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Relationships between urban form and air quality: A reconsideration based on evidence from China’s five urban agglomerations during the COVID-19 pandemic

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ABSTRACT

The outbreak of Coronavirus disease 2019 (COVID-19) led to the widespread stagnation of urban activities, resulting in a significant reduction in industrial pollution and traffic pollution. This affected how urban form influences air quality. This study reconsiders the influence of urban form on air quality in five urban agglomerations in China during the pandemic period. The random forest algorithm was used to quantitate the urban form–air quality relationship. The urban form was described by urban size, shape, fragmentation, compactness, and sprawl. Air quality was evaluated by the Air Quality Index (AQI) and the concentration of six pollutants (CO, O₃, NO₂, PM₂.₅, PM₁₀, SO₂). The results showed that urban fragmentation is the most important factor affecting air quality and the concentration of the six pollutants. Additionally, the relationship between urban form and air quality varies in different urban agglomerations. By analyzing the extremely important indicators affecting air pollution, the urban form–air quality relationship in Beijing-Tianjin-Hebei is rather complex. In the Chengdu-Chongqing and the Pearl River Delta, urban sprawl and urban compactness are extremely important indicators for some air pollutants, respectively. Furthermore, urban shape ranks first for some air pollutants both in the Triangle of Central China and the Yangtze River Delta. Based on the robustness test, the performance of the random forest model is better than that of the multiple linear regression (MLR) model and the extreme gradient boosting (XGBoost) model.

1. Introduction

Air pollution has long been a focus of human concern due to its potential for serious damage to human health. According to data derived from the World Health Organization (WHO) in 2018, nine out of every ten people breathe air containing high concentrations of pollutants (WHO, 2018). Research about air pollution is generally related to meteorology, environmental science, and geography. Climate factors like wind velocity, temperature, and humidity play important roles in urban air quality (Ikram et al., 2015; Hassan et al., 2016; Tian et al., 2020). Additionally, human activities, industrial development, and energy consumption have increased the levels of air pollution (Stankovic et al., 2012; Tuo et al., 2013; Wang et al., 2020a; Miao et al., 2021). From the perspective of the urban economy, urban form—which refers to the spatial structure of the urban physical environment formed by human activities and natural factors—also has a profound effect on air quality.

Several studies have concluded that cities with polycentricity, better continuity, simple shape, and smaller size provide better air quality (Stone, 2008; Li et al., 2019). However, the relationship between urban form and air quality is rather complex (McCarty et al., 2015; Lu et al., 2016; Shi et al., 2019): if one factor influencing air quality changes, it is worth reconsidering the relationship between urban form and air quality under the influence of other factors.

Coronavirus disease 2019 (COVID-19) broke out at the end of 2019. Since this time, many country and city governments have taken lockdown measures to control the source of infection and cut off the spread of the virus (Moritz et al., 2020). In China, the agile and stringent measures proved to be effective and led to a significant decline in the number of infections (Zhang et al., 2020). However, these measures resulted in the closure of many factories and a significant reduction in traffic volume. Due to large reductions in the sources of air pollution, air quality in cities has significantly improved (Bao et al., 2020;
pollution. Consequently, the COVID-19 pandemic provides a good opportunity to reconsider the urban form–air quality relationship.

Existing research relating to the effect of urban form on air quality has mainly focused on individual regions. For example, Yang et al. (2020) took a high-density urban area as the sample to explore the effect of urban form on air pollution at the microscopic building level. She et al. (2017) explored the relationship between urban form and six pollutants in the Yangtze River Delta of China. Rodríguez et al. (2016) investigated the relationship between urban structure and air quality by using 249 larger urban zones (LUZ) across Europe. It has been found that the urban form–air quality relationship varies in areas with different climate conditions and industrial structures (Shi et al., 2019; Li et al., 2021). Tian et al. (2020) compared a linear and a nonlinear model to improve understanding of the urban form–air quality relationship, with results indicating that the urban form–air quality relationship is likely to be nonlinear. However, few studies have explored differences in the urban form–air quality relationship in different regions.

In China, urban agglomerations have large populations and certain industrial clusters, making their air pollution more serious than in other areas (Wang et al., 2017, 2021b). Additionally, different urban agglomerations have significant differences in their geographical conditions and industrial structures, which means that there is significant variation in the dominant factors of urban form that influence air quality. For example, the air quality of the Beijing-Tianjin-Hebei region in China is mainly affected by urban compactness (Liang et al., 2020a), but urban size and urban shape have significant effects on air quality in the Yangtze River Delta of China (She et al., 2017). Therefore, the differences in the effect of urban form on air quality among urban agglomerations in China needs to be clarified.

The current study explored how urban form affects air quality in five urban agglomerations in China during the COVID-19 pandemic. A spatial scale of 20 × 20 km was selected within the regions as the sample unit. Urban form was described by urban size, shape, fragmentation, compactness, and sprawl. Air quality was evaluated using the Air Quality Index (AQI) and the concentration of six pollutants. The random forest algorithm was applied to analyze the urban form–air quality relationship.

The innovative aspects of the current study are as follows. (1) During the pandemic period, due to the widespread stagnation of urban activities, traffic pollution and industrial pollution were significantly reduced. This affected how urban form influences air quality. The pandemic period was utilized as a natural science experiment in which to reconsider the relationship between urban form and air quality. (2) The random forest model was selected to better understand the nonlinear relationship between urban form and air quality. (3) Taking urban agglomerations as the research area, the focus was on differences in the urban form–air quality relationship among urban agglomerations, thereby broadening research on the relationship between urban form and air quality.

