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Assessment of $PM_{2.5}$ exposure risk towards SDG indicator 11.6.2 – A case study in Beijing

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ABSTRACT

The SDG Target 11.6 was committed to "reduce the adverse per capita environmental impact of cities", one of its indicators 11.6.2 mainly focusing on air quality and used to measure the health impacts of fine particulate pollution on urban populations. However, given that this indicator was designed for the assessment and monitoring at national, regional, and global levels, and few studies to quantitively evaluate it at the city-level currently, whether it can be directly applied to the city-level and fully reflects the intensity of the exposure risk of fine particulate pollution is still unknown. In light of this problem, taking Beijing as an example, we use methods such as population-weighted $PM_{2.5}$ concentrations, trend analysis, and geographic spatial distribution measurement to analyze the $PM_{2.5}$ exposure risk in Beijing from the perspective of multiscale spatiotemporal characteristics of $PM_{2.5}$ concentrations and exposure risk intensity, finally realized a localized assessment framework towards SDG 11.6.2 to quantitatively evaluate the progress of Beijing. The results not only clarified the sustainable development status of air quality in Beijing but also provided experience and demonstration for the similar city-level monitoring and assessment towards SDG 11.6.2 in the future.

1. Introduction

To promote the coordinated development of economic growth, social inclusion, and environment friendly, the UN approved and adopted the 2030 Agenda for Sustainable Development in 2015, which covers 17 Sustainable Development Goals (SDGs) with 169 targets (Chen, Shu, Chen, Zhao, Ge, & Li, 2020). To ensure successful implementation of this global agenda, the United Nations has established an Inter-Agency and Expert Group on the SDG indicators (IAEG-SDGs) and researched the indicator design, metadata compilation, indicator classification, etc. (Liu, Bai, & Chen, 2019). In 2017, the SDGs Global Indicator Framework (SGIF), which included 232 indicators, was proposed, providing a globally unified indicator system for quantitative assessment, periodic monitoring, and reporting of the national or regional SDGs (Cheng, et al., 2020).

Owing to the significance of cities and urban settlements in the diversity of aspects that affect sustainable development, SDG 11, which aims at making cities and human settlements inclusive, safe, resilient, and sustainable by 2030, was developed to track performance and encourage deliberate actions to promote sustainability in cities. This goal contains ten targets, of which target 11.6 focuses on reducing the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management. One of its indicators 11.6.2 is “Annual mean levels of fine particulate matter (e.g. $PM_{2.5}$ and PM_{10}) in cities (population weighted)”, which aims to evaluate the impact of fine particulate pollution on the health of urban populations.

With the characteristics of small particle size, wide sources, complex physical properties, and chemical components, particulate matter, especially fine particulate matter with a diameter less than 2.5 μm ($PM_{2.5}$), is recognized as a kind of the most representative air pollutant that is extremely harmful to human health (Fann, Lamson, Ananberg, Wesson, Risley, & Hubbell, 2012; Hoek, Krishnan, Beelen, Peters, Ostro, & Brunekreef, et al., 2013; Li, Dong, Zhu, Li, & Yang, 2019). Air

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Pollution Exposure refers to the state or process by which individual residents are exposed to air pollution in direct contact with air pollutants, essentially due to the overlapping of air pollutants and population distribution in time and space (Ott, 1982). According to the State of the World's Air 2020 released by the American Institute for Health Effects, the number of people dying from various diseases due to long-term exposure to air pollution reached 6.17 million in 2019, and about 500, 000 babies died from air pollution in the first month of life. Cities are particularly vulnerable to the atmospheric environment, as they accommodate more than half of the world's population and consume most of the global energy (Wang, Niu, Fan, & Long, 2022). In the context of the implementation of the 2030 Agenda for Sustainable Development, it is of great practical significance and practical value to carry out a city-level $PM_{2.5}$ pollution population exposure risk assessment based on SDG 11.6.2.

Considering the harm and urgency of air pollution, many scholars have conducted qualitative and quantitative analyses on the risk assessment of $PM_{2.5}$ pollution exposure. Traditional $PM_{2.5}$ pollution exposure risk studies focused primarily on epidemiology and environmental chemistry, and went through a research journey from single pollutants to mixed pollutants, from individual studies to population studies, and from statistical methods to model improvement (Hystad, Setton, Cervantes, Poplawski, Deschenes, & Brauer, et al., 2011; Jing, Liu, Wang, Song, Lee, & Xu, et al., 2020; Kousa, Kukkonen, Karppinen, Aarnio, & Koskentalo, 2002). But these studies are mostly conducted in administrative regions or specific population groups, which is difficult to deeply analyze the spatial heterogeneity of pollution population exposure and quantitatively evaluate the intensity of population exposure risk in the study area (Wang, Guo, & Lang, 2016). Some scholars have carried out experimental exploration studies on the $PM_{2.5}$ exposure risk, and Kousa, Kukkonen, Karppinen, Aarnio, & Koskentalo (2002) have proposed a model for evaluating the population exposure to $PM_{2.5}$ pollution by considering the spatial distribution of $PM_{2.5}$ concentration and the spatial distribution of population. The model can quantify the intensity of $PM_{2.5}$ exposure risk at the pixel scale, thereby obtaining high-precision exposure assessment results in the study area. Furthermore, to better reflect the influence of $PM_{2.5}$ pollution on public health and the exposed public, Wang, Guo, & Lang (2016) proposed population-weighted $PM_{2.5}$ concentrations considering the exposed population to $PM_{2.5}$pollution, and analyzed the $PM_{2.5}$ exposure risk in 31 provinces in China. In general, few risk assessment studies are focusing on $PM_{2.5}$ pollution in recent years, and the evaluation indicators of $PM_{2.5}$ exposure risk used by different researchers and their applicable evaluation scales vary (Hoek, Brunekreef, Goldbohm, Fischer, & Brandt, 2002; Zhang & Hu, 2018). Beside, most of these existing studies are analyses of the pollution status and characters of $PM_{2.5}$ population exposure risk and lack specific quantifiable evaluation targets to apply to the evaluation and monitoring practice of SDG 11.6.2.

In addition, while SDG 11.6.2 is a conceptually clear and quantifiable indicator in the Tier Classification for Global SDG Indicators, it was designed for global and national monitoring and assessment like other indicators in SGIF, and in practice still faces the issue of how to monitor and evaluate at the local level (Burford, Tamás, & Harder, 2016; Chen, Ren, Geng, Peng, & Ye, 2018). Therefore, studies mainly conduct summary analysis of SDG 11.6.2 on a global or national scale (Lozano, Fullman, Abate, Abay, Abbafati, & Abbasi, 2018); to our knowledge, there are few studies and reports on comprehensive evaluation and monitoring of it at a city level. Obviously, for SDG 11.6.2, an indicator for evaluating the adverse environmental impact on a city, it is difficult to accurately reflect the specific progress of the city by only considering the evaluation results at the national level. For example, Akuraju, Pradhan, Haase, Kropp, & Rybski (2020) demonstrate that high levels of pollution tend to be related to high pollution levels in large cities after analyzing how urban indicator values scale with city size within a country. In summary, to avoid concealing local heterogeneities, the perspective of SDG 11.6.2 assessment should be turned from the national and sub-national levels to the city-levels (Utazi, Thorley, Alegana, Ferrari, Nilsen, & Takahashi, 2019), and form a localization index evaluation system adapted to local conditions.

