Spatiotemporal evolution and path selection of decarbonization in the transition of China' s resource-based cities: postprint

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Abstract

The decarbonization of transforming resource-based cities is key to achieving the "dual carbon" goals. By measuring the level of transformation decarbonization in China' s resource-based cities from 2006 to 2021, and employing spatial Markov chains and fuzzy-set qualitative comparative analysis (fsQCA), this study investigates the spatiotemporal evolution characteristics and pathway choices of transformation decarbonization in resource-based cities. The results show that: (1) The level of transformation decarbonization in resource-based cities has risen year by year. The development pattern has evolved from a contiguous distribution centered on lagging areas to a cluster-based distribution centered on leapfrogging and pioneering areas. The overall disparity in transformation decarbonization is significant, with intra-regional differences and mature cities being the main cause and source, respectively, of the widening overall disparity. (2) The transitions among types of transformation decarbonization exhibit stability, indicating a phenomenon of "path dependence" ; the probability of maintaining the initial state is relatively high, presenting a "club convergence" characteristic. A "Matthew effect" is observed in the process of continuous upward transitions, and spatial spillover effects are evident. (3) Technological, organizational, and environmental factors cannot individually constitute necessary conditions for achieving transformation decarbonization. Multiple factors co-occur, forming three configurational pathways for transformation decarbonization in resource-based cities: the "technology-environment" synergistic driving type, the "technology-organization" synergistic driving type, and the "technology-organization-environment" joint driving type, among which green technological innovation plays a core role. (4) Different types of resource-based cities rely on different factors: growth-type cities depend on digital technology and environmental concern; mature cities are jointly driven by multiple dimensions including technological innovation, industrial upgrading, and environmental factors; declining cities are more strongly affected by environmental factors;

and regenerative cities emphasize the synergistic driving role of technological innovation and environmental factors. The findings provide useful experience and practical insights for realizing transformation decarbonization in China’ s resource-based cities.

Full Text

Preamble

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Spatiotemporal Evolution and Pathway Selection of Transformation Decarbonization in China’ s Resource-Based Cities

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Abstract: The transformation decarbonization of resource-based cities is critical for achieving China’ s “dual carbon” goals. This study measures decarbonization levels using the spatial Markov chain and fuzzy-set qualitative comparative analysis (fsQCA) methods to investigate the spatiotemporal evolution and pathway selection of transformation decarbonization in resource-based cities. Results show that: (1) Transformation decarbonization levels in China’ s resource-based cities have risen year by year, with spatial patterns evolving from a concentrated contiguous distribution centered on lagging areas to a clustered distribution centered on transitional and pioneering zones. (2) Overall disparities in transformation decarbonization are significant, with intra-regional differences and mature-type cities serving as the primary causes and sources of widening gaps. (3) Transitions between decarbonization types exhibit stability with clear “path dependence” characteristics; cities show high probabilities of maintaining their initial states, demonstrating “club convergence” features. A “Matthew effect” emerges during continuous upward transitions, with significant spatial spillover effects. (4) No single factor—technological, organizational, or environmental—can independently constitute a necessary condition for transformation decarbonization. Instead, multiple factors interact concurrently to form three configurational pathways: “technology-environment” synergy-driven type, “technology-organization” synergy-driven type, and “technology-organization-environment” jointly-driven type, with green technology innovation playing a core role throughout. (5) Different types of resource-based cities rely on distinct factors: growing cities depend on digital technology and environmental concern; mature cities are jointly driven by technological innovation, industrial upgrading, and environmental factors; declining cities are more heavily influenced by environmental factors; and regenerating cities emphasize the synergistic drive of technological innovation and environmental factors. These findings provide valuable experience and practical insights for China’ s resource-based cities to achieve transformation decarbonization.

