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Carbon Neutrality, International Trade, and Agricultural Carbon Emission Performance in China

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International trade and agricultural development play important roles in carbon neutrality. This study uses the Malmquist index to quantify agricultural carbon emission performance and the panel data regression model to analyze the relationship between international trade and agricultural carbon emission performance. Data from 2005 to 2020 were used. The results show that the agricultural carbon emission of China has increased slowly since 2005. There is still an improvement space for low-carbon agricultural productivity. As for the relationship between agricultural international trade and carbon emission performance, the coefficient of the total trade in agricultural products is 0.0444. Suggestions on agricultural international trade and the development of low-carbon agricultural production are put forward, which will provide technical support for carbon neutrality.

Keywords: carbon neutral, international trade, agricultural carbon emission, spatial pattern, Malmquist index

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1 INTRODUCTION

Carbon reduction has become the inevitable choice and optimal path to dealing with climate change (Chang and Dong, 2016). The balance between agricultural carbon emissions and economic benefits resulting from trade liberalization and economic development has become an important development indicator (Yang, 2019a). The effects of trade liberalization on agricultural carbon emissions need to be quantified.

The development of China's agricultural trade has encountered major obstacles. After two consecutive years of decline (Bu et al., 2018), China's agricultural imports and trade deficit increased again in 2020. The total import and export of agricultural products exceeded US $200 billion, reaching record highs. The trade deficit, which had been shrinking in the past few years, has grown again, driven by rapid import growth (Wang et al., 2018; Sohlberg and Yvon, 2019). In the process of rapid economic growth, environmental pollution has become increasingly prominent, and global climate change caused by anthropogenic greenhouse gas emissions has become a global concern (Yu and Chen, 2017; Wu et al., 2018). On the relationship between environmental degradation and economic growth, various hypotheses, such as the Porter hypothesis, the pollution haven hypothesis, the resource curse, and the environmental Kuznets curve, have been proposed (Fu et al., 2018). The relationship between economic growth and carbon emissions is becoming a hot research topic in academia (Li, 2013; Yang, 2019b). Compared with the transportation and energy sectors, the agricultural sector contributes less to global emissions (Li, 2012). The rural revitalization strategy of China aims to realize sustainable development of rural areas, which contains requirements for environmental protection, such as establishment of environmental governance systems and improvement of living environments (Balsalobre-Lorente et al., 2019). The agricultural carbon budget of China benefits from trade surplus in major agricultural products, while these benefits have been offset recently because of rapid increases in imports of grains, edible oilseeds, and other agricultural products (Pendrill et al., 2019). Therefore, finding low-carbon pathways to develop China's agricultural sector has become an important priority.

Carbon emissions have attracted the attention of different scholars since the 1990s, and many scholars have begun to explore the relationship between carbon emissions and the economy and trade, especially for the effect of carbon emissions caused environmental problems on economic development (Li and Cui, 2017). Generally, in the early stage of industrial development, the leading industries in the economic structure are mainly agriculture. With economic development and the rapid increase in fossil energy use, carbon emissions will also rapidly increase. In the later stages of industrial development, the economy gradually shifted to the secondary and tertiary industries, the emission structure will be gradually improved by efficient energy use, environmental quality will be further improved, and the evolution of the industry process and the environment Kuznets curve will be fully consistent. In the study of urban air quality, Grossman and Kruger (1991) explored the empirical relationship between environmental quality and per capita income and found that when per capita income reaches $4,000–$5,000, there will be a willingness and tendency to reduce environmental pollution, which proves that the relationship between economic growth and environmental carbon emissions is not entirely conflicted.