To minimize air pollution impacts effectively, process assessments of air pollution goals must be implemented in all global cities. As the capital of China, Beijing's urban population, energy consumption, and the number of motor vehicles have grown rapidly over the past few decades, and the consequent problem of air particulate pollution has become more prominent. In response to poor air quality, the Beijing Municipal Government issued the Beijing Clean Air Action Plan 2013–2017, which provides a clear and feasible strategy for air pollution control. Immediately afterward, the "Beijing Blue Sky Defense War 2018 Action Plan" was launched, which further expanded and deepened the air pollution control work (Cheng, Zhang, Li, Xie, Chen, & Meng, et al., 2017). Therefore, to the formulation of more scientific air pollution prevention and control policies, a scientific assessment of the results of air pollution control in Beijing is also necessary.

Based on this, this article is oriented towards SDG 11.6.2, in combination with the $PM_{2.5}$ monitoring site data and population grid data of Beijing in the past 7 years, adopting quantitative of SDG 11.6.2 at the city level from the perspective of multiscale spatial-temporal variations analysis of $PM_{2.5}$ exposure risk, which provides technical support and practical policy suggestions for the control of air pollution in Beijing, and provides research ideas and scientific references for further improving the SDG index system.

2. Materials and methods

2.1. Study area

Beijing is located in the center of Beijing-Tianjin-Hebei and the surrounding area, one of the four major smog areas in China, adjacent to Tianjin to the east and surrounded by six cities in Hebei (Wang, Ning, & Sun, 2012; Wu, 2012). The terrain slopes from northwest to southeast, with plains in the center and east, and hills in the west, north, and northeast surround the small plain where Beijing City is located. The cross-regional transmission of pollutants caused by the southeastern monsoon, coupled with the meteorological conditions that are not conducive to the diffusion of pollutants caused by topography, has caused severe air pollution in Beijing (Liu, Gautam, Yang, Tao, Wang, & Zhao, 2021).

2.2. Data and data processing

2.2.1. Urban population data

Due to the uneven spatial distribution of the population, it is obvious that areas with higher population density have greater exposure risks under the same $PM_{2.5}$ concentration. Therefore, in the assessment of the overall $PM_{2.5}$ exposure risk in Beijing, the WorldPop dataset was used to reflect the geospatial distribution of population data at a fine scale. The spatial resolution of this data set is 1 km, which has been adjusted to match the country's total population from the official United Nations population estimates and is widely used in the fine study of medium and higher population density areas (Lin, Tan, Lin, Liu, & Zhu, 2020; Qiu, Zhao, Fan, & Li, 2019). To verify the accuracy of the WorldPop dataset in Beijing, this paper collects the permanent population data of various districts of Beijing for 2014–2020, of which the data from 2014 to 2019 are derived from the Beijing Statistical Yearbook, and the data in 2020 are from the bulletin of the 7th National Census of Beijing. After that, the zonal statistic method was used to count the total population of each district in each year of Beijing based on the WorldPop dataset, and then calculate the Pearson correlation coefficient with the permanent population statistics of each district in the same year. The results show that the WorldPop dataset has high precision and applicability in reflecting the spatial distribution of population in Beijing, and the lowest correlation coefficient is 0.95 at the level of P value less than 0.001, which can meet the needs of this study.

2.2.2. $PM_{2.5}$ data

To analyze the changing law of $PM_{2.5}$ exposure risk in Beijing on a long-term scale and better reflect the current pollution situation, this paper collected hourly $PM_{2.5}$ mass concentration data from 35 province-level air monitoring stations in Beijing from January 2014 to December 2020 released by the Beijing Environmental Protection Monitoring centre, and the spatial distribution of each site as shown in Fig. 1.

Due to the difference in the spatial distribution of $PM_{2.5}$ concentration, it is not reasonable to only use the $PM_{2.5}$ concentration obtained from the site monitoring to represent the $PM_{2.5}$ concentration in Beijing. Therefore, the kriging method was applied to interpolate the $PM_{2.5}$ concentration site data to generate $PM_{2.5}$ concentration raster surface with spatial resolution and range consistent with the WorldPop dataset, and then calculated the average $PM_{2.5}$ concentration of all pixels in the corresponding $PM_{2.5}$ concentration grid surface in each region as the $PM_{2.5}$ concentration in the region.

2.3. Methods

The SDG indicator is designed for global and national monitoring and assessment, a localization reform must be undertaken when applying it at a city level (such as in Beijing) due to the lack of localized indicators, basic data, and quantitative assessment and analysis models (Liu, Bai, & Chen, 2019). The core philosophy of localization reform is to improve, extend and adjust the original indicator system based on maintaining the connotations of sustainable development indicators (Chen, Peng, Zhao, Ge, & Li, 2019). Since SDG 11.6.2 was designed to reflect air quality and its impact on the health of urban populations, the connotations of this indicator can be extended from the perspective of spatiotemporal change analysis. To tailor it to local circumstances, three criteria of purposefulness, adaptability and measurability were proposed for selecting a localization indicator set combined with SGIF and local geographical characteristics. Among them, purposefulness analysis refers to whether the evaluation index can reflect the connotation of its corresponding target; adaptability analysis means whether the evaluation index has practical significance or value for the research area; measurable analysis is used for determining whether the evaluation index can be quantified and whether it has available authoritative data.

This is followed by spatiotemporal data processing and data-driven indicator calculation based on the full use of statistical, geospatial, and other types of data. Finally, the SDG Dashboard and local action targets are combined to evaluate the progress of SDG 11.6.2 in terms of local sustainable development status, the distance from achieving the SDGs, and the actions taken to achieve the SDGs. The localized framework for the assessment of progress towards SDG 11.6.2 is summarized and illustrated in Fig. 2.

2.3.1. Population-weighted $PM_{2.5}$ concentrations

Before the selection of the indicators, we needed to examine the connotation of the goal in detail and clarify what the goal intends to achieve. In the SDGs Global Indicator Framework (SGIF), SDG 11.6 is "By 2030, reduce the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management", one of its indicators 11.6.2 is "Annual mean levels of fine particulate matter (e.g. $PM_{2.5}$ and PM_{10}) in cities (population weighted)", and the connotation of the indicator is to evaluate the impact of fine particulate pollution on the health of urban populations.

$PM_{2.5}$ mass concentration is a commonly used $PM_{2.5}$ exposure risk assessment index (Ban, Ma, Zhang, & Li, 2021; Qiu, Xu, Song, Luo, Zhao, & Xiang, et al., 2017), but it ignores the unevenness of population spatial

Fig. 1. Study area and the locations of the 35 air-quality monitoring stations.

