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Location Preferences and Changes in Pollution-Intensive Firms from the Yangtze River Economic Belt, China

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Abstract: This study examined the location preferences and changes in pollution-intensive firms by analyzing the spatiotemporal distribution and drivers in the Yangtze River Economic Belt, a transitional manufacturing region in China. To analyze the distribution of firms under natural growth conditions prior to the implementation of the national "Great Protection of the Yangtze River" policy in 2016, this study utilized data on newly expanded industrial land use from 2007 to 2016. The results indicated that new pollution-intensive firms predominantly focused on water pollution, occupying over 40% of the total area annually. The new pollution-intensive firms preferred the geographic agglomeration siting strategy, mostly along the Yangtze River or in urban agglomerations, while gradually moving westward. The total area and number of new pollution-intensive firms in the Yangtze River Economic Belt showed an overall trend of "inverted U-shaped" variation during the study period, and the average size of the pollution-intensive firms gradually decreased. GeoDetector analysis revealed that geographical factors have always been significant. Local economic factors attracted new pollution-intensive firms, but later in the study period, these factors showed some inhibitory effect on the increase in pollution-intensive firms in the lower reaches. Government intervention worked less effectively but was significantly enhanced after interaction with other factors. Finally, the results suggested that local governments should build a stronger synergy between industrial land policies and environmental regulations to ensure sustainable growth and rational allocation of pollution-intensive firms.

Keywords: pollution-intensive industries; location preferences; industrial land use; Yangtze River Economic Belt; GeoDetector

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1. Introduction

As a special category of industries, pollution-intensive industries (PIIs) possess the dual attributes of promoting regional economic growth and causing environmental pollution. On one hand, due to their capabilities to generate substantial tax revenue and create jobs, pollution-intensive firms (PIFs) have become prime targets for local governments. On the other hand, their spatial concentration not only exacerbates environmental risks but also reshapes the geographical distribution of industrial pollutants [1]. Therefore, analyzing the spatial patterns and location preferences of PIFs is crucial to strategically adjust regional economic structures and environmental policies in support of sustainable development.

Since the 1970s, researchers have launched a series of studies on the evolutionary patterns and influencing factors of PIIs. A range of theories and hypotheses have been proposed to explain the importance of government intervention to PII transfers, such as the "Pollution Haven Hypothesis" [2], and the "Porter Hypothesis" [3], alongside governmental interplay [4,5]. In addition to theoretical developments, some scholars have conducted empirical research to explore the influencing factors of PIIs. The price of

industrial land and environmental compliance costs have been identified as significant factors in the location preferences of PIFs [6–8]. However, other studies have revealed that PII relocation have been more affected by economic development levels [9], infrastructure construction [10], R&D investments [11], and digitalization technologies [12,13]. Moreover, the relocation of water and air pollution-related industries is influenced by water sources and wind directions [14,15].

It is evident that numerous factors influence the location choices of PIFs. Nonetheless, the interaction between these factors should not be overlooked, as their combined effects on PIFs are complex. Environmental regulations, for instance, interact with other variables such as labor costs and technological capabilities, jointly shaping firms' decision-making [16]. When environmental regulations tighten, if firms cannot offset rising compliance costs through technological improvements, other factors, such as labor costs, may become the primary drivers for relocating. Additionally, the same factors exert different influences in different cities. The interaction between urban economic development levels and environmental regulations has a nonlinear impact on the spatial distribution of PIFs, with more developed cities experiencing greater regulatory effects [17]. While most existing studies employ econometric models, such as panel regression, geographically weighted regression, and spatial Durbin models, to quantify the contribution of influencing factors, they often fail to fully explore the spatial differentiation and interaction between these factors.

The GeoDetector method, which uses the q-value to measure the intensity of individual factor influences and the strength of interactions between two factors, offers a robust approach to analyzing spatial heterogeneity more effectively [18]. Moreover, current research primarily relies on manufacturing enterprise databases and environmental statistics. However, frequent revisions to statistical indicators and inadequate oversight during the data collection process often compromise data quality. Given that the transfer of polluting industries is accomplished through land development and construction in China, some scholars endeavor to utilize newly expanded industrial land use data for research [19,20], furnishing more objective data for the analysis of industrial transfer.

Globally, PIIs primarily move from developed countries to developing countries in Asia, Latin America, and Africa [21,22], among which Asia hosts the majority of export processing zones and is the continent most affected by pollution [23,24]. China, located in Asia, has absorbed a large amount of PIIs since the reform and opening up, especially in coastal areas [25]. Recently, there is evidence that some of China's PIIs are shifting to the less developed central and western regions [26,27]. The Yangtze River Economic Belt (YREB) is an economic artery that spans eastern, central, and western China. It accommodates a variety of industries with highly interconnected environmental elements, reflecting the siting characteristics of PIIs in China. However, the region faces significant challenges due to the high proportion of PIFs, making the task of managing industrial pollution risks formidable [28,29].

Against this background, this paper utilizes newly expanded industrial land use data from 2007 to 2016 to depict the spatiotemporal distribution patterns and location preferences of PIFs in the YREB. An index system that integrates geographical, economic, and policy factors was constructed, and the GeoDetector model was applied to examine the interactive effects of these factors on the layout of PIIs, as well as potential spatial heterogeneity. This study deepens the understanding of location preferences for PIIs in the YREB, offering recommendations for sustainable development and industrial relocation, which are of significant reference value for both national and international high-quality development.

2. Materials and Methodology

2.1. Study Area

The YREB lies in the subtropics, with rich water and heat resources, and spans three major terrain types in China, namely plateaus, basins and hilly plains, with a trend of high altitude in the west and low altitude in the east. Thus, this region can be divided into three

major areas based on the watershed division: Chongqing, Sichuan, Guizhou and Yunnan provinces in the upper reaches; Jiangxi, Hubei and Hunan provinces in the middle reaches; and Shanghai, Jiangsu, Zhejiang and Anhui provinces in the lower reaches (Figure 1). In total, it covers 110 prefecture-level cities in the whole study area and 33, 36, and 41 cities in the upper, middle and lower reaches, respectively.

