Estimation of Atmospheric PM$_{10}$ Concentration in China Using an Interpretable Deep Learning Model and Top-of-the-Armosphere Reflectance Data From China’s New Generation Geostationary Meteorological Satellite, FY-4A

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Abstract The rapid urbanization in China and the long-range transport dust (LRTD) from arid and semi-arid areas has resulted in an increase of PM$_{10}$ concentration. In this study, an interpretable deep learning model [deep forest (DF)] with FY-4A top-of-the-atmosphere reflectance (TOAR) data were used to obtain the hourly PM$_{10}$ in China. The optimal hourly average $R^2$ of 10-fold cross validation can achieve 0.85 (13:00 Beijing time); The $R^2$ (RMSE, μg/m$^3$) of the daily, monthly, and annual averages were 0.82 (24.16), 0.97 (6.53), and 0.99 (2.30), respectively. Using TOAR data, the DF model performed better than other machine learning models. The feature importance of the TOAR-PM$_{10}$ model showed that TOAR and meteorological elements both contributed significantly to the model. In spring, the PM$_{10}$ in northern China was greater than that in southern China, which may be related to the LRTD. Excluding the dust weather periods, the areas with high PM$_{10}$ values in China were mainly in cities and their suburbs, where were correlated with human activities. During a dust weather process, LRTD increased PM$_{10}$ in northern China by 80.4%. During a mixture haze and dust weather process, the PM$_{10}$ increased by 130.2% in northern China, of which LRTD led to an increase of 73.7%. The sources (from the Taklimakan Desert in China) and transmission paths of these two LRTD processes were similar. The contribution of LRTD to PM$_{10}$ was related to dust intensity and meteorological conditions. The results showed that LRTD and local pollution to PM$_{10}$ was both important in haze periods.

1. Introduction

Atmospheric particulate matter with an aerodynamic diameter less than 10 μm (PM$_{10}$) has a great impact on global environmental (Jiang et al., 2015; Kassomenos et al., 2014; Millán-Martínez et al., 2021; Rastogi et al., 2020), human health (Brook et al., 2010; Ho et al., 2018; Samoli et al., 2011; Tomczak et al., 2016), and climate change (Q. Zhang et al., 2017; C. Zhao & Garrett, 2015). Since 2013, China has successively established more than 1,000 environmental monitoring stations to obtain the particle concentration (Yan et al., 2020; Q. Zhang et al., 2019; T. Zhang et al., 2019). However, because of the uneven spatial distribution of these ground stations, atmospheric PM$_{10}$ concentration data with continuous high spatial and temporal resolution are absent. This limits the research on the atmospheric PM$_{10}$ climate environment (Hu et al., 2014; Y. Zhang & Li, 2015).

Many scholars have obtained atmospheric particle matter concentrations with high spatio-temporal resolution by using machine learning models and satellite data (G. Chen et al., 2018; You et al., 2015; T. H. Zhang et al., 2016; Y. Zhang et al., 2021). Studies showed that there was a strong correlation between aerosol optical depth (AOD) and surface particles (Guo et al., 2009; Z. Li et al., 2016; Q. Xu et al., 2021), which is often used to estimate the particle concentration (Gui et al., 2020; T. Li et al., 2017; Xiong et al., 2021). Using the 5 km resolution AOD of the MediumResolution Imaging Spectrometer (MERIS) sensor in three Malaysian metropolises and an artificial neural network to estimate PM$_{10}$ concentrations, the correlation coefficient of the model had values as large as 0.65 (Kanniah et al., 2014). The daily atmospheric PM$_{10}$ concentration in Israel was estimated based on the mixed effect model and MAIAC AOD, resulting a cross-validation, $R^2$ value of 0.79 (Kloog et al., 2015). Z. Zhang et al. (2018) used land-use regression (LUR) model to estimate the monthly PM10 concentration in China, and the $R^2$ reached 0.71. Based on random forest model and AOD data, G. Chen et al. (2018) successfully
estimated the PM_{10} concentration in China in the past decade. Wei, Li, Xue, et al. (2021) used the space-time extremely randomized trees (STET) to generate PM10 data in China from 2015 to 2019, with a spatial resolution of 1 km, and pointed out that PM_{10} showed a significant downward trend. In addition, researchers have shown the relationship between AOD and particulate matter of polar orbiting satellites in China, such as MODIS (X. Wang et al., 2020), Visible Infrared Imaging Radiometer Suite (VIIRS; Wu et al., 2016), MISR (X. Meng et al., 2018), and Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP; Chen, Song, Pan, & Huang, 2022).

