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$PM_{2.5}$ Spatiotemporal Evolution and Drivers in the Yangtze River Delta between 2005 and 2015

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Abstract: High concentrations of $PM_{2.5}$ are a primary cause of haze in the lower atmosphere. A better understanding of the spatial heterogeneity and driving factors of $PM_{2.5}$ concentrations is important for effective regional prevention and control. In this study, we carried out remote sensing inversion of $PM_{2.5}$ concentration data over a long time series and used spatial statistical analyses and a geographical detector model to reveal the spatial distribution and variation characteristics of $PM_{2.5}$ and the main influencing factors in the Yangtze River Delta from 2005 to 2015. Our results show that (1) The average annual $PM_{2.5}$ concentration in the Yangtze River Delta prior to 2007 displayed an increasing trend, followed by a decreasing trend after 2007 which eventually stabilized; and (2) climate regionalization and geomorphology were the dominant natural factors driving $PM_{2.5}$ concentration diffusion, while total carbon dioxide emissions and population density were the dominant socioeconomic factors affecting the formation of $PM_{2.5}$. Natural factors and socioeconomic factors together lead to $PM_{2.5}$ pollution. These findings provide an interpretation of $PM_{2.5}$ spatial distribution and the mechanisms influencing $PM_{2.5}$ pollution, which can help the Chinese government develop effective abatement strategies.

Keywords: $PM_{2.5}$ pollution; natural pollution factors; socioeconomic pollution factors; Geographical detector model

1. Introduction

Burgeoning industrialization and urbanization have brought sharp rises in industrial exhaust, construction dust and automobile exhaust. Fine-particulate air pollution has manifold effects on people's daily lives and health and on ecosystems, national heritage and the global atmosphere [1–4]. Air pollution causes an estimated 2.0–4.0 million premature deaths per year [5,6]. According to the 2015 Global Burden of Disease (GBD) report, published in the British medical journal The Lancet, fine-particulate air pollution ($PM_{2.5}$) caused 916,000 premature deaths in China in 2013 [7]. The Yangtze River Delta (YRD) is the region of eastern China with the most developed economy, the greatest degree of urbanization and high coal consumption [8]. The region has suffered frequent extreme haze episodes in recent years [9]. Therefore, understanding the characteristics and its driving factors of $PM_{2.5}$ concentrations will be of benefit in the task of regional pollution prevention and control.

At present, the model adopted for determining the spatial distribution and variation characteristics of $PM_{2.5}$ concentrations primarily employs the scale factor method and the statistical model method.

The scale factor method does not require $PM_{2.5}$ monitoring data because researcher used the second simulation of satellite signals in the solar spectrum (6S), which simulates the proportional relationship between Aerosol Optical Depth (AOD) and $PM_{2.5}$. We then calculated $PM_{2.5}$ concentration and analyzed the spatiotemporal distribution characteristics of $PM_{2.5}$ [10]. However, this model has low precision. Moreover, an accurate list of atmospheric emission source is needed, which is not conducive to the model's application [11]. The statistical model method requires a large amount of $PM_{2.5}$ monitoring data. This method establishes a regression model of $PM_{2.5}$ and AOD and then estimates $PM_{2.5}$ concentration to analyze its spatial distribution characteristics [12]. Although this model has high precision, it requires long time series and a large amount of ground site monitoring data to establish a statistical model [13]. Before 2012, due to a small number of monitoring stations with uneven spatial distribution, spatial distribution characteristics could not be fully clarified. Some scholars have used $PM_{2.5}$ grid-data to study $PM_{2.5}$ spatial distribution characteristics but analyses of trends in average annual or multi-year $PM_{2.5}$ concentration patterns and variation are still relatively weak [14].

Other scholars have focused their study on the drivers of $PM_{2.5}$ pollution. These studies used traditional statistical analysis to examine the relationships between $PM_{2.5}$ pollution natural factors and socioeconomic factors and indicated that population agglomeration, economic development levels, industrial production and energy consumption have a significant impact on $PM_{2.5}$ pollution [15,16]. At the same time, some scholars have concluded that $PM_{2.5}$ pollution is a geographical phenomenon that is closely related to the geographical environment [17], finding that natural factors such as geomorphology (Geomor) [4], climate regionalization (CR) [18] and Ecosystem type (ET) [19] have a significant impact on the agglomeration and diffusion of $PM_{2.5}$ concentrations. Current studies mostly focus on signal factors, which are unilateral factors such as natural or socioeconomic factors but quantification of the influences of integrated natural and socioeconomic factors has largely been ignored and a quantitative analysis of impact factors is lacking [19–22]. Moreover, traditional statistical analyses usually do not consider the geographical location and spatial patterns of $PM_{2.5}$ pollution.

Overall, the current research on $PM_{2.5}$ pollution has primarily focused on analyzing pollution characteristics over short time scales, using traditional statistical analyses for single factor analysis. These studies lack large-scale, long-term sequence systems to analyze the temporal and spatial distribution characteristics and the driving factors of $PM_{2.5}$ pollution. The main reasons for this are: (1) The YRD lacks a long-term $PM_{2.5}$ ground monitoring network, making it difficult to obtain large-scale and long-term sequence $PM_{2.5}$ pollution data and greatly limiting research on the temporal and spatial distribution characteristics and driving factors of $PM_{2.5}$ in the YRD; (2) Comprehensive consideration of the impacts of socioeconomic and natural factors on $PM_{2.5}$ pollution is lacking; (3) Traditional statistical analyses usually do not consider the geographical location and spatial patterns of $PM_{2.5}$ pollution.

Therefore, this paper analyzed the spatial distribution and variation characteristics of $PM_{2.5}$ concentrations in the YRD from 2005–2015, then used geographical detectors to quantitatively reveal the influences of socioeconomic factors and natural factors on $PM_{2.5}$ concentrations. This study provides a framework for the rational formulation and effective implementation of China's policies and global atmospheric environment research on $PM_{2.5}$ pollution abatement.

