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Original Research

High-Resolution Population Exposure to $PM_{2.5}$ in Nanchang Urban Region Using Multi-Source Data

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Abstract

Long-term exposure to $PM_{2.5}$ can lead to great adverse health effect on human health. To better guide public policies that aim to reduce $PM_{2.5}$ population exposure, this work combined multi-source data to realize high-resolution $PM_{2.5}$ exposure risk assessment in Nanchang urban region. The land use regression (LUR) model was used to simulate the seasonal-spatial variations of $PM_{2.5}$ concentrations at 100-m resolution, and building information extracted from IKONOS image was applied to spatialize population at 100-m resolution. An improved piece-wise population exposure approach was introduced to evaluate the exposure risk, and results were compared with two classical approaches. In all seasons, results by the absolute concentration approach are very different from the other two, showing obvious spatial smoothing effect. Results by population-weighted and piece-wise exposure approaches are similar in spring and autumn, and different in summer and winter. In winter, the area and population percentages divided to severity level 7 by population-weighted exposure approach are 5.21% and 2.35% lower than that by piece-wise exposure approach. When in summer, the area and population percentages divided to severity level 7 by population-weighted exposure approach are 6.77% and 24.79% higher than that by piece-wise exposure approach. The absolute concentration approach is disadvantageous for the identification of high-risk areas, the population-weighted exposure approach would underestimate or overestimate the population exposure when air is seriously polluted or remarkably clean, and the proposed piece-wise exposure approach would be more reasonable. The integrated methodology is effective in exposure risk assessment and can be applied to other regions and pollutants.

Keywords: $PM_{2.5}$, population exposure, high-resolution, piece-wise population exposure approach

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Introduction

Epidemiological studies have shown that long-term exposure to ambient air pollution is harmful to human health [1-4]. Population exposure to air pollutants especially the fine particulate matter ($PM_{2.5}$), will lead to significant adverse impacts on morbidity and mortality [5, 6]. According to the World Health Organization (WHO), air pollution was responsible for more than 7.6% of global deaths in 2015 [7]. From 2008 to 2015, 92% of the worldwide populations were exposed to $PM_{2.5}$ concentrations that exceeded the WHO Air Quality Guidelines (AQG) levels (10 μg/m^3), and 56% of the populations lived in areas with $PM_{2.5}$ concentrations higher than the Interim Target 1 (IT-1) (35 μg /m^3) [8]. In many Asian cities, the $PM_{2.5}$ concentrations are much higher than in U.S. or Europe, such as India and China, 86% of the populations experienced remarkably serious $PM_{2.5}$ concentrations over 75 μg/m^3 [9]. To better guide public policies that aim to reduce exposure risk and protect people's health, it is of great importance to assess the $PM_{2.5}$ population exposure in densely populated urban areas.

High-resolution population data is essential for conducting researches about population exposure to $PM_{2.5}$ at an urban scale. Previously, for large-scale researches, administrative census-population data have often been evenly allocated to the region, which is inconsistent with the actual population spatial distribution. In complicated small-scale urban landscapes, urban residential buildings are important indicators of population distribution. In recent years, more and more studies have begun to estimate the spatial distribution of population with building information extracted from satellite imagery, since the information is closely related to human activities [10-12].

High-resolution $PM_{2.5}$ data is also critical for population exposure assessment. Traditional studies often use fixed-site monitors data to assess the population exposure. However, the number of fixed-site monitors is limited since the high cost, and the sparsely distributed monitoring sites cannot capture the large spatial variability of the pollutant concentrations [13-15]. The use of average pollutant concentrations derived from scattered station measurements can lead to systematic errors in the estimate of overall population exposure. Several methods have been developed over the last decade to strengthen $PM_{2.5}$ monitoring, including remote sensing image retrieval, spatial interpolation, air dispersion modeling, and land use regression (LUR) technology. Land use regression (LUR) technology are statistical regression models using predictor variables e.g. land use, traffic, and physical characteristics etc. to predict atmospheric pollutants concentration. Studies have proved that LUR modeling is one of the most important and systematic methods to simulate pollutant concentration at the city scale [16-18].

Evaluation of population exposure to ambient air pollution is a classic topic [19, 20]. The earliest study date back to "simulation of human air pollution exposures" in 1985, personal air pollution exposure was defined by the time that people spent in particular concentrations of air pollutants. Then, various evaluation approaches [21-27] have been proposed and can be divided into three categories according to the use of population data: absolute concentration, the intensity of population, and population-weighted exposure. Early approaches pertain to the absolute concentration exposure, which is calculated directly by air pollutant concentrations [19]. Although the approach is simple and effective, the result may be inconsistent with the actual situation because public health risk is not only related to $PM_{2.5}$ concentration but also to exposure

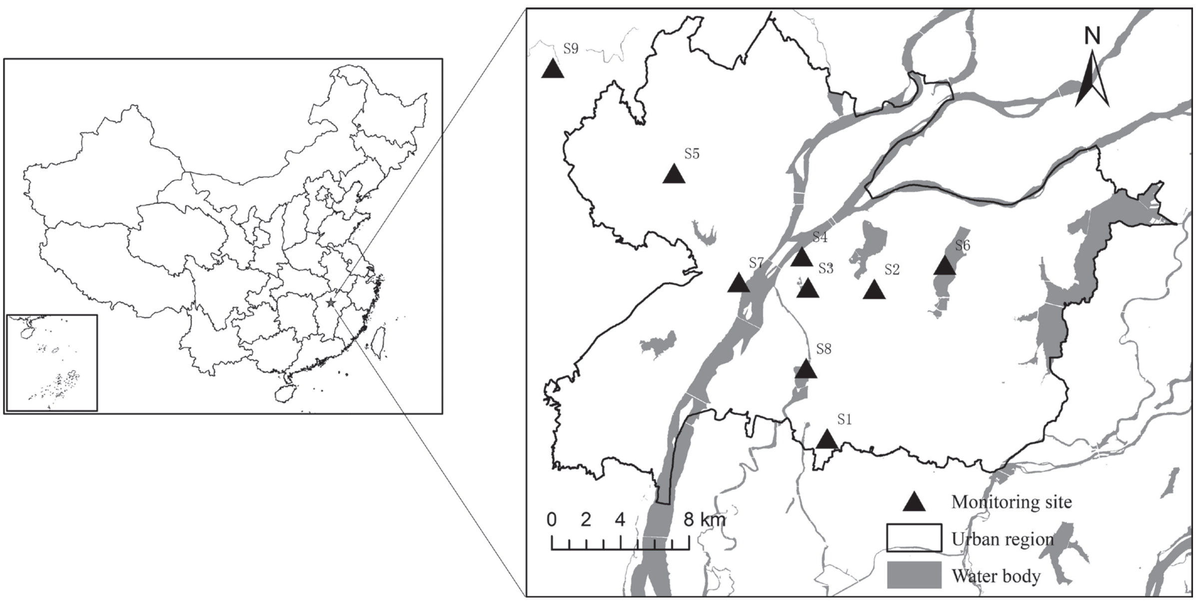

Fig. 1. Geographical location of Nanchang urban region and the nation-standard air pollution monitoring sites.

population [28]. In 2002, Kousa et al. [29] proposed the intensity of population exposure approach, which calculates the people exposure through the product of population density and air pollutant concentration. It was the first exposure approach considering the effect of population data. Nevertheless, population density often has a larger range than pollution concentration, resulting in the polarization of the highest and lowest population exposure [30]. The population-weighted exposure approach improved use of population data by employing relative population weight instead of absolute population density and has become the most widely used population exposure approach [31, 32]. In spite of this, it overrates the influence of population data when ambient air condition is remarkably clean or seriously polluted. Sparsely-populated regions with high pollutant concentration would be evaluated as low exposure risk, and densely-populated regions with clean air tend to be at high exposure risk, which are against the common sense of people.

