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Impact of factor quality improvement on agricultural carbon emissions: Evidence from China's high-standard farmland

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Reducing agricultural carbon emissions is essential to address climate change comprehensively, and improving factor quality reduces agricultural carbon emissions by promoting agricultural transformation. Based on the policy experiment of high standard farmland construction in China, this paper analyzes the role of factor quality in reducing agricultural carbon emissions using the SARAR model and data from 280 urban agricultural sectors. The study finds a significant spatial correlation between agricultural carbon emissions and factor quality improvement. Factor quality improvement can reduce agricultural carbon emissions. The disequilibrium effect analysis finds that the impact of factor quality improvement on agricultural carbon emissions has a disequilibrium effect. In other words, factor quality improvement mainly affects agricultural carbon emissions in areas with a higher level of agricultural development. The mediating test suggests that factor quality reduces the improvement of agricultural carbon emissions and promotes the transformation of agricultural industrial structure through the mediating factor of agricultural carbon emissions. Finally, in addressing global climate change, this paper attempts to provide policy references for developing countries to reduce agricultural carbon emissions from factor quality improvement.

KEYWORDS

factors quality, carbon emission, agriculture, high-standard farmland, industrial structure

1 Introduction

The economic losses caused by extreme weather caused by the greenhouse effect on global agricultural production are increasing yearly. The extreme weather events disrupt the environment (Cruz and Krausmann, 2013), in particular, crop production (Elahi et al., 2021). Therefore, governments are paying attention to agricultural carbon emission reduction. Meanwhile, Article four of the Paris Agreement proposes reducing emissions and increasing foreign exchange to balance anthropogenic greenhouse gas emissions and removals by sinks in the second half of the 21st century (Nations, 2015). More and more countries are turning carbon emission reduction into strategies and actions. More than 100 countries or regions worldwide have committed to carbon neutralization. As agriculture is not only the source of greenhouse climate emissions, but also a contributor to climate change, agriculture has become one of the centers of climate change. Agricultural carbon emissions mainly come from pesticides, chemical fertilizers, and agricultural diesel oil. At the same time, agriculture also has a carbon sink function, increasing farmland soil's organic carbon storage and carbon fixation capacity (Cara and Jayet, 2000). The rational use of production factors not only improves climate change, but also effectively increases output. Therefore, improving the quality of agricultural factors and reducing the input of agricultural factors will reduce agricultural carbon emissions and help achieve the global carbon neutrality goal.

According to the theory of factor quality, factor quality is an essential factor affecting the green development of agriculture (Xiao et al., 2021). Previous studies have found that the higher the quality of land elements, the higher the land efficiency under the same conditions (Leonard et al., 2020), and at the same time, the agricultural carbon emissions will be reduced (Deng et al., 2021). This idea provides a way to promote the green development of agriculture: to improve agricultural efficiency by improving the quality of agricultural factors to realize the green development of agriculture (Pu et al., 2019). For agriculture in developing countries, implementing a factor quality improvement project, namely high-standard farmland construction, is a new driving force to achieve green agricultural development (Zhou and Cao, 2020). In this context, to improve cultivated land quality and reduce agricultural carbon emissions, China put forward the construction task of high-standard basic farmland in 2012. The Ministry of agriculture and rural areas of China issued the national high standard farmland construction plan 2021–2030 in September 2021 (MARA, 2021). This policy states that 190 million acres of high-standard farmland will be built, and 46 million acres of high-standard farmland will be upgraded. Scholars have found that by implementing high-standard farmland construction to improve the quality of factors, China's agricultural carbon emissions have been reduced by 24.4% (Chen and Wang, 2022). In summary, there are two new questions. In the context of green agricultural development, what impact does the improvement of factor quality represented by high standard farmland construction have on agricultural carbon emissions? Where can the improvement of factor quality affect agricultural carbon emissions? Answering these questions will help clarify the relationship between factor quality improvement and agricultural carbon emissions and explore the source of green agricultural development. At the same time, it will provide a theoretical basis and practical reference for developing countries to transform traditional agriculture.

The existing literature discusses the influencing factors of agricultural carbon emissions from the aspects of agricultural land operation scale (Asif and Almagul, 2022), carbon emission reduction policy (Wang et al., 2020), technological progress (Zaman et al., 2012; Cai et al., 2022), marketization (Dumortier and Elobeid, 2021). The agricultural land management scale's expansion induces changes in agricultural chemicals' input intensity and production technology (Koondhar et al., 2021). From the driving source, the improvement of agricultural carbon emission reduction efficiency mainly depends on the progress of cutting-edge technology rather than improving technical efficiency. The advanced technology progress has played a positive role in promoting the improvement of agricultural carbon emission reduction efficiency everywhere (Liu D. et al., 2021). In addition, urbanization is also considered to be an essential factor affecting agricultural carbon emissions (Asif and Almagul, 2022). The impact of urbanization on total agricultural carbon emissions lasts longer and has a more obvious impact effect.

