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Spatial correlation network structure of carbon productivity from the livestock sector in china and its driving factors: a perspective of social network analysis

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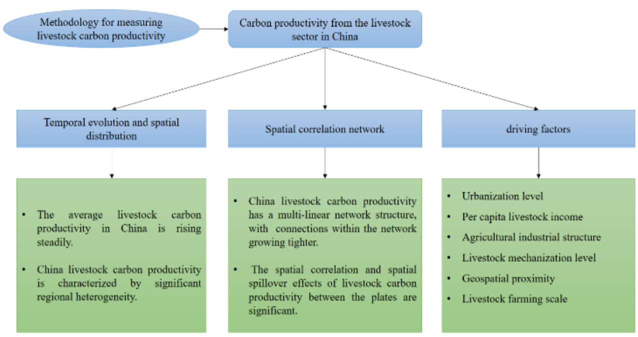
Graphical abstract



Abstract

Exploring the spatial correlation network structure of provincial livestock carbon productivity and its driving factors can provide new policy perspectives for realizing the synergy of regional pollution and carbon reduction. This study constructs 2006-2021 panel data models by social network analysis (SNA) to systematically quantify the spatial correlation network structure of the carbon productivity in livestock sector. Then, the quadratic assignment procedure (QAP) is further utilized to examine its driving factors. The results demonstrate that: (1) The average carbon productivity from the livestock sector in China is rising steadily. (2) The spatial correlation of carbon productivity exhibits a multi-linear network structure, with the spatial correlation network becoming increasingly complex and the connections within the network growing tighter. It has formed a spatial network structure with the eastern coast zone as the core and the north-eastern and north-western zones as the edges. (3) The spatial correlation and spatial spillover effects of carbon productivity from the livestock sector between the plates are significant. (4) The formation and evolution of the spatial correlation network of carbon productivity from the livestock sector is influenced by the urbanization level, per capita livestock income, agricultural industrial structure and livestock mechanization level.

Keywords: livestock sector; carbon productivity; spatial correlation network structure; social network analysis; driving factors

1. Introduction

Recently, the issue of global warming caused by greenhouse gas emissions has attracted widespread attention, with the issue of carbon emissions being widely discussed in all sectors (He *et al.* 2020; Wang *et al.* 2021). Since China proposed the dual carbon goal at the 27th the United Nations General Assembly, the strategic deployment of "carbon peaking" and "carbon neutrality" has gradually gained prominence on the agenda. The 20th National Congress of the Communist Party of China explicitly pointed out the need to "accelerate the green transformation of the economic development model" and "actively and steadily promote carbon peaking and carbon neutrality". The Central Document No.1 in 2023 emphasizes the need to "deepen the promotion of agricultural green development". It is evident that carbon emissions have received attention from the Party and the government in all industries. China's carbon emissions are among the highest in the world, posing a serious challenge to high-quality domestic economic growth and sustainable development of the ecological environment (Xie *et al.* 2017; Hu *et al.* 2023). Among them, emissions reduction and carbon sequestration in agriculture and rural areas play an important role in the "dual carbon" goals and represent great potential (Hansen *et al.* 2019). The livestock sector is an important component of agriculture. While meeting the growing demand for livestock products, it has become a major source of global greenhouse gas emissions. (Xu *et al.* 2021; Jiang *et al.* 2024). In order to promote the green and low-carbon transformation of the livestock sector and to enhance the improvement of the rural ecological environment, it is of practical significance to study the issue of livestock carbon emission in China.

The livestock sector is one of the primary sources of agricultural carbon emissions. Existing studies indicate that the carbon emissions from livestock and poultry farming in

China account for over 30% of the total agricultural carbon emissions, surpassing the carbon emissions generated from agricultural energy use, input of agricultural materials, and rice cultivation (Jiang *et al.* 2023; Zhang *et al.* 2023). Currently, the main academic literature covers carbon emission measurement and comparison, influencing factors and spatial patterns from the livestock sector (Herrero *et al.* 2016; Qambrani *et al.* 2017; Xu *et al.* 2021). In terms of measuring and comparing carbon emissions from the livestock sector, the IPCC coefficient method, the life cycle assessment (LCA) and the carbon footprint method have been more frequently applied (Ross *et al.* 2014; Salvador *et al.* 2017; Horrillo *et al.* 2020). All of the above studies have found that livestock carbon emission reduction is crucial for carbon neutrality in China (Barthelmie, 2022). The scale of the study encompasses the national, provincial and county levels (Josette *et al.* 2019; Cai *et al.* 2019; Zhuang *et al.* 2019). And the results all contribute to the formulation and implementation of national environmental policies on the livestock sector (Yan *et al.* 2023).

In terms of the factors influencing carbon emissions from the livestock sector, the effects of livestock production efficiency, population growth, urbanization, income level, industrial structure and other factors on carbon emissions have been meticulously explored (Li *et al.* 2017; González *et al.* 2020; Zhang *et al.* 2020; Rehman *et al.* 2021; Kumar *et al.* 2023). And some of these factors can spatially contribute to or inhibit the carbon emissions from the livestock sector. Accompanied by the progress of spatial analysis methods and spatial measurement techniques, scholars have discussed the spatial spillover and spatial convergence of carbon emissions from the livestock sector. (Cai *et al.* 2018; Hao *et al.* 2022; Su *et al.* 2022). Relevant studies have found that the spatial correlation of carbon emissions from the livestock sector has been increasing, and there are characteristics of agglomeration and convergence (Willeghems *et al.* 2016; He *et al.* 2023). Further, some scholars have analyzed the distribution pattern of carbon emissions from the livestock sector. in China based on the perspectives of “equity” and “efficiency” (VanderZaag *et al.* 2014; Albert *et al.* 2019; Sun *et al.* 2022). They all believe that China has gradually formed a major carbon emission zone for the livestock sector extending from northeast region to southwest region, with significant regional variations. (Verdi *et al.* 2024).

