



Potential Source Analysis for PM₁₀ and PM_{2.5} in Autumn in a Northern City in China

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ABSTRACT

In this study, PM₁₀ and PM_{2.5} samples were obtained in a northern city in China. The 12-h averaged concentrations of particulate matter and species were analyzed. A PCA-MLR model was applied to identify the potential source categories and to estimate the source contributions for the PM₁₀ and PM_{2.5} datasets. Five factors were extracted for the PM₁₀ samples, and their percentage contributions were estimated as follows: crustal dust—39.87%; vehicle exhaust—30.16%; secondary sulfate and nitrate—14.42%; metal emission source—6.77%; and residual oil combustion source—1.82%. Four factors were resolved for the PM_{2.5} dataset, and their contributions were obtained: crustal dust—35.81%; vehicle exhaust—22.67%; secondary sulfate and nitrate—32.35%; and metal emission and residual oil combustion sources—4.57%. In addition, a Potential Source Contribution Function (PSCF) was used to investigate the possible locations of the major sources. The PSCF results showed that for each source category, PM₁₀ and PM_{2.5} had similar potential source areas.

Keywords: Sources; Potential source contribution function; PM₁₀; PM_{2.5}.

INTRODUCTION

Concentrations of airborne particulate matter (PM) are important because they can cause adverse health effects (Harrison and Yin, 2000; Raman *et al.*, 2007; Lin *et al.*, 2008; Zhang *et al.*, 2008; Zeng *et al.*, 2010). Several studies show that ambient particulate pollution is associated with certain health effects and environmental effects (Mazurek *et al.*, 1997; Polissar *et al.*, 2001; Choosong *et al.*, 2010; Ning *et al.*, 2010). Thus, understanding the level of PM₁₀ (PM with an aerodynamic diameter less than 10 μm) and PM_{2.5} (PM with an aerodynamic diameter less than 2.5 μm) in urban areas is important (Wang *et al.*, 2008; Li *et al.*, 2009). Techniques such as source apportionment have been developed to control PM pollutants.

The receptor model is a useful tool that is widely used to study source information. Principal component analysis/

multiple linear regression (PCA-MLR) is an important receptor model that has been applied in several studies (Harrison *et al.*, 1996; Srivastava *et al.*, 2008; Shi *et al.*, 2009; Chakraborty *et al.*, 2010; Wang *et al.*, 2010). This model does not require information on source profiles. The source categories can be identified according to the PM ambient dataset, and the contribution of each source category can be also estimated.

In addition, identifying the probable locations of emission sources is important for developing effective management strategies of PM. A variety of receptor models that combine meteorology with the measured chemical compositions have been developed to locate potential sources (Seibert *et al.*, 1994; Stohl, 1996; Poirot *et al.*, 2001; Hopke, 2003). The potential source contribution function (PSCF), which is one of the most widely used trajectory ensemble models, can be combined with the results of receptor models (Begum *et al.*, 2010). In several works (Ashbaugh *et al.*, 1985; Zeng and Hopke, 1989; Gao *et al.*, 1993; Polissar *et al.*, 2001; Liu *et al.*, 2003; Begum *et al.*, 2005), this method has been successfully used to find the possible areas of the major source categories identified by the receptor model.

In this study, ambient PM₁₀ and PM_{2.5} samples were

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measured in Ordos, a large northern city in China in the Inner Mongolia Autonomous Region. To date, there has been a lack of studies regarding the Inner Mongolia Autonomous Region. Thus, in this work, the source categories and their contributions to the PM₁₀ and PM_{2.5} datasets were first estimated by the PCA-MLR model; then, the possible source regions were identified by PSCF. The results of source apportionment and potential source regions can provide information to the government for urban air management.

MATERIALS AND METHODS

Sampling Site Description

As shown in Fig. 1, Ordos (37°28'–40°52'N, 106°31'–111°29'E) is an important city in the southwestern Inner Mongolia Autonomous Region. The area of Ordos is 86752 km², and the population of the city is approximately 150 million. The city is on the Ordos Plateau and is adjacent to the Shanxi, Shaanxi and Ningxia provinces. In Ordos, there is a hilly area in the east, high plateaus in the west and center, sandy deserts in the north and south, and plains at the southern bank of the Yellow river. The highest elevation (2,149 m) of Ordos is located in the west, and the lowest point (850 m) is in the east. The annual rainfall is 300–400 mm in the eastern part and 190–350 mm in the western part.

Ambient Sampling Method

Data on the ambient PM₁₀ and PM_{2.5} concentrations were collected throughout the month of September in 2005 from an urban area in Ordos. PM₁₀ and PM_{2.5} were collected with medium-volume samplers manufactured by the Beijing Geological Instrument-Dickel Co., Ltd. (flow rate 78 L/min). Twelve-hour PM samples were measured from 5 sampling sites. After the sampling campaign, a total of 135 PM₁₀ and 122 PM_{2.5} samples without missing data were obtained. To study the source apportionment, the 135 PM₁₀ samples were combined into one PM₁₀ dataset as the input of the PCA-MLR model, and the 122 PM_{2.5} samples were combined for the PM_{2.5} input dataset.

Chemical Analysis

Inductively coupled plasma-atomic emission spectroscopy (ICP-AES, General Electric Co., U.S.A.) was applied to measure the elements (Al, B, Ba, Ca, Cr, Cu, Fe, K, Mg, Mn, Na, Ni, P, Pb, Sr, Ti and Zn) in the ambient samples. Water soluble SO₄²⁻, NO₃⁻ and Cl⁻ were extracted by an ultrasonic cleaner and filtered through 0.47-μm microporous membranes and then analyzed by ion chromatography (IC; Dionex 500, Dionex Co., U.S.A.). The CHN analyzer (Sunset Laboratory Inc., CHN model) was applied to measure organic carbon (OC) and elemental carbon (EC). The sampling methods and chemical analyses were referred to the literatures (Tyler, 1992; Carvalho et al., 1995; Chow et al., 2001; Zhao et al., 2006; Xue et al., 2010).

