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Insights from spatial Markov chain and dynamic QCA into the spatiotemporal evolution and configurational pathways of eco-efficiency in China's coastal megaregions

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As critical zones subject to intensive human activities and significant environmental pressures, coastal megaregions require differentiated improvements in ecological efficiency (EE) to advance sustainable development. Adopting an institutional logics perspective, this study examines China's five major national coastal city clusters and develops a triple-dimensional framework integrating "government–market–technology" forces to enhance EE. By innovatively combining a spatial Markov chain model with dynamic qualitative comparative analysis (QCA), we investigate the dynamic evolution of EE and the spatiotemporal heterogeneity of its configuration pathways. The results indicate that: (1) EE in coastal megaregions exhibited fluctuating growth, with the Pearl River Delta and the West Coast Straits regions consistently leading. The number of high-efficiency cities increased annually, showing a clear pattern of spatial agglomeration. (2) Latitudinally, EE displayed a south-high-north-low gradient with a central trough; longitudinally, it followed a persistent U-shaped distribution. (3) EE demonstrated significant path dependency and club convergence, which constrain short-term rapid improvement. However, spatial spillover effects from adjacent areas facilitated dynamic transitions and gradient leaps. (4) High EE is not determined by any single factor but arises from the synergistic interaction of multiple conditions, manifested through three dominant configuration paths: market-dominated, government–market dual-driven, and market–technology dual-driven. The explanatory power of these pathways strengthens over time, exhibiting pronounced spatial imbalance and geographic dependence within city clusters. This study extends the theoretical framework for promoting EE and offers practical insights for optimizing ecological governance in coastal megaregions, thereby supporting the acceleration of sustainable development goals.

Keywords Institutional logics, Configuration pathways, Ecological efficiency, Spatio-temporal evolution

In 2015, Transforming Our World: The 2030 Agenda for Sustainable Development established 17 Sustainable Development Goals (SDGs) and 169 associated targets across economic, social, and environmental dimensions, explicitly defining sustainable development as encompassing sustained inclusive economic growth, social progress, and environmental protection. Specifically, it emphasizes enhancing human well-being within ecological carrying capacity boundaries. Ecological efficiency (EE) has emerged as a crucial metric for evaluating sustainable development, where higher EE levels indicate greater environmental welfare performance per unit input[1,2]. The concept of EE was originally proposed by Schaltegger and Sturm[3], later refined by organizations including the World Business Council for Sustainable Development (WBCSD), European Environment Agency (EEA), and United Nations Economic and Social Commission for Asia and the Pacific (ESCAP) through perspectives ranging from fulfilling human development needs to reducing natural resource inputs[4]. EE can be

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operationally defined as generating enhanced human well-being and economic value while minimizing resource consumption, capital expenditure, and pollution emissions to improve quality of life.

Recent literature has witnessed growing scholarly interest in ecological efficiency (EE) across diverse sectors, including agriculture[5], energy[6], finance[7], and tourism[8], spanning disciplines from economics to management and geography. Methodologically, researchers predominantly employ ratio analysis[9]or construct EE evaluation index systems based on input-output frameworks, utilizing models such as conventional DEA[10], non-radial Super-SBM incorporating undesirable outputs[10, 11], and Super-EBM[12]. These measurements account for both desirable socioeconomic outputs and undesirable environmental externalities, comprehensively reflecting regional competitiveness. Spatiotemporal analyses have revealed EE dynamics through three-dimensional kernel density estimation[2], standard deviational ellipses for tracking spatial distribution centroids[13], and hot spot analysis coupled with Gini coefficient decomposition for spatial heterogeneity[1, 14]. While studies have examined national[1, 2]and watershed[15]scales, most adopt either temporal or spatial perspectives separately, with limited integration of spatiotemporal interactions. Determinant research has identified digital economy development[16], environmental regulation[17], green innovation[18], and energy conservation policies[19]as key drivers, analyzed through geographical detectors[2], spatial econometrics[18], and difference-in-differences[19, 20]. However, prevailing studies focus on net effects of isolated factors, neglecting the complex combinatorial pathways through which multiple determinants jointly shape EE in urban systems.

