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Changes in $PM_{2.5}$-related health burden in China's poverty and non-poverty areas during 2000–2020: A health inequality perspective

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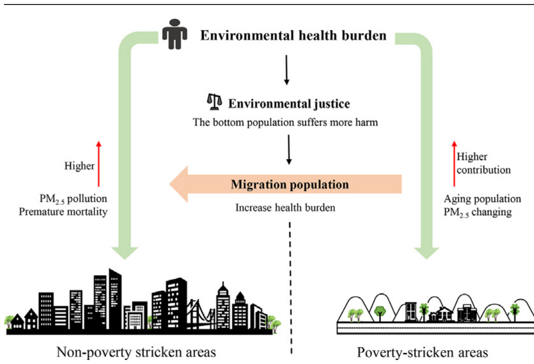
HIGHLIGHTS

- $PM_{2.5}$-related deaths increased initially and then decreased during 2000–2020.
- Populations of low socioeconomic status suffer more from $PM_{2.5}$-related deaths harm.
- Population migration from PAs to developed cities contributed to premature deaths.
- Population aging amplified the $PM_{2.5}$ health burden.

GRAPHICAL ABSTRACT



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ABSTRACT

China suffers from severe $PM_{2.5}$ pollution that has resulted in a huge health burden. Such $PM_{2.5}$-related health burden has long been suspected to differ between China's poverty-stricken areas (PAs) and non-poverty-stricken areas (NPAs). Yet, evidence-based examination of this long-held belief, which is critical as a barrier of environmental injustice to advancing China's sustainability, is still missing. Here our study shows that the $PM_{2.5}$ pollution is more serious in China's NPAs than PAs—with their annual averages being respectively 54.83 $\mu g/m^3$ and 43.63 $\mu g/m^3$—causing higher premature mortality in the NPAs. Compared to economic inequality, China's total $PM_{2.5}$-related premature mortality was relatively evenly distributed during 2000–2015 across regions of varying levels of gross domestic product (GDP) per capita but increased slightly in 2015–2020 owing to the dramatic change in age structure. The elderly population increased by 31 %. $PM_{2.5}$-related premature deaths were more severe for populations of low socioeconomic status, and such environmental health inequalities could be amplified by population aging. Additionally, population migration from China's PAs to developed cities contributed to 638, 779, 303, 954, and 896 premature deaths in 2000, 2005, 2010, 2015, and 2020, respectively. Changes in the age structure (53 %) and $PM_{2.5}$ concentration (28 %) had the greatest impact on premature deaths, followed by changes in population (12 %) and baseline mortality (8 %). The

Abbreviations: BTH, Beijing-Tianjin-Hebei; COPD, chronic obstructive pulmonary disease; GDP, gross domestic product; IER, integrated exposure response; IHD, ischemic heart disease; LC, lung cancer; NPAs, non-poverty-stricken areas; NRPAs, non-relative poverty areas; PAs, poverty-stricken areas; PRD, Pearl River Delta; RPAs, relative poverty areas; RR, relative risk; YRD, Yangtze River Delta.

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contribution rate of changes in the age structure and $PM_{2.5}$ concentration was higher in PAs than in NPAs. Our findings provide insight into $PM_{2.5}$-related premature death and environmental inequality, and may inform more equitable clean air policies to achieve China's sustainable development goals.

1. Introduction

Fine particulate matter less than 2.5 μm in diameter ($PM_{2.5}$) is now a major environmental factor contributing to the global disease burden (Southerland et al., 2022). An estimated global total of 4.1 million deaths, 7.3 % of global deaths in 2019, were attributed to $PM_{2.5}$ exposure (Murray et al., 2020). For China, particularly, its rapid urbanization and industrialization have resulted in even more severe $PM_{2.5}$ pollution, leading to significant impacts on human health (Geng et al., 2021; McDuffie et al., 2021; Xue et al., 2022; Yue et al., 2020). In fact, China's ambient air pollution is the fourth leading risk factor for its premature mortality (Han et al., 2022), having caused >1 million premature deaths per year in the recent years (Hong et al., 2019).

In developed countries, the poor and disadvantaged minorities are systematically exposed to high levels of environmental harms (Kopas et al., 2020). Similar to the uneven exposure to pollution among minorities and poor households in the United States, India's air pollution from coal-fired power plants is heavily concentrated in poor and low-caste communities (Kopas et al., 2020). In Italy, environmental justice issues are not perceived in racial and ethnic terms, but in terms of social categories and the gender composition of households (Germani et al., 2014). In China, a large gap in the level of development exists between different regions, and relatedly, the distribution of polluting enterprises is notably unbalanced across China (Liu et al., 2021b; Ma, 2010b). To date, most studies about environmental pollution and health have focused on the more developed large cities and urban-rural gaps (Chan and Yao, 2008; Lin et al., 2021; Shan et al., 2020; Zhao et al., 2018), but few have examined the environmental pollution and health burden differences between the poverty and non-poverty areas in China. The air pollution caused by China's uneven economic development may have an unequal impact on the entire population (Liu et al., 2021a). As a main environmental factor affecting health, pollution increases the level of health inequality (Yang and Liu, 2018). However, there are few studies analyzing China's environmental health from the perspective of environmental inequality, and it remains unknown how the health effects of $PM_{2.5}$ are distributed among different economic groups.

Population migration could cause changes in the environmental health burden (Shen et al., 2018). Population migration from rural to urban areas owing to urbanization has played a positive role in rural poverty reduction (Pryce et al., 2021; Zhang et al., 2022). Over 290 million people have moved to urban areas in the past three decades (Zhang et al., 2022). Previous studies have shown that 79–98 % of the increase in urban population affected by $PM_{2.5}$ was attributable to rural-urban migration (He et al., 2016). Most of China's migration population prefers to live in modern Chinese cities that are usually heavily polluted, thus suffers from more serious $PM_{2.5}$ health exposure (Schoolman and Ma, 2012), and population aggregation will increase the health burden (Lin et al., 2021; Liu et al., 2021c). Owing to a limited amount of data, research on the relationship between $PM_{2.5}$ pollution and migrant health in China is limited, and existing estimates of migrant health focus on interprovincial migration (Lin et al., 2021; Liu et al., 2021c; Shen et al., 2018). Few studies have examined the health burden of migrants from poverty-stricken areas to developed cities. In the above context, this study aims to examine the $PM_{2.5}$-related health burden caused by population migration from poverty-stricken areas to developed cities in China at the city and county levels.

Importantly, China's population aging, in addition to population migration, has also contributed significantly to its $PM_{2.5}$-related health burden and premature deaths (Geng et al., 2021; Yue et al., 2020). China's aging population increases the number and proportion of at-risk population groups exposed to $PM_{2.5}$ (Xu et al., 2021). Populations are more vulnerable to air pollution when they exceed a reduced age-standardized baseline mortality rate (Geng et al., 2021). A robust and comprehensive understanding of the spatiotemporal dynamics of premature deaths and the relative contributions of drivers on a long-term scale is urgently needed to better mitigate $PM_{2.5}$-related health burden and to guide future air pollution policymaking in China.

Here with more accurate city-level population data and age structure data, we conducted a long-term scale analysis of China's $PM_{2.5}$-related health burden from 2000 to 2020. To our best knowledge, this is the first comparative analysis about the $PM_{2.5}$-related health burden of PAs and NPAs in China on a long-term scale. We quantified the corresponding health disparities at the municipal level using a Gini coefficient based on mortality from a health inequality perspective. We also quantified the impact on $PM_{2.5}$-related premature deaths from the perspective of population aging and migration. Our research questions include: (1) How did the mortality burden due to long-term $PM_{2.5}$ exposure differ between China's poverty-stricken areas (PAs) and non-poverty stricken areas (NPAs), and relatedly, how has the inequality evolved from 2000 to 2020 in China? (2) To what extent has China's population migration from PAs to developed cities contributed to $PM_{2.5}$-related health burden? (3) How did changes in population, age structure, baseline mortality, and $PM_{2.5}$ variously contributed to the premature deaths of PAs and NPAs?

2. Materials and methodology

2.1. Study area

In this study, we considered two types of poverty areas; absolute poverty areas and relative poverty areas. In the first type, we included 832 poverty counties identified by the State Council Leading Group Office of Poverty Alleviation and Development, referred to in our study as PAs [Fig. 1(a)]. This type covered 22 provinces and accounted for 44 % of mainland China. The second type was determined by the GDP per capita at the municipal level and GDP per capita at the provincial level. When the GDP per capita at the municipal level was always lower than the GDP per capita at the provincial level in 2000–2020, the areas were referred to as relative poverty areas (RPAs), including 177 cities [Fig. 1(b)]. This type accounted for 51 % of mainland China. The study area included mainland China, while excluding Taiwan, Hong Kong, and Macao.