However, it is known that scholars have conducted more studies on carbon emissions from the livestock sector, but relatively fewer studies on the efficiency or productivity of carbon emissions in the livestock sector (Landholm *et al.* 2019). Carbon emissions only reflect “environmental benefits”, while carbon efficiency or productivity consider both “environmental benefits” and “economic benefits”. Focusing only on carbon emissions and neglecting the efficiency or productivity of carbon emissions in the livestock sector may lead to a lack of harmony between the livestock economic development in some regions and environmental protection. Therefore, this study will focus on the carbon productivity in the livestock sector. Furthermore, with the increased coordination of regional development in China, the circulation and allocation of factors such as knowledge, technology, and capital have accelerated, and the spatial correlation relationships between provinces have been enhanced. (Huo *et al.* 2022). As a result, the spatial correlation of carbon emissions is no longer limited to geographical proximity but exhibits complexity and network characteristics in space (Cai *et al.* 2022; Rong *et al.* 2023). Although some studies have recognized the spatial spillover and convergence effects of carbon emissions in the livestock sector, reflecting spatial correlation characteristics based on “attribute” data rather than “relationship” data inevitably has certain limitations and fails to fully demonstrate its specific internal structural characteristics. While scholars have employed social network analysis methods to analyze the overall and individual characteristics of spatial correlation networks of carbon emission efficiency in China, involving industries such as transportation, agriculture, and tourism, they have not yet delved into the study of carbon emissions in the livestock sector (Yang *et al.* 2014; Chen *et al.* 2018; Yu *et al.* 2022; Tang and Li, 2024). Therefore, these limitations will pose constraints on the development of carbon emission reduction efforts and policy design in the livestock sector.

Based on the “dual carbon” goal and the context of high-quality development in the livestock sector, this study aims to calculate the livestock carbon productivity in China. Furthermore, it employs social network analysis and QAP regression analysis to examine the spatial correlation network characteristics of livestock carbon productivity in China and identify the driving factors involved. Compared with existing studies, the marginal contributions of this study are: (1) By expanding the concept of “livestock carbon emissions to “livestock carbon productivity”, this study aims to provide a more objective assessment of the balance between “emission reduction” and “economic development” in the regional livestock sector from the perspectives of both “environmental benefits” and “economic benefits (2) By focusing on “relationship” data rather than “attribute” data and emphasizing “numerical validity” over “numerical magnitude”, this study aims to delve into the internal structural characteristics of the spatial correlation network of carbon productivity from the livestock sector in China. (3) This study utilizes the latest data to explore the driving factors of the spatial correlation network of carbon productivity from the livestock sector in China. It analyses the impact of variables characterizing the livestock industry on the spatial correlation network and mitigates the estimation bias that may result from the problem of multicollinearity among variables.

2. Methodology and data

2.1. Methodology for measuring livestock carbon productivity

Drawing the definition of carbon productivity from Kaya *et al*. (1999), this study adopts the livestock industry output created per unit of carbon emissions as the measurement indicator for carbon productivity in the livestock sector. This indicator takes into account both the environmental benefits" and "economic benefits" aspects, providing a comprehensive evaluation of carbon productivity. To measure carbon productivity in the livestock sector, it is necessary to calculate the carbon emissions from the livestock sector in China. Using the IPCC coefficient method, this study calculates the carbon emissions from 10 categories of ruminant and non-ruminant animals from the livestock sector in China, including cows, non-dairy cattle, horses, donkeys/mules, camels, goats, sheep, pigs, rabbits, and poultry. The specific calculation formula is as follows:

$$C_t = C_{CH_4} + C_{N_2O} = \theta_i \times W_{CH_4} \times \sum N_i + \gamma_i \times W_{N_2O} \times \sum N_i \tag{1}$$

Here, C_t is the total carbon emissions from the livestock sector in China; C_{CH_4} C_{N_2O} denote the equivalent of CO_2 after the conversion of CH_4 and N_2O; θ_i, γ_i denote the CH_4, N_2O emission factors of the livestock species in category I W_{CH_4}, W_{N_2O} are global warming potentials (GWPs) with values of 21 and 310 N_i then denotes the average annual stocking of the livestock species in category i. The livestock carbon emissions measured in this study mainly include enteric fermentation and manure treatment. Among them, the data on CH_4 emission factors from enteric fermentation of 10 livestock species were obtained from the United Nations Intergovernmental Panel on Climate Change (IPCC). The data on the emission factor of CH_4 from manure treatment were obtained from FAO, while the data on the emission factor of N_2O from manure treatment were obtained from Hu *et al* (2010).

Based on the available data, different livestock rearing cycles dictate the need to adjust the average annual feeding levels for some livestock species. For breeds with a rearing cycle greater than or equal to 1 year, the end-of-year stocking is the average annual feeding. For breeds with a rearing cycle of less than 1 year, it is necessary to use the rearing cycle of the livestock breed and the end-of-year stocking conversion to obtain. The specific calculation formula is as follows:

$$N_{AF} = \begin{cases} L_{AO},\ RC \geq 365 \\ RC \times \dfrac{N}{365},\ RC < 365 \end{cases} \tag{2}$$

Here, N_{AF} is the average annual feeding; L_{AO} is the end-of-year stocking; RC is the rearing cycle; and N is the year-end output. Of the 10 types of livestock species selected for this study, pigs, rabbits and poultry have rearing cycles of 200, 105 and 55 days (less than 1 year). Therefore, the average annual feeding of the above three types of livestock breeds was converted.

2.2. Modified gravity model

Before analyzing the characteristics of the spatial correlation network of carbon productivity from the livestock sector in China, it is necessary to construct a spatial correlation matrix of carbon productivity in the livestock sector. Drawing on the relevant studies of Cai *et al*. (2022) and Hao *et al*. (2022), a modified gravity model is constructed by combining the traditional gravity model and the carbon productivity of China's livestock sector by province calculated above. Then a spatial correlation matrix of China's livestock sector carbon productivity is obtained. The modified gravitational model is given in the following equation:

$$Q_{ij} = \frac{LG_i}{LG_i + LG_j} \times \frac{LCP_i + LCP_j}{\dfrac{D_{ij}^2}{\left(lg_i - lg_j\right)^2}} \tag{3}$$

Here, Q_{ij} is the gravitational value of livestock carbon productivity between province *i* and province *j* in China, and the matrix formed by each gravitational value reflects the strength of spatial correlation of livestock carbon productivity in China; LG_i and LG_j are the Gross Livestock Production (in million yuan) of province *i* and province *j* in China; LCP_i and LCP_j are livestock carbon productivity of province *i* and province *j* in China; lg_i and lg_j are the per capita GDP of the livestock sector of province *i* and province *j* in China (10,000 yuan); D_{ij} is the geographical distance of the provincial capitals. Using the aforementioned model to construct the spatial correlation network matrix, if the gravity value of each row is greater than its row average, it is assigned a value of 1; otherwise it is assigned a value of 0. This matrix is finally converted into a binary (0-1) matrix.

2.3. Social Network Analysis (SNA)

Social network analysis is an interdisciplinary method that focuses on "relationship" data and has been widely applied in various fields such as management, sociology, psychology, and economics. In this study, the overall network characteristics of the spatial correlation network of carbon productivity from the livestock sector in China are described using five indicators: network density, network contacts, network connectedness, network hierarchy, and network efficiency. The individual network characteristics of the carbon productivity spatial correlation network in the livestock sector are analyzed using three indicators: point centrality, closeness centrality, and betweenness centrality. Additionally, cluster characteristics of the carbon productivity spatial correlation network in the livestock sector are revealed through methods such as block modeling and adjacency matrix analysis. The relevant indicators and their formulae were obtained from He *et al*. (2022) and Rong *et al*. (2023).

