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Spatial transfer and policy leakage of livestock carbon emissions driven by local livestock-free zone policies

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Abstract

Under the global climate governance framework and China's "Dual Carbon" goals, reducing carbon emissions from livestock farming has become an urgent priority. Local environmental regulations, such as "Livestock-Free Zone", aim to control emissions through spatial management but may cause unintended pollution transfer effects. Using Guangdong Province as a case study, this research analyzes the effects of the policy on livestock carbon emissions based on 2014–2023 county-level panel data, combining a spatial Durbin model, a continuous difference-in-differences model and network analysis. The results show that while the policy achieved local carbon reduction (direct effect: −0.047), it triggered significant spatial spillover effects (indirect effect: +0.148), amplifying the environmental cost by 3.14-fold and shifting it to neighboring regions. Further analysis reveals hierarchical emission transfers from Pearl River Delta core cities to less developed northern and western Guangdong regions, with heterogeneous environmental outcomes. Western Guangdong benefits from efficient livestock breeding technology, showing "high total emissions yet low carbon-emission intensity," while northern Guangdong falls into the trap of absorbing industrial capacity without efficiency gains and leading to magnified environmental risks. This study extends the Pollution Haven Hypothesis to land-intensive agricultural sectors, demonstrating how micro-level enforcement disparities drive passive capacity reallocation. It highlights the unintended externalities associated with fragmented policies and suggests that cross-regional governance, coupled with technology-driven capacity transfers, can mitigate leakage risks and promote sustainable development.

Highlights

- Local carbon reduction policies trigger a massive regional emissions spillover.
- The spatial carbon leakage effect is 3.14 times greater than the local reduction.
- Carbon transfer confirms the Pollution Haven Hypothesis at a subnational scale.
- Recipient regions face an "efficiency dilemma", amplifying environmental risks.

Keywords Livestock-free zone, Livestock farming carbon emissions, Policy-induced leakage, Pollution haven hypothesis, Coordinated governance

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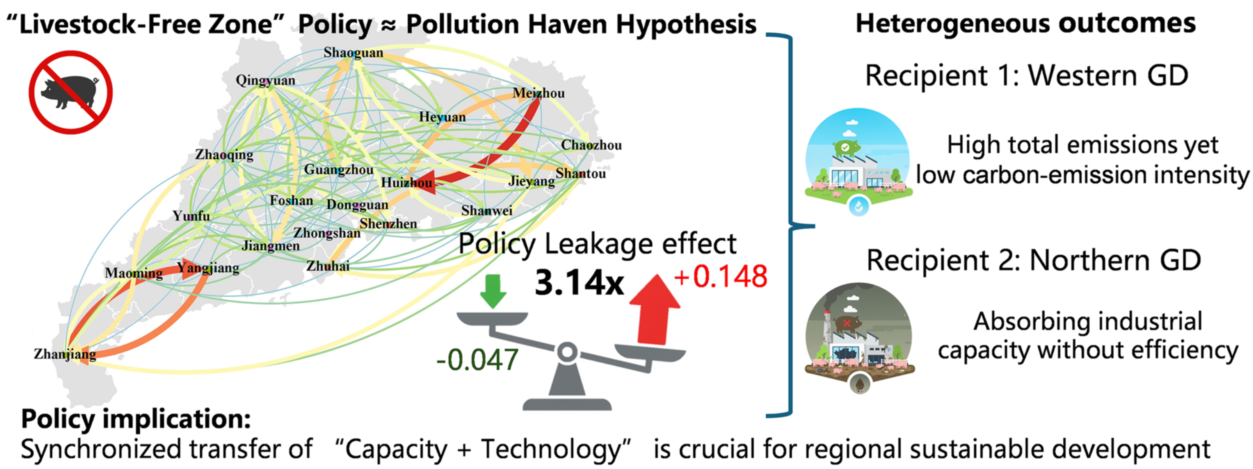
Graphical Abstract



1 Introduction

China's "Dual Carbon" strategy has made deep decarbonization across all economic sectors a crucial national priority (Zhang et al. 2020). While much of the focus remains on industrial and energy sectors (Zhao et al. 2017; Du and Wang 2022; Qian et al. 2022; Hu et al. 2024), the agricultural sector has been largely overlooked. This includes livestock and poultry farming, a major source of potent greenhouse gases like methane and nitrous oxide, which plays a strategic role in achieving the "Dual Carbon" goals (Havlík et al. 2014; Weindl et al. 2015). To tackle the mounting pressures from agricultural non-point source pollution and carbon emissions, local governments have implemented stringent environmental regulations. Among these measures, the establishment of "Livestock-Free Zones" that prohibit livestock and poultry breeding has been widely adopted. This policy acts as a form of regional "shock therapy" by rapidly "cleaning up" targeted areas through operational certainty (Wei et al. 2021). However, its overall effectiveness remains debated. A key uncertainty is whether such spatially targeted regulations generate a net regional environmental benefit or simply trigger pollution leakage by displacing the environmental burden to adjacent, less-regulated jurisdictions.

Theoretically, such spatial transfers in the livestock and poultry farming industry driven by differences in environmental regulations align closely with the classic "Pollution Haven Hypothesis". This hypothesis posits that, within open economies, highly polluting industries tend to relocate from regions with stringent environmental regulations to "havens" with more lenient policies to avoid additional costs (Copeland and Taylor 2004). Extensive research has validated this hypothesis within industrial sectors and on international scales, accumulating substantial empirical evidence (Hu et al. 2022; Jiang et al. 2022; Liu et al. 2022). However, there is insufficient exploration of the hypothesis within the agricultural sector, especially in relation to livestock farming (Liu and Yang 2021; Zheng et al. 2025; Li et al. 2025). Unlike industrial capital, which relocates based on marginal cost differentials, the livestock sector is fundamentally dependent on land resources (Rivera and Oh 2013; Bu and Wagner 2016; Liu et al. 2020; Wei et al. 2023). Consequently, the transfer of its production capacity is predominantly driven by involuntary withdrawal and structural reallocation under stringent spatial regulations, such as ecological redlines (Jiang et al. 2023; Martin et al. 2016). Testing the Pollution Haven Hypothesis within this context broadens the applicability of the theory to land-intensive, policy-constrained sectors, thereby addressing a critical gap in understanding policy-induced spatial spillovers in agriculture. Furthermore, most studies are focused on international trade and carbon tax regimes, while evidence to substantiate the pollution transfer effects driven by policy within a single region with stark socioeconomic disparities is limited (Sapkota and Bastola 2017; Shahbaz et al. 2019; Zhu et al. 2022; Zhou and Wu 2024). Even when geographic migration of pollution is observed, such studies often remain at the level of descriptive patterns, lacking precise quantification of the spatial spillover effects of policies (Yan and Zhang 2023; Zhao et al. 2024; Zhang et al. 2025a, b). Consequently, it is imperative not only to confirm whether pollution transfer exists, but also to elucidate the specific pathways and network structures of such transfers while uncovering the heterogeneity of environmental impacts borne by various "recipient regions".