2.2. Data sources

Data on the resident population and age structure at the municipal level are from the National Institute of Statistics, for 2000, 2010, and 2020 are from the provincial census data, and for 2005 and 2015 are from the 1 % Population Sampling Survey Data (NBSC, 2022). Satellite-derived $PM_{2.5}$ concentration data of 1 km^2 grid cells were collected from the ChinaHighAirPollutants (CHAP) database (Wei et al., 2020, 2021), which can be downloaded from https://doi.org/10.5281/zenodo.3539349. The county-to-county RMW migration data for 2010 were obtained from Shen's research (Shen et al., 2018). Population data of 1 km^2 grid cells used the LandScan population datasets of 2000, 2005, 2010, 2015, and 2019, which are downloaded from https://landscan.ornl.gov/landscan-datasets. The original disease-specific baseline mortality data in different years were obtained from the Global Burden of Disease (GBD) database (https://vizhub.healthdata.org/gbd-results/), and the mortality data in 2019 were used to replace the mortality data of 2020 due to data unavailability. The data of GDP, per capita GDP, average salary of employees, investment in fixed assets, number of students in regular colleges and

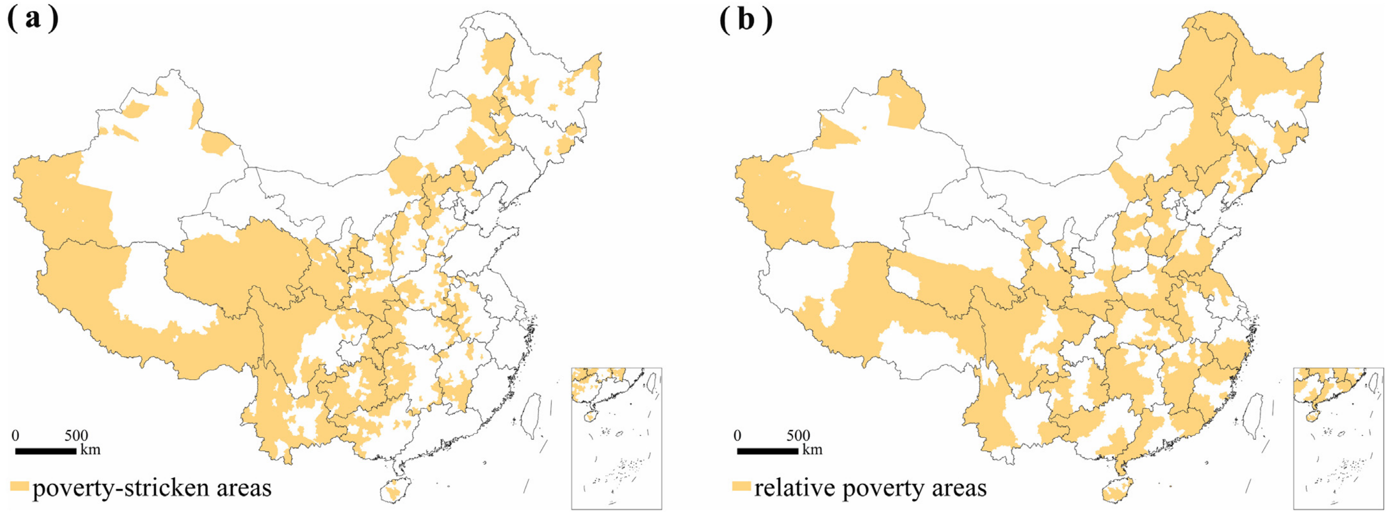

Fig. 1. The research area of this study. (a) Poverty-stricken areas. (b) Relative poverty areas.

universities, passenger traffic, regional area, and population density of each city are obtained from the Chinese Statistic Yearbook (NBSC, 2022).

2.3. Research methods

2.3.1. Estimating deaths attributable to $PM_{2.5}$ pollution

To quantify the environmental health burden of each city exposed to $PM_{2.5}$, we applied the integrated exposure response (IER) model to calculate premature deaths due to $PM_{2.5}$ (Burnett et al., 2014). Many previous studies have used this method to estimate deaths attributable to $PM_{2.5}$ pollution (Lin et al., 2021; Liu et al., 2016; Liu et al., 2021c; Lu et al., 2019). In this study, premature deaths was determined by four factors: population, age structure, disease-specific death rates, and the attributable fraction (*AF*). The premature deaths and premature mortality were calculated according to a formula, as follows:

$$\Delta M_{i,t} = \sum_{i,a,d}\left(Pop_{i,t} \times AgeP_{i,a,t} \times Rate_{i,a,d,t} \times AF_{i,d,t}\right) \tag{1}$$

$$\Delta M_{i,t}^{'} = \frac{\Delta M_{i,t}}{Pop_{i,t}} \times 100,000 \tag{2}$$

where ΔM_t and $\Delta M_t^{'}$ are premature deaths and premature mortality (/ 100,000) for a specific disease attributable to $PM_{2.5}$ exposure in year *t*, *Pop* refers to the population after correcting for census data, *AgeP* refers to the age group ratio, *Rate* refers to the baseline mortality, *AF* refers to the attributable factor, *i* refers to the grid cell, *a* refers to the age group, and *d* refers to the disease. The age structure is divided into three categories: 0–14 years old, 15–64 years old, and 65 years old and above. The most common non-communicable diseases in China are associated with $PM_{2.5}$, including chronic obstructive pulmonary disease (COPD), ischemic heart disease (IHD), lung cancer (LC), and stroke (Zhou et al., 2016). Grids in the same city have shared age structures. The *Rate* and *AF* were calculated using the method described in Section S1 of the supplementary material.

2.3.2. Analyzing environmental inequality

In this study, we estimated environmental and economic inequalities to assess environmental justice. The purpose of environmental justice is to effectively protect the environmental rights of people, which can often be unequal, and minimize the environmental impacts of unequal environmental justice rights, thereby preserving the worth and dignity of people. Increasing changes in the Chinese economy and resulting air pollution could have unequal effects on the entire population. We used the Lorenz curve to describe the distribution of GDP per capita. Owing to the lack of data on per capita income at the municipal level, we chose per capita GDP as a proxy indicator (Liu et al., 2021a; Zhao et al., 2019). All GDP per capita data were counted in constant prices with the base year 2000 (Ma, 2010a; Rokicki and Hewings, 2016), the method was described in Section S2 of the supplementary material. We graded the GDP per capita of different cities according the GDP per capita of low-income, lower-middle-income, low & middle income, middle-income, and upper-middle-income countries as defined by the World Bank (https://data.worldbank.org/) in 2020. And GDP per capita data were calculated in constant prices with the base year 2000, namely, <2.5, 2.5–8, 8–15, 15–20, 20–30, 30–40, and >40 thousand RMB. This method was used to characterize the distribution of premature mortality. Population and premature mortality were ranked by GDP per capita and plotted with their cumulative shares; the cumulative share of the population on the horizontal axis and premature mortality on the vertical axis. Lorenz curves were constructed at the municipal level to evaluate the distribution of mortality between cities as a measure of municipal inequality. As shown in Fig. S1, the Gini coefficient G is equal to the area of A divided by the sum of the areas of A and B or the area of A divided by 0.5. The Gini coefficient represents the degree of inequality, with higher values indicating higher levels of inequality. The Gini coefficient G is calculated as:

$$G = 1 - \sum_{i=1}^{n}(x_i - x_{i-1})(y_i + y_{i-1}) \tag{3}$$

where *n* represents the number of cities; x_i refers to the cumulative percentage of the population in city *i*; y_i refers to the cumulative percentage of the $PM_{2.5}$-attributable premature mortality.

2.3.3. Predicting migrating populations from PAs and estimating immigrant health status

Owing to data limitations, we used a random forest model to predict more granular city-to-city or county-to-county migration data. Random forest (RF) models are an ensemble method of decision trees that can be used for the classification of discrete outcome variables or the regression of continuous variables and are particularly powerful tools when there are strong nonlinearities or interactions between variables in the data (Best et al., 2022). Population migration is a complex process. Studies have demonstrated that migration activities are often influenced by a combination of political, social, economic, and environmental drivers (Cao et al., 2018; Liu et al., 2015; Wang et al., 2021). Random forest models can assess variable importance and account for complex nonlinear interactions between variables, thereby achieving high prediction accuracy without overfitting.

It is also possible to use a combination of categorical, ordinal, and continuous-valued variables as inputs without dummy variables or scaled data. Therefore, the random forest model was used to predict the migration population.

Based on data availability, we used municipal data from 2010 to train the model. The model was trained with the distance between origin and destination, population, GDP, per capita GDP, average salary of employees, investment in fixed assets, number of students in regular colleges and universities, passenger traffic, regional area, and population density as independent variables x, and population migration as the target result variable y. These variables were used to predict migration population. This method was described in Section S3. 80 % of the data were randomly selected as the training dataset, and the remaining 20 % were used to test the accuracy of the model. There were two major hyperparameters affect the prediction ability of the RF model: the number of regression decision subtrees (n_estimators) and the number of features in the feature (max_features) subset randomly selected. The optimal combination was 500 and 10. The NMB and R^2 of the RF model in the test dataset were not far more than those in the training dataset (Table S9), which implied that the model was not overfitting, and has good generalization performance to effectively predict the migration population. The trained model was then used to predict the number of migrants in 2000–2020 and showed that city-to-city population migration must be allocated. We assumed that the migration ratios between counties within the same city to different regions were the same. Using the resident population of the emigrated counties as the distribution basis, the migration population of each city was divided at the county level. In the 2000 and 2010 censuses, the age range of 86.6 % and 85.5 % of the migrant population, respectively, was 15–64. Therefore, we assumed that the age of the migrated population was 15–64 years old and calculated the number of premature deaths using the baseline mortality data of 15–64 year-olds. Finally, we compared premature mortality in the pre-migration and post-migration scenarios.

