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# COVID-19 mortality and exposure to airborne PM<sub>2.5</sub>: A lag time correlation

Longyi Shao<sup>1\*</sup>, Yaxin Cao<sup>1</sup>, Tim Jones<sup>2</sup>, M. Santosh<sup>3,4</sup>, Luis F.O. Silva<sup>5</sup>, Shuoyi Ge<sup>1</sup>, Kátia da Boit<sup>5</sup>, Xiaolei Feng<sup>1</sup>, Mengyuan Zhang<sup>1</sup>, Kelly BéruBé<sup>6</sup>

<sup>a</sup> *State Key Laboratory of Coal Resources and Safe Mining, and College of Geoscience and Surveying Engineering, China University of Mining and Technology (Beijing), Beijing 100083, China*

<sup>2</sup> *School of Earth and Environmental Sciences, Cardiff University, Park Place, Cardiff, CF10 3AT*

<sup>3</sup> *School of Earth Sciences and Resources, China University of Geoscience Beijing, Beijing 100083, China*

<sup>4</sup> *Department of Earth Science, University of Adelaide, Adelaide SA 5005, Australia*

<sup>5</sup> *Department of Civil and Environmental, Universidad de la Costa, Calle 58 #55-66, 080002 Barranquilla, Atlántico, Colombia*

<sup>6</sup> *School of Biosciences, Cardiff University, Museum Avenue, Cardiff, CF10 3AX, Wales, UK.*

**Abstract:** COVID-19 has escalated into one of the most serious crises in the 21<sup>st</sup> Century. Given the rapid spread of SARS-CoV-2 and its high mortality rate, here we investigate the impact and relationship of airborne PM<sub>2.5</sub> to COVID-19 mortality. Previous studies have indicated that PM<sub>2.5</sub> has a positive relationship with the spread of COVID-19. To gain insights into the delayed effect of PM<sub>2.5</sub> concentration ( $\mu\text{gm}^{-3}$ ) on mortality, we focused on the role of PM<sub>2.5</sub> in Wuhan City in China and COVID-19 during the period December 27, 2019 to April 7, 2020. We also considered the possible impact of various meteorological factors such as temperature, precipitation, wind speed, atmospheric pressure and precipitation on pollutant levels. The results from the Pearson's correlation coefficient analyses reveal that the population exposed to higher levels of PM<sub>2.5</sub> pollution are susceptible to COVID-19 mortality with a lag time of more than 18 days. By establishing a generalized additive model, the delayed effect of PM<sub>2.5</sub> on the death toll of COVID-19 was verified. A negative correlation was identified between temperature and number of COVID-19 deaths, whereas atmospheric pressure exhibits a positive correlation with deaths, both with a significant lag effect. The results from our study suggest that these epidemiological relationships may contribute to the understanding of the COVID-19 pandemic and provide insights for public health strategies.

**Keywords:** Correlation analysis; COVID-19; Lag time; Mortality; PM<sub>2.5</sub>.

## 1. Introduction

Since December 2019, the coronavirus disease outbreak (COVID-19) has resulted in a global health catastrophe caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). COVID-19 was first officially reported in Wuhan, but the source of the virus is unknown (Special Expert Group for Control of the Epidemic of Novel & Pneumonia of the Chinese Preventive Medicine, 2020). The disease spread rapidly with much higher infection levels and speed than comparable epidemics such as Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS) (Ganesh et al., 2021), disrupting normal lifestyles and social frameworks (Candido et al., 2020). The SARS-CoV-2 variant strains currently prevalent are Alpha, Beta, Gamma, Delta, Epsilon, Theta, Kappa, Lambda, and Mu, making the epidemic more serious (Chen, Wang, & Wei, 2021). The mortality rates of COVID-19 varies in different regions based on the local conditions and medical facilities, with an average of 2.21% as of March 15, 2021 (<https://covid19.who.int/>). Factors affecting mortality are widely discussed, including air quality, meteorological conditions (Rahman et al., 2021), travel habits (B. Wang et al., 2020) and social distance (Neto et al., 2021). Among them, air quality and meteorological conditions are relatively uncontrollable factors.

PM<sub>2.5</sub> is airborne particulate matter with an aerodynamic diameter of less

than 2.5  $\mu\text{m}$  (Sciences & Centre, 2012), which can be inhaled into the distal regions of the lung, and has a protagonist role (Mehmood et al., 2021), as well as the ability to carry into the respiratory system hazardous elements and organic and organometallic toxic substances; potentially resulting in lung and cardiovascular diseases (Kesic, Meyer, Bauer, & Jaspers, 2012; Mehmood et al., 2021; Xu et al., 2021). It has been found that SARS-CoV-2 RNA exists in urban environmental PM samples (Kayalar et al., 2021). Chronic exposure to certain air pollutants may lead to more severe and lethal COVID-19 outcomes (Domingo, Marques, & Rovira, 2020). Numerous studies have now shown that the inhalation of particulate matter pollution has a strong correlation with the prevalence and mortality of COVID-19 (De Angelis et al., 2021; SanJuan-Reyes, Gomez-Olivares, & Islas-Flores, 2021; Sasidharan, Singh, Torbaghan, & Parlikad, 2020), and could even lead to increased susceptibility to the disease (Chakrabarty et al., 2021; Coccia, 2020; Milicevic et al., 2021). In an Italian case study, it was shown that the daily COVID-19 cases were directly related to the mobility habits of a person(s) 21 days prior to infection (Carteni, Francesco, & Martino, 2020). It was also noted that a small increase in air pollution led to a large increase in COVID-19 infectivity and mortality in England (Travaglio et al., 2021). A study in California found that  $\text{PM}_{2.5}$  pollution caused by wildfires was correlated with mortality rates of COVID-19 (Meo et al., 2021). However, most studies have not considered the lag effect of  $\text{PM}_{2.5}$  on

mortality from COVID-19, particularly in the time interval between exposure to PM<sub>2.5</sub> pollution, and physiological responses to this inhalation hazard.

After the outbreak of the COVID-19 epidemic, the Municipal Government of Wuhan City officially reported the daily number of patients and deaths from January 23<sup>th</sup>, 2020 and implemented strict lockdown measures on the same day. The relationship between fine (i.e., PM<sub>2.5</sub>) and nanoparticulate (i.e., ultrafine) atmospheric matter and COVID-19 in Wuhan has been widely discussed (Lin, Zhang, Xie, Fan, & Liu, 2021). Some studies have observed that the air pollutants, including NO<sub>2</sub>, PM<sub>2.5</sub>, PM<sub>10</sub>, and CO decreased during the epidemic period (J. X. Chen et al., 2021; Sulaymon et al., 2021). Some studies have explored the real-time effect of PM<sub>2.5</sub> on the mortality of COVID-19 in Wuhan (Yao et al., 2020). However, since PM<sub>2.5</sub> is such a critical factor, further investigations are needed. Wuhan City was closed for 76 days and was re-opened on April 8<sup>th</sup>, 2020. During this period, the COVID-19 epidemic was affected by decreased routine human behaviors, and the period can be considered as a complete cycle from the beginning to end of the COVID-19 Wuhan epidemic. Thus, this cycle offers an important opportunity for studying the influence of air pollutants and meteorological factors on that epidemic. In addition, due to the mid-way change in testing standards, the number of confirmed COVID-19 has significantly increased. In addition, some asymptomatic cases or patients with very mild symptoms were not able to be



tested over this period. Therefore, although the number of actual cases of the disease is uncertain, the number of deaths is clearly documented.

