Impacts of Two Dust Storm Events in Northern China on Representative Large Cities: Case Studies of Lanzhou and Beijing (Postprint)

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Abstract

The complex relationship between dust storms and meteorological factors not only constitutes the dominant cause of particulate matter formation and distribution, but also exerts severe impacts on transportation, agriculture and animal husbandry, and public health. Based on HYSPLIT, wavelet coherence, and random forest model, this study investigates the transport pathways of two severe dust storm events in northern China from March 10–25, 2021 (SD1) and March 16–28, 2023 (SD2), as well as the influence of meteorological factors on urban PM10. The results indicate that: (1) During both dust storm events, a high aerosol optical depth (AOD) zone formed across northern China, covering Xinjiang, Gansu, Shaanxi, Shandong, and other regions, primarily attributable to the southward migration of the Mongolian cyclone and the strong westerly circulation over Xinjiang. (2) The overall airflow transport direction ranged from northwest to northeast. At the urban scale, Lanzhou was susceptible to influences from the Xinjiang cyclone, whereas Beijing was significantly affected by the Mongolian cyclone. During SD1, the primary airflow sources for Lanzhou were Qinghai and Xinjiang, while 53.64% of air masses in Beijing were transported to northeastern China, extending into northeastern Russia; during SD2, 51.16% of airflow in Lanzhou originated from Inner Mongolia, and 49.41% of airflow in Beijing was transported to Shandong, Jiangsu, and other regions. (3) PM10 variations in SD1 exhibited higher sensitivity to meteorological factors at longer time scales, while SD2 displayed more variations in meteorological factors at shorter time scales. (4) Lanzhou served as the collision point of the two cyclones, characterized by unstable variations in atmospheric pressure and air temperature, whereas Beijing functioned as the input terminus of the dust storm, being primarily influenced by air temperature. The research findings elucidate the formation mechanisms of dust storms in northern China and contribute to

understanding the interactive relationship between meteorological factors and particulate matter.

Full Text

Preamble

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Impact of Two Sandstorms on Typical Large Cities in Northern China: A Case Study of Lanzhou City and Beijing City

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Abstract: The complex relationship between dust storms and meteorological factors not only dominates the formation and distribution of particulate matter but also severely impacts transportation, agriculture, animal husbandry, and public health. Based on the HYSPLIT model, wavelet coherence analysis, and random forest modeling, this study investigates the transport pathways of two strong dust storms in northern China—one from March 10-25, 2021 (SD1) and another from March 16-28, 2023 (SD2)—and examines how meteorological factors influence urban PM_{10} concentrations. The results show that: (1) During these two dust storm events, a high aerosol optical depth (AOD) belt formed across northern China, covering Xinjiang, Gansu, Shaanxi, Shandong, and other regions, primarily due to the southward movement of the Mongolian cyclone and strong westerly circulation in Xinjiang. (2) The overall airflow transmission direction was from northwest to northeast, with Lanzhou being vulnerable to Xinjiang cyclones while Beijing was significantly affected by Mongolian cyclones. During SD1, Lanzhou' s airflow mainly originated from Qinghai and Xinjiang, while 53.64% of Beijing' s air mass was transmitted to northeastern China, extending into northeastern Russia. During SD2, 51.16% of Lanzhou' s airflow came from Inner Mongolia, while 49.41% of Beijing' s airflow moved toward areas such as Shandong and Jiangsu. (3) PM_{10} variation in SD1 exhibited higher sensitivity to meteorological factors over longer time scales, whereas SD2 showed more diverse responses to meteorological factors over shorter time scales. (4) Lanzhou served as the collision point of the two cyclones, characterized by unstable pressure and temperature changes, while Beijing acted as the endpoint of dust storm input, primarily influenced by temperature. These findings reveal the formation mechanisms of dust storms in northern China and help understand the interactions between meteorological factors and particulate

matter.