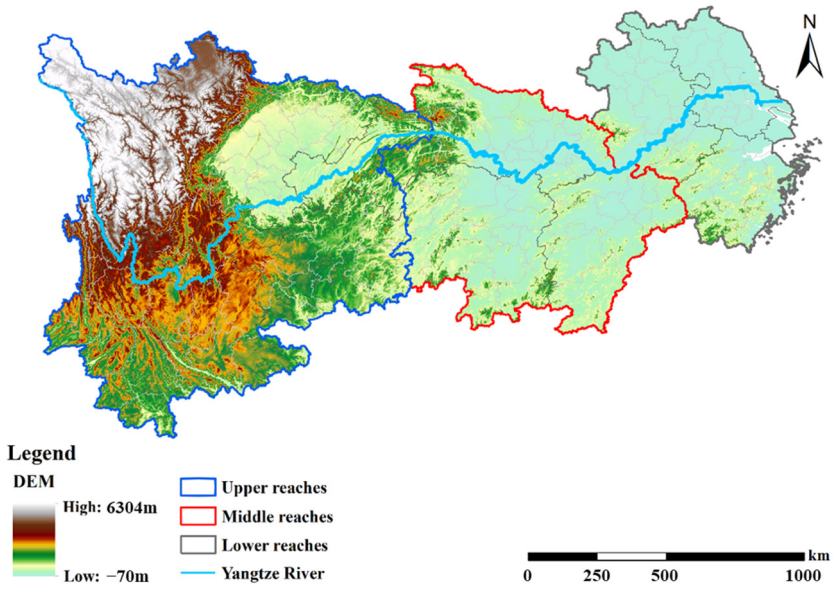

Figure 1. Study area and partitions.

The YREB is the most developed region of China's industrial system and the main distribution area for PIFs. Along the Yangtze River, 30% of the nation's petrochemical industry and 40% of the cement industry are distributed, and 43% of the nation's wastewater and 35% of sulfur dioxide emissions are concentrated in this area [30]. This makes the YREB a typical area for systematically portraying the spatiotemporal distribution of PIFs. With the continuous progress of urbanization along the Yangtze River, long-term extensive development in the past has resulted in high pollution attributed to the geographical concentration of PIIs. In 2016, China adopted the Outline of the Plan for the Development of the YREB, which for the first time put ecological and environmental protection in first place in the planning and design of the YREB, marking the official launch of the national strategy for the Great Protection of the Yangtze River. Although the ecological environment has been continuously improved since the YREB's development strategies were pursued, regional and local environmental problems are still prominent. To put forward more relevant and effective policies for the proper distribution and regulation of PIIs, it is necessary to detect where PIFs are attracted and what the influencing factors are.

2.2. Data Sources

This study used multi-dimensional data such as network capture data, yearbook data and basic geographic information, including the land transfer data of provinces and cities in the YREB from 2007 to 2016, and social and economic data for the corresponding years, as well as regional spatial vector boundary, DEM, river and traffic data. Due to the implementation of the national strategy for the Great Protection of the Yangtze River in 2016, the distribution of PIFs is subject to greater policy intervention. The main purpose of this paper was to obtain the distribution of enterprises under natural growth conditions, providing a reference for the layout of manufacturing division of labor in other countries and regions, so the time frame of years was practically irrelevant.

The newly formed location information was obtained from the newly expanded industrial land data on www.landChina.com (accessed on 22 April 2021), including the

land development project (name and address), land area, deal method, land use type, and amount of deal money. According to the standard of the National Economic Classification of Industries (GB/T 4754–2017), 49602 land parcels were screened as newly expanded pollution-intensive industrial land in this study. The locations of these land parcels were geocoded to obtain their coordinates for plotting.

Currently, there is no uniform standard for the definition of PIIs in academia. In this study, we mainly referred to the classification methods and results of previous scholars, as well as the emissions and treatment data on industrial wastewater, exhaust gases and solids that were provided in the *China Statistical Yearbook* from 2007 to 2016, and we finally selected the pollutant emission scale as the criterion [20]. We considered PIIs as industries whose total emissions accounted for more than 80% of the total pollutant emissions during the decade. Based on the industrial land type screening of the national economic industry classification (GB/T4754-2017), the paper defined the land type corresponding to the pollution-intensive industry, namely the textile industry; chemical fiber manufacturing; the agricultural and sideline food processing industry; leather, fur, feathers, (velvet) and their products; food manufacturing; water production and supply industry; pharmaceutical manufacturing industry; beverage manufacturing; the paper and paper products industry; the gas production and supply industry; petroleum processing, coking and nuclear fuel processing; the non-ferrous metal smelting and rolling industry; the non-metallic mineral products industry; the ferrous metal mining industry; coal mining and washing; non-ferrous metal mining and beneficiation; the production and supply of electricity and heat; chemical raw materials and chemical manufacturing; and the ferrous metal smelting and rolling industry, as PIIs. According to the location information in the announcement, the latitudes and longitudes were obtained from the map and were imported into ArcGIS software 10.4 for the next step of the analysis.

DEM data were obtained from the Resource and Environment Science and Data Center of China (https://www.resdc.cn/ (accessed on 22 April 2021)). For the influencing factors, the data of the variables were collected and calculated from the *China Statistical Yearbook*, the *China City Statistical Yearbook*, and the statistical yearbooks of selected provinces in the corresponding years. In addition, some missing data were effectively supplemented by interpolation.

2.3. Methods

2.3.1. Measuring the Spatiotemporal Distribution of PIFs

To visually analyze the spatial distribution patterns and regional differences of new PIFs, we used ArcGIS 10.4 to show the spatial distribution of new PIFs in YREB cities and used the natural interruption point method to classify the cities into five classes by the areas of new PIFs: low-value areas (0–50 km^2), secondary-low-value areas (50–150 km^2), middle-value areas (150–300 km^2), secondary-high-value areas (300–600 km^2), and high-value areas (>600 km^2).

Kernel density estimation is a widely used nonparametric statistical method in spatial analysis used to produce density estimates of features [31–33]. In this study, we used kernel density estimation to estimate the distribution density and spatial agglomeration of new PIFs. The higher the value is, the more concentrated new PIFs are in the region, and vice versa. The kernel density estimation was implemented in ArcGIS 10.4, and the formula was as follows:

$$F(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \quad (1)$$

where $F(x)$ represents the kernel density equation, n represents the number of points in the search window, h is the threshold value, and d represents the dimension of the data. By using the kernel density analysis function in ArcGIS software 10.4, the highest kernel density of the PIFs was used as the upper limit, and 0 was the lower limit.

For the change characteristics of the temporal distribution of new PIFs, we mainly adopted mathematical and statistical approaches.