The rapid expansion of coastal megacities has emerged as a defining feature of 21st-century global development. These dynamic hubs, predominantly clustered along continental margins, serve as critical engines for national and global economic prosperity while enhancing human well-being[21]. However, the concentration of population and economic activity has simultaneously imposed unprecedented pressure on fragile coastal ecosystems, triggering resource depletion, environmental degradation[22], and heightened vulnerability to climate change impacts, including sea-level rise and extreme weather events. China exemplifies this paradox: Its coastal urban agglomerations represent the nation's most economically advanced yet resource-intensive and carbon-emitting regions, grappling with dual constraints of ecological carrying capacity and developmental demands. The State Council's Carbon Peak Action Plan Before 2030 (2021) explicitly mandates that key regions—the Beijing-Tianjin-Hebei cluster, the Yangtze River Delta, and Guangdong-Hong Kong-Macao Greater Bay Area—pioneer green transitions as growth poles for high-quality development. As pivotal hubs within global networks and frontline zones confronting environmental challenges, addressing the inherent tension between economic development and ecological imbalance in coastal megaregions represents an issue of both regional and global significance.

However, existing studies have not yet fully revealed the spatial transfer laws of EE in China's coastal urban agglomerations at different development stages, nor have they systematically clarified the differentiated configuration paths and their spatio-temporal heterogeneity of multi-factor collaborative driving for improving EE. As a result, a research gap has emerged between theoretical construction and policy practice. By reviewing existing literature, this study focuses on the five major urban agglomerations in China, aiming to explore the following three questions. (1) As engines of national economic development, China's five major coastal urban agglomerations also bear enormous ecological pressure. What evolutionary patterns and gradient differences do EE present from spatio-temporal dimensions? (2) Does the evolution of EE show significant spatial effects? How does the development status of adjacent regions affect the local EE transformation through spillover effects? (3) Under China's unique political system, multiple institutional logics such as government, market, and technology coordinate and interact with each other. What differentiated configuration modes and spatio-temporal heterogeneity exist in the improvement of EE under different combinations of institutional logics? Based on the above research questions, this paper explores the spatio-temporal evolution patterns and dynamic transfer laws of EE in coastal urban agglomerations, and identifies the configuration paths to achieve high EE under institutional logics. This work holds important theoretical value and practical significance for promoting the green growth of coastal urban agglomerations and providing a key paradigm for global sustainable development.

This study advances the existing literature through three key contributions:

First, as growth poles of national economic development, China's five major coastal national-level urban agglomerations host 16 low-carbon pilot cities and 39 ecological civilization demonstration zones. Compared with studies conducted at the national or provincial level, this research focuses on these five coastal urban agglomerations. These regions not only serve as the core engines of national economic development but also emerge as ideal samples for exploring the spatio-temporal evolution patterns and regional heterogeneity of EE, owing to their north-south vertical extension along the coastline and significant internal gradient differences. By systematically depicting the spatio-temporal evolution and gradient characteristics of EE, this study provides refined empirical evidence for understanding the EE evolution in large-scale, high-density urbanized areas. Their development models also hold important reference value for inland regions and even global coastal metropolitan areas.

Second, this paper innovatively applies the spatial Markov chain method, integrating the dynamic transfer in the time dimension and the dependence relationship in the spatial dimension into a unified analytical framework to analyze the spatial dynamic transfer laws of EE in urban agglomerations. This approach not only breaks through the limitations of traditional single-time-series or static spatial analysis but also, more importantly, broadens the research perspective of ecological economics to a certain extent by empirically testing how the spillover effects of adjacent regions affect the transformation of local EE. It further provides an empirical basis for cross-administrative collaborative governance.

Third, based on China's unique political and economic context, this study constructs a three-dimensional analytical framework of "government-market-technology" rooted in institutional logics. It adopts the dynamic Qualitative Comparative Analysis (QCA) method, which differs from the "net effect" thinking of traditional regression. Dynamic QCA can avoid endogeneity problems arising from traditional regression analysis. Through

Boolean operations, it effectively identifies the differentiated configuration paths leading to high EE under the combination of multiple institutional logics and reveals the synergistic mechanisms and combined effects of multiple institutional factors. By comparing inter-group and intra-group consistency, this study deepens the understanding of the spatio-temporal heterogeneity of configuration paths for high EE at the empirical level and provides a decision-making basis for formulating targeted and differentiated regional policies in practice.

The remainder of this paper is organized as follows: Sect. 2 details the theoretical framework, variables, and methodology; Sect. 3 presents the empirical results; Sect. 4 discusses contributions and limitations; and Sect. 5 summarizes the conclusions and policy implications.

