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1. Introduction

PM$_{2.5}$, which represents fine particulate matter with diameter $\leq$ 2.5 $\mu$m suspended in the air, affects air quality by reducing visibility, poses a threat to human health, and is characterized by radiative forcing that can affect the global climate, and would cause great economic losses to society (Guan et al., 2014; Mегаритis et al., 2014). Since 2013, serious haze events, which have attracted widespread concern, have been frequently observed in China. In response, the State Council of China promulgated the Air Pollution Prevention and Control Action Plan in September 2013 (China GOotSC, 2013). Thus, there has been a significant drop in PM$_{2.5}$ concentration over the past few years. Zhai et al. (2019) showed that the annual average PM$_{2.5}$ concentration in China fell by 30–50% overall during the 2013–2018 period, at an average of $\sim$5.2 $\mu$g $\cdot$ m$^{-3}$ $\cdot$ y$^{-1}$. However, heavy haze events still occur occasionally, especially in large cities (Liu et al., 2019; Xiao et al., 2020; Zhang et al., 2018a). Thus, the air quality situation is still grim.

The causes of haze events are complex and primarily include anthropogenic emissions, topography, meteorology, regional transport, and their interactions (Chen and Wang, 2015; Liu et al., 2021; Shi et al., 2019; Zhang et al., 2018a). Reducing human activity-related emissions is the most important air quality improvement strategy. During key events such as the G20 summit in 2016 and the Asia-Pacific Economic Cooperation (APEC) meeting in 2014 (Li et al., 2018; Zhang et al., 2018b), high-emission factories, construction activities, and motor traffic were restricted (Sun et al., 2016); the result was a marked improvement in local air quality. Furthermore, as strict emission control measures continue to be implemented, meteorology and regional transportation...
will play increasingly important roles in PM$_{2.5}$ outbreaks. He et al. (2017) studied the changes in the concentrations of six major pollutants (CO, NO$_2$, O$_3$, PM$_{10}$, PM$_{2.5}$, and SO$_2$) and revealed that meteorology could explain more than 70% of the daily average variations of the concentrations of these pollutants in China. Further, Li et al. (2017) showed that highly aged secondary inorganic aerosols from surrounding regions are responsible (60%) for the rapid increase in surface PM$_{2.5}$ levels in Beijing. Owing to differences in geographical location and topography, the contribution of meteorology to PM$_{2.5}$ levels differs from one region to another; hence, the different pollution potentials observed in different regions. From an efficiency and economic perspective, it is essential to develop targeted pollution prevention measures so as to achieve scientific emission reduction.

In 2020, the outbreak of the coronavirus disease (COVID-19) had an unprecedented impact on the Chinese society. The high infectivity of this disease seriously threatened lives and health of people (Huang et al., 2020; Xu et al., 2020). In response, the Chinese government promptly and forcefully implemented a series of lockdowns, beginning in Wuhan on January 23, followed by other cities and counties. This led to a rapid decline in anthropogenic emissions and a significant improvement in air quality in the months that followed. The Copernicus Atmosphere Monitoring Service (CAMS) detected an approximately 20–30% decrease in PM$_{2.5}$, over large parts of China in February 2020 based on information from satellite observations (CAMS, 2020). This unique period provided an opportunity to assess the contribution of meteorology and anthropogenic emissions to air pollution.

Hubei Province, located in the east-central part of China and downwind of the East Asian winter monsoon, is an important center for pollutant transport. Previous studies have revealed that the regional transportation of pollutants contributed significantly to the occurrence of pollution incidents in Hubei Province during the COVID-19 outbreak (Shen et al., 2021; Xiong et al., 2021). However, a quantitative assessment of the importance of anthropogenic emissions and meteorology is still lacking. Therefore, in our study, we established random forest models between PM$_{2.5}$ concentration and time variables and meteorological variables, and combined the de-weathering method to quantitatively evaluate the contribution of emission reduction and meteorological conditions to the decrease of PM$_{2.5}$ concentration during the epidemic. This provides a way to evaluate the effect of emission reduction, and is of great significance for the formulation and implementation of appropriate emission reduction measures.

