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Spatial and Temporal Effects of Digital Technology Development on Carbon Emissions: Evidence from China

Keyong Zhang [1], Sulun Li [1,*], Peng Qin [2] and Bohong Wang [3]

[1] School of Economics and Management, North University of China, Taiyuan 030051, China
[2] Jinxi Industries Group Co., Ltd., Taiyuan 030024, China
[3] Department of Computer Science, University College London, London WC1E 6BT, UK
* Correspondence: l15835880306@163.com; Tel.: +86-158-3588-0306

Abstract: In the context of digital economy and low carbon economy, digital technology is an important tool to achieve the goal of carbon peaking and carbon neutrality. Based on the panel data of 30 Chinese provinces from 2011–2019, to empirically test the time-lagged effect and spatial spillover effect of digital technology development on carbon emissions, the entropy method was used to measure the comprehensive index of digital technology development after applying the dynamic spatial Durbin model. The research results show that: (1) Carbon emissions have time inertia and positive spatial correlation, specifically the spatial characteristics of "high in the north and low in the south"; the overall level of digital technology development is improving; however, the spatial differences are gradually expanding, showing a spatial layout of east, west and middle gradient decline. (2) In both the short term and long term, digital technology development has a significant positive impact on reducing carbon emissions in the region. The long-term inhibitory effect of digital technology development on carbon emissions is more obvious than the short-term effect. (3) Unlike the existing studies indicating that digital technology development contributes to reduce carbon emissions in neighboring regions, digital technology development does not have a positive spatial spillover effect on carbon emissions in spatially connected regions. Therefore, policy makers should take into account spatial effects when promoting the penetration and application of digital technologies in environmental governance.

Keywords: digital technology; carbon emissions; time lag effect; spatial spillover effect

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1. Introduction

Climate change has potentially threatened human survival and development. The massive emission of greenhouse gases has triggered a series of extreme climate phenomena, such as glacial melt, drought and flood polarization. In the past decades, China's long-term high energy consumption and high-pollution crude economic growth model has led to serious pollution problems [1,2]. The consumption of large amounts of fossil energy has made China's carbon dioxide emissions increase yearly [3]. Furthermore, China became the world's largest carbon emitter in 2009 [4]. China's carbon emissions reached 14.093 million tons in 2019, accounting for about one-third of the total global carbon emissions. In response to the increasingly serious problem of carbon emissions, at the 75th session of the United Nations General Assembly in 2020, the Chinese government had committed to peak carbon emissions by 2030 and strives to achieve carbon neutrality by 2060. This means that China's future development will be gradually "decoupled" from carbon, forcing a new round of energy revolution and industrial structure upgrade. Thus, effective control of carbon emissions has become a priority.

Humanity has now entered the digital age, whilst digital technology is leading a new round of global technological revolution and industrial change [5,6]. The new generation of digital technology with big data, cloud computing, artificial intelligence, etc., as the core is deeply integrated with the green low-carbon industry, promoting the transformation and upgrading of industrial structure from high-carbon to low-carbon and from low-end to high-end. According to the white paper on "Jointly Building a Community of Destiny in Cyberspace" released by the Chinese government, China's digital economy reached $7.05 trillion by 2021, accounting for 39.8% of annual GDP. The Digital Carbon Neutral White Paper (2021) released by the China Academy of Information and Communication Research suggested that digital technology is vital in assisting the global process of combating climate change, bringing a new perspective to environmental governance. Therefore, by studying the impact of digital technology development on carbon emissions in China, the insight into the potential role of digital technology in future environmental governance can be acquired, and an important theoretical basis for the green and sustainable development of China and the world can also be provided.

With the deep integration and application of innovations in digital technologies in the fields of resources, energy and environment, digital technologies have received wide attention from researchers and policymakers for their role in reducing carbon emissions. Some scholars argued that digital technologies contribute to green and sustainable development. Firstly, digital technologies promote the dematerialization of economic activities [7,8], with a great reduction of the demand for resources and energy for economic activities [9], following which carbon emissions could be eliminated to a great extent. Secondly, the advancement and spillover penetration of digital technology can improve energy use efficiency by enhancing innovation efficiency and promoting industrial structure upgrading, and the improvement of energy use efficiency is beneficial to the reduction of carbon emissions. Finally, the application of digital technologies in environmental monitoring, early warning and management is key for reducing carbon emissions [10,11]. The construction of smart cities, intelligent transport systems, smart grids, etc., also rely on digital technologies to reduce carbon emissions [12,13]. However, other scholars claimed that the development of digital technology has the potential to worsen environmental pollution. Zhou et al. [14] found that implied emissions from the information and communication industry are growing rapidly; meanwhile, the development of digital technology is not improving the environment. The construction and operation of digital infrastructures consume large amounts of electricity resources [15], resulting in more carbon emissions [16,17]. The electricity leaned on by electronic products and devices would further generate carbon emissions during the life cycle of production, installation, use and disposal [12,18,19].

It is worth noting that dematerialization, technological innovation output, and industrial restructuring are a dynamic evolutionary process compared to the consumption of energy and electricity to generate carbon emissions. Over time, the emission reduction effects of dematerialization, technological innovation output, and industrial restructuring will continue to increase. Therefore, there may be a lag period for the impact of digital technology development on carbon emissions [3]. However, most studies are less holistic in measuring the comprehensive index of digital technology development, and the overall impact of digital technology development on carbon emissions remains unclear. Furthermore, the trend of the impact of digital technology development on carbon emissions in the time dimension is not fully reported.

In addition, digital technology is based on information and communication technology and uses digital knowledge and information as a production factor. Its important characteristics are inter-temporality [20], permeability and innovation complementarity [21]. Digital technology enables the compression of spatio-temporal distances by virtue of efficient data transmission, enhancing the inter-regional connectivity of digital economic activities [22]. Shao et al. [23] pointed out that the externalities characteristic of environmental pollution determines environmental problems possessing regional correlation effects on a geospatial scale. Hao and Peng [24] supported this assertion. The implementation of China's "coordinated regional development strategy" has revealed a new pattern of comprehensive and interconnected regional development. The breadth and depth of inter-regional linkages were strengthened [25,26]. However, existing studies are less likely to analyze the spillover effects of digital technology development on carbon emissions in a spatial dimension. Moreover, there is a lack of research on the spatial effects of digital technology on inter-provincial carbon emissions in China.

