sustainability

MDPI

Article

A Dynamic Assessment of Manufacturing Low-Carbon Transition in the Chengdu–Chongqing Economic Circle: A Set Pair Analysis with State Transition Matrix

Xin Liao, Yuguo Jiang *, Qiang Lin and Ping Jiang

School of Business, Sichuan Normal University, Chengdu 610101, China; 20251902007@stu.sicnu.edu.cn
* Correspondence: ygjiang2018@sicnu.edu.cn or daocaoren2007@126.com

Abstract

In response to global climate change and China's "Dual Carbon" goals, the transition to low-carbon manufacturing has become a crucial step for achieving high-quality regional development. This study focuses on the Chengdu–Chongqing Economic Circle and constructs a comprehensive evaluation system spanning economic, technological, energy, carbon emission, and environmental dimensions. By applying a dynamic Set Pair Analysis (SPA) model coupled with a state transition matrix, we assess the low-carbon manufacturing performance of eight core cities from 2016 to 2023. The results indicate the following: (1) Strong path dependence characterizes regional low-carbon development, revealing a "Matthew effect" in which leading cities continue to advance while lagging ones face persistent barriers. (2) Cities are evolving into distinct equilibrium patterns: Chongqing is progressing toward full optimization, and Chengdu and Mianyang remain in a high-level equilibrium, whereas Suining and Zigong show signs of long-term low-level lock-in. (3) A three-tier regional structure emerges: Chongqing and Chengdu represent a high-level steady state; Deyang, Mianyang, Yibin, and Luzhou form an intermediate fluctuating tier; and Suining and Zigong constitute a low-level locked tier. (4) The low-carbon transition of manufacturing within the region remains markedly unstable, with cities such as Deyang and Yibin yet to establish steady low-carbon trajectories and remaining susceptible to regression. These findings provide a robust, evidence-based foundation for policymaking aimed at fostering coordinated and sustainable low-carbon development in the Chengdu–Chongqing region's manufacturing sector.

Keywords: Chengdu–Chongqing Economic Circle; low-carbon manufacturing transition; regional disparities; dynamic Set Pair Analysis; state transition matrix

Check for updates

Academic Editor: Radu Godina

Received: 16 February 2026
Revised: 19 March 2026
Accepted: 20 April 2026
Published: 22 April 2026

1. Introduction

Amid intensifying global climate change and growing international consensus on the low-carbon transition, decoupling economic growth from carbon emissions has become central to achieving sustainable development globally [1]. As the world's largest carbon emitter, China formally announced its "Dual Carbon" goals in 2020, aiming to peak carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060 [2]. This commitment not only represents a proactive response to global climate governance but also accelerates the nation's comprehensive socio-economic green transformation. Within this framework, the manufacturing sector—serving as the foundation of the real economy, a primary consumer of energy, and a major source of carbon emissions—plays a pivotal role.

Its transition to low-carbon operations is critical for reshaping the entire economic structure towards sustainability and for enhancing international competitiveness [3]. Therefore, scientifically measuring and effectively promoting this industrial transition is not only a necessary response to resource and environmental constraints but also a crucial pathway for fostering new-quality productive forces and realizing high-quality development.

Regions are key spatial units for implementing the national "Dual Carbon" strategy. China's vast territory leads to significant regional disparities in resource endowments, industrial structure, technological level, and stage of development. These differences inevitably result in heterogeneous pathways, paces, and outcomes in low-carbon transitions. In this context, the new model of coordinated regional development, exemplified by city clusters, provides a crucial platform for achieving synergistic emission reduction and green growth [4]. As a national strategic area leading development and opening-up in western China, the Chengdu–Chongqing Economic Circle is tasked with becoming "a major growth pole and a new source of power driving high-quality development nationwide" [5]. The region possesses a comprehensive industrial system and a robust manufacturing base. However, its long-established industrial structure, dominated by heavy chemical and resource-processing sectors, has led to prominent challenges, including intensive energy consumption and high carbon emission intensity [6]. Therefore, driven by the dual objectives of regional integration and green low-carbon transition, it is both theoretically and practically urgent to conduct an in-depth analysis of the intrinsic low-carbon progression within the region's manufacturing sector and to accurately identify the differential patterns and dynamic evolution among its cities. Such research is essential for formulating differentiated regional industrial policies and addressing the challenges of regional coordination under the "Dual Carbon" goals.

Academic research on low-carbon manufacturing has proliferated, focusing primarily on three key strands. First, regarding evaluation frameworks, the focus has shifted from singular metrics such as energy consumption or carbon intensity toward multi-dimensional systems integrating economic, energy, environmental, and technological dimensions. Concepts such as green total factor productivity and low-carbon competitiveness have been incorporated, highlighting the synergy between economic and environmental performance [7,8]. Nevertheless, the application of such general frameworks to specific regional settings—especially strategic economic zones with considerable internal heterogeneity like the Chengdu–Chongqing Economic Circle—often fails to adequately account for local characteristics and inherent structural weaknesses. Second, studies on regional disparities, often conducted at national or provincial scales, employ methods such as convergence tests and spatial econometrics to examine the spatial heterogeneity of carbon emission performance and its drivers. These studies underscore the critical influence of factors such as economic development level, industrial structure, and technological innovation [9,10]. Nevertheless, most existing studies treat provinces as spatially uniform entities, with inadequate consideration given to the internal evolutionary dynamics within urban clusters. This is particularly relevant for those regions characterized by a typical "twin-core-driven, multi-node-supported" spatial structure. Third, methodological advancements have sought to overcome the limitations of static assessment. Dynamic comprehensive evaluation methods are gaining traction, exemplified by "vertical" approaches that incorporate time weights or integrate trend prediction into traditional models to capture temporal dynamics in system evolution [11,12]. Of particular note is the combined application of Set Pair Analysis (SPA) and the state transition matrix, which offers a reliable analytical framework for examining dynamic systems affected by uncertainty. Nonetheless, despite the theoretical advantages of these approaches, empirical studies that integrate

https://doi.org/10.3390/su18094164

them to investigate the complex, uncertain, and dynamic process of regional manufacturing low-carbon transition are still relatively limited.

In summary, although notable advances have been achieved in the field, several important research gaps still exist when these studies are applied to strategic regions such as the Chengdu–Chongqing Economic Circle. First, the spatial scale employed in most analyses remains overly coarse: detailed empirical examinations of the divergent patterns and evolutionary paths among core cities within such agglomerations are still scarce. Second, the analytical framework lacks dynamic integration: few studies have been able to incorporate both the spatial patterns of regional inequality and the temporal evolution of low-carbon performance within a single consistent model. Third, the practical utility of combined methodological approaches remains underutilized: while the joint use of Set Pair Analysis (SPA) and state transition matrix shows clear strengths in diagnosing system structure and predicting future trends, empirical applications of this integrated framework remain very limited.

To address these gaps, this study examines the Chengdu–Chongqing Economic Circle, with a focus on eight core cities, including Chongqing and Chengdu. We aim to achieve the following objectives. First, we will construct a comprehensive evaluation index system for low-carbon manufacturing that integrates five dimensions: economic benefit, technological input, energy consumption, carbon emission, and environmental pressure. We subsequently propose an integrated dynamic framework that combines Set Pair Analysis (SPA) with a state transition matrix. This method allows us to evaluate the relative position of each city, diagnose the structural attributes of its manufacturing system, identify micro-level transition pathways, and forecast long-term steady-state behavior. By employing this analytical framework that unifies "state diagnosis" and "trend projection," we aim to clarify the sources of regional heterogeneity, the driving forces behind structural evolution, and the future convergence paths associated with low-carbon manufacturing in the Chengdu–Chongqing Economic Circle.

The remainder of this paper is organized as follows. Section 2 provides a literature review. Section 3 describes the research design, including the evaluation index system, methodology, and data. Section 4 presents the empirical results. Section 5 discusses the findings and their implications. Finally, Section 6 concludes the study and outlines limitations and future research directions.

2. Literature Review

The low-carbon transition of the manufacturing sector constitutes a central challenge for global climate action and sustainable development. Its trajectory is shaped by a complex interplay of factors, including economic structure, technological capability, energy systems, and the policy environment. Scholarly research has extensively investigated the measurement, regional variation, and evolutionary dynamics of this transition, providing a critical theoretical foundation while also revealing significant avenues for further inquiry.

Early assessments of low-carbon manufacturing relied heavily on single metrics such as energy or carbon intensity per unit of output. Although straightforward, such measures often fail to capture the synergistic relationship among economic efficiency, technological advancement, and environmental impact that characterizes a genuine low-carbon transition [13,14]. As sustainability paradigms have evolved, comprehensive evaluation frameworks have gained prominence. Researchers increasingly incorporate constructs such as green total factor productivity and low-carbon competitiveness, emphasizing the integration of environmental performance into economic growth [15,16]. For example, Lv and Lu (2022) advanced the assessment of industrial green growth by incorporating energy and environmental factors into productivity analysis, while Xu and Lv (2015) systematically developed a five-dimensional index system covering economic, technological, energy, carbon, and environmental dimensions, which has served as a foundation for macro- and meso-level evaluations [17,18]. More recently, the analytical scope has broadened to include "soft" dimensions such as managerial capability, human capital, and carbon-related intangible assets, aiming to uncover the transition potential at the micro level [11]. Nevertheless, when applied to specific regional contexts—particularly strategic zones with pronounced internal heterogeneity such as the Chengdu–Chongqing Economic Circle—existing index systems rarely account for local particularities, developmental stages, and structural vulnerabilities. As a result, generic indicators may inadequately identify the key constraints and comparative advantages that shape localized low-carbon pathways.

The uneven nature of regional development inevitably leads to heterogeneous pathways and outcomes in low-carbon transition. Extant research, conducted primarily at the national or provincial level, has employed σ-convergence, β-convergence, and club convergence models to examine spatial divergence in carbon emission performance [19,20], while also investigating key drivers such as economic development, industrial structure, energy mix, technological innovation, and environmental regulation [21,22]. These studies confirm the existence of regional disparities in low-carbon development as well as the complexity of underlying factors. However, much of this work treats provinces as homogeneous units, paying little attention to internal dynamics within city clusters—especially those with a distinct "twin-core-driven, multi-node-supported" spatial form. The interactive mechanisms, divergent pathways, and micro-level dynamics between core and peripheral cities in such regions during the manufacturing low-carbon transition remain underexplored. Importantly, regional differences are reflected not only in composite scores but more fundamentally in the composition and dynamic interplay of positive and negative factors within each regional system. Unpacking this structural dimension requires analytical tools capable of diagnosing the internal state of complex socio-technical systems.