In this study, Nanchang urban region was chosen as the study area, LUR model was employed to simulate the seasonal-spatial $PM_{2.5}$ concentrations at 100-m resolution, and building information extracted from IKONOS image was used to spatialize the population distribution at the same resolution. An improved piece-wise population exposure approach was proposed for evaluating the population exposure to $PM_{2.5}$, and the absolute concentration and population-weighted exposure approaches were treated as baselines. Results of three evaluation approaches were compared, and high $PM_{2.5}$ exposure risk areas were identified.

Material and Methods

Study Area

Nanchang City (28°09'N-29°11'N, 115°27'E-116°35'E), the capital of Jiangxi Province, is a typical city of middle China located in the southwest of Poyang Lake. This city experienced rapid urbanization in the past decade. The residential population had reached 5.6 million, and the number of vehicles had exceeded 1.07 million by the end of 2019. Along with the urbanization process, air pollutants (especially $PM_{2.5}$) have become one of the most crucial urban issues. Thus, population exposure to air pollution must be effectively evaluated. The present work chose Nanchang urban region as the study area (as shown in Fig. 1), which covers a region of 562.46 km^2 and includes 2.61 million people. Eight nation-standard air pollution monitoring sites established by the China Environmental Monitoring Center (CEMC) are included in the study area (Fig. 1).

Population Spatialization

High spatial resolution population data, which are indispensable in many activities such as business decision-making, regional planning and development, exposure risk assessment, are one of the most direct indicators of human activity. The population density data in this study were acquired on basis of classification information of buildings from high-resolution remote sensing images. All people were assumed to live on residential land because it is the most representative urban land use type and people spend the longest time in this area, and the mobility of people was not considered [33, 34]. Based on this assumption, the high spatial resolution population density of the Nanchang urban region was estimated through the following four steps. First, residential buildings were extracted and divided into urban residential, rural residential, and student dormitory buildings by employing 1 m spatial resolution IKONOS remote sensing image. Among these buildings, the urban residential buildings were further divided into the four categories: low-rise (1-5 floors), mid-rise (6-10 floors), high-rise (11-20 floors), and super high-rise (more than 20 floors) buildings. Second, the entire study area was split into three parts by expert consultation, and the same residential building type of the same part had the same population density. The population density of every residential building type was acquired by sample investigation. Third, 100 m × 100 m grids were produced by ArcGIS. The population of each grid was then obtained by summing up the products of the area of every residential building type and the corresponding investigated population density [35]. Finally, the indexes of the overall relative error rate and the relative error rate of samples were utilized to verify the accuracy of the estimated results.

$PM_{2.5}$ Concentration Estimation

The LUR model can be used to predict the concentration of air pollutants at a given site by establishing a statistical relationship between pollutant measurements and potential predictor variables, such as land use, traffic, and physical characteristics [17, 36].

The LUR model is expressed

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \quad (1)$$

...where dependent variable y is the pollutant concentrations, independent variables $X_1 ... X_n$ are the potential variables, $\beta_1 ... \beta_n$ are the associated coefficients, ε is the constant intercept.

Following the work of Yang et al. [37], this study applied the LUR model to realize $PM_{2.5}$ simulation across the study area. Four classes of independent variables, including five meteorological factors, three traffic-related factors, three land use factors, and population density were adopted. Specifically, relative humidity, air pressure, water vapor pressure, temperature, and wind speed were used to characterize the meteorological conditions. Monthly average values of the meteorological data were collected from the Chinese Meteorological Data Share Service System (http://data.cma.cn/). The intensity of main roads, secondary roads, and all roads were adopted to indicate the traffic conditions. Traffic-related data were obtained from the Transportation Map of Nanchang Urban Master Planning. The land use situation was reflected by ecological land proportion, industrial land proportion, and distance to large ecological space, whose data were derived from the Nanchang Land Use Map and satellite remote sensing images. The population density data were presented in Section 2.2.

Seasonal average $PM_{2.5}$ concentrations were simulated rather than annual average data considering the variation of $PM_{2.5}$ concentrations in different seasons. The 12 months were categorized into spring (March to May), summer (June to August), autumn (September to November), and winter (December to February). 75% of the samples in every season were used to develop the LUR models based on the backward model-building algorithm. Every seasonal modeling was repeated three times to avoid priori division of samples, and the best fitting model was chosen last. The adjusted R^2 values of seasonal LUR models, average relative error and Root Mean Square Error (RMSE) of the other 25% of samples were used to indicate the effectiveness of the results. After the model validation, 100 m × 100 m grids were produced by ArcGIS, and the $PM_{2.5}$ concentrations of each grid were obtained by final seasonal LUR models.

$PM_{2.5}$ Population Exposure Evaluation

Absolute Concentration $PM_{2.5}$ Exposure Evaluation

Absolute concentration is one of the most commonly used risk evaluation indicators for exposure to air pollution, and it ignores the spatial distribution of population in the assessment unit. It is defined as

$$E_a = c_i \tag{2}$$

...where E_a is the absolute concentration population exposure at grid point i, c_i is the concentration of $PM_{2.5}$ at grid point i.

Population-Weighted $PM_{2.5}$ Exposure Evaluation

The population-weighted exposure evaluation is proposed by Fu et al. [31], which mainly considers population as weights at different exposure to $PM_{2.5}$ concentrations. Now, it has been extensively used to reflect the actual total impact of $PM_{2.5}$ on the population under normalized population conditions for different regions [32]. The population-weighted $PM_{2.5}$ pollution is defined as

$$E_p = \omega_i c_i \tag{3}$$

...where E_p is the population-weighted exposure at grid point i, c_i is the concentration of $PM_{2.5}$ at grid point i and ω_i is the weight of population at grid point i to the average population density in the whole study area. The ω_i is calculated as

$$\omega_i = \frac{np_i}{\sum_{i=1}^{n} p_i} \tag{4}$$

...where p_i is the population at grid point i and n is the total number of grids in the study area.

