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Evaluation on the effectiveness of China's

2013 *Action Plan for Air Pollution Prevention and Control*

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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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Abstract

China promulgated its 2013 *Action Plan of Air Pollution Prevention and Control* in order to remediate the heavily polluted atmosphere. To evaluate the effect of this nationwide policy, a statistical model was developed using ground measurements of fine particulate matter ($PM_{2.5}$) concentration, satellite retrieved Aerosol Optical Depth (AOD), meteorological factors and land cover parameters in northern China between 2013 and 2014. Model predictions suggested that the policy implementation has accounted for 35% or 48% of the total reduction in annual average $PM_{2.5}$ concentrations, based on different scenarios of policy implementation. As data required to develop this model are generally accessible in most cities of China, this model can be applied as a convenient tool to evaluate Chinese air pollution policies.

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Literature Review

1. Air Pollution and Action Plan in Northern China

Ambient fine particulate matter ($PM_{2.5}$, airborne particles with an aerodynamic diameter of less than or equal to 2.5 μm) has been identified as one of the major causes of the severe air pollution in northern China [1, 2]. $PM_{2.5}$ was proved to be associated with different adverse health outcomes including cardiovascular disease and preterm birth [3-6].

In order to relieve the problem of heavy air pollution and reduce the concentration of $PM_{2.5}$, the State Council of China had released the *Action Plan for Air Pollution Prevention and Control* (referred as *Action Plan* in below) in September, 2013 [7]. The *Action Plan* selected ten evidence-based polices to improve air quality. The *Action Plan* attempts to reduce pollutant emission, shift industrial structure, regulate economic power and establish alert systems for exposure protection, etc. Other general laws were either providing indirect legislative approaches, or have failed to keep up with the pace of current environmental problems. For example, the current Air Pollution Prevention and Control Act of China was amended in 2000 to regulate sulfur dioxide emission, and the latest updated version (December 2014) was only a draft proposal released for comments [8]. Therefore, the *Action Plan* was regarded as the only legislative text that was specifically designed to regulate nationwide air pollution emission activities.

Quantitatively, the *Action Plan* had set a list of goals for air quality improvement. Two out of three goals were evaluated by $PM_{2.5}$: (1) by 2017, the annual average concentration of fine particulate matter in the Beijing-Tianjin-Hebei region (also include province of Shanxi, Shandong and Inner Mongolia) should be decreased with by 25%, and (2) the annual average concentration of fine particulate matter in Beijing must be not exceed 60 $\mu g/m^3$. Additionally, mid-term goals were set within the *Action Plan* to ensure the compliance of provincial governments in a timely manner, especially for Beijing-Tianjin-Hebei Region.

The goals are listed as following. By the end of 2015, regional governments are required to complete (a) reconstruction of coal-burning power plants, (b) gasoline and diesel should meet the National V standard, (c) eliminate the 500 million “yellow tag vehicles” (the yellow tag refers to the automobiles who are using gasoline below National I standard, or using diesel below National III standard), (d) phase out the excessive and lagging productivity capacity of iron & steel smelting, cement grinding and glass production, and (e) complete the establishment of fine particulate matter monitoring sites and a heavy pollution weather alerting system.

A decrease in $PM_{2.5}$ concentration should be expected in 2014, the first year of the *Action Plan* implementation, if provincial governments were on track to reach their midterm and final reduction goals. This expectation was based on the following evidence:

Evidence #1. In response to the *Action Plan*, each province of the Beijing-Tianjin-Hebei Region, also referred as northern China, submitted a letter of responsibility including annual plan of industry phase out and emission control to the Minister of Environmental Protection of China (available on CMEP’s official website). By the end of 2014, Beijing had planned to (a) add denitration/ desulfurization/dust removal devices to seven major plants in total, (b) decrease 10,000 tons of VOC emissions, (c) add 5,000 new-energy automobiles and phase out 280,000 old standard automobiles, and (d) shift 44,000 households from coal-burning heating to natural-gas power.

Evidence #2. Each province had either developed its own regional plan or a united plan with adjacent provinces [9-11], or at least delivered the *Action Plan* via its own province level Environment Protection Bureau to local industries [12-14]. These requirements ensured that each province has an individual guideline for implementation.

Evidence #3. In order to urge the implementation of the *Action Plan,* State Council of China had also released a document that requires each province government to submit an annual report on the implementation of *Action Plan* to Ministry of Environmental Protection of China for effect evaluation, in which the goal of reduction in annual average $PM_{2.5}$ concentration is emphasized [15].

2. Evaluating the Particulate Matter with Remote Sensing Data

Air quality measurement stations have been established since 2013 to keep track of the particle pollution. Due to restrictions on research priorities, only major cities in northern China had been prioritized to establish ground measurement stations with the capability of measuring $PM_{2.5}$ concentration. For example, the northern China only prioritized 14 cities, and only less than 50 cities have been established monitoring sites, which could greatly halted the representativeness of the ground measurement data. In order to expand spatial and temporal coverage, satellite remote sensing data has been applied in air quality studies in recent years [16].

With broader coverage, satellite sensors are able to provide aerosol optical density (AOD), a quantitative indicator of particle abundance in the atmospheric column. AOD retrieved at visible wavelength is uniquely sensitive to PM from 0.1-2 μm and therefore is a good indicator for ambient $PM_{2.5}$ concentration [17]. Recent studies have established quantitative relationships between AOD and $PM_{2.5}$ using mathematical models along with meteorological covariates and land use covariates [18-21].

Meteorological parameters are used, either in linear combination with AOD, or fitted in the model as smoothing terms to enhance the performance of the model. In assessing the quantitative relationship between AOD and $PM_{2.5}$, meteorological factors such as surface temperature, wind speed, absolute or relative humidity, planet boundary layer height, and precipitation are commonly included in the models [21-24]. As these meteorological factors affect the physical and chemical properties of the atmospheric aerosols, the retrieval of AOD values will be affected as well.

Similarly, land use terms in models typically includes land use classification/type, population density, traffic information, and vegetation coverage [19, 24, 25]. Specifically, vegetation coverage is assessed using Normalized Difference Vegetation Index (NDVI), which is designed to provide consistent spatial and temporal comparisons of vegetation conditions. According to NASA and the USGS, NDVI retrieved by MODIS instrument, and generated via blue, red, and near-infrared reflectance, centered at 469nm, 645nm, and 858nm, respectively. The NDVI reflects the bio-active content of the land cover, and its value was mainly associated with the live green plant on the land surface.

