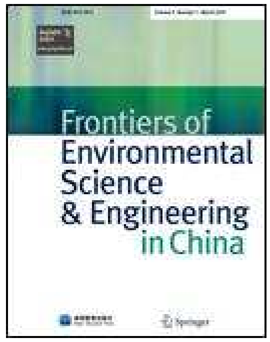

Estimating the effects of meteorology on PM2.5 reduction during the 2008 Summer Olympic Games in Beijing

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Keywords:	meteorology, emission control measures, Beijing Olympic Games, PM2.5, linear statistical models

Estimating the effects of meteorology on $PM_{2.5}$ reduction during the 2008 Summer Olympic Games in Beijing

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Abstract Particulate pollution was a critical challenge to the promise of good air quality during the 2008 Beijing Olympic Games, which took place from the Aug 8 to Aug 24. To ensure good air quality for the Games, several temporary emission control measures were implemented in Beijing and surrounding areas. Ambient PM concentration decreased significantly during the Olympic period; however, it is difficult to distinguish the effectiveness of those control measures since meteorology also affects ambient $PM_{2.5}$ concentration. In this work, a multiple linear regression analysis was conducted to evaluate the effects of meteorology and emission control measures on the reduction of $PM_{2.5}$ during the 2008 Olympic Games. The response variable is $PM_{2.5}$ and the meteorology covariates used in the model were hourly temperature, dew point temperature, wind speed and precipitation. The hourly data set was divided into two time periods, the no control period, Jun 22 to Jul 4, and the control period, Jul 28 to Aug 21. Using the meteorologically-based regression coefficients from the two time periods, meteorology was found to contribute for at least 17.9% on the reduction of $PM_{2.5}$ in the roadside microenvironment; while the pollution control measures contributed for at least 42.1%.

Keywords: meteorology, emission control measures, Beijing Olympic Games, $PM_{2.5}$, linear statistical models

1 Introduction

Particulate matter has been a major air quality concern in Beijing for several decades. The annual average concentration of PM_{10} was first reported in the "Beijing Environmental Bulletin 1999" as 180 μg/m^3, which exceeded the second standard of the National Ambient Air Quality Standards (NAAQS) pertaining to urban areas (100 μg/m^3) by 80%. In order to insure better air quality, the Beijing Municipal Government has implemented numerous pollution control measures since 2000. The annual average PM_{10} concentration decreased to 148 μg/m^3 in 2007; however, it was still a challenge to fulfill the promise of a "Green Olympic Games". To ensure good air quality during the Olympic Games and the Paralympic Games, temporary emission control measures were implemented in both Beijing and the surrounding areas. In neighboring Tianjin municipality, Hebei, Shanxi, Shandong provinces, and the Inner Mongolia Autonomous Region, polluting factories were closed and high-emission vehicles were removed from the roads. Source control measures in Beijing included closing pollution emitting factories, slowing down construction activities and temporary traffic control measures [1]. The temporary traffic control measures, which were implemented in order to reduce congestion and improve air quality, included: (1) Private vehicles could only operate on odd or even days depending on the parity of the last digit on their license plate; (2) 70% of government vehicles were ordered off the road; (3) Trucks could only operate inside the 6th Ring Road between midnight and 6 am unless they were issued special passes; and (4) All high emitting vehicles with a yellow environmental label were banned from the roads throughout Beijing [2].

Significant reductions in PM concentration during the Olympic Games were reported by the Beijing Environmental Protection Bureau. This reduction has been documented by a number of field monitoring projects [3-6]. Daily emissions of PM_{10} during the Aug 2008 Olympics were reported to be 55% lower than during Jun 2008 [1]. The emission of PM_{10} by urban traffic during the Olympics was found to have decreased by 52% compared to the grid-based emission inventory before the Olympics [5]. The road dust-fall was reported to have declined by 65%, 55%, 65% and 84%, respectively, for freeways, major arterial, minor arterial and collector roads from Aug 2007 to Aug 2008 [7]. However, it is difficult to assess the effectiveness of the emission control measures directly from the reduction in PM concentration and emission inventories since both the control measures and meteorology affected the air quality observed during the Games. For example, the combination of precipitation and strong winds can change the air quality in Beijing very quickly. Therefore, the assessment of the effectiveness of control measures requires that we adjust for the effects of meteorology on the air quality in Beijing. The role of meteorology on the reduction of PM concentration has been the focus of a number of recent papers [4, 8-11].

The aim of this paper is to provide a scientific assessment of the effects of the mandated air quality control measures on the reduction of roadside $PM_{2.5}$. Hourly observed data collected near the 4th Ring Road were analyzed using multiple linear regressions. By adjusting for meteorological conditions, we can gain a better understanding of the effectiveness of the control measures which will help us explore the long-term mechanisms needed to achieve lasting air quality improvement in Beijing.

2 Materials and methods

2.1 Monitoring site

The Municipality of Beijing, which is located on the Northeast China Plain (39.54N 116.23E), is the capital of the People's Republic of China. Beijing covers an area of 16,800 km^2, with a resident population of 17.6 million and more than 3.8 million vehicles by the end of 2009. The city is surrounded by the Yanshan Mountains in the north, Taihang Mountain in the west (~1000 m above sea level) and flat plains (20-60 m above sea level) to the south and east. The climate of the city is classified as a warm, semi-humid continental monsoon type climate, with prevailing north winds in winter and prevailing south winds in summer.