Because of strict environmental systems, pollution emissions will slow down at every stage of economic growth below emission levels without institutional impacts. Besides, the inflection point of environmental emissions will occur ahead of time, and the environmental Kuznets curve will become relatively stable, and the curve will be lower. With economic growth, environmental problems will be improved, and in this sense, pollution control is not more important than promoting economic growth. Specifically in terms of carbon emissions, the study points out that the relationship between carbon emissions and GDP per capita is structurally stable, and the relationship between carbon emissions and GDP per capita is upwardly skewed, but economic growth is not sufficient to reduce carbon emissions; thus, all countries should strive to reduce carbon emissions.

2 THEORETICAL FRAMEWORK

Study on the impact of trade on carbon emissions can be divided into three categories **Figure 1**. First, research can be based on the assumption that international trade is conducive to carbon emission reduction (Tian et al., 2016) and that Chinese enterprises will borrow or improve technology (Chen et al., 2019) to meet strict sustainability standards imposed by international clients. Second, some studies are based on the assumption that international trade hinders the reduction of carbon emissions (Cui and Li, 2017); they assume that the pursuit of greater economic benefits in a highly competitive world promotes the adoption of cheaper modes of production at the expense of the environment (Xia, 2014). Third, some studies are based on the assumption that education level, laws, regulations, and other aspects of the country of production jointly determine or influence the national capacity to absorb technology and reduce carbon emissions (Yang and Martinez-Zarzoso, 2014); therefore, these studies assume that the effect of international trade on carbon emissions is ambiguous.

2.1 Capital Formation Resulting From Trade

Agricultural carbon emissions performance is influenced by capital, technology, knowledge, management, and other elements of international trade applied to the national technological level and industrial structure adjustment (Diao et al., 2012). Therefore, in order to understand agricultural trade and mechanisms that influence agricultural carbon emissions performance, it is necessary to first identify spillover effects on the national capital. Existing studies show that the agricultural production of a country is equivalent to that involved in agricultural trade through technology spillovers and industrial connection (Chen and He, 2017). However, this depends on the quantity and quality of the products being exported. If imported products are high in quality or low in cost, they may crowd out the domestic market, while the opposite may happen if imported products are lacking or play a guiding role in the domestic market (Fojtíková, 2018).

2.2 Technology Transfer Resulting From Trade

Technological progress has become an important driving force for industrial development (You and Wu, 2014); especially in modern times, taking advantage of technological progress has become the goal of many governments in the world. The agricultural production of China is impacted by technology transfer from trade, especially when production reaches a certain scale (Cheng et al., 2019). However, extensive agriculture can only meet domestic demands; without an increased focus on pure industrial capital, further development of the agricultural industry would be difficult. Agricultural trade can promote the upgrading of industrial technology through technical assistance and technology licensing and sales, thereby promoting reductions in agricultural carbon emissions (Zhang and Tian, 2019).

2.3 Technology Spillover Resulting From Trade

Technology transfer resulting from trade can lead to agricultural carbon emission reductions across the country. The demonstration and imitation effect and the market competition effect are some of the technology spillover effects of agricultural trade (Jiang et al., 2015; Li et al., 2015). With the development of trade, Chinese enterprises learn from, imitate, and absorb the experience of more technologically advanced countries (Qin, 2013). Therefore, their production and efficiency can be continuously improved, and carbon emissions can be reduced. This demonstration and imitation effect is dependent on the learning capacity of the local production team, as well as the mastery and management of

TABLE 1 | Input and output indicators of agricultural production efficiency index system.

	Variables	Indicators	Units
Input indicators	Labor input	The number of employees in the primary industry	10,000 people
	Land input	Crop planting area	Thousands of hectares
	Fertilizer input	The scalar quantity of agricultural fertilizer	10,000 tons of
	Pesticide input	Pesticide use	Tons of
	Agriculture film input	Agriculture film use	Tons of
	agricultural machinery input	Total power of agricultural machinery	Million kilowatt-hour
Output indicators	Agricultural, forestry, livestock, and fishery output value		100 million yuan
	Agricultural carbon emission		10,000 tons of

