High-Resolution Satellite-Based PM2.5 Concentration Data Acquired During the COVID-19 Outbreak Throughout China: Model, Variations, and Reasons

Hong Guo, Xingfa Gu, Tianhai Cheng, Shuaiyi Shi, Xin Zuo, and Wannan Wang

***Abstract*—High spatial resolution and broad spatial coverage data on fine particulate matter (PM2.5) are of great significance to estimating the exposure to PM2.5. However, this type of data is currently very limited worldwide. In addition, the COVID-19 pandemic in China, starting in January 2020, may have led to significant variations in the PM2.5 concentrations. To identify the variations and causes of PM2.5 concentrations before and after the COVID-19 pandemic from January 23 to March 24 during 2018–2020, in this article, a geographically weighted regression model with a 1 km spatial resolution covering all of mainland China was developed. The overall R and RMSE values of the model cross validation were 0.91 and 17.19 μg/m^3, respectively, indicating that the model performed satisfactorily in estimating the PM2.5 values. Then, based on the satellite-based PM2.5 values, the results show that the PM2.5 values fluctuated significantly across mainland China before and after the COVID-19 outbreak. Additionally, the mean PM2.5 values decreased by 5.41 μg/m^3 in 2020 compared to 2019. In Hubei Province, the mean PM2.5 values increased by 1.85 μg/m^3 in 2019 compared to 2018, whereas they dramatically decreased by 23.18 μg/m^3 in 2020 compared to 2019. Finally, the results show that anthropogenic factors were primarily responsible for the variations in the PM2.5 concentrations in Heilongjiang, Jilin, and Liaoning provinces; whereas, both meteorological and anthropogenic factors were responsible for the variations in Hubei, Henan, Anhui, Shandong, and Jiangsu provinces during the study period. These results provide an important reference for the future development of air pollution control policies in China.**

***Index Terms*—China, COVID-19, high-resolution, particulate matter (PM2.5) concentrations, satellite remote sensing.**

I. Introduction

FINE particulate matter (PM2.5) has become a serious health threat to people worldwide [1]–[3]. For example, the average annual number of PM2.5-induced premature deaths in Southeast Asia totaled 1 447 000 during 1999–2014 [4]. In addition to the adverse health effects, PM2.5 pollution also has significant impacts on the weather and climate systems on earth through aerosol-radiation interactions and aerosol-cloud interactions [5]–[7], albeit these effects have large uncertainties [8]. Therefore, it is necessary to understand the variability in PM2.5 concentrations. In China, PM2.5 concentrations have already caused great public concerns in recent years, and in response, China has enforced strict pollution control laws. As a result, PM2.5 concentrations decreased by 14.5% in 2017 compared to 2015 [9]. Although PM2.5 concentrations in China have decreased significantly, the country still failed to meet the health standard set by the World Health Organization. Therefore, it is still important to study the distribution and causes of PM2.5 concentrations and to monitor and control the atmospheric environment in China.

In January 2020, the city of Wuhan in Hubei Province experienced an outbreak of the COVID-19 virus, which spread quickly to other places across mainland China. China immediately implemented very strict control measures to prevent the widespread transmission of COVID-19. Most factories and malls were closed, and people were not allowed to go out except when absolutely necessary. These measures started on 23 January in Wuhan and then spread across the country. After the COVID-19 pandemic was brought under control, people gradually returned to work and travel, starting on March 25, 2020. During this period, with the implementation of very strict measures, air pollutant emissions were significantly reduced, thus providing China with a relatively pure atmosphere. Therefore, it is of great significance to study the variations and causes of PM2.5 concentrations during this period of slower economic activity across mainland China.

At present, a number of studies have reported variations in the air quality during this period [10]–[13]. For example, Liu *et al.* [14] found a notable downward trend in the Air Quality Index across mainland China from January to March 2020. Tanvir *et al.* [15] demonstrated that the COVID-19 lockdown during 2020 led to a considerable decrease in the densities of HCHO and NO_2 in Shanghai. However, only a few studies have focused on the variations in and driving factors of PM2.5 values

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during the lockdown in China [16]. Nichol *et al.* [17] found that PM2.5 values in Beijing increased by 19.5% during January and February in 2020 compared with 2019. Wang *et al.* [18] showed that PM2.5 concentrations would decrease by ∼20% in Guangzhou and nine other cities in China compared with the situation without a change in emissions. Huang *et al.* [19] reported that PM2.5 values increased in Beijing during the COVID-19 lockdown. These studies were mainly based on ground PM2.5 concentrations. However, the spatial coverage was so limited that it was difficult to capture the spatial variability of the PM2.5 concentrations.

Satellite data, with a broad spatial coverage and high resolution, can provide a new way to study PM2.5 concentrations [20]–[24]. A number of models have been developed to predict PM2.5 values using satellite data, such as the linear mixed effect [25]–[27], generalized additive [28], and geographically weighted regression (GWR) models [29]–[32], along with deep learning methods [33]–[36]. However, most previous studies have been limited to providing PM2.5 values with low spatial resolutions or only covered a part of China. Few studies have provided high spatial resolution PM2.5 values across all of mainland China. Moreover, few studies have covered the main period during the COVID-19 pandemic. Therefore, the main purpose of this article was to construct a new model to provide PM2.5 values with a 1 km spatial resolution across mainland China from 23 January to March 24 , during 2018–2020. Subsequently, the variations in the PM2.5 values during the period were analyzed. Finally, the impact of multiple environmental and economic factors on PM2.5 pollution was investigated.

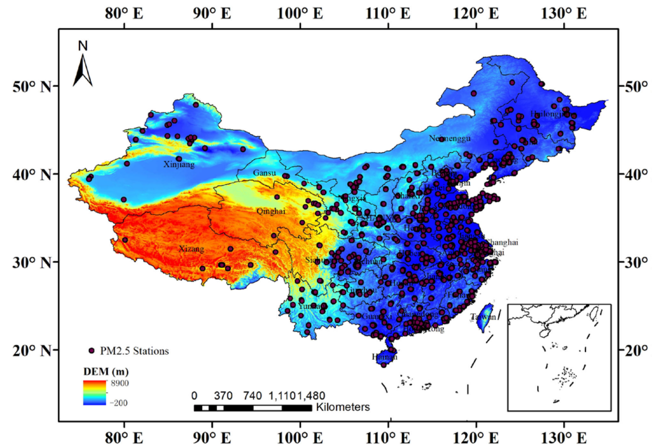

Fig. 1. Ground PM2.5 monitoring stations covering mainland China.