The air quality measurements were made at the curbside of the 4th Ring Road, an eight-lane highway in the urban area of Beijing. The monitoring site was located on the south side of the road (39.99N, 116.35E), with a six-story building 20 m away to the south and a bus stop 100 m away to the west. The bus stop was only used by public city buses, most of which use liquefied petroleum gas and natural gas. Daily traffic counts taken in Jun 2008 were approximately 240,000 vehicles on weekdays and 160,000 vehicles on weekends. Light-duty vehicles (LDVs), which includes cars, vans, buses and light-duty trucks contributed more than 98.5% of the daytime traffic count (07:00 a.m. ~ 20:00 p.m.); while the fraction of heavy-duty trucks (HDTs), most of which were diesel vehicles, increased from 1.4 % in the daytime to 3.9% at night (about 1600 vehicles during the period 21:00 p.m. to 07:00 a.m.). A satellite map of the monitoring site and the surroundings is shown in Fig. 1.

(a) Location of monitoring site (b) Surrounding of monitoring site

Fig. 1 Location and surroundings of the monitoring site and meteorology site

As mentioned above, temporary traffic control measures were implemented in Jul 2008 and lasted until Sep 2008. These temporary traffic control measures resulted in a significant change in the pattern of traffic in Beijing. The daily traffic counts measured in Aug 2008 were less than 190,000 vehicles on weekdays, with a decrease of approximately 21% compared to those in Jun 2008. It should be noted that heavy duty vehicles, which are normally on the road at night, decreased by 66%. This resulted in a further reduction in emissions from diesel engines compared with gasoline engines.

2.2 Data acquisition

Measurements were conducted during two time periods in 2008: Jun 22-Jul 4 (no control period) and Jul 28-Aug 21 (control period). There are totally 818 hourly observations spreading over 38 days. Data are divided into two sets: one for the control period and one for the no control period. The mean meteorological parameters and $PM_{2.5}$ mass concentrations observed during the two periods are given in Table 1.

Table 1 Characteristic meteorology data and $PM_{2.5}$ concentration in no control and control periods

Sampling Period	n*	Temperature (°C)	Wind Speed (m/s)	Relative Humidity (%)	$PM_{2.5}$ ($\mu g/m^3$)
Jun 22 23:00 ~ Jul 4 08:00	274	24.05±3.36	0.52±0.44	76.71±12.44	76.0±32.2
Jul 28 12:00 ~ Jul 31 14:00 Aug 1 10:00~Aug 3 22:00 Aug 4 09:00~ Aug 21 08:00	544	26.09±3.52	1.00±0.68	65.80±15.91	40.3±32.9

* Number of monitoring hours.

Meteorological data were taken about 200 m to the north-northeast of the monitoring site. The instruments were located on the top of a five-story building located across the North 4th Ring Road. An Automatic Weather Station (Vantage Pro2^{TM}, Davis Instruments) was used to collect 10-minute averaged data for ambient temperature, relative humidity, rainfall, wind speed and the dominant wind direction. There were no trees, buildings or other obstructions that were close enough to disturb the measurements at that height. Fig. 2 shows the meteorology observations for both the no control period and the control period. The dew point temperature, which indicates the actual amount of water vapor in the atmosphere, is calculated based on the temperature and relative humidity [12].

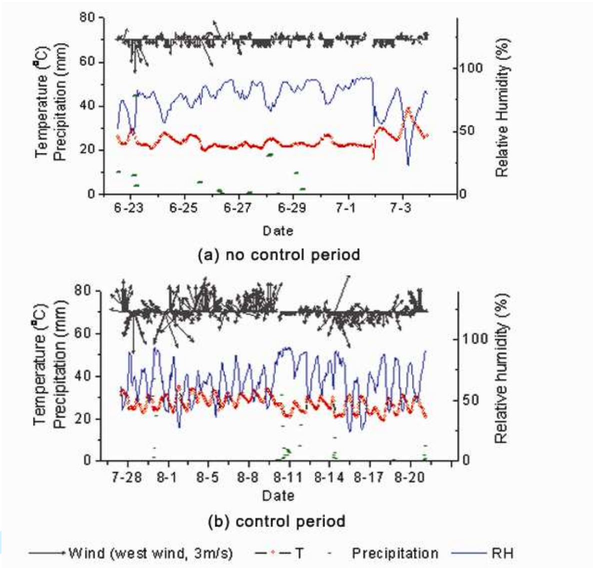

Fig. 2 Hourly averaged meteorological data collected during the no control and control periods

The continuous mass concentration of $PM_{2.5}$ was acquired using a DustTrak Aerosol Monitor (DustTrak 8520, TSI Inc.), and then calibrated by the readings from Tapered Element Oscillating Microbalances (TEOM 1400a, R&P Corp.). Those two instruments were placed within 2 m of the curb; and the sampling inlets were 2.5 m above the ground level. Readings from the DustTrak and TEOM were logged every 10 minutes and averaged over 1 hour. Based on the particle light scattering principle, the DustTrak monitor generates a relative value that usually overestimates the mass concentration of particulate matter [13]. However, once recalibrated, it demonstrates excellent functionality in terms of real-time data acquisition [14, 15]. In this study, the DustTrak readings were recalibrated by TEOM measurements. Good correlations were found between the DustTrak and the TEOM for both the no control and control periods (R^2=0.84 and R^2=0.87, respectively). Details of the calibration procedures used for the $PM_{2.5}$ mass concentration measurements are given in our recent paper [6].

