

Article

Atmospheric Particulate Matter Pollution in the “U-C-S” Urban Agglomeration: Spatio-Temporal Distribution and Source Analysis

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Abstract

This study utilizes backward trajectory cluster analysis, the Potential Source Contribution Function (PSCF), Concentration Weighted Trajectory (CWT), and a random forest model to investigate the pollution characteristics of PM_{2.5} and PM₁₀ in the “Urumqi-Changji Hui Autonomous Prefecture-Shihezi-Wujiaqu (U-C-S)” urban agglomeration. Findings indicate that on an annual basis, higher PM_{2.5} concentrations are observed in the central part of the “U-C-S” urban agglomeration, southern Wujiaqu, and the Shihezi area, whereas PM₁₀ concentrations are lower in the high-altitude regions of the Tianshan and Bogda Mountains. Seasonally, both PM_{2.5} and PM₁₀ concentrations significantly increase during winter, with summer exhibiting the best air quality. On a monthly scale, Urumqi’s central urban area shows a marked rise in PM_{2.5} concentrations during winter, attributed to coal heating and stable weather conditions. Weekly patterns reveal higher pollution levels on weekdays compared to weekends. Daily data show that PM_{2.5} concentrations are notably higher in winter compared to other periods, while elevated PM₁₀ levels in spring are primarily due to dust storms. Cluster analysis indicates that seasonal airflow paths significantly influence particulate matter concentrations. PSCF and CWT analyses demonstrate that the most severe PM_{2.5} pollution in winter is concentrated in the northern part of the Bayingolin Mongol Autonomous Prefecture, southern Yining City, and across all areas of Urumqi. The random forest model provides robust predictions of particulate matter concentrations, aiding in the understanding and mitigation of future pollution trends. This study offers valuable insights for atmospheric particulate matter pollution research in the Xinjiang region and serves as a reference for similar urban agglomerations.

Keywords: PM_{2.5} and PM₁₀; Urumqi; Changji Hui Autonomous Prefecture; Shihezi urban agglomeration; spatiotemporal variations; potential source apportionment



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1. Introduction

Atmospheric particulate matter exists in two primary forms: solid and gaseous. The solid form predominantly comprises total suspended particulates, inhalable particulate matter (PM₁₀), fine particulate matter (PM_{2.5}), and ultrafine particulate matter. PM_{2.5} and PM₁₀ serve as critical indicators for evaluating air pollution levels. Given their small size and large specific surface area, PM_{2.5} particles can remain airborne for extended periods,

posing significant threats to the economy, society, ecology, and human health by contributing to smog formation and increasing the risk of respiratory diseases [1–5]. While some PM_{10} particles can be naturally expelled from the human body, they can still induce respiratory inflammation. The acceleration of industrialization and urbanization has exacerbated complex pollution issues, making atmospheric particulate matter a particularly pressing concern in rapidly developing cities in northern China. Despite some improvements, challenges persist [6,7].

Scholars from various countries have conducted extensive research on $PM_{2.5}$ and PM_{10} , finding that, according to the World Health Organization (WHO) 2021 guidelines, the majority of the world's population resides in areas where $PM_{2.5}$ concentrations exceed the recommended levels [8]. Annual average $PM_{2.5}$ concentrations are markedly lower in developed countries—e.g., $8.5 \mu\text{g}\cdot\text{m}^{-3}$ in the United States [9] and $12.8 \mu\text{g}\cdot\text{m}^{-3}$ in the European Union [10]—whereas severe pollution persists across many developing Asian nations, with peak $PM_{2.5}$ concentrations in Delhi, India, reaching as high as $656.91 \mu\text{g}\cdot\text{m}^{-3}$ [11]. Major anthropogenic sources of $PM_{2.5}$ include coal combustion (contributing over 30% [3]), vehicle emissions (20–25% [1]), industrial processes (30–35% [12]), and biomass burning (15–20% [13]). For PM_{10} , dominant anthropogenic sources comprise road dust (30–35% [13]), construction activities (15–20% [12]), industrial dust (20–25% [13]), and dust storms (30–40% [12]). $PM_{2.5}$ concentrations often exceed standards both before and after winter, exhibiting long-term cyclic patterns characterized by peaks or steps [14]. Studies indicate that large-scale pollution control measures have led to a yearly decrease in particulate matter concentrations [15,16], and meteorological data combined with modeling techniques can effectively track pollution sources and transmission pathways [17,18]. Research in Xinjiang primarily focuses on the exacerbation of pollution due to winter heating [19], but there is relatively limited analysis on weekend effects [20]. Internationally, developing regions such as Southeast Asia have seen significant reductions in $PM_{2.5}$ through innovative control technologies and decreased coal usage [13,21]. However, reductions in PM_{10} are less pronounced due to secondary inorganic aerosols and African dust [22]. Random forest models have been introduced to predict $PM_{2.5}$ in North America [23,24]. Overall, while developed regions boast a wealth of research findings, further in-depth exploration is needed for the Xinjiang region [25].

The Northern Slope of the Tianshan Economic Belt is a key economic region in Northwest China, with the “Urumqi-Changji Hui Autonomous Prefecture-Shihezi-Wujiaqu (U-C-S)” urban agglomeration at its core. As a strategic node in both the “Western Development” and “Belt and Road” initiatives, this area has experienced rapid economic growth. However, this development has been accompanied by severe $PM_{2.5}$ and PM_{10} pollution, the causes and consequences of which remain insufficiently understood [26]. Therefore, this study focuses on the “U-C-S” urban agglomeration as a case study, based on ground monitoring data, to explore the spatiotemporal characteristics and potential sources of $PM_{2.5}$ and PM_{10} pollution, aiming to fill existing research gaps.

2. Study Area

The “Urumqi-Changji Hui Autonomous Prefecture-Shihezi-Wujiaqu (U-C-S)” urban agglomeration is located in the core area of the Northern Slope of the Tianshan Economic Belt, in the northern part of the Xinjiang Uygur Autonomous Region. It encompasses Urumqi City, Changji Hui Autonomous Prefecture (hereafter referred to as Changji Prefecture), Wujiaqu City, and Shihezi City, covering an area of approximately $41,000 \text{ km}^2$ with a total population of about 8 million. As a national innovation demonstration zone, this region plays a pivotal role in China's “Belt and Road” initiative and the economic development of Xinjiang, boasting abundant energy and agricultural resources [27]. How-

ever, rapid economic growth has brought significant environmental challenges, particularly severe atmospheric particulate matter pollution during winter heating periods, which poses serious threats to the ecological environment and public health. According to statistical data from early 2022, the proportion of heavily polluted days in this region reached 30.4%, far exceeding the national average air pollution level, with $PM_{2.5}$ and PM_{10} identified as the primary pollutants. These pollutants originate from multiple sources, including industry, transportation, and residential heating (Figure 1).

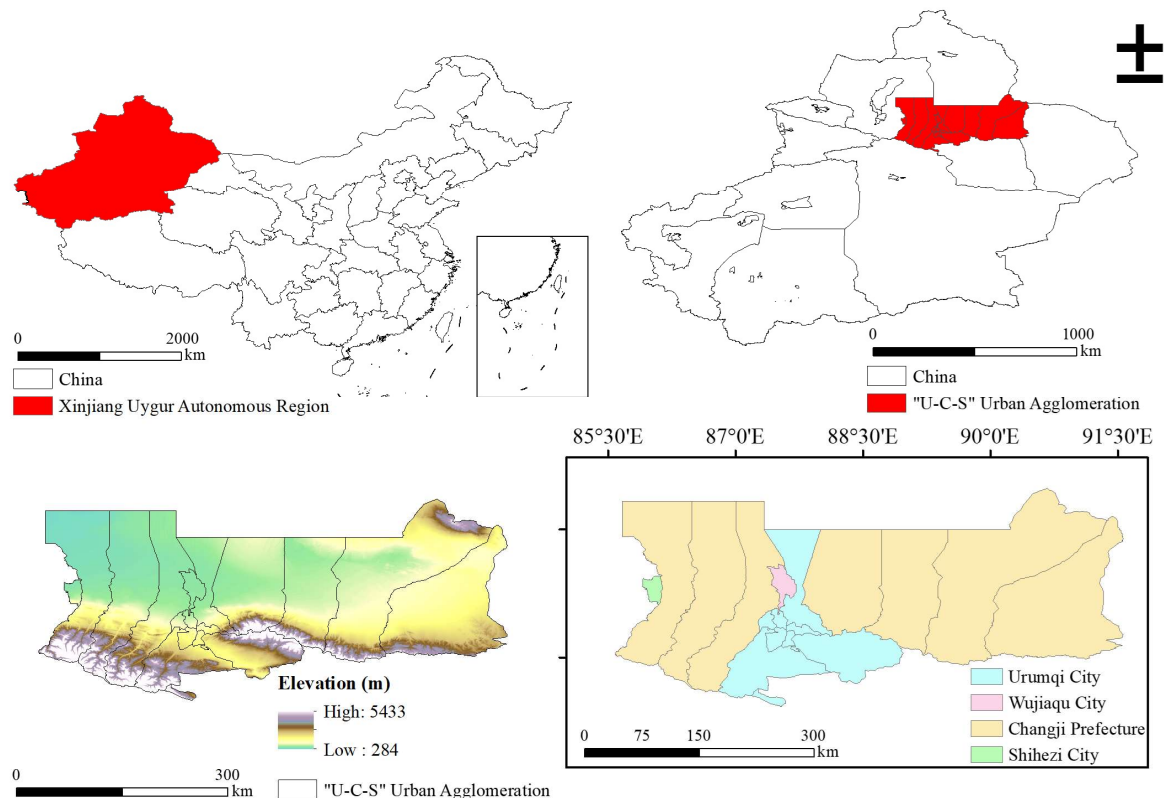


Figure 1. Overview map of the “U-C-S” urban agglomeration study area.

3. Data Sources

The hourly concentration data for $PM_{2.5}$ and PM_{10} used in this paper are sourced from the National Urban Air Quality Monitoring Network operated by the China National Environmental Monitoring Center (<https://air.cnemc.cn:18007/>, accessed on 23 June 2023), covering the period from 1 January 2019 to 31 December 2022. The number of monitoring stations increased from 13 in 2015 to 17 by 2022, distributed across Urumqi City, Changji Prefecture, Shihezi City, and Wujiaqu City, with a data resolution of one hour. This dataset has undergone rigorous quality control procedures, including interpolation for missing values, regression estimation, and the removal of anomalous data points to ensure its accuracy and reliability [28].

The remote sensing monitoring data for $PM_{2.5}$ and PM_{10} are sourced from the Chinese High-Resolution Air Quality (CHAP) dataset (<https://weijing-rs.github.io/product.html>, accessed on 26 June 2023) [29], with a spatial resolution of 1 km, covering the period from 2019 to 2022. Utilizing this dataset, we calculated the average distribution of pollutants within the “Urumqi-Changji Hui Autonomous Prefecture-Shihezi-Wujiaqu (U-C-S)” urban agglomeration. The CHAP dataset is a large-scale, high-precision series focusing on Chinese air pollutants, integrating ground measurements, satellite remote sensing, model predictions, and artificial intelligence technologies, thereby fully accounting for the spatial and temporal variations in pollution levels.

The meteorological analysis data for backward trajectory clustering are sourced from the Global Data Assimilation System (GDAS) of the National Centers for Environmental Prediction (NCEP) (<https://www.ncei.noaa.gov/products/weather-climate-models/global-data-assimilation>, accessed on 30 June 2023), covering the period from December 2018 to January 2022. This dataset includes globally synchronized meteorological elements such as temperature, pressure, precipitation, and wind speed. The Digital Elevation Model (DEM) data is obtained from the Geospatial Data Cloud (<https://www.gscloud.cn/#page1/1>, accessed on 30 June 2023), utilizing ASTER GDEM data with a 30 m resolution, which also provides slope and aspect information.

The data for the random forest prediction comprise daily meteorological records from the “U-C-S” area over the past four years (2019–2022), including temperature, humidity, wind speed, wind direction, and air pressure, along with corresponding PM_{2.5} and PM₁₀ concentration data. After preprocessing steps such as filling missing values and handling outliers, the quality and integrity of the data were ensured. The processed dataset was then divided into training and testing sets in a 7:3 ratio, with the former used for model training and the latter for evaluating the model’s generalization ability. During the training process, model parameters—such as the number of trees, the maximum number of features, and the minimum number of leaf node samples—were tuned to optimize performance. Cross-validation techniques were also employed to further enhance the stability and reliability of the model [30,31]. The spatial delineation of high-concentration pollution zones was based on the 1-km resolution Chinese High-resolution Air Quality (CHAP) dataset. Annual and seasonal mean PM_{2.5} and PM₁₀ concentrations were first calculated for each grid cell across the study period (2019–2022). Grid cells exceeding the China’s National Ambient Air Quality Standard (NAAQS) [32] Grade II annual limit (35 µg·m^{−3} for PM_{2.5}; 70 µg·m^{−3} for PM₁₀) were initially flagged as potential high-pollution areas. To ensure spatial coherence and reduce noise, only contiguous regions with an area ≥ 0 km² (i.e., at least 10 adjacent 1-km² grid cells) were classified as ‘high-concentration zones’. This approach balances sensitivity to local hotspots with robustness against isolated outliers.

The meteorological data were obtained from the Urumqi National Basic Meteorological Station, with measurements taken at a height of 1.5 m above ground level. The meteorological variables during the study period (January–December 2023) are as follows: mean air temperature of 9.6 °C (mean maximum temperature of 14.5 °C and mean minimum temperature of 5.3 °C); mean relative humidity of 51.7%; annual total precipitation of 260.02 mm; annual mean wind speed of 2.1 m·s^{−1}; annual mean surface temperature of 14.1 °C; annual mean sunshine duration of 2744.25 h; and annual mean atmospheric pressure of 915 hPa.