To address these gaps in research, this study selects Guangdong Province, the largest provincial economy (GDP_{2025} = 14.58 trillion CNY) and a pioneering policy demonstration zone in China, as a case study. Guangdong Province contains both the highly developed Pearl River Delta region with the most stringent environmental regulations in the country, and less developed eastern, western, and northern areas that host a significant portion of agricultural activity. This stark regional heterogeneity provides an ideal quasi-natural experimental setting for investigating spatial spillover effects of environmental regulations across regions. Therefore, this study investigates the impacts of the "Livestock-Free Zone" policy in Guangdong. Specifically, it aims to: (1) quantify the policy's effectiveness in reducing local carbon emissions while simultaneously assessing the magnitude of carbon leakage to neighboring regions; (2) identify the network pathways and hierarchical structure of this spatial displacement, pinpointing the primary spillover hubs and absorption zones; and (3) examine the divergent environmental consequences across different recipient regions, exploring how disparities in production efficiency may disproportionately amplify environmental risks. The findings will provide micro-level evidence for the "Pollution Haven Hypothesis" within the agricultural sector at a subnational scale and offer crucial insights for designing coordinated regional governance.

2 Methods

2.1 Data sources

The data used in this study include carbon emission data, policy data, and spatial-geographic data. The carbon emission data were sourced from the Guangdong Province Agriculture and Rural Statistical Yearbook (2014–2023). These data cover metrics such as the GDP from livestock and the annual slaughter and inventory numbers for major livestock categories, including pigs, cattle, sheep, and poultry, at the county level. Data on policies relevant to livestock-free zones were primarily collected from the official websites of the Guangdong provincial government and its municipal governments to ensure authority and reliability. Spatial-geographic data were obtained from the National Platform for Common GeoSpatial Information Services (https://www.tianditu.gov.cn/). To facilitate subsequent temporal-spatial distribution analyses and spatial econometric modeling, Guangdong Province was subdivided into four regions: Western Guangdong (cities of Yunfu, Yangjiang, Maoming and Zhanjiang), Northern Guangdong (cities of Qingyuan, Shaoguan, Heyuan and Meizhou), Eastern Guangdong (cities of Shanwei, Jieyang, Shantou and Chaozhou), and the Pearl River Delta region (cities of Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing) (Fig. 1).

2.2 Livestock carbon emission accounting

This study follows the framework of the IPCC Guidelines for National Greenhouse Gas Inventories (2006 edition

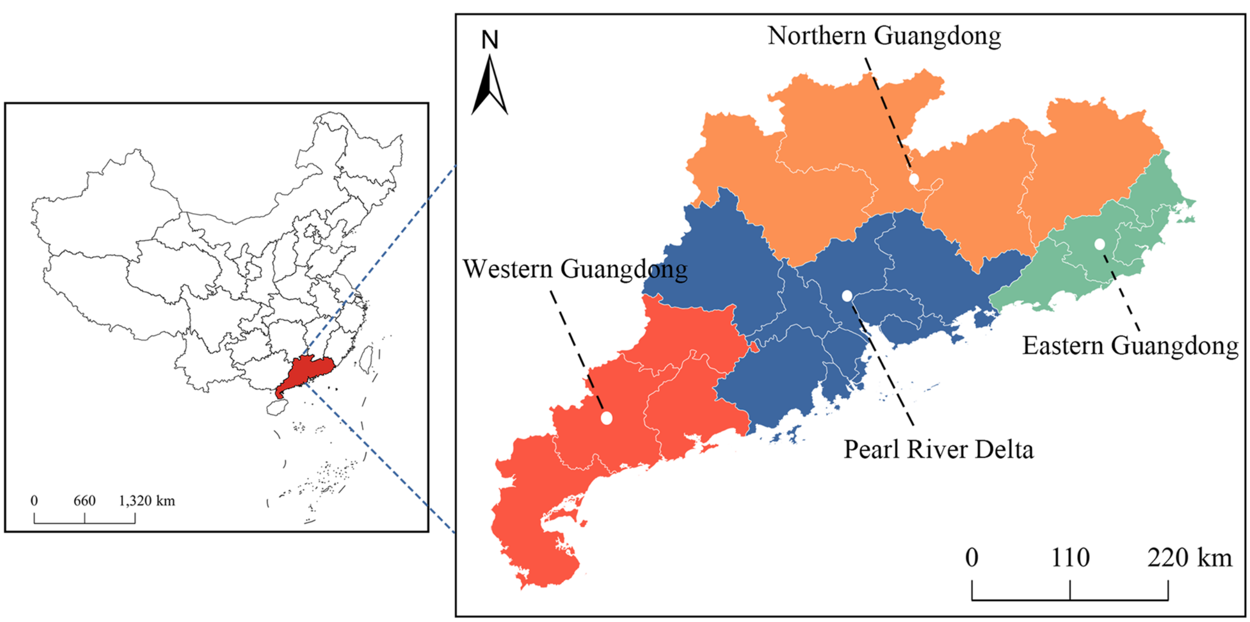


Fig. 1 Schematic map of Guangdong Province's geographic location. Note: this map is based on the standard map with the review number GS (2024) 0650 downloaded from the Standard Map Service website of the National Platform for Common GeoSpatial Information. The base map has not been modified

and the 2019 revision) and further incorporates authoritative documents such as the Emissions Database for Global Atmospheric Research (EDGAR v8.0; Crippa et al. 2023), the China National Greenhouse Gas Inventory (Ministry of Ecology and Environment of the People's Republic of China 2024a, b), and the China national standards on requirements of the greenhouse gas emissions accounting and reporting (Ministry of Ecology and Environment of the People's Republic of China 2024a, b). The accounting scope includes methane emissions from livestock enteric fermentation and methane and nitrous oxide emissions from manure management. The emissions were calculated based on Eqs. (1)–(3):

$$E_{CH_4,\text{enteric}} = \sum_j \left(EF_{CH_4,\text{enteric},j} \times AP_j \times 10^{-3} \right) \times GWP_{CH_4} \tag{1}$$

$$E_{CH_4,\text{manure}} = \sum_j \left(EF_{CH_4,\text{manure},j} \times AP_j \times 10^{-3} \right) \times GWP_{CH_4} \tag{2}$$

$$E_{N_2O,\text{manure}} = \sum_j \left[\left(EF_{N_2O,\text{manure},D,j} + EF_{N_2O,\text{manure},ID,j} \right) \times AP_j \times 10^{-3} \right] \times GWP_{N_2O} \tag{3}$$

where $EF_{CH_4,\text{enteric},j}$ is the enteric fermentation CH_4 emission factor for livestock category j; AP_j is the annual average inventory data for livestock category j; GWP_{CH_4} is the global warming potential of methane; $EF_{CH_4,\text{manure},j}$ is the manure management CH_4 emission factor for livestock category j; $EF_{N_2O,\text{manure},D,j}$ is the direct nitrous oxide emission factor for manure management for livestock category j; $EF_{N_2O,\text{manure},ID,j}$ is the indirect nitrous oxide emission factor for manure management for livestock category j; GWP_{N_2O} is the global warming potential of nitrous oxide. The provincial default values used in this study are shown in Table 1.

To effectively capture the temporal dynamics of livestock carbon emission levels across different regions in Guangdong Province and to assess carbon emission efficiency per unit of output, this study calculates the kernel density and carbon emission intensity for each region. Carbon emission intensity is defined by Eq. (4):

$$I_{carbon} = \frac{E_{carbon}}{GDP_{livestock}} \tag{4}$$

where E_{carbon} is the total livestock carbon emissions, and $GDP_{livestock}$ refers to the output value of the livestock industry. This indicator assesses the relationship between carbon emission levels and industry output, highlighting the extent of low-carbon development within the sector.

