Analysis of the interactive effects of new urbanization and agricultural carbon emission efficiency

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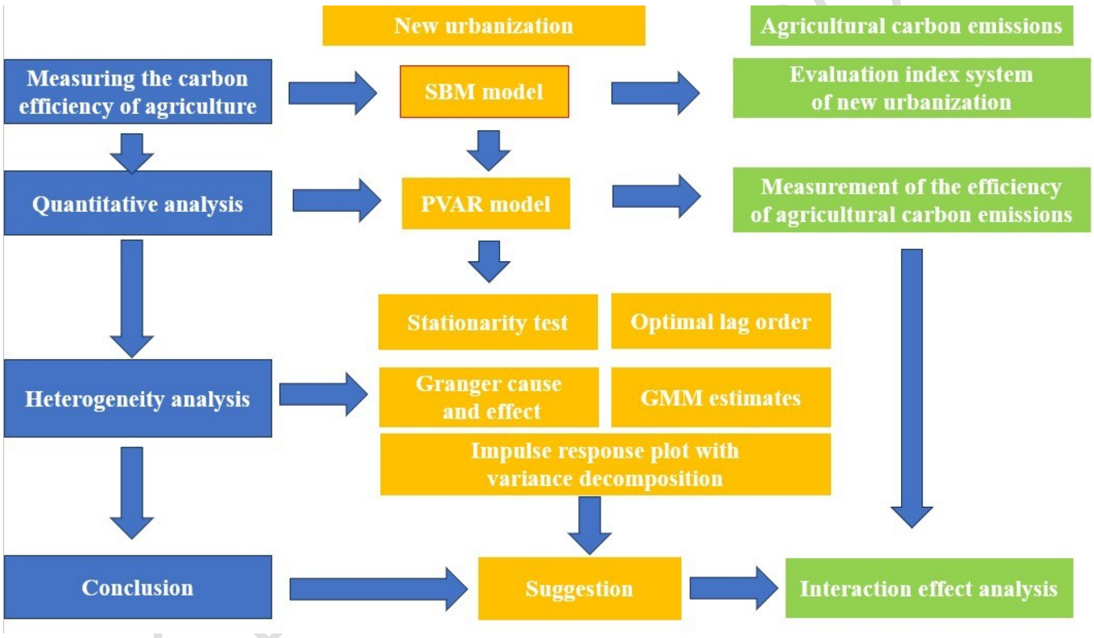
GRAPHICAL ABSTRACT



ABSTRACT: Exploring the relationship between new urbanization and agricultural carbon emission is of great significance to promote the green and low-carbon development of agriculture. The urbanization level was comprehensively assessed by constructing an index system, and the agricultural carbon emission efficiency was measured using the SBM model, and finally, the relationship between urbanization and agricultural carbon emission efficiency was quantitatively analyzed with the help of the PVAR model. The results of the study show that: (1) From a general point of view, new urbanization is the Granger cause of agricultural carbon emission efficiency, and new urbanization has a reverse effect on the improvement of agricultural carbon emission efficiency, while the opposite is not true. (2) Agricultural urbanization is always the Granger cause of agricultural carbon emission efficiency in both main grain-producing and non-main grain-producing areas, but the inhibitory effect of new urbanization on the improvement of agricultural carbon emission efficiency is significantly stronger in main grain-producing areas.

Keywords: new urbanization, agricultural carbon emission efficiency, PVAR model, heterogeneity analysis.

1. Introduction

In the *National New Urbanization Plan 2014-2020*, it is stated that the concept of ecological civilization should be fully integrated into the entire process of urbanization development. In the process of continuously promoting urbanization, it is also necessary to promote the construction of ecological civilization in urban and rural areas. At present, China's urbanization belongs to the stage of accelerated development, which inevitably affects the carbon emission and the ecological environment in urban and rural areas. Therefore, the study of the relationship between new urbanization and carbon emission is not only of great significance to the development of urbanization, but also of great significance to the development of the whole ecological economy. However, most of the current studies mainly focus on the impact of urbanization on the overall carbon emissions, and the research focuses mainly on the relationship between urbanization and carbon emissions in urban areas, with less research on the relationship between urbanization and agricultural carbon emissions. Therefore, this paper will explore the relationship between new urbanization and the efficiency of agricultural carbon emissions, in order to provide reference for the development of urbanization and the realization of carbon reduction goals.

Through the collation of domestic and international literature, it is found that the difference between new urbanization and traditional urbanization lies in the fact that new urbanization mainly measures the level of urbanization from various aspects, such as economy, population, and ecology instead of only through the proportion of the urban resident population to the total population (Chu, Zhang and Wu et al., 2022; Yu et al., 2021). Current research on new urbanization mainly focuses on the study of ecological and economic effects and influencing factors of new urbanization. It is widely believed that new urbanization can not only promote the growth of regional economy, but also promote the growth of the overall economy through the transfer of capital and labor, and innovation (Zhao et al., 2022). It can also promote economic growth by facilitating the optimization of industrial structure (Wang et al., 2022, Cheng et al., 2022) and the narrowing of the income gap (Song and Wang, 2022). The development of urbanization will not only have a multifaceted impact but will also be affected by a variety of factors such as foreign direct investment (Fan and Bai, 2022), financial agglomeration (Quan et al., 2022), and scientific and technological innovation (Ning and Hu, 2022). However, the research related to the ecological effect of new urbanization is relatively single compared to the research angle of the economic effect, and the current research on the ecological effect of new urbanization mainly focuses on the research of the impact of new urbanization on carbon emissions.