This study is therefore vital, because it provides a better understanding of the role of digital technology on carbon emissions in the digital age from both a temporal and spatial perspective. Herein, it is meaningful to provide targeted and specific policy recommendations for China to control carbon emissions and achieve its carbon peak and carbon neutrality targets on schedule. Furthermore, contributions were displayed in the existing literature in the following aspects. First, with China, an emerging economy, as the research target, and using panel data from 30 Chinese provinces for analysis, this study can provide policy recommendations in the area of digital technology for China and the rest of the developing countries to reduce carbon emissions. Second, to ensure the accuracy and reliability of the research results, a comprehensive index of digital technology development was constructed by using as many relevant proxy variables as possible for the reassessment of the overall impact of digital technology development on carbon emissions. Third, differing from existing studies without considering the time lag and spatial correlation of key variables when analyzing the impact of digital technology development on carbon emissions, this study was explored under the analytical framework of dynamic space, avoiding the estimation bias of ordinary econometric models and eliminating the problem of model endogeneity due to two-way causality. Therefore, the results are robust and can provide an important theoretical basis for government environmental policy formulation.

The remainder of the study is presented below. Section 2 reviews the relevant literature, Section 3 describes the methodology and data, Section 4 discusses the results, and Section 5 summarizes and provides policy implications.

2. Literature Review

Scholars have researched the influence of different factors on carbon emissions, such as urbanization, energy consumption, economic growth, etc. [27–31]. With the rapid development of digital technologies and the increasing severity of the global climate, scholars are increasingly focusing on the impact of digital technologies on carbon emissions and related applications. However, existing studies have not reached consensus conclusions.

Several studies have reported that digital technology development has increased carbon emissions and poses a serious threat to the environment. For example, Lee and Brahmasrene [32] explored the impact of ICT (Information and Communications Technology) on carbon emissions in ASEAN countries from 1991–2009 using cointegration regression estimation, and the results showed that ICT development would increase carbon emissions by 0.60% for every 1% increase in development. Park et al. [17] estimated the impact of ICT, financial development, economic growth and trade development on carbon emissions using a pooled mean group (PMG), and the empirical results showed that a long-term relationship was observed between ICT and increased carbon emissions as well as reduced environmental quality. Raheem et al. [33] studied the role of ICT and financial development in carbon emissions and economic growth in G7 countries, and the results showed that ICT has a long-term positive impact on carbon emissions. Salahuddin et al. [34] estimated the impact of economic growth and ICT on carbon emissions in OECD countries from 1991 to 2012. It was found that a 1% increase in ICT would increase carbon emissions by 0.16%.

Other studies have argued that digital technology development reduces carbon emissions and helps improve environmental quality. For example, Zhang and Liu [35] found a significant inhibitory effect of the ICT industry on regional carbon emissions in China based on the STIRPAT model. Asongu et al. [36] studied 44 sub-Saharan African countries and concluded that ICT can be used to curb environmental pollution's potential negative impact on human development. Lu [8] explored the impact of ICT on carbon emissions using panel data for 12 Asian countries from 1993–2013, and ICT was shown as not threatening the environment and not having a significant negative impact from carbon emissions. Zhou et al. [2] examined the impact of the digital economy on haze pollution and its spatial spillover effects using spatial econometric and threshold models. The results showed that haze pollution has spatial spillover effects and high emission aggregation characteristics, and the development of the digital economy has a significant effect on reducing haze pollution. Iqbal et al. [37] explored the impact of ICT and economic globalization on carbon emissions in Pakistan. It was found that ICT has a significant negative impact on carbon emissions and its ability to mitigate climate change. In addition, studies by Ozcan and Apeigis [38], Khan [39] and Chen [40] also provided relevant evidence for the ability of digital technologies to reduce carbon emissions from other perspectives or methods.

Meanwhile, studies exist where the relationship between digital technology development and carbon emissions is non-linear. For example, Higon et al. [41] used a panel dataset consisting of 142 economies to introduce ICT and its squared term study found that ICT and carbon emissions show an inverted U-shaped relationship. Shahnazi and Shabani [42] argued that the direct impact and spatial spillover effects of ICT on carbon emissions showed an inverted U-shaped relationship. Yang et al. [43] explored the impact of internet development on haze pollution and its mechanism using the dynamic spatial Durbin model, and the results showed that there was an inverted U-shaped curve between internet development and haze pollution. Shobande [44] used 32 African countries as a study and also reached similar conclusions.

The reason for the controversial results in these literatures may be the difference in the study period and the study population. NDri et al. [45] found in a survey of 58 developing countries that ICT was environmentally beneficial for relatively low-income developing countries, while there was no significant effect for relatively high-income developing countries. In the inverted U-shaped relationship found by Higon [41], the ICT inflection point is higher for developing countries than for developed countries. Even in the few studies of specific countries at the provincial level, the impact of digital technology development on carbon emissions is not equally consistent. In the case of China, Zhou et al. [14] found that the ICT sector is not an environmentally friendly industry, and its implied carbon impact is tens of times higher than the direct impact. The rapid growth of implied emissions is one of the reasons for the rising carbon emissions. Zhang and Liu [35] found that the ICT industry has a greater inhibiting effect on carbon emissions in central China than in the eastern region, and the inhibiting effect is not significant in the western region.

