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Socioeconomic Drivers of $PM_{2.5}$ in the Accumulation Phase of Air Pollution Episodes in the Yangtze River Delta of China

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Abstract: Recent studies in $PM_{2.5}$ sources show that anthropogenic emissions are the main contributors to haze pollution. Due to their essential roles in establishing policies for improving air quality, socioeconomic drivers of $PM_{2.5}$ levels have attracted increasing attention. Unlike previous studies focusing on the annual $PM_{2.5}$ concentration (C_{year}), this paper focuses on the accumulation phase of $PM_{2.5}$ during the pollution episode (PMAE) in the Yangtze River Delta in China. This paper mainly explores the spatial variations of PMAE and its links to the socioeconomic factors using a geographical detector and simple linear regression. The results indicated that $PM_{2.5}$ was more likely to accumulate in more developed cities, such as Nanjing and Shanghai. Compared with C_{year}, PMAE was more sensitive to socioeconomic impacts. Among the twelve indicators chosen for this study, population density was an especially critical factor that could affect the accumulation of $PM_{2.5}$ dramatically and accounted for the regional difference. A 1% increase in population density could cause a 0.167% rise in the maximal increment and a 0.214% rise in the daily increase rate of $PM_{2.5}$. Additionally, industry, energy consumption, and vehicles were also significantly associated with $PM_{2.5}$ accumulation. These conclusions could serve to remediate the severe $PM_{2.5}$ pollution in China.

Keywords: $PM_{2.5}$; pollution episode; socioeconomic factor; geographical detector; Yangtze River Delta

1. Introduction

In past decades, with the rapid development of industrialization and urbanization, the problem of air pollution has become increasingly severe around the world. In particular, fine particulate matter ($PM_{2.5}$), a type of pollutant, has been verified to be unhealthy for humans and the living environment, as it can cause lung cancer, respiratory and cardiovascular diseases, affect transportation, as well as increase mortality [1–4]. Recently, $PM_{2.5}$ pollution has become the greatest environmental problem in China and is therefore attracting growing public concern. Since 2013, heavy $PM_{2.5}$ pollution events have often occurred in many Chinese cities, as observed via monitoring-site data [5] and satellite imagery [6,7]. For instance, in the Yangtze River Delta (YRD), a developed region in China, Shanghai witnessed a maximum hourly $PM_{2.5}$ concentration of 602 $\mu g/m^3$ [8] in December of 2013. In addition, Nanjing experienced a daily $PM_{2.5}$ concentration (C_{day}, the average concentration of 24 h in a day) of 369 $\mu g/m^3$, which is far above 75 $\mu g/m^3$ (the 24-h standard of Chinese Ambient Air Quality Standards, CAAQS, GB3095-2012). In 2014, 86 million people in some cities of the YRD were exposed to more than 100 pollution days ($C_{day} \geq 75$ μg/m^3), so there is an urgent need to formulate effective policies to improve the severely polluted air environment in China.

A considerable body of literature describes the enormous efforts dedicated to understanding $PM_{2.5}$. It is mainly focused on the chemical composition [9–11] and source apportionment [10,12,13], spatiotemporal variations of ambient concentration [14–16] and various influencing factors (such as human emissions, synoptic conditions, topography, and vegetation, etc.) [8,17–19]. Among them, the analyses regarding the influence of socioeconomic factors (SEFs), such as population, population density, and vehicles, etc., on $PM_{2.5}$ pollution can better assist environmental policy-makers. Several articles have identified industrial activities, fuel combustion, biomass burning, and vehicles as major contributors in the YRD [13,20]. Wang et al. [21] explored $PM_{2.5}$ contributors in Shanghai from 2011 to 2013 and identified three kinds of typical $PM_{2.5}$ episodes, caused by biomass burning, suspended dust, and fireworks. They suggested that gas precursors from human activities and their secondary formation dominated $PM_{2.5}$ pollution. Ye et al. [17] also mentioned some cultural customs, like fireworks and the burning of incense sticks during the Chinese New Year period. They indicated these were the less-obvious factors resulting in $PM_{2.5}$ pollution episodes. Furthermore, using satellite detection Zhang et al. [22] determined that the annual $PM_{2.5}$ emissions from open straw burning were 1.036 metric tons in China during 1997–2013. These studies have all reported strong links between $PM_{2.5}$ pollution and human behavior, although most of them mainly investigated a certain source or a specific period of time. For decision-makers to formulate an environmental control target, it is important to fully understand the impact of socioeconomic development on air pollution from a statistical perspective and recognize the force of local socioeconomic drivers.

However, studies relating to the inextricable links between $PM_{2.5}$ and SEFs are still scarce. It is only in recent years that several articles have tried to apply quantitative analysis methods to this problem. One reason for this could be that high $PM_{2.5}$ concentrations occur most frequently in developing countries, where pollution data was unavailable. According to the latest studies, several articles have argued that some SEFs are closely related to ambient $PM_{2.5}$ concentration. For instance, in 1999, Romero et al. [23] explored the relationship between rapid urban growth and air pollution in Santiago. He suggested that the highest population concentration mainly occurred in the urban area and determined industries and vehicles were the main contributors to smog. Using Pearson Correlation analysis, Han et al. [6] showed the annual $PM_{2.5}$ concentration (C_{year}, the mean concentration of all days in a year) in urban areas was positively related to urban population and an urban secondary industrial fraction at the Chinese prefectures level. Hao and Liu [5] employed the Spatial Lag Model and Spatial Error Model to examine the relationship between urban air quality and the socioeconomic development in China, suggesting that secondary industry and vehicle population positively influenced C_{year}. In addition, Wang and Fang [16] discussed the influence of SEFs on $PM_{2.5}$ in the Bohai Rim urban agglomeration using Geographically Weighted Regression (GWR) and further explored their quantitative relationships. They concluded that in some cities of that region, an increase of 10,000 yuan in the GDP per capita would reduce $PM_{2.5}$ of 1.18 μg/m^3, while a 1% increase in urbanization rate and an increment of 10,000 in the working population could raise $PM_{2.5}$ by 1.25 μg/m^3 and 0.09 μg/m^3, respectively. Generally speaking, these studies addressing the statistical links between SEFs and $PM_{2.5}$ have mainly focused on C_{year}, with discussions on the national scale, as well as urban scale. However, C_{year} is influenced by many factors, such as human emissions, synoptic conditions, surface terrain and vegetation, etc. The difference of these factors may be enormous at the national scale, but not significantly different within a city. Thus, it is considered that C_{year} may not be appropriate to reflect the influence of SEFs under the interference from other factors. To accurately evaluate the impact of SEFs on $PM_{2.5}$, it is necessary to minimize this disturbance as far as possible.

For the aforementioned reasons, we selected the YRD as the sample area, focusing only on the relationship of SEFs with $PM_{2.5}$ in the accumulation stage during in the pollution episodes, called PMAE in this study. Two main aspects were considered. Firstly, each pollution episode was split into an accumulation stage and a diminishing stage, based on the peak concentration. Unlike the diminishing process which is controlled by winds and precipitation [24], the accumulation stage generally occurs under stagnant weather conditions [13,25]. Further, cities in the YRD had similar synoptic conditions, as a pollution episode typically only lasted for a few days. Thus, our focus on PMAE could greatly reduce the interference from the different weather conditions to some extent. Secondly, although the YRD was often regarded as a whole in numerous studies, the socioeconomic development here as well as the atmospheric pollution, did differ among cities in the region. For example, in 2014, Shanghai had a population of 24 million, more than 34 times that of Zhoushan. This difference brings about many distinctions with regard to the other SEFs between the two cities, like the total energy consumption and the number of vehicles in Shanghai, which were found to be 98 and 27 times higher, respectively, than those in Zhoushan. Given the minimal difference in the synoptic environmental conditions in the YRD, the spatial diversity of PMAE may be mainly dominated by socioeconomic drivers. However, to our knowledge, existing studies show a lack of concern about the relationship between PMAE and socioeconomic factors, especially at a regional scale.