Polar orbiting satellites cannot obtain high time resolution data; however, the time resolution of second-generation geostationary satellites is ~15 min with a fine spatial resolution. Recently, some studies have begun to use geostationary satellites to obtain particle concentrations (W. Wang et al., 2017; Wei et al., 2019). Previously, the geostationary satellite AOD was principally used for PM_{2.5} remote sensing (J. Liu et al., 2019; Z. Zhang et al., 2019). The inversion of PM_{10} was initiated in the 2 yr prior to this work. The geographically weighted region models and AOD of the Indian geostationary satellite (INSAT-3D) were used to estimate PM_{10}. The $R^2$ values of the pre-, post-, and winter models were 0.624, 0.718, and 0.633, respectively (Gupta et al., 2021). The AOD data from the Geostationary Ocean Color Imager (GOCI) of the Korean geostationary satellite (GEO-KOMPASAT 2B) was used to estimate the PM_{10} concentration based on two machine learning models [gradient boosted regression trees (GBRT) and light gradient boosting machine (LightGBM)]. The models achieved $R^2$ for daily, monthly, seasonal, and annual averages of atmospheric PM_{10} concentrations of 0.87, 0.91, 0.94, and 0.94, respectively (Chen, Song, Shi, & Li, 2022).

The particle concentration can be effectively estimated using the AOD (Stafoggia et al., 2019). Because AOD was only provided under optimal conditions, there were a large number of missing values (Y. Park et al., 2020). The coverage of satellite top-of-the-atmosphere reflectance (TOAR) was higher than that of AOD, so TOAR was used to directly obtain the particle concentration (L. Yang et al., 2020). Using the TOAR of Himawari-8 and the random forest model, the PM_{2.5} of the Yangtze River Delta (YRD) in 2016 was obtained, and the 10-fold cross validation ($R^2$) was 0.75 (Bai et al., 2021). Using the TOAR of the Himawari-8 and LightGBM models, the $R^2$ of the PM_{2.5} model was 0.86 (Yin et al., 2021). Using TOAR directly increases the effective coverage, and the performance of the model is also very positive.

Since the Himawari-8 satellite cannot cover Xinjiang, China (Song et al., 2021; Wei, Li, Pinker, et al., 2021), China’s second-generation geostationary meteorological satellite FY-4A successfully launched on 11 December 2016, can cover the entire territory of China. Its Advanced Geosynchronous Radiometer Imager (AGRI) imager can provide multi-band full-disk images with a time resolution of 15 min (Y. Chen et al., 2020; Mao et al., 2021; Zhang, Zhu, et al., 2019). As dust is an important component of PM_{10}, the Taklimakan Desert in Xinjiang, China is an important source of dust in East Asia. Using the FY-4A satellite was advantageous in estimating the contribution of dust weather to PM_{10} in East Asia (B. Chen et al., 2010). At the same time, there have been no studies on estimating PM_{10} from the FY-4A satellite. This study used the FY-4A satellite to estimate China’s high spatial-temporal resolution for atmospheric PM_{10} concentrations.

Most studies have shown that nonlinear machine-learning models can more effectively obtain the particle concentration (Paschalidou et al., 2011; Qin et al., 2018; Yin et al., 2021). This study used a deep learning model, the deep forest (DF) model (Zhou & Feng, 2017), which has the structure of a deep neural network (DNN), and replaced DNN neurons with decision tree (DT) models. Combining the advantages of the DNN and DT models, the DF model can better fit nonlinear data and provide the importance of model features to result in a more interpretable deep learning model. The hourly PM_{10} concentrations in China from June 2018 to May 2019 were obtained using the DF model, FY-4A TOAR, meteorological parameters, and geographic information data. Using the results of the FY-4A TOAR-PM_{10} model, the contribution of long-range transport dust (LRTD) originating in the Taklimakan Desert to atmospheric PM_{10} concentrations in China and northern China was evaluated.

2. Data and Methods

2.1. FY-4A TOAR Data

FY-4A is China’s second-generation geostationary meteorological satellite. It contains four advanced instruments: the AGRI, the Geosynchronous Interferometric Infrared Sounder, Lightning Mapping Imager, and Space
Environment Package; X. Zhang et al., 2020; Zhang, Lu, et al., 2019). The satellite provides high-precision data products for weather forecasting, environmental monitoring, climate change, and disaster prevention and reduction (C. Meng & Li, 2019; Min et al., 2017; Xia et al., 2020; J. Yang et al., 2017).

AGRI had 14 channels and a wavelength range of 0.45–13.8 μm. It covers the visible (VIS), near-infrared (NIR), medium infrared, and long infrared, with a spatial resolution of 0.5–4 km. As shown in Table 1, according to the scientific objectives of each spectral channel (channels related to the properties of aerosols), four channels related to particulate matter were selected to estimate PM$_{10}$, including 0.45–0.49 μm (VIS_B), 0.55–0.75 μm (VIS_G), 0.75–0.90 μm (VIS_R), and 2.1–2.35 μm (NIR). Cloud detection products (CLM) provided by the National Satellite Meteorological Center (NSMC) were used to remove the impact of clouds. For the TOAR data, mask processing was performed on the area where clouds or possible clouds were displayed in CLM. In this study, FY-4A Level 1 (L1) 4 km full disk dataset and CLM data with the same resolution obtained from NSMC from 1 June 2018 to 31 May 2019, were utilized.