Keywords: dust storms; Google Earth Engine (GEE); trajectory analysis; wavelet coherence; meteorological normalization

1. Introduction

1.1 Study Area Overview

Northern China (31°-54°N, 103°-135°E) includes Xinjiang, Qinghai, Gansu, Inner Mongolia, Ningxia, Shaanxi, Shanxi, Henan, Hebei, Shandong, Heilongjiang, Jilin, and Liaoning. The region features alternating mountains and basins from west to east and is characterized by temperate continental monsoon climate and warm temperate continental monsoon climate. The average Normalized Difference Vegetation Index (NDVI) in March shows a spatial pattern of high values in the east and low values in the west. Both Lanzhou and Beijing are located on the boundary between high and low AOD value zones. Lanzhou is situated in central China with a temperate continental semi-arid climate at an average altitude of 1,833 m. Its geographic features include a narrow river valley basin and the Hexi Corridor fold belt, serving as an important channel for the mid-latitude westerlies. Beijing is located on the North China Plain with a temperate monsoon climate at an average altitude of 43 m, representing a crucial position for westerly and northwesterly winds transporting air masses to the Pacific region.

1.2 Data Sources

This study utilized aerosol optical depth (AOD) data, meteorological data, and PM_{10} concentration data. Specific sources are as follows:

AOD Data: Derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA' s Terra satellite, with a spatial resolution of 10 km and temporal resolution of 1 day. Google Earth Engine (GEE) is a multi-petabyte, open-source, high-performance processing system (https://developers.google.com/earth). This study processed time-series images from GEE to monitor AOD changes in northern China during dust storm periods.

PM_{10} Concentration Data: Ground station data from the China National Environmental Monitoring Centre (http://www.cnemc.cn/), including data from 5 monitoring stations in Beijing and 4 in Lanzhou. City-level PM_{10} concentrations were obtained by calculating station averages, covering March 10-25, 2021, and March 16-28, 2023, with hourly records.

Meteorological Data: Hourly observations from the China Meteorological Administration (https://weather.cma.cn/), synchronized with pollutant data, recording temperature, pressure, relative humidity, wind speed, wind direction, and visibility. A total of 1,872 records were obtained, with missing data filled using average values, resulting in 1,824 valid records.

1.3 Methods

1.3.1 Dust Movement Path Clustering Analysis The HYSPLIT model uses Global Forecast System (GFS) meteorological data as initial fields to analyze air mass trajectories. This study simulated 72-hour backward trajectories at 1,000 m altitude. The clustering algorithm employed Euclidean distance, and based on trajectory simulation accuracy, the clustering result with the largest variation trend was selected to determine dust storm movement paths. The distance between trajectories was calculated as:

$$TD_{AB} = \sqrt{\sum_{i=1}^{n} [(X_A(i) - X_B(i))^2 + (Y_A(i) - Y_B(i))^2]}$$

where TD_{AB} is the trajectory distance (km), $X_A(i)$ and $X_B(i)$ are longitude coordinates at time point i, $Y_A(i)$ and $Y_B(i)$ are latitude coordinates at time point i, and n is the total number of time steps.

1.3.2 Wavelet Coherence Analysis Wavelet analysis reveals irregular variations between time series variables and identifies their co-movement in time-frequency domains, making it suitable for analyzing unstable time series and understanding dynamic meteorological changes during dust storms. The coherence coefficient was calculated as:

$$R^2(p) = \frac{|S(s^{-1}W_{AB}(p))|^2}{S(s^{-1}|W_A(p)|^2) \cdot S(s^{-1}|W_B(p)|^2)}$$

where $R^2(p)$ is the coherence coefficient indicating the correlation between two time series at wavelet scale k and time position p, and S is the smoothing operator. Phase difference was calculated as:

$$\phi(p) = \tan^{-1}\left(\frac{M\{s^{-1}W_{AB}(p)\}}{N\{s^{-1}W_{AB}(p)\}}\right)$$

where $\phi(p)$ is the phase difference, M is the imaginary part of the wavelet transform, and N is the real part. In wavelet coherence plots, the angle between arrows and the positive X-axis represents lag phase difference and correlation sign. Zero phase difference means the time series move together at a certain frequency, while non-zero values indicate lead-lag relationships.

