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Original Research

Study on the Temporal and Spatial Pattern of Carbon Emissions and Influencing Factors in the Context of the Digital Economy

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Abstract

The digital economy drives China's high-quality economic growth and reduces carbon emissions. Urban carbon emissions reduction is crucial to China's "dual carbon" development goal and climate change adaptation. Spatial econometric modeling, standard deviation ellipse analysis, kernel density estimation, the Moran index, and Moran's index are used to study the effects of the digital economy on provincial carbon emissions in 30 Chinese provinces from 2012 to 2021. The study found that: (1) The digital economy has shown a rising trend over time, with the spatial distribution of "east-center-west" decreasing in space. Carbon emissions, on the other hand, show a decreasing trend, with a spatial distribution characterized by a high north and a low south. (2) As measured by the standard deviation ellipse model, the digital economy and carbon emissions have decreasing ellipse areas, with the former's centers of gravity moving northward and the latter's southward, indicating that their spatial agglomeration characteristics are growing. (3) The spatial Durbin model examined how the digital economy affects carbon emissions. The digital economy is reducing carbon emissions in China significantly. A national spatial spillover effect was also detected, with surrounding provinces' carbon emissions being negatively affected.

Keywords: digital economy, carbon emissions, spatial characteristics, influencing factors

Introduction

Excessive emissions of greenhouse gases (GHGs) are the leading cause of climate change, and it has become one of the most severe and critical challenges of our time as the global economy has developed rapidly [1]. The International Energy Agency's (IEA) "2022 Carbon Dioxide Emissions Report" shows that China's carbon emissions have grown 7.09 times from 1.419 billion tons in 1978 to 11.48 billion tons in 2022. The world's largest carbon dioxide emitter is China [2]. The world's fastest-growing economy, China, faces greenhouse gas emissions issues. Economic growth in China now prioritizes carbon reduction and eco-sustainable development. General Secretary Xi Jinping proposed "peak carbon emissions" and "carbon neutrality." To achieve "dual carbon" development goals, China

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has proposed many programs and proposals. According to the State Council's November 2021 "Opinions on Intensively Advancing the Tough Battle Against Pollution," China's low-carbon and sustainable economy requires critical investments [3]. Therefore, understanding the role of carbon emission reduction is of tremendous practical significance for China's economy to achieve high-quality growth.

As technology continues to evolve, green and low-carbon practices have emerged as the dominant direction and trend in global economic development. The digital economy, as a novel productive element, has established a new economic form centered around digitalization knowledge and information as its core productive elements by incorporating cutting-edge digital technologies in production activities. This transformation is increasingly recognized as a critical driver of high-quality economic growth [4]. According to the "2022 China Digital Economy Development Report," China's digital economy was 45.5 trillion yuan in 2021, or 39.8% of GDP. A 21st-century economic infrastructure must include the digital economy due to its constant growth [5]. Additionally, the digital economy has become more interwoven with many industries as the industrial structure has grown, especially during the new crown epidemic; this integration has dramatically impacted social structure and industrial development. The digital economy has also done well, helping conventional industries modernize and stabilizing China's economic growth and industrial structure [6]. To encourage green growth, the State Council of China issued the "Notice on the 14th Five-Year Plan for the Development of the Digital Economy" in December 2021. China's 20th National Congress of the Communist Party of China report underlined the necessity of leveraging digitalization to collectively support carbon reduction, pollution control, and green measures for low-carbon development and high-quality economic growth. Research reveals that integrated environmental management, ecological conservation, and governance require a digital economy [7]. Considering this, it is essential for policymakers to gain a deeper understanding of the factors influencing the relationship between the digital economy and carbon emissions in order to develop effective carbon reduction policies.

Although the research on digital economy and carbon emission reduction has achieved preliminary results, the research on the spatial correlation between the two is relatively insufficient, which is not conducive to the in-depth study of digital economy and carbon emission reduction. In view of this, this research uses panel data from 30 Chinese provinces from 2012 to 2021 to examine the spatial and temporal evolution of China's digital economy, carbon emissions, and carbon emission reduction path in five sections, with the aim of providing policy recommendations for future layouts of the digital economy. The first section describes China's economic development and carbon emissions, emphasizing the importance of the digital economy in fostering low-carbon urban development. The second section is a literature review of domestic and foreign scholars' research on the digital economy and carbon emissions, briefly explaining the digital economy's impact on carbon emissions in the literature and proposing this paper's research content and marginal contribution. The third section, study design, briefly describes this paper's methodology and data variable selection based on the research goal. The fourth section, the empirical part, uses kernel density estimation and the standard deviation ellipse model to analyze the spatial and temporal evolution of the digital economy and carbon emissions, combined with the spatial econometric model to explore the spatial influence effect of digital economy-enabled carbon emission reduction, and robustly tests model construction and variable selection. The final section finishes the analysis with practical solutions from the digital economy-carbon emission synergy and impact effect.

Literature Review

In the context of the development of the digital economy, the advancement of information technology has provided a new engine for intelligent environmental management. Consequently, the digital economy has integrated various environmental protection and energy consumption aspects. This integration holds significant practical significance for alleviating environmental carrying capacity and energy scarcity issues [8]. In this context, the impact effect of the digital economy empowering carbon emission reduction has attracted extensive attention from scholars [9]. Li et al. [10] and Xu et al. [11] concluded that the development of digital economies effectively reduces the emission of urban pollutants, which is mainly manifested in the significant reduction of the PM2.5 value, and considered that the development of digital economies is of great practical significance for the improvement of environmental quality. Qiu et al. [12] pointed out that the digital economy can effectively promote the development of urban green innovation and provide an effective way to achieve the goal of "dual-carbon" development. Li et al. [10] found that the development of the digital economy has significantly contributed to improving environmental efficiency and sustainability levels. Thus, the digital economy is of great practical significance for improving the environment.

Since 2020, when China formally proposed the goal of "dual-carbon" development, scholars have begun to gradually explore the mechanisms of the digital economy to curb carbon emissions [13]. By summarizing existing literature, current research on the relationship between the digital economy and carbon emissions mainly focuses on three aspects. Firstly, most scholars believe that the digital economy can significantly mitigate the increase in carbon emissions. They have found that the continuous development of the digital economy will accelerate the flow of various production factors among different industries, leading to the accelerated flow of data resources between different sectors. Consequently, this can enhance energy efficiency and reduce carbon emissions [14-16]. One of them, Mulaydinov [17], argues that the digital economy can reduce energy demand and carbon emission levels by driving the dematerialization of social development. Liu et al. [18] explored the effect of the digital economy on carbon emissions based on the SPIRPAT model. They concluded that the digital economy could significantly inhibit the increase in carbon emissions by improving the energy structure. Secondly, some scholars believe there is a non-linear relationship between the impact of the digital economy on carbon emissions. Yi et al. [19] showed that the development of the digital economy has a significant spatial spillover effect on carbon emissions and presents the characteristics of spatial decay. Some other scholars have found that the digital economy promotes and inhibits carbon emissions [20]. Wang et al. [21] show that there is an "inverted U-shaped" relationship between the digital economy and carbon emissions. Zhang et al. [22] believe that the impact of the digital economy on carbon emissions has a double-threshold effect and that the relationship between the digital economy and carbon emissions is "N-shaped." Thirdly, according to the laws of geography, it can be found that geographic things or attributes are interdependent in spatial distribution. At the same time, there are differences in distance, so some scholars believe that the impact of the digital economy on carbon emissions is in the inter-regional variability [23]. This will show a more significant inhibition of carbon emissions in cities with highly developed digital economies, especially in eastern China [24]. Li et al. [25] studied the difference in energy structure. They found that with the digital economy's development, energy structures' effect on carbon emissions is gradually weakening for resource cities.

In summary, although research on the digital economy and carbon reduction has achieved preliminary results, the study of their spatial correlation needs to be revised, which hampers further investigation into the relationship between the digital economy and carbon reduction. Therefore, it is necessary to understand the digital economy's spatial expansion and its impact on other regions. Based on data from 30 provinces in China (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2012 to 2021, this article explores explicitly the spatiotemporal evolution characteristics and spatial spillover effects of the digital economy and carbon emissions. The marginal contributions and innovations of this article mainly lie in three aspects: Firstly, building upon existing research on the digital economy, this article comprehensively reconstructs the comprehensive evaluation index system of the digital economy from five aspects: the level of digital infrastructure, the level of digital industrialization, the level of industrial digitization, the level of digital technology innovation, and the development level of digital finance. This enriches the theoretical research on measuring the digital economy. Secondly, innovatively starting from the spatial distribution pattern, this article explores the spatial aggregation characteristics and evolutionary status of the digital economy and carbon emissions based on kernel density estimation and standard deviation ellipses, which helps relevant departments comprehensively grasp the development status of the digital economy and carbon emissions. Thirdly, based on the spatial Durbin model, this article extends the impact of the digital economy on carbon emissions to spatial spillover effects, which helps relevant departments provide theoretical references for formulating development policies in the carbon reduction process.

