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# Analysis of the Spatial Pattern Evolution and Influencing Factors of Pollution-intensive Industries: A Case Study of the Yangtze River Economic Belt, China

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# Analysis of the Spatial Pattern Evolution and Influencing Factors of Pollution-intensive Industries: A Case Study of the Yangtze River Economic Belt, China

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**Abstract:** This study identifies 17 pollution-intensive industries (PII) by industrial pollution emission intensity and uses latitude and longitude data of 4,663,413 Chinese enterprises to explore the spatiotemporal evolution and driving factors of PII in the Yangtze River Economic Belt (YREB). The result indicates that: First, PII quantity in YREB grew significantly with distinct phased growth differences. Second, the spatial distribution of PII showed prominent imbalance, presenting an east-west stepped-down pattern. water pollution-intensive industries as the core component of PII agglomeration. Third, PII exhibited a weak northeast-southwest migration trend over time, displaying a characteristic pattern of contraction followed by diffusion. Their spatial gravity center

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moved southwest, and layout favored socioeconomic advantages. Forth, three factors, namely institutions, traditional location and new economic geography, will have an impact on the agglomeration of PII in the YREB. Among them, the intensity of environmental regulations, green finance and opening up to the outside world have a negative inhibitory effect on the agglomeration of PII in the YREB, while labor supply and technological progress have a promoting effect. Moreover, these factors have obvious spatiotemporal heterogeneity.

**Keywords:** Pollution-intensive industries; MGWR; The Yangtze River Economic Belt; Spatiotemporal analysis; Influencing factors

## 1 Introduction

The acceleration of industrialization has intensified the complexity and severity of industrial pollution. In 2024, 83% of monitored cities worldwide recorded annual average concentrations of PM2.5 exceeding the World Health Organization’s standard values. Industrial pollution has thus become one of the critical challenges requiring urgent resolution in global ecological governance.

The YREB spans the upper, middle, and lower reaches of the Yangtze River (YREBUR, YREBMR and YREBLR), covering 130 cities as shown in Fig.1 (Guo et al., 2024). It occupies an irreplaceable strategic position in China's overall regional development pattern. However, for a long time, relying on its advantages in resource endowment and labor costs, this region has proactively undertaken the transfer of traditional manufacturing industries from eastern China. This development path has directly led to the high agglomeration of PII such as the chemical industry,

iron and steel industry, and non-ferrous metal smelting within the region. More notably, such industries show a gradient diffusion trend along the main and tributary streams of the Yangtze River, gradually penetrating into the middle and upper reaches where environmental supervision is relatively weak, and eventually forming a severe spatial pattern of chemical industries surrounding the Yangtze River (Fan et al., 2024). Taking the phosphorus chemical industry as an example, the Yangtze River Basin concentrates 93% of China's phosphate fertilizer production enterprises. Among them, the upper reaches of the Min River and Tuo River, as phosphorus ore-rich areas, have become core agglomeration regions for phosphorus ore mining, phosphate fertilizer production, and phosphorus chemical deep processing enterprises (Song et al., 2024). The high intensity of PII activities has directly caused the deterioration of regional water environmental quality. The total phosphorus concentration in water bodies in this region frequently exceeds the standard limit for Class III water bodies (≤0.2 mg/L) specified in the Environmental Quality Standards for Surface Water (GB 3838-2002)(Yan et al., 2021). . In some river sections, the exceedance multiple reaches 2 to 5 times, which further induces severe water eutrophication and poses a significant threat to the stability of the river basin ecosystem (Fan et al., 2024). It is evident that YREB has entered a critical window period for the transformation from an extensive growth model to an intensive development model (Guo et al., 2024). Against this backdrop, promoting the green transformation and upgrading of PII is an inherent necessity for this region to break through resource and environmental constraints, and achieve sustainable development.

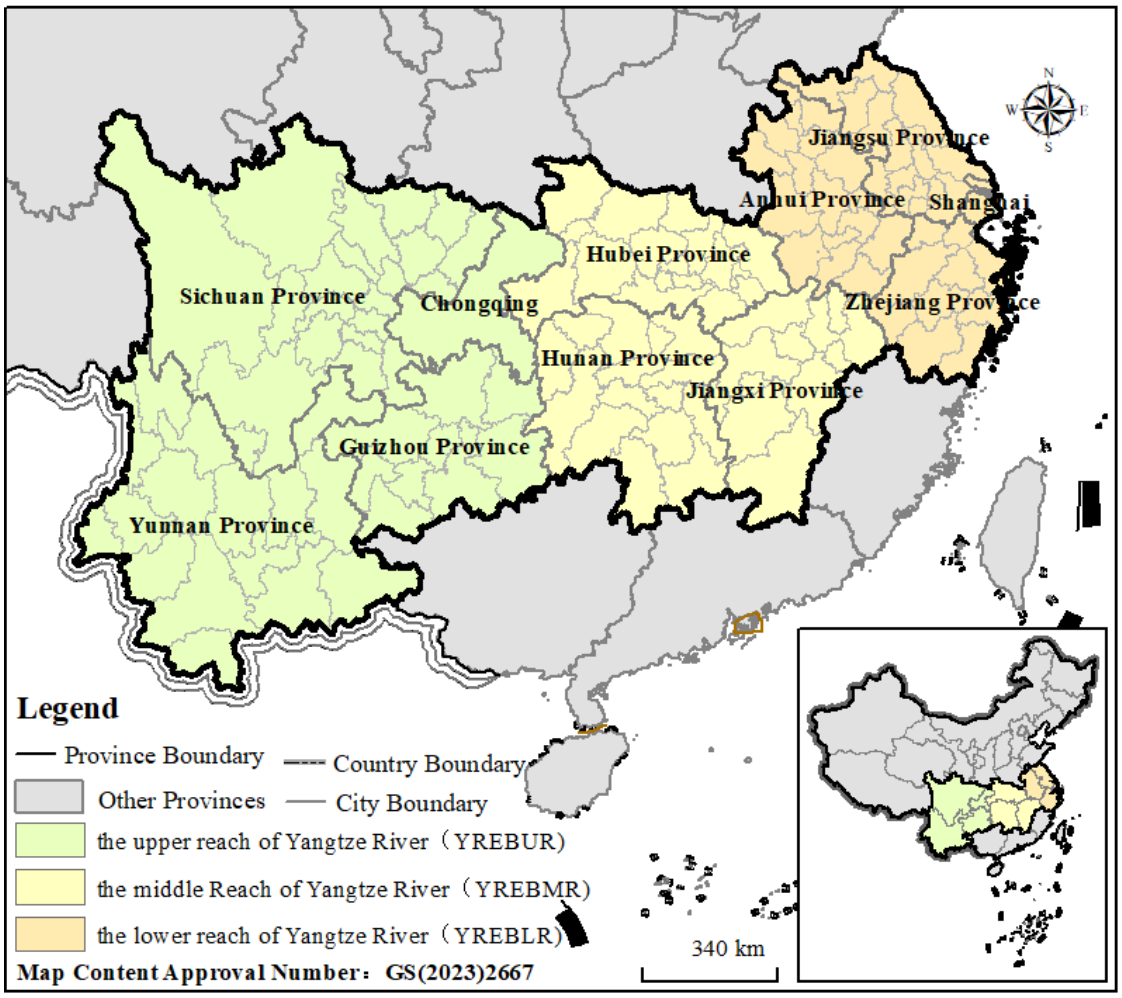



**Fig. 1** Location of the Yangtze River Economic Belt

PII exhibit high pollution emissions during production, imposing significant negative externalities on the environment (Li et al., 2020). They are therefore recognized as the primary source of pollution generation and discharge (Miao et al., 2024). Since the 1980s, scholars have begun to focus on resource and environmental issues caused by spatial changes in PII, with research primarily centered on the identification and governance of such industries. In the field of PII identification research, the academic community has not yet reached a consensus on the definition of PII. Quantitative indicators such as pollutant discharge scale (Becker and Henderson, 2000), emission intensity (Mani and Wheeler, 1998), and treatment costs (Tobey, 1990) are mainly adopted. Based on macro-scales (e.g., national, provincial, and municipal levels) and small-to-medium scales,

