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IMPACT OF DIGITAL ECONOMY DEVELOPMENT ON POLLUTION REDUCTION AND CARBON REDUCTION

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Abstract: Exploring the impact and spatiotemporal characteristics of the digital economy on pollution and carbon reduction is of great significance in the context of the "dual carbon" goal and The digital economy is advancing at a fast pace. Currently, China is facing the dual task of reducing pollution and carbon emissions, and the "technological dividend" of the digital economy provides a new path for achieving environmental governance goals. However, there are still shortcomings in the systematic analysis of the spatial spillover effects, regional adaptation differences, and dynamic mechanisms of pollution and carbon reduction in the digital economy, which urgently require in-depth research from a multidimensional perspective. This study comprehensively utilized entropy weight method, benchmark regression model, mediation effect model, spatial-Durbin-model (SDM), spatiotemporal-geographically-weighted-regression (GTWR), and graph attention network (GAT) to construct a research framework covering impact effect assessment, mechanism identification, and spatiotemporal dynamic analysis. Firstly, This study utilized the entropy weight method for quantifying the development degree of the digital economy, and conducted an analysis on the spatiotemporal features of both pollutant emission intensity and carbon intensity of emissions, the fundamental correlation between the digital economy and environmental performance is revealed; Secondly, through the application of a fixed effects model, the digital economy exerts a direct influence on achieving the twin goals of reducing pollution and carbon emissions, and identifying indirect paths such as industrial structure upgrading, technological progress, and green finance through a mediation effect model; Finally, using spatial econometric models and GAT models, analyze the spatial dependence, regional heterogeneity, and the digital economy's emission reduction effects: Spatiotemporal dynamic evolution characteristics.
Keywords: Digital economy; Pollution reduction and carbon reduction; Spatial effects; Spatiotemporal heterogeneity; Intermediary mechanisms

1 INTRODUCTION

Faced with the requirements of pollution reduction and carbon emission reduction in the new stage, the influence of the digital economy on pollution reduction and carbon emission reduction has increasingly grown into a key concern within academic circles. Research on how the development of the digital economy affects pollution control and carbon emission reduction primarily covers the following four dimensions: firstly, the measurement of the level of digital economy development. Previous studies have often used methods such as factor analysis, entropy method, and B-team method, coupled with the construction of an evaluation indicator system, to measure the level of development of the digital economy[1]. After considering the necessary conditions for the development of the digital economy, the construction and development process of the digital industry, the degree of digital transformation of traditional industries, and the extensive impact of the digital economy on various aspects of society, The Academy of Information and Communications Technology of China has proposed a comprehensive measurement standard - the Digital Economy Index[2-5]. In addition to constructing an evaluation index system, some scholars focus more on quantifying the causal effects between variables and calculating the level of China's digital economy development through methods such as BEA [6-7]. The second is the research on the influencing factors of digital economy on pollutant emissions and carbon emissions. The relationship between the digital economy and environmental pollution is gradually emerging. Based on spatial econometric models, projection pursuit models, and fixed effects models, empirical research has been conducted by scholars to explore the inhibitory role of digital economy development level in three major pollutant emissions[8-9].To investigate how regional carbon emissions are affected by the digital economy, researchers performed in-depth analysis with panel data and revealed that the digital economy notably increases aggregate carbon emissions but diminishes carbon emission intensity [10-12]. The third is the study of the influence mechanism of the digital economy on pollutant emissions and carbon emissions. The research on the impact mechanism of digital economy on carbon emissions continues to deepen, mainly expanding the understanding of its mechanism from the perspectives of technological progress and energy utilization efficiency. However, there is relatively little research on the impact mechanism of the digital economy on pollutant emissions, and the depth is somewhat insufficient. Most scholars consider pollutant reduction, ecological environment improvement, and ecological efficiency enhancement as the main characteristics [13-14]. Another category is the exploration of spatial heterogeneity regarding the role of the digital economy in pollutant and carbon emissions. A number of scholars adopt spatial econometric analytical approaches, including QAP regression and the spatial Durbin model to explore regional linkage relationships and spatiotemporal heterogeneity analysis[15-18]. Research has found that per capita GDP level, geographical proximity, technological

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innovation level, and informatization level all have a significant positive impact on the spatial correlation between pollutant emissions and carbon emissions [19-22].

The existing literature on pollution reduction and carbon reduction in the digital economy has achieved significant results in terms of measurement methods, spatiotemporal evolution characteristics, and exploration of influencing factors. However, there are shortcomings in the analysis of spatiotemporal heterogeneity and spatial effects. The majority of researches have not comprehensively examined spatiotemporal heterogeneity, nor have they separated the spatial spillover effects and local impacts arising from the digital economy's pollution and carbon reduction.Drawing on panel data from 30 Chinese provinces spanning 2011 to 2021, this study employs the entropy weight method to quantify the development level of the digital economy. It uncovers disparities in the spatial distribution of the digital economy via visualization techniques, while leveraging the Spatio-Temporal-Geographically-Weighted-Regression (GTWR) model and Spatial-Durbin-Model (SDM) to analyze the spatiotemporal heterogeneity and dynamic shifts in how the digital economy influences pollution and carbon reduction. Additionally, the mediation effect model is utilized to examine the mechanisms through which the digital economy impacts carbon and pollutant emissions, focusing on channels such as technological advancement, industrial structure upgrading, and green finance indicators.

