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Regional differences and spatio-temporal convergence of environmental regulation efficiency in the Yellow River Basin, China

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Environmental regulation efficiency facilitates environmental governance performance assessment, ecological protection, and high-quality development. Herein, based on the panel data of 75 cities in the Yellow River Basin from 2007 to 2020, this paper constructed an evaluation index system and measured the environmental regulation efficiency using a super-EBM hybrid distance model. We analyzed the regional differences and dynamic evolution characteristics of environmental regulation efficiency with the help of Dagum's Gini coefficient decomposition and kernel density estimation methods. Furthermore, a spatial econometric model explored the spatio-temporal convergence of environmental regulation efficiency. The main findings show that the environmental regulation efficiency of the overall Yellow River Basin and the upper, middle, and lower reaches showed an increasing trend with significant within-region spatial differences. The differences between all regions had a narrowing trend. The primary source of spatial differences in environmental regulation efficiency was the intensity of transvariation. The dynamic evolution characteristics of environmental regulation efficiency in different regions were quite different, and the spatial polarization phenomenon was more evident in the upper reaches. Except for the overall Yellow River Basin, all regions existed σ convergence. The results of spatial convergence estimation indicated absolute and conditional β convergence in all regions. The findings provide a factual reference for policies related to establishing policy systems for environmental regulation efficiency and green coordinated development in similar regions of the world.

KEYWORDS

environmental regulation efficiency, super-EBM model, regional differences, dynamic evolution, spatio-temporal convergence, the Yellow River Basin

1 Introduction

The Yellow River Basin is a distinct geographical region that spans China's three gradient terrains and economic belts, serving as a significant ecological barrier and a key region to defeat poverty in China (Zeng and Hu, 2021). In recent years, the Chinese government has placed the ecological protection and high-quality development of the Yellow River Basin at a prominent national strategic position. It has continued to strengthen environmental regulations, resulting in significant results in eco-environmental protection in the Yellow River Basin. From 2007 to 2020, the total investment in environmental pollution control in nine provinces and regions along the Yellow River in China rose from 5.086 billion USD to 24.144 billion USD, an average annual growth of 1.466 billion USD. However, the Yellow River Basin still faces problems such as a fragile ecological background, severe environmental pollution, and inefficient resource utilization (Liu and Ma, 2020; Zhang and Zhang, 2020). The needs of people continue to vary on how the ecological environment is being improved. According to the 2020 China Ecological and Environmental Bulletin released by the Ministry of Ecology and Environment, 15 of the 20 cities with relatively poor ambient air quality in China are in the Yellow River Basin, indicating that although environmental quality in the basin has improved, its governance performance is not satisfactory. In this context, it is necessary to explore the current development of environmental regulation efficiency in the Yellow River Basin as a whole and by region. However, due to natural and economic factors vary among regions in the Yellow River Basin, there are certain differences in environmental regulation efficiency between regions. So where do the differences originate? What are the evolution characteristics of regional differences in environmental regulation efficiency? Is there any spatial convergence in environmental regulation efficiency among regions? Addressing the above questions can improve our understanding of the current situation and the fundamental characteristics of environmental regulation efficiency in the Yellow River Basin and help us grasp the evolution of the spatial pattern of environmental regulation efficiency, so as to promote relevant research on environmental regulation efficiency in theory and provide a reference basis for the collaborative construction of an environmental regulation system in the Yellow River Basin in practice.

Environmental regulation improves environmental quality and ensures public interest by intervening in the behavior of pollution emission externalities of economic subjects. Implementing environmental regulation for pollution control should consider the technical and economic feasibility. Therefore, as reflected in environmental regulations, good environmental performance must be achieved by relying on the efficiency of pollution control. Facing the growing contradiction between economic development and environmental protection, the role of government regulation in environmental activities has become increasingly apparent, and the concept of environmental regulation efficiency has been developed. Compared with general input–output efficiency, environmental regulation efficiency is the ratio of environmental benefits obtained by the government in exercising its public management function of environmental protection to environmental management costs and is an effective way to assess the performance of government environmental governance (Xue and Liu, 2010; Cheng et al., 2016; Cao, 2021). Environmental regulation efficiency highlights the magnitude of the environmental benefits derived from a particular cost input and measures the effectiveness of the regulation by its value. In recent years, with the continuous deepening of the world's attention to assessing the performance of environmental governance, relevant research on environmental regulation efficiency has become a hot topic in the academic community. Concerning the research on the theory of environmental regulation efficiency, the academic circle has done much productive work. Many scholars have combined the theory of cost-benefit analysis to provide theoretical explanations for environmental regulation efficiency (Erdogan, 2014; Riccardi et al., 2015). Sunstein argued that the cost–benefit analysis theory could promote significant changes in environmental regulation and the combination of environmental science and economics (Sunstein, 1996). Hamamoto constructed an evaluation index system of environmental regulation efficiency through the cost–benefit analysis theory to provide a reference basis for a scientific, reasonable, and comprehensive evaluation of environmental regulation efficiency (Hamamoto, 2006). As for the evaluation of environmental regulation efficiency, existing studies have mainly used the data envelopment analysis (DEA) method (Tang et al., 2017), the stochastic frontier analysis (SFA) method (Xu et al., 2021), the multi-factor comprehensive evaluation method (Cui et al., 2018), the cost elasticity coefficient method (Liu and Wang, 2009), and the data converting function method (Simões et al., 2010) to measure environmental regulation efficiency in terms of the number of environmental policies, the amount of pollution abatement, and the cost of operating pollution control facilities. DEA is widely used in measuring environmental regulation efficiency because it does not require an explicit functional form relating inputs and outputs. It involves the traditional DEA model (Xu et al., 2014; Cheng et al., 2016), the two-stage DEA model (Wu et al., 2017), the three-stage DEA model (Zeng and Niu, 2019), the Malmquist index approach (Tang et al., 2016), the SBM model (Wang and Ma, 2020; Dong and Han, 2021; Wang and Cheng, 2021; Sun et al., 2022a), and the super-SBM model (Huang and Shi, 2015; Yin et al., 2017; Ren et al., 2019).

Regarding regional differences in environmental regulation efficiency, the driving forces mainly include the level of economic development, industrial structure, market environment, urbanization, technology input, and openness to the outside world (Xu et al., 2014; Cheng et al., 2016; Ren et al., 2019). The research methods used to measure regional differences cover the spatial analysis techniques, the Gini coefficient, the indicator observation, and the kernel density estimation (Dong and Han, 2021; Xu et al., 2021). Jia et al. examined the regional differences in the environmental regulation efficiency of the Lanzhou–Xining urban agglomeration in the Yellow River Basin using spatial analysis techniques. They found that the main differences were regional (Jia et al., 2022). Ren et al. used the Gini coefficient to compare the internal differences in the environmental regulation efficiency in three major urban agglomerations in China and found that the Pearl River Delta showed the most apparent internal regional differences (Ren et al., 2019). Although indicators can be observed visually and their differences compared, the spatial analysis techniques, traditional Gini coefficient, and indicator observation method cannot explain the sources of these differences. Wang and Cheng investigated the distribution dynamics of marine environmental regulation efficiency in China using kernel density estimation and pointed out that the internal differences were gradually increasing (Wang and Cheng, 2021). Kernel density estimation presents an intuitive explanation of the spatial distribution dynamics of environmental regulation efficiency, but it fails to take into account the distribution of the sub-samples and uses the mean value for the calculation, which leads to an averaging of the sample differences and reduces the accuracy of the results. The convergence of environmental regulation efficiency has gradually become the focus of research in economics and the environment as scholars continue to study it. Many scholars used the σ convergence model (Li and Luo, 2016), β convergence model (Piao, 2020), and club convergence model (Deng et al., 2021) to investigate the convergence of environmental regulation efficiency. Camarero et al. pointed out that both the most efficient countries for environmental regulation and the worst within the Organization for Economic Co-operation and Development (OECD) tend to form convergence clubs (Camarero et al., 2013). Some scholars have argued that there are spatial spillover effects and convergence in environmental regulation efficiency. Fredriksson and Millimet believed that the environmental regulation efficiency of all states in the United States has spatial spillovers and that the states with more efficient environmental regulations have a "demonstration effect" on their neighbors (Fredriksson and Millimet, 2002). Jia et al. identified both spatial spillover effects of environmental regulation efficiency and spatial β convergence in the Lanzhou–Xining urban agglomeration (Jia et al., 2022).

