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Engineering Coupling Coordination and Spatial-Temporal Evolution of Green Innovation, Ecological Efficiency, and Digital Economy in China

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Abstract: *The synergistic development of green innovation (GI), ecological efficiency (EE), and the digital economy (DE) is pivotal for achieving China's high-quality economic development and ecological civilization goals. This study establishes a comprehensive evaluation index system for these three subsystems. Utilizing panel data from 30 Chinese provinces (excluding Chinese Hong Kong, Chinese Macao, and Chinese Taiwan) from 2012 to 2022, we measure their development levels using the entropy weight method and super-efficiency SBM model. A tri-system coupling coordination degree model (CCDM) is constructed to quantify their interactive relationships. Furthermore, spatial autocorrelation analysis (Moran's I) is employed to uncover their spatial aggregation characteristics. The findings reveal that: (1) The overall development levels of GI, EE, and DE have shown an upward but volatile trend, with significant regional imbalances. (2) The national coupling coordination degree has steadily increased from 0.385 (mild imbalance) in 2012 to 0.465 (on the verge of imbalance) in 2022, yet it remains at a low level with considerable room for improvement. (3) Spatially, the coordination level exhibits a distinct "ladder-like" distribution, descending from the eastern to the western regions. Global spatial autocorrelation is significantly positive, indicating a strong spatial agglomeration effect. Local spatial analysis identifies stable High-High (H-H) agglomerations in the eastern coastal provinces (e.g., Shanghai, Jiangsu, Zhejiang, Shandong) and Low-Low (L-L) agglomerations in the northwestern regions (e.g., Gansu, Qinghai, Ningxia, Xinjiang) since 2019. Based on these spatiotemporal evolution patterns, this study proposes targeted policy recommendations for categorized regional development to foster synergistic advancement and narrow regional disparities.*

Keywords: *Green Innovation; Ecological Efficiency; Digital Economy; Coupling Coordination Degree; Spatial Autocorrelation; Regional Disparity*

1. Introduction

Against the backdrop of a new global technological revolution and China's "dual-carbon" (carbon peak and neutrality) strategic goals, the transition towards a green and digital economy has become an irreversible trend. The 2023 Chinese Government Work Report explicitly set key targets, including a GDP growth rate of around 5%, a continuous reduction in energy consumption per unit of GDP, and stringent control over fossil fuel consumption, highlighting the paramount importance of harmonizing economic growth with ecological preservation [1]. In this context, the digital economy, as a core driver of high-quality development, is profoundly reshaping production methods and lifestyles.

Green innovation, which aims to achieve economic benefits while reducing environmental costs through technological advancement, and ecological efficiency, which measures the economic output per unit of environmental pressure, are two cornerstone indicators for assessing green development [2, 3]. The digital economy can empower both by optimizing resource allocation, improving energy efficiency through big data and IoT, and fostering green technological breakthroughs. However, the rapid processes of industrialization and urbanization have led to resource over-exploitation and environmental pollution, creating a tension between economic growth and ecological protection.This study explores how the digital economy can catalyze green innovation and enhance ecological efficiency is therefore crucial to resolving this contradiction.

Existing literature has extensively studied these three systems individually or in pairs [4-6], but systematic research on the synergistic mechanisms and spatiotemporal evolution of the "Green

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Innovation-Ecological Efficiency-Digital Economy" trinity system remains scarce. Most studies focus on static analyses, lacking dynamic assessments of their coupling coordination and its spatial characteristics. This study aims to fill this gap by: (1) constructing a comprehensive evaluation index system for GI, EE, and DE; (2) developing a tri-system coupling coordination degree model to assess their synergistic development from 2012 to 2022 across 30 Chinese provinces; (3) employing spatial analysis techniques to uncover their spatial-temporal evolution patterns and aggregation features; and (4) proposing differentiated policy recommendations based on the empirical findings. This research provides a scientific basis for promoting the integrated development of these three systems and achieving regional coordinated sustainable development.