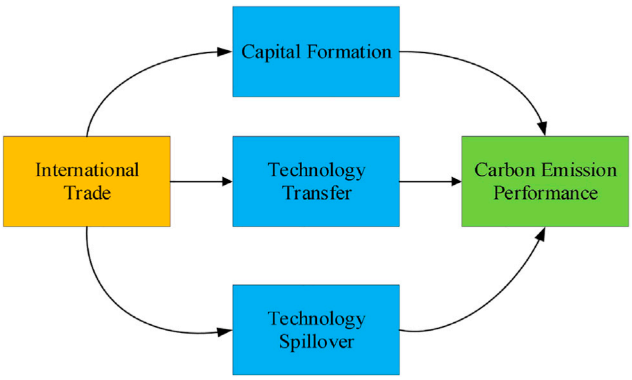

FIGURE 1 | Theoretical framework between international trade and carbon emission performance.

advanced technology (Tian et al., 2014). The market competition effect is an indirect effect, which can be positive or negative. The positive effect leads to more efficient allocation of domestic resources and improvement of national welfare (Rozelle, 2017). Availability of advanced technology from foreign countries intensifies competition among domestic companies, which promotes improved company management, and creates a virtuous circle for the reduction of carbon emissions.

In this study, the mechanism of trade influencing agricultural carbon emission performance is systematically analyzed, the crowding-in and crowding-out effects caused by trade is researched, which can ultimately lead to emission reductions (Zhang et al., 2017). In addition, the structural effect of resource consumption brought about by exports when the country has a dominant market position is examined, which otherwise brings about the imitation of technology and emission reductions.

3 DATA AND METHODS

3.1 Data

On the basis of existing studies, a logical, science-based index system that can evaluate agricultural production efficiency is constructed. It provides a basis for the objective evaluation of agricultural carbon emission performance. Following existing definitions of agricultural production efficiency and similar index systems proposed in other studies and considering data accessibility, purpose, and other factors, the input and output indicators for the index system are identified (**Table 1**). The decision-making unit includes 31 provinces, municipalities, and autonomous regions in China.

Three main categories are included in input indicators: labor, land, and agricultural resources. For each province, municipality, or autonomous region, the number of persons employed in the primary agricultural industry (unit: 10,000 people) is used as the labor indicator. Land indicators include proportions of different crops, proportions of fallow, and abandoned land in different regions. Agriculture consumes resources that mainly include chemical fertilizers, pesticides, agricultural film, farm machinery, and water. The main agricultural resources indicators include quantities of agricultural fertilizer, pesticide, and agricultural film used; total agricultural machinery power (unit: kilowatts); quantity of water used for irrigation; and the surface area of the provincial effective irrigation area.

This study focuses on two output variables: total output of agriculture, forestry, husbandry, and fishery and agricultural carbon emissions.

The data derives from China Statistical Yearbooks from 2000 to 2016, provincial statistical yearbooks in the same period, a collection of agricultural statistical data spanning the last 30 years of reform and opening-up, and a collection of statistical data spanning the 60 years since the establishment of the People's Republic of China. Data availability on use of chemical fertilizers, pesticides, agricultural film, sown area, total power of agricultural machinery, effective irrigation area, and working population involved in the primary agricultural industry varies between years. The total value of agricultural output (gross value of agricultural, forestry, livestock, and fishery output) is calculated using the agricultural producer price index. Constrained by data availability, the study is limited to the provincial level.