2.3 Statistical analysis procedures

2.3.1 Basic linear model techniques

The basic multiple regression equation is given by:

$$Y_i = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i} + \varepsilon_i \qquad \text{for i=1,…,n} \tag{1}$$

In matrix form this becomes:

$$Y = X\beta + \varepsilon \tag{2}$$

where *Y* is the response variable vector. *X* is the design matrix of covariates, which are the meteorological variables in this case plus sine and cosine terms for the daily and weekly cycles [16]. β is a vector of regression coefficients. ε is a random error term with the mean zero and variance σ^2. Under standard assumptions (the Gauss-Markov model), the ε_i and ε_j are independent, so their covariance is zero (i.e., $\sigma(\varepsilon_i, \varepsilon_j) = 0$ for all $i, j; i \neq j; i = 1,\ldots n)$. $\hat{\beta}$ is an unbiased estimator of β. The covariance matrix for $\hat{\beta}$ is given by $\mathrm{cov}(\hat{\beta}) = \sigma^2 (X'X)^{-1}$ provided the conditions placed on the random error term above are valid. More will be said about this below.

The full expression for the covariance of $\hat{\beta}$ is given by:

$$\mathrm{cov}(\hat{\beta}) = (X'X)^{-1} X' \mathrm{cov}(Y) X (X'X)^{-1} \quad (3)$$

If $\mathrm{cov}(Y) = \sigma^2 I$, then the Gauss-Markov assumptions are met, and the expression simplifies to $\mathrm{cov}(\hat{\beta}) = \sigma^2 (X'X)^{-1}$ as indicated above. In our case, the basic model is not applicable because of the presence of temporal correlation, which is typical of time series regression data. The vector of estimated means of the response variable Y for the values of the covariates in the data set is found from $\hat{Y} = X\hat{\beta}$.

The residuals (e) indicate the lack of agreement between the observed Y and the estimated $\hat{Y}$ and are given by $Y - \hat{Y} = e$. These residuals show strong autocorrelation. Unfortunately, $\mathrm{cov}(Y) = \sigma^2 I$ does not hold when working with time series data in the regression setting because of aforementioned autocorrelation. In this case we must use $\mathrm{cov}(Y) = \sigma^2 V$, where $V = 1/(1-\rho^2)(\rho\ matrix)$. The ρ matrix is given by:

$$\rho \quad matrix = \begin{bmatrix} 1 & \rho & \cdots & \rho^{n-1} \\ \rho & 1 & \cdots & \rho^{n-2} \\ \cdots & \rho & 1 & \cdots \\ \rho^{n-1} \cdots & & \rho & 1 \end{bmatrix} \quad (4)$$

σ^2 and ρ are estimated based on the variance of the residuals from the regression of e_i on e_{i-1}. The estimate of ρ, the autocorrelation parameter, is based on an AR (1) structure and obtained from:

$$\rho = \sum e_i e_{i-1} / \sum e_i^2 \quad (5)$$

2.3.2 Collinearity

The initial model contained two terms related to water vapor in the atmosphere, relative humidity and dew point temperature. Unfortunately, there is the potential for significant collinearity when both terms are in the model. We calculated the variance inflation factor and square root of the ratio of the largest eigenvalue to the smallest eigenvalue derived from the singular value decomposition of the design matrix [17]. Both indicated the presence of significant collinearity when both relative humidity and the dew point temperature are retained in the model. The largest values for both collinearity measures were obtained for the relative humidity. Thus only the dew point was retained with the added benefit of its direct relationship to the actual amount of water vapor in the atmosphere. However, the basic model was also analyzed using relative humidity in place of the dew point temperature. Similar results were obtained for the relative humidity model.

2.3.3 Application of the fundamental equations

Equation (2) was applied to assess the effects of the air quality control measures instituted by the Beijing government during the 2008 Olympic Games. Since meteorology is also a factor in determining air quality, we have adjusted for meteorology by including only these variables in our basic model. We have considered two time periods; the no control time period and the period when controls were in effect (see Table 1). The response variable is $PM_{2.5}$ (μg/m^3); the covariates are temperature (°C), dew point temperature (°C), wind speed (m/s) and precipitation (mm). The u and v wind components were also available, but based on the t-statistic were not as good as wind speed alone as a predictor. In addition we have two sin/cos harmonics which help capture the intra-day variability and three sin/cos harmonics which help capture the day to day variability. The equations for the two time periods have the form like equation (1). The response variable is the vector Y, the $PM_{2.5}$ data, and the design matrix is given by *X = (1, T, Td, ws, precip, sind1, sind2, cosd1, cosd2, sinw1, sinw2, sinw3, cosw1, cosw2, cosw3),* where *T* is temperature, *Td* is the dew point, *ws* is wind speed and *precip* is the rainfall. The first four *sin/cos* terms are for the first two harmonics of the diurnal cycle, while the remaining *sin/cos* terms are for first three harmonics of the weekly cycle. No additional harmonics can be added to either the diurnal cycle or the weekly cycle without causing aliasing problems. The sine and cosine functions are in the model to help reduce the effects of autocorrelation. The basic equation above was used for both the no control period and the control period. All calculations were done using the statistical language "R" (http://www.r-project.org/).

