Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Consistency of the relationship between air pollution and the urban form: Evidence from the COVID-19 natural experiment

Mengyang Liu, Di Wei, Hong Chen*
School of Architecture and Urban Planning, Huazhong University of Science and Technology, Wuhan, Hubei 430000, China

ARTICLE INFO

Keywords: COVID-19 Air pollution Urban form Cluster analysis

ABSTRACT

The lockdown measures enacted to control the COVID-19 pandemic in Wuhan, China, resulted in a suspension of nearly all non-essential human activities on January 23, 2020. Nevertheless, the lockdown provided a natural experiment to understand the consistency of the relationship between the urban form and air pollution with different compositions of locally or regionally transported sources. This study investigated the variations in six air pollutants (PM$_{2.5}$, PM$_{10}$, NO$_2$, CO, O$_3$, and SO$_2$) in Wuhan before and during the lockdown and in the two same time spans in 2021. Moreover, a hierarchical agglomerative cluster analysis was conducted to differentiate the relative levels of pollutants and to detect the relationships between the air pollutants and the urban form during these four periods. Several features depicting the urban physical structures delivered consistent impacts. A lower building density and plot ratio, and a higher porosity always mitigated the concentrations of NO$_2$ and PM$_{2.5}$. However, they had inverse effects on O$_3$ during the non-lockdown periods. PM$_{10}$, CO, and SO$_2$ concentrations have little correlation with the urban form. This study improves the comprehensive understanding of the effect of the urban form on ambient air pollution and suggests practical strategies for mitigating air pollution in Wuhan.

1. Introduction

COVID-19, an infectious disease closely connected to the family of coronaviruses, broke out in Wuhan, China, at the end of 2019 (Sohrabi et al., 2020). To control the pandemic, a complete lockdown of the entire city was declared by the Chinese government on the morning of January 23, 2020, in Wuhan (Wilder-Smith & Freedman, 2020). The control lockdown measures that included temporarily banning access to roads were enacted on January 24, 2020. Under this extreme circumstance, only transportation for pandemic prevention and the products of daily use was allowed. Public transportation, including railway stations and national and provincial highways, was also temporarily closed (Wu et al., 2020). Furthermore, non-essential factories, businesses, and commercial spaces that may cause public gatherings were also suspended to lessen the risk of the virus spreading (Lau et al., 2020). All of the residential communities across the city were under management control. After over two months, the lockdown was finally released on April 6, 2020.

Due to this sharp decrease in human activity, the use of private cars and public transportation, as well as the closing of industrial enterprises as a result of the control measures, several existing studies have already discussed the improvement in air pollution levels during this unprecedented period in several big cities in China. Wang et al. (2020) observed a decrease in the ambient PM$_{10}$, PM$_{2.5}$, NO$_2$, and SO$_2$ levels in six megacities during the lockdown phase compared with the same time span in 2019. In addition, over 300 cities in northern China also experienced a noticeable reduction in the air quality index (AQI) during the city control periods (Wang et al., 2020). In another study, the dynamic response of traffic and ambient air pollutants related to the COVID-19 lockdown in Shanghai was reported (Wu et al., 2021). Another study (Li et al., 2021) showed amplified O$_3$ pollution in Chinese cities, highlighting that reduced traffic emissions during the COVID-19 lockdown could not mitigate the severe O$_3$ pollution. General reductions in air pollution caused tangible short-term benefits for human health. However, a large number of studies have primarily focused on the temporal variation of cities caused by the lockdown measures, and few studies have so far discussed the fine-grained spatial variations of a city during the different periods.

Several spatial features related to the urban form depicting the roughness of the urban surface have been shown to be efficient in
promoting wind speed and traffic-related air pollution dispersion (Bottema, 1997; Cariolet et al., 2018). Some studies have also proposed an urban form that can increase urban permeability can help to mitigate traffic-related air pollution from streets (Yang et al., 2020; Yuan et al., 2014). However, higher wind speeds can also inversely promote the regional transmission of external pollutants to a city (Chen et al., 2021). Whether or not the mitigating effect of the urban form is varied based on air pollution with different compositions of local and regional sources is not clearly understood. A recent study revealed greatly increased concentrations of sources from transboundary emissions to PM$_{2.5}$ concentrations in Wuhan during the COVID-19 control period (Zheng et al., 2020). These lockdown measures offered a unique natural experiment to re-evaluate the effect of the urban form on different urban air pollutants. February of 2020 had the least traffic emissions. In addition, February is normally the period of the Spring Festival holiday when people return to their hometowns, and the majority of factories are also shut down during this time (Wang et al., 2020). The entire month of February of the year, except for in 2020, is basically within the holiday time period, and there are less air pollution levels than in other months throughout the year (Salaymon et al., 2021). The data of the different periods are thus more favorable to differentiate the relationship between various air pollution emissions and urban forms. In addition, the existing literature has primarily focused on particle matters instead of gaseous pollutants (Gao et al., 2019; Hankey & Marshall, 2015; Shi et al., 2016). The comprehensive effect of the urban form on multiple pollutants has been less discussed.

In this study, a trend analysis is primarily utilized to investigate changes in pollution levels before and during the lockdown to understand the impact consistency of the urban form. First, this study investigates variations in the concentrations of the six air pollutants before and during the COVID-19 lockdown period in 2020, while the concentrations of air pollutants during the same span in 2021 are also assessed. Each pollutant of a single monitoring station was defined as 24 dimensions for subsequent analysis during four different defined periods. In addition, several urban form features that are widely used in urban management and planning to quantify the physical structure of the urban area are prepared as statistical data. The clustering method is then used to determine the relationship between the air pollutants and the urban form. This research attempts to assess the role of urban morphology in air quality based on various pollutants and selects the most efficient urban form features to instruct strategies for urban air pollutants to deliver consistent impacts on ambient air pollution.

