



Quantitative assessment, spatial and temporal characteristics, and dynamic evolution of carbon emissions from animal husbandry in China: 2001–2020

Jiale Yan¹ · Yuanyuan Zhang²

Received: 23 January 2023 / Accepted: 13 October 2023 / Published online: 1 November 2023
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2023

Abstract

Carbon emissions from animal agriculture are a major source of global greenhouse gases. This paper measures the spatial and temporal characteristics and evolution patterns of carbon emissions from livestock farming in China and 31 provinces from 2001 to 2020 based on IPCC coefficients. The paper also uses Moran's *I* index, kernel density estimation, and spatial Markov chains for the analysis. The results show that the total carbon emissions from China's livestock sector show a fluctuating downward trend. And livestock carbon emissions are concentrated in areas with better resource endowments, with grassland and grain-producing areas dominating China's livestock carbon emissions. The spatial analysis shows that the spatial correlation of the national livestock carbon emissions is increasing, showing prominent local aggregation characteristics, mainly in the form of high-high and low-low aggregation. The transfer of carbon emissions from China's livestock industry shows strong spatial and temporal dependence, and the transfer of regional carbon emissions is limited by the original type and stock of carbon emissions, showing growth inertia and path dependence. The findings of this paper can provide suggestions for planning and modifying policies to reduce carbon emissions in China's livestock industry.

Keywords Carbon emissions · Spatial and temporal characteristics · Dynamic evolution · Livestock

Introduction

Livestock is an essential component of agriculture. While meeting people's demand for animal products, it has become a significant source of global greenhouse gas emissions (Oenema et al. 2005; Grossi et al. 2019). With the massive emissions of greenhouse gases such as CO₂, CH₄, and N₂O, global climate change has become a serious threat to the survival and development of human society (Tollefson 2021; Zheng et al. 2019). China is also under severe pressure to reduce carbon emissions. However, there are many differences between provinces in terms of geographical location, economic base, and development methods. Only

an in-depth study and analysis of the regional differences in carbon emissions from livestock farming in each province can promote the reduction of carbon emissions. Since the reform and opening, China's livestock industry has developed rapidly. However, some problems and hidden dangers have emerged with the continuous development of the livestock industry. The problems of excessive consumption of livestock production capacity, serious pollution of livestock and poultry, and insufficient conversion of new and old dynamics are constraining the development of the livestock industry. Two thousand nineteen agricultural data released by FAO show that China's agricultural greenhouse gas emissions are 667 million tons CO₂ equivalent, of which carbon emissions from animal husbandry accounted for 35.4% (FAO 2019). Carbon emissions from animal husbandry threaten ecological security and hinder the achievement of sustainable development goals. Therefore, clarifying the current situation of greenhouse gas emissions from the livestock industry in China and specifying the spatial distribution pattern and transfer pattern of carbon emissions from the livestock industry are conducive to solving the problems of efficiency and equity. The government needs to formulate

Responsible Editor: V.V.S.S. Sarma

✉ Yuanyuan Zhang
keyneee@sda.u.edu.cn

¹ Irvine Valley College, Irvine, CA 92618, USA

² College of Economics and Management, Shandong Agricultural University, Tai'an 271000, Shandong, China

targeted emission reduction measures while stabilizing the development of the livestock industry.

Reducing carbon emissions is a must for green development. In recent years, scholars have studied the drivers of carbon emissions (Wen 2020), predictive modelling (Liu et al. 2015), and carbon trading (Zhou et al. 2019). Regarding carbon emission influencing factors, economic factors are an essential category of factors affecting carbon emissions (Cai et al. 2015). Demographic factors among social factors are also important factors influencing CO₂ emissions (Sun et al. 2015; Wang et al. 2010; Siddiqi et al. 2007). For example, Akbostancı et al. (2009) used four types of energy consumption, solid fuels, oil, gas, and electricity, in three major industries, agriculture, industry, and services, as indicators to measure carbon emissions in turkey from 1970 to 2006. He used LMDI decomposition model energy carbon emissions influencing factors and pointed out that the most influential factor of carbon emissions is economic activity. Fernandez Gonzalez (2014) also used LMDI decomposition model to analyze the influencing factors of carbon emissions in EU countries. Du et al. (2023) examined the impact of emission reduction policies on agricultural carbon emissions. Scholars have also systematically examined the regional differences and dynamic evolution of carbon emission fluctuations. For example, Fang et al. (2019) applied a carbon factor decomposition model based on the environmental Kuznets curve model to empirically analyze the characteristics and dynamic evolution of carbon emissions in China. Wang et al. (2010) applied the DEA model to measure the carbon emission performance of 28 Chinese provinces and cities from 1996 to 2007. He analyzed the regional differences and influencing factors of China's carbon emissions with the help of convergence theory and panel data regression model. Li et al. (2012) first divided 30 Chinese provinces into three different regions with low, medium, and high emissions, and then examined the non-proportional effects of population, economy, and technology on CO₂ emissions using the spirpat model. He found that there were significant differences in CO₂ emissions among the three regions. Li et al. (2020) evaluated 29 provincial-level regions in China from 1998 to 2008 based on the Ruggiero three-stage model and found that China's carbon emission efficiency gradually improved. Zhang et al. (2023) found that high speed rail can reduce carbon emissions. This effect has a negative spatial spillover effect. Liu et al. (2023) measures the carbon emissions of building materials based on data from 33 cities.

There has been a great deal of research focusing on carbon emissions from sectors such as industry, construction, and agriculture. The livestock industry serves as a pillar industry to promote farmers and herdsmen's income. It is a basic industry in rural areas. It is related to the economic and social development of the countryside and is also closely related

to the ecological environment. However, few studies have focused on the carbon emissions of livestock farming. The main organizations and methods currently conducting carbon accounting for livestock emissions are the Organization for Economic Cooperation and Development (OECD), the Intergovernmental Panel on Climate Change (IPCC), Life Cycle Assessment (LCA), and Input–Output (I-O) (Ruffing 2007; IPCC 2006; Daneshi et al. 2014), which the IPCC coefficient method and the whole-life cycle method are more commonly used. Some other scholars have further explored the influencing factors and spatial differences of carbon emissions of the livestock industry in China based on carbon emission measurement. They found that there are significant regional differences in carbon emissions of the livestock industry in China. In addition, the analysis of carbon emissions in the livestock sector is mainly focused on the trend of changes in the time dimension, but the analysis of the spatial scale is not detailed and in-depth. A certain region is selected as the main object of study, but there is a lack of comparative studies for each region of the country. In terms of research methodology, the existing studies are mainly simple descriptive statistics. Although this can identify regional differences in China's livestock industry to a certain extent, it is difficult to examine them in a detailed and systematic way.

Existing studies provide a mature methodological reference for the quantitative assessment of carbon emissions from livestock. Scholars have conducted livestock carbon emission measurements (Yang et al. 2015; Dominate et al. 2014; Munoz-Rojas et al. 2015), specified mechanisms for the growth of livestock carbon emissions (Schandl et al. 2016; Qin et al. 2016; Panichelli and Gnansounou 2015), regional equity (Kim and Neff 2009; De Vries et al. 2000), and decision-making mechanisms (Dace and Blumberg 2016). However, it fails to reveal the causes and dynamic evolutionary trends of carbon emission distribution patterns in China's livestock sector. It ignores the role of spatial factors on regional carbon emission shifts. Their findings cannot provide an adequate explanation of the dynamic changes in carbon emissions. In this paper, the global and local Moran's *I* indices are used to examine and demonstrate the spatial correlation and agglomeration characteristics of China's livestock carbon emissions from 2001 to 2020. Finally, the dynamic evolution of China's livestock carbon emissions is revealed by kernel density estimation and Markov chain analysis.

Research methods and data sources

Methodology for measuring carbon emissions from the livestock industry

The CO₂ emissions of dairy cattle, non-dairy cattle, horses, mules, donkeys, pigs, camels, goats, sheep, rabbits, and

poultry were measured based on the carbon emission factor method. The equation is:

$$E_t = E_{CH_4} + E_{N_2O} = e_{CH_4} \times \sum N_i \times \alpha_i + e_{N_2O} \times \sum N_i \times \beta_i \tag{1}$$

In Eq. (1), E_t is the total CO₂ emission, E_{CH_4} represents the CO₂ equivalent of CH₄ conversion, E_{N_2O} represents the CO₂ equivalent of N₂O conversion, e_{CH_4} and e_{N_2O} are the global warming potential (GWP) values of 21 and 310, respectively, N_i is the average feeding rate of the i species of livestock, and α_i and β_i is the CH₄ and N₂O emission factors, respectively (Table 1). Due to the different feeding cycles of livestock and poultry, it is necessary to adjust the annual average feeding rate of livestock and poultry in the way shown in Eq. (2). The livestock and poultry species to be adjusted are pigs, rabbits and birds, whose feeding cycles are 200 days, 105 days, and 55 days, respectively. The data on stock and slaughter of various livestock and poultry were obtained from the China Livestock Statistics Yearbook and the China Rural Statistics Yearbook.

$$App = \begin{cases} Herdsend, Days \geq 365 \\ Days_s \times (N/365), Days < 365 \end{cases} \tag{2}$$

The app is the average annual stocking, Herdsend is the year-end stocking, Days is the stocking period, and N is the annual slaughter.