The existing literature provides a valuable reference for regional differences in agricultural carbon emissions. However, these studies mainly focus on technological progress and agricultural policies and seldom analyze the influencing factors of agricultural carbon emissions from the perspective of factor quality improvement. Supporters of technology theory believe that factor quality improvement is a way to change the input structure of agricultural factors (Peng et al., 2017), can change and improve the efficiency of agricultural production (Yuan et al., 2022), improve agricultural productivity and profitability, and then reduce agricultural carbon emissions (Dakpo et al., 2016). However, the substitution theorists believe that factor quality improvement will produce a factor substitution effect (Li et al., 2021). As labor-saving technological progress, with the rise of labor price, the improvement of factor quality plays a more and more important role in replacing labor factors (Zhang et al., 2019). Some studies have shown that reconfiguring agricultural factors will change the agricultural industrial structure, thus improving factor allocation efficiency and ultimately reducing agricultural carbon emissions (Liu and Yang, 2021).

Through the above analysis, this paper finds that the existing literature has the following two points that can be expanded. The first is the relationship between factor quality improvement and agricultural carbon emissions. In the process of traditional agricultural transformation, the improvement of factor quality has become an important way to supplement the weakness of agricultural infrastructure. The improvement of factor quality can promote the green development of agriculture, but whether the improvement of factor quality will affect agricultural carbon emissions needs further discussion. Therefore, this paper attempts to analyze the influencing factors of agricultural carbon emissions from the perspective of factor quality improvement. The second is the agricultural carbon reduction effect of factor quality improvement from the perspective of disequilibrium. Terrain conditions will also restrict the economic impact of factor quality improvement. In areas with slight topographic relief, factor quality improvement is easier to improve agricultural efficiency, thereby reducing agricultural carbon emissions. However, in areas with sizeable topographic relief, it is difficult to improve the quality of factors, so the improvement of factor quality has a limited effect on the improvement of agricultural carbon emissions. The improvement of high factor quality will not only be restricted by the terrain conditions but also be affected by the level of agricultural economic development. The higher the level of agricultural economic growth, the greater the impetus to improve the quality of factors. Therefore, this paper studies the agricultural carbon emission reduction effect of factor quality improvement from the perspective of disequilibrium.

In summary, agricultural production is an important source of carbon emissions, and developing a low-carbon economy is inseparable from low-carbon agriculture. Under the background of transforming traditional agriculture in developing countries, this paper studies the path of reducing agricultural carbon emissions by improving the quality of agricultural factors. The main research questions of this paper are "How does the improvement of factor quality affect agricultural carbon emissions?". Therefore, this paper performs an empirical analysis based on China's policy experiment of high-standard farmland construction and considers the disequilibrium effect to systematically analyze and elaborate on the mechanism behind the impact of factor quality improvement on agricultural carbon emissions. Using the data from 280 urban agricultural sectors and SARAR model, this paper empirically analyzes the spatial and disequilibrium effects of factor quality improvement on agricultural carbon emission. The findings of this paper provide policy references for developing countries to reduce agricultural carbon emissions from factor quality improvement. The possible marginal contributions of this paper are as follows. First, from the perspective of factor quality improvement, this paper studies the path to reducing agricultural carbon emissions. In transforming traditional agriculture, improving the quality of agricultural factors has become a new driving force for agricultural development to complement the shortcomings of agricultural infrastructure. Whether the improvement of the quality of agricultural factors will affect agricultural carbon emissions needs further discussion. Second, further expand the research hypothesis to an unbalanced perspective. Agricultural carbon emissions will not only be affected by the quality of agricultural factors but also by the agricultural natural environment and socio-economic environment. Therefore, this paper analyzes the impact of factor quality improvement on agricultural carbon emissions in which regions. Third, this paper selects the number of high-standard farmland construction documents published by urban agricultural departments as an instrumental variable and uses two-stage least squares regression to discuss the possible endogeneity problems.

The structures of paper are as follows. The second section introduces theoretical framework, data sources, model, and variable selection. The third section discusses the spatial correlation. The fourth section reports the empirical findings on the impact of factor quality improvement on agricultural carbon emissions. The fifth section discusses the disequilibrium effect. The sixth section provides the robustness test. The seventh section examines the mechanism effect of agricultural industrial structure. The eighth section provides conclusions, puts forward some policy recommendations, and suggests future research.