Piece-Wise $PM_{2.5}$ Exposure Evaluation

The piece-wise exposure approach was introduced to evaluate the population exposure to $PM_{2.5}$ in this subsection. The proposed approach can be calculated via the following three steps. First, health and severity thresholds of $PM_{2.5}$ concentrations were defined as c_0 and c_{max}, based on certain air quality guidelines. Second, the population exposure at grid point i was consequently set as Δc_i when $c_i \leq c_0$ or $>c_{max}$. Third, the population exposure at grid point i was determined by an incremental population-weighted function, when $PM_{2.5}$ concentrations were between c_i and c_{max}. The piece-wise exposure approach is defined as

$$E_{p-w} = \begin{cases} \Delta c_i, & c_i \leq c_0 \text{ or } c_i > c_{max} \\ \omega_i \times \Delta c_i, & c_0 < c_i \leq c_{max} \end{cases} \tag{5}$$

...where E_{p-w} is the population exposure at grid point i, c_i is the concentration of $PM_{2.5}$ at grid point i, ω_i is the weight of population at grid point i to the average population density at the whole study area and Δc_i is the difference between c_i an c_0. The ω_i is calculated as Equation (4). The Δc_i is calculated as

$$\Delta c_i = c_i - c_0 \tag{6}$$

In order to show the population exposure risks for different $PM_{2.5}$ concentrations, the results by above three approaches were converted into risk levels according to some air quality standards, show as Table 1. In this study, c_0 and c_{max} were respectively set to 15 μg/m^3 and 75 μg/m^3, according to the air quality standards of the WHO and China [38, 39].

Results and Discussion

Spatial Population Intensity

Fig. 2 shows the estimated population density of the Nanchang urban region at 100-m spatial resolution. Results show the effectively high-resolution population estimation with the overall relative error of 12.58% and the average relative error of the 20 verification samples lower than 15%. Spatial distribution with suburban-urban-downtown differences in population density is

Table 1. Exposure levels and the corresponding conditions of the piece-wise exposure approach.

Exposure level	Corresponding conditions		Reference standard
	E_{p-w}	E_p and E_a	
Health (level 1)	≤0	≤15	WHO IT-3 (15 μg/m³)
Low risk (level 2)	(0,5]	(15,20]	
Low-and-middle risk (level 3)	(5,10]	(20,25]	WHO IT-2 (25 μg/m³)
Middle risk (level 4)	(10,20]	(25,35]	WHO IT-1 (35 μg/m³)
Middle-and-high risk (level 5)	(20,35]	(35,50]	
High risk (level 6)	(35,60]	(50,75]	
Severity (level 7)	>60	>75	WHO IT-1 daily average (75 μg/m³)

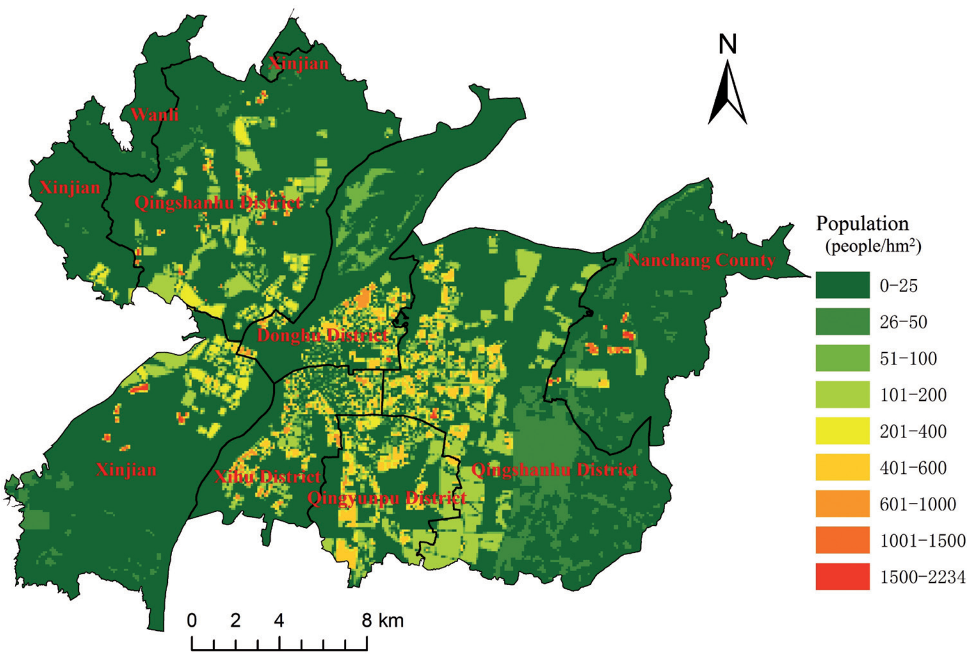

Fig. 2. Spatial distribution of population density in Nanchang urban region.

generally present. Representatively, the most densely populated areas are the student dormitory lands of universities, with population densities larger than 1,000 people/hm². Typical student dormitory lands of universities are distributed in several districts (e.g., Nanchang county, Qingshanhu district, and Xinjian county). Some areas in Donghu and Xihu districts have population densities that ranging from 600 people/hm² to 1,000 people/hm². Most areas in Donghu, Xihu, and Qingyunpu districts have the population densities between 400 and 600 people/hm². The overall population density of North Qingshanhu district is smaller than that of South Qingshanhu district. Most of the rural residential lands have population densities of 51-100 people/hm². The largest proportion is area with population densities of 0-25 people/hm², mainly included water bodies, surrounding farmlands, and forests distributed on the borders.

Seasonal and Spatial $PM_{2.5}$ Concentration

Fig. 3 shows the seasonal and spatial variations in $PM_{2.5}$ concentrations simulated by the LUR modeling. The seasonal adjusted R^2 is 0.803, 0.605, 0.874, and 0.786 in spring, summer, autumn, and winter, respectively. The average relative error of verification samples in four seasons is 15.43%, 16.29%, 10.15% and 8.53%, with RMSE of 3.38, 1.49, 1.93, and 2.38 μg/m³, respectively. The indexes reveal the reliability of the simulated result. $PM_{2.5}$ concentrations of Nanchang urban region in four seasons are all higher than the WHO IT-3 (15 μg/m³), and their temporal distribution is high in winter and low in summer. The minimum value of $PM_{2.5}$ concentrations in winter is greater than the WHO IT-1 (35 μg/m³), and the maximum value exceeds the seriously polluted threshold (75 μg/m³). Air quality is evidently better in summer, and the $PM_{2.5}$

