Analysis of Spatio-temporal Evolution Characteristics and Influencing Factors of Agricultural Carbon Emissions in the Yellow River Basin (Postprint)

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Date: 2026-04-29T00:10:09+00:00

Abstract

To deeply explore the spatiotemporal distribution characteristics of agricultural carbon emissions in the Yellow River Basin, the carbon emission factors provided by the Intergovernmental Panel on Climate Change (IPCC) were adopted to calculate the total agricultural carbon emissions of various provinces (regions) in the Yellow River Basin from 2013 to 2023. Moran' s I was employed to analyze the spatial autocorrelation, and the Logarithmic Mean Divisia Index (LMDI) was used to quantitatively decompose the influencing factors of agricultural carbon emissions, providing an in-depth discussion on the driving and inhibiting effects of various factors on carbon emissions. The results indicate that: (1) From 2013 to 2023, the total agricultural carbon emissions in the Yellow River Basin exhibited a trend of "slow rise - year-on-year decline - slight recovery." Spatially, it presented a distribution pattern of "high in the north and south, low in the central region." (2) The agricultural carbon emission intensity of each province (region) generally showed a downward trend. (3) Except for 2016 and 2017, the global Moran' s I overall exhibited a significant positive spatial correlation, and this spatial agglomeration effect strengthened year by year. Local Moran' s I scatter plots further confirmed the significant spatial autocorrelation of agricultural carbon emission intensity in this region. (4) Economic effects and structural effects exerted a positive driving role on agricultural carbon emissions, while population effects, industrial effects, and technical effects exerted a negative inhibitory role on carbon emissions. Identifying the dominant factors of agricultural carbon emissions and effectively inhibiting carbon emissions from all stages of agricultural production will facilitate precise carbon emission reduction.

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Preamble

Vol. 49, No. 4, April 2026

GEOGRAPHY

49 No. 4

Apr. 2026

Analysis of Spatiotemporal Evolution Characteristics and Influencing Factors of Agricultural Carbon Emissions in the Yellow River Basin

1. Introduction

The Yellow River Basin serves as a critical ecological barrier and a vital economic zone in China, playing a strategic role in the nation’ s food security and ecological civilization construction. As global climate change intensifies, reducing greenhouse gas emissions has become a consensus within the international community. Agriculture is not only a significant source of carbon emissions but also possesses substantial carbon sequestration potential. Therefore, exploring the spatiotemporal evolution of agricultural carbon emissions in the Yellow River Basin and identifying their driving factors is of great theoretical and practical significance for promoting green, low-carbon agricultural development and achieving the “dual carbon” goals.

2. Research Methodology and Data Sources

2.1 Calculation of Agricultural Carbon Emissions In this study, agricultural carbon emissions are calculated based on six primary sources: chemical fertilizers, pesticides, agricultural films, diesel consumption, irrigation, and tilling. The total agricultural carbon emissions are estimated using the following formula:

$$E = \sum E_i = \sum T_i \cdot \delta_i$$

Where E represents the total agricultural carbon emissions, T_i denotes the quantity of the i-th carbon source, and δ_i represents the corresponding emission coefficient. The emission coefficients are derived from established academic standards and relevant literature.

2.2 Spatial Correlation Analysis To analyze the spatial distribution characteristics and clustering effects of agricultural carbon emissions, we employ the Global Moran’ s I index:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} (x_i - \bar{x})^2}$$

In this equation, n is the number of regions, x_i and x_j are the carbon emission values for regions i and j, and w_{ij} is the spatial weight matrix.

2.3 Logarithmic Mean Divisia Index (LMDI) Decomposition To investigate the factors influencing changes in agricultural carbon emissions, we utilize the LMDI decomposition method. This approach decomposes the total change in emissions into several

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摘要

To deeply explore the spatiotemporal distribution characteristics of agricultural carbon emissions in the Yellow River Basin, this study adopts the carbon emission coefficient method proposed by the Intergovernmental Panel on Climate Change (IPCC). By selecting six primary carbon sources—chemical fertilizers, pesticides, agricultural films, diesel fuel, irrigation, and tilling—we calculated the agricultural carbon emissions for nine provinces (autonomous regions) in the Yellow River Basin from 2000 to 2020. Furthermore, we utilized the Theil index and exploratory spatial data analysis (ESDA) to reveal the regional differences and spatial correlation characteristics of agricultural carbon emissions in this area.

The results indicate that from 2000 to 2015, the total agricultural carbon emissions in the Yellow River Basin exhibited a fluctuating upward trend, followed by a significant decline after 2015, reflecting the initial success of China's agricultural green development policies. Spatially, agricultural carbon emissions show a distribution pattern of "high in the east and low in the west," with Henan and Shandong provinces serving as the primary emission centers. The Theil index analysis reveals that the overall differences in agricultural carbon emissions in the Yellow River Basin are gradually narrowing, with intra-regional differences being the main source of the total variation.

The spatial autocorrelation analysis demonstrates a significant positive spatial correlation of agricultural carbon emissions in the Yellow River Basin, characterized by distinct "High-High" and "Low-Low" clustering patterns. Specifically, the lower reaches of the Yellow River are dominated by High-High clusters, while the upper reaches are characterized by Low-Low clusters. These findings provide a scientific basis for formulating differentiated carbon reduction policies and promoting the high-quality development of agriculture in the Yellow River Basin.

Based on the carbon emission factors provided, the total agricultural carbon emissions for each province (region) in the Yellow River Basin from 2013 to 2023 were calculated. This study employs the Moran' s I index to analyze the spatial autocorrelation of these emissions. Furthermore, the Logarithmic Mean Divisia Index (LMDI) was utilized to decompose the driving factors of agricultural carbon emissions.

A quantitative decomposition of the factors influencing agricultural carbon emissions was conducted to deeply explore the driving and inhibitory effects of various factors on carbon emissions. The results are as follows:

(1) From 2013 to 2023, the total agricultural carbon emissions in the Yellow River Basin exhibited a trend of "slow increase, followed by a year-on-year decline, and then a slight recovery." Spatially, the distribution pattern is characterized as "high in the north and south, and low in the central region."

(2) The intensity of agricultural carbon emissions across all provinces and autonomous regions in the basin showed an overall downward trend.

(3) Global···

Except for the years 2016 and 2017, Moran' s I generally exhibits a significant positive spatial correlation, and this spatial clustering effect has demonstrated a steady increase year by year.

Local Moran' s I scatter plots further confirm the significant spatial autocorrelation of agricultural carbon emission intensity within the region. (4) Economic and structural effects act as positive drivers of agricultural carbon emissions, whereas population, industrial, and technical effects exert a negative inhibitory influence. Identifying the dominant factors of agricultural carbon emissions allows for the effective suppression of emissions across all stages of agricultural production, thereby facilitating precision carbon reduction strategies.

Keywords: Spatiotemporal evolution; Agricultural carbon emissions; Spatial autocorrelation; LMDI model; Influencing factors; Yellow River Basin **Article ID:** 1000-6060 (2026) 04-0713-14 (0713–0726)

1. Introduction

Agriculture serves as the fundamental basis for national economic development, yet it is also a significant source of greenhouse gas emissions. As global climate change intensifies, reducing agricultural carbon emissions has become a critical component of sustainable development strategies. The Yellow River Basin, acting as a vital ecological barrier and an essential agricultural production base in China, plays a decisive role in ensuring national food security and ecological stability. However, the region faces challenges characterized by fragile ecological environments and high intensities of resource exploitation. Therefore, exploring the spatiotemporal evolution and driving factors of agricultural carbon emissions in the Yellow River Basin is of great theoretical and practical significance for promoting green agricultural transformation and achieving "dual carbon" goals.

2. Research Methods and Data Sources

2.1 Calculation of Agricultural Carbon Emissions

In this study, agricultural carbon emissions are calculated based on the primary sources of carbon in farming operations, including chemical fertilizers, pesticides, agricultural films, diesel fuel, irrigation, and tilling. The calculation formula is expressed as follows:

$$E = \sum E_i = \sum T_i \cdot \delta_i$$

In the formula, E represents the total agricultural carbon emissions; E_i represents the emissions from the i-th carbon source; T_i denotes the amount of the i-th carbon source utilized; and δ_i is the corresponding emission coefficient for each source.

2.2 Spatial Autocorrelation Analysis

To analyze the spatial distribution characteristics and clustering effects of agricultural carbon emissions in the Yellow River Basin, this paper employs the Global Moran' s I index. The formula is defined as:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n} (x_i - \bar{x})^2}$$

Where n

As global climate change becomes an increasingly severe issue, countries worldwide are establishing greenhouse gas emission reduction targets. China has consistently and proactively addressed the challenges of global climate change. During the United Nations General Assembly in September 2020, China formally committed to its "dual carbon" goals: striving to peak carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060. This strategic commitment underscores China's dedication to sustainable development and its role as a responsible global power in the transition toward a low-carbon economy.

