Assessment of Air Quality Monitoring Stations Locations Based on Satellite Observations

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Abstract

Optimal locations of air quality monitoring stations have great significance in providing high quality data for regional air pollution monitoring. To assess the rationalization of locations for current air quality monitoring stations, in this paper, we proposed a new method which was based on satellite observations data with the stratified sampling approach. Unlike the traditional method which relied on the spatial distribution of air pollutants from the simulated dispersion models, we obtained the sampling population through observations from remote sensing. Firstly, the spatial distribution of aggregated air quality was obtained based on ground concentrations of PM_{10}, $PM_{2.5}$, NO_2 and SO_2 derived from satellite observations. Secondly, rationalization of locations of air quality monitoring stations was assessed by using the method of stratified sampling. Results of paper indicated that combing remote sensing data with the stratified sampling approach have great potential in assessing rationalization of locations for air quality monitoring stations.

Key words: air quality, monitoring stations locations, assessment, remote sensing

1 Introduction

Optimal location of air quality monitoring stations is very important for both monitoring and protecting ambient air quality (Benis and Fatehifar 2015). The data observed by ambient air quality monitoring stations have not only widely applied in evaluating air quality, but also in some other areas such as studying the dynamic behavior of air pollutants, verifying dispersion models and assessing human heath impact caused by air pollution (Elkamel et al. 2008; Maji, Dikshit, and Deshpande

2014). Therefore, monitoring data with good quality is essential for these applications. But, the current distribution of air quality monitoring stations in China tended to be clustered in areas with poor air quality, such as in street canyons and city centers. As a result, the observations are spatially less representative, especially in areas with complex terrains and in the vicinity of pollution sources (Andrews, 2008; Rohde and Muller, 2015). In general, the coverage of the representative area is small, and the monitoring data is also under-represented. Therefore, re-assessing the locations for air quality monitoring stations in China has important implications in improving the quality of the monitoring data.

Assessing and optimizing locations for air quality monitoring stations are one of the most important and indispensable research topics in designing air monitoring networks. Principal component analysis, cluster analysis (Pires et al. 2008; Lu, He, and Dong 2011), geostatistical modeling (Haas 1992; Kanaroglou et al. 2005) and fuzzy set theory (Maji, Dikshit, and Deshpande 2014) were all applied to locating stations and evaluating the predictive error in previous researches. In addition, some economic and social factors, such as population density, land-use, and the city scale were all taken into account to determine the optimum number and location of monitoring stations in some multi-objective optimization approach (Sarigiannis and Saisana 2008; Pope and Wu 2014) and genetic algorithm (Tseng and Chang 2001; Wang et al. 2015). Some studies (Henne et al. 2010; Duyzer et al. 2015) focused on evaluating and comparing the effectiveness of parameters to describe the representativeness. While the others (Lu, He, and Dong 2011; Mofarrah and Husain 2010) put emphasis on the impact of multiple air pollutants when designing the monitoring network, and proposed some optimization methodology based on the distribution of particulate matter, sulfur dioxide and nitrogen dioxide.

Some gaps still exist among those approaches as described in above sections. The one of the most obvious is the difficulty in obtaining the overall regional air quality. The spatial distribution and concentration of air pollutants were mostly obtained from simulated air dispersion models in previous studies (Zheng et al. 2011; Duyzer et al. 2015), these models were constrained by physiochemical processes, changeable meteorological conditions, and the data quality of the sampling stations, therefore, may not be representative, especially in complex terrain areas (Hertel et al. 2001; Wang et al. 2015). It is difficult to evaluate the representativeness when the sampling population, i.e., overall regional air pollutants concentration, is not preferable. To this end, an approach to evaluate the rationalization of locations for air quality monitoring stations by using satellite observations data to estimate air quality has more advantages and was proposed in our research. First of all, the spatial distribution of air pollutants were derived from satellite-based data, this could provide a better spatial coverage. Satellite observation of surface air quality has evolved dramatically in recent years. Regional and global observations are now available for many air pollutants. And many retrieval methods and products have been developed, such as MODIS aerosols, GOME tropospheric NO_2 and SO_2 columns, SCIAMACHY CO columns (Martin, 2008). Use of satellite data could provide some information about location of peak concentrations, the concentration gradients among surface monitoring stations and the transport of air pollutants (Engel-Cox et al., 2004). Second, considering that overall air quality was not only determined by the dominant pollutant, but also determined by the second pollutant and some other pollutant, the Aggregate Air Quality Index (AAQI) (Kyrkilis, Chaloulakou, and Kassomenos 2007) was adopted to evaluate the aggregated effects of four kinds of air pollutants, i.e., PM_{10}, $PM_{2.5}$, NO_2, and SO_2. Finally, the stratified sampling method was used to evaluate the rationality of the spatial distribution of the air quality monitoring stations.

