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The Impact of the Digital Economy on Carbon Emissions from Cultivated Land Use

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Abstract: Is digitalization conducive to promoting carbon reduction in cultivated land use while empowering high-quality socio-economic development and intelligent territorial spatial planning? Derived from China's provincial panel data from the period 2011 to 2019, in this paper, we employ a fixed-effect model to study the impact of the digital economy on carbon emissions from cultivated land use and apply an intermediary-effect model to estimate the impact that the structure of the digital economy has on carbon emissions from cultivated land use. The results indicate the following: (1) The expansion of the digital economy can significantly decrease the carbon emissions caused by cultivated land use. This conclusion is still valid after considering endogenous issues and conducting a series of robustness tests. (2) Green technical renovation has played a significant intermediary role in the effect the digital economy has on the amount of carbon emissions from cultivated land use. (3) Digital economy development has significantly promoted innovation in green technology by increasing the size of green invention patent applications and authorizations, thus effectively curbing carbon emissions from cultivated land use and achieving the carbon emission reduction effect of the digital economy. However, some suggestions are put forward, including speeding up the deep integration of digital technology and cultivated land use planning, strengthening the application of green technical renovation achievements in the agricultural field, and enhancing the government's function in the institutional guarantee of the growth of the digital economy.

Keywords: digital economy; carbon emissions; green technology innovation; cultivated land utilization; low-carbon transformation

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1. Introduction

Climate change has become a global problem. The extreme weather brought about by global warming has brought huge losses to agricultural production, food security, and sustainable human development, which have faced unprecedented challenges. In response to global warming, in September 2020, China made a solemn commitment during the United Nations General Assembly to strive to achieve a carbon peak by 2030 and carbon neutrality by 2060. Although industrial production and energy activities are the main sources of carbon emissions, agricultural carbon emissions cannot be ignored. According to a pioneering study published in the journal *Nature Food*, the greenhouse gas emissions of the food system account for more than one third of the total global greenhouse gas emissions, and about two thirds of global food system emissions come from the land sector. [1]. According to the data of the Third National Communication on Climate Change of the People's Republic of China (2018), the total greenhouse gas (GHG) emissions in China (including land use, land use change and forestry, LULUCF) in 2010 were equivalent to about 9551 million tons of carbon dioxide. The GHG emissions from agricultural activities in China were equivalent to about 828 million tons of carbon dioxide, accounting for about 8.67% of the total, while agricultural land emissions were equivalent to 283 million tons of carbon dioxide, accounting for 34.1% of the GHG from agrarian activities [2]. China's all-round promotion of high-quality development, adherence to a sustainable development strategy, and promotion of the low-carbon transformation of cultivated land use are effective methods to cope with global warming and develop excellent farming practices [3]. Under the guidance of China's low-carbon agriculture policy, total agricultural carbon emissions and carbon emission intensity in China have shown a decline in recent years [4]. However, China's 13 major grain production provinces are dominated by high-emission traditional production methods and they are still the main areas of agricultural carbon emissions [5]. Consequently, it is of great importance to study the influencing factors of carbon emissions arising out of cultivated land utilization.

In the meantime, the digital economy has gradually become a new engine that promotes high-quality economic well-being. According to the Statistical Classification of the Digital Economy and its Core Industries (2021) released by the National Bureau of Statistics of China, the digital economy is defined as a series of economic activities that use digital resources as key production factors and modern information networks as important carriers to achieve efficiency and the optimization of economic structures through the effective use of information and communication technologies. As per the public data collected from the China Digital Economy Development Report (2021) issued by China's Cyberspace Administration, China's digital economy grew from 27.2 to 45.5 trillion yuan from 2017 to 2021, and the proportion of GDP grew from 32.9% to 39.8%. Thus, can the digital economy restrain carbon emissions from cultivated land use while enabling high-quality socio-economic development? What is its mechanism? The exploration of the above issues is of great importance to the practice of carbon footprint mitigation through cultivated land in China.

At present, the research of many scholars can be divided into two groups: (1) carbon emissions from cultivated land utilization and (2) the digital economy and carbon emissions. First, we will discuss the research on carbon emissions from cultivated land utilization. Some scholars' studies mostly focus on carbon emissions from cultivated land use measurements, spatiotemporal differences, and the analysis of influencing factors [6–9]. Their views in their research are that China's carbon emissions from cultivated land have revealed an overall development trend in recent decades, and the differences between provincial and regional carbon emissions have tended to narrow. Agricultural production efficiency and economic size are the main influencing elements on carbon emissions from cultivated land. In the past few years., with the promotion of ecological civilization construction, some scholars have focused their attention on the measurement of carbon emissions and the eco-efficiency of cultivated land use and the analysis of its influencing factors [10–13]. Their investigation findings indicate that China's overall ecological effectiveness from cultivated land displays a downward trend, showing great differences between regions, mainly affected by economic growth, natural circumstances, and production situations. In addition, some scholars also conducted in-depth discussions on issues such as carbon emissions, the carbon sequestration of farmland [14], the impact of carbon emissions from ploughed land on specific growth factors [15], carbon footprints from cultivated land and the decoupling effect [16], the relationship between the appropriate scale operation of cultivated land and carbon emissions [17], and agricultural carbon emissions and the cultivated land use transformation relationship [18]. Secondly, we will discuss the research on the digital economy and carbon emissions. At present, scholars have mainly studied the relationship between the digital economy and carbon emissions from food production [19]; carbon emissions from consumption [20]; carbon emissions from cities [21], carbon emissions from trade [22], carbon emissions from economic development [23]; and regional carbon emissions [24–26], etc. They mainly used the panel regression model [27,28], RVAR model [29], difference-in-differences model [30], machine learning model [31], and intermediary effect model [32] to assess the digital economy and carbon emissions procedure via the in-depth analysis of spatial effects and influencing factors. The mainstream view is that the digital economy has significantly reduced carbon emission intensity through industrial structure upgrading, technological progress, and energy structure improvement [33–35].