2.3.2. Measuring Factors That Determine the Location of New PIFs

Theoretical Framework

A number of studies have explored the various determinants of polluting firm location choices. In general, the location choice of polluting firms is influenced by three types of factors, namely geographical factors (e.g., natural conditions, natural resource endowment), local economic factors (e.g., market conditions and agglomeration economies), and government intervention (e.g., environmental regulation, tax competition, and land use policy) [34].

Geographical factors are fundamental for polluting firms to make location choice decisions, which are usually omitted in previous studies because these factors do not change over time. PIIs are natural resource intensive; thus, they prefer to be located in areas with abundant energy and raw materials. For example, water-polluting firms prefer to locate close to rivers or the ocean to minimize production costs due to their processing requirements and emission capacity [35].

The influence of local economic factors on the location choice of polluting firms has been analyzed mainly in the fields of *Traditional Industrial Location Theory* and *New Economic Geography Theory*. *Traditional Industrial Location Theory* is the basis for exploring industrial layout and development, which focuses on exogenous resource conditions, such as the natural conditions, resources, labor, and technology of each region, determining the location preferences of industries [36]. Firms are assumed to choose the optimal location to maximize their profits and minimize their costs [37]. In this regard, the location choice and industry dynamics of PIIs have a close relationship with transport costs, labor markets and market conditions. In particular, products of PIIs are capital- or labor-intensive; thus, the related industries tend to be located in places with rich capital and low labor costs [38]. *New Economic Geography Theory* introduces and absorbs ideas such as the *Increasing Returns Hypothesis*, *Imperfect Competitive Market*, and *New Trade Theory* to endogenize industrial location and highlight the roles of factors such as industrial agglomeration and market size [39]. Thus, the geographic concentration of PIFs could generate positive externalities and attract even more new PIFs.

The role of government intervention in the siting of PIFs has received considerable attention from researchers, especially in China. Attracting investment is one of the main tasks of local governments. Due to the outstanding effects of PIIs on promoting regional economic growth, local governments tend to attract PIFs when faced with financial burdens. In addition, China's governments exert significant influence over the nation's resources and environmental policies, which are crucial components of the production expenses for PIFs [34]. Although China's government has introduced a series of policies about land marketization, which can limit the unrestrained growth of PIFs to some extent, China's land market is still incomplete because of the government's strong intervention in industrial land transfer. Insufficient competition in the land market has led many industrial enterprises to acquire industrial land at a low price [40]. In recent years, there has been an increasing number of studies on the effects of environmental regulations on PIFs. These studies were mainly based on the Pollution Haven Hypothesis, which argues that differences in environmental regulation levels cause polluting industries to move from developed regions with strict environmental regulations to developing regions with lax environmental regulations [41,42], or based on the Porter hypothesis, which argues that strict but proportionate environmental regulations may attract polluting firms because these regulations can actually lead to the induced innovation and increased competitiveness of these firms by encouraging efficiency improvements and higher productivity, which in turn offset some or all of the compliance costs [34,43].

Construction of the Model and Selection of Factors

In this study, a GeoDetector-based investigation of the relationship between the distribution of new PIFs in the YREB and its influencing factors was conducted. GeoDetector is a spatial statistical method used to detect consistency in spatial divergence patterns between

outcome variables and impact factor variables [18]. It can not only quantitatively detect the relative importance of each driving factor in both spatial and temporal variations but also address the interaction effects of these factors.

The core idea of the model is that if factor X has a significant influence on the distribution of new PIFs Y, then the spatial distribution of this factor should have a more significant similarity with the area of newly expanded pollution-intensive industrial land. The factor detector part of this model quantitatively describes the relative importance of factor X. It measures the explanatory power of the independent variable on the dependent variable by constructing a q statistic. The model is expressed as

$$q_{Y,X} = 1 - \frac{1}{N\sigma^2}\sum_{h=1}^{L} N_h\sigma_h^2 \quad (2)$$

where q indicates the influence of the factor on the distribution of new PIFs; h = 1, ..., L represents the stratification of variable Y or factor X, i.e., classification or partition; N_h and N are the number of cells in subregion h and the whole, respectively; and σ^2 and σ_h^2 are the variance of the area of newly expanded pollution-intensive industrial land in the whole region and subregion h, respectively. $q \in [0,1]$, when q = 0, indicates that the distribution of new PIFs in the YREB is not influenced by this factor; the larger the value of q is, the stronger the explanatory power of this factor, i.e., the greater the impact of this factor X on the distribution of new PIFs Y.

Interaction detection is used to quantitatively identify the interaction between two factors, which assesses whether the effect of factors on attribute Y is independent, enhanced or weakened when they work together by comparing the q values of two factors for Y separately and the q value when they interact [18]. For two factors X_1 and X_2, their post-interaction q values are denoted as $q(X_1 \cap X_2)$. If $q(X_1 \cap X_2) < \text{Min}\,(q(X_1), q(X_2))$, the interaction results are nonlinearly weakening. If $\text{Min}\,(q(X_1), q(X2)) < q(X_1 \cap X_2) < \text{Max}\,(q(X_1), q(X_2))$, the results are unidirectional enhancement. If $q(X_1 \cap X_2) > \text{Max}\,(q(X_1), q(X_2))$, the results are bidirectionally enhanced. If $q(X_1 \cap X_2) = q(X_1) + q(X_2)$, the results are independent of each other. If $q(X_1 \cap X_2) > q(X_1) + q(X_2)$, the results are nonlinear enhancement.

Based on the above theoretical analysis, we selected three types of factors (geographical factors, local economic factors, and government intervention) to explore the influencing factors of new PIF location choice in our study. For geographical factors, the water resource amount and degree of surface steepness were selected. For local economic factors, we chose market size, capital investment, labor cost, transportation infrastructure and science and technology innovation level. For government intervention, we chose the degree of fiscal decentralization, intervention in the land market, and environmental regulation. We calculated the determinant value q for each influence factor on the distribution patterns of new PIFs in the YREB. The explanations and specific descriptions of each factor are shown in the table below (Table 1). Previous work has shown that the strengths of different factors may differ at different geographical scales [44]. We therefore performed our analysis for both the whole region and the three reaches.

Table 1. The selection and description of the influencing factors in this study.

Criterion Layer	Code	Influencing Factors	Index	Description
Geographical factors	Ge_1	Water resource amount	Drainage density	The abundance of water resources can provide sufficient water and energy and convenient waterway transportation conditions to attract PIFs.
	Ge_2	Degree of surface steepness	Regional average slope (°)	The comparatively flat terrain can reduce construction costs.

