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Technical Note

Identifying $PM_{2.5}$-Related Health Burden in the Context of the Integrated Development of Urban Agglomeration Using Remote Sensing and GEMM Model

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Abstract: Integrated development of urban agglomeration is emerging as the main pattern of China's new modernization. Yet, atmospheric pollution continues to have an adverse impact on public health, challenging efforts to promote coordinated regional development. To better understand the interaction between atmospheric pollution-related health burdens and urbanization, this study employed deep learning technology to obtain high-resolution satellite-derived $PM_{2.5}$ concentration data across the Yangtze River Delta (YRD) region. Using the Global Exposure Mortality Model (GEMM), this study estimated premature mortality resulting from long-term exposure to $PM_{2.5}$ and innovatively incorporated exposure factors to improve accuracy. Results indicated that while $PM_{2.5}$ concentrations decreased by 16.13% from 2015 to 2019, the region still experienced 239,000 premature mortalities in 2019, with notable disparities among cities of different economic levels and sizes. Furthermore, it was found through correlation analysis that residential density and GDP per capita were highly associated with premature mortality. In conclusion, these findings highlight the continuing challenge of achieving equitable effectiveness of joint air pollution control across regions in the context of integrated development of urban agglomeration.

Keywords: deep learning; air pollution; premature mortality; Yangtze River Delta; integration development; urban agglomeration

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1. Introduction

Public health concerns have garnered considerable attention on a global scale, particularly in step with unprecedented urbanization and economic development [1,2]. A new annual standard (5 $\mu g/m^3$) for $PM_{2.5}$ (particles with an aerodynamic diameter equal to or less than 2.5 μm) was proposed by the World Health Organization (WHO, Geneva, Switzerland) on 22 September 2021 [3], since emerging evidence demonstrated its strong association with increased morbidity and mortality [4–7]. $PM_{2.5}$ are a prominent component of air pollution, damaging public health and impeding the well-being of the Chinese populace. Although significant progress has been made in curbing $PM_{2.5}$ concentrations in China, levels are still far above 5 $\mu g/m^3$ in most parts of the country, thereby jeopardizing human health.

China has been building comprehensive and influential regional collaboration mechanisms for joint prevention and control of atmospheric pollution since 2010, with the

Beijing–Tianjin–Hebei region (BTH), the Yangtze River Delta (YRD), and the Pearl River Delta (PRD) listed as key regions for improving air quality. In 2013, China released the "Action Plan for the Prevention and Control of Air Pollution" (referred to as "Atmospheric Ten"), proposing a target of reducing fine particulate matter concentrations in the BTH, YRD, and PRD regions by 25%, 20%, and 15%, respectively, and clearly stipulating Joint Prevention and Control of Atmospheric Pollution (JPCAP) as an effective approach to addressing regional environmental issues [8]. Following deeper research on air pollution, the JPCAP policy was revised and updated in 2015 to reflect the changing regional conditions of integrated development and regional characteristics of air pollution [9].

The implementation of the JPCAP policy has given rise to a complex interplay between the imperatives of economic development and environmental protection, as well as regional cooperation. This is because different regions are at varying stages of urban development and exhibit varying levels of connectivity between them [10]. However, existing literature has inadequately examined the impact of jointly controlling air pollution on both environmental and economic outcomes with a disproportionate focus on the $PM_{2.5}$ levels in China's megacities [11]. Furthermore, $PM_{2.5}$-related premature mortality was mainly discussed at the national scale or regional scale, thus potentially overlooking the public health burden faced by lower-level administrative areas in regions undergoing integration development, where priority and beneficiary areas are dominant [1,12,13]. In light of this, more refined and precise data is required to remedy the research gap.

Satellite station hybrid models were widely used to map $PM_{2.5}$ concentrations at various spatiotemporal scales [14]. Unlike in situ $PM_{2.5}$ measurements, this method leverages the high accuracy of ground data and continuous spatial coverage of remote sensing data [15,16]. In previous studies, satellite-derived aerosol optical depth (AOD) products were proven to estimate $PM_{2.5}$ concentrations effectively [17]. Many statistical regression models, such as simple linear regression models, multiple linear regression models, and geographically weighted regression (GWR) models have been employed to retrieve high-quality AOD products [16,18–20]. Nonetheless, these methods may oversimplify the complex non-linear AOD-$PM_{2.5}$ relationships and may also suffer from missing values [21,22]. Thus, non-linear models are increasingly being explored to build a robust correlation between satellite-derived AOD and $PM_{2.5}$, such as generalized additive models (GAM) and random forest models. Unfortunately, these models were likely to be limited by insufficient AOD data, existing emission uncertainties, or incomplete descriptions of chemical transformations. In conclusion, a more efficient and appropriate research method is needed to address the aforementioned challenges.

To estimate the health burden, it is crucial to consider the concentration response mechanism and human activity patterns. Concentration response functions (CRFs) based on epidemiological studies have been widely applied to estimate mortality from air pollution [3]. However, most CRFs adopted in previous studies were derived from cohort studies in North America and Europe, where the annual $PM_{2.5}$ concentrations were relatively low [12,23]. To better reflect highly polluted regions in China, the newly developed Global Exposure Mortality Model (GEMM) based on global exposure range was introduced [24]. In addition, human activity patterns exhibit spatial heterogeneity and should be considered when estimating premature mortality [13,25]. Previous studies have shown that neglecting exposure factors may lead to overestimation of the total number of premature mortalities [12]. Therefore, in this study, provincial-level respiratory rates and time spent outdoors were incorporated into the GEMM model to more accurately estimate premature mortality caused by $PM_{2.5}$.