In this paper, using Beijng-Tianjin-Hebei area of China as the case area, locations of the air quality monitoring stations was assessed. This paper consists of four parts. In the first part, the spatial distribution of ground PM_{10}, $PM_{2.5}$, NO_2, and SO_2 were obtained from satellite observation data. In the second part, the comprehensive air quality was by assessed by using the AAQI. In the third part, using the AAQI value in study area as the sample frame, locations of air quality monitoring stations was further assessed with stratified sampling approach. In the last part, the accuracy of satellite observations data in estimating ground air pollutant concentrations was analyzed, and the advantages of using remote sensing data in assessing air quality monitoring stations locations were discussed.

2 Data and methods

2.1 Study area

Beijing-Tianjin-Hebei, notorious for its air quality, having high and frequent PM_{10}, $PM_{2.5}$, NO_2 and SO_2 pollutions, especially particulate matter (PM) pollutions (Xin et al. 2014), is located in northern China. Mountains, plateaus, basins and plains are all distributed in this area, therefore, making the terrain over this area very complex. And the government funding of air quality monitoring and protection is relatively independent in this area. To monitor air quality and to study the dynamic behavior of air pollutants, a network consisting of 169 air quality monitoring stations were constructed and distributed over this area in recent years. Although the functions and tasks of these stations are different, all of them have the ability to monitor the concentrations of PM_{10}, $PM_{2.5}$, NO_2 and SO_2. The location of Beijing-Tianjin-Hebei area and the distribution of these air quality monitoring stations are shown in Figure 1. It is clearly seen that air quality monitoring stations are mostly concentrated in city centers. The number of stations is much less in northern, northwestern mountainous regions, and southern rural regions.

[Figure 1 near here]

2.2 Data collection and processing

Satellite data

In this study, daily Level-2 OMI/Aura Near UV Aerosol Optical Depth (OMAERUV) products over the time period from 2009 to 2013 were used to estimate ground PM_{10} and $PM_{2.5}$ concentrations. The aerosol optical depth (AOD) products were generated by the OMAERUV algorithm with the spatial resolution of 0.125°×0.125°. These products showed an good quality by comparing to Aerosol Robotic Network (AERONET) observations, with correlation coefficient, slope and intercept in the range 0.79-0.92, 0.63-0.92, and 0.08-0.18, respectively (NASA 2012). Monthly average

AOD was calculated from the daily AOD products.

Monthly average Level-2 OMI tropospheric NO_2 columns, which were derived from satellite observations based on slant column retrievals with the differential optical absorption spectroscopy (DOAS) technique, were used to calculate ground NO_2 concentrations over the time period from 2009 to 2013 in study area. These data had a spatial resolution of 0.125°×0.125°, and the valid range varied from 0 to 20 (10^{15} molecule/cm^2). The fitting error in the NO_2 slant column was estimated to be 0.3-1x10^{15} cm^{-2} (NASA 2012; Celarier et al. 2011).

The ground SO_2 concentrations used in this study for the time period from 2009 to 2013 were derived from monthly Level 2 OMI SO_2 tropospheric columns data. They were derived with DOAS technique, had a spatial resolution of 0.125°×0.125°. The standard deviation was only 1.2DU-1.5 DU (NASA 2012; Yang et al. 2007), indicating that the derived SO_2 tropospheric columns were in good quality.

Ground level field Data

Ground measurement of PM_{10}, NO_2 and SO_2 concentrations from 2009 to 2013 in 11 cities of Beijing-Tianjin-Hebei were collected. These records in each city were from the air monitoring stations in both urban and suburban areas. And these data were recorded daily and published by the environmental protection bureau in these cities. Monthly data were obtained by averaging the daily air pollutants concentrations. Since $PM_{2.5}$ concentrations were not included in the air quality standard until February 2012 in China (MEPC and GAQSIQ 2012), ground measured $PM_{2.5}$ concentrations were only collected in 2013 in these cities.