2.3.4 A two equation approach to the model development

The hourly data set was divided into observations taken during the period before controls were put into effect (no control period) and those that were taken during the time when controls were in effect (control period). Separate equations were used for each time period, which allows us to fit a separate linear relationship between $PM_{2.5}$ and the covariates for the two time periods. The two equation approach was selected for the following reasons: (1) there was a data gap between the end of the no control period (Jul 4) and the beginning of the control period (Jul 28); (2) the correlation structure of the $PM_{2.5}$ observations taken during the no control period differs from the correlation structure of the $PM_{2.5}$ observations taken during the control period. The same can be said for the correlation structure of the covariates when comparing the no control period with the control period. The correlation structures will differ. The procedure that we have used is dependent on the difference in the set of beta values between the two equations, i.e., $\beta_{nc} - \beta_c$, where "*nc*" indicates the no control period and "*n*" indicates the control period. There are 14 covariates in the basic equations plus the intercept. Thus each beta value is a 15 component vector, β_{nc} is the vector of regression coefficients for the no control period and β_c is the vector of regression coefficient for the control period. To determine how the mean levels of $PM_{2.5}$ differ between the no control period and the control period, one multiplies $\beta_{nc} - \beta_c$ by a vector of observed covariate values, e.g., *X* = (1,23.7,72.3,0.46,17.4,0.36,0,0,0,0,0,0,0,0,0). In this example we have used zero values for all the *sin* and *cos* terms. The "1" in this equation is for the intercept term. The input vector is denoted by *X*. The calculation is thus $X'(\beta_{nc} - \beta_c)$. In the input vector, the terms are average meteorology conditions for a specified period of time (*input = intercept, T, rh, ws, Td, precip, sin/cos terms*). If, for example, this calculation yields a positive value of 25, this would indicate that for this particular set of meteorology condition the $PM_{2.5}$ level would be 25 μg/m^3 higher during the no control period than during the control period. The t-statistic can be used to assess whether the apparent differences may be due to random error. The form of this test is:

$$t = \sum (X'(\beta_{nc} - \beta_c)) / (X' \operatorname{cov}(\beta_{nc}) X + X' \operatorname{cov}(\beta_c) X)^{0.5} \tag{6}$$

3 Results and discussion

3.1 Influence of meteorological parameters on $PM_{2.5}$ in two periods

We follow the procedure outlined above, whereby a different regression model was developed for the two time period (no control and control). The response variable in each case is $PM_{2.5}$ and the meteorology and *sin/cos* covariates are the same in each regression formula. Since the $PM_{2.5}$ levels are generally higher in the no control period that in the control period, the regression coefficients for the covariates were different for each equation. The Adjusted Multiple Coefficient of Determination (R^2_a) of the regression model estimated for no control and control time period was 0.401 and 0.397, respectively. It should be noted that the ambient $PM_{2.5}$ concentration depend on many factors, such as local emission, regional emission, secondary formation and meteorology. Emission of primary particles and their precursors from local/regional sources also showed a significant decrease during the control period due to the temporary control measures. In order to evaluate the influence of meteorology, only four meteorological covariates mentioned above (temperature, dew point temperature, wind speed and precipitation) were used in the analysis. According to the regression model, wind speed and precipitation are significantly negatively correlated with $PM_{2.5}$ concentration in both no control and control period ($p<0.05$). The humidity, represented by dew point temperature in the model, is significantly positively correlated with the $PM_{2.5}$ concentration in two time periods ($p<0.05$). However, the relationship between ambient temperature and $PM_{2.5}$ concentration is more complex.

To determine the marginal effects of the temperature covariate, the means of the covariate data (except for temperature) for the entire period (no control and control) including the values for the *sin/cos* functions were found. The temperature for a specific range of values (19 to 30 °C) was allowed to vary while holding the other covariates at their mean values. The estimated meteorologically adjusted $PM_{2.5}$ values for both the no control period and the control period were then calculated versus the varying temperature values. In order to make inferential statistical statements about the relationship between the no control period and the control period the same meteorology data must be used for both periods. Fig.3 shows the marginal effects of temperature on $PM_{2.5}$ mass concentration for both no control and control periods. Confidence intervals were added in order to evaluate the slope of the lines. The confidence bands were tight for both lines, indicating that an acceptance of the indicated orientation of the line was warranted. For the no control period, the line slopes were downward, while for the control period the line slopes were upward.