2. Material and Methods

2.1. Conceptual Framework

The main goal of this study was to analyze the spatial distribution characteristics and main influencing factors of $PM_{2.5}$ from 2005–2015 in the YRD. We used remote sensing retrieval of global annual $PM_{2.5}$ grids in a long-time series to analyze the spatial distribution characteristics of $PM_{2.5}$ pollution. We then used the geographical detector model to reveal the influences of socioeconomic factors and natural factors on $PM_{2.5}$ pollution.

2.2. Data and Data Sources

Spatial variation of $PM_{2.5}$ concentration is significant, its causes are complex and its driving factors are diverse [23]. Previous studies have found that the driving factors include socioeconomic factors such as population density (PD) [24], gross domestic product (GDP) [25], energy consumption and motor vehicle exhaust. At same time, spatial variation of $PM_{2.5}$ concentration is also closely linked to natural factors such as landforms [26], CR [19] and ET [27]. Based on the results of these previous studies, we selected socioeconomic factors and natural factors as potential driving factors of the spatial variation of $PM_{2.5}$ concentration. The socioeconomic factors included PD, GDP and carbon dioxide total emissions (CE) (Figure 1). The natural factors included Geomor, CR and ET (Figure 2).

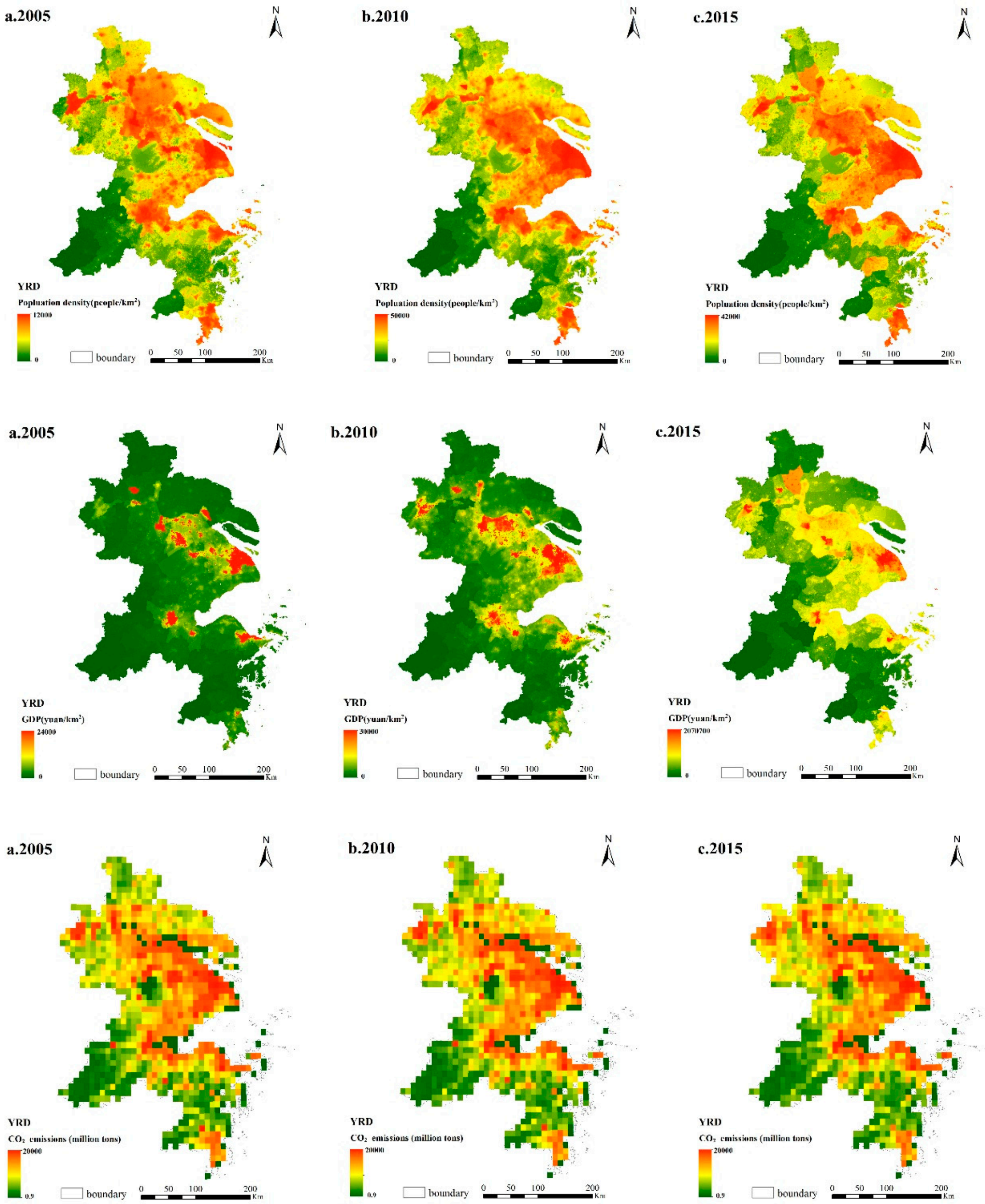

Figure 1. The spatial distribution of socioeconomic factors.