The kernel density function is defined as:

Table 1 Default emission factors for livestock carbon emissions

Livestock type	Enteric CH_4 emissions	Manure management emissions	
		CH_4	N_2O (direct + indirect)
Beef cattle	69.2	4.72	0.84
Dairy cattle	58.6	8.45	1.71
Sheep	9.6	0.31	0.106
Pigs	1.5	5.85	0.157
Poultry	/	0.02	0.007

$$f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{x - x_i}{h} \right) \tag{5}$$

where N is the sample size, x_i is the i-th independent sample, x is the target carbon emission intensity value, h is the bandwidth controlling the smoothness of the kernel density curve, and K is the kernel function. In this study, the Gaussian kernel is employed.

2.3 Spatial autocorrelation analysis

The Global Moran's I index is used to identify the overall spatial clustering pattern of livestock carbon emissions across Guangdong Province. The calculation formula is as follows:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{6}$$

Its value lies within [−1,1]. When Moran's I > 0, the variable demonstrates positive spatial autocorrelation, meaning high-value (or low-value) areas are likely to be clustered. When Moran's I < 0, it implies negative spatial autocorrelation, with high-value and low-value areas interspersed.

The Local Moran's I index effectively reflects the spatial relationship of carbon emissions between individual regions and their neighbors. It is calculated using the following formula:

$$I_i = \frac{n(x_i - \bar{x}) \sum_{j=1}^{n} w_{ij} (x_j - \bar{x})}{\sum_{k=1}^{n} (x_k - \bar{x})^2} \tag{7}$$

where $I_i \geq 0$ implies positive spatial clustering effects for carbon emissions in neighboring regions, while $I_i \leq 0$ indicates negative spatial clustering effects.

The spatial weight matrix w_{ij} plays a pivotal role in spatial econometric models. In this study, to account for spatial interactions between all counties, including geographically non-contiguous or island counties, we constructed an inverse distance weight matrix rather than a binary contiguity matrix. This approach ensures that no isolated nodes exist within the spatial network, thereby avoiding potential biases in Moran's I statistics and SDM estimations. The element is defined as:

$$w_{ij} = \begin{cases} 1/d_{ij}, & i \neq j \\ 0, & i = j \end{cases} \tag{8}$$

where d_{ij} represents the geographical distance between the geometric centroids of county i and county j, calculated based on their longitude and latitude coordinates.

2.4 Spatial econometric model

In the context of the "Livestock-Free Zone" policy and the spatial redistribution of livestock farming, carbon emissions' spatial effects may arise from interactions between dependent variables or from transmission of explanatory variables across regions. To comprehensively characterize these "local effects" and "neighboring effects," this study employs the Spatial Durbin Model (SDM) as the core econometric method.

The general formula for SDM is expressed as:

$$Y_{it} = a_i + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \beta x_{it} + \delta \sum_{j=1}^{n} w_{ij} x_{jt} + \mu_i + \gamma_t + \varepsilon_{it} \tag{9}$$

2.5 Effect decomposition

The regression coefficients of SDM do not directly correspond to the marginal effects of explanatory variables on dependent variables; interpreting results solely based on coefficients may lead to bias (LeSage and Pace 2009). Hence, effect decomposition is essential. Rearranging the matrix form provides the following solution:

$$Y = (I - \rho W)^{-1}(\beta I + \theta W)X + (I - W)^{-1}\alpha + (I - \rho W)^{-1}\varepsilon \tag{10}$$

The partial derivative matrix is given as:

$$\frac{\partial Y}{\partial x_k} = (I - \rho W)^{-1} \begin{bmatrix} \beta_1 & w_{12}\theta_k & \cdots & w_{1n}\theta_k \\ w_{21}\theta_k & \beta_2 & \cdots & w_{2n}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\theta_k & w_{n2}\theta_k & \cdots & \beta_n \end{bmatrix} \tag{11}$$

The average of diagonal elements indicates the direct effect, which measures the impact of an explanatory variable on its own dependent variable in the region. The average of off-diagonal elements represents indirect effects (spillover effects), which reflect the influence of explanatory variables in other regions passed through spatial links. This decomposition enables a comprehensive evaluation of the local and cross-regional effects of the "Livestock-Free Zone" policy on carbon emissions.

2.6 Continuous difference-in-differences model

To rigorously quantify the causal impact of the "Livestock-Free Zone" policy on local carbon emissions and address the potential endogeneity inherent in spatial models, this study employs a continuous Difference-in-Differences (DID) model. Unlike the traditional binary DID approach, which only captures the average treatment effect of policy implementation, the continuous DID model accommodates variations in policy intensity across different regions. This enables us to precisely capture the marginal effect of regulatory strictness. The baseline model is specified as follows:

$$E_{it} = a + \beta\left(Intensity_{it} \times Post_{it}\right) + \gamma X_{it} + \mu_{it} + \delta_t + \epsilon_{it} \tag{12}$$

where E_{it} represents the carbon emission level of city (or county) i in year t; $Intensity_i$ denotes the intensity of the policy implementation; and $Post_{it}$ is a time dummy variable that equals 1 in the year of policy implementation and subsequent years, and 0 otherwise. The interaction term, $Intensity_i \times Post_{it}$, serves as the core explanatory variable, $Policy_{it}$, in this study. X_{it} represents a vector of time-varying control variables; μ_i and λ_t denote the individual (city or county) fixed effects and year fixed effects, respectively; and ε_{it} is the stochastic error term.

To further validate the parallel trend assumption and examine dynamic policy effects, we adopt the event study framework proposed by Sun and Abraham (2021), which provides robust estimators in the presence of heterogeneous treatment effects:

$$Y_{i,t} = a_i + a_t + \sum_{e \neq \bar{e}} \sum_{\ell \neq -1} \delta_{e,\ell} \cdot (1\{E_i = e\} \cdot 1\{t - E_i = \ell\}) + \varepsilon_{i,t} \tag{13}$$

where α_i and α_t represent individual and time fixed effects, respectively; E_i denotes the initial period when unit i is first subjected to the policy shock; $\bar{e}$ represents the latest treated cohort (serving as the control group); $\ell = t - E_i$ indicates the number of periods relative to the treatment timing; and $\delta_{e,\ell}$ captures the cohort-specific average treatment effect on the treated (CATT) for cohort e in relative period ℓ.

$$\widehat{\delta_\ell^{IW}} = \sum_{e \neq \overline{e}} \widehat{w_e} \cdot \widehat{\delta_{e,\ell}} \tag{14}$$

where $\widehat{w_e} = \Pr\{E_i = e \mid E_i \in \mathcal{G}_\ell\}$ represents the sample share of cohort e within the observable relative period ℓ.

2.7 Variable explanation

The explained variable in this study is the carbon emissions from livestock farming at the county level, calculated using the accounting method described in Sect. 2.2:

$$E = \sum\nolimits_i (A_i \times EF_i) \tag{15}$$

where A_i represents the farming scale (inventory or slaughter size) for livestock category i, EF_i is the emission factor for livestock category i, and i = {pigs, poultry, cattle, sheep}.

Since the implementation of the policy, local governments have closed large-scale farms and small household livestock within designated exclusion zones, alleviating issues such as odor and water pollution. However, the policy has also led some enterprises and farmers to relocate outside the exclusion zones. While some have upgraded their operations through greener practices, others have ceased farming altogether. Thus, the intensity of the exclusion measures has significantly influenced livestock productivity and carbon emissions. Regarding published data on Livestock-Free Zone delineations within counties, this study employs various processing methods: for directly measured area data, official statistics are used; for vector file data, spatial overlay analysis and area calculations are performed using ArcGIS; for publicly available image datasets, Python's OpenCV library is utilized to remove background noise, extract exclusion zone pixels, and calculate area. Validation results show that area calculations using ArcGIS and Python approximate government measurements with a relative error of ± 4.19%.

