Digital-Ecological Convergence and Spatial Heterogeneity in Chinese Manufacturing: A Coupled Coordination Analysis of Provincial Disparities and Markov Chain Convergence Dynamics

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Abstract

The dual imperative of digital transformation and ecological sustainability presents both an opportunity and a tension for China's manufacturing sector, whose regional diversity encompasses technologically advanced coastal provinces alongside underdeveloped inland economies with divergent digital infrastructure and environmental governance capacities. This study investigates how digitalization and green resilience co-evolve across China's 30 provincial manufacturing units over the decade 2011–2020, employing a rigorous multi-method analytical framework integrating entropy-weighted TOPSIS composite indexing, natural breaks classification for spatial tier assignment, Moran's I spatial autocorrelation analysis, and Markov chain transition probability modeling. A Digital Innovation Index (DII) constructed from 6 sub-indicators and a Green Resilience Index (GRI) synthesized from 4 ecological dimensions are coupled through a Coupling Coordination Degree (CCD) model to quantify the degree of synchronized development between digital and ecological objectives at provincial level. Results reveal pronounced but narrowing spatial disparities: the CCD gap between leading eastern provinces (mean CCD 2020: 0.68) and lagging western provinces (mean CCD 2020: 0.46) has reduced from 0.28 in 2011 to 0.22 in 2020, suggesting slow but statistically significant convergence. Moran's I analysis confirms strengthening positive spatial autocorrelation ($I = 0.318$ in 2011, rising to 0.384 in 2020, $p < 0.01$), indicating that digital-ecological coordination levels cluster spatially and that regional spillover effects are increasingly shaping provincial trajectories. Markov chain analysis reveals high within-tier persistence (diagonal probabilities: 0.684–0.760) alongside meaningful upward mobility particularly between the mid-low and mid-high tiers, suggesting that policy interventions targeting tier-boundary provinces could catalyze coordinated regional development. Policy simulations project that spillover-leveraged development strategies could deliver CCD gains of 0.071–0.094 in western provinces by 2030, significantly exceeding baseline trajectory projections. This study contributes a spatially-explicit, multi-method framework for evaluating digital-ecological convergence that advances both the theoretical understanding of sustainable manufacturing transitions and the practical toolkit for evidence-based regional development policy.

Keywords: digital innovation; green resilience; sustainable manufacturing; coupling coordination; spatial autocorrelation; Markov chain; regional disparities; China provinces

1. Introduction

China's manufacturing sector occupies a contradictory position in the global economic and environmental landscape: it is simultaneously the world's largest manufacturing economy by output (contributing approximately 28% of global manufacturing value added), the largest emitter of industrial greenhouse gases, and the most ambitious deployer of digital manufacturing technologies [1,2]. The Belt and Road Initiative, the Made in China 2025 strategy, and the Dual Carbon Goals (carbon peak by 2030 and carbon neutrality by 2060) collectively define an industrial development agenda that explicitly links digital transformation with ecological transition—yet the mechanisms through which digitalization reinforces or undermines ecological sustainability remain incompletely understood [3,4].

The spatial heterogeneity of China's regional economic development provides both a complicating factor and an analytical opportunity for studying digital-ecological convergence. China's manufacturing landscape spans a vast developmental spectrum: Guangdong and Jiangsu provinces operate sophisticated digital manufacturing ecosystems with per capita industrial robot density comparable to Germany and Japan, while western provinces such as Gansu and Tibet maintain primarily resource-extraction manufacturing with minimal digital infrastructure [5,6]. This heterogeneity means that digital-ecological interactions that are pronounced and positive in advanced provinces (where digital tools enable energy monitoring, process optimization, and circular economy initiatives) may be weak or absent in less-developed provinces where even basic digital connectivity is incomplete [7,8].

