Advancing green transition: regional gaps, dynamic evolution, and decoupling effects of livestock environmental efficiency in China

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Abstract: Investigating the spatiotemporal heterogeneity of livestock environmental efficiency and its decoupling effect is crucial for fostering the coordinated development of livestock economy and environmental sustainability. This study examines the spatiotemporal distribution, regional gaps, dynamic evolution, and decoupling effect of livestock environmental efficiency across 30 provinces in China from 2006 to 2021. By integrating the super-efficiency EBM-DEA model, the GML index, the Theil index, kernel density estimation, and the decoupling model, we provide a comprehensive analysis of the sector's efficiency dynamics. The findings indicate that while China's livestock environmental efficiency has exhibited an overall upward trend, its absolute level remains relatively low, with a significantly higher number of non-DEA-efficient provinces compared to DEA-efficient ones. The total factor productivity of livestock environmental efficiency has shown continuous improvement, primarily driven by technological progress. The Theil index analysis reveals an uneven regional distribution, with the highest gaps observed in the eastern region (11.93%), followed by the western (10.96%), northeast (8.78%), and central regions (7.37%), with intra-regional gaps being the dominant source of overall gaps. Moreover, provincial gaps in livestock environmental efficiency are substantial and exhibit a polarization trend. During the periods covered by the 11th to 13th Five-Year Plans, the decoupling relationship between livestock environmental efficiency and economic growth predominantly manifested as "strong decoupling," "expansive negative decoupling," and "weak decoupling," with the latter two representing more favorable development states. These findings offer valuable insights for policymakers to optimize regional strategies and enhance the sustainability of the livestock industry.

Keywords: livestock environmental efficiency; regional gaps; dynamic evolution; decoupling effects; green transition

1. Introduction

Given the significant environmental challenges posed by CO_2 emissions and livestock waste pollutants, optimizing input factors, strategically reallocating resources, and enhancing input-output efficiency in livestock production have become critical for advancing green development (Hou et al., 2021). In response, many countries have implemented policies aimed at promoting sustainability within the livestock industry (Costa et al., 2021; Wang et al., 2024). For example, the United States Department of Agriculture (USDA) has introduced various agri-environmental protection programs focused on carbon sequestration, energy conservation, and land preservation. Similarly, the European Union (EU) has enacted policies providing institutional support for greening the livestock sector and promoting circular agricultural practices. In Asia, Japan has established legal frameworks to mitigate agricultural and livestock pollution, reduce environmental impacts, and protect agro-ecological systems. China's Central Government Document No.1 consistently highlights the importance of rural ecological conservation and sustainable livestock development. Scholars further emphasize that improving input-output efficiency is essential for enhancing the overall quality and sustainability of agricultural and livestock industries (Bai et al., 2018; Wen et al., 2025). Therefore, accurately assessing livestock environmental efficiency is crucial for guiding the sector’s transition towards green development.

Accurately assessing livestock input-output efficiency is crucial for developing and implementing effective green development policies (Lemaire et al., 2014; Zeng et al., 2025). Livestock manure generates significant non-point source pollution, exacerbating water contamination and ecological degradation. Therefore, prioritizing sustainable and circular development in the livestock industry has become increasingly important (Wang et al., 2021; Xu et al., 2023; Miller et al., 2021). Additionally, challenges such as forage shortages due to excessive input factors and inefficiencies in aligning output with input structures hinder the sector’s transition toward high-quality and sustainable development (Li et al., 2024; Zhang et al., 2020). Achieving green and efficient livestock production requires rational adjustments to input structures, improved resource utilization, and enhanced ecological performance. In this context, evaluating regional disparities, dynamic evolution, and decoupling effects of livestock environmental efficiency in China provides valuable insights. This evaluation helps reduce resource and environmental dependencies, regulate herders' management practices, and promote the simultaneous achievement of economic and environmental benefits within the livestock sector.

Technical efficiency and total factor productivity (TFP) growth are essential for ensuring the sustainability of industries (Deng et al., 2023; Shen et al., 2024). Despite rapid economic growth, China's livestock industry continues to face significant environmental pollution and waste emission challenges, which hinder its development quality and efficiency. Existing research has extensively examined agri-environmental efficiency, focusing on indicator measurement, spatial-temporal evolution, and influencing factors, particularly in crop cultivation (Liu et al., 2020; Guo et al., 2022; Wen et al., 2024). Studies have also investigated environmental total factor productivity, agricultural green production efficiency, and water-use efficiency, incorporating carbon emissions and non-point source pollution as undesirable outputs (Song et al., 2022; Lei et al., 2023; Sun et al., 2023). Furthermore, research by Xiao et al. (2022) and Wang and Long (2024) has explored endogenous drivers such as industry agglomeration and technological advancements that contribute to improvements in agricultural environmental efficiency. However, while some studies have addressed livestock environmental efficiency and green total factor productivity (Abed and Acosta, 2018; Acosta and Luis, 2019), research in the livestock sector remains relatively limited compared to the agricultural and plantation sectors (Ma et al., 2024). This gap highlights the need for further refinement and enhancement of methodologies to better assess and optimize livestock environmental efficiency.

In recent years, China’s livestock industry has seen steady growth in total output value, coupled with reduced CO_2 and pollutant emissions from waste, indicating improvements in development quality and efficiency (Zhang et al., 2022; Zou et al., 2024). Scholars have examined the sector’s efficiency, focusing on total factor productivity, eco-efficiency, and green total factor productivity (Xu et al., 2019; Li et al., 2024). Common input indicators include labor, capital, technology, and land, with total output value as the desirable output (Wang et al., 2024; Wu et al., 2024). Carbon emissions are often included as undesirable outputs, but non-point source pollution is less frequently considered (Yang et al., 2024). Unlike agriculture, livestock farming traditionally relied on draft animals, rarely integrated into input indicators. From 2001 to 2011, China’s livestock sector showed both strong and weak decoupling between GHG emissions and economic output, with an overall decoupling elasticity of -0.004 (Chen and Shang, 2014). Advancing low-carbon technologies, clean manure treatment, and improved breeds is crucial, along with enhancing environmental technology efficiency (Zhao et al., 2024). While studies explore carbon emissions, non-point source pollution, and economic growth, research linking environmental efficiency to livestock economic growth remains nascent, necessitating further integration for sustainable development.

Existing research has significantly advanced the understanding of environmental input-output efficiency in China's livestock sector, providing valuable insights. However, several gaps remain: (1) Limited Research Focus: Compared to the plantation industry, studies on livestock environmental efficiency are scarce, despite the sector's higher pollutant emissions and distinct input structure. Deeper investigation is urgently needed. (2) Incomplete Measurement Frameworks: Current frameworks often omit draft animal inputs and certain undesirable outputs, such as non-point source pollution, which undermines assessment accuracy. (3) Narrow Scope of Studies: Most studies focus on agricultural carbon emissions and non-point source pollution, with limited attention to the decoupling relationship between livestock environmental efficiency and economic growth.

Addressing these limitations through further research and refining measurement methodologies is crucial for providing robust insights that foster sustainable livestock development.

To address the limitations of previous research, this study introduces several innovations: (1) This study evaluates both input-output efficiencies and their spatiotemporal dynamics, as well as decoupling effects, specifically for China's livestock sector. Previous research primarily focused on large-scale agriculture. (2) By incorporating draft animal inputs and expanding undesirable outputs to include livestock carbon emissions (encompassing energy use) and five types of non-point source pollutants, this study improves measurement accuracy. (3) This study examines the relationship between livestock environmental efficiency and economic growth, helping to reduce inter-regional development gaps and enriching the understanding of livestock environmental efficiency. These innovations aim to provide a more comprehensive and accurate assessment of livestock environmental efficiency, supporting sustainable development efforts.