Research Design

Research Methodology

Kernel Density Estimate

The estimation of the kernel density profile of a random variable is a non-parametric technique used for studying data distributions and describing their dynamic evolution [26, 27]. Kernel density estimation, on the other hand, avoids potential mistakes brought on by arbitrarily selecting the shape of the function by fitting the distribution of the function from the properties of the data itself [28]. Since the subject's prior knowledge can skew model-fitting results, this technique is frequently used in studying regional economic and ecological differences and dynamic evolution [29]. It is expressed in the form of:

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{1}$$

Where: x_i denotes the sample observations selected for this paper; x denotes the mean of the observations; $K(\cdot)$ denotes the functional form, and the Gaussian kernel function is selected in this paper; n denotes the number of sample observations; and the parameter h denotes the bandwidth and has a value greater than 0. The larger the value of h, the smoother the estimated kernel density function, the need to pay attention to whether the bandwidth is too small or too large because the bandwidth is too small or too large will the phenomenon of fitting bias, which has an impact on the experimental results, in this paper, according to the principle of the minimum mean-square error to select the optimal bandwidth.

Standard Deviation Ellipse (SDE)

Lefever [30] standard deviation ellipse is an analytical method for characterizing the spatial distribution of geographic elements. Its four basic parameters – the center of gravity coordinates, rotation angle, and standard deviation of the long- and short-axis, respectively – represent the primary spatial location, the direction of growth, and the degree of discretization of the geographic elements along the major and minor axes, respectively [31], and the calculation formula is as follows:

Average center of gravity ($\bar{X}$, $\bar{Y}$):

$$\bar{X} = \frac{\sum_{i=1}^{m} q_i x_i}{\sum_{i=1}^{m} q_i}, \quad \bar{Y} = \frac{\sum_{i=1}^{m} q_i y_i}{\sum_{i=1}^{m} q_i}, \tag{2}$$

Azimuth θ:

$$\tan\theta = \frac{\left(\sum_{i=1}^{m} q_i^2 \tilde{x}_i^2 - \sum_{i=1}^{m} q_i^2 \tilde{y}_i^2\right) + \sqrt{\left(\sum_{i=1}^{m} q_i^2 \tilde{x}_i^2 - \sum_{i=1}^{m} q_i^2 \tilde{y}_i^2\right)^2 + 4\sum_{i=1}^{m} q_i^2 \tilde{x}_i \tilde{y}_i}}{\sum_{i=1}^{m} 2 q_i^2 \tilde{x}_i \tilde{y}_i}, \tag{3}$$

Coordinate deviation ($\tilde{x}_i$, $\tilde{y}_i$):

$$\tilde{x}_i = x_i - \bar{X}, \quad \tilde{y}_i = y_i - \bar{Y}, \tag{4}$$

Standard deviation of the long and short axes σ_x, σ_y:

$$\sigma_x = \sqrt{\left(2\sum_{i=1}^{m}\left(q_i \tilde{x}_i \cos\theta - q_i \tilde{y}_i \sin\theta\right)^2\right) \Big/ \left(\sum_{i=1}^{m} q_i^2\right)}, \tag{5}$$

$$\sigma_y = \sqrt{\left(2\sum_{i=1}^{m}\left(q_i \tilde{x}_i \sin\theta + q_i \tilde{y}_i \cos\theta\right)^2\right) \Big/ \left(\sum_{i=1}^{m} q_i^2\right)}, \tag{6}$$

Ellipse area S:

$$S = \pi \sigma_x \sigma_y \tag{7}$$

Where ($\bar{X}$, $\bar{Y}$) denotes the latitude and longitude coordinates of each province and city; (x_i, y_i) denotes the spatial location of the study area; q_i denotes the value of the index for each province and city corresponding to the object of study; ($\tilde{x}_i$, $\tilde{y}_i$) denotes the coordinate deviation from the mean center for each study object zone, respectively; σ_x, σ_y denote the standard deviation along the X-axis and Y-axis, respectively.

Moran Index

There is a significant gap in the digital economy's productivity between regions due to constraints imposed by location and other spatial variables. To determine if spatial econometric analyses are justified, the Moran index is used as a criterion for making such a determination; when the result is statistically significant, the analyses are shown to be such. As stated in Equation (8), the global Moran index is utilized to determine if there is agglomeration or outliers in the region under investigation.

$$Moran's\ I = \frac{\sum_{i=1}^{30}\sum_{j=1}^{30} W_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{30}\sum_{j=1}^{30} W_{ij}} \tag{8}$$

where Y_i, Y_j refers to the sample values of the digital economy and carbon emissions of region *i* and region *j*, W_{ij} denotes the spatial weight matrix by normalization. $\bar{Y}$ and S^2 denote mean and variance, respectively.

A typical range for Moran's I is -1 to 1. Positive spatial correlation is indicated when Moran's I value is greater than 0, with more significant values indicating a stronger positive correlation. The opposite is true when the value of Moran's I is less than zero; this implies geographical heterogeneity and a negative correlation between locations. If Moran's I is zero, then the space is entirely random. After computing the global Moran's index, the investigation of local spatial correlation is accomplished by the calculation of the local Moran's index, as illustrated in formula (9).

$$I_i = \frac{(Y_i - \bar{Y})}{\sum_{i=1}^{30}\left(Y_i - \bar{Y}\right)^2} \sum_{j=1}^{30} W_{ij}\left(Y_j - \bar{Y}\right) \tag{9}$$

The Spatial Durbin Model

The traditional panel model in the construction process can only explore the linear or non-linear influence effect of the digital economy on the impact of carbon emissions, and according to the first and second laws of geography, it can be found that the impact of the digital economy on carbon emissions in the process of development will be affected by the geospatial influence effect, so the traditional model did not include the spatial factors into the regression model, while this study is based on the traditional regression model. Considering the potential spatial spillover effects of digital economic development and carbon emissions, this work selects spatial econometric models for investigation as the empirical models of choice. In the field of spatial economics, the spatial lag model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM) are the three most frequent types of models. However, while

SAR primarily investigates the spatial dependency of the dependent variable, spatial error modeling (SEM) concentrates on the spatial dependence of the error term. The SDM is superior to the other two models because it accounts for not only the impact of the lagged factor of the dependent variable on the explanatory variables but also the role of the spatial spillover effects of different factors on the explanatory variables [32]. It is thus more suitable for exploring the spatial role of digital economic development on carbon emissions [33]. Therefore, this paper empirically analyzes the Spatial Durbin Model (SDM), whose formula is shown below:

$$Ban_{it} = \beta_0 + \rho W \times Ban_{it} + \beta_1 Fin_{it} + \rho_1 W \times Fin_{it} + \eta X_{it} + \eta_1 W \times X_{it} + \varepsilon_{it} \quad (10)$$

where: Ban_{it} represents the level of carbon emissions of the corresponding region in this study. Fin_{it} represents the digital economic development level corresponding to the carbon study area. X_{it} denotes the control variable of the paper (see variable selection in 3.2 for details), W denotes the spatial weight matrix, $W \times Fin_{it}$, $W \times Ban_{it}$, $W \times X_{it}$ refer to the spatial lagged variables of the explanatory, interpreted, and control variables of this paper, respectively, ε_{it} is the spatial lag error term.

Variable Selection and Measurement

Dependent Variable: Carbon Emissions

Given its development, carbon reduction is a significant challenge for China and the world. Thus, this article calculates the carbon dioxide emissions for the 30 provinces and municipalities in China (excluding Tibet and the Hong Kong-Macao-Taiwan regions) from 2012 to 2021 using the nine principal energy reference coefficients from the "2006 IPCC National Greenhouse Gas Inventory Guidelines" (see Table 1) and fossil fuel consumption data from the "China Energy Statistical Yearbook." Specific calculation formula:

$$Car = \frac{44}{12} \times \sum_{i=1}^{9} K_i E_i \div GDP \quad (11)$$

In the above equation, *Car* denotes the carbon emissions of each province, *GDP* is the gross domestic product of the provinces, i denotes 9 energy categories, and K_i denotes the carbon emission factor for the i energy source. E_i is i energy use.

