The application of land use regression model to investigate spatiotemporal variations of $PM_{2.5}$ in Guangzhou, China: Implications for the public health benefits of $PM_{2.5}$ reduction

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Abstract

Understanding the intra-city variation of $PM_{2.5}$ is important for air quality management and exposure assessment. In this study, to investigate the spatiotemporal variation of $PM_{2.5}$ in Guangzhou, we developed land use regression (LUR) models using data from 49 routine air quality monitoring stations. The R^2, adjust R^2 and 10-fold cross validation R^2 for the annual $PM_{2.5}$ LUR model were 0.78, 0.72 and 0.66, respectively, indicating the robustness of the model. In all the LUR models, traffic variables (e.g., length of main road and the distance to nearest ancillary) were the most common variables in the LUR models, suggesting vehicle emission was the most important contributor to $PM_{2.5}$ and controlling vehicle emissions would be an effective way to reduce $PM_{2.5}$. The predicted $PM_{2.5}$ exhibited significant variations with different land uses, with the highest value for impervious surfaces, followed by green land, cropland, forest and water areas. Guangzhou as the third largest city that $PM_{2.5}$ concentration has achieved CAAQS Grade II guideline in China, it represents a useful case study city to examine the health and economic benefits of further reduction of $PM_{2.5}$ to the lower concentration ranges. So, the health and economic benefits of reducing $PM_{2.5}$ in Guangzhou was further estimated using the BenMAP model, based on the annual $PM_{2.5}$ concentration predicted by the LUR model. The results showed that the avoided all cause mortalities were 992 cases (95% CI: 221−2140) and the corresponding economic benefits were 1478 million CNY (95% CI: 257−2524) (willingness to pay approach) if the annual $PM_{2.5}$ concentration can be reduced to the annual CAAQS Grade I guideline value of 15 μg/m^3. Our results are expected to provide valuable information for further air pollution control strategies in China.

Keywords: $PM_{2.5}$, Land use regression model, BenMAP, Guangzhou, Health benefit

1. Introduction

Ambient particle matter (PM) has been recognized as a great threat to human health and has received worldwide attention. Numerous epidemiological studies have shown that long-term exposure to fine particulate matter ($PM_{2.5}$, particles with aerodynamic diameter smaller than 2.5μm) is associated with many adverse health effects, such as respiratory and cardiovascular diseases, and an increase of mortality (Beelen et al., 2014; Chen et al., 2018b; Chen et al., 2012; Stafoggia et al., 2014). In addition, $PM_{2.5}$ is also responsible for climate deterioration and haze episodes that exert negative impacts on the living environment (Huang et al., 2014; Wu et al., 2005). Moreover, more than half of the global population live in high-density urban environments where these adverse effects are expected to be stronger (Jin et al., 2019; Yuan et al., 2014). However, intra-city variations of $PM_{2.5}$ have been shown to be significant, thus, it is critical for air quality management and exposure risk assessment to accurately estimate the spatial distribution of $PM_{2.5}$ within cities.

Early studies mostly used data from fixed monitoring stations to present regional $PM_{2.5}$ concentrations, but it is generally difficult to capture intra-city variability due to the limited geographic coverage of monitoring stations (West et al., 2016). To address such challenges, previous studies tried to combine monitoring data and spatial interpolation (e.g. kriging and inverse distance weighted interpolation)(Meng et al., 2015). However, interpolation methods are considered too mechanistic and can produce overly smoothed concentration surfaces, and cannot consider environmental characteristics (Meng et al., 2015; Zou et al., 2015). Alternatively, air quality models (e.g., chemical transport models and dispersion models) could estimate spatiotemporal variations of air pollution concentrations, considering the emission sources, meteorology and topography conditions. However, the simulated results of air quality models are highly reliant on the accuracies of emission inventories, which usually makes the simulation process complicated and high-cost (de Hoogh et al., 2014; Solomos et al., 2015; Zhang et al., 2012). Satellite-based aerosol optical depth (AOD) data has also popularly applied to predict ground-level $PM_{2.5}$, but this method is limited by the imaging time and the spatial resolution is relatively coarse (Ma et al., 2016; Zang et al., 2017). In addition, the relationship between $PM_{2.5}$ and AOD could be affected by PM optical properties, PM vertical and diurnal concentration profiles, and meteorological conditions (Lee et al., 2011). Compared with the above methods, the land use regression (LUR) model was shown to be able to capture intra-city variations of air pollutants at a refined spatial scale with a relatively low demand for data input (Briggs et al., 1997; Hoek et al., 2008). In LUR models, the concentration of air pollutants at unmonitored sites could be predicted by a linear regression framework based on spatial predictors that include emission sources (e.g. land use, traffic, population density and nearby pollutant emissions) and dispersion conditions (e.g. elevation, boundary layer height, meteorology) (Chen et al., 2018b; Meng et al., 2015; Sampson et al., 2013; Wu et al., 2005; Young et al., 2016). Especially, the real time meteorological parameters (e.g., temperature, wind speed and relative humidity) and anthropogenic activities related pollutants (e.g., NO_2 and CO) can be combined into the linear regression frameworks to develop high time resolution grid-scale models (Hsieh et al., 2020; Lee et al., 2016). With the development of Geographic Information System (GIS) technology, LUR models have been shown to be a cost-effective approach to estimate spatial variations of air pollutants in different regions of the world (Briggs et al., 1997; Chen et al., 2018b; Hoek et al., 2008; Meng et al., 2015; Vienneau et al., 2013; Zou et al., 2015). Also, in recent years LUR models have been widely used to assess air pollutants exposures in epidemiological research (Beelen et al., 2014; Chen et al., 2017b).

Evaluating the health impacts and benefits associated with air quality improvements is essential for governments and policy makers. In recent years, the Environmental Benefits Mapping and Analysis Program Community Edition (BenMAP-CE) developed by the United States Environmental Protection Agency (USEPA) has been widely used to estimate health benefits of $PM_{2.5}$ reduction at local, regional, and national scales (Chen et al., 2017b; Kheirbek et al., 2014; Li et al., 2019; Sacks et al., 2018). The reliability of BenMAP estimates highly depend on the accuracy and suitability of air quality exposure fields used in benefit calculations. However, it should be noted that the exposure $PM_{2.5}$ fields in previous studies that used BenMAP were mostly generated by chemical transport models and interpolation methods (Chen et al., 2017b; Luo et al., 2020). Given the advantages of using a LUR model that were mentioned above, the combination of a LUR model and BenMAP could help better estimate health benefits associated with $PM_{2.5}$ reduction.

To reduce the $PM_{2.5}$ concentration and minimize its adverse influence on human health, the China State Council released a 5-year Air Pollution Prevention and Control Action Plan in 2013. From 2013 to 2017, the nationwide-average annual $PM_{2.5}$ concentrations decreased from 67.8 $\mu g/m^3$ to 45.6 $\mu g/m^3$ (Wu et al., 2020). These concentration reductions were seen especially in the Pearl River Delta (PRD) region where in 2017 the annual $PM_{2.5}$ concentration already met the Chinese Ambient Air Quality Standards (CAAQS, GB3095-

2012) Grade II guidelines (35 μg/m^3) (Shen et al., 2020). In Guangzhou, the main city of the PRD region annual $PM_{2.5}$ concentrations in the past three years (2017 to 2019) were lower than 35 μg/m^3, due to emission control measures and favorable meteorological conditions. However, there is still a distance to reach the annual Grade I guideline of 15 μg/m^3 proposed by CAAQS. In addition, the $PM_{2.5}$ concentrations of Guangzhou were higher in fall and winter due to the unfavorable meteorological conditions for pollutant dispersion. Therefore, there remains a need to better understand the spatial and temporal variation of $PM_{2.5}$ in Guangzhou. Moreover, as Chinese air quality has improved a lot in recent years, the $PM_{2.5}$ concentrations in many cities have fallen below Grade II guideline (35 μg/m^3). Guangzhou as the third biggest city in China with relatively lower $PM_{2.5}$, it represents a useful case study city to examine the health and economic benefits of further reduction of $PM_{2.5}$ to the lower concentration ranges. This could provide valuable information for future efforts to reduce air pollution in China.