2. Materials and methods

2.1. Study area description

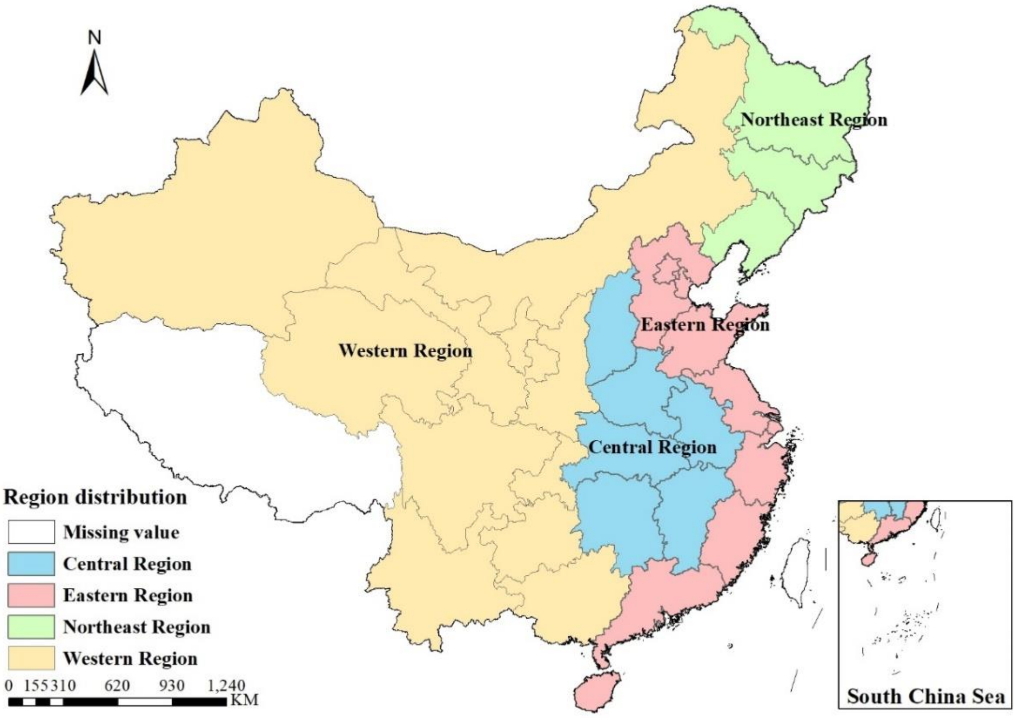


Figure 1. Study area in China under four-regional perspective

Note: The map is based on the standard map with review number GS2019 (1838) downloaded from the website of the Standard Map Service of the Ministry of Natural Resources, with no modifications to the base map. Same as below.

This study covers 30 provinces in mainland China, excluding Hong Kong, Macao, Taiwan, and Tibet. Due to the lack of data on livestock energy consumption in Tibet, accurately measuring its livestock carbon emissions is challenging. To ensure the reliability of the livestock environmental efficiency assessment, Tibet is excluded from the analysis. Drawing upon guidelines issued by the

Central Committee of the Communist Party of China, the State Council's policies for advancing the central region, and directives from the 16th National Congress, China's economy is delineated into four primary regions: Eastern, Central, Western, and Northeast regions. This categorization is grounded in a comprehensive assessment of natural resources, economic foundations, and developmental stages. As shown in Fig. 1, China's regions are divided as follows: the eastern region (10 provinces, including Beijing, Tianjin, and Hebei), the central region (6 provinces, such as Shanxi, Henan, and Anhui), the western region (11 provinces, including Inner Mongolia, Xinjiang, Sichuan, and Yunnan), and the northeast region (3 provinces—Liaoning, Jilin, and Heilongjiang).

2.2. Data collection

This study employs provincial data from 2006 to 2021 to assess livestock environmental efficiency in China. Carbon emissions data are sourced from the China Livestock and Veterinary Medicine Yearbook (2007–2022) and the China Energy Statistics Yearbook (2007–2022). Livestock non-point source pollution emissions data are based on calculations from the National Survey on the Status of Pollution in Large-Scale Livestock and Poultry Breeding and Prevention Countermeasures (SEPA, 2002). Additional calculated data are primarily drawn from the China Statistical Yearbook (2007–2022), China Rural Statistical Yearbook (2007–2022), China Livestock and Veterinary Medicine Yearbook (2007–2022), China Environmental Statistical Yearbook (2007–2022), and China Grassland Yearbook. Missing data are addressed through interpolation.

2.3. Model specification

2.3.1. Super-efficient EBM-DEA model

Data Envelopment Analysis (DEA) is a widely used method for input-output efficiency analysis. The super-efficient DEA model improves upon traditional DEA by allowing efficiency comparisons among multiple effective decision-making units (Andersen & Petersen, 1993). While previous studies often apply the super-efficient SBM-DEA model to account for non-radial slack variables, it lacks information on the ratio between target and actual input or output values (Wei et al., 2021). The EBM model, proposed by Tone and Tsutsui (2010), integrates radial and non-radial distance functions, reducing biases associated with single-distance function models. To comprehensively assess livestock input-output efficiency in China, this study incorporates livestock carbon emissions and non-point source pollution emissions as undesirable outputs to measure environmental efficiency. Accordingly, a super-efficient EBM-DEA model is constructed, integrating both types of undesirable outputs, as detailed below.

$$r^{*} = min\frac{\theta-\varepsilon^{-}\sum_{i=1}^{m}\frac{w_{i}^{-}s_{i}^{-}}{x_{i0}}}{\psi+\varepsilon^{+}\left(\sum_{r=1}^{s}\frac{w_{r}^{+}s_{r}^{+}}{y_{r0}}+\sum_{p=1}^{q}\frac{w_{p}^{-}s_{p}^{-}}{y_{p0}}\right)} \tag{1}$$

$$\text{s.t.}\sum_{j=1}^{n}x_{ij}\lambda_{j}+s_{i}^{-}=\theta x_{i0} \tag{2}$$

$$\sum_{j=1}^{n} y_{ij}\lambda_j - s_r^+ = \varphi y_{r0} \quad (3)$$

$$\sum_{j=1}^{n} u_{pj}\lambda_j + s_p^- = \varphi u_{p0} \quad (4)$$

$$\lambda_j \geq 0;\ s_i^-、s_r^+、s_p^- \geq 0; i = 1,2,\cdots,m; r = 1,2,\cdots,s; p = 1,2,\cdots,q \quad (5)$$

Where r^* denotes the most efficient value measured by the model; x_{i0}, y_{r0}, u_{p0} denote inputs, desirable outputs and undesirable outputs of DMU_0; s_i^-, s_r^+ and s_p^- denote input slack, desirable output slack and undesirable output slack; w_i^-, w_r^+, w_p^- denote the weights of input, desirable outputs and undesirable outputs indicators; θ denotes the efficiency value under radial conditions, which can be obtained through calculation; ε is the key parameter that signifies the significance of the non-radial component within the super-efficient EBM model, with its value ranging from [0,1]. When $\varepsilon = 0$, the EBM model is equivalent to the CCR model; when $\theta = \varepsilon = 0$, the EBM model transforms into the SBM model.

