Greenspace availability or greenspace usability, which matters on PM2.5-related premature deaths: evidence from 360 cities in China

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Abstract

Greenspace exposure is confirmed to reduce air pollution-related negative health impact. However, which type of greenspace exposure matters more on mitigating air pollution-related deaths and whether this effect is regionally different remain unclear. Here we show, greenspace usability exposure plays a more significant role in mitigating PM_{2.5}-related premature deaths in 360 China cities generally speaking. By clustering 360 cities into urban-rural and Deprivation Index groups, we further find that greenspace availability and usability together work on respiratory health in rural regions, and greenspace availability matters more in very low deprived areas or urban and rural regions. Our results that increasing greenspace usability exposure is more helpful in reducing air pollution-related premature deaths may inform more effective and equitable greenspace planning policies in rapidly developing countries like China.

Introduction

Air pollution is the fifth highest leading cause for premature deaths globally^{1,2,3,4}. Nearly 86% populations in expanding developing countries such as China, India, and Bangladesh experienced the extreme PM_{2.5} concentrations^{5,6}. It shows that the problem of PM_{2.5}-related premature deaths are becoming a global respiratory health challenge rather than a regional air pollution issue^{7,8}. Many studies have proved the positive effect of greenspace on reducing PM_{2.5} exposure and promoting environment restoration^{9,10,11,12,13,14}. Whereas no studies have quantified whether greenspace can mitigate PM_{2.5}-related health impact by relieving PM_{2.5} emissions. In response to achieving high-quality development, the epidemiological evidence associating greenspace and respiratory health has put greenspace interventions as a sustainable way to reduce air pollution-related premature mortality on the agenda of planners and policymakers^{14,15}.

Existing literature indicates that exposure to greenspace reduces the risk of all-cause premature mortality^{8,9,12}, and broadly classify the greenspace exposure into two aspects; greenspace availability exposure and greenspace usability exposure^{1,16,17}. Greenspace availability such as normalized difference vegetation index (NDVI) has widely proven to have unequal positive effect on residents' respiratory health in regions with different socioeconomic levels^{18,19}. It still remains unclear that which type of greenspace exposure could matters more on alleviating air pollution-related premature deaths? Although most studies give an overall assessment of greenspace quantity for the entire study area, few studies can reveal residents' actual exposure to greenspace from a large scale²⁰. Besides, differences of local natural base and green infrastructure construction have led to strong inequity of people's access to greenspace^{21,22}. Simply considering the relationship between total amount of greenspace and air pollution-related health seems to have encountered bottlenecks^{1,10,23,24,25}. Thus, working on combining human mobility and greenspace distribution will become an inevitable trend. Additionally, emissions, urban structure, and socioeconomic factors such as PM_{2.5} concentration, population density and GDP are also significantly linked with air pollution-related premature deaths, and their impact on PM_{2.5}-related health effect need to be discussed together with greenspace exposure^{8,19,26,27}. It's also remarkable that these factors and premature deaths have obvious regional heterogeneity because of differences in policy implementation and

socioeconomics^{1, 18}. On account of the inconsistent progress of China's clean air plan in cities, strong emission control of high-density urban areas may thus encourage air pollution to transfer or leak to less developed areas^{2, 7}. Yet these areas have less resources to provide health services and construct green infrastructure, which will further aggravate the health threat caused by air pollution^{7, 28}. Whereas numerous studies have examined the difference in air pollution-related morbidity or deaths in urban and rural areas, or cities with different deprivation indexes^{1, 18, 28}. No investigation has associated the positive effect of greenspace exposure on respiratory health with city structure and socioeconomic differences. Regarding the inequity of respiratory health in different affluent areas, whether greenspace quantity or greenspace experience or a combination of this two has a positive effect will be potential to affect decisions of policymakers on zone planning^{29, 30}.

In the present study, using multiple linear regression model, we quantify the relationship between greenspace exposure and PM_{2.5}-related premature deaths in 360 cities in whole China. First, we identify the outdoor PM_{2.5}-related premature deaths by using the integrated exposure-response (IER) concentration-response relationships⁷. Second, we use big datas including NDVI, LAI, LULC and per capita green space exposure to characterize the greenspace exposure. Then, we cluster group the samples based on Deprivation Index, and identify the differences in the relationship between greenspace exposure and PM_{2.5} related premature death in each group. Our work provides quantitative estimates of greenspace exposure and PM_{2.5} related premature deaths in large scale from a city planning-based perspective, and reveal the different role of greenspace availability and greenspace usability in urban, rural and further deprivation levels. The findings of this study provide implications on targeted and equitable greenspace planning for mitigation plans on public respiratory health in China.

