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Evaluation of Effectiveness of 2013 Action Plan for

Air Pollution Prevention and Control in North China

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Sichuan Agriculture University

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An abstract of
A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
in partial fulfillment of the requirements for the degree of
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Abstract

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By Shuang Wang

As the largest developing country, China has some of the worst air quality in the world. Fine particulate matter (PM 2.5) is one of major components of air pollution. There is a strong association between exposure to PM 2.5 and adverse health outcomes. A linear mixed effect (LME) model was established using satellite remote sensing data, meteorological parameters, and population data to evaluate the effectiveness of 2013 Action Plan for Air Pollution Prevention and Control in North China. The cross validation (CV) R^2 and RMSE of the overall LME model was 0.59 and 34.61 $\mu g/m^3$, respectively. The results showed that the PM2.5 concentration decreased by 19.62 $\mu g/m^3$ and the air pollution prevention policy accounted for 68% of the reduction in PM 2.5 levels during 2013 to 2015 in North China. The data required to develop the model are accessible in most cities of China. Therefore, the LME model could be used as a tool to evaluate the effectiveness of the air pollution control policy in other parts of China.

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1. Introduction

Epidemiological studies have provided evidence for a strong association between exposure to fine particulate matter (airborne particles with aerodynamic diameter less than 2.5 µm, PM 2.5) and adverse health effects on human subjects, such as cardiovascular diseases mortality, cardiometabolic disorders, asthma, lower birth weights, and respiratory infections(Bonzini et al., 2010; I. Kloog, Coull, Zanobetti, Koutrakis, & Schwartz, 2012; Pope et al., 2015; Sheppard, Levy, Norris, Larson, & Koenig, 1999; Zanobetti, Franklin, Koutrakis, & Schwartz, 2009).

As the largest developing country, China has suffered from severe, widespread air pollution due to the rapid economic development and industrial reconstruction in past 30 years. In January 2013, 1.4 million km^3 of China were covered by harmful dense haze and more than 800 million people were affected (Xu, Chen, & Ye, 2013). This heavy haze smog led public concern to the problem of air pollution and health impact of exposure to PM 2.5 that has been recognized as one of major components of air pollution and haze in China. During the heavy haze period in January 2013, one study found an association between exposure to heavy smog and an increased risk of hospital visits(Chen, Zhao, & Kan, 2013). In 2015, Lu et al. published a systematic review and meta-analysis focusing on Chinese population and deduced an increase of 10 $\mu g/m^3$ of PM 2.5 is related to a 0.40% (95% CI: 0.22%, 0.29%) increase in total non-accidental mortality, a 0.75%(95% CI: 0.39%, 1.11%) increase in mortality due to respiratory disease, and a 0.63%(95% CI: 0.35%, 0.91%) increase in mortality of cardiovascular disease(Lu et al., 2015). The Global Burden of Disease Study 2010 revealed that ambient air pollution was the fourth leading risk factor for disability-adjusted life-years (DALYs) (Yang et al., 2013).

To improve air quality concurrently, the State Council of China established the *Action Plan for Air Pollution Prevention* (hereinafter referred to as Action Plan) *and Control* in September 2013. The *Action Plan,* the only legislative text concerning air pollution in China, is designed to regulate nationwide air pollution emission by executing ten evidence-based measures, including enhancing overall treatment, reducing emissions of multiple pollutants, adjusting and optimizing industrial structure, promoting upgrade of economic transition, speeding up technological reform of enterprises, etc. The *Action Plan* had set a list of goals to improve overall air quality across the nation through five years. One of those goals can be quantitatively evaluated by PM 2.5 is by 2017, the annual average concentration of fine particulate matter in Beijing-Tianjin-Hebei region (including province of Shandong, Shanxi, and Inner Mongolia) will be dropped by 25% against 2012 level.

In accordance with the *Action Plan*, a decrease in PM 2.5 concentration will be expected in 2015, which is the second year after the implementation of the *Action Plan.* The objective of this study is to evaluate the effectiveness of the *Action Plan* in Beijing-Tianjin-Hebei region, i.e. North China. North China (Latitude: 34.3°N to 42.7°N; Longitude: 105.5°E to 126.2°E) is a major economic zone in China, including Beijing, Tianjin, the Shanxi, Shandong, and Hebei provinces, and the Inner Mongolia region. From policy makers' perspective, the evaluation of effectiveness of the *Action Plan* is essential and important for promptly modifying current policy and guiding future control measures.

Previous methods of evaluation was to compare two annual means of PM 2.5 concentrations provided by province-level reports based on local monitoring sites. The Ministry of Environmental Protection (MEP) of China began to establish PM 2.5 monitoring sites in major cities of China since the beginning of 2013. North China has an area of 1,782,900 square kilometers. However, there are only no more than 400 monitoring sites within North China, which means each site would represent more than 4,000 square kilometers. In addition, most of monitoring sites are located in capital and big cities, such as Beijing, Tianjin, and Shijiazhuang. Therefore, only using data from ground monitoring sites for evaluation is non-representative and can lead to bias. Since the air pollution levels can be affected by meteorological parameters, the change of PM2.5 concentrations can be caused by seasonal fluctuation or meteorological factors, such as precipitation, wind speed, and wind direction. Therefore, simply comparing annual average PM 2.5 concentrations is unable to provide powerful evidence to evaluate the effectiveness of air pollution control measures. Liu et al. developed a statistical model using remote sensing data and meteorological parameters to evaluate the effectiveness of air pollution control policies during the 2008 Beijing Olympic Games. (Y. Liu et al., 2012) The results showed there was 70% of the PM 2.5 variability can be explained by the model and the emission control policies were able to account for 20-24 $\mu g/m^3$ reduction in PM2.5 levels during the Olympic Games.