During the no control period there are few temperatures above 30 °C given the time of year. During the control period there are many values above 30 °C. A t-test was applied to each temperature level based on the equation given in the methods section. At all temperature values between 19 and 29 °C, the separation between the $PM_{2.5}$ levels are statistically significant (the p values were in the range 0.000003 to 0.027). At temperatures above 29 °C, the separation between the $PM_{2.5}$ levels is not statistically significant. At 30 °C, the p value is 0.075. Thus at any given temperature level up to 29 °C, Fig. 3 indicates a statistically significant difference between $PM_{2.5}$ levels for the no control period and the control period. It is important to note the limitations that accompany this figure and the two others that follow. The results shown in Fig. 3 should not be taken to imply that the indicated changes in $PM_{2.5}$ levels are due solely to changes in temperature. The actual changes are due to many complicated atmospheric processes. Temperature is a contributor to the changes in $PM_{2.5}$, but clearly not the only one. It should also be noted that the two lines in will differ for different meteorological conditions.

As shown in Fig.3, the line separation decreases when the temperature increased. In other words, larger differences between no control and control $PM_{2.5}$ levels could be expected under lower temperatures. This pattern can be attributed to the fact that secondary components, such as sulfate, nitrate and ammonium, were an important component of total $PM_{2.5}$ mass. It has been found that the formation of secondary nitrate is enhanced at low temperatures [18-20]. If there are no other effects, the fraction of secondary nitrate is expected to be higher at low temperatures compared to that at higher temperatures. Compared to Jun 2008, the daily emission of NOx in Beijing decreased by 47% [1] and traffic-related NOx emission decreased by 46% [2] during the Olympic period. It is also found that the NOx and NO_2 concentrations at the monitoring site decreased by 71% and 70%, respectively, in the control period compared to the no control period [21]. The reduction in NOx may result in a related reduction in secondary nitrate. This feedback is expected to be more significant when the fraction of secondary nitrate contributes a larger fraction of total PM mass. Therefore, larger differences in the $PM_{2.5}$ concentrations between the no control and control periods were found at low temperatures rather than high temperatures.

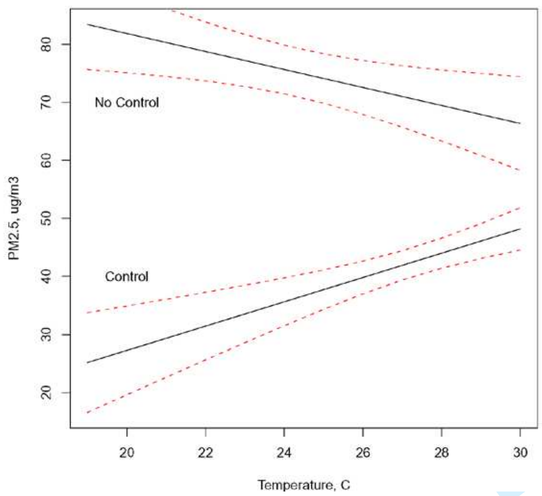

Fig. 3 Marginal effects of temperature on $PM_{2.5}$ mass concentration. The dotted lines show the confidence interval for each regression

Fig.4 is a marginal plot for the dew point temperature using the same method as was used for the temperature plots in Fig. 3. For this covariate, the lines slope upward for both the no control period and the control period, and indicate an increase in $PM_{2.5}$ as the dew point temperature increases. The plot for an additional analysis using relative humidity in place of the dew point temperature showed similar slopes for the two periods. The confidence interval for both lines is tight. An increase in the dew point temperature is a direct indication that the amount of water vapor in the atmosphere is increasing. The increase in the amount of water vapor in the atmosphere would promote the formation of particulate matter concentration and effect the size distributions [22-24]，which appears to be happening in this case. It should be noted that there are two more mechanisms by which the ambient humidity may influence the $PM_{2.5}$ concentration. High relative humidity can promote the formation of secondary organic aerosols though photo-chemical reactions [25, 26]. In addition, high ambient humidity was found to increase the formation of particles in combustion chambers such as diesel and natural gas engines [27-30].

The t-test indicates that the separation between the two lines is statistically significant at all dew point temperatures (the p values were in the range 0.000026 to 0.016). The line for no control has a slightly steeper slope than the line for control, indicating that the effect of an increase in dew point temperature on $PM_{2.5}$ levels is greater during the no control period. This could be attributed to two conditions. First, the concentration of $PM_{2.5}$ in the no control period was significantly higher than that in control period [6]. Higher $PM_{2.5}$ concentration, which results in more coagulation cores in the ambient air, could enhance the influence of humidity on particle mass. Also, as mentioned above, high ambient humidity is found to promote particle formation in vehicle engines and thus increase the PM emission factor for vehicles. The traffic count around the monitoring site was 26.3% larger in the no control period compared with those counts taken in the control period, which may account for the steeper slope in the no control period.