Specific results have been achieved in studying environmental regulation efficiency, but several limitations exist. First, the measurement of environmental regulation efficiency mainly adopts the traditional radial DEA model or the non-radial SBM model. Both models have certain restrictions, which often lead to biased measurements of environmental regulation efficiency, thus affecting the scientificity and accuracy of the conclusion. Second, the study of regional differences mainly applies the traditional Gini coefficient method and cannot reveal the source of regional differences in environmental regulation efficiency. In contrast, the Dagum Gini coefficient method effectively solves this problem. Third, in the aspect of the research object, most of the current environmental regulation efficiency measurements are focused on countries (Tang et al., 2016), provinces (Xu et al., 2014), and urban agglomerations (Ren et al., 2019; Wang and Ma, 2020; Sun et al., 2022b). Less attention has been paid to the environmental regulation efficiency of the Yellow River Basin, which is a significant ecological barrier and a rapidly transmutating economic–environmental system in China. Finally, the spatio-temporal characteristics of environmental regulation efficiency are less widely explored, and spatial econometric models are seldom tested for their spatial spillover effects. Therefore, this paper introduces the super-EBM (epsilon-based measure) model containing the undesirable output to measure the environmental regulation efficiency of 75 prefecture-level cities in the Yellow River Basin from 2007 to 2020. Then, the Dagum Gini coefficient, kernel density estimation method, and spatial convergence model are used to analyze the regional differences, dynamic evolution characteristics, and spatio-temporal convergence of environmental regulation efficiency in detail. This paper also puts forward relevant policy suggestions to promote the environmental management of the Yellow River Basin in China under the strategy of ecological protection and high-quality development of the Yellow River Basin.

2 Materials and methods

2.1 Methods

2.1.1 Super-EBM model

A hybrid EBM model with both radial and non-radial information was proposed by Tone and Tsutsui (2010), which accounts for the influence of non-radial slack variables while retaining the majority of the original proportion information from the front projection value. In addition, it addresses the problem of inconsistent input and output element dimensions, allowing for a more accurate and valuable reflection of the efficiency of decision-making units (DMUs). Considering the ranking problem of undesirable output elements and decision units (Andersen and Petersen, 1993; Tone, 2011; Xie et al., 2018), the super-EBM model based on undesirable outputs is defined as follows (Zou et al., 2019):

$$\gamma^{*} = \min \frac{\theta - \epsilon_x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{ik}}}{\varphi + \epsilon_y \sum_{r=1}^{s} \frac{w_r^+ s_r^+}{y_{rk}} + \epsilon_u \sum_{p=1}^{q} \frac{w_p^{u-} s_p^{u-}}{u_{pk}}}$$
$$\text{s.t.} \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{i0},\ i = 1, 2, \ \dots\ , m$$
$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \varphi y_{i0},\ r = 1, 2, \ \dots\ , s \tag{1}$$
$$\sum_{p=1}^{n} u_{pj}\lambda_j + s_p^{u-} = \varphi u_{pk},\ p = 1, 2, \ \dots\ , q$$
$$\lambda_j \geq 0,\ s_r^+ \geq 0,\ s_i^- \geq 0,\ s_p^{u-} \geq 0$$

where γ^* represents the environmental regulation efficiency, λ_j refers to the linear combination coefficient of DMU$_j$, x_{ij}, y_{rj}, and u_{pj} represent the i-th input, r-th and p-th denote desirable output and undesirable output of DMU$_j$, respectively, s_i^-, s_r^+, and s_p^{u-} represent slack variables, θ represents the radial planning parameter, ϵ_x, ϵ_y, and ϵ_u represent the non-radial weight of input, desirable output, and undesirable output, respectively.

2.1.2 Dagum Gini coefficient and its decomposition

Dagum decomposed the Gini coefficient into the contribution of within-region difference (G_w), between-region difference (G_{nb}), and the intensity of transvariation (G_t) (Dagum, 1997), which effectively solved problems such as the overlap of sample data.

The formula is as follows:

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji} - y_{hr}|}{2n^2\mu} \tag{2}$$

where G represents the overall Gini coefficient, y_{ji} is the environmental regulation efficiency of the city i in region j, and μ is the average environmental regulation efficiency of all cities. The specific formulas of G_w, G_{nb}, and G_t are as follows:

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j \tag{3}$$

$$G_{jj} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}|y_{ji} - y_{jr}|}{2n_j^2 \overline{y_i}} \tag{4}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j) D_{jh} \tag{5}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j)(1 - D_{jh}) \tag{6}$$

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji} - y_{jr}|}{n_j n_h(\overline{y_i} + \overline{y_h})} \tag{7}$$

$$D_{jh} = \frac{(d_{jh} - p_{jh})}{(d_{jh} + p_{jh})} \tag{8}$$

$$d_{jh} = \int_0^{\infty} dF_j(y) \int_0^{y} (y - x) dF_h(x) \tag{9}$$

$$p_{jh} = \int_0^{\infty} dF_h(y) \int_0^{y} (y - x) dF_j(x) \tag{10}$$

where $p_j = n_j/n, \quad s_j = n_j \quad \overline{y_j}/n\overline{y}, \quad \overline{y_j}(\overline{y_h})$ represents the average environmental regulation efficiency of region $j(h)$, d_{jh} represents the difference in gross environmental regulation efficiency influence between regions j and h, and p_{jh} represents the first-order moment of transvariation.

2.1.3 Kernel density estimation

Kernel density estimation is a highly representative method for examining the differences in particular geographic phenomena, which describes the distribution patterns of random variables by estimating their probability densities (Zhang et al., 2022). Suppose the density function of the random variable X is $f(x)$, and the probability density at point x is as follows:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x_i - \bar{x}}{h}\right) \tag{11}$$

where $K(\cdot)$ is the kernel density function, n is the number of observations, $\bar{x}$ is the mean value of observation, and h represents the bandwidth that determines the accuracy and smoothness of the kernel density curve.

2.1.4 σ convergence

Sigma (σ) convergence indicates that the deviation of environmental regulation efficiency tends to decrease over time (Rezitis, 2010; Zhang et al., 2022). The coefficient of variation was used to measure the σ convergence of environmental regulation efficiency in the Yellow River basin and different regions. The calculation formula is:

$$\sigma = \frac{\sqrt{\sum_{i}^{n_j}(ERE_{jt} - \overline{ERE_{jt}})^2/n_j}}{\overline{ERE_{jt}}} \tag{12}$$

where ERE_{jt}represents the environmental regulation efficiency of time t in region j.

2.1.5 Spatial β convergence

β convergence is derived from neoclassical growth theory, including absolute β and conditional β convergence (Liu and Du, 2017; Bigerna et al., 2021; Ram, 2021; Shi et al., 2022). Absolute β convergence refers to a gradual convergence to the same state of environmental regulation efficiency across cities over time, without considering external factors. Conditional β convergence means that the environmental regulation efficiency of each region eventually converges to its respective steady state after controlling for other influencing factors. Considering the increasing flow of environmental resource factors between regions, it is necessary to incorporate spatial dependence in the convergence of environmental regulation efficiency in the Yellow River Basin. The absolute β convergence of the spatial Durbin model (SDM) was built because it can degenerate into the spatial autoregressive model (SAR) and spatial error model (SEM). The proposed model is as follows:

$$\ln\left(\frac{ERE_{i,t+1}}{ERE_{i,t}}\right) = \alpha + \beta \ln(ERE_{i,t}) + \rho\sum_{j=1}^{n} W_{ij} \ln\left(\frac{ERE_{i,t+1}}{ERE_{i,t}}\right) + \theta\sum_{j=1}^{n} W_{ij} \ln(ERE_{i,t}) + \mu_i + \nu_t + \epsilon_{it} \tag{13}$$

The conditional β convergence of SDM was further established. The control variables in this model include the level of economic development (GDP), industrial structure (INS), market environment (MKT), degree of economic openness (OPEN), and technological progress (TP). GDP is reflected by per capita GDP and promotes rapid economic development to the detriment of environmental benefits. INS is the secondary industry's ratio to GDP, increasing industrial pollutant emissions and degrading eco-environmental quality. MKT is expressed by the proportion of private and self-employed employment in total employment, and it can improve the government's decision-making system and reasonably allocate regulatory elements. OPEN is measured *via* foreign direct investment (FDI) to indicate the level of environmental regulation intensity thresholds. TP is characterized by the proportion of public budget expenditure on science and technology, and it stimulates the reduction of regulatory costs and promotes productivity improvement. The conditional β convergence of SDM can be expressed as follows:

$$\ln\left(\frac{ERE_{i,t+1}}{ERE_{i,t}}\right) = \alpha + \beta \ln(ERE_{i,t}) + \rho \sum_{j=1}^{n} W_{ij} \ln\left(\frac{ERE_{i,t+1}}{ERE_{i,t}}\right) + \theta \sum_{j=1}^{n} W_{ij} \ln(ERE_{i,t}) + \gamma X_{i,t+1} + \delta \sum_{j=1}^{n} W_{ij} X_{i,t} + \mu_i + v_t + \epsilon_{it} \quad (14)$$

where β is the convergence coefficient, ρ, θ, and δ are spatial coefficients, W is the spatial weight matrix, ERE_{it} and ERE_{t+1} are the environmental regulation efficiency of region i from t to $t+1$, X_{it} is the control variable, α is the constant term, μ is the spatial fixed effect, v_t is the time effect, and ϵ is the random error term.

