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The Spatial Pattern of Polluting Enterprises and the Effects of Local Regulation in the Guanzhong Plain Urban Agglomeration

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Abstract: In the context of actively undertaking the transfer of domestic and foreign industries in the central and western regions of China, local regulatory behaviors influence the spatial distribution of polluting enterprises (PEs). This study examined the Guanzhong Plain urban agglomeration (GPUA), the largest urban agglomeration in the northwest region of China and one of the main regions that undertakes industrial transfer, using kernel density estimation and geographically and temporally weighted regression to explore the spatial pattern characteristics and evolution of PEs and reveal the effects of local regulatory behaviors, including environmental regulation (ER) and local protection (LP). The results indicate that (1) The distribution of the PEs tended towards energy and mineral resources and agglomerated along the development axes, aligning with the strategic positioning of the major function-oriented zones. Agglomerated areas gradually concentrate in key development zones. Major agricultural production zones exit high-density areas, and those adjacent to high-density areas often become secondary agglomeration core areas. Key ecological functional zones do not form high-density areas. (2) Both ER and LP have a positive impact on the distribution of PEs, and the dominant influence shifts from ER to LP. Counties with strict ER have increased the tendency of PEs to exhibit a certain layout due to better pollution treatment facilities and more mature pollution control technologies. The "pollution haven effect" has not yet formed within the GPUA. (3) The role of LP was more prominent in key development zones and major agricultural production zones, whereas the role of ER was more evident in key ecological functional zones. (4) RE and LP have mutually reinforcing effects on the distribution of PEs; the "innovation compensation effect" gradually manifests, but an increase in ER leads to a decrease in regional industrial clustering. This study provides a reference value for understanding the impact of government regulation on the distribution of PEs in underdeveloped areas.

Keywords: polluting enterprises (PEs); environmental regulation (ER); local protection (LP); Guanzhong Plain urban agglomeration (GPUA)

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1. Introduction

The conflict between economic growth and environmental pollution is a common dilemma that is difficult to avoid in the process of industrialization in all countries in the world. As a double-edged sword of regional development, the spatial agglomeration of polluting enterprises (PEs), while bringing significant economic benefits, also brings huge resource and environmental pressure and socio-economic costs, which have important impacts on the sustainability of regional development [1]. Globally, transfers of PEs have been observed from developed countries to developing countries in Asia, Latin America, and Africa through export processing zones [2–4]. The transformation in developing countries is one of the topical themes in the field of "geography of sustainability transitions" [5]. As the world's largest developing country, China's economy has experienced rapid growth

over the last 40 years, since the reform and opening up. However, the traditional economic operation model, which relies on traditional factors and investment (such as labor, capital and resources), has led to increasingly severe environmental pollution issues [6]. To promote high-quality economic development, upgrade industrial structures, and transform driving forces, the developed eastern coastal regions of China have optimized the industrial structure through industrial transfer, and polluting industries have been the first to be considered for relocation [7]. At the same time, the underdeveloped central and western regions may lower their environmental standards and thresholds to attract more enterprise investment to promote economic development. Over the past 20 years, driven by national macro strategies such as the Western Development Strategy, the Belt and Road Initiative, and policies implemented by the central and western regions to actively undertake domestic and foreign industrial transfers, the pace of industrial adjustment has accelerated. The central and western regions absorbed a large number of industrial transfers from the eastern coastal and northeastern regions [7,8]. During industrial development, the western regions have tended to overemphasize economic development while neglecting ecological environmental benefits; and even sacrificed the environment to accept industries with high pollution and energy consumption, and low technological capacity, easily following the development path of "pollute first, treat later". At a time when China's economic development transformation and ecological civilization construction are highly valued, determining how to develop pollution-intensive industries rationally while protecting the environment and correctly handling the relationship between the two has become an important issue in sustainable development research.

Under China's unique institutional arrangement of fiscal decentralization and environmental decentralization, local government behavior has the dual motivation of economic growth and environmental protection. Therefore, under the stage's macroeconomic policy regulation, the policy institutions are considered a significant factor influencing enterprise location choices [9]. On the one hand, PEs are supported and protected by the local government due to their significant contributions to the GDP, profit, and employment; on the other hand, owing to the increasingly prominent environmental protection requirements and the public's growing environmental awareness, PEs have become the focus of environmental regulation. Therefore, facing the dual pressures of economic growth and environmental quality improvement, the impact of local government's dual regulatory behavior, named environmental regulation (ER) and local protection (LP), on the distribution of PEs and pollution-intensive industries has become a hot topic in the study of environmental economic geography [10–12].

Environmental regulation refers to the means, mechanisms, and actions adopted to control and influence the behavior of target groups in the field of environmental protection [13]. In this study, environmental regulation refers to the government's management of natural resources and environmental pollution through the formulation and implementation of environmental policies, which is known as formal environmental regulation [14]. Different viewpoints have emerged in academic circles regarding the impact of ER on PEs distribution. The well-known "Pollution Haven Hypothesis" (PHH) suggests that regions or countries with lenient ER have a comparative advantage in the production of pollution-intensive industries and can attract these industries from areas with stricter ER [15]. Many studies examining environmental pollution and international trade, ER and FDI, and the transfer of pollution-intensive industries between regions or urban and rural areas support the PHH [16–18]. Millimet and Roy [19] found that pollution-intensive industries were negatively impacted by local ER in the United States. Kahn [20] evidenced that PIEs in America agglomerated at a specific state or international borders where ER is relatively loose. Ma et al. [1] found that the distribution of PEs in the Loess Plateau of China showed a locational preference for settling in rural areas. However, Porter hypothesized the positive impact of ER on PEs. He stated that reasonable ER could stimulate enterprises to further optimize resource allocation efficiency and improve technological levels, triggering the "innovation compensation effect" of enterprises, which can offset the compliance cost of

enterprises in part or as a whole [21,22]. Many studies support Porter's hypothesis [23,24]. Furthermore, some scholars believe that ER has a threshold effect on the location choice of PEs, indicating a reverse U-shaped relationship. Before the threshold is reached, PEs may choose regions with stricter ER but mature pollution control technologies. After the threshold, enterprises' environmental investment increases, and they tend to choose regions with lower environmental costs [25].

LP refers to the utilization of various economic and administrative measures by local governments to support and protect industries that make significant contributions to local tax revenues and economic growth. LP is an important means of competition between regions for economic development under a fiscal decentralized system during China's economic transformation period. It is also a focal and challenging aspect of reshaping government–market relations in economic institutional reform [25]. The performance evaluation mechanism centered on GDP growth incentivizes local governments to blindly introduce PEs in pursuit of political achievements [26]. Empirical studies indicate that governments tend to protect industries with a high proportion of state-owned enterprises, strong industrial relatedness, and high profits [27]. Favorable policies, such as tax reductions or refunds, are provided to locally supported industries (including polluting industries with high tax revenues) to enhance their competitiveness in the market [28].

The impacts of ER and LP on the location choice of PEs are complex. The core issue is the government's need to balance economic growth and environmental protection. Existing studies have mostly focused on large-level and meso-level regions, such as nations, provinces, and cities, when exploring the effects of either ER or LP on the transfer of PEs from developed areas to underdeveloped areas [7,10,18]. Some studies have examined the distribution characteristics of PEs in developed areas at a smaller scale [29,30]. However, there is a noticeable lack of research on the pattern and locational dynamics of PEs within the underdeveloped region of western China, which is one of the main recipients of industrial transfer. Existing studies have indicated that the locational choices of PEs within underdeveloped regions have emerged non-equilibrium evolutionary trends similar to those in developed areas [1]. Nonetheless, there is a lack of comprehensive research from the perspective of the combined effects of ER and LP that originates from government regulatory behavior, particularly in terms of understanding the mechanisms of their impact.

As a strategic pivot for China's westward opening and a key growth pole leading to the development of the northwest region, the Guanzhong Plain urban agglomeration (GPUA) faces issues such as relatively fragile ecosystems and intensified resource and environmental constraints. At the same time, by leveraging the market space oriented towards the northwest and its abundant resource advantages, the GPUA has become one of the main areas in the central and western regions that is involved in undertaking domestic and foreign industrial transfers. Shaanxi, Shanxi, and Gansu are provinces in the GPUA that have received several pollution-intensive industries [31,32]. So, given the multiple constraints of the ecological environment, infrastructure, local fiscal capacity, institutional concepts, and the influence of national macro-industrial transfer policies, what are the spatial and temporal characteristics and evolving trends of the PEs distribution across the GPUA? How do ER and LP, which are both local government regulatory behaviors, impact the distribution of PEs? Therefore, from the perspective of spatial analysis, this paper revealed the spatial pattern of PEs by using kernel density, designed an analytical framework for the distribution of PEs under that background (Figure 1), and applied geographically and temporally weighted regression to explore the impact of local regulations on the distribution of PEs. This study made up for the limitations of traditional statistics research and regression analysis, further enriching the research methods for PEs. The research findings can provide theoretical references for optimizing enterprise distribution decisions and are of significant theoretical and practical value in promoting the high-quality economic and social development of the GPUA, and also have certain reference significance for the government decision-making behavior of underdeveloped countries that undertake industrial transfer.

