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Research article

A new approach to evaluate regional inequity determined by PM$_{2.5}$ emissions and concentrations

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1. Introduction

With the rapid development of industrialization and urbanization in China, the air has become seriously polluted, causing economic losses and health hazards. Among various atmospheric pollutants, PM$_{2.5}$ (particulate matter $\leq 2.5\ \mu m$) has the most severe impacts on human health and can cause a series of diseases. Long-term exposure to PM$_{2.5}$ has been consistently linked to cardiovascular and respiratory diseases, such as asthma, tracheitis and even lung cancer (Kioumourtzoglou et al., 2016; Zhang et al., 2016a). In 2013, China implemented the Air Pollution Prevention and Control Action Plan, which aimed to reduce PM$_{2.5}$ concentrations by 25% by 2017 compared with the level in 2012 (Huang et al., 2014; Zhang et al., 2018). China made great efforts to meet this goal, such as restrictions on road traffic and construction dust, strengthening emission standards for main industries, and closing many factories that caused serious pollution. As a result, the air quality in China’s most populated areas has been considerably improved (Li et al., 2019; Ma et al., 2019). According to a report from the Innovative Green Development Program (IGDP), PM$_{2.5}$ concentrations decreased by 32% in 2017 compared with 2013 for approximately 70% of China’s populated land area (IGDP, 2020). This finding indicates that China’s actions are effective, that PM$_{2.5}$ emissions can predict regional PM$_{2.5}$ concentrations, and that severe air pollution events can be avoided by controlling anthropogenic emissions (Li et al., 2016b; Xue et al., 2018). However, the latest study showed an opposite conclusion. In December 2019, the serious infectious disease Coronavirus 2019 (COVID-19) was initially identified in Wuhan, China, and the infection spread rapidly across China and around the globe. Since late January 2020, various emergency control strategies have been implemented across China, and almost all avoidable anthropogenic activities have been limited,
including transportation, outdoor human activities, industrial production, construction, and agricultural activities; however, severe air pollution has continued to occur in the North China Plain (IGDP, 2020; Wang et al., 2020). Thus, the following questions arise: How do emissions affect concentrations, and what is the spatial heterogeneity of their relationship?

It seems clear that PM$_{2.5}$ concentrations can be reduced through emission source control efforts. However, while high PM$_{2.5}$ concentrations can be attributed to high emissions, many natural factors, such as topography, land coverage, and climate conditions, can also significantly affect its concentrations (Cai et al., 2017; Liu et al., 2017). Among these factors, meteorological conditions are among the most important, especially wind speed, humidity, temperature, and precipitation, and their influence varies with the seasons (Yu et al., 2013; Ozbek et al., 2016; Zhang et al., 2020). Once emitted, the emissions will be influenced by various factors and transported in the atmosphere; therefore, nearby or even faraway regions will also be affected. By considering the main meteorological factors, many models, such as the WRF-Chem model, the GEOS-Chem model, and the CMAQ model, have been developed and used to simulate PM$_{2.5}$ transportation and concentrations (Chemel et al., 2014; Lee et al., 2017; Zhang et al., 2018). However, to reduce regional concentrations, natural factors are unnecessary or difficult to control, and emissions control remains the most effective approach. Thus, it is important to know the structure of the emission sources. According to previous studies, PM$_{2.5}$ emission sources mainly include energy consumption from industrial production, households, and transportation (Stevens and Boucher, 2012; Sheehan et al., 2014; Xu et al., 2016b), along with other sources such as waste and crop straw burning (Xu et al., 2016a). The Emission Database for Global Atmospheric Research (EDGAR) provides data on annual anthropogenic emissions since 1970, including both statistical and spatial data for all countries (Muntean et al., 2014). As one of the most important pollutants, PM$_{2.5}$ is included in this dataset. Including 30 countries and regions in Asia, the Multiresolution Emission Inventory for China (MEIC) provides PM$_{2.5}$ emission estimates for Asia for 2008 and 2010. The emissions are aggregated into the five sectors of power, industry, residential, transportation, and agriculture (Kurokawa et al., 2013; Li et al., 2017). These datasets enable a detailed study of PM$_{2.5}$ emissions, both temporally and spatially, which will support efforts to reduce emissions and concentrations. Additionally, these datasets make it possible to examine the relationship between PM$_{2.5}$ emissions and concentrations at multiple spatial scales, but research on this relationship is lacking.