2. Materials and methods

2.1. Data preparation of the pollutants

Wuhan, the epicenter of COVID-19, was selected to be the study site. Winter and spring in Wuhan are the seasons with the worse air quality (Wang et al., 2018). The ambient concentrations of six air pollutants (PM$_{2.5}$, PM$_{10}$, NO$_2$, CO, O$_3$, and SO$_2$) before (2020B) and during (2020D) the COVID-19 lockdown control measures (enacted on January 23) in Wuhan were compared. The 2020B period was from December 23, 2019 to January 22, 2020. The 2020D period ranged from January 24 to February 23, 2020. These periods were then compared with the same periods of 2021 (2021B and 2021D). The basic statistics of the meteorological variables are briefly summarized (Table S1 in SI). There were no significant differences in the meteorological variables during 2020 and 2021. However, these four periods had different aerosol compositions of the air pollutants, and these were comprehensively used to help evaluate the effect of urban form features on air pollution. 2020D served as the base period with the least transportation, less industrial activity, and less human behaviors. The 2021D period occurred during the Spring Festival with less transportation, less industrial activity, and less human behaviors. The periods of 2020B and 2021B were regular days with emissions from different sources.

We first collected the data from 10 national air quality monitoring stations in Wuhan City. Fig. 1 shows the spatial distribution of these monitoring stations. Donghuliyuan (LY), Hangyangyuehu (YH), Hankouhuai (HQ), Wuchangziyuan (ZY), Hankoujiang (JT), and Minzudadao (MZ) are located in the urban center of Wuhan, and Qingshanganghua (QS), Zhuankouxinqu (ZK), Wujiangshan (WS), and Chenhu (CH) are suburban stations. Significant urban texture variations were noted in the satellite images, as shown in Fig. 1d. CH, with less urban development, served as the background monitor of the city. One-hour data for six pollutants were derived from China’s National Environmental Monitoring Center (http://www.cnenmc.cn). The missing data occupying less than 5% of the entire dataset were imputed using the expectation-maximization (EM) algorithm based on the R package of “midsi” (Junger & De Leon, 2015) with data of the same pollutants measured at other sites. The mean values of the hourly concentrations of the six pollutants were then extracted from the one-month data of the four periods. This 24-dimension vector, including the concentration value of each air pollutant corresponding to 24 hourly average values in a day, was prepared for the following clustering analysis.

2.2. Urban form factors

We utilized the monitoring point as the center of the buffer with a radius of 0.5 km (1 km was the diameter), referring to the scale of neighborhoods with continuous built-up areas in China (Li et al., 2019; Long et al., 2016). Fourteen features were defined and calculated within the buffer to describe the urban form and the built environment with the help of a geographical information system (GIS). Data including the building information and street network for calculation were downloaded from BIGEMAP (http://www.bigemap.com/). Table 1 lists the basic information of these features including the building profiles and street network features. The building profile represents the ventilation potential of each buffer zone. The building density (BD) is a widely used index that represents the percentage of floor area divided by the total area of a specific buffer, and the plot ratio (PR) refers to the area of all floors divided by the area of the buffer. The surface roughness was measured using the mean height (Salamanca et al., 2011) and the standard deviation of the building height (BHD) within a specific urban buffer (Hang et al., 2012). The sky view factor (SVF) represents the degree of planar enclosure (Yang et al., 2013) as derived from a quick 3D GIS-based method (Chen et al., 2012; Gal et al., 2009). In addition, the concept of porosity proposed by Gál and Unger (2009) measures the permeability of the urban space that could be abstracted to the combined indices including the podium level porosity (0–15 m) and the urban canopy level porosity (15–60 m) in Wuhan (Yuan et al., 2014). Five of the station buffers had a waterbody feature that absorbs and minimizes particulate matter (Zhu & Zhou, 2019). Therefore, the waterbody coverage (WB) refers to the water surface coverage divided by the total area of the region, and this was also included for further analysis.

Apart from the urban form features based on the physical built environment, another group of features were determined by the street network as a proxy for the traffic status. First-level and second-level street densities and proximities to the closed first-level and second-level streets were also included in this study. The betweenness centrality is a measurement widely used to assess the potential of a street segment to attract all the other streets in a city network (Wang et al., 2011; Yu, 2017). The betweenness centrality has been shown to capture the essence of traffic and be closely related to the distribution of vehicle volumes and economics within a city network (Escamilla et al., 2016). The betweenness value calculated by the spatial design network analysis (sDNA) model (Cooper, 2015) represents the probability that the path passed by traffic flow is subject to the maximum trip distance determined by the radius (Hillier & Iida, 2005). According to a previous study (Dai et al., 2016), 4, 5 km was considered as the vehicle commuting distance. In this study, the higher betweenness within the radius of 5 km
can be considered to have a higher likelihood of air pollution from commuting traffic (Zhou & Lin, 2019), and the betweenness within the radius of \( n \) indicated the lasting effect of traffic at the entire city scale. The features of the street network were then achieved using a buffer analysis in the geographical information system.

2.3. Clustering analysis

The hierarchical agglomerative cluster analysis (HACA) is used to classify objects into clusters that has been applied widely for air pollution analyses (Govender & Sivakumar, 2020). This clustering method first considers each station as a separated cluster. Then the pairwise distances between clusters are calculated, and the two with the shortest...
stations into three levels based on six air pollutants. These three levels help understand the spatial distribution and the relative concentration magnitude of pollutants in each group. This method was implemented to were then labeled as high, medium, and low based on the mean distance measurement (Lau et al., 2009). The cluster model grouped 10 of the different air pollutants.