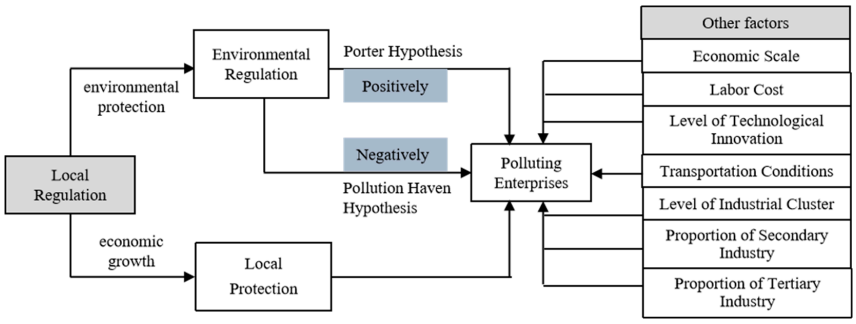


Figure 1. Analytical framework for the distribution of PEs in the GPUA.

2. Research Data and Methodology

2.1. Study Area

The GPUA is the largest urban agglomeration in the northwest region of China and serves as a significant driver of economic growth [33]. It holds a unique strategic position in the overall context of China's modernization and comprehensive opening-up. According to The Development Plan of the Guanzhong Plain Urban Agglomeration (2017–2035), the GPUA spans three provinces: Shaanxi, Shanxi, and Gansu (Figure 2). It includes six cities: Xi'an, Baoji, Xianyang, Tongchuan, Weinan, and Tianshui, as well as parts of Shangluo, Yuncheng, Linfen, Pingliang, and Qingyang, totaling 11 prefecture-level cities and 90 counties (Figure 2). With a land area of 107,100 km^2, the region had a resident population of 39.1925 million at the end of 2021, a regional GDP of CNY 2.30 trillion, and a three-industry structure ratio of 14.0:42.8:43.2. The per capita GDP was CNY 58,739 per capita, accounting for 72.54% of the national per capita GDP. The GPUA possesses a vast market space in the northwest region; abundant mineral resources, such as coal and non-ferrous metals; and significant locational and transportation advantages, providing a solid foundation and potential for industrial development. However, in the course of regional development, the GPUA faces challenges, such as relatively fragile ecosystems and intensified resource and environmental constraints. Air pollution is a pressing issue, as the excellent air-quality rate is only 61.37%. According to The National Master Plan for Functional Zones, the GPUA is categorized into three major function-oriented zones: key development zones, major agricultural production zones, and key ecological functional zones. Differences in the carrying capacity of resources and environment, functional orientation, and development direction of various functional zones have far-reaching impacts on industrial development [34].

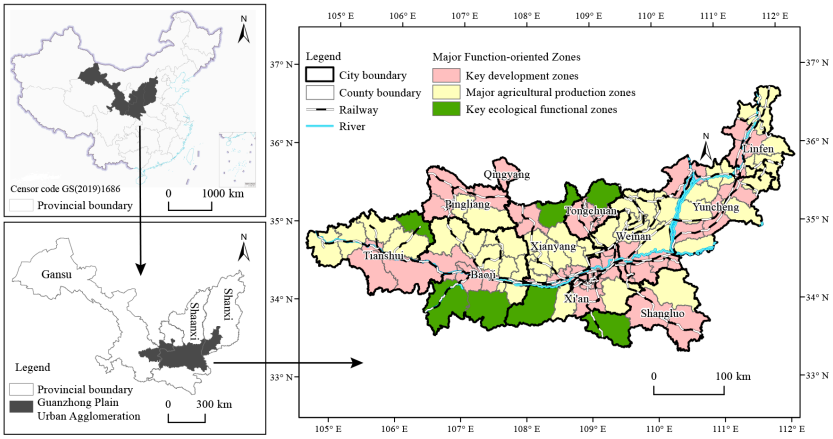


Figure 2. Geographical location and administrative divisions of the GPUA. The Chinese map is created based on the standard map, with approval number GS (2019)1686, downloaded from the standard map service website of the National Administration of Surveying, Mapping, and Geoinformation, with the unmodified base map.

2.2. Data Source and Processing

The data on PEs are derived from The List of National Key Monitoring Enterprises issued by the Chinese Ministry of Ecology and Environment (formerly the Ministry of Environmental Protection) from 2007 to 2017. This list focuses on the monitoring enterprises in each province, which account for over 65% of the total emissions of major pollutants. Between 2007 and 2011, three types of enterprises were operated: wastewater, waste gas, and sewage treatment plants. From 2012 to 2014, a fourth type of heavy metal enterprises was added. In 2015, five types of hazardous waste enterprises were identified. The XGeocoding_v2.0.0.7 software extracted the longitude and latitude coordinates of the PEs from the Baidu map and used the Baidu pickup coordinate system for calibration, and then used ArcGIS10.2 software to construct the enterprise's spatial point database. The basic geographic information data, such as rivers, railroads, administrative boundaries, etc., were sourced from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn) accessed on 2 March 2022; road network data were obtained from Peking University's Geographic Data Platform (https://cuesdata.pku.edu.cn/index.php?c=content&a=show&id=1728) accessed on 2 March 2022; and socio-economic data were obtained from China Urban Statistical Yearbook, China County Statistical Yearbook, and the statistical yearbooks of provinces, cities, and counties within the GPUA.

2.3. Research Method

2.3.1. Kernel Density Estimation

The kernel density estimation is a nonparametric method that reflects the distance decay effect of the spatial distribution of features by calculating the density of features in the surrounding neighborhood. The advantage of this method is that it uses the characteristics and properties of the data itself to fit the distribution without resorting to any prior knowledge about the data distribution; thus, it can avoid the subjectivity of the functional form setting and has the advantages of high robustness and weak model dependence in the application process. Therefore, this method has been widely used in the study of spatial clustering of variables [35]. In this study, ArcGIS 10.2 software was used to abstract the centroids of PEs, and the kernel density estimation method was employed to identify the spatial clusters of PEs. The formula is as follows:

$$f_n(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right), \tag{1}$$

where $f(x)$ is the kernel density estimate value, h is the search radius, n is the number of PEs, $k(\cdot)$ is the kernel function, and $x - x_i$ is the distance from the estimation point to the output grid.

2.3.2. Geographically and Temporally Weighted Regression

According to the second law of geography, spatial heterogeneity may cause the variations in local governments' impact on the distribution of PEs owing to the different geographical locations. The assumption of homogeneity in the traditional regression models may lead to distorted results. Therefore, the geographically weighted regression (GWR) model has been widely applied to the study of spatial heterogeneity. However, the GWR model only considers the spatial dimension and not the time dimension. The geographically and temporally weighted regression (GTWR) model takes into account the non-stationarity of time, which is an extension of the GWR model, and incorporates both temporal and spatial effects into the model, making the model able to deal with spatio-temporal heterogeneity at the same time. Therefore, GTWR has obvious advantages in exploring the spatio-temporal differences in the influencing factors of the distribution of polluting enterprises [36]. The formula for GTWR is as follows:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i, \tag{2}$$

in this formula, Y_i represents the dependent variable, which is the number of PEs in the county; (u_i, v_i, t_i) represents the spatiotemporal coordinates of county i; $\sum_k \beta_k(u_i, v_i, t_i)$ represents the regression coefficient; $\beta_k(u_i, v_i, t_i)$ represents the constant term; and ε_i represents the residual.

The estimation method for $\beta_k(u_i, v_i, t_i)$ is as follows:

$$\beta_k(u_i, v_i, t_i) = \left[X^T W(u_i, v_i, t_i) X\right]^{-1} X^T W(u_i, v_i, t_i) Y, \tag{3}$$

where $W(u_i, v_i, t_i)$ represents the spatiotemporal weight matrix, X and Y represent matrices composed of independent and dependent variables, respectively, and X^T represents the transpose matrix of X.