2.4. Data sources and description

This study employs provincial panel data from 2006 to 2021, covering 31 provinces in China (excluding Hong Kong, Macao, and Taiwan). Data on the number of livestock and poultry at the end of each year and the livestock total output value are obtained from the "China Livestock and Veterinary Yearbook". The geographical distance between provincial capitals is calculated using ArcGIS software tools, combined with the geographical coordinates of provincial capital cities. Other variable data are obtained from sources such as the "China Statistical Yearbook", "China Livestock and Veterinary Yearbook", and "China Rural Statistical Yearbook".

Table 1. Spatial distribution pattern of livestock carbon productivity in 2006, 2011, 2016, and 2021.

Provinces	Livestock carbon productivity (RMB 10,000/t)					Provinces	Livestock carbon productivity (RMB 10,000/t)				
	2006	2011	2016	2021	Average annual rate(%)		2006	2011	2016	2021	Average annual rate(%)
Beijing	0.902	1.499	1.412	2.172	6.037	Hubei	0.452	1.021	1.319	2.367	11.675
Tianjin	0.621	0.828	1.123	1.460	5.861	Hunan	0.409	0.888	1.030	1.600	9.516
Hebei	0.411	1.040	1.207	1.612	9.540	Hubei	0.552	1.143	1.259	2.534	10.695
Shanxi	0.199	0.675	0.742	1.034	11.606	Guangxi	0.339	0.848	1.003	1.382	9.830
Inner Mongolia	0.185	0.394	0.467	0.647	8.710	Hainan	0.321	0.860	1.203	2.543	14.803
Liaoning	0.526	1.169	1.190	1.569	7.565	Chongqing	0.381	0.767	1.034	1.754	10.722
Jilin	0.364	1.016	1.169	1.998	12.023	Sichuan	0.391	0.693	0.827	1.146	7.426
Heilongjiang	0.352	0.865	1.381	1.301	9.112	Guizhou	0.126	0.350	0.670	0.809	13.185
Shanghai	0.790	1.253	1.475	1.738	5.393	Yunnan	0.184	0.422	0.554	0.942	11.491
Jiangsu	0.669	1.799	2.101	2.745	9.874	Tibet	0.023	0.040	0.088	0.108	10.681
Zhejiang	0.740	1.536	1.884	2.406	8.178	Shannxi	0.254	0.989	1.215	1.564	12.872
Anhui	0.502	1.336	1.546	2.586	11.551	Gansu	0.108	0.168	0.229	0.429	9.595
Fujian	0.581	1.094	1.549	2.848	11.176	Qinghai	0.054	0.113	0.152	0.187	8.577
Jiangxi	0.392	0.817	0.811	1.292	8.273	Ningxia	0.161	0.348	0.394	0.530	8.255
Shandong	0.408	1.042	1.167	2.098	11.528	Xinjiang	0.092	0.294	0.367	0.620	13.567
Henan	0.309	0.785	0.941	1.666	11.894						

3. Results and analysis

3.1. Spatiotemporal evolution of livestock carbon productivity

3.1.1. Characterization of temporal evolution

On the whole, the average carbon productivity of the livestock sector in China showed a fluctuating upward trend during the study period. In 2021, the average carbon productivity of the livestock sector in China was 1.54×10^4 yuan/t. It is approximately 3.05 times higher than the 0.38×10^4 yuan/t in 2006. The significant increase of livestock carbon productivity can be attributed to two aspects. On the one hand, it is due to the implementation of carbon emission reduction policies at different stages of development by the government. These policies impose institutional constraints on various production behaviors of breeding entities and providing effective policy support for the green and sustainable development of the livestock sector in China. On the other hand, the increasingly tight resource and environmental constraints and higher farming efficiency are driving the main bodies of farming to learn and adopt advanced green farming techniques. The farming theme has led to increased productivity in livestock and poultry farming through enhanced daily farm cleaning and management. But there were also instances of a decline in carbon productivity in certain years. This suggests that the coordinated economic and environmental development of the livestock sector in China may need to be wary of adverse shocks from major external events. Nevertheless, the carbon productivity of the livestock sector in China continues to steadily increase.

According to the division of three major economic zones in China during the "7th Five-Year Plan", the sample provinces are classified into the eastern coastal zone, central zone, and western zone to analyze the regional differences in the livestock carbon productivity. Comparatively, the average carbon productivity of the livestock sector in the eastern coastal zone has always been higher than the national average, with an average annual growth rate of 8.45%. The average carbon productivity of the livestock sector in the western zone has consistently been lower than the national average, with relatively slower growth rates. The average carbon productivity of the livestock sector in the central zone has been roughly in line with the national average, with a progressively clear increasing trend in recent years. In summary, the average carbon productivity of the livestock sector of different economic zones in China is steadily increasing. This indicates that China is gradually achieving its goal of reducing carbon emissions in the livestock sector, and the livestock and poultry farming industry is moving towards a green, low-carbon, and sustainable direction (Figure 1).

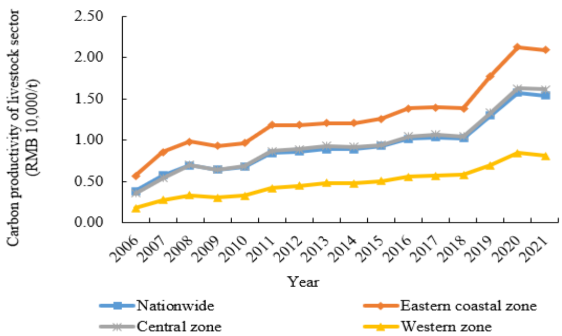


Figure 1. Temporal evolution of livestock carbon productivity in China, 2006–2021

3.1.2. Characterization of spatial distribution

In this study, four representative years (2006, 2011, 2016, and 2021) were selected to analyze the spatial distribution pattern of average carbon productivity in the livestock sector among different provinces (Table 1). It can be observed that the average carbon productivity of livestock sector of different provinces in China has generally increased to varying degrees. Specifically, taking the year 2021 as an example, the three provinces with the highest average carbon productivity in the livestock sector are Fujian, Jiangsu, and Anhui, with values of 2.85×10^4 yuan/t, 2.75×10^4 yuan/t, and 2.59×10^4 yuan/t. The three provinces with the lowest average carbon productivity in the livestock sector are Gansu, Qinghai, and Tibet, with values of 0.43×10^4 yuan/t, 0.19×10^4 yuan/t, and 0.11×10^4 yuan/t. In terms of average annual change rates, the three provinces with the highest average annual growth rates in carbon productivity of livestock sector in China are Hainan, Xinjiang, and Guizhou, with growth rates of 14.803%, 13.567%, and 13.185%. The three provinces with the lowest average annual growth rates in carbon productivity of livestock sector are Beijing, Tianjin, and Shanghai, with growth rates of 6.037%, 5.861%, and 5.393%. The above observations indicate that the high-value areas of average carbon productivity in the livestock sector are mainly located in the eastern coastal and central zones, while the provinces with the largest annual growth rate variations in carbon productivity of livestock sector are mostly in the western zone. Therefore, the western zone is expected to become a key region for improving carbon productivity from the livestock sector and promoting the green transformation and upgrading of livestock sector.