2.2 Environmental regulation efficiency indicators system

The evaluation of environmental regulation efficiency refers to measuring and evaluating the government's environmental regulation behavior using scientific evaluation methods to achieve a specific goal. Based on the cost–benefit analysis theory and related principles, this study divided the evaluation indicators into cost indicators (input indicators) and benefits indicators (output indicators). Cost indicators select labor input, capital input, and physical resource input. Benefit indicators include pollution control situations and environmental quality status. According to the general rule of DEA method indicator selection (Golany and Roll, 1989), the number of DMUs should not be less than the product of the input and output indicators. At the same time, it should be at least three times the number of input and output indicators. Drawing on the selection of indicators in the existing literature (Huang and Shi, 2015; Cheng et al., 2016; Tang et al., 2016; Zeng and Niu, 2019; Jia et al., 2022; Sun et al., 2022a; Sun et al., 2022b), 17 fundamental evaluation indicators of environmental regulation efficiency in the Yellow River basin were selected in this study. In terms of pollution control indicators, the industrial "three waste" emissions indicator is used as an indicator of undesirable output. Since there is too much missing data for the industrial wastewater emission compliance rate indicator for each prefecture-level city in the Yellow River basin, this indicator is not considered. The price-related indicators are deflated using 2007 as the base period to eliminate the effect of price fluctuations. The input–output indicators system is shown in Table 1.

2.3 Overview of the study area

The Yellow River flows through and borders nine provinces and autonomous regions in Qinghai, Sichuan, Gansu, Inner Mongolia, Ningxia, Shanxi, Shaanxi, Henan, and Shandong, with a total length of 5464 km and a basin area of about 2.17 million km^2. It is an essential ecological barrier and economic belt in China, and the ecological protection and high-quality development of the Yellow River Basin were elevated to a major national strategy in 2019. In order to delineate the study area of the Yellow River Basin, 75 prefecture-level cities in the upper, middle, and lower reaches of the Yellow River basin were selected for the study based on the principle of "taking the natural river basin as the basis, considering the

TABLE 1 Indicators system of environmental regulation efficiency.

Indicator type	Indicators name	Indicator characterization
Input indicators	Labor	Number of employees in the environmental sector (person)
	Capital	Investment in sewerage per unit of output (million yuan RMB)
		Total investment in landscaping (million yuan RMB)
		Total investment in environmental sanitation (million yuan RMB)
	Physical resources	Number of wastewater treatment plant (unit)
		Number of harmless treatment plants/grounds (unit)
		The density of water supply pipelines in the built district (km/km^2)
Desirable output indicators	Pollution control	Industrial SO_2 removal rate (%)
		Wastewater treatment rate (%)
		The comprehensive utilization rate of industrial solid waste (%)
		Domestic garbage harmless treatment rate (%)
		Industrial smoke (dust) removal rate (%)
	Environmental quality	The green coverage rate of the built district (%)
		Public recreational green space per capita (m^2)
Undesirable output indicators	Industrial "three waste" emissions	Wastewater emissions per unit of output (million t/billion yuan RMB)
		Industrial smoke (dust) emissions per unit of output (t/million yuan RMB)
		Industrial SO_2 emissions per unit of output (t/million yuan RMB)

integrity of the geographical study unit, and the direct correlation between the regional economy and the Yellow River" (Li et al., 2011) (Table 2). Since Sichuan belongs to the Yangtze River Basin, Hanzhong, Ankang, and Shangluo in Shaanxi, Hulunbeier, Chifeng, and Tongliao in Inner Mongolia are classified as northeast China in a broad sense, and Haidong in Qinghai has more severe missing data, these regions are not included in the Yellow River basin examined in this study. The spatial distribution of the Yellow River Basin is shown in Figure 1.

2.4 Data sources

The panel data of 75 prefecture-level cities in the Yellow River Basin from 2007 to 2020 in this study were mainly obtained from the China City Statistical Yearbook, the China Urban Construction Statistical Yearbook, the China Urban-Rural Construction Statistical Yearbook, and the statistical yearbooks and bulletins of various cities. Linear interpolation was used to supplement the missing data. Considering the continuity of the data, the data of Laiwu before 2019 was merged into Jinan. The acquired data were classified into the Yellow River Basin's upper, middle, and lower reaches.

3 Results

3.1 Results of environmental regulation efficiency measurements

With the help of MaxDEA 9.1 Ultra software, the input and output data of 75 prefecture-level cities in the Yellow River Basin from 2007 to 2020 were substituted into the super-EBM model with undesirable outputs, non-oriented, and variable returns to scale, and the environmental regulation efficiency values of various cities and regions over the years were calculated. The results are shown in Figure 2.

The overall average environmental regulation efficiency in the Yellow River Basin increased from 0.588 in 2000 to 0.776 in 2020, with an average annual increase of 1.861%. Specifically, during the study period, the environmental regulation efficiency of the Yellow River Basin showed a U-shaped trend, which first decreased and then increased, reaching the lowest point in 2011. The possible reason is that in the early stage of economic development, most cities in the Yellow River Basin were dominated by resource-intensive industries such as coal, iron and steel, and chemical industries, which were overly dependent on natural resources, resulting in pollutant emissions that were significantly higher than the national average. At the same time, pollution regulation and control were inadequate, traditional production technology and management modes were relatively backward, and a scientific and complete pollution management system still needed to be established, leading to a gradual decrease in environmental regulation efficiency. Since the 18th National Congress of the Communist Party of China (CPC), the national strategic positioning of the development of the Yellow River Basin has become more prominent, along with the in-depth implementation of ecological civilization construction. Most of the cities in the Yellow River Basin have changed their short-sighted development patterns of the long-term pursuit of economic growth while ignoring resource conservation and eco-environmental protection. They have curbed the development inertia of lagging economic development, local environmental pollution, and significant potential risks. They have also reduced the total amount and intensity of pollutant emissions and the carrying capacity of resources. At the same time, pollution regulation and control were inadequate, traditional production technology and management modes were relatively backward, and a scientific and complete pollution management system still needed to be established, leading to a gradual decrease in environmental regulation efficiency. Thus the environmental regulation efficiency is still fluctuating to a certain degree.

In the sub-regional comparison of environmental regulatory efficiency, the upper reaches had the highest average of 0.801, and the lower reaches was the next highest with 0.748. Both regions have long been higher than the overall average of 0.726 in the Yellow River Basin. The middle reaches ranked lower at 0.641, below the Yellow River Basin average. The time-series trend of the sub-regions shows that the environmental regulatory efficiency of all regions has increased at different rates during the study period, and there is a trend toward further development at higher levels. Further analysis reveals that the environmental regulation efficiency in the middle reaches increased by 0.230 and in the upper reaches by 0.053 during the study period, with the former exceeding the latter by more than four times, indicating that the increase in the regions with low environmental regulation efficiency is higher than that in the regions with high environmental regulation efficiency and that the difference in the average environmental regulation efficiency among regions is significantly reduced, showing some convergence characteristics. However, it was also found that the average

TABLE 2 The division of prefecture-level cities in the upper, middle, and lower reaches of the Yellow River Basin.

