

Supplementary Material

Satellite and ground observations of severe air pollution episodes in the winter of 2013 in Beijing, China

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Text S1: description of the two-stage PM_{2.5} prediction model

A two-stage statistical model was developed to describe the spatiotemporal relationships between PM_{2.5} and satellite AOD. The first-stage linear mixed effect (LME) model includes daily random intercepts and slopes for AOD and meteorological fields:

$$\begin{aligned} PM_{2.5,st} &= (\mu + \mu') + (\beta_1 + \beta_1')AOD_{st} + \beta_2WS_{st} + \beta_3PBLH_{st} + \beta_4PS_{st} + \beta_5RH_PBLH_{st} \\ &+ \beta_6Precip_Lag1_{st} + \beta_7Fire_spots_{st} + \varepsilon_{1,st} \\ (\mu' \beta_1') &\sim N[(0,0), \Psi_1] \end{aligned}$$

where $PM_{2.5,st}$ is the average observed PM_{2.5} concentration at grid cell s on DOY t ; AOD_{st} is combined MODIS AOD; WS_{st} , $PBLH_{st}$, PS_{st} , RH_PBLH_{st} , $Precip_Lag1_{st}$ are meteorological fields; $Fire_spots_{st}$ is the fire count; μ and μ' are the fixed and daily random intercepts, respectively; β_1 - β_7 are fixed slopes for independent variables; β_1' is the daily random slope for AOD; $\varepsilon_{1,st}$ is the error term at grid cell s on day t ; and Ψ_1 is the variance-covariance matrices for the daily random effects, respectively.

The second-stage generalized additive model (GAM) is expressed as follows:

$$PM_{2.5_resid_{st}} = \mu_0 + s(X, Y)_s + s(ForestCover)_s + s(UrbanCover)_s + \varepsilon_{st} \quad [3]$$

where $PM_{2.5_resid_{st}}$ is the residual from the first-stage model at grid cell s on day t ; μ_0 is the intercept term; $s(X, Y)_s$ is the smooth term of the coordinates of the centroid of grid cell s ; $s(ForestCover)_s$ and $s(UrbanCover)_s$ are the smooth functions of percent forest cover and urban area for grid cell s ; and ε_{st} is the error term.

Text S2: Satellite AOD data fusion technique

In order to improve data coverage over urban areas, a three-step customized approach was developed to combine MODIS DT and DB AOD. First, regression coefficients between daily collocated DT and DB AOD were used to predict the missing DB AOD in those pixels with only DT AOD and vice versa (Puttaswamy et al., 2014). Second, level 2 validated AOD observations from 33 Aerosol Robotic Network (AERONET) sites in China were matched with the gap-filled MODIS DT and DB AOD retrievals. The variance of the differences between gap-filled MODIS AOD and AERONET AOD values for each season was calculated. Finally, we combined the gap-filled DT and DB AOD data using an inverse variance weighting (IVW) approach. When compared with the AERONET observations, our combined AOD performs similarly ($R^2 = 0.80$, mean bias = 0.07) to MODIS's operational combined AOD ($R^2 = 0.81$, mean bias = 0.07). Coverage for densely populated southern and eastern China improve by 50-100%.

Reference:

Puttaswamy, S. J., et al., 2014. Statistical data fusion of multi-sensor AOD over the Continental United States. Geocarto International. 29, 48-64.

