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Original Research Article

Evolution in disparity of $PM_{2.5}$ pollution in China

Su Shi [a], Weidong Wang [a], Xinyue Li [a], Chang Xu [a], Jian Lei [a], Yixuan Jiang [a], Lina Zhang [a], Cheng He [a,b], Tao Xue [c], Renjie Chen [a], Haidong Kan [a], Xia Meng [a,d,*]

[a] School of Public Health, Key Laboratory of Public Health Safety of the Ministry of Education and Key Laboratory of Health Technology Assessment of the Ministry of Health, Fudan University, Shanghai 200032, China

[b] Institute of Epidemiology, Helmholtz Zentrum München–German Research Center for Environmental Health (GmbH), Munich D-85764, Germany

[c] Institute of Reproductive and Child Health/Ministry of Health Key Laboratory of Reproductive Health and Department of Epidemiology and Biostatistics, School of Public Health, Peking University Health Science Center, Beijing 100191, China

[d] Shanghai Typhoon Institute/CMA, Shanghai Key Laboratory of Meteorology and Health, Shanghai 200030, China

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ABSTRACT

The spatial disparity of air pollutants is one of the key influential factors for environmental inequality. We quantitatively evaluated the evolution of $PM_{2.5}$ spatial disparity in China during 2013–2020, and investigated the associations between $PM_{2.5}$ spatial disparity and economic indicators. Differences in $PM_{2.5}$ between more- and less-polluted cities declined over time, suggesting decreased absolute disparity. However, the more polluted cities in 2013 remained so in 2017 and 2020, and vice versa, indicating persistent relative disparity. $PM_{2.5}$ pollution levels increased with higher GDP per capita in less-developed areas of China, but such negative effects weakened over time, while economic development tended to promote cleaner air in developed areas of China. Therefore, policies to improve air quality and promote economic development simultaneously are needed in China to reduce the disparity of air pollution and promote all people to enjoy environmental equality.

1. Introduction

Fair treatment is one of the two components of environmental justice, which means no group of people should bear a disproportionate share of the negative environmental consequences [1]. Besides demographic characteristics, the spatial disparity of hazardous environmental factors contributes to exposure inequity among population. Fine particulate matter (particles of aerodynamic diameter $\leq$2.5 μm [$PM_{2.5}$]) is responsible for about 4.14 million deaths worldwide and is the fourth leading risk factor for death globally, according to estimates from the Global Burden of Disease (GBD) 2019 [2]. However, the global disease burden of $PM_{2.5}$ is unevenly distributed due to large inter- and intra-country variations in $PM_{2.5}$. For example, with rapid economic growth and urbanization, $PM_{2.5}$ concentrations in China and India are higher than in well-developed European and American countries [3]. In particular, China has suffered from severe $PM_{2.5}$ pollution, and the $PM_{2.5}$ concentrations show significant spatial variation within the country [4,5]. The spatial variation of $PM_{2.5}$ concentrations, which may be caused by regional differences in economic activity, emission sources, population density, and geophysical conditions, leads to disparity in the risk of exposure to $PM_{2.5}$ pollution [6]. To improve air quality and protect public health, China launched a series of clean air policies, including the Action Plan of Air Pollution Prevention and Control (APPC–AP) in 2013 and Three-year (2018–2020) Action Plan for Cleaner Air in 2017. By virtue of these policies, $PM_{2.5}$ concentrations have dropped significantly in China since 2013 [7,8]. However, few studies have evaluated temporal trends of the spatial disparity of $PM_{2.5}$ concentrations in China.

The spatial disparity of $PM_{2.5}$ concentrations may change over time due to clean air policies. For example, the gap between more- and less-polluted areas in the USA decreased from 1981 to 2016 with decreased absolute spatial disparity of $PM_{2.5}$, but the more- and less-polluted areas in 1981 remained so in 2016, as well as the relative disparity persisted [6]. Previous studies on air quality in China mainly focused on temporal trends in the reduction of $PM_{2.5}$ concentrations, nationwide or in city clusters [9–12]. For example, Xue et al. explored the trends in eight major city clusters and found that $PM_{2.5}$ in these regions decreased by 0.269–1.604 μg/m^3 per year from 2006 to 2017 [9]. Zhao et al. investigated the reduction of $PM_{2.5}$ in 269 Chinese cities from 2015 to 2016; most cities in eastern China saw a decrease in $PM_{2.5}$ concentration [4]. However, few studies have compared changes in spatial disparity of

* Corresponding author.
E-mail address: mengxia@fudan.edu.cn (X. Meng).

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$PM_{2.5}$ concentrations in China in the past few years, which would provide insight into environmental disparities and inform future clean air policies.

Air pollution levels can be influenced by economic development [1,13]. Individuals and communities of low socioeconomic status tend to be exposed to higher air pollution levels [1,14,15]. However, few studies have investigated associations between $PM_{2.5}$ spatial disparity and socioeconomic factors in China and yielded inconclusive results [5,16–18]. For example, Guo et al. reported that people living in areas with high residential property prices were exposed to high $PM_{2.5}$ levels in Shenzhen, China [17]. Huang et al. reported that poor and less-educated residents were exposed to a disproportionally high share of the pollution occurring in 2014 in Beijing, China [18]. Uneven geographic distributions of air quality measurements, as well as the low spatial resolution of economic data, hinder understanding of their relationship. With the development of modeling methodologies [19–22], estimates of air pollutants and economic data at high resolution, with full spatial coverage, will enable a nationwide analysis of the effect of economic development on the spatial disparity of $PM_{2.5}$ pollution.