3.2 Malmquist Productivity Index

Intertemporal dynamics and the geometric mean of the Malmquist productivity index are utilized to account for the undesired output of carbon emissions. The agricultural carbon emission performance index (ACPTFP) is defined as a slack-based measure of efficiency based on directional distance functions:

$$
\begin{aligned}
ACPTFP\left(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}; x_k^t, y_k^t, b_k^t\right) &= \left[\frac{\overrightarrow{S_c^t}\left(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}\right)}{\overrightarrow{S_c^t}\left(x_k^t, y_k^t, b_k^t\right)} \times \frac{\overrightarrow{S_c^{t+1}}\left(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}\right)}{\overrightarrow{S_c^{t+1}}\left(x_k^t, y_k^t, b_k^t\right)}\right]^{\frac{1}{2}} \\
&= \frac{\overrightarrow{S_c^{t+1}}\left(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}\right)}{\overrightarrow{S_c^t}\left(x_k^t, y_k^t, b_k^t\right)} \times \left[\frac{\overrightarrow{S_c^t}\left(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}\right)}{\overrightarrow{S_c^{t+1}}\left(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}\right)} \times \frac{\overrightarrow{S_c^t}\left(x_k^t, y_k^t, b_k^t\right)}{\overrightarrow{S_c^t}\left(x_k^t, y_k^t, b_k^t\right)}\right]^{\frac{1}{2}} \\
&= EC\left(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}; x_k^t, y_k^t, b_k^t\right) \times TC\left(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}; x_k^t, y_k^t, b_k^t\right)
\end{aligned} \tag{1}
$$

where ACPTFP between time period t and $t+1$ is calculated by multiplication, division, and referencing to adjacent time periods and can be decomposed into the technology efficiency change index (EC) and the technology progress index (TC). An ACPTFP value greater than 1 indicates an increase in carbon emission performance; otherwise, it indicates a decrease in performance. An EC value greater than 1 indicates improvement in technical efficiency; otherwise, it indicates deterioration of technical efficiency. A TC value greater than 1 indicates advance of the agricultural production technology frontier; otherwise, it indicates a retreat.

3.3 Panel Data Regression Model

Agricultural trade and carbon emissions performance involve technology spillovers and effects that are similar to those of foreign direct investment. Therefore, the international direct investment model of Coe and Helpman (1995) is also used, which has been widely adopted and has become a classic international technology spillover model:

$$LnTFP_i = \alpha_i^0 + \alpha_i^d \ln S_i^d + \alpha_i^f \ln S_i^f \tag{2}$$

where, i represents the region, $LnTFP$ represents the agricultural carbon emission performance, $\ln S_i^d$ represents the spillover stock of domestic research and development (R&D) investment, and $\ln S_i^d$ represents the spillover stock of foreign R&D investment obtained from agricultural trade. According to this model, national productivity depends on its own R&D investment and knowledge spillover from foreign R&D. Based on an econometric model, the carbon emission performance index (ACPTFP) is defined as follows:

$$ACPTFP = \alpha_0 + \alpha_1 TRADE_{it} + \alpha_2 RDG + \mu_i + \varepsilon_{it} \tag{3}$$

where i and t represent the different provinces and time, respectively; ACPTFP represents the agricultural carbon emission performance; TRADE represents the agricultural product; RDG represents the domestic R&D investment; μ_i is the unobservable regional effects; and ε_{it} is the random disturbance terms. Studies have indicated that human capital can influence technological innovation and the capacity and speed at which foreign technologies can be absorbed. Besides, financial development is able to bring about sufficient capital to satisfy demand and can also provide credit funds to support innovations in production and environmental protection technologies. As more innovations are supported, there is a higher chance that at least some will succeed, guaranteeing carbon emission reductions. Environmental regulation is an important variable and affects agricultural carbon emissions in two ways. On the one hand, regulations can add compliance costs, raising production costs and forcing companies that are unable to bear these new costs to be crowded out of the market. On the other hand, companies that adopt new technology to follow higher environmental standards may become more competitive and be compensated by being chosen by more consumers. Besides, different industrial structures will also have an impact on agricultural carbon emissions. Therefore, human capital, financial development, environmental regulation, and industrial structure are included into the empirical model for agricultural carbon emissions performance:

$$
\begin{aligned}
ACPTFP = \alpha_0 + \alpha_1 TRADE_{it} + \alpha_2 RDG_{it} + \alpha_3 HUM_{it} + \alpha_4 FIN_{it} \\
+ \alpha_5 REG_{it} + \alpha_6 IND_{it} + \mu_i + \varepsilon_{it}
\end{aligned} \tag{4}
$$

where HUN_{it} represents the human capital, FIN_{it} represents the financial development, REG_{it} represents the environmental regulation, IND_{it} represents the industrial structure, and ε_{it} represents the random disturbance term.

