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Study on Spatiotemporal Characteristics of the Impacting Factors of Agricultural Carbon Emissions Based on the GTWR Model: Evidence from the Yellow River Basin, China

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ABSTRACT

Scholars have turned their attention to the ecological protection and high-quality development of China's Yellow River Basin in recent years. The basin is a major agricultural production area in China, hence investigating agricultural carbon emission reduction strategies in the basin is crucial. The research object in this article is the agricultural departmen.ts of China's nine provinces in the Yellow River Basin from 2005 to 2018. Agricultural carbon emissions are measured using agricultural land usage, rice planting, crop planting, straw burning, and livestock breeding as agricultural carbon sources. In addition, the GTWR model is used to examine the spatiotemporal aspects of the impact of five factors on agricultural carbon emissions in this paper. The findings reveal that the five factors have varying degrees and directions of influence.

INTRODUCTION

The human ecological ecosystem has been seriously harmed in recent years. Excessive carbon emissions exacerbate the greenhouse effect, causing the average temperature of the earth's surface to rise, resulting in catastrophic effects such as glacier melting and sea-level rise. The global temperature might rise by 1.5°C in the next 30 years (IPCC 2018). As a result, lowering carbon emissions is critical. Although the carbon emissions of the industrial and service sectors considerably outnumber those of other sectors, agriculture's rapid growth also generates a significant amount of carbon emissions. China's agricultural greenhouse gas emissions, as a significant agricultural country, contributed to a rising proportion of global total emissions. The percentage was as high as 13.07% in 2016 (FAO 2021). As a result, China's efforts to minimize agricultural carbon emissions are critical.

Scholars are increasingly delving into the topic of agricultural carbon emissions. This article categorizes the literature based on three factors.

To begin, scholars have a variety of options when it comes to agricultural carbon emissions sources. Some academics define agriculture in a very narrow way, referring just to the planting sector (Wang et al. 2015). They are primarily interested in the carbon emissions caused by agricultural land use. Pesticides, chemical fertilizers, agricultural plastic films, fossil fuels, electricity, and ploughing were chosen as agricultural carbon sources by Lu et al. (2018) and Zhou et al. (2021). Han et al. (2018), Cui et al. (2021), and Huang et al. (2019) added rice planting, straw burning, and crop planting to the list of sources, respectively. Agriculture is also defined in a broad sense by some researchers, which includes animal husbandry (Xiong et al. 2016, Guo et al. 2021).

Secondly, scholars have studied the influencing factors from various aspects, such as agricultural production (Owusu & Asumadu-Sarkodie 2017), agricultural mechanization (Ismael et al. 2018), agricultural opening (Cui et al. 2018), rural population (Chen et al. 2018), land use area (Zhao et al. 2017), energy consumption (Zhang et al. 2019), urbanization (Ridzuan et al. 2020), agricultural technological progress (Chen et al. 2019) and agricultural industrial structure (Guo et al. 2021).

Thirdly, scholars will adopt different methods according to different purposes and data characteristics to study influencing factors. As for time series, scholars often use the autoregressive distributed lagged (ARDL) model (Saboori et al. 2016) and the ordinary least squares (OLS) model (Danish et al. 2017). As for panel data, scholars often use the fixed effects (FE) model (Nassani et al. 2017). To solve the endogenous problem, some scholars use the generalized method of moments (GMM) model (Qureshi et al. 2017). In addition, some researchers have begun to take into account the regional variability of contributing factors, opting for a geographically weighted regression (GWR) model (Wang & Zhang 2020). Some researchers use the geographically and temporally weighted regression (GTWR) model to analyze elements that are spatially and temporally heterogeneous (Chen et al. 2019).

The Yellow River, the second-longest river in China, with a length of about 5,464 kilometers and a drainage area of about 752,443 square kilometers, is dominated by dryland agriculture. This paper selects nine provinces (autonomous regions) including Shanxi, Inner Mongolia, Shandong, Henan, Sichuan, Shaanxi, Gansu, Qinghai, and Ningxia in the basin as the study area. Agriculture in the nine provinces increased fast between 2005 and 2018, resulting in a large number of carbon emissions. As a result, understanding the factors that influence agricultural carbon emissions in the nine provinces is critical to the Yellow River Basin's biological ecosystem.