2. Literature Review

2.1 Green Innovation Measurement

Scholars have primarily focused on measuring regional green innovation efficiency and its influencing factors. Han et al. (2013) used a four-stage DEA model to analyze inter-provincial differences in green innovation efficiency in China for 2010 [4]. Cao & Yu (2015) improved the SFA model, finding significant regional disparities from 2005 to 2011, a conclusion supported by Yang (2018) [5]. Lv Yanwei et al.(2020) incorporated "innovation failure" into the evaluation system, while Shen & Zhou (2018) considered technological heterogeneity, discovering that factors like industrial structure rationalization significantly impact green innovation [6].

2.2 Ecological Efficiency Measurement

Research on ecological efficiency has evolved from single-indicator to comprehensive evaluations. Wang & Fang (2010) calculated provincial ecological efficiency scores based on economic, resource, and environmental dimensions using factor analysis [7]. Yang & Du (2017) built an urban ecological efficiency indicator system from the perspective of ecological civilization construction [8]. Chen et al. (2020) measured forestry ecological efficiency from 1998 to 2017 using an improved model [9]. Internationally, Färe et al. (1989) first used DEA to assess environmental efficiency, and Kuosmanen (2005) established a super-efficiency DEA model to measure the ecological efficiency of the Finnish road transport industry [10].

2.3 Digital Economy Measurement

With the rise of the digital economy, its measurement systems have become increasingly refined. The China Academy of Information and Communications Technology (CAICT). (2022). White Paper on China's Digital Economy Development (2022). Beijing: CAICT Press. [11]. Cai & Niu (2021) conducted a systematic accounting of the value-added scale of China's digital economy [12]. Many scholars construct indicator systems from dimensions such as digital infrastructure, industrial digitization, and digital industrialization [13].

In summary, while previous studies provide a solid foundation, they often operate in silos. This study integrates these three critical systems into a unified analytical framework, employing coupling coordination and spatial analysis to reveal their interconnected dynamics, thus offering a more holistic perspective.

3. Research Design and Methodology

3.1 Indicator System and Data Sources

Based on a review of relevant literature and theoretical frameworks, we constructed a comprehensive indicator system for GI, EE, and DE, as shown in Table 1.

Data for these indicators were primarily obtained from the China Statistical Yearbook, China Energy Statistical Yearbook, and provincial statistical yearbooks for the period 2012-2022. Missing data were supplemented using linear interpolation. Given significant data gaps, Chinese Hong Kong, Chinese Macao, and Chinese Taiwan were excluded from the study.

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Table 1. Comprehensive Evaluation Indicator System for the Three Systems.

Subsystem	Dimensional Index	Specific Indicator	Unit	Attribute
Green Innovation	Input	R&D Personnel Full-time Equivalent	man-years	+
		R&D Internal Expenditure	10,000 yuan	+
		Energy Consumption	10,000 tons of SCE	-
	Output	Number of Patent Applications	item	+
Ecological Efficiency	Input	Fixed Asset Stock	100 million yuan	-
	Desired Output	Regional GDP	100 million yuan	+
	Undesired Output	Industrial Wastewater Discharge	10,000 tons	-
		Nitrogen Oxide Emissions	10,000 tons	-
Digital Economy	Infrastructure	Internet Broadband Access Ports	10,000 units	+
	Digital Industry	Number of Telecommunications Enterprises	unit	+
	Industry Digitization	Software Business Revenue	100 million yuan	+
		Telecommunications Business Volume	100 million yuan	+
	Digital Environment	Internet Penetration Rate	%	+
		Mobile Phone Penetration Rate	subscribers/100 people	+

Note: SCE = Standard Coal Equivalent; '+' denotes positive indicator, '-' denotes negative indicator.

3.2 Methodology

3.2.1 Entropy Weight Method

To avoid subjectivity in assigning weights, the entropy weight method was used to determine the weight of each indicator and calculate the comprehensive development indices for GI, EE, and DE for each province and year.

3.2.2 Coupling Coordination Degree Model (CCDM)

The coupling degree (C) measures the strength of interaction among the three systems. The coupling coordination degree (D) further reflects the level of benign coordination, considering both the interaction strength and the overall development level.

1) Coupling Degree (C):

$$C=\sqrt[3]{\frac{X\cdot Y\cdot Z}{\left(\frac{X+Y+Z}{3}\right)^3}}=3\times\sqrt[3]{\frac{X\cdot Y\cdot Z}{(X+Y+Z)^3}} \tag{1}$$

where X,Y,Z represent the comprehensive evaluation scores of GI, EE, and DE, respectively. $C\in[0,1]$. A higher C indicates stronger interaction.