2.4. Variable Selection

To explore the influencing factors of the distribution of PEs, with particular emphasis on the dual regulatory behavior of local governments in industrial distribution—the impact of ER and LP—this study takes the number of PEs in each county of the GPUA as the dependent variable and ER and LP as the core explanatory variables to construct the GTWR model. Furthermore, to further explore the interaction of ER and LP and consider whether the "pollution haven effect" or "innovation compensation effect" exist in the process of industrial agglomeration in the GPUA, interaction terms for ER and LP, ER and industrial cluster, and ER and technological innovation are included in the model. The specific variables are selected as follows.

Environmental Regulation (ER): As an important governance tool for the government to address the coordination of rapid economic development and improvement of environmental quality, the intensity of ER has rich connotations, and its measurement dimensions and methods have always been a controversial topic in the academic community [37]. As this study focuses on the environmental pollution caused by PEs, the government's perspective on the ER of PEs mainly involves the promulgation of relevant laws and regulations and the collection of pollution discharge fees to limit the emission of pollutants. Based on the availability of county-level data and referencing the indicator definitions from existing research [38], we selected the county-level reduction rate of SO_2 emissions to measure ER intensity. During the Eleventh Five-Year Plan to the Thirteenth Five-Year Plan period, SO_2 has consistently been identified by the government as one of the main pollutants to be controlled, showing a certain degree of temporal continuity. Additionally, owing to the severe public health issues, economic losses, and environmental pollution problems it causes, SO_2 pollution control is a more urgent task in China than for other pollutants, and emission reduction efforts are the most stringent [28]. Therefore, it is appropriate to use SO_2 emissions as a measure of ER strictness in the GPUA. The formula is as follows:

$$ER_{it} = \frac{(S_{i(t-1)} - S_{it}) \times 100\%}{S_{it-1}}, \tag{4}$$

where $S_{i(t-1)}$ represents the SO_2 emissions in county i in the year $t-1$ and S_{it} represents the SO_2 emissions in county i in year t. The larger the ER_{it} value, the higher the ER intensity.

Local Protection (LP): Local protectionism is an important factor that influences industrial distribution. As they are responsible for economic development, all levels of government are motivated to protect local industries from competition, which exacerbates market segmentation [27]. Due to their high tax revenues, contributions to local income, and stable employment, PEs are prone to becoming the objects of protection and support of local governments in western regions [25]. Due to its covert and diverse nature, it is difficult to measure local protectionism directly. Existing studies have mostly quantified local protectionism at the provincial level from the perspective of industrial specialization, trade barriers, and tax base protection [25,39]. Based on the availability of county-level data and following the approach of Chen et al. [40], this study starts from the perspective

of local finance and enterprises' tax base, using the proportion of fiscal revenue to county GDP as a proxy variable to measure the intensity of government implementation of the LP. Enterprise taxation is one of the main sources of regional fiscal revenue and is an important aspect of local officials' performance assessments. Relative to the total economic activity in the region, the greater the proportion of government fiscal revenue and expenditure, the greater the incentive to protect and support local enterprises through market segmentation [41]. Therefore, the larger the proportion of county fiscal revenue to GDP, the greater the intensity of local protectionism.

Economic Scale (ES): This study considers economic scale as a control variable. Economic scale can characterize the economic strength of a region. Relevant studies indicate that PEs tend to relocate from regions with higher levels of economic development to less-developed areas [38]. We chose the county's gross domestic product (GDP) to represent this variable. The government's economic growth target is usually measured by the GDP, which is one of the direct motivations for local governments to support and protect PEs.

Transportation Conditions (Tra): New trade theory emphasizes the impact of transportation conditions on enterprises' location choices. Accessibility and transportation costs are important factors in business-location decisions. Road network density is a fundamental indicator used to evaluate the advantages of regional transportation networks. Referring to existing research [35], we measured the transportation conditions using the road network density of each county. Considering that the transportation network for industrial enterprises in the western region mainly includes railways and highways, we selected the road density of railways, expressways, national highways, provincial highways, and county roads to calculate the overall road network density for each county. Because of the different capacities of different types of transportation routes, this study applied a weighted approach to the lengths of different road types. The formula is as follows:

$$Tra_i = \frac{\sum_{x=1}^{5} W_x R_X}{A_i}, \tag{5}$$

$$W_x = V_i / \sum_{i=5}^{1} V_i, \tag{6}$$

where Tra_i represents the road network density of county i, A_i represents the land area of county i, R_X represents the mileage of road type x, W_x represents the weight of road type x, and V_i represents the maximum speed limit of road type i. According to Cheng et al. [42] different weights were assigned to different road categories based on their respective maximum speed. The maximum speeds of railways, expressways, national highways, provincial roads, and county roads are 160, 120, 80, 60, and 40 km/h, respectively, and the calculated weights are 0.35, 0.26, 0.17, 0.13, and 0.09, respectively.

As complete organizational entities, PEs, in addition to ER and LP, exhibit similar common patterns in their distribution and site selection to other industrial enterprises. Neoclassical trade theory emphasizes the guiding role of resource endowments in enterprise location decisions. To represent this, labor force and technological innovation levels were included as control variables, and industrial clusters were added to reflect the impact of agglomeration economies on enterprise location decisions. Additionally, the proportions of secondary and tertiary industries increased to reflect the industrial structure of the counties (Table 1).

To ensure the accuracy and authenticity of the regression results, we conducted the following pre-processing steps and checks on various indicators and models. ① Economic indicators were adjusted to constant 2007 prices to eliminate the impact of inflation. ② A multicollinearity test between variables was conducted using SPSS 26 software to analyze the correlation coefficients and variance inflation factors (VIF), and no significant multicollinearity was found between the variables. ③ Interaction terms were decentered to reduce the impact of multicollinearity in the data.

Table 1. Variables selection and measurement.

Variables	Code	Evaluation Method
Environmental Regulation	ER	Reduction rate of SO_2 emissions
Local Protection	LP	The proportion of county fiscal revenue to GDP
Economic Scale	ES	Gross domestic product (GDP)
Labor Cost	Labor	Regional average wage
Level of Technological Innovation	Inn	The proportion of R&D expenditure in county-level areas to the GPUA
Transportation Conditions	Tra	Road network density (Equation (5))
Level of Industrial Cluster	Cluster	The proportion of industrial output value in county-level areas to the GPUA
Proportion of Secondary Industry	Sec	Proportion of secondary industry
Proportion of Tertiary Industry	Ter	Proportion of tertiary industry

3. Evolution of the Spatiotemporal Pattern of PEs in the GPUA

3.1. Temporal Changes in the Number of PEs

From 2007 to 2017, the overall number of PEs first increased, then decreased, with a peak in 2012. The overall changes in the number of PEs, as well as the changes in the number and proportion of wastewater and waste gas enterprises, exhibited distinct two-stage characteristics (Figure 3): (1) From 2007 to 2012, the overall number of PEs showed a fluctuating upward trend, with an average annual growth rate of 5.38%; the number of wastewater enterprises grew at an average annual rate of 7.08%; the proportion of gas-emitting enterprises among the total PEs decreased from 59.88% in 2007 to 27.74% in 2012. (2) From 2012 to 2017, the number of PEs decreased continuously, with an average annual decrease of 4.76%; the reduction rate of wastewater enterprises exceeded half (62.22%), with an average annual decrease of 21.6%; the proportion of gas-emitting enterprises increased from 27.74% in 2012 to 36.24% in 2017.

Since 2012, The National Key Monitoring Enterprises List has included heavy metal enterprises, and their numbers have been more than halved between 2012 and 2017. The numbers and proportions of sewage treatment plants and hazardous waste enterprises have grown continuously. The number of wastewater treatment plants that function as urban and rural public facilities has increased by 12.5 times over the past 10 years.

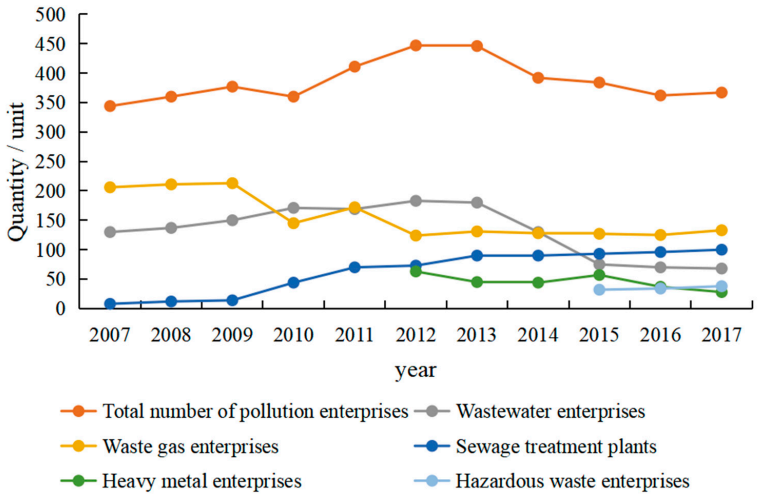


Figure 3. Changes of the number of PEs in the GPUA from 2007 to 2017.