Conventional static evaluation methods, such as entropy weighting, TOPSIS, and DEA, are effective for cross-sectional comparison but generally inadequate for capturing the dynamic evolution and developmental trajectory of systems over time. In response, dynamic comprehensive evaluation approaches have gained traction [23]. For example, Jiang et al. (2019) incorporated a temporal dimension into the TOPSIS framework to dynamically assess low-carbon competitiveness [11]. Particularly noteworthy is the coupled use of SPA and the state transition matrix, which provides a robust analytical tool for dynamic systems characterized by uncertainty. SPA delineates the composition of certain and uncertain elements within a system through degrees of identity, discrepancy (positive and negative), and opposition [24], while the state transition matrix quantifies transition probabilities across performance states, thereby revealing micro-level evolutionary patterns [25]. This combined approach is especially suitable for evaluating and projecting complex dynamic systems such as manufacturing low-carbonization, which are shaped by multi-factor interactions, inherent uncertainty, and path dependence.

In summary, although considerable progress has been made in evaluating manufacturing low-carbonization, understanding its regional disparities, and developing dynamic assessment methods, several critical research gaps persist. First, the scale of analysis remains insufficiently granular. Fine-grained investigations into the differential patterns, interactive mechanisms, and evolutionary trajectories of low-carbon manufacturing among core cities within national strategic regions—such as the Chengdu–Chongqing Economic Circle—are notably lacking. Second, the analytical perspective would benefit from greater dynamic integration. Many studies are confined either to static cross-sectional comparisons or to descriptive trend analyses, failing to couple the "spatial pattern" of regional disparity with the "temporal evolution" of low-carbon performance within a unified framework.

This limitation hinders a deeper characterization of the internal structural state of the system and its transition dynamics. Third, the applied potential of relevant methodologies remains underexploited. Despite the theoretical strengths of dynamic SPA coupled with the state transition matrix, empirical applications of this integrated approach to the complex, dynamic system of regional manufacturing low-carbonization are still scarce. Consequently, its potential to uncover the underlying drivers of regional divergence and to project future evolutionary trends awaits thorough empirical validation and further development.

To address these gaps, this study focuses on the Chengdu–Chongqing Economic Circle as a representative region, with its eight core cities serving as the research units. We develop a multidimensional evaluation system encompassing economic, technological, energy, carbon emission, and environmental dimensions, and introduce an integrated dynamic model combining SPA with the state transition matrix. Beyond statically assessing each city's relative performance, this approach enables a deeper structural diagnosis of their manufacturing systems, a dynamic characterization of state transition patterns, and the projection of long-term steady-state trends. Accordingly, the study provides an analytical framework that integrates "state diagnosis" with "trend projection" to advance the understanding of regional disparities in manufacturing low-carbonization and to address the limitations of prior research.

3. Research Design

3.1. Evaluation Index System

A robust, scientifically grounded, and comprehensive evaluation index system is essential for accurately assessing regional manufacturing low-carbonization and its spatial heterogeneity. Our framework is informed by sustainable development theory and the "Pressure-State-Response" (PSR) model. The former advocates for a balanced approach to industrial transformation that harmonizes economic growth, resource efficiency, and environmental integrity. The latter provides a causal logic: "Pressure" stems from the resource consumption and emissions generated by manufacturing activities; "State" reflects the resulting performance in resource use, environmental quality, and economic output; and "Response" refers to the technological and managerial actions taken by societal actors (e.g., governments, firms) to ameliorate the state. Building on this, we conceptualize manufacturing low-carbonization as a dynamic process in which external pressures elicit systemic responses that progressively optimize both economic and environmental performance, thereby steering the system toward sustainability. Guided by this theoretical foundation, we construct a multi-tiered evaluation system comprising five dimensions and 21 specific indicators, as detailed in Table 1.

Table 1. Evaluation index system for low-carbon manufacturing development level.

Dimension	Measure	Unit	Source
Economic Benefit	A_1. Industrial value added	100 M CNY	Luomaranta & Martinsuo, 2022 [26] Yu et al., 2023 [27]
	A_2. Industrial value added per employee	100 M CNY/10,000 persons	
	A_3. Industrial profit per employee	100 M CNY/10,000 persons	
Technology Input	A_4. R&D expenditure	100 M CNY	Liang et al., 2022 [28] Xu & Lv, 2015 [18]
	A_5. R&D intensity	‰	
	A_6. Full-time equivalent of R&D personnel	Person-year	

Table 1. *Cont.*

Dimension	Measure	Unit	Source
Energy Consumption	A_7. Total energy consumption	tce	Lin & Li, 2022 [29] Xu & Lv, 2015 [18]
	A_8. Raw coal consumption per unit of output	t/100 M CNY	
	A_9. Coke consumption per unit of output	t/100 M CNY	
	A_{10}. Gasoline consumption per unit of output	t/100 M CNY	
	A_{11}. Kerosene consumption per unit of output	t/100 M CNY	
	A_{12}. Diesel consumption per unit of output	t/100 M CNY	
	A_{13}. Fuel oil consumption per unit of output	t/100 M CNY	
	A_{14}. Natural gas consumption per unit of output	10k m^3/100 M CNY	
	A_{15}. Electricity consumption per unit of output	10,000 kWh/100 M CNY	
Carbon Emission	A_{16}. CO_2 emissions	10,000 tons	Wu et al., 2022 [30] Wei et al., 2023 [31]
	A_{17}. CO_2 emissions per unit of energy	%	
	A_{18}. CO_2 intensity (per unit of output)	10,000 tons/100 M CNY	
Environmental Pressure	A_{19}. Wastewater discharge	10,000 tons	Xu & Lv, 2015 [18] Huo et al., 2022 [32]
	A_{20}. Waste gas emissions	100 M m^3	
	A_{21}. Solid waste discharge	10,000 tons	

3.2. Method

3.2.1. Determining Weights

In constructing a comprehensive evaluation model, determining the weights of indicators is crucial. To avoid bias introduced by subjective factors, this study employs the Entropy Weight Method for objective weighting. Based on information entropy theory, this method calculates the information entropy of each indicator to reflect its inherent degree of variation within the dataset, thereby determining its weight. The specific procedural steps are as follows.

Data standardization: Consider a scenario with m evaluation objects and n evaluation indicators, which constitute the original data matrix $X = (x_{ij})_{m\times n}$. Positive (benefit-type) and negative (cost-type) indicators are normalized separately using the following formulas:

For positive (benefit-type) indicator:

$$r_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \tag{1}$$

For negative (cost-type) indicator:

$$r_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \tag{2}$$

Calculating indicator entropy: The entropy value e_j for the j-th indicator is calculated as:

$$e_j = -\frac{1}{lnm}\sum_{i=1}^{m} p_{ij} ln\, p_{ij} \tag{3}$$

where $p_{ij} = r_{ij}/\sum_{i=1}^{m} r_{ij}$, with the stipulation that $p_{ij}\ln p_{ij} = 0$ when $p_{ij} = 0$.

Determining indicator weights: The weight w_j for the jth indicator is then given by:

$$w_j = \frac{1 - e_j}{\sum_{k=1}^{n}(1 - e_k)} \tag{4}$$

This process yields the objective weight for each secondary indicator in the evaluation system, establishing a foundation for the subsequent integrated assessment.

3.2.2. Set Pair Theory, Connection Number, and Set Pair Potential

SPA is a systematic methodology for addressing uncertainty in complex systems. Its core involves constructing a set pair from two interrelated sets and analyzing their relationship in terms of identity, discrepancy, and opposition. To more precisely capture the uncertainty inherent in the discrepancy component, this study employs the four-element connection number proposed by Xu and Lv (2015) [18]:

$$\mu = a + b_1 i_1 + b_2 i_2 + cj \tag{5}$$

where:

a denotes the degree of identity, representing the consistency between the evaluated object and the ideal state;

b_1 denotes the positive discrepancy degree, representing the uncertain component that deviates from the ideal target yet exhibits a tendency toward positive or favorable development;

b_2 denotes the negative discrepancy degree, representing the uncertain component that deviates from the ideal target and tends toward negative or unfavorable development;

c denotes the degree of opposition, representing the extent of conflict between the evaluated object and the ideal state;

i_1 and i_2 are discrepancy coefficients, assigned values within the interval $[-1, 1]$ based on the specific research context to reflect the tendency of the discrepancy;

j is the opposition coefficient, conventionally set to $j = -1$ to signify opposition.

In the dynamic analysis of this study, the focus is placed on the weight distribution and transfer patterns of the four components a, b_1, b_2 and c. Accordingly, i_1 and i_2 are retained as indicative coefficients without assigning specific values to them.

The set pair potential is employed to characterize the relative relationship between the degree of identity and the degree of opposition, thereby reflecting the overall developmental tendency of the system. When $c \neq 0$, it is calculated as:

$$E = {}^{a}/_{c} \tag{6}$$

Based on the value of E, the developmental status of an evaluated object can be classified into three levels: homogeneous potential ($E > 1$), balanced potential ($E = 1$), and opposite potential ($E < 1$). Calculating the set pair potential thus facilitates an intuitive identification of each city's position and trajectory within the low-carbon development process, providing a basis for formulating tailored policies.

3.2.3. Coupled Model of State Transition Matrix and SPA

To dynamically characterize the evolution of low-carbon manufacturing development across cities in the Chengdu–Chongqing region, this study integrates a Markov state transition matrix with the four-element connection number to construct a coupled evaluation model. The specific procedure is as follows.