4. Research Methods

4.1. Weekend Effect Analysis

This paper introduces the formula for calculating the weekend effect deviation [33]:

$$\text{Dev} = \left[(c_{\text{weekend}} - c_{\text{workday}}) / c_{\text{workday}} \right] \times 100 \quad (1)$$

where Dev is the deviation value (%); c_{weekend} is the average daily concentration of pollutants on weekends (µg·m^{−3}); and c_{workday} is the average daily concentration of pollutants on weekdays (µg·m^{−3}). When Dev > 0, it indicates that the pollutant concentration on weekends is higher than on weekdays, representing a “positive weekend effect.” Conversely, if Dev < 0, it indicates a “negative weekend effect,” where pollutant concentrations are lower on weekends compared to weekdays.”

4.2. Backward Trajectory and Cluster Methodology

In this study, the Hybrid Single-Particle Lagrangian Integrated Trajectory (HSPLIT) model was utilized for backward trajectory simulations, employing the Lagrangian coordinate method [34]. Aerosols or gaseous particles are treated as individual particles, and their atmospheric movement trajectories are simulated in conjunction with meteorological parameters such as wind fields [35]. Through backward trajectory simulations, foundational data are provided for Potential Source Contribution Function (PSCF) and Concentration Weighted Trajectory (CWT) analyses [36,37].

In this study, a simulation height of 500 m was selected to consider near-surface atmospheric characteristics. Backward trajectory simulations were calculated every 72 h to track the movement paths of PM_{2.5} and PM₁₀ particles. Additionally, the TrajStat tool was utilized for trajectory cluster analysis to differentiate transport pathways. By integrating trajectory simulations and cluster analyses, the sources, transport paths, and impact ranges of PM_{2.5} and PM₁₀ were elucidated, providing a foundation for understanding pollution processes. Backward trajectories serve as an essential methodological approach for investigating pollution transport and identifying sources [12].

4.3. Potential Source Contribution Function (PSCF) Methodology

The Potential Source Contribution Function (PSCF) is a statistical method based on backward trajectory simulations, used to identify potential source areas of atmospheric pollutants. In this study, the study area was divided into grids, and a concentration threshold was established. When a trajectory's pollutant concentration exceeded this threshold within a grid, that grid was marked as a "pollution point." For each grid, the ratio of "pollution points" to the total number of trajectory endpoints was calculated, yielding the PSCF value for that grid [38,39]. A higher PSCF value indicates a greater likelihood that the grid is a potential source area contributing to pollution in the study region. However, the PSCF method has inherent uncertainties. To enhance the reliability of the results, a trajectory weight function was introduced [40].

The formula is as follows:

$$\text{WPSCF}_{ij} = W_{ij} \cdot (m_{ij}/n_{ij}) \quad (2)$$

$$W_{ij} = \begin{cases} 1.00 (80 < n_{ij}) \\ 0.70 (25 < n_{ij} < 80) \\ 0.42 (15 < n_{ij} < 25) \\ 0.17 (n_{ij} < 15) \end{cases} \quad (3)$$

where WPSCF_{ij} is the weighted potential source contribution function value for grid (i, j); m_{ij} is the number of pollution trajectory endpoints passing through grid (i, j); n_{ij} is the total number of trajectory endpoints passing through grid (i, j); W_{ij} is the empirical weight function; and i, j are the row and column numbers of the grid.

4.4. Concentration Weighted Trajectory (CWT) Methodology

CWT (Concentration Weighted Trajectory) is a method that quantifies the actual pollution contribution of each area to the observation point by considering both the residence time and pollutant concentration of trajectories in each grid [41,42]. In this study, the pollutant concentrations and residence times of each trajectory were jointly analyzed to refine the pollution transmission paths and reveal the absolute contribution values of each area to the observation point. Since the PSCF method cannot directly quantify the contribution strength of potential sources to pollutants, the CWT analysis method was further introduced to enhance the precision of pollution impact measurement. Additionally, a

trajectory weight function was applied during the CWT analysis process to further improve the reliability of the results.

The formula is as follows:

$$CWT_{ij} = \sum_{k=1}^M C_k \tau_{ijk} / \sum_{k=1}^M \tau_{ijk} \quad (4)$$

$$WCWT_{ij} = W_{ij} \cdot \left(\sum_{k=1}^M T_{ijk} \right)^{-1} \cdot \sum_{k=1}^M C_k \tau_{ijk} \quad (5)$$

where CWT_{ij} is the concentration weighted trajectory value for grid (i, j); $WCWT_{ij}$ is the weighted concentration weighted trajectory value for grid (i, j); C_k is the pollutant concentration ($\mu\text{g}\cdot\text{m}^{-3}$) of trajectory k passing through grid (i, j); τ_{ijk} is the residence time (h) of trajectory k in grid (i, j); k is the specific trajectory index; i, j are the row and column numbers of the grid; M represents the total number of trajectories.

4.5. Random Forest

In this study, to achieve robust and accurate predictive performance, the Random Forest (RF) ensemble learning method was employed for data analysis. The objective was to explore the relationship between $\text{PM}_{2.5}$ and PM_{10} concentrations and meteorological conditions in the “U-C-S” area. Random Forest enhances the model’s generalization capability by constructing multiple decision trees and averaging their outputs, effectively mitigating overfitting risks associated with individual decision trees. Specifically, each tree is trained on a different bootstrap sample drawn from the original dataset, using bootstrap aggregation (Bagging), which helps reduce model variance and improve overall stability [43].

Furthermore, when splitting at each node, the algorithm randomly selects only a subset of all available features as candidate features for splitting. This approach not only enhances model diversity but also reduces the correlation among individual trees, thereby further improving overall model performance. In classification tasks, the final prediction is determined by the class that receives the majority of votes from all decision trees; in regression tasks, it is calculated as the average of the outputs from all trees.

During the implementation of the Random Forest model, three key parameters were tuned: the number of trees (ntree), the number of random features considered at each split (mtry), and the minimum node size (nodesize). A larger ntree is generally recommended to ensure model stability and accuracy. The mtry parameter, which determines the number of features randomly sampled at each split when identifying the optimal splitting point, is typically selected through cross-validation to balance bias and variance. The nodesize controls the tree’s growth depth by specifying the minimum number of observations required in a terminal node, thereby influencing model complexity.

To ensure the effectiveness and reliability of the model, the ranger package (version 0.12.1) in R was employed to implement random forest modeling [44]. Ranger is an efficient and fast implementation tool for random forests, particularly well-suited for analyzing large-scale datasets. Through optimized parameter selection, the objective was to develop a random forest model that achieves both low bias and low variance, thereby providing reliable data interpretation and prediction.

5. Results

5.1. Annual Spatiotemporal Distribution Changes of $\text{PM}_{2.5}$ and PM_{10}

In the “U-C-S” urban agglomeration, higher $\text{PM}_{2.5}$ concentrations are observed in the central region, southern Wujiaqu, and Shihezi area (Figure 2). This trend was not significantly alleviated during the pandemic, suggesting that climate, land use patterns,

and human activities are the primary influencing factors. For PM_{10} , lower concentrations are found in the high-altitude zones of the Tianshan and Bogda Mountains, while other regions exhibit elevated levels (The definition of “high” concentrations of $PM_{2.5}$ and PM_{10} varies across regulatory frameworks. The World Health Organization (WHO), representing the United Nations system, recommends 24-h mean guideline values of $15 \mu\text{g}\cdot\text{m}^{-3}$ for $PM_{2.5}$ and $45 \mu\text{g}\cdot\text{m}^{-3}$ for PM_{10} in its 2021 Global Air Quality Guidelines—substantially stricter than China’s National Ambient Air Quality Standards (NAAQS), which set corresponding thresholds at $75 \mu\text{g}\cdot\text{m}^{-3}$ and $150 \mu\text{g}\cdot\text{m}^{-3}$, respectively. Unless otherwise specified, this study adopts China’s official standards to define elevated pollution levels: daily average concentrations exceeding $75 \mu\text{g}\cdot\text{m}^{-3}$ for $PM_{2.5}$ or $150 \mu\text{g}\cdot\text{m}^{-3}$ for PM_{10} are classified as “high” $PM_{2.5}$ concentrations reaching $150 \mu\text{g}\cdot\text{m}^{-3}$ and PM_{10} concentrations reaching $200 \mu\text{g}\cdot\text{m}^{-3}$ indicate heavy pollution.). These differences are associated with natural factors such as lower air density, low pressure, precipitation, and wind speed, as these mountainous areas are generally farther from pollution sources. From 2019 to 2020, PM_{10} concentrations declined in the northwestern and eastern lowland areas of Changji Prefecture (including Jimusaer County, Qitai County, and Mulei Kazakh Autonomous Prefecture). However, in 2021, both the concentration and spatial extent of PM_{10} pollution increased across the “U-C-S” urban agglomeration. In 2022, PM_{10} levels decreased again in the northern part, indicating that the pandemic had a more pronounced impact on PM_{10} than on $PM_{2.5}$, likely due to reduced dust and sandstorm activity. Regions with a $PM_{2.5}/PM_{10}$ ratio greater than 0.5 (represented by orange and red colors) indicate dominance of fine particles ($PM_{2.5}$), reflecting significant fine particle pollution. The $PM_{2.5}/PM_{10}$ ratio aligns with the temporal trends of both $PM_{2.5}$ and PM_{10} mass concentrations, further confirming that atmospheric particulate matter in the study area was predominantly composed of $PM_{2.5}$ from 2019 to 2022.

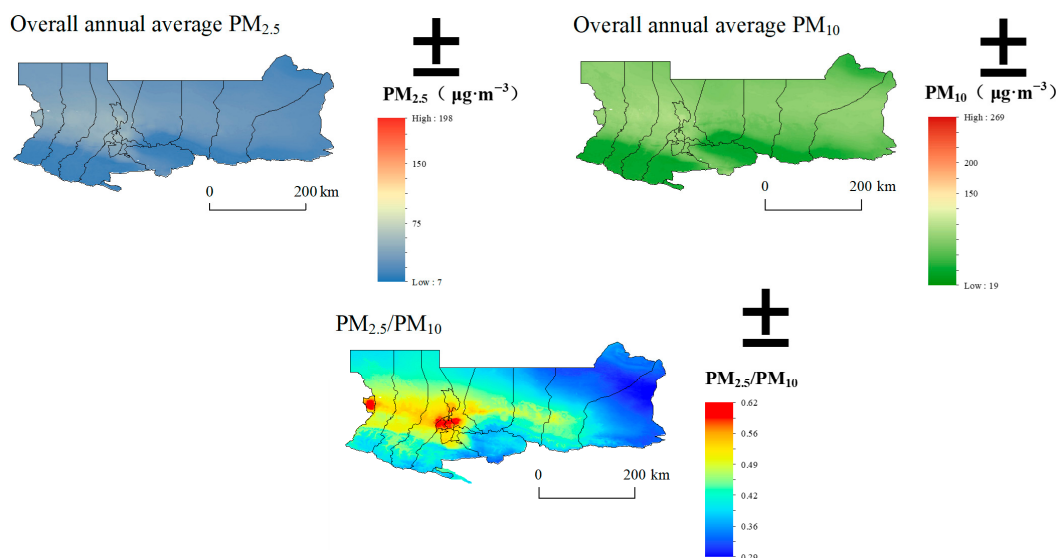


Figure 2. Spatial distribution of the total average concentrations and ratio of $PM_{2.5}$ to PM_{10} over the study period (2019–2022) in the “U-C-S” urban agglomeration. Note: According to China’s Ambient Air Quality Standards, air quality is classified as lightly polluted when $PM_{2.5} \geq 75 \mu\text{g}\cdot\text{m}^{-3}$ or $PM_{10} \geq 150 \mu\text{g}\cdot\text{m}^{-3}$. These thresholds are used consistently throughout this paper.

Between 2019 and 2022, the concentrations of $PM_{2.5}$ and PM_{10} in the “Urumqi-Changji Hui Autonomous Prefecture-Shihezi” (U-C-S) urban agglomeration exhibited significant spatial heterogeneity (Figure 3). In 2019, high $PM_{2.5}$ concentration zones were observed in the central and western parts of Urumqi, the western region of Changji Prefecture, and Shihezi City, with elevated levels also present in the central and southern areas of Wujiaqu

City. PM_{10} concentrations showed an inverse relationship with altitude, with higher values detected in the southwestern part of Urumqi, as well as the eastern and western regions of Changji Prefecture and Shihezi City. In 2020, $PM_{2.5}$ levels remained largely stable overall, although slight increases were noted in the central and northern parts of Urumqi, the western part of Changji Prefecture, and Shihezi City, while Wujiaqu maintained relatively steady conditions. Under the influence of the pandemic, PM_{10} concentrations declined across the region, particularly in the southern part of Urumqi and the eastern part of Changji Prefecture. In 2021, as economic activities resumed, $PM_{2.5}$ concentrations rose significantly in the central and northern parts of Urumqi, the western part of Changji Prefecture, and Shihezi City, and pollution levels in Wujiaqu City worsened. PM_{10} concentrations increased across all four cities, with the most pronounced rise observed in Wujiaqu. By 2022, both $PM_{2.5}$ and PM_{10} levels had decreased compared to 2021, with a reduction in the extent of high-concentration zones in Urumqi and Changji Prefecture; however, a slight increase was observed in the eastern part of Changji Prefecture. $PM_{2.5}$ levels in Shihezi and Wujiaqu also declined slightly. PM_{10} concentrations declined compared to 2021, reaching the lowest level over the four-year period.