Dagum Gini coefficient and decomposition method

This paper uses Dagum’s Gini coefficient decomposition method to describe the regional disparity of carbon emissions in livestock industry. According to the Gini coefficient and its decomposition by subgroups proposed by Dagum (1997), the Gini coefficient is defined as shown in Eq. (3), where y_{ji} (y_{hr}) is the carbon emission intensity of the livestock industry in any province (municipalities, autonomous regions, the same below) within $j(h)$ region. y is the average of carbon emission intensity of livestock industry in all provinces; n is the number of provinces. k is the number of regional divisions. And n_h is the number of provinces within $j(h)$ region.

$$G = \frac{\sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{2n^2\bar{y}} \tag{3}$$

$$\bar{Y}_h \leq \dots \bar{Y}_j \leq \dots \leq \bar{Y}_k \tag{4}$$

When decomposing the Gini coefficient, the regions are first ranked according to the mean value of the intra-regional carbon emission intensity of livestock, as shown in Eq. (4). According to Dagum’s (1997) Gini coefficient decomposition method, the Gini coefficient can be decomposed into three components: the contribution of intra-regional disparity G_w , the contribution of inter-regional net disparity G_{nb} , and the contribution of hyper-variance density G_t . Equations (5) and (6) represent the Gini coefficient G_{jj} and the contribution of intra-regional disparity G_w for region j , respectively. Equations (7) and (8) denote the inter-regional Gini coefficient G_{jh} and the contribution of the inter-regional net worth gap G_{nb} for regions j and h , respectively, while Eq. (9) denotes the contribution of the hypervariable density G_t . where $PJ = nj/n$, $sj = nj Yj/n Yj j = 1, 2 \dots, k$, D_{jh} is the relative impact of carbon emission intensity per unit of livestock between regions j and h , which is defined as shown in Eq. (10).

$$G_{jj} = \frac{\frac{1}{2\bar{Y}_j} \sum_{i=1}^{n_j} \sum_{r=1}^{n_j} |y_{ji} - y_{jr}|}{n_j^2} \tag{5}$$

$$G_w = \sum_{j=1}^k G_{jj} p_j s_j \tag{6}$$

$$G_{jh} = \frac{\sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{n_j n_h (\bar{Y}_j + \bar{Y}_h)} \tag{7}$$

$$G_{nb} = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) D_{jh} \tag{8}$$

$$G_t = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) (1 - D_{jh}) \tag{9}$$

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \tag{10}$$

Table 1 Greenhouse gas emission factors of livestock and poultry in China

Category		Cow	Non-cow	Horse	Donkey	Pig	Camel	Goat	Sheep	Rabbit	Poultry	Source
CH4 emission factor	Intestinal fermentation	68	51.4	18	10	1	46	5	5	0.25	—	IPCC
	Manure disposal	16	1.5	1.64	0.9	3.5	1.92	0.17	0.15	0.08	0.02	FAO
N2O emission factor	Manure disposal	1	1.37	1.39	1.39	0.53	1.39	0.33	0.33	0.02	0.02	Hu.et.al

$$d_{jh} = \int_0^j dF_j(y) \int_0^y (y-x)dF_h(x) \tag{11}$$

$$d_{jh} = \int_0^j dF_j(y) \int_0^y (y-x)dF_h(y) \tag{12}$$

The calculation of d_{jh} and p_{jh} is shown in Eqs. (11) and (12). F_j (F_h) is the cumulative density distribution function of region j (h), respectively. We define d_{jh} as the difference in carbon emission intensity of livestock between regions, which can be interpreted as the mathematical expectation of the sum of all sample values of $y_{ji} - y_{hr} > 0$ in j and h regions. p_{jh} is defined as the hypervariable first-order moment, which can be interpreted as the mathematical expectation of the sum of all sample values of $y_{hr} - y_{ji} > 0$ in j and h regions. We measured and decomposed the Gini coefficients of the spatial distribution of carbon emission intensity of animal husbandry in 31 provinces of China from 2001 to 2020 according to the above method and performed the regional decomposition.

ESDA method

With the help of the GeoDa spatial autocorrelation tool to characterize the spatial agglomeration of carbon emissions from the livestock industry and express the degree of global spatial autocorrelation by Moran's I index, the model is shown in the following equation.

$$I = \frac{n \sum_{j=1}^n \sum_{h=1}^n w_{jh} (x_j - \bar{x})(x_h - \bar{x})}{\sum_{j=1}^n \sum_{h=1}^n w_{jh} \sum_{j=1}^n (x_j - \bar{x})^2} \tag{13}$$

where n is the number of provinces in the study. w_{jh} is the spatial weight. x_j and x_h are the carbon emissions of livestock in province j and province h , respectively, and \bar{x} is the average value of carbon emissions of livestock in 30 provinces (cities and districts) in the study. j and h denote provinces, j and $h = 1, 2, \dots, 30$. This paper chooses the Queen-based spatial adjacency approach to establish the spatial weights. The global Moran's I index is used to reflect the spatial correlation of carbon emissions from the livestock industry, and the local Moran's I index is further used to test whether similar or dissimilar sample values in local areas appear to cluster in space, and the model is as follows.

$$I_j = \left[\frac{(x_j - \bar{x})}{s^2} \right] \times \sum_{j \neq h, j=1}^n w_{jh} (x_j - \bar{x}) \tag{14}$$

$$s^2 = \left[\sum_{j=1}^n (x_j - \bar{x})^2 \right] / n \tag{15}$$

$I > 0$ indicates that the sample values are spatially positively correlated; $I < 0$ indicates that the spatial correlation is negative at this point. $I = 0$ means no correlation, $I = [-1, 1]$.

Kernel density estimation method

Kernel density estimation is a nonparametric estimation method that has become a common method for studying unbalanced distributions because of the robustness of its estimation results (Luo et al. 2014; Fahey 2009). This method is mainly used to estimate the probability density of a random variable, and a continuous density profile describes the distribution pattern of the random variable. Assuming that the density function of the random variable X is $f(x)$, the probability density at the point x can be estimated by Eq. (16). where N is the number of observations, h is the bandwidth, and $K(\cdot)$ is the kernel function, which is a weighting function or a smoothing transformation function, X_i is the independent identically distributed observations, and \bar{x} is the mean value. Thus, the kernel density estimation method was used to analyze the location, pattern, extension, and polarization trends of the national distribution of carbon emissions from livestock (Quah 1993).

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{X_i - x}{h}\right) \tag{16}$$

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \tag{17}$$

According to the different expressions of the kernel density function, the kernel function can be classified into Gaussian kernel, triangular kernel, quadratic kernel, and other types (Lopez-Novoa et al. 2015). In this paper, we choose the more commonly used Gaussian kernel function for estimation, and the expression of the Gaussian kernel function is as in Eq. (17). Since there is no definite function expression for nonparametric estimation, we need to examine the change of distribution by graphical comparison. Generally, based on the kernel density estimation results graphs, we can get three aspects of information about the location, shape, and extension of the variable distribution.

Markov chain analysis method

The Markov chain is a stochastic process that, firstly, the carbon emission intensity of the livestock industry in each province and region is discrete into K types of Markov chain series according to the level of carbon

emission. The Markov chain is a stochastic process that firstly disaggregates the carbon emission intensity of each province and region into K types of Markov chain sequences $\{X_1, X_2, X_3, \dots\}$, The conditional probability distribution of the future state of carbon emissions from livestock in each province and region is independent of the “past state.” It is only related to the “present state.” Let the state probability vector of livestock carbon emissions in year t in each province and region be P_t . If the Markov chain for each province has a transfer matrix $P = (P_{ij})$, $P_{ij} = (n_{ij}/n_i)$, then we have $P = (n/n)$, where P represents the transfer probability of transferring a province of type i to a province of type j , n_{ij} denotes the sum of the number of provinces belonging to type i transferred to type j in the initial year of the study period, and denotes the sum of the number of provinces belonging to type i in all years.

Spatial Markov chains are derived by introducing the concept of “spatial lag” to traditional Markov chains (Anselin et al. 2008). By comparing the Markov transfer matrices of different spatial lag types, we can determine whether the level of livestock carbon emissions of “neighbors” will have an impact on the transfer of regional livestock carbon emissions. Specifically, we need first to determine the spatial weight matrix, which is the spatial adjacency matrix, then decompose the $N \times N$ type probability transfer matrix into the $N \times N \times N$ type probability transfer matrix, and finally find out the spatial transfer probability $P_{ij}(N)$ of the states in two different periods after considering spatial factors, and then reveal the influence of spatial association on the dynamic evolution of livestock carbon emission level.