II. Materials and Methods

A. Materials

1) *Moderate Resolution Imaging Spectroradiometer* (MODIS) *Aerosol Optical Depth:* (AOD) In this article, the MCD19A2 product of MODIS with a 1 km spatial-resolution was collected, which is produced based on the multiangle implementation of atmospheric correction (MAIAC) algorithm [37]. The main points of the MAIAC algorithm include the following: using knowledge of the bidirectional reflectance distribution function and spectral regression coefficient; using smoke and dust tests to discriminate between the absorption of fine-mode and coarse-mode aerosols; optimizing the lookup-table based on radiative transfer model for producing the global AOD; and deriving the AOD was from both Terra and Aqua inputs. As a result, MCD19A2 provides a broader spatial coverage than other MODIS AOD products [38], [39]. This product was selected because it offers a broad spatial coverage and high spatial resolution, and the AOD at 550 nm was used. First, we obtained the daily AOD values with partial coverage across China. Then, after we acquired the mean AOD values from during January 23 to March 24 in 2018, 2019, and 2020, we used the inverse distance weighting method to interpolate the AOD data covering the entire country. However, errors can be introduced into the results when a discrete point is far away from the interpolation point [40], [41].
2) *PM2.5 Concentrations:* The Chinese Ministry of Environmental Protection (MEP) has published hourly PM2.5 concentrations at a national scale since January 2013. A total of ∼1480 monitoring stations are unevenly distributed across China (see Fig. 1). In this article, the hourly mean PM2.5 concentrations from January 23 to March 24, 2020 were obtained from the MEP, and the PM2.5 values from January 23, to March 24 in 2018 and 2019 were also obtained in order to compare the variations in the PM2.5 concentrations before and after the outbreak of COVID-19. Then, the mean PM2.5 concentrations measured at 10:00, 11:00, 13:00, and 14:00 were calculated at each site across the entire country, with the same temporal resolutions as the MAIAC Terra (10:30) and Aqua (13:30) data.
3) *Meteorological Data:* The ERA5 product from the European Centre for medium-range weather forecasts represents the fifth-generation atmospheric reanalysis of the global climate dataset, and it provides hourly values of atmospheric parameters. Because they have a higher spatial and temporal resolution than the National Center for Environmental Prediction data, the ERA5 data have been widely used. Therefore, the boundary layer height (BLH; unit: m), the relative humidity at 950 hPa (RH; unit:%), and the 10 m wind speed (WS; unit: m/s) data from the ERA5 were used in this article. The spatial resolutions of the BLH, RH, and WS were $0.25° \times 0.25°$, $0.25° \times 0.25°$, and $0.1° \times 0.1°$, respectively. To enhance the contrast of the regional variability of the PM2.5, the BLH, RH, and WS data were resampled to a $0.01° \times 0.01°$ spatial resolution grid using the nearest neighbor approach. Finally, the mean values of the meteorological factors measured at 10:00, 11:00, 13:00, and 14:00 were used, which were consistent with the MCD19A2.
4) *Gross Domestic Product:* (GDP) The contribution of the GDP to PM2.5 concentrations has been widely discussed. Generally, PM2.5 values are negatively correlated with

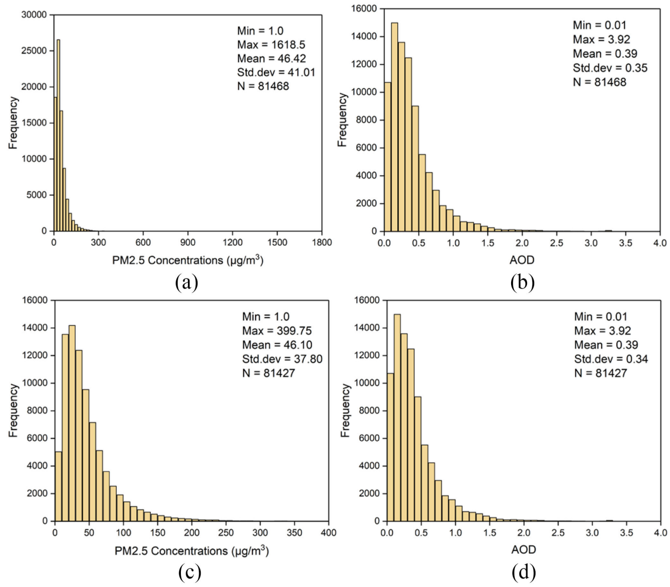

Fig. 2. Histograms and descriptive statistics for AOD and PM2.5 values across mainland China from January 23 to March 24 during 2018–2020. (a) PM2.5 for all data. (b) AOD for all data. (c) PM2.5 for only measurements lower than 400 μg/m^3. (d) AOD for the same records as in Fig. 2(c).

the GDP [42]. The GDP across mainland China has been significantly affected by the COVID-19 pandemic. Thus, in this article, the first quarter GDPs for each province/city in 2018, 2019, and 2020 were obtained from the Chinese National Bureau of Statistics (NBU).

B. Methods

1) GWR Model: Currently, GWR models have been developed to predict PM2.5 concentrations many times. However, at least three parameters have been used in some GWR models, whereas five or more parameters have been widely incorporated into other GWR models [43]–[45]. The AOD represents the aerosol optical properties of the total column. The PM2.5 is defined as the aerosols with aerodynamic diameters of $\leq 2.5\ \mu$m. As Fig. 2 shows, they are highly correlated, so the AOD was used to estimate the satellite-based PM2.5 concentrations. Except for the AOD, most of the parameters were meteorological factors with a low spatial resolution ($1^\circ \times 1^\circ$), which could introduce uncertainties in the model. Therefore, a new GWR model with one parameter was developed to estimate the PM2.5 values. The bandwidth is the distance band or number of neighbors used for each local regression equation, and it controls the degree of smoothing in the GWR model. The optimal distance or optimal number of neighbors can be obtained using the fixed kernel method or the adaptive kernel method. Here, the adaptive kernel method was selected because the monitoring sites were unevenly distributed. The Akaike Information Criterion (AICc) is based on the concept of entropy, and it can weigh the complexity of the estimated model and the goodness of fit of the model to the data [46], [47]. The model with the lowest AICc value provides the best fit to the observed data. A good bandwidth can be obtained by minimizing the corrected AICc values [48], [49]. The smaller the AICc is, the better the bandwidth is. The model can be expressed as follows:

$$\mathrm{PM2.5}_{ij} = \mathrm{a}_{ij} + \mathrm{b}_{ij}\mathrm{AOD}_{ij} + \varepsilon_{ij} \tag{1}$$

where PM2.5 is the ground-based values at location *i* on day *j*, AOD is the average value of the MCD19A2 at location *i* on day *j*, a is the location-specific intercept of the GWR model, *b* is the location-specific slope of the GWR model, and ε is an error term.

Cross validation (CV) is a common method used to evaluate the accuracy of a model. Therefore, a three-fold CV method was used [50]. The entire dataset was divided into three subsets, with approximately 1/3 of the entire records in each subset. In each round of CV, two subsets were selected to fit the model, and the other subset was used as testing samples. In addition, the reduced major axis (RMA) was used to obtain the slope and intercept between the ground PM2.5 concentrations and the satellite estimated values [51], [52]. In the RMA, the slope (β) and intercept (α) were calculated as follows:

$$\beta = \frac{\sigma_y}{\sigma_x} \tag{2}$$

$$\alpha = \bar{Y} - \left(\frac{\sigma_y}{\sigma_x}\right)\bar{X} \tag{3}$$

where X are the ground PM2.5 concentrations, and *Y* are the satellite estimated values. $\bar{X}$ and $\bar{Y}$ are the mean values of *X* and *Y*, respectively; and σ_x and σ_y are the standard deviations of *X* and *Y*, respectively. In addition, the mean absolute error (MAE), root-mean-squared error (RMSE), and mean systematic error (MSE) were computed as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - X_i| \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)^2} \tag{5}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - X_i\right)^2 \tag{6}$$

where $\hat{Y}_i$ is the predicted value based on the RMA relationship ($Y = \beta X + \alpha$) between *X* and *Y*.