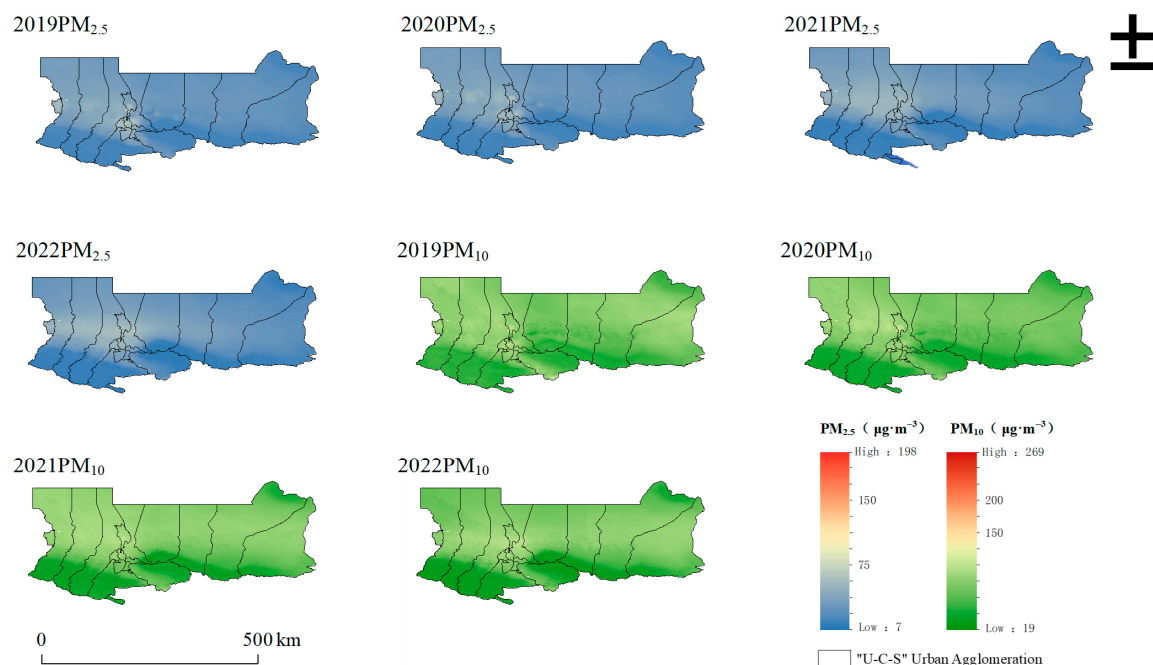


Figure 3. Spatial distribution of annual average concentrations of $PM_{2.5}$ and PM_{10} in the “U-C-S” urban agglomeration.

5.2. Seasonal Spatiotemporal Distribution Changes of $PM_{2.5}$ and PM_{10}

An analysis of the seasonal variations in $PM_{2.5}$ and PM_{10} concentrations in the “U-C-S” urban agglomeration from 2019 to 2022 (Figure 4) reveals a distinct seasonal pattern. $PM_{2.5}$ concentrations are relatively low in spring, decline further to reach their annual minimum during summer, and show a modest increase in autumn while remaining at a generally low level. However, a significant rise occurs in winter—particularly in the central urban area of Urumqi, western Changji Prefecture, southern Wujiaqu, and across Shihezi. The elevated levels in these areas are closely linked to low temperatures, stable atmospheric conditions, and increased coal combustion for heating purposes. For PM_{10} , concentrations tend to be high in spring, drop significantly in summer, exhibit [45] a moderate increase in autumn, and then surge again in winter—spatially overlapping with the high-concentration zones of $PM_{2.5}$. This suggests that although $PM_{2.5}$ and PM_{10} share

some common pollution sources, PM_{10} is more strongly influenced by natural factors such as dust storms and resuspension processes, particularly during spring. The central urban area of Urumqi, western Changji Prefecture, southern Wujiaqu, and the entire Shihezi region consistently exhibit high concentrations of both $PM_{2.5}$ and PM_{10} during winter, which can be attributed to unfavorable meteorological conditions and intensified anthropogenic activities. Low temperatures and stable atmospheric layers restrict pollutant dispersion, while increased coal combustion directly contributes to higher particulate matter levels. In addition, dust storms and related activities in spring have a pronounced impact on PM_{10} concentrations. This phenomenon is closely associated with the vast and sparsely populated geographical features of the Xinjiang region, which makes it more vulnerable to natural environmental influences. In summary, the temporal and spatial variations in $PM_{2.5}$ and PM_{10} concentrations within the “U-C-S” urban agglomeration exhibit clear seasonal characteristics and significant spatial heterogeneity. Winter is identified as the most polluted season, whereas air quality tends to improve markedly during summer.

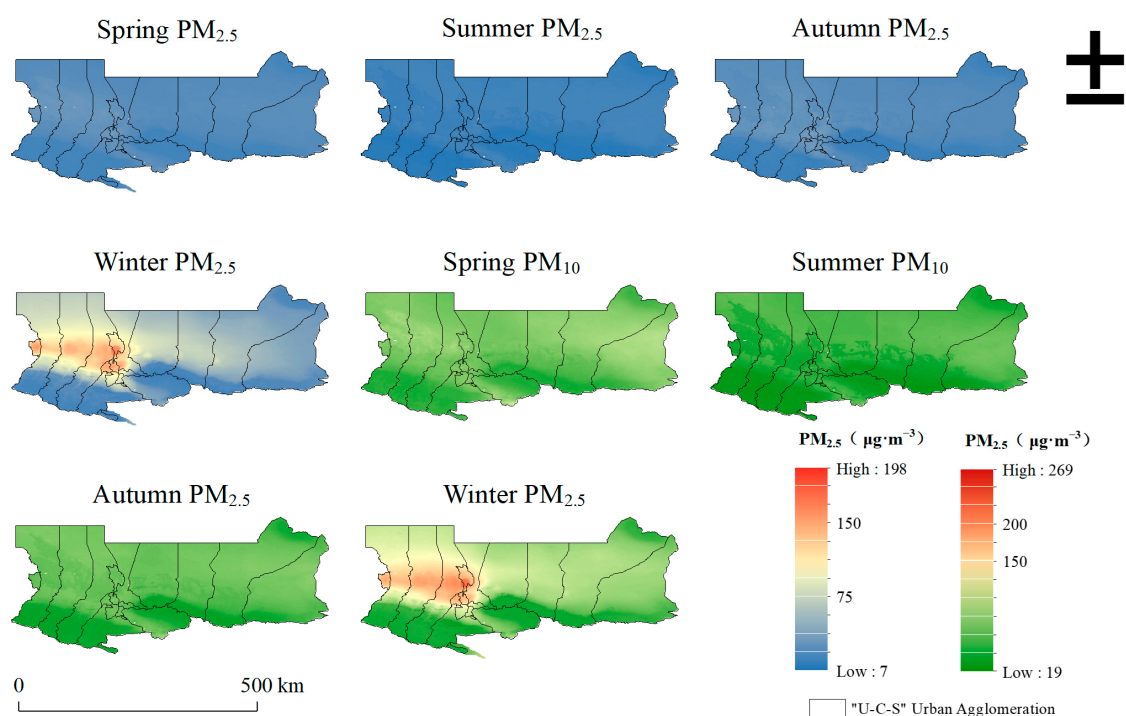


Figure 4. Spatial distribution of seasonal average concentrations of $PM_{2.5}$ and PM_{10} in the “U-C-S” urban agglomeration.

Analyzing the seasonal mean concentrations of $PM_{2.5}$ and PM_{10} across each city within the “U-C-S” urban agglomeration reveals an overall downward trend in both pollutants, with the relative decrease from largest to smallest being spring > summer > autumn > winter (Figure 5). The reduction in Shihezi City and Wujiaqu City is notably less pronounced compared to other areas. High summer temperatures facilitate atmospheric diffusion, a phenomenon observed similarly in other Chinese cities [27,36]. Despite the general decline in concentrations during autumn, variations exist among cities; particularly in Changji Prefecture, where the seasonal mean concentrations of $PM_{2.5}$ and PM_{10} have not decreased, likely due to local weather conditions. Following the resumption of economic activities in 2021, the seasonal mean concentrations of $PM_{2.5}$ and PM_{10} in all cities experienced a rebound, highlighting the influence of economic recovery on air quality [46]. Winter pollution levels for $PM_{2.5}$ and PM_{10} are influenced by temperature inversions and dust transport [47], with Urumqi experiencing the most rapid concentration reductions. In

contrast, Changji Prefecture shows relatively lower concentrations with minimal fluctuation, indicating lesser pressure for pollution control. Conversely, Shihezi City and Wujiaqu City exhibit smaller reductions in seasonal mean concentrations of $PM_{2.5}$ and PM_{10} , coupled with higher overall pollution levels, suggesting the need for further governance measures in these regions.

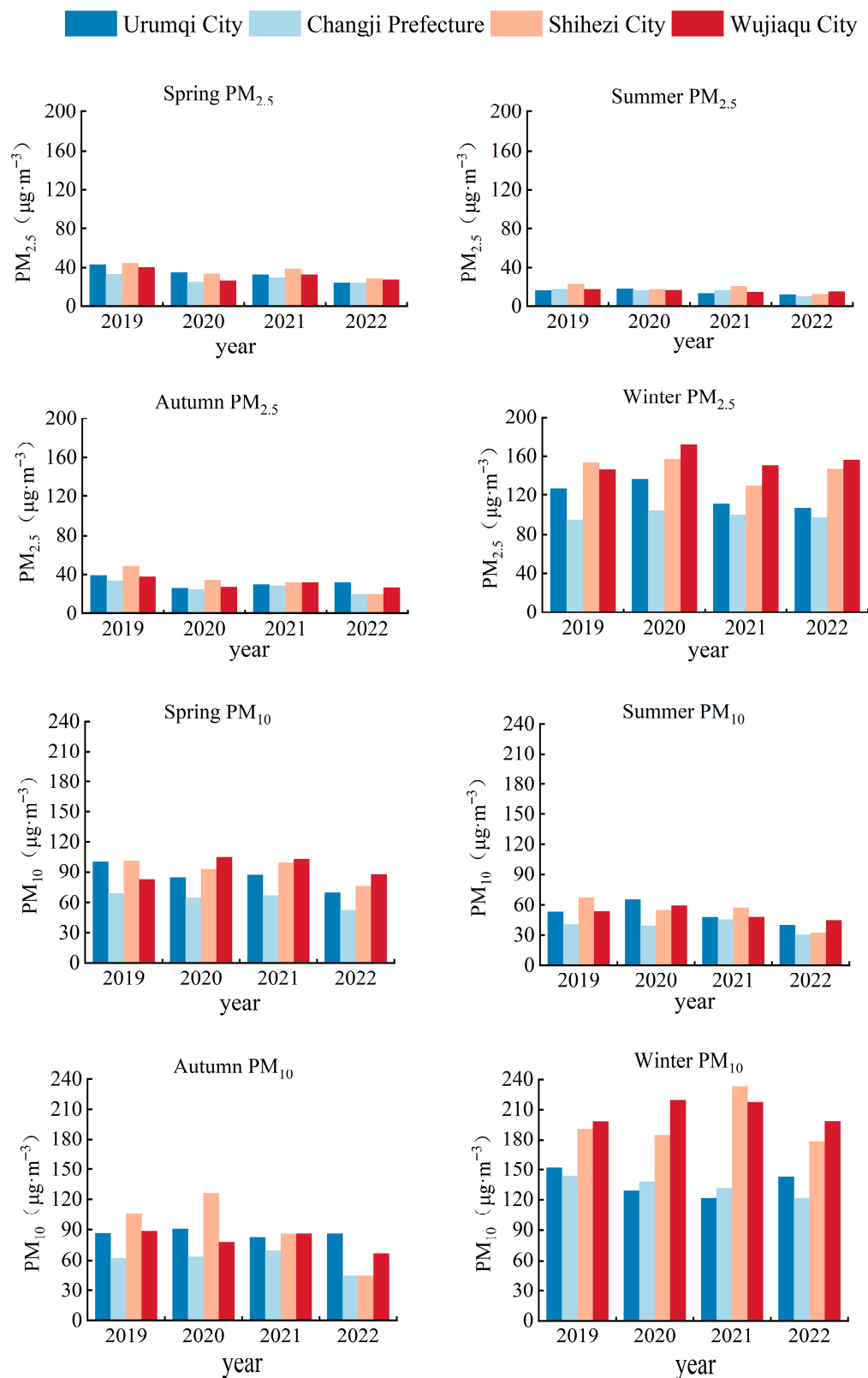


Figure 5. Seasonal mean concentration changes in the “U-C-S” urban agglomeration.

5.3. Monthly Spatiotemporal Distribution Changes of $PM_{2.5}$ and PM_{10}

On a monthly scale, the monthly average concentrations of $PM_{2.5}$ and PM_{10} in the “Urumqi-Changji Hui Autonomous Prefecture-Shihezi” (U-C-S) urban agglomeration exhibited a typical “U”-shaped pattern from 2019 to 2022, with elevated levels observed from December to February of the following year and reduced concentrations recorded between June and August (Figure 6). A significant decline in the monthly average concentrations of both pollutants was noted in January across all cities, indicating that the Spring Festival holiday, effective government control measures, and natural meteorological factors collectively exert a notable influence on air quality. Among these cities, Urumqi experienced the most substantial reduction, followed by Wujiaqu. However, Wujiaqu also displayed greater variability and less distinct seasonal patterns. Meteorological conditions had a more pronounced effect on the monthly average PM_{10} concentrations during spring, summer, and autumn, with the greatest fluctuations occurring specifically in spring, from March to May.