First, the developmental status of each indicator is classified into one of four grades based on its value. These grades correspond to four characteristic states: the identity state (A), the positive discrepancy state (B), the negative discrepancy state (C), and the opposition state (D). Let w_A denote the sum of the weights of indicators classified under state A, with w_B, w_C, and w_D defined analogously. The set pair connection number at time t can then be expressed as:

$$U_t = w_A + w_B i_1 + w_C i_2 + w_D j \tag{7}$$

Second, a state transition matrix is constructed by aggregating the proportional weight shifts of indicators moving between states across consecutive periods (from t to t + 1). For indicators initially in state A at time t, we calculate the proportion of their total weight that remains in A or transitions to B, C, or D at time t + 1. This yields the transition probability vector from state A:

$$\vec{p}_A = (p_{AA}, p_{AB}, p_{AC}, p_{AD}) \tag{8}$$

where each element is calculated as:

$$p_{AA} = \frac{\sum_{k \in A \to A} w(A)}{\sum_{k \in A} w(A)} \tag{9}$$

Similar vectors are derived for transitions starting from states B, C, and D. Combining these row vectors yields the one-step state transition probability matrix P:

$$P = \begin{pmatrix} \vec{p_A} \\ \vec{p_B} \\ \vec{p_C} \\ \vec{p_D} \end{pmatrix} = \begin{pmatrix} p_{AA} & p_{AB} & p_{AC} & p_{AD} \\ p_{BA} & p_{BB} & p_{BC} & p_{BD} \\ p_{CA} & p_{CB} & p_{CC} & p_{CD} \\ p_{DA} & p_{DB} & p_{DC} & p_{DD} \end{pmatrix} \tag{10}$$

The state transition matrix P enables multi-period dynamic forecasting. Given the connection number vector at the base period $U(t) = (a(t), b_1(t), b_2(t), c(t))$, the vector at period $t + \Delta T$ is obtained by:

$$U(t + \Delta T) = U(t) \cdot P \tag{11}$$

Consequently, the connection number vector after n periods is derived as:

$$U(t + n\Delta T) = U(t) \cdot P^n \tag{12}$$

Assuming the Markov chain is ergodic, a steady-state connection number vector $U^* = \left(a^*, b_1^*, b_2^*, c^*\right)$ exists and must satisfy:

$$U^* = U^* \cdot P \tag{13}$$

$$a^* + b_1^* + b_2^* + c^* = 1 \tag{14}$$

Solving this system of linear equations yields the long-term steady-state vector U^*, revealing the steady-state vector, which characterizes the system's inherent developmental trend in the long run.

3.3. Data Basis

Following the construction of the indicator system and the specification of the model, it is necessary to elaborate on the data sources, processing methods, and underlying parameters used in the empirical analysis, so as to ensure the reproducibility and reliability of the results.

3.3.1. Data Sources and Preprocessing

We conducted an empirical analysis focusing on eight major cities in the Chengdu–Chongqing Economic Circle: Chongqing, Chengdu, Deyang, Mianyang, Suining, Yibin, Luzhou, and Zigong. The analysis utilizes panel data for the period 2016–2023, drawn from the *China Statistical Yearbook*, *Chongqing Statistical Yearbook*, *Sichuan Statistical Yearbook*, and the corresponding municipal statistical yearbooks. This study measures the low-carbon manufacturing level of eight core cities in the Chengdu–Chongqing economic circle—Chongqing, Chengdu, Deyang, Mianyang, Suining, Yibin, Luzhou, and Zigong—over the period 2016–2023. The raw data were sourced from the *China Statistical Yearbook*, *Chongqing Statistical Yearbook*, *Sichuan Statistical Yearbook*, and the respective statistical yearbooks of the individual cities.

To ensure scientific validity and comparability, all data in this study were processed uniformly. For instances of missing statistics in certain cities for specific years, interpolation was applied to maintain data continuity and preserve the integrity of the state transition matrix. The total number of missing values accounted for approximately 3% of all observations, a relatively minor proportion. In addition, individual outliers were identified and corrected during the data cleaning process. Comparative analysis indicates that these treatments have a limited impact on the descriptive statistical characteristics of the core indicators and do not compromise the robustness of the study's main conclusions. Furthermore, to maintain consistency, the statistical scope was standardized to "industrial enterprises above a designated size" for all cities and years, mitigating issues arising from incomplete data in municipal yearbooks.

Based on the existing data, this study further investigates the dynamic characteristics of the low-carbon transition process in manufacturing. As an evolution process driven by multiple factors, the state transition patterns across years may exhibit fluctuations. To smooth short-term random noise and extract the average evolutionary trend during the observation period (2016–2023), this study adopts the arithmetic mean of annual transition matrices as the benchmark matrix for dynamic prediction and steady-state analysis. This methodological treatment is justified by two considerations: (1) Long-term steady-state prediction of Markov chains relies on a stable transition probability matrix, and the multi-year average matrix better reflects the empirical probabilities of the system compared with a single-year matrix. (2) The averaging process helps avoid misinterpreting accidental fluctuations in a specific year as long-term trends, thereby enhancing the robustness of the prediction results.

3.3.2. Weight Determination and Grade Classification

After data preprocessing, the objective weights of the 21 indicators within the low-carbon manufacturing evaluation system were calculated via the Entropy Weight Method, as detailed in Equations (1)–(4).

The resulting weights are reported in Table 2. In the absence of a unified benchmark for low-carbon manufacturing assessment, we engaged a panel of experts from academia, industry, and policymaking to classify each indicator into one of four ordered grades (A, B, C, D) based on industry practices and theoretical benchmarks. The expert-defined meaning of each grade is as follows: Grade A indicates that the indicator fully meets the requirements for low-carbon manufacturing development and represents a deterministic positive factor in the industry's low-carbon transition; Grade B indicates that the indicator largely meets the requirements and is regarded as a deviation factor leaning toward identity; Grade C indicates that the indicator largely fails to meet the requirements and is considered a deviation factor leaning toward opposition; and Grade D indicates that the indicator completely fails to meet the requirements and is classified as a deterministic negative factor. The specific numerical thresholds defining these grades for all indicators are provided in Table 3 (benefit-type indicators) and Table 4 (cost-type indicators).

Table 2. Indicator weights.

Indicator	Weight	Indicator	Weight	Indicator	Weight
A_1	0.1806	A_8	0.0139	A_{15}	0.0314
A_2	0.0252	A_9	0.0155	A_{16}	0.0177
A_3	0.1059	A_{10}	0.0188	A_{17}	0.0327
A_4	0.1650	A_{11}	0.0061	A_{18}	0.0158
A_5	0.1059	A_{12}	0.0096	A_{19}	0.0146
A_6	0.1665	A_{13}	0.0065	A_{20}	0.0234
A_7	0.0196	A_{14}	0.0166	A_{21}	0.0087

Table 3. Classification thresholds for benefit-type indicators.

Grade	A_1	A_2	A_3	A_4	A_5	A_6
A (≥)	3415.9330	57.1916	14.3383	177.4437	21.8590	35,853.9500
B (≥)	932.3000	51.1570	10.2346	41.2249	11.5114	9313.5500
C (≥)	646.7675	44.1686	8.6500	13.0016	7.5834	3190.0500
D (<)	646.7675	44.1686	8.6500	13.0016	7.5834	3190.0500

Table 4. Classification thresholds for cost-type indicators.

Grade	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}
A (≤)	3,453,188.5000	317.4697	1.5143	0.9373	0.0128	5.4766	0.2344	19.1611
B (≤)	6,285,664.0000	1264.8390	11.3505	1.5707	0.0241	7.5144	1.1551	32.2595
C (≤)	12,736,419.2500	2102.7060	23.7498	2.6991	0.0713	12.4973	6.8658	53.0455
D (>)	12,736,419.2500	2102.7060	23.7498	2.6991	0.0713	12.4973	6.8658	53.0455
Grade	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}	A_{21}	
A (≤)	216.3186	233,892.7000	0.0560	75.3732	1289.6450	392.4450	0	
B (≤)	260.4887	371,180.5000	0.0691	119.3514	2311.3000	1185.0650	0.0075	
C (≤)	294.2339	837,456.6000	0.0870	171.8798	6673.4130	3451.4450	0.9750	
D (>)	294.2339	837,456.6000	0.0870	171.8798	6673.4130	3451.4450	0.9750	

4. Results

Utilizing the evaluation system and methodological framework developed in the preceding sections, this chapter empirically assesses the manufacturing industry's low-carbon transformation level across eight core cities within the Chengdu–Chongqing economic circle. The analysis encompasses static structural characteristics, dynamic evolutionary patterns, long-term steady-state projections, and comprehensive evaluations accompanied by tiered classifications for these municipalities.

4.1. Static Structural Characteristics

Following the established grading criteria, the four-element connection numbers for each city were computed annually from 2016 to 2023 using Equation (5). Subsequently, the average four-element connection number for each city over the 2016–2023 period was calculated to characterize the static structural attributes of its manufacturing industry's low-carbon development. These averages, derived from multi-year data, are intended to reflect the mean state of each city's manufacturing system during the observation period, thereby establishing a benchmark for subsequent dynamic analyses. The average connection numbers for the eight cities are presented below:

$$\overline{U_{Chongqing}} = 0.474 + 0.1972i_1 + 0.1572i_2 + 0.1716j$$

$$\overline{U_{Chengdu}} = 0.6530 + 0.1127i_1 + 0.1032i_2 + 0.1311j$$

$$\overline{U_{Deyang}} = 0.0967 + 0.6208i_1 + 0.2101i_2 + 0.0724j$$

$$\overline{U_{Mianyang}} = 0.2176 + 0.4657i_1 + 0.1904i_2 + 0.1263j$$

$$\overline{U_{Suining}} = 0.1182 + 0.1362i_1 + 0.0806i_2 + 0.6650j$$

$$\overline{U_{Yibin}} = 0.1358 + 0.2931i_1 + 0.5138i_2 + 0.0573j$$

$$\overline{U_{Luzhou}} = 0.1195 + 0.1575i_1 + 0.4690i_2 + 0.2540j$$

$$\overline{U_{Zigong}} = 0.1555 + 0.053i_1 + 0.2261i_2 + 0.5654j$$

Analysis of these average connection numbers first focuses on the degrees of identity (a) and opposition (c). Chongqing and Chengdu exhibit relatively high identity degrees and low opposition degrees. This indicates a strong alignment between their manufacturing development and low-carbon objectives, implying lower internal systemic conflict and greater structural stability. In contrast, Suining and Zigong are characterized by high opposition and low identity degrees. This reflects significant resistance to low-carbon transition within their current manufacturing systems, suggesting substantial internal tension and structural contradiction. Second, the discrepancy components—the positive discrepancy degree b_1 and the negative discrepancy degree b_2—reveal the underlying drivers and uncertainties in the system's evolution. Deyang and Mianyang show a much higher b_1 than b_2, suggesting their systems possess strong inherent potential to evolve toward low-carbon pathways, with positive momentum. In comparison, Yibin and Luzhou exhibit a much higher b_2 than b_1. This indicates their systems are under greater structural pressure from pronounced negative influences, which introduces considerable uncertainty into their low-carbon transition.