Regarding the analysis methods, various models, such as the traditional Ordinary Least Square model, Land Use Regression [26–28], GWR [16], Panel Data model [29], Spatial Lag model and Spatial Error model [5], were adapted to quantify the relationship between various SEFs and $PM_{2.5}$. However, due to their collinearity, many SEFs were removed in the abovementioned models. To compare the influence of each indicator on $PM_{2.5}$ at the regional level, we used a geographical detector to explore the spatial correlations between PMAE and SEFs.

Overall, we first selected 10 typical pollution episodes from 2014 and averaged them to obtain the characteristics of PMAE in the YRD. Then, using the geographical detector and a linear regression model, the following goals were pursued, as presented in the subsequent sections: to explore the relationship between PMAE and SEFs, as well as to identify the influence of the socioeconomic indicators driving the accumulation of $PM_{2.5}$. Some of the main findings are discussed at the end of this paper. All of these should provide policy-makers with an insight into $PM_{2.5}$ accumulation during pollution episodes in order to formulate appropriate air quality regulations.

2. Methods

2.1. Sample Area and Cities

In our study, the YRD consists of Shanghai, the southern part of Jiangsu Province and the northeastern part of Zhejiang Province, including 16 cities (Figure 1a,b). Being a developed area, although this region covers only 1.1% of China in terms of area, it accounts for 7.47% of its total population (according to the data of 16 cities in 2014). Due to the dense urban clusters and the increasing coal consumption in recent years, the region has frequently suffered from severe $PM_{2.5}$ pollution events. On account of the negative effects on human health, $PM_{2.5}$ concentration has been automatically monitored in many cities in China since 2013. Considering that most of the monitoring sites are located in the urban built-up area. We chose the urban area of 16 prefecture-level cities and 14 counties for this study, including at least one air-monitoring site, as shown in Figure 1c.

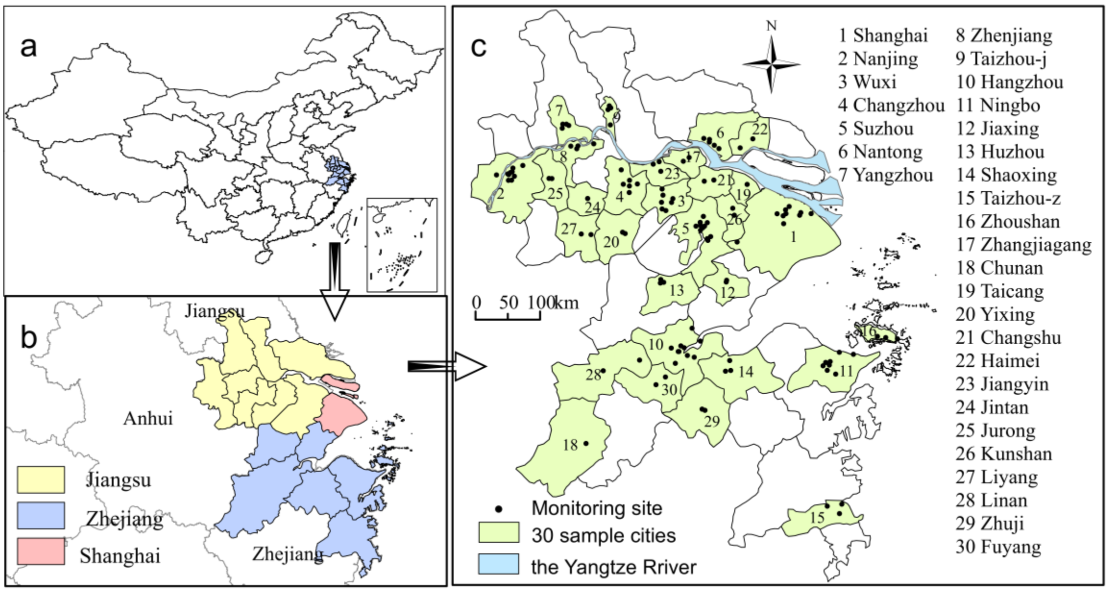

Figure 1. The location of the YRD in China (**a**); the three parts of the YRD in this study; (**b**); and the sample cities and the location of 120 observation sites in the YRD (**c**).

2.2. PM$_{2.5}$ Data

2.2.1. Ambient PM$_{2.5}$ Concentration

Currently, the PM$_{2.5}$ concentration data are updated every hour on the air quality publishing platform of the National Environmental Monitoring Centre in China. This paper derived hourly PM$_{2.5}$ concentrations from 120 monitoring sites in the 30 sample cities in the YRD from 1 January to 31 December in 2014. According to the requirements for the validity of the concentration of air pollutants released in GB3095-2012, firstly, we deleted the values $\leq$0 and the abnormal concentrations in the raw data. Secondly, a daily concentration (C_{day}) was calculated by averaging the value for 24 h from 0:00 to 23:00. If the hourly data were missing for more than 4 h on any day, the C_{day} was considered invalid and excluded. At last, for each monitoring site, the mean of all daily concentrations was seen as its C_{year}, and then the average C_{year} of all sites in a city represented its urban pollution level.

2.2.2. Pollution Day and PM$_{2.5}$ Episodes

To explore the characteristic of pollution episodes clearly, we defined a pollution day as a day with $C_{day} \geq 75$ µg/m^3, and a pollution episode as the pollution period with more than two consecutive pollution days. To reduce abnormality and contingency, ten pollution episodes were carefully picked out to average. The principles of selecting PMAE are as follows: (1) there is no daily data missing during a pollution episode; (2) there is no precipitation, and the wind conditions had a value of less than 3 on the Beaufort scale; and (3) the pollution episodes are distributed in different seasons. Although the C_{day} in part cities perhaps have not reached the pollution level as defined above, the same PM$_{2.5}$ changing period was chosen simultaneously in all cities for comparing. As a result, ten pollution events, EP1-EP10 (during in the time of 1/1–1/6, 1/15–1/21, 2/19–2/23, 3/8–3/11, 5/26–5/30, 10/13–10/17, 11/9–11/13, 11/16–11/21, 12/20–12/26, and 12/27–12/31, respectively) were adapted and selected for this paper (Figure 2) at last. Due to frequent rainfall, no episode was eligible from June to September.