2.3.4. Decomposing the effects of individual factors

We dissected the contributions of population, $PM_{2.5}$, age structure, and the rate of deaths owing to diseases to the change in ΔM using the decomposition method from GBD (GBD 2016 Risk Factors Collaborators, 2017) and the study by Yue et al. (2020). The decomposition method estimates the contribution of the factors by sequentially introducing each factor into the ΔM equation. Based on the four factors in 2000, premature death caused by each factor was estimated by introducing the population, age structure, baseline mortality, and attributable factors in 2005, 2010, 2015, and 2020 into the calculation formula of attributable deaths. The formula is as follows:

$$M_{t_0} = \sum_{i,a,d}\left(Pop_{i,t_0} \times AgeP_{i,a,t_0} \times Rate_{i,a,d,t_0} \times AF_{i,d,t_0}\right) \tag{4}$$

$$A_t = \sum_{i,a,d}\left(Pop_{i,t} \times AgeP_{i,a,t_0} \times Rate_{i,a,d,t_0} \times AF_{i,d,t_0}\right) \tag{5}$$

$$B_t = \sum_{i,a,d}\left(Pop_{i,t} \times AgeP_{i,a,t} \times Rate_{i,a,d,t_0} \times AF_{i,d,t_0}\right) \tag{6}$$

$$C_t = \sum_{i,a,d}\left(Pop_{i,t} \times AgeP_{i,a,t} \times Rate_{i,a,d,t} \times \frac{1-AF_{i,d,t}}{1-AF_{i,d,t_0}} \times AF_{i,d,t_0}\right) \tag{7}$$

$$M_t = \sum_{i,a,d}\left(Pop_{i,t} \times AgeP_{i,a,t} \times Rate_{i,a,d,t} \times AF_{i,d,t}\right) \tag{8}$$

$$C_{A_t} = \frac{|A_t - M_{t_0}|}{|A_t - M_{t_0}| + |B_t - A_t| + |C_t - B_t| + |M_t - C_t|} \tag{9}$$

$$C_{B_t} = \frac{|B_t - A_t|}{|A_t - M_{t_0}| + |B_t - A_t| + |C_t - B_t| + |M_t - C_t|} \tag{10}$$

$$C_{C_t} = \frac{|C_t - B_t|}{|A_t - M_{t_0}| + |B_t - A_t| + |C_t - B_t| + |M_t - C_t|} \tag{11}$$

$$C_{D_t} = \frac{|M_t - C_t|}{|A_t - M_{t_0}| + |B_t - A_t| + |C_t - B_t| + |M_t - C_t|} \tag{12}$$

where t_0 and t refer to the base year (2000 in this study) and target years (2005, 2010, 2015, and 2020), respectively. M_{t0} refers to the annual deaths attributable to $PM_{2.5}$ in the base year, which were calculated based on factors in the base year. A_t, B_t, and C_t are the intermediate variables that consider the changes in population, age structure, and death rate incrementally from the base year to the target year. M_t refers to the annual deaths attributable to $PM_{2.5}$ in the target year, which considers all changes in the four factors. C_{At}, C_{Bt}, C_{Ct}, and C_{Dt} are the contribution rates of population, age structure, baseline mortality, and $PM_{2.5}$, respectively, to changes in the number of deaths (%). A more detailed description of each step showed in the Section S4 of the supplementary material.

3. Results

3.1. Spatial distribution and the inequality of premature deaths attributable to $PM_{2.5}$

3.1.1. Spatial and temporal distribution of $PM_{2.5}$-attributable premature deaths

The spatial distribution of premature deaths caused by $PM_{2.5}$ in China is shown in Fig. 2, and the changes of deaths is shown in Fig. 3. The number of premature deaths from 2000 to 2020 initially increased and then decreased [Fig. 4(a)]. The total numbers of premature deaths in 2000, 2005, 2010, 2015, and 2020 were 1.02, 1.41, 1.52,1.36, and 1.33 million, respectively. For example, in 2015, our results were higher than those of Cohen et al. (2017) and lower than those of Li et al. (2018), Lin et al. (2021), and Song et al. (2017) (Table S2). Specifically, stroke and IHD were the leading causes of death, accounting for 51 % and 26 %, on average, of the total annual deaths, respectively. The number of deaths owing to IHD increased annually. The regions with high premature deaths mainly included Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), Pearl River Delta (PRD), and Central China. And changes in premature deaths were more obvious in these regions [Fig. 3]. From 2000 to 2010, owing to the sharply increase of $PM_{2.5}$ concentration (+13.17 %), premature deaths increased significantly in NPAs in China. During 2010–2015, premature deaths in BTH (−11,304), YRD (−23,713), and PRD (−10,925) decreased due to the reduction of $PM_{2.5}$ concentration. However, after 2015, premature deaths have increased in BTH (+3759), YRD (+3035), and PRD (+2899), mainly because of the population growth and population aging.

The spatial distribution of premature mortality caused by $PM_{2.5}$ in China is shown in Fig. S2. The premature mortality from 2000 to 2020 initially increased and then decreased [Fig. 4(a)]. The regions with high premature mortality mainly included BTH, YRD, and the central and eastern regions of China. Changes in the number of premature deaths and mortality correlated not only with changes in $PM_{2.5}$, but also with changes in age structure, as described in Section 3.3. For example, the $PM_{2.5}$ concentration was lower in Nantong, Jiangsu Province than in most cities in China; however, this region had the highest proportion of the elderly population (age ≥ 65) in China (12.44–22.67 %). Nantong was among the top five Chinese cities in terms of annual premature mortality.

3.1.2. Changes in premature mortality in poverty and non- poverty areas

China's poverty counties are mainly concentrated in the southwest and northwest regions of the country, and developed cities are mainly in the eastern coastal regions [Fig. 1(a)]. In general, the $PM_{2.5}$, concentration, and premature mortality in both regions initially increased and then decreased [Fig. 4(b)]. The $PM_{2.5}$ concentration and premature mortality in China were lower in PAs than in NPAs. This is because, in China, polluting enterprises are mainly located in more developed cities and drive their economic development and accelerated urbanization (Liu et al., 2021b; Ma, 2010b). Premature mortality increased faster in PAs (+44.76 %) than in

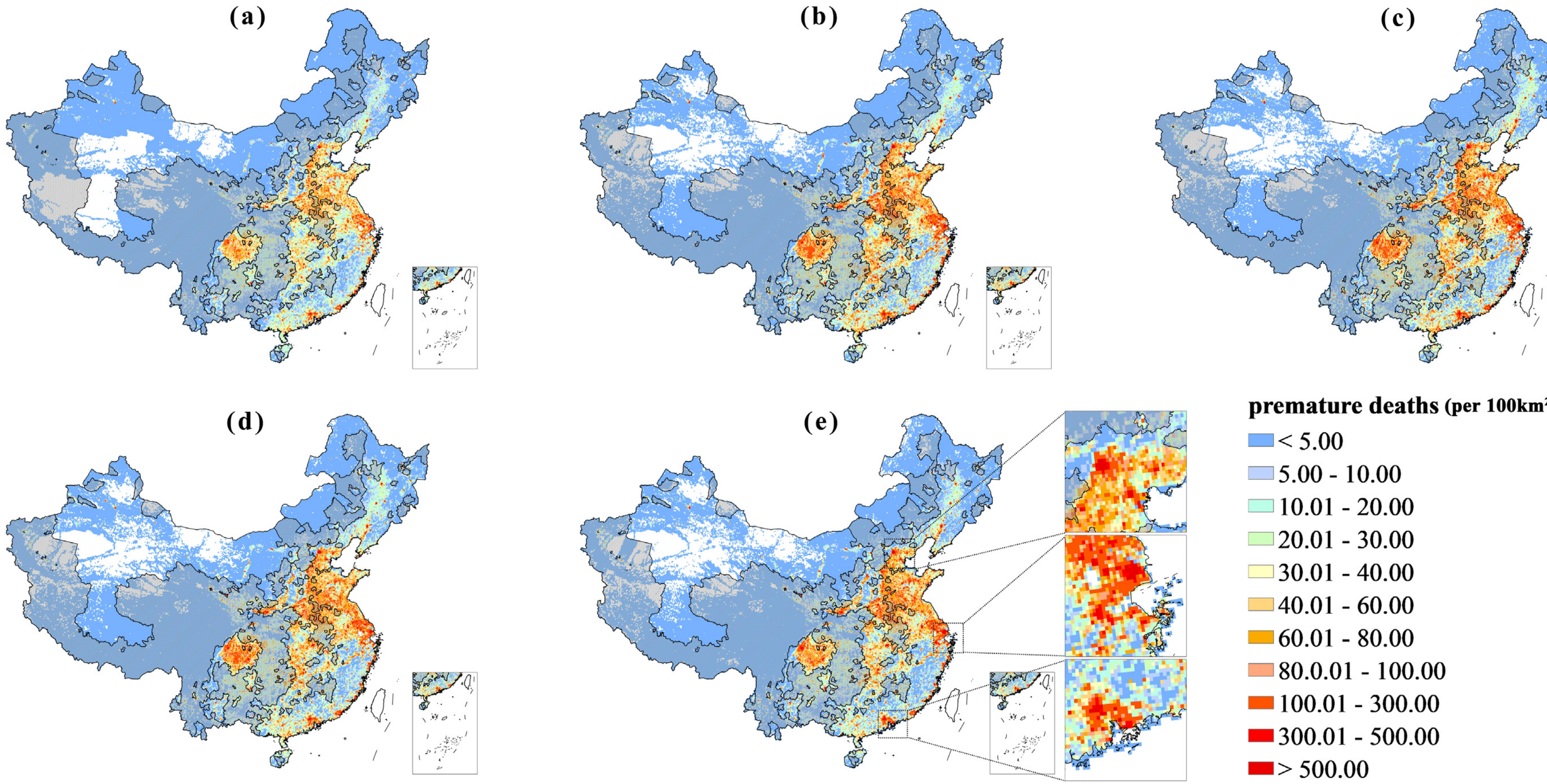

Fig. 2. The spatial distribution of $PM_{2.5}$-attributable premature deaths in 2000, 2005, 2010, 2015, and 2020. The three smaller maps on the right show $PM_{2.5}$-attributable premature deaths in the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions in 2020. (The shaded areas in the figure are PAs.)