2) Analytical Methods: In order to determine the variations in the PM2.5 concentrations and the reasons for these values during the study period, the mean difference (MD) and mean rate of change (MROC) were used to compare the variances in mean values of the PM2.5 concentrations, BLH, RH, WS, and GDP throughout China. The MD and MROC were defined as follows:

$$\mathrm{MD} = Y_{i,j} - X_{i,j} \tag{7}$$

$$\mathrm{MROC} = (Y_{i,j} - X_{i,j}) / X_{i,j} \times 100\% \tag{8}$$

where *i* and *j* indicate the locations in the satellite images. When evaluating the variations in and reasons for the PM2.5 concentrations between 2018 and 2019, $Y_{i,j}$ and $X_{i,j}$ represent the mean values of the PM2.5 concentrations, BLH, RH, WS, and

GDP in 2019 and 2018, respectively; and when evaluating the variations in and reasons for the PM2.5 concentrations between 2019 and 2020, $Y_{i,j}$ and $X_{i,j}$ represent the values in 2020 and 2019, respectively.

III. Results and Discussion

A. *Model for Estimating High-Resolution Satellite-Based PM2.5 Concentrations*

1) Descriptive Statistics: Finally, a total of 81468 observations were included in the dataset during the period described above. The descriptive statistics and histograms for the AOD and PM2.5 values are shown in Fig. 2. For all of the records [see Fig. 2(a) and (b)], the mean value and standard deviation of the AOD were 0.39 and 0.35, respectively; and they were 46.42 and 41.01 μg/m^3 for the PM2.5 concentrations, respectively. The minimum and maximum PM2.5 values were 1.0 and 1618.5 μg/m^3, respectively. The maximum PM2.5 values were found in Xinjiang Province and were very likely caused by dust storms. Furthermore, only 41 records contained PM2.5 values of greater than 400 μg/m^3. For the records with PM2.5 values of less than 400 μg/m^3 [see Fig. 2 (c) and (d)], we found that the frequency distributions of the AOD and PM2.5 were very similar, indicating that they were strongly correlated.

2) Model Performance: Fig. 3 illustrates the results for the model fitting and CV. The *R*, slope, and RMSE were 0.94, 0.91, and 14.19 μg/m^3, respectively, for the model fitting, whereas they were 0.91, 0.91, and 17.19 μg/m^3 for the model CV. Moreover, the MAE and MSE were 8.63 and 12.67 μg/m^3, respectively, for the model fitting, whereas they were 10.17 and 12.78 μg/m^3 for the model CV [see Fig. 3(a) and (b)]. It was found that the residuals were large, with ground PM2.5 values of greater than 400 μg/m^3 [see Fig. 3(c) and (d)]. One potential error in the model is related to the uneven spatial distribution of the ground PM2.5 monitoring sites. Consequently, in the areas with few ground PM2.5 monitoring sites, for example Xizang, Qinghai, and Neimenggu [see Fig. 3(e) and (f)], the model could contain substantial errors. Overall, the results suggest that the model performs well, with a good agreement between the observed and estimated PM2.5 values. However, the accuracy of the model could still be improved by incorporating more parameters into the model.

3) Estimated PM2.5 Concentrations: Fig. 4 shows the mean PM2.5 values across mainland China during the study period. The PM2.5 values were 43.30 $\pm$ 27.53 μg/m^3 in 2019 and 37.89 $\pm$24.94 μg/m^3 in 2020. The most polluted areas were in Xinjiang, the North China Plain, the Northeast China Plain, and the Sichuan Basin, where the PM2.5 values were generally greater than 55 μg/m^3. In contrast, the areas with the cleanest air were mainly in Xizang and Qinghai, where the PM2.5 values were generally less than 15 μg/m^3. Similar results were also found for most of the areas in China in previous studies [21], [44]. However, the Northeast China Plain had much higher PM2.5 values than the others, and the PM2.5 values mainly ranged from 35 to 75 μg/m^3. Overall, the PM2.5 values in most of the areas across mainland China decreased in 2020 compared with 2019, especially in the North China Plain.

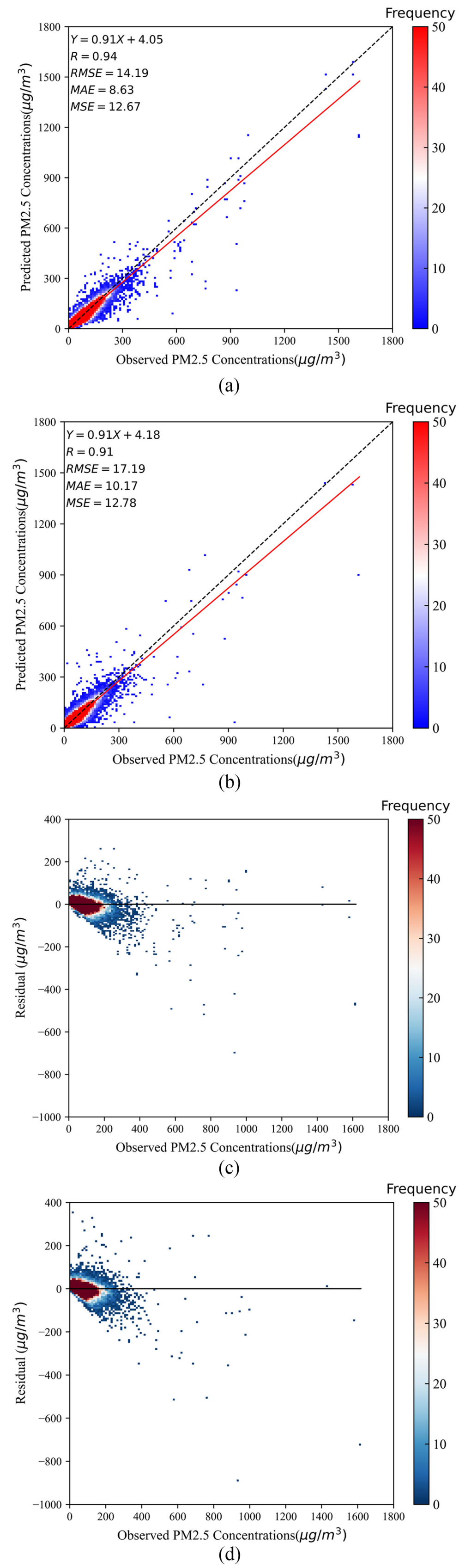

Fig. 3. Model performance across mainland China. (a) model fitting; and (b) model validation. (c) The residuals for the model fitting; and (d) the residuals for the model validation.

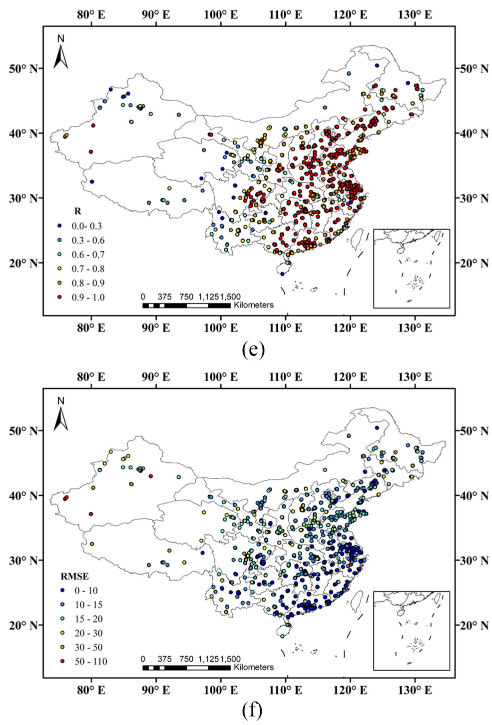

Fig. 3. (Continued.) Model performance across mainland China. (e) The spatial distribution of the R for the model validation; and (f) the spatial distribution of the RMSE for the model validation.