Building on existing research (Martinsson & Hansson, 2021; Li et al., 2024) and the core concept of livestock environmental efficiency, this study selects livestock actual output value as the desirable output indicator for economic growth. Livestock carbon emissions and non-point source pollution emissions are chosen as undesirable output indicators. Input variables include livestock practitioners for labor input, available grassland area for land input, total power of livestock machinery for technological input, livestock fixed asset investment for capital input, and the number of large livestock at year-end for draft animal input (Table 1).

Table 1. Evaluation index system of the livestock environmental efficiency in China

Category	Variable	Explanation
Input	Labor	Livestock practitioners (10^4 person)
	Land	Available grassland area (10^3 ha)
	Technology	Total power of livestock machinery (10^4 Kw·h)
	Fixed assets	Livestock fixed asset investment (10^8 yuan)
	Draft animal	Number of large livestock at year-end (10^4 head)
Desirable output	Livestock actual output value	Constant price 2006 (10^8 yuan)
Undesirable output	Livestock carbon emission	Livestock CO_2 emission (10^4 tons)
	Livestock non-point source pollution emission	Pollutant emissions from livestock and poultry manure (10^4 tons)

2.3.2. Global Malmquist-Luenberger (GML) model

Charnes et al. (1978) enhanced efficiency evaluation by incorporating environmental factors, merging the traditional Malmquist index with a directional distance function to develop the Malmquist-Luenberger (ML) index. This index aligns with the study's goal of increasing desirable outputs while reducing undesirable ones. However, the ML index has limitations, including non-transferable results and infeasible solutions due to geometric averaging of only two efficiency values

(Chung et al., 1997). To address these issues, Oh (2010) introduced the Global Malmquist-Luenberger (GML) index by integrating global production technology with the ML index. The GML index allows for efficiency comparisons over time, overcoming the limitations of the traditional ML index. Therefore, this study applies the GML index model to analyze the dynamic changes and decomposition of livestock environmental efficiency in China. Using the global directional distance function, the GML productivity index from period t to t+1 is defined as follows:

$$GML^{t,t+1}(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1})=\frac{1+D^G(x^t,y^t,b^t)}{1+D^G(x^{t+1},y^{t+1},b^{t+1})}=\frac{1+D^t(x^t,y^t,b^t)}{1+D^{t+1}(x^{t+1},y^{t+1},b^{t+1})}\times$$

$$\left[\frac{1+D^G(x^t,y^t,b^t)}{1+D^t(x^t,y^t,b^t)}\times\frac{1+D^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{1+D^G(x^{t+1},y^{t+1},b^{t+1})}\right]=EC^{t,t+1}\times TC^{t,t+1}=PEC^{t,t+1}\times SEC^{t,t+1}\times TC^{t,t+1} \quad (6)$$

Where $D^G(x,y,b)=max\{\beta|(y+\beta y,b-\beta b)\in P^G(x)\}$ denotes the global directional distance function that depends on the global set of production possibilities $P^G(x)$; $GML^{t,t+1}$ denotes the change in the livestock environmental efficiency in two adjacent decision-making units during the study period; $GML^{t,t+1}>1$ denotes improvement of the livestock environmental efficiency, $GML^{t,t+1}<1$ denotes reduction of the livestock environmental efficiency; $EC^{t,t+1}$ denotes the change in the environmental technology efficiency; $EC^{t,t+1}>1$ denotes improvement of the environmental technology efficiency, $EC^{t,t+1}<1$ denotes reduction of the environmental technology efficiency; $TC^{t,t+1}$ denotes the change in the environmental technology progress; $TC^{t,t+1}>1$ denotes improvement of the environmental technology progress, $TC^{t,t+1}<1$ denotes environmental technology regression; $PEC^{t,t+1}$、$SEC^{t,t+1}$ denote pure technical efficiency and scale efficiency. The GML index and its decomposition can be utilized to delve deeper into the underlying factors driving changes in the livestock environmental efficiency. To measure and decompose the GML index, the directional distance function in Eq. (7) is derived by solving it using the following DEA linear programming model.

$$D^t(x^t,y^t,b^t)=max\beta \quad (7)$$

$$\text{s.t.}\, x_\gamma\le x_k^t, y_\gamma\ge(1+\beta)y_k^t, b_\gamma=(1-\beta)b_k^t, \gamma\ge 0$$

$$D^G(x^t,y^t,b^t)=max\beta \quad (8)$$

$$\text{s.t.}\, x_\gamma\le x_k^t, y_\gamma\ge(1+\beta)y_k^t, b_\gamma=(1-\beta)b_k^t, \gamma\ge 0$$

Similarly, the directional distance function $D^{t+1}(x^{t+1},y^{t+1},b^{t+1})$ for period t+1 and the global directional distance function $D^{G+1}(x^{t+1},y^{t+1},b^{t+1})$ for period t+1 can be obtained.

2.3.3. Theil index model

The Theil index, derived from a generalized entropy measure, is also known as the Theil entropy index when the general entropy standard index equals zero. This index effectively quantifies the contribution of intra- and inter-regional gaps to overall gaps (Lambert et al., 2010). Typically ranging from 0 to 1, a higher value indicates greater regional gaps, while a lower value suggests more uniform distribution. This study applies the Theil index model to evaluate intra- and inter-regional gaps in China's livestock environmental efficiency. It aims to measure national gaps, intra- and inter-regional gaps, and their respective contribution rates. The specific calculation formulas are as follows:

$$T = \frac{1}{k}\sum_{q=1}^{k}\left(\frac{LEE_q}{\overline{LEE}} \times ln\frac{LEE_q}{\overline{LEE}}\right) \tag{9}$$

$$T_p = \frac{1}{k_p}\sum_{q=1}^{k_p}\left(\frac{LEE_{pq}}{\overline{LEE_p}} \times ln\frac{LEE_{pq}}{\overline{LEE_p}}\right) \tag{10}$$

$$T = T_w + T_b = \sum_{p=1}^{4}\left(\frac{k_p}{k} \times \frac{\overline{LEE_p}}{\overline{LEE}} \times T_p\right) + \sum_{p=1}^{4}\left(\frac{k_p}{k} \times \frac{\overline{LEE_p}}{\overline{LEE}} \times ln\frac{\overline{LEE_p}}{\overline{LEE}}\right) \tag{11}$$

Here, T denotes the overall Theil index of the livestock environmental efficiency at the whole country. Its size is at [0,1], the larger Theil index means that the regional gaps are also larger, and vice versa, the smaller the regional gaps are. q denotes province, k denotes the number of provinces, LEE_q denotes the livestock environmental efficiency in province q, and $\overline{LEE}$ denotes the national average of the livestock environmental efficiency. In Eq.(10), T_p denotes the overall Theil index of region p, k_p denotes the number of provinces in region p, LEE_{pq} denotes the livestock environmental efficiency in province q of region p, $\overline{LEE_p}$ denotes average of the livestock environmental efficiency in region p. In Eq. (11), the overall Theil index of the livestock environmental efficiency can be further decomposed into an intra-regional Theil index T_w and an inter-regional Theil index T_b. In addition, define T_w/T and T_b/T as the contribution of intra-regional and inter-regional gaps to the overall gaps; define $(C_P/C) \times (T_p/T)$ as the contribution of each region to the overall gaps within the region. Where LEE_P denotes the sum of the livestock environmental efficiency in each province within region p, and T_p denotes the sum of the livestock environmental efficiency at the whole country.

