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To cite this article: Lijuan Yang 2020 *IOP Conf. Ser.: Earth Environ. Sci.* **619** 012046

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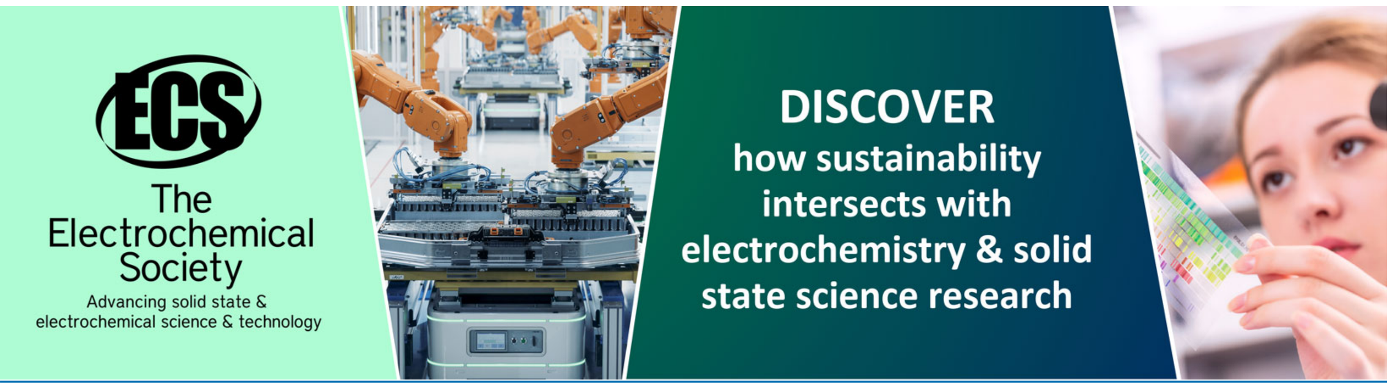

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IOP Conf. Series: Earth and Environmental Science **619** (2020) 012046 doi:10.1088/1755-1315/619/1/012046

A novel approach of Landsat 8 imagery to predict $PM_{2.5}$ concentrations in a south-eastern coastal city of China

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Abstract. Satellite remote sensing data with moderate- to high- resolution has been commonly used in deriving spatial coverage of $PM_{2.5}$ concentrations in urban areas. Previous studies focusing on city-scale $PM_{2.5}$ estimation mainly retrieved aerosol optical depth from moderate- to high- resolution remote sensing data. In this study, the spectral response experiment was carried out to explore the sensitivity of spectral wavelengths to $PM_{2.5}$ concentrations in Fuzhou, China. The results showed that the near-infrared reflectance was much more sensitive to $PM_{2.5}$ than other wavelengths. We also found that the difference vegetation index (DVI) presented higher correlation with $PM_{2.5}$ than other indexes. A linear mixed effects (LME) model was then developed to explain the variability of $PM_{2.5}$, and the results showed that the overall R^2 of LME model using DVI and meteorological parameters reached 0.80 with RMSE of 7.82 μg/m^3. The results suggested that the proposed LME model using DVI from Landsat 8 OLI could be effectively used for predicting $PM_{2.5}$ in a city scale.

1. Introduction

Many previous and recent epidemiological studies have reported a significant association between exposure to fine particles with aerodynamic diameter less than 2.5 um, i.e., $PM_{2.5}$, and various adverse health effects including asthma[1-2], cardiovascular problems[3-4], lung cancer and mortality[5-6]. Typically, the most direct way to obtain the accurate $PM_{2.5}$ concentrations is from the ground $PM_{2.5}$ monitoring sites, which however, cannot be used for retrieving the spatial coverage of $PM_{2.5}$ since the number of these sites is limited and sparse. Satellite with various sensors on board can provide remote sensing imagery with extensive coverage of large area, and the retrieved aerosol optical depth (AOD) representing the atmospheric turbidity has been widely used in assessing the air pollution[7-8].