B. Variations in PM2.5 Concentrations

1) Variations in PM2.5 Concentrations Across Mainland China: To compare the variations in the PM2.5 values before and after the outbreak of COVID-19 across mainland China, the MD and MROC were calculated, and three interesting areas (i.e., regions A–C) were selected for analysis (see Fig. 5a). Region A mainly includes Heilongjiang, Jilin, and Liaoning provinces. Region B mainly includes Hubei, Henan, Anhui, Shandong, and Jiangsu provinces, and region C is Yunnan Province.

The mean PM2.5 values decreased year by year across mainland China, i.e., 3.17 μg/m^3 (43.30 $\pm$ 27.53 μg/m^3) in 2019 compared with (46.47 $\pm$ 22.65 μg/m^3) in 2018 (see Fig. 5a). When compared with 2018, the PM2.5 values increased in nearly half of the areas across mainland China [see Fig. 5(c)]. These areas were mainly located in regions A and B and in Xinjiang, where the PM2.5 values increased by less than 40 μg/m^3 [see Fig. 5(a)]. Thus, the areas with decreases were primarily in the western and southern parts of China, where the PM2.5 values decreased to less than 20 μg/m^3 in 2019.

As was expected, the outbreak of COVID-19 resulted in a significant decrease in the mean PM2.5 values across mainland China, with PM2.5 values decreasing by 5.41 μg/m^3 in 2020 (37.89 $\pm$ 24.94 μg/m^3) compared to 2019, i.e., by a factor of 1.71 (5.41/3.17 = 1.71). Compared with 2019, the PM2.5 values in nearly three-quarters of the areas across mainland China decreased in 2020 [see Fig. 5(b)]. Apparently, the PM2.5 concentrations in regions A and B, which mainly increased by 10–40% in 2019 compared with 2018, [see Fig. 5(d)], mainly

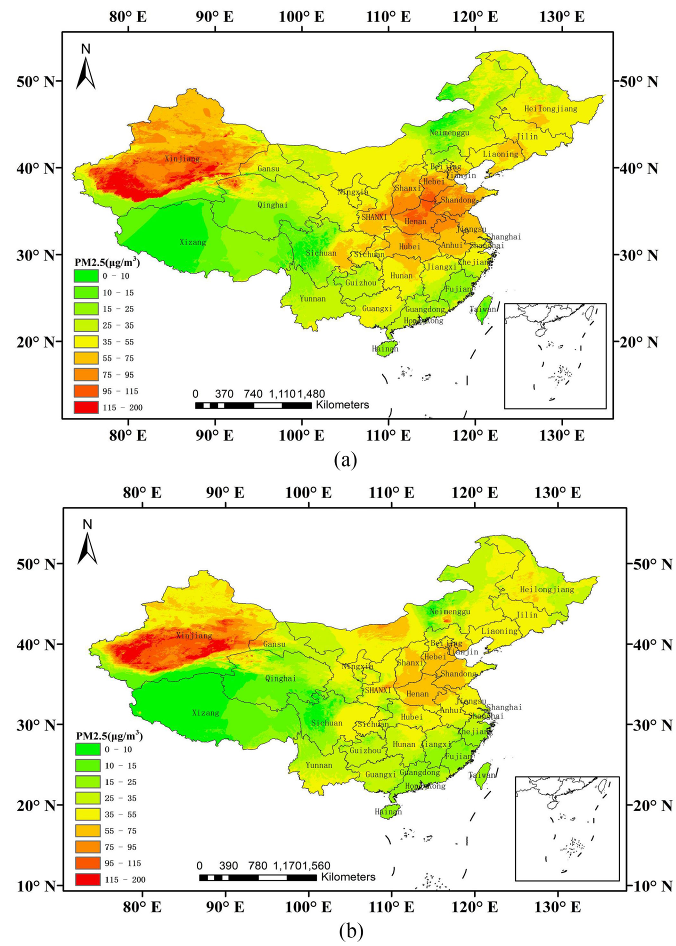

Fig. 4. Spatial distributions of the mean PM2.5 values across mainland China from January 23 to March 24: (a) for 2019 and (b) 2020.

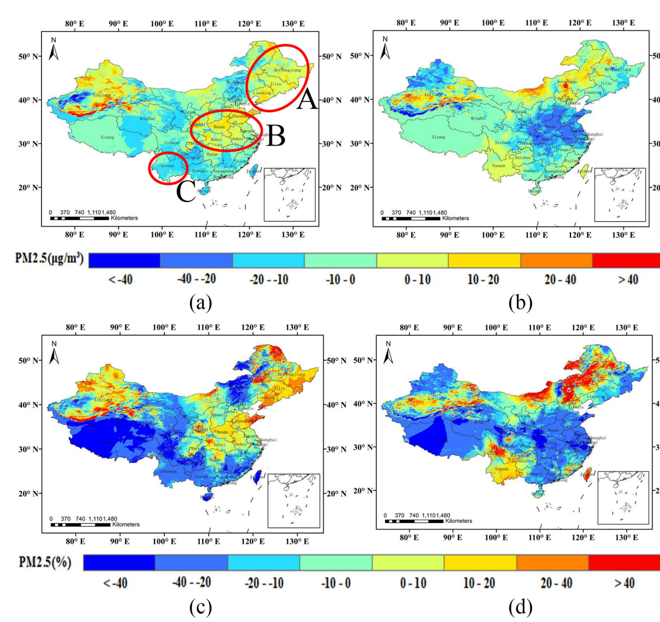

Fig. 5. Variations in the PM2.5 values across mainland China from January 23 to March 24. (a) MD between 2018 and 2019. (b) MD between 2019 and 2020. (c) MROC between 2018 and 2019. (d) MROC between 2019 and 2020.

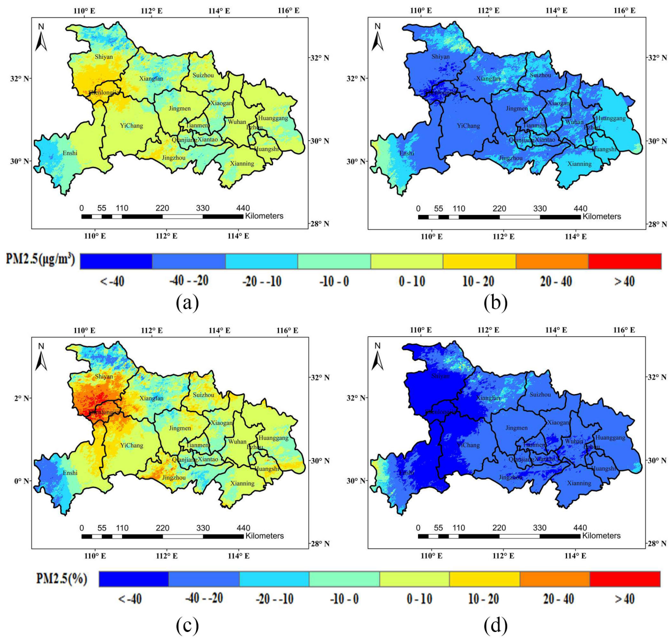

Fig. 6 Variations in PM2.5 values in Hubei Province from January 23 to March 24. (a) MD between 2018 and 2019. (b) MD between 2019 and 2020; (c) MROC between 2018 and 2019. (d) MROC between 2019 and 2020.

