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# POPULATION EXPOSURE TO $PM_{2.5}$ POLLUTION AND ASSOCIATED LUNG CANCER DEATHS IN THE YANGTZE RIVER DELTA BASED ON MULTI-SATELLITE RETRIEVALS: A CASE STUDY IN 2013

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## ABSTRACT

The spatial distribution of $PM_{2.5}$ population exposure is a key factor to the estimation of the health impacts of $PM_{2.5}$. By combining the $PM_{2.5}$ data retrieved from MODIS satellite and the population spatial distribution data in the Yangtze River Delta which were estimated by the random forest model with the night light, vegetation index, elevation and slope of satellite remote sensing, the population exposure intensity of $PM_{2.5}$ and the risk of lung cancer death in 2013 were calculated. The results show that the spatial distribution of $PM_{2.5}$ population exposure intensity is spatially discontinuous, which is consistent with the spatial distribution of population but inconsistent with the spatial distribution of $PM_{2.5}$ concentration. Generally, the regions of high exposure intensity include Shanghai, most of Jiangsu Province, the central and southern half of Anhui Province and some coastal cities in Zhejiang Province. The lung cancer deaths caused by $PM_{2.5}$ pollution are consistent with the spatial distribution of $PM_{2.5}$ exposure intensity. Among the four major cities, relative to the baseline situation, the largest increment in lung cancer deaths caused by $PM_{2.5}$ in 2013 is in Shanghai (1565), and the smallest is in Hefei (570). In 2013, the total number of lung cancer deaths caused by $PM_{2.5}$ exposure in the Yangtze River Delta is 14000. Our findings indicates that moderate-resolution information from multi-satellite retrievals can help to understand the spatiotemporal variability of population exposure and the related health risk in a high-density environment.

  

**Keywords:** $PM_{2.5}$ population exposure level; satellite remote sensing; population spatial distribution; random forest model; lung cancer death.

## 1. INTRODUCTION

Ambient $PM_{2.5}$ air pollution poses a great threat to global human health. The population exposure to $PM_{2.5}$ will increase the risks of a sequence of diseases, affecting respiratory system, cardiovascular system, reproductive system and other organs, ultimately leading to a shortened life expectancy (Pope III C A et al., 2002; Zeng XW et al., 2016; Chen X et al., 2016; Wang, H et al., 2019). According to the WHO report, air pollution with $PM_{2.5}$ as the primary pollutant in 2012 is related to 16% of lung cancer mortality (WHO., 2005).The "Harvard six cities study" points out that for every 10 μg/m3 increase in $PM_{2.5}$ concentration, the mortality of obstinate chronic obstructive pulmonary disease increases by 3.3% (Dockery DW et al., 1993). Cohen et al. found a 10 μg/m3 increase in $PM_{2.5}$ exposure could cause a 5% increase in premature mortality due to lung cancer. (Cohen AJ et al., 2017). Pathogenic mechanism research results demonstrated that $PM_{2.5}$ can cause oxidative damage, and chromosomal aberration of cells, resulting in the formation of tumor cells (Gurgueira SA et al., 2002; Gonzalez-Flecha et al., 2004). To assess the health burden attributable to $PM_{2.5}$, premature mortality has been applied to estimate the regional impacts of $PM_{2.5}$ on lung cancer. For example, Burnett et al. (2014) developed an integrated exposure–response (IER) model to estimate the global burden of disease attributable to $PM_{2.5}$ (Burnett, R. T. et al., 2014).

To evaluate the premature mortality caused by $PM_{2.5}$, it is necessary to accurately estimate the population exposure to $PM_{2.5}$, which is not only an element of environmental quality but also an element of population distribution. Therefore, it may be inaccurate to use just a single value of $PM_{2.5}$ concentration (Gui K et al., 2019). At present, the spatial distribution of $PM_{2.5}$ are released by NASA and other institutions (Kloog, I. et al., 2011) and the census population in administrative region is mostly adopted(Yu S et al., 2018) . However, it maybe still imprecise when population exposure to $PM_{2.5}$ is estimated as the population weighted $PM_{2.5}$ concentration with a single population value of a whole city or a very coarse resolution of air quality data (Wang L et al., 2018; Song C et al., 2017; Zhang F. et al., 2011; Guo, Y. et al., 2016; Wu, J. et al., 2017) , because both ambient $PM_{2.5}$ and population have large spatial variations (Kloog I. et al., 2014; Korhonen, A. et al., 2019).