2.3 Methodology

The aggregated air quality was assessed by using the aggregated air quality index. To do this, the spatial distribution of ground PM_{10}, $PM_{2.5}$, NO_2, SO_2 were firstly derived from satellite observations. Then locations of air quality monitoring stations were assessed by stratified sampling.

2.3.1 Assessing air quality by aggregated air quality index

Considering that traditional air quality index (AQI) is determined mostly by the main air pollutant, this type of index does not take fully into account the possible adverse effects associated with the coexistence of multi-pollutants (Kyrkilis, Chaloulakou, and Kassomenos 2007). Therefore, they could not reflect the overall air pollution level. In this paper, we adopted the aggregated air quality index (AAQI) based on the concentrations of four kinds of air pollutant to evaluate the combined effects of the multiple air pollutants. PM_{10}, $PM_{2.5}$, NO_2, SO_2 are the four main air pollutants in China, and are included in the air monitoring standard (MEPC and GAQSIQ, 2012), so these four kinds air pollutants are selected in this study when assessing the aggregated air quality in this study. The concentration of each air pollutant could be expressed as the ratio of the concentration to standard concentration (Kyrkilis, Chaloulakou, and Kassomenos 2007):

$$AAQI_i = AAQI_s(\frac{q}{q_s}) \tag{1}$$

Where $AAQI_i$ is the sub-index of the i-th air pollutant, $AAQI_s$ is the scaling coefficient, q is the measured concentration of the i-th air pollutant, which could be estimated from the remote sensing data. q_s is the standard concentration, which means the highest concentration that is harmless to human beings. Table 1 shows the standards of these four pollutants recommended by World Health Organization (WHO) (WHO 2006).

[Table 1 near here]

Then a power function model was adopted to describe the overall air quality index (Swamee and Tyagi, 1999):

$$AAQI = (\sum_{i=1}^{n}(AAQI_i)^{\rho})^{\frac{1}{\rho}} \tag{2}$$

Where $AAQI$ is the aggregated air quality index, ρ is a constant set to be 2.5 in this paper.

2.3.2 Estimating ground air pollutants from remote sensing data

AOD is the integration of the extinction coefficient along the vertical direction. The direct correlation between satellite-based AOD and the surface concentrations of particulate matter is usually relatively low. To connect AOD with ground concentrations of particulate matter, the relationship between AOD and surface aerosol extinction coefficient should be considered (Chu et al. 2013). In addition, due to impacts of the hydroscopic growth of aerosols, relative humidity (RH) should be taken into account to improve the accuracy when estimating surface PM_{10} and $PM_{2.5}$ concentrations from satellite observations. We adopted the method proposed by Lin et al. (2015) and Yu et al. (2016) to eliminate the impact of RH and aerosol scaling height in this study.

The main sources of NO_2 and SO_2 are emissions from fossil fuels combustion and biomass burning, therefore, NO_2 and SO_2 in the air are mainly distributed below the planetary boundary layer (PBL), and columns above the top of PBL could be ignored (Boersma et al 2008). Therefore, we could assume that mixing volume ratios of NO_2 and SO_2 are consistent from the ground-level to the top of mixing layer, and the concentrations are zero above the height of mixing level (Boersma et al 2009). In this study, we adopted the method proposed by Yu et al. (2016) to estimate the surface concentrations of NO_2 and SO_2.

2.3.3 Assessing air monitoring locations by stratified sampling

Stratified sampling is the most suitable method when the data population shows gradient features, such as the air quality in study area, which contains large spatial variability and hierarchical characteristics due to the complex terrains. Therefore, stratified sampling approach was adopted to study the location and representativeness of the air quality monitoring stations.

AAQI value based on the satellite-derived concentrations of four types of air pollutant was regarded as the sampling frame. The cumulative square root method was used to stratify the population. This method was introduced as a fast method to determine the optimal stratum boundaries by Dalenius and Hodges (1959). The auxiliary variable x, which represented AAQI value in each grid, was arranged in ascending order. Then $f(x)$, which was the frequency of x was calculated. The method was to form the cumulative of $\sqrt{f(x)}$ and chose the stratified point x_h which divided the summation by the number of strata equally.

