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Spatial spillover effect and heterogeneity of digital economy on agricultural carbon emissions

Yuan Liu, Xinyu Pu & Guiyou Zhang

The development of digital economy not only directly affects agricultural carbon emissions through digital technology input, but also indirectly affects inter-regional agricultural carbon emissions through spatial spillover effect. Based on the panel data of 30 provinces, autonomous regions and municipalities in China from 2012 to 2022 (excluding Tibet, Hong Kong, Macao and Taiwan), this paper uses the entropy method to measure the development level of digital economy, and constructs a spatial econometric model to test the spatial spillover effect and heterogeneity of digital economy on agricultural carbon emissions. The results show that the development of digital economy has a significant inhibitory effect on agricultural carbon emissions. Digital economy has a spatial spillover effect on agricultural carbon emissions. The higher the development level of digital economy in neighboring regions, the less agricultural carbon emissions in the region. In the northeast and central regions, the development level of the digital economy has a significant positive impact on agricultural carbon emissions. In the western region, the impact is significantly negative, while in the eastern region, it is not significant. In addition, there is a spatial spillover effect in the northeast region. This paper puts forward policy suggestions from four aspects: promoting the construction of digital infrastructure, narrowing the development gap among provinces, strengthening the digital literacy of agricultural operators, and promoting financial innovation, so as to further play the role of carbon emission reduction in the digital economy.

Keywords Digital economy, Agricultural carbon emissions, Spatial spillover effect, Spatial econometric model

In recent years, global warming has become increasingly serious and the situation is not optimistic. The 2021 Intergovernmental Panel on Climate Change (IPCC) report pointed out that the global average temperature has been about one degree Celsius higher than that of 100 years ago in the past decade, and further recommended that the global output of carbon emissions should be reduced by 40% by 2030. China is the second largest economy in the world and a large agricultural country. It has made brilliant achievements in the agricultural field, but the marginal benefit of agricultural chemicals input is gradually decreasing[1], which also means that agricultural carbon emission will further increase, and the problem of agricultural ecological environment governance is imminent. Therefore, under the background of coping with ecological environment changes, agricultural carbon emission needs to be paid special attention to. At present, how to reduce agricultural carbon emissions is being explored. Some regions try to establish carbon emission trading centers in the form of "agriculture-carbon-finance" strategic cooperation, aiming to promote agricultural emission reduction and carbon sequestration through financial innovation and further realize the goal of "carbon peak and carbon neutralization". The Implementation Plan for Carbon Reduction and Fixation in Agricultural Rural Areas clearly puts forward that scientific and technological innovation should be used to promote carbon reduction and fixation in rural areas, strengthen technological breakthrough, supplement green and low-carbon scientific and technological shortcomings, and the role of scientific and technological innovation in promoting green agricultural development is increasingly prominent. Digital economy is closely related to scientific and technological innovation. The continuous and rapid development of Internet enables digital economy to rely on advanced underlying science and technology to deeply integrate with green agricultural development, promote digital technology to penetrate into agricultural production and sales links, improve total factor productivity of agriculture, and promote green transformation and upgrading of agriculture.

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At present, the research on digital economy mainly focuses on the high-quality economic development. The construction of digital infrastructure provides important support for the development of digital economy, promotes the upgrading of digital industry and leads the high-quality development of economy[2], and industrial agglomeration plays an active regulatory role in it[3]. Scientific and technological innovation is an important driving force for the development of digital new productivity driven by digital economy. The development of digital economy will make elements flow rapidly between regions. With the help of big data, the information of both supply and demand sides of the market can be accurately grasped, and resources can flow to more reasonable and efficient places, which is conducive to the high-quality development of commerce and trade circulation industry[4]. In terms of manufacturing industry, digital economy can improve the intelligent level of production[5] ,optimize the production process[6], promote industrial synergy[7], and promote the green and high-quality development of manufacturing industry[8]. At the same time, this is conducive to the promotion of China's manufacturing industry to participate in the international value chain[9,10]. The existing research on agricultural carbon emissions mainly focuses on the calculation of agricultural carbon emissions and its influencing factors. Carbon emissions from various carbon emission sources in China are increasing annually, among which the increasing rate of tillage is the largest. Reducing carbon emissions is an urgent problem. At present, the calculation of agricultural carbon emissions has always been a controversial topic in academic circles. At the Oak Ridge National Laboratory in the United States, WEST[11] calculated the unit carbon emissions of pesticides, agricultural film, irrigation, plowing and diesel. However, the carbon emission coefficient of agricultural irrigation varies greatly from scholar to scholar. Guan HL[12] used 18.5 kg (C)/hm2 as the carbon emission coefficient, the calculation result of Li B and Zhang JB [13] is 20.476 kg (C)/hm2, and the calculation result of Duan HP and other scholars[14] is 266.48 kg (C)/hm2. In view of Li Bo's abundant achievements in the field of carbon emission, the agricultural carbon emission coefficient adopted in this paper is 20.476 kg (C)/hm2. In terms of influencing factors of carbon emission, the construction and application of numerical formula is an important method. The reasonable deformation of KAYA identity is used to decompose the influencing factors of carbon emission. It is found that efficiency and structural factors have an inhibitory effect on agricultural carbon emission[15]. Some scholars further point out that scientific and technological innovation efficiency has a significant promotion effect on agricultural carbon emission efficiency, and industrial agglomeration and industrial structure upgrading play an intermediary role[16]. Agricultural production efficiency, agricultural industrial structure, economic structure effect[17] have a significant inhibitory effect on carbon emissions of farmland ecosystem. These all verify the results of factor decomposition of agricultural carbon emissions by mathematical formula. The existing research on carbon emission reduction of digital economy mainly focuses on carbon emissions of urban, energy and manufacturing industries. Digital economy has strong permeability and wide radiation, which can link regional economic development. While driving the development of relevant industries in the region, regions with high comprehensive development level of digital economy can form demonstration effect in adjacent regions, which not only promotes the high-quality development of regional economy, but also affects the regional total factor energy efficiency non-linearly in an inverted N-type manner[18] and has a positive U-shaped relationship with energy consumption scale[19]. In terms of manufacturing, digital economy can optimize production processes, accurately control production links by using big data analysis, reduce material loss, and promote green transformation development of manufacturing industry[20]. The carbon emission reduction effect of digital economy on energy and manufacturing industry will also have a radiation effect on cities, which will help drive the low-carbon transformation of cities[21]. It will also produce green synergy effects, which will not only reduce local carbon emissions, but also drive synchronous carbon emission reduction policies in neighboring cities.

With the development of science and technology, the green transformation of agriculture is inevitable. The existing literature provides theoretical basis and research framework for this paper, but there are still some deficiencies. First, at present, scholars mainly focus on the research on the carbon emission reduction effect of digital economy on cities, energy and manufacturing industries. There is a lack of research on bringing digital economy and agricultural carbon emission into the same framework and analyzing the relationship between them in depth. Its importance lies in the essential difference between agricultural research and research in other industries. Agriculture is both a carbon emission source and a carbon sink system. Digital technology needs to achieve the dual goals of emission reduction and sink increase at the same time. In addition, agriculture also undertakes the function of food security. Digital technologies need to reduce emissions while ensuring output, which is completely different from the goal of "pure emission reduction" in manufacturing and other industries. Second, existing studies mostly use ordinary panel models to analyze the relationship between digital economy and agricultural carbon emissions, ignoring the inter-provincial spatial interaction effects caused by agricultural factor flow, technology diffusion and policy imitation. Third, there is a lack of regional heterogeneity research on the impact of digital economy on agricultural carbon emissions. The development differences between digital economy regions are large. By analyzing regional heterogeneity, relevant countermeasures can be provided for regional carbon emission reduction. Based on this, this paper makes use of 30 provinces of China from 2012 to 2022 (Excluding Xizang, Hong Kong, Macao and Taiwan) panel data, construct spatial econometric model, empirically test the impact of digital economy on agricultural carbon emissions and spatial spillover, and divide the whole country into four economic regions to further study regional heterogeneity, so as to deeply understand regional characteristics, make policies fit the actual needs of regions, and improve the accuracy and implementation effect of decision-making. The marginal contributions of this paper are as follows: First, systematically construct an integrated analysis framework for digital economy and agricultural carbon emissions, effectively filling the theoretical gap in existing research focusing on cities, energy and manufacturing industries while ignoring agriculture. Different from the existing research on the "simple emission reduction" goal, this paper fully bases on the dual characteristics of agriculture bearing food security and ecological protection, deeply analyzes how the digital economy balances the contradictory relationship between carbon reduction and production preservation through differentiated paths, enriches the theoretical dimension of green development of digital economy empowerment, and provides an exclusive analysis method different from manufacturing industry and energy industry for understanding the digital low-carbon transformation in agricultural field. Second, the spatial measurement framework such as Spatial Durbin Model (SDM) is to make the kernel density map of digital economy development in the whole country and in different regions, to construct the local Moran scatter plot of agricultural carbon emissions, to analyze the impact of digital economy development on agricultural carbon emissions in this region and adjacent regions from spatial dimensions, not only to quantify the direct inhibition effect of digital economy on agricultural carbon emissions in this province, but also to identify the indirect spillover effect of digital economy on adjacent provinces. It fills the gap in the study of spatial spillover effects of agricultural carbon emissions and provides a new quantitative analysis paradigm for understanding the synergy of agricultural green transition among regions. Third, the samples were divided into eastern regions, central regions, western regions and northeast regions. Through group regression and interactive term analysis, the differences of action paths of the four regions were systematically compared, in order to provide quantitative support and theoretical basis for different regions to realize agricultural low-carbon transformation and "double-carbon" goal by digital path and promote agricultural green development.