Currently, several AOD products with various resolutionhave been demonstrated as good proxy to retrieve the ground-level $PM_{2.5}$ in large- and global- coverage, however, it cannot provide more detailed information in a city scale due to its low spatial resolution[9-10]. Thus, more and more researchers have diverted to urban $PM_{2.5}$ estimation by using remote sensing data with moderate- to high- resolution. Previous studies of urban $PM_{2.5}$ estimation mainly focused on retrieving AOD from several moderate- to high- resolution data[11], or established the relationship between retrieved AOD and particulate matter concentrations[12]. Several studies also used the remote sensing bands and indices to predict ground-level PM_{10} and $PM_{5.0}$[13-14].One of the limitations of these studies is that they used simple regression models to account for the variability between particulate matter concentrations and other variables (e.g., retrieved AOD, meteorological parameters and land use information), which presented relatively lower predictability in estimating PM concentrations. Therefore, researchers have

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gradually focused on urban PM concentrations estimation by using the advanced statistical models along with the meteorological parameters. For example, researchers used a linear mixed effects (LME) model to explain the variability of the AOD retrieved from GF-1 imageries, meteorological factors and $PM_{2.5}$ in Beijing, Shanghai and Wuhan, respectively, and the R^2 of estimated and observed $PM_{2.5}$ reached 0.96[15].

Previous studies that have linked particulate matter concentrations with ultrahigh resolution AOD, or with remote sensing bands and combined indexes, showed a great capability of remote sensing data with moderate- to high- resolution in monitoring atmospheric aerosols in urban areas. Previous work demonstrated that the aerosol information could be obtained by using visible and near-infrared wavelengths of satellite sensors[16], but the response mechanism of different spectral wavelengths to $PM_{2.5}$ concentration is still unknown. Thus, in this study, we explored the spectral response of different wavelengths of remote sensing images with moderate- to high- resolution to $PM_{2.5}$ concentrations, and discussed the most sensitive spectral wavelengths. Three Landsat 8 imageries with spatial resolution of 30 m covering Fuzhou district, a south-eastern coastal city of China, were used in this study. Unlike the previous studies, we developed a new method that combined the most sensitive spectral wavelengths, instead of AOD, to predict the $PM_{2.5}$ concentrations within a linear mixed effects model in Fuzhou area.

2. Materials and Methods

2.1. Study area

Fuzhou is an important port city that located in the coastal zonal area of Fujian province, between the Yangtze River Delta (YRD) to the north and the Pearl River Delta (PRD) to the south. The study area now includes six urban districts and six surrounding suburban districts (**Fig. 1**). The air quality has declined due to the urban expansion and intensive human activities in Fuzhou, for instance, the daily $PM_{2.5}$ concentration in Fuzhou exceeded the fourth grade standard of China (115 μg/m^3) in 14% of the days during the entire winter in 2015. Moreover, the air pollution in the study area has also been exacerbated by the pollutants originating from YRD region in cold season.

2.2. Data

2.2.1. Landsat 8 satellite data.

The Landsat 8 satellite with two on-board instruments, i.e., Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), was launched on February 11, 2013. It provides digital earth images with nine spectral bands (band1-7, 9: 30 m, band8: 15 m) and two thermal wavelengths (100 m). Three cloud-free Landsat 8 imageries covering Fuzhou area from 2014 to 2016 were collected in this study. The atmospheric correction on the data of Landsat 8 imageries was carried out before the application.

2.2.2. $PM_{2.5}$ observation data.

The corresponding hourly $PM_{2.5}$ concentrations measured at 45 monitoring sites for three days were collected (Fig. 1), and the averaged $PM_{2.5}$ concentrations from 10:00 to 12:00 were used as the dependent variable. Before data modeling, all the abnormal $PM_{2.5}$ data (i.e., $PM_{2.5}$< 0) were discarded to reduce the estimation error.

2.2.3. Meteorological data.

There are only one meteorological station located in the center of study area with available data, thus, the meteorological data from Goddard Earth Observing System Data Forward Processing (GEOS-5 FP) were used in this study. The spatial resolution of GEOS-5 FP data is 0.25° (latitude) × 0.3125° (longitude) in China, and two meteorological variables including relative humidity (RH, %) and wind speed (WS, m/s) were obtained in this study. For data integration, we interpolated these meteorological data to a 30 m grid using the inverse distance weighting method.