In recent years, the remote sensing data of night lights are found closely related to human activities, and high-precision remote sensing data of night lights obtained by satellite remote sensing have been used for analysis of spatial distribution of population (Ye T et al., 2019). Ye et

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al. developed a population random forest model (population RF model) suitable for Chinese high resolution population mapping by setting the points of interest (POIs), nighttime light (NTL) images, road network, MODIS-derived normalized difference vegetation index (NDVI), digital elevation model (DEM) as multiple independent variables and census population as the dependent variable. The R2 of the model is as high as 0.93 and the resolution is 100 m x100 m (Ye T et al., 2019). However, the national census is conducted once every ten years, and some other independent variables are also missing in some years, so this high-precision and high-resolution population can only be mapped in the census year.

Therefore, in order to explore a method to precisely estimate the spatial distribution of $PM_{2.5}$ population exposure and its risk on lung cancer in any given years, we attempt to reasonably simplify the population RF model on the premise of ensuring the accuracy and resolution of the results by taking the situation in 2013 in the Yangtze River Delta (YRD) as an example, First, we combined the machine learning and geographic information system (GIS) technology and eliminated some factors which were difficult to collect and contributed little to the population RF model. Then we estimated the spatial distribution of population with the simplified population RF model. Consequently, the spatial distribution of $PM_{2.5}$ population exposure and lung cancer deaths attributable to $PM_{2.5}$ exposure were assessed by combining the spatial distribution of population and the spatial distribution of $PM_{2.5}$ retrieved from MODIS satellite remote sensing.

## 2. DATA AND METHODS

### 2.1. Data

The YRD is selected as the research area because of its developed economy, dense population, higher correlation between night lights and human activities, and more reliable predicted results of the spatial distribution of population from the population RF model (Ye T et al., 2019). The study area includes three provinces and one municipality, which are Jiangsu Province, Zhejiang Province, Anhui Province and Shanghai City. The three provincial capitals are Nanjing, Hangzhou and Hefei, respectively. These three provincial capitals and Shanghai municipality are the 4 major cities of this study (Figure 1).

  

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**Figure 1: Study area of Yangtze River Delta**

Taking 2013 as an example, we analyzed the spatial distribution of population, $PM_{2.5}$ population exposure level and the lung cancer deaths attributable to $PM_{2.5}$ exposure in the Yangtze River Delta. Table 1 shows the data sources and descriptions. In order to optimize the results and maximize the resolution, the grid size in the study is unified to 1km. To uniform grid attributes including resolution, grid row and column number, coordinate system, etc., all the grid data were projected, masked and resampled by ArcGIS.

The census population data used in this study are the permanent population data of districts and counties. Compared with the permanent population of street blocks (Ye T et al., 2019), the population data at the district and county level have coarser resolution. However, the latter is updated every year and the can meet the 1km resolution requirement.

  

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**Table 1: Summary of data used in the study**

| Data | Description | Data Source |
|---|---|---|
| Annual $PM_{2.5}$ concentration | 0.01˚ x 0.01˚ | http://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod/data-download# |
| The census permanent population | Data of street blocks in 2010, and data of districts and counties in 2013 | National census data in 2010, and annual reports published by the Department of Civil Affairs, National Bureau of Statistics of China in 2013 |
| Normalized Difference Vegetation Index (NDVI) | 1 km x 1 km | https://modis.gsfc.nasa.gov/data/dataprod/mod13.php |
| Digital Elevation Model (DEM) | 1 km x 1 km | http://www.dsac.cn/ |
| Slope | 1 km x 1 km | Calculated from DEM |
| NTL (DMSP/OLS) | 1 km x 1 km | https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html |
| Vector boundary of administrative divisions at Prefecture, city, district and county levels | The scale is 1:250 thousand | China National Basic Geographic Information Center |
| Lung cancer mortality | Age-standardized mortality rate (world) of 347 cancer registrations in China | 2013 Chinese cancer registry annual report |

### 2.2. RF Modelling

To ensure the applicability, accuracy and resolution of the results, we constructed a simplified RF model of population spatial distribution (Ye T et al., 2019). We eliminated factors that contributed little to the model, or difficult to collect, or need long processing time, and finally retained four independent variables including NTL, DEM, NDVI, and slope.