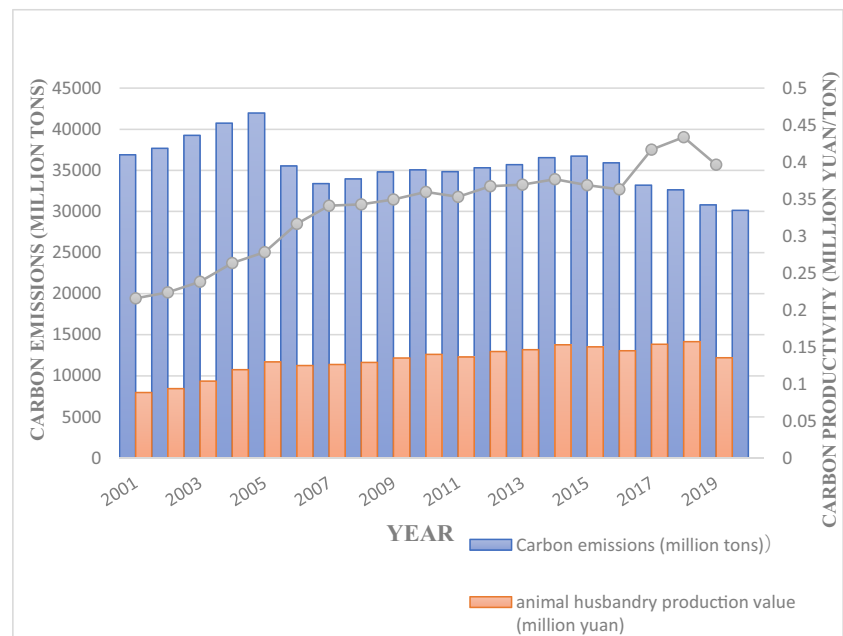
Results and analysis

Time-series characteristics analysis of carbon emissions from the livestock industry at the national level

The trend of the total carbon emission of the national livestock industry from 2001 to 2020 is shown in Fig. 1. The total carbon emission of the national livestock industry shows a decreasing trend, from 36,886.86 million tons in 2001 to 30,138.94 million tons in 2020, a decrease of 6747.92 million tons, or 18.29%. The evolution of the total carbon emission of the national livestock industry is further divided into four stages according to the fluctuation magnitude and change trend.

Rapidly rising stage (2001–2005) The national carbon emissions from animal husbandry increased from 368,886,600 to 41,948,500 tons, an increase of 50,979,800 tons or 13.82%. The increase mainly influenced the significant growth of carbon emissions in this stage in grain production and agricultural policy orientation. A phased and structural surplus of grain appeared in the late 1990s. In response, on the one hand, the state promoted farmers’ income by adjusting the agricultural structure, vigorously developed the livestock industry, effectively transformed grain and other by-products, spurred the development of planting and related industries, stabilized the development of pigs and eggs, accelerated the development of beef, mutton and poultry meat production, highlighted the development of milk and wool production, and strived to promote large-scale, standardized

Fig. 1 CO₂ emissions and livestock CO₂ emissions



and industrialized livestock and poultry farming. On the other hand, the state further reduced the livestock tax, the Slaughter tax, and other related taxes. Such initiatives have fully mobilized farmers' and herders' enthusiasm for production and promoted the development of animal husbandry, which in turn has improved the carbon emissions of animal husbandry.

Rapid decline stage (2005–2007) The national carbon emissions from animal husbandry decreased from 41,948,500 to 33,382,400 tons, a decrease of 86,019,000 tons, or 20.49%, with much higher fluctuations than other stages. The main reason for this situation is that the grain production from 1999 to 2003 was reduced, and the price remained low. Thus, the grain supply gap increased from 2004 onwards, and the grain price rebounded significantly. In addition, due to the serious ecological damage caused by overgrazing, the state implemented the system of determining livestock by grass and the resting period, which led to a significant decrease in livestock breeding, such as cattle and sheep, and eventually led to an overall reduction in carbon emissions from livestock.

The phase of oscillation and rebound (2007–2015) The national carbon emission from the livestock industry increased from 33,382.94 to 36,722.58 million tons, an increase of 3339.64 million tons, or 10.00%. The reason for this is that the steady growth of grain in this period has led to the recovery of the livestock industry, while the demand for livestock products is also steadily increasing due to the improvement of urbanization level and the adjustment of the diet structure of urban and rural residents. However, the growth rate of carbon emission in this period is relatively slow, with an average annual growth rate of only 0.6%. This is mainly due to the improvement of urbanization level, reducing the dependence of farmers and herders on animal husbandry, coupled with the tightening of resources and environment and the introduction of relevant policies to limit the rapid growth of livestock and poultry feeding, but the growth rate is slowing down. The overall expansion is in an orderly manner.

The steady decline stage (2015–2020) The national carbon emissions from livestock farming decreased from 367,225,800 to 301,389,400 tons, a decrease of 65,836,400 tons, or 17.93%. The changes in carbon emissions during this period were mainly influenced by factors such as farming efficiency, disease risk, new epidemic, and environmental regulations. For example, include the low efficiency of pig farming in 2015, the occurrence of the H7N9 epidemic in 2017, African swine fever in 2018, and the new crown epidemic in 2019. Furthermore, the Environmental Protection Tax Law implemented on January 2018 imposed an environmental protection tax on farmers with a stocking size greater than 50 cattle, 500 pigs, and 5,000 chickens and

ducks, which has had a dampening effect on carbon emissions from the livestock industry. In addition, some positive factors have played a positive role in curbing carbon emissions from livestock farming, such as breed improvement and scientific feeding, which have reduced the carbon intensity of livestock farming. Figure 2 shows the quartile chart of carbon emissions from China's animal husbandry industry. From Fig. 2, the carbon emissions from animal husbandry in each province are gradually increasing.

As shown in Table 2, the top 5 provinces in terms of carbon emissions in 2020 are Inner Mongolia (26.186 million tons), Sichuan (23.3958 million tons), Yunnan (2129.25 million tons), Xinjiang (1962.72 million tons), and Henan (16.3673 million tons). All five provinces are central livestock provinces, with Inner Mongolia, Yunnan, and Xinjiang being grassland pasture areas, while Sichuan and Henan are major grain-producing and farming pasture areas. This result indicates that livestock farming is concentrated in areas with good resource endowments, and grassland and grain-producing areas dominate the carbon emissions of China's livestock industry. Zhejiang (170.00 million tons), Hainan (139.15 million tons), Tianjin (93.18 million tons), Shanghai (28.48 million tons), and Beijing (228.2 million tons) ranked in the last five places in order. These five provinces (cities) are the primary grain marketing areas with a high level of economic development, among which Tianjin, Shanghai, and Beijing have limited resources and environmental conditions. Zhejiang and Hainan are southern water network areas. Thus, areas in addition to the high level of urbanization, the development of livestock, and animal husbandry do not play a significant role in increasing farmers' income. Farmers' conditions and enthusiasm to engage in livestock breeding are not enough. Furthermore, the difference in carbon emission changes in different provinces (cities) can be divided into four types: (1) Continuous decline type. In other words, carbon emissions are decreasing compared with the previous year, represented by four provinces (cities), including Beijing, Hebei, Guizhou, and Shaanxi. (2) Fluctuating decreasing type. In other words, carbon emissions as a whole are decreasing. However, in some years, they are increasing, represented by 19 provinces, including Shanghai, Zhejiang, Anhui, Henan, Hainan, Shandong, Jiangsu, Guangdong, Guangxi, Shanxi, Tianjin, Jilin, Fujian, Chongqing, Hunan, Sichuan, Jiangxi, Hubei, and Tibet. (3) Continuous growth type. Carbon emissions are rising compared with the previous year, represented by four provinces, including Qinghai, Gansu, Inner Mongolia, and Ningxia. (4) Fluctuating growth type. In other words, carbon emissions are generally increasing, but there are ups and downs in some years, represented by four provinces (cities), including Heilongjiang, Xinjiang, Yunnan, and Liaoning. This shows that grassland pasture and grain-producing areas are becoming China's core growth areas of carbon emissions from animal husbandry.