At the 75th session of the United Nations General Assembly, President Xi Jinping announced that China aims to reach peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060.

Under the premise of optimizing resource utilization and enhancing soil carbon sequestration capacity, it is essential to promote the implementation of high-quality development strategies within the Yellow River Basin.

Domestic and international scholars have established a relatively mature framework for researching agricultural carbon emissions. Regarding the measurement of agricultural carbon emission volumes, researchers generally⋯

Introduction

The strategic goals of reaching "carbon peak" for major greenhouse gas emission sources and achieving "carbon neutrality" by 2060 represent a significant commitment to global climate action. These objectives necessitate a fundamental transformation of the energy structure and the implementation of advanced technological solutions across various industrial sectors. Achieving these targets requires not only the reduction of direct emissions but also the development of sophisticated monitoring and management systems to track progress and optimize resource allocation.

In the context of these environmental milestones, machine learning and deep learning have emerged as critical tools for modeling complex emission patterns and predicting future trends. By leveraging large-scale datasets, researchers can identify key drivers of carbon intensity and develop more effective mitigation strategies. The integration of these computational approaches into policy-making frameworks is essential for ensuring that the transition to a low-carbon economy is both scientifically grounded and economically viable.

The methodology employed in this study follows the guidelines provided by the Intergovernmental Panel on Climate Change (IPCC).

Agricultural CO_2 emissions, a primary source of greenhouse gases, have long been a subject of significant concern.

Methodology and Coefficients

To accurately quantify carbon emissions in agricultural production, it is essential to identify and categorize various emission sources. These primarily include inputs such as chemical fertilizers, pesticides, agricultural films, and diesel fuel, as well as processes like irrigation and soil tillage.

1.1 Calculation Methods for Agricultural Carbon Emissions

The total carbon emissions from agricultural production are typically calculated using an emission factor approach. This method involves multiplying the quantity of each agricultural input or activity by its corresponding carbon emission coefficient. The general formula for estimating total agricultural carbon emissions (E) is expressed as follows:

$$E = \sum E_i = \sum (T_i \cdot \delta_i)$$

In this equation, E represents the total carbon emissions from the agricultural production system; E_i denotes the emissions from the i-th carbon source; T_i represents the amount of the i-th carbon source utilized (e.g., the weight of fertilizer applied or the area of land tilled); and δ_i signifies the carbon emission coefficient for that specific source.

1.2 Determination of Emission Coefficients

The accuracy of the results depends heavily on the selection of appropriate emission coefficients (δ_i). Based on existing domestic and international research, the coefficients for the primary agricultural emission sources are defined as follows:

- **Chemical Fertilizers:** Emissions result from the energy-intensive manufacturing process and the subsequent release of gases upon application. The coefficient is generally derived from life-cycle assessment (LCA) data.
- **Pesticides:** Carbon emissions are accounted for based on the chemical production and processing requirements of the active ingredients.
- **Agricultural Films:** This includes the carbon footprint associated with the production and disposal of plastic mulching films used in crop cultivation.
- **Diesel Fuel:** Emissions are calculated based on the fuel consumed by agricultural machinery during field operations such as sowing, harvesting, and transportation.
- **Irrigation:** Carbon emissions from irrigation primarily stem from the electricity or fuel consumed by pumping systems to extract and distribute water.
- **Tillage:** Soil organic carbon is released into the atmosphere as CO_2 due to the disturbance of the soil structure during mechanical plowing and land preparation.

By integrating these coefficients with regional statistical data, we can establish a comprehensive profile of agricultural carbon emissions, providing a scientific basis for developing mitigation strategies and promoting sustainable farming practices.

Introduction

The concept of "carbon neutrality" has become a central focus of global environmental policy. Agriculture accounts for approximately 23% of total global carbon emissions. As a critical sector, the mitigation of agricultural emissions is essential for achieving broader climate goals.

The accounting methods provided by the Intergovernmental Panel on Climate Change (IPCC) serve as the standard framework for evaluating greenhouse gas emissions.

Agricultural carbon emissions exert a significant impact on global climate change. As a major source of greenhouse gas emissions, the agricultural sector contributes substantially to the accumulation of atmospheric carbon dioxide, methane, and nitrous oxide. Addressing these emissions is critical for achieving international climate goals and ensuring the long-term sustainability of global food systems.

pesticide application, agricultural machinery energy consumption, livestock enteric fermentation, and manure management.

⋯threatens global food security and ecosystem stability. The Yellow River Basin, as a critical ecological barrier and an important grain production base in China, faces increasingly severe challenges from land degradation and climate change. Understanding the spatiotemporal evolution of vegetation cover and its driving mechanisms in this region is essential for formulating effective environmental protection policies and ensuring sustainable regional development.

Recent studies have demonstrated that machine learning and deep learning techniques offer powerful tools for analyzing complex geographical data. By integrating multi-source remote sensing observations with meteorological datasets, researchers can more accurately quantify the impact of anthropogenic activities and natural factors on the ecological environment. This study aims to utilize these advanced computational methods to evaluate the long-term trends of vegetation dynamics within the Yellow River Basin, providing a scientific basis for ecological restoration and resource management.

accounting for the greenhouse gas emissions generated [?]. Agricultural machinery, irrigation

The Yellow River Basin serves as a critical agricultural production base in China. In recent years, the region has faced significant challenges and transformations. As a cornerstone of national food security and ecological stability, the basin’ s development is increasingly defined by the intersection of traditional agricultural practices and modern sustainability requirements. Efforts to optimize water resource management and improve land-use efficiency have become central to the region’ s strategic planning, particularly in the context of climate change and evolving socio-economic demands.

Energy consumption, chemical fertilizers, pesticides, agricultural film usage, straw burning, and livestock and poultry farming constitute the primary sources of carbon emissions in agricultural production. These factors represent the intensive resource inputs and waste management challenges inherent in modern farming systems. Specifically, the heavy reliance on fossil-fuel-derived inputs such as fertilizers and pesticides contributes significantly to the greenhouse gas footprint, while the open burning of crop residues and methane emissions from livestock further exacerbate environmental pressures. Addressing these emission sources is critical for transitioning toward sustainable and low-carbon agricultural practices.

Although the area affected by soil erosion has decreased significantly, the excessive application of chemical fertilizers and pesticides in agricultural production remains a critical concern. This imbalance in nutrient management not only threatens the long-term fertility of the soil but also poses substantial risks to the surrounding ecosystem through runoff and leaching processes. Addressing these challenges requires a transition toward more sustainable agricultural practices that balance productivity with environmental stewardship.

Sources of carbon emissions, such as livestock farming, have become the primary focus for the majority of scholars conducting research on agricultural carbon emissions.

Carbon emissions associated with processes such as chemical application and irrigation remain significant and cannot be overlooked.

Mid-2025 Progress Report

In the first half of 2025, the field of machine learning has continued to evolve at a rapid pace, particularly in the integration of deep learning architectures with complex physical systems. Current research trends indicate a significant shift toward enhancing the interpretability and robustness of large-scale models. This period has seen a marked increase in the deployment of hybrid models that combine traditional numerical methods with neural network-based approximations to solve high-dimensional partial differential equations.

Recent advancements have focused on optimizing the computational efficiency of transformer-based architectures. By leveraging sparse attention mechanisms and adaptive computation time, researchers have successfully reduced the energy consumption of training cycles without compromising model accuracy. Furthermore, the development of self-supervised learning techniques has allowed for the utilization of vast amounts of unlabeled data, leading to breakthroughs in natural language understanding and computer vision tasks.

The integration of domain-specific knowledge into neural networks remains a primary objective. For instance, incorporating conservation laws directly into the loss functions of deep learning models has proven effective in maintaining physical consistency in fluid dynamics simulations. These "physics-informed" approaches ensure that the predicted solutions satisfy fundamental principles such as the conservation of mass and momentum, which is critical for engineering applications.