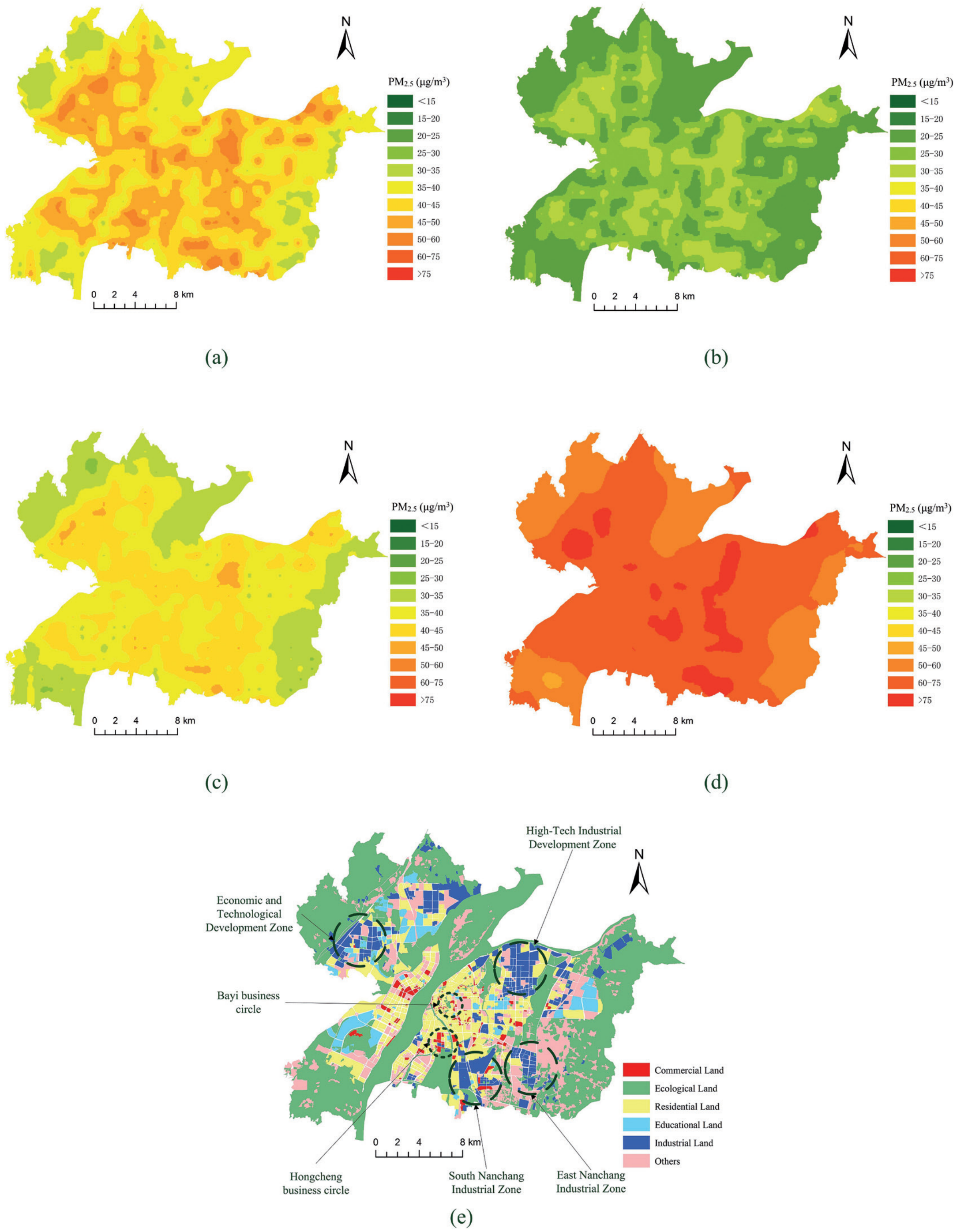

Fig. 3. LUR-based $PM_{2.5}$ concentrations of Nanchang urban region: in a) Spring; b) Summer; c) Autumn; d) Winter. (e) the land use map of Nanchang urban region.

concentrations of most areas are lower than 35 μg/m^3. The air quality in spring and autumn is between that in summer and winter, and the corresponding $PM_{2.5}$ concentrations are almost between 25 and 55 μg/m^3. A discernible spatial variation in $PM_{2.5}$ concentrations is observed in the study area. High-value areas are always located in the center of the study area, while low concentration areas are mainly distributed on city borders. Most of the high-value areas are commercial zones (e.g., Bayi business circle, Hongcheng business circle), and industrial zones (e.g., Economic and Technological Development Zone, High-Tech Industrial Development Zone, East Nanchang Industrial Zone, and South Nanchang Industrial Zone). Some of these areas even experienced $PM_{2.5}$ concentrations of more than 75 μg/m^3 in winter. The majority of low-value areas are forests (e.g., Meiling National Forest Park in the northwest), and farmlands (e.g., Yangtze Island in the north, Luojia town in the southeast and Shengmi town in the southwest). $PM_{2.5}$ concentrations of Meiling

National Forest Park remained the lowest in the entire study area, which is less than 20 μg/m³ in summer.

Result Comparisons of Population Exposure to $PM_{2.5}$

Figs 4, 5, 6, and 7 show the spatial distribution of population exposures to $PM_{2.5}$ based on the piece-wise exposure approach and baselines in four seasons. Two characteristics can be summarized. First, spatial characteristics by the absolute concentration exposure approach are totally different from those by the population-weighted and piece-wise exposure approaches. The absolute concentration exposure result concentrates on a few exposure levels, while the two other exposure results usually cover most of the exposure levels. This finding illustrates that population data considerably affect the exposure results. Second, spatial characteristics of population-weighted and piece-wise exposure results are respectively approximate in spring and autumn and different to some extent in summer and winter. The area of severity level 7 in summer by the piece-wise exposure approach is remarkably smaller than that by the population-weighted exposure approach. In winter, the difference is mainly distributed in areas where $PM_{2.5}$ concentrations exceed the severity level threshold (75 μg/m³), such as the Economic and Technological Development, High-Tech Industrial Development, East Nanchang Industrial, and South Nanchang Industrial Zones. The above-mentioned areas are divided into severity level 7 by the piece-wise exposure approach while health level 1 by the population-weighted exposure approach. The result by the proposed approach is consistent with the goal that population exposure should be independent of population density when the pollutant concentrations exceed a severity threshold.