Materials and methods

Theoretical analysis

The concept of institutional logics was initially developed by Alford and Friedland[23]as the core principles guiding organizational behavior that emerge from cultural and practical foundations across different institutions or societies. Focusing on how multiple institutional logics shape individual actions, this theoretical perspective has proven particularly effective in explaining organizational heterogeneity arising from the long-term coexistence of diverse institutional arrangements within specific systems, leading to its widespread application across various disciplines[24]. Empirical studies have established that China's economic growth and sustainable development are fundamentally influenced by the dynamic interactions among governmental, market, and technological dimensions[25,26], with this tripartite framework demonstrating strong explanatory power through its integration of multidisciplinary research findings[24,27]. Numerous studies have identified environmental regulation, industrial structure, and technological innovation as key determinants of EE[2,28]. Significantly, these factors inherently belong to the institutional logics framework. However, current research has largely overlooked their interactive effects and failed to integrate them into a coherent system. Addressing this gap, our study constructs a comprehensive analytical framework grounded in institutional logics theory, synthesizing existing empirical evidence. This approach provides crucial insights into how different institutional logics combine and interact to generate multiple configuration pathways for enhancing urban EE. The theoretical framework is illustrated in Fig. 1.

(1) Government logic. The government logic refers to the exercise of political authority through policies, regulations, and other instruments based on governance and legitimacy principles to enhance EE, which can be categorized into regulatory and supportive measures. Regulatory approaches manifest as the central government imposing political pressure on local governments through performance evaluation systems to achieve environmental targets[29], where environmental regulations supervise, constrain, and standard-

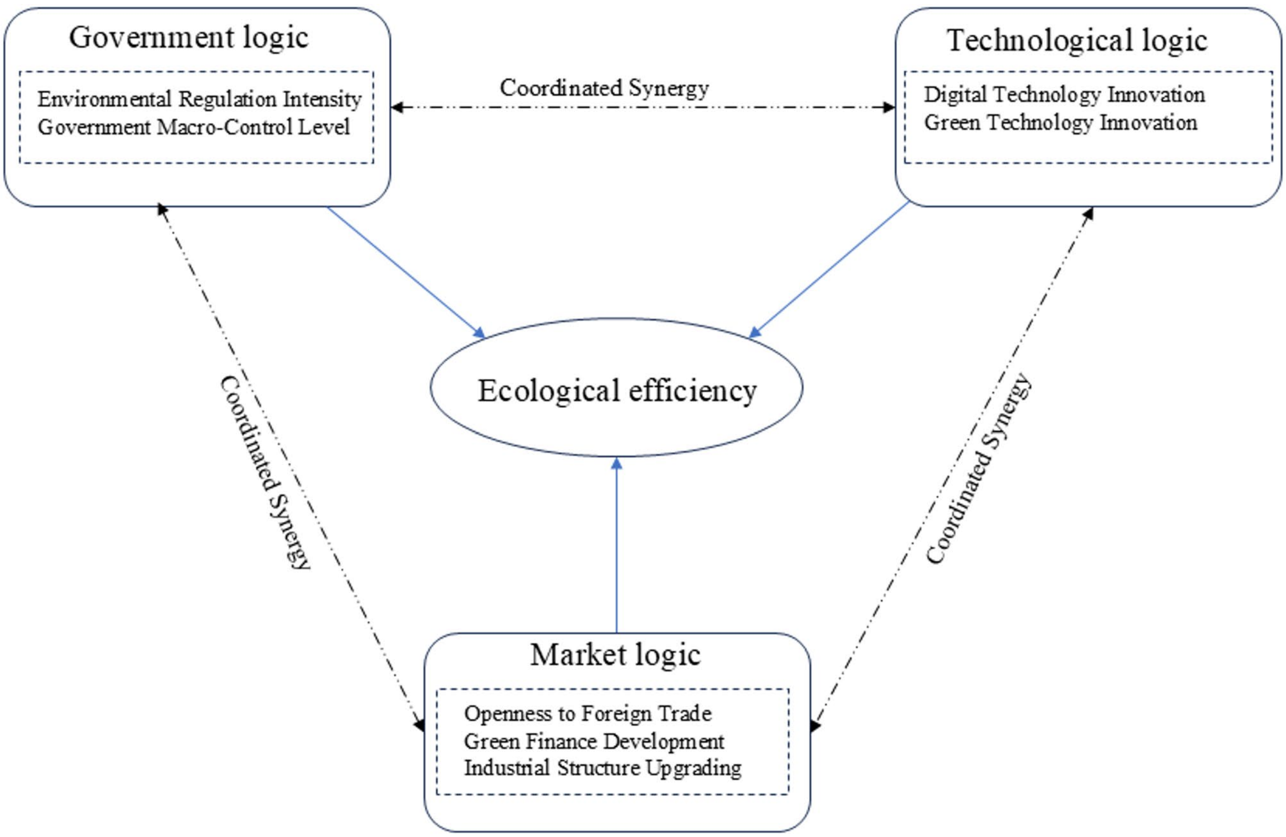

Fig. 1. Theoretical framework diagram.