Understanding the correlation of the COVID-19 deaths,  $PM_{2.5}$  and meteorological variables improves our understanding of the incubation period of the SARS-CoV-2 virus contracted by airborne transmission. In this study, we focus on the period from December 27<sup>th</sup>, 2019 to April 7<sup>th</sup>, 2020, collated air pollutants and meteorological data during the Wuhan epidemic, and collected information on the case fatality rate of one COVID-19 epidemic cycle in Wuhan from January 23<sup>th</sup>, 2020 to April 7<sup>th</sup>, 2020. Based on these data, the cumulative correlation between  $PM_{2.5}$  and COVID-19 mortality were assessed.

## **2. Methods and Data sources**

### **2.1 Methods**

All analysis were performed with IBM SPSS Statistics for Windows, Version 25.0 (IBM Corp. Armonk, NY, USA) and OriginPro, Version 2019 (OriginLab Corp., Northampton, MA, USA).

#### **2.1.1 Pearson correlation analysis**

Correlation analysis was employed to determine whether there was a relationship between the following two variables: (1)  $PM_{2.5}$  concentration and (2) COVID-19 mortality rate. The *Pearson's correlation coefficient* was utilised to measure the *statistical relationship between these two continuous variables*. Correlation coefficients were applied to define the relationship between air



pollutants and human disease (Seposo, Ueda, Sugata, Yoshino, & Takami, 2020), including COVID-19 (Choi, Peters, & Mueller, 2010; Daniele & Francesco, 2020). The formula for the correlation coefficient was as follows:

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

Where  $x_i$  and  $y_i$  are the  $i$ -th sample values of variables  $X$  and  $Y$  respectively.  $\bar{x}$ ,  $\bar{y}$  are the mean value of variables  $X$  and  $Y$  correspondingly.  $R$  is a dimensionless value with a range  $[-1, 1]$ . If the  $R$  value is positive the two variables are positively correlated, and negative  $R$  values show a negative correlation. The larger the  $|R|$  value (the closer to 1 or -1), the stronger the correlation between the two variables. If the  $R$  value is +1 or -1, it indicates that the two variables have a strict linear relationship (Choi et al., 2010).

### 2.2.2 Principal Component Analysis

PCA (Principal Component Analysis) uses dimensionality reduction to transform multiple indicators into a few Principal components. By simplifying the data structure, the index load and variance contribution rate on the principal components are used to calculate the index weight, so as to achieve comprehensive evaluation (Eder, Bash, Foley, & Pleim, 2014; Groth, Hartmann, Klie, & Selbig, 2013). PCA is widely used in the study of atmospheric pollutants and meteorological factors (Mor et al., 2021; Nguyen et al., 2021; Xiao et al.,

2014). This study first determined the correlation between the number of COVID-19 deaths and variables such as air pollutants and meteorological factors based on Pearson's analysis results. PCA was used to reduce the dimensionality of relevant variables to obtain the synergistic relationship among variables.

The parameters involved in the main factor analysis were determined according to the correlation between individual factors and the number of deaths. Principal components were determined and the load of each principal component was calculated according to the measurement criteria of eigenvalue > 1 and variance contribution rate reaching 80%.

### **2.1.3 Generalized additive model**

GAM (Generalized additive model) represents a method of fitting a smooth relationship between two or more variables. GAMs are useful when the relationship between the variables is expected to be of a complex form (Verbeke, 2007). The GAM (Generalized additive model) analysis was performed by the 'mgcv' package (v 1.8-31) in R v4.0.3. The main advantage of this model is its flexibility to allow non-parametric fittings with relaxed assumptions on the actual association between response and predictor that provides the potential for better fitting to data than purely parametric models. This model has been widely used in air pollution research and epidemiology (Manoj, Satheesh Kumar, Valsaraj, Sivan, & Vijayan, 2020; Rahman et al.,

2021). The GAM is used in this study to analyze the additive relationship between  $PM_{2.5}$  and meteorological factors COVID-19. The core GAM equation is:

$$g(E(Y|X_1, X_2, \dots, X_p)) = s_0 + s_1(X_1) + s_2(X_2) + \dots + s_p(X_p)$$

Where,  $Y$  is the dependent variable and  $X$  is the independent variable  $s_i(X_i), i = 1, 2, \dots, p$  are smooth functions which are obtained by the backfitting algorithm. In this study,  $X_i$  was set as  $PM_{2.5}$ , temperature, air pressure, FAC1, FAC2 and FAC3 according to the linear correlation.

## 2.2 Data sources

Wuhan is in the east of Hubei Province, China, at the intersection of the Yangtze River and the Hanshui River (coordinates:  $29^{\circ}58'$ -  $31^{\circ}22'N$  and  $113^{\circ}41'$ -  $115^{\circ}05'E$ ). Wuhan has a humid climate with four distinct seasons. Winter is cold (December to February  $4^{\circ}C$  average) and summer is hot (June to August  $29^{\circ}C$  average), with an annual average rainfall of 644.7mm year (1985-2015; Climate & Weather Averages in Wuhan, Hubei, China; timeanddate.com). The study period (January 23<sup>th</sup>, 2020, to April 7<sup>th</sup>, 2020) covers the winter and spring seasons in Wuhan.

The daily COVID-19 death data (i.e., January 23<sup>th</sup> to April 7<sup>th</sup>, 2020) in Wuhan was obtained from the website of the China Health Committee

(<http://www.gov.cn/fuwu/bm/wsjkw/index.htm>). The mass concentration data of PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, NO<sub>2</sub>, O<sub>3</sub>, and CO represents the average value of urban national control points from the Wuhan air quality real-time release system (<http://gis.hbj.wuhan.gov.cn:8088/Air/Default.aspx>). Meteorological data were obtained from the open data platform (<http://hz.zc12369.com/home/>). The relevant urban meteorological stations to obtain the required meteorological variables, included temperature (°C), humidity (%), precipitation (mm), wind speed (m/s), and atmospheric pressure (hPa).

### **3. Results**

#### **3.1 Real-time analysis**

##### **3.1.1 Daily new death toll of COVID-19**

Since January 23<sup>th</sup>, 2020, Wuhan City has officially counted and released the number of new daily deaths caused by the COVID-19 epidemic. As shown in Figure 1, the deaths in Wuhan from January 23<sup>th</sup>, 2020 to April 7<sup>th</sup>, 2020, presented a quasi-normal distribution. According to the changing trends, three stages were identified, including (1) the increased period of deaths (January 23<sup>th</sup> to February 4<sup>th</sup>) with the average death cases of 27.85, (2) the outbreak peak period (February 5<sup>th</sup> to February 24<sup>th</sup>) with the average death cases of 89.45, and (3) the declined period of deaths (February 25<sup>th</sup> to April 7<sup>th</sup>) with the average death cases of 12.30. These three stages defined a relatively complete epidemic cycle, and categorized as Stage 1, Stage 2, and Stage 3 in

Figure 1. “The New Coronavirus pneumonia diagnosis and treatment plan” (trial version fifth) has added “clinical diagnosis cases” in the case diagnosis classification of Hubei(China & Medicine, 2020), so that patients receive standardized treatment as early as possible. On February 12<sup>th</sup>, 13436 new confirmed cases were reported in Wuhan, and the corresponding new deaths on February 12<sup>th</sup> increased to 216.

