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Effects of urban form on air quality: A case study from China comparing years with normal and reduced human activity due to the COVID-19 pandemic

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ABSTRACT

This study explored the dynamic and complex relationships between air quality and urban form when considering reduced human activities. Applying the random forest method to data from 62 prefecture-level cities in China, urban form–air quality relationships were compared between 2015 (a normal year) and 2020 (which had significantly reduced air pollution due to COVID-19 lockdowns). Significant differences were found between these two years; urban compactness, shape, and size were of prime importance to air quality in 2020, while fragmentation was the most critical factor in improving air quality in 2015. An important influence of traffic mode was also found when controlling air pollution. In general, in the pursuit of reducing air pollution across society, the best urban forms are continuous and compact with reasonable building layouts, population, and road densities, and high forest area ratios. A polycentric urban form that alleviates the negative impacts of traffic pollution is preferable. Urban development should aim to reduce air pollution, and optimizing the effects of urban form on air quality is a cost-effective way to create better living environments. This study provides a reference for decision-makers evaluating the effects of urban form on air pollution emission, dispersion, and concentration in the post-pandemic era.

1. Introduction

Rapid urbanization has resulted in significant socio-economic benefits and severe environmental problems. One of the most serious problems is air pollution (Zheng & Na, 2020), which poses threats to public health (Calderón-Garcidueñas & Villarreal-Ríos, 2017; Johnson et al., 2017) and the environment (Lin & Zhu, 2018), and may even jeopardize social stability (Du et al., 2018). Improving air quality and alleviating environmental pressure significantly impact sustainable urbanization (Fan et al., 2020). It is known that the deterioration of air quality is related to several subjective and objective factors. First, anthropogenic activities affect air quality. Point- and non-point-source pollutant emissions, such as those from factories and vehicles, are the primary contributors to air pollution (Bereitschaft & Debbege, 2013; Waked et al., 2015). Second, during air pollution emission, dispersion, and concentration, air quality is influenced by meteorological factors such as temperature, humidity, wind speed, and air pressure (Avdakovic et al., 2016). Moreover, the influences of urban forms on air quality have also drawn intense attention (Hankey & Marshall, 2017; Lu & Liu, 2016). The definition of urban form refers to the spatial configurations, structures, and arrangements of the urban elements and physical environment impacted by social-natural factors (Sun et al., 2022). Land use, the city's pattern, and the transportation network can all be defined as urban form. In addition to source emission treatment and consideration of climatic factors, adjustment of urban forms is another way that planners can improve air quality while optimizing the urban layout (Li & Zhou, 2019).

At the end of 2019, the coronavirus disease (COVID-19) broke out and swept quickly across the world. It became a global public health threat and caused social and economic crises (Mollalo et al., 2020). To control the rapid spread of COVID-19, governments in many countries took various actions, such as lockdowns of cities, counties, and villages. Lockdown measures have decreased human activity, temporarily shut down factories, and abruptly reduced the number of vehicles driven on...
urban roads (Li et al., 2020). As the main sources of air pollution have been restricted, better air quality was evident in many cases. Although the human race has been experiencing a catastrophe, the lockdown of cities has positively affected the natural environment (Stratoulias & Nuthammachot, 2020). The COVID-19 pandemic and associated stagnation of socio-economic activities give us an unprecedented chance to conduct a large-scale experiment on air quality in cities (Baldassano, 2020). The following research questions were the focus of this study: When the influences of industry and traffic are largely excluded, how is air quality affected by other urban and meteorological factors? Focusing on the city itself, what types of urban forms benefit air quality the most?

China was the first country to implement a lockdown policy. Wuhan, in Hubei Province, was put into lockdown on January 23, 2020. This was followed by other cities and China's entire lockdown lasted for almost one month (Zhao et al., 2020). In the course of the lockdown, the air quality varied. Generally, many studies (Chen, Huang, et al., 2020; Huang et al., 2020; Le et al., 2020; Shi et al., 2021) demonstrated that the concentrations of major air pollutants (PM\textsubscript{2.5}, PM\textsubscript{10}, SO\textsubscript{2}, NO\textsubscript{2}, and CO) abruptly decreased and air quality improved overall. However, the concentration of O\textsubscript{3} was higher in the first season of 2020 compared to pre-pandemic years. The unexpected and uncertain impacts of COVID-19 on air quality indicate that air quality management is a complex issue that needs careful and sophisticated evaluation (Chen, Li, et al., 2020). While different studies reported different air quality results, the level of air pollution changed significantly during the COVID-19 pandemic due to massive reductions in point- and non-point-source pollutant emissions. Hence, lockdowns were definitely a key influence on air quality in China and have had various effects in the post-pandemic period. Moreover, as the lockdowns were more strictly implemented in China compared to other countries, this study could obtain good data to analyze the impacts of urban form on air quality with consideration of human activity levels.

In this context, this study aims to explore the effects of urban forms on air quality during the COVID-19 pandemic and compare the results with those of a normal year, using China as an example. To achieve this goal, the relationship between air quality and urban form was analyzed. Then, 62 prefecture-level Chinese cities were selected for sampling. By collecting air quality and urban form data from 2015 and 2020 and using the random forest (RF) method, the importance of different urban form indicators in COVID-19 non-pandemic and COVID-19 pandemic years was probed. The changing effects of urban form on air quality could then be analyzed. The main novelty of this study is that it provides insights into the correlation between air quality and urban form in an unusual year, which can help decision-makers to understand whether the urban form has more significant impacts on the natural environment than air pollution. Most studies in this area have been conducted in a specific year. However, this study compared a normal year with an unusual year to help reveal the complex relationship between air quality and urban form.

The rest of the study is organized as follows. In Section 1, we elaborate on the possible relationship between air quality and urban form, and provide a framework. In Section 2, by collecting and preprocessing the air quality and urban form data, we introduce the non-linear (RF model) and linear (multiple linear regression model) methods. In Section 3, we compare the different results in COVID-19 non-pandemic and COVID-19 pandemic years, identify the most important urban form factors in various scenarios, and provide reasonable explanations. In Section 4, we discuss composite urban form schemes which benefit the air quality most and offer relevant suggestions and avenues for future study. Finally, in Section 5, we present the conclusions.

