SPATIOTEMPORAL EVOLUTION OF THE COUPLED AND COORDINATED DEVELOPMENT BETWEEN DIGITAL ECONOMY AND CARBON EMISSION GOVERNANCE CAPABILITY: EVIDENCE FROM 30 PROVINCES OF CHINA

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Abstract. Existing research predominantly focuses on the impact of the digital economy on carbon emissions; however, there is a distinct lack of studies exploring the relationship between the digital economy and carbon emission governance capability, especially in terms of their coupled and coordinated development levels, which are crucial for sustainable economic and environmental development. This study addresses this gap by innovatively optimizing the traditional entropy weight method and coupling coordination degree model, alongside spatial analysis techniques and dynamic models, to analyze the spatiotemporal evolution patterns, development trends, and regional disparities of this relationship across China from 2015 to 2022. The empirical results show the following: (1) significant progress has been made in the coupled and coordinated development of these two systems in China, currently at an intermediate coordination level; (2) The imbalance in regional coordinated development has intensified, with the eastern coastal areas demonstrating high-high clustering, while most of the central and western regions display low-low clustering; (3) high-level states of coupled and coordinated development have high stability and sustainability, while low-level states have considerable potential for improvement. These findings underscore the importance of tailored regional policies and technological innovations in promoting synergistic development between the digital economy and effective carbon management strategies. By enhancing the theoretical framework for assessing coupled and coordinated development and employing a comprehensive suite of analytical tools, this research offers strategic insights for achieving balanced economic growth and environmental sustainability, applicable to both China and other regions globally facing similar challenges.
Keywords: *sustainable development, regional disparities, spatial analysis, coupling coordination degree, carbon emission*

Introduction

In recent years, the environmental and economic challenges posed by greenhouse gas emissions, such as carbon dioxide, have become increasingly severe. Although the digital economy, through technologies like the internet, big data, and artificial intelligence, has enhanced resource efficiency and productivity, it has also led to increased energy consumption and carbon emissions (Wang et al., 2023a). This dual-edged sword effect has sparked in-depth academic research into the relationship of the digital economy and carbon emission governance capability. According to statistics, China’s carbon emissions in 2022 increased by 5.3% year-on-year, accounting for 30.9% of the world’s total carbon emissions (Ma et al., 2021). This indicates that China’s long-standing high-carbon dependency still has significant inertia, creating immense pressure to balance economic growth with the goals of achieving “carbon peaking” and “carbon neutrality.” As global climate change intensifies and environmental awareness rises, carbon emission issues have become a focal point of global attention. As the largest developing country and the largest emitter of carbon dioxide, China faces substantial pressure to reduce emissions (Azam et al., 2022). To achieve sustainable development, the Chinese government has set goals for carbon peaking and carbon neutrality, actively promoting economic restructuring and green development (Hongchun et al., 2023). Against this backdrop, studying the coupled and coordinated development between digital economy and carbon emission governance capability, and understanding its role and potential risks in carbon reduction, is of great theoretical and practical significance.

The rapid development of the digital economy has not only revolutionized traditional production and consumption patterns but also had profound impacts on energy use and carbon emissions. On one hand, the application of digital technologies can optimize resource allocation and improve energy efficiency, thus reducing carbon emissions (Liu et al., 2023a). On the other hand, the expansion of the digital economy may create new energy demands, leading to increased carbon emissions (Li et al., 2021c). Therefore, in-depth research into the dynamic relationship of the digital economy and carbon emission governance capability, revealing its evolution across different times and spaces, is crucial for promoting green and low-carbon development. This study aims to establish a coordination model between the digital economy and carbon emission governance capability to analyze the impact of China’s digital economy development on carbon emissions, exploring its mechanisms and policy implications. Specifically, the study seeks to answer the following key questions: Is there a significant dynamic coupling relationship between the digital economy and carbon emission governance capability? Are there significant regional differences in their coordinated development levels? Does this level of coordinated development exhibit spatial effects? What are the long-term and short-term evolution patterns of their coordinated development?

To address these questions, this study will combine quantitative and qualitative analyses to empirically reveal the coupling effect between China’s digital economy and carbon emissions. This paper offers three main contributions over existing research: (1) Optimization of Models: It refines the traditional entropy weight model and CCD model, significantly boosting computational efficiency and interpretability. This enhancement addresses distortions caused by extreme data, leading to improved model accuracy and robustness; (2) Application of Advanced Algorithms: The paper utilizes unsupervised learning algorithms and spatial analysis models to examine the spatiotemporal evolution characteristics of coupled and coordinated development. This approach provides both theoretical and practical insights for enhancing the level of such development; (3) Policy Recommendations: by integrating theoretical analysis with empirical research, the paper suggests policy innovations to foster coupled and coordinated development. These recommendations offer practical pathways for achieving the dual objectives of economic growth and environmental protection.

The rest of this paper is organized as follows: The second section reviews relevant literature. The third section constructs the indicator evaluation system for digital economy and carbon emission governance capability. The fourth section outlines the model and methodology used. The fifth section presents the empirical analysis and discusses the findings. The sixth section concludes the study with policy recommendations.

Literature reviews

The impact of the digital economy on carbon emissions

With the digital transformation of the global economy, digital economy emerged as a key driver of economic growth. In recent years, scholars have explored the impact of the digital economy on carbon emissions from three main perspectives: mechanisms of influence, emission reduction effects, and regional differences.

Impact mechanisms

Digital economy affects carbon emissions through various pathways. First, the development of the digital economy promotes technological innovation and industrial upgrading, thereby reducing carbon emissions. For instance, Zhu et al. (2022) found that China’s digital economy played a crucial role in curbing carbon emissions mainly through innovation and industrial upgrading. Additionally, Cheng and Qu (2023) pointed out that the impact of digital economy on carbon emissions exhibits dynamic effects, showing an inverted U-shaped trend: it may increase carbon emissions at the early stages but will reduce them as it further develops. The digital economy also influences carbon emissions by optimizing the energy structure and reducing energy consumption. Research by Lyu et al. (2023a) demonstrated that the digital economy significantly curbs carbon emissions by lowering energy consumption and improving carbon emission efficiency. Moreover, Sun and Chen (2023) found that the development of the digital economy mainly reduces carbon emissions by driving energy structure transformation, with its impact following an inverted U-shaped relationship. This mechanism was also validated in the study by Li and Wang (2022), which discovered a U-shaped correlation between the digital economy and carbon emissions in China’s logistics industry. Furthermore, the digital economy enhances carbon emission efficiency by mitigating factor mismatches and promoting low-carbon and green transitions (Ge et al., 2022).

Internationally, similar impact mechanisms have been validated. Mei et al. (2023), analyzing data from 100 countries, found that the growth of the digital economy significantly curbs carbon emissions, primarily by enhancing energy efficiency and optimizing energy structures. Research by Li et al. (2021b), which examined global panel data from 190 countries, revealed an inverted U-shaped relationship between the digital economy and CO_2 emissions: during the early stages of digital economic development, emissions may increase, but after reaching a certain threshold, emissions begin to decrease. Additionally, the analysis by Wang et al. (2022a) of 94 countries indicates that nations actively advancing digital technologies and digital trade are more likely to achieve carbon emission reductions.

