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Spatial correlation network characteristics and driving factors of carbon emissions from cultivated land use in the yellow river basin

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The study aimed to investigate the spatial correlation network of carbon emissions from cultivated land use in the Yellow River Basin(YRB) and its driving factors, which is conducive to promoting collaborative carbon emission reduction in cultivated land use across the region. The study utilized the carbon emission coefficient method to calculate carbon emissions from cultivated land use in the YRB between 2008 and 2022. A modified gravity model and social network analysis method were then employed to analyze the characteristics of the spatial correlation network of carbon emissions from cultivated land use in the YRB. Additionally, the Quadratic Assignment Procedure (QAP) method was utilized to identify driving factors. The research findings indicate that: (1) Between 2008 and 2022, the overall carbon emissions from cultivated land use in the YRB increased by 27.6%. The proportion of carbon emissions from different sources, from largest to smallest, was as follows: straw burning (over 60%), agricultural inputs (over 20%), and crop cultivation (around 13%). (2) According to the overall network characteristics, the spatial correlation network underwent an evolution from dispersion to concentration and then to adjustment. The network connectivity was good, efficiency fluctuated and rose to stability, centrality showed an inverted "U" shaped change, with Shandong and Henan remaining at the core of the network throughout. (3)Based on individual network characteristics, the network structure showed a core-periphery hierarchy, with Gansu and Inner Mongolia identified as the core provinces. (4) QAP analysis indicated that factors such as geographical proximity, urbanization levels, and agricultural machinery input intensity positively influenced the spatial correlation network, while factors like agricultural economic levels, farmer income levels, and environmental regulations had negative effects. Based on the findings of this study, feasible pathways are proposed from aspects including the three sources of carbon emissions, regional cooperation within the YRB, and policy optimization.

Abbreviations
YRB   The Yellow River Basin
CLCD   Chinese Life Cycle Database
IPCC   Intergovernmental Panel on Climate Change

Over the past century, the accelerated process of global industrialization has driven rapid economic development, but has also brought serious environmental issues. The emissions of a large amount of greenhouse gases, especially carbon dioxide (CO_2), have led to an increasingly significant greenhouse effect. According to the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report, the global average surface temperature has risen by 1.09℃ from 1850-1900 to 2011-2020, and is projected to exceed 1.5℃ by 2050[1]. This change not only has profound implications for the global climate system, but also presents serious challenges to the sustainable development of human society.

China, as a traditional agricultural nation, accounts for approximately 24% of total carbon emissions from agriculture[2], representing about 12% of global agricultural emissions and making it the world's second largest

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agricultural emitter[3]. In recent years, in order to support carbon emissions reduction in agricultural production, China has issued a series of policy documents to support green development in agriculture. In 2024, the Ministry of Agriculture and Rural Affairs issued the "Guiding Opinions on Accelerating the Comprehensive Green Transformation of Agricultural Development and Promoting the Ecological Revitalization of Rural Areas", proposing to "implement rural carbon emission reduction and carbon sequestration actions, and strengthen the carbon sequestration functions of farmland and soil"[4]. In 2025, the State Council issued the "Rural Revitalization Comprehensive Plan (2024-2027)", which proposed to "steadily advance agricultural carbon emission reduction and carbon sequestration, popularize no-till or reduced-till seeding technologies"[5].By properly utilizing and protecting arable land, it not only can improve agricultural production efficiency but also enhance carbon sink capacity effectively, making contributions to addressing climate change.

The Yellow River Basin (YRB) is an important grain producing region in China with abundant arable land resources, but currently faces significant carbon emission pressure from its land use. Specifically, carbon emissions from land use in the YRB stem from three areas.

The first is carbon emissions from agricultural inputs. Taking fertilizers as an example, in 2022, the nitrogen fertilizer usage per hectare of farmland in the United States was 59.07 kg, compared to China's high usage of 191.55 kg/ha[6], this not only caused resource waste, but also increased carbon emissions. In addition to fertilizers, inputs such as pesticides, plastic film and other elements also generate a large amount of carbon emissions.

The second is the carbon emissions during the cultivation process of crops. The vast agricultural land in the YRB has significant differences in nitrous oxide (N_2O) emissions flux from different crops. Studies have found that soil N_2O emissions account for 38% of agricultural greenhouse gas emissions[7], and N_2O has a global warming potential 310 times higher than CO_2[8]. Therefore, in this study, we focus on this key greenhouse gas -"N_2O".

Third, carbon emissions from straw burning. In 2021, the comprehensive utilization rate of crop straw in China reached 88.1%[9], indicating that straw resources have been relatively fully utilized. However, there is still a large amount of straw accumulating in the fields or being burned in concentrated areas, leading to the production of significant carbon emissions.

In order to study the carbon emissions from cultivated land use, it is first necessary to quantify it. Scholars in existing literature have calculated the carbon emissions from cultivated land use at different times and spaces. Scholars in China have conducted research at the provincial[10], municipal[11], county levels[12], as well as in different river basins at different time periods[13]. Foreign scholars have also conducted relevant research. For example, Sha et al. (2022) found that optimizing land management can increase land vegetation carbon sinks by 3.5–4 billion tons on a global scale[14]. Ning et al. (2023) identified the sources, directions, and spatial changes of carbon emissions from land use in Nepal, using ESA/CCI (European Space Agency/Climate Change Initiative) data for their analysis[15]. These studies had all revealed that carbon emissions from cultivated land use cannot be ignored, provided theoretical support for subsequent scholars to conduct research. In their research process, they innovatively applied many research methods. The methods for calculating carbon emissions from land use mainly include carbon emission coefficient method[16], remote sensing assessment[17], and model calculation[18]. When studying the spatiotemporal distribution characteristics of carbon emissions from land use, scholars mainly use spatial correlation analysis, LISA temporal path analysis[19], spatiotemporal transition methods[20], standard deviation ellipses[21], and centroid migration[22]. In the research on influencing factors of carbon emissions from land use, methods such as the Kaya constant equation[23], Logarithmic Mean Divisia Index (LMDI) model[24], and GTWR[25] analysis are mainly used. Scholars have further advanced research in this field using these methods, and research results can be presented in a more intuitive way through numbers, tables, images, and soon. At the same time, it can also make people realize that the issue of greenhouse gas emissions from cultivated land use under different time and space conditions cannot be ignored. In order to improve this situation, researchers have conducted studies on the driving factors of carbon emissions from cultivated land use, aiming to pinpoint the reasons and address the issue effectively. Aziz et al. (2023) believed that demographic, socioeconomic, and technological factors in the agricultural sector are positively correlated with the emissions of CO_2, CH_4, and N_2O[26]. Lu et al. (2023) has found that the impact of open agricultural product trade on agricultural carbon emissions exhibits a significant environmental regulation threshold effect[27]. Li et al. (2025) found that Green finance policies play an important role in promoting regional carbon reduction[28].

In conclusion, existing literature has explored carbon emissions from land use in China, but most studies focus on static analysis of the spatial relationships of carbon emissions from land use, neglecting the structural evolution of spatially related carbon emissions from land use, and failing to discuss the driving factors of the spatially related structural evolution of carbon emissions from land use. Therefore, the overall objective of this paper is to analyze the spatial correlation network characteristics of carbon emissions from land use in the YRB from 2008 to 2022 and their driving factors, and provide relevant suggestions for carbon reduction from land use in the YRB.

This paper has numerous innovative aspects, mainly reflected in the following areas. First, innovation in the research subject. Although existing literature on carbon emissions is quite extensive, it mostly focuses on other regions and industries. This study is the first to take carbon emissions from cultivated land use in the YRB as an independent research subject, filling a gap in this field. Second, innovation in methodology. Existing research in this region has concentrated on the spatiotemporal variation of carbon emissions and efficiency, with little discussion on inter-regional carbon flow and spatial correlation. This paper innovatively applies a combined SNA and QAP approach in this region for the first time, systematically depicting the spatial network characteristics of carbon emissions from cultivated land use in the YRB, and deeply analyzing influencing factors, providing a scientific basis for formulating regional collaborative carbon reduction strategies. Third, innovation in the indicator system. In the process of constructing the modified gravity model, this paper fully considered the actual conditions of the YRB, incorporating cultivated land use carbon emissions into the key

indicator system. This innovation not only enhances the model's explanatory power but also provides a new perspective for accurately assessing regional carbon emissions.

The specific objectives of this paper are as follows: (1) Calculate the carbon emissions from land use in the YRB from 2008 to 2022 using the carbon emission coefficient method; (2) Analyze the spatial correlation network characteristics of carbon emissions from land use in the YRB using a modified gravity model and social network analysis methods; (3) Identify the driving factors of the spatial correlation network of carbon emissions from land use in the YRB using the Quadratic Assignment Procedure (QAP) method; (4) Provide relevant suggestions for carbon reduction from land use in the YRB.