In summary, selecting nine provinces in the Yellow River Basin as the research area, this paper chooses agricultural land use, rice planting, crop planting, straw burning, and livestock breeding as agricultural carbon sources, and estimates the agricultural carbon emissions of the basin from 2005 to 2018. And then appropriate influencing factors are chosen to analyze the spatiotemporal characteristics based on the GTWR model.

MATERIALS AND METHODS

Estimation of Agricultural Carbon Emissions

Carbon emissions from agricultural land use: The carbon sources, coefficients, and references are shown in Table 1. The six-carbon sources are measured by the amount of pesticides, agricultural fertilizers, agricultural plastic film, agricultural diesel fuel, the effective irrigation area, and the total sown area of crops.

Carbon emissions from rice planting: This research relates to Min et al. (2012)'s study, which considers the CH4 emission coefficients of different types of rice in different regions, as indicated in Table 2 to assess carbon emissions from rice cultivation. The yields of early rice (ER), late rice (LR), and in-season rice (IR) in each region are measured by their sown area.

Carbon emissions from crop planting: During the process of crop planting, the soil will emit N_2O. This paper refers to

Table 1: The agricultural land use carbon source coefficients and references.

Source	Coefficient	Reference
Pesticides	4.9341kg $CE.kg^{-1}$	Oak Ridge National Laboratory
Fertilizers	0.8956kg $CE.kg^{-1}$	Oak Ridge National Laboratory
Agricultural Film	5.1800kg $CE.kg^{-1}$	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University
Diesel fuel	0.5927kg $CE.kg^{-1}$	IPCC
Irrigation	20.4760kg $CE.hm^{-2}$	Dubey and Lal (2009)
Plowing	312.6000kg $CE.km^{2}$	College of Biology and Technology, China Agricultural University

Table 2: CH_4 emission coefficients of rice in nine provinces of the Yellow River Basin ($g.m^{-2}$).

Province	ER	LR	IR	Province	ER	LR	IR	Province	ER	LR	IR
Shanxi	0	0	6.62	Henan	0	0	17.85	Gansu	0	0	6.83
Inner Mongolia	0	0	8.93	Sichuan	6.55	18.5	25.73	Qinghai	0	0	0
Shandong	0	0	21	Shaanxi	0	0	12.51	Ningxia	0	0	7.35

Table 3: N_2O emission coefficients of various crops ($kg.hm^{-2}$).

Crop	Coefficient	Crop	Coefficient
Rice	0.24	Corn	2.532
Spring Wheat	0.4	Vegetables	4.944
Winter Wheat	1.75	Other Upland Crops (Potato, Peanut, Rapeseed, Cotton, Sugar cane, Beet)	0.95
Soybean	2.29		

the study of Min et al. (2012), and considers the N_2O emission coefficients of different types of crops, as shown in Table 3. The yield of various crops is measured by their sown area.

Carbon emissions from straw burning: Straw burning also produces carbon emissions. This paper refers to the study of He et al. (2018), which considers the carbon emission coefficients of different types of crop straw burning, as shown in Table 4. The amount of various crop straw burning is represented by its total output.

Carbon emissions from livestock breeding: In the process of livestock breeding, the enteric fermentation will produce CH_4, and the manure emissions will produce CH_4 and N_2O. The greenhouse gas emission coefficients of several cattle breeds are provided in Table 5 in this work, based on Min et al. (2012) and Xu et al. (2019) research.

Since the feeding cycles of livestock are different, the average annual feeding amount of livestock should be adjusted. The slaughter rates of rabbits, pigs, and poultry are greater than 1, and their average life cycles are 105 days, 200 days, and 55 days respectively. Therefore, the average feeding amount is adjusted as follows (Equation (1)):

$$N_i = D\_alive_i \times \frac{M_i}{365} \quad \ldots(1)$$

N_i is the annual average breeding amount for livestock. D_alive_i is the average life cycle for livestock. M_i is the annual production amount for livestock.

