LONG-TERM TREND OF GROUND-LEVEL PM2.5 CONCENTRATIONS OVER 2012-2017 IN CHINA

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***Abstract* - Ambient suspended fine particulate matter (PM2.5) is a greatest environmental risk factor for premature mortality. We adopted aerosol optical depth (AOD) retrieved from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument to produce annual-mean PM2.5 concentrations from 2012 to 2017 with a spatial resolution of 3km. A geographically weighted regression model was conducted using vertical- and hydroscopic-corrected AOD and meteorological data. The PM2.5 estimates were validated by the ground measurements, with R^2 and RMSE (MPE) of 0.79 and 18.26 (12.03) μg/m^3. The results show that national average of PM2.5 concentration represented a 31% decline over five years, from 69.37 μg/m^3 in 2013 to 43.85 μg/m^3 in 2017, after a slightly rise (6%) during 2012-2013. Significant reduction was revealed in the Beijing-Tianjin-Hebei region, decreasing by 37.31% from 2013 to 2017. Despite low decline in some southeastern provinces, the national-mean PM2.5 concentration has decreased by 31%, indicating the effectiveness of the control policies issued by Chinese government in 2013. Nevertheless, efforts to improve air quality are still required to further reduce the mass concentration in China.**

Index Terms* - *PM2.5, satellite remote sensing, air pollution, trend

I. INTRODUCTION

China has suffered severe fine particulate matter (with aerodynamic diameters lower than 2.5μm, PM2.5) pollution due to urbanization and economic development [1]. Exposure to PM2.5 could increase the mortality risk from respiratory diseases, cardiopulmonary diseases and lung cancer [2], since these small particles could penetrate into the respiratory tract, even the alveoli and the blood stream [3]. The Global Burden of Diseases (GBD) study reported that PM2.5 poses the fourth highest risk factor for premature mortality in China, resulting in 11.1% of all deaths in 2016 [4].

Chinese government introduce a series of control policies to improve the air quality. Following the World Health Organization (WHO) air quality guidelines [5], fine particulate matter was included into the Ambient Air Quality Standard (GB3095-2012) in 2012. Since then, "Action Plan for Air Pollution Prevention and Control" were published as the guideline for air quality improvement, intending to reduce PM2.5 concentration by 25% from 2012 to 2017 [6].

Therefore, long-term PM2.5 estimation is inevitable to ensure the implementation of these strategies in China. Although air quality monitoring network could accurately quantify ground PM2.5 concentrations, it cannot reflect the spatial variation of the concentrations. Satellite remote sensing technique provide a possibility to estimate large-scale outdoor PM2.5 concentration based on the relationship between satellite-observed aerosol optical depth (AOD) and PM2.5. Various statistical models have been conducted using satellite observations, such as land use regressions [7], mixed effects models [8], generalized additive models [9] and artificial neural networks [10]. However, few models considered the aerosol physical characteristics, resulting in weak interpretability. Although chemical transport models could simulate PM2.5 concentrations with strong physical mechanism, the accuracy is influenced by initial parameters (such as emission inventory) and incomplete description of the processes [11].

In this study, the satellite-observed AOD was corrected based on aerosol vertical distribution and hydroscopic growth characteristics for PM2.5 estimation using geographical weighted regression (GWR) model. Annual PM2.5 concentrations from 2012 to 2017 were estimated over China, with spatial resolution of 3km. The long-term PM2.5 trend was explored to assess the implementation of current air control policy in China, providing scientific basis for future policy-making.

The rest of paper is structured as follows. Section II introduces the adopted datasets and the main retrieval method. The validation results of ground PM2.5 retrieval and the trend during 2012-2017 are explored in Section III. Section IV concludes the paper.

II. METHOD

A. Data Collection

Hourly ground PM2.5 measurements were obtained and calibrated with quality control according to "National Ambient Air Quality Standard" and "Environmental Protection Standard". Annual PM2.5 concentrations were averaged from hourly concentrations when the satellite is passing by.