Accordingly, this study took the YRD region as the study area and investigated the spatiotemporal evolution of public health burden of exposure to long-term $PM_{2.5}$ in the context of regional integration development and the JPCAP policy. To evaluate $PM_{2.5}$-related exposure more reliably, this study first applied an interpretable self-adaptive deep neural network (SADNN) to obtain high-resolution satellite-derived $PM_{2.5}$ concentrations. The GEMM model was then combined with exposure factors and age-grouped population data to estimate premature mortality caused by $PM_{2.5}$. The spatiotemporal variations in $PM_{2.5}$-related premature mortality at the city level in the YRD region from 2015 to 2019 were analyzed, and potential correlations between health risks induced by long-term exposure to $PM_{2.5}$ and urban development features were explored. Findings from this study will support assessing the effectiveness of JPCAP policy in the YRD region from 2015 to 2019 and guide the optimization of future regional joint governance of atmospheric pollution problems. Ultimately, these results will promote the integrated development of urban agglomerations and facilitate high-quality modernization.

2. Study Area

The YRD region is an alluvial plain situated in the lower Yangtze River basin and proximate to the Yellow Sea and the East China Sea (Figure 1). The whole region covers a vast area of 3.58 × 106 km^2, including Shanghai Municipality, the central city of integrated development, and Zhejiang, Jiangsu, and Anhui Provinces. This region, which constitutes merely 4% of the total land area of China, is inhabited by around 1/6 of the population and generates 1/4 of the nation's total economic output. Despite being set up as one of the "key regions" conducting the Joint Prevention and Control Action Plan (JPCAP) policy to address point source pollution and regional pollution, the YRD region continues to face challenges in terms of environmental quality, with annual $PM_{2.5}$ concentrations exceeding WHO guidelines (5 $\mu g/m^3$) and occasional heavy pollution events. In light of its development trajectory, it is imperative to evaluate the impact of environmental factors on public health within the YRD region, with a particular emphasis on promoting high-quality integration development.

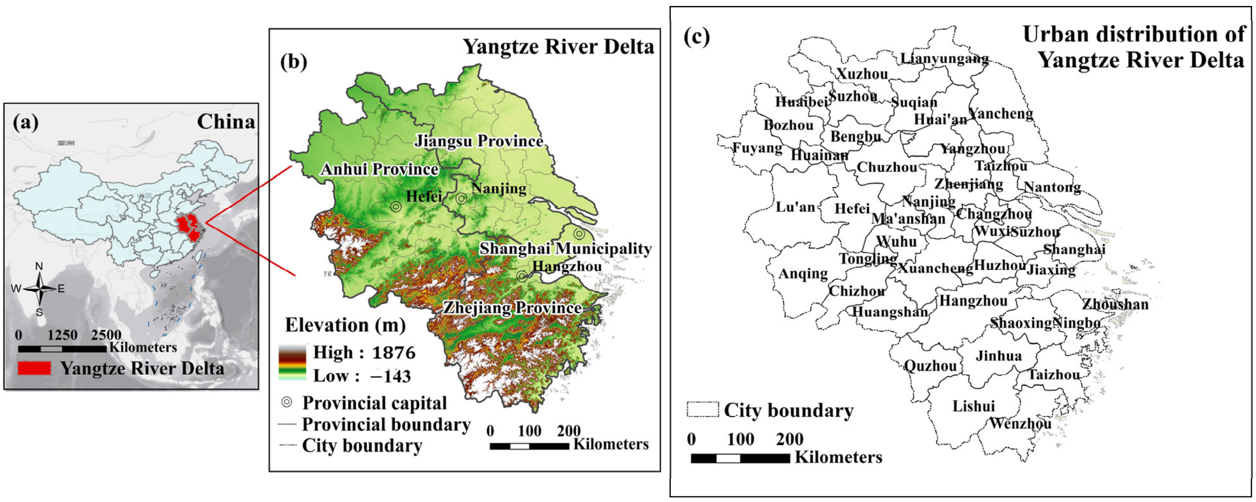

Figure 1. (**a**) Location of the Yangtze River Delta; (**b**) Digital elevation map of the YRD region; (**c**) Urban distribution of the YRD region.

3. Materials and Methods

This study developed a comprehensive approach to estimate $PM_{2.5}$ concentrations and evaluate their health burden on the public in the YRD region from 2015 to 2019 (Figure 2). The technical framework combined an interpretable self-adaptive deep neural network (SADNN) and GEMM NCD + LRI with exposure factors and age-grouped population data to accurately calculate premature mortality caused by $PM_{2.5}$. To investigate population aggregation and air pollution levels in different regions, we conducted a Bivariate Local Moran Index analysis which identifies areas with dense populations simultaneous with severe $PM_{2.5}$ pollution. Then correlation analysis was utilized to find out the potential relationship between $PM_{2.5}$ pollution and urban characteristics in the context of YRD integration development.

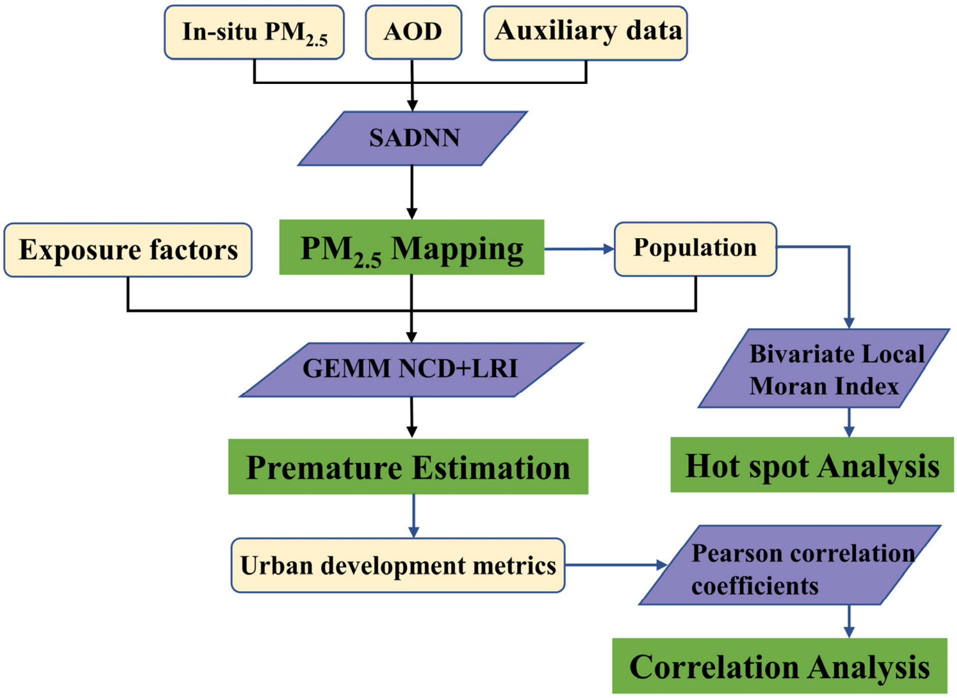

Figure 2. Technical framework.