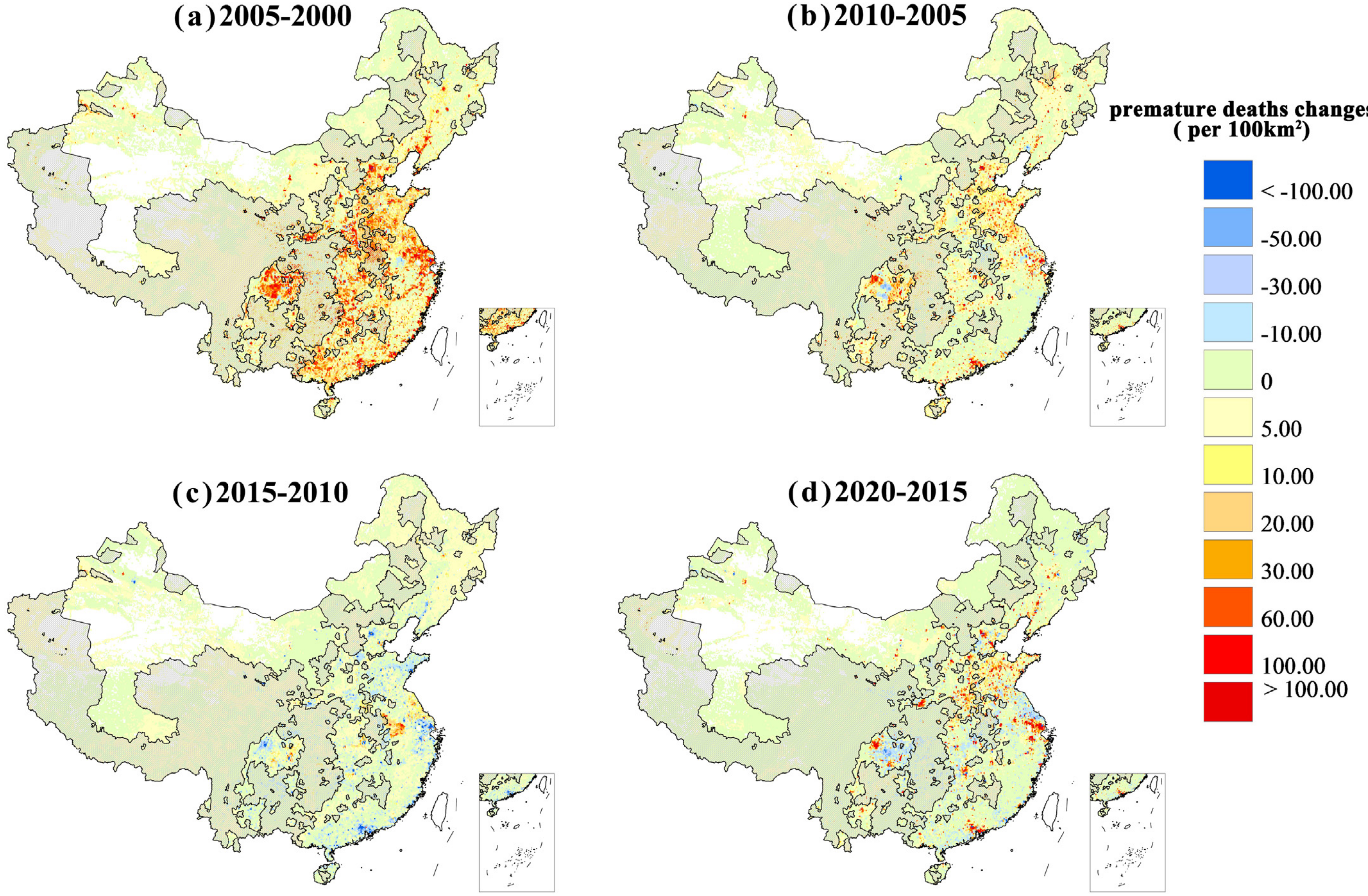

Fig. 3. The spatial distribution of the changes in $PM_{2.5}$-attributable premature deaths (the shaded areas in the figure are PAs).

NPAs (+38.38 %) from 2000 to 2010 and decreased faster in PAs (−23.75 %) than in NPAs (−15.85 %) from 2010 to 2020. From 2000 to 2010, the growth rate of premature mortality in most provinces was higher in PAs than in NPAs owing to the faster aging population and increasing $PM_{2.5}$ pollution in PAs. From 2010 to 2020, the decline rate of $PM_{2.5}$ pollution was slower in PAs (−23.05 %) than in NPAs (−50.26 %), but rapid population aging in NPAs (+56.44 %) slowed the reduction in premature mortality.

The premature mortality in some provinces was higher in PAs than in NPAs in the same province. For example, in 2010, in Jilin and Gansu Province, premature mortality was higher in the PAs than in the NPAs of the province [Table S6] owing to the difference in the proportion of the elderly population between PAs and NPAs. Even though the $PM_{2.5}$ concentration was higher in NPAs than in PAs, the proportion of the elderly population in PAs was larger, which resulted in higher premature mortality in PAs than in NPAs. The difference in premature mortality between the two areas within Sichuan province was the largest; the average annual premature mortality in NPAs of the province was 44.97/100,000 higher than that in PAs. Owing to the much higher $PM_{2.5}$ concentrations of NPAs and the proportion of the elderly population compared to PAs, this difference increased the gap in premature mortality between the two areas [Fig. 4]. From 2000 to 2010, the growth rate of premature mortality in the PAs in Guangxi and Hainan provinces (+70.20 % and 68.94 %, respectively) was the highest, and it was higher than that in NPAs (+52.35 % and 55.75 %, respectively). However, the growth rate of premature mortality in NPAs of the Xinjiang and Qinghai provinces (+46.79 % and + 46.36 %, respectively) was higher than in PAs (+19.63 % and + 32.93 %, respectively) owing to the higher growth rate of the proportion of the elderly population in NPAs (PAs: +8.25 %, +25.72 %; NPAs: +47.28 %, 49.79 %). From 2010 to 2020, the decline rate of premature mortality in PAs (−23.05 %) was higher than this in NPAs (−15.85 %), because PAs had a relatively low proportion of the elderly population, and the $PM_{2.5}$ concentration also decreased significantly (−47.92 %) in these years.

Similar to PAs and NPAs, the $PM_{2.5}$ concentration and premature mortality in both RPAs and non-relative poverty areas (NRPAs) initially increased and then decreased [Fig. 4(c)]. Both $PM_{2.5}$ concentrations and premature mortality were lower in the RPAs. RPAs account for 51 % of mainland China, but the population in this region is less than that of NRPAs, and its proportion is gradually decreasing. The population of RPAs in 2020 accounted for only 43 % of the total population owing to the population migration and concentration in developed cities. There were more premature deaths in NRPAs between 2000 and 2020. As the population was concentrated and $PM_{2.5}$, pollution was serious in NRPAs, the economy of regions such as BTH, YRD, and PRD, was relatively developed. Consequently, these contributed to a higher number of premature deaths in the three regions. Premature mortality increased faster in RPAs (+44.29 %) than in NRPAs (+38.93 %) from 2000 to 2010, but decreased faster in NRPAs (−19.07 %) than in RPAs (−18.62 %) from 2010 to 2020. When pollution increases, population aging accelerates the increase in premature mortality, and when pollution decreases, population aging slows down the decline in premature mortality. Comparing the RPAs and NRPAs within each province, we found that the difference between the two regions in Guangdong Province was the largest [Table S7]. The proportion of the elderly population in developed cities within Guangdong Province was 4.53 % lower than that in relatively poor cities, and the difference in concentration was not significant. Therefore, premature mortality was lower in NRPAs than in RPAs within Guangdong Province, and this difference was the largest compared with other provinces.

3.1.3. Environmental health equality during 2000–2020

With rapid urbanization and industrialization, the uneven distribution of polluting enterprises among different socioeconomic groups has become