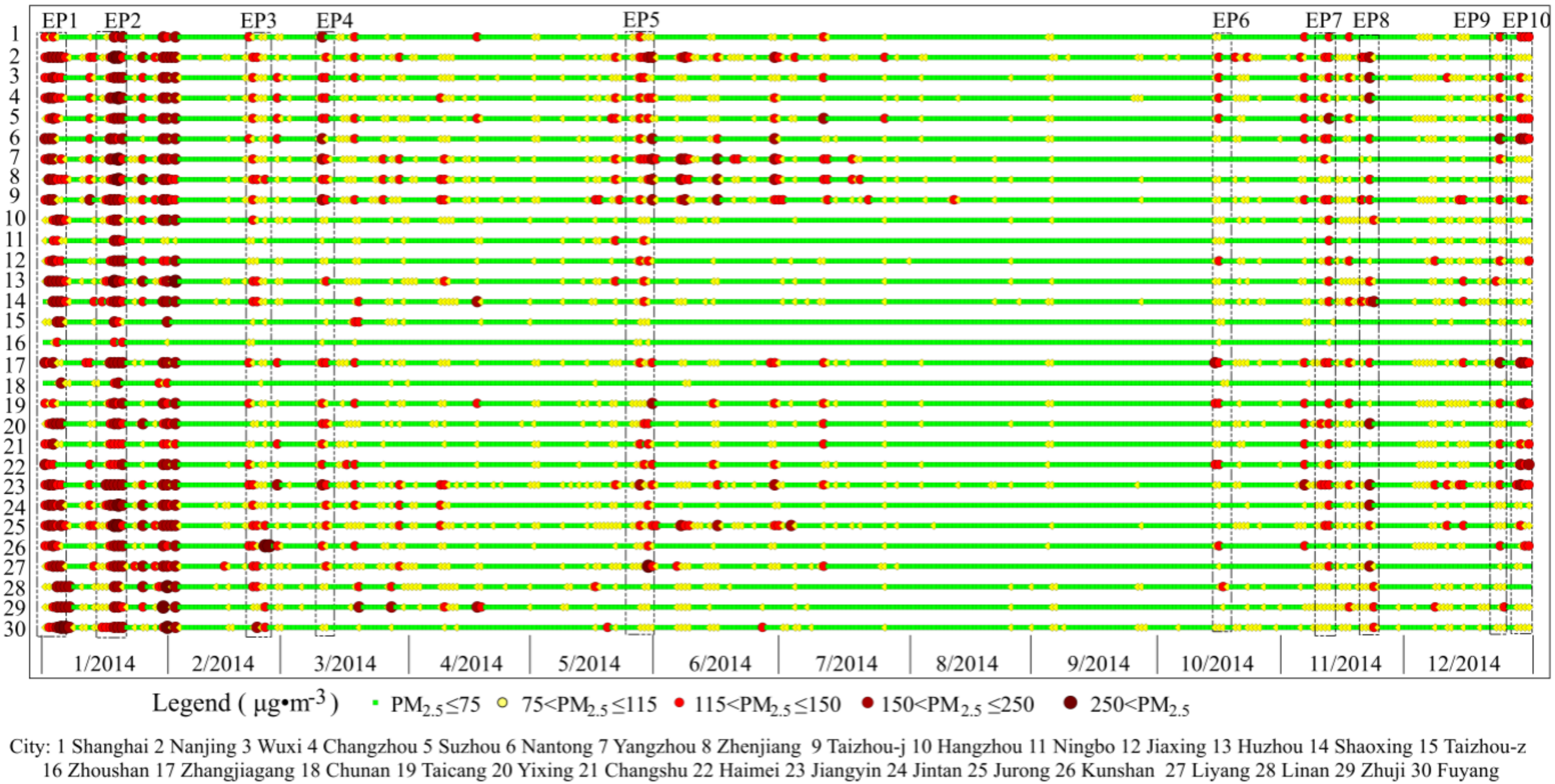

Figure 2. Daily $PM_{2.5}$ concentrations and ten pollution episodes selected in 2014.

2.3. Method

2.3.1. $PM_{2.5}$ Episode Indexes

To exhibit the characteristic of PMAE, We defined three episode indexes, MI_{ep}, DI_{ep}, and AD_{ep}, which are written as follows:

$$MI_{ep} = \frac{1}{n}\sum_{i=0}^{n}(C_{(max,i)} - C_{(0,i)}) \tag{1}$$

$$DI_{ep} = \frac{1}{n}\sum_{i=0}^{n}\frac{MI_{ep,i}}{d_i} \tag{2}$$

$$AD_{ep} = W_1 MI_{ep} + W_2 DI_{ep} \tag{3}$$

where, MI_{ep}, DI_{ep}, and AD_{ep} refer to the maximum increment, the daily increase rate and the accumulation degree of $PM_{2.5}$ during a pollution episode, respectively. i = 1, 2, 3 . . . . . . n (n = 10). $C_{(0,\ i)}$ and $C_{(max,\ i)}$ refer to the beginning and the peaking concentration of $PM_{2.5}$ in EPi, respectively. d_i is the days of duration before $PM_{2.5}$ concentration reaching the peak in EPi. In Equation (3), W_1 and W_2 represent the weight of MI_{ep} and DI_{ep}, respectively. In this study, considering MI_{ep} and DI_{ep} were significantly positively related to each other (R^2 = 0.79), we defined W_1 = W_2 = 0.5. When the Equation (3) was applied, MI_{ep} and DI_{ep} were normalized to the region of (0, 1) first. The higher value of AD_{ep} indicates $PM_{2.5}$ in that city is easier to accumulate.

2.3.2. Geographical Detector Model

The geographical detector proposed by Wang et al. [30] is a novel and suitable spatial analysis method to detect the influential force on certain geographic and environmental phenomena, which has been applied in many fields in recent years [31–33]. We used factor detector, one module of the geographical detector, to determinate the impact of socioeconomic indicators on PMAE in our study. Let one SEF be D, which is categorized into several sub-region D_i (i = 1, 2, 3 . . . . . . m, m is the number of sub-region, and m = 5 in this study), and let an episode index (i.e., MI_{ep}, DI_{ep}, or AD_{ep}) be H, then the determinant power of factor D to H ($PD_{D,H}$) could be expressed as follows [30,31,33]:

$$PD_{ep} = 1 - \frac{1}{n\sigma^2}\sum_{i=1}^{m} n_{D,i}\sigma_{D,i}^2 \tag{4}$$

where, n and $n_{D,i}$ are the number of samples in the total study area and in the divisional D_i, respectively; σ^2 and $\sigma_{D,i}^2$ refer the variations of H in the total study area and in the divisional D_i. The higher value of $PD_{D,H}$, which is between 0 and 1, indicates the impact of the factor D on $PM_{2.5}$ is stronger.

2.3.3. Factor Detector Indicators

The analysis of $PM_{2.5}$ sources was a focus in previous articles. Firstly, pursuant to several papers, industry, coal combustion, private vehicles, gas combustion, iron and steel manufacturing, and biomass burning were regarded as the main sources generating fine particulate matter in the YRD [13,34]. Secondly, some studies have suggested that city size impacts air quality. For instance, Stone [35] and Martins [36] suggested that urban sprawl led to changes in population, energy consumption and air emissions, which would finally result in a worsening of air quality. Thirdly, population density was considered an influencing factor, but it is unclear whether the population density plays a positive or negative role with regard to $PM_{2.5}$. On the one hand, a higher density in a large city is helpful for pollution-concentrated disposal, which will improve environment [35]. On the other hand, a higher density of population would cause more energy consumption and more emissions. As reported in many studies, the ambient $PM_{2.5}$ concentration is higher in an urban area than in a rural region [6,37], indicating that higher population density can aggravate $PM_{2.5}$ pollution. To further explore the effects of social and economic factors on PMAE, we chose five pollution sources, including

12 indicators, as detector factors (Table 1). Considering the monitoring sites were located in the urban built-up district, each variable in this paper was considered at an urban area scale to match the $PM_{2.5}$ data. All the SEFs data, which was captured as annual values, came from the Statistical Yearbook (2014) [38–40] or the National Economic and Social Development Statistics Bulletins of 30 cities (http://www.stats.gov.cn/tjgz/wzlj/dftjwz/). Figure 3 shows the spatial distributions of the twelve SEFs. In the remainder of this paper, the abbreviations of the indicators as follows: X_{11}, Sec_indu; X_{12}, Indu_L; X_{21}, Energy; X_{22}, Elec_tot; X_{23}, Elec_indu; X_{31}, Pop_tot; X_{32}, Den_pop; X_{33}, Area; X_{41}, Vehicles; X_{42}, Road; X_{51}, Prim_indu; X_{52}, Sown.

Table 1. Indicators of potentially influential factors.