3. Modelling effort between AOD and $PM_{2.5}$ concentration

In the beginning, attempt were made to evaluate the quantitative relationship between AOD and $PM_{2.5}$ using Linear Regression [25-27]. In order to improve the performance of the model with linearity assumption, additional models were used. Both a geological weighted model and generalized linear model yielded fairly good result with R^2 ranging from 0.51 to 0.71 [18, 28]. Generalized Additive Model (GAM) have been used to enhance the performance by applying smoothing terms into the model. Liu et al. used GAM with lag terms of AOD and precipitation to illustrate the autocorrelative nature of the data [21]. Yanosky et al., created separate generalized additive mixed models with different time intervals [22]. Hamer et al. compared the performance of linear regression, GAM, and Multivariate Adaptive Regression Splines (MARS) and improve retrieval of $PM_{2.5}$ from linear to non-linear methods [26]. In the work of Zou et al., a Neural Network model was established based on limited observations of $PM_{2.5}$ concentration [29]. In the research of Reid et al., 11 models, including GLM, GAM, lasso regression, random forest and others were fitted using up to 29 variables, and the performances of these models were compared [24].

Several statistical parameters were calculated to evaluate the fitness of the proposed model. Adjusted R squared, Mallow's C_p, Akaike Information Criterion (AIC), Deviance and Bayesian Information Criterion are commonly used to illustrate the feasibility and fitness of the model. Apart from these parameters, Cross Validation (CV) is also an important technique to examine the performance of the candidate models. Specifically, CV is used in the format of Leave-one-out Cross Validation, *k*-fold Cross Validation (*k*-fold CV) and Generalized Cross Validation. Based on CV, there are several parameters that are used for evaluation of the models: R squared of CV (CV-R^2), Root of Mean Square of Prediction Error (CV-RMSPE or CV-RMSE), Mean Prediction Error (MPE) or Mean Absolute Error (MAE) [30]. Xin et al. reported the linear relationship between $PM_{2.5}$ and AOD using measurements from ground sensors and from MODIS retrieval, with R^2 equals to 0.58 and 0.57, respectively [27]. Non-linear approaches have improved the performance of the model comparing to linear approaches. Reid et al. have produced a Generalized Boosting Model (GBM) out of 11 models with CV-R^2 = 0.80 and CV-RMSE = 1.50 $\mu g/m^3$using Geostationary Operational Environmental Satellite Aerosol/Smoke Product (GASP) AOD as the main predictor. Similarly, using GASP AOD, Liu et al. had built a GAM describing the relationship between $PM_{2.5}$ concentration and GASP AOD with CV-R^2 = 0.78 and CV-RMSE = 3.6. Using Collection 5 MODIS AOD as the major predictor, Chang et al. used statistical downscaling to generated improved model with CV-R^2 = 0.78 and CV-RMSE = 3.61. [31].

1. Introduction

The first decade of 21^{st} century has witnessed the great economic development of China, as well as emerging environment issues. The challenge of the heavy haze, which might remaining and accumulating in the atmosphere of cities of China for days, had forced the air pollution problem be put onto the priority list of the China's government. After severe air pollution since 2012, China promulgated a responsive action plan as a comprehensive solution.

The State Council of China released *Action Plan for Air Pollution Prevention and Control* in September, 2013 (abbreviated as *Action Plan* in the following content) [7]. The *Action Plan* attempts to regulate in several aspects covering reducing pollutant emission, shifting industrial structure, economical regulating power and alert system for exposure protection, etc.

Quantitatively defined by the *Action Plan*, the control was measured by $PM_{2.5}$ concentration. $PM_{2.5}$ has been identified as one of the major causes of the severe air pollution and the grey haze that decrease the visibility in northern China [1, 2]. Recent studies also revealed that $PM_{2.5}$ is associated with a series of adverse health effect covering respiratory disease, cardiovascular disease and also birth-related conditions. Due to the small size of the $PM_{2.5}$, it is capable to go through the defense system of the respiratory tract, and reached as deep as alveoli, causing irreversible damage to the tissues and inducing respiratory-related diseases [6]. It also has the ability to invade into the circulation system, and move along the blood vessels, finally causing cardiovascular disease. Ping revealed that because of the heavy pollution of hazy weather, in which the $PM_{2.5}$ reached its peak value, the hospital visit had significantly grew in bronchitis, bronchial asthma, upper respiratory infection, COPD, and pneumonia [32]. Yamazaki et al. had observed an increased asthma attack in Japan due to the transboundary air pollution from Beijing's January 2013 episode [33]. Using time series data in Beijing, Xie et al concluded that 10 μg/m3 increase in PM2.5 was associated with a 0.27% (95% CI 0.21 to 0.33%, $p<0.0001$) increase in ischaemic heart disease morbidity and a 0.25% (95% CI 0.10 to 0.40%, $p<0.0001$) increase in mortality on the same day [34]. Yang et al. conducted a meta-analysis on the lung cancer effect due to air pollutant, and concluded that the risk of lung cancer mortality or morbidity increased 7.23 (95% CI: 1.48–13.31) % per10 μg/m3 increase in $PM_{2.5}$ [35]. In another meta-analysis study focusing Chinese population, the author summarized A 10 μg/m3 increase inPM2.5 was associated with a 0.40% (95% CI: 0.22%, 0.59%) increase in total non-accidental mortality, a 0.63% (95% CI: 0.35%, 0.91%) increase in mortality due to cardiovascular disease, and a 0.75% (95% CI: 01.39%, 1.11%) increase in mortality due to respiratory disease [36]. Also, Xu et al. had reported that $PM_{2.5}$ is associated with the variation of heart rate in elderly people with heart disease in Beijing, China [37]. Besides the respiratory and cardiovascular disease, the $PM_{2.5}$ also contribute to the adverse effect on neonatal. A study using WHO survey data had suggested a threshold effect between $PM_{2.5}$ concentration and the condition of low birth weight [38]. Additionally, Zhu et al. conducted a meta-analysis and found association between the maternal exposure to $PM_{2.5}$ and the occurrence of low birth weight, preterm birth, and small for gestational age [39]. With the evidence of a variety of adverse effect on human health, it is crucial to implement a policy that aim to reduce the ambient $PM_{2.5}$ concentration within a small period of time.

According to the *Action Plan*, the goals for controlling ambient $PM_{2.5}$ concentrations are: (1) by 2017, the annual average concentration of fine particulate matter in the Beijing-Tianjin-Hebei region (also include province of Shanxi, Shandong and Inner Mongolia) should be decreased with by 25%, and (2) the annual average concentration of fine particulate matter ($PM_{2.5}$) in Beijing must be not exceed 60 $\mu g/m^3$.