1.3.3 Meteorological Normalization Based on Random Forest Model Random forest is an algorithm that effectively controls decision tree overfitting through bootstrap sampling. Each prediction randomly selects meteorological parameter explanatory variables from original observations, which are then input into the random forest model to predict PM_{10} concentrations at specific time points. Averaging the regression results from these datasets yields the meteorological normalization trend.

The model randomly splits datasets into training (70%) and testing (30%) subsets. After model construction and validation, the number of explanatory variables per tree was set to 3, and minimum node size to 5. Meteorological normalization can calculate the importance of meteorological factors on pollutant concentrations in time series, thereby quantifying parameter impacts. This study used the "rmweather" package in R to implement normalization, leveraging random forest's computational power to handle collinearity between meteorological variables in the normalization model. For specific time points, PM_{10} concentrations were predicted 100 times using randomly resampled explanatory variables and then averaged.

2. Results

2.1.1 AOD Spatiotemporal Variation

To understand aerosol variation patterns, the study period was divided into four stages: pre-dust storm (March 10-13, 2021, and March 16-19, 2023), dust storm outbreak (March 14-18, 2021, and March 20-24, 2023), and post-dust storm (March 19-25, 2021, and March 25-28, 2023). During the pre-dust storm period, AOD in Hebei and Shandong was significantly higher than other regions, showing an east-high-west-low pattern (Figure 2a, 2d), mainly due to large industrial emissions. During the outbreak period, AOD values decreased significantly, forming an east-west high-value belt (AOD > 0.6) covering Xinjiang, Gansu, Shaanxi, and Shandong (Figure 2b, 2e). In the post-dust storm period, the spatial pattern gradually returned to the pre-dust storm state, with high values concentrated in Xinjiang's desert areas (Figure 2c, 2f) due to frequent local dust events in the Taklamakan Desert.

The AOD spatiotemporal variation in SD2 was similar to SD1, occurring under similar climatic conditions, though the high-value area proportion was relatively smaller. During the outbreak period, a high AOD belt also formed across China, but with less extensive high-value regions compared to SD1 (Figure 2h). Post-dust storm, only localized high AOD values remained in Xinjiang and Hebei (Figure 2i).

2.1.2 Atmospheric Circulation Characteristics

During SD1, rapid pressure drops in northwestern Mongolia formed a Mongolian low-pressure cyclone (Figure 3b). The northerly winds on the cyclone' s western side combined with upper-level northwesterly airflow, pushing cold air southward and causing near-surface cooling effects. Dust from the Gobi Desert spread southeastward. Simultaneously, the pressure center in West Asia moved eastward (Figure 3a), triggering dramatic pressure changes in Xinjiang and forming a Xinjiang high-pressure cyclone (Figure 3c). Strong winds carried dust from Mongolia to Inner Mongolia and Ningxia, and from Xinjiang to Shaanxi and Shanxi (Figure 3b). When the dust storm ended, the cyclone moved northeastward, transporting the dust belt to northeastern China.

SD2 also experienced large-scale pressure gradient changes over Mongolia and Siberia, with sharp pressure gradients fueling strong winds that lifted dust particles to higher altitudes. The Mongolian cyclone formation may be related to the Asian spring monsoon entering a strong cyclonic phase. During SD2, surface wind speeds in dust source areas further increased, lifting dust particles into the airflow and transporting them long distances to Shanxi, Shandong, and Hebei (Figure 3e). As cold air activity increased, the aftereffects of the Mongolian cyclone became more intense (Figure 3f), with cold air moving eastward and southward.

2.1.3 Dust Storm Movement Paths

Based on the above analysis, both dust storm events were triggered by the southward movement of the Mongolian cyclone and eastward movement of the Xinjiang cyclone. During SD1, Lanzhou's airflow trajectory showed that 28.64% originated from the Taklamakan Desert, crossing the Hexi Corridor to reach Lanzhou, while 71.36% came from Qinghai and extended to Shandong and Hebei, with relatively short transport distances (Figure 5a). Beijing' s airflow included 26.56% from southern Mongolia, with 58.34% of air masses moving southeast to Shaanxi, Henan, and Hebei, eventually reaching the North Pacific (Figure 5b).

