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Agricultural carbon emission efficiency and agricultural practices: Implications for balancing carbon emissions reduction and agricultural productivity increment

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ABSTRACT

The current Ukraine War underlines the importance of grain self-sufficiency. After the adoption of the Paris Agreement, two major challenges developing countries are facing in the coming decades are increasing agricultural production to ensure food security and reducing carbon emissions (CE). The key to such an "environment-development dilemma" is to improve agricultural carbon emission efficiency (CEE). Using China as the study site, we systematically analyze the impacts of agricultural management activities on agricultural CEE from 1997 to 2019. Global and local Moran's *I* index tests provide evidence of a positive spatial dependence of agricultural CEE. Using the LISA cluster map, we observe that high CEE regions tend to be distributed together, dominated by environmental conditions. However, with the promotion of agricultural management activities, such a clustering pattern vanished. Our spatial Durbin model (SDM) estimation results indicate that there are significant nonlinear relationships between agricultural practices and agricultural CEE. While the consumption of fertilizers and pesticides has economies of scale effects, the deployment of agricultural machinery and irrigation have diseconomies of scale effects on local CEE. Based on the SDM results, the direct and indirect effect estimation results suggest that the significant direct and spillover effects of many practices on agricultural CEE have opposite nonlinear shapes, implying a more complicated situation in promoting these activities, as the positive regional effect of an agricultural activity might have a negative impact on adjacent regions. All the results indicate that local policymakers should carefully tailor agricultural development policies based on local environmental conditions.

1. Introduction

In recent years, a global food crisis fuelled by the COVID-19 pandemic has been growing because of the ripple effects of the war in Ukraine driving rising prices of food (World Food Programme, 2022). According to the United Nations (UN), approximately 50 countries rely on Russia and Ukraine for at least 30% of their total wheat imports (Welsh, 2022). Due to the fragile food self-sufficiency system, developing countries are clearly more vulnerable to these crises. Approximately 95% of the war-affected population are from

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developing countries (Deng et al., 2022). Since such international political, economic, and public health events constantly pose uncertainties on developing countries' food supply, it is crucial for developing countries to strengthen their food self-sufficiency, where increasing agricultural productivity plays a key role.

It is beyond debate that many agricultural activities, e.g., the consumption of fertilizers and pesticides and the deployment of agricultural machinery, are vital to promoting agricultural production efficiency, which is the key to securing the domestic food supply. However, agricultural production management in many developing countries is still very primitive, and the rate of adoption of new agricultural technologies has remained low in most of these countries (Mwangi and Kariuki, 2015). In addition, as empirically found by many scholars, these agricultural practices are positively correlated with carbon emissions (CE). In December 2015, the Paris Agreement was adopted by 196 parties (United Nations, 2020). All the participating countries agreed to limit global warming to well below 2 °C above preindustrial levels and to pursue efforts to limit the temperature increase to 1.5 °C (Gota et al., 2019). Since carbon dioxide (CO_2) accounts for approximately 76% of total greenhouse gas emissions, mitigating carbon emissions (CE) is a shared responsibility for every country worldwide (United States Environmental Protection Agency, 2016).

As noted by Grubb et al. (2011), from the perspective of economic and social development, CE rights are synonymous with a country's development (Grubb et al., 2011; Yang, 2012; Pei et al., 2013). Increasing agricultural productivity is thus inevitably accompanied by an increase in CE. Although agriculture-related CO_2 does not account for a large amount of total emissions, each unnecessary unit of CE is too much. In addition, it must be borne in mind that the adoption of agricultural management activities is also closely related to the investment of resources, which are scarce in underdeveloped countries. Currently, there are 152 developing countries, accounting for approximately 85.43% of the world's population (International Monetary Fund, 2023). Among these 152 countries, 46 are on the UN's list of least developed countries (United Nations, 2022). Thus, the key to such an "environment-development dilemma" is to improve agricultural carbon emission efficiency (CEE), defined as the gross output value (GOV) or gross domestic product (GDP) per unit of emitted CO_2 in the agriculture sectors.

With only 7% of the world's farmland, China has to feed approximately 20% of the world's population. Both per capita arable land, i.e., 0.09 ha, and water, i.e., 2050 m^3, are far below the global average. However, with the adoption of new agricultural management technologies, the total grain output in China increased 74%, from 354 million tons in 1982 to 618 million tons in 2017, surpassing the growth of the Chinese population by approximately 34% (Cui and Shoemaker, 2018). Nevertheless, with the repealing of the "one child policy", increasing life expectancies and changes in the dietary patterns of the growing middle class, food security still has the highest priority in the foreseeable future in China (Carter et al., 2012). Moreover, as the largest CO_2 emitter, accounting for approximately 33% of the global total, China announced its commitment to reach a carbon peak before 2030 and carbon neutrality before 2060 (IEA, 2022). Therefore, among developing countries, China is under greater pressure than other countries to improve agricultural CEE. A clear answer to the question of how agricultural management practices affect CEE could help China and other developing countries effectively make and adjust their plans for future agricultural development to achieve more sustainable agricultural production.

In the literature, studies of agricultural CO_2 emissions have been very limited. Some scholars have focused on the spatial pattern and spatiotemporal characteristics of primary industry CE (Tian et al., 2014; Huang et al., 2019; Cui et al., 2021; Liu and Yang, 2021). Other researchers have investigated the factors influencing agricultural CE at both the national and regional levels (Xiong et al., 2016, 2020; Han et al., 2018; Zhang et al., 2019; Chen et al., 2020; Liu et al., 2021; Yang et al., 2022). Regarding research on CEE, an indicator combining both economic and environmental aspects, among different research fields, the CEE index has been estimated, and its influencing factors have been analyzed but only regarding some certain industrial sectors (Zhou et al., 2019; Li and Cheng, 2020; Wang and Feng, 2021; Du et al., 2022). Only two studies have addressed the topic of agricultural CEE, both of which have attempted to measure agricultural CEE for different regions using data envelopment analysis and the Malmquist index models (Wang and Feng, 2021; Fan et al., 2022). To date, no study has investigated the spatial pattern of agricultural carbon efficiency. In addition, the spillover effects of some agricultural CEE influencing factors in China or other countries have not been examined, leaving a vast research gap. Previous studies generally adopted standard econometric models, restricting spillovers to be zero, ignoring thus potential interregional interactions. Spatial econometric models, in contrast, bring this valuable aspect back in the estimation to empirically assess the magnitude and significance of spatial spillovers (Vega and Elhorst, 2013). Furthermore, the relationship between costs and output levels is not strictly linear. By adding the squared variable, a recent study conducted by Sporkmann et al. (2023) revealed that there is a "sustainability sweet spot" in the relationship between transportation infrastructure and transportation CE on the European countries. Such understanding is crucial for effective transportation infrastructure planning and management. In the agricultural industry, however, there is still no research investigating whether such "sweet spots" also exist in the agricultural inputs and CEE relationship and whether some agricultural management activities have favorable economies of scale effects on CEE.

To fill these three research gaps, in this study, we aim to systematically investigate the spatial pattern of agricultural CEE and the direct and indirect impacts of different agricultural practices in China. We compile a panel covering China's 30 provincial administrative regions from 1997 to 2019. By employing global and local Moran's *I* index tests and LISA cluster maps, we document that agricultural CEE shows a significantly positive spatial correlation pattern among the studied provinces. However, the strength of the spatial correlation is observed to be weaker in more recent years. To account for this spatial pattern and understand the potential interregional interactions, we deploy the individual and time fixed effects spatial Durbin model (SDM) to study both the direct and indirect effects of various agricultural activities, i.e., fertilization, irrigation, deployment of agricultural machinery, etc. To explore the potential economies of scale or even diseconomies of scale effects of agricultural management activities on CEE, we further add quadratic terms into the regression model to examine the potential nonlinear relationships. Based on the SDM results, we estimate the direct and indirect effects of the studied practices to analyze the spillover effects.

Our study has both research and practical significance. In recent decades, different agricultural management practices have been strongly promoted in most regions of China where agricultural production management was primitive at the beginning of the focused period. Thus, using data from China, we could obtain more robust results on how these activities affect agricultural CEE. In addition, China id selected as our study site due to its vast territory and diverse environmental conditions. As the second-largest country by area, China has the most complex agricultural production structure. Thus, by employing different spatial econometric methods, we can comprehensively investigate the impacts of agricultural management activities deployed in different agricultural production areas on CEE from both spatial and temporal dimensions. Furthermore, the results of the current study can provide vital implications for policymakers not only in China but also in underdeveloped countries to achieve sustainable development in agricultural sectors.

The remainder of the paper is organized as follows. In the next section, we describe the sample data and the methodologies deployed in this research. In the third section, we report our empirical results. In the fourth section, we discuss the key findings in this research and provide some important policy implications. In the last section, we conclude this study.

