Spatiotemporal Variation and Potential Source Analysis of PM2.5 and PM10 in the Urumqi-Changji-Shihezi Urban Agglomeration, 2015-2023: Postprint

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Abstract

Using the HYSPLIT model and other methods, this study analyzed the spatiotemporal variations and sources of PM2.5 and PM10 in the "Urumqi-Changji Hui Autonomous Prefecture-Shihezi (U-C-S)" urban agglomeration from 2015 to 2023. The results indicate: (1) At the spatial scale, during 2019-2022, PM2.5 and PM10 concentrations in the U-C-S urban agglomeration were relatively high in urban centers and northwestern regions, with PM10 concentration being inversely proportional to altitude. (2) At the temporal scale from 2015-2023, at the interannual scale, the annual average concentrations of PM2.5 and PM10 in Urumqi City and Changji Hui Autonomous Prefecture exhibited an overall downward trend, while those in Shihezi City and Wujiaqu City did not decrease significantly until 2023. At the seasonal scale, seasonal average concentrations of PM2.5 and PM10 generally declined, with the largest relative decrease occurring in spring, followed by summer and autumn, and the smallest in winter. At the monthly scale, monthly average concentrations of PM2.5 and PM10 displayed a "U-shaped" distribution, with a significant reduction in January. At the weekly scale, factors such as heavy traffic congestion during weekdays caused weekly average PM2.5 concentrations in the four cities to exhibit a "negative weekend effect", whereas weekly average PM10 concentrations only showed a "positive weekend effect" in Urumqi. At the daily scale, daily average concentrations of PM2.5 and PM10 in winter were substantially higher than in other seasons; daily average PM2.5 concentrations showed an overall decline with fewer high-concentration days, while daily average PM10 concentrations fluctuated considerably due to dust storm impacts. (3) The pollution sources for the U-C-S urban agglomeration during 2019-2021 were characterized as follows: in 2019, local sources dominated with widespread and high-concentration pollution sources; in 2020, due to the implementation of epidemic prevention and control measures, local emissions decreased and pollution sources shifted toward Central Asia; in 2021, pollution sources expanded again and shifted back to domestic origins. This research can provide data support for air pollution control and environmental policy optimization in the U-C-S urban agglomeration, contributing to the promotion of ecological environment protection and high-quality economic growth in the region.

Full Text

Preamble

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Spatiotemporal Variations and Potential Source Apportionment of PM2.5 and PM10 in the "Urumqi-Changji-Shihezi" Urban Agglomeration from 2015 to 2023

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Abstract

Using the HYSPLIT model and other analytical methods, this study investigated the spatiotemporal variations and potential sources of PM2.5 and PM10 in the Urumqi-Changji Hui Autonomous Prefecture-Shihezi urban agglomeration from 2015 to 2023. The results reveal several key patterns: (1) At the spatial scale, PM2.5 and PM10 concentrations were higher in the central and northwestern regions of the urban agglomeration from 2019 to 2022, with PM10 concentrations showing an inverse relationship with elevation. (2) At the temporal scale, annual average concentrations of PM2.5 and PM10 in Urumqi City and Changji Hui Autonomous Prefecture exhibited an overall declining trend during 2015–2023. In contrast, Shihezi City and Wujiaqu City did not show significant decreases until 2023. On a seasonal scale, average concentrations generally declined, with the largest relative reduction occurring in spring, followed by summer and autumn, and the smallest in winter. Monthly average concentrations displayed a "U-shaped" distribution, with notable decreases in January. On a weekly scale, heavy traffic congestion during weekdays produced a "negative weekend effect" for PM2.5 across all four cities, while PM10 showed a "positive weekend effect" only in Urumqi City. On a daily scale, winter concentrations were significantly higher than other seasons. PM2.5 concentrations decreased overall with fewer high-pollution days, whereas PM10 fluctuated considerably due to dust events. (3) Regarding pollution sources (2019–2021), local sources dominated in 2019, resulting in widespread high concentrations. In 2020, pandemic control measures reduced local emissions, shifting pollution sources toward Central Asia. By 2021, source regions expanded again and re-

turned to domestic areas. These findings provide critical data for air pollution control and environmental policy optimization in the Urumqi-Changji-Shihezi urban agglomeration, supporting regional ecological protection and sustainable economic development.