3.2. Overall characterization of the spatial correlation network

This study selected four sample years (2006, 2011, 2016, and 2021) to construct the spatial correlation network of carbon productivity from the livestock sector in China among provinces using the Netdraw module of UCIENT 6 (Figure 2). Overall, the spatial correlation of carbon productivity in the livestock sector exhibits a multi-linear network structure, with the spatial correlation network becoming increasingly complex and the connections within the network growing tighter. Provinces in the eastern coastal zone such as Beijing, Shanghai, and Tianjin are located at the core of the network, while provinces like Jiangsu, Zhejiang, and Fujian occupy sub-core positions. It indicates stronger connections with other regions in terms of carbon productivity in livestock sector and belonging to the core area of the network. Certain provinces in western and central zones in China, such as Inner Mongolia and Ningxia, have weaker connections with other regions in terms of carbon productivity in livestock sector and are situated on the network's periphery.

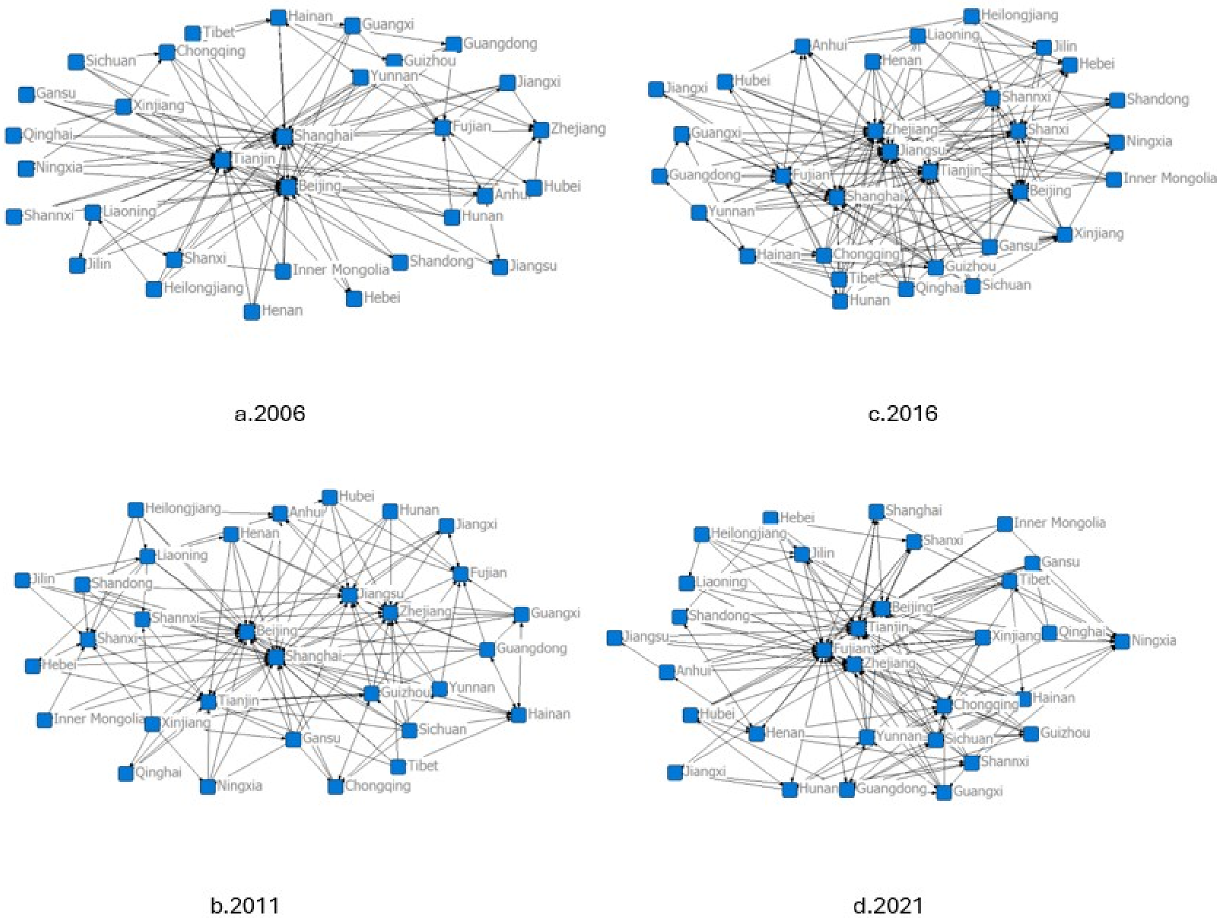


Figure 2. Evolution of spatial correlation network of livestock carbon productivity in China

Table 2 presents the overall network structure and evolutionary characteristics of the spatial correlation network of carbon productivity from the livestock sector in China. The network density increased from 0.139 in 2006 to 0.218 in 2021, indicating a growth of 56.83%. The network contacts also increased from 129 connections in 2006 to 203 connections in 2021, showing a growth of 57.36%. These findings reflect the increasing interconnectedness of the spatial correlation network in the livestock sector carbon productivity, with a strengthening of spatial spillover effects.

The largest increases in network density and contacts occurred in 2020-2021, possibly due to the government's issuance of the 'Opinions on Promoting High-Quality Development of Livestock Sector' in 2020. The implementation of this policy has facilitated communication and cooperation in the development of livestock sector among provinces and cities, promoted the circulation of factors and the dissemination of breeding technologies, thereby strengthening internal connections among provinces nationwide. However, the maximum number of network contacts at this stage is 211, which is less than 1/3 of the maximum number of possible relationships of 930. It implies that the spatial correlation network relationship of carbon productivity in the livestock sector needs to be further improved. It is worth noting that while the network density is increasing, excessive growth in network density may lead to network redundancy. Therefore, it is necessary to increase the number of network connections on one hand, and gradually enhance network density on the other hand to reduce the interference caused by network redundancy in the circulation of factors related to carbon productivity in livestock sector among provinces.

