International Journal of Statistics and Probability; Vol. 12, No. 5; September 2023
ISSN 1927-7032 E-ISSN 1927-7040
Published by Canadian Center of Science and Education

China's Provincial Digital Economy and Carbon Emissions: A Spatio-Temporal Analysis During 2013–2019

Jiahui Wang[1], Tong Bai[1], Jie Yang[1], Baoguo Shi[2], Chuanhua Wei[1]

[1]School of Science, Minzu University of China, Beijing 100081, China

[2] School of Economics, Minzu University of China, Beijing 100081, China

*Correspondence: Chuanhua Wei, chweisd@163.com

Received: July 19, 2023 Accepted: September 20, 2023 Online Published: September 30, 2023

doi:10.5539/ijsp.v12n5p22 URL: https://doi.org/10.5539/ijsp.v12n5p22

Abstract

Today, with the rapid development of the digital economy, China is also working with the world to deal with the huge challenges brought about by the deteriorating climate environment. In the context of the "dual carbon" development goal, the digital economy is in a new era of integration with environmental protection and other fields. Studying how the development of the digital economy has an impact on carbon emissions is the key to solving the current coordinated development of the economy and the environment.

This paper firstly takes 30 provinces in China (except Tibet, Hong Kong, Taiwan, and Macau due to data unavailability) as the research object, and takes 2013-2019 as the research time to construct an index system for measuring the development level of digital economy, and calculates the level of digital economy development at different time points in each region based on the entropy weight TOPSIS method. It is found that the average annual development level of the digital economy is the eastern coastal area, the central area, the northeast area and the western area from high to low. Then, considering that China's carbon emissions and digital economy development have certain spatial patterns, and at the same time doing a spatial autocorrelation test based on Moran's I, geographically and temporally weighted regression (GTWR) model with the dependent variable being carbon emission intensity and the independent variables being digital economy development level, population, urbanization rate, secondary production ratio, industrial solid waste utilization rate and per capita GDP was established.

Finally, we obtained that the temporal and spatial evolution of the influence has weakened from the promotion in the west to the surrounding areas to the inhibition in the eastern coastal and northeastern regions; the overall promotion decreased and the inhibition increased with time.

Keywords: digital economy, carbon emissions, spatiotemporal evolution, entropy weight topsis method, geographically and temporally weighted regression

JEL Classification: R12, C14; C31

1. Introduction

1.1 Research Background

In recent years, artificial intelligence, the Internet and other new technologies have played a key role in many aspects of China's economic and social development, the White Paper on the Development of China's Digital Economy (2021) shows that the proportion of China's total digital economy in GDP has risen from 30.3% in 2016 to 38.6% in 2020 and the development of digital economy is an inevitable trend in the development of China's times. From the perspective of digital industrialization and industrial digitalization, in 2020, China's digital industry will account for 19.1% of the digital economy, and industrial digitalization will account for 80.9%, and industrial digitalization will play an important role in the development of the digital economy. At present, the scale of China's market is large, which has created a wealth of application scenarios for the vigorous development of the digital economy, and the digital economy is deeply integrated with multiple application fields such as production and operation, environmental protection and so on.

At the same time as the rapid development of the digital economy, China is also working with the world to cope with the huge challenges brought about by the deterioration of the climate environment, in order to promote the sustainable development of mankind, a very important point is to reduce the emission of greenhouse gases, in September 2020, China announced that "strive to achieve carbon peak by 2030, carbon neutrality by 2060".

In this context, it is significant to measure the development level of the digital economy, and figure out what is the impact of the digital economy on carbon emissions, whether there is spatial heterogeneity etc. Answering the above questions will help us more target digital economy construction, and better complete the "30·60" plan.

1.2 Literature Review

Based on the above research hotspots, this paper analyzes the relevant literature from the three perspectives of digital economy, carbon emissions and the interrelationship between digital economy and carbon emissions.

In terms of digital economy, Zhao *et al.* (2020) measured the comprehensive level of digital economic development from the aspects of digital inclusive finance and Internet development, and studied the mechanism of promoting the high-quality development of cities by the digital economy. Many scholars have examined the development level of the digital economy from the two aspects of digital industrialization and industrial digitalization, among which Yang *et al.* (2021) used the panel data of China's provinces from 2004 to 2017 to examine the role of the development of the digital economy on total factor productivity. Some scholars have studied the spatio-temporal evolution of the development of the digital economy, and Wu *et al.* (2022) used the entropy law to construct a digital economy development index, and analyzed the spatio-temporal characteristics of the development of the digital economy in 30 provinces in China. Liu *et al.* (2022) used the entropy right TOPSIS method to measure the development level of digital economy in various provinces in China, and used exploratory spatial data analysis and nuclear density estimation method to study the spatio-temporal pattern evolution of the new kinetic energy index of digital economic development.

In terms of carbon emissions, Li *et al.* (2021) studied the spatiotemporal heterogeneity of the influence of various influencing factors on carbon emissions in Zhejiang Province through Geographically and temporally weighted regression models. Guo et al. (2022) used total carbon dioxide emissions to measure carbon emissions, using two-way fixed effect and intermediary effect models to explore how digital inclusive finance affects carbon emissions. Cheng *et al.* (2022) and many other domestic and foreign scholars have used carbon emission intensity to measure carbon emissions, using panel data from 30 provinces in China from 2011 to 2019 to explore whether digital inclusive finance promotes agricultural carbon emission reduction, and the results show that the development of digital inclusive finance has an agricultural carbon emission reduction effect.

In terms of the relationship between the two, domestic and foreign scholars have mostly used spatial econometic models to study them. Sun and Kim (2021) analyzed the impact of ICT on reducing carbon emission intensity in various regions of China based on the improved STIRPAT model and the spatial Dubin model. Wang and Guo (2022) used data from 272 Chinese city-level panels from 2011 to 2017 to study the impact of digital financial inclusion on carbon emissions. Xie (2022) studied the impact and mechanism of digital economy development on carbon emission intensity in various regions through a two-way fixed-effect model. Xu *et al.* (2022) used the spatial Dubin model and the spatial DID model to study the impact of digital economy development on urban carbon emissions, and the results showed that the development of digital economy has significantly improved carbon emissions, but this impact is different between various economic circles.

Recently, some scholars have studied the impact of the development of the digital economy on carbon emissions, but many scholars use the constant coefficient models to study, and few use the varying-coefficient models, this paper uses the geographical and temporal weighted regression (GTWR) model to study the impact of digital economy development on carbon emissions, and compares it with ordinary least squares regression (OLS) model and geographical weighted regression (GWR) model to select the most appropriate model, which is the innovation of this paper.

2. Overview of Research Methods and Variables

2.1 Introduction to Research Methods

2.1.1 Entropy Weight TOPSIS Comprehensive Evaluation Method

In order to measure the development level of digital economy, we use the entropy weight method and TOPSIS model, namely entropy weight TOPSIS comprehensive evaluation method.

(i). Entropy weight method

Entropy weight method is a method of giving objective weight. According to each evaluation index and depending on the discreteness of data itself, more objective weight can be obtained. The specific process is as follows:

Step 1: According to the evaluation index system, select the statistical data, build the original matrix, set up the m evaluation objects and n evaluation indicators. is the (i, j)-th element of the original matrix X. The original matrix X is as Eq.(1):

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & x_{ij} & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}_{m\times n} \tag{1}$$

Step 2: Normalize the data

$$\begin{cases} \text{Positive indicator: } y_{ij}^{+} = \dfrac{x_{ij} - \min\left(x_{ij}\right)}{\max\left(x_{ij}\right) - \min\left(x_{ij}\right)} \\ \text{Negative indicator: } y_{ij}^{-} = \dfrac{\max\left(x_{ij}\right) - x_{ij}}{\max\left(x_{ij}\right) - \min\left(x_{ij}\right)} \end{cases}, i = 1, \cdots, m; j = 1, \cdots, n$$

$\min\left(x_{ij}\right)$ and $\max\left(x_{ij}\right)$ indicate the minimum and maximum value of the element of X respectively

The indicators in this paper are all positive indicators.

Step 3: Calculate the proportion p_{ij} of the i th evaluation object in the j th index:

$$p_{ij} = y_{ij} / \sum_{k=1}^{n} y_{ik}$$

where n is the number of indicators.

Step 4: Calculate the entropy e_j of the j th index:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \cdot \ln p_{ij}$$

where $k = 1/\ln m$.

Step 5: Calculate the weight w_j of the j th index:

$$w_j = \left(1 - e_j\right) \Big/ \sum_{l=1}^{n} \left(1 - e_l\right).$$

(ii). TOPSIS method

TOPSIS is a relatively efficient comprehensive evaluation method, which is helpful to solve the multi-level and multi-index decision-making problems. The method is constructed as follows:

Step 1: Normalize the original data $X = \left(x_{ij}\right)_{m\times n}$, and form the final decision matrix $Y = \left(y_{ij}\right)$.