Keywords: PM2.5 and PM10; Urumqi-Changji-Shihezi urban agglomeration; spatiotemporal variations; potential source apportionment

Introduction

Atmospheric particulate matter exists in both solid and gaseous forms, with solid components primarily including total suspended particulates, inhalable particulates (PM10), fine particulates (PM2.5), and ultrafine particles. PM2.5 serves as a crucial indicator for assessing air pollution severity. Due to its small particle size and large specific surface area, PM2.5 can remain suspended in the atmosphere for extended periods, posing serious threats to the economy, society, ecosystems, and human health by contributing to haze formation and increasing respiratory diseases. Although some PM2.5 can be naturally expelled from the human body, it still causes respiratory inflammation. With accelerated industrialization and urbanization, compound pollution has intensified, making atmospheric particulate matter a prominent environmental issue. Despite improvements in rapidly developing northern Chinese cities, they continue to face severe challenges, with pollution characteristics often showing peak or step-like patterns.

Research demonstrates that large-scale pollution control efforts have gradually reduced particulate concentrations year by year. Meteorological data and modeling technologies can effectively track pollution sources and transport pathways, while innovative control technologies and reduced coal consumption have significantly lowered PM2.5 levels, though secondary inorganic aerosols and African dust influences have limited the reduction magnitude. Previous studies on PM2.5 in Xinjiang have primarily focused on pollution exacerbation during winter heating seasons, with relatively limited analysis of long-term trends and weekend effects. Research in other regions, such as Southeast Asia, has shown that PM2.5 frequently exceeds standards with long periodicity, and its concentration variability exhibits mountainous or step-like patterns. While the Beijing-Tianjin-Hebei region has abundant research findings, studies in Xinjiang require further deepening.

The Tianshan North Slope Economic Belt represents a crucial economic zone in northwestern China. Taking the Urumqi-Changji Hui Autonomous Prefecture-Shihezi (Urumqi-Changji-Shihezi) urban agglomeration as the core area, this region serves as a key node in the "Western Development" and "Belt and Road" initiatives, experiencing rapid economic growth. However, it faces severe PM2.5 pollution problems whose causes and impacts remain unclear. Distributed across Urumqi City, Changji Prefecture, Shihezi City, and Wujiaqu City, PM2.5 data resolution has been limited. Therefore, this study utilizes ground-based PM2.5

monitoring data to investigate the spatiotemporal characteristics and potential sources of pollution in this region, filling existing research gaps.

1.1 Study Area Overview

The Urumqi-Changji-Shihezi urban agglomeration is located in the core area of the Tianshan North Slope Economic Belt in northern Xinjiang, covering Urumqi City, Changji Hui Autonomous Prefecture (hereinafter referred to as Changji Prefecture), Wujiaqu City, and Shihezi City. The region spans an area of 2 and has a total population of approximately 800$×$10^4. As a national independent innovation demonstration zone, this area plays a vital role in the "Belt and Road" initiative and Xinjiang' s economic development, boasting abundant energy and agricultural resources. However, economic development has brought significant environmental challenges, particularly severe atmospheric particulate pollution during winter heating seasons that threatens the ecological environment and public health. Statistics indicate that heavy pollution days account for 30.4% of the total, far exceeding the national average, with PM2.5 as the primary pollutant originating from industrial, transportation, and heating sources.

1.2 Data Sources

Hourly PM2.5 concentration data used in this study were obtained from the China National Environmental Monitoring Centre' s National Urban Air Quality Monitoring Network (https://air.cnemc.cn:18007/), covering monitoring stations from 2015 to 2023. The data underwent rigorous quality control, including interpolation for missing values, regression estimation, and outlier removal to ensure accuracy and reliability.

