TYPE Original Research
PUBLISHED 18 November 2025
DOI 10.3389/fenvs.2025.1659608

Check for updates

OPEN ACCESS

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RECEIVED 08 July 2025
REVISED 20 October 2025
ACCEPTED 20 October 2025
PUBLISHED 18 November 2025

CITATION
Xia Y, Ji K, Ren C and Jiang L (2025) Spatiotemporal variations of carbon emissions in digital economy: evidence from China. *Front. Environ. Sci.* 13:1659608.
doi: 10.3389/fenvs.2025.1659608

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Spatiotemporal variations of carbon emissions in digital economy: evidence from China

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The last few decades witnessed the tremendous growth of Chinese digital economy. How to calculate and estimate the carbon footprints of this rising economic formation, naturally becomes an issue. Based on the provincial panel from China spanning 2016 to 2021, we conduct an in-depth analysis of the spatial characteristics of carbon emissions in China's digital economy and empirically investigates the driving forces of the spatial differentiation. The results indicate that carbon emissions show rapid growth and a distinct "T-shaped" spatial pattern, with high-emission areas expanding and carbon footprints becoming more dispersed. The spatial variation is driven by six key dimensions with strong interactive effects. By constructing a new emission measurement framework, this study offers spatiotemporal insights into digital carbon footprints, providing relevant implications for enhancing the sustainability of the digital industry and supporting global carbon reduction goals.

KEYWORDS

carbon emission, digital economy, spatiotemporal differentiation, geographical detector, regional disparity

1 Introduction

The unchecked accumulation of greenhouse gas (GHG) emissions becomes a worldwide issue in the last few decades. The Twenty-Sixth Conference of Parties (COP26), held in Glasgow in November 2021, provided the demonstration of the 2015 Paris Agreement's mechanism to regularly revisit and enhance national climate strategies. 151 countries submitted updated and new nationally determined contributions (NDCs) outlining plans to cut GHG emissions by 2030. As the world's second-largest entity, China shows its responsibility and ambition to participate in the global governance process, by presenting "dual-carbon" goals to limit carbon emissions, including reaching its peak emissions by 2030 and realizing carbon neutral by 2060.

Meanwhile, the development of Industry 4.0 is in progress. Innovations in information technology are driving the digital transformation of traditional industries (Bowman, 1996). In China, the scale of the digital economy has expanded significantly as a primary engine of economic growth. From 2016 to 2023, China's digital economy maintained rapid growth with a compound annual growth rate (CAGR) of 14.2%, and its contribution to GDP has reached a level comparable to that of the secondary industry (Tian et al., 2024). Within this context, new business models and formats driven by the digital economy have proliferated competitively. Digital technologies have been adopted to various industrial sectors (Kolpak et al., 2021). Meanwhile, novel productions - such as mobile payments, online education, e-commerce and livestreaming - are deeply influencing consumers' habits.

The balance between industrial expansion and environmental concern has been always discussed. On the one hand, digital economy enhances efficiency and then seems to support sustainable production, on the other hand, due to its proliferation pattern it may still confront significant carbon emission challenges. According to the Global e-Sustainability Initiative's SMARTer 2030 report, the global ICT sector accounted for approximately 2.3% of total carbon emissions in 2020 (GESI, 2021). Greenpeace research further reveals that in 2020, China's data centers and 5G base stations generated approximately 120 million tons of CO_2 emissions, constituting around 1% of the nation's total carbon footprint.

Although existing literature has explored into digital economy emissions, most researches calculate emissions from a global perspective, say, with variations from country-level. Some literatures describe the distribution of digital GHG emissions within countries, but they usually focus on developed countries Pang and Zhu (2013). This paper, however, tries to provide evidence from China, the largest developing entity of the world. We construct a framework for measuring carbon emissions in Chinese digital economy, in order to characterize the distribution of it and then dig into the triggers of the spatiotemporal dynamics. We construct a new framework for measuring carbon emissions in Chinese digital economy, combining initiatively the "top-down" approach and the "bottom-up" approach. Then we unveil a distinct "T-shape" pattern in the emission distribution and dig into the triggers (driving factors) of the spatiotemporal dynamics. The triggers are systematically categorized into six dimensions, whose interactions are rigorously tested to explain the observed heterogeneity, thereby providing unique evidence from the world's largest developing economy.

The subsequent sections of the paper are organized as follows. Section 2 lays out the literature review and theoretical analyses. Section 3 presents a boundary system for emission calculation based on the research data and methodology. Section 4 analyses the spatiotemporal characteristics of carbon emission in Chinese digital economy. Section 5 discusses the triggers. Finally, we present conclusions and policy recommendations.

2 Literature review

As digital technologies integrate into various industrial sectors, the digital industry system driven by technologies such as big data, cloud computing, artificial intelligence, and the Internet of Things (IoT) is rapidly emerging (Xu and Zhang, 2020; Li et al., 2024). The swift expansion of these technologies leads to the escalating demand for energy. Current literature primarily extends the theory of carbon footprints of digital economy.

Walsh emphasized the substantial energy demands of digital products such as computers and mobile phones during their production and usage phases (Walsh, 2013). Bieser and Hilty contended that the production, utilization, and disposal of ICT hardware result in direct environmental impacts, including resource usage and emissions (Bieser and Hilty, 2018). Similarly, Roussilhe et al. also held the view that ICT generates significant electricity consumption and greenhouse gas (GHG) emissions (Roussilhe et al., 2023). Cosar pointed out that digital lifestyles such as the internet and e-commerce have imposed substantial electricity demands on data centers, thereby increasing carbon footprints (Cosar, 2019). Subsequently, Bordage expanded the scope of the digital carbon footprint to include three main parts: user-end, network-end, and data centers (Bordage, 2019). Belkhir and Elmeligi further enriched this perspective, arguing that the increasing number of ICT devices leads to a corresponding increase in carbon footprints, primarily due to the energy consumption required for manufacturing and operating these devices (Belkhir and Elmeligi, 2018). Mewes broadened the scope of digital carbon footprints even further, including areas influenced by ICT such as digital devices, digital services, and digital society (Mewes, 2023).

Based on literature regarding digital carbon footprints and digital economy carbon emissions, this paper regards digital economy carbon emissions to be highly consistent with the connotation of digital carbon footprints. Therefore, digital economy carbon emissions should be understood as the energy (mainly electricity) consumed and the volume of greenhouse gas emissions released during the production and usage processes of digital technologies.

2.1 Calculation and spatiotemporal analysis

In terms of carbon emission estimation, research primarily employs bottom-up and top-down methods, focusing on sub-domains of the digital economy (manufacturing, digital products, data centers, communication networks (Wang and Wang, 2022), 5G, etc.). The bottom-up approach, often based on life cycle analysis (LCA), is one of the main methods for estimating carbon emissions from digital products. Life cycle assessment is a tool for evaluating the environmental impact of products or services from the extraction of raw materials to production and use phases, to waste management. It mainly uses experimental test results or product energy consumption reports to assess the carbon emissions of digital economy projects or products. The top-down method typically uses overall energy consumption data and corresponding carbon emission coefficients to calculate carbon emissions. The carbon emission coefficient method provided by the Intergovernmental Panel on Climate Change (IPCC) is a widely recognized method for calculating carbon emissions, which multiplies energy consumption by carbon emission coefficients to obtain the corresponding carbon dioxide emissions, applicable to various industries. Additionally, some papers calculate ICT industry carbon emissions through macro industry statistics data, but most still rely on the IPCC's methods for research (Yang, 2022). Furthermore, some scholars use input-output tables to calculate ICT industry carbon emissions. Therefore, many literatures have conducted numerous studies on digital economy carbon emissions using single methods or a combination of methods. For example, Qu Shenning et al., according to the "Digital Economy Core Industry

Classification 2021," constructed a digital economy carbon emission accounting framework, estimated the carbon emissions of China's digital product production and use stages based on life cycle analysis, and estimated the carbon emissions of China's data centers and communication networks through macroeconomic data (Qu et al., 2022). Ding et al. divided the boundaries of a single 5G base station through LCA, combined with the total number of 5G base stations in China, discussed the carbon emissions of 5G base stations from a full life cycle perspective, and estimated the carbon emissions of China's 5G network (Ding et al., 2022). Dong et al., based on national energy data and inter-country input-output tables, calculated the CO_2 emissions and intensity of the global ICT industry from 2000 to 2014 (Dong et al., 2022).