Affected by emissions from anthropogenic activities and natural factors, the actual level of regional PM$_{2.5}$ emissions may not match their concentrations. The emissions from different regions will spread and be transported in the atmosphere, and since the distribution and effect of emissions are uneven, regional inequality occurs. Furthermore, because many industrial products in high-emission regions are used or consumed in other regions, the high PM$_{2.5}$ emissions produced in source areas are driven, in part, by consumption in external regions. This process is usually driven by regional economic links through trade among various sectors and regions, resulting in considerable indirect resource consumption and environmental pollution (Guan et al., 2014; Kanemoto et al., 2016; Nagashima et al., 2017). The transfer of resources pressure and the allocation of responsibility along with the total resource consumption among regions and throughout the supply chain have attracted considerable attention, and regional inequality has been analyzed from this perspective (Hertwich and Peters, 2009; Kanemoto et al., 2012). Multiregional input-output (MRIO) models have been developed and used widely in environmental assessments by considering the economy links among regions and sectors (Bey et al., 2001; Albrecht et al., 2018; Wiedmann and Lenzen, 2018; Tramberger et al., 2019). This inequality hinders harmonious development and social stability; therefore, it is important to diagnose inequities and find solutions. To evaluate inequality, some scholars have combined the MRIO and GEOS-Chem chemical transport models to obtain the fractional contribution of each region to the near-surface PM$_{2.5}$ concentrations along the trade chain (Zhang et al., 2017). Based on large datasets, the integrated linked models can provide a more accurate examination of the PM$_{2.5}$ flow in trade and its transmission in the atmosphere; however, this is not practicable since it involves a complex calculation process. To guide the government in both regional coordinated development and environmental protection, a relatively simple and more applicable research framework and method must be developed.

Innovatively, this study attempts to examine the relationship between PM$_{2.5}$ emissions and concentrations at multiple scales, both temporally and spatially; develop a new research framework; and integrate related models to evaluate regional inequity from a different perspective. The objectives of this study include the following: 1) comprehensively evaluate the changes in PM$_{2.5}$ emissions and concentrations, both temporally and spatially; 2) explore the relationship between PM$_{2.5}$ emissions and concentrations at multiple scales; and 3) develop a new approach to diagnose regional inequality caused by PM$_{2.5}$ by integrating the relationship of PM$_{2.5}$ emissions/concentrations and the indirect emissions driven by domestic trade. This study can provide a new research perspective from which to reevaluate the responsibility for PM$_{2.5}$ emissions and their influence on regional air quality, provide detailed guidance for PM$_{2.5}$ spatial control, and provide a convenient method and application references for coordinated regional development.

2. Methods

2.1. Data and study area

The data used in this study include PM$_{2.5}$ emission data, PM$_{2.5}$ concentration data, and multiregional input-output (MRIO) tables. The initial PM$_{2.5}$ emission data were obtained from the Emissions Database for Global Atmospheric Research (EDGAR) dataset (Crippa et al., 2018), which includes not only PM$_{2.5}$ emission quantities but also their spatial distribution with a resolution of 0.1° × 0.1° (https://edgar.jrc.ec.europa.eu/). The PM$_{2.5}$ concentrations data between 1998 and 2016 were obtained from a dataset from the Global Annual PM$_{2.5}$ Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) with GWR, released by NASA (http://data.sedac.ciesin.columbia.edu/dataset/sde i-global-annual-gwr-pm2.5-midis-seawifs-aod), with a resolution of approximately 1 km × 1 km. It was reported that this dataset has high consistency with ground-monitored PM$_{2.5}$, with $R^2 = 0.81$. Additionally, the dataset has been widely used in PM$_{2.5}$-related research (Peng et al., 2016; Lavigne et al., 2017; Guo et al., 2019). The MRIO table in 2012 is the latest for China, which was compiled by Liu et al. (2018). The table includes the economic connections among 31 regions and 42 sectors.

This study uses China’s mainland as the study area. The PM$_{2.5}$ emissions and concentrations are analyzed in six regions of China: North China, Northeast China, East China, Mid-south China, Southwest China and Northwest China. The relationship between PM$_{2.5}$ emissions and concentrations and regional inequality is examined at the provincial level. In addition to the administrative levels, changes in PM$_{2.5}$ emissions/concentrations and their relationship are examined at the grid level. This study does not include Hong Kong and Macao. The spatial distribution of regions and provinces is shown in Fig. S1.

2.2. Methodology

2.2.1. Trend analysis

Trend analyses for PM$_{2.5}$ emission intensity and concentrations are performed for different regions and individual spatial grids. For the regions of North China, Northeast China, Northwest China, East China, Mid-south China and Southwest China, the mean regional values of PM$_{2.5}$ emission intensity and concentrations for each year within the study period are displayed. To analyze the trends in PM$_{2.5}$ emission intensity and concentrations for each grid, a simple linear regression.
analysis model of the slope is used (Eq. (1)).

\[
\text{slope} = \frac{n \times \sum_{i=1}^{n} t_i \times p_i - \sum_{i=1}^{n} t_i \sum_{i=1}^{n} p_i}{n \times \sum_{i=1}^{n} t^2 - (\sum_{i=1}^{n} t)^2}
\]  

(1)

where slope is the PM\textsubscript{2.5} emission intensity/concentration trend; \(n\) is the number of studied time intervals (years); \(p\) is the annual PM\textsubscript{2.5} emission intensity/concentrations for year \(i\); and \(\text{slope} > 0\) and \(\text{slope} < 0\) represent the increasing and decreasing tendencies of the PM\textsubscript{2.5} emission intensity/concentrations, respectively. The calculations were completed using coded programming in MATLAB software.