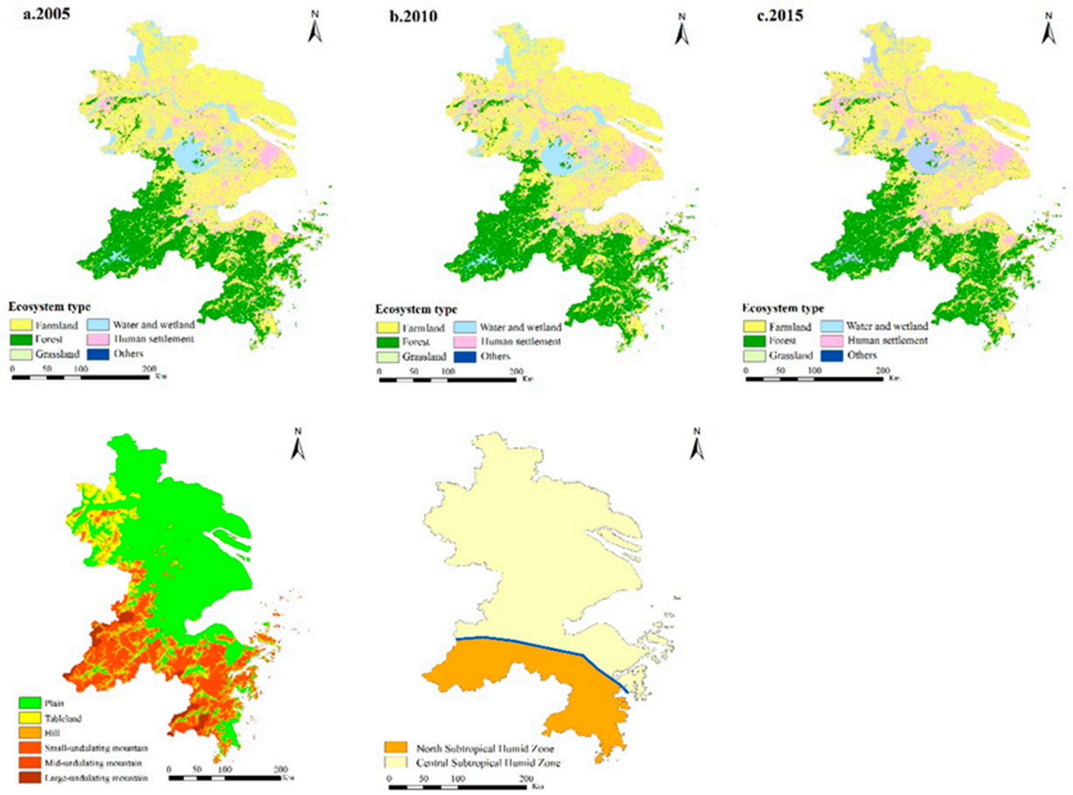

Figure 2. The spatial distribution of natural factors.

PD represents population scale. GDP represents the level of economic development. CE is closely related to human activities and energy consumption has received considerable attention from climate scientists [28,29]. In this study we used CO_2 emissions to represent energy consumption. Table 1 provides a description of each factor analyzed.

Table 1. Socioeconomic and natural factors analyzed as potential driving factors of the spatial variation of $PM_{2.5}$ concentration.

Explanatory Variable	Name	Symbol	Unit	Brief Description
Socioeconomic Factors	Population density	PD	peoples/km^2	Population scale
	Gross Domestic Product	GDP	yuan/km^2	Level of economic development
	Total CO_2 emissions	CE	ton	Energy consumption
Natural Factors	Geomorphology	Geomor	-	Topographical features
	Climate regionalization	CR	-	Precipitation and temperature
	Ecosystem type	ET	-	Ecosystem functions

2.2.1. $PM_{2.5}$ Data

Global annual $PM_{2.5}$ data were obtained from the Atmospheric Composition Analysis Group at Dalhousie University [30]. The resolution of the data is 0.1° × 0.1°. The accuracy of the global annual $PM_{2.5}$ data is highly consistent (R^2 = 0.81) by sample cross-validated $PM_{2.5}$ concentrations [31]. This dataset has been used in many studies at national and regional scales [32–34].

2.2.2. Socioeconomic Factors

The PD and GDP grid-data used in this study were obtained from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn).

Energy demand, energy consumption and urbanization may underlie the staggering increases in CO_2 emissions over the last three decades, so in this study we used CE to represent energy consumption. The spatial and time resolution of the PD and GDP grid-data are 1 km × 1 km and one year, respectively. The CE grid-data used in this study were obtained from the China Emission Accounts and Datasets [35,36]. The spatial resolution of CE was 0.1° × 0.1°.

2.2.3. Natural Factors

The Geomor, CR and ET grid-data used in this study were obtained from RESDC [37]. The spatial and time resolution of the ET and Geomor grid-data are 1 km × 1 km for ET and 0.1° × 0.1° for Geomor and one year, respectively.

2.3. Data Preprocessing

All research data were raster data except for the boundary data of the YRD. The raster and vector data differed in structure and form and are therefore difficult to integrate. Thus, we used converting transforming coordinates and applied geometric corrections to standardize the data in ArcGIS 10.3.1. Because the resolution of PD and GDP grid-data and the other data were not the same, we converted the 1 km × 1 km data (PD grid-data, GDP grid-data and ET grid-data) to 0.1° × 0.1° in ArcGIS 10.3.1 to ensure consistent spatial resolution.

We used a subset of the global annual $PM_{2.5}$ grid-data, Geomor grid-data, ET, CE grid-data, PD grid-data and GDP grid-data in raster format for the YRD from 2005–2015 to produce a 0.1° × 0.1° grid covering the YRD urban cluster using ArcGIS 10.3.1. The 0.1° × 0.1° grid-data was used as the basic spatial unit.

2.4. Methodology

The geographical detector model is a method used to explore differences in graphical elements and their influencing factors on the spatial distributions of a research object [38]. The geographical detector model consists of four parts: factor detectors, interaction detectors, ecological detectors and risk detectors. The factor detectors are mainly used to test whether socioeconomic factors and natural factors are the causes of haze formation. Risk detectors are mainly used to reveal the high and low mean values of the sub-regions of the driving factors. The advantages of the geographical detector model are that it relies on few assumptions and can effectively overcome the limitations of traditional statistical methods for dealing with categorical variables. At present, it is widely used in the ecological and environmental fields [39–41].

In our study, we used factor detectors and risk detectors to evaluate socioeconomic factors and natural factors associated with $PM_{2.5}$ pollution as determined by spatial variance analysis (SVA). The fundamental purpose of SVA is to assess the spatial consistency of $PM_{2.5}$ concentration distributions versus socioeconomic factors (e.g., PD, GDP, CE) and natural factors (e.g., Geomor, CR, ET).