These figures also show the percentage cumulative distribution of the population (0%-100%) at different $PM_{2.5}$ exposure thresholds. In four seasons, nearly 100% of the populations are exposed to $PM_{2.5}$ concentrations that exceed the WHO AQG (10 μg/m³), and the

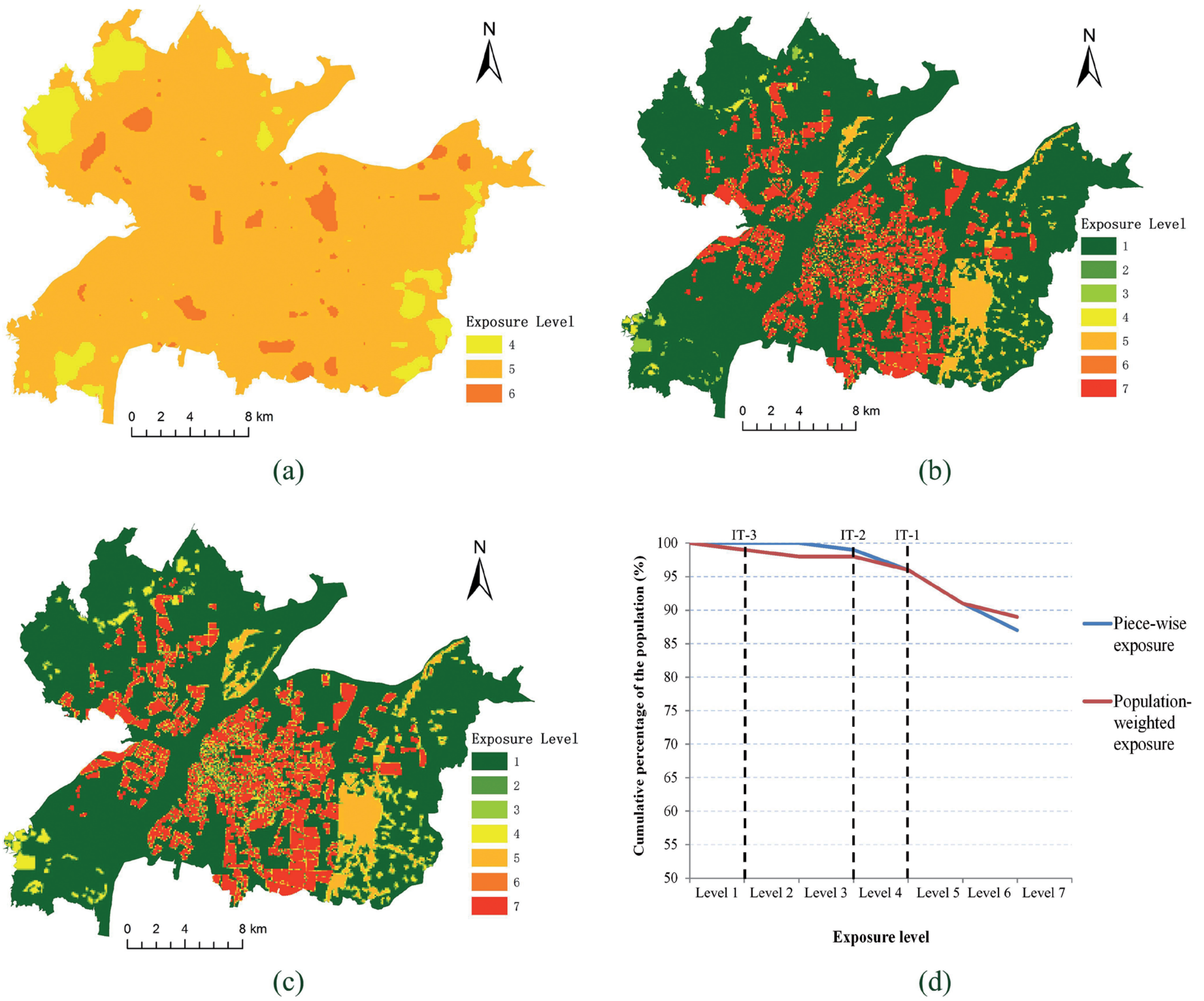

Fig. 4. Spatial distribution of population exposure in spring based on evaluation approaches: a) absolute concentration exposure; b) population-weighted exposure; c) piece-wise exposure. d) the cumulative percentages of the population at different $PM_{2.5}$ exposure levels.

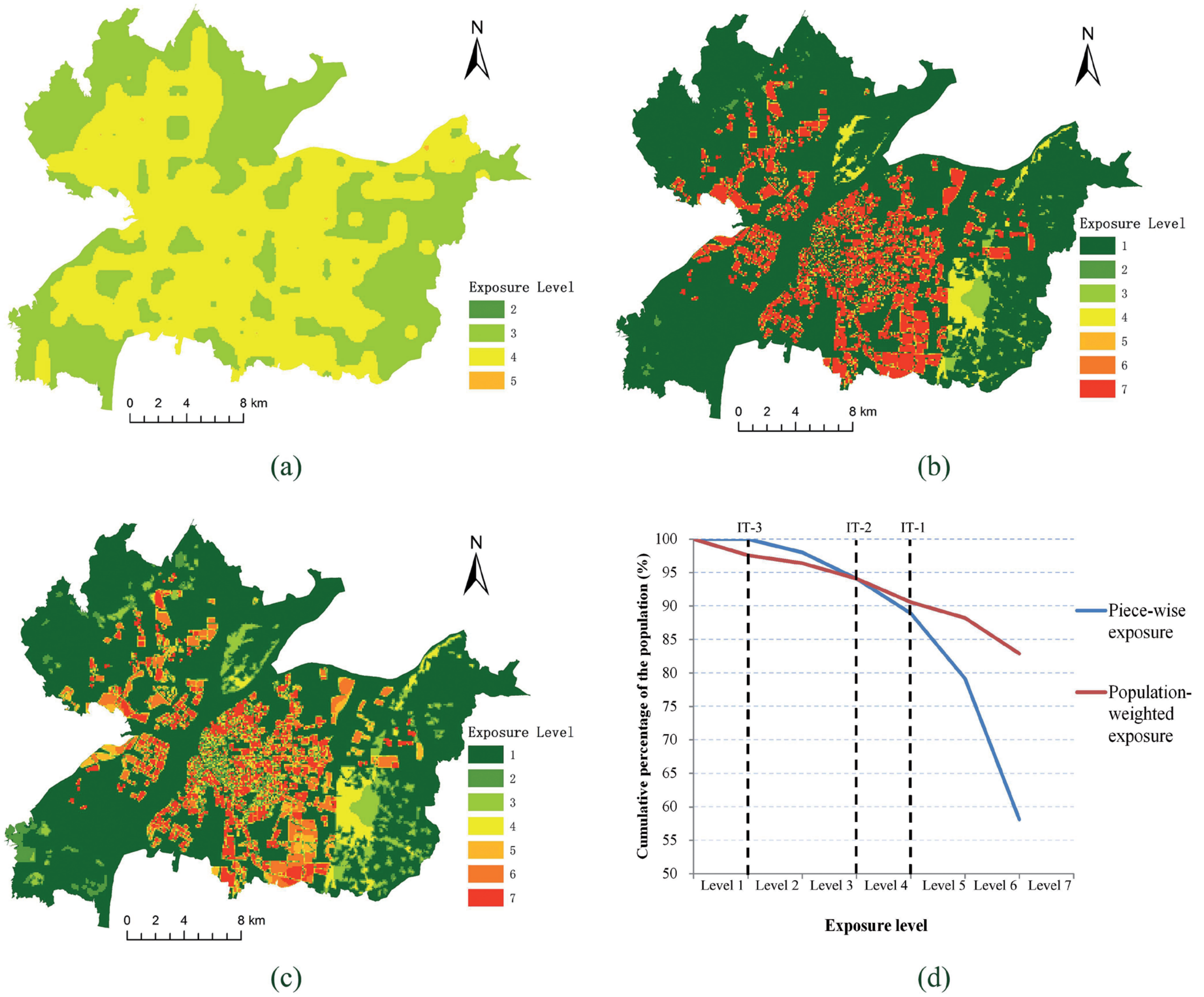

Fig. 5. Spatial distribution of population exposure in summer based on evaluation approaches: a) absolute concentration exposure; b) population-weighted exposure; c) piece-wise exposure. d) the cumulative percentages of the population at different $PM_{2.5}$ exposure levels.