The purpose of this study was therefore to: (1) develop seasonal and annual LUR models based on 49 routine air quality monitoring stations, to investigate the spatiotemporal variation of $PM_{2.5}$ in Guangzhou; (2) estimate public health benefits of reducing $PM_{2.5}$ to CAAQS Grade I guidelines (15 μg/m^3) by combining LUR modelling and BenMAP. Our results are expected to help policymakers to improve air quality and achieve health and economic benefits for citizens.

2. Methodology

2.1 Study area

Guangzhou (22°26′–23°56′N, 112°57′–114°3′E, Figure 1) is the capital and most populous city of the province of Guangdong in Southern China. On the Pearl River about 120 km north-northwest of Hong Kong and 145 km north of Macau, Guangzhou serves as a major port and transportation hub. Guangzhou is China's third largest city with a population of 14.9 million in 2018, covering an area of 7,434 km^2 with a typical subtropical monsoon climate.

2.2 Ground $PM_{2.5}$ monitoring data

The daily $PM_{2.5}$ concentration data of 2018 were obtained from the air pollution monitoring network operated by the Guangdong Environmental Monitoring Centre. There are 49 routine monitoring stations included in this study (Figure 1). The daily concentrations were only included in calculations when there were at least 18 hours of valid data per day. The $PM_{2.5}$ measurement and quality control follow the regulation of the CAAQS (No. GB3095-2012). To investigate the spatiotemporal variation of $PM_{2.5}$ in Guangzhou, the seasonal average $PM_{2.5}$ concentrations were calculated and served as dependent variables of seasonal LUR models.

2.3 Geographical data

As presented in Table 1, we employed a combination of point, buffer, and proximity based geographic variables. A total of 352 predictor variables were considered. Each predictor variable was first given an expected direction of the regression coefficient (e.g., positive or negative). We used the ESRI ArcGIS 10.5 to extract predictor variables from GIS layers.

We obtained the road data from OpenStreetMap (https://www.openstreetmap.org). Considering the jurisdiction and function, we divided the roads into four categories: main roads (freeways, such as motorways and trunk ways, usually with limited access), highways (primary roads, important roads that often link towns or main road within cities), ancillary (tertiary roads, such as residential roads, which serve as an access to housing or within a community), and alley (residential roads, pedestrian walkways, and tracks). It should be noted that, because it is difficult to obtain the traffic intensity, we used the distance to nearest road and length of road to represent traffic related variables. Compared to traffic intensity which could indicate the number of vehicles, the road information in GIS just represented as one-dimensional lines that cannot reflect the number of vehicles, width of road, and the number of lanes. However, previous studies have found that the performance of LUR models developed with lengths of road were comparable to those using traffic intensity data for explaining the refined spatial variability of pollutant concentrations (Henderson et al., 2007; Rosenlund et al., 2007). Therefore, we considered distance to nearest road and road length as appropriate traffic related variables, in the absence of traffic intensity.

Land use data were derived from International Symposium on Land Cover Mapping (http://data.ess.tsinghua.edu.cn/), with a resolution of 30 m. The land use types were classified into bare land, cropland, forest, grassland, impervious surfaces, shrubland, water bodies, and wetland. The impervious surfaces were further separated into residential area, commercial area, industrial area, transportation area, public management and service aera. The nearest distance to the coast of each monitoring site was also calculated based on the coastline shapefile of China.

The population density data with approximately 1 km resolution in 2015 were obtained from the Landscan global population database, which was developed by the United States Department of Energy's Oak Ridge National Laboratory (https://www.worldpop.org/). Meanwhile, the gridded GDP data were provided by Resources and Environment Data Cloud Platform (http://www.resdc.cn). We downloaded the Digital Elevation Model (DEM) data from Shuttle Radar Topography Mission (SRTM, http://srtm.csi.cgiar.org), and the spatial resolution was 90 m. The locations of bus stops and parking areas were extracted using Amap Application Programming Interface (API) based on categories and keywords (https://lbs.amap.com/api/uri-api) The monthly meteorological data (e.g. boundary layer height, temperature, precipitation, pressure, and wind speed) were extracted from the Third Pole Environment Database (http://en.tpedatabase.cn/).

2.4 LUR model development, validation and mapping

The annual and seasonal concentrations of $PM_{2.5}$ and geographic variables were used for the LUR model development. We followed the manually supervised forward multiple linear regression method to develop the LUR models for $PM_{2.5}$ (Eeftens et al., 2012a). Briefly, the $PM_{2.5}$ concentrations were considered as dependent variables, while the geographic variables were used as independent variables. The model construction started by including predictor variables with the highest adjusted R^2 in univariate regressions analysis. Thereafter, the candidate variables were added into the model if they satisfied the following criteria; (1) the adjusted R^2 of the model increased by at least 1%; (2) the *p* value of the variable was < 0.05; (3) the variance inflation factor (VIF, a check for multi-collinearity) of the variable was < 3; (4) the coefficient of the variable accorded with the prior direction and variables already in the model did not change their regression directions. All possible predictor variables were added until no predictor variables added more than 1% to the adjusted R^2 of the previous regression model.

We used the 10-fold cross-validation method to evaluate overall model performance. The adjusted R^2 and root mean squared error (RMSE) between the predicted and measured concentrations for all sites were calculated to present the model's fit. In addition, Moran's I was calculated to evaluate the spatial autocorrelation of the residuals. All the statistical analyses were conducted by R software (Version 3.2.2).

The predicted $PM_{2.5}$ concentration surfaces were created according to the final LUR models. The study area was divided into 7,225 1000×1000 m grid cells. The predictor variables of LUR model were drawn around the centroids of each grid cell and the $PM_{2.5}$ concentrations were calculated by the final LUR model coefficients. At last, we applied universal kriging interpolation to draw $PM_{2.5}$ concentrations map across Guangzhou. It should be noted that the reliability of predicted $PM_{2.5}$ concentrations maybe lower in areas with sparse monitoring stations, especially for the Northeast of Guangzhou (Figure 1).

2.5 Health impacts and economic benefits estimates

In this work, BenMAP-CE 1.5 was used to estimate the health and economic benefits of $PM_{2.5}$ reductions. Since previous studies showed that more than 90% of health impacts of $PM_{2.5}$ were from mortality, we selected avoidable premature mortality to present the health benefits of $PM_{2.5}$ reductions (DeMocker, 2003). According to the International Classification of Diseases Revision 10 (ICD-10), the causes of death in this study are classified into all causes (A00–R99), cardiovascular diseases (I00–I99), and respiratory diseases (J00–J98). The health impacts are estimated by BenMAP-CE according to following the equation (Davidson et al., 2007):

$$\Delta Y = Y_0\left(1 - e^{-\beta \Delta PM}\right) * Pop \qquad (1)$$

$$\beta_{min} = \beta - \left(1.96 \times \sigma_\beta\right) \qquad (2)$$

$$\beta_{max} = \beta - \left(1.96 \times \sigma_\beta\right) \qquad (3)$$

where ΔY is the avoided premature mortalities due to the $PM_{2.5}$ reductions, Y_0 is the baseline incidence rate for the health endpoint (mortality), ΔPM ($\mu g/m^3$) is the annual $PM_{2.5}$ concentration change, Pop (person) is the exposed population, β is the exposure concentration-response coefficient, representing the percent change in a certain health impact per unit of $PM_{2.5}$ concentration, and σ_β is the standard error of β (Table S1).