2.3.4. Kernel density estimation

Kernel density estimation is a key nonparametric method for analyzing the distribution characteristics of environmental efficiency in China through continuous density curves (Heidenreich et al., 2013). The horizontal position of the kernel density curve within a single period reflects livestock environmental efficiency, while vertical comparisons across multiple periods reveal its dynamic evolution. Additionally, horizontal comparisons across regions highlight gaps in efficiency change trajectories. The kernel density function for livestock environmental efficiency in region j is defined as follows:

$$f_j(y) = \frac{1}{n_j h}\sum_{i=1}^{n_j} K\left(\frac{y_{ji} - y}{h}\right) \tag{12}$$

Here, $K(\cdot)$ denotes the kernel density function which describes the proportion of all sample points y_{ji} in the y neighbourhood. h denotes the window width for kernel density estimation. Common kernel density functions include the Gaussian, Epanechnikov, biweight, and triangular kernels. However, the choice of kernel function generally has minimal impact on estimation results. Therefore, this study employs the commonly used Gaussian kernel function, expressed as follows:

$$K(x) = \frac{1}{\sqrt{2\pi}} exp\left[-\frac{x^2}{2}\right] \tag{13}$$

For window width selection, a smaller width increases estimation accuracy but reduces sample size, leading to higher variance and a smoother density curve. This study adopts Silverman's (1986) optimal window width selection method to determine the appropriate bandwidth.

2.3.5. Decoupling model

The concept of decoupling, originally from physics, describes the weakening or disconnection of relationships between variables over time (Bai et al., 2021). This study applies the Tapio decoupling model to examine the relationship between livestock environmental efficiency and economic growth. The calculation formula is as follows:

$$T_i = \frac{\%\triangle\gamma}{\%\triangle\mu} = \frac{\triangle\gamma/\gamma}{\triangle\mu/\mu} = \frac{(\gamma_{i+1}-\gamma_i)/\gamma_i}{(\mu_{i+1}-\mu_i)/\mu_i} \tag{14}$$

Where T_i denote the decoupling index for period i, i.e. the type of decoupling status between the livestock environmental efficiency and economic growth; $\%\triangle\gamma$ and $\%\triangle\mu$ denote the change rate of livestock environmental efficiency and economic growth in period i; $\triangle\gamma$ and $\triangle\mu$ denote the change amount of livestock environmental efficiency and economic growth in period i; γ_i and γ_{i+1} denote the value of the livestock environmental efficiency in the beginning and end years of period i; μ_i and μ_{i+1} denote the value of the livestock total output value in the beginning and end years of period i. Based on relevant research, critical values of 0.8 and 1.2 were used to define the decoupling state. Accordingly, classification criteria were established to identify the decoupling relationship between livestock environmental efficiency and economic growth in China (Table 2).

Table 2. The criteria of decoupling indicator.

Typology		$\triangle\gamma$	$\triangle\mu$	Tapio
Negative decoupling	Strong negative decoupling	+	–	(–∞,0)
	Weak negative decoupling	–	–	(0,0.8)
	Expansive negative decoupling	+	+	(1.2,+∞)
Decoupling	Strong decoupling	–	+	(–∞,0)
	Weak decoupling	+	+	(0,0.8)
	Recessive decoupling	–	–	(1.2,+∞)
Coupling	Expansive coupling	+	+	(0.8,1.2)
	Recessive coupling	–	–	(0.8,1.2)

3. Results

3.1. Static analysis of livestock environmental efficiency in China

3.1.1. Spatial and temporal distribution of livestock environmental efficiency

China livestock environmental efficiency was evaluated using MaxDEA Ultra software for the years 2006, 2011, 2016, and 2021. As shown in Fig. 2, the average efficiency values for these years were 0.376, 0.452, 0.581, and 0.585, reflecting a steady upward trend. This improvement aligns with China's transition toward environmentally sustainable livestock farming, driven by policies such as the 13th Five-Year Plan for Ecological and Environmental Protection. These initiatives emphasize pollution control, resource optimization, and integrated breeding-husbandry approaches, contributing to enhanced environmental efficiency. Among all provinces, Jiangsu is the only one achieving DEA efficiency, with an environmental efficiency value of 1.019. In contrast, all other provinces exhibit values below 1, indicating inefficiencies in livestock environmental management. This suggests that while progress has been made, a substantial gap remains in achieving efficient and sustainable livestock development nationwide.

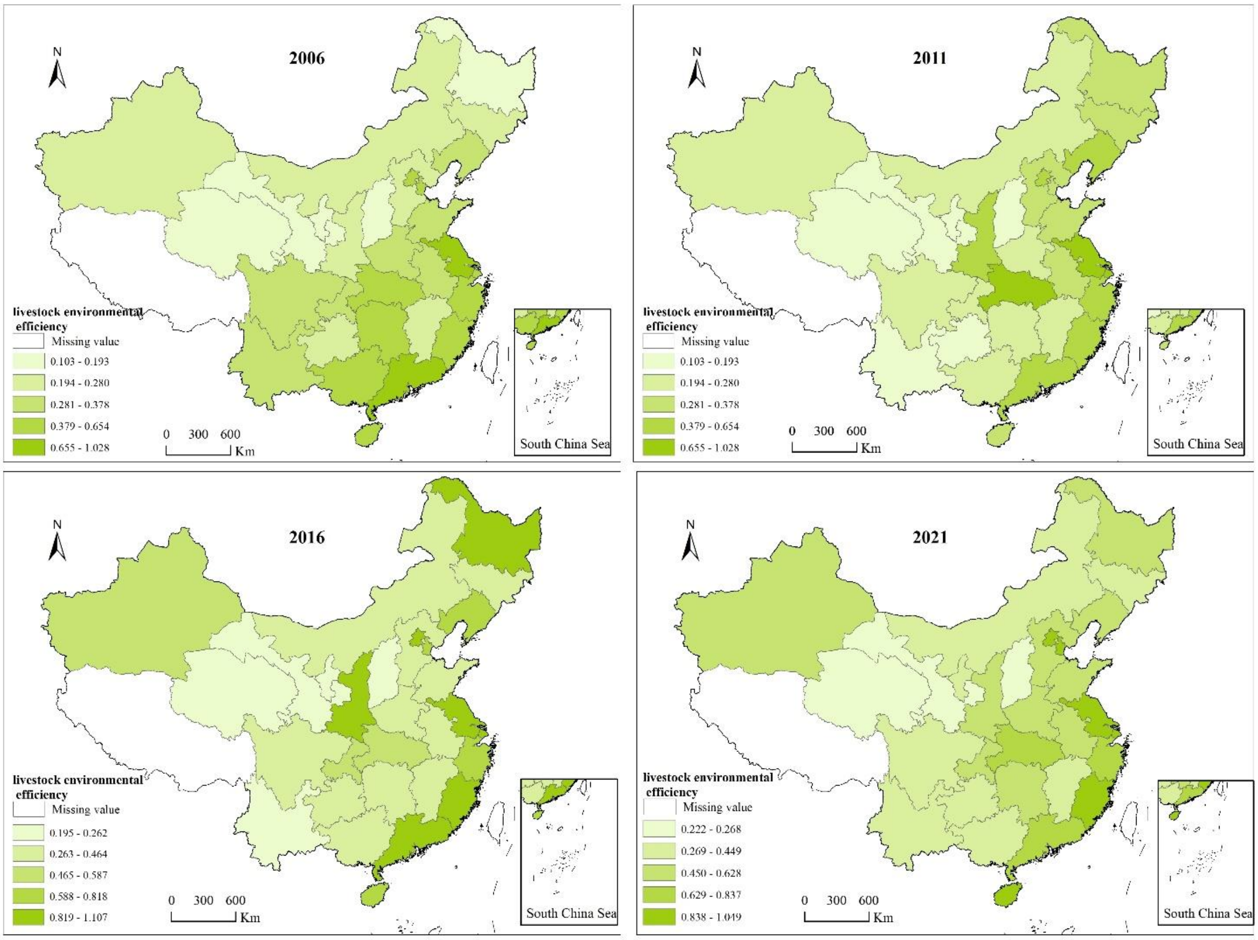


Figure 2. Spatial distribution of the livestock environmental efficiency in China (2006, 2011, 2016, 2021)

Regarding provincial efficiency classifications, only two provinces achieved DEA efficiency (efficiency >1) in 2006, accounting for just 6.67% of the total sample. By 2011, 2016, and 2021, the number of DEA-efficient provinces increased to 3, 6, and 6, representing 10%, 20%, and 20% of the total. This trend indicates that in most provinces, environmental inputs in the livestock sector have not yet translated into proportionally high outputs, highlighting significant room for efficiency improvement. Notably, provinces with higher livestock environmental efficiency are primarily concentrated in eastern China. This region benefits from advantageous geographical conditions, which attract foreign investment and facilitate the adoption of advanced breeding technologies. Additionally, the more efficient utilization of production inputs in the eastern region contributes to its higher environmental efficiency.

