Original Research

Agricultural Carbon Emissions in China: Estimation, Influencing Factors, and Projection of Peak Emissions

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Abstract

Agricultural carbon emissions significantly contribute to global greenhouse gases. Enhancing green and low-carbon agricultural practices is crucial for China's high-quality economic progression and achieving its "carbon peaking and carbon neutrality" objectives. This study focuses on agriculture's ecological role, incorporating 18 primary carbon sources across agricultural materials, soil, water fields, and animal husbandry into an evaluative framework. It assesses the total agricultural carbon emissions in 31 Chinese provinces from 2000 to 2021. Employing the STIRPAT environmental pressure model, the paper investigates the determinants of China's agricultural carbon emissions. Additionally, it utilizes the BP neural network model for forecasting emission peak trends under various development scenarios and validates these predictions through the Geographically and Temporally Weighted Regression (GTWR) model, among other methods. The findings reveal a reverse U-shaped pattern in China's total agricultural carbon emissions over the study period, marked by initial growth followed by a decline and significant regional variations. The primary drivers of these emissions are the agricultural population, per capita agricultural GDP, and agricultural technology level. Under green development initiatives, China's agricultural sector is projected to achieve its "peak CO_2 emission" goal by around 2030, with minimal peak variations. This research offers valuable insights into Chinese agriculture's carbon sequestration capabilities within the context of carbon peak and neutrality goals. It guides governmental agencies in devising flexible, precise, and moderate agricultural carbon sink strategies, enhancing regional agricultural collaborations, and promoting pollution and carbon reduction in China's agriculture towards realizing its "carbon peaking and carbon neutrality" ambition.

Keywords: peak carbon dioxide emissions, agricultural carbon emissions, STIRPAT model, BP neural network

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Introduction

As modernization intensifies and human society rapidly evolves, the issue of climate change, primarily driven by escalating carbon dioxide emissions, has emerged as a significant global challenge. The urgency of reducing carbon emissions gains prominence amidst the ongoing global warming crisis. Agriculture, a key economic sector, is recognized as a substantial contributor to carbon emissions. Data from the United Nations Food and Agriculture Organization (FAO) indicate that emissions from agricultural activities and land-use changes constitute approximately one-fourth of total human-induced carbon emissions [1]. The Intergovernmental Panel on Climate Change's (IPCC) Fourth Assessment Report underscores that agriculture accounts for nearly one-third of global greenhouse gas emissions, making it the second-largest source [2, 3]. In response, nations worldwide have established targets for climate change mitigation and adaptation. Demonstrating its commitment to environmental stewardship, China, at the 2021 15th Conference of the Parties to the Convention on Biological Diversity (CBD), advanced the integration of "carbon peaking and carbon neutrality" into its ecological civilization blueprint, with an aim to peak carbon emissions by 2030 and achieve carbon neutrality by 2060. As the leading emitter of greenhouse gases globally, China attributes 17% of its carbon emissions to agriculture, which, in 2017, constituted 29.01% of Asia's and approximately 12.54% of the world's agricultural emissions [4]. In facing the formidable task of realizing its "dual-carbon" objectives, China urgently seeks a transition to a green, low-carbon, and sustainable development pathway, identifying the reduction of agricultural carbon emissions as a critical strategy.

The examination of agricultural carbon emissions is pivotal to addressing global climate change and understanding the carbon cycle. Agriculture not only represents a significant source of worldwide greenhouse gas emissions but is also a crucial component of the carbon cycle. Thorough research into agricultural carbon emissions is essential for devising effective strategies to reduce emissions and optimize agricultural practices, contributing to the mitigation of global warming. Furthermore, such research is key to meeting international environmental commitments and fostering sustainable agricultural development. Realizing the 'dual-carbon' objective necessitates comprehensive studies of carbon emissions across various sectors. While agricultural carbon emissions have garnered less focus compared to those from the industrial and service sectors, their impact on the overall carbon cycle is considerable. Traditional methods of measuring carbon emissions, which often concentrate on energy consumption, tend to overlook the distinctive emission characteristics inherent in agricultural processes like cultivation and livestock rearing. For instance, the emission dynamics in rice farming and animal husbandry, which release substantial greenhouse gases, differ markedly from those in industrial and service activities. Consequently, applying carbon emission reduction models from the industrial and service sectors directly to agriculture is ineffective. This paper, therefore, undertakes an analysis of agricultural carbon emissions across 31 provinces in China. It aims to comprehensively assess the current state and unique features of China's agricultural emissions, examine their spatial and temporal dynamics, identify influencing factors, and provide practical, well-grounded recommendations. This analysis will offer theoretical insights for reducing agricultural carbon emissions, aiding in the reduction of China's agricultural emissions, and helping meet its international carbon emission reduction commitments.

Literature Review

Agricultural carbon emissions encompass both direct and indirect greenhouse gas emissions that arise from the use of fertilizers, pesticides, fossil fuels, and waste management in agricultural production. Agriculture uniquely functions as both a carbon source and a carbon sink. As a carbon source, it generates greenhouse gas emissions through activities like crop cultivation, livestock farming, aquaculture, and forestry. As a carbon sink, it sequesters carbon via photosynthesis in ecosystems such as fields, forests, and grasslands. This dual role bestows on agriculture a distinct position in the context of carbon emissions, setting it apart from other industries. Consequently, accurately measuring agricultural carbon emissions requires a comprehensive approach, considering various factors such as the use of agricultural inputs, land management, rice cultivation, and animal husbandry, rather than solely focusing on the net carbon emissions from crops [5]. Current scholarly research predominantly explores the quantification, temporal dynamics, determinants, and predictive analyses of agricultural carbon emissions.

The primary methodologies for measuring agricultural carbon emissions include the IPCC inventory method, the life cycle assessment (LCA) method, and the input-output analysis method. The IPCC's Guidelines for National Greenhouse Gas Inventories are the most extensively adopted for national GHG emission inventories, encompassing emission sources and factors. Anwar et al. utilized the IPCC method for analyzing GHG emissions in sectors like agriculture and forestry [6]. The LCA method evaluates carbon intensity and emission factors, with Li et al. demonstrating fluctuating carbon emissions trends in China's dairy industry [7]. The input-output approach, focusing on energy demand and emission factors, was employed by Yuan et al. to assess the carbon emission dynamics in various Chinese industries [8]. Additionally, models such as Agri-LCI, SPAC, and DNDC have been instrumental in estimating carbon emissions across diverse regions and sectors [9].

Goglio et al. conducted a comparative analysis of the IPCC method and DNDC model, leveraging field trial data [10].

The analysis of the spatial and temporal evolution of agricultural carbon emissions frequently employs the kernel density method and the Malmquist index method [11]. Ma et al. examined the spatio-temporal dynamics of agricultural carbon emission efficiency using the DEA-Malmquist index decomposition approach [12]. They dissected the Agricultural Mechanization Carbon Productivity Index (AMCPI) into the technical efficiency index and the technical progress index, integrating agricultural carbon emissions into the agricultural economic accounting system. This method was used to assess the trends in agricultural carbon emission efficiency across 31 Chinese provinces, cities, and districts from 2000 to 2011. To align with China's objective of achieving "carbon peak and carbon neutrality," Wang et al. selected Guangdong Province, China's most industrially advanced region, and employed a kernel density estimation model. This model was used to analyze the composition of industrial fossil energy consumption and the total carbon dioxide emissions from industrial enterprises [13]. In addition, the Malmquist index has been widely used to measure the efficiency of agricultural carbon emissions [14].