Table 1. *Cont.*

Criterion Layer	Code	Influencing Factors	Index	Description
Local economic factors	Le_1	Market potential	GDP per capita (CNY)	On one hand, the high level of economic development has a large market capacity, which promotes the development of PIFs; on the other hand, after a certain stage of economic development, people will be more likely to buy cleaning products, which promotes the relocation of PIFs.
	Le_2	Capital investment	Fixed assets investment (10,000 CNY)	The higher the fixed assets investment is, the better the local economic base and infrastructure development are.
	Le_3	Labor cost	Average wage of employees (CNY)	Being in a capital-intensive industry, PIFs prefer places where labor is cheaper.
	Le_4	Transportation infrastructure	Road network density ①	Improved transportation infrastructure facilitates the flow of production factors, reduces transaction costs and attracts industries.
	Le_5	Industrial agglomeration level	The proportion of total industrial output value above the scale to GDP (%)	Regions with higher levels of agglomeration economies can attract more PIFs [45].
	Le_6	Science and technology innovation level	Technology Innovation Index	This reflects the development of regional science and technology. The development of high-tech industries is bound to have a suppressive effect on PIFs.
Government intervention	Gi_1	Degree of fiscal decentralization	Municipal government budgetary revenue/total budgetary expenditure (%)	When faced with financial burdens, local governments tend to attract PIFs to locate here by way of industrial land supply.
	Gi_2	Intervention in land market	Market development level of industrial land ②	A high degree of land marketization means that local land transfers are mainly market-driven and subject to little government intervention, which will restrict the distribution of PIFs.
	Gi_3	Environmental regulation	Environmental regulation index by municipality ③/environmental regulation index of the study area	Environmental regulation tools are a key aspect of government regulation of PIFs, and their potential "pollution haven" effect may drive industries to areas with low levels of regulation.

Note: ① Considering that the data of some years were difficult to obtain directly, for the calculation of the weight of each city's graded road, we divided the total graded road length of the province by the ratio of urban road area to the total provincial volume. We combined the transport capability of different types and graded roads, and the road network density was calculated in accordance with the weights of 1.2, 0.8 and 0.6 for railroads, national roads and provincial roads, respectively. ② The market development level of industrial land was measured by the product of the standardized premium rate of industrial land transfer and the proportion of the area offered for "bidding, auction, and sale" to the total of industrial land transfer, following the method of Zhao et al. [46]. ③ Based on the availability of municipal-scale data, the pollutant emissions per unit of industrial output were selected for the calculation of the environmental regulation index.

3. Results

3.1. The Spatial Variation Characteristics of PIF Location Preferences in the YREB

From a whole-basin perspective, the high-value areas were mainly distributed along the Yangtze River or in the urban agglomerations (Figure 2). The overall number of new PIFs showed a trend of increasing from 2007 to 2013 and then decreasing after 2013. The overall high-value areas and secondary-high-value areas gradually expanded in coverage and shifted to the west, but the number was still greater in the eastern region during the study period.

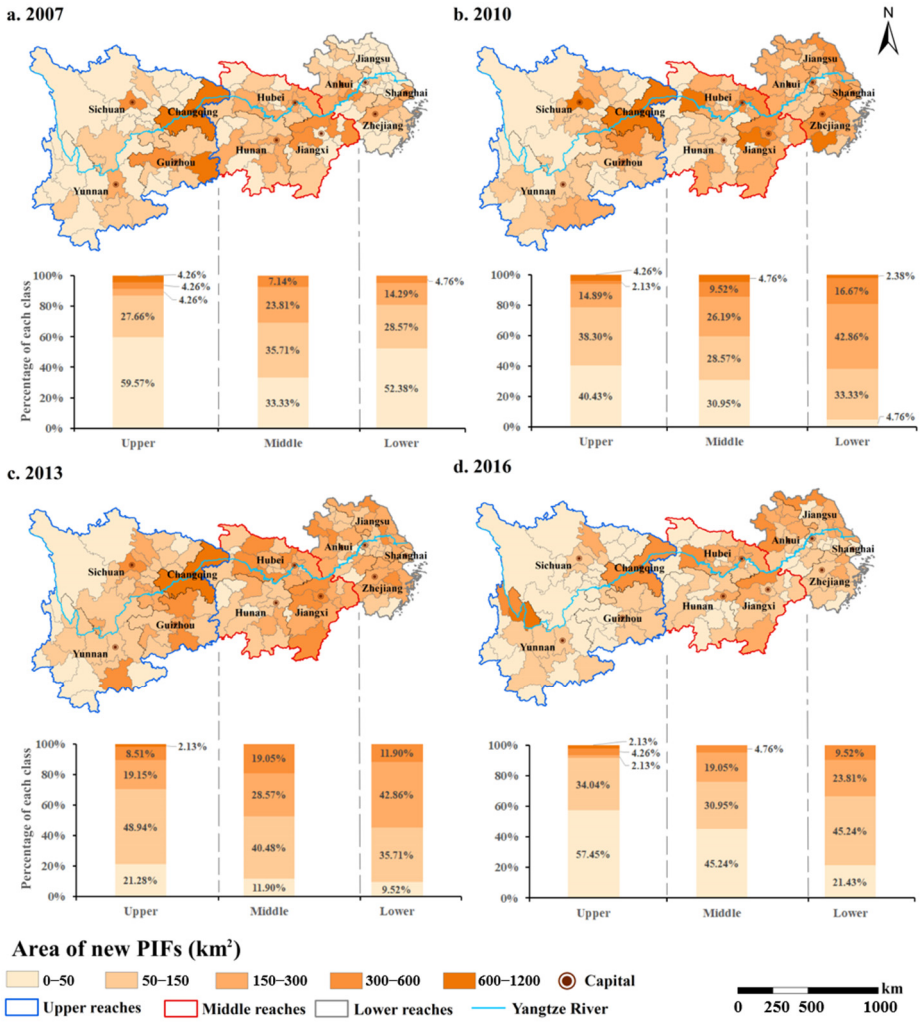

Figure 2. The distribution of new PIFs by city in the YREB in 2007, 2010, 2013 and 2016.

By region, most cities in the upper reaches had very few new PIFs and were concentrated in the low-value area. However, the Chengdu–Chongqing urban agglomeration, with Chongqing as the leader, has always been one of the high-value areas in the basin. The number of high-value areas in the middle and lower reaches varied in the same way as in the whole region. The trend of new PIFs in the middle reaches was low in the southwest and high in the northeast. In the lower reaches, the area was low in 2007. After 2010, most cities basically belonged to the middle-value areas with a more even distribution, and the high-value areas and the secondary-high-value areas gradually shifted from southeast to northwest.