2. Literature review

2.1. The measurement of urban form

Urban form refers to the physical form of a city; that is, how spatial elements are distributed within a city. When exploring the relationship between urban form and air quality, previous studies have usually described urban form using ecological landscape indicators. These can reflect the content of remote sensing images and contribute to understanding the landscape status and land-use patterns of the region. Ecological landscape indicators are usually used to describe urban size, urban shape, urban fragmentation, urban compactness, and urban sprawl. Urban size has been represented by indicators such as the Class Area (CA; She et al., 2017; Tian et al., 2020) and the Percentage of Landscape (PLAND; Ku, 2020; Li et al., 2021). Previous studies have shown that urban size has a significant impact on urban air quality (Liu et al., 2018b). Urban shape has been measured by the Mean Perimeter Area Ratio (PARA_MN; Fang et al., 2015; She et al., 2017) and Landscape Shape Index (LSI; Fan et al., 2018). Li et al. (2019) indicated that irregularly shaped cities have lower air pollution. Urban fragmentation has been measured by the Number of Patchs (NP; McCarty et al., 2015; Li et al., 2021), Largest Patch Index (LPI; Tian et al., 2020), and Patch Density (PD; Ku, 2020; Tian et al., 2020). It has been demonstrated that urban fragmentation significantly affects air quality (Shi et al., 2019). Urban compactness has been measured by Clumpiness (CLUMPY; Liu et al., 2018a) and the Mean Euclidean Nearest Neighbor Distance (ENN_MN; She et al., 2017). Urban sprawl has been measured by Contagion (CONTAG; Li et al., 2021) and the Aggregation Index (AI; Fang et al., 2015; Liang et al., 2020a; Tian et al., 2020). Cities with more compact and sprawled form have severer air pollution (Liu et al., 2017).

2.2. The relationship between urban form and air quality

Many studies have explored how urban form affects urban air quality. The relationship between urban form and air quality is the comprehensive result of how the urban form affects the air pollution generation, diffusion, and purification. An overview of previous studies is provided below to enable a better understanding of the mechanisms by which urban form influences air quality.

2.2.1. The mechanism by which urban form influences the generation of air pollution

The generation of air pollution includes point-source pollution and non-point-source pollution. Point-source pollution mainly includes domestic pollution and industrial pollution. Non-point-source pollution refers to traffic pollution. Generally, the diffusion distance of point-source pollution is limited but it causes regional differences in air pollutant concentrations in a city. The spatial distribution of non-point-source pollution in a city is relatively homogeneous. The total amount and spatial distribution of air pollution sources are strongly related to urban form. Previous studies have proven that urban form affects the generation of air pollution through direct and indirect paths.

In terms of urban size, the expansion of cities increases the concentration of air pollutants as a result of increasing energy consumption, industrial production, and traffic volume (Chen et al., 2011; Shi et al., 2020). However, McCarty et al. (2015) reached the opposite conclusion; that is, that urban size has a negative effect on air pollution, probably due to reduced biogenic emissions. From the perspective of urban shape, irregular urban landscapes significantly increase the amount and duration of traffic by increasing the movement of people from living areas to work areas (Fang et al., 2015). On the contrary, She et al. (2017) showed that cities with a large perimeter-to-area ratio have good air quality. Lu et al. (2016) demonstrated that the air quality of “X”- or “H”-shaped cities is much better than that of rhomboid cities, as “X”- or “H”-shaped cities usually have more than one city center which is conductive to reducing traffic distance. Urban fragmentation also plays a significant role in air pollution sources, being positively correlated with air pollution, such as NO2, PM2.5, and PM10 (McCarty et al., 2015; Rodríguez et al., 2016; Liu et al., 2018b; Zhou et al., 2018). When activities are distributed in different urban patches, the potential traffic demand increases (Bartholomew et al., 2009; Chen et al., 2011). Simultaneously, urban compactness is closely related to air pollution (Higgins et al., 2019). A more compact city has less air pollution due to its improved industrial efficiency and reduced traffic volume (Lu et al., 2016; Fan et al., 2018; Mou et al., 2018); additionally, non-motorized transportation—such as cycling and walking—is more commonly used compared to in less compact cities (Rodríguez et al., 2016). In contrast, several studies also revealed that a compact urban form produces more...
Air pollution because of increased fossil fuel consumption (Liu et al., 2017; Zhao et al., 2022). In terms of urban sprawl, Bereitschaft et al. (2013) found that cities with higher levels of urban sprawl generally exhibit higher concentrations and emissions of air pollution. This may be because people rely more on private cars and more infrastructure needs to be built, resulting in more air pollution. However, Tao et al. (2020) demonstrated that urban sprawl does not necessarily lead to worse air pollution in the Yangtze River Delta of China, which might be due to the development of public transport. In general, urban size, compactness, and sprawl affect the number of point-pollution sources and non-point-pollution sources. Urban shape and urban fragmentation mainly influence the amount of traffic pollution.

In addition to its effect via direct paths, there is also evidence that urban form has an indirect effect on the generation of air pollution. Urban form—such as urban size, shape, compactness, and sprawl—is positively related to the urban heat island effect (Dobbie et al., 2015; Zhao et al., 2016; Liang et al., 2020b). Chen et al. (2018) demonstrated that an increase in temperature contributes to the synthesis of pollutants. Li et al. (2021) reported that temperature is related to energy consumption, such as heating and cooling, and their air pollutants affecting the urban temperature. According to previous studies, urban fragmentation has notable effects on urban form changes due to the proportions of impervious surface areas. Furthermore, cities with higher humidity are more likely to generate air pollutants such as PM2.5, as the formation of secondary aerosol is affected (Cheng et al., 2015). Therefore, urban form affects air pollution generation through its effect on urban humidity.

2.2.2. The mechanism by which urban form influences the diffusion and purification of air pollution

Previous studies have shown that wind velocity, temperature, precipitation, and other climate factors have a significant impact on air quality (Cheng et al., 2015; Rodriguez et al., 2016; Liu et al., 2018a; Kang et al., 2019; Wang et al., 2019).