In accordance with the *Action Plan*, a decrease in $PM_{2.5}$ concentration should be expected in 2014, which is the first year after the enforcement of the *Action Plan*. This assumption was supported by the following evidence. (1) The letter of responsibility from each regional government had denoted their first year's annual plan of industry phase out and emission control, which was available on China's Minister of Environmental Protection's (CMEP) website. For example, by the end of 2014, Beijing had planned to (a) add denitration/desulfurization/dust removal device to 7 major plants in total, (b) decrease 10,000 tons of VOC emission, (c) add 5,000 new-energy automobiles and phase out 280,000 old-standard automobiles, and (d) shift 44,000 households from coal-burning heating to natural-gas power. (2) Some province has already published its own regional plan or united plan with adjacent provinces [9-11], and (3) In order to urge the implementation of the *Action Plan,* State Council of China had released a document demanding that each government of province should submit an annual report to CMEP for effect evaluation, in which the goal of deduction in annual average $PM_{2.5}$ concentration is emphasized [15].

Since air pollution is affected by meteorological conditions, and may have differences that is caused by seasonal fluctuation or annual variation, it is therefore not sufficient to evaluate the effect by comparing solely the annual average concentration of $PM_{2.5}$. In order to eliminate the interference of the annual variation, it is necessary to apply statistic models to control for meteorological effects. Liu et al. developed a statistical model to evaluate the effectiveness of a temporary $PM_{2.5}$ control method during the Olympic Game events in Beijing, and was able to isolate the effect of control policy from the effect of meteorological impact. The model could explained 70% of the temporal variability in $PM_{2.5}$, and according to the fitted coefficient, the emission control policies is accounted for 27-33% reduction of the $PM_{2.5}$ concentration during the game [21].

The purpose of the study is to evaluate the effectiveness of the *Action Plan* implementation on northern China. northern China contains one of the China's five main metropolitan areas, the Beijing-Tianjin-Hebei Triangle. Also, this region resided nearly 25% of China's population, and covers nearly one fifth of the China's land territory. Due to its importance, the *Action Plan* should be evaluated in a legitimate approaches. Current evaluation method only asks for direct comparison between the two annual means generated from province-level reports, which could only be resulted from local monitoring sites. However, as far as the author is concerned, no more than 400 monitoring sites were built in the six provinces of northern China, which has a total area as approximately 1,782,901 square kilometers. This means each observation sites is representing averagely more than 4,000 square kilometers, which is very non-representative and biased. In addition, as it could be found from Figure 1, most of the observations sites are located in more developed metropolitan areas (in where the regional Environment Protection Bureau would have the ability to conduct such observation and record). Therefore the result from the government report would be highly biased to more developed cities. In order to solving these problems, satellite remote sensing data could be used because of its ability to expand to a great coverage on space and on time.

The evaluation will be conducted using a statistical approach to analyzing data retrieved from both ground measurement and satellite observations. We first develop a linear mixed model which contains both satellite AOD and corresponding meteorological and land use parameters to estimate ground level daily average $PM_{2.5}$ concentrations in Beijing. After the model describes the association between these predictors and $PM_{2.5}$ levels, a categorical variable labeling the time before and after the implementation of the *Action Plan* will be added into the model. The performances of models with and without the period variable will both be evaluated with cross-validation techniques. The better model will be able to illustrate whether or not the *Action Plan* had successfully affect the $PM_{2.5}$ concentration within the 2013-2014 time period.

The study objective is to evaluate the impact of the policy implementation of China's 2013 *Action Plan for Air Pollution Prevention and Control* using statistical modelling with the data combined from ground measurement $PM_{2.5}$ concentration and satellite remote sensing data of AOD values, meteorological parameters and land covers status.

2. Data and Methods

With the purpose of evaluating the effect of *Action Plan* conducted in Beijing-Tianjin-Hebei Region, i.e. northern China, the Region of Interest was defined as the geographic region that covers this area. In total, the Region of Interest includes 42 cities, whose ground measurement $PM_{2.5}$ data have been successfully been extracted and matched to other meteorological and land use parameters. This study region covers an area of approximately 890,000 square kilometers in land, and is located between a latitude of 34.3°N – 42.7°N and a longitude of 105.5° E – 126.2° E. This region contains six provinces or direct-controlled municipalities in northern China, including Beijing, Tianjin, Hebei, Shandong, Shanxi, and Inner Mongolia.

The data in this study consist of ground measured particulate matter concentrations, satellite retrieved aerosol optical density, and satellite observation of meteorological and land cover parameters. The retrieval, processing and the integration of these dataset are described briefly in the following contents.

2.1 Ground $PM_{2.5}$ Measurement Data

Daily average $PM_{2.5}$ measurements from January 1, 2013 to December 31, 2014 were primarily collected from the official real-time data portal of the China Environmental Monitoring Center (CEMC) (http://113.108.142.147:20035/emcpublish/). Some provinces (such as Shandong and Shanxi province) and municipalities (such as Beijing and Tianjin City) have newly established measurement sites that are not included in the CEMC's system. Data from those additional sites were also collected. Ground $PM_{2.5}$ measurements in China are required to follow the most recent promulgated Chinese National Ambient Air Quality Standard (GB 3095-2012 and HJ 316-2011, available on Chinese Ministry of Environmental Protection (MEP) website http://kjs.mep.gov.cn/), in which the measurements are required to be conducted either by the tapered element oscillating microbalance method or the beta-attenuation method.

Several illegitimate observations were marked as invalid values including (1) observations with $PM_{2.5}$ concentration below 1 μg/m^3, which is very rare in countries with pollution issues like China and possibly caused by detection error, and (2) observations with great leverage and marked as outliers in the diagnostic plots – three observations were removed in this way since they are observed in the exceptional event. Two of them were observed when a heavy dust storm hits nearly half of China in early May, 2014, and the other one was observed when there was an extremely heavy haze hit northern China in November, 2014. After excluding invalid values, a total of 336 $PM_{2.5}$ monitoring sites in 42 cities are included in the region of interest within the northern China. These 42 cities covers most part of the six provinces except only 3 out of 12 cities from the Inner Mongolia Province are included (Figure 1).

2.2 Remote Sensing Data

The Moderate Resolution Imaging Spectroradiometer (MODIS) instrument is operating on the Aqua spacecraft launched by National Aeronautics and Space Administration (NASA). The MODIS is capable of scanning a swath of 2,330 km and has a global coverage of 1-2 days [40]. Aqua MODIS approximately crosses the equator at 1:30 p.m. local time, and AOD were retrieved at 10 kilometer spatial resolution by the MODIS instrument. The Level 2 MODIS Aerosol Product (Collection 6), which contains the AOD variables from January 1, 2013 to December 31, 2014, were obtained from the Level 1 and Atmospheric Archive and Distribution

System (LAADS Web; http://ladsweb.nascom.nasa.gov/), and subset according to the latitude and longitude range of region of interest. Specifically, AOD data (MODIS parameter name: Image_Optical_Depth_Land_And_Ocean) at 550 nm were extracted using IDL 8.4 and used Quality Assurance Confidence Flag equals to 3 to yield better AOD retrieval value (AOD, unitless).