To accurately capture the spatiotemporal evolution of environmental regulations, this study constructs "policy intensity" ($Policy_i$) as a time-varying continuous variable. The quantification follows a dynamic stepwise approach: for years preceding the policy's official implementation ($t < T_{start}$), the variable is assigned a value of 0. From the year of enforcement onward ($t \geq T_{start}$), it is measured as the ratio of the livestock exclusion zone area to the total administrative area. Furthermore, to account for policy volatility, if local governments promulgated new regulations to adjust exclusion zone boundaries during the observation period, the ratio is updated synchronously. This dynamic process is formally defined in Eq. (16):

$$Policy_i = \begin{cases} 0, & t < T_{start} \\ \frac{A_{ban,i}}{A_{total,i}}, & t \geq T_{start} \end{cases} \tag{16}$$

where $Policy_i$ represents the policy intensity of the Livestock-Free Zone in administrative region i, $A_{ban,i}$ is the area of exclusion zones in region i, and $A_{total,i}$ is the total area of region i.

To mitigate omitted variable bias, the study incorporates the following control variable: livestock GDP, which reflects the scale-economy effect of the livestock industry. A higher GDP indicates greater output and industrial intensification, which positively influences carbon emissions.

For a comprehensive overview of the research design, the definitions, measurement units, and data sources for all primary and control variables are summarized in Table 2.

3 Results and discussion

3.1 Spatio-temporal dynamics of livestock carbon emissions

During the study period from 2014 to 2023, total carbon emissions from livestock farming in Guangdong Province decreased significantly, dropping from 11.809 to

Table 2 Definitions and descriptive statistics of main variables

Variable type	Variable name	Symbol	Definition	Unit	Data source
Dependent variable	Total livestock carbon emissions	$\ln E_{it}$	Total county-level greenhouse gas emissions from livestock	10^4 tons CO_2e	Calculated based on IPCC (2006) and provincial coefficients
Independent variable	Policy intensity	$\ln Policy_i$	Ratio of exclusion zone to total area	/	Compiled from official government documents
Control variable	Livestock industry output	lnCGDP	Annual gross regional product of the livestock industry	10^4 CNY	Guangdong Province Agriculture and Rural Statistical Yearbook (2014–2023)
Derived variable	Carbon emission intensity	I_{carbon}	Livestock carbon emissions per unit of output value	tons CO_2e/ CNY	Calculated by authors

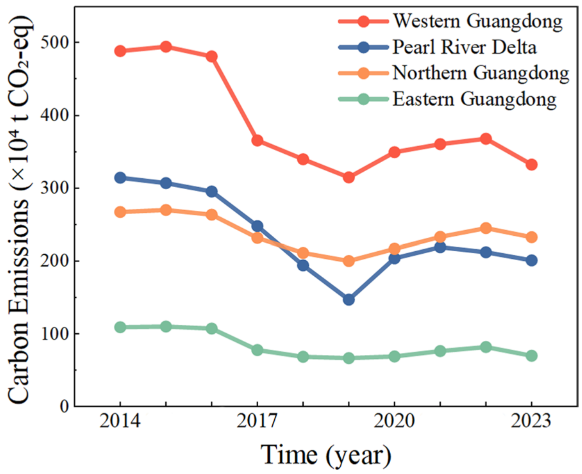


Fig. 2 Total livestock carbon emissions in various regions of Guangdong Province, 2014–2023

9.081×10^6 t. This decline coincided with a decoupling trend characterized by a steady rise in livestock GDP, as demonstrated by the reduction in emission intensity from 3.51 to 1.35×10^6 t/CNY. This shift is closely associated with advancements in livestock farming technologies (Su and Li 2025). The spatial pattern of emissions underwent significant restructuring, marked by a reduction in the central core and an expansion in the peripheral regions. As illustrated in Figs. 2 and 3, total carbon emissions in the Pearl River Delta region consistently decreased, falling from 3.149 to 2.017×10^6 t, gradually transforming into a "low-emission zone." In contrast, while the western Guangdong region exhibited the largest absolute reduction in emissions (from 4.314 to 2.874×10^6 t), its initially high baseline means it still maintains one of the highest emission levels in the province. The northern Guangdong region saw a relatively slow progression in emission reductions, achieving only a total decrease of 0.347×10^6 t during this period. Notably, carbon emissions in cities of Shaoguan and Qingyuan increased by 0.133 and 0.067×10^6 t, respectively, between 2018 and 2023, making them the only regions in the province where emissions increased. These changes align closely with Guangdong Province's rapid urbanization process and increasingly stringent environmental regulations during this period (Ren et al. 2023). This suggests that the observed spatial transformation is likely driven by significant external interventions rather than merely natural industrial evolution.

To quantify and verify the observed spatial restructuring trends, this study further employed kernel density estimation to analyze regional carbon

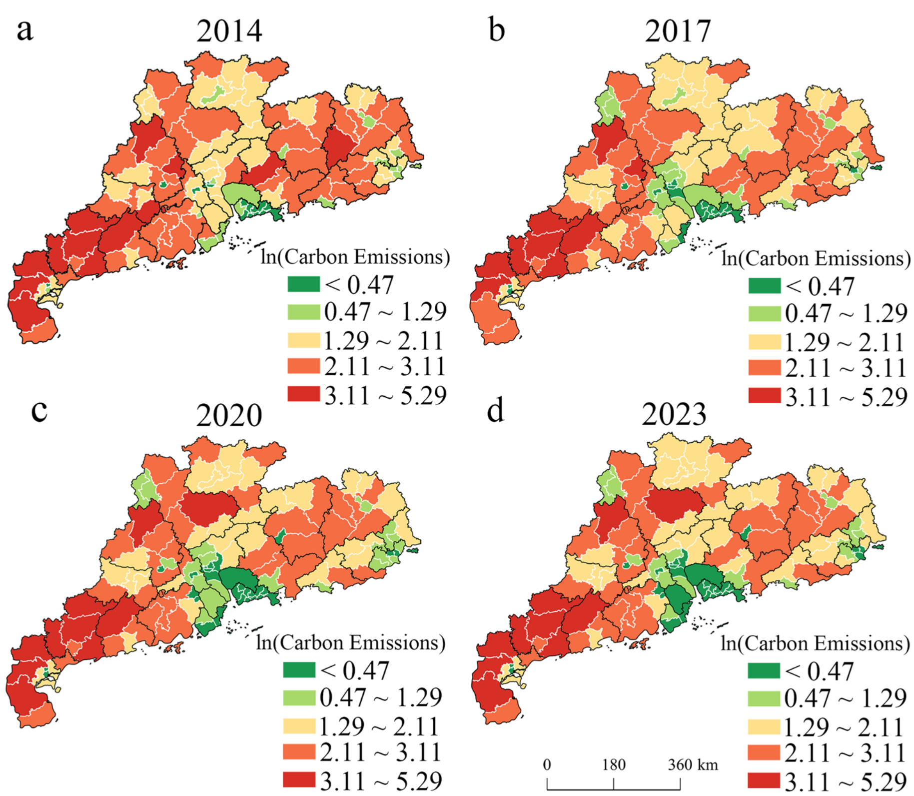


Fig. 3 **a**–**d** Temporal-spatial distribution of carbon emissions across Guangdong Province over four stages