Although these studies have successfully estimated the impact of digital technology development on carbon emissions using different methodologies, most of these studies have ignored the temporal and spatial effects of digital technology development on carbon emissions. In addition, as in the case of the "Solow paradox" [46], the different measures of digital technology development in these studies may also lead to uncertainty in the results. For example, Altinoz et al. [6] explored the relationship between ICT, total factor productivity and carbon dioxide emissions in the top ten emerging market economies for 1995–2014, showing that internet use and fixed-line subscriptions have a positive effect on carbon emissions, while mobile phone subscriptions and total factor productivity have a negative effect on carbon emissions.

Therefore, considering the relative lack of research on the carbon reduction effects of digital technology development in emerging countries, the temporal and spatial effects of digital technology development on carbon emissions in China are not fully understood. In this study, panel data of 30 Chinese provinces was utilized and the comprehensive index of digital technology development was measured using the entropy method to provide a new reference for decision making for sustainable development in other emerging countries.

3. Methodology and Data

3.1. Spatial Correlation Test

The externality characteristic of environmental pollution and the inter-temporal and permeability characteristics of digital technology determine the possible spatial effects between the two. The empirical results of ordinary econometric models would be biased. Therefore, the study tests the spatial correlation of carbon emissions and digital technology development before empirical analysis. Spatial correlation can quantitatively describe the spatial characteristics of variables. In this paper, the "Global Moran Index" was used to characterize the degree of spatial correlation between inter-provincial carbon emissions and digital technology development in China. The calculation formula is as follows:

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{1}$$

where x_i and x_j denote the variable values of the i and j provinces, $\overline{x}$ denotes the average of the variable values of all provinces, and W_{ij} is the spatial weight matrix. $Moran's\ I$ takes values in the range of [–1,1], when $Moran's\ I = 0$ indicates no spatial correlation; when $Moran's\ I > 0$, there is spatial positive correlation; and when $Moran's\ I < 0$, there is spatial negative correlation. Additionally, the larger its absolute value, the higher the spatial correlation.

This paper uses the "Local Moran Index" to characterize the spatial clustering of inter-provincial carbon emissions and digital technology development in China. The calculation formula is as follows:

$$Local\ Moran's\ I = \frac{n(x_{it} - \overline{x_t})\sum_{j=1}^{n} W_{jt}(x_{jt} - \overline{x_t})}{\sum_{i=1}^{n}(x_{it} - \overline{x_t})^2} \tag{2}$$

where x_{it} is the variable value of the t year for the i province, $\overline{x_t}$ is the average of the variable values of all provinces in the t year, and W_{ij} is the spatial weight matrix. When $Local\ Moran's\ I > 0$, it means that there is positive spatial agglomeration in the neighboring areas; when $Local\ Moran's\ I < 0$, it means that there is negative spatial agglomeration in the neighboring areas.

3.2. Spatial Econometric Models

To examine the spatial spillover effects of digital technology development on carbon emissions, a dynamic spatial Durbin model (SDM) based on the STIRPAT model was constructed [47]. The model took into account the time-lag and spatial correlation of core variables, which could effectively avoid the problem of model endogeneity caused by two-way causality and ensure the accuracy and reliability of the model estimation results. The expression is as follows:

$$\begin{aligned} LnCE_{it} = \ & \alpha_0 + \rho W_{ij}LnCE_{jt} + \varphi LnCE_{i,t-1} + \theta W_{ij}LnCE_{j,t-1} + \alpha_1 DT_{it} + \alpha_2 X_{it} \\ & + \alpha_3 W_{ij}DT_{it} + \alpha_4 W_{ij}X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{3}$$

Next, a two-period lag treatment of digital technology development was conducted, which is meant to further examine the time-lagged effect of digital technology development on carbon emissions. The following dynamic spatial Durbin model (SDM) was constructed.

$$\begin{aligned} LnCE_{it} = \ & \alpha_0 + \rho W_{ij}LnCE_{jt} + \varphi LnCE_{i,t-1} + \theta W_{ij}LnCE_{j,t-1} + \alpha_1 DT_{i,t-2} + \alpha_2 X_{it} \\ & + \alpha_3 W_{ij}DT_{i,t-2} + \alpha_4 W_{ij}X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{4}$$

where i is the province; t is the time; α_0 is the constant term; α_1 to α_4 are the estimated coefficients; W_{ij} is the spatial weight matrix; μ_i and γ_t are the spatial and temporal fixed effects, respectively; ε_{it} is the residual term; ρ is the spatial autoregressive coefficient, reflecting the impact of carbon emissions from spatially linked areas on carbon emissions in the region; φ is the time-lagged regression coefficient, reflecting the impact of carbon emissions in the previous period on carbon emissions in the current period; and θ is the time-lagged regression coefficient of the spatial lag term, which reflects the impact of the previous period's carbon emissions on the current period's carbon emissions in the region.

3.3. Variables and Data Description

As digital technology is an emerging technology, the statistics of its relevant indicators is relatively new. Thus, this study chooses to conduct the relevant research at the provincial level rather than the city level. This study covers all provinces in China as far as possible. However, the study sample was finally determined to be 30 provinces due to the absence of digital technology indicators in individual provinces, excluding Tibet, Hong Kong, Macau and Taiwan. Meanwhile, the temporal and spatial effects of digital technology development on carbon emissions were empirically analyzed using panel data for 30 Chinese provinces from 2011 to 2019. The availability and completeness of data measuring digital technology development was then ensured. The carbon emission data were obtained from the China Carbon Emission Accounts & Datasets (CEADs), a multi-scale carbon accounting inventory including socio-economics and trade covering China and other developing economies with the joint support of the National Natural Science Foundation of China, the Ministry of Science and Technology of China, and the UK Research Council. The digital inclusive finance index, one of the digital technology development indicators, uses the aggregate index from the Peking University Digital Inclusive Finance Index (2011–2020). Other research data were obtained from the China Statistical Yearbook, provincial statistical yearbooks and the website of the National Bureau of Statistics. Data processing and model regression were conducted using Stata16.0 software.

