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Analysis of the Spatiotemporal Evolution and Driving Factors of China's Digital Economy Development Based on ESDA and GM-GWR Model

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Abstract: Research on the geographical aspects of the digital economy is valuable. We base our study on 10 consecutive years of panel data from 2011–2020 for 31 Chinese provinces. First, we measure the Digital Economy Index using the entropy weight method and analyze its spatiotemporal heterogeneity characteristics using the Exploratory Spatial Data Analysis (ESDA) method. Next, the Grey Model (GM) is utilized to conduct time series predictions of each geographical unit. Finally, we use the GM predicted values and Geographic Weighted Regression (GWR) model to explore the spatial heterogeneity effects of external factors. This study finds that: (1) The overall development shows a trend of vigorous growth, with significant spatial heterogeneity. The gradient difference shows a decreasing trend from the eastern coastal areas to the western inland areas. (2) There is an obvious "digital divide" and a "Matthew effect" in regional development, with agglomeration and spillover effects gradually increasing. (3) Considering the influencing factors, technological progress has a positive impact, and the technology-oriented spatial spillover is obvious, showing a pattern of high in the south and low in the north. The industrial structure is significantly positive, and increases year by year, showing a distribution characteristic of high in the north and low in the south in general, with a clear effect of reducing the "bipolar" distribution. The marginal effects of government support and foreign investment are reduced and there is spatial non-stationarity. This study provides a scientific basis for further research on the spatial development of the digital economy.

Keywords: digital economy; spatial heterogeneity; driving factors; predictive analysis; geographically weighted regression (GWR)

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1. Introduction

With the widespread and profound infiltration of digital technology, the evolution of information technology represented by big data, artificial intelligence, Web 3.0 technology, human–computer interaction technology, and other digital information technologies has been extensive in various fields. This has promoted the rapid progression of social industries, and human civilization is now living in a time of digital development [1–3]. Every area of human politics, business, society, and culture has changed because of the digital revolution. Digital and internet technologies have completely changed and revolutionized humans' daily existence [4]. The digital economy is the most dynamic field, with its integration into various economic and social sectors constantly expanding in both breadth and depth. It plays a crucial role in stimulating consumption, driving investment, creating employment, and more [5]. As the digital economy continues to develop, the boundaries between the industrial and service sectors are being blurred. This has facilitated the restructuring and modernization of the real estate economy, reduced the economic gap between developed and underdeveloped countries, broken the barriers of traditional industries, and promoted global economic integration [6]. The value of the digital economy in China expanded from USD 1.31 trillion in 2011 to USD 5.4 trillion in 2020, with an increase in its GDP contribution from 20.3% to 38.6%, ranking it second in the world. In the US, it reached USD 13.6 trillion, or about 65% of the US GDP, ranking first in the world [7]. The global economy is now largely being driven by the digital economy. In terms of regional digital economy growth, 13 Chinese provinces developed a combined digital economy worth more than CNY 1 trillion by 2020, while eight other provinces' combined digital economies were worth more than CNY 500 billion. All of China's regions have seen strong success in the digital economy, which is fueling regional economic expansion [8]. Digital transformation has become a new area of global competitiveness in the era of Industry 4.0. Many countries have embraced the development of the digital economy.

The term "digital economy" was originally used by Don Tapscott in his 1996 book "*The Digital Economy*". He emphasized that during the previous economic era, information flow appeared in physical form, while in the new economy, it appeared in digital form. Therefore, the digital economy is essentially equivalent to the new economy or knowledge economy [9]. The economic development model relies on information, ICT, and digital technologies, and utilizes the Internet and mobile communication networks. The use of the Internet as part of an economic development model that depends on information, ICT, and digital technologies to advance social and economic goals has emerged as a significant worldwide economic development trend [10–12]. It has garnered significant attention within the scholarly community. Notably, the novel economic geography theory put forth by Paul Krugman introduces a spatial dimension that has traditionally been disregarded in mainstream economic studies [13]. This theory delves into the spatial configuration of economic activities and offers explanations for phenomena like industrial clustering and regional economic integration. In contrast, the emerging growth theory posits that technological progress plays a pivotal role in driving economic expansion. It effectively amplifies productivity and capital investment, fosters technological advancements and innovations, and ultimately leads to economic growth. Consequently, with the context provided by the new growth theory and new economic geography theory, the digital economy can be more comprehensively elucidated and thoroughly analyzed.

Academic research has focused on both its measurement and its economic impact. Numerous nations and institutions have conducted extensive research and studies regarding its measurement, aiming to comprehend its magnitude, composition, and impact. However, due to variations in the definitions of crucial concepts, an all-encompassing and authoritative theory or indicator system is yet to be established. On the other hand, scholars primarily examine how the digital economy presents novel prospects for businesses to generate value by employing inventive business models and technological applications [14]. This prompts companies to actively investigate and implement fresh technologies and methodologies to augment their capacities [15]. Concurrently, the digital economy has also facilitated the emergence of financial technology [16], leading to favorable ramifications for efficient resource allocation, diminished environmental pollution, and the advancement of the green economy [17].

Several academics use spatial analysis to examine the digital economy. In spatial differentiation analysis, commonly used methods include the Theil index, Moran index, Dagum Gini coefficient, kernel density estimation, Markov transition probability matrix technology, and spatial beta convergence models for spatial differentiation analysis. Some researchers also use GWR to examine China's eight main economic zones [18], spatial econometric analysis to examine the link between the digital economy and urban growth [19], and geographic detectors to conduct factor analyses [20].

There are several underlying factors that contribute to the geographical differences, encompassing a broad range of historical, geographical, technological, economic, and policy factors. Historical and geographical factors are among the key drivers of spatial disparities, with the eastern coastal regions benefiting from their proximity to overseas markets and the impact of coastal opening policies. In contrast, the central and western areas have experienced infrastructural and geographic limits, which have caused a considerable delay in growth [21]. The impact of technological advancements on spatial disparities in China's digital economy cannot be overlooked. The emergence and widespread use of innovative technologies have reduced the influence of historical and geographical factors on digital economic development. Instead, clustering and networking are becoming increasingly prevalent in the industry, leading to more pronounced spatial heterogeneity. Technology's contribution to the digital economy is reshaping the sector and creating new chances for expansion and improvement [22]. Economic issues are important contributing elements to geographical inequality. Adequate market demand and industry chain support are essential for the growth of a strong digital economy. Disparities in economic development across provinces can also result in varying levels of digital economy development [23]. Policy factors are also one of the important reasons affecting spatial heterogeneity. Government support and encouragement policies for the digital economy can promote its development, and the degree of policy preferences among different provinces can also lead to differences [24,25].

Based on the above analysis, research on the digital economy is still in its infancy. It focuses mainly on measuring its scale and economic impact. However, there is a significant lack of research on spatial analysis and driving factors. Due to its importance, its spatial characteristics are closely related to the stability and sustainability of regional development. Therefore, we analyze it further in terms of spatial vision, with a detailed spatial presentation of the results. First, this article combines the meaning of development with a geographical heterogeneity viewpoint to create the China Digital Economy Index. To examine the geographical distribution features, we employ the Exploratory Spatial Data Analysis (ESDA) approach, including Moran's I index and the Getis-Ord G* index. Secondly, the application of the Grey Model (GM) shall be employed for the purpose of performing time series forecasts for every geographical entity at hand. Finally, we use the GM predicted value and geographically weighted regression (GWR) to analyze the spatiotemporal distribution characteristics of the effect of external influencing factors in Chinese provincial regions, with industrial structure, foreign openness, government support, and technological progress. We hope that this study will help to understand the main factors influencing spatial development. The primary objective of this scholarly inquiry is to augment the spatiotemporal pattern of the digital economy, mitigate the regional digital schism, and establish a rational basis for the optimal development of the digital economy and the design of policies combining economic geography.

The remainder of this paper is structured as follows. Section 2 presents the data and methods. Section 3 reports the results of the spatial analysis, including temporal evolution, spatial distribution, and spatial correlation. Section 4 reports the driver results, including forecasting results and driving force space analysis. Section 5 summarizes the paper, containing the conclusions, policy implications, and limitations and future directions.

2. Data Sources and Methods

2.1. Study Area and Data Sources

This study centers on the evolution of the regional digital economy in China, with a particular emphasis on the determinants and heterogeneity characteristics of its expansion across the country's provincial regions. The research will focus on the examination of 31 provinces in China as the sample for investigation. The study areas are illustrated in Figure 1.