### 2.2. PM$_{10}$ Data and Auxiliary Data

The hourly atmospheric PM$_{10}$ observation data were obtained from the China Environmental Monitoring Center (CEMC; China, 2012). Figure S1 in Supporting Information S1 showed the distribution of the 1,641 CEMC ground PM$_{10}$ stations. The box in the figure shows six typical urban agglomerations in China: the Guanzhong Plain (GZP), Pearl River Delta (PRD), Central China (CC), Beijing-Tianjin-Hebei (BTH), Sichuan Basin (SCB), and Yangtze River Delta (YRD).

Auxiliary data include meteorological parameters, geographic information, and time variables. Previous studies have shown that meteorological parameters and geographic information have an impact on pollutant transmission and accumulation of pollutants (Fu et al., 2008; Gao et al., 2016; Sun et al., 2016). Meteorological parameters include boundary layer height (BLH, m; Han et al., 2018), 2 m air temperature (TM, K; K; Ma et al., 2021), relative humidity (RH, %; F. Liu et al., 2019), $u$ and $v$ components of 10 m wind ($U_{10}$, $V_{10}$, m/s; B. Xu et al., 2020), and surface air pressure (SP, Pa; G. Xu et al., 2020). These data were obtained from ERA-5 ECMWF reanalysis data (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land). The temporal resolution of per hour and a spatial resolution of 0.25° × 0.25° or 0.1° × 0.1° (Table 2 for more details). Geographic information, including ECMWF’s high and low vegetation index (LV, LH), NASA’s height (HEIGHT), and population density (PD; M. Chen et al., 2020), were obtained from NASA’s socio-economic data and Applications Center (SEDAC).

| Channel | Wavelength | Spatial resolution (km) | Main scientific objectives |
|---------|------------|-------------------------|---------------------------|
| 1       | 0.45–0.49  | 1                       | Small particle aerosol, true color |
| 2       | 0.55–0.75  | 0.5–1                   | Vegetation                |
| 3       | 0.75–0.90  | 1                       | Vegetation, aerosols      |
| 4       | 1.36–1.39  | 2                       | Cirrus cloud              |
| 5       | 1.58–1.64  | 2                       | Low cloud/snow identification, water cloud/ice cloud identification |
| 6       | 2.1–2.35   | 2–4                     | Cirrus cloud, aerosol, particle size |
| 7       | 3.5–4.0 (High) | 2       | Cloud and other high albedo targets, fire point |
| 8       | 3.5–4.0 (Low) | 4       | Low albedo target, surface |
| 9       | 5.8–6.7    | 4                       | Upper layer water vapor   |
| 10      | 6.9–7.3    | 4                       | Middle layer water vapor  |
| 11      | 8.0–9.0    | 4                       | Total water vapor and cloud |
| 12      | 10.3–11.3  | 4                       | Cloud, surface temperature, etc. |
| 13      | 11.5–12.5  | 4                       | Cloud, total water vapor, surface temperature |
| 14      | 13.2–13.8  | 4                       | Cloud and water vapor     |

**Table 1**

Details of 14 Channels Information of the Advanced Geosynchronous Radiation Imager (AGRI) Instrument on FY-4A Satellite
The time variable (TIME) refers to the hour difference between the current time and 0:00 on 1 January 1900. The data used in the model are listed in Table S1 in Supporting Information S1.

### 2.3. Deep Forest Model

Zhou and Feng (2017) proposed the DF model, which uses an extreme tree (ET; Geurts et al., 2006) and random forest (RF; Breiman, 2001) as neurons of the model, and multiple neurons formed a hidden layer. The DF model includes N hidden layers, and the output of the last hidden layer is connected to a separate estimator LightGBM (Ke et al., 2017) to output the results of the model. Because the DF model neurons were tree models (such as RF and ET), the DF model can output the importance of features, which makes the DF model interpretable. In this study, a DF model with three hidden layers was designed. Each layer contained 12 neurons (6 ETs and 6 RFs). Figure 1 is a structural diagram of the PM$_{10}$ concentration obtained by the DF model.

| Area                  | $R^2$ | RMSE (µg/m$^3$) | MAE (µg/m$^3$) | $N$   |
|-----------------------|-------|----------------|----------------|-------|
| Beijing-Tianjin-Hebei | 0.86  | 22.04          | 13.57          | 58,857|
| Guanzhong Plain       | 0.85  | 22.29          | 13.78          | 36,714|
| Centra China          | 0.87  | 18.05          | 11.96          | 128,167|
| Sichuan Basin         | 0.81  | 15.08          | 10.44          | 49,801|
| Pearl River Delta     | 0.80  | 13.73          | 9.44           | 48,263|
| Yangtze River Delta   | 0.86  | 15.70          | 10.69          | 155,458|

**Table 2** Model Validation Results for Six Large Urban Agglomerations

**Figure 1.** The schematic diagram of estimating PM$_{10}$ using FY-4A TOAR data and deep forest (DF) model. The upper part of the right column is the distribution of input features, such as VIS$_B$, VIS$_G$, VIS$_R$, NIR, RH, SP, TM, and BLH on 28 April 2019, 12:00 (Beijing Time), and the lower part of the right column is the structure of the neuron [extreme tree (ET) and random forest (RF)].
2.4. Data Preprocessing

The spatial resolution of meteorological elements and geographic information was adjusted to 0.04° × 0.04° of FY-4A data by bilinear interpolation. The PM$_{10}$ hourly mean data of CEMC were compared with those of the TOAR of FY-4A. After data matching, the total number of samples was 937,974, of which the number of samples in spring (MAM), summer (JJA), autumn (SON), and winter (DJF) were 229,769, 259,037, 300,717, and 148,451, respectively.

