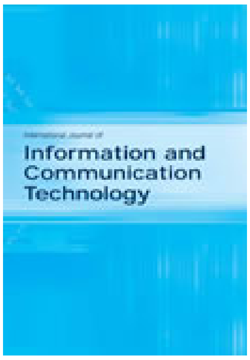

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Spatio-temporal evolution analysis of the coupling and coordination of digital economy and green development based on computer intelligence analysis

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Abstract: This paper combines computer intelligence technology to propose a spatiotemporal evolution analysis model that couples and coordinates digital economy (DE) and green development (GD), thereby providing new insights and enlightenment for the development of related fields and providing theoretical support for the transformation and high-quality development of green economy (GE). This paper combines subgroup decomposition Gini coefficient to improve the algorithm and proposes a Dagum-coupling model, and verifies the effect of the model with experiments. This paper uses the Dagum-coupling model to analyse the influencing factors of the CAD (CAD) level between DE and GD, and tests the robustness of the model. The experimental results verify that this paper uses Dagum-coupling model to analyse the CAD level of DE and GD, which has good practical effect. The strategic improvement adopted by the model proposed in this paper can promote the coordinated development of DE and GE in this region.

Keywords: intelligent analysis; digital economy; DE; green development; GD; coupling; spatio-temporal evolution.

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1 Introduction

Against the background of global environmental pressure and resource constraints, the deep integration of DE and GE shows great potential to solve contemporary challenges. In particular, in the area of regional development, this convergence not only helps to optimise the allocation of resources, but also promotes the green transformation of the economic structure. Through analysis, this paper explores the application of digital technology in promoting regional sustainable development and the innovation opportunities it brings, and further understands how to realise the win-win strategy of economic growth and environmental protection through scientific and technological innovation and the promotion of environmental awareness, so as to open up a new path for regional development (Luo et al., 2022).

The DE has the characteristics of high technology, synergy and penetration, and can promote job creation, innovation and development, stimulate consumption and drive investment through continuous and in-depth integration with various fields of society, including integration with the GE (Ma and Zhu, 2022). Under the increasingly severe global climate problem, countries around the world generally realise that the integrated development of DE and GE will become an important breakthrough in addressing climate challenges, and have launched a series of measures for the strategic collaborative development of DE and GE (Luo et al., 2023).

With the development of electronic information, electronic waste has increased significantly in the process of production and life. In addition, the energy consumed by the development of the DE cannot be ignored. Therefore, whether the impact of the DE on the environment is negative has become a question. In fact, using information technology to build smart grids, detecting carbon absorption and managing carbon emissions through big data can promote the green and efficient transformation of energy, and vigorously promoting the GD of the DE can curb the adverse impact of the DE on the climate. Moreover, adhering to GD is an objective requirement to deal with the deterioration of the ecological environment, and it is also the only way to achieve the ‘double carbon’ goal. The emerging technologies and innovation capabilities contained in the DE can improve the efficiency of environmental supervision and resource utilisation, contribute to industrial economic development and social ecological governance, and GD can guide the healthy development of the DE, which is a development concept that should always be upheld. Therefore, studying the coordination relationship between DE and GD is of great significance for promoting the coordinated development of the two, and then promoting the high-quality development of China’s economy (Yang et al., 2024).

Traditional financial services have some problems, such as liquidity stratification of financial resources, mismatch between allocation structure and efficiency, etc., which lead to low quality and efficiency of financial services. As a product of financial innovation, digital inclusive finance, on the basis of strengthening the application of digital technology and big data, can improve resource use efficiency and slow down environmental pollution by optimising resource allocation, alleviating financing constraints, and stimulating innovation. On the other hand, as the threshold of financial services is lowered, financing channels are widened, financing costs are reduced, and the coverage of financial services is expanded, production and consumption will be further stimulated, leading to an increase in energy consumption and environmental pollutant emissions.

This paper combines computer intelligence technology to propose a spatiotemporal evolution analysis model that couples and coordinates DE and green development (GD), thereby providing new insights and enlightenment for the development of related fields and providing theoretical support for the transformation and high-quality development of GE. At the same time, this paper combines subgroup decomposition Gini coefficient to improve the algorithm and proposes a Dagum-coupling model, and verifies the effect of the model with experiments. By comparing the goodness of fit of different models, this paper confirms that the Dagum-coupling model has a better effect on the analysis of influencing factors of panel data.

2 Related works

2.1 The relationship between DE and GD

Ren et al. (2022) discussed the benefits of DE to GD from the perspective of the internet of things, and believed that using the internet of things for information transmission and remote control could reduce the use of human resources, and its convenience and intelligent management avoided the consumption of huge resources, which was conducive to the development of low-carbon economy. Hao et al. (2023b) analysed the energy consumption and environmental impact characteristics of the DE, and analysed from multiple perspectives that the greening of the DE is an inevitable choice for China's high-quality development. Li et al. (2022) believed that the continuous implementation of technology integrating DE and GE created opportunities for the construction of urban infrastructure, the improvement of sectoral productivity, and the development of knowledge economy and experience economy, and improved the quality of urban environment and urban life, thus achieving sustainable development. Wang et al. (2022), from the perspective of green stimulus, believed that the GE and the DE can promote each other, and the coordinated development of the two can promote the economic recovery after the epidemic.

2.2 Quantitative analysis

Liu et al. (2022) empirically found that technological innovation is an important means for DE to improve the efficiency of GE. Lyu et al. (2023) studied the relationship between economic recovery and GD during the epidemic, and believed that the development of DE and clean energy can increase my country's economic aggregate, but the challenges in the process of labour transformation will slow down the progress of economic recovery to a certain extent. Xu et al. (2022) constructed the Malmquist-Luenberger productivity index based on the DDF model for analysis, and believed that the DE can significantly improve the green total factor productivity of my country's industry. Ran et al. (2023) used DFGMM model and threshold regression model to conduct empirical research, and the results showed that the level of DE can generally promote green economic efficiency.