4.2. Dynamic Evolutionary Patterns

The state transition matrix captures the micro-level evolution of indicator grades over time, thereby revealing systemic inertia, transformation momentum, and latent risks from a dynamic perspective. Following Equations (7)–(10), we calculated the annual state transition probabilities for the low-carbon manufacturing indicators in each city. These annual matrices were then averaged across the 2016–2023 period to derive an aggregate transition matrix for each city, representing its predominant dynamic pattern during the study period. The resulting aggregate matrices are as follows:

$$\overline{P_{Chongqing}} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0.1317 & 0.8011 & 0.0672 & 0 \\ 0 & 0.2682 & 0.6290 & 0.1028 \\ 0 & 0.0041 & 0.1794 & 0.8165 \end{pmatrix}$$

$$\overline{P_{Chengdu}} = \begin{pmatrix} 0.9487 & 0.0382 & 0.0062 & 0.0069 \\ 0.2654 & 0.5517 & 0.0905 & 0.0924 \\ 0 & 0.2177 & 0.6362 & 0.1461 \\ 0.0351 & 0.0296 & 0.1894 & 0.7459 \end{pmatrix}$$

$$\overline{P_{Deyang}} = \begin{pmatrix} 0.8159 & 0.1841 & 0 & 0 \\ 0.0683 & 0.8041 & 0.1276 & 0 \\ 0 & 0.5287 & 0.4594 & 0.0119 \\ 0 & 0 & 0.1677 & 0.8323 \end{pmatrix}$$

https://doi.org/10.3390/su18094164

$$\overline{P_{Mianyang}} = \begin{pmatrix} 0.7996 & 0.2004 & 0 & 0 \\ 0.0950 & 0.8632 & 0.0418 & 0 \\ 0.0041 & 0.1282 & 0.8396 & 0.0281 \\ 0 & 0 & 0.0338 & 0.9662 \end{pmatrix}$$

$$\overline{P_{Suining}} = \begin{pmatrix} 0.8459 & 0.0874 & 0 & 0.0667 \\ 0.1866 & 0.6133 & 0.1362 & 0.0639 \\ 0.0979 & 0.2094 & 0.2637 & 0.4290 \\ 0 & 0.0235 & 0.0871 & 0.8894 \end{pmatrix}$$

$$\overline{P_{Yibin}} = \begin{pmatrix} 0.8503 & 0.1497 & 0 & 0 \\ 0.1139 & 0.7714 & 0.1147 & 0 \\ 0.0039 & 0.1339 & 0.8430 & 0.0192 \\ 0 & 0.0077 & 0.2943 & 0.6980 \end{pmatrix}$$

$$\overline{P_{Luzhou}} = \begin{pmatrix} 0.8329 & 0.1671 & 0 & 0 \\ 0.2241 & 0.6560 & 0.1199 & 0 \\ 0 & 0.0822 & 0.8557 & 0.0621 \\ 0 & 0.0462 & 0.3653 & 0.5885 \end{pmatrix}$$

$$\overline{P_{Zigong}} = \begin{pmatrix} 0.8188 & 0.1006 & 0.0543 & 0.0263 \\ 0.1243 & 0.6647 & 0.1661 & 0.0449 \\ 0.0423 & 0.0817 & 0.5239 & 0.3521 \\ 0 & 0.0042 & 0.1642 & 0.8316 \end{pmatrix}$$

Analysis of these aggregate transition matrices yields the following key insights:

First, the diagonal elements reflect the system's inertia, i.e., the tendency to remain in its current grade. Two notable patterns of path dependence emerge:

(1) Self-reinforcing stability in Grade A: Retention probabilities in Grade A are consistently high across all cities (all above 0.79). This is particularly pronounced in Chongqing ($p_{AA} = 1$) and Chengdu ($p_{AA} = 0.9487$). Once an indicator reaches an advanced low-carbon level, it exhibits strong stability within the local industrial ecosystem and policy environment, showing low susceptibility to regression.

(2) Structural lock-in in Grade D: Most cities show persistence probabilities in Grade D, especially Chongqing, Deyang, Mianyang, and Zigong, with retention probabilities (p_{DD}) all exceeding 0.85. Among them, Mianyang's p_{DD} reaches 0.9662, indicating that once structural barriers to low-carbon development are entrenched, the system struggles to escape this state through endogenous dynamic change within the prevailing technological, industrial, and institutional frameworks, demonstrating a powerful lock-in effect.

Second, the off-diagonal elements characterize the system's transition behavior. Their distribution and magnitude reveal the activity and directionality of system evolution. Chongqing, for instance, has relatively few non-zero off-diagonal elements, with transitions largely confined to adjacent grades, suggesting a concentrated and orderly evolutionary process. Chengdu exhibits a broader distribution of non-zero off-diagonal elements and active inter-grade exchanges, hinting at more complex, multi-path evolutionary dynamics. Notably, it displays an overall optimizing trend; for example, the total probability of transition from Grade C to A or B (0.2177) substantially exceeds the probability of regression to Grade D (0.1461). In Deyang, Mianyang, Yibin, and Luzhou, off-diagonal elements are concentrated near the main diagonal. This reflects a pattern of gradual, stepwise adjustment and an overall tendency toward optimization. In contrast, Suining and Zigong show non-negligible transition probabilities between non-adjacent grades, indicating potential for leapfrog changes. However, their probabilities of regression outweigh those of improvement. In Suining, for instance, the probability of regression from Grade C to D (0.4290) exceeds the total probability of improvement to A or B (0.3073).

4.3. Long-Term Steady-State Trends

Before exploring the long-term evolutionary trends of low-carbon development in the manufacturing sectors of each city, we first conducted ergodicity tests on the average state transition matrices for all cities, to verify the existence and uniqueness of the stationary distribution underlying the homogeneous Markov chains. Ergodicity requires that the chain satisfy both irreducibility and aperiodicity. Using the isergodic function in MATLAB R2025a, we found that the average transition matrices of all seven other cities satisfy ergodicity (return value = 1), with the only exception being Chongqing.

The first row of Chongqing's average transition matrix is [1, 0, 0, 0], indicating that Grade A acts as an absorbing state: once an indicator reaches Grade A, it will no longer regress to lower grades in subsequent periods. Although this absorbing structure renders the chain non-ergodic, the theory of absorbing Markov chains demonstrates that a unique limiting distribution still exists, with all probability mass eventually concentrated in the absorbing state A. Based on the analysis of the absorbing chain, the long-run equilibrium state of Chongqing is characterized by a unity degree $a^* = 1$, corresponding to $U^* = 1 + 0i_1 + 0i_2 + 0j$.

To project the long-term evolutionary trajectory of low-carbon manufacturing in each city, this study conducted a dynamic forecast for 2024–2026 based on the constructed average state transition matrix, following Equations (11)–(14), and further solved for the steady-state connection number U^* for all cities except Chongqing. These projections reflect the short-term path and potential long-term equilibrium, assuming current transition patterns persist. The predicted and steady-state connection numbers are presented in Table 5.

Table 5. Predicted connection numbers (2024–2026) and steady-state values (U^*).

City	Four-Element Connection Number	City	Four-Element Connection Number
Chongqing	$U_{2024} = 0.5000 + 0.2009i_1 + 0.1429i_2 + 0.1562j$ $U_{2025} = 0.5264 + 0.1999i_1 + 0.1314i_2 + 0.1423j$ $U_{2026} = 0.5528 + 0.1960i_1 + 0.1216i_2 + 0.1296j$ $U^* = 1 + 0i_1 + 0i_2 + 0j$	Suining	$U_{2024} = 0.1333 + 0.1264i_1 + 0.0977i_2 + 0.6426j$ $U_{2025} = 0.1459 + 0.1247i_1 + 0.0989i_2 + 0.6305j$ $U_{2026} = 0.1564 + 0.1247i_1 + 0.0980i_2 + 0.6209j$ $U^* = 0.2177 + 0.1322i_1 + 0.0907i_2 + 0.5594j$
Chengdu	$U_{2024} = 0.6540 + 0.1135i_1 + 0.1047i_2 + 0.1278j$ $U_{2025} = 0.6551 + 0.1142i_1 + 0.1052i_2 + 0.1255j$ $U_{2026} = 0.6562 + 0.1147i_1 + 0.1051i_2 + 0.1240j$ $U^* = 0.6685 + 0.1136i_1 + 0.1007i_2 + 0.1172j$	Yibin	$U_{2024} = 0.1508 + 0.3157i_1 + 0.4836i_2 + 0.0499j$ $U_{2025} = 0.1661 + 0.3313i_1 + 0.4585i_2 + 0.0441j$ $U_{2026} = 0.1807 + 0.3422i_1 + 0.4375i_2 + 0.0396j$ $U^* = 0.2935 + 0.3753i_1 + 0.3113i_2 + 0.0198j$
Deyang	$U_{2024} = 0.1213 + 0.6280i_1 + 0.1879i_2 + 0.0628j$ $U_{2025} = 0.1419 + 0.6267i_1 + 0.1769i_2 + 0.0545j$ $U_{2026} = 0.1585 + 0.6236i_1 + 0.1704i_2 + 0.0475j$ $U^* = 0.2277 + 0.6137i_1 + 0.1481i_2 + 0.0105j$	Luzhou	$U_{2024} = 0.1348 + 0.1736i_1 + 0.5130i_2 + 0.1786j$ $U_{2025} = 0.1512 + 0.1868i_1 + 0.5250i_2 + 0.1370j$ $U_{2026} = 0.1678 + 0.1973i_1 + 0.5217i_2 + 0.1132j$ $U^* = 0.3449 + 0.2572i_1 + 0.3457i_2 + 0.0522j$
Mianyang	$U_{2024} = 0.2190 + 0.4700i_1 + 0.1836i_2 + 0.1274j$ $U_{2025} = 0.2205 + 0.4732i_1 + 0.1780i_2 + 0.1283j$ $U_{2026} = 0.2220 + 0.4755i_1 + 0.1736i_2 + 0.1289j$ $U^* = 0.2334 + 0.4857i_1 + 0.1534i_2 + 0.1275j$	Zigong	$U_{2024} = 0.1435 + 0.0717i_1 + 0.2286i_2 + 0.5562j$ $U_{2025} = 0.1361 + 0.0831i_1 + 0.2308i_2 + 0.5500j$ $U_{2026} = 0.1315 + 0.0901i_1 + 0.2324i_2 + 0.5460j$ $U^* = 0.1246 + 0.1015i_1 + 0.2354i_2 + 0.5387j$

Note: The steady-state connection number U^* for Chongqing is derived based on the theory of absorbing Markov chains.