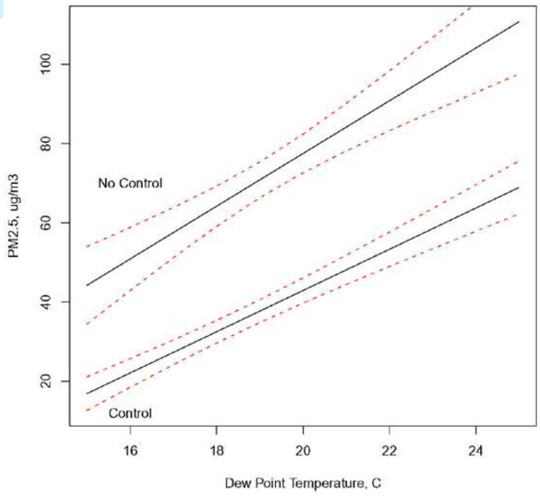

Fig. 4 Marginal effects of dew point temperature on $PM_{2.5}$ mass concentration. The dotted lines showed the confidence interval for each regression.

The third covariate in the basic statistical model is wind speed. Fig. 5 shows a two line plot for that covariate. Basically, both lines show that the $PM_{2.5}$ levels decrease as the wind speed increases. The slope of the two lines is the same, which indicates that the marginal effect of wind speed was the same in both the no control period and the control period. The separation between the two lines in the figure is statistically significant at all wind speeds. The negative correlation between wind speed and $PM_{2.5}$ concentration is mainly due to the processes of diffusion and dilution. Previous studies found that the size distribution and mass concentration of particles changed dramatically in the downwind direction due to dilution in roadside microenvironment [31, 32]. Hourly precipitation was the fourth meteorology covariate used in this analysis. The plot of marginal effect of precipitation is not given here because of the large number of hours with no rain. Simple plots of $PM_{2.5}$ versus rain events clearly show the scavenging properties of rain events during both the no control and control periods.

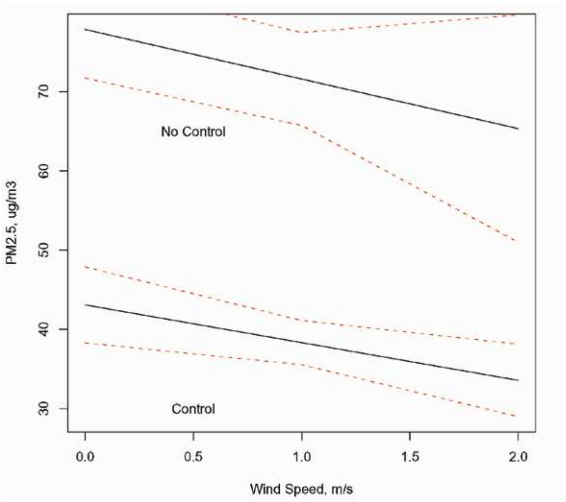

Fig.5 Marginal effects of wind speed on $PM_{2.5}$ mass concentration. The dotted lines showed the confidence interval for each regression

3.2 Contribution of meteorology to PM2.5 reduction

As mentioned above, low $PM_{2.5}$ levels in roadside environments during the control period are related to many air quality control measures, including emission restrictions for local sources and surrounding areas. It was found that the daily emissions of SO_2, NOx, PM_{10} and NMVOC in the control period were reduced by 41%, 47%, 55% and 57%, respectively, compared to emissions in the no control period [1]. In addition to the emission control effects, meteorology helped to reduce $PM_{2.5}$ levels during the control period. As mentioned above, the contribution of meteorology to the reduction of $PM_{2.5}$ was assessed based on the difference between the vectors of regression coefficients for the two models (no control and control). Multiplied by a vector of input meteorology data, it provides us with the difference in $PM_{2.5}$ levels between the two time periods (no control and control) for the given set of meteorology conditions.

It was of interest to apply the regression coefficients for the no control period to the control period data to see what the $PM_{2.5}$ levels would have been during the control period if there had been no controls (Scenario I). A combination of regression coefficients for no control period and the meteorology data for the control period was used for Scenario I. The estimated $PM_{2.5}$ concentration for Scenario I is calculated to be 69.6 μg/m^3, which indicates the $PM_{2.5}$ level in the control period if there had been no emission control measures (denoted by C_3). As shown in Table 1, the observed $PM_{2.5}$ levels during the no control period and control period were 76.0 μg/m^3 (denoted by C_1) and 40.3 μg/m^3 (denoted by C_2), respectively. The contribution of the meteorology to reduce $PM_{2.5}$ in the control period, denoted by η_1, can be calculated by the equation below:

$$\eta_1 = \frac{C_1 - C_3}{C_1 - C_2} \tag{7}$$

Based on the observational results and simulation results, meteorology contributed for 17.9% of the reduction of $PM_{2.5}$ in the control period. The contribution of emission control measures on the $PM_{2.5}$ reduction during the control period, denoted by η_2, can be calculated by a similar equation:

$$\eta_2 = \frac{C_3 - C_2}{C_3} \tag{8}$$

According to equation (8), the emission control measures contributed for 42.1% of the $PM_{2.5}$ reduction in the control period. It should be noticed that the estimated $PM_{2.5}$ values (C_3) is based on the assumption that we have the best regression coefficients for each time period.