3. Results and discussion

3.1. A spatial-temporal comparison of the six criteria urban air pollutants

Fig. 2 shows the statistical distributions of the hourly samples of all six air pollutants before and during the lockdown period in 2020 and 2021 among the 10 monitoring stations. The white cross mark represents the average of the hourly pollutant concentrations in a specific period, while the number at the top indicates the amplitude of the concentration variation (ACV) from before to during the lockdown. The ACV was derived based on the equation, \(\text{ACV} = \frac{y - x}{x} \times 100\%\), where \(x\) and \(y\) represent the average concentrations of one air pollutant before and during the control period for COVID-19, respectively.

As shown in Fig. 2a, there is an apparent spatial variation among the 10 monitors of the PM\(_{2.5}\) concentrations. The concentration of nearly all the stations decreased between \(-41\%\) and \(-22\%\) after the imposition of lockdown in 2020. The ACV of PM\(_{10}\) (Fig. 2b) in 2020 ranged from \(-46\%\) to \(-35\%\), which was approximately equivalent to that of PM\(_{2.5}\). There was a similar decline trend for PM\(_{2.5}\) and PM\(_{10}\) from 2021B to 2021D, and this was because the Spring Festival holiday also resulted in a substantial decrease in anthropogenic emissions (Wang et al., 2020).

NO\(_2\) showed the most significant reduction, as shown in Fig. 2c, considering that the value of the ACV in 2020 ranged from \(-70\%\) to \(-44\%\). This indicated that the limitation of local human activities, which is the primary source of NO\(_2\) pollution, was significantly decreased during lockdown. In addition, the NO\(_2\) concentration of CH (the background station) was drastically smaller than those of the other stations. The declining trend from 2020B to 2020D also occurred for CO, while the trend for CO in 2021 was not consistent with that in 2020. The incomplete combustion of fossil fuel and biomass combustion contributed to the majority of CO. The ACVs of CO between 2021B and 2021D of LY, HQ, QS, and JT were near zero, indicating that the CO emissions at these stations were not greatly affected by the Spring Festival holidays in 2021. Gaseous SO\(_2\) primarily originates from the combustion of sulfur-containing fuels (oil, coal, and diesel) (Huang et al., 2012), especially from coal heating in winter (Kuerban et al., 2020). The ACV of SO\(_2\) in 2020 ranged from \(-18\%\) to \(-3\%\), and the concentration of SO\(_2\) decreased the least. This suggested that the control measures did not have a great influence on the emissions from coal heating activities. However, SO\(_2\) is not the primary component of air pollutants in Wuhan because industries based on coal and central heating pollution are relatively few (Lian et al., 2020).

A pairwise t-test was used to compare the hourly samples of 2020B and 2020D, 2021B and 2021D, 2020B and 2021B, and 2020D and 2021D (Figs. S1–S6 in SI). In a comparison of the hourly samples of 2020B and 2020D, only the p-values of the SO\(_2\) distribution in MZ were greater than 0.05. When comparing the hourly samples of 2021B and 2021D, only the p-values of the CO distribution in LY and JT were greater than 0.05. The air quality benefit caused by the substantial

### Table 1
Description of the urban form features.

| Urban form features | Abbreviation | Units | Description | Calculation unit |
|---------------------|--------------|-------|-------------|------------------|
| Building density    | BD           | ratio | The ratio of floor area divided by the total area of a specific buffer. | Buffer |
| Plot ratio          | PR           | ratio | The area of all floors divided by the area of the buffer. | Buffer |
| Mean height         | MH           | m     | The average floors of all buildings within the buffer zone. | Buffer |
| Building height     | BHD          | m     | The standard deviation of all building floors within the buffer zone. | Buffer |
| Sky view factor     | SVF          | ratio | Degree of planar enclosure. | Predicted value |
| Podium-level porosity (0-15 m) | P15       | ratio | The non-building volume under 15 m divided by the buffer volume. | Buffer |
| Canopy-level porosity (15-60 m) | P60   | ratio | The non-building volume between 15 and 60 m divided by the buffer volume. | Buffer |
| Water body          | WB           | ratio | Water surface coverage divided by the total area of the region. | Buffer |
| First-level road density | RD1   | km/km\(^2\) | The total length of first-level roads within the buffer zone divided by the area of the buffer. | Buffer |
| Second-level road density | RD2       | km/km\(^2\) | The total length of second-level roads within the buffer zone divided by the area of the buffer. | Buffer |
| Proximity to nearest first-level road | RP1 | m | Distance from the monitoring station to the nearest first-level road. | Euclidean distance |
| Proximity to nearest second-level road | RP2 | m | Distance from the monitoring station to the nearest second-level road. | Euclidean distance |
| Betweenness (radius of 5 km) | BT5 | n/a | Mean betweenness within the radius of 5 km | Buffer |
| Betweenness n | BTn | n/a | Mean betweenness within the radius of n km | Buffer |

distance will be combined to generate the new clusters. The similarity levels of classification for the monitoring stations were illustrated in a dendrogram that was calculated using Ward’s method and the Euclidean distance measurement (Lau et al., 2009). The cluster model grouped 10 stations into three levels based on six air pollutants. These three levels were then labeled as high, medium, and low based on the mean magnitude of pollutants in each group. This method was implemented to help understand the spatial distribution and the relative concentration of the different air pollutants.
declines in PM2.5, PM10, and NO2 during the lockdown was partially offset by an amplified O3 pollution of 88%–163% during the same period. The consistency in the direction of change indicated that the O3 concentration increases were ubiquitous over Wuhan. The temporal variation in O3 among all the monitoring stations increased the concentration during the lockdown compared with those of the pre-lockdown periods in both 2020 and 2021, which was opposite to the variations in the other five pollutant types. This general trend of decreased PM2.5, PM10, NO2, CO, SO2, and increased O3 during the lockdown has been confirmed in different metropolitan areas including Beijing, Chengdu, Shenzhen, and Xi’an (Wang et al., 2020). This study is the first to discuss that this variation was similar among all the stations at the city scale.

