Applied Energy Symposium 2020: Low carbon cities and urban energy systems
October 10-17, 2020
Paper ID: CUE2020-D-028

Unequal city resident's exposure to PM $_{2.5}$ -A case study of Shanghai

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ABSTRACT

Due to speeding up urbanization and increasing living standards of city residents, environmental consequence of both production and consumption activities have raised air pollution issue as one of major concern worldwide. Among varied air pollutants, $PM_{2.5}$ does only contribute to respiratory diseases, but also causing cardiopulmonary, ischemic disease, etc. It may further cause extremely unequal impact on age or affluence-based population groups, due to its varying spatial concentration. To investigate its exposure to citizens from economical aspect, we firstly extract affluence-based residents in Shanghai city, China, based on the most recent housing price and population data, then analyzed its potential exposure to $PM_{2.5}$ across the year of 2019. Direction analysis is applied to comparing the varied exposure levels to $PM_{2.5}$ by affluence-specific population. Results suggest the highest $PM_{2.5}$ exposure is found in the central wards of Shanghai, which is also featured by average housing price over 40,000 yuan. People living in 60,000 yuan above housing of Shanghai city are exposed to the highest $PM_{2.5}$ pollution, in winter in particular.

Keywords: City; $PM_{2.5}$; Spatial distribution; Citizen Affluence; Standard deviational ellipse.

1. INTRODUCTION

In recent decades, air pollution becomes an essential contributor to respiratory disease, or even can convert into premature death. Studying the population exposure to air pollution is of great importance to mitigate the adverse impact on both physical and psychological health, especially that of fine particulate matter smaller than 2.5 µm ($PM_{2.5}$). Previous studies have found that $PM_{2.5}$ does only contribute to respiratory diseases, but also cardiopulmonary, ischemic disease, etc(Chen et al., 2018; Liu et al., 2016). Given this, exploration on $PM_{2.5}$ distribution and influential factors have been widely discussed. However, the correlation between $PM_{2.5}$ and mortality has been found to vary spatially, even from a community-level can be very different (Kioumourtzoglou et al., 2016). Therefore, revealing the spatial distribution and people's exposure should be simultaneously conducted, for better avoiding its harmful impact for residents.

On the other hand, city is the major place for both production and consumption, which is also vulnerable for air pollution due to its substantial amount of urban dweller. In Chinese cities, particulate matter is accounting for 85%–90% of primary pollutants (Jiang et al., 2020; Wang et al., 2014). Considering its sensitivity toward air pollution, urban-scale analysis should carefully include both $PM_{2.5}$ and population distribution. Even within the same city, different groups of population may exposure of different level of $PM_{2.5}$ considering its inner features such as living habit and lifestyles. Among different groups of population, citizen affluence has been found as the major reason of where the live and how the spend a day. Similar with income-level, housing price is also can represents citizen's affluence by distinguishing purchasing power. Therefore, housing price distribution can be taken as a reference of city affluence distribution. In this study, we firstly grab the housing price data from Internet and re-evaluate the population distribution based on the residential building

Selection and peer-review under responsibility of the scientific committee of CUE2020

cluster. Next, district-specific $PM_{2.5}$ data is collected by month, and we generate exposure index according to both population and $PM_{2.5}$ concentration. Furthermore, the direction analysis is conducted by dividing population into different affluence level. Finally, the result will not only provide total population exposure, but also detailing that into different affluence levels.