### 2.2.2. Correlation analysis

Pearson’s correlations were determined between PM\textsubscript{2.5} emissions and concentrations to examine their relationship, and two-tailed \(p\)-values were used to determine the significance of each relationship. A high \(R\)-value indicates a high correlation relationship, while a low \(R\)-value represents a low correlation relationship. A positive \(R\)-value implies that PM\textsubscript{2.5} emissions have the same trend as PM\textsubscript{2.5} concentrations, while a negative \(R\)-value implies the opposite trend. To check the validity of the model, the \(p\)-test was used, and the tendencies were classified into 5 categories: highly significant (\(-\)), \((R < 0\) and \(p < 0.01\)); significant (\(-\)) \((R < 0\) and \(0.01 < p < 0.05\)); no significant change \((\pm \)) \((R > 0\) and \(0.01 < p < 0.05\)); and highly significant (\(+\)) \((R > 0\) and \(p < 0.01\)).

The correlation analysis was performed both temporally and spatially. For the time series, the resolution of the initial PM\textsubscript{2.5} concentration grid maps between 1998 and 2012 were compiled in the MRIO table by integrating PM\textsubscript{2.5} emissions and concentrations, and this study also examined the spatial correlations for each year between 1998 and 2012.

### 2.2.3. Inequity analysis based on an input-output model

To analyze the inequity by considering the PM\textsubscript{2.5} emission endowments associated with China’s interregional trade network, the MRIO simulation was used. By adding the direct PM\textsubscript{2.5} emissions of each province as one component of intermediate use, the study compiled an MRIO table by integrating PM\textsubscript{2.5} emission flows with economic data.

Based on the fundamental relationship of rows in the MRIO table, the balanced input and output relationship for each province can be expressed by Eq. (2).

\[
\sum_{j=1}^{n} T_{ij} + f_i = T_i
\]  

(2)

where \(T_{ij}\) is the economic flow from province \(i\) to \(j\); \(f_i\) is the final use of the province; and \(T_i\) is the total output of the province \(i\).

Direct consumption coefficients \(a_{ij}\) of provinces were defined as Eq. (2), and \(A\) is the direct consumption coefficients matrix.

\[
a_{ij} = T_{ij}/T_i
\]  

(3)

\[
A = [a_{ij}]_{n \times n}
\]  

(4)

Eq. (3) was transformed as follows:

\[
T_{ij} = a_{ij} T_i
\]  

(5)

If we replace \(T_{ij}\) with \(AT\), Eq. (2) can be expressed as Eq. (7) through the transformation of Eq. (6).

\[
AT + F = T
\]  

(6)

\[
T = (I - A)^{-1} F
\]  

(7)

where \(T\) refers to the total output matrix, \(I\) is an \(n \times n\) identity matrix, \(A\) is the direct requirement matrix based on a multiregional economy, \((I - A)^{-1}\) is a Leontief inverse matrix, and \(F\) is the final use matrix.

The PM\textsubscript{2.5} emissions triggered by domestic consumption are calculated by Eq. (8).

\[
C_F = (I - A)^{-1} F
\]  

(8)

where \(I\) is the direct PM\textsubscript{2.5} emission intensity, \(C_F\) is the indirect PM\textsubscript{2.5} emissions of provinces triggered by consumption, and \(F\) is the final use matrix.

### 2.2.4. Inequity index

By considering both the trade-pulled PM\textsubscript{2.5} emissions and the diffusion effect in the atmosphere, this study developed the inequity index to analyze regional inequity caused by PM\textsubscript{2.5} emissions. The calculation process is shown in Eq. (9).

\[
i = C \left( E + \frac{E}{A} \right)
\]  

(9)

where \(i\) is the inequity index for a specific province; \(C\) and \(E\) are PM\textsubscript{2.5} emission intensity and concentrations of a specific province, respectively; \(E\) is the PM\textsubscript{2.5} emissions pulled by external province \(i\); import\(_i\) is the PM\textsubscript{2.5} emissions one specific province pulled from external provinces \(i\); and \(E\) and \(import_i\) are calculated by Eq. (8). \(A\) is the land area of a specific province, and \(n\) is the number of other provinces (not including the province itself). The final calculated \(i\) has no unit. Higher values indicate greater disadvantages according to the regional inequity analysis, and conversely, lower values indicate greater advantages.