2.5. Model Validation

A 10-fold cross-validation method was used to test the model performance (Rodriguez et al., 2010). The parameters used to describe the model performance included the determination coefficient ($R^2$), root mean square error (RMSE), and mean absolute error (MAE; Chen, Song, Pan, & Huang, 2022; Chen, Song, Shi, & Li, 2022). The expected error (EE, Equation 1) was used to evaluate the accuracy of the TOAR-PM$_{10}$ model. The better EE value (close to 100%) indicated that the estimated value of the model is agree with the observation value (Chu et al., 2003; X. Yang et al., 2020).

$$EE = (1 \pm 0.15)y_i \pm 0.05$$

$y_i$ represents the observed value of PM$_{10}$ from CEMC.

3. Model Validation Results

3.1. Time Scale Results (Hourly, Daily, Monthly, Seasonal, and Annual Mean)

The TOAR-PM$_{10}$ model was established using the DF model, and the estimated atmospheric PM$_{10}$ concentration values were compared with the observed values of the CEMC. The results were shown in Figure 2. Except at 09:00 a.m. Beijing time, the 10-fold cross validation $R^2$ was greater than 0.8. At 13:00, the $R^2$ value of the model reached a maximum of 0.85, and 55% of the samples fell within EE. The fitting slope comparing the estimated value and the observed value was >0.8, indicating that the TOAR-PM$_{10}$ model estimated most atmospheric PM$_{10}$ samples well, and the estimated value was consistent with the observed value. The RMSE of the model was 18.44–34.72 µg/m$^3$ with a MAE is 10.91–16.92 µg/m$^3$. This showed that it was feasible to directly obtain PM$_{10}$ concentration data using FY-4A TOAR data, and the model performance was mainly related to pollutant
emissions and meteorological conditions (J. Chen et al., 2019; Zang et al., 2019; C. Zhao et al., 2020). As shown in Figure 2 (I), the $R^2$ of the out-of-station cross validation results was 0.66, which was worse than the data based on grid points. This was because some stations did not participate in the training data of the model, so that the model could not obtain the effective information of the region. In general, considering the overall performance of the model, the DF model could effectively estimate the PM$_{10}$ concentration in the area without sites.

As shown in Figures 3a–3d, the TOAR-PM$_{10}$ estimation model performed best in autumn with a cross validation $R^2$ was 0.84 (RMSE was 21.66 µg/m$^3$). Performance was poor during summer $R^2$ with a value of only 0.66 (RMSE was 22.57 µg/m$^3$). $R^2$ in spring and winter were 0.75 and 0.83, respectively; however, RMSE in these two seasons was relatively high, 27.19 and 29.04 µg/m$^3$, respectively. This may be related to the frequent occurrence of dust weather in spring and the large combustion of fossil fuels for heating in winter (Xiao et al., 2015; Y. Yang et al., 2016). In addition, the estimated atmospheric PM$_{10}$ concentrations was compared with station observations on daily, monthly, seasonal, and annual average PM$_{10}$. The results were shown in Figures 3e–3h. The daily, monthly, seasonal, and annual validation results $R^2$ (RMSE) of TOAR-PM$_{10}$ model were 0.82 (24.16 µg/m$^3$), 0.97 (6.53 µg/m$^3$), 0.98 (4.17 µg/m$^3$), and 0.99 (2.30 µg/m$^3$), respectively. The results showed that the PM$_{10}$ estimated using the TOAR-PM$_{10}$ model was reliable.

### 3.2. Spatial Scale Results

Figure 4 showed the spatial performance of the TOAR-PM$_{10}$ model. In most stations in eastern China, model $R^2$ was relatively high (>0.8), while in western China, the model performance was degraded, especially in the Qinghai Tibet Plateau, which has very complex terrain. There was a large difference in the number of stations in eastern and western China. The model performed relatively well in areas with large samples, and $R^2$ showed a high distribution in eastern China and low distribution in western China. The distribution of RMSE and MAE in China was high in the North and low in the South, especially in Northwest China, and RMSE and MAE were greater than 18 and 24 µg/m$^3$, respectively. The validation results of the six typical urban agglomerations in China were shown in Table 2. The Yangtze River Delta, Beijing Tianjin Hebei and Central China demonstrated good model performance, with $R^2$ (RMSE) of 0.86 (15.70 µg/m$^3$), 0.86 (22.04 µg/m$^3$), and 0.87 (18.05 µg/m$^3$), respectively. The $R^2$ values in the Sichuan Basin and Pearl River Delta were less than 0.82. $R^2$ performed well, mainly
in urban agglomeration areas, and performed poorly, mainly in areas with complex topographic conditions, such as the western Sichuan Basin.