Emission reduction effects

Scholars have found that the impact of the digital economy on carbon reduction mainly manifests in lowering total carbon emissions and reducing carbon emission intensity. Research shows that for every unit increase in the digital economy, carbon

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emissions decrease by 0.417 units, with this effect being particularly pronounced in less developed regions of China (Tian et al., 2024). Chen et al. (2023) analyzed data from 30 provinces in China from 2011 to 2021 and discovered that a 1% growth in the digital economy results in approximately a 1.09% decrease in total carbon emissions. Additionally, the digital economy significantly improves China's carbon emission efficiency, thus reducing the carbon intensity per unit of GDP (Zhao et al., 2023). This positive effect of the digital economy on carbon reduction is evident not only in China but also in other countries. For instance, studies by Li et al. (2024) and Chen and Jiang (2023) on 46 countries and the G20 nations found that digital trade substantially reduces overall carbon emissions. Research by Ahmed and Le (2021) on the ASEAN-6 countries revealed that information and communication technology (ICT) within the digital economy significantly lowers carbon emission intensity. However, this effect varies according to a country's economic development level: high-income countries experience particularly strong reductions, while some low-income countries see limited reductions due to weaker technological foundations (Bruckner et al., 2022).

Regional differences

The digital economy can alleviate carbon emissions both locally and in neighboring areas (Nan and Luo, 2023). Therefore, the impact of the digital economy on carbon emissions shows significant heterogeneity across different regions (Zou and Zou, 2023). Through technology diffusion and information sharing, the digital economy creates spatial spillover effects, which not only reduce local carbon emissions but also positively influence neighboring regions (Shen et al., 2024). In more developed areas, the digital economy has a stronger suppressive effect on carbon emissions, while in less developed areas, despite a smaller digital economy scale, its impact on emissions remains notable (Lyu et al., 2023b). At the urban level, the digital economy also contributes to emissions reduction, especially in resource-based cities (Zhang et al., 2022), where it helps optimize resource allocation and promotes industrial transformation, effectively lowering carbon emission intensity (Zha et al., 2022). Additionally, research also indicates that the long-term development of digital technology has a significant suppressive effect on regional carbon emissions, while the short-term impact is relatively weaker (Zhang et al., 2023).

Traditional coupling coordination degree (CCD) model

The method of calculating the CCD is pivotal for understanding how the digital economy coordinated with carbon emission governance capability. This comprehensive metric evaluates the structural and functional interactions, dependencies, and coordinated development among multiple systems (Li et al., 2021a). Originating from systems science and synergy theory, the CCD concept examines the dynamic relationships and mutual influences between systems, particularly their coordination during development (Li et al., 2020). By studying CCD, researchers can identify discordant factors between systems and implement corrective measures to promote synergistic growth and long-term sustainability. Scholars often use traditional entropy weight methods and coupling coordination models in their analyses. For example, Wang et al. (2023b) used traditional models to assess the coordination between resilience and efficiency in the digital economy. Tomal (2021) used the traditional entropy weight model and the CCD model to evaluate the coordination of development among local governments in Poland.

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Despite their widespread use, traditional measurement models have significant limitations. Primarily, the traditional entropy weight method can struggle to capture the complex dynamic changes in time series data in certain scenarios (Flood and Grimm, 2021), particularly lacking sensitivity to the temporal evolution of data in decision-making or evaluation processes (Zhu et al., 2020). The traditional formula assumes that data from all time points are equally important, failing to consider the dynamic changes in time series. This oversight can lead to assessment results that do not accurately reflect the temporal dynamics of the system. Since economic data is inherently time-related, ignoring this factor can distort evaluation outcomes. The traditional formula of entropy value is as followed:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}) \quad \text{(Eq.1)}$$

where, $p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$, $k = \frac{1}{\ln m}$. p_{ij} is the proportion of the *i-th* sample within the *j-th* indicator. k is a normalization constant used to ensure that the entropy calculation remains within a certain range. m is the total number of samples.

Secondly, traditional CCD models encounter validity issues in calculating the CCD. Although CCD theoretically ranges from 0 to 1, its distribution is not uniform and often clusters near 1, undermining the accuracy of assessments (Shen et al., 2018). This tendency to cluster can lead to misleading conclusions about the level of coordination between systems. The traditional formula for calculating the CCD is:

$$\mathrm{C}=\left[\frac{\prod_{i=1}^{n} U_i}{\frac{1}{n}\sum_{i=1}^{n} U_i}\right]^{\frac{1}{n}} \quad \text{(Eq.2)}$$

where n represents the number of subsystems and U_i indicates the value of each subsystem, the formula shows that as subsystem values rise, the C gets closer to 1. This could potentially overstate the CCD if the subsystem performances are not consistently high, leading to skewed assessments. To tackle these issues, Wang et al. (2021) built upon earlier research by introducing a revised CCD model to boost computational validity. Although this improved the model’s validity, its computational efficiency remains moderate, especially during significant social and environmental changes, where it lacks numerical stability and robustness. This highlights the necessity for further refinement in model design to address the complexities of calculations and the range of real-world scenarios, ensuring both theoretical soundness and operational stability in diverse environmental conditions.

Knowledge gaps

In summary, although the academic community generally recognizes the importance of the digital economy in relation to carbon emissions governance capability, research on their coupled and coordinated development is relatively scarce. When calculating the

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CCD between systems, only a few scholars have applied the Wang's modified CCD model. However, Wang's modified model faces several challenges. Firstly, before assessing the CCD, it is necessary to calculate the index for each system. Most scholars still rely on the traditional entropy weight method, which does not fully account for the impact of the time variable on economic data, potentially leading to inaccurate reflections of the system's temporal dynamics. Secondly, although Wang's model has shown improvements in effectiveness, its computational efficiency remains limited. Particularly, during significant social and environmental fluctuations, its numerical stability and robustness are suboptimal. Moreover, there is a lack of in-depth research on the coupled and coordinated development of the digital economy and carbon emissions governance capability across different temporal and spatial dimensions, including their evolutionary characteristics, regional differences, and developmental stages.

This underscores the necessity for future research to develop more advanced models. These models should not only enhance computational efficiency and robustness but also integrate time series analysis to better capture and explain the dynamic interactions between the digital economy and carbon emissions within various environmental and temporal frameworks.

Materials and methods

Construction of indicators system

The primary data of *Table 1* and *Table 2* are sourced from the CSMAR database, the China Statistical Yearbook (2015 to 2022), the China Energy Statistical Yearbook (2015 to 2022), the China Industrial Yearbook (2015 to 2022), the China Environmental Statistical Yearbook (2015 to 2022), and the statistical yearbooks of various provinces from 2015 to 2022. Due to data availability, the sample includes 30 provincial-level administrative regions in China, excluding Tibet, Hong Kong, Macau, and Taiwan. In China, the eastern region includes the provinces and municipalities of Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, Liaoning, Jilin, and Heilongjiang. The central region comprises Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region consists of Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

This study adopts a rigorous and comprehensive approach to explore the coupling and coordinated effects between the digital economy and carbon emission governance capability Drawing on the research frameworks of Su et al. (2023), Wang (2023), Liu et al. (2023b), and the Digital Economy Research Module of CSMAR database, a complete indicator system was established. Specifically, this study selects 32 indicators across three core dimensions: digital industrialization, industry digitization, and innovation foundation, to assess the development level of the digital economy, as shown in *Table 1*. Digital industrialization (Xu and Xu, 2023), as the fundamental component of the digital economy, primarily reflects the widespread application of information technology in production and service sectors, as well as the growth potential of the digital industry itself. Industry digitization (Matt et al., 2023) focuses on how traditional sectors leverage digital technologies for transformation and upgrading, achieving efficiency gains and optimized resource allocation. Innovation foundation emphasizes the driving force and sustainability of digital economic development, reflecting a country's or region's foundational capability in technological innovation, R&D investment, and innovation ecosystem (Mohamed Abdel Razek Youssef, 2022).