Remote sensing PM2.5 monitoring data were derived from the China High-resolution Air Quality Dataset (https://weijing-rs.github.io/product.html), with a spatial resolution of 1 km. This long-term, large-scale, high-precision dataset integrates ground measurements, satellite remote sensing, model predictions, and artificial intelligence technology, fully considering spatial and temporal variations in pollution. The dataset was used to calculate the average distribution of pollutants in the Urumqi-Changji-Shihezi urban agglomeration from 2019 to 2022.

Meteorological data for backward trajectory clustering analysis were obtained from the National Centers for Environmental Prediction (NCEP) Global Data Assimilation System (GDAS1) at ftp://ftp.arl.noaa.gov/pnb/archives/gdas1, providing global synchronous meteorological elements including temperature, pressure, precipitation, and wind speed.

Digital Elevation Model (DEM) data were sourced from the Geospatial Data Cloud (https://www.gscloud.cn/#page1/1) using ASTER GDEM data with 30 m resolution, containing slope and aspect information.

1.3 Methods

1.3.1 Weekend Effect Analysis

This study introduced a deviation formula for weekend effect analysis: $Dev = [(c_{weekend} - c_{weekday})/c_{weekday}] \times 100\%$, where Dev represents the deviation value (%), $c_{weekend}$ is the average daily pollutant concentration on weekends, and $c_{weekday}$ is the average daily pollutant concentration on weekdays. When $Dev > 0$, it indicates that weekend pollutant concentrations exceed weekday levels, representing a "positive weekend effect"; conversely, $Dev < 0$ indicates a "negative weekend effect."

1.3.2 Backward Trajectory Model Simulation

The HYSPLIT (Hybrid Single-Particle Lagrangian Integrated Trajectory) model treats aerosols or gas particles as mass points and combines meteorological parameters such as wind fields to simulate their atmospheric movement trajectories. The model was run at a 500 m height to consider near-surface atmospheric characteristics, with daily 24-hour backward trajectory simulations conducted to track PM2.5 particle movement paths. Through backward trajectory simulation, the model enables potential source contribution analysis (PSCF) and concentration-weighted trajectory analysis.

1.3.3 Potential Source Contribution Function (PSCF) Analysis

The Potential Source Contribution Function (PSCF) is a statistical analysis method based on backward trajectory simulation used to identify potential source regions of atmospheric pollutants. In this study, the research area was first gridded and a concentration threshold was established. When the pollutant concentration of a trajectory exceeded this threshold within a grid cell, the grid was marked as a "polluted point." For each grid, the ratio of polluted points to total trajectory endpoints was calculated to obtain the potential source contribution value. Since PSCF cannot directly quantify the contribution intensity of potential sources, this study further introduced concentration-weighted trajectory analysis to improve the precision of pollution impact measurement. Trajectory weighting functions were also applied during analysis to enhance result reliability.

The calculation formulas are as follows:

$$WPSCF_{ij} = W_{ij} \times (m_{ij} / n_{ij})$$

where W_{ij} is the empirical weighting function: - $W_{ij} = 1.0$ when $n_{ij} > 80$ - $W_{ij} = 0.7$ when $15 < n_{ij} \leq 80$ - $W_{ij} = 0.4$ when $n_{ij} \leq 15$

$WPSCF_{ij}$ represents the weighted potential source contribution function value for grid (i, j); m_{ij} is the number of polluted trajectory endpoints passing through grid (i, j); n_{ij} is the total number of trajectory endpoints in grid (i, j); and i, j are grid row and column indices.

1.3.4 Concentration Weighted Trajectory (CWT) Analysis

The Concentration Weighted Trajectory (CWT) method quantifies the actual pollution contribution from each region to the observation site by comprehensively considering the residence time and pollutant concentration of trajectories within each grid cell. This approach refines pollution transport pathways and reveals the contribution intensity of different regions. In this study, pollutant concentrations of each trajectory were combined with residence time for analysis.

The calculation formula is:

CWT_{ij} = (k C_k × τ{ijk}) / (k τ{ijk})

where CWT_{ij} is the concentration-weighted trajectory value for grid (i, j); C_k is the pollutant concentration of trajectory k (g · m^-3); τ_{ijk} is the residence time of trajectory k in grid (i, j); k is the trajectory index; and M is the total number of trajectories.

