Potential Source Analysis for PM$_{10}$ and PM$_{2.5}$ in Autumn in a Northern City in China

Zong-shuang Wang$^{1,2,3,*}$, Ting Wu$^4$, Guo-liang Shi$^{5,*}$, Xiao Fu$^1$, Ying-ze Tian$^5$, Yin-chang Feng$^5$, Xue-fang Wu$^2$, Gang Wu$^1$, Zhi-peng Bai$^{2,5}$, Wen-jie Zhang$^2$

$^1$ State Key Laboratory of Urban and Regional Ecology, Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing 100085, China
$^2$ Chinese Research Academy of Environmental Sciences, Beijing 10012, China
$^3$ Graduate University of Chinese Academy of Sciences, Beijing 100049, China
$^4$ Publicity and Education Center, Tianjin Environmental Protection Bureau, China
$^5$ State Environmental Protection Key Laboratory of Urban Ambient Air Particulate Matter Pollution Prevention and Control, College of Environmental Science and Engineering, Nankai University, Tianjin, 300071, China

ABSTRACT

In this study, PM$_{10}$ 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 PM$_{10}$ and PM$_{2.5}$ datasets. Five factors were extracted for the PM$_{10}$ 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, PM$_{10}$ and PM$_{2.5}$ had similar potential source areas.

Keywords: Sources; Potential source contribution function; PM$_{10}$; 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 PM$_{10}$ (PM with an aerodynamic diameter less than 10 $\mu$m) and PM$_{2.5}$ (PM with an aerodynamic diameter less than 2.5 $\mu$m) 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 PM$_{10}$ and PM$_{2.5}$ samples were
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 PM$_{10}$ 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 km$^2$, 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 PM$_{10}$ and PM$_{2.5}$ concentrations were collected throughout the month of September in 2005 from an urban area in Ordos. PM$_{10}$ 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 PM$_{10}$ and 122 PM$_{2.5}$ samples without missing data were obtained. To study the source apportionment, the 135 PM$_{10}$ samples were combined into one PM$_{10}$ 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 SO$_4^{2-}$, NO$_3^-$ 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 PM$_{10}$ 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:

$$x_{ik} = \sum_{j=1}^{p} g_{ij} f_{jk} + e_{ik}$$  

where $x_{ik}$ is the $i$th species concentration measured in the $k$th sample; $f_{jk}$ is the contribution of the $p$th source to the $k$th sample; $g_{ij}$ 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.](image-url)
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 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° × 0.5° 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:

\[
PSCF_{ij} = \frac{m_{ij}/N}{n_{ij}/N} = \frac{P[B_{ij}]}{P[A_{ij}]} \tag{2}
\]

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:

\[
J-PSCF_{ij} = \frac{\sum_{n=1}^{10} (P[B_{ij}]_n)}{\sum_{n=1}^{10} (P[A_{ij}]_n)} \tag{3}
\]

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:

\[
W(n_{ij}) = \begin{cases} 
1.00 & \text{if } n_{ij} \geq 4 \\
0.75 & \text{if } n_{ij} = 3 \\
0.50 & \text{if } n_{ij} = 2 \\
0.10 & \text{if } n_{ij} = 1
\end{cases} \tag{4}
\]

**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 μg/m\(^3\), and the PM\(_{2.5}\) concentration was 51.81 μg/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 (μg/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.*
by PCA for the PM$_{10}$ 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 NO$_3^-$ and SO$_4^{2-}$, so this factor can be identified as secondary sulfate and nitrate sources. Sulfate and nitrate in the atmosphere are generated through the oxidation of SO$_2$ 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 PM$_{2.5}$ 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 NO$_3^-$ and SO$_4^{2-}$, 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 PM$_{10}$ and PM$_{2.5}$ ambient datasets are also shown in Tables 3 and 4. For the PM$_{10}$ ambient dataset, crustal dust obtained the largest contribution: 35.53 µg/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 µg/m$^3$ (30.16%). Secondary sulfate and nitrate were 12.85 µg/m$^3$ (14.42%) of PM$_{10}$. The contributions of the metal emission and residual oil combustion sources were 6.04 µg/m$^3$ (6.77%) and 1.62 µg/m$^3$ (1.82%), respectively.

Similar to the PM$_{10}$ ambient dataset, crustal dust was the largest contributor of PM$_{2.5}$ at 18.56 µg/m$^3$ (35.81%). Secondary sulfate and nitrate was the second highest contributor at 16.76 µg/m$^3$ (32.35%). Vehicle exhaust was 11.75 µg/m$^3$ (22.67%), and the metal emission and residual oil combustion sources were 2.37 µg/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 for each sample for the PM$_{10}$ 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 PM$_{10}$ 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 PM$_{10}$ 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 PM$_{10}$ samples resolved by PCA-MLR are shown in Fig. 3. The J-PSCF result for the PM$_{10}$ 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 PM$_{2.5}$ 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 Shannxi province, the northern area of Shaanxi province, etc.). Some relatively economically developed urban cities (near sampling sites) are in these regions. Thus,

| cities                  | year            | PM$_{10}$ concentration | PM$_{2.5}$ concentration | references         |
|------------------------|-----------------|--------------------------|---------------------------|--------------------|
| Beijing, China         | 2002, September | 153.5                    | 31                        | Duan et al., 2005  |
| 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                    | 17.92                     | Liu et al., 2005   |
| Birmingham, UK         | 2000–2002       | 223.0                    | 47.4                      | Li et al., 2009    |
| Münster, Germany       | 2006, January   | 31                       | 66                        | Gietl et al., 2008 |
| Malaysian              | 2000–2006, September | 133                   | 223.0                     | Xue et al., 2010   |
| Panzhuhua, China       | 2007, summer    | 59.2                     | 47.4                      | Wang et al., 2008  |
| Tianjin, China         | 2007, winter    | 223.0                    | 47.4                      | Zhang et al., 2008 |
| Taiwan                 | 2005            | 59.2                     | 47.4                      | Wang et al., 2008  |
| Lahore, Pakistan       | 2006, spring    | 459                      | 17.8                      | Boogaard et al., 2011 |
| Haarlemmerweg, Netherlands | 2008          | 27.5                     | 17.8                      |                    |
### Table 3. Varimax rotated factor loadings for PM$_{10}$ ambient dataset in Erods.

| Factor | 1 | 2 | 3 | 4 | 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 | –0.01 |
| 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 ($\mu$g/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 emission metal 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 | 2 | 3 | 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 ($\mu$g/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 combustion
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
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.

**ACKNOWLEDGEMENTS**

This Study is supported by National Major Program of Science and technology: 2008ZX07633-03-04; 2008ZX07208-001-01-03; and the Fundamental Research Funds for the Central Universities.
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.

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Received for review, April 15, 2011
Accepted, September 22, 2011