### 3.1.2 Meteorological conditions during COVID-19

The dominant wind direction in Wuhan throughout the year is from the north. Figure 2 shows the variation of several meteorological factors during COVID-19 in Wuhan. Table 1 lists the average values of these meteorological factors in the three stages of the COVID-19 epidemic cycle. In addition, the coefficient of variance(CV) describes the volatility of the data. During the study period, the temperature (T), range was 2.2-19.8°C, with an average at 10.7°C. The data show an overall upward trend. The temperature in Stage 2 had an opposite trend in comparison with daily new deaths. The relative humidity (RH) range was 60.0-94.0%, with an average of 78.1%. The range was large with a downward trend. The wind speed (WS) range was 0.3-4.6m/s, with an average of 1.3m/s and shows an upward trend in general. The atmospheric pressure (AP) range was 1006.0-1032.0hPa, (average 1019.4hPa) and is highest in Stage 1 and Stage 2, with an overall downward trend. The pressure in Stage 2 had a similar trend based on a comparison with daily new deaths. The

atmospheric rainfall (AR) range was 0-26.7mm, with an average 2.7mm, with less and irregular rainfall during the period under study. According to the comparison of coefficient of variation, among the five meteorological factors, AR has the largest volatility and the other four have smaller volatility.

### 3.1.3 Air quality during COVID-19

Although some studies have shown that the level of air pollutants was lower during COVID-19 lockdown compared with the period before the onset of COVID-19 epidemic (Sulaymon et al., 2021), there were positive and negative excursions during the COVID-19 epidemic period in Wuhan (Figure 3).

The concentration of  $PM_{2.5}$  varied from 8 to 97  $\mu g/m^3$  with an average of 38.3  $\mu g/m^3$  and was higher during the outbreak and increasing periods of the epidemic, with a downward trend in general. The concentration of  $PM_{10}$  varied from 12 to 103  $\mu g/m^3$  with an average of 51.6  $\mu g/m^3$ . The trend of  $PM_{10}$  was similar to  $PM_{2.5}$ , but with a distinct increase during Stage 3. The concentration of  $NO_2$  varied from 10 to 43  $\mu g/m^3$  with an average of 21.9  $\mu g/m^3$ , with a steady trend in Stage 1 and 2, and a sudden increase in the latter part of Stage 3. The concentration of CO varied from 0.5 to 14  $\mu g/m^3$  with an average of 0.9  $mg/m^3$ , reflecting no major change. The  $O_3$  concentration ranged from 39 to 157  $\mu g/m^3$  with an average of 85.3  $\mu g/m^3$ , and  $SO_2$  was from 5 to 17  $\mu g/m^3$  with an average of 8.1  $\mu g/m^3$ . The changes of  $O_3$  and  $SO_2$  were relatively synchronous, showing an upward trend overall (Table 2). According to the comparison of

coefficient of variance, among the six pollutants,  $PM_{2.5}$  and  $O_3$  have the greatest volatility. Although  $PM_{2.5}$  decreased, the increase in  $SO_2$  and  $NO_2$  increased the proportion and risk of secondary aerosol  $PM_{2.5}$  (Sun et al., 2020). The formation efficiencies of secondary aerosols were enhanced during the lockdown due to the increase of atmospheric oxidation capacity, as also noted in another recent study (Tian et al., 2021). As shown in Figure 3, these pollutants do not display significant correlations with the daily death toll.

Table 3 shows the correlation between  $PM_{2.5}$  and meteorological factors such as air temperature, humidity, wind speed, air pressure and rainfall.  $PM_{2.5}$  is affected by several meteorological factors in Stage 1 and Stage 3, but not in Stage 2. From the correlation coefficient of the whole stage,  $PM_{2.5}$ , air temperature and air pressure are independent of each other. This also provides a basis for selecting variables in the next “GAM” analysis.

#### **3.1.4 Results of principal factor analysis**

The principal component analysis of air pollutants and meteorological factors was carried out, and KMO and Bartlett spherical test were selected to confirm the applicability of the data. KMO is 0.638 and greater than 0.6. The p value of Bartlett's spherical test was 0.00, which was less than the significance test limit of 0.05. Therefore, the input data are suitable for principal component analysis. In this study, the maximum variance method is used to rotate the initial load matrix, and the factor with load value greater than 0.5 is selected as



the corresponding principal factor.

Three factors with eigenvalues  $> 1$  are selected as the main factors (Figure 4). Component 1 mainly includes  $PM_{10}$ ,  $PM_{2.5}$ ,  $NO_2$  and  $CO$ , accounting for 35.02%. Component 2 mainly includes  $RH$  and  $O_3_{8h}$ , accounting for 24.22%. Component 3 mainly includes  $AP$ ,  $T$  and  $SO_2$ , accounting for 23.7%.

### **3.2 Lag time analysis**

#### **3.2.1 Analysis results of linear correlation for the lag effect of Meteorology and $PM_{2.5}$ on COVID-19 deaths**

The study of the lagged correlation of the COVID-19 deaths,  $PM_{2.5}$  and meteorological variables may indicate the incubation period of the SARS-CoV-2 virus caused by airborne transmission. Pearson correlations were used to evaluate the linear correlation in Wuhan during the COVID-19 epidemic. Some studies have attempted to establish a lag correlation between the number of cases per day and pollutants in COVID-19 infection. A study on the possible influence of a pollutant to an infection lag time of 0-14 days found a lag effect for  $PM_{2.5}$  (Q. Wang & Li, 2021). In this study, we increased the potential lag time, by using the SPSS software to adjust  $PM_{2.5}$  over the range of 0 to 28 days with a view to quantify its impact on the number of deaths per day. We observed a cumulative relationship between  $PM_{2.5}$  and death rates from December 27<sup>th</sup>, 2019, to April 7<sup>th</sup>, 2020, using 28 correlation analyses,

and conducted a two-tailed test. At the same time, we considered the influence of meteorological factors. In Figure 5,  $PM_{2.5}$ , temperature, humidity, wind speed, atmospheric and pressure precipitation demonstrated the influence of coefficient curves under different lag days.

Our results indicate a significant positive correlation between  $PM_{2.5}$  and the number of deaths per day at the level of 0.05 (two-tailed) on the 14<sup>th</sup> to 17<sup>th</sup> day of adjustment, and at the level of 0.01 (two-tailed) on the 18<sup>th</sup> to 27<sup>th</sup> day of adjustment; with the highest correlation coefficient on the 18<sup>th</sup> day (Figure 5a). The temperature was negatively correlated with the number of deaths (G. Zhu et al., 2021). With the increase of adjustment days, the absolute value of the correlation coefficient between the temperature and the number of deaths reveals an increasing trend, with the highest value on the 26<sup>th</sup> day (Figure 5b). A positive correlation was seen between atmospheric pressure and the number of deaths, and the correlation coefficient uncovered a peak on day 3 (Figure 5e).