Result

Descriptive data. Figure 1 presented the outdoor PM_{2.5}-related premature deaths (person), greenspace availability exposure and greenspace usability exposure in 360 Chinese cities. A total of 2,841,180 PM_{2.5}-related premature deaths were obtained in all 360 cities in china during the study period, and 503,905 PM_{2.5}-related premature deaths from 17 megacities accounted for 17.74% of the total. The greenspace usability exposure ranged from 3.22E-07to 3.30 E-03 square meter per person and the greenspace availability exposure ranged from 0.22 to 0.68. We observed that high greenspace usability exposure regions were mostly concentrated in woodland-rich cities while high greenspace availability exposure regions were mostly concentrated in cities with a medium economic level, sufficient green space and moderate population density (Fig.1, Fig. 4). High PM_{2.5} concentrations regions were also noticed that distributing in cities with developed industries or dense populations (Fig.4). Descriptive information on the number of PM_{2.5} related premature deaths and the greenspace exposure are presented in Source Data.

Fig.1 Outdoor PM_{2.5}-related premature deaths (person), Greenspace availability exposure (dimensionless) and Greenspace usability exposure (square meter per person) in 360 China cities. The colors represent different ranges of **a** annual premature deaths in 2017, **b** annual greenspace availability exposure (GAVE) in 2017 and **c** annual greenspace usability exposure (GUE) in 2017.

Overall correlation differences. Table 1 presented the estimated attributable deaths due to outdoor near-ground PM_{2.5} concentrations by China's cities with demographic characteristic in 2017. The overall multiple linear regression demonstrated that greenspace usability exposure was negatively associated with PM_{2.5}-related premature deaths, -0.195 ($p < 0.001$) while PM_{2.5} concentration, population density and GDP had significant positive correlation with them, 0.150, 0.116, 0.720 ($p < 0.001$). In the regression analysis, we found that there existed certain outliers which were megacities with a population of more than 10 million. Thus we separated these megacities and compared them with the result of most cities (Supplementary Table 1). We observed that greenspace usability exposure had excellent health benefits generally speaking while the positive effect of greenspace availability exposure on air-pollution health impact was not obvious. For most China cities, greenspace usability as the only negative impact factor -0.194 ($p < 0.001$) could significantly reduce the number of PM_{2.5}-related premature mortalities. PM_{2.5} concentrations, population density and GDP had positive correlation with air-pollution premature deaths, 0.145, 0.112 and 0.441 ($p < 0.001$). In case diagnosis, greenspace had little effect on premature mortality in 17 megacities and GDP as the only significant factor amplified the negative effects of PM_{2.5} on health 0.619 ($p < 0.001$). This phenomenon had also been reported that capital cities usually showed a high health burden, but greenspace was not sufficient to prevent deaths for the high variability of green levels and interactive influence of multiple factors among capital cities ¹⁵.

Table 1 Multiple linear relationship between PM _{2.5} related premature deaths and main impact factors (greenspace availability exposure, greenspace usability exposure, PM _{2.5} concentrations, population density and GDP) based on the overall city classification.				
Cities		All (n=360)	Megacities (n=17)	Other cities (n=343)
Factors	Greenspace availability	0.047	0.850	0.015
	Greenspace usability	-0.195***	-0.404	-0.194***
	PM _{2.5} concentrations	0.150***	0.065	0.145***
	Population Density	0.116***	0.266	0.112***
	GDP	0.720***	0.619**	0.441***
R ²		0.635	0.709	0.509
Note: n Represented number of cities. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$				

