Spatiotemporal Variation Characteristics and Influencing Factors of Agricultural Carbon Emissions in the Yellow River Basin: Postprint

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Abstract

Based on six carbon sources in agricultural production including chemical fertilizer, pesticide, agricultural film, diesel, tillage, and agricultural irrigation, this study measures and analyzes the agricultural carbon emissions and spatiotemporal characteristics at provincial and municipal scales in the Yellow River Basin from 2005 to 2020 using the carbon emission coefficient method proposed by the Intergovernmental Panel on Climate Change (IPCC), and employs a Geographically Weighted Regression (GWR) model to dissect the spatial heterogeneity of influencing factors. The results show: (1) From 2005 to 2020, agricultural carbon emissions in the Yellow River Basin exhibited a pattern of first increasing then decreasing, with an overall upward trend, increasing from 4431.95$×104tin2005to4915.87×104tin2020.Chemicalfertilizerandtillagearethemaincarbonsources,account
t, while Qinghai Province consistently had the lowest agricultural carbon emissions. In 2020, agricultural carbon emissions at the municipal scale in the Yellow River Basin displayed a spatial differentiation pattern of stepped decrease from east to west. (3) The positive impact of agricultural production efficiency on agricultural carbon emissions in the Yellow River Basin shows spatial variation characteristics of being high in the southeast and northwest and low in the northeast; the high-value area of negative impact from agricultural structure is Shanxi Province; the high-value area of positive impact from agricultural economic development level is the border region of Shaanxi Province, Shanxi Province, and Henan Province; the positive impact of agricultural labor force scale exhibits spatial characteristics of being high in the southeast and northwest and low in the southwest.

Full Text

Spatio-temporal Characteristics and Influencing Factors of Agricultural Carbon Emissions in the Yellow River Basin

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Abstract: Based on six carbon sources in agricultural production, namely fertilizers, pesticides, agricultural films, diesel oil, plowing, and agricultural irrigation, this study applied the carbon emission coefficient method proposed by the United Nations Intergovernmental Panel on Climate Change to measure and analyze the spatio-temporal variation in agricultural carbon emissions at provincial and municipal scales in the Yellow River Basin of China from 2005 to 2020. The spatial heterogeneity of the influencing factors was assessed using a geographically weighted regression model. The conclusions are as follows: (1) From 2005 to 2020, agricultural carbon emissions in the Yellow River Basin initially increased before declining, following an overall upward trend. Emissions rose from 4431.95×10^{4} t in 2005 to 4915.87×10^{4} t in 2020. Among the carbon sources, fertilizers and plowing were the primary contributors, accounting for more than 65% of total agricultural carbon emissions. Pesticide-related carbon emissions consistently remained the lowest. (2) In 2005, Shandong Province was the leading contributor to agricultural carbon emissions in the Yellow River Basin, with emissions of 1241.68×10^{4} t. However, from 2010 to 2020, Henan Province became the largest emitter, with annual emissions ranging from 1360×10^{4} t to 1470×10^{4} t. Qinghai Province consistently recorded the lowest agricultural carbon emissions. In 2020, agricultural carbon emissions at the municipal scale exhibited a stepped decline from east to west in the Yellow River Basin. (3) The positive effect of agricultural production efficiency on agricultural carbon emissions was stronger in the southeast and northwest and lower in the northeast of the Yellow River Basin. The negative impact of agricultural structure was most pronounced in Shanxi Province. The highest positive impact of agricultural economic development was observed at the borders of Shaanxi Province, Shanxi Province, and Henan Province. The positive effect of the agricultural labor force was higher in the southeast and northwest and lower in the southwest.