Neyman allocation was then employed to determine the value of sample sizes n_h in respective stratum. If the relative error limit r was given under a given confidence level of $1-\alpha$, the total sample size could be determined. If we defined N as the total number of units, $\bar{Y}$ as the population mean, W_h as the stratum weight, S_h^2 as the population variance of stratum h, then the estimator of total sample size could be expressed as follows:

$$n = \frac{(\sum W_h S_h)^2}{\frac{(r\bar{Y})^2}{(u_{\alpha/2})^2}+\frac{1}{N}\sum W_h S_h^2} \tag{3}$$

The sample sizes in stratum h could then be calculated as:

$$n_h = n\frac{W_h S_h}{\sum W_h S_h} \tag{4}$$

After the sample size within each stratum was determined, a simple random sample was taken in each stratum independently. Then the estimator of the statistical population could be formulated as below:

$$\hat{X} = \mathrm{N}\bar{x}_{st} = \sum_{h=1}^{L} N_h \bar{x}_h \tag{5}$$

where $\bar{x}_h = \sum_{i=1}^{n_h} x_{hi}$. According to the characteristics of Neyman allocation, this variance was defined as a minimum variance.

$$v_{min}(\hat{X}) = N^2\left(\frac{1}{n}\left(\sum_{h=1}^{L} W_h s_h\right)^2 - \frac{1}{N}\sum_{h=1}^{L} W_h s_h^2\right) \tag{6}$$

Although the whole process of stratified sampling is based on statistical basis, the strata have some physical meaning. Specially, the first stratum is related to areas with the minimum AAQI, where the quality is the best. While the last stratum is related to areas with the maximum AAQI, where the air pollution is most serious.

3 Results

3.1 Distribution of air pollutants

In general, air pollution is mainly concentrated in southern and southeastern areas in Beijing-Tianjin-Hebei area, as shown in Figure 2. It is seen that air pollution in cities is heavier than those in suburbs, rural areas and mountain areas as a result of the emissions from the heavy industry and the large number of vehicles. More specifically, the highest PM concentrations, with the average concentration of PM_{10} higher than 120 μg/m^3 and the average concentration of $PM_{2.5}$ higher than 85μg/m^3, are located at Beijing, Tianjin, Shijiazhuang and Handan. Since the main sources of troposphere NO_2 and SO_2 are emissions from fossil fuels combustion, biomass burning and the vehicle exhaust emissions (Liang et al. 1998), the most heavy NO_2 and SO_2 pollution concentrate over heavy industry cities in the southern and southeastern cities, such as Handan, Xingtai and Shijiazhuang, with the average concentration of NO_2 from 2009 to 2013 is about 65 μg/m^3, and the average concentration of SO_2 is about 50 μg/m^3. It is worth noting that PM_{10}, $PM_{2.5}$ and NO_2 pollution are all very serious in Beijing, but SO_2 pollution is much more less. This is due to the heavy industry, which is the main source of SO_2 pollution, had moved out of Beijing since the Olympic Games in 2008. In northern and northwestern areas, there is less air pollution, benefited from high forest coverage rate and less heavy industry and vehicles. In this region, concentrations of PM_{10}, $PM_{2.5}$, NO_2 and SO_2 are less than 50 μg/m^3, 35 μg/m^3, 20 μg/m^3 and 15 μg/m^3, respectively.

[Figure 2 near here]

3.2 Validation of satellite derived air pollutant concentrations

The uncertainties of the satellite-derived air pollutant concentrations lead to the uncertainties of AAQI. To estimate the accuracy of the satellite derived air pollutant concentrations, we compared the satellite derived air pollutant concentrations with the ground measured concentrations, as shown in Figure 3. In general, a good linear relationship exists between the satellite derived air pollutant concentrations and the ground measured concentrations. Coefficient of determination between surface measurement PM_{10}, $PM_{2.5}$, NO_2, SO_2 concentrations and corresponding satellite derived concentrations can be as high as 0.68, 0.66, 0.72 and 0.72, respectively. While root mean square error (RMSE) is about 20.33, 16.45, 7.94 and 10.91, respectively. According to equation (2), corresponding transferred bias for AAQI was less than 13. The small bias of satellite derived air pollutions and AAQI demonstrate that estimating ground air pollutant concentrations using satellite observations data is reliable.