In conclusion, many scholars have conducted research on carbon emissions from cultivated land use, and the impact of the digital economy on carbon emissions, but few scholars have discussed the digital economy's effect on carbon emissions from cultivated land utilization. Taking this into consideration, this study talks about the connection between the digital economy and carbon emissions from cultivated land use by expanding the digital economy development indicator process using a fixed-effect model and intermediary-effect model and analyzes its procedure, aiming to provide a basis for decision making and a reference for China's smart land space governance and for the low-carbon transformation of cultivated land use.

2. Theoretical Mechanism and Research Hypothesis

2.1. Digital Economy and Carbon Emissions from Cultivated Land Use

Existing studies have shown that the digital economy can effectively reduce carbon emissions through the infrastructure effect, structural optimization effect, technological innovation effect, and resource allocation effect [31,32]. In agriculture, the digital economy relies on the 'technology effect' and the 'structural effect' of optimizing the proportion of crops grown, which reduces "high-carbon" production factor inputs and improves production factors [19]. Cultivated land is one of the primary sources of carbon emissions from agriculture. Carbon emissions from cultivated land use are mainly derived from direct and indirect carbon emissions in the agricultural cultivation process. Direct carbon emissions include diesel consumed during the use of agricultural machinery, while indirect ones include those caused by the use of pesticides, fertilizers, agricultural films, etc. In addition, carbon emissions are generated by the organic carbon released into the air during tilling, and indirectly by the use of electricity during irrigation. Combining the influence mechanism of the digital economy on agricultural carbon emissions, this paper argues that the digital economy affects carbon emissions from cultivated land use at three levels: producer, government, and market. Among them, the producer level mainly affects the behavior of cultivated land use, the government level primarily affects the efficiency of cultivated land use decisions, and the market level principally involves the agricultural carbon sink market transaction.

Specifically, the impact of the digital economy on carbon emissions from cultivated land use mostly includes the following three features: First of all, from the producer's perspective, the digital economy has promoted a digital transformation in cultivated land use as well as improved cultivated land use efficiency and green transformation development, which will be good for reducing the carbon emissions from cultivated land use. On the one hand, the digital economy development will speed up the construction of soil digital application scenarios, guide farmers to apply fertilizer scientifically, enable the rational use of drugs, and allow for accurate irrigation by mastering high-precision soil scientific data such as soil quality, properties, and utilization status, which will help to reduce pollution and carbon while increasing production and efficiency. On the other hand, digital economy development has greatly broadened information channel dissemination and reduced the cost of information acquisition. Producers can obtain new farming and management technologies in time, implement green farming practices, and reduce carbon emissions from the source of cultivated land use. Secondly, from the government's perspective, digital economy development will accelerate digital government construction, improve administrative decision-making efficiency relating to the land and cultivated land use, and thus reduce carbon emissions from cultivated land use. Digital economy expansion will be advantageous for promoting the construction of a digital government, encouraging the construction and implementation of a digital territorial spatial planning information system. This type of system uses cloud computing, big data, artificial intelligence, and other digital technologies to digitize cultivated land use, enabling government to accurately grasp the information on the use of cultivated land, greatly improving the efficiency and level of cultivated land use decision-making, improve the utilization efficiency of cultivated land resources, and reducing energy consumption from the use of cultivated land. For example, Hangzhou has built a “cloud of cultivated land” digital platform to collect and sort out data related to the city’s cultivated land utilization, providing data assistance for the planning and utilization of cultivated land. Third, from the market’s perspective, digital economy growth will facilitate the establishment of an agricultural carbon sink trading market, thereby reducing carbon emissions. In recent years, China has successively established seven pilot carbon markets. As reported in the relevant China’s Carbon Market Review and Outlook (2022) data, by the end of 2021, the cumulative turnover quotas of carbon emissions in the seven pilot carbon markets in China have reached 483 million tons, estimated at 8.622 billion yuan, with remarkable results. However, it is difficult to include agricultural carbon sinks in the carbon sink trading market system due to technical reasons, namely emissions monitoring, reporting, and verification. Digital economy progress shall lead to a breakthrough in the above-mentioned areas. With the help of online technology, we will establish a monitoring system for agricultural carbon emissions, improve the accounting and evaluation methods of agricultural carbon sinks to improve the carbon trading market, promote the establishment of agricultural carbon sink markets, realize the ecological development of the agricultural economy, and reduce carbon emissions.

Hypothesis 1 (H1). *The development of the digital economy helps reduce carbon emissions from cultivated land use.*

2.2. Green Technology Innovation and Carbon Emissions from Cultivated Land Use

Green innovation of cultivated land mainly embodies two aspects of agricultural technology and agricultural factor input. (1) Green innovation in agricultural technology mainly includes the research, development, promotion, and application of new agricultural green technologies and innovation in modern agricultural production and management methods; (2) Innovation in factor input mainly refers to the reasonable allocation of agricultural production input factors to achieve the best efficiency through the innovation of information access channels and production factor circulation channels. The digital economy can reduce carbon emissions through green technical renovation [36]. The effect of green technical renovation on carbon emissions from cultivated land use mainly includes the following three aspects: First of all, the impact of green technology innovation on carbon emissions is first reflected in resource utilization efficiency, specifically in the precise control of chemical fertilizers, pesticides, and other resources, improving resource utilization efficiency, and indirectly reducing the level of carbon emissions from cultivated land use. For example, agricultural drip irrigation technology has greatly improved resource utilization efficiency by using digital technology to accurately determine the time and amount of utilization, using sensing technology to record and build crop growth models, implementing precise planting and breeding, and achieving high-quality and high-yield agricultural production. Secondly, the achievements of green technology innovation are provided to agricultural producers through digital platforms, which improves the utilization rate of green innovation technologies and brings about significant effects in terms of innovation. Simultaneously, the widespread application of green innovation technologies further reduces carbon emission levels from cultivated land use. For example, pheromones, biopesticides, and biostimulants are publicized through digital platforms such as big data and mobile Internet to replace traditional pesticides and fertilizers, reducing carbon emissions and providing high-quality green food. Third, the digital economy accurately spreads and shares knowledge about sustainable innovation through the Internet, improving agricultural enterprises’ green innovation through talent gathering, as well as scientific and technological financing, improving the innovation environment of agricultural enterprises. This promotes agricultural enterprises that conduct green technical renovations, catalyzing innovation and carbon emission reduction.