Spatiotemporal analysis is a method that combines spatial (geographic location) and temporal dimensions, aimed at studying how phenomena dynamically evolve with changes in time and space. By using tools like autocorrelation analysis, machine learning, geographically weighted regression (GWR) and so on, spatiotemporal analysis has become a normally welcomed method to drawing the distribution of the target elements, such as, in the field of environment, identifying pollution source dispersion pathways and predicting future extreme weather events. Some researches focus on the spatiotemporal evolution of digital economy (Zhong and Mao, 2020; Hu et al., 2022), with the help of Moran's I index (Pan et al., 2021; He et al., 2023), Dagum Gini coefficient (Shu et al., 2022; Chen, 2022) and kernel density (Zhang and Shi, 2023; Guo et al., 2023). As for carbon emissions, spatiotemporal evolution is also popular in terms of industry, tourism, construction and agriculture (Deng and Ren, 2017; Zheng, 2019; Bai et al., 2023). For instance, Huang et al. (2025) identified the regional disparities of agricultural carbon emission differences in China. In the urban context, (Du et al., 2022), demonstrated that low-carbon city policies significantly improved urban ecological efficiency through the mechanism of green technology innovation. However, there is little literature on the spatiotemporal evolution of the combination of carbon emissions and digital economy. However, there is little literature on the spatiotemporal evolution of the combination of carbon emissions and digital economy.

2.2 Influencing factors

Existing literature has explored the driving factors of the growth of digital economy (Zhang et al., 2023; Lv and Fan, 2023; Yu et al., 2023; Cai et al., 2022; Mao et al., 2022). Zhong Yexi and Mao Weisheng, used GWR model to identify that the level of informatization, urban hierarchy, and industrial structure positively influence the development of the digital economy in the Yangtze River Economic Belt, while the impact of human capital is found to be unstable (Zhong and Mao, 2020). Zhang Pei et al., based on the Spatial Durbin Model (SDM), pointed out the key drivers of China's digital infrastructure (Chen, 2022). Szeles and Simionescu noted that education level and R&D expenditure are significant drivers of the digital economy level in the EU (Szeles and Simionescu, 2020). Besides, there are studies discussing the regional and industry heterogeneity of carbon emissions (Li et al., 2023; Zhao et al., 2023; Wei et al., 2017). Song Xu et al., based on the LMDI logarithmic mean Divisia index decomposition method, studied the impact of energy structure, economic growth, population, and other factors on the decoupling of energy consumption and carbon emissions (Song et al., 2020).

2.3 Summary

In aggregate, the existing literature on the digital economy and carbon emissions has achieved notable progress in theoretical exploration, estimation methodologies, and the identification of influencing factors. Researches on carbon footprint theories encompass a broad spectrum of carbon footprints and primary carbon sources, with a focus on carbon footprints influenced by Information and Communication Technology (ICT), including key sectors such as digital manufacturing, digital products, communication networks, and data centers, which provides a foundation for the calculation of carbon emissions in this paper.

In terms of calculation method, researches generally employ top-down or bottom-up approach for estimation, each with its own set of advantages and disadvantages. Specifically, the bottom-up approach faces challenges such as ill-defined research boundaries and incomplete lifecycle databases, but it has a favorable framework and complete methods. The top-down approach, based on macro energy consumption data, has easy access to data but suffers from ambiguity. Therefore, this paper aims to construct a new carbon emission boundary system combining the bottom-up and top-down approaches, which takes the advantages of both approaches. We will adopt the province-level sample of China, estimating their carbon emission of digital economy, aiming to further enrich related literature and provide a scientific reference for carbon emission reduction and sustainable development of the digital economy.

3 Data

3.1 The boundary system for carbon emission calculation

Given the unique nature of the digital economy, this study constructs a framework for the boundaries of carbon emission calculation based on relevant research, as well as the "Classification of Digital Economy and Core Industries (2021)" and "National Economic Industry Classification GB/T 4754-2017". The emissions are further decomposed into four types: carbon footprint of digital products, carbon emissions from digital manufacturing, carbon emissions from communication networks, and carbon emissions from data centers. The complete boundary system for carbon emission calculation and detailed explanation can be found in the Supplementary Appendix SA.

The first category includes the carbon footprint of digital products and devices, covering the main types of digital products currently

TABLE 1 Carbon footprints for major digital products during the usage stage.

Product/Device	Carbon footprint per year (kg)	References
Smartphone	5	Apple/Samsung
Computer (Home Use)	72	Qu Shenning
Computer (Commercial)	105	Qu Shenning
Monitor	116	Apple
Camera	0.2	Urban
Tablet	5	Qu Shenning
Television	74	Urban
Audio system	39.5	Urban
Router	32	Urban
Wearable products	1.5	Apple

available. The second category corresponds to the computer, communication, and other electronic equipment manufacturing industries. The third category involves carbon emissions from communication networks, including communication stations under mobile communication networks and communication optical cables under fixed communication networks. The fourth category is carbon emissions from data centers, which lay the foundation for new information and communication technologies such as 5G, artificial intelligence, cloud computing and blockchain. These four categories essentially correspond to the main sources of carbon emissions in China's digital economy at present.

There are two major methods for emission boundaries in literature: the "top-down" approach and the "bottom-up" approach. The bottom-up method is generally based on life cycle analysis. The energy consumption parameters related to the digital economy are obtained through experimental testing or analysis of product energy consumption reports, and the individual carbon emissions are calculated respectively, and then the total data can be obtained by summing up. The top-down rule estimates the carbon emissions of the digital economy directly from the macro or industry level based on macro statistics or input-output tables. The two approaches are not antagonistic, but complementary. In applications, the "mixed" approach is a very recommended strategy (Yang et al., 2025). Some studies have already combined the "bottom-up" approach with the "top-down" approach to obtain more comprehensive and reliable results (Wang and Zhu, 2024; Liao et al., 2022).

The article also follows this path, using the bottom-up method for digital products that can obtain energy consumption parameters, and the top-down method for new infrastructure that is difficult to obtain energy consumption parameters (Equation 1). In particular, the carbon emissions of the digital economy are the sum of the carbon emissions from digital products (C_{dp}), digital manufacturing (C_{dpm}), communication networks (C_{cn}), and data centers (C_{dc}). The remaining parts of this chapter will provide a detailed introduction to the calculation methods of carbon emissions for each category.

$$C_{de} = C_{dp} + C_{dpm} + C_{cn} + C_{dc} \tag{1}$$

3.2 Digital products

For digital products, we use the bottom-up approach (life cycle). The entire life cycle of digital products includes raw materials, manufacturing, usage, and recycling stages[1]. In this paper, the production and usage stages of digital products are measured, with the production stage calculated by digital manufacturing section. Considering the availability of data, the carbon footprint of raw materials and waste recycling is not included[2]. According to the life cycle analysis method, this study collates the annual carbon footprint of different literatures to determine the carbon footprint during the usage stage of digital products, referring to existing literature, and taking the average value for individual digital product carbon footprints.

The carbon emission from digital products is as follows Equation 2:

$$C_{dp} = C_{dpi} \cdot N_i \tag{2}$$

Where C_{dp} is the carbon emissions from digital products, C_{dpi} is the carbon footprint of the digital products of category i and N_i is the quantity of the products of category i. The footprints are detailed in the table below (Table 1).

1 The carbon footprint of digital products is limited by the product brand, product model, consumer behavior and product upgrading. There are some differences in quantitative accounting based on the whole life cycle theory. We add the specific calculation process to Supplementary Appendix SB.

2 This paper ignores the carbon footprint generated by digital product recycling. However, according to Qu Shenning, Shi Dan and Yang Danhui (2022)'s carbon accounting system for China's digital economy, the carbon footprint in the recovery phase is often much smaller than that in the production and use phase. Therefore, the method in this paper will not have a great impact on the basic results.