Changes of correlations in urban-rural groups. Table 2, Supplementary Figure 2 showed the changes of greenspace role on estimated attributable deaths due to outdoor near-ground PM_{2.5} concentrations by urban and rural in Chinese cities, which were divided into urban and rural regions by region code respectively. Because of the existence of megacity cases, we still analyzed them separately. For most cities in China, we observed that greenspace casted a positive impact on mitigating the negative health effects of PM_{2.5}, whether in urban or rural areas. Greenspace usability exposure had a greater negative impact on premature deaths than greenspace availability (Table 2). As the central area transitioned to the countryside, there existed a shift from single mitigation effect of greenspace usability [-0.098 ($p < 0.05$)] to a dual mitigation effect of greenspace availability and greenspace usability [-0.184 ($p < 0.05$), -0.280 ($p < 0.01$)]. Remarkably, the role of GDP in promoting premature deaths weakened [0.344 ($p < 0.001$)] and the positive role of PM_{2.5} concentrations [-0.160 ($p < 0.001$)] began to increase with the deceleration of urbanization in rural regions. These shifts might be attributed to the sufficient greenspace for small permanent

population and inadequate promotion of clean energy in rural areas ^{7, 26}. For megacities, the significantly positive effect of GDP on PM_{2.5} premature deaths was shown in urban regions, 0.595 ($p < 0.001$) while greenspace usability turned to be clearly negatively correlated with premature deaths in rural regions, -7.960 ($p < 0.05$). This strong disparity could be explained by the highly-developed greenspace system and protected forest land in the suburbs to limit urban expansion . In general, greenspace exposure had a greater effect on reducing premature deaths in rural areas than urban areas, and greenspace usability played a better role than greenspace availability. The attributable numbers of greenspace exposure and PM_{2.5}-related deaths by urban and rural, and the differences in other impact factors in 2017 were shown in Source Data.

Table 2 Multiple linear relationship between PM_{2.5} related premature deaths and main impact factors further based on the urban and rural classification.

Cities groups ^a		Megacities (n=17)		Most cities (n=343)	
		Urban	Rural	Urban	Rural
Factors	Greenspace availability	0.983	1.491	0.023	-0.184*
	Greenspace usability	0.806	-7.960*	-0.098*	-0.280**
	PM_{2.5} concentrations	-0.029	0.438	0.059***	0.160***
	Population Density	-0.032	351.034	0.017	-0.024
	GDP	0.595***	0.011	0.415***	0.344***
R²		0.786	0.478	0.343	0.154
Note: n Represented number of cities. ^a Classified according to urban and rural code. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$					

Deprivation Index on PM_{2.5}-related premature deaths. Fig. 2 showed the inequity in greenspace exposure and PM_{2.5}-related health burden in 360 cities and four Deprivation Index groups scale. We clustered 360 cities in China based on the Deprivation Index (DI) and divided them into four groups from high to low (Supplementary Figure 3). The higher the DI, the poorer the areas. In general, unequal distribution of greenspace usability in the four DI groups was more obvious than that of greenspace availability, and this inequity corresponded to the difference of PM_{2.5}-related premature deaths in DI groups. Across all urban regions, greenspace availability exposure was highest in highly deprived group and greenspace usability exposure decreased with increasing urban affluence. Across all rural regions, greenspace availability exposure was also highest in ‘High’ group, greenspace usability exposure was extremely uneven and rising with increasing urban affluence. Through observation we could find that greenspace usability exposure and premature death showed a clear opposite trend, and more inequity was reflected in green usability among DI groups. This results indicated that it was imminent to increase the equivalent opportunities of using greenspace for different poverty level. The clustering subdivision based on Deprivation Index were provided in Supplementary Table 2 & 3.

Fig.2 Greenspace exposures and PM_{2.5}-related premature deaths were inequitable in different deprived areas of China. The average greenspace exposure and average PM_{2.5}-related health burden of 360 cities and four Deprivation Index groups were presented with 95% confidence interval. **a** average greenspace availability exposure for all cities and four DI groups, **b** average greenspace usability exposure for all cities and four DI groups and **c** average PM_{2.5}-related premature deaths for all cities and four DI groups.