National development strategies, such as the Western Development Program and the urgent economic needs of the western region, have played a positive guiding role in the growth of the number of PEs from 2007 to 2012. However, since 2010, with the successive introduction of national strategies such as the major function-oriented zones planning, pollution prevention and control policies, and laws and regulations [38,43], in

2012, China began to gradually incorporate environmental protection indicators into the performance evaluation system of local governments at all levels [44], prompting a shift in local industrial policies from encouragement to gradually phasing out outdated production capacity, leading to a decreasing trend in the number of PEs after 2012.

3.2. Spatial Agglomeration Characteristics Analysis of PEs

Based on the survey type standards and the characteristics of the changing number of PEs, three time points (2007, 2012, and 2017) were selected. Using the kernel density analysis tool in ArcGIS and applying the natural break classification method, kernel density analysis results for the three years (Figure 4) were obtained to depict the spatial agglomeration distribution characteristics and evolutionary trends of PEs.

The results of the kernel density analysis (Figure 4a–c) indicate that the distribution of PEs exhibits a clear orientation towards energy and mineral resources and a tendency to agglomerate along development axes. It also aligns with the strategic positioning of the major function-oriented zones. From the perspective of the entire GPUA, the overall spatial pattern of PEs shows a "dense in the east, sparse in the west" trend, evolving from a multi-core agglomeration to the domination of a central city and a gradual increase in the level of agglomeration in the western region. In 2007, PEs clearly followed this pattern, with clustering areas located in the eastern part of the GPUA, delineated by the boundary of the western part of Xi'an and Xianyang. The highest kernel density was observed in Yaodu District, extending north to Huozhou City and south to Houma City along the Jingkun Development Belt, forming a "bead-like" agglomeration pattern in the resource-based city of Linfen. Secondary agglomeration areas with relatively high kernel densities were located in the resource-endowed northeastern core cities of the Hancheng–Hejin Integrated Development Zone. Additionally, multiple agglomeration core areas were formed in Shaanxi Province, including the central urban areas of Xi'an, such as the Weiyang, Lianhu, and Yanta Districts, as well as Pucheng and Dali Counties along the Jingkun Development Belt; and Yaozhou District along the Baomao Development Belt. In 2012, with a significant reduction in the number of PEs in the urban area of Linfen City, the kernel density along the Jingkun Development Belt decreased, leading to the withdrawal of the agglomeration zone. The Hancheng–Hejin Integrated Development Zone witnessed a significant increase in the number of PEs, especially in Hejin City, which nearly doubled and became the agglomeration zone with the highest kernel density, highlighting its position as a regional agglomeration center in the northeast. The Xi'an agglomeration zone experienced an increase in kernel density and expanded its scope to encompass the urban area of Xianyang, forming a large Xi'an Metropolitan agglomeration zone. In addition, with an increase in the number of PEs in the western part of the GPUA, the agglomeration zone expanded westward along the Longhai Industrial and Urban Development Axis, forming an agglomeration zone in the node city of Baoji. Furthermore, core agglomeration zones were formed in Toguan County, located in the eastern part of the Longhai Industrial and Urban Development Axis, and in Luonan County, located in the Fuyin Development Belt. In 2017, despite a noticeable decrease in the number of PEs in the eastern region of the GPUA and an overall decrease in kernel density values, the Hancheng–Hejin and the Xi'an Metropolitan remained in the agglomeration zones with the highest kernel density, maintaining their position as regional agglomeration centers. The radiating effect of the Xi'an Metropolitan agglomeration zone was prominent, extending its reach to the counties surrounding the old city area, such as Huyi District, Xingping City, and Liquan County. Simultaneously, there was a significant increase in the number of PEs in the western part of the GPUA, primarily located in the energy-resource city of Qingyang and coal-rich city of Pingliang. Multiple medium-density and low-density agglomeration zones have emerged in urban areas and resource-based counties (such as Huating and Feng County).

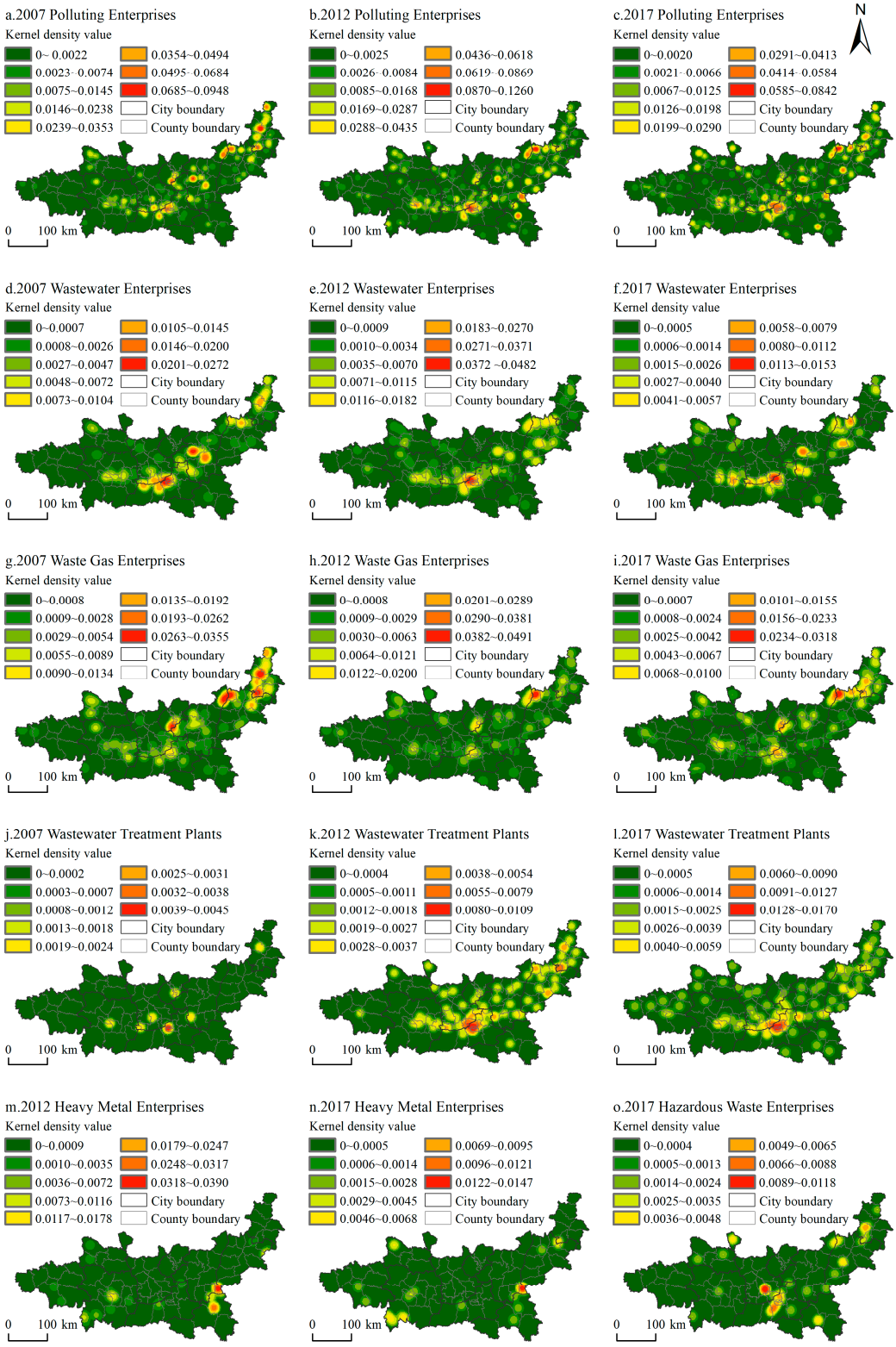


Figure 4. Kernel density estimation of PEs in the GPUA, 2007–2017.