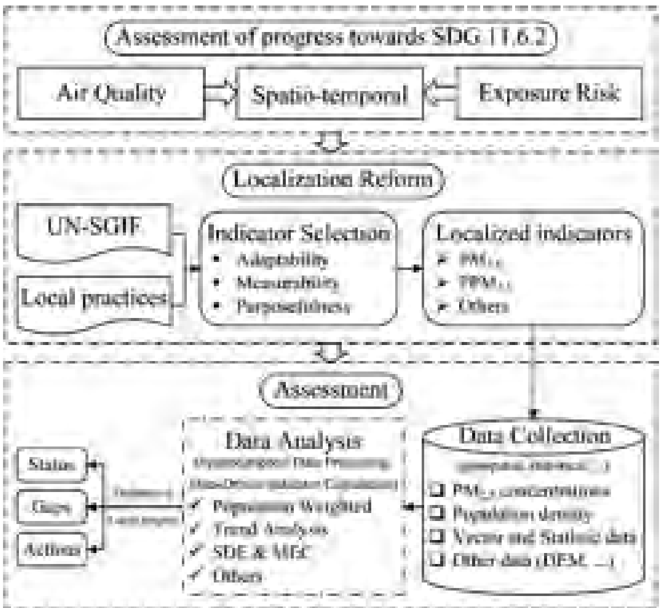

Fig. 2. The localized framework for the assessment of progress towards SDG 11.6.2.

distribution and is difficult to reflect the difference in $PM_{2.5}$ exposure risk in areas with different population densities under the same $PM_{2.5}$ concentration. Theoretically, compared with the exposure assessment that only considers mass concentrations, population-weighted $PM_{2.5}$ concentrations weigh the population at different exposure concentrations, which not only comprehensively reflect the mass concentration of particulate matter and the spatial distribution of population density but also quantify the intensity of the air pollution exposure risk in a certain spatial unit (Lin, Li, Lau, Deng, Tsa, & Fung, et al., 2016; Zhong, Louie, Zheng, Yuan, Yue, & Ho, et al., 2013). Therefore, population-weighted $PM_{2.5}$ concentrations can better reflect the actual impact of $PM_{2.5}$ pollution on population health, the expression as follows:

$$PPM_{2.5}^{t} = \sum_{j=1}^{n}\left(PM_{2.5}^{i,\,t} \times P^{i,t}\right) \Bigg/ \sum_{j=1}^{n} P^{i,t} \tag{1}$$

where, $PPM_{2.5}^{t}$ (unit: ug/m^3) represents the population-weighted mean $PM_{2.5}$ concentrations for a given time t; $PM_{2.5}^{i,\,t}$ (unit: ug/m^3) denotes the mean $PM_{2.5}$ concentrations of grid point i; $P^{i,t}$ (unit: person) stands for the population count at grid point i.

The calculation of the difference between $PPM_{2.5}$ and $PM_{2.5}$ are presented as follow:

$$D^{i,t} = \left(PPM_{2.5}^{i,\,t} - PM_{2.5}^{i,\,t}\right) / PM_{2.5}^{i,\,t} \times \ 100\% \tag{2}$$

where, $D^{i,t}$ is the difference between $PPM_{2.5}$ and $PM_{2.5}$.

2.3.2. *Trend analysis*

The seasonal Kendall test (Hirsch, Slack, & Smith, 1982), which is a generalized form of nonparametric Mann–Kendall (MK) test (Kendall, 1948; Mann, 1945), does not require the sample to follow any distribution and is less affected by outliers, and hence more applicable for trend test to data sets with seasonality (Ahmad, Fatima, Awan, & Anwar, 2014). The seasonal Kendall slope estimator (Hirsch, Slack, & Smith, 1982) is an unbiased estimator of linear trend magnitude, reflecting the long-term trends of data with complicated seasonality and has considerably higher precision than a regression estimator (Tsirkunov, Nikanorov, Laznik, & Zhu, 1992). In this study, the seasonal Kendall test and seasonal Kendall slope tests were used to identify trends in the $PM_{2.5}$ time series from January 2014 to December 2020. Firstly, we performed the seasonal Kendall test to detect whether the $PM_{2.5}$ time series has a significant trend. If the p-value is less than 0.05, the corresponding trend is considered significant. Then, the slope values of the $PM_{2.5}$ data were calculated by performing seasonal Kendall slope estimator in order to indicate the direction and the magnitude of the temporal changes in $PM_{2.5}$ concentration.

2.3.3. *Measuring geographic distributions methods*

In this paper, the kriging method was used to map the $PM_{2.5}$ concentrations distribution from 35 air monitoring stations with $PM_{2.5}$ concentrations, and the standard deviation ellipse (SDE) and median center (MEC) are employed to trace the spatial pattern changes of $PM_{2.5}$ concentrations distribution across a time series. Kriging is a geostatistical method widely used in air pollution research that generates an estimated surface from a scattered set of points with z-values (Li, Song, Zhai, Lu, Kong, & Xia, et al., 2019; Shao, Ma, Wang, & Bi, 2020). SDE was firstly proposed by Lefever (1926) in 1926, including three basic parameters: mean center, azimuth, and long-short half axis length, which are typically used to summarize the geospatial distribution characteristics of discrete point data (He, Zhang, Song, & Huang, 2021). Among the parameters of SDE, the mean center is the center of spatial data, which indicates the gravity of the distribution; the azimuth reflects the main trend directions; and the long and short half axis represents the direction and range of geospatial elements distribution, respectively. Accordingly, the size of long-short axis ratio can reflect the tendency of the directional about the distribution of geospatial elements (Cheng, Zhang, Chen, Li, Wang, & Hu, et al., 2020). The median center is a measure of the central tendency and feature distribution, identifying the location that minimized travel from it to all other features in a dataset (Li, Li, Chen, Zhou, Cui, & Liu, et al., 2019). Compared with the average center, the median center is less influenced by data outliers, which can better reflect the spatiotemporal trend of the dataset (Cao, Gao, Li, Wu, Guan, & Ho, 2021).

3. Results

3.1. *Spatial pattern of $PM_{2.5}$ concentrations in Beijing*

The spatial distribution of annual average $PM_{2.5}$ concentrations from 2014 to 2020 in Beijing is presented in Fig. 3. Overall, the average annual $PM_{2.5}$ concentration in Beijing shows a spatial distribution characteristic that decreases from south to north, reflecting the influence of industrial layout and cross-regional transmission of pollutants on air quality. The northern part of Beijing is backed by the Taihang Mountains and Yanshan Mountains, with low population density and low emissions, coupled with the location of the northwest monsoon entry channel that helpful to the diffusion of pollutants, so the overall concentration of particulate matter is low (Ji, Wang, & Zhuang, 2019); the southern region has the worst air quality due to its proximity to several heavy industrial cities in Hebei and Shandong, and the cross-regional transmission of pollutants under the action of the southeast monsoon in summer (Xu & Zhang, 2020); the population and vehicles in the central urban area are dense, and the emission of air pollutants is large, so the air pollution situation is also more serious.