Independent Variable: Digital Economy

There are discrepancies between how various academics and institutions measure and evaluate the digital economy. This article synthesizes fundamental ideas of the digital economy based on the "Digital Economic Development Index" released by the National Bureau of Statistics of China. According to [34] and [35], the digital infrastructure level, digital industrialization level, industrial digitization level, digital technology innovation level, and digital finance development level are selected as secondary indicators, and the specific indicators and descriptions are shown in Table 2.

Control Variables

In the regression equation model, according to the role of the digital economy on carbon emissions, it can be found that the influence of the digital economy on carbon emissions affects other variables' co-influence. Referring to [17] and [36], this study selects five indicators, namely, industrial structure upgrading, human capital level, economic development level, industrialization level, and foreign direct investment, as the control variables of this research. The method for controlling variables is as follows: The measurement of industrial structure upgrading involves assessing the ratio of value added from the tertiary to the secondary industry. The human capital level is calculated by the ratio of students in higher education institutions to the total population. The economic development level is computed using the logarithm of per capita GDP. The level of industrialization is measured by the proportion of industrial value added to the regional gross domestic product. The ratio of the actual use of foreign capital to GDP assesses foreign direct investment. All relevant indicator data are sourced from the "China Statistical Yearbook" and the EPS database.

Data Sources and Processing

Table 1. Carbon emission factors for various energy sources.

Energy	Raw coal	Coke	Crude	Gasoline	Kerosene	Diesel fuel	Fuel oil	Natural gas	Electricity
Convert to standard coal (t standard coal/t)	0.714	0.971	1.429	1.471	1.471	1.457	1.429	1.330	0.345
Carbon emission factor K_i (million tonnes/million tons of standard coal)	0.756	0.855	0.586	0.534	0.571	0.592	0.619	0.448	0.272

Table 2. Indicators for measuring the digital economy.

Level 1 indicators	Secondary indicators	Level 3 indicators	Unit
Digital economy	Digital infrastructure level	Number of mobile phone base stations	10,000
		Fiber optic cable line length	kilometres
		Number of domain names	10,000
		Postal outlets	place
		Number of Internet broadband access ports	10,000
		Mobile phone penetration	Department/100 people
	Digital industrialization level	Number of ICT companies	piece
		Average number of people employed in the ICT industry	person
		Operating income of the ICT industry	100 million yuan
		Total volume of postal services	100 million yuan
		Total telecommunications services	100 million yuan
		Software business revenue	100 million yuan
	Industrial digitization level	Proportion of enterprises with e-commerce transaction activity	%
		Enterprise e-commerce sales	100 million yuan
		Number of websites per 100 businesses	person
		Number of computers used per 100 people	stand
		Number of terminals in the electronic reading room	person
		Technology Market Turnover	100 million yuan
	Digital technology innovation level	Full-time equivalent of R&D personnel	person-years
		R&D funding	10,000 yuan
		Number of valid invention patents	matter
		Employees of the unit	person
		Information transmission, software, and information technology services	person
	Digital finance development level	Breadth of digital financial inclusion	-
		The depth of use of digital inclusive finance	-
		Digital Inclusive Finance: Degree of Digitalization	-

The 30 provinces of China (excluding Tibet, Hong Kong, Macau, and Taiwan) serve as the primary data for this research. Using the “China Energy Statistical Yearbook,” the “China Science and Technology Statistical Yearbook,” the “China Education Statistical Yearbook,” the “China National Economic and Social Development Statistical Bulletin,” and the statistical yearbooks and EPS data platforms of each province, it compiles panel data for these regions from 2012 to 2021. Our data is up to 2021 because current CO_2 emissions statistics are up to 2021. Table 3 displays descriptive statistics for the empirical variables.

Carbon emission, an explanatory variable, ranges from a high of 13.788 to a low of 0.168, with a mean of 2.468 and a standard deviation of 2.507. The difference between the high and low values is 11.320, or nearly 4.59 times, indicating substantial variations in carbon emissions across regions and years. These data are presented in Table 3. There is still some inequity in the growth of the digital economy since its primary explanatory variable has a maximum value of 0.659 and a minimum value of 0.223, with the difference between these two values being almost 1.96 times. Subsequent empirical studies can be conducted because the values for the control variables – upgrading the industrial structure, the quantity and quality of human capital, the rate of economic development, the degree to which industries are industrialized, and the level of foreign direct investment – fall within a normal, non-outlying range.

Table 3. Descriptive statistical analysis of variables.

Variable	Obs	Mean	Std. dev.	Min	Max
Carbon emissions	300	2.468	2.507	0.168	13.788
Digital economy	300	0.311	0.085	0.223	0.659
Industrial structure upgrading	300	2.386	0.127	2.176	2.836
Human capital level	300	0.208	0.055	0.085	0.425
Economic development level	300	9.325	0.464	8.598	10.70
Industrialisation level	300	0.316	0.079	0.101	0.523
Foreign direct investment (FDI)	300	0.182	0.045	0.001	0.796

Empirical Analyses

Characteristics of the Spatial and Temporal Evolution

Time-Varying Characteristics of the Digital Economy and Carbon Emissions

This research uses a kernel density estimation method to create maps of China's digital economy and carbon emission composite index from 2012 to 2021 (Fig. 1 and Fig. 2, respectively). Kernel density curve shifts reveal the state of the digital economy and the trend of carbon emissions over the study period, revealing the following characteristics from a geographic, distributional, and temporal perspective:

(1) The digital economy and carbon emissions are two areas whose relative positions change in opposite directions. The digital economy has been actively developing as the center of the kernel density curve shifts to the right from year to year. Meanwhile, there is a general leftward shift in the kernel density curve for carbon emissions, suggesting that emissions are falling and the rate at which they are falling is accelerating. This indicates an inverse relationship between the digital economy and greenhouse gas production.

(2) According to the distribution, the digital economy change curve peaked relatively high in 2012, and its peak height change has been fluctuating ever since, appearing to first decrease, then increase, and then decrease in a cycle of three years for cyclic change, with the peak height change tending towards stability in 2018-2021. As the height of the prominent peak of the curve of carbon emission change has increased, its width has decreased, and the absolute difference within the region still exists, but it is on a downward trend; the gap between the two regions has shrunk.

(3) Both the digital economy and carbon emissions exhibit a right-trailing trend, and from the perspective of distribution extensibility, the width of both is increasing; this suggests that the absolute spatial difference between China's digital economic development level and carbon emission level is widening, that is, the gap between the digital economic development level and carbon emission level of some regions and the rest of the country is growing. It is easy to see why, given the wide range of differences between regions and even provinces and municipalities regarding government spending, economic development, foreign country status, geographical environment, population distribution characteristics, resource endowment, and other factors. This is especially true now when the provincial

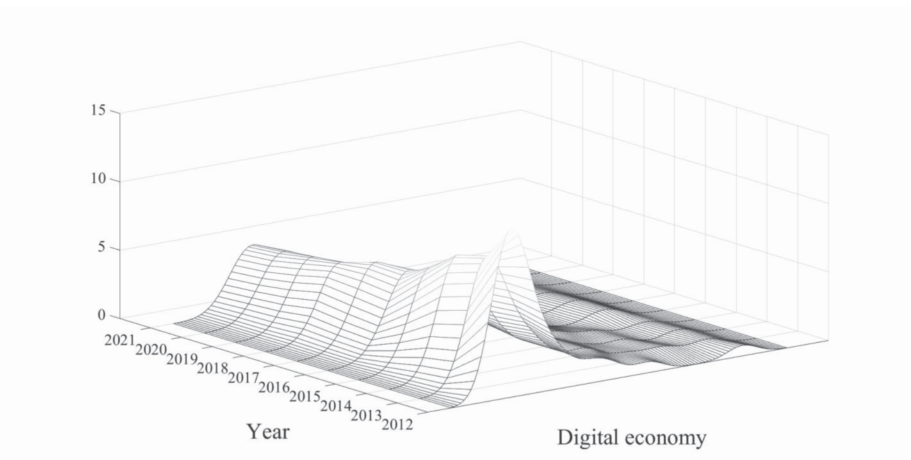

Fig. 1. Kernel density estimation of the digital economy index.