There are fewer studies on agricultural carbon emissions. The small amount of existing literature mainly focuses on the study of factors influencing agricultural carbon emissions and the accounting of agricultural carbon emissions. The influencing factors of agricultural carbon emissions mainly include the level of agricultural science and technology, the level of development of rural finance, agricultural insurance and industrial agglomeration. Scholars have found that the development of rural finance, agricultural insurance, the level of agricultural mechanization, and agricultural science and technology innovation can play a significant role in suppressing agricultural carbon emissions (Xie and Su, 2022; Wang et al., 2021; Ma and Cui, 2021; Xu and Mao, 2022). However, agricultural industrial agglomeration has contributed to agricultural carbon emissions, but as the level of agglomeration develops to a higher degree, agricultural carbon emissions will gradually decrease (He and Zhang, 2021).

At present, the accounting of agricultural carbon emissions mainly includes the measurement of total agricultural carbon emissions as well as carbon emission intensity. The measurement of agricultural carbon emissions is mainly accounted for by carbon emission sources and carbon emission coefficients (Zhang, 2021; Hu and Zhang, 2020; Zhang and Yin, 2020), and the measurement of the efficiency of agricultural carbon emissions is mainly derived from the measurement of input-output indicators using the SBM model (Tian and Lin, 2022; Tian and Wang, 2020).

There are fewer studies on the correlation between new urbanization and agricultural carbon emissions, and the findings of the existing literature show that new urbanization negatively affects the intensity of agricultural carbon emissions (He and Zhang, 2022). Most of the current literature mainly explores the relationship between new urbanization and urban carbon emissions based on the traditional coupled coordination model. It is widely believed that carbon emissions constrain the development of urbanization, but the impact of new urbanization on carbon emissions is not yet conclusive, some scholars believe that the development of urbanization on carbon emissions its facilitating effect (Dogan & Turkekul, 2016; Wang et al., 2016), but scholars such as Khan & Su (2021) and other scholars believe that urbanization development plays an inhibitory role on agricultural carbon emissions.

From the above analysis, the relationship between new urbanization and agricultural carbon emissions is not clear and there is little literature on new urbanization and agricultural carbon emission efficiency and almost no one has considered the differences in the relationship between the two between different regions. In view of this, this paper will adopt the entropy value method to conduct a comprehensive evaluation of new urbanization and explore the relationship between new urbanization and agricultural carbon emission efficiency, and will explore the relationship between the two. In addition, the heterogeneity will be analyzed for different regions.

2. Theoretical analysis

The development of urbanization will not only have an impact on the flow of rural labor but will also have an impact on all aspects of the rural economy, politics and ecology. The ecological impact is mainly reflected in the impact on the efficiency of agricultural carbon emissions. The development of urbanization will firstly bring a large number of agricultural people to the towns and cities directly, which leads to a decline in the rural population. The number of people and the amount of human activities will reduce the amount of agricultural carbon emissions, which in turn affects the efficiency of agricultural carbon emissions. And urbanization will also lead to the continuous adjustment of industrial structure in the process of continuous development (Zhou and Ding, 2019), and more labor will be transferred from agriculture to industry and services. The relative reduction of the proportion of agriculture can also promote the reduction of agricultural carbon emissions. Secondly, agricultural carbon emissions mainly come from straw burning and the use of fertilizers, pesticides, plastic films and large agricultural machinery (Zhang et al., 2021). The development of urbanization will lead to the shortage of rural labor, which will lead to the increase in the use of fertilizers, pesticides and agricultural machinery, which will also lead to the increase in agricultural carbon emissions and thus affect the efficiency of agricultural carbon emissions.