(1) Factor detector

The power of determinants of driving factors on $PM_{2.5}$ concentration can be expressed using the following equation:

$$\mathrm{P}_{D,P} = 1 - \frac{1}{n * \sigma^2} \sum_{h=1}^{L} n_h * {\sigma_h}^2$$

where, $\mathrm{P}_{D,P}$ is the power of determinant of a driving factor on $PM_{2.5}$ concentration. D is the driving factor for the change in average annual concentration of $PM_{2.5}$. n, σ^2 are sample size and variance of the study area as a whole, respectively. n_h, σ_h are sample size and variance of stratum $h(h = 1, 2 \ldots, L)$, respectively. The value of $\mathrm{P}_{D,P}$ ranges from 0 to 1. As the value of $\mathrm{P}_{D,P}$ approaches 1, the stronger the influence of factor D on changes in average annual concentration of $PM_{2.5}$.

(2) Risk detector

Risk detectors are mainly used to reveal the high and low mean values of the sub-regions of the driving factors.

$$t_{ij} = \frac{R_i - R_j}{\sqrt{\frac{\delta_i^2}{n_i} + \frac{\delta_j^2}{n_j}}}$$

where, R_i, R_j represents average $PM_{2.5}$ concentrations in subregion R; n represents the size of the sample in subregion R; and δ represents the variance of subregion R. The geographical detector models used in this study are freely available from (http://www.geodetector.cn/). Since the model requires input data to be type data, the resolution criteria for various data can be found in the Supplementary Materials. The spatial statistical methods used in this paper are mainly raster statistical analysis. Specifically, the statistical analysis was performed using a raster calculator. Because it is simple, it is not described in detail here.

3. Results

3.1. Spatial Distribution Characteristics of $PM_{2.5}$ Concentrations

The trend of $PM_{2.5}$ concentrations in the YRDpresented complex trend from 2005 to 2015 (Figure 3). The raster calculation method for spatial statistical analysis showed that the trend increased from 2005 to 2007, decreased from 2007 to 2010 and fluctuated around 50.22 μg/m^3 between 2010 and 2015. The average annual $PM_{2.5}$ concentration increased from 48.89 μg/m^3 in 2005 to 55.56 μg/m^3 in 2007, with an average annual increase of 3.33 μg/m^3, showing a significant upward trend. This trend became suppressed and turned into a downward trend after 2007. After 2010, average annual $PM_{2.5}$ concentration fluctuated relatively stable. This indicates that 2007 was an important "inflection point" for the trend in average annual $PM_{2.5}$ concentration in the YRD, which is consistent with the results released by the Chinese Ministry of Environmental Protection in 2007. The main reasons for the inflection were national ecological civilization construction projects, ecological compensation pilot projects, a pollution census and environmental protection policies. Adjustments to the national industrial structure and improvements in energy efficiency have inhibited particulate emissions to a certain extent.

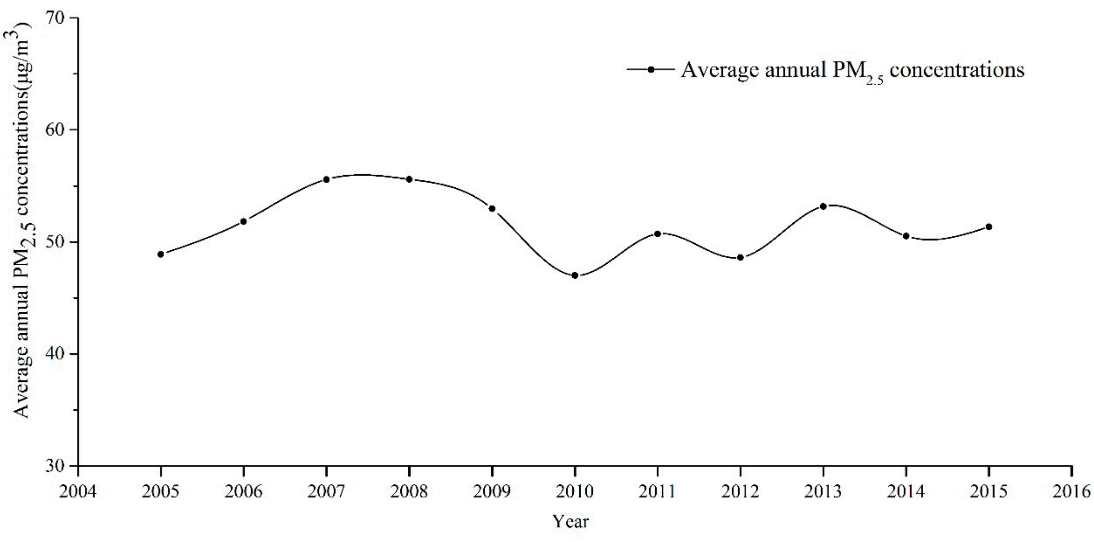

Figure 3. Overall trend for $PM_{2.5}$ concentrations in the Yangtze River Delta (YRD) from 2005–2015.

Using the annual average concentration limit of $PM_{2.5}$ concentrations in China's Environmental Air Quality Standards (GB3095-2012), we divided the average annual $PM_{2.5}$ concentrations into five intervals [42]: level I (<25 μg/m^3), level II (25–35 μg/m^3), level III (35–50 μg/m^3), level IV (50–70 μg/m^3) and level V (>70 μg/m^3). Further analysis of the area ratio of each interval grid revealed that during the period from 2005 to 2015, the proportion of level I concentrations increased from 1.98% in 2005 to 10.34% in 2015. The proportion of level III concentrations and higher continuously decreased from 78.59% in 2005 to 72.39% in 2015. The proportion of level V concentrations continuously increased from 0.00% in 2005 to 7.75% in 2015, showing a rapid expansion trend in the YRD (Figure 4). The proportion of level I and level V concentration gradually increased from 2005 to 2010. The combined total of level III and level IV concentrations covered about half of the study area. The proportion of the study area that reached the level III and level IV limit was 78.59% in 2005 and 64.64% in 2015 based on the ambient air quality standard (GB3095-2012). The combined total of II concentrations covered about one fifth of the study area. The proportion of the study area that reached the level II limit was 21.41% in 2005 and 27.61% in 2015.