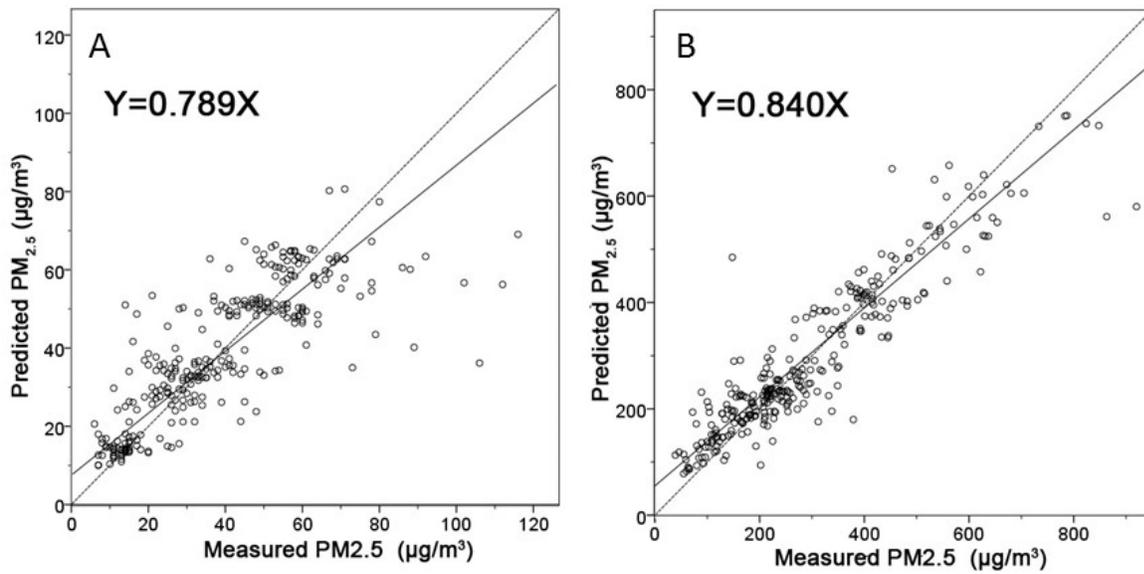


Figure S1. Cross validation of ordinary kriging used to develop the PM_{2.5} concentration contours in this study. (a) Result for Jan 2nd, the least polluted day during the study period; (b) result for Jan 12th, the most polluted day during the study period. Dotted lines represent the 1:1 reference lines.