Urban form mainly affects the diffusion of air pollution by taking climate factors as intermediary factors (Stone, 2008). Wind velocity plays an important role in the relationship between urban form and air quality. A more fragmented city has more street canyons, which changes the wind direction, wind velocity, and other factors. Yang et al. (2020) indicated that high density urban areas affect wind velocity and ventilation conditions. As an increase in wind velocity is conductive to the diffusion of pollutants (McCarty et al., 2015), urban fragmentation and compactness may influence the diffusion of air pollution through the wind environment. Then, as mentioned above, urban form factors such as urban size, shape, compactness, and sprawl are related to the formation of the urban heat islands. In the relationship between temperature and air pollution diffusion, Chen et al. (2018) indicated that increased temperatures contribute to the diffusion of air pollution. However, Liang et al. (2020b) proposed that the heat island effect is not conducive to the diffusion of air pollutants. In addition to wind velocity and temperature, precipitation is another important mediating factor. Urban size and fragmentation are correlated with precipitation (Zhang et al., 2019) and precipitation may hinder the diffusion of air pollutants by increasing air humidity (Zeng et al., 2017). Thus, urban size and fragmentation have an indirect effect on the diffusion of air pollutants through precipitation.

Air can be purified through the absorption and transformation of pollutants by plants. Zhang et al. (2016) proposed that the rapid expansion of impervious surface leads to a relative reduction in the green plant area. Urban shape, fragmentation, and sprawl may increase the interspersion of urban and forested land, which promotes the purification of air pollutants (Shi et al., 2019; Tao et al., 2020; Huang et al., 2021). Additionally, precipitation can also purify air pollutants due to its effect of washing away some particulate pollutants in the air. Thus, urban form is related to air pollution purification through precipitation.

Based on these studies, urban size, shape, fragmentation, and sprawl may have an indirect effect on the purification of air pollution. It is worth reconsidering the underlying mechanism of urban form on air quality during the pandemic period, as some factors have been affected by the epidemic. On the one hand, the transportation-related air emission—an important channel by which urban form affects air quality—was significantly weakened in this period. Based on how urban form influences the generation of air pollution during non-pandemic periods, urban form factors are all strongly related to the traffic demand. Therefore, the impact of different urban form indicators on air quality may have changed during the pandemic. Additionally, home electricity consumption increased when people underwent home isolation (Jiang et al., 2021). Therefore, the impact of urban size, compactness, and sprawl on air pollution, which are related to the amount of domestic pollution may have increased. On the other hand, fossil fuel energy consumption is responsible for greenhouse gas emissions (Wang et al., 2021a). When human activities notably decreased, the urban heat island effect is reduced (Rosshan et al., 2021). Thus, the effect of urban form indicators on temperature may have affected the urban form–air quality relationship during the COVID-19 outbreak.

The mechanisms by which urban form influenced air quality during the pandemic period are worthy of further study. Based on the above theoretical analysis, the mechanism by which urban form influenced air quality in the normal period and the pandemic period was compared (Fig. 1).

3. Data and method

3.1. Study area

The top five urban agglomerations with great development potential in China, including Beijing-Tianjin-Hebei (BTH), Chengdu-Chongqing (CC), Pearl River Delta (PRD), Triangle of Central China (TCC), and Yangtze River Delta (YRD) were selected (Fig. 2). There are two main reasons for choosing these five urban agglomerations in China. First, Beijing-Tianjin-Hebei, the Pearl River Delta, and the Yangtze River Delta are the earliest urban agglomerations, with better economic conditions and social development foundation. Second, urban size, shape, and sprawl are related to the formation of the urban heat islands. In the relationship between temperature and air pollution diffusion, it is indicated that increased temperatures contribute to the diffusion of air pollution. However, Liang et al. (2020b) proposed that the heat island effect is not conducive to the diffusion of air pollutants. In addition to wind velocity and temperature, precipitation is another important mediating factor. Urban size and fragmentation are correlated with precipitation (Zhang et al., 2019) and precipitation may hinder the diffusion of air pollutants by increasing air humidity (Zeng et al., 2017). Thus, urban size and fragmentation have an indirect effect on the diffusion of air pollutants through precipitation.

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3.2. Data

3.2.1. Air quality

Air quality is usually evaluated by the AQI, which is divided into six categories according to the “Ambient Air Quality Standard” in China: excellent (0–50), moderate (51–100), slightly polluted (101–150), moderately polluted (151–200), heavily polluted (201–300), and grossly polluted (> 300). It is a single indicator based on the concentrations of different air pollutants. The main pollutants are carbon monoxide (CO), ozone (O3), nitrogen dioxide (NO2), inhalable particulate matter (PM2.5), fine particulate matter (PM10), and sulfur dioxide.
Fig. 1. Mechanisms by which urban form influences air quality during normal and pandemic periods.
According to the measured concentrations of each pollutant, the Individual Air Quality Index (IAQI) is calculated according to Eq. 1:

$$IAQI_p = \frac{IAQI_{Hi} - IAQI_{Lo}}{BP_{Hi} - BP_{Lo}} (C_p - BP_{Lo}) + IAQI_{Lo},$$

(1)

Here, IAQI_p represents the IAQI of pollutant P; $C_p$ is the concentration of pollutant $P$; $BP_{Hi}$ and $BP_{Lo}$ refer to the high and low values of pollutant concentration limits close to $C_p$, respectively; $IAQI_{Hi}$ and $IAQI_{Lo}$ represent the IAQIs corresponding to $BP_{Hi}$ and $BP_{Lo}$, respectively.

IAQI is the maximum value of IAQI. A higher AQI indicates that air pollution is more serious. It is calculated according to Eq. 2, where $n$ is the number of pollutants.

$$AQI = \max (IAQI_1, IAQI_2, IAQI_3, \ldots, IAQI_n)$$

(2)

Air quality data, which was obtained from the China National Environmental Monitoring Center, included real-time data from each monitoring station in each city. In addition to the AQI, the monitoring stations also provided the concentrations of six pollutants. However, because $20 \times 20$ km study units were defined by creating a fishnet, air quality data in each study area was not monitored effectively. Because of the strong spatial correlation of air quality, the Krigeing interpolation method was used to obtain air quality data in each spatial unit.