2 EMPIRICAL ANALYSIS AND VERIFICATION OF THE IMPACT OF PROVINCIAL DIGITAL ECONOMY ON POLLUTION REDUCTION AND CARBON REDUCTION

2.1 Analysis of Benchmark Regression Model Results

Firstly, to guard against estimation inaccuracies caused by multicollinearity, the variance inflation factor (VIF) test is implemented alongside the least squares method for every explanatory variable. According to Table 1, the VIF values of all explanatory variables are less than 10, which can rule out serious multicollinearity issues between explanatory variables.

Table 1 Variance Inflation Factor Test

Variable	VIF	1/VIF
DIG	5.408	0.184
ED	5.087	0.196
FDI	1.228	0.814
PD	1.418	0.705
ECI	1.048	0.954
Average VIF	2.837	

After F-test and Hausman test, this article ultimately chose the fixed-effects model for analysis. According to Table 2, the development of digital economy can significantly reduce the pollutant emission intensity and carbon emission intensity of each province, and the R2 model shows robust regression results. Each unit increase in the digital economy is associated with an average reduction of 0.2575 units in pollutant emission intensity and 0.2773 units in carbon emission intensity. This empirical outcome provides solid support for the validation of Hypothesis H1.

Economic development standards and population density exert a suppressive impact on both pollutant intensity and carbon emission intensity. With the improvement of economic development level, agglomeration effect promotes efficient allocation of resources and intensive utilization of public facilities (such as centralized heating and sewage treatment), reducing dispersed emissions; The increasing of population density is accompanied by the process of urbanization, and the promotion of green planning, low-carbon buildings, and renewable energy further reduces emission intensity.

The per capita energy consumption is significantly positively correlated with two types of intensity. The energy structure and high energy consumption production mode dominated by coal in our country directly lead to an increase in pollutant and carbon emission intensity, reflecting the pressure of high pollution production mode on the environment. Pollutant emission intensity is subject to a restraining effect from foreign investment, demonstrating its positive effect in reducing pollution by promoting industrial upgrading and the application of environmental protection technologies, effectively controlling pollutant emissions.

Table 2 Benchmark Regression Results

Variable	C	P
DIG	-0.2773***	-0.2575***
	（0.0287）	（0.0430）
ED	-0.0441	-0.1375***
	（0.0300）	（0.0448）
PD	-1.927***	-1.7247***
	（0.2320）	（0.3466）
ECI	0.4467***	0.0064
	（0.2320）	（0.1253）
FDI	-0.0188	-0.0576***
	（0.0121）	（0.0181）
R2	0.7720	0.6981

Note: The parentheses indicate standard errors；*P<0.10,**P<0.05,***P<0.01

2.2 Endogeneity Test

To ensure the accuracy of the empirical analysis results, this article uses the instrumental variable method for endogeneity testing to minimize the impact of these potential issues on the research conclusions.

The research selects the Internet broadband access rate of each province and city in 2012 as the tool variable of the digital economy. First, as the early core infrastructure, its popularity level directly determines the subsequent development of the Internet, which can be regarded as a measure of the historical development of the digital economy; Secondly, there is no direct causal relationship between this indicator and the intensity of pollutants and carbon emissions, which satisfies the condition of exogeneity of instrumental variables. In order to adapt to the panel data, further construct the interaction term between this indicator and the Internet penetration rate lagging one year as a tool variable. This method, while increasing the time dimension of data, captures the dynamic correlation of infrastructure penetration through interaction design to more accurately reflect the development characteristics of the digital economy, and uses the two-stage least square method (2SLS) for estimation.

As shown in Table 3,through instrumental variable regression, it is observed that the regression coefficient corresponding to the digital economy achieves significance at the 1% statistical level. Such a result demonstrates that the digital economy continues to exert a significant inhibitory effect on pollutant emission intensity and carbon emission intensity, without being compromised by endogeneity-related biases.The RKF test result exceeds the 10% critical threshold specified for the weak identification test.This outcome verifies the validity of the instrumental variable selected in this study and confirms the absence of issues related to weak instrumental variables.

Table 3 Results of Endogeneity Test Regression

	Phase One Return to the Digital Economy	Two-stage regression P	C
DIG		-0.4918*** （0.0509）	-0.3043*** （0.0355）
instrumental variable（IV）	0.2069*** （0.0302）		
RKF inspection		93.4300	
R^2		0.2443	0.2031

Note: The parentheses indicate standard errors；*P<0.10,**P<0.05,***P<0.01

2.3 Robustness Test

2.3.1. Exclude special samples

Considering the administrative specificity of municipalities directly under the central government, they have advantages in policy support and resource allocation, which may interfere with the robustness of research conclusions. To ensure the reliability of the research results, this study excluded Beijing, Tianjin, Shanghai, and Chongqing from the sample and re estimated the remaining samples to eliminate the influence of administrative specificity and more accurately analyze the development trend of non municipalities directly under the central government.

2.3.2. Shorten time window

In 2020, the global COVID-19 epidemic will break out, which is set to have a marked effect on the evolution of the digital economy and related industries and will affect pollutant emissions and carbon emissions. Such factors may interfere with the reliability of research conclusions. To test the stability of the model, this study excluded data from the special year of 2020, in order to weaken the impact of abnormal data caused by the epidemic on the research results.