Key words: Yellow River Basin; agricultural carbon emissions; spatial-temporal variation; influencing factors; geographically weighted regression model

In recent years, global warming has become a focal point of international concern. Greenhouse gas emissions triggered by human activities are recognized as the dominant factor driving climate change, making emission reduction a global consensus and responsibility. According to calculations by the United Nations Intergovernmental Panel on Climate Change (IPCC), as the largest source of greenhouse gas emissions, China's agricultural sector accounts for a significant portion of total carbon emissions. Facing this severe situation, China has committed to playing an active role in carbon reduction, proposing the "dual carbon" goals of peak emissions before 2030 and carbon neutrality before 2060. From the perspective of emission sources, agricultural carbon emissions constitute a substantial share of China's total greenhouse gas emissions. The "Implementation Plan for Emission Reduction and Carbon Sequestration in Agriculture and Rural Areas" issued by the National Development and Reform Commission in 2022 states that "green and low-carbon development in agriculture and rural areas is key to reducing greenhouse gas emission intensity and actively exploring pathways for emission reduction and carbon sequestration." The report from the 20th National Congress of the Communist Party of China also emphasizes "coordinately advancing carbon reduction, pollution control, green expansion, and growth" to consolidate food security. Therefore, investigating the spatio-temporal patterns of agricultural carbon emissions and understanding the differences among various emission sources are crucial for effectively tapping emission reduction potential, implementing targeted policies, and promoting green and low-carbon agricultural development to achieve the dual carbon goals.

Current research on agricultural carbon emissions primarily focuses on three aspects: emission accounting, spatio-temporal variation characteristics, and influencing factor analysis. Academics typically employ various methods for agricultural carbon emission accounting, including the carbon emission coefficient method, model simulation, and field measurements. The carbon emission coefficient method determines carbon emission sources based on different agricultural production activities and conducts comprehensive measurement using emission factors. Due to its technical simplicity and ease of regional comparison, this method has been widely applied across multiple scales. Li et al. constructed a carbon source inventory involving six emission factors: fertilizers, pesticides, agricultural films, plowing, diesel, and irrigation. Other studies have examined agricultural carbon emission increases resulting from human interventions such as production factor inputs, with fertilizers identified as the primary carbon source. Some research has adopted a broader agricultural perspective, conducting China's agricultural carbon emission measurements based on four major sources: agricultural material inputs, rice paddies, soil, and livestock breeding. Additional studies have incorporated straw burning into the agricultural carbon emission accounting system.

Regarding spatio-temporal variation characteristics, existing research typically analyzes temporal differences and dynamic evolution of agricultural carbon emissions at the national level using provinces as basic units, or focuses on specific provinces using prefecture-level cities as basic units. Numerous studies have revealed that agricultural carbon emissions exhibit strong spatial heterogeneity due to differences in natural conditions, production methods, and technological levels. Research at the provincial scale has found that agricultural carbon emissions in China's major grain-producing areas of the Yellow River Basin are higher than those in the Yangtze River and Songhua River Basins, with high-emission areas concentrated in Henan and Shandong Provinces. This difference primarily stems from variations in agricultural production layout, planting structure, and resource input conditions across basins. Similar conclusions indicate that regions with favorable water and land resources conditions have larger agricultural carbon emissions, with Henan, Anhui, Shandong, and other provinces showing significant "high-high agglomeration areas." Many scholars have used the STIRPAT identity, β-convergence, and LMDI methods to study influencing factors of agricultural carbon emissions, identifying agricultural economic development level, agricultural structure, agricultural labor force scale, and agricultural production efficiency as primary drivers. Agricultural economic development level typically constitutes the main driver of agricultural carbon emission increments, while agricultural industrial structure demonstrates certain inhibitory effects. Production efficiency and agricultural labor force scale may exhibit negative spatial spillover effects on agricultural carbon emissions but could also promote emission increases. Other studies suggest that farmland transfer area and urbanization rate also contribute to agricultural carbon emissions.