A comparison of the spatial distribution and temporal changes in China's livestock environmental efficiency since 2006 reveals notable improvements in Beijing, Shanghai, and Fujian, where efficiency reached DEA levels. Additionally, some central and western provinces, such as Shaanxi and Hubei, exhibited efficiency values exceeding 1 in specific years. However, in several provinces, environmental efficiency has shown a fluctuating downward trend or followed an inverted "U" or positive "U" pattern. For instance, Liaoning, Jilin, and Heilongjiang demonstrated an inverted "U" trend, likely due to the region's relatively small livestock sector and the persistence of resource-intensive, pollution-prone farming models. In contrast, Sichuan and Guangxi exhibited an inverted "N" and a positive "U" pattern, reflecting ecological constraints that hinder sustainable grass-fed livestock development.

3.1.2. Cluster analysis of livestock environmental efficiency

This study employed the systematic clustering method in SPSS 17.0 to classify the mean livestock environmental efficiency of 30 Chinese provinces into four distinct groups, as indicated by the clustering results (Table 3). Category I includes Shanghai and Jiangsu, which lead in production with environmental efficiency scores exceeding 0.90, indicating a high level of efficiency. Category II comprises five provinces—Beijing, Fujian, Zhejiang, Guangdong, and Hainan—where efficiency ranges from 0.65 to 0.90. While these provinces achieve DEA efficiency in some years, occasional inefficiencies highlight the need for further improvement. Category III consists of Shaanxi, Liaoning, Tianjin, Heilongjiang, and Hubei, with efficiency scores between 0.50 and 0.65, exhibiting minimal fluctuation but significant potential for enhancement. Category IV encompasses 18 provinces, including Xinjiang, Anhui, and Shandong, with efficiency values below 0.50, reflecting a considerably low environmental performance and substantial room for improvement.

Provinces in Categories I and II are predominantly located in the eastern region, exhibiting higher livestock environmental efficiency and ranking among the top nationwide. In contrast, Categories III and IV mainly include provinces in the central, western, and northeast regions, where efficiency levels are notably lower. However, livestock environmental efficiency does not strictly follow the conventional geographical division of China’s four major regions. For instance, despite their advanced economic development, Tianjin, Shandong, and Hebei in the eastern region do not reach the DEA efficiency frontier. This indicates that economically strong provinces may still face inefficiencies due to irrational input structures and excessive resource consumption. Additionally, Sichuan, Henan, and Hunan—major livestock producers—fall into Category IV, highlighting the urgent need for resource-efficient and environmentally friendly development strategies.

Table 3. Clustering results of the livestock environmental efficiency in China

Classification	Provinces
Category I	Shanghai, Jiangsu
Category II	Beijing, Fujian, Zhejiang, Guangdong, Hainan
Category III	Shaanxi, Liaoning, Tianjin, Heilongjiang, Hubei
Category IV	Xinjiang, Anhui, Shandong, Hebei, Chongqing, Jilin, Hunan, Henan, Sichuan, Guangxi, Inner Mongolia, Jiangxi, Guizhou, Yunnan, Ningxia, Shanxi, Qinghai, Gansu

3.2. Dynamic analysis of livestock environmental efficiency in China

The super-efficiency EBM-DEA model provides a static analysis of livestock environmental efficiency. To capture dynamic trends, we evaluated total factor productivity and its decomposition across 30 provinces for 2006, 2011, 2016, and 2021 using the Global Malmquist-Luenberger (GML) index, as detailed in Table 4.

Table 4 presents the annual average values of TFP and its decomposition indices for livestock environmental efficiency across provinces during the study period. Overall, China's livestock environmental TFP remains above 1, indicating a positive productivity trend. Both efficiency change (EC) and technological change (TC) exceed 1 on average, with TC surpassing EC, suggesting that technological progress contributes more to TFP than technological efficiency. Notably, TC remains above 1 in all provinces, whereas EC falls below 1 in four provinces, highlighting the need to enhance both technology adoption and its effective utilization. Provincial-level analysis shows an overall upward trend in TFP, TC, and EC, though the primary drivers of efficiency change vary. In Beijing, Guangdong, Anhui, Hubei, Guangxi, Sichuan, Yunnan, and Ningxia, efficiency improvements are driven mainly by pure technical efficiency, while in Liaoning and Jilin, scale efficiency is the dominant factor.

Table 4. The GML index and its decomposition of the livestock environmental efficiency in China

Province	GML	TC	EC	PEC	SEC
Beijing	1.127	1.125	0.999	1.003	0.997
Tianjin	1.146	1.152	1.047	1.050	1.011
Hebei	1.136	1.150	1.082	1.000	1.080
Shanxi	1.133	1.133	1.029	1.020	1.009
Inner Mongolia	1.124	1.154	1.031	1.024	1.015
Liaoning	1.079	1.103	1.021	0.976	1.052
Jilin	1.098	1.115	0.998	0.998	1.026
Heilongjiang	1.151	1.159	1.075	1.067	1.008
Shanghai	1.065	1.059	1.003	1.237	1.306
Jiangsu	1.096	1.094	1.002	1.000	1.002
Zhejiang	1.150	1.170	1.017	1.006	1.014
Anhui	1.146	1.156	1.088	1.111	0.968
Fujian	1.117	1.108	1.024	1.004	1.020
Jiangxi	1.119	1.139	1.027	1.017	1.016
Shandong	1.102	1.097	1.011	1.001	1.009
Henan	1.109	1.091	1.027	1.010	1.035
Hubei	1.166	1.123	1.053	1.067	0.989
Hunan	1.117	1.198	1.021	1.013	1.019
Guangdong	1.091	1.125	1.000	0.999	0.997
Guangxi	1.081	1.151	0.999	1.024	0.991
Hainan	1.117	1.175	1.056	1.031	1.010
Chongqing	1.114	1.111	1.026	1.018	1.010
Sichuan	1.066	1.119	0.990	0.999	0.991
Guizhou	1.111	1.146	1.045	1.024	1.024
Yunnan	1.100	1.120	1.019	1.053	0.974
Shannxi	1.173	1.122	1.103	1.086	1.018
Gansu	1.110	1.157	1.035	1.017	1.022
Qinghai	1.143	1.146	1.056	1.045	1.013
Ningxia	1.202	1.159	1.110	1.104	0.998
Xinjiang	1.131	1.145	1.076	1.050	1.019

Fig. 3 presents the annual trends of TFP and its decomposition indices for livestock environmental efficiency in China across four phases: 2006–2009, 2010–2013, 2014–2017, and 2018–2021. The TFP trajectory follows an 'N'-shaped pattern, with both the GML and TC indices consistently exceeding 1, indicating a sustained improvement in livestock environmental efficiency. Except for 2006–2009, technical efficiency change remained above 1 in all periods, demonstrating a steady upward trend. However, technical progress change played a more dominant role than technical efficiency change in driving environmental efficiency, except in 2014–2017. This suggests that while technical efficiency contributes positively, its impact remains secondary to technical progress. The decomposition indices reveal that pure technical efficiency change exhibited an average annual growth rate of 2.9%, peaking at 5.59% in 2010–2013, underscoring continuous improvements in production efficiency. In contrast, scale efficiency change remained below 0.1%, highlighting its negligible contribution to livestock environmental efficiency.