Due to data availability, this research chooses data from 31 Chinese provinces covering the years 2011 to 2020 for analysis. The primary data sources for this study include the "*China Statistical Yearbook*", "*China Information Yearbook*", "*China Science and Technology Statistical Yearbook*", "*Statistical Report on the Development of China's Internet*", provincial statistical yearbooks, and the CNRDS database. These sources were utilized to extract relevant data that align with the research objectives. Some of the indicators are weighted based on raw data, the resulting data are manually collated and cleaned, and some missing data are supplemented using statistical methods. We used MATLAB to generate the predictions. We used ArcGIS for spatial analysis.

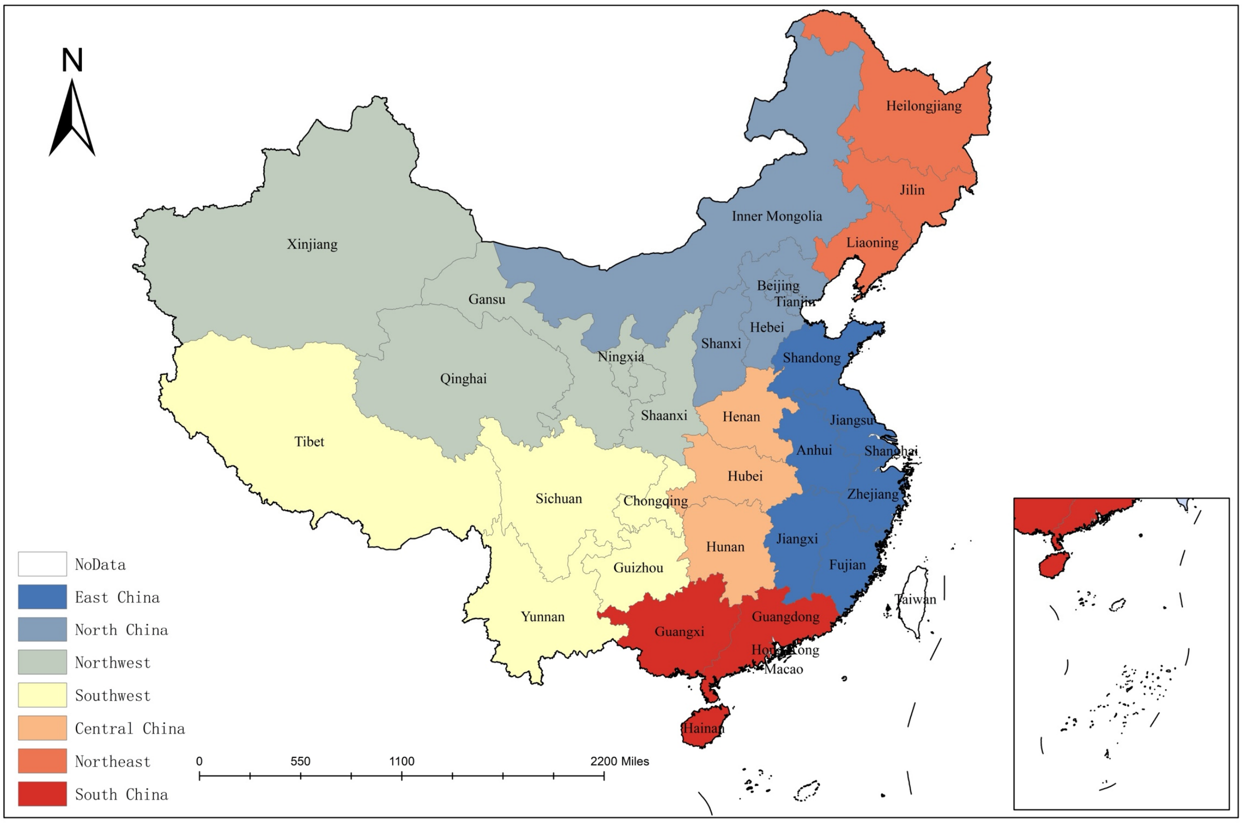

Figure 1. Spatial Distribution of Study Areas.

2.2. Construction of a Comprehensive Indicator System

2.2.1. Selection and Construction of Indicators

A digital economy is a new type of economy whose significance is continuously expanded by continual scientific and technological progress. Additionally, it possesses a dynamic and complex nature stemming from the evolving times. This study develops an index system for evaluating the digital economy by integrating multiple indicators at the target level based on relevant research findings [21,26] considering the principles of data accessibility, quantifiability, and the representativeness of indicators. The choice of digital infrastructure construction is basic, including the construction of cloud, network, terminal, and other information infrastructures [27,28]. Regarding the digital industrialization of electronic information manufacturing, telecommunications, software, IT services, and other related sectors [29], as well as the integration and use of digital technology with traditional industries, e-commerce, and rural integration, among other things, the financial aspect is selected from the Peking University Digital Inclusive Finance Index, which constitutes the digital aspect of the industry. The combination of technology and management, typically characterized by "digital technology + governance", is also considered, including the level of digital government, the number of various technology contracts, the level of R&D spending, the quantity of digital employees and enterprises, etc. Therefore, this paper provides a comprehensive assessment in four dimensions: digital infrastructure construction (DC), digital industrialization (DI), industry digitization (ID), and the digital governance environment (DGE) [25–27]. A total of 21 indicators were selected for this assessment (Table 1).

Table 1. Construction of the indicator system of the Digital Economy Index.

Total Index	Primary Indicators	Secondary Indicators	Units	Attributes
Digital Economy Index	Digital Infrastructure Construction (DIC)	Internet penetration rate	%	+
		Telephone penetration rate	Pcs/100 People	+
		Length of long-distance fiber optic cable lines	Km	+
		Internet broadband access ports	10 thousand Pcs	+
		Number of internet domain names	10 thousand Pcs	+
		Mobile telephone exchange capacity	10 thousand Pcs	+
	Digital Industrialization (DI)	Total telecom services	CNY 100 million	+
		Software business revenue	CNY 10 thousand	+
		Scale of information service revenue	CNY 100 million	+
		Number of digital TV subscribers	10 thousand Pcs	+
		Technology market turnover	CNY 100 million	+
	Industry Digitization (ID)	Expenditure on technology acquisition and technological transformation of industrial enterprises	Pcs/Person	+
		Rural broadband users	CNY 10 thousand	+
		Digital inclusive finance index	–	+
		E-commerce sales	CNY 100 million	+
		Number of computers per 100 people	Pcs	+
	Digital Governance Environment (DGE)	Digital government level	Pcs	+
		Number of technology contracts of various types	Pcs	+
		R&D investment intensity	%	+
		Average number of employees in high-tech industries	People	+
		Number of digital economy enterprises	Pcs	+

Notes: This table displays the construction of the Digital Economy Index. The second and third columns represent the selection of primary indicators (including 4 items) and secondary indicators (specific refinement of the primary indicators, including 21 items). The fourth and fifth columns correspond to the units and attributes (+ for positive; − for negative) of the secondary indicators.

2.2.2. Entropy Value Method for Assigning Weights

Firstly, the indicator data are standardized. As the indicators have different units and dimensions, to ensure comparability over time, the indicators with various characteristics and measurement systems are converted into dimensionless values [26,30]. To avoid the subjectivity of weight assignment and ensure high objectivity, relevance, and matching principles in the selection of indicators, the entropy value approach is used to assign weights to the indicators. This represents a method of weighing that is objective. The following shows the precise computation process:

$$X_{ij} = \frac{a_{ij} - \min(a_{ij})}{\max(a_{ij}) - \min(a_{ij})} (i = 1, 2, 3, \cdots ; j = 1, 2, 3, \cdots) \tag{1}$$

$$E_j = \ln \frac{1}{n} \sum_{i=1}^{n} \left(\frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}} \ln \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}} \right) \tag{2}$$

$$W_j = \frac{(1 - E_j)}{\sum_{j=1}^{m} (1 - E_j)} \tag{3}$$

$$D_i = \sum_{j=1}^{m} W_j X_{ij} \tag{4}$$

where a_{ij} represents the original data of each indicator in the digital economy indicator system, X_{ij} denotes the value of the standardized province i and indicator j, E_j represents the information entropy, n represents the 31 provinces, and m represents the 21 indicators. W_j is the weight assigned to each indicator through the entropy value method. D_i is the digital economy development index.

2.3. Exploratory Spatial Data Analysis

2.3.1. Global Spatial Autocorrelation

Moran's I index, commonly utilized to assess the global spatial autocorrelation, was implemented to examine the patterns of spatial clustering exhibited by the elements analyzed in the given region. By computing the index, a technique used to assess the total geographical correlation of digital economic growth levels, we can determine whether the changes in digital economic development levels in each province are related to adjacent regions. The formula for the calculation is as follows [31–33]:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{5}$$

where I is Moran's I index; x_i and x_j are the observations of regions i and j; S^2 is the variance of the observations; W_{ij} is the spatial weight matrix, and we use the neighborhood standard spatial weight; $\overline{x}$ is the mean; and n is the number of study areas.