During SD2, 51.16% of Lanzhou' s airflow originated from Inner Mongolia, with 53.64% transmitted to Shaanxi, Henan, and Hebei, ultimately reaching the North Pacific (Figure 5c). Beijing' s airflow was 49.41% from southern Mongolia, with 73.81% transmitted to northeastern China and extending to northeastern Russia, and 50.59% extending to Shandong and Jiangsu (Figure 5d). The common feature of both events was that Lanzhou was susceptible to Xinjiang cyclones while Beijing was significantly affected by Mongolian cyclones, with airflow transmission mainly from northwest to northeast.

2.2 Temporal Correlation Between PM_{10} and Meteorological Factors

To investigate the vertical relationship between urban particulate matter and meteorological factors during dust storms, this study calculated the weights of ground station data for PM_{10}, temperature, wind speed, and relative humidity in Lanzhou and Beijing, using wavelet coherence to analyze periodicity, lag effects, and correlations.

During SD1, temperature and wind speed showed strong correlations with PM_{10} at time scales of 16-64 hours, while relative humidity and pressure exhibited strong negative correlations at 8–32-hour scales. Increased relative humidity may enhance particle adhesion in the atmosphere, and pressure instability strengthens cross-regional dust deposition. At scales greater than 64 hours, wind direction was negatively correlated with PM_{10} concentration, with some periods showing 8–16-hour lag relationships, while correlations with temperature and visibility gradually weakened.

During SD2, the coherence coefficients between meteorological factors and PM_{10} concentration exceeded 0.8 over longer time scales, with temperature and wind speed showing positive correlations. This may be because rising temperatures increase soil aridity and wind speeds remove soil moisture. At scales less than 16 hours, relative humidity, pressure, and wind speed showed coherence coefficients partially above 0.6, with relative humidity negatively correlated and showing 4–8-hour lag cycles. Visibility was negatively correlated overall, with strong negative correlations at scales greater than 32 hours and phase differences of about π. Throughout SD2, coherence coefficients between temperature, relative humidity, pressure, wind speed, wind direction, and PM_{10} concentration varied, with different phase differences (Figure 6).

2.3.1 Model Validation

The random forest model was used to analyze the intrinsic relationship between PM_{10} and meteorological factors in Beijing and Lanzhou. Model reliability evaluation metrics (Table 3) showed determination coefficients (R^2) ≥ 0.85, indicating that the random forest model effectively normalized PM_{10} concentrations. Mean absolute error (MAE) values were within 4.29 $g \cdot m^{-3}$, and root mean square error (RMSE) remained low, confirming good model performance and supporting further application.

2.3.2 Meteorological Normalization Results

Wavelet analysis revealed that visibility was significantly negatively correlated with PM_{10}. To better simulate dust storm processes, visibility was introduced as a meteorological factor. After normalization, the model was established with temperature, relative humidity, and visibility as independent variables and PM_{10} concentration as the dependent variable. Hourly calculations were performed on test data and compared with actual observations.

During both dust storms, normalized and observed PM_{10} values in Lanzhou and Beijing showed fluctuations, with most variations within \$$\pm 500\mu g \cdot m^{\{-3\}.Lanzhouexperiencedthreepeaksexceeding200\mu g \cdot m}$\{-3\}\$ during SD1 (Figure 7a), while Beijing’ s concentration rapidly rose to 1,500 $g \cdot m^{-3}$ within

24 hours. During SD2, Lanzhou showed two peaks reaching 1,500 $g \cdot m^{-3}$, but most fluctuations remained within 200 $g \cdot m^{-3}$ (Figure 7c). Beijing' s concentration was significantly lower than Lanzhou' s, with only one period exceeding 800 $g \cdot m^{-3}$ (Figure 7d).

2.3.3 Importance of Meteorological Factors in Dust Storms

The relative importance of meteorological factors explains their anomalous effects on PM_{10} concentrations. After normalizing meteorological factors from both dust storms, the random forest model output the importance of each factor.