Satellite remote sensing with broad spatial and temporal coverage can fill the spatiotemporal gaps of PM 2.5 left by ground monitors. National Aeronautics and Space Administration (NASA) lunched two Earth Observing System satellites, Terra and Aqua, in 1999 and 2002, respectively (Remer et al., 2005). The Moderate Resolution Imaging Spectroradiometer (MODIS) aboard Terra and Aqua satellites measure aerosol optical depth (AOD) that reflects particle abundance in the atmospheric column. Early studies have showed that satellite-derived AOD can be used as an effective tool for estimating ground PM 2.5 concentration (Xuefei Hu et al., 2013; X. Hu, Waller, Lyapustin, Wang, & Liu, 2014; Koelemeijer, Homan, & Matthijsen, 2006). Statistical models have been established to assess the relationship between satellite-derived AOD and ground PM 2.5 concentrations (Y. Liu, Paciorek, & Koutrakis, 2009; Ma, Hu, Huang, Bi, & Liu, 2014; Mao, Qiu, Kusano, & Xu, 2012; You, Zang, Zhang, Li, & Wang, 2016). Studies have showed the relationship between satellite-derived AOD and ground PM 2.5 concentrations can be affected by meteorological parameters such as temperature, relative humidity, wind speed, precipitation, and planet boundary layer height(I. Kloog, Nordio, Coull, & Schwartz, 2012; Lee, Liu, Coull, Schwartz, & Koutrakis, 2011; Y. Liu, Sarnat, Kilaru, Jacob, & Koutrakis, 2005; Yanosky et al., 2014). Adding land use variables (road network, population density, vegetation coverage) can improve the spatial resolution of the model.(I. Kloog, Nordio, et al., 2012; Ma et al., 2014; Mao et al., 2012; Wu et al., 2014).

A linear mixed-effects (LME) model is a generalization of the standard linear model that consists of both fixed and random effects in the same analysis. A basic assumption is that the relationship between PM2.5 concentrations and AOD varies daily because of time-varying parameters.(Chudnovsky, Lee, Kostinski, Kotlov, & Koutrakis, 2012) The mixed-effects model approach can provide higher accuracy than a simple regression model. (Lee et al., 2011) Studies that applied LME model in the

United States and European cities estimated both the average effect of AOD on PM for all study days and the daily variability in the relationship between PM and AOD.(Chudnovsky et al., 2012; Itai Kloog, Koutrakis, Coull, Lee, & Schwartz, 2011; Nordio et al., 2013) Meng et al. used a LME model to predict ground PM10 levels in a Chinese metropolis on high spatiotemporal resolution(Meng et al., 2016).

The objective of this study is to evaluate the effectiveness of the *Action Plan* in North China using a statistical method. Firstly, a linear mixed effects (LME) model is devolved for each year (i.e. 2013,2014,2015) using satellite-derived AOD, meteorological parameters, and land use variable to estimate PM 2.5 concentrations. Then PM2.5 concentrations in areas where had no ground PM2.5 data but had the data of all predictors were estimated using the built year-specific models. Since there is no ground PM 2.5 measurements before 2013 in China, we estimated PM 2.5 levels in 2012 based on the built developed in 2013. A paired t-test was performed to test whether there was a significant decrease in PM 2.5 concentrations after the implementation of the *Action Plan*. Furthermore, a time period variable was added into the model and its statistical significance was calculated to illustrate whether or not this variable is statistically significant under the model.

2. Material and methods

2.1 Study domain

The spatial domain of this study consists of Beijing, Tianjin, the Shanxi, Shandong, and Hebei provinces, and the Inner Mongolia region, is located in between 34.3°N to 42.7°N latitude and 105.5°E to 126.2°E longitude. (Figure1) They cover an area of approximately 890,000 km^2 and have a population of 388,900,000. Economic development in this area is highly dependent on heavy industries that are main sources for PM 2.5 emission (Zhang et al., 2009).

2.2 Ground PM 2.5 measurements

Data for daily average PM 2.5 concentrations from January 1, 2013 to December 31, 2015 were obtained from the official Web site of the China Environmental Monitoring Center (CEMC)(http://113.108.142.147:20035/emcpublish/). There are some additional monitoring sites established in Shandong and Shanxi provinces, Beijing, and Tianjin that are not included in the CEMC's Web site. Data from these monitoring sites are also obtained in this study. The ground PM 2.5 concentration from these sites are measured using Tapered Element Oscillating Microbalance (TEOM) or the beta-attenuation method. A total of 463 monitoring sites are included in the present study.

2.3 Satellite AOD data

The Moderate Resolution Imaging Spectroradiometer (MODIS) is aboard the Terra satellite and Aqua satellite. The MODIS instruments scan the swath of 2330 km with a global coverage of 1 – 2 days, providing nearly two measurements of AOD per day.