3.3 Digital manufacturing

Carbon emissions from the digital manufacturing industry are calculated using a top-down approach. Both direct energy consumption and indirect energy consumption are taken into account (Table 2). The specific formula is as follows Equation 3:

$$C_{dpm} = \sum_i A_i * c_i \tag{3}$$

Where: C_{dpm} is the carbon emissions from digital manufacturing. A_i is the consumption of energy i (in units of tons, kilograms, or cubic meters). c_i is the carbon dioxide emission coefficient for energy i, with emission coefficients for various fossil fuels referenced from the "IPCC Guidelines for National Greenhouse Gas Inventories."

The carbon emission coefficient for electricity is referenced from the "Notice on Key Work Related to the Management of Corporate Greenhouse Gas Emission Reporting for the Year 2022″ issued by the Ministry of Ecology and Environment, which cites the national electricity carbon emission factor for the year 2021, with a factor of $0.6101tCO_2/MWh$.

The carbon emission coefficient for thermal energy is referenced from the "Pilot Guidelines for the Accounting and Reporting of Greenhouse Gas Emissions from Electronic Equipment Manufacturing Enterprises," with a factor of $0.11tCO_2/GJ$.

3.4 Telecommunication networks

The calculation for the telecommunication networks section takes "top-down" approach, which primarily draws on the macro-energy consumption data and related data ratio estimation approach at the regional scale, as demonstrated by Zhu Songli, Tan Xian Chun, and Qu Shen Ning[3]. The carbon emission calculation formula is as follows Equation 4:

$$C_{cn} = E_{cn} \cdot B_i * c_i \tag{4}$$

Where: E_{cn} denotes the carbon emissions of the communication network, defined as the energy consumption intensity per unit of telecommunication services (in billions of yuan/KWh). B_i denotes the total volume of telecommunication services in a given province (in billions of yuan). c_i denotes the carbon dioxide emission coefficient for electricity $(0.6101 kgCO_2/KWh)$.

3.5 Data centers

Data center rack is mainly used to accommodate it equipment such as data center server, storage, hub and network switch. The number of data center racks used in this paper is the number of available single racks[4].

The main indicator to measure the energy consumption of the data center is PUE (i.e., power utilization efficiency). The higher the PUE value, the lower the overall efficiency of the data center. IT load utilization rate refers to the ratio of the power actually required by IT equipment to the power required at rated load. The higher the IT load, the greater the power required to maintain its operation, and the more power consumption. Single rack design power refers to the power consumption of the data center rack.

Due to the variation of key energy consumption data, it is inaccurate to directly calculate the energy consumption through the number of existing racks. Therefore, in order to measure the total energy consumption of provincial data centers over the years relatively objectively, the above key factors affecting energy consumption and energy consumption are compared and corrected with comprehensive reference to various institutions[5].

The formula is as follows Equation 5:

$$C_{dc} = N_i \cdot PUE_i \cdot a_i \cdot P_{dci} \cdot t \cdot c_i \tag{5}$$

Assuming that the design power per rack, IT load utilization rate, and power usage effectiveness are the same in each region. Wherein: E_{dc} represents the total energy consumption of data centers nationwide, N_i is the total number of racks in region i, PUE_i is the average power usage effectiveness (PUE) of data centers in region i, a_i is the average IT load utilization rate of data centers in region i, P_{dci} is the average design power per rack in region i, t is the

3 The carbon emissions of communication networks are calculated using a top-down approach, which is difficult to measure in a standardized manner like the carbon footprint of digital products. Considering the difficulty in measuring the carbon emissions of building materials involved in the construction phase of communication network infrastructure, its carbon emissions are only calculated during the operation phase. The energy consumption during the operation phase of the communication network is mainly the use of electricity. Due to the lack of energy consumption inventory data for provincial units, it is difficult to quantify the carbon emissions of communication networks at the provincial level. However, the energy consumption and telecommunications business volume at the national level can be estimated from relevant yearbooks. Among them, the electricity consumption of national communication network and telecommunications services is sourced from the "China Electricity Yearbook" from 2016 to 2021, and the total amount of telecommunications services in each province is sourced from the "China Third Industry Yearbook" from 2016 to 2021. The missing values are supplemented by an average annual growth rate.

4 The total number of data center racks in each province over the years comes from the national data center application development guidelines 2017–2020 prepared by the Ministry of industry and information technology. This paper selects the time series data of the data center from 2016 to 2021, and uses the annual average growth rate to supplement the missing value and abnormal value.

5 The region where the rack belongs refers to the guidelines for the application and development of national data centers 2017–2020 issued by the Ministry of industry and information technology; The average it load utilization rate, average pue, average single frame power, etc. refer to the existing achievements of the Fifth Institute of electronics of Greenpeace and the Ministry of industry and information technology.

TABLE 2 Energy carbon emission coefficients.

Energy type	Average low heating value (KJ/Kg)	Conversion factor to standard coal (kg/kgce)	Carbon content per unit heat (t-c/TJ)	Carbon oxidation rate	Carbon emission coefficie nt
Raw coal	20,908	0.7143	26.37	0.94	1.9003 kg – CO2/kg
Coking coal	26,344	0.9000	25.41	0.93	2.2829 kg – CO2/kg
Blast furnace gas	17,354	0.5929	13.58	0.98	0.8469 kg – CO2/m3
Coke oven gas	3,763	0.1286	12.1	0.98	0.1636 kg – CO2/m3
Other gases	16,308	0.5571	12.1	0.98	0.7091 kg – CO2/m3
Crude oil	41,816	1.4286	20.08	0.98	3.0202 kg – CO2/kg
Gasoline	43,070	1.4714	18.9	0.98	2.9251 kg – CO2/kg
Kerosene	43,070	1.4714	19.6	0.98	3.0179 kg – CO2/kg
Diesel	42,652	1.4571	20.2	0.98	3.0959 kg – CO2/kg
Fuel oil	41,816	1.4286	21.1	0.98	3.1705 kg – CO2/kg
Petroleum gas	50,179	1.7143	17.2	0.98	3.1013 kg – CO2/kg
Refinery dry gas	46,055	1.5714	18.2	0.98	3.0119 kg – CO2/kg
Natural gas	38,931	1.3300	15.32	0.99	2.1622 kg – CO2/m3

The carbon emission coefficients are referenced from the "IPCC Guidelines for National Greenhouse Gas Inventories".

time, taken as 8,760 h, and c_i is the carbon dioxide emission coefficient for electricity (0.6101 kg/KWh). The division of regions and main indicators such as average IT load utilization rate, average design power per rack, and average PUE are shown in Table 3.

4 Spatiotemporal dynamics

4.1 Temporal trend

From 2016 to 2021, the emissions of Chinese digital economy have shown a significant upward trend, with a growth rate of 59.8% and an average annual growth rate of 8.36%. Further analysis of the structure and growth trends of the four sections of digital economy reveals that although there is not much change in the proportion within the internal structure of the emissions, the total of each section has shown fierce growth. This reflects that the development of the digital economy has a great impact on energy consumption and carbon emissions (Figures 1, 2).

From 2016 to 2021, the regional carbon emission structure remained relatively stable, with the eastern region, western region, central region, and northeastern region maintaining their respective shares at around 62%, 18%, 16%, and 4% (Figure 3). Specifically, the eastern region, as the most developed region in China, has a large number of data centers and large-scale digital industries, which to some extent has driven the increase in its emissions. The total carbon emissions in the western region have also shown a significant growth trend, reflecting the layout of cloud computing and big data centers in the process of promoting the development of the digital economy in the western region, resulting in an increase in energy consumption and corresponding carbon emissions. The central region, at the same time, has undertaken the transfer of digital manufacturing industry from the eastern region and promoted the construction of digital infrastructure, which has also led to an increase in overall energy demand and carbon emissions. However, the Northeast region has shown relatively small increase in total emissions, implicating that the degree and scale of the new structure remain limited, as well as the large proportion of traditional heavy industry.