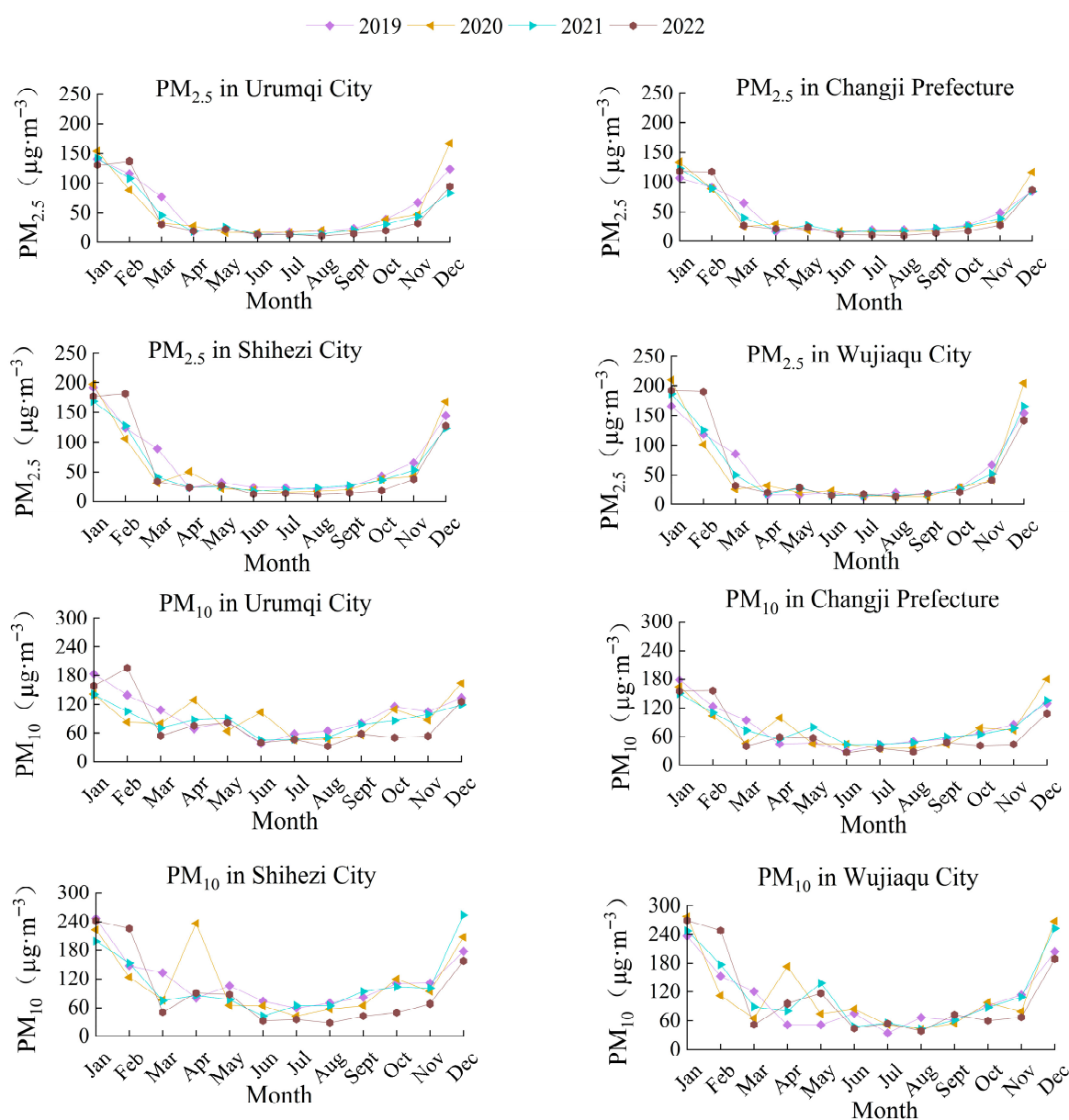


Figure 6. Monthly mean concentration variation in the “U-C-S” urban agglomeration.

An analysis of the monthly spatiotemporal distribution of $PM_{2.5}$ concentrations in the “U-C-S” urban agglomeration from 2019 to 2022 (Figure 7) reveals significant seasonal and spatial heterogeneity. The central urban area of Urumqi exhibits a marked increase in $PM_{2.5}$ concentrations during winter, particularly in January, when levels reach their annual peak. This phenomenon is likely associated with increased coal heating and stable atmospheric conditions. In western Changji Prefecture—specifically Manas County, Hutubi County, and Changji City—elevated $PM_{2.5}$ levels are also observed in winter, influenced by local topography and climate. Similarly, the southern parts of Wujiaqu and the Shihezi region experience high $PM_{2.5}$ concentrations during this season, aligning with the high-pollution zones identified in the annual mean distribution. As shown in the figure, $PM_{2.5}$ concentrations remain relatively low during spring (March–May) and summer (June–August), with only a gradual rise becoming evident in autumn (September–November). These seasonal patterns indicate that the winter high-concentration trend remains consistent over time, reflecting the strong influence of the region’s specific climatic conditions—such as low temperatures and atmospheric stability—as well as human activities like intensified coal combustion for heating. Notably, despite the reduction in social and industrial activities during the pandemic, the upward trend in $PM_{2.5}$ concentrations persisted, further underscoring that meteorological and anthropogenic factors are the dominant drivers of $PM_{2.5}$ pollution in the region.

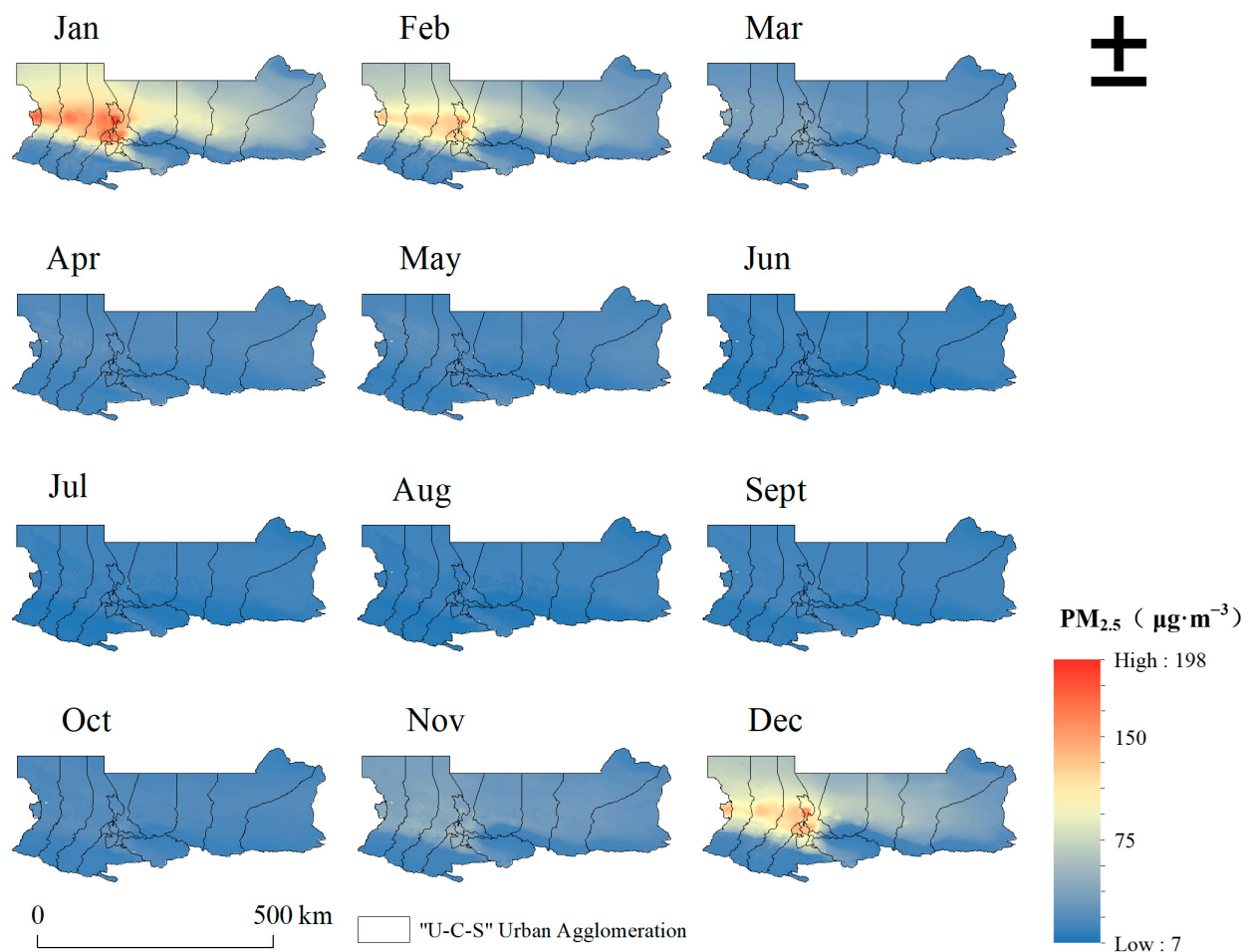


Figure 7. Spatial distribution of monthly mean $PM_{2.5}$ concentrations in the “U-C-S” urban agglomeration.

The spatiotemporal variations in monthly mean PM_{10} concentrations within the “U-C-S” urban agglomeration from 2019 to 2022 (Figure 8) exhibit patterns broadly similar

to those of $PM_{2.5}$, with elevated levels observed in the central urban area of Urumqi during December, January, and February—often exceeding $200 \mu\text{g}\cdot\text{m}^{-3}$. However, compared to $PM_{2.5}$, PM_{10} concentrations are not only higher across the “U-C-S” region but also remain elevated during additional periods, particularly in June, July, and August. Even in the eastern mountainous areas included within the urban agglomeration, PM_{10} levels remain relatively high. This phenomenon can be largely attributed to frequent windblown dust events, as PM_{10} is more strongly associated with sand and dust storms. This is especially evident in the sparsely populated regions of Xinjiang, which are more vulnerable to such natural meteorological events due to their arid climate and expansive land cover.

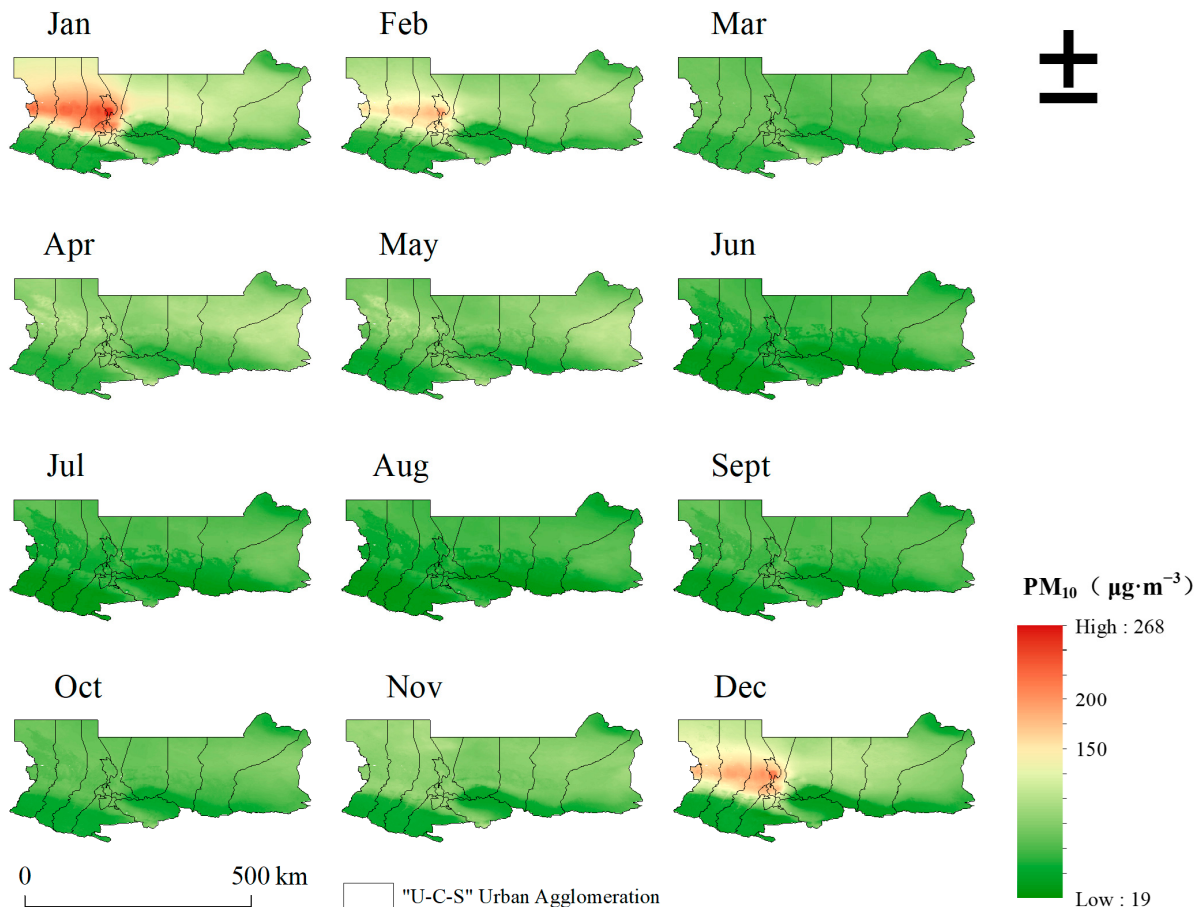


Figure 8. Spatial distribution of monthly mean PM_{10} concentrations in the “U-C-S” urban agglomeration.