3.1. $PM_{2.5}$ Concentration Mapping

In this study, we utilized a validated modeling approach for estimating $PM_{2.5}$ concentrations, specifically an interpretable self-adaptive deep neural network (SADNN), which was published previously in our research [21]. The SADNN model was employed to estimate annual $PM_{2.5}$ concentrations in the YRD region at a spatial resolution of 0.01° from 2015 to 2019. This SADNN model, which was developed from traditional deep neural networks (DNN), has the capacity to self-adaptively model and correct the complicated non-linear AOD-$PM_{2.5}$ relationships by innovatively introducing the attention module after the input layer. Essentially, this attention module adopts a gating activation function to classify the input predictors by different importance weights and additionally analyze the interactions of predictors, and is thus able to improve the interpretability of the modeling results. Five-fold sample-based cross-validation results showed a high estimation accuracy of the SADNN model, with a coefficient of determination value of 0.86. The specific structure and detailed procedures of the SADNN model are included in the Supplementary Materials.

The input predictors in this study mainly consist of in situ $PM_{2.5}$, AOD products and auxiliary data. The in situ $PM_{2.5}$ data was deployed as the dependent variable for modeling with the time spanning from January 2015 to December 2019. The AOD products were retrieved from MODIS Terra and Aqua satellites, and the data gaps were filled by means of random forest (RF). According to our previous research [21], the correlation coefficient of the filled AOD data was 0.89 with a low RMSE value of 0.24. Except for AOD products and $PM_{2.5}$ monitoring data, data used as potential variables to map $PM_{2.5}$ concentrations also included Normalized Difference Vegetation Index (NDVI) data, Digital Elevation Model (DEM) data, and ERA-5 hourly meteorological data. ERA-5 is the fifth generation European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis of global climate and weather for the past 4 to 7 decades [25]. The following were selected as predictors in this study: 2-meter temperature (T2M), 10-meter U wind component (WU10M), 10-meter V wind component (WV10M), boundary layer height (BLH), surface pressure (SP), and relative humidity (RH). All data were resampled to a spatial resolution of 0.01° by employing bi-linear interpolation. Table S1 summarizes the details of the datasets used in the SADNN model and validation of the results can be found in the Supplementary Materials. Detailed analysis of spatial–temporal variations of $PM_{2.5}$ concentrations in the YRD region from 2015 to 2019 is included in the Supplementary Materials (Figures S1–S3).

3.2. Hot Spot Analysis

We utilized a Bivariate Local Moran Index (I_i^{ab}) in conjunction with significance analysis and cluster analysis to investigate the spatial association between air pollution and population density. Those pixels with high z scores and small p values were defined as hotspots showing spatial agglomeration features. Bivariate Local Moran Index analysis was completed on GeoDa software, a widely used platform for spatial data analysis [26]. The formula is calculated as follows:

$$I_i^{ab} = x_i^a \sum_{j=1, j\neq i}^{n} w_{ij} x_i^b \tag{1}$$

$$Z(I_i^{ab}) = \frac{I_i^{ab} - E\left(I_i^{ab}\right)}{\sqrt{Var\left(I_i^{ab}\right)}} \tag{2}$$

$$E\left(I_i^{ab}\right) = -\frac{\sum_{j=1,j\neq i}^{n} w_{ij}}{n-1} \tag{3}$$

$$Var\left(I_i^{ab}\right) = E\left({I_i^{ab}}^2\right) - E\left(I_i^{ab}\right)^2 \tag{4}$$

$$n = \sum_{i=1}^{n} \sum_{j\neq 1}^{n} w_{ij} \tag{5}$$

where x_i^a and x_i^b represent the mean standardized (z-scores) values of variable a and variable b, respectively, at the ith and jth pixels, and w_{ij} is the spatial weight value of 1 or 0 depending on the distance between pixel i and j and was refined through multiple experiments to identify the most pronounced spatial aggregation features within a 10 km radius.

3.3. Public Health Burden Analysis

3.3.1. Demographic Data Correction

The demographic data in the YRD region from 2015 to 2019 was obtained from WorldPop (https://www.worldpop.org, accessed on 15 January 2022), which provides high-resolution geospatial data on population distributions, demographic, and dynamics. In this study, the datasets of population containing age and sex structures at a spatial resolution of 3 arc (approximately 100 m at the equator) were collected. To ensure accuracy, we also utilized statistics from the China Population and Employment Statistical Yearbook (https://navi.cnki.net/knavi/yearbooks/YZGRL/detail?uniplatform=NZKPT, accessed on 12 January 2022) to correct the population distribution data. Details of the correction process are explained in the Supplementary Materials.

3.3.2. Exposure Factors

As air pollution exposure involves complicated interactions including both air quality and individual-level factors such as daily physical activity, we introduced respiratory rates and time spent outdoors into the GEMM model based on our previous study [12]. These parameters were drawn from the first Chinese Environment Exposure-Related Human Activity Patterns Survey (CEERHAPS), with provincial-level statistics used in this study [27,28].