### 3. Results

#### 3.1. Spatial-temporal variations in PM\textsubscript{2.5} emissions and concentrations

#### 3.1.1. Change trends for regions

PM\textsubscript{2.5} emissions intensities between 1990 and 2012 for different regions are shown in Fig. 1(a) and (b). Overall, China’s mean PM\textsubscript{2.5} emissions intensities increased, with the values rising from 55.32 t/grid in 1990 to 92.74 t/grid in 2012; this trend passed the significance test at the \(p < 0.01\) level. The six regions all showed a similar trend, and the increases were all significant. Between 1995 and 2002, a decrease occurred in all regions, but the values increased rapidly after 2002. East China had the highest emission intensity values of 212 t/grid in 1990 and 351 t/grid in 2012. Mid-south China showed the second-highest emission intensity values, with 144 t/grid in 1990 and 246 t/grid in 2012. North China and Northeast China had similar values, with the Northeast having slightly higher values and a more obvious increase. In 2012, the values were 77.97 t/grid and 113.53 t/grid for the North and Northeast, respectively. The Southwest presented the second-lowest emission level among regions, with 27.59 t/grid in 1990 and 42.34 t/grid in 2012. Its increase was slightly weaker than those of other regions, with \(R = 0.79\). The Southwest was the only region with an \(R\) lower than 0.8. Northwest China’s mean regional emission intensity values were much lower than those of the other regions; they varied from 12.1 t/grid in 1990 to 18.48 t/grid in 2012. Fig. 1 (c) and (d) show PM\textsubscript{2.5} concentration changes between 1998 and 2016 for different regions. Compared with the emissions, the concentrations fluctuated obviously for most regions but continued increasing. The increase in East China, Northeast China and North China all passed the significance test at the \(p < 0.01\) level, while the other regions were at the \(p < 0.05\) level. Similar to emissions, East China had the highest concentration values, and the second highest was Mid-south...
China; their peak values both appeared in 2007, with values of 48.29 μg/m³ and 42.84 μg/m³, respectively. The PM\textsubscript{2.5} concentrations of Northeast China and North China also showed similar values for most years; however, in recent years, the values of Northeast China increased more obviously, with the peak value of 37.33 μg/m³ appearing in 2015. The values for Southwest China and Northwest China were much lower than in other regions. The peak value of 12.11 μg/m³ appeared in Southwest China in 2006, but a decrease appeared in recent years; the peak value in Northwest China occurred in 2016.

3.1.2. Change trends in grids

To match the study periods of the PM\textsubscript{2.5} concentrations, images of PM\textsubscript{2.5} emission slopes were produced for the periods between 1990 and 1997 and 1998 and 2012. Between 1990 and 1997, the mean annual PM\textsubscript{2.5} emissions increased by 0.96 t/grid/year for all of China, while 86.47% of China’s total emissions showed a decrease, with a mean value of −0.08 t/grid/year. Decreasing values between −2 and 0 t/grid/year covered a large percentage of the total area of China. The range of −5 to −2 t/grid/year occurred mainly in East China, Mid-south China, and in the Sichuan Basin within Southwest China. Decreasing values higher than −10 t/grid/year were also distributed partly within these three regions. For the area with an increase, the mean increase was 7.2 t/grid/year; most of the increasing area was in the range of 0–50 t/grid/year (Fig. 2 (a)). Between 1998 and 2012, the mean annual PM\textsubscript{2.5} emissions increase reached 2.9 t/grid/year. The area under the increase accounted for 99.31% of the total, with a mean increase rate of 2.96 t/grid/year. The remaining decreasing area showed a mean value of −5.46 t/grid/year. For the spatial distribution, high increases were more intensively concentrated in the North China Plain, the Sichuan Basin, and the cities of Guangzhou and Shanghai. In Northeast China, the distribution of the high values was much narrower; Liaoning Province showed more intensity than Jilin and Heilongjiang Provinces (Fig. 2 (b)).

Since China implemented the Air Pollution Prevention and Control Action Plan in 2013 to improve air quality, the time breakpoint for PM\textsubscript{2.5}
concentrations has been set to 2013. During the first period between 1998 and 2012 (Fig. 2 (c)), China showed an increase, with a mean value of 0.46 μg/m³/year overall. Approximately 84.61% of the total area experienced an increase, with a mean value of 0.54 μg/m³/year. High increases were mainly located in East China, Mid-south China, and portions of Northeast China and North China; the increase was especially high in Hebei and Shandong Provinces. The 15.39% of the area experiencing a decrease was mainly located on the fringe of China’s northern boundary, with a mean decrease of 0.15 μg/m³/year. Between 2013 and 2016, most of the areas presented obvious increases between 1998 and 2012 and then began to show decreases, with a mean value of 0.13 μg/m³/year. The decrease was especially obvious in the Sichuan Basin and portions of Anhui and Henan Provinces. Approximately 53.4% of the total area continued to increase, with a mean value of 1.09 μg/m³/year, mainly located in West China, Northeast China, and a portion of North China. The high increases were mostly located in Northeast China (Fig. 2 (d)).