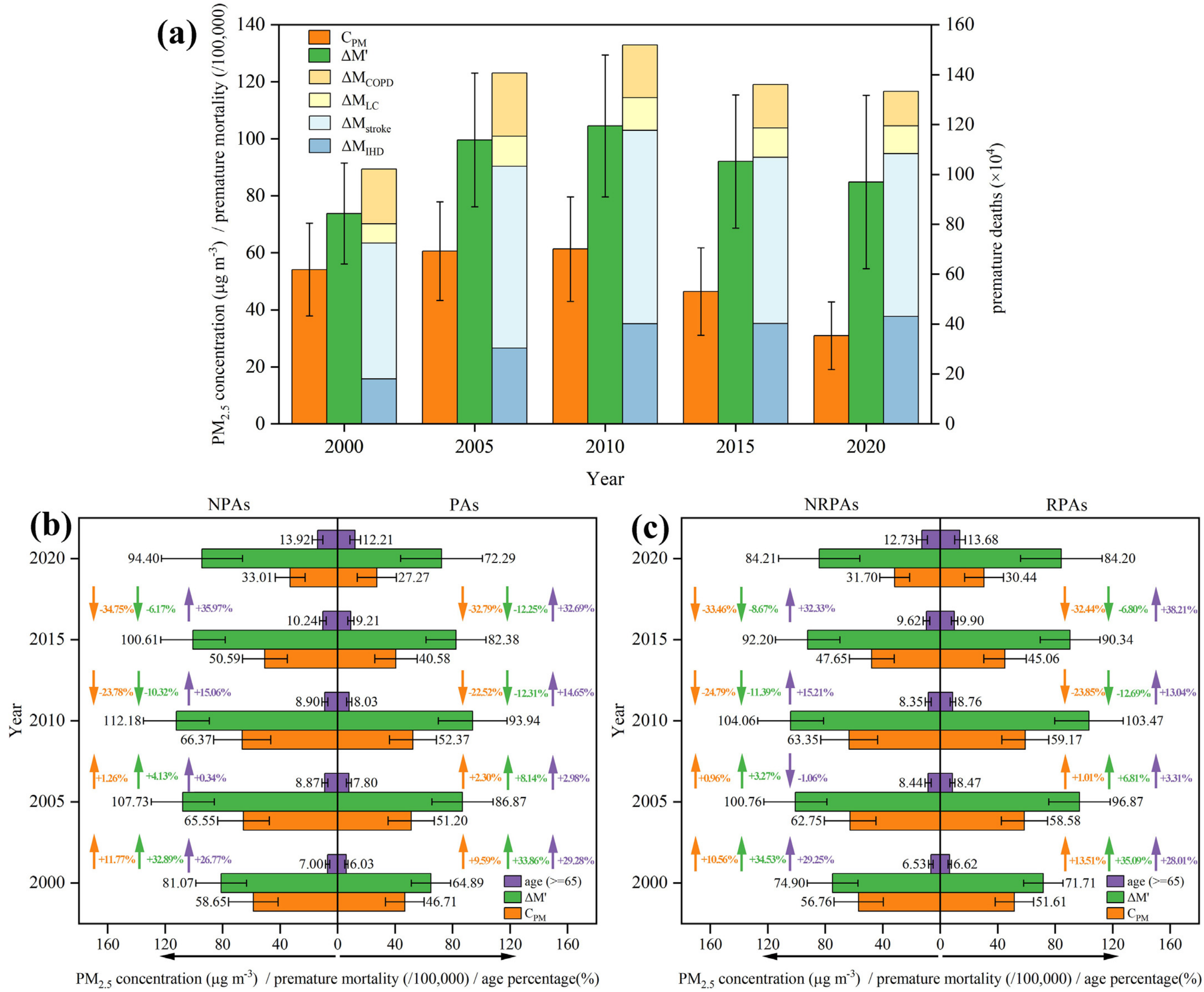

Fig. 4. Changes in premature death. (C_{PM} refers to the $PM_{2.5}$ concentration, ΔM' refers to premature mortality, ΔM refers to premature deaths, and age (≥ 65) refers to the elderly population percentage.)

a prominent environmental and social problem in China during the transition period (Liu et al., 2021b). Additionally, the health burden caused by air pollution is not evenly distributed in China and air pollution exposure has different health effects on different socio-economic groups in China; these differences result from environmental and health inequalities (Jiao et al., 2018). In this study, we used city-level indicators to test whether poorer cities bear a disproportionate public health burden owing to $PM_{2.5}$. Fig. 5 shows the Lorenz curves of municipal inequality for 2000, 2005, 2010, 2015, and 2020.

Premature deaths related to $PM_{2.5}$ disproportionately harm populations of low socioeconomic status [Fig. 5]. During the period 2000–2020, the bottom 20 % of China's population (ordered by GDP per capita) earned an average of only 10 % of the total GDP per capita, yet experienced an average of 22 % of premature deaths caused by $PM_{2.5}$. In comparison, the upper 20 % of China's population earned an average of 33 % of the total GDP per capita and experienced 14 % premature deaths caused by $PM_{2.5}$. The municipal GDP Gini coefficient, G, gradually became more balanced from approximately 0.31 in 2000 to 0.09 in 2020. Especially, Gini coefficient dropped dramatically from 0.18 in 2015 to 0.09 in 2020. The rapid population aggregation of the medium- and high-GDP per capita cities, and the slowing down of overall GDP per capita growth in these medium- and high-GDP per capita cities led to an equalization of economic development between cities. The equity in GDP per capita improved across Chinese cities (Table S8). The population with a GDP per capita of <8000 decreased from 67.3 % in 2000 to 0.07 % in 2020. This population experienced premature deaths, which decreased from 70.6 % in 2000 to 0.2 % in 2020. The rate of decline was as high as 99.7 %.

Compared with economic inequality, $PM_{2.5}$-related premature mortality was relatively evenly distributed across the GDP per capita in China's cities between 2000 and 2015. However, the equity of premature mortality showed a downward trend among Chinese cities and its Gini coefficient in 2020 exceeded that of GDP per capita. With the increasing severity of air pollution (from 2000 to 2010), the health disparities between people of different socioeconomic statuses will increase (Jiao et al., 2018). The fairness in the distribution of premature mortality was highest in 2020. There was a smaller gap in premature mortality between RPAs and NRPAs in 2020 [Fig. 4(c)]. This means that lower economic levels of the population bear the brunt of higher pollution exposure. The elderly population who are most vulnerable to $PM_{2.5}$, are more concentrated in economically underdeveloped areas [Fig. 4(c)]. Population aging may amplify

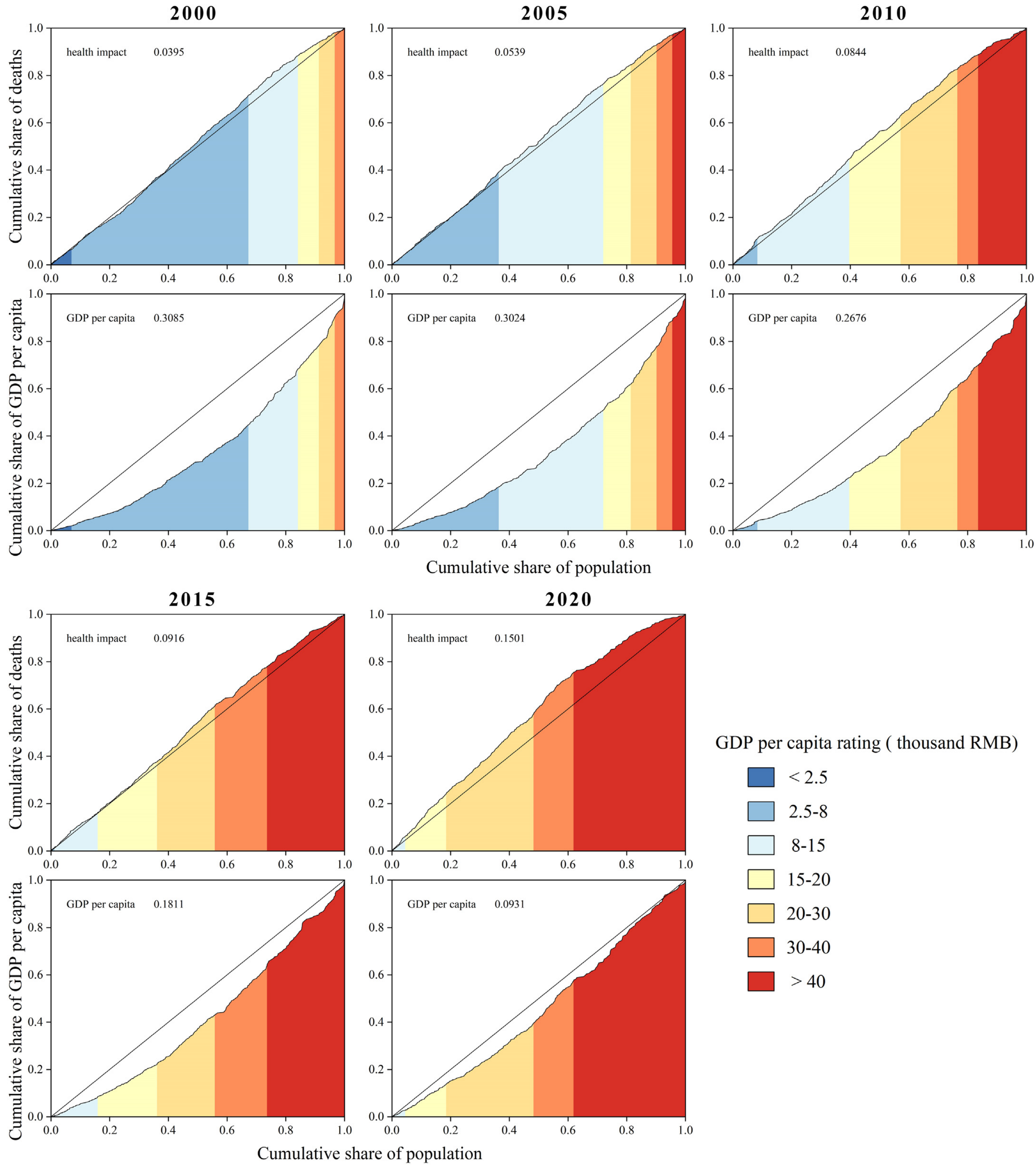

Fig. 5. Municipal Lorenz curves for $PM_{2.5}$-attributable premature mortality and economic inequality. The diagonal is the line of perfect equality. The economic inequality initially increased and then decreased from 2000 to 2020. The premature mortality was distributed fairly more equitably than the GDP per capita. The poor population (GDP per capita <8000) experienced quickly decreasing premature deaths.

inequalities in environmental health in the context of relatively balanced economic development.

Similar to the mortality-based Gini coefficient, the Lorenz curve shows that each disease has a disproportionate impact on cities with low GDP per capita (Fig. S4). LC mortality was distributed relatively uniformly, and IHD mortality was the most inhomogeneous. The bottom 40th percentile of the Chinese population experienced premature deaths from IHD caused by $PM_{2.5}$, increasing from 43 % in 2000 to 50 % in 2020.