3.3.3. Premature Mortality Estimation

Since GEMM was built relying on long-term exposure to $PM_{2.5}$ and focused on non-communicable diseases (NCDs) and lower respiratory infections (LRIs), the model was denoted as GEMM NCD + LRI in this study. First, premature mortality attributed to long-term exposure to $PM_{2.5}$ for the total population group (aged $\geq$ 25 years) in grid j was calculated:

$$M_j(C_j) = P_j \times B \times AF(C_j) \tag{6}$$

where C_j is the concentration in grid j; P_j represents the total population amount in grid j; B represents the baseline mortality incidence rates of NCD+LRI for a population group, which were selected from the GBD data on the Global Health Data Exchange (GHDx) website (http://ghdx.healthdata.org/gbd-results-tool, accessed on 28 October 2021); and $AF(C_j)$ is the fraction of NCD + LRI attributed to long term $PM_{2.5}$ exposure at a given concentration level C_j, which was obtained from the Supplementary Materials.

In the second stage, exposure factors including respiratory rates and time spent outdoors were introduced to correct premature mortality at the provincial level. The weighted coefficient E_j was determined by the following equation:

$$E_j = \frac{L_j}{L_{ave}} \times \left(\frac{t_j + \beta \times (24 - t_j)}{t_{ave} + \beta \times (24 - t_j)} \right) \tag{7}$$

where L_j is the respiratory rate for a given population in the grid j and L_{ave} is the national average value of the respiratory rates across mainland China; similarly, t_j is the time spent outdoors for the given population in the grid j, and t_{ave} is the national average value of time spent outdoors; and β represents the ratio of indoor $PM_{2.5}$ (in residential buildings) to outdoor $PM_{2.5}$. These parameters have been validated, and more details are explained in the study by Zou et al., (2019) in China [12].

Finally, the estimation of premature mortality was calculated as:

$$\text{Mortality}_j = M_j \times E_j \tag{8}$$

where Mortality_j represents final premature mortality estimation in the grid j for a population group.

4. Results

4.1. Hot Spot Analysis of $PM_{2.5}$ Concentrations and Population Density

High-density populations exposed to air pollution tend to bear the greatest public health burden. Figure 3 illustrates the spatial inconsistency analysis between $PM_{2.5}$ concentrations and population density with a 10-km spatial resolution in the YRD region from 2015 to 2019. The results were classified into four distinct types based on the aggregation features.

In general, the spatial patterns of the four types showed distinct regional characteristics. The high-high type, characterized by significantly high population density and annual $PM_{2.5}$ concentrations, was observed in the northern YRD region, represented by Shanghai Municipality and its surrounding areas. It also included Hangzhou, the provincial capital of Zhejiang Province, as well as some cities in the east of Jiangsu Province, such as Nanjing, Wuxi, Nantong, Yancheng, Lianyungang, and cities such as Hefei, Bozhou, Fuyang, Huainan, Tongling, and Wuhu in Anhui Province. The low-low type, where both population density and annual $PM_{2.5}$ concentrations were relatively low, was centered in the southwestern mountainous and hilly areas of the YRD region, featuring high forest coverage and less human activity. The low-high type was primarily found in coastal areas, mainly in Zhejiang Province, including Ningbo, Taizhou, and Wenzhou, where annual $PM_{2.5}$ concentrations were relatively low while population density was distinctively high. On the other hand, the high-low type was mainly observed in Chuzhou City, which is situated on the border between Anhui Province and Jiangsu Province and is one of the core cities in the integrated development of the YRD region.

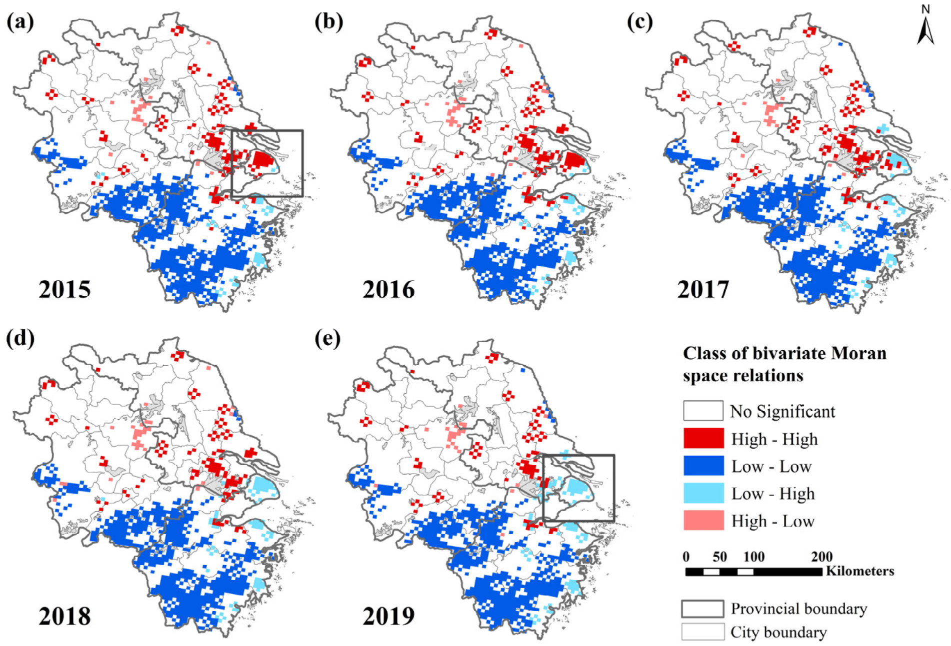

Figure 3. $PM_{2.5}$-population autocorrelation clustering diagram in the Yangtze River Delta from 2015 to 2019: (**a**) 2015; (**b**) 2016; (**c**) 2017; (**d**) 2018; (**e**) 2019. The high–high type is characterized by both high population density and high annual $PM_{2.5}$ concentrations. The low–low type is characterized by both low population density and annual $PM_{2.5}$ concentrations. The low–high type features regions where annual $PM_{2.5}$ concentrations are relatively low but population density is significantly high. The high–low type represents regions where annual $PM_{2.5}$ concentrations are distinctively high but population density is relatively low. Gray squares on the graph show areas of significant change.