It is for this reason that more and more scholars have begun to explore the interrelationship between urbanisation and agricultural carbon emissions, with the results mainly focusing on the following two aspects. Firstly, exploring the mechanism of urbanisation on agricultural carbon emissions (Wen et al.,2024). Based on the perspective of carbon reduction, Yan et al. (2023) believed that urbanisation has formed the scale effect of pollution control through industrial upgrading and technological spillover, which helped to feed back the carbon reduction in agriculture. On the other hand, based on the carbon increase perspective, urbanisation has exacerbated the degree of aging, feminisation and part-time employment in rural areas, so that farmers are forced to increase the intensity of agricultural materials and machinery inputs to avoid agricultural production reduction, which has resulted in an increase in carbon emissions. In addition, scholars also studied the spatial effects of urbanisation on agricultural carbon emissions, finding that urbanisation has intensified the large-scale movement of rural labour (Huang et al., 2023). This has led to the inter-provincial transfer and dissemination of concepts, knowledge and capital, effectively promoting the embedding of green and low-carbon agricultural science and technology into agricultural production, and generating obvious spatial spillover effects on neighbouring regions' agricultural carbon emissions. The second is to analyse the impact of urbanisation on agricultural carbon emission efficiency. Existing studies have shown that urbanisation is an important factor affecting agricultural carbon emission efficiency, but the differences in the choice of regions to be examined and the determination of input-output indicators have led to differences in the research conclusions reached by scholars. Among them, Wang et al. (2023) found that urbanisation can positively affect the efficiency of agricultural carbon emissions, while the negative effect of urbanisation on agricultural carbon efficiency is more significant in areas with high concentration of agricultural industries. Meanwhile, Huang et al. (2022) explored the spatial autocorrelation of urbanisation development and found that urbanisation has a negative spatial spillover effect on agricultural carbon efficiency in the neighbouring areas.

Therefore, from the above analysis, the direction of the impact of urbanization on the efficiency of agricultural carbon emissions is still uncertain.

3. Indicator construction and data processing

3.1 New urbanization indicator system

Based on the research of Shao and Leng (2022) and combined with the relevant national planning for new urbanization, the entropy method is used to assign values to each index from the four dimensions of population, economy, society and ecology, and the index system of new urbanization is constructed. (as shown in Table 1 below).

Table 1. New urbanization evaluation index system

Target level	Level 1 indicators	Level 2 indicators	Description of indicators	Indicator properties
New type of urbanization	Urbanization of population	Urbanization rate of resident population (%)	Urban resident population/total population at the end of the year	+
		Employment in secondary and tertiary industries (%)	Employment in secondary and tertiary industries/Total social employment	+
		Urban registered unemployment rate (%)	Number of urban registered unemployed/total number of urban employees + number of urban registered unemployed at the end of the period	-
	Economic of urbanization	Percentage of value added of secondary and tertiary industries	Value added of secondary and tertiary industries/Regional GDP	+
		Urban per capita disposable income (yuan)	——	+
		Urban per capita consumption expenditure (yuan)	Consumption expenditure of urban residents/Number of urban population	+
	Social urbanization	Retail sales of social consumer goods per capita (yuan)	Total consumer goods/Total social population	+
		Expenditures on basic urban old-age insurance	——	+

		premiums (ten thousand yuan)		
		Urban road area per capita (m^2 /person)	——	+
	Ecological urbanization	Green space per capita (m^2 /person)	——	+
		Rate of harmless treatment of municipal domestic waste (%)	——	+
		Industrial sulphur dioxide emissions per capita (kg/person)	Industrial sulphur dioxide emissions/population of society at the end of the year	-

3.2 Measurement of carbon emission efficiency in agriculture

3.2.1 Measurement of total agricultural carbon emissions

Referring to the research of Xu et al (2022), Chen (2022), etc., and combining the input of materials and land in agricultural production, fertilizers, pesticides, the use of agricultural plastic film, effective irrigation area, the use of diesel fuel for agricultural machinery, and the area of sown crops in the process of agricultural production were selected as the six sources of carbon in agriculture for the discounting of the total amount of carbon emissions. The conversion coefficients are 0.8956 kg/kg, 4.9341 kg/kg, 5.1800 kg/kg, 25 kg/hm^2, 312.60 kg/km^2, and 0.5927 kg/kg, respectively, and the formula for calculating the carbon emissions from agriculture is shown in equation (1).

$$E = \sum E_i = \sum T_i * \delta_i \quad (1)$$

Where E represents the total carbon emissions, E_i represents the emissions from various carbon sources, T_i represents the total amount of various carbon sources, and δ_i represents the carbon emission conversion factor.

3.2.2 Measurement of carbon emission efficiency in agriculture

The industry indicators in the traditional DEA model do not consider the non-desired outputs, which is easy to cause the inaccuracy of the measurement results. Therefore, in reference to the research method of Tian and Wang (2020) selected the SBM directional distance function model that includes non-expected outputs to measure the efficiency of agricultural carbon emissions. Taking fertilizer, pesticide, agricultural machinery, land, labor, irrigation as inputs, agricultural carbon emissions as non-desired outputs, and total agricultural output value as desired outputs to measure the agricultural carbon emission efficiency. Among them, agricultural machinery inputs use the total power of agricultural machinery as a specific indicator, land inputs are replaced by the total sown area of agriculture, irrigation indicators are selected as the effective irrigated area, and labor indicators are selected as the number of employed people at the end of the year in agriculture. The specific model is as follows:

$$\rho *= min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{p+q}\left(\sum_{r=1}^{p}\frac{s_r^g}{y_{r0}^g}+\sum_{t=1}^{q}\frac{s_t^b}{u_{t0}^b}\right)} \dots\dots\dots (2)$$

$$x_0 = X\lambda + S^-$$
$$y_0^g = Y^g\lambda - S^g$$
$$u_0^h = U^b\lambda + s^h$$

$$e\lambda = 1$$
$$\lambda \geq 0, s^- \geq 0, s^g \geq 0, s^b \geq 0$$

Where $\rho*$ is the efficiency value, *m, p and q* are inputs, desired and non-desired outputs respectively; X, Y_g, U^b are decision unit inputs, desired and non-desired outputs respectively. The matrices x_0, y_0^g, u_0^b are the input variables in *m dimension*, the desired output variables in *ρ dimension* and the non-desired output variables in *q* dimension; s^-, s^g, s^b are the inputs, desired and non-desired outputs respectively, and λ is the intensity vector.