2.3 Impact of information technology on energy

Dou and Gao (2022) believed that with the development of DE, the impact of coal-based energy structure on carbon emissions gradually weakens. Zhao et al. (2023) used the data of Chinese manufacturing enterprises for analysis, and believed that the increase of ICT technology application would reduce the energy intensity of enterprises. Liu et al. (2024) believed that information technology can indeed improve the operation efficiency of traditional industries, thus reducing resource utilisation and environmental pollution in the process of product production. However, the information manufacturing industry itself will consume a lot of energy, and the accelerated upgrading of information equipment will also produce more electronic waste, which will increase the waste of natural resources. Hao et al. (2023a) pointed out that digital technology shows an inhibitory effect by improving energy efficiency and optimising industrial structure to reduce part of energy consumption. The improvement of energy efficiency will have a rebound effect, and the ICT industry itself is an energy-intensive industry, so it has a growth effect on energy consumption. Regarding the relationship between the two, Guo et al. (2023) found that there is a U-shaped relationship between ICT development and energy consumption. Meng and Zhao (2022) found through empirical research on China's inter-provincial panel data that the level of economic greening first increases and then decreases with the improvement of the level of DE, and there is a quadratic curve relationship between DE and energy intensity. Nusratovich and Shermatov (2022) believed that the DE can promote GD by reducing energy consumption, reducing pollution emissions and improving production efficiency.

From the above analysis, it can be seen that in the construction of digital infrastructure level indicators, few studies consider new infrastructure indicators. This paper uses most commonly used angles, and combines the digital industrialisation and industrial digitisation level into the degree of digital industry integration to construct the index system of DE development level, and takes the number of national data exchanges and the number of national supercomputing centres as new infrastructure indicators into the de infrastructure evaluation system. In terms of measurement methods, previous studies mostly use entropy method, while in recent years, subjective weighting method and principal component analysis method are rarely used.

3 Regional differences and evolution trends in industrial GD efficiency

This part measures and analyses the characteristics of digital economy and industrial green development level. Firstly, the evaluation index system of digital economy is constructed, and the entropy weight method is used to measure the development level of digital economy, and then the super efficiency SBM model is used to measure the efficiency of industrial green development; this paper analyses the characteristics of digital economy development level and industrial green development efficiency from two dimensions of time and space, and finally analyses the regional differences and sources of industrial green development efficiency by measuring Gini coefficient.

Taking digital economy and green development as two systems, this paper analyses the coupling coordination mechanism between them, calculates their coupling coordination scheduling, and displays their coupling coordination level; then, the spatio-temporal evolution characteristics of coupling coordination degree are analysed, and the development status and development differences of provinces and cities are revealed from the perspective of time and space; finally, the spatial autocorrelation of the coupling coordination degree between digital economy and green development in each region is analysed.

3.1 Dagum Gini coefficient and its decomposition method

Based on the problem that the traditional Gini coefficient cannot be decomposed, the overlapping problem between subgroups can be reflected according to the distribution of subgroups.

This paper assumes that there are *k* regions and *w* provinces (Yu et al., 2022):

$$G = \frac{\sum_{v=1}^{k}\sum_{j=1}^{k}\sum_{u=1}^{w_v}\sum_{i=1}^{w_j}\left|Y_{vu} - Y_{ji}\right|}{2w^2\overline{Y}} \tag{1}$$

G is the Gini coefficient of the whole region, $v(j)$ represents the $v(j)^{\text{th}}$ region in k regions, $u(i)$ represents the $u(i)^{\text{th}}$ province in w provinces, $w_v(w_j)$ represents the number of provinces in the $v(j)^{\text{th}}$ region, $Y_{vu}(U_{ji})$ represents the GD efficiency of the $u(i)^{\text{th}}$ province in the $v(j)^{\text{th}}$ region, and $\overline{Y}$ represents the average GD efficiency of each region.

$$G_{vv} = \frac{\sum_{u=1}^{w_v}\sum_{i=1}^{w_v}\left|Y_{vu} - Y_{vr}\right|}{2w_v^2\overline{Y}_v} \tag{2}$$

In the formula, G_{vv} is the Gini coefficient within the region, which is used to measure the difference of GD efficiency within the region, Y_{vr} represents the GD efficiency of the r^{th} province in the v^{th} region, and $\overline{Y}_v$ represents the average GD efficiency of each province in the v^{th} region.

$$G_{vj} = \frac{\sum_{u=1}^{w_v}\sum_{i=1}^{w_j}\left|Y_{vu} - Y_{ji}\right|}{\left(\overline{Y}_v + \overline{Y}_j\right)} \qquad (v \neq j) \tag{3}$$

In the formula, G_{vj} is the Gini coefficient between regions, which is used to measure the difference of GD efficiency between regions, and $\overline{Y}_j$ represents the average value of GD efficiency in the j^{th} region. When dividing the overall Gini coefficient G of a region, in order to avoid negative values in calculation, the sorting method is as follows (Che and Wang, 2022):

$$\overline{Y}_j \leq \ldots \leq \overline{Y}_v \leq \ldots \leq \overline{Y}_k \tag{4}$$

The contribution is divided into three parts, including the contribution of intra regional differences G_w, the contribution of inter regional differences G_{nb}, and the contribution of inter regional hyper variable density G_t:

$$G = G_w + G_{nb} + G_t \tag{5}$$

G_t indicates the total contribution of the difference in GD efficiency between regions to the overall regional difference when there is cross-overlap between regions (that is, the efficiency value of the high-efficiency province in the low-efficiency region is greater than that of the low-efficiency province in the high-efficiency region).

$$G_w = \sum_{V=1}^{K} G_{vv} p_v s_v \tag{6}$$

$$G_{nb} = \sum_{V=2}^{K} \sum_{j=1}^{v-1} G_{vj} \left(p_v s_j + p_j s_v \right) D_{vj} \tag{7}$$

$$G_t = \sum_{V=2}^{K} \sum_{j=1}^{v-1} G_{vj} \left(p_v s_j + p_j s_v \right) \left(1 - D_{vj} \right) \tag{8}$$

$$p_v = \frac{w_v}{w}, \ p_j = \frac{w_j}{w} \tag{9}$$

$$S_v = \frac{w_v \overline{Y}_v}{w \overline{Y}}, \ S_j = \frac{w_j \overline{Y}_j}{w \overline{Y}} \tag{10}$$