[Figure 3 near here]

3.3 Distribution of aggregated air quality index

According to equation (2), we obtained the spatial distribution of AAQI in Beijing-Tianjin-Hebei area, shown in Figure 4. Since the PM_{10} and $PM_{2.5}$ pollution is very heavy, the spatial distribution of AAQI is just like the distribution of PM_{10} and $PM_{2.5}$ generally. High AAQI value is mainly located in the southern and southeastern cities, while low AAQI value is concentrated in the northern mountainous areas. AAQI value in all cities, except for Zhangjiakou, Chengde and Qinhuangdao in the northern areas, are higher than 100, indicating a serious threat and great risk to the life of the citizen. Especially, Beijing, Tianjin and Handan, with the highest PM_{10}, $PM_{2.5}$ and NO_2 concentrations, AAQI value can be as high as 220. Followed by Xingtai, Hengshui, Cangzhou, Tangshan and Baoding, which all are cities with heavy industry with AAQI value about 170. Chengde, Zhangjiakou and Qinhuangdao, AAQI is less than 80, which means the air quality is good and suitable to live.

[Figure 4 near here]

3.4 Assessment of air quality monitoring stations locations

AAQI value based on satellite-derived concentrations of four type of air pollutant was regarded as the sampling frame. According to the sampling approach proposed in section 2.3.3, we compared the existing air quality monitoring stations number with the sample size in stratified sampling, as shown in Table 2. In most cases, the existing air quality monitoring stations numbers are less than the sample numbers in stratified sampling in the first and second stratum. While the first and second stratum represents the areas with good air quality. It is indicated that the number of air quality monitoring stations is insufficient in areas with good air quality, such as Zhangjiakou, Chengde and Qinhuangdao in study area. The existing air quality monitoring stations numbers are much more than the needed sample numbers in stratified sampling in the last stratum. The last stratum represents the areas with heavily polluted air. It is clear that the number of air quality monitoring stations is too much in areas with bad air quality.

[Figure 5 near here]

[Table 2 near here]

Based on the above studies, the optimized locations of air quality monitoring stations were given, shown in Figure 5. It is clear that the existing air quality monitoring stations are mostly located in the inner of cities, such as Beijing, Tianjin and Shijiazhuang, while in the suburb areas, northern mountainous areas, number of air quality monitoring stations is too few to be representative. Table 3 demonstrates the precision of optimization for air monitoring stations locations. With the increasing of the stratum, the minimum variance and relative error (RE) is decreasing, demonstrating that representativeness of the air monitoring stations is increasing. When stratum number is 6, air quality in study area could be calculated with the minimum variance and RE from optimized air monitoring stations. When stratum number is 5, RE is only 6.77%, and the minimum variance is only 1420.20. At this time, just 16 stations need to be set except existing stations. And the air quality in study area could be estimated with small RE. As the difference of air pollutants concentrations is small in a pixel, the monitoring stations could be set at anywhere in the pixel.

[Table 3 near here]

4 Discussion

4.1 Advantages of using remote sensing data in assessing air quality monitoring stations locations

Some advantages exist when assessing locations of air quality monitoring stations using satellite observations data. To compare the method proposed in this paper with the method which relied on the simulated air dispersion models to obtain the data population, we optimized the locations of air quality monitoring stations by applying the method of fuzzy set theory (Maji, Dikshit, and Deshpande 2014). Then we compared the optimal locations of air quality monitoring stations between using this method and the method proposed in our paper. The results are given in Figure 6. It is clearly shown that the number of proposed stations is larger in northern areas with good air quality based on method proposed in this paper. In addition, method proposed in our research suggested some stations located in southeastern areas, while no stations are given from fuzzy set theory. The total number of proposed stations by fuzzy set theory is 61, while the number of proposed stations by our research is only 40. The relative error of the optimized stations based on fuzzy set theory is about 15.52%, much large than the relative errors 7.65% in this paper.