Therefore, in this study, we aimed to evaluate temporal trends of the spatial disparity in $PM_{2.5}$ concentrations from 2013 to 2020, and their associations with socioeconomic factors in China based on full-coverage, high-resolution $PM_{2.5}$ estimates. First, we compared changes in $PM_{2.5}$ concentrations between more- and less-polluted regions at the city level to explore temporal trends of absolute and relative $PM_{2.5}$ spatial disparities. Second, we investigated the association between $PM_{2.5}$ spatial disparities and socioeconomic factors.

2. Methods

2.1. $PM_{2.5}$ predictions

$PM_{2.5}$ concentrations were predicted by random forest models at the daily scale and 1-km spatial resolution from 2013 to 2019 in Mainland China with full spatiotemporal coverage, as reported previously [23], and $PM_{2.5}$ concentrations in 2020 were predicted using the same methodology. Ground $PM_{2.5}$ measurements, Multi-Angle Implementation of Atmospheric Correction aerosol optical depth (MAIAC AOD), MERRA–2 simulated $PM_{2.5}$ concentrations, meteorological parameters, land-use data, and population density were used to develop the models. Given the high missing rate of AOD, a gap-filling method was applied to generate full-coverage $PM_{2.5}$ concentrations and reduce bias in exposure assessment following previous studies [24,25]. The overall 10-fold cross-validation R^2 and root-mean-square error (RMSE, defined as the standard deviation of model residuals) values of random forest model-predicted $PM_{2.5}$ and measurements from 2013 to 2020 were 0.85 and 15.29 μg/m^3; and the slope and intercept were 1.09 and −4.50 μg/m^3, respectively. The annual mean $PM_{2.5}$ concentration for each grid cell at 1 km × 1 km resolution was averaged from daily $PM_{2.5}$ concentrations. The APPC-AP was launched in 2013 and ended in 2017, and the Three-year Action Plan for Cleaner Air was implemented between 2018 and 2020. Therefore, we used 2013, 2017, and 2020 as the time points to analyze changes in $PM_{2.5}$ disparity.

2.2. Socioeconomic data

Several socioeconomic factors, including race, gross domestic product (GDP), household income, and tertiary industry, have been used to assess the effect of economic development and human activities on air pollutants [4,5,26–28]. In this study, considering the data availability, we used urban/rural classification and GDP data to indicate urbanization and economic development. Land-cover classification data for urban and rural regions, classified based on impervious surfaces with a 30-m resolution, were downloaded from http://data.ess.tsinghua.edu.cn to reflect urbanization development [29,30]. GDP data for 2010, 2015, and 2019 at 1-km resolution were downloaded from the Resource and Environmental Science Data Registration and Publication System (https://www.resdc.cn/DOI/) [22] and linearly interpolated to 2013, 2017, and 2020, to directly reflect economic development. Urban/rural and GDP data were matched or integrated into the 1-km grid cells. The disposable income per capita of cities was collected from the website of the statistics bureau of each city if the data were available. The expected targeted $PM_{2.5}$ reduction in the province in 2017, which was set in 2014, was collected from the official websites of provincial governments to represent the stringency of local policies, which was utilized in the previous study [31]. The total coal consumption at the city level was collected from China Energy Statistical Yearbook and Chinese Urban Statistical Yearbook to reflect the coal burning levels.

2.3. Temporal trends of $PM_{2.5}$ spatial disparities

Changes in $PM_{2.5}$ concentrations in 2013, 2017, and 2020 between more- and less-polluted regions were compared at the city level to explore the temporal trends of $PM_{2.5}$ spatial disparities. Considering the population exposure distributions, population-weighted $PM_{2.5}$ concentrations at the city level in 2013, 2017, and 2020 were calculated as follows:

$$PM_{POPi} = \left(\sum PM_{2.5ij} \times POP_{ij}\right) \Big/ \sum POP_{ij} \quad (1)$$

where i denotes city i; j denotes grid cell j spatially joint with city i; PM_{POPi} represents the population-weighted $PM_{2.5}$ concentration in city i; $PM_{2.5ij}$ and POP_{ij} represent the annual mean $PM_{2.5}$ concentration and the population at grid cell j within city i, respectively. Population density data at 1-km resolution were obtained from LandScan Global Population Database [32].

To assess changes in the absolute disparity of $PM_{2.5}$ pollution, the differences between the 99th–1st percentiles (P99–P1), 95th–5th percentiles (P95–P5), and 90th–10th percentiles (P90–P10) of $PM_{2.5}$ concentrations at the city level were calculated for each year from 2013 to 2020.