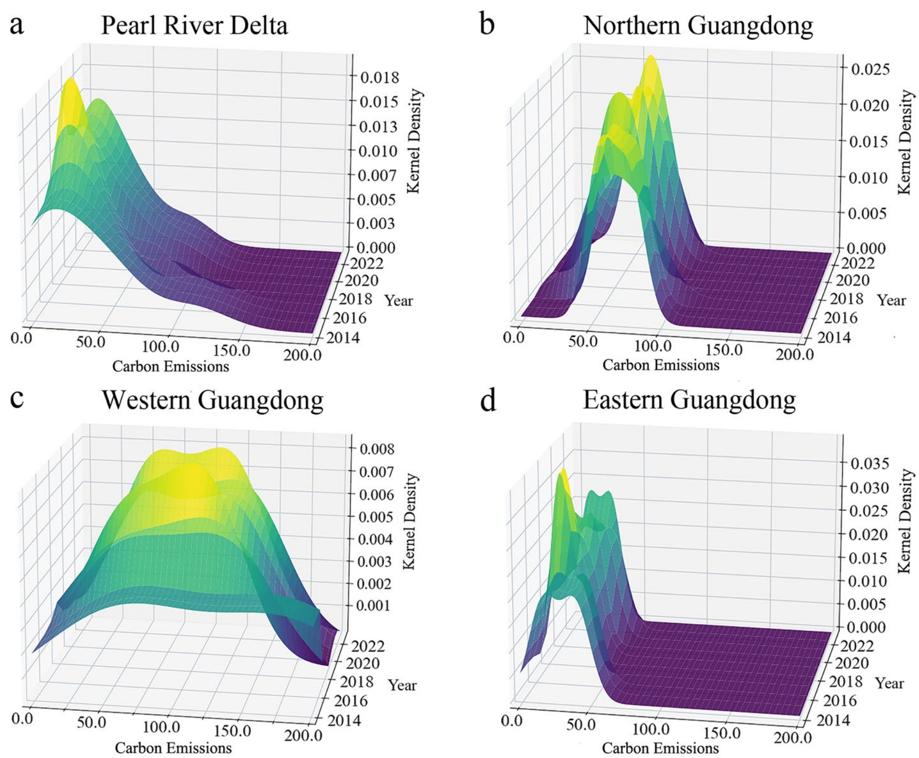


Fig. 4 a–**d** Evolution of livestock carbon emissions across regions of Guangdong Province, 2014–2023

emission dynamics. As illustrated in Fig. 4, the kernel density curve for the Pearl River Delta region exhibited a clear leftward shift, with increasingly steep peaks concentrated in lower emission areas. This indicates that, in addition to the substantial reduction in total emissions, county-level units in the region are converging towards a homogenous, low-emission level. In contrast, the curve for the northern Guangdong region revealed a distinct rightward shift, with peaks becoming flatter over time, indicating widespread increases in emission levels and the formation of new clusters within the medium-to-high emission range. Meanwhile, the western Guangdong region, a traditional livestock farming hub, consistently displayed its kernel density curve in the high-emission range. Over time, the curve's peak contours became steeper, evolving from a single peak to a double-peak pattern. This reveals a growing polarization within the region, indicating internal differentiation despite maintaining a high level of emissions. In comparison, emission levels in the eastern Guangdong region remained relatively stable. These results further corroborate the geographic transfer of carbon emissions and illustrate the regional differentiation in livestock farming's transformation paths and functional roles. A new spatial pattern of "core purification, peripheral burden" has emerged, highlighting the distinct roles played by different regions in accommodating industrial transitions and environmental pressures.

3.2 Emission transfers created a new geographical clustering pattern

To investigate whether the spatial restructuring discussed earlier follows specific spatial dependency patterns, this study first conducted a global spatial autocorrelation analysis to examine the spatial dependency of livestock carbon emissions in Guangdong Province. As shown in Table 3, the Global Moran's I indices for all years during the study period were significantly positive ($p < 0.001$),

Table 3 Results of Global Moran's I for Guangdong Province's livestock carbon emissions, 2014–2023

Year	Moran's I index	Variance	Z-score	*p*-value
2014	0.231	8.58×10^{-4}	8.19	$p < 0.0001$
2015	0.233	8.57×10^{-4}	8.25	$p < 0.0001$
2016	0.233	8.58×10^{-4}	8.24	$p < 0.0001$
2017	0.213	5.86×10^{-4}	9.16	$p < 0.0001$
2018	0.265	8.61×10^{-4}	9.33	$p < 0.0001$
2019	0.276	8.66×10^{-4}	9.67	$p < 0.0001$
2020	0.267	8.73×10^{-4}	9.32	$p < 0.0001$
2021	0.249	8.74×10^{-4}	8.70	$p < 0.0001$
2022	0.254	8.77×10^{-4}	8.86	$p < 0.0001$
2023	0.242	8.77×10^{-4}	8.46	$p < 0.0001$

indicating that livestock carbon emissions in Guangdong Province exhibit significant positive spatial autocorrelation. This means that regions with high emissions tend to cluster together geographically, as do regions with low emissions. Notably, the dynamic changes in Moran's I reveal clear stage characteristics: a noticeable trough was observed in 2017, where the Moran's I index dropped to 0.213, signaling a weakening of spatial clustering intensity. However, this trend rebounded and peaked in 2019, with the index reaching 0.276. This turning point aligns closely with the implementation timeline of several critical policies in 2016–2017, including the Regulations on Prevention and Control of Pollution by Scaled Livestock and Poultry Breeding Industry (The State Council of the People's Republic of China (2013), the Action Plan for Prevention and Control of Water Pollution (The State Council of the People's Republic of China 2015), and the China National Sustainable Agricultural Development Plan (2015–2030) (The State Council of the People's Republic of China 2015). These findings suggest that policy interventions temporarily disrupted the original spatial patterns, subsequently leading to the emergence of new and stronger spatial clusters associated with industry relocation and reorganization.

The Local Indicators of Spatial Association (LISA) further identified the specific geographic locations and types of clustering. As shown in Fig. 5, the LISA cluster map clearly delineates the "hotspots" and "coldspots" in Guangdong Province's livestock carbon emissions. The "Low-Low (LL)" clusters, representing emission "coldspots," were stably centered in the Pearl River Delta region throughout the study period and displayed an expanding trend. This is consistent with the region's role as a high-pressure area for policy enforcement. Conversely, the "High-High (HH)" clusters, or emission "hotspots," were located in western Guangdong's traditional livestock farming cities, including Zhanjiang and Maoming, reaffirming their status as primary industry hubs. Additionally, transitional zones such as areas on the periphery of the Pearl River Delta and certain parts of northern Guangdong emerged as "Low-High (LH)" and "High-Low (HL)" spatial anomaly units. These regions represent "buffer zones" between different types of areas, reflecting the dynamic spatial trade-offs and relocation processes occurring within the livestock industry under the pressure of environmental regulations. Thus, the spatial redistribution of livestock carbon emissions across Guangdong Province does not follow a pattern of random diffusion. Rather, it is closely linked to local environmental regulations—represented most notably by the designation of "Livestock-Free Zone"—and has resulted in a highly differentiated and rigidified new geographical clustering pattern.