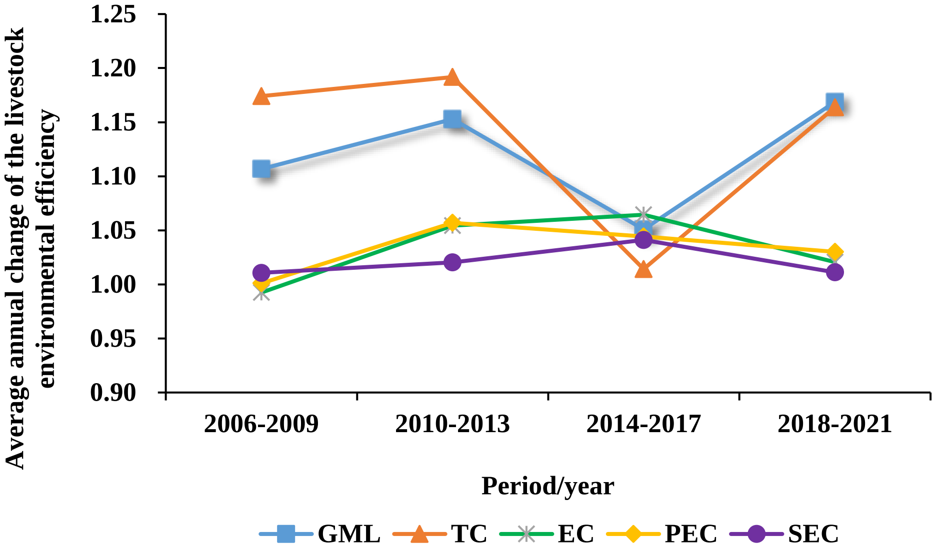


Figure 3. Annual changes of provincial livestock environmental efficiency in China

3.3. Decomposition and contribution rate analysis

The livestock environmental efficiency in China exhibits notable spatial and temporal gaps, as reflected by the Theil index, with an average value of 12.92% (Fig. 4). The index reached its highest regional gap of 19.64% in 2011 and its lowest at 9.24% in 2021. Over time, the Theil index followed a fluctuating upward trend before declining, indicating a gradual narrowing of regional gaps since 2011. However, a slight increase in the Theil index in 2019 and 2020 suggests the need for vigilance against exogenous shocks that could hinder improvements in livestock productivity and environmental efficiency.

The analysis of livestock environmental efficiency across China's four regions reveals significant regional heterogeneity, each following a distinct evolutionary trajectory. Based on the Theil index, the average ranking of regional gaps in livestock environmental efficiency is as follows: eastern region (11.93%) > western region (10.96%) > northeast region (8.78%) > central region (7.37%). This indicates that gaps are most pronounced in the eastern region, followed by the western region, while the northeast and central regions exhibit relatively smaller gaps. Notably, the Theil index in the eastern region shows a fluctuating downward trend, suggesting decreasing intra-regional gaps and increasing inter-provincial cooperation in the livestock industry. The western region exhibits an inverted "V" pattern, reflecting initial divergence followed by improved synergy and coordination. In contrast, the northeast and central regions demonstrate consistently smaller gaps with a significant downward trend in recent years. Furthermore, a general trend of convergence is observed in both intra- and inter-regional gaps, though intra-regional gaps remain the dominant source of overall gaps. The average Theil index for intra-regional gaps (10.24%) is substantially higher than that of inter-regional gaps (2.53%).

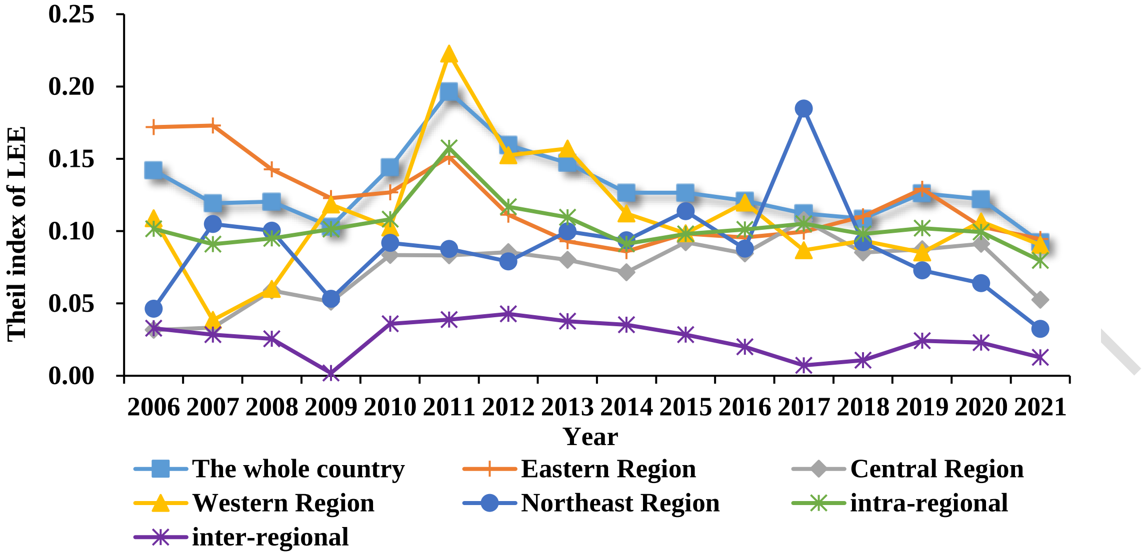


Figure 4. The Theil index of the livestock environmental efficiency and its evolution trend in the whole country and four regions of China (2006-2021)

In terms of contribution rate, the Theil index of livestock environmental efficiency is the highest in the eastern region (45.56%), followed by the western (43.76%) and central (41.20%) regions, with the northeast region exhibiting the lowest value (9.42%) (Table 5). This indicates that intra-regional gaps are the primary drivers of efficiency gaps in the eastern, central, and western regions, whereas their impact is relatively minor in the northeast region. Furthermore, the contribution of intra-regional gaps has been increasing, while that of inter-regional gaps has declined, underscoring the urgent need to address intra-regional gaps, particularly in the eastern and western regions.