a series of studies have been conducted on the spatial diffusion and transfer characteristics of regional PII (Cole and Elliott, 2005). Research methods mainly include the Gini coefficient, geographic concentration index, location quotient, industrial concentration ratio, and industrial shift-share coefficient, with multi-dimensional explorations carried out at different levels such as national, provincial, and municipal (Shen et al., 2017). Further studies have found that PII exhibit cross-regional migration behavior in space, which essentially reflects pollution-intensive enterprises seeking optimal production locations (Weber, 1909). Due to their higher sensitivity to changes in labor costs and environmental policies (Jiang and Lyu, 2021), PII tend to be distributed in less developed regions and shift from core cities to non-core cities (Shen et al., 2017). This leads to the transfer of industrial pollution-related environmental problems from developed regions to less developed regions, a phenomenon known as the "pollution haven" effect (Dechezleprêtre and Sato, 2017; Shen et al., 2019). Considering the factor dependence, industrial transfer conditions, and economic efficiency of PII, scholars generally agree that environmental regulation (Shu et al., 2024), Environmental investment (Shu et al., 2024), digital transformation (Zhang et al., 2024), green finance (Tian et al., 2022; Zhang et al., 2022) are the main factors driving the migration of PII. Guidance should therefore be provided during the migration process of PII. Additionally, some scholars of new economic geography have focused more on the geographical characteristics of PII, aiming to effectively regulate the migration and unordered development of PII by identifying the dominant factors driving their migration (Caballero et al., 2024).

Existing studies have conducted in-depth discussions on the identification and governance of PII, yet there remain aspects that require further expansion: First, the identification of PII lacks systematicity. Most existing studies tend to define PII from the perspective of local regions and

specific short-term periods, lacking comprehensive judgments from a long-cycle and global perspective, which means the accuracy of industrial identification can be further improved. Second, insufficient attention has been paid to the agglomeration of PII in major strategic regions. In particular, specialized research on the agglomeration trend of PII in the Yangtze River Economic Belt—an important economic support belt in China—urgently needs to be deepened. Third, analyses of governance mechanisms mostly focus on traditional location selection or institutional factors, while ignoring the role and costs of new economic geography factors in the agglomeration of PII, as well as the impact of knowledge or technology externalities on economic agglomeration. In view of the above research gaps, this study systematically identifies 17 PII based on the pollution emission intensity of industrial sectors. By integrating the longitude and latitude data of 4,663,413 Chinese enterprises registered with industrial and commercial administrative departments, it further conducts an in-depth analysis of the spatiotemporal evolution characteristics of PII in YREB. Additionally, this study employs the Multiscale Geographically Weighted Regression (MGWR) model to explore the decisive factors influencing the spatial layout of PII from three dimensions, namely the systematic dimension, traditional location dimension, and new economic geography dimension.

# 2 Identification and spatial pattern evolution of PII

## 2.1 Identification of PII

At present, the identification of PII primarily relies on quantitative indicators such as the scale of pollutant discharge (Becker and Henderson, 2000), emission intensity (Mani and Wheeler, 1998), and treatment costs (Tobey, 1990). While the scale of pollutant emissions takes into account the

total volume of emissions, it fails to reflect the intensity of pollutant discharge (Jin and Lin, 2014). Conversely, emission intensity considers only the density of pollution-generating industries, neglecting the overall emission levels. Furthermore, the high pollution characteristics of PII are strictly endogenous, determined by the intrinsic attributes of the industries themselves (Piersanti et al., 2021). In contrast, the costs associated with pollution control are significantly influenced by various external factors, including geographical location, policies, and institutional standards (Cheng et al., 2025), making it challenging to directly represent the inherent high pollution attributes of these industries.

Based on this, this paper considers both the scale of pollutant emission and the intensity of pollutant emission, and calculates the pollution-intensive indices corresponding to industrial exhaust gas, wastewater and solid waste of 38 industrial sectors, using the relevant data of 2015, in order to identify PII pollution-intensive. The formula for calculating the index is as follows:

$$Pollution_{mn} = \sqrt{A_{mn} \times X_{mn}} \quad (1)$$

Where, $A_{mn}$ is the total amount of pollutant emissions from $m$ industry n, characterized by the total amount of pollutant emissions from M industrial industry n categories, and $X_{mn}$ is the pollutant emission intensity from M industry n, characterized by the ratio of the total amount of pollutant emissions from M industrial industry n categories to the value added of M industrial industry. Among them, the relevant data are from the China Environmental Statistics Yearbook.

**Table 1** Catalogue list of different types of PII

| Order | Water Pollution Intensive Industries | Solid Pollution Intensive Industries | Air Pollution Intensive Industries |
|---|---|---|---|
| 1 | Paper and paper products industry | Ferrous Metal Ore Mining | Electricity and heat production and supply |

| | | | |
|---|---|---|---|
| 2 | Wine, Beverage and Refined Tea Manufacturing | Non-ferrous metal mining | Non-metallic mineral products industry |
| 3 | Agricultural Food Processing Industry | Other Mining | Ferrous metal smelting and rolling processing industry |
| 4 | Food Manufacturing | Coal Mining and Washing | Non-ferrous metal smelting and rolling processing industry |
| 5 | Chemical fibre manufacturing | Non-metallic mineral processing | Petroleum Processing, Coking and Nuclear Fuel Processing Industry |
| 6 | Textile industry | Electricity and heat production and supply | Chemical raw materials and chemical products manufacturing industry |
| 7 | Chemical raw materials and chemical products manufacturing | Ferrous metal smelting and rolling processing industry | Paper and paper products industry |

As shown in Table 1, the top 7 industries in the pollution-intensive index of waste gas, waste water and solid waste are defined as PII, which contain the following 17 industries: coal mining and washing industry (B06), ferrous metal ore mining and processing industry (B08), non-ferrous metal ore mining and processing industry (B09), non-metallic ore mining and processing industry (B10), non-metallic mineral product industry (B10), other mining industries ( B12), Agricultural and Food Processing Industry (C13), Food Manufacturing Industry (C14), Alcohol, Beverage and Refined Tea Manufacturing Industry (C15), Textile Industry (C17), Paper and Paper Products Industry (C22), Petroleum Processing, Coking and Nuclear Fuel Processing Industry (C25), Chemical Materials and Chemical Products Manufacturing Industry (C26), Chemical Fiber Manufacturing Industry (C28), Ferrous Metals Smelting and Rolling processing industry (C31), non-ferrous metal smelting and

rolling processing industry (C32) electricity and heat production and supply industry (D44). the numbers in parentheses are the corresponding industry codes of each industry in the National Economic Industry Classification and Codes (GB/4754-2011). This is basically consistent with the classification of heavily polluting industries issued by the Notice of the General Office of the State Council on the Issuance of the First National Census on the Sources of Pollution and the List of Listed Companies for Environmental Verification of the Classification and Management of Industries (Environmental Affairs Office Letter [2008] No. 373), which suggests that the polluting industries identified in this paper are reasonable.