Materials and methods
Overview of the study area
The Yellow River is the second longest river in China, originating in Qinghai Province and flowing through Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, and Shandong, ultimately emptying into the Bohai Sea. The YRB is not only a core area for China's food security but also one of the most carbon emission-intensive regions in global agriculture. In 2022, the cultivated land area in the YRB was 446 million hectares, with significant differences in spatial distribution among provinces (see Fig. 1). The upper and middle reaches of the YRB are characterized by widespread plateau and mountainous areas, making them prone to soil erosion, with fragile ecological environments and limited arable land, posing significant constraints on agricultural production and economic development[29].Henan and Shandong, two major agricultural provinces, are located in the lower reaches of the Yellow River with natural geographic and climatic conditions suitable for crop growth. However, the high degree of intensive agriculture and dense population in these two provinces result in relatively high total agricultural carbon emissions. Currently, the conflict between environmental protection and economic development in the YRB is particularly prominent, with economic growth still to some extent coming at the expense of sacrificing the ecological environment. Data shows that for every 1% increase in per capita output, ecological efficiency decreases by 0.54%[30]. Therefore, research on carbon emissions in the YRB contributes to a deeper understanding of the impact of agricultural activities on climate change, proposes corresponding emission reduction strategies, and thus promotes sustainable agricultural development.

Methodology
This study constructs an analytical framework for the spatial correlation network and driving factors of cultivated land use carbon emissions in the YRB, and the research framework is illustrated in Fig. 2.
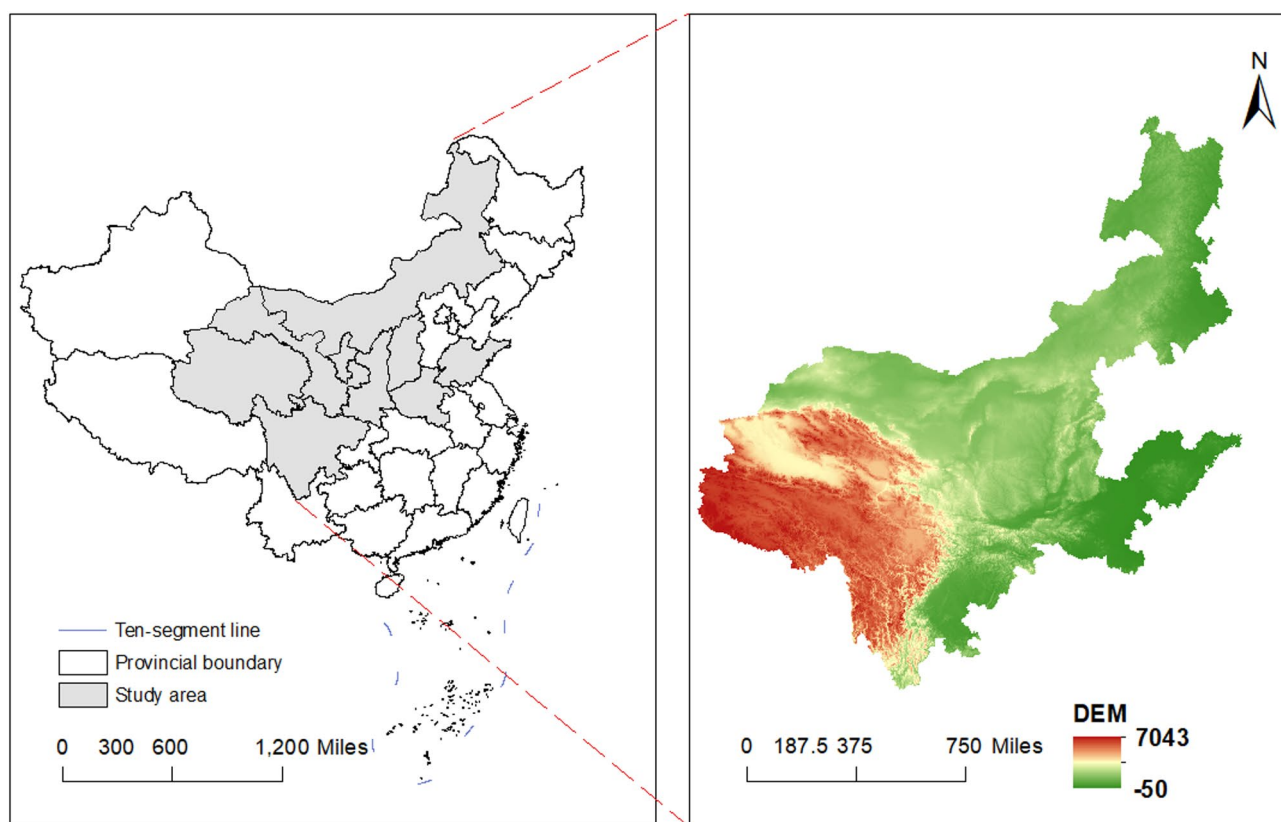
Fig. 1. Geographical location of the study area. Note: The base map is produced using the standard map from the Ministry of Natural Resources, with a map approval number of GS(2024)0650, and no modifications were made to the base map boundaries, the same as below.
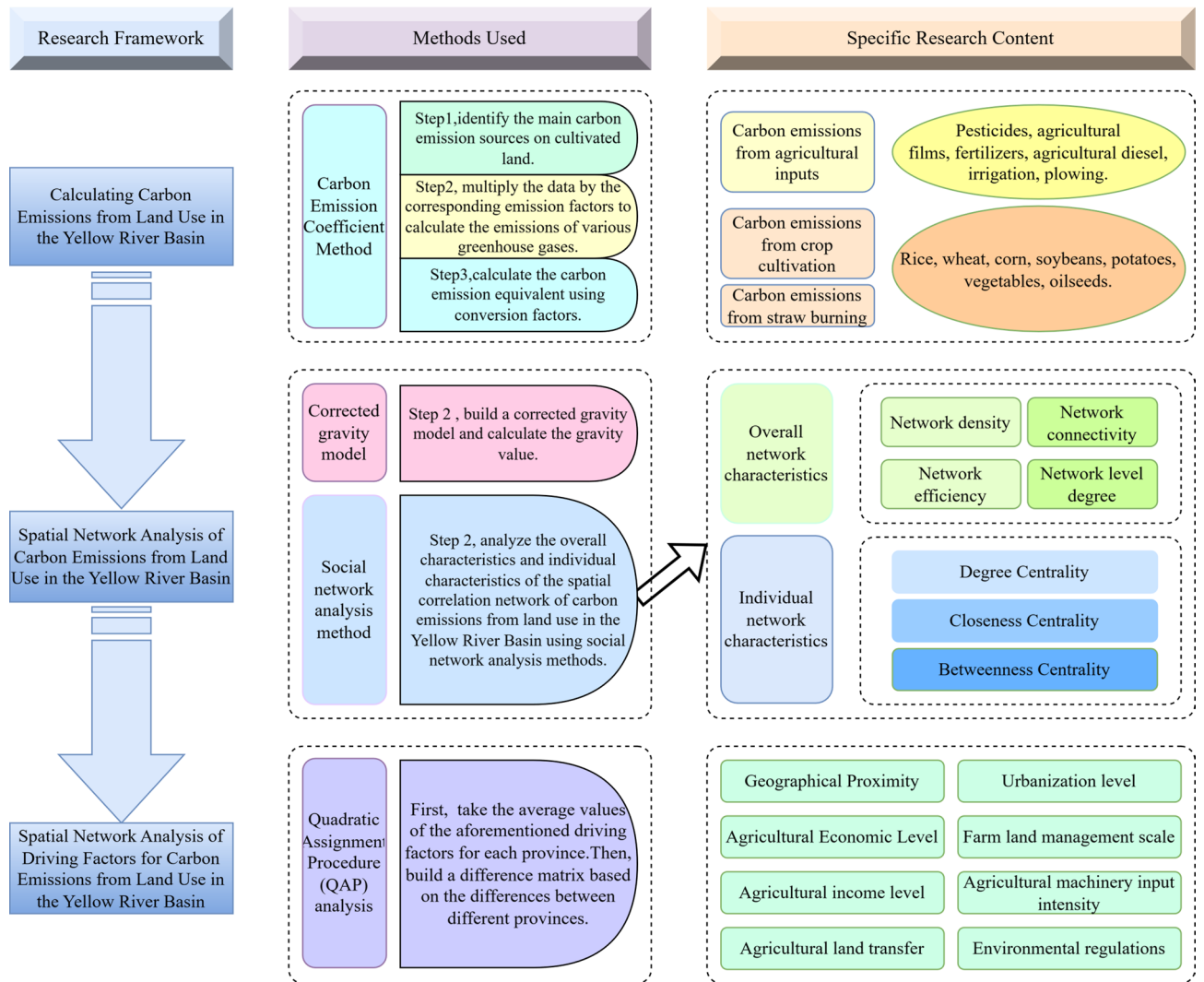
Fig. 2. Geographical location of the study area.