3.3. Importance of Model Features

The deep learning DNN model is a “black box,” which cannot provide interpretability to the model. The neuron of the deep learning DF model is a tree model, which can obtain the importance of model features and the contribution of model input variables. To evaluate the importance of each input feature in different seasons (or regions), we used the same DF architecture (as described in Section 2.3) and retrained the data in seasons (or regions) to obtain the feature importance. Except for Figure 5a (spring, summer, autumn, and winter) and Figure 5b, the other results of the model in this article were the results of the same TOAR-PM$_{10}$ model constructed based on the whole sample, such as Figure 5a (Annual).

As shown in Figure 5a, the feature importance of TOAR (the sum of the feature importance of the four channels) was the highest, followed by the TIME variable. Among the meteorological elements, BLH, RH, and TM made significant contributions to the model. Generally speaking, the feature importance of each input was different in seasons, but in the season with poor model performance, the contribution of other importance features was low except for TOAR. Figure 6 showed the variation trend of uncertainty (RMSE) with important features. The results indicate that the uncertainty of derived PM$_{10}$ varies with TOAR and meteorological elements. In general, various factors (including TOA and meteorological factors) influence the uncertainty of derived PM$_{10}$. RMSE decreased with the increase of VIS$_{B}$, VIS$_{G}$, VIS$_{R}$, BLH, and TM. The effect of NIR and RH on RMSE was about 20 µg/m$^3$. Furthermore, based on the feature importance, the main influencing factors of each region will change. In addition, we performed linear fitting for each estimation factor and model bias, and the regression coefficient obtained is shown in Figure S2 in Supporting Information S1. The results indicated that the factors such as VIS$_{G}$, VIS$_{R}$, RH, LL, SP, TM, and height contributed more (absolute value of the regression coefficient > 1) to the uncertainty of the estimation results.

In addition, as shown in Figure 5b, the feature importance of TOAR in each region was ~0.15, while meteorological elements, geographic information, and time variables changed significantly. BLH and RH had a significant impact on the BTH region, but their contributions to other regions were relatively low. The contribution of TM to
Figure 5. The feature importance of DF in (a) annual and seasons and (b) six urban agglomerations. The color and number of each grid point on the panel represent the feature importance score in the DF model.

Figure 6. The variation trend of RMSE with important features and color bar indicates the number of points.
CC, SCB, PRD, and YRD exceeded 0.1. The importance of SP was only >0.1 in the SCB area with poor model performance. For the YRD and GZP regions, the TIME variable was a very important variable. The dominant features of the model would change in different seasons and regions, which also explained why the out-of-station cross validation result of the model was relatively poor, as shown in Figure 2 (I).

4. **PM$_{10}$ Distribution Results**

4.1. **Spatial Distribution of Hourly and Seasonal Average for Atmospheric PM$_{10}$ Concentrations**

The average PM$_{10}$ concentration distribution from 09:00 to 16:00 Beijing during the study period was shown in Figure 7. The estimation results of TOAR-PM$_{10}$ showed that the Tarim Basin had the highest concentration of atmospheric PM$_{10}$ concentration in China, with a daily average concentration of 100 µg/m$^3$, which is correlated with frequent local dust aerosols. The concentration of PM$_{10}$ in BTH region showed obvious diurnal variation: it was the greatest from 09:00 to 10:00 (73.15 ± 22.81 µg/m$^3$), then decreased to 56.22 ± 9.87 µg/m$^3$ at 13:00. At 16:00 it increased slightly (63.03 ± 13.71 µg/m$^3$). The PM$_{10}$ concentration in GZP had the same diurnal variation as that in the BTH area (61.10 ± 19.96 µg/m$^3$, 55.87 ± 10.98 µg/m$^3$, and 58.01 ± 12.53 µg/m$^3$). The concentration of PM$_{10}$ in southern China continued to decline from 09:00 to 16:00, but there were great differences among regions: the concentration of PM$_{10}$ in the YRD region was 65 µg/m$^3$ and greater; The hourly variation range of PM$_{10}$ concentration in CC region was 60.38 ± 17.53 µg/m$^3$; The hourly PM$_{10}$ of SCB region was 53.22 ± 11.25 µg/m$^3$; The concentration of atmospheric PM$_{10}$ in the YRD region was less than 50 µg/m$^3$. In addition, the concentration of PM$_{10}$ in other parts of China was relatively low, especially in Northeast China and the Qinghai Tibet Plateau. The results indicated that the estimated results were in good agreement with the observed results.

As shown in Figure S3 in Supporting Information S1, the average atmospheric PM$_{10}$ concentration values during the four seasons in China were 67.90 ± 25.78, 49.8 ± 20.06, 58.68 ± 22.16, and 73.46 ± 26.27 µg/m$^3$, respectively. Because of the frequent dust weather in spring, the atmospheric PM$_{10}$ concentration in the Tarim Basin, one of the dust sources in East Asia, was very high, and the PM$_{10}$ concentration in North China was generally greater than that in South China. In winter, due to low wind speeds, meteorological conditions were not conducive to pollutant diffusion. Winter is the heating season in northern China. The PM$_{10}$ concentrations in the BTH, GZP, YRD, and SCB regions were greater in winter. Compared with those of winter, the anthropogenic emissions in summer and autumn were lower. In addition, there was more precipitation during summer and autumn resulting in a moisture-based elimination, wet deposition, of atmospheric PM$_{10}$. This elimination resulted in a lower atmospheric PM$_{10}$ concentration during summer and autumn.