Step 2: Calculate the weight $W = \left(w_1, w_2, \cdots, w_n\right)^T$ according to the entropy weight method. The weighted decision evaluation matrix $R = \left(r_{ij}\right)$ is obtained by multiplying W with the normalized decision matrix. r_{ij} is calculated as

$$r_{ij} = w_j \cdot y_{ij}, \quad i = 1, \cdots, m; j = 1, \cdots, n. \tag{2}$$

Step 3: Calculate the positive ideal solution(r_j^*) and negative ideal solution(r_j^0) of each index as follows:

Positive ideal solution is calculated as:

$$r_j^{+} = \begin{cases} \max\left\{r_{ij}\right\}, j \text{ is the benefit index} \\ \min\left\{r_{ij}\right\}, j \text{ is a cost indicator} \end{cases}, j = 1, \cdots, n \tag{3}$$

Negative ideal solution is calculated as:

$$r_j^{-} = \begin{cases} \min\left\{r_{ij}\right\}, j \text{ is the benefit index} \\ \max\left\{r_{ij}\right\}, j \text{ is a cost indicator} \end{cases}, j = 1, \cdots, n \tag{4}$$

Step 4 :Calculate the distance from each object to the positive ideal solution and the negative ideal solution.

The Euclidean distances from the object r_{ij} to the positive ideal solution and the negative ideal solution are respectively expressed as:

$$d_i^+ = \sqrt{\sum_{j=1}^{n}\left(r_{ij} - r_j^+\right)^2}, i = 1, \cdots, m \tag{5}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}\left(r_{ij} - r_j^-\right)^2}, i = 1, \cdots, m \tag{6}$$

Step 5: Calculate the comprehensive evaluation index of each object:

$$C_i^* = d_i^- \Big/ \left(d_i^- + d_i^+\right), i = 1, \cdots, m$$

2.1.2 Ordinary Least Squares Regression (OLS) Model

The traditional regression model is the multiple linear model, written as $Y = X\beta + \varepsilon$,with

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix}, X = \begin{pmatrix} 1 & X_{11} & \cdots & X_{1p} \\ 1 & X_{21} & \cdots & X_{2p} \\ \vdots & \vdots & & \vdots \\ 1 & X_{n1} & \cdots & X_{np} \end{pmatrix}, \beta = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}.$$

where $rank(X) = p+1$, error term ε satisfies Gauss-Markov condition: $E(\varepsilon) = 0$, $Var(\varepsilon) = \sigma^2 I$ .It is known that the ordinary least squares (OLS) estimator of β is $\hat{\beta}_{OLS} = (X^{\mathrm{T}}X)^{-1}X^{\mathrm{T}}Y$.

This model can not reflect the spatial location attribute of data, but can only represent the correlation between dependent variables and independent variables in the average sense, and can not effectively reflect the spatial heterogeneity characteristics. Therefore, it is of great significance to include the spatial location attribute of data into the regression model to analyze the characteristics of regression relationship changing with spatial location in spatial data regression.

2.1.3 Geographically Weighted Regression (GWR) Model

GWR model of Brunsdon et al. (1996) is an improvement of the traditional linear regression model, which can reflect the spatial heterogeneity of the regression relationship.

Generally , set Y as the dependent variable , $X_1, X_2, \cdots, X_p$ as independent variables, $(Y_i; X_{i1}, X_{i2}, \cdots, X_{ip})$ as the observation value of the independent variables and dependent variable at the geographical location $(u_i, v_i), i = 1, 2, \cdots, n$, where (u_i, v_i) represents longitude and latitude. Then the GWR model is written as:

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p}\beta_k(u_i, v_i)X_{ik} + \varepsilon_i\ , \quad i = 1, 2, \cdots, n \tag{7}$$

where $\beta_k(u,v)$ is the unknown function of the geographical location; ε_i is an independent and identically normal distributed error term, and $E(\varepsilon_i) = 0$, $\mathrm{Var}(\varepsilon_i) = \sigma^2$.

Let (u_0, v_0) be any point in the studied geographical area , d_{oi} is the distance between (u_0, v_0) and the geographical location (u_i, v_i) where the i th observation $(Y_i; X_{i1}, X_{i2}, \cdots, X_{ip})$ is located (this distance is usually taken as Euclidean distance). Construct a set of weights at the point (u_0, v_0) , $w_i(u_0, v_0) = K(d_{oi}/h)$, $i = 1, 2, \cdots, n$, where $K(\cdot)$ is a kernel function ,we usually taking Gauss kernel or epanechnikov kernel ,and h is bandwidth. Then, for the estimation of regression coefficient, the traditional GWR estimation method is as follows:

From the constructed weights $w_i(u_0, v_0) = K(d_{oi}/h)$, we get the spatial weight matrix which is a diagonal matrix is shown as:

$$W=\begin{pmatrix} w_1(u_0,v_0) & & \\ & \ddots & \\ & & w_n(u_0,v_0) \end{pmatrix}. \tag{8}$$

Then the estimators of the coefficient functions at (u_0,v_0) is expressed as:

$$\hat{\beta}_{GWR}(u_0,v_0)=(X^{\mathrm{T}}W(u_0,v_0)X)^{-1}X^{\mathrm{T}}W(u_0,v_0)Y. \tag{9}$$

The predicted value of the dependent variable Y at (u_0,v_0) is expressed as:

$$\hat{Y}(u_0,v_0)=X_0^{\mathrm{T}}\hat{\beta}_{GWR}(u_0,v_0)=X_0^{\mathrm{T}}(X^{\mathrm{T}}W(u_0,v_0)X)^{-1}X^{\mathrm{T}}W(u_0,v_0)Y. \tag{10}$$

where $X_0^{\mathrm{T}}=(1,X_{01},\cdots,X_{0p})$ is the values of the independent variables $X_1,X_2,\cdots,X_p$ at (u_0,v_0).

Here are some common selection methods of kernel function bandwidth:

(i). Cross validation method

For a given h, remove the i th observation value, and use some fitting method to calculate the fitting value of the regression function $m(x)$ at point X_i with the remaining $n-1$ group of data under a given h, which is recorded as:

$$\hat{Y}_{(-i)}(h)=\hat{m}_{(-i)}(X_i) \tag{11}$$

Execute the above process for $i=1,2,\cdots,n$ in sequence, and we have $\hat{Y}_{(-1)}(h),\hat{Y}_{(-2)}(h),\cdots,\hat{Y}_{(-n)}(h)\cdot$

Let

$$CV(h)=\frac{1}{n}\sum_{i=1}^{n}\left(Y_i-\hat{Y}_{(-i)}(h)\right)^2,$$

cross validation method selects h_0 to make $CV(h_0)=\min\limits_{h>0}CV(h)$.

(ii). ***AICc*** **criterion**

AICc criterion is modified on the basis of general *AIC* criterion, that is, for a given h, at n design points $X_1,X_2,\cdots,X_n$,the vector formed by the fitting value of the dependent variable can be expressed as $\hat{Y}(h)=(\hat{Y}_1(h),\hat{Y}_2(h),\cdots,\hat{Y}_n(h))^{\mathrm{T}}=L(h)Y\cdot$

Let

$$AIC_c(h)=\log(\hat{\sigma}^2(h))+\frac{n+\mathrm{tr}(L(h))}{n-2-\mathrm{tr}(L(h))},$$

and $\hat{\sigma}^2(h)=\frac{1}{n}\hat{\varepsilon}^T\hat{\varepsilon}=\frac{1}{n}Y^T(I-L(h))^T(I-L(h))Y$,then h_0 needs to satisfy $AIC_c(h_0)=\min\limits_{h>0}AIC_c(h)$.

2.1.4 Geographically and Temporally Weighted Regression (GTWR) Model

GTWR model of Huang *et al.* (2010) is an extension of GWR Model, which incorporates the time dimension on the basis of the original spatial information. The model can reflect spatiotemporal heterogeneity at the same time. The model is shown as:

$$Y_i=\beta_0(u_i,v_i,t_i)+\sum_k\beta_k(u_i,v_i,t_i)X_{ik}+\varepsilon_i, i=1,\cdots,n \tag{12}$$

where (u_i,v_i) still indicates the latitude and longitude ,and t_i represents the time dimension.

The estimation method of this model is similar to that of GWR, we have Eq.(13)

$$\hat{\beta}_{GTWR}(u_0,v_0,t_0)=(X^{\mathrm{T}}W(u_0,v_0,t_0)X)^{-1}X^{\mathrm{T}}W(u_0,v_0,t_0)Y \tag{13}$$

where the space-time weight matrix $W(u_i,v_i,t_i)$ is a $n\times n$ diagonal matrix, $W(u_i,v_i,t_i)=\mathrm{diag}(W_{i1},W_{i2},\cdots,W_{in})$. $W_{ij}(1\le j\le n)$ is spatiotemporal distance decay function. The calculation formula is shown as:

$$W_{ij}=\exp\left[-\frac{(d_{ij}^{ST})^2}{h^2}\right] \tag{14}$$

d_{ij}^{ST} is space-time distance, and the calculation formula is expressed as:

$$d_{ij}^{ST}=\sqrt{\lambda\left[(u_i-u_j)^2-(v_i-v_j)^2\right]+\mu(t_i-t_j)^2} \tag{15}$$

where h is the space-time bandwidth, and the selection method of the optimal bandwidth is consistent with the bandwidth selection method of the GWR method above.