TABLE I. DETAILED INFORMATION OF ADOPTED DATASETS

Dataset	Unit	Spatial resolution	Data source
Ground-level $PM_{2.5}$	μg/m^3	N/A	China National Environment Monitoring Center (http://www.cnemc.cn),
MODIS AOD	Unitless	3km; 10km	NASA Atmosphere Archive and Distribution System
T	K	0.25 degree	NCEP GDAS/FNL 0.25 Degree Global Tropospheric Analyses and Forecast Grids (https://rda.ucar.edu/datasets/ds083.3/)
WS	m/s		
P	kg/m^2		
RH	%		
PBLH	m		
VIS	m	N/A	NCEP ADP Global Surface Observational Weather Data (http://rda.ucar.edu/datasets/ds461.0/)
DEM	m	1km	Resources and Environmental Science Data Center

The Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 6 AOD data was adopted in our study. MODIS provides three AOD retrieval algorithms overland: the "Dark Target (DT)", the "Deep Blue (DB)" and the "Multi-Angle Implementation of Atmospheric Correction (MAIAC)" algorithm. Considering the spatial extent and the computational efficiency, we employed MODIS 3km DT and 10 km DB AOD in our study. DB algorithm excels DT in bight surface AOD retrieval, therefore, we employed DB 10km AOD to fill the missing pixels in DT 3km AOD images. An inverse variance weighting (IVM) approach was adopted for gap- filling [12]. We also adopted AERONET (Aerosol Robotic Network) level 2.0 AOD measurements to calibrate MODIS AOD products.

Meteorological data was acquired from NCEP/NCAR reanalysis dataset to perfect the AOD-PM2.5 relationship, which includes air temperature (K), surface wind speed (WS), precipitation (P), relative humidity (RH), planetary boundary layer height (PBLH) and visibility (VIS) (m). The 1km DEM data was also adopted in this study. The detailed information is shown in Table I. The VIS data was interpolated to 3km spatial resolution using the inverse distance weighted algorithm. All adopted datasets were unified with spatial resolution of 3 km for modelling using cubic convolution resampling algorithm.

B. Satellite-derived PM2.5 estimation

According to [13], both RH and PBLH could affect the AOD-PM relationship. Since satellite-observed AOD is the aerosol optical property in the atmosphere column, it should be corrected the ground-level extinction via eliminating the effect of height. The majority of atmospheric aerosols evenly suspend in the PBL due to the active mixing was demonstrated in [14]. Meanwhile, aerosol hygroscopic characteristic affects extinction through changing the particle size, leading to the overestimation of mass concentration. Therefore, we corrected satellite-observed AOD to 'meteo-scaled' optical depth using the following formula.

$$AOD^* = AOD/(PBLH*f(RH)) \quad (1)$$

where f(RH) refers to hygroscopic growth function with independent variables of relative humidity RH, which is calculated based on the previous studies [15-17].

The GWR model was conducted to estimate PM2.5 across China based on the corrected AOD, which was developed according to the following model structure:

$$PM_{2.5(i,j)} = \beta_{0(i,j)} + \beta_{AOD^*_{(i,j)}} AOD^*_{(i,j)} + \beta_{T(i,j)} T_{(i,j)} + \beta_{WS(i,j)} WS_{(i,j)} + \beta_{P(i,j)} P_{(i,j)} + \beta_{VIS(i,j)} VIS_{(i,j)} + \beta_{DEM(i,j)} DEM_{(i,j)} + \varepsilon_{(i,j)} \quad (2)$$

where $PM_{2.5(i,j)}$ is the annual ground-level PM2.5 concentration at location (i, j); β_0 is the intercept for each year; β with different subscripts denote the slope of corresponding variables. $\varepsilon_{(i,j)}$ is the error term at location (i,j). The Gaussian distance decay functions were adopted to determine the weight.

The model was developed based on the PM2.5 ground measurements from 2013 to 2017 due to the limited number of measurements in 2012. Considering the spatial autocorrelation, the 10-fold block cross validation (CV) were adopted to evaluate the model performance.