In summary, existing agricultural carbon emission research primarily targets national-scale studies based on provincial units or specific provinces based on municipal units. Relatively few studies have examined larger regions such as river basins or even the entire country using meso- and micro-scale geographical units like prefectures and counties. Furthermore, influencing factor research tends to focus on analyzing driving or inhibiting intensities of agricultural carbon emissions, with less attention paid to spatial heterogeneity in factor impacts. The Yellow River Basin represents a crucial grain-producing region in China and a significant source of agricultural carbon emissions. Agricultural emission reduction and carbon sequestration in the basin serve as important entry points and breakthroughs for implementing national strategies such as ecological protection and high-quality development in the Yellow River Basin. Therefore, this study takes the Yellow River Basin as the research object, employing the IPCC carbon emission coefficient method to measure and analyze agricultural carbon emissions and their spatio-temporal characteristics at provincial and municipal scales from 2005 to 2020 based on six carbon sources: fertilizers, pesticides, agricultural films, diesel, plowing, and irrigation. Using geographically weighted regression (GWR), we analyze the spatial heterogeneity of influencing factors. The findings provide important theoretical and practical reference value for understanding spatio-temporal differentiation patterns of agricultural carbon emissions in the Yellow River Basin, achieving green and low-carbon agricultural transformation, and promoting ecological protection and high-quality development in the basin.

1.1 Study Area Overview

The Yellow River Basin flows through nine provincial-level regions: Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, and Shandong, with terrain gradually descending from west to east. Considering the integrity of research units and the relationship between the Yellow River and regional economic development, we define the nine provinces and regions through which the Yellow River flows as our provincial-scale study area, and the 78 prefecture-level cities (states, leagues) in these provinces as our municipal-scale study area (Figure 1). The Yellow River Basin encompasses 1627.48$\times10^{4}$ hm^2 of cultivated land, with per capita cultivated area of 0.23 hm^2, approximately 2.43 times the national rural average. The basin includes major grain-producing plains such as the Huang-Huai-Hai Plain, Fen-Wei Plain, and Hetao Plain. In 2020, grain output in the nine provinces reached 3586.11$\times10^{4}$ t, accounting for 35.33% of national grain production; agricultural output value reached 12518.95$\times10^{4}$ yuan, representing 13.64% of the national total; and agricultural labor force totaled 346.11$\times10^{4}$ persons, comprising 17.13% of the national agricultural labor force. However, agricultural production in the Yellow River Basin has long relied on massive inputs of chemicals and agricultural materials such as fertilizers, pesticides, agricultural films, and machinery, resulting in substantial greenhouse gas emissions that exacerbate ecological environmental degradation and increase production risks for grain and other crops. In 2020, agricultural carbon emissions in the Yellow River Basin accounted for 10.92% of the national total, making it a crucial source of agricultural carbon emissions and a key region for emission reduction and carbon sequestration. Meanwhile, significant differences in natural conditions, land use efficiency, agricultural production methods, and technological levels within the Yellow River Basin have created obvious spatial heterogeneity in agricultural carbon emissions. Consequently, research on spatio-temporal differentiation characteristics and influencing factors of agricultural carbon emissions in the Yellow River Basin can provide important practical references for policy formulation regarding agricultural emission reduction and carbon sequestration.

1.2 Data Sources

Data on carbon sources including fertilizers, pesticides, agricultural films, diesel, plowing, and irrigation at provincial and municipal scales were obtained from the China Statistical Yearbook, China Rural Statistical Yearbook, and statistical yearbooks of various provinces and cities. Fertilizer data were based on annual 折纯量 (pure quantity) of chemical fertilizers, plowing data on annual crop sowing area, and irrigation data on effective agricultural irrigation area. Missing data were estimated using the Kriging method.

1.3.1 Agricultural Carbon Emission Calculation Method

Due to data availability limitations, this study defines agriculture in its narrow sense, namely crop farming. Since emission sources from human activities possess strong emission reduction potential, this research focuses on measuring agricultural carbon emissions generated by human activities. Based on existing research findings, we primarily employ the IPCC carbon emission coefficient method to calculate agricultural carbon emissions in the Yellow River Basin. Considering the current agricultural development status in the study area, we selected six carbon emission sources: fertilizers, pesticides, agricultural films, diesel, plowing, and irrigation. The calculation method is as follows:

$$E_i = \sum_j E_{ij} = \sum_j T_{ij} \times \delta_j$$

where E_i represents the agricultural carbon emissions of the ith research unit (10^4 t), E_{ij} represents the carbon emissions from the jth carbon source in the ith research unit (10^4 t), T_{ij} represents the usage of the jth carbon source in the ith research unit (10^4 t or 10^4 hm^2), and δ_j represents the emission coefficient of the jth carbon source.