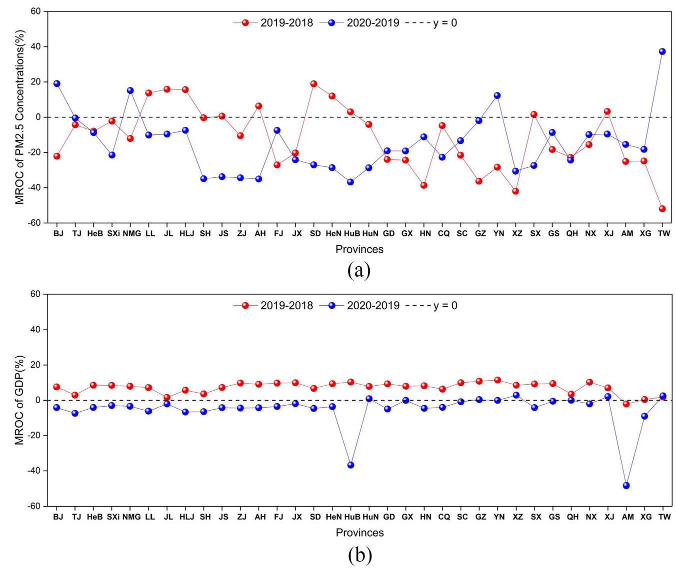

Fig. 7. Variations in the PM2.5 values and GDP across mainland China from January 23 to March 24 during 2018–2020. (a) PM2.5 concentrations, (b) Gross domestic product.

decreased by 10–40% in 2020 [see Fig. 5(d)]. Additionally, in region C, the PM2.5 values mainly decreased by 20–40% in 2019 compared with 2018; however, the PM2.5 values primarily increased by 10–40% in 2020 compared with 2019.

2) Variations in PM2.5 Concentrations in Hubei Province: Hubei Province experienced the worst effects caused by the outbreak of COVID-19 in China. Benefiting from PM2.5 values with a 1 km spatial resolution, many detailed characteristics of the PM2.5 concentrations in Hubei were also identified (see Fig. 6). As Fig. 6 shows, the mean PM2.5 values in Hubei were significantly different before and after the outbreak of COVID-19, with a 1.85 $\mu g/m^3$ increase in 2019 ($63.06 \pm 9.51 \mu g/m^3$) compared to 2018 (61.21 ± 9.81 $\mu g/m^3$). However, PM2.5 values decreased dramatically by 23.18 $\mu g/m^3$ in 2020 to 39.88 $\pm$ 10.01$\mu g/m^3$ when compared with 2019 levels. Spatially, the variations of PM2.5 values in 2019 generally ranged from -10 to 10 $\mu g/m^3$, with most areas increasing by $\sim$10% compared to 2018. The outbreak of the COVID-19 pandemic in 2020 caused the PM2.5 values in almost all of Hubei Province to decrease significantly by over 20%, with the values mainly dropping by 10–40 $\mu g/m^3$ compared with 2019.

C. Reasons for the Trends in the PM2.5 Concentrations

1) Contribution of the GDP to the Variations in the PM2.5 Concentrations: The variations in the PM2.5 values were caused by both natural and anthropogenic factors. Rapid socioeconomic development has been tied to the increasing PM2.5 pollution across mainland China. The mean PM2.5 values for each province across mainland China were initially calculated to identify correlations between the GDP and PM2.5 values. Then, we obtained the MROC values of the PM2.5 values and the GDP during 2018–2020 (see Fig. 7). As Fig. 7 shows, although the GDP increased steadily in 2019 compared with 2018, the PM2.5 values decreased in 24 out of 34 provinces and other administrative areas in China, indicating that the enforcement of environmental protection laws in China had a positive effect, which is in agreement with the findings of Wang *et al.* [53] and Zhang and Wu [54]. Additionally, the number of provinces with increasing GDPs decreased substantially from 33 in 2019 to only 5 in 2020 with the outbreak of COVID-19. As a result, the provinces with decreased PM2.5 values increased from 24 in 2019 to 30 in 2020. Furthermore, a total of 14 provinces experienced decreases in PM2.5 values of greater than 20%. For example, Hubei Province experienced a large decrease in PM2.5 values (-36.72%) in part because it experienced a large decrease in its GDP (-36.75%). It seems that the PM2.5 values were positively associated with the GDPs across mainland China; however, combined with the results shown in Fig. 8, it can be inferred that there is no obvious correlation between the PM2.5 values and GDP, which is different from the findings of Zhou *et al.* [42].

2) Effects of Meteorological Factors on Variations in PM2.5 Concentrations: In addition to anthropogenic effects, PM2.5 values are also significantly affected by meteorological factors, especially the BLH, WS, rainfall, and RH. The evolution of BLH affects the vertical diffusion of PM2.5 particles [55], [56]. Generally, a higher BLH implies stronger turbulent diffusion, which results in lower PM2.5 values [57]. In addition, the horizontal diffusion of PM2.5 particles varies greatly with the WS [58]. Moreover, the washing process caused by rainfall strongly affects atmospheric PM2.5 values [59]. A 5 mm rain event led to a 10–30 $\mu g/m^3$ decrease in the PM2.5 values in Beijing [60]. In addition, the formation of PM2.5 is also affected by the RH, and a high RH is conducive to the conversion of gaseous pollutants, such as SO_2 and NO_x, into particulate matter, thus aggravating

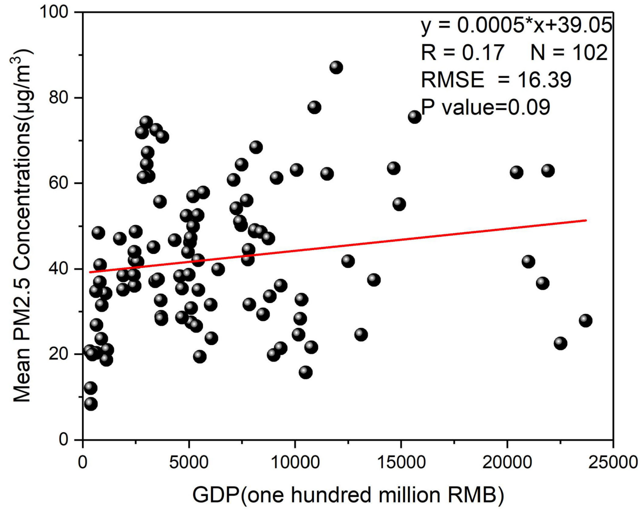

Fig. 8. Correlation between the mean PM2.5 values and GDPs in the provinces/cities during 2018–2020.