2) Comprehensive Coordination Index (T):

$$T=\alpha X+\beta Y+\gamma Z \tag{2}$$

Considering the systems are of equal importance, we set $\alpha=\beta=\gamma=1/3$.

3) Coupling Coordination Degree (D):

$$D=\sqrt{C\cdot T} \tag{3}$$

$D\in[0,1]$. A higher D indicates better coordinated development. The classification criteria for D are shown in Table 2.

Table 2: Coupling Coordination Degree Classification Criteria

D Value Range	Coordination Level	D Value Range	Coordination Level
0.00 - 0.09	Extreme Dysfunction	0.50 - 0.59	Barely Coordinated
0.10 - 0.19	Severe Dysfunction	0.60 - 0.69	Primary Coordination
0.20 - 0.29	Moderate Dysfunction	0.70 - 0.79	Intermediate Coordination
0.30 - 0.39	Mild Dysfunction	0.80 - 0.89	Good Coordination
0.40 - 0.49	On the Verge of Dysfunction	0.90 - 1.00	Quality Coordination

3.2.3 Spatial Autocorrelation Analysis

Spatial autocorrelation assesses whether a variable is spatially clustered. Global Moran's I reveals the overall spatial pattern, while Local Moran's I (LISA) identifies local clusters and outliers.

1) Global Moran's I:

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$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij(x_i-\overline{x})(x_j-\overline{x})}}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\sum_{i=1}^{n}(x_i-\overline{x})^2} \tag{4}$$

where n is the number of provinces, x_i and x_j are the coupling coordination degrees of provinces i and j, $\overline{x}$ is the mean, and ω_{ij} is the spatial weight matrix (inverse distance matrix used in this study). $I>0$ indicates positive spatial autocorrelation (clustering), $I<0$ indicates negative spatial autocorrelation (dispersion), and $I \approx 0$ suggests a random spatial distribution.

2) Local Moran's I (LISA):

$$I_I = \frac{(x_i-\overline{x})}{S^2}\sum_{j=1}^{n}\omega_{ij}\left(x_j-\overline{x}\right) \tag{5}$$

where S^2 is the variance. LISA clusters are categorized into four types: High-High (H-H), Low-Low (L-L), High-Low (H-L), and Low-High (L-H).

4. Empirical Results and Analysis

4.1 Analysis of Subsystem Development Levels

4.1.1 Green Innovation (GI)

Nationally, the GI comprehensive index showed a clear upward trend, rising from 0.499 in 2012 to 0.726 in 2022, with an average annual growth rate of 3.11%. However, growth was volatile, peaking in 2017 (8.32%) and slowing thereafter. Spatially, provinces like Chongqing, Zhejiang, Guangdong, Jiangsu, and Shandong led the rankings due to strong economic foundations and significant S&T investment. In contrast, Heilongjiang, Gansu, Hebei, Ningxia, and Liaoning, often reliant on traditional resource-based industries, lagged behind, constrained by limited funding and technology (Figure 1).