2.2 Variable Selection and Data Sources

2.2.1 Variable Selection

Based on STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model, this model studies the relationship between economic development level, population, technology level and other related factors and a certain environmental index. In terms of the selection of independent variables, the level of economic development selects the level of digital economic development and per capita GDP, the population factor selects the population size and urbanization rate, the technical level selects the level of technological innovation, and the industrial structure, traffic scale, and government supervision are selected as other relevant factors. For the explained variable, we choose carbon emission intensity to study. The following is the selection method of each index.

(i).Explained variable: carbon emission intensity (CEI)

The carbon dioxide emissions are estimated according to the accounting scope of the Intergovernmental Panel on climate change (IPCC) based on administrative regions. The following two parts constitute the total carbon dioxide emissions: energy related and process related (cement) carbon dioxide emissions.

Energy related emissions refer to carbon dioxide emitted during the combustion of fossil fuels. According to IPCC guidelines, see Eq.(16) for details:

$$CE_{ij}^{a}=AD_{ij}\times NCV_i\times CC_i\times O_{ij} \tag{16}$$

where CE_{ij}^{a} represents the carbon dioxide emission of fossil fuel i used in area j; AD_{ij} represents the fossil fuel consumption of corresponding fossil fuels and regions; NCV_i refers to the net calorific value, that is, the calorific value generated by the combustion of fossil fuels in each physical unit; CC_i (carbon content) is the emission of each net calorific value produced by fossil fuel i; O_{ij} is the oxygenation efficiency, which refers to the oxidation rate of fossil fuels during combustion.

Process related emissions refer to CO_2 emitted due to physical and chemical reactions in the production process, rather than the energy of industrial combustion. We only investigated cement production, which accounts for about 75% of China's total process related CO_2 emissions. The calculation formula of CO_2 emission related to cement is shown as:

$$CE_{it}^{b}=EC_{it}\times EF_{it} \tag{17}$$

where EC_{it} is the cement production of each region, and EF_{it} refers to the carbon emission coefficient related to cement in the process of cement production.

Therefore, the carbon emission *CE* of each region is the sum of the above two parts, that is expressed as:

$$CE=CE^{a}+CE^{b} \tag{18}$$

The carbon emission intensity CEI is expressed as the ratio of carbon emissions of each region to its actual GDP, representing the proportion of carbon emissions in unit output. Its calculation formula is shown as:

$$CEI = \frac{CE}{GDP} \tag{19}$$

(ii). Core explanatory variable: digital economy development level (DE)

According to the definition of digital economy in *the white paper on the development and employment of China's digital economy*, we measure the development level of digital economy from the four aspects of digital infrastructure, digital industrialization, industrial digitization and digital innovation ability. Also according to the research of Yang et al.(2021) and Xu et al.(2022), we describe digital infrastructure from the basic elements of the Internet and Internet popularization, from the electronic information manufacturing industry, telecommunications industry, software industry Information service industry and Internet related industries describe the development of digital industrialization from the development of agriculture, industry, the tertiary industry and the inclusive development of digital finance, and express the ability of digital innovation from two perspectives: the support of digital innovation elements and the output level of digital innovation.

(iii). Control variable

The selection of control variables is as follows: population size (PS)-- the total population at the end of year each region is used as the proxy variable; urbanization rate (UR)-- select the ratio of regional urban population to regional population to measure; industrial structure (SI)--select the proportion of the secondary industry in each region to express; traffic scale (CAR)-- select the civil vehicle ownership in each region as the proxy variable; government supervision (WU)-- use the utilization rate of industrial solid waste as the proxy variable; economic development status (PGDP)-- select per capita GDP as the proxy variable; technological innovation (NP)-- select the number of technology patents authorized to express.

2.2.2 Data Sources

The indicators of the above data are from the National Bureau of statistics, the China Statistical Yearbook, the digital finance research center of Peking University, the national carbon emissions accounting database (CEADs), the official database of the website of the Ministry of industry and information technology, the China Industrial Economy Statistical Yearbook, etc. Considering the availability of data and ensuring the consistency of corresponding data time, some missing data are filled by linear interpolation method, and some index data in Tibet, Hong Kong, Macao, Taiwan and 2020 are seriously missing, so they are eliminated. Therefore, we use the relevant data of 30 provinces in China from 2013 to 2019 for research.

3. Measurement and Space-Time Analysis of the Development Level of Digital Economy

3.1 Measuring the Development Level of Digital Economy

At present, there is no fixed measurement index for the development level of digital economy. Therefore, we should establish a scientific and reasonable evaluation index system and use certain evaluation methods to evaluate it. Based on the principle of objective science and the availability of data, we set up a three-level index evaluation system according to the development category of digital economy. Combined with entropy weight method and TOPSIS model, we measure and evaluate the development level of digital economy of each sample.

According to the white paper on the development and employment of China's digital economy issued by the China Academy of communications, the concept and calculation method of digital economy are understood in this paper. Based on the two dimensions of digital industrialization and industrial digitization, digital infrastructure and digital innovation capacity are added. The four criteria layers reflect the comprehensive development level of digital economy more comprehensively. The specific indicators are as follows (see Table 1):

Table 1. Evaluation index system of digital economy development level based on four criteria

Target layer	Criterion layer	Index layer	Index description	Efficacy
Development level of digital economy	Digital infrastructure	Basic elements of Internet	Optical cable line length (km)	+
		Internet popularization	Number of IPv4 addresses (10000)	+
	Digital industrialization	Electronic information manufacturing industry	Business income of electronic information manufacturing owners above designated scale (100 million yuan)	+
		Telecommunication industry	Total telecom business volume (100 million yuan)	+
		Software industry	Software business income (10000 yuan)	+
		Information service industry	Information technology service revenue (100 million yuan)	+
		Internet related industries	E-commerce sales (100 million yuan)	+
			Number of employees in information transmission, computer service and software industry (10000)	+
	Industry digitization	Agriculture	Agricultural added value (100 million yuan)	+
			Rural electricity consumption (100 million kwh)	+
		Industry	Industrial added value (100 million yuan)	+
			Proportion of new product sales revenue of Industrial Enterprises above designated scale in main business income of industrial enterprises	+
		The service sector; the tertiary industry	Added value of tertiary industry (100 million yuan)	+
			Per capita transportation and communication consumption expenditure (yuan)	+
			Quantity of express delivery (10000 pieces)	+
		Inclusive development of digital Finance	Digital inclusive finance index	+
	Innovation capability	Digital innovation elements support	Local fiscal expenditure on science and Technology (100 million yuan)	+
		Output level of digital innovation	Number of invention patents per 10000 people	+

According to the evaluation index system and entropy weight TOPSIS method, weights are given to the relevant indicators to measure the development level of digital economy, and the development level of digital economy in 30 provinces is evaluated, as shown in Table 2.

Table 2. The development level of digital economy is divided into East, West and Northeast China