A subsequent analysis of the spatiotemporal distribution of monthly average PM_{10} concentrations in the “U-C-S” urban agglomeration from 2019 to 2022 was conducted and compared with concurrent changes in $PM_{2.5}$ concentrations. The results indicate that both PM_{10} and $PM_{2.5}$ exhibit elevated levels during winter (December–February), particularly in the central urban area of Urumqi, where PM_{10} concentrations frequently exceed $200 \mu\text{g}\cdot\text{m}^{-3}$. However, the spatial extent of high PM_{10} concentrations is broader and not confined to the winter season. Although particulate matter concentrations generally decline during summer (June–August), PM_{10} levels remain relatively high in the eastern mountainous regions encompassed by the “U-C-S” urban agglomeration. Moreover, PM_{10} concentrations surpass the secondary air quality standard during spring (April–May) and late autumn (November), indicating persistent high values beyond typical seasonal variations. The natural characteristics of the Xinjiang region—such as its vast land area and sparse population—contribute to frequent dust events, particularly under strong wind conditions, which significantly influence PM_{10} concentrations. Dust storms and resuspended

dust are the primary natural factors driving increases in PM_{10} levels, especially in open, vegetation-scarce areas. In summary, the variations in PM_{10} concentrations within the “U-C-S” urban agglomeration are shaped by a combination of seasonal climatic conditions and socio-economic activities.

5.4. Weekly Spatiotemporal Distribution Changes of $PM_{2.5}$ and PM_{10}

Figure 9 illustrates the spatial patterns of the weekend effect for $PM_{2.5}$ and PM_{10} across the Urumqi-Changji-Shihezi (U-C-S) urban agglomeration. Overall, $PM_{2.5}$ concentrations are generally lower on weekends than on weekdays, with peak levels typically occurring on Wednesdays. This pattern reflects the combined influence of anthropogenic emission peaks and recurrent unfavorable meteorological conditions—such as reduced boundary layer height and decreased wind speeds—that commonly occur from Tuesday to Thursday in northern China [48,49]. Consequently, pollutant concentrations usually reach their maximum before Friday, when emission intensity begins to decline and/or atmospheric dispersion conditions improve. In contrast, the weekend effect for PM_{10} exhibits pronounced spatial heterogeneity: only Urumqi shows higher PM_{10} concentrations on weekends compared to weekdays, while other cities display either negative or near-zero deviations. This anomaly in Urumqi may be attributed to its unique urban activity patterns—such as intensified construction site clean-ups, increased recreational vehicle traffic on unpaved roads, and expanded outdoor markets during weekends—which enhance local dust resuspension and elevate coarse particulate matter (PM_{10}) emissions. In Changji, Shihezi, and Wujiaqu, PM_{10} is predominantly influenced by natural dust sources, with limited anthropogenic disturbance; thus, the weekend effect is either insignificant or slightly negative [50].

To further investigate the weekend effect of particulate matter, this study classified and computed daily mean $PM_{2.5}$ and PM_{10} concentrations in the U-C-S region from 2015 to 2023 according to weekdays and weekends. The relative deviations between weekend and weekday concentrations are presented in Table 1. During this period, the daily mean $PM_{2.5}$ concentrations consistently exhibited negative deviations, ranging from -1.26% to -2.66% . This finding aligns with previous studies conducted in Beijing [51], indicating a widespread “negative weekend effect”—i.e., higher $PM_{2.5}$ levels on weekdays—likely driven by intensified traffic congestion during morning and evening rush hours. Collectively, these results highlight that fine particulate matter ($PM_{2.5}$) is primarily governed by systematic anthropogenic emissions, whereas coarse particulate matter (PM_{10}) is more susceptible to localized and episodic human activities on weekends, particularly in the core city of Urumqi.

Table 1. The relative deviation of daily average pollutant concentrations among cities on weekends and weekdays.

City	The Daily Average Concentration Deviation of $PM_{2.5}$ (%)	The Daily Average Concentration Deviation of PM_{10} (%)
Urumqi	−1.26	4.27
Changji Prefecture	−2.66	0.84
Shihezi	−2.14	−0.50
Wujiaqu	−2.32	0.18

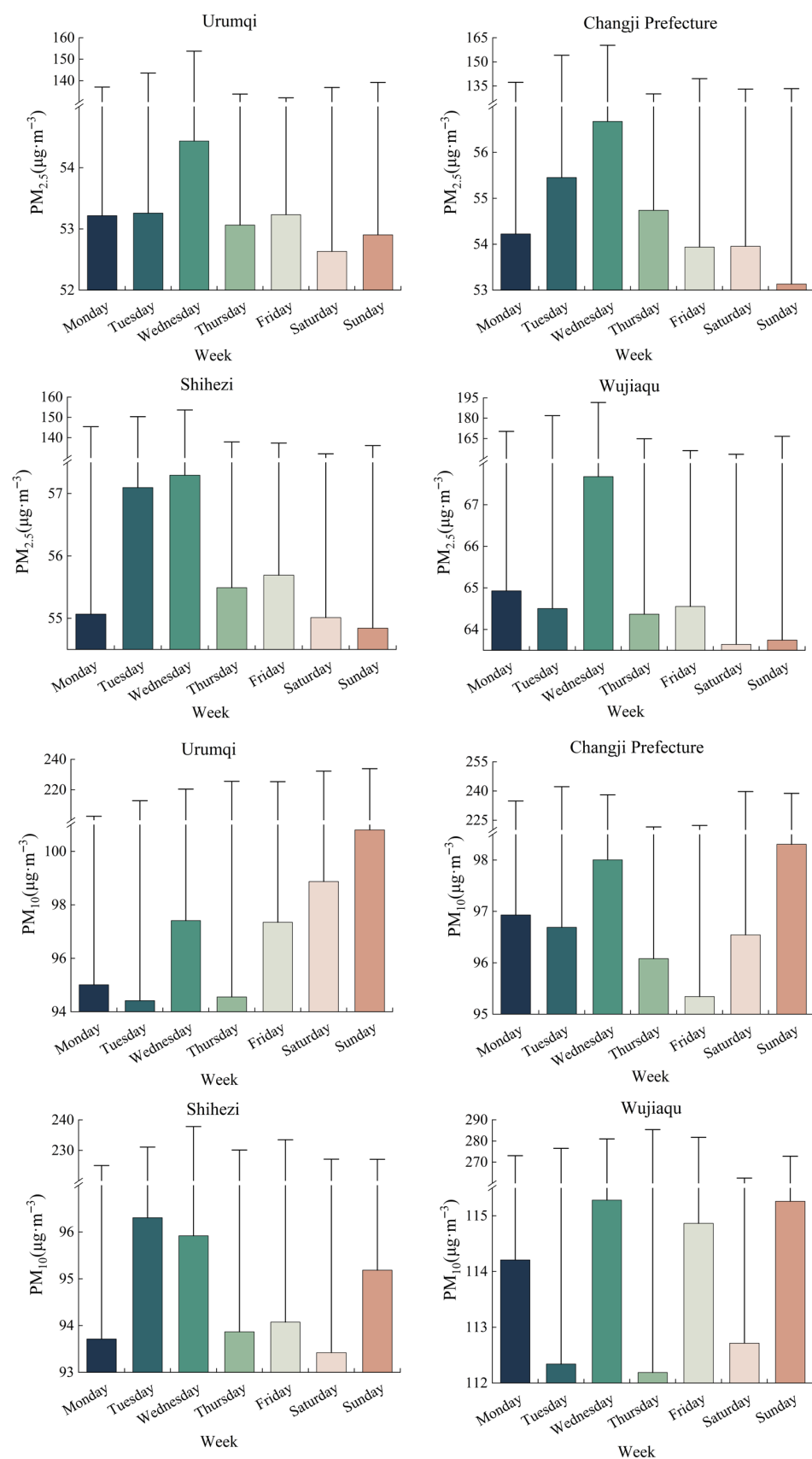


Figure 9. Changes in weekly mean concentrations in the “U-C-S” urban agglomeration. Note: The y-axis in each subplot starts from a value close to the median concentration rather than zero to enhance visual clarity of the weekly variation patterns. This scaling does not affect the interpretation of relative differences between days, as all data are presented on the same scale within each panel.

5.5. Daily Spatiotemporal Distribution Changes of $PM_{2.5}$ and PM_{10}

As illustrated in Figure 10, the daily mean concentrations of $PM_{2.5}$ and PM_{10} across the four cities within the “U-C-S” urban agglomeration exhibit clear temporal heterogeneity and pronounced spatial variability. Temporally, since 1 January 2019, $PM_{2.5}$ concentrations have displayed a distinct seasonal pattern, with significantly elevated levels observed during winter months. Following winter, particulate matter concentrations gradually decline to below $35 \mu\text{g}\cdot\text{m}^{-3}$, remaining low until the onset of the next winter season. Although minor fluctuations occur throughout the year, the overall trend remains relatively stable. In contrast, PM_{10} concentrations demonstrate more pronounced seasonal variability, with peak values often occurring in spring—sometimes even surpassing those recorded in winter. This phenomenon is primarily attributed to the frequent dust storms described earlier, which cause sharp increases in PM_{10} levels. Furthermore, during winter, the $PM_{2.5}$ concentration ranking among the cities follows the order: Wujiaqu > Shihezi > Changji Prefecture > Urumqi. This suggests that Urumqi, as the core city of both the “U-C-S” urban agglomeration and the Xinjiang region, has implemented more effective pollution control measures compared to other cities. Meanwhile, Shihezi, located at the westernmost part of the urban agglomeration, exhibits greater PM_{10} fluctuations than the other three cities, indicating its heightened vulnerability to windblown dust events.

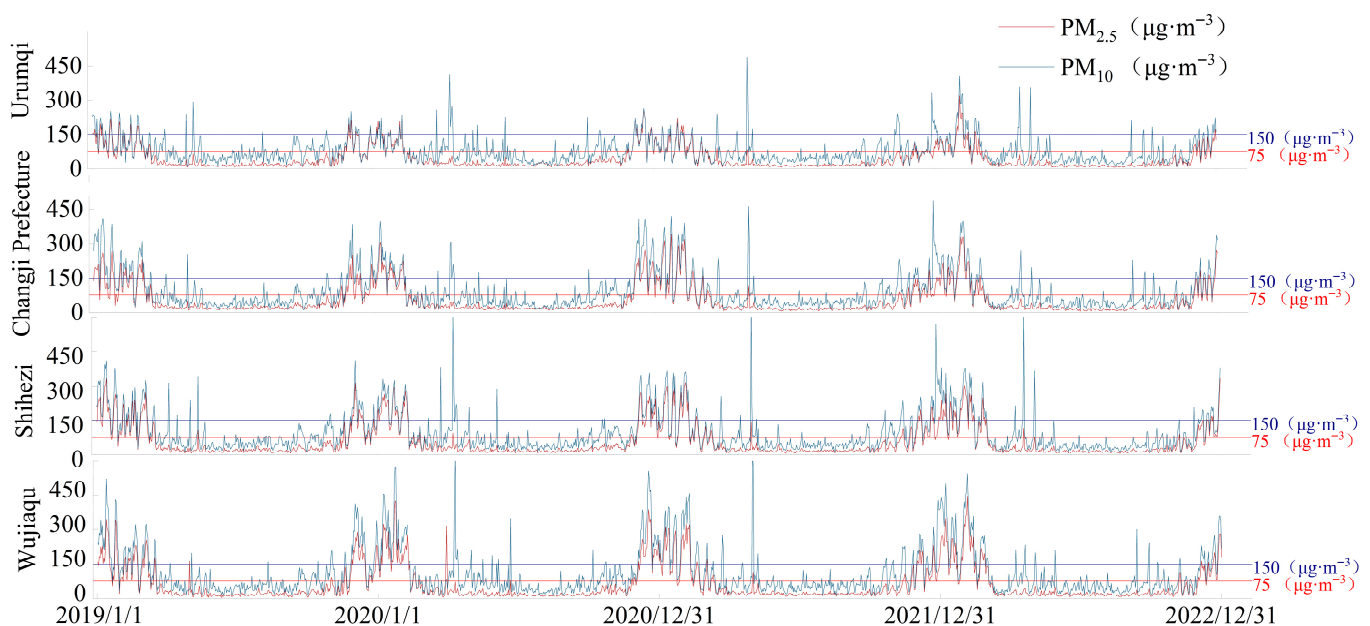


Figure 10. Daily mean concentration changes in the “U-C-S” urban agglomeration.

The “China’s National Ambient Air Quality Standard (NAAQS)” (GB 3095-2012) specifies the secondary standards for daily average $PM_{2.5}$ and PM_{10} concentrations as $75 \mu\text{g}\cdot\text{m}^{-3}$ and $150 \mu\text{g}\cdot\text{m}^{-3}$, respectively. Exceeding these thresholds is classified as air pollution. According to the Air Quality Index (AQI) calculation criteria, the concentration thresholds for different levels of pollution are defined as follows: Level One Standard ($PM_{2.5}$: $35 \mu\text{g}\cdot\text{m}^{-3}$, PM_{10} : $50 \mu\text{g}\cdot\text{m}^{-3}$), Level Two Standard ($PM_{2.5}$: $75 \mu\text{g}\cdot\text{m}^{-3}$, PM_{10} : $150 \mu\text{g}\cdot\text{m}^{-3}$), Light Pollution ($PM_{2.5}$: $115 \mu\text{g}\cdot\text{m}^{-3}$, PM_{10} : $250 \mu\text{g}\cdot\text{m}^{-3}$), Moderate Pollution ($PM_{2.5}$: $150 \mu\text{g}\cdot\text{m}^{-3}$, PM_{10} : $350 \mu\text{g}\cdot\text{m}^{-3}$), Heavy Pollution ($PM_{2.5}$: $250 \mu\text{g}\cdot\text{m}^{-3}$, PM_{10} : $500 \mu\text{g}\cdot\text{m}^{-3}$), and anything beyond Heavy Pollution is considered Severe Pollution. Analysis of compliance with the standards (Figure 11) reveals that approximately 80% of days across the cities meet either the Level One or Level Two standards for $PM_{2.5}$. Urumqi shows the highest compliance rate, followed by Changji Prefecture, Shihezi City, and Wujiaqu City. In contrast, PM_{10} ex-

hibits higher compliance rates compared to $PM_{2.5}$, with fewer instances of severe pollution. Moreover, PM_{10} concentration fluctuations lack a clear temporal pattern.