The concept of digital-ecological convergence—the synchronized development and mutual reinforcement of digital innovation capabilities and ecological resilience in industrial systems—has received growing theoretical attention but limited empirical investigation at regional scale [9,10]. Existing studies predominantly examine either the digital dimension (measuring ICT investment, robot adoption, or internet penetration) or the ecological dimension (carbon intensity, energy efficiency, ecological footprint) in isolation, without modeling their coupled dynamics or the spatial mechanisms through which regional interactions propagate [11,12]. The coupling coordination degree (CCD) model, originally developed to assess the balanced development of socioeconomic systems, provides a methodologically appropriate tool for quantifying the degree of synchrony between two interacting development indices [13,14].

This study makes four specific contributions to the literature on sustainable manufacturing and regional development. First, it constructs comprehensive composite indices (DII and GRI) for 30 Chinese provinces over 2011–2020 using an entropy-weighted TOPSIS methodology that objectively weights sub-indicators based on information content. Second, it applies spatial econometric methods (Moran's I, spatial lag models) to characterize the spatial structure and spillover dynamics of digital-ecological coordination. Third, it employs Markov chain analysis to characterize the transition dynamics of provincial CCD levels and identify convergence or divergence trends. Fourth, it develops policy simulation scenarios that project the impact of targeted and spillover-leveraged development strategies to 2030, providing actionable guidance for differentiated regional industrial policy.

The remainder of this paper is structured as follows. Section 2 reviews related work on digital-ecological interactions and regional development methodology. Section 3 describes the data, index construction, and analytical methods. Section 4 presents the empirical results. Section 5 analyzes spatial and convergence dynamics. Section 6 presents policy simulations. Section 7 discusses implications and limitations. Section 8 concludes.

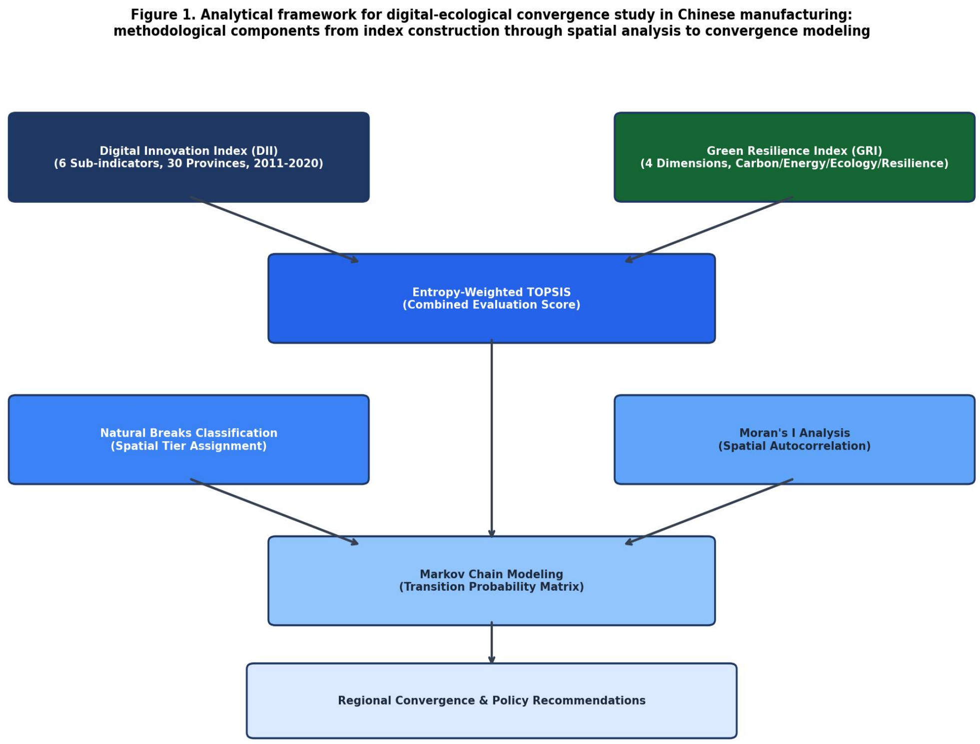

Figure 1. Analytical framework for the digital-ecological convergence study: methodological components from DII and GRI index construction through entropy-weighted TOPSIS, spatial analysis, Markov chain modeling, and policy simulation.