ize organizational behavior by implementing environmental policies and establishing reward-punishment mechanisms, demonstrating strong enforcement and rapid effectiveness within China's bureaucratic system. Supportive measures are embodied through fiscal incentives, as peer cities engage in mimetic behaviors due to "race-to-the-top" competition, with local governments increasing fiscal expenditures to participate in green GDP tournaments30. The core mechanism lies in utilizing fiscal incentives to drive technological and institutional innovation, optimize resource allocation, and strengthen sustainable development competitiveness, thereby improving urban EE.

(2) Market logic. The market logic emphasizes the decisive role of market mechanisms in resource allocation, leveraging market forces to coordinate environmental and economic development, thereby influencing EE. Under this logic, three key market-driven factors collectively shape EE: First, foreign openness affects EE through two competing hypotheses. The "Pollution Halo Hypothesis" posits that increased openness introduces advanced concepts, equipment, technologies, and capital, thereby enhancing factor allocation efficiency and promoting sustainable development28. Conversely, the "Pollution Haven Hypothesis" suggests that developed countries relocate pollution-intensive industries to developing nations with lower environmental standards through foreign investment to avoid stringent regulation costs, resulting in economic growth accompanied by environmental degradation and reduced EE31. Second, to support green and low-carbon transition, China's Central Bank issued the Guidelines for Establishing the Green Financial System (2016), which utilizes market-based instruments to direct green capital toward nationally prioritized sustainable sectors32. Third, industrial upgrading effectively displaces high-pollution, low-efficiency enterprises through competitive crowding-out and demonstration effects, driving green transformation of industrial structures33. This process reduces undesirable outputs while systematically improving EE.

(3) Technological logic. The technological logic represents the reconfiguration of production factors through technological advancement to decouple economic growth from environmental pollution, thereby enhancing EE. This logic operates through two synergistic pathways: digital technology innovation and green technology innovation, both fundamentally transforming the triad of input factors, desirable outputs, and undesirable outputs. Firstly, digital technological development introduces data and computing power as novel production factors that augment traditional inputs like resources and labor34. The convergence of digital technologies enables real-time monitoring of energy consumption and pollution emissions while fostering emerging economic paradigms, substantially alleviating resource constraints and ecological pressures during urban clusters' sustainable transition35. Secondly, compared to conventional technological innovation, green technology innovation specifically reduces resource/energy intensity through developing and applying environmentally sound technologies, simultaneously improving resource productivity and promoting clean production technologies/renewable energy adoption to minimize undesirable outputs at source26, 36. This dual mechanism resolves the economy-environment paradox by generating economic value while systematically elevating urban EE through technological solutions.

Variable measurement

Outcome variable: EE

EE is grounded in the "input-output" logic, with its essence being to maximize economic benefits while minimizing resource consumption and environmental costs. To comprehensively, accurately, and transparently measure EE, this paper adheres to this core connotation and synthesizes established authoritative research[2, 18]to systematically construct a comprehensive evaluation framework encompassing multidimensional inputs, desirable outputs, and undesirable outputs.

First, input indicators should encompass core production factors such as economic activities and energy consumption. This paper selects input indicators from four dimensions: labor, capital, technology, and resources. "Year-end employed population" more accurately reflects the scale of human resources actually engaged in economic production[12]. "Fixed asset investment" measures the capital stock in the process of social reproduction[2]. "Local government expenditure on science and technology" represents the level of governmental support for technological green transformation. Simultaneously, "built-up area," "total water supply," and "total electricity consumption of the whole society" are included to characterize the occupation and consumption of land, water resources, and energy, respectively[12]. Second, regarding output indicators, the ideal outputs are economic growth and environmental friendliness. In addition to per capita GDP as the core economic output indicator, this study incorporates "green coverage rate of built-up areas" into the indicator system. The rationale is that urban green space is a primary provider of ecosystem services. In densely urbanized coastal areas, the trade-off between green spaces and gray infrastructure is particularly salient. Treating green space as a desirable output helps assess a city's capacity to maintain and enhance ecological livability amidst intensive development[2]. Undesirable outputs primarily represent the environmental costs of economic activities. These include two major categories of industrial pollutants: " industrial sulfur dioxide emissions " and " industrial smoke and dust emissions"[11]. Furthermore, "carbon dioxide emissions" are specifically incorporated to directly align with China's strategic goals of addressing climate change through "carbon emission reduction" and "carbon neutrality." The EE indicator system is presented in Table 1.