During SD1, visibility was the most important factor for PM_{10} in both cities, validating model reliability. In Lanzhou, pressure (16.7%) and temperature (12.6%) were important, while wind speed importance was significantly lower at 7.4%. In Beijing, wind speed (22.6%) and temperature (17.4%) were key factors.

During SD2, pressure (13.3%) and temperature (13.3%) remained important in Lanzhou, though slightly less than in Beijing. Wind speed and relative humidity had smaller impacts at 12.8% and 12.4%, respectively. In Beijing, temperature importance increased dramatically to 39.4%, becoming the dominant factor, far exceeding others. Overall, temperature, pressure, and wind speed were the main meteorological factors affecting PM_{10} concentrations, with varying relative importance across cities and events. Lanzhou maintained dominance of pressure and temperature across both events, while Beijing saw temperature impacts intensify significantly during SD2.

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3. Discussion

This study analyzed dust storm causes and transport paths in northern China by calculating geopotential height and airflow trajectories during dust storm periods. The findings show that both strong dust storms were primarily influenced by the southward movement of the Mongolian low-pressure cyclone and strong westerly circulation in Xinjiang, consistent with Yang et al.' s research. However, trajectory clustering analysis revealed that 71.36% of Lanzhou' s airflow originated from Qinghai during SD1, possibly because the Tibetan Plateau' s massive uplift creates a strong low-pressure center that attracts airflow from the Indian Ocean, which then transports dust to northern China via southwesterly winds.

Both dust storms formed high-AOD belts across Xinjiang, Gansu, Inner Mongolia, and Hebei, consistent with the China Atmospheric Environment and Meteorology Bulletin, which recorded floating dust on March 15, 2021, and strong dust storms on March 22, 2023, affecting Xinjiang, Gansu, Shaanxi, and Hebei. The March 2023 event reached the highest AOD values since 2000 observations, demonstrating the strongest impact intensity and scope. AOD values thus reflect dust storm impact to some extent. Combined with NDVI analysis (Figure 1), dust storms typically affect areas with lower vegetation coverage. Therefore, governments should continue implementing the "Three-North" Shelter Forest Program and other sand control policies, closely monitoring cyclone movement paths and impact ranges during strong dust storms for comprehensive disaster prevention.

Dust storms not only damage agriculture, animal husbandry, and transportation but also seriously harm urban ecosystems and residents' health. This study focused on analyzing temporal correlations between meteorological factors and PM_{10} in Lanzhou and Beijing, finding that dust storms significantly affect meteorological conditions in different cities, with temperature, pressure, and wind speed showing high contributions. This may occur because cold air changes alter soil dryness, wind speeds, and pressure systems, significantly affecting particulate concentrations. Additionally, horizontal and vertical pressure fluctuations cause wind speed and direction changes, leading to prolonged particle residence in urban air and increasing health risks for urban residents. Therefore, policymakers should develop targeted urban air quality management strategies to address natural disasters like dust storms.

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4. Conclusion

(1) During SD1 and SD2, AOD spatiotemporal distributions in northern China showed significant dust storm impacts on aerosol concentrations, forming a high-value belt across Xinjiang, Gansu, Shaanxi, and Hebei. SD2 was similar to SD1 but with relatively fewer high-value areas. The southward movement of the Mongolian cyclone and strong westerly circulation in Xinjiang were the main causes of both dust storms.

(2) Airflow transmission moved from northwest to northeast overall. Lanzhou and Beijing experienced expanded intensity and scope of cyclone impacts, with SD2 showing longer transport distances than SD1. During SD1, Lanzhou's airflow originated from Xinjiang and Qinghai, crossing the Hexi Corridor to Shandong and Hebei. Beijing's airflow was 26.56% from southern Mongolia, with 58.34% transmitted to northeastern China and 53.64% extending to northeastern Russia. During SD2, 51.16% of Lanzhou's airflow came from Inner Mongolia, transmitting to Shaanxi and Henan and ultimately reaching the North Pacific. Beijing's airflow was 49.41% from southern Mongolia, with 73.81% transmitted to northeastern China and 50.59% extending to Shandong and Jiangsu.