Carbon emission coefficient method

Currently, the most commonly used method for calculating carbon emissions from land use is the emission coefficient method. The carbon emission coefficient method can directly quantify the carbon emissions of different energy sources, numericalize them in terms of energy units, has clear calculation methods and data sources, making the results more objective and comparable, and more accurate and reliable compared to other methods. The core process of this method is to determine the main sources of carbon emissions from land use, multiply relevant data by emission coefficients, calculate the emissions of various greenhouse gases, and then calculate the carbon emission equivalents using conversion factors[31]. Land use carbon emissions mainly include three aspects: agricultural input carbon emissions, crop growth carbon emissions, and straw burning carbon emissions. The formula for calculating total carbon emissions is as follows:

$$CE = CE_{Inputs} + CE_{Growth} + CE_{Burning} \tag{1}$$

In the equation: CE represents total carbon emissions (t); CE_{Inputs} represents agricultural input carbon emissions (t); CE_{Growth} represents crop growth carbon emissions (t); and $CE_{Burning}$ represents straw burning carbon emissions (t).

<u>Carbon emissions from agricultural input</u>   Inputs of agricultural elements are one of the main sources of agricultural carbon emissions. These elements release greenhouse gases during their utilization, and to a certain extent, they also affect the efficiency and structure of land use, thereby influencing carbon emissions. The calculation formula is as follows:

$$CE_{Inputs} = \sum\nolimits_{m=1}^{M} \sum\nolimits_{i=1}^{I} E_{mi} \cdot \delta_i \tag{2}$$

Carbon emission sources	Carbon emission coefficient	Coefficient source
Pesticides	4.943 kg/kg	Oak Ridge National Laboratory[32]
N Fertilizer	1.53 kg/kg	CLCD
P Fertilizer	1.63 kg/kg	CLCD
K Fertilizer	0.65 kg/kg	CLCD
Compound Fertilizer	1.77 kg/kg	CLCD
Agricultural Film	5.18 kg/kg	Oak Ridge National Laboratory[32]
Agricultural Diesel	0.593 kg/kg	IPCC
Agricultural Irrigation	266.48 kg/hm^2	Duan et al[33].
Agricultural Tillage	312.6 kg/km^2	Wu et al[34].

Table 1. Carbon emission coefficients of agricultural factor inputs.

Province	Rice	Wheat	Corn	Soybeans	Potatoes	Vegetables	Oilseeds
Shanxi	0.24	1.30	2.53	2.29	0.950	4.94	0.95
Inner Mongolia	0.24	0.50	2.53	2.29	0.950	4.94	0.95
Shandong	0.24	1.75	2.53	2.29	0.950	4.94	0.95
Henan	0.24	1.75	2.53	2.29	0.950	4.94	0.95
Sichuan	0.24	0.40	2.53	2.29	0.950	4.94	0.95
Shaanxi	0.24	1.20	2.53	2.29	0.950	4.94	0.95
Gansu	0.24	0.80	2.53	2.29	0.950	4.94	0.95
Qinghai	0.24	0.40	2.53	2.29	0.950	4.94	0.95
Ningxia	0.24	0.60	2.53	2.29	0.950	4.94	0.95

Table 2. N$_2$O background emission fluxes of various crops (kg/hm^2). Note: Data sourced from Min(2012)[36].

In the equation: CE_{Inputs} represents the carbon emissions from agricultural inputs (t); E_{mi} represents the amount of the i-th agricultural input in the m province, including pesticides, fertilizers (classified as N fertilizer, P fertilizer, K fertilizer, compound fertilizer), agricultural film, agricultural diesel, irrigation, and tillage; and δ_i represents the carbon emission coefficient of the i-th agricultural input (Table 1). When calculating carbon emissions, it is necessary to convert various agricultural inputs into equivalent units based on the units of different carbon emission coefficients, and then multiply these coefficients with the corresponding indicators and sum them up.

Carbon emissions from crop cultivation   In the process of crop cultivation, in addition to the carbon emissions produced by agricultural inputs, crops also release certain greenhouse gases during their growth, with a focus on N$_2$O in this study. Based on the agricultural statistical yearbooks of provinces in the Yellow River basin and actual planting conditions, seven crops including rice, wheat, corn, soybeans, potatoes, vegetables, and oilseeds are selected as research subjects to calculate carbon emissions from crop cultivation. The calculation formula is as follows:

$$CE_{Growth} = \sum_{m=1}^{M} Crop_{mi} \cdot \theta_{mi} \cdot 298 \tag{3}$$

In the equation: CE_{Growth} represents carbon emissions from crop growth (in tons); $Crop_{mi}$ represents the area of the i-th crop in province m (in hectares); θ_{mi} represents the N$_2$O baseline emission flux of the i-th crop in province m. After calculating the N$_2$O emissions, it needs to be converted into CO$_2$ equivalent emissions. According to the Intergovernmental Panel on Climate Change (IPCC) data, typically has a Global Warming Potential (GWP) of 298 over a 100-year timeframe[35]. Different types of crops have different N$_2$O baseline emission fluxes (as shown in Table 2). For example, wheat can be divided into winter wheat and spring wheat based on the growing season, with N$_2$O baseline emission fluxes of 1.75 and 0.4, respectively. Based on the characteristics of wheat cultivation in the YRB and historical data, this study obtained the N$_2$O baseline emission flux of wheat in each province using a weighted average method.

Carbon emissions from straw burning   Currently, in China, a large amount of straw is still disposed of by burning, which generates a significant amount of greenhouse gases such as CO$_2$, CH$_4$, and N$_2$O. This not only pollutes the ecological environment but also poses health risks to humans. In this study, when calculating carbon emissions from land use, straw burning is taken into account. The specific calculation method is as follows:

$$CE_{Burning} = \sum_{m=1}^{M} \sum_{n=1}^{N} Burning_{mn}$$

Crop categories	CO_2	CH_4	N_2O
Rice	1.11	0.0058	0.00007
Wheat	1.47	0.0034	0.00007
Corn	1.35	0.0044	0.00014
Soybeans	1.58	0.0058	0.00007
Potatoes	1.58	0.0058	0.00007
Oilseeds	1.58	0.0058	0.00007

Table 3. Greenhouse gas emission factors from straw combustion. Note: Data sourced from Du(2019)[38].

Province	Rice	Wheat	Corn	Soybeans	Potatoes	Oilseeds
Shanxi、Inner Mongolia、Shandong、Henan	0.85	1.34	1.73	1.57	1	1.5
Sichuan	1	1.31	1.29	1.05	0.6	1.5
Shaanxi、Gansu、Qinghai、Ningxia	1.23	1.23	1.52	1.07	1.22	1.5

Table 4. Grass-to-grain ratios of various crops. Note: Data sourced from Office of the National Development and Reform Commission[39].

$$Burning_{mn} = \pi_n \cdot \sum_{i=1}^{I} \beta_{in} \cdot p_{mi} \cdot \alpha_{mi} \cdot \gamma_m \cdot \epsilon \tag{4}$$

In the formula, $CE_{Burning}$ represents the carbon emissions from straw burning (t); $Burning_n$ represents the carbon emissions of the nth greenhouse gas generated from straw burning in province m; π_n represents the conversion coefficient of the nth greenhouse gas to carbon dioxide, with CH_4 needing to be converted to N_2O first, and N_2O being taken as 298; β_{in} represents the combustion carbon emission coefficient of the nth greenhouse gas for the i-th crop (Table 3); p_{mi} represents the yield of the i-th crop in province m; α_{mi} represents the grass-to-grain ratio of the i-th crop in province m (Table 4); γ_m and ϵ respectively represent the percentage of open-field burning and the combustion efficiency of straw in province m. Both CH_4 and N_2O need to be converted to carbon dioxide emissions based on conversion coefficients, with related coefficients and calculation methods referring to the "Provincial Greenhouse Gas Inventory Compilation Guide". The open-field burning percentages for Shanxi, Shandong, Henan, Shaanxi, Gansu, Qinghai, and Ningxia are taken as 18.2%, with Inner Mongolia at 31.9% and Sichuan at 9.1%, while the combustion efficiency is set at 0.9 for all[37].

Modified gravity model
Before conducting spatial correlation network analysis, it is necessary to first build a gravity model. The gravitational values calculated through this model are used to construct a spatial correlation matrix, allowing for the analysis of factors influencing spatial correlation networks. Existing research on carbon emission spatial correlations has primarily utilized traditional spatial econometric methods (such as VAR models[40] and gravity models. However, conclusions from VAR models often focus on geographically adjacent or close regions, neglecting potential correlations between non-adjacent regions, which may lead to biased results[41]. In contrast, the gravity model is not only suitable for aggregate data but also better at capturing spatial dynamic trends.

Given that cropland carbon emissions are influenced by multiple factors and interstate carbon emission interactions vary, this study introduces a carbon emission proportional coefficient into the gravity model[42], constructing a modified gravity model:

$$Q_{ij} = K_{ij} \cdot \frac{\sqrt[3]{G_i \cdot C_i \cdot P_i} \cdot \sqrt[3]{G_j \cdot C_j \cdot P_j}}{D_{ij}^2 / (g_i - g_j)^2} \tag{5}$$

$$K_{ij} = \frac{C_i}{C_i + C_j}$$

In the equation, Q_{ij} represents the gravitational value of cropland carbon emissions between province i and province j; K_{ij} is the weight coefficient used to adjust the strength of the connection between region i and region j, reflecting the relative attractiveness of region i in the two regions; G_i and G_j respectively represent the GDP of province i and province j (in hundred million yuan); C_i and C_j respectively represent the cropland carbon emissions of province i and province j (in ten thousand tons); P_i and P_j respectively represent the population of province i and province j (in ten thousand people); D_{ij} represents the geographical distance (in kilometers) between the capital cities of province i and province j; g_i and g_j respectively represent the per capita GDP of province i and province j (in yuan).