The decomposition of factors influencing agricultural carbon emissions primarily involves models such as the LMDI index decomposition model, Kaya identity, STIRPAT model, Divisia index decomposition method, and the Input-Output Structural Decomposition Analysis (I-O SDA) [15-18]. Furthermore, research indicates that agricultural carbon emissions are impacted by factors at both the market and governmental levels [19]. Additionally, at the micro level, variables including population, industrial structure, economic development level, educational attainment, mechanization degree, agricultural advancement, and urbanization extent also play significant roles in determining agricultural carbon emissions [20-23].

The projection of future trends and peak times for carbon emissions is a topic extensively explored by scholars. Common methodologies for these predictions encompass the gray prediction model, the input-output model, the STIRPAT model, and the Long-Range Energy Alternatives Planning (LEAP) model. Zhang employed the gray prediction model GM (1, 1) to forecast agricultural carbon emissions in Shandong Province from 2021 to 2045, deducing that emissions would peak by 2030 [24]. Chang conducted a projection for Henan Province's agricultural carbon emissions between 2021-2030, indicating a potential achievement of carbon neutrality by 2029 [25]. The LEAP model, recognized as a comprehensive energy-economic-environmental assessment tool, is utilized for projecting energy demands and carbon emissions. Hong applied the LEAP model to simulate China's carbon peaking trajectory [26]. Additionally, other scholars have adopted the logistic growth model, the BP neural network model, and the LSTM model for carbon peak modeling [27-29]. Scenario prediction models [30] have also gained increasing prominence in the field of carbon emission forecasting.

In conclusion, the research into agricultural carbon emissions appears to be systematic and comprehensive, yielding significant findings in various dimensions. Nonetheless, as research progresses, certain limitations in existing studies persist. To address these, this study employs the established IPCC guidelines and the STIRPAT model to guarantee accuracy and comparability. Innovatively, it also utilizes the BP neural network model and the Geographically and Temporally Weighted Regression (GTWR) model for enhanced prediction and robustness assessment. These methodologies augment the precision and dependability of forecasts, contributing to a more profound understanding of the current state and future trajectory of agricultural carbon emissions.

This study's key contributions are manifold. Firstly, it addresses the regional disparities in agricultural carbon emissions within China's varied topographical landscape. It delves into the differences in resource availability and agricultural production patterns across regions, thereby offering a nuanced understanding of the regional emission variances. Secondly, it expands the analytical framework to include a broader range of carbon source indicators, enabling a more systematic and holistic evaluation of China's agricultural carbon emissions. Thirdly, it investigates the socio-economic factors influencing the trends in agricultural carbon emissions, incorporating the STIRPAT environmental stress model to unravel the intricate interplay between regional development imbalances and carbon emissions. This approach allows for a multifaceted exploration of the determinants of agricultural carbon emissions in China. Fourthly, by employing BP neural networks for forecasting, the study not only assesses China's agricultural carbon emissions but also anticipates their peak and suggests context-specific carbon reduction measures. Overall, this research fills existing gaps in the literature by providing a thorough, comprehensive, and integrated socio-economic analysis of China's agricultural carbon emissions. This contributes significantly to the formulation of effective carbon reduction strategies and the achievement of carbon emission peak goals.

Methods and Data Sources

Research Methods

Measurement of Agricultural Carbon Emissions

This study employs the IPCC's (2006) guidelines and pertinent literature to quantify China's agricultural carbon emissions from four perspectives. The first involves agricultural inputs such as fertilizers,

pesticides, agricultural films, machinery, and diesel fuel, recognized as significant carbon sources [31]. The second perspective focuses on land use, specifically the carbon emissions resulting from plowing activities, with metrics including the total sown area of crops and the irrigated area [32]. Thirdly, the study assesses methane emissions from rice fields, accounting for hydrothermal conditions in various regions. The chosen indicators for this assessment are the cultivation of early, middle, and late rice [33]. Lastly, the livestock sector is evaluated, considering the enteric fermentation and fecal emissions from animals including cattle (both beef and dairy), horses, donkeys, mules, pigs, and sheep (encompassing goats and sheep). Integrating these factors, the study formulates the following agricultural carbon emission measurement model:

$$c = \sum c_i = \sum e_i \times \varepsilon_i \tag{1}$$

In Equation (1), c is the total amount of agricultural carbon emissions; c_i is the carbon emissions from source i; e_i is the total amount of inputs from source i; and ε_i is the carbon emission coefficient of source i. For the convenience of accounting, the estimated GHGs are converted to CO_2 uniformly, and according to the IPCC Fifth Assessment Report, 1tC, CH_4, and N_2O can be converted to 44/12, 28, and 265 t CO_2, respectively.

Kernel Density Estimation

Kernel density estimation, a crucial nonparametric technique, has gained prominence in analyzing uneven distributions[34]. This method primarily estimates the probability density of a random variable, representing the variable's distribution pattern through a continuous density curve. Employing kernel density analysis aids in elucidating the dynamic evolution of China's agricultural carbon emissions, thereby supporting the development of tailored emission reduction strategies. The functional form of this method is presented below:

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{x_i - \bar{x}}{h}\right) \tag{2}$$

In Equation (2), $f(x)$ is the density function; $k\left(\frac{x_i - \bar{x}}{h}\right)$ is the kernel function, h is the bandwidth, and n is the number of observations (i.e., the total number of provinces), i denotes individual provinces, x_i denotes independently and identically distributed observations, and $\bar{x}$ is the mean.Regarding the selection of kernel density functions, commonly utilized options include the Gaussian kernel, the Epanechnikov kernel, the biweight kernel, and the triangular kernel. Generally, the choice of different kernel density functions has a minimal impact on estimation outcomes. Therefore, this study opts for the widely used Gaussian kernel function as the basis for discussion. In terms of selecting the window width, the study employs an optimal window width selection method to determine this parameter [35].