Principal Component Analysis/Multiple Linear Regression (PCA-MLR)

The potential source categories of the PM₁₀ and PM_{2.5} ambient samples in Ordos were analyzed by the principal component analysis/multiple linear regression (PCA-MLR) model (Thurston and Spengler, 1985). The PCA-MLR model is a receptor model, which is a useful tool for identifying potential source categories and estimating source contributions (Harrison et al., 1996; Watson et al., 2008). The PCA-MLR model can extract certain factors from an ambient dataset. The factors can be identified as the actual source categories according to the source markers (Zeng et al., 2010).

The general receptor model can be described as all m chemical species in the n samples are contributions from p independent sources:

$$x_{ik} = \sum_{j=1}^p g_{ip} f_{pk} + e_{ik} \quad (1)$$

where x_{ik} is the i th species concentration measured in the k th sample; f_{pk} is the contribution of the p th source to the k th sample; g_{ip} is the concentration of the i th species from the p th source; and e_{ik} is the error (Hopke, 2003).

The factor loading and score matrices can be obtained by PCA-MLR. The source profile and contribution matrix can be calculated from the factor loading and score matrices.

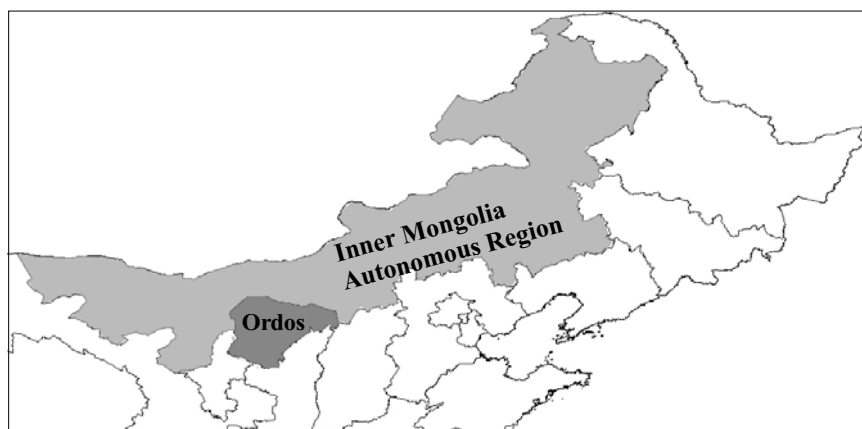


Fig. 1. Maps of studying area.

The detailed methods of PCA-MLR were introduced from the literature (Hopke, 2003; Guo *et al.*, 2004).

Potential Source Contribution Function (PSCF)

PSCF is the conditional probability that a parcel with a certain level of pollutant concentration arrives at a receptor site after having passed through a specific upwind source area (Ashbaugh *et al.*, 1985; Hwang and Hopke, 2007). In this work, air mass back trajectories are generated by HYSPLIT 4 model (NOAA's Air Resources Laboratory, 2009) first, and then the trajectory points are combined with the source contributions to estimate conditional probabilities over a region (Hopke *et al.*, 1995; Crawford *et al.*, 2007). The Back trajectories were computed using HYSPLIT4 model and the archived meteorological data from National Oceanic Atmospheric Administration's (NOAA) Air Resources Laboratory (ARL) web site (Hwang and Hopke *et al.*, 2007; Xia *et al.*, 2007; Bhanuprasad *et al.*, 2008).

In this study, a database of 3-day back trajectories (for every hour in one day) for each sampling site was generated by Hysplit (Hybrid Single-Particle Lagrangian Integrated Trajectory) 4.9. The Hysplit 4.9 trajectory model software can be downloaded from NOAA, and the detailed description of the process can be found in Hysplit4 User's Guide-Version 4.9 (NOAA's ARL, 2009).

For the PSCF model, the number of trajectory segment end points falling within grid cells ($0.5^\circ \times 0.5^\circ$ in this work) was calculated (the possible source region is subdivided into a number of grid cells, i by j), where n_{ij} is the total number of endpoints falling within the ij -th grid cell. After the PCA-MLR study, the source contributions for each sample were obtained. If the contribution of an endpoint (corresponds to a sample) is higher than the threshold level (average contribution for one source category in one sampling site), then the endpoints can be considered "high" (Liu *et al.*, 2003). m_{ij} is the number of "high" endpoints falling within the ij -th grid cell. Thus, the PSCF for the ij -th grid cell is:

$$\text{PSCF}_{ij} = \frac{m_{ij}/N}{n_{ij}/N} = \frac{P[B_{ij}]}{P[A_{ij}]} \quad (2)$$

In another study (Kim *et al.*, 2005), the source contributions in one day were assigned to each hour of a given day to match to the hourly endpoint.

In this work, a joint PSCF (J-PSCF) (Han *et al.*, 2008) was applied to identify the important influencing areas affecting the PM_{10} and $PM_{2.5}$ source contributions at all five sites:

$$\text{J-PSCF}_{ij} = \frac{\sum_{n=1}^{10} (P[B_{ij}]_n)}{\sum_{n=1}^{10} (P[A_{ij}]_n)} \quad (3)$$

In addition, a weight function for n_{ij} was used to calculate

the J-PSCF values (Hwang and Hopke, 2007). The weight function is defined as follows:

$$W_{(n_{ij})} = \begin{cases} 1.00 & \text{if } n_{ij} \geq 4 \\ 0.75 & \text{if } n_{ij} = 3 \\ 0.50 & \text{if } n_{ij} = 2 \\ 0.10 & \text{if } n_{ij} = 1 \end{cases} \quad (4)$$

RESULTS AND DISCUSSION

PM_{10} and $PM_{2.5}$ Concentrations

The PM_{10} and $PM_{2.5}$ concentrations are listed in Table 1. The average concentration of PM_{10} was $89.12 \mu\text{g}/\text{m}^3$, and the $PM_{2.5}$ concentration was $51.81 \mu\text{g}/\text{m}^3$. Table 2 compares the PM_{10} and $PM_{2.5}$ concentrations in different cities. The PM concentration values show that Ordos has higher PM level than some southern cities in China (such as Hong Kong and Shenzhen) (Cao *et al.*, 2004). The PM_{10} value in Ordos was lower than that in Beijing (Duan *et al.*, 2005), and the $PM_{2.5}$ concentration in Ordos was higher than the concentrations in some cities in the USA and the UK (Liu *et al.*, 2005).