2. Data and methods

2.1. Data source

The lockdown in Hubei lasted approximately two months. It was implemented on January 23 and uplifted on March 20. Thus, we chose February and March 2020 as the study period, and at the same time chose February and March 2019 as a period for comparison. PM$_{2.5}$, SO$_2$, NO$_2$, and CO concentration data with hourly resolution were obtained from the Ministry of Ecology and Environment of China (http://10.6.37.208.233.20035/) and from https://quotsoft.net/air/. The Multi-resolution Emission Inventory for China version 1.3 (MEICv1.3) was used to obtain the anthropogenic emission data. Furthermore, Gao et al. (2020) built a random forest classification model for the distribution of pollution incidents in Hubei Province during the COVID-19 outbreak. Therefore, in our study, we established random forest models to assess the contributions of meteorology and anthropogenic emissions to air pollution.

2.2. The random forest regression model

In recent years, machine learning has been widely used in the study of air pollutants. Specifically, Feng et al. (2020) using the multilayer sensing method, sufficiently predicted PM$_{2.5}$ levels in several major cities in China, and found that the main factors that influence PM$_{2.5}$ concentrations during the study period were precursor pollutants. Furthermore, Gao et al. (2020) built a random forest classification model and successfully evaluated the contribution of relative humidity, aerosol pH, and precursor pollutants to secondary inorganic aerosol formation during different levels of pollution. Thus, machine learning has great potential in predicting PM$_{2.5}$ levels and assessing the importance of influencing factors. In this study, we used a random forest (RF) regression model to predict PM$_{2.5}$ levels. The predictors used in the model included time variables, i.e., day of year (0, 1, ..., 364 or 365), day of the week (0, 1, ..., 6), hour of day (0, 1, ..., 23), and meteorological variables, including 2-m temperature (2m), relative humidity (rh), direction of 10-m wind (wd), speed of 10-m wind (ws10), surface pressure (sp), total precipitation (tp), downslope surface solar radiation (ssrd), and boundary layer height (blh). We selected 151 air quality sites in the range of 107–117°E and 28–34°N (covering the geographic area of Hubei) (Fig. S3), and then established random forest models for these sites in two periods (February and March of 2019 and 2020), a total of 302 models. In the process of model building, we used 75% of the data to train the model, and the remaining 25% as the test set to evaluate the accuracy of the model.

2.3. De-weather method

Obviously, due to the different meteorological conditions in February and March in 2019 and 2020, the reduction in PM$_{2.5}$ is not entirely the effect of emission reduction. In order to keep the meteorological conditions consistent between the two periods, we have followed a method called meteorological normalization (Grange and Carslaw, 2019; Grange et al., 2018; He et al., 2021). Specifically, for any one moment (for example, 8:00), we randomly resample the meteorological variables at that moment from all the meteorological variables at the same moment in February and March in 2019 and 2020 (sampling with replication). After that, the time variables and meteorological variables are substituted into the model of the site to re-predict, and new PM$_{2.5}$ concentration is obtained. Repeat the above process 1000 times, and take the average of the results as the de-weathered PM$_{2.5}$ concentration. This value represents the PM$_{2.5}$ concentration under the average meteorological conditions in February and March in 2019 and 2020. Method S1 is a more detailed description of the process of model building and de-weather methods.

The difference between the de-weathered PM$_{2.5}$ concentration in the two periods reflected the impact of anthropogenic emission reductions during the pandemic, while the decrease in observed PM$_{2.5}$ concentration represented the dual impact of anthropogenic emission reductions and meteorology. Thus, we used the following formulas to assess the contribution of emission reduction and meteorology to the changes in PM$_{2.5}$ concentrations.