3.2. Diurnal variation of the six criteria urban air pollutants

Fig. 3 shows the diurnal variation based on the average hourly data for all of the six pollutants for four periods. The error bar indicates the standard deviation of the hourly concentrations of air pollutants among the 10 monitoring stations. The trend in the diurnal variation for PM2.5 during the lockdown of 2020 was similar to that before. However, a significant decrease occurred after the afternoon peak time (Fig. 3a). This trend was attributed to the vertical expansion of the boundary layer and the vertical diffusion of pollutants during the day (Shi & Brasseur, 2020). The decrease in anthropological activity due to the Spring Festival also caused a relatively equal drop in the PM2.5 concentration of each hour. The diurnal variation of PM2.5 (Fig. 3a) and PM10 (Fig. 3b) shared a similar pattern, although PM10 had less amplitude in the variation and the hourly standard deviation. The reason might be

Fig. 2. Statistical distributions of the (a) PM2.5, (b) PM10, (c) NO2, (d) CO, (e) O3, and (f) SO2 concentrations for the 10 monitoring stations before and during the lockdowns in 2020 and 2021.
because the PM$_{10}$ concentrations had no observable increasing trend close to the street and were not highly variable in space (Pasquier & André, 2017; Patton et al., 2014). A peak emerged in the morning and evening in the diurnal concentration of NO$_2$ during the non-lockdown periods (Fig. 3c). However, NO$_2$ did not exhibit peaks associated with traffic rush hours during the lockdown. Unlike PM$_{2.5}$, PM$_{10}$, and NO$_2$, the concentration of CO in 2020B was always the highest. The trend of CO during 2021D was nearly the same as in 2021B (Fig. 3d). Prior to the lockdown, there was an apparent sink during the morning rush hour. The morning increasing trend of O$_3$ began at 7:00 and reached the highest peak at 15:00 due to the increasing solar radiation. This peak was retained during these four periods. In comparison with the period prior to the lockdown, O$_3$ showed a smoothed downward trend from 00:00 to 10:00, and this may have been related to a reduction in NO$_2$ during the morning period. O$_3$ and SO$_2$ seemed to accumulate and reach the highest of the day during the afternoon and decrease after 17:00 and 12:00, respectively.

3.3. Relative levels of the six criteria urban air pollutants

The primary dendrogram for the HACA results is shown in Figs. S7–S12 in the SI. In this study, the 24-dimension vectors of the monitoring stations within a cluster were close to each other, while the variations in the monitoring stations of the other clusters were different from each other. Table 2 summarizes the cluster results of the four periods for the six pollutants and the five hours with the best alignments. The top five aligned hours of the six air pollutants varied largely among the different periods, indicating that the relative levels for each hour varied in some specific hours. This phenomenon confirmed the necessity of the clustering analysis of the 24-dimension vectors instead of the
average of a day or the peak time. The cluster map is shown in Fig. 4, and this demonstrates the spatial distributions of each pollutant according to the HACA results in Table 2.

For the cluster results of PM<sub>2.5</sub>, QS remained at a high level, while CH remained at a low level. During the lockdown in 2020 (2020D), the stations, except for QS and CH, were all at the middle level. From 2021B to 2021D, only ZY and WJS changed their classification results. The clustering results for 2020B were in the same classification. The stations with high levels during 2020B H L M L M M M M M M 5, 11, 4, 8, 10, and confirmed the explainable information. With the levels of the specific air pollutants following a trend from low to high, some features demonstrated an increasing trend (synthetic trend), and some features behaved in reverse (crosscurrent trend). Based on Tables S2–S8 in SI, Table 3 summarizes the urban form features that delivered consistently synthetic or crosscurrent trends with the four periods. This also includes the features whose trends during the lockdown (2020D) were different from that during the non-lockdown periods. There were 7, 11, and 5 urban features that emerged for the four periods that are summarized in Table S2 in SI. The average wind speed was less than 3.3 m/s the majority of the winter in Wuhan (Hu et al., 2018), which has also been shown in the meteorological features of these four periods. This might be that the wind speeds were less sensitive. The second-level road density and the road proximity had no significant effect on all six air pollutants. The features of the building density, plot ratio, porosity, and sky view vector can be considered the detailed description of the urban permeability, and these were more conducive to urban air pollution than the features related to the urban surface roughness (MH and BHD). The features related to the street network betweenness emerged in the analysis on NO<sub>x</sub> and O<sub>3</sub> and confirmed the explainable power of these features in the research of urban air pollution.

The PM<sub>2.5</sub> level was negatively related to P15, P60, SVF, WB, and P19, seemed sensitive to the urban form features, while PM<sub>10</sub>, CO, and SO<sub>2</sub> were less sensitive. The second-level road density and the road proximity had no significant effect on all six air pollutants. The features of the building density, plot ratio, porosity, and sky view vector can be considered the detailed description of the urban permeability, and these were more conducive to urban air pollution than the features related to the urban surface roughness (MH and BHD). The features related to the street network betweenness emerged in the analysis on NO<sub>x</sub> and O<sub>3</sub> and confirmed the explainable power of these features in the research of urban air pollution.