Table 3, Table 4 and Figure 3 showed the different relationship of greenspace exposure, other factors and PM_{2.5}-related premature deaths due to Deprivation Index (DI) in urban or rural regions. In general, the common features of urban and rural regions were that greenspace had a significant effect on mitigating PM_{2.5}-related premature deaths in Low and Very low deprived areas. Unlike greenspace exposure, positive effect of GDP and PM_{2.5} positive weakened as the deprivation level decreased. For urban regions, the richer the area, the more obvious the positive effect of greenspace usability exposure on residents' health, -0.612 ($p < 0.001$) and -1.212 ($p < 0.01$). However, greenspace availability hardly contributed to the health of urban residents related to air pollution (Table 3, Fig. 3). This phenomenon could be explained by that although the urban greenspace was abundant, large amount of greenspace was distributed in the periphery of cities¹. Meanwhile, high density of urban center construction and uneven distribution of greenspace resources greatly reduced the chances of people being exposed to green environment (Fig. 2), which ultimately led to only increasing greenspace availability was not enough to improve respiratory health^{25, 31}. A more scientific and effective path was to increase the exposure of green space. Population density had an increasing positive effect of premature deaths in rich area, because high-density human activities would lead to resource shortages and large amount of pollutants emission⁹. High GDP were related to more premature deaths in very highly and highly deprived cities, and PM_{2.5} concentrations positively influence premature deaths in medium deprived cities. This phenomenon might be explained by the toughest-ever clean air actions in China between 2012-2017, when the combined contributions of strict energy-climate and policy-mandated adjustment were carried out for economic structure³². For rural regions, we observed that the positive effect of greenspace availability on PM_{2.5}-related health crisis was on the rise with the increase of affluence. However, greenspace usability showed the opposite trend, and it had no obvious relationship with premature deaths in Very low rural cities. Different from the above results, in the wealthiest rural cities, greenspace availability was the most influential factor for premature deaths and the positive effect on residents' health was much greater than the greenspace availability -0.397 ($p < 0.05$) (Table 4, Fig. 3). This phenomenon could be comparable to another studies, which found that a 1-unit addition in greenspace availability would led to a certain reduction of potential life, especially in least and greater deprived areas¹. In addition, an increase in the relationship between PM_{2.5} concentrations and the promotion of premature death was also observed. This phenomenon had been reported on other researches, which could be attributed to solid fuel consume and resource-intensive

consumption patterns for rich families ^{7, 33, 34}. The distribution of greenspace exposure and PM_{2.5}-related deaths by DI groups were provided in Source Data.

Table 3 Multiple linear relationship between PM_{2.5} related premature deaths and main impact factors in urban regions of 360 cities based on four subdivision groups of deprivation index.

Cities groups ^b		Urban regions			
		Very high (n=13)	High (n=108)	Low (n=176)	Very low (n=63)
Factors	Greenspace availability	-0.012	-0.058	0.073	0.333
	Greenspace usability	-0.014	-0.058	-0.612*	-1.212*
	PM_{2.5} concentrations	0.011	0.073*	0.056*	0.110
	Population Density	0.041	0.186*	-0.089**	0.224***
	GDP	1.289***	0.205	0.608***	0.696***
R²		0.987	0.234	0.444	0.837
Note: n Represented number of cities. ^c Classified according to deprivation index. *p<0.05, **p<0.01, ***p<0.001					

Table 4 Multiple linear relationship between PM_{2.5} related premature deaths and main impact factors in urban regions of 360 cities based on four subdivision groups of deprivation index.

Cities groups ^b		Urban regions of 360 cities			
		Very high (n=13)	High (n=108)	Low (n=176)	Very low (n=63)
Factors	Greenspace availability	-0.105	-0.129	-0.251*	-0.397*
	Greenspace usability	-7.145	-0.673	-3.836**	-0.135
	PM_{2.5} concentrations	-0.003	0.090	0.155*	0.000
	Population Density	-32.447	14.092	21.726*	-0.062
	GDP	6.092***	3.372***	0.707***	0.025
R²		0.963	0.468	0.301	0.165
Note: n Represented number of cities. ^c Classified according to deprivation index. *p<0.05, **p<0.01, ***p<0.001

Fig.3 Negative impact of greenspace exposure on PM_{2.5}-related premature deaths showed urban-rural and DI differences. Coefficient values from multiple linear model for the relationship between PM_{2.5}-related premature deaths and greenspace availability exposure (GAVE), greenspace usability exposure (GUE), PM_{2.5} concentrations, population density and GDP. Coefficient values were represented as dots, bars represent 95% CIs, greenspace exposures were shown in green and other variables were shown in purple.