The Aqua and the Terra cross the equator at 13:30 p.m. and 10:30 a.m. local time, respectively. Level 2 Aqua MODIS Aerosol Product (Collection 6, C6) with spatial resolution of 10×10 km from January 1, 2012 to December 31, 2015 was downloaded from Level 1 and Atmosphere Archive and Distribution System (LAADS Web, https://ladsweb.nascom.nasa.gov/). The AOD data that cover the study domain was extracted using IDL 8.4. Finally, the combined AOD data at 550nm with Quality Assurance Confidence flag of 2 and 3 were used in the study.

2.4 Meteorological data

The relationship between AOD and PM 2.5 can be modified by meteorological parameters such as relative humidity, temperature, and wind speed(I. Kloog, Nordio, et al., 2012; Lee et al., 2011; Y. Liu et al., 2005; Yanosky et al., 2014). On the other hand, these meteorological parameters act as temporal predictors for estimating concentration of PM 2.5. Hourly meteorological data including planetary boundary layer height above surface (PBLH), relative humidity in PBLH (RH_PBLH), wind speed at 10m(Wind_10m), temperature at 2m(Temp_2m), and total precipitation during 1- 2 p.m. local time (PRETOT) were obtained from the Goddard Earth Observing System Model, Version 5(GEOS-5) and Goddard Earth Observing System-Forward Processing (GEOS-FP). The spatial resolution of meteorological data is 0.25° latitude × 0.3125° longitude.

2.5. Land Cover and Population Data

Normalized difference vegetation index (NDVI) and population density were used in the analysis. The MODIS level 3 monthly mean NDVI with a 0.25°× 0.25° spatial resolution were downloaded from NASA Earth Observation (NEO)(http://neo.sci.gsfc.nasa.gov/). The population data were obtained from the WorldPop project (http://www.worldpop.org.uk/) The WorldPop project offers high spatial resolution data on human population distributions in the world. Gridded population maps, whereby population numbers per 100×100m grid square are estimated based the census, survey, cellphone, and other spatial datasets by WorldPop project. The 2010 and 2015 estimates of numbers of people with 100×100m spatial resolutions in China were downloaded from the WorldPop website. Since the resolution of population data is 100×100m, which is relatively high when compared with the resolution of remote sensing and meteorological data.

We use the aggregate tool in ArcGIS 10.3 to convert the original resolution of 100×100m to a resolution of 0.25°× 0.25° and numbers of population per pixel were calculated as well. We assumed that the change of population between 2010 and 2015 could be described by a simple linear regression. So the population density of 2012, 2013 and 2014 were estimated based on the population data of 2010 and 2015.

2.6 Data integration

A 0.25°× 0.25° resolution grid (2882 grid cells in total) covering our study domain (Latitude: 34.3°N to 42.7°N; Longitude: 105.5°E to 126.2°E) was created using fishnet tool in ArcGIS 10.3 and each grid cell was assigned a unique grid cell ID. The gridded satellite daily AOD values were assigned to the grid cell where the centroid of AOD retrieval was located using R function “over” of package “sp”. If there were more than one AOD retrievals fell into the same grid cell, the average AOD value was calculated for that grid cell. PM 2.5 measurements, meteorological parameter, NDVI, and population data were assigned a grid cell ID and averaged over the 0.25°× 0.25° grid cells using the same method. Finally, AOD, PM2.5, NDVI, PBLH, Temp_2m, Wind_10m, RH_PBLH, PRETOT, and population density for all days and all grid cells were matched by grid cell ID and day of year (DOY) for model fitting. All procedures were conducted in R 3.1.3 environment.

2.7 Model development and validation

A linear mixed effects (LME) model of each year is developed using AOD, NDVI, population density, planetary boundary layer height above surface (PBLH), relative humidity in PBLH (RH_PBLH), wind speed at 10m(Wind_10m), temperature at 2m(Temp_2m), and total precipitation (PRETOT) during 1- 2 p.m. local time (PRETOT) as independent variables. The dependent variable of the model was PM2.5 concentration. The LME model with AOD allows us to explore the day-to-day variability in the PM 2.5-AOD relationship. The AOD in the LME model has both fixed and random effects, which represent daily variability in the relationship between PM2.5 and AOD and the average effect of AOD on PM 2.5 for the whole year, respectively. Fixed and random slops of AOD and temperature were estimated:

$$\text{PM } 2.5_{gt} = (b_0 + b_{0,t}) + (b_1 + b_{1,t})\,\text{AOD}_{gt} + (b_2 + b_{2,t})\,\text{Temp\_2m}_{gt} + b_3\text{PBLH}_{gt} + b_4\text{RH\_PBLH}_{gt} + b_5\text{Wind\_10m}_{gt} + b_6\text{PRETOT}_{gt} + b_7\text{NDVI}_{gt} + b_8\text{pop\_density}_{gt} + \varepsilon_{gt} \quad (1)$$

Where PM 2.5_{gt} is the daily average ground measurement of PM 2.5 concentration (μg/m^3) in grid cell g on day t; b_0 and $b_{0,t}$ (day-specific)are the fixed and random intercepts, respectively; AOD_{gt} is the AOD value (unitless) in grid cell g on day t; b_1 and $b_{1,t}$ (day-specific) are fixed and random slopes for AOD; Temp_2m_{gt}(K), PBLH_{gt}

(m), RH_PBLH_{gt} (%), $Wind\_10m_{gt}$(m/s), $PRETOT_{gt}$ (mm), $NDVI_{gt}$(unitless), $pop\_density_{gt}$ (N/cell)corresponding to grid cell *g* on day *t*, respectively; b_2 and $b_{2,\,t}$ (day-specific) are the fixed and random slopes for Temp_2m, respectively; b_3 to b_8 are the fixed slopes for their corresponding variables; ε_{gt} is the error term in grid cell *g* on day *t*.