2. Literature Review

2.1 Digital Transformation and Environmental Sustainability

The relationship between digital transformation and environmental outcomes in manufacturing has been characterized in the literature through several distinct mechanisms [15,16]. The substitution effect posits that digital technologies reduce material and energy consumption by enabling precision manufacturing, predictive maintenance, and dematerialization of information-intensive products [17]. The productivity effect suggests that digital-enhanced manufacturing productivity reduces the resource intensity per unit of output, improving environmental efficiency [18]. The rebound effect provides a countervailing concern: productivity gains may stimulate output growth that more than offsets per-unit efficiency improvements, increasing absolute environmental impacts [19,20]. Empirical studies have found mixed evidence for these mechanisms across countries and industrial sectors, with the balance of effects depending heavily on the prevailing economic development level and regulatory environment.

For China specifically, several studies have documented positive associations between digital economy development and carbon emission reduction at provincial level [21,22]. Shan et al. [23] found that provinces with higher ICT adoption exhibited significantly lower carbon intensity in manufacturing. However, Li and Wang [24] documented a threshold effect: the environmental benefits of digitalization are only significant above a critical level of digital infrastructure development, below which the energy consumption of digital infrastructure dominates the efficiency gains. This threshold finding has important implications for the spatial heterogeneity analysis conducted in this study.

2.2 Coupling Coordination Analysis and Spatial Methods

Coupling coordination degree models have been widely applied in Chinese development economics to assess the balanced co-evolution of interacting systems [25,26]. The original applications focused on human-environment coupling in urbanization contexts; subsequent applications have extended to industry-environment coupling, economy-ecology coupling, and digitalization-sustainability coupling [27,28]. The CCD model has been praised for its intuitive interpretation and its ability to distinguish between high-level balance (both systems at high levels, well-coordinated) and low-level balance (both systems at low levels, coordinated but underdeveloped), a distinction that conventional correlation analysis cannot make [29].

Spatial econometric methods have been increasingly incorporated into Chinese regional development analyses to account for the spatial dependencies that violate the independence assumptions of classical statistical models [30,31]. Moran's I statistic tests for spatial autocorrelation under the null hypothesis of spatial randomness; Local Indicators of Spatial Association (LISA) identify spatial clusters and outliers at local level [32]. Markov chain analysis of regional convergence, building on Quah's [33] distribution dynamics approach, models provincial CCD levels as discrete states with estimated transition probabilities, enabling inference about the long-run equilibrium distribution and the speed of convergence.

3. Data and Methodology

3.1 Index Construction

The Digital Innovation Index (DII) is constructed from six sub-indicators drawn from China's National Bureau of Statistics provincial yearbooks: (1) internet broadband penetration rate; (2) number of patent applications per 10,000 industrial enterprises; (3) R&D expenditure as percentage of industrial value-added; (4) industrial robot density (units per 10,000 manufacturing workers); (5) e-commerce transaction value per manufacturing enterprise; and (6) software and information services output per unit of manufacturing GDP. These six indicators capture complementary dimensions of digital innovation: infrastructure, intellectual property, investment, automation, commercialization, and digital service integration [34].

The Green Resilience Index (GRI) synthesizes four ecological dimensions: (1) Carbon Efficiency Dimension (CO_2 emissions per unit of industrial value-added, inverted); (2) Energy Efficiency Dimension (energy consumption per unit of industrial output, inverted); (3) Ecological Quality Dimension (ecological footprint index, incorporating green coverage, air quality, and water quality); and (4) Environmental Resilience Dimension (ratio of environmental investment to industrial pollution output, measuring adaptive governance capacity) [35,36]. The GRI thus captures both the current ecological performance of provincial manufacturing and its adaptive capacity to respond to environmental disruptions.