Abbreviation	Interpretation of Indicators (Unit)	Max	Min	Mean
Industrial factors				
Secondary industry/X_{11}	The secondary industry DGP (100 million yuan)	8167	71	1258
Industry above size/X_{12}	Gross industry output value above designated size (100 million yuan)	32,665	241	5098
Energy consumption				
Energy consumption/X_{21}	Total energy consumption (10,000 ton standard coal)	11,084	62	1494
Electricity power/X_{22}	Total electricity power (100 million kWh)	1367	10	205
Industry electricity/X_{23}	Industry consumption of electricity power (100 million kwh)	785	6	145
Population and City				
Population/X_{31}	Permanent Resident Population (10,000 persons)	2425	46	264
Population Density/X_{32}	Density of Population(person/km^2)	4341	98	1399
Built-up area/X_{33}	Area of urban Built-up (km^2)	1563	13	216
Transportation				
Vehicles/X_{41}	Possession of Civil Vehicles (10,000 vehicles)	304	2	44
Road/X_{42}	Total length of roads (km)	17,797	1296	3353
Agricultural factors				
Primary industry/X_{51}	The primary industry DGP (100 million yuan)	205	27	58
Sown/X_{52}	Total sown area of crops (1000 hm^2)	358	17	98

2.3.4. Univariate Linear Regression

It is noteworthy that a positive or negative correlation did not indicate causality completely. To express the force of each SEF on PMAE, we employed univariate linear regression to determinate the influence. Linear regression is a model used for data following a normal distribution. Due to the skewed distribution of many socioeconomic data (Figure 3), we select a log transformation to process the raw indicators. Compared with SK (the skewness of initial data), the values of SK-Log (the skewness of data in a logarithmic form), as shown in Figure 3, had a significant decrease from 2.68 ± 1.38 to 0.24 ± 0.93. Thus, a log transformation is considered to be a better effective method for processing the data and was selected in this study. The linear fitting formula is written as Equation (5):

$$Ln(Y) = \mathrm{a} + \mathrm{b}Ln(X) \tag{5}$$

where, Y is an episode index (MI_{ep}, DI_{ep}, or AD_{ep}); X means the socioeconomic indicators in Table 1; a is constant, and b stands for the slope of the regression line. This paper used the slope b to express the elasticity of Y growth caused by per unit of X added.

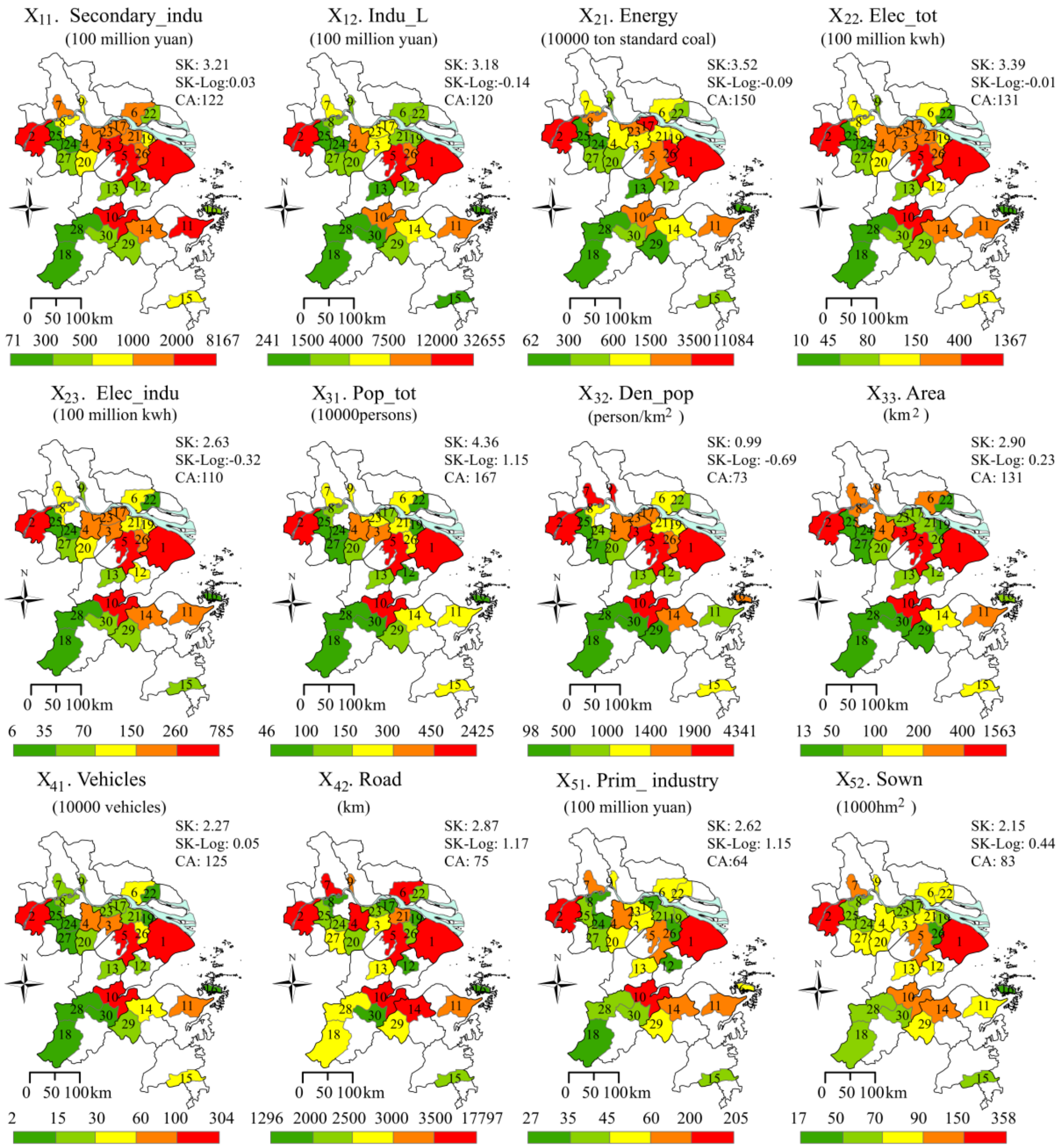

Figure 3. Spatial distributions of socio-economic factors. (SK is the skewness of the SEFs; SK-Log refers the skewness of SEFs used in a logarithmic form. CA is the coefficient of variation, which is calculated by the equation "CA = (Mean/Standard Deviations) × 100". Each city was numbered as in Figure 1. The blue color is the Yangtze River.)

3. Results

3.1. Characteristics of $PM_{2.5}$ Pollution in the YRD

In 2014, the YRD experienced long-duration $PM_{2.5}$ pollution, as shown in Figure 2. The regional C_{year} was 62.57 μg/m^3, which is higher than the national average (61 μg/m^3) [16] and obviously exceeds the CAAQS 35 μg/m^3 C_{year} standard. Affected by various factors, the $PM_{2.5}$ concentration was highest in winter (100.52 μg/m^3), followed in spring (62.28 μg/m^3) and in fall (52.49 μg/m^3), and lowest in summer (49.61 μg/m^3). Figure 4a,b show the spatial variation of C_{year} and pollution days, respectively. Figure 4 indicates that the cities with higher C_{year} were mainly located in the northwest of the region. For example, the top four cities, Nanjing, Taizhou, Jurong, and Jiangyin, which were located along the Yangtze River, had the higher C_{year} of 74.63, 73.53, 73.17, and 73.17 μg/m^3, respectively. Only one out of 30 sample cities, i.e., Zhoushan, witnessed a C_{year} of less than 35 μg/m^3. There were 16 cities with more than 100 pollution days. Figure 5 shows the statistical results of C_{day}. In the highly-polluted days, the C_{day} reached a peak of 454 μg/m^3 in Zhuji, 449 μg/m^3 in Lin'an, and 143–352 μg/m^3 in other cities, far in excess of 75 μg/m^3. Regarding spatial distribution, the value of C_{year} and pollution days all decreased from the northwest to the southeast, which may be related to the coastal location.

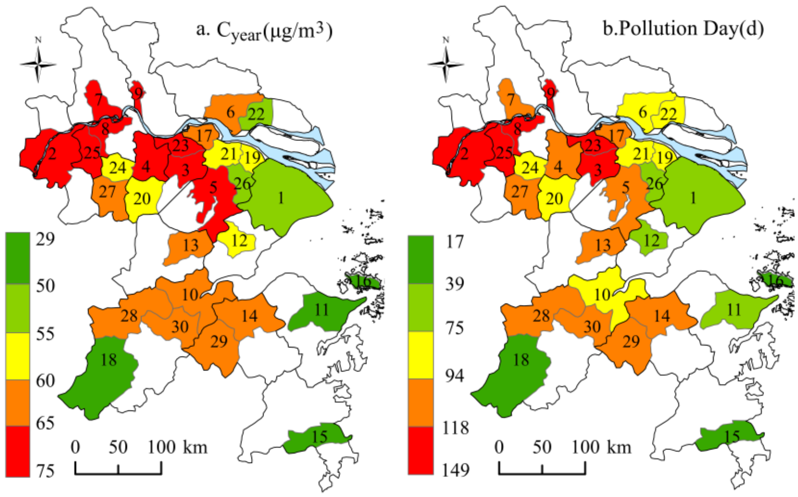

Figure 4. Spatial distribution of the annual $PM_{2.5}$ concentrations and pollution days in sample cities in 2014. (Each city was numbered as Figure 1. The blue color is the Yangtze River.)