Additionally, we calculated the kernel density of cumulative new PIFs (Figure 3). The higher the density value was, the more concentrated the new PIFs. It can be seen that new PIFs in the YREB showed a clear "multipoint-strip" clustering distribution during the study period, and the high-density clustering areas were mainly concentrated along the Yangtze River or in the capital cities of each province. The number of clusters increased and then decreased, and a trend of "clustering-spreading-reclustering" was observed. By region, new PIFs in the upper reaches were mainly concentrated in the central Chengdu–Chongqing urban agglomeration. In the middle reaches, new PIFs mainly gathered in the northeastern urban agglomerations. The "reclustering" effect in the lower reaches was not obvious compared with that in the upper and middle reaches, and the clustering area gradually shifted to the north.

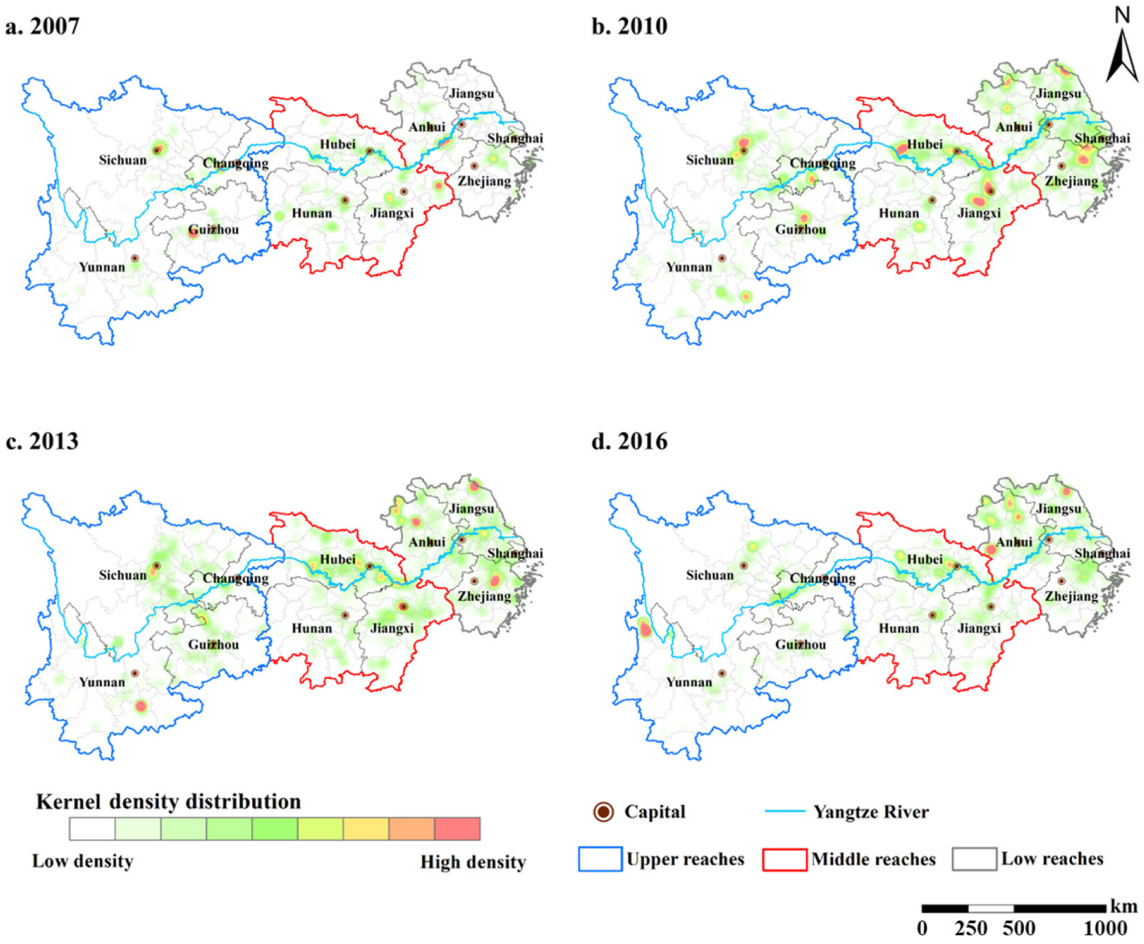

Figure 3. The distribution of the kernel densities of new PIFs in the YREB in 2007, 2010, 2013 and 2016.

3.2. The Time Variation Characteristics of New PIFs in the YREB

The results showed that from 2007 to 2016, a total of 49,602 new PIFs were added to the YREB, with a total area of 190,698.42 ha (Figure 4). During the decade, the change in total area and number of new PIFs could be roughly divided into two parts: the general growth phase from 2007 to 2011 and the continuous decline phase from 2012 to 2016. In terms of industrial land use, the average size of new PIFs had a decreasing trend.

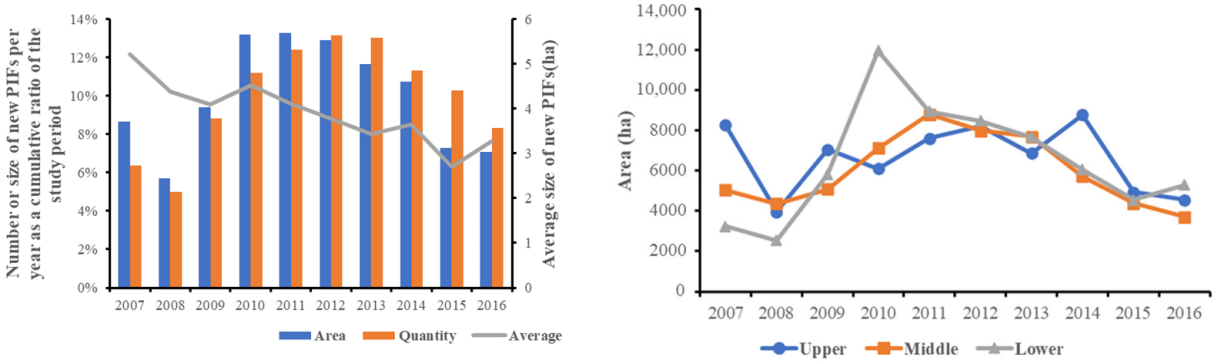

Figure 4. The number and area of new PIFs in the YREB during the study period.