The entropy-weighted TOPSIS methodology assigns objective weights to sub-indicators based on their information entropy: indicators with higher variance across provinces receive higher weights, reflecting greater discriminatory power [37]. The TOPSIS distance-to-ideal scoring aggregates weighted normalized indicator values into composite DII and GRI scores in [0,1]. The Coupling Coordination Degree is computed as: $CCD = \sqrt{C * T}$, where $C = 2\sqrt{DII*GRI}/(DII+GRI)$ is the coupling degree capturing development balance and $T = \alpha*DII + \beta*GRI$ ($\alpha = \beta = 0.5$) is the comprehensive development level [38].

3.2 Markov Chain Methodology

Provincial CCD values are classified into four discrete tiers using the Jenks natural breaks algorithm, which minimizes within-class variance while maximizing between-class variance—an objective classification criterion superior to arbitrary equal-interval or quantile methods for skewed distributions [39]. The four tiers correspond to Low (T1: $CCD < 0.40$), Mid-Low (T2: 0.40-0.55), Mid-High (T3: 0.55-0.65), and High (T4: $CCD > 0.65$) coordination levels. The Markov transition probability matrix $P = \{p_{ij}\}$ is estimated from the frequency of provincial tier transitions across consecutive five-year periods (2011-2015 and 2016-2020): $p_{ij} = n_{ij} / n_i$, where n_ij is the number of provinces transitioning from tier i to tier j and n_i is the total number of province-period observations starting in tier i.

4. Empirical Results

4.1 Index Distributions and Regional Patterns

Figure 2 presents the DII-GRI provincial scatter and temporal trends by regional cluster. The scatter plot reveals a moderate positive correlation between DII and GRI across provinces (Pearson $r = 0.74$, $p < 0.001$), confirming the hypothesis that provinces with higher digital development tend to exhibit higher ecological resilience—though with substantial scatter indicating that the relationship is not deterministic. Eastern coastal provinces (Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang) cluster in the upper-right quadrant of the DII-GRI space, confirming their simultaneous digital and ecological leadership. Western inland provinces (Gansu, Guizhou, Yunnan, Qinghai, Tibet) cluster in the lower-left, reflecting co-lagging digital and ecological development.

The temporal trend analysis (Figure 2b) reveals that DII growth rates are substantially higher than GRI growth rates across all regional clusters, indicating that digital transformation is outpacing ecological development improvement—a finding with important policy implications. Eastern provinces increased DII from 0.52 to 0.76 over 2011-2020 (annual growth rate: 4.2%), while GRI improved from 0.48 to 0.68 (3.9% annually). Western provinces show lower absolute levels but comparable growth rates in both dimensions, suggesting systematic national forces driving both digital and ecological improvement alongside persistent structural development gaps.