Notably, during the study period, only Shanghai and its surrounding areas changed from the high-high type to the low-high type as the grey square in Figure 3a,e demonstrates, indicating that annual $PM_{2.5}$ concentrations were not accompanied by an increase in population density. In contrast, other types remained stable. This suggests that the public health burden associated with air pollution has been effectively alleviated in the metropolitan areas under the JPCAP, while the lower-level administrative cities have not experienced significant changes.

Overall, the findings highlight the regional characteristics of the spatial inconsistency between population density and $PM_{2.5}$ concentrations in the YRD region and provide valuable insights for policymakers to develop targeted strategies to mitigate the adverse effects of air pollution on public health.

4.2. Provincial and City Level Variations of Premature Mortality

Utilizing annual $PM_{2.5}$ concentrations, population, baseline mortality rates, and the GEMM NCD + LRI model, we estimated premature mortality in the YRD region from 2015 to 2019. In 2015, the total $PM_{2.5}$-related premature mortality was estimated to be 242,859 (95% CI: 190,520; 290,782), and this figure decreased to 239,257 (95% CI: 186,481; 288,278) by 2019, representing a reduction of 1.48%. There were obvious variations among the different provinces. Figure 4 illustrates $PM_{2.5}$-related premature mortality and premature mortality per 100,000 inhabitants at the provincial level, depicted by the bar chart and folding line chart, respectively. Specifically, in 2019, Jiangsu Province and Anhui Province had much higher rates of premature mortality per 100,000 inhabitants, estimated at 172 (95% CI: 134; 207) and 171 (95% CI: 134; 205) respectively, followed by Shanghai Municipality and Zhejiang Province, with estimates of 152 (95% CI: 117; 182) and 139 (95% CI: 108; 168), respectively. Over the past five years, Shanghai Municipality showed the most notable sharp downward trend in premature mortality per 100,000 inhabitants, which corresponds to the results of the hot spot analysis demonstrating a reduction of 29.79% in

$PM_{2.5}$ concentrations. However, Anhui Province had the smallest reduction in premature mortality per 100,000 inhabitants, even with an increasing trend in total premature mortality. Regarding interannual variability, premature mortality per 100,000 inhabitants in Shanghai Municipality and Zhejiang Province continued to decrease, whereas the rest of the provinces experienced fluctuations, particularly in 2017 in Anhui Province. This trend is consistent with the rebound of $PM_{2.5}$ concentrations observed in 2017.

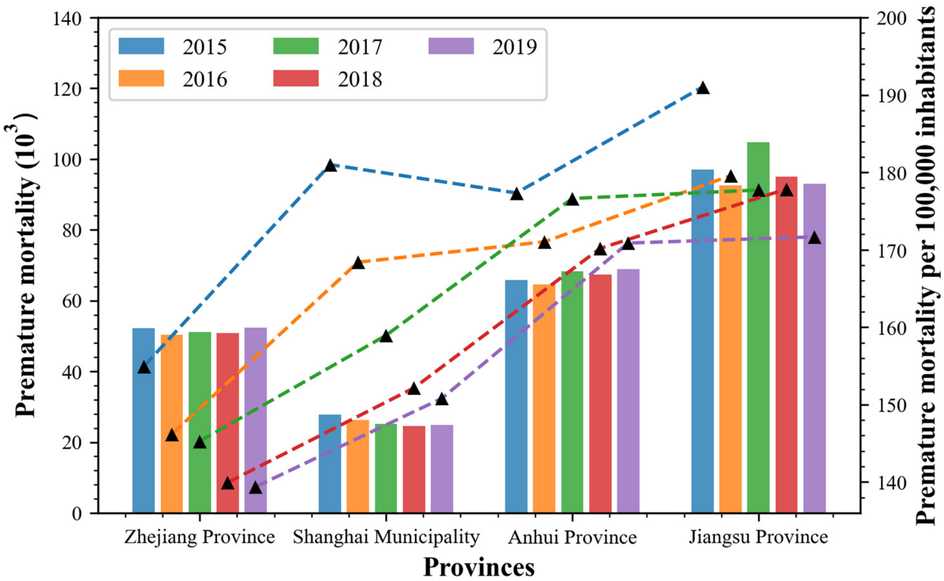

Figure 4. $PM_{2.5}$-related premature mortality at the provincial level from 2015 to 2019. The bar chart represents premature mortality, while the folding line chart with black triangles represents premature mortality per 100,000 inhabitants.

Figure 5 displays the spatiotemporal changes in premature mortality per 100,000 inhabitants attributed to $PM_{2.5}$ at the city level from 2015 to 2019 with the YRD region. Most cities in the region exhibited a decreasing trend, except Fuyang, Anqing, and Chuzhou, which are in the western region of Anhui Province. The largest reduction in mitigating the health burden associated with air pollution was observed in Shanghai and its surrounding areas, including Suzhou, Jiaxing, Wuxi, and Nantong. Moreover, the capitals of the other three provinces, as well as the eastern coastal regions, demonstrated relatively effective mitigation, forming a "mitigation corridor" connected by four central cities, thereby illustrating the radiation effect of a central developed city on the surrounding areas. The overall pattern suggests a decreasing progression from coastal cities to inland areas in reducing premature mortality per 100,000 inhabitants. However, in 2019 the top five cities with the most extensive premature mortality were Shanghai Municipality, Suzhou, Nanjing, Hangzhou, and Hefei, including all the capital cities, as shown in Figure S5. This underscores that the capital cities of each province in the YRD region are still at a higher risk of premature mortality attributed to $PM_{2.5}$ pollution due to their high population density and advanced economy, despite the achieved mitigation effectiveness. These findings highlight the need for tailored interventions for different types of regions. Continued efforts are required to reduce $PM_{2.5}$ concentrations in capital cities and their surrounding areas due to their large population size. Moreover, it is worthwhile to continue playing a radiating role in developed areas. Above all, targeted policies and attention should be directed towards the areas under development that may face a deteriorating trend of health burden exposed to air pollution.