Hypothesis 2 (H2). *The digital economy reduces carbon emissions from cultivated land use by promoting green technical renovations.*

3. Methodology

3.1. Variable Selection

The core variables included explained and explanatory variables. Among them, the explained variable was carbon emissions from cultivated land use (*ce*), and the explanatory variables consisted of the development of the digital economy (*dig*) and green technology innovation (*gretech*).

3.1.1. Core Interpreted Variable

The core explained variables in this research mainly referred to Kuang B et al. [37] and the measurement of carbon emissions associated with data availability. Six agricultural carbon emission sources were selected, namely farming, chemical fertilizer, pesticide, agricultural diesel, agricultural film, and agricultural irrigation, to calculate carbon emissions from cultivated land in all provinces of the country. The following equation was applied to estimate the cultivated land carbon emissions:

$$E = \sum E_i = \sum T_i \times \delta_i$$

E stands for the overall carbon emissions from cultivated land use; E_i is the emissions of carbon from carbon-based sources utilized by class i of cultivated land; T_i represents agricultural carbon emission consumption sources of category i; δ_i represents a carbon source's emission coefficient of category i. The calculation system is displayed in Table 1.

Table 1. Carbon emission measurement system for agricultural cultivated land use.

Carbon Source of Cultivated Land Utilization	Expressions	Explanations
Cultivation (C_1)	$T_1 \times \delta_1$	T_1 Sown area of grain crops; the coefficient δ_1 is 312.6 kg CE/hm^2 [38]
Chemical fertilizer (C_2)	$T_2 \times \delta_2$	T_2 The amount converted from fertilizer application; the coefficient δ_2 is 0.8956 kg CE/kg^2 [39]
Pesticides (C_3)	$T_3 \times \delta_3$	T_3 Pesticide usage; the coefficient δ_3 is 4.9341 kg CE/kg [40]
Agricultural diesel (C_4)	$T_4 \times \delta_4$	T_4 Agricultural diesel consumption; the coefficient δ_4 is 0.5927 kg CE/kg [41]
Agricultural film (C_5)	$T_5 \times \delta_5$	T_5 Amount of agricultural film used; the coefficient δ_5 is 5.18 kg CE/kg [42]
Agricultural irrigation (C_6)	$T_6 \times \delta_6$	T_6 Agricultural irrigation amount; the coefficient δ_6 is 20.476 kg CE/hm^2 [43]

3.1.2. Core Explanatory Variables

Utilizing the previous approaches developed by academics such as Zhao Tao [44], Li Xue, and others [45], in this paper, we evaluated the growth of the digital economy mainly in two dimensions: the internet development level and digital financial inclusion. Among them, the dimensions of the degree of internet advancement include: (1) internet penetration, as measured by the proportion of Internet subscribers with high-speed access per 100 individuals; (2) the number of Internet-related industries, expressed as the percentage of city dwellers who work in computer services and software businesses; (3) Internet-related output, characterized by the total telecom services per person; and (4) the number of mobile Internet subscribers, measured by the quantity of cell phone subscribers per 100 people. In order to calculate the three digital financial inclusion dimensions—digital financial coverage breadth, digital financial use depth, and digitalization level—the provincial digital financial inclusion index in China, created by Guo Feng et al. [46], was used as a proxy. In this research, we computed a total of 5 indicators for the 2 aspects mentioned above to determine how the digital economy is evolving, by using the entropy approach to construct China's interprovincial digital economy growth index.

Intermediary Variables

This paper considers green technical renovation (*gretech*) as an intermediary variable, including patent applications for green inventions (*gretech1*) and patent authorizations for green inventions (*gretech2*).

Control Variables

Given that the carbon emissions from the development of the digital economy on cultivated land use are influenced by several factors, these were the control variables that were considered for this study: opening level, planting structure, human capital, rural electricity consumption, waste disposal, environmental regulation, and infrastructure construction. Among them, the opening level (*openlevel*) was calculated from the percentage of the whole foreign trade in the regional GDP; the planting structure was represented as a percentage of food crop area sown in relation to the total crop area sown; human capital (*hucap*) was defined as the portion of the province's population with higher education as a percentage of the total population; rural energy consumption (*encon*) was described as the total electricity consumption of rural residents; domestic garbage disposal (*waste disposal*) was expressed by the harmless disposal rate of domestic garbage; environmental regulation (*eg*) was proxied as a share of GDP by investment in pollution control; the highway mileage of the province characterized the infrastructure construction (*road*). All the above control variables were logarithmized to mitigate the heteroscedasticity interference caused by data fluctuation.

3.2. Model Settings

3.2.1. Fixed-Effect Model

The manuscript developed the model with a fixed effect, as follows, to investigate the effects of digital economy development on carbon emissions from cultivated land use based on theoretical analysis and data characteristics:

$$clu_{it} = \lambda_0 + \lambda_1 dig_{it} + \lambda_2 controls_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

The subscript i stands for various provinces. The subscript t accounts for various years, and the clu_{it} is an explained variable, representing the amount of carbon emissions from cultivated land usage in i the province during period t. The primary explanatory variable dig_{it} is the growth of the digital economy of the i region in the t period. λ_1 is the parameter to be estimated. λ_1 is the key concern coefficient of this paper, if λ_1 is strongly negative, which indicates that the digital economy rise can successfully cut the carbon emissions of China's cultivated land use. The control variable group $controls_{it}$ shows a number of control variables at the provincial level in the region. In addition, μ_i indicates an individual fixed effect, while ν_t denotes a time fixed effect, and ε_{it} demonstrates the random error term.