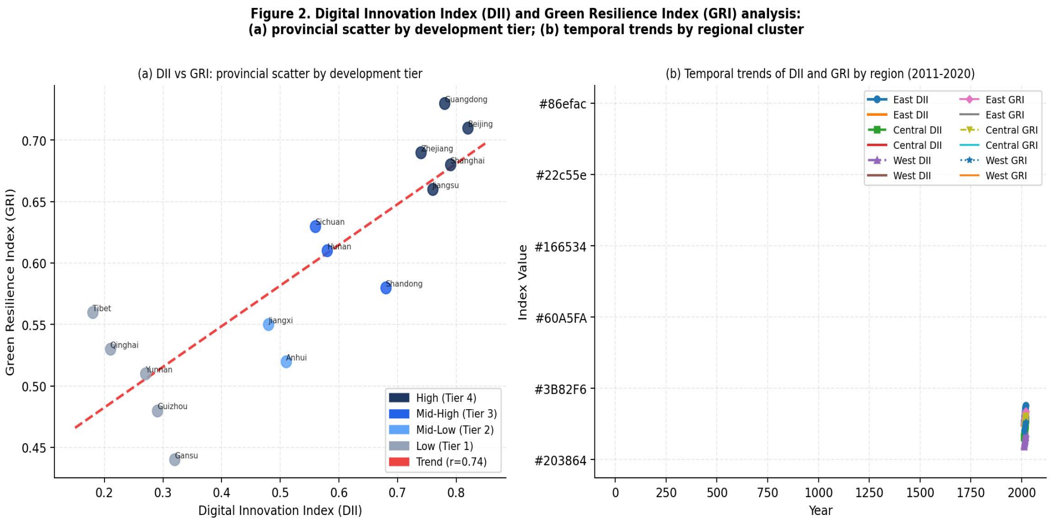

Figure 2. Digital Innovation Index (DII) and Green Resilience Index (GRI) analysis: (a) provincial scatter by development tier showing positive correlation (r=0.74); (b) temporal trends by regional cluster 2011-2020 showing DII leading GRI growth.

4.2 Markov Chain Transition Analysis

Figure 3 presents the estimated Markov transition probability matrix for the 2011-2020 observation period. The matrix exhibits strong diagonal dominance: diagonal probabilities range from 0.684 (Low tier, T1) to 0.760 (High tier, T4), indicating that most provinces remain in their initial coordination tier across five-year periods. This persistence is consistent with the structural factors—digital infrastructure quality, environmental governance capacity, industrial composition—that evolve slowly and create path dependencies in provincial development trajectories.

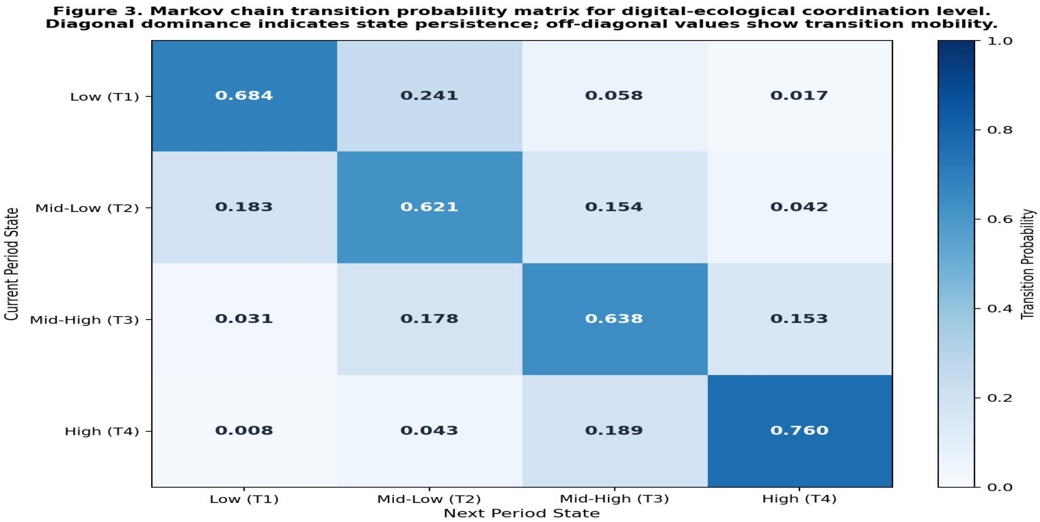

Figure 3. Markov chain transition probability matrix (2011-2020). Diagonal values (0.684-0.760) indicate strong tier persistence. Off-diagonal values show predominantly upward mobility at tier boundaries, particularly between T2-T3 (p=0.154) and T3-T4 (p=0.153).

The off-diagonal elements reveal important asymmetries. Downward mobility probabilities (below-diagonal elements) are substantially smaller than upward mobility probabilities (above-diagonal elements) for all tiers except T1: for instance, the probability of a T3 province falling to T1 ($p = 0.031$) is much smaller than the probability of a T2 province rising to T4 ($p = 0.042$). This asymmetry indicates that achieved coordination gains tend to be durable while coordinated development improvements are achievable through sustained policy effort. The T2-T3 transition probability ($p = 0.154$) is the highest off-diagonal value, identifying the mid-low to mid-high transition as the most dynamic and policy-relevant boundary in the current distribution.