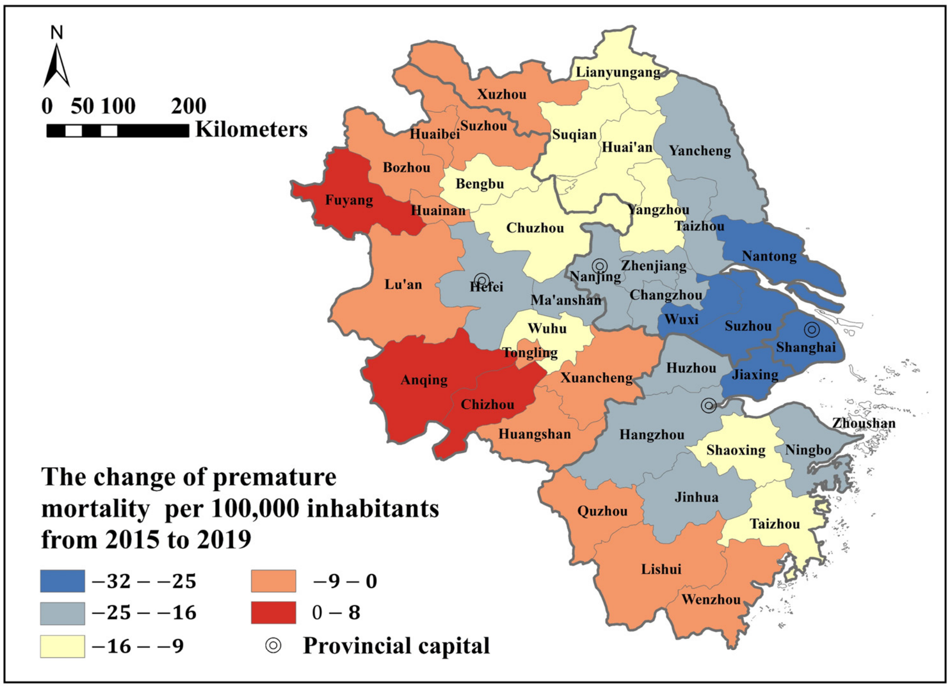

Figure 5. The changes in $PM_{2.5}$-related premature mortality per 100,000 inhabitants in the Yangtze River Delta from 2015 to 2019.

4.3. Potential Influence of Urban Development on Premature Mortality

Urban agglomerations are composed of cities of different natures, types, and scales. To better understand the effectiveness of the JPCAP policy and identify potential discrepancies that need to be considered in the context of YRD integration development, this section explores the correlation between $PM_{2.5}$ pollution and urban characteristics among cities in the YRD region. Using data from the China Urban Statistical Yearbook (https://navi.cnki.net/knavi/yearbooks/YZGCA/detail, accessed on 11 May 2022), several urban development metrics, including GDP per capita (GDPpc), residential density (RD), urban greening rate (URG), and share of secondary industry in GDP (SSIG), were selected. Collinearity analysis was conducted, and the Variance Inflation Factor (VIF) was used to check the collinearity between the selected factors, which was found to be low (VIF = 2). Pearson correlation coefficients of these factors in forty cities of the YRD region were calculated for each year from 2015 to 2019 (Table 1). The results show that residential density had the highest correlation with premature mortality density at a significance level of $p < 0.01$. GDP per capita was also positively correlated with mortality, and the correlation coefficient increased over time. In contrast, a significant negative correlation was found between the share of secondary industry in GDP and mortality. As for the urban greening rate, there was a significant negative correlation ($p < 0.05$) with mortality in 2017 and 2019. Moreover, the correlation between urban greening rate and mortality increased during the study period.

Table 1. The correlation coefficient between potential factors and mortality density from 2015 to 2019 (Pearson correlation).

	GDP per Capita	Residential Density	Urban Greening Rate	Secondary Industry
2015	0.494 **	0.787 **	−0.268	−0.504 **
2016	0.538 **	0.789 **	−0.249	−0.496 **
2017	0.564 **	0.808 **	−0.363 *	−0.502 **
2018	0.552 **	0.815 **	−0.295	−0.391 *
2019	0.560 **	0.813 **	−0.366 *	−0.476 **

** Significant correlation at 0.01 level (bilateral); * Significant correlation at 0.05 level (bilateral).

These findings suggest that urban development metrics can significantly influence premature mortality attributed to $PM_{2.5}$ pollution in the YRD region. Higher levels of residential density and GDP per capita were associated with an increased risk of premature mortality. Therefore, it is essential for economically developed metropolitan areas and densely populated regions to prioritize environmental health issues. However, the Pearson correlation coefficient of the SSIG, which is known as a significant pollution source though [29], was observed to be significantly negative. One plausible explanation for this result is that despite having a more developed tertiary industry, premature mortality in metropolises were still higher than those observed in smaller cities due to the larger population size. In light of the development characteristics of the correlation between SSIG and mortality, it can be inferred that cities in industrial development tended to suffer higher mortality as the share of secondary industry in GDP increased. Thus, policymakers must prioritize controlling air pollution from the source and developing a higher-quality economic mode for relatively backward areas. In summary, these findings have important implications for urban planning and public health policy in the YRD region and underscore the need for a comprehensive approach to address the adverse health impacts of urban development in the YRD region and beyond.