Source Apportionment

To identify the potential source categories of PM_{10} and $PM_{2.5}$, the ambient samples in Ordos were analyzed by PCA-MLR. The varimax rotated factor loadings obtained

Table 1. Ambient Receptors ($\mu\text{g}/\text{m}^3$) for PM_{10} and $PM_{2.5}$ in Ordos.

	PM_{10}		$PM_{2.5}$	
	mean	sd*	mean	sd
Al	0.58	0.41	0.34	0.23
B	0.02	0.01	0.01	0.01
Ba	0.73	1.55	0.01	0.01
Ca	2.90	3.14	1.89	1.36
Cr	0.03	0.05	0.01	0.02
Cu	0.19	0.35	0.03	0.03
Fe	0.84	0.78	0.47	0.45
K	0.54	0.43	0.31	0.26
Mg	0.53	0.62	0.40	0.31
Mn	0.09	0.10	0.03	0.02
Na	0.34	0.36	0.23	0.20
Ni	0.02	0.07	0.00	0.01
P	0.05	0.04	0.03	0.03
Pb	0.77	1.66	0.04	0.05
Sr	0.02	0.01	0.01	0.01
Ti	0.06	0.10	0.01	0.01
Zn	0.13	0.13	0.11	0.10
Cl ⁻	0.20	0.18	0.10	0.09
NO ₃ ⁻	0.60	0.65	0.29	0.24
SO ₄ ²⁻	1.81	1.31	1.07	0.81
OC	19.87	12.77	12.80	8.75
EC	3.80	2.38	2.46	1.55
mass	89.12	53.13	51.81	30.92

*sd: standard deviation; OC: organic carbon.

Table 2. PM₁₀ and PM_{2.5} concentrations ($\mu\text{g}/\text{m}^3$) in different cities.

cities	year	PM ₁₀ concentration	PM _{2.5} concentration	references
Ordos, China	2005, September	89.12	51.81	This study
Beijing, China	2002, September	153.5		Duan et al., 2005
Hong Kong, China	2002, summer	41.4	31	Cao et al., 2004
Guangzhou, China	2002, summer	124.7	78.1	Cao et al., 2004
Shenzhen, China	2002, summer	75.1	47.1	Cao et al., 2004
Atlanta, USA	2000–2002		16.72	Liu et al., 2005
Birmingham, UK	2000–2002		17.92	Liu et al., 2005
Münster, Germany	2006, January	31		Gietl et al., 2008
Malaysian	2000–2006, September	66		Juneng et al., 2009
Panzhihua, China	2007, summer	133		Xue et al., 2010
Tianjin, China	2007, winter		223.0	Li et al., 2009
Taiwan	2005	59.2	47.4	Wang et al., 2008
Lahore, Pakistan	2006, spring	459		Zhang et al., 2008
Haarlemmerweg, Netherlands	2008	27.5	17.8	Boogaard et al., 2011

by PCA for the PM₁₀ ambient dataset are listed in Table 3. Five factors (eigenvalue greater than 1.0) were obtained by PCA. Factor 1 obtained high loading values for Al, Ca, Fe and Mg. These species are the markers for the crustal dust source (Yuan et al., 2006). Thus, factor 1 can be identified as crustal dust. Factor 2 was heavily weighted in Ba, Cr, Mn, Pb and Ti, so this factor could be the metal emission source. Factor 3 was mostly associated with OC and EC. These two species were the source markers for vehicle exhaust (Yuan et al., 2006). Thus, factor 3 might be the vehicle exhaust source. Factor 4 obtained high loadings for NO₃⁻ and SO₄²⁻, so this factor can be identified as secondary sulfate and nitrate sources. Sulfate and nitrate in the atmosphere are generated through the oxidation of SO₂ and nitrogen oxides produced from fossil fuel combustion (Yuan et al., 2006). Factor 5 obtained high levels of Ni. This species is the marker for residual oil combustion (Chow and Watson, 2002; Yuan et al., 2006). Thus, this factor can be identified as the residual oil combustion source.

Table 4 shows the rotated loadings for the PM_{2.5} ambient dataset. Four factors were obtained by PCA. Similar to the results of the PM₁₀ ambient dataset, factor 1 obtained high loadings for Al, Ca, Fe and Mg. Thus, this factor might be the crustal dust source. Factor 2 was associated with OC and EC, which can be identified as the vehicle exhaust emission source. Factor 3 was heavily weighted in NO₃⁻ and SO₄²⁻, so it might be the secondary sulfate and nitrate. Factor 4 obtained high loadings for Cr, Cu and Ni, so factor 4 might be the metal emission and residual oil combustion source.

The estimated source contributions for the PM₁₀ and PM_{2.5} ambient datasets are also shown in Tables 3 and 4. For the PM₁₀ ambient dataset, crustal dust obtained the largest contribution: 35.53 $\mu\text{g}/\text{m}^3$ (39.87%). This result is reasonable because crustal dust is usually an important source category in northern China (Bi et al., 2006). The second highest contributor was vehicles, at 26.88 $\mu\text{g}/\text{m}^3$ (30.16%). Secondary sulfate and nitrate were 12.85 $\mu\text{g}/\text{m}^3$ (14.42%) of PM₁₀. The contributions of the metal emission and residual oil combustion sources were 6.04 $\mu\text{g}/\text{m}^3$ (6.77%) and 1.62 $\mu\text{g}/\text{m}^3$ (1.82%), respectively.

Similar to the PM₁₀ ambient dataset, crustal dust was the largest contributor of PM_{2.5} at 18.56 $\mu\text{g}/\text{m}^3$ (35.81%). Secondary sulfate and nitrate was the second highest contributor at 16.76 $\mu\text{g}/\text{m}^3$ (32.35%). Vehicle exhaust was 11.75 $\mu\text{g}/\text{m}^3$ (22.67%), and the metal emission and residual oil combustion sources were 2.37 $\mu\text{g}/\text{m}^3$ (4.57%) of PM_{2.5}.