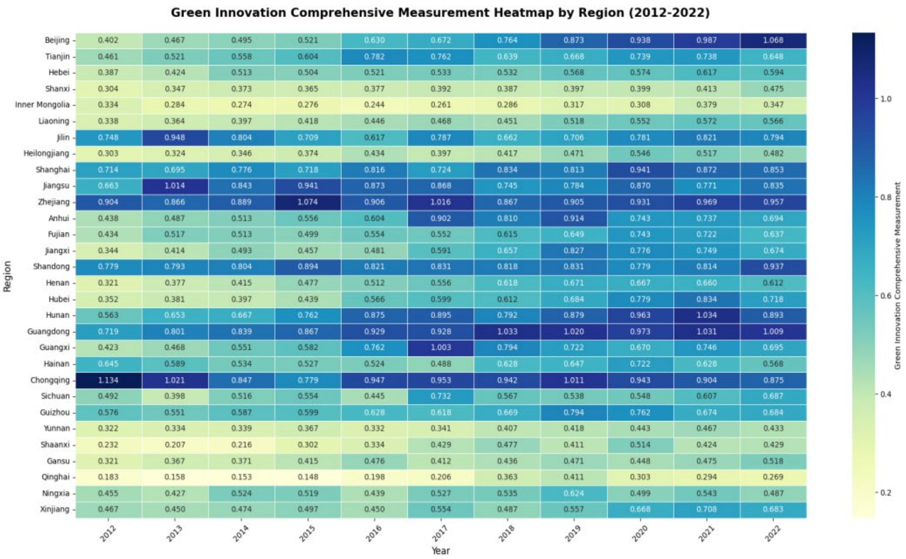

Figure 1. Heat Map of Comprehensive Green Innovation Measurement Values by Region

4.1.2 Ecological Efficiency (EE)

The national EE index experienced fluctuations, increasing from 0.497 in 2012 to 0.746 in 2022. Growth was stable around 2% from 2012-2015, declined, then recovered before being impacted by the pandemic in 2020. Regional disparities widened significantly. In 2022, the top five provinces (e.g., Jiangsu, Shandong) had an average EE score of 1.338, while the bottom five (e.g., Gansu) averaged 0.581—a gap of 0.762, much larger than the 0.144 gap in 2012. Developed eastern provinces benefited from advanced technology and capital for industrial upgrading, whereas less developed western regions struggled with resource-intensive industrial structures and insufficient environmental investment (Figure 2).

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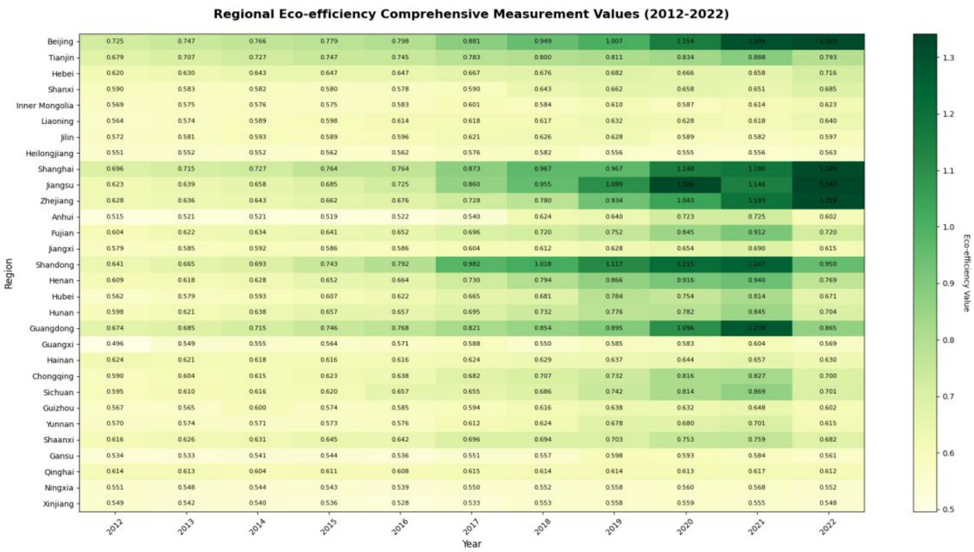

Figure 2. Heat Map of Comprehensive Ecological Efficiency Measurement Values by Region

4.1.3 Digital Economy (DE)

The DE comprehensive index demonstrated the most stable growth, increasing from 0.364 in 2012 to 0.528 in 2022, with a cumulative growth of 47.73%. Despite this progress, the absolute level remained relatively low, indicating substantial potential for future development. Growth rates were volatile, peaking at 9.64% in 2018. The regional divide was stark: Guangdong, Beijing, and Shanghai were the frontrunners, while Qinghai, Ningxia, and Xinjiang trailed due to geographical and economic constraints (Figure 3).