Additionally, changes in the relative disparities of $PM_{2.5}$ concentrations were explored. First, cities were ranked from lowest to highest according to their corresponding population-weighted $PM_{2.5}$ concentrations in 2013, 2017, and 2020. The ranks of the cities in 2013 and 2017, 2017 and 2020, and 2013 and 2020 were compared using linear regression to assess changes in the relative disparities of $PM_{2.5}$ pollution [6,33]. Second, a quantitative analysis of $PM_{2.5}$ relative disparity was conducted based on the Gini coefficient. The Gini coefficient was developed to measure the inequality of population wealth distribution [34]. It was subsequently used to examine disparities in the distributions of environmental pollutants [35–37]. The geographic distribution of $PM_{2.5}$ concentrations among cities in 2013, 2017, and 2020 was explored using the Gini coefficient. The cities were ranked from lowest to highest in terms of their population-weighted $PM_{2.5}$ concentrations, and the Gini coefficient was calculated as follows:

$$G = 1 - \sum (X_{k+1} - X_k)(Y_{k+1} + Y_k) \quad (2)$$

where G is the Gini coefficient; k represents the k^{th} city ranking by $PM_{2.5}$ concentration; X_k denotes the cumulative proportion of cities with fewer ranks than city k; and Y_k denotes the cumulative proportion of $PM_{2.5}$ concentrations in cities with fewer ranks than city k; when k is equal to 1, (X_k, Y_k) is (0, 0). The Gini coefficient ranges from 0 to 1, with 1 representing complete disparity and 0 represents complete parity. We plotted Lorenz curves to visualize the Gini coefficients, with the cumulative proportion of cities as the x-axis, and the cumulative proportion of the population-weighted $PM_{2.5}$ concentrations of corresponding cities as the y-axis. A diagonal Lorenz curve indicates complete parity.

Finally, the concentrations and percentages of $PM_{2.5}$ reductions at the city level from 2013 to 2020 were compared to help understand changes in the absolute and relative disparities of $PM_{2.5}$ pollution.

2.4. Associations between $PM_{2.5}$ spatial disparity and socioeconomic factors

To assess the associations between $PM_{2.5}$ spatial disparity and socioeconomic factors, the differences in $PM_{2.5}$ concentrations were compared between urban and rural areas.

Next, the associations between $PM_{2.5}$ spatial disparity and GDP per capita were assessed. Grossman and Krueger introduced the Environmental Kuznets Curve (EKC) to assess the association between economic development and environmental quality [38]. The EKC assumption is that in the early stage of economic development, environmental degradation increases in parallel with economic growth but decreases (while environmental quality increases) with economic growth after a certain point. Whether the EKC assumption is applicable to the relationship between $PM_{2.5}$ concentration and GDP per capita was tested. GDP and population values in grid cells inside the city boundary were summed and assigned to the corresponding city, and GDP per capita was calculated by dividing the GDP by the population values at the city level. The EKC model was established using the following formula:

$$PM_{i,t} = \alpha_0 + \beta_1 \times SES_{i,t} + \beta_2 \times (SES_{i,t})^2 + \varepsilon_{i,t} \tag{3}$$

where i represents the city i; t denotes the year (2013, 2017, or 2020); $PM_{i,t}$ is the mean $PM_{2.5}$ concentration for city i in year t; $SES_{i,t}$ denotes the value of GDP per capita for city i in year t; $(SES_{i,t})^2$ denotes the squared value of GDP per capita for city i in year t; α_0 is the intercept term; β_1 and β_2 are the coefficient estimates of regressors; and $\varepsilon_{i,t}$ denotes the error term. According to Eq. 3, the relationship between $PM_{2.5}$ level and GDP per capita can be explained as follows.

(1) If β_1 and $\beta_2 = 0$, there is no relationship between $PM_{2.5}$ and GDP per capita.
(2) If $\beta_1 > 0$, $\beta_2 = 0$, there is a positive monotonic relationship between $PM_{2.5}$ and GDP per capita.
(3) If $\beta_1 < 0$, $\beta_2 = 0$, there is a negative monotonic relationship between $PM_{2.5}$ and GDP per capita.
(4) If $\beta_1 > 0$, $\beta_2 < 0$, there is an inversed U-shaped relationship between $PM_{2.5}$ and GDP per capita.
(5) If $\beta_1 < 0$, $\beta_2 > 0$, there is a U-shaped relationship between $PM_{2.5}$ and GDP per capita.

To further examine the correlation between $PM_{2.5}$ concentrations, GDP levels, targeted $PM_{2.5}$ reduction, and coal burning, the Spearman correlation coefficients were calculated.

2.5. Sensitivity analysis

We conducted several sensitivity analyses to validate our findings. For exploring $PM_{2.5}$ disparity, we used population-weighted $PM_{2.5}$ predictions at the provincial level, arithmetic averaging of $PM_{2.5}$ predictions, and averaged $PM_{2.5}$ measurements at the city level from national monitoring stations to present the $PM_{2.5}$ pollution levels to evaluate the changes in absolute and relative disparity of $PM_{2.5}$. For exploring the association between $PM_{2.5}$ pollution levels and economic development, we tested the association between $PM_{2.5}$ concentrations and GDP per capita at the provincial level; we used disposable income per capita to represent the economic development instead; meanwhile, we tested the association between $PM_{2.5}$ concentrations and GDP per capita in 2010, 2015, and 2019 without interpolation of GDP data.