Region	Prefecture-level city
Upper reaches	Lanzhou, Baiyin, Wuwei, Jinchang, Pingliang, Zhangye, Jiayuguan, Jiuquan, Qingyang, Dingxi, Longnan, Tianshui, Xining, Yinchuan, Guyuan, Wuzhong, Shizuishan, Zhongwei
Middle reaches	Hohhot, Baotou, Wuhai, Ordos, Ulanqab, Bayannur, Taiyuan, Datong, Yangquan, Changzhi, Linfen, Jinzhong, Yuncheng, Jincheng, Xinzhou, Shuozhou, Lvliang, Xi'an, Xianyang, Yulin, Baoji, Tongchuan, Weinan, Yan'an
Lower reaches	Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Jiaozuo, Hebi, Xinxiang, Anyang, Puyang, Xuchang, Luohe, Sanmenxia, Nanyang, Shangqiu, Xinyang, Zhoukou, Zhumadian, Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Weifang, Jining, Tai'an, Weihai, Rizhao, Binzhou, Dezhou, Liaocheng, Linyi Heze

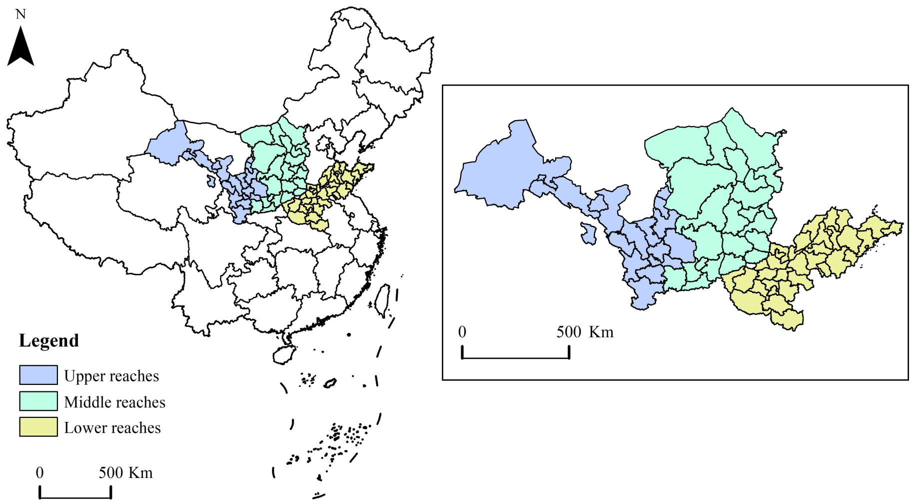

FIGURE 1
Location of the study area in China. The map projection system is World Geodetic System (WGS) 84.

annual increase of environmental regulation efficiency in the upper reaches was 0.460%, much lower than the overall level of the Yellow River Basin. In comparison, the average annual increase in the middle reaches was 2.422%, which shows that the increase in the regions with high environmental regulation efficiency failed to exceed that of the regions with low environmental regulation efficiency. The catching-up effect was noticeable, and then different regions may converge to the same steady state.

3.2 Regional differences in environmental regulation efficiency and their sources

The Dagum Gini coefficient and its decomposition method were used to reveal the overall difference in environmental regulation efficiency in the Yellow River Basin, the differences within and among the three regions, and the primary contribution sources. The specific results are shown in Table 3. In particular, the names of the three regions in the table were abbreviated here to provide more result information.

3.2.1 Overall and within-region differences

Figure 3 depicts the Gini coefficient and characteristics of change in environmental regulation efficiency for the Yellow River Basin and the three regions considered. During the inspection period, the difference in environmental regulation efficiency in the Yellow River Basin showed an inverted U-shaped fluctuation. The overall Gini coefficient had an average value of 0.253, reaching a maximum value of 0.372 and a minimum value of 0.098 in 2012 and 2018, respectively,

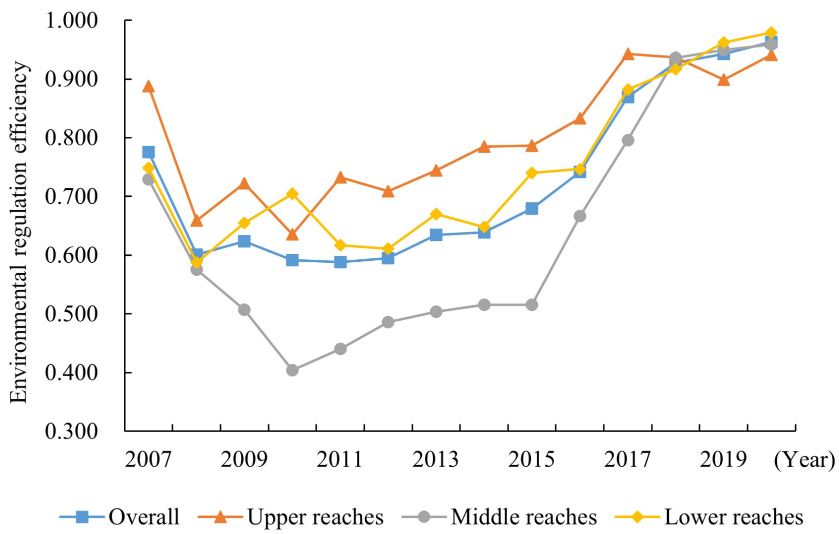

FIGURE 2
Trends of average environmental regulation efficiency by region in the Yellow River Basin.

TABLE 3 The Gini coefficient of environmental regulation efficiency and results of its decomposition.

Year	Overall	Within-region Gini coefficient			Between-region Gini coefficient			Contribution (%)		
		Upper	Middle	Lower	Upper-Middle	Upper-Lower	Middle-Lower	G_w	G_{nb}	G_t
2007	0.115	0.182	0.290	0.256	0.247	0.231	0.273	34.575	15.152	50.091
2008	0.331	0.262	0.304	0.371	0.289	0.336	0.351	35.279	7.881	56.840
2009	0.322	0.244	0.396	0.300	0.338	0.281	0.345	34.210	22.087	43.704
2010	0.364	0.340	0.524	0.245	0.453	0.280	0.371	31.313	31.272	37.414
2011	0.365	0.247	0.483	0.329	0.392	0.303	0.398	33.264	27.720	39.016
2012	0.372	0.286	0.471	0.336	0.396	0.324	0.395	33.825	20.345	45.830
2013	0.346	0.248	0.480	0.293	0.387	0.278	0.375	33.421	22.602	43.976
2014	0.333	0.244	0.415	0.298	0.357	0.288	0.350	33.138	25.360	41.502
2015	0.277	0.217	0.204	0.393	0.332	0.213	0.289	31.737	30.488	37.816
2016	0.229	0.193	0.292	0.189	0.255	0.198	0.234	33.246	19.054	47.250
2017	0.151	0.103	0.175	0.147	0.154	0.135	0.160	34.148	22.625	43.200
2018	0.098	0.089	0.106	0.095	0.101	0.094	0.100	34.743	5.233	60.024
2019	0.115	0.128	0.149	0.078	0.143	0.097	0.110	32.877	11.358	55.765
2020	0.117	0.130	0.136	0.090	0.135	0.105	0.111	33.309	7.406	59.285
Average	0.253	0.208	0.316	0.244	0.284	0.226	0.276	33.506	19.185	47.265

indicating that the environmental regulation efficiency in the Yellow River Basin had noticeable differences between cities and that the differences were shrinking.