Scenario II was designed to see what the $PM_{2.5}$ levels would have been during the no control period if control measures had been in effect. Control period regression coefficients were applied to three time periods during the no control period when $PM_{2.5}$ levels were high (see Table 2). It is found that the high $PM_{2.5}$ concentrations in the no control period could be substantially reduced by more than 67.0% if the temporary control measures had been implemented then. In Scenario III, we estimated what the $PM_{2.5}$ level would have been at the time of the opening ceremony (Aug 8, 20:00 p.m.) if no controls had been in effect. The estimated $PM_{2.5}$ level was 85.4 μg/m^3, while the observed value for $PM_{2.5}$ was 61.1 μg/m^3. Therefore, a decrease of 28.5% in $PM_{2.5}$ level occurred with the emission control measures implemented during the opening ceremony.

Table 2 Mean $PM_{2.5}$ concentration of heavy pollution days in the no control period

Time Period	Observed $PM_{2.5}$ (μg/m^3)	Estimated $PM_{2.5}$ (μg/m^3)	% Reduction
Jun 25, 03:00-18:00	127.3	41.1	67.7%
Jun 27, 08:00-22:00	117.5	28.3	75.9%
Jun 29, 14:00-Jun30, 04:00	126.8	40.4	68.1%

Based on the results of multiple linear regression analysis, meteorology and emission control measurements accounted for at least 17.9% and 42.1%, respectively, of the reduction of roadside $PM_{2.5}$ concentration during the Olympic period. The sources for the remaining 40% of the reduction could not be identified due to the limitation of the multiple linear regression analysis. Several recent papers also focus on the influence of meteorology on the air quality in Beijing during the Olympic Games. However, to determine the contributions of emission controls and meteorology to the reduction of air pollutants concentration is complicated, and subject to debate. Wang et al found that the reduction in the emission of ozone precursors associated with the Olympic Games accounted for 45% of the O_3 reduction during the Olympics Games (Aug 8-24) [33]. Wang et al reported that more than 60% of decrease in $PM_{2.5}$ concentration could be attributed to the emission control measures during the Olympic Games based on the simulation results from CMAQ [1]. Wang et al found that meteorological parameters accounted for 40% of the total variation in PM_{10} concentration, while source control accounted for only 16% [4]. However, shortly after that publication, Tang et al and Yao et al published comments on this paper and questioned its conclusions [9, 11].

4 Conclusions

Based on the statistical methodologies employed, we have demonstrated that the air quality control measures instituted by the Beijing government to control particulate matter levels were effective in providing good air quality conditions for the 2008 Olympic period. We also acknowledge that meteorological events also played a role in providing good air quality conditions. However, it is shown that meteorology alone could not have accounted for the good air quality conditions. We have also found that air quality conditions during the no control period would have been improved had control measures been in effect, and that conditions during the control period would not have been as good as they were if control measures had not been effect. Moreover, it is estimated that at the time of the opening ceremonies for the Games $PM_{2.5}$ levels would have been 39.5% higher had no controls been in effect.

For future work related to air quality experiments, we think it is important to expand the collection of meteorology data. It is recommended that meteorology data be collected both at the location of the air quality sampling instrument, but also in a location that provides background meteorological conditions. It is also recommended that a numerical mesoscale meteorological model be run during the data collection period. The fusion of the observed data and mesoscale model may provide a better representation of the meteorology conditions that prevailed during the experiment [34]. The mesoscale model output also provides many other meteorology variables (e.g., boundary layer height) that can be useful in analyzing the results of the air quality experiment.

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References

[1] Wang S, Zhao M, Xing J, et al. Quantifying the air pollutants emission reduction during the 2008 Olympic Games in Beijing. Environmental Science & Technology. 2010, 44(7): 2490-2496

[2] Zhou Y, Wu Y, Yang L, et al. The impact of transportation control measures on emission reductions during the 2008 Olympic Games in Beijing, China. Atmospheric Environment. 2010, 44(3): 285-293

[3] Sun J, Zhang Q, Canagaratna M R, et al. Highly time- and size-resolved characterization of submicron aerosol particles in Beijing using an Aerodyne Aerosol Mass Spectrometer. Atmospheric Environment. 2010, 44(1): 131-140

[4] Wang W, Primbs T, Tao S, et al. Atmospheric particulate matter pollution during the 2008 Beijing Olympics. Environmental Science & Technology. 2009, 43(16): 6440-6446

[5] Wang X, Westerdahl D, Chen L C, et al. Evaluating the air quality impacts of the 2008 Beijing Olympic Games: On-road emission factors and black carbon profiles. Atmospheric Environment. 2009, 43(30): 4535-4543

[6] Yang L, Wu Y, Song S J, et al. Characteristics of ambient particulate matters near major urban roads in Beijing-Part I: Mass concentrations and temporal profiles of PM10, PM2.5 and PM1. Submitted to Journal of the Air & Waste Management Association. 2010

[7] Fang G C, Wu Y S, Chang S Y, et al. Size distributions of ambient air particles and enrichment factor analyses of metallic elements at Taichung Harbor near the Taiwan Strait. Atmospheric Research. 2006, 81(4): 320-333

[8] Simonich S L M. Response to comments on "Atmospheric particulate matter pollution during the 2008 Beijing Olympics". Environmental Science & Technology. 2009, 43(19): 7590-7591

[9] Tang X, Shao M, Hu M, et al. Comment on "Atmospheric particulate matter pollution during the 2008 Beijing Olympics". Environmental Science & Technology. 2009, 43(19): 7588-7588