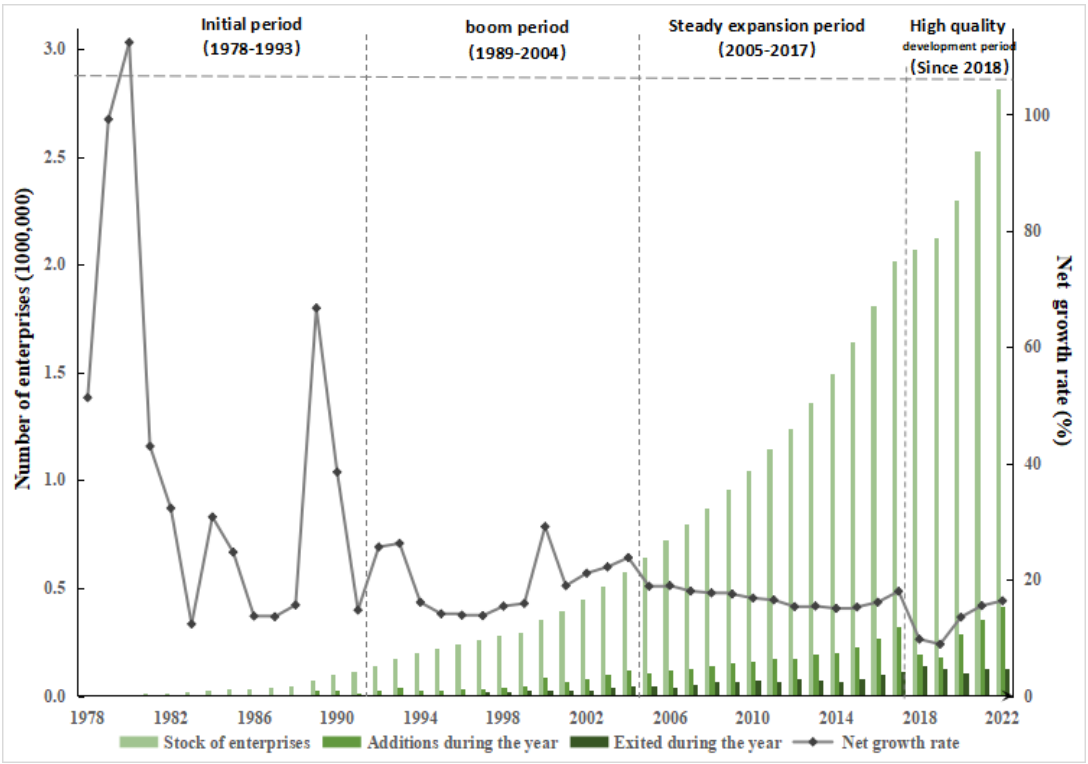
## 2.2 The spatio-temporal evolution characteristics of PII

### 2.2.1 Change in the number of PII enterprises

According to the industry catalogue list of PII, a total of 4 663 413 enterprises in 130 cities in YREB from 1978 to 2022 were obtained through the China Industrial and Commercial Enterprises Registration Database.

As shown in Fig. 2, there exhibits a pronounced characteristic of distinct phases over time basing the net growth rate of polluting enterprises. The period from 1978 to 1991 can be characterized as the initial formation stage, during which PII were established sporadically. The overall scale within YREB remained relatively small, with the number of such enterprises amounting to merely 147,500 in 1991. Notably, the net growth rate maintained a high level of development, albeit accompanied by significant fluctuations. The subsequent phase, spanning from 1992 to 2004, marked a period of rapid development. During this interval, the net growth rate of PII exhibited a steep upward trajectory, escalating from 14.71% in 1991 to 23.78% by 2004.

Consequently, the number of enterprises burgeoned to 577,400 by 2004, signaling the near formation of a concentrated cluster of PII. The period from 2005 to 2017 is described as a phase of stable expansion, where the growth rate stabilized around 17%, notwithstanding a slight downward trend. The total number of enterprises continued to expand further, reaching 2.0161 million by 2017. By this point, a significant aggregation of PII had been established, concomitantly giving rise to prevalent ecological risks, including issues related to chemical pollution along the river and haze. The intensive development stage since 2018, in which the net growth rate of PII is only 9.74% and 8.88% in 2018 and 2019, and although the net growth rate rises after 2020, it is always lower than the growth rate in 2017 (23.78%), which is due to the implementation of the pollution prevention and control war by provinces and cities along the YREB, which reduces, by means of renovation, shutting down, and relocation of undesired outputs such as industrial wastewater, industrial sulfur dioxide and industrial solid waste, improving production efficiency and promoting the transformation and upgrading of PII.




177

178 **Fig. 2** Changes in the Number of PII in YREB from 1978 to 2022

179 2.2.2 Characteristics of spatial distribution

180 Next, we queried and transformed 4.66 million pollution-intensive enterprise addresses into
181 enterprise latitude and longitude coordinates via Google Maps API interface, constructed the
182 enterprise spatial location database, and then referring to the approach of Henderson et al. (2021),
183 we choose the kernel density estimation to measure PII agglomeration from the perspective of
184 enterprise location big data as follows:

185
$$D_{ij} = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x - X_i}{h}\right) \quad (2)$$

186 Among them, $k$ is the kernel density function, n is the number of known business location
187 points within the search area, $x$-$X_i$ denotes the distance from the valuation point $x$ *to* $X_i$.

As shown in Fig. 3a, PII shows a stepped-down distribution pattern in YREB in 2022 from east to west. Among them, the value of the kernel density of PII in YREBLP is as high as 41353.7, which is much higher than the average level of YREB (14,537.12). The value of the kernel density of PII in YREBMP is 13,008.68, which is nearly double of that in YREBUP (6589.16).

From the perspective of major basin, the characteristics of continuous distribution of central agglomeration have gradually taken shape in the lower reaches of Yangtze River, and the overlapping area formed by Shanghai-Nanjing and Nantong-Shaoxing is the main plate of PII, around which PII are gradually spreading to the peripheral areas. PII in the YREBMP as a whole show the development character of multi-center agglomeration and multi-point dispersion, Wuhan, Changsha, Ezhou and Nanchang are the core cities of PII in the YREBMP, and the nuclear density value in 2022 will be 65,720, 41,248, 39,528 and 37,256, respectively, and the cities of Jingdezhen, Pingxiang, Huangshi, Ma'anshan, Xiangtan, Wuhu, Bozhou City, Xiantao City, etc. The characteristics of the agglomeration sub-center are increasingly formed, and the distribution of PII in other cities is relatively balanced. PII in the Chengdu-Chongqing Twin Cities Economic Circle have a slow trend of concentration and show the characteristics of high-capacity single-center concentration. Chengdu is the center of PII agglomeration, with an industrial agglomeration degree of 52,483.8 in 2022, which is more than one times that of other cities.

In terms of specific pollution types, as shown in Fig. 3b-3d, water pollution-intensive industrial (WPII) are the main component of PII agglomeration in YREB, with a high kernel density level of 10113, contributing to 67.86% of PII agglomeration in YREB, followed by air pollution-intensive industrial (APII) with a kernel density value of 5836, and the lowest degree of solid waste pollution-intensive industrial (SPII) agglomeration, with a kernel density level of only 1779. The spatial

distribution patterns of enterprises across the three pollutant types are broadly consistent with the full sample.

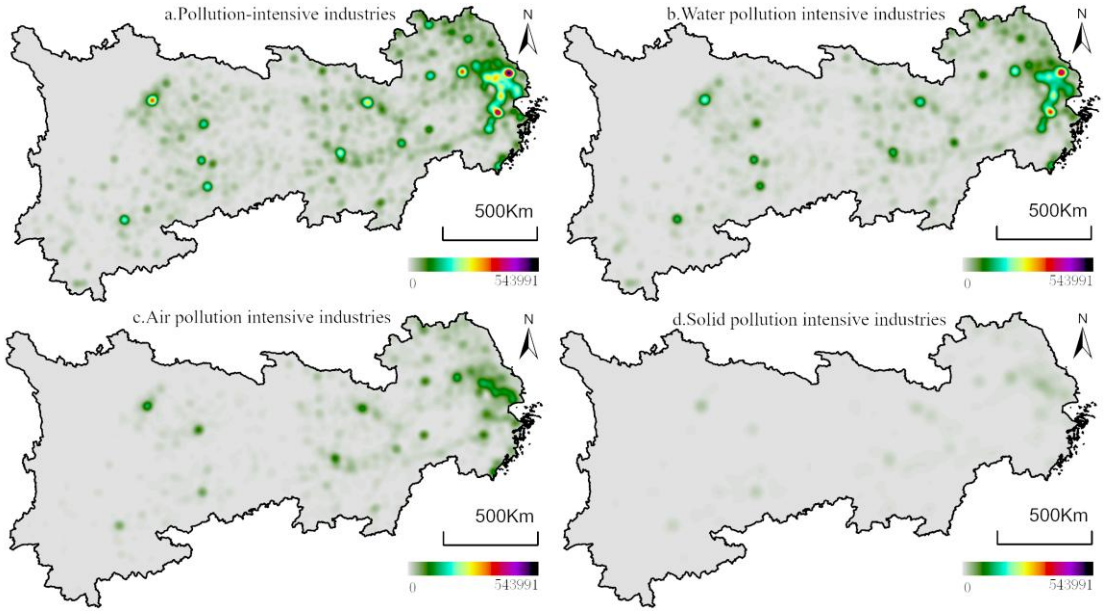



**Fig. 3** Kernel density values for different types of PII in YREB

### 2.2.3 Characteristics of temporal evolution

Referring to Duman et al. (2023), the standard deviation ellipse method is used to quantify the temporal evolution characteristics of PII in YREB as follows:

$$X_{\mathrm{w}}=\sum_{i=1}^{n} w_i x_i \Big/ \sum_{i=1}^{n} w_i ; \qquad Y_{\mathrm{w}}=\sum_{i=1}^{n} w_i \mathrm{y}_i \Big/ \sum_{i=1}^{n} w_i \tag{3}$$

$$\tan\theta=\left(\sum_{i=1}^{n} w_i^2\tilde{x}_i^2-\sum_{i=1}^{n} w_i^2\tilde{y}_i^2+\sqrt{\left(\sum_{i=1}^{n} w_i^2\tilde{x}_i^2-\sum_{i=1}^{n} w_i^2\tilde{y}_i^2\right)^2+4\times\sum_{i=1}^{n} w_i^2\tilde{x}_i^2\tilde{y}_i^2}\right)\Big/ 2\times\sum_{i=1}^{n} w_i^2\tilde{x}_i^2\tilde{y}_i^2 \tag{4}$$

$$\sigma_x=\sqrt{\sum_{i=1}^{n}(w_i\tilde{x}_i\cos\theta\text{-}w_i\tilde{y}_i\sin\theta)^2 \Big/ \sum_{i=1}^{n} w_i^2} \tag{5}$$

$$\sigma_y=\sqrt{\sum_{i=1}^{n}(w_i\tilde{x}_i sin\theta\text{-}w_i\tilde{y}_i cos\theta)^2 \Big/ \sum_{i=1}^{n} w_i^2} \tag{6}$$

Among them, $w_i$ indicates the level of concentration of PII; $(x_i, y_i)$ is the latitude and longitude coordinates of the spatial center of the basin, $(X_w, Y_w)$ indicates weighted average center, $\theta$ is the elliptic azimuth, $\tilde{x}_i$ and $\tilde{y}_i$ denote the difference between the weighted average center and the latitude and longitude coordinates of the center of the space, respectively, $\sigma_x$, $\sigma_y$ is the standard deviation of the x-axis from the y-axis.

As can be seen from Fig. 4, the degree of concentration of PII in YREB has been increasing, with the value of its nuclear density increasing from 10.39 in 1978 to 14,903 in 2022, a 637.17-fold increase, but the growth rate has gradually levelled off, decreasing from 102 per cent in 1978 to 11 per cent in 2022. Among them, the average annual growth rate of the nuclear density of SPII is 15.81 per cent, which is significantly lower than the average growth rate of the YREB (17.96%).

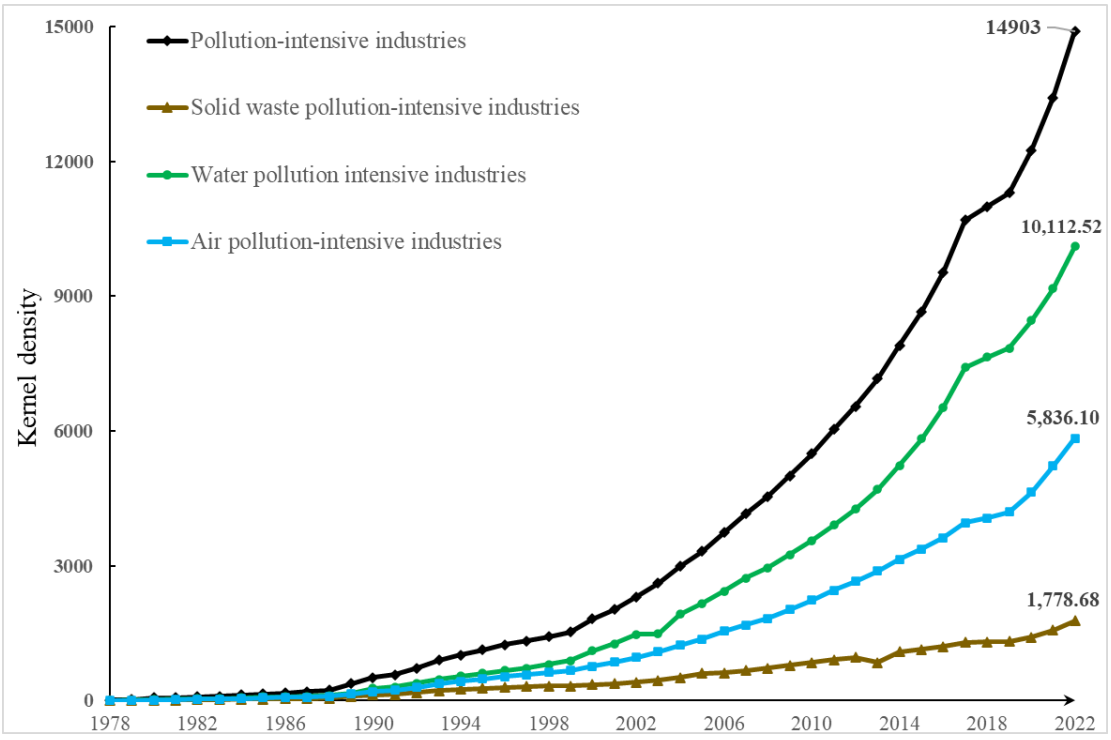



**Fig. 4** Kernel density levels of different types of PII in the YREB from 1978 to 2022

As can be seen from Table 2, In terms of the evolution of the center of gravity of agglomeration, the distribution of PII in YREB from 1978-2022 shows an overall spatial distribution pattern in the 'east-west' direction, and the azimuthal turn angle decreases from 84.59° in 1978 to 75.80° in 2022, indicating that there is a weak tendency for the spatial distribution pattern of PII in the region to shift to the northeast-southwest direction. The area of the ellipse and the standard distance of the long half-axis and the short half-axis of the ellipse show a trend of decreasing and then increasing, indicating that PII in YREB show a development trend of agglomeration and then diffusion. The trajectory of the center point of the ellipse shifted from Linxiang City, Yueyang City, to the northeast by 247 km to Herb County, Huangshi City, in 1978, and then shifted to the south-west by 116 km to finally migrate to Daye City, Huangshi City, in 2006, which shows that there is an obvious socio-economic preference for the agglomeration of pollution-intensive enterprises.

**Table 2** Elliptical Standard Deviation of PII in the YREB

| Year | Central coordinate | Central city | Long axis (km) | Short axis (km) | Directionality (km) | Circumference (km) | Area ($km^2$) |
|---|---|---|---|---|---|---|---|
| 1978 | 113.37,29.47 | Linxiang City, Yueyang City | 9.00 | 2.55 | 84.59 | 721884 | 72.19 |
| 1991 | 114.40,30.40 | Jiangxia District, Wuhan City | 8.98 | 2.60 | 80.21 | 733416 | 73.34 |
| 2004 | 115.69,30.35 | Qichun County, Huanggang City | 8.89 | 2.54 | 78.25 | 708861 | 70.89 |
| 2017 | 114.98,30.11 | Daye City, Huangshi City | 9.08 | 2.69 | 76.51 | 766694 | 76.67 |
| 2022 | 114.60,30.05 | Daye City, Huangshi City | 9.26 | 2.78 | 75.80 | 809043 | 80.90 |

