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Measurement and Spatiotemporal Dynamics Analysis of the Coupling Coordination Between New Quality Productive Forces and Emission Reduction Efficiency

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Abstract: This study elucidates the significance of new quality productive forces(NQPF) in achieving emission reduction efficiency, providing theoretical and empirical foundations for synergizing economic transformation with climate goals. Existing research on new quality productive forces suffers from three key limitations: (1) inadequate multidimensional measurement systems failing to capture their technological-institutional complexity, (2) overreliance on isolated bivariate analyses that ignore systemic coordination mechanisms, and (3) disconnected treatment of spatial and temporal dimensions in impact assessments. Our study addresses these gaps through an integrated spatiotemporal framework. This study pioneers a multidimensional framework to quantify new quality productive forces, overcomes the limitation of traditional bivariate analysis by investigating their systemic coordination, and innovatively assesses these relationships through integrated spatial and temporal approaches. This study establishes a multidimensional evaluation system for new quality productive forces, develops a systemic coordination testing model that transcends traditional bivariate analysis, and creates a spatiotemporal coupling framework integrating spatial kernel density estimation with temporal Markov chain analysis. This study identifies three key findings on new quality productive forces and carbon reduction synergy: (1) Significant east-west disparity in coordination (Coupling Coordination Degree: 0.552 vs 0.433), with high-tech clusters excelling; (2) Path-dependent evolution (90% provinces stable/improving) with policy-induced bifurcation (2015); (3) Positive spatial spillovers (Moran's I>0) but western geographical constraints cause low-value lock-in.

Keywords: New quality productive forces, Emission reduction efficiency, Coupling coordination, Markov chain, Spatial econometrics

1. Introduction

In January 2024, the General Secretary emphasized at the 11th collective study session of the Political Bureau of the CPC Central Committee on promoting high-quality development that “We must accelerate the development of new forms of productive forces to promote high-quality development.” [1]. New quality productive forces (NQPF) combine digital and green technologies, exhibiting regional disparities between China's advanced east and developing west. Emission reduction efficiency varies regionally, with eastern areas benefiting from industrial and clean energy advantages. Their coordination shows economic growth and emissions control are compatible, emphasizing

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promoting the green and low-carbon economic transformation by improving total factor productivity and optimizing the energy structure [2].

Current research lacks comprehensive NQPF measurement, productivity-emission synergy assessment, and spatiotemporal analysis. This study: (1) builds a multidimensional NQPF evaluation system, (2) establishes a coupling coordination model, and (3) combines kernel density and Markov chain methods. Key contributions include: a novel NQPF assessment framework, an original synergy evaluation model, and an integrated spatiotemporal analysis approach.

The structure of the remaining sections of this paper is as follows. Section 2 is Literature Review. Section 3 is the Method. Section 4 is the Data. Section 5 is Result. Section 6 is Conclusion. Section 7 is Discussion.

2. Literature review

Existing NQPF studies focus narrowly on three aspects: technological innovation (patents/R&D), labor quality (education/skills), and digital/green transition (ICT/renewables) [3]. Key limitations include: (1) overemphasis on GDP over institutional factors, (2) isolated dimensional analysis lacking integration, and (3) inadequate spatiotemporal dynamic assessment (e.g., regional evolution/policy impacts).

Emission reduction efficiency is commonly measured using input-output models (e.g., SBM-DEA) [4] with variables like energy intensity, industrial structure, and clean tech adoption. Despite these efforts, limitations persist. The reliance on static analysis rather than dynamic efficiency trends is a significant issue. Additionally, aggregated data often mask regional disparities, such as those between the east and west of China [5]. Moreover, these methods overlook non-linear synergies, such as technology spillovers across sectors. Existing NQPF-emission studies predominantly employ bivariate regressions or panel models, but suffer three key gaps: (1) Unexamined institutional mechanisms, (2) Lacking spatial-temporal analyses (e.g., econometrics/Markov chains), and (3) No coordination assessment between NQPF growth and emission trajectories.