Keywords: resource-based cities; transformation decarbonization; spatial Markov chain; fsQCA; different paths leading to the same destination

At the 28th United Nations Climate Change Conference, nations reached consensus on advancing transformation decarbonization—a core pathway for mitigating climate change and achieving green development. As the world’ s largest energy consumer and carbon emitter, China plays a pivotal role in this global effort. However, with coal still dominating its energy consumption, China must accelerate transformation decarbonization to achieve its “dual carbon” goals and address energy security risks. China’ s resource-based cities, long dependent on resource extraction and heavy industry, face multiple challenges including resource depletion, high energy consumption, severe pollution, and high emissions, creating substantial pressure for green transformation and insufficient decarbonization momentum. The “14th Five-Year Plan for High-Quality Development of Resource-Based Regions” emphasizes the need to promote transformation based on local conditions. Therefore, advancing transformation decarbonization in resource-based cities is both an inevitable choice for sustainable urban development and a key priority for driving high-quality economic development and achieving China’ s “dual carbon” targets. Given that resource-based cities differ in resource endowments, economic foundations, and development trajectories, accurately grasping their spatiotemporal evolution characteristics and identifying effective transformation pathways becomes crucial.

Existing literature on transformation decarbonization falls into two main categories: first, conceptual discussions of transformation and decarbonization and their interrelationships; second, examinations of implementation pathways. Scholars define “transformation” as either a shift in technological systems or the co-evolutionary outcome of economic, technological, and institutional development. In sustainability and low-carbon contexts, research focuses on energy transition, technological transformation, and industrial transformation, where technological innovation drives low-carbon transitions to achieve decarbonization goals. “Decarbonization” is defined as the process of reducing carbon intensity in primary energy consumption, with deep decarbonization representing the replacement of inefficient high-carbon infrastructure with efficient low-carbon technologies. Studies argue that global deep decarbonization is essential for climate risk mitigation, with transformation being a prerequisite. Proposed pathways include: (1) energy structure transformation as the core foundation for deep decarbonization; (2) technological innovation as the key driver; (3) industrial restructuring as a critical pathway, since industrial structure determines energy demand; and (4) improved policy systems to support transformation decarbonization.

Research on China’ s resource-based cities has examined transformation performance, influencing factors, spatiotemporal evolution characteristics, and carbon emission patterns. Studies have mapped spatiotemporal differentiation in carbon emissions and identified carbon reduction pathways for resource-based regions. However, while existing scholarship provides valuable insights, three key gaps remain: First, most studies focus exclusively on either transformation or decarbonization, lacking integrated quantitative assessment. Given their interdependence and mutual reinforcement, treating them as two dimensions of a unified system enables more comprehensive understanding of their dynamics and complexity. Second, existing pathway analyses rely heavily on theoretical induction or scenario simulation, emphasizing single-factor effects while failing to capture causal complexity. How do multiple interacting factors shape transformation decarbonization processes? What are the diverse configurational pathways and differential characteristics under varying regional conditions? These questions remain underexplored.

This study addresses these gaps by integrating transformation and decarbonization within a unified measurement framework. We construct a quantitative evaluation system for resource-based city transformation decarbonization, analyze its differential sources and spatiotemporal evolution, and examine the dynamic complexity of the process. Using a configurational perspective, we investigate how multiple factor combinations promote transformation decarbonization, identify dominant factors, and reveal the “different paths leading to the same destination” for diverse city types.

1. Data and Methods

1.1 Data Sources

The 2013 “National Plan for Sustainable Development of Resource-Based Cities” identified 262 prefecture-level resource-based cities, classified into four types: growing, mature, declining, and regenerating. Based on data availability, this study examines 111 prefecture-level resource-based cities from 2006 to 2021 (including 19 growing, 68 mature, 16 declining, and 8 regenerating cities). Data primarily come from the *China City Statistical Yearbook*, *China Energy Statistical Yearbook*, the National Intellectual Property Administration, and municipal statistical bulletins on national economic and social development.

1.2 Evaluation Index System for Resource-Based City Transformation Decarbonization

Drawing on Fang et al. and Gao et al., we construct a transformation decarbonization evaluation index system (Table 1). The transformation subsystem comprises three dimensions: energy transition, industrial transformation, and technological transformation. Energy transition is measured by coal consumption share and energy utilization efficiency—the former reflecting the degree of low-carbon energy structure, the latter representing energy-saving technological progress and management effectiveness, calculated following Shi et al. Industrial transformation is measured by industrial structure rationalization and upgrading, following Gan et al. Rationalization reflects improved resource allocation efficiency and environmental sustainability, while upgrading reflects technological innovation and value-added enhancement. Technological transformation includes green technology innovation and digital technology innovation, measured by green patent and digital patent applications, respectively. Green patents reflect low-carbon R&D investment and innovation output, while digital patents capture digital technology contributions to energy efficiency and industrial upgrading.