4.2 Spatial distribution

We use ArcGIS 10.2 to visualize the spatial distribution of the emissions from 30 provinces and cities in China from 2016 to 2021. Due to space limitations, visualization results for specific categories (digital products, digital manufacturing, communication networks and data centers) can be found in Supplementary Appendix SC.

According to Figure 4, the carbon emissions from digital economy are higher in the eastern regions and lower in the western regions, overall presenting a "T"-shaped spatial configuration along the eastern coastal axis and the Yangtze River Economic Belt. Specifically, the provinces with prominent carbon emissions in the digital economy include coastal provinces, as well as provinces or nearby regions along the Yangtze River Economic Belt. In 2016, high carbon emission areas were concentrated in Guangdong and Jiangsu provinces forming a spatial configuration that gradually spread towards the central and western regions. By 2018, there was a significant increase in national digital economy carbon emissions, particularly in the Beijing-Tianjin-Hebei region, coastal areas, and central and

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TABLE 3 Main indicators of data center energy consumption.

Region	Average IT Load Utilization rate (%)	Average rack design power (kW)	Average PUE	Provinces
Beijing	64	6.7	1.43	Beijing, Hebei, Tianjin, Inner Mongolia
Shanghai	53	5.4	1.47	Shanghai, Zhejiang, Jiangsu
Guangzhou	45	5.6	1.58	Guangdong, Fujian, Hainan
Central	32	4.9	1.62	Anhui, Henan, Hubei, Hunan, Jiangxi, Shanxi, Shandong
Western	38	5	1.51	Guizhou, Sichuan, Chongqing, Gansu, Guangxi, Yunnan, Shaanxi, Qinghai, Xinjiang, Ningxia
Northeast	43	4.2	1.47	Heilongjiang, Jilin, Liaoning

The main indicators refer to The Road to Decarbonization of China's Digital Infrastructure: Decarbonization Potential and Challenges of Data Centers and 5G (2020–2035).

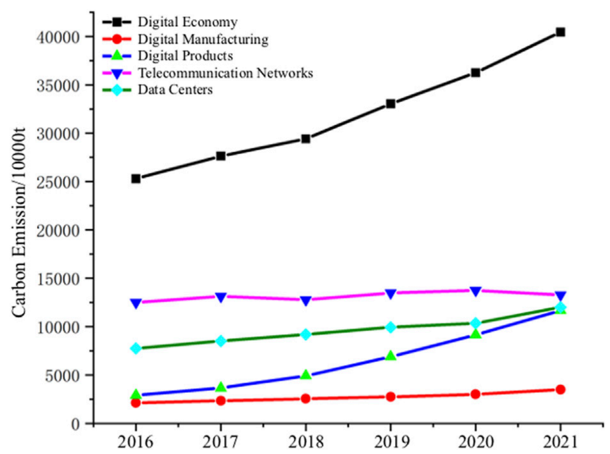

FIGURE 1
Carbon emission trend of digital economy from 2016 to 2021.

western cities. In 2021, the high carbon emission zone formed along the north-south coastal belt, while the secondary high-value aggregation areas emerged in the central region and western region.

The "T" pattern formation is highly consistent with the historical context and spatial structure of China's regional economic development. Since the reform and opening up, the eastern coastal regions have attracted a large amount of capital, technology and highly skilled labor due to their geographical advantages and policy preferences, forming digital economy clusters represented by information technology, the internet, artificial intelligence, etc. Although these industries are of the "low physical consumption" type, the digital infrastructure behind them, such as data centers, cloud computing platforms and communication networks, has high energy consumption characteristics, especially being highly dependent on electricity. At the same time, the Yangtze River Economic Belt regions (such as Jiangsu, Zhejiang, Hubei, Sichuan) benefit from the water transportation and industrial chain collaboration, as well as the agglomeration effects of talents, technology and markets, thus forming the second-highest carbon emissions.

Also, from the industrial perspective, digital economy enterprises tend to cluster in regions with well-developed infrastructure, complete industrial chains, and abundant innovation resources. However, this agglomeration leads to the concentration of energy consumption and carbon emissions. Provinces such as Guangdong, Jiangsu, and Zhejiang, as the pioneering regions and core carriers of the digital economy, have the highest total carbon emissions and growth rates in the country, reflecting the reality that the relationship between economic growth and carbon emissions has not yet been completely decoupled.

Although the "T" structure has a certain degree of stability, its internal structure is still undergoing dynamic adjustments. For instance, in recent years, provinces in the central and western regions (such as Hebei, Inner Mongolia, Guizhou, etc.) have significantly accelerated their carbon emission growth by industrial transfer. This reflects the "carbon leakage" effect brought about by the diffusion of the digital economy from the eastern region to the central and western regions. Under the impetus of policies, these provinces are becoming new carbon emission growth poles. This not only brings regional development opportunities but also poses a challenge to the national carbon reduction target.

4.3 Spatial agglomeration

This paper uses Moran's I index to measure the emission agglomeration of the digital economy. Moran's I is a classic statistical analysis in spatial autocorrelation analysis, to measure the similarity or clustering degree of a variable in spatial distribution. It is quite popular in fields such as geography and environmental science to identify patterns in spatial data, say, random distribution, clustering, or dispersion.

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \boldsymbol{w}_{ij}\,(x_i - \bar{x})\left(x_j - \bar{x}\right)}{\sigma^2 \sum_{i=1}^{n}\sum_{j=1}^{n} \boldsymbol{w}_{ij}} \tag{6}$$

In Equation 6, I is the global Moran's I index, W_{ij} is the proximity relationship between province i and $j.x_i$ and x_j represent the emissions values of province i and j, respectively. And $\bar{x}$ is the average carbon emissions of provinces within the study area, and n is the number of selected provinces. The standardized Moran's I index values are between −1 and 1, with a tendency towards −1 indicating stronger negative correlation, a tendency

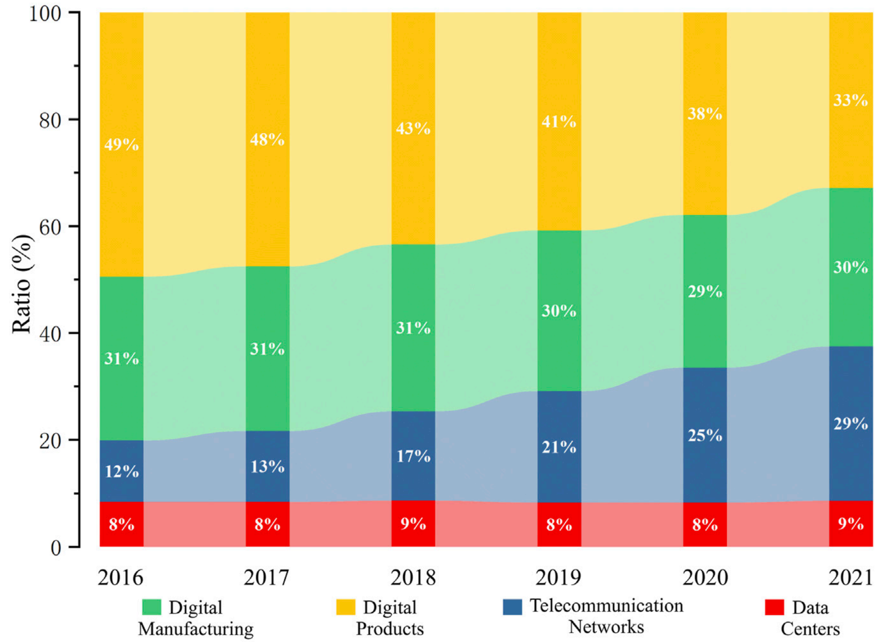

FIGURE 2
Changes in carbon emission structure of digital economy from 2016 to 2021.