2 Materials and methods

2.1 Theoretical framework

According to the agricultural production theory, the green development of agriculture mainly comes from three aspects: first, the increase of agricultural factor input; Second, improve the production efficiency of agricultural factors; Third, improve the quality of agricultural factors. From the current situation of global agricultural production, the input of agricultural factors has reached a certain degree. Therefore, it is difficult for the government to promote the green development of agriculture by increasing the input of agricultural factors. At the same time, it is difficult to promote agriculture's green development by improving agricultural factors' production efficiency due to the lack of power to promote the progress of agricultural technology. Based on the above analysis, the way to reduce agricultural carbon emissions by improving the quality of factors is a new way to promote agricultural green development. Factor quality improvement reduces agricultural factor input (increases agricultural output) under the condition that agricultural output (agricultural factor input) remains unchanged by improving factor quality. The factor quality improvement can promote the large-scale agricultural production. The large-scale agricultural production will inhibit the excessive application of pesticides and fertilizers caused by farmers' pursuit of output, and make the protective agricultural farming measures applied in a wider range. Therefore, the factor quality improvement reduces agricultural carbon emissions by reducing agricultural factor input.

Under the assumption of rational people, the change in the relative output efficiency of agricultural factors will further affect the factor input of the agricultural sector, and then change the agricultural industrial structure. According to the agricultural production theory, the reallocation of agricultural factor resources among different regions is an important way to promote agricultural economic growth and reduce agricultural carbon emissions. The factor quality improvement can change the agricultural industrial structure by affecting the allocation structure of agricultural factors. Under the background of optimization of agricultural industrial structure and green development of agriculture, traditional agriculture with large carbon emissions will be gradually reduced. Modern agriculture with small carbon emissions will develop rapidly, thus reducing the overall carbon emissions in the agricultural sector.

2.2 Data sources

This paper focuses on the impact of factor quality improvement on agricultural carbon emissions. The panel data of 280 cities in China from 2018 to 2020 are used as the sample. The data of this paper mainly includes two parts. The agricultural carbon emissions data and control variables are one part, mainly from the China Statistical Yearbook for years 2019–2021, the statistical yearbook of various provinces and cities. The other part of the data is the factor quality improvement data, mainly from the high standard farmland construction data published by the Provincial Department of agriculture and rural affairs and the Municipal Bureau of agriculture and rural affairs. For cities that have not published high-standard farmland construction data, this paper sends a letter to the urban Bureau of Agriculture and rural affairs or the Department of agriculture and rural experiences of the province to which the city belongs.

2.3 Model

As a government policy, factor quality improvement has an exogenous nature. Still, the delimitation of the scope of factor quality improvement, completion quality, and the impact on agricultural production in surrounding areas will also have a spatial correlation. At the same time, agricultural carbon emissions are not independent in space (Cai et al., 2022). Therefore, when studying factor quality improvement and agricultural carbon emissions, we must consider its spatial attributes. We need to use spatial econometric models to analyze the impact of factor quality improvement on agricultural carbon emissions. The mainstream spatial econometric models mainly include spatial autoregressive (SAR), spatial error (SEM), and spatial Durbin (SDM) models, which subsumes all the spatial autoregressive and error terms. However, the spatial autoregressive and error terms may exist in the process of the impact of factor quality improvement on agricultural carbon emissions simultaneously. Based on this, this paper uses the research method of Xie et al. (2019) and Li et al. (2022) for reference. We use the spatial autoregressive model with spatial autoregressive disturbances (SARAR) model to study the impact of factor quality improvement on agricultural carbon emissions. The equation is set as follows:

$$SARAR: \begin{cases} ACE = \rho W \cdot ACE + \beta FQI + \kappa Control + \mu \\ \mu = \lambda W \mu + \varepsilon \end{cases} \quad (1)$$

where *ACE* is agricultural carbon emissions; *FQI* is factor quality improvement; *Control* is control variable, which includes seven variables. ρ is the spatial autoregressive coefficient of agricultural carbon emissions, stands for the impact of agricultural carbon emissions in adjacent areas on the region; β is the regressive coefficient of *FQI* on *ACE*; μ and ε are the spatial error term; λ is the regressive coefficient of spatial error term on agricultural carbon emissions; *W* is the spatial weight matrix (n×n), which is the urban spatial distance calculated based on the urban centroid coordinates, and the reciprocal of this distance is the weight between cities. The mathematical expression of *W* is:

$$W = \begin{cases} 1/d_{ij} & i \neq j \\ 0 & i = j \end{cases} \quad (2)$$

where *i* and *j* are city; d_{ij} is the spatial distance between city *i* and city *j*.

2.4 Measures

2.4.1 Agricultural carbon emissions

Agricultural carbon emissions are the dependent variable of this paper. Based on the availability of urban agricultural data, this paper attempts to choose the carbon emissions per unit of GDP method as the measurement method of agricultural carbon emissions. According to Zaman et al. (2021), the carbon sources in this paper include fertilizers, pesticides, agricultural film, agricultural diesel, irrigation and plowing. Due to the lack of data on pesticides, agricultural film, and agricultural diesel within the urban, this paper attempts to calculate those data based on provincial unit cultivated land area and actual urban cultivated land area. The total agriculture carbon emission is equal to the sum of the product of the pure amount of fertilizers, pesticides, agricultural film, agricultural diesel, total sown area, and actually irrigated area and the emission coefficient respectively. In other words, the total agricultural carbon emission is equal to the sum of the product of the above usage and emission coefficient. The formula of the total agriculture carbon emission is $E = \sum E_i = \sum S_i \cdot C_i$, among which E_i refers to the carbon emissions of various carbon sources, S_i refers to the values of various carbon sources, and C_i is the emission coefficient of various carbon sources. For the convenience of subsequent quantitative analysis, the agricultural carbon emission in this paper is expressed by the ratio of the total agricultural carbon emission (kg) to the total agricultural output value (one hundred thousand yuan). According to relevant research (West and Marland, 2002; Dubey and Lal, 2009; Liu Y. et al., 2021), the carbon emission coefficient showed in Table 1.