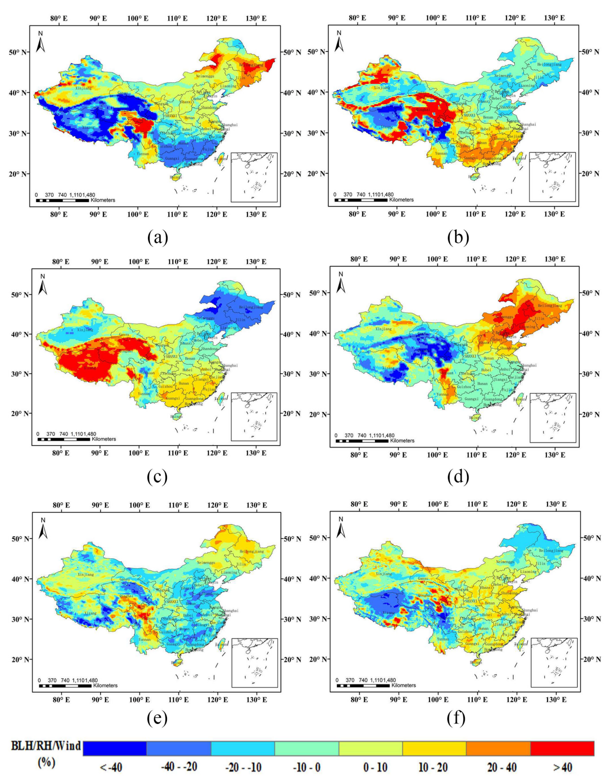

Fig. 9. Variations in the meteorological factors across mainland China from January 23 to March 24. (a) MROC of the BLH between 2018 and 2019. (b) MROC of the BLH between 2019 and 2020. (c) MROC of the RH between 2018 and 2019. (d) MROC of the RH between 2019 and 2020. (e) MROC of the wind between 2018 and 2019. (f) MROC of the wind between 2019 and 2020.

PM2.5 pollution [61]. Given the complicated wet scavenging effect on PM2.5 concentrations, all of the cases in the presence of rainfall were discarded from the subsequent analysis, thus, only the contributions of the BLH, WS, and RH to the PM2.5 concentrations were analyzed (see Fig. 9). In this section, the causes of the PM2.5 values in the three representative regions (A–C) are discussed (see Fig. 5).

As Fig. 9 shows, compared with 2018, the BLH and WS in most areas of region A both increased by $\sim$20% in 2019, whereas the RH decreased by $\sim$30%, suggesting that some meteorological conditions are helpful in diffusing PM2.5 pollutants. However, the PM2.5 values increased by $\sim$20% in 2019. Considering that the GDP increased by 5.71%, 1.62%, and 7.18% in Heilongjiang, Jilin, and Liaoning, respectively, it could be that the anthropogenic factors were responsible for the variations in the PM2.5 values in 2019. As for region B, compared with 2018, the variations in the BLH and RH in most areas ranged from -10% to 10%, whereas the WS decreased by $\sim$20%, indicating that the meteorological conditions adversely affected the diffusion of PM2.5 pollutants. Combined with the GDP growth of $\sim$8.5%, it can be inferred that the $\sim$10% increase in the PM2.5 values in 2019 may have been caused by both meteorological and anthropogenic factors. As for region C, compared with 2018, the meteorological conditions were conducive to the diffusion of PM2.5 pollution, with an increase of $\sim$10% for both the BLH and WS, whereas the RH remained almost unchanged. Considering that the GDP increased by 11.48%, the meteorological factors may have led to the $\sim$10% decrease in the PM2.5 values in 2019.

Compared to 2019, the meteorological conditions in region A in 2020 severely limited the diffusion of the PM2.5 pollutants, with the BLH decreasing by $\sim$10% and the RH increasing by more than 20%, whereas the WS remained nearly steady. Considering the fact that the GDP decreased by 6.67%, 2.02%, and 6.13% in Heilongjiang, Jilin, and Liaoning, respectively, suggests that anthropogenic factors may have been responsible for the $>$ 10% decrease in the PM2.5 concentrations in 2020. As for region B, compared with 2019, overall, the BLH and RH remained steady, whereas the WS increased by more than 10%, indicating that the meteorological conditions were conductive to the diffusion of PM2.5 pollution. Combined with the $\sim$4% decrease in the GDP, except in Hubei (decrease of 36.75%), it can be inferred that the $>$20% decrease in the PM2.5 values in 2020 may have been the result of both meteorological and anthropogenic factors. As for region C, compared with 2019, the meteorological conditions were conducive to the diffusion of PM2.5 pollution, with the BLH increasing by $\sim$10% and the WS and RH remaining almost unchanged in 2020. Considering that the GDP remained steady (-0.06%), anthropogenic factors may have caused the $>$ 10% increase in the PM2.5 values in 2020. Overall, only a qualitative analysis of the causes of the PM2.5 concentrations was conducted in this article, and the detailed causes of the changes in the PM2.5 still need to be quantitatively studied in the future. Moreover, the study period including the Spring Festival may have also influenced the results.

IV. Conclusion

In this article, in order to determine the variations and the causes of the variations in the PM2.5 concentrations before and after the outbreak of COVID-19 across mainland China, ground PM2.5 concentrations, AOD, GDP, and meteorological data from January 23 to March 24 during 2018–2020 were selected for analysis.

TABLE I

Original Name	abbr. Name	Original Name	abbr. Name
Beijing	BJ	Hubei	HuB
Tianjing	TJ	Hunan	HuN
Hebei	HeB	Guangdong	GD
Shānxi	SXi	Guangxi	GX
Neimenggu	NMG	Hainan	HN
Liaoning	LL	Chongqing	CQ
Jilin	JL	sichuan	SC
Heilongjiang	HLJ	Guizhou	GZ
Shanghai	SH	Yunnan	YN
Jiangsu	JS	Xizang	XZ
Zhejiang	ZJ	Shǎnxi	SX
Anhui	AH	Gansu	GS
Fujian	FJ	qinghai	QH
Jiangxi	JX	Ningxia	NX
Shandong	SD	Xinjiang	XJ
Henan	HeN	Xianggang	XG
Aomen	AM	Taiwan	TW

First, unlike previous GWR models, in this article, only the AOD was used to predict the PM2.5 concentrations. The GWR model using satellite data was developed to provide the PM2.5 values with a 1 km spatial resolution during the outbreak of COVID-19 across mainland China. The overall R and RMSE values for the model fitting were 0.94 and 14.19 μg/m^3, respectively, whereas those for the model CV were 0.91 and 17.19 μg/m^3, respectively, suggesting that the model performed satisfactorily when estimating the PM2.5 values.

Second, we found that the PM2.5 concentrations fluctuated significantly across mainland China during the study period, with a 5.41 μg/m^3 decrease in the PM2.5 values in 2020 compared to 2019. Due to the availability of PM2.5 values with a high spatial resolution, the variations in the PM2.5 values in Hubei Province were also available. The results indicate that the PM2.5 values increased by 1.85 μg/m^3 in 2019 compared to 2018. However, the PM2.5 values decreased dramatically by 23.18 μg/m^3 in 2020 compared to 2019.

Finally, the reasons for the variations in the PM2.5 values were investigated. The anthropogenic factors could be responsible for the variations in the PM2.5 values in region A during 2018–2020, whereas both the meteorological and anthropogenic factors were involved in region B. As for region C, the meteorological factors led to the decrease in the PM2.5 values in 2019 compared with 2018, whereas the anthropogenic factors resulted in the increase in the PM2.5 values in 2020 compared with 2019. These results provide an important reference for the future development of air pollution control policies in China.