After the sources were identified by the PCA-MLR model, the extracted source profiles and source contributions were obtained. Thus, the estimated concentrations were calculated from the source contributions and source profiles according to Eq. (1). The plots of the estimated concentration vs. measured concentration of each sample for the PM₁₀ and PM_{2.5} datasets are described in Fig. 2. The fit between the estimated and measured concentrations is presented on the plots. For the PM₁₀ plot, the regression ($p < 0.01$) was 1:1.0, and the value of r was 0.97. For the PM_{2.5} plot, the regression ($p < 0.01$) was 1:1.0, and the value of r was 0.97. The regression results indicate that the estimated concentrations were close to the measured concentrations.

Potential Source Contribution Function (PSCF) Study

As discussed above, the crustal dust, vehicle exhaust and secondary sulfate and nitrate sources were the important source categories for both the PM₁₀ and PM_{2.5} samples in Ordos. Therefore, in this section, the potential areas for each source category were identified by the potential source contribution function (PSCF).

The J-PSCF plots for the PM₁₀ samples resolved by PCA-MLR are shown in Fig. 3. The J-PSCF result for the PM₁₀ crustal dust source is presented in Fig. 3(A). The plot shows that the major potential source area might be in the Inner Mongolia, Xinjiang and Gansu provinces. These provinces are located in Northwestern China. Crustal dust is the important source category in these areas.

The J-PSCF plot of the PM₁₀ vehicle exhaust source is shown in Fig. 3(B). The most likely source regions were at the southeast of the monitoring sites (including the center area of Shanxi province, the northern area of Shaanxi province, etc.). Some relatively economically developed urban cities (near sampling sites) are in these regions. Thus,

Table 3. Varimax rotated factor loadings for PM₁₀ ambient dataset in Erods.

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Al	0.91	0.16	0.17	0.08	0.01
B	0.32	0.11	0.83	0.02	-0.02
Ba	-0.16	0.89	0.26	-0.15	0.07
Ca	0.83	-0.38	0.21	0.09	0.14
Cr	0.02	0.73	0.18	-0.08	-0.02
Cu	-0.11	0.90	0.27	-0.12	0.07
Fe	0.96	0.11	0.06	0.07	0.00
K	0.20	0.50	0.56	0.32	0.07
Mg	0.82	-0.30	0.11	0.16	0.13
Mn	0.21	0.91	0.17	0.08	0.11
Na	0.69	-0.39	0.45	0.23	-0.03
Ni	0.06	0.16	0.03	0.00	0.95
P	0.77	0.33	0.28	0.16	-0.09
Pb	-0.06	0.92	-0.06	0.10	0.07
Sr	0.87	0.11	0.44	0.09	0.01
Ti	0.09	0.88	-0.12	0.09	0.01
Zn	0.33	-0.45	0.29	0.44	-0.14
Cl ⁻	0.44	-0.15	0.26	0.71	-0.10
NO ₃ ⁻	-0.03	-0.01	-0.01	0.94	-0.10
SO ₄ ²⁻	0.20	0.12	0.23	0.80	0.30
OC	0.50	0.31	0.70	0.29	0.04
EC	0.46	0.21	0.72	0.32	0.10
Estimated contribution (µg/m ³)	35.53	6.04	26.88	12.85	1.62
Percentage (%)	39.87	6.77	30.16	14.42	1.82
Source	crustal dust	metal emission	vehicle exhaust	secondary sulfate and nitrate	residual oil combustion

Table 4. Varimax rotated factor loadings for PM_{2.5} ambient dataset in Erods.

	Factor 1	Factor 2	Factor 3	Factor 4
Al	0.85	0.28	0.15	0.17
B	0.22	0.79	0.23	-0.03
Ba	0.44	0.55	0.11	0.31
Ca	0.79	0.49	0.13	0.18
Cr	0.13	0.05	0.06	0.97
Cu	0.08	0.06	0.27	0.91
Fe	0.92	0.25	0.05	0.12
K	0.33	0.27	0.78	0.25
Mg	0.83	0.24	0.23	0.04
Mn	0.78	0.33	0.40	0.11
Na	0.54	0.75	0.18	-0.03
Ni	0.09	0.00	0.00	0.89
P	0.75	0.45	0.20	0.16
Pb	0.08	-0.18	0.59	0.01
Sr	0.76	0.59	0.12	0.04
Ti	0.64	0.00	0.02	0.01
Zn	0.15	0.23	0.73	0.20
Cl ⁻	0.52	0.76	0.20	-0.04
NO ₃ ⁻	0.03	0.40	0.85	-0.07
SO ₄ ²⁻	0.07	0.31	0.88	0.06
OC	0.42	0.62	0.53	0.20
EC	0.35	0.64	0.54	0.14
Estimated contribution (µg/m ³)	18.56	11.75	16.76	2.37
Percentage (%)	35.81	22.67	32.35	4.57
Source	crustal dust	vehicle exhaust	secondary sulfate and nitrate	metal emission and residual oil