3.3 Data sources and processing

The data related to new urbanization in this paper come from the China Rural Statistical Yearbook and the National Bureau of Statistics. Data related to new urbanization are mainly from the National Bureau of Statistics, China Urban Statistical Yearbook, and statistical yearbooks of provinces. The data mainly cover 31 provinces (excluding Hong Kong, Macao and Taiwan) from 2007 to 2022.

Table 2. Data descriptive statistics

Variable name	Sample size	Average value	Standard deviation	Minimum value	Maximum values
urb	496	0.3312515	0.1408379	0.1040262	0.7771854
car	496	0.7372516	0.2525147	0.2048	1

Note: New urbanization is denoted by urb and agricultural carbon efficiency is denoted by car.

4. Analysis of interactive effects

4.1 Benchmark regression

4.1.1 Model settings

Based on the previous literature (Liu and Ma et al., 2022), combined with the data and variable characteristics of this thesis, a PVAR model (e.g., equation 3) is constructed to explore the correlation between new urbanization and agricultural carbon emission efficiency. The PVAR model combines the advantages of the panel analysis and the time-series analysis, and does not need to consider the variable endogeneity, exogeneity, and causality, that is, the endogeneity problem of the panel data can be avoided effectively. The PVAR model combines the advantages of panel analysis and time series analysis without considering the endogeneity, exogeneity and causality of variables, i.e. it can effectively avoid the endogeneity problem in panel data.

$$y_{i,t} = \alpha_0 + \sum_{j=i}^{k} \beta_i y_{i,t-j} + \eta_i + u_i + \varepsilon_{i,t} \tag{3}$$

In the formula, $y_{i,t}$ denotes the column vector of the two endogenous variables of new urbanization and agricultural carbon emission efficiency,α_0 is the intercept term, k denotes the lag order of the variable,β_i is the parameter to be estimated, η_i is the time effect,μ_i is the individual fixed effect, and ε_i is the random error term.

4.1.2 Smoothness test of variables

In order to avoid the occurrence of pseudo-regression phenomenon, it is necessary to carry out the smoothness test first. Referring to the relevant papers, combined with the data characteristics, HT, IPS, LLC and ADF tests were conducted on the panel data at the same time, and the test results are shown in Table 3 below. According to the results of the pre-test of unit root, out of the consideration of data smoothness, this paper takes the logarithm of new urbanization and agricultural carbon emission efficiency and carries out the first-order difference treatment for the variables after taking the logarithm. As can be seen from Table 3, the test results of the four tests after differencing the two variables show that the P-value shows that the two variables are significant at the 1% level, so it can be judged that both dlnurb and dlncar are smooth.

Table 3. Results of the stability test

Variant	HT inspect	P-value	IPS inspect	P-value	LLC inspect	P-value	ADF inspect	P-value	Conclusion
dlnurb	-0.251	0.000	-11.207	0.000	-11.467	0.000	252.236	0.000	smoothly
dlncar	-0.027	0.000	-9.833	0.000	-6.975	0.000	207.984	0.000	smoothly

4.1.3 Optimal lag order determination

Next, the optimal lag order needs to be determined, and the results from AIC, BIC, and QIC show that the minimum values are -5.143, -75.412, and -33.430, respectively, the optimal lag order for the model is 1st order. Therefore, order 1 is chosen as the lag order.

Table 4. Optimal lag order selection

Lag order	AIC	BIC	HQIC
1	-5.143*	-75.412*	-33.430*
2	-3.718	-59.933	-26.348
3	-1.215	-43.376	-18.187
4	1.101	-27.006	-10.214
5	7.982	-6.072	2.324

Note: The labeled * is the optimal lag order.

4.1.4 Granger causality test

Granger causality is a method of inferring the existence of a causal relationship between two variables in time series analysis by observing and testing their correlations. This method is largely based on the assumption that if one variable is a better predictor of the other, then the former can be assumed to be causally related to the latter. The traditional Granger causality test examines the linear causality between variables, and, since the traditional Granger causality test implicitly assumes that the underlying data generating process (DGP) is linear, the linear causality between variables is often tested with the help of the F-test within the framework of the VAR analysis in practical application analyses.