# 3 Analysis of Influencing Factors of PPI in the YREB

## 3.1 Model design

Traditional Geographically weighted regression (GWR) is based on the theoretical foundation of the non-parametric method of local weighted regression. It extends the traditional regression model to a regression model including spatial positions, and then estimates the parameters of the model point by point through the local weighted least squares method to explore the regression relationship varying with space (Zhou et al., 2019). However, the GWR model ignores the reality that the data are not evenly distributed on the spatial scale, and thus fails to test the heterogeneity relationship of local coefficients under the condition of spatial process scale variation (Shabrina et al., 2021). Therefore, Multi-scale Geographically weighted regression (MGWR) conducts regression modeling by using the generalized addition ability model and the golden search algorithm to explore the variation of different variables with spatial scale under their respective optimal bandwidth conditions (Fotheringham et al., 2017), thereby personalizing the scale size of the action of different spatial processes Form a spatial process model that is closer to the real situation and more explanatory (Lu et al., 2023), avoid the mismatch between bandwidth and the scale of variable action, thereby reducing the noise of the model in parameter estimation (Rong et al., 2022). The calculation formula of the MGWR model is as follows:

$$Y_i = \sum_{j=1}^{k} \beta_{bwj}\left(u_i, v_i\right) X_{ij} + \varepsilon_i \quad (7)$$

In the above formula, $Y_i$ represents the number of PII in the $i$ city. $(u_i,v_i)$ represents the longitude and latitude of the $i$ city. $X_{ij}$ represents the $j$ variable of the $i$ city. $\varepsilon_i$ represents the random error term; $k$ represents the number of variables; $bwj$ represents the bandwidth used by the $j$ variable. The

267 difference in its magnitude indicates the sensitivity of different variables to distance, that is, the
268 scale of each variable's effect. The smaller the bandwidth for the optimal fitting effect, the more the
269 variable affects the number of PII within a local range. Conversely, it indicates the number of PII
270 affected by the variable in a larger area or even a global range. $\beta_{bwj}$ is the local regression coefficient
271 of the *j* variable. Its magnitude and positive or negative represent the size and influence direction of
272 the *j* variable in different cities, reflecting the benefits or losses and their intensity of each city in
273 the region. If the regression coefficient of the *j* variable in each city is different, there will be spatial
274 heterogeneity, and the greater the difference, the stronger the heterogeneity.

275 **3.2 Variable selection**

276 PII will take into account a variety of factors when choosing their location and layout to ensure the
277 maximization of their own profits. Therefore, based on the consideration of data availability and in
278 combination with existing research and theories such as location theory and new economic
279 geography, this paper classifies the factors influencing layout into the following three categories
280 (Table 3).

281 **Table 3** Variable Names and Meanings

| Factor category | Variable name | Variable symbol | Index selection |
|---|---|---|---|
| Institutional factors | Intensity of environmental regulations | IER | Number of environmental protection penalties (times) |
| | Ecological monitoring point | EMP | The number of ecological monitoring stations (number) |
| | The level of green finance | GF | Green Finance Index (no unit) |
| | Digital attention | DA | Digital technology word frequency |

| | | | |
|---|---|---|---|
| Traditional location factors | Cost of production factors | CPF | Per capita disposable income of urban residents (yuan) |
| | Labor supply | LS | Human capital level (no unit) |
| | Technological innovation ability | TECH | Internal expenditure on R&D (Ten thousand yuan) |
| New economic geographical factors | Degree of openness to the outside world | OPEN | Foreign investment amount (billion yuan) |
| | Industrial structure | IND | The proportion of the tertiary industry in GDP (%) |
| | Path dependence | DEP | Total energy consumption (Ten thousand tons of standard coal) |

The first factor is institutional. PII are characterized by high energy consumption, large amounts of waste generation, and severe environmental pollution. The government will set up ecological monitoring points and apply digital technologies such as big data, the Internet of Things, and artificial intelligence to precisely monitor and control the pollutants discharged by enterprises. Furthermore, environmental protection penalties are imposed on enterprises that discharge pollutants in violation of regulations (Lv et al., 2024; Yang and Umair, 2024). Meanwhile, the government will also provide specialized green financial products such as green credit and green bonds for polluting enterprises to assist these enterprises in transformation and upgrading in aspects such as green production, energy conservation and emission reduction, and utilization of clean energy (Zhang et al., 2024). Therefore, this article measures institutional factors from four aspects: the intensity of environmental regulations (IER), ecological monitoring point (EMS), the level of green finance (GF), and the attention paid to digitalization (DA). The second is traditional location factors, referring He et al. (2022), Song and Feng (2023) and Li et al. (2021), the costs of production factor (CPF), labor supply (LS) and technological innovation capabilities (TECH) are selected. The third is the new economic geographical factors. Industrial agglomeration of PII is an objective

phenomenon with measurability and identifiability. It manifests itself in the aspects of spatial location distribution and functional synergy patterns, resulting from the multi-dimensional and in-depth dynamic interactions between the internal production characteristics of these industries (such as their production technology attributes and factor dependence characteristics) and external systems, including environmental, social, and economic systems (Gu et al., 2024; Liu et al., 2024). Referring He et al. (2022), three variances are respectively selected for characterization, such as opening up to the outside world (OPEN), industrial structure (IND) and path dependence (DEP). Fig. 5 illustrates the reasons behind the shift in the spatial distribution of PII.

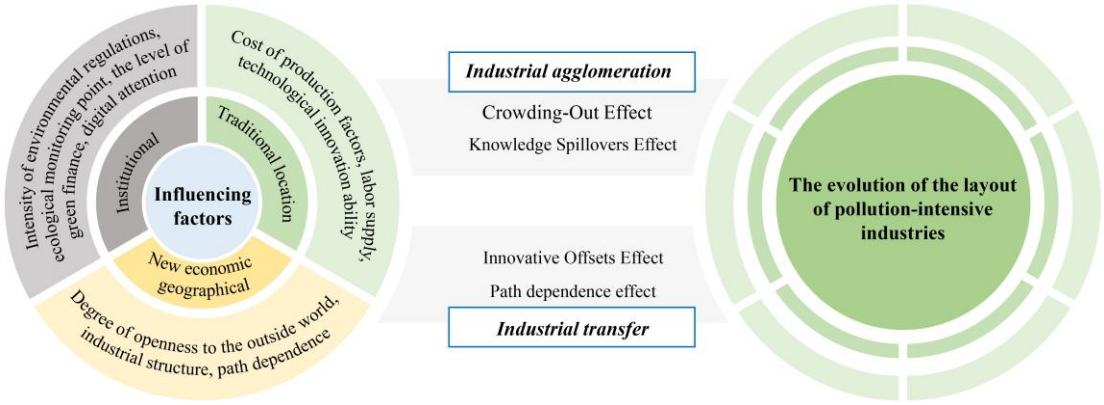



**Fig.5** The reasons behind the shift in the spatial distribution of PII.

To eliminate the influence of different dimensions on the regression results, the Z-score standardization method was adopted in this paper to standardize all indicators (Song et al., 2022). The descriptive statistical results of each variable after standardization are shown in Table 2. Meanwhile, to avoid the multicollinearity problem caused by the redundancy of explanatory variables and to ensure that the number of explanatory variables included in each model at each time cross-section is the same, this paper first uses the OLS model to conduct VIF tests on all the above explanatory variables in 2008 and 2022 respectively. The test results (Table 4) indicate that

314 the VIF values of all explanatory variables at the two-time sections are all less than 5, meaning there
315 is no possibility of multicollinearity.