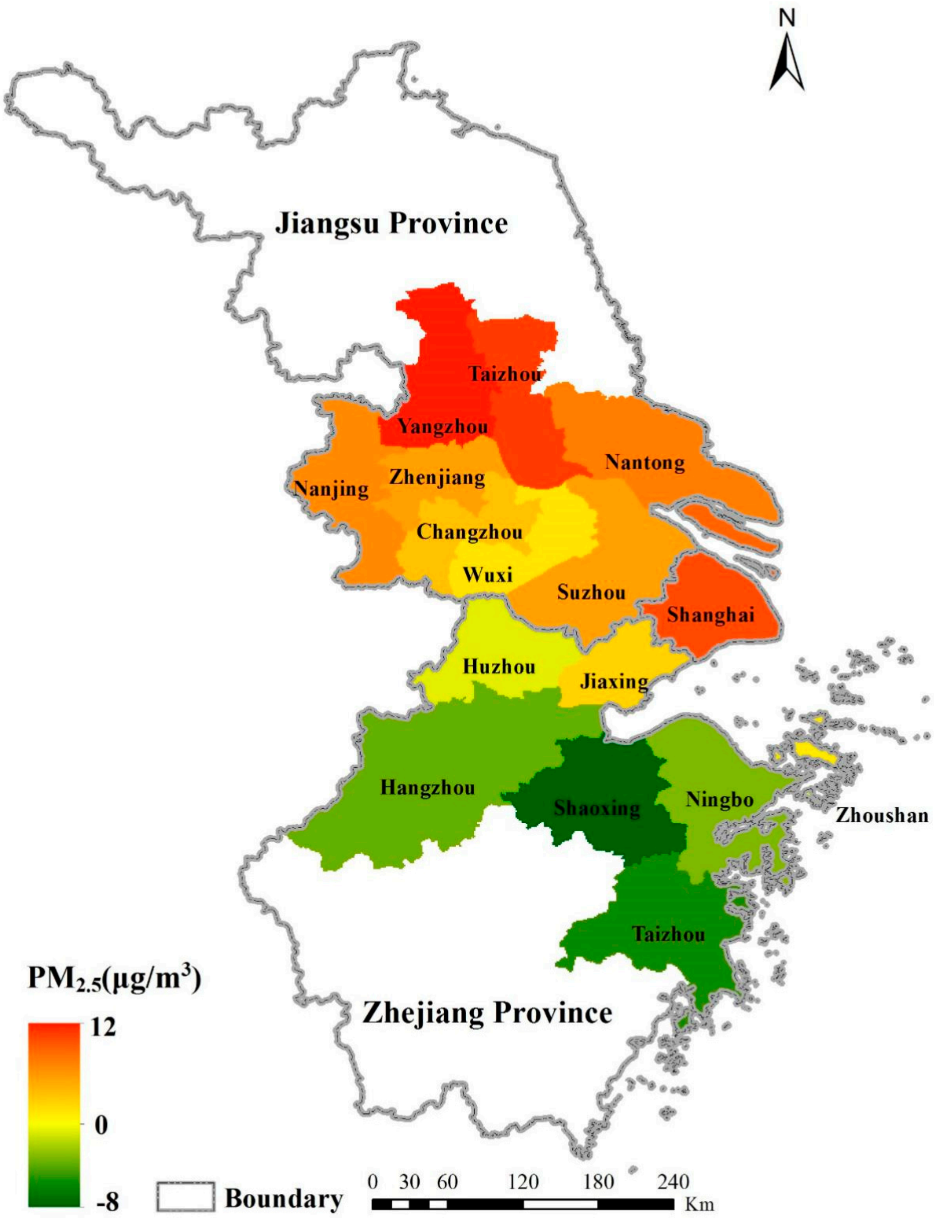

Figure 4. The spatial distribution of changes in annual average $PM_{2.5}$ concentrations in different YRD cities from 2005 to 2015.

Regions with increasing $PM_{2.5}$ concentrations were primarily located in the provinces of Jiangsu and Shanghai and included the cities of Yangzhou, Taizhou and Shanghai. The areas with decreasing $PM_{2.5}$ concentrations were mainly located in Zhejiang Province and included the cities of Hangzhou, Taizhou and Shaoxing (Figure 5). Specifically, average annual $PM_{2.5}$ concentrations in Yangzhou and Taizhou increased by more than 10 μg/m^3 from 2005 to 2015. The average annual $PM_{2.5}$ concentrations in Shaoxing decreased by more than 5 μg/m^3 from 2005 to 2015 (Figure 5).

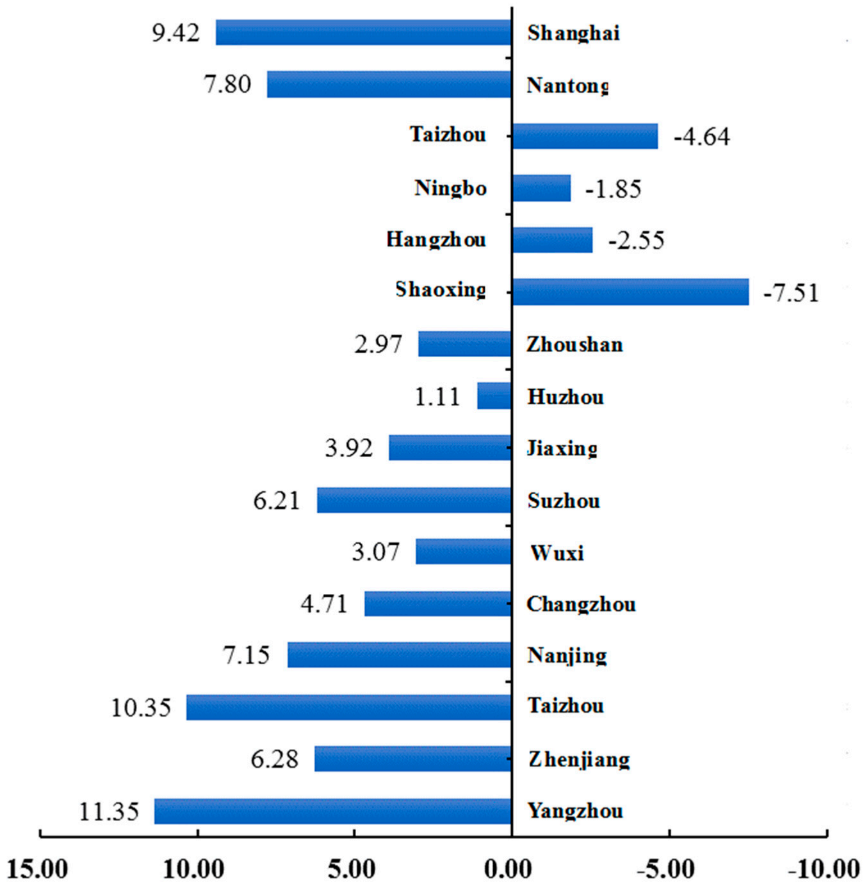

Figure 5. Average annual changes in $PM_{2.5}$ concentrations (μg/m^3) in different YRD cities from 2005 to 2015.