Beside, the annual average concentration of $PM_{2.5}$ in Beijing showed a significant downward trend in time changes from 2014 to 2020, reflecting the achievements of air pollution control in Beijing. In 2014, the annual average concentration of $PM_{2.5}$ in Beijing was 41~128 ug/m3, the annual average $PM_{2.5}$ concentrations in all areas of Beijing exceeded the CAAQS Grade II (35 μg/m^3). With the implementation of the Beijing 2013–2017 Clean Air Action Plan, the annual average concentration of $PM_{2.5}$ in Beijing was 33–80 ug/m^3 in 2017, a decrease of about 31% compared with the average annual concentration in 2014. Based on the five-year $PM_{2.5}$ pollution action plan, the capital city implemented the Beijing Blue Sky Defense War 2018 Action Plan, which continued to focus on $PM_{2.5}$ pollution control. By 2020, the annual

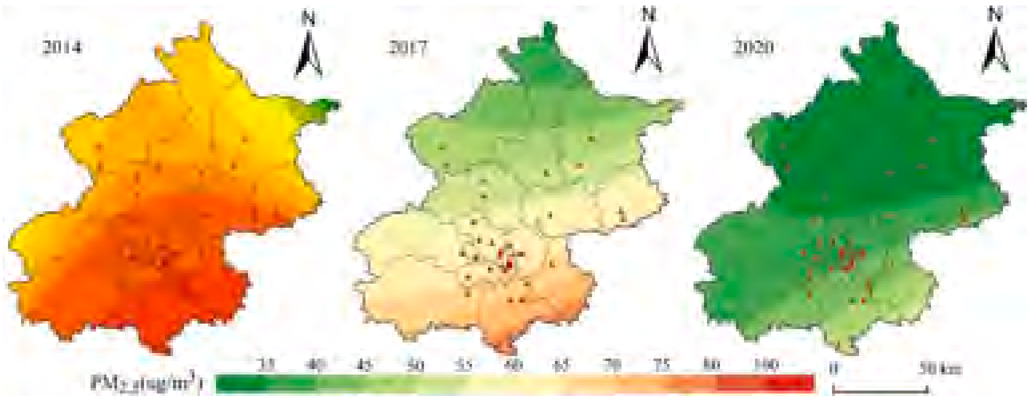

Fig. 3. Spatial distribution of $PPM_{2.5}$ annual average concentrations in Beijing from 2014 to 2020.

average concentration of $PM_{2.5}$ in Beijing will be 23–54 ug/m^3 with a decrease of about 28% compared with 2017, and the $PM_{2.5}$ concentrations in Huairou, Miyun, Yanqing, and north Changping districts was lower than 35 ug/m^3.

The overall spatial pattern changes of annual $PM_{2.5}$ concentrations in Beijing from 2014 to 2020 were evaluated by standard deviation ellipse and median center analysis (Fig. 4). The distribution pattern of the median center found in southeastern Changping with an obvious north-south change and the small east-west change, which reflects the characteristics of $PM_{2.5}$ distribution in Beijing mainly changed in the north-south direction. This is primarily because the west, east, and north of Beijing are surrounded by mountains, making it difficult for pollutants that spread from the south to diffuse in east-west directions (He, Liu, Zhao, He, Liu, & Mu, 2022). The azimuth of SDE reflects the $PM_{2.5}$ concentration in Beijing showed a significant distribution pattern in the "northeast-southwest" direction, which is also parallel to the mountains in the southwest, reflecting the effect of terrain on the spatial distribution of $PM_{2.5}$ concentration. Furthermore, the long-short axis ratios changed from 1.51 to 1.62 in 2014–2017, which means that air pollution has spread in the main direction during this period; then gradually dropped to 1.54 in 2020, reflecting that the directionality of the $PM_{2.5}$ pollution was weakened.

Fig. 4. Standard deviational ellipses and median center of $PM_{2.5}$ concentrations in Beijing from 2014 to 2020.

3.2. Overall $PM_{2.5}$ exposure risk assessment in Beijing

3.2.1. Yearly variations of $PM_{2.5}$ exposure risk

The concentrations of $PPM_{2.5}$ and $PM_{2.5}$ in Beijing from 2014 to 2020 are shown in Fig. 5, the concentrations of $PPM_{2.5}$ and $PM_{2.5}$ in Beijing in 2014 were 92.6 and 83.7 ug/m^3, respectively, and then dropped to 38.9 and 35.4 ug/m^3. Overall, the concentrations of $PPM_{2.5}$ and $PM_{2.5}$ in Beijing from 2014 to 2020 showed a downward trend year by year. $PM_{2.5}$ concentration value was higher than $PPM_{2.5}$ every year, which means that the $PM_{2.5}$ mass concentration underestimated the actual impact of $PM_{2.5}$ pollution on the health of the population in Beijing. From the perspective of the difference between $PM_{2.5}$ and $PPM_{2.5}$, the overall trend from 2014 to 2018 showed a significant downward trend, which was mainly due to a series of air pollution control measures in Beijing that led to a decrease in the difference between $PM_{2.5}$ concentration in high population density areas and low population density areas; the difference from 2018 to 2020 has increased slightly, which is mainly due to the further reduction of the difference in the spatial distribution of $PM_{2.5}$ concentrations that leads to the transfer of high pollution areas to the central and southern high population density areas.

According to the traffic light method of the SDGs Index and Dashboard in the Sustainable Development Report 2020, released by the Bertelsmann Foundation and the United Nations Sustainable Development Solutions Network (SDSN). Most of the SDGs indicators were quantitatively graded, the scores were divided into four grades, i.e., the green (basically fulfilling the requirements of the indicator), the yellow (to be upgraded), the orange (challenging), and the red (far from achieving the 2030 requirements). It enables SDGs indicators to be compared across regions, helping countries or regions assess the relative progress of SDGs. Among it, SDG 11.6.2 is divided into four grades according to the average annual population-weighted $PM_{2.5}$ concentration (ug/m^3), of which the average annual $PPM_{2.5}$ concentration represented by green, yellow, orange, and red is $PPM_{2.5} \leq 10$, $10 < PPM_{2.5} \leq 17.5$, $17.5 < PPM_{2.5} \leq 25$ and $25 < PPM_{2.5}$, respectively. Although the concentration of $PPM_{2.5}$ in Beijing has continued to decrease in recent years, the average annual concentration of $PPM_{2.5}$ (38.9 ug/m^3) in 2020 still far exceeds the 25 ug/m^3 required by the red grade of the SDG 11.6.2 Dashboard.