The robustness test results for the exclusion of special samples are provided in column (1) of Table 4, and those for the shortened time window are listed in column (2) of Table 4. The findings indicate that after removing special samples and narrowing the time frame, both pollutant emission intensity and carbon emission intensity are continuously positively affected by the digital economy in terms of reduction.

Table 4 Robustness Test Table

Variable	(1) Exclude special samples P	C	(2) Shorten Time Window P	C
DIG	-0.2724*** （0.0303）	-0.3048*** （0.0303）	-0.2597*** （0.0418）	-0.3016*** （0.0294）
ED	-0.1036** （0.0462）	-0.0137 （0.0307）	-0.1332*** （0.0428）	-0.0331 （0.0302）
PD	-1.8017*** （0.3510）	-1.8961*** （0.2333）	-1.6623*** （0.3425）	-1.7961*** （0.2415）
ECI	-0.0320 （0.1337）	0.4716*** （0.0888）	-0.0209 （0.1252）	0.3824*** （0.0883）
FDI	-0.0518*** （0.0183）	-0.0066 （0.0122）	-0.0589*** （0.0173）	-0.0234* （0.0122）

R^2	0.7094	0.8940	0.7222	0.8642

2.4 Mechanism Verification of the Impact of Provincial Digital Economy on Pollution Reduction and Carbon Reduction

2.4.1 Inspection of advanced industrial structure mechanism

According to Table 5, firstly, the level of digital economy development significantly promotes the upgrading of industrial structure (7.364), while the upgrading of industrial structure reduces the intensity of pollutant emissions (-1.351) and carbon emissions (-0.210), confirming H2a.

Secondly, the digital economy shows a weak positive impact on pollutant emission intensity (with a coefficient of 1.123), but it exerts a significant inhibitory effect on carbon emission intensity (-1.245), highlighting its positive function in promoting carbon reduction.

Thirdly, in terms of controlling variables, economic development significantly reduces pollutant emissions and has a slight positive impact on carbon emissions; Population density has a slight positive impact on both types of emission intensity; The energy consumption intensity significantly inhibits industrial structure upgrading and pollutant emissions (-0.413, -1.192), but significantly promotes carbon emissions (1.668); Foreign investment significantly reduces pollutant emissions (-77.570) and has a slight negative impact on carbon emissions (-0.094).

Table 5 Regression Results of Intermediate Effects of Advanced Industrial Structure

variable	（1） IS	（2） P	（3） C
DIG	7.364*** -15.197	1.123* (1.098)**	-1.245** (-2.153)**
ED	-0.000*** (-16.711)	-0.000** (-2.496)	0.000* (0.567)**
PD	0.000*** -4.608	0.000** (1.314)**	0.000* (0.786)**
ECI	-0.413*** (-5.645)	-1.192** (-2.337)**	1.668*** -13.824
FDI	-0.95* (-0.605)**	-77.570*** (-7.431)	-0.094* (-0.038)**
IS		-1.351*** (-3.602)	-0.210** (-2.119)**
constant term	1.579*** （-16.534）	19.777*** （-22.776）	0.341** （-1.662）**
N	330	330	330
R2	0.589	0.296	0.55
F	90.034	27.895	62.375

Note: The parentheses indicate standard errors；*P<0.10,**P<0.05,***P<0.01

2.4.2 Testing the mechanism of technological progress

According to Table 6, the digital economy significantly promotes technological progress (8.256), and technological progress can significantly reduce pollutants (0.000) and carbon emission intensity (0.000). The digital economy exerts a significant inhibitory effect on both types of emission intensity, with the impact coefficients being -10.567 and -1.125 respectively.

When the digital economy and technological progress are both introduced into the model, their coefficients retain significance, indicating that technological progress operates as a partial mediating factor in the influence exerted by the digital economy on emission intensity and corroborating the H2b hypothesis.

Table 6 Regression Results of Mediating Effects of Technological Progress

variable	（1） TD	（2） P	（3） C
DIG	8.256* (16.51)	-10.567** (-2.894)**	-1.125** (-2.678)**
ED	3.273*** -14.305	0.000* (2.496)	0.000*** (4.109)
PD	-14.731*** (-3.340)	-0.001** (-1.827)**	0.000* (0.786)
ECI	13559.850* (1.703)	-0.736** (-1.488)**	1.761*** （-15.183）
FDI	40545.009* （0.237）	-76.591*** (-7.247)	0.13* （0.052）
TD		0.000** （2.153)	0.000* (1.987)
constant term	-8.90e+04***	18.312***	-0.055

	(-8.562)	（25.636）	(-0.331)
N	330	330	330
R2	0.904	0.278	0.526
F	588.715	20.069	57.913

Note: The parentheses indicate standard errors；*P<0.10,**P<0.05,***P<0.01

2.4.3 Verification of the green finance index mechanism

According to Table 7, the digital economy exerts a significant promotional effect on the advancement of green finance, with a coefficient of 2.156. Meanwhile, green finance demonstrates a notable negative impact on both pollutant emission intensity (with a coefficient of -0.397) and carbon emission intensity (with a coefficient of -1.252), which indicates that green finance is capable of lowering these two types of emission intensity.