2. Methodologies and data

2.1. Empirical methods

2.1.1. Spatial dependence models

To examine the overall spatial dependence of agricultural CEE, we use the global Moran's I index (Moran, 1950). As a test index, the global Moran's I index is commonly defined as follows:

$$I = \frac{\Sigma_i \Sigma_j w_{ij}(z_i - \bar{z})(z_j - \bar{z})}{S^2 \Sigma_i \Sigma_j w_{ij}},$$
$$\text{with } S^2 = \frac{\Sigma_i (z_i - \bar{z})^2}{n} \text{ and } w_{ij} = \begin{cases} 1, \textit{if provinces i and j are adjacent} \\ 0, \textit{otherwise} \end{cases}, \tag{1}$$

where S^2 is the sample variance. z_i and z_j are the observed values of regions i and j, $\bar{z}$ denotes the sample average, and w_{ij} is the ith and jth element of a spatial weight matrix W, specifying the degree of dependence between regions i and j. When i and j are neighboring regions, $w_{ij} = 1$, and when regions i and j are not adjacent, $w_{ij} = 0$.[1] The hypothesis test of Moran's I index is defined as follows:

$$Z = \frac{I - I_0}{\sqrt{Var(I)}},$$
$$\text{with } E(I) = I_0 = -\frac{1}{n-1}. \tag{2}$$

A positive significant Moran's I index is a signal of spatial clustering, while a negative index implies spatial dispersion pattern (Anselin and Florax, 1995). In addition to the global Moran's I index, we employ the local Moran's I test proposed by Anselin and Florax (1995) to study the cluster effect of agricultural CEE in local areas. The expression of the local Moran's I test is as follows:

$$I_i = \frac{z_i - \bar{z}}{\frac{1}{n}\Sigma_i (z_i - \bar{z})^2} \sum_j w_{ij}(z_j - \bar{z}),$$
$$\text{with } w_{ij} = \begin{cases} 1, \textit{if provinces i and j are adjacent} \\ 0, \textit{otherwise} \end{cases}. \tag{3}$$

$I_i > 0$ indicates that region i is adjacent to region j in a similar situation. In the context of the present study, $I_i > 0$ indicates that region i is surrounded by region j with similar agricultural emission efficiency, indicating a high with high (H–H) or low with low (L-L) cluster. In contrast, when $I_i < 0$, region i is adjacent to region j in a different situation, forming a high-low (H-L) or low-high (L-H) spatial correlation mode. Using Moran's scatter, we plot all the four spatial correlation forms in the four quadrants. The first and third quadrants represent H–H and L-L clusters, whereas the second and fourth quadrants are L-H and H-L spatial correlation modes, respectively (Li and Li, 2020).

2.1.2. Spatial econometric models

If the existence of a spatial dependence pattern is evidenced, it is necessary to adopt a spatial econometric model for the regression estimation. Generally, three spatial models are used to analyze the inner mechanism of spatial correlation, i.e., the spatial autoregressive model (SAR), spatial error model (SEM) and spatial Durbin model (SDM) (Elhorst, 2012, 2014). We start with a universal model defined as follows:

$$Y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \varphi X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{ijt} + \varepsilon_{it},$$
$$\text{with } w_{ij} = \begin{cases} 1, \textit{if provinces i and j are adjacent} \\ 0, \textit{otherwise} \end{cases} \text{ and } \varepsilon_{it} = \gamma \sum_{j=1}^{n} w_{ij} \varepsilon_{it} + \epsilon_{it}, \tag{4}$$

[1] It is worth noting that in our study, in the spatial weight matrix, we set Hainan province adjacent to Guangdong province.

where i and j denote regions i and j, respectively, and t represents year t. Y_{it} is an $N\times 1$ matrix of the dependent variable, and X_{it} is an $N\times K$ matrix of the independent variables. w_{ij} is the element of the constructed spatial weight matrix W. ρ indicates the spatial autoregression coefficient on the spatial lag dependent variable, and γ is the spatial autocorrelation coefficient of the random error term. φ and θ are the estimated coefficients of the independent and spatial lag independent variables, respectively. α is the constant term, and ϵ is the random error term with an independent and identical distribution.

When in Eq. (4) $\gamma = 0$ and $\theta = 0$, the model is reduced to the SAR, assuming that the autoregressive process is just on the dependent variable, as described in Eq. (5). When $\rho = 0$ and $\theta = 0$, Eq. (4) is reduced to SEM, which can be derived as shown in Eq. (6):

$$Y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \varphi X_{it} + \epsilon_{it}, \tag{5}$$

$$\begin{gathered} Y_{it} = \alpha + \varphi X_{it} + \varepsilon_{it}, \\ \text{with } w_{ij} = \begin{cases} 1, \textit{if provinces i and j are adjacent} \\ 0, \textit{otherwise} \end{cases} \text{ and } \varepsilon_{it} = \gamma \sum_{j=1}^{n} w_{ij}\varepsilon_{it} + \epsilon_{it}. \end{gathered} \tag{6}$$

When only $\gamma = 0$, Eq. (4) describes the SDM:

$$\begin{gathered} Y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \varphi X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{ijt} + \epsilon_{it}, \\ \text{with } w_{ij} = \begin{cases} 1, \textit{if provinces i and j are adjacent} \\ 0, \textit{otherwise} \end{cases}. \end{gathered} \tag{7}$$

To control the potential individual and time effects in the data, μ and λ, representing these two effects, can be added into the SDM, leading to the individual and time fixed effects SDM derived as follows:

$$\begin{gathered} Y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + \varphi X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{ijt} + \mu_i + \lambda_t + \epsilon_{it}, \\ \text{with } w_{ij} = \begin{cases} 1, \textit{if provinces i and j are adjacent} \\ 0, \textit{otherwise} \end{cases}. \end{gathered} \tag{8}$$

Furthermore, the SDM allows researchers to study the direct and indirect (spillover) impacts of the studied factors by interpreting the estimates on independent variables, i.e., φ, and spatial lag independent variables, i.e., θ (Yang et al., 2015). However, using the SDM to test whether a variable has a spillover effect might result in biased findings (LeSage and Pace, 2010). Thus, we adopt the partial derivative method to estimate the direct and indirect effects based on the SDM estimation (LeSage and Pace, 2009; Elhorst, 2010). As the starting point, the SDM can be rewritten as follows:

$$Y_t = (I_n - \rho W)^{-1}\alpha + (I_n - \rho W)^{-1} X\varphi + (I_n - \rho W)^{-1} WX\theta + (I_n - \rho W)^{-1}\varepsilon, \tag{9}$$

where I_n is an $N\times K$ identity matrix. The partial derivatives of the dependent variable Y relative to the kth explanatory variable X_k across n observations can then be expressed as follows:

$$\begin{bmatrix} \frac{\partial Y}{\partial X_{1k}} & \cdots & \frac{\partial Y}{\partial X_{Nk}} \end{bmatrix} = (I_n - \rho W)^{-1}[\varphi_k I_n + \theta_k W]. \tag{10}$$

Direct impact is the average of the main diagonal elements of the $(I_n - \rho W)^{-1}[\varphi_k I_n + \theta_k W]$ matrix, and indirect impact is the average of the off-diagonal elements of the matrix.

2.2. Data

Our study covers 30 provincial administrative divisions of China from 1997 to 2019.[2] We define the agriculture as the practice of growing food, including plants, such as rice, corn and vegetables, animals, including sheep, cows, pigs and fishes, forestry products, e.g., hazelnuts, and even insects like bees. China's annual province-level agricultural CE is proxied by rural CO_2 emissions, as in most years of the studied period, the industrial structure was dominated by the agricultural practices in China's rural areas (Zhu et al., 2018; Yu et al., 2023). The data on agricultural CE is sourced from Shan et al. (2016, 2018, 2020) and Guan et al. (2021), who constructed panel data following the Intergovernmental Panel on Climate Change energy-related sectoral approach, which can be understood as an "apparent energy consumption" approach (Eggleston et al., 2006). The sources of other data for deriving the agricultural activity variables are the China Statistical Yearbook (National Bureau of Statistics of China, 2022). A detailed description of the collected raw data can be found in Table A1 in the Appendix.