The emission coefficients for the six carbon sources are: 0.8956 kg(C)$\cdot$kg^{-1} for fertilizers, 0.5927 kg(C)$\cdot$kg^{-1} for pesticides, 5.18 kg(C)$\cdot$kg^{-1} for agricultural films, 4.9341 kg(C)$\cdot$kg^{-1} for diesel, 312.6 kg(C)$\cdot$hm^{-2} for plowing, and 266.48 kg(C)$\cdot$hm^{-2} for irrigation. It should be noted that temporal variation characteristics and provincial-scale spatial variation characteristics of agricultural carbon emissions in the Yellow River Basin were analyzed for the nine provinces from 2005 to 2020. Due to data availability constraints, municipal-scale spatial variation characteristics and influencing factor analysis were conducted only for 2020.

1.3.2 Kaya Decomposition Model

The Kaya identity attributes carbon emissions to carbon emission intensity, energy use intensity, economic development level, and population size. Drawing on the STIRPAT analytical framework and incorporating characteristics of agricultural carbon emissions, we decompose agricultural carbon emissions as follows:

$$C_i = \frac{C_i}{AGRI_i} \times \frac{AGRI_i}{AGR_i} \times \frac{AGR_i}{EI_i} \times EI_i = AI_i \times EI_i \times EL_i \times PI_i$$

where C_i, $AGRI_i$, AGR_i, and EI_i represent agricultural carbon emissions (10^4 yuan), agricultural output value (10^4 yuan), crop farming output value (10^4 yuan), and agricultural labor force size (10^4 persons) in the ith research unit, respectively. AI_i, EI_i, EL_i, and PI_i represent agricultural production efficiency

(10^4 t $\cdot$ 10^4 yuan^{-1}), agricultural structure (10^4 persons $\cdot$ 10^4 yuan^{-1}), agricultural economic development level (10^4 yuan $\cdot$ 10^4 persons^{-1}), and agricultural labor force (10^4 persons), respectively.

1.3.3 Geographically Weighted Regression (GWR) Model

GWR is a local linear regression method based on spatially varying relationships. It generates local regression models within space to explain local spatial relationships and spatial heterogeneity of variables. The calculation formula is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i$$

where y_i is the global dependent variable, representing agricultural carbon emissions in the ith research unit (10^4 t); x_{ik} is the observed value of the kth variable in the ith research unit; (u_i, v_i) represents the geographic coordinates of the ith research unit; $\beta_0(u_i, v_i)$ is the regression constant term; $\beta_k(u_i, v_i)$ is the regression coefficient of the kth variable in the ith research unit; and ε_i is the random error term.

This study applies the GWR model to analyze spatial heterogeneity of influencing factors of agricultural carbon emissions in the Yellow River Basin. We selected agricultural production efficiency, agricultural structure, agricultural economic development level, and agricultural labor force size as influencing factors. By examining the spatial heterogeneity of each factor's impact on agricultural carbon emissions, we clarify how different factors affect emissions across regions and explain the reasons for spatial differentiation patterns of carbon emissions.

2.1 Temporal Variation Characteristics of Agricultural Carbon Emissions in the Yellow River Basin

From 2005 to 2020, agricultural carbon emissions in the Yellow River Basin exhibited an initial increase followed by a decrease, with an overall upward trend (Figure 2). Emissions increased from 4431.95$×10^{4}$ t in 2005 to 5282.14$×10^{4}$ t in 2015, then decreased to 4915.87$×10^{4}$ t in 2020, representing a total increase of 10.92%. The early increase in agricultural carbon emissions resulted from low agricultural production efficiency and excessive input of chemicals and agricultural materials. Following the proposal of transforming agricultural development patterns and promoting green agricultural development at the 18th National Congress of the Communist Party of China, agricultural carbon emissions began to decline, though emissions remain high and reduction tasks are arduous.