[Figure 6 near here]

In this paper, sampling population with high precision was obtained by using concentrations of air pollutants derived from satellite observations. As the population, i.e., the overall air quality of the region, was not easy to obtain, it is a difficult thing to assess the representativeness of data from air quality monitoring stations. Compared with methods relied on simulated air dispersion models to obtain the data population (Mofarrah and Husain 2010; Zheng et al. 2011), which were constrained by changeable meteorological conditions and terrains, especially in mountainous areas, the method proposed in our research has great advantage in obtaining the spatial distribution of the air pollutants. Air pollutant concentrations derived from satellite observations data provided better spatial coverage, therefore, overcame the shortcoming of the dispersion models. Above all, some simulated air dispersion models depended on samplings of air pollutants concentration, locations of these samplings, i.e., the air quality monitoring stations, had influence on the accuracy of the dispersion models.

4.2 Future work

The method proposed by our study may has great potential in assessing and optimizing air monitoring networks with the development of remote sensing. In the future, some aspects of this research still need to be improved. First of all, images with high spatial resolution will be used in the future, which could help improve the accuracy of locations of the optimized air quality monitoring stations. Second, the location of monitoring stations is a complex and exact matter. Some other considerations may be also taken into account in future work when using statistical methods, for example land-use, epidemiology and city planning.

5 Conclusions

In this study, concentrations of ground PM_{10}, $PM_{2.5}$, NO_2 and SO_2 were firstly derived from satellite observations over Beijing-Tianjin-Hebei area of China. The aggregated air quality was represented by using AAQI with the concentrations of four main pollutants. The spatial distribution of air quality monitoring stations was then assessed and optimized using the method of stratified sampling. Finally, the accuracy of satellite derived air pollutant concentrations was discussed, and the advantages of remote sensing in evaluating rationalization of air quality monitoring stations locations were analyzed. Results of this paper demonstrated that air quality monitoring stations were clustered in areas with heavily polluted air, while the number of air quality monitoring stations was insufficient in areas with good air quality. After optimization, the minimum relative error was only 6.77% and the minimum variance was only 1420.20. Compared with previous studies, the improvements in our study are shown in two aspects. First, overall ground air quality was evaluated based on the air pollutant concentrations derived from satellite observations, which has the advantages of large spatial coverage. Therefore, the accuracy of sampling population was higher compared with the dispersion models which were constrained by meteorological conditions and terrains. Second, the spatial distribution of air quality monitoring stations was optimized using the method of stratified sampling. And, the representativeness of the stations was evaluated according to sampling results.

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References

Benis, K. Z., and E. Fatehifar. 2015. "Optimal design of air quality monitoring network around an oil refinery plant: a holistic approach." *International Journal of Environmental Science and Technology* 12(4):1331-1342.

Boersma, K. F., D. J. Jacob, E. J. Bucsela , A. E. Perring , R. Dirksen , R. J. Van Der A, R.M.Yantosca, R.J.Park, M.O.Wenig, T.H.Bertram, and R.C.Cohen. 2008. "Validation of OMI tropospheric NO_2 observations during INTEX-B and application to constrain NO_x emissions over the eastern United States and Mexico." *Atmospheric Environment* 42(19):4480-4497.

Boersma, K. F., D. J. Jacob, M. Trainic, Y. Rudich, I. DeSmedt, R. Dirksen, and H. J. Eskes. 2009. "Validation of urban NO_2 concentrations and their diurnal and seasonal variations observed from the SCIAMACHY and OMI sensors using in situ surface measurements in Israeli cities." *Atmospheric Chemistry and Physics* 9(12):3867-3879.

Celarier, E.A., L. Lamsal, N.A. Krotkov , E.J. Bucsela, J.R. Herman, R.R. Dickerson,

Chu, D. A., T. C. Tsai, J. P. Chen, S. C. Chang, Y. J. Jeng, W. L. Chiang, and N. H. Lin. 2013. "Interpreting aerosol lidar profiles to better estimate surface $PM_{2.5}$ for columnar AOD measurements." *Atmospheric Environment* 79:172-187.

Dalenius, T., and J. L. Hodges Jr. 1959. "Minimum variance stratification". *Journal of the American Statistical Association* 54(285):88-101.

Duyzer, J., D. van den Hout, P. Zandveld, and S. van Ratingen. 2015. "Representativeness of air quality monitoring networks." *Atmospheric Environment* 104:88-101.