3. Results

3.1. Temporal trends of $PM_{2.5}$ spatial disparity in China in 2013–2020

$PM_{2.5}$ concentrations have decreased markedly in China since 2013. Fig. 1a and b shows the spatial distributions of predicted annual mean $PM_{2.5}$ concentrations in 2013 and $PM_{2.5}$ reductions from 2013 to 2020, respectively, at 1 km × 1 km spatial resolution. The annual mean $PM_{2.5}$ concentration decreased from 55.71 ± 17.92 μg/m^3 in 2013 to 39.75 ± 17.68 μg/m^3 in 2017, and then to 28.74 ± 15.10 μg/m^3 in 2020, according to the high-resolution predictions. Areas with high levels of $PM_{2.5}$ pollution decreased, and areas with middle levels of $PM_{2.5}$ pollution increased (Fig. 1c). The percentages of grid cells with $PM_{2.5}$ concentrations higher than the interim target 1 (35 μg/m^3) recommended by the WHO [39] decreased from 90.39% in 2013 to 47.30% in 2017, and then to 23.17% in 2020. The percentages of grid cells with $PM_{2.5}$ concentrations between 10 μg/m^3 (recommended by WHO in 2005 [40]) and 35 μg/m^3 increased from 9.61% in 2013 to 52.70% in 2017, and then to 75.57% in 2020. During 2013–2020, none of the grid cells with $PM_{2.5}$ concentrations reached the air quality guidelines (5 μg/m^3) recommended by WHO in 2021 [39].

The gap in $PM_{2.5}$ concentrations between more- and less-polluted areas narrowed, suggesting a decline in the absolute disparity in $PM_{2.5}$ pollution. Fig. 1d shows the difference of the P99–P1, P95–P5, and P90–P10 of $PM_{2.5}$ concentrations at the city level from 2013 to 2020. The difference of P99–P1 of $PM_{2.5}$ concentrations decreased from 76.63 μg/m^3 in 2013 to 49.43 μg/m^3 in 2017, and to 45.48 μg/m^3 in 2020. The difference in the P95–P5 and P90–P10 of the $PM_{2.5}$ concentrations at the city level showed similar trends, and the difference of P95–P5 decreased from 64.51 μg/m^3 in 2013 to 33.95 μg/m^3 in 2020, while that of P90–P10 decreased from 46.21 μg/m^3 in 2013 to 28.53 μg/m^3 in 2020.

More- and less-polluted cities in 2013 tended to remain so in 2017 and 2020, indicating the persistence of the relative disparity in $PM_{2.5}$ pollution over time. Fig. 2 shows the ranks of cities according to $PM_{2.5}$ concentration in 2013 against 2017 (a), in 2017 against 2020 (b), and in 2013 against 2020 (c). The R^2 values in Fig. 2a–c were 0.89, 0.92, and 0.83, respectively, with statistical significance ($P < 0.0001$). Regression analysis showed that the relative ranks for air pollution levels remained stable among cities from 2013 to 2020. Fig. 2d shows Lorenz curves between the cumulative proportions of cities and the cumulative proportion of population-weighted $PM_{2.5}$ concentrations thereof in 2013, 2017, and 2020. The Gini coefficient was 0.17 in 2013, 0.17 in 2017, and 0.19 in 2020. In 2013, 2017, and 2020, the $PM_{2.5}$ concentrations in 60.95%, 56.51%, and 89.35% of all cities were higher than the national average $PM_{2.5}$ concentration of that year (2013, 55.71 μg/m^3; 2017, 39.75 μg/m^3; 2020, 28.74 μg/m^3), respectively. The Gini coefficients and Lorenz curves supported the persistence of the relative disparity in $PM_{2.5}$ pollution, which tended to increase from 2013 to 2020.

The decline of $PM_{2.5}$ was proportional at the city level, possibly explaining the persistence of the relative disparity. Fig. 3a shows that $PM_{2.5}$ concentrations in cities with higher pollution levels in 2013 decreased more from 2013 to 2020, respectively, and vice versa for cities with lower pollution. The values of reductions of $PM_{2.5}$ concentrations increased at a rate of 0.0861 μg/m^3 per rank (95% confidence interval [CI]: 0.0803, 0.0918) during 2013–2020. Fig. 3b shows that percentages of $PM_{2.5}$ reductions were comparable across cities from 2013 to 2020 with the coefficient not statistically significant.

Results from sensitive analysis based on population-weighted $PM_{2.5}$ predictions at the provincial level (Figs. S1–S2), arithmetic averaging of $PM_{2.5}$ predictions at the city level (Figs. S3–S4), and averaged $PM_{2.5}$ measurements at the city level (Figs. S5–S6) validated the findings that the absolute disparity in $PM_{2.5}$ pollution has decreased, and the relative disparity has persisted over time.