Table 5. Theil index contribution rate of the livestock environmental efficiency in China

	2006-2009	2010-2013	2014-2017	2018-2021
Contribution rate of intra-regional	0.8119	0.7571	0.8168	0.8462
Contribution rate of inter-regional	0.1881	0.2429	0.1832	0.1538
Contribution rate of Eastern Region	0.2965	0.5989	0.5361	0.3909
Contribution rate of Central Region	0.6080	0.4099	0.2876	0.3424
Contribution rate of Western Region	0.6806	0.3222	0.3670	0.3808
Contribution rate of Northeast Region	0.0946	0.0857	0.0717	0.1248

3.4. Kernel density estimation analysis

This study utilized Stata 17.0 and the Kernel density function to estimate livestock environmental efficiency for the years 2006, 2011, 2016, and 2021 in China, resulting in the generation of corresponding Kernel density curves (Fig. 5). The kernel density curve of livestock environmental efficiency consistently shifts rightward, indicating an overall improvement across most provinces. This reflects increased governmental emphasis on green livestock development, structural optimization, and the transition to low-carbon practices. The primary peak of the kernel density curve shows a fluctuating decrease in height and a slight increase in width. This widening absolute gap highlights challenges in coordinating green development efforts nationwide and disparities in policy implementation. Additionally, the distribution curves exhibit a persistent right-skewed pattern, indicating substantial regional gap. Over time, the transition from single peaks in earlier years to double peaks in 2006, 2016, and 2021 suggests increasing polarization in livestock environmental efficiency, further emphasizing the need for targeted policy interventions to bridge regional gaps.

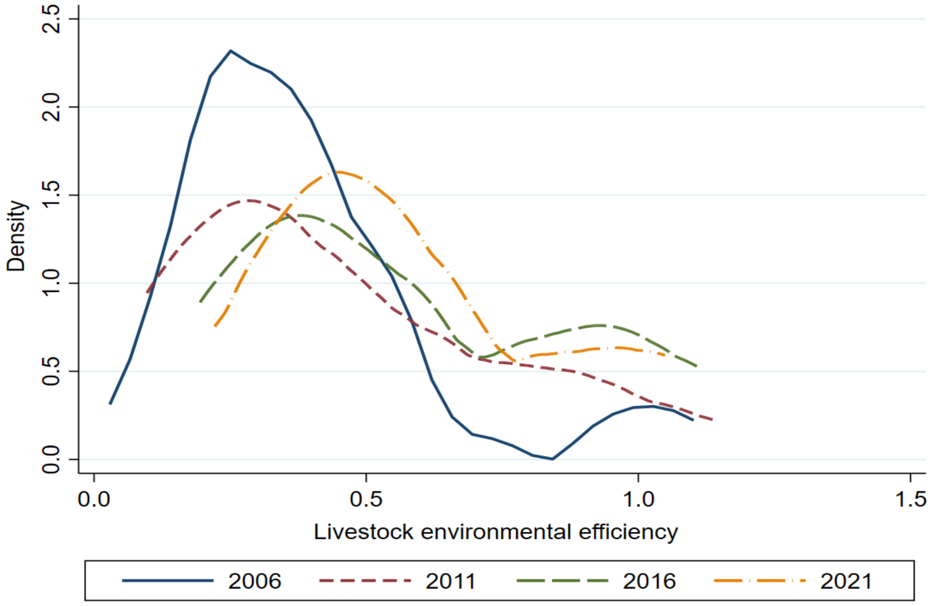


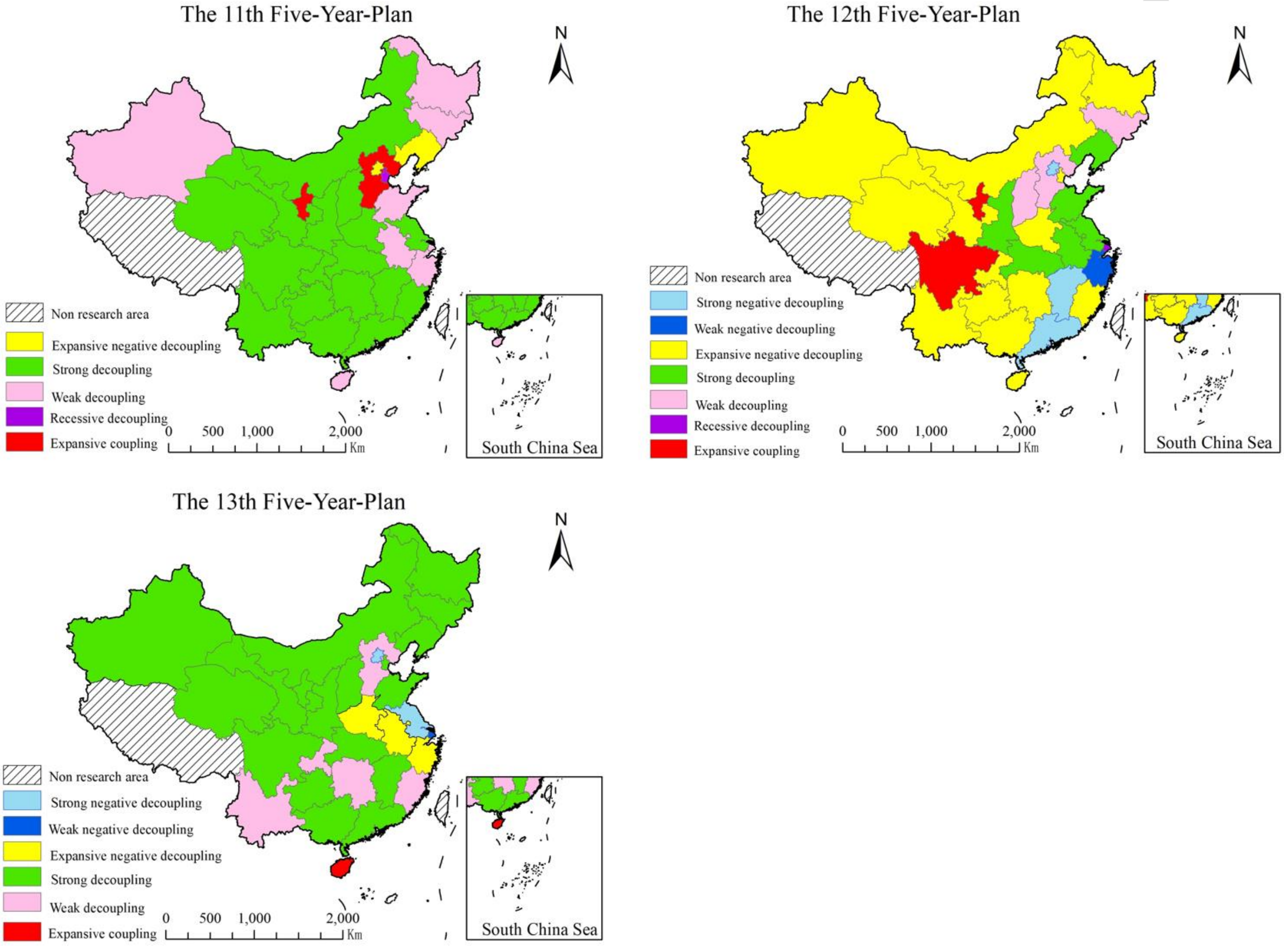
Figure 5. Kernel density curves for the livestock environmental efficiency in China

3.5. Decoupling analysis

The sample period is segmented according to the "11th Five-Year Plan," "12th Five-Year Plan," and "13th Five-Year Plan." The decoupling index between livestock environmental efficiency and livestock economic growth in China is calculated for each period using Eq. (14), with the results presented in Fig. 6.

During the 11th Five-Year Plan period, "strong decoupling" was the dominant trend, observed in 56.67% of provinces. This indicates that in these regions, the growth rate of livestock environmental efficiency was significantly lower than that of livestock economic growth, or even negative, with economic expansion largely dependent on resource consumption and environmental inputs. Additionally, 26.67% of provinces experienced "weak decoupling," where livestock environmental efficiency growth slightly lagged behind economic growth, representing an ideal form of decoupling. Regionally, Beijing and Liaoning exhibited "expansive negative decoupling," while Hebei and Ningxia were in an "expansive coupling" state. Tianjin, meanwhile, experienced "recessive coupling," reflecting varying degrees of environmental and economic interdependence across different provinces.