In terms of within-region differences, the average Gini coefficient values of environmental regulation efficiency in the upper, middle, and lower reaches were 0.208, 0.316, and 0.244, respectively, with the most considerable difference in the middle reaches owing to the convergence of industrial structures in the upper reaches and the relatively balanced input of environmental regulation factors. However, the problem of unbalanced environmental regulation efficiency in the region was prominent in the middle reaches due to its wide coverage area and the heterogeneity of economic level, population characteristics, government regulation, and other factors, the pace of industrial transformation and upgrading and pollution control in core cities was not uniform. In addition, the Gini coefficients of the upper and lower reaches did not exceed the overall Gini coefficient, indicating that the imbalance among

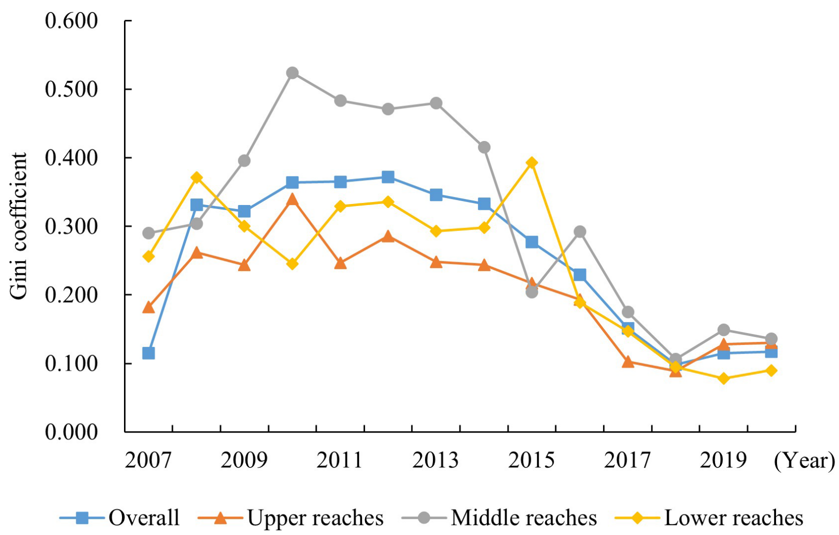

FIGURE 3
Trends in the overall and within-region Gini coefficient of environmental regulation efficiency.

cities within the upper and lower reaches was relatively low. The Gini coefficients of environmental regulation efficiency in the upper, middle, and lower reaches all showed a fluctuating decreasing trend from 0.182, 0.290, and 0.256 in 2007 to 0.130, 0.136, and 0.090 in 2020, with a decrease of 28.571%, 53.103%, and 64.844%, respectively. The difference in the Gini coefficients of the three regions was narrowing, and the regions with a low environmental regulation efficiency were getting closer to the regions with a high environmental regulation efficiency.

3.2.2 Between-region differences

As shown in Figure 4, the average Gini coefficient values of environmental regulation efficiency in the upper-middle, upper-lower, and middle-lower reaches were 0.284, 0.226, and 0.276, respectively. Among them, the most considerable differences were found in the upper-middle reaches and the smallest in the upper-lower reaches. From the dynamic evolution trend, the Gini coefficients of environmental regulation efficiency in the upper-middle, upper-lower, and middle-lower reaches exhibited a fluctuating decreasing trend from 0.247, 0.231, and 0.273 in 2007 to 0.135, 0.105, and 0.111 in 2020, with a decrease rate of 45.344%, 54.545%, and 59.341%, respectively, reflecting the evolution of the fluctuating increasing and decreasing trends. This indicates that the differences in the upper-middle, upper-lower, and middle-lower reaches have narrowed significantly from 2007 to 2020. Still, the difference in the upper-middle reaches has narrowed relatively little.

3.2.3 Sources and contributions of differences

The contribution rates of the intensity of transvariation (G_t), within-region difference (G_w), and between-region difference (G_{nb}) were measured separately in this paper to reveal the sources of the overall difference in environmental regulation efficiency in the Yellow River Basin. The evolution of these three contribution rates is reflected in Figure 5.

For the magnitude of the contribution rates, the average annual contribution rates of within-region difference, between-region difference, and the intensity of transvariation were 33.506%, 19.185%, and 47.265%, respectively, from 2007 to 2020. The sources of the overall difference in environmental regulation efficiency in the Yellow River Basin were, in order, the contributions of the intensity of transvariation, within-region difference, and between-region difference. Therefore, the most crucial cause of the overall difference in environmental regulation efficiency in the Yellow River Basin is the intensity of transvariation. In other words, reducing the intensity of between-region transvariation should be the focus of future efforts to promote the development of environmental regulation efficiency in the Yellow River Basin. This means the environmental regulation efficiency in the upper, middle, and lower reaches has a particular intersection. In addition, the environmental resource endowment and development levels of certain cities in different regions are similar. As a result, a city with a lower environmental regulation efficiency in the higher-rank region may be lower than a city with a higher value in the lower-rank region. Regarding the dynamic evolution trend, the contribution rate of within-region difference was relatively stable at about 33%. In contrast, the contribution rates of between-region difference and the intensity of transvariation fluctuated more during the observation period. The contributions of within-region difference and the intensity of transvariation have a complementary fluctuating relationship that reinforces each other. The contribution rate of the intensity of transvariation showed a U-shaped trend, and correspondingly, the contribution rate of within-region difference showed an inverted U-shaped trend. The former reached the minimum value of 37.414% in 2010, while the latter reached the maximum value of 31.272% in 2010.

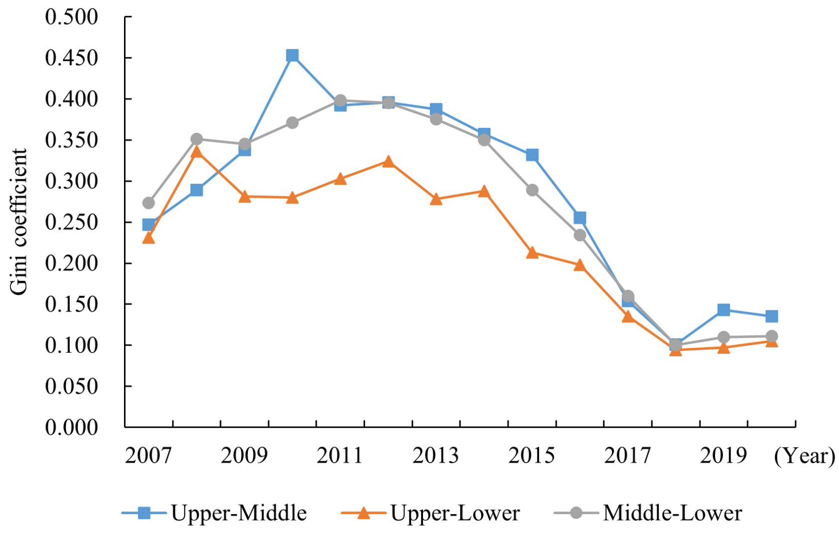

FIGURE 4
Trends in the between-region Gini coefficient of environmental regulation efficiency.

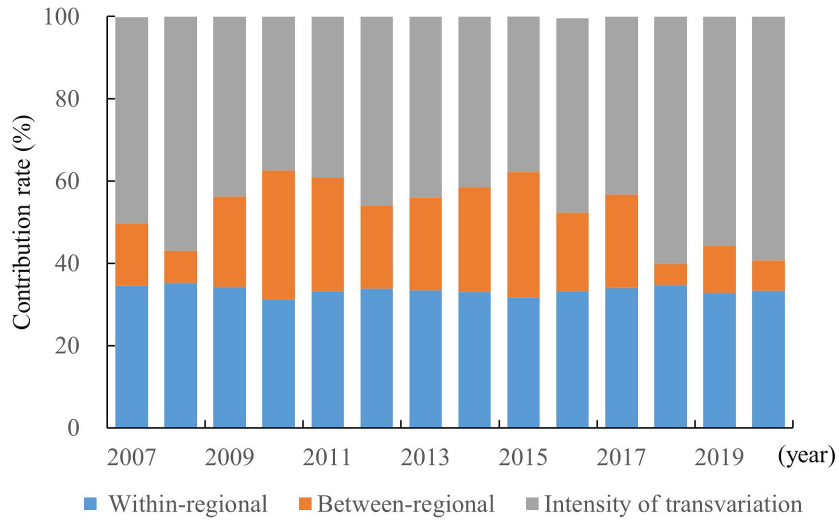

FIGURE 5
Sources of regional difference and their contributions.

3.3 Distribution dynamics of environmental regulation efficiency

The Gini coefficients revealed the magnitude and source of environmental regulation efficiency in the Yellow River Basin and represented the relative differences in environmental regulation efficiency but could not describe the dynamic changes in the absolute differences. In this study, we applied the kernel density estimation method to characterize the distribution dynamics of environmental regulation efficiency in the Yellow River Basin and the three regions in terms of location, pattern, extension, and polarization trends. Figure 6 presents a 3D kernel density map of environmental regulation efficiency in the Yellow River Basin from 2017 to 2020.