[10] Wang T, Gao J, Nie W, et al. Effect of anti-pollution measures and meteorology on air quality during the Beijing Olympic Games-An overview of the results from surface and satellite measurements. In: Proceedings of the 11th International Conference on Atmospheric Science and Applications of Air Quality 2009, Ji'nan. Ji'nan: Shandong University Press, 2009, 77

[11] Yao X, Xu X, Sabaliauskas K, et al. Comment on "Atmospheric particulate matter pollution during the 2008 Beijing Olympics". Environmental Science & Technology. 2009, 43(19): 7589-7589

[12] Stull R B. Meteorology for Scientists and Engineers. Pacific Grove (CA): Brooks/Cole Publishing Company, 2000

[13] Yanosky J D, Williams P L, MacIntosh D L. A comparison of two direct-reading aerosol monitors with the federal reference method for PM2.5 in indoor air. Atmospheric Environment. 2002, 36(1): 107-113

[14] Park J M, Rock J C, Wang L, et al. Performance evaluation of six different aerosol samplers in a particulate matter generation chamber. Atmospheric Environment. 2009, 43(2): 280-289

[15] Kingham S, Durand M, Aberkane T, et al. Winter comparison of TEOM, MiniVol and DustTrak PM10 monitors in a woodsmoke environment. Atmospheric Environment. 2006, 40(2): 338-347

[16] Monahan J F. A Primer on Linear Models. New York: Chapman & Hall/CRC, 2008

[17] Belsley D A. Conditioning Diagnostics: Collinearity and Weak Data in Regression. New York: John Wiley, 1991

[18] Giroux M, Esclassan J, Arnaud C, et al. Analysis of levels of nitrates and derivatives of ammonia in an urban atmosphere. Science of the Total Environment. 1997, 196(3): 247-254

[19] Russell A G, McRae G J, Cass G R. Mathematical modeling of the formation and transport of ammonium nitrate aerosol. Atmospheric Environment. 1983, 17(5): 949-964

[20] Stelson A W, Seinfeld J H. Relative humidity and temperature dependence of the ammonium nitrate dissociation constant. Atmospheric Environment. 1982, 16: 983-992

[21] Kong Q, Wu Y, Yang L, et al. Characteristics and intake dose of gaseous pollutants near a major Beijing road during the 29th Olympic Games. Acta Scientiae Circumstantiae. 2010, 30(2): 281-286

[22] Hanel G, Landsberg H E, Van Mieghem J. The Properties of atmospheric aerosol particles as functions of the relative humidity at thermodynamic equilibrium with the surrounding moist air. Advances in Geophysics. 1976, 19: 73-188

[23] McMurry P H, Stolzenburg M R. On the sensitivity of particle size to relative humidity for Los Angeles aerosols. Atmospheric Environment. 1989, 23(2): 497-507

[24] Pillai P S, Suresh S, Krishna Moorthy K. A study of PM, PM10 and PM2.5 concentration at a tropical coastal station. Atmospheric Research. 2002, 61(2): 149-167

[25] Kang C M, Lee H S, Kang B W, et al. Chemical characteristics of acidic gas pollutions and PM2.5 species during the hazy episodes in Seoul, South Korea. Atmospheric Environment. 2004, 38: 4749-4760

[26] Sun Y, Zhuang G, Tang A, et al. Chemical characteristics of PM2.5 and PM10 in haze-fog episodes in Beijing. Environmental Science & Technology. 2006, 40(10): 3148-3155

[27] Chan S H, Zhu J. Exhaust emissions based air–fuel ratio model (I): literature reviews and modeling. SAE Transactions. 1996, 105(4): 408-417

[28] Jamriska M, Morawska L, Mergersen K. The effect of temperature and humidity on size segregated traffic exhaust particle emissions. Atmospheric Environment. 2008, 42(10): 2369-2382

[29] Kubesh J T, Podnar D J. Humidity effects and compensation in a lean burn natural gas engine. In: Proceedings of International Spring Fuels & Lubricants Meeting & Exposition 1997, Dearborn, USA. Product Code: 971706

[30] McCormick R L, Graboski M S, Newlin A W, et al. Effect of previous termhumiditynext term on heavy-duty transient emissions from diesel and natural gas engines at high altitude. Journal of the Air & Waste Management Association. 1997, 47: 784-791

[31] Zhang K M, Wexler A S, Zhu Y F, et al. Evolution of particle number distribution near roadways- Part II: the “Road-to-Ambient” process. Atmospheric Environment. 2004, 38: 6655-6665

[32] Wu Y, Hao J M, Fu L X, et al. Vertical and horizontal profiles of airborne particulate matter near major roads in Macao, China. Atmospheric Environment. 2002, 36: 4907-4918

[33] Wang Y X, Hao J M, McElroy M B, et al. Ozone air quality during the 2008 Beijing Olympics: Effectiveness of emission restrictions. Atmospheric Chemistry and Physics. 2009, 9: 5237-5251

[34] Garcia V C, Foley K M, Gego E, et al. A comparison of statistical techniques for combining modeled and observed concentrations to create high-resolution ozone air quality surfaces. Journal of the Air & Waste Manage Association. 2010, 60: 586-595