Theoretical analysis and research hypothesis

Data, as a new production factor, combined with traditional factors, can stimulate the vitality of traditional factors, such as digital finance, digital technology, digital talents, and enable the further development of traditional factors. On the one hand, it can reduce agricultural operation costs, optimize the allocation of factors, improve the output efficiency of traditional factors, and realize value extension[22]. On the other hand, it can reduce the unexpected output of agriculture and reduce agricultural carbon emissions through rational allocation of resources. In addition, the strong penetration and wide radiation of digital economy not only promote the economic development of the region, but also form the same group, learning and diffusion effects in the surrounding areas, link the economic development of neighboring areas, and produce spatial spillover effects geographically. Therefore, this paper constructs a theoretical analysis framework of the impact of digital economy on agricultural carbon emissions, covering how digital economy affects agricultural carbon emissions and spatial spillover effects of digital economy on agricultural carbon emissions, and divides the country into four economic regions for regional heterogeneity analysis.

Impact of digital economy on agricultural carbon emissions

The continuous improvement of digital infrastructure and the extensive and deep application of digital technology make the digital economy affect agricultural carbon emissions through penetration into all aspects of agricultural production, management, transportation and sales. In Cobb Douglas production function, labor, capital and technology directly affect agricultural production. Data, land, labor force, capital and technology together constitute the five major production factors. Therefore, data, as a new production factor, will trigger new factor allocation reform in agricultural production. Data itself is an advanced production factor and can be combined with traditional agricultural production factors to revitalize idle resources and innovate factor allocation methods[23]. Promote research and development of green production technology, reduce agricultural carbon emissions, and lead green and high-quality development in rural areas. By establishing intelligent management facilities in agricultural production bases and scientifically analyzing crop yield demand information, we can balance information asymmetry, reduce waste of agricultural resources and reduce unnecessary losses. Farmers can communicate and share resources through digital platforms, obtain information about agricultural production and sales[24], and then improve the personal quality of workers, giving play to the most active and dominant role of workers among production factors. At the same time, farmers can make scientific decisions by using the information on the digital platform, which can make other production factors such as land and capital reasonably allocated, thus changing the problem of blind and extensive management of agricultural production and reducing the production of agricultural carbon emissions. Meanwhile, the development of digital economy builds a platform for the establishment of carbon trading market and further suppresses the output of agricultural carbon emissions[25,26].

Therefore, this paper proposes research hypothesis H1: the development level of digital economy can reduce the production of agricultural carbon emissions.

Spatial spillovers of digital economy impacts on agricultural carbon emissions

According to the first law of geography[27], things distributed in space are related, and this property is more obvious between things adjacent to each other. Carbon emissions are externalities, affecting not only local areas but also neighboring areas. At the same time, digital economy has strong penetrability and wide radiation, which can break the spatial constraints and promote the flow of production factors among regions, thus driving the development of economy between regions, so digital economy has strong positive externalities. Therefore, the comprehensive development level of digital economy in this region will have an impact on carbon emissions in neighboring regions[28]. This spatial spillover can be realized through cluster effect, learning effect and diffusion effect. Agricultural carbon emissions in one region will be adjusted by agricultural carbon emissions in neighboring regions[29], regional economic development and environmental policies are usually synchronized, and the development of digital economy in the region reduces agricultural carbon emissions, which will drive neighboring regions to learn digital technology and adjust agricultural carbon emission policies. The learning effect is that the region will learn advanced digital carbon reduction technologies from neighboring regions[30], so as to reduce the cost of environmental governance and improve the efficiency of local agricultural carbon emission. At the same time, the development of digital economy has built a platform for technology sharing among regions, so the convenience and efficiency of digital carbon reduction technology learning between adjacent regions are improved without technical barriers. Diffusion effect means that economically developed regions will have conditions for developing digital infrastructure. These regions will form benchmarks in the process of exploring the development of digital economy. Neighboring regions will compete to imitate. The speed and process of digital economy development will accelerate, and will accelerate the diffusion of agricultural carbon emission experience. Technology learning will improve agricultural carbon emission efficiency.

Therefore, this paper proposes research hypothesis H2: The impact of digital economy on agricultural carbon emissions has spatial spillover.

Heterogeneity of Spatial spillover effects of digital economy on agricultural carbon emissions

There are differences in economic development level, agricultural development orientation and agricultural resource endowment among different regions, which leads to obvious regional heterogeneity in the impact of digital economy on agricultural carbon emissions. Digital infrastructure construction can drive regional economic development, with the strongest technological innovation effect in the central region and the strongest economic benefit in the eastern region. Meanwhile, there are differences in driving methods among different regions, with the eastern region driven by capital factors and the central and western regions dominated by labor factors[31]. The eastern region is a non-grain producing area, and the development center is in high-tech industries. The digital economy has limited effect on reducing agricultural carbon emissions. The northeast and central regions are the core areas of national grain production. In order to stabilize the national grain output, the application of digital economy may maintain the principle of “efficiency first, emission reduction lag”. In addition, the simplification of agricultural structure in Northeast China will amplify the carbon emission effect. The planting industry accounts for a high proportion of the total agricultural output value, while the remaining straw is still burned due to insufficient supporting facilities for straw return. Although the digital platform can optimize the production and marketing connection, it fails to extend to the straw resource utilization link, resulting in the development of digital technology, the expansion of production scale, and the higher the total emission amount. Although this “production-preserving”-oriented digital empowerment has increased the coverage rate of digital agriculture, the amount of fertilizer applied is still increasing every year, resulting in an increase in agricultural carbon emissions. However, digital infrastructure investment in the west has been deeply bound to ecological targets since the initial stage, avoiding the old road of “pollution before treatment” in the eastern and central regions, so that the development of digital economy can significantly reduce carbon emissions. Hence, this paper divides the whole country into four economic regions, namely eastern, northeast, central and western regions, which have different economic development water, agricultural basic conditions and agricultural industrial structure, and the effects of digital economy on agricultural carbon emission reduction in these different regions are different.

Therefore, this paper proposes research hypothesis H3: The spatial spillover effect of digital economy on agricultural carbon emissions is heterogeneous in four economic regions.

Data sources, research methods and variable selection

Data sources

Based on the availability of data, this paper selects panel data composed of 30 provinces, autonomous regions and municipalities (excluding Xizang, Hong Kong, Macao and Taiwan) from 2012 to 2022 as research samples. The digital inclusive financial index comes from the Digital Finance Research Center of Peking University, and the rest data come from China Statistical Yearbook, China Information Yearbook, provincial statistical yearbooks, National Bureau of Statistics, CNRDS database, EPS database and China Internet Development Statistical Report. Interpolation method is used to supplement individual missing values in the sample.