Looking forward to the latter half of 2025, the community expects further convergence between reinforcement learning and autonomous systems. The challenge remains to bridge the gap between simulation environments and real-world deployment, particularly regarding safety guarantees and out-of-distribution generalization. As hardware capabilities continue to expand, the focus will likely shift toward decentralized training protocols and privacy-preserving machine learning frameworks to address the growing concerns over data security and ethics.

carbon sources for measurement [8-9]. Additionally, some studies have utilized novel types of···

The Central Document No. 1 emphasizes the continued strengthening of rural ecological environmental governance. This directive underscores the critical importance of protecting and restoring the natural environment in rural areas as a cornerstone of sustainable agricultural development and rural revitalization. By prioritizing ecological health, the policy aims to harmonize agricultural productivity with environmental conservation, ensuring that rural landscapes remain resilient and productive for future generations.

The governance strategy involves a multi-faceted approach, targeting key issues such as soil quality preservation, water resource management, and the reduction of agricultural non-point source pollution. These efforts are essential not only for maintaining biodiversity but also for improving the overall quality of life for rural residents. Furthermore, the document highlights the need for innovative governance models that integrate modern technology and community participation to achieve long-term ecological stability.

Technologies such as Geographic Information System (GIS) technology are utilized to process and analyze agricultural carbon emission data.

Strengthen the systematic governance of regions with prominent agricultural non-point source pollution, and enhance the management of livestock and poultry manure.

Spatial visualization provides an intuitive representation of the distribution characteristics of carbon emissions within a watershed.

The resource utilization of sewage and the treatment of aquaculture tailwater are critical components of sustainable environmental management. Achieving these goals requires the integration of agricultural practices with advanced engineering solutions. By treating wastewater not merely as a pollutant but as a potential source of nutrients, it is possible to recover valuable components such as nitrogen and phosphorus for crop irrigation or fertilizer production. Simultaneously, the effective management of aquaculture tailwater is essential to prevent the eutrophication of receiving water bodies and to ensure the long-term viability of aquatic ecosystems. This dual approach promotes a circular economy and enhances the overall efficiency of water resource management in rural and industrial sectors.

[10]. Some studies have integrated Life Cycle Assessment (LCA) methodologies to evaluate agricultural inputs from a comprehensive perspective.

Abstract

Agricultural production plays a critical role in reducing carbon emission intensity and enhancing the resource utilization of agricultural waste. By optimiz-

ing production processes and implementing sustainable management practices, the agricultural sector can significantly contribute to global climate mitigation goals. This study examines the mechanisms through which modern agricultural techniques facilitate the transition toward a low-carbon economy while simultaneously addressing the challenges of waste management.

Introduction

As global concerns regarding climate change intensify, the agricultural sector faces the dual challenge of ensuring food security and minimizing its environmental footprint. Reducing carbon emission intensity is no longer merely an environmental objective but a fundamental requirement for sustainable development. Central to this transformation is the effective management of agricultural waste, which, when properly utilized, can serve as a valuable resource for energy production and soil enhancement.

1.1 Carbon Emission Intensity in Agriculture

The reduction of carbon emission intensity involves decoupling agricultural growth from greenhouse gas emissions. This can be achieved through the adoption of precision agriculture, improved nutrient management, and the integration of machine learning for resource optimization. By leveraging data-driven approaches, farmers can minimize the use of carbon-intensive inputs such as synthetic fertilizers and fossil fuels.

1.2 Resource Utilization of Agricultural Waste

Agricultural waste, including crop residues and livestock manure, represents a significant untapped resource. Transforming these materials into bioenergy, organic fertilizers, or industrial raw materials not only mitigates the environmental hazards associated with improper disposal but also creates a circular economy within the rural sector. Strengthening the resource utilization of such waste is essential for achieving a carbon-neutral agricultural cycle.

Methodology

This research employs a comprehensive framework to analyze the relationship between production efficiency and emission reduction. We utilize various models to quantify the impact of waste-to-energy technologies on the overall carbon balance of the agricultural system.

The mathematical representation of the carbon sequestration potential in these systems is given by:

$$C_{total} = \sum_{i=1}^{n} (S_i + R_i - E_i)$$

where C_{total} represents the total carbon balance, S_i denotes the carbon sequestered in the soil, R_i represents the emissions avoided through waste recycling, and E_i accounts for the emissions generated during the production process.

Results and Discussion

Our findings indicate that integrated waste management systems can reduce carbon emission intensity by up to 30% compared to traditional disposal methods. Furthermore, the

From the perspective of the entire industrial chain, encompassing the production, processing, transportation, and consumption of products [**?**],

[2-3]

[4-5]

Supported by the 2025 Undergraduate Innovation and Entrepreneurship Training Program (General Project No. 202505026).

Comprehensive Evaluation of Agricultural Carbon Emissions: Enhancing Accounting Completeness and Accuracy

A comprehensive evaluation of agricultural carbon emissions is essential for ensuring that accounting results achieve a high degree of completeness and accuracy. This process involves a systematic analysis of various emission sources across the entire agricultural production cycle, ranging from land preparation and input application to livestock management and waste disposal. By integrating multi-dimensional data and refined emission factors, researchers can better capture the nuances of carbon dynamics within agroecosystems.

To improve the precision of these assessments, it is necessary to move beyond simplified estimation models and incorporate site-specific variables such as soil characteristics, climate conditions, and regional farming practices. Achieving completeness requires the inclusion of indirect emissions—such as those derived from the production of chemical fertilizers, pesticides, and the energy consumed by irrigation systems—alongside direct emissions like methane from rice paddies and nitrous oxide from nitrogen fertilization.

Furthermore, the adoption of advanced methodologies, including life cycle assessment (LCA) and high-resolution remote sensing, allows for a more granular understanding of spatial and temporal emission patterns. By refining these accounting frameworks, policymakers and stakeholders can develop more effective, evidence-based strategies for carbon reduction, ultimately supporting the transition toward sustainable and low-carbon agricultural development.

Drivers and Inhibitors of Emissions and Agricultural Carbon Reduction within the Watershed

The analysis of drivers and inhibitors is crucial for understanding the dynamics of agricultural carbon emissions within the watershed. By identifying the primary factors that either propel or mitigate emission levels, policymakers can develop more targeted strategies for sustainable agricultural development and carbon reduction.

Analysis of Emission Drivers

Agricultural carbon emissions are primarily driven by several interconnected factors related to production intensity and economic structure. The expansion of cultivated land area and the increased application of chemical inputs—such as fertilizers, pesticides, and agricultural films—remain significant contributors to rising emission levels. Furthermore, the mechanization of farming processes, while improving efficiency, often leads to higher fossil fuel consumption, thereby increasing the overall carbon footprint of the sector. Economic growth within the agricultural sector also tends to correlate with higher emissions, as intensified production methods are frequently employed to meet rising market demands.

Inhibitors and Mitigation Factors

Conversely, several factors act as inhibitors to carbon emissions, playing a vital role in the transition toward low-carbon agriculture. Technological progress is the most significant inhibitor; innovations in precision farming, improved irrigation techniques, and the development of high-efficiency, low-emission fertilizers help decouple agricultural growth from carbon output. Additionally, the optimization of the agricultural industrial structure—shifting from high-emission livestock or crop varieties to more sustainable alternatives—contributes to emission reductions. Policy interventions, including subsidies for green farming practices and stricter environmental regulations, also serve as critical constraints on emission growth.

Strategies for Agricultural Carbon Reduction

To achieve effective carbon reduction within the watershed, a multi-faceted approach is required. First, it is essential to promote the adoption of conservation tillage and organic fertilization methods to enhance soil carbon sequestration. Second, the integration of renewable energy sources into agricultural machinery and infrastructure can significantly reduce the reliance on carbon-intensive fuels. Third, strengthening the monitoring and management of agricultural non-point source pollution will not only improve water quality but also mitigate the release of greenhouse gases. Finally, fostering regional cooperation within the watershed is necessary to ensure that carbon reduction efforts are synchronized and that best practices are shared across different administrative boundaries.

Through these coordinated efforts, the watershed can transition toward a more resilient and low-carbon agricultural economy.

curacy. In terms of temporal evolution, as the process of agricultural modernization intensifies, the traditional production models are undergoing significant transformations. This shift is characterized by the integration of advanced technologies and data-driven decision-making frameworks, which collectively enhance the efficiency and sustainability of farming practices.

The progression of agricultural modernization has led to a substantial increase in the adoption of precision agriculture techniques. By leveraging machine learning and deep learning algorithms, researchers and practitioners can now analyze complex environmental variables with unprecedented precision. This evolution not only optimizes resource allocation but also mitigates the environmental impact of intensive farming, ensuring long-term food security in a rapidly changing global climate.

Based on the findings of this study, we propose the following targeted recommendations:

First, it is essential to strengthen the integration of machine learning and deep learning techniques within the existing analytical framework. By leveraging advanced algorithms, researchers can more effectively identify complex patterns and non-linear relationships that traditional statistical methods might overlook. This transition not only enhances predictive accuracy but also provides a more robust foundation for data-driven decision-making in scientific research.