10-fold Cross Validation (CV) was performed to test for potential model overfitting, that is, the model could have better predictive performance in the data set used in model fitting than the data from the rest of the study domain. 90% of the data were randomly selected for model building and the remaining 10% of the data formed a test data for prediction. This procedure was repeated 10 times. Root mean squared error (RMSR) and overall fit R-square were used to evaluate the model performance.

2.8 Evaluation of the effectiveness of the *Action Plan*

Although the Action Plan was published on September 2013, we allowed some time for regional governments to form a plan that would achieve compliance with the *Action Plan*. We chose February 1, 2014 as the cut-off date of the *Action Plan*. Namely, we defined February 1, 2014 was the day that the *Action Plan* had real effects on the aerosol fine particulate matter concentration. There are two reasons for choosing February 1, 2014 as the cut-off point. The first reason was to keep the same sample sizes of before and after groups for further paired t-test. The other reason was February 1, 2014 was the day that all regional government were required to deliver the *Action Plan* to local industries and submit their letter of responsibility to the CMEP.

Based on the equation (1), there were three annual LME models built for 2013, 2014, and 2015, respectively. The PM 2.5 concentrations were estimated for the grid cells lack ground PM2.5 measurements but with values of all independent predictors based on the built model of each year. Since there was no ground PM 2.5 measurements before 2013 in China, the established model of 2013 using data from 2013 was adopted to predict the PM 2.5 concentrations in 2012. The dataset was divided into two parts according to the cut-off point. One was composed of the data before February 1, 2014; the second part was formed of the data after February 1, 2014. For each part, the monthly average concentrations of PM2.5 in each grid cell were calculated from both measurements and predicted PM 2.5. A paired t-test was performed to test the difference in PM 2.5 concentrations between two datasets. The data was paired with each other based on the month and grid cell ID. The null hypothesis was that the difference of the means is equal to zero. The alternative hypothesis was the average PM 2.5 concentration of the data after February 1, 2014 is greater than the average PM 2.5 concentration of the data before February 1, 2014.

Furthermore, an overall LME model was built using the data from 2013, 2014, and 2015. A new variable “POLICY” was added into the model, with POLICY = 0 for the time before the policy implementation and POLICY = 1 for the time after the policy implement. Ultimately, we performed the likelihood ration test to analysis the statistical significance of the POLICY variable and determine whether or not the variable should be included in the final model.

3. Results and Discussion

3.1 Descriptive Statistics

Table 1(a) to Table 1(d) show the descriptive statistics of the model variables in the LME model fitting datasets of 2013, 2014, 2015, and overall, respectively. A total of 11,586, 12,741, and 16,883 data records were included in the 2013, 2014, and 2015 model fitting dataset, respectively. The overall dataset covers 1095 sample days (from January 1, 2012 to December 31, 2015). Within this time interval, the overall mean PM 2.5 concentration was 69.29 μg/m^3, and the mean values of AOD was 0.58. The year specific mean PM 2.5 concentrations were 83.80 μg/m^3, 68.26 μg/m^3, and 60.12 μg/m^3 for 2013, 2014, and 2015, respectively. The corresponding annual mean AOD values were 0.64, 0.60, and 0.54,respectively. The annual average PM 2.5 concentrations show a decreasing trend from 2013 to 2015.

The seasonal mean PM2.5 concentration was highest in winter and lowest in summer (Table 2(a) to Table 2(d)), which was consistent with previous study.(Lv, Hu, Chang, Russell, & Bai, 2016) The highest mean AOD was in summer and the lowest in fall. The seasonal patterns of PRECTOT, PBLH, RH_PBLH and NDVI were similar that the highest value occurred in summer and the lowest in winter. The seasonal patterns of PM2.5 and AOD were different. The relationship between PM2.5 and AOD is complex, which can be strongly affected by geographical, meteorological, and seasonal conditions. (Yang Liu, Franklin, Kahn, & Koutrakis, 2007)