Pollutant emission intensity (-6.608) and carbon emission intensity (-2.309) are still influenced by the digital economy in terms of reduction, and both influences reach statistical significance. Overall, the digital economy exerts an indirect promotion effect on emission reduction by virtue of its direct impact and the boosting of green finance, validating H2c.

Table 7 Regression Results of Green Finance Index

variable	（1） GF	（2） P	（3） C
DIG	2.156* (3.214)	-6.608** (-2.010)	-2.309*** (-3.050)
ED	0.000* (2.496)	0.000* (2.496)	0.000*** (4.109)
PD	-0.001* (-2.191)	-0.001* (-2.191)	0.000* (0.786)
ECI	-0.156*** (-10.438)	-0.572* (-1.488)	1.941*** (15.183)
FDI	-1.110*** (-3.456)	-75.846*** (-6.993)	1.474* (0.052)
GF		-0.397* (2.153)	-1.252*** (1.987)
constant term	0.425*** -21.73	17.474*** -17.046	-0.487** (-2.064)
N	330	330	330
R2	0.476	0.335	0.55
F	57.075	27.895	62.735

Note: The parentheses indicate standard errors；*P<0.10,**P<0.05,***P<0.01

3 SPATIAL EFFECT ANALYSIS OF PROVINCIAL DIGITAL ECONOMY ON POLLUTION REDUCTION AND CARBON REDUCTION

3.1 Global Moran Index Test

This article uses ArcGIS 10.8 software to conduct spatial autocorrelation tests on provincial pollutant emission intensity, carbon emission intensity, and digital economy development level. Moran's index is utilized to test whether spatial autocorrelation exists among various regions. The range of Moran's I values is (-1,1). When Moran's I > 0, this denotes that spatial positive autocorrelation exists, and when Moran's I<0, it indicates the existence of spatial negative autocorrelation.

Table 8 Global Moran Index Test Table

year	P Moran’s I	C Moran’s I	DIG Moran’s I
2011	0.3626***	0.0384	0.0724
2012	0.3057**	0.0290**	0.0753
2013	0.2860***	0.0277*	0.0658*
2014	0.2524***	0.0214**	0.0594**
2015	0.2262***	0.0371*	0.0464**
2016	0.2182***	0.0393*	0.0614**
2017	0.4050***	0.0485**	0.0586*
2018	0.5571***	0.0531***	0.0390*

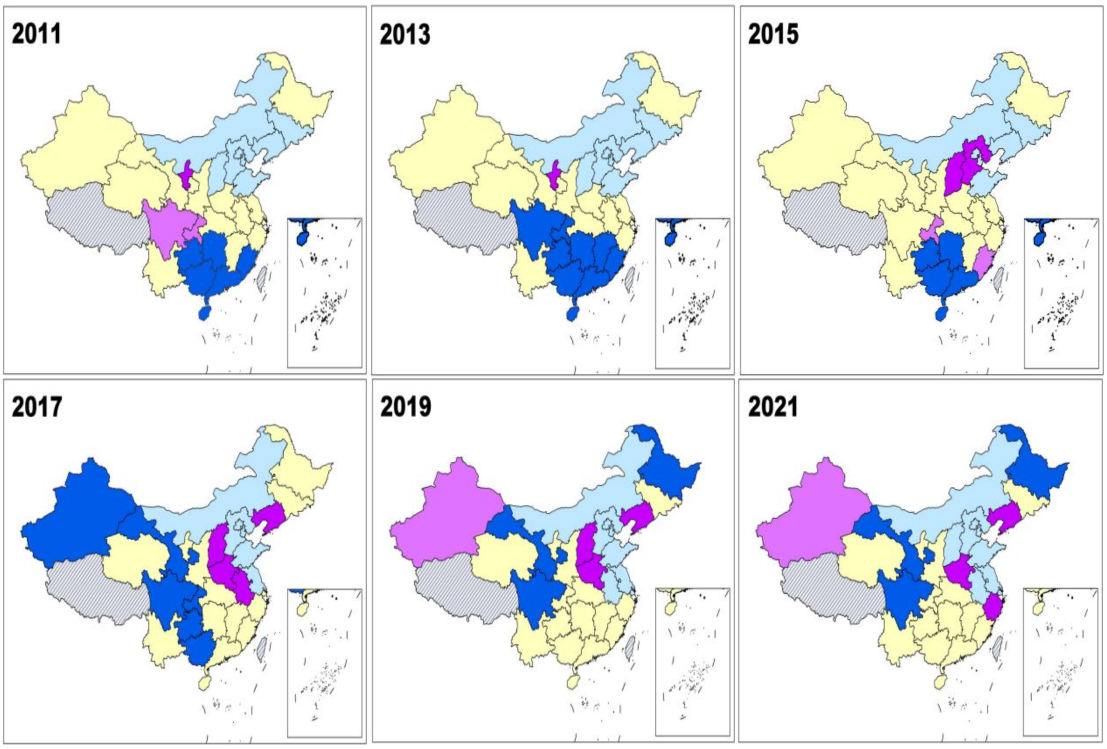
2019	0.5381***	0.0912**	0.0341**
2020	0.5009***	0.0957***	0.0365***
2021	0.3346***	0.0931***	0.0571***