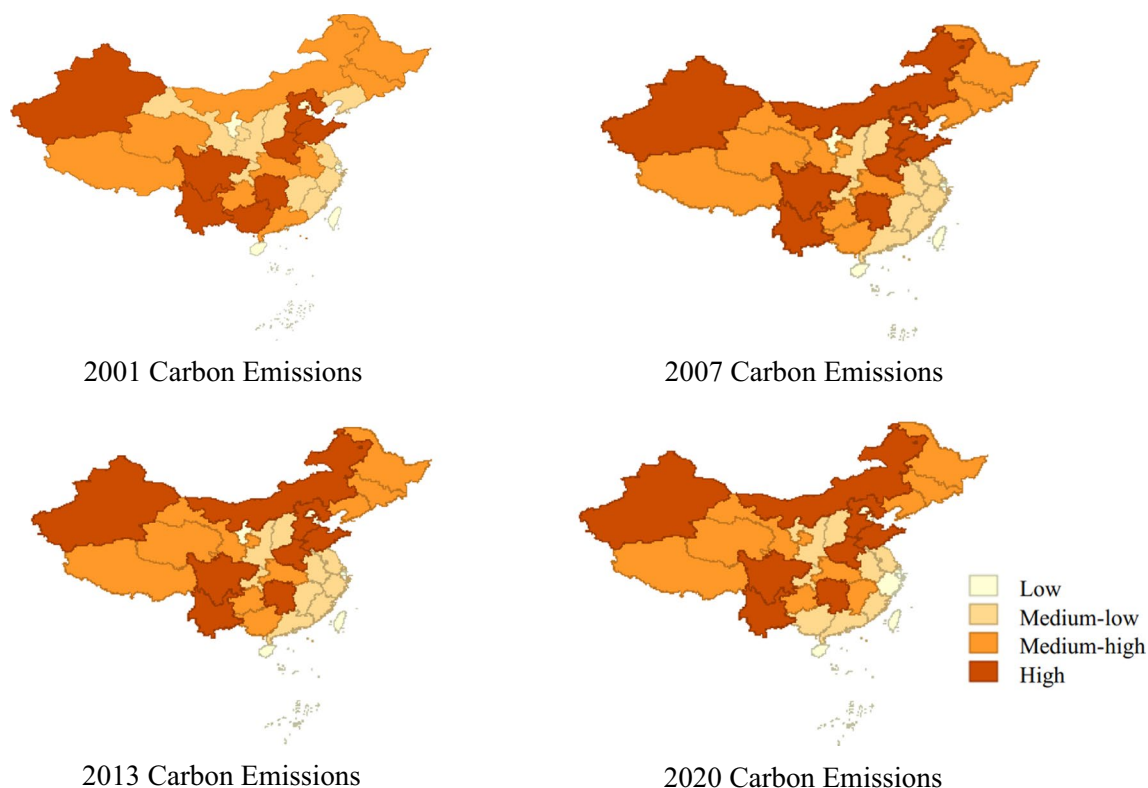


Fig. 2 Quartile chart of carbon emissions from animal husbandry production 31 provinces (cities) of China

Gini coefficient decomposition

In order to further characterize the regional disparity in the distribution of agricultural carbon emissions in China, we measured the Gini coefficient of agricultural carbon emission intensity in China from 2001 to 2020 according to the Gini coefficient and its decomposition by subgroups (Fig. 3). We decomposed it according to the three major regions in the east, central, and west, and the results are shown in Table 3. In general, the regional gap in the spatial distribution of agricultural carbon emissions in the eastern region is the smallest. In comparison, the regional gap in agricultural carbon emissions in the central region is more significant than in the western region before 2010 and smaller than in the western region after 2010. Among them, the regional gap of agricultural carbon emissions in the eastern region has decreased slightly for three consecutive years since 2001 and then increased significantly in 2004, reaching the maximum value of 0.165 in the whole sample period, and then decreased in 2006 and then increased for two consecutive years to 0.157 in 2008, and then showed an apparent downward trend despite minor fluctuations. So the gap in the eastern region is generally narrowing. If we take 2001 and 2016 as the base periods, the regional gap of agricultural carbon emissions in the eastern region decreases by 0.696% and 4.

737% annually, respectively. The regional gap of agricultural carbon emissions in the central region generally shows a decreasing trend during the sample period; if we take 2001 and 2016 as the base periods, the regional gap of agricultural carbon emissions in the central region decreases by 0.852% and 4.704% per year, respectively. From its evolution, after two rounds of increase and decrease from 0.190 in 2001, it reached the minimum value of 0.163 in 2006, and then showed an apparent upward trend and reached the maximum value of 0.232 in 2009, after which it fluctuated but showed an apparent downward trend in general. Unlike the eastern and central regions, the regional gap of agricultural carbon emissions in the western region shows a widening trend during the sample period, with an average annual increase of 1.086% in the base period of 2001 and an average annual decrease of 3.081% in the base period of 2016, respectively. From the evolutionary trend, the regional gap of agricultural carbon emissions in the western region also changes more obviously from 0.171 in 2001 to 0.195 in 2005, then decreases to 0.181 in 2007, and then rises to the maximum value of 0.233 in 2013 after a slight fluctuation, and finally shows a continuous decreasing trend.

The inter-regional gap of agricultural carbon emissions and its evolution trend is further described (Fig. 4). The inter-regional disparity of agricultural carbon emissions

Table 2 Carbon emissions from animal husbandry production and their ranking in 31 provinces of China

State	2001		2007		2013		2020	
	Carbon emissions	Rank	Carbon emissions	Rank	Carbon emissions	Rank	Carbon emissions	Rank
Beijing	163.56	29	116.18	29	105.20	30	22.82	31
Tianjin	122.71	30	101.18	30	121.33	29	93.18	29
Hebei	2351.85	4	1722.99	6	1664.84	8	1363.71	8
Shanxi	716.70	22	459.23	23	502.69	25	543.61	22
Inner Mongolia	1630.98	9	2418.53	3	2474.02	3	2618.66	1
Liaoning	843.73	20	1150.45	13	1249.71	14	1036.55	14
Jilin	1068.89	15	1203.05	11	1096.36	16	786.37	17
Heilongjiang	1155.43	14	1276.49	10	1362.97	10	1313.93	10
Shanghai	110.02	31	52.55	31	61.75	31	28.48	30
Jiangsu	818.40	21	565.86	22	670.27	21	458.48	23
Zhejiang	372.23	26	318.64	26	347.71	26	170.00	27
Anhui	1356.26	10	727.31	19	863.21	20	691.33	19
Fujian	424.39	25	377.01	25	511.57	24	348.74	26
Jiangxi	887.67	19	726.73	20	969.29	19	809.68	15
Shandong	2931.39	2	2134.75	4	2234.10	4	1533.10	7
Henan	3448.26	1	2778.21	2	2804.32	2	1636.73	5
Hubei	1064.37	16	1032.69	17	1324.15	12	809.41	16
Hunan	1684.94	7	1455.25	8	1687.92	6	1554.72	6
Guangdong	1205.37	13	914.53	18	1052.35	18	664.09	20
Guangxi	1680.22	8	1142.22	14	1377.56	9	705.56	18
Hainan	296.19	27	198.78	28	245.60	28	139.15	28
Chongqing	556.41	24	443.77	24	558.80	23	442.52	25
Sichuan	2831.18	3	2947.97	1	3083.28	1	2339.58	2
Guizhou	1347.71	11	1136.82	15	1125.28	15	1102.82	13
Yunnan	1852.00	5	1808.38	5	1966.99	5	2129.25	3
Tibet	1260.17	12	1378.08	9	1333.11	11	1138.43	12
Shaanxi	694.80	23	583.28	21	579.85	22	578.32	21
Gansu	1030.63	18	1174.11	12	1271.52	13	1359.13	9
Qinghai	1034.35	17	1052.68	16	1060.60	17	1310.73	11
Ningxia	231.25	28	270.54	27	307.93	27	447.14	24
Xinjiang	1714.80	6	1714.66	7	1669.29	7	1962.72	4

fluctuates during the sample period. However, the inter-regional disparity between east and central and east and west shows a decreasing trend, except for the slightly increasing inter-regional disparity between central and west. Taking 2001 as the base year, the inter-regional gap of agricultural carbon emissions in central and western China increased by 0.377% annually, while the inter-regional gaps in eastern and central China and eastern and western China decreased by 0.959% and 0.600%, respectively, and in 2010 as the base year, they decreased to 4.836%, 5.163%, and 4.597%, respectively. In terms of the evolution of the inter-regional gap in agricultural carbon emissions, the gap between the central and western regions has shown a significant increase since 2001 and reached 0.303 in 2005. Then, it has experienced repeated fluctuations but is in the range of 0.250~0.300, with a significant decrease after reaching the

maximum value of 0.314 in the sample period in 2014. The gap between the eastern and central regions has the same changes as the central and western regions at the beginning; i.e., it starts to show a significant increase in 2003 and reaches the maximum value of 0.217 in 2005, then fluctuates around 0.200 in the next 3 years and shows a significant decrease in 2010, while it experiences a slight increase from 2012, reaches 0.184 in 2014, and then shows a decreasing trend, 0.184 after showing a decreasing trend. Compared with the eastern and central and the central and western regions, the inter-regional disparity between the eastern and western regions fluctuates more widely, starting at a similar stage and reaching a maximum value of 0.384 within the sample period, and then decreasing significantly, reaching 0.263 in 2011 and then showing a rising and decreasing trend and reaching a minimum value of 0.243 in 2018.