Second, we recommend the establishment of standardized data processing protocols to ensure consistency across different experimental setups. The implementation of rigorous data cleaning and normalization procedures is critical for minimizing noise and reducing the risk of overfitting. Furthermore, adopting open-source tools and maintaining transparent documentation will facilitate reproducibility and foster collaboration within the broader academic community.

Finally, policy-makers and institutional leaders should prioritize investment in high-performance computing infrastructure. As the scale of datasets continues to grow, the computational demands of sophisticated models will increase accordingly. Providing researchers with the necessary hardware and software resources is vital for maintaining a competitive edge in the rapidly evolving landscape of modern science.

The total volume of agricultural carbon emissions exhibits an "inverted U-shaped" trend, characterized by an initial increase followed by a subsequent decline, which is consistent with the Environmental Kuznets Curve (EKC) [**?**]. In the early stages of agricultural development, the widespread adoption of agricultural machinery and the intensive use of chemical inputs contributed significantly to rising emission levels. However, as technological advancements and sustainable practices have been integrated into the sector, a decoupling of agricultural growth from carbon emissions has begun to emerge.

The chemicalization of agriculture and the expansion of industrial processes have driven an increase in carbon emissions. In later stages, however, agricultural carbon emissions have gradually decreased due to advancements in agricultural technology, the implementation of energy-saving and emission-reduction measures, and adjustments to agricultural structures.

Scholars have conducted increasingly sophisticated research on agricultural carbon emissions in the Yellow River Basin. From a temporal perspective, the total volume of agricultural carbon emissions in the Yellow River Basin has shown an overall upward trend [?]. The input of agricultural materials has already become the primary source of carbon emissions within the crop cultivation industry [?]. However, in recent years, certain regions have seen progress due to the promotion of energy-saving and emission-reduction technologies.

The growth rate of carbon emissions has slowed down significantly. In terms of spatial distribution, due to variations in agricultural production types and resource endowments across different regions, the agricultural carbon emission intensity in the Yellow River Basin exhibits a "high in the west, low in the east" pattern. Conversely, the level of agricultural technological innovation demonstrates a spatial distribution characterized as "low in the west, high in the east" [?].

Agricultural provinces such as Henan and Shandong exhibit high total carbon emissions. In contrast, water-scarce regions—including the Ningxia Hui Autonomous Region (hereinafter referred to as Ningxia) and parts of the Inner Mongolia Autonomous Region (hereinafter referred to as Inner Mongolia)—demonstrate relatively high carbon emission intensity per unit area. Conversely, regions characterized by robust ecological protection and advanced agricultural technology maintain lower emission intensities.

Regarding the analysis of influencing factors, large-scale agricultural operations, the optimization of planting structures, the research and application of modern agricultural machinery, and the promotion of precision agriculture technologies have significantly reduced agricultural energy consumption and carbon emissions. However, factors such as rural resident income and the overall level of agricultural economic development exert a clear driving effect on agricultural carbon emission intensity [?]. In terms of research methodology, academic studies on agricultural carbon emissions primarily utilize Logarithmic Mean Divisor Index (LMDI) methods, stochastic frontier analysis, and various econometric models to decompose and analyze these trends.

1.1 研究区概况

The Yellow River Basin (95°E $\sim$ 119°E, 32°N $\sim$ 42°N) is located in northern China. It serves as a vital ecological barrier and a significant economic zone, playing a crucial role in the country' s environmental security and socioeconomic development. The basin spans across nine provinces and autonomous regions, characterized by complex topographical features and diverse climatic conditions, ranging from the arid and semi-arid regions in the northwest to the humid and semi-humid zones in the southeast. Given its strategic importance, understanding the hydrological patterns and ecological dynamics of the Yellow River Basin is essential for sustainable water resource management and regional environmental protection.

The Yellow River flows through nine provinces and autonomous regions in northern China, including Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shanxi, Shaanxi, Henan, and Shandong, before finally emptying into the Bohai Sea.

The Yellow River basin covers an area of approximately 79.5×10^4 km^2. As the second longest river in China, it spans a total length of approximately···

5,464 km ([Figure 1: see original paper]). Considering the intensity of economic ties and geographical proximity···

Due to the integrity of the spatial scope, this paper conducts a study on agricultural carbon emissions across the nine provinces (and autonomous regions) of the Yellow River Basin at the provincial level. The Yellow River Basin occupies a critical position in China' s national food security, particularly regarding grain output and total cultivated area. Specifically, the regions along the river···

The grain production of provinces such as Henan and Shandong contributes significantly to national food security. As of 2023, the grain output of the Yellow River Basin has reached

2.44×10^8 t. As a primary source of agricultural carbon emissions, livestock farming accounts for a significant proportion of total agricultural emissions. In 2023, the total livestock production in the Yellow River Basin···

The output value is approximately 5×10^{11} yuan, accounting for about 17% of the total output value of the national livestock industry. Currently, the degree of agricultural intensification in the Yellow River Basin is high, and the inputs into farmland are substantial.

The extensive use of production inputs such as chemical fertilizers and pesticides, coupled with the annual growth in livestock and poultry farming, has significantly exacerbated greenhouse gas emissions. However, due to substantial differences in topography, land-use patterns, and agricultural production efficiency across the provinces within the Yellow River Basin, agricultural carbon emissions in this region exhibit marked spatial heterogeneity. Consequently, conducting a spatio-temporal analysis of agricultural carbon emissions in the Yellow River Basin is essential.

Various methodologies have been employed to study agricultural carbon emissions, including the Logarithmic Mean Divisia Index (LMDI) model [?], Geographically Weighted Regression (GWR) [?], and the Kaya identity [?].

In summary, academic research regarding agricultural carbon emissions in the Yellow River Basin has been relatively comprehensive. The selection of agricultural carbon sources primarily focuses on two sectors: crop production and livestock husbandry. Within the crop production sector, the input of agricultural materials has emerged as the most significant carbon source, while in the livestock sector, the rearing of large livestock also generates substantial carbon emissions. However, livestock···

Research focusing on carbon emissions from the livestock industry remains relatively scarce. However, existing studies have identified livestock production as the primary source of carbon emissions within the agricultural sector. Given that the development of animal husbandry in the Yellow River Basin has made significant contributions to China' s overall agricultural growth, it is essential to examine its environmental impact. Consequently, this paper conducts an analysis of the planting and livestock industries across the nine provinces (and autonomous regions) of the Yellow River Basin from 2013 to 2023.

The agricultural carbon emissions from various carbon sources were calculated. Based on the agricultural carbon emission intensity, the Moran' s I index was computed to test its spatial autocorrelation.

spatial autocorrelation. Regarding the analysis of factors influencing agricultural carbon emissions, the Logarithmic Mean Divisia Index (LMDI) model has become the preferred choice for many scholars. This paper utilizes the LMDI model to analyze agricultural carbon emissions across the nine provinces (regions) of the Yellow River Basin from 2013 to 2023.

By decomposing the factors influencing carbon emissions, this study analyzes the agricultural carbon emissions within the Yellow River Basin.

1. Introduction

The Yellow River Basin serves as a vital ecological shield and a significant agricultural production base in China. Under the strategic framework of "Ecological Protection and High-Quality Development of the Yellow River Basin," achieving a green and low-carbon transformation in agriculture has become a critical objective. To effectively formulate emission reduction policies, it is essential to systematically decompose the driving factors behind carbon emissions and understand their underlying mechanisms.

2. Methodology and Data

2.1 Decomposition of Carbon Emission Factors

To identify the primary drivers of agricultural carbon emissions, this study employs the Logarithmic Mean Divisia Index (LMDI) method. This approach allows for the decomposition of total carbon emissions into several key components, including agricultural technology levels, agricultural structural effects, economic development levels, and population size effects. The decomposition model is expressed as follows:

$$C = \sum_i \frac{C_i}{Q_i} \times \frac{Q_i}{Q} \times \frac{Q}{P} \times P$$

Where: - C represents the total agricultural carbon emissions; - C_i denotes emissions from specific agricultural activities; - Q_i represents the output value of specific agricultural sectors; - Q is the total agricultural output value; - P is the total population.

2.2 Data Sources

The data utilized in this analysis spans the period from 2000 to 2022, covering the nine provinces and autonomous regions through which the Yellow River flows. Data regarding agricultural inputs (such as fertilizers, pesticides, and diesel), crop yields, and economic indicators were primarily sourced from the *China Statistical Yearbook* and the *China Agricultural Yearbook*.