3.3.1. Explained Variable

Since the carbon peak and carbon neutral target are limits on total carbon emissions, it makes sense to take carbon emissions (CE) as the explained variable. Currently, the two main methods applied to measure carbon emissions are the sectoral accounting method and the apparent emissions accounting method. This study uses the apparent carbon emissions data provided by CEADs for empirical analysis. The dynamic evolution and spatial pattern of carbon emissions can be seen in Figure 1.

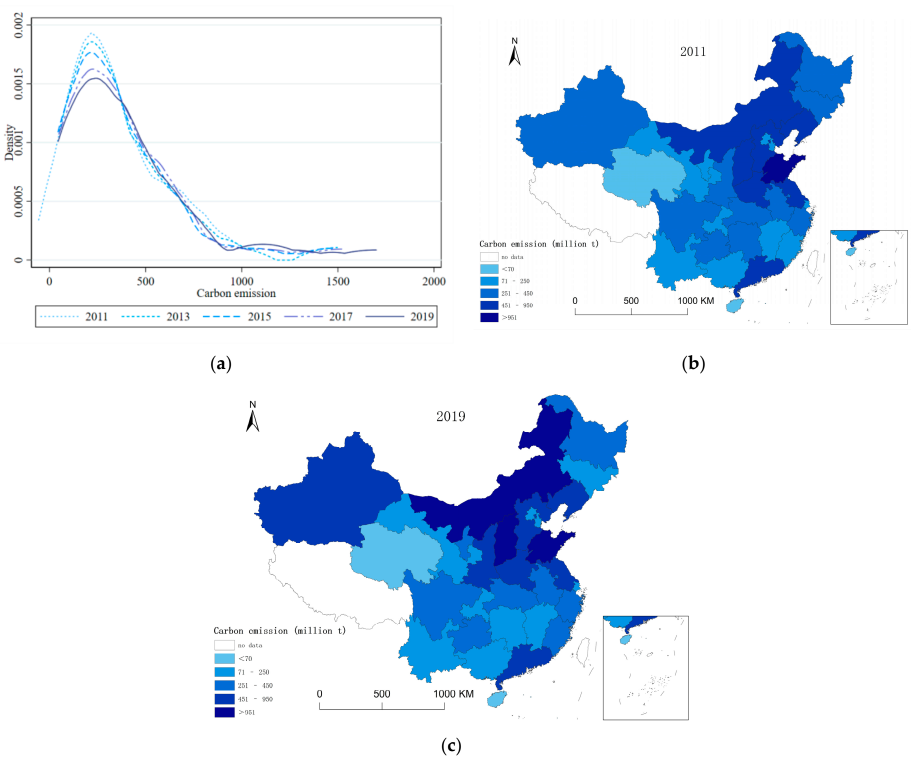


Figure 1. The dynamic evolution and spatial pattern of carbon emissions in China (province).

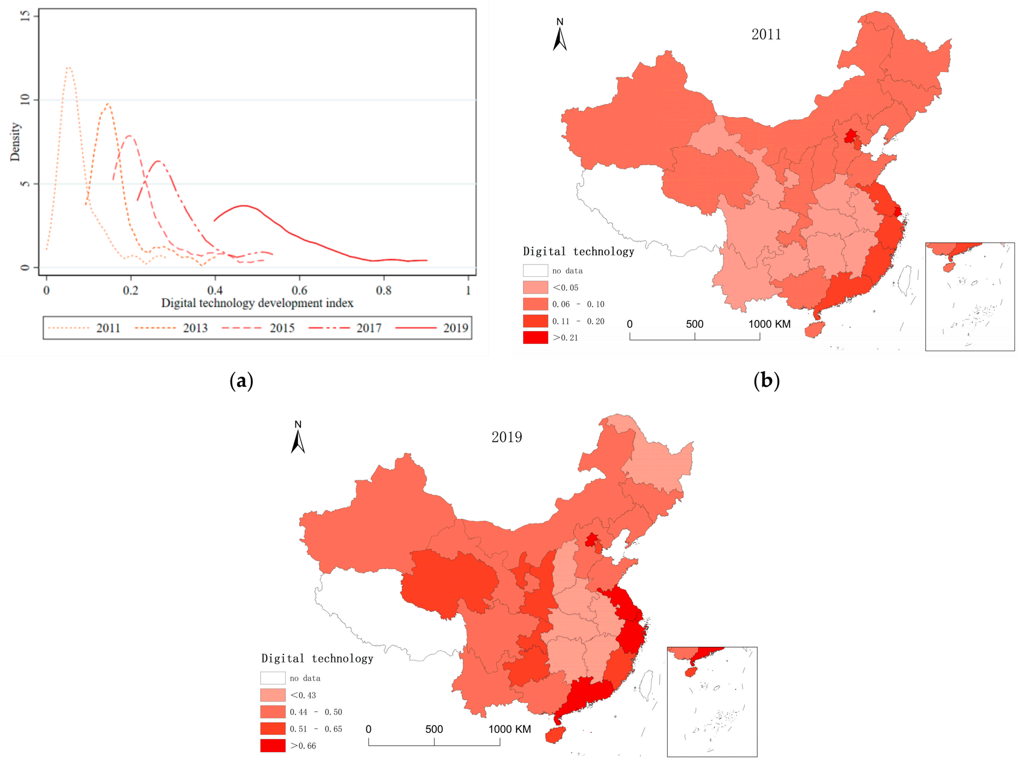
First, the kernel density plot of carbon emissions (Figure 1a) shows that the center of the kernel density curve has not shifted significantly, indicating that the overall level of carbon emissions in China is relatively stable during the sample period. Second, the wave height is decreasing, and the right tail is elongating, demonstrating that the spatial gap in China's carbon emissions is gradually widening. The spatial distribution of China's inter-provincial carbon emissions in 2011 and 2019 (Figure 1b,c) drawn by Arcgis10.7 also shows a gradual increasing in the north, with a decreasing trend in the south. Meanwhile, it can be observed that China's carbon emissions show a characteristic of "high in the north and low in the south". This is consistent with the reality of dense heavy industrial locates in the north.