3.2.2. Mediation Effect Model

To investigate the potential mechanisms of the influence of digital economic growth on carbon emissions, we further tested the intermediary effect to estimate how digital economic development affects cultivated land use carbon emissions through the path of green technology innovation. This manuscript refers to the approach of Wen Zhonglin et al. [47], who take cultivated land use carbon emissions (*clu*) as a dependent variable, digital economy growth (*dig*) as an independent variable, and green technology innovation (*gretech*) as an intermediary variable. The following intermediary-effect model was constructed:

$$clu_{it} = \alpha_0 + \alpha_1 dig_{it} + \alpha_2 controls_{it} + \epsilon_{it} \quad (2)$$

$$gretech_{it} = \beta_0 + \beta_1 dig_{it} + \beta_2 controls_{it} + \eta_{it} \quad (3)$$

$$clu_{it} = \gamma_0 + \gamma_1 dig_{it} + \gamma_2 gretech_{it} + \gamma_3 controls_{it} + \theta_{it} \quad (4)$$

The stepwise regression method was adopted in this paper to confirm the intermediary effect. Equations (3) and (4) represent the green technology innovation intermediary variable.

3.3. Data Description

The research data range of this manuscript included 30 Chinese provinces, municipalities, and autonomous regions, over the period from 2011 to 2019. Because of the obvious shortage of statistics for the Tibet Autonomous Region, Hong Kong, Macao, and Taiwan for many years, we eliminated the data and obtained 270 samples from 30 provinces and cities. What calls for special attention is that although some regions are more economically developed and have a high urbanization rate, they still retain a large amount of arable land and agricultural production practices. For instance, in 2019, the arable land area in Beijing was about 93,500 ha, and grain production reached 288,000 tons [48]. In the same year, the cultivated land area in Shanghai was about 162,000 ha, and grain production reached 914,000 tons [49]. This study used farming, chemical fertilizer, agricultural film, pesticide, diesel oil, and agricultural irrigation data collected from the China Rural Statistical Yearbook. The data on the intermediary variables came from the Green Patent Database (GPRD) in the China Research Data Service Platform. Digital economy development data were from the China Urban Statistical Yearbook, China provincial digital inclusive financial index, and China Science and Technology Statistical Yearbook. Moreover, the rest of the data on the majority of the control variables originated from the China Statistical Yearbook and various provinces. There were a few missing values in individual years in some provinces. The interpolation method was applied to this manuscript to complete the sample data. Table 2 shows descriptive statistics for the data listed above.

Table 2. Descriptive Statistics.

Variable Name	Variable Symbol	Sample Size	Average Value	Standard Deviation	Minimum	Maximum
Carbon emissions from cultivated land use	*clu*	270	29.129	19.773	1.195	87.088
Digital economy development	*dig*	270	0.341	0.150	0.077	0.895
T inclusive financial index	*df*	270	0.203	0.092	0.018	0.410
Opening level	*openlevel*	270	4.842	1.121	1.869	6.987
Planting structure	*planting_structure*	270	4.168	0.222	3.576	4.575
human capital	*hucap*	270	−2.074	0.400	−2.925	−0.683
rural energy consumption	*encon*	270	4.853	1.328	1.411	7.575
Domestic waste disposal	*waste_disposal*	270	4.510	0.160	3.731	4.605
Environmental regulation	*eg*	270	1.342	0.751	0.300	4.240
Highway mileage	*road*	270	7.064	0.847	4.605	8.123

4. Results

4.1. Spatial and Temporal Aspects of China's Carbon Emissions from Cultivated Land Usage

4.1.1. Time-Series Pattern of Carbon Emissions from Cultivated Land in China

This paper accounts for carbon emissions from cultivated land use across China's 30 regions, municipal governments primarily under the central state, and independent regions from 2011 to 2019 (except Tibet, Hong Kong, Macao, and Taiwan), and draws trends of total carbon emissions (Figure 1). The results show that China's carbon emissions from cultivated land use in the period 2011–2019 show an overall decreasing trend and are expected to continue to decrease in the future. In 2011, carbon emissions from cultivated land use were 85.6011 million tons, while in 2019, emissions decreased to 80.9643 million tons, with a −5.73% growth rate and a yearly growth of −0.694%. China's total carbon emissions from cultivated land use show a two-stage change of "slow rise—peak—slow decline", with the first stage (2011–2015) showing an annual upward growth rate in the period of about 27.54%. The second phase (2015–2019), a declining period, has a yearly growth rate of −37.25%. Among others, 2015 was the inflection point when carbon emissions from cultivated land use turned from rising to falling, mainly because China adopted the "Proposal of the 13th Five-Year Plan of the Central Committee of the Communist Party of China on the Formulation of National Economic and Social Development" in that year. Green development became the national development concept, the green development of agriculture was further emphasized, and the green utilization of cultivated land became a new concept of cultivated land utilization.

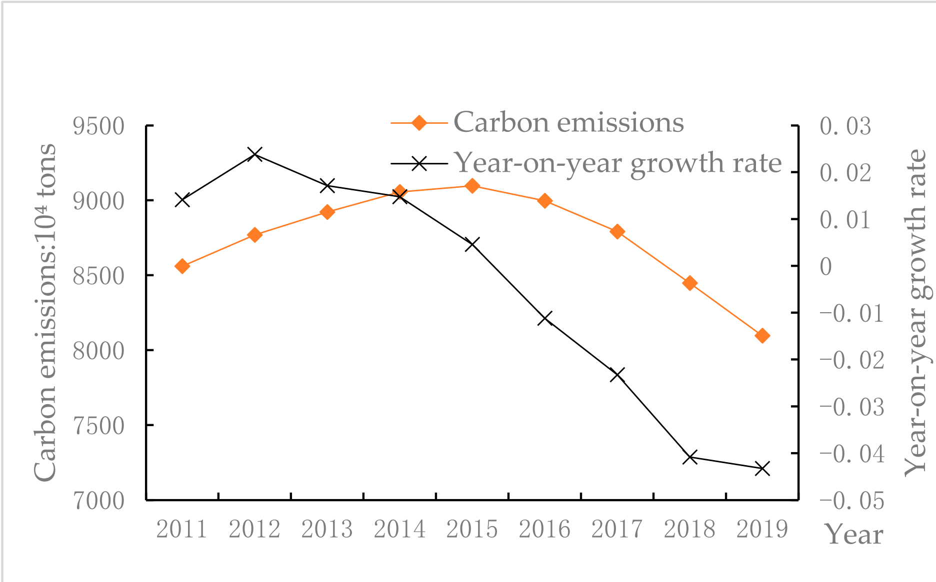

Figure 1. Total carbon emissions from cultivated land use and year-on-year growth rate in China.