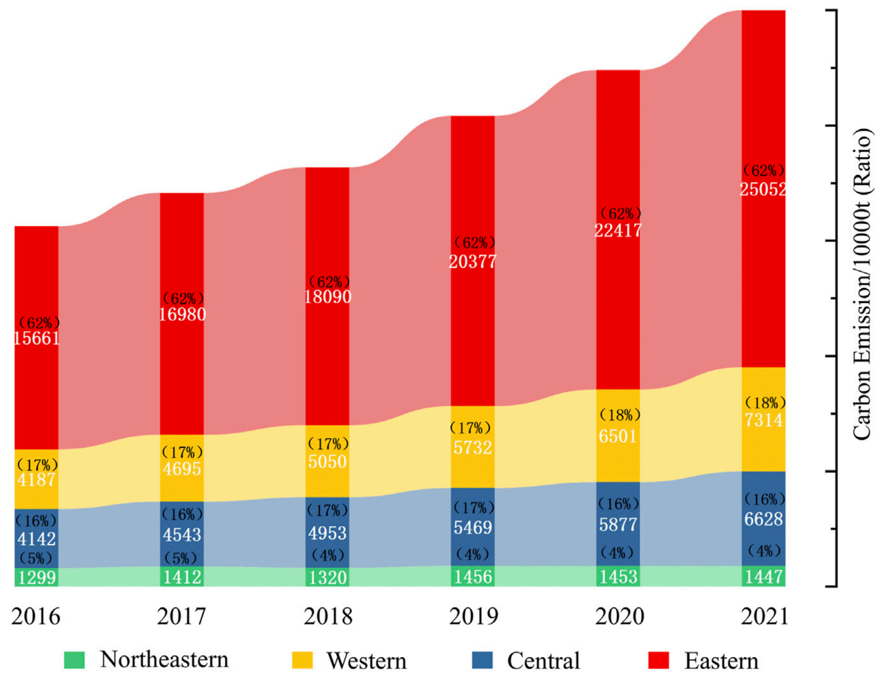

FIGURE 3
The proportion of carbon emission regions in the digital economy from 2016 to 2021.

towards 1 indicating stronger positive correlation, and 0 indicating no correlation.

In addition, the global Moran's index can reflect the overall characteristics of the spatial correlation of various variables, and to study the phenomenon of local clustering in space, it is necessary to use the local Moran's index for analysis (Equation 7).

$$I = Z_i \sum_{j=1}^{n} W_{ij} Z_j \tag{7}$$

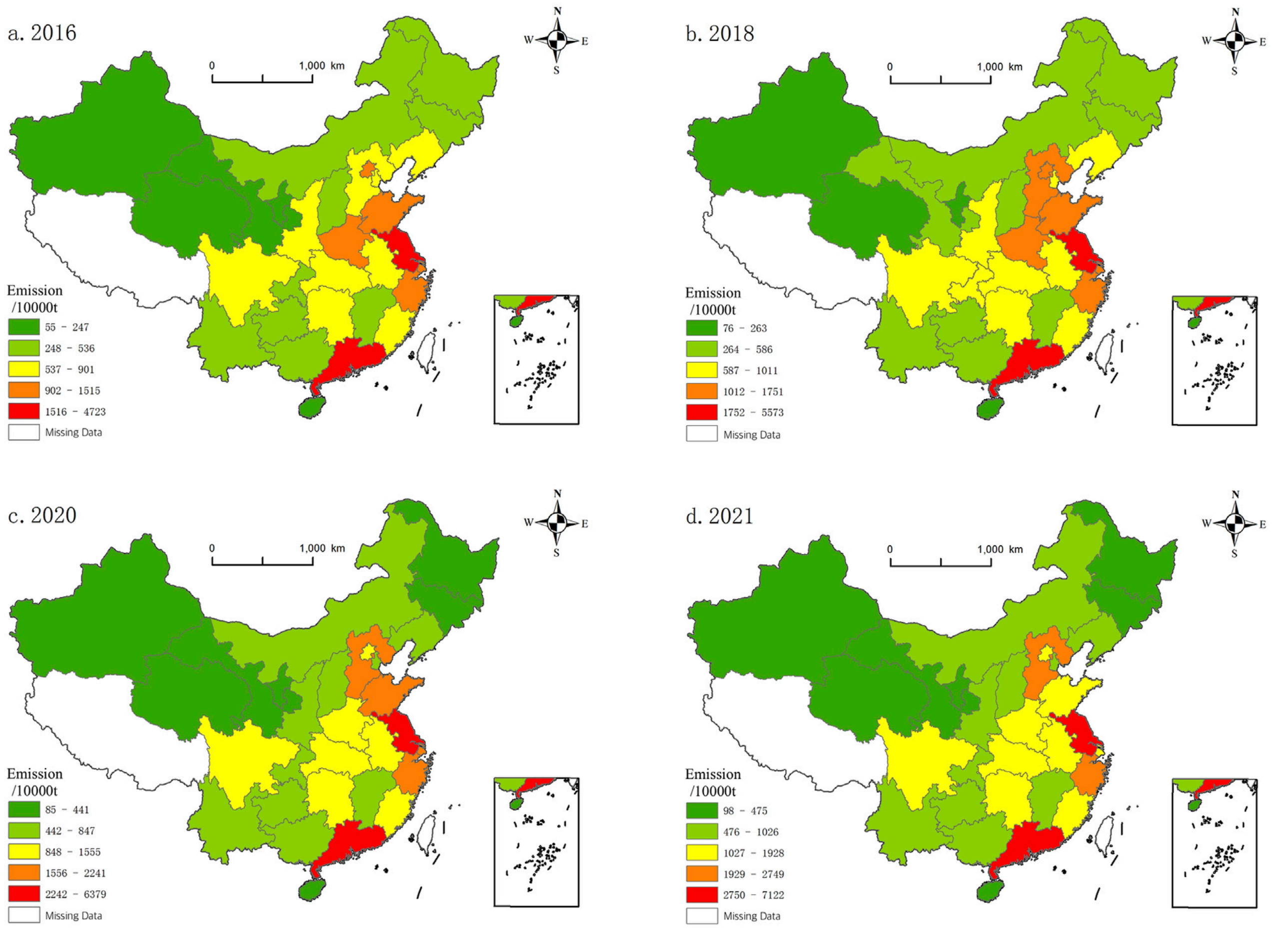

FIGURE 4
Spatial distribution of carbon emissions in the digital economy in 2016, 2018, 2020, and 2021. Note: The figure is based on the standard map approved by the Ministry of Natural Resources with the reference number GS (2023) 2,767, and the boundaries of the base map have not been modified.

Where: Z_i and Z_j are the standardized carbon emissions of province i and province j. The research units can be divided into four spatial correlation types: HH clustering area, LH outlier area, LL clustering area, and HL outlier area.

From 2016 to 2021, the global Moran's I for carbon emissions from China's digital economy was positive (Table 4), with the Z-value exceeding the threshold of 1.96 and the P -value less than 0.05. At the 5% significance level, the P -value rejects the null hypothesis of spatial randomness, indicating that there is a positive spatial autocorrelation in the carbon emissions from China's digital economy. In other words, there is a spatial agglomeration phenomenon in the carbon emissions from the digital economy across provinces in China, meaning that provinces with high carbon emissions from the digital economy tend to be adjacent to each other, and similarly, provinces with low carbon emissions also tend to be adjacent to each other.

TABLE 4 Spatial autocorrelation statistics from 2016 to 2021.

Year	I	E(I)	sd(I)	Z	P-value
2016	0.229	−0.034	0.118	2.229	0.013**
2017	0.222	−0.034	0.118	2.173	0.015**
2018	0.210	−0.034	0.118	2.072	0.019**
2019	0.217	−0.034	0.118	2.125	0.017**
2020	0.211	−0.034	0.118	2.079	0.019**
2021	0.210	−0.034	0.118	2.058	0.020**

***, **, * represent the significance levels of 1

4.4 Regional disparities

The Dagum Gini coefficient can decompose the overall differences of a sample into three parts: Gini within-group component (Gw), Gini between-group component (Gb), and Gini transvariation component (Gt). Dagum Gini overcomes the limitation of traditional Gini coefficients that cannot decompose the contribution of each region to the overall differences, which is a supplement to traditional Gini coefficients.

We use the Dagum Gini coefficient to measure the degree of difference in carbon emissions between the national and regional

TABLE 5 Dagum gini coefficient and contribution rate results.