percentages of populations for IT-3 (15 μg/m^3) are over 97%. In winter, when $PM_{2.5}$ pollution is the highest of four seasons, over 98% of the populations by the piece-wise and population-weighted exposure approaches are exposed to $PM_{2.5}$ concentrations that exceed the WHO IT-1 (35 μg/m^3). Even in summer when $PM_{2.5}$ pollution is the lowest of four seasons, there are still more than 88% of the populations by the two approaches exposed to $PM_{2.5}$ concentrations that surpass the WHO IT-1. These results highlight the severity of the $PM_{2.5}$ exposure problem in Nanchang urban region.

Table 2 describe the numerical result comparisons of the piece-wise exposure approach and baselines in four seasons. An evident feature is that area percentages obtained by the absolute concentration exposure approach cover a few exposure levels and always concentrate on two certain exposure levels or less, such as level 5 in spring, levels 3 and 4 in summer, levels 4 and 5 in autumn, and level 6 in winter. By comparison, area percentages obtained by the population-weighted and piece-wise exposure approaches over all exposure levels and usually concentrate on health level 1. Hence, the population-weighted and piece-wise exposure approaches would be more effective than the absolute concentration exposure approach for identifying the high exposure risk areas.

The population-weighted and piece-wise exposure approaches are then compared. The following three points can be concluded. First, in all four seasons, the area and population percentages of health level 1 in all four seasons by the population-weighted exposure approach are larger than those by the piece-wise exposure approach. This finding suggests that health level 1 by the piece-wise exposure approach is more stringent than that of the population-weighted exposure approach. Second, the area and population percentages of severity level 7 in spring, summer and autumn by the piece-wise exposure approach are all smaller than those by the population-weighted exposure approach, while the situation is opposite in winter. This result further illustrated the characteristic in Figure 7. This figure shows that additional areas and populations

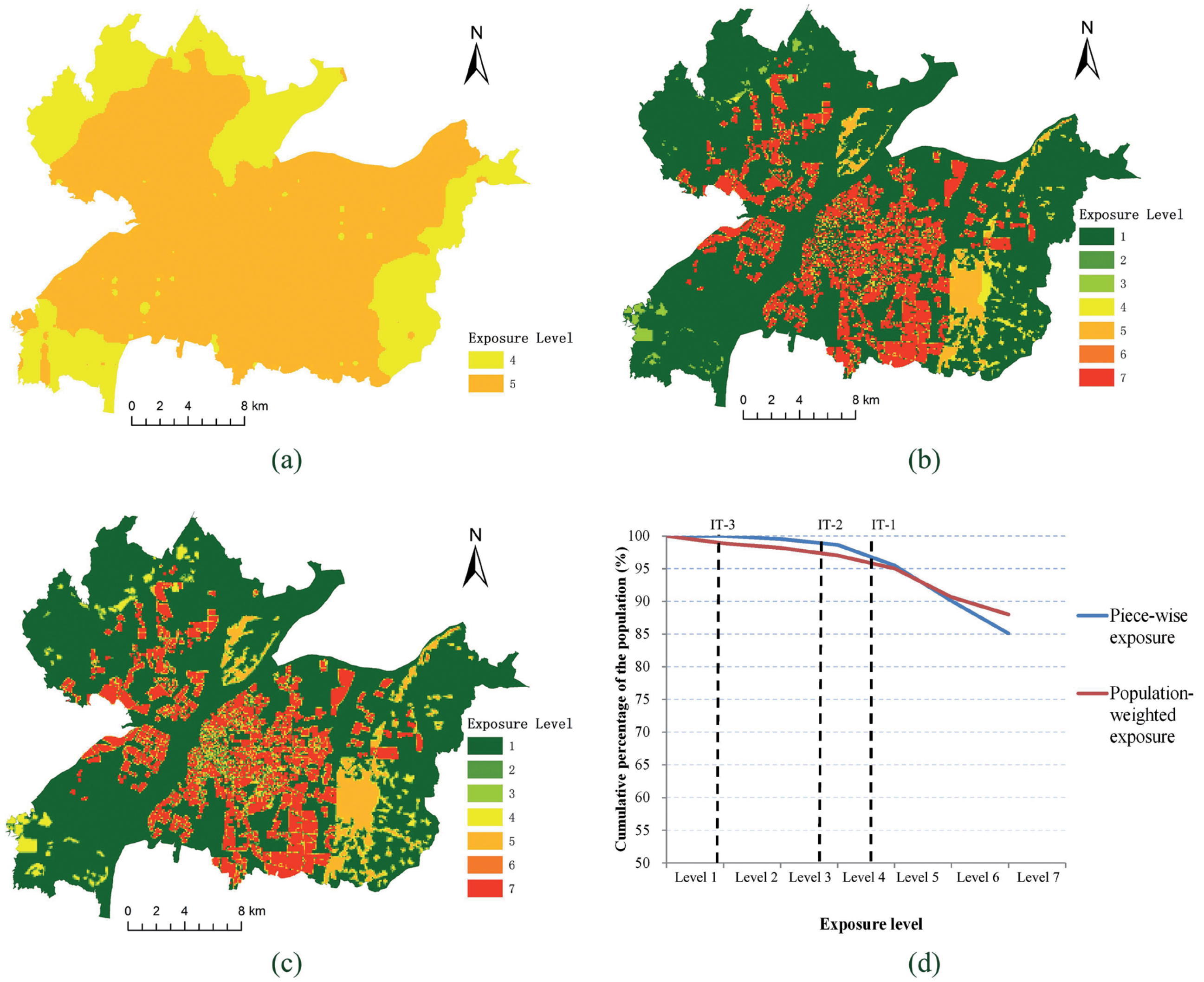

Fig. 6. Spatial distribution of population exposure in autumn based on evaluation approaches: a) absolute concentration exposure; b) population-weighted exposure; c) piece-wise exposure. d) the cumulative percentages of the population at different $PM_{2.5}$ exposure levels.

would be divided to severity level 7 by the piece-wise exposure approach than population-weighted exposure approach, when the $PM_{2.5}$ concentration is relatively high such as in winter (64.46 ± 6.75 μg/m^3). Third, the area and population percentages in summer, which are divided into health level 1 and severity level 7 by piece-wise exposure approach, are smaller than those by population-weighted exposure approach. The obtained results by the piece-wise exposure approach tend to distribute in the middle levels when the $PM_{2.5}$ concentration is relatively low but higher than the health threshold.