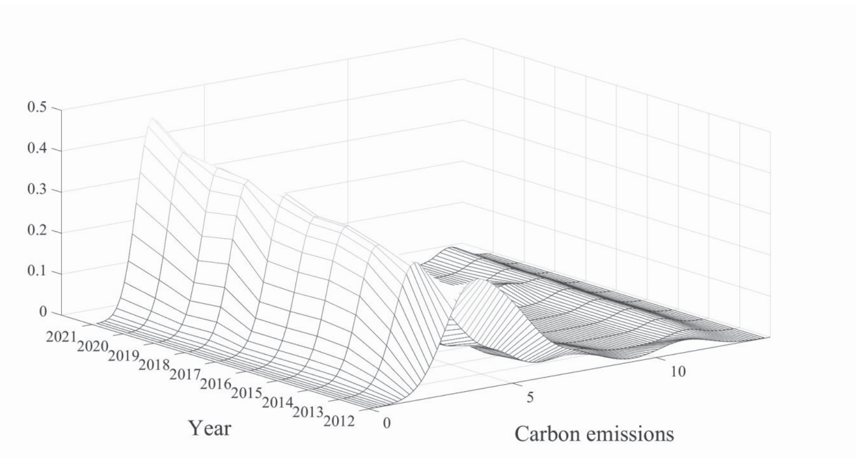

Fig. 2. Carbon emission kernel density estimates.

and municipal levels are so low. Within a specific time frame, the chasm will almost certainly deepen further.

Characteristics of the Spatial Distribution and Correlation Between the Digital Economy and Carbon Emissions

This research delves into the historical evolution of the connection between the growth of China's digital economy and regional carbon emissions. The investigation includes carbon emissions data from 30 Chinese provinces and cities and vector data for these areas in 2012, 2015, 2018, and 2021. Red, orange, and yellow represent provinces and cities with relatively high levels of the variable. At the same time, light green and green reflect relatively low levels, as determined by the natural breakpoint approach. With this method, it is shown that, in Fig. 3 and 4, the digital economy index and greenhouse gas emissions are distributed over time and space.

China's digital economy is not well established but is growing, as indicated by the index's spatial and temporal distribution patterns. In 2018, Beijing (red) had the highest digital economic development level among

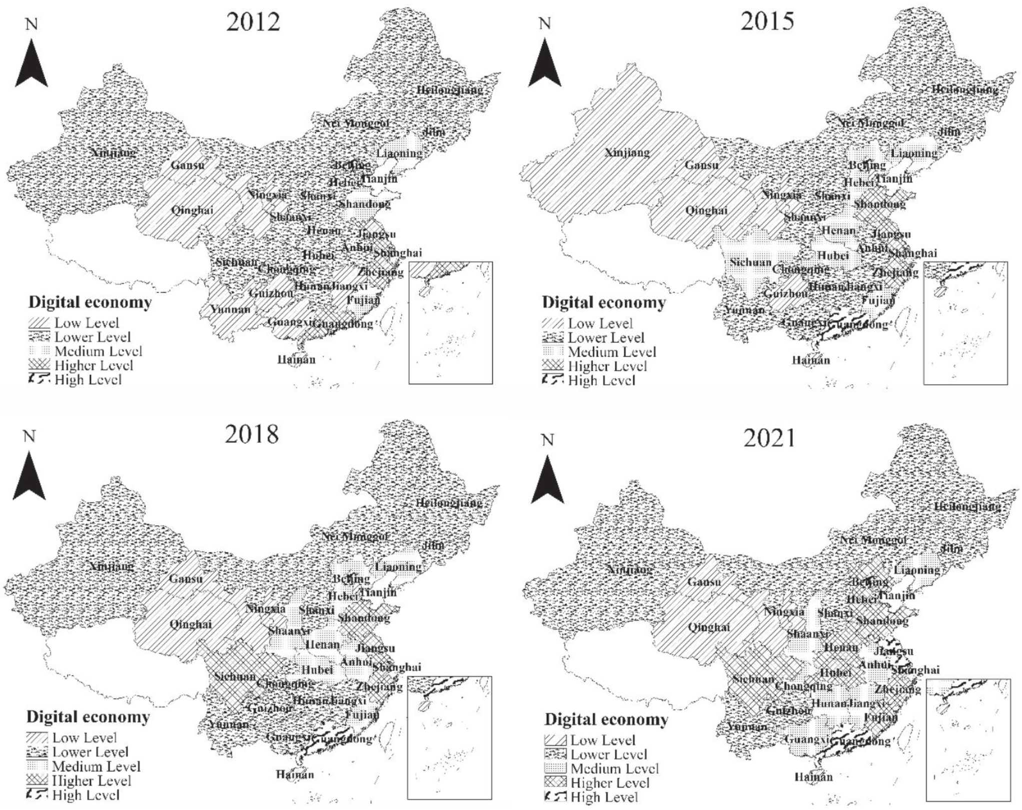

Fig. 3. Spatial and temporal distribution pattern of digital economy indices.

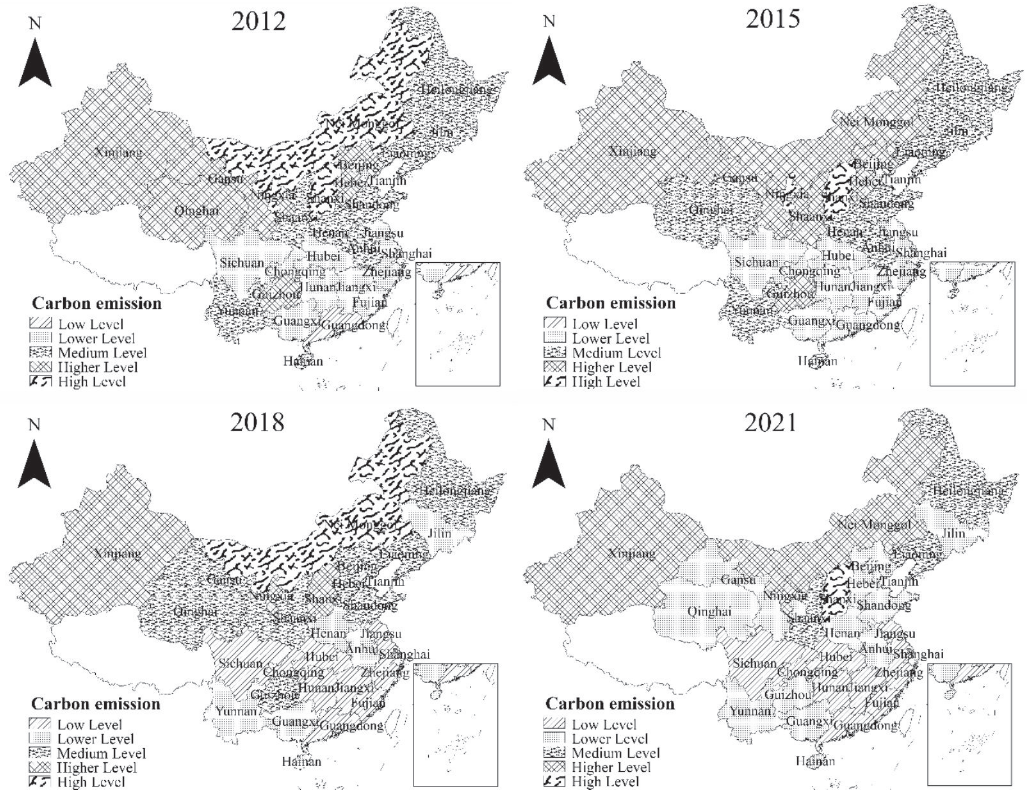

Fig. 4. Spatial and temporal distribution pattern of carbon emissions.

China's 30 provinces and municipalities; a few eastern regions (orange), including Guangdong, Zhejiang, Shanghai, and Jiangsu, also have a high level of digital economic development. Guangdong Province (red) will have a high digital economic development level in 2021. Slowly but surely, the yellow area is catching up to the orange province of Sichuan in terms of digital economic growth. In 2018, Sichuan joined the ranks of provinces with a more advanced degree of digital development. The number of regions in China with highly developed digital economies is expected to skyrocket by 2021 compared to 2012, with the orange zone in the middle of the country seeing the fastest growth. The digital economy in China is highly spatially heterogeneous, with a decreasing law reflecting the link between the country's three main regions (East, Central, and West).