The PM<sub>2.5</sub> level was negatively related to P15, P60, SVF, WB, and P19, while it was positively associated with BD and PR. In addition, these features related to increasing the urban permeability showed a consistent impact on assisting the dispersion of the PM<sub>2.5</sub> concentrations across the four periods. The reason might be that the wind speeds were less than 3.3 m/s the majority of the winter in Wuhan (Hu et al., 2018), which has also been shown in the meteorological features of these four periods that are summarized in Table S2 in SI. The average wind speed was far enough from 5 m/s to promote the regional transmission of particles to the city (Chen et al., 2021), indicating that the impact of increasing urban permeability on the increasing wind speed and mitigation of local PM<sub>2.5</sub> concentrations weighed more than its effect to introduce external transmission all the time because the contribution of transboundary sources increased during the lockdown (Sulaymon et al., 2021). Moreover, the findings that the decreased magnitude of BD, PR, and increased porosity mitigated the PM<sub>2.5</sub> concentrations agreed with some measurements and simulations conducted during a normal winter in Wuhan based on land use regression and computational simulations (Liu et al., 2021; Xu & Chen, 2021). Large areas of water with no

### Table 2: Clustering results.

| ZK | WJS | JT | HQ | MZ | YH | CH | ZY | LY | QS | Similarities in top 5 h (entanglement) |
|----|-----|----|----|----|----|----|----|----|----|-------------------------------------|
| PM<sub>2.5</sub> | 2020B | M | H | M | H | M | L | H | H | H | 1, 3, 16, 17, 4 |
| 2020D | M | M | M | M | M | L | M | M | M | H | 9, 11, 4, 23, 10 |
| 2021B | H | M | M | M | M | L | H | M | H | H | 5, 1, 6, 4, 9 |
| 2021D | H | H | M | H | M | L | M | M | M | H | 3, 4, 0, 12, 11 |
| PM<sub>10</sub> | 2020B | M | M | M | M | H | L | H | L | M | 10, 11, 23, 7, 8 |
| 2020D | L | M | M | H | H | H | M | L | H | L | 0, 2, 15, 14, 10 |
| 2021B | H | H | M | M | M | L | M | M | H | L | 3, 6, 4, 5, 10 |
| NO<sub>2</sub> | 2020B | H | H | H | H | M | L | H | H | H | 9, 10, 7, 20, 11 |
| 2020D | M | M | H | H | M | M | L | M | H | H | 9, 10, 2, 18, 8 |
| 2021B | H | H | H | H | H | H | L | H | H | H | 1, 0, 2, 21, 23 |
| 2021D | H | H | H | H | H | H | L | H | H | H | 0, 20, 21, 19, 17 |
| CO | 2020B | M | L | M | L | M | H | L | L | H | 12, 18, 4, 3, 20 |
| 2020D | L | M | L | M | M | H | L | L | L | 2, 10, 1, 16, 9 |
| 2021B | M | H | L | H | M | M | L | M | L | M | 23, 22, 10, 21, 13 |
| 2021D | L | L | L | M | M | L | H | M | M | H | 10, 9, 8, 1, 21 |
| O<sub>3</sub> | 2020B | L | M | M | L | M | L | H | L | M | 15, 17, 11, 9, 22 |
| 2020D | H | H | H | M | M | H | M | L | M | 22, 3, 4, 18, 20 |
| 2021B | M | M | M | M | M | H | L | M | L | 23, 6, 11, 16, 15 |
| 2021D | M | M | M | H | L | H | L | L | H | L | 20, 22, 12, 18, 19 |
| SO<sub>2</sub> | 2020B | H | L | L | M | L | H | M | L | H | 10, 15, 11, 16, 18 |
| 2020D | M | L | M | L | M | L | H | M | L | M | 15, 1, 4, 0, 10 |
| 2021B | H | L | M | M | M | L | M | M | L | M | 15, 21, 16, 15, 10 |

* L = Low, M = Medium, H = High; The bold numbers in the last column highlight the morning and evening peak time.
Fig. 4. Mapping of the clustering results.
The tendency analysis of the urban form features with consistent impacts.

| Year | PM | BD | PR | PIS | SVF | WB | BT5 | RB1 | NOx | O3 | PO | P15 | P60 |
|------|----|----|----|-----|-----|----|-----|-----|-----|----|----|-----|-----|
| 2018 | 0.21 | 0.20 | 0.29 | 0.28 | 0.88 | 0.74 | 0.72 | 0.88 | 0.74 | 0.88 | 0.74 | 0.72 | 0.88 |
| 2019 | 0.29 | 0.28 | 0.88 | 0.74 | 0.72 | 0.88 | 0.74 | 0.88 | 0.74 | 0.72 | 0.88 | 0.74 | 0.88 |
| 2020 | 0.28 | 0.28 | 0.74 | 0.74 | 0.72 | 0.88 | 0.74 | 0.88 | 0.74 | 0.72 | 0.88 | 0.74 | 0.88 |

Underlined represents a synthetic trend, while the bold show a crosscurrent trend.

Table 3 illustrates that the levels of NO2 had the same trend as MH, BHD, BD, PR, WB, B5, B7, and B11 but were contrary to P15, P60, and SVF. These identified features and their response to NO2 levels were partially similar to the features associated with PM2.5. This result indicates that NO2 also has difficulty in dispersing in a built environment consisting of dense buildings. Compared to PM2.5, NO2 is relatively less affected by external pollution sources (Zhu & Zhou, 2019), and this can explain its higher sensitivity to more urban form features that depict the physical structure of a neighborhood. In addition, the building profile of the upper level was more contributive to NO2 than to PM2.5, since the factors related to the building height (MH & BHD) emerged in the tendency analysis with NO2. The reaction to B5, B7, and B11 also reflected that the cumulative effect of traffic was significant for the NO2 concentration. The aforementioned features defined within the neighborhood scale had consistent impacts on the NO2 concentrations because the sources of NO2 were primarily from local communities, and the aerosol composition was less affected by the lockdown action.

