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The Impact of the Digital Economy on Municipal Air Quality: Insights from Spatial Analysis

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Abstract: Air quality is a core element concerning public health and sustainable development. As the backbone of new quality productive forces, the digital economy is quietly emerging as a significant driver of air quality improvement. Based on prefectural-level city data in China from 2020–2023, and after confirming the spatial correlation between the digital economy and air quality, this paper first employs bivariate Moran's index to examine the spatial association characteristics between them. Subsequently, variance inflation factors are used to diagnose multicollinearity among annual variables. By constructing an ordinary least squares regression model, we investigate the overall impact effect. We then introduce a geographically weighted regression model to identify and estimate the spatial heterogeneity inherent in their relationship. Furthermore, the influence coefficient of the digital economy is utilized to analyze the spatial pattern and evolutionary trend of its impact on air quality. The results indicate a significant spatial dependence between the development of the digital economy and urban air quality, with this correlation pattern exhibiting a directional shift during the sample period. The geographically weighted regression model demonstrates superior goodness-of-fit and overall model adaptability compared to the ordinary least squares model, underscoring the robust spatial non-stationarity of the digital economy's impact on air quality. Further analysis reveals a clear East-West differentiation pattern in the spatial distribution of the digital economy's influence coefficients. This study not only provides spatial empirical support for exploring the complex relationship between the digital economy and environmental quality but also offers certain policy reference value for promoting regionally coordinated emission reductions and accelerating the green digitalization process.

Keywords: Digital Economy; Air Quality; Air Quality Index; Moran's Index; Geographically Weighted Regression Model

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1. Introduction

Air quality constitutes a fundamental public resource for human survival and development, directly impacting global public health, sustainable development of economy and society, and regional ecological security. According to estimates by the World Health Organization (WHO), air pollution causes over two million premature deaths annually worldwide, highlighting its severity as a major environmental health risk factor [1]. In China, the rapid economic and social development since the reform and opening-up has also accumulated a series of ecological and environmental issues, with air pollution being particularly prominent, forming a critical constraint on high-quality development. According to the 2024 Report on the State of the Ecology and Environment in China, 117 out of 339 cities at prefecture level and above still failed to meet the air quality standards in 2024, accounting for 34.5% of the total, indicating that the task of improving air quality remains arduous[2]. In response to this challenge, China has integrated air quality improvement into the core agenda of its national development strategy. In November 2023, the State Council issued the Action Plan for Continuous Air Quality Improvement, outlining a systematic approach to use sustained air quality improvement to drive high-quality economic development. By strengthening pollution source control and fostering green, low-carbon production and lifestyle, the plan strives to achieve a triple win of environmental, economic, and social benefits[3]. Concurrently, the Proposal of the Central Committee of the Communist Party of China on Formulating the Fifteenth Five-Year Plan for National Economic and Social Development, adopted at the Fourth Plenary Session of the 20th CPC Central Committee, explicitly emphasized accelerating the comprehensive green transformation of economic and social development to build a Beautiful China [4].Furthermore, the coordinated development of the economy and environment remains a central topic in sustainability research. Studies indicate an overall upward trend in the coupling coordination level between China's regional economy and air quality[5]. Simultaneously, promoting green development and improving air quality have been shown to help narrow the consumption gap between urban and rural residents, thus providing significant support for promoting common prosperity[6]. Therefore, air quality is not only a key factor in addressing environmental and health crises, but also serves as a strategic pivot for driving high-quality economic development, promoting social equity, and achieving harmonious coexistence between humanity and nature.

Digital technology, as a core driver of economic transformation and upgrading, is profoundly reshaping modes of production, lifestyles, and the patterns of socioeconomic development. Over the past decade, rapid advancements in information and communication technologies have propelled the digital economy to become a primary engine and key driver of global economic growth. The outbreak of the COVID-19 pandemic has further accelerated the adoption and application of digital technologies, prompting a large-scale shift of work, daily life, and consumption activities online. The deep penetration of digital technologies has reconfigured production and lifestyles, and their role in promoting carbon emission reduction, driving high-quality development, and narrowing development gaps is increasingly prominent, making them a priority in national policy frameworks[7][8].In China, the growth momentum of the digital economy is particularly pronounced. In 2024, the value-added output of core digital economy industries reached 14.0891 trillion yuan, accounting for 10.5% of GDP—a 5.7% increase from the previous year—demonstrating its substantial contribution to the national economy[9]. Policy initiatives have advanced in parallel. The Guidelines on Accelerating the Comprehensive Green Transition of Economic and Social Development, issued by the Central Committee of the Communist Party of China and the State Council in the same year, explicitly calls for strengthening green and low-carbon technological innovation and enhancing the quality, efficiency, and resource-energy utilization efficiency of economic and social development. This document charts the course for the deep integration of digital technology and the green transition[10].Academia has conducted extensive and in-depth research on the digital economy. Existing studies focus on its role in promoting post-pandemic sustainable development, encompassing its positive impacts on economic growth, resource use efficiency, and environmental protection [11]. In recent years, the impact of the digital economy on air quality has gradually become a significant research topic. Empirical studies indicate that, overall, the development of the digital economy helps reduce air pollutant emissions and improve urban air quality[12]. The core mechanism behind this improvement, however, is not the direct reduction of emissions. Instead, it is achieved by reshaping the economic structure and driving innovation. Specifically, the digital economy enhances the technical efficiency of pollution control by promoting green technological innovation. It promotes green technology innovation, thereby enhancing the technical efficiency of pollution control[13]. Concurrently, it drives the advancement and optimization of industrial structure, fostering the growth of service and high-tech industries while reducing the share of traditional, heavily polluting, and high-emission industries, thus curbing emissions at source. Furthermore, through the synergistic effects of digital platforms, the digital economy optimizes resource allocation and reduces redundant energy consumption [14]. Collectively, this research provides a crucial foundation for understanding the impact of the digital economy on air quality.

The above studies collectively indicate the positive role of digital economy development in improving air quality.

However, current studies on the impact of the digital economy on air quality still face several critical limitations that need to be addressed. Firstly, there are limitations in research scale. Most existing studies focus on macro-level analysis at the national or provincial level, with relatively few exploring more detailed scales such as the city level. This makes it difficult to reveal specific patterns such as local heterogeneity. Secondly, the existing literature pays insufficient attention to the spatial correlation between air quality and the digital economy itself, as well as the spatial heterogeneity arising from their interaction. This inadequacy hinders a deeper understanding of the complex relationship between the two.·

2. Theoretical Analysis

2.1 Air Quality

Air quality denotes the concentration levels and integrated states of various air pollutants within a specific region. It is typically assessed based on environmental standards and health guidelines. In academic research and policy application, air quality is usually quantified by monitoring the concentrations of a set of key pollutants. Common core indicators include particulate matter and gaseous pollutants. Particulate matter, especially fine particulate matter (PM2.5) and inhalable particulate matter (PM10), is the primary culprit responsible for the formation of haze and poses a major threat to human respiratory health. It is also widely used as a proxy variable for air pollution in current research[15]. Gaseous pollutants, such as sulfur dioxide (SO2), nitrogen oxides (NOx), carbon monoxide (CO), and ozone (O3), predominantly originate from fossil fuel combustion and industrial processes. They serve as precursors to the formation of acid rain and photochemical smog. This paper focuses on “air quality” as a comprehensive environmental condition, which is characterized principally by the concentrations of the aforementioned pollutants.