### 3.2.2. Urban form

The present study explored the influence of urban form on air quality from a meso perspective, so the land-use data obtained from remote sensing images were most suitable. The current study further clarified the mechanism by which urban form impacted air quality, which was evaluated according to urban size, shape, fragmentation, compactness, and sprawl. Based on a review of existing research, ten indicators were selected to describe urban form: total area (CA), percentage of landscape (PLAND), mean perimeter-area ratio (PARA_MN), landscape shape index (LSI), number of patches (NP), largest patch index (LPI), clumpiness (CLUMPY), mean Euclidean nearest neighbor distance (ENN_MN), contagion index (CONTAG), and aggregation index (AI). CA is the total built-up area in the spatial units. PLAND is the proportion of built-up area in the spatial units. PARA_MN is the mean perimeter-area ratio, LSI represents the landscape shape indicating that the urban shape is more complex. NP is the total number of patches in the landscape. LPI is the proportion of the largest built-up area in the whole landscape area. CLUMPY represents the probability of different types of patches appearing on a map; a CLUMPY value of 1 indicates that patch types are dispersed to the greatest extent whereas a value of +1 indicates that patch types are aggregated to the greatest extent. ENN_MN is the relative index of the distance between patches of urban build-up land, with a higher ENN_MN indicating that the same patch types are further apart. CONTAG represents the extension trend of different patch types in a landscape, with a high value generally indicating that a certain patch type in the landscape has good connectivity. AI refers to the length of the common boundary between all pixels of the same patch type; the AI value is lowest when pixels have no common boundary.

Urban form metrics were based on 2020 land coverage data with a resolution of 30 m from the Ministry of Natural Resources of the People’s Republic of China (http://www.globallandcover.com). The land is divided into 10 types: cultivated land, woodland, grassland, shrub, wetland, water, tundra, artificial surface, bare land, glacier, and permanent snow. Artificial surface refers to the built surface formed by human activities and covered by asphalt, concrete, gravel, and other building materials, and is similar to urban and rural build-up land as defined by the Ministry of Natural Resources of the People’s Republic of China. Urban form metrics were derived from Fragstats 4.2.

The data set collected in the present study included one dependent variable and ten independent variables. After data collection, the data was preprocessed to improve data quality. With no missing values in the data set, the data was normalized using the max-min normalization method to eliminate the influence of dimension. This transformed the original data linearly so that all resulting data were between 0 and 1. Eq. 3 was used, where $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the variable $X$. 

![Fig. 2. Location of the five sampled urban agglomerations in China.](image-url)
The relationship between urban form and air quality is usually explored using linear models, such as the multiple linear regression model and the spatial lag model. In recent years, machine learning models have begun to be applied in urban development or air pollution research (Mia et al., 2020; Nyamkhey et al., 2020; Tian et al., 2020). In this study, the random forest algorithm was selected to analyze the impact of urban form indices on air quality. The main reasons for choosing this method were as follows. (1) Previous studies have shown that the relationship between urban form and air quality is likely to be nonlinear (Tian et al., 2020), so random forest is more suitable than a linear regression model. (2) In a linear regression model, control variables are needed to ensure the significance of the relationship between urban form and air quality. As the period selected for the current study was only two months, it was difficult to obtain accurate control variable values related to air quality during this period. However, random forest trains samples based on given features, which effectively avoids the restriction of requiring control variables.

The random forest model was proposed by Leo Breiman in 2001 (Breiman, 2001). It is composed of many decision trees with no correlation between the decision trees; the final result of the model relies on each decision tree. The construction of the random forest model includes the following steps. First, the decision tree is constructed: K features are randomly selected from the data set, which contains M features; The decision tree is established according to the K features. Second, the training set is generated using a bootstrap method to train the sample set by randomly selecting N samples from all samples. To avoid the local optimal solution, the size of the training set extracted each time is about two-thirds of the total amount, and the rest is “out of bag” (OOB). Third, as far as regression is concerned, each decision tree in the random forest predicts an output value. The final prediction value is calculated from the average value of all decision trees in the random forest. Compared with ordinary least squares (OLS) regression, random forest has higher accuracy and better prediction ability.

Next, the mean squared error (MSE), root mean square error (RMSE), and R-squared ($R^2$) were selected to test the fitting degree and applicability of the random forest outcome. MSE is the mean squared sum of the difference between the estimated value and the real value, and RMSE is the arithmetic square root of the MSE. A smaller value of RMSE indicates that the model has greater accuracy. The MSE and RMSE were calculated from Eqs. (4) and (5), respectively.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$  \hspace{1cm} (4)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$  \hspace{1cm} (5)

Here, $n$ is the number of samples, $y_i$ is the actual value and $\hat{y}_i$ is the predicted value. $R^2$ is the coefficient of determination was calculated according to Eq. (6), where $\bar{y}_i$ is the predicted value, $\bar{y}$ is the mean value and $y_i$ is the actual value.

$$R^2 = 1 - \frac{\sum (\bar{y}_i - y_i)^2}{\sum (\bar{y} - y_i)^2}$$  \hspace{1cm} (6)

Random forest regression was performed using Python. Urban form metrics were selected as independent variables and air quality parameters as dependent variables, which were all included in the random forest calculation. First, the parameter dictionary was constructed, and the number of decision trees, maximum tree depth and maximum
eigenvalue were determined by random forest training. The feature importance of the independent variables was analyzed based on the best model, and the importance order of different features was obtained. The next step was to assess the predicted results of the test set; for this purpose, the values of MSE, RMSE, and $R^2$ were obtained. Finally, the influence of urban form on air quality in the five urban agglomerations was determined.

4. Results

4.1. Statistical characteristics of air quality and urban form in the urban agglomerations

Tables 1 and 2 show the values of the AQI and the average concentrations of the six pollutants in the five urban agglomerations in 2019 and 2020. Table 3 shows the recommended annual air quality guideline (AQG) levels and interim targets for the concentrations of the six pollutants according to the WHO global air quality guidelines (WHO, 2021). By comparing the statistical results with the guidelines, it was apparent that the concentrations of NO$_2$, PM$_{2.5}$, and PM$_{10}$ exceeded the AQG levels both in 2019 and 2020.