In terms of emission structure, fertilizers and plowing were the primary carbon sources in the basin throughout the study period, accounting for more than 65% of total agricultural carbon emissions. The trend of fertilizer carbon emissions was similar to that of total agricultural carbon emissions, while plowing carbon emissions showed a continuous increasing trend, ranging between 1680×10^{4} t and 1690×10^{4} t annually. Carbon emissions from agricultural irrigation, agricultural films, diesel, and pesticides were relatively low. Among these, agricultural irrigation carbon emissions remained relatively stable with a slight upward trend, ranging between 420×10^{4} t and 670×10^{4} t annually. Carbon emissions from agricultural films, diesel, and pesticides showed an initial increase followed by a decrease. Notably, pesticide carbon emissions consistently remained the lowest, ranging between 170×10^{4} t and 250×10^{4} t.

2.2.1 Spatial Variation Characteristics at Provincial Scale

From 2005 to 2020, agricultural carbon emissions varied significantly across provinces in the Yellow River Basin (Figure 3). Shandong and Henan provinces, as major agricultural and population centers, had far higher emissions than other regions, both exceeding 1000×10^{4} t. In 2005, Shandong Province had the highest agricultural carbon emissions at 1241.68×10^{4} t, accounting for 28.02% of total emissions in the Yellow River Basin, with fertilizers being the primary source at 418.78×10^{4} t (33.73% of provincial emissions). From 2010 to 2020, Henan Province became the highest emitter, with emissions ranging between 1360×10^{4} t and 1470×10^{4} t, accounting for 26%–28% of total basin emissions. Henan's agricultural carbon emissions were also dominated by fertilizers, which accounted for 42%–44% of provincial emissions. Sichuan and Inner Mongolia also had relatively high emissions, generally ranging between 420×1010^{4} t and 670×10^{4} t, with plowing and fertilizers as the main sources, each accounting for more than 50% of total emissions. Qinghai and Ningxia had relatively low emissions, particularly Qinghai, where agricultural carbon emissions remained below 65×10^{4} t. This is because Ningxia is located in arid and semi-arid regions, while Qinghai lies on the Qinghai-Tibet Plateau with harsh natural conditions and fragile ecological environments, resulting in relatively small crop planting areas and limited use of chemicals and agricultural materials. Except for 2005 when fertilizer carbon emissions accounted for the highest proportion, plowing carbon emissions ranked first in all other years, with proportions exceeding 27.40%. In terms of emission structure, aside from being concentrated in Henan, Shandong, and Sichuan provinces, fertilizer carbon emissions were also high in Shaanxi Province; plowing and irrigation carbon emissions were high in Inner Mongolia; film and pesticide carbon emissions were high in Gansu Province; and diesel carbon emissions were high in Shaanxi and Inner Mongolia.

2.2.2 Spatial Variation Characteristics at Municipal Scale

Spatial Differentiation of Agricultural Carbon Emissions. Using ArcGIS 10.5 software and the natural breaks method, we classified agricultural carbon emissions into five levels based on the classification standards of 39.87×10^{4} t, 23.89×10^{4} t–39.87×10^{4} t, 7.53×10^{4} t–23.89×10^{4} t, 3.64×10^{4} t–7.53×10^{4} t, and $<3.64\times10^{4}$ t (Figure 4). Agricultural carbon emissions at the municipal scale in the Yellow River Basin showed a stepped decreasing pattern from east to west. Ten cities (states, leagues) had emissions exceeding 39.87×10^{4} t, collectively accounting for 64.56% of total emissions in the study area. These were concentrated in the lower Yellow River region, with patchy distributions in northern Inner Mongolia, southern Shaanxi, and southern Shanxi. The distribution was most concentrated in Shandong and Henan provinces, where highly mechanized agriculture, extensive fertilizer use, and large-scale crop cultivation resulted in significantly higher emissions than other regions. Fourteen cities had emissions between 23.89×10^{4} t and 39.87×10^{4} t, collectively accounting for 29.96% of total emissions, concentrated in central parts of the Yellow River Basin. Cities with emissions between 7.53×10^{4} t and 23.89×10^{4} t were scattered around the periphery of higher-emission areas, including central-northern Shanxi, Xining, Lanzhou, and Yan'an. Cities with emissions between 3.64×10^{4} t and 7.53×10^{4} t were scattered across Alxa League, Haixi Mongolian and Tibetan Autonomous Prefecture, and Aba Tibetan and Qiang Autonomous Prefecture. Cities with emissions below 3.64×10^{4} t were concentrated in Qinghai Province in the upper Yellow River Basin, totaling 13 cities. Due to natural environmental constraints, these regions typically employ traditional farming methods with minimal chemical and agricultural material use, resulting in the lowest overall emissions.