To estimate the spatial variability of prediction population density, first, the NTL, DEM, NDVI, and slope data are resampled to 1km grid. And the population of each administrative division was converted to the population density in each square kilometer for the estimation of prediction density based on the unit of administrative division. In addition, Natural logarithm was also

  

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applied to the population density in order to create a dependent variable of density considering the curve-linearity of population patterns. Data of 2010 are set as the training sample of the RF model and data of 2013 are the prediction sample. Considering the running time and the accuracy, according to the sensitivity test, the number of trees to grow (ntree) in the RF model is set to 500, and the number of variables randomly sampled as candidates at each split (mtry) is set to 2. The output prediction population density of simplified RF model is used to create a prediction density surface, which is the final dasymetric population map after redistribution by the controlling with the total population.

**2.3. Accuracy Assessment**

According the percentage of variables explained (% Var explained) and the percentage of increment of mean square error (% IncMSE), the accuracy and the contribution of each variable of the simplified RF model constructed in 2.2.1 were assessed. In addition, a space-based validation approach was applied to the 2010 data in order to determine whether the dasymetric data could be matched with census data in a smaller spatial unit. Specifically, data of street block, township, town and county were used for the validation. The linear regression and error analysis were carried out between the estimated results and the statistical results to report the R-square (R2) and root mean square error (RMSE).

**2.4. $PM_{2.5}$ Population Exposure Estimation**

The $PM_{2.5}$ population exposure at grid level in the Yangtze River Delta region in 2013 is represented by the product of population density and the concentration of selected pollutants, which is defined as $PM_{2.5}$ population exposure intensity (unit: μg·people/m3·km2) and proposed by Kousa et al. (Kousa A et al., 2002). The equation is:

$$E_i = P_i C_i \quad (1)$$

where  is the population exposure intensity of grid i,  is the annual $PM_{2.5}$ concentration in grid i extracted from the global $PM_{2.5}$ concentration data by ArcGIS,  is the population density in grid i output from the simplified RF model in 2.2.1.

**2.5. The lung cancer deaths caused by $PM_{2.5}$ exposure in the Yangtze River Delta**

In order to estimate lung cancer deaths caused by $PM_{2.5}$ in YRD in 2013, first we applied the IER with equation (2) for estimating premature mortality (Burnett, R. T. ea al., 2014), Then we estimated the lung cancer deaths caused by $PM_{2.5}$ exposure with the equation (3) (Lu, X. et al., 2017):

$$RR_i = 1 + \alpha \times (1 - e^{-\beta (C_i - C_0)^{\gamma}}) \quad (2)$$

  

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$$F_i = \frac{RR_i - 1}{RR_i} \times M_0 \times P_i \quad (3)$$

where  is the relative risk (RR) of lung cancer mortality caused by $PM_{2.5}$ exposure in grid i,  is the annual $PM_{2.5}$ concentrations in grid i, is the theoretical minimum risk exposure level, and α, β, γ and C0 are parameter estimates reported in (Cohen, A. J. et al., 2017). Fi is the premature mortality caused by lung cancer due to the exposure to $PM_{2.5}$ in grid i, M0 represents the baseline mortality rate; Pi is the population in grid i.

## 3. DATA AND METHODS

### 3.1. The Simplified RF Model and Its Accuracy

The %IncMSE of the simplified RF model, percent reduction in prediction accuracy due to random variation of variables, represents the contribution of variables and shows that NTL and NDVI contribute the most to the simplified population RF model (Table 2). And the % Var explained of the simplified RF model in 2010 and 2013 is 86.32% and 87.84%, respectively (Table 2), which means the selected four variables explained over 80% of the population density in 2013.

**Table 2: The percentage of variables explained and the contribution of each factor in the simplified population RF model**

| Year | % Var explained | %IncMSE | | | |
|---|---|---|---|---|---|
| | | NTL | NDVI | DEM | Slope |
| 2010 | 86.32 | 38.22 | 20.78 | 14.41 | 18.31 |
| 2013 | 87.84 | 33.61 | 25.45 | 14.32 | 19.09 |

The validation results of estimated population and census population of county, town, township, street blocks results in 2010 show that the predicted population based on the simplified RF model is acceptable. In detail, R2 and RMSE are 0.64 and 35166.79 persons (Figure 2a), respectively, which are comparable with previous studies that produced dasymetric population data across China (Pope III C A et al., 2002) [Korhonen, A. et al., 2019; Gaughan, A. E. et al., 2016]. Compared with the census population, 70% relative error (RE) of the predicted population are less than 40% (Figure 2b).