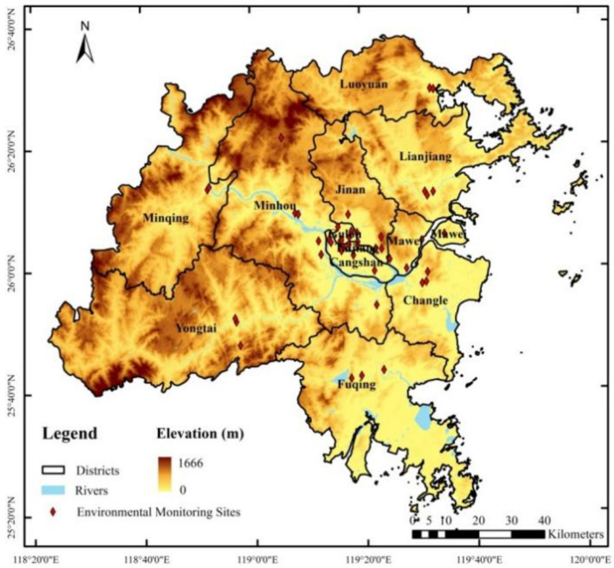

Fig. 1. Map of the study area and $PM_{2.5}$ monitoring sites

2.3. model development.

For comparison, we defined $PM_{2.5}$ concentrations with ≤30, 30-50, and >50 μg/m^3 as low, moderate, and high level, respectively. Three land-cover types including vegetation, bare soil and built-up area were selected for spectral response analysis. By comparing the spectral response curve of three land-cover types in different $PM_{2.5}$ levels, the most sensitive spectral wavelengths, or the combined wavelengths, which presented the highest correlation coefficient with $PM_{2.5}$ concentrations were finally determined.

A simple regression model incorporating the most sensitive spectral wavelength/combined wavelengths and meteorological variables was first developed in this study. A linear mixed effects (LME) model that contains two effects, i.e., fixed effect and random effect, was further applied to predict the $PM_{2.5}$ concentrations. Here in the LME model, we defined the fixed effect as the average impact of all the independent variables on $PM_{2.5}$ for the entire period, while the random effect explains the variation between $PM_{2.5}$ and the independent variables. The LME model was performed in R language:

$$PM_{2.5ij} = (a + b_j) + (c + d_j)\cdot SSW_{ij} + (x + y_j)\cdot WS_{ij} + (k + z_j)\cdot RH_{ij} + \varepsilon_{ij} \quad (1)$$

where $PM_{2.5ij}$, SSW_{ij}, WS_{ij} and RH_{ij} are the four variables in LME model, which represent the hourly average $PM_{2.5}$, the value of the sensitive spectral wavelength, the wind speed and relative humidity on day j at site i, respectively. a and b_j represent the fixed and random intercept for the entire period; c, x and k are the fixed slopes for the sensitive spectral wavelength, WS and RH, respectively; d_j, y_j and z_j are the random slopes for the sensitive spectral wavelength, WS and RH, respectively; and ε_{ij} represents the random error.

3. Results and Discussion

3.1. DataSpectral response analysis

Three days representing three different $PM_{2.5}$ levels, i.e., September 27, 2015 (28 μg/m^3), June 25, 2016 (40 μg/m^3) and April 17, 2014 (87 μg/m^3), were selected for the spectral characteristics analysis. The results showed that three types all presented higher near-infrared reflectance (i.e., NIR or b5) in clear days with low $PM_{2.5}$ concentrations than those with high $PM_{2.5}$, namely, the NIR reflectance decreased with the increase of $PM_{2.5}$ concentrations. The mid-infrared reflectance varied much and presented unstable relationship in different $PM_{2.5}$ levels for three land-cover types.

We achieved a statistical correlation coefficient (*r*) value of 0.50, 0.61 and 0.56 ($P<0.01$), respectively. These *r* values were much higher than those obtained from other days with less available $PM_{2.5}$ data (r=0.30~0.50, $P<0.05$). Eight NIR-related indexes including ratio vegetation index (RVI), difference vegetation index (DVI), normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), atmospherically resistant vegetation index (ARVI), modified normalized difference vegetation index (MNDVI), normalized difference moisture index (NDMI) and normalized difference built-up index (NDBI) were also employed to validate their relationship with $PM_{2.5}$ concentrations. Our results indicated that six vegetation indexes were generally stronger relative to $PM_{2.5}$ than NDMI and NDBI, while DVI presented the highest *r* value of ~0.50 in three $PM_{2.5}$ levels.