Antecedent variables

Based on the theoretical framework established earlier, this study adopts an institutional logic perspective to identify antecedent variables affecting EE across three constitutive dimensions: governmental, market, and technological factors. The variable names, measurement methods, and reference sources are presented in Table 2.

Category	Primary input indicators	Specific indicators	Unit
Input indicators	Labor	Year-end employed population	10^4 persons
	Capital	Fixed asset investment	10^7 yuan
	Technology	Local government expenditure on science and technology	10^6 yuan
	Resource	Built-up area	km^2
		Total water supply	10^6 m^3
		Total electricity consumption	10^7 kWh
Output indicators	Desirable	GDP per capita	10^8 yuan
		Urban green space area	ha
	Undesirable	Industrial sulfur dioxide emissions	t
		Industrial smoke and dust emissions	t
		Carbon dioxide emissions	10^8 t

Table 1. Ecological efficiency evaluation index system.

Category	Dimension	Variable name	Measurement method	References
Antecedent variables	Government	X1 Environmental regulation intensity	Frequency count of environmental protection keywords (15 keywords) extracted from government reports using Python web scraping	37, 38
		X2 Government macro-control level	Government fiscal expenditure/GDP	39, 40
	Market	X3 Openness to foreign trade	Total import and export volume/GDP	28
		X4 Green finance development	Comprehensive weighted score of: green credit, green investment, green insurance, green bonds, green support, green funds, and green equity	41, 42
		X5 Industrial structure upgrading	Value-added of the tertiary industry/Value-added of the secondary industry	33
	Technology	X6 Digital technology innovation	Number of digital economy patent applications	43
		X7 Green technology innovation	Number of green patent applications (Green invention patents + Green utility model patents)	26, 44

Table 2. Names of antecedent variables and description of their measures.

Research methodology

Super-Efficiency Epsilon-Based measure (EBM) model

Currently, the mainstream methods for efficiency measurement are primarily divided into two categories: parametric approaches, represented by Stochastic Frontier Analysis (SFA), and non-parametric approaches, represented by Data Envelopment Analysis (DEA). The SFA method requires a pre-specified production function form. If the functional form is misspecified, it can lead to significant measurement bias. Furthermore, SFA is typically limited to handling problems with multiple inputs and a single output, which imposes significant limitations. In contrast, the DEA method effectively addresses these shortcomings of SFA. It does not depend on a specific functional form, is based on dimensionless data processing, helps reduce model bias, and is capable of solving efficiency problems involving multiple inputs and multiple outputs. Specifically, traditional DEA models can be classified into radial and non-radial types. Since traditional radial DEA models cannot effectively resolve inefficiency issues caused by input-output slacks, Tone and Tsutsui[45]proposed a hybrid distance function model, namely the Epsilon-Based Measure model (EBM). The EBM model combines both radial and non-radial approaches in DEA. It fully accounts for non-radial slack variables in inputs and outputs while maintaining the radial proportion between frontier values and actual values, resulting in more accurate efficiency measurements for decision-making units. Therefore, this study employs a Super-EBM model incorporating undesirable outputs to calculate the EE of urban agglomerations as the outcome variable, with the specific formula as follows[12].

$$E^* = \min \frac{\theta - \varepsilon_x \sum_{i=1}^{m} w_i^- s_i^- / x_{i0}}{\varphi + \varepsilon_y \sum_{r=1}^{s} w_r^+ s_r^+ / y_{r0} + \varepsilon_z \sum_{p=1}^{q} w_p^{z-} s_p^{z-} / z_{p0}}$$
$$s.t. \begin{cases} \sum\limits_{j=1}^{n} x_{ij}\lambda_j + S_i^- = \theta x_{i0} \, (i = 1, 2, \ldots, m) \\ \sum\limits_{j=1}^{n} y_{rj}\lambda_j - S_r^+ = \varphi y_{r0} \, (r = 1, 2, \ldots, s) \\ \sum\limits_{j=1}^{n} z_{pj}\lambda_j + S_p^- = \varphi z_{p0} \, (p = 1, 2, \ldots, q) \\ \qquad \lambda_j \geq 0, S_i^-, S_r^+, S_p^- \geq 0 \end{cases} \tag{1}$$

In Eq. (1): E^* represents the efficiency value; *x*, *y* and *z* denote input factors, desirable outputs, and undesirable outputs, respectively; *m*, *s* and *q* indicate their respective quantities; λ signifies the relative importance weight of decision-making units; θ and ϕ are key parameters for the radial component; ϵ is the critical parameter for the non-radial component, with a value range of [0,1]; w_i, w_r and w_p represent the weights assigned to the *i*th input, *r*th desirable output, and *p*th undesirable output, respectively.