If the p-value is less than the level of significance (i.e., $p < 0.05$), the null hypothesis can be rejected and a causal relationship is considered to exist. According to the results of Granger causality test in Table 4, it shows that the P-value of the first row passes the significance test, but the P-value of the second row does not pass the significance test. That is to say new urbanization is the cause of agricultural carbon emission efficiency but the reverse is not true. This indicates that the development of urbanization affects the agricultural carbon emission efficiency, but the agricultural carbon emission efficiency cannot affect the development of urbanization in turn, i.e., there is a unidirectional causal relationship between the two.

Table 5. Results of Granger causality test

Original hypothesis	Chi2	P-value	Conclusion
Granger reasons why dlnurb is not dlncar	9.142	0.002	Rejection
Granger reasons why dlncar is not dlnurb	2.145	0.143	Acceptance

4.1.5 GMM estimation

Table 6. GMM estimation results

Variable name	L.dlnurb	L.dlncar
L.dlnurb	-0.234*** (-5.36)	-0.051*** (-3.02)
L.dlncar	0.307 (1.46)	0.104 (0.77)

Note: * indicates significant at the 0.1 level, ** indicates significant at the 0.05 level, *** indicates significant at the 0.01 level, and t-values are in parentheses.

Table 5 shows that the development of urbanization has an inhibiting effect on the improvement of agricultural carbon emission efficiency, which may be due to the fact that the process of urbanization leads to a reduction in the agricultural population, which correspondingly brings about a large number of agricultural machinery and an increase in the use of pesticides and chemical fertilizers, which in turn increases agricultural carbon emissions. The increase in agricultural carbon emissions greatly exceeds the reduction in agricultural carbon emissions brought about by the transfer of the rural population, which leads to a reduction in the efficiency of agricultural carbon emissions.

4.1.6 Impulse response function

The impulse response diagram is mainly to respond to the impact of a change in one variable on another variable under the condition that other variables remain unchanged, which can be more intuitive to see the relationship between the two. As can be seen from Figure 1 below, the agricultural carbon emission peaks around the 2nd period when it is affected by new urbanization, and then decreases gradually, and the response tends to 0 around the 5th period, and it can be learned from the figure that its impact is mainly negative, which is also consistent with the results of GMM regression.

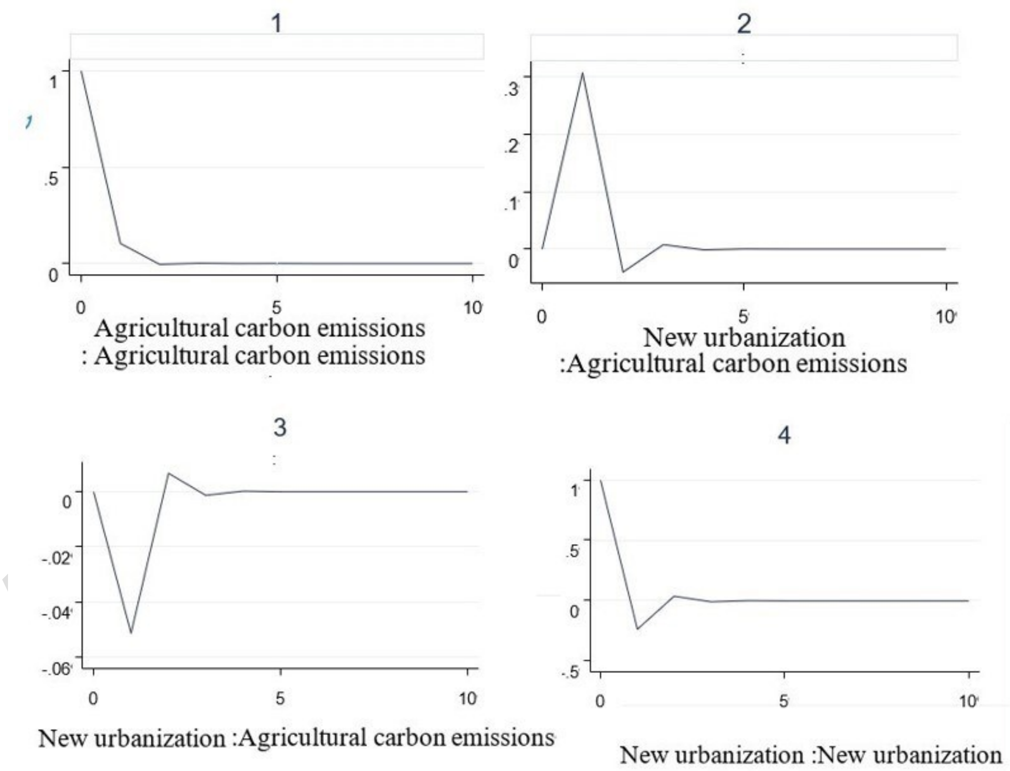


Figure 1. National pulse response map

4.1.7 Variance decomposition

Compared with the impulse response plot, the variance decomposition better reflects the contribution of the explanatory variables to the explanatory variables. As can be seen in Table 6 below, the impact of new urbanization on the efficiency of agricultural carbon emissions increases gradually, the first period is 0.26%, the second period increases to 2.86%, the third period reaches a maximum of 2.9%, and the later period increases gradually. The new urbanization has a significant impact on the efficiency of agricultural carbon emissions, but the duration of this impact is not too long, only about 5 periods.