From the perspective of the major function-oriented zones, agglomeration zones in the key development zones such as Hancheng–Hejin and the core urban area of Xi'an consistently maintained high kernel densities. The degree of agglomeration increased in the urban areas of Shangluo, Baoji, Pingliang, and Qingyang, as well as in counties along the development axes, such as Tongguan County and Shangzhou District, forming

scattered agglomeration areas with relatively low values. In the agglomeration areas of the major agricultural production zones, the fluctuation in kernel density values decreased in Huozhou City, Quwo, Pucheng, and Dali Counties, leading to their withdrawal from the high-density zones. However, the major agricultural production zones adjacent to high-density zones are susceptible to becoming secondary core areas for the agglomeration of PEs, such as Jishan County adjacent to the Hancheng–Hejin Agglomeration Zone and Huyi District and Liquan County surrounding the Xi'an Metropolitan agglomeration zone. High-value agglomeration zones have not formed in key ecological functional zones, but counties with excellent energy and mineral resources, such as Feng County, one of China's four major lead–zinc mining bases, have experienced continuous deepening of agglomeration, forming medium-density agglomeration zones.

In terms of types of differentiation: (1) The evolution of the agglomeration pattern of wastewater enterprises shows similarities with the overall evolution of the PEs agglomeration pattern (Figure 4d–f), presenting a trend of "dense in the east and sparse in the west", with the level of agglomeration gradually increasing in the western regions. High-density areas are consistently located within the Xi'an Metropolitan agglomeration and continue to expand westward along the Longhai Industrial and Urban Development Axis to the nodal city of Baoji. Additionally, agglomeration areas formed in Linwei District, Pucheng, Linyi, and Jishan Counties along the Jingkun Development Belt. (2) The high-value core density areas of waste gas enterprises were consistently located in Hancheng–Hejin and gradually formed secondary agglomeration areas within the Xi'an Metropolitan agglomeration (Figure 4g–i). (3) The spatial distribution of sewage treatment plants shifted from scattered to agglomerated; however, the level of agglomeration was relatively low. Apart from agglomerations that formed in the main urban areas of Xi'an and Xianyang, they were relatively evenly distributed elsewhere (Figure 4j–l). (4) Heavy metal enterprises were mainly distributed in the southern part of the GPUA. In 2012, two agglomeration areas formed in Tongguan and Luonan Counties in Shaanxi Province. However, by 2017, the number in Luonan County had decreased, and it ceased to be part of the agglomeration area. A new agglomeration area formed in Feng County, which is a key ecological functional zone (Figure 4m,n). (5) In 2017, hazardous waste enterprises exhibited a spatial pattern characterized by a core-belt-scattered distribution. The highest core density was found in Liquan County, while the second-highest core density, which formed a relatively high-density area, centered around the Chang'an District in the main urban area of Xi'an. Additionally, small scattered agglomeration areas appeared in the Shangzhou District, Hancheng–Hejin, and Xiangfen County (Figure 4o).

4. The Local Regulatory Effect on the Distribution Pattern of PEs

Tables 2 and 3, respectively, show the estimation results of the OLS model and GTWR model. I presents the regression coefficients of ER and LP, and the impact of control variables on the distribution of PEs. II presents the regression results after adding the interaction terms ER and LP (ER×LP) to the model. III presents the regression results after adding the interaction terms of ER with Inn and Cluster (ER× Inn and ER× Cluster) to the model.

Table 2. Estimation results of OLS model.

Variables	Estimated Value		
	I	II	III
ER	0.156 **	0.027	0.160
LP	0.092	0.166 *	0.157 *
Labor	−0.124	−0.141 *	−0.121
Inn	−0.340 **	−0.378 ***	−0.431 ***
Cluster	0.375 ***	0.399 ***	0.420 ***
Tra	0.291	0.281	0.269
ES	1.181 **	0.212 *	0.287 *
Sec	0.345 **	0.316 **	0.299 **
Ter	−0.087	−0.097 **	−0.114 **
ER×LP	/	0.194 **	0.165 *
ER× Inn	/	/	0.010
ER× Cluster	/	/	−0.186
R^2	0.252	0.266	0.281
Adj R^2	0.226	0.238	0.247

Note: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.001$.

Table 3. Estimation results of GTWR model.

Variables	Minimum Value	Maximum Value	I			II	III
			Mean Value	Percentage of Positive Values (%)	Percentage of Negative Values (%)	Mean Value	Mean Value
ER	0.479	1.918	0.936	100	0	0.389	1.060
LP	−0.220	1.022	0.487	90	10.	0.902	0.909
Labor	−0.770	0.743	−0.385	9.259	90.741	−0.455	−0.409
Inn	−4.487	7.031	−1.734	2.963	97.037	−1.934	−2.263
Cluster	−1.510	2.735	1.372	94.074	5.926	1.465	1.523
Tra	−0.908	1.794	0.904	88.889	11.111	0.882	0.823
ES	0.894	4.454	1.400	100.000	0	1.512	2.186
Sec	−0.841	2.011	0.933	88.148	11.852	0.847	0.769
Ter	−1.140	2.294	−0.270	24.444	75.556	−0.317	−0.399
ER×LP	/	/	/	/	/	1.594	1.411
ER× Inn	/	/	/	/	/	/	0.132
ER× Cluster	/	/	/	/	/	/	−1.362
R^2			0.734			0.644	0.629
Adj R^2			0.725			0.630	0.612

4.1. Analysis of the Results of the Traditional Regression Model

To discuss the overall impact of local regulations on the PEs' distribution, estimates using the Ordinary Least Squares (OLS) method were made (Table 2I). The results indicated that the intensity of the ER was significantly positively correlated with the number of PEs, whereas the role of the LP was not significant. This suggests that the distribution of PEs is mainly influenced by ER and tends to be located in counties with stricter ER. This may occur because counties with stricter ER in the GPUA have better pollution treatment facilities and more mature pollution control technologies. This also indicates that, during the study period, the intensity of ER in the GPUA did not form a restrictive threshold for the entry of PEs, and their impact is in the rising stage of the reverse U-shape. The "pollution haven effect" has not yet formed within the GPUA. Among the control variables, the estimated coefficients of the industrial cluster, regional economic level, transportation conditions, and proportion of secondary industry are all positive, indicating that an increase in the relevant indicators will increase the tendency of PEs being located. However, the estimated coefficients of labor cost and proportion of tertiary industry are negative, indicating that an increase in labor cost and the proportion of tertiary industry will decrease the tendency of PEs being located in these areas.

To further explore the interaction between ER and LP, as well as the interaction between ER, Inn, and Cluster, the decentralized interaction terms were added to the model. The results show the following: (1) The coefficient of the interaction term between ER and LP (ER×LP) is significantly positive (Table 2II). According to the principle of interaction terms, a significantly positive value indicates that the impact of ER on the distribution of PEs is influenced by LP, which increases with LP. This suggests that the LP in the GPUA promotes the impact of ER on the relocation of PEs. (2) The coefficient of the interaction term between ER and level of technological innovation (ER× Inn) is a non-significant positive value, and the coefficient of the interaction term between ER and level of industry cluster (ER× Cluster) is a non-significant negative value (Table 2III). This indicates that ER stimulates technological innovation by enterprises and reduces the level of agglomeration of regional PEs to some extent.

4.2. Analysis of the GTWR Model Results

By calculating Moran's I value of the number of PEs in the counties of the GPUA, we found that the Moran's I values for 2007, 2012, and 2017 were 0.126, 0.137, and 0.109, respectively, which are all greater than zero and significantly strong, indicating the existence of a strong spatial autocorrelation in the distribution of PEs in the GPUA. Therefore, the GTWR model can be used to further explore the influencing mechanisms.

The GTWR model was constructed using ArcGIS 10.2, and the analysis results of the relevant parameters are shown in Table 3. Compared with the OLS model, the adjusted R^2 for the GTWR model was 0.725, which was much higher, indicating a better fit. In the GTWR model, each county had specific estimated values for each year. Table 3 provides a statistical summary of the estimation results for different variables, including the minimum, median, maximum, and mean values, as well as the percentages of positive and negative values for each variable coefficient. In terms of the average value, the direction of the coefficients for both the core and control variables in the GTWR model did not change compared with the OLS, but the magnitude of the coefficients changed significantly. Except for ER and ES, the signs of the minimum and maximum values of the coefficients for each variable differed, indicating directional differences in the impact of the variables on counties in different years. In terms of the percentages of positive and negative values, ER has a positive effect on the distribution of PEs for all spatiotemporal units. The maximum value of the coefficient is 1.918, indicating that for every 1% increase in ER intensity, the corresponding number of PEs increases by 1.918%. For 90% of the spatiotemporal units, LP had a positive effect on the distribution of PEs, with a maximum value of 1.022, indicating that for every 1% increase in the intensity of LP, the corresponding number of PEs increases by 1.022%. Additionally, for 10% of the spatiotemporal units, there was a negative correlation between the LP and the number of PEs. There are several possible reasons for this. Firstly, LP tends to protect industries with a higher proportion of state-owned capital, such as resource- and energy-intensive industries and automobile manufacturing. At the same time, the government's tax revenue expectations are met, and there is not much enthusiasm with regard to the idea of introducing small and micro-polluting industries, such as the cement and paper industries.