3. Method

3.1. Entropy weight method

Measuring new quality productivity requires multidimensional indicators with scientifically determined weights. While traditional methods like AHP are subjective, the Entropy Weight Method objectively calculates weights based on data dispersion, eliminating human bias—making it ideal for multi-province, longitudinal evaluations [6]. First, this study distinguishes indicators into positive and negative ones, and standardizes the data using different methods respectively (In Eqs. 1). Second, calculate the entropy value e_j of the j-th indicator, reflecting the degree of data dispersion (In Eq. 2). Third, assign the weight for each indicators (In Eq. 3). In the end, give annual new quality productivity index for each province (In Eq. 4).

$$x'_{ijt} = \frac{x_{ijt} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad \text{(Positive)} \tag{1}$$

$$x'_{ijt} = \frac{\max(x_j) - x_{ijt}}{\max(x_j) - \min(x_j)} \quad \text{(Negative)} \tag{2}$$

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

$$S_{it} = \sum_{j=1}^{m} \omega_j \cdot x'_{ijt} \tag{4}$$

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3.2. SBM-DEA

Conventional DEA models ignore slack variables, while the SBM method [7], effectively addresses non-radial improvements in efficiency evaluation by directly handling input/output slack, and evaluates decision-making units (DMUs) by simultaneously considering slack variables in both dimensions (In Eqs. 5).

$$\rho^* = \min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1+\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{rk}}} \tag{5}$$

$$\text{s.t.}\begin{cases} \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{ik}, & i = 1,\ldots,m \\ \sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = y_{rk}, & r = 1,\ldots,s \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0 \end{cases}$$

Where ρ^* donate Efficiency score ($0 \leqslant \rho^* \leqslant 1$); x_{ik}, y_{rk} donate Inputs/outputs of DMU k; s_i^-, s_r^+ donate Input excess and output shortfall slack; λ_j donate Weight coefficient.

3.3. Coupling coordination degree

The coupling coordination degree evaluates synergistic development between multiple systems [8]. The calculation involves two steps (In Eq. 6, Eq. 7).

$$C = n \times \left[\frac{(u_1 \times u_2 \times \ldots \times u_n)}{\left(\frac{u_1+u_2+\ldots+u_n}{n}\right)^n}\right]^{\frac{1}{n}} \tag{6}$$

Where C donate Coupling degree ($0 \leqslant C \leqslant 1$), higher values indicate stronger interaction; u_i donate Standardized score of subsystem i; n donate Number of subsystems (typically n=2 for pairwise analysis).

$$D = \sqrt{C \times T},\ \ T = \alpha u_1 + \beta u_2 + \ldots + \gamma u_n \tag{7}$$

Where D donate Coordination degree ($0 \leqslant D \leqslant 1$), classified into 5 levels (see table below); T donate Comprehensive index weighted by subsystem importance; $\alpha, \beta, \ldots, \gamma$ donate Weights (sum to 1), determined via entropy weight/AHP.

3.4. Moran's index

Moran's I is a widely used spatial autocorrelation statistic that measures the degree of clustering or dispersion for geographic data [9]. It quantifies whether similar values tend to concentrate (positive autocorrelation), diverge (negative autocorrelation), or distribute randomly across space. Values range from -1 to 1, where 1 indicates perfect clustering of similar values, -1 represents perfect dispersion, and 0 suggests no spatial pattern [10]. This index is extensively applied in fields like epidemiology, urban planning, and environmental studies to identify hotspots, spatial trends, or anomalies. This study distinguishes indicators into Global (In Eq. 8) and Local ones (In Eq. 9).

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \text{ (Global)} \tag{8}$$

Where n donate Number of spatial units (provinces); x_i donate Observation value at location ii; $\bar{x}$ donate Mean value of observations; ω_{ij} donate Spatial weight matrix element (binary or distance-based).