Table 7. Results of variance decomposition

Number of periods	Agricultural carbon emissions to shocks variance decomposition	
	dlnurb	dlncar
1	0.0026	0.9974
2	0.0286	0.9714
3	0.0290	0.9710
4	0.0290	0.9710
5	0.0290	0.9710
6	0.0290	0.9710
7	0.0290	0.9710
8	0.0290	0.9710
9	0.0290	0.9710
10	0.0290	0.9710

4.2 Heterogeneity analysis

The different weights of agriculture in different regions may result in different carbon emissions from agriculture, which in turn may lead to different carbon emission intensities from agriculture. In order to verify this point, the country will next be divided into main grain-producing areas and non-grain-producing areas according to different regions, in which the main grain-producing areas mainly include thirteen provinces and cities, such as Heilongjiang, Henan, Shandong, Sichuan, Jiangsu, Liaoning, etc., and the rest of the provinces and cities are non-grain-producing areas. On this basis, the interactive effects of new urbanization and agricultural carbon emission efficiency in the two regions are further explored. Again, the smoothness test, determination of optimal lag order, Granger causality test, GMM estimation, impulse response function, and variance decomposition are performed sequentially.

4.2.1 Smoothness test

From Table 7 below, it can be seen that for both food-producing and non-food-producing regions, for the endogenous variables dlnurb and dlncar are significant at the 1% level, which shows the smoothness of the sample data, i.e., the sample data also meets the conditions for the applicability of the PVAR model.

Table 8. Stability tests

	Variant	HT inspect	P-value	IPS inspect	P-value	LLC inspect	P-value	ADF inspect	P-value	Conclusion
Foodstuff main production area	dlnurb	-0.246	0.000	-7.150	0.000	-6.784	0.000	104.994	0.000	Smoothly
	dlncar	0.044	0.000	-6.616	0.000	-4.097	0.000	74.587	0.000	Smoothly
Non-food-producing regions	dlnurb	-0.240	0.000	-8.152	0.000	-9.453	0.000	163.813	0.000	Smoothly
	dlncar	-0.048	0.000	-6.122	0.000	-9.133	0.000	196.601	0.000	Smoothly

4.2.2 Determination of optimal lag order

Again, based on the results of AIC, BIC, and HQIC, the first order is selected as the optimal lag order, and subsequent regressions are performed with this.

Table 9. Optimal lag order selection

Lag order	Major agricultural region			Non-food-producing regions		
	AIC	BIC	HQIC	AIC	BIC	HQIC
1	-16.657	-69.545*	-38.084*	-11.239*	-70.635*	-35.374*
2	-19.168*	-61.478	-36.309	-8.726	-56.243	-28.034
3	-12.146	-43.879	-25.002	-3.894	-39.532	-18.376
4	-6.798	-27.954	-15.370	-0.555	-24.314	-10.209
5	-2.627	-13.204	-6.912	1.611	-10.268	-3.2164

Note: The labeled * is the optimal lag order.

4.2.3 Granger causality test

The test results for food-producing areas show that new urbanization is the Granger cause of agricultural carbon emission efficiency, i.e., the development of urbanization has an impact on agricultural carbon emissions, and vice versa does not hold, which is consistent with the baseline regression. However, the test results for non-food-producing areas show that new urbanization is causally related to agricultural carbon emission efficiency, i.e., the efficiency of agricultural carbon emissions will in turn also have an impact on new urbanization.

Table 10. Granger causality test

Original hypothesis	Major agricultural region			Non-food-producing regions		
	Chi2	P-value	Conclusion	Chi2	P-value	Conclusion
Granger reasons why dlnurb is not dlncar	2.813	0.093	Rejection	6.523	0.011	Rejection
Granger reasons why dlncar is not dlnurb	0.030	0.863	Acceptance	6.666	0.010	Rejection

4.2.4 GMM estimation

The estimation results of GMM in Table 10 show that new urbanization inhibits the improvement of agricultural carbon emission efficiency in both main grain producing areas and non-main grain producing areas, which is also consistent with the results of the benchmark regression. However, the value of -0.032 is significantly larger than that of -0.062, which means that new urbanization has a stronger inhibitory effect on agricultural modernization in the main food-producing areas. This is mainly because the process of urbanization will make the main grain producing areas use agricultural machinery more intensively than before, and use more pesticides, fertilizers and mulch films, which leads to greater agricultural carbon emissions, and thus leads to the inhibition of agricultural carbon emission efficiency in the main grain producing areas compared with the non-main grain producing areas more significantly.