Studies show that agricultural trade and financial development have effects on agricultural carbon emissions. Reduction in carbon emissions can lead to more sustainable and competitive products, which, in turn, impact economic growth and trade. Besides, economic growth can also increase demands for financial and other products. Therefore, the empirical model for agricultural carbon emissions performance is further modified. A first-order lag term of agricultural carbon emission performance is introduced to address possible endogeneity issues and time series data gaps:

$$
\begin{aligned}
ACPTFP_{it} = \beta_0 + \beta_1 ACPTFP_{i,t-1} + \beta_2 TRADE_{it} + \beta_3 RDG_{it} \\
+ \beta_4 HUM_{it} + \beta_5 FIN_{it} + \beta_6 REG_{it} + \beta_7 IND_{it} + \mu_i \\
+ \varepsilon_{it}
\end{aligned} \tag{5}
$$

where $ACPTFP_{i,t-1}$ represents the first-order lag term of agricultural carbon emission performance. To ensure the consistency of coefficient and standard error estimates without having to determine the form of conditional variance functions, the ordinary least squares (OLS) regression is performed, and heteroscedasticity-robust standard errors of coefficients are calculated.

4 RESULTS AND DISCUSSION

4.1 Agricultural Carbon Emission Performance

The ACPTFP is calculated on the basis of relative efficiency. Therefore, interpretation and analysis of ACPTFP values are a form of dynamic analysis that takes into account relative effects.

Low-carbon agricultural productivity has increased slowly since 2005 (**Table 2**). The average annual contribution of technical efficiency (EFF) to productivity is only 0.04%. The average annual contribution of scale efficiency (SECH) to productivity has been increasing slightly, by 0.10% annually, while that of pure technical efficiency (PECH) has been

TABLE 2 | Agricultural carbon emission performance, 2005–2020.

Time Period	ACPTFP	EC	TC
2005–2006	1.0290	0.9880	1.0427
2006–2007	1.0202	1.0338	0.9955
2007–2008	1.0561	1.0156	1.0480
2008–2009	1.0879	1.0196	1.0725
2009–2010	1.0825	1.0122	1.0737
2010–2011	1.0831	1.0063	1.0805
2011–2012	1.0946	1.0067	1.0911
2012–2013	1.1031	1.0081	1.0974
2013–2014	1.1029	1.0088	1.0962
2014–2015	1.1073	1.0085	1.1006
2015–2016	1.1142	1.0071	1.1089
2016–2017	1.1138	1.0065	1.1089
2017–2018	1.1115	1.0064	1.1065
2018–2019	1.1080	1.0055	1.1039
2019–2020	1.1036	1.0053	1.0996

decreasing by 0.06% annually. There is still an improvement space for low-carbon agricultural productivity.

4.2 Impact of Agricultural Trade on Agricultural Carbon Emission Performance

To identify the most appropriate model for the data, the F test and the Hausman (H) test are utilized. The null hypothesis of the F test is that the mixed regression model is superior, and it is rejected because of the *p* value of 0.00 (**Table 3**). The null hypothesis of the H test is that the random-effects model is superior, and it is rejected because of the *p* value of 0.00. Therefore, the fixed effect model is chosen.