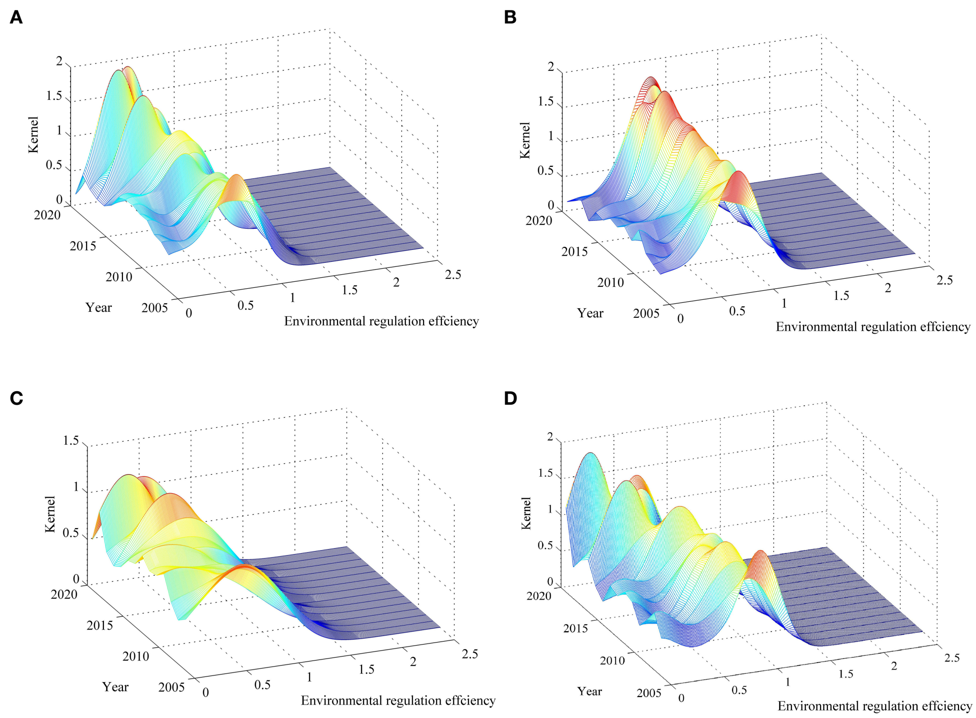

FIGURE 6
Dynamic evolutionary trends of environmental regulation efficiency. **(A)** Overall, **(B)** Upper reaches, **(C)** Middle reaches, and **(D)** Lower reaches.

As illustrated in Figure 6, the distribution curves of the overall Yellow River Basin and the three regions tended to move to the right, indicating that the environmental regulation efficiency of the overall Yellow River Basin and the three regions improved, which is consistent with the trend of environmental regulation efficiency measured in the previous paper. The distribution curves of the upper and lower reaches did not move significantly to the right over time. The efficiency of environmental regulation still needs to be improved, especially with the tightening of resource and environmental constraints and the acceleration of green transformation. Considering the shape of the kernel density curves, the height of the main peak of the distribution curves of the overall Yellow River Basin and the three regions increased. At the same time, the width narrowed, indicating that the absolute difference in the environmental regulation efficiency of the overall Yellow River Basin and the three regions had a particular diminishing trend. The height of the main peak in the middle reaches first decreased as the width widened and then increased as the width narrowed, implying that the dispersion of environmental regulation efficiency tended to increase at the beginning of the inspection period and that the dispersion trends had diminished in recent years. In terms of the extension of the main peak, there was an apparent right-trailing phenomenon in the distribution curves for the overall Yellow River Basin and the three regions, which was mainly due to the existence of cities with high environmental regulation efficiency in each region, such as Qingyang in the upper reaches, Linfen in the middle reaches, and Sanmenxia in the lower reaches. Furthermore, the distribution curves of the overall Yellow River Basin and the three regions had the characteristics of extended convergence, and the gap between the cities with higher environmental regulation efficiency and the cities with average efficiency had been reduced, i.e., the probability of extreme values of environmental regulation efficiency became increasingly unlikely. From the perspective of the polarization characteristics, the distribution curves of the overall Yellow River Basin and the lower reaches had a bimodal peak phenomenon at the beginning of the inspection period. Still, at the end of the period, the distribution curves had a single peak pattern, indicating that the polarization within these regions tended to weaken. The degree of within-regional difference gradually decreased. The distribution curve of the upper reaches consistently showed a bimodal peak, and the difference between the main peak and the side peak was relatively large, indicating a significant spatial polarization phenomenon in the environmental regulation efficiency of this region. On the other hand, the distribution curve of the middle reaches showed a single peak characteristic with a more moderate divergence trend.

3.4 Spatio-temporal convergence of environmental regulation efficiency

3.4.1 Time series convergence analysis

The σ convergence of environmental regulation efficiency in each region of the Yellow River Basin is shown in Figure 7. The coefficient of variation of environmental regulation efficiency in the overall Yellow River Basin showed a repeated rise and declined from 0.195 in 2007 to 0.248 in 2020. In general, there is no σ convergence because the variation coefficient at the period's end was higher than at the beginning. The coefficient of variation of the upper reaches had a rising–declining–rising–declining, indicating that there is σ convergence in the environmental regulation efficiency of the upper reaches. The coefficient of variation of environmental regulation efficiency in the middle reaches only increased from 2007 to 2010 and showed cyclical ups and downs from 2010 to 2020. Moreover, the coefficient of variation of environmental regulation efficiency in the lower reaches only increased slightly from 2007–2008, 2010–2011, and 2019–2020, and decreased in other years. Therefore, there is σ convergence in the middle and lower reaches. The convergence

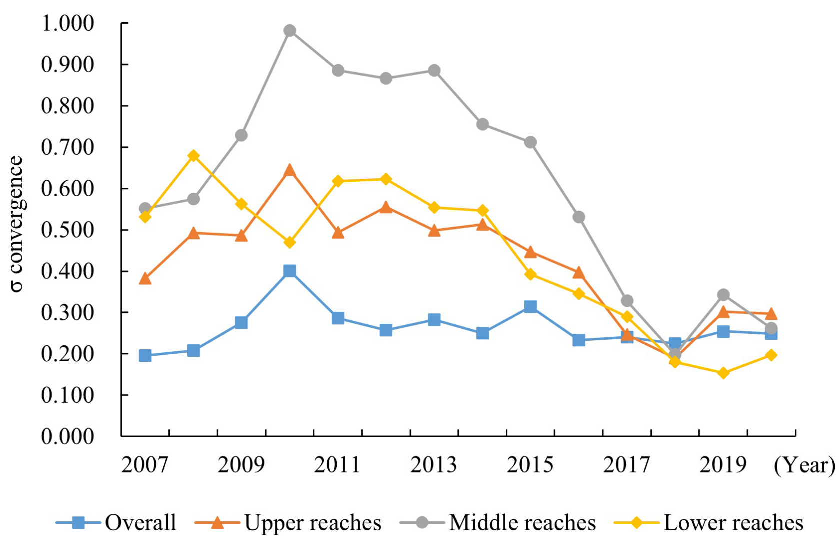

FIGURE 7
Trends of σ convergence of environmental regulation efficiency.

speed in the lower reaches was 0.6287, nearing that of the upper and middle reaches, in a "catch-up" situation.

3.4.2 Spatial convergence analysis

3.4.2.1 Spatial autocorrelation test

According to Formula (8), the spatial autocorrelation of environmental regulation efficiency in the Yellow River Basin was tested and analyzed using the Rook spatial weight matrix. In order to avoid the "island phenomenon", Xining and Weiwu were set as neighbors. Stata 16.0 software was used to calculate the global Moran's I for the environmental regulation efficiency in the Yellow River Basin from 2017 to 2020 (Table 4). Except for 2007 and 2017, the global Moran's I values were significantly positive during the observation period, indicating that the environmental regulation efficiency in the Yellow River Basin was not randomly distributed. Instead, it showed that the spatial distribution of environmental regulation efficiency tended to exhibit significant spatial correlation and regional clustering. The results of the spatial autocorrelation test indicated that the environmental regulation efficiency in the Yellow River Basin could be analyzed using a spatial econometric model for convergence.

3.4.2.2 Spatial convergence model setting

The spatial convergence model involves spatial lag terms. When solving spatial problems, the traditional least squares regression method presents difficulty acquiring unbiased estimates. Thus, a suitable spatial econometric model was selected using the Wald and Lagrange multiplier (LM) tests. The Hausman test results were for determining whether the model utilized fixed effects or random effects. The Likelihood ratio (LR) test was further judged for the fixed effects model for time-fixed, spatial-fixed, and spatial-time double-fixed. Because of the space limitation, the specific model setting process was not listed in this study. The corresponding author is available upon request.