By comparing the AQI and the average concentration of the six pollutants from February to March in 2019 and 2020, the ratio of change in air quality was obtained (Fig. 3). Compared with air quality data in 2019, the air quality of the five urban agglomerations was significantly improved in 2020, especially in the Yangtze River Delta. Additionally, the air quality was improved to varying degrees in terms of the concentrations of the five pollutants in different regions. NO$_2$ had the most markedly decreased concentration of more than 15%. The decrease in industrial and traffic pollution in the pandemic period might explain the markedly decrease in NO$_2$ concentrations (Zhang et al., 2021). The concentrations of PM$_{2.5}$, PM$_{10}$, and SO$_2$ decreased significantly in the Beijing-Tianjin-Hebei and the Yangtze River Delta. However, the concentration of O$_3$ increased. This may be because the reduction of particulate matters in the air enhanced solar radiation on the Earth’s surface, which contributes to photochemistry and O$_3$ generation (Wang et al., 2020b; Wang et al., 2021c).

Table 4 shows the statistical characteristics of urban form in the urban agglomerations. According to the land-use data in 2020, urban form metrics varied among urban agglomerations. Average CA and PLANL values in Chengdu-Chongqing and the Triangle of Central China were lower than in other urban agglomerations, indicating that these generally had lower artificial land cover and lower urban land use density. Beijing-Tianjin-Hebei, the Pearl River Delta, and the Yangtze River Delta had a good urbanization foundation, with large urban size. In terms of urban fragmentation, the average NP value in the Yangtze River Delta was lower than in other urban agglomerations, indicating that the land-use patterns in the Yangtze River Delta were relatively less complex. Chengdu-Chongqing had the lowest average LSI, which indicated that the urban shape of CC was relatively simple. Furthermore, ENN_MN was greatest for Chengdu-Chongqing and the Triangle of Central China, which indicated that there was less spatial connection in these agglomerations.

4.2. Relationships between air quality and urban form in urban agglomerations during the COVID-19 pandemic

Based on the random forest model, the importance of urban form indicators to AQI and the six air pollutants was ranked. Additionally, the evaluation index value of the model was obtained through the prediction results of the test group. The results are presented in Fig. 4, with the top three of ten urban form indicators highlighted. The results showed similarities and differences in the degree of influence of urban form on air quality in different agglomerations.

Based on the empirical results, NP was the indicator that had a marked influence on the AQI and the concentration of the six air
which urban form influenced air quality varied in the five urban agglomerations. In the Triangle of Central China, the Pearl River Delta, and the Yangtze River Delta, AI played vital roles for some air pollutants in the Beijing-Tianjin-Hebei, Chongqing and the Yangtze River Delta. Additionally, AI was found to be the most important factor impacting on AQI in Chengdu-Chongqing. By analyzing the extreme important indicators related to the six pollutants, NP still had an extreme effect on air pollutants. In addition to this finding, some differences between urban agglomerations were further clarified. The mechanism by which urban form influenced air quality was complicated in Beijing-Tianjin-Hebei, with significant differences in the importance of the effect of different urban form factors on different air pollutants. In Chengdu-Chongqing, urban sprawl proxied by CONTAG strongly influenced the concentrations of PM$_{2.5}$ and PM$_{10}$. In the Pearl River Delta, CLUMPY—representing urban compactness—was an extremely important indicator affecting CO. In the Triangle of Central China, PARA_MN ranked first among the urban form indicators in relation to the concentrations of PM$_{2.5}$ and PM$_{10}$. In the Yangtze River Delta, LSI strongly influenced the concentrations of PM$_{10}$.

### 4.3. Robustness test

Generally, previous studies have tested the robustness of the results by reselecting the proxy variables, methods, or sample sizes (Cole et al., 2020; Wu et al., 2021; Zhang, 2021). In this study, five urban form factors were proxied by two indicators. The results showed that indicators representing the same urban form factor had different effects on air quality depending on how they were measured. Therefore, reselection of the methods and sample size were chosen to test the robustness of the results. According to the approaches of Joharestani et al. (2019) and Ma et al. (2020), the multiple linear regression model (MLR) and the extreme gradient boosting model (XGBoost) were chosen to explore.

| Table 1 | Statistical characteristics of air quality in 2019. |
|---------|-----------------------------------------------|
| Urban Agglomeration | Average AQI | Average CO | Average NO$_2$ | Average O$_3$ | Average PM$_{2.5}$ | Average PM$_{10}$ | Average SO$_2$ |
| BTH     | 91.36192 | 0.95982 | 34.07947 | 58.11229 | 60.61418 | 103.25850 | 14.91344 |
| CC      | 69.97192 | 0.79109 | 32.07574 | 43.88211 | 49.87969 | 72.66737 | 8.19768 |
| PRD     | 41.13509 | 0.79698 | 26.91730 | 41.87234 | 50.96764 | 60.60562 | 6.78822 |
| TCC     | 63.85874 | 0.88854 | 23.76717 | 46.08769 | 43.49872 | 63.45570 | 9.11473 |
| YRD     | 72.95056 | 0.79579 | 31.85054 | 59.95183 | 48.96764 | 74.05413 | 8.46573 |

| Table 2 | Statistical characteristics of air quality in 2020. |
|---------|-----------------------------------------------|
| Urban Agglomeration | Average AQI | Average CO | Average NO$_2$ | Average O$_3$ | Average PM$_{2.5}$ | Average PM$_{10}$ | Average SO$_2$ |
| BTH     | 71.95851 | 0.85528 | 25.98936 | 58.17136 | 46.71010 | 71.15413 | 10.38690 |
| CC      | 65.90601 | 0.68348 | 17.16702 | 53.76818 | 35.45906 | 48.93482 | 8.78970 |
| PRD     | 37.16210 | 0.81727 | 24.56207 | 53.76818 | 35.45906 | 48.93482 | 8.78970 |
| TCC     | 53.61947 | 0.81727 | 17.16702 | 53.76818 | 35.45906 | 48.93482 | 8.78970 |
| YRD     | 50.93944 | 0.66455 | 24.50339 | 59.95183 | 48.96764 | 74.05413 | 8.46573 |