To measure the impact of agricultural trade on carbon emission performance, the OLS and the generalized method of moments (GMM) are used to estimate parameters in the model and calculate heteroscedasticity-robust standard errors of the coefficients. In order to minimize errors and effects of missing variables, all variables are entered into the model to determine the role of agricultural trade. Then, to estimate model parameters, other control variables were added in order, so that the effect of each control variable could be identified. Models (1)–(3) are calculated using the OLS and robust standard errors (**Table 4**). Only the impacts of trade and human capital on emission performance are included in Model (1). Some variables of industrial development and environmental regulation are included in Model (2), and more variables are included in Model (3). All variables are statistically significant in both models. For Model (4), the Wald test is statistically significant at the 1% level. The Sargan test fails to reject the null hypothesis; therefore, all instruments are valid. The AR (1) and AR (2) tests fail to reject the null hypotheses; therefore, there is no first- or second-order autocorrelation. These test results prove the robust dynamic panel model and reliable estimates of parameters. In addition, the coefficient of the first-order lag term of agricultural carbon emission performance is positive and large, indicating that emission performance is affected by the variables in the model and is also negatively affected by emission performance of the previous period.

Columns 2–4 show results from the OLS regression; numbers in brackets are *t*-values of the standard error of the variable. Column 5 shows results from the GMM; numbers in brackets are *Z*-values of the variable or *p*-values of the Wald, AR (1), AR (2), and Sargan tests.

Model (4) is examined more closely to explore its economic significance. The coefficient of total agricultural trade is 0.0444, which is statistically significant at the 5% level, indicating that agricultural trade significantly promotes emission performance. The results are consistent with findings reported in other studies, the agricultural sector of China is at the stage of learning and adopting advanced technology from foreign countries; its production systems are being upgraded in the process.

Trade has led to a large number of foreign products entering the Chinese market, meeting the needs of Chinese people. It has also brought advanced technology and management standards to China. Although these technologies are less advanced compared with those of foreign countries, they have considerably increased average domestic production. Therefore, trade has had a strong effect on the increase in agricultural carbon emission performance, validating the hypothesis of technology spillover. In addition, some agricultural enterprises will move into the agricultural service sector to help other companies to upgrade their technologies. Through the demonstration and imitation effect, domestic agricultural production will be transformed, and competition in the domestic market will be accelerated.

Through comparative analysis among different regions, it can be found that from the perspective of regional heterogeneity, the proportion of the tertiary industry to the performance of agricultural carbon emissions has a difference in the eastern region, the central region, the western region, and the northeast region. Besides, in the eastern and northeast regions, the proportion of the first industry to the performance of agricultural carbon emissions shows a negative effect, while in the central and western regions, the proportion of the first industry to the performance of agricultural carbon emissions shows a positive effect, which is due to the development of the region. From a national perspective, the performance of agricultural carbon emissions showed a downward trend with the increase of the proportion of the agricultural output value, indicating that the development of agriculture needs to achieve green transformation and high-quality development, rather than the current high-emission, high-energy consumption. It is

TABLE 3 | F and Hausman (H) tests of fixed effects and random effects.

Inspection Method	Null Hypothesis	Statistics	Value of *P*
F test	Mixed regression model is better	3.46	0.0000
H test	The random-effects model is better	201.16	0.0000

TABLE 4 | Results of multiple regression models.

Variable	OLS Regression			System GMM
	(1)	(2)	(3)	(4)
ACPTFP (−1)				−2.5393***
				(−7.16)
ATD (−1)	0.0027*	−0.0033*	−0.0046**	0.0444**
	(1.02)	(−1.76)	(−2.03)	(3.86)
HUM	1.26**	1.7225***	1.7031***	4.2143***
	(2.54)	(2.89)	2.86	(3.14)
IND		2.7446***	2.7475***	0.08178
		(5.38)	(5.39)	(0.55)
IND (−1)		−2.5198***	−2.5148***	−0.0034**
		−5.63	(−5.62)	(−2.94)
REG			0.0658	0.3613
			(1.05)	(1.21)
F	3.34	10.15	8.34	
Wald				59.23*** (0.000)
AR (1)				−1.04 (0.30)
AR (2)				−1.33 (0.18)
Sargan				14.77 (0.32)

*Note: *, **, and *** represent statistical significance at the 10, 5, and 1% levels, respectively.*

necessary to turn to more energy-saving and low-consumption links; at the same time, the central and western regions of fertilizer, pesticides, and other agricultural carbon emissions performance is the main reason for the low.