For this work, Guangzhou was divided into 7,225 1000×1000 m grids. The $PM_{2.5}$ annual mean concentration in each grid was estimated based on the LUR model. The control case concentration was rolled back to annual Grade I guidelines of 15 $\mu g/m^3$ proposed by CAAQS. The gridded population data in 2018 with 1 km^2 resolution was calculated by multiplying the each 1 km^2 grid in 2015 by the Guangzhou population ratio of 2018/2015. The baseline incidence data for all-cause, cardiovascular diseases, and respiratory diseases in 2018 were obtained from the Guangdong Statistical Yearbook (http://stats.gd.gov.cn/gdtjnj/).

BenMAP-CE uses a Monte Carlo approach (5000 times) and specifies Latin hypercube points to generate 95% confidence intervals around mean prediction of β values of each health endpoint. Then the BenMAP-CE estimates the incidence of changes in each grid according to the assumption value of β and generates the distribution of the incidence changes.

We further evaluated the economic benefits of the health impacts associated with the $PM_{2.5}$ reduction. The willingness to pay (WTP), cost of illness (COI), and human capital (HC) methods are commonly used to quantify the economic benefits associated with avoided mortality. Generally, WTP is the most widely preferred used method, because it takes intangible losses into account, such as pain, suffering and other adverse effects due to illness (Robinson, 2011). Thus, the WTP method was used to evaluate the economic benefits from avoided premature mortality, and the unit economic values associated with premature mortality were summarized in Table S2. We converted the US dollar to Chinese Yuan (CNY) based on Purchasing Power Parity adjusted exchange rates, and the unit value for various currency years was adjusted to the year 2018 by multiplying by the annual consumer price index (CPI) in China.

3. Results and discussion

3.1 Descriptive statistics for $PM_{2.5}$ concentrations

The monitored annual average concentration of $PM_{2.5}$ was 34.4 ± 21.0 μg/m^3, which was lower than annual CAAQS Grade II guidelines (35 μg/m^3). However, it should be noted that, the concentration of $PM_{2.5}$ exhibited significant seasonal variation (Figure 2), which showed highest concentrations in winter (46.7 ± 31.0 μg/m^3), followed by the fall (37.0 ± 14.0 μg/m^3), spring (35.6 ± 16.8 μg/m^3), and summer (22.6 ± 8.0 μg/m^3). The higher concentrations of $PM_{2.5}$ in winter are associated with the unfavorable meteorological conditions (e.g. lower wind speed, precipitation, and boundary layer height) for pollutants dispersion (Chen et al., 2018a; Chen et al., 2018c). In addition, the emissions of $PM_{2.5}$ would also increase due to cold start-up of automobiles in the lower winter temperatures (Zhang et al., 2015b). In fact, there were 52 days (57.8%) and 14 days (15.7%) of daily $PM_{2.5}$ concentrations in winter above current daily CAAQS Grade I (35 μg/m^3) and II (75 μg/m^3) guidelines, followed by fall (48.9% and 1.1%), spring (38.9% and 4.4%), and summer (10% and 0%). It is therefore important to investigate spatiotemporal variation of $PM_{2.5}$ and further strengthen efforts to control the atmospheric pollutants in Guangzhou.

3.2 $PM_{2.5}$ LUR models and evaluation

The annual and seasonal LUR models for $PM_{2.5}$ in Guangzhou are shown in Table 2. There were 4 to 5 predictive variables in the final LUR models. The VIF values of all the variables were < 3, indicating a relatively low multicolinearity between the predictive variables. The Moran's I value of the models ranged from 0.01 to 0.12 with *p* values lower than 0.05, which indicated no significant spatial autocorrelation of the residuals.

For the annual $PM_{2.5}$ models, five predictive variables remained in the final LUR model, including the length of main roads (4000m buffer), DEM, distance to nearest ancillary, commercial area (1000m buffer), and wind speed. The predicted annual average $PM_{2.5}$ concentrations are mapped in Figure 3. The predicted annual $PM_{2.5}$ concentrations were 35.5 ± 9.29 μg/m^3, which are close to the measured values across 49 monitoring stations. As expected, the $PM_{2.5}$ concentrations increased with the length of main road and commercial area, while DEM, distance to nearest ancillary and wind speed were negatively correlated with $PM_{2.5}$ concentrations. Thus, we found that the higher $PM_{2.5}$ concentrations occurred in the center of Guangzhou with a relatively intensive road network and commercial area, whereas lower concentrations areas distributed in the north and south Guangzhou suburbs with fewer roads (Figure 3).

For the seasonal models, we found that the predicted seasonal and annual $PM_{2.5}$ concentrations across 7,225 1000×1000 m grids exhibited a good correlation with each other (Table S3). This indicated that the $PM_{2.5}$ concentrations might be affected by similar factors throughout the year. Indeed, the predictive variables of seasonal models were similar to those in the annual model. In addition, the predictive variables left in the models could also be used to identify potential sources of air pollutants. In this work, we found that all the models contained traffic related variables (e.g. distance to nearest ancillary and length of main road), suggesting that vehicle emissions were an important contributor to $PM_{2.5}$ and controlling vehicle emissions would be an effective way to reduce $PM_{2.5}$ in Guangzhou. That is consistent with previous studies which reported that 20 to 47% of $PM_{2.5}$ in Guangzhou derived from mobile sources (Liu et al., 2014; Yuan et al., 2018). The distance to nearest ancillary entered all the LUR models and was a strong predictor variable. That may be because the speed of vehicles on ancillary roads is usually limited to below 40 km/h in China, and the emissions of $PM_{2.5}$ and gaseous precursors of $PM_{2.5}$ from vehicles tend to be higher at lower speeds (Jones and Harrison, 2006; Wang et al., 2013). Another important traffic related variable is the length of main road. Although the speed of vehicles on main roads is relatively high, traffic on main roads is much higher. Therefore, the length of main roads was treated as a predictive variable in 3/5 of LUR models.

Meteorology has been shown to play a significant role in the distribution of air pollution (Chen et al., 2018a; Chen et al., 2018c). However, most previous studies did not incorporate meteorological variables in LUR models in China. In this work, all the LUR models contained the meteorological variables (e.g. wind speed and precipitation). We found that the $PM_{2.5}$ concentration decreased with the increasing wind speed and precipitation. In fact, the wind would facilitate dispersion of $PM_{2.5}$, while the rain would clean ambient $PM_{2.5}$ through the wash-out effect.

In this study, only three buffer predictive variables with buffer sizes < 700 m enter the final LUR model (Table 2), while most of buffer predictive variables (7/10) in the final LUR models have a larger buffer buffers size (> 1000 m). Therefore, the final LUR models might be sensitive to variables with larger buffers. In general, $PM_{2.5}$ could be directly emitted from primary sources, and secondarily formed from precursors by various atmospheric chemical reactions (Lai et al., 2016; Liu et al., 2014; Wang et al., 2018; Yuan et al., 2018). Moreover, primary pollutants (e.g., black carbon and heavy metals) tend to be more linked with variables with smaller buffers, whereas secondary pollutants (e.g., O_3 and NO_3^-) are more associated with variables with larger buffers (Cai et al., 2020; Wu et al., 2015; Zhang et al., 2015a). Thus, the larger buffer size of variables for $PM_{2.5}$ models may suggest the significant contribution from secondary sources in Guangzhou. Additionally, the larger buffer may reflect the long-range transport of $PM_{2.5}$ from emission sources.