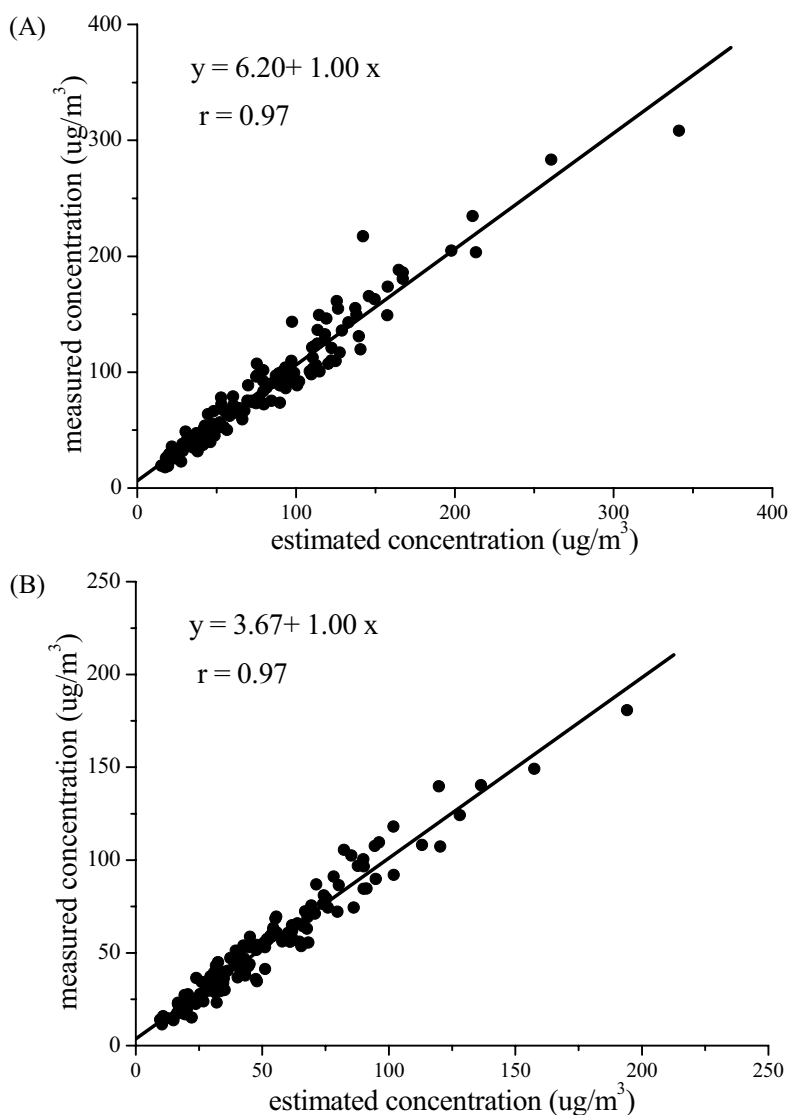


Fig. 2. The plot of least squares regression between estimated concentration and measured concentration of each sample for PM_{10} (A) and $PM_{2.5}$ (B) dataset. The estimated concentration is the sum of the extracted factors (sources) contributions ($\mu\text{g}/\text{m}^3$) for each sample.

heavy vehicle activity is present in these areas. According to the J-PSCF plot, local areas cannot be ignored either.

Fig. 3(C) shows the J-PSCF result for the PM_{10} secondary sulfate and nitrate. The potential areas identified by J-PSCF are to the southeast of the monitoring sites. The locations of coal-fired power plants are usually consistent for the secondary sulfate source (Liu *et al.*, 2003; Kim *et al.*, 2007), which shows that these areas might be the most likely potential source areas of secondary sulfate and nitrate.

Fig. 4 shows the J-PSCF plots for the $PM_{2.5}$ samples. For each source category, the J-PSCF result of the $PM_{2.5}$ sample is similar to that of the PM_{10} sample, which indicates that the potential source areas for $PM_{2.5}$ and PM_{10} are similar. For vehicle, the most influencing area of Fig. 4(B) is relative different from Fig. 3 (B). In Fig. 4(B), the most influencing area is on the southwest of the sampling sites. Of course, similar to Fig. 3(B), southeast was also an important source region for vehicle.

According to the results of the source apportionment, crustal dust is the most important source for Ordos in summer, which agrees with other studies in northern Chinese cities such as Yinchuan and Urumqi (Bi *et al.* 2007). In addition, the areas of origin of the important sources of the sampling sites were studied. These studies can provide valuable information for government air management.

CONCLUSION

Twelve-hour PM_{10} and $PM_{2.5}$ samples were collected at Ordos in China. The potential source categories for the PM_{10} and $PM_{2.5}$ datasets were identified, and the contributions were then estimated by the PCA-MLR model. For both datasets, the major source categories were crustal dust, vehicle exhaust and secondary sulfate and nitrate. Crustal dust was the largest contributor for both PM_{10} and $PM_{2.5}$, at 39.87% and 35.81%, respectively. The contributions of