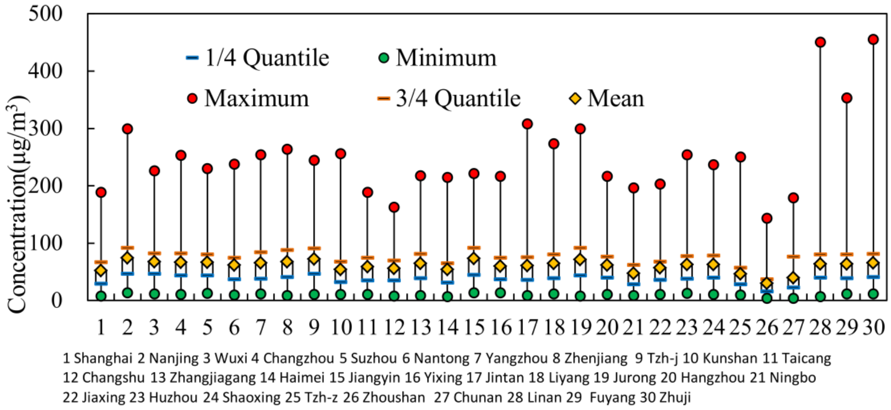

Figure 5. Statistics of daily $PM_{2.5}$ concentrations in sample cities in 2014.

3.2. Characteristics of PMAE

To express the results intuitively, the 30 cities were divided into five groups based on their GDP in 2014. Ten selected pollution episodes from these cities have been shown in detail in Figure 6. Table 2 showed the statistics of pollution indicators during the ten episodes in the YRD. The results indicated that severe episodes mainly occurred in January. In particular, during EP1 and EP2, the C_{day} peaked at 143–307 μg/m^3 in the sample cities. During the ten selected episodes, the maximum *of* MI_{ep} and DI_{ep} reached 217 μg/m^3 and 55.42 μg/(m^3·d) (observed in Nanjing). Notably, a peak was noticed in May, during EP5, for instance, when the maximum C_{day} reached 84–273 μg/m^3 in all the cities.

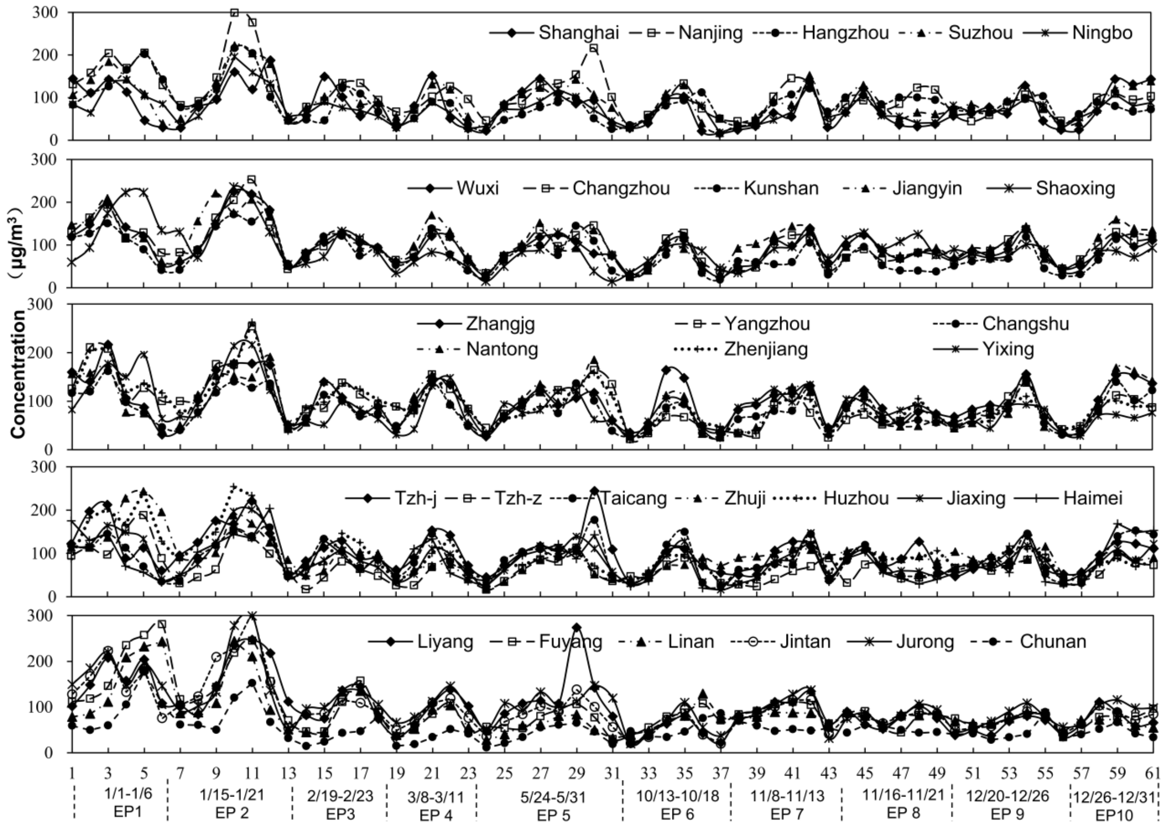

Figure 6. Ten $PM_{2.5}$ episodes from the sample cities in the YRD.

Table 2. Descriptive statistics of accumulation indicators during ten episodes in the YRD.

Episode	Month	MI_{ep}			DI_{ep}			AD_{ep}		
		Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
EP1	January	14	167	85	4.67	42.50	23.53	0.00	0.96	0.48
EP2	January	80	217	144	21.09	55.42	32.92	0.06	0.98	0.40
EP3	February	29	107	59	9.67	42.85	18.44	0.00	0.86	0.33
EP4	March	36	131	83	9.37	40.04	22.57	0.01	0.94	0.46
EP5	May	31	187	73	7.01	37.49	15.37	0.01	1.00	0.27
EP6	October	43	129	79	9.73	43.09	20.77	0.02	1.00	0.37
EP7	November	2	117	61	0.70	25.25	15.09	0.01	0.96	0.55
EP8	November	3	56	24	1.43	28.00	10.46	0.00	1.00	0.36
EP9	December	13	98	50	2.60	24.50	12.32	0.00	1.00	0.44
EP10	December	2	141	69	0.78	46.94	22.07	0.00	1.00	0.47
Average	annual	54	90	72	13.46	25.67	19.38	0.00	0.96	0.26

From Figure 6, it can be seen that every $PM_{2.5}$ pollution episode in each city in the YRD showed a similar, but not identical, tendency. This means the upward and downward trends in each city were similar, while their peak concentrations and the corresponding time of appearance were different. Unlike the spatial variations of C_{year} (decreasing from northwest to southeast), the high values of MI_{ep}, DI_{ep}, and AD_{ep} (obtained by averaging ten episodes) were concentrated on both sides of the Yangtze River, in addition to being characterized by a downward trend from north to south (Figure 7a–c). For instance, in Shanghai, $PM_{2.5}$ reached the peak faster, during six out of ten episodes, than in the other cities. Although Shanghai experienced a relatively lower C_{year} at 51.97 μg/m^3, it saw the highest MI_{ep} at 88.73 μg/m^3, DI_{ep} at 23.78 μg/(m^3·d) and AD_{ep} at 0.97 among the 30 cities. That is probably because of the dense population and vast industrial activities, which would cause more air emissions compared to the other cities. Another example, Nanjing, not only suffered from the highest C_{year} at

74.64 μg/m^3, but also experienced a high MI_{ep} at 88.43 μg/m^3, DI_{ep} at 21.33 μg/(m^3·d), and AD_{ep} at 0.87. Thus, it was a typical city with severe pollution that would easily accumulate. The reason for that might be related to the high humidity, local multiple emissions, and unfavorable diffusion here [13,20,41]. $PM_{2.5}$ was also easily accumulated in Nantong, Kunshan, Suzhou, as well as Taicang. However, it was low or hard to accumulate in some cities, such as Zhoushan and Chun'an. Among the remaining cities, the $PM_{2.5}$ accumulation degree was at a moderate level.