For the convenience of subsequent research, when constructing the spatial correlation matrix based on the gravitational values, calculate the row average of the original gravitational matrix. Using the row average value as the threshold. When the gravitational value is greater than the threshold, assign a value of 1 to indicate a carbon

emission correlation relationship between the two cities; when it is less than the threshold, assign a value of 0 to indicate no carbon emission correlation relationship between the two cities.

Spatial correlation network analysis method
Social network analysis is an interdisciplinary analysis method aimed at "relationship data" and has been widely applied in multiple fields. This article aims to study the temporal and spatial distribution characteristics of carbon emissions from land use in the YRB, and based on this, propose regional carbon reduction paths. The Spatial Correlation Network Analysis Method, by taking into account spatial correlations, can more accurately reveal the relationships between different regions, thus providing more comprehensive references and decision support for regional development planning. Compared to other methods, it is more comprehensive and practical. The description of overall characteristics selects four indicators: network density, network connectivity, network efficiency, and network centrality, while individual characteristics are reflected through node degree centrality, closeness centrality, and betweenness centrality.

Overall network characteristics indicators   Network density is the ratio of the actual number of connections in the network to the theoretical maximum number of connections, ranging from 0 to 1. A value closer to 1 indicates a tighter spatial correlation among the nodes in the network. Network connectivity measures the strength of connections between nodes through the average degree of nodes. A higher degree implies a tighter connection, and a value of 1 indicates that there are no unreachable points between cropland carbon emissions nodes in the YRB, making the spatial correlation network more robust. Network efficiency reflects the efficiency of information transmission, with higher efficiency indicating more effective information transmission. Network centrality, based on node centrality (such as degree centrality and betweenness centrality), shows the hierarchical structure of the network. Nodes with higher centrality levels have a greater impact on the entire network, potentially leading to network instability. Therefore, a lower network centrality indicates a more stable spatial correlation network of cropland carbon emissions in the YRB.

Individual network characteristics indicators   Node degree centrality reflects the direct number of connections a node has. A higher value indicates wider direct connections, making the node more likely to be a core node in the network. Closeness centrality calculates the reciprocal of the average shortest path length from a node to all other nodes, with a higher value indicating closer proximity to other nodes in the network, promoting economic and cultural exchanges between regions. Betweenness centrality measures the frequency of a node acting as an intermediary in the shortest paths between nodes. A higher value indicates the importance of the node as an intermediary in connecting different regions. To standardize the measurement of node importance in the network, this study normalized degree centrality, closeness centrality, and betweenness centrality, scaling their values to between 0 and 1 for easier comparison and analysis.

QAP regression analysis
The impact variables studied in this paper are relational data, which can easily lead to multicollinearity issues. This may affect the estimation results of regression models, rendering significance tests meaningless and causing bias in the estimation results of variables. Therefore, this paper employs the Quadratic Assignment Procedure (QAP) method, where the explanatory variables are "difference matrices" rather than original numerical vectors, significantly reducing the risk of multicollinearity compared to traditional Ordinary Least Squares (OLS).The QAP model, which does not require parameter setting, can perform pairwise comparisons and permutations of elements in matrices in social networks, revealing potential associations or patterns between two or more matrices through similarity comparison[43]. Furthermore, this model does not require explanatory variables to meet the assumption of independence, allowing for effective treatment of potential multicollinearity and endogeneity issues between variables[44]. Regarding the selection of influencing factors, Wei et al. (2024) found that geographical proximity, economic development level, urbanization rate, industrial configuration, technological innovation level, and the intensity of environmental protection significantly impact the spatial correlation network[45]. Shan et al. (2025) discovered that geographical proximity and economic development have a notable influence on the spatial association network of agricultural carbon emissions[46]. Yang et al. (2025) believed that geographical proximity, economic development level, openness level, industrial structure, and population density are all related to spatial carbon emissions[47]. Tian et al.(2024)[48], Qiu et al.(2025)[49] and others argued that the scale of farmland management, level of land transfer, level of agricultural mechanization, and environmental regulations also affect carbon emissions and their spatial correlation. Combining the above studies, the study focuses primarily on three dimensions: natural, economic and social, selected 8 factors to investigate the driving factors of spatial correlation of carbon emissions from cultivated land use in the YRB (Table 5).

①Geographical proximity: Directly influences the diffusion of agricultural technology, resource flow and policy coordination between regions, promoting convergence of carbon emission patterns between adjacent regions;②Agricultural economic level: Regions with different agricultural economic levels will also have varying levels of agricultural development and production methods, leading to differentiated carbon emission levels;③Farmers' income level: Farmers' income level affects the cost of their investments in agricultural production, thus influencing carbon emission levels;④Farmland circulation: Land circulation can improve land management practices, thereby affecting carbon emission levels;⑤Urbanization level: Urban areas have richer human capital and other resources compared to rural areas, and urbanization can affect land use through labor force migration and industrial substitution;⑥Farmland management scale: Large-scale operation is conducive to the promotion of low-carbon technologies, but excessive scale may lead to ecological damage;⑦Mechanization intensity of agriculture: The level of mechanization directly affects energy consumption and carbon emissions;⑧Environmental regulations: Environmental policies influence agricultural behavior through

Type	Driving factors	Indicators
Natural	Geographic proximity	Spatial adjacency matrix
Economic	Agricultural economic level	Agricultural output growth rate
	Farmer' income level	Rural per capita disposable income growth rate
	Land transfer	Land transfer rate
Social	Urbanization level	Urbanization rate
	Agricultural operating scale	Cultivated land area/agricultural population
	Agricultural machinery input intensity	Total agricultural machinery power/crop planting area
	Environmental regulation	Investment completion of industrial pollution control

Table 5. Driving factors of the spatial correlation network of carbon emissions from cultivated land use in the YRB.

constraints or incentives, strict environmental regulations may push farmers to adopt low-carbon technologies, but regions with weak enforcement may lack substantive implementation. Based on these indicators, the QAP model was constructed:

$$Q_{ij} = f(X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8)$$

In the equation, Q_{ij} represents the spatial network relationship matrix of carbon emissions from cultivated land use in the YRB; X_1 is the spatial adjacency matrix, with adjacent provinces labeled as 1 and non-adjacent provinces labeled as 0; X_2, X_3, X_4, X_5, X_6, X_7, X_8 respectively represent the difference matrices of each driving factor. The specific operational steps are as follows: First, the study selects data from 2008 to 2022 as samples, due to the long time span of the samples, the method of taking the average value is used to eliminate some associated effects[50].Second, a difference matrix is constructed based on inter-provincial differences, which is then binarized into a 0-1 adjacency matrix to reduce numerical multicollinearity among variables. Finally, Ucinet 6 software is used to conduct QAP analysis on each influencing factor with 5,000 random permutations, a process that does not rely on the assumption of independence of explanatory variables, thus fundamentally avoiding multicollinear interference in traditional regression and ensuring robust estimation.

In summary, this paper employs the "carbon emission coefficient method-SNA-QAP" combined model to deeply study the spatial correlation characteristics of cultivated land use and carbon emissions in the YRB, but this method combination still has some limitations. Firstly, the carbon emission coefficient method has certain applicability restrictions. Since carbon emission coefficients may vary across different regions, time periods, and even activities, using them may introduce errors. Moreover, the update speed of carbon emission coefficients may not keep pace with technological and policy changes, leading to inaccurate estimations. Secondly, SNA has certain constraints at the provincial scale. Although SNA is commonly used to study relationships and influences between individuals or organizations, at the provincial scale, the larger scale of research subjects and social network structure may be influenced by factors such as geography and culture, increasing the challenge of the research. Lastly, QAP is more sensitive to non-linear relationships. As QAP is mainly used for linear relationship testing, there is a problem of not being able to accurately capture complex non-linear relationships. At this time, it is necessary to combine non-parametric statistical methods or machine learning algorithms, etc., to better understand the associations between data. Future research needs to optimize these issues to improve the accuracy and applicability of the study, providing certain references for agricultural carbon emission reduction.

Data source

The main focus of this study is the spatial correlation network characteristics and driving factors of carbon emissions from land use in the YRB from 2008 to 2022. Various agricultural input elements, crop planting areas, crop yields, and other data sources are from the "China Statistical Yearbook", "China Environmental Statistical Yearbook", "China Agricultural Statistical Yearbook", as well as provincial statistical yearbooks and statistical bulletins. The Geospatial Data Cloud Platform provides DEM data with a spatial resolution of 30 m (http://www.gscloud.cn/, accessed on 13 May 2025). In cases where data are missing, linear interpolation method was used for supplementation.