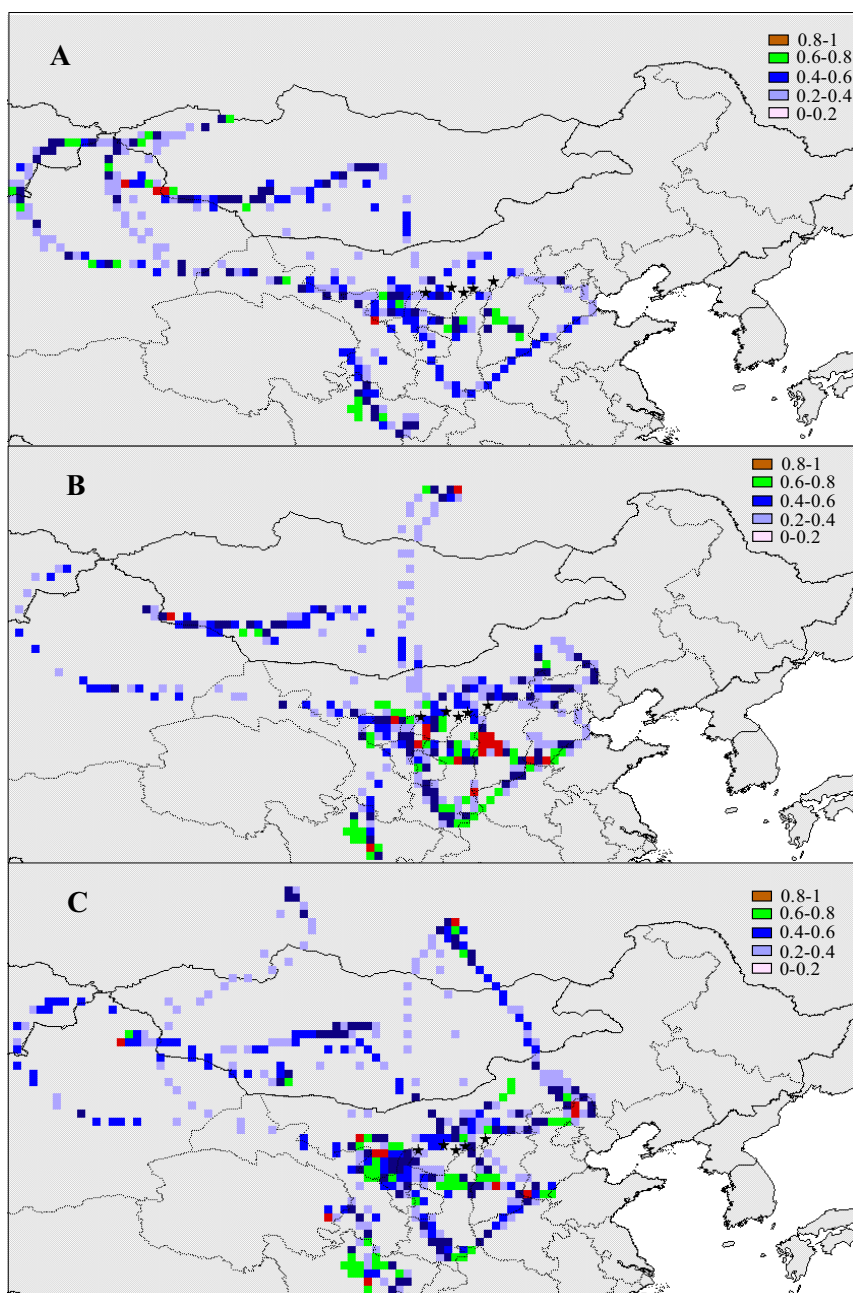


Fig. 3. J-PSCF plots for PM_{10} samples resolved by PCA-MLR. A: crustal dust source; B: vehicle exhaust source; C: secondary sulfate and nitrate sources. The areas with high J-PSCF values show the high probability for source origin.

vehicle exhaust were 30.16% for PM_{10} and 2.67% $PM_{2.5}$; the contributions of secondary sulfate and nitrate were 14.42% and 32.35% for PM_{10} and $PM_{2.5}$, respectively.

The potential source areas impacting the sampling sites were analyzed by J-PSCF. PM_{10} and $PM_{2.5}$ obtained similar results for each source category. The plot results show that the possible source areas of crustal dust were regions in Northwestern China. For vehicle exhaust, major urban cities with heavy vehicle activity might be the potential impacting areas. For secondary sulfate and nitrate, the east and south regions of Ordos, where coal-fired power plants are located, might be important areas.

According to this study, the potential source contributions

and probable locations of the identified source categories were studied by PCA/MLR combined with J-PSCF. The possible origin areas were found for each important source. Finding these sources would be highly useful for reducing pollutant concentrations in the atmosphere and for supporting government management strategies.

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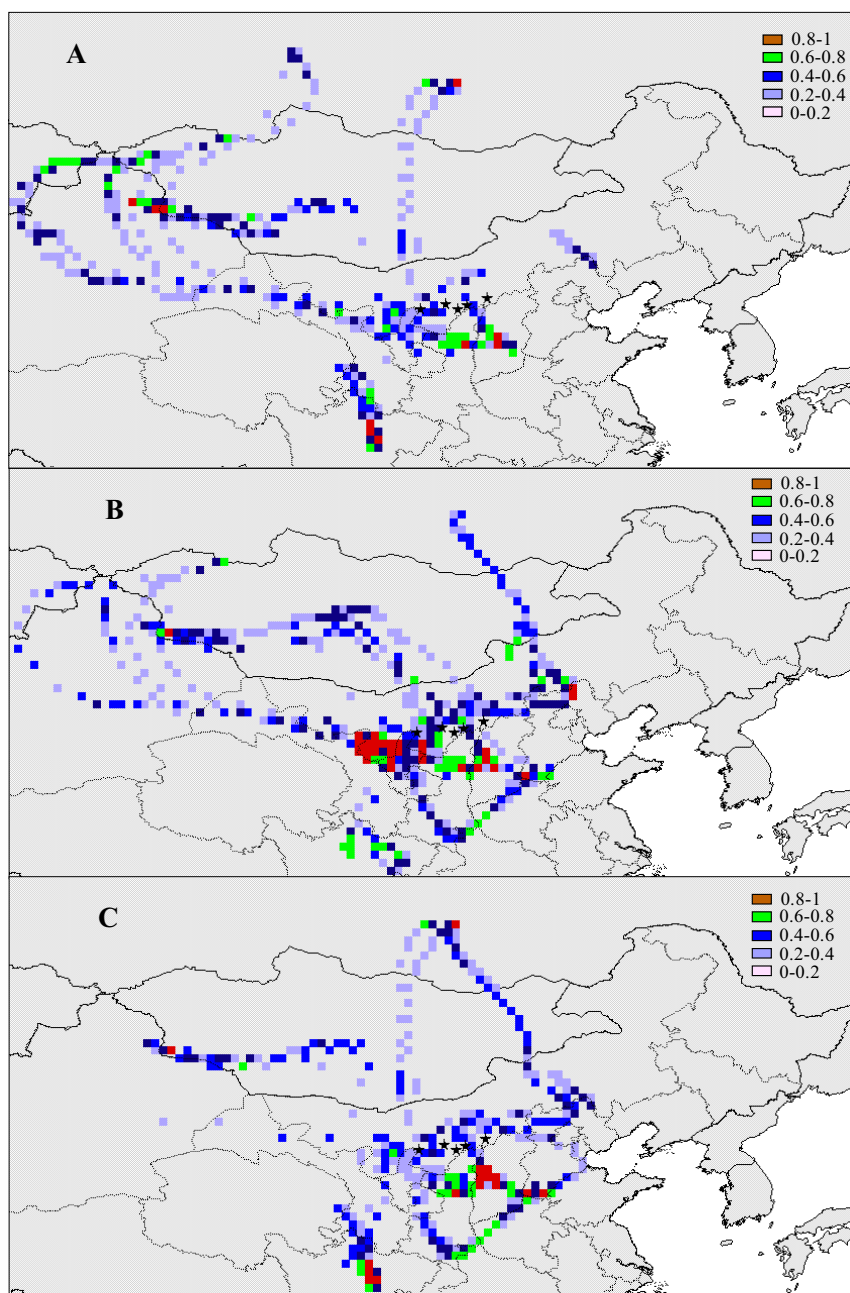


Fig. 4. J-PSCF plots for $PM_{2.5}$ samples resolved by PCA-MLR. A: crustal dust source; B: vehicle exhaust source; C: secondary sulfate and nitrate sources. The areas with high J-PSCF values show the high probability for source origin.