Year	Dagum gini				Contribution rate (%)		
	Total	Gw	Gb	Gt	Gw	Gb	Gt
2016	0.473	0.113	0.321	0.038	23.900%	67.976%	8.124%
2017	0.465	0.111	0.315	0.038	23.873%	67.855%	8.273%
2018	0.466	0.111	0.318	0.038	23.737%	68.165%	8.098%
2019	0.459	0.105	0.318	0.036	22.884%	69.309%	7.807%
2020	0.462	0.106	0.320	0.036	22.921%	69.275%	7.804%
2021	0.467	0.108	0.324	0.035	23.094%	69.501%	7.405%

***, **, * represent the significance levels of 1%, 5%, and 10%, respectively.

digital economies, and statistically analyze the results from 2016 to 2021 (Table 5).

During the sample period, the overall Gini coefficient in China showed a slight downward trend. Specifically, from 2016 to 2019, the Gini coefficient decreased, indicating that the imbalance in carbon emissions from the digital economy in China was gradually diminishing. However, from 2019 to 2021, there was a slight increase, suggesting that the imbalance among regions intensified during this period. Overall, the Gini coefficient was relatively high during the sample period, which indicates a significant imbalance in regional carbon emissions. This may be related to the lack of coordination in economic development levels, digital infrastructure endowment, and the scale of the digital industry across different regions in China. The decline in the intra-group Gini coefficient suggests that the gap in carbon emission levels within regions has narrowed to some extent. The increase in the inter-group Gini coefficient indicates that the gap in carbon emission levels between regions has slightly widened.

Figure 5 illustrates the sources of differences and the trend of contribution rates in carbon emissions from China's digital economy. During the research period, the inter-regional differences (Gb) contributed the most to the disparities in carbon emissions from the digital economy, followed by intra-regional differences (Gw), with the super variance density (Gt) having the smallest contribution rate. Specifically, the contribution rate of inter-regional differences (Gb) showed an upward trend, increasing from 67.98% in 2016 to 69.50% in 2021, making it the largest contributor to total carbon emissions. In contrast, intra-regional differences (Gw) showed a downward trend during the sample period, decreasing from 23.9% to 23.09%. The super variance density (Gt) also showed a downward trend, dropping from 8.12% to 7.40%, and remained at a relatively low level overall, indicating the presence of extreme carbon emissions in regions with generally low (or high) overall carbon emission levels, and these extreme values are significant. This corresponds to provinces such as Sichuan in the western region and Jiangsu, Guangdong in the eastern region, which have relatively high carbon emissions within their respective areas. Therefore, the analysis of the contribution rates of the Gini coefficient components indicates that regional differences are mainly influenced by inter-regional differences, while the impact of intra-regional differences and super variance density is relatively smaller. The carbon emissions from the digital economy are expected to continue to grow, and it is important to focus on the issue of collaborative emission reduction between regions. It is foreseeable that digitalization will continue to transform people's lives and promote industrial upgrading, and attention should be paid to the growth of carbon emissions from the digital economy across different regions.

5 Triggers

5.1 Selection of indicators

Based on relevant literature and theories, this paper identifies and analyzes six major core factors[6]. Considering the distinctiveness and availability of data, we established a system of independent variables affecting factors (Table 6).

From six aspects: digital user scale, economic development, consumption, digital infrastructure, digital industry scale, and digital investment intensity, a total of 17 indicators are listed, which are summarized into 12 factors. These factors include the sum of mobile internet users and internet broadband users for digital user scale, GDP *per capita*, the proportion of urban population, *per capita* consumption expenditure, mobile internet data usage, online retail sales, number of internet broadband access ports, the proportion of data centers, number of mobile base stations, length of optical cables, digital industry scale (the sum of main business income from electronic information manufacturing, software business income, internet business income, and telecommunications main business income), and digital investment intensity (the total of fixed asset investment in information transmission, computer services, and software industry, as well as the total fixed asset investment in the manufacturing of computers, communication, and other electronic equipment industry) to analyze the influencing factors of carbon emissions in China's digital economy.

5.2 Impact factor detection analysis based on geodetector

5.2.1 Factor detection

Factor detection is used to explore the spatial differentiation of the dependent variable and to identify the extent to which each detected factor explains the spatial differentiation of the dependent variable. The influence of the detected factor is represented by the q-value, which ranges from [0, 1]. The larger the q-value, the stronger the explanatory power of the independent variable on the dependent variable, and *vice versa*. The specific calculation formula is as follows Equation 8:

$$q_k = 1 - \frac{\sum_{h=1}^{L} N_{k,h}\sigma_{k,h}^2}{N\sigma^2} \tag{8}$$

6 The emission transmission pathways of these factors are detailed in Supplementary Appendix SD. The main text will not be elaborated further, due to space limitations.

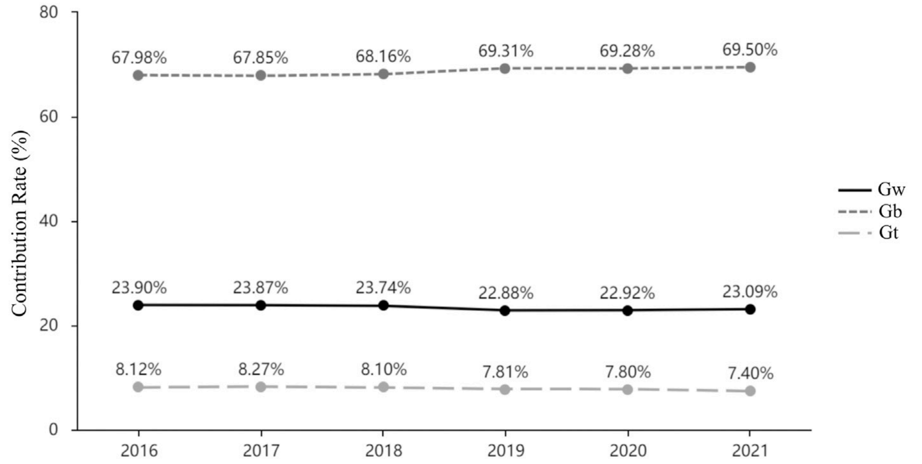

FIGURE 5
Decomposition of Dagum Gini coefficient contribution rate.

TABLE 6 Indicator system of influencing factors for the digital economy.

Primary indicator	Secondary indicator	Variable	Data source
Digital user scale	Secondary indicator	PP	China internet development report
	Mobile internet users (10,000) internet		China statistical yearbook
	Broadband users (10,000 thousand)		
Economic	Per capita GDP (billion yuan)	GDP	China statistical yearbook
Development	Urbanization rate (%)	UR	China statistical yearbook
Consumption	Per capita consumption expenditure (yuan)	PC	China labor statistics yearbook
	Online retail sales (billion yuan)	IS	China statistical yearbook
	Mobile internet data consumption (million GB)	GB	China statistical yearbook
Digital infrastructure	Internet broadband access ports (10,000)	IP	China statistical yearbook
	Mobile base stations (10,000)	BS	China statistical yearbook
	Data center rack total ratio (%)	DC	Application development yearbook
	Optical cable length (10,000 km)	OC	China statistical yearbook
Digital industry scale	Electronic information manufacturing main	DI	China high-tech industry yearbook
	Software business income (10,000 yuan)		China tertiary industry yearbook
	Internet business income (10,000 yuan)		China communication industry statistical annual report
	Telecommunications main business income (10,000 yuan)		China tertiary industry yearbook
Digital investment intensity	Fixed asset investment in information transmission, computer services, and software	ST	China fixed asset investment statistical yearbook
	Industry (10,000 yuan)		
	Industry (10,000 yuan) fixed asset investment in computer, communication,and other electronic equipment manufacturing (10,000 yuan)		

In the formula above, q_k represents the influence of the driving factor k, the larger the value, the greater the impact of the driving factor k on the carbon emissions of the digital economy, with a range of $[0, 1]$; N and $N_{k,h}$ represent the number of provinces involved in the regression and the number of samples of the driving factor k in province h, respectively; σ^2 and $\sigma^2_{k,h}$ are the global variance of carbon

TABLE 7 Univariate detection statistics for 2016 and 2021.