The slaughter rates of the other livestock are less than 1, so the average feeding amount is adjusted as follows (Equation (2)):

$$N_i = (C_{i,t} + C_{i,t-1})/2 \quad \ldots(2)$$

N_i is the annual average breeding amount for livestock. $C_{i,t}$, $C_{i,t-1}$ are the stocks of livestock at the end of year t and t-1, respectively.

Estimation of the scale and intensity of agricultural carbon emissions: The greenhouse effect produced by 1 ton of CH_4 is equivalent to the greenhouse effect produced by approximately 6.82 tons of carbon, and the greenhouse effect produced by 1 ton of N_2O is approximately equal to the greenhouse effect produced by 81.27 tons of carbon (IPCC 2008). Therefore, when calculating agricultural carbon emissions, CH_4 and N_2O emissions can be converted into carbon equivalent.

The calculation method of the agricultural carbon emission scale is shown in Equation (3):

$$\begin{aligned} ACE &= \Sigma ACE_l + \Sigma ACE_r + \Sigma ACE_p + \Sigma ACE_b + \Sigma ACE_s \\ &= \Sigma\omega_l\alpha_l^C + \Sigma\mu_r\beta_r^{CH_4} \times 6.82 + \Sigma\theta_p\gamma_p^{N_2O} \times 81.27 + \Sigma\eta_b\alpha_b^C \\ &\quad + \Sigma\left(\lambda_s\beta_s^{CH_4} \times 6.82 + \lambda_s\gamma_s^{N_2O} \times 81.27\right) \end{aligned} \quad \ldots(3)$$

ACE is the scale of agricultural carbon emissions. *ACEl, ACEr, ACEp, ACEb, ACEs* are the carbon emissions from agricultural land use, rice planting, crop planting, straw

Table 4: Carbon emission coefficients of major crop straw burning（kg.CE.kg^{-1}）.

Crop	Coefficient	Crop	Coefficient	Crop	Coefficient
Rice	0.18	Corn	0.17	Soybean	0.15
Wheat	0.16	Rapeseed	0.22	Cotton	0.13

Table 5: Greenhouse gas emission coefficients of various species of livestock (kg.(head·a)$^{-1}$).

Livestock	CH_4 Emission Coefficients		N_2O Emission Coefficients
	Enteric Fermentation	Manure Emissions	Manure Emissions
Dairy Cow	68	16	1
Non-dairy Cow	51.4	1.5	1.37
Mule	10	0.9	1.39
Camel	46	1.92	1.39
Donkey	10	0.9	1.39
Horse	18	1.64	1.39
Sheep	5	0.16	0.33
Rabbit	0.254	0.08	0.02
Live Pig	1	3.5	0.53
Poultry	-	0.02	0.02

burning, and livestock breeding. ω_l, μ_r, θ_p, η_b, λ_s are the amounts of carbon sources for agricultural land use, rice planting, crop planting, straw burning, and livestock breeding. $\alpha_l^C, \beta_r^{CH_4}, \gamma_p^{N_2O}, \alpha_b^C, \beta_s^{CH_4}, \gamma_s^{N_2O}$ are the greenhouse gas emission coefficients corresponding to the carbon sources.

Agricultural carbon emission intensity is measured by the ratio of the scale of agricultural carbon emissions to the total output value of agriculture, forestry, animal husbandry, and fishery.

Selection of Influencing Factors

Agricultural technological progress (TECH): TECH has an important impact on ACE reduction (Chen et al. 2019). TECH can increase energy utilization and reduce the waste of agricultural materials. And it can optimize the allocation of elements and improve production efficiency, thereby improving agriculture productivity. This paper uses the DEA-Malmquist model (Fare et al. 1994) to measure TECH from the perspective of input and output. The input indicators are selected from the four aspects of labor, land, capital, and mechanization input, which are the number of employees in the primary industry, the total sown area of crops, the fixed asset investment in the primary industry, and the total power of agricultural machinery. The total output value of the primary industry is selected as the output indicator.