Methods

Integrated modeling framework. Our work has combined multiple data and models from different sources to quantified the impacts of green availability exposure and green usability exposure on PM_{2.5}-related premature deaths in 360 cities of China, and grouped cities according to Deprivation Index for detailed analysis, as listed in [Supplementary Table 3](#). The datasets used in this study include Normalized Difference Vegetation Index (NDVI) from 500 m resolution MODND1T ten-day synthetic products, Leaf Area Index (LAI) from 1 km resolution MYD15A2 eight-day synthetic products, Land Use-Land Cover (LULC) data from LANDSAT 8 remote sensing image, the dynamic population data in 2017 of China from LandScan (<https://landscan.ornl.gov/>), the ground-level PM_{2.5} mass concentrations data in 2017 from previous study^{35,36}, the parameters of IRE model are from the study of Zhao³⁷, statistics demographic data in 2017 from the World Population website, the GDP, Per capita disposable income, employment rate, housing prices data are from the National Bureau of Statistics in 2015, the illiteracy rate and the number of education years per person in each city from the data of the 6th National Population Census.

Greenspace availability exposure and Greenspace usability exposure. The greenspace availability exposure index (GAVI) can be expressed by Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI) and Land Use-Land Cover (LULC)³⁸. Previous studies have proved that NDVI could represents the greenspace density, LAI could measures greenspace quantity, and LULC accounts for the overall presence or absence of greenspace^{39,40}. NDVI was obtained from 500m resolution, LAI and LULC were obtained with a spatial resolution of 1 km, compared to other moderate resolution, the data were selected due to better higher accuracy. The LULC data contained six land cover types (arable land; woodland; grassland; water; urban-rural, industrial, mining and residential land; unused land), for each land cover type, woodland and grassland was assigned with a value of 1, other types of land were assigned with a value of 0, and for each metric, we calculate the proportion of grids with a value of 1. The previous research interprets that the three indicators had the same weights for contribution of greenspace availability exposure, thus we used the min-

max normalization method to process these three indicators

At last, we took the three maps to build our availability exposure index through Eq. (1).

$$GAVE_i = \frac{(G_{NDVIi} + G_{LAII} + G_{LULCI})}{P} \quad (1)$$

In Eq. (1), $GAVE_i$ is the green availability exposure index value for cell i , and G_{NDVIi} , G_{LAII} and G_{LULCI} are greenspace metric ‘exposure’ values for corresponding cell i . P is the number of metrics (in our case, $P = 3$). In this study, $GAVE_i$ values ranged between 0 and 1, in which 1 indicates the highest availability exposure of greenspace, and 0 means the lowest level, or no available of greenspace exposure. Remarkably, we removed and set the negative NDVI values to zero in our computation, as these values expressed water or other non-green covers. We resampled the GAVE map to 1km resolution using ArcGIS (v 10.2) to be consistent with other exposure layers.

The greenspace usability exposure (GUE) is described by dynamic population and land use data in 2017, China¹⁷. Since the individual location is temporally varied, the model to objectively reflect people's real-time use of greenspace is established for evaluating the greenspace usability exposure. Thereby presenting a more reasonable way to access population exposure to greenspace²⁰. By integrating the dynamic population distribution and land use data into the assessment with a spatial resolution of 1km, we further modified the model in Eq. (2) in a dynamic population-weight manner. The green usability exposure (GUE_i) is estimated as Eq. (2).

$$GUE_i = \frac{\sum_{i=1}^n S_i}{\sum_{i=1}^n P_i} \quad (2)$$

In Eq. (2), S_i represents the green area of cell i , P_i is the dynamic population within cell i . GUE_i is greenspace metric ‘usability exposure’ values for corresponding cell i . In this study, GUE_i values also ranged between 0 and 1, in which 1 indicates the highest usability exposure of greenspace, and 0 means the lowest level.