Driving factor	2016		2021	
	q-value	p-value	q-value	p-value
Digital user scale (PP)	0.800	0.003***	0.794	0.003***
GDP per capita (GDP)	0.436	0.033**	0.292	0.294
Urbanization rate (UR)	0.274	0.235	0.336	0.146
Per capita consumption expenditure (PC)	0.348	0.217	0.458	0.041**
Online retail sales (IS)	0.664	0.010***	0.852	0.000***
Mobile internet data usage (GB)	0.856	0.000***	0.746	0.010***
Internet broadband access ports (IP)	0.891	0.000***	0.765	0.009***
Number of mobile base stations (BS)	0.717	0.000***	0.765	0.009***
Data center proportion (DC)	0.443	0.074*	0.658	0.000***
Length of optical cables (OC)	0.540	0.126	0.542	0.012**
Digital industry scale (DI)	0.930	0.000***	0.821	0.000***
Digital investment intensity (ST)	0.486	0.234	0.483	0.252

***, **, * represent the significance levels of 1%, 5%, and 10%, respectively.

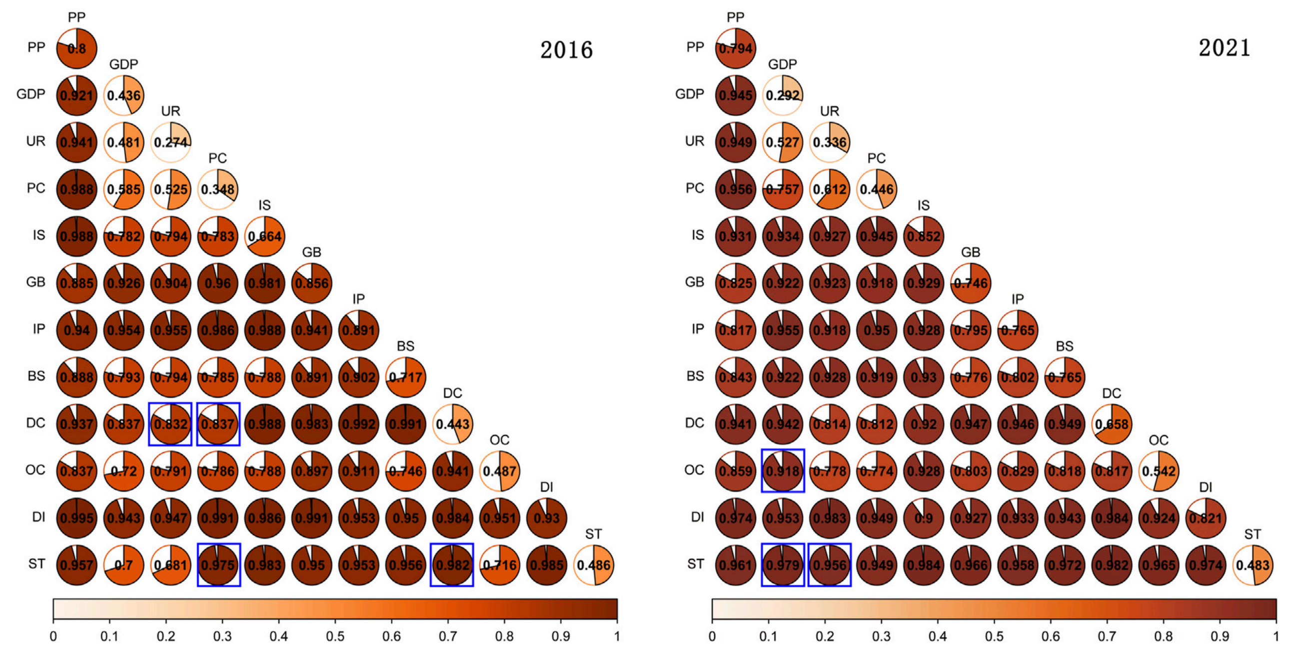

FIGURE 6
Factor interaction detection in 2016 and 2021.

emissions from the digital economy and the variance of carbon emissions from the digital economy in the province *h*, respectively.

The identification results of the impact factors on the spatial differentiation of carbon emissions from the digital economy in 2016 and 2021, as detected by the Geodetector, are shown in the table (Table 7). The P-value results indicate that among the six dimensions of driving factors, most were significant at the 1% level in both 2016 and 2021, with a few factors being significant at the 5% level, and a minority not significant. This suggests that the majority of these factors have a strong explanatory power regarding the spatial differentiation of carbon emissions from the digital economy. To be more specific, firstly, the expansion of the digital industry relies on the development of industries such as digital manufacturing. Then the digital products (digital infrastructure equipment) produced are ultimately invested as part of digital investment in the construction of digital infrastructure and the

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digital manufacturing industry, which in turn promotes the expansion of digital production scale and has a significant impact on carbon emissions in the digital economy. In addition, consumers have more access to digital life, which affected their lifestyle and entertainment, and also led to the increase of digital consumption (online retail sales) and Internet traffic. The increase of digital consumption capacity and mobile Internet traffic requires faster and stronger computing infrastructure and communication infrastructure to support, leading to the construction and high intensity operation of digital infrastructure such as data centers and mobile base stations, and further promoting the increase of carbon emissions of digital infrastructure.

5.2.2 Interaction detection

The core of interaction detection analysis is to assess the nature of the change in the explanatory power of the dependent variable when two factors act in combination, that is, to explore whether this combination enhances or diminishes the explanatory power of the dependent variable, or whether they maintain their independent effects. Interaction detection compares the explanatory power (q-value) of the new variable generated by the combination of two factors with the q-values of the explanatory power of each factor alone.

Factor interaction detection assesses the explanatory power of the dependent variable after the interaction of different influencing factors, reflecting the impact of multi-factor interactions on carbon emissions from the digital economy (Figure 6). Among the 66 types of interactions formed by the detection of interactions between 12 influencing factors in 2016, 62 were of the dual-factor enhancement type (orange circles), accounting for 94% of all types; 4 were of the non-linear enhancement type (blue-outlined), accounting for 4% of all types. In 2021, among the 66 types of interactions formed by the detection of interactions, 63 were of the dual-factor enhancement type (orange circles), accounting for 98% of all types; 3 were of the non-linear enhancement type (blue-outlined), accounting for 2% of all types.

Specifically, in 2016, among the dual-factor enhancement states, there were 14 pairs with a q-value influence above 0.98, with the highest being PP∩DI, reaching an influence of 0.995 (the combination still reached 0.974 in 2021). The interaction between the digital user scale (PP) and the digital industry scale (DI) is extremely strong, indicating that the coordinated expansion of both the supply and demand sides has a significant amplifying effect on the emissions of digital economy. On the one hand, the expansion of user scale stimulates the demand for digital products and services, promoting the expansion of the digital industry, especially in high-energy-consuming sectors such as hardware manufacturing and data center construction. On the other hand, the development of the digital industry (such as 5G, cloud computing, and e-commerce platforms) lowers the threshold for users to access and use digital services, further attracting more users and forming a feedback cycle.

In 2021, among the dual-factor enhancement types, there were 18 pairs with a q-value influence above 0.95, with the highest being DC∩DI, reaching an influence of 0.984, which indicates the core hub role of data centers is becoming increasingly prominent. To be more specific, the growth of digital industries (such as artificial intelligence and big data) highly relies on the computing power support of data centers, and their energy consumption and carbon emissions increase sharply as the business volume grows. Based on 4.2, the interaction also reflects the energy structure issues brought about by the regional concentration of digital industrialization: Data centers are mostly located in the eastern regions with high energy consumption, and they rely on fossil fuel electricity, which amplifies their carbon footprint. This result is consistent with “Energy Return Deterioration” theory, that is, the infrastructure investment made in the early stage of digital economic development may lock into a high-carbon path for a long time.

Overall, the q-values on the diagonal are all less than the q-values of the two factors interacting in their respective rows or columns both in 2016 and 2021, which means that the interactive effect of each factor is greater than the explanatory power of a single factor on emissions. This indicates that the spatial differentiation of carbon emissions from China’s digital economy is the result of the combined effects of multiple aspects.