The LUR models have been widely applied to describe spatial variability in air pollution concentrations worldwide (Beelen et al., 2013; Chen et al., 2018b; Eeftens et al., 2012b; Eeftens et al., 2012c; He et al., 2018; Meng et al., 2015; Wu et al., 2015). The percentage of explained spatial variability ranged from 51% to 88% in the PM LUR models in Chinese cities (Table 3), which was associated with quality of predictive variables and measured data, the model development approaches, and the complexity of the study areas. Our $PM_{2.5}$ models' performance was comparable to previous studies in China, which has an R^2 of 0.62 to 0.82, adjusted R^2 of 0.56 to 0.80, and 10-fold cross-validation (CV) R^2 of 0.50 to 0.78 (Table 3). The model R^2 values were close to those of CV R^2, suggesting the good robustness of our LUR models. Moreover, the CV RMSE ranged from 2.29 to 3.00 μg/m^3, indicating the predicted values coincided well with the measured values. We found that the performance of the models exhibited significant seasonal variation, which showed highest explained spatial variability in winter (80%), followed by fall (62%), spring (60%) and summer (56%). This may be due to the fact that it is difficult for the LUR model to predict $PM_{2.5}$ formed from secondary sources, and the contribution of secondary sources to $PM_{2.5}$ would be higher in warm seasons.

As shown in Table 3, most PM LUR models in China were developed by the routine monitoring stations data from government (Chen et al., 2018b; He et al., 2018; Meng et al., 2015; Wu et al., 2015). However, the number of routine monitoring stations is limited in most Chinese cities, which cannot meet the minimum required number of sampling sites suggested for LUR model development (40 to 80 sites) (Hoek et al., 2008). In addition, routine monitoring stations were generally designed for regulatory purposes, with few sites situated close to traffic or industrial sources. To overcome such challenges, some studies have used purposefully designed monitoring networks to build their LUR models (Cai et al., 2020; Eeftens et al., 2012c; Jin et al., 2019; Zhang et al., 2015a). Although the purpose-designed monitoring sites have sufficient geographic coverage to capture the gradients of spatial predictive variables, it should be noted that purpose-designed monitoring campaigns can be money- and time-consuming (Beelen et al., 2013; Briggs et al., 1997; Eeftens et al., 2012a). Additionally, the sampling period for purpose-designed monitoring campaigns is usually within several weeks, which can introduce uncertainties in the models.

In this study, the number of routine monitoring stations (49 stations) was more than previous LUR models for Chinese cities based on routine monitoring stations data, and comparable to other studies with purpose-designed monitoring data. In addition, we obtained the $PM_{2.5}$ data from routine monitoring stations is a relatively cost-effective procedure without additional sampling, and the measurements were continuous in temporal coverage. Moreover, most of the routine monitoring stations in Guangzhou were located in the urban centre with high population density, suggesting the data and the LUR models are suitable for $PM_{2.5}$ human exposure assessment.

3.3 Seasonal and spatial variation of predicted $PM_{2.5}$

The seasonal pattern of predicted average $PM_{2.5}$ concentrations was consistent with that of measured values, which exhibited highest values in winter (43.8 ± 9.6 μg/m^3), followed by fall (35.6 ± 7.2 μg/m^3), spring (35.3 ± 12.7 μg/m^3), and summer (20.7 ± 5.8 μg/m^3). In addition, the intercept of LUR models showed similar variation patterns to the predicted values (Table 2), which is higher in winter and fall. This suggested that the intercept of LUR models could be employed to reflect the seasonal variations (Chen et al., 2017c; Sabaliauskas et al., 2015; Wu et al., 2015).

The spatial variations of $PM_{2.5}$ were similar across seasons. The $PM_{2.5}$ was higher in the center of Guangzhou where there is a more intensive road network, and a larger commercial area (Figure 4). The north and south of Guangzhou had lower $PM_{2.5}$ concentrations, which may be due to them being away from the pollutant sources. In addition, the more forested areas in the north may help filter the $PM_{2.5}$, while proximity to the coast in the south may promote dispersion of $PM_{2.5}$.

Previous studies have reported that PM concentrations could be influenced by land use types (Anand and Monks, 2017; Tang et al., 2018), so it is important to investigate the distribution of PM in different land use types. Due to less than 1% of the areas being bare land and wetland we did not take these two land use types into account. In addition, the grassland and shrubland are usually used as roadside and in parks in the cities, so the grassland and shrubland were combined as green land in this study. The contribution of forest, cropland, green land, impervious surface, and water area was 45.3%, 22.7%, 4.5%, 21.3% and 6.0%, respectively. Figure 5 shows the predicted $PM_{2.5}$ concentration in different land use types. Regardless of the land use type, we found that all the predicted annual $PM_{2.5}$ concentrations were above the annual CAAQS Grade I guide line, so there is a need to further reduce the $PM_{2.5}$ emissions at source in Guangzhou. In this study, the highest annual $PM_{2.5}$ concentration occurred over impervious surfaces (42.3 ± 6.3 μg/m^3), followed by green land (38.0 ± 8.0 μg/m^3), cropland (36.2 ± 7.4 μg/m^3), forest (33.1 ± 10.9 μg/m^3), and water bodies (28.1 ± 11.0 μg/m^3). Industrial, commercial and transportation activities and hence sources are mainly carried out on impervious surfaces, which leads to the highest $PM_{2.5}$ concentrations. The lowest $PM_{2.5}$ concentrations were found in water areas, including rivers and lakes, which is likely related to the water surface removing $PM_{2.5}$ via the absorption effect (Zhu and Zeng, 2018).

Vegetation in urban areas (e.g. urban forests, urban parks, and roadside vegetation) is known to efficiently remove PM (Nowak et al., 2018; Selmi et al., 2016; Wang et al., 2019). However, the predicted $PM_{2.5}$ concentrations varied a lot among the green land, cropland, and forest. That may be due to the removal efficiency of vegetation being highly dependent on tree species, leaf surface properties, and seasons (Chen et al., 2017a; Nguyen et al., 2015; Vos et al., 2013; Wang et al., 2019). The vegetation mainly captures the $PM_{2.5}$ via the leaf surface, and the growth of leaves varies seasonally (Nguyen et al., 2015). However, it should be noted that Guangzhou has a warm climate, and the vegetation is lush throughout the year. Thus, it seems the season is not main reason for such differences here. The shrubs and grasses with lower leaf surface areas and height are the main vegetation species in the green land, usually found by the roadside and in urban parks close to traffic sources. Thus, the predicted $PM_{2.5}$ concentration in green land is only second to that in impervious surface. For the cropland, the combustion of straw residuals may contribute to the relatively high predicted $PM_{2.5}$ concentration. Indeed, despite open straw burning being prohibited, biomass burning is still an important source of $PM_{2.5}$ in Guangzhou (Lai et al., 2016; Liu et al., 2014). The forest vegetation in Guangzhou is dominated by tall evergreen trees with large leaf surface area. These trees are far away from the urban centre area with high pollution. Thus, the relatively low predicted $PM_{2.5}$ concentration was observed in the forest area.