Therefore, we conclude that  $PM_{2.5}$  pollution has a greater impact on the mortality rates of COVID-19 after 18 days (Figure 6). Among the meteorological factors, temperature shows a strong negative correlation with the number of deaths, whereas atmospheric pressure displays positive correlation. The influence of  $PM_{2.5}$  has a more obvious delay effect.

The adjusted time series analysis showed that  $PM_{2.5}$  with a lag time of 18

days is significantly correlated with the daily death toll (Figure 6), at Stage 1 and the first half of Stage 3, with a significant correspondence between the number of COVID-19 deaths and  $PM_{2.5}$ . Overall, the adjusted daily  $PM_{2.5}$  and death toll show a low-high-low trend in these three stages. The corresponding change in pattern was not very clear in Stage 2 when the COVID-19 epidemic was in the early Stage of the outbreak. The number of newly confirmed cases increased sharply, which may be the reason for the observed increase in mortality in Stage 2. At the end of Stage 3, the effect of  $PM_{2.5}$  was not obvious, which could be attributed to the rapid development of the epidemic preventative measures during the epidemic (e.g., masks, hand washing, social distancing and lockdowns). As a result of these public health interventions, the daily death toll gradually approached zero, which curbed the larger-scale spread of COVID-19 in the region. In general,  $PM_{2.5}$  played a greater role at the beginning of the rising and declining stages of COVID-19.

### **3.2.2 Analysis of generalized additive model for the lag effect of meteorology and $PM_{2.5}$ on COVID-19 deaths**

The generalized additive model is used to study the additive correlation and influence of various factors on the death toll of COVID-19. We used the  $PM_{2.5}$ , temperature, and atmospheric pressure of lag 18 days to establish a generalized additive model. The family is set to "quasipoisson", and the smoothing parameter "k" is set to 3.

The additive relation of  $PM_{2.5}$  on daily COVID-19 deaths and its relationships with  $PM_{2.5}$  concentration, air temperature, air pressure, FAC1, FAC2, and FAC3 are shown in Figure 7. The additive positive correlation between  $PM_{2.5}$  and death of COVID-19 is significant, which is consistent with the results of the Pearson correlation analysis. However, it does not increase monotonically, which may be affected by the change of statistical mode in the second stage. There is an opposite relationship between temperature and COVID-19 deaths. Similarly, the temperature changes in the generalized additive model are consistent with the results of the Pearson correlation analysis. The deaths of COVID-19 decrease with the increase of temperature. The degree of freedom (EDF) of  $AP$  is 1 (Table 4), which means that there is a linear correlation between  $AP$  and death toll, but there is no additive relationship. FAC1 related to  $PM_{10}$ ,  $PM_{2.5}$ ,  $NO_2$  and  $CO$  was positively additive correlated with the number of deaths. FAC2 associated with  $RH$  and  $O_3\_8h$  had no additive correlation with the number of deaths. FAC3 related to  $AP$ ,  $T$  and  $SO_2$  was negatively additive correlated with the number of deaths. We used the subgroup analysis method for sensitivity analysis. The analysis results show that (Table S4), the sensitivity is low and the model is relatively stable.

#### 4. Discussion

$PM_{2.5}$  can act as a vehicle or nucleation site to transport harmful

substances directly into the respirable regions of the human lung, ultimately resulting in the translocation of pollutants into the systemic circulation. Exposure to ambient PM may also reduce the resistance to infection in the population (Maleki, Anvari, Hopke, Noorimotlagh, & Mirzaee, 2021). People exposed to higher levels of PM<sub>2.5</sub> pollution are more likely to suffer from cardiopulmonary diseases (Manojkumar & Srimuruganandam, 2021), including IHD (Ischemic Heart Disease) (Nirel et al., 2021), COPD (Chronic Obstructive Pulmonary Disease) (Guo et al., 2021), lung cancer (Hvidtfeldt et al., 2021), and strokes (Niu, Liu, Yu, Wu, & Xiong, 2021). The adverse health outcomes are more significant for persons who have these pre-existing diseases (Cheng et al., 2021; Mahmood et al., 2021; W. T. Zhu et al., 2021). A recent study suggested that long-term exposure to poor air quality may aggravate the clinical symptoms of COVID-19 (Al-Kindi et al., 2021).

Airborne particles can act as the possible carriers of the SARS-CoV-2 virus into the human body, resulting in increased morbidity and mortality (Cao et al., 2021; Maleki et al., 2021; Nguyen Thanh et al., 2021; Nor et al., 2021). It has been revealed that the interaction of SARS-CoV-2 with PM is possible in moist environments. After drying, PM can serve as a carrier for transmission of SARS-CoV-2 immobilized on their surface (Borisova & Komisarenko, 2020). The SARS-CoV-2 virus has been detected in hospitals, buses, subways and other environments (Hadei et al., 2021; Moreno et al., 2021; Nor et al., 2021;

Yarahmadi et al., 2021).

The increase of secondary aerosols may also lead to an increase in the death toll of COVID-19. Some studies have noted that during the lockdown,  $O_3$  in Wuhan has increased by more than two times compared with the values before the lockdown (C. W. Huang et al., 2021; Lian et al., 2020), which can boost atmospheric oxidizing capacity and further enhance the formation of secondary organic aerosols (X. Huang et al., 2021; Li et al., 2020; Meng et al., 2021). An increase in the formation efficiency of secondary aerosols represented by nitrate and secondary OA was observed in Wuhan and many other areas during the COVID-19 lockdown (Sun et al., 2020; Tian et al., 2021; Z. L. Wang et al., 2021; Zheng et al., 2020). It has been found that secondary aerosols can carry toxic bacteria (Jiang, Xia, & Liu, 2021) and are more harmful to humans than primary aerosols (Lin et al., 2016). Therefore, the increase of secondary aerosol may be an important factor in  $PM_{2.5}$  role in the mortality of COVID-19.

In addition,  $PM_{2.5}$  can upregulate ACE-2 (Du et al., 2020), the receptor of the SARS-CoV-2 virus (Baidya, Ghosh, & Chattopadhyay, 2021), and increase the chance of viral RNA entering cells (Nguyen Thanh et al., 2021). Thus, the potential role of fine particles in the transmission of COVID-19 is of increased importance. The findings in this study support the urgent need to implement environmental mitigation strategies for reducing airborne particulate pollution.

There is a lag time between the inhalation of  $PM_{2.5}$  and the onset of adverse respiratory responses (Dong, Wang, Wang, & Bao, 2021; X. L. Zhu et al., 2021). A Mexican study, at an individual level, did not find robust evidence for short-term  $PM_{2.5}$  exposure increasing the chances of dying from COVID-19 (Lopez-Feldman, Heres, & Marquez-Padilla, 2021). This supports findings that COVID-19 mortality seems to be driven mainly by longer-term (i.e., lagging, chronic or cumulative) rather than the short-term (i.e., acute) factors. Our results also suggest that the COVID-19 epidemic was established in Wuhan before any mobility restrictions were implemented.