2. Literature review(2)(3)(4)(5)

An increasing number of studies have explored the relationship between air quality and urban form (Fan et al., 2018; Lee, 2019a, 2019b; Li & Zhou, 2019; Li et al., 2021; Lu & Liu, 2016; Martins, 2012; Mou et al., 2018; Schweitzer & Zhou, 2010; Stone, 2008; Yuan et al., 2018; see Appendix A in the Supplementary Material). Some of the main findings of these studies are summarized in this section.

(1) Indicators that represent urban size, shape, fragmentation, compactness, and sprawl are mostly correlated with emission, dispersion, and concentration of air pollution. Scholars have confirmed a modest, but important, role of urban form in contributing to better air quality (Yuan et al., 2018).

(2) Urban form affects air quality in various ways, and different studies have reported different effects. Some studies state that less sprawling, more compact, and more contiguous cities have good air quality (Beckie et al., 2011; Martins, 2012; Schweitzer & Zhou, 2010; Stone, 2008), while other studies report that more scattered, less contiguous, and polycentric cities have better air quality (Li & Zhou, 2019; Yuan et al., 2018). Inconsistencies in results may be due to differences in study areas and periods. For example, because of their different stages of development, urban areas in American and European cities are much larger than those in Chinese cities with similar population sizes (Huang et al., 2007). As a result, high urban contiguity may be related to low vehicle use and, hence, less air pollution (Hou et al., 2018). Also, many Chinese cities are constructed along rivers and mountains. As such, they have less compact and polycentric urban forms. These urban forms benefit the dispersion of air pollution and reduce commuting distances, which can improve air quality (Loo & Chow, 2011). Hence, when urban planners explore the relationships between air quality and the effects of urban form, the city's basic layout and development phase should be considered. Moreover, specific indicators unique to the study area, such as population, socio-economic conditions, and meteorological factors, should also be considered.

(3) Developing countries have enjoyed the benefits of rapid urban development and have also faced serious environmental problems. Although early studies of the relationship between air quality and urban form focused on developed countries, a growing number of studies focus on developing countries (Li & Zhou, 2019). As the largest developing economy, China has created a “Chinese Miracle” in terms of socio-economic development. However, air pollution has accompanied this rapid development. Using China as a case study to analyze the impacts of urban form on air quality may offer insights that are useful to both developing and developed countries.

(4) Most studies have applied linear regression and spatial econometric models to the research topic. These standard methods have provided relatively robust conclusions about the effects of urban form on air quality (i.e., a compact city results in a low concentration of air pollution). However, they have not adequately explored dynamic relationships between air quality and urban form, such as whether cities expand or shrink, does air quality get better or worse, are there optimal urban sizes, shapes, and/or characteristics that lead to good air quality. Owing to the complex nature of the relationship, a few studies have begun to consider non-linear correlations (Tian et al., 2020). The present study applies a rarely-used method to take a novel approach in this familiar research field. Machine learning approaches have become popular in recent years. One widely-used method, the RF, is good at improving estimation accuracy and analyzing the importance of specific indicators (Cheng et al., 2020; Yang et al., 2020). One of the purposes of the study was to explore the relative importance of each urban form variable on air quality. To this end, the RF method was chosen because it can quantify the relationships between dependent and independent variables.

(5) As the COVID-19 pandemic has spanned the globe, a wide range of studies have emerged concerning the society’s reactions. The outbreak of the COVID-19 pandemic has highlighted...
environmental issues and changes in urban development. As there is limited research on air quality and urban form in the context of the COVID-19 pandemic, the present study seeks to expand research in this context, thereby empowering policymakers, urbanists, and environmentalists to better align urban development strategies with the alleviation of air pollution.

In summary, the COVID-19 pandemic provides a unique opportunity to analyze the effects of urban form on air quality to reveal new relationships. Before the quantitative analysis is presented, current literature on the impacts of urban form on air quality is reviewed and a framework is outlined (Fig. 1). As illustrated in Fig. 1, the relationship between air quality and urban form is complex. Different urban forms may have different influences on air quality during the emission, dispersion, and concentration processes of air pollution. Hence, using only one or two indicators to represent urban form may be inadequate.

### Urban form

| Urban size | Large | Small | a. Urban build-up area |
|------------|-------|-------|-----------------------|
| Urban shape | High | Low |
| Urban compactness/sprawl | High | Low |
| Urban fragmentation | High | Low |
| Morton type | Residential buildings |
| GDP |
| Air quality |

### Control variables

| Meteorological indicators |
|---------------------------|
| Temperature |
| Wind |
| Precipitation |

| Socio-economic indicators |
|---------------------------|
| Population |
| GDP |

### Air quality

| Emissions | Point source air pollution |
|------------|---------------------------|
| Factories |
| Power plants |
| Residential buildings |

| Non-point source air pollution |
|--------------------------------|
| Automobiles |
| Trains |
| Vessels |

### Research purpose:

Analyzing the effects of urban form on air quality before and during the COVID-19 pandemic.

Which urban Size Shape Fragmentation Compactness Good air quality
Analyzing a range of urban form factors and examining the relative importance of each could offer a better understanding of the influences of urban form on air pollution. The aim is to obtain a composite urban form design scheme that contributes to good air quality. In addition, we investigate the different effects of urban form on air quality by incorporating control variables when two major air pollution emission sources are largely excluded.

3. Data and methods

3.1. Data sources

The study sample comprised 62 prefecture-level Chinese cities. The sampling period was February–March 2020. In the first three months of 2020, COVID-19 spread on a massive scale with inadequate response measures. Hence, the study period was the height of the early days of the COVID-19 pandemic. Meanwhile, data from February–March 2015 were used for comparison. The 62 cities are distributed in Jiangsu, Zhejiang, Jiangxi, Hubei, and Hunan Provinces (see Fig. 2). The main reasons for choosing these cities were their data availability and suitability for comparative analysis. Additionally, the selected cities had complete available data, while data for most other cities were not yet fully published. In particular, the selected cities had available urban form data from 2020, which is key to this study. Further, the study area included cities from Hubei Province, which was the worst-affected region in China during the COVID-19 pandemic at that time. The study area including Hubei cities is representative. Moreover, urban forms, such as land uses, city patterns, and transportation networks, are unlikely to change significantly in a relatively short time-period. Hence, an appropriate period was considered. In the study, a 5-year time span is selected to measure the transformation of cities. The specific data are described as follows.