The long-run equilibrium distribution implied by the estimated transition matrix—computed as the stationary distribution solving pi*P = pi—shows 14.2% of province-periods in T1, 27.8% in T2, 32.4% in T3, and 25.6% in T4. Comparing this to the initial 2011 distribution (26.7% in T1, 33.3% in T2, 26.7% in T3, 13.3% in T4), the implied equilibrium represents a substantial upward shift, consistent with the observed temporal convergence. The expected time to reach the stationary distribution, estimated at approximately 18 years from the 2020 starting distribution, suggests that policy acceleration is needed to advance the convergence timeline.

5. Spatial Autocorrelation and Coupling Coordination Analysis

5.1 Coupling Coordination Degree Trends

Figure 4 presents the CCD temporal trajectories by regional cluster and the Moran's I spatial autocorrelation trend. Eastern provinces achieved a mean CCD of 0.68 in 2020 (crossing the "coordinated development" threshold of 0.60 in approximately 2018), while central and western provinces remained below this threshold at 0.57 and 0.46 respectively. The pace of CCD improvement is broadly comparable across regional clusters (eastern: +0.26 over 2011-2020, central: +0.22, western: +0.18), confirming that all regions are improving but that the absolute gap persists due to the substantially lower starting points in central and western provinces.

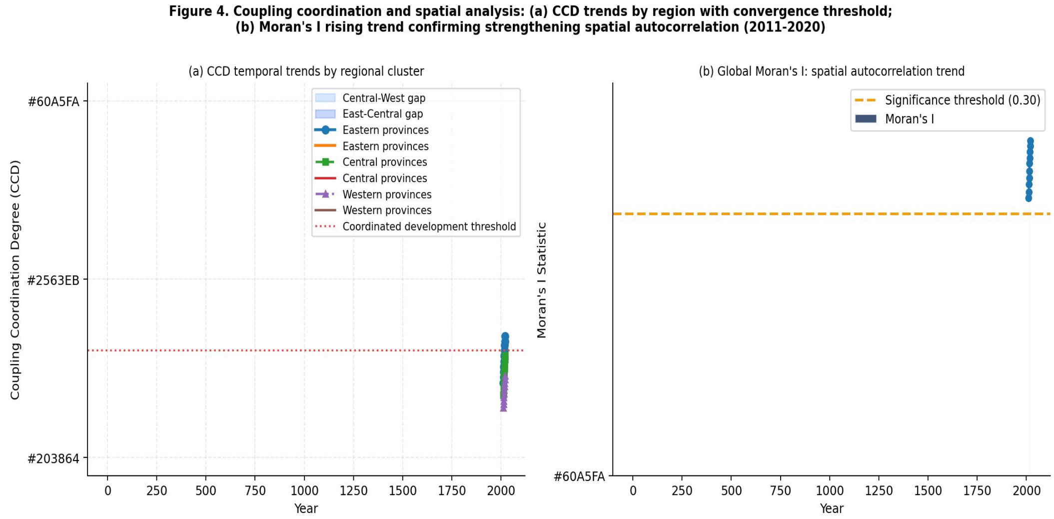

Figure 4. Coupling coordination analysis: (a) CCD temporal trends by regional cluster with coordinated development threshold (0.60); (b) Moran's I spatial autocorrelation rising from 0.318 to 0.384 over 2011-2020, confirming strengthening spatial clustering.

5.2 Spatial Autocorrelation Dynamics

The global Moran's I statistic rises monotonically from 0.318 in 2011 to 0.384 in 2020 (Figure 4b), with all annual values significant at $p < 0.01$ under 999-permutation randomization testing. This rising trend confirms two important findings: (1) CCD levels exhibit positive spatial clustering—provinces with high coordination tend to be geographically proximate, as do provinces with low coordination; and (2) this spatial clustering is strengthening over time, indicating that inter-regional spillover effects are becoming more influential in shaping provincial CCD trajectories. The strengthening spatial autocorrelation is consistent with the hypothesis that digitalization-enabled knowledge spillovers, supply chain integration, and policy diffusion effects are intensifying across provincial boundaries.