Measurement results of urban agricultural carbon emissions are shown in Table 2. Table 2 shows that China's agricultural

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TABLE 1 Agricultural carbon sources, carbon emission coefficient and reference sources.

Carbon sources	Coefficient	Reference
Fertilizer	0.8956	American Oak Ridge National Laboratory
Pesticide	4.934	American Oak Ridge National Laboratory
Agricultural film	5.18	Institute of Resource, Ecosystem and Environment of Agriculture in Nanjing Agricultural University
Agricultural diesel	0.5927	Intergovernmental Panel on Climate Change
Irrigation	25	Dubey and Lal (2009)
Plowing	312.6	College of Agronomy and Biotechnology in China Agricultural University

TABLE 2 Measurement results of urban agricultural carbon emissions.

Time	All regions	Eastern regions	Central regions	Western regions
2018	0.5782	0.8731	0.5603	0.4981
2019	0.5730	0.8208	0.5509	0.4870
2020	0.5691	0.7932	0.5334	0.4631
Mean	0.5734	0.8290	0.5482	0.4827

carbon emissions have been continuously reduced from 2018 to 2020. The agricultural carbon emissions reduction rate in the eastern region has been faster than in the central and western regions. Regarding spatial differences, agricultural carbon emissions in the eastern region are significantly higher than those in the central and western regions. The possible explanation is that the total agricultural output in the eastern regions is relatively high so the agricultural carbon emissions will be higher. Still, at the same time, the implementation of agricultural carbon reduction policies in the eastern region is also relatively large. Hence, the agricultural carbon emissions reduction rate in the eastern regions is also higher than in the other regions.

2.4.2 Factor quality improvement

Factor quality improvement (FQI) is the independent variable of this paper. This paper attempts to use the proportion of high standard farmland construction area in urban cultivated land area to express.

2.4.3 Control variables

The control variable selected in this paper cover seven aspects, informatization (Infor) is measured by the number of netizens in the city; Human capital (HC) is measured by the ratio of the number of middle school students to the total urban population; Urbanization (Urb) is measured by the ratio of the urban permanent population to the total population; Financial development (FD) is measured by the ratio of the balance of various deposits of financial institutions to the total population at the end of the year. Government intervention (GI) is measured by the ratio of fiscal expenditure to regional GDP. Industrial development (ID) is measured by the ratio of the total industrial output value above scale to the regional GDP. Social consumption (SC) is measured by the total retail sales of social consumer goods to the total population. The descriptive statistics of the variable are shown in Table 3.

3 Discussion of spatial correlation

According to the previous analysis, there may be a spatial correlation between the improvement of factor quality and agricultural carbon emissions, so it is necessary to test its spatial correlation. Suppose the factor quality improvement or agricultural carbon emission has a spatial correlation. In that case, it is necessary to use a spatial econometric model to discuss the impact of factor quality improvement on agricultural carbon emission. According to Jung and Vijverberg. (2019), this paper adopts Moran's I index to analyze the spatial correlation test results between factor quality improvement and agricultural carbon emissions. Table 4 provides the test results of spatial correlation.

As shown in Table 4, there is a significant spatial correlation between factor quality improvement and agricultural carbon emissions. It shows that although the factor quality improvement is an independent policy choice of each region, other regions will also affect the quality improvement in the different regions. At the same time, changes in agricultural carbon emissions will also be affected by other regions. Therefore, when analyzing the impact of factor quality

TABLE 3 Descriptive statistics of variables.

Variable	Var-Des	Mean	S.D.	Min	Max
FQI	Factor quality improvement (%)	0.3140	0.2631	0.0008	0.4631
Infor	Informatization level (ten thousand households)	3.9831	0.3690	2.8805	5.0932
HC	Human capital (person/ten thousand persons)	10.7281	0.4910	8.3814	11.9831
Urb	Urbanization level (%)	0.5732	0.4268	0.1023	0.9879
FD	Financial development (RMB million/person)	0.3241	0.1892	0.1893	1.3981
GI	Government intervention (%)	0.0791	0.0267	0.0234	0.1901
ID	Industrial development (%)	0.5031	0.5876	0.0564	11.8732
SC	Social consumption (RMB million/person)	10.0911	0.6581	7.7647	13.1102

TABLE 4 Spatial correlation test.