REFERENCES

- Ashbaugh, L.L., Malm, W.C. and Sadeh, W.D. (1985). A Residence Time Probability Analysis of Sulfur Concentrations at Grand Canyon National Park. *Atmos. Environ.* 19: 1263–1270.
- Begum, B.A., Biswas, S.K., Markwitz, A. and Hopke, P.K. (2010). Identification of Sources of Fine and Coarse Particulate Matter in Dhaka, Bangladesh. *Aerosol Air Qual. Res.* 10: 345–353.
- Begum, B.A., Kim, E., Jeong, E.K., Lee, D.W. and Hopke, P.K. (2005). Evaluation of the Potential Source Contribution Function Using the 2002 Quebec Forest fire Episode. *Atmos. Environ.* 39: 3719–3724.
- Bhanuprasad, S.G., Venkataraman, C. and Bhushan, M., (2008). Positive Matrix Factorization and Trajectory Modeling for Source Identification: A New Look at Indian Ocean Experiment Ship Observations. *Atmos. Environ.* 42: 4836–4852.
- Bi, X.H., Feng, Y.C., Wu, J.H., Wang, Y.Q. and Zhu, T. (2007). Source Apportionment of PM_{10} in Six Cities of Northern China. *Atmos. Environ.* 41: 903–912.
- Cao, J.J., Lee, S.C., Ho, K.F., Zou, S.C., Fung, K., Li, Y., Watson, J.G. and Chow, J.C. (2004). Spatial and Seasonal Variations of Atmospheric Organic Carbon and Elemental Carbon in Pearl River Delta Region, China. *Atmos.*

- Environ.* 38: 4447–4456.
- Carvalho, L.R.F., Souza, S.R., Martinis, B.S. and Korn, M. (1995). Monitoring of the Ultrasonic Irradiation Effect on the Extraction of Airborne Particle Matter by Ion Chromatography. *Anal. Chim. Acta* 317: 171–179.
- Chakraborty, A. and Gupta, T. (2010). Chemical Characterization and Source Apportionment of Submicron (PM_{10}) Aerosol in Kanpur Region, India. *Aerosol Air Qual. Res.* 10: 433–445.
- Choosong, T., Chomanee, J., Tekasakul, P., Tekasakul, S., Otani, Y., Hata, M. and Furuuchi, M. (2010). Workplace Environment and Personal Exposure of PM and PAHs to Workers in Natural Rubber Sheet Factories Contaminated by Wood Burning Smoke. *Aerosol Air Qual. Res.* 10: 8–21.
- Chow, J.C. and Watson, J.G. (2002). Review of $PM_{2.5}$ and PM_{10} Apportionment for Fossil Fuel Combustion and other Sources by Chemical Mass Balance Receptor Model. *Energy Fuels* 16: 222–260.
- Chow, J.C., Watson, J.G., Crow, D., Lowenthal, D.H. and Merrifield, T. (2001). Comparison of IMPROVE and NIOSH Carbon Measurements. *Aerosol Sci. Technol.* 34: 23–24.
- Crawford, J., Chambers, S., Cohen, D.D., Dyer, L., Wang, T. and Zahorowski, W. (2007). Receptor Modeling Using Positive Matrix Factorisation, Back Trajectories and Radon-222. *Atmos. Environ.* 41: 6823–6837.
- Duan, F.K., He, K. B., Ma, Y.L., Jia, Y.T., Yang, F.M., Lei, Y., Tanaka, S. and Okuta, T. (2005). Characteristics of Carbonaceous Aerosols in Beijing, China. *Chemosphere* 60: 355–364.
- Gao, N., Cheng, M.D. and Hopke, P.K. (1993). Potential Source Contribution Function Analysis and source Apportionment of Sulfur Species measured at Rubidoux, CA during the Southern California Air Quality Study, 1987. *Anal. Chim. Acta* 277: 369–380.
- Guo, H., Wang, T., Simpson, I.J., Blake, D.R., Yu, X.M., Kwok, Y.H. and Li, Y.S. (2004). Source Contributions to Ambient VOCs and CO at a Rural Site in Eastern China. *Atmos. Environ.* 38: 4551–4500.
- Han, Y.J., Kim, T.S. and Kim, H. (2008). Ionic Constituents and Source Analysis of $PM_{2.5}$ in Three Korean Cities. *Atmos. Environ.* 42: 4735–4746.
- Harrison, R.M. and Yin, J.X. (2000). Particulate Matter in the Atmosphere: Which Particle Properties are Important for its Effects on Health? *Sci. Total Environ.* 249: 85–101.
- Harrison, R.M., Smith, D.J.T. and Luhana, L. (1996). Source Apportionment of Atmospheric Polycyclic Aromatic Hydrocarbons Collected from an Urban Location in Birmingham, U.K. *Environ. Sci. Technol.* 30: 825–832.
- Hopke, P.K. (2003). Recent Developments in Receptor Modeling. *J. Chemom.* 17: 255–265.
- Hopke, P.K., Li, C.L., Ciszek, W. and Landsberger, S. (1995). The Use of Bootstrapping to Estimate Conditional Probability Fields for Source Locations of Airborne Pollutants. *Chemom. Intell. Lab. Syst.* 30: 69–79.
- Hwang, I. and Hopke, P.K. (2007). Estimation of Source Apportionment and Potential Source Locations of $PM_{2.5}$ at a West Coastal IMPROVE Site. *Atmos. Environ.* 41: 506–518.
- Kim, E., Hopke, P.K., Kenski, D.M. and Koerber, M. (2005). Source of Fine Particles in a Rural Midwestern U.S. Area. *Environ. Sci. Technol.* 39: 4953–4960.
- Kim, M., Deshpande, S.R. and Crist, K.C. (2007). Source Apportionment of Fine Particulate Matter ($PM_{2.5}$) at a Rural Ohio River Valley Site. *Atmos. Environ.* 41: 9231–9243.
- Li, W.F., Bai, Z.P., Liu, A.X., Chen, J. and Chen, L. (2009). Characteristics of Major $PM_{2.5}$ Components during Winter in Tianjin, China. *Aerosol Air Qual. Res.* 9: 105–119.
- Lin, C.H., Wu, Y.L., Lai, C.H., Watson, J.G. and Chow, J.C. (2008). Air Quality Measurements from the Southern Particulate Matter Supersite in Taiwan. *Aerosol Air Qual. Res.* 8: 233–264.
- Liu, W., Hopke, P.K., Han, Y.J., Yi, S.M., Holsen, T.M., Cybart, S., Kozlowski, K. and Milligan, M. (2003). Application of Receptor Modeling to Atmospheric Constituents at Potsdam and Stockton, NY. *Atmos. Environ.* 37: 4997–5007.
- Liu, W., Wang, Y.H., Russell, A. and Edgerton, E.S. (2005). Atmospheric Aerosol over Two Urban-rural Pairs in the Southeastern United States: Chemical Composition and Possible Sources. *Atmos. Environ.* 39: 4453–4470.
- Mazurek, M., Masonjones, M.C., Masonjones, H.D., Salmon, L.G., Cass, G.R., Hallock, K.A. and Leach, M. (1997). Visibility-reducing Organic Aerosols in the Vicinity of Grand Canyon National Park: Properties Observed by High Resolution Gas Chromatography. *J. Geophys. Res.* 102: 3779–3793.
- Ning, Z. and Sioutas, C. (2010). Atmospheric Processes Influencing Aerosols Generated by Combustion and the Inference of Their Impact on Public Exposure: A Review. *Aerosol Air Qual. Res.* 10: 43–58.
- NOAA's Air Resources Laboratory (2009). Hysplit4 User's Guide, Version 4.9. Last Revision: January, http://www.arl.noaa.gov/HYSPLIT_pubs.php.
- Poirot, R.L., Wishinski, P.R., Hopke, P.K. and Polissar, A.V. (2001). Comparative Application of Multiple Receptor Methods to Identify Aerosol Sources in Northern Vermont. *Environ. Sci. Technol.* 35: 4622–4636.
- Polissar, A.V., Hopke, P.K. and Poirot, R.L. (2001). Atmospheric Aerosol over Vermont: Chemical Composition and Sources. *Environ. Sci. Technol.* 135: 4604–4621.
- Raman, R.S. and Hopke, P.K. (2007). Source Apportionment of Fine Particles Utilizing Partially Speciated Carbonaceous Aerosol Data at Two Rural Locations in New York State. *Atmos. Environ.* 41: 7923–7939.
- Seibert, P., Kromp-Kolb, H., Baltensperger, U., Jost, D.T., Schwikowski, M., Kasper, A. and Puxbaum, H. (1994). *Transport and Transformation of Pollutants in the Troposphere*, Academic Publishing, Den Haag, p. 689–693.
- Shi, G.L., Li, X., Feng, Y.C., Wang, Y.Q., Wu, J.H., Li, J. and Zhu, T. (2009). Combined Source Apportionment, Using Positive Matrix Factorization–Chemical Mass Balance and Principal Component Analysis/Multiple Linear Regression–Chemical Mass Balance Models. *Atmos. Environ.* 18: 2929–2937.