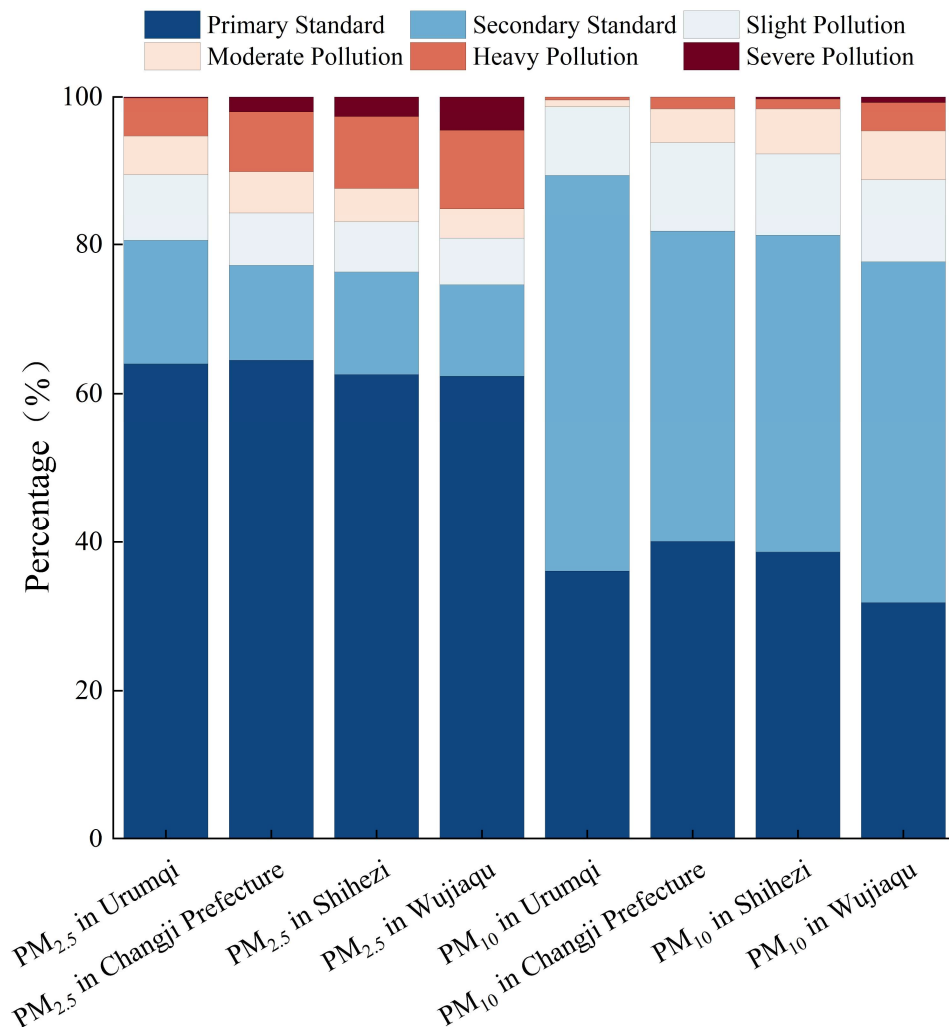


Figure 11. Proportion of daily average concentration of each pollution degree in the “U-C-S” urban agglomeration.

5.6. Backward Trajectory Cluster Analysis

Based on backward trajectory data analysis, this study investigated the dominant air mass pathways affecting the Urumqi area across different seasons and their influence on $PM_{2.5}$ and PM_{10} concentrations (Figure 12). The results reveal that there are six major trajectory clusters in both spring and summer, four in autumn, and five in winter. The source directions of air masses during spring, summer, and autumn are generally similar, with the northwest and north being the most prominent. Specifically, in spring, trajectories 5 and 6 (accounting for 20.02%) and autumn trajectory 4 (13.18%) originate from the northwest, while spring trajectory 4 (14.43%) and autumn trajectory 3 (18.63%) come from the north. These pathways are associated with relatively low $PM_{2.5}$ concentrations, suggesting they are not significant contributors to fine particulate matter. Notably, airflow from the direction of Kazakhstan in spring (trajectory 6) is characterized by higher average PM_{10} concentrations and standard deviations—but not $PM_{2.5}$ —indicating that this pathway may serve as a major transport channel for dust storms.

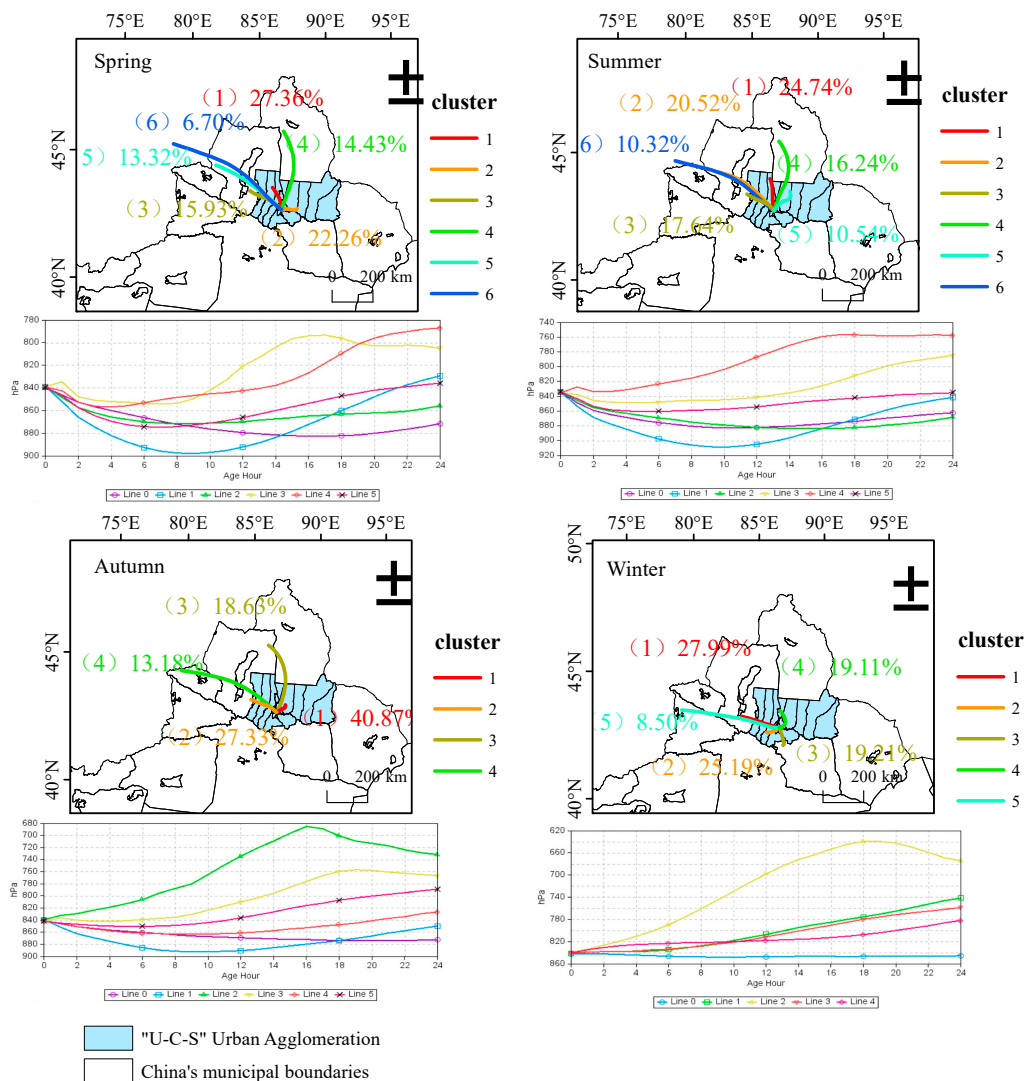


Figure 12. Backward trajectory and air pressure in the “U-C-S” urban agglomeration.

During spring and autumn, local airflows—represented by trajectories 1, 2, and 3 in spring and trajectories 1 and 2 in autumn—account for a substantial proportion (65.55% in spring and 68.20% in autumn), with correspondingly higher $PM_{2.5}$ and PM_{10} concentrations. This suggests that these local airflows are key contributors to air pollution in Urumqi during these two seasons. Although the “U-C-S” region experiences relatively better air quality during summer, airflow originating from the direction of Kazakhstan (trajectory 6) still exhibits elevated average PM_{10} concentrations and higher standard deviations, indicating that dust storms from the northwest may continue to exert a notable influence on local air quality even in this season.

Unlike other seasons, winter airflows in the study area exhibit distinct characteristics. The frequency and travel distance of northern airflows (trajectory 3, accounting for 19.21%) decrease during this season, and these airflows are associated with the lowest $PM_{2.5}$ and PM_{10} concentrations, which may contribute to a reduction in local air pollution. In contrast, airflows from the west (trajectories 1 and 5, accounting for 36.49%) exhibit moderate pollutant levels. Additionally, newly observed wintertime airflows originating from the southern Dabancheng direction (trajectories 2 and 3, accounting for 44.40%) are characterized by higher pollution concentrations, suggesting that they play a significant role in exacerbating air pollution during winter (Table 2).

Table 2. Trajectory numbers and mean concentrations and standard deviations of PM based on all trajectories.

Season	Clusters	The Number of All Trajectories	The Percentage of All Trajectories(%)	The Source Area of Air Masses	Mean Concentrations and Standard Deviation of PM _{2.5} ($\mu\text{g}\cdot\text{m}^{-3}$)	Mean Concentrations and Standard Deviation of PM ₁₀ ($\mu\text{g}\cdot\text{m}^{-3}$)
Spring	1	2517	27.36%	Xinjiang, China northern	32.21 ± 33.85	74.36 ± 59.89
	2	2048	22.26%	Xinjiang, China eastern	32.80 ± 33.08	83.24 ± 57.20
	3	1466	15.93%	Xinjiang, China western	32.64 ± 29.05	77.38 ± 69.07
	4	1328	14.43%	Xinjiang, China northern	19.68 ± 14.22	67.53 ± 85.71
	5	1225	13.32%	Xinjiang, China western	24.05 ± 20.44	68.56 ± 78.82
	6	616	6.70%	Kazakhstan northeast	25.57 ± 28.99	99.72 ± 194.79
Summer	1	2276	24.74%	Xinjiang, China northern	15.42 ± 6.42	47.65 ± 26.97
	2	1888	20.52%	Xinjiang, China western	13.31 ± 5.93	40.88 ± 29.52
	3	1623	17.64%	Xinjiang, China western	14.64 ± 6.04	42.99 ± 26.80
	4	1494	16.24%	Xinjiang, China northern	15.35 ± 6.06	43.74 ± 20.73
	5	970	10.54%	Xinjiang, China northeast	15.87 ± 7.24	48.30 ± 27.39
	6	949	10.32%	Kazakhstan northeast	14.98 ± 16.56	52.31 ± 109.49
Autumn	1	3719	40.87%	Xinjiang, China northeast	32.18 ± 20.81	77.83 ± 45.27
	2	2487	27.33%	Xinjiang, China western	33.18 ± 21.90	74.16 ± 46.39
	3	1695	18.63%	Xinjiang, China northern	18.30 ± 10.79	52.71 ± 39.26
	4	1199	13.18%	Kazakhstan northeast	25.21 ± 20.21	67.33 ± 74.86
Winter	1	2526	27.99%	Xinjiang, China western	104.1 ± 53.62	117.10 ± 66.57
	2	2273	25.19%	Xinjiang, China Southern	116.64 ± 58.50	132.77 ± 70.19
	3	1734	19.21%	Xinjiang, China Southern	124.76 ± 60.04	147.82 ± 73.82
	4	1725	19.11%	Xinjiang, China northern	90.65 ± 53.92	101.57 ± 67.30
	5	767	8.50%	Xinjiang, China western	102.92 ± 64.35	107.64 ± 66.34

5.7. Potential Source Contribution Function (PSCF) Analysis

Although cluster analysis is effective in identifying the primary transport pathways and source directions of PM_{2.5} and PM₁₀, it has limitations in visually representing potential pollution source regions and distinguishing pollution intensity levels. To address these limitations, this study incorporates the Probability Weighted Contribution Function (PSCF) and Conditional Weighted Trajectory (CWT) models to provide a more precise assessment of pollution contributions across different seasons (Figure 13).