2.3 Meteorological Data and Land Cover Data

Meteorological data were downloaded from the Goddard Earth Observing System-Forward Processing (GEOS-FP). GEOS-FP is the latest GEOS-5 meteorological data product provided by NASA/Global Modeling and Assimilation Office (GMAO). Current GESO-FP uses the 5.11.0 version of the GEOS Data Assimilation System. GEOS-FP data was gridded in a native spatial resolution of 0.25˚ latitude × 0.3125˚ longitude, and temporal resolution of one hour or three hour. In accordance with the local time of the satellite retrieval, the mean values between 1:00 p.m. and 2:00 p.m. of the following variables were extracted from the dataset “tavg3_3d_asm_Nv” in the China 0.25˚ × 0.3125˚ nested gridded file from FTP location ftp://rain.ucis.dal.ca : planetary boundary layer height above surface (PBLH, m), mean relative humidity in PBLH (RH, %), temperature at 2 m above displacement height (T, K), wind speed at 10 m above displacement height regardless of direction (Wind, m/s), and total precipitation (Precip, kg m^{-2} s^{-2}).

Land cover status also has impact on the relationship between the $PM_{2.5}$ concentration and satellite AOD value, and was taken into consideration in the present study. In order to address the effect of land cover, NDVI was chosen to indicate the influence of vegetation change. The MODIS Level 3 monthly mean normalized difference vegetation index (NDVI) products were downloaded from NASA Earth Observations (NEO) (http://neo.sci.gsfc.nasa.gov/). The data provided by NEO was already aggregated into monthly period and gridded into 0.25° × 0.25° spatial resolution.

2.4 Data Preparation and Integration

The raw dataset varied in format. Several steps were used to prepare and combined the data into ready-to-use dataset. Aqua MODIS AOD data were extracted using IDL 8.4 from .HDF format to .CSV format with a latitude/longitude coordinates and date of year (DOY) associated with each observation. Also the Quality Assurance flag is kept to filter out bad observations. GEOS-FP data were extracted using IDL from .nc format to .CSV format with the meteorological parameters in need and again geological coordinates and temporal date marks associated. $PM_{2.5}$ concentration data were summarized as daily average from hourly record, and prepared as long-format data so that each observations is marked with one pair of latitude/longitude coordinates and one date of year value, which could be used to match with two set of predictors above. As Land cover data were represented by NDVI, the dataset is retrieved as aggregated data stored in excel file, with latitude as rows and longitude as columns. Using coordinate as matching variable, the NDVI value was assigned to each observations. These two steps of matching was conducted in R 3.1.3 environment with no additional package installation required.

In order to reduce the burden of processing data, all downloaded datasets were first subset using geological range of the northern China, which is a spherical rectangle with the border of latitude 34.3° N – 42.7° N and longitude 105.5° E – 126.2° E. For data integration, different variables were matched to build each observation using their unique spatial and temporal parameters. The Julian dates of the $PM_{2.5}$ dataset were converted into the variable of date of year (DOY) to help matching other datasets. Based on DOY, a weekend variable was created to demonstrate the weekend effect.

MODIS AOD value were matched to $PM_{2.5}$ that was measured on the same date of year, and within the distance of 0.25 degree approximately. As GEOS-FP was gridded in the 0.25˚ × 0.3125˚ cell, the five meteorological parameters (Temperature, Precipitation, PBLH, Relative Humidity and Wind speed) were assigned to the observation that share the same date of year value, and have latitude and longitude covered within. Using similar matching mechanism, the NDVI value representing a 0.25° × 0.25° cell was also assigned to each $PM_{2.5}$ observation according to geological coordinates and date of year variable.

2.5 Model Development and Validation

The model is developed based on the relationship between the $PM_{2.5}$ concentration and AOD value along with meteorological factors and the land use parameter. In order to address the temporal and spatial variation of the relationship above, temporal and spatial variables were added as random effect into the model as follows:

$$PM_{2.5} = \beta_0 + \beta_1\,\mathrm{AOD} + \beta_2\log(\mathrm{PBLH}) + \beta_3\,\mathrm{Wind} + \beta_4\log(\mathrm{T}) + \beta_5\log(\mathrm{Precip}+1) + \beta_6\,\mathrm{RH} + \beta_7\,\mathrm{NDVI} + \beta_8\,\mathrm{Weekend} + (b_{0,i,j} + b_{1,i,j}\,\mathrm{AOD} + b_{2,i}\log(\mathrm{PBLH})) + \varepsilon \quad \ldots\ldots (1)$$

where $PM_{2.5}$ ($\mu g/m^3$) is the daily average ground measurement of $PM_{2.5}$ concentration, β_0 is the intercept of fixed effect, $\beta_1 - \beta_8$ are the slopes of the corresponding predictors. AOD (unitless) is the AOD value retrieved from Aqua MODIS Collection 6 Aerosol Product; Log(PBLH) (m), Wind (m/s), log(T) (K), log(Precip + 1) (mm), RH (%) are the meteorological parameters (as defined in the "Meteorological Data" section above) with proper log transformation to decrease the range of these variables. NDVI (unitless) is the NDVI value collected from Terra MODIS NDVI value. Weekend is a categorical variable, indicating the difference of effect on weekdays (Weekend = 0) and weekends. b_0 is the random intercept in particular City and on a particular day of year (DOY), b_1 and b_2 are the random slopes for AOD and log(PBLH), respectively. In order to take temporal and spatial variation into consideration, city and week of year are used to address such issues. In the above model, the subscript *i* denotes the effect from city, and *j* denotes the effect from week of year. Therefore the $b_{1,i,j}$ is the random effect on AOD in *i*-th City and on *j*-th DOY, while $b_{2,I}$ is the random effect on log(PBLH) in *i*-th City. The selection of the meteorological and land use variables in the final model is based on the reference of parameter combination from previous studies, and statistical parameters for model selection including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Deviance.