3.3.2. Core Explanatory Variable

The core explanatory variable is the Digt. At present, relevant research has not yet formed a unified standard for measuring the development of digital technology. Indicators for measuring digital technology development can be divided into two main categories, non-monetary type variables reflecting the intensity of use and monetary type variables reflecting the degree of application [7]. This study considers the comprehensiveness, accuracy and availability of data to construct a comprehensive index of digital technology development (Digt) in terms of both the intensity of use and the degree of application of digital technology. Among them, the indicators of digital technology usage intensity include mobile phone penetration rate (number of mobile phone subscribers per 100 people), internet penetration rate (number of internet users per 100 people), and the proportion of employees in the information and communication industry in urban units; the indicators of digital technology application degree include total post and telecommunications business per capita and the digital financial inclusion index.

The entropy value method determines the weights based on the influence of the relative change degree of each indicator on the system as a whole, which reduces the influence of subjective factors in the process of weight determination and the possible problem of multiple covariance among indicators and can reflect not only the differentiation ability of indicators, but also the change of indicator weights over time. The entropy value method was used to measure the comprehensive index of digital technology development on the basis of determining the weights of each indicator. Figure 2 shows the dynamic evolution and spatial pattern of digital technology development.

First, Figure 2a shows an overall rightward shift of the kernel density curve from 2011–2019, indicating that the level of digital technology development in China is increasing. Second, the peak of the kernel density curve keeps decreasing, and the width increases, indicating that the regional differences in digital technology development in China are widening. These can be observed visually in the spatial distribution of China's inter-provincial digital technology development in 2011 and 2019 (Figure 2b,c) drawn by Arcgis10.7. In addition, the level of digital technology development in China is highest in the eastern coastal region, followed by the western region and lowest in the central region. It is reasonable that the eastern coastal region of China has the highest level of digital technology development, and it has the advantage of greater capital, policy and digital infrastructure. The level of digital technology development in the western region has been greatly enhanced. The superior natural conditions and policy support are possible reasons for the good development of digital technology in the western region. Currently, the eight national computing hubs and ten national data center clusters of China's "East Digital West Computing" strategy are all located in the eastern and western regions.



(**a**) (**b**) (**c**)

Figure 2. The dynamic evolution and spatial pattern of digital technology development in China (province).

3.3.3. Control Variables

Considering that there are many factors affecting carbon emissions, this paper introduces some important control variables to ensure the accuracy of the research results. The EKC curve suggests that carbon emissions may decrease when economic growth exceeds a certain inflection point. The level of economic development (eg) was measured by regional GDP per capita. Technological innovation is a key factor in achieving green development, and the level of technological innovation (ti) was measured by the intensity of R&D investment reflecting the innovation process. Rapid urbanization is also an important factor affecting environmental pollution. The level of urbanization (urb) was measured by the share of urban year-end population in the total regional population. Foreign direct investment is the use of capital by investors in one country for production or operations in another country, and in the process, it also affects socio-economic activities and carbon emissions. Foreign direct investment (fdi) was measured by the amount of actual foreign direct investment. There is a high correlation between industrial structure and environmental pollution. The industrial structure (is) was measured by the share of value added in the secondary industry in regional GDP. A rational energy mix will help to reduce carbon emissions. However, China's economic development still has a strong reliance on traditional energy, and coal-based fossil energy is still the main source of carbon emissions. The energy consumption structure (es) was measured by the share of coal consumption in total energy consumption.

To avoid the effect of possible heteroskedasticity in the data, the data was logarithmically processed using Stata16.0 software. Table 1 shows the results of descriptive statistics of the variables.

Table 1. Descriptive statistics of the variables.

Variable	Unit of Measurement	Mean	Std. Dev.	Min	Max
lnCE	Million Tons	5.647	0.774	3.785	7.438
lnDigt		−1.575	0.702	−4.169	−0.103
lneg	RMB/Person	10.811	0.435	9.706	12.009
lnti	Percent	0.308	0.595	−0.892	1.842
lnurb	Percent	4.033	0.201	3.554	4.495
lnfdi	Billion RMB	5.463	1.727	−1.220	9.259
lnis	Percent	3.757	0.235	2.785	4.078
lnes	Percent	4.081	0.570	0.573	5.169

4. Results and Discussion

4.1. Results of the Spatial Correlation Test

Stata16.0 software was used to calculate the global Moran index of carbon emissions and digital technology development from 2011 to 2019 based on the adjacency spatial weight matrix (bin), geographic distance spatial weight matrix (geo), and economic distance spatial weight matrix (eco). From Table 2, the Moran s I index for carbon emissions and digital technology development was shown to be always greater than 0 under bin matrix and statistically significant at the 5% level.

Table 2. Carbon emissions and digital technology development index global Moran (2011–2019).

Year	Carbon Emissions			Digital Technology Development Index		
	Bin	Geo	Eco	Bin	Geo	Eco
2011	0.266 ***	0.200 ***	−0.015	0.248 ***	0.188 ***	0.413 ***
	(2.476)	(2.484)	(0.209)	(2.502)	(2.535)	(5.166)
2012	0.253 ***	0.204 ***	0.003	0.240 ***	0.169 **	0.421 ***
	(2.378)	(2.545)	(0.403)	(2.385)	(2.289)	(5.170)
2013	0.251 ***	0.212 ***	−0.046	0.113 *	0.067	0.389 ***
	(2.566)	(2.862)	(−0.130)	(1.285)	(1.141)	(4.813)
2014	0.227 ***	0.197 ***	−0.033	0.155 **	0.048	0.365 ***
	(2.376)	(2.714)	(0.023)	(1.567)	(0.935)	(4.559)
2015	0.231 ***	0.201 ***	−0.032	0.172 **	0.083 *	0.330 ***
	(2.359)	(2.706)	(0.030)	(1.785)	(1.310)	(4.112)
2016	0.218 **	0.187 ***	−0.029	0.215 **	0.125 **	0.341 ***
	(2.212)	(2.504)	(0.060)	(2.136)	(1.759)	(4.200)
2017	0.201 **	0.166 **	−0.030	0.233 **	0.116 *	0.307 ***
	(2.093)	(2.302)	(0.054)	(2.237)	(1.624)	(3.732)
2018	0.182 **	0.167 ***	−0.007	0.185 **	0.083	0.256 ***
	(1.945)	(2.333)	(0.318)	(1.836)	(1.268)	(3.171)
2019	0.172 **	0.161 **	0.007	0.215 **	0.122 **	0.238 ***
	(1.846)	(2.244)	(0.479)	(2.087)	(1.692)	(2.975)

Notes: (i) z statistics are in parentheses. (ii) *, **, *** represent significance at 10%, 5%, and 1% level, respectively.