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Table 1. *Evaluation index system of the digital economy*

Subsystem	Criterion layer	Indicator layer	Index attribute
Digital economy development (U_1)	Digital industrialization	Penetration rate of fixed-line telephones X1	+
		Penetration rate of Mobile phones X2	+
		Total telecommunications services revenue X3	+
		Number of SMS messages X4	+
		Number of Mobile phone users X5	+
		Number of cellular Base Stations X6	+
		Length of fiber optic cable line X7	+
		Number of personal computers per 100 people X8	+
		Number of websites per 100 companies X9	+
		Number of internet users X10	+
		Number of internet broadband access port X11	+
		Number of Mobile internet users X12	+
		Number of Mobile internet traffic X13	+
		Number of users with Internet broadband access X14	+
		Software service revenue X15	+
		Software product revenue X16	+
		Service revenue from information technology X17	+
		Software export revenue X18	+
	Industrial digitalization	Total assets X19	+
		Operating revenue X20	+
		Total income X21	+
		the coverage breadth of digital finance X22	+
		the usage depth of digital finance X23	+
		Digitalization degree of digital finance X24	+
		online mobile payment level X25	+
	Foundation of technological innovation	R&D personnel FTE X26	+
		R&D expenditure X27	+
		expenditure of new product development X28	+
		number of patent applications granted X29	+
		number of new product development projects X30	+
		sales revenue of new product X31	+
		export revenue of new product X32	+

The assessment of carbon emission governance capability reflects the overall performance of a country or region in addressing climate change, reducing greenhouse gas emissions, and promoting a low-carbon economy (Ronaghi et al., 2020; Wang et al., 2022b). This capability encompasses not only technological and policy measures but also involves institutional development, public awareness, economic structure optimization, and international cooperation. Therefore, this paper draws on the research findings of scholars such as Fan et al. (2019), Dong et al. (2021), and He et al. (2021), constructing an evaluation index system for carbon emission governance capability from four dimensions: economic, social, technological, and environmental, as detailed in *Table 2*.

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Table 2. *Evaluation index system of the carbon emission governance capability*

Subsystem	Criterion layer	Indicator layer	Index attribute
Carbon emission governance capability (U2)	Economic	Energy Intensity of GDP X1	-
		Degree of Energy Structure Optimization X2	-
	Social	Number of Relevant Policies X3	+
		Frequency of Media Reports X4	+
	Technological	Public Transportation Usage Rate X5	+
		Level of Low-Carbon Technology Application X6	+
		Number of Green Invention Patents X7	+
		Number of Green Utility Model Patents X8	+
		Intensity of R&D Expenditure X9	+
	Environmental	R&D Investment/GDP X10	+
		Total Carbon Emissions/GDP X11	-
		Per Capita Carbon Emissions X12	-
		Carbon Productivity X13	-
		Carbon Dioxide Emission Intensity X14	-

Research methods

Optimized entropy weight method (EWM)

To calculate the coupled and coordinated development levels of the digital economy and carbon emission governance capability, this study optimizes the traditional entropy method. This paper introduces a temporal weighting factor, w_θ, to assign greater weight to recent data, enhancing the model's sensitivity to temporal changes and improving its accuracy for time series analysis. The specific calculation process is detailed as follows:

(1) Data standardization:

$$\text{Positive indicators: } x_{ij}^{*} = \frac{x_{ij} - min_j x_{ij}}{max_j x_{ij} - min_j x_{ij}} \tag{Eq.3}$$

$$\text{Negative indicators: } x_{ij}^{*} = \frac{max_j x_{ij} - x_{ij}}{max_j x_{ij} - min_j x_{ij}} \tag{Eq.4}$$

(2) Calculate the standardized probability distribution:

$$p_{ij} = \frac{x_{ij}^{*}}{\sum_{i=1}^{m} x_{ij}^{*}} \tag{Eq.5}$$

(3) Calculate the entropy value of each indicator, incorporating the time variable:

$$e_j(adjusted) = -\frac{1}{\ln(m \times T)} \cdot \sum_{\theta} w_\theta \sum_{i} \frac{x'_{\theta ij}}{\sum_{\theta} w_\theta \sum_{i} x'_{\theta ij}} \ln\left(\frac{x'_{\theta ij}}{\sum_{\theta} w_\theta \sum_{i} x'_{\theta ij}}\right) \tag{Eq.6}$$

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where w_ϑ is the time-weighting factor. m is the number of samples (or individual observations) within each time period. The term $m \times T$ in the formula represents the total sample space, encompassing all time periods and samples in the entropy calculation.

(4) Calculate the weights of each evaluation indicator:

$$w_j = \frac{1-e_j}{n-\sum_{j=1}^{n} e_j} \tag{Eq.7}$$

(5) Calculate the comprehensive index:

$$U_i = \sum_{j=1}^{n} w_j \times \left(\sum_{t=1}^{T} x_{ij}{}^{*} \right) \tag{Eq.8}$$

Optimized CCD model

Building on Wang’s research, this paper optimizes the CCD model. The newly optimized CCD model (OCCD) is detailed as follows:

$$C_{\text{optimized}} = \sqrt{\left[1 - \frac{\sum_{i>j}^{n} |U_i - U_j|}{\frac{n(n-1)}{2}} \right] \times \frac{\max_{k=1}^{n} U_k}{\max_{k=1}^{n} U_k + \left(\prod_{i=1}^{n} U_i \right)^{1/n}}} \tag{Eq.9}$$

$$T = \sum_{i=1}^{n} \alpha_i \times U_i, \sum_{i=1}^{n} \alpha_i = 1 \tag{Eq.10}$$

$$D_{optimized} = \sqrt{C_{optimized} \times T} \tag{Eq.11}$$

In the formula, U represents the development index, C denotes the degree of coupling, D signifies the degree of coordination, and T is the composite evaluation index. With n set to 2 and α at 0.5, reflecting equal importance of both domains, the optimized model improves precision, structural integrity, and clarity.

Compared to the Wang model, the optimized coupling model offers the following advantages: (1) By incorporating max U_i and $\prod_{i=1}^{n} U_i$, it reduces the impact of individual minimal values on the overall result, enhancing the model’s robustness to outliers. Additionally, the use of geometric mean smooths data fluctuations, making the model less sensitive to minor variations and improving result stability; (2) the optimized model simplifies the calculation process, relying only on the geometric mean and basic algebraic operations, thereby reducing computational complexity; (3) the optimized model has clear physical significance, broad applicability, and high computational efficiency, making it convenient for practical use.