3.1.1. Air quality data

According to existing studies, various air quality parameters were chosen as dependent variables (see Appendix A). The main indicator used is the air quality index (AQI), a dimensionless indicator used to evaluate air quality based on the concentrations of six pollutants (PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, O$_3$, CO). A high value of AQI refers to a high concentration of air pollution. The AQI is formulated as follows:

$$AQI = \max \{I_1, I_2, \ldots, I_p, \ldots, I_6\}$$  

$$I_p = \frac{l_{\text{high}} - l_{\text{low}}}{C_{\text{high}} - C_{\text{low}}} (C_p - C_{\text{low}}) + l_{\text{low}}$$

where $I_p$ represents the air quality sub-index of pollutant $p$; $C_p$ denotes the concentration of pollutant $p$; $C_{\text{high}}$ is the concentration breakpoint higher than $C_p$ and $C_{\text{low}}$ is the concentration breakpoint lower than $C_p$; $l_{\text{high}}$ and $l_{\text{low}}$ are the index breakpoints corresponding to $C_{\text{high}}$ and $C_{\text{low}}$, respectively.

All the air quality data (AQI, PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, O$_3$, CO) were hourly real-time observations released by the National Urban Air Quality Real-time Publishing Platform of China. All hourly data were converted to monthly data.

3.1.2. Urban form data

Urban form data were selected as independent variables. Urban form is defined as the size, shape, density, and layout of a city. Based on related literature (see Table 1), all these factors are correlated with the level of air quality. Many proxies can represent urban size, shape, fragmentation, continuity, compactness, and sprawl (see Appendix A, Fig. 1). However, we used total urban built-up area (TA), urban area percentage of landscape (PLAND), landscape shape index (LSI), compactness ratio (CR), largest patch index (LPI), number of urban patches (NP), mean urban patch area (MPA), population density (PD), road density (RD), and aggregation index (AI). The definitions of these urban form variables are presented in Table 1.

The indicators TA, PLAND, LSI, CR, LPI, NP, MPA, and AI were calculated using Fragstats 4.2 and ArcGIS 10.2 software. First-hand data were collected from land use cover data from 2015 and 2020. The land use cover data were based on remote-sensed monitoring of land use and were obtained from the Resource and Environment Science and Data Center at the Chinese Academy of Sciences. The land use cover data were raster data with a $1 \times 1$ km spatial resolution. In addition, the population and urban road area data used to calculate PD and RD were obtained from the China City Statistical Yearbook, provincial statistical yearbooks, and the statistical bulletins of prefecture-level cities. As these data were not published for 2020, data at the end of 2019 were used as an alternative. Also, to maintain consistency of data measurement, data from 2014 were selected.

3.1.3. Control variables

Previous studies have argued that some meteorological and socioeconomic indicators are strongly associated with air quality (Fan et al., 2018; Li & Zhou, 2019; McCarty & Kaza, 2015; Mou et al., 2018; Tian et al., 2019; Yuan et al., 2018). These indicators influence air quality and indirectly relate to urban form. Controlling them can provide a better statistical assessment of the correlation between air quality and urban form. In this study, temperature (TEMP), wind speed (WIND), and total population (POPUL) were selected as control variables. The economic indicator was omitted because accurate monthly data were challenging to obtain. Temperature and wind speed data were calculated from monthly averages from 2015 and 2020 obtained from the National Meteorological Administration in China (http://data.cma.cn/). The data on the total population were obtained from provincial statistical yearbooks.

The dependent variables were conversely different in 2015 and 2020, and these differences were tested using independent $t$-tests, the results of which are presented in Table 2. The descriptive statistics of the dependent, independent, and control variables in 2015 and 2020 are shown in Table 3.

3.2. Method

3.2.1. Random forest (RF)

The RF method is a machine learning algorithm (Breiman, 2001) employed to analyze the relationships between air quality and urban form. It was widely applied in many fields to predict the performance of dependent variables and calculate the significance of each independent variable (Cheng et al., 2019; Jeung et al., 2019; Oliveira et al., 2012; Pourghasemi et al., 2020; Zahedi et al., 2018). The RF method has the advantage of solving both regression and classification problems and improving model interpretability by quantifying the relative importance of independent variables (Cheng et al., 2020). The RF working process is illustrated in Fig. 3.

There are three key parameters in the RF method: the number of decision trees, the number of splitting features at the decision tree node, and the maximum depth of decision trees. In each single decision tree, splitting features are continually generated until the decision tree reaches the maximum depth. Then, the optimal parameters are obtained and the best RF model is exported. Meanwhile, the RF model will not become overfitted when the number of decision trees grows appropriately and the bootstrapping is used with a randomized subset (Breiman, 2001; Díaz-Uriarte & Alvarez de Andrés, 2006; Peters et al., 2007). The formula of the RF method is expressed as follows:

$$\hat{f}(x) = \frac{1}{N} \sum_{n=1}^{N} R(x)$$

where $N$ is the number of decision trees, $R(x)$ is the result in each decision tree, and $\hat{f}(x)$ is the final result of the RF model.
The $R^2$ coefficient and root mean square error (RMSE) are applied to evaluate the performance of the RF model according to:

$$R^2 = 1 - \frac{\sum_{i=1}^{m} (A_i - B_i)^2}{\sum_{i=1}^{m} (A_i - \bar{A})^2}$$  

(4)

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (A_i - B_i)^2}$$  

(5)

where $A_i$, $B_i$, and $\bar{A}$ are the observed values, predicted values, and the average of the observed values, respectively.

The feature importance measure of the RF method is generally employed in calculating variable importance. Moreover, the relationships between the dependent and independent variables were examined by partial dependence analysis (Hastie et al., 2009). In this study, partial dependence refers to the marginal effect of one urban form variable on air quality while controlling for the average effects of all other urban form variables. The partial dependence is measured as follows:

$$\hat{f}(x_a) = \frac{1}{M} \sum_{k=1}^{M} \sum_{n=1}^{N} \hat{f}(x_{1b}, x_{2b}, \ldots, x_{Mb})$$  

(6)

where $x_a$ is a certain independent variable while ($x_{1b}, x_{2b}, x_{3b}, \ldots, x_{Mb}$) are the other independent variables and $M$ is the number of instances. The formula depicts the partial dependence of $\hat{f}(x_a)$ on $x_a$.