Trend surface analysis
Trend surface analysis is based on regression principles and employs the least squares method to fit a two-dimensional nonlinear function. This method uses mathematical surfaces to simulate the spatial distribution and variation trends of geographic elements. By transforming two-dimensional sampling points into a three-dimensional smoothed surface, it takes geographic coordinates (x, y) as independent variables and the observed value z as the dependent variable to analyze the spatial variation patterns of *z*. The calculation formula is as follows:

$$Z_I\left(X_I, Y_I\right) = z_i\left(x_i, y_i\right) + \varepsilon_i \tag{2}$$

In Eq. (2): $\left(x_i, y_i\right)$ represents the geographic coordinates of the sampling points; ϵ_i is the residual term.

Spatial Markov chain
Traditional Markov chains utilize transition probability matrices to calculate the probability distribution of each type, reflecting the upward or downward mobility of regional characteristics. With reference to relevant literature[46, 47], this paper adopts the quartile method (with the three breakpoints set at the 75th, 50th, and 25th percentiles, respectively) to discretize EE into four state types: I (low), II (relatively low), III (relatively high), and IV (high). The reasons are as follows. First, the quartile method ensures a roughly balanced number of cities within each state category. Simultaneously, it naturally forms a performance hierarchy of low, relatively low, relatively high, and high, which can comprehensively reflect a city's relative position within the overall sample and thereby allow for the observation of mobility across tiers. Finally, compared to classification based on absolute values or fixed thresholds, the quartile method is less sensitive to outliers and enhances comparability over time. However, since a city's efficiency type is influenced not only by its state changes but also by the efficiency types of neighboring cities, the spatial Markov chain incorporates a spatial lag term. This method discretizes regional states into *k* types and constructs *k* transition probability matrices of size *k*×*k*, clearly revealing the probabilities of EE improvement or decline under different neighborhood conditions. This study selects the geographic contiguity matrix as the spatial weight matrix. Based on Tobler's First Law of Geography, which states that "near things are more related than distant things." The geographic contiguity matrix directly captures this spatial proximity relationship. Furthermore, by considering only directly adjacent units, it effectively mitigates interference from spurious long-distance correlations, thereby enhancing the interpretability of the results. The formula is as follows[48]:

$$Lag_i = \sum_{j=1}^{n}\left(Y_j W_{ij}\right) \tag{3}$$

In Eq. (3): Lag_i represents the spatial lag value for city *i*; Y_j denotes the observed value for city *j*; W_{ij} is the spatial weight matrix defining the spatial relationship between cities *i* and *j*. This study adopts a binary contiguity matrix (0 = no adjacency, 1 = adjacency)¨ n indicates the total number of cities.

Spatial effects test formula:

$$Q_b = -2\log\left\{\prod_{l=1}^{k}\prod_{i=1}^{k}\prod_{j=1}^{k}\left[\frac{m_{ij}}{m_{ij}\left(S\right)}\right]^{n_{ij}\left(S\right)}\right\} \tag{4}$$

In Eq. (4): k represents the number of EE categories (in this study, =4), $n_{ij}\left(S\right)$ denotes the count of cities undergoing spatial Markov transitions with neighborhood state *S*, m_{ij} indicates the traditional Markov transition probability; $m_{ij}\left(S\right)$ signifies the spatial Markov transition probability conditioned on neighborhood state *S*.

Dynamic qualitative comparative analysis (QCA)
The QCA method combines the strengths of qualitative and quantitative analysis. Based on Boolean algebra and set theory principles, it focuses on logical relationships between sets rather than simple correlations, enabling identification of "equifinal" driving mechanisms under different combinations of antecedent conditions while avoiding estimation bias caused by endogeneity[27, 49]. Traditional static QCA analysis examines only a single temporal cross-section, neglecting changes over time. This limitation may lead to sampling time selection bias and reduced reliability of conclusions. Since urban EE is a dynamic process involving temporal evolution, this study adopts dynamic QCA to investigate how multiple antecedent conditions generate differentiated configurations of outcome variables across different periods, thereby obtaining more accurate empirical evidence on urban sustainable development drivers. By calculating between-group, within-group, and overall consistency measures along with adjusted distances, the analysis identifies temporal effects and case effects of configurations[50]. The formulas for consistency and coverage are as follows:

$$\left(X_t \leq Y_t\right) = \sum\left[\min\left(X_t, Y_t\right)\right] / \sum\left(X_t\right) \tag{5}$$

$$\left(X_t \leq Y_t\right) = \sum\left[min\left(X_t, Y_t\right)\right] / \sum\left(Y_t\right) \tag{6}$$

In Eqs. (5) and (6): X_k and Y_k represent the subordination of the k antecedent condition and the subordination of the resultant set, respectively.