4.1.2. Spatial Characteristics of Carbon Emissions from Cultivated Land in China

The spatial pattern of carbon emissions from cultivated land use in China in major years is shown in Figure 2. This manuscript applies the natural breakpoint approach to classify the inter-provincial carbon emissions from cultivated land use in 2011 and 2019 into levels I-V. It can be seen that level I is the lowest level and level V is the highest, to compare the variability of carbon emissions between regions more intuitively. There were 6 carbon emission areas in level I, 6 in level II, 12 in level III, 4 in level IV, and 2 in level V in China in 2011, and 6, 6, 10, 6, and 2 in 2019 in that order. The number of low-emission areas (Class I and Class II) remained stable, the number of medium-emission areas (Class III) decreased, and the number of high-emission areas (Class IV and Class V) increased over the 9 years, and in general, the distribution of China's carbon emissions from cultivated land use displayed a rugby-ball shape.

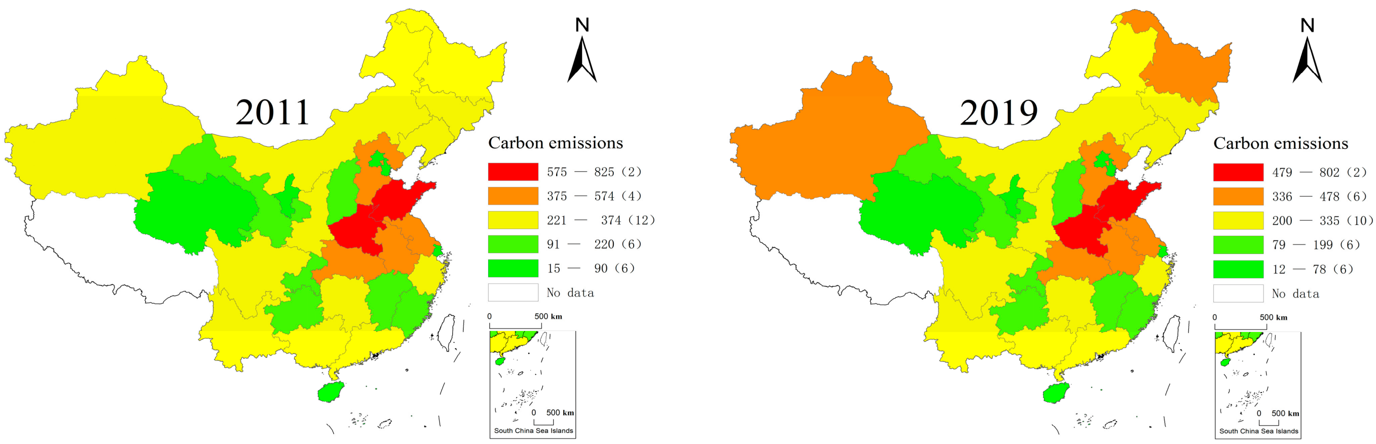

Figure 2. Carbon emission patterns of cultivated land use in 30 Chinese provinces and cities in 2011 and 2019.

Specifically, the six level I provinces in terms of carbon emissions remained stable, including Beijing, Tianjin, Shanghai, and Qinghai Province, in 2011 and 2019; the six level

II provinces in terms of carbon emissions remained unchanged in 2011 and 2019, including Gansu, Chongqing, and Guizhou; the 12 level III provinces in terms of carbon emissions, including Xinjiang, Inner Mongolia, Sichuan and Yunnan, remained unchanged in 2011, but decreased to 10 in 2019; the level IV provinces in terms of carbon emissions increased from four in 2011 to six in 2019. In 2011, there were 12 provinces emitting carbon, including Xinjiang, Inner Mongolia, Sichuan, and Yunnan, and the number of provinces that emitted carbon dioxide dropped to 10 in 2019; those at level IV increased from four in 2011 to six in 2019 (Xinjiang and Heilongjiang were added); those at level V remained unchanged, including Henan Province and Shandong Province. On the whole, China's overall carbon emissions from cultivated land use revealed considerable spatial and temporal divergences. In 2011, the characteristics of East > Central > Northeast were shown by the spatial variance of carbon emissions from cultivated land use, while in 2019, the spatial diversity of carbon emissions from cultivated land use indicated the characteristics of West > East > Central > Northeast.

4.2. Benchmark Regression

The calculated outcomes of the growth of the digital economy here on carbon emissions from cultivated land usage are shown in Table 3. For model selection, the fixed-effect model was chosen for estimation based on the findings of the Hausman test. Models (1) to (3) are the results of fixed effects without control variables, fixed effects with control variables, and random effects. From the results of columns (1) to (3), we can see that dig's regression coefficients are −3.936, −9.362, and −10.91, respectively, which pass the 1% significance level test. It can be seen that the digital economy growth of the empirical results can effectively reduce the level of carbon emissions from cultivated land use in China, which preliminarily proves Hypothesis 1 of this study. The amount of China's digital economy growth has improved the digital transformation of cultivated land use and the innovation and growth of cultivated land use technology, especially green technology innovation, which effectively promotes the efficiency of cultivated land use and the improvement of green transformation Therefore, it will decrease the level of carbon emissions from cultivated land use.

Table 3. The consequences of the growth of the digital economy on carbon emissions from cultivated land usage as assessed by benchmark regression findings.

Variables	(1)	(2)	(3)
	fe_non Control	fe	re
dig	−3.936 ***	−9.362 ***	−10.91 ***
	(−4.34)	(−5.76)	(−6.77)
openlevel		1.448 ***	1.564 ***
		(2.79)	(2.98)
planting_structure		−15.82 ***	−13.13 ***
		(−5.19)	(−4.34)
hucap		0.533	−0.210
		(0.54)	(−0.21)
encon		1.871 ***	2.338 ***
		(2.69)	(3.46)
waste_disposal		2.838 **	2.710 **
		(2.34)	(2.17)
eg		0.234	0.199
		(0.92)	(0.76)
road		3.496	8.441 ***
		(1.59)	(4.73)
_cons	30.47 ***	45.45 **	−3.903
	(91.46)	(2.20)	(−0.21)
N	270	270	270
R^2	0.073	0.267	

Note: **, *** denote the significance level of 5%, and 1%, respectively, and the brackets are T values.