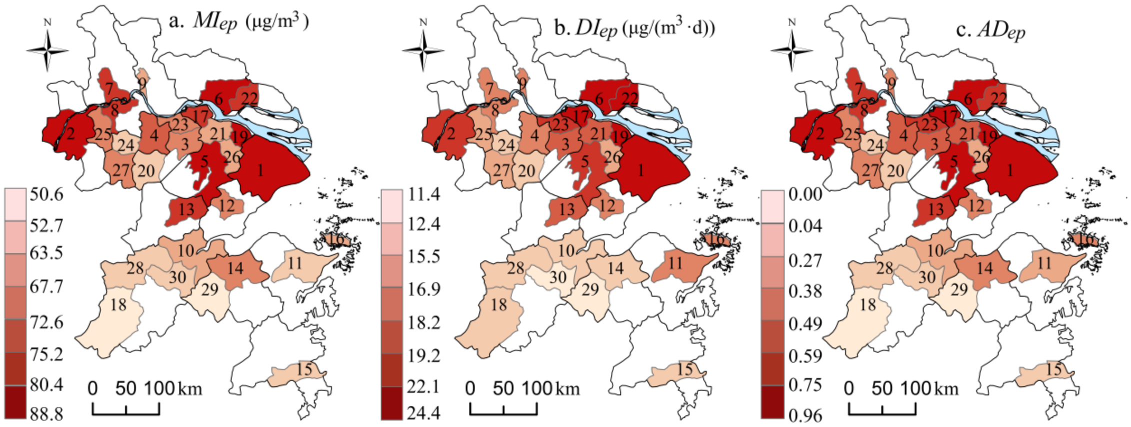

Figure 7. Spatial patterns of $PM_{2.5}$ episode indexes in the YRD. (Each city was numbered as Figure 1. The blue color is the Yangtze River.)

Based on the equal interval classification method, let the C_{year} of 30–47, 48–65 and 66–74 μg/m^3 represent the slight, moderate and heavy pollution level, respectively, and let the AD_{ep} of 0–0.33, 0.34–0.67 and 0.67–1 refer to the lower, moderate and higher accumulating degree, respectively. A figure indicating $PM_{2.5}$ pollution type was prepared (Figure 8).

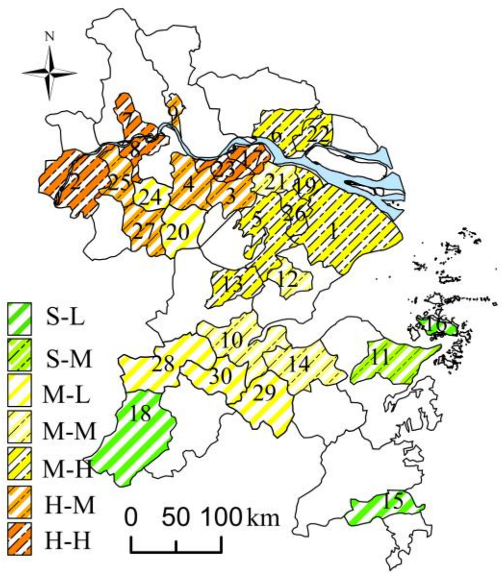

Figure 8. Pollution types of the sample cities. (In this figure, the H, M, and S before "-" refer heavy, moderate and slight pollution, respectively; the H, M, and L after "-" refer high, moderate, and low accumulation degree, respectively. Each city was numbered as Figure 1. The blue color is the Yangtze River.)

Overall, a more heavily polluted city had a higher degree of accumulation of $PM_{2.5}$, although, a less polluted city did not necessarily indicate "lack of ease of accumulation". In other words, severe pollution was dominated by the ease of $PM_{2.5}$ accumulation in certain spaces. However, in the cities with low C_{year}, like Shanghai, there were still highly-polluted periods. During the pollution episodes, the increase and decrease of $PM_{2.5}$ were rapid here.

In a word, the difference of the $PM_{2.5}$ accumulation, as well as that of C_{year}, is significant in the YRD. Unlike the trend of C_{year}, "higher in the northwest, lower in the southeast", the tendency of the degree of $PM_{2.5}$ accumulation is "higher in the north, lower in the south".

3.3. Impacts of Socioeconomic Factors on $PM_{2.5}$ Pollution

3.3.1. Pearson Correlation Analysis

Table 3 shows the Pearson correlation coefficients of SEFs with $PM_{2.5}$ episode indexes. From Table 3, it can be seen that no SEF was significantly related to the C_{year} (R ranging from 0.13 to 0.34), indicating weak correlations between them. However, for PMAE, the coefficients increased remarkably and presented a significant positive relationship. Taken together, three sources, including industrial factors, energy consumption, and population and city, had a stronger influence on PMAE than transportation and agricultural factors. Specifically, nine out of twelve SEFs except for road (X_{42}) and agricultural factors (X_{51} and X_{52}) were significantly related to MI_{ep}, as well as to DI_{ep} and to AD_{ep} at the level of $p < 0.01$ or $p < 0.05$. Among these nine indicators, firstly, population density (X_{32}) had the highest coefficients with MI_{ep} (0.68), DI_{ep} (0.67) and AD_{ep} (0.64), respectively, suggesting that population density could be an important factor driving the rapid increase of $PM_{2.5}$, compared to other factors, when pollution occurs. Although the impact of population density was unclear in previous literature, our results suggested that a higher density of population may influence $PM_{2.5}$ and cause it to increase rapidly, within a short period. Secondly, secondary industry (X_{11}), industry above designated size (X_{12}), energy consumption (X_{21}), total electricity power (X_{22}), and electricity power of industry consumption (X_{23}) had a high coefficient of 0.53–0.56 with MI_{ep}, 0.60–0.62 with DI_{ep} and 0.55–0.58 with AD_{ep}, indicating these five factors also influence $PM_{2.5}$ accumulation significantly. Overall, compared with C_{year}, PMEA was more sensitive to the influence of socioeconomic indicators.

Table 3. Correlations between SEFs and $PM_{2.5}$.