Carbon emissions have decreased in intensity across the board during the study period, as shown by the spatial and temporal distribution map. There is a clear trend for the grade of carbon emissions to evolve from high carbon emission intensity to low carbon emission intensity. Western regions, including Inner Mongolia, Ningxia, and Shaanxi (shown in red), had a disproportionately large number of cities with high carbon emission intensities in 2018 because of their abundant coal resources and the prevalence of high-carbon businesses. Although high-value carbon emission intensity has resurfaced in the Inner Mongolia region (orange) in 2018, the number of cities with medium or lower carbon emission levels (green and li) has increased. The west and northwest regions have seen a decrease in carbon emission intensity since 2015, while Ningxia and Shanxi have seen an increase. It is important to remember, though, that China's northern and southern regions continue to diverge in terms of carbon emission intensity, with the latter showing a clear spatial hierarchy. During the study, China's urban areas have been reducing their carbon emission intensity year over year, with the most significant reductions occurring in several eastern and central cities.

Center of Gravity Shift and Discrete Trends in the Digital Economy and Carbon Emissions

While the above analysis of spatial distribution characteristics provides some insight into the relationship between China's level of digital economic development and the intensity of its carbon emissions, a more complete understanding will require consulting Fig. 5 and 6, which use ArcGIS software to depict the spatial evolution characteristics of China's digital economy and carbon emissions over time. The following diagrams examine the spatial development of the digital economy and carbon emissions from four different angles: the shift in the ellipse's mean center of gravity, the ellipse's shape, the ellipse's long and short axes, and the ellipse's azimuthal angle.

Upon careful examination of the map depicting the spatial evolution characteristics of the digital economy (Fig. 5 and Table 4), it becomes evident that: (1) The average center of gravity shifted during the study period from Hubei Province to

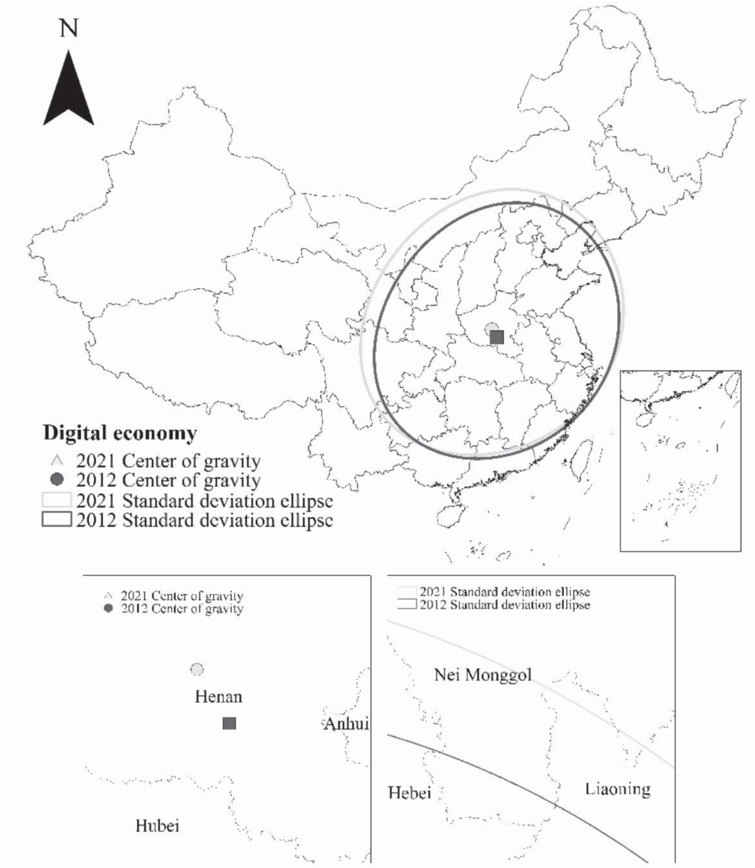

Fig. 5. Characteristics of the spatial evolution of the digital economy.

Henan Province, indicating that the development of the digital economy was centered in the central and northwestern regions of the country. Fig. 3 displays the dynamic spatial-temporal distribution pattern of the digital economic index, revealing a north-westward shift in China's digital economic development level during the study period, emphasizing central-region development. (2) The area of the ellipse experienced a decrease from 4,098,223.45 km² in 2012 to 3,695,880.15 km² in 2021, resulting in a total reduction of 402,343.30 km². Furthermore, the growth of digital economic development outside the ellipse was comparatively lower than that within the ellipse. This observation supports the idea that China's digital economy has exhibited a trend of economic concentration in the overall spatial context. (3) The analysis reveals that both the long and short semi-axes of the ellipse exhibit a declining pattern over time. Notably, the long semi-axis experiences a more pronounced decrease. This observation suggests that China's digital economic agglomeration is expected to further intensify during the period spanning from 2012 to 2021. (4) The standard deviation ellipse azimuth of digital economic development exhibits a drop from 69.80° in 2012 to 64.83° in 2021, suggesting a south-east-north-west orientation in the high-quality development level of China's digital economy.

Fig. 6 depicts our ongoing use of ArcGIS to chart the spatial evolution of carbon emissions, and Table 5 details the paper's use of the standard deviation ellipse's parameters. Similarly, the spatial evolution characteristic map of carbon emission can be observed and reasonably interpreted from four viewpoints: the shift in the ellipse's mean center of gravity, the ellipse's area, the ellipse's long half-axis, its short half-axis, and its azimuthal angle (1). The study area's mean center of gravity shifts southward over time, with the same general pattern seen in both carbon emissions and the digital economy. This shift occurs as the former begins to dominate in Hubei Province and the latter begins to dominate in Henan

Table 4. Table of standard deviation ellipse parameters for the digital economy.

Year	Centre of gravity longitude	Latitude of the centre of gravity	Semi-major axis (km)	Short half shaft (km)	Area (km^2)	Azimuth (degrees)
2012	113.32	33.55	1281.05	1018.31	4098223.45	69.80
2021	113.72	32.98	1204.08	977.04	3695880.15	64.83

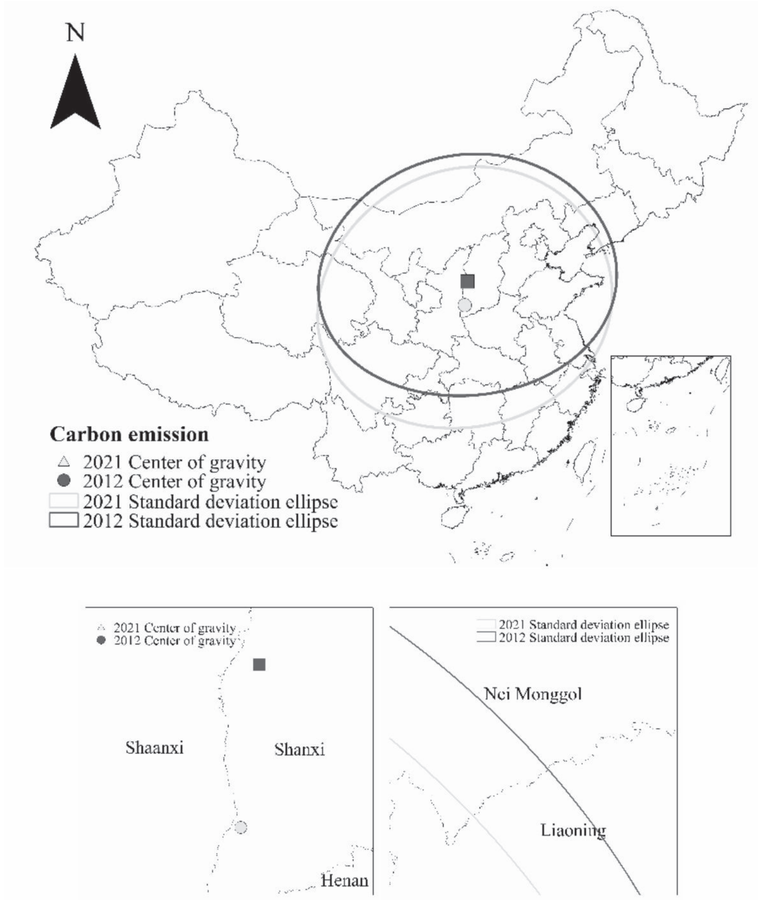

Fig. 6. Characteristics of spatial evolution of carbon emissions.