Spatial Measurement Analysis

Global Spatial Autocorrelation

To more effectively represent the spatial autocorrelation of agricultural carbon emissions and their influencing factors, this study utilizes Global Moran's I for measurement [36]. The calculation formula employed is as follows:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{3}$$

In Equation (3) $S^2 = \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X})^2$, $\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$, and X_i are the observed values of region i, and n is the total number of regions.The global Moran index, denoted as I, typically ranges between [-1,1]. A value of $I>0$ signifies positive autocorrelation, suggesting that agricultural carbon emission values in provinces and their neighbors are spatially clustered, either as high-value or low-value agglomerations. Conversely, $I<0$ indicates negative autocorrelation, where the spatial distribution of agricultural carbon emissions in adjacent provinces is more dispersed. A value of $I = 0$ reflects no correlation. The spatial weights matrix, w_{ij}, is essential in this analysis, and this paper employs the Composite Spatial Weights Matrix. The global Moran index's calculation undergoes a Z-value significance test, as depicted in Equation (4):

$$Z = \frac{I - E(I)}{\sqrt{VAR(I)}} \tag{4}$$

Modeling of Factors Influencing Carbon Emissions in STIRPAT Agriculture

In this study, the STIRPAT model is employed to analyze the influence of China's rural population, affluence, and technological advancements on the carbon emissions from its agricultural sector [37]. The model is structured as follows:

$$I = aP^b A^c T^d e \tag{5}$$

Where I, P, A, and T represent environmental impact, population, affluence, and technology level, respectively; a is a constant term; b, c, and d are indices to be estimated; and e is the error term. The model is a multivariate nonlinear model, after taking the logarithm of both sides of the model, we can get:

$$\ln I = \ln a + b\ln P + c\ln A + d\ln T + \ln e \qquad (6)$$

A multivariate linear regression analysis was conducted on the refined model, with the natural logarithm of I ($\ln I$) as the dependent variable and the natural logarithms of $P(\ln P)$, $A(\ln A)$, and $T(\ln T)$ as independent variables. The model includes a constant term ($\ln a$) and an error term ($\ln e$). In this model: I represents the total carbon emissions from Chinese agriculture (in tons); P denotes the agricultural population (in 10,000 individuals); A signifies the degree of affluence, measured by per capita agricultural GDP (in yuan per person); and T indicates the level of agricultural technology, reflected by the power of agricultural machinery.

Agricultural Carbon Emission Trend Projection Model

The BP (back propagation) neural network model, inspired by the principles of the biological neuron system, comprises three components: an input layer, a hidden layer, and an output layer[38]. This model is distinguished by its minimal error margin and high accuracy. In this study, the number of neurons in the hidden layer of the BP neural network model is determined using the following empirical formula:

$$l = (n + m)^{1/2} + h \qquad (7)$$

In Equation (7), n and m are the number of nodes in the input and output layers, respectively; h is a constant with a value in the range of [1, 10]. The parameters are iterated continuously through training, and finally the network converges to complete the training.

Study Area and Data Sources

LLocated in the eastern part of Asia, China is one of the largest countries in the world, with the largest population in the world. China's agricultural production is mainly concentrated in its vast rural areas, which include a number of provinces such as Henan, Shandong, Hebei, etc. In 2021, China's realized gross output value of agriculture, forestry, animal husbandry, and fishery reached 14,701.34 billion yuan, with a year-on-year growth rate of 6.7%. In terms of ecological functions, China is recognized as a country that responds and acts positively in global assessment studies of the development process of a low-carbon economy. As a major economic power in the world, China's contribution to the promotion of a low-carbon economy and sustainable development is obvious [39].

The basic data in this paper comes from the China Statistical Yearbook, the China Energy Statistical Yearbook, the China Rural Statistical Yearbook, and so on. The sample covers 31 provinces and cities, and the examination period is from 2000 to 2021. Among them,

fertilizers (pure amounts), pesticides, agricultural films, and agricultural diesel are the actual amounts used in that year, and plowing is replaced by the actual sown area of crops in that year. For the amount of livestock and poultry breeding, it is calculated according to the median value of 130 days that the number of pigs, cattle, goats, sheep, etc. is based on the number of stocks at the end of the year, and the total value of agricultural output is discounted based on the year 2000 as the base period. For individual missing data, moving averages, mean interpolation, and linear interpolation were used to fill in the gaps. Hong Kong, Macao, and Taiwan were not included in the study due to data availability constraints.

Characterization of the Current Status

Characterization of the Time-Series of Agricultural Carbon Emissions

Table 1 illustrates that between 2000 and 2021, China's total agricultural carbon emissions escalated from 102.668 million tons to 118.6 million tons, marking an increase of 0.16%. In 2021, the distribution of carbon sources was as follows: agricultural materials accounted for 63.39%, land use for 19.99%, paddy fields for 5.6%, and animal husbandry for 10.99%. Notably, while land use carbon emissions exhibited an upward trend, the emissions from other sources declined. Regarding the year-over-year growth rate, the overall trend for ttotal agricultural carbon emissions were decreasing. A notable exception occurred in 2007, attributed primarily to the reduction in large-scale livestock breeding and the gradual refinement of industrial structures within the livestock sector.

Carbon emissions from China's agricultural sector can be categorized into four distinct stages: a period of rapid growth from 2000-2006, steady growth from 2007-2010, slowing growth from 2011-2015, and a decline from 2016-2021.

In the initial rapid growth phase, the peak annual growth rate of total carbon emissions reached 5.11% in 2004. This surge was primarily due to the issuance of the Central Government's Document No. 1 in 2004, which implemented the "two reductions, three subsidies" policy. This policy invigorated farmers' production enthusiasm, leading to increased agricultural input usage and consequently accelerating carbon emissions in agriculture.

The second phase, characterized by steady growth, saw a slight reduction in total carbon emissions in 2007 compared to 2006, yet the overall upward trend persisted. This period was more stable than the first. The downturn in 2007 coincided with the 17th National Congress of the Communist Party of China's emphasis on resource conservation and ecological protection, contributing to the temporary decline.

In the third stage, the growth rate of emissions slowed significantly. Although total agricultural carbon

Table 1. Structure, total amount and intensity of agricultural carbon emissions, 2000-2021.

Year	Agricultural Materials	Land	Paddy Land	Livestock and Poultry Farming	Total Carbon Emissios	Growthm Rate	Carbon Emission Intensity	Carbon Emission Intensity Growth Rate Year
2000	7843.18	1922.80	939.60	1561.27	10266.8	——	1023.80	——
2001	6042.69	1932.39	903.57	1567.05	10445.7	0.01742	942.20	-0.08
2002	6192.39	1931.84	884.41	1606.10	10614.7	0.01618	872.10	-0.07
2003	6334.57	1915.82	831.28	1659.30	10740.9	0.01189	781.60	-0.10
2004	6755.07	1931.75	889.96	1713.39	11290.1	0.05113	697.60	-0.11
2005	6998.44	1952.48	904.66	1749.12	11604.7	0.02786	619.50	-0.11
2006	7235.10	1942.04	907.51	1732.75	11817.4	0.01833	538.50	-0.13
2007	7543.17	1985.83	906.90	1352.38	11788.2	-0.0024	436.50	-0.19
2008	7642.36	2046.65	917.00	1355.63	11961.6	0.01471	374.70	-0.14
2009	7887.86	2075.11	929.10	1373.99	12266.0	0.02545	351.90	-0.06
2010	8137.77	2110.42	936.83	1359.94	12544.9	0.02274	304.40	-0.13
2011	8361.98	2150.99	942.59	1339.52	12795.0	0.01994	262.20	-0.14
2012	8566.91	2190.64	945.10	1342.73	13045.3	0.01956	242.20	-0.08
2013	8714.46	2206.06	950.59	1348.85	13219.9	0.01338	222.90	-0.08
2014	8850.32	2237.03	950.52	1372.44	13410.3	0.01440	208.40	-0.07
2015	8886.33	2275.46	947.56	1392.55	13501.9	0.00683	196.00	-0.06
2016	8783.12	2311.01	936.62	1362.94	13393.7	-0.0080	179.40	-0.08
2017	8578.07	2327.10	964.23	1219.85	13089.2	-0.0227	157.30	-0.12
2018	8233.35	2337.91	946.74	1199.26	12717.2	-0.0284	138.30	-0.12
2019	7885.32	2348.85	931.19	1173.25	12338.6	-0.0297	125.10	-0.10
2020	7650.66	2366.55	943.16	1253.61	12213.9	-0.0101	120.50	-0.04
2021	7517.97	2370.32	668.02	1303.73	11860.0	-0.0289	103.20	-0.14
Cumulative	-4%	23%	-29%	-16%	16%	——	-0.8992	——
Average Rate	-0.18%	1.045%	-1.31%	-0.72%	0.727%	——	-0.0408	——