$$D_{vj} = \frac{d_{vj} - q_{vj}}{d_{vj} + q_{vj}} \tag{11}$$

$$d_{vj} = \int_0^{\infty} dF_v(y) \int_0^{y} (y - x) dF_j(y) \tag{12}$$

$$q_{vj} = \int_0^{\infty} dF_j(y) \int_0^{y} (y - x) dF_v(y) \tag{13}$$

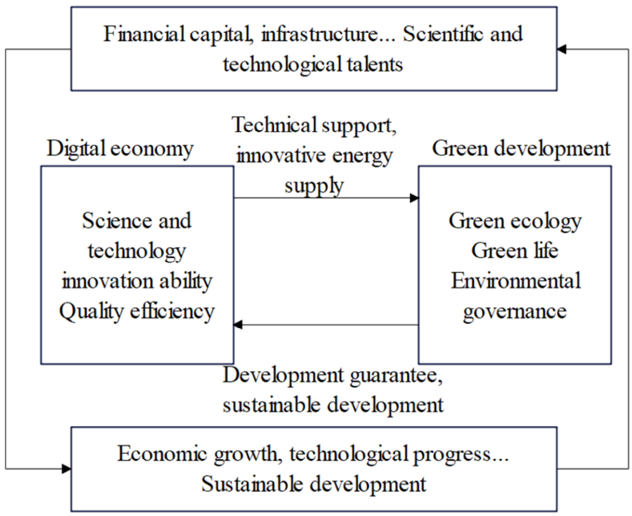
In the formula, $p_v(p_j)$ is the ratio of the number of regions included in the $v(j)^{th}$ region to the total number of regions, $s_v(s_j)$ is the ratio of the sum of the GD efficiency of the $v(j)^{th}$ region to the GD efficiency of the total region, and D_{vj} represents the relative influence of the GD efficiency between the v^{th} region and the j^{th} region. d_{vj} is the total influence between the v^{th} region and the j^{th} region.

3.2 CAD mechanism between DE and GD

As shown in Figure 1, DE and GD constitute a coupling system, and the two are interrelated and influence each other. Vigorously developing the DE is a strategic choice in the face of industrial structure upgrading and technological change. Moreover, it is a key measure to improve the level of economic development and international competitiveness. Adhering to GD is an objective requirement to deal with the deterioration of the ecological environment and a necessary requirement to meet the needs of a better life for the people (Zhang et al., 2021).

On the one hand, the DE is the key to improving the efficiency of GD. The emerging technologies and innovation capabilities contained in the DE can improve the efficiency of environmental supervision and resource utilisation, and contribute to industrial economic development and social ecological governance. Using information technology to build smart grids, detecting carbon absorption and managing carbon emissions through big data can promote the green and efficient transformation of energy, and vigorously promoting the GD of the DE can curb the adverse impact of the DE on the climate. On the other hand, GD is the guarantee for promoting the sustainable development of the DE. Although the DE improves the efficiency of GD and is an important means to promote low-carbon development, it does not mean absolute low-carbon. With the development of electronic information, e-waste has increased significantly in the process of production and life. In addition, the new digital infrastructure and the application industries it carries are high in electricity consumption and carbon emissions, so the large amount of energy consumed by the development of the DE cannot be ignored. GD aims at sustainability, takes into account both efficiency and fairness, and can guide the healthy development of the DE. It is a development concept that should always be upheld. Moreover, the two rely on each other and influence each other.

Figure 1 Diagram of coordination mechanism between DE and GD



However, coupling is an open and complex process, and the interaction between DE and GD will be affected by many factors. As can be seen from Figure 1, the input of external factors such as financial funds and scientific and technological talents will make them compete with each other, thus transferring limited resources between them. Only when the two work together and balance the allocation of resources can a virtuous circle of coupling system be formed, thereby promoting high-quality economic development and maintaining the sustainability of development while improving the overall economic benefits. Therefore, this paper further studies the dynamic coordination relationship between DE and GD.

Coupling coordination degree model is widely used in studying the coordination of multiple systems. This paper assumes that there are r subsystems ($r = 1, 2, \ldots, R$) under study, U_r is the comprehensive development index of the subsystem, and the calculation formula of the coupling degree C is shown in formula (14):

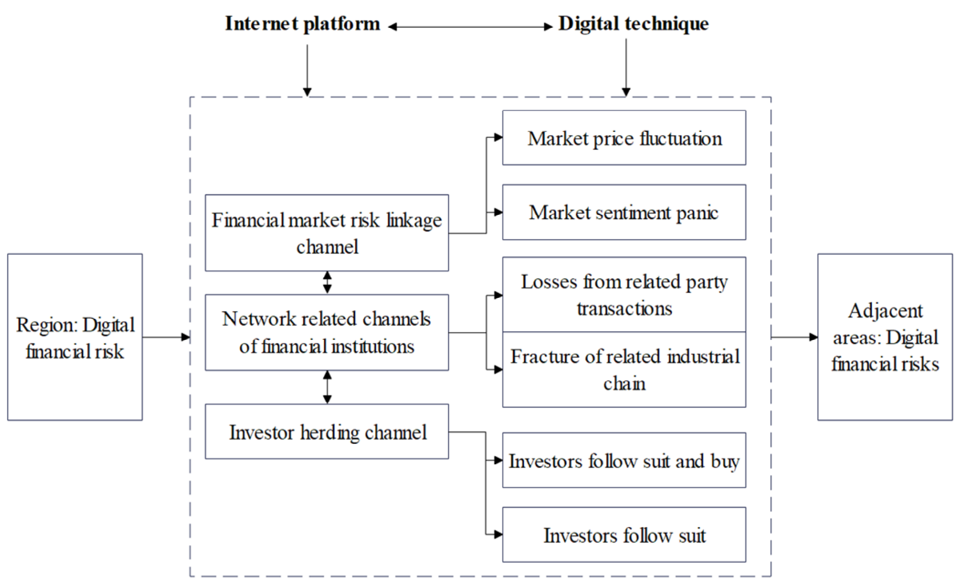
$$C = \left[\frac{\prod_{r=1}^{R} U_r}{\left(\frac{1}{R} \sum_{r=1}^{R} U_r \right)^R} \right]^{\frac{1}{R}} \tag{14}$$

When the comprehensive level of subsystems is low, the coupling degree will be virtually high. Therefore, it is necessary to construct a coupling coordination model between the DE and GD to reflect the internal coordination of the DE. The formula is shown in formula (15):

$$\begin{cases} D = \sqrt{C \times T} \\ T = \sum_{r=1}^{R} \alpha_r \times U_r \\ \sum_{r=1}^{R} \alpha_r = 1 \end{cases} \tag{15}$$

Among them, α_r is the weight reflecting the importance of the subsystem. Since this paper measures the coordination level of DE and GD without bias, they are given equal weights, namely $\alpha_1 = \alpha_2 = \frac{1}{2}$. T is the comprehensive development index that integrates the evaluation values of each subsystem, reflecting the overall level of the system, and D is the coupling coordination degree, $D \in [0, 1]$.