Analysis of results

Temporal and Spatial evolution characteristics of carbon emissions from land use in the YRB

Trends in carbon emissions from land use in the YRB as a whole

Table 6 presents the changes in carbon emissions from land use in the YRB from 2008 to 2022, as well as their composition. From an overall perspective, carbon emissions from land use in the YRB showed a fluctuating upward trend from 2008 to 2022, forming an "N" shape. In 2008, carbon emissions from land use in the YRB were 204.87 million tons, reaching a peak in 2017, slightly decreasing in 2018 and 2019, but starting to rise again in 2020 and 2021, reaching the highest value of 261.46 million tons in 2022, with an overall increase of 27.6% over the entire study period. The reason for this trend is mainly that in 2016, the State Council issued the "13th Five-Year Plan for Controlling Greenhouse Gas Emissions" and made specialized deployment for the development of low-carbon agriculture, after which the carbon emissions in the basin as a whole tended to stabilize.

Year	Agricultural input carbon emissions	Straw burning carbon emissions	Crop planting carbon emissions	Cultivated land utilization carbon emissions
2008	5284.95	12378.59	2823.92	20487.47
2009	5416.85	12574.57	2889.83	20881.25
2010	5552.79	13100.42	2937.57	21590.78
2011	5697.27	13749.62	2983.44	22430.34
2012	5839.72	14274.56	3032.68	23146.96
2013	5934.59	14960.37	3085.78	23980.74
2014	5973.20	15172.31	3124.86	24270.37
2015	6030.19	15638.85	3158.21	24827.25
2016	6033.32	16153.56	3277.01	25463.88
2017	5915.56	16106.01	3254.05	25275.63
2018	5775.93	16558.03	3249.55	25583.51
2019	5589.24	16646.78	3245.91	25481.92
2020	5487.25	16916.23	3272.44	25675.93
2021	5471.09	16961.73	3312.77	25745.59
2022	5393.38	17380.58	3372.11	26146.07

Table 6. Carbon emissions from cultivated land use in the YRB and their composition from 2008 to 2022 (in 10,000 tons).

From different components, the largest source of cultivated land use carbon emissions in the YRB is straw burning, which has consistently been the largest source of carbon emissions over the 15-year period, with its proportion increasing from 60.4% in 2008 to 66.5% in 2022, with an average annual growth rate of 2.1%, reaching 17,380.58 million tons in 2022. The second is agricultural input carbon emissions, which increased continuously from 2008 to 2015, remained almost stable in 2016, and then continued to decline. This may be because in 2015, the Ministry of Agriculture and Rural Affairs of China issued the "Action Plan for Zero Growth of Fertilizer Use by 2020" and launched a series of reduction plans for other agricultural production factors, which improved the utilization efficiency of various agricultural inputs and reduced their usage. The third is crop planting carbon emissions, Subject to the constraints of relatively stable crop structure and area in various regions, it shows a slow rising trend, with a cumulative increase of 19.4% over 15 years.

Temporal and Spatial evolution characteristics of carbon emissions from land use in various provinces in the YRB
The study period in this paper is from 2008 to 2022. During the study period, in 2015, the signing of the Paris Agreement and the introduction of China's overall plan for ecological civilization reform provided a policy basis for carbon emissions control, while in 2020, China's goal of "peak carbon emissions and achieve carbon neutrality" further accelerated the process of emission reduction. With the introduction of these important policy objectives, the spatial and temporal distribution of carbon emissions from cultivated use in the YRB has also changed. Based on this, using ArcGIS software, distribution maps of carbon emissions from land use in the YRB for the years 2008, 2015, 2020, and 2022 were plotted (Fig. 3), providing a visual representation of the changes in carbon emissions from land use in the YRB.

According to Fig. 3, Henan and Shandong are at the forefront of carbon emissions from land use, belonging to the highest emission level in the first tier. This study result is consistent with Ren's (2023) study result[51], mainly due to the high agricultural population and large farmland area in these two regions, which consume a large amount of energy in the process of farmers' production and daily life, thereby driving carbon emissions. Gansu, Qinghai, and Ningxia are located in the northwest region of China with low population, arid climate, and predominant land types such as deserts, Gobi, and alpine meadows, with a relatively low proportion of farmland area. Therefore, the carbon emissions from cultivated use in these regions have always been at a low level. The carbon emissions from cultivated use in other provinces fluctuated, with Shaanxi and Shanxi showing small changes in carbon emissions from cultivated use. From 2008 to 2015, Inner Mongolia's carbon emissions from cultivated use showed a significant increase, rising from 34.19 million tons to 54.08 million tons, an increase of 58.2%, and remained at a high level in subsequent years.

Spatial correlation network of carbon emissions from land use in the YRB
Characteristics of the overall network structure
Using ArcGIS software, the spatial correlation strength of carbon emissions from land use in the YRB for the years 2008, 2015, 2020, and 2022 was visualized based on gravity values, as shown in Fig. 4.