Note: The parentheses indicate standard errors；*P<0.10,**P<0.05,***P<0.01

According to Table 8, Moran's I for pollutant emission intensity is greater than 0.2, indicating strong spatial autocorrelation; Although the initial value of Moran's I of carbon emission intensity is not high, it shows a continuous upward trend in 2011-2021,signifying that the spatial clustering effect of carbon emission intensity across provinces is gradually growing in significance; The Moran's I index for the development level of the digital economy exceeds 0, indicating a positive spatial correlation tendency but the value is relatively low. When using the economic spatial weight matrix proposed by Du Jingai [23], Moran's I is significantly greater than the geographically adjacent or distance weight matrix, which denotes that the digital economy's agglomeration is more inclined to depend on economic level similarity rather than geographical proximity. This is related to the characteristics of the digital economy, which uses information networks as carriers and is less constrained by geography, and regions with similar economic levels are more likely to form division of labor, cooperation, and scale effects in terms of resources and industrial models.

3.2 Local Moran's Index Test

After the global Moran index test in the previous section, it was found that pollutant emission intensity, carbon emission intensity, and the digital economy's development level demonstrates the attribute of spatial autocorrelation. Next, a local Moran index test will be conducted using ArcGIS 10.8 software to identify specific regions with clustering.



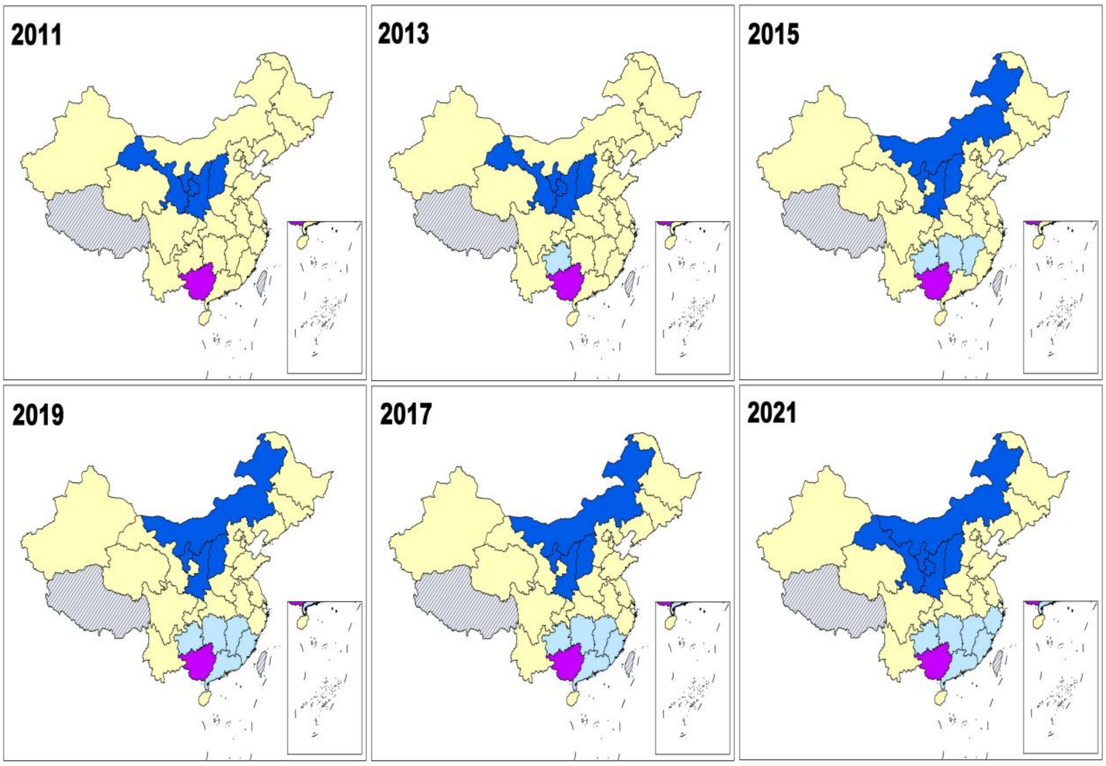
Note: Based on the standard map production of Gaode Map Review No. GS (2019) 756, the base map has not been modified.

Figure 1 LISA Aggregation Chart of Pollutant Emission Intensity

As shown in Figure 1, the LISA concentration map of China's pollutant emission intensity in 2011-2021 shows significant distribution characteristics and dynamic changes:

High high concentration areas: In 2011, they were concentrated in traditional industrial provinces in the central, northern, and southern regions (with high pollution industries such as steel and chemical), distributed in a north-south pattern; After 2017, with the promotion of the Western Development, resource-based regions such as Xinjiang were included and evolved into an east-west distribution, which is related to the layout of the heavy chemical industry. High low outlier area (such as North China in 2013): There are large high polluting enterprises in the region, and the surrounding areas have formed a "low valley" of emissions due to industrial cleanliness or strong environmental protection efforts. Low high outlier area (East China after 2015): The local area has taken the lead in promoting industrial upgrading and environmental governance, with emission intensity lower than the surrounding areas.

Trend of change: High high concentration areas are expanding from traditional industrial core areas in central and southern China to resource-based areas in northeast and northwest China. The main reason is that the upgrading of industries in the east drives the westward migration of highly polluting industries, coupled with the introduction of resource dependent industries in regional development strategies such as the revitalization of Northeast China, leading to the reconstruction of the spatial pattern of emission intensity.