- Srivastava, A., Gupta, S. and Jain, V.K. (2008). Source Apportionment of Total Suspended Particulate Matter in Coarse and Fine Size Ranges over Delhi. *Aerosol Air Qual. Res.* 8: 188–200.
- Stohl, A. (1996). Trajectory Statistics—A New Method to Establish Source–Receptor Relationships of Air Pollutants and its Application to the Transport of Particulate Sulfate in Europe. *Atmos. Environ.* 30: 579–587.
- Thurston, G.D. and Spengler, J.D. (1985). A Quantitative Assessment of Source Contributions to Inhalable Particulate Matter Pollution in Metropolitan Boston. *Atmos. Environ.* 19: 9–25.
- Tyler, G. (1992). ICP vs. AA: How Do you Choose. *Environmental Laboratory*, p. 31–34.
- Wang, H.K., Huang, C.H., Chen, K.S., Peng, Y.P. (2010). Seasonal Variation and Source Apportionment of Atmospheric Carbonyl Compounds in Urban Kaohsiung, Taiwan. *Aerosol Air Qual. Res.* 10: 559–570.
- Wang, W.C., Chen, K.S., Chen, S.J., Lin, C.C., Tsai, J.H., Lai, C.H., and Wang, S.K. (2008). Characteristics and Receptor Modeling of Atmospheric PM_{2.5} at Urban and Rural Sites in Pingtung, Taiwan. *Aerosol Air Qual. Res.* 8: 112–129.
- Watson, J.G., Chen, L. W. A., Chow, J. C., Doraiswamy, P. and Lowenthal, D. H. (2008). Source Apportionment: Findings from the U.S. Supersites Program. *J. Air Waste Manage. Assoc.* 58: 265–288.
- Xia, X., Chen, H. and Zhang, W. (2007). Analysis of the Dependence of Column-integrated Aerosol Properties on Long-range Transport of Air Masses in Beijing. *Atmos. Environ.* 41: 7739–7750.
- Xue, Y.H., Wu, J.H., Feng, Y.C., Dai, L., Bi, X.H., Li, X.A., Zhu, T., Tang, S.B. and Chen, M.F. (2010). Source Characterization and Apportionment of PM₁₀ in Panzhuhua, China. *Aerosol Air Qual. Res.* 10: 367–377.
- Yuan, Z.B., Lau, A.K.H., Zhang, H.Y., Yu, J.Z., Louie, P.K.K. and Fung, J.C.H. (2006). Identification and Spatiotemporal Variations of Dominant PM₁₀ Sources over Hong Kong. *Atmos. Environ.* 40: 1803–1815.
- Zeng, F., Shi, G.L., Xiang, L., Feng, Y.C., Bi, X.H., Wu, J.H. and Xue, Y.H. (2010). Application of a Combined Model to Study the Source Apportionment of PM₁₀ in Taiyuan, China. *Aerosol Air Qual. Res.* 10: 177–184.
- Zeng, Y. and Hopke, P.K. (1989). A study on the Sources of Acid Precipitation in Ontario, Canada. *Atmos. Environ.* 23: 1499–1509.
- Zhang, Y.X., Quraishi, T., and Schauer, J.J. (2008). Daily Variations in Sources of Carbonaceous Aerosol in Lahore, Pakistan during a High Pollution Spring Episode. *Aerosol Air Qual. Res.* 8: 130–146.
- Zhao, P.S., Feng, Y.C., Zhu, T. and Wu, J.H. (2006). Characterizations of Resuspended Dust in Six Cities of North China. *Atmos. Environ.* 40: 5807–5814.

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