Comprehensive Discussion

Numerous epidemiological studies have proven the significant association between exposure to $PM_{2.5}$ and adverse health effects. It is of significant importance to assess the $PM_{2.5}$ population exposure in urban areas. Three kinds of population exposure approaches, including absolute concentration, intensity of population, and population-weighted exposure had been proposed to examine the adverse health influence. This study claims that population data should always be considered, except in cases of clean and high morbidity air conditions. The piece-wise approach, which can combine characteristics of the absolute concentration and population-weighted exposure approaches, is then put forward.

High spatial resolution population data is necessary to obtain reliable exposure evaluation results at the intra-urban scale. The commonly used methods for population spatialization include areal weighting, dasymetric mapping, and statistics regression models [40, 41]. In this study, residential buildings were screened and classified on the basis of high-resolution remote sensing images. The population densities of different residential building types were obtained through investigation, and population spatialization data were calculated through areal weighting method. The overall relative error is 12.58% based on the census population data, and the average relative error of sample

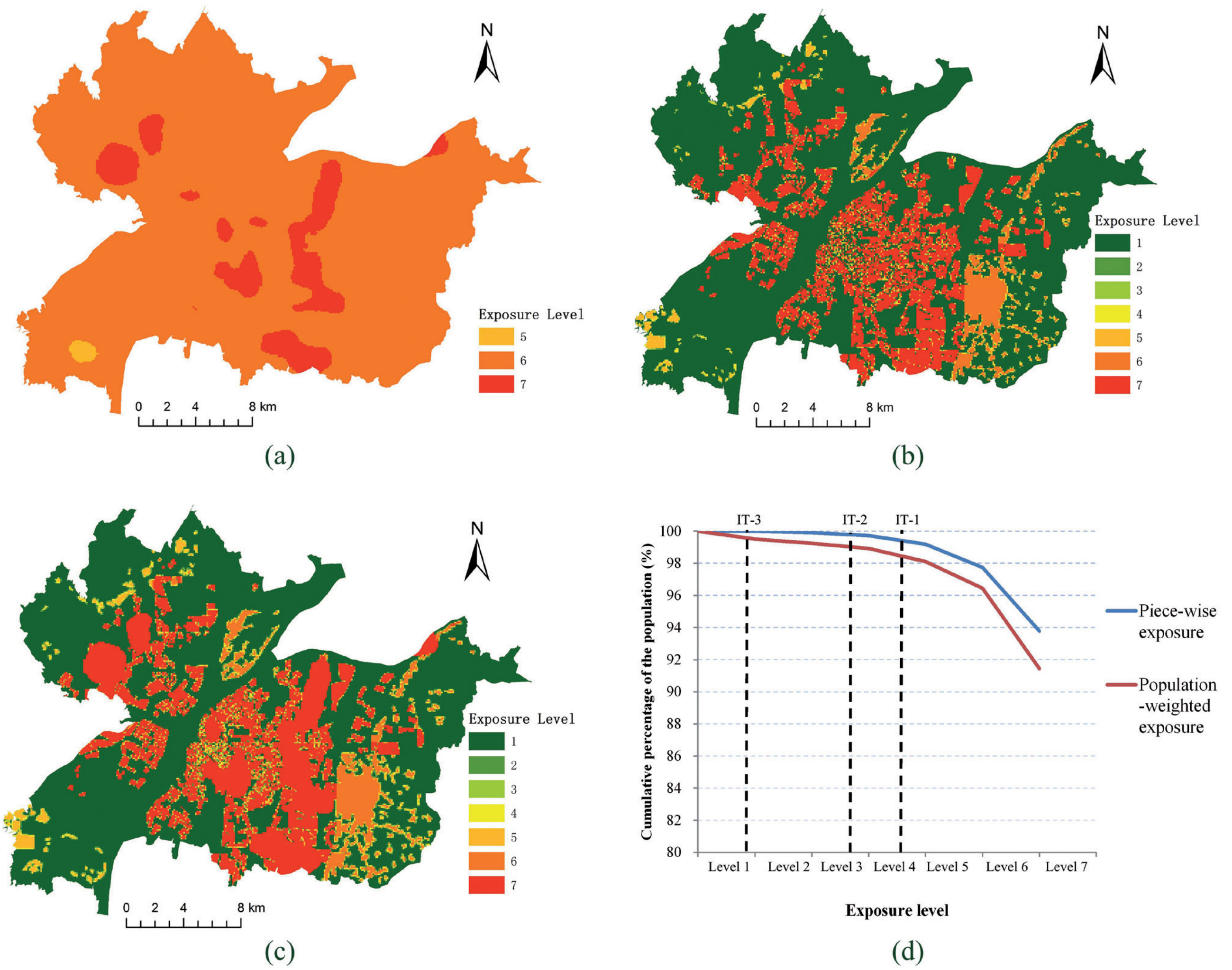

Fig. 7. Spatial distribution of population exposure in winter based on evaluation approaches: a) absolute concentration exposure; b) population-weighted exposure; c) piece-wise exposure. d) the cumulative percentages of the population at different $PM_{2.5}$ exposure levels.

investigation is less than 15%. This finding indicates the reliability of the estimated population result. However, the population result does not incorporate human mobility; for example, people working, relaxing, and commuting. The temporal factors can be added to improve the precision of population data in future work [42].

High-resolution $PM_{2.5}$ concentration data is also crucial for exposure evaluation [43]. Many approaches, including spatial interpolation, dispersion modeling, satellite-derived modelling and LUR, have been developed to cope with the challenge. The LUR model has received increasing attention in recent years and has been proven to be a valid and cost-effective alternative for the simulation of the intra-urban pollutant concentration [33, 44]. Therefore, the LUR models were employed to simulate the spatial $PM_{2.5}$ concentration of four seasons in the Nanchang urban region. The adjusted R^2, average relative error and RMSE demonstrated the effectiveness of LUR modeling. A uniform standard regarding the number of monitoring sites for LUR modeling is currently unavailable [17]. Although the number of monitoring sites in the study area is small, eight monitoring sites cover a region of 562.46 km^2, resulting in a monitoring site for every 70 km^2. The spatial coverage of the monitoring sites in this study is comparable with other LUR models reported in the literature [14, 18].