Note: Based on the standard map production of Gaode Map Review No. GS (2019) 756, the base map has not been modified

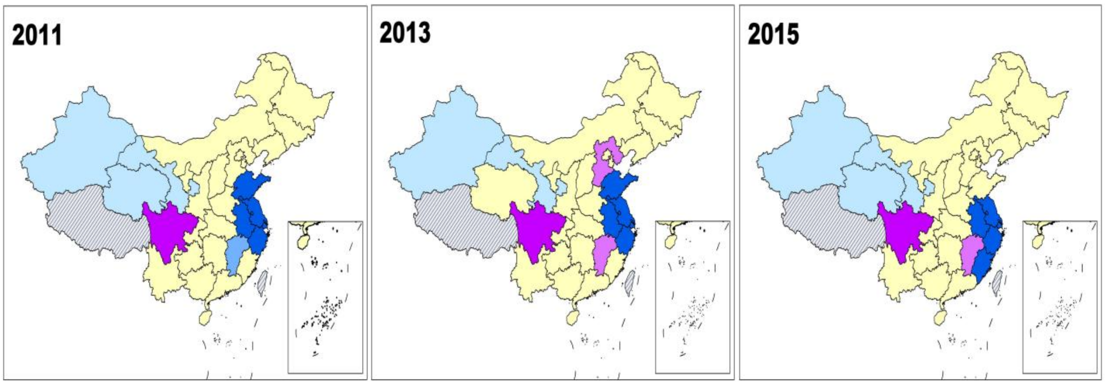
Figure 2 LISA Aggregation Plot of Carbon Emission Intensity

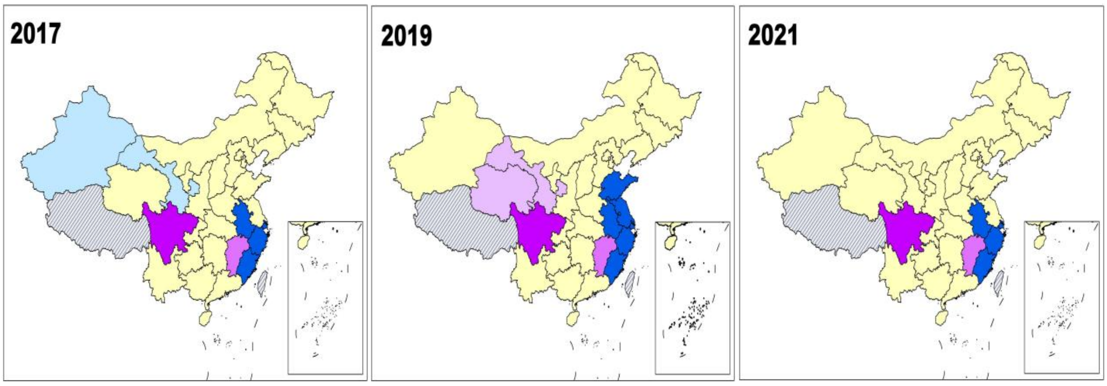
As shown in Figure 2, the LISA aggregation map of China's carbon emission intensity in 2011-2021 shows significant temporal and spatial differences:

Distribution characteristics: In 2011, high high concentration areas were concentrated in North China (Shanxi coal industry and related high energy consuming industries), Northwest (traditional energy development areas), and Northeast old industrial bases (heavy industries such as steel and machinery manufacturing with lagging energy efficiency), displaying an initial distribution pattern characterized by "higher levels in the north and lower levels in the south".

Dynamic changes: After 2015, the range of high high concentration areas in some parts of Northeast China has expanded, reflecting the carbon emission pressure brought about by industrial development in the process of industrialization; After 2017, low low concentration areas appeared in East China (Zhejiang, Jiangsu, etc.), thanks to the elimination of outdated production capacity, high-tech industry development and the escalation of environmental protection investment, leading to a substantial decrease in regional emission intensity.

Driving factors: High emission clusters are constrained by traditional energy dependence (coal mining, heavy chemical industry) and heavy industrial structure, resulting in low energy utilization efficiency; Low emission areas achieve breakthroughs in emission reduction through industrial upgrading and the application of clean energy.





Note: Based on the standard map production of Gaode Map Review No. GS (2019) 756, the base map has not been modified

Figure 3 LISA Agglomeration Chart of Digital Economy Development Level

As shown in Figure 3, the LISA aggregation map of the digital economy in 2011-2021 shows significant regional differences:

Distribution characteristics: since 2011, the eastern coastal areas (such as the Yangtze River Delta) have formed high high concentration areas. Relying on strong economic foundation, scientific and technological talents and improving Internet facilities, leading enterprises lead the development of digital economic clusters; Jiangxi and other regions have long been characterized by low to high concentration, reflecting the industrial radiation effect of surrounding developed areas.As a result of the rapid growth of its endogenous digital economy, a province in central China has formed a high low outlier zone, while its surrounding areas are limited by lagging development in technology, funding, and other areas.

Dynamic changes: From 2013 to 2017, some areas in Northwest China formed low low clustering areas due to a single economic structure and a late start in informatization; After 2019, some cities gradually moved away from low-level clustering by deploying data centers through the "East Data West Calculation" project. The high high concentration areas continue to consolidate in the east, while spreading to central cities, reflecting the trend of regional gradient transfer and coordinated development.