2.3.2. Local Spatial Clustering

To reveal the geographical heterogeneity of analytical components in various places, local Moran's I can be employed to discover spatial clustering in limited areas. The Getis-Ord G* index is calculated to quantify the degree of spatial dependence of the variables, thus forming an intuitive analysis and an understanding of the high- and low-aggregation areas of spatially high (hotspots) and low (coldspots) values of digital economy development levels, calculated as follows [34]:

$$G_i^*(d) = \sum_{i=1}^{n} w_{ij}(d)x_i / \sum_{i=1}^{n} x_i \tag{6}$$

where x_i is the observed value of region i and W_{ij} is the spatial weight matrix. If the index is significantly positive, then region i is a hotspot; otherwise, it is a coldspot.

2.4. Grey Prediction Model

As time series data are utilized for short-term forecasting in this paper, the grey prediction method can be implemented. The grey prediction method is a technique used to predict systems that contain uncertain factors. By identifying the differences in the development trends of various system elements (such as residuals, relative errors, etc.), the method generates processed data from the original data to seek patterns of system changes and generate a series of data sequences with strong regularity. To predict the future development tendency, a matching differential equation model is then built, which is particularly appropriate for short-term time series data prediction to enhance the rationality and effectiveness of the forecast [35–37]. Appendix A lists the specific formulae for the calculations.

2.5. Geographically Weighted Regression Analysis

The GWR model may be classified as a commonly employed statistical regression model within the field of quantitative analysis that incorporates geographical distance weighting. Recognizing that the regression coefficients of different spatial units are not the same, GWR embeds the spatial attributes of the observed values into the regression parameters, enabling a more effective reveal of the spatial heterogeneity characteristics and evolutionary rules of the influencing factor regression coefficients in different geographic locations, and reflecting the non-stationarity and mutual differences in spatial data. In the model equation:

$$\mathrm{DE}_i = \beta_0(\mu_i, v_i) + \sum \beta_k(\mu_i, v_i)x_{i,k} + \varepsilon_i \tag{7}$$

DE_i is the digital economic index of the explained variable province i; the coordinate of the geographic unit i is (μ_i, v_i); $\beta_0(\mu_i, v_i)$ is the intercept term; $x_{i,k}$ is the $k-$th explanatory variable on unit i; the function $\beta_k(\mu, v)$ has a value of $\beta_k(\mu_i, v_i)$ on unit i, and ε_i represents the random error.

3. The Spatiotemporal Distribution Characteristics of China's Digital Economy

3.1. Temporal Evolution Characteristics

Figure 2 shows the evolution and modifications in the provincial digital economies of China from 2011 to 2020. The results obtained from this study demonstrate that the digital economy is now operating at a much higher level overall, as is each dimension's level of growth. Among these, the development of digital infrastructure is advancing consistently. The incorporation of the digital economy has brought forth a novel economic paradigm that heavily utilizes digital technology, and depends on the creation of a reliable digital economic infrastructure [38]. The establishment of a comprehensive information infrastructure, encompassing the development of cloud, network, and terminal facilities, is a pivotal component in modern technological systems [39,40]. This demonstrates China's dedication to strengthening its infrastructure and treating data as a production resource that is included in the allocation system. The country has also implemented a nationwide big data strategy, which has yielded significant results. The development of digital industrialization has shown rapid growth in this context and has become a central area. This trend demonstrates the growing confluence of technological developments, economic strategies, and societal requirements, with digital industries playing a crucial part in the digital transformation of the current economy as a support for the quick growth of the digital economy. Despite the major advancements achieved in the evolution of technology, industrial digitalization still has a lot of potential for expansion. In forthcoming times, it is imperative that we expedite the comprehensive integration of digital technology into the tangible economic sphere and capitalize on the instrumental capacity of the digital economy. This innovation may grow quickly and healthily thanks to the digital environment. Even though the digital governance landscape has not undergone significant development and there is still a considerable gap in some areas, we can actively utilize digital technology to explore a brand-new digital governance transformation strategy. On this basis, we can establish a standardized and orderly digital governance system, increasing support for the digital economy's healthy growth [41].

3.2. Spatial Distribution Characteristics

The "natural breakpoints classification method" was used to create a five-level spatial map of the digital economic levels from 2011 to 2020. This visualization is based on the observation years of 2011 and 2020 (Figure 3). There is significant spatial heterogeneity for each province, as well as in their sub-dimensions, which display unique characteristics over time and space. The overall Digital Economy Index exhibits a decreasing trend from the coast to the inland areas, with coastal areas and relatively developed core provinces showing a significant advantage. The development of digital infrastructure has advanced in each province, according to the digital infrastructure index, with high-value areas gradually spreading. The regions of Sichuan and Chongqing, the Yangtze River Delta region merging the provinces of Jiangsu, Zhejiang, and Shanghai, and the Pearl River Delta region are all experiencing marked development, and the overall digital infrastructure is gradually taking shape [42]. The overall development of digital industrialization has significantly improved, with a trend toward the spatial overflow of high-value areas. Over time, there has been a distinctive emergence of three primary core regions, which are located around the central regions of "Beijing-Tianjin-Hebei", "Jiangsu-Zhejiang-Shanghai", and the "Pearl River Delta". The "Twin City Economic Circle" in the southwestern region, centered around Chengdu and Chongqing, has significant development potential, while the northeastern region has shown a decline. The development of industrial digitalization has shown a trend of low-value areas expanding while high-value areas contract, especially with low-value areas such as Inner Mongolia and the northeastern region significantly expanding, and high-value areas along the coast showing a continuous convergence trend. However, the Pearl River Delta region still maintains a high-value area [43]. The development of the digital governance environment has shown a trend of low-value areas gradually expanding from western regions, while high-value areas are mostly concentrated in Guangdong and Jiangsu provinces [44].

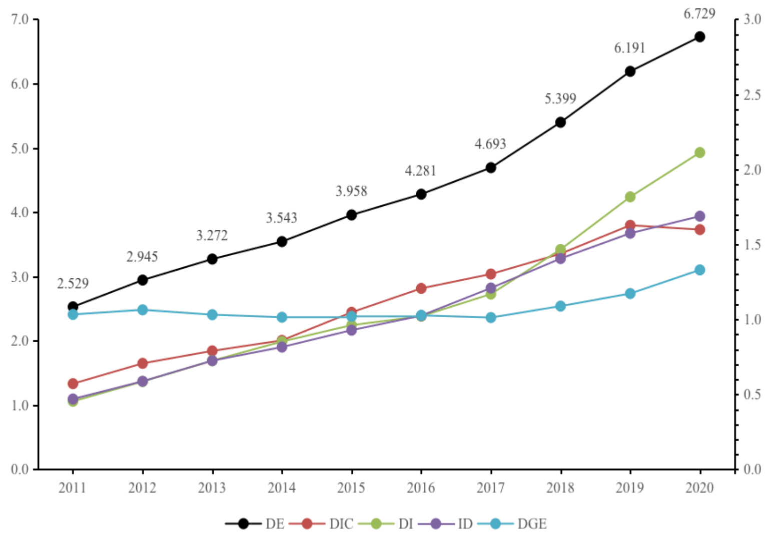

Figure 2. The trend of China's Digital Economy Development from 2011 to 2020.