Moreover, when it comes to the control variables, the coefficient values of regression for the degree of openness to the external world, rural electricity use, domestic waste treatment, and infrastructure construction are significantly positive, which shows that for this sample, with the growth of the above control variables, the carbon emissions from cultivated land use also increase, proving the "pollution refuge" hypothesis, which is similar to previous research findings [50]. As the amount of openness to the external world, rural electricity consumption, domestic waste disposal, and infrastructure construction increase, it will directly or indirectly promote the consumption of cultivated land resources and the consumption of energy, thus expanding the emissions of carbon. The regression coefficient of the planting structure is −13.13, which is significantly negative, indicating that the enhancement of planting structure can help to enhance the efficiency of cultivated land usage and industrial optimization, thus effectively reducing the level of carbon emissions from cultivated land usage.

4.3. Robustness Test

4.3.1. Replacing Explanatory Variables and Remove Some Samples

In the above benchmark regression, the index of digital economic growth is chosen as the explained variable to conduct the benchmark regression. To test the robustness of the estimated results and investigate further the implications of digital economic growth on carbon emissions from cultivated land use, the first step is to replace the explanatory variable to minimize the potential effect of a single variable on the outcomes of the estimation. Gauging the digital economic growth level, this study examines the possibility of substituting the digital economic growth index with the digital open financial index. For regression, the fixed-effect model must be utilized. Column (2) of Table 4 presents the findings. Column (1) is the result obtained before replacing the index of digital economic growth. The comparison findings show that after substituting the explained variables, the digital economy growth regression coefficient is −6.664, which is still dramatically negative at the 5% level, in line with the estimated outcomes of the benchmark model. Therefore, after replacing the explanatory variables, the digital economic growth level improvement can significantly reduce carbon emissions from cultivated land use.

Because there are large differences between municipalities directly under the Central Government and ordinary provinces in terms of the level of digital economy development, economic development, technological innovation, and green technological innovation, the samples from municipalities directly under the Central Government are not included in this article. It only retains the benchmark model for the re-estimation of ordinary province samples. The regression findings for Table 4's column (3) remove four municipalities (Beijing, Tianjin, Shanghai, and Chongqing). As can be seen, dig's regression coefficient value is still notably negative at 1%, and its absolute value is higher than the regression coefficient before excluding municipalities that fall under the direct authority of the Central Government, which indicates that the improvement of digital economic development in provinces not directly under the Central Government has a stronger inhibition effect on carbon emissions from cultivated land use, thus further strengthening the core conclusions of this paper.

4.3.2. Random Sampling and Adjust Sample Period

Based on benchmark analysis, this paper conducts a random sampling of samples to further strengthen the regression findings' robustness, and the estimation of the sampling is shown in Table 4's column (4). The significance levels of each control variable and the regression coefficients of the dig are similar to the regression outcome, indicating that the selected sample data are representative, the outcomes of benchmark regression are more reliable, and the amount the digital economic growth can decrease the carbon emissions from cultivated land use.

Table 4. Robustness Test I.

Variables	(1)	(2)	(3)	(4)	(5)
	fe	thfe	xtfe	bsfe	tzfe
dig	−9.362 ***		−10.43 ***	−9.362 ***	−13.74 ***
	(−5.76)		(−5.43)	(−5.30)	(−8.78)
openlevel	1.448 ***	1.714 ***	1.765 ***	1.448 **	0.742
	(2.79)	(3.13)	(3.17)	(2.25)	(1.48)
planting_structure	−15.82 ***	−13.17 ***	−18.63 ***	−15.82 ***	−17.26 ***
	(−5.19)	(−4.15)	(−4.86)	(−3.62)	(−3.89)
hucap	0.533	−0.447	0.778	0.533	−0.413
	(0.54)	(−0.42)	(0.77)	(0.60)	(−0.33)
encon	1.871 ***	1.601 **	5.889 ***	1.871 *	0.783
	(2.69)	(2.13)	(4.83)	(1.93)	(0.96)
waste_disposal	2.838 **	1.992	4.094 ***	2.838 **	−5.410 **
	(2.34)	(1.53)	(3.17)	(2.19)	(−2.37)
eg	0.234	0.502 *	0.399	0.234	−0.125
	(0.92)	(1.90)	(1.43)	(0.69)	(−0.52)
road	3.496	0.472	−2.776	3.496	0.781
	(1.59)	(0.20)	(−0.94)	(1.59)	(0.34)
df		−6.664 **			
		(−2.35)			
_cons	45.45 **	55.39 **	79.95 ***	45.45 **	117.8 ***
	(2.20)	(2.46)	(2.90)	(2.24)	(4.47)
N	270	270	234	270	150
R^2	0.267	0.182	0.364	0.267	0.588

Note: *, **, *** denote the significance level of 10%, 5%, and 1%, respectively, and the brackets are T values.

Taking into account the fact that digital economic growth was relatively slow before 2015, this essay employs the methodology of shortening the sample period to lead the robustness test and strengthen the persuasiveness of the regression evaluation. Since 2015, the digital economy in China has grown rapidly. Using the research methods of Dang Lin et al. [51] for reference, the sample period was shortened. Taking 2015 as the starting year for research on the digital economy, the time series sample in this study was changed to include 2015–2019 and the regression estimation was carried out again. The consequences of the estimation are given in Table 4's column (5). The findings demonstrate that dig's regression coefficient is still strongly negative, and the absolute value exceeds the benchmark regression results by a substantial margin, which is in keeping with the aforementioned premises, further proving the consistency of the primary findings presented in this research paper.