3.2 Model fitting and cross validation

Figure 2 shows the scatter plots for the model fitting and cross validation of 2013, 2014, 2015, and overall. The R^2 and 10-fold CV R^2 of the 2013 LME model were 0.73 and 0.68, respectively. The RMSE was 34.46 μg/m^3 for the 2013 LME model and 37.00 μg/m^3 for CV. Comparing to the model fitting, the CV R^2 decreases by 0.05 and CV RMSE increases by 2.54 μg/m^3 for the 2013 LME model. The R^2 and 10-fold CV R^2 of the 2014 LME model were 0.68 and 0.62, respectively. The RMSE was 29.39 μg/m^3 for the 2013 LME model and 31.76 μg/m^3 for CV. Comparing to the model fitting, the CV R^2 decreases by 0.06 and CV RMSE increases by 2.37 μg/m^3 for the 2014 LME model. The R^2 and 10-fold CV R^2 of the 2015 LME model were 0.67 and 0.63, respectively. The RMSE was 25.32 μg/m^3 for the 2013 LME model and 26.58 μg/m^3 for CV. Comparing to the model fitting, the CV R^2 decreases by 0.04 and CV RMSE increases by 1.26 μg/m^3 for the 2013 LME model. The R^2 and CV R^2 of the overall LME model were 0.62 and 0.59. The RMSE was 33.51 μg/m^3 and CV-RMSE was 34.61 μg/m^3. Compared with the year-specific model, the R^2 and CV R^2 were relatively low.

The application of AOD data allowed us to substantially expand the temporal flexibility and resolution of the model. In our model, AOD was positively associated with daily PM 2.5 concentrations. Since the relationship between AOD and PM 2.5 can be influenced by meteorological conditions, meteorological parameters were added to improve the model performance. The application of AOD in predicting ground PM 2.5 concentration is rare in China. A study by Ma et al. (2014) used geographical weighted regression (GWR) method to predict PM 2.5 concentration in the entire China in 2013 with CV R^2 = 0.64 and RMSE=32.98 μg/m^3 and concluded that over 96% of the Chinese population lives in areas that exceed the Chinese National Ambient Air Quality Standard (Ma et al., 2014). The CV R^2 of 2013 in our study is higher than that value. It is mainly because of the study domain of our study is smaller than the entire China, which could decrease the variability. A developed Bayesian hierarchical model was developed by Lv et al. (2016) to estimate spatio-temporal relationship between AOD and PM2.5 in North China in 2014. They got a CV R^2= 0.61 when a novel interpolation-based variable, PM 2.5 Spatial Interpolator (PMSI2.5), was included, and a CV R^2=0.48 without PMSI2.5(Lv et al., 2016).

3.3 Effectiveness of the *Action Plan*

The cut-off date of the policy implementation is February 1, 2014. Using the developed LME model of 2013, the PM 2.5 concentrations of 2012 were estimated. There were a total of 160,743 estimations of 2012. The estimated annual PM2.5 concentration of 2012 is 59.37 μg/m^3 (Table 3). The seasonal pattern of 2012 was similar to 2013, 2014, and 2015. The highest seasonal mean value of 91.75 μg/m^3 occurred in winter and the lowest seasonal mean value of 52.14 μg/m^3 occurred in summer. A summary of descriptive statistics of predicted PM 2.5 in grid cells without ground PM 2.5 measurements for 2013, 2014, and 2015 was provided in Table 3 as well. The annual predicted PM2.5 levels of 2012, 2013, and 2014 are showed in Figure 3. We noticed that the annual PM 2.5 concentrations of 2013 were highest in both ground measurements group and predictions group. The high PM2.5 levels in 2013 were mainly caused by the high-intensity emissions in winter, and the relative humidity, continuous low temperature, and the allocation of the surface pressure field also have effects on PM2.5 concentrations. (Wang, Liao, Wang, & Sun, 2016)

A paired t-test was performed to compare mean monthly mean PM 2.5 concentrations before the cut-off date and after the cut-off date in each grid cell. There were a total of 20,171 pairs. The results of one tailed paired t-test showed there was a significant difference in PM 2.5 concentration for days before February 1, 2014 (M=66.14 $\mu g/m^3$, SD= 35.73) and days after cut-off date (M=52.33 $\mu g/m^3$, SD=24.57); p-value <0.0001. The mean difference was 13.81 $\mu g/m^3$ (95%CI: 13.51 $\mu g/m^3$, 14.11 $\mu g/m^3$).

A new model with a variable called “POLICY” was built based on the equation (1) using the multiyear dataset. The R^2 and CV R^2 of the new model were 0.63 and 0.60, respectively. The RMSE was 33.15 $\mu g/m^3$ for the new model and 34.13 $\mu g/m^3$ for CV. Compared with the R^2 and CV R^2 of the overall LME model without the variable “POLICY” the R^2 and CV R^2 of the new model were increased due to adding the period variable. The Likelihood ratio test indicated the *Action Plan* affected annual PM2.5 concentration ($\chi^2(1)=30.40$, p-value<0.0001), lowering it by about 13.5 ± 0.42 $\mu g/m^3$. The annual average PM 2.5 level of 2013 was 83.80 $\mu g/m^3$. The average PM 2.5 level of 2014 and 2015 was 64.19 $\mu g/m^3$. Therefore, the annual PM 2.5 levels decreased by 19.61 $\mu g/m^3$ since the implication of the *Action Plan*. Our model suggested that the implementation of policy was responsible for about 68.84% of the reduction in PM2.5 level.

Liu et al. conducted an evaluation of effectiveness of emission control measures during the Beijing Olympic Games in 2008, and reported a 27-33% reduction in daily PM 2.5 concentration because of the control policies (Y. Liu et al., 2012). Our study showed a higher relative reduction in PM 2.5 level due to the Action Plan implementation. It is because the effect of extremely high PM2.5 levels of 2013 and the Action Plan is long-term policy.