emissions continued to rise, the annual increase ranged between 0.683%-1.994%, indicating a marked deceleration. This stage aligned with China's 12th Five-Year Plan, which focused on agricultural modernization, enhanced agro-ecological environment management, and promoted resource-efficient and environmentally friendly farming practices.

The fourth stage marked a decline. During this period, China's total agricultural carbon emissions decreased by 13%, with the largest annual reduction being 2.97%. Notably, emissions from agricultural materials and paddy fields saw a substantial decrease, from 9,366,300 tons to 6,680,200 tons. This reduction can be attributed to the implementation of China's "Zero Growth in Fertilizer Use by 2020" and "Zero Growth in Pesticide Use by 2020" policies in 2015. These initiatives led to improved efficiency in energy and agricultural material use and a considerable decrease in the number of large livestock holdings [5].

As shown in Fig. 1, from 2000 to 2021, China's total agricultural carbon emissions demonstrated an upward trend, yet the emissions intensity markedly decreased from 10,238,200 tons per 10,000 yuan to 103.20 tons per 10,000 yuan. This decline can be attributed to several factors: Firstly, technological advancements [40], such as the enhancement of seed quality, precision in fertilizer application, and the adoption of water-saving irrigation technologies, including the propagation of super rice planting in Jiangsu and Zhejiang provinces and drip and sprinkler irrigation systems in arid regions like Gansu. Secondly, significant improvements in management practices [41], such as modernized approaches to agricultural management encompassing better land management, crop rotation, and reduced tillage frequency, have increased soil carbon storage and lowered greenhouse gas emissions. Thirdly, a strategic shift in cropping patterns [42], including corn and soybean rotations in Northeast China and the expansion
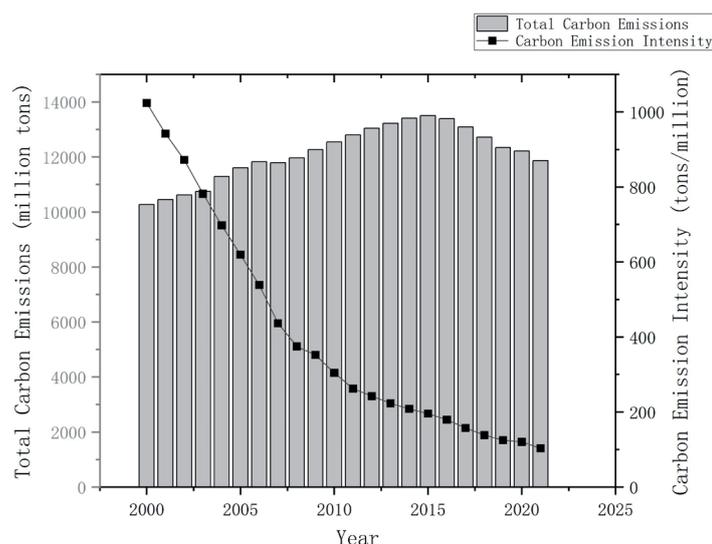
Fig. 1. Trends in total agricultural carbon emissions and intensity.

of economic forestry in Yunnan and Guizhou, has reduced dependence on water- and energy-intensive crops. Fourthly, the move towards large-scale production in regions like Hebei and Henan has improved resource use efficiency and reduced carbon emissions per unit of output [43]. Finally, policy and regulatory initiatives by the Chinese government, designed to foster low-carbon agriculture [44], enhance energy efficiency, and encourage renewable energy adoption, have been crucial. Collectively, these elements have led to a steady decrease in the intensity of agricultural carbon emissions in China, a trend that is expected to persist in future years.

Analysis of Regional Differences in the Administrative Geography

Table 2 delineates the total volume and intensity of agricultural carbon emissions across various provinces in China. In 2021, the total agricultural carbon emissions across China's provinces varied significantly. Henan, Shandong, Heilongjiang, Xinjiang, Anhui, Jiangsu, Hebei, Hunan, Inner Mongolia, and Sichuan were the top ten emitting provinces, collectively contributing 66.9407 million tons of carbon emissions. This accounted for 56.44% of the total national agricultural emissions. In contrast, the lowest emissions were recorded in Beijing, Shanghai, Tianjin, Tibet, Qinghai, Hainan, Ningxia, Chongqing, Guizhou, and Shanxi. Together, these ten provinces contributed only 10.4936 million tons, representing a mere 8.85% of China's total agricultural carbon emissions.

The distribution of agricultural carbon emissions across China's provinces reveals a concentration in major grain-producing areas such as Henan, Jiangsu, and Sichuan. The extensive cultivation of grain in these regions necessitates the use of pesticides, fertilizers, and other agrochemicals, leading to substantial carbon

emissions. Moreover, the carbon emissions from agriculture are notably high in Xinjiang, Inner Mongolia, and Sichuan, partly due to the prevalence of animal husbandry. Remarkably, Inner Mongolia experienced the most significant increase in agricultural carbon emissions, surging by 117.33%, the highest among all Chinese provinces. Conversely, regions like Beijing and Shanghai have relatively low agricultural carbon emissions, attributed to geographical and landscape constraints that limit the use of extensive agricultural machinery.

From 2000 to 2021, there has been a general decline in the carbon emission intensity of agriculture across all Chinese provinces. This trend, aligning with Li's study [37], demonstrates economic growth alongside a decrease in carbon emissions per unit of output. The reduction in carbon emission intensity is particularly notable in economically advanced regions such as Shanghai, Tianjin, and Beijing. This decline can be attributed to two primary factors: the adoption of advanced agricultural technologies and management practices, enhancing production efficiency while reducing carbon emissions per output unit, and the optimization and upgrading of the industrial structure[45], leading to more efficient and lower-emission agricultural production. Overall, China's agricultural carbon emission intensity displays a marked regional disparity, characterized as "high in the west and low in the east." In 2000, Tibet had the highest intensity at 5,869.95 tons per ten thousand yuan, compared to Shanghai's lowest at 120.46 tons per ten thousand yuan, a nearly 49-fold difference. By 2021, Heilongjiang had the highest intensity at 481.5007 tons per million yuan, whereas Beijing had the lowest at only 3.8539 tons per million yuan, a disparity of approximately 125 times.

