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Using geographical semi-variogram method to quantify the difference between NO_2 and $PM_{2.5}$ spatial distribution characteristics in urban areas

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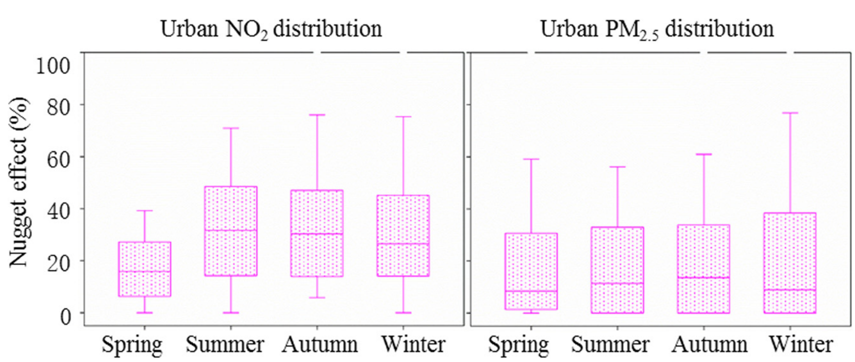
HIGHLIGHTS

- Spatial variations in NO_2 and $PM_{2.5}$ in Foshan were assessed by semi-variogram.
- The local-scale spatial variance of $PM_{2.5}$ is smaller than that of NO_2.
- The spatial range of NO_2 autocorrelation is larger than that of $PM_{2.5}$
- The NO_2 and $PM_{2.5}$ influencing factors have different spatial scale dependence.
- The study provides scientific evidence for buffering selection of LUR predictors.

GRAPHICAL ABSTRACT



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ABSTRACT

Urban air pollutant distribution is a concern in environmental and health studies. Particularly, the spatial distribution of NO_2 and $PM_{2.5}$, which represent photochemical smog and haze pollution in urban areas, is of concern. This paper presents a study quantifying the seasonal differences between urban NO_2 and $PM_{2.5}$ distributions in Foshan, China. A geographical semi-variogram analysis was conducted to delineate the spatial variation in daily NO_2 and $PM_{2.5}$ concentrations. The data were collected from 38 sites in the government-operated monitoring network. The results showed that the total spatial variance of NO_2 is 38.5% higher than that of $PM_{2.5}$. The random spatial variance of NO_2 was 1.6 times than that of $PM_{2.5}$. The nugget effect (i.e., random to total spatial variance ratio) values of NO_2 and $PM_{2.5}$ were 29.7 and 20.9%, respectively. This indicates that urban NO_2 distribution was affected by both local and regional influencing factors, while urban $PM_{2.5}$ distribution was dominated by regional influencing factors. NO_2 had a larger seasonally averaged spatial autocorrelation distance (48 km) than that of $PM_{2.5}$ (33 km). The spatial range of NO_2 autocorrelation was larger in winter than the other seasons, and $PM_{2.5}$ has a smaller range of spatial autocorrelation in winter than the other seasons. Overall, the geographical semi-variogram analysis is a very effective method to enrich the understanding of NO_2 and $PM_{2.5}$ distributions. It can provide scientific evidences for the buffering radius selection of spatial predictors for land use regression models. It will also be beneficial for developing the targeted policies and measures to reduce NO_2 and $PM_{2.5}$ pollution levels.

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1. Introduction

Urban air pollutant distribution is a concern in environmental and health studies. Particularly, the spatial distribution of NO_2 and $PM_{2.5}$, which represent photochemical smog and haze pollution in urban areas, is of concern. NO_2 and $PM_{2.5}$ experience totally different atmospheric processes from emissions, transport, chemical reactions, and deposition (Chen et al., 2018; Jiang and Christakos, 2018; Liu et al., 2016; Strak et al., 2017; Wang et al., 2014b). There have been a number of studies on NO_2 and $PM_{2.5}$ distribution. These studies mainly focus on source apportionment, concentration mapping, formation and transport mechanisms, the effects of meteorological elements on distribution, and interaction analysis between $PM_{2.5}$, NO_2 and other air pollutants (Callen et al., 2014; Hoek et al., 2008; Liao et al., 2017; Song et al., 2014; Wu et al., 2017b). However, whether NO_2 and $PM_{2.5}$ have different spatial distribution characteristics has not been addressed in the previous literature.

On the other hand, the geographical semi-variogram has been widely used for the development of kriging interpolation (KI) model (Badaro-Saliba et al., 2014; Cao et al., 2017; Qu et al., 2010). The geographical semi-variogram has been used for assessing the spatial variation of heavy metal pollution in soils, groundwater level, as well as optimization of air quality monitoring network (Ahmadi and Sedghamiz, 2007; Guo et al., 2001; Lin, 2002; Liu et al., 2013; Pahlavani et al., 2017; Wang et al., 2014a). However, it has not been used to quantify the difference between NO_2 and $PM_{2.5}$ spatial variations, or to analyze the spatial scale-dependence of influencing factors.

Here, we considered that the spatial variation in air pollutant concentrations could be split into different components related to multiple spatial scales (Alary and Demougeot-Renard, 2010; Lv et al., 2014; Spokas et al., 2003). Then, the geographical semi-variogram was developed based on daily measurements. This may be a simple and effective way to analyze the spatial distribution characteristics of NO_2 and $PM_{2.5}$ in a complex urban environment. The geographical semi-variogram parameters can also quantify the multi-scale spatial variation, spatial autocorrelation distance, as well as the spatial scale dependence of influencing factors in NO_2 and $PM_{2.5}$ concentrations.