Elkamel, A., E. Fatehifar, M. Taheri, M. S. Al-Rashidi, and A. Lohi. 2008. "A heuristic optimization approach for Air Quality Monitoring Network design with the simultaneous consideration of multiple pollutants." *Journal of Environmental Management* 88(3):507-516.

Engel-Cox, J. A., Hoff, R. M., & Haymet, A. D. J. 2004. "Recommendations on the use of satellite remote-sensing data for urban air quality." *Journal of the Air & Waste Management Association* 54(11):1360-1371.

H. He, L. C. Brent, C. Retscher, W. H. Swartz, and J. F. Gleason. 2011. "Evaluation of improved operational standard tropospheric NO_2 retrievals from Ozone Monitoring Instrument using in situ and surface-based NO_2 observations." In AGU Fall Meet. Abstr 1:0360.

Haas, T. C. 1992. "Redesigning continental-scale monitoring networks." *Atmospheric Environment* 26A(18):3323-3333.

Henne, S., D. Brunner, D. Folini, S. Solberg, J. Klausen, and B. Buchmann. 2010. "Assessment of parameters describing representativeness of air quality in-situ measurement sites." *Atmospheric Chemistry and Physics* 10(8):3561-3581.

Hertel, O., F. A. De Leeuw, S. S. Jensen, D. Gee, O. Herbarth, S. Pryor, F. Palmgren, and E. Olsen. 2001. "Human exposure to outdoor air pollution (IUPAC technical report)." *Pure and Applied Chemistry* 73(6):933-958.

Joly, M., and V. H. Peuch. 2012. "Objective classification of air quality monitoring sites over Europe." *Atmospheric Environment* 47:111-123.

Kanaroglou, P. S., M. Jerrett, J. Morrison, B. Beckerman, M. A. Arain, N. L. Gilbert, and J. R. Brook. 2005. "Establishing an air pollution monitoring network for intra-urban population exposure assessment: A location-allocation approach." *Atmospheric Environment* 39(13):2399-2409.

Kyrkilis, G., A. Chaloulakou, and P. A. Kassomenos. 2007. "Development of an aggregate Air Quality Index for an urban Mediterranean agglomeration: Relation to potential health effects." *Environment International* 33(5):670-676.

Liang, J., L. W. Horowitz, D. J. Jacob, Y. Wang, A. M. Fiore, J. A. Logan, G. M. Gardner, and J. W. Munger. 1998. "Seasonal budgets of reactive nitrogen species and ozone over the United States, and export fluxes to the global atmosphere." *Journal of Geophysical Research: Atmospheres (1984–2012)*103(D11):13435-13450.

Lin, C., Y. Li, Z. Yuan, A. K. Lau, C. Li, and J. C. Fung. 2015. "Using satellite remote sensing data to estimate the high-resolution distribution of ground-level $PM_{2.5}$." *Remote Sensing of Environment* 156:117-128.

Lu, W. Z., H. D. He, and L. Y. Dong. 2011. "Performance assessment of air quality monitoring networks using principal component analysis and cluster analysis." *Building and Environment* 46(3): 577-583.

Maji, K. J., A. K. Dikshit, and A. Deshpande. 2014. "Can fuzzy set theory bring complex issues in sizing air quality monitoring network into focus?." *International Journal of System Assurance Engineering and Management* :1-11.

Martin, R. V. 2008. "Satellite remote sensing of surface air quality." *Atmospheric Environment* 42(34): 7823-7843.MEPC and GAQSIQ (Ministry of Environmental Protection of the People's Republic of China, General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China). *Ambient air quality standards*. Beijing: China Environmental Science Press.

Mofarrah, A., and & T. Husain. 2010. "A holistic approach for optimal design of air quality monitoring network expansion in an urban area." *Atmospheric Environment* 44(3):432-440.

NASA (National Aeronautics and Space Administration). 2012. *Ozone Monitoring Instrument (OMI) Data User's Guide*. Washington DC: NASA.

Pires, J. C. M., S. I. V. Sousa, M. C. Pereira, M. C. M. Alvim-Ferraz, and F. G. Martins. 2008. "Management of air quality monitoring using principal component and cluster analysis-Part I: SO_2 and PM_{10}." *Atmospheric Environment* 42(6):1249-1260.