2.2 Digital Economy

The digital economy refers to a series of economic activities that utilize digitalized knowledge and information as a key production factor, modern information networks as an important carrier, and the effective use of information and communication technologies to enhance economic efficiency and optimize the economic structure [16]. Its core can be divided into two dimensions: digital industrialization and industrial digitalization. Digital industrialization refers to industries that provide technology, products, and services for digital transformation. These primarily include the electronic information manufacturing industry, the information and communication technology industry, the software and information technology service industry, and the internet industry. This constitutes the “hardcore” foundation of the digital economy. Industrial digitization, conversely, focuses on the increased output and enhanced efficiency derived from applying digital technologies in traditional industries, spanning a broad spectrum such as smart manufacturing, industrial internet, smart agriculture, e-commerce, digital finance, smart logistics, and telemedicine across the national economy. This dimension is central to the enabling role of the digital economy, driving the intelligent and efficient transformation of conventional sectors [17].Current academic and policy practices employ several mainstream methods to measure the development level of the digital economy. These mainly include the value-added approach, the index approach, the supply-demand perspective assessment approach, the international comparison and satellite account approach, and the regional disparity and structural analysis approach. The value-added approach, the most fundamental and widely adopted method, typically decomposes the digital economy into “digitalization of industry” and “industrial digitization,” separately estimating their contributions to economic growth and summing them to derive the digital economy’s added value [18]. The index approach, on the other hand, constructs a multi-dimensional evaluation system that covers features such as digital industrialization, industrial digitalization, and the penetration, collaboration, and substitution of digital technologies. This method aims to comprehensively reflect both the breadth and depth of digital economy development [19]. The supply-demand perspective assessment method offers a dual-path assessment from both supply and demand sides, addressing limitations of traditional unidirectional metrics and yielding more systematic and comprehensive results [20]. The international comparison approach focuses on cross-national comparisons, often using developed economies like the US and Australia as references to assess China’s international competitiveness and relative position via indicators such as digital economy added value [21]. The satellite account approach draws on the statistical frameworks of international organizations such as the Organisation for Economic Co-operation and Development (OECD). It treats the digital economy as a “satellite account” within the system of national economic accounting to specifically measure its output scale and economic impact [22]. The regional disparity approach primarily employs tools like the Gini coefficient and Dagum decomposition to analyze disparities in digital economy progression among China's eastern, central, and western regions and across different development tiers, revealing the spatial distribution of the digital divide [23]. The structural analysis approach focuses on the internal industrial composition of the digital economy. By examining the proportional relationship between core industries and related supporting industries, as well as their dynamic evolution, this method captures the internal structure and development trends of the digital economy [24].

2.3 Socioeconomic Factors

The relationship between economic development and environmental pollution is a central topic in environmental economics. The most classic theoretical framework is the Environmental Kuznets Curve (EKC) hypothesis. This hypothesis posits that in the early stages of economic development, environmental pollution intensifies as per capita income increases. However, once economic development reaches a certain level, the degree of environmental pollution gradually decreases with further income growth. This shift is driven by factors such as industrial structure optimization, technological progress, and increased public environmental awareness, presenting an inverted "U-shaped" relationship[25]. In academia, per capita GDP is commonly employed as the core proxy variable for a region's economic development level[26].

Urbanization, the concentration of population, capital, and land in cities, exerts a dual impact on air quality [27]. Studies indicate increased urban population density leads surging energy consumption for daily living and transportation demand, thereby increasing pollutant emissions and degrading air quality [28]. Concomitantly, rapid growth in vehicle ownership and traffic congestion substantially increases motor vehicle exhaust emissions [29].

Industrialization is the most direct and primary driver of environmental pollution, particularly air pollution. Examining the energy consumption structure, relevant studies indicate that industrial production is the main consumer of energy, and China's energy structure has long been dominated by coal [30]. Coal combustion emits significant amounts of SO2, NOx, and soot, key precursors and components of PM2.5. Regarding industrial structure, studies note that secondary industries, represented by heavy chemicals, steel, and building materials, is a typical resource-intensive and pollution-intensive sector. A higher proportion of secondary industry in a region often correlates with a "crude" growth model and greater environmental pressure [28]. Therefore, the level of industrialization, particularly its structure and quality, directly determines the intensity of pollution emissions in a region.

Government expenditure is a critical instrument for promoting environmental governance and reducing pollution and carbon. Research demonstrates that structural adjustments in fiscal spending can markedly enhance regional environmental governance capacity, with specific environmental protection expenditures significantly improving pollution control outcomes [31]. In addition to direct environmental spending, expenditures on economic construction, science, education, culture, and health, as well as social security, can also improve the quality of regional development and indirectly support environmental governance [32].

Scientific and technological innovation is the fundamental pathway for resolving environmental issues, primarily by fostering a "technique effect." Technological progress is core to improving energy efficiency, reducing energy consumption per unit of GDP, thereby mitigating pollutant emissions from energy use [27]. Furthermore, innovation activities in a region can generate positive spillover effects on the green technology level of surrounding areas through channels such as talent mobility and technology diffusion [33].

Opening-up influences the environmental quality of host countries through international trade and foreign direct investment (FDI). The environmental impact of FDI is heterogeneous [34]. In technology-intensive and high value-added sectors, FDI typically brings positive environmental technology spillovers; in labor-intensive or resource-based industries, negative scale effects may still dominate [35]. Meanwhile, influenced by international environmental pressures and domestic policy orientation, FDI is accelerating its shift away from traditional "high-pollution, high-energy-consumption" sectors toward "green energy, digital economy, and advanced manufacturing"[36].