III. RESULTS AND DISCUSSION

A. Validation of PM2.5 concentrations

We obtained available ground-level PM2.5 measurements across China over 2012-2017. Fig.1 presents the spatial pattern of the 6-year average PM2.5 concentrations. The spatial distribution of ground-level measurements is consistent with that of satellite-derived results, with severe PM2.5 pollution in the eastern China. Four hotspots (including three city clusters and one desert region) are also presented to highlight the details. Among the three city hotspots, the highest concentration occurred in the Beijing-Tianjin-Hebei (BTH) metropolitan area, with six-year mean concentration higher than 75 μg/m^3, followed by the Yangtze River Delta region (YRD) region and the Pearl River Delta (PRD) region. These three city clusters contribute over 28 % of the total Chinese population, with only 6% of the total area. PM2.5 concentrations in these densely populated regions result from the rapid urbanization and industrial development, while dust and sand are the primary sources of the PM2.5 in the Taklamakan Desert [18].

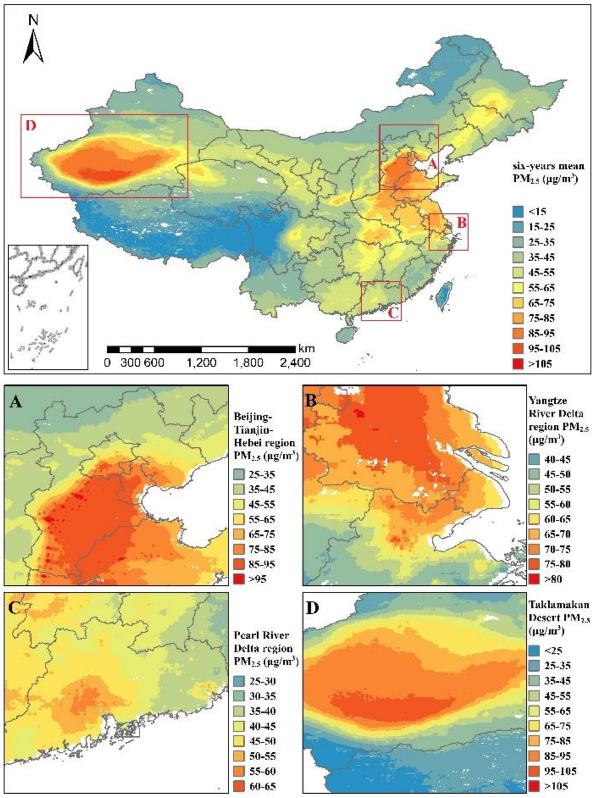

Fig. 1Spatial pattern of the 6-year average of PM2.5 concentrations

TABLE II. VALIDATION RESULTS OF ANNUAL MEAN PM2.5 CONCENTRATION

	N	R^2	RMSE (μg/m³)	MPE(μg/m³)
Model-fitting	5468	0.83	15.22	9.87
Cross-validation	5468	0.79	18.26	12.03

Note: N - sample numbers; R^2 - determination coefficient; RMSE - root mean square error; MPE - mean predictive error

Table II shows the validation results of annual mean PM2.5 concentrations. The model fitting and CV R^2 are 0.83 and 0.79, respectively. The performance is comparable to those in other studies [9, 18]. We selected three mega cities (Beijing, Shanghai and Guangzhou) corresponding to three hotspots (the BTH, YRD and PRD regions) in Fig. 1 to highlight the temporal pattern of PM2.5 concentrations during 2012-2017. The inter-annual variation of the retrieved and measured PM2.5 concentrations in three mega cities including Beijing, Shanghai, and Guangzhou are plotted in Fig. 2. The trends of estimated concentrations are similar with those of measured values. The mean differences between ground measurements and satellite estimations in these three cities are 4.63±3.81 μg/m³, 2.21±3.02 μg/m³ and 1.66±2.93 μg/m³, respectively. The result shows that the method combined the GWR model with corrected AOD based on aerosol vertical distribution and hydroscopic growth characteristics could effectively estimate ground-level PM2.5 concentration in national scale.