10-fold Cross validation (CV) was conducted to test for potential overfitting of the proposed model by comparing the predictive performance in the training dataset and the test dataset with a 10-time repetition. In each fold, approximately 10% of the total dataset were randomly sampled and forms a test data to determine model performance, while the other 90% of the dataset were used as training dataset to fit a model. After a 10-fold repetition, the statistics used to help determine the performance of the model were used to detect model performance were calculated as a mean value from these 10-fold values. Furthermore, in order to evaluate the model prediction accuracy and CV results, R^2 of the CV (CV-R^2), Mean Fractional Bias (FBIAS) and Mean Fractional Error (FERROR) were calculated to help demonstrate the model performance in our study. The approaches to obtain these parameters are provided as follows:

$$\text{CV-R}^2 = \frac{1}{N}\sum_{i=1}^{N} \mathrm{R}_i^2$$

$$FBIAS = \frac{2}{N}\sum_{i=1}^{N}\frac{(M_i - O_i)}{(M_i + O_i)} \times 100\%$$

$$FERROR = \frac{2}{N}\sum_{i=1}^{N}\frac{|M_i - O_i|}{(M_i + O_i)} \times 100\%$$

Where M_i refers to fitted value using our model, and O_i refers to the observation value, N equals to the total observation and is 52,974 in our case.

After fitting the model, a policy implementation period variable (PERIOD) was added into the model, and its statistical significance was calculated to illustrate whether or not this variable is statistically significant under such model. Statistical significance of the PERIOD variable will determine if the *Action Plan* has been sufficiently effective to reach the desired $PM_{2,5}$ reduction.

2.6 Evaluation of the Effectiveness of the *Action Plan*

Based on equation (1), the policy implementation period variable (PERIOD) was added into the model. Several definitions of the policy implementation were tested due to the ambiguous implementation date that could be identified from governmental documents.

Although the *Action Plan* was published on September, 2013, we allowed some time for regional governments to form a responsive plan that would achieve compliance with the *Action Plan*. Two cut-offs dates (February 1, 2014 and May 1, 2014) were picked to determine the PERIOD variable value and define the date the *Action Plan* had real effects on the aerosol fine particulate matter concentrations. The dates as February 1, 2014 was chosen because it is the date that all regional governments were required to deliver the *Action Plan* to local industries and submit their letter of responsibility to the CMEP, and May 1, 2014 is the date that the Regional United Action Strategy for the six provinces involved in this study region was published as a response to the national-level *Action Plan*. With these cut-off dates, the PERIOD variable was added into the model, with PERIOD = 0 for the time before the policy implementation and PERIOD = 1 for the time after the policy implementation. The *Action Plan* was first considered, and subsequently the Regional United Action Strategy was added into model instead of the previous one to demonstrate its effect. Statistical significance of the PERIOD variable will be calculated as inclusion criterion, and the reduction of annual average $PM_{2.5}$ concentration from 2013 to 2014 accounted by impact of policy implementation alone will be determined comparing to the reduction in total.

3 Result and Discussion

3.1 Descriptive Analysis and Summary Statistics

Summary statistics are provided in Table 1(a) for the response variable $PM_{2.5}$ and major predictor AOD value. Overall, the full dataset covers temporally 730 sample days (January 1, 2013 to December 31, 2014) and spatially 42 cities in the six provinces. Within this time interval, the overall mean $PM_{2.5}$ concentration is 71.57 $\mu g/m^3$, while the year specific mean values are 77.41 and 64.86 $\mu g/m^3$ in 2013 and 2014, respectively. Mean values for AOD are 0.767, 0.762 and 0.772 for overall, 2013-specific and 2014-specific, respectively. A city-specific summary data can be found in Table 1(b). Additionally, histograms of other predictors are also provided in Figure 2 for each model variables in the model fitting dataset.

Comparing the annual average $PM_{2.5}$ concentration between the 2013 and 2014, we could see a small decrease from 2013 to 2014, although this decrease could be caused by either annual variations due to change in climate and weather conditions, or by the immediate implementation of the *Action Plan*. Given that the effect from these two factors are both influencing the variation of $PM_{2.5}$ concentration, the modelling approach is used to control for the effects from each variable.

3.2 Model Development

In order to develop a model with good fitness, several attempts were made to improve the performance. Predictors were added into the model either in its original format or with natural log transformation to rescale the predictor so that the range of the value is shrunk to a proper magnitude. Different combinations of the predictors in original format and with log transformations were tried (Table 2(a)). After figuring out several predictors, i.e. PBLH, Temperature and Precipitation, serves better in log-transformed format, the random effect is added into the model. Several grouping factors have been tried to demonstrate effect, including day of year, week of year, city, cities group, province, etc. Also, the random effects were added on different predictors to help determine the model with the best performance (Table 2(b) and Table 2(c)). With the outcome from ANOVA, and comparison of several statistical criteria including AIC, BIC, deviance, df, etc. the final model came in this format: natural log transformation were used on predictors of PBLH, Precipitation and Temperature. Random effect were added as random intercept, random slope on AOD and random slope on log(PBLH). Finally, as a supplementary adjustment, Date of week (DOW) variable is substituted by Weekend variable (=1 on weekend and =0 on weekdays) since it improves the model by demonstrating the difference between weekdays and weekends in the scenarios of emission from human activities.

In order to fit a model with random effect (i.e. Linear Mixed Effects model), a R package named *lme4* were installed in the R 3.1.3 environment and the function of *lmer()* were mainly utilized to build the model. For coefficient estimation, Maximum Likelihood (MLE) were used. Although there are other choice such as Restricted Maximum Likelihood (REML) or Generalized Estimation Equation (GEE), we pick MLE method for the purpose of enable the comparison capacity of MLE, while other approaches don't have. As there are broad discussions about the uncertainty and the approximation method to retrieve an R^2 in a linear mixed model with the consideration of random effect, an approach to retrieve a R^2 is derived by Jarrett Byrnes and could be referenced in http://glmm.wikidot.com/faq . Similarly, there is some controversy in estimating a confidence interval with the consideration of random effect, and the approach to estimate these intervals were also referenced in the web link above.

3.3 Model Performance

First, a model without the policy implementation period variable was built to describe the impact of weather conditions and land cover status. As indicated by adjusted R^2 value, the fitted model explained 68.7% of the temporal and spatial variation. A linear regression between fitted and observed values of $PM_{2.5}$ concentration could be found on Figure 3.

Comparing the following parameters between model and Cross Validation (CV), we would have Mean Fractional Bias (FBIAS) increased from 0.071 in the fitted model to 0.202 in CV, Mean Fractional Error (FERROR) decreased from 0.296 in the model to 0.211 in CV, and Root of Mean Square Error (RMSE) increased by 10.2 $\mu g/m^3$ from the model fitted to the result in the 10-fold cross validation. This probably suggests a slight overfitting in our model.