There were also some similarities and differences in the temporal distribution of new PIFs among the upper, middle and lower regions. As shown in Figure 4, the area of new PIFs in the middle and lower reaches followed an "inverted U-shape" similar to the whole

region, while the change in the upper reaches presented a continuous fluctuating trend. In addition, the lower reaches had the largest proportion of the area in most years. Although for the cumulative total area of new PIFs, the upper reaches had the most for 66,249.37 ha, it was probably the lower reaches that dominated the region-wide time-series change trend.

3.3. The Influencing Factors on the Location Choice of New PIFs in the YREB

3.3.1. Factor Detection Results

As shown in Figure 5, for the YREB as a whole, the effect of geographical factors has been the most significant. In terms of the effects of individual factors, the water resource amount (Ge_1) and capital investment (Le_2) have always been important factors, which echoes the phenomenon that the high-value areas and agglomerations of new PIFs were mostly distributed along the Yangtze River or in urban clusters. The water resource amount was the primary consideration for new PIFs when making site selections. Places with more capital investment tended to have more developed infrastructure and better economic development, which would attract PIFs. The effect of the science and technology innovation level (Le_6) was also comparatively significant. A higher science and technology innovation level often suggests that the region is more welcoming to "low-input, high-output, low-pollution" types of firms, while there is a certain degree of exclusion of PIFs. This may have led to the gradual shift of PIFs from the east, where the science and technology innovation level is higher, to the west during the study period.

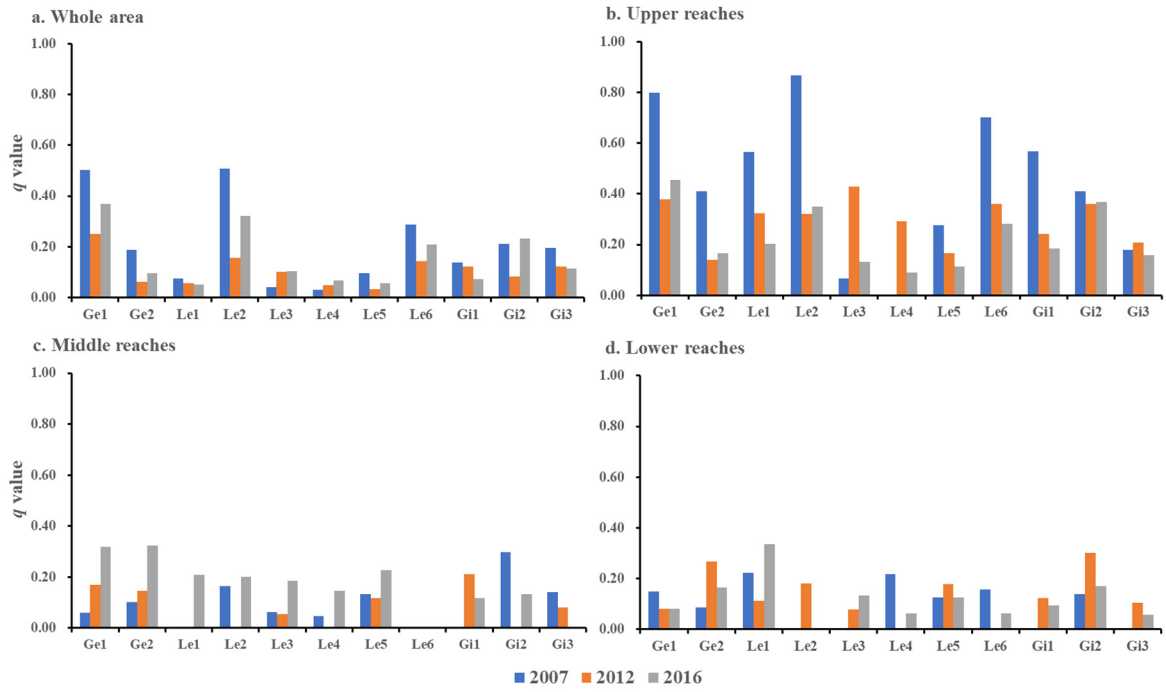

Figure 5. The detection value *q* of the influence factors on the location choice of new PIFs in the YREB. Note: Only points that passed the test at the 10% significance level are shown in the figure.

The detected value *q* basically had a decreasing tendency in the upper reaches during the study period. This suggests that in the upper reaches, there were several dominant factors influencing the distribution of new PIFs in 2007. By 2016, the influence of all factors became more complex and balanced. The effect of geographical factors was significant because the amount of water resource (Ge_1) was the dominant influencing factor. Compared to the middle and lower reaches, government intervention was more significant in the upper reaches. Among these factors related to government intervention, intervention in the land market (Gi_2) has also been an important factor in the upper reaches. In Guizhou Province, where intervention in the land market (Gi_2) was high, there were some clustered

high-value areas of new PIFs. However, new PIFs were more frequently located in the Chengdu–Chongqing urban agglomeration, which had a low level of intervention in the land market (Gi_2). This may be because PIFs preferred areas with better economic development and larger market potential. This can be supported by the high q value of market potential (Le_1) and capital investment (Le_2).

In the middle reaches, the effect of government intervention weakened during the study period, and geographical factors and local economic factors strengthened during the study period. The industrial agglomeration level (Le_5) was the most influential factor from 2007 to 2016, suggesting that new PIFs preferred to cluster around urban agglomerations. At the same time, we found that in 2007, the effect of intervention in the land market (Gi_2) was strong, while the effect of the degree of fiscal decentralization (Gi_1) was insignificant. By 2012, it was the opposite, and by 2016, the q value of intervention in the land market (Gi_2) rebounded again, while the q value of the degree of fiscal decentralization (Gi_1) declined. Theoretically, a low level of intervention in the land market and a high level of fiscal decentralization can indicate that land transfer in the region is mainly guided by the market rather than controlled by the government, and the phenomenon of "attracting capital with land" is unlikely to occur. However, in the 2007–2012 period, there was a tendency for the PIFs to move westward—mainly from the lower reaches to the middle reaches—probably because of the "land attracting investment" in the middle reaches, which had a high level of intervention in the land market and a low level of fiscal decentralization. This tendency was suppressed by 2016, when the role of land marketization was emphasized again.

In the lower reaches, the effect of local economic factors was significant. The most influential factors were market potential (Le_1) and intervention in the land market (Gi_2). The q value of market potential (Le_1) was higher in 2007 and 2016 than in 2012, while the q value of intervention in the land market (Gi_2) showed the opposite trend. In 2007, favorable economic fundamentals and great market potential were very attractive to PIFs. As PIFs continued to increase, the land market became increasingly competitive. Meanwhile, local residents became more inclined to buy cleaner products. By 2016, the lower reaches had already entered the late stage of industrialization. Expensive production costs and shrinking markets restricted the location of "high-input and high-pollution" PIFs.