Year	FQI		ACE		Residual	
	Moran's I	S.D (I)	Moran's I	S.D (I)	Moran's I	S.D (I)
2018	0.018**	0.010	0.067***	0.009	0.047***	0.010
2019	0.017**	0.010	0.089***	0.009	0.041***	0.010
2020	0.019**	0.010	0.083***	0.009	0.048***	0.010

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

improvement on agricultural carbon emissions, it is necessary to use a spatial econometric model for discussion. In addition, according to Anselin et al. (2004), this paper uses the OLS model to calculate the residual term in different years and discusses the spatial correlation of the residual. It can be seen from the residual spatial correlation test in Table 4, the residual has a significant spatial correlation. It shows that the impact of factor quality improvement on agricultural carbon emissions estimated by the OLS model is not a real estimation result. To accurately reflect the impact of factor quality improvement on agricultural carbon emissions, this paper attempts to select an econometric model that can reflect the spatial correlation between regions for estimation.

4 Benchmark regression

Since the data in this paper are panel data, it is necessary to judge which is more suitable for this study: fixed effect, random effect, and mixed effect. According to Anselin et al. (2004), BP and Hausman tests are used to test the fitting result of the spatial econometric model in this paper. The results show that both BP and Hausman tests passed the significance test. Thus, the benchmark regression of this paper is based on the fixed effect, using the SARAR model for empirical analysis. Table 5 provides the estimated results of FQI on ACE. Columns (1), (2), (3), and (4) report the results of all regions, eastern regions, central regions, and western regions.

Firstly, column (1) in Table 5 is the estimation result of FQI on ACE. We find that factor quality improvement significantly reduces agricultural carbon emissions. On the one hand, under certain output conditions, the factor quality improvement will lead to the continuous reduction of the number of factors invested in the agricultural sector. When the number of factor inputs is reduced, the carbon emissions of the agricultural sector will also be reduced (Tian et al., 2016; Chen et al., 2020). On the other hand, with the improvement of agricultural land quality, the government's investment in the agricultural sector will continue to increase, thereby improving the factor efficiency. When the factor efficiency of the agricultural sector is improved, this will reduce the undesirable output, which will be reflected in the reduction of agricultural carbon emissions.

Secondly, column (1) in Table 5 shows the spatial spillover effects of FQI on ACE. The spatial autoregressive term (rho) estimation coefficient is significantly positive. It shows that the reduction of agricultural carbon emissions will not lead to the decrease of agricultural carbon emissions in adjacent regions but will increase agricultural carbon emissions in adjacent areas. The possible explanation is that there is no driving effect on agricultural carbon emissions. The improvement of factor quality will drive the improvement of the input quality of agricultural factors in this region. Still, it will also attract

TABLE 5 Results of the benchmark regression.

Variable	(1)	(2)	(3)	(4)
	All regions	Eastern regions	Central regions	Western regions
FQI	−0.0166***	−0.0505***	−0.0296***	−0.0021***
	(0.0008)	(0.0179)	(0.0094)	(0.0002)
Infor	−0.0077	−0.0205	−0.0164	−0.0016
	(0.0083)	(0.0169)	(0.0107)	(0.0199)
HC	−0.2481***	−0.1612	−0.3567***	−0.1104
	(0.0506)	(0.1542)	(0.0767)	(0.0901)
Urb	−0.0028	−0.0015	−0.0696*	−0.1076***
	(0.0025)	(0.0022)	(0.0400)	(0.0295)
FD	−0.0108***	−0.0074	−0.0148***	−0.0051
	(0.0025)	(0.0065)	(0.0042)	(0.0060)
GI	−0.0463***	−0.1329**	−0.0008	−0.0316**
	(0.0063)	(0.0678)	(0.0294)	(0.0160)
ID	0.0218***	0.0108*	0.0459***	0.0114**
	(0.0031)	(0.0056)	(0.0062)	(0.0047)
SC	−0.0035	−0.0111**	−0.0044	−0.0388***
	(0.0025)	(0.0048)	(0.0030)	(0.0138)
rho	0.8980***	0.7813***	0.8961***	0.8371***
	(0.0109)	(0.0863)	(0.0177)	(0.0192)
lambda	−0.8534***	−0.9413***	−0.6175***	−1.0997***
	(0.0420)	(0.0146)	(0.0738)	(0.0712)
sigma2_e	0.0145***	0.0092***	0.0152***	0.0161***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Pseudo R^2	0.5483	0.6013	0.6756	0.7013
Log	735.1779	250.5340	255.4166	250.5199
N	840	291	300	249

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Numbers in parenthesis are standard error.

advantageous agricultural factors in adjacent regions, which will increase agricultural carbon emissions in adjacent regions. In other words, reducing agricultural carbon emissions is at the cost of the rise of agricultural carbon emissions in the adjacent regions.