To improve reliability, a weighted version was applied:

WCWT_{ij} = W_{ij} × CWT_{ij}

where WCWT_{ij} is the weighted concentration-weighted trajectory value for grid (i, j), and W_{ij} is the empirical weighting function as defined above.

2.1.1 Spatial Distribution of PM2.5 and PM10

The spatial distribution of PM2.5 and PM10 concentrations in the Urumqi-Changji-Shihezi urban agglomeration showed significant heterogeneity from 2019 to 2022. High PM2.5 concentration areas were located in central-western Urumqi City, western Changji Prefecture, and Shihezi City, with elevated levels also observed in central-southern Wujiaqu City. PM10 concentrations were inversely correlated with elevation, with higher concentrations in southwestern Urumqi City, eastern and western Changji Prefecture, and Shihezi City.

At the seasonal scale, PM2.5 concentrations showed little change, with increased levels in north-central Urumqi City, western Changji Prefecture, and Shihezi City, while Wujiaqu City remained stable. The pandemic impact led to overall concentration reductions, particularly in southern Urumqi City and eastern Changji Prefecture. In 2021, with economic recovery, PM2.5 concentrations rose substantially in north-central Urumqi City, western Changji Prefecture, and Shihezi City, with worsening pollution in Wujiaqu City. By 2022, all four cities experienced increases, most notably in Wujiaqu City.

Seasonal average PM2.5 concentrations generally declined, with relative reduction magnitudes decreasing from spring to summer to autumn to winter. In spring 2015, Urumqi City had the highest PM2.5 concentration, while Shihezi City and Wujiaqu City showed relatively smaller reduction magnitudes. Summer' s high temperatures facilitated atmospheric diffusion, consistent with patterns observed in other Chinese cities. Although autumn concentrations generally decreased, the reduction magnitude varied by city, with Changji Prefecture's seasonal average concentration showing little decline, primarily due to meteorological factors. After work resumption in 2020, PM2.5 concentrations fell but remained higher than pre-pandemic levels.

[Figure 1: see original paper] Overview of the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration

[Figure 2: see original paper] Spatial distributions of annual average PM2.5 and PM10 concentrations in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration from 2019 to 2022

2.1.2 Temporal Distribution of PM2.5 and PM10

At the interannual scale, Urumqi City and Changji Prefecture in the Urumqi-Changji-Shihezi urban agglomeration showed significant declining trends in annual average PM2.5 and PM10 concentrations, though they remained above national secondary standards. In contrast, Shihezi City and Wujiaqu City did not show clear declines in annual average concentrations until 2023. According to Wujiaqu City's statistical yearbook, GDP increased from 230.09$\times 10^{8} yuan to 426.27\times 10^{8} yuan between 2015 and 2023, while civilian vehicle ownership grew from 36.55\times 10^{4}$ suggesting that the lack of decline in PM2.5 and PM10 concentrations may be related to rapid economic development and vehicle growth.

On a monthly scale, PM2.5 and PM10 concentrations displayed a typical "U-shaped" distribution, with high concentrations in winter months and low concentrations in summer months. January showed particularly significant reductions, especially in Urumqi City, likely due to Spring Festival holidays, effective government control measures, and natural factors. During the pandemic, reduced human activities led to decreased PM2.5 concentrations, though post-2020 work resumption caused concentrations to rebound above pre-pandemic levels. Wujiaqu City exhibited large fluctuations with less distinct seasonal trends.

At the weekly scale, PM2.5 and PM10 concentrations showed higher pollution levels on weekdays (particularly Wednesdays) and lower levels on weekends across all four cities. This pattern likely results from increased traffic flow and industrial activities during weekdays, combined with unfavorable meteorological conditions that facilitate pollutant accumulation, while reduced weekend activities and more favorable weather conditions improve air quality. This indicates that traffic, industrial emissions, and meteorological factors play crucial roles in the spatiotemporal distribution of air pollution.