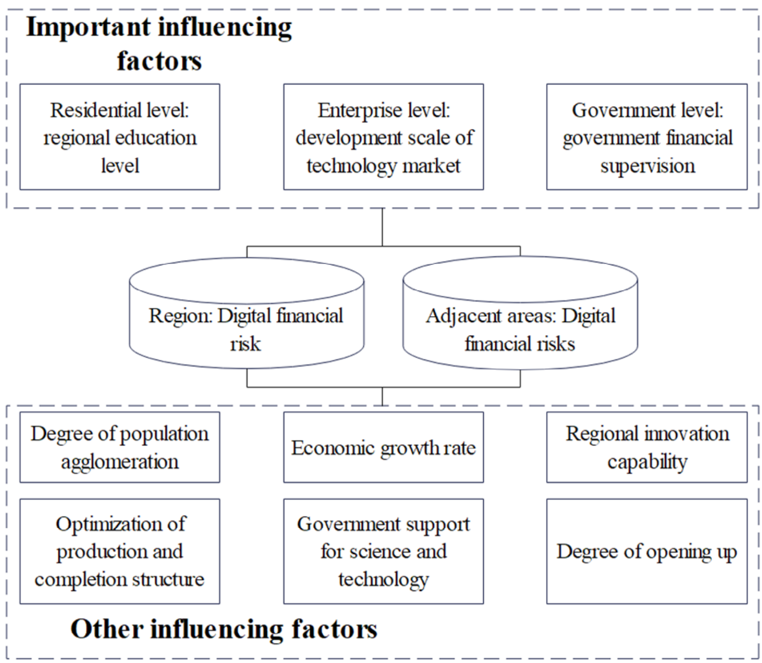
Figure 2 Conceptual mechanism of digital financial risk spatial spillover



The spatial spillover effect of digital financial risks refers to the process in which the risks generated by digital financial activities gradually spread in geographical space and affect other regions or fields. The conceptual diagram of the spatial spillover mechanism of digital financial risks is shown in Figure 2. When digital financial risks occur in the region, relying on internet platforms and digital technologies, digital financial risks will spread rapidly through financial market risk linkage channels, financial institution network association channels, and investor herd channels. Under the interaction of multiple risk channels, the contagion of digital financial risks among regions has accelerated and escalated, thus having spatial spillover effects on digital financial risks in neighbouring regions. The contagion and spread of digital financial risks among regions are more likely to have a serious impact on systemic financial risks. Therefore, it is necessary to further explore the spatial spillover effects of digital financial risks, which is crucial for the effective prevention of digital financial risks.

The mechanism of the influencing factors of digital financial risk spatial spillover is shown in Figure 3. The influencing factors of digital financial risk spatial spillover may also include population agglomeration, regional innovation capabilities, government scientific and technological support, economic growth rate, industrial structure optimisation and opening up to the outside world.

Figure 3 Mechanism of influencing factors of digital financial risk spatial spillover (see online version for colours)



3.3 *Intelligent computer analysis model*

The data formats of simulation systems in the time dimension and space dimension are very different. Taking regional economic simulation as an example, the time series data is in the form of a one-dimensional array, such as GDP, population, etc., while the spatial data is raster data or vector data. Therefore, it is necessary to define the data conversion method between the two. In GIS, this is achieved through 'attributes', dividing the overall space into different blocks (such as administrative divisions in regional economy), and each block can define its attributes. The time series data is assigned to the attributes of the block according to the time node, as shown in Figure 4, so that the time series data of the system dynamics is linked to the spatial data of the spatial module.

Figure 4 Schematic diagram of conversion between temporal data and spatial data

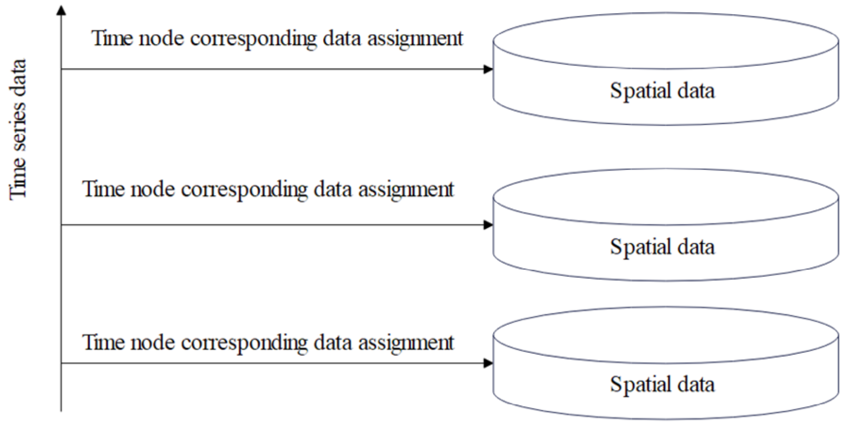
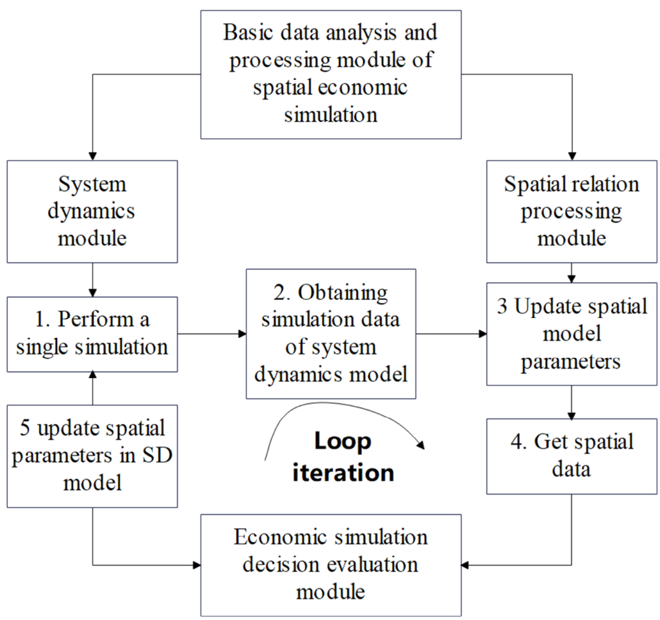


Figure 5 Schematic diagram of spatial economic simulation framework



The basic data processing module integrates data processing functions and is mainly responsible for processing simulation data, including data cleaning, data regression analysis, spatial data processing, etc. The processed initial simulation data will be imported into the system dynamics module, which mainly provides functions related to system dynamics. After receiving the initial data, the system dynamics module will perform a single simulation, save the simulation data and pass it to the spatial relationship processing module. After processing the simulation data, the spatial relationship processing module obtains spatial parameters, and then returns to the system dynamics module to participate in the next simulation, so that multiple cycles of simulation are carried out between the system dynamics module and the spatial relationship processing module until the time boundary is reached. During the simulation process, the economic simulation decision evaluation module can obtain simulation data in real time for real-time visualisation, as shown in Figure 5.