Fig. 3 Gini coefficient

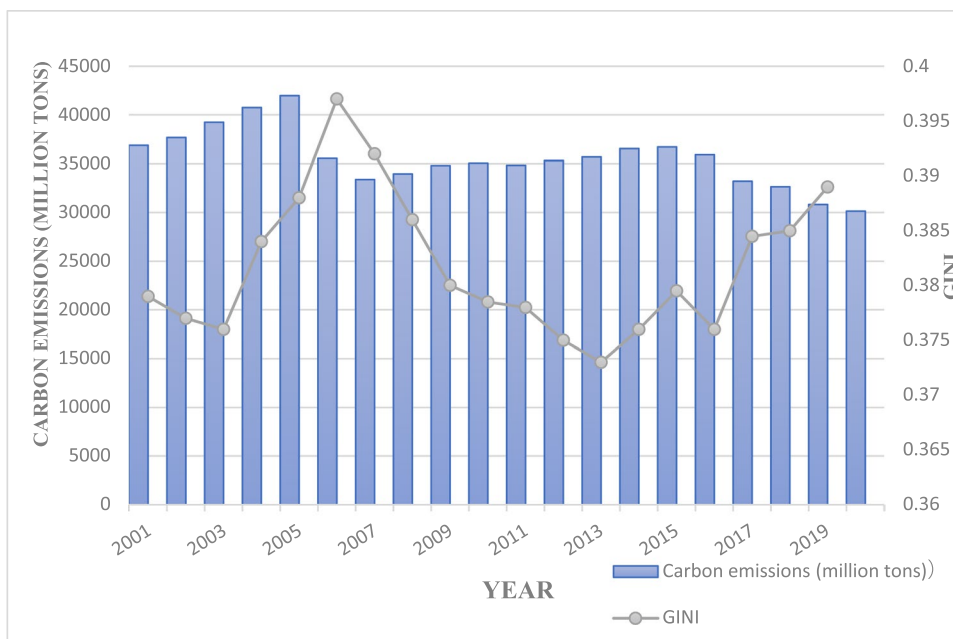


Table 3 Gini coefficient decomposition

Year	Total	Intra-regional gap			Inter-regional gap			Contribution rate		
		East	Middle	West	E-M	E-W	M-W	Intra	Inter	Den
2001	0.379	0.129	0.190	0.171	0.176	0.269	0.242	25.975	54.902	19.123
2002	0.377	0.127	0.204	0.175	0.182	0.268	0.251	26.019	53.821	20.159
2003	0.376	0.127	0.218	0.176	0.190	0.281	0.272	25.508	52.981	21.511
2004	0.384	0.164	0.187	0.184	0.212	0.384	0.295	23.316	64.588	12.096
2005	0.387	0.165	0.220	0.195	0.217	0.363	0.303	24.732	59.425	15.843
2006	0.396	0.134	0.163	0.195	0.193	0.346	0.260	23.064	64.261	12.674
2007	0.391	0.146	0.207	0.181	0.200	0.343	0.286	24.182	59.562	16.256
2008	0.385	0.157	0.232	0.220	0.210	0.307	0.283	27.152	50.011	22.837
2009	0.380	0.135	0.232	0.202	0.199	0.300	0.290	25.918	51.644	22.438
2010	0.378	0.131	0.201	0.218	0.174	0.276	0.279	26.809	47.706	26.144
2011	0.377	0.136	0.188	0.216	0.169	0.263	0.260	27.615	44.297	28.088
2012	0.374	0.140	0.191	0.218	0.172	0.282	0.287	26.675	45.457	27.868
2013	0.372	0.142	0.191	0.223	0.178	0.273	0.285	27.049	40.827	32.124
2014	0.376	0.139	0.199	0.233	0.184	0.293	0.314	26.068	43.369	30.563
2015	0.379	0.129	0.194	0.224	0.174	0.284	0.285	26.313	41.214	32.473
2016	0.378	0.125	0.175	0.227	0.158	0.285	0.286	25.962	41.854	32.183
2017	0.385	0.125	0.187	0.213	0.166	0.272	0.278	26.354	41.132	32.514
2018	0.385	0.115	0.164	0.206	0.149	0.243	0.258	26.655	41.849	31.496
2019	0.389	0.124	0.177	0.214	0.152	0.256	0.276	26.466	41.257	32.458
2020	0.383	0.114	0.182	0.211	0.158	0.263	0.281	26.535	41.895	31.985

During the sample period, although the contribution rate of inter-regional disparity fluctuated more obviously, it was always higher than that of intra-regional disparity and super-variable density, which indicates that inter-regional disparity is the main source of regional disparity in agricultural carbon emissions in China (Fig. 5). However, the contribution rate of inter-regional disparity to

the overall regional disparity tends to decrease yearly. In contrast, the contribution rate of intra-regional disparity to the overall regional disparity is greater than that of hyper-variable density before 2010 and less than that of hyper-variable density after 2010. If we take 2001 and 2016 as the base periods, the contribution of intra-regional disparity to the overall regional disparity decreases by 1.584%

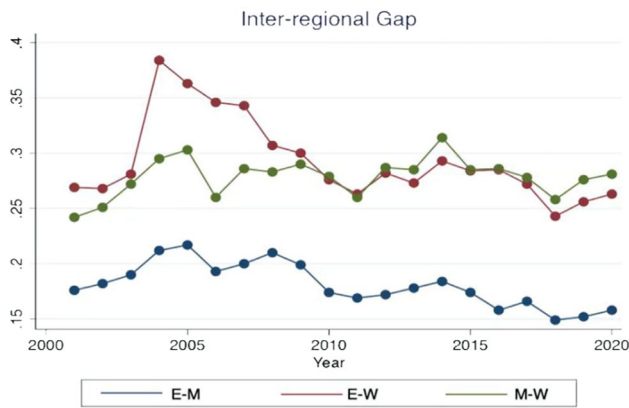


Fig. 4 Inter-regional Gap

and 0.888% annually. The contribution of intra-regional disparity to the overall regional disparity, although relatively stable, tends to increase over the sample period, with the contribution of intra-regional disparity to the overall regional disparity increasing by 0.153% per annum in 2010 relative to 2001, and reaching 0.559% relative to 2010. The contribution of hypervariable density to the overall regional gap shows a clear upward trend over the sample period, with the contribution of hypervariable density to the overall regional gap increasing by 2.979% per annum in 2020 relative to 2001, compared to 0.754% in 2010.

Spatial correlation and agglomeration patterns of carbon emissions from the livestock sector in China

Global correlation analysis The global Moran’s *I* index showed that the Moran’s *I* index of China’s livestock emissions was more significant than 0. Moran’s *I* index of China’s livestock emissions was more significant than 0 during the study period (Table 4). Moran’s *I* index of China’s livestock

carbon emissions during the study period was more significant than 0. Except for the Moran’s *I* indexes of 2005, 2006, and 2008–2014, which did not pass the significance test, the Moran’s *I* indexes of the remaining years rejected the original hypothesis, which indicates that there is some spatial correlation in livestock carbon emissions in most years. Moran’s *I* index for livestock carbon emissions from 2001 to 2019 shows an overall fluctuating growth trend. This indicates that the carbon emissions of a region are not only influenced by the resource endowment, economic development level, and livestock development strategy of the region but also by the influence of the surrounding “neighbors”; i.e., the spatial correlation of China’s livestock carbon emissions is increasing. The root causes of this are (1) the openness and connectivity of regions and the solid spatial coupling between economic development levels and carbon emissions, which determines that any economically interconnected region cannot be isolated in terms of carbon emissions. (2) The increasing infrastructure improvement and the close interaction of economic activities, knowledge, technology, and experience related to livestock and poultry farming are more likely to flow between regions. It creates a demonstration effect on neighboring regions. (3) According to the “pollution paradise hypothesis,” pollution-intensive industries are likely to move from provinces with solid environmental regulations to provinces with less intense environmental regulations, which determines the spatial dependence of carbon emissions from livestock farming. (4) The accelerated regional integration process and the regional agglomeration effect

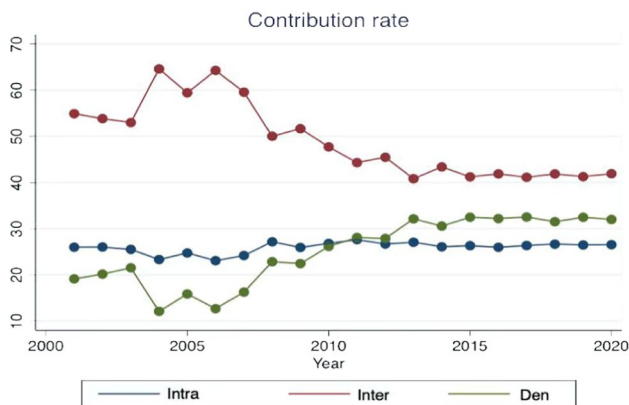


Fig. 5 Contribution rate

Table 4 Moran’s *I* of carbon emissions from animal husbandry in China

Year	Moran’s <i>I</i>	<i>p</i> -value
2001	0.160	0.046
2002	0.162	0.044
2003	0.155	0.050
2004	0.138	0.068
2005	0.130	0.078
2006	0.124	0.085
2007	0.151	0.056
2008	0.128	0.081
2009	0.134	0.073
2010	0.131	0.077
2011	0.130	0.079
2012	0.126	0.085
2013	0.130	0.080
2014	0.132	0.077
2015	0.140	0.068
2016	0.155	0.052
2017	0.169	0.041
2018	0.178	0.035
2019	0.216	0.016
2020	0.248	0.008

will promote cross-regional cooperation, the movement of resource endowments (feed, labor, etc.), and the spillover of farming technology. It makes carbon emissions from the livestock industry spatially dependent.