Research methods

Spatial autocorrelation analysis

Firstly, the global Moran index is used to test whether there is spatial autocorrelation in agricultural carbon emissions of all provinces, autonomous regions and municipalities in China, and then the Moran index of local spatial autocorrelation is used to analyze the local spatial autocorrelation of agricultural carbon emissions in China. The Moran index is between [-1,1]. If it is less than 0, it means negative correlation; if it is greater than 0, it means positive correlation; if it is equal to 0, it means spatial uncorrelation. The formula of the global Moran index is as follows:

$$I = \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(s_i - \bar{s}\right) - \left(s_j - \bar{s}\right)}{\frac{1}{n}\sum_{i=1}^{n}\left(s_i - \bar{s}\right)^2} \tag{1}$$

The local Moran index formula is as follows:

$$I = \frac{\left(s_i - \bar{s}\right)}{\frac{1}{n}\sum_{i=1}^{n}\left(s_i - \bar{s}\right)^2} \sum_{j\neq 1}^{n} w_{ij}\left(s_j - \bar{s}_j\right) \tag{2}$$

In Eq. (1)(2), $s_i$is the agricultural carbon emission of region i, $\bar{s}$ represents the national average agricultural carbon emission level, $w_{ij}$is the spatial weight matrix, and n is the total number of regions.

Carbon source	Carbon emission coefficient	Reference source
Fertilizer	0.89 kg(C)/kg	WEST et al.[11]
Pesticide	4.93 kg(C)/kg	Oak Ridge National Laboratory
Agricultural film	5.18 kg(C)/kg	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University
Irrigation	20.476 kg(C)/hm^2	Li B et al.[13]
Tillage	312.60 kg(C)/km^2	College of Biology and Technology, China Agricultural University
Diesel oil	0.59 kg(C)/kg	IPCC

Table 1. Agricultural carbon emissions, carbon sources and their coefficients.

First level indicator	Secondary indicator (unit)	Indicator attribute	Indicator weight
Construction of digital infrastructure	Number of Internet broadband access users (10000 households)	Positive	0.0554
	Length of long-distance optical cable per unit area (kilometers/square kilometer)	Positive	0.1096
	Number of websites owned by each hundred enterprises	Positive	0.0091
	Number of domain names owned by each hundred people	Positive	0.1159
The degree of application of digital economy	Mobile phone penetration rate (units/100 people)	Positive	0.0216
	Internet penetration rate (%)	Positive	0.0216
	Digital Inclusive Finance Index	Positive	0.0203
	Enterprise e-commerce transaction volume (100 million yuan)	Positive	0.1077
Scale of digital economy development	Number of employees in the information service industry (10000 people)	Positive	0.1002
	Volume of telecommunications business (ten billion yuan)	Positive	0.1082
	Proportion of information technology service income in GDP (%)	Positive	0.1287
	Per capita express delivery volume (pieces)	Positive	0.2018

Table 2. Comprehensive index system of digital economy.

Spatial econometric model

In order to fully consider the influence of spatial factors and characterize the spatial spillover effect of digital economic development level on agricultural carbon emissions, referring to the research of Chen ZW et al.[1], control variables such as economic society and agricultural development of each region are selected to further construct Spatial Durbin Model (SDM). The model is as follows:

$$lnCAR_{it} = \rho\, wlnCAR_{it} + \beta_{1}DIG_{it} + \beta_{2}wDIG_{it} + \beta_{3}X_{it} + \beta_{4}wX_{it} + \delta_{i} + \tau_{t} + u_{it} \tag{3}$$

In Eq. (3), ρ represents spatial autocorrelation coefficient, $\beta_{2}$and β_{4} represent elasticity coefficient of interaction between core explanatory variable and control variable and space respectively, w represents spatial weight matrix, and geographical distance matrix is mainly used for regression in this paper.

Variable selection

***Explained variable** agricultural carbon emissions*

Since there is no uniform standard for the calculation of agricultural carbon emissions at present, based on the accuracy and availability of data, this paper selects fertilizer, pesticide, agricultural film, irrigation, tillage and diesel oil as the main carbon emissions sources of agriculture, and and adopts the carbon emission coefficient studied by Li B [13]. The total carbon emission of each province in different years can be measured by formula (4):

$$C = \sum {}_{i}^{n}C_{i} = \sum {}_{i}^{n}AB_{i} \times GF_{i} \tag{4}$$

C is the total agricultural carbon emission, $C_i$is the carbon emission of various carbon sources, $AB_i$is the amount of various carbon sources, GF_i is the carbon emission coefficient of various carbon sources, and the carbon emission coefficients of various carbon sources are shown in Table 1.

Explanatory variables

Digital economic development level. Drawing lessons from existing research, this paper constructs a comprehensive index system of digital economy from three dimensions: digital infrastructure construction, digital economy application degree and digital economy development scale, and measures the development level of digital economy by entropy weight method. The results are shown in Table 2.

The specific index construction is as follows: (1) Digital infrastructure construction is the foundation of digital economy development. The construction of broadband, optical cable and website makes the development of digital economy have material carriers and give birth to the rapid development of digital economy. Therefore, this paper selects the number of Internet broadband access users, the length of long-distance optical cable per unit area, the number of websites owned by each hundred enterprises and the number of domain names owned by each hundred people as measurement indicators. (2) The application degree of digital economy can reflect the extensive use of digital tools in a region or business entity, which is the embodiment of digital economy after digital infrastructure construction. Therefore, this paper selects mobile phone penetration rate, Internet penetration rate, digital inclusive financial index and enterprise e-commerce transaction volume as measurement indicators. (3) The scale of digital economy development can reflect the total value created by various fields and industries included in digital economy, which is the further embodiment of the digital economy after the application of digital technology. Therefore, this paper selects the number of employees in the information service industry, the volume of telecommunications business, the proportion of information technology service income in GDP and the per capita express delivery volume as measurement indicators.

Control variables

Considering that agricultural carbon emissions will be affected by other factors, referring to Du X [32] and Chen ZW[1], the level of financial support for agriculture, planting structure, gross domestic product, urbanization rate, industrial structure upgrading index and advanced industrial structure are selected as control variables. The results are shown in Table 3. Among them, the measurement index of financial support for agriculture (FSA) is the ratio of local financial expenditure on agriculture, forestry and water affairs to the total output value of agriculture, forestry, animal husbandry and fishery, the measurement index of planting structure (PS) is the proportion of grain sown area to crop sown area, the gross domestic product (GDP) is the total value of final products produced in the region, the urbanization rate (UR) is the proportion of urban population to the total population, and the industrial structure upgrading index (ISU) is the proportion of the total added value of secondary and tertiary industries to GDP. Advanced industrial structure (AIS) is measured by the ratio of output value of tertiary industry to output value of secondary industry.

Empirical results and discussion

Digital economic measurement results

This paper uses entropy method to measure the digital economy development level of 30 provinces in China from 2012 to 2022, and divides them into four economic regions for horizontal comparison. As can be seen from Fig. 1, the comprehensive development level of digital economy in the four economic regions is on the rise as a whole, and fluctuates in individual years. Among them, the comprehensive development level of digital economy in the four economic regions is declining in 2021. As can be seen from Table 4, compared with 2012, the comprehensive development level of digital economy in the four major economic regions has increased significantly in 2022, with the central region having the fastest growth rate of 356.250%, much higher than that of the eastern region and the whole country. The comprehensive development level of digital economy in the four major economic regions is ranked in the eastern region, the central region, the northeast region and the western region in turn. The comprehensive development level of digital economy in the eastern region is in an absolute dominant position, while there is a big development gap between the central and western regions and the northeast. The eastern region has developed economy, started early in digital infrastructure construction, and invested more, which provides important support for the development of digital economy.

It can be seen from Table 5 that, taking the comprehensive development level of national digital economy in 2022 as an example, there are 13 provinces in the top 15 eastern and central regions, and the top seven provinces are all eastern provinces, and the ranking of these seven eastern provinces has not changed compared with the previous year, which indicates that the comprehensive development level of digital economy in most eastern regions is relatively high and the trend is stable at the same time. Compared with 2021, except Shaanxi and Hainan Province, the development level of digital economy in other regions has improved, with Guangdong Province having the largest increase. This may be because Guangdong Province, as a major manufacturing province, ranks among the top in the country in terms of output of new energy vehicles and industrial robots, which has promoted the digital transformation of industries. In addition, digital industries such as electronic information, software and information technology services are also very developed, such as Tencent, Huawei and other well-known enterprises gathering. At the same time, Guangdong is located in the coastal area and can communicate and cooperate with domestic and foreign markets, attract more technology, capital and talents, and promote the international development of digital economy.