To investigate the weekend effect, this study calculated relative deviations of daily average PM2.5 concentrations. The results showed negative deviations ranging from -1.26% to -2.66% across the urban agglomeration, consistent with Beijing studies, indicating a "negative weekend effect" due to weekday traffic congestion. In contrast, PM10 daily concentrations in Urumqi City showed a "positive weekend effect," possibly related to more active weekend economic activities. Other cities showed less significant weekend effects due to greater influence from natural factors.

On a daily scale, winter PM2.5 and PM10 concentrations were significantly higher than other seasons, frequently reaching levels above light pollution. However, overall PM2.5 concentrations showed a declining trend with fewer high-concentration days, while PM10 concentrations fluctuated considerably due to dust events. A sandstorm in early March 2020 significantly elevated PM10 levels while PM2.5 remained normal, demonstrating the dominant role of natural factors on PM10 and its asynchronous variation with PM2.5.

[Figure 3: see original paper] 3D annual average PM2.5 and PM10 concentration changes in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration from 2015 to 2023

[Figure 4: see original paper] Seasonal average PM2.5 and PM10 concentration changes in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration from 2015 to 2023

[Figure 5: see original paper] Monthly average PM2.5 and PM10 concentration changes in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration from 2015 to 2023

[Figure 6: see original paper] Daily average PM2.5 and PM10 concentration variations in a week in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration

Relative deviation of daily average pollutant concentrations among cities on weekends and weekdays

[Figure 7: see original paper] Daily average concentration changes in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration from January 1, 2015 to December 31, 2023

[Figure 8: see original paper] Proportions of various pollution levels for daily average PM2.5 and PM10 concentrations in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration

2.2 Pollutant Potential Source Contribution

The HYSPLIT model was used to analyze potential source regions for PM2.5 and PM10 pollution in the Urumqi-Changji-Shihezi urban agglomeration during different pandemic control phases from 2019 to 2021, assessing pandemic impacts on pollution sources.

In 2019, potential source regions were extensive with high concentrations, indicating predominantly local sources with widespread and high-level pollution. In 2020, pandemic prevention and control measures significantly reduced local emissions, causing potential source regions to shrink and shift from central Xinjiang to natural dust source areas in northern Xinjiang, eastern Kazakhstan, and southern Russia. In 2021, source regions expanded again and returned to domestic areas.

Monthly analysis revealed that in January 2020, potential source regions were concentrated in central and western Xinjiang and northern Kazakhstan, affected by heating periods and unfavorable meteorological conditions, with increased local pollution and intensified cross-border transport. In March 2020, source regions expanded northward due to dust and topography. In July 2020, sources stabilized in the northwest direction, occasionally affected by clean air masses but still influenced by dust sources in northern Xinjiang and Central Asia. In November 2020, potential source regions further expanded to multiple Central Asian countries, demonstrating cross-regional pollution characteristics.

Since PSCF analysis can only display pollution trajectory frequencies but cannot quantify source contributions, Concentration Weighted Trajectory (CWT) analysis was applied to estimate pollution levels from different trajectories. The results showed that in 2019, high WCWT values were concentrated in central and western Xinjiang and southeastern Kazakhstan, primarily affected by mining activities and industrial emissions. In 2020, WCWT values were more influenced by western Mongolia and southern Russia, affected by natural dust sources and meteorological conditions. In 2021, WCWT values shifted from Central Asia to southern Russia, with reduced ranges and maximum values, while being significantly affected by natural dust sources and spring sandstorms.

[Figure 9: see original paper] Contribution distributions of potential source areas for PM2.5 and PM10 in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration from 2019 to 2021

[Figure 10: see original paper] Monthly distributions of potential source areas contribution for PM2.5 in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration in 2020

[Figure 11: see original paper] Monthly distributions of potential source areas contribution for PM10 in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration in 2020

[Figure 12: see original paper] Weighted trajectory distributions of PM2.5 and PM10 concentrations in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration from 2019 to 2021

[Figure 13: see original paper] Monthly distributions of PM2.5 concentration weighted trajectory in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration in 2020

[Figure 14: see original paper] Monthly distributions of PM10 concentration weighted trajectory in the Urumqi, Changji Hui Autonomous Prefecture, and Shihezi urban agglomeration in 2020

3 Conclusions

This study analyzed the spatiotemporal variations and potential pollution sources of PM2.5 and PM10 in the Urumqi-Changji-Shihezi urban agglomeration from 2015 to 2023, yielding the following conclusions:

(1) At the spatial scale, PM2.5 concentration distribution showed significant spatial heterogeneity. Central-western Urumqi City, western Changji Prefecture, and Shihezi City were high-concentration areas, while PM10 concentrations increased with decreasing elevation, primarily concentrated in southwestern Urumqi City and eastern and western Changji Prefecture.