Based on these results, the evolutionary patterns of the eight cities can be categorized into four distinct types, revealing structural divergence in regional low-carbon pathways. (1) Strong-Convergence Type (Chongqing): The identity degree increases continuously throughout the forecast. At steady state, the system converges entirely to Grade A ($U^* = 1 + 0i_1 + 0i_2 + 0j$). This indicates a robust, self-reinforcing pathway toward an ideal low-carbon state. (2) Balanced-Stable Type (Chengdu, Mianyang): Probabilities across grades show minimal fluctuation in the near term, and the steady-state vector aligns closely with near-future projections. This suggests the system has attained a phase of dynamic equilibrium with a stable internal structure. (3) Gradual-Improvement Type (Deyang, Yibin, Luzhou): These cities exhibit a slow but steady increase in the identity and positive discrepancy degrees (a and b_1) alongside a decline in opposition (c). Their steady states are characterized by a dominance of intermediate grades with low opposition, indicating ongoing positive structural adjustment. (4) Low-Level Lock-in Type (Suining, Zigong): The opposition degree remains persistently high with little change, mirroring the steady-state value. This implies an entrenched structural barrier, where long-term development is likely to remain at a relatively low level without significant external intervention or systemic overhaul.

The above analysis has revealed the evolutionary direction of each city during the forecast period from a numerical perspective. To more intuitively demonstrate the dynamic evolution of representative cities at the internal structural level of the system, Figure 1 further presents the four-element connection number stacked area charts of Chongqing, Chengdu, Deyang, and Suining from 2016 to 2026. These four cities correspond to four evolutionary patterns—"strong convergence type", "balanced stable type", "gradual improvement type", and "low-level lock-in type"—which can well reflect the typical paths of low-carbon development in the regional manufacturing industry.

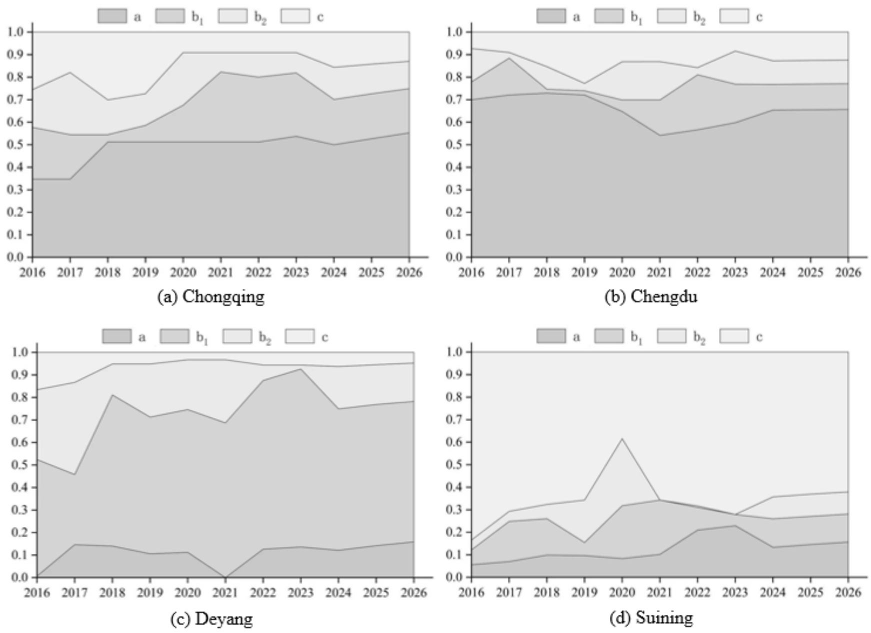

Figure 1. Stacked area charts of four-element connection number structural evolution for representative cities (2016–2026).

In Figure 1a, the proportions of identity degree and positive discrepancy degree in Chongqing continuously expanded from 2016 to 2026, with the dark-colored segment representing identity degree showing particularly pronounced growth, while negative discrepancy degree and opposition degree contracted accordingly. This evolutionary trend is highly consistent with its "strong convergence" characteristic: positive factors within the system accumulate continuously, negative factors gradually recede, and the system ultimately tends toward an ideal state dominated by identity degree. In Figure 1b, the proportion of identity degree in Chengdu is significantly larger than other components, and its structure exhibits almost no drastic fluctuations over time, with the opposition degree region consistently suppressed at a low level. This intuitively reflects the typical feature of a "balanced and stable" city: the system has entered a dynamic steady stage, where positive factors dominate and the structure is robust. In Figure 1c, the proportion of positive discrepancy degree in Deyang shows a slow expansion trend, while negative discrepancy degree fluctuates noticeably and gradually declines. This visually embodies the typical characteristic of a "gradual improvement" city: the system is adjusting toward a low-carbon direction, with positive factors accumulating step by step, but the transformation process remains unstable. In Figure 1d, the opposition degree in Suining occupies a dominant position for a long time, the dark-colored segment (identity degree) remains at a low proportion, and no obvious improvement is observed within the forecast period. This clearly presents the structural dilemma of a "low-level lock-in" city: negative factors within the system are overwhelmingly dominant, making it difficult for positive forces to grow. A comparison of the stacked area charts of the four cities intuitively reveals the core characteristics of low-carbon development in the manufacturing industry of the Chengdu–Chongqing region: Chongqing's structure continues to optimize, Chengdu maintains a high-level stable state, Deyang improves slowly amid fluctuations, and Suining is trapped in a structural predicament.

4.4. Comprehensive Trend Analysis

Calculating the set pair potential using Equation (6) and analyzing its distribution and dynamics allows us to classify the eight cities into three distinct tiers, as presented in Table 6.

Table 6. Set pair potential (E) and corresponding grades by city and year.

Year	City	E	Grade	City	E	Grade
2016	Chongqing	1.3585	Sl. Homo. (12)	Suining	0.0672	St. Oppo. (47)
2017		1.9326	Sl. Homo. (12)		0.0990	St. Oppo. (47)
2018		1.7025	St. Homo. (6)		0.1462	St. Oppo. (47)
2019		1.8731	St. Homo. (6)		0.1471	St. Oppo. (49)
2020		5.6399	St. Homo. (4)		0.2161	St. Oppo. (42)
2021		5.6399	St. Homo. (2)		0.1551	St. Oppo. (47)
2022		5.6399	St. Homo. (2)		0.3068	St. Oppo. (45)
2023		5.9174	St. Homo. (2)		0.3179	St. Oppo. (45)
2024		3.2001	Sl. Homo. (9)		0.2074	St. Oppo. (47)
2025		3.7007	St. Homo. (4)		0.2314	St. Oppo. (47)
2026		4.2634	St. Homo. (4)		0.2518	St. Oppo. (47)
2016	Chengdu	9.5628	St. Homo. (4)	Yibin	0.7282	Sl. Oppo. (33)
2017		7.9646	St. Homo. (2)		0.7545	Sl. Oppo. (33)
2018		4.7549	St. Homo. (6)		2.1792	Sl. Homo. (14)
2019		3.1656	St. Homo. (6)		6.6979	Sl. Homo. (18)
2020		4.9269	St. Homo. (4)		2.6357	Sl. Homo. (18)
2021		4.1304	St. Homo. (4)		6.4979	Sl. Homo. (20)
2022		3.5916	St. Homo. (2)		3.7859	Sl. Homo. (18)
2023		7.1167	St. Homo. (4)		3.7859	Sl. Homo. (18)
2024		5.1194	St. Homo. (4)		3.0224	Sl. Homo. (20)
2025		5.2178	St. Homo. (4)		3.7625	Sl. Homo. (20)
2026		5.2903	St. Homo. (4)		4.5595	Sl. Homo. (18)

https://doi.org/10.3390/su18094164

Table 6. *Cont.*

Year	City	E	Grade	City	E	Grade
2016	Deyang	0.0393	Sl. Oppo. (31)	Luzhou	0.1327	Wk. Oppo. (44)
2017		1.1006	Sl. Homo. (20)		0.1603	Wk. Oppo. (44)
2018		2.7204	Sl. Homo. (18)		0.2626	Wk. Oppo. (44)
2019		2.0563	Sl. Homo. (18)		0.6193	Sl. Oppo. (33)
2020		3.4373	Sl. Homo. (18)		2.2109	Sl. Homo. (14)
2021		0.0000	Sl. Oppo. (31)		0.7854	Sl. Oppo. (33)
2022		2.2513	Wk. Homo. (11)		2.4501	Sl. Homo. (20)
2023		2.4225	Wk. Homo. (11)		2.1287	Sl. Homo. (20)
2024		1.9322	Sl. Homo. (18)		0.755	Sl. Oppo. (33)
2025		2.6035	Sl. Homo. (18)		1.1040	Sl. Homo. (20)
2026		3.3407	Sl. Homo. (18)		1.4825	Sl. Homo. (20)
2016	Mianyang	1.7945	Sl. Homo. (18)	Zigong	0.2875	St. Oppo. (47)
2017		1.7945	Sl. Homo. (18)		0.1821	St. Oppo. (45)
2018		1.5118	Sl. Homo. (18)		0.2633	St. Oppo. (47)
2019		2.6735	Sl. Homo. (12)		0.2231	St. Oppo. (47)
2020		2.6903	Sl. Homo. (12)		0.4917	Wk. Oppo. (40)
2021		0.6053	Sl. Oppo. (31)		0.4788	Wk. Oppo. (40)
2022		0.9112	Sl. Oppo. (31)		0.3690	St. Oppo. (47)
2023		1.4233	Sl. Homo. (18)		0.1494	St. Oppo. (47)
2024		1.7192	Sl. Homo. (18)		0.2580	St. Oppo. (49)
2025		1.7195	Sl. Homo. (18)		0.2474	St. Oppo. (49)
2026		1.7221	Sl. Homo. (18)		0.2409	St. Oppo. (49)

(Note: E= set pair potential; Sl.= slightly; St.= strong; Wk.= weak; Homo.= homogeneous; Oppo.= opposite.)

Tier 1: Persistently Strong Homogeneous Potential (Chongqing, Chengdu).