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Dagum Gini coefficient

This study utilizes the Dagum Gini coefficient decomposition method (Huang et al., 2022) to analyze the spatial differences and sources of coupling coordination between the digital economy and carbon emission governance capability. The calculation and decomposition process of the Dagum Gini coefficient are as follows:

$$G = \frac{1}{2n^2\bar{D}} \sum_{j=1}^{k}\sum_{h=1}\sum_{i=1}^{n_j}\sum_{r=1}\sum_{i=1}^{n_h} |D_{ji} - D_{hr}| \quad \text{(Eq.12)}$$

G represents the overall Gini coefficient. k is the number of regions. n is the total number of samples across all regions. n_j is the number of samples in the *j-th* region. D_{ji} is the value of the *i-th* sample in the *j-th* region. D_{hr} is the value of the *r-th* sample in the *h-th* region.

$$G_{jj} = \frac{1}{2n_j^2\bar{D}_j^i = 1} \sum_{r=1}^{n_j} |D_{ji} - D_{hr}| \quad \text{(Eq.13)}$$

where, G_{jj} denotes the intra-regional Gini coefficient.

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h} |D_{ji} - D_{hr}|}{n_j n_h (\bar{D}_j + \bar{D}_h)} \quad \text{(Eq.14)}$$

where, G_{jh} stands for the inter-regional Gini coefficient.

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j \quad \text{(Eq.15)}$$

where, G_w indicates the contribution of the intra-regional Gini coefficient.

$$G_b = \sum_{j=2}^{k}\sum_{h=1}\sum_{j=1}^{j-1} G_{jh}(p_j s_h + p_h s_j) \quad \text{(Eq.16)}$$

G_b signifies the contribution of the inter-regional Gini coefficient. p_j and s_j are the weighting factors for the *j-th* region, used to weight both the within-group and between-group Gini coefficients.

$$G = G_w + G_b \quad \text{(Eq.17)}$$

Moran's I index

This study utilizes Moran's I index (Chen, 2013) to investigate the spatial correlation features and the dynamics of spatial clustering in relation to the coordinated and coupled development between the digital economy and carbon emission governance capacity.

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$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad \text{(Eq.18)}$$

where, n is the total number of provinces. w_{ij} is the spatial weight between regions i and j, which indicates the spatial relationship between these regions.

Kernel density estimation (KDE)

Kernel Density Estimation (KDE) is an advanced, non-parametric method for estimating probability density functions (Chen, 2017). Through KDE, the distribution characteristics of the coupling and coordination degree between digital economy indicators and carbon emission governance capability can be intuitively observed.

$$\hat{f}_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h\left(x - x_i\right) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \quad \text{(Eq.19)}$$

In the formula, $f(x)$ the probability density function. n is the total number of provinces. h is the bandwidth, which is the smoothing parameter of the curve. $K(x)$ is the basic form of the Gaussian kernel function.

Spatial Markov chain analysis

This research employs spatial Markov chain analysis to investigate the dynamics and evolution of coupled and coordinated development (Liu and Wu, 2023). By integrating conventional Markov chain analysis with spatial correlation, this method allows for the examination of how spatial influences impact state transitions.

$$P(X_{t+1} = j \mid X_t = i, N_t = k) = p_{ij|k} \quad \text{(Eq.20)}$$

In the formula, X_{t+1} is the state of the system at the next time step, and $t + 1$ is the future state the system is transitioning to. Nt is the spatial neighborhood condition at time t, which influences the transition probabilities. $P_{ij|k}$ is the transition probability.

Research results

Results of coupling coordination degree (CCD)

Based on optimized EWM and CCD model (*Eqs. 3–11*), this study calculated the CCD between the digital economy and carbon emission governance capability for 30 provinces in China from 2015 to 2022. *Table 3* categorizes the CCD levels. As shown in *Figure 1*, the coordination level between the digital economy and carbon emission governance capacity across China's provinces has been steadily improving year by year, now reaching a primary coordination state. However, there are still significant regional differences. Over time, the CCD values in the eastern regions have shown a faster growth trend. Benefiting from strong economic foundations and robust technological innovation capacities, these regions maintain consistently higher levels of coupling and

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coordination. In contrast, the western regions, constrained by geographic and economic conditions, exhibit relatively slower growth in CCD values and lower levels of coordination.

Tabe 3. *Classification of CCD*

CCD value	State level	CCD value	State level
(0.0, 0.2]	Serious disorders	(0.4, 0.6]	Primary coordination
(0.2, 0.3]	Slight disorders	(0.6, 0.8]	Intermediate coordination
(0.3, 0.4]	Barely coordination	(0.8, 0.10]	Senior coordination

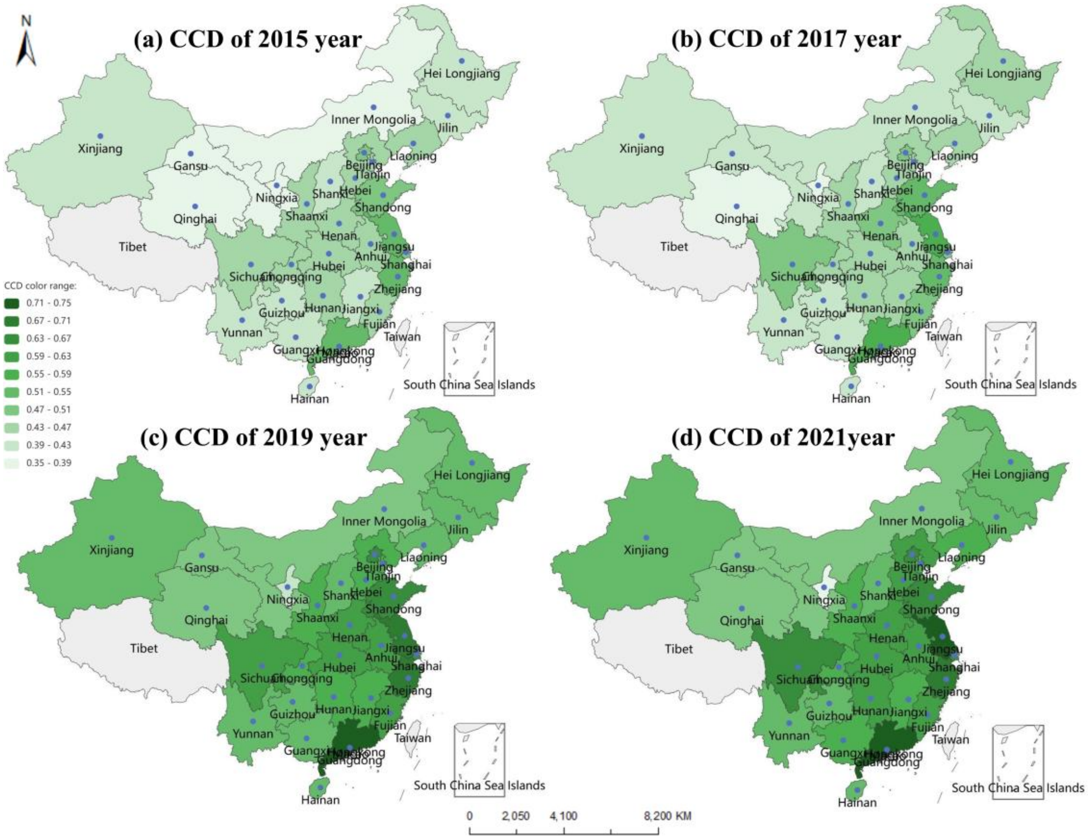

Figure 1. *Temporal and spatial distribution of CCD values of 2015, 2017, 2019, 2021*

Figure 2 illustrates that the mean and median values in the box plots rise over the years, indicating an overall annual improvement in CCD. The violin plots show that the shape becomes more symmetrical and concentrated as the years progress, suggesting that data distribution is becoming more consistent and the differences in CCD between provinces are gradually increasing. The upward trend in CCD is linked to China's enhanced policy support for a green economy and sustainable development in recent years. For example, the significant increase in investments in the digital economy and the intensified efforts in carbon emission governance are reflected in government policies such as the "Carbon Neutrality Strategy" and digital economy development plans, which provide policy support and financial investment for the provinces.