Decarbonization aims to reduce carbon emissions toward net-zero. We characterize it through three aspects: total carbon emissions, carbon emission intensity, and decarbonization rate, with carbon emission data following Cong et al. Total emissions directly reflect actual discharge volumes, forming the basis for assessing mitigation effectiveness. Emission intensity reflects economic activity decarbonization efficiency. Decarbonization rate, measured by carbon intensity change rate, reflects emission reduction speed.

The coupling coordination model comprehensively evaluates synergistic trends and overall coordination between subsystems. After calculating transformation and decarbonization subsystem scores using the entropy weight method, we measure the comprehensive transformation decarbonization index through the coupling coordination model:

$$\begin{aligned} C_{it} &= 2 \times \sqrt{\frac{TR_{it} \times DC_{it}}{TR_{it} + DC_{it}}} \\ S_{it} &= \sqrt{TR_{it} \times DC_{it}} \\ TD_{it} &= \sqrt{C_{it} \times S_{it}} \end{aligned}$$

where C_{it} is the coupling degree between transformation and decarbonization systems for city i in year t; TR_{it} and DC_{it} are transformation and decarbonization scores, respectively; S_{it} is the coordination degree; and TD_{it} is the coupling coordination degree representing the transformation decarbonization level, with $0 \leq TD_{it} \leq 1$. Higher TD_{it} values indicate higher transformation decarbonization levels.

1.3 Analysis Methods

1.3.1 Methods for Analyzing Spatiotemporal Evolution Characteristics

Theil Index. Following Zhou et al., we use the Theil index to decompose overall disparities in transformation decarbonization levels into within-group and between-group differences, analyzing trends and contributions:

$$
\begin{aligned}
T &= \sum_{r=1}^{4}\sum_{i=1}^{n_r}\frac{TD_{ir}}{n\times\overline{TD}}\ln\left(\frac{TD_{ir}}{\overline{TD}}\right)\\
T_r &= \sum_{i=1}^{n_r}\frac{TD_{ir}}{n_r\times\overline{TD}_r}\ln\left(\frac{TD_{ir}}{\overline{TD}_r}\right)\\
x &= \sum_{r=1}^{4}\frac{n_r\times\overline{TD}_r}{n\times\overline{TD}}\times T_r\\
y &= \sum_{r=1}^{4}\frac{n_r\times\overline{TD}_r}{n\times\overline{TD}}\ln\left(\frac{\overline{TD}_r}{\overline{TD}}\right)\\
z &= \frac{n_r\times\overline{TD}_r}{n\times\overline{TD}}\times T_r
\end{aligned}
$$

where T is the overall Theil index; T_r $(r = 1, 2, 3, 4)$ represents Theil indices for growing, mature, declining, and regenerating cities; n is total city count; n_r is city count by type; TD_i is city i' s transformation decarbonization level; $\overline{TD}_r$ and $\overline{TD}$ are type-specific and overall means; x and y are within-group and between-group contribution rates; and z is each type' s contribution to within-group differences.

Spatial Markov Chain. To examine spatial correlations with neighboring cities during dynamic evolution, we follow Xu et al. by classifying cities into k types based on initial-year spatial lag values. Neighborhood states are represented by spatial lag values, which are incorporated into traditional $k\times k$ Markov matrices to construct k $k \times k$ probability transition matrices. The spatial lag formula is:

$$
Lag_j = \sum_i TD_i W_{ij}
$$

where Lag_j is the spatial lag value for neighboring city j, and W_{ij} is the spatial weight matrix indicating adjacency between cities i and j (1 if adjacent, 0 otherwise).

1.3.2 Methods for Analyzing Transformation Decarbonization Pathways

The Technology-Organization-Environment (TOE) framework comprehensively considers interactions among technological, organizational, and environmental factors, offering advantages in comprehensiveness, quantifiability, and applicability. Based on identified key influencing factors, we construct a configurational analysis framework (Figure 1). Technological factors—green technology innovation, digital technology innovation, and energy efficiency—are critical for improving resource utilization efficiency and promoting low-carbon development. Organizational factors include industrial structure upgrading as a strategic adaptation to diversify from single-resource dependence. Environmental factors encompass environmental regulation and public environmental concern, representing governmental policies and societal pressure. The outcome variable is transformation decarbonization level.