3.2. The relationship between PM$_{2.5}$ emissions and concentrations

3.2.1. Spatial relationship

Fig. 3 displays the spatial distributions of PM$_{2.5}$ emissions and concentrations in 2012. The values show a similar distribution pattern. The higher values for both figures are intensively concentrated in the North China Plain, the Sichuan Basin, the Yangtze River Delta Plain, and a portion of Northeast China. In a large area of the west, the emissions and concentrations levels were much lower. There were also different distribution patterns; for example, Guangzhou City had a high PM$_{2.5}$ emission level but a relatively lower concentration.

To further examine the relationship, a linear regression analysis was performed for each year between 1998 and 2012, which used the provincial mean PM$_{2.5}$ emissions and concentrations as variables. The analyzed results in Table 1 show that the correlation coefficients of $R$ were stable and ranged between 0.68 and 0.79. The significance test shows that each year passed the $p<0.01$ level, indicating that PM$_{2.5}$ emissions and concentrations have a close correlation at the provincial

Fig. 2. Mean annual trend of PM$_{2.5}$ emission intensity (a, b) (t/grid/year) and PM$_{2.5}$ concentrations (c, d) (μg/m³/year) of each grid for different periods.
level. For year differences, 1999 showed the lowest correlation coefficient, which was the only year with an $R$ lower than 0.7.

To show the relationship differences among provinces, scatterplots were developed for 2012 and the mean values between 1998 and 2012 (Fig. 4). The plots show that some provinces deviate from the relationship more obviously than others. Using Fig. 4 (b) as an example, the

![Fig. 3. Spatial distribution of PM$_{2.5}$ emissions (a) (t/grid) and concentrations (b) ($\mu$g/m$^3$) in 2012.](image)

### Table 1

Linear regression analysis for China’s provincial regions between PM$_{2.5}$ emissions and concentrations for each year between 1998 and 2012.

| Year   | R     | P-test | Linear regression model          | Year   | R     | P-test | Linear regression model          |
|--------|-------|--------|----------------------------------|--------|-------|--------|----------------------------------|
| 1998   | 0.72  | 0      | $y = 0.06x + 10.2$               | 2006   | 0.76  | 0      | $y = 0.10x + 12.6$               |
| 1999   | 0.68  | 0      | $y = 0.07x + 11.1$               | 2007   | 0.75  | 0      | $y = 0.09x + 13.9$               |
| 2000   | 0.71  | 0      | $y = 0.07x + 9.9$                | 2008   | 0.77  | 0      | $y = 0.09x + 15.7$               |
| 2001   | 0.79  | 0      | $y = 0.10x + 11.5$               | 2009   | 0.77  | 0      | $y = 0.09x + 14.6$               |
| 2002   | 0.74  | 0      | $y = 0.09x + 12.6$               | 2010   | 0.75  | 0      | $y = 0.08x + 15.1$               |
| 2003   | 0.77  | 0      | $y = 0.10x + 13.6$               | 2011   | 0.78  | 0      | $y = 0.08x + 13.6$               |
| 2004   | 0.75  | 0      | $y = 0.08x + 13.3$               | 2012   | 0.73  | 0      | $y = 0.08x + 13.9$               |
| 2005   | 0.72  | 0      | $y = 0.08x + 16.2$               | 1998–2012 | 0.76 | 0   | $y = 0.08x + 13.4$               |

![Fig. 4. Scatterplots of PM$_{2.5}$ emissions and concentrations among China’s provincial regions and the linear regression analysis for 2012 (a) and the mean values between 1998 and 2012 (b).](image)
emissions intensities of Hainan, Fujian, Liaoning, Guangdong, Zhejiang and Shanxi were all relatively high, with values of 158.56, 160.02, 277.68, 454.12, 341.62, and 306.84 t/grid, respectively, while their PM$_{2.5}$ concentrations ranged between 12.45 and 29.78 μg/m$^3$, which were not always higher than those in other provinces. Among these regions, all are coastal provinces except Shanxi Province.