In the control variables, (1) an increase in the level of technological innovation (Inn) in over 97% of the spatiotemporal units reduced the influx of PEs. This occurred because counties with higher levels of technological innovation have higher environmental awareness and barriers to entry for enterprises. At the same time, in the western regions, an increase in the level of technological innovation mainly promotes the development of tertiary and other service industries, thereby exerting a crowding-out effect on pollution-intensive industries. (2) The labor cost and proportion of the tertiary industry have a negative impact on the distribution of PEs in most spatiotemporal units, whereas the proportion of the secondary industry has a positive impact. Accordingly, PEs tend to be located in counties dominated by secondary industries with low labor costs. (3) The level of industrial clusters, transportation conditions, and economic development level all increase the influx of PEs.

Industries clusters generate effects, such as factor sharing, technological spillovers, and economies of scale, which can effectively improve the efficiency of resource allocation for enterprises, reduce production costs, and enhance regional industrial competitiveness and path dependence. A convenient transportation infrastructure not only meets the transportation needs of products and raw materials, promoting industrial development, but it serves as attractive infrastructure that will attract foreign investment. Underdeveloped areas that are rich in energy and mineral resources tend to invest the most in pollution-intensive projects. The economic development level has a positive impact on the influx of PEs in all spatiotemporal units, indicating that the current regional development in the GPUA is in the upward phase of the Environmental Kuznets Curve (EKC) and is also a stage of regional industrialization dominated by secondary industries. There is a strong dependency relationship between local economies and PEs.

To analyze the local regulatory effects on the distribution of PEs more intuitively, the GTWR estimation results for 2007, 2012, and 2017 are visually represented in Figure 5. This analysis examines the distribution characteristics of the regression coefficients for EP, LP, ER×LP, ER× Inn, and ER× Cluster. (1) From 2007 to 2017, the coefficient of ER has shown evident regional clustering, evolving from a pattern of "dense in the central and east regions, sparse in the west region" to "dense in both the east and west regions, sparse in the central region", with the coefficient values continuously decreasing. This indicates that, overall, the positive impact of ER on the distribution of PEs in the GPUA is gradually weakening, especially in the central region. This further confirms that the influence of ER on PEs in the GPUA is still in the ascending phase of an inverted U-shaped curve, and the central region with a relatively high level of economic development may be the first to surpass the threshold. (2) Unlike the ER coefficient, the LP coefficient has continued to increase, with the average coefficient value surpassing that of ER in 2017 (Table 3). This indicates shifts in the dominant influence of local regulation on the GPUA from ER to LP. The coefficients of some counties in Xi'an, Xianyang, Baoji, and Shangluo centered around the Xi'an Xianyang Metropolitan Area changed from negative to positive, indicating a shift in the direction of the impact of the LP on the distribution of PEs in these regions. These areas belong to the Guanzhong region, a manufacturing industry cluster in the Shaanxi Province. For a long time, state-owned capital had a relatively large share in the manufacturing industry, which has, to some extent, limited market competition and increased new enterprises' difficulty in entering the market. However, with the introduction of The Guanzhong-Tianshui Economic Zone Development Plan in 2009 and the advancement of the Western Development Policy, the Guanzhong region, centered around Xi'an, has shown increased enthusiasm for undertaking industrial transfers due to policy guidance and economic growth demands. This led to a shift in the LP coefficient from negative to positive, with a continuous increase in its value. (3) The coefficient of ER×LP continued to increase, and the average coefficient value in 2017 was much higher than that of ER and LP during the same period. This indicates that in the GPUA, ER and LP mutually reinforced the entry of PEs. The spatial distribution of ER×LP coefficients shows an "dense in the east, sparse in the west" pattern with the boundary of Xi'an and Xianyang as the dividing line, which is consistent with the spatial distribution of PEs. (4) The coefficient values of ER× Inn showed significant spatial distribution differences across different periods. In general, in the eastern and western regions, the coefficient values are mostly negative, whereas in the central region, the coefficient values are mostly positive, and the number continues to increase. In 2007, approximately half the counties had positive coefficient values, and by 2017, the number of counties with positive coefficient values exceeded two-thirds. The coefficient values for the core area of the GPUA, represented by the Xi'an Metropolitan area, remained consistently high. This indicates that ER in the GPUA can stimulate technological innovation in enterprises to a certain extent, and the innovation compensation effect is increasingly evident in different counties. (5) The coefficient values of ER× Cluster were negative in all counties, with minimal numerical changes over the study period, and the

spatial distribution was relatively stable. This suggests that an increase in ER leads to a decrease in the level of industrial clusters in all counties.

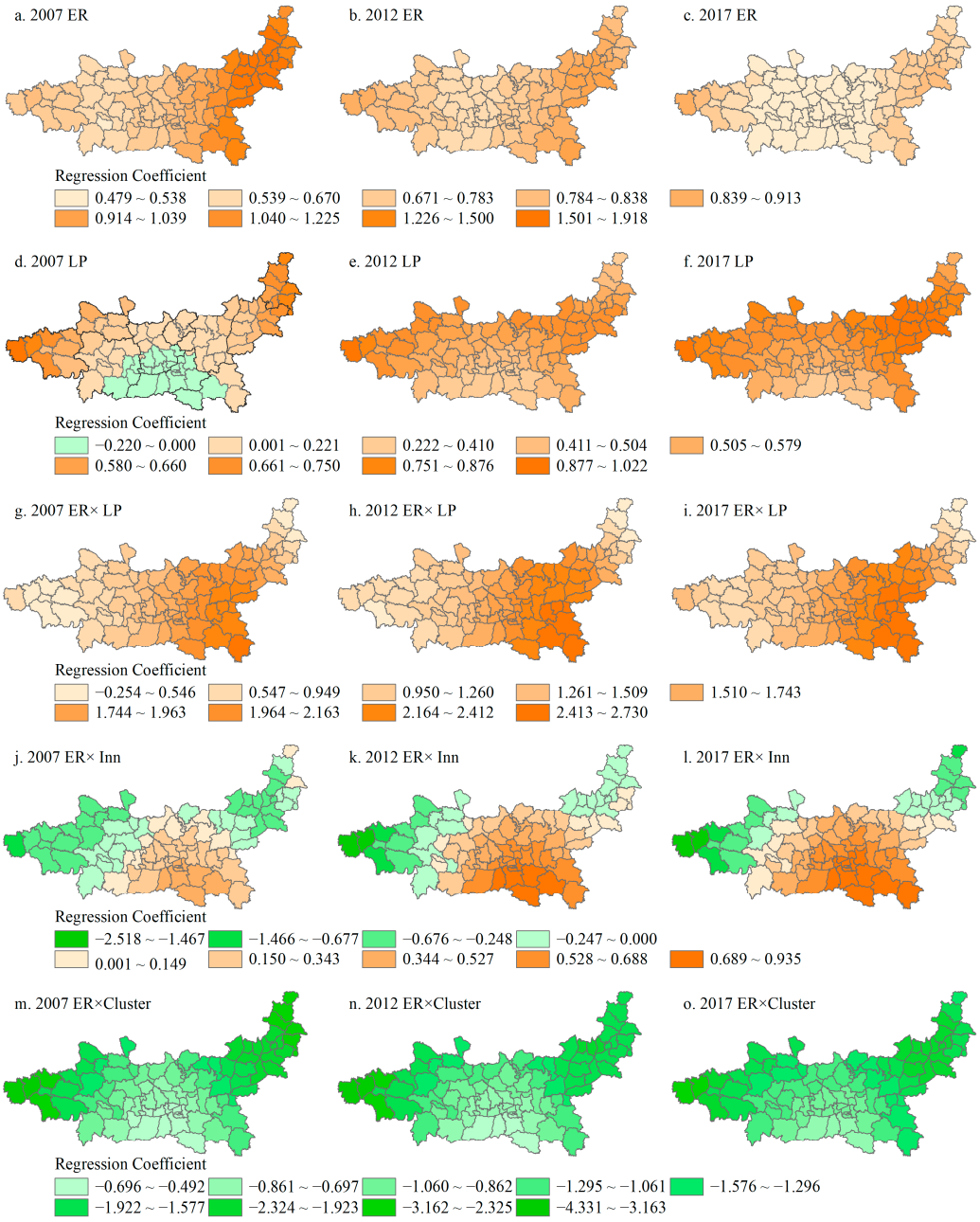


Figure 5. Regression coefficient distribution of some influencing factors.