Appendix

See Table I.

Acknowledgment

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References

[1] L. A. McGuinn *et al.*, “Fine particulate matter and cardiovascular disease: Comparison of assessment methods for long-term exposure,” *Environ. Res.*, vol. 159, pp. 16–23, 2017.
[2] H. Guo *et al.*, “Assessment of PM2.5 concentrations and exposure throughout China using ground observations,” *Sci. Total Environ.*, vol. 601/602, pp. 1024–1030, 2017.
[3] Y. Zhou *et al.*, “Long-term effect of personal PM2.5 exposure on lung function: A panel study in China,” *J Hazard Mater*, vol. 393, 2020, Art. no. 122457.
[4] Y. Shi, T. Matsunaga, Y. Yamaguchi, A. Zhao, Z. Li, and X. Gu, “Long-term trends and spatial patterns of PM2.5-induced premature mortality in South and Southeast Asia from 1999 to 2014,” *Sci. Total Environ.*, vol. 631-632, pp. 1504–1514, 2018.
[5] D. Rosenfeld *et al.*, “Flood or drought: How do aerosols affect precipitation?,” *Science,* vol. 321, pp. 1309–1313, 2008.
[6] O. Boucher *et al.*, “Clouds and aerosols. In: Climate change 2013: The physical science basis. Contribution of working group i to the fifth assessment report of the intergovernmental panel on climate change,” Cambridge Univ. Press, Cambridge, U.K., 2013.
[7] J. Guo *et al.*, “Declining summertime local-scale precipitation frequency over China and the United States, 1981–2012: The disparate roles of aerosols,” *Geophys. Res. Lett.*, vol. 46, pp. 13281–13289, 2019.
[8] Z. Li *et al.*, “East Asian study of tropospheric aerosols and their impact on regional clouds, precipitation, and climate (EAST-AIR CPC),” *J. Geophys. Res. Atmos.*, vol. 124, pp. 13026–13054, 2019.
[9] H. Guo *et al.*, “Spatial and temporal variations of air quality and six air pollutants in China during 2015-2017,” *Sci. Rep.*, vol. 9, 2019, Art. no. 15201.
[10] Q. Liu *et al.*, “Spatiotemporal impacts of COVID-19 on air pollution in California, USA,” *Sci. Total Environ.*, vol. 750, 2021, Art. no. 141592.
[11] P. Chowdhury, S. K. Paul, S. Kaisar, and M. A. Moktadir, “COVID-19 pandemic related supply chain studies: A systematic review,” *Transp. Res. E.,* vol. 148, 2021, Art. no. 102271.
[12] D. Liang *et al.*, “Urban air pollution may enhance COVID-19 case-fatality and mortality rates in the United States,” *Innovation*, vol. 1, 2020, Art. no. 100047.
[13] R. Wang *et al.*, “Daily CO_2 Emission reduction indicates the control of activities to contain COVID-19 in China,” *Innovation*, vol. 1, 2020, Art. no. 100062.
[14] Q. Liu *et al.*, “Spatiotemporal patterns of COVID-19 impact on human activities and environment in mainland China using nighttime light and air quality data,” *Remote Sens.*, vol. 12, no. 10, 2020, Art. no. 1576.
[15] A. Tanvir *et al.*, “Ground-based MAX-DOAS observations of tropospheric NO2 and HCHO during COVID-19 lockdown and spring festival over Shanghai, China,” *Remote Sens.*, vol. 13, no. 3, 2021, Art. no. 488.
[16] C. Fan *et al.*, “The impact of the control measures during the COVID-19 outbreak on air pollution in China,” *Remote Sens.*, vol. 12, no. 10, 2020, Art. no. 1613.
[17] J. E. Nichol, M. Bilal, M. A. Ali, and Z. Qiu, “Air pollution scenario over China during COVID-19,” *Remote Sens.*, vol. 12, no. 13, 2020, Art. no. 2100.
[18] P. Wang, K. Chen, S. Zhu, P. Wang, and H. Zhang, “Severe air pollution events not avoided by reduced anthropogenic activities during COVID-19 outbreak,” *Resour. Conserv. Recycling*, vol. 158, 2020, Art. no. 104814.
[19] X. Huang *et al.*, “Enhanced secondary pollution offset reduction of primary emissions during COVID-19 lockdown in China,” *Nat. Sci. Rev.*, vol. 8, no. 2, 2021, Art. no. nwaa137.
[20] A. van Donkelaar, R. V. Martin, M. Brauer, and B. L. Boys, “Use of satellite observations for long-term exposure assessment of global concentrations of fine particulate matter,” *Environ. Health Perspectives*, vol. 123, no. 2, pp. 135–143, 2015.
[21] J. Wei *et al.*, “Estimating 1-km-resolution PM2.5 concentrations across China using the space-time random forest approach,” *Remote Sens. Environ.*, vol. 231, 2019, Art. no. 111221.
[22] X. Hu *et al.*, “Estimating ground-level PM2.5 concentrations in the Southeastern United States using MAIAC AOD retrievals and a two-stage model,” *Remote Sens. Environ.*, vol. 140, pp. 220–232, 2014.

[23] Y. Guo, Q. Tang, D. Y. Gong, and Z. Zhang, “Estimating ground-level PM2.5 concentrations in Beijing using a satellite-based geographically and temporally weighted regression model,” *Remote Sens. Environ.*, vol. 198, pp. 140–149, 2017.

[24] T. Li, H. Shen, C. Zeng, Q. Yuan, and L. Zhang, “Point-surface fusion of station measurements and satellite observations for mapping PM2.5 distribution in China: Methods and assessment,” *Atmos. Environ.*, vol. 152, pp. 477–489. 2017.

[25] Z. Ma, Y. Liu, Q. Zhao, M. Liu, Y. Zhou, and J. Bi, “Satellite-derived high resolution PM2.5 concentrations in Yangtze River delta region of China using improved linear mixed effects model,” *Atmos. Environ.*, vol. 133, pp. 156–164, 2016.

[26] Y. Zheng, Q. Zhang, Y. Liu, G. Geng, and K. He, “Estimating ground-level PM2.5 concentrations over three megalopolises in China using satellite-derived aerosol optical depth measurements,” *Atmos. Environ.*, vol. 124, pp. 232–242, 2016.

[27] D. Fu *et al.*, “Mapping nighttime PM 2.5 from VIIRS DNB using a linear mixed-effect model,” *Atmos. Environ.*, vol. 178, pp. 214–222, 2018.

[28] B. Zou, J. Chen, L. Zhai, X. Fang, and Z. Zheng, “Satellite based mapping of ground PM2.5 concentration using generalized additive modeling,” *Remote Sens.*, vol. 9, no. 1, pp. 1–16, 2017.

[29] B. Zou, Q. Pu, M. Bilal, Q. Weng, L. Zhai, and J. Nichol, “High resolution satellite mapping of fine particulates based on geographically weighted regression,” *IEEE Trans. Geosci. Remote Sens.,* vol. 13, no. 4, pp. 495–499, Apr. 2016.