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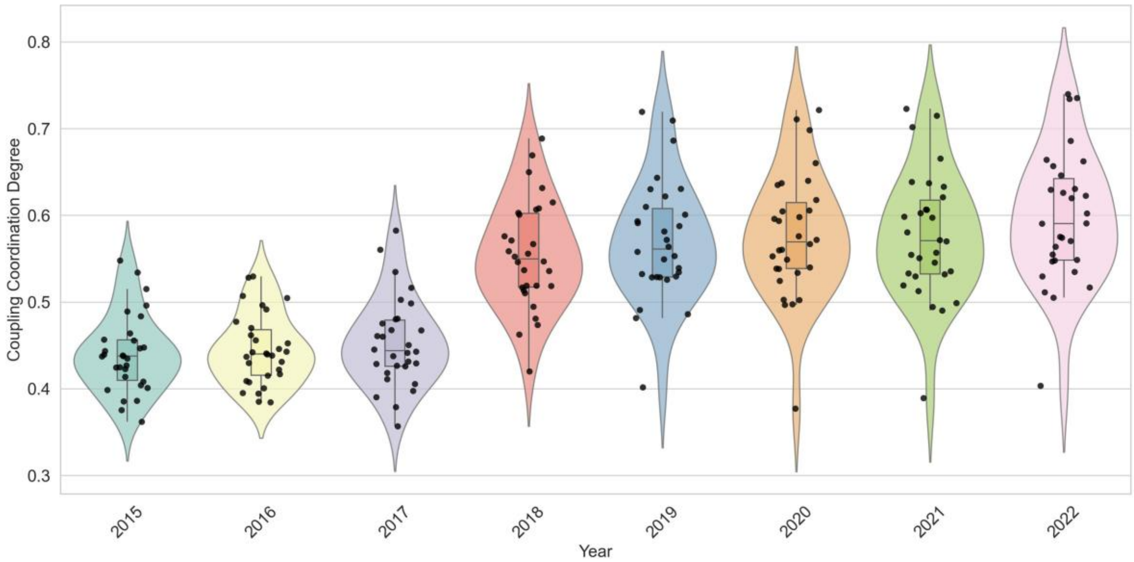

Figure 2. *Descriptive statistical value of CCD from 2015 to 2022*

Analysis of regional differences

To further analyze the regional differences in the coupling and coordinated development of the digital economy and carbon emission governance capability, this study divided China into three major regions—Eastern, Central, and Western—based on the regional classification standards of the National Bureau of Statistics. Using the Dagum Gini coefficient method, we measured and analyzed the sources of regional differences from the perspectives of intra-regional differences, inter-regional differences, and hypervariability density. The Dagum Gini coefficient and contribution rates were calculated according to *Equations 13–17*, with results shown in *Table 4*. As seen in *Figure 3*, the overall Gini coefficient has been rising annually, indicating that although the coupled and coordinated development level of China's digital economy and carbon emission governance capability is improving, the issue of uneven development is also becoming more pronounced. This may be because regions with rapid digital economy development also have advantages in carbon emission governance, thereby widening regional inequalities. The intra-regional Gini coefficient shows a slow upward trend overall, suggesting that the degree of imbalance within provinces is increasing. The inter-regional Gini coefficient also shows some fluctuations, but overall, it does not change significantly, indicating that the differences between provinces have not changed markedly. This could be related to the balanced implementation of national policies across different provinces. The increase in hypervariability density implies that the role of extreme inequality in overall inequality is becoming more significant. This might reflect that a few provinces have made substantial progress in the digital economy and carbon emission governance capability, thus widening the gap with other provinces.

Figure 4a demonstrates a fluctuating upward trend in the intra-regional Gini coefficients for both the eastern and western regions from 2015 to 2022, indicating that internal inequality within the eastern region is gradually increasing. The intra-regional Gini coefficient for the central region remains relatively stable, suggesting that internal inequality levels in this region are relatively consistent. *Figure 4b*

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illustrates the widening inequality between the eastern and the central and western regions, indicating that the development gap between these regions is expanding. The eastern region's leading position in the digital economy and carbon emission management capability may further exacerbate the development disparity with the central and western regions.

Table 4. *The Dagum Gini coefficient and contribution rate*

Year	Gini coefficient				Contribution rate（%）		
	Overall	Intra-regional	Inter-regional	Hyper-variable density	Intra-regional	Inter-regional	Hyper-variable density
2015	0.055	0.016	0.035	0.004	28.181	63.803	8.017
2016	0.051	0.014	0.033	0.005	26.910	64.106	8.985
2017	0.062	0.018	0.037	0.006	29.268	60.436	10.296
2018	0.062	0.018	0.036	0.008	29.158	58.261	12.581
2019	0.065	0.020	0.036	0.009	31.002	54.601	14.397
2020	0.067	0.021	0.037	0.01	30.706	54.380	14.914
2021	0.069	0.021	0.036	0.012	31.152	52.056	16.799
2022	0.069	0.022	0.035	0.012	31.130	51.069	17.804