Chongqing's set pair potential rose steadily from 1.3585 in 2016 to 4.2634 in 2026, with its potential grade advancing from "slightly homogeneous" to "strong homogeneous (grade 6)" and finally stabilizing at "strong homogeneous (grade 4)." As further shown in Figure 2a, Chongqing's upward trajectory exhibits a two-phase pattern of "acceleration followed by stabilization": it surged rapidly from 1.6874 to 5.7219 between 2018 and 2020, and then maintained a stable high-level operation thereafter. This pattern is highly consistent with the "high-level lock-in" characteristic reflected by its $p_{AA} = 1$. Chengdu's set pair potential fluctuated between 3.5916 and 9.5628, yet consistently remained within the "strong homogeneous" range (grades 2–6). Figure 2b reveals that Chengdu's fluctuations display a distinct "elastic recovery" feature: its decline from 7.96 to 3.16 during 2017–2019 did not persist, and strong rebounds occurred in both 2020 (rising to 4.77) and 2023 (rising to 7.11), indicating that Chengdu's system possesses strong resilience and self-repair capabilities. Notably, the development modes of the two cities differ significantly: Chongqing shows a steady upward trend, while Chengdu exhibits a high-level steady-state trend.

Tier 2: Fluctuating Balanced Potential (Mianyang, Deyang, Yibin, Luzhou).

Their set pair potentials mostly oscillate below 3.0, hovering around the equilibrium point, with frequent shifts among grades such as "slightly homogeneous," "weak homogeneous," and "slightly opposite." For instance, Mianyang's potential dropped sharply from "slightly homogeneous (grade 12)" to "slightly opposite (grade 31)" in 2021 before recovering, reflecting that these systems are undergoing significant dynamic adjustment and facing notable transitional volatility.

Deyang's potential jumped to "slightly homogeneous (grade 18)" in 2018 but fell back to "slightly opposite (grade 31)" in 2021, also indicating notable dynamic volatility. As further observed in Figure 2c, two key features emerge: first, the synchronization of sharp declines—all four cities experienced a substantial drop around 2021, suggesting that external shocks exerted a more pronounced impact on the middle-tier cities; second, the divergence in recovery speed—Yibin recovered relatively quickly, returning to 3.61 by 2023, while Mianyang's recovery was slower, only rising to 1.29 by 2023.

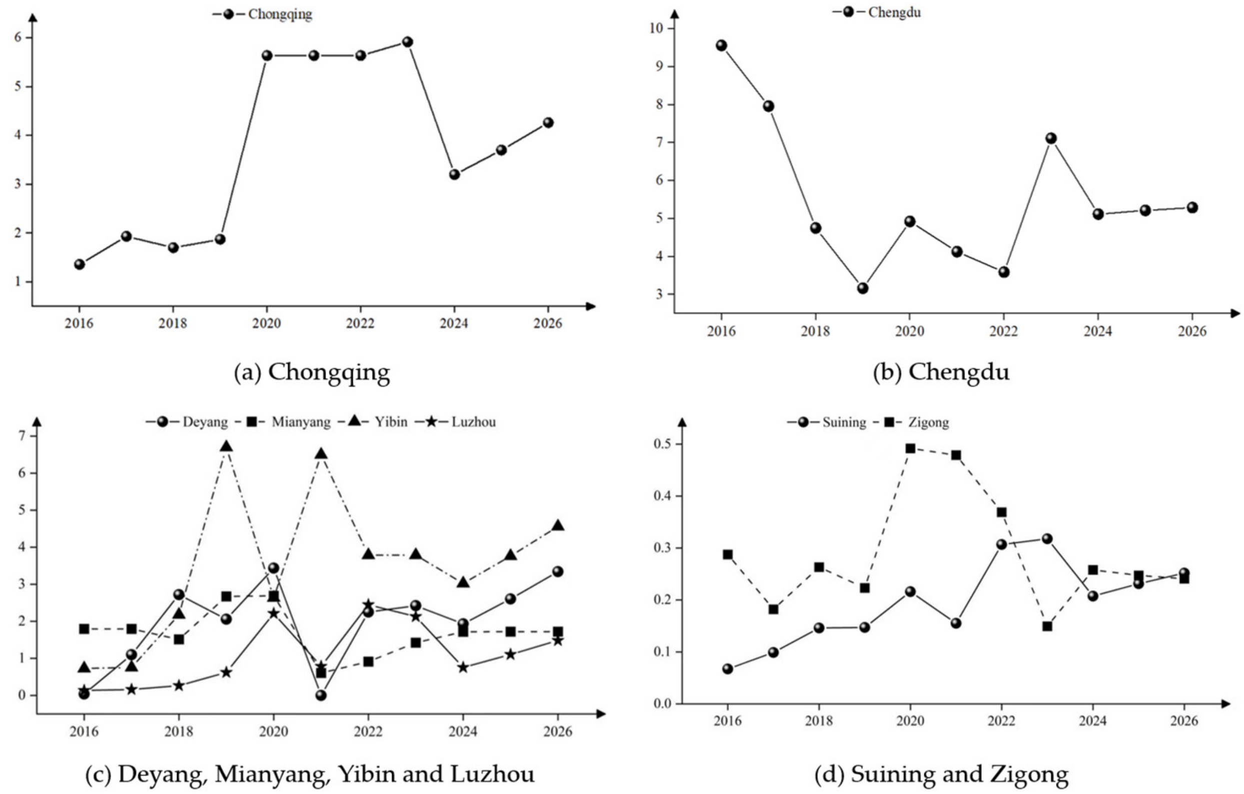

Figure 2. Temporal trends in set pair potential across cities.

Tier 3: Long-Term Strong Opposite Potential (Suining, Zigong).

Their set pair potentials remain consistently below 0.5, with grades entrenched in the "strong opposite (grades 45–49)" category. As visually demonstrated in Figure 2d, the curves of these two cities exhibit a "low-level flat" pattern, running nearly parallel to the horizontal axis with no substantive breakthroughs observed over the 11-year period. This steady state is not a dynamic equilibrium, but rather a reflection of the system's lack of endogenous momentum and its high dependence on external intervention. This indicates that low-carbon manufacturing development in these cities is characterized by long-term systemic disadvantage, with the overall trend leaning strongly negative, suggesting deeply embedded structural challenges.

In summary, the tier classification and dynamic development patterns reveal the evolutionary characteristics of low-carbon manufacturing in the Chengdu–Chongqing region from multiple dimensions: The first tier, represented by Chongqing and Chengdu, follows two distinct paths: "steady upward" and "high-level stable." Chongqing demonstrates robust growth momentum through continuous structural optimization, while Chengdu exhibits strong system resilience amid high-level fluctuations. The second tier displays an overall "medium-position oscillation" pattern, with the four cities frequently shifting around the equilibrium point. The synchronization of sharp declines and divergence in recovery speed jointly reflect the fragility of the transformation process. The third tier is a typical "low-level steady state" group, where Suining and Zigong have long lingered in the strong opposite potential range, trapped in a low-level equilibrium. The coexistence of these four development patterns not only corroborates the core judgment on regional differentiation and multi-equilibrium convergence presented earlier, but also provides a more targeted basis for the formulation of subsequent differentiated policies.

4.5. Robustness Test

To ensure the core conclusions are not overly dependent on the indicator grading criteria, this study adopted three alternative grading schemes—quartile, lenient quintile, and strict quintile—to conduct a sensitivity analysis. The specific grading thresholds for each scheme are as follows: (1) Quartile scheme: The 75th, 50th, and 25th percentiles of the dataset are used as cutoffs for grades A, B, C, and D, respectively. (2) Lenient quintile scheme: The 60th, 40th, and 20th percentiles are used as cutoffs (expanding the range of Grade A and narrowing that of Grade D). (3) Strict quintile scheme: The 80th, 60th, and 40th percentiles are used as cutoffs (narrowing the range of Grade A and expanding that of Grade D).

Under these three schemes, we recalculated each city's average four-element connection number, state transition matrix, and steady-state prediction, then compared the results with the original findings: results from the quartile scheme are fully consistent with the original conclusions, confirming the inherent rationality of the original grading criteria. The classification of the first tier (Chongqing, Chengdu) and third tier (Suining, Zigong) remains stable across all three schemes, indicating that the core tier structure is insensitive to threshold selection.

Middle-tier cities (Deyang, Mianyang, Yibin, Luzhou) exhibit sensitivity: under the strict quintile scheme, their composite scores are slightly lower than the original results; under the lenient quintile scheme, their composite scores are slightly higher. The sensitivity of middle-tier cities to evaluation criteria corroborates our judgment that they are "in a critical transition period with an unstable development path." These cities are in the transitional phase of old-to-new kinetic energy conversion, where positive and negative factors coexist within the system, making them more vulnerable to changes in evaluation standards. In contrast, the stability of the first and third tier cities reflects the "lock-in" characteristic of their development paths—whether high-level lock-in or low-level lock-in, they exhibit strong structural inertia.

In summary, the sensitivity analysis verifies the robustness of the core conclusions of this paper and further deepens the understanding of the volatile characteristics of middle-tier cities.

5. Discussion and Implications

5.1. Discussion

Employing a constructed multidimensional evaluation system and a coupled model integrating dynamic SPA with a state transition matrix, this study assesses the low-carbon manufacturing levels of the eight core cities in the Chengdu–Chongqing Economic Circle from 2016 to 2023. The analysis uncovers their regional disparities, static structural features, and dynamic evolutionary patterns.

5.1.1. Path Dependence and the "Lock-In" vs. "Unlocking" of Low-Carbon Transition

The findings reveal significant path dependence in the region's low-carbon manufacturing transition, manifesting a Matthew effect where "the strong get stronger and the trapped become more trapped." The state transition matrices show extremely high self-maintenance probabilities for both high-level (Grade A) and low-level (Grade D) states (e.g., $p_{AA} = 1$ for Chongqing, $p_{DD} = 0.9662$ for Mianyang). This aligns with theories in New Institutional Economics and Evolutionary Economic Geography on the co-evolution of technology–institution complexes and regional "lock-in" [33,34]. Leading cities like Chongqing and Chengdu, leveraging first-mover advantages, have established a positive feedback loop that encompasses green technology accumulation, clean energy infrastructure, regulatory frameworks, and market recognition, thereby consolidating their low-carbon competitiveness.

Conversely, lagging cities (e.g., Suining, Zigong) risk being "locked in" to carbon-intensive industrial structures, entrenched energy consumption patterns, and weaker governance capacities, potentially falling into a "low-level equilibrium trap."