Spatial Differentiation of Emissions from Different Carbon Sources. Similarly using the natural breaks method and expert consultation, we classified agricultural carbon emissions from different sources into five levels at the municipal scale (Figure 5). Overall, fertilizer and plowing carbon emissions showed a pattern of high values in the east and central regions and low values in the west. Pesticide carbon emissions demonstrated a decreasing trend from east to west. Agricultural film carbon emissions formed a "cross-shaped" high-value zone stretching across the upper, middle, and lower reaches, connecting northern Inner Mongolia and northern Shanxi. Diesel carbon emissions formed a belt-shaped high-value zone in the southeast-northwest direction and a low-value zone in the west. Agricultural irrigation carbon emissions showed a pattern of high values along the river in the middle and lower reaches and low values in the upper reaches.

Specifically, 21 cities had fertilizer carbon emissions exceeding 18.36×10^{4} t, collectively accounting for 59.85% of total fertilizer carbon emissions in the Yellow River Basin. These were distributed in belt-shaped patterns across Shandong Province and southern Shanxi and Shaanxi provinces. Cities with fertilizer emissions between 7.45×10^{4} t and 18.36×10^{4} t were distributed in clustered patterns at the "几"-shaped top of the Yellow River Basin and in central Shanxi and eastern Gansu. Plowing carbon emissions exceeded 16.16×10^{4} t in 21 cities, collectively accounting for 61.42% of total plowing emissions, concentrated in Shandong and Henan provinces, with patchy distributions in southern Shanxi, northern Shaanxi, and Dingxi City in Gansu Province. Agricultural irrigation carbon emissions exceeded 4.49×10^{4} t in 14 cities, collectively accounting for 77.33% of total irrigation emissions, concentrated in the middle and lower reaches of the Yellow River Basin. Diesel carbon emissions exceeded 2.44×10^{4} t in 21 cities, collectively accounting for 76.45% of total diesel emissions, mainly distributed in Shandong Province, Guanzhong Plain, border areas between Ningxia and Shaanxi, and Xinxiang, Kaifeng, and Shangqiu cities in Henan Province. Agricultural film carbon emissions exceeded 5.69×10^{4} t in 14 cities, collectively accounting for 98.5% of total film emissions, distributed across northern Qinghai, southeastern Gansu, Henan, and Shandong provinces, forming a north-south corridor through eastern Inner Mongolia and northern Shaanxi. Compared with other sources, most municipal units had relatively low pesticide carbon emissions, with high values concentrated in Shandong and Henan provinces. As a major pesticide production and use province, Shandong ranks first nationally in pesticide production enterprises and registered products, with Jining and Weifang cities having the highest emissions.

2.3 Spatial Heterogeneity of Influencing Factors of Agricultural Carbon Emissions in the Yellow River Basin

To deeply explore the spatial heterogeneity characteristics of influencing factors of agricultural carbon emissions in the Yellow River Basin, this study used the GWR model and visualized regression coefficients for different factors using the natural breaks method in ArcGIS 10.5 (Figure 6).

Agricultural Production Efficiency. The positive effect of agricultural production efficiency on agricultural carbon emissions showed a distinct spatial pattern of high values in the southeast and northwest and low values in the northeast (Figure 6a), indicating that efficiency improvements in Shandong and Henan provinces had greater impact on carbon emissions than surrounding areas. With advanced agricultural technology and high mechanization, these provinces have higher production efficiency than other regions, making carbon emissions more sensitive to efficiency changes. Additionally, Wuwei and Baiyin cities in Gansu Province are arid regions where, despite active promotion of efficient water-saving and smart irrigation, agricultural irrigation and film carbon emissions remain high, making carbon emissions in these areas also significantly affected by production efficiency.