Finally, column (2), (3), and (4) in Table 5 shows the results of the subdivision sample. We find that factor quality improvement significantly reduces agricultural carbon emissions in eastern, central, and western regions. The comparison of the results shows that the factor quality improvement has the largest impact on the coefficient of agricultural carbon emissions in the eastern region and the smallest effect on the coefficient of agricultural carbon emissions in the western regions. Land leveling in the eastern regions is suitable for large-scale mechanized farming. Improving the quality of land factors will reduce the input of labor factors, pesticides, fertilizers, and other factors and then optimize the input structure of agricultural factors, reducing agricultural carbon emissions in the eastern region from the perspective of agricultural factor input (Xiong et al., 2020). On the other hand, the natural conditions of agricultural production in the western region are relatively poor, and the agricultural unit output in the western regions is relatively low. Improving the quality of land factors will have a relatively small impact on agricultural production in the western regions (Huang et al., 2019).

5 Disequilibrium effect analysis

According to the previous analysis, factor quality improvement can reduce agricultural carbon emissions, but the impact of factor quality improvement on agricultural carbon emissions in different regions is significantly different. Based on the facts of agricultural development in the East, central and western regions, and according to He et al. (2020), we suspect that the impact of factor quality improvement on agriculture in the different regions may be subject to the level of agricultural

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TABLE 6 Results of disequilibrium effect.

Variable	(1) All regions	(2) Affluent regions	(3) General regions	(4) Poor regions
FQI	−0.0039***	−0.4665***	−0.0145***	−0.0173**
	(0.0011)	(0.0463)	(0.0048)	(0.0068)
FQI*AGDP	−0.0563**	−0.0334***	−0.0469***	−0.0037**
	(0.0222)	(0.0086)	(0.0109)	(0.0015)
Infor	−0.0784	−0.2291	−0.0076	−0.0076
	(0.1393)	(0.3815)	(0.0083)	(0.0083)
HC	−0.1217	−1.3448	−0.2441***	−0.2441***
	(0.9003)	(2.4517)	(0.0484)	(0.0484)
Urb	−0.2530***	−0.6633***	−0.0012	−0.0015
	(0.0044)	(0.0121)	(0.0030)	(0.0030)
FD	−0.1353***	−0.3763***	−0.0106***	−0.0106***
	(0.0496)	(0.1325)	(0.0023)	(0.0023)
GI	−0.8788***	−0.2008***	−0.0415***	−0.0428***
	(0.0105)	(0.0029)	(0.0082)	(0.0077)
ID	−0.1651***	−0.4262***	−0.0222***	−0.0221***
	(0.0549)	(0.1496)	(0.0030)	(0.0030)
SC	−0.0956**	−0.2049*	−0.0036	−0.0036
	(0.0428)	(0.1170)	(0.0025)	(0.0025)
rho	−0.0038	−0.0076	−0.8985***	−0.8985***
	(0.0402)	(0.0410)	(0.0108)	(0.0108)
lambda	0.2098***	−0.1271*	−0.8537***	−0.8537***
	(0.0682)	(0.0688)	(0.0420)	(0.0420)
sigma2_e	0.3846***	0.2890***	0.0145***	0.0145***
	(0.0045)	(0.0034)	(0.0002)	(0.0002)
Pseudo R^2	0.7821	0.8091	0.8193	0.7901
Log	−782.981	−780.673	727.872	719.872
N	840	291	300	249

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Numbers in parenthesis are standard errors. The cities in the top 93 are rich, and the cities in the bottom 93 are poor.

economic development. Therefore, this paper attempts to introduce agricultural economic growth into the model to study the unbalanced effect of factor quality improvement on agricultural carbon emissions. We use the output value of the urban primary industry in 2017 as the initial level of agricultural economic development (AGDP) and introduce the interaction term between AGDP and FQI into the model to analyze the disequilibrium effect. Table 6 presents the results.

As shown in column (1) of Table 6, considering the initial level of agricultural economic development, FQI significantly negatively affects ACE. At the same time, comparing the results of Table 6 and Table 5 (0.0039 < 0.0166), we can find significant differences in the impact of factor quality improvement on agricultural carbon emissions in different regions. This difference will also affect the economic effect of factor quality improvement. In addition, FQI*AGDP has a significant negative impact on ACE, indicating that compared with poor regions, the factor quality improvement can reduce agricultural carbon emissions in affluent regions. On the one hand, the agricultural economy needs transformation and upgrading in regions with high agricultural economic development. Therefore, the factor quality improvement of land directly optimizes the input structure of agricultural factors, and agricultural carbon emissions will be reduced (Han et al., 2018). On the other hand, regions with low agricultural economic development need to increase agricultural factor investment. Thus, factor quality improvement has smaller impact on agricultural carbon emissions.