From 2008 to 2022, the spatial correlation network of carbon emissions from cultivated use in the YRB has exhibited a continuously changing multi-centric distribution. The correlation network, initially centered around "Henan-Shandong", gradually evolved into a high-intensity triangular relationship involving "Henan-Shandong-Shanxi", and then returned to being centered around "Henan-Shandong" in2020.By 2022, in addition to the original centers, Inner Mongolia and Sichuan have emerged as new hub regions. Henan and Shandong have maintained their high-intensity central positions due to their geographical advantages and abundant resources, while Qinghai has consistently shown weaker correlations with other regions. These changes are influenced by the improvement of infrastructure and the rapid agricultural and rural development in various regions. Significant
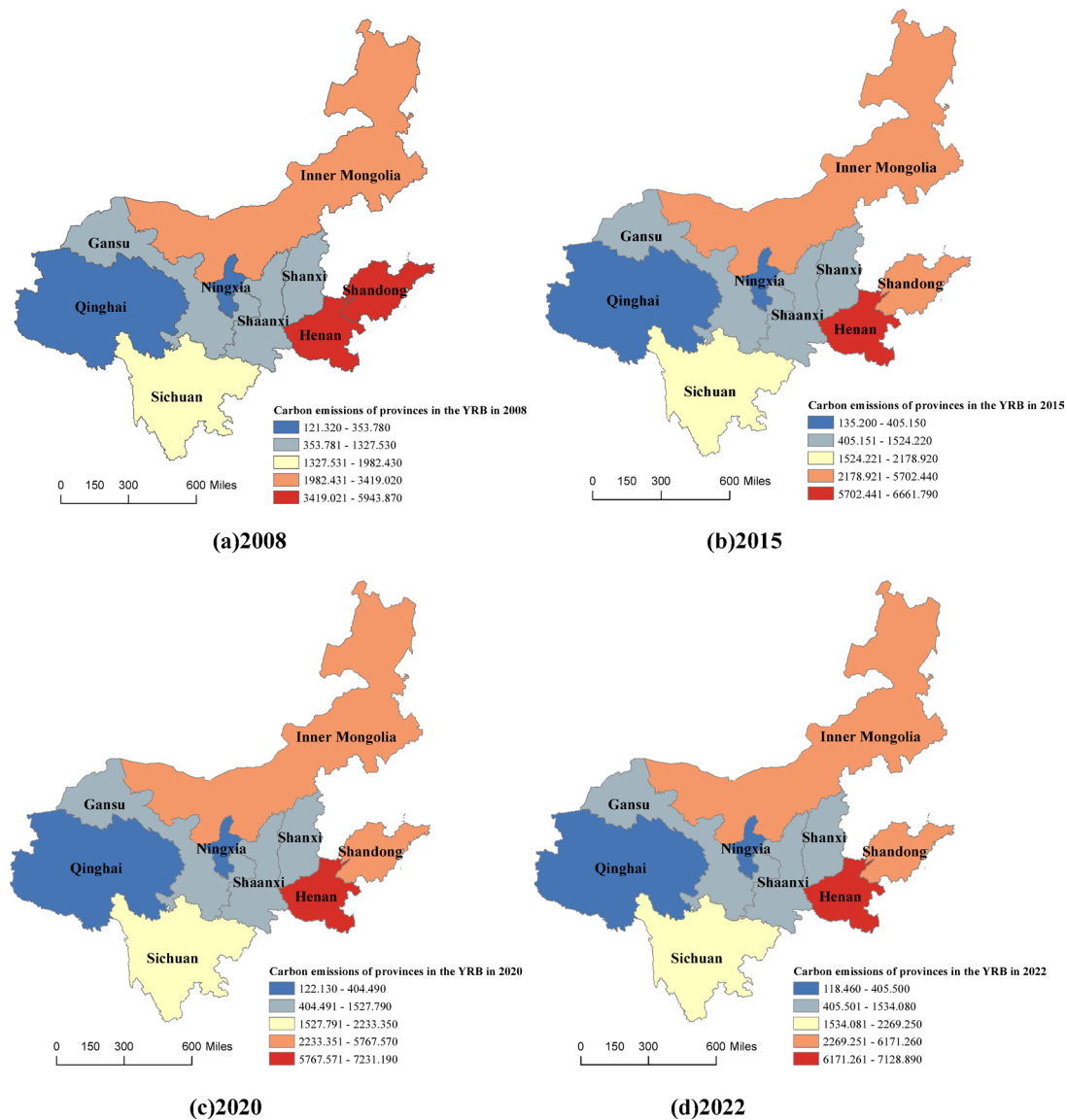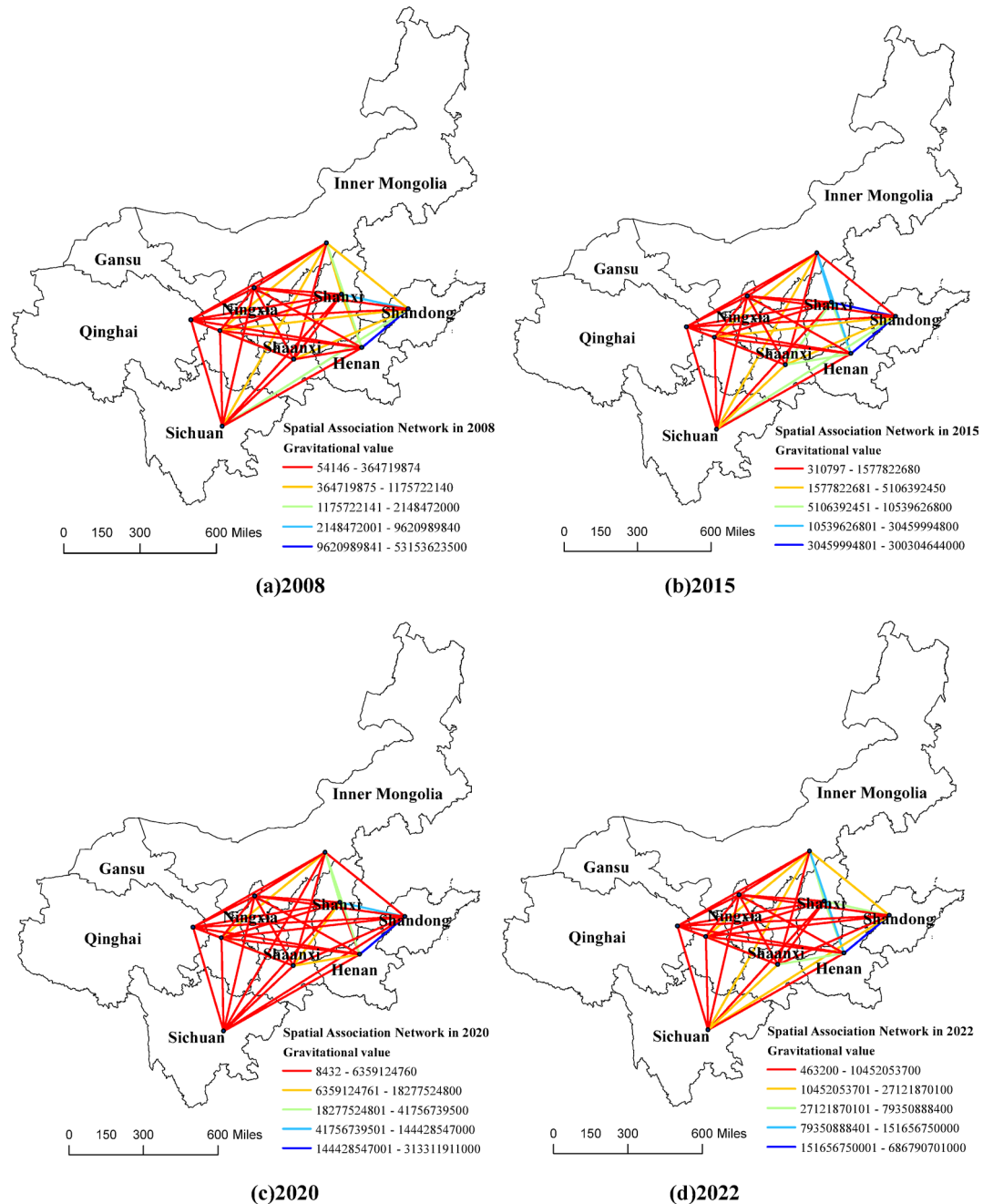
Fig. 3. Evolution of carbon emissions from cultivated land use in the YRB (in 10,000 tons). (**a**) 2008, (**b**) 2015, (**c**) 2020, (**d**) 2022.

differences in correlation strength between different regions are evident, and the evolution of network centers reflects the complexity and dynamics of the spatial correlation network of carbon emissions from cultivated use in the YRB. In future development, it is crucial to further enhance cooperation and communication between regions to promote the sustainable development of the entire area.

Using "Ucinet" software, characteristic indicators of the overall network structure of carbon emissions from land use in the YRB for the years 2008, 2015, 2020, and 2022 were calculated, as shown in Table 7. Overall, the network structure of carbon emissions from land use in the YRB underwent significant changes from 2008 to 2022, displaying a trend of dispersion, then concentration, and adjustment. Fluctuations in network density, efficiency, and degree centrality reflect the dynamic evolution of interregional correlations and hierarchical patterns.

First, between 2008 and 2022, the spatial correlation network density of carbon emissions from cropland use in the YRB experienced fluctuations. From 2008 to 2013, the network density hovered around 0.333. In November 2013, the Third Plenary Session of the 18th Central Committee of the Communist Party of China proposed deepening the reform of the ecological civilization system. This policy direction demonstrated positive effects in 2014, when the network density rose to 0.375, the highest point during the study period. However, due to significant disparities in agricultural development levels within the YRB and the lagging effects of industrial restructuring, the network density dropped to 0.278 in 2015, the lowest value in the study period. Subsequently, from 2016 to 2022, with the implementation of the 13th Five-Year Plan, policies related to ecological protection and sustainable agricultural development in the YRB were successively introduced. These policies promoted the

Fig. 4. Evolution of the spatial correlation network of carbon emissions from cultivated land use in the YRB. (**a**) 2008, (**b**) 2015, (**c**) 2020, (**d**) 2022.

widespread adoption of agricultural technologies and carbon emission control in the region, leading to a gradual recovery in network density.

Secondly, the stability of the spatial correlation network of carbon emissions from cropland use in the YRB exhibits fluctuations. The network centrality has consistently remained at 1, indicating strong connections among various regions in terms of land use carbon emissions, with significant spatial correlations and spillover effects. However, from 2008 to 2014, the network hierarchy level fluctuated between 0.2222 and 0.4, without forming a distinct hierarchical structure. In 2015, influenced by a series of policies, the network hierarchy level reached 0.818, suggesting the emergence of core provinces in carbon emissions within the YRB, particularly Henan and Shandong. Subsequently, as provinces such as Inner Mongolia and Shanxi became secondary centers, the network hierarchy level returned to its original range.

Thirdly, the efficiency of the spatial correlation network of carbon emissions from cropland use in the YRB experienced a fluctuating trend, initially decreasing and then increasing, reflecting the influence of different factors during various periods. In 2008, the network efficiency was 0.6071. After fluctuations, it increased to 0.7143 in 2015 and further improved to 0.75 in 2020, indicating a significant enhancement in information flow

Year	Network density	Network centrality	Network efficiency	Network degree centrality
2008	0.361	1	0.6071	0.222
2009	0.333	1	0.6429	0.400
2010	0.319	1	0.7143	0.222
2011	0.361	1	0.6071	0.222
2012	0.333	1	0.6786	0.222
2013	0.333	1	0.6429	0.400
2014	0.375	1	0.5714	0.400
2015	0.278	1	0.7143	0.818
2016	0.333	1	0.6429	0.400
2017	0.319	1	0.6786	0.400
2018	0.347	1	0.7143	0.222
2019	0.347	1	0.7143	0.222
2020	0.319	1	0.7500	0.222
2021	0.333	1	0.7143	0.400
2022	0.347	1	0.6429	0.400

Table 7. Characteristics of the overall network structure of carbon emissions from cultivated land use in the YRB.