3.4. Limitations

The study has several limitations. Firstly, missing AOD values due to clouds can limit the temporal coverage of the predicted PM 2.5 concentration. The PM2.5 concentrations were highest in winter due to fuel combustion. The extremely high concentration of PM 2.5 limits eligibility of remote sensing retrieval of AOD values. Therefore, days with extremely high PM 2.5 levels are more likely to lose AOD data, which could cause a bias. Secondly, there is no regulatory monitoring data of PM 2.5 in China before 2013. In order to keep the same time interval before and after the policy implementation, we had to use the developed LME model of 2013 to estimate PM2.5 concentrations in 2012. The overall LME model was built based on the data of 2013, 2014, and 2015, which means the distribution of data was not balanced. Namely, there was one-year data before the cut-off date but two-year data after the cut-off point.

Conclusion

The LME model described in this study aimed to evaluate the effective of *the China's 2013 Action Plan for Air Pollution Prevention and Control*. The model attempted to estimate PM2.5 levels by incorporating AOD data, meteorological data, land cover status, and population density. Additionally, temporal and spatial variation was resolved by applying random effect terms. According to the predictions of the year-specific models, the mean difference of monthly PM 2.5 concentrations in between days before and after the implementation of the Action Plan was 13.81 $\mu g/m^3$. Our model indicates that the Action Plan was accounted for 68% of the reduction of PM2.5 levels. The data used as predictors in this model are accessible for most cities in China, which suggests that the model could be applied as a tool to expand the assessment of PM 2.5 levels to a greater spatial coverage, as well as an approach for evaluation other air pollution control measurements.

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Tables and Figures

Figure 1 Study domain.

Table 1(a) Summary statistics of the variables in the whole LME model fitting dataset, 2013

Statistic	N	Mean	St. Dev.	Min	Max
PM2.5	11,586	83.80	65.74	3.00	863.00
PRECTOT	11,586	0.25	1.70	0.00	60.78
PBLH	11,586	1,821.17	627.61	60.62	5,623.15
Temp_2m	11,586	293.10	11.53	263.40	317.10
Wind_10m	11,586	4.50	2.43	0.084	18.12
RH_PBLH	11,586	0.41	0.15	0.081	0.94
AOD	11,586	0.64	0.59	-0.05	4.65
NDVI	11,586	0.36	0.17	-0.10	0.83
pop_density	11,586	804,694	744,310	10,804	4,244,479

Table 1(b) Summary statistics of the variables in the whole LME model fitting dataset, 2014

Statistic	N	Mean	St. Dev.	Min	Max
PM2.5	12,741	68.26	51.98	3.00	615.50
PRECTOT	12,741	0.17	1.44	0.00	112.84
PBLH	12,741	1,922.90	674.15	63.50	4,903.70
Temp_2m	12,741	294.00	11.82	262.00	317.40
Wind_10m	12,741	4.37	2.50	0.038	16.30
RH_PBLH	12,741	0.42	0.15	0.069	0.91
AOD	12,741	0.60	0.55	-0.050	4.50
NDVI	12,741	0.37	0.16	-0.10	0.79
pop_density	12,741	859,900	826,410	9,002	4,829,235

Table 1(c) Summary statistics of the variables in the whole LME model fitting dataset, 2015

Statistic	N	Mean	St. Dev.	Min	Max
PM2.5	16,883	60.12	44.000	4.44	476.08
PRECTOT	16,883	0.37	2.800	0.00	99.44
PBLH	16,883	1,795.75	708.000	63.46	4,879.86
Temp_2m	16,883	292.80	11.000	261.70	316.90
Wind_10m	16,883	4.33	2.500	0.012	15.76
RH_PBLH	16,883	0.43	0.150	0.10	0.95
AOD	16,883	0.54	0.510	-0.050	4.25
NDVI	16,883	0.36	0.170	-0.10	0.88
pop_density	16,883	746,785	752,025.000	6,567	4,829,235

Table 1(d) Summary statistics of the variables in the whole LME model fitting dataset, overall

Statistic	N	Mean	St. Dev.	Min	Max
PM2.5	41,210	69.29	54.17	3.00	863.00
PRECTOT	41,210	0.28	2.14	0.00	112.84
PBLH	41,210	1,842.22	677.86	60.62	5,623.15
Temp_2m	41,210	293.30	11.54	261.70	317.40
Wind_10m	41,210	4.39	2.45	0.012	18.12
RH_PBLH	41,210	0.42	0.15	0.069	0.95
AOD	41,210	0.58	0.55	-0.050	4.65
NDVI	41,210	0.36	0.17	-0.10	0.88
pop_density	41,210	798,038	775,138	6,567	4,829,235

Table 2(a) Seasonal patterns of measured PM 2.5, AOD, NDVI and meteorological variables in the whole LME model fitting dataset, 2013