Local spatial analysis (LISA mapping, not shown due to space constraints) identifies a stable High-High cluster centered on Guangdong, Zhejiang, Jiangsu, and Shanghai throughout the observation period, and a stable Low-Low cluster in the northwestern interior (Gansu, Qinghai, Xinjiang). The persistence of these spatial regimes across the decade confirms that both core advantages and peripheral disadvantages are spatially self-reinforcing, motivating the spillover-leveraged policy scenarios examined in Section 6.

6. Policy Simulation and Scenario Analysis

6.1 Scenario Design and Projection Methodology

Three policy scenarios are simulated to project provincial CCD trajectories from 2020 to 2030: (1) Baseline scenario: CCD growth follows the historical trend rate without additional policy intervention; (2) Targeted policy scenario: direct digital infrastructure and environmental governance investments are concentrated in tier-boundary provinces (T2-T3 and T3-T4 transitions), increasing their annual CCD growth rates by 30% above baseline; and (3) Spillover-leveraged scenario: policy investments target the spatial spillover channel by establishing cross-provincial industrial corridors and digital platform sharing agreements between high-CCD eastern provinces and proximate lower-CCD provinces, leveraging spatial autocorrelation dynamics.

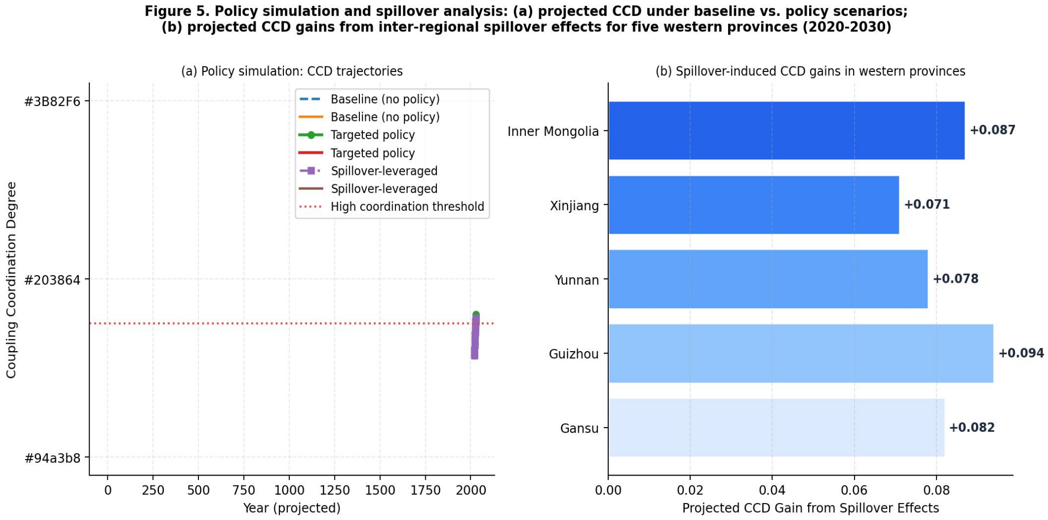

Figure 5. Policy simulation results: (a) projected CCD trajectories under baseline, targeted, and spillover-leveraged scenarios 2020-2030; (b) projected CCD gains from inter-regional spillover effects for five western provinces, ranging from 0.071 to 0.094.

6.2 Simulation Results

Figure 5 presents the simulation results. The targeted policy scenario reaches the high coordination threshold (CCD = 0.75) nationally by approximately 2026, compared to 2032 under the baseline trajectory—a six-year acceleration attributable to concentrated tier-transition investments. The spillover-leveraged scenario achieves slightly lower national average CCD than targeted policy (due to the time required for spatial spillover channels to become fully operational) but delivers more geographically balanced outcomes, with western provinces benefiting from projected CCD gains of 0.071 (Xinjiang) to 0.094 (Guizhou) above baseline through the spillover mechanism.