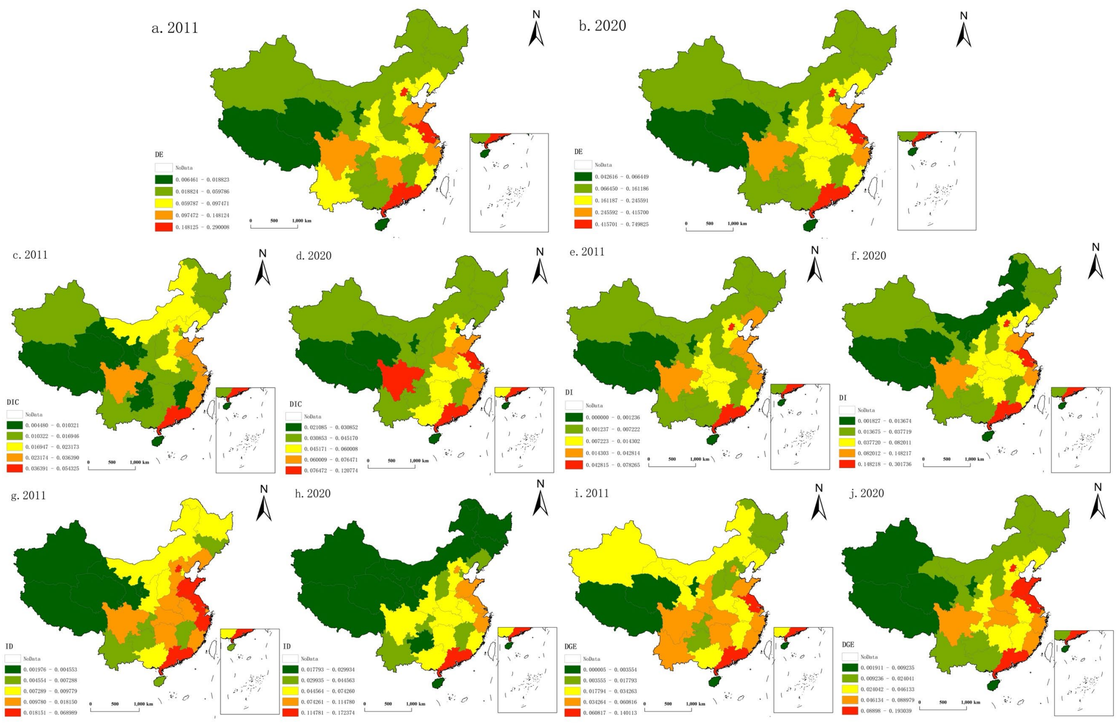

Figure 3. Spatial distribution map of the development index of the digital economy. (**a**,**b**) stand for digital economy (DE); (**c**,**d**) stand for digital infrastructure construction (DIC); (**e**,**f**) stand for digital industrialization (DI); (**g**,**h**) stand for Industry digitization (ID); (**i**,**j**) stand for digital governance environment (DGE).

3.3. Spatial Correlation Analysis

3.3.1. Global Spatial Autocorrelation

The geographical correlation and agglomeration features of the digital economy between each province and its neighboring provinces were examined in this study. The outcomes of the Moran's I index computation and associated Z value are shown in Figure 4. Our findings lead to the conclusion that Moran's I index during the research period was significantly positive and ranged between 0.048 and 0.088. The overall mean Moran's I index even reached 0.072, indicating that the spatial distribution is not random and that there are significant positive spatial correlation characteristics between regions, as well as spatial dependence and agglomeration phenomena. This further confirms that cities with higher levels are geographically closer, forming a strong alliance. However, cities with lower levels also cluster together, becoming a "funnel zone". This is consistent with the previous spatial pattern analysis conclusion.

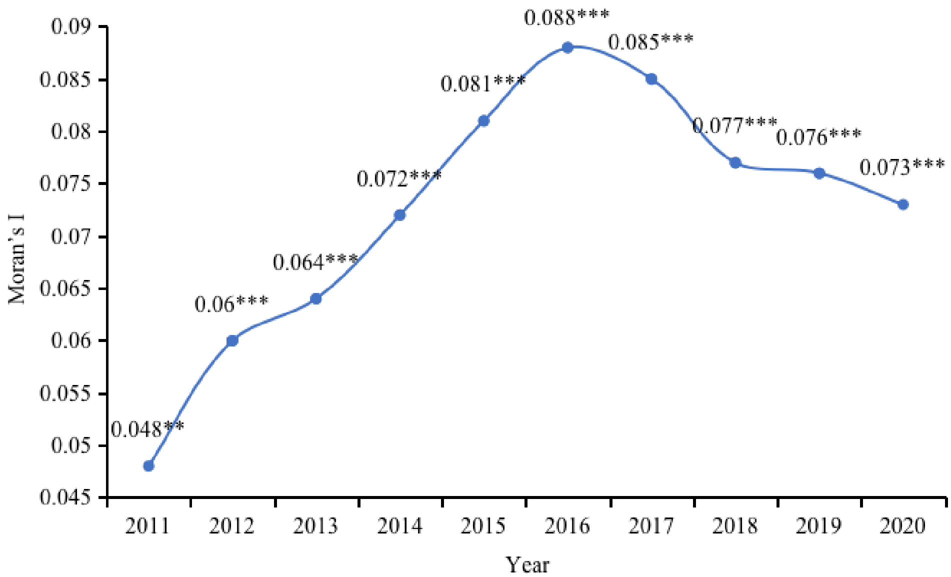

Figure 4. Global Moran's I index of the level of new economic development in China's provinces. Note: *** and ** indicate that the Z values are significant at the 1% and 5% levels, respectively.

However, the trend shows a "convex" shape, increasing first, and then, decreasing slightly. The spatial agglomeration gradually decreases after continuous enhancement. This shows that the provincial agglomeration development pattern is evolving in a way that is consistent with the fundamental rule of economic growth and development. In the phase of rapid economic growth in China, various regions, including provinces and cities, exhibit an ardent pursuit of progress through various initiatives to enhance their economic standing accumulated capital, labor, technology, and other factors through their endowment advantages, forming a low-level equilibrium. Each province's and city's digital economy development circumstances steadily improve as China's economy enters a high-quality development stage, digital technology continues to be popularized and applied, and relevant factors are reconfigured. This leads to an evolution path from low-level equilibrium to polarization, and then, to high-level equilibrium.

In 2011, this was basically in a low-level equilibrium state, but it has already shown a trend of spatial polarization. With the implementation of relevant policies, provinces with comparative advantages, such as Beijing, Shanghai, Guangdong, and Zhejiang, as well as provinces with early-mover advantages, such as Sichuan and Hubei, were able to develop more quickly. Therefore, the spatial polarization process accelerated, reaching its peak in 2016. Noteworthy is the assertion that the terminology "digital economy" was initially employed within the framework of the Chinese government's 2017 work report and suggests that China's growth of the digital economy has progressed from theory to practice. Moreover, as the spatial spillover effects gradually emerge, the agglomeration pattern has begun to shift toward high-level equilibrium. In the future, to promote more balanced and orderly development across the country, it is important to optimize the industrial layout and strengthen policy coordination, thereby forming a digital economy development pattern with multiple synergies and coordinated development.

3.3.2. Localized Spatial Autocorrelation Analysis

Based on the hot- and coldspot analysis in Figure 5, it is evident that the overall level, as well as the hotspots in each dimension, are primarily concentrated in the main provinces of the Yangtze River Basin. In terms of the comprehensive index, there is no significant difference in the overall distribution of hot- and coldspots between 2011 and 2020. The hotspots are primarily concentrated in the Yangtze River Delta region, such as Shanghai, Jiangsu, and Anhui, and have gradually expanded outward to coldspots, forming a spatial heterogeneity pattern resembling a "mountain peak". The coldspots are primarily found in China's western and northern areas, such as Xinjiang, Sichuan, Yunnan, and Guangxi.