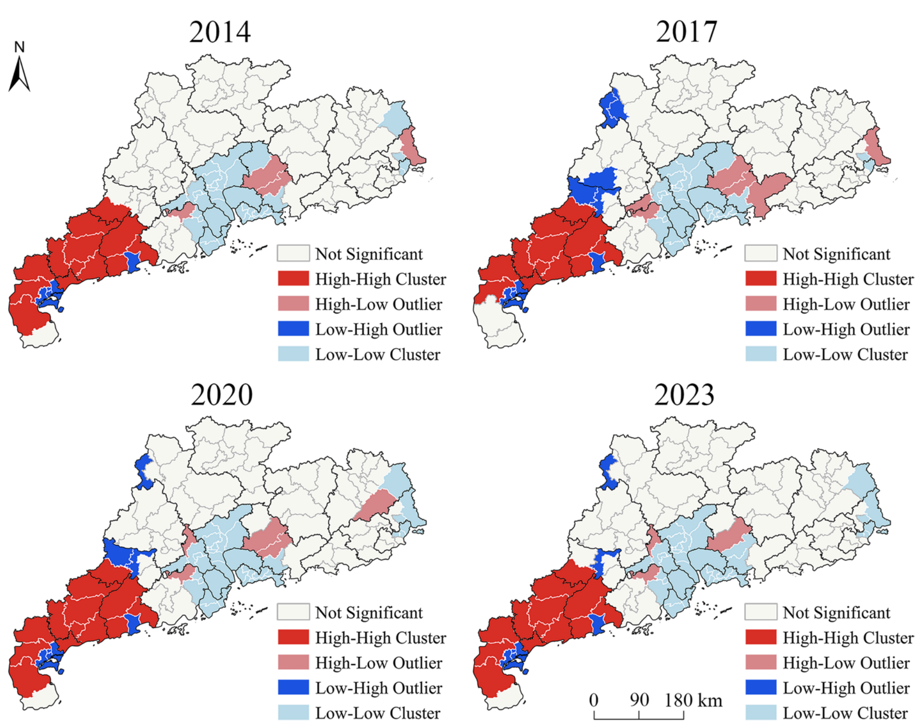


Fig. 5 Hotspot analysis of livestock carbon emissions across four stages in Guangdong Province

Table 4 Baseline regression results

Variables	(1)	(2)
Policy	−0.032***	−0.035***
	(0.01)	(0.01)
CGDP		0.049***
		(0.01)
Observations	1230	1230
Individual FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.965	0.968

The symbols *** indicate significance at the 1% level

Table 5 Direct, indirect, and total effects of the SDM

Variable	Direct effect	Indirect effect	Total effect
Policy	−0.047***	0.148**	0.101*
	(−7.55)	(2.55)	(1.76)
CGDP	0.054***	0.858**	0.912***
	(11.94)	(3.33)	(3.50)

The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

3.3 Livestock-free zone policy as the key driver of spatial spillover of carbon emissions

To rigorously evaluate the impact of the "Livestock-Free Zone" policy on local carbon emissions, Table 4 presents the baseline regression results of the continuous DID model. The coefficient for the core explanatory variable, Policy, is significantly negative (−0.035, p < 0.01). This result indicates that the implementation and intensifying strictness of the spatial regulations are robustly associated with a decline in local livestock carbon emissions. Furthermore, the dynamic event-study analysis (Figs. S1 and S2) confirms the parallel trend assumption prior to the policy shock and reveals a distinct temporal pattern: the local reduction effect peaked within the first two years of enforcement before gradually dissipating by the third year. This specific temporal dynamic suggests that the displaced high-emission production capacity may have rapidly relocated to loosely regulated neighboring regions during the initial phase of the policy shock, thereby prompting the subsequent investigation into spatial spillover effects.

To test the aforementioned hypothesis and quantitatively assess the impact of policies on the spatial patterns of carbon emissions, this study subsequently constructed a SDM. Compared to traditional econometric models, the SDM has the unique advantage of decomposing the total effect of a policy into “direct effects” on the local region and “indirect/spillover effects” transmitted to neighboring regions. This allows us to identify and test whether environmental regulations are associated with phenomena such as “pollution transfer” or “policy-induced leakage” (Ingalls et al. 2018; Hou et al. 2023; Yao et al. 2024). The decomposition results from the SDM show that the "Livestock-Free Zone" policy has a significant negative direct effect on local livestock carbon emissions (coefficient: −0.047, p < 0.01), indicating that the policy succeeded in achieving its expected emission reductions in the regulated areas by clearing livestock farms and limiting farming scales. However, this local success comes at a significant regional cost. The SDM model also reveals a notable positive spatial spillover effect (coefficient: +0.148, p < 0.05), which means a 1% increase in the intensity of the Livestock-Free Zone policy in a given region leads, on average, to a 0.148% increase in livestock carbon emissions in neighboring regions. Detailed model diagnostics and the decomposition of direct, indirect, and total effects are presented in Tables 5 and 6. Remarkably, the absolute value of this spillover effect is nearly 3.14 times the local reduction effect (0.148/0.047). This striking contrast demonstrates that the spatial transfer of carbon emissions associated with the Livestock-Free Zone policy far exceeds the amount of local reductions achieved. Such a discrepancy reveals a significant disconnect between the policy’s design and its real-world impacts. While the policy may align with local ecological conditions, it fails to sufficiently account for spatial scales and feedback mechanisms. This mismatch, known as a lack of social fit, drives unintended incentives that not only exacerbate cross-regional carbon leakage but may also result in a net increase in overall emissions—a classic case of “policy-induced leakage” (Epstein et al. 2015; Alpízar et al. 2017; Bastos Lima et al. 2019; Xiong and Wang 2022).

Table 6 Diagnostic tests for spatial econometric model selection

Method	Statistic
Moran’s I	46.94***
Lagrange multiplier (error)	2038.46***
Robust LM (error)	1524.39***
Lagrange multiplier (lag)	603.11***
Robust LM (lag)	89.04***
Hausman test	21.59***
Wald test for SAR	13.27***
Wald test for SEM	7.47**
LR test for SAR	41.24***
LR test for SEM	33.08***

The symbols *** and ** indicate significance at the 1%, 5% levels, respectively

Table 7 Results of sample structure perturbation test: comparison of direct and indirect effects (main explanatory variable)

Sample	Direct effect	Indirect effect	Indirect/direct
Baseline Sample (Province-Wide)	−0.047***	0.148**	3.14
Excluding the Pearl River Delta	−0.025***	−0.082**	/
Excluding Northern Guangdong	−0.047***	0.113*	2.4
Excluding Western Guangdong	−0.047***	0.138**	2.9

The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

To further evaluate the robustness of these SDM estimates and identify regional heterogeneity, a sample structure perturbation test was conducted (Table 7). We systematically excluded the Pearl River Delta, Northern Guangdong, and Western Guangdong from the sample. The results indicate that when the Pearl River Delta is excluded, both the direct and indirect effects become negative. However, when Northern or Western Guangdong is excluded, the indirect effect remains positive and larger than the direct effect. This confirms that the policy shock in the Pearl River Delta is the primary driver of the carbon emission transfer, aligning with the policy leakage and Pollution Haven hypotheses. Furthermore, excluding the recipient regions proves that the spatial transfer pattern is robust across the overall network and not entirely dependent on extreme localized samples.