2.4 The Impact of the Digital Economy on Air Quality

The digital economy contributes to reducing air pollution[37]. It takes data as a key production factor and relies on digital infrastructure such as the Internet, 5G, and the Internet of Things. Through technology empowerment, it promotes the intelligent integration of industries and the development of virtualized services. By leveraging network effects for open sharing, it significantly enhances resource allocation efficiency and promotes low-carbon development[38][39]. As a new type of production factor, data has the characteristics of low reproduction cost and a marginal cost of use approaching zero. This feature is often likened to “digital oil,” giving it an advantage in resource allocation efficiency that traditional factors cannot match [40]. As economic activities extend from physical to virtual spaces, the operational virtuality of the digital economy reduces reliance on physical logistics and production, inherently enabling reductions in energy consumption and carbon emissions. Simultaneously, the digital economy relies heavily on high-speed, low-latency network infrastructure (such as 5G) and ubiquitously connected IoT systems. This enables real-time data collection and intelligent responses across all stages of production, circulation, and consumption, laying the technical foundation for refined resource management and precise environmental monitoring [41]. Furthermore, digital technologies like artificial intelligence and big data are rapidly embedding into traditional manufacturing and services, promoting the proliferation of smart manufacturing and intelligent services. By optimizing processes, reducing waste, and enhancing output efficiency, they further drive low-carbon and intensive transformation of industrial chains [42]. Moreover, the data openness, sharing, and collaborative mechanisms championed by the digital economy allow platform-based models to leverage network effects, effectively lowering market transaction costs and improving total factor productivity. thereby creating conditions for synergistic achievement of environmental and economic benefits.

3. Methodology

3.1 Data Sources

This study utilizes panel data for prefecture-level cities in China from 2020 to 2023. The primary data sources are the China City Statistical Yearbook, the“China City Digitalization Evolution Index (DEI) White Paper published by H3C, the Science Data Bank, and the statistical yearbooks of various provinces and prefecture-level cities.

3.2 Variable Selection

3.2.1 Dependent Variable

To comprehensively measure regional air pollution, the annual average of the Air Quality Index (AQI) for each prefecture-level city is selected as the dependent variable. The Air Quality Index is a composite metric for assessing air pollution severity, based on the concentrations of six key pollutants: PM2.5, PM10, SO2, NO2, O3, and CO. The AQI is an important metric widely adopted internationally for the quantitative evaluation of ambient air quality. The data is derived from real-time monitoring at air quality stations across China between 2014 and 2024. The city’s daily AQI is first calculated from station-level daily averages, then aggregated to an annual average, and finally compiled into a dataset of annual AQI values for Chinese prefecture-level cities.

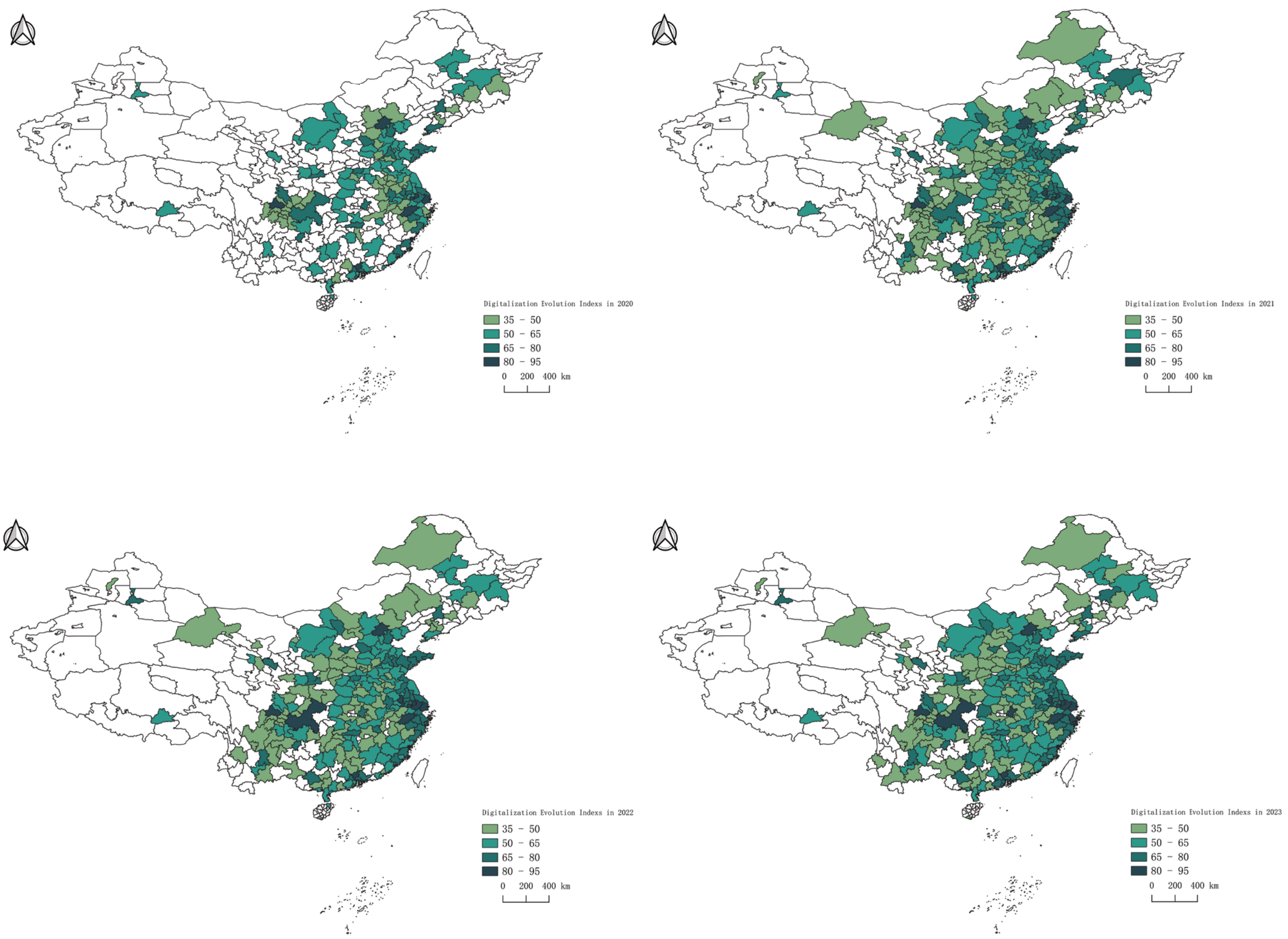
3.2.2 Core Explanatory Variable

To precisely characterize the comprehensive development level of the digital economy in each city, the core explanatory variable is the Urban Digitalization Evolution Index. Based on relevant literature, this study measures it using the Urban Digitalization Evolution Index (DEI) published in the “China City Digitalization Evolution Index (DEI) White Paper” released by H3C for the years 2020-2023. This index systematically evaluates the integrated development of the digital economy in major Chinese cities using a framework of four primary indicators—Data and IT Infrastructure, City Services, City Governance, and Industrial Integration—along with 12 secondary and 40 tertiary indicators. It is widely recognized and timely. The assigned weights are 20% for Data and IT Infrastructure, 35% for City Services, 20% for City Governance, and 25% for Industrial Integration. The white paper covered 147, 226, 231, and 240 prefecture-level cities in 2020-2023, respectively. This index is highly compatible with the prefecture-level city research scale of this paper and can be directly obtained and applied to empirical analysis.