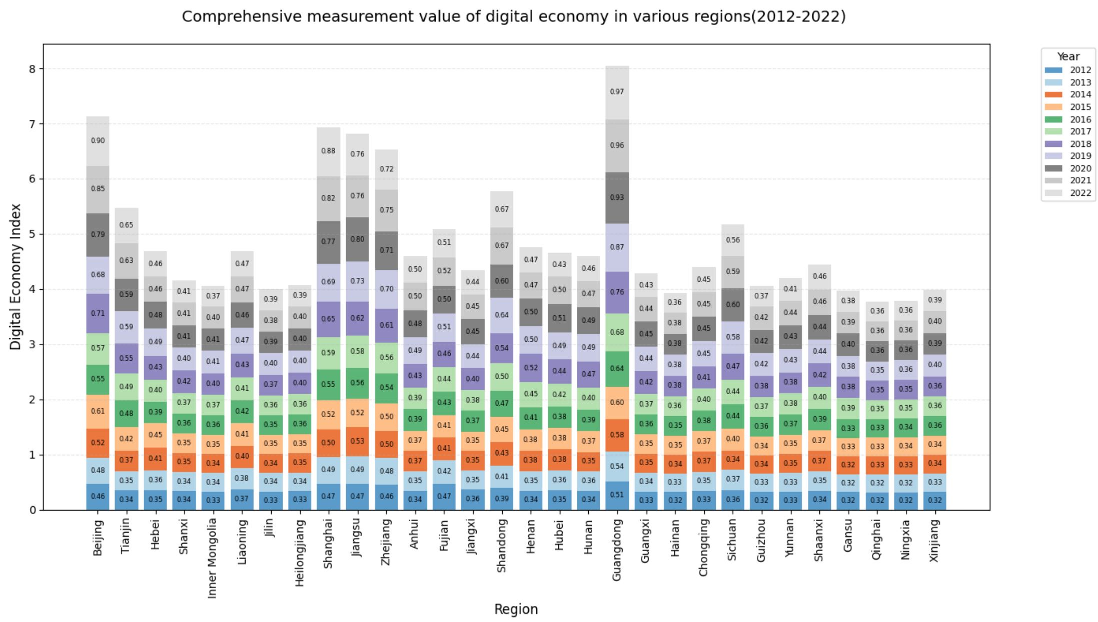

Figure 3. Heat Map of Comprehensive Digital Economy Measurement Values by Region

4.2 Coupling Coordination Degree Analysis

4.2.1 Temporal Evolution

As shown in Table 3, the national average coupling coordination degree (D) steadily increased from 0.385 (Mild Dysfunction) in 2012 to 0.465 (On the Verge of Dysfunction) in 2022, with a cumulative growth of 18.31%. However, the growth rate exhibited an "M-shaped" fluctuation, slowing notably after 2019, likely due to the economic impacts of the COVID-19 pandemic. This indicates that while the synergistic development of the three systems is improving, the pace is slow, and the overall level remains precarious, requiring further effort to achieve a stable coordinated state.

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Table 3: National Average Coupling Coordination Degree and Growth Rate (2012-2022)

Year	2012	2013	2014	2015.	2016	2017	2018	2019	2020	2021	2022
D	0.385	0.395	0.405	0.410	0.415	0.430	0.440	0.463	0.455	0.460	0.465
Growth Rate(%)	-	2.60	2.53	1.23	1.22	3.61	2.33	4.55	-1.73	1.10	1.09

4.2.2 Spatial Pattern and Provincial Evolution

The spatial distribution of the coupling coordination degree exhibited a clear "east-high, west-low" gradient. In 2012, most eastern coastal provinces were "On the Verge of Dysfunction," forming a "V-shaped" development belt with Guangdong as the core, while central and western provinces were predominantly in "Mild Dysfunction." By 2022, significant progress was made. The spatial pattern evolved into a dual-core structure radiating from Guangdong and Shanghai. The number of provinces in "Mild Dysfunction" decreased from 16 to 5, while those achieving "Barely Coordinated" (5 provinces) and "Primary Coordination" (2 provinces, Beijing and Guangdong) emerged. However, the absolute disparity (range) in D values among provinces widened from 0.14 in 2012 to 0.24 in 2022, indicating intensifying regional polarization (Figure 4).