Province. As can be observed from Fig. 4's spatial-temporal distribution pattern map, carbon emission intensity in China decreases as one travels southward within the research area. (2) Overall, the ellipse's area will decrease from 4513310.66 km^2 in 2012 to 4153224.58 km^2 in 2021, a reduction of 360086.08 km^2; the rate of change of carbon emission intensity outside the ellipse area will be less than that inside the ellipse area, proving that China's level of carbon emission intensity is decreasing in the overall spatial performance of agglomerations. (3) By comparing the long and short semi-axes, it is evident that the long semi-axis is growing more prominent over time while the short semi-axes are shrinking; this suggests that China's carbon emission intensity will continue to rise between 2012 and 2021. (4) The standard deviation ellipse azimuthal angle of carbon emission intensity rises from 83.00° in 2012 to 86.41° in 2021, showing a northeastern-southern bias in China's carbon emission intensity level. In 2021, this angle will have risen to 86.41°, demonstrating a northeast-to-southwest trend in the intensity of China's carbon emissions.

Spatial Econometric Analysis

Spatial Correlation Test

(1) Global autocorrelation

Verifying whether the digital economy and the carbon emissions used for this study have any spatial connection is essential before utilizing the spatial econometric model to analyze the spatial effects between the independent and dependent variables. The spatial autocorrelation between the two is first tested in this work using the global Moran index; the results are presented in Table 6. The analysis shows that the

Table 5. Standard deviation ellipse parameterisation of carbon emissions.

Year	Centre of gravity longitude	Latitude of the centerre of gravity	Semi-major axis (km)	Short half shaft (km)	Area (km^2)	Azimuth (degrees)
2012	110.65	35.46	1419.09	1012.36	4513310.66	83.00
2021	110.89	37.11	1433.98	921.92	4153224.58	86.41

Table 6. Global Moran's I index table.

Year	Digital economy			Carbon emissions		
	Moran's I	Z_values	P_values	Moran's I	Z_values	P_values
2012	0.108	2.551	0.005	0.197	4.358	0.000
2013	0.091	2.360	0.009	0.157	4.005	0.000
2014	0.085	2.262	0.012	0.146	3.892	0.000
2015	0.089	2.309	0.010	0.143	3.786	0.000
2016	0.081	2.145	0.016	0.151	3.919	0.000
2017	0.070	1.967	0.025	0.173	4.141	0.000
2018	0.064	1.875	0.030	0.170	4.033	0.000
2019	0.070	1.962	0.025	0.188	4.388	0.000
2020	0.067	1.954	0.025	0.181	4.304	0.000
2021	0.067	1.991	0.023	0.187	4.355	0.000

digital economy and carbon emissions have always been positively spatially correlated, and both exhibit high or low (surrounding similarity) spatial agglomeration during 2012-2021, as measured by the Moran index. The worldwide Moran index of carbon emissions is much larger than the digital economy's, suggesting that carbon emissions are more susceptible to geographical agglomeration. In terms of the change of the global Moran index over time, although the digital economy and carbon emissions show up and down fluctuations, the overall trend is gradually decreasing, indicating that the spatial correlation between the level of the digital economy and the intensity of carbon emissions in Chinese cities is gradually weakening in the fluctuation.

(2) Local autocorrelation

China's digital economy and carbon emissions show robust spatial agglomeration features when tested with the global Moran index. This allows for a deeper

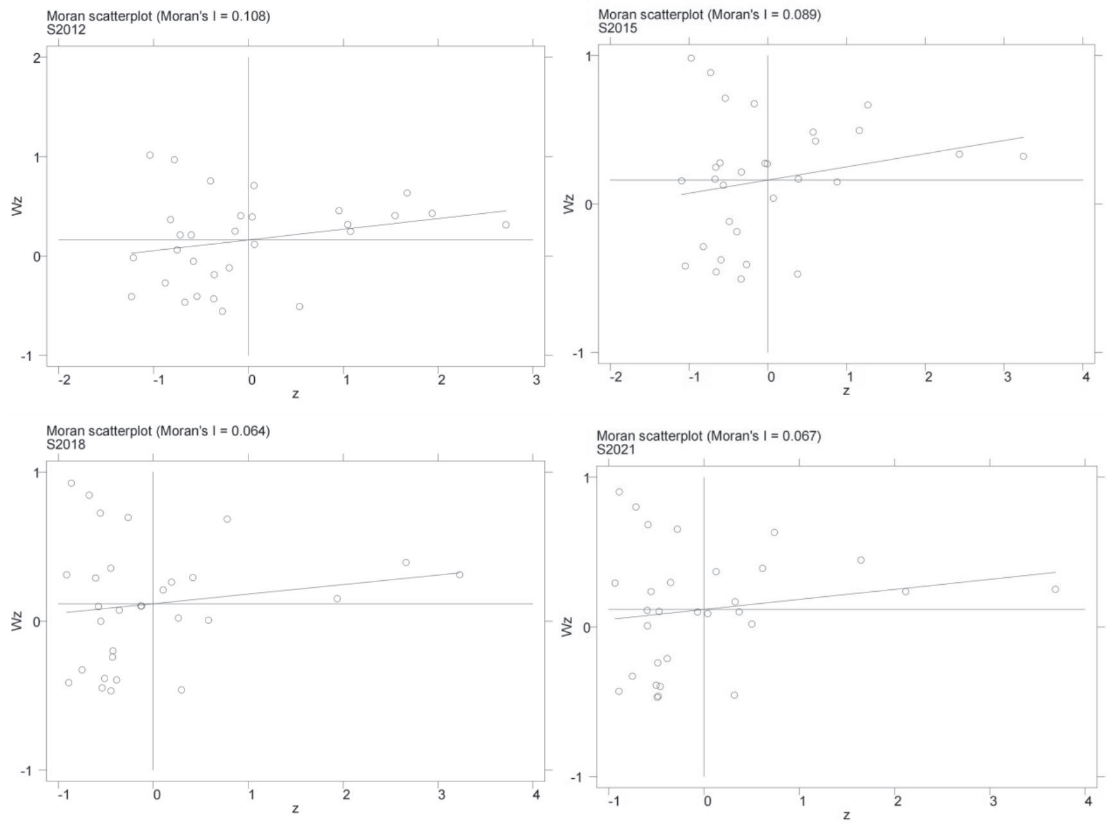

Fig. 7. Localised Moran's I scatterplot for the digital economy.

investigation into the regional concentration of the digital economy and carbon emissions. To resolve the local autocorrelation characteristics of the level of the digital economy and the intensity of carbon emissions in cities, this paper first draws the local Moran scatterplot of the digital economy for four-time nodes, namely 2012, 2015, 2018, and 2021, as shown in Fig. 7 and 8, respectively. By looking at the scatter plots, it is shown that both the digital economy index and the carbon emission index tend to cluster in the first and third quadrants and that there is a positive correlation between the high and low distributions; this suggests that both the digital economy and carbon emissions are more likely to occur in cities with a high (or low) level of development. Results further reveal a significant association between the digital economy and carbon emissions in the 30 provinces of China, confirming findings from both the local and global Moran Indices.

Benchmark Regression Results

Table 7 provides a statistical overview of the baseline regression results from the spatial Durbin model of the digital economy's impact on carbon emissions, where column (1) represents the main effect of the digital economy's impact on carbon emissions and column (2) represents the spatial spillover effect. At the 1% level of significance, the results show that the regression coefficient of the main effect test result of the impact of the digital economy on carbon emissions is -13.643, indicating that the digital economy has an apparent inhibitory effect on carbon emissions; that is, the level of carbon emissions will decrease by 13.643% for every unit increase in the digital economy. The regression coefficient of the test result is -7.517, which is statistically significant at the 5% level, demonstrating that expanding the digital economy will reduce not only local carbon emissions but also those in neighboring provinces; more specifically, the rate of decrease in carbon emissions will be one unit for every unit increase in the level of digital economic development. For every unit of progress in the digital economy, the regional emission level will decrease by 7.517 percent. One possible explanation for this trend is that as the region's digital economy grows, more and more data is pouring into it from adjacent areas. This, in turn, will cut the neighboring areas' carbon emission levels.

The regression coefficient of human capital level is significant at 1% level; the coefficient of upgrading industrial structure is positive and significant at 1% level, indicating that upgrading industrial structure will lead to the growth of carbon emissions through the investment in new equipment and technology, which in turn affects the enterprise's fixed assets that are not easy to discard and the change in market demand. This can result in less reliance on carbon-intensive sectors and power, leading to greener industrial practices.