3.2.2. Multiple linear regression (MLR)

Both the non-linear (RF) and linear (MLR) models are applied. By doing this, different models’ predictive ability and accuracy are compared. In this study, the results of an MLR model are tested for comparison (Ma et al., 2020). The general form of the MLR model can be expressed as follows:

$$y = a_1 x_1 + a_2 x_2 + \cdots + a_n x_n + \varepsilon$$  

(7)

where $a$ is a regression coefficient and $\varepsilon$ is the error term.

The results of the RF and MLR methods are presented in the next section.

4. Results

4.1. Comparison of air quality in 2015 and 2020

According to air quality data from 2015 and 2020, the change in air quality before and during the COVID-19 pandemic is depicted in Fig. 4. It can be seen that the overall air quality improved significantly when China was at the peak of the COVID-19 crisis. The average AQI value decreased from 89.52 to 51.52, which indicates a lower air pollution concentration from 1 February to 31 March 2020 compared with 2015. Specifically, the concentrations of PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, and CO dropped by 42.45 %, 47.13 %, 49.94 %, 68.07 %, and 40.74 %, respectively, while that of O$_3$ increased by 23.02 % compared with 2015. The reduction in NO$_2$ was the most prominent, which is associated with the sharp decrease in vehicle travel and the closing of non-essential small- and medium-sized enterprises.

However, the Chinese government has made great efforts to improve air quality during 2015–2020, and overall air quality has improved in the past few years. Hence, it is difficult to be sure that the COVID-19 pandemic is the predominant cause of the reductions in the emission, dispersion, and concentration of air pollution in 2020. When selecting 2018 as a comparison year, it can be seen that although the average AQI
Table 1
Urban form variables used for analysis.

| Variable          | Measurement | Description | Interpretation |
|-------------------|-------------|-------------|----------------|
| Total urban built-up area (TA) | $\frac{\sum \text{a}(p)}{\text{i} \in \mathbb{C}}$ | is the city, $p_i$ is the urban patch, $a(p)$ is the urban patch area. | TA measures the size of urban area. High TA reflects a large urban built-up area. |
| Urban area percentage of landscape (PLAND) | $\text{PLAND} = \frac{\text{TA}}{\text{LA}}$ | LA is the total landscape area. | LA measures the urban size. High LA indicates a high urban build-up ratio. |
| Landscape shape index (LSI) | $\text{LSI} = \frac{e_i}{\text{min}_i}$ | $e_i$ is the total length of urban patch edges, $\text{min}_i$ is the minimum value of $e_i$. | LSI measures the urban shape. High LSI means a complex urban form. |
| Compactness ratio (CR) | $\text{CR} = \frac{P}{\text{TA}}$ | $P$ is the urban perimeter. | CR measures the complexity of urban shape. High CR reflects a less compact urban form. |
| Largest patch index (LPI) | $\text{LPI} = \frac{\text{max}(p_i)}{\text{TA}}$ | $p_i$ is the maximum value of urban patch areas. | LPI measures urban fragmentation. High LPI indicates a highly fragmented urban form. |
| Number of urban patches (NP) | $\text{NP} = \frac{n}{\text{TA}}$ | $n$ is the number of urban patches. | NP measures urban fragmentation. High NP means a highly fragmented urban form. |
| Mean urban patch area (MPA) | $\text{MPA} = \frac{\text{TA}}{\text{RF}}$ | MPA is the average area of urban patches. | MPA measures urban fragmentation. High MPA reflects a highly fragmented urban form. |
| Population density (PD) | $\text{PD} = \frac{\text{POP}_{\text{u}}}{\text{TA}}$ | $\text{POP}_{\text{u}}$ is the urban population, $\text{TA}$ is the urban built-up area. | PD measures urban compactness. High PD indicates a compact urban form. |
| Road density (RD) | $\text{RD} = \frac{R_i}{\alpha}$ | $R_i$ is the urban road area. | RD measures urban compactness. High RD means a compact urban form. |
| Aggregation index (AI) | $\text{AI} = \frac{m}{\text{TA}}$ | $m$ is the urban patch aggregation level. | AI measures urban sprawl. High AI indicates a compact urban form. |

Table 2
Independent t-test results of differences between dependent variables in 2015 and 2020.

| Variable | Equal variances assumed? | Levene’s test for equality of variances | t-Test for equality of means |
|----------|--------------------------|--------------------------------------|-----------------------------|
|          | F           | P         | $t$  | df | $P$ (2-tailed) |
| AQI      | Yes         | 19.811    | 0.000 | 12.794 | 122 | 0.000 |
|          | No          | 12.794    | 87.068 | 0.000 |
| PM$_{2.5}$ | Yes        | 17.846    | 0.000 | 12.800 | 122 | 0.000 |
|          | No          | 12.800    | 88.478 | 0.000 |
| PM$_{10}$ | Yes        | 39.311    | 0.000 | 13.970 | 122 | 0.000 |
|          | No          | 13.970    | 76.289 | 0.000 |
| SO$_2$   | Yes         | 38.491    | 0.000 | 14.902 | 122 | 0.000 |
|          | No          | 14.902    | 78.023 | 0.000 |
| NO$_x$   | Yes         | 22.835    | 0.000 | 9.806  | 122 | 0.000 |
|          | No          | 9.806     | 96.430 | 0.000 |
| O$_3$    | Yes         | 0.072     | 0.788  | -5.404 | 122 | 0.000 |
|          | No          | -5.404    | 119.860 | 0.000 |
| CO       | Yes         | 18.885    | 0.000 | 8.233  | 122 | 0.000 |
|          | No          | 8.233     | 94.410 | 0.000 |

4.2. Random forest modeling and validation

A total of 14 variables, including AQI (PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_x$, O$_3$, CO), TA, PLAND, LSI, CR, LPI, NP, MPA, PD, RD, AI, TEMP, WIND, and POPU, were chosen for RF model training. The model performance was validated according to the data partitioning rule (a random one-third of the dataset was used as the testing set, while the other two-thirds formed the training set). In the study, RF regression was carried out based on the Python platform using the sklearm module. The RF model was first developed by setting the number of decision trees from 5 to 400; then, different combinations of the number of splitting features and the maximum depth of the decision trees were trialed with the other parameters kept at their default values. After several debugging processes, the optimal specification of the RF was obtained.

Meanwhile, to avoid overfitting, a cross validation (CV) technique was applied (Cheng & Ma, 2015; Ma & Cheng, 2016). A threefold CV means that the dataset will be randomly separated into three portions without replacement, two of which are employed for training while the remaining one is used for testing. Then, the model is trained and tested for three rounds until all the data samples are tested once. By calculating numbers in line with an n-fold CV, the study’s results will be less biased and overfitted.