Spatially, from 2020 to 2023, the development level of China’s urban digital economy consistently exhibited a pattern of “higher in the east and lower in the west, and higher in coastal areas than inland”. Specifically, high-value zones (index 80-95) are predominantly clustered in eastern coastal urban agglomerations such as Beijing-Tianjin-Hebei region, the Yangtze

River Delta, and the Pearl River Delta, forming core growth poles. Medium-high value zones (index 65–80) are widely distributed in the hinterlands of the eastern coast and surrounding provincial capitals in central and western China, indicating an initial diffusion of digital technology from core cities. In contrast, most cities in central, western, and northeastern regions remain in low-level development zones, forming contiguous “digital lowlands”. This pattern reveals significant spatial imbalance in China’s digital economy development, with digital dividends largely confined to a few developed regions, while many small and medium-sized cities and traditional industrial cities have not yet deeply integrated into the digitalization process.

Figure 1: Spatial Distribution of China’s Prefecture-Level City Digitalization Evolution Index, 2020-2023



3.2.3 Control Variables

To conduct a in-depth analysis of the digital economy’s impact on air quality, the following control variables are selected: (1) Economic development level, measured by per capita GDP of each city in the given year ; (2) Urbanization level, measured by the proportion of urban population in each city’s total population for that year; (3) Industrialization level, measured by the proportion of secondary industry in the regional GDP of each city; (4) Government intervention level, measured by the scale of local general public budget expenditure; (5) Technological innovation level, measured by the number of invention patents granted in each city for that year;(6) Openness level, measured by total import and export volume of each city for the year.

Table 1: Attributes of Control Variables

Variable Abbreviation	Variable Name	Measurement Method	Unit
EL	Economic Development Level	Annual per capita GDP	100 million yuan per person
UL	Urbanization Level	The proportion of the urban population in the total population each year	%

Variable Abbreviation	Variable Name	Measurement Method	Unit
LI	Industrialization Level	The proportion of the added value of the secondary industry in the regional GDP each year	%
GIL	Government Intervention Level	Scale of Local General Public Budget Expenditure by City	hundred million yuan
TIL	Technological Innovation Level	Number of authorized invention patents	piece
OL	Openness Level	Total import and export volume	hundred million yuan

3.3 Model Specification

3.3.1 Ordinary Least Squares

To preliminarily examine the overall directional impact and basic association between the digital economy and air quality, an Ordinary Least Squares (OLS) baseline model is first constructed. The model is specified as follows:

$$lnAQI_{i,t} = \alpha + \beta_1 lnDEI_{i,t} + \beta_2 lnEL_{i,t} + \beta_3 lnUL_{i,t} + \beta_4 lnLI_{i,t} + \beta_5 lnGIL_{i,t} + \beta_6 lnTIL_{i,t} + \beta_7 lnOL_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $lnAQI_{i,t}$ represents the air quality index of prefecture-level city i in year t, α is the intercept term, the core explanatory variable $lnDEI_{i,t}$ is the logarithmic value of the Digitalization Evolution Index, and $\varepsilon_{i,t}$ is the random error term. Given that the macroeconomic environment and policies may fluctuate annually during the study period, the model essentially conducts separate regressions on four independent cross-sections from 2020 to 2023 to capture the distinct characteristics of each year.

3.3.2 Moran's I Analysis

To investigate whether a systematic spatial co-variation relationship exists between the digital economy and air quality, a bivariate Moran's I analysis is employed. Moran's I includes Global Moran's I and Local Moran's I. The Global Moran's I assesses whether spatial dependence is pervasive across the entire study area, while the Local Moran's I further identifies specific local spatial association patterns and clustering types for individual cities. Therefore, this study uses the bivariate Moran's I to reveal the spatial correlation between a region's digital economy development level and the air quality of its neighboring regions, thereby identifying their spatial dependency pattern.

The formula for the bivariate Global Moran's I is:

$$I_b = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(y_j - \bar{y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (2)$$

Here, $S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$, x_i denotes the Digitalization Evolution Index for city i, y_j denotes the Air Quality Index for city j, w_{ij} are the elements of the spatial weight matrix (constructed using the Queen contiguity criterion), and n is the number of spatial units. Moran's I ranges from [-1, 1]. If An $I_b > 0$, it indicates a positive spatial correlation;if $I_b = 0$, there is no spatial correlation; and if $I_b < 0$, it signifies a negative spatial correlation.

Based on the global spatial autocorrelation analysis, it is possible to determine whether the digital economy and air quality exhibit a spatial clustering trend across the entire study area. Furthermore, by employing the local Moran's I, the heterogeneity in spatial association patterns among different cities can be revealed. This allows for the identification of locally significant cluster types, including four typical patterns: "High-High" clusters, "Low-Low" clusters, "High-Low" outliers, and "Low-High" outliers. This approach facilitates an in-depth analysis of the spatial synergistic or divergent characteristics between the development of the digital economy and air pollution. The formula for the Local Moran's I is:

$$I_i^L = \frac{(y_i - \bar{y})}{S^2 \sum_{j\neq 1}^{n} w_{ij}(y_j - \bar{y})} \quad (3)$$

The local spatial autocorrelation index focuses on detecting small-scale spatial clustering or dispersion patterns. Unlike the Global Moran's I, it reveals spatial correlation for individual locations, analyzing clusters of high or low values within specific areas.

3.3.3 Geographically Weighted Regression

Geographically Weighted Regression (GWR) is a spatial regression analysis method that incorporates spatial variation into traditional global regression models. GWR uses environmental covariates to perform local linear regression on sample points within a bandwidth range. It estimates a set of regression parameters at each location, thereby generating a series of local regression models. The formula for GWR is as follows:

$$lny_{GWR_i} = \alpha(\mu_i, v_i) + \beta_1(\mu_i, v_i)lnDEI_i + \beta_2(\mu_i, v_i)lnEL_i + \beta_3(\mu_i, v_i)lnUL_i + \beta_4(\mu_i, v_i)lnLI_i + \beta_5(\mu_i, v_i)lnGIL_i + \beta_6(\mu_i, v_i)lnTIL_i + \beta_7(\mu_i, v_i)lnOL_i + \beta_8(\mu_i, v_i)lnOL_i + \varepsilon_i \quad (4)$$

Here, $lny_{GWR_i} = 1$ is the predicted value of the model at location i; $\alpha(\mu_i + v_i)$ is the intercept term; i denotes the i-th city; μ_i and v_i represent the longitude and latitude coordinates of the i-th city, respectively; and ε_i is the regression residual.

4. Analysis of Empirical Results

4.1 Analysis of Spatial Correlation

4.1.1 Bivariate Global Moran's I Analysis

This study employs the bivariate global Moran's I, with the Air Quality Index (AQI) as the benchmark variable, to examine its spatial association characteristics with both the Digitalization Evolution Index and various control variables. The test results are presented in the table below.