5. Discussion

5.1. Evaluation of the Integrated Development of the Urban Agglomeration

The regional atmospheric environment is a vital part of the integration development process due to the transfer of pollutants between adjacent cities [30]. The results of the study suggest that the integrated development of urban agglomerations is crucial for managing the regionality and spillover of environmental problems. China's establishment of a joint prevention and control mechanism for air pollution has been effective in reducing $PM_{2.5}$ concentrations in the Yangtze River Delta region since 2015. However, the changes in $PM_{2.5}$ concentrations varied significantly at the sub-regional level, with the largest reductions occurring in Shanghai Municipality due to changes in the industrial structure and layout of the YRD region. According to the Yangtze River Economic Belt Economic Development Report, by 2019, the output value of the tertiary sector in Shanghai Municipality was 45.7% higher than that of secondary industry, with the secondary sector accounting for the least in the YRD region. This shift towards the tertiary sector in Shanghai Municipality has led to a significant improvement in air quality and a reduction in public health burden.

Despite the overall success of the joint prevention and control mechanism, regional disparities still exist. The hot spot analysis revealed that the conflict between humans and the environment had been alleviated first in the metropolis, while non-priority cities, particularly in the northern part of the YRD region, bore a more severe public health burden due to exposure to air pollution. This disparity can be attributed to the integration policy, with Anhui and northern Jiangsu Provinces taking over many traditional industries phased out from Shanghai Municipality and southern Jiangsu Province. Specifically, Su-Huai urban agglomeration (Figure 6), as a particular policy area of Northern Anhui Province to undertake industrial transfer, has rapidly developed due to the advantages of traffic location conditions and original industrial base. Thus, $PM_{2.5}$ concentrations were likely to increase with the acceleration of socioeconomic development. Similarly, Xuzhou Metropolitan Area actively undertook industrial transfer in the YRD region, becoming the primary economic growth pole. Its traditional heavy chemical industries, heavy machinery, traffic, and other industrial clusters have developed in the past ten years, contributing to the primary production of air pollution. Therefore, more efforts are needed to implement coordinated clean air policies and to ensure their effectiveness in all regions under integration.

In conclusion, the study highlights the importance of coordinated efforts in managing environmental problems in urban agglomerations, particularly with regards to air pollution. The successful implementation of joint prevention and control mechanisms can lead to significant improvements in air quality and public health. However, the regional disparities in the effectiveness of these policies underscore the need for a more comprehensive and tailored approach to environmental management in different regions under integration.

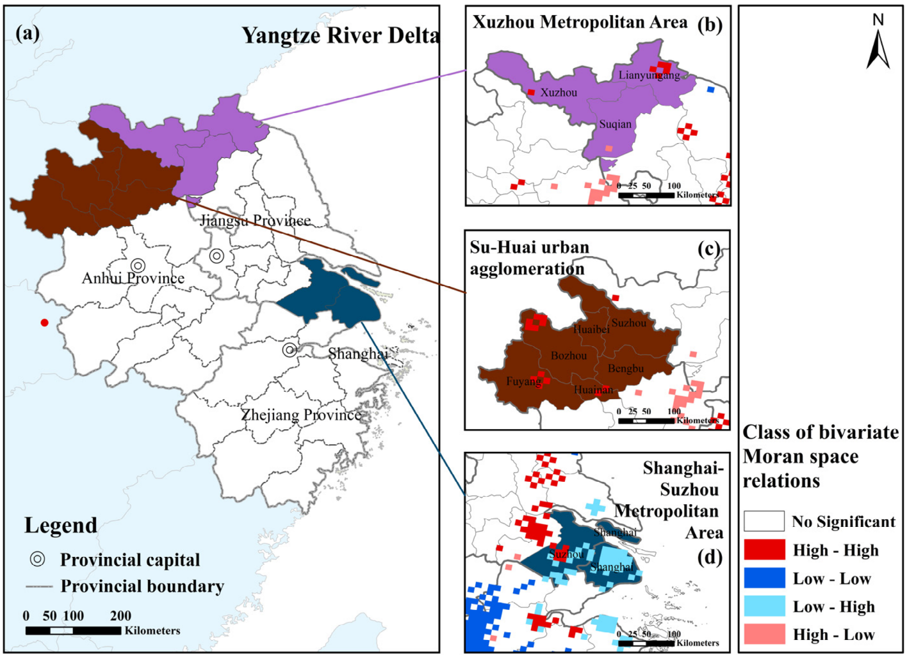

Figure 6. Locations of Xuzhou Metropolitan Area, Su-Huai urban agglomeration, and Shanghai-Suzhou Metropolitan Area. (**a**) The YRD region; (**b**) Xuzhou Metropolitan Area in the YRD region; (**c**) Su-Huai urban agglomeration in the YRD region; (**d**) Shanghai-Suzhou Metropolitan Area in the YRD region.

5.2. New Periods of the Integrated Development of Urban Agglomeration

However, it is worth noting that the level of $PM_{2.5}$ concentrations all over the YRD region was still far from the WHO-recommended AQG levels (5 $\mu g/m^3$) after adopting measures such as industrial transfer and clean transfer heating projects, construction site shutdowns, diesel vehicle bans. This highlights the need for new strategies to address air pollution in the context of integrated development. At present, Chinese ecological civilization construction has entered a critical period with the aim of achieving carbon neutrality. The YRD region, as one of the top three urban agglomerations, plays an exemplary role in this process. Studies suggest that by 2030, China could reach a $PM_{2.5}$ air quality annual standard of 35 $\mu g/m^3$ and reduce $PM_{2.5}$ exposure of most of the population to below 10 $\mu g/m^3$ by 2060 in a carbon-neutral scenario [31]. Thus, investigating the relationships between air pollution and carbon emissions, and their coupling relationship with economic and social energy, is an urgent need. By understanding the mechanisms of synergistic reduction of pollution and carbon, policymakers can develop effective strategies for improving air quality and promoting sustainable regional socioeconomic development and environmental protection. Measures such as promoting renewable energy, implementing low-carbon transportation, and encouraging green building construction should be considered in the future integrated development of the YRD region.