Study area and data sources

This research encompasses 96 cities within China's five national-level coastal megaregions during the 2011–2022 timeframe, distributed as follows: Beijing-Tianjin-Hebei (13 cities), Shandong Peninsula (16 cities), Yangtze River Delta (38 cities), West Taiwan Strait (20 cities), and Pearl River Delta (9 cities). Figure 2 presents a map of the study area. Megaregion boundaries align with authoritative planning documents, including the Beijing-Tianjin-Hebei Coordinated Development Plan, Shandong Territorial Spatial Plan (2021–2035), Yangtze River Delta Integration Plan, West Taiwan Strait Urban Cluster Plan, and Guangdong-Hong Kong-Macao Greater Bay Area Framework. Notably, the cities of Wenzhou, Quzhou and Lishui appearing in both Yangtze River Delta and West Taiwan Strait megaregions were assigned to the latter jurisdiction for analytical balance. For the convenience of reference, a complete list of the city samples is provided in Appendix A.

Empirical data were procured from China's Urban Statistical Yearbook, Energy Statistical Yearbook, and Urban Construction Statistical Yearbook, supplemented by municipal socioeconomic bulletins. Upon reviewing the raw data, we found that missing values accounted for no more than 2% of the total. These gaps were addressed using linear interpolation. Patent metrics originated from the National Intellectual Property Administration (https://www.cnipa.gov.cn), while CO_2 emissions were compiled from EDGAR (Emissions Database for Global Atmospheric Research) and spatially aggregated to prefectural-level totals through raster-based processing in ArcGIS 10.8.