(2) At the temporal scale, annual average PM2.5 and PM10 concentrations in the urban agglomeration showed an overall declining trend from 2015 to 2023. However, under strict policy implementation and rapid economic development, Urumqi City and Changji Prefecture, benefiting from more stringent policies and better natural environments, showed more pronounced declines compared to Shihezi City and Wujiaqu City. Seasonal average PM2.5 concentrations were highest in winter, followed by spring and autumn, and lowest in summer. Monthly average PM2.5 concentrations displayed a "U-shaped" distribution, with high winter values and low summer values, showing significant January reductions particularly in Urumqi City. Wujiaqu City exhibited large fluctuations, indicating that Spring Festival holidays, government control measures, and natural factors all influence air quality.

(3) At the weekly scale, PM2.5 concentrations showed a "negative weekend effect" across the urban agglomeration, while PM10 concentrations exhibited a "positive weekend effect" only in Urumqi City, demonstrating that traffic and economic development affect weekend patterns.

(4) At the daily scale, winter PM2.5 and PM10 concentrations were significantly higher than other seasons, frequently exceeding light pollution levels. However, overall PM2.5 concentrations declined with fewer high-pollution days. PM10 daily concentrations fluctuated considerably due to dust events, indicating that natural factors have more significant impacts on PM10, with variations asynchronous from PM2.5 changes.

(5) Analysis of potential pollution sources revealed that in 2019, sources were widespread with high concentrations. In 2020, pandemic controls reduced local emissions, shifting potential source regions to natural dust source areas in eastern Kazakhstan and southern Russia. In 2021, source regions expanded again and returned to domestic areas. Throughout different control phases in 2020, seasonal factors such as sandstorms and meteorological conditions remained influential. Overall, pandemic prevention effectively reduced local pollution, but cross-border input from Central Asia became the primary external pollution source. Although pollution range expanded, pollutant concentrations showed a declining trend.

References

[1] Gao X, Li W D. A graph based LSTM model for PM2.5 forecasting[J]. Atmospheric Pollution Research, 2021, 12(9): 101150, doi: 10.1016/j.apr.2021.101150.

[2] Guo X H, Wang Y F, Mei S Q, et al. Monitoring and modelling of PM2.5 concentration at subway station construction based on IoT and LSTM algorithm optimization[J]. Journal of Cleaner Production, 2022, 360: 132179, doi: 10.1016/j.jclepro.2022.132179.

[3] Shamsollahi H R, Yunesian M, Kharrazi S, et al. Characterization of persistent materials of deposited PM2.5 in the human lung[J]. Chemosphere, 2022, 301: 134774, doi: 10.1016/j.chemosphere.2022.134774.

[4] Wu Y Y, Zhang T, Wang Y Y, et al. Spatial heterogeneity in health risks of illness related absenteeism associated with PM2.5 exposure for elementary students[J]. Environmental Research, 2022, 212: 113473, doi: 10.1016/j.envres.2022.113473.

[5] Bu X, Xie Z L, Liu J, et al. Global PM2.5 attributable health burden from 1990 to 2017: Estimates from the global burden of disease study 2017[J]. Environmental Research, 2021(1): 111123, doi: 10.1016/j.envres.2021.111123.

[6] Liu Wen, Zhan Qingming, Qiu Chundi, et al. Spatio temporal variations of PM2.5 and PM10 pollution in winter and summer: A case of Xiangyang, China[J]. Environmental Science & Technology, 2023, 46(Suppl. 1): 8-18.