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$$I_i = \frac{(x_i - \overline{x})}{S^2} \sum_{j=1}^{n} \omega_{ij}(x_j - \overline{x}) \; (S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2) \; \text{(Local)} \tag{9}$$

4. Data

The data used in this study were primarily obtained from the China Statistical Yearbook like China Industrial Statistical Yearbook, China City Statistical Yearbook, China Population and Employment Statistical Yearbook, China Labour Statistical Yearbook, China Energy Statistical Yearbook, China Water Resources Bulletin, China Meteorological Yearbook, China Tertiary Industry Statistical Yearbook, China Statistical Yearbook on Science and Technology, China Statistical Yearbook on Education for the period 2010–2020, covering all 31 provincial-level administrative regions in mainland China (excluding Hong Kong, Macao, and Taiwan). The study analyzes a balanced provincial panel (31 provinces × 11 years; N=341) measuring five core dimensions: New-Type Laborers, Labor Objects, Production Means, Sustainable Development, and Input-Output indicators. All monetary values use 2010 constant prices, with missing data handled via linear interpolation. The dataset passed rigorous consistency checks for empirical reliability.

5. Result

5.1. Measurement result

5.1.1. Measurement of new quality productivity

In order to assess the impact of new quality productive forces on emission reduction efficiency, this study construct a multidimensional evaluation index system for new quality productive forces [11]. The details are shown below: The new-type laborers dimension (including 3 secondary dimensions - skills, productivity, and awareness - with 5 indicators: average years of education, proportion of population with higher education, GDP, average wage of employed workers, and value-added of tertiary industry); The new-type labor objects dimension (including 3 secondary dimensions - industrial development, upgrading, and greening - with 4 indicators: industrial structure sophistication index, business revenue of high-tech industries, industrial water consumption, and total CO_2 emissions); The new-type means of production dimension (including 3 secondary dimensions - green innovation, technological innovation, and digitalization level - with 4 indicators: number of authorized green invention patents, number of domestic patent applications, R&D expenditure of industrial enterprises above designated size, and internet broadband access ports); The sustainable development capacity dimension (including 3 secondary dimensions - resources conservation, environmental planning, and protection - with 4 indicators: renewable energy consumption, afforestation area, industrial smoke (dust) emissions, completed investment in industrial pollution control, and daily capacity of harmless domestic waste treatment).

5.1.2. Measurement of emission reducing efficiency

This study employs an input-output analysis approach to establish an evaluation system comprising five key indicators. The productivity indicator is calculated using the perpetual inventory method, with 2010 as the base year (initial capital stock at 10%, depreciation rate at 9.6%), measured in 100 million yuan. The industrial pollution control indicator adopts the comprehensive utilization rate of industrial solid waste (%). The environment-related investment indicator represents the proportion of environmental infrastructure construction investment to GDP (%). The desired output indicator is provincial GDP deflated to 2010 prices (100 million yuan), while the undesirable output indicator is CO_2 emissions (10,000 tons).

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All monetary value indicators are calculated at constant 2010 prices to eliminate the effects of price fluctuations. CO_2 emissions are estimated following IPCC guidelines, and the industrial solid waste utilization rate reflects the performance of circular economy development. This indicator system quantifies the relationship between production efficiency and environmental constraints, providing essential data support for assessing green total factor productivity.

5.1.3. Measurement of Coupling Coordination Degree

This study classifies Coupling Coordination Degree (CCD) into tiers (Table 1). The Table 2 shows the CCD of the east, west and central. Longitudinal analysis indicates China's overall coordination reached moderate levels: transitioning from barely coordinated (2010-2016) to moderately coordinated status. For instance, Shanghai's index grew from 0.445 (2010) to 0.527 (2020), while the national average rose from 0.435 to 0.500 during 2010-2016.

Table 1: Coupling level classification

Interval	Coupling Coordination Degree	Coordination Degree
0<D<0.2	Severe Dysregulation (SD)	Low-level Stage
0.2<D<0.4	Mild Dysregulation (MD)	
0.4<D<0.6	Barely Coordinated (BC)	Adaptation Stage
0.6<D<0.8	IntermediateCoordination (IC)	High-level Stage
0.8<D<1	High-quality Coordination (HC)	

Regional comparisons show all three zones (eastern/central/western China) improved CCD between input-output and NQPF, but with pronounced "east-high, west-low" divergence. Eastern regions led (avg. 0.552), exemplified by Jiangsu's high coordination (0.809), while central areas followed (0.489). Western provinces trailed (0.433), with Qinghai notably low (0.270).