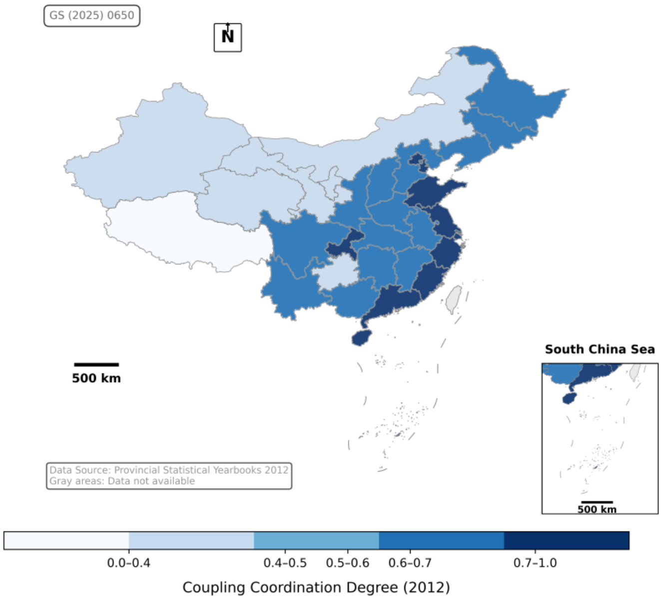

Figure 4. Spatial Distribution of Coupling Coordination Degree by Province (2012)

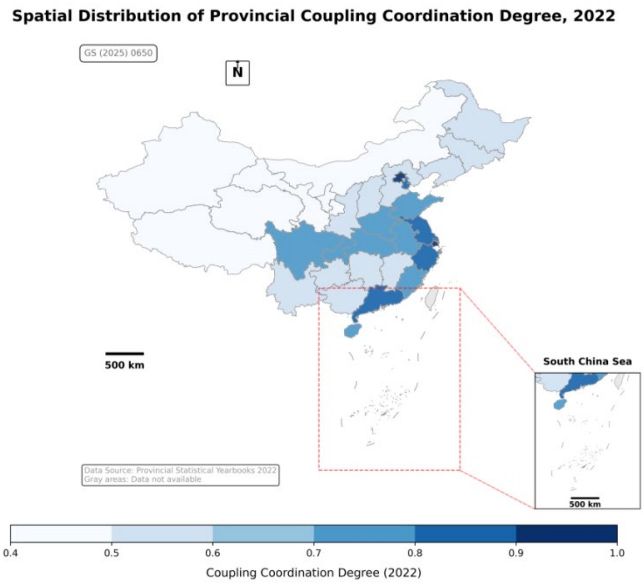

Figure 5. Spatial Distribution of Coupling Coordination Degree by Province (2022)

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Based on changes in coordination levels from 2012 to 2022, provinces can be divided into three types:

Improvement Type (17 provinces): e.g., Beijing, Guangdong, and Tianjin, which jumped two levels; Hebei, Sichuan, etc., which improved by one level. Stable Type (8 provinces): e.g., Fujian, Hainan (stable at "On the Verge"), Qinghai, Ningxia (stable at "Mild Dysfunction"). Fluctuation Type (e.g., Heilongjiang): Experienced fluctuations between levels (Figure 5).

4.3 Spatial Correlation Analysis

4.3.1 Global Spatial Autocorrelation

As presented in Table 4, the Global Moran's I indices from 2012 to 2022 are all positive and statistically significant ($p < 0.05$), confirming a significant positive spatial correlation in the coupling coordination degree across China. The index generally increased from 0.058 in 2012 to a peak of 0.118 in 2020, indicating a strengthening spatial agglomeration effect over this period. The slight decline in 2021-2022 suggests a potential moderation of this trend, but the overall spatial clustering pattern remains robust (Table 4).

Table 4: Global Moran's I Index of Coupling Coordination Degree (2012-2022)

Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Moran's I	0.058	0.069	0.078	0.079	0.092	0.087	0.101	0.107	0.118	0.111	0.089
P-value	0.005	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Z-score	2.497	2.700	2.890	3.191	3.531	3.571	3.700	3.941	4.220	3.910	3.630

4.3.2 Local Spatial Autocorrelation (LISA)

LISA analysis reveals the formation and stability of specific local agglomeration areas.

High-High (H-H) Agglomeration: Initially observed in Shanghai, Jiangsu, and Zhejiang in 2012. By 2015, Tianjin and Shandong joined this cluster. From 2018 to 2022, the H-H agglomeration stabilized in Shanghai, Jiangsu, Zhejiang, and Shandong. These provinces, with their strong economic and technological capabilities, create positive spillover effects, forming a high-level synergistic development zone in the eastern coastal region.