3.4 Health and economic benefits of $PM_{2.5}$ reduction

The Chinese air quality has greatly improved after the 5-year Air Pollution Prevention and Control Action Plan that initiated in 2012. Actually, many Chinese cites' $PM_{2.5}$ concentration achieved CAAQS Grade II guideline at the end of 2017. However, it is noteworthy that the number of cities' $PM_{2.5}$ concentration that meet CAAQS Grade I is very limited. To further improve the air quality in China, it is important to assess the public health benefits of further reduction of $PM_{2.5}$ to the lower concentration ranges. Guangzhou as the third largest city with densely populated in China, of which $PM_{2.5}$ concentration has achieved CAAQS Grade II guideline. Therefore, Guangzhou is an ideal case study city to estimate health and economic benefits of further reduction of $PM_{2.5}$ to lower concentration ranges, which can provide valuable information for policy makers to analyze cost and benefits of air pollution management programs in China. In previous studies, the PM exposure surfaces imported in the BenMAP were estimated by interpolation methods or chemical transport models. However, the performance of interpolation methods was affected by the number and distribution of the monitoring sites, and the stimulation process of chemical transport models was complicated and expensive. Recently, LUR models have been shown to be an efficient method to assess air pollution exposures in epidemiologic studies (Chen et al., 2017b; Sampson et al., 2013; Vienneau et al., 2013). Therefore, we estimated the health and economic benefits of reducing $PM_{2.5}$ in Guangzhou using BenMAP based on the annual $PM_{2.5}$ concentration predicted by the LUR model.

The estimated values of avoided premature mortality and corresponding economic benefits are summarized in Table 4. The estimated avoided mortalities from all causes, cardiovascular, and respiratory were 992 (95% CI: 221−2140), 362 (95% CI: 124−768) and 92 (95% CI: -18−176) cases in 2018 by reducing the annual $PM_{2.5}$ concentration to annual CAAQS Grade I guideline (15 μg/m^3) respectively. The contribution of cardiovascular and respiratory to all cause mortalities were 36.5% and 9.3%, respectively. Correspondingly, economic benefits due to avoided premature mortalities by reducing $PM_{2.5}$ were 1478 million CNY (95% CI: 257−2524) based on WTP approach, accounting for 0.064% GDP of Guangzhou in 2018. Although the BenMAP was widely applied to investigate the public health benefits of reducing $PM_{2.5}$, there are very limited studies on the estimation of premature mortalities related to $PM_{2.5}$ in Chinese cities. In Shanghai, the avoided all cause mortalities were estimated to range from 180 to 3500 per year, assuming the $PM_{2.5}$ concentration achieved the annual CAAQS Grade II guideline (35 μg/m^3), which had an estimated monetary value ranging from 170 to 1200 million CNY (Voorhees et al., 2014). For the same scenario, the avoided premature mortalities ranged from 1100 to 4800 per year in Tianjin, the corresponding economic benefits ranged from 270 to 7200 million CNY (Chen et al., 2017c). The estimated health and economic benefits of the above two studies just considered the achievement of meeting the annual CAAQS Grade II guideline. However, due to the annual $PM_{2.5}$ concentration in Guangzhou having already achieved the annual CAAQS Grade II guideline in the past few years, it is difficult to compare the results of these two studies with Guangzhou. In Guangzhou, the $PM_{2.5}$-related premature mortalities were estimated to be 1926 cases in 2012, and the reduction of annual $PM_{2.5}$ concentration being greater than 15 μg/m^3 from 2013 to 2015.(Li et al., 2019; Pan et al., 2012). The estimated avoided mortalities from all causes ranged from 791 to 1473 (Li et al., 2019) which is comparable to the results of this work. In addition, we only chose mortality as the health endpoint, while morbidity was not included in this study. Therefore, the health and economic benefits will be underestimated, and there is a need to further improve the air quality and public health benefits by reducing $PM_{2.5}$ concentration.

3.5 Limitation and further works

There are several limitations to this study. Source-specific emissions were not considered in this work, which may be important predictors in the study areas. In addition, the performance of LUR models in warm seasons was poorer, which may be because the predictors cannot indicate the secondary formations of $PM_{2.5}$ as well. Therefore, to improve the performances of LUR models, data from air quality models which has considered emission source inventories and chemical reactions should be incorporated into future LUR models in Guangzhou (de Hoogh et al., 2016; Yang et al., 2017).

For the health benefits estimation, we only selected all cause, cardiovascular, and respiratory mortality as the health endpoints in this work. Moreover, the sex and age of the population was not considered when estimating the avoided premature mortality. In addition, the LUR models only predict the ambient air pollution concentrations, and the use of ambient concentration to estimate people's exposure to air pollution may not provide a reliable result, because more than 80% of people's lives is typically spent indoors (Lim et al., 2011). All of these may introduce uncertainties into estimation of potential health benefits of $PM_{2.5}$ reduction. Therefore, to enhance the accuracy of health benefits estimation in future, there is a need to develop the dynamic exposure models that consider differential exposures between population subgroups (e.g. age and sex) and exposure characteristics in different microenvironments (Tang et al., 2018).

4. Conclusion

In this work, we applied LUR models to study the spatiotemporal variations of $PM_{2.5}$ in Guangzhou. The results showed that all the LUR models had a high accuracy and predictive ability, and the traffic variables (e.g., length of main roads and the distance to nearest ancillary) were most common among the LUR models, suggesting that vehicle emissions were an important source for $PM_{2.5}$. The R^2, adjusted R^2 and 10-fold cross validation R^2 of the annual $PM_{2.5}$ LUR model were 0.78, 0.72 and 0.66, respectively, which could provide useful spatial information for air quality management and air pollution exposure assessment. Therefore, we estimated the health and economic benefits of reducing $PM_{2.5}$ in Guangzhou using BenMAP based on the annual $PM_{2.5}$ concentration predicted by the LUR model. The results showed that, by achieving the annual CAAQS Grade I guideline (15 μg/m^3), the avoided all cause mortalities due to exposure to $PM_{2.5}$ were 992 cases (95% CI: 221−2140) and the corresponding economic benefits were 1478 million CNY (95% CI: 257−2524) (willingness to pay approach) in 2018 in Guangzhou.

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Figure 1. The distribution of air quality monitoring stations, land use types, and main roads in the study area.