Table 2. Total agricultural carbon emissions and intensity

Region	2000 year				2021 year				Change in Total Carbon Emissions	Change in Carbon Intensity
	Total Emissions	Rank	Intensity	Rank	Total Emissions	Rank	Intensity	Rank		
Beijing	42.70	31	130.27	30	15.82	31	3.8539	31	-62.95	-97.04
Tianjin	46.25	30	290.57	29	34.40	29	21.9317	29	-25.62	-92.45
Hebei	660.94	3	1428.07	16	601.30	7	148.8462	12	-9.02	-89.58
Shanxi	187.05	23	1013.44	22	221.28	22	96.7532	23	18.30	-90.45
Inner Mongolia	258.94	18	1682.41	12	562.76	9	265.8784	6	117.33	-84.20
Liaoning	281.32	16	602.51	26	343.33	16	124.5332	15	22.04	-79.33
Jilin	256.90	19	1466.83	13	414.59	15	314.9448	4	61.38	-78.53
Heilongjiang	380.41	11	1332.2	20	715.43	3	481.5070	1	88.07	-63.86
Shanghai	57.97	28	120.46	31	23.76	30	5.4420	30	-59.01	-95.48
Jiangsu	642.30	4	750.9	24	602.94	6	51.3607	25	-6.13	-93.16
Zhejiang	328.85	14	533.43	27	282.40	20	38.1408	27	-14.12	-92.85
Anhui	562.56	5	1800.02	7	608.67	5	142.9962	13	8.20	-92.06
Fujian	261.59	17	694.89	25	231.08	21	46.6209	26	-11.66	-93.29
Jiangxi	346.92	13	1731.92	9	335.06	18	112.3325	17	-3.42	-93.51
Shandong	946.48	1	1143.35	21	817.96	2	98.6974	22	-13.58	-91.37
Henan	852.27	2	1686.66	11	1008.92	1	173.7372	10	18.38	-89.70
Hubei	516.38	8	1456.48	15	547.01	11	109.2025	19	5.93	-92.50
Hunan	518.34	7	1459.5	14	565.05	8	123.6065	16	9.01	-91.53
Hubei	428.90	9	396.75	28	415.39	14	33.3057	28	-3.15	-91.61
Guangxi	408.42	10	1963.56	5	448.06	13	177.7376	9	9.71	-90.95
Hainan	70.33	25	1335.04	19	91.22	26	140.2435	14	29.70	-89.50
Chongqing	164.10	24	900.61	23	183.23	24	65.2587	24	11.66	-92.75
Sichuan	554.88	6	1412.56	17	553.71	10	102.3730	21	-0.21	-92.75
Guizhou	203.72	21	1978.06	4	212.17	23	109.0345	20	4.15	-94.49
Yunnan	347.34	12	1710.95	10	455.04	12	167.5295	11	31.01	-90.21
Xizang	67.97	26	5769.95	1	80.56	28	387.2678	3	18.52	-93.29
Shannxi	252.09	20	1397.39	18	336.44	17	111.6932	18	33.46	-92.01
Gansu	187.61	22	1781.84	8	308.25	19	301.4571	5	64.30	-83.08
Qinghai	67.04	27	2542.28	2	87.53	27	258.5891	7	30.56	-89.83
Ningxia	56.60	29	1918.64	6	99.39	25	216.6228	8	75.60	-88.71
Xinjiang	309.67	15	2270.97	3	657.33	4	402.9841	2	112.27	-82.25

Analysis of Spatial and Temporal Evolution

Fig. 2 presents a kernel density analysis of China's agricultural carbon emissions. In 2001, the emissions displayed a dense, single-peak distribution. By 2006, the curve's center had shifted rightward, maintaining a certain level of inter-provincial disparity. In 2011, the emission curve continued its rightward shift,

transitioning from a single peak to a double peak. This indicated a decrease in emissions in some regions and a widening of the inter-provincial gap. By 2016, the curve had evolved into a "primary and secondary" bimodal pattern with further rightward movement of the center, suggesting an overall increase in intensity but with reductions in some areas, amplifying provincial differences. In 2021, the curve's center moved leftward,
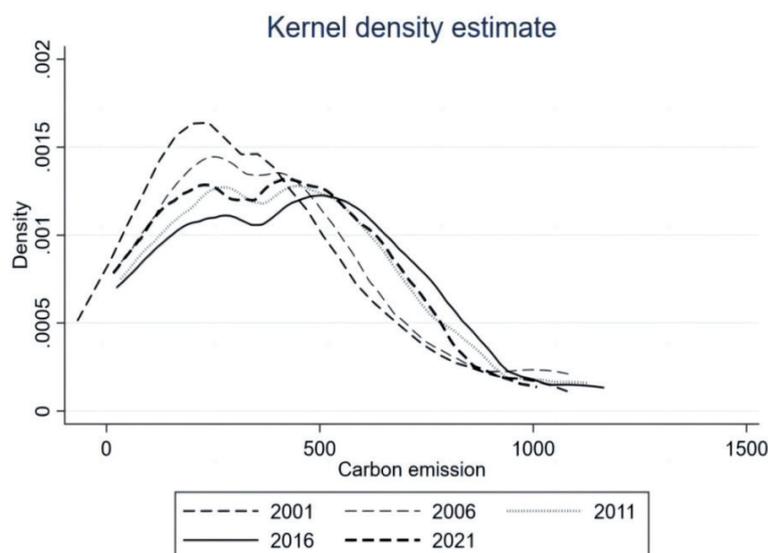
Fig. 2. Results of kernel density analysis of agricultural carbon emissions.

and the pattern developed into a "primary with two smaller" triple-peak, signifying a significant overall reduction in emissions, yet with increases in certain areas, leading to a more dispersed distribution of carbon emissions. Overall, China's agricultural carbon emissions have transitioned from an increasing to a decreasing trend, but the gap between provinces has grown annually. This shift is likely attributable to varying agricultural development strategies, industrial restructuring, and agricultural modernization processes across provinces, where diverse strategies and models have resulted in an expanding inter-provincial disparity in carbon emission intensity.

In addition to analyzing the national overview, this study also delves into the agricultural carbon emissions from four primary sources: agricultural materials, soil, paddy fields, and animal husbandry, with detailed analysis results to follow.

1. The trend of carbon emissions from agricultural materials experienced a significant fluctuation from 2001 to 2021, initially increasing and then decreasing. This trend exhibited a bimodal characteristic in the carbon emission density, signifying simultaneous increases and decreases in different regions and resulting in a varied overall distribution. This shift can be attributed to the 19th Congress of the Communist Party of China (CPC) promoting eco-friendly agriculture and efficient energy use, along with the adoption of renewable energy contributing to the reduction of agricultural carbon emissions.

2. Regarding land carbon emissions, there has been a slight overall decrease, with more noticeable peak variations and growing regional disparities. From 2001 to 2021, these emissions showed a multipolar trend, influenced by industrialization and urbanization processes. Urbanization in the eastern coastal areas and major cities has altered rural land-use patterns, leading to varied carbon emission levels.