316 **Table 4** Descriptive statistics of variables and VIF test results

| Variable | Mean | Std | Min | Max | VIF (2008) | VIF (2022) |
|---|---|---|---|---|---|---|
| IER | -1.8846E-08 | 0.9981 | -1.8221 | 5.1159 | 1.242 | 1.227 |
| EMP | -9.3088E-17 | 0.9981 | -1.2710 | 8.5656 | 1.805 | 2.266 |
| GF | 3.0385E-08 | 0.9981 | -2.2655 | 2.2645 | 1.515 | 1.412 |
| DA | 6.9231E-08 | 0.9981 | -2.0241 | 1.8347 | 2.296 | 2.838 |
| CPF | -5.5385E-08 | 0.9981 | -1.9356 | 2.0950 | 2.884 | 3.894 |
| LS | -5.7692E-09 | 0.9981 | -0.7566 | 4.4786 | 1.620 | 1.566 |
| TECH | 6.5385E-09 | 0.9981 | -0.4749 | 9.2373 | 2.412 | 3.264 |
| OPEN | -2.1154E-08 | 0.9981 | -0.1473 | 11.1525 | 1.096 | 1.111 |
| IND | -8.8462E-09 | 0.9981 | -6.1459 | 3.3771 | 1.298 | 1.363 |
| DEP | -2.3077E-09 | 0.9981 | -0.8306 | 7.7192 | 1.679 | 4.966 |

317 **3.3 Model comparison**

318 To screen out the optimal model that can better explain the influencing factors of the layout of PII
319 in the Yangtze River Economic Belt, this paper respectively uses the OLS, GWR and MGWR
320 models to conduct regression on the above 10 independent variables. In terms of model Settings,
321 both the GWR and MGWR models adopt the Gaussian function as the spatial kernel function and
322 use the golden section to search for the optimal bandwidth. If the variation gap of the regression
323 coefficients during the iterative process is within 0.00001, the model is considered to have

convergent. The final regression results are shown in Table 5. From the regression results, on the two-time sections, the R2 and AD-R2 of the MGWR model are both greater than those of the OLS and GWR models, while the AICc, BIC, and RSS are all smaller than those of the OLS and GWR models. This indicates that the MGWR model is closer to the regression results of the true values and is more suitable for explaining the factors influencing the distribution of PII. Meanwhile, to ensure the reliability of the MGWR model and not to omit important variables, spatial autocorrelation analyses were conducted on the residuals of the two-time sections respectively. The P-values of all residuals were greater than 0.1, indicating that there was no spatial autocorrelation among the residuals. Therefore, the reliability of the MGWR model was further verified. At this point, at least based on this case, the results of the MGWR model are superior to those of the OLS and GWR models. Therefore, the model establishment is complete.

**Table 5** Regression Results of OLS, GWR and MGWR models

| Inspection | 2008 | | | 2022 | | |
|---|---|---|---|---|---|---|
| standard | OLS | GWR | MGWR | OLS | GWR | MGWR |
| $R^2$ | 0.642 | 0.833 | 0.922 | 0.636 | 0.824 | 0.869 |
| AD-$R^2$ | 0.612 | 0.785 | 0.880 | 0.606 | 0.775 | 0.819 |
| AICc | 258.333 | 211.878 | 177.392 | 260.370 | 217.470 | 205.759 |
| BIC | 288.027 | 193.824 | 94.360 | 290.065 | 200.195 | 161.694 |
| RSS | 46.218 | 21.570 | 10.036 | 46.949 | 22.653 | 16.847 |
| P-value | — | — | 0.350 | — | — | 0.665 |

### 3.4 Scale and significance analysis

On a spatial scale, the MGWR model can reflect the differentiated spatial interaction scales among different variables by estimating the optimal bandwidth of each variable. A larger bandwidth indicates that the variable has an impact on PII over a larger range or globally, while a smaller bandwidth indicates that the variable has an impact on PII within a region or a local range.

**Table 6** Bandwidth of Each Variable in GWR and MGWR Models (Unit: Kilometers)

| Variable | 2008 | | 2022 | |
|---|---|---|---|---|
| | GWR | MGWR | GWR | MGWR |
| IER | 4.0 | 2.0 | 4.0 | 1.7 |
| EMP | 4.0 | 8.6 | 4.0 | 991.9 |
| GF | 4.0 | 986.8 | 4.0 | 986.8 |
| DA | 4.0 | 995.0 | 4.0 | 995.0 |
| CPF | 4.0 | 991.0 | 4.0 | 991.9 |
| LS | 4.0 | 0.9 | 4.0 | 1.2 |
| TECH | 4.0 | 909.8 | 4.0 | 978.7 |
| OPEN | 4.0 | 5.0 | 4.0 | 6.2 |
| IND | 4.0 | 978.7 | 4.0 | 4.8 |
| DEP | 4.0 | 2.2 | 4.0 | 11.2 |

However, the GWR model can only reflect the average value of the spatial action scale of each variable (Senyel Kurkcuoglu, 2023; Wu et al., 2024). As can be seen from Table 6, the optimal bandwidth selected by the GWR model in both 2008 and 2022 was 4.0. From the bandwidth of each

345 variable calculated by the MGWR model, it can be seen that there are differentiated spatial
346 interaction scales among different variables.

347 Meanwhile, this paper conducts descriptive statistical analysis on the regression coefficients of
348 each variable in the MGWR model, and the results are shown in Table 7. Based on the estimation
349 results of the MGWR model in 2008 and 2022, it can be seen that the action scale of GF and TECH
350 has always been greater than 900 (greater than 970 in 2022), and the significance ratio has always
351 been 100%. It indicates that these two variables can significantly influence the spatial layout of PII
352 almost throughout the entire YREB, that is, there is no spatial heterogeneity. Secondly, the
353 bandwidths of IER, LS, and OPEN are 1.7-2.0, 0.9-1.2, and 5.0-6.2 respectively, with significance
354 ratios ranging from 36% to 100%. This indicates that the influence of these three variables is highly
355 regionalized and shows strong spatial heterogeneity. Thirdly, IND changed from being insignificant
356 in 2008 to being locally significant in 2022 (bandwidth 4.8), while EMP and DEP reversed from
357 being locally significant in 2008 to being insignificant in 2022. Fourth, DA and CPF failed the
358 significance test in 2008 and 2022 respectively. In conclusion, IER, GF, LS, TECH, and OPEN
359 constitute the stable core explanatory variables that influence the layout of PII, while the scope or
360 significance of the other variables change significantly over time.

361 **Table 7** Descriptive statistical results of regression coefficients of the MGWR model

| Variable | Mean | | Std | | Min | | Median | | Max | | Significant ratio | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2008 | 2022 | 2008 | 2022 | 2008 | 2022 | 2008 | 2022 | 2008 | 2022 | 2008 | 2022 |
| IER | -0.263 | -0.259 | 0.129 | 0.153 | -0.474 | -0.586 | -0.297 | -0.272 | 0.088 | 0.129 | 80.77% | 73.08% |
| EMP | -0.089 | 0.024 | 0.032 | 0.000 | -0.136 | 0.024 | -0.094 | 0.024 | -0.037 | 0.024 | 63.85% | 0% |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GF | -0.098 | -0.180 | 0.000 | 0.000 | -0.098 | -0.180 | -0.098 | -0.180 | -0.098 | -0.180 | 100% | 100% |
| DA | -0.013 | 0.071 | 0.000 | 0.000 | -0.013 | 0.071 | -0.013 | 0.071 | -0.013 | 0.071 | 0% | 0% |
| CPF | -0.027 | 0.034 | 0.000 | 0.000 | -0.027 | 0.034 | -0.027 | 0.034 | -0.027 | 0.034 | 0% | 0% |
| LS | 0.365 | 0.327 | 0.585 | 0.396 | -0.647 | -0.141 | 0.093 | 0.189 | 1.782 | 1.366 | 39.23% | 36.15% |
| TECH | 0.115 | 0.203 | 0.000 | 0.000 | 0.115 | 0.203 | 0.115 | 0.203 | 0.115 | 0.203 | 100% | 100% |
| OPEN | 0.377 | -0.364 | 0.071 | 0.094 | 0.270 | -0.449 | 0.391 | -0.417 | 0.468 | -0.178 | 100% | 97.69% |
| IND | -0.002 | -0.180 | 0.000 | 0.246 | -0.002 | -0.624 | -0.002 | -0.030 | -0.002 | 0.022 | 0% | 40.00% |
| DEP | -0.074 | 0.007 | 0.123 | 0.013 | -0.483 | -0.014 | -0.034 | 0.006 | 0.076 | 0.030 | 21.54% | 0% |

### 3.5 Analysis of coefficient spatial pattern

As can be seen from the previous text, the spatial distribution characteristics of PII in the YREB are obvious. Through the fitting of the MGWR model, it is found that the factors influencing their distribution show obvious spatial heterogeneity. There are both influential factors with relatively stable significant changes and those with large fluctuations. Therefore, this paper conducts spatial visualization analysis on the variables with significance at each time section. The result is shown in Fig. 6.