Low-Low (L-L) Agglomeration: In 2012, this cluster included Shaanxi, Gansu, Qinghai, and Ningxia. By 2015, Shaanxi was replaced by Xinjiang. From 2018 to 2022, the L-L agglomeration stabilized in Gansu, Qinghai, Ningxia, and Xinjiang. These northwestern provinces face similar challenges, such as a fragile ecological environment, a less developed economy, and weaker digital foundations, trapping them in a low-level equilibrium state (Figure 6).

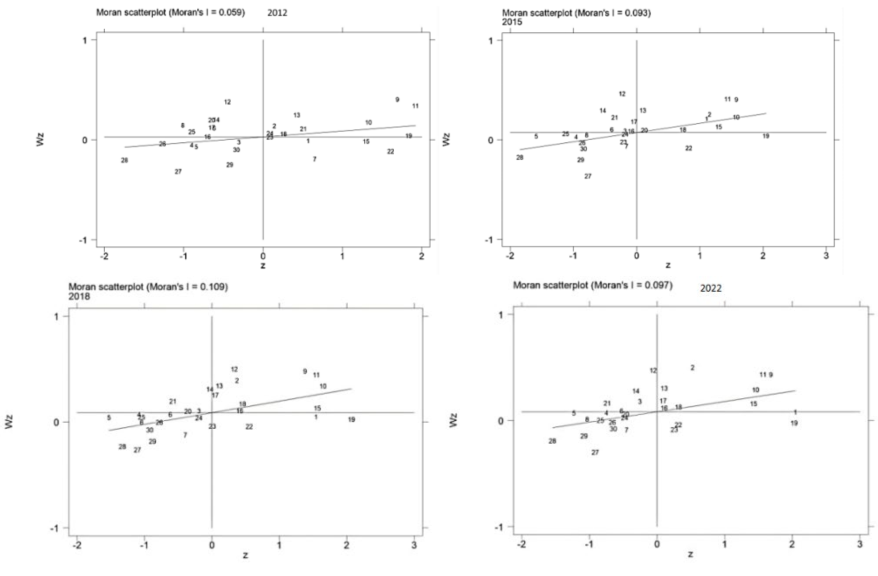

Figure 6. Moran Scatter Plots for the Years 2012, 2015, 2018, and 2022

Annotation: 1.Beijing, 2. Tianjin, 3. Hebei Province, 4. Shanxi Province, 5. Inner Mongolia Autonomous Region, 6. Liaoning Province, 7. Jilin Province, 8. Heilongjiang Province, 9. Shanghai, 10. Jiangsu Province, 11. Zhejiang Province, 12. Anhui Province, 13. Fujian Province, 14. Jiangxi Province,

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15. Shandong Province, 16. Henan Province, 17. Hubei Province, 18. Hunan Province, 19. Guangdong Province, 20. Guangxi Zhuang Autonomous Region, 21. Hainan Province, 22. Chongqing, 23. Sichuan Province, 24. Guizhou Province, 25. Yunnan Province, 26. Autonomous Region, 27. Shaanxi Province, 28. Gansu Province, 29. Qinghai Province, 30. Ningxia Hui Autonomous Region, 31. Xinjiang Autonomous Region

5. Conclusion and Policy Implications

5.1 Conclusion

This study systematically evaluates the coupling coordination and spatiotemporal evolution of green innovation, ecological efficiency, and the digital economy in China from 2012 to 2022. The main conclusions are as follows:

1) The development levels of GI, EE, and DE have generally improved but are characterized by volatility and significant regional inequality, with eastern provinces consistently outperforming their western counterparts.

2) The coupling coordination degree of the three systems has shown a steady but slow upward trend. However, by 2022, the national average remained "On the Verge of Dysfunction," indicating a fragile state of synergy with considerable room for improvement.

3) The spatial distribution of coordination is uneven, showing a clear "step-like" decrease from east to west. The spatial agglomeration effect is significant and intensified during the study period, forming stable H-H and L-L agglomeration areas, which has led to a widening gap in regional synergistic development levels.