Regarding the core explanatory variable, the bivariate Moran's I between the Digitalization Evolution Index and Air Quality Index exhibits a trend of transitioning from negative to positive and strengthening annually over the sample period. In 2020, the Moran's I was -0.007, failing to pass the significance test. In 2021, the index turned positive to 0.011 and became significant at the 5% level. It continued to rise in subsequent years, reaching 0.025 in 2022 and further increasing to 0.028 in 2023. This evolutionary trend indicates that the spatial dependence between the digital economy and air quality is gradually forming and intensifying. Regions with a developed digital economy are increasingly co-located in space with surrounding areas experiencing higher pollution levels, suggesting a solidifying pattern of homogeneous agglomeration characterized by "high digitalization–high pollution."

For the control variables, most exhibit a significant positive spatial correlation with air quality. The Moran's I for economic development level has remained above 0.05 and statistically significant since 2021, indicating that areas with higher economic development tend to be surrounded by regions with similar air quality characteristics. Industrialization level and the level of government intervention both show a significant positive correlation with air quality across all years examined. This indicates that industrial agglomeration and the scale of government expenditure exhibit distinct spatial homogeneity, and they share a synergistic relationship with the regional distribution of air quality. The Moran's I for technological innovation level is significantly positive in 2020, 2021, and 2023, implying that areas with active innovation activities tend to cluster spatially and are associated with the air quality conditions in surrounding areas. The significance level for urbanization is relatively weaker but shows a significant positive correlation in 2022 and 2023. The Moran's I for the level of openness to foreign trade is negative in most years and significant in 2021 and 2023, reflecting that foreign trade-active regions may exhibit a pattern of heterogeneous spatial distribution.

These results collectively demonstrate the widespread existence of significant spatial autocorrelation in air quality and its influencing factors. Consequently, following the baseline regression, it is necessary to further introduce models capable of handling spatial dependence to more accurately identify the impact mechanism of the digital economy on air quality.

Table 2: LeBron's advantages in rebounds and assists are particularly obvious

Year	Variable	lnDEI	lnEL	lnUL	lnLI	lnGIL	lnTIL	lnOL
2020	lnAQI	-0.007	0.006	0.007	0.017**	0.014**	0.017*	-0.002
2021		0.011**	0.052*	0.007	0.010*	0.016**	0.087**	-0.008*
2022		0.025*	0.076*	0.018*	0.038**	0.032**	-0.004	0.001
2023		0.028**	0.062**	0.013*	0.061***	0.035***	0.100***	-0.008*

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

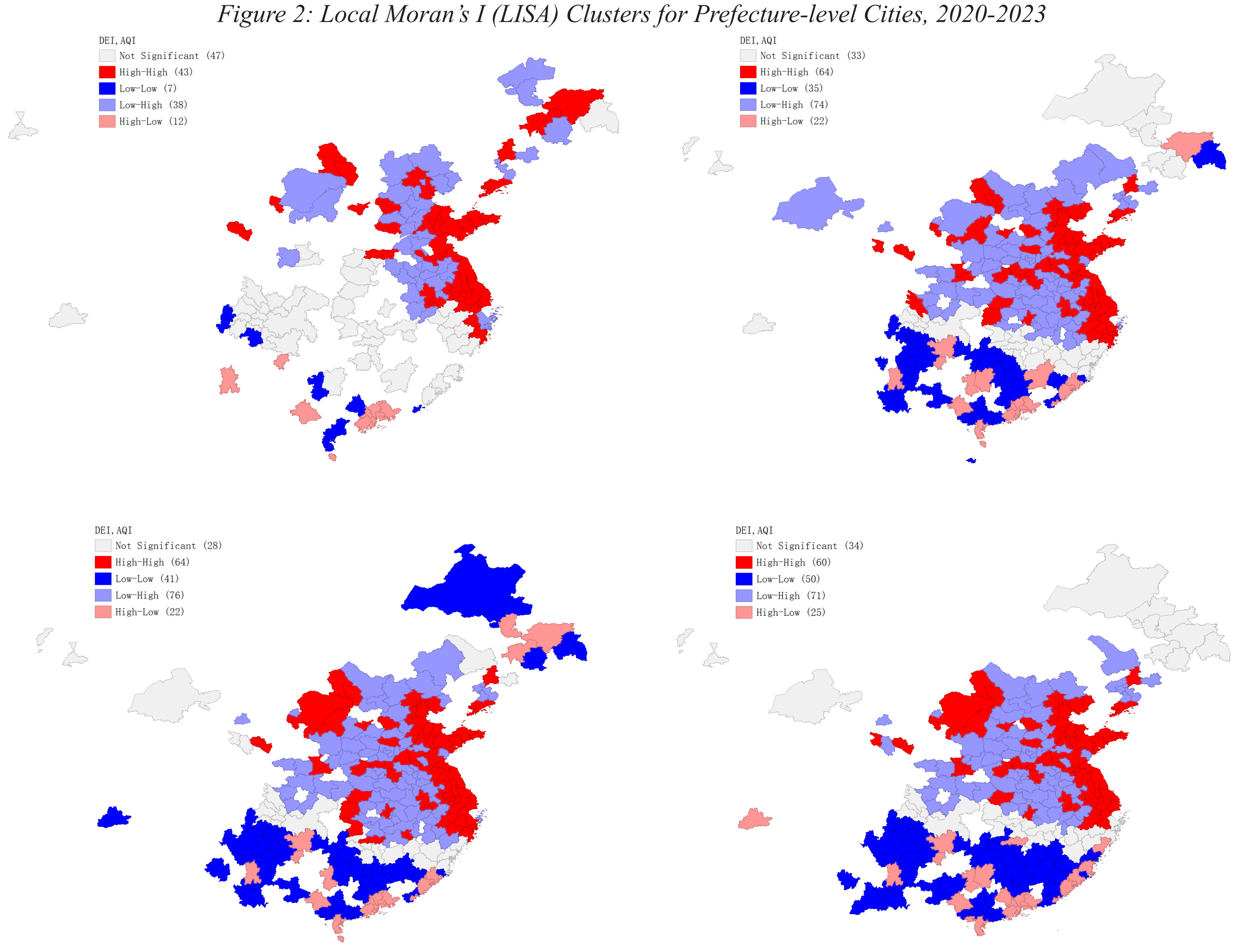
4.1.2 Local Moran's I Analysis

The analysis of Local Moran's I（LISA）can further reveal the specific spatial positions and cluster types of different cities within the spatial association framework, providing a more detailed perspective for understanding the internal structure of the relationship between digital economic development and air quality. The figure presents the LISA cluster maps for the prefecture-level cities studied from 2020 to 2023.