Urbanization (URBAN): The improvement of URBAN will promote ACE (Cui et al. 2018). The increase in URBAN means more farmers will move to cities, and they will lease land to farmers who still stay in the countryside, thus integrating agricultural land and helping farmers to use land more efficiently. Then the income of rural households has increased, and farmers can purchase and use more energy in agricultural production, thereby increasing ACE (Chen et al.2013). This article uses the proportion of the urban population in the permanent population at the end of the year to measure URBAN.

Rural education (EDU): The improvement of EDU can curb ACE. The improvement of EDU helps to strengthen farmers' understanding of low-carbon agriculture and improve their ability to use agricultural production technologies, thereby improving production efficiency and reducing ACE (Guo et al. 2021). This article uses per capita of number of years of education in rural areas to measure EDU.

Agricultural industrial structure (STRU): The agricultural materials used in the process of planting crops are an important source of ACE (Tian et al. 2016). That means the higher the proportion of the planting industry is, the more ACE will be. This paper uses the ratio of the total output value of the planting industry to the total output value of agriculture, forestry, animal husbandry, and fishery to measure STRU.

Rural economic development(RGDP): The improvement of RGDP would curb ACE, because the study area changed the way of agricultural development, ensuring the development of the agricultural economy while also preventing damage to the ecological environment (Cui et al. 2018). This article uses the per capita gross production value of agriculture, forestry, animal husbandry, and fishery to measure RGDP.

Research Methodology

Huang et al. (2010) proposed the GTWR model, which can better analyze the spatiotemporal non-stationary characteristics of each variable. The model is as follows:

$$y_i = \beta_0(\mu_i, v_i, t_i) + \sum_k \beta_k(\mu_i, v_i, t_i) x_{ik} + \varepsilon_i \quad \ldots(4)$$

i is the serial number of the point. . (μ_i, v_i, t_i) is the coordinate of the point. y_i is the dependent variable. x_k is the independent variable. ε_i is the error term. β_k is the function related to the coordinate (μ_i, v_i, t_i). See Equation (5) for details:

$$\hat{\beta}(\mu_i, v_i, t_i) = \left(X^T W(\mu_i, v_i, t_i) X\right)^{-1} X^T W(\mu_i, v_i, t_i) y \quad \ldots(5)$$

W is a diagonal matrix. Each element in the matrix represents the weight of the corresponding observation point i. The Gaussian spatiotemporal kernel function is used to determine the weight, as shown in Equation (6):

$$W_{ijs,T}^t = \exp\left(-\frac{d_{s_{ij}}^2}{b_S^2}\right) \times \exp\left(-\frac{d_{t_{ij}}^2}{b_T^2}\right) \quad \ldots(6)$$

$d_{s_{ij}}^2$ and $d_{t_{ij}}^2$ represent the spatial distance and time distance between the data point j and the regression point i respectively. See Equations (7) and (8) for details:

$$d_{s_{ij}}^2 = (\mu_i - \mu_j)^2 + (v_i - v_j)^2 \quad \ldots(7)$$

$$d_{t_{ij}}^2 = (t_i - t_j)^2 \quad \ldots(8)$$

b_S and b_T represent the spatial bandwidth and the temporal bandwidth respectively. The method of selecting the optimal bandwidth is cross-validation (CV). See Equation (9) for details:

$$CV(b_S, b_T) = \sqrt{\sum_{i=1}^{n} \left(y_i - \hat{y}_{-i}(b_S, b_T)\right)^2 / n} \quad \ldots(9)$$

$\hat{y}_{-i}$ is the fitted value of y_i. The point i does not include in the calibration process. b_S and b_T are the optimal space bandwidth and time bandwidth respectively when CV takes the minimum value.