Table 2: Result of Coupling Coordination Degree

Region	2010	CCT	2011	CCT	2012	CCT	2013	CCT
East	0.484	BC	0.506	BC	0.510	BC	0.537	BC
Central	0.444	BC	0.448	BC	0.449	BC	0.482	BC
West	0.380	MD	0.388	MD	0.393	MD	0.422	BC
-	2014	CCT	2015	CCT	2016	CCT	2017	CCT
East	0.547	BC	0.566	BC	0.565	BC	0.576	BC
Central	0.488	BC	0.490	BC	0.492	BC	0.505	BC
West	0.435	BC	0.428	BC	0.441	BC	0.465	BC
-	2018	CCT	2019	CCT	2020	CCT	-	-
East	0.585	BC	0.591	BC	0.600	IC	-	-
Central	0.529	BC	0.532	BC	0.525	BC	-	-
West	0.465	BC	0.473	BC	0.474	BC	-	-

At the local coordination level from 2010 to 2020, Jiangsu Province achieved the highest coupling coordination degree in China with an average of 0.809, reaching the premium coordination stage. It was closely followed by Guangdong (0.801) and Shandong (0.740), all three far exceeding the national average of 0.492.

Jiangsu and Guangdong lead in high-tech clusters: Guangdong in electronics and smart manufacturing; Jiangsu in nanotechnology and biomedicine. Both have perfected the "R&D-transformation-upgrading" cycle, achieving high productivity-output synergy. Their innovation ecosystems thrive through industry-university-research integration—Guangdong via the Greater Bay Area tech corridor and Jiangsu through the Sunan Innovation Zone, with top universities (e.g.,

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Nanjing University, SCUT) partnering with firms (Huawei, DJI, Hengrui) to drive commercialization. Guangdong's "Chain Leader System" and Jiangsu's "Industrial Chain Strengthening" initiative optimize resource allocation by supporting key industries and leveraging private enterprises (e.g., Tencent, Shagang). Both provinces enhanced energy transitions (2010-2020)—Jiangsu by expanding clean energy, Guangdong by boosting renewables—while Shandong capitalized on industrial/agricultural strengths to align NQPF growth with emission cuts. Other provinces outperforming the national average include Fujian, Hebei, Liaoning, Zhejiang, Anhui, Henan, Hubei, Hunan, Inner Mongolia, Sichuan, and Yunnan, with coupling coordination degrees ranging from 0.492 to 0.647 and an average of 0.583. In contrast, Hainan, Ningxia, Qinghai, Jilin, and Gansu ranked as the bottom five provinces, showing significantly lower coordination levels between 0.209 and 0.364, with an average of just 0.291, indicating substantial room for improvement in their development models.

5.2. Analysis of time evolution trend

Figure 1 explains the 3 key evolutionary characteristics of the coupling coordination degree (2010–2020) by using kernel density [12]: (1) Initial scattered distribution (low-density peaks) transitioned to high-value clustering by 2020, indicating strengthened synergy; (2) A transitional bimodal pattern emerged in 2015 (peaks at 0.4/0.8), reflecting policy/technology-induced differentiation; (3) Sustained high-value convergence in later stages demonstrates successful integration of green policies with technological innovation.