Estimating PM_{2.5}-related premature deaths. We use satellite-based ground-level PM_{2.5} concentrations data and the IER model to estimate PM_{2.5}-related premature deaths. The IER model is developed by Burnett, it describes the concentration–response relationship for the overall range of PM_{2.5} concentration observed in the world⁴¹. And it also has been used in many influential studies to estimate the PM_{2.5}-related premature deaths^{42, 43, 44}. In this study, we use IER model to estimate the total number by four main causes of the PM_{2.5}-related premature deaths: ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), and lung cancer (LC). The relative risk (RR) for each disease is calculated as Eq. (3).

$$RR(C_{PM2.5}) = \begin{cases} 1 + a_1(1 - e^{-a_2(C_{PM2.5} - C_0)^{a_3}}), & \text{if } C_{PM2.5} > C_0 \\ 1, & \text{else} \end{cases} \quad (3)$$

where $C_{PM2.5}$ is the satellite-based PM_{2.5} concentrations in 2017; C_0 is the counterfactual concentration, in this study, there is assumed to be no additional risk below C_0 ; a_1 , a_2 and a_3 are parameters to describe the overall shape of the concentration response, the parameters which we used in this study are adopted from Lee et al.⁴⁵, and the values are listed in [Supplementary Table 4](#). The deaths due to PM_{2.5} pollution are calculated as Eq. (4).

$$M_{PM2.5} = \frac{RR(C_{PM2.5}) - 1}{RR(C_{PM2.5})} \times B_C \times P_C \quad (4)$$

where $M_{PM2.5}$ is the total deaths related to PM_{2.5}; $\frac{RR-1}{RR}$ is the attributable proportion to PM_{2.5} pollution; derived from the national average data in GBD 2013⁴⁶, B_C is the baseline incidence for

all age group of a given health endpoint; P_C is the scale of the exposed population gathered from the Word Population database in 2017 at a 1km resolution. Value for B_C used in this study are in [Supplementary Table 4](#).

Linking premature deaths to different influencing factors. In this study, multiple linear regression is used to identify the relationship between influencing factors PM_{2.5}-related premature deaths: green availability exposure, green usability exposure, PM_{2.5} concentrations, population density and GDP. The PM_{2.5} concentrations, GDP and population density maps of 360 China cities in 2017 are presented in [Fig. 1](#). PM_{2.5} concentrations has been proved to be strongly associated with premature death ⁴⁷. Except for greenspace exposure, previous studies have shown that PM_{2.5} concentrations, population density and GDP also had a strong correlation with air pollution-related health impact ⁴⁸.

Fig.4 PM_{2.5} concentrations (microgram per cubic meter), Population density (person per square kilometer) and GDP (100 million yuan) in 360 China cities. The colors represent different ranges of **a** annual mean PM_{2.5} concentrations in 2017, **b** annual population density in 2017 and **c** annual Gross Domestic Product in 2015.

The regression coefficients derived from the MLR analysis can fully reflect the sensitivity of the dependent variable (PM_{2.5}-related premature deaths) to multiple independent variables (green availability exposure, green usability exposure, PM_{2.5} concentrations, GDP and population density) ⁴⁹. The MLR models were constructed as Eq. (4).

$$M_{PM2.5} = \gamma_1 \times GAVE_i + \gamma_2 \times GUE_i + \gamma_3 \times C_{PM2.5} + \gamma_4 \times PD + \gamma_5 \times GDP \quad (5)$$

where $GAVE_i$ is the greenspace availability exposure; GUE_i is the greenspace usability exposure; $C_{PM2.5}$ is the PM_{2.5} concentrations; PD represent the population density; GDP represent the Gross Domestic Product; $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5$ are the regression coefficient values represent the influence degree of the independent variable. The regression coefficient represents the positive and negative correlation between dependent variables and independent variables, and the magnitude of the coefficient indicates the strength of the correlation.

Subdivided groups. Previous study provided the correlation of PM_{2.5} with mortality risks and illustrated urban-rural difference of PM_{2.5}-related premature death ⁵⁰. In this study, we use the ‘Zoning and Urban and Rural Codes’ of the National Bureau of Statistics for 2017 to divide urban and rural areas among 360 cities of China to discuss the disparities PM_{2.5}-related premature death between urban and rural areas under different dependent variables. The code is widely used in various statistical surveys and urban and rural management, which is of great significance to multiple statistical works.