4.2. **PM$_{10}$ Distribution of Six Large Urban Agglomerations in China**

The spatial resolution of the TOAR data provided by FY-4A was 4 km, which reflected the atmospheric PM$_{10}$ concentration distribution at the city level. Figure 8 showed the annual average atmospheric PM$_{10}$ concentration distribution of six large urban agglomerations in China. The results showed that the concentration of atmospheric PM$_{10}$ was higher in BTH (66.66 ± 16.92 µg/m$^3$), CC (64.22 ± 1.478 µg/m$^3$), and YRD (79.34 ± 15.86 µg/m$^3$) region. The concentration of atmospheric PM$_{10}$ in GZP and SCB was relatively low, ~59.05 ± 14.71 µg/m$^3$. The annual atmospheric concentration of PM$_{10}$ in the PRD region was only 49.76 ± 6.53 µg/m$^3$. According to the distribution of atmospheric PM$_{10}$ areas of high atmospheric PM$_{10}$ concentrations in each region generally occurred in large cities and surrounding areas, which were closely related to local human activities.

4.3. **Case 1: Contribution of Long-Range Transport Dust to Atmospheric PM$_{10}$ Concentration**

From 14 to 17 May 2019, a large-scale dust storm occurred in northern China (35°N–45°N, 70°E–135°E). Combined with the spaceborne lidar CALIOP data, the results of the TOAR-PM$_{10}$ model were used to analyze the dust weather process. Figure 9 (Part 1) showed the three-dimensional transmission diagram of CALIOP’s observational data of the dust weather process. The red transmission line was the forward trajectory line of the HYSPLIT mode. It can be observed that the dust weather originated in Taklimakan desert of China, traversed northern China to the Yellow Sea on May 17.
Figure S4 in Supporting Information S1 showed the cloud and aerosol profiles obtained by CALIOP during this dust weather process. The dust aerosol ascended to an altitude greater than 8 km; consequently, it could be transmitted downstream for long distances. There was a wide range of dust aerosols at an altitude of 0–8 km in northern China, and on the 17th, there was a large area of polluted continental aerosols and polluted dust aerosols in the southern Yellow Sea. The red line in Figure 10 was the orbit of CALIOP, and the left column was the FY-4A true color map. There were many white clouds in the map, which resulted in the vacancy value of the estimated atmospheric PM$_{10}$ concentration. It can also be seen from the figure that there was a large quantities of dust...
aerosols in northern China (earthy yellow). Station observations (Figure 10, middle column) and model estimation (Figure 10, right column) showed that the atmospheric PM$_{10}$ concentration first increased and then decreased from the 14th to 17th. From 14 to 17 May 2019, the estimated values of atmospheric PM$_{10}$ concentrations in China were 98.53, 91.02, 99.95, and 77.22 µg/m$^3$ (northern China: 123.82, 121.98, 139.77, and 106.90 µg/m$^3$). The observed values of PM$_{10}$ concentration stations were 102.81, 96.00, 91.88, and 60.90 µg/m$^3$ (northern China: 134.49, 169.54, 130.04, and 77.86 µg/m$^3$). Figure S5 in Supporting Information showed the 10 m wind field during dust weather, and PM$_{10}$ was the estimated value of the TOAR-PM$_{10}$ model. The wind speed in northern China was significantly greater than that in southern China. The surface wind in northern China was generally westerly. The area with high surface wind speed corresponded to the high atmospheric PM$_{10}$ concentration and dust transmission path.

As shown in Figure 9 (Part 2), it was the atmospheric PM$_{10}$ concentration (Figure 9a, Dust period) during the dust weather process (14–17 May 2019) and the atmospheric PM$_{10}$ concentration (Figure 9b, None_Dust period) without dust weather in May 2019. In addition, the difference (Figure 9c, Dust period—None_Dust period) between the two periods was presented. The left column was the station observation value, and the right column was the estimated value of the TOAR-PM$_{10}$ model, and through the difference (Figure 9c), we can estimate the contribution of LRTD to atmospheric PM$_{10}$ concentration during dust weather. During this dust weather process (Dust Period), the estimated and observed atmospheric PM$_{10}$ concentrations in China were 87.53 and 87.78 µg/m$^3$, respectively (northern China: 116.64 and 127.96 µg/m$^3$). The estimated and observed atmospheric PM$_{10}$ concentration values in None_Dust period in May 2019 were 57.46 and 55.49 µg/m$^3$, respectively (northern China: 64.64 and 64.91 µg/m$^3$). Based on the model results, during the dust weather, the atmospheric PM$_{10}$ concentration in 64% of China’s regions increased by 20%. In 39% of China’s regions, it increased by 50%. In 28% of China’s regions, it increased by 70%. Finally, 17% of China’s regions it increased by 100%. Based on the CEMC stations, the atmospheric PM$_{10}$ concentration at 827 stations (accounting for 52% of the total stations) increased by 20%. At 592 stations (37%), it increased by 50%. At 484 stations (30%), it increased by 70%. Finally, at 379 stations (23%), it increased by 100%. The model estimates were consistent with station observations for atmospheric PM$_{10}$ concentrations.
4.4. Case 2: Changes in PM$\text{_{10}}$ Concentration Under the Combined Conditions of Dust and Haze Weather