3.2. Individual Effects of Different Factors on $PM_{2.5}$ Concentrations

The influence of the six natural and socioeconomic risk factors on $PM_{2.5}$ concentrations were detected using the geographical detector model and are presented in Figure 6. Our results show that Geomor exerted the greatest influence on $PM_{2.5}$ concentrations, followed by another natural factor, CR. CE was the main socioeconomic factor affecting $PM_{2.5}$ concentration, followed by PD. The natural conditions exerted a greater influence over $PM_{2.5}$ concentrations in the YRD than did socioeconomic conditions in 2005, 2010 and 2105. Specifically, Geomor(0.45) > CR(0.43) > ET(0.36) > CE(0.25) > PD(0.23) > GDP(0.085) in 2005; Geomor(0.50) > CR(0.44) > ET(0.42) > PD(0.28) > CE(0.27) > GDP(0.10) in 2010; CR(0.54) > Geomor(0.49) > ET(0.40) > CE(0.22) > PD(0.17) > GDP(0.10) in 2015.

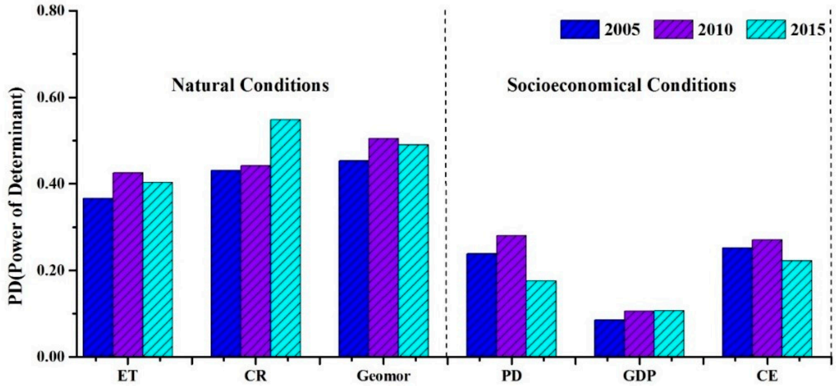

Figure 6. The power of determinants of different impact factors (ET, CR, Geomor, PD, GDP and CE) on $PM_{2.5}$ concentrations in the YRD (p-values < 0.01 for all factors).

3.3. The Leading Impact Areas of Factors Influencing $PM_{2.5}$ Concentrations

For the years 2005, 2010 and 2015, average $PM_{2.5}$ concentrations were highest in the subregion of the human settlement ecosystem (54.87 μg/m^3, 53.97 μg/m^3 and 59.98 μg/m^3), followed by the farmland ecosystem (54.62 μg/m^3, 53.27 μg/m^3 and 58.77 μg/m^3) and the wetland ecosystem (54.58 μg/m^3, 51.77 μg/m^3 and 57.96 μg/m^3). Average $PM_{2.5}$ concentrations were highest in the north subtropic humid climate subregion (52.92 μg/m^3, 51.27 μg/m^3 and 57.52 μg/m^3) and the central subtropic humid climate subregion (35.11 μg/m^3, 31.89 μg/m^3 and 29.23 μg/m^3). And finally, average $PM_{2.5}$ concentrations were highest in the geomorphological plain subregion (54.43 μg/m^3, 54.49 μg/m^3 and 60.71 μg/m^3), followed by the platform subregion (53.97 μg/m^3, 51.6 μg/m^3 and 56.21 μg/m^3) and the hilly subregion (Figure 7).

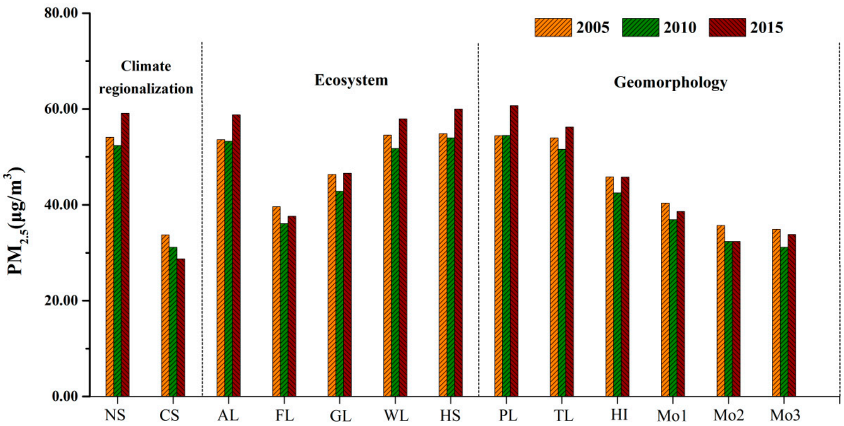

Figure 7. Annual average $PM_{2.5}$ concentrations in different climate, ecosystem and geomorphological subregions (NS = North subtropical humid zone, CS = Central subtropical humid zone, AL = Arable land ecosystem, FL=Forest ecosystem, GL = Grassland ecosystem, WL = Water and wetland ecosystem, HS = Human settlement ecosystem, PL = Plain, TL = Tableland, HI = Hills, Mo1 = Small-undulating mountain, Mo2 = Mid-undulating mountain, Mo3 = Large-undulating mountain).