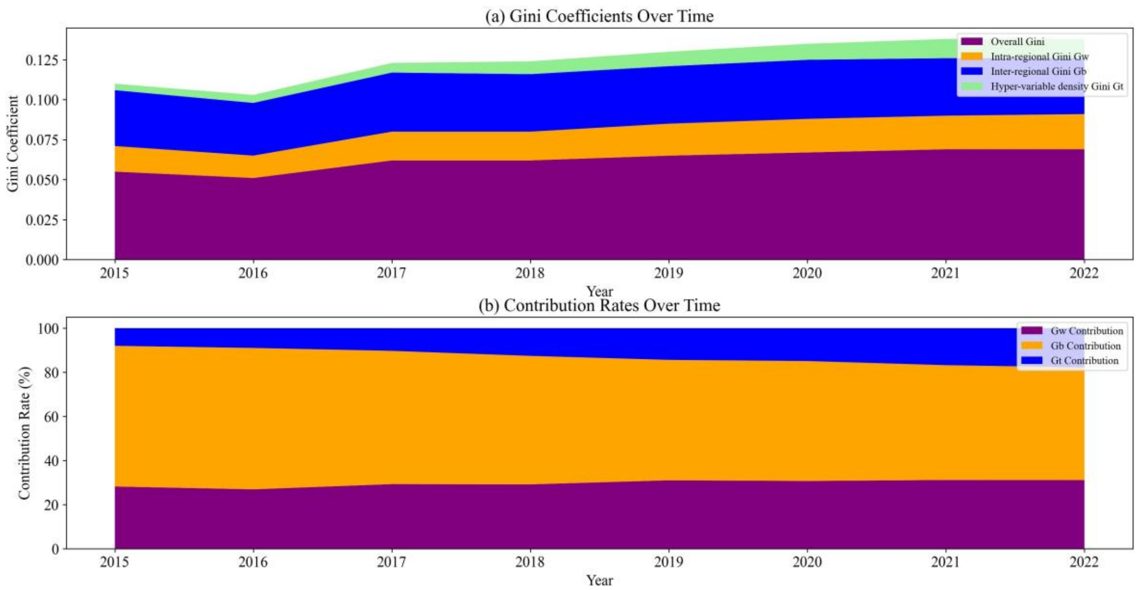

Figure 3. *Trends of Gini coefficients and contribution rate from 2015 to 2022*

KDE results analysis

Following the regional disparity analysis, to visually display the dynamic distribution of coupling coordination degrees between the digital economy and carbon emission management across regions, this study further utilizes the KDE method (*Eq. 19*) to analyze the distribution changes and evolutionary trends of the CCD in the eastern, central, and western regions. *Figure 5a* shows that between 2015 and 2022, the kernel density curve for the eastern region shifts significantly to the right, indicating a rapid improvement in the coupling coordination between the digital economy and carbon emission management capability. Over time, the main peak of the curve widens, suggesting an increase in inter-provincial disparities. *Figure 5b* illustrates that the

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kernel density curve in the central region initially becomes more concentrated before dispersing. From 2015 to 2018, the CCD in the central region rose quickly, with the main peak of the curve increasing and the distribution becoming more concentrated. However, after 2019, the curve gradually flattens, and by 2020-2022 it shows a multi-peaked pattern, reflecting a rapid increase in coupling coordination levels in some provinces, while others lag behind. *Figure 5c* reveals that in the western region, the kernel density curve shifts slowly to the right over the study period, but at a slower pace. The main peak width expands significantly, evolving from a single peak to multiple fluctuations. This suggests substantial disparities in the coordinated development of digital economy and carbon emission management capability across the western region, with varying CCD levels among different provinces.

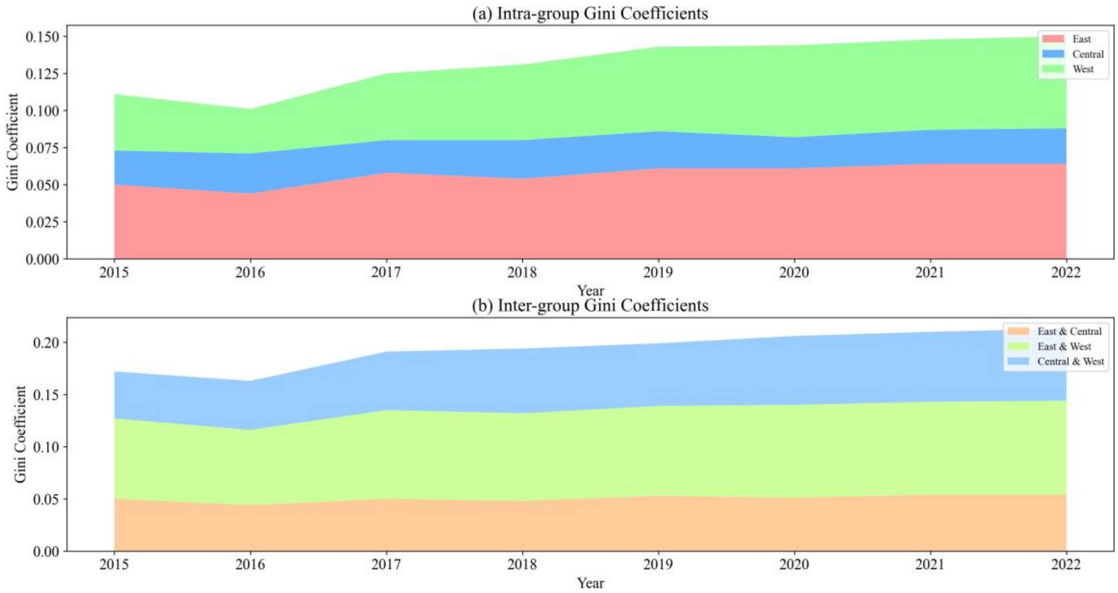

Figure 4. *Decomposition of Dagum Gini coefficient difference*

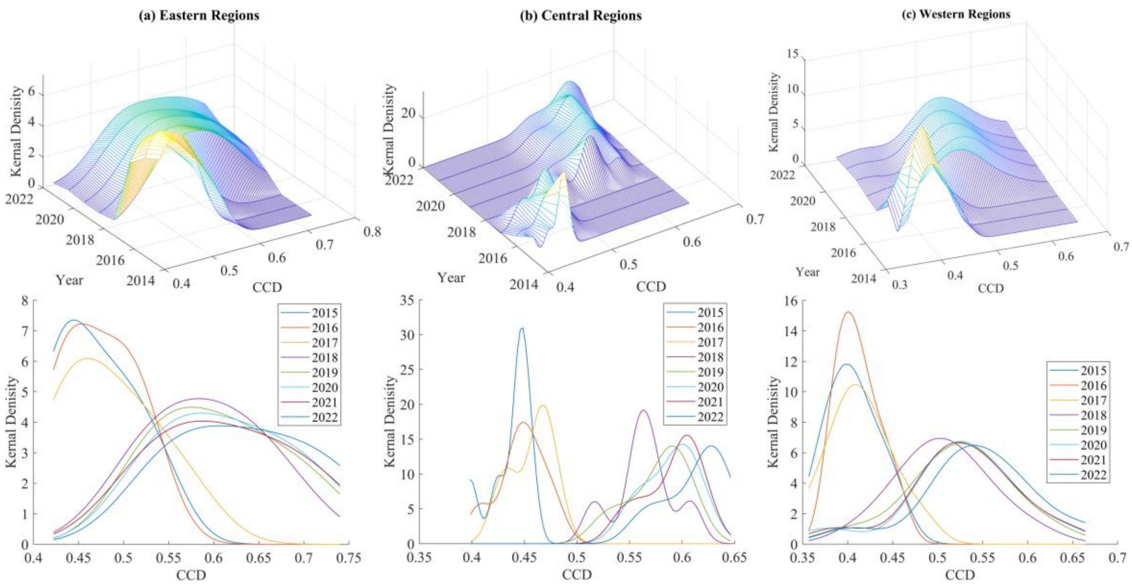

Figure 5. *KDE Curve of CCD for Eastern, Central and Western regions from 2015 to 2022*

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In terms of distribution spread, the left tail of the eastern region's curve gradually shortens, while the right tail extends significantly, indicating an increase in high-coordination provinces and widening disparities within the region. In the central region, the left tail progressively shortens, and the right tail extends, reflecting intensifying internal differentiation. In the western region, both tails remain throughout the period, with limited extension on the right side, suggesting slow overall improvement and notable internal disparities.