Further, Moran scatter plots were drawn to visualize the local spatial correlation of carbon emissions and digital technology development. Figure 3 consists of four Moran scatterplots showing the spatial heterogeneity of inter-provincial carbon emissions and digital technology development in China in 2011 and 2019, respectively. The trend lines in Figure 3 are all located in the first and third quadrants, indicating that carbon emissions and digital technology development have significant spatial clustering characteristics. Specifically, provinces with high (small) carbon emissions cluster together, and provinces with high (low) levels of digital technology development cluster together. In summary, the global Moran index and the Moran scatter plots indicate that carbon emissions and digital technology development have a significant positive spatial correlation. Therefore, it is necessary to construct a spatial econometric model for empirical analysis.

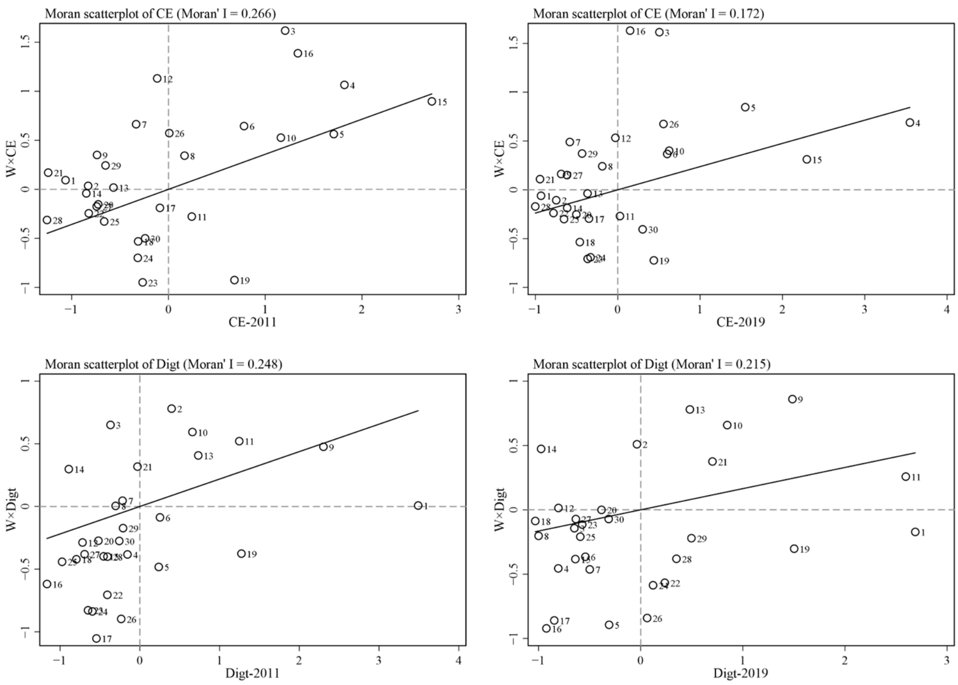


Figure 3. Moran scatter plots of Chinese (province) carbon emissions and digital technology development in 2011 and 2019.

4.2. Results of Spatial Econometric Model Selection

Ignoring the spatial correlation between variables, regression results using classical econometric models may be biased [48]. In this paper, spatial econometric models were conducted to explore the impact of digital technology development on carbon emissions. Currently, there are three main spatial econometric models commonly used: the spatial autoregressive model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). The spatial Durbin model includes the effects of both spatially lagged dependent variables and spatially lagged independent variables, which is more broadly applied. First, the Lagrange multiplier (LM) tests in Table 3 are all significant at the 1% level, meaning that it is reasonable to construct a spatial econometric model. Second, both the LR likelihood ratio test and the Wald test reject the original hypothesis at the 1% level of significance, proving that the spatial Durbin model is therefore more suitable in this study. Finally, the Hausman test rejects the original hypothesis at the 1% level, indicating that the fixed effects are better than random effects. Based on the above tests, this research would use the fixed effects dynamic spatial Durbin model to empirically test the impact of digital technology development on carbon emissions.

Table 3. Diagnostic tests for spatial econometric models.

Test	Statistic	*p*-Value
LM—Spatial lag	135.873	0.000
Robust LM—Spatial lag	17.533	0.000
LM—Spatial error	143.120	0.000
Robust LM—Spatial error	24.781	0.000
LR—SDM—SLM	58.020	0.000
LR—SDM—SEM	57.960	0.000
Wald	27.190	0.000
Hausman	43.540	0.000

4.3. Empirical Results on Time Lag Effects

Column (1)–column (4) in Table 4 present the estimation results of the static spatial Durbin model and three dynamic spatial Durbin models. The regression coefficients of digital technology development in columns (1)–(4) are all significantly negative at the 1% level. This indicates that digital technology development can effectively suppress carbon emissions in Chinese provinces when spatial effects are considered. Meanwhile, the regression coefficients of the time-lagged terms in columns (2) and (4) are positive at the 1% level of significance. It can be inferred that carbon emissions have significant "time inertia", which is manifested as the "snowball effect". The regression coefficients of the spatial and temporal lags are significantly positive at the 5% level. Hence, the carbon emissions of the previous period in the spatially related regions can suppress the carbon emissions of the current period in the region, which is a "warning effect".