Firstly, the variables with relatively stable significant changes include IER and GF in institutional factors, LS and TECH in traditional location factors, and OPEN in new economic geographical factors. Moreover, the regression coefficients of the other four variables except LS on the two-time sections can all show significant results in most prefecture-level cities.

Specifically, (1) IER has a significant negative inhibitory effect on the PII layout of most prefecture-level cities in the YREB, and the inhibitory intensity decreases layer by layer from west

to east. The average coefficients of the YREBUP and YREBLP have strengthened from -0.348 and -0.114 in 2008 to -0.383 and -0.152 in 2022, respectively. The YREBMP weakened from -0.314 in 2008 to -0.226 in 2022. The possible reason for this is that the YREBUP is a key national ecological barrier area, so environmental regulations have been continuously strengthened. The YREBLP, due to its geographical advantages and competitive pressure, has forced enterprises to upgrade their technologies, so environmental regulations are relatively mild. The YREBMP takes over a large number of industries from the YREBLP. Moreover, there is law enforcement flexibility, which weakens environmental rules and leads to a heterogeneous distribution pattern in PII.

(2) GF has a significant negative inhibitory effect on the layout of PII in the YREB, and it shows an integrated situation throughout the region. Its coefficient has changed from -0.098 in 2008 to -0.18 in 2022, uniformly raising the threshold for pollution financing throughout the region. The reason might be that the national unification of green finance standards and the full coverage of cross-regional information sharing platforms (such as the Yangtze River Delta Green Project Database) have led to a simultaneous increase in the financing costs of polluting projects throughout the entire river basin, resulting in a "full-domain integration" suppression.

(3) LS has a significant positive promoting effect on PII in the YREBLP and some prefecture-level cities in the YREBMP and YREBUP. The average value of its coefficient in the YREBLP has decreased from 0.972 to 0.825, in the YREBMP from -0.057 to 0.091, and in the YREBUP from 0.211 to 0.105. The reason might be that the labor costs in the YREBLP have been continuously rising, and the upgrading of the industrial structure has squeezed out low-end polluting jobs, reducing the coefficient. The YREBMP takes over a large number of industries from YREBLP, and a large number of laborers return, thus turning the coefficient from negative to positive. However,

in the YREBUP, due to the contraction of industrial scale and the accelerated outflow of population, the positive effect has weakened.

(4) TECH has had a significant positive promoting effect on PII in the YREB, and has also shown a phenomenon of all-round integration. Its coefficient has risen from 0.115 to 0.203. The reason for this might be that technological innovation has significantly enhanced the productivity and competitiveness of PII, enabling them to survive and expand under stricter environmental protection and cost constraints.

(5) The impact of OPEN on PII in the YREB has shifted from "significant positive promotion" to "significant inhibition". This inflection points stems from the fact that the export-oriented economy has completed the role switch from "emphasizing technology" to "emphasizing ecology". The average coefficients of the YREBUP, YREBMP and YREBLP also changed sharply from 0.292, 0.393 and 0.456 to -0.247, -0.416 and -0.446 in sequence. However, compared with the YREBMP and YREBLP, the YREBUP has a relatively lagging degree of openness, so the negative effect of the coefficient is lower, thus forming a gradient misalignment that decays layer by layer from east to west.

Secondly, the variables with significant fluctuations include EMP in institutional factors and IND and DEP in new economic geographical factors. Specifically, (1) EMP has a significant negative inhibitory effect on PII in the YREBMP and YREBLP in the first cross-section. The inhibitory intensity decreases from the YREBLP (-0.125) to the YREBMP (-0.096), but its effect continues to weaken in the later stage until it loses its significance. (2) The coefficient of IND changed from global insignificance in 2008 to local negative values in the YREBMP and YREBLP

in 2022. The YREBLP (-0.522) had the greatest inhibitory intensity, followed by the YREBMP (-0.071). (3) DEP mainly exerted a significant negative inhibitory effect on dye-intensive industries in most prefecture-level cities in the YREBLP in 2008, with an average coefficient of -0.213. Subsequently, the inhibitory intensity continued to decline until it lost its significance. In short, the early environmental protection law enforcement and the hard constraints of emission reduction, combined with the pressure of downstream transformation, have significantly suppressed PII through EMP and DEP. Subsequently, regional gradient transfer, technological upgrading and market-oriented policy tools weakened the binding force of the first two, while the inhibitory effect of IND on PII gradually became prominent.

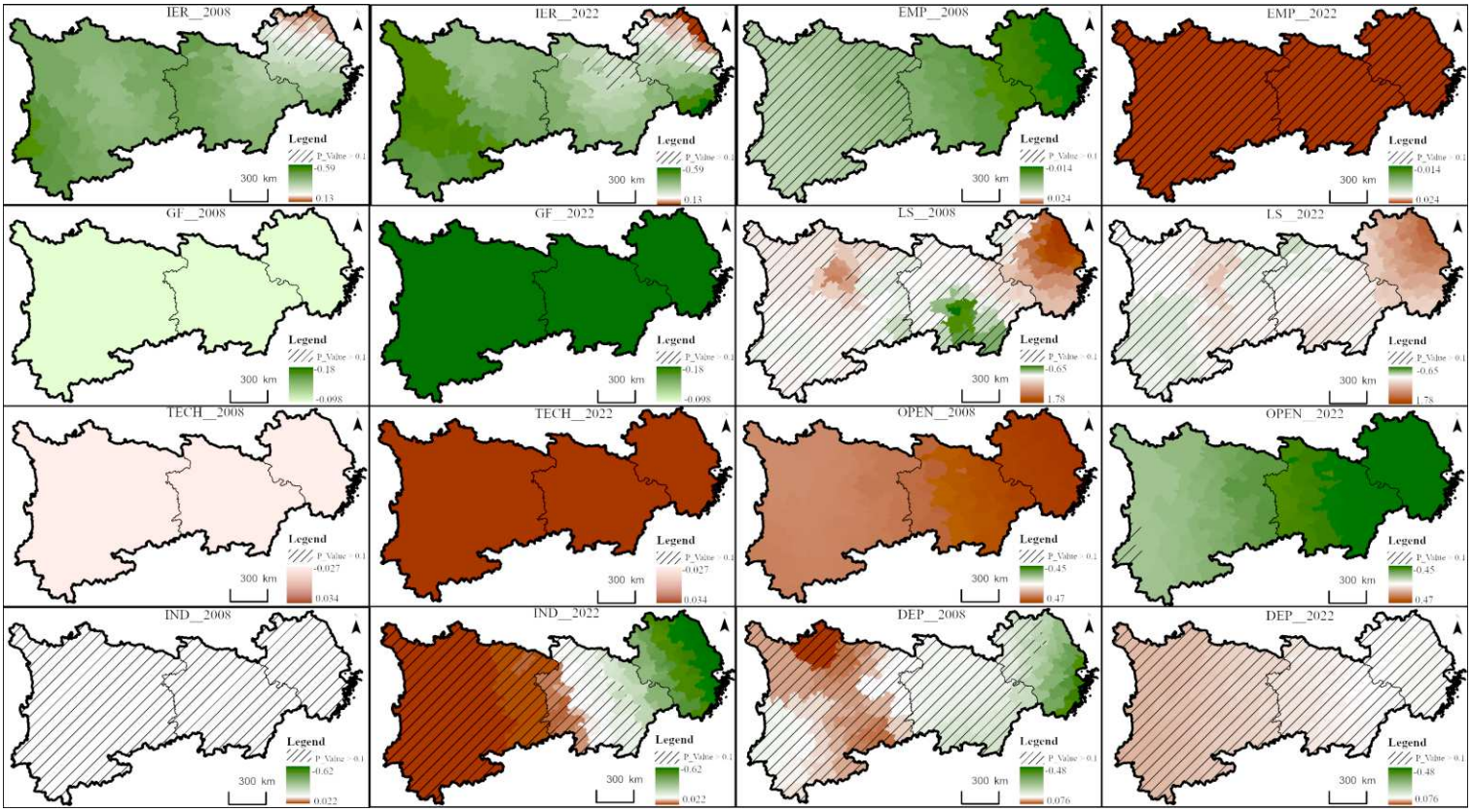



**Fig. 6** Spatial patterns of regression coefficients and significance of each variable

## 4 Discussion

Firstly, regarding the "spatial attenuation" effect of IER, it highly echoes the "regulation last mile" hypothesis proposed by (Kahn and Zhang, 2016), which holds that the law enforcement flexibility of local governments will gradually expand with geographical hierarchy, resulting in the regulatory effect decreasing from the center to the periphery. However, this paper further refines this hypothesis to a gradient scenario of "YREBUP - YREBMP - YREBLP ", and uses the coefficient changes of two cross-sections to prove that the law enforcement elasticity is not linearly decreasing and may rebound due to reasons such as industrial gradient transfer and differences in ecological barrier positioning.