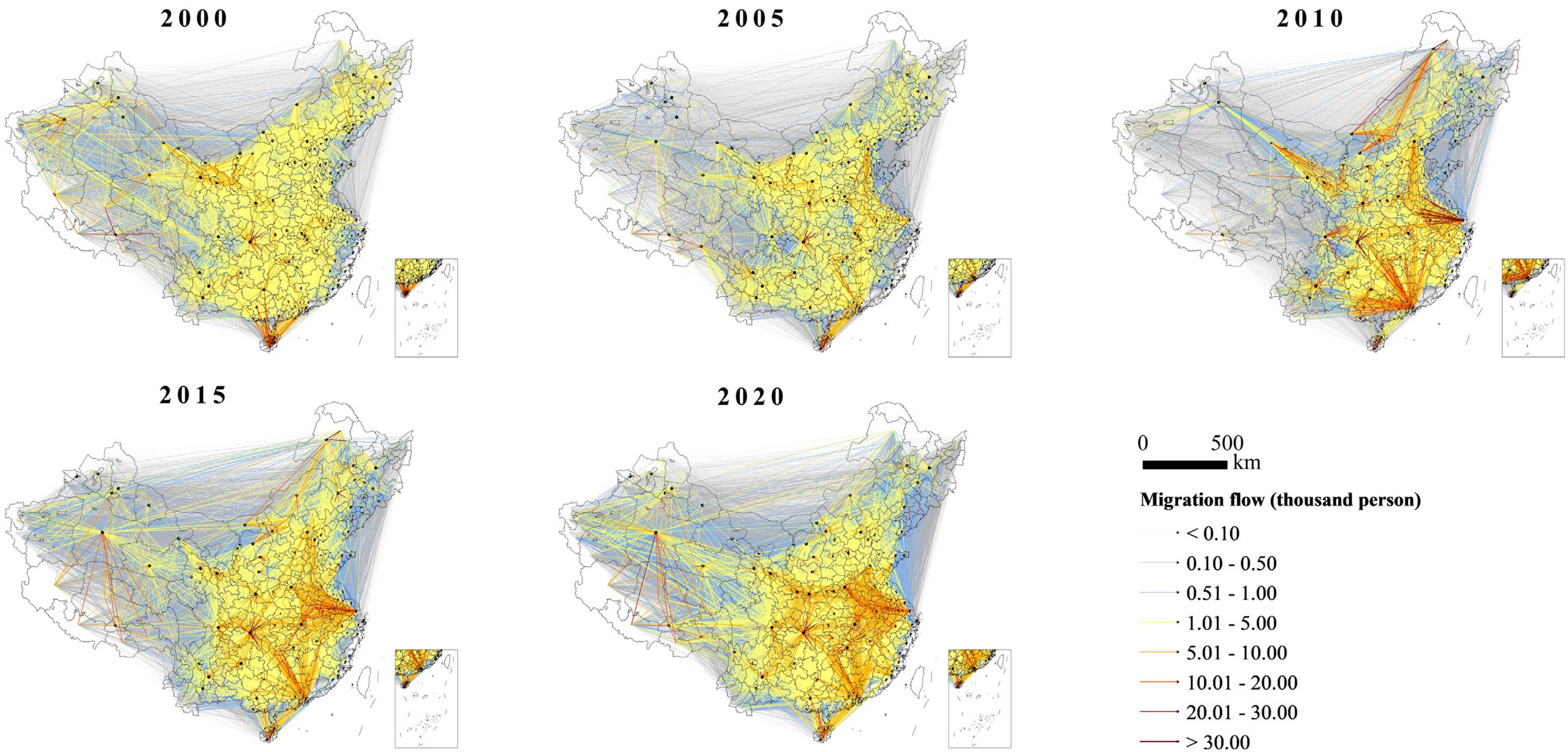

Fig. 6. China's population migration network representation. The width of the arrow represents the number of migration flows. The largest migration flow is displayed on the top layer of the figure.

3.2. Changes in the environmental health burden of migration from PAs

3.2.1. Changes in the characteristics of the migration process

The predictions of the random forest model were in good agreement with the actual data, with very high data accuracy (0.94 in R^2, 5.8 % in NMB; Fig. S5). The distance between the origin and destination, population of origin, and destination were the three most important variables, which were determined by identifying the feature importance among the variables (Table S10). The proportions of these three variables in the final migration population were 42.82 %, 10.58 %, and 7.12 %, respectively.

The number of people who moved from PAs to developed cities from 2000 to 2020 initially decreased and then increased [Fig. 6]. These numbers were 24, 19, 21, 32, and 42 million in 2000, 2005, 2010, 2015, and 2020, respectively. In terms of the choice of migration destination, the population that migrated across provinces was mainly concentrated in the eastern coastal areas (annual average of 25.4 %), while the population moving to the northeast areas was lower (annual average of 3.7 %). Northeast China is an inactive immigrant area, while developed cities in the eastern coastal area have multiple advantages, such as policy, location, industrial agglomeration, historical foundation, and resource and environmental carrying capacity (Cheng et al., 2019).

It is worth noting that >20 % of large-scale migration flows of >10,000 people choose to move to developed cities in the southwest every year. This is mainly because there are nearly 32 % poor counties in Southwest China, and the most important factor affecting migration is distance. The migration destination was selected based on the principle of proximity. The super-large migration flows of >30,000 people were mainly intra-city and intra-provincial migrations. The largest number of super-large migration flows occurred in Chongqing, and the number of people who moved to Chongqing from PAs annually (including intra-city migration) remained in the top five (Table S11). Chongqing is not only located in the central encirclement of PAs but also has many poverty-stricken counties in the city. Intra-city population flow and out-of-city immigration activities occur more actively in Chongqing.

3.2.2. Changing trend of air pollution health effects accompanying population migration

Before 2015, $PM_{2.5}$ pollution was serious in most developed cities. Thus, 72–95 % of the migration behavior was concentrated in moving from high pollution areas to high pollution areas (Table S12). In 2020, the $PM_{2.5}$ concentration was reduced to 30.92 μg/m^3 nationwide, and 40 % of people moved from light pollution areas to light pollution areas, while 29 % moved from light pollution areas to high pollution areas. A comparison of the places of origin and destination showed that 71 %, 74 %, 68 %, 68 %, and 63 % of the migration occurred from less polluted areas to heavier polluted areas in the years 2000, 2005, 2010, 2015, and 2020, respectively (Table 1). Air pollution had little effect on people's willingness to move.

The total population moving from poor areas to developed cities initially decreased and then increased; the number of premature deaths exhibited the same trend [Fig. 7(a)]. After the population of PAs moved to developed cities, they became affected by the health burden of the city. In 2005, the premature mortality caused by $PM_{2.5}$ was the highest at 37.19 per hundred thousand people [Fig. 7(c)], owing to 74 % of the migrating population moving from low pollution areas to high pollution areas, with the highest average $PM_{2.5}$ concentration of 65.83 μg/m^3 in developed cities. After moving into developed cities, high concentrations of $PM_{2.5}$ pollution were associated with higher premature mortality (Fig. S6). Developed cities in central China had more serious $PM_{2.5}$ pollution and higher premature mortality in the migrant population. Conversely, less polluted southwestern China had the lowest premature mortality rate.

The comparison before and after migration revealed that the number of premature deaths and the mortality of people in PAs before moving out were lower than those after moving out owing to the more serious $PM_{2.5}$ pollution in developed cities. In 2005, the difference in $PM_{2.5}$ concentration between poor areas and developed cities was the largest, with a difference of 13.52 μg/m^3. This led to a large gap in premature mortality caused by $PM_{2.5}$, with a gap of 4.15/100 thousand people [Fig. 7(c)]. The overall premature mortality in 2020 was lower than that in other years, but the premature mortality in impoverished areas in Xinjiang was higher than that in previous years, which was different from the pattern in other regions [Fig. 7(d)]. Because the $PM_{2.5}$ concentration in Xinjiang in 2020 was higher than in previous years.

Migrating from high-pollution areas to low-pollution areas would reduce the premature deaths of the migrated population while migrating from low-pollution areas to high-pollution areas would increase premature deaths. Premature deaths increased by 638, 779, 303, 954, and 896 in 2000, 2005, 2010, 2015, and 2020, respectively, as >63–74 % of the migration direction was from lower pollution areas to higher pollution areas from 2000 to 2020.

Table 1
Numbers of migrants and the associated net health impacts.

Year	Migration population	Premature deaths		Premature mortality/(100,000)		The proportion of migrants moving from less polluted areas to heavily polluted areas
		Before migration	After migration	Before migration	After migration	
2000	23,513,039	6468	7106	27.51	30.22	71 %
2005	18,784,295	6206	6986	33.04	37.19	74 %
2010	20,775,188	6626	6929	31.89	33.35	68 %
2015	31,663,433	8829	9783	27.89	30.90	68 %
2020	41,858,166	9133	10,029	21.82	23.96	63 %

3.3. Driving factors of the $PM_{2.5}$-related premature deaths

The results obtained from the preliminary analysis of contribution rates are shown in Fig. 8. Changes in age structure contributed most to the number of deaths, followed by changes in $PM_{2.5}$ concentration, population, and baseline mortality. Aging in the Chinese population resulted in increasing annual premature deaths among the elderly population caused by $PM_{2.5}$ pollution. The proportion of China's population aged 65 years and over increased from 7.0 % in 2000 to 13.5 % in 2020. Changes in the age structure of the population caused an increase of 782 thousand premature deaths in 2020 compared to 2000 [Fig. 8(a)]. Changes in the age structure contributed the most to the number of deaths. And compared to 2000, the changes in age structure in 2015 contributed the most to the change in premature deaths (65.26 %) [Fig. 8(b)]. Compared with 2000, changes in $PM_{2.5}$ concentration resulted in approximately 111 thousand premature deaths in 2010 and 668 thousand in 2020 [Fig. 8(a)]. The population of mainland China increased from 1.27 billion in 2000 to 1.41 billion in 2020, an increase of approximately 11 %. As the population increased, so did the annual premature deaths. Compared with 2000, the population increase resulted in an increase of 148 thousand premature deaths in 2020.