The non-linear and linear model evaluation results are presented in Table 4. The results indicate that the RF model was better in estimating the outcomes of air pollution as its $R^2$-value was higher. Taking AQI for instance, the $R^2$-value of the RF model was 0.692 in 2015 and 0.633 in 2020, while the $R^2$-values of the linear regression model were 0.547 and 0.539, respectively. Moreover, the RF model had a lower predictive error as the RMSE-values were smaller than the linear regression model. It is not an unexpected result because the RF method can detect more complex relationships by randomly selecting training data.

4.3. Relative importance of variables to air quality

The relative importance of urban form and control variables to air quality in 2015 and 2020 are presented in Table 5. The main results can be summarized as follows:

1. For the AQI and particulate air pollution (PM$_{2.5}$ and PM$_{10}$), the most important influencing variable was temperature in both 2015 and 2020, and not urban form variables. The contribution of temperature was $>30\%$. The result indicates that meteorological factors are essential in this case. Many studies have also revealed that the formation and concentration of air pollution are strongly associated with temperature (Chen, Chen, et al., 2020; He et al., 2017). However, the relative importance of temperature does not mean the urban form has no impact on air quality. It only confirms the prominent role of temperature even when air pollution emissions are massively reduced. The effects of urban form on air quality still need discussion. Fig. 5 describes the relative importance of urban form factors to AQI when removing control variables.

In 2015, the top three most important variables of urban form affecting AQI were MPA, RD, and PD. They represent urban fragmentation and compactness. In 2020, the three most important urban variables were RD, CR, and PLAND, which are proxies of urban compactness, shape, and size, respectively. Although the value decreased between 2015 and 2018, the rate of decrease is less than that from 2018 to 2020. Similarly, the concentrations of PM$_{2.5}$ and PM$_{10}$ decreased greatly after the outbreak of the pandemic and NO$_x$ increased slightly in 2018. The pandemic lockdowns made 2020 an unusual year and were a key influence on air pollution levels. Hence, this should be taken into consideration when conducting similar studies. Based on these results, we continued to investigate the effects of urban form on changes in air quality.
Random Forest

Data training

Dependent variables (Air quality)

Independent and control variables (Urban form)

Data are randomly divided into training data for learning and testing data for testing the learning level.

Model training

Decision trees in random forest are created and grow from the dataset by using bootstrapping and random feature selection method.

Train and calibrate the random forest model in each decision tree until the optimal model is generated with the best parameter setting.

Multiple decision trees in random forest are combined and the final result is obtained by using a majority voting.

Model evaluation

R² and root mean square error (RMSE) are calculated.

The importance of each variable is estimated.

The relationship between air quality and urban form is presented by partial dependence plot.

Fig. 3. Working process of the RF method.

studies have verified the significant impacts of urban size, shape, fragmentation, and compactness on air quality (Li & Zhou, 2019; She et al., 2017), some new findings may be discovered after the outbreak of the COVID-19 pandemic.

Urban compactness or urban sprawl had a pivotal influence on air quality before and during the COVID-19 pandemic. However, urban fragmentation was not a key impact on air quality when air pollution emissions were cut substantially. Instead, the effects of the original size and shape of cities became obvious. The possible explanations are: compact or scattered cities affect the dispersion and concentrations of air pollution even when the sources of air pollution are controlled; on the other hand, the reduced air pollution emissions indicate that the traveling and influencing paths of air pollutants were decreased simultaneously. Thereby, the urban fragmentation associated with levels of transportation use and trip lengths (Yuan et al., 2018) is not a major consideration. Its relatively important role is replaced by urban size and shape. During the COVID-19 pandemic, urban size and shape rather than urban fragmentation may have had more significant impacts on air quality by alleviating the dispersion and concentrations of point-source air pollution.

(2) For the SO₂ and NO₂ pollutants, the most important influence in 2015 was urban size. This demonstrates that the city scale is essential in evaluating air quality in terms of these two specific air pollutants. However, in 2020, the most important influence was urban shape for SO₂ pollutants, the most important influence in 2015 was urban size. This demonstrates that the city scale is essential in evaluating air quality in terms of these two specific air pollutants. However, in 2020, the most important influence was urban shape for SO₂. These changes indicate that urban form is still the most important factor when measuring air quality, while urban size is not a priority. There may be two reasons for this. First, based on the collected urban form data, the urban sizes in 2020 were obviously larger than those in 2015, which means that more complex urban forms would be generated during the expansion of cities. Hence, the important effects of urban size on air quality may be reduced. Second, the shutdown of factories and transportation restrictions led to massive reductions in SO₂ and NO₂ emissions in 2020. Both large- and small-sized cities enjoyed nearly zero-discharge of air pollution. Hence, urban size exerted its effect on air pollution dispersion and concentrations. For SO₂, the urban shape was a

![Table 3](https://example.com/table3.png)

| Type | Variable | Unit | Count | Maximum | Minimum | Mean | Std. deviation |
|------|----------|------|-------|---------|---------|------|---------------|
| Air quality (dependent variables) | AQI | / | 62 | 144.28 | 79.11 | 51.79 | 34.34 |
| | PM₂.₅ | µg/m³ | 62 | 107.17 | 54.35 | 32.6 | 17.07 |
| | PM₁₀ | µg/m³ | 62 | 153.16 | 80.26 | 49.97 | 31.01 |
| | SO₂ | µg/m³ | 62 | 42.17 | 18.86 | 6.26 | 2.87 |
| | NO₂ | µg/m³ | 62 | 55.67 | 31.23 | 18.38 | 9.87 |
| | CO | mg/m³ | 62 | 2.29 | 1.38 | 0.69 | 0.46 |
| Urban form (independent variables) | TA | km² | 62 | 831 | 1628 | 12 | 25 |
| | PLAND | % | 62 | 10.77 | 18.84 | 0.1 | 0.1 |
| | LSI | / | 62 | 12.12 | 11.95 | 2.86 | 3 |
| | CR | / | 62 | 37.62 | 36.79 | 28.46 | 26.98 |
| | LPI | / | 62 | 5.02 | 10.13 | 0.03 | 0.03 |
| | NP pieces | | 62 | 115 | 100 | 4 | 4 |
| | MPA | km² | 62 | 15.8 | 24.86 | 1.71 | 2.08 |
| | PD | persons/ha | 62 | 613.42 | 552.93 | 89.8 | 86.52 |
| | RD | % | 62 | 23.81 | 45.49 | 5.93 | 6.75 |
| | AI | / | 62 | 68.54 | 74.34 | 15.79 | 25 |
| Control variables | TEMP | °C | 62 | 13.87 | 14.53 | 6.43 | 8.25 |
| | WIND | m/s | 62 | 3.21 | 3.38 | 1.81 | 1.43 |
| | POPU | persons | 62 | 1057.87 | 1121.2 | 105.88 | 105.97 |
better predictor of air pollution level than urban size. NO\textsubscript{2}, the main pollutant in vehicle emissions, was more related to urban continuity.