The network connectedness of the spatial correlation network of carbon productivity in the livestock sector remains at 1, indicating that there are no unreachable pairs of nodes within the network. This suggests that the carbon productivity relationships among provinces in the livestock sector are relatively close, and each network node can be connected and spillover within the network. In other words, the spatial correlation network of carbon productivity in the livestock sector has good robustness.

Although the network hierarchy showed an upward trend in 2011, 2016, and 2019, it generally exhibited a downward trajectory. It fluctuated from 0.820 in 2006 to 0.237 in 2021. This indicates that the internal structure of the spatial correlation network of carbon productivity in the livestock sector is gradually moving towards diversification, with a decrease in the number of nodes occupying an absolute dominant position and a weakening of their 'radiation' effect on other nodes within the network.

Table 2. Overall structural characteristic indicators of the spatial correlation network of livestock carbon productivity, 2006-2021

Year	Network density	Network contacts	Network connectedness	Network hierarchy	Network efficiency
2006	0.139	129	1	0.820	0.814
2007	0.167	155	1	0.768	0.759
2008	0.176	164	1	0.581	0.747
2009	0.184	171	1	0.579	0.731
2010	0.172	160	1	0.575	0.756
2011	0.165	153	1	0.806	0.759
2012	0.198	185	1	0.626	0.710
2013	0.216	201	1	0.463	0.692
2014	0.216	201	1	0.463	0.694
2015	0.227	211	1	0.459	0.683
2016	0.218	203	1	0.503	0.685
2017	0.215	200	1	0.422	0.692
2018	0.209	194	1	0.420	0.690
2019	0.178	166	1	0.614	0.740
2020	0.178	166	1	0.571	0.747
2021	0.218	203	1	0.237	0.726

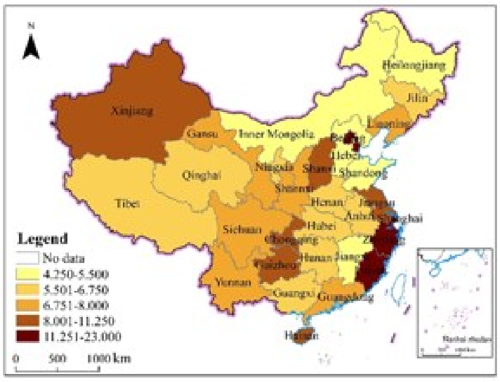
The overall network efficiency has shown a downward trend, decreasing from 0.814 in 2006 to 0.726 in 2021. This indicates that the number of correlation lines between provinces in the spatial correlation network of carbon productivity in the livestock sector has increased, and mutual interactions have continued to strengthen, with network connections becoming increasingly close. However, since 2019, network efficiency has slightly increased, indicating that while strengthening internal connections and interactions within the network, it is necessary to avoid adverse impacts on network stability caused by external events.

3.3. Individual characterization of spatial correlation networks

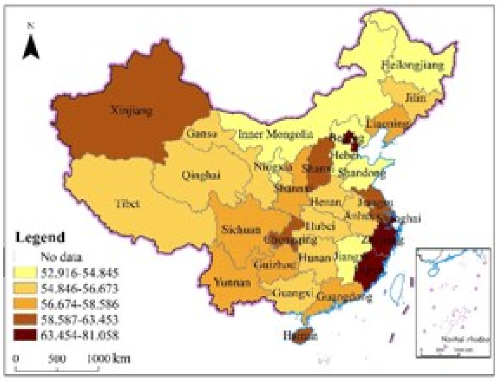
To explore the individual-level status and role of different provinces in the spatial correlation network of carbon productivity in the livestock sector, four time cross-sections were selected for analysis, namely 2006, 2011, 2016, and 2021. Three centrality indicators were used to calculate the individual network characteristics of the spatial network of carbon productivity in the livestock sector (Figure 3). It can be observed that the spatial correlation network of carbon productivity from thelivestock sector forms a network structure with the eastern coastal region as the core and the northeastern and northwestern regions as the periphery. With the increase in the livestock sector output value and the continuous implementation of policies promoting high-quality development in the livestock sector, the status of central and western regions in the spatial correlation network of carbon productivity in the livestock sector has become increasingly prominent.

3.3.1. Point centrality

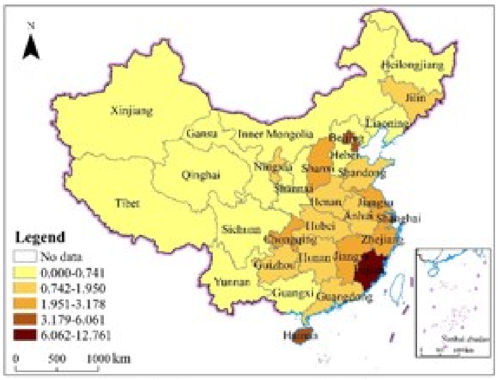
In 2006, 2011, 2016, and 2021, the average point centrality values of each province were 7.16, 8.71, 10.77, and 9.61, showing an overall increasing trend. This indicates that the spatial correlation between the carbon productivity of the livestock sector in different provinces has been continuously increasing, leading to a closer network connection between provinces. In terms of regions, provinces such as Beijing, Shanghai, Tianjin, Jiangsu, and Zhejiang consistently held high positions in point centrality throughout the study period, positioning them at the core of the network.



a. Point centrality



b. Closeness centrality



c. Betweenness centrality

Figure 3. Individual structural characteristic indicators of spatial correlation network of livestock carbon productivity in 2006, 2011, 2016, and 2021

Possible reasons for this include their developed economic levels, advantageous geographical locations, rapid urbanization rates, and efficient resource utilization, resulting in more frequent flows of factors and resources with neighboring regions. In some years, provinces in central and western regions such as Chongqing, Guizhou, Shanxi, and Xinjiang had point centrality values higher than the average. Xinjiang may rely on its abundant grassland resources and the support of the Western Development Strategy to establish spatial network connections with other regions. Provinces in the northwest region like Inner Mongolia, Qinghai, Gansu, and those in the northeast region like Jilin and Heilongjiang generally had lower point centrality values in most years. This can be attributed to factors such as their remote geographical locations, relatively underdeveloped economic levels, and inefficient energy utilization structures, placing these regions at the periphery of the spatial correlation network.