Variable type	Variable	Symbol	Mean	Standard deviation	Minimum	Maximum
Explained variable	Agricultural carbon emissions	LNCAR	5.270	1.055	2.456	6.766
Explanatory variable	Digital economy	DIG	0.123	0.105	0.013	0.613
Control variable	Financial support for agriculture level	FSA	0.294	0.716	0.031	6.602
	Planting structure	PS	0.648	0.145	0.355	0.971
	Gross domestic product	LNGDP	9.906	0.887	7.332	11.772
	Urbanization rate	UR	0.608	0.117	0.364	0.896
	Industrial structure upgrading Index	ISU	2.406	0.121	2.132	2.836
	Advanced industrial structure	AIS	1.384	0.751	0.611	5.283

Table 3. Descriptive statistics of variables.

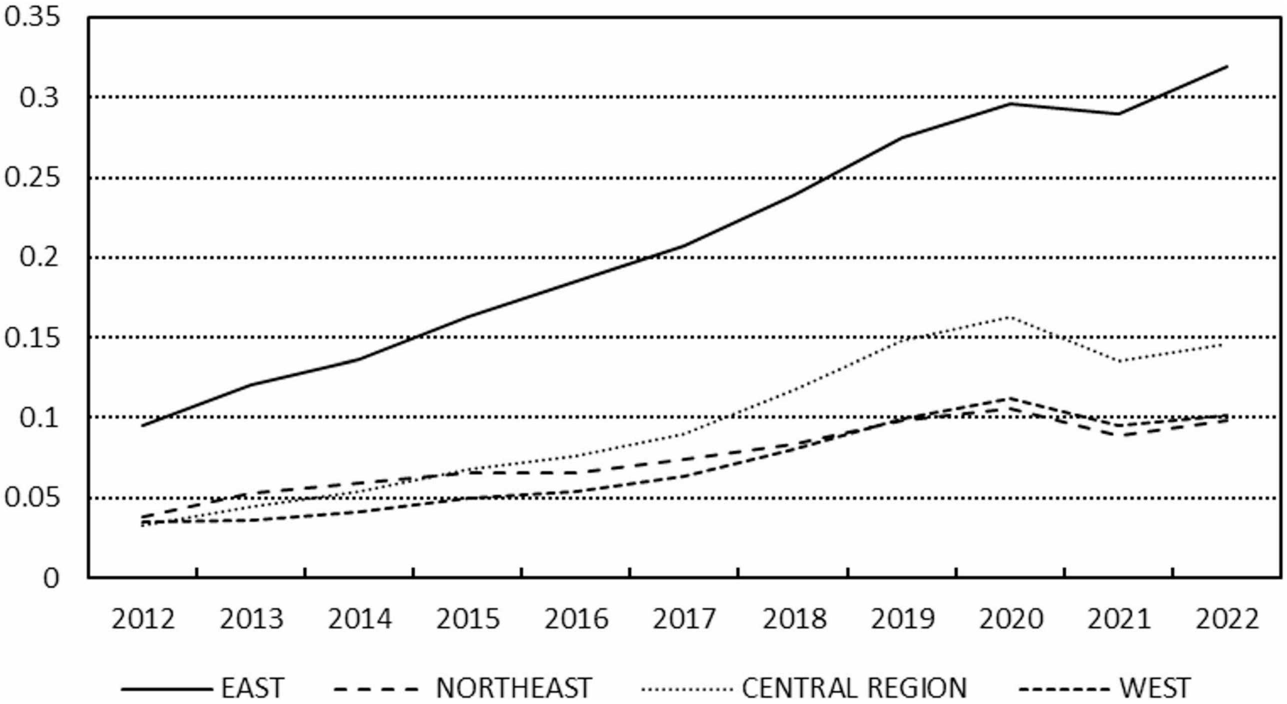


Fig. 1. Changes in comprehensive development level of digital economy in four economic regions from 2012 to 2022.

Region	2012	2022	Average value	Growth rate
Eastern region	0.096	0.319	0.212	232.292%
Northeast region	0.038	0.098	0.076	157.895%
Central region	0.032	0.146	0.097	356.250%
Western region	0.035	0.102	0.070	191.429%
Nationwide	0.050	0.166	0.114	230.846%

Table 4. Comprehensive development level of digital economy in the four major economic regions in 2012 and 2022. Eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Northeast region includes Liaoning, Jilin, and Heilongjiang. Central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. Western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

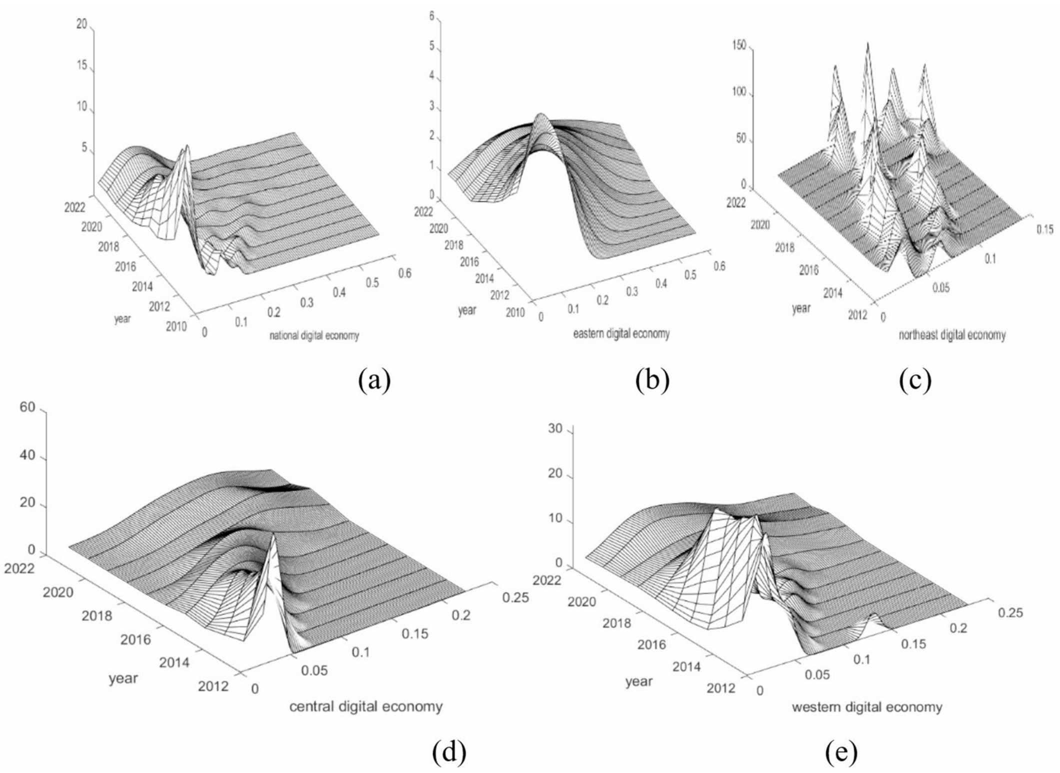
Kernel density estimation method is used to draw kernel density maps of digital economic development level in China and four economic regions from 2012 to 2022, mainly to explore the spatiotemporal evolution characteristics of digital economic development level in different regions.

Figure 2 (a) shows the kernel density map of the national digital economic development level distribution. From 2012 to 2017, the kernel density map maintains a multi-peak shape, with peaks increasing first, then decreasing and finally stabilizing. The peaks are high on the left and low on the right. From 2018 to 2022, the kernel density curve maintains a single-peak shape. The density center is to the left and the tail is elongated year by year. This shows that the digital economic development levels in different regions in the early stage are independent. In addition, differences in development patterns and levels lead to multiple centralized distribution patterns. Overall, the development level of digital economy in China gradually tends to be unified from 2012 to 2022, and differences between regions are narrowing, showing a relatively uniform distribution.