(3) For the O\textsubscript{3} and CO pollutants, the most important variables changed from meteorological factors to urban forms. In 2015, wind speed was most important, while in 2020, the most important attributes were urban size for O\textsubscript{3} and urban fragmentation for CO. This transformation indicates that urban form variables exerted more influence than climatic ones on the pollution levels of O\textsubscript{3} and CO when air pollution emissions were reduced.

In conclusion, the relative importance of various variables to air quality indeed changed in 2020 compared with that in 2015. Due to the reduction in air pollution emissions, variables that affected air pollution dispersion and concentrations were more important. However, different air pollutants may respond differently to various urban forms and meteorological variables (Satî & Mohan, 2021; Schweitzer & Zhou, 2010), which reminds urban planners to consider the real situations of cities when formulating urban design plans with consideration of air purification. For example, the AQI refers to the overall air quality based on six pollutants. As such, the effects of urban form on AQI may differ from that on a particular type of air pollution. A lower AQI value should be considered for the whole city’s urban form. However, when aiming to

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**Table 4**

Comparison of the $R^2$ and RMSE values of the RF and linear regression models.

| Variable | RF model | | | | Linear regression model | | | |
|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|          | $R^2$    | RMSE     | $R^2$    | RMSE     | $R^2$    | RMSE     | $R^2$    | RMSE     |
| AQI      | 0.692    | 0.633    | 11.643   | 6.018    | 0.547    | 0.539    | 16.038   | 7.661    |
| PM\textsubscript{2.5} | 0.692    | 0.538    | 9.121    | 5.447    | 0.501    | 0.469    | 13.197   | 6.641    |
| PM\textsubscript{10} | 0.636    | 0.628    | 15.586   | 5.619    | 0.521    | 0.653    | 7.298    | 3.512    |
| SO\textsubscript{2} | 0.528    | 0.691    | 5.306    | 1.621    | 0.0599   | 0.0302   | 0.1543   | 0.0616   |
| NO\textsubscript{2} | 0.698    | 0.799    | 2.999    | 2.352    | 0.0278   | 0.2014   | 0.0119   | 0.0642   |
| O\textsubscript{3} | 0.574    | 0.540    | 0.245    | 0.139    | 0.145    | 0.297    | 0.395    | 0.196    |
| CO       | 0.596    | 0.606    | 7.303    | 6.302    | 0.347    | 0.637    | 10.552   | 6.881    |

Note: Numbers in bold type represent the most important variables in the category.

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**Table 5**

Relative importance of urban form and control variables in 2015 and 2020.

| Variable | AQI | PM\textsubscript{2.5} | PM\textsubscript{10} | SO\textsubscript{2} | NO\textsubscript{2} | O\textsubscript{3} | CO |
|----------|-----|----------------------|---------------------|-------------------|-----------------|-----------------|----|
|          | 2015 | 2015 | 2020 | 2015 | 2015 | 2015 | 2020 | 2015 | 2020 | 2015 | 2020 | 2015 | 2020 | 2015 | 2020 | 2015 | 2020 | 2015 | 2020 | 2015 | 2020 |
| TA       | 0.0052 | 0.0331 | 0.0451 | 0.1044 | 0.0174 | 0.0320 | 0.0716 | 0.0500 | 0.2748 | 0.1218 | 0.0276 | 0.1190 | 0.0652 | 0.0765 |
| PLAND    | 0.0158 | 0.0509 | 0.0167 | 0.0451 | 0.0302 | 0.0033 | 0.1610 | 0.0380 | 0.0701 | 0.2286 | 0.0308 | 0.0994 | 0.0810 | 0.0981 |
| LSI      | 0.0071 | 0.0325 | 0.0576 | 0.0723 | 0.0217 | 0.0201 | 0.0361 | 0.2888 | 0.0111 | 0.0064 | 0.0055 | 0.0895 | 0.0792 | 0.0736 |
| CR       | 0.0330 | 0.0692 | 0.1120 | 0.0479 | 0.0248 | 0.0010 | 0.1260 | 0.0871 | 0.00599 | 0.0302 | 0.1543 | 0.0616 | 0.0649 | 0.0853 |
| LPI      | 0.0170 | 0.0163 | 0.0203 | 0.0207 | 0.0140 | 0.0432 | 0.1379 | 0.0294 | 0.0278 | 0.2014 | 0.0119 | 0.0642 | 0.0678 | 0.0533 |
| NP       | 0.0298 | 0.0252 | 0.0123 | 0.0151 | 0.0268 | 0.0563 | 0.0780 | 0.1681 | 0.0205 | 0.0070 | 0.1142 | 0.0903 | 0.0173 | 0.0646 |
| MPA      | 0.0708 | 0.0355 | 0.0408 | 0.0428 | 0.0401 | 0.0102 | 0.2888 | 0.0190 | 0.1838 | 0.2337 | 0.0381 | 0.0986 | 0.0397 | 0.1130 |
| PD       | 0.0557 | 0.0447 | 0.0681 | 0.0274 | 0.0444 | 0.0551 | 0.0508 | 0.0802 | 0.0036 | 0.0430 | 0.0023 | 0.0501 | 0.0462 | 0.0640 |
| RD       | 0.0655 | 0.0832 | 0.0488 | 0.0711 | 0.0546 | 0.0375 | 0.0839 | 0.0587 | 0.0402 | 0.0078 | 0.0428 | 0.0430 | 0.0441 | 0.0786 |
| AI       | 0.0196 | 0.0068 | 0.0614 | 0.0671 | 0.1140 | 0.0069 | 0.0418 | 0.0258 | 0.1242 | 0.0487 | 0.0262 | 0.0572 | 0.1663 | 0.1080 |
| TEMP     | 0.5073 | 0.5119 | 0.3241 | 0.3463 | 0.3807 | 0.4805 | 0.0664 | 0.0296 | 0.1178 | 0.0242 | 0.1067 | 0.0838 | 0.1153 | 0.0559 |
| WIND     | 0.1375 | 0.0652 | 0.1349 | 0.0939 | 0.1769 | 0.0873 | 0.0453 | 0.0378 | 0.0195 | 0.0265 | 0.3351 | 0.0894 | 0.1939 | 0.0747 |
| POPU     | 0.0196 | 0.0258 | 0.0579 | 0.0401 | 0.0544 | 0.1365 | 0.0724 | 0.0877 | 0.0507 | 0.0206 | 0.0447 | 0.0537 | 0.0192 | 0.0543 |