4. Discussion

A better understanding of the factors influencing the spatial distribution of $PM_{2.5}$ concentrations benefits managers tasked with formulating air pollution control strategies. Using spatial statistical analysis and a geographical detector model, this study emphasizes the importance of socioeconomic and natural factors in determining $PM_{2.5}$ concentrations. Socioeconomic development is a main cause of $PM_{2.5}$ formation and Geomor, CR and ET factors significantly affected its distribution, aggregation and diffusion. We next discuss the impacts of socioeconomic and natural factors on $PM_{2.5}$ concentrations.

4.1. Analysis of The Socioeconomic Drivers of $PM_{2.5}$ Pollution

Socioeconomic activities profoundly impact air pollution and regional emissions of polluting gases are closely related to socioeconomic activities. GDP, CE and PD data represent the level of industrialization and urbanization in the YRD and are important drivers of $PM_{2.5}$ concentrations. Our factor detector results show that CE and PD were the main influencing factors in all three years of the study and their influence was significantly greater than that of GDP. The relationship between CE and PD exhibited an inverted U-shaped with the inflection point occurring in 2010.

Many studies have shown that socioeconomic factors are the most significant factors influencing $PM_{2.5}$ concentrations [19,43], with the power of the determinant greater than 50% [44]. Our findings are consistent with these studies. Energy consumption, as represented by CE, was the most important factor triggering $PM_{2.5}$ formation. The reason that energy consumption exerts the strongest influence is that total energy consumption has significantly increased from 2005 to 2015. Coal is the largest source of energy production in the YRD. For example, total coal consumption in Jiangsu Province has increased by more than 58% from 2005 to 2015. China's steel industry, which consumed huge amounts of coal from 2005–2015, is mainly located in the YRD, with Jiangsu and Shanghai serving as primary centers of the steel industry. The high level of steel production in Jiangsu Province and Shanghai accounted for an overall increase in national steel production from 17.71% in 2005 to 19.08% in 2015. The spatial agglomeration of the coal and steel industries is a key factor driving increases in $PM_{2.5}$ concentrations. The curve showing the effects of socioeconomic factors (CE and PD) on $PM_{2.5}$ contains an inflection point between 2005 and 2015. The reason for the formation of the inflection point may be that the government vigorously controls sulfur dioxide, so that measures such as desulfurization of coal-fired power plants and replacement of coal-fired boilers with clean energy technologies reduces smog. Therefore, China has further opportunities to reduce smog by altering its industrial and energy structures, reducing coal emissions, developing new energy sources and encouraging residents to use mass transportation [45].

In addition to CE, many studies have found that PD affects $PM_{2.5}$, which is also consistent with our findings. PD may affect $PM_{2.5}$ through population agglomeration, which leads to increased industrial agglomeration and production activities (e.g., catering industry, service industry, construction industry) and increased pollutant emissions and energy consumption [9]. For example, traffic jams that result from dense population agglomeration reduce the combustion efficiency of motor fuels. In addition, densely packed housing reduces wind speeds and dispersal of pollutants, thereby trapping high $PM_{2.5}$ concentrations and indirectly aggravating $PM_{2.5}$ pollution. The reason for the formation of the inflection point may be that increasing PD will also have an agglomeration effect, which will increase the rate of public transportation and the efficiency of resource use, leading to alleviation of $PM_{2.5}$ pollution. The results of this study suggest that the counter scale effect of population agglomeration played a significant role in $PM_{2.5}$ pollution before 2010, while the scale effect of population agglomeration played a greater role in $PM_{2.5}$ pollution after 2010.

4.2. Analysis of The Natural Drivers of $PM_{2.5}$ Pollution

Our factor detection results show that Geomor and CR are the main factors affecting $PM_{2.5}$ diffusion and that their explanatory power is greater than that of ET. This result demonstrates large-scale spatial heterogeneity and indicates that geomorphology and climate regionalization have an important influence on the agglomeration and diffusion of $PM_{2.5}$ [20]. Our findings are consistent with many studies [46,47]. Geomor and CR likely affect $PM_{2.5}$ agglomeration and diffusion by affecting air flow, air pressure, temperature and precipitation [26,46]. There are several possible explanations for this finding. As a fine particle, $PM_{2.5}$ floats easily in low altitudes compared with high altitudes due to gravity. On the other hand, as altitude increases, temperature gradually decrease and air convection increases, resulting in increased mobility of $PM_{2.5}$ particles. Therefore, $PM_{2.5}$ concentrations in low altitudes areas are higher than in high altitude areas [48].

The effect of CR on $PM_{2.5}$ concentrations is mainly via temperature and precipitation. This may be related to the uneven rainfall and temperature differences in the YRD. There are significant differences in precipitation and temperature between the north and the south (Figures 8 and 9). The YRD is spread over two climatic zones. The northern part is a north subtropical humid zone, while the south is a central subtropical humid zone. There are several possible explanations for the impact of temperature and precipitation on $PM_{2.5}$ concentrations: (1) Raindrops (or other precipitation particles) capture aerosol particles from the atmosphere during Brownian diffusion, inertial collision and other processes, resulting in a decrease in $PM_{2.5}$ concentration [49–52]. This may explain the decline in $PM_{2.5}$ concentration in 2010 (Table 2); (2) The primary mode of diffusion of suspended particulates in the air is Brownian motion. The intensity of Brownian motion is related to temperature. Therefore, the higher the atmospheric temperature, the more intense the Brownian motion of the fine particles and the more favorable the diffusion of the particles [53,54]. The results of this study are limited to the YRD region from 2005 to 2015. Although the impact of ET was lower than the other two impact factors, we cannot assume that it is not important, especially in the northern plains where fertilizers used in farmland ecosystems strongly affect $PM_{2.5}$ [55].