2. METHOD

2.1 Interpolation and direction analysis

To understand the residential affluence and its correlation with air pollution, we firstly extraced the housing price from Lianjia.com, which is the largest real estate brokerage firm in China (Li et al., 2019), to generate citizen affluence indicator. Relying on web-crawling program, sale price of housing is collected by July 2020. Original population data is derived from Socioeconomic Data and Application Center by 1 kilometer resolution, from Data Center in NASA's Earth Observing System Data and Information System (EOSDIS). Consequently, we use Standard Deviational Ellipse (SDE) and inverse distance-weighted (IDW) to detect the spatial relationship of housing price. Both analyses are processed by ESRI ArcMap 10.4. After grabbing the building cluster point data from Lianjia.com, the general housing price and population distribution in Shanghai can be calculated as:

$$\bar{I} = \sum_{i=1}^{n} \frac{D_i^{-w}}{\sum_{i=1}^{n} D_i^{-w}} \quad (1)$$

where D_i is the geographic distance calculated by $d_i = \sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2}$, w is a weighting term, $\bar{I}$ is the interpolation value, and n refers to the number of available data points.

As an effective trend analysis tool, the standard deviational ellipse (SDE) is widely applied for capturing spatial feature of targeted elements(Lefever, 1926; Yuill, 1971). By calculating the standard distance of multiple points by two direction. The ellipse intuitively describes the dynamic trends of the points (Du et al., 2019). After capturing the housing price distribution, we used SED to analyze the spatial distribution by classifying housing price into nine categories. Level 1 to 8 indicates the housing price from 10,000 to 80,000 yuan while Level 9 refer to housing above 80,000/m^2. SED is applied to investigate the direction and spatial-temporal features of housing price. The ellipse center, x and y-axis and azimuth are estimated as follows:

$$A = \sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2 \quad (2)$$

$$B = \sqrt{\left(\sum_{i=1}^{n} \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2\right)^2 + 4\left(\sum_{i=1}^{n} \tilde{x}_i \ \tilde{y}_i\right)^2} \quad (3)$$

$$C = 2\sum_{i=1}^{n} \tilde{x}_i \ \tilde{y}_i \quad (4)$$

$$\theta = arctan\frac{A+B}{C} \quad (5)$$

$$\partial^x = \sqrt{\sum_{i=1}^{n} (w_i\tilde{x}_i \ \cos\theta - w_i\tilde{y}_i \ \sin\theta)^2 / \sum_{i=1}^{n} w_i^2} \quad (6)$$

$$\partial^y = \sqrt{\sum_{i=1}^{n} (w_i\tilde{x}_i \ \sin\theta - w_i\tilde{y}_i \ \cos\theta)^2 / \sum_{i=1}^{n} w_i^2} \quad (7)$$

where $\tilde{x}_i$ and $\tilde{y}_i$ indicate the gap between weighted-mean center and the coordinates of housing i, and ∂^x and ∂^y refers to standard deviations along x and y-axis.

2.2 Aggregated exposure indicator

In this study, monthly air quantity data across 2019 are provided by Shanghai Municipal Bureau of Ecology and Environment. Here, $PM_{2.5}$ concertation is collected by district unit. In this study, the exposure indicates the aggerated $PM_{2.5}$ of total population in each building cluster. Here, $\alpha_{j,m}^{\theta}$ means in ward θ month j, population from affluence level m's exposure to $PM_{2.5}$. $PM2.5_j^{\theta}$ is the $PM_{2.5}$ concertation in district θ month j. p_i^{θ} refers to population of building cluster i in ward θ. Then, the exposure can be expressed as:

$$\alpha_{j,m}^{\theta} = PM2.5^{\theta} \sum_{i=1}^{n} p_{i,j,m}^{\theta} \quad (8)$$

3. RESULT

3.1 Citizen affluence distribution in Shanghai

Fig.1 shows the results of interpolation for both housing price and building cluster-based population. Here,

Fig.1(a) gives out the housing price distribution in Shanghai. To note, housing price data from Chongming island is not included due to its data limitations, which is excluded in the following direction analysis. Not surprisingly, the highest housing price is in the central area of Shanghai. Fig.2(b) shows the population reallocation based on the household information provided by housing building cluster. The hotspots of population indicate the highest concertation locate in Jinjiang, Yangpu, Xuhui, Hongkou, Huangpu, Changning and northwest area of Pudong new area. Although other wards of Shanghai also have population hotspots, they are found distributed less continuously, such as Jinshan and Fengxian.