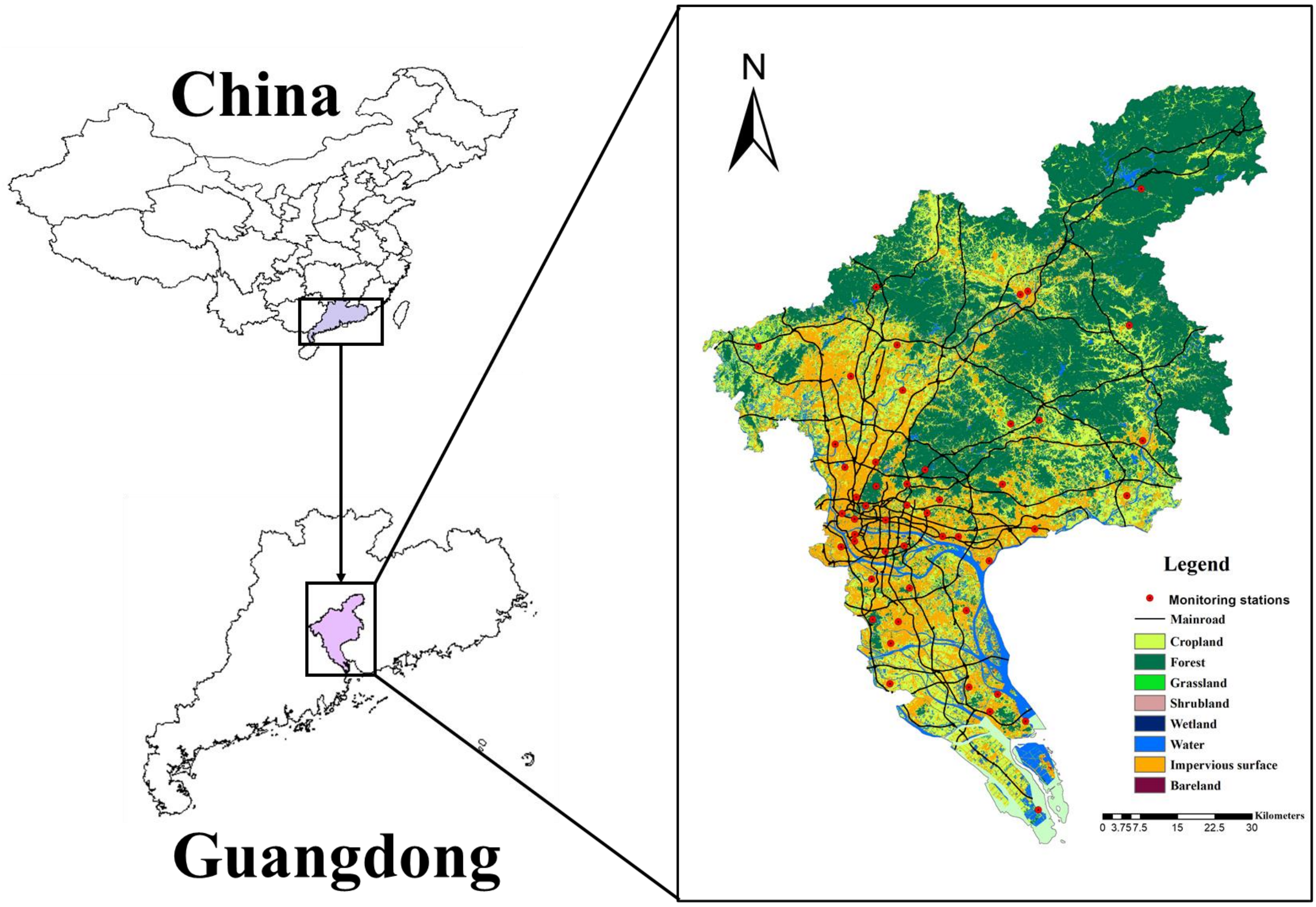

Figure 2. The monthly average concentrations of $PM_{2.5}$ in Guangzhou, China, 2018. The mean (filled circle), median (horizontal line in the box), 25th and 75th percentiles (lower and upper end of the box), 10th and 90th percentiles (lower and upper whiskers) are shown.

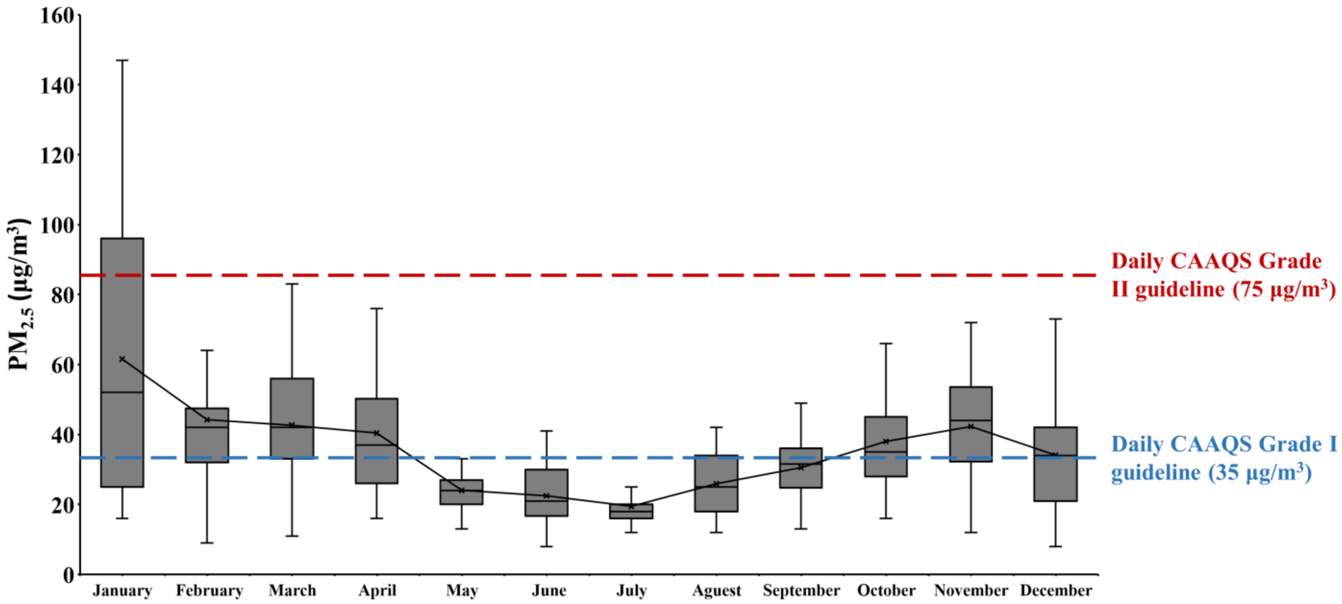

Figure 3. The spatial variation of predicted annual average $PM_{2.5}$ concentrations by land use regression model in Guangzhou.