Figure 2 (b) shows the kernel density map of the development level of digital economy in eastern China. From 2012 to 2022, the kernel density curve in eastern China keeps a "single peak" shape, the peak value decreases and finally tends to be stable, the density center of the kernel density curve shifts to the right, and the tail increases. This indicates that with the passage of time, the development level of digital economy in eastern China is shifting and spreading from high-level areas to other areas, the concentration of digital economy development is weakened, the development differences between regions are narrowed, and this development trend remains stable in the later period, while the development level of digital economy in each region is improving year by year.

Province	Digital economy	Ranking	Place	Level	Province	Digital economy	Ranking	Place	Level
Guangdong	0.613	1	0	0.073	Liaoning	0.135	16	− 1	0.015
Beijing	0.528	2	0	0.049	Shaanxi	0.122	17	2	− 0.010
Shanghai	0.429	3	0	0.040	Guangxi	0.117	18	− 2	0.010
Zhejiang	0.411	4	0	0.045	Guizhou	0.117	19	1	0.005
Jiangsu	0.330	5	0	0.033	Jiangxi	0.114	20	1	0.007
Shandong	0.276	6	0	0.034	Shanxi	0.101	21	0	0.013
Fujian	0.210	7	0	0.014	Yunnan	0.089	22	0	0.004
Sichuan	0.203	8	0	0.019	Jilin	0.081	23	0	0.005
Henan	0.188	9	0	0.014	Heilongjiang	0.078	24	− 2	0.006
Anhui	0.167	10	− 1	0.011	Inner Mongolia	0.078	25	0	0.005
Hebei	0.166	11	− 1	0.012	Xinjiang	0.069	26	− 1	0.005
Tianjin	0.163	12	2	0.002	Hainan	0.068	27	3	− 0.006
Hubei	0.163	13	0	0.012	Gansu	0.065	28	0	0.003
Chongqing	0.153	14	− 2	0.022	Ningxia	0.057	29	0	0.001
Hunan	0.141	15	1	0.008	Qinghai	0.048	30	0	0.007

Table 5. Ranking and level change of comprehensive development level of National digital economy in 2022.



(a) (b) (c)

(d) (e)

Fig. 2. Dynamic evolution of digital economy development level. (**a**) National kernel density map, (**b**) Eastern kernel density map, (**c**) Northeast kernel density map, (**d**) Central kernel density map, (**e**) Western kernel density map.

Figure 2 (c) shows the kernel density map of the development level of digital economy in Northeast China. From 2012 to 2022, the core density curve is in the state of “multi-peak”, and the core density center shifts to the right, which indicates that there are obvious differences in the development level of digital economy in Northeast China, the regional development is relatively scattered, and the development level of digital economy in each region is constantly improving.

Figure 2 (d) shows the kernel density diagram of the digital economy development level in the central region. The kernel density curve from 2012 to 2022 is in a “single peak” state, with the peak decreasing and the kernel density center shifting to the right. This indicates that the digital economy development level in the central region

Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Moran's I	0.277	0.270	0.247	0.235	0.226	0.222	0.220	0.214	0.215	0.206	0.199
P value	0.005	0.006	0.011	0.014	0.018	0.020	0.021	0.024	0.023	0.029	0.035

Table 6. Global autocorrelation coefficient of agricultural carbon emissions from 2012 to 2022.

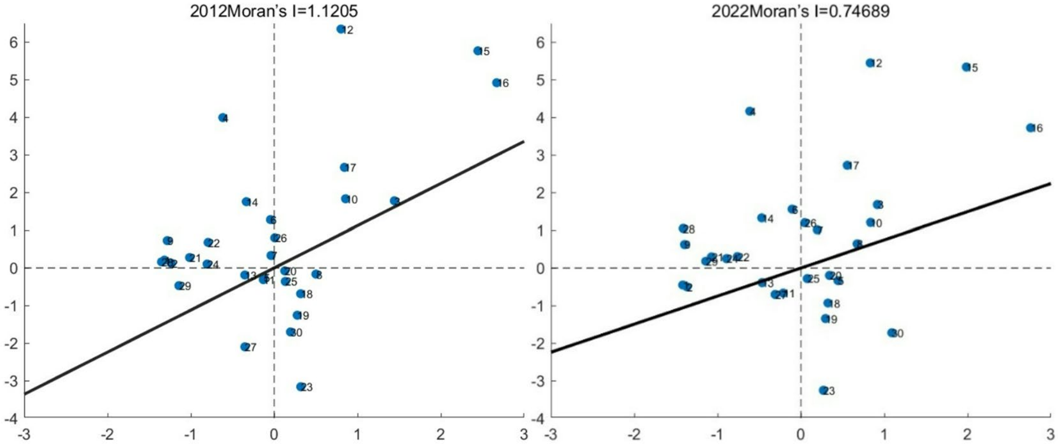


Fig. 3. Local Moran scatter plot of agricultural carbon emissions in 2012 and 2022. From 1 to 30 respectively represent Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

is in a relatively concentrated and mainstream interval, without obvious polarization, and the development is relatively unified, and the overall development trend is towards a higher level.

Figure 2 (e) shows the kernel density diagram of the digital economy development level in the west, which is in the state of "multi-peak" from 2012 to 2017 and in the state of "single-peak" after 2017. The density center of the kernel density distribution curve is to the left, indicating that the digital economy development in the west has great differences in the early stage, relatively concentrated in the later stage, and the overall development level is low and relatively backward.

Spatial correlation analysis

The global Moran index is used to test the spatial correlation of agricultural carbon emissions. If the P value is significant, it indicates that the sample area has obvious spatial autocorrelation. It can be seen from Table 6 that the global Moran index of agricultural carbon emissions from 2012 to 2022 shows a continuous downward trend, and all of them show significant spatial positive correlation. Therefore, this paper uses spatial econometric model to empirically test the spatial heterogeneity of agricultural carbon emissions.

As shown in Fig. 3, the local Moran index of agricultural carbon emissions in 2012 and 2022 is positive, indicating that there is a positive spatial correlation. The decrease of local Moran index indicates that the positive spatial correlation is gradually weakening. For example, different regions formulate differentiated emission reduction policies according to their own resource endowments, which will break the original convergence production mode and lead to the widening of carbon emission gap between adjacent regions. The agricultural carbon emissions of most provinces, autonomous regions and municipalities are located in the first, second and fourth quadrants, among which Anhui, Jiangsu, Henan, Shandong and Hubei are always located in high-high concentration areas during the study period. The reason is that Henan and Shandong are all major grain producing provinces in China, with high proportion of planting industry, high input intensity of chemical fertilizer, pesticide and agricultural machinery energy consumption, and are located in major agricultural producing areas such as Huanghuaihai Plain and the middle and lower reaches of Yangtze River Plain. The agricultural patterns of neighboring provinces are similar, forming a "high emission linkage effect". Gansu, Fujian and Zhejiang are located in low-low agglomeration areas, because Fujian and Zhejiang have high industrialization degree, small agricultural scale, Gansu has large agricultural area, but the climate is dry, planting is mainly water-saving crops (such as potato), animal husbandry is mostly scattered breeding, and carbon emission intensity is low. Shanxi, Jiangxi, Chongqing and Guizhou are located in low-high concentration areas, because Shanxi and Chongqing are mainly mountainous and hilly, cultivated land fragmentation, low agricultural scale, Guizhou and Jiangxi are affected by karst landform, planting output is limited, and ecological protection policies (such as returning farmland to forests) restrict agricultural expansion, but most of the surrounding areas of these provinces are agricultural provinces, forming a spatial pattern of "low emission but surrounded by high emission areas". Hunan, Guangdong, Sichuan and Yunnan are located in high-low concentration areas, because Sichuan and Hunan are large provinces of grain and animal husbandry, with high double emissions from planting and breeding.

Test	Coefficient	*P* value
LM-error	9.487***	0.002
Robust LM-error	34.980***	0.000
LM-lag	10.033***	0.002
Robust LM-lag	35.527***	0.000

Table 7. LM test results.

Test	Null hypothesis	Coefficient	*P* value
LR	SDM degenerates into SAR	55.29***	0.000
	SDM degenerates into SEM	54.43***	0.000
Wald	SDM degenerates into SAR	58.49***	0.000
	SDM degenerates into SEM	57.74***	0.000

Table 8. LR and Wald test results.