| Table 3 | Recommended long- and short-term AQG levels and interim targets for the concentration of six pollutants. |
|---------|-----------------------------------------------|
| Pollutants | Averaging time | Interim target | AQG level |
| CO (µg m$^{-3}$) | 24-hour | 7 | 120 | 100 |
| NO$_2$ (µg m$^{-3}$) | Annual | 40 | 10 | 100 |
| O$_3$ (µg m$^{-3}$) | Peak season | 100 | 70 | 100 |
| PM$_{2.5}$ (µg m$^{-3}$) | Annual | 35 | 15 | 10 |
| PM$_{10}$ (µg m$^{-3}$) | Annual | 75 | 37.5 | 15 |
| SO$_2$ (µg m$^{-3}$) | 24-hour | 75 | 50 | 100 |

Notes: AQG means the air quality guideline level.

| Table 4 | Statistical characteristics of urban form. |
|---------|-----------------------------------------------|
| Urban Agglomeration | Average CA | Average PLAND | Average PARA_MN | Average LSI | Average NP | Average LPI | Average Average | Average CLUMPY | Average CONTAG | Average AI |
| BTH     | 4850.204 | 11.419 | 609.803 | 13.721 | 2276.284 | 53.600 | 0.908 | 637.189 | 67.350 | 91.601 |
| CC      | 1189.054 | 2.970 | 681.191 | 6.873 | 3220.648 | 59.211 | 0.828 | 851.151 | 69.393 | 82.959 |
| PRD     | 4527.337 | 12.224 | 709.589 | 11.847 | 3220.648 | 59.211 | 0.828 | 851.151 | 69.393 | 82.959 |
| TCC     | 1794.118 | 4.431 | 654.219 | 10.719 | 3246.315 | 59.211 | 0.828 | 851.151 | 69.393 | 82.959 |
| YRD     | 4652.480 | 11.485 | 690.003 | 1621.032 | 1621.032 | 59.211 | 0.828 | 851.151 | 69.393 | 82.959 |

Beijing-Tianjin-Hebei, and the Pearl River Delta, respectively.

Fig. 3. The ratio of change in AQI and six pollutants in February to March, 2019 and 2020.
relationships between urban form and air quality. Comparison of the evaluation indicators—R² and RMSE—of MLR and XGBoost with those of the random forest algorithms (Table 5), it indicated that the performance of the random forest algorithm was better overall than that of MLR or XGBoost.

Additionally, the five urban agglomeration samples were combined into a sample set, and the random forest model was further used to explore the robustness of the results. As shown in Fig. 5, NP and ENN_MN played important roles in the urban form–air quality relationship in China’s urban agglomerations, which indicated that the results were robust.
Table 5
Evaluation results of AQI and six air pollutants by different models.

| Categories | Urban agglomerations | Random Forest | MLR | XGBoost |
|------------|----------------------|--------------|-----|---------|
|            |                      | R²        | RMSE | R²     | RMSE   | R²     | RMSE   |
| AQI        | BTH                  | 0.817     | 5.454 | 0.454 | 9.495  | 0.858 | 4.799  |
|            | CC                   | 0.643     | 3.502 | 0.173 | 5.376  | 0.421 | 4.457  |
|            | PRD                  | 0.730     | 0.793 | 0.279 | 1.331  | 0.474 | 1.108  |
|            | TCC                  | 0.686     | 6.469 | 0.207 | 10.342 | 0.688 | 6.450  |
|            | YRD                  | 0.697     | 4.450 | 0.332 | 6.610  | 0.656 | 4.741  |
| CO         | BTH                  | 0.689     | 0.102 | 0.114 | 0.175  | 0.469 | 0.134  |
|            | CC                   | 0.661     | 0.039 | 0.306 | 0.056  | 0.359 | 0.054  |
|            | PRD                  | 0.705     | 0.024 | 0.435 | 0.035  | 0.768 | 0.022  |
|            | TCC                  | 0.590     | 0.099 | 0.052 | 0.152  | 0.607 | 0.098  |
|            | YRD                  | 0.696     | 4.459 | 0.111 | 0.217  | 0.716 | 0.122  |
| NO₂        | BTH                  | 0.774     | 2.954 | 0.166 | 5.734  | 0.775 | 2.959  |
|            | CC                   | 0.430     | 2.862 | 0.119 | 3.594  | 0.442 | 2.834  |
|            | PRD                  | 0.591     | 3.110 | 0.352 | 4.020  | 0.482 | 3.498  |
|            | TCC                  | 0.597     | 0.597 | 0.095 | 2.076  | 0.386 | 1.702  |
|            | YRD                  | 0.657     | 0.657 | 0.148 | 0.231  | 0.567 | 0.163  |
| O₃         | BTH                  | 0.697     | 2.799 | 0.140 | 4.757  | 0.814 | 2.188  |
|            | CC                   | 0.547     | 4.271 | 0.230 | 5.622  | 0.508 | 4.452  |
|            | PRD                  | 0.707     | 3.648 | 0.284 | 5.849  | 0.489 | 4.813  |
|            | TCC                  | 0.649     | 4.243 | 0.296 | 6.045  | 0.437 | 5.375  |
|            | YRD                  | 0.739     | 0.063 | 0.287 | 0.161  | 0.739 | 0.063  |
| PM₁₀       | BTH                  | 0.887     | 3.396 | 0.433 | 7.686  | 0.887 | 3.396  |
|            | CC                   | 0.439     | 3.521 | 0.196 | 4.258  | 0.439 | 3.521  |
|            | PRD                  | 0.483     | 1.333 | 0.267 | 1.630  | 0.483 | 1.333  |
|            | TCC                  | 0.573     | 6.134 | 0.194 | 8.471  | 0.573 | 6.134  |
|            | YRD                  | 0.601     | 0.139 | 0.292 | 0.186  | 0.601 | 0.139  |
| SO₂        | BTH                  | 0.808     | 7.569 | 0.482 | 12.563 | 0.808 | 7.569  |
|            | CC                   | 0.644     | 3.512 | 0.174 | 5.398  | 0.644 | 3.512  |
|            | PRD                  | 0.836     | 0.725 | 0.293 | 1.542  | 0.836 | 0.725  |
|            | TCC                  | 0.678     | 4.716 | 0.231 | 7.321  | 0.678 | 4.716  |
|            | YRD                  | 0.744     | 0.100 | 0.347 | 0.162  | 0.744 | 0.100  |
| PM₂₅       | BTH                  | 0.595     | 1.858 | 0.145 | 2.725  | 0.506 | 2.053  |
|            | CC                   | 0.708     | 0.602 | 0.192 | 1.011  | 0.793 | 0.506  |
|            | PRD                  | 0.602     | 0.530 | 0.495 | 0.613  | 0.837 | 0.349  |
|            | TCC                  | 0.620     | 1.245 | 0.197 | 1.820  | 0.622 | 1.242  |
|            | YRD                  | 0.646     | 0.138 | 0.137 | 0.217  | 0.450 | 0.172  |