3. Analysis of Agricultural Carbon Emissions in the Yellow River Basin

3.1 Temporal Evolution of Emissions

The analysis reveals that agricultural carbon emissions in the Yellow River Basin have undergone distinct phases of growth and gradual stabilization. In the early 2000s, emissions rose steadily due to the intensive use of chemical inputs. However, in recent years, the implementation of "zero-growth" policies for fertilizers and pesticides has led to a noticeable deceleration in emission growth rates.

[Figure 1: see original paper]

3.2 Spatial Distribution

Note: This map is produced based on the standard map with the approval number GS(2019)1837 from the Standard Map Service website of the Ministry of Natural Resources. The boundaries of the base map have not been modified. The same applies hereafter.

1 Schematic diagram of the study area

E1 =∑E i =∑(T i × δ i)

Researching the spatial evolution characteristics and clarifying their influencing factors is conducive to implementing targeted carbon emission reductions in the Yellow River Basin, thereby facilitating the early achievement of "dual carbon" goals.

In the formula: E_1 represents the total carbon emissions from the agricultural planting industry in the nine provinces (regions) of the Yellow River Basin; E_i represents the carbon emissions from various carbon sources; T_i represents the quantity of each type of carbon source; and δ_i represents the emission factor for carbon source type i.

1.2 数据来源

The data for this study are sourced from the statistical yearbooks publicly released by the National Bureau of Statistics and the statistical yearbooks of various provinces (–).

Carbon source agricultural carbon emission factors. The indicator data selected for this paper cover the nine provinces (autonomous regions) of the Yellow River Basin.

Missing data, such as agricultural diesel consumption and pesticide consumption, were supplemented using the interpolation method.

The 2013–2023 data include the net amount of agricultural nitrogen fertilizer and the usage of agricultural plastic film.

Certain data, such as agricultural output value, were calculated by summing the output values of the planting and animal husbandry industries.

Consumption and pesticide consumption. The calculation of carbon emissions from animal husbandry measures the animal husbandry industry.

The output value was obtained through summation. Agricultural carbon emissions were calculated by combining the aforementioned yearbook data with the carbon emission accounting data published by the IPCC. 1 Planting industry carbon emission factors and

Chen Wenxuan et al.: Analysis of the Spatiotemporal Evolution Characteristics and Influencing Factors of Agricultural Carbon Emissions in the Yellow River Basin

reference sources

Carbon emission factors

Chemical fertilizer / $kg \cdot kg^{-1}$; Pesticide / $kg \cdot kg^{-1}$

Oak Ridge National Laboratory (ORNL), USA

Institute of Agricultural Resources and Environment, Nanjing Agricultural University [24]

Intergovernmental Panel on Climate Change (IPCC) [24]

Intergovernmental Panel on Climate Change (IPCC) [24]

Agricultural plastic film / $kg \cdot kg^{-1}$; Agricultural diesel / $kg \cdot kg^{-1}$

Agricultural sown area / $kg \cdot hm^{-2}$; Agricultural irrigation area / $kg \cdot hm^{-2}$

Oak Ridge National Laboratory (ORNL), USA [23]

College of Biological Sciences, China Agricultural University [9]

reference sources

Enteric fermentation, manure management.

N_2O emission factors and reference sources.

Camels, pigs, and small ruminants (categorized into goats and sheep). The calculation formula is:

E 2 =∑ GWPCH × D i × $ 1i+ $ GWPCH × D i × δ 2i +

∑(GWP

×D ×δ)

In the formula: E_2 represents the total carbon emissions from animal husbandry; GWP_{CH_4} and GWP_{N_2O}

represent the global warming potential (GWP) indices for CH_4 and N_2O, respectively. For CH_4, the GWP is applied to the year-end livestock population; δ_{1i}, δ_{2i}, and δ_{3i} denote the agricultural carbon emission factors for CH_4 from enteric fermentation, CH_4 from manure management, and N_2O from manure management, respectively.

The indicator data selected for this study cover the nine provinces (autonomous regions) of the Yellow River Basin.

The data encompass the populations of major livestock—including cattle, horses, donkeys, mules, camels, pigs, and sheep—from 2013 to 2023.

2 Animal husbandry carbon emission factors and CH_4 emission factors.

The sources of carbon emissions include cattle (categorized as dairy and non-dairy), horses, donkeys, mules,

The index for CH_4 is 25, while the global warming potential index for N_2O is 298; D_i represents the population of large livestock.

Carbon source indicator / $kg \cdot head^{-1} \cdot a^{-1}$

The volume, the sown area of major crops, the irrigated area of cultivated land, and the consumption of agricultural diesel.

The year-end livestock population, in which sheep are further categorized into sheep and goats. The agricultural carbon emission factors are detailed in Table 1 and Table 2 .

1.3.2 空间相关性使用 Moran’ s I 检验黄河流域农

The spatial autocorrelation of industrial carbon emission intensity is analyzed using the global Moran’ s I index. The calculation formula for the global Moran’ s I is as follows:

1.3.1 农业碳排放系数法根据 IPCC 官方提供的碳

Emission Factors and Agricultural Production Data in the Yellow River Basin

To accurately assess the environmental impact of agricultural activities in the Yellow River Basin, it is essential to integrate various types of data related to agricultural production with specific emission factors. This process involves the systematic collection and analysis of data concerning crop cultivation, livestock farming, and land management practices across the region. By applying localized emission factors to these activity datasets, researchers can quantify the total greenhouse gas emissions and nutrient runoff associated with the basin' s agricultural sector.

The methodology relies on high-resolution data regarding the consumption of chemical fertilizers, pesticides, and agricultural film, as well as the energy used for irrigation and machinery. Furthermore, the spatial distribution of different crop types and livestock populations must be accounted for to reflect the geographical diversity of the Yellow River Basin. These datasets, when combined with emission factors derived from empirical studies or standardized guidelines (such as those provided by the IPCC), allow for a comprehensive evaluation of the carbon footprint and environmental load of the region' s agriculture.

Accurate quantification is critical for developing targeted mitigation strategies. For instance, identifying sub-regions with disproportionately high emission intensities enables policymakers to implement more effective conservation measures, such as promoting precision agriculture or optimizing fertilizer application rates. This data-driven approach ensures that the ecological protection and high-quality development of the Yellow River Basin are supported by robust scientific evidence.

∑∑W (X - X)(X - X)

I = n nn

i=1 i=1

i=1 j=1

∑(Xi - X)

The formula for calculating the local Moran' s I is as follows:

$$I_i = \frac{x_i - \bar{x}}{S^2} \sum_{j=1, j \neq i}^{n} w_{i,j}(x_j - \bar{x})$$

where n is the total number of spatial units, x_i and x_j represent the observed values of the variable at locations i and j respectively, $\bar{x}$ is the mean value of the observations, $w_{i,j}$ denotes the spatial weight between units i and j, and S^2 is the sample variance, defined as:

$$S^2 = \frac{\sum_{j=1,j\neq i}^{n}(x_j - \bar{x})^2}{n-1}$$

$\sum$ n-1

In the formula: n represents the number of spatial units; W_{ij} denotes the spatial weight between the i-th and j-th spatial units.

Based on the calculated agricultural carbon emissions, the planting and livestock industries in the Yellow River Basin in 2023 exhibited specific spatial and structural characteristics. These sectors represent the primary sources of carbon output within the region's agricultural framework. The calculation methodology accounts for various emission factors, including chemical fertilizer application, pesticide use, and agricultural film in the planting sector, as well as enteric fermentation and manure management in the livestock sector.

The spatial distribution of these emissions reveals significant heterogeneity across the upper, middle, and lower reaches of the Yellow River. Provinces with extensive agricultural activities, such as Henan and Shandong, continue to contribute a substantial portion of the total carbon load due to their intensive cultivation practices and large-scale livestock production. Conversely, the upper reaches, characterized by pastoral systems, show a different emission profile dominated by methane from ruminants.

To achieve the dual goals of food security and carbon reduction, it is essential to optimize the industrial structure of the Yellow River Basin. This involves promoting green production technologies, such as precision fertilization and improved feed efficiency. Furthermore, the integration of the planting and livestock sectors—specifically through the circular utilization of waste—remains a critical strategy for mitigating the overall carbon footprint of the region' s agricultural system.

The spatial weight matrix defines the relationships between different spatial units. In this context, X_i and X_j represent the observed values for the i-th and j-th spatial units, respectively, while $\bar{X}$ denotes the mean value across all observed spatial units.

Carbon emissions are primarily calculated through two major categories: the crop cultivation industry and the livestock industry.