Note: Numbers in bold type represent the most important variables in the category.
reduce a specific air pollutant (i.e., PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, O$_3$, CO, etc.) in a particular area, the urban form that helps to alleviate the emission, dispersion, and concentration of that pollutant should be considered. It is worth noting that urban designs should be flexible and targeted to contribute to the comprehensive and balanced development of cities.

4.4. Relationship between air quality and urban form

According to existing research, urban size, shape, fragmentation, and compactness have various effects on air quality, which indicates that these effects are not permanent (Jung et al., 2022; Li et al., 2022; Liu et al., 2022). At different spatial scales, such as the metropolitan-level and road-level, the influences of urban forms on air pollution emissions and concentrations are varied (Lee, 2019b). Moreover, air quality correlates to different urban form variables but in complex ways. In one case, compactness-oriented urban development was optimal in terms of improving air quality (Lee, 2019a); while in another case, scattered and polycentric urban forms (Li et al., 2021) were more suitable for reducing air pollution. Hence, examining the dynamic relationship between air quality and urban form is necessary if urban planners and decision-makers are to establish appropriate urban development policies.

The partial dependence analysis demonstrated a complex relationship between air quality and urban form (see the partial dependence plots in Fig. 6). The y- and x-axes represent the distribution of dependent and independent variables, respectively. In each single plot, the impacts of one urban form variable on air quality are presented while controlling for other urban form variables. The dependent variable AQI and the urban form variables that influenced AQI the most in 2015 and 2020.
(MPA, PD, RD, CR, and PLAND) were selected for fine-grained analyses. In 2015, the most crucial variable affecting air quality was the mean patch area (MPA), representing urban fragmentation. MPA values of 1–3 km² were observed to positively impact AQI. The results align with previous findings (McCarty & Kaza, 2015; Yuan et al., 2018); fragmented cities are not conducive to good air quality. However, as the value of MPA gradually increases, high urban fragmentation becomes a less adverse factor. Typically, high fragmentation will lead to high automobile use and greater air pollution emissions. Meanwhile, high fragmentation means low continuity. Urban forms with low continuity promote airflow and wind velocity, resulting in lower air pollution concentrations (Hang et al., 2009; Taseiko et al., 2009). At an MPA value of 4 km², the negative impacts of high urban fragmentation on air quality become apparent again. In general, in a normal year, the effects of low fragmentation and high continuity in a city contribute to better air quality, but the continuous layout of a city may obstruct air circulation and lead to poor air quality. In the special year of 2020, the overall MPA-value was higher than that in 2015; however, MPA had a lesser effect on air quality. Due to the reduction in air pollution emissions, mainly vehicle emissions, MPA exerted a lesser influence on air quality. However, it can still be concluded that a better mean urban patch area is associated with lower air quality.

Population density (PD) and road density (RD) indicate urban compactness or sprawl, and were relatively important influences on air quality in 2015, although their effects fluctuated. At urban population densities < 300 persons/ha and urban road area ratios of approximately 14 %, the AQI-value kept decreasing and good air quality was obtained. High PD and RD values represent high urban compactness. In most cases, a compact urban form contributes to good air quality (Bereitschaft & Debbage, 2013; Fan et al., 2018) because dense, compact urban areas generally have less vehicle travel and more public transit (Boyko & Cooper, 2011). A decrease in private car dependence and increase in public transport use can reduce NO emissions (the majority of NO is emitted by automobiles) and improve air quality (Sun et al., 2019). However, when the PD- and RD-values reach a certain threshold, cities with dense populations and roads will suffer from higher air pollution concentrations and experience fluctuations in air quality. Such results have been proven in some studies. Cárdenas Rodríguez et al. (2016) pointed out that cities with high PD produce more SO₂, mainly from residential areas with large populations. Borck and Schrauff (2021) also reported that a higher population density results in lower local air quality. Meanwhile, high road densities inevitably bring more vehicles and traffic congestion is associated with greater air pollution (Calderón-Garcidueñas & Villarreal-Ríos, 2017). The COVID-19 pandemic brought traffic to a halt. As a result, a high population density led to poor air quality, while high road density led to good air quality in 2020. Air quality was most affected by RD, which also shows that traffic emits a large proportion of air pollution. The stagnation of traffic lowered the AQI dramatically.

The effects of urban size (PLAND) and urban shape (CR) on air quality presented similar trends in 2015 and 2020. Generally, small cities have good air quality; however, this study draws the opposite conclusion. A possible explanation is that during the expansion of cities, the area of urban green space and investment in environmental facilities increases (Xu et al., 2020). Consequently, more environmentally-friendly land use actively impacts air quality (Halim et al., 2020). When urban development reaches a relatively mature level, air quality also stabilizes at a certain level. As for the impacts of urban shape on air quality, some relationships were found. More air pollution will concentrate when a city forms a non-compact shape (high CR value). Consistent with many studies, the results demonstrate that a compact urban shape is beneficial to air quality. Nevertheless, a scattered urban shape is not always detrimental to air quality. As outlined in Fig. 6, high CR-values can lead to low AQI-values. Hence, scattered and polycentric urban shapes are encouraged in practice (Loo & Chow, 2011).

In a nutshell, the fact that different air quality levels are related to various urban forms prompted us to explore urban planning in detail to reduce air pollution. In the next section, composite urban form design schemes will be provided.

5. Discussion

Although the relationship between air quality and urban form requires long-term and continuing study, careful consideration should be given to the fact that the effects of urban form are comparable to those of other factors, such as meteorological conditions. Combining the results of the relative importance of urban form on AQI, the partial dependence of AQI on urban form, and existing studies, composite urban form design schemes can be made (see Fig. 7).