Fuzzy-set Qualitative Comparative Analysis (fsQCA) is suitable for analyzing multiple concurrent causal relationships in complex social phenomena, enabling identification of multiple pathways driving high transformation decarbonization levels and distinguishing core versus peripheral conditions.

2. Results

2.1 Spatiotemporal Evolution Characteristics of Transformation Decarbonization

2.1.1 Overall and Structural Differences The Theil index shows an overall upward trend from 2006–2021, indicating widening disparities in transformation decarbonization levels. Both within-group and between-group differences fluctuated upward, with within-group contributions exceeding 85% and between-group contributions below 15% (Figure 2). Within-group differences dominate total disparities, primarily due to uneven resource endowments, economic development, technological innovation, industrial optimization, and policy implementation across cities within the same region. This creates divergent decarbonization progress, amplifying intra-regional gaps.

Decomposing within-group differences by city type reveals mean Theil indices of 0.023, 0.041, 0.028, and 0.032 for growing, mature, declining, and regenerating cities, respectively. Growing, declining, and regenerating cities contribute less than 20% each, with declining contributions for growing and declining cities. Mature cities' contributions exceed 40% but fluctuate downward (Figure 3). Mature cities are the primary source of overall disparities, followed by declining and regenerating cities, with growing cities contributing least. After 2015, regenerating cities' Theil index surpassed others, with rising contribution rates, indicating growing internal disparities likely due to differential technological innovation and policy support. Mature cities have strong industrial bases but high energy-consuming industry shares and significant technological development gaps, contributing most to overall disparities. Declining cities suffer from resource depletion, insufficient capital and technology investment, and uneven environmental regulation, showing high but decreasing contributions. Regenerating cities exhibit rising internal differences due to varying innovation and policy support. Growing cities, with later starts but clearer digital and environmental pathways and more balanced economic-policy foundations, show the smallest internal disparities.

2.1.2 Spatial Distribution Patterns Following Xu et al., we use the 2006–2021 average transformation decarbonization level to classify cities into lagging, initial, transitional, and pioneering zones, visualized using ArcGIS 10.8 (Figure

4). In 2006, overall levels were low, with lagging zones forming concentrated contiguous clusters, initial zones scattered nearby, and transitional zones sporadically emerging due to low economic development, weak technological support, and lax policy enforcement. By 2013, levels improved noticeably: lagging zones decreased from 76 to 58 cities, while initial and transitional zones increased through low-carbon technology promotion, industrial optimization, and regional policy coordination. By 2021, deepening green technology innovation and environmental policies accelerated decarbonization, significantly raising transformation decarbonization levels. Lagging zones further decreased while transitional zones increased substantially, with 4 pioneering zones emerging. Overall, transformation decarbonization levels continuously upgraded across the four categories, evolving from lagging-zone-centered contiguous distribution to transitional and pioneering-zone-centered clustered distribution.

2.1.3 Spatiotemporal Dynamic Evolution Static Spatial Markov Chain Analysis. To analyze spatiotemporal evolution, we construct Markov transition probability matrices. Traditional matrix results show diagonal elements exceeding non-diagonal elements, indicating stable state transitions with high probabilities of maintaining original states—demonstrating "path dependence." Upward transitions refer to moves from lower to higher values, downward transitions the opposite, while unchanged states include stable (remaining in original type) and oscillating (temporarily leaving but returning).

The traditional Markov matrix reveals: (1) Diagonal probabilities exceed off-diagonal, confirming stability and "path dependence." (2) Lagging and pioneering zones show significantly higher diagonal probabilities than intermediate types, indicating "club convergence." (3) Intermediate types have higher upward than downward transition probabilities, especially transitional zones, suggesting favorable upward mobility. (4) A "Matthew effect" exists during continuous upward transitions.

Incorporating spatial lags, spatial Markov chain analysis further reveals: (1) Spatial spillover effects are significant—cities are influenced by neighbors, with higher neighbor levels increasing upward transition probabilities. (2) Resource-based cities and their neighbors show coordinated transitions, with higher probabilities of moving in the same direction, particularly upward. (3) Spatial distribution maps (Figure 5) show neighboring cities exhibit convergence, with local development influenced by neighbors, displaying "high-high" and "low-low" clustering.