Then, the variables selected above are introduced into Equation (1) to obtain Equation (10):

$$\ln ACEI_i = \beta_0(\mu_i,\nu_i,t_i) + \beta_1(\mu_i,\nu_i,t_i)\ln TECH_i + \beta_2(\mu_i,\nu_i,t_i)\ln URBAN_i + \beta_3(\mu_i,\nu_i,t_i)\ln EDU_i + \beta_4(\mu_i,\nu_i,t_i)\ln STRU_i + \beta_5(\mu_i,\nu_i,t_i)\ln RGDP_i + \varepsilon_i \quad \ldots(10)$$

$\beta_1(\mu_i, \nu_i, t_i)$, $\beta_2(\mu_i, \nu_i, t_i)$, $\beta_3(\mu_i, \nu_i, t_i)$, $\beta_4(\mu_i, \nu_i, t_i)$, $\beta_5(\mu_i, \nu_i, t_i)$ are the change rates of the ACEI of each province with TECH, URBAN, EDU, STRU, and RGDP, respectively.

Data Sources

The above data are from China Statistical Yearbook, China Livestock Industry Yearbook, China Rural Statistical Yearbook, China Agricultural Statistics, China Agricultural Machinery Industry Yearbook, China Population and Employment Statistics Yearbook, and open data from the National Bureau of Statistics. Some missing values are filled by interpolation. All the variables are taken to the logarithm to unify the magnitude. The descriptive statistics of variables are shown in Table 6.

RESULTS AND DISCUSSION

Empirical Results of GTWR

This paper uses the GTWR model to analyze the spatiotemporal characteristics of the influencing factors. Firstly, SPSS was used to analyze the variance inflation factor (VIF) showing that there was no obvious multicollinearity. Then, use OLS, TWR, GWR, GTWR models in ArcGIS. The evaluation indicators are shown in Table 7. The R^2 of the GTWR model is the largest. The AIC of the GTWR model is the smallest. Therefore, the GTWR model is a better choice. Finally, the GTWR model is used to obtain the estimated results of the coefficients of variables. The descriptive statistics of the coefficients are shown in Table 8.

Spatiotemporal Evolution of Influencing Factors

(1) The coefficients of lnTECH in most provinces are negative, indicating that TECH has an inhibitory effect on ACEI (Table 9). In 2005 and 2009, TECH in all provinces inhibited ACEI. In 2005, for every 1% increase in lnTECH, ACEI fell by 0.16%-1.65%. In 2009, for every 1% increase in lnTECH, ACEI fell by 0.17%-0.77%. In 2013, only five provinces' TECH had an inhibitory effect on ACEI, while the TECH in Shanxi, Inner Mongolia, Shandong, and Qinghai became the promotion of ACEI. In 2018, TECH in 6 provinces has a depressing effect on ACEI, while TECH in Shanxi, Shandong, and Henan has a promoting effect on ACEI. On the whole, the inhibitory effect of TECH on ACEI is weakening, or even turning into a promotion effect, which shows that

Table 6: Descriptive statistics of variables.

Variable	Symbol	Obs	Mean	Std. Dev.	Min	Max
Agricultural Carbon Emission Intensity	lnACEI	126	15.5446	0.5856	14.5707	17.3966
Agricultural Technological Progress	lnTECH	126	0.2646	0.5404	-1.6801	1.0856
Urbanization	lnURBAN	126	-0.7633	0.1724	-1.2033	-0.4667
Rural Education	lnEDU	126	1.9816	0.1032	1.6387	2.1671
Agricultural Industrial Structure	lnSTRU	126	-0.5993	0.1523	-0.9576	-0.2420
Rural Economic Development	lnRGDP	126	15.1942	1.3355	12.7714	18.7010

Table 7: The comparison of evaluation indicators of OLS, TWR, GWR, GTWR.

	OLS	TWR	GWR	GTWR
R^2	0.8907	0.9487	0.9846	0.9944
AIC	-37.0986	-78.3997	-184.9170	-203.6920

Table 8: The descriptive statistics of the regression coefficients of the GTWR model.