In order to align with the emission scope, we define the agricultural CEE as the amount of primary industry GOV that can be generated from one unit of emitted CE (Shi et al., 2022). Since The carbon emission efficiency CEE_t^i (Yuan/ton) for province i in year t is

[2] Data on Tibet (Xizang), Taiwan, Hongkong and Macao are not available in this database.

derived as follows:

$$CEE_t^i = \frac{TGV_t^i}{CEM_t^i}, \tag{11}$$

where TGV_t^i and CEM_t^i are the total GOV of the primary industry and CE in year t in province i, respectively. The studied CO_2 emissions efficiency influencing agricultural activities include the consumption of fertilizers, pesticides and agricultural films, the deployment of agricultural machinery, and irrigation. FER_t^i is the consumption of fertilizers (tons per thousand hectares) in year t in province i, derived as follows:

$$FER_t^i = \frac{TFC_t^i}{TSA_t^i}, \tag{12}$$

where TFC_t^i and TSA_t^i are the total consumption of fertilizers, including nitrogenous, phosphate, potash and compound fertilizers, and the total sown area in year t and province i, respectively. In a similar vein, we calculate the consumption of pesticides PES_t^i (kg per thousand hectares) and agricultural films AGF_t^i (tons per million hectares). ARM_t^i is the power of agricultural machinery (kW per million yuan), constructed as follows:

$$ARM_t^i = \frac{TMP_t^i}{TGV_t^i}, \tag{13}$$

where TMP_t^i is the total agricultural machinery power (kW), including the power of tractors and diesel engines of, for instance, fishing vessels, in year t in province i. The last studied agricultural activity is irrigation IRA_t^i, which is measured by the proportion of irrigated area in the total cultivated area in year t and province i. In total, we derive five agricultural activity variables, with each containing 690 observations covering 30 of China's provincial administrative regions from 1997 to 2019. In Table A2 in the Appendix, we provide an overview of the province-level agricultural practices.

2.3. Model specification

We specify our model based on the constructed variables proxying agricultural activities. To eliminate possible heteroscedasticity in the data, we take the natural logarithm of the studied variables. Our model, Model (1), is defined as follows:

$$log\left(CEE_t^i\right) = \alpha + \beta_1 log\left(FER_t^i\right) + \beta_2 log\left(ARM_t^i\right) + \beta_3 \log\left(IRA_t^i\right) + \beta_4\, log\left(PES_t^i\right) + \beta_5 log\left(AGF_t^i\right) + \varepsilon_t, \tag{14}$$

where FER_t^i, ARM_t^i, IRA_t^i, PES_t^i and AGF_t^i are five agricultural practices in year t in province i; α and ε are the intercept and random error terms, respectively. One drawback of Model (1) is that this model can only capture the linear relationship. If agricultural activities have (dis)economies of scale effects on CEE, (inverted) U-shaped relationships should be observed. In addition, since all the studied agricultural activities are tightly coupled with energy consumption, technological advancement and economic growth, their relationships with agricultural CEE might follow the hypothesized shape of the environmental Kuznets curve (EKC) (Grossman and Alan, 1991; Sarkodie and Strezov, 2018). Thus, to capture potential nonlinear relationships, we further add the quadratic terms of agricultural management activities as nonlinear components in Model (1), leading to Model (2) as follows:

Table 1
Descriptive statistics and correlation matrix.

	FER	ARM	IRA	PES	AGF
Panel A: Descriptive Statistics					
Minimum	111.83	39.46	0.1391	226.58	120.52
Median	314.47	217.75	0.3601	9349.34	10,332.23
Mean	330.39	257.35	0.3996	13,402.08	15,726.06
Maximum	799.60	1024.80	1.00	91,065.07	86,944.89
Std. Dev.	121.16	172.62	0.1630	13,621.03	13,216.17
Panel B: Correlation Matrix					
FER	1.00				
ARM	−0.4009	1.00			
IRA	0.4045	−0.0503	1.00		
PES	−0.1744	0.1448	0.0181	1.00	
AGF	0.4235	−0.3360	0.6458	0.0414	1.00

Note: Std. Dev. stands for standard deviation. FFR, ARM, IRA, PES and AGF represent the consumption of fertilizers, the power of agricultural machinery, the share of irrigation, and the consumption of pesticides and agricultural films, respectively.

$$log\left(CEE_t^i\right) = \alpha + \beta_1 log\left(FER_t^i\right) + \beta_2\left(log\left(FER_t^i\right)\right)^2 + \beta_3 log\left(ARM_t^i\right) + \beta_4\left(log\left(ARM_t^i\right)\right)^2 + \beta_5 log\left(IRA_t^i\right) + \beta_6\left(log\left(IRA_t^i\right)\right)^2 + \beta_7\, log\left(PES_t^i\right) + \beta_8\left(\log\left(PES_t^i\right)\right)^2 + \beta_9 log\left(AGF_t^i\right) + \beta_{10}\left(log\left(AGF_t^i\right)\right)^2 + \varepsilon_t. \tag{15}$$

The descriptive statistics and the correlation matrix for all the variables are reported in Table 1. To enhance the credibility of the regression results, we conduct a stationarity test for each of the studied variables to rule out potential spurious regression results. Since our panel is constructed of 30 provinces (N) for 23 years (T), i.e., a large N and small T pattern, we select the panel data stationarity test method proposed by Levin et al. (2002). The results of the stationarity test listed in Table A3 in the Appendix indicate that the null hypothesis that the unit root exists can be rejected. Furthermore, we deploy the variance inflation factor (VIF) test to examine the degree of multicollinearity in our model (O'brien, 2007). The results listed in Table A4 in the Appendix indicate that the VIF for each variable is clearly lower than the conventional threshold level of five, implying that our specified model does not have a multicollinearity problem.

3. Empirical results

3.1. Overview of agricultural CEE and agricultural practices

We first provide maps of province-level agricultural CEE in China for 1997 and 2019 in Fig. 1. As shown, in 1997, provinces in Southeast China generally had higher agricultural CEE than did the central and western provinces. Two reasons behind this, from our point of view, are economic development and climatic and natural conditions. Compared to other regions, economic development in coastal provinces was much more advanced at the end of the last century. Better economic conditions led to more investments in agricultural management activities, which significantly improved agricultural productivity. In addition, the environmental conditions in southeastern China are more favorable for agricultural production, leading to higher agricultural productivity. Compared to that in 1997, the agricultural CEE increased in each province in 2019. In particular, provinces in central China with comparably less favorable agricultural production conditions had significantly improved agricultural CEE. Provinces in North and Northwest China also displayed more efficient agricultural CE, and the gap to other regions was reduced. All these observations indicate that with the adoption of agricultural management practices, environmental conditions are no longer the dominant factor of agricultural CEE.

Regarding agricultural management activities, in Table 2, we report the results of the mean and median comparisons between 1997 and 2019 for each practice. As listed in Table 2, from 1997 to 2019, a clear increasing trend of fertilizer consumption was observed in China. In contrast, the intensity of agricultural machinery tended to decrease during the same period. In terms of irrigation, a nationwide increase in the irrigation share from 1997 to 2019 is evident. Compared to 1997, the use of pesticides did not become more popular in China in 2019. The mean and median comparison results provide evidence that despite an increase in pesticide consumption, the change is not statistically significant. In contrast, the consumption of agricultural films significantly increased in China during the studied period. Taken together, except for the deployment of agricultural machinery, all the other agricultural activities became more prevalent from 1997 to 2019.

In Fig. 2, we further visualize the temporal changes in the five agricultural management practices. Fig. 1 a) shows that while the eastern provinces had clearly higher fertilizer consumption intensity than did the other regions in 1997, a clear cluster of provinces with high fertilizer consumption in central China was evident in 2019. The identified decrease in agricultural machinery intensity was more significant in southern provinces, which is more likely due to the rapid urbanization and mountainous landforms in these areas. Large amounts of useable land were urbanized in favor of secondary industry development, and the remaining arable lands were fragmented such that they were not suitable for the large use of agricultural machinery. In contrast, in the northern provinces, agricultural machinery deployment intensity remained high during the focused period. As illustrated in Fig. 2 c), the increase in the share of irrigated area was more pronounced in coastal provinces. In addition, we observe that in Northwest China, the proportion of

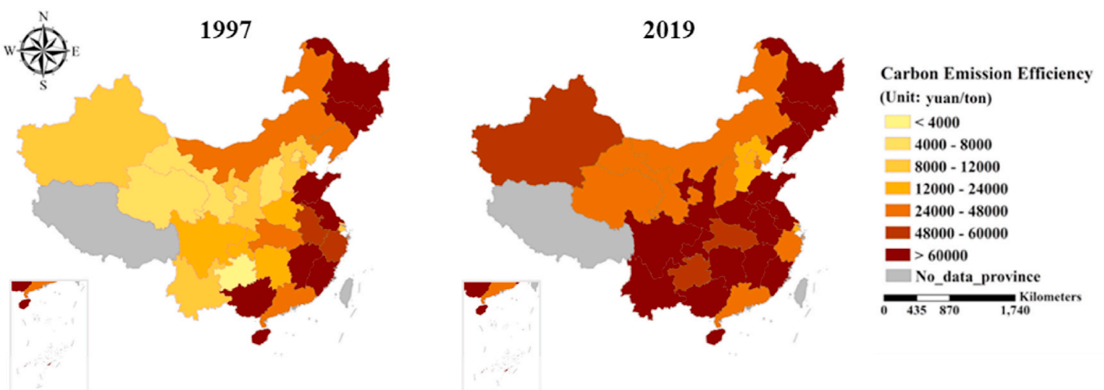

Fig. 1. Province-level agricultural CEE in 1997 and 2019.