[30] M. Jiang, W. Sun, G. Yang, and D. Zhang, “Modelling seasonal GWR of daily PM2.5 with proper auxiliary variables for the Yangtze River delta,” *Remote Sens.*, vol. 9, no. 4, pp. 1–20, 2017.

[31] A. van Donkelaar *et al.*, “Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors,” *Environ. Sci. Technol.*, vol. 50, pp. 3762–3772, 2016.

[32] M. S. Hammer *et al.*, “Global estimates and long-term trends of fine particulate matter concentrations (1998-2018),” *Environ. Sci. Technol.*, vol. 54, pp. 7879–7890, 2020.

[33] K. Huang *et al.*, “Predicting monthly high-resolution PM2.5 concentrations with random forest model in the North China plain,” *Environ. Pollut.*, vol. 242, pp. 675–683, 2018.

[34] X. Li and X. Zhang, “Predicting ground-level PM2.5 concentrations in the Beijing-Tianjin-Hebei region: A hybrid remote sensing and machine learning approach,” *Environ. Pollut.*, vol. 249, pp. 735–749, 2019.

[35] H. Liu and C. Chen, “Prediction of outdoor PM2.5 concentrations based on a three-stage hybrid neural network model,” *Atmos. Pollut. Res.*, vol. 11, no. 3, pp. 469–481, 2020.

[36] J. Wei *et al.*, “Reconstructing 1-km-resolution high-quality PM2.5 data records from 2000 to 2018 in China: Spatiotemporal variations and policy implications,” *Remote Sens. Environ.*, vol. 252, 2021, Art. no. 112136.

[37] A. Lyapustin, Y. Wang, S. Korkin, and D. Huang, “MODIS collection 6 MAIAC algorithm,” *Atmos. Meas. Techn.*, vol. 11, no. 10, pp. 5741–5765, 2018.

[38] N. C. Hsu *et al.*, “Enhanced deep blue aerosol retrieval algorithm: The second generation,” *J. Geophys. Res., Atmos.*, vol. 118, no. 16, pp. 9296–9315, 2013.

[39] R. C. Levy *et al.*, “The collection 6 MODIS aerosol products over land and ocean,” *Atmos. Meas. Techn.*, vol. 6, no. 11, pp. 2989–3034, 2013.

[40] G. M. Philip and D. F. Watson. “A precise method for determining contoured surfaces,” *Australian Petroleum Exploration Assoc. J.*, vol. 22, pp. 205–212, 1982.

[41] D. F. Watson and G. M. Philip. “A refinement of inverse distance weighted interpolation,” *Geoprocessing*, vol. 2, pp. 315–327, 1985.

[42] C. Zhou, J. Chen, and S. Wang, “Examining the effects of socioeconomic development on fine particulate matter (PM2.5) in China’s cities using spatial regression and the geographical detector technique,” *Sci. Total Environ.*, vol. 619/620, pp. 436–445, 2018.

[43] Z. Ma, X. Hu, L. Huang, J. Bi, and Y. Liu, “Estimating ground-level PM2.5 in China using satellite remote sensing,” *Environ. Sci. Technol.*, vol. 48, no. 13, pp. 7436–7444, 2014.

[44] W. Song, H. Jia, J. Huang, and Y. Zhang, “A satellite-based geographically weighted regression model for regional PM2.5 estimation over the Pearl River Delta region in China,” *Remote Sens. Environ.*, vol. 154, pp. 1–7, 2014.

[45] W. You, Z. Zang, L. Zhang, Y. Li, X. Pan, and W. Wang, “National-Scale estimates of ground-level PM2.5 concentration in China using geographically weighted regression based on 3 km resolution MODIS AOD,” *Remote Sens,* vol. 8, no. 3, 2016, Art. no. 184.

[46] H. Akaike, “A new look at statistical model identification,” *IEEE Trans. Control,* vol. 19, no. 6, pp. 716–723, Dec. 1974.

[47] A. W. Hughes and M. L. King, “Model selection using AIC in the presence of one-sided information,” *J. Stat. Plan. Inference*, vol. 115, pp. 397–411, 2003.

[48] X. Hu *et al.*, “Estimating ground-level PM 2.5 concentrations in the southeastern U.S. using geographically weighted regression,” *Environ. Res.*, vol. 121, pp. 1–10, Feb. 2013.

[49] Q. Zhou, C. Wang, and S. Fang, “Application of geographically weighted regression (GWR) in the analysis of the cause of haze pollution in China”. *Atmos. Pollut. Res.,* vol. 10, pp. 835–846, 2019.

[50] A. P. R. Juan Diego Rodríguez and J. A. Lozano, “Sensitivity analysis of k-fold cross validation in prediction error estimation,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 3, pp. 569–575, Mar. 2010.

[51] J. Bohonak Andrew and K. van der Linde, “RMA: Software for reduced major axis regression, java version,” 2004, [Online]. Available: http://www.kimvdlinde.com/professional/rma.html

[52] M. Bilal *et al.*, “A simplified and robust surface reflectance estimation method (SREM) for use over diverse land surfaces using multi-sensor data,” *Remote Sens.*, vol. 11, no. 11, 2019, Art. no. 1344.

[53] S. Wang, J. Xing, B. Zhao, C. Jang, and J. Hao, “Effectiveness of national air pollution control policies on the air quality in metropolitan areas of China,” *J. Environ. Sci.,* vol. 26, no. 1, pp. 13–22, 2014.

[54] P. Zhang and J. Wu, “Impact of mandatory targets on PM2.5 concentration control in Chinese cities,” *J. Cleaner Prod.*, vol. 197, pp. 323–331, 2018.

[55] Z. Li *et al.*, “Aerosol and boundary-layer interactions and impact on air quality,” *Nat. Sci. Rev.*, vol. 4, pp. 810–833, 2017.

[56] M. Lou *et al.*, “On the relationship between aerosol and boundary layer height in summer in China under different thermodynamic conditions,” *Earth Space Sci.*, vol. 6, pp. 887–901, 2019.

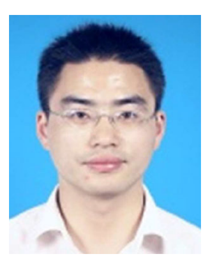
[57] Z. Zang, W. Wang, X. Cheng, B. Yang, X. Pan, and W. You, “Effects of boundary layer height on the model of ground-level PM2.5 concentrations from AOD: Comparison of stable and convective boundary layer heights from different methods,” *Atmosphere*, vol. 8, no. 12, 2017, Art. no. 104.

[58] Y. Zhang *et al.*, “Impact of control measures and Typhoon weather on characteristics and formation of PM2.5 during the 2016 G20 summit in China,” *Atmos. Environ,* vol. 224, 2020, Art. no. 117312.

[59] L. C. Guo *et al.*, “The washout effects of rainfall on atmospheric particulate pollution in two Chinese cities,” *Environ. Pollut.*, vol. 215, pp. 195–202, 2016.

[60] W. Ouyang *et al.*, “The washing effect of precipitation on particulate matter and the pollution dynamics of rainwater in downtown Beijing,” *Sci. Total Environ.*, vol. 505, pp. 306–314, 2015.

[61] Z. Wang, L. Chen, J. Tao, Y. Liu, X. Hu, and M. Tao, “An empirical method of RH correction for satellite estimation of ground-level PM concentrations,” *Atmos. Environ.*, vol. 95, pp. 71–81, 2014.



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