Spatial correlation analysis

Based on *Equation 17*, the calculation results of the Moran's I index are shown as *Table 5*. According to *Table 5*, the CCD between the digital economy and carbon emission governance capability across 30 provinces in China exhibited significant positive spatial autocorrelation. This indicates that during this period, provinces with high coupling coordination degrees were generally adjacent to other provinces with high coupling coordination degrees, while provinces with low CCD were typically adjacent to other provinces with low CCD.

Table 5. *Moran's I index from 2015 to 2022*

Year	Moran's I	Z-value	P-value	Variance
2015	0.2382	4.1185	0.000	0. 006618
2016	0.3032	4.0360	0.000	0.006998
2017	0.2629	3.6110	0.000	0.006784
2018	0.2722	4.0474	0.000	0.006918
2019	0.2966	3.2982	0.000	0.006753
2020	0.3169	3.3287	0.000	0.006648
2021	0.3426	3.3708	0.000	0.006760
2022	0.3906	3.4582	0.000	0.006798

Figure 6 further reveals the spatial patterns and clustering characteristics of different regions in terms of digital economy development and carbon emission governance capability. Overall, economically developed eastern coastal provinces, such as Shanghai and Zhejiang, form high-high clusters. These regions exhibit high levels in both digital economy and carbon emission governance, showing significant positive spatial autocorrelation. This indicates that their synergistic development in these two areas is particularly prominent. In contrast, western and central provinces like Ningxia, Gansu, and Qinghai form low-low clusters. These regions lag behind in both digital economy and carbon emission governance capability, also displaying positive spatial autocorrelation, which reflects weaker synergistic development in these areas. They require more policy support and resource investment to enhance their overall capability. Additionally, a few provinces show high-low and low-high distribution characteristics, indicating significant disparities in either digital economy development or carbon emission governance capability.

Analysis of trends in spatial displacement

Based on *Equation 20*, the results of spatial Markov transition probability matrix for the CCD are shown as *Table 6*. According to *Table 6*, we can analyze the state

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transition probabilities under different lag periods (from no lag to a lag of three periods) and examine the impact of spatial proximity on these transitions. *Figure 7* shows that as the lag period increases, the retention probabilities of the low state and lower-middle state gradually decrease, while the transition probabilities to the upper-middle state and high state increase. This indicates that over time, provinces in the low state and lower-middle state are more likely to improve their coupling coordination degree and transition to the upper-middle state and high state. Notably, provinces in the high state maintained a 100% retention probability across all lag periods, suggesting that once these provinces reach a high state, they exhibit strong stability and sustainability in their coupling coordination degree. Moreover, the influence of spatial weights in the lag periods also reveals the significant impact of spatial proximity on state transitions. For instance, in the one, two, and three lag periods, the transition probabilities from the low state and lower-middle state to the upper-middle state significantly increase, indicating that proximity to high state provinces has a positive influence on neighboring provinces.

These findings provide important references for formulating regional economic and environmental governance policies. They suggest that in promoting the improvement of the CCD in low state and lower-middle state provinces, it is essential to consider regional synergistic effects and leverage the demonstration and driving effects of high state provinces to promote coordinated development across the region.

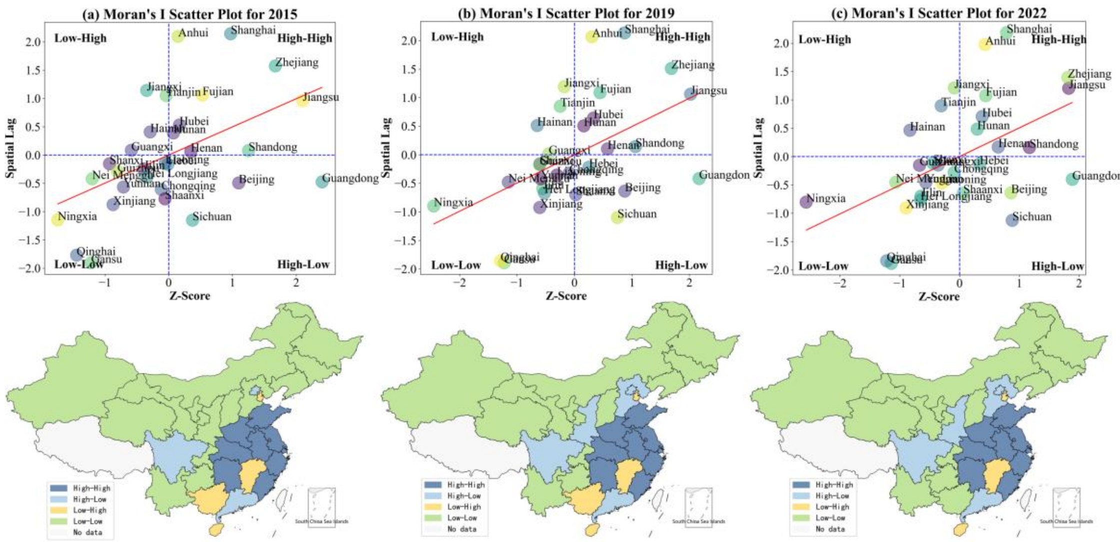

Figure 6. *Moran scatter plot for 30 provincial regions*

Discussion

Results discussion

This study reveals a sustained upward trend in the CCD between digital economic development and carbon emission governance capacity across China’s provinces from 2015 to 2022. This trend is especially pronounced in the eastern regions, where stronger economic foundations and robust technological innovation capability have resulted in significantly higher CCD levels compared to the central and western regions. Notably, the eastern region has shown faster improvements in the synergistic development of digital transformation and environmental governance capacity, while CCD growth in the western region has been relatively slower due to geographic and economic

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constraints. This disparity highlights regional imbalances and indicates that the potential for the digital economy to enhance carbon emission management varies significantly across different areas. These findings lay the groundwork for a deeper exploration of how digital economic development can support regional green growth.

Tabe 6. *The spatial Markov transition probability matrix*

Lag type	State level	Low	Lower-middle	Upper-middle	High
No lag	Low	0.533	0.467	0.000	0.000
	Lower-middle	0.025	0.620	0.354	0.000
	Upper-middle	0.000	0.018	0.954	0.028
	High	0.000	0.000	0.000	1.000
Lag I	Low	0.214	0.714	0.071	0.000
	Lower-middle	0.039	0.342	0.618	0.000
	Upper-middle	0.000	0.000	0.930	0.070
	High	0.000	0.000	0.000	1.000
Lag II	Low	0.077	0.769	0.154	0.000
	Lower-middle	0.014	0.068	0.919	0.000
	Upper-middle	0.000	0.000	0.869	0.131
	High	0.000	0.000	0.000	1.000
Lag III	Low	0.154	0.615	0.231	0.000
	Lower-middle	0.000	0.029	0.971	0.000
	Upper-middle	0.000	0.000	0.730	0.270
	High	0.000	0.000	0.000	0.000