During the 12th Five-Year Plan period, "expansive negative decoupling" was the dominant trend, observed in 46.67% of provinces. This indicates that in these regions, the growth rate of livestock environmental efficiency exceeded livestock economic growth by more than 1.2 times, demonstrating significant environmental improvements alongside economic expansion in the livestock sector. Additionally, 20% of provinces experienced "strong decoupling," while 13.33% exhibited "strong negative decoupling." The proportions of provinces in "weak decoupling" and "expansive coupling" states were 10% and 6.67%, while 3.33% fell into the category of "recessive coupling." These findings highlight the diverse regional dynamics in balancing economic growth and environmental efficiency during this period.



The 11th Five-Year-Plan

The 12th Five-Year-Plan

The 13th Five-Year-Plan

Figure 6. Changes of the decoupling types between livestock environmental efficiency and livestock economic growth in China

During the 13th Five-Year Plan period, the predominant trend observed in the livestock sector was characterized by "strong decoupling." Notably, approximately 60% of provinces exhibited a state of strong decoupling, indicating that the growth rate of livestock environmental efficiency was negative and significantly lagged behind the economic growth rate of the livestock industry. The inefficiency observed may be attributed to an irrational structure of factor inputs and excessive resource consumption, both of which hinder improvements in livestock environmental efficiency. Furthermore, the distribution of provinces across other decoupling states was as follows: "weak decoupling" (16.67%), "expansive negative decoupling" (10%), "strong negative decoupling" (6.67%), "weak negative decoupling" (3.33%), and "expansive coupling" (3.33%). These findings underscore the need for more sustainable and efficient resource allocation strategies to enhance environmental performance in the livestock industry.

4. Discussion

China's livestock environmental efficiency shows notable spatial and temporal variations, influenced by factors such as grassland resource distribution, breeding structures, production technologies, and economic foundations. The recent average rankings are: eastern region (0.707) > northeast region (0.499) > central region (0.363) > western region (0.328). The eastern region, with its strong economic base and advanced livestock technologies (Bruckner, 2019; Feyisa, 2020), exhibits the highest efficiency. The northeast region, benefiting from a developed agricultural sector and smaller livestock industry, exerts less ecological pressure, resulting in higher efficiency compared to the central and western regions (Zhao et al., 2022). In contrast, the central and western regions, especially the western provinces, face harsh natural conditions and scarce forage resources, leading to unsustainable practices that prioritize resource consumption over environmental protection (Han et al., 2020; Wöhler et al., 2023). Addressing pollution emissions, enhancing resource utilization, and improving environmental performance in these regions are crucial priorities for future development (Zhang et al., 2020).

Intra-regional gaps are the primary driver of overall gaps in China's livestock environmental efficiency, surpassing inter-regional gaps. Within regions, free flow of labor, capital, and technology facilitates cooperation and exchanges (Acharya et al., 2020; Chen et al., 2023). However, widening intra-regional gaps concern stakeholders such as governments, enterprises, and farmers/herders. Issues like population aging, low education levels, and imperfect benefit linkage mechanisms hinder cooperation and exacerbate efficiency gaps (Boudalia et al., 2023; Ren et al., 2023). The Theil index shows that the eastern and western regions have higher livestock environmental efficiency gaps compared to the northeast and central regions, highlighting the need for enhanced inter-provincial synergies. Notably, intra-regional gaps in the eastern, central, and western regions similarly contribute to overall gaps. Therefore, these regions, especially the eastern and western areas, are crucial for mitigating pollution and optimizing input/output efficiency.

It's noteworthy that this study identified a shift in the relationship between China livestock environmental efficiency and its economic growth from the 12th to the 13th Five-Year Plan periods. Initially characterized by a predominantly ' expansive negative decoupling ' this relationship transitioned to a predominantly 'strong decoupling.' This shift indicates that while the value of livestock production increased, the growth rate of the livestock environmental efficiency in China lagged behind, suggesting that the livestock scale expansion may entail unforeseen environmental costs (Chen et al., 2023; Li et al., 2024). Therefore, during the 14th Five-Year Plan period, adopting low-energy consumption and high-output production methods is imperative for mitigating environmental impacts. Furthermore, efforts must concentrate on addressing any discrepancies between factor input structures and environmental outputs.

Nevertheless, it is crucial to acknowledge the limitations of this study. Firstly, although the Theil index reveals absolute gaps in livestock environmental efficiency within and among regions, it does not explain multi-region crossover phenomena, resulting in a lack of analysis of relative gaps. The Dagum Gini coefficient can address this limitation by more effectively identifying sources of regional gaps. Consequently, future research should integrate multiple methodologies to explore both absolute and relative gaps in livestock environmental efficiency. Secondly, while this study emphasizes the decoupling relationship between livestock environmental efficiency and economic growth, it does not delve into the factors influencing this relationship. Future studies should examine the driving and hindering factors of this decoupling, considering governmental regulation, environmental governance, and policy support perspectives.

5. Conclusions and policy implications

5.1. Conclusions

The main conclusions drawn from this study can be summarized as follows: Firstly, while China's livestock environmental efficiency has exhibited an overall upward trend, its absolute level remains relatively low, with a significantly higher number of non-DEA-efficient provinces compared to DEA-efficient ones. Secondly, the TFP of livestock environmental efficiency has shown continuous improvement, primarily driven by technological progress. Thirdly, the Theil index analysis reveals an uneven regional distribution, with the highest gaps observed in the eastern region (11.93%), followed by the western (10.96%), northeast (8.78%), and central regions (7.37%), with intra-regional gaps being the dominant source of overall gaps. Fourthly, provincial gaps in livestock environmental efficiency are substantial and exhibit a polarization trend. Finally, during the periods covered by the 11th to 13th Five-Year Plans, the decoupling relationship between livestock environmental efficiency and economic growth predominantly manifested as "strong decoupling," "expansive negative decoupling," and "weak decoupling," with the latter two representing more favorable development states.

5.2. Policy implications

To this end, this study provides follow-up policy recommendations to guide policymakers involved in actions to green livestock development.

(1) Effective planning for sustainable livestock development, tailored to regional conditions, is crucial. In the economically advanced eastern region, balance efficient production with ecological conservation while fostering secondary and tertiary sector growth. In the western region, prioritize environmental preservation and resource optimization. Central and northeast regions should reduce excessive resource inputs and optimize breeding structures to balance economic growth with sustainability.

(2) Bridging regional gaps in livestock environmental efficiency is crucial for sustainable development. This study shows higher efficiency in the eastern and northeast regions, with a significant gap between the eastern and western regions. Promoting cross-regional synergy through a robust inter-provincial cooperation platform can facilitate knowledge exchange on best practices in production, management, and environmental conservation. Strengthening such collaboration will align livestock economic growth with environmental sustainability.

(3) Green development policies for the livestock industry should be tailored to regional decoupling statuses. In weak decoupling areas, focus on breeding superior livestock, developing emission-reducing additives, and promoting cleaner farming techniques and optimized manure management. In strong decoupling areas, strengthen legislative measures to sustain environmental improvements. In expansive negative decoupling regions, prioritize innovative green practices and document successful cases. Technological advancements are crucial for enhancing environmental efficiency and ensuring long-term ecological balance.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

Author Contributions

Ming Li: Conceptualization, Methodology, Software, Visualization, Formal analysis, Data curation, Writing-original draft. **Haifeng Xiao:** Supervision, Writing-review & editing, Funding acquisition.

Data availability

Data are available from the author on reasonable request.

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