The impacts of various factors on China's PAs and NPAs are different. Compared to 2000, the change in age structure caused an increase in premature deaths in 2005–2020 [Fig. 8(a)]. The largest increase was in 2020, with changes in age structure resulting by 145 and 637 thousand premature deaths in PAs and NPAs, respectively. It is worth noting that the change in the population of PAs in 2020 compared to that in 2000 resulted in 6321 fewer deaths. However, its contribution to NPAs was high and added 154 thousand deaths. Compared with 2000, the $PM_{2.5}$ concentration in NPAs in 2020 decreased by 26.27 μg/m^3 and the number of deaths decreased by 572 thousand. The four factors had different degrees of influence on PAs and NPAs, among which the difference in the impact of population changes was the largest [Fig. 8(c)]. The contribution rate of population change was smaller in PAs than in NPAs, but the contribution rate of changes in age structure and $PM_{2.5}$ concentration was higher in PAs than in NPAs.

Therefore, the changes in age structure and $PM_{2.5}$ concentration contributed significantly to the change in the number of premature deaths in China from 2000 to 2020 [Fig. 8(b)]. Older people are more susceptible

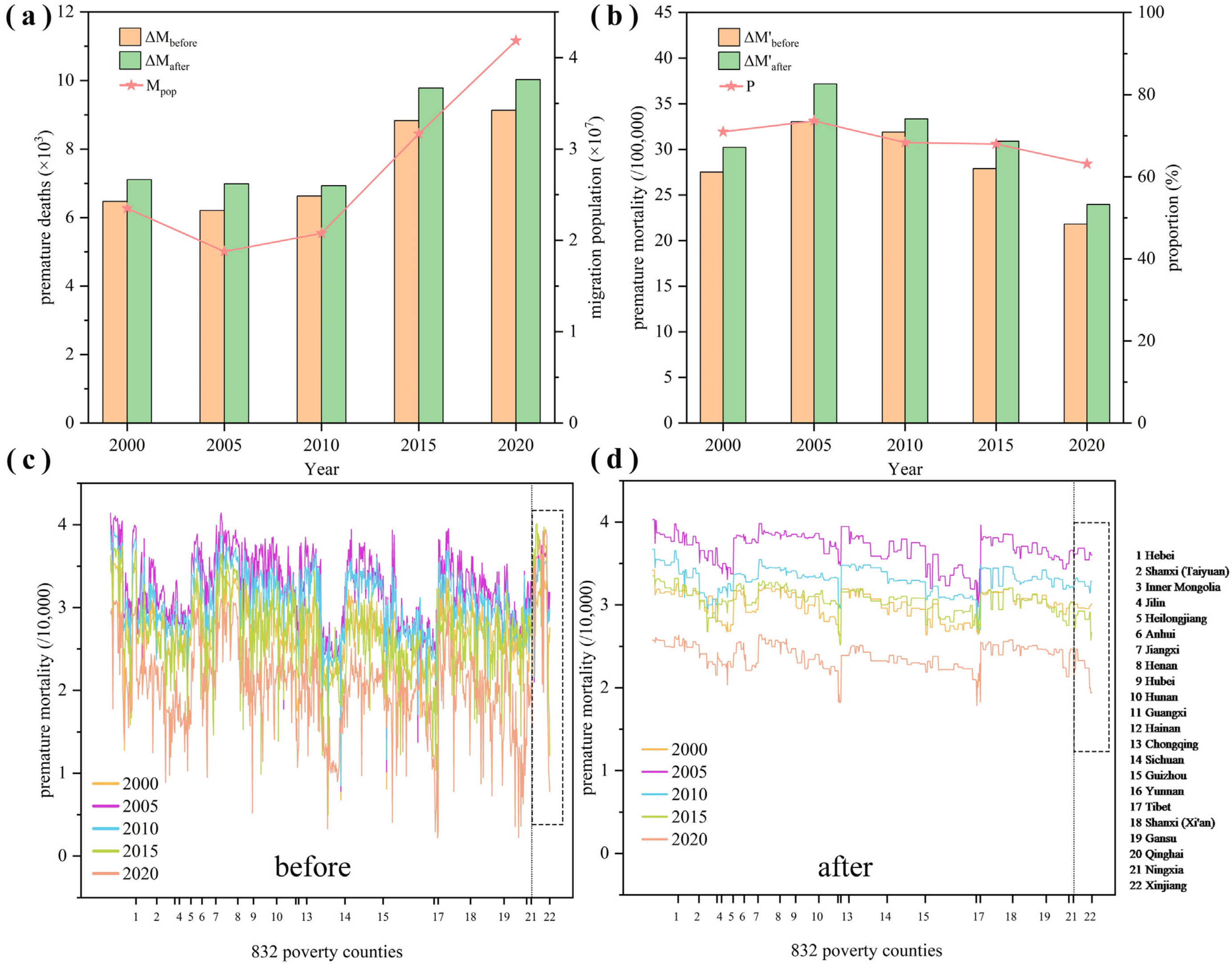

Fig. 7. Change in the migration characteristics. (a) The total population migrated from PAs to developed cities and the premature deaths of the migrated population caused by $PM_{2.5}$ (ΔM_{before} and ΔM_{after} indicate premature deaths before and after migration, respectively) (b) Premature mortality of migrating populations caused by $PM_{2.5}$ and the proportion of migrants moving from low-pollution areas to high-pollution areas. ($\Delta M'_{before}$ and $\Delta M'_{after}$ indicate premature mortality before and after migration, respectively). (c) and (d), the premature mortality caused by $PM_{2.5}$ before and after migration, respectively (the part enclosed by the black dashed frame is the Xinjiang region).

to $PM_{2.5}$ exposure. Furthermore, as the population ages, the prevalence of chronic diseases associated with $PM_{2.5}$, such as cardiovascular diseases, will be higher (Xu et al., 2021). The overall mortality level of a region or population is not only determined by the mortality rate of each age group but also by the age composition of the local population. For the same region or population, even if the mortality rate in each age group remains unchanged, the overall mortality rate may increase owing to an increase in the proportion of the elderly. Although China's $PM_{2.5}$ concentration has decreased under the constraints of policy, as the population continues to grow, the contribution of China's population to the number of deaths cannot be ignored. The results of the driver decomposition analysis suggest that the health benefits of improved air quality may be offset by population change. The decline in $PM_{2.5}$ concentrations was not enough to offset the effect of population age changes on $PM_{2.5}$-related deaths. The aging Chinese population is expected to increase the estimated number of premature deaths.

The influence of each factor on the migrating population is illustrated in Fig. S7. The increase in the migrating population resulted in an increasing number of deaths among the population. The number of deaths in 2020 increased by 5501 compared with 2000. Before 2010, increasing $PM_{2.5}$ concentrations increased premature deaths; after 2010, decreasing $PM_{2.5}$ concentrations reduced premature deaths. Compared with 2000, the decreasing $PM_{2.5}$ concentrations resulted in 4959 fewer premature deaths among migrants in 2020. Changes in the number of migrants had the most significant contribution to premature deaths in 2015 (62.09 %) [Fig. S7(b)]. The size of the migrant population is constantly increasing, which has become the main factor affecting the change in premature deaths. Declines in $PM_{2.5}$ concentrations were not enough to offset the impact of growing migratory populations on premature deaths.

4. Discussion

This study aimed to evaluate the mortality burden related to long-term exposure to $PM_{2.5}$, in China's PAs and NPAs, and identify environmental justice from 2000 to 2020. We also considered the impact of population migration on premature mortality owing to exposure to $PM_{2.5}$ pollution. Compared with other studies, in this study, we used more accurate and granular municipal census data to increase the accuracy of our findings.

The change in premature deaths from 2000 to 2020 initially exhibited an increasing trend and then a decreasing one; additionally, premature