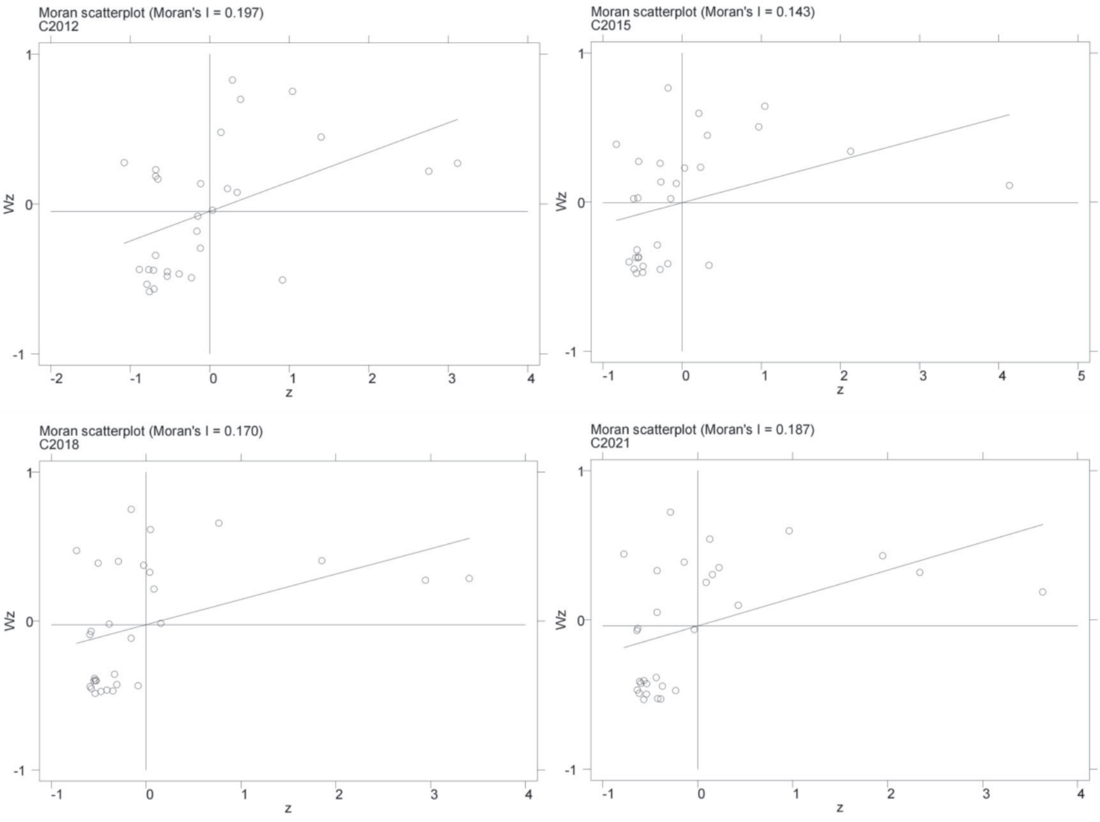

Fig. 8. Localised Moran's I scatterplot of carbon emissions.

Table 7. Benchmark regression results table.

VARIABLES	(1)	(2)
	Main	Wx
L.W Carbon Emissions	1.395***	
	(5.11)	
Digital economy	-13.643***	-7.517**
	(-6.91)	(-1.96)
Industrial structure upgrading	1.624***	0.525
	(4.43)	(0.54)
Human capital level	-1.988***	0.355
	(-2.86)	(0.22)
Economic development level	0.949*	0.234
	(1.92)	(0.28)
Industrialisation level	1.975***	-1.774**
	(6.50)	(-2.53)
Foreign direct investment (FDI)	-2.939**	10.965**
	(-2.32)	(2.36)
rho	0.054**	
	(2.27)	
sigma2_e	4.152***	
	(12.91)	
Observations	270	
R-squared	0.383	
Number of id	30	

Note: ***, **, * denote significance tests passed at 1%, 5% and 10% significance levels, respectively; parameters in parentheses are t-test values.

Table 8. Table of results on spatial spillover effects.

VARIABLES	(1)	(2)	(3)
	Direct effect	Indirect effect	Total effect
Digital Economy	-13.829***	-9.312**	-23.141**
	(-7.11)	(-1.98)	(-2.21)
Industrial structure upgrading	1.678***	0.829	2.507*
	(4.67)	(0.63)	(1.72)
Human capital level	-2.026***	0.115	-1.912**
	(-3.03)	(0.06)	(-1.92)
Economic development level	0.942**	0.283	1.225**
	(2.06)	(0.29)	(2.07)
Industrialisation level	2.007***	-1.660**	0.347
	(6.55)	(-2.07)	(0.47)
Foreign direct investment (FDI)	-2.839**	11.328**	8.489
	(-2.11)	(2.15)	(1.43)
Observations	270		
R-squared	0.383		
Number of id	30		

Note: ***, **, * denote significance tests passed at 1%, 5% and 10% significance levels, respectively; parameters in parentheses are t-test values.

The analysis shows that the coefficient associated with the economic development level exhibits a positive relationship, albeit only meeting the 10% significance threshold. Economic development will likely depend on energy consumption, leading to increased carbon emissions. Furthermore, the regression coefficient linked to the industrialization level demonstrates a positive association and passes the significance test at the 1% level. This indicates a substantial influence of the industrialization level on carbon emissions.

The human capital regression coefficient is statistically significant and negative at the 1% significance level – a positive link between development and carbon emissions. Industrialization increases carbon emissions significantly. Industrialization usually involves large industrial output, mining, construction, and a heavy reliance on fossil fuels due to increased demand. Because these activities employ carbon-intensive energy sources like coal, oil, and gas, they emit a lot of carbon. Industrialization has led to urbanization and transport infrastructure expansion, increasing carbon emissions. At 5% significance, the regression coefficient for foreign direct investment (FDI) is negatively correlated. This shows that foreign direct investment (FDI) can significantly reduce carbon emissions. Foreign Direct Investment (FDI) may have introduced new technologies and management expertise. This boosts production and resource efficiency in receiving countries, reducing carbon emissions.

Spatial Spillover Effects

This section uses the partial differential decomposition method proposed by [37] to further investigate the spatial spillover effect of the impact of the digital economy on carbon emissions, building on the results of the preceding test and regression analysis. This method breaks down the spillover effect into the direct effect of the digital economy of the study area on the average impact of carbon emissions and the indirect effect of the digital economy of the neighboring area in Table 8. The results of decomposing the spatial spillover effect into three components are: the direct effect of the digital economy in the study area on the average carbon emissions the indirect effect of the digital economy in neighboring areas on the average carbon emissions and the total effect of the digital economy in the study area on the average carbon emissions of the whole region.

It can be seen from the regression results that the direct and indirect effects of the digital economy on carbon emissions, as well as the total effect of the regression results, are -13.829, -9.312, and -23.141, respectively, and are significant under different conditions, indicating that the development of the digital economy will inhibit the carbon emissions of the entire region, albeit with a slightly weaker inhibition in the neighboring regions. The regression results for the control variables also coincide with the reference regression findings in Table 6. The positive test coefficients of the direct, indirect, and total effects of upgrading the industrial structure and the economic development level provide further evidence that the control variables encourage increasing carbon emissions in the study area and the neighboring regions. Both the main effect and the total effect of human capital level are shown to be negative, whereas the spillover effect is found to be positive. This indicates that increased human capital reduces the intensity of carbon emissions throughout the region while increasing emissions in neighboring areas. The primary effect test of industrialization level is positive. However, the spillover effect is negative, suggesting that a higher industry level influences carbon emissions in the study area or the overall region. However, less affects carbon emissions in neighboring regions. While FDI was found to have a negative main effect, it was found to have a positive spillover effect and a positive total effect, suggesting that, while FDI may have a dampening effect on local carbon emissions, it will have a stimulating effect on emissions in neighboring areas and across the region.

The findings collectively indicate that the digital economy has a spatial spillover impact on the carbon emissions of adjacent regions. This can be attributed to the absence of spatial constraints within the digital economy, which represents a distinct advantage over the conventional economy. This advantage facilitates the diffusion of the digital economy from the region to its

Table 9. Benchmark regression results.