Table 2
National-level changes in agricultural activities from 1997 to 2019 in China.

	Mean				Median			
	2019	1997	Difference	Test-statistic	2019	1997	Difference	Test-statistic
FER	327.75	238.60	89.15***	3.21	344.85	246.85	98.00***	9.92
ARM	120.21	254.56	−134.35***	−5.45	109.72	229.68	−119.96***	−19.41
IRA	42.84	32.54	10.30***	2.70	39.89	32.56	7.33***	7.56
PES	7299.94	5490.26	1809.68	0.85	10,830.97	6089.88	4741.09	1.69
AGF	16,254.61	6020.00	10,234.61***	4.73	13,119.12	6295.74	6823.38***	20.07

Note: This table presents the annual mean and median values and the results of the mean and median difference tests of different agricultural practices in 1997 and 2019. The test statistics, i.e., t-statistics and Kruskal−Wallis χ^2, are also reported. FFR, ARM, IRA, PES and AGF stand for consumption of fertilizers, the power of agricultural machinery, the share of irrigation, and the consumption of pesticides and agricultural films, respectively. ***, **, and * indicate significance at the 1% and 5% and 10% levels, respectively.

irrigated area in the total cultivated area was the highest. The increasing trend of using agricultural films was, in particular, clearer in the northern and northwestern regions, where the climatic conditions are less favorable for agricultural productions. In Table A2 and Fig. A1 in the Appendix, more information on these five agricultural practices at the province level can be found.

3.2. Agricultural CEE spatial dependence test

The results of the agricultural CEE global Moran's I index test are listed in Table 3. As shown, the global Moran's I index values are positive over the studied period, and in 12 years, the indexes are statistically significant, indicating a significantly positive spatial correlation pattern of the provincial agricultural CEE in China. The observed significantly positive Moran's I index implies the potential spatial agglomeration feature of agricultural CEE, i.e., regions with high or low agricultural carbon efficiency tend to be distributed together. Furthermore, this observation indicates that the agricultural CEE of one province might be affected not only by local factors but also by the surrounding environment. By plotting the Moran's I values in Fig. A2 in the Appendix, it can be seen that the observed pattern is similar to the Moran's I index for the provincial-level agricultural CEs in Chen et al. (2020). To check whether the positive spatial pattern of agricultural CEE is robust, we further conduct a GDP-based agricultural CEE spatial dependence test, and the results are listed in Table A5 in the Appendix.

In addition to the global Moran's I index test, we also conduct the local Moran's I index test to examine the spatial mode of each studied province for 1997, 2008 and 2019. The results of the local Moran's I index are listed in Table A6 in the Appendix. Using local Moran's I indices and their spatial lag terms as the horizontal and vertical axes to construct coordinate systems, we plot Moran's scatter diagrams for 1997, 2008 and 2019 in Fig. 3 (Sun et al., 2018). As shown, in 1997, 12 out of a total of 30 studied provinces were located in the third quadrant, where provinces with low agricultural CEE are surrounded by other low agricultural CEE provinces, i.e., an L-L spatial correlation mode. Similarly, we observe that 11 provinces were distributed in the first quadrant, indicating that these high agricultural CEE provinces were adjacent to provinces with high CEE, namely an H–H spatial mode. Therefore, in 1997, the global Moran's I index was significant and positive, as most provinces showed H–H or L-L agglomerations. Compared to 1997, in 2008, more provinces were in the second quadrant, which is the L-H mode. In sharp contrast, all 30 provinces were distributed evenly in all four quadrants in 2019. In particular, in the second and fourth quadrants, namely the L-H and H-L modes, we observe eight provinces, respectively. As mentioned before, the L-H and H-L modes indicate a spatial dispersion pattern. Thus, in 2019, the global Moran's I index decreased and became nonsignificant.

In Fig. 4, we illustrate the spatial correlation mode of each province and LISA cluster maps for 1997 and 2019. As shown, in 1997, high agricultural CEE provinces were located in southeastern coastal areas, where both environmental and economic conditions are better. In Northwest China, we observe a significant cluster of L-L in the LISA cluster map, indicating that these regions have significantly low agricultural CEE. In 2019, in contrast, we find that more provinces were in the H–H and H-L spatial correlation modes, indicating that with the promotion and development of agricultural management activities, more provinces in southern China have higher agricultural CEE. In addition, according to the LISA cluster map, the cluster effect was less strong in 2019, indicating that environmental and economic conditions were not the dominant factors affecting agricultural CEE. Therefore, less significant positive spatial dependence in 2019 is identified. Based on the results of global and local Moran's I index tests, it is necessary to adopt a spatial model to investigate the agricultural CEE influencing factors and estimate their potential direct and indirect effects.

3.3. CEE SDM estimation

Based on the panel data nature of our collected sample, before we make our choice among the spatial models, i.e., SAR, SEM and SDM, we first estimate the underlying econometric models for both Models (1) and (2). In Table 4, we list the estimation results of the models. In addition to the classic pooled ordinary least square model (OLS), we estimate the panel data random effects model (REM), which can account for unobserved heterogeneity in the data. Then, we continue with the three fixed effects panel data models, namely the individual fixed effects model (SFM), the time fixed effects model (TFM) and the individual and time fixed effects model (STM). The fixed effects models can control for the effects of those time- and individual-invariant data characteristics. Following the procedures of previous studies, we conduct log-likelihood, likelihood ratio (LR), Durbin-Wu-Hausman (Hausman test) and Lagrange multiplier (LM)

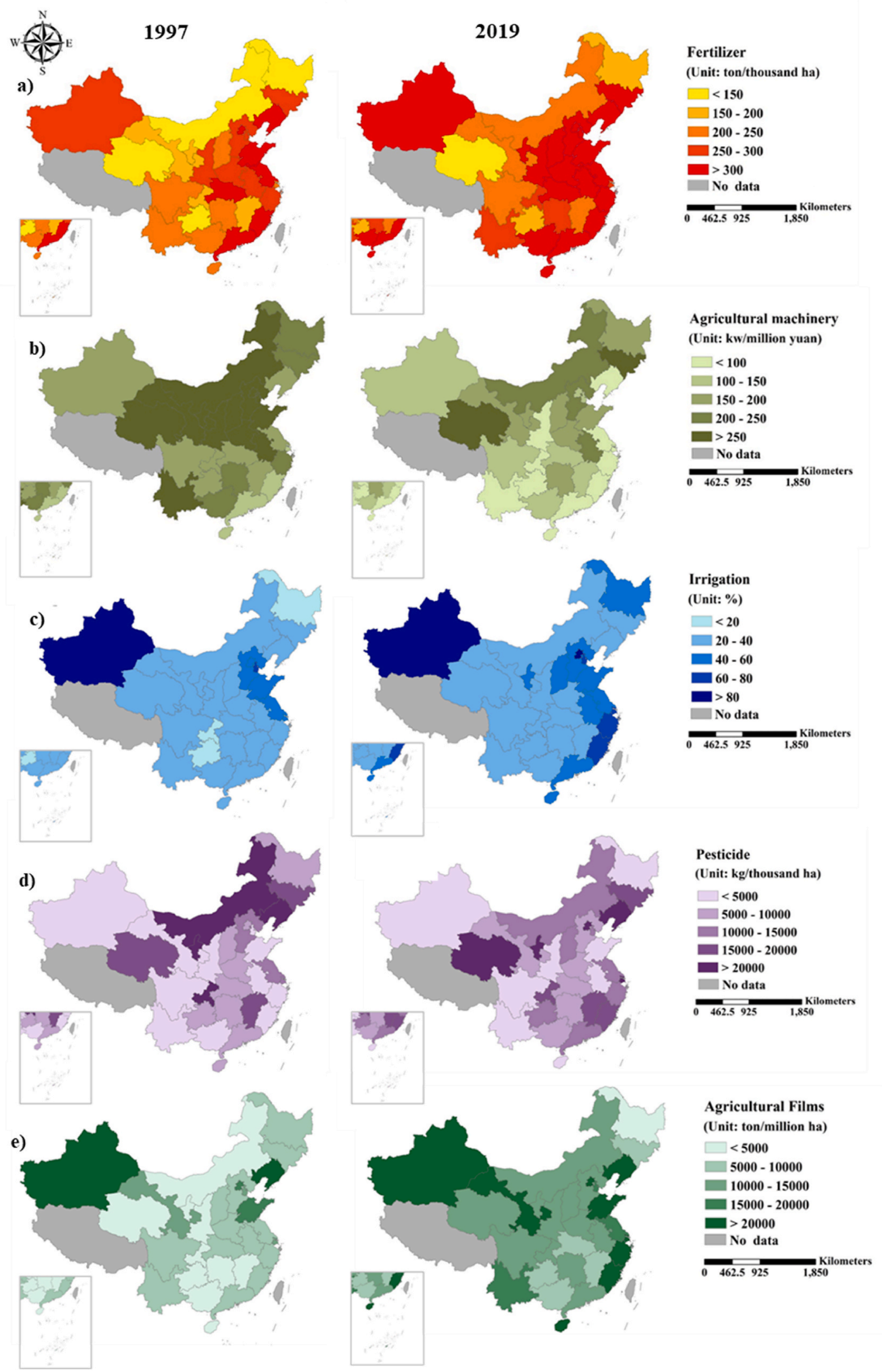

Fig. 2. Provincial-level development of agricultural practices in 1997 and 2019 in China.