Although Guangdong's agricultural scale is smaller than that of traditional large provinces, the intensive degree of cash crops and the intensity of fertilizer and pesticide application are high. The surrounding areas are affected by topography and ecological policies, and agricultural carbon emissions are relatively low, forming a spatial pattern of "high emissions but surrounded by low emission areas ".

Spatial metrology method test

In order to determine which model to use, the following tests are carried out in this paper, and the results are shown in Tables 7 and 8. (1) LM test is used to judge whether there is spatial relationship between variables and the type of spatial relationship. It is obtained that LM-error and LM-lag significantly reject the null hypothesis, so the next robust LM test is adopted. (2) Robust LM test uses Robust LM-Lag and Robust LM-Error as criteria. The results show that Robust LM-Error and Robust LM-Lag also reject null hypothesis significantly. (3) Finally, Wald test and LR test are performed to avoid spatial Durbin model (SDM) degenerating into spatial lag model (SAR) or spatial error model (SEM). If the statistical results of both tests are significant, spatial Durbin model (SDM) should be selected.

Model Estimation results

Table 9 shows the regression results based on the geographical distance matrix. The impact of digital economic development level on agricultural carbon emissions is significantly negative, and hypothesis H1 is verified. In SDM model, the estimation coefficient of digital economic development level(DIG) on agricultural carbon emission is-0.410, which is significant at 1% level, which means that when other conditions remain unchanged, agricultural carbon emission in this region decreases by 41% on average for every unit increase of digital economic development level, indicating that digital economy has a positive effect on promoting agricultural carbon emission reduction. The higher the digital economic development level, the lower agricultural carbon emission in this region. This may be because areas with a high level of digital economic development can promote precision agriculture technology[36], using sensors, satellite positioning and other accurate control of fertilization, irrigation and other links to reduce fertilizer, water waste, and thus reduce carbon emissions caused by related energy consumption in production. The estimation coefficient of financial support level(FSA) on agricultural carbon emission is-0.102, which is significant at 1% level, which means that when other conditions remain unchanged, agricultural carbon emission in this region decreases by 10.2% on average for every unit increase of financial support level, indicating that increasing financial support level helps to reduce agricultural carbon emission, which may be due to the environmental regulation effect imposed by local government expenditure on agricultural production[33]. Moreover, the improvement of financial support level will affect the penetration speed of digital economy in agricultural field, and further expand the suppression effect of digital economy on agricultural carbon emission[35]. The estimation coefficient of planting structure(PS) on agricultural carbon emission is-0.756, which is significant at 1% level, which means that under other conditions unchanged, agricultural carbon emission in this area will decrease by 75.6% on average for every optimized unit of planting structure, indicating that the higher the proportion of grain crop planting area, the lower the agricultural carbon emission. This result is consistent with the research conclusion of Chen Zhongwei and other scholars[1], which may be because food crops (such as corn and wheat) have high straw yields, In recent years, low-carbon treatment methods such as straw returning to field and biomass energy utilization have been widely promoted. Therefore, the increase of grain proportion may be accompanied by the increase of straw low-carbon utilization ratio, indirectly reducing carbon emissions. The estimation coefficient of industrial structure upgrading index(ISU) to agricultural carbon emission is 0.640, which is significant at 1% level, which means that when other conditions remain unchanged, agricultural carbon emission in this region increases by 64.0% on average for every unit of industrial structure upgrading index. This indicates that the higher the industrial structure upgrading index, the higher the agricultural carbon emission in this region. The reason may be that industrial structure upgrading drives the expansion of related industries such as agricultural product processing

Variable	SAR		SEM		SDM	
	Regression coefficient	Standard error	Regression coefficient	Standard error	Regression coefficient	Standard error
DIG	−0.226**	0.110	−0.243**	0.112	−0.410***	0.132
FSA	−0.066***	0.014	−0.079***	0.015	−0.102***	0.015
PS	−1.231***	0.152	−1.268***	0.148	−0.756***	0.164
LNGDP	−0.308***	0.067	−0.304***	0.065	−0.130	0.094
UR	1.198***	0.323	1.188***	0.325	0.306	0.374
ISU	0.529**	0.233	0.511**	0.231	0.640***	0.244
AIS	−0.242***	0.040	−0.235***	0.041	−0.223***	0.043
W×DIG					−2.463**	1.095
W×FSA					−0.290***	0.063
W×PS					0.306	0.988
W×LNGDP					−0.241	0.495
W×UR					−0.731	2.501
W×ISU					3.000*	1.578
W×AIS					−0.255	0.264
Rho/Lambda	0.175	0.171	−0.345	0.256	−0.213	0.223
Sigma2_e	0.003***	0.000	0.003***	0.000	0.003***	0.000
τ_t	Yes		Yes		Yes	
δ_i	Yes		Yes		Yes	
Log-likelihood	482.497		482.924		510.141	
Observations	330		330		330	

Table 9. Results of Spatial spillover effect test. "*", "**", and "***" respectively indicate significant levels at the 10%, 5%, and 1% levels.

and the expansion of agricultural production scale. More land use, farm machinery use, etc. increase energy consumption, which in turn increases carbon emissions. The estimation coefficient of advanced industrial structure (AIS) to agricultural carbon emission is-0.223, which is significant at 1% level, which means that when other conditions remain unchanged, agricultural carbon emission in this region decreases by 22.3% on average for every unit increased by advanced industrial structure, indicating that the higher the advanced industrial structure, the lower the agricultural carbon emission in this region. The reason is that the primary industry shifts to the secondary and tertiary industries, and the proportion of agricultural output value and employment in the national economy gradually decreases. In addition, the advanced industrial structure will promote technological innovation, and the development of secondary and tertiary industries will feed back agriculture, such as drip irrigation technology and unmanned aerial vehicle plant protection, which will make agricultural production from extensive to intensive, and agricultural production efficiency will be improved, further reducing agricultural carbon emissions[37].

From the regression results of spatial interaction term, it can be seen that the spatial lag coefficient of digital economy development level is-2.463, and it is significant at 5% level, which means that when other conditions remain unchanged, the agricultural carbon emission in the adjacent area decreases by 246.3% on average for every unit of digital economy development level, indicating that digital economy has significant spatial spillover effect on agricultural carbon emission. Hypothesis H2 is verified, that is, the higher the digital economy development level in the adjacent area, The less carbon emissions from agriculture in the region. Specifically, the rapid development of digital economy in surrounding areas will drive the region to learn advanced digital carbon emission reduction technology[38], synchronize carbon emission reduction policies, and incorporate carbon emissions in neighboring areas into adjustment standards. At the same time, the establishment of digital platforms will make it easier and faster for agricultural operators to learn advanced carbon emission reduction experience and technology in neighboring areas, which fully demonstrates the spatial spillover of the impact of digital economy on agricultural carbon emissions through the same group. learning and diffusion effects. The spatial lag coefficient of financial support for agriculture is-0.290, which is significant at 1% level, which means that when other conditions remain unchanged, the agricultural carbon emission in this region decreases by 29.0% on average for every unit increase of financial support for agriculture in adjacent areas, indicating that the higher the financial support level in adjacent areas, the lower the agricultural carbon emission in this region. The reason is that the increase of financial funds will improve the agricultural infrastructure level, especially the large-scale application of low-carbon agricultural technologies. For example, precision fertilization and the use of new energy agricultural machinery will significantly reduce agricultural carbon emissions in the region, and neighboring regions will adjust environmental policies due to co-group effect and learning effect, and increase capital investment in low-carbon agriculture to promote technological progress[34], so that carbon emissions in neighboring regions will also decrease. For example, green agricultural subsidy policies in neighboring provinces in the Yangtze River Delta will trigger follow-up by neighboring provinces, forming regional carbon emission reduction synergy. The spatial lag coefficient of the industrial structure upgrading index is 3.000, which is significant at the level of 10%, which means that when other conditions remain unchanged, the agricultural

	Direct effect		Spillover effect		Total effect	
Variable	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
DIG	−0.384***	0.132	−2.092**	1.031	−2.475**	1.101
FSA	−0.100***	0.014	−0.229***	0.074	−0.329***	0.075
PS	−0.746***	0.158	0.453	0.868	−0.293	0.871
LNGDP	−0.126	0.096	−0.179	0.412	−0.305	0.400
UR	0.315	0.381	−0.607	2.263	−0.293	2.343
ISU	0.610***	0.234	2.416*	1.408	3.026**	1.449
AIS	−0.219***	0.042	−0.163	0.234	−0.382	0.251

Table 10. Spatial effect decomposition results. "*", "**", and "***" respectively indicate significant levels at the 10%, 5%, and 1% levels.