For the AOD variable in our model, as the optical property is greatly influenced by the physical and chemical status of the atmospheric aerosol, the random effect from spatial and temporal terms could help explain these variations between cities and between weeks. The aerosol $PM_{2.5}$ is basically generated from the city's local emission, thus a difference in the distribution and the type of emission source can resulted in different association between $PM_{2.5}$ concentration and AOD retrieval. Similarly, the week of year variable could be linked to the seasonal variation and its subsequent effect on the weather condition. These difference in weather condition could also help explain the variation. The Planetary Boundary Layer Height is another factor that is greatly associated with the $PM_{2.5}$ as its height affect the mixing effect of aerosol, and thus impact the elimination and removal process of the $PM_{2.5}$. While aggregating the weather effect into city-level, it is legitimate to have the PBLH as random effect to help address the different association between $PM_{2.5}$ level and AOD value.

3.4 Effectiveness of the Implementation of the *Action Plan*

The cut-off dates of the study period was defined as February 1, 2014 for the first definition of policy implementation period, and defined as May 1, 2014 for the second definition of period Both models containing period terms for each definition are both statistically significant at $\alpha = 0.05$ level. With the addition of the policy implementation impact variable, the RMSE of the model did not decline compared to the model (1) (Table 3).

The annual average PM2.5 concentration decrease by 12.0 $\mu g/m^3$ from 2013 to 2014. We also used our model to predict the annual average $PM_{2.5}$ concentration without the policy impact variable, the annual average $PM_{2.5}$ concentration level would have been 5.7 $\mu g/m^3$ higher than the scenario with policy being implemented. Our model also indicated that the policy implemented by January, 2014 is responsible for 48% of the reduction in $PM_{2.5}$ concentration. Similarly, if the second policy impact is considered to be the main factor that altering $PM_{2.5}$ concentration, then we would see a 4.2 $\mu g/m^3$ reduction in 2014. This implies that the Responsive Strategy of the *Action Plan* accounts for 35% of the total reduction. Both models including policy impact variable did not alter RMSE largely, yet the magnitude of Mean Fractional Error (FERROR) increased, which indicated that the real scenario might not be as simple as a two-stage levels in our study. A possibility in real scenario would be the regional governments would gradually bring out regulations on emission control and progressively shutting down facilities, other than having all policy sections implemented in one day. Therefore the actual reduction of $PM_{2.5}$ concentration could follow a multi-stage pattern or have a linear association with temporal parameter, which is not illustrated in our model.

Comparatively, Liu et al. conducted an evaluation of the effectiveness of emission control policies during the Beijing Olympic Games in 2008, and reported a reduction in 24±4 μg/m^3 or 27–33% in daily $PM_{2.5}$ concentration due to the emission control measures [21]. Our result shows $PM_{2.5}$ reductions are lower in magnitude, indicating that current type of long-term and permanent policy is still in its preliminary phase of implementation, and may have only generated a partial effect in controlling air pollution. The higher percentage in our results, when comparing to the total reduction amount of a 12 μg/m^3 reduction, might result from the different magnitude of the total reduction.

3.5 Limitations

In February 2015, CMEP released a report indicating the decrease in annual average $PM_{2.5}$ concentration from 2013 to 2014 in the Northern China Region was 12%. This CMEP report also reported the annual average $PM_{2.5}$ concentration was 93 μg/m^3 in 2014 [41]. In contrast, our model suggested that there was a 15% reduction and that the $PM_{2.5}$ level for 2014 is 65 μg/m^3, which should be noted as an underestimation of the $PM_{2.5}$ level. Several factors could contribute to this difference.

(1) The CMEP report did not provide criteria for the inclusion of the data according to observation legitimacy or definition of cities, while our dataset had excluded obviously invalid observations and gathered data from all possible sites in this region. For example, there is a large proportion of $PM_{2.5}$ observations detected with a daily average value less than 1 $\mu g/m^3$, which would be uncommon even for cities worldwide that had drastically reduced emissions.

(2) Additionally, extremely high concentrations of $PM_{2.5}$ may limit eligibility of remote sensing retrieval of AOD values, because the algorithm of the AOD retrieval would regard heavy haze as thin clouds and report missing values instead. Therefore, the extremely heavy pollution episodes would generate invalid and missing values in the dataset. In order to fit models, observations with these missing values or obtained during exceptional events have been filtered out. Thus resulted in an estimation bias towards cleaner days with lower mean $PM_{2.5}$ concentrations.

Another reason for the bias of $PM_{2.5}$ reduction is the lack of $PM_{2.5}$ ground measurement sites in rural areas in 2014 – As the demand for monitoring sites is satisfied in urban region, the new sites built in 2014 is more likely to be located in urban areas, where the $PM_{2.5}$ level could be close to background values which is very low. If the subset of 2014 data is contained with much of these rural sites, it is very easy to detect a lower mean value compared to 2013 even there is no reduction in atmospheric aerosol $PM_{2.5}$ at all. A remedy for this phenomenon would be accumulating more observations, so that separate analyses of urban and rural areas can be performed.

At last, there is also a limitation in the time interval covered by our dataset. As China only begin its $PM_{2.5}$ observations in massive cities till very end of 2012, we cannot retrieve data before that time point. Thus, the sample size is insufficient to demonstrate daily effect. In order to satisfy the demand of sensitivity to detect the effect, temporal variable is defined as "week of year" instead of "day of year" to help resolve this issue.

4. Conclusion

In this study a statistical model aimed to evaluate the effectiveness of the *China's 2013 Action Plan for Air Pollution Prevention and Control* is demonstrated. These estimates were obtained by controlling the meteorological parameters and land cover status. Additionally, temporal and spatial variation is also resolved by applying random effect terms. Our model indicates that the *Action Plan* policy is accounted for 48% or 35% of the reduction of annual average $PM_{2.5}$ levels, respectively depending on an implementation date based on the selection of either nationwide legislation or regional united responsive action.

The data used as predictors in this model are accessible for most cities in China, suggesting that this model could be used as a tool to expand the evaluation of the $PM_{2.5}$ concentration to a greater spatial and temporal coverage, as well as an approach to assess the effectiveness of other Chinese air pollution policies. Due to reliance on satellite data, cloud cover is an important limiting factor in data availability. It is advised that this model be used with fewer extreme pollution scenarios.