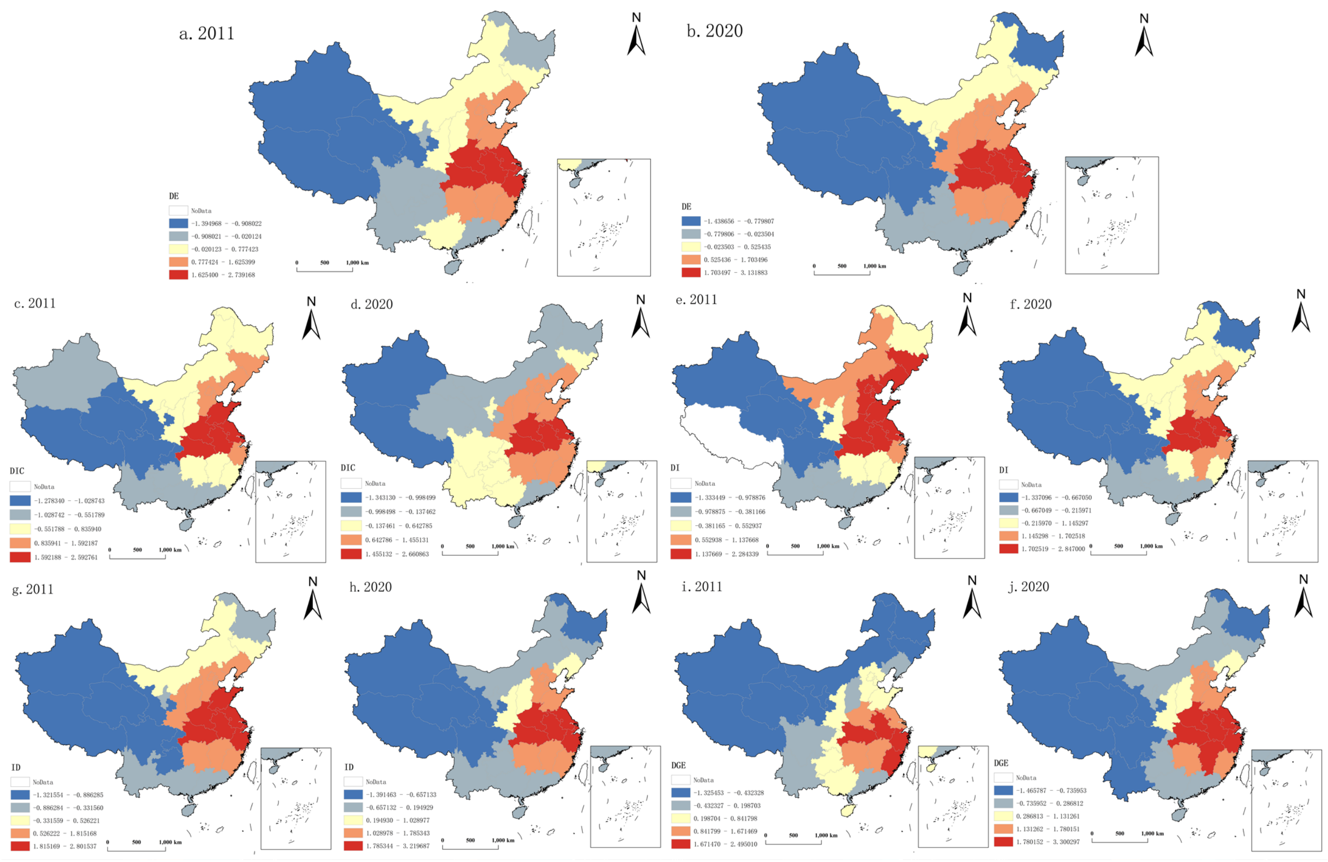

Figure 5. Distribution of hot- and coldspots of China's provincial digital economy development level. (**a**,**b**) stand for digital economy (DE); (**c**,**d**) stand for digital infrastructure construction (DIC); (**e**,**f**) stand for digital industrialization (DI); (**g**,**h**) stand for Industry digitization (ID); (**i**,**j**) stand for digital governance environment (DGE).

The development of digital infrastructure has undergone significant changes over time, with the hotspots in the areas centered around Shanghai, Jiangsu, Anhui, Hubei, and Henan gradually expanding outward. Meanwhile, Inner Mongolia and the northeastern region have transitioned from being a transition zone to a sub-coldspot area. The distribution range of hotspots and sub-hotspots in the development of digital industrialization is gradually becoming concentrated in the Yangtze River Basin. In particular, the northern regions, such as the Beijing–Tianjin–Hebei region, Shandong, and Liaoning surrounding the Bohai Sea, were the main hotspots in 2011, but transitioned into sub-hotspots in 2020. In 2011, the hotspots and sub-hotspots in the development of industrial digitization were mainly distributed in the central provinces. However, in 2020, the overall distribution range slightly reduced, with the sub-hotspots shrinking relative to the Beijing–Tianjin–Hebei region, while the hotspots have shrunk relative to the Jiangsu, Zhejiang, and Shanghai areas. The distribution range of hotspots and sub-hotspots in the digital governance environment is generally expanding. In 2011, the hotspots were mainly distributed in three belt-shaped regions, including Zhejiang, Hubei, and Anhui, while the sub-hotspots were distributed in a manner surrounding the hotspots and expanding outward. However, by 2020, the range of hotspots had gradually expanded to the surrounding areas and extended southward.

In summary, the spatial agglomeration characteristics and their four sub-dimensions have been quite significant over the past decade, primarily manifesting in the expansion of hotspots and sub-hotspots, as well as the stability of coldspots and sub-coldspots. The focal areas and subsidiary clusters are notably centered in the geographical locale of the "Beijing-Tianjin-Hebei," "Jiangsu-Zhejiang-Shanghai", the Yangtze River Delta, and the coastal regions towards the east, thereby evidencing a clustered dispersion pattern. Meanwhile, the western and northeastern areas are where the majority of the coldspots and sub-coldspots are located, which are large and contiguous agglomeration areas (Figure 5).

4. Analysis of the Predictions and Influencing Factors

4.1. Predictions of the Digital Economy

On the basis of the results of the measuring index for 10 consecutive years from 2011–2020 and using the GM grey degree forecasting model to forecast and analyze the index levels for 2021–2025 (Table 2), the Posterior Difference Ratio (C-Value) can verify the accuracy of the grey prediction. The model's accuracy is generally considered to be high when the grey prediction value is less than 0.35, qualified when it is less than 0.5, basically qualified when it is less than 0.65, and unqualified when it is greater than 0.65. The C-value of the prediction model in this study has an average of 0.053, and the average relative error (Error.) is 0.049, indicating that the model's accuracy is high.

Table 2. Forecast results for China's Digital Economy Index.

Province	2021	2022	2023	2024	2025	Average	C-Value	Error.
Guangdong	0.780	0.844	0.910	0.979	1.050	0.913	0.050	0.057
Beijing	0.636	0.708	0.789	0.879	0.979	0.798	0.002	0.012
Jiangsu	0.576	0.628	0.685	0.748	0.815	0.690	0.010	0.022
Shandong	0.430	0.463	0.496	0.530	0.565	0.497	0.015	0.034
Zhejiang	0.417	0.449	0.481	0.514	0.547	0.482	0.031	0.044
Shanghai	0.359	0.394	0.433	0.475	0.522	0.437	0.012	0.031
Sichuan	0.335	0.363	0.391	0.420	0.449	0.392	0.030	0.048
Hubei	0.276	0.310	0.348	0.391	0.438	0.353	0.008	0.019
Fujian	0.280	0.301	0.323	0.345	0.367	0.323	0.088	0.071
Henan	0.256	0.279	0.302	0.326	0.350	0.303	0.008	0.030
Hebei	0.233	0.263	0.296	0.334	0.376	0.300	0.004	0.017
Anhui	0.223	0.242	0.262	0.282	0.302	0.262	0.033	0.061
Shaanxi	0.221	0.238	0.255	0.273	0.291	0.256	0.073	0.076
Hunan	0.194	0.206	0.219	0.231	0.243	0.219	0.165	0.089
Liaoning	0.176	0.184	0.192	0.200	0.209	0.192	0.059	0.026
Chongqing	0.163	0.176	0.190	0.204	0.218	0.190	0.007	0.026
Guangxi	0.159	0.173	0.187	0.201	0.215	0.187	0.114	0.123
Jiangxi	0.156	0.169	0.183	0.197	0.211	0.183	0.030	0.063
Tianjin	0.150	0.159	0.169	0.178	0.188	0.169	0.014	0.022
Guizhou	0.121	0.131	0.141	0.151	0.162	0.141	0.069	0.089
Shanxi	0.119	0.127	0.136	0.145	0.154	0.136	0.054	0.064

Table 2. *Cont.*

Province	2021	2022	2023	2024	2025	Average	C-Value	Error.
Yunnan	0.118	0.124	0.130	0.136	0.142	0.130	0.429	0.118
Jilin	0.110	0.117	0.125	0.132	0.140	0.125	0.036	0.037
Heilongjiang	0.110	0.116	0.122	0.128	0.134	0.122	0.029	0.034
Gansu	0.098	0.105	0.113	0.120	0.128	0.113	0.067	0.076
Inner Mongolia	0.097	0.103	0.109	0.116	0.124	0.110	0.035	0.025
Xinjiang	0.087	0.092	0.097	0.102	0.107	0.097	0.156	0.074
Hainan	0.073	0.079	0.085	0.091	0.097	0.085	0.018	0.043
Ningxia	0.064	0.069	0.074	0.079	0.085	0.074	0.011	0.035
Qinghai	0.060	0.064	0.069	0.073	0.078	0.069	0.007	0.027
Tibet	0.048	0.052	0.056	0.060	0.064	0.056	0.006	0.029

Notes: This table presents the forecast results of the Digital Economy Index. It includes the predictions for 31 provinces in China from 2021 to 2025. The values are sorted in descending order based on the five-year average forecast. The Posterior Difference Ratio (C-value) is used to validate the accuracy of the model's predictions. A lower C-value indicates higher accuracy, with values less than 0.35 considered high, less than 0.5 being qualified, less than 0.65 being qualified, and anything above 0.65 deemed unqualified. In this study, the average C-value of the prediction model is 0.053, and the average relative error (Error.) is 0.049, indicating a high level of accuracy for the model.