Symbol	Obs	Mean	Std. Dev.	Min	Max
lnTECH	126	-0.2424	0.4803	-1.6497	1.1801
lnURBAN	126	-0.2326	0.9201	-2.0003	1.8497
lneEDU	126	-0.5974	1.4059	-3.1683	3.2775
lnSTRU	126	-0.2169	0.7319	-2.2913	1.0592
lnRGDP	126	-0.3141	0.1528	-0.7426	-0.0088

TECH in nine provinces is more inclined to the expansion of agricultural production while ignoring the development of low-carbon technology.

(2) The coefficients of lnURBAN in most provinces are negative, which indicates that URBAN has an inhibitory effect on ACEI (Table 10). In 2005, the coefficients of Sichuan and Qinghai were positive. For every 1% increase in lnURBAN of the remaining provinces, ACEI fell by 0.36%-1.65%. In 2009, the coefficients of Sichuan, Gansu, and Qinghai were positive. For every 1% increase in lnURBAN of the remaining provinces, ACEI fell by 0.43%-1.46%. In 2013, the coefficients of Sichuan, Gansu, and Qinghai were positive. For every 1% increase in lnURBAN of the remaining provinces, ACEI fell by 0.21%-1.16%. The province with the most restraining effect was Henan. In 2018, the coefficients of Inner Mongolia, Gansu, and Qinghai were positive. For every 1% increase in lnURBAN of the remaining provinces, ACEI fell by 0.30%-2.00%. The province with the most restraining effect was still Henan. The coefficients of Sichuan, Gansu, and Qinghai have been positive for a long time. This may be because the URBAN in these provinces is in an extensive model. The lifestyles of rural households have changed, resulting in higher income and higher energy consumption, which has led to an increase in ACEI.

(3) In 2005, only Shandong, Sichuan, Gansu, and Qinghai had negative coefficients (Table 11). For every 1% increase in lnEDU, ACEI fell by 0.84%-2.68%. And the coefficients for the remaining five provinces were positive. In 2009, only Shaanxi had a positive coefficient. For every 1% increase in lnEDU in the remaining provinces, ACEI fell by 0.31%-2.60%. The province with the most restraining effect was Shandong. In 2013, only Henan had a positive coefficient. For every 1% increase in lnEDU in the remaining provinces, ACEI fell by 0.68%-1.98%. In 2018, the coefficients of Inner Mongolia, Henan, and Shaanxi were positive. For every 1% increase in lnEDU in the remaining provinces, ACEI fell by 0.85%-1.65%. The province with the most restraining effect is still Shandong. The coefficients of Inner Mongolia, Henan,

Table 9: The comparison of coefficients of lnTECH.

Year	Coefficient	Province	Year	Coefficient	Province
2005	-1.649679	Shaanxi	2009	-0.773829	Inner Mongolia
	-1.649678~-1.314597	Shanxi		-0.773828~-0.495197	Shanxi, Sichuan, Ningxia
	-1.314596~-0.738838	Inner Mongolia, Shandong, Ningxia		-0.495196~-0.287975	Shandong
	-0.738837~-0.422202	Henan, Sichuan		-0.287974~-0.179086	Henan, Shaanxi, Gansu
	-0.422201~-0.161031	Gansu, Qinghai		-0.179085~-0.142997	Qinghai
2013	-0.225517	Henan	2018	-0.382916~-0.367305	Sichuan, Shaanxi
	-0.225516~-0.124885	Sichuan, Ningxia		-0.367304~-0.224435	Inner Mongolia, Gansu
	-0.124884~ 0.006878	Shaanxi, Gansu, Qinghai		-0.224434~-0.076516	Qinghai, Ningxia
	0.006879~ 0.173274	Inner Mongolia, Shandong		-0.076515~ 0.464161	Shandong, Henan
	0.173275~ 0.422710	Shanxi		0.464162~ 1.180101	Shanxi

Table 10: The comparison of coefficients of lnURBAN.