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Tables and Figures

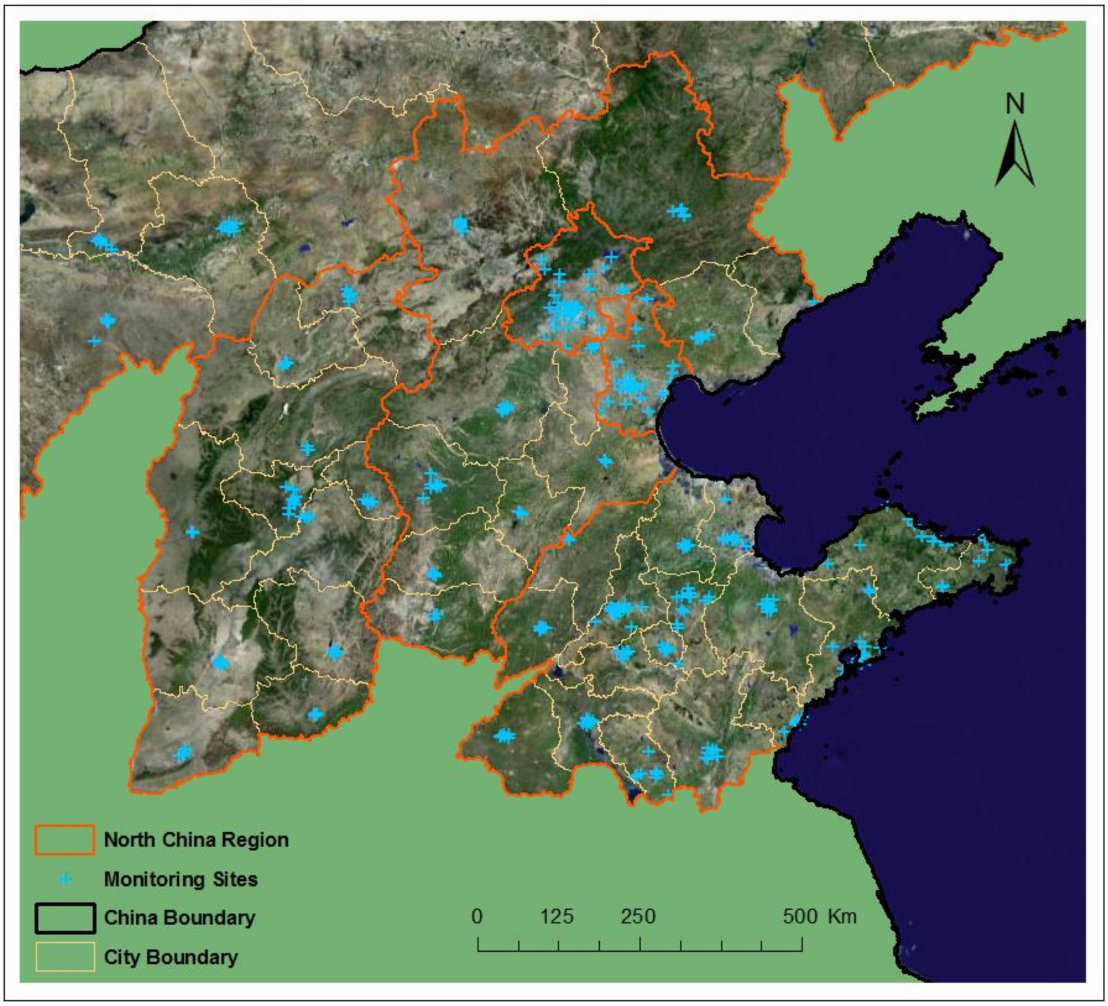

Figure 1. Study domain – northern China (circled with orange border). Monitoring sites for ground level $PM_{2.5}$ are marked out with light blue cross.

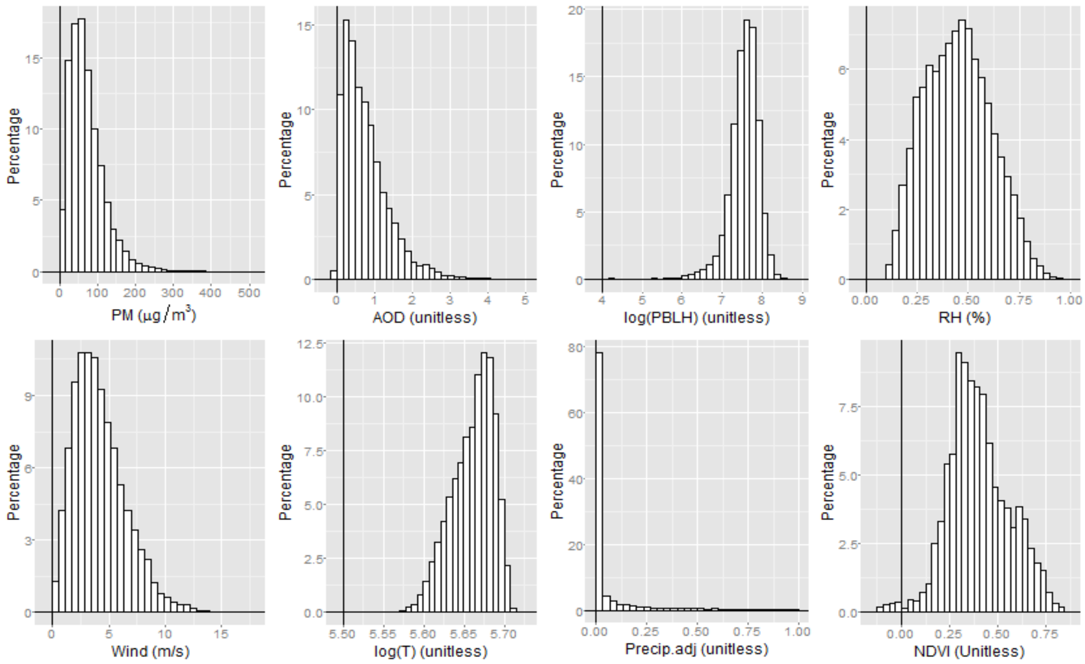

Figure 2. Distribution of the model variables. Several variables have been log-transformed to improve model performance. (Note: Precip.adj = Log(precip +1)

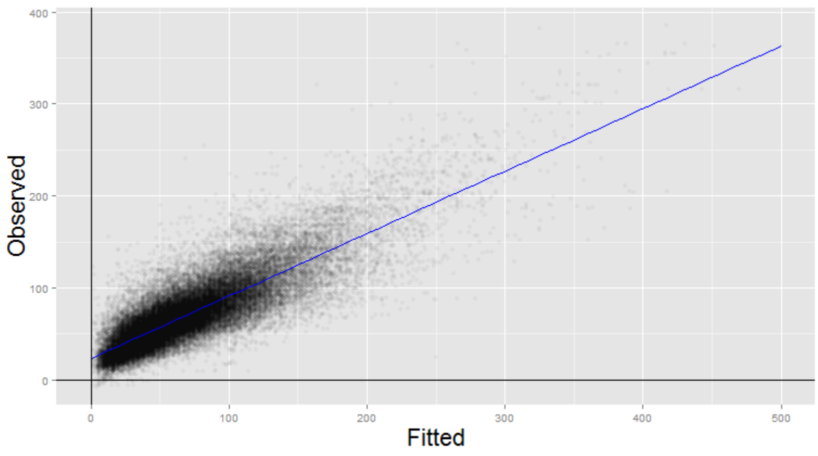

Figure 3. Linear regression between fitted value and observed $PM_{2.5}$ concentration using model (1). Fitted $PM_{2.5}$ = 0.66 × Observed $PM_{2.5}$ + 24.03, R^2 = 0.698.