According to predictions, Guangdong, Beijing, Jiangsu, Shandong, Zhejiang, and Shanghai will be ranked as the top six provinces in terms of digital economic development over the next five years. The Bohai Rim, Yangtze River Delta, and Pearl River Delta regions are significant areas of concentration with respect to the three primary economic circuits, have significant development potential, but other areas may also present new opportunities for growth and breakthroughs.

4.2. Driving Force Space Analysis

A model plausibility analysis is first required. Based on relevant studies, to circumvent the presence of multicollinearity within the chosen indicators, and thus, bias the regression results, a multicollinearity test must be performed on the chosen variables, excluding variables with a VIF greater than 5 and OLS regression with low significance. Finally, four external influential variables of spatial differences were obtained, namely industrial structure, degree of openness, government support, and technological progress [21,22,24,45]. To further prove the rationality of the model selection, Moran's I index was calculated in 2011, 2015, 2020, and 2025, and all were significantly positive. This indicates they are clustered in space and have a strong positive spatial correlation. Additionally, the R^2 values for the OLS model are 0.859, 0.907, 0.923, and 0.858, respectively, indicating that, as a whole, the GWR model outperforms the OLS model. The model selection is reasonable (Table 3).

Table 3. Parameter results of the GWR model.

Parameters	2011	2015	2020	2025
Bandwidth	1,557,473.526	1,892,852.163	1,700,628.703	3,672,588.992
AICc	−144.020	−110.225	−92.846	−33.522
R^2	0.907	0.913	0.931	0.820
Adjusted R^2	0.872	0.887	0.910	0.785

Notes: The table presents the parameter results of the GWR model for conducting model credibility analysis. It includes bandwidth, AICc, R^2, and adjusted R^2 for the years 2011, 2015, 2020, and 2025.

Within this realm of explanatory variables, the indicator of the ratio between tertiary industry added value and Gross Domestic Product (GDP) within a given region, specifically known as the Industrial Structure (IS), constitutes a measure of the level of industrial structure present. The proportion of foreign-invested enterprises' aggregate imports and exports with respect to a region's GDP (FDI) functions as a metric to measure the level of external accessibility of said region. The ratio of public spending to GDP in each area (GS) is used to gauge the level of government assistance. The number of patent authorizations per ten thousand people (TP), which, combined, make up the external influencing variables for growth, serves as a measure of technical advancement. At the same time, based on the indicator data of external influential factors for 10 consecutive years from 2011 to 2020, the numerical value was predicted until 2025 using the GM grey degree method, and we analyzed the evolution of external influential factors in the temporal and spatial dimensions.

4.2.1. Spatial Patterns of IS

The data presented in Figure 6 reveal that regional outcomes regarding the influence of industrial structure exhibit some level of variation. Specifically, in relation to temporal patterns, the regression coefficient pertaining to industrial structure displays a prominent, upward trend throughout the years 2011 to 2025, indicating that regional industrial structure optimization has contributed to development and influence. The coefficient values from a geographical standpoint exhibit a broad pattern of high in the north and low in the south, with the high-value area extending from the northeast and the Beijing–Tianjin–Hebei region to the southwest. In 2011, the regression coefficient is between −0.0417 and 0.1299 and spatially shows a pattern of decreasing positivity from northeast to northwest. In Xinjiang, Tibet, and Yunnan, the coefficient is negative, indicating that the positive impact of industrial structure on the northeast region is greater than that on the southwest region, and it harms the Xinjiang, Tibet, and Yunnan regions. In 2015, the regression coefficient is between 0.0512 and 0.1772, with the high-value area being positive and contracting, while the low-value area is negative and pushes towards the southern coastal areas. In 2020, the regression coefficient is between 0.0854 and 0.4203, and the overall regression coefficient increases slightly, with high-value and transitional areas expanding, and low-value areas concentrated on the southwestern border. The impact of industrial structure on the digital economy of each province is gradually deepening. The predicted regression coefficient for 2025 is between 0.2240 and 0.4044, with a significant increase in the regression coefficient for the low-value area, further reducing the size of the low-value area. Moreover, the optimization of the industrial structure has yielded considerable progress in the digital economy of each province, drawing them closer together and thereby narrowing the gap of effects between them.

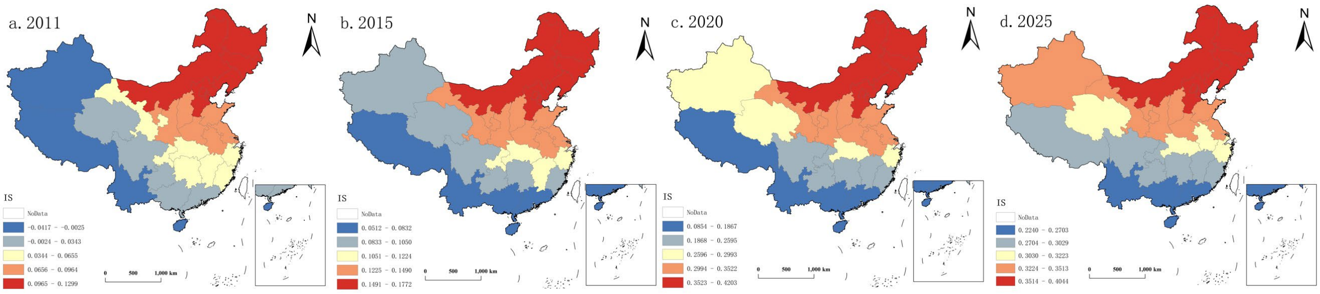

Figure 6. Spatial distribution of IS regression coefficients in 2011, 2015, 2020, and 2025.

As a whole, the movement towards knowledge- and technology-centric sectors by labor and capital incentivize the enhancement of industrial structure, thereby catalyzing progress within the digital economy [21]. As the globe transitions towards the post-industrial age, modern service sectors, such as retail and e-commerce, are developing more quickly and are becoming more crucial to economic growth. This is intricately linked to the level of sophistication exhibited by the industrial structure, and the degree of development witnessed within the tertiary industry. These factors are of utmost importance in determining the magnitude and direction of the digital economy's evolution. However, in the northeast region of China, resource-based industries and heavy industry have long dominated, and the transformation of industries has been slow. The tertiary industry is developing quite slowly, and the degree of industrial sophistication is relatively low. The region's modification of its industrial structure profoundly influences its respective area, rendering it exceedingly receptive to the burgeoning advancement of the digital economy [43]. Additionally, the industrialization process in the regions of the center and west has increased with the adoption of the Western Development Strategy and the emergence of the central region in the latter time. However, because of their slow economic growth, these areas lack top talent and the conditions necessary for significant industrial innovation. Short-term technological advances are not possible, and there are conflicts between their growth and that of some old sectors. The lack of technological innovation capabilities in the industrial structure will, to some extent, restrict development [46]. As the industrial structure gradually optimizes and the efficiency of each province improves, the gap between provinces is expected to further narrow.

4.2.2. Spatial Patterns of FDI

As shown in Figure 7, from a temporal perspective, the regression coefficient of foreign investment dependence from 2011 to 2025 is significant and has both positive and negative values, indicating that this factor has spatial non-stationarity in its impact on the digital economy. In terms of geographical context, the coefficient values show a general tendency of increasing in the southern sub-regions as opposed to a drop in the northern parts. Furthermore, there is a notable change in the high-value area from the southern coastal places to the northwest regions throughout time. In 2011, the contextual regression coefficient varies between 0.0040 and 0.1670, with the bulk of the high-value zone located south of the Yangtze River, and the low-value region concentrated mostly in the northeastern and Inner Mongolia sub-regions. In 2015, the regression coefficient is between −0.0031 and 0.1509, and there is a significant high-value area moving towards the southeast coastal areas, and a pattern of low-value area expansion. In 2020, the regression coefficient ranges from −0.1698 to 0.1180, with most regions having negative coefficients. Furthermore, there are significant changes in the breakdown of high- and low-value locations, along with the high-value areas showing a positive trend and forming a "striped belt" in the Guangdong, Guangxi, Yunnan, and Tibet regions. Due to factors such as international trade frictions, global economic slowdown, and the impact of the pandemic, economic instability and uncertainty have intensified, limiting the investment and innovation willingness of businesses in the sector, and hindering development [47]. However, key provinces of the "Belt and Road" initiative, such as Guangxi, Yunnan, and Tibet, have unique geographical and resource advantages, and through economic complementarity and cooperation with neighboring countries and regions, they have promoted foreign trade and investment cooperation. In 2025, the predicted regression coefficient is expected to range from 0.1696 to 0.3198, with an overall significant increase in positive regression coefficients.