3.3.1. Inequity from interregion trade

Fig. 6 (a) displays the interregion exported and imported PM$_{2.5}$ emissions embodied in domestic trade, and the net values of the imported emissions amount minus the exported emissions. The following 15 provinces had negative net PM$_{2.5}$ emissions: Hebei, Shandong, Shanxi, Inner Mongolia, Guizhou, Guangxi, Anhui, Hunan, Jilin, Shaanxi, Henan, Gansu, Liaoning, Heilongjiang, and Hebei. Among these provinces, Hebei and Shandong showed much higher net PM$_{2.5}$ emissions than the others. For the amount of interregion exports and imports, provinces such as Hebei, Shandong, Henan, Shanxi, Jiangsu, Inner Mongolia, Zhejiang and Guangdong presented high PM$_{2.5}$ flows among provinces.

Fig. 6 (b) illustrates the source-receiver relationship of PM$_{2.5}$ emissions between provinces. As the largest net producer, several high values appear in Hebei’s contribution to other provinces; for example, its contributions to Jiangsu, Zhejiang, and Shandong were higher than 1 × 10$^4$ t, and its contributions to Henan and Guangdong Provinces were also high. A similarity was found for Shanxi, Inner Mongolia, Liaoning, Shandong, and Henan Provinces, with considerable contributions to China’s more developed regions, mainly including Jiangsu, Zhejiang, Guangdong, Beijing, and Shanghai. Additionally, the abovementioned contributors have considerable PM$_{2.5}$ emission flows with each other. Conversely, the developed regions have significant PM$_{2.5}$ emission flows with each other, but their contributions to the source regions were lower. For example, Jiangsu Province provided 1.03 × 10$^4$ t and 0.71 × 10$^4$ t to Guangdong and Zhejiang, respectively, while its contributions to its main source regions were not always high. Thus, the regional inequity can be well reflected in domestic trade; more developed regions take obvious advantage of the sacrifices of the less developed regions.

3.3.2. Comprehensive inequity analysis

Fig. 7 shows the inequity index difference among provinces, which is calculated by Eq. (10). The lowest level of 0.02–0.04 includes Beijing and Shanghai, and the second lowest level includes Liaoning, Tianjin, Jiangsu, Zhejiang, Guangdong and Hainan Provinces, which are China’s coastal provinces. The provinces with high inequity values are mostly concentrated in the north and west. Among them, Tibet had the highest values, followed by Xinjiang, Inner Mongolia, Jilin, Guizhou, Heilongjiang, Qinghai and Gansu also have relatively high values, with inequity index values ranging from 0.6 to 0.42. As the largest PM$_{2.5}$ emissions contributor to other regions, Hebei also has a high inequity index value of 0.36; however, Shandong and Henan have moderate values of 0.17 and 0.16, respectively. Generally, lower values were shown for provinces along the coastline, especially provinces with high economic levels; most of the high values appeared in inland China, especially in the west and north.

![Fig. 5. Spatial pattern of the correlation coefficients (a) and significance test (b) between PM$_{2.5}$ emissions and concentrations](image-url)
4. Discussion and policy implications

Both the emissions and concentrations increased overall because of the high amount of energy consumption to satisfy the demand for continuous economic and population growth and the rapid urbanization and industrialization processes (Li et al., 2016a; Xu and Lin, 2018; Wang et al., 2018). Lower PM$_{2.5}$ emissions are generally observed at the end of the last century and the beginning of this century; this is because PM$_{2.5}$ emissions are mostly generated from anthropogenic activities, especially from energy consumption. However, during this period, the Asian Financial Crisis in 1997 significantly affected China’s economy, and the economic depression decreased coal-reliant energy consumption and thus lowered PM$_{2.5}$ emissions. After China joined the World Trade Organization (WTO) in 2001, its economy began to recover and develop rapidly, which corresponds well with the change in PM$_{2.5}$ emissions. The PM$_{2.5}$ concentration trend does not correspond well with China’s economic development, because once PM$_{2.5}$ is emitted into the atmosphere, it will be affected by weather and climate conditions and can be transported far away (Ozbek et al., 2016). To better understand PM$_{2.5}$ emission reduction, it is critical to know the structure of emission sources. According to the data from EDGAR, manufacturing industries and construction were the largest emission sources; they accounted for 40.61% of the entire emission budget in 2012. Residential and other sectors, public electricity and heat production, and other energy industries were the three next highest industries, with percentages of 13.26%, 11.93% and 12.25%, respectively. Another notable emission source is cement production. For transportation, the percentage was much lower, among road transportation accounted for the highest percentage (Crippa et al., 2018; EDGAR, 2020). This emission source structure is generally similar to the PM$_{2.5}$ emission data from the MEIC in Asia (Kurokawa et al., 2013; Li et al., 2017), indicating that our analysis is credible. Thus, PM$_{2.5}$ emission reduction should be focused on these sectors, and effective measures should be strictly implemented, such as using clean energy to replace coal-burning power plants (Zhang et al., 2018), strengthening industrial and vehicle emission standards, closing small and polluting factories, and upgrading industrial boilers (Zhang et al., 2019; Wang et al., 2020).