3.2. Results of model fitting and validation

In view of the high correlation of the difference vegetation index and $PM_{2.5}$ concentrations, the difference vegetation index, instead of NIR, was employed as the main variable to predict the $PM_{2.5}$ concentrations in Fuzhou. In addition to DVI, two meteorological parameters including wind speed and relative humidity were also added as ancillary variables in our models. We aimed to develop an advanced statistical model, i.e., the linear mixed effects (LME) model, to explain the variability of $PM_{2.5}$ concentrations and other independent variables, which has previously been demonstrated to present high predictability in $PM_{2.5}$ estimation by using AOD with coarse resolution. We achieved an overall R^2 of 0.80 between the estimated $PM_{2.5}$ and observed values in LME model (**Fig. 2**).

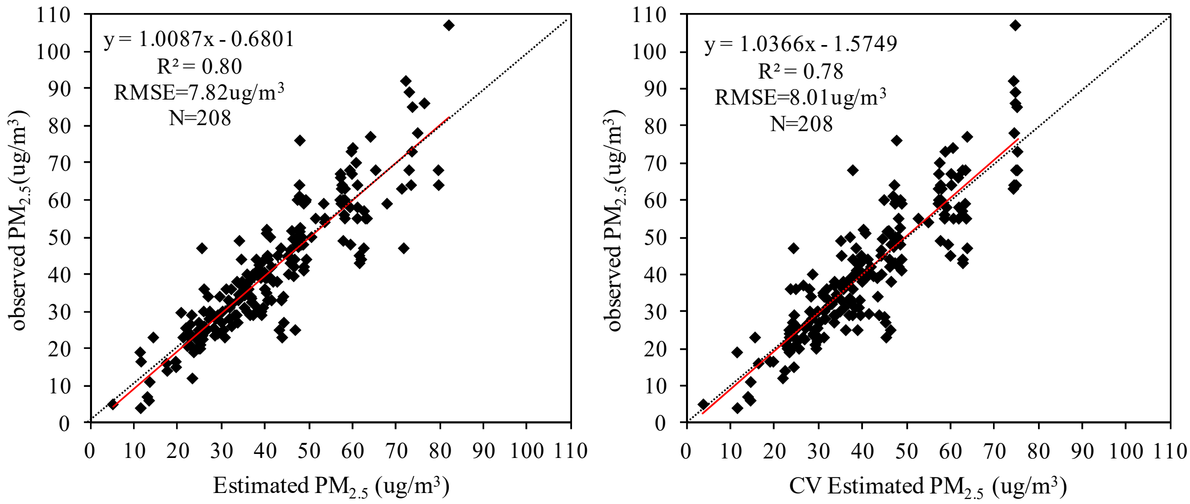

Fig. 2. The model fitting and cross validation of LME model

The RMSE of the LME model was 7.82 μg/m³. The slopes of fixed effect for DVI, WS and RH were -46.15, -3.39 and -9.76, respectively, indicating that DVI, wind speed and relative humidity were all generally negatively related to $PM_{2.5}$. The WS was generally negatively correlated with $PM_{2.5}$ concentrations, indicating that higher wind speed would facilitate the dilution of particulate matter concentrations. The RH, representing the mass proportion of water vapor in the atmosphere, can also reduce the pollutant concentrations to some extent, such as the heavy rainfall with RH great than 80%. Furthermore, the results of the 10-fold cross validation showed that the average CV R^2 values for LME model was 0.78, with CV RMSE of 8.01 μg/m³, indicating the significant predictability of our LME model.