Agricultural Structure. The negative impact of agricultural structure on agricultural carbon emissions showed a spatial pattern gradually weakening outward from Shanxi Province as the core (Figure 6b), indicating that structural effects on carbon emissions were stronger in Shanxi than elsewhere. This likely stems from Shanxi's deepened agricultural supply-side structural reforms, vigorous development of organic dry farming, and achievement of mutual benefits between production and ecology through agricultural structure transformation and upgrading. Agricultural structure transformation has helped maintain relatively low carbon emissions in Shanxi Province.

Agricultural Economic Development Level. The positive effect of agricultural economic development level on agricultural carbon emissions showed a spatial pattern gradually weakening outward from the border region of Shaanxi, Shanxi, and Henan provinces (Figure 6c), indicating that agricultural economic development in these border areas had greater impact on carbon emissions than other regions. Despite having better agricultural foundations than upstream areas, cities such as Zhengzhou, Jiaozuo, Changzhi, Linfen, and Weinan remain on the left side of the environmental quality-agricultural economic development turning point, where agricultural economic development has greater impact on emission increases than elsewhere. Additionally, since Qinghai's agricultural development focuses on animal husbandry, and our agricultural carbon emission calculation does not include carbon emissions from ruminant breeding, agricultural development level shows a negative impact on carbon emissions in Qinghai.

Agricultural Labor Force Scale. The positive effect of agricultural labor force scale on agricultural carbon emissions showed a spatial pattern of high values in the southeast and northwest and low values in the southwest (Figure 6d), indicating that labor force expansion in Henan and Shandong provinces had greater impact on emission increases than other regions. As both major agricultural and populous provinces, Henan and Shandong collectively account for 37.56% of the Yellow River Basin's agricultural labor force, with abundant labor reserves making carbon emissions more sensitive to labor force scale than in other regions. Additionally, Alxa League and Bayannur City in Inner Mongolia have continuously optimized population distribution in recent years, adopting a development model of "retreating people to advance sand control," where agricultural labor force scale shows a strong positive effect on carbon emissions.

3 Discussion

At the 2023 symposium on comprehensively promoting ecological protection and high-quality development in the Yellow River Basin, President Xi Jinping emphasized the need to promote comprehensive green transformation of development patterns, improve the coordinated protection pattern of the Yellow River Basin's ecology, and strengthen the national ecological security barrier. As an important grain-producing region in China, the Yellow River Basin is also a significant source of agricultural carbon emissions. Agricultural emission reduction and carbon sequestration in the basin represent crucial entry points and breakthroughs for implementing national strategies of ecological protection and high-quality development in the Yellow River Basin. Therefore, this study on spatio-temporal differentiation characteristics and influencing factors of agricultural carbon emissions in the Yellow River Basin holds important theoretical and practical significance.

Consistent with existing research findings, this study also identifies major agricultural provinces such as Henan and Shandong as primary high-emission areas. Our research further confirms the driving effect of agricultural economic development level on emission increments and the inhibitory effect of agricultural structure. However, Qinghai Province, focusing on animal husbandry, shows negative impacts of agricultural development level on carbon emissions since our calculation excludes carbon emissions from ruminant breeding. Additionally, this study finds that agricultural production efficiency and labor force scale have non-negligible driving effects on carbon emissions, demonstrating that technological progress does not necessarily promote agricultural carbon reduction. Increased labor scale and improved efficiency may lead to increased emissions from carbon sources such as irrigation, diesel, fertilizers, plowing, and agricultural films, causing fluctuating changes in agricultural carbon emissions over certain periods. Beyond analyzing positive or negative impacts of different factors, this study deeply explores spatial heterogeneity of factor impacts on agricultural carbon emissions within the Yellow River Basin, thereby improving theoretical methods and practical applications in agricultural carbon emission research.