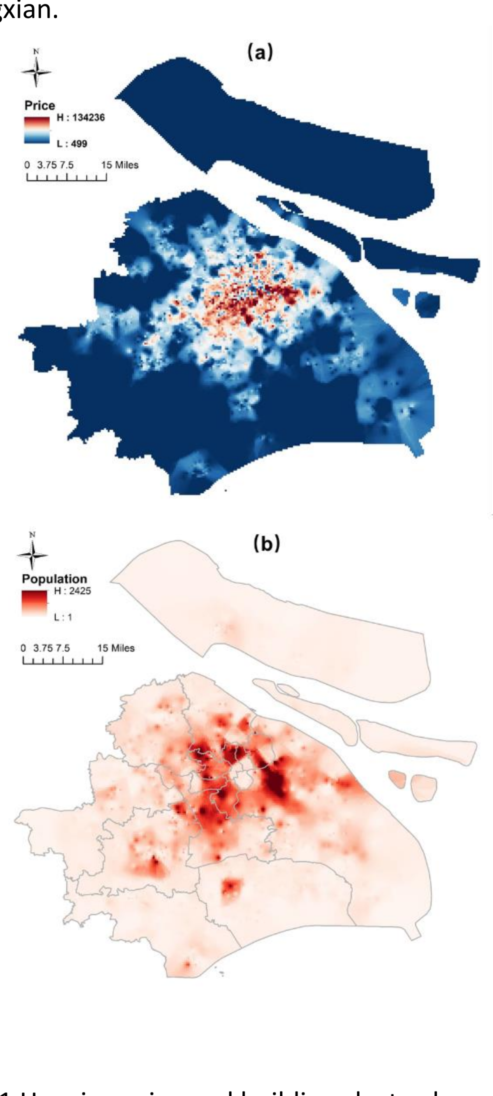

Fig.1 Housing price and building cluster-based population

3.2 PM $_{2.5}$ exposure distribution

According the exposure index calculated by Section 2.2, Fig.2 gives out the general population exposure and its affluence-based directions. First, Fig.2(a) shows the aggregated $PM_{2.5}$ exposure considering both $PM_{2.5}$ concentration and population. Except for the central areas, Baoshan and Minhang wards are also found higher exposure volume. However, although population hotspot is also found in the center of Songjiang ward, the exposure level is lower than other wards. When we dividing population into different housing price level, the citizen affluence-specific information can be generated. Fig.2(b) show the affluence-specific exposure direction in Shanghai. As the price getting lower, the ellipse area is enlarged, the direction is changing from northeast to northwest (See Table 1), which indicate the highest city affluence is concentrated into five wards: Huangpu, Changning, Hongkou, Putuo and Xuhui. Affluence-specific $PM_{2.5}$ exposure shows similar with housing price distribution. Therefore, people living in central areas of Shanghai are simultaneously facing higher housing price and $PM_{2.5}$ concentration.