region	region	2013	2014	2015	2016	2017	2018	2019	average value
Eastern Coastal Area	Beijing	0.242	0.339	0.316	0.351	0.452	0.485	0.529	0.388
	Tianjin	0.079	0.080	0.092	0.102	0.112	0.122	0.132	0.103
	Hebei	0.114	0.120	0.118	0.123	0.134	0.144	0.164	0.131
	Shanghai	0.200	0.230	0.252	0.286	0.309	0.342	0.373	0.284
	Jiangsu	0.353	0.378	0.407	0.438	0.463	0.495	0.521	0.436
	Zhejiang	0.195	0.215	0.247	0.285	0.336	0.393	0.454	0.304
	Fujian	0.109	0.107	0.121	0.136	0.154	0.176	0.193	0.142
	Shandong	0.172	0.195	0.212	0.235	0.257	0.280	0.296	0.235
	Guangdong	0.357	0.401	0.449	0.517	0.602	0.682	0.737	0.535
	Hainan	0.030	0.026	0.032	0.033	0.040	0.045	0.054	0.037
	average	0.185	0.209	0.225	0.251	0.286	0.316	0.345	0.260
Central Region	Shanxi	0.043	0.042	0.043	0.048	0.058	0.069	0.079	0.055
	Anhui	0.073	0.080	0.089	0.109	0.121	0.142	0.167	0.112
	Jiangxi	0.058	0.057	0.062	0.069	0.088	0.099	0.117	0.079
	Henan	0.106	0.118	0.125	0.135	0.146	0.166	0.189	0.140
	Hubei	0.086	0.099	0.109	0.124	0.140	0.159	0.184	0.129
	Hunan	0.085	0.094	0.102	0.109	0.117	0.128	0.151	0.112
	average	0.075	0.081	0.088	0.099	0.112	0.127	0.148	0.104
Northeast China	Liaoning	0.143	0.144	0.145	0.125	0.137	0.124	0.131	0.135
	Jilin	0.041	0.044	0.049	0.053	0.059	0.066	0.075	0.055
	Heilongjiang	0.057	0.059	0.062	0.065	0.079	0.080	0.089	0.070
	average	0.080	0.082	0.085	0.081	0.092	0.090	0.098	0.087
Western Region	Inner Mongolia	0.047	0.046	0.051	0.054	0.065	0.070	0.083	0.060
	Guangxi	0.059	0.057	0.063	0.070	0.079	0.092	0.115	0.076
	Chongqing	0.060	0.070	0.079	0.089	0.104	0.112	0.128	0.092
	Sichuan	0.115	0.128	0.138	0.151	0.177	0.199	0.233	0.163
	Guizhou	0.032	0.034	0.045	0.053	0.062	0.079	0.097	0.057
	Yunnan	0.050	0.053	0.059	0.060	0.070	0.088	0.115	0.071
	Shaanxi	0.060	0.067	0.076	0.084	0.100	0.123	0.154	0.095
	Gansu	0.025	0.029	0.032	0.033	0.039	0.046	0.058	0.037
	Qinghai	0.012	0.014	0.026	0.027	0.033	0.040	0.042	0.028
	Ningxia	0.030	0.019	0.028	0.036	0.041	0.049	0.051	0.036
	Xinjiang	0.038	0.040	0.045	0.049	0.054	0.066	0.073	0.052
	average	0.048	0.050	0.058	0.064	0.075	0.088	0.105	0.070
	Total average	0.103	0.114	0.124	0.138	0.158	0.177	0.199	0.145

Next, we ranked the digital economy development levels of 30 provinces in China from 2013 to 2019 (see Table 3).

Table 3. Top 10 provinces in digital economy development

Ranking	2013	2014	2015	2016	2017	2018	2019
1	Guangdong	Guangdong	Guangdong	Guangdong	Guangdong	Guangdong	Guangdong
2	Jiangsu	Jiangsu	Jiangsu	Jiangsu	Jiangsu	Jiangsu	Beijing
3	Beijing	Beijing	Beijing	Beijing	Beijing	Beijing	Jiangsu
4	Shanghai	Shanghai	Shanghai	Shanghai	Zhejiang	Zhejiang	Zhejiang
5	Zhejiang	Zhejiang	Zhejiang	Zhejiang	Shanghai	Shanghai	Shanghai
6	Shandong	Shandong	Shandong	Shandong	Shandong	Shandong	Shandong
7	Liaoning	Liaoning	Liaoning	Sichuan	Sichuan	Sichuan	Sichuan
8	Sichuan	Sichuan	Sichuan	Fujian	Fujian	Fujian	Fujian
9	Hebei	Hebei	Henan	Henan	Henan	Henan	Henan
10	Fujian	Henan	Fujian	Liaoning	Hubei	Hubei	Hubei

3.2 Spatial and Temporal Evolution Analysis of the Development Level of Digital Economy

From Table 2 and Table 3, it can be seen that from the perspective of horizontal regional development differences, the region with the highest level of digital economic development in China is Guangdong Province, which is as high as 0.737 in 2019, while Qinghai Province has the lowest level of development, which is 0.042, and the highest region is 18 times of the lowest region, indicating that there is still a large gap in the development level of digital economy among different regions in China.The annual average value of the eastern coastal area is 0.26, that of the central region is 0.104, that of the northeast region is 0.087, and that of the western region is 0.07.This is mainly due to the early development of digital economy in the eastern coastal areas, which has a number of leading digital economy enterprises such as Tencent, Alibaba, Huawei, byte hop, etc., which have a certain driving role. Due to the geographical factors in northeast, western and central China, the foundation of digital industrialization is weak, and due to the lack of technology and talent introduction, industrial digitization can not be accelerated(Zhao et al.,2020)。

Then, according to the changes of digital economic development level in eastern coastal, central, northeast and western regions, the trend chart is drawn below (see Fig.1).

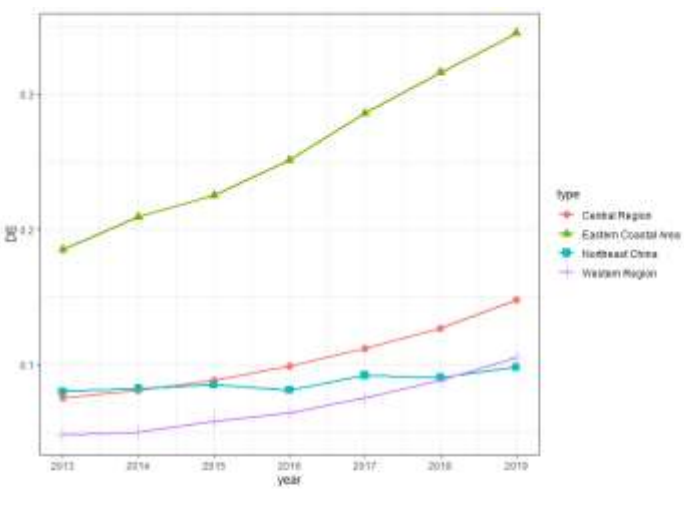


Figure 1. Development trend of digital economy in different regions

It can be seen that from the perspective of vertical time, the development of digital economy is becoming more and more optimistic and the level is gradually improving, especially in the eastern coastal areas, which has nearly doubled in seven years. This shows that regions with good development foundation have good conditions and advantages in developing digital industry or accelerating industrial digital transformation in the later stage. Although the digital economy in the western and central regions is not developed in the early stage, it is also in the process of steady growth by continuously optimizing the industrial structure, accelerating the process of industrial digitization, improving the talent incentive mechanism, and increasing the investment in digital scientific research. However, the growth rate and growth rate of digital economy in northeast China are not very optimistic. There are many traditional industries in northeast China, so it is difficult to carry out industrial digital transformation. Due to the comprehensive factors of geography and economy, the population outflow in northeast China is serious, which leads to the lack of talents.

Fig.2 illustrates the spatial-temporal evolution of digital economy development level in different provinces from 2013 to 2019.

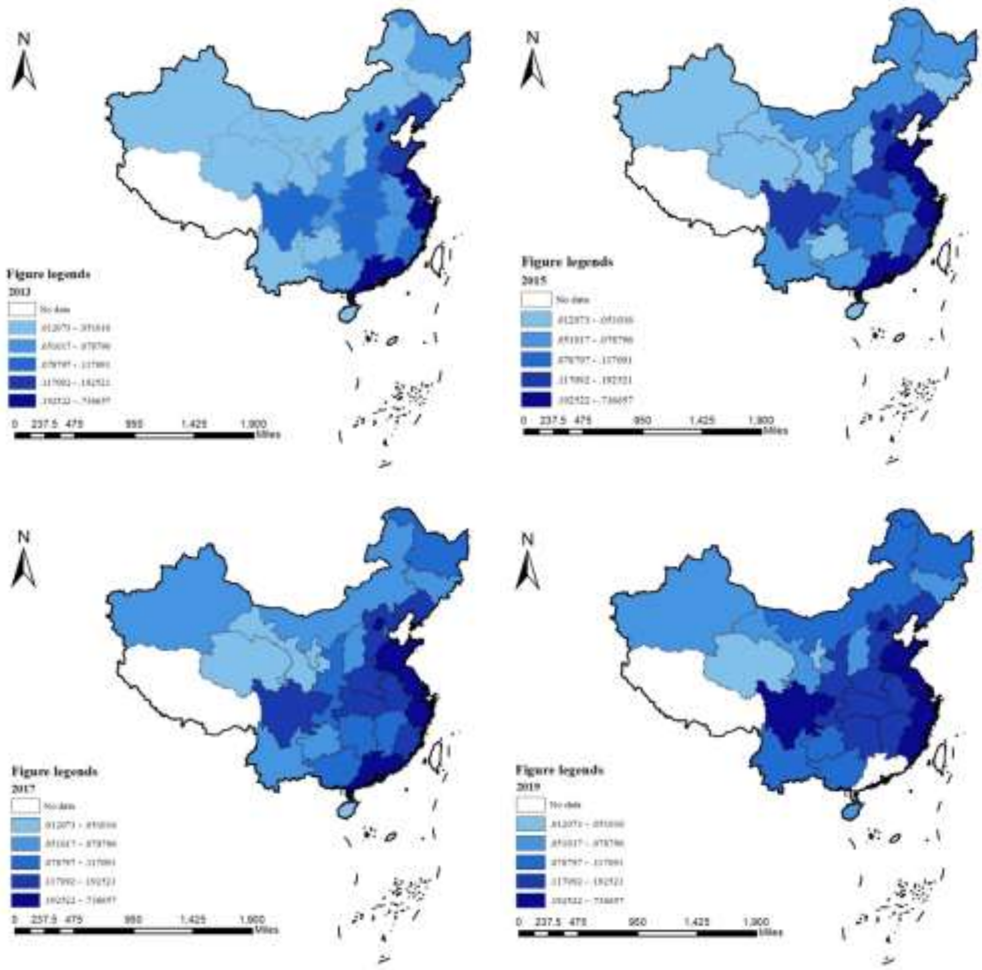


Figure 2. Spatial distribution of digital economy development level in 2013, 2015, 2017 and 2019

4. Research on the Impact of the Digital Economy on Carbon Emissions

4.1 Spatio-temporal Evolution Analysis of Carbon Emissions in China

This paper uses ArcGIS10.8 software to visualize the carbon intensity of 30 provinces in 2013, 2015, 2017 and 2019.