As shown in columns (2), (3), and (4) of Table 6, FQI has a significant negative impact on ACE in affluent, general, and poor regions. Through the regression coefficient, the impact of factor quality improvement on agricultural carbon emissions in affluent

TABLE 7 Results of robustness test.

Variable	(1) Plains	(2) Hilly regions	(3) Mountainous regions	(4) ACE
FQI	−0.7170***	−0.1319***	−0.0505***	−0.0021***
	(0.0478)	(0.0005)	(0.0179)	(0.0002)
Infor	−0.0205	−0.0174***	−0.0451***	−0.0016
	(0.0169)	(0.0065)	(0.0164)	(0.0199)
HC	−0.1612	−0.0076	−0.7434***	−0.1104
	(0.1542)	(0.0083)	(0.0190)	(0.0901)
Urb	−0.0015	−0.2461***	0.0123***	−0.1076***
	(0.0022)	(0.0510)	(0.0002)	(0.0295)
FD	−0.0074	−0.0012	−0.0015	−0.0051
	(0.0065)	(0.0030)	(0.0030)	(0.0060)
GI	−0.1329**	−0.0108***	0.0152***	−0.0316**
	(0.0678)	(0.0025)	(0.0004)	(0.0160)
ID	−0.0108*	−0.0415***	−0.0428***	−0.0114**
	(0.0056)	(0.0082)	(0.0077)	(0.0047)
SC	−0.0111**	−0.0221***	−0.1100***	−0.0388***
	(0.0048)	(0.0031)	(0.0071)	(0.0138)
rho	−0.7813***	−0.0036	0.0161***	−0.8371***
	(0.0863)	(0.0025)	(0.0003)	(0.0192)
lambda	−0.9413***	−0.8984***	−0.8983***	−0.6175***
	(0.0146)	(0.0108)	(0.0108)	(0.0738)
sigma2_e	0.0092***	−0.8538***	0.0145***	−0.0152***
	(0.0002)	(0.0420)	(0.0002)	(0.0003)
Pseudo R^2	0.6931	0.7903	0.8083	0.6756
Log	730.0937	767.8012	770.091	255.4166
N	390	174	276	840

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Numbers in parenthesis are standard errors.

regions is greater than that in poor regions. The results further reveal that FQI can significantly reduce ACE and confirm the robustness of the results.

6 Robustness test

This paper uses two robustness test methods to verify the reliability of the results. Firstly, because the topographic conditions in eastern, central, and Western are different, we divide cities into plains, hilly regions, and mountainous regions. Secondly, we adapt the instrumental variable approach to solve the possible endogeneity problems.

Columns (1), (2), and (3) of Table 7 report the results of the subdivision sample through topographic differences. We find that factor quality improvement significantly reduces agricultural carbon emissions in plains, hilly, and mountainous regions. By comparing the estimated coefficient of factor quality improvement, it finds that factor quality improvement has the greatest impact on agricultural carbon emissions in plains, followed by hilly regions, and the smallest impact on agricultural carbon emissions in mountainous regions. Thus, the above results show that the results of benchmark regression are robust.

According to Daniel et al. (2020), the instrumental variable selected in this paper is the number of high-standard farmland construction documents published by urban agricultural departments. Columns (4) of Table 7 present the result of the endogeneity test. FQI still plays a steady role in reducing agricultural carbon emissions, which indicates that the results are robust. In addition, we verify the rationality of the instrumental variable selection through Pseudo R^2 (0.7103), indicating that the instrumental variables contribute greatly to the fitting degree of factor quality improvement.

TABLE 8 Results of mechanism analysis.

Variable	(1)	(2)	(3)
	AIS	ACE	ACE
FQI	0.0235***		−0.0148***
	(0.0020)		(0.0042)
AIS		−0.0240*	−0.0338***
		(0.0130)	(0.0107)
Infor	−0.0057	−0.0067	−0.0087
	(0.0078)	(0.0090)	(0.0088)
HC	−0.2161***	−0.3180***	−0.2520***
	(0.0455)	(0.0566)	(0.0598)
Urb	−0.0021	−0.0032	−0.0039
	(0.0023)	(0.0028)	(0.0028)
FD	−0.0097***	−0.0135***	−0.0078**
	(0.0022)	(0.0030)	(0.0036)
GI	−0.0445***	−0.0449***	−0.0411***
	(0.0059)	(0.0066)	(0.0066)
ID	−0.0197***	−0.0228***	−0.0218***
	(0.0028)	(0.0034)	(0.0036)
SC	−0.0039*	−0.0025	−0.0033
	(0.0024)	(0.0027)	(0.0027)
rho	−0.9303***	−0.7166***	0.3567***
	(0.0076)	(0.0193)	(0.0767)
lambda	−1.6936***	−0.0696*	0.0296***
	(0.0693)	(0.0400)	(0.0094)
sigma2_e	0.0459***	0.0123***	0.0896***
	(0.0062)	(0.0002)	(0.0018)
Pseudo R^2	0.5474	0.5227	0.6111
Log	733.8183	728.3806	721.6807
N	840	840	840

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Numbers in parenthesis are standard errors.