A further analysis of the differentiation from the perspective of indicator dimensions reveals that core indicators of economic benefit and technological investment dimensions, such as manufacturing output value added (A1) and R&D expenditure (A4), though not directly equivalent to low-carbon transition effectiveness, lay a solid foundation for urban low-carbon transition. Chongqing and Chengdu have consistently maintained A or B levels in these two indicators, indicating stronger economic strength and innovative resources. These advantages enable them to support the upgrading of industrial structures toward high-end and green orientation, and provide financial and technical support for clean energy substitution and energy-saving technological transformation. From the perspective of actual outcomes, the two cities generally show low levels in efficiency indicators such as unit output value energy consumption (A8–A15) and carbon emission intensity (A18), suggesting that their economic and technological advantages have not been fully transformed into low-carbon performance to a certain extent. In contrast, Suining and Zigong have long been stuck at C or D levels in A1 and A4. The insufficient economic scale and innovative investment restrict the pace of their industrial structure upgrading. The traditional industrial pattern dominated by heavy chemical industry is difficult to break through, and the comprehensive energy consumption (A7) remains persistently high, leading to more severe structural constraints on low-carbon transition. Meanwhile, R&D investment intensity (A5) and environmental pressure indicators (e.g., A19 wastewater discharge, A21 solid waste discharge) also reflect the gradient differences in policy environment and governance capacity. Specifically, Chongqing, as a municipality directly under the central government, enjoys stronger policy support, with both A5 investment intensity and environmental regulation intensity at a high level. The Chengdu–Deyang–Mianyang region exhibits prominent performance in innovative investment by virtue of its scientific and educational resources and industrial foundation. In contrast, Suining and Zigong face insufficient innovation momentum and relatively weak governance capacity, which further exacerbates the structural dilemma of their low-carbon transition. The dual effects of industrial structure foundation and policy environmental capacity jointly solidify the differentiated low-carbon development paths among cities.

Theoretically, this underscores that the low-carbon transition is not a linear, homogeneous process but a path-dependent one, deeply shaped by historical accumulation and initial conditions. Consequently, marginal improvements (e.g., in firm-level energy efficiency) may be insufficient to break systemic lock-ins. Therefore, policy must transcend conventional "one-size-fits-all" or incremental approaches, shifting towards structural and transformative interventions that reshape regional technological trajectories and institutional environments.

5.1.2. Intra-Regional Heterogeneity and Pluralistic Equilibrium

The analysis reveals profound heterogeneity in low-carbon manufacturing development across the region. Statically, cities fall into three tiers: high-level stable (Chongqing, Chengdu), mid-level fluctuating (Deyang, Mianyang, Yibin, Luzhou), and low-level locked-in (Suining, Zigong). Dynamically, long-term steady-state projections indicate a trend toward pluralistic equilibrium: Chongqing tends toward complete optimization ($U^* = 1$), Chengdu and Mianyang maintain a high-level equilibrium, while Suining and Zigong converge to a low-level state dominated by opposition. This pattern of pluralistic equilibrium challenges the traditional convergence theory assumption that regional disparities automatically diminish over time [35]. It suggests that under prevailing conditions, regional low-carbon manufacturing levels may not converge naturally but rather form a persistent hierarchical structure. This reflects underlying structural disparities in resource endowments, industrial positioning, innovation capacity, policy efficacy, and integration into green value chains. For instance, as a national central city, Chongqing benefits from superior policy resources and strategic positioning, driving its manufacturing system toward sophistication, intelligence, and green transformation. In contrast, cities like Chengdu, Deyang, and Mianyang, leveraging solid educational and scientific resources and distinctive industrial bases, are positioned in a critical transformation phase. Traditional industrial cities like Suining and Zigong face greater pressure from industrial restructuring and carry significant historical burdens.

This finding alerts researchers and policymakers to the necessity of acknowledging and respecting intrinsic heterogeneity when promoting regionally coordinated low-carbon development. Pursuing absolute convergence is neither realistic nor efficient. A more rational objective is to foster a differentiated development pattern characterized by comparative advantage, functional complementarity, and coordinated synergy. Concurrently, efforts should prevent further deterioration in locked-in areas to avoid their becoming a drag on the regional transition.

5.1.3. Systemic Vulnerability: The Instability of Intermediate States

A key finding is the high vulnerability and uncertainty of indicators in intermediate states, particularly those contributing to the negative discrepancy degree (b_2). The state transition matrices reveal concurrent probabilities of upgrade and degradation for these indicators, with the risk of degradation substantially exceeding the potential for improvement in some cities (e.g., Suining). This underscores the dynamic complexity and latent risks of the transition process. An intermediate state signifies a system under transitional stress, where the old model is not fully dismantled and a new green pathway is not yet firmly established. This phase is susceptible to external shocks (e.g., economic fluctuations, policy inconsistency) and internal resistance (e.g., cost pressures, organizational inertia), which may trigger regression. For instance, the persistent predominance of b_2 over b_1 in Yibin and Luzhou suggests their systems face greater structural pressure and possess a more fragile transitional foundation.

This finding deepens the understanding of transition drivers and barriers. It indicates that assessing transition progress requires looking beyond leading indicators (identity degree a) or final outcomes (opposition degree c) to closely monitor the dynamics and quality of the intermediate process. Thus, policy interventions must provide stable expectations and enhance resilience for actors in critical transitional phases, helping them withstand risks, consolidate positive trends, and prevent systemic regression.

5.2. Implications

The empirical findings offer a clear understanding of the complex dynamics of the low-carbon transition in the region's manufacturing sector, characterized by strong path dependence, profound regional divergence, and inherent vulnerability. Building on the integrated "state diagnosis and trend projection" framework, we propose the following systematic, targeted, and forward-looking policy insights to inform coordinated regional low-carbon development and overcome transition challenges.

First, implement differentiated and precise regional intervention strategies tailored to the path-dependent characteristics of different tiered cities. The state transition matrix reveals that both high-level (Grade A) and low-level (Grade D) states exhibit extremely high self-sustaining probabilities (e.g., $p_{AA} = 1$ for Chongqing and $p_{DD} = 0.9662$ for Mianyang), indicating that the low-carbon advantages of leading cities and the low-carbon disadvantages of lagging cities both possess self-reinforcing inertia. This implies that "one-size-fits-all" policies are inherently ineffective, and policy design must adopt a "stratified governance" approach based on the dynamic positioning of cities.

For leading cities (e.g., Chongqing), policy should shift from "maintaining advantages" to "leading and diffusion." Such cities consistently maintain Grade A or B in high-weight indicators such as economic efficiency (A1) and scientific and technological investment (A4, A6), endowing them with the capacity to radiate influence to surrounding areas. This involves establishing regional green technology standards and carbon footprint systems, and leveraging their market and capital advantages to channel green investment into regional supply chains, thereby activating "growth pole" spillover effects.

For fluctuating cities (e.g., Deyang, Yibin) in a critical yet fragile transitional stage, the policy core is "stabilizing expectations and preventing regression." Essential measures include providing long-term green financial instruments (e.g., transition finance bonds, risk compensation funds) to mitigate the risk of firms discontinuing green investments during short-term economic downturns. Concurrently, technical adaptability should be enhanced through regional technology transfer and service centers to facilitate the absorption of advanced low-carbon technologies.

For locked-in cities (e.g., Suining, Zigong), set-pair analysis reveals that they have long been trapped in a strong reverse potential interval (with potential values below 0.53) and maintain a degree of opposition (c) consistently above 0.6, rendering conventional policies are ineffective. A robust strategy combining "external intervention and endogenous cultivation," orchestrated by higher-level governments, is imperative. Externally, a "Structural Transformation Fund" could be established to support the phased retirement of outdated production capacities under preferential terms, alongside targeted programs for worker retraining and relocation assistance. Endogenously, strategic planning should leverage local resource endowments to foster emerging low-carbon industries, with the goal of advancing green technology-led industrial restructuring to fundamentally reshape developmental pathways.

Second, establish a dynamic monitoring and resilience enhancement mechanism to address the volatility and degradation risks of middle-tier cities. The state transition matrix demonstrates that middle-tier cities such as Deyang, Mianyang, Yibin, and Luzhou face a dual probability: the likelihood of the negative discrepancy indicator (b_2) degrading to Grade D, alongside the possibility of optimizing to Grade A or B. Notably, in the four-element connection numbers of Yibin and Luzhou, the negative discrepancy has long exceeded the positive discrepancy, indicating that the urban system is under substantial structural pressure. This necessitates a policy shift from static outcome assessment to dynamic management of transition "process quality."

We recommend establishing a regional dynamic monitoring and early-warning platform for the low-carbon manufacturing transition. Informed by models such as the SPA-state transition framework employed here, this platform would track in real-time the structural changes in the "identity-discrepancy-opposition" composition for cities, key industries, and critical enterprises. Upon detecting a significant rise in negative discrepancy (b_2) or a high probability of regression to opposition (Grade D), the platform would trigger automatic warnings, activating targeted guidance and rapid response mechanisms.

Third, advance a functionally complementary regional collaborative governance system in response to the solidification of regional differentiation. Long-term steady-state predictions indicate that the low-carbonization level of manufacturing industries in the Chengdu–Chongqing region will not naturally converge; instead, a pluralistic equilibrium pattern will emerge, characterized by the coexistence of four types: strong convergence, balanced stability, gradual improvement, and low-level lock-in. Recognizing this trend toward pluralistic equilibrium does not mean accepting ever-widening regional disparities. A higher-level policy objective should be to guide the formation of a development pattern that is differentiated, functionally complementary, and synergistic.

This requires establishing a higher-level regional coordination mechanism. First, formulate a Green Synergistic Development Plan for Chengdu–Chongqing Manufacturing to clarify each city's positioning and division of labor within regional green industrial chains, avoiding homogeneous competition. Second, innovate regional ecological compensation and market-based emission reduction mechanisms. For example, explore a cross-regional market for carbon and energy-use rights, allowing less developed areas to earn revenue through ecological conservation or by hosting green industrial projects transferred from leading areas. This would ensure reasonable compensation for the positive externalities of low-carbon development within the region. Third, jointly develop and share regional green infrastructure and innovation platforms, such as cross-regional clean energy grids, collaborative waste treatment facilities, and joint green technology R&D centers. By lowering the green transition threshold—especially for less developed cities—these initiatives foster positive factor interaction and enhance overall regional efficiency.

6. Conclusions and Limitations

Through an empirical assessment of eight core cities in the Chengdu–Chongqing Economic Circle, this study identifies three core characteristics of the regional manufacturing low-carbon transition, directly addressing the research propositions. Firstly, this study confirms strong path dependence and a Matthew effect. Second, long-term projections indicate a trend toward pluralistic equilibrium: Chongqing tends toward complete optimization ($U^* = 1$); Chengdu and Mianyang maintain a high-level equilibrium, while Suining and Zigong are likely to remain locked in a low-level state. Third, this study delineates pronounced regional differentiation and a solidified tiered structure. Based on set pair potential analysis, cities are grouped into three tiers: high-level stable (Chongqing, Chengdu), mid-level fluctuating (Deyang, Mianyang, Yibin, Luzhou), and low-level locked-in (Suining, Zigong). Long-term steady-state projections suggest this differentiation is persistent. Finally, it highlights the high vulnerability and risks inherent in the transition process.