Pope, R., and J. Wu. 2014. "A multi-objective assessment of an air quality monitoring network using environmental, economic, and social indicators and GIS-based models." *Journal of the Air & Waste Management Association* 64(6):721-737.

Sarigiannis, D. A., and M. Saisana. 2008. "Multi-objective optimization of air quality monitoring." *Environmental Monitoring and Assessment* 136(1-3):87-99.

Swamee, P. K., and A. Tyagi. 1999. "Formation of an air pollution index." *Journal of the Air & Waste Management Association* 49(1): 88-91.

Tseng, C. C., and N. B. Chang. 2001. "Assessing relocation strategies of urban air quality monitoring stations by GA-based compromise programming." *Environment International* 26(7):523-541.

Wang, K., H. Zhao, Y. Ding, T. Li, L. Hou, and F. Sun. 2015. "Optimization of air pollutant monitoring stations with constraints using genetic algorithm." *Journal of High Speed Networks* 21(2):141-153.

Wang, W., T. Yu, P. Ciren, and P. Jiang. 2015. "Assessment of human health impact from PM_{10} exposure in China based on satellite observations." *Journal of Applied Remote Sensing* 9(1): 096027-096027.

WHO (World Health Organization). 2006. *Air quality guidelines: global update 2005: particulate matter, ozone, nitrogen dioxide, and sulfur dioxide.* Geneva: World Health Organization.

Xin, J., Q. Zhang, L. Wang, C. Gong, Y. Wang, Z. Liu, and W. Gao. 2014. "The empirical relationship between the $PM_{2.5}$ concentration and aerosol optical depth over the background of North China from 2009 to 2011." *Atmospheric Research* 138:179-188.

Yang, K., N. A. Krotkov, A. J. Krueger, S. A. Carn, P. K. Bhartia, and P. F. Levelt. 2007. "Retrieval of large volcanic SO_2 columns from the Aura Ozone Monitoring Instrument: Comparison and limitations." *Journal of Geophysical Research: Atmospheres* 112: D24S43.

Yu, T., W. Wang, P. Ciren, and Y. Zhu. 2016. "Assessment of human health impact from exposure to multiple air pollutants in China based on satellite observations." *International Journal of Applied Earth Observation and Geoinformation* 52:542-553.

Zheng, J., X. Feng, P. Liu, L. Zhong, and S. Lai. 2011. "Site location optimization of regional air quality monitoring network in China: methodology and case study." *Journal of Environmental Monitoring* 13(11):3185-3195.

Tables with captions

Table 1 Annual air pollutants concentrations recommended by WHO

	PM_{10}(μg/m^3)	$PM_{2.5}$(μg/m^3)	NO_2(μg/m^3)	SO_2(μg/m^3)
Annual average concentration	20	10	40	20

Table 2 Comparison of existing air quality monitoring stations numbers and sample numbers in stratified sampling

Stratum Number	existing number/ number in the 1st stratum	existing number/ number in the 2nd stratum	existing number/ number in the 3rd stratum	existing number/ number in the 4th stratum	existing number/ number in the 5th stratum	existing number/ number in the 6th stratum
3	9/17	42/13	67/10	-	-	-
4	10/45	16/25	43/29	49/26	-	-
5	3/40	15/41	16/28	44/38	40/27	-
6	3/52	9/40	15/22	29/47	32/27	30/14

Table 3 Accuracy of optimization for air quality monitoring stations locations

Stratum number	Sample size	Estimator of population	Minimum variance	Relative error
3	41	134.32	1721.33	9.71%
4	125	131.80	1493.83	7.65%
5	185	130.72	1420.20	6.77%
6	210	129.35	1229.46	5.65%

Figure captions

Figure 1 Distribution of the existing air quality monitoring stations in Beijing-Tianjin-Hebei area

Figure 2 Distribution of air pollutants in Beijing-Tianjin-Hebei area

Figure 3 Comparison of ground measured air pollutants concentrations and satellite derived air pollutants concentrations

Figure 4 Distribution of AAQI in Beijing-Tianjin-Hebei area

Figure 5 Locations of the existing and proposed air quality monitoring stations (a: stratum number is 3; b: stratum number is 4; c: stratum number is 5; d: stratum number is 6)

Figure 6 Comparison of locations of air quality monitoring stations (a: locations of stations based on remote sensing; b: locations of stations based on fuzzy set theory)