$$E_i = \frac{C_{2020}^b - C_{2019}^b}{C_{2019}^b} \times 100\%$$

$$M_i = \frac{(C_{2020}^b - C_{2020}^{\text{ob}}) - (C_{2019}^b - C_{2019}^{\text{ob}})}{C_{2019}^b} \times 100\%$$

where $C_{2020}^b$ and $C_{2019}^b$ represent the observed PM$_{2.5}$ concentration and de-weathered PM$_{2.5}$ concentration in February and March 2020, respectively. And $C_{2019}^{\text{ob}}$ and $C_{2020}^{\text{ob}}$ represent the observed PM$_{2.5}$ concentration and de-weathered PM$_{2.5}$ concentration in February and March 2019, respectively.
Fig. 1. (a) Geographical location of Hubei Province in China, (b) location distribution map of air quality monitoring sites in Hubei Province, and (c) changes of average mass concentrations of PM$_{2.5}$, NO$_2$ and SO$_2$ in Hubei Province in February and March from 2015 to 2021.

Fig. 2. (a) Spatial distribution of PM$_{2.5}$ concentration in Hubei Province in February and March 2019, (b) spatial distribution of PM$_{2.5}$ concentration in Hubei Province in February and March 2020, and (c) the PM$_{2.5}$ concentration changes in Hubei Province from January 15 to March in 2019 and 2020, the error band is 2 times the standard deviation, which represents the difference in PM$_{2.5}$ concentration between different sites. The dashed line represents the average daily PM$_{2.5}$ concentration standard of China (75 μg/m$^3$).
3. Results and discussion

3.1. Spatial and temporal distribution of PM$_{2.5}$ in Hubei Province

Since 2015, the average concentrations of PM$_{2.5}$, SO$_2$, and NO$_2$ in February and March in Hubei have shown an overall decreasing trend (Fig. 1(c)), with an average annual decrease of 7.15, 2.81, and 2.68 $\mu\text{g}/\text{m}^3$, respectively, indicating that the recently implemented emission reduction measures are effective (Zhai et al., 2019). Furthermore, owing to the severe lockdown imposed during the COVID-19 pandemic, PM$_{2.5}$ levels dropped to about 39.6 $\mu\text{g}/\text{m}^3$ in February and March 2020, representing a 30% decrease compared with the level observed during the same period in 2019, but it was still higher than the secondary standard of China (35 $\mu\text{g}/\text{m}^3$). After the lockdown was uplifted and the cities returned to normal operation (2021), the PM$_{2.5}$ level rebounded.

From the perspective of spatial distribution, whether it is in 2019 or 2020, the average PM$_{2.5}$ concentration corresponding to the two months study period is significantly higher in central cities (Fig. 2(a) and (b)), with the high value center of PM$_{2.5}$ concentration predominantly located in Xiangyang, Jingmen, and Yichang (Fig. S6), and with the highest concentration reaching 79 $\mu\text{g}/\text{m}^3$ in 2019, 56 $\mu\text{g}/\text{m}^3$ in 2020. Comparing the spatial distribution of pollutant emission intensity in Hubei Province (Fig. S1), the central and eastern regions are the key areas for pollutant emission, which explains the high PM$_{2.5}$ concentration in the central region. However, PM$_{2.5}$ concentration in the central region is higher than that in the eastern region, which may indicate the influence of other factors, such as severe weather conditions, more regional transport, topographic effects, etc. In terms of time, the changes of concentration of PM$_{2.5}$ in 2019 and 2020 also have similar patterns.

The PM$_{2.5}$ pollution incidents in Hubei Province are mainly concentrated in January and February, which are usually attributed to the unfavorable weather conditions in winter, such as the inversion layer that often occurs in winter, which makes it difficult for pollutants to dissipate. Although during the COVID-19 outbreak in 2020, that is, in the context of low anthropogenic emissions, relatively high levels of PM$_{2.5}$ also appeared around February 5 and February 25. Entering March, the average concentration of PM$_{2.5}$ changed below 75 $\mu\text{g}/\text{m}^3$, and the change range was even smaller.