Year	Coefficient	Province	Year	Coefficient	Province
2005	-1.647911	Inner Mongolia	2009	-1.461374	Shaanxi
	-1.647910~-1.153687	Shaanxi, Ningxia		-1.461373~-0.854348	Shanxi, Shandong, Henan, Ningxia
	-1.153686~-0.580577	Shandong		-0.854347~-0.436276	Inner Mongolia
	-0.580576~-0.362097	Shanxi, Henan, Gansu		-0.436275~ 0.490700	Gansu
	-0.362096~ 0.920961	Sichuan, Qinghai		0.490701~ 0.935310	Sichuan, Qinghai
2013	-1.155129	Henan	2018	-2.000269	Henan
	-1.155128~-0.528612	Shanxi, Inner Mongolia, Shaanxi		-2.000268~-1.085537	Shanxi, Shaanxi
	-0.528611~-0.213141	Shandong, Ningxia		-1.085536~-0.299831	Shandong, Sichuan, Ningxia
	-0.213140~ 0.686070	Sichuan, Gansu		-0.299830~ 0.412768	Gansu
	0.686071~ 1.195260	Qinghai		0.412769~ 1.751666	Inner Mongolia, Qinghai

and Shaanxi have changed from positive to negative, and then to positive again, indicating that their EDU is not stable enough. Shandong's coefficient has always been negative, and its inhibitory effect ranked first in 2018. This is because Shandong has good educational resources. On the whole, the effect of EDU in each province on ACEI is changing from a promoting effect to a restraining effect, but the EDU of some provinces still needs to be improved.

(4) In 2005, only Inner Mongolia, Shandong, and Henan had positive coefficients (Table 12). For every 1% increase in lnSTRU in the remaining provinces, ACEI fell by 0.12%-0.76%. In 2009, the coefficients of Shanxi, Inner Mongolia, Shandong, Henan, and Sichuan were positive. For every 1% increase in lnSTRU in the remaining provinces, ACEI fell by 0.32%-0.64%. In 2013, only Inner Mongolia, Shandong, and Henan had positive coefficients. For every 1% increase in lnSTRU in the remaining provinces, ACEI fell by 0.29%-2.05%, and the province with the most restraining effect was Shaanxi. In 2018, the coefficients of Inner Mongolia, Shandong, Sichuan, and Gansu were positive. For every 1% increase in lnSTRU in the remaining provinces, ACEI fell by 0.26%-2.28%, and the province with the most restraining effect was still Shaanxi. The coefficients of Inner Mongolia and Shandong have always been positive, indicating that their planting industry contributes a lot to ACEI. The coefficients of Shaanxi, Qinghai, and Ningxia have always been negative, indicating that their planting industries don't contribute much to ACEI. The signs and sizes of the coefficients in different provinces are different, indicating that for different provinces, the contribution of planting to ACEI is different.

(5) The coefficients of all provinces from 2005 to 2018 are negative (Table 13). In 2005, for every 1% increase in lnRGDP of each province, ACEI fell by 0.27%-0.50%. In 2009, for every 1% increase in lnRGDP of each province, ACEI fell by 0.25%-0.57%. The province with the most restraining effect was Qinghai. In 2013, for every 1% increase in lnRGDP of each province, ACEI fell by 0.02%-0.70%. The province with the most restraining effect was Qinghai.

Table 11: The comparison of coefficients of lnEDU.

Year	Coefficient	Province	Year	Coefficient	Province
2005	-2.678585~-2.405002	Gansu, Qinghai	2009	-2.599254	Shandong
	-2.405001~-1.757907	Sichuan		-2.599253~-2.027379	Henan, Gansu
	-1.757906~-0.838910	Shandong		-2.027378~-1.784293	Sichuan, Qinghai
	-0.838909~ 0.778079	Inner Mongolia, Henan, Ningxia		-1.784292~-0.312775	Shanxi, Inner Mongolia, Ningxia
	0.778080~ 2.618964	Shanxi, Shaanxi		-0.312774~ 1.355597	Shaanxi
2013	-1.982982~-1.705128	Inner Mongolia, Gansu	2018	-1.645274	Shandong
	-1.705127~-1.081102	Shandong		-1.645273~-0.852317	Shanxi, Gansu, Qinghai, Ningxia
	-1.081101~-0.847841	Shaanxi, Qinghai		-0.852316~ 0.260609	Inner Mongolia, Sichuan
	-0.847840~-0.676302	Shanxi, Sichuan, Ningxia		0.260610~ 1.426912	Shaanxi
	-0.676301~ 1.923003	Henan		1.426913~ 3.219786	Henan

Table 12: The comparison of coefficients of lnSTRU.