Local correlation analysis To further characterize the spatial clustering of carbon emissions from the livestock sector in China, the local Moran’s *I* was used to reflect the clustering characteristics of neighboring regions. Table 5 shows the spatial clustering of carbon emissions in some years. From this, it can be seen that (1) the clustering patterns are mainly high-high and low-low, and the distribution patterns are converging in two clubs, mainly in the “high carbon club” and the “low carbon club.” (2) The areas with high-high carbon emissions from livestock farming are mainly located in the southwest and the southwest of China. The remaining provinces are mainly grain-producing areas, where grain and its processing by-products are used as support, forming the carbon emission belt for livestock farming. (3) Low-low carbon emission agglomerations are mainly located in the southeastern coastal areas, which have obvious advantages in terms of location, industrial structure, and economic development patterns, and therefore have similar and low carbon emission levels and a relatively stable agglomeration trend. (4) High-low and low–high agglomerations are shrinking, with the number of provinces in the former stabilizing, while the latter leapfrogging under the influence of high-carbon areas, such as Heilongjiang, Gansu, and Qinghai, resulting in a decrease in the number of such areas. This has led to a decrease in the number of such areas.

Dynamic evolution of the distribution of carbon emissions from livestock

As mentioned earlier, carbon emissions from the livestock sector in China are spatially dependent and agglomerative. To further explore the dynamic evolution of the distribution of carbon emissions from the livestock sector in China, this paper uses the Kernel density estimation method to analyze the convergence of regional carbon emission growth. From this, the following conclusions are drawn. (1) In terms of

the movement of the peaks, the position of the central peak of the distribution curve of carbon emissions from China’s livestock industry shows a trend of “shift left-shift right-shift left,” indicating that the overall level of carbon emissions from China’s livestock industry is on a downward trend; the average values of carbon emissions from China’s livestock industry in 2001, 2007, 2013, and 2019 are 118.990 million tons, 10.768 million tons, 11.510 million tons, and 993.9646 million tons, respectively. The centre of the central peak is to the left of 10 million tons, indicating that the carbon emissions of most provinces are lower than the national average. (2) The shape of the central peak has changed from “flat and flat” to “sharp and narrow,” indicating that with the free flow of production factors, the spillover of farming technology, and the acceleration of the regional integration process. There is a clear trend of convergence within the medium level carbon emission regions. (3) Although there was a small side peak in 2001, it disappeared afterwards, indicating that the polarization of carbon emissions from China’s livestock industry was not apparent during the study period. The number of areas with high carbon emissions has increased and shows a specific gradient effect. (iv) The four curves in Fig. 6a do not show any significant variation in their location patterns, indicating that the distribution pattern of carbon emissions from China’s livestock industry is stable across a wide range of low a high-carbon emitting regions.

Since regional carbon emissions are correlated, in order to reflect the influence of the proximity effect on regional livestock carbon emissions, this paper further plots the Kernel density curve of the spatial lag of livestock carbon emissions in each province (Fig. 6b), the meaning of which is the distribution of the ratio of livestock carbon emissions to the spatial lag term in a particular province. From Fig. 6b, the kernel density curve of the spatial lag of carbon emissions from livestock in China is centered around 0.6, indicating that the carbon emissions from livestock in most regions are closed. It is challenging to compare livestock production with industrial production, and livestock production is closely related to the land area, climatic conditions, and resource endowment of each province, which determines the

Table 5 Lisa concentration pattern of carbon emissions from animal husbandry in China

Cluster Type	2001	2007	2013	2020
(H–H)	XZ YN GZ GX HN HE SD HA AH	HL JL LN HE SD HA XJ XZ YN GZ GX GS	HL LN HE SD HA HB XJ XZ YN GX GS	HL HE SD XJ XZ YN GX GS QH SC GZ
(H–L)	IM XJ SC	IM SC HN	IM SC HN	IM HA HN
(L–L)	JL NX SH ZJ JX FJ GD HI	BJ TJ SZ SH ZJ JX FJ GD HI	BJ TJ SZ SH ZJ JX FJ GD HI	BJ TL JS SH ZJ JX FJ GD HI HB AH
(L–H)	HL LN BJ TJ JS SX SN HB CQ GS QH	SX AH CQ SN QH NX HB	JL AH SX CQ SN QH NX GZ	JL LN SX SN SC NX

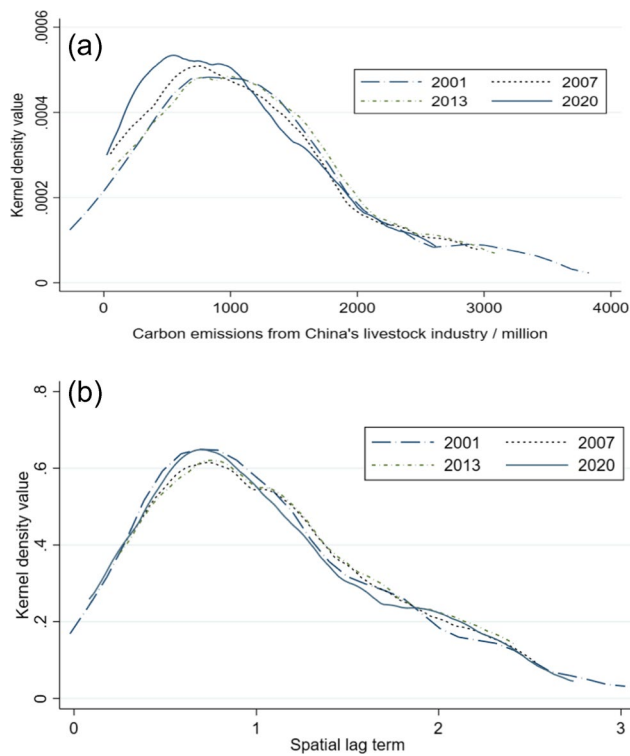


Fig. 6 Kernel density curves of absolute value (a) and the spatial lag (b) of China's animal husbandry carbon emissions

ratio of livestock carbon emissions to the spatial lag term in each province is hardly close to 1. However, this does not deny the near-neighbor effect of China's livestock carbon emissions. From the calculation results of the spatial lag ratio, for the neighboring from the results of spatially lagged ratio calculation, for neighboring provinces with more similar regional backgrounds, such as the eastern provinces, Hunan and Hubei, and Qinghai and Gansu, the proximity effect still has a more substantial explanatory power for regional livestock carbon emissions.

Dynamic evolution of the distribution of carbon emissions

The kernel density estimation method can directly examine the dynamic evolution of the distribution of carbon

emissions in China's livestock industry from the time dimension and reveal its non-equilibrium characteristics. However, it cannot reflect the specific transfer pattern and long-term evolution of the distribution of carbon emissions in the livestock industry. Therefore, based on the existence of spatial correlation and agglomeration of carbon emissions, the traditional Markov chain and spatial Markov chain analysis methods are used to calculate the transfer probability matrix to reveal the role of own carbon emissions and “neighboring” carbon emissions on the transfer of carbon emission types in the livestock industry. Firstly, the carbon emission levels of the livestock industry in each province were classified into four types: high level, medium–high level, medium–low level, and low level. This paper measures the state shift probability of China's livestock carbon emissions during the study period based on the traditional Markov chain without considering the influence of spatial factors. The results are shown in Table 6. The values on the diagonal line when T is taken at different durations in Table 6 indicate the probability of a smooth shift in regional carbon emissions after T years. In contrast, the values on the non-diagonal line indicate the probability of a shift in regional carbon emissions between different types. We can obtain the following results: (1) the values on the diagonal line (T is taken at different durations) are all greater than those on the non-diagonal line, the maximum value on the diagonal line is 97%, and the minimum value is 74%, which means that the probability that the type of carbon emissions from livestock in each region remains unchanged at different durations is at least 74%, much greater than the probability that the type of carbon emissions shifts. It indicates that the original type of carbon emissions limits the change in regional carbon emissions, and this indicates that the change in regional carbon emissions is limited by the original carbon emission types and stocks, showing growth inertia and path dependence. (2) The values on the non-diagonal line (T at different times) are not all zero, and most of the non-zero values are located in the “neighboring areas of the diagonal line,” indicating that regional carbon emissions have the possibility of shifting upwards or downwards at different times, but do not jump. This may be the effect of the development of animal husbandry. (3) The reason for this may be that the development of the livestock industry is continuous. In the

Table 6 Traditional Markov transition probability of carbon emissions from animal husbandry in China

Time	$T=1$				$T=3$				$T=5$					
	L	M-L	M-H	H	Category	L	M-L	M-H	H	Category	L	M-L	M-H	H
L	0.90	0.10	0.00	0.00	L	0.88	0.12	0.00	0.00	L	0.89	0.11	0.00	0.00
M-L	0.03	0.84	0.13	0.00	M-L	0.08	0.79	0.13	0.00	M-L	0.09	0.75	0.16	0.00
M-H	0.00	0.06	0.88	0.06	M-H	0.00	0.15	0.77	0.08	M-H	0.00	0.16	0.76	0.08
H	0.00	0.00	0.03	0.97	H	0.00	0.00	0.12	0.88	H	0.00	0.00	0.16	0.84

absence of major national strategies and opportunities for industrial development, it is unlikely that there will be a leap in the type of carbon emissions from the livestock industry across levels. The probability of maintaining a smooth shift between low and high-level areas is 90%, 88%, 89% and 97%, 88%, and 84% after 1, 3, and 5 years. It indicates that both low and high-level areas have an internal convergence. The trend is toward internal convergence in both low and high-level regions. The probability of carbon emission types shifting between low and medium-level areas is relatively higher. Most of the carbon emission types in low and medium-level areas will shift upwards. In contrast, most of the carbon emission types in medium and high-level areas will shift downwards, which indicates that under the state of “spatial locking” between low and high-level areas, low and medium level areas and high-level areas will have a greater impact on the carbon emissions of the livestock industry. This indicates that in areas where low and high carbon emissions are “spatially locked,” medium–low and medium–high carbon emissions have a “reconciling” effect on the total carbon emissions of the livestock industry. And in the future, the focus should be on optimizing the carbon emissions of these two types of areas in order to reduce carbon emissions.