3.3.2. Interaction Detection Results

As shown in Figure 6, most pairs of factors had enhancement effects with q values higher than those of the single factors, that is, the interaction between pairs of factors had a stronger impact on the location choice of new PIFs.

On a basin-wide basis, government intervention can show stronger effects after the interaction. The influence of the degree of surface steepness and environmental regulation was significantly enhanced after interacting with other factors. This proves that although these two factors had weak explanatory power on their own, their synergistic effects could exert a stronger influence. The results were similar in the upper reaches. For example, the q value after the interaction of Ge_2 and Gi_3 reached 0.92 in 2016, suggesting that places with relatively flat topography and lower levels of environmental regulation in the upper reaches may be more attractive to new PIFs.

In the middle reaches, the influence of environmental regulation was significant after interacting with other factors in 2007. The q value after the interaction of Gi_1 and Gi_3 was 0.63. New PIFs were mostly distributed in Jiangxi Province, which had a low level of environmental regulation and a low degree of fiscal decentralization. By 2016, economic growth had a significant impact after interacting with other factors. The q value after the interaction of Le_1 and Le_5 reached 0.71, and new PIFs were more inclined to cluster in the urban agglomerations of Hubei and Jiangxi, which were better developed economically in the northwestern region. In the lower reaches, the post-interaction effects of economic growth were also significant. These interaction effects showed some attraction to new PIFs during this study but some repulsion later in this study.

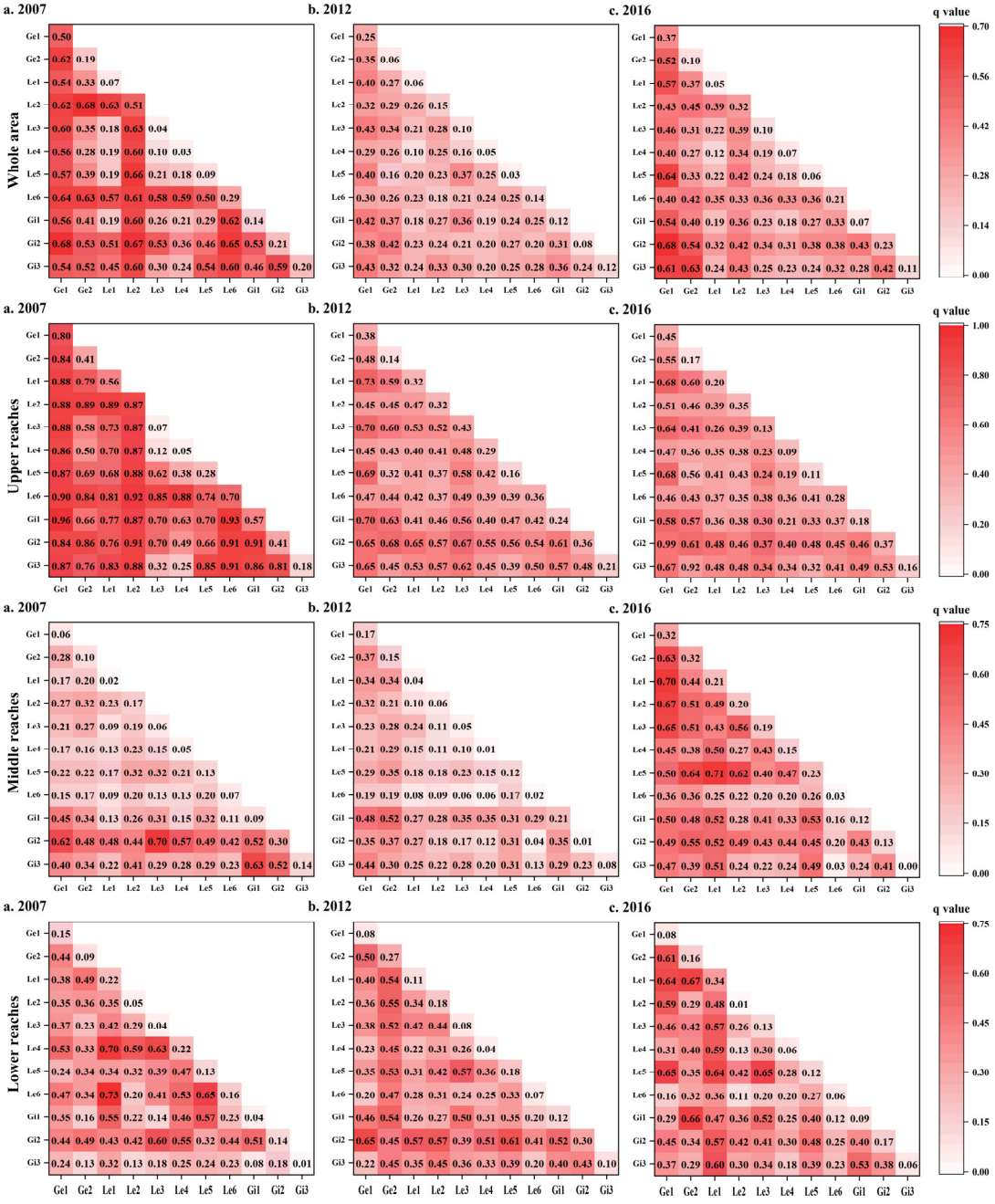

Figure 6. The interaction detection results for the influence factors on the location choice of new PIFs in the YREB. The nondiagonal element (different factors) depicts the interaction of two elements.

4. Discussions

4.1. "Factor Endowment" and the "Crowding-Out Effect" May Exist in the YREB

Our results showed that there was fluctuating growth of industrial land for new PIIs in the YREB, and new PIFs preferred to locate along the Yangtze River or in urban agglomerations. The areas with abundant water resource, strong economic power, and high market potential did appeal in terms of location choice for new PIFs, which confirms the "Factor Endowment Hypothesis". This hypothesis was proposed by economists Antweiler [47] and Copeland and Taylor [48]. They pointed out that pollution-intensive industrial products were capital-intensive; thus, the related industries tended to be located in more capital-rich places. Similar conclusions were obtained from the studies of Constantini and Crespi [38]. For the whole basin, new PIFs in the lower reaches, which had better economic fundamen-

tals and higher market potential, dominated the time series, and regionally, new PIFs in the upper reaches tended to locate in the Chengdu–Chongqing urban agglomeration, which had higher land marketization but better economic development, which can also reflect this hypothesis.