Table 1(a). Summary statistics of MODIS AOD and ground measurement of $PM_{2.5}$

	Overall		2013		2014	
	Mean (SD)	Range	Mean (SD)	Range	Mean (SD)	Range
$PM_{2.5}$ (μg/m^3)	71.9 (46.1)	1.1 – 500.0	77.0 (48.1)	3.0 – 500.0	65.4 (42.9)	1.1 – 469.0
MODIS AOD	0.77 (0.62)	-0.05 – 4.84	0.76 (0.62)	-0.05 – 4.64	0.77 (0.62)	-0.05 – 4.84

Table 1(b). Descriptive statistics for each city in northern China

City	Central longitude	Central Latitude	Observation Sites	Average $PM_{2.5}$	Average AOD
Baoding	115.2	39.0	6	90.0	1.0
Beijing	116.4	40.2	7	63.3	0.7
Binzhou	117.9	37.6	6	83.0	0.9
Cangzhou	116.8	38.3	3	72.4	0.8
Changzhi	112.9	36.5	5	59.3	0.5
Chengde	117.5	41.3	5	39.5	0.3
Datong	113.7	39.9	6	39.2	0.3
Dezhou	116.6	37.2	6	93.8	0.9
Dongying	118.6	37.6	9	73.2	1.0
Handan	114.5	36.6	4	89.9	1.1
Hengshui	115.8	37.8	3	87.9	0.9
Heze	115.7	35.2	6	91.8	0.9
Hohhot	111.4	40.6	19	37.6	0.3
Jinan	117.1	36.7	16	77.0	0.9
Jincheng	112.7	35.6	5	88.2	0.6
Jining	116.7	35.4	7	95.7	0.9
Jinzhong	113.0	37.3	4	85.4	0.6
Laiwu	117.7	36.3	7	78.6	0.7
Langfang	116.6	39.3	4	70.4	0.8
Liaocheng	115.9	36.5	6	94.5	1.0
Linfen	111.4	36.2	16	67.7	0.8
Linyi	118.3	35.3	8	87.2	0.9
Luliang	111.3	37.7	3	57.5	0.3
Qingdao	120.1	36.5	14	63.2	0.8
Qinhuangdao	119.2	40.1	1	65.2	0.8
Rizhao	119.1	35.6	7	71.8	0.8
Shijiazhuang	114.4	38.1	8	89.2	1.0
Shuozhou	112.6	39.6	4	53.1	0.4
Tai'an	117.0	36.0	7	73.7	0.8
Taiyuan	112.3	38.0	9	58.2	0.5
Tangshan	118.3	39.7	6	84.0	0.8
Tianjin	117.3	39.3	27	74.7	0.9
Weifang	119.1	36.5	9	78.1	0.8

Table 1(b). (Continued)

City	Central longitude	Central Latitude	Observation Sites	Average $PM_{2.5}$	Average AOD
Weihai	122.0	37.1	10	49.2	0.6
Xingtai	114.8	37.2	4	99.6	1.1
Xinzhou	112.4	38.9	3	103.4	0.5
Yangquan	113.5	38.1	6	56.9	0.5
Yantai	120.8	37.2	11	52.0	0.7
Yuncheng	111.1	35.2	5	91.4	0.8
Zaozhuang	117.3	35.0	8	89.3	0.8
Zhangjiakou	115.0	40.9	5	27.9	0.3
Zibo	118.0	36.6	13	88.6	0.8

Table 2(a). Stepwise Linear Selection of candidate models.

Model Specification*	Residual Sum of Squares	Keep Log transformed term in the model?
All terms in Linear	67204120	/
+Log transform: PBLH	66448481	YES
+Log transform: RH	66766120	NO
+Log transform: Wind	66602354	NO
+Log transform: Temp.	66446907	YES
+Log transform: Precip.	66366831	YES**
+Log transform: RH &Wind	66761408	NO

* Only a proportion of the candidate models are presented here.

** After selection, the predictors of PBLH, Temperature and Precipitation are determined to be added as log-transformed terms into the model.

Table 2(b). Selecting terms to add random effect

Model Specification*	DF	AIC	BIC	logLik	deviance
1.Random intercept from Site	17	529678	529829	-264822	529644
2.Random intercept and slope on AOD from Site	18	528921	529081	-264442	528885
3.Random slope on AOD from Site	19	528922	529091	-264442	528884
4.Random slope on AOD from Site & Random intercept from City	20	528604	528782	-264282	528564
5.Random intercept and slope, nested group on City & Site	21	528606	528793	-264282	528564
6.Random slope on AOD, random intercept and slope on PBLH**	23	527729	527933	-263842	527683
7.Random slope on AOD, random intercept and slope on RH	23	528138	528343	-264046	528092
8.Random slope on AOD, random intercept and slope on Wind	23	528360	528564	-264157	528314
9.Random slope on AOD, random intercept and slope on Temp.	23	528278	528483	-264116	528232
10.Random slope on AOD, random intercept and slope on Rain	60	528510	529043	-264195	528390

* Only a proportion of the candidate models are presented here.

** Model 6 in Table 2(b) is decided to use to develop model in next step.

Table 2(c). Selecting terms to add random effect

Model Specification	**Df**	**AIC**	**BIC**	**logLik**	**deviance**
1. Day of Year and City as grouping factor	25	482601	482823	-241276	482551
2. Week of Year and City as grouping factor*	25	506624	506846	-253287	506574
3. Week of Year and City as nested grouping factor	25	507840	508062	-253895	507790
4. Week of Year and Cities Group as grouping factor	25	508979	509201	-254464	508929
5. Week of Year and Cities Group as nested grouping factor	26	508983	509213	-254465	508931

*Model 2 in Table 2(c) is selected as the model with best performance.

Table 3. Performance of the Models and Cross Validation results.

Model	RMSE	R^2	CV-R^2	CV-RMSE	FERROR	FBIAS
(1) PM~AOD+Met*+Land**	25.4	0.698	0.699	35.4	19.5%	20.2%
(2) PM~AOD+Met+Land +PERIOD1	25.2	0.702	0.702	34.4	53.9%	-12.9%
(3) PM~AOD+Met+Land +PERIOD2	25.4	0.701	0.702	34.0	30.9%	9.4%

* Met: Meteorological parameters.

** Spatial and temporal variables are not demonstrated in these three equations.