3.3.2. Closeness centrality

In 2006, 2011, 2016, and 2021, the average closeness centrality values of each province were 58.16, 59.47, 61.75, and 59.86, showing an overall increasing trend, with a convergence range in closeness centrality values. This indicates that the spatial correlation network of carbon productivity in the livestock sector exhibits more pronounced agglomeration characteristics. In terms of regions, provinces such as Beijing, Shanghai, Tianjin, Jiangsu, and Zhejiang had closeness centrality values far above the average. This suggests that these provinces play a central role in the spatial correlation network of livestock carbon productivity in China, enabling them to establish more connections with other provinces in the spatial correlation network. As a result, they are better positioned to acquire and distribute relevant factors and influence the carbon productivity of the livestock sector in neighboring or other provinces. Additionally, provinces like Fujian, Liaoning, and Shanxi had closeness centrality values higher than the average in most years, indicating a trend of catching up with the central actors. Provinces in the northwest region such as Gansu, Ningxia, Qinghai, and those in the northeast region like Jilin and Heilongjiang had closeness centrality values lower than or equal to the average in most years. This highlights the role of these regions as peripheral actors in the spatial correlation network of livestock carbon productivity in China.

3.3.3. Betweenness centrality

In 2006, 2011, 2016, and 2021, the average betweenness centrality values of each province were 1.067, 1.00, 2.98, and 3.22, showing an overall upward trend, with an expanding range in betweenness centrality values. This indicates signs of local differentiation expansion in the spatial correlation network, reflecting the need to further enhance the degree of balance in the spatial network structure of livestock carbon productivity in China. In terms of different regions, provinces such as Fujian, Jiangsu, and Tianjin had betweenness centrality values higher than the average, showing an increasing trend. This implies that these provinces have a significant influence on the carbon productivity of the livestock sector in various regions within the spatial correlation network. These provinces can promote the green and low-carbon transformation of the livestock production in other regions through the dissemination of breeding technologies, funding, and labor. Additionally, provinces like Guangdong, Jilin, Shanxi, and Chongqing experienced rapid growth in betweenness centrality. This is mainly attributed to the introduction of provincial policies promoting green and low-carbon development in the livestock sector and their geographical accessibility. Provinces in the northwest such as Qinghai, Tibet, Inner Mongolia, and in the northeast like Heilongjiang had betweenness centrality values mostly lower than the average. This indicates that these regions occupy marginal positions in the spatial correlation network, making it challenging for them to influence and control the carbon productivity of the livestock sector in other regions.

3.4. Block model analysis

With the CORNOR operation tool of UCINET software, 31 provinces in China were divided into four segments for spatial clustering with the criteria of maximum depth of 2 and concentration degree of 0.2 to clarify the internal structure of the spatial correlation network of carbon productivity in China's livestock sector (Table 3). The spatial correlation network of carbon productivity in China's livestock sector consists of a total of 203 relationships, including 38 within-board relationships and 165 between-board relationships. This indicates that the spatial correlation and spillover effects of carbon productivity in the livestock sector between different regions are significant.

Table 3. Segmentation of spatial correlation network of livestock carbon productivity

Plate	Relationships received				Number of provinces	Inflow external relationships	Outflow external relationships	Expected internal relationship ratio (%)	Actual internal relationship ratio (%)	Role
	I	II	III	IV						
I	17	5	58	3	14	20	66	43.333	20.482	Main outflow
II	0	17	36	15	9	28	51	26.667	25.000	Main outflow
III	17	6	4	2	5	97	25	13.333	13.793	Main inflow
IV	3	17	3	0	3	20	23	6.667	0.000	Agent

Note: Calculated and collated by the authors.

Sectors I and II belong to the 'main outflow' sectors within the spatial correlation network of livestock carbon productivity in China. Both sectors have a higher expected internal relationship ratio than the actual internal relationship ratio, and the number of outflow external relationships is significantly greater than the number of inflow external relationships. Regions belonging to this sector type are mostly provinces in the central and western regions where there is abundant grassland resources and large energy reserves. In recent years, the orderly advancement of the Western Development Strategy and the Rise of Central China Strategy has strengthened the flow and allocation of resources and factors between different regions, resulting in a main outflow status for these regions. Sector III includes Beijing, Tianjin, Zhejiang, Ningxia, and Fujian. These regions have a much higher number of inflow external relationships than outflow external relationships, and the actual internal relationship ratio is essentially in line with the expected internal relationship ratio, making them 'main inflow' sectors. Beijing, Tianjin, and Zhejiang may be able to effectively attract resources and factors from other regions due to their superior geographical location and relatively high level of economic development, forming a rational pattern of resource allocation. Fujian may benefit from the ripple effects of the Yangtze River Economic Belt development strategy and gradually align with Zhejiang in various aspects, thus creating a certain attractiveness. Ningxia, located in the Hexi Corridor, may have overcome local economic development difficulties through its factor endowment advantages, attracting factors from surrounding areas and becoming a main inflow. Sector IV includes Henan, Guangdong, and Hunan, where the number of inflow and outflow external relationships is relatively balanced, but the actual internal relationship ratio is lower than the expected internal relationship ratio. Therefore, these provinces belong to the 'agent' sector within the spatial correlation network of livestock carbon productivity in China, primarily playing a 'linking' role.

Table 4. Density matrix and image matrix of spatially correlated segments of livestock carbon productivity

Plate	Density matrix				Image matrix			
	I	II	III	IV	I	II	IIII	IV
I	0.093	0.04	0.829	0.071	0	0	1	0
II	0.000	0.236	0.8	0.556	0	1	1	1
III	0.243	0.133	0.2	0.133	1	0	0	0
IV	0.071	0.63	0.2	0.000	0	1	0	0

The density of the spatial correlation network of carbon productivity in the livestock sector is 0.218. The matrix composed of sector densities is transformed into an image matrix (Table 4). In summary, while each sector emits spatial overflow to other sectors, they also receive spatial overflow from other sectors. Sector I receives spatial overflow from Sectors III and IV while emitting overflow to Sectors II, III, and IV. Sector II receives spatial overflow from Sectors I, III, and IV while emitting overflow to Sectors III and IV. Due to the significantly lower number of receiving relationships compared to emitting relationships, Sectors I and III are both classified as ‘main outflow’ sectors. Sector III experiences mutual spatial overflow effects with the other three sectors but its outflow to inflow ratio is much lower, placing it in the ‘main inflow’ category. The relationships from Sectors I and II dominate the total overflow relationships in the three sectors Similarly to Sector III, Sector IV also exhibits mutual spatial overflow effects with the other three sectors, but its outflow to inflow ratio is very close, categorizing it as a ‘agent'' sector within the spatial correlation network of livestock carbon productivity in China.