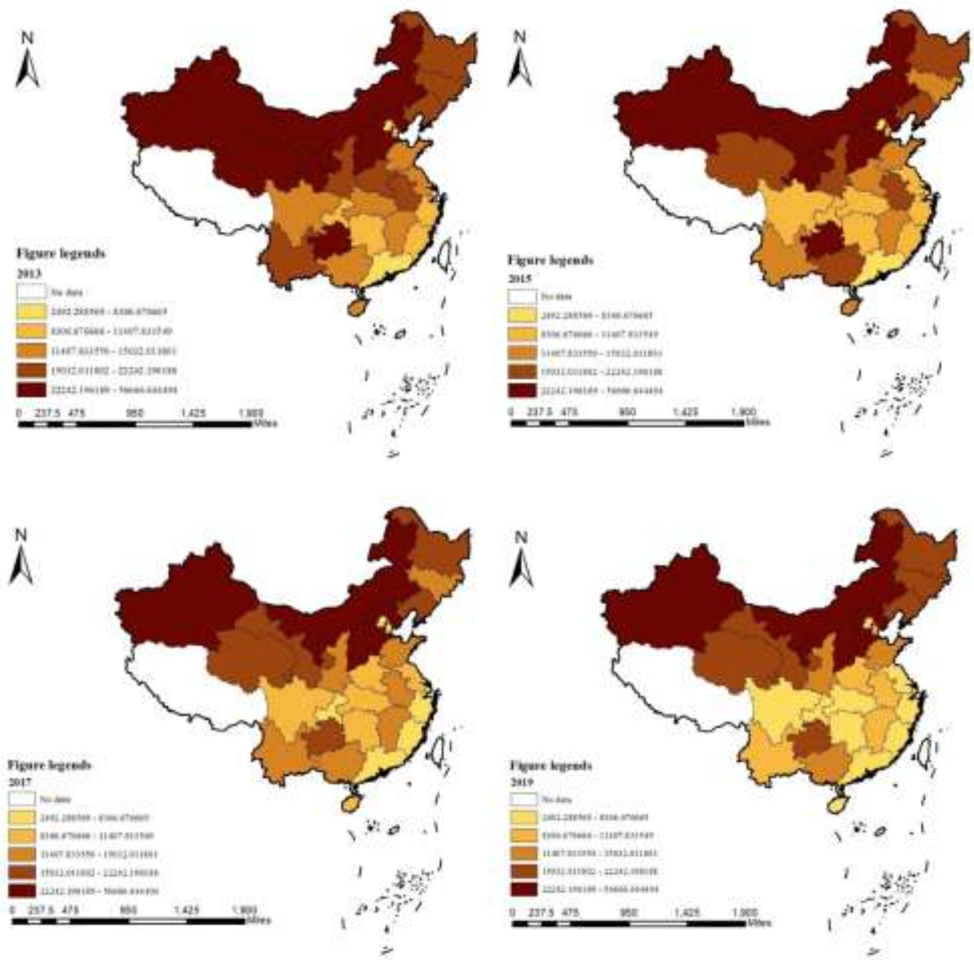


Figure 3. Spatial distribution of carbon emission intensity in 2013, 2015, 2017 and 2019

Change law of carbon emissions during the study period is shown Fig.3, horizontally, China's carbon emission intensity has shown a spatial distribution pattern of high north and low south for several years during the study period(Yunfei Xie,2022), and the provinces with large carbon emission intensity are mainly Xinjiang, Qinghai, Gansu, Ningxia, Shanxi, Hebei and the three northeastern provinces. From a longitudinal point of view, China's carbon emission intensity showed a good trend overall during the study period, and the central and eastern regions were more obvious. Specifically, during the study period, in addition to the carbon emission intensity of Shanxi, the carbon emission intensity of the other provinces in the central region has been significantly improved, which may be due to the fact that with the continuous promotion of industrial structure optimization and upgrading by the government in recent years, the comparative advantages of the central region can be fully utilized, and the rapid economic growth has been guaranteed while ensuring the low-speed growth of carbon emissions. In addition to Hebei and Shandong, the carbon emission intensity of the rest of the places continues to decline in the case of a low level, on the one hand, because the eastern region has a suitable climate and significant geographical advantages, on the other hand, there are more emerging industries in the eastern region, and there are fewer carbon emissions while the economy is developing at a high speed.

4.2 Empirical Analysis of the Impact of Digital Economy on Carbon Emissions

4.2.1 Multicollinearity Test

Before establishing the model, in order to ensure the rationality of the model and avoid multicollinearity. The variance inflation factor (VIF) of each variable was calculated by Stata17.0 Generally, we believe that if VIF is between 1 and 10 for all independent variables, there is no strict multicollinearity between independent variables, and regression analysis can be carried out. Through the test, we removed the two independent variables of the number of civil vehicles and the number of patents with VIF of more than 10, and used the independent variables shown in Table 4 to establish the model. The following table also shows the VIF values of the respective variables after removing these two variables.

Table 4. VIF value of independent variables

variables	VIF	1/VIF
lnPGDP	8.81	0.113502
lnUR	7.39	0.135275
DE	3.65	0.273882
lnPS	2.11	0.473401
lnWU	1.49	0.671981
lnSI	1.44	0.693319

4.2.2 Spatial Autocorrelation Test

Spatial autocorrelation analysis can study whether the data to be investigated has spatial dependence and spatial heterogeneity. In this paper, the global Moran's *I* is used to analyze the spatial autocorrelation of carbon emission intensity and digital economy. The calculation formula of the global Moran index is shown as:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(y_i - \bar{y} \right) \left(y_j - \bar{y} \right)}{\sum_{i=1}^{n} \left(y_i - \bar{y} \right)^2} \tag{20}$$

Among them, w_{ij} is the (i, j)-th element of the spatial weight matrix , y_i represents observed value. The value range of *I* is [-1,1]. When I >0, it indicates that the observed variables have spatial positive correlation; I <0 indicating a negative correlation; *I* closes to 0, there is no spatial correlation feature.

(i). Global spatial correlation analysis

According to the carbon emission intensity and the development level of digital economy of 30 provinces in China from 2013 to 2019, we calculated the global Moran's *I* of each year, and carried out spatial autocorrelation test.According to Table 5 and Table 6, it can be seen that the p value from 2013 to 2019 is less than 0.05, so they passed the test and have spatial autocorrelation.

Table 5. Global Moran's I of carbon emission intensity

Year	2013	2014	2015	2016	2017	2018	2019
global Moran's I	0.173	0.188	0.203	0.188	0.153	0.163	0.166
p value	0.040	0.037	0.025	0.037	0.049	0.045	0.047

Table 6. Global Moran's I of development level of digital economy

Year	2013	2014	2015	2016	2017	2018	2019
global Moran's I	0.158	0.169	0.188	0.177	0.198	0.205	0.199
p value	0.047	0.044	0.037	0.039	0.028	0.024	0.027

(ii). Local spatial correlation analysis

Taking 2019 as an example, the local Moran index scatter charts of the development level of digital economy and carbon emission intensity are given respectively in Fig.4-5. For the development level of digital economy (DE) (see Fig.4), 9 of the 30 provinces and cities are in the second and fourth quadrants, and most of them are in the first and third quadrants. Therefore, the spatial distribution of digital economy presents the situation of high concentration and low concentration.