Driving factors: High concentration areas rely on economic foundations, policy support, and leading enterprises to drive; Low concentration areas are limited by insufficient input of factors, and breakthroughs in infrastructure construction will be achieved through national strategies such as "counting from the east to the west" in the later stage.

3.3 Estimation Results and Analysis of Spatial Durbin Model

Table 9 Estimation Results of Spatial Durbin Model

VARIABLES	(1)lnP	(2)lnC
lnDIG	-0.024*** （-5.92）	-0.033*** （-5.08）
lnPD	0.039** （2.19）	0.135***
lnIS	-0.059*** （-1.59）	-0.744*** （-12.51）
lnECI	-0.014* (-0.37)	1.054*** (17.28)
lnFDI	-0.017*** (-1.40)	-0.115*** (-5.68)
lnTD	-0.081*** (-3.49)	0.171*** (4.68)
lnED	-0.384*** (-8.86)	-0.021* (-0.31)
rho	0.121* (1.89)	0.287*** (3.51)

Note: The parentheses indicate standard errors；*P<0.10,**P<0.05,***P<0.01

In order to ensure that the model reflects the actual diffusion process of pollutants and effectively explains spatial spillover effects, 0-1 spatial adjacency matrix and economic geographic distance weight matrix are used in the SDM model. The results are shown in Table 9.

The digital economy has a significant negative impact on pollutant and carbon emission intensity, and promotes emission reduction through factor allocation, green technology diffusion, and energy structure adjustment, which is consistent with the "dual carbon" and "Digital China" policies; Population density has a stronger impact on carbon emission intensity, reflecting the pressure of carbon governance in high-density urban areas and responding to the requirements of urbanization during the 14th Five Year Plan period; The level of economic development is negatively correlated with two types of emission intensity. Developed regions have significant advantages in pollution control, while carbon emission control needs to deepen institutional incentives due to lagging energy structure adjustments; The

significant suppression of carbon emission intensity by industrial structure highlights the key role of high energy consuming industries in transformation, which is in line with the Industrial Green Development Plan; The positive and significant impact of energy consumption intensity on carbon emission intensity confirms that energy structure is the core factor; Foreign direct investment demonstrates a significant negative influence on both types of emission volumes, verifying the 'pollution halo hypothesis'; Technological progress effectively reduces pollutants,but demonstrates a positive effect on the volume of carbon emissions.
The spatial lag term (rho) is significantly positive, supporting regional collaborative governance strategies such as the Beijing Tianjin Hebei and Yangtze River Delta regions, and providing empirical evidence for cross regional environmental policy coordination.
In summary, the model reveals how factors such as the digital economy and industrial structure contribute to reducing pollution and carbon emissions, along with the mechanisms of their spatial spillover. This is in line with China's policy focus on regionally coordinated green development and serves as a reference for policy improvement.
This study used the SDM model to estimate pollutant intensity (lnP) and carbon emission intensity (lnC), and decomposed the total effect into direct and indirect effects, so as to further explore the mechanisms of various influencing factors in regional environmental pollution and carbon emissions.

Table 10 Decomposition of Spatial Durbin Model Effects

VARIA-	direct effect		indirect effect		total effect	
BLES	lnP	lnC	lnP	lnC	lnP	lnC
lnDIG	-0.123***	-0.133***	-0.060***	-0.069***	-0.183***	-0.065***
	(1.46)	(5.89)	(0.42)	(-1.54)	(1.42)	(1.47)
lnPD	-1.755***	-0.398***	1.616**	-1.495***	-0.139	-1.893***
	(-4.99)	(-4.14)	(2.00)	(-5.63)	(-0.18)	(-6.85)
lnIS	-0.234***	-0.023	-0.093	-0.017	-0.327*	-0.040
	(-3.06)	(-1.06)	(-0.58)	(-0.33)	(-1.94)	(-0.69)
lnECI	-0.070	0.264***	-0.320	0.029	-0.390	0.294***
	(-0.64)	(8.76)	(-1.25)	(0.36)	(-1.55)	(3.43)
lnFDI	-0.058***	-0.013***	-0.043	-0.024*	-0.101**	-0.036**
	(-3.87)	(-2.99)	(-1.10)	(-1.78)	(-2.32)	(-2.41)
lnTD	-0.150***	-0.029***	-0.044	-0.025	-0.195**	-0.054*
	(-4.08)	(-2.80)	(-0.54)	(-0.89)	(-2.12)	(-1.69)
lnED	-1.031***	-0.749***	-0.079	0.241***	-1.110***	-0.509***
	(-6.17)	(-16.44)	(-0.28)	(2.65)	(-3.93)	(-5.29)