Table 3
Global Moran's *I* index for agricultural CEE.

Year	*I*	*p*-Value	Year	*I*	*p*-Value
1997	0.2307**	0.01	2009	0.1403*	0.07
1998	0.2177**	0.02	2010	0.1215*	0.10
1999	0.2734***	0.01	2011	0.1455*	0.10
2000	0.2369**	0.01	2012	0.0870	0.16
2001	0.2263**	0.01	2013	0.0357	0.28
2002	0.1845**	0.03	2014	0.0369	0.28
2003	0.1861**	0.03	2015	0.0450	0.25
2004	0.1488*	0.06	2016	0.0579	0.22
2005	0.0482	0.24	2017	0.0359	0.28
2006	0.0238	0.31	2018	0.0559	0.22
2007	0.0283	0.30	2019	0.0504	0.24
2008	0.1321*	0.10			

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

tests for spatial lags and errors to help us select our model (Durbin, 1954; Wu, 1973; Hausman, 1978).

In both Models (1) and (2), it is observed that the STM has the highest value of log-likelihood. The results of the LR test imply that the REM, SFM, TFM and STM better fit the data for both linear and nonlinear model estimations, compared to the OLS. In addition, we deploy the Hausman test to determine whether random or fixed effects model should be employed to investigate our data. The results reported in Table 4 clearly indicate the superiority of the fixed effects models. Based on the results of the log-likelihood, LR and Hausman tests, it is necessary to fix both the spatial and time effects, leading us to the STM. Furthermore, we examine whether it is necessary to include both spatial lag independent variables (LM spatial lags) and spatial autocorrelated error terms (LM spatial errors) in the STM. As reported, the test statistics of both the LM spatial lags and errors and the robust LM spatial lags and errors are significant. In such circumstances, the use of SDM is recommended (LeSage and Pace, 2009; Li and Li, 2020). Based on all these test results, we deploy the individual and time fixed effects SDM for our analysis.

The results of the SDM and direct and indirect effects estimation are reported in Table 5. As mentioned previously, the estimated direct and indirect effects based on the SDM might be imprecise. Thus, we only interpret the sign and significance of the estimated coefficients in the SDM and measure the effect size according to the estimated effects. We start with the linear model, i.e., Model (1) in Table 5. The coefficient on fertilization is negative but not significant at the conventional levels; however, the estimate on the spatial lag *FER* is positive and highly significant, indicating a significant spillover effect of fertilizer application on agricultural CEE. The estimated direct and indirect effects of fertilization confirm the findings in the SDM. Since we have a double-log model, the estimated indirect effect can be interpreted as a 1% increase in fertilizer consumption that is correlated, on average, with a 0.2004% increase in CEE in neighboring regions. A similar result is found for the consumption of pesticides, where only the coefficient on the spatial lag *PES* is significant. In contrast, the deployment of agricultural machinery is only associated with local agricultural CEE, and the nature of this correlation is negative. Irrigation is negatively correlated with both local and interregional CEE, and a 1% increase in the proportion of irrigated area in the total cultivated area is related to, on average, 0.3355% and 0.3569% decreases in local and surrounding CEEs, respectively. The only agricultural activity that is found to have nonsignificant effect on agricultural CEE is the consumption of agricultural films. The estimates on both *AGF* and spatial lag *AGF* are found to be nonsignificant, which is confirmed by the estimation of direct and indirect effects.

Columns 5 to 8 are the estimation results of the nonlinear model. As shown, the coefficients on both fertilization and squared fertilization are highly significant. Using the estimated effect sizes, the relationship between the consumption of fertilizers (*FER*) and local agricultural carbon efficiency (*CEE*) has the form of $CEE = 0.3455FER^2 - 4.0084FER$, which implies that this relationship takes the U shape. This indicates that the slope of the fertilization and CEE relationship depends on the levels of fertilizer consumption itself. Differentiating this equation: $\partial_{CEE}/\partial_{FER} = 0.6910FER - 4.0084$, and setting $\partial_{CEE}/\partial_{FER} = 0$, i.e., $0.6910FER - 4.0084 = 0$, we calculate where the agricultural CEE minimizes, namely, at $FER = 5.8009$, corresponding to $exp\,(5.8009) = 330.60$ tons per thousand hectares. At low levels of fertilization, the slope is negative, such that the agricultural CEE decreases with the consumption of fertilizers. After reaching the minimum, the CEE increases with fertilizer application. Recall that in the linear model, it is observed that the coefficient on *FER* is not significant. As illustrated in Fig. 5 a), where we plot the nonlinear relationships between fertilizer consumption and agricultural CEE, the sample mean and median are located close to the vertex of the parabola in the direct effect estimation. Since the slope of the point near the axis of symmetry is close to zero, in the linear model, the coefficient is thus tested to be nonsignificant. In contrast, we identify that the spillover effect of fertilizer consumption takes an inverted U shape. By setting the first-order differentiated equation to zero, we obtain the maximum agricultural CEE at $FER = 6.1751$, corresponding to 480.63 tons per thousand hectares. After reaching this point, the agricultural CEE in neighboring regions decreases with further consumption of fertilizers. As shown in the indirect effect plot in Fig. 5, the sample average is on the left side of the vertex where the slope is positive. Thus, in the linear model, we observe positive coefficient on the spatial lag *FER*.

Regarding the deployment of agricultural machinery, we also observe significant nonlinear relationships for both direct and indirect effects. The relationship with the local CEE takes an inverted U form in which the agricultural CEE increases with the deployment of agricultural machinery until it reaches 70.43 kW per million yuan and falls afterward. In contrast, the spillover effect has a U shape, with the minimum being calculated at 347.27 kW per million yuan. The consumption of pesticides only has a significant U-shaped relationship with local CEE, and the minimum is at a consumption of 6803.55 kg per thousand hectares. Regarding the