7 Mechanism analysis

Previous empirical results have shown that FQI significantly reduces ACE. We further discuss the agricultural industrial structure (AIS) in which FQI affects ACE. Table 8 presents the results. As shown in columns (1) of Table 8, FQI significantly promotes the transformation of AIS. The factor quality improvement can improve the efficiency of unit factor output to enhance agricultural output and optimize agricultural industrial structure (Liu and Yang, 2021). As shown in columns (2) and (3) of Table 8, FQI and AIS significantly reduce ACE, indicating that AIS plays a part in the plausible channel in the path of FQI to reduce ACE. Combining theory with practice, it can be seen that the optimization of agricultural industrial structure means that traditional agriculture is gradually transitioning to modern agriculture, which will reduce the factor input of traditional agriculture. With the reduction of factor input of traditional agriculture, agricultural carbon emissions will also be gradually reduced (Guo et al., 2021).

8 Conclusion, recommendations and future research

The factors reducing carbon emissions are critical to resolving the environmental problem. Based on panel data of cities, this paper discusses the impact of factor quality improvement on agricultural carbon emissions. We find that factor quality improvement can significantly reduce agricultural carbon emissions. Further heterogeneity analysis finds that factor quality improvement has a greater effect on agricultural carbon emissions for eastern regions. The disequilibrium effect results show significant differences in the impact of factor quality improvement on agricultural carbon emissions in different economic development regions. Compared with poor regions, the factor quality improvement has a greater impact on affluent regions. After conducting the robustness test from two aspects, factor quality improvement still significantly reduces agricultural carbon emissions. The results of the mechanism analysis show that factor quality improvement reduces not only agricultural carbon emissions but also agricultural carbon emissions by optimizing agricultural industrial structures. This paper focuses on high-standard farmland and expounds on the impact of factor quality on carbon emission reduction. It provides a reference basis for understanding the effect of factor quality in carbon emission reduction and has vital practical significance for the study of agricultural carbon emission.

Based on the above conclusion, this paper puts forward policy suggestions for reducing agricultural carbon emissions from the perspective of factor quality improvement. Government departments should actively introduce relevant policies to improve the quality of agricultural factors. To solve the market failure problem in agricultural development by improving the quality of agricultural factors and then promoting the green development of agriculture. Meanwhile, the transformation of the agricultural industrial structure will also reduce agricultural carbon emissions. Therefore, the government and agricultural companies should continue promoting the transformation from traditional to modern agriculture. All regions must continue to promote agricultural modernization and the development of low-carbon agriculture. The government should pay attention to differences in agricultural economic development and geographical location in the carbon emission reduction effect of factor quality. Different regions should use factor quality improvement differently to promote agricultural carbon reduction. For developed regions, the government should reduce agricultural carbon emissions by improving the quality of agricultural factors. For backward areas, the government should first improve the economic level and then promote the quality of agricultural factors. On the other hand, the government should adopt modern production factors to carry out intensive production, which is the key to improving agricultural output. The government promotes reducing and synergizing fertilizers and pesticides, which is critical to reducing carbon emissions. At the same time, the government should actively establish a green and low-carbon economic system for circular development, and actively explore the agricultural circular production mode, the agricultural and animal husbandry combined circular mode, and the agricultural enterprise circular industry mode. Finally, the government should improve the quality of arable land to achieve the role of carbon fixation, such as using organic fertilizer, promoting the return of straw to the field, and strengthening the management of degraded arable land. The government should also develop clean energy (hydropower, wind power, or solar energy) and new energy technologies (electric vehicles) to replace the original agricultural diesel. At the same time, the government should actively develop smart agriculture (artificial intelligence and big data). Those emerging information technologies help farmers make efficient judgments to promote sustainable agricultural production and reduce agricultural carbon emissions.

This paper complements the lack of relevant research on factor quality improvement and carbon emissions and provides a theoretical reference for studying the environmental improvement effect of factor quality. However, the limitations of this paper need to be further improved. First, the impact of factor quality improvement on carbon emissions of industries is different (such as industry, construction industry, transportation industry). Future studies should expand in data richness and advance the research on carbon emissions in various industries. Meanwhile, future studies should improve the measurement of factor quality and carbon emissions. Second, this paper does not discuss other specific mechanisms (such as resource misallocation, the operational environment, and technological innovation) of the relationship between factor quality and carbon emissions. Finally, the research on carbon emissions should not only focus on the macro level, but also explore the micro level, such as farmers' agricultural low-carbon production behavior, residents' low-carbon life behavior, and so on. Therefore, further studies based on obtaining relevant data are suggested to expand the research on carbon emissions.

Data availability statement

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

Author contributions

NY: literature review, empirical analysis, software, revision. XS: conceptualization, methodology, software, critical review. QQ: data curation, literature collection.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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