1. Calculation of Carbon Emissions from the Crop Cultivation Industry

Carbon emissions from the crop cultivation industry mainly originate from six sources: fertilizers, pesticides, agricultural films, diesel consumption, irrigation, and tillage. The specific calculation formula is as follows:

$$E = \sum E_i = \sum T_i \cdot \delta_i$$

In this formula, E represents the total carbon emissions from the crop cultivation industry; E_i represents the emissions from the i-th carbon source; T_i represents the consumption or scale of the i-th carbon source; and δ_i represents the emission coefficient for the i-th carbon source. Based on existing research and the specific characteristics of the study area, the carbon emission coefficients for each source are determined as follows:

- **Fertilizers:** 0.8956 kg/kg
- **Pesticides:** 4.9341 kg/kg
- **Agricultural Films:** 5.1800 kg/kg
- **Diesel:** 0.5927 kg/kg
- **Irrigation:** 20.4760 kg/hm^2
- **Tillage:** 312.6000 kg/km^2

2. Calculation of Carbon Emissions from the Livestock Industry

Carbon emissions from the livestock industry primarily consist of methane (CH_4) and nitrous oxide (N_2O) produced during the gastrointestinal fermentation and manure management processes of livestock. To facilitate a unified analysis, these emissions are typically converted into carbon equivalents based on their global warming potential (GWP). The calculation formula is:

$$E_{animal} = \sum N_j \cdot (\phi_j + \theta_j)$$

In this formula, E_{animal} represents the total carbon emissions from the livestock industry; N_j represents the population of the j-th type of livestock; ϕ_j is the emission coefficient for gastrointestinal fermentation; and θ_j is the emission coefficient for manure management. Common livestock types include cattle, sheep, and pigs, each with specific emission factors defined by international or national standards.

The range of Moran’ s I values is as follows: $I > 0$ indicates positive spatial autocorrelation (clustering), while $I < 0$ indicates negative spatial autocorrelation (dispersion). When $I = 0$, the spatial distribution is random.

The formula for calculating Moran’ s I is:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\right) \sum_{i=1}^{n} (x_i - \bar{x})^2}$$

Where: - n is the number of spatial units. - x_i and x_j are the observed values of the variable at locations i and j, respectively. - $\bar{x}$ is the mean value of the variable across all units. - w_{ij} represents the spatial weight between units i and j.

The gross output value of animal husbandry accounts for 86.14% of the total agricultural output value within the region. Consequently, this study···

and the livestock industry. The carbon sources involved in the calculation of carbon emissions from the crop cultivation industry primarily include agricultural inputs such as chemical fertilizers, pesticides, agricultural films, diesel fuel usage, tillage operations, and agricultural irrigation. The formula for calculating these emissions is as follows:

the mean value of the measured observations; $W(i,j)$ represents the spatial weight matrix between provinces; $I < 0$ indicates negative spatial correlation (dispersion), while $I \approx 0$ suggests a random spatial distribution.

1.3.3 LMDI 模型依据黄河流域农业生产特点，基

Factors influencing agricultural carbon emissions in the Yellow River Basin based on the Kaya identity

the corresponding contribution rates.

$E = P \times G \times B \times A \times E$ In this formula: E represents the total agricultural carbon emissions (10^4 t); P represents the population engaged in the agricultural sector.

2 结果与分析

(104 persons); G represents the Gross Regional Product (10^8 yuan); B represents the total agricultural output

2.1.1 Agricultural Carbon Emissions in the Nine Provinces (Regions) of the Yellow River Basin from 2013 to 2023

value (10^8 yuan); A represents the total output value of the planting and animal husbandry industries (10^8 yuan). The additive model of the LMDI can be expressed as:

ΔE = ΔE P + ΔEG + ΔE B + ΔE A + ΔET

In the formula: ΔE represents the change in carbon emissions; ΔE_P denotes the population effect, reflecting the impact of changes in the agricultural labor force [10^4 t $\cdot$ (10^4 persons)$^{-1}$];

ΔE_G represents the economic effect, referring to the change in per capita regional gross domestic product [10^8 yuan $\cdot$ (10^4 persons)$^{-1}$];

ΔE_B represents the industrial structure effect, which accounts for the change in the proportion of agricultural output value relative to the total regional economic output value.

2.1 黄河流域农业碳排放时空演化特征

1. Calculation of Agricultural Carbon Emissions

1.1 Total Agricultural Carbon Emissions

In this study, the total agricultural carbon emissions in the Yellow River Basin are calculated using the agricultural carbon emission factor method. Based on the specific characteristics of agricultural production in the nine provinces of the Yellow River Basin, we identify six primary sources of carbon emissions: chemical fertilizers, pesticides, agricultural plastic films, diesel consumption, irrigation, and tillage. The specific calculation formula is as follows:

$$E = \sum E_i = \sum T_i \cdot \delta_i$$

In this formula, E represents the total agricultural carbon emissions; E_i denotes the emissions from the i-th carbon source; T_i represents the original quantity of the i-th carbon emission source; and δ_i is the corresponding carbon emission coefficient. Based on a synthesis of existing research [**?**, **?**], the carbon emission coefficients for each source are determined as follows: chemical fertilizer (0.8956 kg/kg), pesticide (4.9341 kg/kg), agricultural film (5.1800 kg/kg), diesel fuel (0.5927 kg/kg), irrigation (20.476 kg/hm^2), and tillage (312.6 kg/km^2).

1.2 Agricultural Carbon Emission Intensity

To better reflect the relationship between agricultural production and environmental impact, this paper utilizes agricultural carbon emission intensity as a key indicator. Agricultural carbon emission intensity is defined as the ratio of total agricultural carbon emissions to the total agricultural value added. This metric allows for a comparative analysis of the low-carbon development levels across different regions within the Yellow River Basin, accounting for variations in economic scale. The formula is expressed as:

$$CI = \frac{E}{GDP_{agri}}$$

Where CI represents the agricultural carbon emission intensity, E is the total agricultural carbon emissions calculated previously, and GDP_{agri} refers to the added value of the primary industry (specifically the agriculture, forestry, animal husbandry, and fishery sectors) adjusted to constant prices to ensure temporal comparability.

[Figure 1: see original paper]

By applying these methodologies, we can quantitatively assess the spatial and temporal evolution of carbon emissions in the Yellow River Basin, providing a scientific basis for formulating regional emission reduction policies and promoting sustainable agricultural transformation

Table 3 presents the agricultural carbon emissions for the provinces (autonomous regions) from 2013 to 2023. The data indicates that livestock farming remains a significant contributor to these emissions.

Industry has become a significant source of agricultural carbon emissions in the Yellow River Basin. Notably, carbon emissions from the livestock industry in this region have consistently remained higher than those from the crop cultivation industry, establishing it as the primary contributor to agricultural carbon emissions within the Yellow River Basin.

(%); ΔEA represents the structural effect, defined as the proportion of the total output value of the crop and livestock industries within the region.

As the primary source of agricultural carbon emissions, livestock production in the Yellow River Basin presents a critical challenge for regional carbon reduction efforts.

1. Introduction

The livestock industry serves as the largest contributor to agricultural carbon emissions. Analyzing the characteristics and drivers of these emissions in the Yellow River Basin is essential for achieving "dual carbon" goals and promoting sustainable agricultural development.

2. Analysis of Livestock Carbon Emissions

Livestock carbon emissions primarily originate from enteric fermentation and manure management. In the Yellow River Basin, the intensity and scale of livestock farming vary significantly across different provinces, leading to distinct spatial patterns in emission distribution.

2.1 Emission Sources and Mechanisms

The primary greenhouse gases emitted by the livestock sector include methane (CH_4) and nitrous oxide (N_2O). Methane is largely produced during the digestive processes of ruminants, such as cattle and sheep, through enteric fermentation. Conversely, N_2O emissions are predominantly associated with the storage and treatment of animal waste.

[Figure 1: see original paper]

2.2 Spatial Distribution Characteristics

Research indicates that carbon emission intensity in the Yellow River Basin follows a gradient, often correlating with the level of industrial intensification and local environmental regulations. Provinces in the upper reaches often face different ecological constraints compared to the intensive farming hubs in the middle and lower reaches.

3. Drivers of Carbon Emission Reduction

To effectively reduce carbon emissions from livestock in the Yellow River Basin, several key factors must be addressed:

1. **Technological Innovation**: Implementing advanced feeding strategies and improving manure treatment technologies can significantly lower the emission factors per head of livestock.
2. **Scale and Structure**: Optimizing the structure of livestock populations—balancing ruminants and non-ruminants—helps manage the overall methane output.
3. **Policy Support**: Government subsidies for green farming practices and stricter environmental standards are vital for incentivizing low-carbon transitions.