(3) Over longer time scales, SD1's PM_{10} showed higher sensitivity to meteorological factors with longer temporal correlations. Over shorter time scales, SD2 displayed more diverse meteorological factor changes, with temperature shifting from positive to no correlation and wind speed from positive

to negative correlation.

(4) In both dust storms, meteorological factors showed significantly different impacts on PM_{10} across cities. Visibility was the most important factor in both Lanzhou and Beijing. During SD1, Lanzhou was dominated by pressure (16.7%) and temperature (12.6%), while Beijing' s PM_{10} was mainly affected by wind speed (22.6%) and temperature (17.4%). During SD2, Lanzhou continued to be dominated by pressure (13.3%) and temperature (13.3%), while Beijing' s temperature importance increased dramatically to 39.4%, becoming the most critical factor.

References

[1] Darvishi B A, Soleimani M, Papi R, et al. Dust and health[M]. Islamabad: COMSATS University Islamabad, 2023: 31-49.
[2] Yu H, Yang W, Wang X H, et al. A seriously sand storm mixed air polluted area in the margin of Tarim Basin: Temporal spatial distribution and potential sources[J]. Science of the Total Environment, 2019, 676: 436-446.
[3] Aswini M A, Tiwari S, Singh U, et al. Aeolian dust and sea salt in marine aerosols over the Arabian Sea during the southwest monsoon: Sources and spatial variability[J]. ACS Earth and Space Chemistry, 2022, 6(4): 1044-1058.
[4] Yu H, Yang W, Wang X H, et al. A seriously sand storm mixed air polluted area in the margin of Tarim Basin: Temporal spatial distribution and potential sources[J]. Science of the Total Environment, 2019, 676: 436-446.
[5] Yang Y, Wang Z L, Lou S J, et al. Strong ozone intrusions associated with super dust storms in East Asia[J]. Atmospheric Environment, 2022, 290: 119355, doi: 10.1016/j.atmosenv.2022.119355.
[6] Zhao Hongfei, Yang Yi, Dong Jiaqi, et al. Variation of aerosol and its effects on precipitation in China based on CMIP5 models[J]. Arid Zone Research, 2019, 36(4): 953-962.
[7] Lü Yanxun, Zhao Hongmin, Wang Xiaojun, et al. Dust weather changes in northwest Chinese cities: Lanzhou as a case study[J]. Arid Zone Research, 2024, 41(7): 1112-1119.
[8] Li Yuman, Li Lei, Xie Jielan, et al. Study on variation characteristics of O_3 at different time scales in Shaoguan City based on KZ filter method[J]. Journal of Environmental Science, 2023, 43(1): 128-139.
[9] Han X, Ge C, Tao J H, et al. Air quality modeling for a strong dust event in East Asia in March 2010[J]. Aerosol and Air Quality Research, 2012, 12(4): 615-628.
[10] Han Lihun, Lan Tong, Chen Shuiyuan, et al. The variations and influencing factors of atmospheric particulate matter and O_3 at multiple scales in Tangshan[J]. China Environmental Science, 2024, 44(3): 1185-1194.
[11] Liu L, Wang Z L, Che H Z, et al. Climate factors influencing springtime dust activities over northern East Asia in 2021 and 2023[J]. Atmospheric Research, 2024, 303: 107342, doi: 10.1016/j.atmosres.2024.107342.