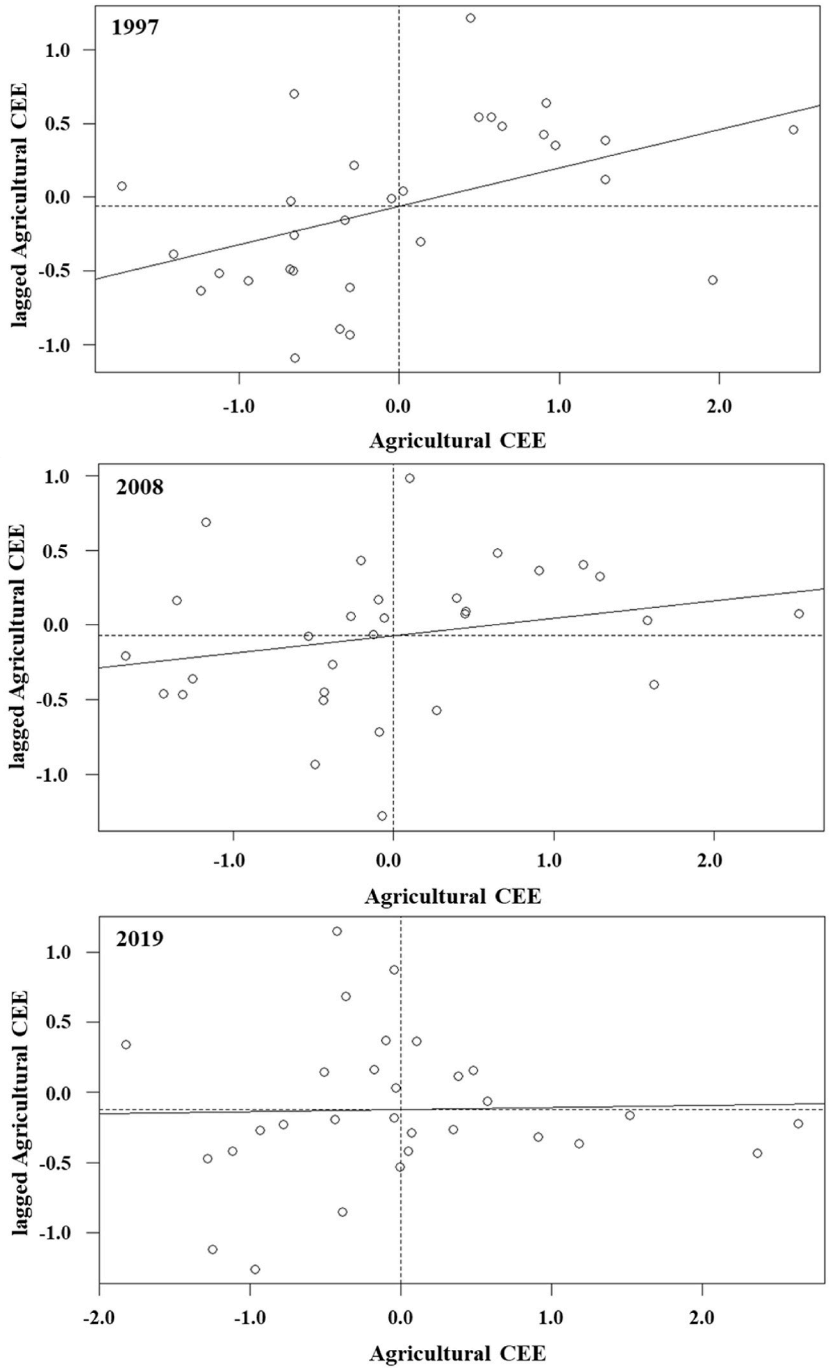

Fig. 3. Moran's scatter plots of agricultural CEE in 1997, 2008 and 2019.

indirect effect, the factor loadings on *PES* and *PES* squared are not significant. Recall that in the linear model, the estimate on *PES* is significant. However, these observations do not allow us to draw the conclusion that there is only a linear relationship between pesticide consumption and interregional agricultural CEE. These findings only indicate that the vertex of the U-shaped nonlinear relationship lies outside of our data range. Within our data range, we only have part of the parabola that is a curvilinear function, which does not reach a peak or nadir and turns around. Thus, we observe that the coefficient on *PES* is significant only in the linear model. Irrigation is the only agricultural activity that is observed to have the same nonlinear shape in terms of both direct and indirect effects. In Fig. 5 c), we plot the nonlinear relationships between irrigation and agricultural CEE for both direct and indirect effects. This observation suggests that both local and agricultural CEE in neighboring provinces first increase with the proportion of irrigated area;

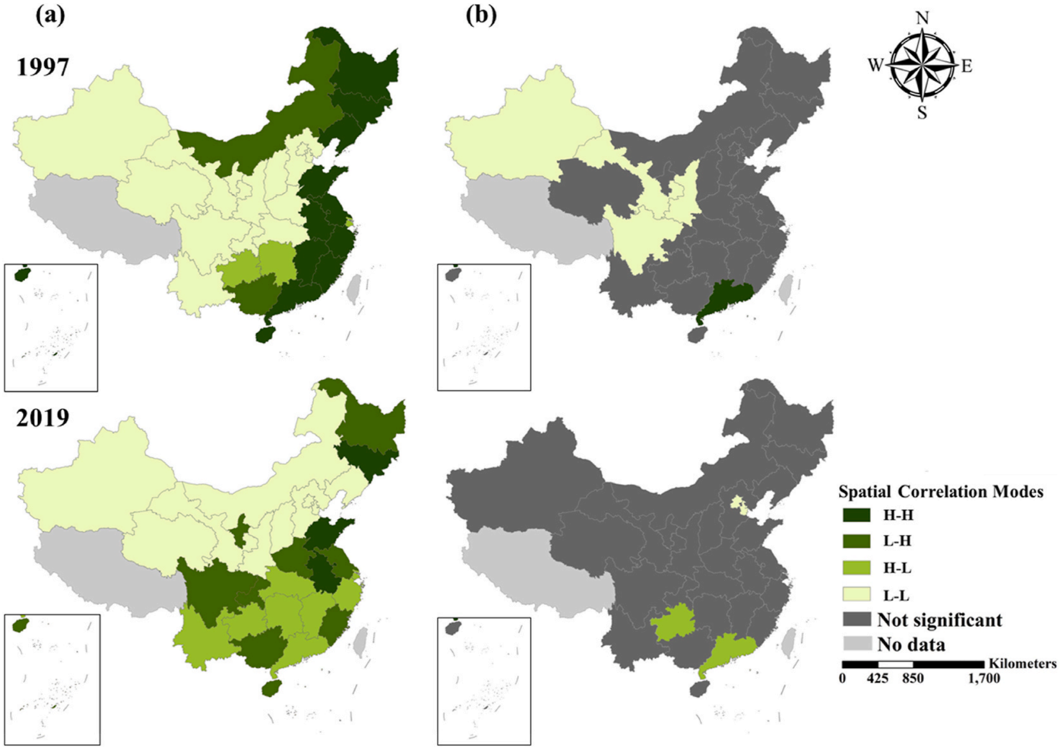

Fig. 4. (a) Map of spatial correlation modes and (b) LISA cluster map for 1997 and 2019.
Note: For the LISA cluster map, we use the 10% significance level.

after reaching the turning points, they start to fall. Following the same procedure, we calculate the maximums for both direct and spillover effects occurring at irrigated area shares of 25.40% and 18.57%, respectively.

To check whether the identified nonlinear relationships between agricultural activities and CEE disappear when other explanatory variables are introduced, we conduct a robustness study by adding livestock farming variables, i.e., sheep, cattle and pig breeding, into the model. The results are provided in the Animal husbandry controlled model section in the Appendix. With the presence of these three livestock farming variables, the U-shaped relationships of fertilization, deployment of agricultural machinery, irrigation and pesticide consumption on agricultural CEE remain robust, and only the size of their estimated coefficients is marginally affected by the three animal husbandry variables, although these three newly added variables are themselves significant.

4. Discussion and policy implications

Our study yields many valuable insights. In this section, we discuss the key findings of the current study. First, the Moran's scatter plot for 1997 provides evidence that most of the provinces were distributed in the first and third quadrants so that the global Moran's I index is significant and positive. More specifically, we observe a clustering pattern in which provinces in the H–H quadrant were the eastern provinces where climatic and environmental conditions are better. In contrast, provinces distributed in the third quadrant were the provinces in central and northwestern China. Only a handful of provinces in the second and fourth quadrants imply a clear boundary between high and low CEE areas. This observation indicates that environmental conditions dominated agricultural CEE in 1997. In 2019, however, we do not observe a clear pattern of agricultural CEE spatial correlation because all the studied provinces were evenly distributed in the four quadrants. More than half of the studied provinces are in the H-L and L-H quadrants, implying a mixed geographical distribution of different levels of CEE provinces. In recent decades, not only has an increase in agricultural practice intensity been witnessed in China, but it has also accelerated interregional integration, which has removed barriers between provinces to facilitate capital, labor and technology exchanges (Ang, 2017). Thus, our findings suggest that the promotion of agricultural management activities can improve agricultural CEE in regions with less favorable environmental conditions. In addition, with the support of interregional integration projects, more intensified experience and technical exchanges between regions can significantly accelerate the improvement of agricultural CEE countrywide.

As shown in Fig. 5, the direct effect of fertilizer consumption on CEE has a U shape, while the indirect effect takes an inverted U shape. This implies that fertilizer application has an economies of scale effect on local agricultural CEE and a diseconomies of scale effect on CEE in adjacent regions. It is beyond debate that fertilization can positively affect agricultural productivity. However, when considering the CO_2 emissions of this activity, i.e., emissions during fertilization and from soil after fertilization, the consumption of fertilizers might no longer be efficient in the sense that the emitted CO_2 cannot be compensated by the improvement in agricultural

Table 4
Estimation results of nonspatial models for Models (1) and (2).