Table 3 shows that O3 had an inverse relationship to BD, PR, and BTS, but a positive relationship with P15 and P60 during the three lockdown periods. Ozone formation at the ground level in the urban context typically depends on the intensity of the solar radiation, the absolute concentration of NOx and volatile organic compounds (VOCs), and the ratio between NOx and VOCs (Han et al., 2011). During the non-lockdown periods, the decreased building density, plot ratio, and increased porosity could probably increase solar radiation directly first and promote the diffusion of PM2.5. Therefore, this could also have enhanced the photochemical reaction of solar radiation to facilitate the generation of O3. Therefore, as shown in Fig. 5a, PM2.5 was typically negatively correlated with O3 in winter, which was consistent with previous findings (Wang et al., 2014). A similar finding of an increased urban ozone concentration was highly correlated with a higher solar radiation intensity during the lockdown periods. Ozone formation at the ground level in the urban environment factors as important predictors in urban ozone concentrations (Han et al., 2022; Schweitzer & Zhou, 2010), and the consistency of the effect is crucial to this analysis based on the limited periods of ozone data. However, in this study, the effect of the urban form for O3 during the control period was not consistent with that of the non-epidemic (Table 3). We found that under situations where NOx was not sufficiently emitted, the selected urban form affected the O3 concentration differently. This was likely because a reduction in cars led to a significant reduction in NOx, and the radical titration of NOx was then significantly decreased. Fig. 5b also indicates that the concentration of the surface O3 decreased substantially with the increased concentration of NOx, and the formation from O3 to NOx always existed (Monks et al., 2011). However, the generated NOx during the lockdown in Wuhan City also decreased by 30%, and the NOx emissions had a worse reduction of 43% (Huang et al., 2021; Yin et al., 2021). The increased ratio of VOC–NOx provided favorable conditions for the generation of O3 for Wuhan during the pandemic. During the lockdown, this might have been due to the low NOx rather than the high solar radiation that prompted an increase in the surrounding O3. In addition, the ozone–PM2.5 correlation switched from negative to positive during the lockdown (Fig. 5a). This may have been due to the increase in O3 that obstructions were also found to provide natural winds and provide good conditions for pollutant dispersal (Crosman & Horel, 2016). However, no urban feature displayed a discernable trend with the PM10 concentration. This result further revealed that local intense built environments contributed to PM2.5 while having less of an influence on the PM10 concentrations. This finding confirmed that PM10 concentrations in winter are not primarily affected by local built environmental features.
promoted the growth of atmospheric oxidation, accelerated gas-particle transformation, and increased the secondary PM\textsubscript{2.5} concentration (Huang et al., 2021; Sun et al., 2020). Therefore, this study has demonstrated that the effect of the urban form on ozone is far more complicated. However, due to the lack of data on VOC from different monitoring stations, the effect of the urban form on ozone requires further analysis with the consideration of the NO\textsubscript{x} and VOC concentrations.

4. Conclusion

This study comprehensively assessed the spatial variation of six air pollutants among 10 national monitoring stations throughout Wuhan and discussed the relationships of the urban form features with each pollutant. Furthermore, the COVID-19 pandemic provided a natural experiment to evaluate the consistency of impacts of the urban form on air pollutants from different aerosol compositions. We conducted multiple comparisons to determine the contribution of the urban form and assess the effects on the spatial variation of air quality. We arrived at the following conclusions:

- This study provided the first step to comprehensively understand the effect of the urban form on six criteria air pollutants using a clustering analysis. Urban form features depicting the physical structure of the neighborhood seem to have been less contributive to the urban PM\textsubscript{10}, CO, and SO\textsubscript{2} concentrations, while PM\textsubscript{2.5}, NO\textsubscript{2}, and O\textsubscript{3} were more sensitive to these features.
- The cluster analysis demonstrated to be feasible with an outcome similar to the land use regression model used in Wuhan in the past. A decreased building density, plot ratio, increased porosity, sky view factors, and waterbodies promoted the diffusion of PM\textsubscript{2.5} and NO\textsubscript{2} consistently under the condition of substantial aerosol composition changes due to the COVID-19 outbreak and the Spring Festival. Increased urban roughness features, including the mean height and building height standard deviation, also helped mitigate NO\textsubscript{2}. This study also offered supplemental information for urban management for mitigating urban PM\textsubscript{2.5} and NO\textsubscript{2} consistently.
- The relationship between the urban form and O\textsubscript{3} concentrations was not consistently the same due to the complicated formation process of ozone. A decreased building density, plot ratio, and increased canopy level porosity promoted the formation of O\textsubscript{3} inversely during the un-lockdown periods. However, under the condition of low levels of NO\textsubscript{x} during the lockdown, these features failed to influence the O\textsubscript{3} concentrations efficiently.
- This study offers more information for future research design. With the optimization of traffic policies that may continuously decrease NO\textsubscript{x} emissions, the aforementioned urban strategies that contributed to minimizing the formation of ozone may fail to reduce the pollution, even in winter, without the efficient control of VOC emissions. Our future research on air-quality-oriented urban management and design will have a greater emphasis on ozone under different ratios of NO\textsubscript{x} and VOCs.

CRediT authorship contribution statement

Mengyang Liu: Conceptualization, Methodology, Data curation, Investigation, Writing – original draft. Di Wei: Visualization, Investigation. Hong Chen: Supervision, Writing – review & editing.

Declaration of Competing Interest

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

Acknowledgment

This study was supported by the National Natural Science Foundation of China (No. 51778251 & 51538004), and the Fundamental Research Funds for the Central Universities, HUST (No. 2021JYCXJ009).