4. Conclusion and Policy Recommendations

The Yellow River Basin’ s livestock industry is at a crossroads. To transition toward a low-carbon model, it is necessary to integrate machine learning and deep learning technologies for precision livestock farming. By monitoring animal health and optimizing feed efficiency, producers can reduce waste and emissions simultaneously.

Future policies should focus on regional cooperation across the basin, ensuring that carbon reduction strategies are tailored to the specific ecological and

The variation in industrial carbon emission intensity [10^4 t • (10^8 yuan)$^{-1}$].

The impact of chemical fertilizer use on agricultural carbon emissions in the Yellow River Basin is significant. Based on current trends, fertilizer application remains a primary driver of the overall carbon footprint within the region’ s agricultural sector.

the change in the proportion of the total agricultural output value (%); ΔET represents the technical effect, reflecting the impact of agricultural technological progress on carbon emissions.

The impact of agricultural input factors on agricultural carbon emissions, ranked by their contribution, is as follows:

The calculation formulas for each component are as follows:

(E - E)ln Pt - 1 ΔE P =$\sum$ ln E it - ln E it - 1

Agricultural plastic film, agricultural diesel, pesticides, agricultural irrigation area, and agricultural sown area.

(G/P) (G/P)t - 1 ln E it - ln E it - 1

(E it - E it - 1)ln

ΔEG =$\sum$

(E A)t (E A)t - 1 ln E it - ln E it - 1

The development of low-carbon agriculture has achieved significant results. The overall trend is characterized by an initial rise, followed by a year-on-year decline, and a subsequent slight recovery [Figure 3: see original paper]. Since 2013,

the total production increased from 19348.22×10^4 t to 19856.78×10^4 t in 2023. There are significant disparities in emission volumes across different regions; specifically, the agricultural carbon emissions of Sichuan, Henan, and Inner Mongolia all rank among the highest, with each exceeding 2500×10^4 t. According to

statistics, in 2013, the crop cultivation and livestock industries in Sichuan, Henan, and Inner Mongolia

(E it - E it - 1)ln

ΔET =$\sum$

The consumption of plastic mulch has decreased, indicating that traditional crop farming within the basin is shifting toward intensive···

The growth rate is approximately 2.6%. The agricultural carbon emissions of the nine provinces (autonomous regions) in the Yellow River Basin···

(A/B)t (A/B)t - 1 ln E it - ln E it - 1

(E it - E it - 1)ln

ΔE A =$\sum$

development, and positioning agricultural green development as a core component of the green development strategy.

The agricultural carbon emissions of the nine provinces (autonomous regions) in the Yellow River Basin exhibit a

(B/G) (B/G)t - 1 ln E it - ln E it - 1

ΔE B =$\sum$

The total planting area is illustrated in [Figure 2: see original paper]. Since the 18th National Congress of the Communist Party of China, the promotion of green agricultural development has been actively advocated and implemented across various regions. During the research period, the consumption of chemical fertilizers, pesticides, and agricultural film in each province has been recorded.

(E it - E it - 1)ln

The task of reducing emissions remains arduous. Carbon emissions from the crop cultivation industry have exhibited a trend of fluctuating decline.

The total industrial output values were 5154.04×10^8 yuan, 6439.74×10^8 yuan, and···

The economy' s agricultural output value (the sum of the output values of the crop cultivation and livestock industries) accounts for approximately

This is a significant reason for its leading position. In 2013, agricultural carbon emissions reached their peak.

In the formula: E_{it} and E_{it-1} represent the values for the i-th region in year t and year $t-1$, respectively.

The total agricultural output value reached 2539.75×10^8 yuan. Notably, Sichuan and Henan, as major agricultural hubs, account for 44.27% of the total agricultural output value of the Yellow River Basin. Henan stands out as the province with the highest agricultural carbon emissions, totaling 4067.45×10^4 t, with a significant portion originating from livestock carbon emissions.

The total agricultural carbon emissions reached 3208.48×10^4 t, accounting for 78.88% of the total agricultural carbon emissions in Henan Province. In 2015, the four provinces with the highest agricultural carbon emissions were Henan, Si…

Sichuan, Inner Mongolia, and Shandong. With the exception of Sichuan, all other provinces and autonomous regions have exhibited a clear downward trend in agricultural carbon emissions [Figure 3: see original paper]. Following the initial proposal of green agricultural development at the Fifth Plenary Session of the 18th CPC Central Committee in 2015, agricultural carbon emissions in Henan, Inner Mongolia, and Shandong have decreased. This reflects a positive response to…

agricultural carbon emissions; RE_1, RE_2, RE_3, RE_4, and RE_5 are respectively

The implementation of China' s national green development philosophy has yielded significant results. In Shaanxi and Qinghai provinces, these efforts have led to substantial advancements in ecological preservation and sustainable industrial practices.

Analysis of Socioeconomic Effects

The dynamics of regional development are driven by a complex interplay of various factors, primarily categorized into demographic, economic, industrial, structural, and technological effects. Understanding these drivers is essential for formulating effective policy and achieving sustainable growth.

Population Effects

The population effect refers to the impact of demographic changes—including total population size, age structure, and migration patterns—on socioeconomic outcomes. A growing population can expand the labor force and increase consumer demand, thereby stimulating economic activity. Conversely, an aging population or significant brain drain can lead to labor shortages and increased social welfare burdens, potentially hindering long-term development.

Economic Effects

Economic effects encompass the broad impacts of macroeconomic variables such as GDP growth, investment levels, and consumption patterns. These effects represent the overall scale of economic activity and its capacity to generate wealth. High economic growth typically provides the necessary capital for infrastructure development and public services, creating a feedback loop that further enhances regional competitiveness.

Industrial Effects

The industrial effect focuses on the contribution of specific sectors—such as agriculture, manufacturing, and services—to the overall economy. This involves analyzing how the expansion or contraction of particular industries influences employment and output. Shifts toward high-value-added industries often lead to higher productivity levels and more robust economic resilience against external shocks.

Structural Effects

Structural effects relate to the composition and optimization of the economic system. This includes the transition from primary and secondary industries toward a service-oriented tertiary economy, as well as the balance between urban and rural development. Effective structural transformation ensures that resources are allocated to the most efficient sectors, reducing systemic redundancies and fostering balanced regional growth.

Technological Effects

Technological effects are the primary drivers of intensive growth and productivity gains. These effects result from innovation, the adoption of new digital tools, and improvements in research and development (R&D) capabilities. By enhancing the efficiency of production processes and enabling the creation of new products, technological advancement allows for increased output without a proportional increase in resource consumption, which is critical for achieving sustainable development goals.

The agricultural carbon emissions in Qinghai and Ningxia have consistently remained at relatively low levels.

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

1. Introduction

The Yellow River Basin serves as a critical ecological barrier and an essential agricultural production base in China. Achieving green and low-carbon development in this region’ s agriculture is of great significance for national food security and ecological civilization construction. As global climate change intensifies, reducing greenhouse gas emissions has become a consensus within the international community. Agriculture is not only a significant source of carbon emissions but also possesses vast potential for carbon sequestration. Therefore, exploring the spatio-temporal evolution characteristics and influencing factors of agricultural carbon emissions in the Yellow River Basin is crucial for formulating differentiated carbon reduction policies and promoting the high-quality development of the basin.

2. Research Methods and Data Sources

2.1 Calculation of Agricultural Carbon Emissions This study accounts for agricultural carbon emissions based on four primary sources: agricultural inputs, soil cultivation, livestock and poultry breeding, and rice cultivation. The basic calculation formula is as follows:

$$E = \sum E_i = \sum T_i \cdot \delta_i$$

In this formula, E represents the total agricultural carbon emissions, E_i represents the emissions from the i-th carbon source, T_i is the amount of the i-th carbon source, and δ_i is the corresponding emission coefficient. The emission coefficients are derived from established domestic and international research standards.

2.2 Spatial Correlation Analysis To analyze the spatial distribution characteristics of agricultural carbon emissions, this paper utilizes the Global Moran’ s I index to test for spatial autocorrelation. The formula is expressed as:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} (x_i - \bar{x})^2}$$

Where n is the number of regions, x_i and x_j are the carbon emission values of regions i and j respectively, and w_{ij} is the spatial weight matrix.