Secondly, the "omni-domain integration" inhibitory pattern presented by GF is consistent with the conclusion of (Chen et al., 2020), which takes the European Union as an example and finds that once the green classification catalogue and information platform are shared across regions, the financing premium of polluting enterprises will converge rapidly. The findings of this paper in the YREB confirm that this mechanism also holds true within non-EU unitary states, and the convergence speed is extremely fast (the coefficient has increased by approximately 83.67% in 14 years), reinforcing the view that "institutional convergence can reduce spatial arbitrage in polluting industries".

Thirdly, the significant positive effect of TECH on PII is contrary to the theory of "environmental innovation compensation" proposed by (Porter and van der Linde, 1995). However, it is consistent with the empirical conclusion of "pollution-enhanced technological progress" of (Dechezleprêtre et al., 2014). This paper further illustrates that when technology leans towards

449 improving the efficiency of high energy-consuming and high-emission processes, green-oriented
450 innovation has not yet taken the lead, and the compensation effect is offset by the "scale expansion
451 effect". This finding serves as a warning about the applicable boundary of the Porter hypothesis:
452 only when the intensity of green innovation exceeds a certain threshold will TECH turn to industries
453 that suppress pollution.

454 Fourth, the significant positive effect of labor supply (LS) on polluting industries and its
455 gradient change of "weakening in the downstream and turning positive in the midstream" echo the
456 conclusions of (Matlaba et al., 2014; Ray and Harvey, 1995) that the increase in labor costs induces
457 the gradient transfer of industries. However, this paper further points out: When the return of labor
458 force occurs simultaneously with industrial succession (such as in the YREBMP), LS can quickly
459 turn from negative to positive, thereby supplementing the dynamic perspective of the tripartite
460 relationship of "quantity - cost - spatial transfer" of labor force.

461 Fifth, the effect of OPEN has changed from "significant positive promotion" to "significant
462 inhibition", verifying the hypothesis of "ecologicalization inflection point of export-oriented
463 economy" proposed by (Dean et al., 2009), and for the first time providing the empirical coordinates
464 of the occurrence of the inflection point at the basin scale. Meanwhile, this inflection point gradually
465 decays from east to west, indicating that the difference in openness determines the timing of
466 ecological transformation, providing new evidence for the asynchrony of "pollution transfer -
467 ecological upgrading".

468 Finally, IND was not significant globally in 2008 but was significantly negative in the
469 YREBMP and YREBLP in 2022, indicating that there is a "threshold effect" in the suppression of

PII by IND. Only when the high-level development of regional manufacturing exceeds a certain critical point does the negative effect of IND become prominent. Therefore, this paper supplements the pollution transfer hypothesis of (Copeland and Taylor, 2003), pointing out that the IND does not take effect immediately but gradually emerges over time gradients, which has enlightenment significance for major developing countries to formulate phased emission reduction policies.

# 5 Conclusions and Implications

## 5.1 Conclusions

This study systematically identifies 17 PII based on industrial sector pollution emission intensity. By integrating the latitude and longitude data of 4,663,413 Chinese enterprises registered with the Administration for Industry and Commerce, it examines the spatiotemporal evolution characteristics and the key factors driving the development of PII within YREB. This study found that:

First, in terms of enterprise scale, the number of PII in YREB has increased significantly, with obvious differences in the growth rate across different years, showing distinct phased characteristics. The period from 1978 to 1991 can be characterized as the initial formation stage, during which PII were established sporadically. The subsequent phase, spanning from 1992 to 2004, marked a period of rapid development, during which the concentration had largely taken shape. The period from 2005 to 2017 is described as a phase of stable expansion, accompanied by widespread ecological risks. Following 2018, the period entered a phase of intensive development, with cities implementing a series of measures to promote the green transformation and upgrading of the industrial sector, control pollutant emissions, and enhance production efficiency.

Second, from the perspective of spatial distribution, the pollution-intensive industries in YREB exhibit a prominent unbalanced spatial distribution feature, showing a stepped-down distribution pattern from east to west. YREBLP exhibits a pronounced pattern of continuous distribution of central settlement areas, and the overlapping area formed by Shanghai-Nanjing and Nantong-Shaoxing serves as the main sector of PII. YREBMP shows a development pattern of multi-center agglomeration and multi-point dispersion. YREBUP witnesses high-capacity single-center agglomeration. Among them, water pollution-intensive industries are the main component of PII agglomeration in YREB.

Third, from the perspective of temporal evolution, the PII show a weak tendency to shift in the northeast-southwest direction. The industrial development exhibits an obvious directional feature, presenting a development trend of first contraction and then diffusion—with the degree of diffusion exceeding that of contraction. Over time, the spatial gravity center of PII has gradually moved toward the southwest, and the industrial layout demonstrates a distinct socioeconomic preference.

Forth, there is obvious spatiotemporal heterogeneity in the factors influencing the distribution of PII in the YREB. Specifically, the variables with relatively stable significant changes include: IER, GF, LS, TECH, and OPEN. Among them, IER has a significant negative inhibitory effect on the layout of PII in most prefecture-level cities, and the inhibitory intensity decreases layer by layer from west to east. GF has a significant negative inhibitory effect on the layout of PII in the YREB, and presents an integrated situation throughout the region. LS has a significant positive promoting effect on PII in the YREBLP and some cities in the YREBMP and YREBUP. TECH has a significant positive promoting effect on PII in the YREB, presenting a phenomenon of all-round integration. The impact of OPEN on PII in the YREB has shifted from a significant positive promotion

throughout the region to a significant inhibition throughout the region. The variables with significant fluctuations are: EMP, IND, and DEP. Among them, both EMP and DEP had a significant negative inhibitory effect on PII in the YREBMP and YREBLP in 2008. In 2022, IND had a significant negative inhibitory effect on PII in the YREBMP and YREBLP.

### 5.2 Policy Implications

First, establish the Yangtze River Green Process Upgrading Fund. By combining fiscal interest subsidies with low-interest bank loans, it will focus on investing in midstream PII. Through a subsidy and return mechanism linked to energy consumption and emission performance, it will guide enterprises to complete clean transformation, thereby amplifying the crowding-out effect of the industrial structure on polluting industries and promoting the negative impact of IND to spread throughout the midstream from the downstream.

Second, a "segmented dynamic pollution discharge fee" system will be implemented. Based on the PM2.5, energy consumption and green credit data of each city, the environmental regulation coefficients of each region will be dynamically adjusted and linked to the bank interest rate to ensure that the suppression intensity of IER and GF is adjusted in real time with the annual performance, continuously raising the pollution cost and avoiding regional "bottom-line competition".

Third, we will implement a zero-tariff plan for green foreign investment in the upstream sector. For foreign investment projects that meet the clean list, import tariffs will be exempted and value-added tax will be refunded immediately upon collection. We will also provide medium - and long-term green credit. We will encourage downstream development zones to set up co-construction parks in the upstream sector to share output value and emission quotas. By leveraging the negative

effect of OPEN, we will transform the ecological threshold into an accelerator for the upgrading of the upstream industrial structure. Promote the global saliency of IND.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Meanwhile, all authors contributed equally.

## CRediT authorship contribution statement

**Junyin Tan:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision, Project administration. **Yang Xiang:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision, Project administration. **Lihua Huang:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision, Project administration, Funding acquisition.

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## Data availability

Data will be made available on request.

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