Spatial Markov chain analysis This paper uses spatial Markov chains to analyze the spatial transfer pattern of livestock carbon emissions and to identify the influence of spatial factors on the dynamic evolution of regional livestock carbon emissions, i.e., to determine whether the level of livestock carbon emissions in the surrounding areas affects the level of livestock carbon emissions in the region. Table 7 gives the significance test results for the spatial Markov shift probabilities of different time durations. The Q statistic is significant at the 1% level for time durations of 1, 2, 3, 4, and 5 years. The significance of this spatial influence (Q value) increases with time, which indicates that the influence of spatial factors on the level of livestock carbon emissions in each region cannot be ignored. There is a spatial effect in the dynamic evolution of livestock carbon emissions in China.

In order to further analyze the specific impact of this spatial effect, a geographical weight matrix was introduced to measure the spatial shift probability matrix of China’s livestock carbon emissions under different time lengths. The shift in the type of regional livestock carbon emissions does not exist in isolation in space but shows a more significant correlation with the carbon emission levels of the surrounding “neighbors.” The probability of transferring carbon emissions from the livestock sector varies among provinces in different regional contexts. For example, suppose the “neighbors” of a low-level region are also low-level. In that case, the probability of upward shift is only 6% after 1 year ($p_{12/1}^{T=1} = 6\%$), while when the regional background is

Table 7 Results of the spatial Markov transfer probability significance test for carbon emissions from animal husbandry

Time (Year)	Q	Degree of freedom	Chi-square value	
1	57.79	6	16.81	0.00
2	72.52	8	20.09	0.00
3	79.06	9	21.67	0.00
4	100.07	8	20.09	0.00
5	108.41	7	18.48	0.00

high-level, this probability will be higher than that of the “neighbors” of a low-level region. When the regional context is high, this probability increases to 45%. Conversely, the probability of a downward shift in livestock emissions is smaller for areas with a high regional background than for areas with low regional background. However, this effect is less pronounced at one year and more pronounced at five years, e.g., at 5 years, the probability of a shift from a high to a medium to low regional background is 9%, while at a low regional background, this probability increases to 5%. When the regional context is low, this probability increases to 44%. This indicates that regional background plays a vital role in the dynamics of regional livestock carbon emissions. It is necessary to explore the evolution of China’s livestock carbon emission pattern from the perspective of spatial correlation. Different regional contexts play different roles in the process of carbon emission increase and decrease in livestock. A high-level regional context has a facilitating effect on regional livestock carbon emissions, and when a region is surrounded by a high-level region, the probability of an upward shift of carbon emissions in that region is higher than that of being surrounded by a low-level region. For example, $p_{32/1}^{T=5} = 44\% > p_{32/4}^{T=5} = 9\%$, $p_{43/1}^{T=5} = 50\% > p_{43/4}^{T=5} = 6\%$ indicates that low-level areas have a suppressing effect on carbon emissions in surrounding areas; the resource endowment, industrial structure, and economic development patterns of neighboring areas are more similar. The acceleration of the economic integration process promotes the common carbon suppression effect. The high carbon spillover effect is stronger than the low carbon lock-in effect. For example, $p_{12/4}^{T=5} = 71\% > p_{43/1}^{T=5} = 50\% > p_{32/1}^{T=5} = 44\%$, indicating that areas with high carbon emissions are more likely to pull up the carbon emissions of Livestock in the surrounding areas, while areas with low carbon emissions are more likely to pull down the carbon emissions of livestock in the surrounding areas. This shows that it is easy to increase carbon but challenging to reduce it in the process of livestock development, and it is difficult to break the “path dependence” of livestock carbon emissions in a short period. The more significant the gap between the level of carbon emissions of the livestock industry and that of its neighbors, the stronger the spatial interaction between the livestock industry’s

carbon emissions. For regions that shift up or down, the probability of shifting increases as the gap with “neighbors” increases, e.g., $p_{12/3}^{T=5} = 13\% < p_{12/4}^{T=5} = 71\%$, $p_{43/2}^{T=5} = 13\% < p_{43/1}^{T=5} = 50\%$ which indicates that the greater the difference in regional carbon emission levels, the stronger the power of low carbon regions to catch up with high carbon regions or low carbon regions to limit high carbon regions (Table 8).

Discussion

- (1) There is an apparent correlation between regional carbon emissions from animal husbandry. Therefore, governments at all levels should face the fundamental differences in regional carbon emissions from livestock farming, make full use of the interdependence between regions, place the low-carbon development of livestock farming within a unified and coordinated framework, and build a collaborative emission reduction mechanism.
- (2) As the core growth areas for carbon emissions from livestock farming, grassland pastoral areas and grain-producing regions are responsible for supplying important livestock products. Therefore, to stabilize the livestock industry’s development, these regions should moderately control the growth rate of carbon emissions through management and technical means.
- (3) The spatial dependence of China’s carbon emission shift is strong, and the regional analysis shows that the regional context clearly influences the shift of regional carbon emission types, and the “high carbon spillover

effect” and “low carbon lock-in effect” are both significant. The “high carbon spillover effect” and the “low carbon lock-in effect” coexist.

Conclusion

This paper presents a comprehensive analysis of the spatial characteristics and dynamic evolution of carbon emissions from animal husbandry using data from 31 provinces in China from 2001 to 2020. We draw the following four conclusions. (1) Total national carbon emissions from livestock farming have fallen amid fluctuations, from 368,886,600 tons in 2001 to 308,129,900 tons in 2019, a decrease of 60,739,600 tones, or 16.47%. In terms of distribution patterns, China’s livestock farming is being enriched to areas with superior resource endowments, with grassland pastoral areas and major grain-producing regions dominating China’s livestock carbon emissions. (2) The overall spatial distribution pattern of carbon emissions in the livestock industry is “high in the west and low in the east,” with more low-carbon areas and fewer high-carbon areas, with obvious regional differences and the possibility of further expansion. The spatial correlation of carbon emissions in the national livestock industry is increasing, showing obvious local clustering characteristics, mainly manifesting as high-high and low-low clustering trends. (3) The evolution of national livestock carbon emission pattern shows obvious path dependency, regional carbon emission is limited by the original carbon emission type and stock, showing strong growth inertia and path dependency, but there is still the possibility of upward or downward shift. (4) The “high carbon spillover effect”

Table 8 Spatial transfer probabilities of carbon emissions from animal husbandry in China ($T=1, T=5$)

Background	$T=1$					$T=5$					
	Category	L	M-L	M-H	H	Category	L	M-L	M-H	H	
L	L	0.94	0.06	0.00	0.00	L	L	0.92	0.08	0.00	0.00
	M-L	0.02	0.98	0.00	0.00		M-L	0.03	0.97	0.00	0.00
	M-H	0.00	0.00	0.78	0.22		M-H	0.00	0.44	0.11	0.44
	H	0.00	0.00	0.00	1.00		H	0.00	0.00	0.50	0.50
M-L	L	1.00	0.00	0.00	0.00	M-L	L	1.00	0.00	0.00	0.00
	M-L	0.00	0.81	0.19	0.00		M-L	0.00	0.65	0.35	0.00
	M-H	0.00	0.08	0.75	0.17		M-H	0.00	0.06	0.67	0.28
	H	0.00	0.00	0.03	0.97		H	0.00	0.00	0.13	0.87
M-H	L	0.75	0.25	0.00	0.00	M-H	L	0.88	0.13	0.00	0.00
	M-L	0.02	0.86	0.12	0.00		M-L	0.09	0.84	0.06	0.00
	M-H	0.00	0.06	0.94	0.00		M-H	0.00	0.23	0.78	0.00
	H	0.00	0.00	0.03	0.97		H	0.00	0.00	0.17	0.83
H	L	0.55	0.45	0.00	0.00	H	L	0.29	0.71	0.00	0.00
	M-L	0.08	0.67	0.25	0.00		M-L	0.21	0.45	0.34	0.00
	M-H	0.00	0.07	0.90	0.03		M-H	0.00	0.09	0.91	0.00
	H	0.00	0.00	0.06	0.94		H	0.00	0.00	0.06	0.94

and the “low carbon lock-in effect” coexist. These two effects have reinforced the trend of convergence in China’s livestock emission clubs, with grassland pasture areas and major grain producing areas in southwest, northwest, and northeast China becoming high carbon emission areas in the livestock sector based on their resource advantages.