Table 11. GMM estimation

Variable name	Food growing area		Non-food-producing areas	
	L.dlnurb	L.dlncar	L.dlnurb	L.dlncar
L.dlnurb	-0.253***	-0.032*	-0.219***	-0.062**
	(-3.75)	(-1.68)	(-3.93)	(-2.55)
L.dlncar	-0.106	-0.064	0.444**	0.156
	(-0.17)	(-0.62)	(2.58)	(0.89)

Note: * indicates significant at the 0.1 level, ** indicates significant at the 0.05 level, *** indicates significant at the 0.01 level, and t-values are in parentheses.

In order to verify the above hypothesis, the line graphs of the two production areas are drawn separately for comparative analysis. From Figure 3 below, it can be seen that the agricultural carbon emissions of non-food producing areas are mainly concentrated in the range of 0-2500, and the only provinces with agricultural carbon emissions over 2000 are Xinjiang, Guangxi and Yunnan. However, the agricultural carbon emissions of food producing areas are mainly concentrated in the range of 3000, and the only provinces with emissions less than 2000 are Jiangxi, Jilin and Liaoning. Therefore, on the whole, agricultural carbon emissions in major grain-producing areas are much larger than those in non-major grain-producing areas.

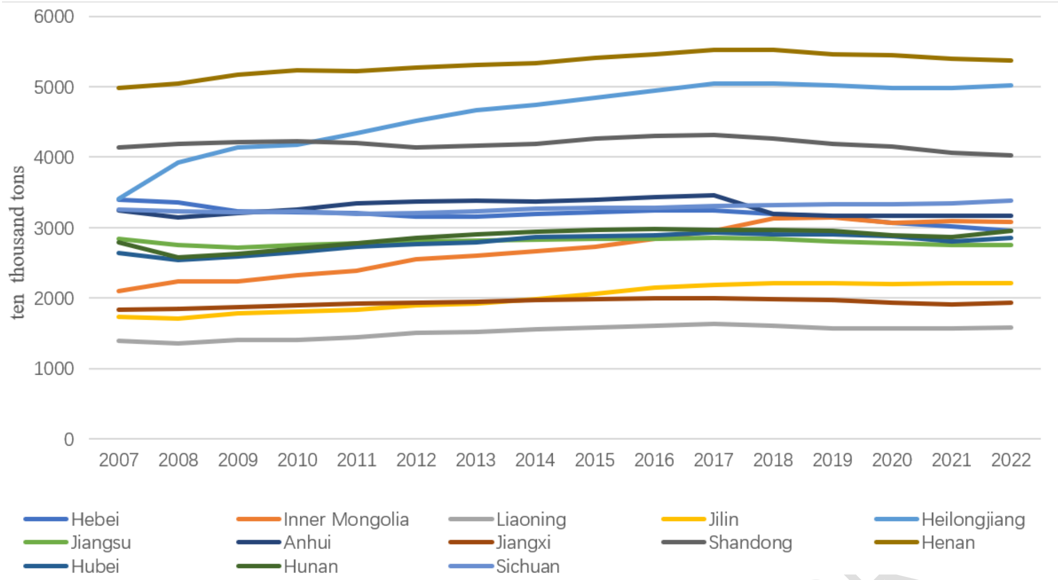


Figure 2. Carbon emissions from agriculture in major food-producing regions 2007-2022

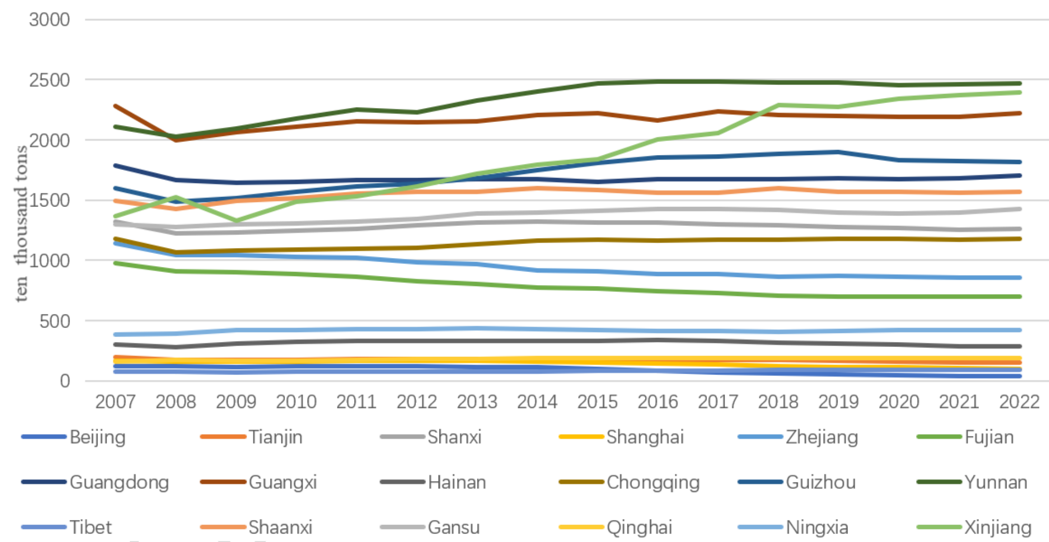


Figure 3. Agricultural carbon emissions in non-food producing regions, 2007-2022

4.1.5 Impulse response plots and variance decomposition

From Figure 4, Figure 5 and Table 11, it can be seen that the response of new urbanization and agricultural carbon emission efficiency in both main food-producing areas and non-main food-producing areas reaches a peak in the second period, and then gradually decreases, and gradually tends to zero after the fifth period, and its effect is generally negative, which is consistent with the benchmark regression.