Absolute concentration and population-weighted exposure approaches were selected as the baselines in the case study rather than the intensity of population exposure approach. This selection is due to the following: the absolute concentration exposure approach, a typical approach disregard population factor; the population-weighted exposure approach, a state-of-the-art approach and the most widely used at present considered the population data; while the intensity of population exposure approach easy produces the polarization problem, thus limiting its application to cities with low concentrations of pollutants [30].

In all seasons, exposure results by the absolute concentration approach focused on a few exposure levels, the obvious spatial smoothing effect is disadvantageous for the identification of high-risk areas

Table 2. Numerical comparisons of the piece-wise exposure approach and baselines in four seasons.

Season	Exposure Level	Absolute concentration		Population-weighted		Piece-wise	
		Area (%)	Population (%)	Area (%)	Population (%)	Area (%)	Population (%)
Spring	Health level 1	0	0	72.79	0.98	66.36	0
	Level 2	0	0	1.29	0.56	4.15	0.35
	Level 3	0	0	1.61	0.93	2.45	0.71
	Level 4	7.66	0.19	2.19	1.59	4.29	2.52
	Level 5	88.15	94.96	4.75	4.75	5.67	5.58
	Level 6	4.19	4.85	1.73	2.44	2.40	3.96
	Severity level 7	0	0	15.64	88.76	14.68	86.88
Summer	Health level 1	0	0	75.60	2.42	66.36	0
	Level 2	0.02	0	1.75	1.20	8.26	2.00
	Level 3	46.14	21.92	2.48	2.29	4.94	3.90
	Level 4	53.79	78.06	3.32	3.52	4.58	5.20
	Level 5	0.05	0.02	1.51	2.36	3.79	9.73
	Level 6	0	0	2.33	5.36	5.84	21.11
	Severity level 7	0	0	13.01	82.85	6.24	58.06
Autumn	Health level 1	0	0	73.18	1.13	66.36	0
	Level 2	0	0	1.47	0.70	4.64	0.46
	Level 3	0	0	1.84	1.15	2.69	0.91
	Level 4	28.92	2.75	2.41	2.01	4.68	3.16
	Level 5	71.08	97.25	4.19	4.36	5.14	5.38
	Level 6	0	0	1.71	2.66	2.63	4.99
	Severity level 7	0	0	15.20	87.99	13.86	85.10
Winter	Health level 1	0	0	71.16	0.49	62.41	0
	Level 2	0	0	0.96	0.26	2.26	0.09
	Level 3	0	0	0.93	0.32	1.57	0.18
	Level 4	0	0	1.70	0.81	2.33	0.54
	Level 5	0.41	0	2.55	1.67	3.26	1.44
	Level 6	90.86	82.80	5.13	5.01	5.39	3.95
	Severity level 7	8.73	17.20	17.58	91.44	22.79	93.79

and the implementation of targeted corrective measures. Hence, the population-weighted and piece-wise exposure approaches would be more effective than the absolute concentration approach for public pollution exposure evaluation. The results obtained by population-weighted and piece-wise exposure approaches are similar in spring and autumn. The calculation equations, the $PM_{2.5}$ concentration in the study area, and threshold setting in the case study jointly contribute to this result. First, the second segment of Equation (5) is an incremental population-weighted function. This segment determines that the result of the piece-wise exposure approach would be similar to that of the population-weighted exposure approach. Second, all areas in Nanchang urban region have $PM_{2.5}$ concentrations between 15 (c_0) and 75 μg/m³ (c_{max}) in spring and autumn. Thus, the final exposure levels are mostly calculated by the second segment of Equation (5) rather than its first or third segment.

The results by the population-weighted and piece-wise exposure approaches are different in summer and winter, and the differences in winter are considerably large. The $PM_{2.5}$ concentration in winter is higher than those in the three other seasons, and some areas even have $PM_{2.5}$ concentrations higher than 75 μg/m³. The areas with $PM_{2.5}$ concentrations >75 μg/m³ but low population densities, such as the Economic and Technological Development and South Nanchang Industrial Zones, are evaluated as severity level 7 by the piece-wise exposure approach, which is equivalent to the absolute concentration exposure approach. However, these areas are still divided into health level 1 by the population-weighted exposure approach due to the low population density. The place should be designated as a severity area (severity level 7) despite the population density once $PM_{2.5}$ concentration exceeds 75 μg/m^3 to protect public health effectively. Similarly, once the $PM_{2.5}$ concentration ≤WHO IT-3 (15 μg/m^3), the place should be designated as a health area (level 1) without considering the population density. Hence, the population-weighted exposure approach would underestimate or overestimate the population exposure when the air is seriously polluted or remarkably clean, and the proposed piece-wise exposure approach would be more reasonable than the population- weighted exposure approach.

The thresholds setting of c_0 and c_{max} have considerable influence on the result. Fig. 3 shows that the WHO IT-3 (15 μg/m^3) is exceeded in all regions of four seasons, while the WHO IT-1 (35 μg/m^3) is exceeded in all regions of winter, most areas of spring and autumn, and small areas of summer. If the c_0 is reset (e.g., 35 μg/m^3), then the result comparisons would be distinctly different. Take summer for example. Areas with $PM_{2.5}$ concentration ≤35 μg/m^3 would be determined as health level 1. Thus nearly 100% of the populations would be divided into health level 1 by the piece-wise exposure approach. By comparison, less than 5% of the populations were divided to health level 1 by the population-weighted exposure approach. c_0 is still set to 15 μg/m^3 in this study, because the WHO AQG (10 μg/m^3) is an overly-high standard for China at present and the WHO IT-1 (35 μg/m^3) is an unsafe threshold for many developed countries.

Conclusions

The evaluation of population exposure to $PM_{2.5}$ is of considerable importance because long-term exposure would have significant adverse effects on public health. In this study, we combined multi-source data to realize high-resolution $PM_{2.5}$ exposure risk assessment in Nanchang urban region. The population and $PM_{2.5}$ data were estimated using the areal weighting method and LUR models, respectively. An improved piece-wise exposure approach was proposed to evaluate the population exposure to ambient air pollution. The proposed approach has improved the use of population data. The absolute concentration exposure approach ignoring the population data in all cases, result of which would has clear theoretical bias and lead to obvious spatial smoothing effect, which is disadvantageous for the identification of high-risk areas and the implementation of targeted corrective measures. The population-weighted exposure approach employing the population data in all air pollution conditions, result of which can reveal the spatial microcosmic difference of the exposure risk in the study area, but it would underestimate or overestimate the population exposure when the air is seriously polluted or remarkably clean. The proposed approach takes population into account merely when air pollutant concentrations are between the health and the severity thresholds, result of which is more helpful to reveal the spatial variation of exposure risk accurately and would be more responsible according to the people-oriented principle. The integrated methodology is effective in exposure risk assessment and can be applied to other regions and pollutants.

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Conflict of Interest

The authors declared no conflict of interest.

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