Pollution Sources	Detector Indicator	Pearson Coefficients				*PD*			
		C_{year}	MI_{ep}	DI_{ep}	AD_{ep}	C_{year}	MI_{ep}	DI_{ep}	AD_{ep}
Industry factors	Sec_indu/X_{11}	0.18	0.56 **	0.62 **	0.58 **	0.13	0.27	0.37	0.36
	Indu_L/X_{12}	0.34	0.54 **	0.61 **	0.55 **	0.19	0.26	0.31	0.32
Energy consumption	Energy/X_{21}	0.19	0.55 **	0.61 **	0.58 **	0.12	0.30	0.32	0.31
	Elec_tot/X_{21}	0.20	0.53 **	0.60 **	0.55 **	0.17	0.18	0.18	0.19
	Elec_indu/X_{23}	0.33	0.53 **	0.62 **	0.57 **	0.15	0.29	0.31	0.34
Population and city	Pop_tot/X_{31}	0.22	0.46 *	0.56 **	0.54 **	0.13	0.31	0.29	0.33
	Den_pop/X_{32}	0.22	0.68 **	0.67 **	0.65 **	0.12	0.36	0.33	*0.39*
	Area/X_{33}	0.13	0.47 **	0.48 **	0.47 **	0.11	0.33	0.29	0.31
Transportation	Vehicles/X_{41}	0.21	0.43 *	0.50 **	0.46 *	0.10	0.19	0.20	0.23
	Road/X_{42}	0.23	0.32	0.31	0.31	0.09	0.18	0.19	0.22
Agriculture factors	Prim_indu/X_{51}	0.15	0.25	0.29	0.27	0.12	0.21	0.14	0.18
	Sown/X_{51}	0.34	0.36	0.37	0.36	0.18	0.23	0.17	0.22

** $p < 0.01$, * $p < 0.05$.

3.3.2. *PD* of SEFs to PMAE

The Factor Detector module was used to quantify the *PD* of SEFs to PMAE. The specific process was listed as follows: (1) the SEFs were discretized into five categories (Figure 3); (2) the spatial figures of SEFs were overlaid on the figures of episode indexes (Figure 7) in ArcGIS; and (3) the *PD* of each factor was calculated by the Equation (4). It should be noted we have compared four discretization methods, system cluster, equal interval break, quantile break, and natural break. *PD* values by the system cluster method were larger than the others, thus, we considered it be suitable for the actuality. Furthermore, we also compared four clusters and five clusters and discovered no significant difference between them. Accordingly, this paper chose the system cluster method to discretize the quantitative data into five clusters (Figure 3).

As shown in Figure 3, the twelve SEFs experienced a great difference in the 30 sample cities. The values of CA ranged from 64–167, which indicated that the social and economic gap in the YRD did exist. Generally speaking, the region had an average population of 2.64 million, secondary industry of 1257 billion yuan, urban built-up area of 222 km^2, and vehicles of 44 million in 2014. Driven by a population of 24 million in Shanghai, most of other SEFs, such as secondary industry, built-up area, vehicles, and energy consumption etc., were more than 100 times higher than that of Chun'an, a city with the minimum of SEFs. In spatial distribution, cities, with a high value of secondary industry, energy consumption, population and population density, were apparently concentrated on both sides of the Yangtze River.

According to Table 3, the *PD* of SEFs to C_{year} was between 0.09–0.19, while it was in the range of 0.18–0.37 for PMAE, showing an extraordinary increase. Similar to the Pearson correlation analysis, the Factor Detector reached the conclusion that SEFs had a larger explanatory power with regard to the spatial diversity of PMAE than C_{year}. For MI_{ep}, population density had the highest *PD* value (0.36), followed by the built-up area (0.33) and population (0.32), suggesting that city size and the population degree could better explain the spatial difference of $PM_{2.5}$ increment compared to the other SEFs. That also means $PM_{2.5}$ accumulates more easily in a larger and more populous city. Similarly, for DI_{ep}, the high *PD* value belonging to secondary industry (0.37), industry above designated size (0.31), energy consumption (0.32), population (0.30) and population density (0.33), was higher than the other detector factors. Apparently, industry and energy consumption had a very significant influence on the rate of $PM_{2.5}$ increase, as well as population. Synthesizing this information to AD_{ep}, the *PD* values were sequenced as: X_{32} (0.39) > X_{11} (0.36) > X_{23} (0.34) > X_{31} (0.33) > X_{12} (0.32) > X_{21} (0.31) = X_{33} (0.31) > X_{41} (0.23) > X_{42} (0.22) = X_{52} (0.22) > X_{22} (0.19) > X_{51} (0.18). The sequence means that $PM_{2.5}$ was more sensitive to industry factors, energy consumption, population and city size than to transportation and agricultural factors.

The close correlations between PMAE and industrial factors, population and city, and energy consumption could also be observed clearly in Figure 9. Overall, the two upward-sloping fitting lines in each figure (except the last three) mean that a positive interrelationship exists between them. Similar to the Pearson analysis and Factor Detector, population density had the highest slope among the twelve factors, suggesting that a higher increment and rising rate occurred with an increase in population density compared to the other factors. The slopes, 0.17 for MI_{ep}, and 0.214 for DI_{ep} showed that an increment of 1% in population density would cause an increase of 0.17% in MI_{ep} and 0.21% in DI_{ep}. The other major slopes belonged to industry factors, energy consumption, and vehicles, in that order, showing the importance of these SEFs to $PM_{2.5}$ response during the episodes. From Figure 9, it can be seen that there were no significant linear trends for episode indexes with road and with agricultural factors.

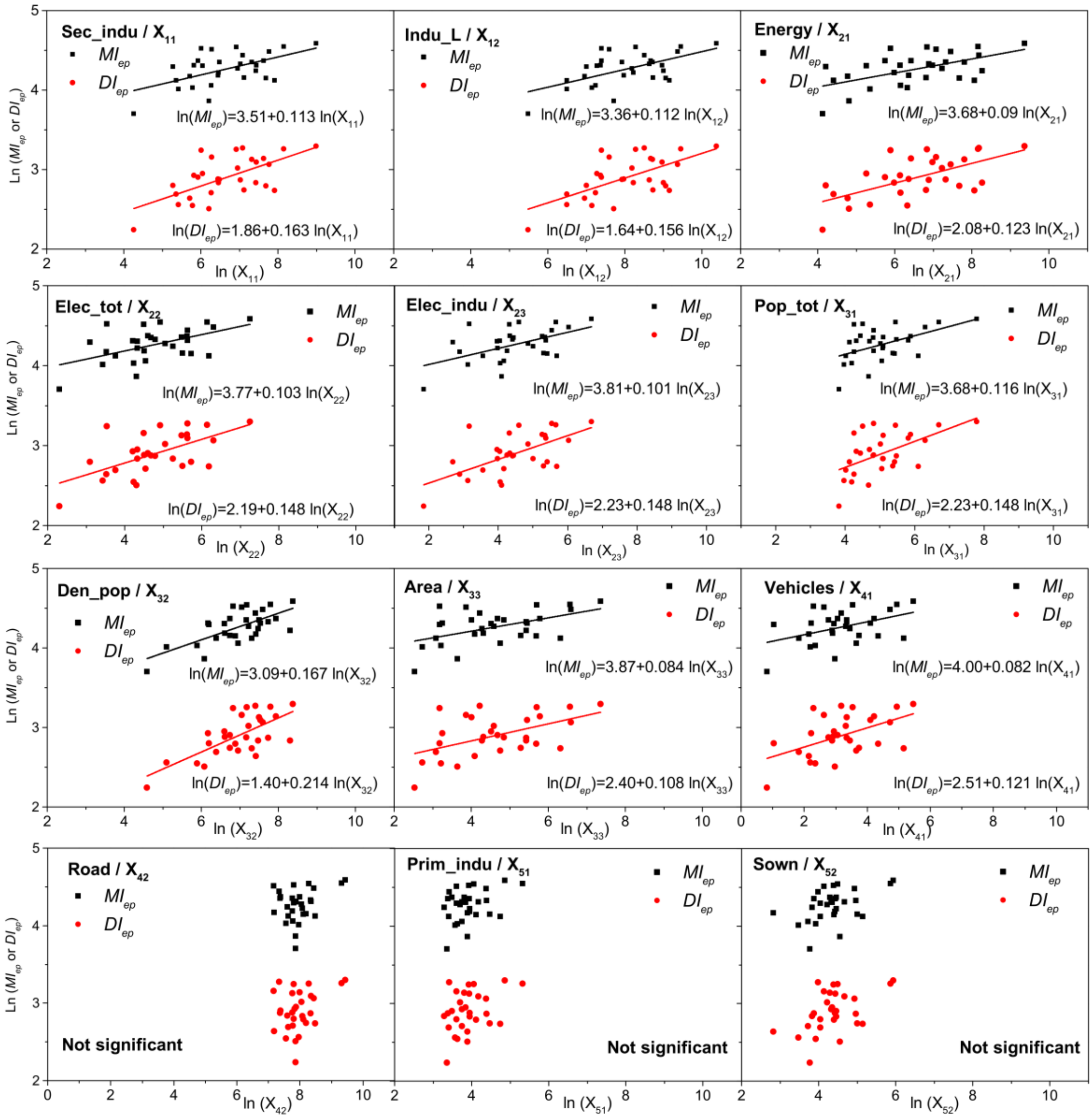

Figure 9. The scatterplots of SEFs with MI_{ep} (black squares), and with DI_{ep} (red circles). (Linear fitting between two variables without significant relation was not exerted in this figure.)