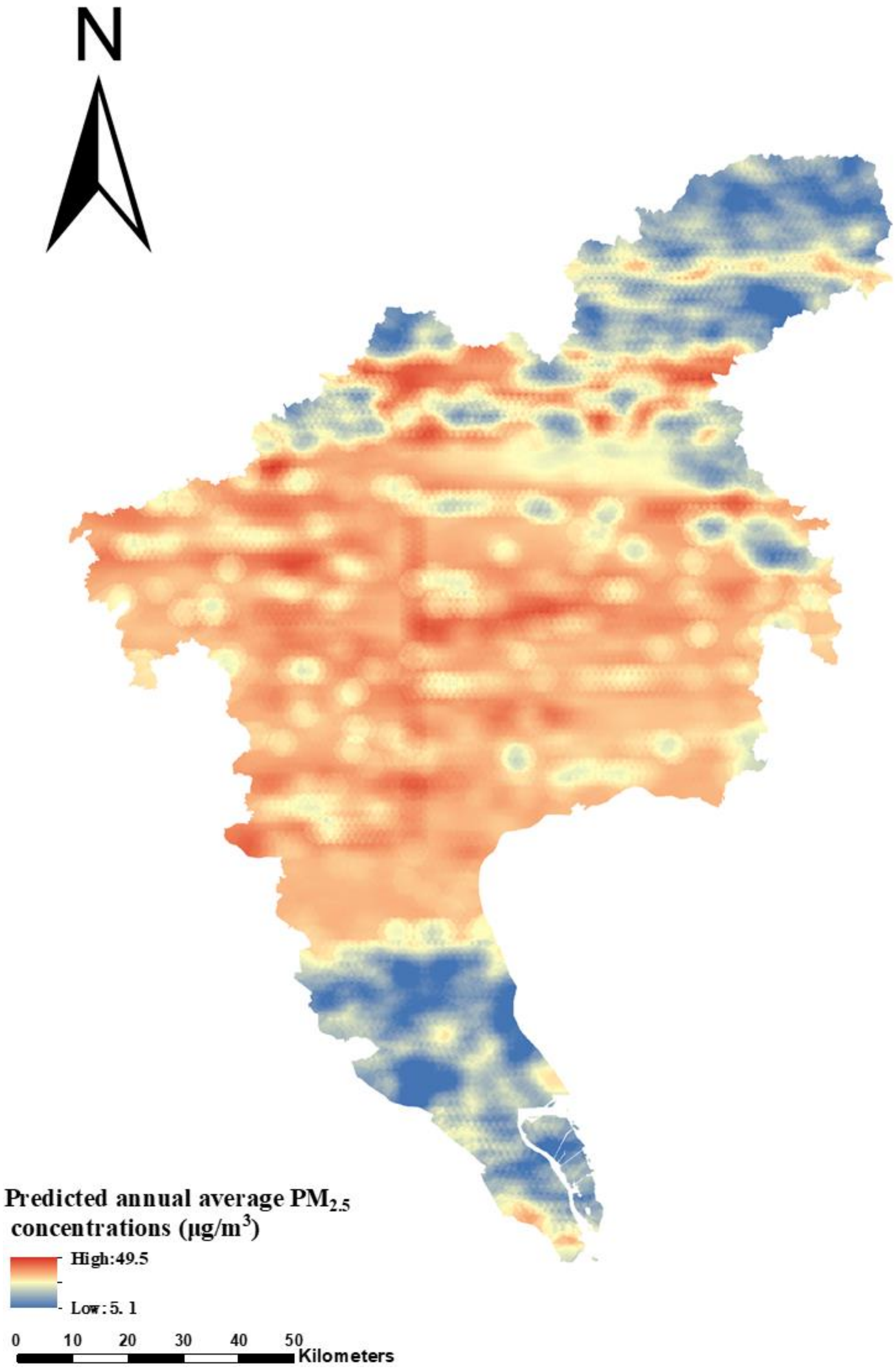

Figure 4. The seasonal averages of $PM_{2.5}$ concentrations predicted by land use regression models in Guangzhou.

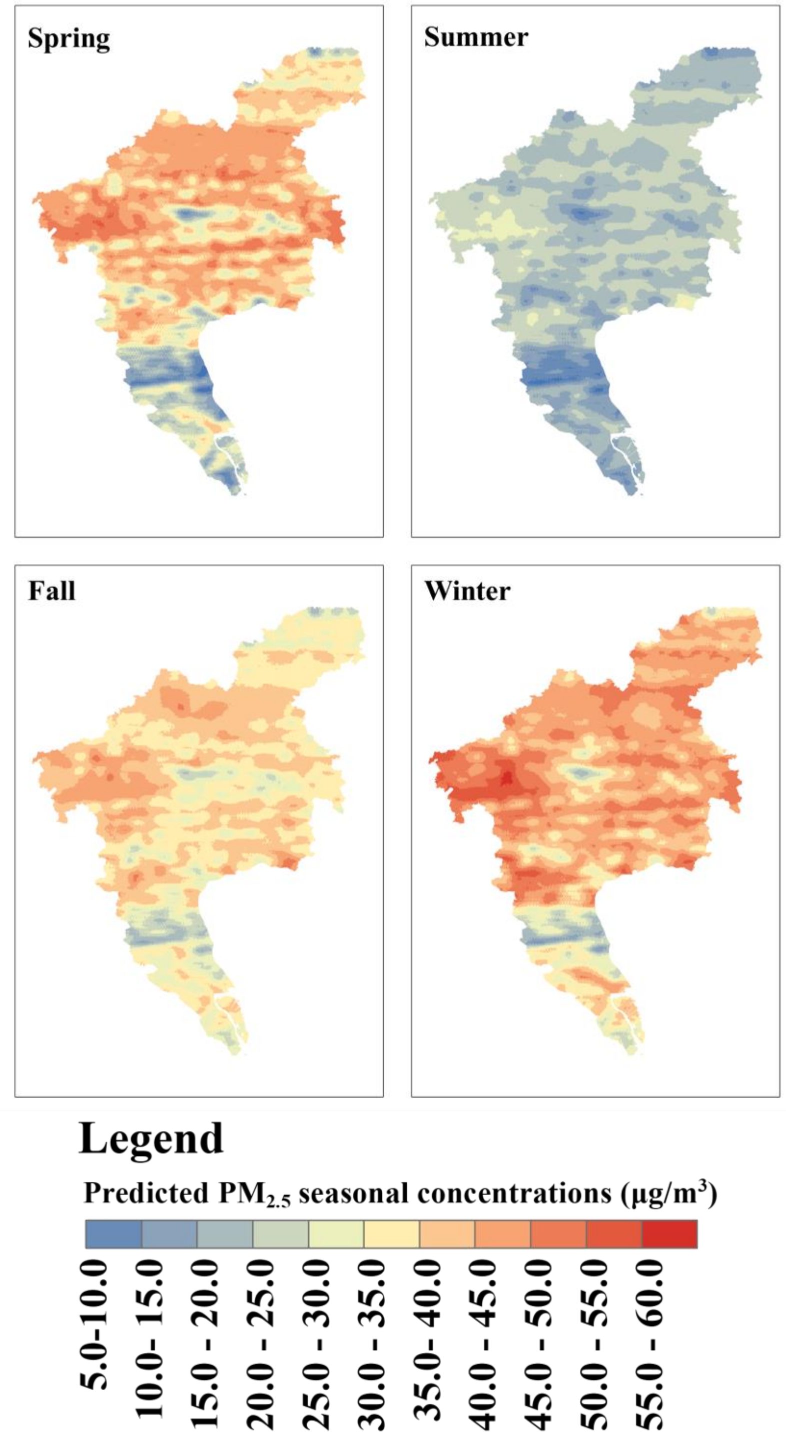

Figure 5. The seasonal and annual predicted concentrations of $PM_{2.5}$ in different land use types in Guangzhou. The green land is the sum of shrubland and grassland.

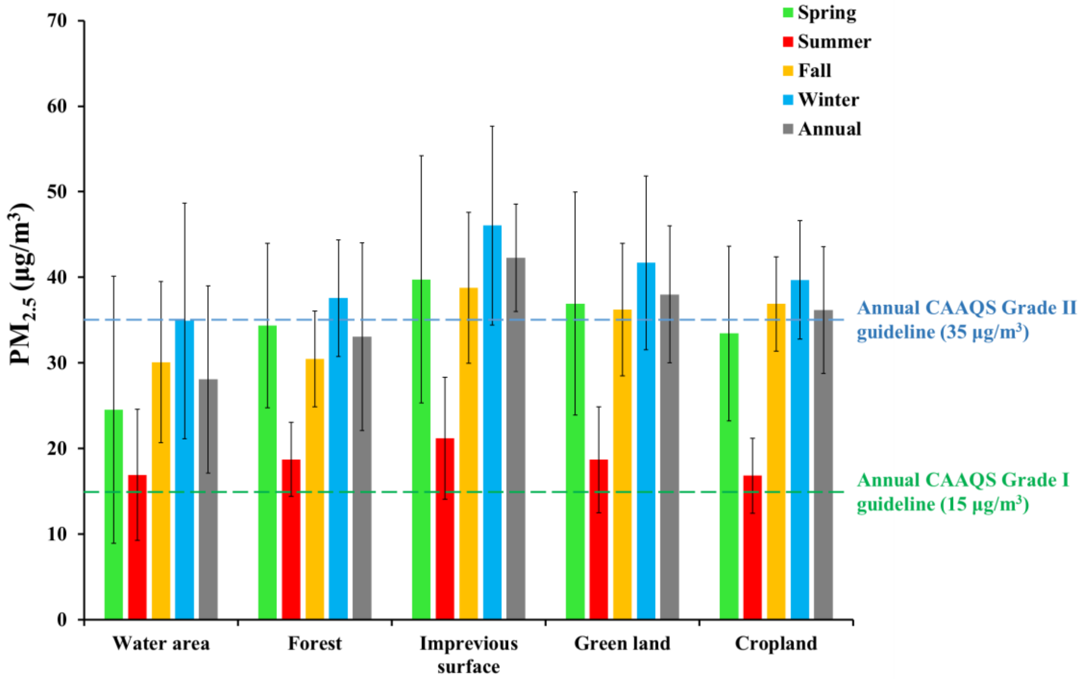

Table1. Potential predictor variables and expected direction of the regression coefficient considered for the LUR model.