Province	Point out degree centrality				Point in degree centrality				Intermediary centrality			
	2008	2015	2020	2022	2008	2015	2020	2022	2008	2015	2020	2022
Gansu	0.5	0.375	0.5	0.375	0.625	0.625	0.625	0.75	0.455	0.345	0.686	0.357
Henan	0.125	0.125	0.25	0.375	0.25	0.375	0.375	0.5	0.009	0.024	0.193	0.369
Inner Mongolia	0.5	0.375	0.375	0.375	0.75	0	0.5	0.75	0.482	0	0.383	0.488
Ningxia	0.375	0.125	0.25	0.25	0.125	0.125	0.125	0.125	0	0	0	0
Qinghai	0.375	0.375	0.375	0.375	0	0	0	0	0	0	0	0
Shandong	0.25	0.25	0.25	0.125	0.875	0.625	0.375	0.375	0.411	0.214	0.131	0.012
Shanxi	0.375	0.125	0.25	0.5	0.25	0.375	0.375	0.125	0.366	0.024	0.193	0.06
Shaanxi	0.375	0.375	0.375	0.25	0.25	0.375	0.375	0.5	0.036	0.143	0.288	0.143
Sichuan	0.375	0.375	0.25	0.5	0.125	0	0.125	0	0.027	0	0.055	0
Province	Out-degree centrality				In-degree centrality							
	2008	2015	2020	2022	2008	2015	2020	2022				
Gansu	0.533	0.421	0.533	0.4	0.667	0.471	0.667	0.727				
Henan	0.308	0.296	0.4	0.4	0.571	0.571	0.615	0.667				
Inner Mongolia	0.533	0.471	0.5	0.421	0.727	0.25	0.615	0.8				
Ningxia	0.5	0.348	0.444	0.381	0.421	0.381	0.421	0.444				
Qinghai	0.615	0.471	0.571	0.471	0.2	0.25	0.2	0.2				
Shandong	0.4	0.308	0.364	0.32	0.889	0.727	0.533	0.5				
Shanxi	0.5	0.296	0.4	0.444	0.571	0.571	0.615	0.471				
Shaanxi	0.5	0.421	0.5	0.381	0.471	0.421	0.571	0.667				
Sichuan	0.471	0.471	0.471	0.533	0.444	0.25	0.421	0.2				

Table 8. Network centrality of carbon emissions from cultivated land use in the YRB.

and resource allocation efficiency. However, due to the adaptation period required for policy adjustments during the "14th Five-Year Plan" period, the network efficiency dropped to 0.6429 in 2022, showing a decline during the policy transition phase.

Individual characteristics of the Spatial correlation network
Using "Ucinet" software, individual characteristics indicators of the carbon emissions spatial correlation network associated with land use in the YRB for the years 2008, 2015, 2020, and 2022 were calculated, as shown in Table 8.

Overall, from 2008 to 2022, the changes in the degree of out-degree centrality and in-degree centrality of provinces in the YRB varied, and the carbon emission network associated with land use in the YRB exhibited a clear core-periphery structure.

Gansu and Inner Mongolia occupy important geographical positions in the network in the YRB. With the support of the Western Development Policy, they have formed connections with other regions, holding core positions and possessing strong comprehensive influence. Additionally, Inner Mongolia's abundant coal

Variables	Non-standardized Coefficients	Standardized Coefficients	P-Value	Probability1	Probability2
Geographical proximity matrix	0.419	0.394***	0.006	0.006	0.994
Agricultural economic level	−0.092	−0.504***	0.009	0.992	0.009
Farmer income level	−0.147	−0.302***	0.001	0.999	0.001
Agricultural land transfer	−0.007	−0.125	0.151	0.849	0.151
Urbanization level	0.035	0.580***	0.000	0.000	1.000
Farm operating scale	−0.355	−0.484***	0.003	0.997	0.003
Agricultural machinery input intensity	0.018	0.107**	0.033	0.033	0.967
Environmental regulation	−0.016	−1.025***	0.000	1.000	0.000
R^2	0.335		0.000		
Adj-R^2	0.251				

Table 9. QAP regression results of the driving factors of the Spatial correlation network of cultivated land use carbon emissions in the YRB. Note: *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.

resources further promote its connections with other regions. Shandong has higher in-degree centrality and closeness centrality than other nodes, indicating that it is most influenced by other provinces.

As a downstream province in the YRB, Shandong plays a significant role in regional economic cooperation due to its relatively developed economy, making it susceptible to the carbon emissions of other provinces. Furthermore, Shandong also has a high out-closeness centrality, suggesting a high level of closeness to other provinces, likely related to its economic development level and strong external connections.

Henan has lower out-degree centrality and out-closeness centrality, but performs well in in-degree centrality and in-closeness centrality, indicating a greater influence from other provinces but weaker influence on other nodes. Being a densely populated province, Henan may face significant pressure in agricultural development and land use carbon emissions, making it more susceptible to the influence of other provinces.

Qinghai performs best in out-closeness centrality but worst in in-degree centrality and intermediary centrality, indicating it is more likely to influence other provinces but is less influenced by them with limited intermediary effects, possibly due to its lower participation in the carbon emission network based on its geographic location and economic development level, relatively independent.

Shanxi and Shaanxi also have higher out-degree centrality, exerting strong influence on other provinces. As midstream provinces in the YRB, they play crucial roles in regional economic cooperation and carbon emissions.

Analysis of driving factors of carbon emission Spatial correlation network

By utilizing the QAP method with 5000 random permutations, the driving factors of the carbon emission spatial correlation network associated with land use in the YRB from 2008 to 2022 were studied, as shown in Table 9. In the regression results, the adjusted R^2 is 0.251, significant at the 1% level, indicating that the selected influencing factors in this study can explain 25.1% of the spatial correlation relationship of carbon emissions associated with land use in the YRB.

The impact of natural factors on the Spatial correlation network of carbon emissions from cultivated land use in the YRB
Geographic proximity represents a natural factor, with a standardized coefficient of 0.394, which is significant at the 1% level. This indicates that spatial correlation between neighboring provinces can promote communication and cooperation between regions, thereby facilitating the formation of the spatial correlation network of carbon emissions from cultivated land use in the YRB.

The impact of economic factors on the Spatial correlation network of carbon emissions from cultivated land use in the YRB
The agricultural economic level and farmer income level are significantly negatively correlated with the formation of the spatial correlation network of carbon emissions from cultivated land use in the YRB at a significance level of 1%. The smaller the difference in economic development levels between different regions, and the more similar the farmer income situation, the more similar the factors needed for agricultural production, which is conducive to communication and joint development between the two areas. In this case, it is conducive to promoting the formation of the spatial correlation network of carbon emissions from cultivated land use in the YRB. Land circulation does not have a significant role in this regard.

The impact of social factors on the Spatial correlation network of carbon emissions from cultivated land use in the YRB
The urbanization level and agricultural machinery input intensity are both significantly positively correlated with the formation of the spatial correlation network of carbon emissions from cultivated land use in the YRB at a significance level of 1%. The greater the difference in urbanization levels between two regions, the more likely, based on spatial spillover effects, it is to promote the flow of various resource elements between regions, thereby promoting the formation of the spatial correlation network of carbon emissions from cultivated land use in the YRB. Generally, areas with higher levels of urbanization also have higher agricultural technology levels

and surplus agricultural machinery resources. In such cases, the flow of agricultural machinery equipment from high-level areas to low-level areas occurs, leading to seasonal "cross-regional operations" and further promoting the formation of the spatial correlation network of carbon emissions from cultivated land use in the YRB.

The scale of agricultural land management and environmental regulations are both significantly negatively correlated with the formation of the spatial correlation network of carbon emissions from cultivated land use in the YRB at a significance level of 1%. Large-scale agricultural production helps unify cultivation and management. At an appropriate scale, a scientifically unified production method helps reduce carbon emissions. However, excessive large-scale management may lead to excessive land use further increasing carbon emissions. The smaller the differences in the scale of agricultural land management between regions, the more conducive it is for mutual learning and exchange, thereby promoting the formation of the spatial correlation network of carbon emissions from cultivated land use in the RB. In the developmental process environmental regulations will also affect carbon emission levels. The greater the differences in environmental regulations between regions, the more likely it is to increase the difficulty of cooperation in environmental governance, which is detrimental to the formation of spatial correlation networks.

Discussion

This study focuses on the YRB, employing the carbon emission coefficient method and Social Network Analysis (SNA) to construct a modified gravity model, analyzing the spatiotemporal characteristics of carbon emissions from cropland use in the YRB from 2008 to 2022.Additionally, this research applies QAP regression to examine the driving factors of spatial correlation of cultivated land use carbon emissions in the YRB, aiming to enhance the objectivity of variable selection and provide references for carbon emission reduction in cultivated land use in the YRB.

Spatiotemporal characteristics of cultivated land use carbon emissions in the YRB

The YRB spans a large distance from east to west. Spatially, due to differences in rural development levels, arable land areas, and cropping structures between the eastern and western regions, research findings indicate that overall, cultivated land use carbon emissions are higher in the east and lower in the west, which is consistent with existing research results[52]. Temporally, in line with the findings of Li et al.(2024), emissions have shown a declining trend after 2016 and gradually stabilized[53], following an "N"-shaped pattern of first rising, then falling, and rising again. This is primarily because, in the early stages, China's agricultural production model was generally extensive, characterized by high usage of various polluting agricultural inputs and a high rate of straw burning, leading to increases year by year in carbon emissions from cultivated land use. In recent years, with the promotion of agricultural technology and the implementation of relevant carbon emission reduction policies, the overall growth rate of carbon emissions has slowed down and shown fluctuations. In terms of emission sources, the proportion of various carbon emissions from largest to smallest is as follows: straw burning > agricultural inputs > crop planting. This result differs from the study by Cao et al. (2025) on the Yangtze River Economic Belt[54],mainly due to differences in crop planting structures and straw disposal methods between the two basins. Overall, carbon emissions from cultivated land use in the YRB remain at a relatively high level.