3.5. Drivers of the spatial correlation network of livestock carbon productivity

3.5.1. Model configuration and variable selection

According to the block model analysis, there exists a mutual overflow correlation of carbon productivity in the livestock sector between different sectors. Based on relevant theories in economics and geography, combined with previous research, it is known that carbon productivity is closely related to factors such as geographical proximity, urbanization level, income level, industrial structure, industry scale, and technological level. Geographical proximity facilitates the geographic agglomeration of resources and factors, thereby enhancing the attractiveness of the local area to surrounding or other regions. Population migration and agglomeration towards urban areas can stimulate the consumption of livestock products such as meat, eggs, and dairy, thereby influencing the spatial pattern of carbon productivity in the livestock sector. Income level serves as the foundation for the economic development of the livestock sector in each province, promoting the cross-provincial flow of related resources and factors and positively impacting the spatial correlation network structure of carbon productivity in the livestock sector. Industrial structure plays a significant role in determining the speed, scale, and quality of livestock industry development. Therefore, the industrial structure and scale also determine the formation and distribution of the spatial network of carbon productivity in the livestock sector. Differences in technological levels may affect the adoption and diffusion of new technologies across regions. Hence, the study constructs a model for the driving factors of the spatial correlation network of carbon productivity in China’s livestock sector, including indicators such as geospatial proximity, urbanization level, per capita livestock income, agricultural industrial structure, livestock farming scale, and livestock mechanization level. The specific calculation formula is as follows:

$$Q = F\left(D, U, R, I, S, M\right) \tag{4}$$

Here, the dependent variable Q is the spatial correlation matrix of carbon productivity from the livestock sector in China; independent variable D denotes geospatial proximity, as measured by the matrix of geographic distances of provincial capital cities between provinces; U denotes urbanization level, as measured by the network matrix of differences in urbanization rates between provinces; R denotes per capita livestock income, as measured by the network matrix of differences in per capita denotes income between provinces; I denotes agricultural industrial structure, as measured by a network matrix of differences between provinces in the share of livestock GDP in agricultural, forestry and fisheries GDP; S denotes livestock farming scale, measured by a network matrix of differences in year-end large livestock stocking between provinces; M denotes livestock mechanization level, as measured by a network matrix of differences in the total power of livestock machinery between provinces. The total power of livestock machinery is derived from the total power of agricultural machinery. Since both the dependent and independent variables are in the form of a “relationship” data matrix, using traditional statistical methods to test causality would inevitably encounter problems with multicollinearity, resulting in estimation bias. Therefore, a non-parametric method called QAP regression was utilized to explore the driving factors of the spatial correlation network of carbon productivity from the livestock sector. This method is more robust than traditional statistical methods. The meaning and data sources of each variable are shown in Table 5.

3.5.2. QAP correlation analysis

The matrices of the dependent and independent variables were imported into the UCINENT software, and 5000 random permutations were selected to obtain the correlation analysis results between the spatial relationship matrix of carbon productivity in the livestock sector and its driving factors (Table 6). It can be seen that the correlation coefficient between geospatial proximity and the spatial correlation of carbon productivity in the livestock sector is significant at the 10% level, while the correlation coefficients between urbanization level, per capita livestock income, agricultural industrial structure, livestock farming scale, and livestock mechanization level and the spatial correlation of carbon productivity in the livestock sector are all significant at the 1% level. This indicates that these variables drive the formation and evolution of spatial correlation network of livestock carbon productivity in China. Hence, the study also tested the correlation between the explanatory variables and found that all explanatory variables are significantly correlated with each other. Therefore, QAP regression is needed to find the driving factors behind the formation of spatial correlation network of carbon productivity in the livestock sector.

3.5.3. QAP regression analysis

The QAP regression results were obtained after 5000 random permutations (Table 7). It can be observed that:

(1) The regression coefficient of the urbanization level difference is significantly negative, indicating that the degree of population urbanization can to some extent measure current level of new urbanization construction in China and generate spatial spillover effects on the economy and society. However, a larger difference in urbanization levels can lead to significant differences in resource and factor demands among relevant personnel. It is not conducive to communication, exchange, and cooperation among various regions in livestock production and environmental protection aspects.

(2) The regression coefficient of the per capita livestock income difference is significantly negative, indicating that the smaller the differences in the level of livestock economic development among provinces in China, the more similar the income situation of herdsmen, and the more conducive it is to promoting the formation of the spatial correlation network of carbon productivity in the livestock sector. A smaller difference in livestock output value leads to similar demands for livestock labor and breeding technology among provinces. It is helpful for the cross-regional allocation and circulation of various related factors and resources and further promotes the formation of spatial network correlation among regions.

Table 5. Description of variables for spatial correlation network of livestock carbon productivity

Variable	Meaning of variable	Calculation method and description	Data source
D	Geospatial proximity	Matrix of geographic distances of provincial capital cities between province i and province j	Measured by ARCGIS software
U	Urbanization level	Network matrix of differences in urbanization rates between province i and province j	China Statistical Yearbook
R	Per capita livestock income	Network matrix of differences in per capita pastoral income between province i and province j	China Livestock and Veterinary Yearbook
I	Agricultural industrial structure	Network matrix of differences in the share of pastoral GDP in agricultural, forestry and fisheries GDP between province i and province j	China Rural Statistics Yearbook
S	Livestock farming scale	Network matrix of differences in year-end livestock stocks between province i and province j	China Livestock and Veterinary Yearbook
M	Livestock mechanization level	Network matrix of differences in total power of livestock machinery between province i and province j	China Rural Statistics Yearbook

Table 6. QAP correlation analysis for spatial correlation network of livestock carbon productivity

Variable	Coefficient	Significance	Average	Std Dev	Minimum	Maximum	P≥0	P≤0
D	-0.077	0.075	-0.000	0.058	110.003	3639.514	0.924	0.075
U	-0.313	0.000	-0.001	0.090	-52.690	52.690	1.000	0.000
R	-0.273	0.001	0.001	0.087	-16.374	16.374	0.999	0.001
I	0.292	0.000	-0.002	0.089	-45.248	45.248	0.000	1.000
S	0.334	0.000	0.001	0.091	-917.100	917.100	0.000	1.000
M	0.208	0.001	-0.001	0.090	-2966.544	2966.544	0.001	0.998

(3) The regression coefficient of the difference in agricultural industrial structure is significantly positive at the 5% level, indicating that the uneven industrial structure between regions under certain conditions affects the spatial correlation relationship of carbon productivity in the livestock sector. The greater the differences in the proportion of livestock development in agricultural development among regions, the more favorable it is for factors and resources to flow from provinces and departments with high production efficiency to those with low production efficiency, forming a positive spatial spillover effect. This ample spatial transfer and exchange of factors and resources help optimize and upgrade the structure of the spatial correlation network of carbon productivity in the livestock sector.