Note: The standard error is in parentheses; *P<0.10,**P<0.05,***P<0.01

According to Table 10, the digital economy (lnDIG) significantly suppresses pollution and carbon emissions, with both local pollution reduction and regional technology spillover effects. Therefore, it is necessary to strengthen its strategic support; The total effect of population density (lnPD) is significantly negative, reflecting the intensive infrastructure and regional technology coordinated emission reduction, echoing the policies of green infrastructure and joint prevention and control. The industrial structure (lnIS) only significantly reduces the intensity of pollutants and has no significant impact on carbon emissions, and green upgrading needs to be promoted; The significant increase in energy consumption intensity (lnECI) has led to higher carbon emissions, confirming that energy structure is the core factor and the need to accelerate low-carbon transformation. The total negative effect of foreign direct investment (lnFDI) on two types of emission intensity is significant, which verifies the "pollution halo hypothesis" and should guide foreign investment towards the green sector; Technological progress (lnTD) mainly focuses on direct emission reduction and requires a focus on green technology innovation; Emissions are significantly negatively impacted by the level of economic development (lnED), a finding that is consistent with the Environmental Kuznets Curve and the orientation of high-quality development. The model reveals the local and spatial spillover effects of variables, supports regional green linkage governance, and provides empirical evidence for optimizing the "dual carbon" policy.

4 CONCLUSION

Based on the panel data of 30 provinces in China from 2011-2021, this study systematically explored the impact of digital economy development on pollution reduction and carbon reduction, its mechanism and spatio-temporal heterogeneity by using entropy weight method, benchmark regression model, mediation effect model, spatial Durbin model (SDM), spatio-temporal geographical weighted regression (GTWR), and map attention network (GAT). The main conclusions are as follows:
Firstly,A direct facilitative effect of the digital economy is exerted on the reduction of pollution and carbon emissions. The improvement of the digital economy's development level enables a remarkable reduction in both pollutant and carbon emission intensity, and indirectly facilitates the reduction of pollutant levels and carbon emission intensity through multiple mechanisms including industrial structure upgrading, technological progress, and green finance. The test results show that for every unit of growth in the digital economy, the average decrease in pollutant and carbon emission intensity is 0.2575 and 0.2773 units, respectively, which is the core driving force for achieving pollution reduction and carbon reduction.

Secondly, the pollution reduction and carbon reduction effects exhibit significant spatial dependence and regional heterogeneity. There is a clear spatial autocorrelation between pollutant and carbon emission intensity, with high emission clusters concentrated in traditional industrial provinces and resource-based areas, while low emission clusters are mostly distributed in the eastern coastal industrial upgrading areas. The emission reduction effect of the digital economy shows a gradient difference of "strong in the east and weak in the west", and over time, the emission reduction effect gradually emerges in the central and western regions due to the promotion of digital infrastructure.
Thirdly, multiple mechanisms drive pollution reduction and carbon reduction, and energy structure remains a key constraint factor. The digital economy plays a dual role through technological empowerment and structural optimization. Meanwhile, population density, the degree of economic development, and foreign direct investment all exert a notable influence on the process of emissions reduction, but energy consumption intensity remains the main positive driving factor for carbon emissions, reflecting the urgency of energy structure adjustment.
Fourthly, the digital economy’s role in promoting emission reduction demonstrates both spatiotemporal dynamism and differentiated characteristics in regional responses. The GTWR model shows that the impact coefficient of the digital economy on pollution reduction and carbon reduction varies dynamically over time and space. After 2017, the marginal effect in the eastern region stabilized, while the effect gradually increased in the central and western regions due to industrial absorption and digital transformation. GAT clustering identifies four types of regional response patterns, reflecting regional adaptation differences between digital economy and environmental performance.

5 FUTURE DIRECTION

While this study systematically examines the impact mechanisms and spatiotemporal heterogeneity of the digital economy on pollution and carbon reduction, several avenues for future research remain:
(1).Micro-level Mechanisms and Firm Behavior
Future research could incorporate firm-level data to explore specific pathways through which the digital economy influences corporate emission reduction decisions, such as digital technology adoption, incentives for green innovation, and intelligent energy management, to reveal the role of micro-level actors in digital-driven emission reduction.
(2).Synergistic Effects Between Digital Economy and Energy Structure
This study highlights that energy structure remains a key constraint on carbon emissions. Future work could investigate how the digital economy promotes the integration of renewable energy, smart grid development, and energy internet systems to facilitate low-carbon energy transition.
(3).Regional Coordination and Policy Linkage Mechanisms
Building on the spatial spillover effects identified in this study, future research could develop cross-regional collaborative policy frameworks for digital emission reduction, exploring mechanisms for joint digital infrastructure development, data sharing, and green technology cooperation in regions such as the Beijing-Tianjin-Hebei Region, the Yangtze River Delta Region, and the Guangdong-Hong Kong-Macao Greater Bay Area.
(4).Research on the “Rebound Effect” of Digital Technology Applications
While the digital economy enhances efficiency, it may also lead to a “rebound effect” due to increased energy consumption or expanded production scale. Future studies should assess the net emission reduction effects of digital technologies from a lifecycle perspective and propose strategies to mitigate rebound effects.
(5).International Comparisons and Global Governance Perspectives
Extending the analysis to cross-country panel data allows for comparisons of the digital economy’s emission reduction effects in various national contexts, providing insights for China’s participation in global digital-green governance and the greening of the “Digital Silk Road.”
(6) Dynamic Forecasting and Policy Simulation
Integrating machine learning, system dynamics, or adopting other computational methods to build dynamic forecasting models for the digital economy and carbon emissions allows for the simulation of emission reduction outcomes under multiple policy scenarios, supporting the optimization of medium- to long-term “dual carbon” pathways.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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