Categories	Predictor variables	Unit	Buffer size (radius in meters)	Assigned direction
Physical geography	DEM	m	NA	-
Socioeconomic	Population	Population/km^2	NA	+
	GDP	CNY/km^2	1000, 2000, 3000, 4000, 5000	+
Meteorology	Wind speed	m/s	NA	-
	Relative humidity	%	NA	NA
	Pressure	kPa	NA	NA
	Temperature	°C	NA	NA
	Boundary layer height	m	NA	-
	Precipitation	mm	NA	-
	Short wavelength radiation	W/m^2	NA	NA
POI	Bus stops	Number	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Parking areas	Number	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
Land use types	Bare land	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Cropland	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	-
	Forest	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	-
	Grassland	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	-
	Impervious surfaces	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Shrubland	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	-

	Water body	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	-
	Wetland	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	-
Impervious surfaces	Residential area	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Commercial area	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Industrial area	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Transportation area	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Public management and service area	m^2	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
Traffic	Length of main road	m	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Length of highway	m	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Length of ancillary	m	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
	Length of alley	m	100, 300, 500, 700, 1000, 2000, 3000, 4000, 5000	+
Distance	Distance to nearest main road	m	NA	-
	Distance to nearest highway	m	NA	-
	Distance to nearest ancillary	m	NA	-
	Distance to nearest alley	m	NA	-
	Distance to nearest coastline	m	NA	+

Table 2. Annual and seasonal LUR models for $PM_{2.5}$ based on 49 monitoring stations in Guangzhou, China.

Predictive variables	Annual			Spring			Summer			Fall			Winter		
	β[a]	*p* value	VIF[b]	β	*p* value	VIF	β	*p* value	VIF	β	*p* value	VIF	β	*p* value	VIF
Intercept	44.2	< 0.001	–	41.8	< 0.001	–	28.8	< 0.001	–	45.4	< 0.001	–	55.8	< 0.001	–
Length of main road (4000m)	2.56×10^{-5}	0.001	1.50	–	–	–	–	–	–	–	–	–	–	–	–
Length of main road (3000m)	–	–	–	6.09×10^{-5}	< 0.001	1.26	–	–	–	–	–	–	4.50×10^{-5}	< 0.001	1.14
Length of ancillary (500 m)	–	–	–	0.001	0.01	1.3	–	–	–	–	–	–	–	–	–
DEM	-0.46	< 0.001	1.33	–	–	–	–	–	–	–	–	–	–	–	–
Distance to nearest ancillary	-8.08×10^{-3}	< 0.001	1.04	-0.011	0.002	1.16	-0.05	0.03	1.07	-5.66×10^{-3}	0.02	1.04	-6.34×10^{-3}	0.03	1.05
Shrubland (5000 m)	–	–	–	–	–	–	-9.04×10^{-7}	0.002	1.93				$1. 84 \times 10^{-6}$	0.02	1.69
Forest (3000 m)	–	–	–	–	–	–	–	–	–	-4.29×10^{-7}	< 0.001	1.17	–	–	–
Water (500 m)	–	–	–	-9.13×10^{-6}	0.02	1.04	–	–	–	–	–	–	–	–	–
Commercial area (1000 m)	4.18×10^{-6}	0.009	1.39	–	–	–	–	–	–	6.31×10^{-6}	< 0.001	1.22	–	–	–
Commercial area (700 m)	–	–	–	–	–	–	1.07×10^{-5}	< 0.001	1.02	–	–	–	–	–	–
Wind speed	-5.52	0.001	1.32	-5.51	0.015	1.17	-3.41	0.01	1.95	–	–	–	-6.21	0.001	1.78
Precipitation	–	–	–	–	–	–	–	–	–	-66.8	0.049	1.18	–	–	–

[a] β is the regression coefficient of each predictor variable.

[b] VIF is the abbreviation of Variance Inflation Factor.

Table 3. Comparison of performance statistics of land use regression models for $PM_{2.5}$/PM_{10} in China.

Study area	Type of monitoring data	Number of monitoring sites	$PM_{2.5}$/ PM_{10}	Adjusted R^2	RMSE ($\mu g/m^3$)	Cross Validation R^2	Cross Validation RMSE ($\mu g/m^3$)	References
Annual Guangzhou				0.72	2.20	0.66	2.50	
Spring Guangzhou				0.60	2.90	0.56	2.42	
Summer Guangzhou	routine monitoring stations	49	$PM_{2.5}$	0.56	1.95	0.50	2.29	This study
Fall Guangzhou				0.62	2.63	0.55	3.00	
Winter Guangzhou				0.80	2.48	0.78	2.77	
Pearl River Delta	routine monitoring stations	69	$PM_{2.5}$	0.88	–	0.87	2.75	Yang et al. (2017)
Hong Kong	routine monitoring stations	15	$PM_{2.5}$	0.67	–	–	2.62	Shi et al. (2017)
Hong Kong	mobile monitoring	222	$PM_{2.5}$	0.63	6.52	0.61	–	Shi et al. (2016)
Hong Kong	purpose-designed monitoring	63	$PM_{2.5}$	0.54	4.00	0.43	4.70	Lee et al. (2017)
Nanjing	routine monitoring stations	9	$PM_{2.5}$	0.72	2.10	0.38	2.58	Huang et al. (2017)
Tianjin	routine monitoring stations	28	$PM_{2.5}$	–	–	0.73	6.38	Chen et al. (2017c)
Shanghai	routine monitoring stations	35	$PM_{2.5}$	0.88	–	–	–	Liu et al. (2016)
Beijing	routine monitoring stations	35	$PM_{2.5}$	0.68	–	–	–	Hu et al. (2016)
Beijing	routine monitoring stations	35	$PM_{2.5}$	0.58	–	–	9.30	Wu et al. (2015)
Lanzhou	purpose-designed monitoring	38	$PM_{2.5}$	0.73	9.60	0.67	–	Jin et al. (2019)
Yantai	purpose-designed monitoring	29	$PM_{2.5}$	0.65	3.12	0.56	–	Cai et al. (2020)
Changsha	routine monitoring stations and purpose-designed monitoring	36	PM_{10}	0.62	9.00	0.58	–	Liu et al. (2015)
Changsha	purpose-designed monitoring	40	PM_{10}	0.51	5.60	0.60	–	Li et al. (2015)

Tianjin	routine monitoring stations	30	PM_{10}	0.84	0.21	−	−	Shang et al. (2012)
Wuhan	routine monitoring stations	9	PM_{10}	0.59	−	−	−	Xu et al. (2016)
Shanghai	routine monitoring stations	28	PM_{10}	0.80	4.20	0.73	5.00	Meng et al. (2016)

Table 4. Estimated avoided premature mortality and benefits of health effects associated with $PM_{2.5}$ reduction in Guangzhou.

Health endpoints	Avoided cases (person)		Benefits (Million CNY)	
	Mean	95% CI	Mean	95% CI
All cause	992	221−2140	1478	257−2425
Cardiovascular	362	124−768	567	48−924
Respiratory	92	-18−176	139	24−278

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