The influence of meteorological factors has also been widely studied. The longevity of SARS-CoV-2 outside hosts decreases at high temperature and under sunlight (Yap, Liu, Shreeva, & Preston, 2020). Respiratory-related mortality will increase with decreasing temperatures (Dadbakhsh, Khanjani, Bahrampour, & Haghighi, 2017). In a cold environment, the susceptibility of the host may be higher due to slower mucociliary clearance or decreased immune function under these conditions (Ficetola & Rubolini, 2021; Lowen & Steel, 2014). Areas with high atmospheric pressure are generally more moist compared to lower pressure areas, thereby providing more transport potential for active and invasive pathogens (Aidoo, Adebajji, Awashie, & Appiah, 2021). The investigations conducted in India (Kulkarni, Khandait, Narlawar, Rathod, & Mamtani, 2021) and in Italy (Lolli, Chen, Wang, & Vivone, 2020) considered



that temperature was negatively correlated with the risk of COVID-19; these findings are consistent with our results. The study conducted in Ghana (Aidoo et al., 2021) had similar conclusions with our study in that there was a positive correlation between air pressure and the risk of contracting COVID-19. However, our results do not agree with studies that suggest that high temperature is conducive to the spread of the virus (Jain, Sharma, Goyal, Kaushal, & Sethi, 2021), or atmospheric pressure has a negative correlation (Sharma, Bansal, Yadav, Jain, & Garg, 2021). Researchers have suggested that air humidity is the most important climatic factor in spreading the virus, while temperatures do not have a strong influence (Crema, 2021).

Although the lag time correlation between the COVID-19 mortality and exposure to airborne  $PM_{2.5}$  has been proposed, the limitation of this study still exists. Firstly, we have not considered impacts from personal behaviors like social distancing and personal hygiene (Bang et al., 2021; Magnan, Gibson, & Bryan, 2021). Secondly, the current study only considered the Wuhan city, lack of research in the neighboring regions which might have a trans-regional influence for the COVID-19 transmissions. Finally, the model needs to be tested in other high incidence areas in the world.

## 5. Conclusion

In conclusion, the concentration of  $PM_{2.5}$  is related to the risk of contracting COVID-19, and its delayed effect on the mortality of COVID-19 is

identified to be more than 18 days. COVID-19 mortality in Wuhan was driven mainly by the longer-term rather than the short-term factors. Relevant administration departments and policy makers should consider that the incubation period of the SARS-CoV-2 is longer than 18 days, which is even longer than the public think of 14 days. The temperature has a strong negative correlation with COVID-19 deaths in Wuhan, while atmospheric pressure has a positive correlation.

### **Code availability**

Source code, with full documentation and examples, are freely available under the GNU General Public License on the WeirauchLab GitHub page: <https://github.com/Fossette-x/COVID-19-and-PM2.5-in-Wuhan.git>

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### **Author contributions**

L.Y.S: funding acquisition, visualization, supervision, review and editing; Y.X.C: conceptualization, writing original draft, investigation, visualization; T. J: investigation, review and editing; M.S.: review and editing; L.F.O.S: supplementing argument; S.Y.G: collecting and arranging the literature; K.D.B:

collecting and arranging the literature; X.L.F: investigation, data curation;

M.Y.Z: review and editing; K.B: review and editing.

### Competing interests

The authors declare no competing interests.

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**Declaration of interests**

☒ 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.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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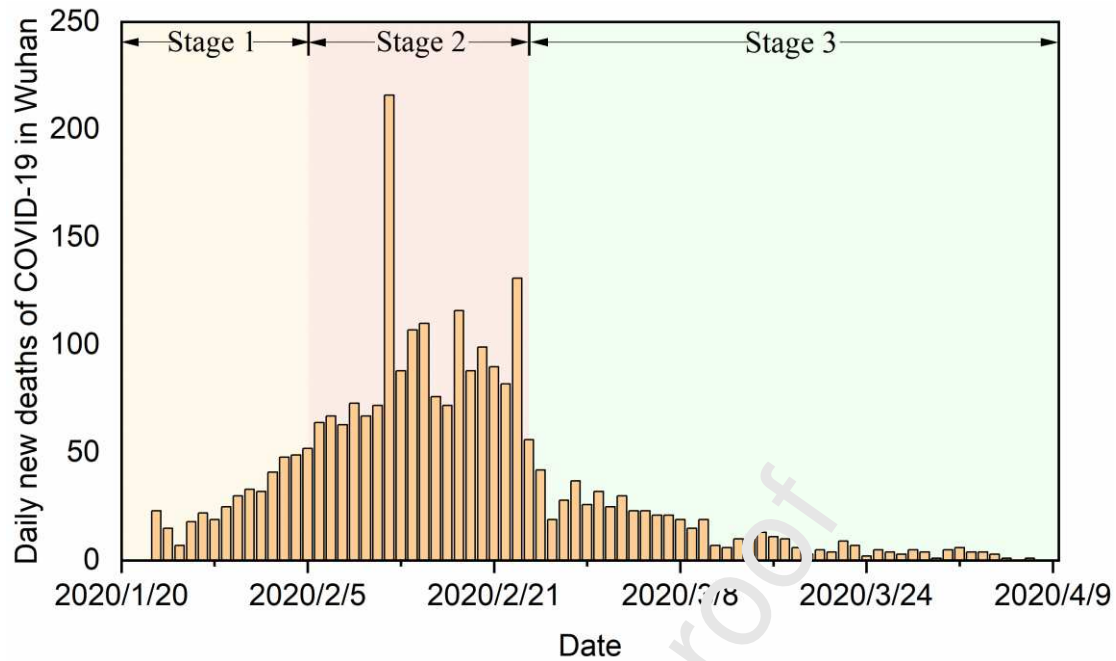


Figure 1. The number of new deaths per day during the COVID-19 epidemic cycle in Wuhan, divided into three stages

The death data in the figure cover the period from January 23, 2020 to April 7, 2020. The yellow shaded region indicates the increased period of deaths, the red region corresponds to the outbreak peak period, and the green region shows the declined period of death.