At the regional level, the ratio of agricultural exports to the total value of primary industry is negatively related to agricultural carbon emission performance, which shows that the main role of agricultural exports in agricultural carbon emission performance is the increase of agricultural carbon emissions. Although the size of the role is different among regions, the central region has the greatest role and the negative effect at the national level.

The ratio of agricultural imports to the first industry has a positive effect on the performance of agricultural carbon emissions at the regional level, where the central region exerts the greatest role, which is linked to the regional geographical location and characteristics. Besides, agricultural imports can bring advanced management and technical experience to the region, thus further improving the performance of agricultural carbon emissions.

The proportion of agricultural labor force to the national labor force has a negative effect on the performance of agricultural carbon emissions, except for the western region. It is closely related to the large area of local land and sparsely populated area, and the increase of agricultural labor force in the western region will strengthen the existing labor force's efforts in agriculture, thereby reducing agricultural carbon emissions and improving agricultural carbon emission performance.

The urbanization rate has a negative effect on the performance of agricultural carbon emissions, except for the western region. It is due to the increase of agricultural production demand in the process of urbanization, resulting in the blind expansion of regional production, thus reducing the performance of agricultural carbon emissions. For the western region, the level of agricultural carbon emission performance still needs to be further improved, and for this reason, the expanded agricultural production demand will drive the performance of agricultural carbon emissions in the western region.

5 CONCLUSION AND DISCUSSION

In this study, carbon emission performance is calculated, and the effect of international trade on carbon emission performance is assessed. agricultural carbon emission performance has increased slowly since 2005. The average annual contribution of EFF to productivity is only 0.04%. The average annual contribution of SECH to productivity has been increasing slightly, by 0.10% annually, while that of PECH has been decreasing by 0.06% annually. There is still an improvement space for low-carbon agricultural productivity. In the econometric model of agricultural carbon emission performance, the coefficient of total trade in agricultural products is 0.0444, which is statistically significant at the 5% level, indicating that agricultural trade significantly promotes emission performance. The results are consistent with findings reported in other studies. The agricultural sector of China is at the stage of learning and adopting advanced technology from foreign countries; its production systems are being upgraded in the process. The results disclose the relationship among carbon neutrality, international trade, and carbon emission performance, which is of vital importance to future carbon neutrality. The countryside is the main area of the ecological environment, and the ecology is the biggest development advantage of the countryside. Rural industries should be greener. We must really make good use of the "two mountains" concept; continuously improve the "value" of green waters and green mountains; explore the "value" of Jinshan Yinshan; accelerate the development of forest and grassland tourism, river and lake wetland tourism, and other emerging industries; actively develop tourism agriculture, green health, ecological education, and other services; and walk out of a sustainable rural development path of ecological beauty, industrial prosperity, and people's prosperity. Agricultural emission reduction does not mean not to apply fertilizer, not to spray medicine, or not to raise pigs but to work the reduction cycle and turn waste into treasure. It is necessary to continue promoting the reduction of chemical fertilizers and pesticides, the replacement of chemical fertilizers with organic fertilizers for fruit and vegetable tea, and green prevention and control products and technologies. It is necessary to promote the resource utilization of agricultural waste, so that livestock and poultry manure can be turned into biogas power generation, biogas slurry and biogas residue can be used as organic fertilizer, and straw can be used as biomass fuel.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

GL and XZ conceived the study and wrote the paper. GL and CH analyzed data for figures and tables. All authors contributed to manuscript development and edited the final version.

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