3. Carbon emissions from rice cultivation have generally declined, with a relatively narrow curve span and minimal changes in emissions. However, there was a notable peak in 2021, potentially due to advancements in China's rice cultivation technology and agricultural supply-side structural reforms that reduced rice cultivation and, consequently, its carbon emissions.

4. As for carbon emissions from livestock and poultry farming, the overall trend is downward, with a small curve span. A significant decrease was observed between 2001-2006, which coincides with the implementation of stricter "livestock and poultry farming pollution prevention and control regulations" in China. For instance, the rigorous environmental protection standards led to a notable shift in pig farming, exemplified by the "southern pig north" phenomenon.

Overall, the trends in China's agricultural carbon emissions are shaped by a combination of policy guidance, technological progress, industrialization, urbanization, and heightened environmental awareness. These factors have collectively contributed to a complex and dynamic emission pattern, reflecting the regional and intra-industry variability within China's agricultural sector.

Influencing Factors and Peak Carbon Prediction

Global Spatial Autocorrelation Test

Prior to delving into the factors influencing agricultural carbon emissions in China, this study first examines the spatial distribution characteristics of these emissions using the global spatial autocorrelation test. The Moran's I index for agricultural carbon emissions was consistently and significantly positive across all years, oscillating between 0.24 and 0.35. This indicates

a substantial positive spatial autocorrelation. Notably, the value of Moran's I progressively increased from 0.25 in 2000 to 0.323 in 2021. This trend signifies a strengthening of positive correlation over time, implying that the similarity in agricultural carbon emissions among Chinese provinces and their neighboring regions has intensified. Furthermore, the spatial distribution pattern of carbon emissions has increasingly become more clustered. Although there were fluctuations in individual years, the overall trend clearly points towards a rising degree of aggregation.

Regression Analysis of Influencing Factors

The analysis utilized the constructed model as outlined in Equation (8), employing Stata 17.0 for fitting. The resulting mean Variance Inflation Factor (meanVIF) of 4.06 indicates the absence of multicollinearity issues. Within the STIRPAT model framework, all data were logarithmically transformed to enhance linearity and mitigate the effects of heteroskedasticity on time series data, thereby improving the regression results' fit. Table 3 presents the t-test results for the independent variables. These results demonstrate a highly significant linear relationship between the dependent variable, carbon emissions from agricultural land inputs, and the independent variable, the agricultural population. Additionally, the other two variables show a positive correlation with agricultural carbon emissions, lending significance to the regression equation. The model's R-squared (R^2) value of 0.712 suggests that the model fit is adequate. Furthermore, the F-statistic stands at 182.33, and all P-values are below 0.05, collectively affirming the regression equation's robustness and statistical significance.

The regression analysis results reveal that the coefficient for the agricultural population is 0.495. When compared to the effects of other variables on agricultural carbon emissions, the agricultural population emerges as the most significant factor influencing these emissions in China, followed in descending order by per capita agricultural GDP, forestry area, and the level of agricultural technology. Holding other factors constant, a 1% increase in the agricultural population corresponds to a 0.495% increase in carbon emissions. This trend highlights the growing conflict between humans and land resources, necessitating increased agricultural land inputs to boost food production. Nonetheless, China's advancing urbanization is expected to gradually reduce the size of the agricultural population, which may, in turn, dampen carbon emissions from agricultural land inputs. The influence of agricultural technology level on carbon emissions from farmland inputs primarily stems from agricultural economic development, including the sector's transformation and upgrading. The escalated use of agricultural machinery for production purposes inevitably leads to increased energy consumption, which indirectly contributes to a rise in carbon emissions from farmland inputs.

Scenario Design and Trend Forecasting of Agricultural Carbon Emissions

Scenario Design for Agricultural Carbon Emissions

BP neural networks offer an efficient, accurate, and flexible approach for predicting agricultural carbon emissions and are, particularly adept at handling complex datasets and identifying nonlinear relationships. In this study, four BP neural networks were developed using MATLAB. The transfer functions for the hidden and output layers were set as 'tansig' and 'purelin', respectively, with 'trainlm' as the training function. The data samples were initially divided into 15 training and 6 testing groups, and the number of nodes in the hidden layer was optimized through multiple training iterations to finalize its configuration. The resulting model structure was determined to be 3-7-1, exhibiting a training sample mean square error of 0.0396 and an R^2 value of 0.998. Both training and testing outcomes were favorable (as shown in Fig. 3), validating the model's applicability for measurement purposes. Consequently, the study's 683 samples will be analyzed using this optimally trained BP neural network.

Scenario analysis, a prevalent method in carbon emission projection studies, hinges on the scientific rigor of its design for accuracy in predictions. Previous research and policy documents have identified population, economy, and technology level as significant determinants of carbon emissions. Given the challenge of manually adjusting demographic and economic factors within existing policy frameworks and economic contexts, this study forecasts China's agricultural carbon emissions under varying scenarios by modifying the technology level parameter. The technological advancement in agriculture is quantified as the degree of mechanization, measured by the ratio of total agricultural machinery power to the total sown area.

Table 3. Results of regression analysis.

Variable	Regression coefficient	Standard error	T-value	P-value
P	0.495***	0.118	4.12	0.000
A	0.386***	0.081	4.76	0.000
T	0.176**	0.065	2.73	0.011
Constant	-2.559**	1.248	-2.05	0.049
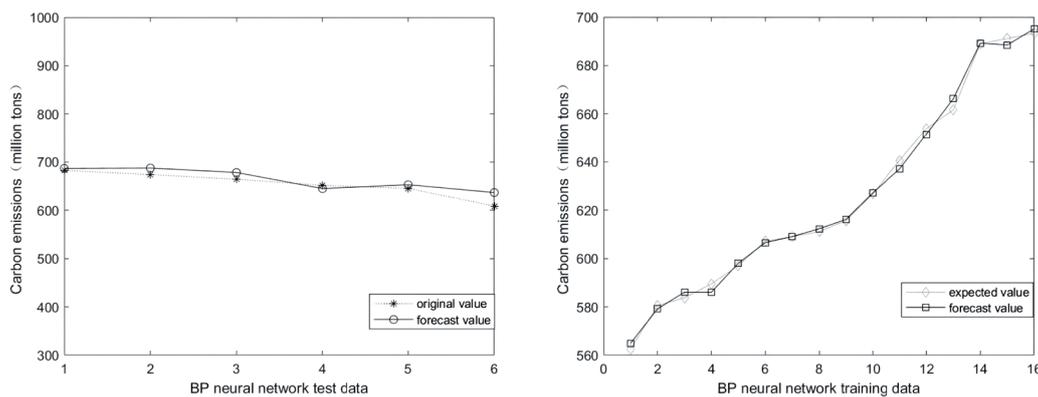
Fig. 3. Training results and prediction data of the BP neural network.

The Chinese government's National Agricultural Mechanization Development Plan for the 14th Five-Year Plan stipulates a target mechanization rate of 75% by 2025. While the contribution rate of agricultural technological progress in developed countries typically exceeds 80%, with the United States and Germany surpassing 90% and the Netherlands reaching up to 97%, China achieved over 60% in 2020 and 70.3% in 2021. Consequently, the projected benchmarks for China's agricultural mechanization in 2022, 2025, 2028, and 2033 are set at 72%, 74%, 77%, and 80% for standard growth; 73%, 80%, 87%, and 95% for high-speed growth; and 71%, 72%, 74%, and 76% for low-speed growth. The baseline mechanization level for 2025, at 74%, aligns closely with the 75% policy target, validating the robustness of the technology level scenario settings employed in this research.