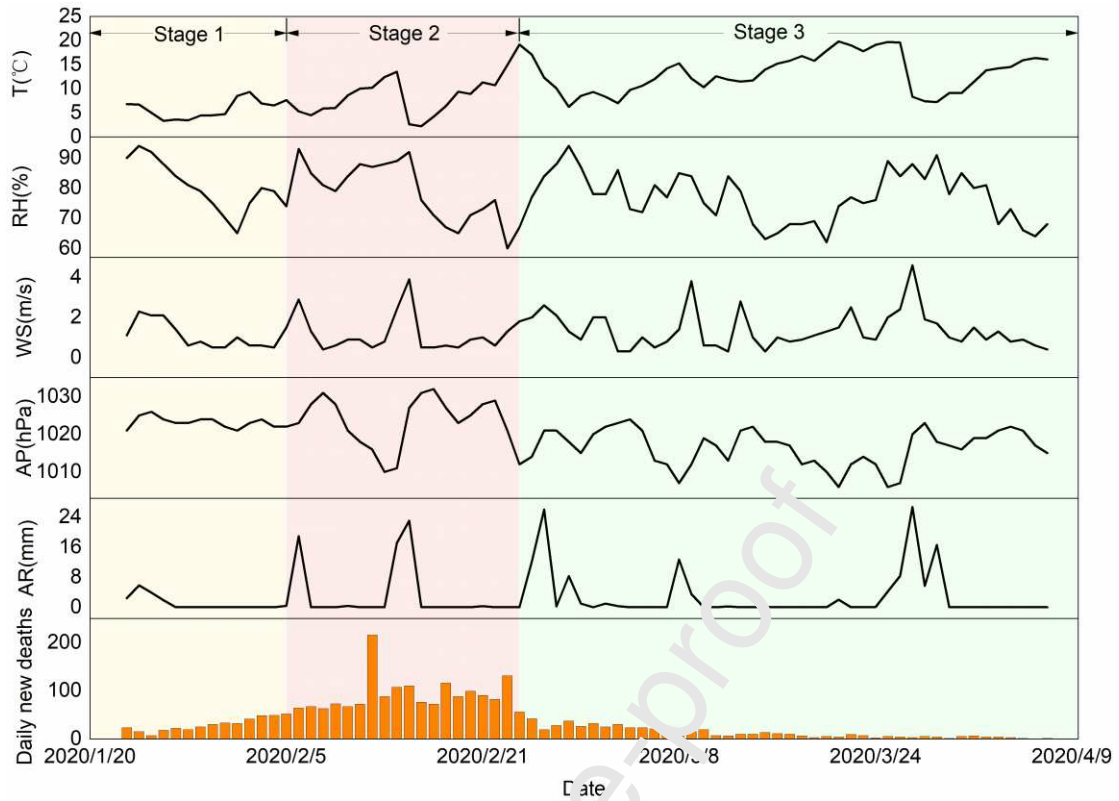


Figure 2. Changes in meteorological factors during COVID-19 in Wuhan.

The figure shows the data of temperature (T), relative humidity (RH), wind speed (WS), atmospheric pressure (AP) and atmospheric rainfall (AR) from January 23, 2020 to April 7, 2020, as well as the corresponding daily death number. The yellow shaded region indicates the increased period of deaths, the red one indicates the outbreak peak period, and the green one shows the declined period of deaths.

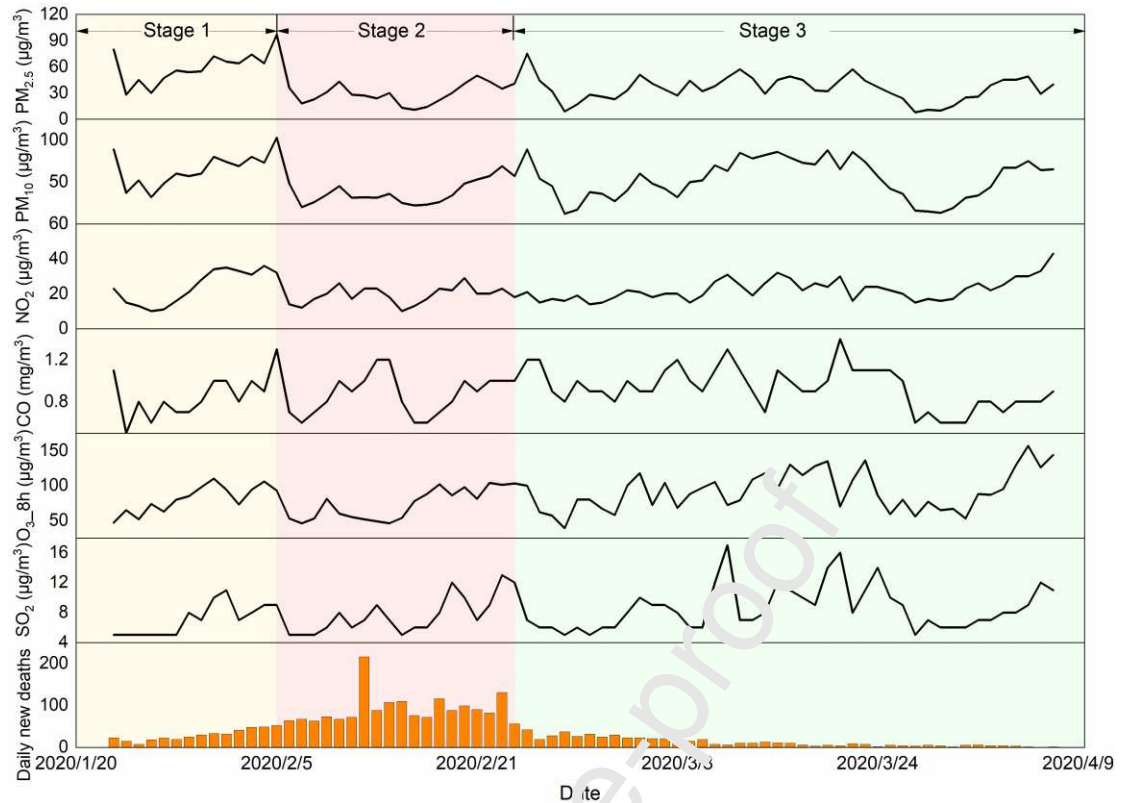


Figure 3. Changes in the concentration of air pollutants during COVID-19 in Wuhan.

The air pollutants data include  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ ,  $\text{NO}_2$ ,  $\text{SO}_2$ ,  $\text{CO}$  and  $\text{O}_3$  from January 23, 2020 to April 7, 2020. The yellow shaded region indicates the increased period of deaths, the red one shows the outbreak peak period, and the green one corresponds to the declined period of deaths.



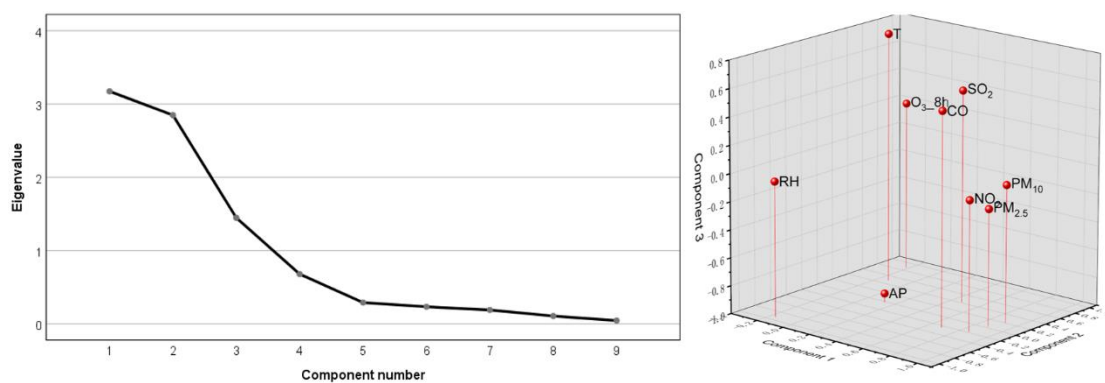


Figure 4. Scree Plot and Component diagram in rotated space.

The rotated component matrix is shown in table S2 Table S2.