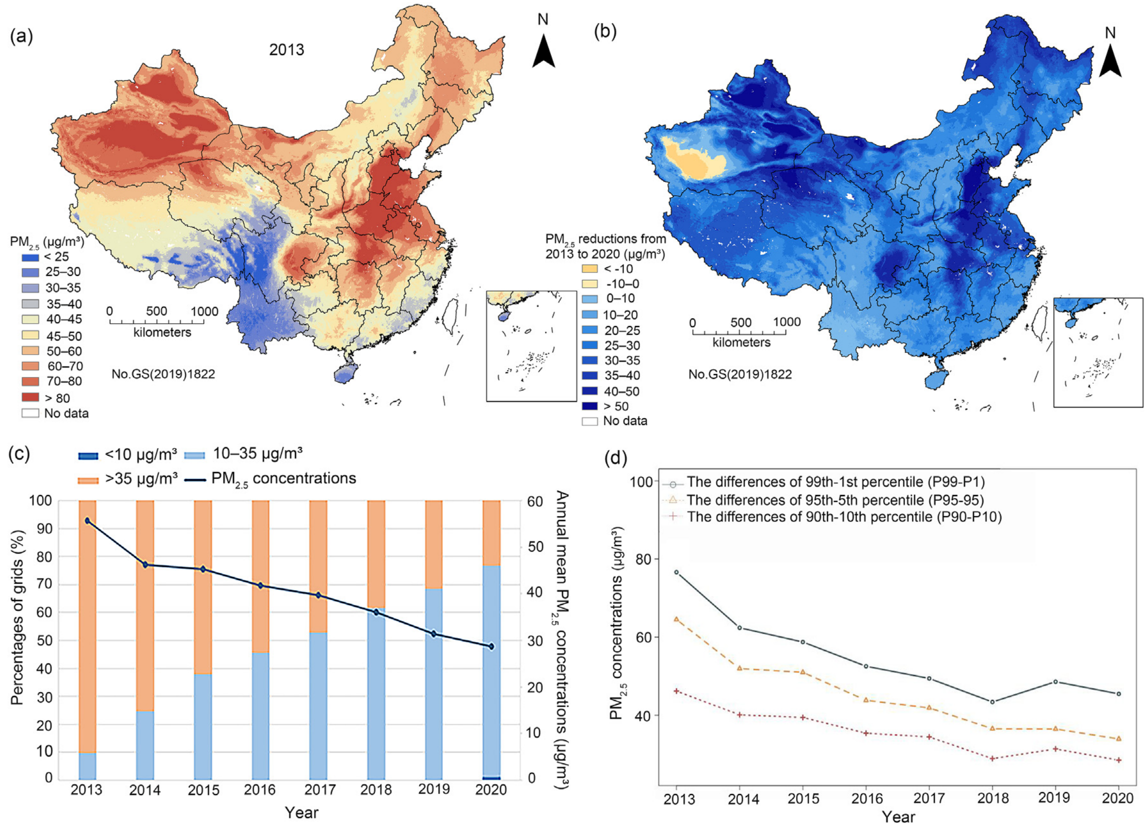

Fig. 1. The spatial distributions of predicted annual mean $PM_{2.5}$ concentrations in Mainland China in 2013 (a); the spatial distributions of $PM_{2.5}$ reductions from 2013 to 2020 (b); percentages of grid cells with $PM_{2.5}$ concentrations less than 10 μg/m^3, between 10 μg/m^3 and 35 μg/m^3, higher than 35 μg/m^3, and the annual mean $PM_{2.5}$ concentration for each year from 2013 to 2020 based on $PM_{2.5}$ predictions in China (c); differences of P99–P1 (blue line), P95–P5 (yellow line), and P90–P10 (red line) of $PM_{2.5}$ concentrations at the city level during 2013–2020 (d).

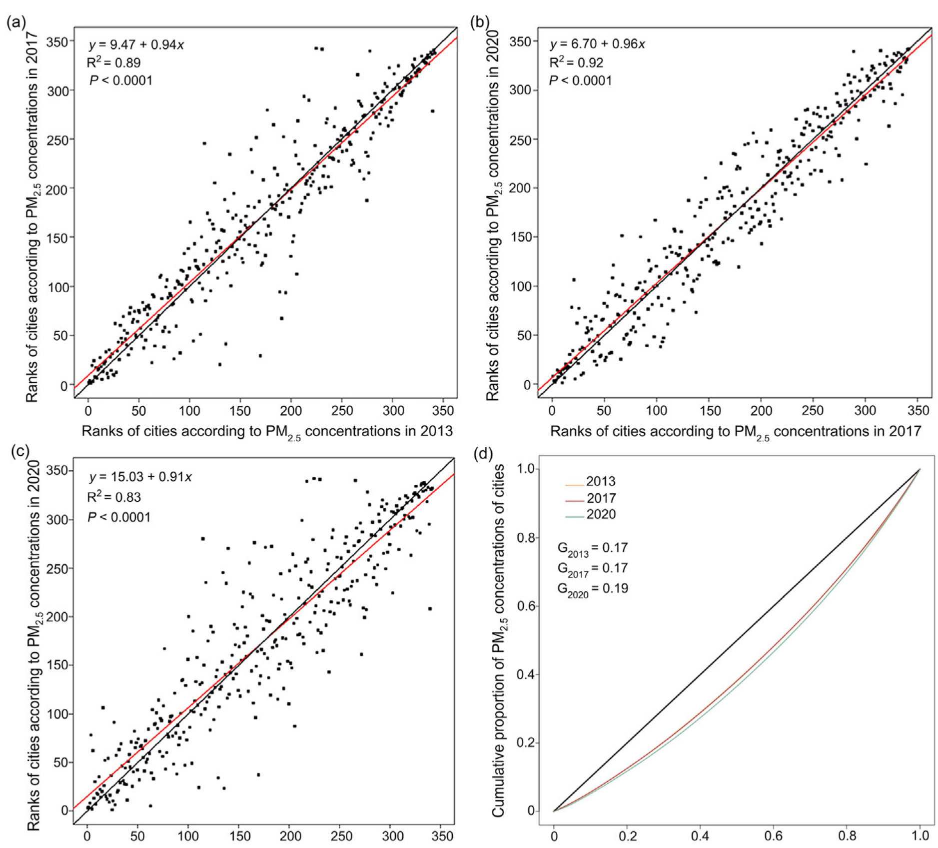

Fig. 2. Regressions between the ranks of cities according to $PM_{2.5}$ concentration in 2013 against 2017 (a), in 2017 against 2020 (b), and in 2013 against 2020 (c), and Lorenz curves between the cumulative proportions of cities and the cumulative proportion of the population-weighted $PM_{2.5}$ concentrations thereof in 2013 (yellow line), 2017 (red line), and 2020 (blue line) (d). The black line is a 1:1 line in (a–c) and indicates complete parity in (d).