	Model (1)					Model (2)				
	OLS	REM	SFM	TFM	STM	OLS	REM	SFM	TFM	STM
Intercept	15.3574***	11.3641***				13.3036**	−1.5855			
	(0.9384)	(0.9274)				(6.2004)	(4.5434)			
log(FER)	1.0583***	0.5107***	0.4480***	0.9650***	0.0435	−9.8884***	1.7947	2.1876	−9.7657***	−0.6495
	(0.1181)	(0.1306)	(0.1341)	(0.1212)	(0.1515)	(2.1940)	(1.5303)	(1.5360)	(2.2122)	(1.5721)
(log(FER)) ^{2}						0.9474***	−0.1161	−0.1574	0.9303***	0.0760
						(0.1936)	(0.1338)	(0.1343)	(0.1954)	(0.1357)
log(ARM)	−0.7685***	−0.6038***	−0.5885***	−0.7337***	−0.3034***	4.8045***	0.8590**	0.8235**	4.9841***	1.7160***
	(0.0664)	(0.0551)	(0.0561)	(0.0725)	(0.0878)	(0.7064)	(0.4374)	(0.4385)	(0.7218)	(0.4514)
(log(ARM)) ^{2}						−0.5269***	−0.1323***	−0.1265***	−0.5433***	−0.1860***
						(0.0656)	(0.0397)	(0.0397)	(0.0671)	(0.0395)
log(IRA)	−0.1975	−0.3010**	−0.2727*	−0.1423	−0.5153***	12.3609***	7.7053***	7.5101***	12.1761***	6.8601***
	(0.1218)	(0.1368)	(0.1418)	(0.1239)	(0.1442)	(1.2919)	(1.1548)	(1.1713)	(1.3127)	(1.2000)
(log(IRA)) ^{2}						−1.7102***	−1.1125***	−1.0824***	−1.6790***	−1.0182***
						(0.1775)	(0.1602)	(0.1627)	(0.1804)	(0.1669)
log(PES)	−0.0764***	0.0796	0.1046**	−0.0984***	0.0571	−0.1902	−1.0074**	−1.0781**	−0.0485	−0.9520**
	(0.0275)	(0.0486)	(0.0525)	(0.0278)	(0.0555)	(0.2771)	(0.4043)	(0.4358)	(0.2856)	(0.4263)
(log(PES)) ^{2}						0.0057	0.0620***	0.0669***	−0.0035	0.0604**
						(0.0166)	(0.0229)	(0.0244)	(0.0172)	(0.0240)
log(AGF)	−0.5616***	−0.0028	0.0190	−0.6512***	−0.0338	−1.3665***	−0.9806***	−1.0747***	−1.6830***	−0.7991**
	(0.0598)	(0.0472)	(0.0479)	(0.0622)	(0.0470)	(0.4871)	(0.3283)	(0.3319)	(0.4914)	(0.3311)
(log(AGF)) ^{2}						0.0488*	0.0567***	0.0642***	0.0630**	0.0442**
						(0.0273)	(0.0200)	(0.0203)	(0.0274)	(0.0203)
Log-Likelihood	−918.71	−344.85	−327.30	−903.16	−286.39	−854.06	−307.44	−286.25	−839.92	−251.00
LR Test		1148***	1183***	31.09*	1265***		1093***	1136***	28.27	1206***
Hausman Test			28.04***	30.04***	59.07***			27.98***	178.62***	63.31***
LM Spatial Lag					46.23***					29.88***
Robust LM Spatial Lag					20.98***					27.03***
LM Spatial Error					38.55***					18.21***
Robust LM Spatial Error					13.30***					15.36***

Note: This table presents the nonspatial model estimation results for both linear and nonlinear models. The standard errors for the coefficients are reported in parentheses. FFR, ARM, IRA, PES and AGF represent the consumption of fertilizers, the power of agricultural machinery, the share of irrigation, and the consumption of pesticides and agricultural films, respectively. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5
SDM and direct and indirect effect estimation results for models (1) and (2).

	Model (1)				Model (2)			
	SDM		Estimated Direct Effect	Estimated Indirect Effect	SDM		Estimated Direct Effect	Estimated Indirect Effect
	Independent Variable	Spatial Lag Variable			Independent Variable	Spatial Lag Variable		
log(CEE)		0.0874***				0.0925***		
		(0.0228)				(0.0163)		
log(FER)	−0.2038	0.1886***	−0.2014	0.2004***	−3.7998**	2.2875***	−4.0084**	2.4120***
	(0.1388)	(0.0573)	(0.1562)	(0.0601)	(1.4837)	(0.6922)	(1.6206)	(0.7069)
(log(FER))^2					0.3276**	−0.1866***	0.3455**	−0.1953***
					(0.1279)	(0.0609)	(0.1374)	(0.0618)
log(ARM)	−0.2059***	−0.0081	−0.2250**	−0.0076	1.1483***	−1.0490***	1.2585**	−1.1747***
	(0.0793)	(0.0227)	(0.0909)	(0.0258)	(0.4431)	(0.2144)	(0.4887)	(0.2422)
(log(ARM))^2					−0.1343***	0.0896***	−0.1479***	0.1004***
					(0.0401)	(0.0191)	(0.0440)	(0.0215)
log(IRA)	−0.3355**	−0.3569***	−0.3697**	−0.3854***	3.0462***	1.5555***	3.3170***	1.8194***
	(0.1381)	(0.0690)	(0.1671)	(0.0761)	(1.1585)	(0.5783)	(1.1762)	(0.5666)
(log(IRA))^2					−0.4671***	−0.2685***	−0.5127***	−0.3114***
					(0.1615)	(0.0804)	(0.1661)	(0.0808)
log(PES)	0.0345	0.1008***	0.0336	0.1148***	−1.8533***	0.1715	−2.0877***	0.1344
	(0.0498)	(0.0296)	(0.0572)	(0.0322)	(0.3903)	(0.2352)	(0.4612)	(0.2400)
(log(PES))^2					0.1050***	−0.0037	0.1085	−0.0011
					(0.0220)	(0.0133)	(0.0262)	(0.0136)
log(AGF)	−0.0023	0.0277	−0.0005	0.0290	−0.3790	−0.1809	−0.4307	−0.1810
	(0.0421)	(0.0262)	(0.0434)	(0.0285)	(0.2922)	(0.2004)	(0.3023)	(0.2369)
(log(AGF))^2					0.0180	0.0108	0.0210	0.0108
					(0.0180)	(0.0118)	(0.0186)	(0.0139)

Note: This table presents the SDM estimation results for agricultural CEE from 1997 to 2019. In addition, the results of the direct and indirect effect estimations are also listed. The spatial lag variables indicate the $W \bullet Y$ and $W \bullet X$ components in Eq. (4). The standard errors for the coefficients are reported in parentheses. FFR, ARM, IRA, PES and AGF represent the consumption of fertilizers, the power of agricultural machinery, the share of irrigation, and the consumption of pesticides and agricultural films, respectively. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

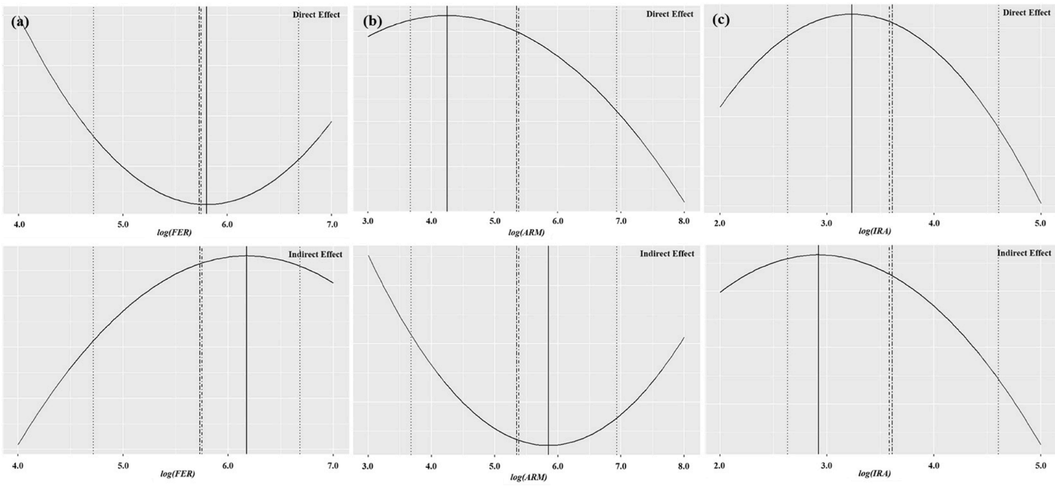

Fig. 5. Nonlinear relationships between fertilization, agricultural machinery and irrigation and agricultural CEE.
Note: The dotted line indicates the sample range, the dashed line indicates the sample mean, the dotted-dashed line indicates the sample median, and the solid line indicates where the minimum or maximum occurs. (a) consumption of fertilizers; (b) deployment of agricultural machinery; (c) irrigation.

productivity. Thus, based on our results, fertilizer consumption should be increased such that a positive impact on local agricultural CEE can be generated. However, it must be noted that higher levels of consumption can positively influence local CEE but also have a negative effect on CEE in adjacent regions. In addition, in our study, we do not consider the CO_2 emissions during the fertilizer production process, which might increase the fertilizer consumption threshold for local CEE and decrease the threshold for neighboring CEE. Furthermore, traditional chemical fertilizers have other significant negative impacts on the environment, such as causing soil structure deterioration and groundwater pollution, and thus indirectly affect the agricultural production (Kandpal, 2021). Therefore, it is vital that local governments and agricultural technicians effectively educate farmers to efficiently use fertilizers for cultivation.