  

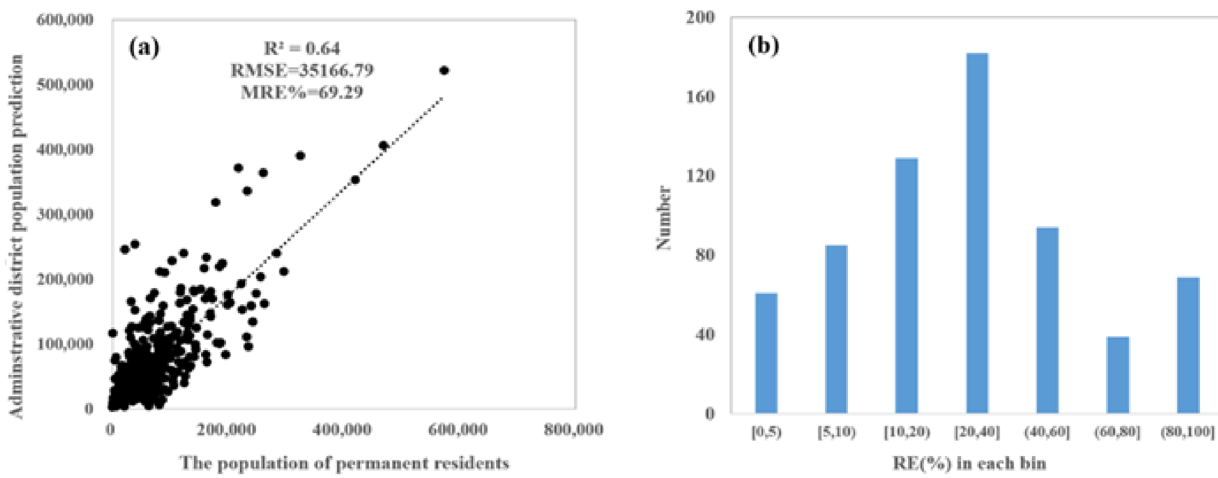


**Figure 2: Accuracy analysis of RF model for estimating population. (a) Linear regression of estimated population and census population of county, town, township, street blocks in 2010; (b) Error analysis of estimated population and census population of streets in 2010.**

### 3.2. $PM_{2.5}$ Population Exposure

The Yangtze River Delta was higher in the north and lower in the south, which means $PM_{2.5}$ pollution was severer in the north and lighter in the south in 2013. in the central and northern regions, including most of Jiangsu, Shanghai and Anhui, the $PM_{2.5}$ concentration exceeded 35 µg/m3 (Interim target-1, proposed by WHO for developing countries), while in the southern regions, including most of Zhejiang Province and a small part of southeast Anhui Province, the $PM_{2.5}$ concentration met or approached IT-1. As the economic center of a province, the provincial capital city is also the seriously polluted center in the province (Figure 3a).

The population in the Yangtze River Delta are mainly distributed in cities, especially in urban centers, which means the spatial distribution of the population is spatially discontinuous. In the centers of the 4 major cities, the population densities are more than 15,000 people/km2, while in the areas far away from downtown, the population density is much smaller. Specifically, the maximum population density in Shanghai, Nanjing, Hangzhou and Hefei exceeds 190,000, 90,000, 50,000 and 20,000, respectively (Figure 3b), whereas in a large number of vegetation covered areas, the population density is less than 200 people/km2. The result indicates that in the center of these provincial capitals, pollution events within one square kilometer can endanger up to tens of thousands or even hundreds of thousands of people. Whereas the pollution events in the sparsely populated areas including both where $PM_{2.5}$ concentration meets IT-1 and where $PM_{2.5}$ concentration exceeds IT-1 may not cause serious public health problems. In addition, under the similar pollution sources, the areas with high $PM_{2.5}$ concentration usually coincide with

  

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those with high population density, which implies that in the YRD, most of the high $PM_{2.5}$ concentration are related to human activities.