VARIABLES	(1) First-order inverse distance	(2) Spatial adjacency matrix	(3) Alternate measurement methods	(4) Culling the lag of the first order
L.W Carbon Emissions	1.649***	0.652**	2.657***	
	(2.84)	(2.28)	(4.68)	
Digital economy	-12.843***	-13.547***	-14.206***	-14.577***
	(-5.50)	(-7.22)	(-5.04)	(-7.76)
Industrial structure upgrading	1.091***	1.804***	1.060***	1.089***
	(2.84)	(5.20)	(2.72)	(3.21)
Human capital level	-1.372*	-2.192***	-1.750**	-1.496**
	(-1.93)	(-3.57)	(-2.40)	(-2.31)
Economic development level	1.389***	0.666	1.287**	1.282***
	(2.70)	(1.53)	(2.47)	(2.72)
Industrialisation level	2.063***	2.282***	2.026***	1.423***
	(7.28)	(8.59)	(7.10)	(5.33)
Foreign direct investment (FDI)	-5.584***	-1.947	-4.824***	-4.337***
	(-3.65)	(-1.50)	(-3.13)	(-3.75)
rho	0.496***	0.317***	0.516***	0.394***
	(3.02)	(3.08)	(3.06)	(3.44)
sigma2_e	4.057***	3.643***	4.166***	3.767***
	(12.91)	(12.91)	(12.91)	(12.13)
Observations	270	270	270	300
R-squared	0.112	0.329	0.135	0.151
Number of id	30	30	30	30

Note: ***, **, * denote significance tests passed at 1%, 5% and 10% significance levels, respectively; parameters in parentheses are t-test values.

neighboring regions, resulting in spatial spillover. This is evident in the phenomenon where regions with a higher level of digital economy can stimulate the development of adjacent regions by transferring talents, technologies, and other factors to regions with a lower level of digital economy. This process strengthens interregional exchanges and connections, and promotes the flow of resources between regions, ultimately leading to overall common development and progress.

Robustness Testing

This research study uses a robust type test to determine whether the empirical results are reliable by replacing the distance-based neighborhood spatial weight matrix with a first-order inverse distance spatial weight matrix and a neighborhood spatial weight matrix based on the number of nearest neighbors, and by recalibrating how the digital economy is measured (primarily by applying the TOPSIS comprehensive evaluation method to the results). As can be seen from the analysis in Table 9, the digital economy's regression coefficients on carbon emissions remain negative, and all of them pass the significance test under the condition of 1%, demonstrating that the baseline regression results are of a robust type and that the digital economy has a clear inhibition effect on carbon emissions. Conclusions generated from the baseline regression are robust since the control variables are consistent with the outcomes of these methods.

Conclusions and Recommendations

Discussion and Deficiencies

This study mainly focuses on the data of 30 provinces in China from 2012 to 2021, explores the spatial and temporal evolution characteristics of the digital economy and carbon emissions from a spatial and temporal perspective, and analyses the path of carbon emission reduction empowered by the digital economy using the spatial Durbin model, which enriches the existing theories on carbon emission reduction empowered by the digital economy and has important theoretical and practical significance for the achievement of the "dual-carbon" development goal in China. It is of great theoretical and practical significance for China to achieve the "dual carbon" development goal. Therefore, this study may have the following innovative points and marginal contributions: First, in the process of measuring the digital economy, existing studies mainly construct the indicator system from two to three levels of the five aspects of digital infrastructure level, digital industrialization level, industrial digitization level, digital technology innovation level, and digital finance development level, which cannot comprehensively measure the comprehensive development of the digital economy in the process of measurement. Therefore, this study comprehensively reconstructs the comprehensive evaluation index system of the digital economy by combining the above five aspects, which enriches the research theory on digital economy measurement. Secondly, existing studies mainly focus on exploring the development characteristics of the digital economy and carbon emissions in time sequence. However, according to the first and second laws of geography, there is a spatial influence effect in the process of evolution of various things. Therefore, this study innovatively starts from the pattern of spatial and temporal distribution and is based on the kernel density estimation and the standard deviation ellipse to explore the spatial economic agglomeration characteristics and evolution trends of the digital economy and carbon emissions, which is conducive to the relevant departments grasping the digital economy and carbon emissions comprehensively and exploring the development trend of the digital economy and carbon emissions. Thirdly, most existing studies use panel regression models to explore the linear or non-linear relationship between the digital economy and carbon emissions, and only some literature has explored the spatial spillover effect between the two. Therefore, based on the spatial Durbin model, this study extends the effect of the digital economy on carbon emissions to the spatial spillover effect, which is conducive to providing theoretical references for the relevant departments in formulating development policies for the process of carbon emission reduction.

However, there are some limitations to this paper: First, in terms of data availability, the sample of this study is provincial data from 2012-2021, and the latest data and more detailed samples have not been obtained; therefore, in future studies, mathematical modeling needs to be used to obtain brand new first-hand data and update the research data to ensure the timeliness of the study. Second, due to the limitation of the number of research samples, this study only analyzes the spatial and temporal evolution characteristics and impact effects of the digital economy and carbon emissions based on the data at the provincial level in China and does not explore the impact effects of the digital economy-enabled carbon emission reduction from the perspective of prefecture-level cities or county-level cities in a more detailed way. Third, comprehensively verifying the impact of the digital economy on carbon emission reduction is a comprehensive and systematic work that requires long-term and stable data and experience accumulation and even more methodological innovations to be applied to empirical research. Therefore, the impact of the relationship between the digital economy and carbon emissions will be explored in depth in future research, and the research method will be innovated.

Research Conclusions

By empirically analyzing the panel data of 30 Chinese provinces from 2012 to 2021, this paper uses kernel density estimation, standard deviation ellipse, the Moran index, and the spatial Durbin model to study the spatial-temporal evolution and spatial influence effects of the digital economy and carbon emissions. It comes to the following conclusions:

Firstly, the spatial difference between the digital economy and carbon emissions in terms of time-series changes is empirically examined through a kernel density estimation model, refined to complement the existing studies regarding time-series research. It was found that China's digital economy showed an increasing trend during the study period, while carbon emissions showed the opposite trend to the digital economy. From the distribution pattern and trailing condition, it can be seen that the spatial difference between the digital economy and carbon emissions is in a shrinking trend of change.

Secondly, the standard deviation ellipse model is used to draw the spatial distribution pattern and evolutionary characteristics of the digital economy and carbon emissions to explore the evolutionary characteristics of the research object in terms of spatial change, which is conducive to the relevant departments to comprehensively grasp the development status of the digital economy and carbon emissions. The study finds apparent differences in the spatial distribution of digital economic development levels, with a decreasing trend of "East-Centre-West." Comparing the spatial distribution patterns of the digital economy and carbon emissions in different years, it is found that the digital economy shows an upward trend. In contrast, carbon emissions show a downward trend. From the trend of the standard deviation ellipse, the results show that the digital economy moves to the north, indicating that the digital economic development level is higher in the north than in the south, while the carbon emission moves to the south-west, indicating that the carbon emission level in the south of China is higher than that in the northern region.

Thirdly, the spatial Durbin model is used to explore the effect of the digital economy on carbon emissions in order to explore the spatial spillover effect between the two from a spatio-temporal perspective. The results show that the development of the digital economy has a significant inhibitory effect on carbon emissions, i.e., the development of the digital economy can reduce carbon emissions to a certain extent. At the same time, there is a significant spatial spillover effect on the impact of carbon emissions in neighboring regions.

Research Recommendations

The conclusion of the study leads to the formulation of the following subsequent recommendations:

First, we need to quicken the pace at which digital infrastructure is built. Achieving the dual-carbon target requires cutting-edge digital infrastructure, which is essential to a low-carbon transformation of the digital economy. Therefore, to improve energy efficiency and minimize energy consumption while fostering the high-quality development of the digital economy, the government should raise investment, improve the quality of human resources, and increase foreign direct investment.

Second, the favorable geographical spillover effect of the digital economy should be brought into full play. The digital economic growth of surrounding regions benefits from proximity to more advanced locations. Therefore, to improve the overall efficiency of carbon emissions, it is necessary to strengthen the links and exchanges between different regions, to fully play the radiation effect of the digital economy in the core regions, and to use effects such as technological spillovers to promote the development of the digital economy in the peripheral regions.

Third, it's crucial to make sure that digital economies are growing at roughly the same rate everywhere in the world. High-quality development is in conflict with the uneven distribution of our digital economy and carbon emissions across the country. Therefore, the government should take multiple steps to address the issue. Government policy assistance, greater investment in infrastructure building, technical and financial support, stronger talent training, and preferential policies for foreign direct investment can all contribute to the rapid expansion of the digital economy in undeveloped areas. The government should encourage faster-growing areas to invest in infrastructure, technology, and human capital to help drive and support slower-growing areas so that the development gap can be narrowed, a more balanced and high-quality digital economy can be achieved, and China can achieve its dual-carbon goals.

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Conflict of Interest

The authors declare no conflict of interest.

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