---

***, **, *Statistically significant at the 0.1%, 1%, and 5% levels, respectively.

Fig. 5. The correlation coefficients (a) between PM\textsubscript{2.5} and O\textsubscript{3}; and (b) between NO\textsubscript{2} and O\textsubscript{3} during the four periods.***, **, *Statistically significant at the 0.1%, 1%, and 5% levels, respectively.
Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scset.2022.103972.

References

Bottema, M. (1997). Urban roughness modelling in relation to pollutant dispersion. Atmospheric Environment, 31(18), 3059–3075.

Cariot, J. M., Colombet, M., Vuillert, M., & Diab, Y. (2018). Assessing the resilience of urban areas to traffic-related air pollution in Greater Paris. Science of the Total Environment, 616, 749–759.

Chen, J., Hu, H., Wang, F., Zhang, M., & Huang, H. (2021). Air quality characteristics in Wuhan (China) during the 2020 COVID-19 pandemic. Environmental Research, 195, Article 110879.

Chen, L., Ng, K., An, X., Ren, C., Lee, M., Wang, W., et al. (2012). Sky view factor analysis of street canyons and its implications for daytime intra-urban air temperature differentials in high-rise, high-density urban areas of Hong Kong: A GIS-based simulation approach. International Journal of Climatology, 32(1), 121–136.

Cooper, C. (2019). Spatial Design Network Analysis (GDNA) version 4.0 manual. Retrieved from http://www.cardiff.ac.uk/sdna/software/documentation.

Cromson, E. T., & Horel, J. D. (2016). Winter lake breezes near the Great Salt Lake. Boundary-Layer Meteorology, 159, 439–464.

Dai, D., Zhou, C., & Ve, C. (2016). Spatial-temporal characteristics and factors influencing commuting activities of middle-class residents in Guangzhou City, China. Chinese Geographical Science, 26(3), 410–428.

Escamilla, J. M., Cos, C. C., & Cereceda, J. S. (2016). Contesting Mexico City’s alleged polycentric coordination through a centrality-mixed land-use composite index. Urban Studies, 53(11), 2380–2396.

Gal, T., Lindberg, F., & Unger, J. (2009). Computing continuous sky view factors using 3D urban raster and vector databases–Comparison and application to urban climate. Theoretical and Applied Climatology, 95(1), 111–123.

Gal, T., & Unger, J. (2009). Detection of ventilation paths using high-resolution roughness parameter mapping in a large urban area. Building and Environment, 44(1), 198–206.

Galili, T. (2015). dendextend–An R package for visualizing, adjusting and comparing trees of hierarchical clustering. Bioinformatics (Oxford, England), 31(22), 3718–3720.

Gao, Y., Wang, Z., Li, C. Y., Zheng, T., & Peng, Z. R. (2021). Assessing neighborhood variations in ozone and PM2.5 concentrations using decision tree method. Building and Environment, 187, Article 107497.

Gao, Y., Wang, Z., Liu, C., & Peng, Z. R. (2019). Assessing neighborhood air pollution exposure and its relationship with the urban form. Building and Environment, 155, 15–24.

Govender, P., & Sivakumar, V. (2020). Application of k-means and hierarchical clustering techniques for analysis of air pollution–A review (1980–2019). Atmospheric Pollution Research, 11(1), 40–56.

Han, L., Zhao, J., Gao, Y., & Gu, Z. (2022). Prediction and evaluation of spatial distributions of ozone and urban heat island using a machine learning modified land use regression method. Sustainable Cities and Society, 78, Article 103643.

Han, S., Bian, H., Feng, Y., Liu, A., Li, X., Zeng, F., et al. (2011). Analysis of the relationship between NO and NO2 in Tianjin, China. Aerosol and Air Quality Research, 11(2), 128–139.

Hang, J., Li, Y., Sandberg, M., Buccelleri, R., & Di Sabatino, S. (2012). The influence of building height variability on pollutant dispersion and pedestrian ventilation in idealized high-rise areas. Building and Environment, 56, 346–360.

Hankey, S., & Marshall, J. D. (2015). Land use regression models of on-road particulate matter pollution: a review. Environmental Modeling & Assessment, 20, 1047–1061.

Hillier, B., & Iida, S. (2005). Network and psychological effects in urban movement. In Pivotal role for old-style public health measures in the novel coronavirus COVID-19. National Academy of Sciences, U.S.A, 118(10), 1–7, https://doi.org/10.1073/pnas.2015579118.

Li, X., Huang, J., Huang, R., Liu, C., Wang, L., & Zhang, T. (2020). Impact of city lockdown on the air quality of COVID-19-hit of Wuhan city. Science of the Total Environment, 742, Article 106556.

Liu, M., Chen, H., Wei, D., Wu, Y., & Li, C. (2021). Nonlinear relationship between urban form and street-level PM2.5 and CO based on mobile measurements and gradient boosting tree models. Building and Environment, 205, Article 108265.

Long, Y., Shen, Y., & Jin, X. (2016). Mapping block-level urban areas for all Chinese cities. Annals of the American Association of Geographers, 106(1), 96–113.

Ma, K., Tan, Z., Lu, Y., Yang, X., Liu, Y., Li, S., et al. (2019). Winter photochemistry in Beijing–Observation and model simulation of OH and HO2 radicals at an urban site. Science of the Total Environment, 685, 85–95.

Monks, P. S., Archibald, A. T., Cooper, O., Coyle, M., Derwent, R., et al. (2015). Tropospheric ozone and its precursors from the urban to the global scale from air quality to short-lived climate forcer. Atmospheric Chemistry and Physics, 15(15), 8889–8973.