The standard of deprivation level has changed from single dimension to multi-dimension in recent years, the identification dimensions and methods of deprivation level have been relatively improved, and the method Alkire and Foster have proposed is widely used to measure deprivation level of a certain area from the aspects of income, education, health and other aspects ⁵¹. Based on many

relative studies ^{52, 53, 54}, we choose the following four aspects as the measures of deprivation index, income level, educational level, employment level and living standard. Limited to data acquisition, we select one or two indicators for each aspect, we use urban and rural per capita disposable income, illiteracy rate, average years of education, urban unemployment rate and commodity housing price to estimate the deprivation level, and different deprivation indexes are obtained through min-max. Through K-means cluster analyze, we divided the deprivation index into four groups, very high, high, low and very low, the result of k-means is listed in [Supplementary Table 2](#).

Discussion

This work developed the correlation between greenspace exposure and PM_{2.5}-related premature death for the first time, and the per capital greenness was firstly used to characterize greenspace usability exposure. Using the urban-rural code and cluster analysis method, we divided 360 China's cities into urban-rural and deprivation level group. Although substantial contribution of greenspace availability on residents' respiratory health in global has been investigated ^{10, 15, 16, 24, 55}, we found that the positive impact of greenspace usability exposure on premature death was significantly stronger than that of greenspace availability exposure in most situations, while greenspace availability exposure only worked in the more affluent rural areas. These findings further emphasize the great importance of increasing per capital greenspace exposure, given that current policies focus more on greenspace equality instead of paying much attention to the greenspace availability exposure ^{1, 26, 56}. Additionally, PM_{2.5} concentrations, population density and GDP promoted PM_{2.5}-related premature deaths as expected, but the positive effect of PM_{2.5} concentrations was greatly weakened compared with other studies ^{8, 32}. From 2013 to 2017, the Chinese government was committed to air pollution control, but the latest research showed that a sharp drop in PM_{2.5} will lead to the rise of other types of pollutants, which would increase health burdens ⁵⁷. This reminds us that from the perspective of promoting residents' health, policies of controlling pollution source were important, but improving city ecological environment to increase slow-release pathways for emissions was much more important and sustainable.

Our work provides unprecedented insight into the different positive effects of greenspace availability and usability exposure on PM_{2.5}-related premature death with urban-rural changes. Moreover, we highlight systematic differences in the impacts of greenspace exposure on PM_{2.5}-related premature deaths according to city deprivation level and location. For example, we show that greenspace usability exposure in richest urban regions affects mortalities most while greenspace availability exposure in richest rural regions affect mortalities most. These findings point to targeted opportunities for greenspace increment, such as construct informal green spaces to increase the per capita green space exposure of urban residents and increase the green patch area to alleviate the air pollution-related health impact of rural residents ¹⁵. But more importantly, our work offers a basis for greenspace planning policies that avoid and redress socioeconomic regional inequities. For urban regions, high concentration of urbanization makes it difficult to build large areas of greenspace, and the total amount of greenspace is no longer a major factor in improving the living environment of residents. We suggest that focus on improving the community proximity and quality of urban green space, and building roof gardens or other public open greenspace in the affluent urban regions to relieve the high-density population and increase the opportunities of greenspace exposure ⁵⁶. Such as Beijing inserting greenspace policy and the UK's 300-meter accessible natural green space plan ⁵⁸. For rural regions, the direct emissions from solid fuels burned by rural residents and the lack of

greenspace availability in residential clusters remind that we should increase the equity of rural residents' greenspace exposure and vigorously promote the use of clean energy^{7, 25, 59}. For example, in Kondo of USA, increasing the tree canopy cover made the poorer rural neighborhoods benefit more^{15, 58}. Since these changes must be borne by highly-deprived regions, consumption-based policies can better support the required technology transfer and capital investment^{7, 60}.

Our study is subject to several uncertainties and limitation from the use of multiple datasets and analyzing method. First, the IER model used in mortality estimates are uncertain due to that the adaptation degree of IER model to PM_{2.5}-related indexes in China is not clear yet⁶¹. Using concentration-response relationships based on local cohort studies would improve the accuracy in estimating of premature deaths in the future⁷. Second, deprivation level assessment is not comprehensive enough due to the lack of complete data of residential and crime rate statistics. Improvement of statistical data collection system or conducting field surveys could remedy this situation in the future. Third, multiple linear regression contributes to the uncertainties in estimating the relationship between greenspace exposure and PM_{2.5} related mortalities for each group. Explaining the cross-correlation among latent variables by structural equation model could improve the identification of correlation of greenspace exposure and premature mortalities in the future⁶².

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