4 Conclusions and Recommendations

4.1 Conclusions

From 2005 to 2020, agricultural carbon emissions in the Yellow River Basin showed an initial increase followed by a decrease, with an overall upward trend, rising from 4431.95×10^{4} t to 4915.87×10^{4} t. In terms of emission structure, fertilizers and plowing were the primary sources, accounting for more than 65% of total emissions. The trend of fertilizer carbon emissions was similar to that of total agricultural carbon emissions, while plowing carbon emissions showed a continuous increasing trend, ranging between 1680×10^{4} t and 1690×10^{4} t annually. Agricultural irrigation carbon emissions remained relatively stable overall, while carbon emissions from agricultural films, diesel, and pesticides showed an initial increase followed by a decrease. Pesticide carbon emissions consistently remained at the lowest level.

At the provincial scale, Shandong Province had the highest agricultural carbon emissions in 2005 at 1241.68×10^{4} t. From 2010 to 2020, Henan Province became the highest emitter, with emissions ranging between 1360×10^{4} t and 1470×10^{4} t, while Qinghai Province consistently had the lowest emissions, remaining below 65×10^{4} t. At the municipal scale in 2020, agricultural carbon emissions showed a stepped decreasing spatial pattern from east to west. Fertilizer and plowing carbon emissions displayed a spatial pattern of high values in the east and central regions and low values in the west. Pesticide carbon emissions showed a decreasing trend from east to west. Agricultural film carbon emissions formed a "cross-shaped" high-value zone across the upper, middle, and lower reaches, connecting northern Inner Mongolia and northern Shanxi. Diesel carbon emissions formed a belt-shaped high-value zone in the southeast-northwest direction and a low-value zone in the west. Agricultural irrigation carbon emissions showed a pattern of high values along the river in the middle and lower reaches and low values in the upper reaches.

The positive effect of agricultural production efficiency on agricultural carbon emissions showed a spatial pattern of high values in the southeast and northwest and low values in the northeast. The negative impact of agricultural structure showed a spatial pattern gradually weakening outward from Shanxi Province as the core. The positive effect of agricultural economic development level showed a spatial pattern gradually weakening outward from the border region of Shaanxi, Shanxi, and Henan provinces, with negative impacts in Qinghai Province. The positive effect of agricultural labor force scale showed a spatial pattern of high values in the southeast and northwest and low values in the southwest.

4.2 Recommendations

Continuously increase investment in agricultural modernization and promote agricultural technology innovation. Agricultural production in the upper Yellow River Basin relies on water from the Yellow River system. We should actively promote efficient water-saving irrigation technologies such as drip and infiltration irrigation. The lower basin has high agricultural development levels and should accelerate the development of new energy sources for agricultural mechanization, research and develop high-quality agricultural materials such as pesticides and fertilizers, maximize the utilization efficiency of agricultural inputs, and fully utilize modern information technologies including remote sensing and the Internet of Things to develop smart agriculture. This will enable precise fertilization and pesticide application, promote scientific, precise, and rational input of agricultural factors, and minimize agricultural carbon emissions.

Integrate regional resource condition differences and tap the potential of agricultural carbon trading markets. Drawing on experiences from carbon trading markets in other industries, we should fully utilize the development potential of agricultural carbon emission trading markets, facilitating the transformation of "carbon tickets" into cash to advance carbon reduction efforts. Pilot programs for agricultural carbon trading could be launched in typical cities or counties in high-emission provinces such as Henan and Shandong, establishing trading platforms that use "carbon tickets" as an entry point to create new income pathways for farmers and enhance the enthusiasm of agricultural enterprises and farmers to participate in carbon reduction initiatives.

Strengthen regional coordination and communication, and leverage the demonstration effect of green technologies. We should give full play to regional resource advantages, establish and improve cooperation mechanisms among provinces and cities, share best practices and technologies for agricultural carbon reduction, and enable low-emission regions to share their experiences in green and low-carbon agricultural development with other regions. High-emission regions should learn from the development achievements of low-emission regions and research agricultural development models suitable for their own areas, thereby achieving low-carbon agricultural transformation across the entire basin.

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Note: Figure translations are in progress. See original paper for figures.