Fig. 5. The impact of urban form on AQI and six pollutants.
5. Discussion

5.1. The relationship between urban form and air quality during the COVID-19 pandemic

During the pandemic period, urban form played a certain important role in air quality in five urban agglomerations. Based on the degree of importance of urban form indicators affecting AQI and six air pollutants, urban fragmentation was found to be the extremely important factor affecting air quality. Other urban form factors were also very important for several air pollutants.

Urban fragmentation was a very important factor affecting AQI and the six pollutants during the pandemic period. Similarly, Lee (2020), McCarty et al. (2015), and Rodriguez et al. (2016) found that higher urban fragmentation is associated with higher concentrations of air pollutants during normal periods. However, Li et al. (2021) found that the effect of NP on AQI is not significant in Northern China. In the present study, urban fragmentation was strongly related to air quality. Based on the literature review, urban fragmentation results in more channels that affect the generation, diffusion, and purification of air pollution compared with other types of urban form. When the effect of urban form on air quality through traffic pollution and the heat island effect is weakened, the importance of urban fragmentation on air quality through other channels may be increased.

Urban size had a significant effect on air quality, especially in the Beijing-Tianjin-Hebei, the Pearl River Delta, and the Yangtze River Delta. The notable positive effect of urban size on air pollution has often been demonstrated in previous studies (Liu et al., 2018b; Shi et al., 2019), with this result generally explained by the generation of domestic, industrial, and traffic pollution. In contrast, urban size has no significant effect on the AQI of Northern China, which is likely attributable to the decoupling effect of population urbanization and land urbanization (Li et al., 2019). In this study, the reason underpinning the finding of the urban size-airequality relationship in the Beijing-Tianjin-Hebei, the Pearl River Delta, and the Yangtze River Delta during the pandemic period may have been that cities with large urban areas contain more people, who generated more domestic pollution in the pandemic period.

Additionally, it is noteworthy that urban shape had a relatively strong influence on air quality. Some empirical studies during non-pandemic periods have quantified the impacts of urban shape on air quality. Fan et al. (2018) identified that cities with polycentricity and irregularity usually have better air quality because traffic connections between different patches are reduced. Li et al. (2019) found that irregular urban shapes with high population density improve air quality, while monocentric, scattered, and irregularly shaped cities tend to have higher air pollution. This could be attributable to the fact that urban shape needs to be combined with other urban form indicators to have an impact on air quality. In contrast, Clark et al. (2011) and McCarty et al. (2015) found there to be little relationship between urban shape and air pollution. During the pandemic period, urban shape played an important role in air quality. This may have been because urban shape is significantly related to the urban heat island effect. Liang et al. (2020b) found that urban geometric complexity has a greater impact on the urban heat island effect than urban size and compactness when comparing the coefficients of their proxy variables.

Urban compactness was vital to the concentration of air pollutants in the Beijing-Tianjin-Hebei, the Pearl River Delta, and the Yangtze River Delta. Previous studies have shown that the compactness of cities is strongly related to better air quality because it can reduce the frequency of people driving (Borrego et al., 2006; Ewing et al., 2018). Also, it has been concluded that higher urban compactness is related to severer urban air pollution (Liu et al., 2017; Lee, 2019) because cities that are too compact are not conducive to the dispersion of air pollutants. However, Li et al. (2021) found that there is little correlation between ENN_MN and AQI. This may be because the decreased spatial scale of the research area weakens the impact of ENN_MN on air quality. During the pandemic period, the result may have been due to more compact urban form in urban agglomerations with better economic development levels being more conducive to improving energy efficiency in the case that the urban form had little effect on the generation of air pollutants.

Urban sprawl was also related to air quality for some air pollutants during the pandemic period. Similar research was conducted by Tao et al. (2020), who identified that more sprawling cities have lower PM_{2.5} concentrations. Shi et al. (2020) believed that PM_{2.5} concentrations would continue to increase with the ongoing expansion of China’s urban areas. In contrast, Fan et al. (2018) found that urban sprawl has little association with air pollution. Additionally, it is noteworthy that AI was negligibly correlated with AQI or the six pollutants during the pandemic period. This result was inconsistent with the findings of Liang et al. (2020a), in which AI has a significantly negative effect on air quality. It is likely that, as AI is closely related to the traffic flow of a city, it affects the air pollution emissions caused by traffic. The reason for negligible correlation between AI and air quality in the present study may have been because of the significant impact of COVID-19 on traffic volume, which greatly decreased the AI mechanism of air pollution.