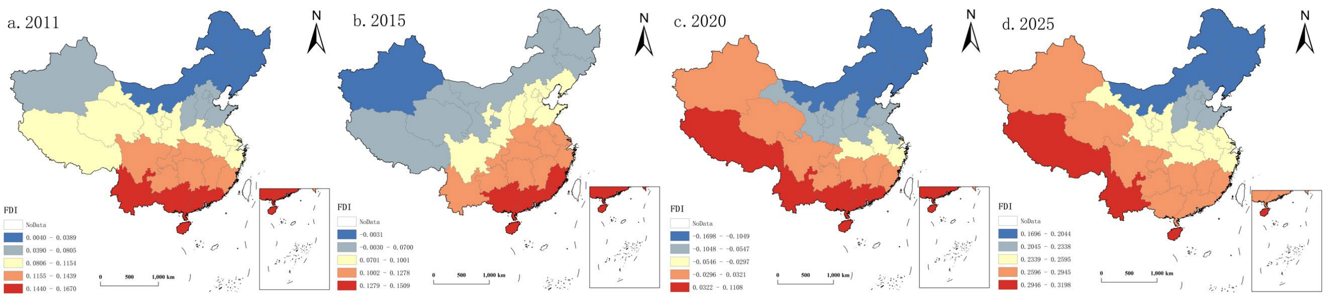

Figure 7. Spatial distribution of FDI regression coefficients in 2011, 2015, 2020, and 2025.

External openness serves as a vital impetus for advancement. By bringing in foreign investment, promoting international collaboration, and broadening market reach, it can effectively bolster regional digital economic development [22]. Increasing the degree of external openness is beneficial for attracting additional capital investment, as well as facilitating the introduction of foreign technology and services. This can aid in integrating advanced digital economy management experience into local digital economic development, promoting digital technology innovation, facilitating the flow of digital resources, and advancing regional digital economic development. Due to their early and high degree of openness, the southern coastal regions and some of the "Belt and Road" areas in the supported free trade pilot zones have outstanding advantages in development, greater development space, and more opportunities and potential. These regions can achieve closer economic connections and cooperation with neighboring countries and regions. However, in some regions of China that have relatively late openness, the impact of technology introduction guided by openness on the local economy has temporal and spatial lag and limitations, especially in areas of China with lower degrees of openness, such as the northeastern region. This suppressive effect is more pronounced, resulting in a relatively small development space for the digital economy. In addition, coastal regions face more intense competition, higher market saturation, and greater difficulty in developing the digital economy over a certain period [48]. This also implies that in accelerating high-quality development, we must be guided by promoting the spillover of knowledge and technology, adhering to the principle of "bringing in and going out", and achieving leapfrog development of the digital economy through international cooperation and competition.

4.2.3. Spatial Patterns of GS

As shown in Figure 8, over time, from 2011 to 2025, the government-supported regression coefficients have significant positive and negative effects, indicating that the impact of government support has spatial non-stationarity. The coefficient values' pattern of distribution tends to show greater values in the western areas and lower values in the eastern regions. Geographically speaking, the western and eastern portions of this distribution pattern are often characterized by a high-value concentration and a low-value concentration, respectively. The lower-value areas tend to accumulate through time from the center coastal regions to the northeastern parts. In 2011, the coefficient ranges from 0.0149 to 0.0292, showing a significant low-value area clustering in the Jiangsu, Zhejiang, and Shanghai regions, with a "funnel-shaped" distribution pattern. This shows that the Jiangsu, Zhejiang, and Shanghai regions are less positively affected by government assistance for the digital economy than the other regions are. In 2015, the regression coefficient ranges from 0.0144 to 0.0264, with a trend of low-value areas spreading to the Bohai Sea region. In 2020, the coefficient ranges from −0.0039 to 0.0388, with some regions having negative coefficients and significant changes in the low-value areas. This forms two "striped belts", mainly in the northeastern and Bohai Sea regions, indicating significant changes in the impact of government support. The predicted regression coefficient in 2025 is expected to range from −0.0090 to 0.0153, with some negative coefficients and an expansion of low-value areas, mostly in North China and the northeast.

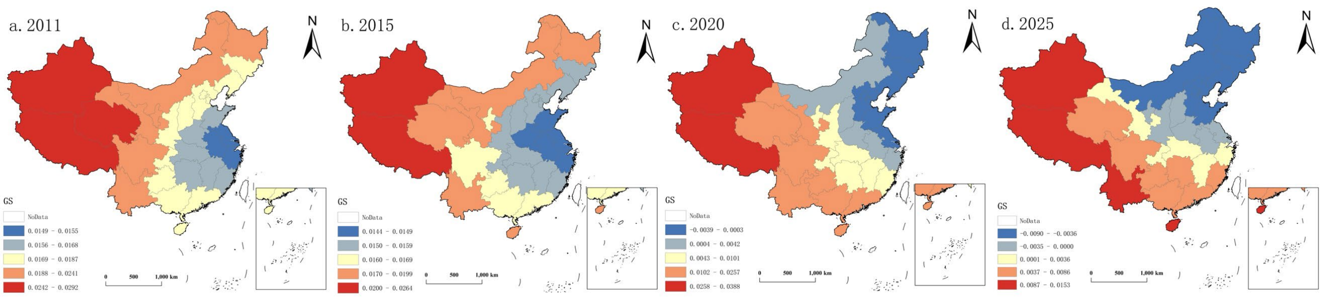

Figure 8. Spatial distribution of GS regression coefficients in 2011, 2015, 2020, and 2025.

The government plays a crucial role by providing support, leading innovation, and promoting integration. The construction of digital infrastructure, including network infrastructure and information technology infrastructure, is the key foundation. The government's actions and policies will directly affect the development and construction of digital infrastructure, which, in turn, will impact the speed and quality of development. It should be noted that government actions play a significant role. However, when regional digital markets have developed to a certain extent, inflexible policy-making and implementation, failure to keep up with technological and market changes, a lack of funding, and insufficient financial support may lead to problems such as lagging digital infrastructure development and inadequate talent cultivation. To a certain extent, these issues may constrain development. In addition, the allocation and use of government financial support also need to be planned reasonably to fully utilize funding resources. Otherwise, it may lead to resource waste, hinder innovation and technological progress, and may not necessarily achieve the desired results [49].

4.2.4. Spatial Patterns of TP

Based on Figure 9, it can be observed that from 2011 to 2025, technological advancement has a positive impact on Chinese provinces, and this impact coefficient gradually increases. In terms of region, different provinces exhibit varying distribution characteristics at different times, with coefficient values generally higher in the south and lower in the north. As time progresses, the low-value area gradually shrinks while the high-value area spreads from the southern coastal regions to the northeast. In 2011, the coefficient ranges from 0.0094 to 0.0130 and the high-value area is concentrated in Guangdong, Hainan, Guangxi, Yunnan, and Xinjiang, while the low-value area is concentrated in the regions north of the Yangtze River. In 2015, the coefficient ranges from 0.0136 to 0.0277, and significantly increases. The high-value area is mainly in Hainan and Yunnan, while the low-value area is concentrated in the northeastern provinces and the Bohai Rim region. In 2020, the coefficient ranges from 0.0206 to 0.0439 and spatially shows a decreasing pattern from south to north along the Yangtze River. The predicted regression coefficient for 2025 ranges from 0.0577 to 0.0740, with the coefficient further increasing. The high-value area encompasses Guangdong, Hainan, Guangxi, and Yunnan, and spatially, it shows a trend of expanding towards the northeast region.

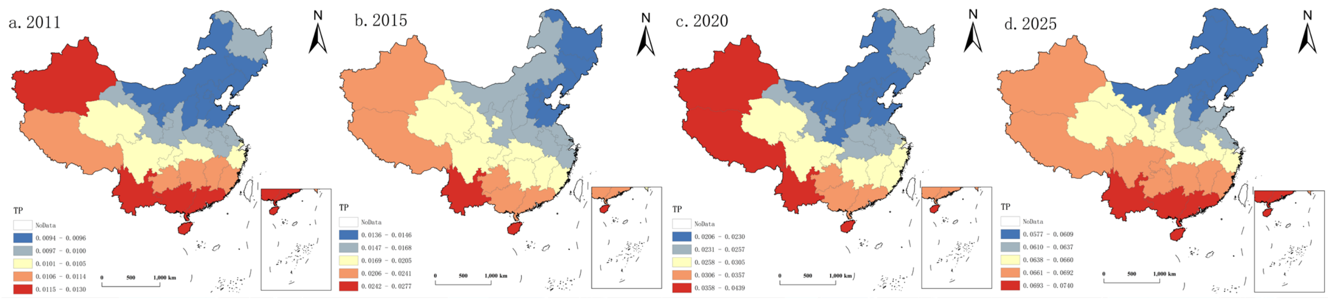

Figure 9. The spatial distribution of TF regression coefficients in 2011, 2015, 2020, and 2025.