3.4.2.3 Spatial absolute β convergence analysis

The spatial absolute β convergence test of environmental regulation efficiency in each region is listed in Table 5. The parameter $s=-\ln(1+\beta)/T$ represents the convergence speed, and $\tau=\ln(2)/s$ represents the half-life cycle (Pan, 2010). It can be seen from Table 4 that, first, the convergence coefficient β of the test in the overall Yellow River Basin and the upper, middle, and lower reaches were significantly negative at the 1% level, indicating that there was absolute β convergence in environmental regulation efficiency in all of them. Suppose the influence of a series of economic, environmental, and social factors on environmental regulation efficiency is not considered. In that case, the environmental regulation efficiency of the overall Yellow River Basin and the three reaches will converge to their respective steady-state levels in the long run. Combined with the fact that environmental regulation efficiency increases from year to year (see Figure 2), even though the coefficient of variation increases in the short term for each study object (see Figure 7), the trend of increasing and long-term convergence of environmental regulation efficiency is already apparent. Second, there were differences in the convergence speed of environmental regulation efficiency across regions. The convergence speed was 0.0702, 0.0862, 0.0770, and 0.0646 for the overall Yellow River Basin and the upper, middle, and lower reaches. At the same time, the half-life cycle was 9.867, 8.038, 8.971, and 10.737 years, respectively. In other words, the upper reaches had the fastest convergence speed. The cities with lower environmental regulation efficiency in the region had the shortest time to "catch up" with the cities with higher environmental regulation efficiency, followed by the middle reaches and the overall Yellow River Basin. In contrast, the lower reaches had the slowest convergence speed. The environmental regulation efficiency in the upper and middle reaches can maintain a high convergence speed despite the relatively high coefficient of variation, which can be attributed to the interaction within cities through spatial effects. Finally, the Yellow River Basin and the three reaches exhibited different spatial effects. Both independent and dependent variables' spatial lags existed in the Yellow River Basin and lower reaches. The ρ and θ coefficients of each model were significantly positive at the 5% level, demonstrating that the positive spatial spillover of both environmental regulation efficiency in other cities and the rates of change of environmental regulation efficiency in other cities had an impact on the rate of change of environmental regulation efficiency in this city within the region. The spatial lags of the dependent variable existed in the upper and lower reaches. The ρ coefficients of the models for both regions were significantly positive at the 5% level, indicating that the rate of change of environmental regulation efficiency in this city within the region was affected by positive spatial spillovers from the rates of change in other cities. It should be noted that the absolute β convergence of

TABLE 4 The results of Moran's I of environmental regulation efficiency in the Yellow River Basin from 2005 to 2020.

Year	Moran's I	Zscores	P-value	Year	Moran's I	Zscores	P-value
2007	0.087	1.279	0.101	2014	0.137	1.902	0.029
2008	0.104	1.809	0.046	2015	0.083	2.625	0.004
2009	0.102	1.459	0.072	2016	0.147	1.829	0.034
2010	0.113	1.595	0.055	2017	0.078	0.833	0.203
2011	0.250	3.335	0.000	2018	0.175	2.399	0.008
2012	0.091	1.325	0.093	2019	0.137	2.053	0.020
2013	0.143	2.132	0.019	2020	0.099	1.484	0.069

TABLE 5 Absolute β convergence test results of the environmental regulation efficiency in the Yellow River Basin.

Model	Overall	Upper	Middle	Lower
	Spatial-time double-fixed effects SDM	Spatial-time double-fixed effects SAR	Spatial-time double-fixed effects SAR	Spatial-time double-fixed effects SDM
β	−0.626***	−0.701***	−0.661***	−0.595***
ρ/λ	0.125***	0.021**	0.065**	0.093**
θ	0.141**			0.261***
Hausman	84.03***	58.29***	114.75***	73.21***
Wald-lag	5.94**	0.03	2.97*	23.88***
Wald-error	8.72***	0.10	0.46	13.39***
LM-lag		10.238***	7.464***	
Robst-LM-lag		22.156***	19.350***	
LM-error		2.386	1.585	
Robst-LM-error		14.304***	13.471***	
Spatial effects	73.52***	27.09***	66.57***	34.84***
Time effects	159.49***	54.51***	53.91***	50.80***
Log-likelihood	427.9634	114.6240	113.6536	224.3129
sigma^2	0.024***	0.022***	0.028***	0.021***
s	0.070	0.086	0.077	0.065
τ	9.867	8.038	8.971	10.737
N	975	234	312	429
R^2	0.186	0.190	0.227	0.217

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

environmental regulation efficiency across the regions was conducted under the assumption that the level of economic development, industrial structure, market environment, degree of economic openness, and technological progress were similar across regions, which is not the case, so further analysis on conditional β convergence is needed.

3.4.2.4 Spatial conditional β convergence analysis

Table 6 presents the results of the conditional β convergence test for the environmental regulation efficiency of 75 cities and regions in the Yellow River Basin. The selection process for the different spatial econometric models is the same as for the absolute β convergence analysis. The results show that taking into account the different economic, environmental, and social characteristics of the overall Yellow River Basin and the three regions, the β coefficients of the overall Yellow River Basin and the upper, middle, and lower reaches were all still significantly negative at the 5% level, indicating that the environmental regulation efficiency of all of them showed significant conditional β convergence, with the convergence speed of 0.071, 0.092, 0.080, and 0.066, while the half-life cycle was 9.760, 7.571, 8.618, and 10.504 years, respectively. With the inclusion of control variables, the convergence speed of all regions was accelerated to varying degrees. At the same time, the half-life cycle was shortened, indicating that the control variables can effectively promote the β convergence of environmental regulation efficiency in the overall Yellow River Basin and the three regions so that the cities with lower environmental regulation efficiency needed less time to "catch up" with the cities with higher environmental regulation efficiency. The overall Yellow River Basin and the three regions also exhibited different spatial effects. In contrast, the spatial effects in individual regions differed from those in the absolute β convergence analysis. In particular, the type of spatial effect in the overall Yellow River Basin changed from SDM to SAR, indicating that the spatial spillover of environmental regulation efficiency in other cities disappeared. Otherwise, the type of spatial effect in the upper reaches changed from SAR to SDM. Apart from these, it did not differ from the absolute β convergence analysis.

3.4.3 Robustness tests

The Pyatt Gini coefficient was used to measure the regional differences in environmental regulation efficiency and the primary sources of contribution in the Yellow River Basin to examine the findings of the previous study based on the Dagum Gini coefficient

TABLE 6 Conditional β convergence test results of the environmental regulation efficiency in the Yellow River Basin.

Variables	Overall	Upper	Middle	Lower
	Spatial-time double-fixed effects SAR	Time-fixed effects SDM	Spatial-time double-fixed effects SAR	Spatial-time double-fixed effects SDM
β	−0.629***	−0.705***	−0.673***	−0.603***
ρ/λ	0.073**	0.044**	0.056***	0.079**
θ		0.083**		0.219***
Hausman	106.81***	147.20***	158.12***	64.55***
Wald-lag	10.55	16.66**	11.76*	23.20***
Wald-error	6.30	16.80**	9.88	18.86***
LM-lag	8.849***		7.756***	
R-LM-lag	43.838***		24.315***	
LM-error	0.267		1.160	
R-LM-error	35.256***		17.719***	
Spatial effects	36.32***	9.62	34.26***	18.87**
Time effects	155.49***	41.79***	45.75***	51.71***
Log-likelihood	427.1545	125.1941	92.8780	228.6742
$sigma^2$	0.024***	0.020***	0.032***	0.020***
s	0.071	0.092	0.080	0.066
τ	9.760	7.517	8.681	10.504
N	975	234	312	429
R^2	0.164	0.100	0.159	0.199

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

(Pyatt, 1976). It can be easily seen that the Pyatt Gini coefficient and decomposition were generally consistent with the Dagum Gini coefficient, which indicates that the conclusions drawn from the Dagum Gini coefficient were robust and reliable. Due to space constraints, the composition of the Pyatt Gini coefficient needed to be more detailed here, and specific Gini coefficient data needed to be reported. The corresponding author is available upon request.

The spatial conditional β convergence analysis was conducted using the geographic distance weight matrix and the economic geography nested weight matrix to examine the robustness of spatial convergence, and the results are shown in Table 7. The β coefficients of the overall Yellow River Basin and the upper, middle, and lower reaches were all significantly negative at the 5% level under both types of weight matrices, implying that the spatial convergence conclusion of this paper was robust.

4 Discussion

Environmental regulation efficiency facilitates environmental governance performance assessment, ecological protection, and high-quality development. Based on the input–output indicators system, this study identified the differences and convergence of environmental regulation efficiency in the Yellow River Basin.