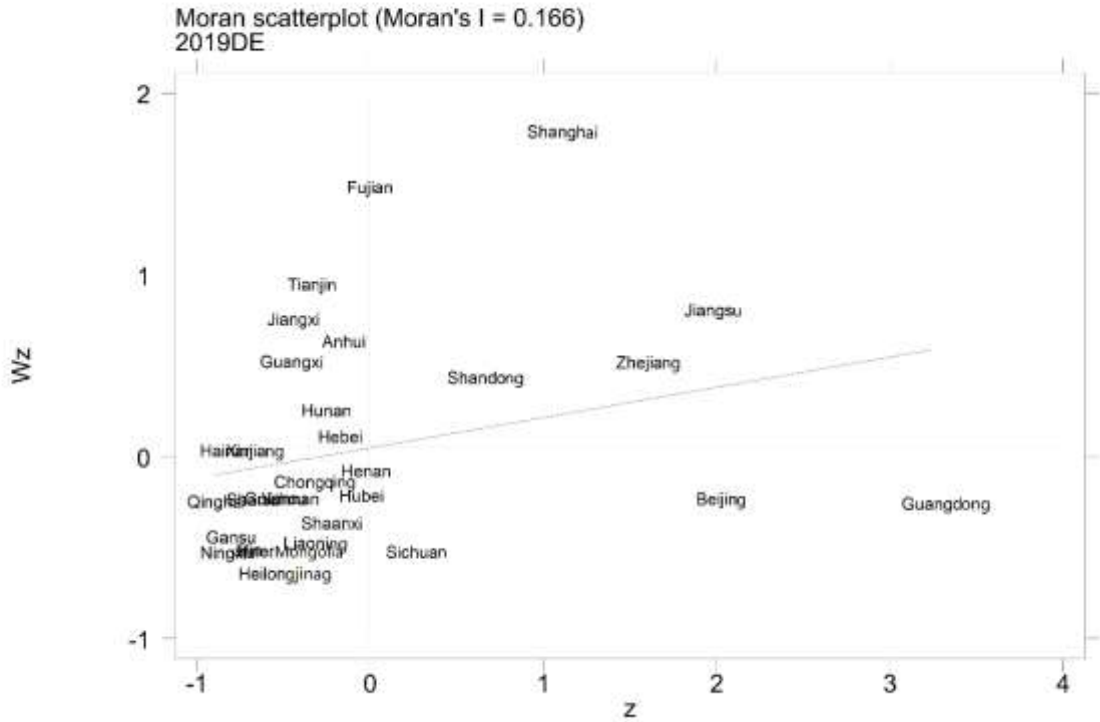


Figure 4. Partial scatter chart of the development level of digital economy in 2019

For carbon emission intensity (see Fig.5), only nine provinces are in a high-low or low-high aggregation state, so the spatial distribution of carbon emission intensity presents the situation of high-high and low-low aggregation situation.

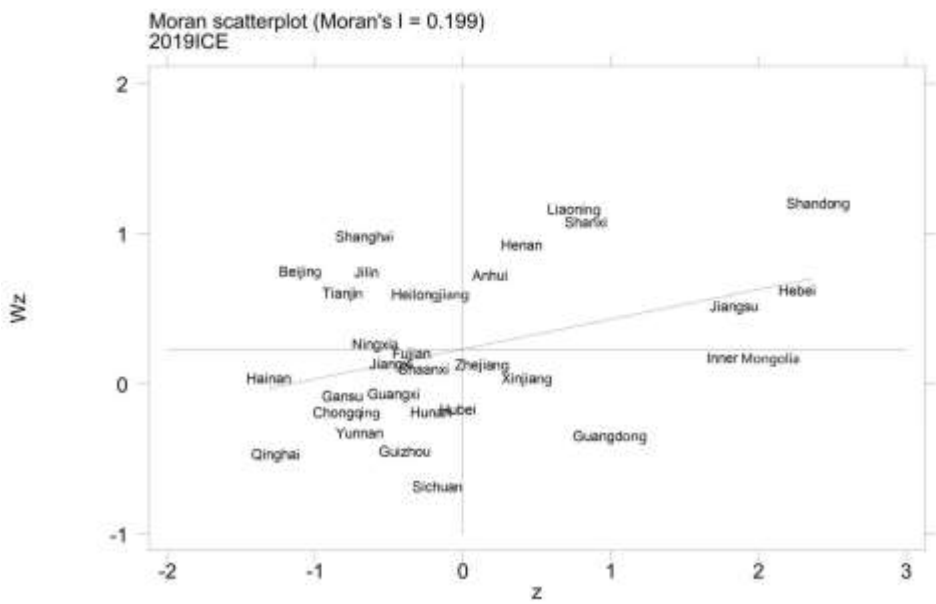


Figure 5. Partial scatter diagram of carbon emission intensity in 2019

4.2.3 Model Establishment

According to the selection of variables, in order to weaken the heteroscedasticity of data, consider logarithmic processing of variables, because the development level of digital economy is quite different from other variables. We take logarithms of carbon emission intensity and control variables, and do not deal with core explanatory variables. We build the following three models, as shown in Eq.(21)-(23).

(i). OLS model

$$\ln CEI = \beta_0 + \beta_1 DE + \beta_2 \ln PS + \beta_3 \ln UR + \beta_4 \ln SI + \beta_5 \ln WU + \beta_7 \ln PGD \quad (21)$$

(ii). GWR model

$$\begin{aligned}\ln CEI_i = \beta_0(u_i,v_i) + \beta_1(u_i,v_i)DE_i + \beta_2(u_i,v_i)\ln PS_i + \beta_3(u_i,v_i)\ln UR_i \\ + \beta_4(u_i,v_i)\ln SI_i + \beta_5(u_i,v_i)\ln WU_i + \beta_7(u_i,v_i)\ln PGDP_i\end{aligned} \quad (22)$$

where i refers to the selected province.

(iii). GTWR model

$$\begin{aligned}\ln CEI_{it} = \beta_0(u_i,v_i,t_i) + \beta_1(u_i,v_i,t_i)DE_{it} + \beta_2(u_i,v_i,t_i)\ln PS_{it} + \beta_3(u_i,v_i,t_i)\ln UR_{it} \\ + \beta_4(u_i,v_i,t_i)\ln SI_{it} + \beta_5(u_i,v_i,t_i)\ln WU_{it} + \beta_7(u_i,v_i,t_i)\ln PGDP_{it}\end{aligned} \quad (23)$$

where i represents the selected province and t represents the selected study year.

4.2.4 Results and Analysis

(i) Model selection

After multicollinearity and spatial autocorrelation test, this paper mainly establishes OLS model, GWR Model and GTWR model to analyze the impact of the development level of digital economy on the intensity of carbon emissions in each province.

Table 7. Estimation of regression coefficients in OLS model

DE	lnPS	lnUR	lnPGDP	lnSI	lnWU	Intercept
-0.3688	-0.2416	1.1893	-0.9258	1.0504	-0.3186	14.1623

As shown in Table 7, on the whole, the development level of digital economy inhibits the intensity of carbon emissions. Population size, per capita GDP and the level of government regulation can effectively curb the intensity of carbon emissions. Urbanization rate and the proportion of secondary industry will promote carbon emission intensity.

Then the fitting effects of the above three models are compared (see Table 8) and analyzed accordingly.

Table 8. Relevant diagnostic indicators of the model

model	AICc	Adjusted R^2	Residual Sum of Squares(SSE)
OLS	230.782	0.567317	34.51955
GWR	-61.5373	0.925259	5.7072
GTWR	-69.2666	0.945002	4.19967

Among the relevant diagnostic indicators of the model, the higher the Adjusted R^2 value, the smaller the AICc value and SSE value, indicating that the independent variable has a stronger interpretation of the dependent variable. The AICc value and RSS value of GTWR model are smaller than those of other models. Therefore, from the above indicators, GTWR model can better explain the impact of digital economy on carbon emission intensity, and can fit the regression coefficient for each year of each province, so we finally choose this model for analysis.

(ii)Spatial and temporal characteristics of regression coefficient of digital economy development level

The explanatory variables selected by GTWR model change with the change of space and time. Through the plug-in of a ArcGIS10.8 in geographical and temporal weighted regression, we use AICc criteria to select the optimal bandwidth $h = 0.115$. In order to study the impact of the development level of digital economy on carbon emissions in each province, the regression coefficient of digital economy is visually analyzed in time and space.

Time characteristics

We divided the selected 30 provinces into eastern coastal, central, western and northeast regions, and mapped the change trend of the regression coefficients of the development level of digital economy in the four regions from 2013 to 2019. We set 0 as the critical value of promoting carbon emission intensity and inhibiting carbon emission intensity, and believe that the greater the absolute value of the regression coefficient, the stronger the impact. Specifically, when the parameter is greater than 0, the larger the parameter, the stronger the promotion of carbon emissions by the development level of digital economy; when the parameter is less than 0, the smaller the parameter, the stronger the inhibition of carbon emissions by the development level of digital economy.