Spatial correlation network characteristics of cultivated land use carbon emissions in the YRB

Henan and Shandong are the most populous and transportation-developed provinces in the YRB. To promote the improvement of the ecological environment in the YRB, these two provinces have taken on corresponding social responsibilities. According to the results of social network analysis, Henan and Shandong have always been at the center of the spatial correlation network of cultivated land use carbon emissions in the YRB due to their geographical advantages and resource endowments. Over time, Shanxi, Inner Mongolia, and Sichuan have successively become sub-centers, but the level of association has fluctuated. Based on the overall and individual characteristics of the network, the network is fully connected and effective. However, during different time periods, the stability and efficiency of the network are in a state of fluctuation. Therefore, in the future process of cultivated land use carbon emission reduction in the YRB, Henan and Shandong need to further strengthen their connections and cooperation with other provinces to jointly promote low-carbon development in the YRB across various industrial fields.

Driving factors of the spatial correlation network of cultivated land use carbon emissions in the YRB

QAP analysis revealed that the geographical proximity matrix, agricultural economic level, farmer income level,urbanization level, farm operating scale, agricultural machinery input intensity, and environmental regulation have significant impacts on the spatial correlation network of carbon emissions from cultivated land use in the YRB. Geographical proximity and urbanization level show a positive correlation with the spatial correlation network of carbon emissions, which is consistent with the findings of Chen et al. (2024)[55].However, urbanization level is positively correlated with the spatial correlation network of carbon emissions, this finding is contrary to the research results of Huang et al. (2025)[56]. This discrepancy is primarily due to their study area being Hubei Province, where the overall urbanization differences within the province are relatively small and the initial urbanization level is higher than that of the YRB.Therefore, when formulating carbon emission reduction strategies, it is necessary to take into account the dynamic changes of these factors to achieve more effective carbon emission control and regional coordinated development.

Optimize path

The above conclusions provide a reference path for carbon emission reduction in the YRB's agricultural land utilization.

Promote comprehensive utilization of straw
Straw burning accounts for a significant proportion of total carbon emissions in the YRB. In accordance with the goals outlined in the YRB Ecological Protection and High-Quality Development Plan, the comprehensive utilization rate of straw in the YRB should exceed 90% by 2030[57]. Therefore, the government should provide various subsidies, technical support, and training to encourage farmers to participate in straw utilization initiatives. Additionally, research institutions across the YRB should strengthen collaboration with enterprises to develop and promote efficient straw utilization technologies, such as converting straw into bioenergy, producing organic fertilizers, or using it as animal feed. Finally, infrastructure for straw collection, transportation, and processing should be established to reduce logistical costs associated with straw utilization. Through these measures, the YRB can not only reduce carbon emissions from straw burning but also improve soil physicochemical properties, increase soil organic matter content[58], and promote green agricultural development.

Reduce the use of agricultural inputs
Currently, agricultural production in the YRB still heavily relies on inputs such as pesticides and chemical fertilizers. While these inputs enhance agricultural productivity, they also contribute significantly to carbon emissions. As China approaches the "16th Five-Year Plan" period, local governments in the YRB should refer to the National Agricultural Green Development Pioneer Zone Implementation Plan for Comprehensive Prevention and Control of Agricultural Non-Point Source Pollution when formulating their next five-year plans, further promoting the reduction of agricultural input usage. Specific measures include promoting precision fertilization and pesticide application technologies to improve the efficiency of input use and reduce overapplication. A strict monitoring and evaluation system should be established to ensure the achievement of reduction targets. Furthermore, farmers should be encouraged and supported to adopt eco-friendly agricultural practices, such as crop rotation, intercropping, and organic farming, to promote sustainable agricultural development and reduce carbon emissions during agricultural production.

Optimize crop planting structure
Existing research has shown that adjusting crop planting structures can effectively enhance the net carbon sink of farmland[59]. Therefore, the planting structure can be optimized according to local conditions in different regions of the YRB. For example, in arid areas of the basin, drought-tolerant crops such as rapeseed and wheat can be appropriately increased to reduce irrigation water demand and lower carbon emissions. In regions with humid climates, the cultivation of rice can be expanded to increase soil organic matter content and enhance carbon storage. Additionally, farmers can be guided to adopt suitable farming models that not only increase the diversity of farmland ecosystems but also improve soil carbon storage capacity, thereby contributing to carbon emission reduction.

Establish a regional carbon trading market
China began preparing for carbon trading in 2011 and officially launched the national carbon market on July 16, 2021. In 2023, the national carbon emission allowance trading volume reached 212 million tons, with a transaction value of RMB 14.444 billion[60]. This demonstrates the strong feasibility and significant economic potential of carbon trading markets. Given the regional disparities and spatial correlations of carbon emissions in the YRB, a cross-provincial carbon trading market can be established. This market would allow high-emission provinces to purchase carbon sinks from less developed regions, incorporating technology transfer clauses to facilitate the diffusion of emission reduction technologies. Blockchain technology can be employed to monitor data in real time and record it on the chain, while smart contracts can automatically execute quota settlements and penalize violations, ensuring transparency and credibility in transactions.

Improve farmland transfer policies
According to existing research, farmland transfer can, to some extent, promote agricultural carbon emissions[61]. Therefore, it is necessary to further refine farmland transfer policies, standardize land transfer practices, and promote green agricultural development. On one hand, a robust contract system for land transfer should be established to clarify the rights and responsibilities of both parties involved[62], ensuring rational land use and environmental protection. This would mitigate the negative environmental externalities of farmland transfer and enhance its stability and green sustainability. On the other hand, strengthened supervision and evaluation of transferred land are essential to ensure that post-transfer farmland management and operations do not increase carbon emissions. Through these optimized measures, the management level of agricultural carbon emissions can be improved, driving agriculture toward a more environmentally friendly and sustainable development path.

Future research directions

Although this study has achieved certain results, it still has limitations, including insufficiently comprehensive analysis of influencing factors, lack of concrete feasibility in carbon emission reduction strategy recommendations, and inadequate consideration of carbon sink effects. To address these shortcomings, future research needs to be optimized in the following aspects.

First, expand the scope of influencing factors. Subsequent studies should further quantify potential influencing factors such as human capital, financial support for agriculture, and natural disasters, and use QAP analysis to more comprehensively evaluate the impact of these factors on carbon emission reduction.

Second, develop practical and feasible emission reduction strategies. Focusing on carbon emission reduction from cultivated land use in the YRB, in-depth analysis should be conducted to propose more targeted and actionable emission reduction measures.

Third, incorporate carbon sink mechanisms. Integrating carbon sinks into the research framework, key crops should be studied in terms of their economic coefficients, carbon absorption rates, moisture content, and other parameters to calculate carbon sink capacity, thereby enhancing the comprehensiveness of carbon emission reduction analysis.

Through these systematic improvements and in-depth analyses, future research will provide more scientific, rigorous, and feasible recommendations for regional collaborative emission reduction in the YRB, thereby promoting green transformation and sustainable development in the region.

Conclusions

The carbon emission coefficient method was used to calculate the carbon emissions from agricultural land use in the YRB from 2008 to 2022. Based on this, a modified gravity model and social network analysis method were used to analyze the spatial correlation network characteristics of carbon emissions from agricultural land use in the YRB. Furthermore, the QAP method was used to identify the driving factors. The study found that:

(1) The overall carbon emissions from agricultural land use in the YRB showed an increasing trend, with straw burning being the main source of carbon emissions. The total carbon emissions from agricultural land use in the YRB from 2008 to 2022 showed an overall increasing trend, with an increase of 27.6%. Straw burning was the largest source of carbon emissions, with its proportion increasing from 60.4% to 66.5%. Carbon emissions from each province showed an increasing trend, especially significant growth in Inner Mongolia, while Henan and Shandong, despite minor fluctuations, still had the highest carbon emissions levels in the region.

(2)The overall characteristics of the spatial correlation network of carbon emissions from agricultural land use in the YRB showed a trend of initial dispersion, followed by concentration and then adjustment. The connectivity within the network was good, with network efficiency fluctuating upward and gradually stabilizing, while the network hierarchy exhibited an inverted U-shaped pattern. Throughout the evolution of the spatial relational network, Shandong and Henan consistently remained at the center of the network.

(3) Individual characteristics of the spatial correlation network of carbon emissions from agricultural land use in the YRB show that the network exhibits a core-periphery structure. Provinces such as Gansu and Inner Mongolia played core roles in the network due to factors such as their geographical location, policy orientation, and economic development level, showing strong influence and intermediary roles. Shandong, due to its developed economy and high level of openness, became the province most influenced by other provinces in the network. Conversely, provinces like Qinghai and Ningxia displayed limited influence and intermediary roles in the network, showing lower participation and independence.

(4) The QAP analysis results showed that geographic proximity, differences in urbanization levels, and variations in agricultural machinery input intensity promote the formation of the spatial correlation network of carbon emissions from agricultural land use in the YRB. Differences in agricultural economic levels, farmer income levels, agricultural land operation scale, and environmental regulations inhibit the formation of the spatial correlation network of carbon emissions from agricultural land use in the YRB, while land transfer had no significant impact.

Data availability

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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