4.3.3. Quantile Regression

As the above regression model focuses on mean regression, which cannot give an accurate picture of the distribution of the reaction conditions, to enhance the reliability of the regression outcomes, this study considers using quantile regression for analysis. Using the quantile regression technique [52] developed by Roger Koenker and Gilbert Bassett as a guide, we can eliminate the extreme values that affect the regression findings by observing the head and tail of the explained variables to reflect the data more comprehensively. By setting three quantiles (0.30, 0.60, and 0.90), the 30 provinces, municipalities, and autonomous areas of China are categorized into regions with low, medium, and high carbon emissions for cultivated land use. The outcomes of regression are in Table 5's columns (2)–(4). To compare the errors and differences between the original benchmark regression and quantile regression, column (1) of Table 5 also shows the benchmark regression findings. The regression coefficients of dig at the three quantiles can be seen to be significantly negative, and the absolute values are broadly from the findings of the benchmark regression. The findings remain robust and support the universal applicability of the core conclusions in this paper.

Table 5. Robustness Test II.

Variables	(1)	(2)	(3)	(4)
	fe	fe30	fe60	fe90
dig	−9.362 ***	−9.456 ***	−9.275 ***	−9.156 ***
	(−5.76)	(−3.39)	(−5.54)	(−3.89)
openlevel	1.448 ***	1.663 *	1.249 **	0.978
	(2.79)	(1.91)	(2.39)	(1.33)
planting_structure	−15.82 ***	−16.09 **	−15.57 ***	−15.22 **
	(−5.19)	(−2.22)	(−3.58)	(−2.49)
hucap	0.533	0.292	0.756	1.061
	(0.54)	(0.18)	(0.76)	(0.76)
encon	1.871 ***	2.500 *	1.289	0.493
	(2.69)	(1.76)	(1.51)	(0.41)
waste_disposal	2.838 **	2.999	2.691 **	2.488
	(2.34)	(1.41)	(2.11)	(1.39)
eg	0.234	0.362	0.116	−0.0466
	(0.92)	(0.58)	(0.31)	(−0.09)
road	3.496	3.540	3.456 *	3.400
	(1.59)	(1.17)	(1.90)	(1.33)
_cons	45.45 **			
	(2.20)			
N	270	270	270	270
R^2	0.267			

Note: *, **, *** denote the significance level of 10%, 5%, and 1%, respectively, and the brackets are T values.

4.4. Endogeneity Test

In this research, we adopted the instrumental variable method to demonstrate the robustness of benchmark regression analysis while limiting endogenous problems due to missing variables, reverse causality, and unobservable factors. Referring to the practice of Li Xue et al. [45], we selected the one-period lag of the index of the digital economic development index as a tool variable of the current digital economy. We used the fixed-effect 2SLS model for regression. Since the digital economic index lagging behind one period is highly related to the current sample and is unlikely to have an influence on the current level of carbon emissions from cultivated land use, the digital economic index lagging behind one period was selected as a tool variable to meet the relevance and exogeneity requirements.

Table 6 displays the instrumental variable regression estimates. Among them, column (1) is the first stage of the estimation. The findings represent that the lagged first-order digital economic index as a tool variable has good explanatory power for endogenous variables, and at the 1% level of statistical significance, the regression coefficient is positive. The second stage estimate is listed in column (2). It can be seen that after considering the endogenous problem, the level of digital economy development level still has a negative effect on the carbon emissions of cultivated land use and has passed the significance test. The benchmark regression's main finding is once more supported by the absolute value, which is much higher than the 9.362 of the benchmark regression coefficients.

Table 6. Regression of instrumental variables.

Variables	(1)	(2)
	Phase I	Phase II
IV	1.044 ***	
	(32.02)	
dig		−11.03 ***
		(−6.55)
control variables	yes	yes
_cons	0.885 **	
	(2.37)	
N	240	240
R^2	0.951	0.390

Note: **, *** denote the significance level of 5%, and 1%, respectively, and the brackets are T values.

4.5. Mechanism Analysis

It can be seen from the previous analysis that digital economic growth dramatically reduces carbon emissions from the usage of cultivated land. We further analyze this transmission mechanism and whether digital economic growth can reduce the carbon emissions from cultivated land use by influencing green technology innovation, and because the technological progress closely related to the carbon emissions from cultivated land use is bound to be related to the degree of innovation in green technologies, in order to prevent a single indicator from measuring the results from bias. As a result, we use the two indicators of patent applications for green inventions (*gretech1*) and green invention patent authorizations (*grdtech2*) as proxy variables of the creation of green technology to investigate the mechanism of innovation in green technology.

The intermediary mechanism analysis findings are presented in Table 7, which highlights the innovation in green technology and the influence of digital economic growth on carbon emissions from cultivated land use. Among them, the regression findings are represented in column (1) for the two indicators in the first stage, and columns (2)–(3) and (4)–(5) are the second- and third-step tests of the number of green invention patent applications and authorizations, respectively. The regression results show that in terms of the number of filings for patents for environmentally friendly innovations, the estimated coefficients of dig and *gretech1* are significant at 1%, demonstrating that the rise of the digital economic system can substantially boost the number of patent applications for environmental inventions, thus effectively curbing the carbon emissions from the use of cultivated land; as far as the number of green invention patents granted is concerned, the regression coefficients of dig and *grdtech2* are still significant. It is evident that digital economic growth also significantly facilitated the advancement of environmental technological innovation based on the number of green invention patents awarded. This confirms the idea that the growth of the digital economy will indirectly restrain the carbon emissions of cultivated land use through environmental technological innovation, and it plays an essential role in this transmission mechanism. This result effectively validates Hypothesis 2. By improving the growth of innovation in green technology, the digital economy provides new impetus for cultivated land use and emission reduction and reduces the carbon emission level of cultivated land use.