The $PM_{2.5}$ population exposure intensity in the YRD is also spatially discontinuous, which is mostly consistent with the spatial distribution of population (Figure 3c). The $PM_{2.5}$ population exposure intensity in Shanghai, most of Jiangsu Province, the central and southern half of Anhui Province and some coastal cities in Zhejiang Province are greater. Among the four major cities, the maximum population exposure intensity and area occurred in Shanghai, followed by Nanjing, Hefei and Hangzhou in turn.

### 3.3. The lung cancer deaths caused by $PM_{2.5}$ exposure in the Yangtze River Delta

Among the 4 major cities, relative to the baseline situation, the lung cancer deaths caused by $PM_{2.5}$ exposure in 2013 were 1565 in Shanghai, 585 in Nanjing, 580 in Hangzhou, and 570 in Hefei (Figure 4). The city with the most lung cancer deaths caused by $PM_{2.5}$ exposure is Shanghai. Five of the top ten cities with the most lung cancer deaths caused by $PM_{2.5}$ exposure are in Jiangsu Province, two are in Anhui Province, and the other two are in Zhejiang Province.

  

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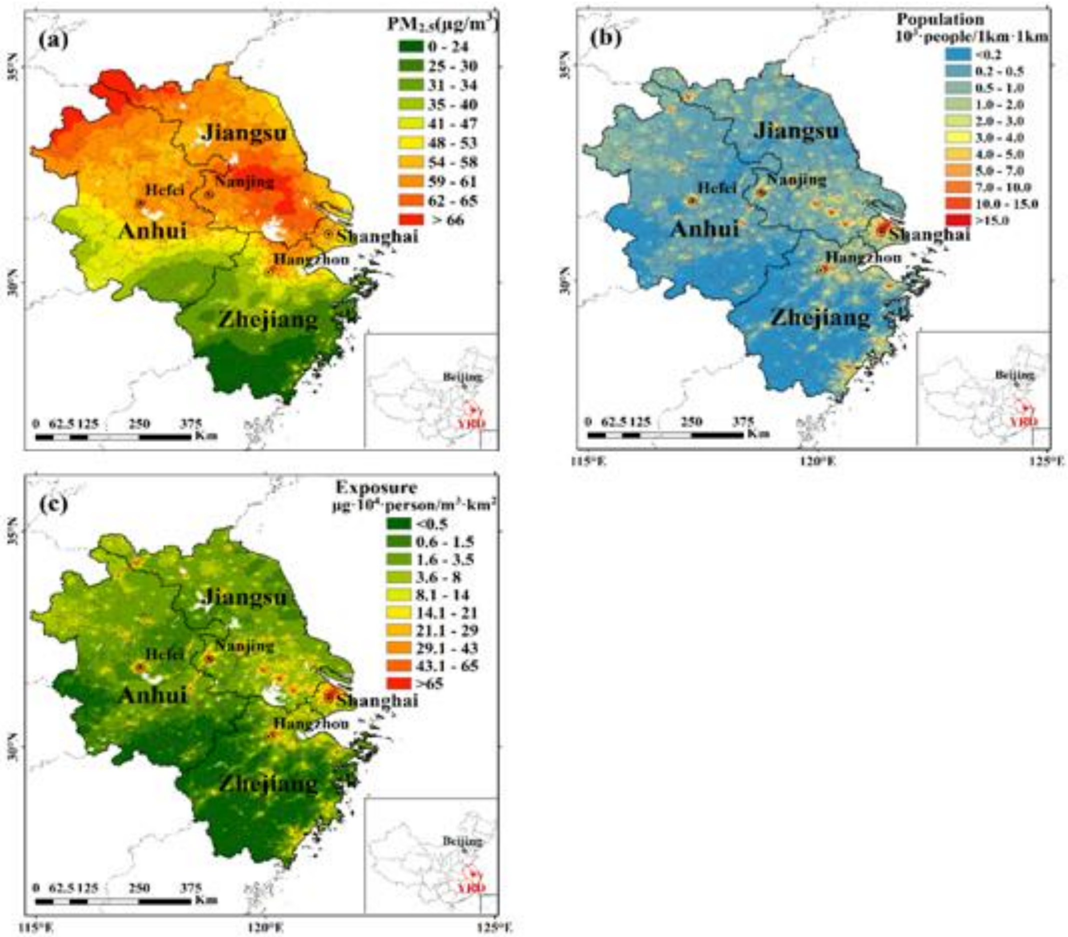