This study is subject to several notable limitations, which also point to promising directions for future research. First, constrained by data availability, the evaluation system does not fully incorporate more forward-looking "soft" indicators like supply-chain carbon management and product carbon footprints. Second, the grade classification relies primarily on intra-regional relative performance and expert judgment, lacking an absolute benchmark aligned with national "Dual Carbon" targets or international standards. Third, the analysis focuses on intra-regional comparison and does not benchmark the region against other advanced clusters like the Yangtze River Delta, limiting broader contextual understanding. Lastly, the Markov chain-based long-term projections assume stationary transition probabilities and do not account for the effects of exogenous shocks like major policy interventions or technological breakthroughs. Future research could enrich data dimensions, develop evaluation standards integrating absolute and relative benchmarks, conduct cross-regional comparisons, and build non-homogeneous forecasting models that incorporate policy variables.

Author Contributions: Conceptualization, Y.J. and X.L.; methodology, X.L. and Q.L.; software, X.L.; validation, Y.J. and Q.L.; formal analysis, X.L.; investigation, X.L. and Q.L.; resources, Y.J.; data curation, X.L.; writing—original draft preparation, X.L.; writing—review and editing, Y.J., P.J. and Q.L.; visualization, X.L. and P.J.; supervision, Y.J.; project administration, Y.J.; funding acquisition, Y.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was financially supported by the Sichuan Science and Technology Program (SCJJ25RKX028), Sichuan Normal University College Students' Innovation and Entrepreneurship Training Program (202510636049) and National Philosophy and Social Sciences Foundation of China (22BGL131).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Saglam, M.S.; Yilanci, V.; Kongkuah, M. Decoupling economic growth and carbon emissions: A time-varying analysis of the environmental Kuznets curve hypothesis in France (1890–2019). *Environ. Dev. Sustain.* **2025**, 1–33. [CrossRef]
2. Wang, J.; Qiao, L.; Zhu, G.; Di, K.; Zhang, X. Research on the driving factors and impact mechanisms of green new quality productive forces in high-tech retail enterprises under China's Dual Carbon Goals. *J. Retail. Consum. Serv.* **2025**, *82*, 104092. [CrossRef]
3. Liu, J.; Zhang, P.; Wang, X. Exploring the mechanisms and pathways through which the digital transformation of manufacturing enterprises enhances green and low-carbon performance under the "Dual Carbon" goals. *Sustainability* **2025**, *17*, 1162. [CrossRef]
4. Feng, X.; Li, F.; Somenahalli, S.; Zhao, Y.; Li, M.; Zhou, Z.; Li, F. Analysis of the Coupling Trend Between the Urban Agglomeration Development and Land Surface Heat Island Effect: A Case Study of Guanzhong Plain Urban Agglomeration, China. *Sustainability* **2025**, *17*, 5239. [CrossRef]
5. Hou, L.; Cui, M. A new insight to investigate the developmental resilience of Chengdu-Chongqing twin-city economic circle based on ecological niche theory. *J. Asian Archit. Build. Eng.* **2025**, *24*, 4213–4225. [CrossRef]
6. Guo, X. Spatial Polarization and Coordinated Development Pathways in the Chengdu-Chongqing Economic Circle: A Structuralist Perspective on Interstitial Regional Dynamics. *J. Interdiscip. Insights* **2025**, *3*, 31–50.
7. He, J.J.; Yang, Q.Y.; Zhao, Y.H. Research on the diffusion effects of data value in supply chains. *J. Asian Econ.* **2025**, *101*, 102064. [CrossRef]
8. Gómez-Mejía, L.R.; Muñoz-Bullón, F.; Requejo, I.; Sanchez-Bueno, M.J. Ethical correlates of family control: Socioemotional wealth, environmental performance, and financial returns. *J. Bus. Ethics* **2025**, *198*, 893–917. [CrossRef]
9. Yousaf, T. Balancing act: Examining the trade-offs between regional convergence and economic growth in China's province managing county reform. *Econ. Transit. Inst. Change* **2025**, *33*, 339–368. [CrossRef]
10. Li, S.; Wu, Y.; Dai, G.; Chen, X. Research on Spatial-Temporal differences and convergence characteristics of ecological total factor productivity of cultivated land use in China. *Agriculture* **2025**, *15*, 1172. [CrossRef]
11. Jiang, Y.; Zhang, J.; Asante, D.; Yang, Y. Dynamic evaluation of low-carbon competitiveness (LCC) based on improved Technique for Order Preference by similarity to an Ideal Solution (TOPSIS) method: A case study of Chinese steelworks. *J. Clean. Prod.* **2019**, *217*, 484–492. [CrossRef]
12. Wu, X.; Hu, F. Analysis of ecological carrying capacity using a fuzzy comprehensive evaluation method. *Ecol. Indic.* **2020**, *113*, 106243. [CrossRef]
13. Ma, X.; Wang, C.; Dong, B.; Gu, G.; Chen, R.; Li, Y.; Zou, H.; Zhang, W.; Li, Q. Carbon emissions from energy consumption in China: Its measurement and driving factors. *Sci. Total Environ.* **2019**, *648*, 1411–1420. [CrossRef] [PubMed]
14. Emir, F.; Bekun, F.V. Energy intensity, carbon emissions, renewable energy, and economic growth nexus: New insights from Romania. *Energy Environ.* **2019**, *30*, 427–443. [CrossRef]
15. Zhang, C.; Zhu, H.; Li, X. Which productivity can promote clean energy transition-total factor productivity or green total factor productivity? *J. Environ. Manag.* **2024**, *366*, 121899. [CrossRef]
16. Jiakui, C.; Abbas, J.; Najam, H.; Liu, J.; Abbas, J. Green technological innovation, green finance, and financial development and their role in green total factor productivity: Empirical insights from China. *J. Clean. Prod.* **2023**, *382*, 135131. [CrossRef]
17. Lv, X.; Lu, X. Green Growth or Gray Growth: Measuring Green Growth Efficiency of the Manufacturing Industry in China. *Systems* **2022**, *10*, 255. [CrossRef]
18. Xu, J.; Lv, X. Evaluation of low-carbon development in China's manufacturing industry based on a dynamic set pair analysis model. *Sci. Technol. Manag. Res.* **2015**, *35*, 49–55.
19. Ko, P.S.; Chen, K.S. Discovering AI tokens in the Fractal Markets Hypothesis and their time-frequency co-movements with the leading high-carbon cryptocurrency. *Data Sci. Financ. Econ.* **2025**, *5*, 293–319. [CrossRef]
20. Baležentis, T.; Butkus, M.; Štreimikienė, D. Energy productivity and GHG emission in the European agriculture: The club convergence approach. *J. Environ. Manag.* **2023**, *342*, 118238. [CrossRef]

21. Xu, C. Towards balanced low-carbon development: Driver and complex network of urban-rural energy-carbon performance gap in China. *Appl. Energy* **2023**, *333*, 120663. [CrossRef]
22. Chen, Q.; Wang, Q.; Zhou, D.; Wang, H. Drivers and evolution of low-carbon development in China's transportation industry: An integrated analytical approach. *Energy* **2023**, *262*, 125614. [CrossRef]
23. Yan, X.; Shi, X.; Fang, X. The internal dynamics and regional differences of China's marine economic evolution based on comprehensive evaluation. *Alex. Eng. J.* **2022**, *61*, 7571–7583. [CrossRef]
24. Yuan, L.; Liu, C.; Wu, X.; He, W.; Kong, Y.; Degefu, D.M.; Ramsey, T.S. A set pair analysis method for assessing and forecasting water conflict risk in transboundary river basins. *Water Resour. Manag.* **2024**, *38*, 775–791. [CrossRef]
25. Reynolds, R.G. Direct solution of the Keplerian state transition matrix. *J. Guid. Control Dyn.* **2022**, *45*, 1162–1165. [CrossRef]
26. Luomaranta, T.; Martinsuo, M. Additive manufacturing value chain adoption. *J. Manuf. Technol. Manag.* **2022**, *33*, 40–60. [CrossRef]
27. Yu, L.; Wang, Y.; Wei, X.; Zeng, C. Towards low-carbon development: The role of industrial robots in decarbonization in Chinese cities. *J. Environ. Manag.* **2023**, *330*, 117216. [CrossRef]
28. Liang, S.; Yang, J.; Ding, T. Performance evaluation of AI driven low carbon manufacturing industry in China: An interactive network DEA approach. *Comput. Ind. Eng.* **2022**, *170*, 108248. [CrossRef]
29. Lin, B.; Li, Z. Towards world's low carbon development: The role of clean energy. *Appl. Energy* **2022**, *307*, 118160. [CrossRef]
30. Wu, X.; Zhou, S.; Xu, G.; Liu, C.; Zhang, Y. Research on carbon emission measurement and low-carbon path of regional industry. *Environ. Sci. Pollut. Res.* **2022**, *29*, 90301–90317. [CrossRef]
31. Wei, X.; Jiang, F.; Yang, L. Does digital dividend matter in China's green low-carbon development: Environmental impact assessment of the big data comprehensive pilot zones policy. *Environ. Impact Assess. Rev.* **2023**, *101*, 107143. [CrossRef]
32. Huo, W.; Qi, J.; Yang, T.; Liu, J.; Liu, M.; Zhou, Z. Effects of China's pilot low-carbon city policy on carbon emission reduction: A quasi-natural experiment based on satellite data. *Technol. Forecast. Soc. Change* **2022**, *175*, 121422. [CrossRef]
33. Kogler, D.F.; Evenhuis, E.; Giuliani, E.; Martin, R.; Uyarra, E.; Boschma, R. Re-imagining evolutionary economic geography. *Camb. J. Reg. Econ. Soc.* **2023**, *16*, 373–390. [CrossRef]
34. Mondal, R. Inter-temporal co-evolution of divergent economic activities and spatial economic resilience embedded in informal institutions. *Reg. Stud. Reg. Sci.* **2023**, *10*, 763–777. [CrossRef]
35. Kremer, M.; Willis, J.; You, Y. Converging to convergence. *NBER Macroecon. Annu.* **2022**, *36*, 337–412. [CrossRef]

https://doi.org/10.3390/su18094164