2.3 Logarithmic Mean Divisia Index (LMDI) Decomposition To further explore the

3 Carbon Emissions of Animal Husbandry and Cultivation in the Nine Provinces (Autonomous Regions) (10^4 t)

of the Yellow River Basin from 2013 to 2023

[Figure 1: see original paper]

Analysis of Total Volume Trends

The line chart illustrating the total volume provides a comprehensive overview of the temporal evolution and growth patterns within the dataset. By observing the fluctuations and general trajectory of the line, we can identify key periods of acceleration, stabilization, or decline. This visualization is essential for understanding the overarching trends and serves as a foundational reference for the subsequent detailed analysis of individual variables.

2 Temporal characteristics of carbon sources and

3 Line graph of total agricultural carbon emissions in

emissions in crop cultivation across the Yellow

nine provinces (autonomous regions) of the Yellow

River Basin from 2013 to 2023

River Basin from 2013 to 2023

(2) Agricultural Carbon Emission Intensity

In this study, agricultural carbon emission intensity is calculated based on total agricultural carbon emissions and agricultural output value. The specific calculation formula is as follows:

$$EI = \frac{E}{GDP_A}$$

In the formula, EI represents the agricultural carbon emission intensity; E denotes the total agricultural carbon emissions; and GDP_A represents the total output value of the agricultural sector (calculated at constant prices to ensure comparability over time). Agricultural carbon emission intensity serves as a key indicator of the relationship between agricultural production and environmental impact, reflecting the carbon efficiency of agricultural economic activities. A lower intensity value indicates higher resource utilization efficiency and a more sustainable transition toward low-carbon agricultural development.

Calculation of Agricultural Carbon Emission Intensity in the Nine Provinces (Regions) of the Yellow River Basin (2013–2023)

The calculation of agricultural carbon emission intensity is a critical metric for evaluating the coordination between agricultural economic development and environmental sustainability. For the nine provinces and regions within the Yellow River Basin (Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, and Shandong) from 2013 to 2023, the calculation process is divided into two primary components: the measurement of total agricultural carbon emissions and the determination of agricultural economic output.

1. Calculation of Total Agricultural Carbon Emissions

Agricultural carbon emissions are primarily derived from six key sources: chemical fertilizers, pesticides, agricultural films, diesel fuel consumption, irrigation, and tilling. The total emissions are calculated using the following formula:

$$E = \sum E_i = \sum T_i \cdot \delta_i$$

In this equation, E represents the total agricultural carbon emissions; E_i denotes the emissions from the i-th carbon source; T_i represents the consumption or scale of the i-th source; and δ_i is the corresponding emission coefficient. Based on established academic standards (such as those from the IPCC and the Institute of Resource, Ecosystem and Environment of Agriculture at Nanjing Agricultural University), the coefficients are generally defined as: fertilizers (0.8956 kg/kg), pesticides (4.9341 kg/kg), agricultural films (5.1800 kg/kg), diesel fuel (0.5927 kg/kg), irrigation (20.476 kg/hm^2), and tilling (312.6 kg/km^2).

2. Calculation of Agricultural Carbon Emission Intensity

Agricultural carbon emission intensity is defined as the ratio of total carbon emissions to the total value of agricultural production. This metric reflects the amount of carbon dioxide equivalent produced per unit of agricultural economic output. The formula is expressed as follows:

$$CI = \frac{E}{GDP_{agri}}$$

Where CI represents the agricultural carbon emission intensity, E is the total agricultural carbon emissions calculated in the previous step, and GDP_{agri} is the gross value of agricultural production (specifically for the farming sector). To ensure temporal comparability across the 2

The intensity of agricultural carbon emissions within the watershed exhibits a consistent downward trend year by year [Figure 1: see original paper]. This decline suggests a decoupling of agricultural economic growth from carbon emissions, likely driven by improvements in agricultural technology and more efficient resource management.

This indicates that the carbon emission reduction effects of agricultural production in the Yellow River Basin are significant. From the perspective of spatial distribution, there are clear regional differences in the intensity of carbon emissions across the basin. High-intensity areas are primarily concentrated in the middle and lower reaches, where traditional intensive farming practices and higher inputs of chemical fertilizers and pesticides are more prevalent. Conversely, the upper reaches exhibit relatively lower emission intensities, which can be attributed to the dominance of extensive pastoral farming and the implementation of ecological protection policies.

The temporal evolution of these emissions reveals a gradual decoupling between agricultural economic growth and carbon output. This trend suggests that the transition toward green and low-carbon agricultural practices is yielding positive results. Key drivers for this transformation include the promotion of conservation tillage, the optimization of fertilizer application structures, and the increasing adoption of renewable energy in rural areas. Furthermore, the implementation of national strategies for ecological protection and high-quality development in the Yellow River Basin has provided a robust policy framework for sustaining these emission reduction trends.

To further enhance the efficiency of carbon reduction, it is essential to consider the heterogeneous resource endowments of different provinces within the basin. Future efforts should focus on strengthening technological innovation in climate-smart agriculture and establishing a cross-regional compensation mechanism for carbon sequestration. By integrating modern agricultural management with digital monitoring technologies, the Yellow River Basin can serve as a model for achieving the dual goals of food security and environmental sustainability.

The spatial distribution pattern is characterized by being "sparse in the north and south, and dense in the central region" [Figure 5: see original paper]. Specifically, the provinces of Sichuan and He-

It has consistently remained in the top position, stabilizing at 2.5×10^4 t $\cdot$ $(10^8$ yuan$)^{-1}$.

Natural conditions and socio-economic foundations have facilitated the rapid development of agriculture in this region, leading to a significant increase in productivity and output.

Moreover, this may be related to the fragile ecological environment of Qinghai. Qinghai is located in···

The input of agricultural materials has also caused agricultural carbon emissions to be higher than those within the watershed.

In the Sanjiangyuan region of Northwest China, the soil organic matter content is significantly higher than that in the eastern regions of the country.

other provinces (regions). Similarly, other provinces (regions) with high agricultural carbon emissions include

To increase soil fertility and improve crop yields, it is necessary to invest more resources into agricultural management and soil health optimization. In modern agricultural systems, the application of fertilizers and the implementation of sustainable farming practices are essential for maintaining the nutrient balance required for high-productivity farming. However, excessive or improper application can lead to environmental degradation, such as soil acidification and nutrient runoff.

Recent advancements in machine learning and deep learning offer promising solutions for precision agriculture. By integrating multi-source data—including soil composition, weather patterns, and historical yield records—researchers can develop predictive models to optimize nutrient delivery. These data-driven approaches allow for the precise calculation of fertilizer requirements, ensuring that inputs are maximized for crop growth while minimizing environmental impact.

Furthermore, the integration of automated monitoring systems and remote sensing technology provides real-time insights into soil conditions. These technologies enable farmers to respond dynamically to changes in soil moisture and nutrient levels, facilitating a more resilient and efficient agricultural production cycle. As the global demand for food continues to rise, the synergy between traditional agronomy and advanced computational techniques will be critical for achieving food security and sustainable development.

In Inner Mongolia, the total volume of agricultural carbon emissions has been increasing year by year. This trend reflects the region' s expanding agricultural production and the intensification of farming practices. As a critical agricultural and livestock hub in northern China, the growth in emissions is closely linked to the increased use of chemical fertilizers, pesticides, and agricultural machinery, as well as the methane and nitrous oxide emissions associated with large-scale livestock husbandry. Addressing this rising trend is essential for achieving regional carbon neutrality goals and promoting sustainable agricultural development.

excessive agricultural supplies such as fertilizers and pesticides, thereby exacerbating agricultural carbon emissions.

The proportion of animal husbandry output value within the primary industry in Inner Mongolia is significantly higher than the national average.

The livestock population in Qinghai Province has experienced a steady year-on-year increase from 2013 to 2023. This growth trend reflects the continuous expansion of the region' s animal husbandry sector and the evolving scale of its agricultural economy.

level, and as the primary source of carbon emissions within the agricultural sector, the livestock industry significantly impacts overall environmental sustainability. Given its substantial contribution to greenhouse gas emissions, addressing the carbon footprint of livestock production is essential for achieving broader climate goals. Strategies aimed at mitigating these emissions often involve optimizing feed efficiency, improving manure management practices, and integrating advanced technological solutions to monitor and reduce methane and nitrous oxide outputs. Consequently, transforming the livestock industry into a more carbon-efficient sector is a critical component of modern agricultural policy and sustainable development.

reached 632.01 $\times 10^4$ head, an increase of approximately 39.77%, becoming a significant component of agricultural carbon emissions in Qinghai.

Agricultural carbon emissions in Gansu and Shanxi provinces exhibit a trend of fluctuating growth.

relatively low, which results in its agricultural carbon emission intensity being lower than that of the entire river basin.

Total emissions remained at a low level from 2013 to 2023. Sh

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