Environmental Pollution 241 (2018) 494–503

Contents lists available at ScienceDirect

Environmental Pollution

journal homepage: www.elsevier.com/locate/envpol

Identifying the socioeconomic determinants of population exposure to particulate matter ($PM_{2.5}$) in China using geographically weighted regression modeling[☆]

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A R T I C L E I N F O

Article history:
Received 23 March 2018
Received in revised form
15 May 2018
Accepted 23 May 2018

Keywords:
Population exposure
Geographically weighted regression
Socioeconomic determinants
China

A B S T R A C T

Air pollution contributes significantly to premature death in China. However, only a limited number of studies have identified the potential determinants of population exposure to $PM_{2.5}$ from a socioeconomic perspective. This paper analyses the socioeconomic determinants of population exposure at the city level in China. We first estimated population exposure to $PM_{2.5}$ by integrating high resolution spatial distribution maps of $PM_{2.5}$ concentrations and population density, using data for 2013. Then, geographically weighted regression (GWR) modeling was undertaken to explore the strength and direction of relationships between the selected socioeconomic factors and population exposure. The results indicate that approximately 75% of the population of China lived in an area where $PM_{2.5}$ concentrations were over 35 $\mu g/m^3$ in 2013. From the GWR models, we found that the percentages for cities that showed a statistically significant relationship ($p < 0.05$) between population exposure and each of the six factors were: urbanization, 91.92%; industry share, 91.58%; construction level, 88.55%; urban expansion, 73.40%; income disparity, 64.98%; and private vehicles, 27.27%. The *R*-squared value for the six factors in the multivariable GWR model was 0.88, and all cities demonstrated a statistically significant relationship. More importantly, the association between the six factors and population exposure was found to be spatially heterogeneous at the local geographic level. Consideration of these six drivers of population exposure can help policy makers and epidemiologists to evaluate and reduce population exposure risks.

1. Introduction

China's high air pollution levels constitute a stigma in the country's achievements in urban and economic development. That is because China's economic expansion is mainly driven by the use of fossil fuels, which dramatically increase emissions of ambient pollutants (Kan et al., 2012). Air pollution, and especially fine particulate matter smaller than 2.5 μm ($PM_{2.5}$), has led not only to gray skies across the country and global climate change but also to significant health risks for residents (Xu et al., 2000; Pope et al., 2002; Venners et al., 2003; Pope and Dockery, 2006; Guo et al., 2009; Chen et al., 2010). For instance, researchers have argued that increased $PM_{2.5}$ levels increase the risk of many kinds of disease, such as cardiopulmonary diseases, lung cancer, stroke, ischemic disease, hypertension, and heart rate variability, and ultimately, even premature death (Liu et al., 2016; Pope et al., 2002; Guo et al., 2009; Wu et al., 2010). More than 3 million people died prematurely due to ambient air pollution across the world in 2010 and there were 1.37 million adult premature mortalities in China in 2013 (Forouzanfar et al., 2015; Liu et al., 2016). Consequently, estimating the determinants of population exposure to $PM_{2.5}$ concentrations in China is of great benefit for policy makers and epidemiologists in formulating feasible policies to mitigate population exposure risk (Pope et al., 2009).

However, research into population exposure mainly focuses on assessing population exposure and its adverse consequences. For example, estimations of population exposure have relied on data that assessed exposure risk and the hazards of exposure. Generally,

☆ This paper has been recommended for acceptance by Haidong Kan.
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https://doi.org/10.1016/j.envpol.2018.05.083
0269-7491/

population exposure to $PM_{2.5}$ concentrations is obtained by overlaying population densities (obtained from static administrative address data) and $PM_{2.5}$ concentrations levels (Friedrich and Bickel, 2001). Therefore, population data and $PM_{2.5}$ concentrations data is very important in calculating population exposure. Population density data include static data and dynamic data. Especially for dynamic data, compared with static data, scholars suggest that since people move, temporal population maps designed for activity-based transport modeling can be combined with pollution data from a dispersion model to more accurately estimate exposure risk. This approach can be seen in a study by Beckx et al. (2009) that estimated population exposure for the cities of the Netherlands. The results demonstrated that the difference of the hours spent exposed to $PM_{2.5}$ levels over 20 $\mu g/m^3$ differed more than 20% between static data and dynamic data.

Moreover, pollution data is also important for assessing population exposure, which includes monitoring data, census data, remote sensing data, and calculated data. Liu et al. (2016), conducted research which employed monitoring data of $PM_{2.5}$ concentrations to estimate the adult mortality attributed to $PM_{2.5}$ exposure. The results found that 83% of the population lived in an area where $PM_{2.5}$ concentrations were over 35 $\mu g/m^3$, contributing to 1.37million adult premature mortalities. Scholars employing household fuel use obtained through census for 2000 and 2010 to explore variations of population exposure to household air population, suggested that population exposure dramatically declined over that decade (Aunan and Wang, 2014). Research undertaken by Lin et al. (2016), whereby the authors utilized high-quality, 1-km MODIS data to compare simple average $PM_{2.5}$ concentrations to estimate long-term population exposure in the Pearl River Delta, found that more than 90% of the population were exposed to $PM_{2.5}$ concentrations higher than 35 $\mu g/m^3$ in each individual city, except for Jiangmen and Huizhou. In contrast to the ready-made pollution data, scholars have used models to calculate the data. For instance, looking at population exposure to pollutants in Canada, Hystad et al. (2011) created a national air pollution model able to address pollution variation at regional and local scales, finding average $PM_{2.5}$ levels to be 8.93 $\mu g/m^3$ in Canada.