There is significant spatial heterogeneity in PM$_{2.5}$ emissions and concentrations across China. China’s three highly developed regions—Beijing-Tianjin-Hebei (BTH), the Yangtze River Delta (YRD) and the Pearl River Delta (PRD)—where there are intense concentrations of large populations and industries, all have high PM$_{2.5}$ emissions and concentrations levels and thus have become the regions of greatest attention for China’s PM$_{2.5}$ reduction. The Chinese government aimed to decrease their levels by 25%, 20% and 15% by 2017 relative to 2012 (Wang et al., 2020). According to our analysis in Fig. 2 (d), between 2013 and 2016, PM$_{2.5}$ concentrations in a large area of the three regions exhibited a decrease, indicating that the Air Pollution Prevention and Control Action Plan released in 2013 was effective and that the considerable effort that the Chinese government has expended will continue to improve air quality in China. The three regions mentioned above have obvious differences determined by their locations. The BTH in North China is a region where heavy industry is intensively concentrated, in which nitrate and sulfate account for a large proportion, which can promote PM$_{2.5}$ accumulation (Wang et al., 2014). In South China, the aerosol type is predominantly a clean-ocean type (Hu et al., 2010), and NaCl is one of the main components in the PM$_{2.5}$.
According to related studies, NaCl is more likely to absorb large amounts of moisture and fall to the ground under high-humidity conditions (Dawson et al., 2007; Ye and Chen, 2013); thus, although PM$_{2.5}$ emissions in East China and Mid-south China are high (Fig. 1), they have relatively lower PM$_{2.5}$ concentration pressure than that in North China. Although various factors bias the regional PM$_{2.5}$ concentrations compared with their emissions, the relationship examination indicates that PM$_{2.5}$ emissions can significantly determine their concentrations in China, indicating that regional PM$_{2.5}$ emission reduction will alleviate their concentrations. This finding is helpful for local air quality improvement efforts. Although a recent study showed that high PM$_{2.5}$ concentrations have continued to be found in the North China Plain during the period of Coronavirus disease 2019 (COVID-19) (Wang et al., 2020), this does not prove that the emissions have no decisive role in the concentration. This finding might be explained by the fact that the concentration has been accumulating for many years, and a short period without emissions may not cause an immediate change.

To check the regional inequity, the inequity analysis in this study considered both the concentration/emission level and the influence of domestic trade; this is a relatively simple but effective method to elevate regional inequity in China. Generally, provinces along the coastline, especially developed provinces, are at an advantage, while most of the inland regions are at a disadvantage, especially in the west and north. First, it is well established by China’s domestic trade and PM$_{2.5}$ emission characteristics among different regions that the interregional exported or imported PM$_{2.5}$ emissions are determined by both economic connections and regional PM$_{2.5}$ emissions. For example, Hebei, Shandong, Henan, Liaoning, Jiangsu and Guangdong all have a high amount of PM$_{2.5}$ emissions, but due to their economic connection differences, the first four are the main PM$_{2.5}$ emission providers to serve the other regions’ development. Although these regions may gain some economic profits compared with the external regions from which they import emissions, the environmental and human health cost is considerable. Additionally, this study only examined PM$_{2.5}$ emissions; however, various air pollution and greenhouse gases will also be imported because they are mainly energy consumption-generated emissions (Wang et al., 2017; Lenzien et al., 2018; Pendrill et al., 2019). Thus, the environmental costs may be more severe. Conversely, developed regions such as Jiangsu, Zhejiang and Guangzhou were obvious net PM$_{2.5}$ emissions receivers, which means that they imported much more emissions from other regions than they exported to their providers. During this process, emissions were transferred to other regions, and they gained environmental benefits. Beijing, Shanghai, Tianjin and Chongqing are municipalities directly under the central government with relatively small regional areas; however, they were also obvious net PM$_{2.5}$ emissions receivers, and the advantages they have taken are also obvious. From another perspective, there is the phenomenon of population outflow mainly to China’s large cities and the more developed regions, especially from Northeast China and North China (You et al., 2018), which causes the developed regions to have large populations (Huang et al., 2018; Song et al., 2018). By transferring a portion of the emissions externally, air pollution damage to human health may be alleviated to some extent; in this way, the regional inequity may be somewhat offset.