Whether in space or time, it can be found that the PM$_{2.5}$ level in 2020 is significantly lower than that in 2019. This is largely due to the reduction of man-made emissions during the epidemic lockdown. According to Zheng et al. (2021) on anthropogenic emissions inventory of China, major pollutant emissions in February and March 2020 in Hubei Province have significantly decreased compared to the same period in 2019. Among them, the emissions of NO$_x$, VOC, CO, SO$_2$, and primary PM$_{2.5}$ decreased by 44, 32, 23, 23, and 21% respectively (Fig. S2). On the other hand, the occurrence of high PM$_{2.5}$ levels under low-emission scenarios is likely to indicate an important contribution from meteorological conditions (Shen et al., 2021; Xiong et al., 2021). Therefore, the decline in PM$_{2.5}$ concentration in 2020 is the result of the combined effect of emission reduction and meteorological conditions. Quantitative assessment of their contributions is of great significance for the formulation and implementation of future emission reduction policies.

3.2. Random forest model prediction of PM$_{2.5}$ concentration

There have been many applications of machine learning in predicting PM$_{2.5}$ concentration, and many of these algorithms have also been
proven to have good prediction accuracy, such as random forest models, multilayer perceptron, neural network, and so on (Gupta and Christopher, 2009; Hu et al., 2017; Zhong et al., 2021). Here, we chose the random forest model, a method with high prediction accuracy and can produce more interpretable results (Hu et al., 2017), to build models for predicting PM$_{2.5}$ concentration. The average RMSE of all models on the test set is 10.75 $\mu$g/m$^3$, and the average $R^2$ is 0.86 (Table S1). Generally, the model has a good prediction of the hourly PM$_{2.5}$ concentration, indicating that the model well recognizes the complex relationship between PM$_{2.5}$ and explanatory variables.

When selecting explanatory variables, considering that the concentration of gaseous pollutants cannot represent the contribution of anthropogenic emissions, we chose to use time variables instead. The time variable represents the mode of anthropogenic emissions to a certain extent, and this approach has also been adopted in some previous studies (Grange et al., 2018; He et al., 2021). Judging from the good performance of the model, this approach is reasonable. Fig. 3 shows the feature importance results of the model output. Regardless of the year, the day of year in the time variable shows the greatest importance, which represents the main trend of anthropogenic emissions. For day of week and hour of day, the importance of the two is much smaller, representing some periodic fluctuations superimposed on the trend. As we have seen, the importance of meteorological variables is obvious. The total percentage of importance of meteorological variables in the models exceeds 50%, which may explain why the phenomenon of excessive PM$_{2.5}$ concentration occurs from time to time under low emission scenarios. In addition, in the 2019 and 2020 models, the importance of meteorological variables has a similar spatial distribution in space, with high value areas in the central and eastern regions. And in 2020, the importance of meteorological variables has shown a significant increase in the central region.

![Fig. 4. Spatial distribution of PM$_{2.5}$ concentration in Hubei Province in February and March (a) 2019 and (b) 2020. Spatial distribution of de-weathered PM$_{2.5}$ concentration in Hubei Province in February and March (c) 2019 and (d) 2020. The spatial distribution of the difference between PM$_{2.5}$ concentration and de-weathered PM$_{2.5}$ concentration in Hubei Province in February and March (e) 2019 and (f) 2020. Here we selected 11 sites distributed in Hubei Province for the significance level test and the sites with black circles indicate that they have passed the 0.05 significance level test.](image-url)
3.3. The role of emission and meteorology on the decrease in PM$_{2.5}$ concentrations

In order to separate the contribution of man-made emissions and meteorological conditions, we used a de-weather method to obtain the PM$_{2.5}$ level under the average meteorological conditions in February and March of 2019 and 2020, and the observed PM$_{2.5}$ concentrations are compared to assess the impact of meteorological conditions on PM$_{2.5}$. After de-weather, the PM$_{2.5}$ level of Hubei Province in February and March 2019 increased by 4.49 $\mu$g/m$^3$ as a whole, and the highest increase was in the central region, with a maximum of 9.46 $\mu$g/m$^3$ (Fig. 4(e)). On the contrary, the PM$_{2.5}$ level in February and March 2020 changed relatively little, with an average decrease of 0.62 $\mu$g/m$^3$ (Fig. 4(f)). The most obvious decrease was in the central region, with the largest decrease of 2.95 $\mu$g/m$^3$. However, the PM$_{2.5}$ concentration in the northwest has increased but not significantly. The results after de-weather represent the PM$_{2.5}$ concentration under average weather conditions, so the above results largely indicate that the weather conditions in February and March 2020 are worse than those in the same period in 2019, and this phenomenon seems to be more significant in the central region.