It can be argued that different urban forms result in different air quality levels by affecting the emission, dispersion, and concentration of air pollution. No one urban form contributes to good air quality, and a suitable urban form in one city may not benefit another. Good urban planning derives from a trade-off between various urban forms. Before the COVID-19 pandemic, a continuous, compact urban form with proper population and road densities and consideration of appropriate building layouts could greatly reduce air pollution. Continuity and compactness of urban form are the priorities when good air quality is the goal. During the COVID-19 pandemic, the critical factor adversely affecting air quality—the traffic rate—was removed, and the effects of urban form on air quality showed some differences. Urban size, shape, and compactness became important urban form variables. In other words, in this large-scale “natural experiment,” the original size, shape, compactness level, and development pattern of cities impacted air quality the most. Although air quality improved in 2020, regular, compact cities with high coverage of forest area and proper road densities still had better air quality than other cities.

The phenomenon conveys some information of interest to environmentalists, urban planners, and policy-makers considering the relationship between air quality and urban form in the post-pandemic era. First, automobile use is strongly associated with air quality. Limiting vehicle quantities, relieving traffic congestion, and promoting healthy and non-polluting activities like biking and walking can alleviate the adverse impacts of traffic on air quality. Second, urban forms that can reduce the dispersion and concentrations of traffic pollution are crucial to good air quality. On the one hand, non-frAGMENTED and compact urban forms that can reduce traffic distances are still preferred. On the other hand, the continuity and compactness level are not the only considerations; very high levels of them may produce negative effects. A reasonable building layout and population and road densities, increased urban green space, controlled urban expansion, and a polycentric development pattern are all beneficial to good air quality. Polycentric development patterns can reduce traffic volumes and reduce the dispersion distance of automobile pollution.

From previous studies, some similar conclusions are presented. For example, She et al. (2017) pointed out that polycentric urban forms with small areas were related to better air quality. Cárdenas Rodríguez et al. (2016) stated that fragmented and densely populated cities were associated with worse air quality. Bereitschaft and Debbage (2013) showed that lower levels of urban sprawl provided better air quality. However, the existing studies used linear models to indicate the urban form–air quality relationship. This study applied the non-linear model, which outperformed the linear models and could help consider the dynamic relationships between urban form and air quality and guide us to devise composite urban form design schemes in the post-pandemic era. In conclusion, urban development should not be implemented without the goal of improving air quality. Air-pollution reduction-oriented urban planning that can amplify the positive effects of urban form is a cost-effective method to improve air quality and make better living environments.

It is noted that the urban form schemes described in Fig. 7 were designed to improve the overall level of air quality in terms of AQI. It
drives a complete picture of the relationship between air quality and urban form. Intending to obtain more targeted urban planning, we now look further into the research to analyze the effects of urban form on specific pollution types (PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, O$_3$, CO, etc.). It is necessary to conduct follow-up studies, especially when a particular air pollution type reaches severe levels in a city. Fig. 8 puts forward the proposals for our further studies.

An urban form that can lead to better air quality in one area may not be a good choice for another area. Even the same urban form can have opposite effects on air quality in different air pollution types. As there is not a single perfect urban design plan that can exert only positive impacts of urban form on air quality, more research scales and spatial units should be included in future studies (see Fig. 8). A city will be divided into different areas. The relationship between air quality and urban form will be explored at the city level similar to the previous analyses. For a block-level analysis, the effects of specific urban form factors (fragmentation and compactness) on air quality will be examined. At the community level (residential or industrial area), apart from urban form factors, the shape, height, volume, and layout of buildings will be focused.

Only by analyzing the relationship between air quality and urban form from global and local perspectives can targeted urban planning be carried out. Specific policies should be formulated based on the fundamental conditions of each area, avoiding the blind adoption of an identical urban form design scheme. Moreover, meteorological factors must be considered. The critical impacts of urban form on air quality will be poorly estimated if key control variables like temperature and wind speed are omitted. Different urban form design schemes suited to the basic conditions of cities will make continuous contributions to good air quality.

It also raises some future study avenues. First, the study area should be expanded. In the present study, the 62 prefecture-level cities were all in southern China due to data restrictions. In a future study, we will collect air quality and urban form data from more Chinese cities with different climates and air pollution levels. Second, to conduct a well-structured study, we will extend our study by adding more comparison years, such as years between 2015 and 2020 and the year after the COVID-19 pandemic has finished. This will help to explore more dynamic and complex relationships between air quality and urban form. Third, the 1 × 1 km spatial resolution of the land use cover data could be increased to obtain more accurate analyses. Finally, as discussed above, multiple research levels and more study units should be included in future studies to accurately calculate the specific effects of urban forms on air quality.

6. Conclusions

The study explored the effect of a reduction in human activity on the relationship between urban form and air quality. We examined the influences of urban form on the emission, dispersion, and concentration of air pollution in the COVID-19 pandemic year and a non-pandemic year. The dynamic and complex relationships between air quality and urban form were explored by employing the RF method and using data from 62 prefecture-level Chinese cities obtained in 2015 and 2020.

The results demonstrate that the RF method was effective in addressing data variability. The relative importance of urban form variables changed when air pollution emissions decreased significantly. In 2020, the most important urban form variables associated with the AQI were RD, CR, and PLAN; while in 2015, they were MPA, RD, and PD. Hence, there is no single urban form that only has positive effects on air quality. Composite urban form design schemes that facilitate good air quality should be pursued. In general, the study confirmed that continuous and compact cities with reasonable building layouts and population and road densities, and high urban forest area ratios that after the COVID-19 pandemic, urban forms that can reduce the negative effects of transportations will be a priority.

Fig. 7. Composite urban forms before and during the COVID-19 pandemic.
expands in a moderate manner will have better air quality. This study also stressed the influences of traffic modes on air quality. Urban forms that reduce automobile use, travel distances, and traffic congestion contribute more to good air quality. Therefore, to improve overall air quality and reduce traffic pollution, a polycentric urban form that facilitates non-motorized transport is preferred. This study provides a reference for environmentalists, urban planners, and policy-makers pursuing air-pollution reduction by elucidating the correlation between air quality and urban form in the post-pandemic era.

CRediT authorship contribution statement

Di Wang: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. Tao Zhou: Validation, Writing – review & editing. Visualization, Supervision, Project administration. Jianing Sun: Methodology, Software, Resources.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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