In our study, both the direct and indirect effects of irrigation on agricultural CEE are found to have an inverted U shape. In addition, the results of the linear model imply that during the studied period, the average direct and indirect impacts of irrigation on agricultural CEE are negative. These findings indicate that irrigation has a diseconomies of scale effect on agricultural CEE and that the average proportions of irrigated area in many regions are too large. As the second-largest country in the world by area, China's landscape is vast and diverse. Both geographical and climatic conditions vary significantly across China's territory. As shown in Fig. 6, the precipitation and sunshine conditions in China have a clear pattern: Southeast China has more rainfall and fewer sunshine hours, while Northwest China has less rainfall and more sunshine hours. Thus, in relatively dry Northwest China, large-scale irrigation systems have been established to assist the production of crops (Yu et al., 2011). Vast amounts of energy are consumed to run such irrigation systems, escalating CO_2 emissions (Chen et al., 2019; Xu et al., 2020). In addition, the strong evaporation effect in these regions decreases irrigation efficiency (Wu et al., 2014). However, due to the very limited arable land resources and high alternative cost, i.e., transporting agricultural products from other regions, it is almost impossible for China to give up on irrigation systems in these areas. Thus, based on our results, the decision regarding which crop should be cultivated in these regions must be made based on both market demand and local environmental conditions. Promoting the cultivation of more drought-resistant crops in such areas can reduce the unnecessary capacity of irrigation systems. Furthermore, increasing irrigation efficiency and combining the use of agricultural films are also measures to be considered. As shown in Fig. 2, the consumption of agricultural films is also the highest in Northwest China. However, all of these factors require the local government to assess the technology feasibility and earn the trust and acceptance of local farmers.

The results of the spatial dependence analysis and the estimated direct and indirect effects of the influencing factors indicate that the agricultural CEE of one province is affected not only by local agricultural activities but also by those of surrounding regions. As found in previous studies, agricultural CO_2 emissions show a significantly positive spatial autocorrelation pattern (Chen et al., 2020). Thus, it is impossible to attribute the responsibility of emissions to a certain region due to spatial correlation and agglomeration effects. CE hotspots are not easy to identify, and regions with high agricultural carbon efficiency might be negatively influenced by neighboring emission hotspots. In addition, we find that some agricultural practices have significant spillover effects on the emission efficiency in adjacent regions. Due to these spillover effects, the costs of the agricultural CE cannot be internalized in the sense of "who pollutes who controls". In addition, the effects of agricultural activities, such as fertilization and the deployment of agricultural machinery, on local and interregional agricultural CEE have opposite U shapes, indicating that improving local CEE performance might occur at the expense of decreasing CEE in neighboring regions. Given these facts, it is almost unrealistic that one region could improve its agricultural carbon efficiency alone. Thus, an effective improvement in emission efficiency requires an interregional joint effort. In such circumstances, national level coordination is needed, and the barriers between regions must be removed to facilitate the

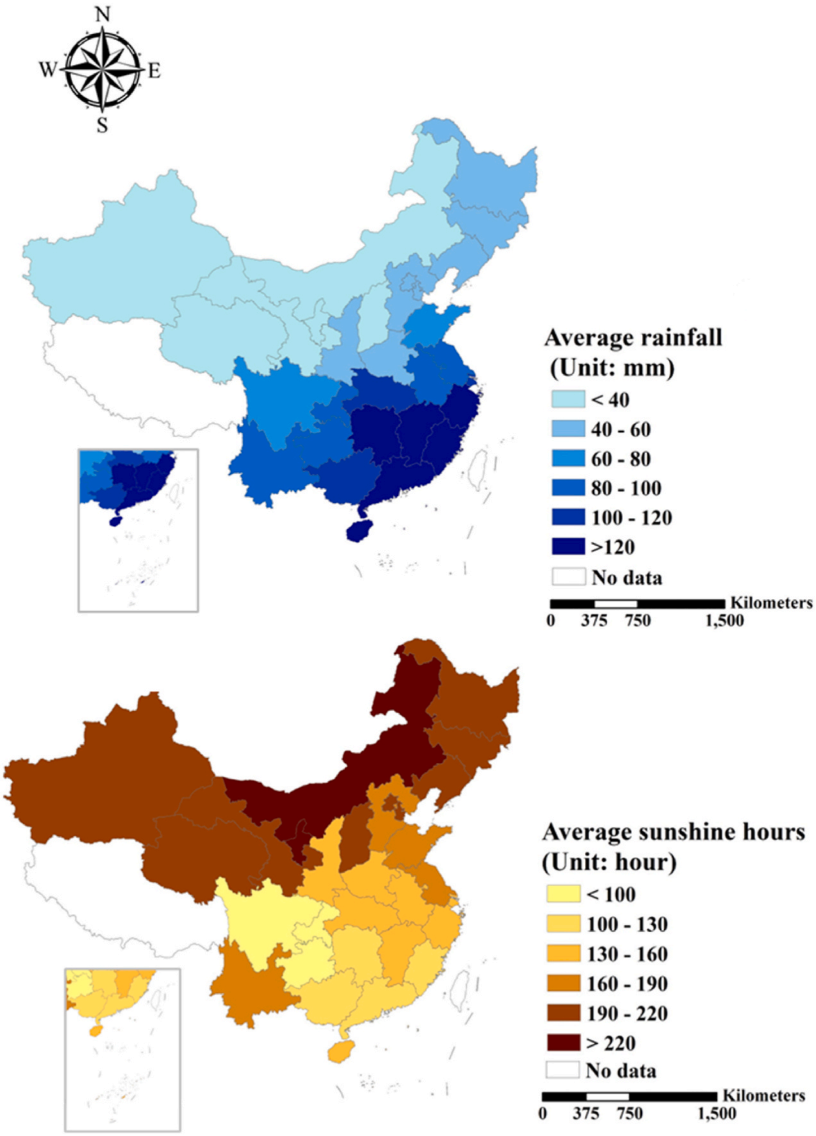

Fig. 6. The average monthly rainfall and sunshine hours from 1997 to 2019.
Note: The monthly rainfall and sunshine hour data are collected from China Meteorological Data Service Centre (2022).

transfer of agricultural labor, technologies, etc.

5. Conclusion

The two major challenges developing countries are facing in the coming decades are improving agricultural production to ensure food security and mitigating CO_2 emissions. It seems that these two tasks are irreconcilable, as any social or economic development is inevitably accompanied by increased CO_2 emissions, in particular for developing countries (Tucker, 1995; Heil and Quentin, 1997). Thus, the only way out is to improve agricultural CEE. To address this issue, in this study, we employ spatial dependence tests, i.e., global and local Moran's *I* index tests, LISA cluster maps and individual and time fixed effects SDM to systematically study agricultural emission efficiency and its influence on agricultural practices in China from 1997 to 2019. We find that CEE in China's agriculture industry displays a positive spatial dependence pattern. However, this dependence has weakened in the last decade. Our results of the SDM estimation suggest nonlinear relationships between agricultural CEE and agricultural practices, such as the consumption of fertilizers and pesticides, the use of agricultural machinery and irrigation. Based on the SDM results, we further estimate the direct and indirect effects of these activities and find that most of these agricultural practices have significant spillover effects on CEE in adjacent regions.

Based on our results, we provide several political implications for developing countries. First, although agricultural practices lead to CO_2 emissions, the positive effects on agricultural productivity can offset these effects and lead to overall improvements in production-emission efficiency. Thus, it is advisable to promote agricultural management activities. Second, adopting agricultural management activities can break the dominance of environmental conditions in agricultural CEE by improving productivity; however, local conditions still play an important role in CEE. Thus, local policymakers should tailor their agricultural development policies based on the local environmental and economic conditions. Third, in our study, the shapes of the relationships between many agricultural practices and local CEE are nonlinear. This finding suggests both diseconomies and economies of scale effects of these activities. Thus, it is vital for policymakers to carefully design their local agricultural development plans to avoid "overdose". Fourth, we find clear evidence that many agricultural activities have significant spillover effects. Thus, improving agricultural CEE in one region also requires interregional joint efforts. In addition, exchanges regarding labor and technology between high- and low-CEE regions should be promoted to improve overall agricultural CEE.

To our knowledge, this study is the first to analyze the spatial pattern and factors influencing agricultural CEE. Based on the present study, we would like to provide some suggestions for future research in this field. In this study, we define the agricultural CEE as the amount of GOV or GDP that can be generated from one ton of emitted CO_2. As mentioned in the introduction section, many researchers have evaluated agricultural carbon efficiency using data envelopment analysis and Malmquist index models. Therefore, it is advisable that future studies use other agricultural CEE metrics to conduct their analysis. In addition, to understand GOV- or GDP-based CEE in agriculture and other sectors, it is important to control for the inflation effect in the analysis. Using the interest rate or sovereign bond yield as a discounting factor is recommended in such circumstances. Furthermore, future studies should consider the carbon sink effect of forests in their analysis.

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CRediT authorship contribution statement

Xueqing Yang: Conceptualization, Funding acquisition, Visualization, Writing – original draft, Writing – review & editing. **Yang Liu:** Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Alberto Bezama:** Conceptualization, Supervision, Writing – review & editing. **Daniela Thrän:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared the influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envdev.2024.101004.

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