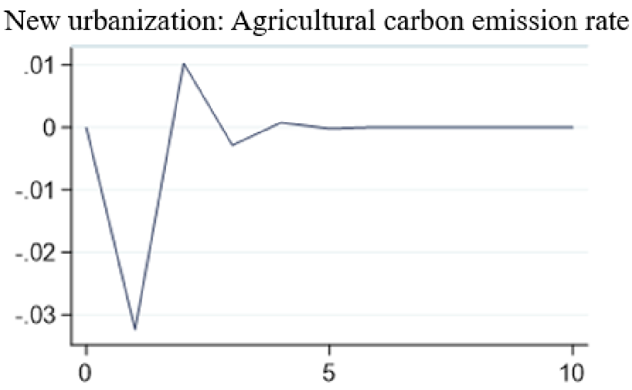


Fig 4. Pulse map of main food producing areas

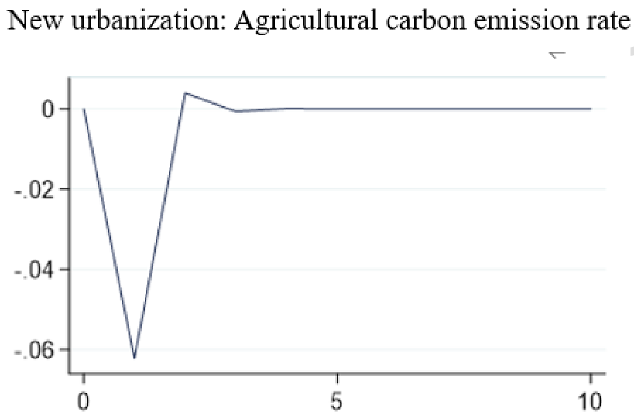


Fig 5. Pulse map of non-main food producing areas

Table 12. Variance decomposition

Number of periods	Variance decomposition in the main grain producing areas		Variance decomposition in non-major food producing areas	
	dlnurb	dlncar	dlnurb	dlncar
1	0.0030	0.9970	0.0106	0.9894
5	0.0215	0.9784	0.0443	0.9557
8	0.0216	0.9784	0.0443	0.9557
9	0.0216	0.9784	0.0443	0.9557
10	0.0216	0.9784	0.0443	0.9557

5. Conclusions and recommendations

5.1 Conclusions

From the above analysis, it can be seen that, in general, new urbanization is the Granger cause of agricultural carbon emission efficiency, and new urbanization inhibits the improvement of agricultural carbon emission efficiency. It is mainly due to the increase of pesticides, fertilizers and machinery used in agricultural production in the process of urbanization, which leads to the increase of agricultural carbon emissions and thus inhibits the improvement of agricultural carbon emission efficiency. From a regional perspective, the inhibitory effect of new urbanization on the improvement of agricultural carbon emission efficiency in non-food-producing areas is significantly weaker than that in food-producing areas. This is mainly due to the fact that the overall agricultural carbon emissions of the main food-producing areas are significantly stronger than those of the non-main food-producing areas, which makes the agricultural carbon emission efficiency of the main food-producing areas be pulled down.

5.2 Recommendations

(1) While promoting urbanization, attention should be paid to the protection of the rural ecological environment. Increase agricultural science and technology investment and financial support, promote the research and development of low-carbon agricultural technology, and improve the efficiency of agricultural carbon emissions. Optimize the agricultural planting structure to reduce agricultural carbon emissions. Formulate relevant regulations to restrain farmers from engaging in highly polluting activities. At the same time, it should also strengthen the efforts to publicize low-carbon development to farmers, and improve the low-carbon awareness of farmers.

(2) The promotion of low-carbon agricultural development should be tailored to local conditions. Especially for agricultural production areas, we should vigorously promote the development of pesticide and chemical fertilizer reduction and strengthen

the control of carbon emission sources. A scientific carbon compensation mechanism should be constructed, and appropriate subsidies should be given to farmers for their low-carbon activities.

(3) Provinces should bring together expert think tanks to establish a sound policy system for the synergistic development of new urbanisation and agricultural carbon emission reduction. The two tasks should be systematically laid out and planned, action strategies and implementation paths should be clarified, supporting policies should be strengthened, and relevant monitoring and evaluation mechanisms and government performance appraisal mechanisms should be improved.

(4) Provinces have taken advantage of the dividends of urbanisation to improve the modern agricultural technology innovation system, and have accelerated the application of highly efficient and low-carbon agricultural technologies such as carbon sequestration and sink enhancement in the planting industry, and pollution reduction and carbon reduction in the animal husbandry industry.

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