In terms of the clustering pattern, the four types of spatial association modes show distinct quantitative differences and spatial differentiation. Among them, the "Low-High" type is the most numerous and stable in distribution, widely found around traditional industrial agglomerations and energy bases. The digital economy development level of these cities lags relatively behind, yet they bear the pressure of high air pollution from surrounding areas, demonstrating a distinct characteristic of "passive pollution bearing." The "High-High" type ranks second in number. These cities are primarily located in regions where the digital economy is developing rapidly but has not yet fully decoupled from the heavy chemical industry, such as the Shandong Peninsula, the southern part of the Beijing-Tianjin-Hebei region, and some peripheral cities in the Yangtze River Delta. These areas reflect that the spatial overlap between the digital economy and pollution emissions remains relatively common, and the agglomeration of digital industries has not yet effectively translated into a driving force for air quality improvement. The "Low-Low" type is moderate, mainly distributed in regions with good ecological conditions and lower industrialization levels. Examples include some ecological function zones in southwest China and forestry cities in the northeast. In these areas, digital economic development is slow, but the air quality is inherently better, forming a state of relatively low-level equilibrium. The "High-Low" type is the smallest in number and shows no significant growth over time. This indicates that only a few cities have achieved a positive synergy between a leading digital economy and improved air quality in surrounding areas, with most of these being core cities in the Yangtze River Delta and the Pearl River Delta.

The local spatial association analysis demonstrates that the relationship between the digital economy and air quality is not a simple linear one. It not only validates the robustness of the global conclusion but also reveals a multi-level and multi-type spatial dependence structure beneath the same global trend.

Figure 2: Local Moran's I (LISA) Clusters for Prefecture-level Cities, 2020-2023



4.2 Collinearity Test

Before conducting the regression analysis, it is necessary to diagnose whether there is a multicollinearity issue among the explanatory variables. When a high correlation exists between independent variables, it can lead to inflated standard errors of the coefficient estimates and unstable estimation results, thereby affecting the reliability of statistical inference. This paper employs the Variance Inflation Factor (VIF) to test for collinearity among the explanatory and control variables for each year. The table presents the VIF test results for the variables from 2020 to 2023. The findings indicate that all VIF values for all variables in each year are below 10, with most values concentrated between 2 and 6. Only the VIF for technological innovation level in 2023 is 7.38, slightly elevated compared to other years but still within an acceptable range. This indicates that there are no severe multicollinearity issues among the variables selected in this paper, allowing for subsequent baseline regression and Geographically Weighted Regression analysis.

Table 3: Multicollinearity Test

Variable	2020 VIF	2021 VIF	2022 VIF	2023 VIF
lnDEI	3.46	5.13	5.95	5.16
lnEL	3.22	2.72	2.86	3.44
lnUL	3.03	2.31	3.13	3.31
lnLI	1.38	1.41	1.16	1.46
lnGIL	3.28	2.99	3.13	3.31
lnTIL	4.79	4.95	5.95	7.38
lnOL	4.47	4.01	3.89	3.54

4.3 Comparison of Baseline and Geographically Weighted Regression Models

To clarify the correlation between the digital economy and local air quality across prefecture-level cities, this study conducts an empirical analysis based on the baseline regression model. Overall, the digital economy demonstrates an improving effect on air quality in each year, although its statistical significance fluctuates. The coefficients for 2021 and 2022 are significant at the 5% and 10% levels, respectively, while those for 2020 and 2023 are positive but fail to meet conventional significance thresholds. In terms of overall explanatory power, the R2 values range from 0.09 to 0.18 annually, indicating that the OLS model explains a small portion of the variation in air quality. Thus, the baseline regression provides preliminary support for the digital economy's beneficial impact on air quality, but it has the following limitations: insufficient annual stability, limited explanatory capacity, and omission of spatial correlation controls.

However, the OLS model is inadequate for precise estimation. This section introduces the Geographically Weighted Regression (GWR) model and systematically compares its performance with that of the OLS model to statistically demonstrate the superiority of GWR in addressing spatial non-stationarity.

Comparing OLS and GWR model results for each year from 2020 to 2023 yields a clear and consistent conclusion: the Geographically Weighted Regression model comprehensively outperforms the Ordinary Least Squares model in characterizing the digital economy–air quality relationship.

Firstly, regarding goodness of fit, the explanatory power of the GWR model substantially exceeds that of OLS. Over the four-year span, the R^2 values of the OLS model range only from 0.094 to 0.179, implying that the traditional global regression can explain less than 18% of the variation in air quality at most, indicating a relatively poor model fit. In contrast, the R^2 values of the GWR model remain consistently high , between 0.837 and 0.858, accounting for over 80% of spatial variation in air quality and markedly enhancing real-data representation. This demonstrates a significantly enhanced ability to capture real-world data patterns. This substantial gap indicates that the impact of the digital economy on air quality exhibits pronounced spatial non-stationarity, and global regressions that ignore spatial heterogeneity risk losing a considerable amount of valuable information. Secondly, from a model adequacy perspective, the AICc values of the GWR model are substantially lower than those of the OLS model annually. The AICc is a commonly used criterion for balancing goodness of fit and model simplicity, where lower values indicate a better model specification. The data show that the AICc values of the GWR model are more than 140 points lower than those of the OLS model annually. This difference provides strong statistical evidence that the GWR model, which incorporates spatial heterogeneity, is a more scientifically sound specification. Thirdly, regarding residual magnitude, the fitted residuals of the GWR model are far smaller than those of the OLS model. For instance, in 2020, the residual of the OLS model is 131.154, while that of the GWR model drops to 23.895—an over 80% reduction. Similar patterns persist in other years, with GWR model residuals consistently stabilizing around 30, compared to OLS model residuals often exceeding 200. This significant reduction in residuals further confirms that the GWR model captures the underlying data characteristics far more effectively. Additionally, the bandwidth of the GWR model remains between 57 and 68 across all years, indicating that local estimation employs a moderate number of neighboring cities, which ensures an adequate capture of local characteristics while avoiding the problem of overfitting. Meanwhile, although the number of observations has gradually increased from 147 to 240 over the four-year period, with a continuously expanding sample coverage, the goodness of fit of the GWR model remains consistently stable. This demonstrates that the estimation results of the model possess strong robustness.

Collectively, this analysis confirms that he impact of the digital economy on air quality is not globally homogeneous; rather, it exhibits significant spatial non-stationarity. Employing GWR model for local estimation enables a more authentic and nuanced revelation of the spatial differentiation in this relationship, thereby laying a solid methodological foundation for subsequent in-depth analysis of the heterogeneous effects across different regions.