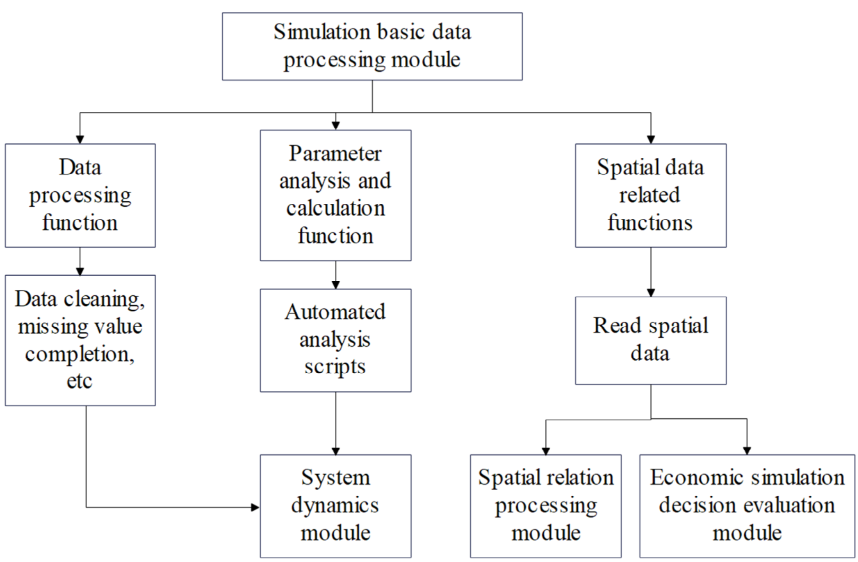
The main functions of the basic simulation data processing module are: processing simulation data, analysing and calculating simulation variable parameters and processing spatial data, as shown in Figure 6.

1 Processing simulation data: system dynamics modelling requires the collection of historical data of the study area, which needs to be collected from yearbooks, statistical bulletins, official websites, etc. However, due to changes in format and statistical calibre, the data may have obvious anomalies, which may cause large errors in the model. Therefore, it is necessary to clean the data before simulation to remove anomalies. In addition, some data may not be available, and reasonable estimation and extrapolation are also required.

2 Analysing and calculating simulation variable parameters: in system dynamics, the relationship between variables can be logical or quantitative description. At this time, it is necessary to carry out correlation analysis and regression analysis on variables to determine the quantitative relationship between variables.

3 Processing spatial data: when spatially analysing the research area, it is necessary to read the raster data of the research area, it is necessary to import the simulation data of each simulation cycle into the spatial module. This part of the function is provided by the data processing module (Han et al., 2022).

Figure 6 Functional diagram of simulation basic data processing module



4 Test

4.1 Test methods

In this paper, the Windows version of VensimPLE5.11 is used as the initial model construction tool of system dynamics, the toolkit provided by ArcGIS is used as the spatial analysis tool, and the social network analysis function of Ucinet is coupled. The above software and functions are all coupled by Python3.6 as the development tool. In the choice of simulation tools, this paper chooses python as the development language, python has extremely low development cost because of its easy-to-understand syntax, and its rich third-party toolkit makes python have powerful functions.

The model proposed in this paper is named Dagum-coupling. During the simulation process, the framework can automatically save the simulation results of each system dynamics, as well as the calculation results of the spatial module. These results will be imported into the economic simulation decision evaluation module. The decision evaluation module includes spatial analysis function, social network analysis function and simulation data visualisation function, which cannot only display the attribute data of the system along the time axis, but also display and process the spatial analysis results in the form of a specified time interface, as shown in Figure 7.

Figure 7 Schematic diagram of spatio-temporal analysis of frame

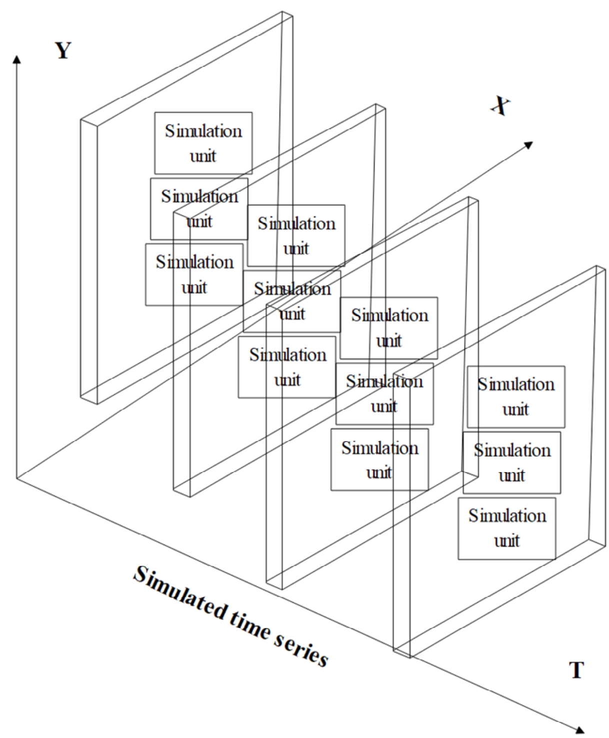
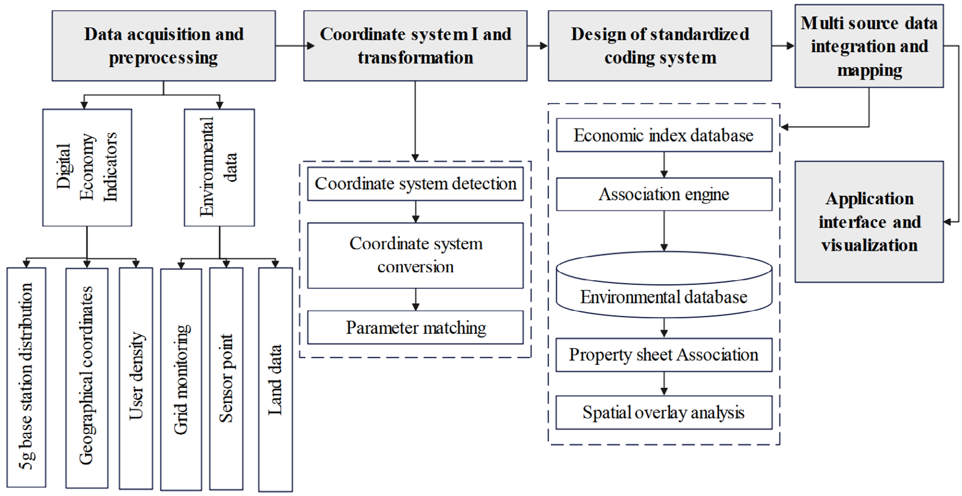