[7] Ning G, Yim S H L, Yang Y, et al. Modulations of synoptic and climatic changes on ozone pollution and its health risks in mountain basin areas[J]. Atmospheric Environment, 2020, 240: 117808, doi: 10.1016/j.atmosenv.2020.117808.

[8] Xu Yong, Guo Zhendong, Zheng Zhiwei, et al. Spatio temporal variation and multi dimensional detection of driving mechanism of PM2.5 concentration in the Chengdu Chongqing urban agglomeration from 2000 to 2021[J]. Environmental Science, 2023, 44(7): 3724-3737.

[9] Xiao Zhimei, Li Yafei, Gao Jingyun, et al. Analysis of change trend and influencing factors of PM2.5-O3 pollution in Tianjin from 2013 to 2020[J]. Environmental Science, 2023, 44(8): 4211-4219.

[10] Li S, Zhou C H, Qu M X. Spatiotemporal variations and mechanism of PM2.5 pollution in urban area: The case of Guiyang, Guizhou, China[J]. Journal of Environmental Management, 2023, 341: 118030, doi: 10.1016/j.jenvman.2023.118030.

[11] Li Le, Liu Minxia, Xiao Shirui, et al. Temporal and spatial variation in O3 concentration near the surface of Shandong Peninsula and analysis of potential source areas[J]. Environmental Science, 2022, 43(3): 1256-1267.

[12] Mu Shilei, Yang Yuhuan, Wuritaoketaohu. Spatiotemporal evolution and

influencing factors of PM2.5 in the five major urban agglomerations in the Yellow River Basin[J]. Arid Land Geography, 2024, 47(4): 707-719.

[13] Shi Xiaocui. Analysis of chemical composition characteristics and sources of atmospheric PM2.5 in Urumqi[D]. Urumqi: Xinjiang Agricultural University, 2021.

[14] Miao Yunge. Analysis of atmospheric particulate matter composition characteristics during dust storm and non dust storm seasons in the southern margin of Xinjiang[D]. Tianjin: Tianjin Normal University, 2017.

[15] Salvador P, Artíñano B, Viana M, et al. Spatial and temporal variations in PM10 and PM2.5 across Madrid metropolitan area in 1999–2008[J]. Procedia Environmental Sciences, 2011, 4(10): 198-208.

[16] Othman M, Latif M T, Hamid H H A, et al. Spatial temporal variability and health impact of particulate matter during a 2019–2020 biomass burning event in Southeast Asia[J]. Scientific Reports, 2022, 12(1): 7630, doi: 10.1038/s41598-022-11409-z.

[17] Pengchai P, Chantara S, Sopajaree K, et al. Seasonal variation, risk assessment and source estimation of PM10 and PM10 bound PAHs in the ambient air of Chiang Mai and Lamphun, Thailand[J]. Environmental Monitoring and Assessment, 2009, 154: 197-210.

[18] Yi Wei. Temporal and spatial distribution characteristics of PM2.5 concentrations in the Tianshan north slope economic belt in 2018 and their meteorological influencing factors[D]. Lanzhou: Northwest Normal University, 2021.

[19] Fu Zhenghui, Liu Ting, Tang Ye, et al. Analysis on cause of atmospheric pollution and control measures in Wuchang region[J]. Environmental Science and Management, 2013, 38(12): 35-39.

[20] An Xinxin, Cao Yang, Wang Qin, et al. Chemical characteristics and source apportionment of PM2.5 in urban area of Beijing[J]. Environmental Science, 2022, 43(5): 2251-2261.

[21] Wei J, Li Z Q, Lyapustin A, et al. Reconstructing 1 km resolution quality PM2.5 data records from 2000 to 2018 in China: Spatiotemporal variations and policy implications[J]. Remote Sensing of Environment, 2021, 252: 112136, doi: 10.1016/j.rse.2020.112136.

[22] Wei J, Li Z Q, Cribb M, et al. Improved 1 km resolution PM2.5 estimates across China using enhanced space time extremely randomized trees[J]. Atmospheric Chemistry and Physics, 2020, 20(6): 2006.