Table 4: Comparison Between the OLS Model and the GWR Model, 2020–2023

Model	**OLS**				**GWR**			
Year	2020	2021	2022	2023	2020	2021	2022	2023
AICc	419.714	628.334	664.072	666.732	280.640	379.563	418.531	397.242
R^2	0.118	0.179	0.094	0.129	0.837	0.852	0.847	0.858
AIC	416.400	625.508	661.257	663.949	239.888	333.913	359.485	345.133
Residual	131.154	193.398	220.933	209.045	23.895	33.801	35.421	34.133
Observation	147	226	231	240	147	226	231	240
Bandwidth					57	68	58	65

4.4 Spatial Differentiation Analysis of the Digital Economy's Influence Coefficients

This section further visualizes the distribution of the influence coefficients of the digital economy on air quality, as estimated by the GWR model from 2020 to 2023, across different prefecture-level cities. This allows for the identification of the spatially differentiated performance of the digital economy's environmental effects.

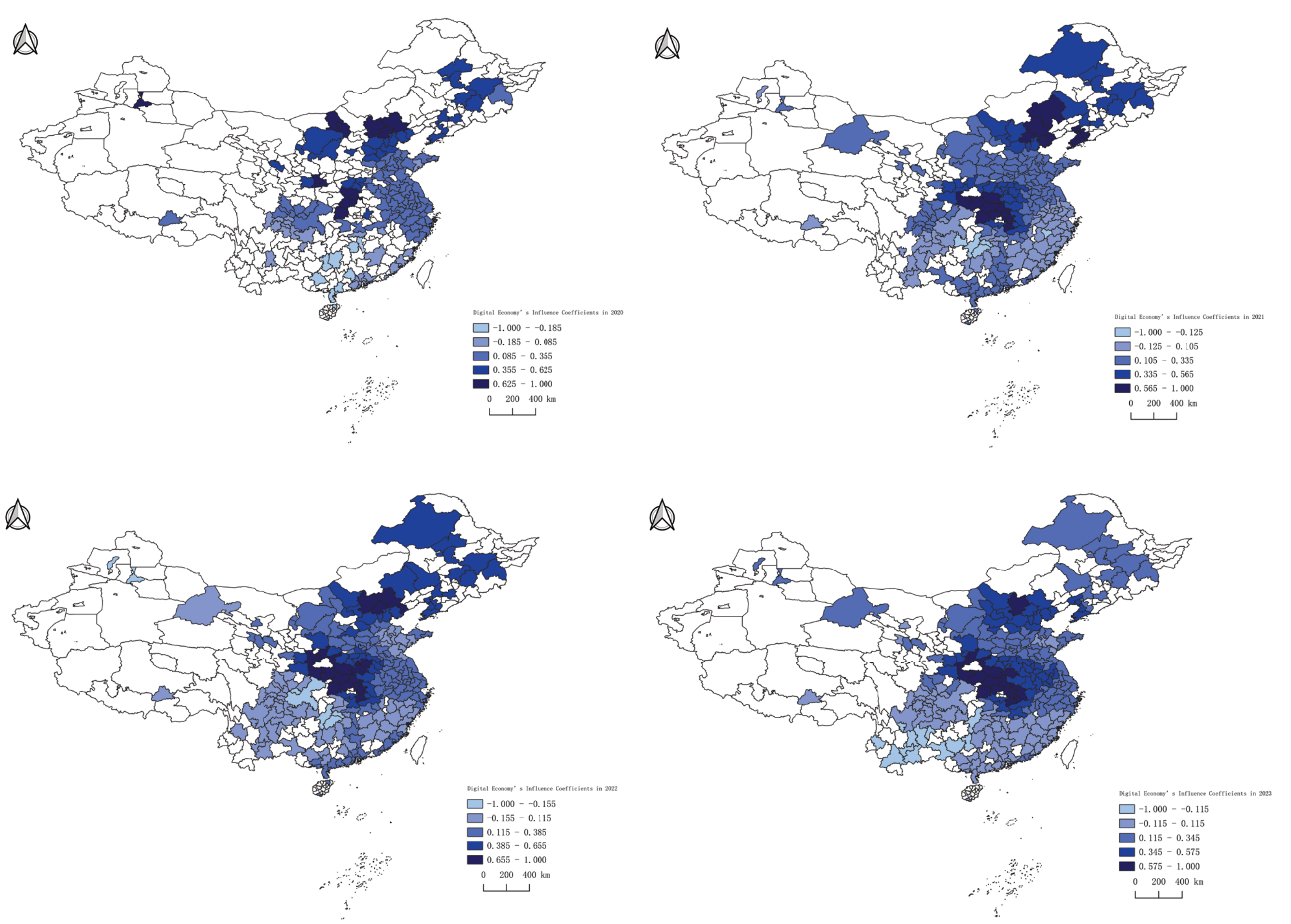
To intuitively present the spatial distribution differences in the influence coefficients of the digital economy on air quality, this paper adopts the method of "mean ± multiplier × standard deviation" to classify the local GWR estimation coefficients of each prefecture-level city. Specifically, using the mean of the influence coefficients of all sample cities as the benchmark, and taking 0.5 and 1.5 times the standard deviation as the critical thresholds, all cities are divided into five categories: regions below the mean minus 1.5 times the standard deviation are defined as significant inhibition zones, indicating that the digital economy has a significant negative impact on air quality; regions between the mean minus 1.5 times and the mean minus 0.5 times the standard deviation are defined as low-value zones, indicating that the digital economy has a weak positive or a slight negative effect on air quality improvement; regions between the mean minus 0.5 times and the mean plus 0.5 times the standard deviation are defined as medium-value zones, indicating that the impact is at an average level; regions between the mean plus 0.5 times and the mean plus 1.5 times the standard deviation are defined as medium-high-value zones, indicating that the digital economy has a relatively obvious effect on improving air quality; regions above the mean plus 1.5 times the standard deviation are defined as significant promotion zones, indicating that the digital economy has the most significant effect on improving air quality.

From an overall spatial perspective, the influence coefficients of the digital economy on air quality exhibit a distinct east-west divergence, a pattern that remains relatively stable throughout the sample period. The figure presents the spatial distribution of these influence coefficients from 2020 to 2023, mapped according to the classification criteria outlined above. Specifically, the medium-high-value zones and significant promotion zones are mainly concentrated in the eastern coastal areas, particularly in the core cities of the Yangtze River Delta, the Pearl River Delta, and the Beijing-Tianjin-Hebei region. These areas have a leading level of digital economy development, and the improving effect of the digital economy on air quality is most prominent here. In contrast, the low-value zones and even significant inhibition zones are widely distributed across the central and western regions, covering most prefecture-level cities in Northeast China, the western part of North China, the Northwest, and the Southwest. In these regions, the influence coefficients are negative or only weakly positive. This indicates that the environmental dividends of digital technology have not yet been effectively realized, and in some areas, there is even a coexistence of digital expansion and pollution accumulation.