Table 4. Results of parameter estimation for the spatial Durbin model.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CE_{t\text{-}1}$		0.668 ***		0.669 ***		0.737 ***		0.710 ***
		(0.046)		(0.046)		(0.062)		(0.061)
$W \times CE_{t-1}$			−0.228 **	−0.266 **			−0.469 ***	−0.319 **
			(0.147)	(0.120)			(0.170)	(0.148)
$W \times CE$	0.041	0.017	0.036	0.054	0.058 *	0.019 *	0.043 *	0.058 **
	(0.094)	(0.089)	(0.105)	(0.095)	(0.102)	(0.099)	(0.077)	(0.081)
$W \times Digt$	0.278 ***	0.110 **	0.262 ***	0.115 **	0.063	0.054	0.064	0.059
	(0.056)	(0.058)	(0.071)	(0.058)	(0.048)	(0.064)	(0.073)	(0.063)
Digt	−0.235 ***	−0.071 ***	−0.161 ***	−0.064 ***	−0.287 **	−0.086 *	−0.170 **	−0.083 *
	(0.047)	(0.050)	(0.061)	(0.049)	(0.041)	(0.050)	(0.058)	(0.049)
eg	−0.110	−0.013	−0.126	−0.017	−0.079	0.015	−0.019	0.039
	(0.104)	(0.080)	(0.099)	(0.080)	(0.090)	(0.082)	(0.095)	(0.081)
ti	−0.051	0.116 **	−0.008	0.132 ***	0.061	0.064	0.084	0.093 *
	(0.063)	(0.051)	(0.062)	(0.051)	(0.059)	(0.051)	(0.060)	(0.051)
urb	0.699 **	−0.336	0.239	−0.324	−0.264	−0.728 **	−0.721 **	−0.731 **
	(0.312)	(0.268)	(0.329)	(0.266)	(0.316)	(0.318)	(0.365)	(0.313)
fdi	0.026 **	−0.001	0.027 **	0.001	0.021 *	−0.020 **	0.015	−0.016
	(0.013)	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)	(0.011)	(0.010)
is	0.222**	0.123	0.345 ***	0.123	0.308 ***	−0.017	0.224 **	−0.032
	(0.103)	(0.087)	(0.106)	(0.086)	(0.103)	(0.096)	(0.108)	(0.095)
es	0.267 ***	0.099 ***	0.240 ***	0.102 ***	0.197 ***	0.091 ***	0.215 ***	0.106 ***
	(0.036)	(0.030)	(0.035)	(0.029)	(0.033)	(0.031)	(0.034)	(0.031)
sigma2_e	0.006 ***	0.004 ***	0.006 ***	0.004 ***	0.004 ***	0.003 ***	0.003 ***	0.002 ***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.393	0.574	0.357	0.580	0.338	0.505	0.370	0.521
Log-likelihood	299.778	340.246	292.650	341.709	287.794	289.085	269.943	291.790
Observations	270	240	240	240	210	180	180	180

Notes: (i) standard errors are in parentheses. (ii) *, **, *** represent significance at 10%, 5%, and 1% level, respectively.

However, the spatial autoregressive coefficients are not statistically significant; the spatial correlation of carbon emissions is therefore insignificant, which is inconsistent with the results of the spatial correlation test. This phenomenon may be caused by the problem of identification of the spatial Durbin model itself and the problem of endogeneity of the model due to the two-way causality between variables.

This study re-runs the model regression by replacing the core explanatory variable with the digital technology development index with a two-period lag. Then, the above issues can be addressed and the time-lagged impact of digital technology development on carbon emissions can be explored. The results in Table 4 column (5)–column (8) demonstrate that the spatial autoregressive coefficient is significantly positive, suggesting that carbon emissions exhibit a significant spatial correlation. The result is consistent with the findings of Kang et al. [49] and Zhang et al. [50]. More importantly, the impact of digital technology development on carbon emissions in China does have a time lag effect. The absolute values of the regression coefficients of the two lagged periods of digital technology development in column (5)–column (8) in Table 4 increase compared to column (1)–column (4), indicating that there is a trend of increasing marginal effect of the inhibitory effect of digital technology development on carbon emissions.

4.4. Empirical Results of Spatial Spillover Effects

According to the theory of Lesage and Pace [51], simple point estimates cannot unbiasedly capture the impact of digital technology development on carbon emissions when carbon emissions are significantly spatially correlated. In this paper, we decompose the impact into direct, indirect and total effects based on the micro-bias method. The direct effect is the local impact of digital technology development on carbon emissions in the region, the indirect effect is the impact of digital technology development in spatially correlated regions on carbon emissions in the region, and the total effect is the overall impact of digital technology development in all regions on carbon emissions in the region. The direct, indirect and total effects of the dynamic spatial Durbin model can be decomposed into short-term and long-term effects.

Table 5 gives the results of the decomposition of the spatial spillover effects of the impact of digital technology development on carbon emissions. Column (1)–column (8) have significantly negative direct effects and positive indirect effects on carbon emissions for both short-term and long-term effects of digital technology development, indicating that the empirical test results of this study are robust. Additionally noting the time lagged shocks of the impact of digital technology development on carbon emissions, column (5)–column (8) compared to column (1)–column (4), the direct inhibitory effect of digital technology development on carbon emissions in the region is enhanced to different degrees in both the short and long term. The indirect promotion effect of digital technology development in spatially linked regions is weakened to different degrees in both the short and long term, and all regression coefficients become insignificant.

Table 5. Results of the decomposition of spatial spillover effects.