Agricultural Carbon Emissions Trend

The parameters defined in the scenario analysis were integrated into Equation (7) to forecast China's carbon emissions from 2022 to 2033. The projections indicate that for the year 2022, carbon emissions under the baseline, high-speed, and low-speed technology level scenarios are expected to be 12,044, 12,242, and 11,942 tons, respectively. Similarly, for 2028, these projections are 13,344, 14,683, and 12,101 tons, respectively. Utilizing this forecast data, graphical representations were created to illustrate the variations in carbon emissions across the different technology level scenarios.

Fig. 4 presents the carbon emission projections under various technological level scenarios from 2022 to 2034. Relative to the baseline scenario, scenarios with high-speed and low-speed technology levels demonstrate the potential for earlier attainment of carbon emission peaks and reduced peak values. In the baseline technology level scenario (T1), carbon emissions initially peak around 2026, followed by a decline, then a resurgence in 2028, and eventually start decreasing after reaching a second peak in 2030. Under the high-speed technology level scenario (T2), carbon emissions are projected to increase beginning around 2024, peaking in 2028,
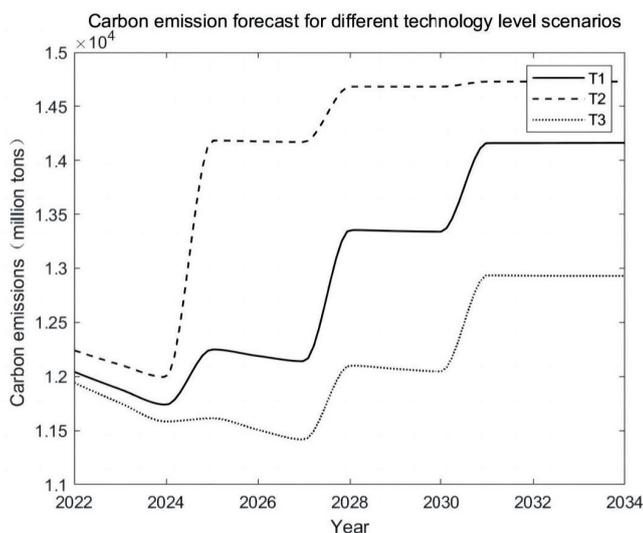
Fig. 4. Carbon Emissions in China under Different Technology Level Scenarios.

Table 4. Results of the robustness test.

Variable	GTWR	Variable	IV	Trimming 1%
Bandwidth	0.115	I	____	0.490*** (0.110)
Residual Squares	1249020	P	0.472*** (0.047)	0.340*** (0.078)
Sigma	42.795	A	0.378*** (0.031)	0.161** (0.059)
AICc	7191.450	T	0.179*** (0.024)	-2.058* (1.157)
Spatio-temporal Distance Ratio	0.642	Constant term	____	-0.846 (2.007)
Trace of S Matrix	58.782	Individual effect	YES	YES
Adjusted R^2	0.974	Time effect	YES	YES
R^2	0.974	R^2	0.681	0.687
N	682	Sample size	651	682

and subsequently diminishing gradually. Conversely, the low-speed technology level scenario (T3) shows a more gradual growth trend, with carbon emissions escalating sharply in 2022, dipping slightly, then increasing again in 2024, peaking around 2026, and thereafter experiencing a steady decrease. Overall, the baseline (T1), high-speed (T2), and low-speed (T3) technology level scenarios indicate a consistent trend: China's agricultural sector's carbon emissions are expected to reach their peak around 2030 within the framework of green development. While the exact peak values may vary, these trajectories underscore the crucial impact of technological advancements in reducing carbon emissions and addressing climate change. By embracing technological upgrades, earlier peaking of carbon emissions can be facilitated, and the magnitude of emissions at the peak can be diminished, offering a viable strategic approach to combating climate change.

Robustness Test

To validate the feasibility and robustness of the empirical findings, this study employs three methods for robustness assessment. Firstly, the analytical model is substituted with the Geographically and Temporally Weighted Regression (GTWR) model for robustness analysis. GTWR is a statistical technique adept at handling spatial heterogeneity, offering significant spatial sensitivity and flexibility. This is crucial since the baseline STIRPAT model does not adequately account for the influence of geographic location on agricultural carbon emissions. Given China's vast and diverse landscape, regions vary in the characteristics and determinants of agricultural carbon emissions. Employing the GTWR model enables the identification of inter-regional differences, thereby enhancing the scientific validity and precision of the research. This approach provides a robust scientific foundation for formulating more targeted and effective regional strategies to mitigate agricultural carbon emissions. Secondly, this study utilizes instrumental variables,

specifically using the lagged values of each explanatory variable as instrumental variables. The two-stage least squares method is then applied to perform a robustness test on the carbon emission efficiency across the three major regions. Thirdly, to factor in the impacts of extreme values and non-randomness, the data undergo a before-and-after 1% trimming process, and the robustness is tested accordingly. The robustness test results, as indicated in Table 4, reveal that the GTWR model exhibits a good fit. The direction and magnitude of its estimated coefficients align closely with those of the original STIRPAT model. Additionally, results from employing lagged instrumental variables and tail-trimming indicate that the nature and significance of the factors remain largely consistent with the initial regression outcomes. These findings collectively reinforce the reliability of the empirical analysis conducted in this study.

Conclusions and Policy Recommendations

Conclusions

This study delves into the spatial and temporal evolution of China's agricultural carbon emissions, based on a comprehensive measurement of these emissions. It examines the influencing factors and dynamic trends, leading to the following key findings:

1. Spatial and Temporal Evolution of Agricultural Carbon Emissions:

From 2000 to 2021, China's aggregate agricultural carbon emissions followed an inverted "U" pattern, initially increasing and then decreasing. During this time frame, emissions from agricultural materials, paddy fields, and livestock and poultry farming exhibited a downward trajectory, while emissions from land use escalated. Spatially, the intensity of agricultural carbon emissions across all Chinese provinces generally declined, with a prominent "high in the west and low in the east" spatial distribution. The spatial autocorrelation

test reveals a significant positive correlation in emissions among provinces, which has strengthened over time. This suggests an increasing similarity in emission patterns across provinces and a rising trend in the spatial concentration of agricultural carbon emissions.

2. Analysis of Influencing Factors and Peak Prediction:

The study identifies the agricultural population as the primary driver of China's agricultural carbon emissions, followed by per capita agricultural GDP and the level of agricultural technology. Population growth intensifies land-use conflicts and influences agricultural inputs and outputs. Urbanization trends, which lead to a decreasing agricultural population, are expected to curtail agricultural carbon emissions. Projections indicate that, despite the challenges posed by agricultural population growth, China's agricultural carbon emissions are likely to reach their peak by 2030 under a scenario driven by technological advancement.