From the perspective of the various major function-oriented zones, the trends in the changes in the five coefficients in the three major function-oriented zones are consistent with the overall situation of the GPUA, but there are differences in the magnitude of the coefficients in the different major function-oriented zones (Table 4). The coefficients of LP in the key development zones and major agricultural production zones increased rapidly, and by 2017, the average values had exceeded those of the ER coefficients. The average ER coefficient in the key ecological functional zones has always been greater than the LP and was significantly lower than the overall average. This indicates that the role of LP is more prominent in key development zones and major agricultural production zones, whereas the role of ER is more pronounced in key ecological functional zones.

The key development zones are the main regions that are undertaking domestic and foreign industrial transfers in the GPUA. Given the abundant resource endowments, heavy chemical industries are the pillar industries in the key development zones, with PEs as their main component. The government is responsible for protecting and supporting the development of these industries. Therefore, in the game between economic growth and environmental protection, the government tends to prioritize the former, weakening the influence of ER on the distribution of PEs. The average values of both the ER and LP coefficients in the major agricultural production zones were higher than those of the GPUA as a whole, but the coefficient value of the ER× Cluster was the lowest. As the key region for agricultural product supply security, these areas are affected by objective factors, such as low agricultural profits and high risks. Local governments still have the impetus to develop industries to improve the local economy; therefore, they tend to attract PEs and encourage them to settle and develop. However, owing to the restrictions on large-scale and high-intensity industrial development, the government should establish higher environmental standards to regulate PEs. Additionally, influenced by the limitations of the industrial land, the impact of the increase in ER on the decrease in the industrial cluster level is more pronounced. The role of ER is more prominent in key ecological functional zones, and the average value of ER× Inn is relatively high, indicating that ER has a more significant stimulating effect on technological innovation. The key ecological functional zones belong to a restricted (or prohibited) development zone and are important for safeguarding national ecological security. Simultaneously, each zone must utilize its unique resource advantages to develop its economy. For example, Feng County, one of China's four major lead–zinc mining bases, has become a high-density agglomeration area for heavy metal enterprises in the traditional mining industry. To minimize the negative impacts on the ecological environment as much as possible during economic development, promoting green development through technological innovation is an inevitable trend for industrial enterprises to establish themselves and for regional development in the key ecological functional zones.

Table 4. GTWR model regression parameter mean statistics, 2007–2017.

Major Function-Oriented Zones	Year	ER	LP	ER×LP	ER× Inn	ER× Cluster
Whole area	2007	1.186	0.218	1.468	−0.002	−1.353
	2012	0.968	0.552	1.641	0.195	−1.306
	2017	0.654	0.693	1.673	0.2	−1.427
Key development zones	2007	1.19	0.163	1.593	0.047	−1.22
	2012	0.969	0.539	1.776	0.289	−1.216
	2017	0.64	0.778	1.804	0.32	−1.365
Major agricultural production zones	2007	1.227	0.298	1.367	0.055	−1.553
	2012	0.986	0.578	1.525	0.087	−1.441
	2017	0.684	0.726	1.56	0.055	−1.534
Key ecological functional zones	2007	0.923	0.076	1.318	0.069	−0.986
	2012	0.857	0.48	1.518	0.265	−1.065
	2017	0.684	0.56	1.557	0.321	−1.166

4.3. Robustness Test

This study used the reduction rate of SO_2 emissions at the county level as a measure of ER stringency. The impact of SO_2 emissions reduction requirements may vary for different types of PEs, potentially leading to biased estimates of government regulatory effects. To further verify the influence of local government regulatory behavior on the distribution of PEs, we selected waste gas enterprises, which are closely related to SO_2 emission reduction and account for a large proportion of the overall PEs as the dependent variable. The core and control variables remained unchanged, and a GTWR model was constructed. The

mean values of the core explanatory variables for the entire GPUA and the three major function-oriented zones for 2007, 2012, and 2017 were calculated (Table 5).

Table 5. Statistics of mean regression parameters for GTWR model of waste gas enterprises, 2007–2017.

Major Function-Oriented Zones	Year	ER	LP	ER×LP	ER× Inn	ER× Cluster
Whole area	2007	0.569	0.218	2.056	0.789	−1.599
	2012	0.495	0.641	2.084	0.697	−1.601
	2017	0.415	0.760	2.229	0.802	−1.720
Key development zones	2007	0.551	0.452	2.167	0.715	−1.560
	2012	0.467	0.634	2.192	0.645	−1.581
	2017	0.385	0.754	2.326	0.760	−1.697
Major agricultural production zones	2007	0.451	0.495	1.943	0.445	−1.708
	2012	0.388	0.647	1.977	0.367	−1.687
	2017	0.303	0.775	2.144	0.475	−1.813
Key ecological functional zones	2007	0.607	0.455	2.047	0.924	−1.201
	2012	0.543	0.652	2.062	0.806	−1.219
	2017	0.465	0.716	2.138	0.901	−1.311

The results indicate that, throughout the GPUA and the three major function-oriented zones, the GTWR results with waste gas enterprises as the dependent variable are generally consistent with the results and trends obtained when using overall PEs as the dependent variable. The coefficients of ER and ER× Cluster continued to decrease, whereas the coefficients of LP, ER× LP, and ER× Inn continued to increase. As waste gas enterprises in key ecological functional zones have a relatively large proportion of capital, such as Shaanxi Daxigou Mining Co., Ltd. (Fengzhen, China), and Dongling Zinc Industry Co., Ltd. (Baoji, China), the role of LP is more prominent than that of ER. This differs from the results obtained when using the overall PEs as the dependent variable. However, the changing trends in the coefficients of ER and LP remained consistent. Therefore, it can be concluded that the research findings are robust.

5. Discussion

5.1. Summary of Findings and Discussion

China is currently in a critical period of economic transformation, and large-scale industrial relocation is imperative. Unlike developed countries, such as Japan and South Korea, which have abundant experience in overseas relocation [7], China, with its vast territory, exhibits significant differences in economic structure, resource endowment, and development paths among its eastern, central, and western regions, making industrial relocation between regions unavoidable. In addition, national pollutant emission reduction tasks are decomposed step by step through the administrative system, which causes spatial, temporal, and industrial differences in the environmental regulatory activities of the polluting industries, which is the fundamental cause of the differences in the distribution of polluting industries in China [29]. This study examined the Guanzhong Plain urban agglomeration (GPUA), the largest urban agglomeration in the northwest region of China and one of the main regions that undertakes industrial transfer, to explore the spatial pattern characteristics and evolution of PEs and reveal the effects of local regulatory behaviors. The research results not only enrich the research content of environmental economics and industrial geography, but also have great significance for the government, contributing to the formation of industrial development policies, rational optimization of the allocation, and promotion of the high-quality development of the GPUA. Meanwhile, it also has certain reference significance for the government decision-making behavior of underdeveloped countries that undertake industrial transfer.

The results of this paper showed that the number of PEs in the GPUA from 2007 to 2017 shows an obvious two-phase change, with a fluctuating increase from 2007 to 2012 and a continuous decrease after 2012. This process is closely related to the country's policies and strategies. National development strategies, such as the Western Development Program and the urgent economic needs of the western region have facilitated the distribution of PEs in the GPUA. However, since 2010, with the successive introduction of national strategies such as the major function-oriented zones planning, pollution prevention and control policies, and laws and regulations [38,43], in 2012, China began to gradually incorporate environmental protection indicators into the performance evaluation system of local governments at all levels [44], prompting a shift in local industrial policies from encouragement to gradually phasing out outdated production capacity, leading to a decreasing trend in the number of PEs after 2012.