Figure 8 Implementation block diagram of standardised coding framework based on GIS



Spatiotemporal research requires high-resolution data. However, digital economic indicators (such as ICT infrastructure) and environmental data are often different in spatial and temporal granularity. To solve this problem, this paper establishes a GIS-based standardised coding framework to solve this problem. Figure 8 is the implementation block diagram of the GIS-based standardised coding framework A standardised coding framework based on geographic information system (GIS) is established, which maps digital economic indicators (such as regional 5G coverage) and environmental data (such as carbon emission grid data) to the same spatial coordinate system, and supports cross-scale data overlay analysis. The 'grid + administrative division' dual track data integration mode is adopted, which is compatible with different granularity data sources.

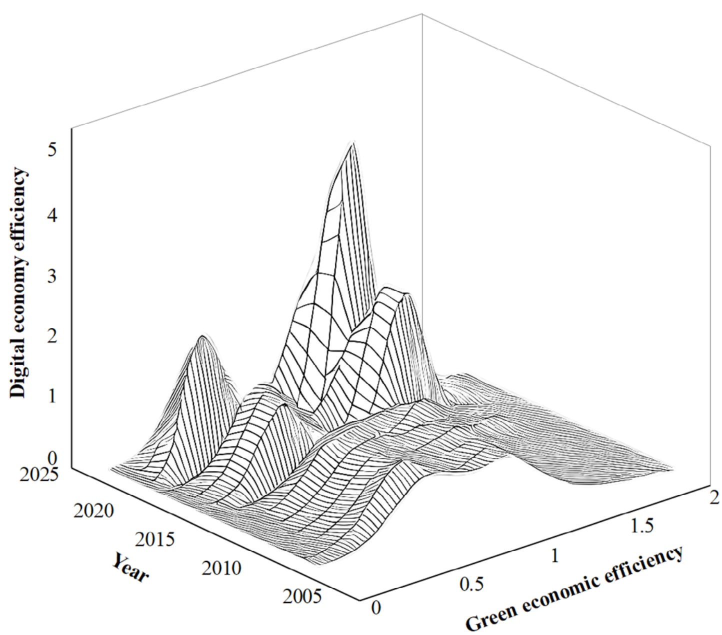
Spatial data is mainly raster data and vector data. The spatial relationship processing module needs to study regional spatial data to establish economic network. The economic simulation decision evaluation module also needs spatial data for visualisation and spatial analysis. It mainly uses the python library provided by ArcGIS: arcpy, to realise it. arcpy integrates most functions of ArcGIS, including reading and operating spatial data, providing spatial analysis functions, etc. In order to facilitate the later comparative analysis of the DE and GD levels in different regions, this paper refers to China's economic regional division standards and divides China into four major regions: eastern, central, western and northeast. The indicator data are mainly taken from China's High-tech Industry Statistical Yearbook, China's Internet Development Statistical Report, Ecological Environment Statistical Annual Report, China's Labor Statistical Yearbook and China's Regional Economic Statistical Yearbook, as well as national data, Qianzhan Industry Research Institute, EPS database, China Macroeconomic Database, Qichacha and other websites. In the DE indicator system, data on the number of companies in the fields of blockchain and artificial intelligence, the number of companies in big data technology and analysis, the number of companies in the field of intelligent manufacturing, the number of companies providing digital financial services, the number of companies in the field of smart agriculture, the number of companies in the smart education industry, and the number of companies providing digital medical services are derived from the official website of Qichacha. The data are retrieved by searching keywords to retrieve the number of corresponding industries in each province over the years and the data are added up.

When analysing the spatial effect of the development of digital economy, the spatial economic geography nested matrix is used to discuss the spatial Dobbin model. However, considering that different weight matrices may have different effects on the regression results, in order to analyse this problem more comprehensively, this paper replaces the original spatial economic geography nested matrix with spatial adjacency matrix to further explore the spatial effect of digital economy development on industrial green development. Such adjustment aims to ensure the preciseness of the research and the accuracy of the results. The open source tool TensorFlow is used to accelerate the model optimisation, which is convenient to analyse the influence of regional specific factors on the analysis results of the team model.

4.2 Results

In order to deeply analyse the dynamic evolution trend of China's green economic efficiency, this paper uses MATLAB software to draw the kernel density map of China's green economic efficiency in each period, and shows its distribution dynamics, as shown in Figure 9.

Figure 9 Distribution dynamics of green economic efficiency



To further explore the distribution pattern, polarisation phenomenon and dynamic development trend of each region, deeply analyses the dynamic evolution characteristics of green economic efficiency in eastern, central, western and northeast China.

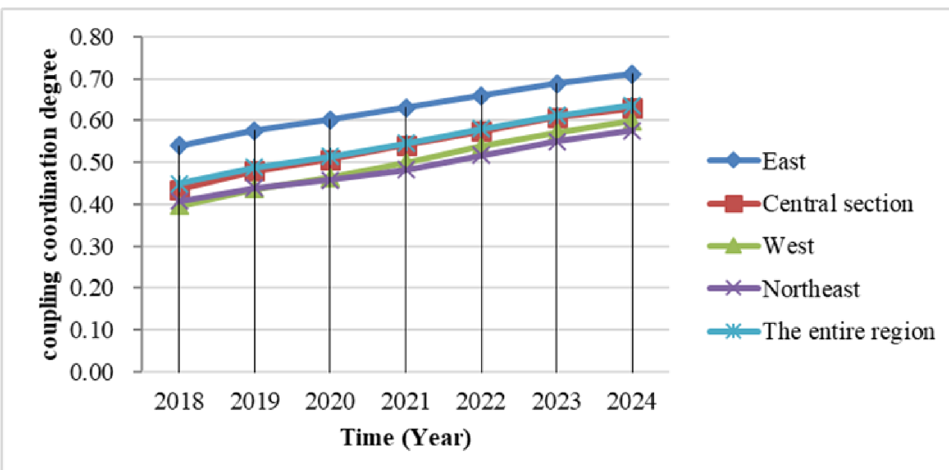
Based on the DE and GD index calculated above, the coupling degree between the two is calculated, and then equal weights are assigned to calculate the corresponding coordination degree. The results are shown in Table 1. Overall, the level of CAD between DE and GD in various regions has gradually improved, and the coordination situation has become increasingly good.