Fig. 6 presents the cumulative distribution plot of population numbers at different $PM_{2.5}$ concentrations in Beijing from 2014 to 2020. The results show that the proportion of people exposed to areas with excessive $PM_{2.5}$ concentration in Beijing from 2014 to 2020 shows a significant downward trend year by year, indicating that the $PM_{2.5}$ exposure risk in Beijing is decreasing. However, before 2019, the proportion of the population in the areas exceeding the CAAQS Grade II (35 μg/m^3) was 100%, indicating that there was a high $PM_{2.5}$ exposure risk among residents in Beijing; by 2020, this proportion dropped to 90%, but the downward trend was significantly slower than in previous years.

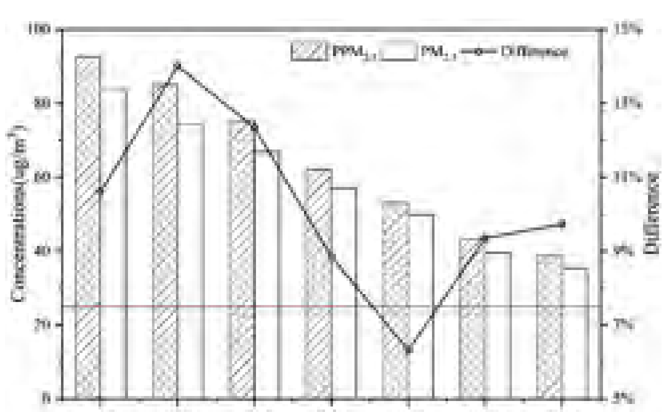

Fig. 5. Comparison of annual average concentrations of $PPM_{2.5}$ and $PM_{2.5}$ in Beijing from 2014 to 2020 (the red line in the figure indicates the red grade of SDG 11.6.2).

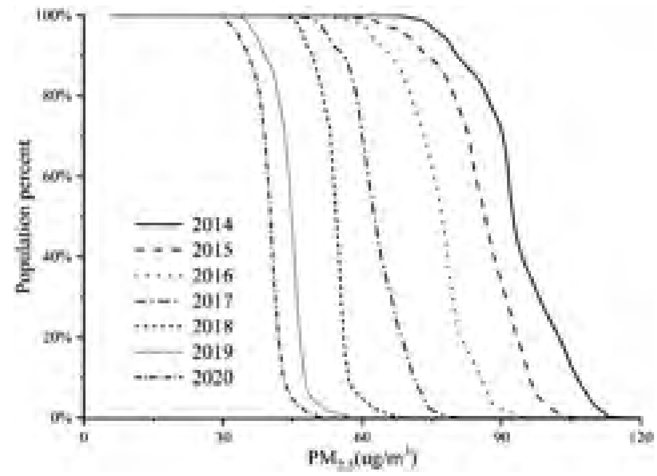

Fig. 6. Cumulative distribution plot of population numbers at different $PM_{2.5}$ concentrations in Beijing from 2014 to 2020.

3.2.2. Monthly variations of $PM_{2.5}$ exposure risk

On the assumption that the spatial distribution of monthly population density in Beijing remains unchanged and consistent with the annual, we calculate the monthly average $PPM_{2.5}$ concentration in Beijing from 2014 to 2020 to analyze the variation characteristics of $PM_{2.5}$ exposure risk on a monthly scale. Subsequently, the seasonal Kendall test method is used to test the significance of the changing trend of $PM_{2.5}$ and $PPM_{2.5}$, and the slope value of the long-term trend of the two is calculated using the seasonal Kendall slope estimator method, then the trend line is plotted as shown in Fig. 7. The Z values obtained by the trend test were -7.3 and -7.5, respectively, and both passed the significance test of 0.01, indicating that the average monthly $PM_{2.5}$ and $PPM_{2.5}$ concentrations in Beijing from 2014 to 2020 showed a significant downward trend. What's more, the monthly average concentration of $PPM_{2.5}$ in each month from 2014 to 2020 was higher than the $PM_{2.5}$, but the gap between the two decreased year by year. From the trend lines of $PPM_{2.5}$ and $PM_{2.5}$, it can be seen that the downward trend of $PPM_{2.5}$ is more obvious, and the trend lines of the two in 2020 are almost overlapping, reflecting the decline of the $PM_{2.5}$ exposure risk in Beijing

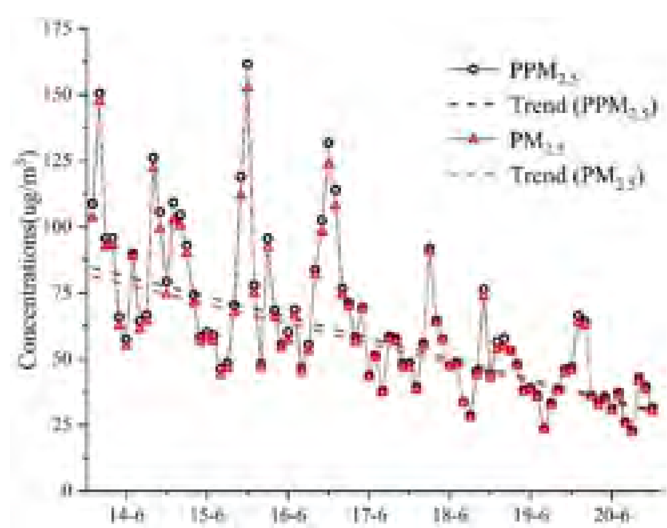

Fig. 7. Trends of monthly average concentrations of $PPM_{2.5}$ and $PM_{2.5}$ in Beijing from 2014 to 2020.

and a high degree of consistency in the changing trend of $PPM_{2.5}$ and $PM_{2.5}$.

In addition, the average monthly $PPM_{2.5}$ concentrations in individual months (August 2019 and September 2020) in Beijing reached the target of less than 25 ug/m^3 required for the orange grade of the SDG 11.6.2 Dashboard, and the concentration of $PPM_{2.5}$ in September 2020 was lower than that in August 2019. The shift from red (far from achieving the 2030 requirements) to orange (challenging) reflects not only the determination and effectiveness of Beijing's air pollution control but also the gradual narrowing of the gap between Beijing and the realization of SDG 11.6.

3.3. $PM_{2.5}$ exposure risk assessment in various districts of Beijing

3.3.1. Yearly variations of $PM_{2.5}$ exposure risk

The annual average concentration of $PPM_{2.5}$ in all districts of Beijing from 2014 to 2020 is shown in Fig. 8. On the whole, the annual average $PPM_{2.5}$ concentration in all districts of Beijing showed obvious spatial distribution characteristics of high in the south and low in the north with a significant downward trend year by year, which was roughly the same as the distribution characteristics of $PM_{2.5}$. And the $PPM_{2.5}$ concentrations in all districts of Beijing in 2014 were 72~106 ug/m^3, 50~71 ug/m^3 in 2017, and 30~44 ug/m^3 in 2020. In 2020, there were four districts in Beijing (Huairou, Miyun, Yanqing, and Mentougou) with an average annual concentration of $PPM_{2.5}$ below 35 ug/m^3, but is still in the red grade (> 25 ug/m^3) of the SDGs Dashboard, indicating that the $PM_{2.5}$ exposure risk in Beijing remains at a high level.