To analyze the transmission paths and spatial configurations of the "policy-induced leakage", this study extracted the non-diagonal elements of the spatial weight spillover matrix based on the SDM decomposition results. These elements were then used as directed edge weights to construct a spatial correlation network for carbon emissions from livestock farming in Guangdong Province. It is important to note that the edge weights in this network are derived from the average spatial spillover effects estimated by the SDM. Consequently, these weights characterize the averaged spillover intensity and connectivity patterns throughout the entire study period (2014–2023), reflecting the long-term structural properties of emission transfers rather than short-term temporal fluctuations. As shown in Fig. 6, the network topology reveals the "sources" and "sinks" of spillover effects. The strongest input effect (weighted in-degree) is highly concentrated in northern Guangdong, with cities of Shaoguan (27.6) and Qingyuan (27.3) serving as the primary receptor areas for livestock carbon emission spillovers in the province. In addition, Zhanjiang City in western Guangdong, Zhaoqing City on the outskirts of the Pearl River Delta, and Jieyang City in eastern

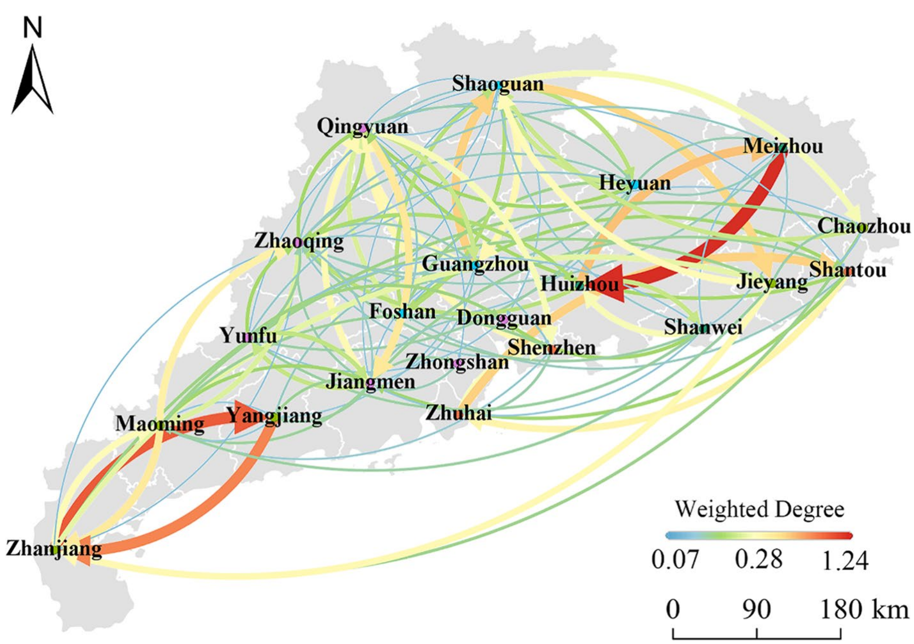


Fig. 6 Spatial correlation network of carbon emissions from livestock farming in Guangdong Province

Guangdong form secondary input centers. Regarding output effects (weighted out-degree), the core cities of Jiangmen and Guangzhou in the Pearl River Delta have become the primary sources of spillover emissions, largely due to their stringent policy restrictions and the relocation of industries. Notably, Maoming City in western Guangdong represents a unique case; it functions as both a major input node and a secondary transmitter of spillovers. Leveraging its strong industrial base and market influence, Maoming transmits emissions to surrounding areas, particularly within western Guangdong. This "source-sink" distribution pattern precisely quantifies and validates the macro migration trends observed in Sect. 3.1.

The “source-sink” distribution revealed by the network topology strongly aligns with the Pollution Haven Hypothesis, which posits that pollution-intensive industries relocate from regions with stringent regulations to regions with weaker regulatory environments. Fundamentally, this pattern reflects the rational choices of enterprises seeking ways to mitigate regulatory costs. There are two primary mechanisms driving this dynamic. (i) Market Substitution Effect: When local livestock products in core consumption markets like the Pearl River Delta are reduced due to policy restrictions, unmet market demand drives neighboring regions with less stringent regulations and lower production costs to scale up production to meet the supply deficit (Liu et al. 2024). (ii) Industry Relocation Effect: Faced with strict environmental standards, high pollution control costs, and limited land resources, livestock enterprises, as rational economic actors, are incentivized to transfer their production capacities to regions with more lenient policies and lower factor costs, minimizing costs in the process (Fu et al. 2021). These findings illustrate how localized environmental policies, when lacking coordinated design across broader spatial scales, may generate unintended negative externalities, including exacerbated cross-regional carbon leakage.

3.4 Asymmetry in spatial spillover paths and policy implications

The mechanisms shaping regional carbon emission linkages are characterized by asymmetrical bidirectional interactions rather than simple unidirectional flows. For instance, the relationships between cities such as Zhanjiang and Yangjiang, as well as Guangzhou and Shaoguan, exhibit bidirectional spillovers with significant differences in intensity. Zhanjiang City demonstrates a particularly strong spillover effect on Yangjiang City, which is markedly greater than the feedback it receives, positioning Zhanjiang as the central node driving regional dynamics within the western Guangdong livestock farming cluster. Similarly, Guangzhou City exerts considerable spillover dominance over Shaoguan City, highlighting a clear unidirectional pressure transmission from the core of the Pearl River Delta to the northern ecological development region. These asymmetric feedback loops reveal that the spatial network of livestock carbon emissions in Guangdong is not a homogeneous structure but has a distinct hierarchical nature. Beneath the complex surface of bidirectional interactions lies a chain of carbon emission transfers dominated by core cities and gradually diffused outward to peripheral regions.

Moreover, the environmental consequences of spillovers differ across regions receiving the emissions. As seen in Figs. 7 and 8, incorporating carbon emission intensity (carbon emissions per unit of GDP) into the analysis uncovers a critical issue of “efficiency”. Western Guangdong (represented by cities like Zhanjiang and Maoming) exhibits a "high total emission, low emission intensity" characteristic, benefiting from long-established large-scale, intensive farming practices that maintain high production efficiency when absorbing new capacities. However, northern Guangdong (represented by cities such as Qingyuan and Shaoguan), the major spillover recipient, suffers from a dilemma of “capacity absorption without sufficient efficiency”. According to 2025 statistics from the Guangdong Provincial Department of Agriculture and Rural Affairs, northern Guangdong has only half as many leading enterprises (38) as western Guangdong and merely one-third of the agricultural patents (430). Yet, it accounts for four out of five cities in Guangdong with the highest carbon emission intensities (cities of Heyuan, Shaoguan, Meizhou, Qingyuan and Yangjiang), illustrating a striking imbalance between industry capacity absorption and low-carbon efficiency. Northern Guangdong is constrained by mountainous terrain, which hampers the rapid establishment of large-scale standardized farming

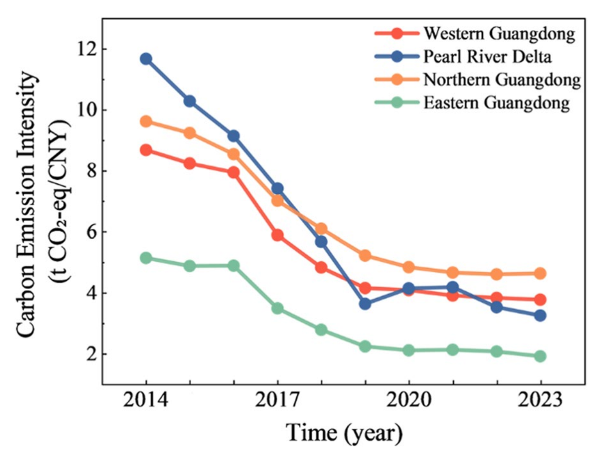


Fig. 7 Temporal trends of livestock carbon emission intensity by region in Guangdong Province