[12] Karimian H, Li Q, Wu C L, et al. Evaluation of different machine learning approaches to forecasting $PM_{2 \cdot 5}$ mass concentrations[J]. Aerosol and Air Quality Research, 2019, 19(6): 1400-1410.
[13] Gagliardi R V, Andenna C. Analysis of changes in pollutant concentrations levels using a meteorological normalisation technique based on a machine learning algorithm[J]. Environmental Sciences Proceedings, 2021, 8(1): 16, doi: 10.3390/ecas2021-10691.
[14] Jiao Meiling, Han Jing, Cao Yanchao, et al. Characteristics of air pollution and meteorological factors in Qingyang City[J]. Arid Land Geography, 2024, 47(6): 932-941.
[15] Kang J H, Suh M S, Kwak C H. Land cover classification over East Asian region using recent MODIS NDVI data (2006–2008)[J]. Atmosphere, 2010, 20(4): 415-426.
[16] Amani M, Ghorbanian A, Ahmadi S A, et al. Google Earth Engine cloud computing platform for remote sensing big data applications: A comprehensive review[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2020, 13: 5326-5350.
[17] Bao C L, Yong M, Bueh C, et al. Analyses of the dust storm sources, affected areas, and moving paths in Mongolia and China in early spring[J]. Remote Sensing, 2022, 14(15): 3661, doi: 10.3390/rs14153661.
[18] Fattah M A, Morshed S R, Kafy A A, et al. Wavelet coherence analysis of $PM_{2 \cdot 5}$ variability in response to meteorological changes in South Asian cities[J]. Atmospheric Pollution Research, 2023, 14(5): 101737, doi: 10.1016/j.apr.2023.101737.
[19] Verma P, Verma R, Mallet M, et al. Assessment of human and meteorological influences on PM_{10} concentrations: Insights from machine learning algorithms[J]. Atmospheric Pollution Research, 2024, 15(1): 101957, doi: 10.1016/j.apr.2023.101957.
[20] Muthukumar P, Cocom E, Nagrecha K, et al. Predicting $PM_{2 \cdot 5}$ atmospheric air pollution using deep learning with meteorological data and ground based observations and remote sensing satellite big data[J]. Air Quality, Atmosphere and Health, 2021, 2021: 1-14.
[21] Talbot N, Takada A, Bingham A, et al. An investigation of the impacts of a successful COVID-19 response and meteorology on air quality in New Zealand[J]. Air Quality and Climate Change, 2022, 56(1): 30-31.
[22] Wang Y J, Tang J K, Wang W H, et al. Long-term spatiotemporal characteristics and influencing factors of dust aerosols in East Asia (2000–2022)[J]. Remote Sensing, 2024, 16(2): 318, doi: 10.3390/rs16020318.
[23] Yang Mei, Li Yanying, Zhang Chunyan, et al. Variation characteristics of spring sandstorm and its typical case analysis in the middle east of Hexi Corridor[J]. Arid Land Geography, 2021, 44(5): 1339-1349.
[24] Yin Z C, Wan Y, Zhang Y J, et al. Why super sandstorm 2021 in north China?[J]. National Science Review, 2022, 9(3): 165, doi: 10.1093/nsr/nwab165.
[25] Meng H F, Bai G Z, Wang L W. Analysis of the spatial and temporal distribution characteristics of AOD in typical industrial cities in northwest China and the influence of meteorological factors[J]. Atmospheric Pollution

Research, 2024, 15(1): 101957, doi: 10.1016/j.apr.2023.101957.
[26] Gao J, Ding T, Gao H. Dominant circulation pattern and moving path of the Mongolian cyclone for the severe sand and dust storm in China[J]. Atmospheric Research, 2024, 301: 107272, doi: 10.1016/j.atmosres.2024.107272.
[27] Filonchyk M, Peterson M P, Zhang L F, et al. An analysis of air pollution associated with the 2023 sand and dust storms over China: Aerosol properties and PM_{10} variability[J]. Geoscience Frontiers, 2024, 15(2): 101762, doi: 10.1016/j.gsf.2023.101762.
[28] You Q L, Jiang Z H, Moore G W K, et al. Revisiting the relationship between observed warming and surface pressure in the Tibetan Plateau[J]. Journal of Climate, 2017, 30(5): 1721-1737.
[29] Shi Jianyang, Liu Minxia, Pan Jinghu, et al. The impact of aerosols in Jizi Bay of the Yellow River on the total primary productivity of vegetation[J]. China Environmental Science, 2024, 44(6): 3314-3324.
[30] China Meteorological Administration. Bulletin on atmospheric environment and meteorology (2021)[M]. Beijing: China Meteorological Press, 2021: 8-13.

Note: Figure translations are in progress. See original paper for figures.