[23] Diao Chunna. Monitoring and exploration of major pollutant characteristics in atmospheric particulate matter of the Wu Chang region[D]. Urumqi: Xinjiang University, 2006.

[24] Fan Shenghu, Liu Ning, Zhang Feiyun. Analysis of the weekend effect characteristics and trend of air pollution in Urumqi[J]. Xinjiang Environmental

Protection, 2021, 43(2): 1-7.

[25] Li Zhipeng, Chen Jian. Remote sensing retrieval of atmospheric fine particle PM2.5 based on GOCI satellite and its temporal and spatial distribution[J]. Remote Sensing Technology and Application, 2020, 35(1): 163-173.

[26] Lei Yu, Zhang Xiaoling, Tang Yixi, et al. Holiday effects on PM2.5 and other major pollutants in Beijing[J]. Acta Scientiae Circumstantiae, 2015, 35(5): 1520-1528.

[27] Liu Ning, Zhang Feiyun, Fan Shenghu. Analysis on change of air quality and cause of pollution in Urumqi City during the 13th Five Year Plan period[J]. Environmental Protection of Xinjiang, 2021, 43(3): 17-25.

[28] Zhao Q W, He Q, Jin L L, et al. Potential source regions and transportation pathways of reactive gases at a regional background site in northwestern China[J]. Advances in Meteorology, 2021, 2021(1): 9933466, doi: 10.1155/2021/9933466.

[29] Fu Chuanfu, Dan Li, Tang Jiaxiang, et al. Analysis of air polluted transportation and potential source in Haikou City based on trajectory model[J]. Acta Scientiae Circumstantiae, 2020, 40(1): 36-42.

[30] Ren Puhui, Xie Jingfang, Jiang Hongjin, et al. Transport pathways and potential sources of PM2.5 in different seasons in Taiyuan City[J]. China Environmental Science, 2019, 39(8): 3144-3151.

[31] Wang Guochen, Wang Jue, Xin Yujie, et al. Transportation pathways and potential source areas of PM10 and NO2 in Tianjin[J]. China Environmental Science, 2014, 34(12): 3009-3016.

[32] Hopke P K, Gao N, Cheng M D. Combining chemical and meteorological data to infer source areas of airborne pollutants[J]. Chemometrics and Intelligent Laboratory Systems, 1993, 19(2): 187-199.

[33] Zeng Y, Hopke P K. A study of the sources of acid precipitation in Ontario, Canada[J]. Atmospheric Environment, 1989, 23(7): 1499-1509.

[34] Seibert P, Kromp-Kolb H, Baltensperger U, et al. Trajectory analysis of aerosol measurements at high alpine sites[J]. Transport and Transformation of Pollutants in the Troposphere, 1994, 15(9): 689-693.

[35] Hsu Y K, Holsen T M, Hopke P K. Comparison of hybrid receptor models to locate PCB sources in Chicago[J]. Atmospheric Environment, 2003, 37(4): 545-562.

[36] Sun Mingxia. Air quality influence factors and trend forecasting in the Wujiaqu[D]. Shihezi: Shihezi University, 2016.

[37] Hao Jufei, Qi Jiahui, Li Yongzhan, et al. Variability characteristics and backward trajectory analysis of particulate pollutants in Xingtai City[J]. Chinese Environmental Monitoring, 2018, 34(5): 46-53.

[38] Feng haiying. Impact of epidemic prevention and control measures on atmospheric particulate concentration and distribution in Urumqi[J]. Environmental Pollution & Control, 2021, 43(5): 606-610.

[39] Zhang Qian, Pang Ke, Ma Caiyun, et al. Analysis of transportation path and potential sources of atmospheric particulate matter over Gansu Province in spring and winter: Based on HYSPLIT4 model and TraPSA analysis platform[J]. China Environmental Science, 2022, 42(2): 509-518.

[40] Li Shuting, Li Xia, Ayikan Mauren, et al. Characteristics of air pollution and its polluted weather types of urban agglomeration on the north slope of the middle Tianshan Mountains from 2017 to 2019[J]. Arid Land Geography, 2022, 45(4): 1082-1092.

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