During 2006–2021, 59 cities experienced type transitions: 51 upward, 8 oscillating, and no downward transitions. Among these, 35 cities saw both local and neighboring types rise; 11 saw local rises while neighbors remained unchanged; 9 saw neighbors rise while locals remained stable; and 4 saw both unchanged. Resource-based cities in Northeast and Southwest China show transition inertia. Overall, transformation decarbonization levels primarily moved upward with good development momentum, though improvement potential remains.

2.2 Pathway Analysis of Transformation Decarbonization

2.2.1 Variable Calibration and Necessary Condition Analysis We conduct configurational analysis using 2006–2021 mean values of outcome and condition variables. Following existing research, we set the 95th, 50th, and 5th percentiles as "full membership," "crossover," and "full non-membership" anchors to transform data into [0,1] fuzzy membership values. Necessary Condition Analysis (NCA) examines whether condition variables are necessary for high transformation decarbonization levels. Results (Table 3) show effect sizes for green technology innovation, digital technology innovation, energy efficiency, industrial structure upgrading, environmental regulation, and public environmental concern all below 0.9, indicating none constitute necessary conditions—allowing configurational analysis to proceed.

2.2.2 Configurational Analysis Using fsQCA 4.0, we analyze condition variables affecting transformation decarbonization levels. With a consistency threshold of 0.8 and case threshold of 1, results meet configurational analysis standards. Three configurations achieve high transformation decarbonization levels (Table 4). Configurations 1 and 2 represent "technology-environment" synergy pathways with core technological and environmental conditions. Configuration 3 represents a "technology-organization-environment" jointly-driven pathway. Green technology innovation appears in all three configurations, confirming its catalytic role.

Technology-Environment Synergy Pathway (Configuration 1). Green technology innovation, digital technology innovation, energy efficiency, and public environmental concern are core conditions. This suits cities with high energy consumption and severe historical pollution, such as Dongying, Suqian, Nanyang, and Baotou. Compared to other pathways, energy efficiency improvement is critical, while stronger environmental regulation guides corporate environmental investment and green transformation.

Technology-Organization Synergy Pathway (Configuration 2). Green technology innovation, digital technology innovation, and industrial structure upgrading are core conditions. Cases include Jilin, Zhangjiakou, Datong, and Suzhou. These cities leverage technological innovation while possessing advantages in industrial structure upgrading, gradually forming green, low-carbon industrial structures that significantly drive transformation decarbonization.

Technology-Organization-Environment Joint Pathway (Configuration 3). Green technology innovation, environmental regulation, and public environmental concern are core conditions, with industrial upgrading as a peripheral condition. Cases include Yuncheng, Jinzhong, Changzhi, and Jiaozuo. Green technology innovation provides emission reduction solutions, environmental regulation ensures effective implementation, public concern supplies external pressure, and industrial upgrading enables the final shift from high-carbon to green industries.

Robustness checks confirm these findings. Raising the consistency threshold to 0.85 yields identical solutions. Using 75th, 50th, and 25th percentiles as anchors with case threshold 2 and consistency threshold 0.75 produces substantially similar results, with minimal changes in coverage and consistency.

2.2.3 Heterogeneity Analysis To examine pathway differences across city types, we analyze each type separately using their respective high transformation decarbonization levels as outcome variables (Table 5).

Growing Cities primarily follow a “technology-environment” synergy pathway, driven by digital technology innovation, energy efficiency, and public environmental concern, as exemplified by Nanchong.

Mature Cities show three pathways: (1) “Technology-environment” synergy, represented by Jining and Ganzhou, which leverage strong innovation capacity to improve energy efficiency; (2) “Technology-organization” joint pathway, represented by Yuncheng and Ganzhou, combining innovation, public concern, industrial upgrading, and environmental regulation; (3) “Technology-organization” synergy, represented by Jilin and Chizhou, which achieve transformation despite deficiencies in energy efficiency and regulation through green and digital technology innovation plus industrial upgrading.

Declining Cities follow one “technology-environment” synergy pathway, exemplified by Jiaozuo and Puyang. Due to weak innovation capacity and insufficient internal transformation momentum, environmental regulation and public concern become critical drivers.