Statistic	Fall	Spring	Summer	Winter
PM2.5	77.56(51.39)	74.02(46.56)	63.62(36.42)	129.27(102.28)
PRECTOT	0.13(0.88)	0.14(1.24)	0.74(3.09)	0.019(0.13)
PBLH	1777.58(459.87)	2103.275(746.34)	2035.30(515.09)	1294.36(449.76)
Temp_2m	292.99(8.35)	293.41(8.81)	306.03(4.08)	278.09(4.47)
Wind_10m	4.27(2.27)	5.69(2.75)	3.71(1.86)	4.29(2.31)
RH_PBLH	0.3(0.13)	0.33(0.13)	0.54(0.12)	0.37(0.13)
AOD	0.54(0.50)	0.68(0.58)	0.75(0.60)	0.62(0.70)
NDVI	0.35(0.11)	0.30(0.12)	0.56(0.13)	0.20(0.07)

Table 2(b) Seasonal patterns of measured PM 2.5, AOD, NDVI and meteorological variables in the whole LME model fitting dataset, 2014

Statistic	Fall	Spring	Summer	Winter
PM2.5	59.73(42.00)	68.31(41.81)	55.00(30.25)	99.14(80.35)
PRECTOT	0.084(0.44)	0.12(0.84)	0.42(2.64)	0.03(0.27)
PBLH	1665.11(430.27)	2330.57(673.60)	2311.87(530.18)	1289.54(434.61)
Temp_2m	292.23(7.54)	295.86(8.08)	306.25(4.07)	276.88(4.53)
Wind_10m	4.27(2.35)	5.16(2.75)	3.48(1.76)	4.66(2.60)
RH_PBLH	0.43(0.14)	0.32(0.12)	0.53(0.12)	0.37(0.12)
AOD	0.44(0.41)	0.63(0.47)	0.84(0.62)	0.47(0.60)
NDVI	0.35(0.12)	0.34(0.13)	0.54(0.13)	0.21(0.06)

Table 2(c) Seasonal patterns of measured PM 2.5, AOD, NDVI and meteorological variables in the whole LME model fitting dataset, 2015

Statistic	Fall	Spring	Summer	Winter
PM2.5	50.54(38.42)	57.35(31.45)	45.28(25.62)	86.13(61.01)
PRECTOT	0.21(1.12)	0.27(1.79)	1.06(5.26)	0.03(0.20)
PBLH	1623.66(514.69)	2087.75(646.84)	2176.69(703.66)	1244.54(511.30)
Temp_2m	294.60(6.74)	294.12(8.39)	305.28(3.87)	278.25(4.53)
Wind_10m	3.87(2.12)	5.24(2.67)	3.32(1.92)	4.53(2.51)
RH_PBLH	0.43(0.14)	0.36(0.14)	0.52(0.13)	0.42(0.13)
AOD	0.41(0.43)	0.58(0.42)	0.70(0.58)	0.46(0.55)
NDVI	0.36(0.13)	0.33(0.15)	0.55(0.13\5)	0.22(0.08)

Table 2(d) Seasonal patterns of measured PM 2.5, AOD, NDVI and meteorological variables in the whole LME model fitting dataset, overall

Statistic	Fall	Spring	Summer	Winter
PM2.5	62.45(45.59)	64.72(39.45)	53.60(31.35)	100.95(80.88)
PRECTOT	0.14(0.91)	0.19(1.44)	0.75(3.97)	0.03(0.20)
PBLH	1687.87(474.13)	2160.11(689.46)	2183.64(609.27)	1269.97(475.86)
Temp_2m	293.28(7.63)	294.71(8.53)	305.82(4.02)	277.83(4.55)
Wind_10m	4.14(2.26)	5.33(2.72)	3.48(1.86)	4.50(2.50)
RH_PBLH	0.42(0.14)	0.34(0.13)	0.53(0.13)	0.39(0.13)
AOD	0.46(0.45)	0.62(0.48)	0.76(0.60)	0.51(0.61)
NDVI	0.36(0.12)	0.32(0.14)	0.55(0.14)	0.21(0.07)

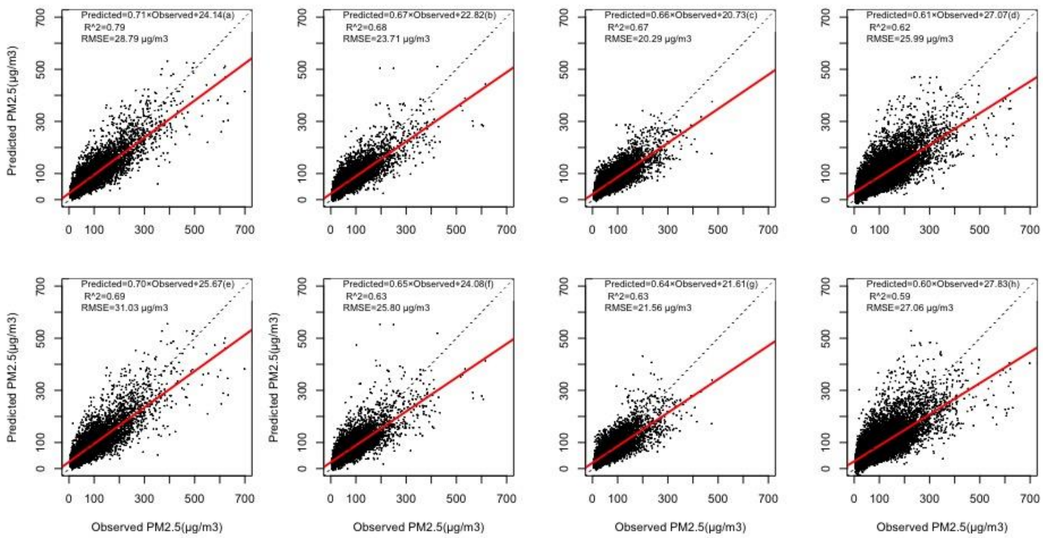

Figure 2. Results of model fitting and cross validation. RMSE: root mean squared prediction error (μg/m^3). The dash line is the 1:1 line as a reference. (a)-(d) are model fitting results of 2013, 2014, 2015, and overall, respectively; (e)-(h) are CV results of 2013, 2014, 2015, and overall, respectively.