On 24–30 November 2018, there was a large area of haze in China. In addition, there was an LRTD weather process in northern China on November 25–27 (the largest area of dust on November 26). This event was a
composite pollution weather event of dust and haze weather. The haze period was November 24–30 (haze period), the dust weather period was November 25–27 (dust period), and the period of no dust nor haze weather was November 1–23 (None_Haze_Dust period). As shown in Figure 11 (Part 1), CALIOP observed the three-dimensional transmission of the dust weather process. The source and transmission path of the dust weather were similar to the dust weather process in May 2019 (as shown in Figure 9, Part 1), but the dust intensity and transmission height were less.

In Figure S6 in Supporting Information S1, a large area of dust aerosols and pollution dust aerosols were found at an altitude of 0–4 km in China from the 24th to 27th, and a small amount of dust aerosol was found at an altitude of 8 km on the 26th, which also showed that the dust intensity was less. The FY-4A true color (RGB) map in Figure 12 showed clouds (white), which was consistent with the observation of CALIOP (Figure S6 in Supporting Information S1). From 24 to 27 November 2018, the estimated atmospheric PM$_{10}$ concentrations in China were 81.98, 95.23, 198.47, and 142.84 μg/m$^3$ (northern China: 101.32, 107.38, 292.72, and 207.59 μg/m$^3$), and the observed atmospheric PM$_{10}$ concentrations were 99.32, 130.18, 174.98, and 171.59 μg/m$^3$ (northern China: 122.50, 193.56, 302.76, and 276.10 μg/m$^3$). The difference between the estimated and observed values was due to the missing values of the estimated PM$_{10}$ caused by cloud cover. Figure S7 in Supporting Information S1 showed the wind field of the dust-weather process. The wind speed was low in the southern region and high in the northern region of China. The wind speed was greatest on November 26, which was also consistent with the
Figure 11. Identical Figure 9, Part I showed mixed pollution event of dust weather and haze weather (24–27 November 2018). And Figure line (a–e) showed the average atmospheric PM$_{10}$ concentration during the Haze period (November 24–30), None_Haze_Dust period (November 1–23), Dust period (November 25–27), the difference between Haze period and None_Haze_Dust period, and difference between Dust period and Haze period, respectively.
larger range of the dust weather observed on November 26 and the dust transmission path. On November 27, the wind speed in northern China decreased, and the dust weather ceased.

Figure 11 (Part 2) showed the atmospheric PM$_{10}$ concentration distribution estimated by the model and observed by the station. The atmospheric PM$_{10}$ concentration on haze days (Figure 11a, haze period) was much greater than that on the None_Haze_Dust days (Figure 11b), and the PM$_{10}$ concentration on dust days (Figure 11c, dust period) was the greatest. The estimated and observed PM$_{10}$ in Haze period were 122.60 and 146.42 μg/m$^3$ (northern China: 162.60 and 209.36 μg/m$^3$), respectively. During the dust period the values were 154.07 and 158.98 μg/m$^3$ (northern China: 214.62 and 257.31 μg/m$^3$), respectively. In November 2018, the estimated and observed atmospheric PM$_{10}$ concentration in the None_Haze_Dust period were 62.28 and 65.37 μg/m$^3$ (northern China: 70.62 and 88.11 μg/m$^3$). There were two principal reasons why the estimated value of the model was less than the observed value of the station. A reason for this was the lack of data in some areas due to the existence of clouds. Second, the sample size of the model average was much larger than the number of stations on the station average.

Figure 11d showed the difference in atmospheric PM$_{10}$ concentration between the haze period and the None_Haze_Dust period. Based on the model PM$_{10}$, during the haze period, the PM$_{10}$ in 74% of China increased by 20%, 53% of China increased by 50%, 43% of China increased by 70%, 17% of China increased by 100%, and 10% of China increased by 200%. The observed atmospheric PM$_{10}$ concentration increased by 20% at 1,327 stations (accounting for 83% of the total number of stations). That of 1,109 stations (69%) increased by 50%, that of 948 stations (59%) increased by 70%, that of 713 stations (44%) increased by 100%, and that of 204 stations
(13%) increased by 200%. Figure 11e showed the results of the atmospheric PM$_{10}$ concentration comparison between the dust and haze periods, which one may estimate the contribution of LRTD to haze weather. Based on the model results, due to the LRTD transport of dust, atmospheric PM$_{10}$ concentration increased by 20% in 33% and 50% in 11% of China. Based on surface station data, atmospheric PM$_{10}$ concentration observations at 352 stations (22% of the total number of stations) increased by 20%, and that at 116 stations (7%) increased by 50%. As shown in Figure 11e, the dust weather mainly affected the PM$_{10}$ concentration in the dust transmission path areas, such as China’s Hexi Corridor and Inner Mongolia.