Regenerating Cities follow a “technology-environment” synergy pathway. Digital technology innovation significantly impacts Tangshan, Xuzhou, Suqian, and Luoyang, while green technology innovation and public environmental concern effectively boost transformation decarbonization in Zibo and Ma’ anshan.

3. Discussion

Transformation and decarbonization are interdependent, mutually reinforcing dimensions of a unified system. While existing literature has preliminarily explored their concepts, relationships, pathways, and application to China’ s resource-based cities, three limitations persist: (1) fragmented perspectives lacking integrated quantitative evaluation; (2) absence of heterogeneity analysis for differentiated pathways; and (3) insufficient examination of dynamic processes. This study innovates by integrating transformation and decarbonization within a unified evaluation framework, analyzing differential sources and spatiotemporal evolution from a holistic perspective, and investigating key influencing factors and differentiated pathways through a configurational lens.

Our spatiotemporal analysis reveals that intra-regional differences are the primary source of overall disparities, consistent with Xu et al.’ s findings on transformation performance. The evolution from dispersed to clustered distribution patterns reflects green technology diffusion, validating Xu et al.’ s conclusions. Spatial Markov chain analysis confirms significant spatial spillover effects, aligning with Xia et al.’ s research. Pathway analysis demonstrates that due to differences in natural resources, industrial structure, low-carbon technology, and historical development, resource-based cities exhibit sequential differentiation in transformation decarbonization performance. This suggests that universal transformation pathways must account for urban heterogeneity and accommodate multiple factor configurations and strategic combinations.

Despite these contributions, limitations remain. The study lacks dynamic simulation and prediction of transformation decarbonization pathways and fails to fully reveal performance under varying policy scenarios across city types. Future research should incorporate dynamic simulation models to enrich the theoretical framework.

4. Conclusions and Implications

4.1 Conclusions

From 2006–2021, China’ s resource-based cities showed rising transformation decarbonization levels, evolving from lagging-zone-centered contiguous distribution to transitional and pioneering-zone-centered clustered patterns. The Theil index increased overall, with widening disparities primarily driven by intra-regional differences, and mature-type cities contributing most to overall gaps.

Transformation decarbonization type transitions exhibit stability with “path dependence” and “club convergence” characteristics. Upward transitions show a “Matthew effect,” with spatial neighborhoods significantly influencing state changes.

High transformation decarbonization levels result from synergistic interactions among technological, organizational, and environmental factors. Three pathways emerge: “technology-environment” synergy, “technology-organization” synergy, and “technology-organization-environment” joint pathways, with green technology innovation playing a pivotal role across all configurations.

Different city types rely on distinct factors: growing cities depend on digital technology and environmental concern; mature cities are jointly driven by technological innovation, industrial upgrading, and environmental factors; declining cities are more heavily influenced by environmental factors; and regenerating cities emphasize synergistic technological-environmental drivers.

4.2 Implications

Differentiated, Layered Policy Implementation. Lagging-zone cities should strengthen green infrastructure and environmental regulation to guide low-carbon technology adoption. Initial-zone cities need increased support for green technology R&D and industrialization. Transitional-zone cities should focus on industrial structure upgrading and low-carbon transformation of high-energy-consuming industries. Pioneering-zone cities should encourage frontier green technology exploration, support digital-green finance integration, and expand technology demonstration effects.

Regional Collaboration Platforms. Establish cross-regional transformation decarbonization networks for technology transfer and sharing. Encourage upstream-downstream industrial chain coordination to optimize resource allocation and reduce logistics-related emissions. Strengthen cross-regional environmental supervision and clarify carbon emission responsibilities to avoid "race-to-the-bottom" competition and foster positive green development interactions.

Type-Specific Pathways. Growing cities should integrate digital technology with environmental governance to support green tech enterprises. Mature cities should achieve transformation through industrial optimization, technological upgrading, and environmental synergy, guiding traditional industries toward low-carbon models. Declining cities must strengthen environmental regulation to drive corporate green transformation. Regenerating cities should intensify green technology R&D and low-carbon industry development. Successful experiences should be summarized and shared through a "knowledge-sharing platform" and case library for broader reference.

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Note: Figure translations are in progress. See original paper for figures.