The effect of meteorology in aggravating haze is mainly reflected in two aspects. One is that static and high-humidity weather conditions will promote the secondary generation and local accumulation of particulate matter, and the other is that the regional transport of pollutants leads to high levels of particulate matter. Compared with the same period in 2020, the local anthropogenic emissions in February and March 2019 were higher, which means that PM$_{2.5}$ has a greater contribution from local sources. From the comparison of the meteorological conditions in the same period of the two years, the height of the boundary layer in the central region of Hubei Province has experienced a significant drop in 2020, accompanied by a significant increase in relative humidity (Fig. 5). This change in meteorological conditions is conducive to the local accumulation of pollutants, which explains the increase in PM$_{2.5}$ concentrations during this period in 2019 after de-weather.

During the 2020 lockdown of the epidemic in Hubei Province, even though man-made emissions have dropped significantly, pollution incidents still occurred. Shen et al. (2021) studied six PM$_{2.5}$ pollution incidents during the lockdown of Hubei Province and found that three of them were mainly caused by the regional transport of pollutants from northern China, and the remaining three were caused by local pollution in Hubei Province. In addition, the increase in PM$_{2.5}$ in the three regional transport events was even greater, which illustrates the important role of the regional transport process during this period. In February and March of 2019 and 2020, the northeast wind prevailed in Hubei Province (Figs. S4(a) and S4(b)), and due to the topography of high west and low east, the wind speed in the low and flat central and eastern regions was higher, which provided conditions for the regional transport of pollutants. The wind speed in 2020 has increased significantly in the central and eastern regions (Fig. 5), which may have promoted this process even more. Interestingly, there was a significant southerly wind anomaly in 2020 compared to the same period in 2019 (Fig. 5(d), Figs. S4(c) and S4(d)). As found in previous studies (Shen et al., 2021), the regional transport of pollutants in Hubei Province is mainly from northern China, while the concentration of PM$_{2.5}$ in the southern region was generally low during this period. To this end, we selected 11 sites located in Hubei Province and analyzed the relationship between PM$_{2.5}$ concentration and wind speed and direction in February and March 2020 (Fig. S5). Obviously, many sites have high concentrations of PM$_{2.5}$ during the southerly winds. On the one hand, this may represent the migration of pollutants from the southern part of Hubei Province to the north. On the other hand, this phenomenon also appears in the site in the south, such as 1844A, this largely indicates the transport of pollutants from southern China.

After de-weather, we get the PM$_{2.5}$ concentration under average
The difference in de-weathered PM$_{2.5}$ concentration between the two years reflects the real effect of reduced anthropogenic emissions. Furthermore, the difference in the decrease in de-weathered PM$_{2.5}$ concentration and the actual decrease reflects the contribution caused by meteorology. Overall, the actual decrease in PM$_{2.5}$ concentration in February and March 2020 compared to the same period in 2019 is about 14.3 $\mu$g/m$^3$. The decrease in PM$_{2.5}$ concentration reaches 19.4 $\mu$g/m$^3$ after de-weather, so it can be inferred that the meteorological conditions contributed to the increase of PM$_{2.5}$ by about 5 $\mu$g/m$^3$. Furthermore, as shown in Fig. 6, there are spatial differences in this contribution. In the central part of Hubei Province, the change in meteorological conditions has the most obvious effect on the increase of PM$_{2.5}$, followed by the eastern region, and finally the western region. Obviously different from other sites, at site 2455A, the PM$_{2.5}$ concentration during the epidemic was higher than in the same period in 2019. From the relationship between PM$_{2.5}$ and wind speed and direction, it can be seen that in February and March 2020, the site has obvious local pollution sources, and at the same time it is also affected by the transport process (Fig. S5).