Effect		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short-term effect	direct effect		−0.072 **	−0.162 ***	−0.057 **		−0.087 **	−0.171 **	−0.076 *
			(0.047)	(0.058)	(0.046)		(0.047)	(0.055)	(0.046)
	indirect effect		0.114 **	0.270 ***	0.114 *		0.053	0.063	0.051
			(0.057)	(0.071)	(0.061)		(0.067)	(0.075)	(0.069)
	aggregate effect		0.042	0.108 **	0.057		−0.034	−0.107	−0.024
			(0.040)	(0.052)	(0.043)		(0.061)	(0.067)	(0.061)
Long-term effect	direct effect	−0.231 ***	−0.215 **	−0.177 ***	−0.245 **	−0.288 **	−0.374	−0.181 **	−0.322 *
		(0.048)	(0.145)	(0.061)	(0.183)	(0.044)	(1.157)	(0.061)	(0.222)
	indirect effect	0.275 ***	0.358 *	0.264 ***	0.347 *	0.266	0.276	0.090	0.276
		(0.058)	(0.196)	(0.069)	(0.201)	(0.049)	(6.472)	(0.070)	(0.249)
	aggregate effect	0.043	0.143	0.087 **	0.102	−0.022	−0.098	−0.091	−0.046
		(0.037)	(0.163)	(0.042)	(0.078)	(0.029)	(6.585)	(0.044)	(0.123)

Notes: (i) standard errors are in parentheses. (ii) *, **, *** represent significance at 10%, 5%, and 1% level, respectively.

It can be concluded that digital technology development has a significant dampening effect on carbon emissions in the region, and the long-term dampening effect is significantly strengthened. This is consistent with the previous empirical results on the time lag effect. The digital technology development in spatially connected regions has a positive spatial spillover effect on carbon emissions in the region. Our results are inconsistent with the findings of Shahnazi and Shabani [42], which can be explained mainly from two aspects.

On the one hand, the development of digital technology has driven industrial change marked by digital industrialization and digitization of industries. Regions with higher levels of digital technology development usually choose to move out high-energy-consuming and high-emission industries when carrying out industrial restructuring [52], achieving industrial upgrading while also solving energy and environmental problems. However, the undertaking of these high-energy and high-emission industries by spatially connected regions is inevitably not conducive to their low-carbon development. Therefore, as mentioned above, China's long-standing unbalanced economic development pattern has not only exacerbated the spatial disparity in digital technology development, but has also created a spatial pattern of "high in the north and low in the south" in carbon emissions. Compared to the technology dividend caused by technology spillovers in the environmental field, the environmental pollution problem caused by taking over high-energy and high-emission industries is more serious.

On the other hand, digital technology development is highly significantly spatially correlated in terms of economic distance, and the spillover effects of emerging technologies depend heavily on the learning, imitation and absorption capabilities of the technology absorbers [23]. The empirical test of this study is partly carried out based on the neighboring spatial weight matrix, and the uneven economic and social development of China at the geospatial scale makes digital technology not synergistic between spatially connected regions. Therefore, insignificant technology penetration leads to the positive externality effect of digital technology development on energy saving, and emission reduction in other regions is not reflected.

5. Conclusions and Policy Implications

5.1. Conclusions

Digital technology development in the digital era is an important pathway to reaching the goal of carbon peaking and carbon neutrality. However, current studies on the impact of digital technology development on carbon emissions rarely take into account the time and spatial effect. This study is based on inter-provincial panel data in China from 2011–2019. Firstly, the entropy method was used to comprehensively and accurately measure the comprehensive index of digital technology development. Secondly, the temporal evolution and spatial correlation of carbon emissions and digital technology development were explored using kernel density analysis and exploratory spatial data analysis methods. Finally, the time lag effect and spatial spillover effect of digital technology development on carbon emissions were examined using dynamic spatial Durbin model.

The main conclusions are as follows: (1) China's carbon emissions show a spatial characteristic of "high in the north and low in the south", while its digital technology development shows a spatial layout of decreasing in the east, west and middle. In addition, both carbon emissions and digital technology development have a significant positive spatial correlation. (2) In both the short and long term, digital technology development has a significant positive impact on the reduction of carbon emissions. (3) The test results of the time lag effect show that the long-term inhibitory effect of digital technology development on carbon emissions is more obvious than the short-term effect. (4) The test results of the spatial spillover effect distinguish that the digital technology development of neighboring regions did not have a positive spatial spillover effect on the reduction of carbon emissions in the region. This is different from the conclusions of existing studies that digital technology development helps reduce carbon emissions in neighboring regions.

5.2. Policy Implications

First, the role of digital technology as a new driving force for energy conservation and emission reduction should be effectively brought into play. Furthermore, the penetration and application of digital technology in environmental governance should be accelerated. The government should strengthen the development of basic, cutting-edge and applicable technologies; use digital technology to empower various industries to reduce carbon; and promote the enhancement of innovation using digital technology to manage carbon and reduce carbon. Second, considering the widening spatial gap in digital technology development, local governments must implement dynamic and differentiated digital technology development strategies based on local conditions. The central and western provinces of China should seize the opportunity of the "East Digital West Computing" project to vigorously develop cutting-edge technologies and promote a more ecological development model of digital industrialization and industrial digitization. Third, digital technology will function more significantly in supporting green and sustainable development in the future. The government should lay out the digital technology supply chain in advance in its development planning and increase R&D investment of cloud computing, big data, artificial intelligence, etc. Finally, the lack of positive impact of digital technology development on reducing carbon emissions in neighboring regions shows the importance of regional synergy mechanisms. Carbon reduction policies should take into account the spatial boundaries of administrative regions, while based on the actual geographical location, resource endowment, economic level, and strategic positioning characteristics of each province.

Notably, the statistical limitations of indicators related to digital technology have resulted in a sample period of only nine years for this study and even fewer years for the analysis of time effects. Therefore, the findings of this study are significantly limited. In the future, as more statistics become available, it will be possible to investigate the spatial and temporal effects of digital technology development on carbon emissions in greater depth. In addition, exploring the relationship between digital technology and carbon emissions at the city and even enterprise level is an important direction for further research, which will help to capture the key role of digital technology in environmental governance in a more detailed and microscopic way.

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