Pasquier, A., & André, M. (2017). Considering criteria related to spatial variabilities for the assessment of air pollution from traffic. Transportation Research Procedia, 25, 3354–3369.

Patton, A. P., Perkins, J., Zanore, W., Levy, J. I., Brugge, D., & Durant, J. L. (2014). Spatial and temporal differences in traffic-related air pollution in three urban neighborhoods near an interstate highway. Atmospheric Environment, 99, 309–321.

Salamanca, F., Martelli, A., Tewari, M., & Chen, F. (2011). A study of the urban boundary layer using different urban parameterizations and high-resolution urban canopy models with WRF. Journal of Applied Meteorology and Climatology, 50(5), 1107–1128.

Schweitzer, L., & Zhou, J. (2010). Neighborhood air quality, respiratory health, and vulnerable populations in compact and sprawled regions. Journal of the American Planing Association, 76(2), 146–157.

Shi, X., & Brasseur, G. P. (2020). The response in air quality to the reduction of Chinese economic activities during the COVID-19 outbreak. Geophysical Research Letters, 47(11). Article e2020GL088670.

Shi, L., Liu, K. L., & Ng, C. M. (2014). Developing street-level PM2.5 and PM10 air pollution regression models in high-density Hong Kong with urban morphological factors. Environmental Science & Technology, 50(15), 8178–8177.

Sohrabi, C., Alashi, Z., O Neil, N., Khan, M., Kerwan, A., Al Jabir, A., et al. (2020). World Health Organization description of emergency: A review of the novel coronavirus COVID-19. International Journal of Surgery, 76, 71–76.

Sulymanyon, I. D., Zhang, Y., Hokep, P. K., Zhang, Y., Hua, J., & Mei, X. (2021). COVID-19 pandemic in Wuhan–Ambient air quality and the relationships between criteria air pollutants and meteorological variables before, during, and after lockdown. Atmospheric Environment, 250, Article 105362.

Sun, Y., Lei, L., Zhou, W., Chen, C., He, Y., Sun, J., et al. (2020). A chemical cocktail during the COVID-19 outbreak in Beijing, China: Insights from six-year aerosol particle composition measurements during the Chinese New Year holiday. Science of the Total Environment, 742, Article 140739.

Wang, F., Antipova, A., & Porta, S. (2011). Street centrality and land use intensity in urbanized Baton Rouge, Louisiana. Journal of Transport Geography, 19(2), 265–269.

Wang, W., Huang, J., Gong, S., Kong, D., & Jie, Y. (2018). Spatio-temporal distribution characteristics and influencing factors of atmospheric pollutants in Wuhan in 2016. Environmental and Technische Parameter-Environmental Monitoring, 6, 20–24 (in Chinese), 2016. Wang, Y., Shen, Y., Wang, Y., Zhang, K., & Zhang, M. (2016). Four-month changes in air quality during and after the COVID-19 lockdown in six megacities in China. Environmental Science & Technology Letters, 7(1), 802–808.

Wang, Y., Ying, Q., Hu, J., & Zhang, H. (2014). Spatial and temporal variations of six criteria air pollutants in capital cities in China during 2013–2014. International Environment, 73, 413–422.

Wang, Y., Yuan, W., Wang, Q., Liu, C., Zhi, Q., & Cao, J. (2020b). Changes in air quality related to the control of coronavirus in China–Implications for traffic and industrial emissions. Science of the Total Environment, 731, Article 139133.

Wilder-Smith, A., & Freedman, D. O. (2020). Isolation, quarantine, social distancing and community containment–Pivotal role for old-style public health measures in the novel coronavirus (2019-nCoV) outbreak. Journal of Travel Medicine, 27, https://doi.org/10.1093/ijtm/taaa120.

Wu, C. L., Wang, H. W., Cai, W. J., Ni, A. N., & Peng, Z. R. (2021). Impact of the COVID-19 lockdown on roadside traffic-related air pollution in Shanghai, China. Building and Environment, 194, Article 107718.

Wu, J. T., Leung, K., & Leung, G. M. (2020). Nowcasting and forecasting the potential dominant emissions of COVID-19 in Wuhan, China: Modeling of the novel coronavirus COVID-19. Atmospheric Environment, 289, Article 117899.
Yu, W. (2017). Assessing the implications of the recent community opening policy on the street centrality in China—A GIS-based method and case study. Applied Geography, 89, 61–76.

Yuan, C., Ng, E., & Norford, L. K. (2014a). Improving air quality in high-density cities by understanding the relationship between air pollutant dispersion and urban morphologies. Building and Environment, 71, 245–258.

Yuan, C., Ren, C., & Ng, E. (2014b). GIS-based surface roughness evaluation in the urban planning system to improve the wind environment—A study in Wuhan, China. Urban Climate, 10, 585–593.

Zheng, H., Kong, S., Chen, N., Yan, Y., Liu, D., Zhu, B., et al. (2020). Significant changes in the chemical compositions and sources of PM2.5 in Wuhan since the city lockdown as COVID-19. Science of the Total Environment, 739, Article 140000.

Zhou, S., & Lin, R. (2019). Spatial-temporal heterogeneity of air pollution—The relationship between built environment and on-road PM2.5 at micro scale. Transportation Research Part D: Transport and Environment, 76, 305–322.

Zhu, D., & Zhou, X. (2019). Effect of urban water bodies on distribution characteristics of particulate matters and NOx. Sustainable Cities and Society, 50, Article 101679.

Further reading

Sannigrahi, S., Kumar, P., Molter, A., Zhang, Q., Ratu, B., Basu, A. S., et al. (2021). Examining the status of improved air quality in world cities due to COVID-19 led temporary reduction in anthropogenic emissions. Environmental Research, 196, Article 110927.