**Figure 3: Spatial distribution of $PM_{2.5}$, population and population exposure intensity in the YRD in 2013. (a) Spatial distribution of $PM_{2.5}$ concentration; (b) Spatial distribution of population; (c) Spatial distribution of $PM_{2.5}$ population exposure intensity.**

  

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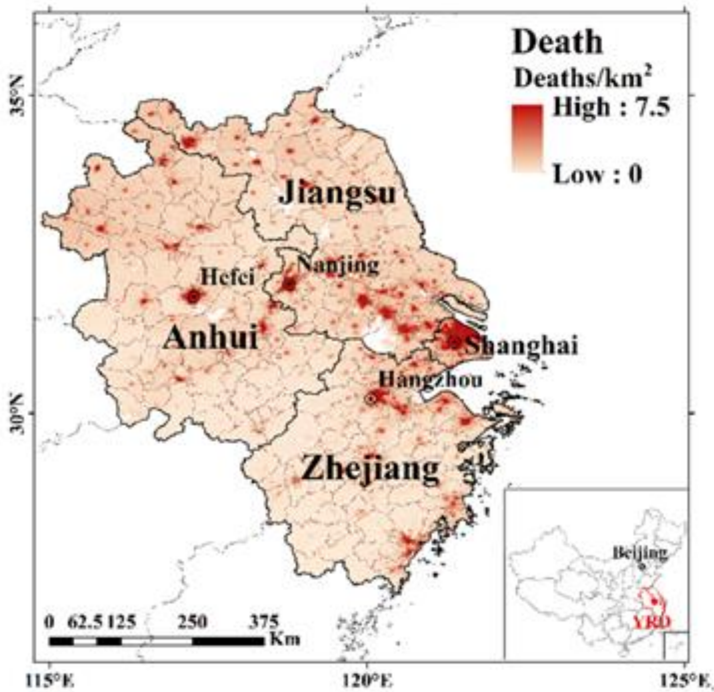


**Figure 4: The lung cancer deaths caused by $PM_{2.5}$ exposure in the Yangtze River Delta in 2013.**

## 4. CONCLUSIONS

To explore a method to efficiently and accurately estimate the spatial distribution of $PM_{2.5}$ population exposure and its risk on lung cancer in any given years, a simplified the population RF model is proposed in this study. The simplified population RF model retains four independent variables: NTL, DEM, NDVI and slope. Taking the census population of districts and counties as the dependent variable, the simplified RF model accurately estimate the population spatial distribution of 1km grid. It shows that NTL and NDVI contribute the most to the simplified RF model, and % Var is 86.32% in 2010 and 87.84% in 2013, respectively. The results indicate that the model is suitable for the estimation of population spatial distribution with no census population in blocks. Taking 2013 as an example, the spatial distribution of $PM_{2.5}$ population exposure intensity is spatially discontinuous, which is highly consistent with the spatial distribution of population, while the spatial distribution of $PM_{2.5}$ concentration is a continuous spatial distribution, which is different from the former. These differences suggest that people living in areas with high $PM_{2.5}$ concentration are not necessary associated with high $PM_{2.5}$ population exposure intensity, but high density population distribution is often a sign of high $PM_{2.5}$ population exposure intensity. In the YRD, the highest $PM_{2.5}$ population exposure intensity appears in Shanghai, most of Jiangsu Province, the central and southern half of Anhui Province

  

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and some coastal cities in Zhejiang Province. The spatial distribution of lung cancer deaths caused by $PM_{2.5}$ is highly consistent with that of $PM_{2.5}$ population exposure intensity. In 2013, relative to the baseline situation, the highest increase in lung cancer deaths was in Shanghai with 1565 deaths, and the lowest was in Hefei with 570 deaths. The total number of lung cancer deaths caused by $PM_{2.5}$ exposure in the YRD was 14180 in 2013. In general, our results indicate that moderate-resolution information derived from multi-satellite retrievals can help to understand the spatiotemporal variability of population exposure and related health risk in a high-density environment.

## 5. ACKNOWLEDGMENTS

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