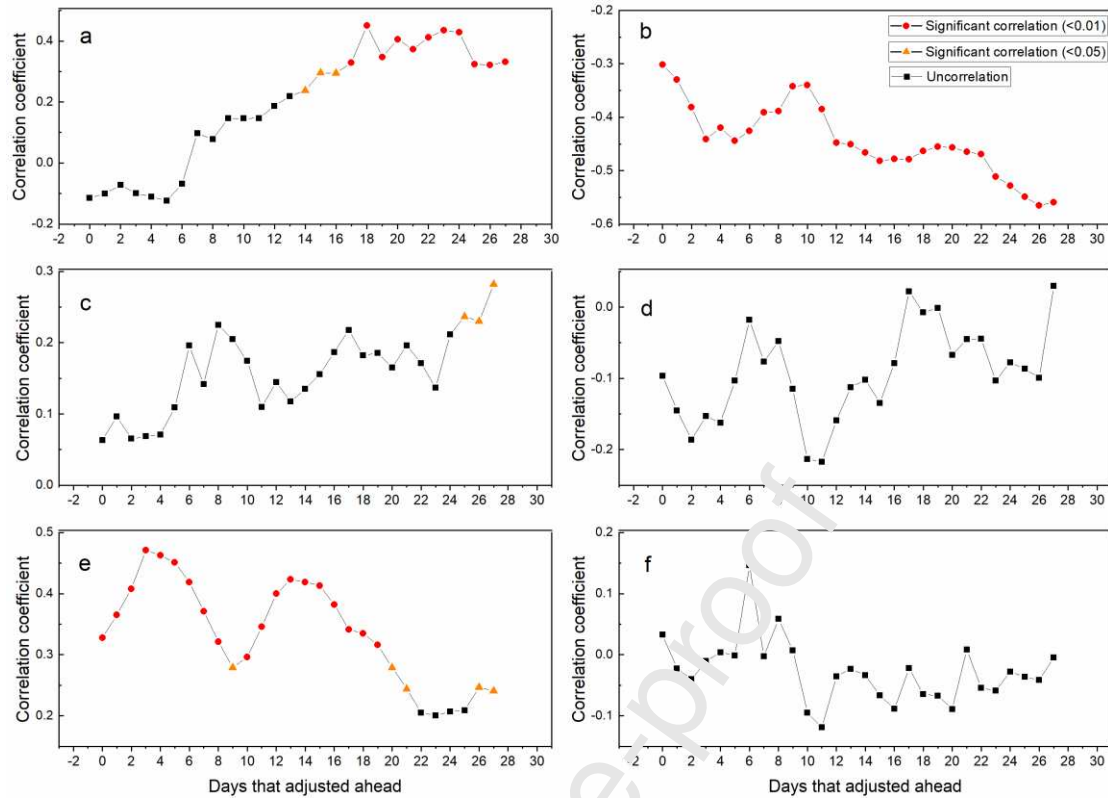


Figure 5. The correlation coefficient on the cumulative impact of  $PM_{2.5}$  and meteorological factors on the number of COVID-19 deaths per day.

The horizontal coordinates are the number of days forward, and the vertical coordinates are the correlation coefficient. The figure shows the correlation between  $PM_{2.5}$  (a), temperature (b), relative humidity (c), wind speed (d), atmospheric pressure (e) and atmospheric rainfall (f) and daily death number with different adjustment days.  $PM_{2.5}$  has a significant lag effect on the number of COVID-19 deaths. The related sig. value (two tails), covariance and standard deviation are in Table S3.

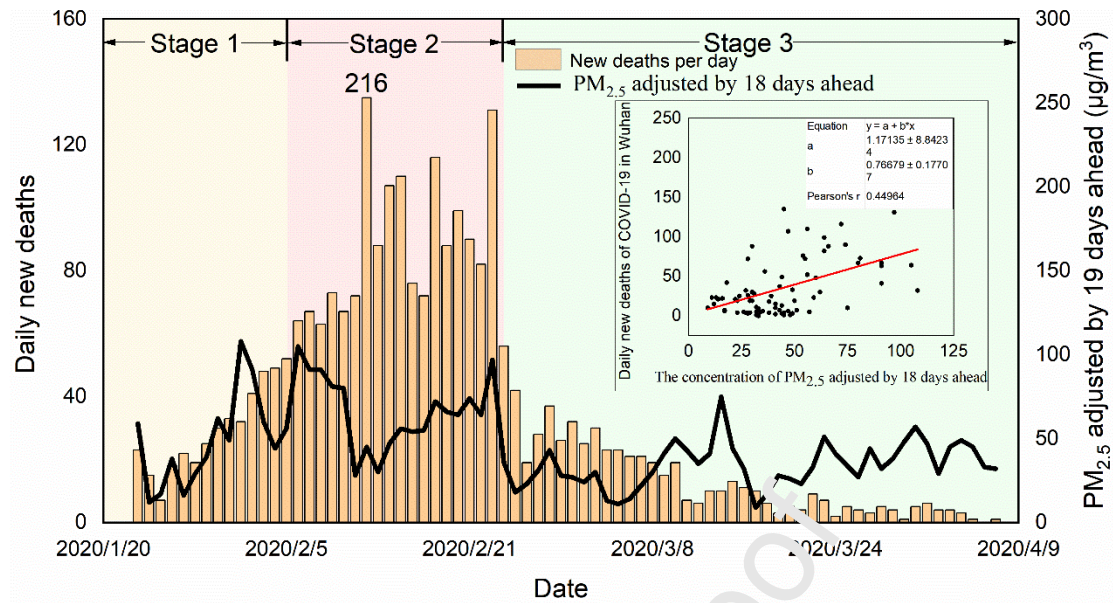


Figure 6. Comparison of PM<sub>2.5</sub> concentration and daily COVID-19 deaths. Note that values of the PM<sub>2.5</sub> concentrations are 18 days ahead.