5.3. Comparison with Similar Studies

In terms of the technical framework of this study, the incorporation of exposure-related human activity patterns and the reallocation of exposure factors to the GEMM NCD + LRI model resulted in theoretically more accurate estimates of premature mortality than previous studies. Previous $PM_{2.5}$-related results estimated by different methods were compared, as illustrated in Figure 7 [12,23,32,33]. It was found that previous studies, such as the one conducted by Maji KJ. (2020), which barely used the GEMM NCD + LRI model, tended to overestimate premature mortality. On the other hand, compared to the results estimated by the IER model, the mortality estimated by GEMM was much higher. This can be attributed to the fact that GEMM employed new cohort studies, including those conducted in China, and hazard ratio predictions increased with $PM_{2.5}$ concentration, showing a near-linear association at higher concentrations [24,33]. Moreover, satellite-based $PM_{2.5}$ mapping combined with the DNN model, taking advantages of high-resolution capabilities, could accurately capture the spatial variations of air pollution, thereby providing reliable data support for analysis.

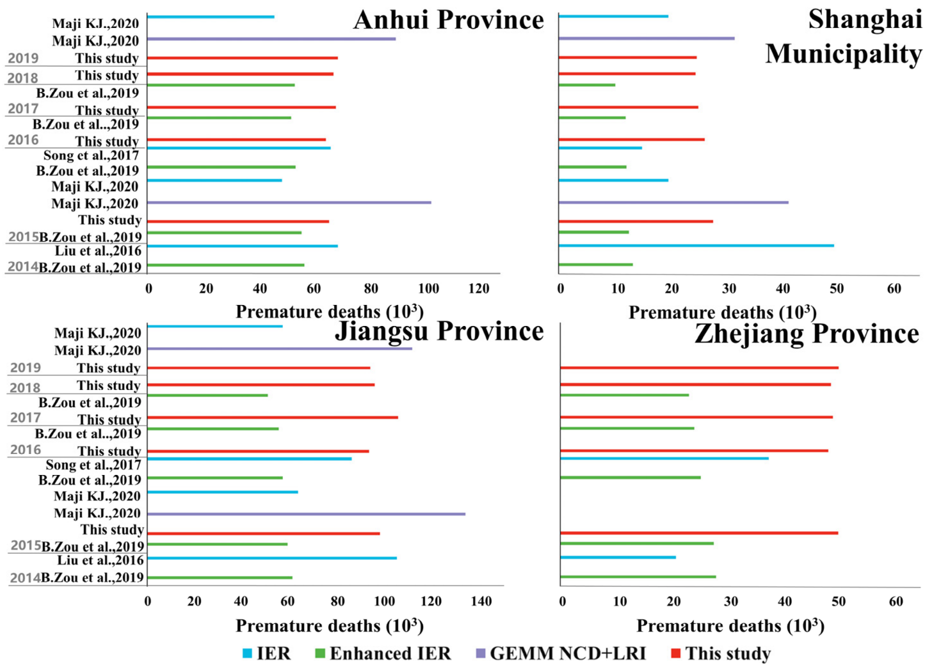

Figure 7. Comparison of premature mortality in the YRD region from different studies. Maji KJ. (2020) [33]; B. Zou et al., 2019 [12]; Song et al., 2017 [23]; Liu et al., 2016 [32].

5.4. Limitations and Future Improvements

There are some limitations and uncertainties in this study. Firstly, the composition of air pollution is complex and dynamic, and the current approach using satellite remote sensing in combination with chemical transport models and ground-based measurements needs to be further developed to better capture pollution levels, factors, and their synthesized impact. Therefore, future research should integrate carbon emissions and other pollution factors into a comprehensive model to serve the goal of synergistic reduction of pollution and carbon emissions, and to improve public health outcomes. Secondly, the adverse impact of short-term exposure to $PM_{2.5}$ was investigated by previous research and should also be considered in future studies [34]. Moreover, while this study analyzed several urban development factors and their potential impact on health risks exposed to $PM_{2.5}$, more potential factors covering industry, energy, transport, and land structure, should be analyzed using more sophisticated methods to better understand the mechanisms and provide evidence-informed recommendations for governments and policymakers.

6. Conclusions

In summary, $PM_{2.5}$ concentrations have decreased significantly in the YRD region from 2015 to 2019 under the implementation of the JPCAP policy, while the effectiveness of the joint policy at the sub-regional level was demonstrated with a distinct geographical characteristic. Developed cities, such as Shanghai Municipality, took the lead in lightening the health burden of exposure to $PM_{2.5}$ while some relatively backward cities, particularly in northern Anhui and Jiangsu Provinces, still faced significant risks. The conflict between humans and the environment has been alleviated primarily in metropolises, such as Shanghai–Suzhou Metropolitan Area, while non-priority cities become more prominent with the expansion of urban areas and economic development. Therefore, more attention should be paid to non-priority cities, such as by adopting differentiated and focused integration development measures, green economic models, and low-carbon energy structures under the integrated development of the YRD region. Findings in this study provided valuable insights for the YRD region to achieve green, shared, and harmonious development during the stage of high-quality modernization.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs15112770/s1, Figure S1: The annual $PM_{2.5}$ concentrations in the Yangtze River Delta from 2015 to 2019, Figure S2: The spatiotemporal variations of annual $PM_{2.5}$ concentrations in the Yangtze River Delta from 2015 to 2019, Figure S3: The change in annual $PM_{2.5}$ concentrations from 2015 to 2019, Figure S4: Spatial distribution of $PM_{2.5}$-related premature mortality in the Yangtze River Delta in 2015, Figure S5: Spatial distribution of $PM_{2.5}$-related premature mortality in the Yangtze River Delta in 2019, Figure S6: The changes in $PM_{2.5}$-related premature mortality in the Yangtze River Delta from 2015 to 2019, Figure S7: Structure of the SADNN model and the attention module, Table S1: Detail description of the datasets used in SADNN model, Table S2: Baseline mortality incidence rates of NCD+LRI for 25 plus population group, Table S3: Provincial-level statistics of air pollution related exposure factors in this study, Table S4: Parameters for GEMM NCD+LRI model in this study.

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