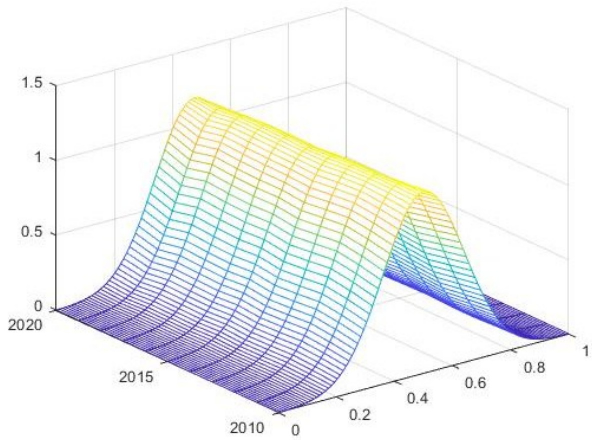

Figure 1: Time evolution trend

5.3. Analysis of temporal and spatial transfer trend

To further analyze the spatial evolution characteristics of the coordinated development level between new quality productive forces and emission reduction efficiency, a Markov chain was introduced. Based on the coupling coordination level between emission reduction efficiency and new quality productive forces, provinces during the sample period were divided into five tiers: severely imbalanced provinces (0-0.2), mildly imbalanced provinces (0.2-0.4), barely coordinated provinces (0.4-0.6), moderately coordinated provinces (0.6-0.8), and premium coordinated provinces (0.8-1). MATLAB 2023a software was used to study the spatial evolution characteristics of coordinated development. The traditional and spatial Markov transition probability matrices for the coordinated development of emission reduction efficiency and new quality productive forces are shown in Table 3.

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Table 3: Global Markov's index

t/(t+1)	Severe	Mild	Barely	Inter-mediate	High	N
Severe Dysregulation	0.000	0.000	0.000	0.000	0.000	0
Mild Dysregulation	0.000	0.899	0.101	0.000	0.000	89
Barely Coordinated	0.000	0.000	0.902	0.098	0.000	123
Intermediate Coordination	0.000	0.000	0.030	0.939	0.030	66
High-quality Coordination	0.000	0.000	0.000	0.000	1.000	9

The traditional Markov transition probability matrix reveals that provinces at the mildly imbalanced, barely coordinated, moderately coordinated, and premium coordinated levels have probabilities of 89.9%, 90.2%, 93.9%, and 100%, respectively, of maintaining their current coordination level after one year, indicating relative stability in the coordinated development between emission reduction efficiency and new quality productive forces across provinces.

The transition probability matrix reveals two key patterns: (1) Diagonal probabilities dominate (e.g., 10.1%,9.8%,3% upward vs. 0%,3%,0% downward between adjacent levels), demonstrating gradual, stepwise progression without leapfrog improvements; (2) Upward transition likelihoods systematically exceed downward risks, indicating sustainable coordination advancement with minimal regression potential.

The spatial Markov transition probability matrix further demonstrates that provinces at the premium coordinated level exhibit extremely stable states and are less susceptible to influence from neighboring provinces.

5.4. Analysis of spatial synergy

Figure 2 shows the calculation results of the global Moran's I index for the coordinated development between emission reduction efficiency and new quality productive forces in various provinces from 2010 to 2020. It can be seen that the global Moran's I index was significantly positive in each year of the sample period, with the average value concentrated between 0.995 and 0.997, showing fluctuating trends overall.

Since the global Moran's I index cannot reflect the spatial clustering characteristics of local regions, we calculated the local Moran's I index to further analyze the degree of spatial correlation between the coordinated development level of each province and its neighboring provinces, shown in the Figure 3 and the Fig 4.

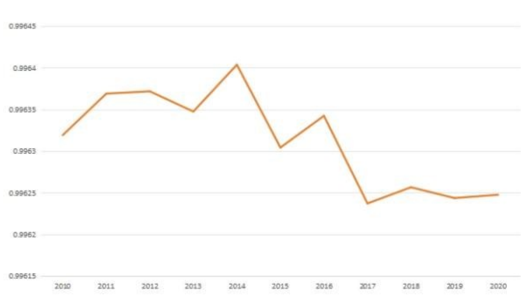

Figure 2: Global Moran's index

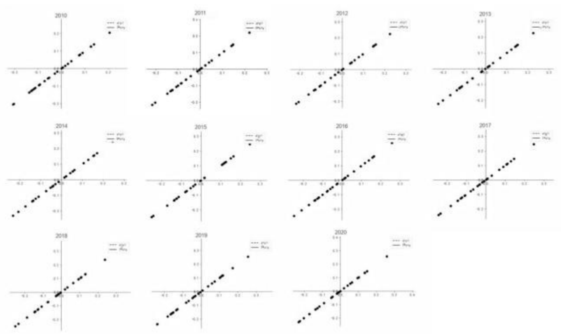

Figure 3: Local Moran's index scatter plot

The spatial distribution of coordinated development levels are shown in Figure 4. The analysis reveals that provinces with geographical proximity tend to exhibit similar Moran's I indices. For instance, Shanxi and Shaanxi maintained consistently low and comparable Moran's I values