5.2 Policy Recommendations

Based on the findings, we propose the following targeted policy recommendations:

1) Implement Precision Governance to Activate Synergistic Potential:

For the Green Innovation subsystem, the government should strengthen policies such as R&D tax deductions, deepen industry-university-research collaboration, and establish green technology transfer platforms to accelerate the commercialization of innovations; for the Ecological Efficiency subsystem, it should tighten environmental regulations, increase investment in pollution control, promote clean production technologies, and encourage the scale-up of green and low-carbon industries; for the Digital Economy subsystem, it should prioritize investments in digital infrastructure (5G, data centers) in central and western regions, implement specialized talent programs to build a multi-level digital workforce, and empower the digital transformation of traditional industries.

2) Promote Differentiated Development Based on Spatiotemporal Characteristics:

Primary Coordination Areas (e.g., Guangdong, Beijing): These regions (local governments and enterprises) should focus on consolidating advantages and radiating influence, strengthen technological exchanges and industrial collaboration with neighboring Chinese provinces to drive regional synergistic development, and also explore higher-level regional integration models tailored to the characteristics of Primary Coordination Areas; Barely Coordinated Areas (e.g., Shanghai, Jiangsu, Zhejiang): Local governments and regional collaborative alliances should increase investment in next-generation infrastructure and strategic emerging industries, and foster deeper regional cooperation to break down administrative barriers and enhance the level of coordination; Areas on the Verge of Dysfunction (accounting for 63.3% of all provinces, the largest proportion): Local authorities should leverage local resource endowments to cultivate characteristic industries (e.g., eco-tourism, clean energy), improve talent introduction and retention policies, and actively introduce external capital and technology to achieve a breakthrough in green and digital development.

References

[1] The State Council of the People's Republic of China. Report on the Work of the Government (2023). http://www.gov.cn.

[2] Li, H., Xiang, G., & Gao, Z. (2005). A Preliminary Study on the Institutional Conditions for the

ISSN 2616-5902 Vol. 7, Issue 12: 109-117, DOI: 10.25236/AJBM.2025.071214

Transformation of Environmental Benefits from Green Innovation in Manufacturing into Enterprise Economic Benefits. Science Research Management, (2), 46-49.
[3] Wang, B., & Fang, C. (2010). Research on Regional Ecological Efficiency Based on Economic and Environmental Coordination. China Population, Resources and Environment, 20(3), 122-127.
[4] Han, J., et al. (2013). Research on China's Regional Green Innovation Efficiency. Finance Research, (11), 130-137.
[5] Cao, X., & Yu, J. (2015). Regional Differences and Convergence of Green Innovation Efficiency in China. R&D Management, 27(1), 23-32.
[6] Shen, N., & Zhou, J. (2018). Research on the Impact of Technological Heterogeneity and Environmental Regulation on Green Innovation Efficiency. Science of Science and Management of S.& T., 39(5), 28-41.
[7] Yang, L., & Du, P. (2017). Evaluation of Urban Ecological Efficiency from the Perspective of Ecological Civilization Construction. Statistics and Decision, (18), 103-106.
[8] Chen, Z., Zhang, Y., & Zhu, H. (2020). Evaluation of Forestry Ecological Footprint, Ecological Pressure and Ecological Efficiency in China. Issues of Forestry Economics, 40(5), 510-517.
[9] Färe, R., Grosskopf, S., Lovell, C. A. K., & Pasurka, C. (1989). Multilateral Productivity Comparisons When Some Outputs are Undesirable: A Nonparametric Approach. The Review of Economics and Statistics, 71(1), 90-98.
[10] Kuosmanen, T. (2005). Measurement and Analysis of Eco-Efficiency: An Economist's Perspective. Journal of Industrial Ecology, 9(4), 15-18.
[11] China Academy of Information and Communications Technology (CAICT). (2022). White Paper on China's Digital Economy Development (2022).Beijing: CAICT Press.
[12] Cai, Y., & Niu, X. (2021). Scale Measurement and Structural Analysis of China's Digital Economy. Social Sciences in China, (11), 4-30.
[13] Cui, K., & Feng, X. (2020). Research on the Design of a Rural Digital Economy Indicator System from the Perspective of Digital Village Construction. Agricultural Modernization Research, 41(6), 899-909.