Overall, the aim of this study is to compare the differences between NO_2 and $PM_{2.5}$ spatial distribution characteristics. The specific objectives are (1) identify the differences between NO_2 and $PM_{2.5}$ variation; (2) identify the difference in the spatial scale-dependence of NO_2 and $PM_{2.5}$ dominant influencing factors; (3) identify the differences in spatial range of NO_2 and $PM_{2.5}$ autocorrelation.

2. Materials and methods

2.1. Study area characteristics

The study was conducted in Foshan, China. The geographical extent is 22°38′–23°34′N, and 112°22′–113°23′E. The total area is 3848.48 km^2. The study area is located south of the Tropic of Cancer. The annual mean temperature, relative humidity, and wind speed are 22.5 °C, 76%, and 2 m/s, respectively. The rainy season is from April to September during which 80% of the total annual rainfall is received. Winds are mainly northerly in winter and spring, and mainly southerly in summer. The southwest and northwest areas are mountainous (up to 785 m), while the remaining area is generally flat. Fig. 1 shows the locations of government-operated NO_2 and $PM_{2.5}$ monitoring stations.

2.2. Air quality measurements

Daily NO_2 and $PM_{2.5}$ measurements were collected from the Foshan air quality monitoring network (http://www.foshanepb.gov.cn/). The network consists of 38 fixed government-operated monitoring stations with simultaneous measurements, which have strict quality assurance and control procedures. The minimum and maximum distance between monitoring stations are 484.2 and 21,993.7 m, respectively. The averaged distance between all monitoring stations is 8117.5 m. The lowest and highest altitude of the monitoring stations is 28 and 58 m respectively. NO_2 and $PM_{2.5}$ were measured using the Ogawa badges method and the tapered element oscillating microbalance (TEOM) method, respectively (Li et al., 2017; Liu et al., 2017; Tessum et al., 2018; Wang et al., 2013). The measurements met the corresponding Ogawa and TEOM analysis protocol, and passed the criteria of the quality assurance and controls according to the environmental protection standard of China (HJ 618-2011; MEPCN) (Xie et al., 2015).

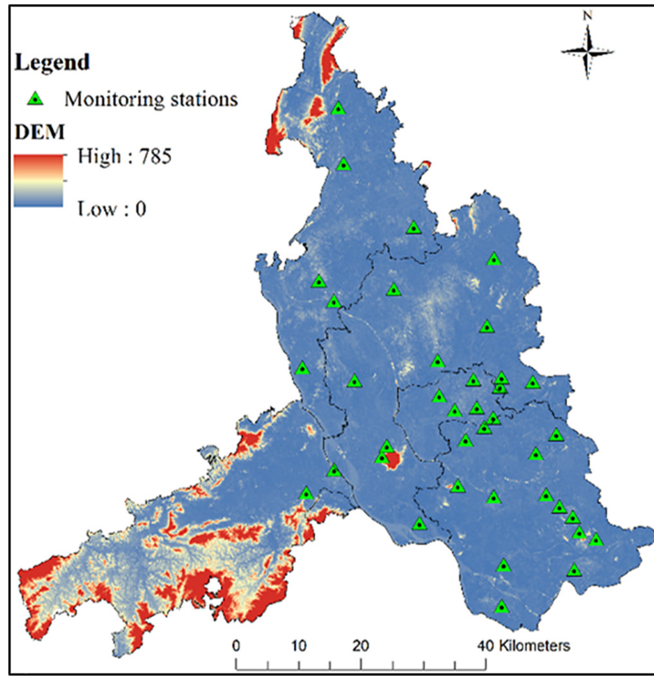

Fig. 1. Location of NO_2 and $PM_{2.5}$ monitoring stations.

2.3. Geographical semi-variogram analysis

The geographical semi-variogram model is a geostatistical analysis method, and is the most common measure for characterizing spatial variability of a regionalized variable (Lin et al., 2018). It is used here to understand the multi-scale spatial variation of urban air pollutants. The semi-variogram model can describe air pollutant variations as in graphical form, and a schematic diagram is presented in Fig. 2. Three major parameters, sill, partial sill, and nugget, are used to quantify the spatial variability of an air pollutant. The nugget parameter (C_0) represents the random spatial variance of the air pollutant. The partial sill parameter (C_1) represents the structural spatial variance of the air pollutant. A high partial sill means that a large proportion of the spatial variation is caused by regional-scale influencing factors. The sill parameter ($C_0 + C_1$) represents the total degree of spatial variation of the air pollutant. Additionally, h indicates the spatial distance between monitoring stations. The range parameter (α) represents the maximum spatial distance of air pollutant autocorrelation, because air pollutant is spatially autocorrelated. Samples separated by distances less than the range are spatially related, whereas those separated by a distance greater than the range are considered not to be spatially related. In short, the semi-variogram parameters effectively depict the spatial structure of air pollutant variations and enrich the understanding of air pollutant distribution. A full discussion of the semi-variogram parameters can be found in the literature (e.g. Burgos et al., 2006; Hu and Xu, 2018; Lin et al., 2018; Ye et al., 2018).

The nugget effect (the ratio of random to total spatial variance) indicates whether regional or local-scale factors are more important for air pollutant distribution. The value of nugget effect ranges from 0 to 100%,