The comparative results of the annual average concentrations of $PPM_{2.5}$ and $PM_{2.5}$ in various districts of Beijing were shown in Table 1. It can be seen that the difference between $PPM_{2.5}$ and $PM_{2.5}$ in Dongcheng and Xicheng is the smallest, which is mainly due to the small change in population density and $PM_{2.5}$ concentration because of the small area, and part of the reason is that the 1 km resolution WorldPop dataset is difficult to reflect the change of population distribution on a smaller scale. In addition, the $PPM_{2.5}$ concentrations in Huairou and Changping are significantly greater than $PM_{2.5}$, which is mainly due to the gentle terrain and high population density in the south of Huairou and Changping, coupled with the overall trend of $PM_{2.5}$ concentration decreasing from north to south. It is worth noting that the $PPM_{2.5}$ concentrations in the most polluted Daxing distinct are much smaller than the $PM_{2.5}$ concentrations, and its difference shows a gradually increasing trend. This is mainly due to the increase in the spatial distribution difference of $PM_{2.5}$ concentration in Daxing District caused by the reduction of pollutant transmission from the south, coupled with the distribution of population that is high in the north and low in the south.

3.3.2. Monthly variations of $PM_{2.5}$ exposure risk

On the assumption that the spatial distribution of monthly population density in Beijing remains unchanged and consistent with the annual, we calculate the monthly average $PPM_{2.5}$ concentration in various districts of Beijing from 2014 to 2020, and the months with $PPM_{2.5}$ concentration in the red grade were extracted as shown in Table 2. The result shows that more and more months have reached the orange grade of SDG 11.6.2 Dashboard in various districts of Beijing from 2018 to 2020, which is closer to international standards and also reflects the effectiveness of air pollution control in Beijing.

4. Discussion

4.1. Progress assessment methodology towards SDG 11.6.2 at city-level

The progress assessment of the SDGs should include the following three aspects, one is to indicate the gap from achieving the sustainable development goal, the other is to be able to take into account the different geographical and technological levels between regions, and the third is to reflect whether the evaluation body has made efforts to achieve the sustainable development goal. The SDGs Dashboard, which is designed based on the degree of achievement of the observation target, has a strong contrast function and a clear and intuitive advantage in reflecting the progress of SDGs (Janoušková, Hák, & Moldan, 2018; Flückiger & Seth, 2016; Simon, Arfvidsson, Anand, Bazaz, Fenna, & Foster, et al., 2015). However, it does not take into account the differences in geographical and technical levels between regions, making it difficult for the SGIF to "translate" for specific application areas (Koch & Krellenberg, 2018). Therefore, to clarify the sustainable development status of air quality in Beijing, a localized assessment framework for Beijing towards SDG 11.6.2 was designed, rather than any rigid global-level indicator with unclear local value.

The SDGs adhere to the core principle of "Leave no one behind", so the indicators of each target are often combined with production and life. SDG 11.6 focuses on reducing the adverse per capita environmental impact of cities, one of its indicators SDG 11.6.2 aims to evaluate the harm of air pollution to public health. Due to the uneven spatial distribution of the population, it is obvious that areas with higher population density have greater exposure risks under the same $PM_{2.5}$ concentration. Based on the concept, population-weighted $PM_{2.5}$ concentrations weigh the population at different exposure concentrations, so the result can better reflect the harm of air pollution on public health. In addition, the calculation method of $PPM_{2.5}$ can be used to construct exposure risk assessment indicators for other atmospheric pollutants such as O_3. However, plenty of air pollution control measures in Beijing are based on $PM_{2.5}$ concentrations, so it is unreasonable to use $PPM_{2.5}$ as an assessment index to analyze the effectiveness of Beijing's air pollution control measures and reflect the efforts made by Beijing to promote the realization of SDG 11.6.

Based on this, to more reasonably assess the progress of Beijing to

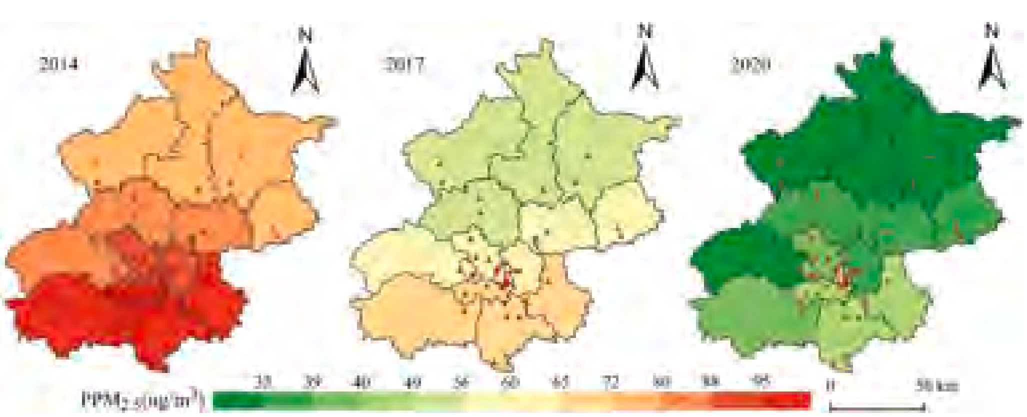

Fig. 8. Spatial distribution of $PPM_{2.5}$ annual average concentrations in all districts of Beijing from 2014 to 2020.

Table 1
The annual average concentrations of $PPM_{2.5}$ and $PM_{2.5}$ in each district of Beijing in 2014, 2017 and 2020.

Districts	2014			2017			2020		
	$PPM_{2.5}$	$PM_{2.5}$	Difference (%)	$PPM_{2.5}$	$PM_{2.5}$	Difference (%)	$PPM_{2.5}$	$PM_{2.5}$	Difference
Beijing	92.59	83.72	10.60	61.11	57.06	8.85	38.86	35.42	9.73%
Dongcheng	90.96	91.48	−0.57	61.87	62.12	−0.39	39.96	39.92	0.09%
Xicheng	92.51	92.90	−0.43	62.42	62.63	−0.34	40.32	40.25	0.16%
Chaoyang	94.65	95.89	−1.29	64.01	65.04	−1.60	38.35	38.26	0.25%
Haidian	89.62	85.93	4.29	58.73	57.77	1.66	40.08	38.78	3.35%
Fengtai	98.51	96.89	1.67	65.98	64.53	2.25	40.11	38.57	4.01%
Shijingshan	87.66	85.46	2.57	60.65	59.75	1.51	39.55	38.50	2.73%
Mentougou	80.37	81.70	−1.62	58.48	58.19	0.50	33.45	34.58	−3.27%
Fangshan	104.06	100.28	3.77	70.91	70.26	0.92	40.05	39.45	1.54%
Tongzhou	105.78	106.29	−0.48	70.78	70.93	−0.22	43.62	44.66	−2.31%
Daxing	106.31	108.62	−2.12	67.93	70.82	−4.08	41.33	45.40	−8.97%
Shunyi	85.27	84.61	0.77	58.29	58.60	−0.52	36.09	35.86	0.64%
Changping	83.98	77.88	7.83	55.33	52.28	5.83	36.38	34.52	5.40%
Pinggu	79.42	77.69	2.24	60.22	58.14	3.57	36.88	36.35	1.46%
Huairou	76.88	72.37	6.24	50.44	47.15	6.98	31.78	30.40	4.51%
Miyun	72.04	70.03	2.87	50.57	48.29	4.72	29.72	30.20	−1.57%
Yanqing	74.49	73.57	1.25	50.09	48.47	3.34	32.47	31.57	2.85%

Table 2
The months with average monthly $PPM_{2.5}$ concentrations less than 25 ug/m^3 in various districts of Beijing from January 2014 to December 2020.