		Eastern region		Northeast region		Central region		Western region	
Test	Null hypothesis	Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficient	P value
Wald	SDM degenerates into SAR	49.67***	0.000	38.67***	0.000	80.89***	0.000	51.56***	0.000
	SDM degenerates into SEM	36.07***	0.000	14.89**	0.037	37.65***	0.000	43.93***	0.000

Table 11. Wald test results.

carbon emission in the region increases by 300.0% on average for every unit of the industrial structure upgrading index in adjacent areas, indicating that the higher the industrial structure upgrading index in adjacent areas, the higher the agricultural carbon emission in the region, because the industrial upgrading in adjacent areas may promote high energy consumption. The spatial spillover effects of planting structure, GDP, urbanization rate and upgrading of industrial structure on agricultural carbon emissions are not significant.

The spatial effects are decomposed by partial differential method. Table 10 shows the effect decomposition results of SDM with two-way fixed effect. From the perspective of core explanatory variables, the influence coefficients of direct effect and spillover effect of digital economic development level on agricultural carbon emissions are-0.384 and-2.092, respectively, which pass the significance level test of 1% and 5% respectively, indicating that the promotion of digital economic development level in this region will reduce agricultural carbon emissions in this region and neighboring regions. From the direct effects of control variables, financial support level, planting structure and advanced industrial structure have negative effects on agricultural carbon emissions and pass the 1% significance level test; industrial structure upgrading index has positive effects on agricultural carbon emissions and pass the 1% significance level test; the direct effects of regional GDP and urbanization rate are not significant. From the perspective of spillover effects of control variables, planting structure, regional GDP, urbanization rate and advanced industrial structure have no significant impact on agricultural carbon emissions. The level of financial support for agriculture is significantly negative at the 1% level, and the industrial structure. The upgrade index is significantly positive at the 10% level. The spillover effect of the digital economy on agricultural carbon emissions is significantly greater than the direct effect. This difference is driven by multiple mechanisms: First, the non-competitive characteristics of digital technology enable it to spread across regions at low cost through platform sharing and technology imitation, breaking through the direct effect constraints such as insufficient local digital literacy and limited equipment investment; second, digital economy accelerates the spatial flow of agricultural machinery cross-regional dispatching, industrial chain coordination and other elements, and the emission reduction effect is more reflected as indirect transmission to neighboring regions; Third, the imitation behavior of local digital agricultural policies and cross-regional coordinated implementation, such as regional echo of subsidy policies, thus forming emission reduction cluster effect and further amplifying spillover effects. The regression results are consistent with Table 9.

Heterogeneity analysis

In order to scientifically reflect the social and economic development of different regions in China, this paper divides China's economic regions into four major regions: eastern, central, western and northeast regions. From Table 11, it can be seen that the Wald test results show that Spatial Durbin Model (SDM) has not degenerated into Spatial Lag Model (SAR) or Spatial Error Model (SEM), so the two-way fixed effect Spatial Durbin Model (SDM) is still used for heterogeneity analysis, and the results are shown in Table 12.

As can be seen from Table 12, the estimation coefficients of the digital economic development level of Northeast and Central China on agricultural carbon emissions are 4.063 and 2.205 respectively, and significant at the level of 1%, which means that when other conditions remain unchanged, the agricultural carbon emissions of Northeast and Central regions will increase by 406.3% and 220.5% respectively for each unit of digital economic development level. The estimation coefficient of Western region is-0.910, and significant at the level of 5%. It means that when other conditions remain unchanged, the agricultural carbon emission in the western region will decrease by 91.0% on average for every unit increase in the digital economic development level, while that in the eastern region is not significant, indicating that the digital economic development level in the northeast and central regions will promote the agricultural carbon emission, while the digital economic

Variable	Eastern region	Northeast region	Central region	Western region
DIG	−0.064 (0.347)	4.063*** (1.353)	2.205*** (0.685)	−0.910** (0.393)
FSA	−0.066*** (0.018)	5.673*** (1.235)	−0.950 (0.651)	−0.214 (0.245)
PS	−0.142 (0.261)	−2.326*** (0.761)	0.091 (0.339)	−0.575 (0.371)
LNGDP	0.611*** (0.190)	1.758** (0.821)	−0.039 (0.070)	0.423** (0.178)
UR	1.816** (0.773)	11.756*** (3.119)	21.832*** (3.618)	−1.990 (1.952)
ISU	1.166* (0.696)	0.012 (0.349)	2.441** (1.058)	3.336*** (0.842)
AIS	−0.100 (0.061)	0.187 (0.119)	−0.762*** (0.250)	−0.687*** (0.187)
W×DIG	−1.332 (1.204)	8.680*** (2.653)	3.211 (2.030)	−2.504 (2.778)
W×FSA	−0.215*** (0.043)	9.214*** (2.570)	−3.351* (2.028)	−0.342 (1.195)
W×PS	−0.599 (0.857)	−3.480* (1.980)	0.590 (1.326)	3.153* (1.875)
W×LNGDP	1.499* (0.909)	3.399*** (1.297)	−0.412 (0.327)	−0.718 (0.924)
W×UR	0.400 (2.997)	19.176*** (5.004)	59.568*** (11.377)	6.216 (9.387)
W×ISU	−0.128 (2.449)	−0.678 (0.739)	14.505*** (3.399)	12.642*** (3.620)
W×AIS	−0.011 (0.184)	0.646*** (0.233)	−3.736*** (0.788)	−3.075*** (0.717)
Rho/Lambda	−0.569*** (0.193)	−0.298 (0.186)	−0.794*** (0.276)	−0.302 (0.280)
τt	YES	YES	YES	YES
δi	YES	YES	YES	YES
Log-likelihood	195.231	124.683	200.392	219.545
Observations	110	33	66	121

Table 12. Heterogeneity analysis results of four major economic regions. "*", "**", and "***" respectively indicate significant levels at the 10%, 5%, and 1% levels, standard error in brackets. The eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan. The western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The northeastern region includes Liaoning, Jilin and Heilongjiang.

development level in the western region will inhibit the agricultural carbon emission. The reason is that the northeast and central regions, as the main grain producing areas, mostly focus on "ensuring output and solving labor shortage": the northeast region relies on large-scale cultivated land to promote intelligent agricultural machinery to improve farming efficiency, but due to long-term dependence on high-carbon input mode such as chemical fertilizer, insufficient coverage of emission reduction technologies such as straw returning to fields, the demand for grain processing increases under the superposition of digital empowerment, driving agricultural carbon emission to rise; In the central region, it is restricted by the decentralized operation of small farmers, digital technology is concentrated on labor substitution scenarios such as unmanned aerial vehicle plant protection, emission reduction equipment such as precision fertilization is difficult to play a role due to high cost and low penetration rate, and the expansion of animal husbandry scale and the absence of manure control under the stimulation of "order breeding" further aggravate emissions. In the western region, due to the attribute of non-main grain producing areas and the policy inclination at the initial stage of development, the digital economy focuses on green emission reduction from the beginning, promotes intelligent drip irrigation, digital fence and other adaptation technologies relying on the advantages of high added value of characteristic agriculture, and superimposes subsidy policies to lower the threshold of emission reduction equipment, showing significant carbon inhibition effect. In the eastern region, due to the dominance of non-agricultural industries, digital resources mostly flow to industry and service industry, agriculture accounts for a low proportion and digital energy is concentrated in high value-added cash crops and circulation links, uneven coverage of emission reduction technologies at the production end and the increase of cold chain logistics emissions form an effect offset, and finally the impact on agricultural carbon emissions is not significant, which is consistent with the research conclusions of Meng Weifu[39] and other scholars.