In addition, we found that there may be a "Crowding-out Effect" in the YREB caused by economic growth and the science and technology innovation level. With the gradual development of the economy, local people's living standards have improved, and they have become more concerned about the quality of their living environment. The demand for a better environment will lead to structural changes in the economy and the exclusion of PIFs [49,50]. The development of science and technology innovation levels can reduce the pollution emissions of firms and promote the transition in a cleaner and greener direction [51], which runs against the definition of PIFs in this paper. Therefore, new PIFs in the study period showed a tendency to gradually shift westward, mainly from the lower reaches, where economic development and science and technology innovation levels were better, to the middle reaches, where the phenomenon of "attracting capital with land" may have existed.

4.2. Synergy of Industrial Land Use Policies and Environmental Regulation Should Be Enhanced

Government intervention is one of the most direct means by which local governments can regulate PIIs. Local governments can optimize the industrial distribution by introducing relevant land policies to guide firms in site selection from various aspects, such as land planning, land supply and land administration [52]. Among the factors related to government intervention, the role of environmental regulation has been of great interest to the academic community in recent decades. From a theoretical perspective, environmental regulation may directly affect the distribution of PIFs [53,54], which consequently affects the pattern of industrial pollution emissions [55]. From a practical perspective, the introduction of environmental regulations is one means for governments to regulate PIFs despite the limitations of enforcement [20].

Nevertheless, the role of environmental regulation was relatively insignificant in our study. The q values were almost always below 0.2, whether in the whole region or in the upper, middle and lower regions. A similar conclusion was reached in some earlier studies, with the explanation that the compliance cost of environmental regulations was too small to have a significant impact on the location decisions of firms [56]. In the case of China, some local governments have offered industrial land to PIFs at excessively low prices to attract investment and promote economic development, which may not be aligned with environmental regulation goals. Moreover, the government adopted an accommodating attitude toward these firms and did not manage them properly, which eventually led to the failure of relevant environmental regulations designed to restrain the distribution of new industrial land [57].

However, we found that the influence of environmental regulations was significantly enhanced after interacting with other factors. This shows that under appropriate industrial land policies, environmental regulations can play their proper role. Therefore, the synergy between industrial land policies and environmental regulations should be strengthened. In formulating industrial land policies, we should strengthen the management of the whole life cycle, achieving an interlocking linkage from planning to supply and post-supply supervision. When planning industrial land, the overall ecological sensitivity should be evaluated, and the distribution of PIFs in ecologically sensitive areas should be strictly restricted. When carrying out industrial land supply, the trade-off between economic development and environmental protection should be considered, and the regulation of the industrial land market should be enhanced. When conducting industrial land administration, the utilization status of pollution-intensive industrial land during the use period should be dynamically evaluated and regulated in the whole process.

4.3. Water-Polluting PIFs Should Be the Focus of Future Industrial Land Use Planning

Our statistical analysis reveals that new PIFs in the YREB predominantly focus on water pollution, occupying over 40% of the total area annually. Notably, the amount of water resources is a key driver behind this trend. Although the YREB is not a water-scarce region, the limited water resources available still make it difficult to support the endless increase in new PIFs. In addition, as an important water supplier, the Yangtze River and its coastal lakes have serious pollution problems. For example, the concentration of heavy metals in water sediments from the middle and lower reaches has potential ecological risks [58,59]. The "Microplastics" pollution of Lake Taihu has also aroused great repercussions in the academic community [60]. Considering firm attributes, water-polluting PIFs are most likely to exacerbate water pollution situations. Therefore, administrators should pay special attention to water-polluting PIFs in future industrial land use.

To protect water resource, local governments can formulate relevant land use policies to limit the distribution of new water-polluting PIFs. For example, for areas near water sources, administrators can appropriately reduce the area of land available for sale or increase the minimum land price, thereby increasing competition for land, raising the threshold for new PIFs and forcing firms to become cleaner and greener. Moreover, eco-industrial parks are able to improve resource utilization efficiency through interfirm cooperation and reduce pollution emissions while promoting economic development [61]. Therefore, the construction of eco-industrial parks can be encouraged and supported under the premise of scientific planning of industrial distribution in conjunction with local environmental and social conditions and promoting the symbiotic relationship between PIFs to minimize overall pollution.

This study can inform corporate governance in pollution-heavy sectors across other developing nations. In India, for instance, Greenstone and Hanna found that national river protection initiatives largely fail due to inadequate environmental protection funding, frail environmental institutions and challenges in regional or sectoral cooperation [62]. Similarly, Brazil's decentralized water management faces significant free-rider issues [63]. Moreover, our analysis did not examine the influence of specific firm characteristics; it generalized across all new PIFs without addressing variances among different PIF types. Future research should more thoroughly investigate these distinctions, particularly for water-polluting PIFs.

5. Conclusions

This study employed the newly expanded industrial land use data of 110 cities in the YREB from 2007 to 2016, examined the location preferences of and changes in new PIFs by portraying the spatiotemporal distribution and identified its influencing factors. The conclusions obtained from the study are as follows:

During the study period, new PIFs presented a clustered distribution trend, mostly concentrated along the Yangtze River or in agglomerations such as the Chengdu–Chongqing urban agglomeration, and they gradually moved westward. The total area and number of new PIFs in the YREB showed an overall inverted U-shaped trend from 2007 to 2016, and the average size of PIFs gradually decreased. The annual change in new PIFs in the middle and lower reaches maintained a similar trend to that of the whole, while the upper reaches showed a continuous fluctuating change.

For the YREB, the amount of water resource as a geographical factor has always been an important factor that affects the location choice of new PIFs. Local economic factors such as market potential and capital investment attracted new PIFs, but later in the study period, these factors showed some inhibitory effect on the increase in PIFs in the lower reaches. The effect of government intervention was significantly enhanced after the interaction with other factors, especially environmental regulation.

Therefore, to guide the location choice of new PIFs in a more reasonable way and achieve a balance between regional development and environmental protection, local governments need to start from the following aspects in the future: paying attention to the

improvement of the industrial land transfer system, promoting "standardized" industrial land transfer and setting a reasonable land price ladder. The interface between industrial land policies and environmental regulations should be strengthened, and the management of the whole life cycle should be strengthened. Building eco-industrial parks can be encouraged and supported as a way to promote the symbiotic relationship between PIFs and minimize overall pollution.

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