5. Conclusions

The hourly atmospheric PM$_{10}$ concentrations in China were obtained using an interpretable deep learning model (DF model) and FY-4A TOAR data from June 2018 to May 2019. The main conclusions were as follows:

The optimal hourly $R^2$ of 10-fold cross validation of TOAR-PM$_{10}$ DF model can reach 0.85 (13:00 Beijing time); The $R^2$ (RMSE) of daily, monthly, seasonal, and annual average were 0.82 (24.16 µg/m$^3$), 0.97 (6.53 µg/m$^3$), 0.98 (4.17 µg/m$^3$), and 0.99 (2.3 µg/m$^3$), respectively. The model performance ($R^2$, RMSE) was better in the YRD (0.86 and 16.91 µg/m$^3$), BTH (0.86, 22.04 µg/m$^3$), and CC (0.87, 18.05 µg/m$^3$) region. The average PM$_{10}$ concentrations in spring, summer, autumn, and winter in China were 67.90 ± 25.78, 49.8 ± 20.06, 58.68 ± 22.16, and 73.46 ± 26.27 µg/m$^3$, respectively. In spring, the PM$_{10}$ concentration in northern China was higher than that in southern China, which may be related to the LRTD (Tao et al., 2021; L. Zhao et al., 2020). Excluding the dust weather periods, the areas with high PM$_{10}$ values in China were mainly in large cities and suburban areas, which were related to local human activities (Tao et al., 2014).

The DF model can obtain the importance of the model features. The results of the FY-4A TOAR-PM$_{10}$ model showed that TOAR, BLH, RH, surface wind speed (U10 and V10), TM, and TIME contributed significantly to the model. The performance of the model was related to the contributions of these important features (Chen, Song, Shi, & Li, 2022). The performance of the model would be worse in areas with a large contribution to surface pressure (SP). As shown in Table 3, the performance of the FY-4A TOAR-PM$_{10}$ model was better than that of other researchers using the AOD-PM$_{10}$ model. Using the same FY-4A TOAR and other auxiliary data, the DF model performed better than other traditional machine learning models (such as DT, RF, and ET).

China’s arid and semi-arid regions account for ~57% of the country’s land (Y. Yang et al., 2019). The dust transmitted from these regions every year has an important impact on China’s air pollutants (such as PM$_{10}$). Using
the results of the TOAR-PM$_{10}$ model, the contribution of LRTD to local atmospheric PM$_{10}$ concentrations was quantified. During the weather promoting dust disturbance and transport (14–17 May 2019), the contributions of LRTD to PM$_{10}$ in China and northern China were 30.07 (52.3%) and 52.02 (80.4%) μg/m$^3$, respectively. When haze weather and dust weather were mixed (24–30 November 2018), the PM$_{10}$ concentrations in China and northern China increased by 60.32 (96.9%) and 91.98 (130.2%) μg/m$^3$, respectively. Compared with PM$_{10}$ on haze days, PM$_{10}$ on dust days in China and northern China increased by 31.47 (50.5%) and 52.02 (73.7%) μg/m$^3$, respectively. The results were similar to those of others (Chen, Song, Shi, & Li, 2022; Gobbi et al., 2013; Guan et al., 2019; Remoundaki et al., 2013). The source (originating from the Taklimakan Desert in China) and transmission path of the two dust weather processes were similar, and the contribution to atmospheric PM$_{10}$ concentration in China and northern China was the same, but the intensity of the second dust weather was weaker than that of the first dust weather. In other words, the contribution of LRTD to local PM$_{10}$ was not only related to the intensity of dust weather, but also to meteorological conditions such as ground wind speed (Dimiritrou & Kassomenos, 2018; Gobbi et al., 2019). In the first dust weather, the ground wind speed was large, which was conducive to the diffusion of ground pollutants and the reduction of atmospheric PM$_{10}$ concentration; The second, the low wind speed was conducive to the dry settlement of dust and the increase of PM$_{10}$ concentration. The results showed that the contribution of LRTD and local pollution to PM$_{10}$ in haze days was both important.

Data Availability Statement

The PM$_{10}$ data were obtained from the China Environmental Monitoring Center, http://www.cnemc.cn (CEMC, 2022). The FY-4A TOAR data provided by the National Satellite Meteorological Center of China, http://satellite.nsmc.org.cn/PortalSite/Data/Satellite.aspx (NSMC, 2022). ERA5 meteorological data can be downloaded from the European Centre for Medium-Range Weather Forecasts, https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land (ECMWF, 2022). The height data downloaded from CCSI Consortium for Spatial Information, https://srtm.csi.cgiar.org/srtmdata/ (CCSI, 2022). Population density data provided by NASA’s Socioeconomic Data and Applications Center, http://sedac.ciesin.columbia.edu/data/collection/gpw-v4/documentation (SEDAC, 2022). The estimated data and data reading codes are available from https://doi.org/10.5281/zenodo.6459693. All programs in this study are implemented based on Python3, https://www.python.org/ (Python3, 2022).

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