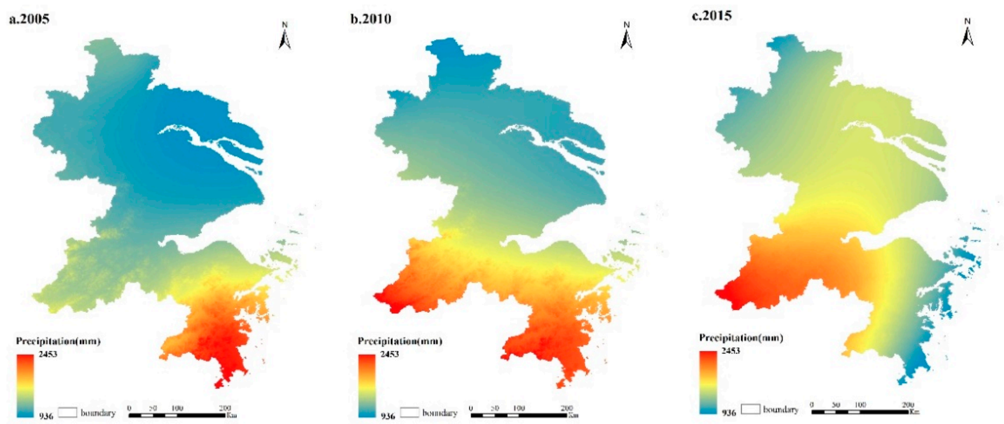

Figure 8. Spatial distribution of average annual precipitation in (**a**) 2005, (**b**) 2010, (**c**) 2015 in the YRD.

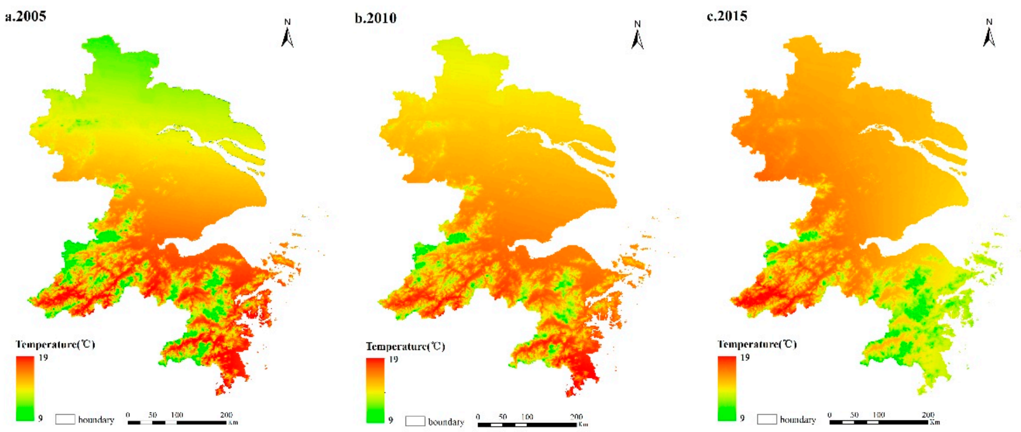

Figure 9. Spatial distribution of average annual temperature in (**a**) 2005, (**b**) 2010, (**c**) 2015 in the YRD.

Table 2. Average annual precipitation from 2005 to 2015 ($mm \cdot a^{-1}$).

Year	Precipitation			
	Max	**Min**	**Mean**	**Standard Deviation**
2005	2220	528	1104	321
2006	1712	834	1188	244
2007	1412	584	1058	180
2008	1613	771	1138	107
2009	1702	632	1286	179
2010	2648	718	1416	360
2011	1712	294	831	244
2012	2339	535	1369	490
2013	2646	396	1156	307
2014	2163	850	1422	254
2015	2389	964	1643	240

Note: The precipitation for 2005–2013 comes from Xu [56] and the precipitation for 2014–2015 was obtained from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn).

4.3. Limitations of This Study

The first limitation of this study is the $PM_{2.5}$ grid-data. Although the resulting $PM_{2.5}$ estimates were highly consistent, there is some uncertainty resulting from the sparse dispersal of $PM_{2.5}$ monitoring sites and the challenging nature of data retrieval and validation [31]. The second limitation comes from the socioeconomic data. In this study, the socioeconomic factors included only GDP, PD and CE, which cannot comprehensively express the characteristics of socioeconomic factors. The third limitation is that the GDP and population density products used in this study were derived from national economic census and national population census data. Because the survey periods for these censuses are long, the time resolution for the data is rough. In order to balance the spatial resolution and temporal resolution of the various socioeconomic and natural ecological factors, five years was chosen as the research cycle. In addition, we only focused on the spatial variation characteristics and driving factors of $PM_{2.5}$ at three time points, which limits the scope of this study. In future research, we will focus on longer time series of annual $PM_{2.5}$ data to more accurately delineate the spatial variation characteristics of $PM_{2.5}$ and quantitatively reveal the influences of socioeconomic and natural factors on $PM_{2.5}$ concentrations in the YRD.

5. Conclusions

Based on remote sensing inversion of $PM_{2.5}$ concentration data over a long time series, our spatial statistical analyses and geographical detector model revealed the spatial distribution and variation characteristics of $PM_{2.5}$ and the main influencing factors of $PM_{2.5}$ concentrations in the YRD from 2005 to 2015. Our main findings and conclusions are as follows:

(1) Average annual $PM_{2.5}$ concentrations in the YRD displayed an increasing trend prior to 2007, a downward trend after 2007 and then eventually stabilized. The proportion of highly polluted areas ($PM_{2.5}$ greater than 70 $\mu g/m^3$) gradually increased between 2005 and 2015 andwere mainly located in the northern regions of the YRD, especially Yangzhou, Taizhou and Zhenjiang. The proportion of low-pollution areas ($PM_{2.5}$ less than 35 $\mu g/m^3$) gradually decreased and were mainly located in southern YRD, especially Shaoxing, Taizhou and Ningbo. (2) The natural driving factors CR and Geomor were the dominant individual factors affecting $PM_{2.5}$ concentration diffusion, while CE and PD were the dominant individual factors affecting $PM_{2.5}$ formation. Natural factors and socio-economic factors together lead to increased $PM_{2.5}$ pollution. Natural factors and socioeconomic factors together lead to $PM_{2.5}$ pollution. Although our research data are from the YRD, our research method and framework can be applied in pollution prevention and control efforts in other regions. These findings extend our understanding of potential socioeconomic and natural drivers of $PM_{2.5}$ concentrations

and can help policy makers in their tasks of formulating pollution control strategies and improving air quality.

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