Table 1 CAD degree of DE and GD in various regions from 2018 to 2024

	2018	*2019*	*2020*	*2021*	*2022*	*2023*	*2024*	*Level of coordination*
East	0.5396	0.5767	0.6023	0.6313	0.6593	0.6888	0.7109	Intermediate coordination
Middle part	0.4347	0.4792	0.5067	0.5419	0.5750	0.6083	0.6294	Primary coordination
Western	0.3966	0.4368	0.4639	0.5001	0.5387	0.5716	0.5990	Primary coordination
Northeast	0.4081	0.4401	0.4589	0.4820	0.5165	0.5505	0.5764	Reluctant coordination
All-region	0.4492	0.4883	0.5143	0.5461	0.5801	0.6120	0.6368	Primary coordination

In Table 1, the development trend chart of the CAD degree of DE and GD in the four major regions of the country is drawn (Figure 10).

Figure 10 Trend chart of CAD degree between regional DE and GD (see online version for colours)



To further verify the role of the mode in the CAD of DE and GD, the geographically weighted regression (GWR) model and the spatiotemporal geographically weighted regression (GTWR) model are used to fit the data, Through CPPGD, intelligent carbon, wind database is used as experimental data to verify the effectiveness and generalisation ability of this model, and compared with the model in this paper to obtain the following comparison results shown in Table 2.

This paper selects education level, scientific and technological innovation level, economic development level, government investment intensity, and economic structure differences as the main research factors, and makes descriptive statistics on the regression coefficients of each explanatory variable. As shown in Table 3.

Table 2 Comparison of model fitting effects

Dataset	*Model*	R^2	*Adjusted* R^2	*AIC*	*Sigma*
CPPGD	GWR	0.8061	0.8051	–707.6140	0.0189
	GTWR	0.9389	0.9377	–824.1621	0.0220
	Dagum-coupling	0.9752	0.9749	–991.5345	0.0119
Intelligent carbon	GWR	0.8091	0.7904	–715.6963	0.0190
	GTWR	0.9260	0.9472	–832.6240	0.0218
	Dagum-coupling	0.9759	0.9917	–984.5297	0.0120
wind	GWR	0.7935	0.8032	–702.9168	0.0188
	GTWR	0.9390	0.9339	–816.5942	0.0222
	Dagum-coupling	0.9632	0.9940	–971.3196	0.0118

Table 3 Descriptive statistical results of regression coefficients of Dagum-coupling model

Variable	*Mean value*	*Minimum*	*Lower quartile*	*Median number*	*Upper quartile*	*Maximum*	*Extremely poor*
Ln_eco	0.0790	–0.1285	0.0091	0.0776	0.1372	0.3044	0.4329
Ln_str	–0.0217	–0.3648	–0.0556	–0.0152	0.0027	0.2260	0.5908
tec	0.1804	–1.0189	0.0095	0.1720	0.3233	1.7737	2.7926
Ln_gov	0.0420	–0.1393	0.0130	0.0469	0.0744	0.1478	0.2871
edu	0.2069	–1.1953	0.0181	0.2221	0.4118	1.2054	2.4008

Table 4 Spatial econometric optimal model test

	Inspection method	*Statistic*	*P*
LM-test	LM-spatial error	158.20	0.003
	Robust LM-spatial error	9.36	0.002
	LM-spatial lag	207.00	0.002
	Robust LM-spatial lag	58.15	0.002
Wald-test	Wald-lag	67.92	0.000
	Wald-error	55.18	0.000
LR-test	LR-lag	58.96	0.002
	LR-error	50.26	0.000

When building spatial econometric models, three commonly used models are usually used: spatial error model (SEM), spatial lag model (SAR) and spatial Durbin model (SDM). In order to ensure the accuracy of the selected model, LM Test and robust LM test are carried out first. The test results show that all statistics can effectively reject the original hypothesis, which indicates that there is a significant spatial correlation between variables, so the spatial econometric model is appropriate. In addition, the test results of LM lag and RobustLM lag rejected the original hypothesis, and the tests of LM error and RobustLM error also showed significance, indicating that the constructed model has the dual spatial correlation of spatial error model and spatial lag model. Because the spatial Dobbin model can have both the above two spatial effects, this paper chose to use the spatial Dobbin model. In order to further enhance the robustness of the model, we also conducted Wald and LR tests to ensure that the spatial Dobbin model will not degenerate into a spatial error model or a spatial lag model. As shown in Table 4, all statistics reject the original hypothesis at the significance level of 1%, which further verifies the stability of the spatial Dobbin model.

4.3 Analysis and discussion

Coupling coordinated development path of digital economy and green development

The collaborative evolution of digital economy and green development is the core engine to promote high-quality economic growth. It is necessary to build a systematic framework from the four dimensions of technological innovation, resource allocation, demand traction and industrial transformation.

1 Deep integration of AI technology and green low carbon industry

   The iteration of artificial intelligence technology injects new momentum into the intelligent upgrading of manufacturing industry. Through the construction of intelligent factory and industrial internet platform, AI can monitor the running status of equipment in real time, dynamically optimise the production process, and achieve accurate control of energy consumption and carbon emissions. For example, technology integration not only promotes the greening of manufacturing, but also extends the life cycle of equipment through intelligent operation and maintenance, forming a low-carbon closed loop of the whole industrial chain.

2 Reconstruction of resource allocation system by digital technology

   The supply and demand matching platform based on big data and cloud computing can effectively solve the stubborn problem of resource mismatch. By integrating idle capacity resources, the sharing economy model has increased the utilisation rate of manufacturing equipment from 55% to more than 80%, reducing the waste of resources caused by repeated investment. On the consumer side, the carbon footprint tracking system guides consumers to choose low-carbon products.

3 Green demand drives digital technology innovation

   The rigid constraint of carbon neutralisation goal leads to new digital solutions. The carbon asset trading platform enabled by blockchain technology has realised the digitalisation of the whole process of carbon emission rights confirmation, trading and write off. In the field of environmental monitoring, the sky ground integrated monitoring network composed of 5g + UAVs can improve the positioning accuracy of pollution sources to meter level and shorten the response speed to minute level. These innovative achievements are not only the product of green governance demand, but also feed back the development of digital economy through technology spillover effect, forming a positive cycle of 'demand innovation application'.