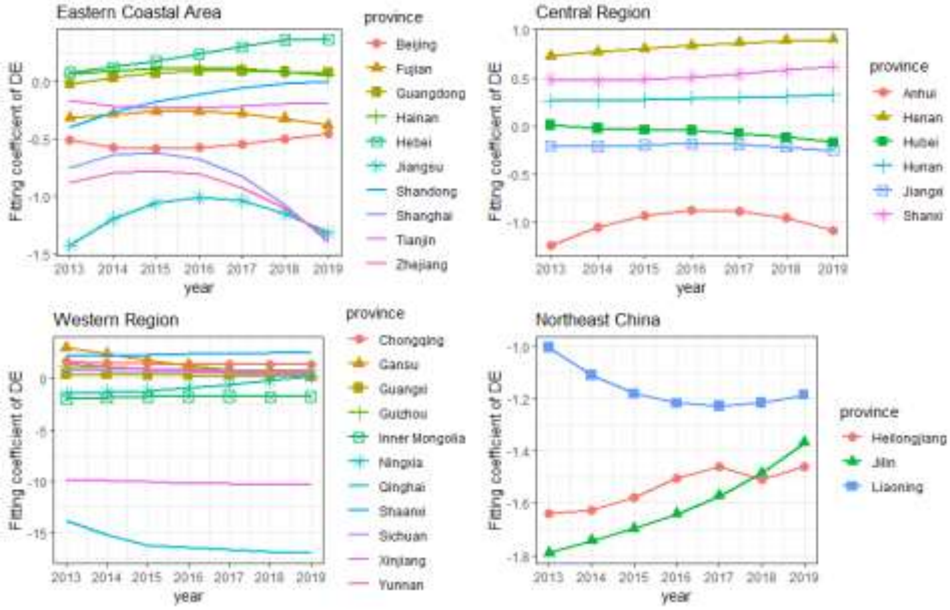
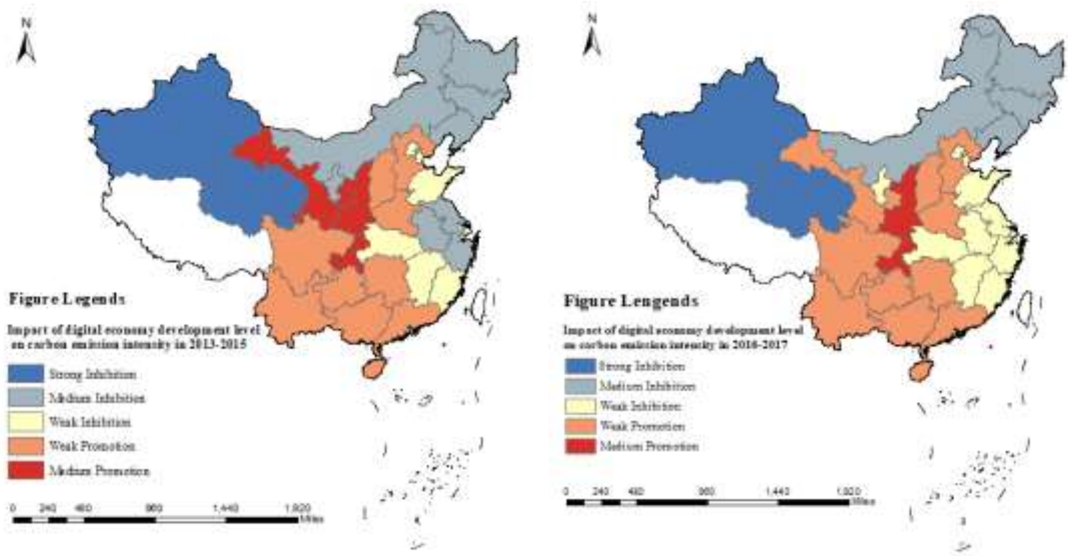


Figure 6. Regression coefficient change curve of digital economy development level in eastern coastal, central, western and northeast China from 2013 to 2019

As shown in Fig.6, among the 30 selected provinces, the change trend of the regression coefficient of digital economy development level in most provinces is relatively flat, and the impact of digital economy development on carbon emissions changes slightly during the study period; since 2016, the high-speed development of digital economy in some provinces has increased the inhibition of carbon emissions, such as Shandong, Zhejiang, Anhui and so on. However, there are also a few provinces, such as Hebei, Ningxia and so on, where the development of digital economy has enhanced the promotion of carbon emission intensity over time.

(2) Spatial characteristics

Using ArcGIS10.8 visualization, calculate and visualize the average value of the regression coefficient of the development level of digital economy in the three time periods of 2013-2015, 2016-2017 and 2018-2019. See Table 8 for the specific value. The influence degree of the development level of digital economy on carbon emission intensity is divided into five levels: strong inhibition, medium inhibition, weak inhibition, medium promotion and weak promotion. The spatio-temporal change diagram is shown in Fig.7 and the correlation analysis is carried out.



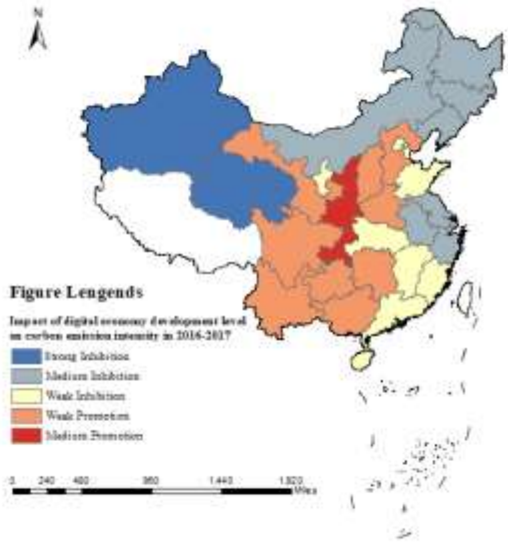


Figure 7. Spatial and temporal changes of the development level of digital economy on carbon emission intensity

During the study period, the development level of digital economy not only inhibited but also promoted the carbon emission intensity of each province, and the space-time evolution weakened from the promotion centered on the west to the inhibition of the eastern coastal and northeast regions. With the change of time, the overall promoting effect decreased and the inhibitory effect increased. The specific analysis is as follows:

From 2013 to 2015, the development level of digital economy in most provinces in the western region focused on the role of medium promotion; the provinces in the central region have great differences in the impact of carbon emission intensity; the provinces in northeast China all show the intensity of restraining carbon emissions; except for a few provinces, the eastern coastal area mainly displays carbon inhibition.

From 2016 to 2017, the promotion of digital economy development level on carbon emission intensity in most provinces in the western region weakened; the impact of provinces in the central region on carbon emission intensity has changed in a small range, and the promotion effect has slightly increased; the provinces in northeast China still show the intensity of restraining carbon emissions; except for a few provinces, the eastern coastal areas mainly restrain carbon emission intensity, but some provinces have fluctuations in the direction of promoting carbon emission intensity.

From 2018 to 2019, the role of the development level of digital economy in most provinces in the western region in promoting carbon emission intensity was further weakened; provinces in the central region have little impact on carbon emission intensity; the provinces in northeast China still show the intensity of restraining carbon emissions; the eastern coastal areas have further expanded the areas that inhibit the intensity of carbon emissions, and some provinces have a strong inhibitory effect.

The economic development of western and some central provinces is relatively backward, and the development mainly depends on traditional energy. The popularity of digital economy is low, and the development of digital economy is more reflected in industrial digitalization. The combination of digital economy and traditional industry and agriculture has promoted the development of the industry, and the expansion of industrial scale has further promoted carbon emissions. However, with the passage of time, the regional development tends to be balanced, the application and popularity of digital economy are improved, the ability of digital innovation is further enhanced, and the increase of energy utilization significantly reduces the intensity of carbon emissions. The development of digital economy has a strong late developing advantage in the process of reducing carbon emissions.

The economic development level of the central provinces varies greatly, and the impact of the development level of digital economy on carbon emissions is also significantly different. The development level of the provinces located in the south is generally higher than that in the north. The development of digital industry in southern provinces started earlier, and the digital innovation ability and infrastructure construction are better than those in the north. The development of northern provinces mostly relies on traditional energy. Taking Shanxi as an example, this has resulted in different degrees of impact on carbon emissions. In recent years, the economy of central provinces has developed rapidly and caught up, but its digital economy development is still backward, and the scope of application is relatively narrow, so there is still a gap in the impact.

As a traditional industrial base, northeast China plays a mainstay role in China's industrial system. The transformation of industrial digitalization can effectively solve the problem of carbon emissions in this region.

The economic development level of the eastern coastal areas is high and fast, and the development level of digital economy in most provinces is in the leading position in the country, which has an inhibitory effect on carbon emissions, and for some provinces, the inhibitory effect is further enhanced over time, indicating that the eastern coastal areas are eating digital economic dividends. However, the development of digital economy in a few provinces, such as Hebei, Guangdong and Hainan, has promoted carbon emissions. The introduction of technology and talents in Hebei is insufficient, and the digital transformation of industry is more difficult. The promotion effect of digital economy on carbon emissions in Guangdong Province is weak, which may be due to the rapid development of economic aggregate while the vigorous development of digital economy, the continuous inflow of population and the accumulation of resources, which weaken the inhibitory effect of digital economy on carbon emissions. But overall, the development of digital economy in the eastern coastal areas has a more significant inhibitory effect on carbon emissions.