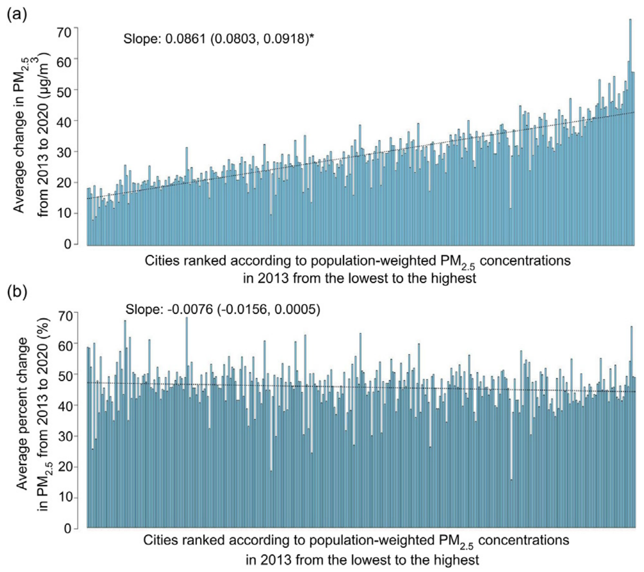

Fig. 3. Values (a) and percentages (b) of reductions of the population-weighted $PM_{2.5}$ concentrations from 2013 to 2020 at the city level. The columns from left to right in x-axis are cities ranked according to population-weighted $PM_{2.5}$ concentrations in 2013 from the lowest (31.04 $\mu g/m^3$) to the highest (113.08 $\mu g/m^3$). * is statistical significance at the 5% level.

3.2. Associations between $PM_{2.5}$ disparities and socioeconomic factors

$PM_{2.5}$ concentrations in urban regions were higher than in rural regions from 2013 to 2020. The annual mean $PM_{2.5}$ concentrations in urban and rural regions from 2013 to 2020 are shown in Fig. S7. Although the $PM_{2.5}$ concentrations in urban and rural areas decreased significantly, urban regions had persistently higher $PM_{2.5}$ concentrations than rural regions. For example, the annual mean $PM_{2.5}$ concentrations in urban and rural areas were 60.45 $\mu g/m^3$ and 55.89 $\mu g/m^3$ in 2013, as well as 32.60 $\mu g/m^3$ and 28.76 $\mu g/m^3$ in 2020, respectively.

Fig. 4 shows the curves between $PM_{2.5}$ concentration and absolute values of GDP per capita in 2013, 2017, and 2020. $PM_{2.5}$ concentrations were positively associated with GDP per capita in areas with lower GDP levels, whereas the slope of their relationship was flat in economically well-developed regions. In general, as GDP per capita increased, the $PM_{2.5}$ concentration first increased and then plateaued. However, the curve decreased slightly in economically well-developed regions in 2020. Overall, there is an inverted U-shaped relationship between $PM_{2.5}$ and GDP per capita. Temporally, the positive slopes in the first stages of the curves in regions with lower socioeconomic status decreased from 2013 to 2020.

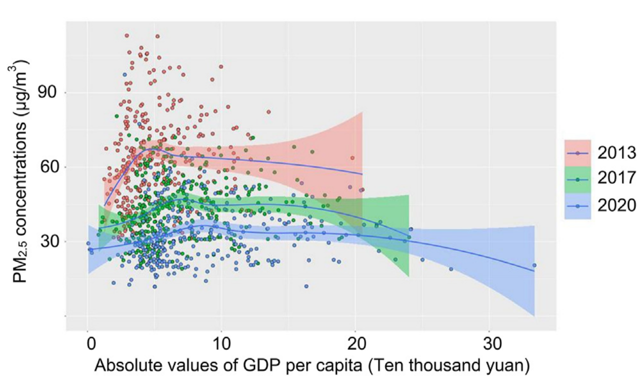

Fig. 4. The associations between $PM_{2.5}$ concentrations and absolute values of GDP per capita in 2013 (red points), 2017 (green points), and 2020 (blue points) at the city level.

The spatial disparities of $PM_{2.5}$ concentrations were significantly related to economic indicators. Table 1 shows the simulated $PM_{2.5}$ concentrations and GDP per capita at the city and provincial levels in 2013, 2017, and 2020 under the EKC assumption. The β_1 (coefficient of GDP per capita values) was 1.38, and the β_2 (coefficient of the square of GDP per capita values) was −0.05 in 2020 at the city level. The $PM_{2.5}$ concentrations and GDP per capita values at the city level in 2013 and 2017, and at the provincial level in 2013, 2017, and 2020 showed similar patterns, with positive values of β_1 and negative values of β_2 (Table 1). According to the EKC hypothesis, a positive value of β_1 and a negative value of β_2 indicate an inverted U-shaped curve between $PM_{2.5}$ concentration and GDP per capita in China.