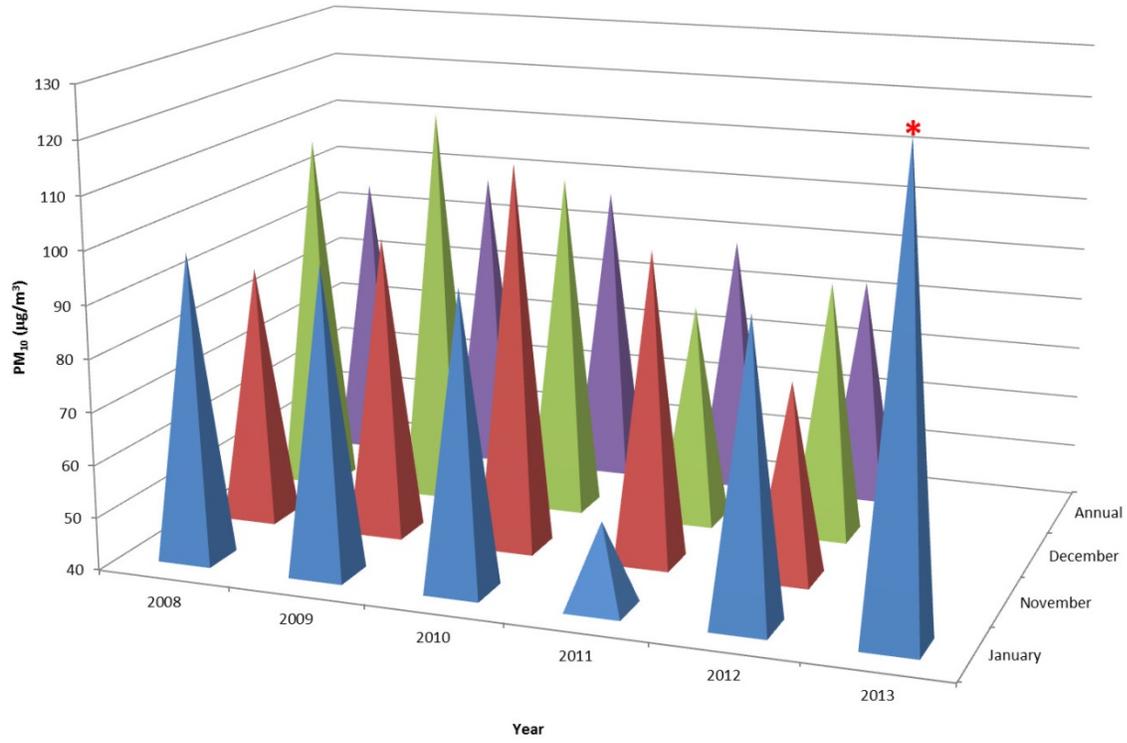


Figure S2. Monthly and annual mean PM₁₀ levels in Beijing inferred from Air Pollution Index data.

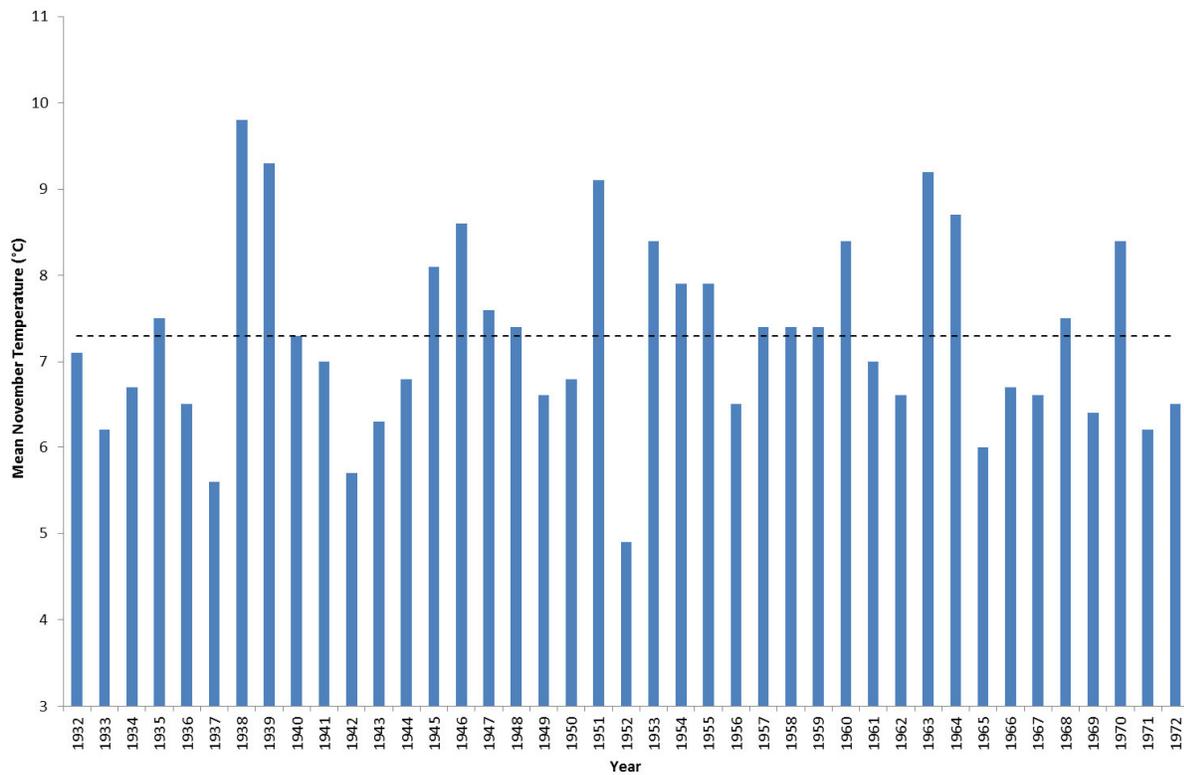


Figure S3. Average November temperature of London, UK. Dashed line indicates mean monthly temperature between 1932 and 1973. Historic monthly data was obtained from the London Weather Channel (<http://www.london-weather.eu/>, accessed on September 20, 2013).