In addition, the adverse consequences of pollution have also been studied by a range of researchers. Research undertaken by Lipfert et al. (2006) demonstrates this. Similarly, Kan et al. (2007) and Pope and Dockery (2006) also found that even short-term exposure to PM2.5 could increase mortality rates, and one empirical study of Shanghai in China found that long-term exposure to PM2.5 is responsible for a proportion of lung cancer mortality among non-smokers. Another study showed a statistically significant relationship whereby a 10 $\mu g/m^3$ increase would lead to a 10% increase in all-cause mortality (Brook et al., 2010).

In contrast, relationship studies have to date been predominantly conducted in relation to $PM_{2.5}$ concentrations, rarely addressing population exposure. A growing number of literature have demonstrated that $PM_{2.5}$ concentrations are closely related to human activities. For instance, Li et al. (2016) investigated the influence mechanisms of industrialization on $PM_{2.5}$ concentrations due to intensive energy consumption. Moreover, Lin et al. (2014) have argued that population growth, economic growth, and urbanization were important drivers of $PM_{2.5}$ concentrations from 2001 to 2010 in China. Vehicular impact on $PM_{2.5}$ concentrations has been exemplified by Hao and Liu (2016) and Hua et al. (2015). While the influence of urban expansion, real estate and rural-urban migration on $PM_{2.5}$ emissions has also been analyzed (Wang et al., 2017; Mao et al., 2012; Guan and Reiner, 2009; Lou et al., 2016; Aunan and Wang, 2014). Much of the existing scholarship agrees that urbanization affects $PM_{2.5}$ concentrations by increasing the urban population, especially in highly populated urban agglomerations. This position can be seen in a study by Wang et al. (2017) that argued that high urban population is an intensity factor for $PM_{2.5}$ concentrations, and a study by Han et al. (2014) which considered the impacts of urbanization on $PM_{2.5}$ concentrations due to higher standards of infrastructure which requires higher energy consumption. More importantly, rural to urban migration will continue due to better job opportunities and a diverse range of public services, which may heavily increase $PM_{2.5}$ concentrations in urban areas (Aunan and Wang, 2014). Similarly, He et al. (2016) argued that migration is the key factor for population exposure to $PM_{2.5}$ concentrations on the national scale in China.

However, studies identifying factors of population exposure are limited. Only a handful of studies have addressed this issue. Aunan and Wang (2014), for example, have identified the influence of internal migration on population exposure to indoor pollution, arguing that rural-urban migrants were subject to the greatest exposure reductions between 2000 and 2010 in China. Their results show that population exposure reduction was greater for rural-urban migrants than non-migrants in this period. Research undertaken by Zou et al. (2009) analyzed population exposure from the perspective of pollution sources, finding that vehicle sources were moderately correlated with population exposure, and that industrial sources had a weak impact on total exposure levels. In addition, scholars have also shown that urban sprawl is positively associated with population exposure; this linkage has been demonstrated by analyzing land-use changes, traffic, and atmospheric dispersion and chemistry (De Ridder et al., 2008).

Given that, previous studies of population exposure mainly relied on monitor air pollution data or low-resolution (e.g. 3 km × 3 km) simulated air pollution data, which may cannot be generalized to population exposure for all cities or obtain actual population exposure data (Kousa et al., 2002; Wang et al., 2008; Beckx et al., 2009). Moreover, these problems hinder such research in usefully assisting policy makers in the task of formulating efficient strategies to reduce population exposure risk (Wilson et al., 2005). More importantly, most researchers mainly focus on the relationship between socioeconomic factors and $PM_{2.5}$ concentrations, not the influence of socioeconomic variables on population exposure. Addressing this gap in the research, this paper uses high-resolution (i.e. 1 km × 1 km) $PM_{2.5}$ concentration data and geographically weighted regression models (GWR) to identify the relationship between population exposure and socioeconomic factors. GWR modeling is a regression technique employed to explore spatially varying relationships and to provide parameter estimates of local variations in a relationship between independent and dependent variables (Wang et al., 2014). The technique has been widely applied in a number of fields, including environmental studies, economics, health, pathology, and the social sciences (Hu et al., 2013; Yu, 2006; Gilbert and Chakraborty, 2011; Hu et al., 2012; Cahill and Mulligan, 2007).

In short, by combining 1 km × 1 km high-resolution data for $PM_{2.5}$ concentrations, population distribution data based on Land Scan, and socioeconomic statistical data, a cross-sectional approach was established. First, we created a map of population exposure. GWR modeling was then utilized to explore the magnitude of the socioeconomic drivers of population exposure for most Chinese cities. To the best of our knowledge, mechanism research on population exposure using high-resolution data and GWR modeling is rare. The results of this analysis could provide benefits for policy makers and planners in the mitigation of China's population's exposure risk to $PM_{2.5}$ concentrations.