Table 7. Regression results of intermediary mechanism.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	fir	**sec1**	**thir1**	**sec2**	**thir2**
dig	−9.362 ***	3.034 ***	−11.51 ***	2.377 ***	−10.43 ***
	(−4.66)	(11.69)	(−5.54)	(11.48)	(−4.87)
openlevel	1.448	−0.0973	1.571	−0.0313	1.500
	(1.44)	(−1.34)	(1.60)	(−0.54)	(1.50)
planting_structure	−15.82 **	1.326 **	−16.23 **	0.891 *	−15.60 **
	(−2.44)	(2.29)	(−2.53)	(1.97)	(−2.33)
hucap	0.533	0.190	0.795	0.125	0.903
	(0.54)	(1.13)	(0.82)	(0.75)	(0.93)
encon	1.871	0.349	1.772	0.179	1.986 *
	(1.61)	(1.68)	(1.61)	(1.47)	(1.77)
waste_disposal	2.838 *	0.0409		−0.106	
	(1.76)	(0.26)		(−0.66)	
eg	0.234	0.0206	0.226	0.0831 ***	0.175
	(1.02)	(0.61)	(1.01)	(2.80)	(0.76)
road	3.496	1.683 ***	1.539	1.740 ***	1.730
	(1.21)	(3.51)	(0.53)	(5.61)	(0.60)
gretech1			1.030 ***		
			(2.90)		
gretech2					0.880 *
					(1.85)
_cons	45.45 *	−12.11 **	67.36 **	−10.88 ***	64.91 **
	(1.80)	(−2.52)	(2.68)	(−3.20)	(2.50)
N	270	270	270	270	270
R^2	0.267	0.824	0.269	0.813	0.259

Note: *, **, *** denote the significance level of 10%, 5%, and 1%, respectively, and the brackets are T values.

5. Discussion

Because of increasing global warming, it is vital to enhance the carbon emission reduction effect of the digital economy to promote high-quality economic development. Therefore, this manuscript systematically discusses the intrinsic link between the digital economy and carbon emissions from cultivated land use and empirically investigates the mechanism of the effect between the two by using data from 30 provincial panels from 2011 to 2019. This paper's main contributions are as follows: (1) It analyzes, in detail, the mechanism through which the digital economy influences carbon emissions from cultivated land use, highlighting that green technology innovation can effectively suppress greenhouse gases from cultivated land utilization. We also corroborate the reduction effect that greenhouse gases have of green technology applications. Additionally, it provides a theoretical basis for green technology innovation to encourage the low-carbon transformation of cultivated land use in China. (2) This paper further enriches the research results in the digital economy field and the field of carbon emission reduction. Furthermore, it provides a feasible theory for the expansion function of the digital economy in reducing carbon emissions from cultivated land use and simultaneously provides China with a new path to achieve carbon neutrality.

This paper has some similarities with existing studies, but also some novel ideas. First, existing studies point out that the digital economy greatly promotes green technology innovation [53–56] and that green technology innovation can effectively curb regional carbon emissions [57–60]. The above studies provide theoretical support for the selection of mediating variables in this paper, but the above studies do not explore the relationship between the digital economy and carbon emissions, nor do they answer whether green technology innovation can similarly curb carbon emissions from cultivated land use. Therefore, this paper connects the digital economy and carbon emissions from cultivated land use, expanding the scope of research on the digital economy and the application scenarios of green technology innovation. Second, existing studies show that the digital economy effectively reduces regional carbon emissions through green technology innovation [61], the upgrading of industrial structures [62,63], and regional economic growth [64]. This paper not only corroborates the carbon reduction effect of the digital economy, which is consistent with the results of existing studies [23,65,66], but also extends the carbon reduction effect of the digital economy even further to the field of carbon emissions from cultivated land use, and confirms that green technology innovation can effectively reduce carbon emissions from cultivated land use.

The digital economy gives a brand-new vision for the reduction of carbon emissions from cultivated land use, and this investigation can, to a certain extent, fill the theoretical deficiencies and give a reference foundation for the energy-efficient alteration of cultivated land application in China.

Of course, there are certain shortcomings in this paper's research, which can be further improved in following studies. Specifically, (1) established studies show that technological advancement has a dual effect on energy consumption and carbon emissions. Technological progress can promote energy saving and emissions reduction, but it may lead to a higher energy demand and weaken the effect of energy saving and emission reduction as well, i.e., the "rebound effect" [67,68]. Given this, will the digital economy induce an energy "rebound effect" while decreasing carbon emissions from cultivated land application through technical renovation, thus leading to a rise in carbon emissions from cultivated land use? This needs to be further studied. (2) Studies have shown that there are many mechanisms through which the digital economy can lessen carbon emissions; for example, the digital economy decreases carbon emissions via a sharing economy [69], the optimization of energy consumption structures [70,71], resource allocation efficiency [72,73] and the optimization of industrial structures [74], but in the case of carbon emission reduction from cultivated land, this paper has not been able to fully address them due to the lack of relevant theoretical and empirical studies. Therefore, further research is needed.

In conclusion, as the worldwide digital economy is still in the early development phase, it faces many risks and challenges in the development process, and we should urgently conduct extensive research on theories, policies, laws, and other aspects of the digital economy to enable green and energy-saving expansion.

6. Conclusions and Suggestions

In this research, considering China's inter-province panel data from 2011 to 2019, we analyze the process underlying the effect of the digital economy on carbon emissions from cultivated land usage, as well as the influencing factors. The results are as follows:

(1) The development of the digital economy significantly reduces carbon emissions from cultivated land use, and even after considering endogeneity and conducting robustness tests, this conclusion is still valid.

(2) Green technology evolution plays a significant mediating role in the effect of digital economic growth on carbon emissions from cultivated land use. The growth of the digital economy considerably enhances green technical renovation, which can effectively reduce carbon emissions from cultivated land use by promoting increasing green invention patent applications and licenses, thus bringing into play the carbon emissions effect of the digital economy.

Based on the findings of this study, we have made advanced policy recommendations. First and foremost, we suggest actively promoting the construction of digital economy infrastructure, promoting smart planning construction and the intelligent governance of land space, and accelerating the deep integration of digital technology and cultivated land use. Second, the government should strengthen policy support for the expansion of the digital economy and provide institutional guarantees for the role of the digital economy in encouraging green technology innovation. Finally, we suggest applying green technology innovations in agriculture and the improvement of low-carbon technology for use on cultivated land. Additionally, green technical renovations should be applied in agriculture, and the utilization of low-carbon technologies for use on cultivated land should be increased.

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