In short, our statistical results indicated that, firstly, PMAE could better explain the distribution of socioeconomic forces on $PM_{2.5}$ compared with the annual average concentration in the YRD on the basis of statistical analysis. Secondly, the population density and total population played important roles in promoting the accumulation of $PM_{2.5}$ during a pollution episode and causing the spatial diversity in the YRD. Thirdly, industrial factors and energy consumption also led to the dramatic increase in $PM_{2.5}$, especially the daily rise rate. Fourthly, as a reflection of the traffic factor, PMAE was significantly related to vehicles, suggesting that the impact of vehicles cannot be ignored. Lastly, although straw burning and agricultural biomass burning have been verified to be a key source in the YRD, we found that the effect of agricultural factors on PMAE was not statistically significant.

4. Discussion

During the last few decades, a growing number of scientific papers and reports have explored the socioeconomic drivers of air pollutant emissions, which are important for the development of pollution control strategies. As one of these cases, to better express the socioeconomic impact on haze pollution, we chose to focus only on $PM_{2.5}$ in accumulation stage (PMAE) in this study, unlike previous studies focusing on C_{year}. The reason was that we considered it may be more reasonable to employ PMAE to reflect the spatial differentiation of socioeconomic impact than C_{year}.

The following two inferences can be drawn. On the one hand, $PM_{2.5}$ was significantly affected by natural factors such as climate, topography, and surface vegetation [42–44] besides socio-economic drivers. C_{year} is a combined effect of these factors. Particularly, the reduction of $PM_{2.5}$ concentration often depended on precipitation or gales. It is very difficult to identify the influence of each factor on C_{year}. On the other hand, firstly, the YRD has similar climate conditions. In 2014, the annual average temperature in the 30 cities was between 14–19 °C and the yearly relative humidity was from 71% to 76%. Compared with SEFs in the region, the CA of temperature (6%) and relative humidity (3%) had a sharply decrease, which indicated the difference in weather factors among cities was much smaller than the SEFs. Secondly, one pollution episode only lasts for several days. In a few days, especially during the accumulation phase of a pollution episode, the synoptic conditions are relatively stagnant, which is one of the prerequisites of $PM_{2.5}$ pollution occurrence. Lastly, the ten pollution episodes were strictly picked out for this study under the principle without the interference of inclement weather (rainfall, winds, etc.). Thus, we believe that it can reduce the interference from natural factors as far as possible to focus on PMAE at the regional scale.

Even so, the disturbance caused by the difference in synoptic conditions in the YRD could not be removed completely. In addition, although we realize that the significant distinction of topography and landscape structure in the study area also contributed to the spatial variation of PMAE, this paper had to exclude these factors due to the lack of data. Furthermore, we selected the urban district as the sample assessment unit to minimize the coverage of $PM_{2.5}$, while it is still a limitation that using the data from a small number of fixed monitoring stations to represent the $PM_{2.5}$ pollution of a large area. With reference to existing, similar papers on the relationship of SEFs with $PM_{2.5}$, many articles also explored the relationship between socioeconomic factors and monitoring-site $PM_{2.5}$ [16,29], in which the influence of natural factors are rarely included [5,6]. Further, the data in the logarithmic form in our study could efficiently minimize the potential heteroscedasticity. Therefore, we considered that the exclusion of the influence of natural factors may not result in a serious evaluation bias.

On basis of this, our results showed that SEFs were more closely related to the episode indexes than to the C_{year}. In view of socioeconomic factors, firstly, although there has been no conclusive result about the positive or negative effects of population density on $PM_{2.5}$ from the existing articles so far, our statistical results indicated that population and its density have a significant influence on PMAE in the sample region. This may be because the population is the leading factor driving the increase in other social and economic factors. For example, in cities with a higher population density, more energy consumption, more private vehicles, and more industrial activities are required to satisfy the needs of a considerable population, which will, in turn, generate more emissions and deteriorate the air quality. When fine particles accumulate to a certain extent under stagnant synoptic conditions, $PM_{2.5}$ pollution will occur or be aggravated. According to existing research [6,38], the conclusion that $PM_{2.5}$ concentration was higher in urban areas than in rural regions also indicated population and its density may cause urban air quality deteriorating. Secondly, indicators of industrial factors, such as secondary industry, industry above designated size and energy consumption showed an important impact on PMAE in our study. In fact, industry, especially heavy industry, and its energy consumption could discharge many pollutants. As Zhao et al. [45] pointed out, a 1% increase in industrial added value will result in an increase of nearly 0.847% in relative pollution density. Therefore, the difference in industrial activities was also responsible for the spatial diversity of PMAE in the YRD. Thirdly, the number of motor vehicles, private vehicles in particular, has increased dramatically in recent years. As many studies have suggested, vehicular emissions include the main components of $PM_{2.5}$, such as particles or the precursor gases [46–48]. Through this paper, we also found the significant impact from vehicles on PMAE, based on statistical information. Lastly, the influence of agricultural factors was deemed as a vital source of $PM_{2.5}$ in previous studies [49,50]. However, it was not found to be strong enough to be statistically significant in our study. We inferred that the comparative stability of the agricultural effect could not lead to the extreme increase in $PM_{2.5}$, except in the harvest season, a few episodes during which time were appropriate for our study.

In brief, socio-economic factors heavily influenced the PMAE, with all contributors being tied to each other with the abovementioned analysis. There were two main contributions in this study. Firstly, we proved that the socio-economic influence on pollution episodes was more significant compared to the annual pollution level, which is rarely mentioned in previous studies. Secondly, the influence of each factor on $PM_{2.5}$ episodes was explored by the suitable techniques, geographical detector and linear regression. All of this information would be useful for developing policies for the improvement of air quality, especially during periods of serious haze episodes.

5. Conclusions

Using the $PM_{2.5}$ concentrations and twelve socioeconomic indicators in 2014, we have explored, for the first time, the characteristics of $PM_{2.5}$ accumulation during pollution episodes and its links with socioeconomic factors in the YRD from a statistical perspective. To compare, we employed the C_{year} as the annual average pollution level and defined the episode indexes, MI_{ep}, DI_{ep} and AD_{ep} to represent the degree of accumulation of $PM_{2.5}$ (the average of ten adopted episodes). In general, the spatial pattern of C_{year} indicated "higher in the northwest, lower in the southeast", while the high value of $PM_{2.5}$ accumulation degree was mainly distributed among the northern cities located along the Yangtze River. Pearson coefficients and *PD* values suggested a similar conclusion, that the variation in $PM_{2.5}$ during the episodes was more sensitive to socioeconomic impact than C_{year}. Scatter plots and linear regression further verified the influence of population density in causing PMAE variation in the YRD.

Overall, larger and more populous cities will generate more emissions, with $PM_{2.5}$ accumulation being easier there compared with the smaller ones. It may be time to think about controlling the scale of city expansion and population density in urban planning. Of course, China should also accelerate industrial restructuring, reduce coal consumption and develop new, cleaner energy sources. At the same time, motor vehicles did have a significant effect on $PM_{2.5}$ accumulation, and hence, should not be taken lightly. Although the explanatory power of agriculture was relatively weak in this study, the particles contributed by biomass burning identified by many other studies should be strictly controlled. Furthermore, air pollution was driven by all social and economic activities and their interaction. More studies about understanding the potential mechanism of socio-economic factors need to be conducted for improving the quality of our environment in the future.

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Conflicts of Interest: The authors declare no conflict of interest.

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