From the spatial interaction term, we can see that the spatial lag term coefficient of the digital economic development level in Northeast region is 8.680, and it is significant at 1% level, while it is not significant in the eastern, central and western regions. The impact of the digital economy development level in Northeast region on agricultural carbon emissions has positive spatial spillover, indicating that the digital economy development level in neighboring regions will promote agricultural carbon emissions in this region. The reason may be that Northeast region is in the revitalization stage and will face the high carbon problem brought about by industrial transfer. The development of digital economy in neighboring regions will optimize its own industrial structure and produce agricultural machinery parts with high energy consumption. High-carbon agricultural links such as large-scale farms with imperfect manure treatment facilities are shifting to Northeast region, where land and labor costs are lower; At the same time, the siphon effect of digital economy in the early stage of development is obvious, and the digital platform, technical talents and policy resources in adjacent areas are more attractive, which leads to the transfer of rural digital technicians in Northeast region to Liaoning and other adjacent provinces. Due to lack of digital energy, local agricultural production can only rely on traditional high-carbon mode, such as excessive fertilization and straw burning, which makes it difficult to upgrade production mode.

Effect type	Variable	Eastern region		Northeast region		Central region		Western region	
		Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Direct effect	DIG	− 0.057	0.280	3.112**	1.421	2.054***	0.537	− 0.838**	0.384
Spillover effect	DIG	− 0.946	0.761	7.082***	2.690	1.070	1.227	− 1.894	2.302
Total effect	DIG	− 0.888	1.011	10.194**	4.054	3.124*	1.671	− 2.732	2.475

Table 13. Spatial effect decomposition results. "*", "**", and "***" respectively indicate significant levels at the 10%, 5%, and 1% levels.

Variable	(1) Increase control variables	(2) Shorten the time window width	(3) The independent variable lags behind by one period
DIG	− 0.918** (0.417)	− 0.817* (0.496)	− 1.048* (0.546)
Controls	Yes	Yes	Yes
_cons	8.375*** (1.540)	7.477*** (0.990)	7.564*** (1.070)
Observations	330	210	300
R-squared	0.882	0.885	0.883

Table 14. Robustness test. "*", "**", and "***" respectively indicate significant levels at the 10%, 5%, and 1% levels, standard error in brackets.

The spatial spillover effect of the development level of digital economy in the central region on agricultural carbon emissions is not significant, because the agricultural applications of digital economy in the central region are mostly concentrated in pilot projects led by the local government and have not formed docking with similar projects in adjacent provinces. Moreover, there are obvious administrative divisions in the 5G coverage rate and agricultural big data platform in the central rural areas, the data interfaces are not unified, the monitoring indicators are inconsistent, and cross-regional coordinated control of agricultural carbon emissions cannot be realized. The spatial spillover effect of digital economy development level on agricultural carbon emission in western region is not significant, because western region is still in the early stage of digital economy development, and presents "core-edge" extreme imbalance pattern, and there is digital divide effect. At the same time, western agriculture is dominated by characteristic cash crops and ecological animal husbandry. Digital technology in adjacent areas is difficult to adapt and popularize due to differences in crop types and breeding methods. Even if there are emission reduction technologies exported from adjacent areas, it is difficult to effectively adopt them locally, and the carbon emission reduction effect cannot be transmitted. The spatial spillover effect of digital economy development level on agricultural carbon emission in eastern region is not significant, because the industrial development in eastern region is diversified, the core resources of digital economy flow to industrial Internet and service industry e-commerce, the proportion of agricultural digital investment in total regional digital investment is small, and the influence of digital economy development in neighboring areas is dispersed by non-agricultural industries. In addition, the proportion of agriculture in GDP in the east is low. Even if the digital economy has the effect of emission reduction, it is difficult to highlight due to the limited scale of agriculture. At the same time, the scale of agricultural products e-commerce cold chain logistics driven by the digital economy expands, and its new emissions partially offset the emission reduction effect at the production end, resulting in no prominent spillover effect. Hypothesis H3 is verified.

This paper divides the sample into eastern region, northeast region, central region and western region, and further analyzes the spatial spillover effect of regional heterogeneity. As can be seen from Table 13, in terms of direct effects, the impact of digital economic development level on agricultural carbon emissions in northeast and central regions is significantly positive at 5% and 1% level respectively, and the direct effect impact coefficient is 3.112 and 2.054 respectively; the western region is significantly negative at 5% level, and the direct effect impact coefficient is-0.838, while the direct effect of eastern region on agricultural carbon emissions is not significant. In terms of spillover effect, the spatial spillover effect of digital economic development level on agricultural carbon emissions in Northeast region is significantly positive at 1% level, and the spillover effect coefficient is 7.082, while it is not significant in eastern, central and western regions. The results are consistent with Table 12.

Robust test

In order to further verify the validity of the conclusions of this paper, this paper adopts the method of increasing the control variable, shortening the time window width and delaying the independent variable by one stage to carry out robustness test. The results are shown in Table 14. (1) Increase the control variable. On the basis of the original control variable, increase the R&D expenditure as the control variable. The results are shown in Column (1) of Table 14. (2) Shorten the time window width. The sample time range selected in this paper is from 2012 to 2022. In order to reduce the influence of other factors, the time range is shortened by one year at the beginning and one year at the end, that is, the time interval is shortened to 2013 to 2021. The regression results are shown in column (2) of Table 14. (3) Independent variables lag by one period. In this paper, the core explanatory variable digital economic development level lags by one period for regression, and the regression results are shown in column (3) of Table 14. The results of columns (1) to (3) in Table 14 show that the significant direction of the impact of digital economic development level on agricultural carbon emissions is negative, which is consistent with the test results mentioned above, indicating that the model is robust.

Conclusions and recommendations

This paper focuses on the impact of digital economy on agricultural carbon emissions, taking 30 provinces in China from 2012 to 2022. (Excluding Xizang, Hong Kong, Macao and Taiwan) as data samples, this paper analyzes how digital economy affects agricultural carbon emissions from the aspect of mechanism, and focuses on analyzing the spatial spillover of digital economy to agricultural carbon emissions by establishing spatial econometric model. The whole country is divided into four economic regions, and regional heterogeneity is further studied. The following conclusions are drawn: First, digital economy level has a significant inhibitory effect on agricultural carbon emissions. In addition, increasing urbanization rate and industrial structure upgrading index will increase agricultural carbon emissions; while improving financial support level, regional GDP and advanced industrial structure, and improving planting structure can significantly inhibit agricultural carbon emissions. Second, digital economy has spatial spillover to agricultural carbon emissions. The higher the development level of digital economy in adjacent areas, the less agricultural carbon emissions in this region. Third, the impact of digital economy on agricultural carbon emissions is heterogeneous. The effect of digital economy development level on agricultural carbon emissions in Northeast and Central region is significant positive and spatial spillover effect exists; the effect of digital economy development level on agricultural carbon emissions in Western region is significant negative, but not significant in Eastern region. Based on the above conclusions, the following recommendations are made:

First, promote the construction of digital infrastructure, use digital technology to optimize agricultural production processes, guide and encourage enterprises and farmers to use advanced digital equipment, accurately control pesticide and irrigation use standards, and avoid excessive waste of resources. Moreover, it is necessary to build a digital supply chain platform, so that digitalization can run through all links of agricultural production, transportation, processing and sales, improve storage and circulation efficiency, so as to reduce energy consumption and logistics costs of cold storage and further reduce agricultural carbon emissions.

Second, narrow the digital economic development gap between provinces, strengthen investment in the western and northeast regions, eastern developed cities should avoid technical barriers, share advanced digital emission reduction technologies to the backward regions in the northeast and west through digital platforms, and further enhance the interoperability of digital economic space, so that the same group, learning and diffusion effects of digital economy can be better exerted.

Third, government departments can strengthen the digital training of agricultural business entities, vigorously do a good job in publicity work, enhance farmers' awareness of actively using digital emission reduction technologies, and formulate agricultural low-carbon incentive policies, give appropriate price subsidies to farmers who purchase digital equipment for agricultural production, and give tax incentives to agricultural enterprises that apply digital technology to significantly reduce agricultural carbon emissions.

Fourth, through financial innovation to promote agricultural carbon fixation and emission reduction, financial institutions should play an investment-oriented role, vigorously develop green finance and digital inclusive finance, scientifically evaluate agricultural production projects, invest more funds into digital economy for agricultural production, and provide more convenient and lower interest rate loan support for agricultural business entities adopting low-carbon technology. In addition, in the form of "agriculture-carbon-finance" strategic cooperation, a carbon emission trading center has been established to promote the realization of digital emission reduction targets.

Data availability

Data is provided within the manuscript or supplementary information files.

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Author contributions

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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