We have carried out de-weather method on the PM$_{2.5}$ concentration of all sites (Fig. S3), and calculated the contribution of changes in meteorology and anthropogenic emissions to the changes in PM$_{2.5}$ concentration according to formula (1) and (2), and performed ordinary kriging interpolation in space (Fig. 6(b) and (c)). The reduction of anthropogenic emissions has led to the reduction of PM$_{2.5}$ concentration. This effect is more pronounced in the central and eastern parts of Hubei Province. In general, the reduction in emissions has reduced PM$_{2.5}$ concentration in February and March 2020 by about 33.3% compared to the same period in 2019, with a maximum drop of about 46.2%. On the contrary, the meteorological conditions during lockdown can promote the increase of PM$_{2.5}$ concentration in Hubei Province, causing the PM$_{2.5}$ concentration to increase by about 8.8% compared to the same period in 2019, and this positive contribution is more obvious in the central region, reaching a maximum of 15%.

As mentioned earlier, the concentration of PM$_{2.5}$ in Hubei Province in February and March 2020 was about 39.6 $\mu$g/m$^3$, which actually dropped by about 14.3 $\mu$g/m$^3$ compared to the same period in 2019. After excluding the influence of meteorological conditions, the decrease can reach 19.4 $\mu$g/m$^3$, which means that under the same meteorological conditions, the PM$_{2.5}$ concentration during this period in 2020 would reach the secondary standard of China (35 $\mu$g/m$^3$). In 2019, the annual average PM$_{2.5}$ concentration in Hubei Province was 44.39 $\mu$g/m$^3$, approximately 10 $\mu$g/m$^3$ higher than the Chinese standard for PM$_{2.5}$. The lockdown during the epidemic represented an overly strict emission reduction measure. It is estimated that the reduction of human activities during the lockdown can lead to a 19.4 $\mu$g/m$^3$ drop in PM$_{2.5}$ concentration, which means that under similar weather conditions in February and March 2019, an emission reduction intensity equivalent to about 48% of the emission reduction intensity during the lockdown may bring the annual average PM$_{2.5}$ concentration to the standard.

4. Conclusions

Evaluating the contribution of meteorological and anthropogenic emissions to PM$_{2.5}$ concentration has always been a research focus, which has important guiding significance for the formulation and implementation of emission reduction policies. In our research, we used a random forest regression model combined with a de-weather method to evaluate the contribution of meteorological and emission reduction to the decline of PM$_{2.5}$ concentration during COVID-19 outbreak in Hubei Province. The results show that the meteorology in February and March 2020 are more conducive to the increase of PM$_{2.5}$ concentration compared to the same period in 2019, and have a positive contribution of about 8.8% to the PM$_{2.5}$ concentration, while the reduction of...
anthropogenic emissions can lead to a 33.3% drop in PM$_{2.5}$ concentration. In February and March 2020, the concentration of PM$_{2.5}$ in Hubei Province was 39.6 g/m$^3$. After excluding the contribution of meteorology, the PM$_{2.5}$ concentration was about 34.5 g/m$^3$, which reached the annual average concentration standard of PM$_{2.5}$. The contribution of meteorological conditions to PM$_{2.5}$ concentration is more obvious in the central region, which is consistent with the conclusion that the central region is the most significant area affected by regional transport, indicating the important contribution of the regional transport of pollutants during COVID-19 outbreak has compensated to some extent for the impact of the reduction of anthropogenic emissions.

As we know, the lockdown during COVID-19 outbreak represents an overly strict emission reduction measure. According to model estimates, under similar meteorological conditions, an emission reduction intensity equivalent to about 48% of the emission reduction intensity during the epidemic may make the annual average concentration of PM$_{2.5}$ in Hubei Province reach the standard.

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Credit author statement
Hongwei Liu: Formal analysis, Investigation, Visualization, Writing – original draft. Fange Yue: Formal analysis, Writing – review & editing. Zhourong Xie: Conceptualization, Formal analysis, Funding acquisition, Supervision, Writing – review & editing.

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

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Appendix A. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2022.118932.

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