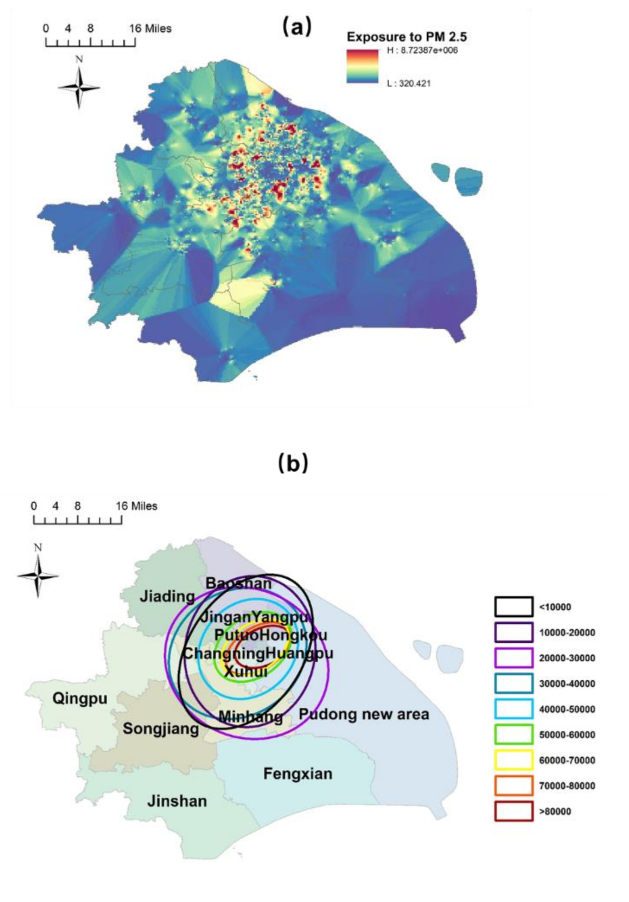

Fig.2 Total population exposure to $PM_{2.5}$ (a) and affluence-specific direction (b)

Table 1 Result of Standard Deviational Ellipse

Housing price (Yuan)	CenterX	CenterY	XStdDist	YStdDist	Rotation
<10000	135.1803819	36.6081245	17311.11	27676.25	25.89859
10000-20000	135.1926016	36.608564	19146.81	25527.39	5.340182
20000-30000	135.1828954	36.5700242	26251.93	23318.98	151.6603
30000-40000	135.1563992	36.6021928	19387.1	22847.36	28.58639
40000-50000	135.1877058	36.6174019	14022.25	17449.28	25.09384
50000-60000	135.2013029	36.6241235	9572.675	13253.2	41.95123
60000-70000	135.2074475	36.6227463	7529.671	11515.83	47.64864
70000-80000	135.2163846	36.6186722	6776.813	11082.94	49.43713
>80000	135.2309107	36.6243377	6070.85	9047.523	56.09098

4. DISCUSSION AND CONCLUSION

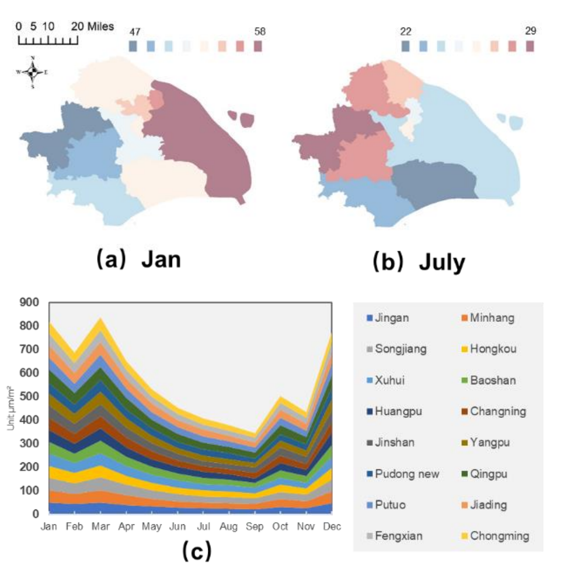

Fig.3 Ward-specific pm 2.5 in January (a); July (b); across 2019 (c)

By analyzing both household population and housing price distribution in Shanghai, this study quantitively give out the results of population's exposure to $PM_{2.5}$. This result shows wards with the denser citizen affluence, which is represented by higher housing price, is facing highest total exposure of its residents. From the Fig.3, (a) and (b) shows the January and July situations and (c) is the continuous value by month. Summer time is obvious not comparable with that in winter. To the local governments, how to cope with the high $PM_{2.5}$ concertation in winter and lower the exposure level in center wards should be the top priority.

ACKNOWLEDGEMENT

The authors acknowledge funding offered by the Japan Science and Technology Agency (JST) through project SASSI (A Systems Approach to Sustainable Sanitation Challenges in Urbanising China) (Project Number: JPMJBF18T3)

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