6 Conclusion

6.1 Main findings

This paper focuses on the carbon emissions from the digital economy, combining bottom-up and top-down approaches to estimate the carbon emissions from China’s provincial digital economy from 2016 to 2021. Firstly, it utilizes ArcGIS spatial analysis and spatial autocorrelation methods to analyze the spatial differentiation and spatial agglomeration characteristics of carbon emissions from China’s digital economy. Secondly, we explore the spatial agglomeration and disparities of the emissions by Moran’s I and Dagum Gini coefficient. Finally, we analyze the triggers of the spatial differentiation by Geodetector model. The main conclusions are as follows:

1. The carbon emissions from Chinese digital economy show a rapidly increasing trend, with the total carbon emissions growing from 25.29 million tons in 2016 to 40.41 million tons in 2021, a growth rate of 59.8%, and an average annual growth rate of 8.36%.
2. The carbon emissions from Chinese digital economy are not randomly distributed. Instead, they show a significant pattern of spatial positive correlation and agglomeration. The overall distribution pattern shows more in the east and less in the west, mainly concentrated along the eastern coastal axis and the Yangtze River Economic Belt, and this pattern exhibits a certain stability.
3. There is significant regional disparity in carbon emissions, mainly attributed to inter-regional differences, and the contribution rate of these differences is continuously increasing. And the variations in the east and west are always greater than those in the central and northeastern regions.
4. Multiple factors drive the spatial differentiation of carbon emissions from the digital economy. From them we extract six primary indicators - digital users scale, economic development, consumption, digital infrastructure, scale of

the digital industry, and the intensity of digital investment all have a significant impact on the spatial differentiation. What's more, the interactive effects of these factors perform greater explanatory power, indicating that the spatial differentiation of emissions is the result of the combined effects of multiple aspects.

6.2 Policy recommendations

Based on our findings, the carbon emissions from Chinese digital economy face severe challenges. The emission structure embodies both regional differences and common characteristics. It is necessary to understand the characteristics and future trends of emissions in different regions, and then make concerted efforts. Only in this way can we promote the low-carbon development of Chinese digital economy.

6.2.1 Establish low-carbon orientation for digital infrastructure

i. Improve the level of inter-regional computing power dispatch. For the eastern regions, the large user base and strong application demands expand the growth space for computing power. And for the western regions, it is necessary to fully leverage resource advantages, improving the quality and utilization efficiency of computing power, and non-real-time computing power (such as back-end processing, off-line analysis, and storage backup). The collaborative operation system of Southern Power Grid[7] is an excellent example of this, which realizes the linkage and scheduling of provincial power, computing power, and carbon emissions. The system is expected to reduce the comprehensive operating costs of the computing power network by over 10% annually.
ii. Guide the rational layout of data centers. Induce the non-real-time computing power to the regions rich in renewable energy, with ample space and suitable climate. Establish data centers in special geographical areas conducive to energy saving and emission reduction, such as caves, mountain passes, and along rivers and lakes, to fully utilize natural cold sources. For example, Guizhou Province, based on its energy advantages, is rapidly promoting data center industry. At present, Guizhou has 49 vital data centers, making it one of the regions with the strongest intelligent computing capabilities and the most concentrated intelligent computing resources in China.
iii. Accelerate the energy-saving and carbon reduction transformation of digital infrastructure. Standards should be established to encourage enterprises and institutions to use clean energy in digital infrastructure and operations, leveraging the clean alternative role of renewable energy sources such as wind, solar, tidal, and biomass energy. China is making great efforts to develop green energy saving technologies and transplant them to the communication industry and Internet infrastructure, such as the application of photovoltaic power generation technology by mainstream mobile operators.

6.2.2 Promote greening collaborations of digital manufacturing industry

i. Establish a green manufacturing system. Support enterprises in implementing green manufacturing technology transformations. Promote the application of intelligent manufacturing technologies, like Internet of Things, big data and artificial intelligence.
ii. Build a green supply chain management system. Promote the full life cycle green development of the digital manufacturing phase. Prioritize low-carbon, environmentally friendly technologies and materials in product design and manufacturing stages. The ESG platform built by Lenovo, say, has achieved full lifecycle carbon management of products, reducing its carbon footprints considerably[8].

6.2.3 Strengthen the research and innovation of low-carbon technologies

i. Create a set of low-carbon technology standards and regulations. Strengthen the cooperation among government departments, industry associations, leading enterprises, research institutes, and high-end think tanks and improve standards for energy-saving certification. China's low-carbon technology standards started relatively late and are still gradually being revised and improved. Still by 2025, China has established national standards such as "Evaluation of Green Data Centers" (GB/T 44989-2024) and "Energy Efficiency Limits and Grades for Data Centers" (GB40879-2021), providing detailed specifications for green technology innovation and construction.
ii. Support the low-carbon technologies. Focus on key low-carbon technologies like wind power, solar power generation and low-carbon power grid. Cultivate laboratories and technology

7 The system links Guizhou, Guangdong and Jiangsu with electricity and emission. In the August 2025 test, the system successfully transferred approximately 500 kWh of intelligent computing tasks from Guangzhou, where electricity costs are higher, to Guizhou, where electricity prices are lower, and from peak to off peak periods, resulting in a 36% reduction in overall electricity costs.

8 The ESG platform has achieved green management throughout the entire product lifecycle: in the product design phase, the platform supports the management of harmful substances to reduce environmental compliance risks; in the production stage, combining AI with artificial intelligence can save 60% of data acquisition and modeling costs, and reduce product carbon footprint/environmental footprint certification costs by 40%; in the logistics stage, support carbon emission data management and carbon emission simulation for different transportation modes, reducing 200 h of manual labor per year and improving work efficiency by 10%; in supplier management stage, the business coverage has expanded from Tier 1 suppliers to key Tier 2/3 suppliers, resulting in a 50% increase in data processing efficiency.

innovation centers. At the same time, protect of intellectual property rights for low-carbon technologies, establish a testing, evaluation, and certification system for low-carbon technologies and products.

6.3 Discussions

i. The emission calculation boundary system still needs to be supplemented. As an emerging economic form, the connotation of the digital economy is still rapidly expanding. Therefore, future research should combine updated industry census data and relevant carbon emission theories to further improve the calculation system.
ii. The theoretical analysis of the influencing factors of carbon emissions still needs to be deepened. This paper analyzes the factors affecting carbon emissions in the digital economy from six dimensions, which is still a relatively macro path. So in the future, it is necessary to analyze the mechanism of carbon emissions in the digital economy from more perspectives.
iii. Due to data limitations[9], this paper failed to consider the spatial spillover effects of emissions. If we can obtain county-level digital economy variables (or longer spans) in the future, we will use methods such as Geographically Weighted Regression (GWR) and Spatial Durbin Model (SDM) for empirical testing to obtain more realistic conclusions.
iv. Future research on carbon emissions from the digital economy can deepen forward-looking thinking on the impact mechanism and management system on the basis of exploring the "dual roles" of emerging technologies such as artificial intelligence. For example, accurately quantify the "net carbon effect" of AI. Besides, the research perspective needs to move from macro to micro. More attention should be paid to the specific mechanism at the enterprise level, such as how AI promotes low-carbon transformation by promoting green innovation and alleviating financing constraints, and reveals the possible "carbon rebound effect".

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

YX: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. KJ: Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review and editing. CR: Software, Validation, Visualization, Writing – review and editing. LJ: Investigation, Writing – review and editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was funded by National Social Science Foundation of China, grant number 22BJY139.

Acknowledgements

During the preparation of this manuscript, the authors used ArcGIS 10.2 for the purposes of visualizing the spatial distribution of the emissions from 30 provinces and cities in China from 2016 to 2021. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2025.1659608/full#supplementary-material

9 As for the variables of digital economy, our database is relatively crude. We are using data from 34 provincial-level administrative regions in China. If we use spatial econometric models such as the spatial Durbin model, it will result in a rough definition of "neighbors" and reduce the effectiveness of statistical testing.

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