First, the average value of environmental regulation efficiency in the Yellow River Basin from 2007 to 2020 was 0.726, which is lower than the results of the Yangtze River Economic Belt and coastal urban agglomerations in China (Ren et al., 2019; Wang and Ma, 2020). The results are lower because our study considered the impact of undesirable output indicators such as industrial "three waste" emissions on environmental regulation, which makes our calculation more scientific. Second, the environmental regulation efficiency in the Yellow River Basin has great within-region differences, and the differences within the middle reaches are the largest. The average contribution to the intensity of transvariation was 47.265%, indicating that the intensity of transvariation is the main source of spatial differences in environmental regulation efficiency. Compared with traditional empirical analysis, the difference and contribution analysis in this study can more scientifically show the characteristics of environmental regulation efficiency in the Yellow River Basin. Finally, the environmental regulation efficiency in the Yellow River Basin has obvious characteristics of spatial absolute and conditional β convergence, and the environmental regulation efficiency of each city tends to a

TABLE 7 Spatial convergence robustness test results.

	Weight type	β	ρ/λ	R^2
Overall	Geographic distance weight matrix	−0.710***	0.123***	0.160
	Economic geography nested weight matrix	−0.585***	0.266***	0.193
Upper	Geographic distance weight matrix	−0.591***	0.685***	0.162
	Economic geography nested weight matrix	−0.513***	0.128*	0.127
Middle	Geographic distance weight matrix	−0.510***	0.018***	0.090
	Economic geography nested weight matrix	−0.669***	0.211***	0.178
Lower	Geographic distance weight matrix	−0.731***	0.119*	0.168
	Economic geography nested weight matrix	−0.425***	0.165**	0.173

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

common steady state. Among them, the upper reaches has the fastest convergence speed, and the lower reaches has the slowest convergence speed. Under the influence of the level of economic development, industrial structure, market environment, degree of economic openness, and technological progress, the convergence speed of all regions is accelerated to varying degrees, which indicates that the control variables can promote the steady-state convergence of environmental regulation efficiency in the overall Yellow River Basin and the three regions. The analysis based on spatial convergence significantly shows the characteristics of the spatial evolution of environmental regulation efficiency in the Yellow River Basin, which can compensate for the lack of research on the dynamic evolution trend of environmental regulatory efficiency (Cheng et al., 2016; Jia et al., 2022).

Our contribution includes three aspects. First, the super-EBM model was used to measure the environmental regulation efficiency in the Yellow River Basin from multiple dimensions of cities, regions, and overall, solving the problem of non-radial slack, radial ratio information, and the pros and cons of various effective decision-making units (DMUs), which helped to enrich the measurement method to some extent. Second, we analyzed the regional differences in environmental regulation efficiency in the Yellow River Basin from the perspectives of composition and source. We also revealed the dynamic evolution characteristics of regional differences, which can provide empirical support for policies based on regional circumstances. Finally, the spatial absolute and conditional β convergence across regions in the Yellow River Basin were verified in light of the spatial effects, which provided guidance and reference for establishing environmental regulation efficiency policy systems and green coordinated development. Our findings and research methodology can provide references for similar regions to select appropriate environmental regulation tools based on local conditions and explore a new way of economic development and eco-environmental protection.

5 Conclusions and policy implications

In this paper, we calculated the environmental regulation efficiency of 75 cities in the Yellow River Basin from 2007 to 2020 using the super-EBM model containing the undesirable output. Further, we analyzed the regional differences, dynamic evolution, and spatio-temporal convergence of environmental regulation efficiency among regions using the Dagum Gini coefficient, kernel density estimation method, and spatial econometric model. The main findings are as follows: First, the average environmental regulation efficiency of the overall Yellow River Basin and the upper, middle, and lower reaches had an increasing trend. The average environmental regulation efficiency in the upper and lower reaches was higher than the overall average, while that in the middle reaches was lower than average but increased fastest. Second, the overall Yellow River Basin and the three regions had obvious within-region differences, and the differences within the middle reaches were the largest. The differences between all regions had a narrowing trend. The regional differences between the upper and middle reaches and the middle and lower reaches were higher than those between the upper and lower reaches. The intensity of transvariation was the main source of spatial differences in environmental regulation efficiency, and the within-regional difference was the second source, with the lowest contribution to the between-regional difference. Third, the gap between the cities with higher environmental regulation efficiency and those with average efficiency had been reduced in the Yellow River Basin. The upper reaches had a significant spatial polarization phenomenon and maintained a certain level. The dynamic evolutionary characteristics of the overall Yellow River Basin and the lower reaches were relatively similar, the within-region polarization tended to weaken, and the differences gradually decreased. Finally, the coefficient of σ convergence of environmental regulation efficiency in the overall Yellow River Basin was increasing to some extent, so there is no σ convergence. Meanwhile, the coefficients of σ convergence for environmental regulation efficiency in the upper, middle, and lower reaches showed a fluctuating decreasing trend, which indicates σ convergence, and the convergence speed in the lower reaches was fast. Overall, the upper, middle, and lower reaches all had significant spatial absolute and conditional β convergence, and they will converge to their respective steady-state levels over time. Their conditional β convergences were faster than absolute β convergences with shorter half-life cycles, indicating that economic, environmental, and social factors such as the level of economic development, industrial structure, market environment, degree of economic openness, and technological progress accelerated the convergence of regional differences.

To further improve the environmental regulation efficiency in the Yellow River Basin, the following policy implications are derived based on the results: First, it is necessary to increase environmental investment and support in the middle reaches of the Yellow River to continuously narrow the gap in environmental regulation efficiency between the middle and lower reaches. As one of the regions with the most significant and fastest-growing pressures on resources and the environment, the middle reaches should optimize the combination of environmental regulation tools, strictly control the scale of highly polluting and energy-consuming industries, and curb the transfer of polluting industries to it, and taking the development of a circular, low-carbon, and green economy as an opportunity to promote the transformation of the economic growth mode to a low consumption and pollution economic development mode. Second, through administrative means such as breaking regional boundaries, improving the property rights trading system for resources and the environment, and optimizing the supply of services, we will facilitate the cross-regional flow of urban input factors, environmental information sharing, and policy coordination, especially by creating conditions and preferential policies for environmental governance exchange and cooperation between cities with lower environmental regulation efficiency and higher cities. Innovative explorations can be considered in constructing resource-sharing platforms, eco-environmental restoration, policy co-benefits, and other win-win benefits. Third, we should be wary of the dangers of over-polarization and the widening disparity in environmental regulation efficiency in the upper reaches of the Yellow River Basin and instead concentrate on improving the diffusion and radiation effects of cities at the growth poles of environmental regulation efficiency to neighboring cities. By establishing a collaborative governance mechanism, breaking the "siphon effect" and reasonably weakening the polarization effect, we can achieve a balanced development of environmental regulation efficiency in the upper reaches. The two core cities of Lanzhou and Xining, in particular, play the role of radiation diffusion of industrial structure transformation and upgrading with the implementation of the western development strategy and accelerate the neighboring cities to improve the proportion of strategic new industries to continuously promote the synergistic improvement of environmental regulation efficiency with the environmental construction of the Lanzhou–Xining urban agglomeration. Finally, the rate of change in environmental regulation efficiency is influenced by various factors. We should fully implement the new development concept, strengthen the development potential according to our own environmental resources endowment and comparative advantages, accelerate the convergence speed of environmental regulation efficiency by transforming and upgrading industrial structures, enhancing independent innovation capability, improving the market economy system and harmonizing fiscal and environmental policies, and then promote the economic development and ecological protection of the Yellow River Basin.

There are still limitations to the study of differences and convergence in environmental regulation efficiency in the Yellow River Basin. Due to the difficulty of data acquisition, this study selected research samples from 75 prefecture-level cities in the Yellow River Basin, but the research on regional differences and convergence in environmental regulation efficiency at the county level based on micro-perspectives will be the focus of our future research. In addition, the club convergence of environmental regulation efficiency at the county level should also be further analyzed on the basis of their initial values. Meanwhile, the number of control variables can also restrict the spatial conditional β convergence conclusions. In future research, we intend to increase the number of control variables and continuously improve the research results.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

FL: conceptualization, software, data curation, and writing—original draft preparation. HR: methodology and writing—reviewing. XZ: editing and visualization. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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