Based on these conclusions we present the following constructive suggestions for the development of China’s livestock industry. Firstly, the government should pay attention to the differences in carbon emissions between regions. Improve the technological level and industrial upgrading of the livestock industry to reduce carbon emissions in some regions. At the same time, the government should coordinate the differences between high-emission areas and low-emission areas to promote the common development of the livestock industry. Secondly, enterprises and individuals in grassland and grain-producing areas should strengthen their management techniques to control the increase in carbon emissions. The government should introduce relevant tax and fee compensation policies to incentivize enterprises to engage in technological innovation. At the same time, the government should increase subsidies to individuals to promote the stable development of the livestock industry. Although the paper considers the provinces, the availability of information and the complexity of the issues do not allow for a comprehensive consideration of all factors. For example, most of the cattle feed is made from grass, but the carbon emissions from growing it are not accounted for. In addition, the factors that influence carbon emissions from livestock should be further analyzed. Factors such as production factors, population growth factors, and farming behavior are areas for further research.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Jiale Yan and Yuanyuan Zhang. The first draft of the manuscript was written by Jiale Yan, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding This work was supported by the National Social Science Foundation youth project “Research on ecological compensation system construction and supporting policies for cleaner production of animal husbandry” (No. 20cgl029).

Data availability All authors ensure that all data and materials as well as software application or custom code support the published claims and comply with field standards.

Declarations

Ethics approval The submitted manuscript is original and have not been published elsewhere in any form or language.

Consent to participate Done.

Consent for publication All authors agreed with the content and that all gave explicit consent to submit.

Competing interests The authors declare no competing interests.

References

- Akbostancı E, Türüt-Aşık S, Tunç Gİ (2009) The relationship between income and environment in Turkey: is there an environmental Kuznets curve? *Energy Policy* 37(3):861–867
- Anselin L, Le Gallo J, Jayet H (2008) Spatial panel econometrics. The econometrics of panel data fundamentals and recent developments in theory and practice. *Matayas L and Sevestre P* 46:625–660
- Cai Q, Zhang D, Zheng W et al (2015) A new fuzzy time series forecasting model combined with ant colony optimization and autoregression. *Knowl-Based Syst* 74:61–68
- Dace E, Blumberg D (2016) How do 28 European Union Member States perform in agricultural greenhouse gas emissions? It depends on what we look at: Application of the multi-criteria analysis. *Ecol Ind* 71:352–358
- Dagum C (1997) Decomposition and interpretation of Gini and the generalized entropy inequality measures. *Statistica* 57(3):295–308
- Daneshi A, Esmaili-Sari A, Daneshi M et al (2014) Greenhouse gas emissions of packaged fluid milk production in Tehran. *J Clean Prod* 80:150–158
- De Vries B, Bollen J, Bouwman L, den Elzen M, Janssen M, Kreileman E (2000) Greenhouse gas emissions in an equity-, environment- and service-oriented world: an image-based scenario for the 21st century. *Technol Forecast Soc Chang* 63(2–3):137–174
- Dominante E, Mackay A, Green S, Patterson M (2014) A soil change-based methodology for the quantification and valuation of ecosystem services from agro-ecosystems: a case study of pastoral agriculture in New Zealand. *Ecol Econ* 100:119–129
- Du Y, Liu H, Huang H et al (2023) The carbon emission reduction effect of agricultural policy—evidence from China. *J Clean Prod* 406:137005
- Fahey TZ (2009) On the use of kernel-based nonparametric probability density functions in electrochemical process analysis. *Electrochim Acta* 54(14):3759–3765
- Fang D, Hao P, Wang Z et al (2019) Analysis of the influence mechanism of CO₂ emissions and verification of the environmental Kuznets curve in China. *International Journal of Environmental Research and Public Health* 16(6):944
- FAO, from <http://www.fao.org>, 2019
- Fernandez Gonzalez P (2014) The driving forces behind changes in CO₂ emission levels in EU-27. Differences between member states. *Environ Sci Policy* 38:11–16
- Grossi G, Goglio P, Vitali A et al (2019) Livestock and climate change: impact of Livestock on climate and mitigation strategies. *Anim Front* 9(1):69–76
- IPCC (2006) IPCC Guidelines for National Greenhouse Gas Inventories Volume 4: Agriculture, Forestry and other Land Use. Geneva, Switzerland: IPCC
- Ipek G, Tun G, Serap R, Tiritas LK (2009) A decomposition analysis of CO emissions from energy use: Turkish case. *Energy Policy* 37(11):4689–4699
- Kim B, Neff R (2009) Measurement and communication of greenhouse gas emissions from U.S. food consumption via carbon calculators. *Ecol Econ* 69(1):186–196
- Li H, Mu H, Zhang M et al (2012) Analysis of regional difference on impact factors of China’s energy-Related CO₂ emissions. *Energy* 39(1):319–326

- Li J, Ma J, Wei W (2020) Analysis and evaluation of the regional characteristics of carbon emission efficiency for China. *Sustainability* 12(8):3138
- Liu LW, Chen CX, Zhao YF et al (2015) China's carbon-emissions trading: overview, challenges and future. *Renew Sustain Energy Rev* 49:254–266
- Liu T, Zhao R, Xie Z et al (2023) Carbon emissions from accumulated stock of building materials in China. *Build Environ* 240:110451
- Lopez-Novoa U, Sáenz J, Mendiburu A, Miguel-Alonso J, Errasti I, Esnaola G, Ezcurra A, Ibarra-Berastegi G (2015) Multi-objective environmental model evaluation by means of multidimensional kernel density estimators: efficient and multi-core implementations. *Environ Model Softw* 63:123–136
- Luo XP, Lu Z, Xu X (2014) Non-parametric kernel estimation for the ANOVA decomposition and sensitivity analysis. *Reliab Eng Syst Saf* 130:140–148
- Munoz-Rojas M, Doro L, Ledda L, Francaviglia E (2015) Application of Carbo SOIL model to predict the effects of climate change on soil organic carbon stocks in agro-silvo-pastoral Mediterranean management systems. *Agr Ecosyst Environ* 202:8–16
- Oenema O, Wrage N, Veldhof GL et al (2005) Trends in global nitrous oxide emissions from animal production systems. *Nutr Cycl Agroecosyst* 72(1):51–65
- Panichelli L, Gnansounou E (2015) Impact of agricultural-based biofuel production on greenhouse gas emissions from land-use change: key modelling choices. *Renew Sustain Energy Rev* 42:344–360
- Qin XB, Li YE, Wang H, Liu C, Li JL, Wan YF, Gao QZ, Fan FL, Liao YL (2016) Long-term effect of biochar application on yield-scaled greenhouse gas emissions in a rice paddy cropping system: a four-year case study in south China. *Sci Total Environ* 569–570:1390–1401
- Quah D (1993) Galton's fallacy and tests of the convergence hypothesis. *The Scand J Econ* 95:427–443
- Ruffing K (2007) Indicators to measure decoupling of environmental pressure from economic growth. *Sustain Indic: A Sci Assess* 67:211
- Schandi H, Hatfield-Dodds S, Wiedmann T, Geschke A, Cai Y, West J, Newth D, Baynes T, Lenzen M, Owen A (2016) Decoupling global environmental pressure and economic growth: scenarios for energy use, materials use and carbon emissions. *J Clean Prod* 132:45–56
- Siddiqi SM, Gordon GJ, Moore AW (2007) Fast state discovery for HMM model selection and learning. *Assistants* 2:492–499
- Sun B, Guo H, Karimi HR et al (2015) Prediction of stock index futures prices based on fuzzy sets and multivariate fuzzy time series. *Neurocomputing* 151:1528–1536
- Tao L, Qiang F (2011) Study on China's carbon dioxide emissions efficiency. *Stat Res* 28(7):62–71
- Tapio P (2005) Towards a theory of decoupling: degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transp Policy* 12(2):137–151
- Tollefson J (2021) IPCC climate report: Earth is warmer than it's been in 125,000 years. *Nature* 596(7871):171–172
- Wang S, Zhao Y (2001) Online Bayesian tree-structured transformation of HMMs with optimal model selection for speaker adaptation. *IEEE Trans Speech and Audio Processing* 9(6):663–677
- Wang QW, Zhou P, Zhou DQ (2010) Research on dynamic carbon dioxide emissions performance, regional disparity and affecting factors in China. *China Industrial Economics* 1:45–54
- Wen L (2020) Li Z Provincial-level industrial CO₂ emission drivers and emission reduction strategies in China: combining two-layer LMDI method with spectral clustering. *Sci Total Environ* 700:134374
- Yang XM, Chen HQ, Gong YS, Zheng XH, Fan MS, Kuzyakov Y (2015) Nitrous oxide emissions from an agro-pastoral ecotone of northern China depending on land uses. *Agr Ecosyst Environ* 213:241–251
- Zhang W, Zeng M, Zhang Y et al (2023) Reducing carbon emissions: can high-speed railway contribute? *J Clean Prod* 413:137524
- Zheng JL, Mi ZF, Coffman D et al (2019) The slowdown in China's carbon emissions growth in the new phase of economic development. *One Earth* 1(2):240–253
- Zhou B, Zhang C, Song HY et al (2019) How does emission trading reduce China's carbon intensity? An exploration using a decomposition and difference-in-differences approach. *Sci Total Environ* 676:514–523

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.