The directions of β_1 and β_2 at the provincial level are similar to those at city levels, but without statistical significance, probably due to the small amount of data points (Table 1, Fig. S8). Results from sensitive analysis based on disposable income per capita (Fig. S9), as well as GDP per capita in 2010, 2015, and 2019 (Fig. S10, Table S1), have validated the findings that the relationship between $PM_{2.5}$ pollution and socioeconomic factors tended to be an inverted U-shape in China.

Table S2 shows the Spearman correlation coefficients between $PM_{2.5}$ concentrations, GDP levels, targeted $PM_{2.5}$ reduction (indicating stringency of local policies), and coal burning. The correlation coefficients between $PM_{2.5}$ and local policies ranged from 0.63 to 0.64, while between $PM_{2.5}$ and coal consumption ranged from 0.27 to 0.28. The correlation coefficients between GDP per capita and local policies ranged from 0.56 to 0.59, while between GDP per capita and coal consumption ranged from 0.60 to 0.65.

4. Discussion

We quantitatively evaluated temporal trends of the spatial disparity in $PM_{2.5}$ concentrations and their associations with socioeconomic factors in China based on full-coverage, high-resolution $PM_{2.5}$ predictions from 2013 to 2020. The gap in $PM_{2.5}$ concentrations between more- and less-polluted cities decreased, indicating that the absolute disparity has decreased over time. However, cities with high $PM_{2.5}$ pollution levels in 2013 also had high levels in 2017 and 2020, and vice versa, indicating that the relative disparity persisted. The $PM_{2.5}$ concentrations in urban regions were higher than in rural ones from 2013 to 2020. There is a weak inverted U-shaped relationship between $PM_{2.5}$ pollution and economic development in China.

The absolute disparity of the $PM_{2.5}$ distribution has decreased in China. This could be attributed to the more substantial decline of $PM_{2.5}$ in high-pollution areas compared to low-pollution areas (as shown in Fig. 3a). This trend might be a result of the implementation of stringent air pollution control policies, such as the APPC-AP and Three-year Action Plan for Cleaner Air, which placed significant emphasis on reducing emissions and pollutant concentrations in regions across China that experience high ambient air pollution levels [9,41–43]. The high correlation between local policies and $PM_{2.5}$ pollution levels quantificationally supported that areas with severe $PM_{2.5}$ pollution adopted more rigorous measures to combat air pollution. Consequently, the decline in $PM_{2.5}$ levels in high-pollution areas

Table 1
The regression results between $PM_{2.5}$ concentrations and GDP per capita at the city and provincial levels in 2013, 2017, and 2020, respectively.

Variables	GDP per capita at the city level			GDP per capita at the provincial level		
	2013	2017	2020	2013	2017	2020
Intercept	48.79**	32.00**	25.67**	42.04*	32.48**	24.61**
β_1	4.04**	2.54**	1.38**	5.09	1.86	1.28
β_2	−0.21**	−0.11**	−0.05**	−0.20	−0.05	−0.03

β_1 denotes the coefficient of GDP per capita values; β_2 denotes the coefficient of the square of GDP per capita values. ** is statistical significance at the 5% level; * is statistical significance at the 10% level.

has been greater than in low-pollution areas, which could explain the reduction in absolute disparity observed in this study.

The relative disparity of $PM_{2.5}$ pollution has persisted in China from 2013 to 2020, which meant that cities with high $PM_{2.5}$ pollution levels in 2013 also had high levels in 2017 and 2020, and vice versa. We found that although cities with higher $PM_{2.5}$ levels had higher reductions, all these cities have comparable reduction proportions in $PM_{2.5}$ pollution levels. Therefore, cities with higher $PM_{2.5}$ levels in 2013 still tended to have leading $PM_{2.5}$ pollution levels in 2020. Furthermore, $PM_{2.5}$ pollution levels might be attributed to economic activity, emission sources, population density, and geophysical conditions [6]. Anthropogenic emissions (e.g., emissions from industry, power plants, traffic, and residents) would be high to satisfy the needs of economic development and residential routines in these regions with dense populations and industries [5,27], leading to the persistence of relative disparity.

$PM_{2.5}$ concentrations in urban regions were persistently higher than in rural ones, as reported previously [5,44]. Due to rapid urbanization, the urban proportion of the Chinese population increased from 54.49% in 2013 to 63.89% in 2020, and the risk of $PM_{2.5}$ exposure was redistributed between urban and rural regions [45]. Thus, residents of urban areas are more likely to be exposed to high $PM_{2.5}$ levels, likely leading to a higher disease burden attributable to $PM_{2.5}$ pollution than in rural areas. The State of Global Air, focusing on urban air pollution and health, reported that 15 of the 20 cities with the highest death rates attributable to $PM_{2.5}$ exposure worldwide are from China, which has highlighted the threats from air pollution in urban residents in China [46]. Additionally, the State of Global Air reported that about 68 percent of the world's population will live in urban areas by 2050. Therefore, continuous improvement of air quality in urban regions could decrease spatial disparity of $PM_{2.5}$ exposure and benefit more people in the context of urbanization in the future.