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throughout 2010-2020. This spatial similarity likely stems from their shared geographical characteristics: both located on the Loess Plateau with predominantly mountainous/rugged terrain and arid/semi-arid climates, resulting in fragile ecosystems that constrain land use patterns (e.g., Grain-for-Green program implementation) and agricultural development. Their economies remain heavily dependent on energy and heavy chemical industries (Shanxi's coking vs Shaanxi's coal chemistry), with industrial output spatially concentrated in few urban centers (Taiyuan/Datong in Shanxi; Yulin/Yan'an in Shaanxi), creating similar "hotspot" distribution patterns.

At the national level, eastern provinces demonstrated significantly stronger spatial clustering than western regions. The peak Moran's I values emerged in Guangdong (5.814) and Jiangsu (5.113) in 2020, likely benefiting from policy-driven interregional coordination like the Greater Bay Area and Yangtze River Delta integration, which enhanced factor mobility (e.g., Shanghai-Hangzhou-Nanjing high-speed rail network enabling 1-hour connectivity). Superior transportation and digital infrastructure in eastern regions—including expressways, HSR, and 5G coverage—accelerated the diffusion of information, technology, and capital, thereby strengthening spatial dependence.

Provinces like Guangdong and Jiangsu could establish cross-regional green technology alliances to uplift neighboring provinces (e.g., Fujian, Hunan). Temporally, the local spatial clustering patterns remained remarkably stable, with only sporadic province-level transitions between cluster types occurring in isolated years without forming sustained evolutionary trends.

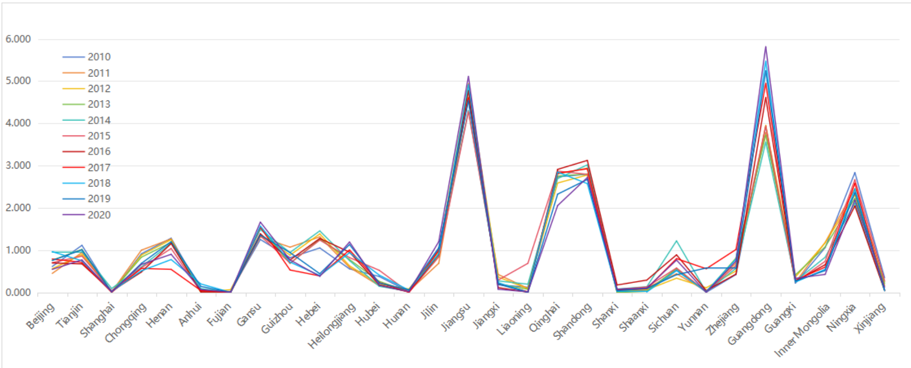

Figure 4: Local Moran’s index

6. Conclusion

This study develops a novel three-dimensional (digitalization, high-end, intelligent) evaluation system for productive forces, quantifying provincial development across China. Using SBM-DEA and coupling coordination models, it assesses emission reduction efficiency and synergy. Spatial-temporal dynamics are analyzed via KDE, Markov chains, and Moran's I, providing policy optimization insights.

Key findings reveal: (1) NQPF lowers energy/GDP and emissions via tech innovation and industrial upgrading; (2) Digitalization improves precision and reduces waste, boosting emission efficiency; (3) Green tech adoption requires strong policy/market support; (4) Regional disparities highlight advanced areas' outperformance, urging better tech transfer and cooperation.

7. Discussion

The innovations of this study lie in the multi-dimensional quantification of new quality productive forces, the addressing the gap in prior research by examining their coordination rather than isolated bivariate analysis, and the multi-perspective coordination assessment through spatial (KDE) and temporal (Markov transition) dimensions.

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Key findings show NQPF enhances emission reduction efficiency via tech innovation, digitalization, and industrial upgrading, though limited by data gaps and model simplicity. Future work should refine methods, while policymakers must boost green tech adoption and regional cooperation for sustainable industrialization.

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