Examining temporal evolution trends from 2020 to 2023, the environmental effects of the digital economy are undergoing a gradient diffusion from core cities to peripheral regions, although the pace of this diffusion remains relatively slow. The scope of the significant promotion zones is expanding gradually. Some secondary coastal cities, such as Qingdao and Yantai on the Shandong Peninsula, and Quanzhou and Zhangzhou in Fujian Province, have progressively advanced from medium-value zones to medium-high-value or significant promotion zones. Concurrently, while the extent of significant inhibition zones has contracted somewhat, vast areas in central and western China remain covered by low-value zones. This is particularly evident in the northwestern region and the old industrial bases in the northeast, where the degree of improvement has been relatively limited.

The spatial differentiation pattern described above reinforces the core judgment made earlier: the impact of the digital economy on air quality is not globally homogeneous. This finding also provides clear geographical targeting for the policy recommendations that follow.

Figure 3: Spatial Distribution of the Digital Economy's Influence Coefficients Across Chinese Prefecture-Level Cities, 2020–2023



5. Conclusions and Policy Recommendations

5.1 Conclusions

First, there is a significant spatial dependence between the digital economy and air quality, and this correlation pattern has undergone a directional shift and continued strengthening during the sample period. The global Moran's I shows that the spatial correlation between the two gradually transitioned from a weak negative correlation in 2020 to a positive spatial agglomeration after 2021, exhibiting a co-agglomeration characteristic of "high digital economy - high air pollution." Meanwhile, most control variables, such as the level of economic development, industrialization, government intervention, and technological innovation, also show significant positive spatial correlations. This indicates that these factors have distinct spatial homogeneity in their regional distribution and exhibit a synergistic relationship with the regional pattern of air quality.

Second, the local spatial association analysis reveals a more complex internal structure. The vast majority of cities in China remain in a state of spatial overlap between the digital economy and environmental pollution, or are passively bearing pollution pressure, indicating that achieving coordinated development between the two still has a long way to go. Among the four types of agglomeration patterns, "Low Digital Economy - High Air Pollution" cities are the most numerous. Widely distributed around traditional industrial agglomerations and energy bases, these cities exhibit a distinct characteristic of "passively bearing pollution," where their own digital economy development lags while they suffer from high pollution pressure originating from surrounding areas. The "High Digital Economy - High Air Pollution" type ranks second. These cities are mainly located in regions where the digital economy is developing rapidly but has not yet decoupled from the heavy chemical industry. "Low Digital Economy - Low Air Pollution" cities are concentrated in areas with a good ecological environment and a low degree of industrialization. In contrast, "High Digital Economy - Low Air Pollution" cities, representing a positive synergy, are extremely rare and are only sparsely distributed in core cities such as the Yangtze River Delta and the Pearl River Delta.

Thirdly, model superiority of the Geographically Weighted Regression (GWR) is confirmed. The explanatory power of the traditional global OLS model is limited. In contrast, the GWR model demonstrates significant advantages, with a goodness-of-fit (R^2) consistently between 0.837 and 0.858 across the four years, explaining over 80% of air quality variation, compared to a maximum R^2 below 0.18 for OLS. Furthermore, the GWR model's corrected Akaike Information Criterion (AICc) values were, on average, more than 140 points lower, and residuals decreased from above 200 to around 30. This underscores that incorporating spatial heterogeneity substantially improves model accuracy and better reflects the true data structure, confirming significant spatial non-stationarity in the impact of the digital economy on air quality and the potential for global models to obscure localized realities.

Fourthly, the influence coefficients of the digital economy estimated by the GWR model reveal a clear pattern of spatial differentiation. In the eastern coastal areas, particularly the core cities of the Yangtze River Delta, the Pearl River Delta, and the Beijing-Tianjin-Hebei region, the digital economy has the most significant effect on improving air quality, forming "significant promotion zones." In contrast, vast areas in central and western China are covered by "low-value zones" or even "significant inhibition zones." Although the scope of the significant promotion zones expanded somewhat between 2020 and 2023, the pace of diffusion has been relatively slow. This pattern indicates that in the developed eastern regions, the digital economy has begun to release green dividends, while in most central and western regions, it remains in a phase characterized by scale expansion coupled with energy consumption.

5.2 Policy Recommendations

Based on the findings, the following policy recommendations are proposed:

First, implement differentiated regional governance strategies based on the type of spatial association. For the most numerous "Low Digital Economy - High Air Pollution" cities, efforts should focus on addressing shortcomings in digital infrastructure and promoting the low-cost adoption of green digital technologies to alleviate their predicament of passively bearing pollution. For "High Digital Economy - High Air Pollution" regions, it is necessary to accelerate the substantive decoupling of the digital economy from polluting industries. This can be achieved by tightening environmental access thresholds, implementing carbon performance evaluations, and employing other means to compel the green transformation of traditional industries. For “High Digital Economy - Low Air Pollution” core cities, their experiences in integrating digital governance with environmental regulation should be promptly summarized to form replicable institutional achievements. For “Low Digital Economy - Low Air Pollution” ecological areas, ecological priorities should be upheld, with a moderate development of environmentally friendly digital industries while avoiding blind expansion.

Second, acknowledge spatial spillover effects and establish a framework for cross-regional collaborative governance. The “High-High” co-agglomeration of the digital economy and air pollution is not an isolated local phenomenon; rather, it is the result of the interplay between interregional factor flows and the cross-boundary transmission of pollution. It is recommended to establish “Digital-Environment” collaborative governance zones, using city clusters and metropolitan areas as the basic units. This would promote the sharing of emissions data, joint judgment of pollution sources, and shared responsibility for emission reduction. Simultaneously, guide the strategic distribution of digital infrastructure, such as data centers and computing hubs, to western regions rich in clean energy. This would help alleviate the spatial binding of “High Digital Economy” and “High Air Pollution” at the source.

Third, respect spatial non-stationarity to facilitate the precise adaptation of local policies. The estimation results of the GWR model indicate that the same set of digital economy policies can produce vastly different environmental outcomes in different cities. Therefore, the top-level national design should leave sufficient room for local adaptation, avoiding the assessment of all regions using uniform indicators. Local governments should be encouraged to conduct “Environmental Impact Pre-assessments for the Digital Economy.” Before the implementation of major digital industry projects, spatial econometric methods should be used to simulate their potential impact on local and neighboring air quality, providing scientific support for project site selection and scale regulation.

Fourth, align with the gradient diffusion pattern of the digital economy’s environmental effects to promote the orderly transfer of green dividends from the eastern to the western regions. Support for digital technology transfer and green innovation in the central and western regions should be strengthened. This can be achieved by establishing cross-regional digital transformation guidance funds and creating “Digital Pairing” assistance mechanisms between the eastern and western regions, thereby facilitating the adoption and adaptation of mature smart environmental protection and intelligent manufacturing solutions from the east in the central and western regions. At the same time, as the central and western regions undertake industrial transfers from the east, advanced air quality monitoring and treatment technologies should be introduced in tandem. This will prevent “digital divides” from becoming new “pollution sinks” and truly realize the cross-regional sharing of digital dividends and air quality benefits.

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