Year	Coefficient	Province	Year	Coefficient	Province
2005	-0.761454~-0.702788	Shaanxi, Gansu	2009	-0.646380	Gansu
	-0.702787~-0.554412	Ningxia		-0.646379~-0.322537	Shaanxi, Qinghai, Ningxia
	-0.554411~-0.123488	Shanxi, Sichuan, Qinghai		-0.322536~ 0.351141	Shanxi, Sichuan
	-0.123487~ 0.031850	Inner Mongolia, Henan		0.351142~ 0.487373	Inner Mongolia, Henan
	0.031851~ 0.951604	Shandong		0.487374~ 0.882900	Shandong
2013	-2.046561	Shaanxi	2018	-2.279289	Shaanxi
	-2.046560~-0.790560	Qinghai, Ningxia		-2.279288~-0.745337	Shanxi, Henan, Ningxia
	-0.790559~-0.291478	Shanxi, Sichuan, Gansu		-0.745336~-0.264268	Qinghai
	-0.291477~ 0.033379	Inner Mongolia		-0.264267~ 0.132499	Sichuan, Gansu
	0.033380~ 0.965521	Shandong, Henan		0.132500~ 0.698138	Inner Mongolia, Shandong

Table 13: The comparison of coefficients of lnRGDP.

Year	Coefficient	Province	Year	Coefficient	Province
2005	-0.498422~-0.480462	Gansu, Qinghai	2009	-0.568232	Qinghai
	-0.480461~-0.445609	Ningxia		-0.568231~-0.415056	Shaanxi, Gansu
	-0.445608~-0.411152	Sichuan, Shaanxi		-0.415055~-0.320603	Shanxi, Henan, Ningxia
	-0.411151~-0.305165	Shandong, Henan		-0.320602~-0.278390	Inner Mongolia, Sichuan
	-0.305164~-0.273368	Shanxi, Inner Mongolia		-0.278389~-0.250648	Shandong
2013	-0.704922	Qinghai	2018	-0.422290	Qinghai
	-0.704921~-0.570335	Gansu		-0.422289~-0.329806	Shanxi
	-0.570334~-0.267433	Shanxi, Inner Mongolia, Sichuan, Ningxia		-0.329805~-0.214790	Shandong, Gansu, Ningxia
	-0.267432~-0.187673	Shandong, Shaanxi		-0.214789~-0.154043	Inner Mongolia, Sichuan
	-0.187672~-0.021435	Henan		-0.154042~-0.008765	Henan, Shaanxi

In 2018, for every 1% increase in lnRGDP of each province, ACEI fell by 0.01%-0.42%, and the province with the most restraining effect was still Qinghai. Although the coefficients of all provinces are negative, as time goes by, the gap in absolute values has increased. This demonstrates that each province's rural economy has been turned into a low-carbon economy, although the degree of the transformation varies by province, and some provinces may have experienced a transformation bottleneck.

CONCLUSION

This paper estimates the agricultural carbon emissions of nine provinces in the Yellow River Basin from 2005 to 2018 and uses the GTWR model to analyze the spatiotemporal characteristics of influencing factors of agricultural carbon emissions. The main conclusions are as follows:

Agricultural carbon emissions in the nine provinces of the Yellow River Basin increased slowly from 2005 to 2018. Agricultural carbon emissions continued to decrease in intensity. \

The share of agricultural carbon emissions from diverse carbon sources has changed from 2005 to 2018.

3. The five parameters have distinct directions and magnitudes of impact on agricultural carbon emissions throughout the nine provinces of the Yellow River Basin, according to the GTWR model's regression results. As a result, each province should take specific steps to minimize carbon emissions depending on the local conditions.

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