4 Digital low carbon transformation of traditional industries

   The transformation of high energy consuming industries relies on digital twins and technological breakthroughs in process simulation. Iron and steel enterprises establish a digital image system of smelting process. Such transformation not only reduces the intensity of carbon emissions in the production process, but also realises the cascade utilisation of energy through the equipment IOT, and builds a cross process energy optimisation network.

To realise the deep coupling of digital economy and green development, it is necessary to establish a collaborative system of technology research and development, policy incentives and market mechanisms. By building a national green digital innovation centre to overcome key common technologies, improve the linkage mechanism between carbon tax and digital infrastructure investment, and cultivate an ecosystem covering technological innovation, industrial transformation and consumption upgrading. This multi-dimensional collaborative model will accelerate the formation of a two-way driving pattern of 'digital enabling green transformation, green demand driving digital innovation', and provide lasting impetus for sustainable economic development.

In Figure 9, the green economic efficiency generally shows a trend of shifting to the right. It shows that the efficiency of the GE is gradually increasing and showing a good momentum overall. The economy is actively taking the path of GD, and the 'green content' of economic development has been significantly improved. From the distribution pattern, the right tail is getting shorter year by year, and the width of the main peak is gradually decreasing while the height is constantly increasing, indicating that the gap in green economic efficiency among regions is gradually narrowing. From the peak number, it can be seen that the kernel density map presents a bimodal state, indicating that the green economic efficiency is polarised. The reason is that the geographical location, resource environment and economic development of each region are different, which makes the green economic efficiency have certain differences. In general, the green economic efficiency shows an upward trend as a whole, and there is a certain volatility and instability in some aspects.

As shown in Figure 10, the coupling coordination between the DE and GD in various regions of China has shown a steady growth trend. Among them, the coupling coordination level of the central region has always been close to the national average, and the eastern region is far ahead of the other three regions and has entered the coordinated improvement type in 2020. In 2019, the two were almost the same. In recent years, the western region has shown a rising trend in many aspects, and the coordination degree between the DE and GD has also achieved latecomer catch-up. Since surpassing the northeastern region in 2020, the coupling coordination situation has become increasingly good. By 2024, only the northeastern region is still in the barely coordinated stage, and the rest of the regions have entered the coordinated improvement stage, the eastern region is in the intermediate coordination.

In Table 2, the test was conducted through the CPPGD dataset, the fitting effect of the GTWR model as an advanced version of the GWR model is significantly better than that of GWR. The goodness of fit of GTWR model and Dagum-coupling model is 0.9389 and 0.9752, respectively, and the AIC of Dagum-coupling model is smaller than that of GTWR model, so it can be seen that the effect of Dagum-coupling model is better. Because Dagum-coupling model considers both temporal and spatial effects, it can not only reflect the spatial differences of explanatory variables, but also reflect the characteristics of estimated parameters changing with time, and has stronger explanatory ability. In view of this, this paper uses the Dagum-coupling model to analyse the CAD level of DE and GD, which has good practical effect. From the test results of intelligent carbon and wind, the performance of this model is basically consistent with the test results in CPPGD dataset, which verifies the generalisation ability of this model.

From the absolute value of the mean value of the regression coefficient in Table 3, the influence intensity of each factor on the coupling coordination level as a whole is ranked as follows: education level > scientific and technological innovation level > economic development level > government investment intensity > economic structure difference, among which the influence intensity of education level and scientific and technological innovation level is much greater than other factors. In addition, the impact of economic structure differences on the level of CAD is negative, the lower the degree of CAD between the DE and GD. It shows that on the whole, the more reasonable the industrial structure is, that is, the coordinated development of the three industries can improve the coordination level between the DE and GD. The range of the regression coefficient reflects the stability of the impact intensity of each variable. The regression coefficients of scientific and technological innovation level and education level vary greatly, indicating that the impact of scientific and technological innovation level and education level on the coupling coordination degree of DE and GD varies greatly in time and space.

From the statistical data in Table 4, all statistics rejected the original hypothesis at the significance level of 1%, which further verified the stability of the spatial Dobbin model.

The synergy lag between digital economy and green development is essentially the systematic mismatch of technology iteration, policy framework and energy structure. Through standardised data governance, cross departmental policy linkage and green technology integration, the operation bottleneck of the real-time monitoring system can be gradually eliminated, providing accurate support for high-quality development.

5 Conclusions

Based on the overall and regional perspective, this paper comprehensively considers the spatial and temporal elements, studies the differences of development levels and changes of development trends in different regions horizontally and vertically, and grasps the temporal and spatial evolution characteristics of their development. By measuring the CAD degree of DE and GD in various regions in recent years, and by comparing the goodness of fit of different models, it is once again confirmed that the Dagum-coupling model has a better effect on analysing the influencing factors of panel data. The Dagum-coupling model is used to analyse the influencing factors of the CAD level between DE and GD, and the robustness of the model is tested. It is verified that this paper uses Dagum-coupling model to analyse the CAD level of DE and GD has good practical effect.

By quantifying the relationship between carbon emissions and economic growth, the model helps the government identify bottlenecks in high-carbon industries, optimise the combination of policy tools (such as carbon tax and green subsidies), and improve the efficiency of policy implementation. The model can simulate the substitution effect of low-carbon technologies (such as clean hydrogen energy and synthetic fuels) on traditional industries, reveal the critical point and cost threshold of the transformation of high energy consuming industries such as steel and chemical industry, and guide capital to the fields of renewable energy and smart grid.

In this paper, the selection of influencing factors is not comprehensive enough, and it is only analysed from five aspects. However, in practice, the factors affecting the DE and GD are complex and diverse. In addition to economic factors and social factors, they also include value orientation and policy measures that are difficult to measure and quantify. Therefore, the future research can be analysed from a deeper and broader perspective.

The interaction between digital economy and green development has significant nonlinearity and lag. It is necessary to break through the short-term perspective of traditional policy evaluation and turn to the governance mode of 'prediction adaptation iteration'. Through long-term data accumulation, interdisciplinary method integration and flexible policy design, we can more accurately capture the deep value of the two synergies and avoid systemic risks caused by short-term miscalculation. In the future, we can further study this lag and improve the prediction ability of the model through a lot of learning to improve the practicability of the model.

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Declarations

Conflict of interest: The author in this paper declares that he does not have any conflict of interest.

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