Districts	Sep-2018	Aug-2019	Aug-2020	Sep-2020	Dec-2020
Dongcheng	**30.31**	**25.61**	**28.28**	**26.60**	**30.80**
Xicheng	**31.07**	**25.04**	**29.29**	**26.84**	**30.83**
Chaoyang	**30.23**	24.54	**27.60**	**25.49**	**30.41**
Fengtai	**30.53**	23.53	**27.13**	24.82	**33.10**
Shijingshan	**26.51**	21.72	**25.83**	22.67	**31.04**
Haidian	**28.46**	23.35	**28.91**	**25.59**	**30.12**
Mentougou	24.60	18.29	23.91	20.77	**27.58**
Fangshan	**30.64**	19.90	24.24	21.17	**37.93**
Tongzhou	**32.37**	**27.07**	**27.64**	23.13	**35.95**
Shunyi	**27.15**	21.73	**26.59**	22.25	**25.29**
Changping	**26.30**	21.64	**26.87**	23.48	**26.49**
Daxing	**32.74**	23.96	**25.85**	23.78	**39.12**
Huairou	23.50	19.44	24.16	19.66	21.24
Pinggu	**25.34**	21.80	**25.64**	20.69	**29.08**
Miyun	22.57	19.53	22.91	18.88	20.95
Yanqing	**25.60**	18.31	21.43	18.66	**28.87**

promote the realization of SDG 11.6.2, this study takes $PM_{2.5}$ as the main evaluation index scientifically evaluates the air pollution control measures and effectiveness of Beijing from 2014 to 2020. The $PPM_{2.5}$ concentration will be used as a supplementary indicator to reflect the impact of air pollution on the exposed population of Beijing and refer to SDGs Dashboard to reflect the gap between Beijing and the achievement of the Sustainable Development Goals.

4.2. Progress towards SDG 11.6.2 in Beijing

Beijing was surrounded by mountains on three sides, the unique topographical conditions make it susceptible to air pollution. At the turn of the last century, the sharp increase in the scale of construction, the surge in road motor vehicles, the continuous increase in the number of urban people, and the consequent increase in coal-burning have all contributed to the worsening trend of air pollution in Beijing. Beijing's air pollution control actions on this basis are facing great difficulties and challenges in itself.

Since 2013, Beijing has carried out a series of air pollution control actions with specific targets focusing on the prevention and control of $PM_{2.5}$ pollution. In September 2013, the "Beijing 2013–2017 Clean Air Action Plan" was implemented, which put forward the overall goal of "after five years of efforts, the $PM_{2.5}$ concentration in Beijing will be controlled at about 60 ug/m^3 by 2017″, and specific targets for each district based on the pollution status of each district. By 2017, the $PM_{2.5}$ and $PPM_{2.5}$ concentrations in Beijing were 59.7 and 61.7 ug/m^3, respectively, achieving the goal of controlling the $PM_{2.5}$ concentration in Beijing at about 60 ug/m^3. And the difference between $PPM_{2.5}$ and $PM_{2.5}$ was also declining, reflecting the decreasing impact of air pollution on the health of urban residents.

The annual average concentrations of $PPM_{2.5}$ and $PM_{2.5}$ in all districts of Beijing in 2017 were shown in Fig. 9. It can be seen that the $PM_{2.5}$ concentrations in Huairou, Miyun, and Yanqing in the northern region all dropped below the target line of 50 ug/m^3, but $PPM_{2.5}$ concentrations in these three districts were higher than 50 ug/m^3, indicating that the population of the three northern districts was mainly distributed in areas with higher $PM_{2.5}$ concentrations. For the three districts of Shunyi, Changping, and Pinggu in the central region, the $PM_{2.5}$ concentrations in the other two districts except for Changping is still far from the target line of 55 ug/m^3, and the $PPM_{2.5}$ concentrations in the other two districts except for Shunyi are higher than the $PM_{2.5}$ concentrations, but the average annual concentration of $PPM_{2.5}$ in all the three districts is greater than 55 ug/m^3. Among the six districts in the central area of Beijing, only the $PM_{2.5}$ concentrations in Haidian was lower than the target line of 60 ug/m^3, the difference between $PPM_{2.5}$ and $PM_{2.5}$ in Dongcheng, Xicheng, and Chaoyang was not much different, and $PPM_{2.5}$ concentrations in Haidian, Fengtai, and Shijingshan was significantly higher than the $PM_{2.5}$. Furthermore, only the $PM_{2.5}$ concentrations in Mentougou among the four districts in the south

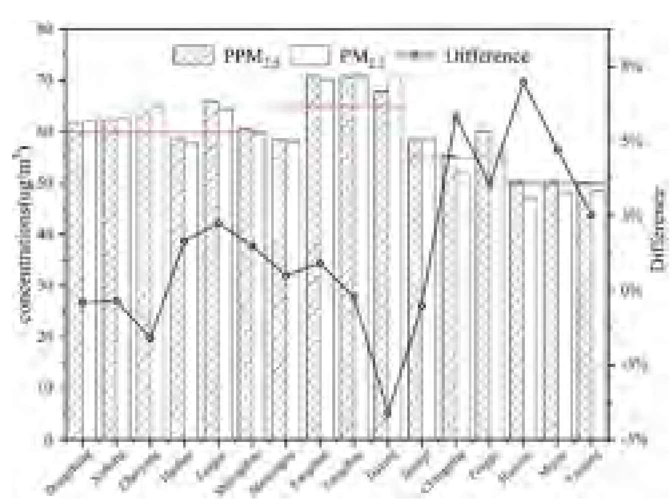

Fig. 9. Comparison of $PPM_{2.5}$ and $PM_{2.5}$ concentrations in various districts of Beijing in 2017 (the red line in the figure indicates the annual average $PM_{2.5}$ concentration target proposed by the Beijing 2013–2017 Clean Air Action Plan for each district to be achieved in 2017).

was lower than the target line of 65 ug/m^3, and the other three districts (Fangshan, Tongzhou, and Daxing) were the three districts with the highest $PM_{2.5}$ concentration among the 16 districts in Beijing, of which the $PPM_{2.5}$ concentrations in Daxing District was much lower than the average annual $PM_{2.5}$ concentrations, indicating that most of the population in Daxing District was concentrated in the area with relatively low $PM_{2.5}$ concentrations.