We found the relationship between $PM_{2.5}$ pollution and socioeconomic factors tended to be an inverted U-shape in China, suggesting that economic development deteriorates air quality at the beginning and further economic development promotes the improvement of air quality after reaching a plateau, a phenomenon that is consistent with the Environmental Kuznets Curve. Our findings were consistent with previous studies [4,5]. The inverted U-shaped relationship might be explained by the complicated associations between economic development and environmental quality. For example, first, in the early stage of economic growth, governments and residents focus on how to escape poverty and achieve rapid economic growth; therefore, their environmental awareness is low. Second, limited by low productivity and technological development, environmental quality is typically sacrificed in exchange for economic development and improved living standards. Third, when economic development reaches a certain threshold, environmental quality can be improved by technological development, enhanced production efficiency, use of clean energy, government regulations, public awareness of environmental protection, and other factors [38]. We found that targeted $PM_{2.5}$ reduction was highly related to both local GDP levels and $PM_{2.5}$ pollution levels, which indicated that economic development may facilitate the implementation of stringent policies in areas with severe $PM_{2.5}$ pollution and therefore contributed to the second stage in the inverted U-shape in China. Specially, the association between $PM_{2.5}$ concentration and disposable income per capita exhibited a weaker inverted U-shape compared to that observed between $PM_{2.5}$ concentration and GDP per capita. This difference may be attributed to the limited number of cities with available income data at the city level included in the analysis, and the included cities were not consistent in the three years. Consequently, future validation is needed when the income data becomes available in more cities.

Temporally, we found that the negative relationship between economic development and air quality in less-developed areas has been weakened. This change is probably attributed to the extension of areas implementing air quality policies [47]. The APPC-AP implemented in 2013 designated the Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Pearl River Delta as key regions. Subsequently, the Three-year Action Plan for Cleaner Air implemented in 2018 extended its focus to include the Fen–Wei Plain and introduced target planning for cities that had not yet met the $PM_{2.5}$ standards [5]. Therefore, more areas have benefited from the intervention of air quality control policies. However, the negative association between air quality and economic development still exists, suggesting that policies for economic development and air pollution control need to be considered simultaneously to improve air quality and minimize spatial disparities, thereby protecting public health from $PM_{2.5}$ pollution and preventing exposure inequalities. Advanced air pollution control in economically developed regions could provide helpful experiences to improve air quality in less economically developed regions of China in the next stage.

This study had several limitations. First, high-resolution GDP data were available only for 2010, 2015, and 2019, and their interpolation to other years may introduce uncertainty. However, we tested the relationship between $PM_{2.5}$ and GDP per capita in 2010, 2015, and 2019. The results were similar to our main findings. Thus, the conclusion should not be changed by the interpolation of GDP data. Second, the association between air quality and economic development established in this study is assumed to have some uncertainty. On the one hand, we used GDP per capita and disposable income per capita as indicators of economic development, which could not provide a comprehensive picture of economic development. On the other hand, some influential factors, such as the natural source of $PM_{2.5}$ or sandstorm, may affect the association but was not considered in this study without source appointment to quantify the contribution of natural source to $PM_{2.5}$ concentrations. More studies, including more indicators of economic development and influential factors, are needed to further validate our findings. Third, the targeted $PM_{2.5}$ reduction used in this study at the provincial level was set during the APPC-AP period. As local policies may have changed during the period from 2018 to 2020, the targeted $PM_{2.5}$ reduction used in this study might not entirely reflect the stringency of local policies. Fourth, the analysis was based on ambient $PM_{2.5}$ concentrations, which may not represent personal exposure to $PM_{2.5}$ pollution unless indoor exposure scenarios are considered. Therefore, the results should be explained with caution when it comes to personal exposure.

5. Conclusion

The gap in $PM_{2.5}$ concentrations between more- and less-polluted cities decreased from 2013 to 2020, indicating that absolute disparity has decreased over time. However, cities with high $PM_{2.5}$ levels in 2013 retained them in 2017 and 2020, and vice versa for cities with low levels, indicating that relative disparity has persisted. There is a weak inverted U-shaped relationship between the spatial disparity of $PM_{2.5}$ pollution and economic development in China. The spatial disparity of air pollution might contribute to exposure inequality; therefore, policies to reduce the disparity are needed to protect health from the deleterious effects of air pollution and promote all people to enjoy environmental equality in China.

Author contributions

S.S.: methodology, formal analysis, validation, writing–original draft, writing–review & editing, visualization. W.D.W.: methodology, data curation. X.Y.L., C.X., L.N.Z., C.H.: data curation. J.L., Y.X.J.: methodology. T.X., R.J.C.: supervision, writing–original draft. H.D.K.: supervision, funding acquisition, resources, writing–original draft. X.M.: conceptualization, methodology, supervision, funding acquisition, resources, writing–original draft, writing–review & editing.

Data sharing statement

The $PM_{2.5}$ dataset at 1-km resolution from 2013 to 2020 is available from the corresponding author upon reasonable request. Population density data at 1-km resolution were available from LandScan Global Population Database [32]. Land-cover classification data for urban and rural regions, classified based on impervious surfaces with a 30-m resolution, were available from http://data.ess.tsinghua.edu.cn [29,30]. GDP data for 2010, 2015, and 2019 at 1-km resolution were available from the Resource and Environmental Science Data Registration and Publication System (https://www.resdc.cn/DOI/) [22].

Declaration of competing interests

The authors declare that they have no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eehl.2023.08.007.

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