5.2. Differences in the urban form–air quality relationship among five urban agglomerations

The empirical results showed that the urban form–air quality relationship of the five urban agglomerations were quite different, this may have been due to the difference in urbanization levels, energy-resource structures, and air pollutant emissions efficiency in the urban agglomerations (Du et al., 2018; Miao et al., 2021).

By comparing extremely important factors, the mechanism by which urban form influenced air quality in the Beijing-Tianjin-Hebei was found to be more complex than in other urban agglomerations. Five types of urban form factors significantly affected air quality or the six pollutant concentrations. The result was similar to Shi et al. (2019), who found that five indicators representing urban form are significantly correlated with air pollution in Beijing-Tianjin-Hebei. This means that Beijing-Tianjin-Hebei needs to systematically optimize different urban form dimensions to improve air quality.

In the Chengdu-Chongqing, it is noteworthy that urban sprawl, proxied by CONTAG, was of significance for NO2 and PM_{2.5} concentrations. A similar result was found by Liu (2019), who suggested that a less sprawling city helps to reduce PM_{2.5} concentration in Western China. However, Shi et al. (2019) indicated that LSI is the highest negative indicator affecting PM_{2.5} concentrations. In the pandemic period, the relationship between urban sprawl and air pollutants (NO2 and PM_{2.5}) may have been more sensitive in areas with higher concentrations of NO2 and PM_{2.5} (e.g., Chengdu-Chongqing), while urban sprawl did not have much impact when the concentrations were relatively low (e.g., Pearl River Delta).

In the Pearl River Delta, urban compactness—as measured by the CLUMPY variable—had a considerable influence on the AQI and CO concentration. Huang et al. (2021) proved that urban compactness is positively associated with air pollutants in the Guangdong-Hong Kong-Macao Greater Bay Area, which developed from the Pearl River Delta. The explanation for this relationship between urban compactness and air quality may be that the urban compactness of the Pearl River Delta is strongly correlated with meteorological factors such as wind velocity and temperature, which affect the diffusion or purification of urban air pollution.

In the Triangle of Central China, urban shape, proxied by PARA_MN, also played an extremely important role in the AQI, PM_{2.5} pollutants, and PM_{10} pollutants. As shown in Table 3 from the comparison of the average PARA_MN values, the urban shape of the Triangle of Central China is more complex than those of other urban agglomerations. The Triangle of Central China has many mountains and varied topography. Accordingly, changes in its urban shape result in the mixing of urban and
forested land, which may contribute to the diffusion of urban air without increasing the pollution sources.

In the Yangtze River Delta, urban fragmentation had the greatest impact on air quality, only LSI was the most important indicator for the concentration of PM$_{10}$. Similarly, Shi et al. (2019) concluded that NP affects air pollutants at the 1% level in winter in the Yangtze River Delta, while other indicators such as CA and AI have little effect on air pollutants. She et al. (2017) also indicated that NP plays an important role for air pollutants in the Yangtze River Delta. The results of the current study showed that urban fragmentation still has a significant impact on the air quality in the Yangtze River Delta through various channels (e.g., wind velocity, the urban heat island effect) with the reduction of pollution sources.

5.3. Limitations and future research

The present study provides a good perspective for reconsidering the relationship between urban form and air quality. However, it has some limitations and further research needs to be carried out in the future. First, urban air quality is affected by many factors. The present study does not consider, for example, non-urban-form indicators such as temperature and rainfall; future research could establish a more comprehensive index system to evaluate the relationship between urban form and air quality. Second, due to the limitations of cities in urban agglomerations, the present study divides the study area into samples with a spatial scale of 20 × 20 km. The results might not apply to city administrative units or on sub-city scales (Li et al., 2021) as the impact of urban form on air quality varies at different spatial scales (Shi et al., 2019). Additionally, the values of air quality in each sample are obtained by interpolation based on data from air quality monitoring stations. Thus, the data accuracy should be improved. Future studies could explore the urban form–air quality relationship on the mesoscale or urban scale by using more accurate data (e.g., high resolution remote sensing data). Third, the present study only explores the impact of urban form on air quality based on air quality data during the pandemic period; the results are unable to reveal any differences in the mechanisms impacting the urban form–air quality relationship in a region between pandemic and non-pandemic periods. Future research using longitudinal data could explore differences in the urban form–air quality relationship in a certain region during pandemic and non-pandemic periods.

6. Conclusions

The present study contributes to knowledge of the relationship between urban form and air quality. First, the COVID-19 pandemic provides a large data set that enables the reconsideration of how urban form affects air quality. This study discusses the effect of urban form on air quality during the normal and pandemic periods, thus enriching the existing theoretical system. Second, the random forest model was used to explore the nonlinear relationship between urban form and air quality, which was proven to be better than MLR and XGBoost. Third, this study compares the impact of urban form on the air quality of China’s five urban agglomerations, thus providing a research basis for improving air quality in different regions.

The results showed that urban fragmentation is an important factor affecting air quality and the concentration of six pollutants during the pandemic. Furthermore, the mechanism by which urban form influences air quality varies in different urban agglomerations. The underlying mechanism by which urban form affects air quality in Beijing-Tianjin-Hebei is rather complex. In Chengdu-Chongqing and the Pearl River Delta, urban sprawl and urban compactness are extremely important indicators for several air pollutants, respectively. Additionally, urban shape ranks first in some aspects when analyzing the importance of urban form indicators to air pollutants both in the Triangle of Central China and the Yangtze River Delta.

The present study informed how urban planning sets out urban forms and how governments formulate land-use policies in the context of advocating green social development and promoting the development of new energy sources to better reduce air pollution and improve air quality. The empirical results showed that, to guide air quality improvement, more attention should be paid to the impact of urban fragmentation on air quality. Additionally, urban planning and land-use policies should attach importance to the spatial connections between different land-use patterns and encourage more reasonable urban form. Simultaneously, the relationship between urban form and air quality varies in different areas, so urban planning and land-use policies should be formulated in accordance with the industrial structure, climate conditions, lifestyles, and other factors in different regions.

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