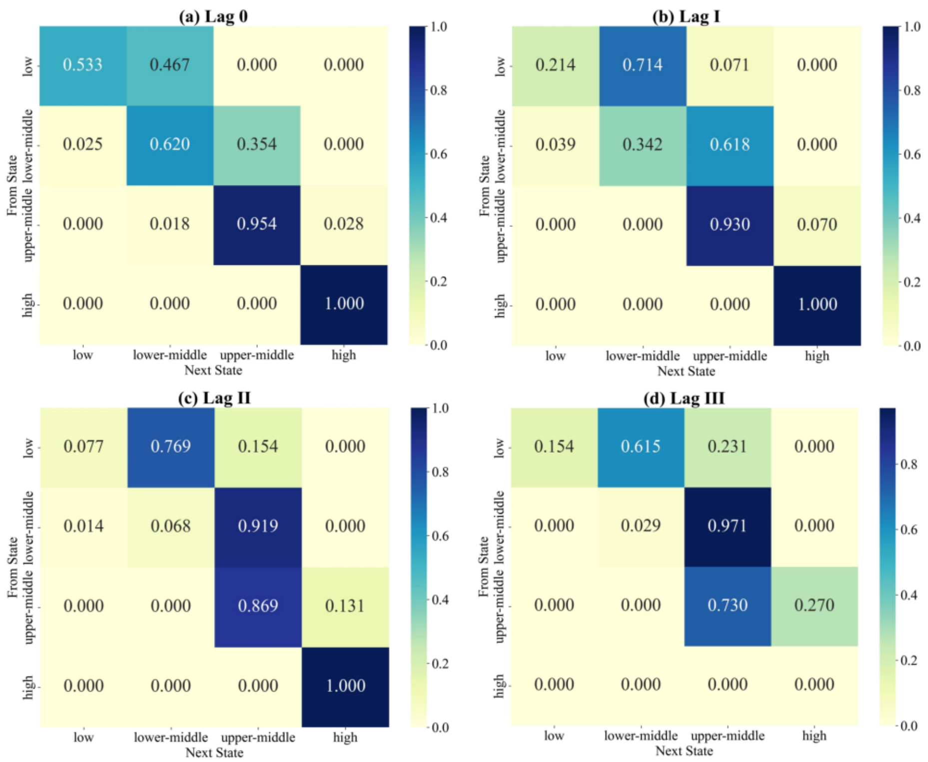

Figure 7. *The state transition probability matrix*

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This study finds a sustained upward trend in the coupling coordination degree between the digital economy and carbon emission management capacity across the country, indicating that the growth of the digital economy has played a positive role in promoting carbon emission management. This aligns with the findings of Zhang et al. (2024), which pointed out that the digital economy contributes to reducing carbon emissions through pathways such as improving energy efficiency and optimizing industrial structure. Although the overall coupling coordination level has improved, significant regional disparities remain. The eastern region, with its strong economic foundation and technological innovation capacity, has experienced faster growth in coupling coordination degree, consistently maintaining a high level. In contrast, the western region, constrained by geographic and economic conditions, shows slower growth and lower coordination levels. This finding differs from Chen et al. (2020), who proposed that the influence of government policy priorities gradually weakens across regions, indicating that the regional impact of the digital economy still exhibits significant disparities. However, this aligns with the findings of Du and Wang (2024), who observed that digital economic development is uneven across regions, with the eastern region holding advantages in digital infrastructure and technology application. Analysis using the Gini coefficient reveals that internal regional imbalances have also intensified, particularly within the eastern region, where disparities are widening. This result reflects that a few provinces have made significant progress in digital economy development and carbon emission management, while others lag behind. This finding aligns with Guo (2023), who argued that the rapid development in the eastern region may lead to the concentration of resources and capital in more developed provinces, thereby widening internal disparities.

Research limitations and future research

While this study sheds light on the regional coupling and coordinated development between the digital economy and carbon emission management capacity, it has certain limitations. For instance, the analysis is restricted to a macro-level perspective, lacking an in-depth exploration of how specific digital economy measures and carbon management initiatives in each province directly influence the coupling degree. Future research could delve into the micro-level mechanisms by which specific digital technologies and policy tools impact environmental governance. Additionally, incorporating more dynamic factors, such as the degree of marketization and industrial upgrading, could enhance understanding of regional coupling and coordinated development.

Research conclusions and suggestions

Conclusions

This study optimizes the traditional entropy weight method and the CCD model. By using relevant data on China’s digital economy and carbon emission governance capability from 2015 to 2022, it calculates the CCD between the two and empirically examines the spatiotemporal evolution characteristics of their coordinated development levels. The research findings reveal the following points:

(1) From 2015 to 2022, the average CCD between the digital economy and carbon emission governance capability across 30 provinces showed an upward trend, overall reaching an intermediate coordination state, but with significant regional differences.

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(2) The imbalance in the coupled and coordinated development level of the two systems has intensified across regions, reflecting a significant expansion in regional development disparities. The eastern region has a higher coupled and coordinated development level, the central region shows greater complexity and variability, and the western region has gradually improved but still exhibits noticeable development imbalances.

(3) The coupled and coordinated development level of the two systems exhibit significant spatial autocorrelation, showing a clear spatial clustering effect. The eastern coastal areas form high-high clusters, while most western and central regions display low-low clusters, with a few provinces showing high-low and low-high distribution characteristics.

(4) The coupled and coordinated development level of the two systems exhibit significant dynamic characteristics in state transitions. Provinces in low and lower-middle levels are more likely to improve their CCD, while provinces in high levels show strong stability and sustainability.

Suggestions

Based on the main findings identified in the research, the following suggestions are proposed:

(1) Strengthen regional policy coordination to promote balanced development: to address the imbalance in the coupled and coordinated development of digital economy and carbon emission governance capability across regions in China, it is recommended that the government increases policy support for the central and western regions. This can be achieved through the implementation of region-specific support policies, increasing fiscal transfers, providing more technical and financial assistance, and encouraging these regions to accelerate the development of the digital economy and carbon emission governance. Additionally, the transfer of advanced experiences and technologies from the eastern regions to the central and western regions should be encouraged to promote regional synergistic development and reduce regional disparities.

(2) Enhance technological innovation to improve coordination level: the coordinated development of the digital economy and carbon emission governance relies on technological innovation. It is recommended that regional governments increase investment in scientific research, particularly in the areas of green technology and digital transformation. Establishing regional innovation centers, nurturing and attracting high-level scientific talent, and promoting independent innovation among enterprises can enhance the competitiveness of the digital economy and the technological level of carbon emission governance, thereby improving the coupling coordination level.

(3) Optimize spatial layout to enhance regional synergy: based on the spatial autocorrelation and dynamic transition characteristics found in the study, it is recommended that the government fully considers the optimization of spatial layout when formulating regional development plans. This can be achieved by establishing regional industrial clusters and cross-regional cooperation platforms to promote resource sharing and collaborative innovation among regions, forming synergistic effects. For example, high-tech industrial parks can be established in the eastern regions, and green industry demonstration zones can be set up in the central and western regions to create complementary and interactive development across regions, thereby enhancing overall coupled and coordinated level.

(4) Increase green financial support to promote sustainable development: to facilitate the coordinated development of the digital economy and carbon emission governance capability, it is recommended that governments and financial institutions at all level increase support for green finance. This can be achieved by setting up special green funds, providing low-interest loans, and offering tax incentives to encourage investment in green technology and digital transformation. Additionally, advancing the implementation of green financial policies, improving the regulatory and incentive mechanisms of the green financial market, and attracting more private capital to invest in green development can promote the coordinated development of the digital economy and carbon emission governance capability, ultimately achieving sustainable development goals.

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