Considering the relationship of PM$_{2.5}$ concentrations and emissions, the regional inequity index in Fig. 7 shows an obvious pattern. The provinces along the coastline have the advantage, while the inland regions have unfavorable conditions. In addition to the effect of domestic trade, the heterogeneity of physical conditions, especially the differences in meteorological factors, plays a critical role. According to previous studies, wind speed, humidity, rainfall and temperature can significantly affect PM$_{2.5}$ concentrations. First, a negative correlation was found between wind speed and PM$_{2.5}$ widely across China; higher wind speed can reduce the concentrations (Stortini et al., 2009; Zhang et al., 2018). The coastline regions, where there are better atmospheric diffusion conditions, benefit from emissions transportation in the atmosphere, which reduces regional pollution. This process can explain why regions with high PM$_{2.5}$ emission levels but not high concentrations are mostly located on the coastline (Fig. 4). Additionally, most of China’s developed regions are located along the coastline; along with the influence of domestic trade, the advantages for these provinces were expanded. Studies have found that temperature is negatively correlated with PM$_{2.5}$ concentrations; an increase in temperature will help reduce PM$_{2.5}$ emissions (Zhang et al., 2016b, 2018). Another important factor is rainfall; annual accumulative rainfall was also found to be negatively correlated with the PM$_{2.5}$ emissions (Ozbek et al., 2016; Chen et al., 2018). Determined by the distribution of China’s climate zones, Southern and Southeastern China have rich hydrothermal conditions, which will aid in the concentration reduction. However, inland China, especially North China, Northwest China and Northeast China, is cold in the winter, resulting in additional coal consumption. Less rainfall and low temperatures in these inland areas are not beneficial for reducing PM$_{2.5}$ concentrations. Such meteorological conditions provide spatial heterogeneity and, along with the emissions distribution pattern, can determine the distribution of China’s PM$_{2.5}$ spatial concentration. Due to data limitations, this study examined the relationship between PM$_{2.5}$ concentrations and emissions yearly. For further studies, if higher-resolution PM$_{2.5}$ concentration and emission data are available (such as monthly), more detailed analysis can be performed, and their connections can be revealed on a synoptic scale.

Accordingly, there are some suggestions both for PM$_{2.5}$ reduction and regional inequity alleviation. First, additional environmental protection strategies, especially air quality improvement plans, should be designed by central and local governments. The emission reduction task must be allocated to different administrative regions and focused on key industries and factories. Second, the supervision and management system must be improved, and the implementation of reduction tasks must be strengthened. Third, China’s main PM$_{2.5}$ emissions were from certain industries, as mentioned above (Crippa et al., 2018; EDGAR, 2020), and they were generated by a large amount of coal burning; thus, energy consumption structure optimization has become the most critical factor for PM$_{2.5}$ emission reduction, and exploitation of new clean energies should be encouraged, such as nuclear power generation (Zhang et al., 2018). Additionally, industrial technology improvement is required, for example, the upgrading of industrial boilers and adding dust removal equipment. Although these measures may bring some economic loss, they are worth the cost to protect the environment and human health. The central government needs to provide financial grants to implement these measures and to compensate certain industries and associated workers making economic sacrifices. To address the issues that hinder harmonious development caused by regional inequity, some policies can be proposed. First, many of the PM$_{2.5}$ emission-generating industries are located in an area with unfavorable meteorological conditions but with high population densities, such as the North China Plain and the Sichuan Basin. Thus, one suggestion is to transfer a portion of the seriously polluting industries to the west, where there is a sparse population. Third, more developed regions should provide technological support to less developed regions to help them improve industry efficiency and reduce emissions. Fourth, less developed regions should receive economic compensation from more developed regions. The central government needs to establish some integrated compensation policies or mechanisms, such as resources, environmental taxes, and cross-area emissions trading (Yip, 2018).

5. Conclusions

The following conclusions are drawn: China’s PM$_{2.5}$ emissions and concentrations have both increased rapidly over time, and the increase in emissions is obvious. Obvious regional differences exist for PM$_{2.5}$ emissions/concentrations levels. Regionally, high values of both emissions and concentrations are more concentrated in a large area of East China, Mid-south China, Northeast China, the North China Plain and the Sichuan Basin, which also presented high annual increasing mean
values. After 2013, PM$_{2.5}$ concentrations decreased to below 16.0 μg/m$^3$ in most of the coastline provinces due to reduction of PM$_{2.5}$ emissions; this is one reason regional inequity occurs. Through economic connections among regions, domestic trade is another reason for regional inequity. Both the meteorological conditions and economic connections in domestic trade in most of the coastline provinces are beneficial for reducing PM$_{2.5}$ concentrations; advantages in these regions are expanded, but they aggravate regional inequity for many of the other regions.

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.

Acknowledgements

This research was funded by the Ministry of Education, Humanities, and Social Science Fund of China (19YJAZH008) and the National Natural Science Foundation of China (71921003).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.111335.

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Xiaowei Chuai: Conceptualization, Methodology, Supervision, Writing - original draft. Yue Lu: Data curation. Fangjian Xie: Visualization, Investigation. Feng Yang: Software. Rongqin Zhao: Writing – review & editing. Baoxin Pang: Writing – review & editing.

Journal of Environmental Management 277 (2021) 111335

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