5. Conclusions and Suggestions

5.1 Conclusions

We statistically measure the carbon emission intensity and digital economy development level of 30 provinces in China from 2013 to 2019, and analyzes the temporal and spatial evolution of the two. By selecting relevant variables, this paper focuses on the spatial-temporal heterogeneity of the development level of digital economy in each province on its carbon emission intensity through GTWR model. The main conclusions are as follows:

(1) During the study period, China's carbon emission intensity showed a high level in the north and low level in the south in the spatial distribution pattern. With the passage of time, the overall trend is positive, especially in the central and eastern coastal areas.

(2) During the research period, from the perspective of horizontal regional development differences, China's digital economy development gap is large, the eastern coastal area has the highest average development level, and the western region is in a backward position. From the perspective of vertical time passage, the development level of the overall digital economy has gradually improved, the eastern coast has nearly doubled during the study period, the development trend of the central and western regions is strong, and the development of the northeast region is slow.

(3) During the study period, the impact of the development of digital economy on carbon emissions in various provinces showed obvious heterogeneity. On the whole, it has an inhibitory effect on carbon emissions, and the space-time evolution has weakened from the promotion centered on the west to the surrounding areas to the inhibition of the eastern coastal and northeast regions. With the change of time, the overall promoting effect decreased and the inhibitory effect increased.

5.2 Suggestions

(1) While the digital economy is developing, it has also brought environmental dividends to our country. We should take advantage of regional advantages to further develop the digital economy, speed up the construction of digital infrastructure, and improve the ability of digital innovation. We should not only make "industrial digitalization" and "digital industrialization" go hand in hand, but also have different emphases, adjust measures to local conditions, in order to better complete the "30 60" plan provides implementable solutions. For example, the eastern coastal areas can vigorously develop digital industries, while the central and western regions can gradually transform from the mode of combining traditional industries with digital technology to digital industries. The northeast region can consider how to improve the ability of digital innovation and reduce the environmental pollution brought by traditional industries in the process of industrial Digitalization.

(2) Since 2016, the restraining effect of digital economy on carbon emissions in eastern regions such as Jiangsu and Zhejiang has increased year by year. These regions should be encouraged to continue to give full play to the advantages of digital economy in environmental protection and expand the carbon reduction effect of digital economy. For Hebei, Ningxia and other places, we should improve the talent training mechanism, speed up industrial transformation, pursue development quality rather than quantity, reduce environmental pollution, and achieve win-win economic development and environmental protection.

(3) For the central and western regions, we recommend introducing relevant policies to promote the development of the digital economy in the central and western regions, encourage the training of relevant talents, reduce the dependence on their traditional industries in the process of economic development, make comprehensive use of digital technology to change the mode of production, reduce the proportion of traditional energy consumption, optimize the structure of energy consumption, and strive to find a new way that is conducive to both the environment and the economy in the process of transformation and development.

Acknowledgments

Chuanhua Wei's research was supported by the National Social Science Foundation of China (No.21BTJ005).

References

Bin, X., & Boqiang, L. (2016). *What cause a surge in China's CO 2 emissions? A dynamic vector autoregression analysis.* Journal of Cleaner Production.

Chen, Q. (2014). *Advanced Econometrics with STATA Applications* (2nd Ed.). Beijing: Higher Education Press.

Cheng, Q., X, A., & Chen, Q. (2022). The realization path of agricultural carbon emission reduction under the background of "double carbon" target: Verification based on digital financial inclusion. *Journal of Southwest Minzu University(Humanities and Social Science), 43*(02),115-126.

Guo, G., & Zhang, Y. (2022). A study on the relationship between digital inclusiveFinance and carbon emission reduction. Price:Theory & Practice, (01), 135-138.

Huang, B., Wu, B., & Barry, M. (2010). Geographically and Temporally Weighted Regression for Modeling Spatio-Temporal Variation in House Prices. *International Journal of Geographical Information Science, 24*(3), 383–401. https://doi.org/10.1080/13658810802672469

Intergovernmental Panel on Climate Change (IPCC). (2019). 2019 Refinement to 2006 IPCCGuidelines forNational Greenhousu Gas Inventoties, p. 2019. Available at: http://www.ipcc-nggip.iges.or.jp/.

Jing,W., & Sun, B. (2019). Digital economy promotes high-quality economic development: A theoretical analysis framework. Economist, (02), 66-73.

Li, Z., Ren, L., Ma, R., Liu, Y., & Yao, D. (2021). Analysis of spatial -temporal pattern and driving factors of carbon emissions in Zhejiang Province based on spatial-temporal geographic weighted regression model. *Journal of Ningbo University(Natural Science & Engineering Edition), 34*(06), 105-113.

Liu, C., Jiang, Y., Zhang, Q., & Zhu, X. (2022). Research on the statistical measure and spatiotemporal trend of the development level of digital economy. *Journal of Industrial Technological Economics, 41*(02), 129-136.

Mei, C., & Wang, N. (2012). *Modern regression analysis method.* Beijing: Science Press.

Min, L., Xu, Z. (2022). Digital economy, innovation performance and high-quality economic development -- Empirical evidence from Chinese cities. *Statistics & Decision, 38*(03), 11-15.

Sun, H., & Kim, G. (2021).The composite impact of ICT industry on lowering carbon intensity: From the perspective of regional heterogeneity. Technology in Society. https://doi.org/10.1016/j.techsoc.2021.101661

Wang, H., & Guo, J. (2022). Impacts of digital inclusive finance on CO2 emissions from a spatial perspective: Evidence from 272 cities in China. *Journal of Cleaner Production, 355*(355). https://doi.org/10.1016/j.jclepro.2022.131618

Wang, S., Xie, Z., & Wang, Z. (2021). The spatiotemporal pattern evolution and influencing factors of CO2 emissions at the county level of China. *Acta Geographica Sinica, 76*(12), 3103-3118.

Wei, Z., Wei, K., & Liu, J. (2023).Decoupling relationship between carbon emissions and economic development and prediction of carbon emissions in Henan Province: based on Tapio method and STIRPAT model. Environmental science and pollution research international (18). https://doi.org/10.1007/s11356-023-26051-z

Wu, J., & Wang, X. (2022). Measurement on digital economy development level based on the latest statistical classification standards. *Statistics & Decision, 38*(03), 16-21.

Xie, Y. (2022). The effect and mechanism of digital economy on regional carbon emission intensity. *Contemporary Economic Management, 44*(02), 68-78.

Xu, W., Zhou J., & Liu, C. (2022). The impact of digital economy on urban carbon emissions: Based on the analysis of spatial effects. *Geographical Research, 41*(01), 111-129.

Yang, H., & Jiang, L. (2021). Digital economy, spatial effect and total factor productivity. *Statistical Research, 38*(04), 3-15.

Yang, Z., & Li, Z. (2022). Research on the measurement of carbon emissions and dynamic characteristics of its driving factors in central regions of China. *Ecological Economy, 38*(05), 13-20.

Zhao, T., Zhang, Z., & Liang, S. (2020). Digital economy, entrepreneurship, and high-quality economic development: Empirical evidence from urban China. *Journal of Management World, 36*(10), 65-76.

Table 8. Spatio-temporal geographical weighted model 2013-2019 DE average regression coefficient of each time period

Province	Average regression coefficients for DE,2013-2015	Average regression coefficients for DE,2016-2017	Average regression coefficients for DE,2018-2019
Beijing	-0.55574	-0.55859	-0.4754
Tianjin	-0.20946	-0.22407	-0.19803
Hebei	0.123331	0.266669	0.357658
Shanxi	0.478817	0.523056	0.597888
Inner Mongolia	-1.86557	-1.73912	-1.74704
Liaoning	-1.09701	-1.22116	-1.19922
Jilin	-1.74394	-1.60669	-1.42647
Heilongjiang	-1.62544	-1.5062	-1.4062
Shanghai	-0.66928	-0.75033	-1.23688
Jiangsu	-1.22327	-1.02033	-1.22968
Zhejiang	-0.8174	-0.86378	-1.2277
Anhui	-1.07357	-0.87584	-1.01477
Fujian	-0.28893	-0.26988	-0.35455
Jiangxi	-0.20351	-0.18589	-0.233
Shandong	-0.28439	-0.08637	-0.01317
Henan	0.765881	0.84951	0.892267
Hubei	-0.01814	-0.0599	-0.14322
Hunan	0.265223	0.295989	0.318562
Guangdong	0.025171	0.090379	0.077907
Guangxi	0.396337	0.303112	0.242644
Hainan	0.086167	0.111121	0.068336
Chongqing	1.531596	1.410924	1.395365
Sichuan	0.76093	0.598487	0.482564
Guizhou	1.048006	0.847134	0.767893
Yunnan	1.198764	0.813872	0.653275
Shaanxi	2.267496	2.401289	2.535568
Gansu	2.383627	1.065898	0.421037
Qinghai	-5.05886	-6.5505	-6.90653
Ningxia	-1.31139	-0.76803	0.017155
Xinjiang	-3.13347	-3.20629	-3.32579