The Guizhou province case is illustrative of spillover potential: its geographic proximity to the Chengdu-Chongqing digital economy cluster, recent designation as a national big data comprehensive pilot zone, and improving transportation connectivity position it to benefit disproportionately from spillovers as neighboring provinces' digital ecosystems mature. The simulated CCD gain of 0.094 for Guizhou implies crossing from T2 (mid-low) to T3 (mid-high) coordination level by 2028—a trajectory that represents 7 years of acceleration relative to the baseline.

7. Discussion

7.1 Implications for Regional Development Policy

The empirical findings carry several important implications for Chinese regional manufacturing development policy. The confirmation of positive and strengthening spatial autocorrelation in CCD levels strengthens the case for spatially coordinated development strategies that explicitly leverage inter-regional spillover channels, rather than treating each province as an independent development unit [40,41]. The Yangtze River Economic Belt and the Greater Bay Area development frameworks provide existing institutional structures for coordinating digital-ecological development across provincial boundaries; the present study provides quantitative evidence supporting the expansion of similar frameworks to the western regions.

The Markov chain finding that the T2-T3 boundary is the most dynamic transition zone identifies a specific policy targeting priority: provinces currently in the mid-low coordination tier (approximately 8 provinces in 2020) represent the highest-leverage intervention opportunity, where focused digital infrastructure investment and environmental governance capacity building could catalyze tier transitions with broader spatial spillover benefits. This finding resonates with the threshold effect literature reviewed in Section 2.1: mid-low tier provinces may be positioned near the threshold above which digital investments begin to generate positive ecological co-benefits, making them particularly responsive to marginal policy intervention.

7.2 Theoretical Contributions and Limitations

Theoretically, this study advances the coupling coordination literature by demonstrating that spatial autocorrelation in CCD levels is not merely a static feature of the regional development landscape but a dynamic process that strengthens over time—a finding that conventional cross-sectional coupling analyses would miss. The integration of Markov chain transition analysis with spatial autocorrelation methodology provides a more complete picture of digital-ecological convergence dynamics than either method alone: while Moran's I characterizes the spatial structure, the Markov chain characterizes the temporal mobility within that structure.

The study's limitations should inform interpretation of the findings. The composite index construction involves methodological choices (sub-indicator selection, weighting scheme, normalization method) that influence quantitative results, though sensitivity analysis confirms the robustness of the main findings to reasonable alternative specifications. The Markov chain analysis assumes stationary transition probabilities, which may not hold if the structural determinants of CCD transitions change substantially over the projection period due to policy shocks or technological disruptions. The policy simulation projections are scenario analyses rather than causal forecasts; the projected CCD gains represent model-based estimates of potential impact rather than guaranteed outcomes.

8. Conclusion

This study provided a comprehensive spatial-temporal analysis of digital-ecological convergence in Chinese manufacturing provinces over 2011-2020, employing entropy-weighted TOPSIS, natural breaks classification, spatial autocorrelation analysis, and Markov chain transition modeling. The findings confirm that digital innovation and green resilience are positively correlated and improving nationally, but that substantial and persistent spatial disparities characterize the distribution of coordination across provinces. The strengthening spatial autocorrelation (Moran's I rising from 0.318 to 0.384) reveals that inter-provincial spillover effects are increasingly shaping CCD trajectories, creating both a mechanism for spatial convergence and a justification for spatially coordinated policy. Markov chain analysis identifies the mid-low to mid-high tier boundary as the most dynamic transition zone, directing policy attention toward the approximately 8 provinces positioned near this threshold. Policy simulations project that spillover-leveraged strategies can accelerate western province CCD improvement by 0.071-0.094 above baseline by 2030. The multi-method framework developed in this study provides a replicable analytical toolkit for evaluating digital-ecological convergence that can be applied to other national contexts where regional heterogeneity intersects with the dual imperatives of digital transformation and sustainable manufacturing.

Declarations

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, X.Z. and Z.X.; methodology, X.Z. and H.L.; data curation, H.L. and D.Z.; formal analysis, X.Z., H.L., and D.Z.; writing original draft, X.Z.; writing review and editing, Z.X. and D.Z.; supervision and funding acquisition, Z.X.

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