Research indicates that the spatial trajectory of industrial relocation in China is gradually shifting away from "east to west along the economic belts" [7]. We found that the distribution of PEs in the GPUA exhibits a clustering trend along the development axes, which is largely aligned with the strategic positioning of the major function-oriented zones, reflecting the pivotal role of top-down local government regulatory actions in China's industrial distribution. The regional central cities of the GPUA have gradually evolved into high-density clusters of PEs. Combined with the regression results of GTWR, the economic development level has a positive impact on the influx of PEs in all spatiotemporal units, indicating that the current regional development in the GPUA is in the upward phase of the Environmental Kuznets Curve (EKC) and is also a stage of regional industrialization dominated by secondary industries. There is a strong dependency relationship between local economies and PEs.

Furthermore, we found the coefficient of the impact of ER on the distribution of PEs in the GPUA is positive, indicating that PEs tend to be located in regions with higher ER intensity, which is consistent with the findings of Song et al. [35] on pollution-intensive industries in the urban agglomeration in the middle reaches of the Yangtze River. Existing research suggests that the ER has an inhibitory effect on the placement of PEs. The disparity in these results reflects the close relationship between the spatial agglomeration of PEs and the level of regional development. For underdeveloped areas in western China, regions with strict regulations often have better pollution treatment facilities and more mature pollution control technologies and are more likely to adopt protective policies to attract PEs. Additionally, environmental protection is a widespread policy trend, and enterprises have a more critical understanding of short-sighted "pollute first, treat later" behavior, placing greater emphasis on ER factors when choosing relocation sites and willingly increasing environmental investment and improving technology to meet higher environmental standards within certain environmental costs. The findings of this study provide supplementary value to existing literature.

5.2. Policy Recommendations

During the process of industrial relocation, how host areas can avoid the development path of "pollute first, treat later" remains a pressing issue. The impact of local regulation on the distribution of PEs is primarily determined by the government's ability to balance economic development with environmental protection goals and motivations. Although environmental protection indicators have gradually been included in performance assessment systems at all levels of government since 2012, economic indicators still dominate the performance assessment system in the current promotion evaluations of officials. For underdeveloped urban agglomerations in the western region, local governments prioritize the economic benefits provided by PEs. Green innovation is an effective way to promote regional economic growth and environmental protection simultaneously. However, the long duration, high risk, and large investments associated with technological innovation reduce PEs' willingness to innovate in the pursuit of short-term economic goals. The government also needs to increase environmental subsidies for polluting enterprises and

support for green innovation resources and promote the formation of "innovation compensation effects" by means of external knowledge and technology spillover. Simultaneously, it is necessary to strengthen the pollution control role of ER, weaken the LP intensity, break the path dependence of high-polluting industry development, and create an effect in which ER drives the green innovation development of enterprises. Additionally, as an important policy tool for attracting enterprise investment and promoting industrial entry, the large-scale and low-priced industrial land transfer is a crucial means by which local governments participate in regional competition and develop the local economy [45,46], but they also significantly increase the emission of industrial pollutants [47]. Therefore, it is necessary to strictly control the supply of newly added industrial land; promote conservation and intensive utilization; make full use of the advantages of industrial parks; and build more pollutant treatment facilities to promote the sustainable development of industries.

Furthermore, the GPUA must strengthen its policy responses to the planning of its major function-oriented zones and accurately implement area strategies for these areas at the county level. Key development zones should fully leverage their resource endowment advantages, enhance the intensity of economic connections between regions, and harness the spillover effects of regional central cities to drive economic growth in the surrounding areas. Moreover, the major agricultural production zones need to be encouraged to invite agricultural and sideline food processing industries that are closely related to people's livelihoods and to control resource-intensive industries with large-scale and industrialized operations. In addition, there needs to be strict control of all types of development activities in key ecological functional zones, with continuous enhancement of green innovation, while minimizing the environmental pollution caused by existing enterprises. Local governments in the GPUA should improve collaborative mechanisms, enhance unified industrial transfer policies, establish integrated development mechanisms, promote joint prevention, control, and governance of pollution, and enhance the resilience of the GPUA. The findings of this study provide references for optimizing the distribution of PEs, comprehensive governance, and control of the environment in underdeveloped areas of China.

Other developing countries could also learn from this study when spatially reorganizing polluting industries. First, appropriately setting stricter levels of environmental regulation through improved pollution treatment facilities and pollution control technologies would increase industrial entry. Second, green industrial transformation is accelerated through support for green innovation resources and external knowledge and technology spillovers.

5.3. Limitation and Prospects

Due to limitations in length and data, this article has the following shortcomings: (1) Due to the restrictions of The National Key Monitoring Enterprises List published by the Chinese Ministry of Ecology and Environment between 2007 and 2017, the research results based on these data may not fully reflect the current situation. Subsequent research will continue to follow up on the list of pollution units released by the Ministry of Ecology and Environment, and longer time-series studies will be conducted. (2) This study is mainly based on the quantitative indicators of polluting enterprises and does not involve attribute information such as enterprise size, industry category, registration type (state-owned, collective, private, foreign-funded enterprises, etc.), as well as major pollutants and emissions, which may affect the precision of the spatial depiction of pollution in the study area and the depth of the study. With the advancement of China's Emission Trading System (ETS) and public announcement system, as well as the disclosure of enterprise information on commercial websites such as Tianyecha and Qicha, there is potential for data enhancement to support a more detailed analysis based on polluting enterprise attributes and emission data. It is proposed to carry out research on the spatial pattern and influencing factors of single types of PEs based on enterprise attribute information, and to explore inter-type variations in subsequent studies. (3) The measurement dimensions and methods for ER and LP are diverse. In this study, based on the availability of county-level data, the

intensities of ER and LP were measured by the reduction rate of SO_2 emissions in each county and the proportion of fiscal revenue to local GDP, respectively, referring to existing research results [38,40]. However, different measurement methods may yield different results. Subsequent research could adopt different measurement dimensions and methods based on changes in the research scale, data availability, etc., to enhance comparative studies and further improve the accuracy and scientific validity of the results.

6. Conclusions

While considering the active transfer of domestic and foreign industries in the central and western regions of China, this study used data from The List of National Key Monitoring Enterprises from 2007 to 2017, to reveal the spatial pattern of PEs by using kernel density, and applied geographically and temporally weighted regression to explore the impact of local regulations on the distribution of PEs. The main conclusions are as follows.

The number of PEs in the GPUA exhibited a clear two-stage pattern. The number of PEs fluctuated and increased between 2007 and 2012. However, with the successive introduction of national major function-oriented zones planning, pollution prevention, and control policies, laws, and regulations after 2010, and the incorporation of environmental protection indicators into the performance assessment system of local governments at all levels, the number of regional PEs continued to decrease after 2012.

The distribution of PEs tends toward energy and mineral resources and to ag-glomerate along development axes, as well as with the strategic positioning of the major function-oriented zones. Spatially, it follows a pattern of "dense in the east and sparse in the west," and temporally, it has evolved from a multi-core agglomeration to the dominance of regional central cities (such as the Greater Xi'an metropolitan area and the Hancheng–Hejin integrated development area), with a continuous increase in the level of clustering on the western side. Wastewater enterprises are mainly concentrated in the Xi'an Metropolitan area, whereas waste gas enterprises form high-density clusters in the Hancheng–Hejin Integrated Development Zone. Agglomerated areas are gradually concentrated in key development zones. Major agricultural production zones exit high-density areas, whereas those adjacent to the high-density areas are highly prone to becoming secondary agglomeration core areas. Key ecological functional zones have not formed high-density areas.

Local regulatory behaviors are significant factors influencing the distribution of PEs in the GPUA. ① From the perspective of the entire GPUA, the government's dual regulatory behaviors—ER and LP—both have a positive impact on the distribution of PEs, with the dominant influence shifting from ER to LP. Counties with strict ER tend to attract more PEs due to better pollution treatment facilities and more mature pollution control technologies. Thus, the GPUA has not yet formed the "pollution haven effect". ② When each major function-oriented zone was examined, LP was notably influential in key development zones and major agricultural production zones, whereas the role of ER was more pronounced in key ecological functional zones. ③ ER and LP mutually reinforced their impact on the PEs distribution. To some extent, ER can stimulate technological in-novation among enterprises, and the innovation compensation effect gradually manifests in the distribution of PEs in the GPUA. An increase in ER intensity leads to a decline in the level of regional industrial clusters, and major agricultural production zones, constrained by the scale of industrial land use, are more significantly affected by the role of ER at the industrial clustering level.

The research findings can provide theoretical references for optimizing enterprise distribution decisions and are of significant theoretical and practical value in promoting the high-quality economic and social development of the GPUA. They also have a certain reference significance for the government decision-making behavior of underdeveloped countries that undertake industrial transfer.

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