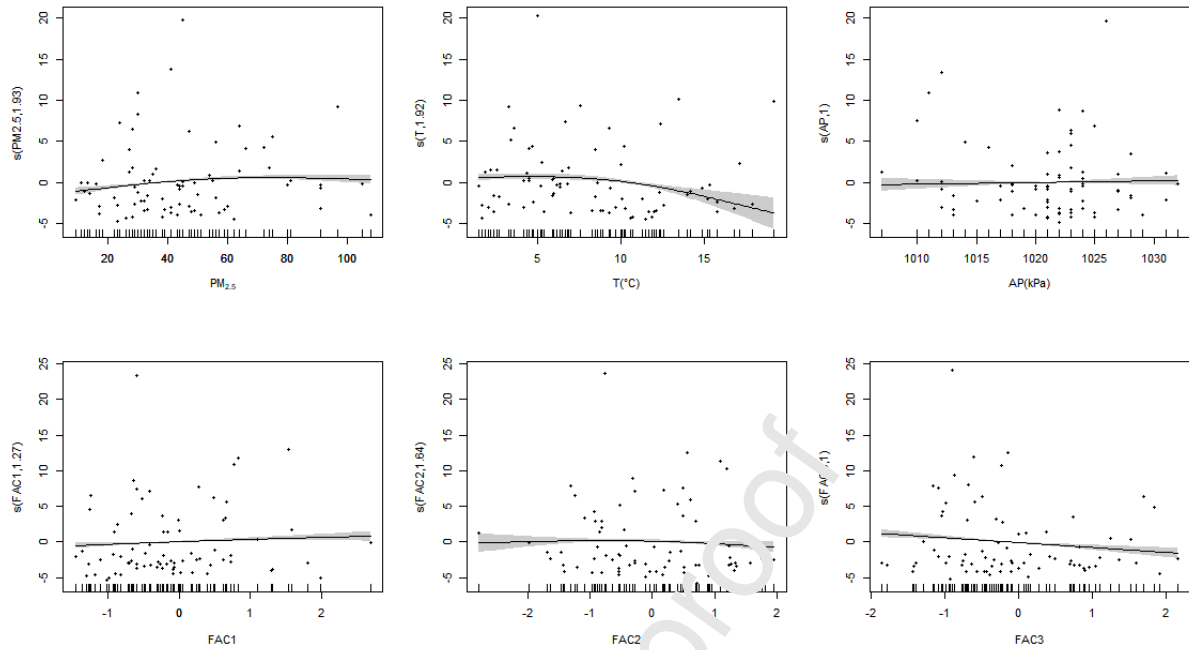


Figure 7. The results of the generalized additive model showing the additive relationships between daily COVID-19 deaths and the  $PM_{2.5}$  concentration, air temperature, air pressure, FAC1 ( $PM_{10}$ ,  $PM_{2.5}$ ,  $NO_2$  and  $CO$ ), FAC2 (RH and  $O_3_{8h}$ ) and FAC3 (AP, T and  $SO_2$ ). The upward trend of the curve indicates that term has a positive effect on the daily death number, and the downward trend of the curve indicates that term has a negative effect on the daily death number.

Table 1. Average values of meteorological factors in the three stages

Meteorology	Stage 1	Stage 2	Stage 3	Whole stage	Coefficient of Variance
Temperature (°C)	5.66	8.69	13.13	10.68	0.45
Relative humidity (%)	80.92	78.3	77.12	78.08	0.11
Wind Speed (m/s)	1.08	1.19	1.36	1.27	0.70
Air pressure (hPa)	1023.23	1023.15	1016.47	1019.38	0.01
Air rainfall (mm)	1.08	3.01	3.00	2.68	2.31

Table 2. Average value of pollutants in each Stage of the Wuhan epidemic cycle

Pollutant	Stage 1	Stage 2	Stage 3	Whole Stage	Coefficient of Variance
PM <sub>2.5</sub> (µg /m <sup>3</sup> )	54.6	32.9	35.3	39.2	0.45
PM <sub>10</sub> (µg /m <sup>3</sup> )	60.2	41.1	53.2	51.6	0.38
SO <sub>2</sub> (µg /m <sup>3</sup> )	7.1	7.8	8.6	8.1	0.36
CO (mg /m <sup>3</sup> )	0.8	0.9	0.9	0.9	0.25
NO <sub>2</sub> (µg /m <sup>3</sup> )	23.6	19.9	22.4	21.9	0.39
O <sub>3_8h</sub> (µg /m <sup>3</sup> )	82.8	74.2	92.1	85.3	0.49

Table 3. Influence of the correlation coefficient of on the meteorological factors on PM<sub>2.5</sub> in each Stage

	PM <sub>2.5</sub> in Stage 1	PM <sub>2.5</sub> in Stage 2	PM <sub>2.5</sub> in Stage 3	PM <sub>2.5</sub> in Whole Stage
Temperature	0.432	0.321	0.542**	0.099
Relative humidity	-0.539	-0.216	-0.461**	-0.271*
Wind Speed	-0.773**	0.034	-0.072	-0.15
Air pressure	-0.684**	-0.18	-0.097	-0.004
Air rainfall	-0.564*	-0.161	-0.258	-0.253*

Significance codes: 0.01 '\*\*', 0.05 '\*'. The related sig. value (two tails), covariance and standard deviation are in Table S1.

Table 4. Approximate significance of smooth terms

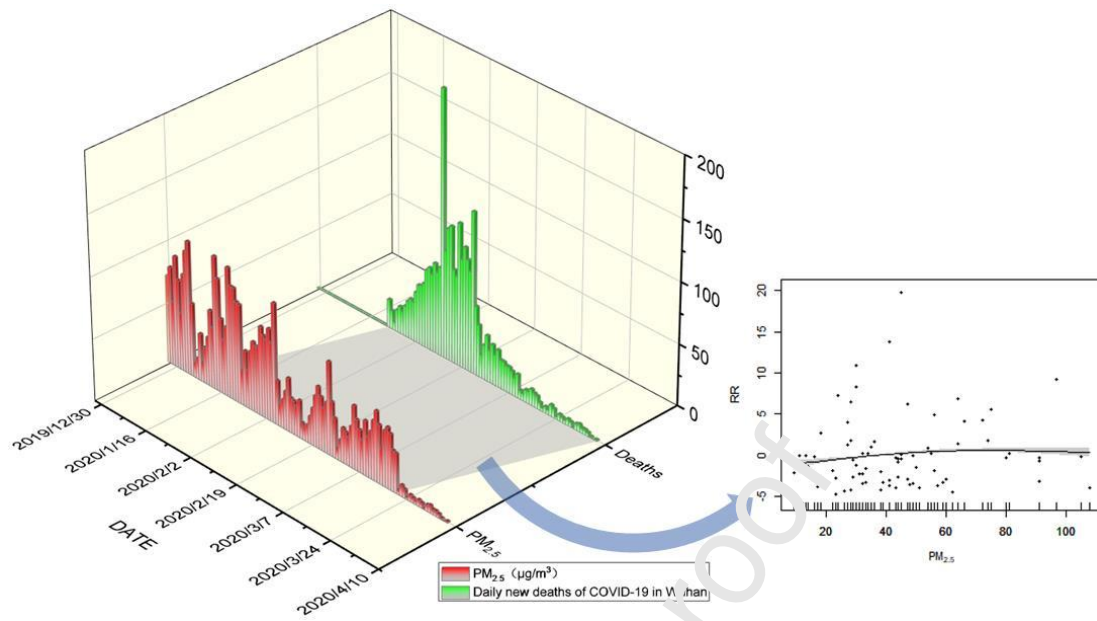
Terms	EDF <sup>a</sup>	P-value	Deviance explained <sup>b</sup>
PM <sub>2.5</sub>	1.98	1.03*10 <sup>-5***</sup>	
Temperature	1.92	2.14*10 <sup>-4***</sup>	57.8%
Air pressure	1.00	0.47	
FAC1	1.27	6.6*10 <sup>-3**</sup>	39.5%

<b>FAC2</b>	1.64	0.19
<b>FAC3</b>	1.00	5.7*10-5 ***

Significance codes: 0 '\*\*\*', 0.001 '\*\*', 0.01 '\*'.

<sup>a</sup>: EDF represents the estimated degree of freedom. Higher EDF values represent more complex splines.

<sup>b</sup>: Deviation explained refers to the degree of interpretation of the model to the data.

*Graphical abstract*

**Highlights:**

- The influence and importance of  $PM_{2.5}$  on the risk of COVID-19 mortality.
- 18 days delay on COVID-19 mortality after high  $PM_{2.5}$  exposure.
- Mortality is partially driven by long term  $PM_{2.5}$  exposure.
- Negative correlation between temperature and COVID-19 mortality
- Positive correlation between atmospheric pressure and COVID-19 mortality