Through the application and innovation of technology, productivity can be increased, costs can be reduced, and market size can be expanded. This can be aided through the introduction of new technology, goods, and services as a result of technical innovation [50]. The influence of technological progress varies significantly from province to province, with strength showing a decreasing pattern from high-value areas in the southwest to low-value areas in the northeast. For example, in technologically advanced regions in the south such as Guangdong and Hainan, the industrial chain may be further optimized using artificial intelligence, and the quality and productivity can be raised. In provinces such as Guangxi, Yunnan, Tibet, and Xinjiang, technological innovation plays an even more important role. This is because these provinces are in the early stages, where innovation investment can significantly contribute to marginal development, making the innovation-driven effect even more apparent. Technological progress has therefore played a more positive role. In contrast, relatively underdeveloped regions in the north need to further enhance investment in infrastructure construction, talent development, and other aspects, to improve their capacity for technological innovation and better promote it.

5. Results and Discussion

5.1. Conclusions

(1) In the past decade, the overall trajectory of China's digital economy has shown an increasing tendency over time. All four sub-dimensions have demonstrated positive trends, although the issue of uneven development persists. Among them, the rapid growth of digital industrialization has shown significant advantages, while the level of digital environmental governance has not received strong development. China's digital economy continues to grow, and its digitalization process is advancing in all aspects. According to predictions, Guangdong, Beijing, Jiangsu, Shandong, Zhejiang, and Shanghai will be ranked as the top six provinces in terms of digital economic development over the next five years. The Bohai Rim, Yangtze River Delta, and Pearl River Delta regions are significant areas of concentration with respect to the three primary economic circuits and have significant development potential, but other areas may also present new opportunities for growth and breakthroughs.

(2) Regarding regional distribution, it is clear that there is substantial spatial variability across the various provinces' degrees of development, with a gradient that gradually narrows as one moves from coastal to inland areas. The Bohai Rim, the Yangtze River Delta, and the Pearl River Delta, which mostly comprise Beijing, Shanghai, and Guangdong, are the three main economic circles that make up the digital economy. The "Twin Cities Economic Circle" in the southwest region, mainly consisting of Chengdu and Chongqing, has great development potential. At the same time, there is a significant "digital divide" and "Matthew effect".

(3) From our spatial correlation analysis, Moran's I index calculation reveals that the index is strongly positive in all years, with a "convex" shape. Economically developed and mature provinces show spatial distribution characteristics that are characterized by agglomeration. The agglomeration phenomenon shows a gradually shifting trend from low-value high agglomeration to high-value relative dispersal, forming significant non-equilibrium. As time passes, the development of the spatial spillover effect among provinces has gradually become stronger. Additionally, our examination of hot- and coldspots reveals a more pronounced spatial clustering pattern that is mostly seen in the dispersion of hotspot areas as well as the stabilization of coldspot locations. The spatial agglomeration and spillover of the four sub-dimensions also exhibit different geographical characteristics.

(4) We considered the external influencing factors and forecasted spatial distribution, with industrial structure, foreign openness, government support, and technological progress. Technological progress is a positive driving factor with an increasing impact. Technology-oriented spatial spillovers are evident, with high-value areas advancing from south to north. The industrial structure regression coefficient is highly positive and rising annually, showing a distribution pattern of north–south differences, and the optimization of industrial structure has, to some extent, narrowed the development gap among provinces. Government support plays an important role and there is spatial non-stationarity. As time progresses, the low-value area advances from east to north. The impact of FDI is relatively small and there is spatial non-stationarity. This was hindered in most regions in 2020 due to external environmental factors, but it is predicted to have an overall positive promoting effect for all provinces by 2025.

5.2. Policy Implications

(1) To adapt to local conditions, the objective is to modify the industrial structure as effectively as possible. The optimization of industrial structure has somewhat mitigated the variation in the growth of the digital economy among provinces. By leveraging their respective strengths and advantages, different regions can promote the expansion of the digital sector in a focused manner. This may involve transforming traditional manufacturing into digital intelligent manufacturing and cultivating clusters of industries associated with the digital economy. The "Bohai Rim", "Yangtze River Delta", and

"Pearl River Delta" serve as the focal areas of these three main economic circles, and the dispersion effect is crucial in spreading and promoting regional digital activities. Local features may serve as a basis for the western and northeastern areas. To accomplish greater adoption and improve the strength of a certain area of the digital economy, and to realize the goal of leading the surface, breakthrough development is necessary.

(2) Relevant policies promote development. Development relies on government support and external cooperation. To effectively address uneven development, with the advancement of artificial intelligence technologies, relevant policies should be implemented to promote coordinated regional development, seize the new opportunities for international competition brought about by the new Industry 4.0 era, and actively participate in cross-border digital economy cooperation. At the same time, it requires strong digital technology as a guarantee. The government can promote innovation and development by advancing relevant policies and regulations, enhancing digital infrastructure development, supporting innovative digital technologies, and expanding digital business models. However, data, networks, and media are exchanged and shared in large quantities in the process, so it is also vital to protect digital privacy and data security.

(3) Promoting the transformation of digital industries. Investment in innovation serves as a catalyst for scientific progress and technological innovation, playing a pivotal driving role. At the macro level, conventional industries' digital transformation has emerged as a significant tool and a crucial connection in fostering rapid growth. At the micro level, digital transformation can aid traditional industries in enhancing production efficiency, optimizing management processes, improving product quality, and increasing innovation capabilities. This can enable them to better adapt to market demand and enhance competitiveness. The process of digital transformation takes time and will evolve gradually, requiring constant adaptation and adjustment by organizations and businesses in terms of technology, models, and formats. Therefore, companies in various industries and fields must face the important choice of "rebirth from the ashes" and continually enhance their awareness of the importance of digital transformation.

5.3. Limitations and Future Prospects

Due to the lack of a unified understanding and definition of the digital economy, further in-depth analysis is needed to quantify its development considering the complexity of the digital economy. Additionally, the digital economy is influenced by various factors, particularly spatial factors, which require further investigation. Moving forward, our research will focus on the following areas: (1) Developing a more comprehensive indicator system for the digital economy, and exploring more comprehensive and scientific measurement methods to accurately assess its development level and potential. (2) Conducting in-depth research on the diverse driving factors of the digital economy, including spatial factors, to gain a better understanding of its development trends and enable more accurate predictions.

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Appendix A. The Formula for the GM Model

The specific method of the GM model is as follows:

First, first-order cumulative generation is performed. A raw sample data column is constructed for a set of digital economic indicators: $X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right\}$, where $x^{(0)}(k) \gg 0(k = 1, 2, \cdots, n)$. Performing first-order cumulative generation on $x^{(0)}$ yields the following equation, where: $x^{(1)}(k) = \sum\limits_{i=1}^{k} x^{(0)}(i), k = 1, 2, \cdots, n$.

$$X^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right\} \tag{A1}$$

Next, a whitening differential equation is established. The neighbor mean generation sequence of $X^{(1)}$ is defined as follows: $Z^{(1)} = \left\{z^{(1)}(2), z^{(1)}(3), \cdots, z^{(1)}(n)\right\}$, where $z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(1)}(k-1)\right), k = 2, 3, \cdots, n$. Therefore, the corresponding differential equation for the GM model can be obtained as follows:

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{A2}$$

where a is the development parameter of the model, reflecting the trend of $X^{(1)}$ and the original series $X^{(0)}$; b is the coordination coefficient of the model, reflecting the changing relationship of the data. Since the generating series $X^{(1)}(k)$ has an approximate exponential growth law, and the solution of the first-order differential equation happens to be in exponential form, the $X^{(1)}$ series is considered to be able to satisfy the first-order linear differential equation model as follows:

$$\frac{\mathrm{d}x^{(1)}}{\mathrm{d}t} + ax^{(1)} = b \tag{A3}$$

Data matrix B and data vector Y are constructed, and are defined as follows:

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} Y = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix} \tag{A4}$$

The least squares estimate parameter column for the grey differential equation satisfies the following equation:

$$\Phi = [a, b]^{\mathrm{T}} = \left(B^{\mathrm{T}}B\right)^{-1}B^{\mathrm{T}}Y \tag{A5}$$

Finally, by performing a cumulative reduction on the above equation, the grey prediction model for the original sequence $x^{(0)}(n)$ can be obtained as follows:

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1 - \mathrm{e}^{a})\left(x^{0}(1) - \frac{b}{a}\right)\mathrm{e}^{-a(k-1)}, k = 1, 2, \cdots, n \tag{A6}$$

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