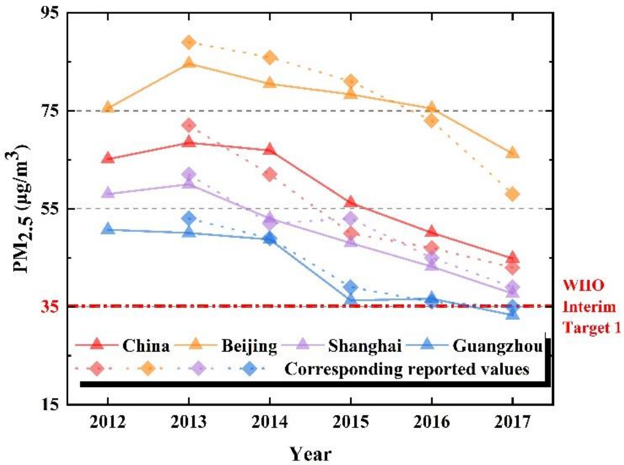

Fig. 2 Interannual variations of the estimated and measured PM2.5 mass concentrations in China and three mega cities (marked by solid and dashed lines respectively)

B. *PM2.5 trend*

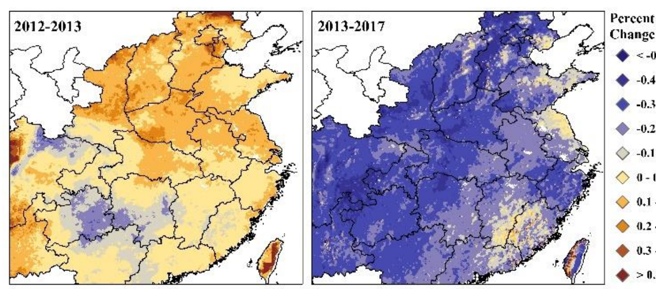

Fig. 3 Percentage changes over the eastern China during 2012-2013 and 2013-2017

The interannual variation shows that the annual mean PM2.5 concentration in China was slightly increased from 65.66 μg/m³ in 2012 to 69.37 μg/m³ in 2013 before decreasing to 43.85 μg/m³ in 2017 (Fig. 2). The result is consistent with the previous studies [6, 19]. Hence, the spatial distributions of PM2.5 percentage changes from 2012-2013 and 2013-2017 are separately plotted to highlight the trends in the densely-populated areas (Fig. 3). PM2.5 concentrations were increased by 20%-30% in the northeastern China during 2012-2013, while values in the southeast were rise slowly. After 2013, when "Action Plan for Air Pollution Prevention and Control" was issued, the PM2.5 concentrations in most provinces were decreased significantly. The concentrations in the BTH regions are decreased by 37.31%, with decreasing rates of -5.79 μg/m³/year in Beijing and -6.08 μg/m³/year in Tianjin. The significant decline in the BTH region is due to the intense air quality policies. Although some provinces, such as Fujian, Jiangxi and Jiangsu province, showed much less change, it is encouraging that the annual-mean PM2.5 concentration in China has decreased by 31%, indicating the effectiveness of Chinese government control policies. However, the efforts of air quality improvement are still required to meet the WHO standard.

IV. Conclusion

This paper investigated the annual average ground-level PM2.5 concentrations from 2012 to 2017 over China obtained from the corrected AOD and meteorological data using the GWR model. The PM2.5 estimation has been validated, with CV R^2 and RMSE (MPE) of 0.79 and 18.26 (12.03) μg/m^3. The spatial patterns of six-year average PM2.5 concentration across China have been presented. Among three metropolitan city clusters with highly dense population, the highest concentration occurred in the BTH region, followed by the YRD and PRD regions. The percentage changes of PM2.5 concentrations during 2012-2013 and 2013-2017 were explored to assess the variation trends. The results show that the national-average PM2.5 concentration was decreased by 31% during 2013-2017 after a slightly rise (6%) during 2012 to 2013. Significant reduction was revealed in the BTH region, decreasing by 37.31% from 2013 to 2017. However, some provinces (e.g.S Jiangsu and Guizhou) showed little change. It is suggested that further efforts should be made to improve air quality in order to meet the WHO standard.

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