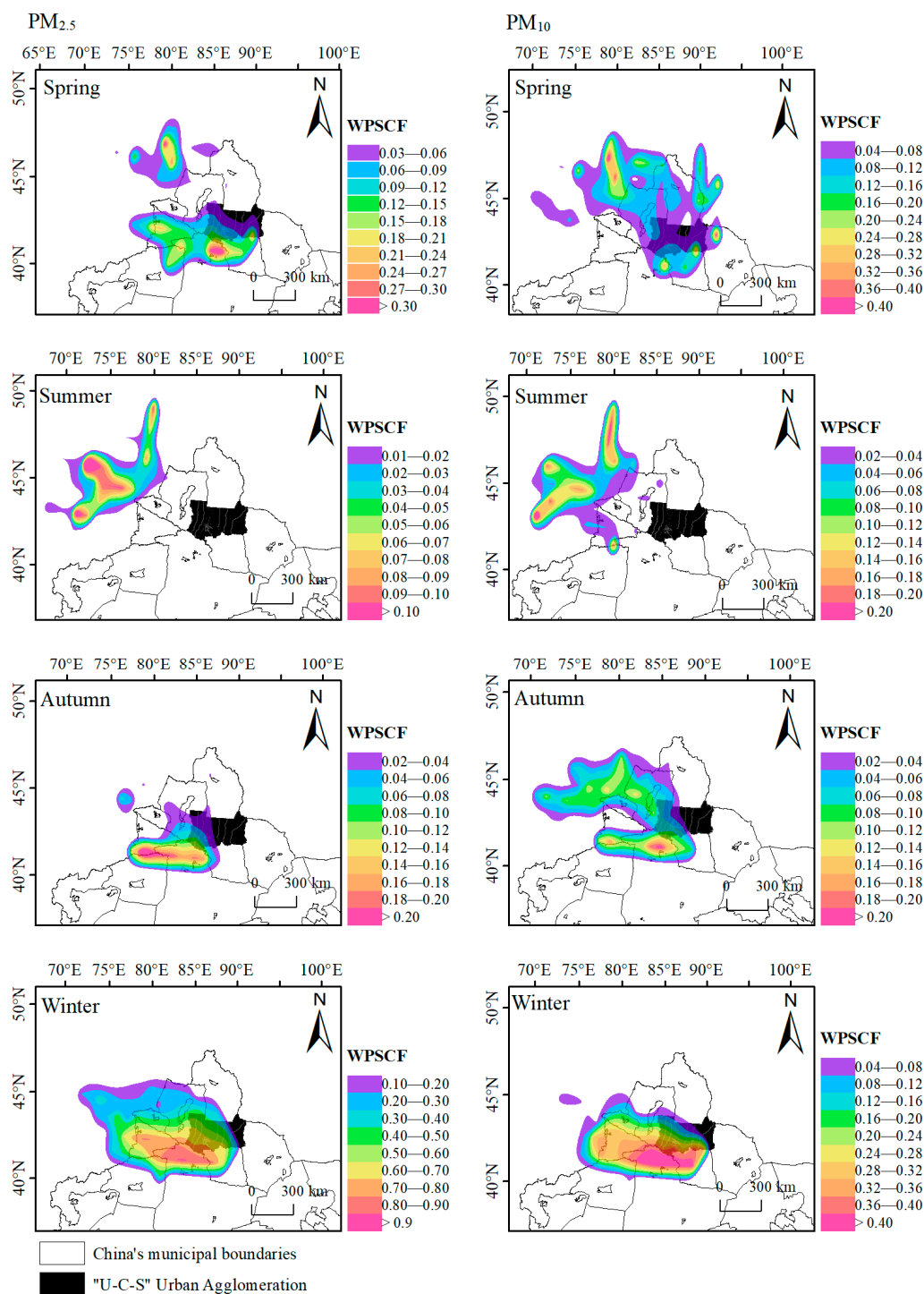


Figure 13. Distribution of contributions from potential source areas in the "U-C-S" urban agglomeration. Note: WPSCF refers to the PSCF(potential source contribution function) weighted by an empirical weight function.

The results from the Weighted PSCF (WPSCF: WPSCF is the PSCF weighted by an empirical weighting function.) model analysis indicate that higher WPSCF values correspond to greater potential source contributions from a given area (High WPSCF values (close to 1) indicate that air masses passing through a given grid cell are frequently associated with high PM_{2.5} or PM₁₀ concentrations at the receptor site, suggesting that the grid cell is a probable source region contributing significantly to pollution. Conversely, low WPSCF values (close to 0) imply that trajectories passing through that area rarely coincide with high

pollution episodes, indicating it is unlikely to be a major source). The spatial distributions of potential pollution sources for $PM_{2.5}$ and PM_{10} exhibit a certain degree of similarity; however, their patterns vary across seasons, with the overall trend following the order: Winter > Spring > Autumn > Summer. This seasonal variation is primarily attributed to differences in dominant air mass pathways and their associated source region influences.

Spring: Although the spatial extent of potential pollution sources is relatively large during spring, regions with high WPSCF values are relatively limited in area and predominantly concentrated in the eastern part of Kazakhstan and the Dabancheng region near Urumqi City. This indicates that these specific areas may serve as significant source regions for air pollution during the spring season.

Summer: As the season with the best overall air quality in the “U-C-S” region, summer is characterized by generally low WPSCF values, with potential source areas primarily located in the southern regions of Kazakhstan and southern Russia. When combined with previous cluster analysis results, these findings suggest that air quality improves during this season, indicating minimal local generation of $PM_{2.5}$ and PM_{10} . Instead, pollution issues during summer are predominantly linked to the influence of dust storms.

Autumn: In autumn, the potential pollution sources of $PM_{2.5}$ are mainly concentrated in the northern part of the Bayingolin Mongol Autonomous Prefecture and the southern part of Yining City. For PM_{10} , the source regions not only include the aforementioned areas but also extend to parts of southeastern Kazakhstan. This indicates a more extensive spatial distribution of PM_{10} pollution during autumn compared to $PM_{2.5}$.

Winter: Winter is the most severe season for $PM_{2.5}$ pollution, with WPSCF values significantly higher than those observed in other seasons. The spatial patterns of $PM_{2.5}$ and PM_{10} pollution in winter are largely consistent with each other, and this combined high-pollution zone is more extensive than the $PM_{2.5}$ hotspot region identified in autumn. In addition to the northern part of the Bayingolin Mongol Autonomous Prefecture and the southern region of Yining City, higher pollution concentrations are also observed across the entire Urumqi City area, including Changji City, Hutubi County, and Manas County in Changji Prefecture, as well as Shihezi City and Wujiaqu City. These areas warrant particular attention due to their significant contribution to regional air pollution.

5.8. Concentration Weighted Trajectory (CWT) Analysis

Although the Probability Concentration Function (PSCF) method is capable of identifying the frequency of pollution-affected trajectories, it lacks the ability to quantify the specific contribution levels of individual source regions. To address this limitation, this study further applies the Concentration Weighted Trajectory (CWT) method to evaluate the pollution intensity associated with different air mass pathways. It should be noted that the WCWT values are expressed in $\mu g \cdot m^{-3}$, as they represent the average observed concentration at the receptor site linked to trajectories passing through each grid, rather than an emission flux. Consequently, high WCWT values suggest that air masses traversing a given region are consistently associated with elevated pollution levels in the “U-C-S” agglomeration, identifying it as a potential source or transport corridor of particulate matter. Conversely, low WCWT values correspond to cleaner air masses and minimal pollution contribution. The CWT analysis (Figure 14) shows that both $PM_{2.5}$ and PM_{10} exhibit the same seasonal ranking of pollution intensity: Winter > Spring > Autumn > Summer.

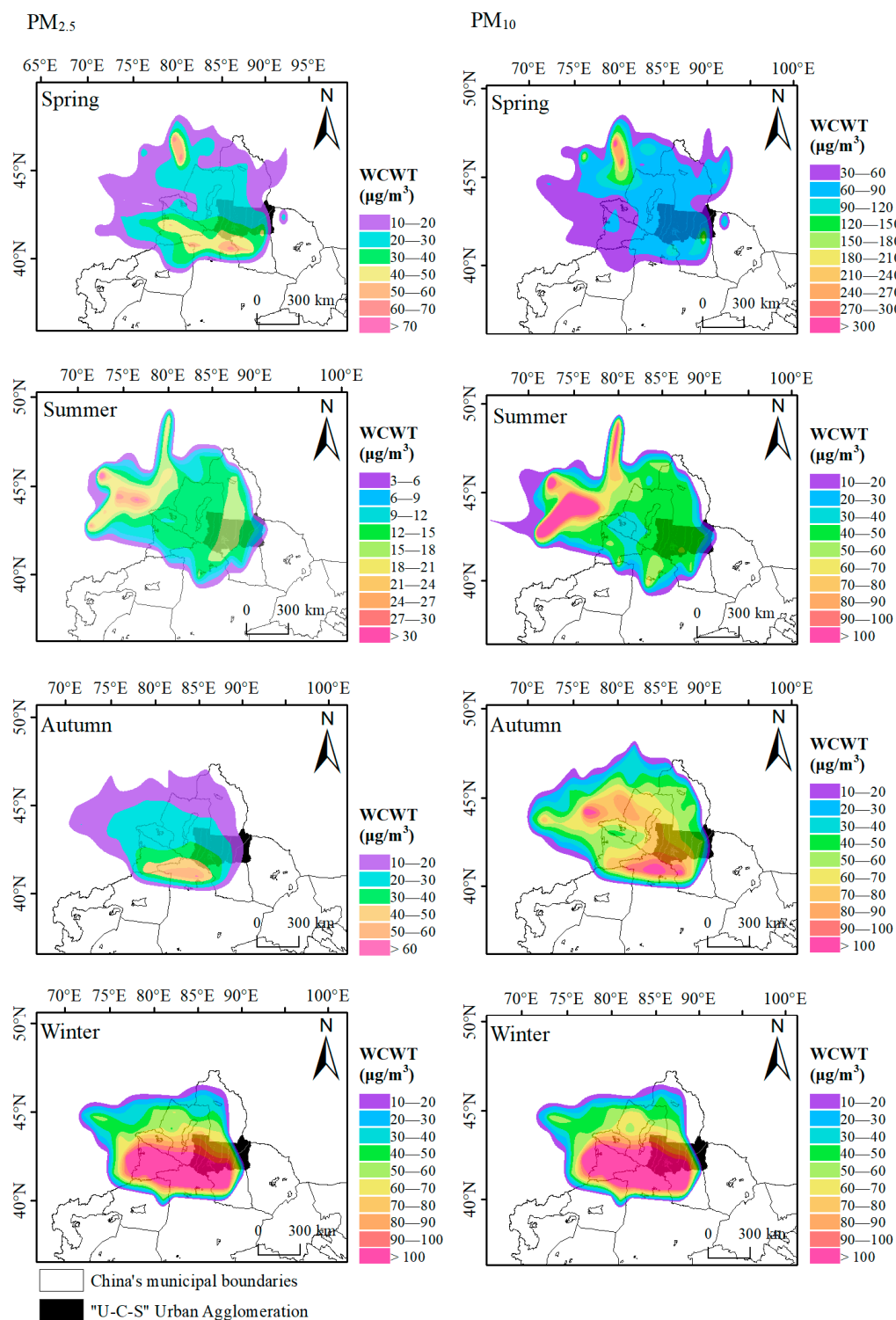


Figure 14. Concentration weight trajectory distribution in the "U-C-S" urban agglomeration. Note: WCWT refers to the CWT (concentration weighted trajectory) weighted by an empirical weight function. WCWT values (unit: $\mu\text{g}\cdot\text{m}^{-3}$) reflect the mean PM concentration at receptor sites associated with air masses passing through each grid cell.

Spring: The highest WCWT (WCWT is the CWT weighted by an empirical weighting function) values for PM_{2.5} are primarily concentrated in the northeastern region of Kazakhstan, the northwestern part of Turpan City, the northern part of the Bayingolin Mongol Autonomous Prefecture, the southern part of Yining City, and the southern part of Urumqi City. These regions exhibit significantly elevated values, indicating that they serve

as primary source areas for $PM_{2.5}$ during spring. For PM_{10} , the highest WCWT values are also observed in the eastern part of Kazakhstan, with peak values exceeding 300. This suggests that this region is not only a key contributor to $PM_{2.5}$ pollution but also a major origin of dust storm events. In addition, higher WCWT values are found in the domestic Turpan Desert area in China and the western part of Mongolia, implying their potential role as significant pollution sources.

Summer: WCWT values for $PM_{2.5}$ remain relatively low during summer, whereas the highest values for PM_{10} persist, mainly concentrated in the southeastern part of Kazakhstan and southern Russia. These regions continue to act as major potential sources of dust storms during the summer season. Although the contribution of $PM_{2.5}$ is relatively minor, the elevated levels of PM_{10} indicate that dust storm activity remains a serious environmental concern during this period.

Autumn: For $PM_{2.5}$, high WCWT value areas are predominantly located within previously identified domestic regions in China, such as the northern part of the Bayingolin Mongol Autonomous Prefecture and the southern part of Yining City. In contrast, high WCWT values for PM_{10} display a clear transport pathway: starting from the southeastern part of Kazakhstan and extending through Bortala City and Karamay City in China, ultimately reaching Urumqi City. The northwestern part of Turpan City, the northern part of the Bayingolin Mongol Autonomous Prefecture, the southern part of Yining City, and the southern part of Urumqi City remain critical potential source areas. This spatial pattern highlights the long-range transport characteristics of PM_{10} pollution during autumn.

Winter: The spatial distribution of WCWT values for both $PM_{2.5}$ and PM_{10} shows a high degree of consistency, with only minor variations between the two pollutants. High-value areas extend from the southern part of Urumqi City and the northern part of Turpan City into the southeastern region of Kazakhstan, forming a continuous high-pollution belt. Both $PM_{2.5}$ and PM_{10} concentrations exceed 100 during winter, indicating severe pollution levels. These findings confirm that winter is the most polluted season of the year and requires particular attention in terms of air quality management and pollution control strategies.