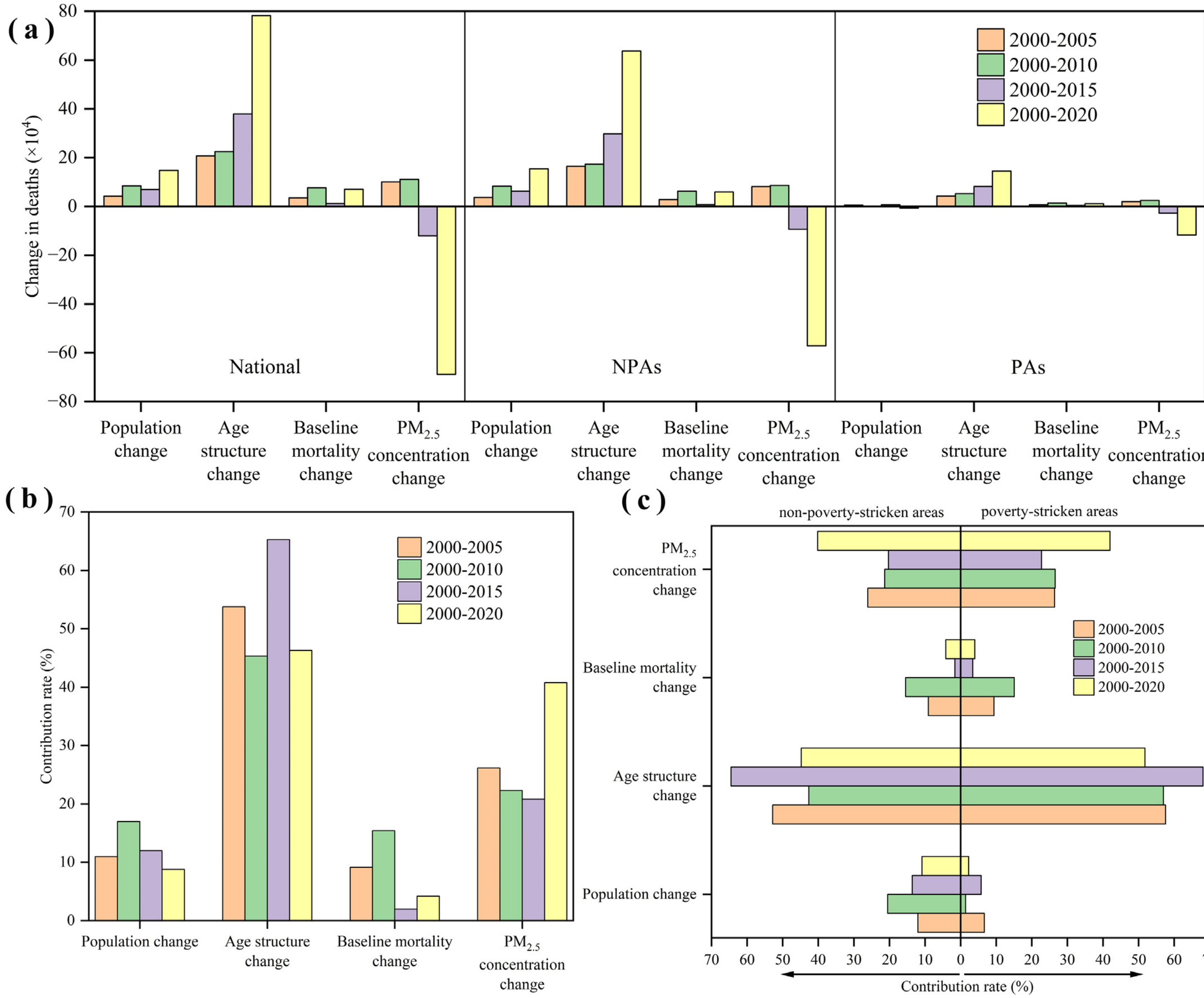

Fig. 8. Contributions of different factors to changes in deaths attributable to $PM_{2.5}$ pollution in China. (a) Changes in the number of premature deaths caused by different factors at the national level, PAs and NPAs. (b) The contribution of different factors to the change in the number of premature deaths, %. (c) Comparison of the contribution of different factors to the change in the number of premature deaths in PAs and NPAs, %.

deaths decreased by 12.19 % from 2010 to 2020. In general, the $PM_{2.5}$ concentration and premature mortality were lower in PAs than in NPAs in China. Polluting enterprises are located in relatively developed areas in China, thereby not only driving economic development but also causing serious pollution. However, the changes in pollution and health burden were not the same in poor and non-poor areas. China has prioritized urban development at the expense of the rural economy, thereby widening the gap between urban and rural areas for a long time (Yuan et al., 2018). From 2000 to 2010, the rapidly aging population in PAs accelerated the increase in premature mortality, and the migration of the working-age population to developed cities and the elderly population in rural areas in eastern and central China caused a rapid increase in premature mortality in the RPAs (Cheng et al., 2019). Premature mortality in poorer areas is more susceptible to changes in the $PM_{2.5}$ concentration and the proportion of the elderly population. The proportion of the elderly population has the greatest impact. Regional differences hinder the establishment of harmony and equality in China, and population aging increases the vulnerability of PAs (Zang et al., 2020). Air pollution exposure in China is affected differently by different socioeconomic groups. Increased air pollution widens health disparities among people of different economic statuses, and population aging increases inequalities in environmental health. Compared to other countries, China's cities appear to be moving toward greater economic equality. While premature mortality associated with $PM_{2.5}$, showed an increasingly unequal trend from 2000 to 2020, it was relatively evenly distributed across GDP per capita before 2015. Premature deaths related to $PM_{2.5}$ harm more seriously populations of low socioeconomic status. In economically underdeveloped cities, aging populations can exacerbate premature deaths caused by $PM_{2.5}$.

Internal population mobility, especially from rural to urban areas, has resulted in huge economic growth and severe socioeconomic inequality in China (Pryce et al., 2021). The migration of workers may lead to increased health burdens in megacities (Shen et al., 2018). In this study, the migration of people from PAs to developed cities was affected by $PM_{2.5}$ exposure in the city. Comparing the origin and destination of migration, an average of 69 % of the migration activities occurred from lower-to higher-pollution areas. At the same time, worker migration to developed cities also affects local air pollution levels (Pryce et al., 2021; Schoolman and Ma, 2012). This added 638, 779, 303, 954, and 896 premature deaths in 2000, 2005, 2010, 2015, and 2020, respectively.

After analyzing the impact of various factors on the number of premature deaths by driving factor decomposition, compared with 2000, we found that the change in the age structure contributed the most to the change in premature deaths in 2005–2020, with an average contribution rate of 52.65 %. These results are similar to those reported by Yin (2022) and Xu et al. (2021). The vulnerability of China's aging population will further increase the estimated premature deaths caused by $PM_{2.5}$ (Hong et al., 2019). China's population is aging gradually, with the elderly population increasing from 7.0 % in 2000 to 13.5 % in 2020; this has resulted in the addition of 782 thousand premature deaths. China launched its Air Pollution Prevention and Control Action Plan in late 2013. The $PM_{2.5}$ concentration dropped rapidly and caused premature deaths to decrease by 121 and 689 thousand in 2000 and 2020, respectively, compared with 2000. The contribution rate of changes in age structure and the $PM_{2.5}$ concentration was higher in PAs than in NPAs. Additionally, economic development and population migration caused the larger population changes within NPAs and contributed to greater changes in premature deaths in PAs. The gap in the contribution rate between the two regions is the largest.

The age structure of the population is the main driver of $PM_{2.5}$-related premature deaths in China after 2005. Due to the aggravation of population aging, the significantly decreased $PM_{2.5}$ concentration cannot be sufficient to decrease $PM_{2.5}$-related premature mortality. Population growth and aging might not be effectively intervened by policies in the short term. Therefore, China needs to focus on reducing pollutant emissions to decrease $PM_{2.5}$-related premature deaths. In addition, stroke and IHD were the leading $PM_{2.5}$-related premature deaths in China, and they showed an increasing trend. In the future, health resources and policies should target the elderly population and those at a high risk of stroke and IHD. Lastly, the population growth caused by urbanization and the expansion of population migration from PAs to NPAs have increased $PM_{2.5}$-related premature deaths, because most migrants in China prefer to migrate to heavily polluted cities, such as Shanghai, Chengdu, and Chongqing. The key to achieving the Sustainable Development Goals is to achieve a win-win situation for health and the economy by effectively reducing the environmental health burden of the migrant population. So relevant policies could be formulated to improve the attractiveness of lower-pollution cities, for example, providing migration subsidies, developing diversified industries, raising wages, reasonably allocating education and medical resources, etc. It can also provide migrants for migration guidance to meet the health and economic needs on the premise of respecting their will.

However, this study still has several limitations. First, there are regional differences in the distribution of population susceptibility and medical level, which may impact health outcomes. However, the effect of these differences on the overall results is very small (Lin et al., 2021; Liu et al., 2021c), thus would not affect the comparative findings. In addition, due to the lack of mortality data in 2020, we used the mortality data in 2019 to replace it. It should be note that the mortality data used in this study is not related to COVID-19, because this study only focused on premature mortality of stroke, IHD, COPD and LC attributable to ambient $PM_{2.5}$ exposure (Hao et al., 2021; Lin et al., 2021; Yue et al., 2020). Second, owing to the limited city-to-city migration data, we used a random forest model for prediction and obtained good results, but the allocation work will lead to certain errors. However, compared to other studies (Lin et al., 2021; Liu et al., 2021c; Shen et al., 2018), we considered a relatively more minor level of migration. Lastly, owing to the COVID-19 epidemic, the implementation of lockdown and control policies across the country will have a huge impact on population migration in 2020. However, owing to data limitations, in this study we did not consider the influence of this factor.

5. Conclusions

In recent decades China's economy has developed rapidly, with the consequent air pollution posing huge health risks. The results of this study showed that China's NPAs were more polluted than PAs and that these NPAs had higher rates of premature deaths owing to population aggregation. China's GDP per capita has been gradually moving toward greater equality, while China's environmental health was comparatively more equally distributed. However, environmental inequalities were amplified by factors such as the long-term trend of population aging in China. Besides, population migration from PAs to developed cities also contributed to higher incidences of premature death and higher premature mortality. The results of the driver factorization analysis indicated that the health benefits of improved air quality may be offset by population change, and that the decrease in the $PM_{2.5}$ concentrations is not sufficient to offset the effect of population age change on $PM_{2.5}$-related deaths. Taken together, our findings suggest that China's policymakers of air pollution need to take into account the scale of population migration and increasingly serious population aging for advancing urban environmental sustainability and justice. In this regard, particularly needed are to adopt stricter management measures and set more ambitious emission control targets.

CRediT authorship contribution statement

Yan Li: Conceptualization, Methodology, Software, Writing – original draft, Data curation. **Baojie Li:** Conceptualization, Writing – review & editing, Resources, Supervision. **Hong Liao:** Supervision. **Bing-Bing Zhou:** Writing – original draft. **Jing Wei:** Resources. **Yuxia Wang:** Resources. **Yuzhu Zang:** Resources. **Yang Yang:** Supervision. **Rui Liu:** Investigation. **Xiaorui Wang:** Resources.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.160517.

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