Table 3 Summary statistics of the predicted PM 2.5 concentration (μg/m^3) of 2012-2015

	Mean	**SD**	**Minimum**	**P25**	**Median**	**P75**	**Maximum**
2012	59.37	37.92	-16.92	36.14	51.87	72.90	728.40
2013	62.56	42.57	-26.15	37.26	53.73	75.94	794.01
2014	54.80	39.86	-19.95	30.53	46.39	67.65	735.36
2015	48.30	30.60	-12.60	27.94	41.67	60.86	619.89

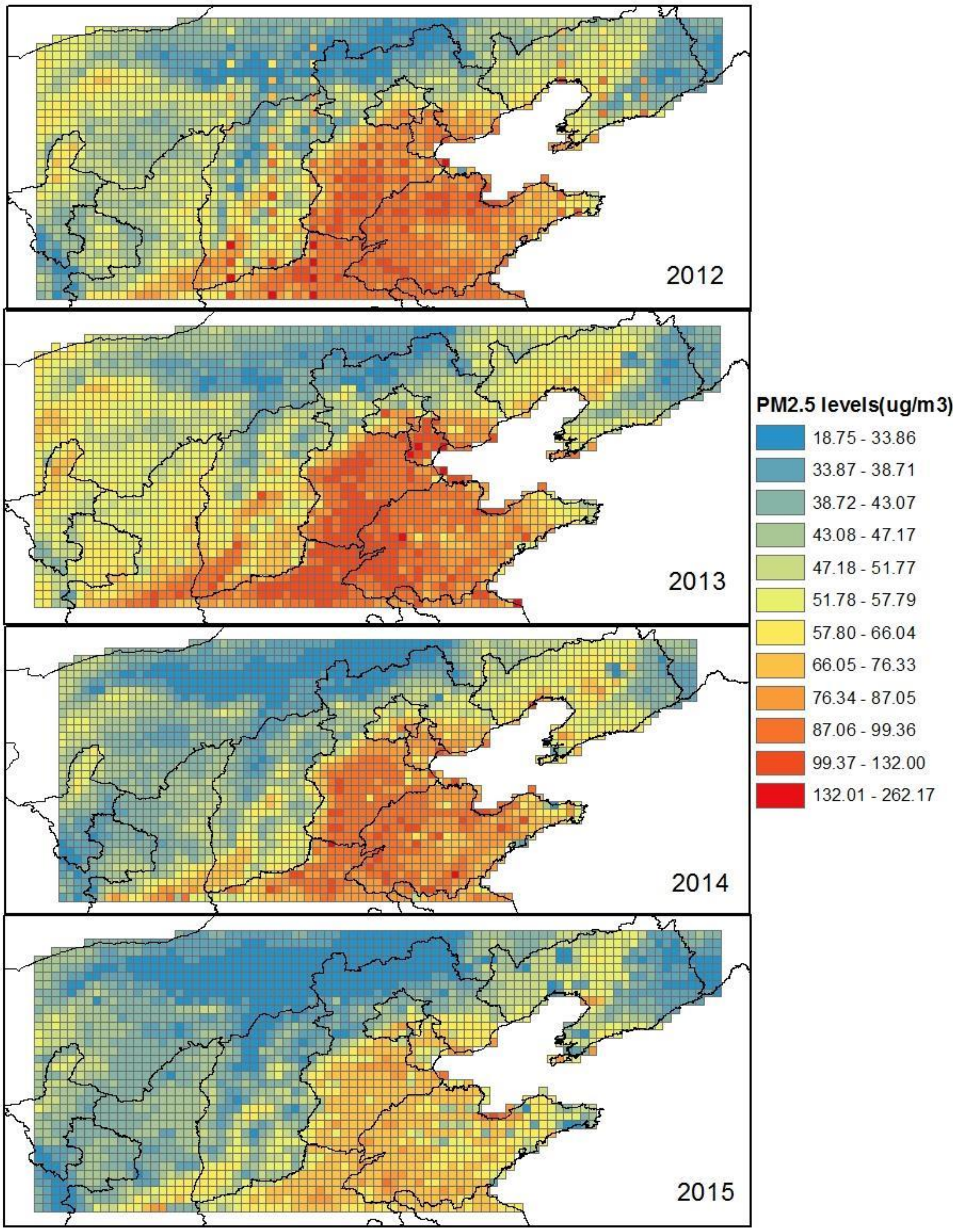

Figure 3 Predicted PM2.5 annual concentration of 2012-2015