Policy Recommendations

Based on the above conclusions, this paper puts forward the following suggestions:

Optimization of agricultural industry structure and transition to sustainable production modes. To facilitate carbon emission reduction in agriculture, optimizing the industry's structure, encompassing planting, animal husbandry, and forestry, is essential. In the realm of crop production, strategic adjustments to the crop structure can mitigate high-carbon emissions. Implementing practices such as water-saving and drought-resistant crop rotation and diversifying crop types are pivotal measures. For the livestock sector, reconfiguring breeding practices to limit high-emission livestock breeds is advisable, alongside the promotion of low-carbon feed technologies and advanced manure management techniques. In the field of forestry, the efficient utilization of forest resources is key, coupled with the development of ecological forestry and a green economy, including biomass energy and forest-based ecotourism. Additionally, this strategy advocates for the adoption of intensive recycling agriculture and low-carbon agricultural practices, which pivot away from traditional farming methods. This transformation aims to reduce unnecessary energy and material consumption, thereby decreasing agricultural carbon emissions and simultaneously boosting the agricultural economy's quality and efficiency.

To promote carbon emission reduction in agriculture, it is essential to optimize the agricultural industry's structure, encompassing planting, animal husbandry, and forestry. In the planting sector, adjustments should focus on crop diversification to reduce high-carbon emission crops. Strategies like crop rotation and crop type optimization can effectively lower carbon emissions. For livestock, it's advisable to modify breeding practices by decreasing high-carbon emission livestock breeds, adopting low-carbon feed technology, and implementing

advanced manure treatment methods. In forestry, rationalizing forest resource usage and emphasizing ecological forestry and green economy initiatives, such as biomass energy and forest eco-tourism, are encouraged. Furthermore, promoting intensive recycling and low-carbon agriculture is pivotal, transforming traditional agricultural production methods to reduce energy and material inefficiencies, thus decreasing carbon emissions while enhancing agricultural economic quality and efficiency. Agricultural technological innovation aligned with local conditions is pivotal for realizing green agricultural development, encompassing precision techniques, new crop varieties, and ecological models. The research also advocates for green and low-carbon agricultural machinery and equipment development, tailored to geographical conditions, and the adoption of clean energy sources to ensure sustainable and efficient agricultural carbon emission reduction.

To ensure the effectiveness of low-carbon agriculture, it is imperative to conduct a precise analysis of agricultural carbon emissions in each region and develop scientifically sound agricultural carbon reduction plans. These plans should align with regional strategies for rural revitalization and land resource management, incorporating specialized layouts with well-defined objectives and milestones for each phase. Consideration must be given to the geographical variations in the efficiency of agricultural carbon reduction. In major grain-producing regions, promoting agricultural consolidation is vital to reducing the use of chemical fertilizers and pesticides. Meanwhile, regions with high carbon emissions per unit area, such as South China, should receive government support for establishing recycling systems for agricultural waste and data management platforms, along with the advancement of smart agriculture practices. Tailored emission reduction plans should be devised based on the region's unique agricultural development and resource capabilities. The establishment of regional cooperation mechanisms is essential to assimilate the experiences of industrialization and large-scale agriculture development from more advanced regions, thus fostering green and high-quality agricultural growth. Strengthened inter-regional collaboration and mutually beneficial arrangements can leverage the advantages of individual agricultural resource endowments, generate economies of scale, alleviate "resource congestion," and create a conducive environment for advancing agricultural carbon emission reduction across neighboring areas.

The establishment of a comprehensive legal framework for carbon emissions and the development of specialized environmental regulations for agricultural emissions reduction are crucial steps. While China has made initial strides in its environmental legal system, it still requires significant enhancements to align with the goals of carbon reduction and low-carbon agriculture, akin to the legal systems in developed nations. To address this, there is a need to enhance the enforcement efficacy of existing laws and

regulations. This involves bolstering command-type environmental regulations, crafting punitive measures for environmental pollution and degradation, and introducing incentivizing policies aimed at encouraging agricultural enterprises to invest in environmentally friendly practices and energy-efficient low-carbon initiatives, thereby enhancing the overall sustainability of green agricultural production. Furthermore, the introduction of a dedicated Low Carbon Agriculture Law is essential to delineating the responsibilities of legal entities and the roles of law enforcement agencies. This would facilitate the creation of a distinctive low-carbon agriculture legal framework tailored to China's specific circumstances. Such legislation should encompass the oversight of the lawful use and production of materials, including fertilizers, pesticides, plastic mulch, and agricultural energy, by agricultural product manufacturers, farmers, pesticide and chemical fertilizer producers, and agricultural tool manufacturers involved in agricultural production activities. Additionally, it should address the responsible management of livestock and poultry manure through scientifically sound practices.

Elevating awareness of low-carbon development within the agricultural community and fostering the concept of sustainable, eco-friendly practices are pivotal in achieving agricultural carbon emission reduction and the overarching "dual-carbon" objectives. To bolster farmers' understanding of low-carbon and sustainable agriculture, it is essential to amalgamate traditional smallholder farming with modern green agricultural practices. This convergence aims to instill ecological mindfulness and prompt transformative shifts in production methodologies. Concrete steps involve facilitating the organization of farmers, reinforcing agricultural cooperatives, nurturing emerging agricultural production entities, providing comprehensive skills training, offering financial support for agricultural emission reduction initiatives, and upgrading agricultural production technologies. Simultaneously, there is a pressing need to augment investments in the dissemination of agricultural science and technology. This entails optimizing the utilization of chemical fertilizers and pesticides, curbing the deployment of carbon-intensive agricultural materials and equipment, and enhancing the competence of agricultural personnel through targeted training and technology exchanges. Moreover, it is imperative to heighten consumers' cognizance of low-carbon agriculture and guide individuals to embrace a low-carbon consumption pattern through educational campaigns and public outreach efforts. This strategic approach is instrumental in realizing the dual objectives of reducing agricultural carbon emissions and bolstering agricultural carbon sequestration. By implementing these measures systematically, the fruition of agricultural carbon emission reduction and the attainment of the "dual-carbon" goals can be effectively facilitated.

Limitations and Future Perspective

This paper primarily utilizes data from China, constrained by data availability and accuracy. Consequently, the analysis of agricultural carbon emissions may not fully represent global variations. Future research should aim to broaden the geographic scope of data collection to enhance the richness and diversity of the sample. Additionally, while this study employed the STIRPAT model to assess the impacts of population, affluence, and technology level on carbon emissions, it did not comprehensively explore other factors influencing agricultural carbon emissions and their interplay. Future studies could improve upon this by considering the roles of policies, market forces, and technological advancements. Moreover, the current research predominantly concentrates on the general trend of agricultural carbon emissions in China, neglecting the regional nuances. Future investigations should delve into the specific characteristics of agricultural carbon emissions in distinct regions, including their reactions to local policy shifts and environmental changes. This would enable the provision of more precise and tailored recommendations for emission reduction strategies.

Acknowledgments

Data Availability Statement

All of the data are publicly available, and proper sources are cited in the text. The data used to support the findings of this study are available from the corresponding author upon request.

Conflict of Interest

The authors declare no conflict of interest.

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