6. Discussion

This study employed correlation analysis to investigate the relationship between $PM_{2.5}$ (Figure 15) and PM_{10} (Figure 16) concentrations and key meteorological factors in the “U-C-S” urban agglomeration from 2019 to 2022. The results reveal that atmospheric pressure (including average, maximum, and minimum pressure) exhibits a weak correlation with both $PM_{2.5}$ and PM_{10} concentrations, suggesting that its influence on particulate matter levels may be minimal. In contrast, temperature (including average, maximum, and minimum temperature) demonstrates a significant negative correlation with both $PM_{2.5}$ and PM_{10} . This implies that rising temperatures may contribute to a reduction in $PM_{2.5}$ and PM_{10} levels. Higher temperatures can enhance atmospheric turbulence and mixing, thereby promoting the dispersion and dilution of pollutants. Wind speed and maximum wind speed also show a weak negative correlation with $PM_{2.5}$ and PM_{10} concentrations. This suggests that increased wind intensity may moderately facilitate the transport and dispersion of pollutants, thus reducing their local accumulation. Sunshine duration displays a slightly negative correlation with both pollutants, which may be associated with the elevated height of the atmospheric boundary layer during prolonged sunshine periods—favoring vertical pollutant dispersion [52]. The correlation between precipitation and $PM_{2.5}/PM_{10}$ is relatively weak, and shows a negative correlation; this result is similar to Zhang et al.’s [53] research findings. However, precipitation can exert an indirect effect

through wet deposition, particularly under heavy rainfall conditions, which can effectively remove airborne particles from the atmosphere.

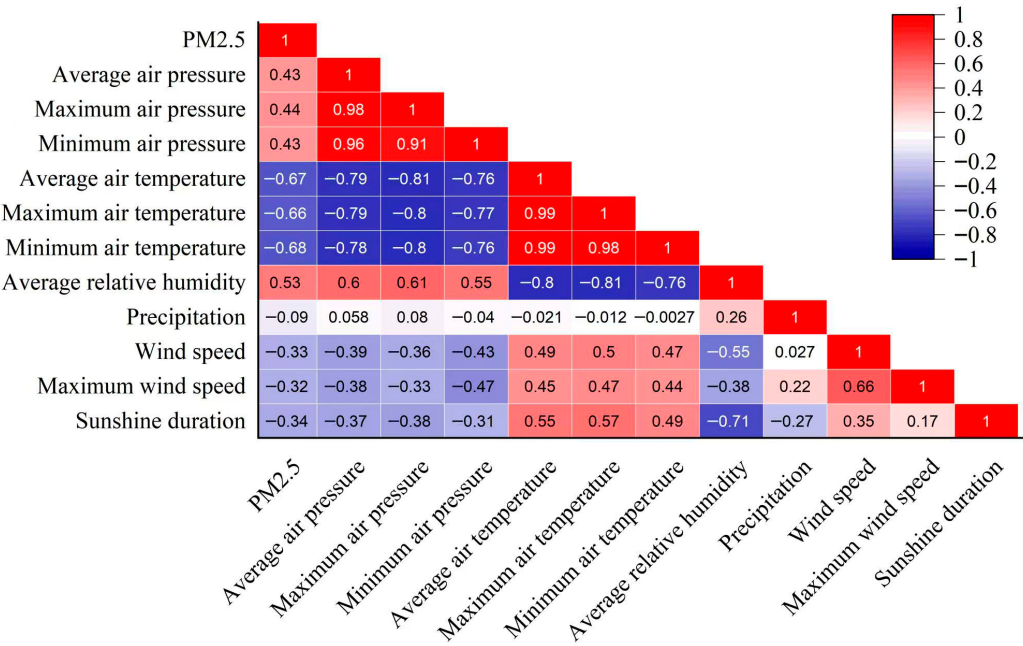


Figure 15. Correlation Matrix of PM_{2.5} with Meteorological Factors in the “U-C-S” urban agglomeration.

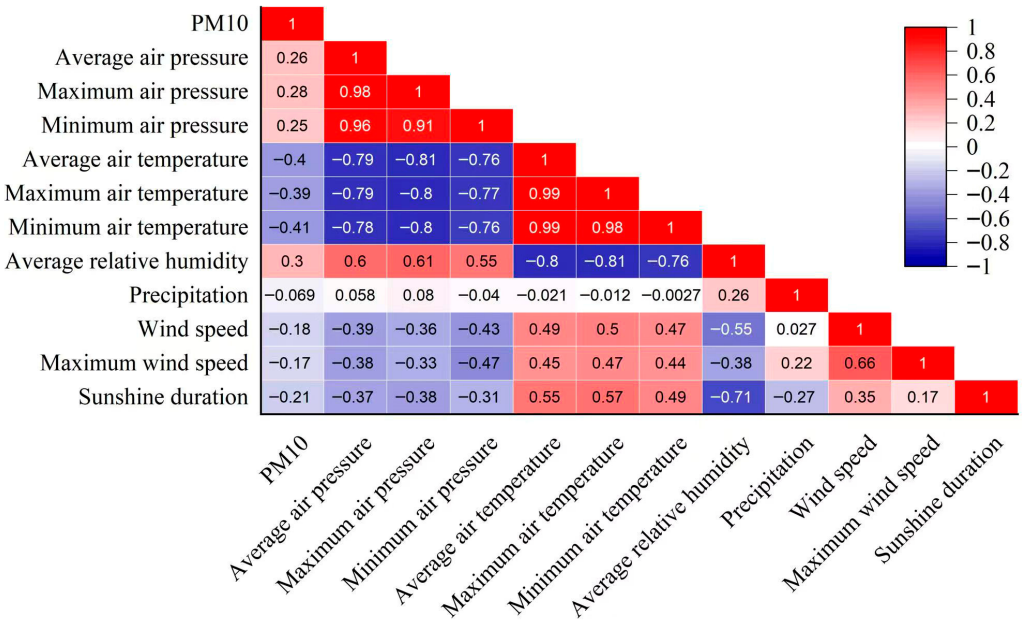


Figure 16. Correlation Matrix of PM₁₀ with Meteorological Factors in the “U-C-S” urban agglomeration.

The Random Forest model-based analysis of the importance of influencing factors on PM_{2.5} and PM₁₀ concentrations reveals significant seasonal variations in particulate pollution mechanisms (Figure 17). During winter, average relative humidity (18.3%) is identified as the primary driving factor for PM_{2.5}, followed by minimum temperature (15.2%) and maximum temperature (14.3%), indicating that low-temperature, high-humidity conditions tend to enhance atmospheric stability, inhibit pollutant dispersion, and promote aerosol hygroscopic growth. In contrast, PM₁₀ concentration is primarily influenced by minimum temperature (18.9%), suggesting intensified surface emissions (e.g., coal heating, road dust) under cold conditions; wind speed (11.1%) and precipitation (0.5%) play minor

roles, highlighting the limited cleansing effect under dry, cold climates. Conversely, in summer, PM_{2.5} concentration is most significantly impacted by average relative humidity (25.4%), far outweighing other variables, alongside elevated average temperature (17.5%) and maximum temperature (10.2%). This suggests that high temperature and humidity favor the formation of secondary organic aerosols, nitrates, and sulfates, thereby increasing PM_{2.5} levels. Factors affecting PM₁₀ are more balanced during summer, with maximum temperature (14%), minimum temperature (14%), and average temperature (14.2%) all contributing substantially. Additionally, the contributions of precipitation (3.1%) and wind speed (11.1%) are slightly increased, indicating that frequent convective weather enhances dilution and wet deposition of pollutants. Overall, PM_{2.5} concentrations are dominated by humidity across both seasons, albeit through different mechanisms: physical adsorption and condensation growth in winter versus photochemical transformation processes in summer. Meanwhile, PM₁₀ concentrations are more controlled by temperature-driven surface emissions in winter but show a stronger response to temperature fluctuations and meteorological cleansing effects in summer. These findings suggest that differentiated control strategies should be adopted for particulate pollution based on season and particle size, with particular emphasis on humidity regulation and the critical role of temperature-humidity coupling effects in air quality prediction and management.

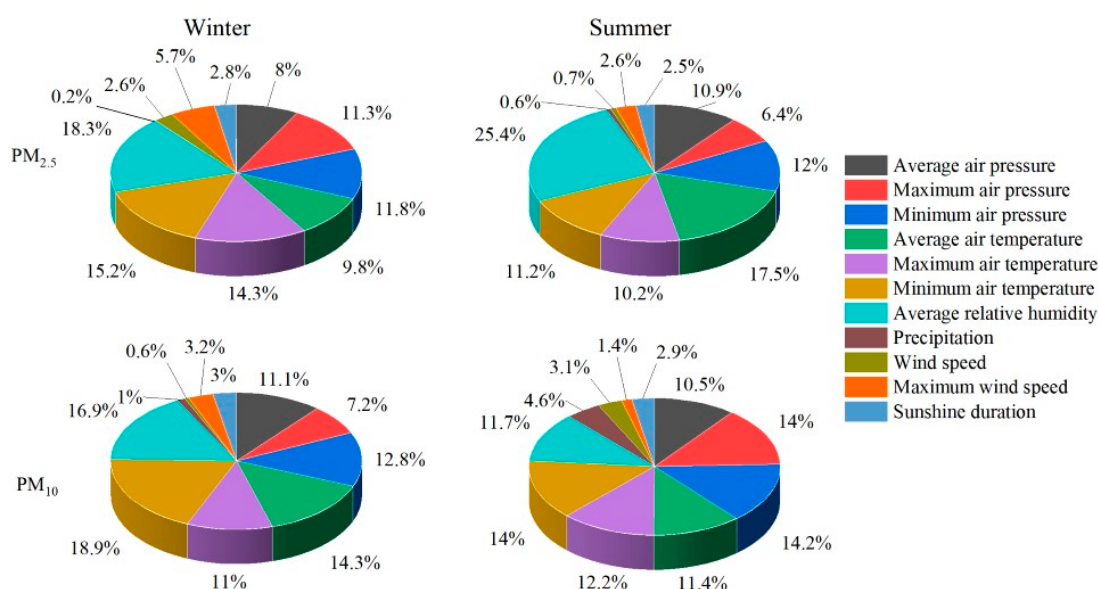


Figure 17. Meteorological Factor Importance for PM_{2.5} and PM₁₀ in Random Forest Model in the “U-C-S” urban agglomeration.

7. Conclusions

This study systematically analyzed the spatio-temporal distribution characteristics and pollution sources of PM_{2.5} and PM₁₀ in the “U-C-S” urban agglomeration, employing backward trajectory clustering analysis, PSCF/CWT models, and random forest prediction methods to elucidate the spatiotemporal patterns and underlying driving mechanisms of particulate matter pollution. The main findings are summarized as follows:

On an annual scale, high-concentration areas of both PM_{2.5} and PM₁₀ are concentrated in the central part of the “U-C-S” urban agglomeration, with PM_{2.5} reaching up to 70 $\mu\text{g}\cdot\text{m}^{-3}$ and PM₁₀ peaking at 124 $\mu\text{g}\cdot\text{m}^{-3}$. In contrast, PM₁₀ concentrations are relatively lower in the high-altitude regions of the Tianshan and Bogda Mountains, where values can drop as low as 20 $\mu\text{g}\cdot\text{m}^{-3}$. On a seasonal basis, both PM_{2.5} and PM₁₀ concentrations rise significantly during winter, with PM_{2.5} levels reaching approximately four times those

observed in spring and autumn and eight to nine times higher than in summer. PM_{10} concentrations in winter are about twice those in spring and autumn and three to four times higher than in summer, while summer exhibits the best air quality. Spring is characterized by elevated PM_{10} levels—often exceeding $500 \mu\text{g}\cdot\text{m}^{-3}$ —due to frequent sandstorms, primarily originating from southern Urumqi and northern Turpan. On a monthly scale, $PM_{2.5}$ and PM_{10} concentrations reach their annual peaks in January, particularly in the central area of Urumqi and Wujiaqu, where $PM_{2.5}$ concentrations in Wujiaqu reached as high as $200 \mu\text{g}\cdot\text{m}^{-3}$ and PM_{10} approached $124 \mu\text{g}\cdot\text{m}^{-3}$. Concentrations remain elevated in December, February, March–May, and September–November, while the lowest levels occur during June–August, forming a distinct “U”-shaped pattern. On a weekly scale, pollution levels on weekdays are generally higher than on weekends, reflecting significant contributions from traffic emissions and industrial activities. At the daily level, $PM_{2.5}$ concentrations are markedly higher in winter compared to other seasons, with peak values reaching $300 \mu\text{g}\cdot\text{m}^{-3}$, while PM_{10} peaks in spring, mainly driven by frequent sandstorm events.

Winter $PM_{2.5}$ pollution is primarily attributed to air masses originating from southern Bayingolin Mongol Autonomous Prefecture and southern Yining City, along with local emissions (e.g., in western Urumqi) and cross-border transport pathways (e.g., from north-eastern Kazakhstan), all of which contribute synergistically to pollutant accumulation. For PM_{10} , springtime increases are largely driven by frequent sandstorms and local dust resuspension activities. High-concentration zones are closely aligned with dust transport pathways, particularly evident in spring and winter. Backward trajectory clustering further reveals that seasonal variations in airflow paths significantly influence particulate matter concentrations. Notably, short-path local air masses during winter are associated with the highest pollution levels, with $PM_{2.5}$ and PM_{10} reaching $124 \mu\text{g}\cdot\text{m}^{-3}$ and $147 \mu\text{g}\cdot\text{m}^{-3}$, respectively. The combined effect of local air masses and transboundary transport during winter plays a critical role in exacerbating pollution levels.

The relationship between $PM_{2.5}$ and PM_{10} concentrations and meteorological factors indicates that air temperature exhibits a strong negative correlation with pollutant levels, suggesting that warmer conditions may enhance atmospheric turbulence and facilitate pollutant dispersion. Wind speed emerges as the most influential factor affecting particulate matter concentrations, confirmed by the model as having the highest predictive importance. Air pressure shows a weaker association with pollutants, while precipitation has a direct but limited impact; however, heavy rainfall can indirectly reduce particulate levels through wet deposition processes. Sunshine duration displays a slight negative correlation with pollutant concentrations, potentially linked to boundary layer lifting and enhanced vertical mixing.

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