3.3. Predictions of $PM_{2.5}$ concentrations

We achieved the spatial coverage of ground-level $PM_{2.5}$ concentrations by using DVI and LME model for three days in Fuzhou. **Figure 3** illustrates the map of the $PM_{2.5}$ concentrations on September 27, 2015 and June 25, 2016, which also represents three different $PM_{2.5}$ levels. The derived-mean $PM_{2.5}$ concentrations for the entire study area were 28 μg/m^3, and 40 μg/m^3 on these two dates, respectively, exhibiting higher mean $PM_{2.5}$ concentrations in the center and southeast of the study area, and lower values in west and north. For comparison, the average $PM_{2.5}$ concentrations for each district was then derived, and finally, we obtained much higher $PM_{2.5}$ concentrations in Taijiang, Gulou and Cangshan than other surrounding districts. These three urban districts are the most frequent areas of human activities in the socio-economic, which are characterized by high population density and road density. To sum up, the large population and road density, as well as the weak urban ventilation, are the key reasons for high $PM_{2.5}$ values in three urban districts.

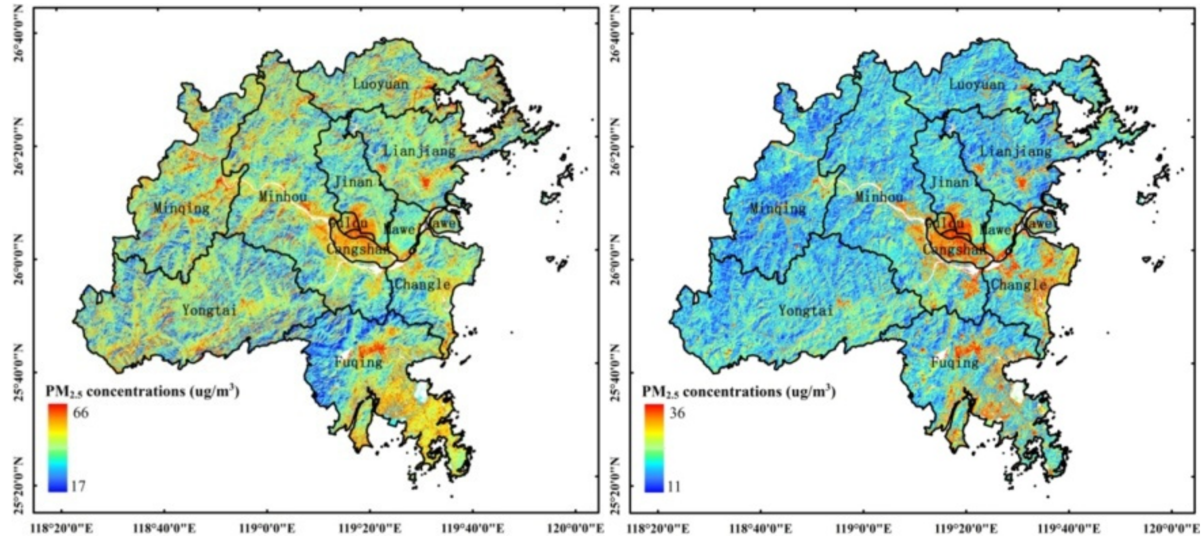

Fig. 3. Spatial distribution of derived $PM_{2.5}$ concentrations for the Fuzhou area (left: 2015/09/27; right: 2016/06/25)

4. Conclusion

In this study, a spectral response experiment was first launched to explore the sensitivity of spectral wavelengths to $PM_{2.5}$ concentrations, by which the most sensitive remote sensing wavelength (i.e., NIR) and combined index (i.e., different vegetation index) were determined. The linear mixed effects model that incorporated the DVI and two meteorological parameters was further developed, and our results revealed that the LME model could explain 80% of the variability between $PM_{2.5}$ and other independent variables. Moreover, the retrieved $PM_{2.5}$ concentrations was also consistent with the urban pattern, showing high $PM_{2.5}$ concentrations in urban districts with large population density and relatively low $PM_{2.5}$ values in suburban districts. In summary, this is the first study that uses the spectrum response experiment aiming moderate- to high- resolution remote sensing data, along with a linear mixed effects model to assess the fine particles pollution in a small scaled region. The results of this thesis would provide a brand new methodology in estimating $PM_{2.5}$ concentrations with more details in city-scale.

Acknowledgement

The authors would like to thank GSFC/NASA for the use of Landsat 8 data. This work was supported by the National Key Research and Development Project (No: 2016YFA0600302).

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