Through strict emission reduction measures, in just five years from 2013 to 2017, the annual average concentration of $PM_{2.5}$ in Beijing dropped by about 35%, and the peak $PM_{2.5}$ concentrations in Beijing reduced by 20%, but the $PM_{2.5}$ concentrations remained at a very high level. Therefore, Beijing municipality issued the "Three-year Action Plan for Beijing to Win the Blue Sky Defense War" in 2018, which put forward the overall goal of "by 2020, the city's air quality improvement target will be further improved based on the '13th Five-Year Plan', and the $PM_{2.5}$ concentrations will be significantly reduced". At the same time, combined with the actual situation, the air quality improvement goals of each district were formulated.

2020 is the final year of the "13th Five-Year Plan" and the "Beijing Blue Sky Defense War 2018 Action Plan", the $PM_{2.5}$ concentrations in Beijing decreased by 52% compared with 2015 to 35.4 ug/m^3, and the gap with the orange grade (<25 ug/m^3) of the SDG 11.6.2 Dashboard has been further narrowed. At the same time, the "13th Five-Year Plan" proposed the overall goal of "by 2020, the average annual concentrations of $PM_{2.5}$ in Beijing will drop by about 30% compared with 2015, controlling it at about 56 ug/m^3" has also completed.

The annual average $PPM_{2.5}$ and $PM_{2.5}$ concentrations in all districts of Beijing in 2020 were shown in Fig. 10. The Daxing and Tongzhou district is still the most pollutant distinct in Beijing, largely due to their proximity to the Hebei Heavy Industrial Zone in the south, where the import of foreign pollutants has led to severe $PM_{2.5}$ pollution. In addition, it's functional positioning in Beijing is the New Urban Development Zone, an important area for the development of the manufacturing industry and the evacuation of industries and population in the urban center area of Beijing, and the emission of various pollutants is relatively large. On the other hand, the Daxing district with the highest annual average $PM_{2.5}$ concentrations among all districts was only 45 ug/m^3, which was lower than the specific target of 46 ug/m^3 set for Huairou, Miyun, and Yanqing in the three northern districts with the best air quality in Beijing. All districts have exceeded the air quality improvement targets set by the "Three-year Action Plan" for the pollution situation in the region, and the "Beijing Blue Sky Defense War 2018 Action Plan" has come to a perfect end. However, the $PPM_{2.5}$ concentrations in all the 16 districts of Beijing exceeded 25ug/m^3 which still in the red grade (> 25 ug/m^3) in the SDG 11.6.2 Dashboard, and only 5 districts (Mentougou, Changping, Huairou, Miyun, Yanqing) had annual average $PM_{2.5}$ concentrations of less than the CAAQS Grade II (35 μg/m^3).

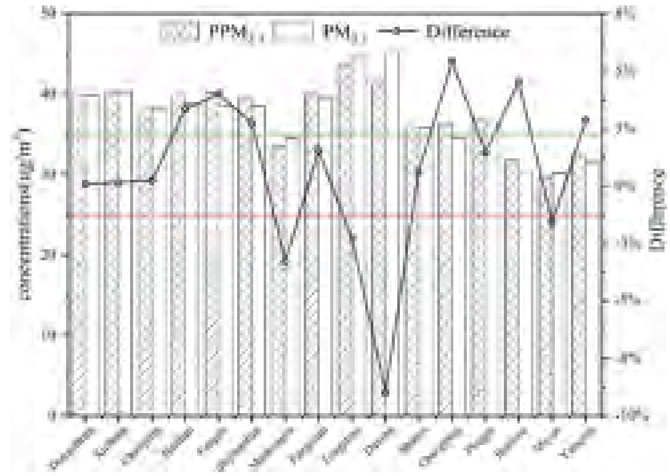

Fig. 10. Comparison of $PPM_{2.5}$ and $PM_{2.5}$ concentrations in various districts of Beijing in 2020 (the green line in the figure indicates the CAAQS Grade II (35 μg/m3), and the red line indicates the orange grade (<25 ug/m3) of the SDG 11.6.2 Dashboard).

5. Conclusions

Based on the measured $PM_{2.5}$ monitoring site data in Beijing and population grid data, using the population-weighted $PM_{2.5}$ concentration algorithm, trend analysis, and measuring geographic distributions methods, etc., we analyze the multiscale exposure risk of $PM_{2.5}$ concentrations in Beijing at the city-level. On this basis, We quantitatively evaluated the progress of Beijing by using a localized assessment framework towards SDG 11.6.2, which not only clarified the sustainable development status of air quality in Beijing but also provided experience and demonstration for similar city-level assessments in the future, and the main conclusions are as follows:

(1) The spatial distribution of $PM_{2.5}$ concentrations in Beijing showed a general trend of decreasing from north to south with significant spatial differences. In addition, due to factors such as terrain, meteorological conditions, and cross-regional transmission of pollutants, $PM_{2.5}$ pollution in Beijing generally shows a significant geospatial trend from northeast to southwest, and the pollution center is located in the southeast of Changping District.

(2) The results of the $PM_{2.5}$ exposure risk assessment show that the population in Beijing had a higher $PM_{2.5}$ exposure risk from 2014 to 2020, and a larger population was distributed in heavily polluted areas, but the $PM_{2.5}$ exposure risk in Beijing showed a significant downward trend year by year. In addition, due to the spatial distribution characteristics difference between $PM_{2.5}$ concentrations and population density, the exposure risk assessment based on population density can better reflect the actual impact of $PM_{2.5}$ pollution on population health.

(3) Finally, the assessment results of SDG 11.6.2 show that although Beijing has a low level of air quality compared to the SDG 11.6.2 Dashboard and is far from the goal of the United Nations 2030 Agenda for Sustainable Development, it is making rapid progress in promoting the implementation of SDG 11.6.2. Therefore, Beijing should continue to promote air pollution control actions, fundamentally change the regional industrial structure, energy structure, transportation structure, and promote continuous improvement of air quality.

Although this study achieved the goal that quantitatively evaluating the progress of SDG 11.6.2 at the city level, some limitations to the study should be clarified to assist future studies. Firstly, to ensure the accuracy of population data, we use the 1 km WorldPop dataset that has been adjusted to match the country's total population, and the differences between it and higher spatial resolution population datasets (such as LandScan, GPW v4, etc.) in the $PM_{2.5}$ exposure risk assessment have yet to be explored. Secondly, although the population-weighted $PM_{2.5}$ concentration can better contrast with the air pollution control targets of various districts in Beijing, it still has certain shortcomings for high-precision spatial change analysis. Finally, this paper only considers the most representative atmospheric pollutant $PM_{2.5}$, but the $PM_{2.5}$ exposure risk evaluation system based on SDG 11.6.2 proposed in this paper can still provide a certain reference for the quantitative assessment of other atmospheric pollutants such as PM_{10}, O_3, CO, etc.

Declaration of Competing Interest

All authors disclosed no relevant relationships.

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