(4) The regression coefficient of the difference in the livestock mechanization level is significantly positive and has passed the 5% significance level test, indicating that provinces with greater differences in the livestock mechanization level are more likely to have spatial correlations in carbon productivity in the livestock sector. This is because the level of mechanization to some extent reflects the regional level of technological development in the livestock sector, and these differences help in the overflow and absorption of capital, technology, and knowledge across regions. Thereby it promotes personnel exchanges and service spillovers in the livestock mechanization level among provinces.

(5) The regression coefficient for the difference in geospatial proximity is negative but not significant, indicating that it does not significantly impact the

formation of the spatial correlation network of carbon productivity in the livestock sector. Possible explanations are that the widening gap in geographical distance leads to higher costs of interregional factor mobility and poor transport of livestock products, which affects the degree of interprovincial livestock development correlation (Hao *et al.* 2022). The regression coefficient for the difference in livestock farming scale is positive but not significant. This suggests that similar farming scales imply similar conditions and environments for livestock development in different provinces, and similar demands for resources and factors, which in turn promote the formation of spatially linked networks. However, the difference in farming scale will cause regional carbon emissions to differ, and carbon productivity will also be affected by the regional economic development level and the basis of livestock development (Rehman *et al.* 2021), so this effect is not significant.

Table 7. QAP regression analysis for spatial correlation network of livestock carbon productivity

Variable	Unstandardized coefficient	Standardized coefficient	Significance	Probability 1	Probability 2
Constant	0.208	0.000			
D	-0.000	-0.041	0.280	0.720	0.280
U	-0.003	-0.117	0.066	0.934	0.066
R	-0.007	-0.099	0.075	0.925	0.075
I	0.003	0.116	0.044	0.044	0.956
S	0.000	0.102	0.116	0.116	0.884
M	0.000	0.099	0.045	0.045	0.955
R^2	0.154		0.000		
Observations	930				

4. Discussion

The average carbon productivity from the livestock sector in China has demonstrated a consistent upward trend, aligning with the existing studies (Huo *et al.* 2022). As government regulations have intensified, livestock and poultry farmers have gradually curbed and regulated their farming practices, resulting in a convergence of livestock carbon emissions. Concurrently, the expansion of the economic scale of livestock farming has contributed to the increased level of carbon productivity. The spatial network of carbon productivity from the livestock sector has become increasingly intricate, with strengthened connections within the network. This underscores the significance of removing barriers to inter-provincial factor flows and advancing regional cooperation and exchange (Rong *et al.* 2022). Notably, the carbon productivity from the livestock sector in China has formed a spatial network structure, with the eastern coastal region serving as the core and the northeastern and northwestern regions as the periphery. Therefore, it is crucial to develop tailored carbon emission reduction programs for the livestock industry (Xu *et al.* 2021). Provinces and cities situated in the eastern coastal zone, at the core of the network, should lead in implementing environmentally friendly and low-carbon initiatives, while continuing to drive the optimization and upgrading of the agricultural industrial structure. The northeastern and northwestern regions should enact more stringent environmental regulations and policies and be open to the transfer of resource elements from other regions. Central and western regions should attract talent and livestock technologies from developed areas to enhance the efficiency of local livestock production, while simultaneously serving as intermediaries in spatially linked networks.

Comparing with previous literature, this study has made advancements in several aspects. Firstly, the research focus has shifted from “livestock carbon emissions” to “livestock carbon productivity” and the perspective has evolved from emphasizing “environmental benefits” to promoting the “synergistic development of environmental and economic benefits”. Secondly, this study has revealed the spatial correlation network structure of livestock carbon productivity, including its overall structure, individual structures, and clustering structures. This enriches the research content on spatial correlation of carbon productivity in the livestock sector, expanding the scope of spatial relationships from “proximity” to a nationwide “network”. However, this study still has some limitations. Firstly, the lack of access to livestock data at the county level hinders the calculation of carbon productivity in livestock sector at that granularity. Therefore, the study of the spatial correlation network of livestock carbon productivity only at the provincial level may be considered somewhat crude. Future research should aim to refine these findings to enhance the value of research related to carbon productivity in the livestock sector. Secondly, the spatial correlation network is the result of multiple driving factors working together. Analyzing the driving forces based solely on variables such as geospatial proximity, urbanization level, per capita livestock income, agricultural industrial structure, livestock farming scale, and livestock mechanization level may be somewhat biased. Future research should delve deeper into discussions on mechanisms, considering factors like the degree of openness and the intensity of environmental regulations.

5. Conclusion

The main conclusions are as follows:

(1) Overall, the average carbon productivity of the livestock sector in China has shown an upward trend with fluctuations, indicating that China is gradually achieving its carbon emission reduction targets in the livestock sector. Among them, the carbon productivity of the livestock sector in the eastern coastal zone is higher than that in

the central and western zones. A series of policies related to carbon emission reduction in the livestock sector and the adoption of green production methods by related farming entities have played an important role in this trend.

(2) The spatial correlation of carbon productivity in the livestock sector exhibits a multi-linear network structure, with the spatial correlation network becoming increasingly complex and the internal connections within the network growing tighter. There is an increasing fluctuation in network density and network contacts, while the network connectedness remains stable at 1, and the network hierarchy and network efficiency show a decreasing trend. This indicates that the spatial correlation network of carbon productivity in the livestock sector is becoming more complex and balanced, while efforts should be made to avoid adverse impacts on network stability from uncertain exogenous events.

(3) The spatial correlation network of carbon productivity in the livestock sector is centered around the eastern coastal provinces and cities, with the northeastern and northwestern regions forming the periphery of the spatial correlation network structure. Additionally, the position of the central and western regions in the spatial correlation network of carbon productivity in the livestock sector is gradually strengthening.

(4) The spatial correlation and spatial spillover effects of carbon productivity in the livestock sector between the plates are significant. Twenty-three provinces, including Inner Mongolia, Gansu and Guizhou, belong to the “main outflow” plate. Beijing, Zhejiang, Tianjin, Fujian and Ningxia belong to the “main inflow” segment. Henan, Guangdong and Hunan belong to the “agent” plate.

(5) Differences in urbanization levels, per capita livestock income, agricultural industry structure, and livestock mechanization level significantly influence the dynamic changes of the spatial correlation network of carbon productivity from the livestock sector in China. In addition, differences in geospatial proximity and livestock farming scale do not significantly impact the formation of the spatial correlation network of livestock carbon productivity.

Competing interests

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

Author Contributions

M. L.: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing-original draft. H. X.: Supervision, Writing-review & editing, Funding acquisition. Z. P.: Visualization, Software, Writing-review and editing.

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