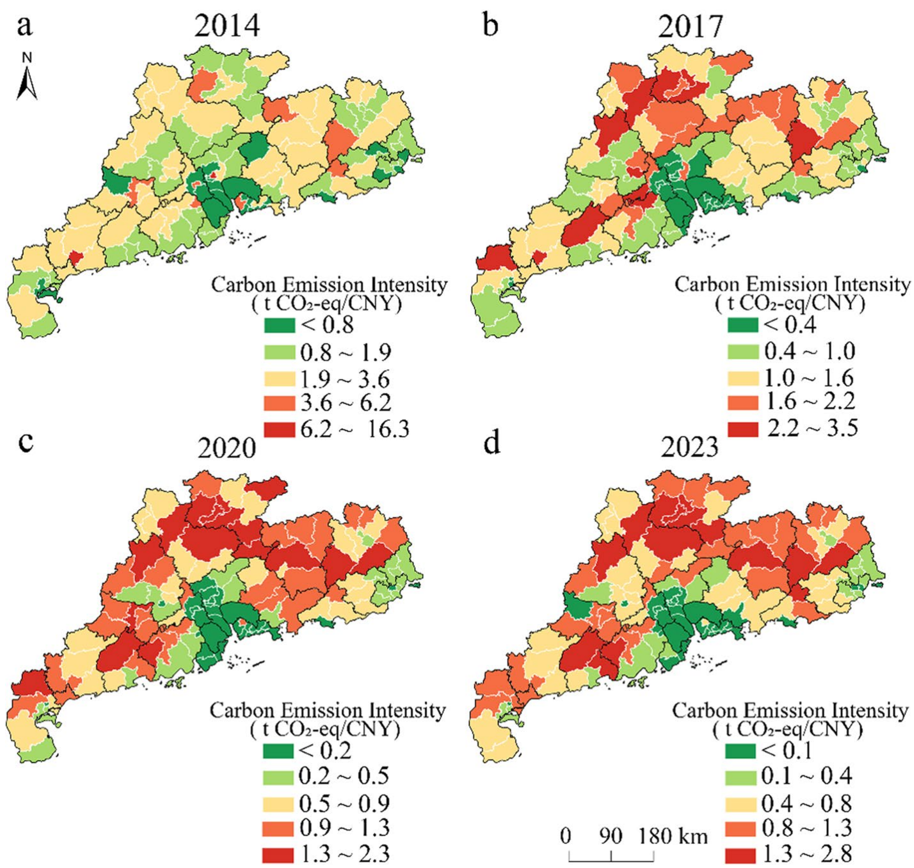


Fig. 8 a–**d** Spatio-temporal distribution of livestock carbon emission intensity across four stages in Guangdong Province

facilities. Consequently, most of the absorbed production capacity is distributed in dispersed, small-to-medium-scale forms, resulting in unsynchronized upgrades to farming practices and environmental protection technologies. This aligns with findings from related research: while the Pearl River Delta region has achieved rapid decoupling (reductions in carbon emissions outpacing economic growth) due to strict policy enforcement, northern Guangdong has shown slower progress in decoupling or even negative decoupling (Zhang et al. 2025a, b). This indicates that what is being transferred is not only "capacity" but also amplified "environmental risks".

These results demonstrate that local environmental regulations, when lacking regional coordination, disproportionately shift the costs to peripheral regions with weaker environmental governance capacities and technological foundations. This study suggests that future environmental governance must shift from a simple "spatial squeeze" approach to a regional collaborative development strategy centered on "efficiency improvement". Policy design should move beyond fragmented thinking and establish top-level coordination mechanisms at the regional level. Measures such as ecological compensation, joint investment in technology, and the establishment of shared industrial parks should be implemented to guide synchronized capital and advanced technology flows into spillover regions. The core goal should no longer be merely transferring capacities but transforming industry relocation into an opportunity for regional green upgrading. Specifically, the Pearl River Delta and western Guangdong regions should be encouraged to export mature large-scale farming models, waste resource utilization technologies, and digital management practices to help northern and eastern Guangdong bypass the "small, scattered, and underdeveloped" early-stage development phase. Instead, these regions should directly establish high-efficiency, low-emission, modern livestock farming industries. Only through these measures can the negative environmental externalities of industrial relocation be converted into a driving force for promoting regional balance and green development, resolving the conflict between environmental protection and economic development, and achieving true sustainable regional development.

This study is subject to several limitations regarding data precision, methodology, and scope. First, the construction of the "policy intensity" variable relied partially on image recognition techniques, introducing a potential measurement error of approximately ± 4.19%. While cross-validation confirms the overall reliability, the estimated coefficients should be interpreted primarily in terms of their significance and direction. Second, the use of IPCC Tier 1 emission factors effectively characterizes macroscopic patterns but may underrepresent the mitigation effects of specific technological upgrades (e.g., anaerobic digesters) compared to Tier 2 methods. Third, data availability constraints prevented the inclusion of city-level technological indicators (e.g., patents) in the county-level regression, suggesting a need for future research to employ more granular proxy variables. Finally, the spatial network constructed via the SDM represents statistical correlations of spillover effects rather than physical livestock flows; future studies incorporating real-time transport big data could further validate these topological relationships.

4 Conclusions

This study employed kernel density estimation, continuous difference-in-differences, and spatial econometric models to characterize the geographical restructuring of livestock carbon emissions in Guangdong Province following the implementation of the "Livestock-Free Zone" policy. The results reveal a significant policy paradox: while the regulation successfully reduced local carbon emissions, this achievement was offset by a far more pronounced "policy leakage" effect. The environmental burden was displaced to neighboring regions at a scale approximately 3.14 times greater than the local reduction, potentially undermining the overall regional mitigation efforts. This finding provides strong micro-level evidence for the Pollution Haven Hypothesis within the agricultural sector at a subnational scale. It uncovers the underlying mechanism of a hierarchical transfer of production capacity, driven by regulatory disparities, from the economically advanced and strictly regulated Pearl River Delta to the environmentally less resilient Northern and Western Guangdong regions. Critically, the study identifies an "efficiency dilemma" in recipient areas, where regions with weaker technological foundations absorbed production capacity without concurrent technological upgrades. This has created a development trap of "capacity absorption with deteriorating efficiency," leading to a disproportionate amplification of environmental risks. Consequently, this study advocates for a policy shift from simple "spatial squeezing" to a regionally coordinated approach centered on "efficiency improvement." This entails ensuring the synchronized transfer of both production capacity and advanced technology to facilitate a green transition during the industry's spatial restructuring. Future research could track the migration decisions of individual farms at the micro-level and assess the co-transfer effects of multiple pollutants to formulate more comprehensive pathways for regional sustainable development.

Supplementary Information

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Supplementary Material 1

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Authors' contributions

All authors contributed to the study conception and design. Conceptualization, funding acquisition, and project administration were led by Xunan Yang. Methodology design, investigation, and visualization were conducted by Zhiyi Ye and Xunan Yang. Data curation and formal analysis were performed by Zhiyi Ye, Xunan Yang, Yadong Cao, and Qihua Liang. The first draft of the manuscript was written by Zhiyi Ye and Xunan Yang. Xunan Yang, Ai-Jun Ma, and Meiying Xu critically reviewed and edited the manuscript. All authors read and approved the final manuscript.

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Data availability

The raw data used in this study were obtained from publicly available sources as described in the Methods section. The carbon emission dataset analyzed in this study was derived from these sources through the authors' own calculations and is available from the corresponding author upon reasonable request.

Declarations

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 paper.

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