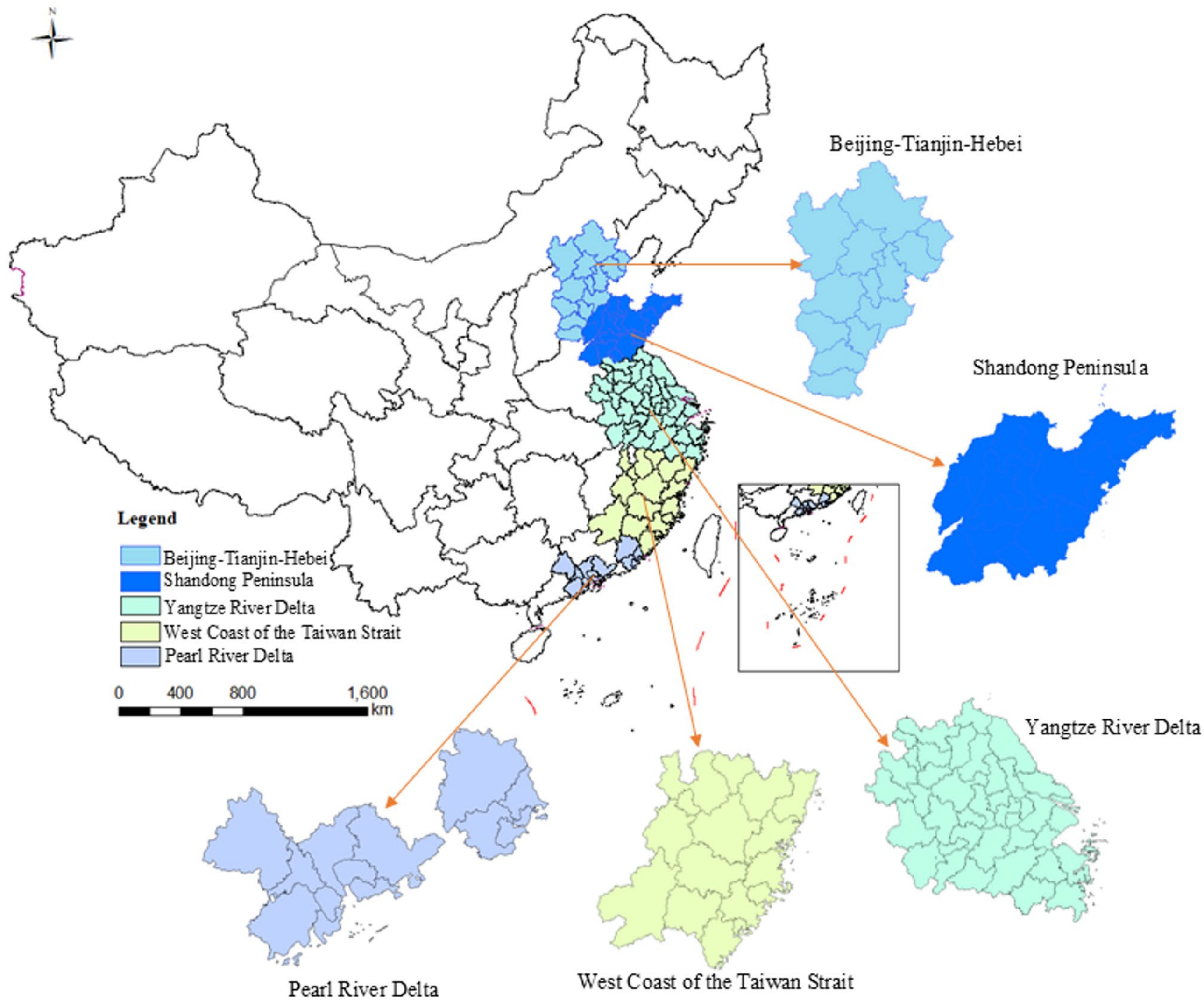

Fig. 2. Map of the study area. Software version: ArcMap 10.8, URL: https://www.esri.com/zh-cn/arcgis/products/index. This map is produced based on the standard map with the review number GS(2024)0650, downloaded from the National Geographic Information Public Service Platform (website: https://www.tianditu.gov.cn/). No modifications were made to the original base map.

Results

Temporal evolution of EE

As illustrated in Fig. 3 (The data corresponding to Fig. 3 can be found in Table 1 of Online Appendix A), the average EE across China's five coastal megaregions exhibited a fluctuating upward trajectory during 2011–2022. Efficiency rankings consistently positioned Pearl River Delta highest, followed by West Taiwan Strait, Shandong Peninsula, Yangtze River Delta, and Beijing-Tianjin-Hebei. A marked efficiency decline occurred universally in 2016–2017, attributable to China's inaugural central environmental inspection campaign. This initiative, recognized as one of the nation's most stringent environmental enforcement actions[51], manifested through institutional innovations, enhanced accountability mechanisms, and comprehensive regulatory coverage. These measures prompted widespread closures of high-pollution enterprises, causing immediate industrial output contraction. Concurrently, pollution control investments such as environmental facility retrofits had not yet yielded measurable efficiency improvements during this transitional phase, resulting in temporary efficiency reductions. From 2017 onward, all megaregions demonstrated sustained efficiency growth, reflecting successful adaptation to environmental governance standards and industrial restructuring.

Spatial evolution of EE

Using the natural breaks method in ArcGIS 10.8, we visualized cross-sectional data from 2011, 2015, 2019, and 2022 to identify the spatial distribution patterns of EE in the five coastal megaregions. Figure 4(a-d) shows that all four time points exhibited a spatial differentiation characteristic of decreasing efficiency from coastal to inland areas (The data corresponding to Fig. 4 can be found in Table 2 of Online Appendix A). In 2011 and 2015, high-efficiency zones were sporadically distributed. By 2019, high-efficiency areas showed localized clustering trends, with significantly enhanced synergy and balance of EE, likely benefiting from the implementation of green development strategies in the 13th Five-Year Plan (2016–2020). In 2022, high-efficiency zones formed continuous distribution patterns, completing the transition to a "core-periphery" gradient structure, indicating effective sustainable development cooperation and policy coordination among urban agglomerations and accelerated regional integration. The spatial evolution characteristics can be summarized as: overall value improvement (continuous increase in proportion of high-value zones), reduced development gaps (upper limit of low-efficiency zones increased from 0.410277 in 2011 to 0.546287 in 2022), and significant spatial agglomeration (evolution from scattered distribution to continuous clustering).

Spatial gradient evolution

The coastal megaregions demonstrate unique geographical positioning, economic agglomeration, and ecological sensitivity, with significant latitudinal variations along the north-south axis exhibiting distinct gradient characteristics, directional patterns, and clustering features that were effectively captured through trend surface

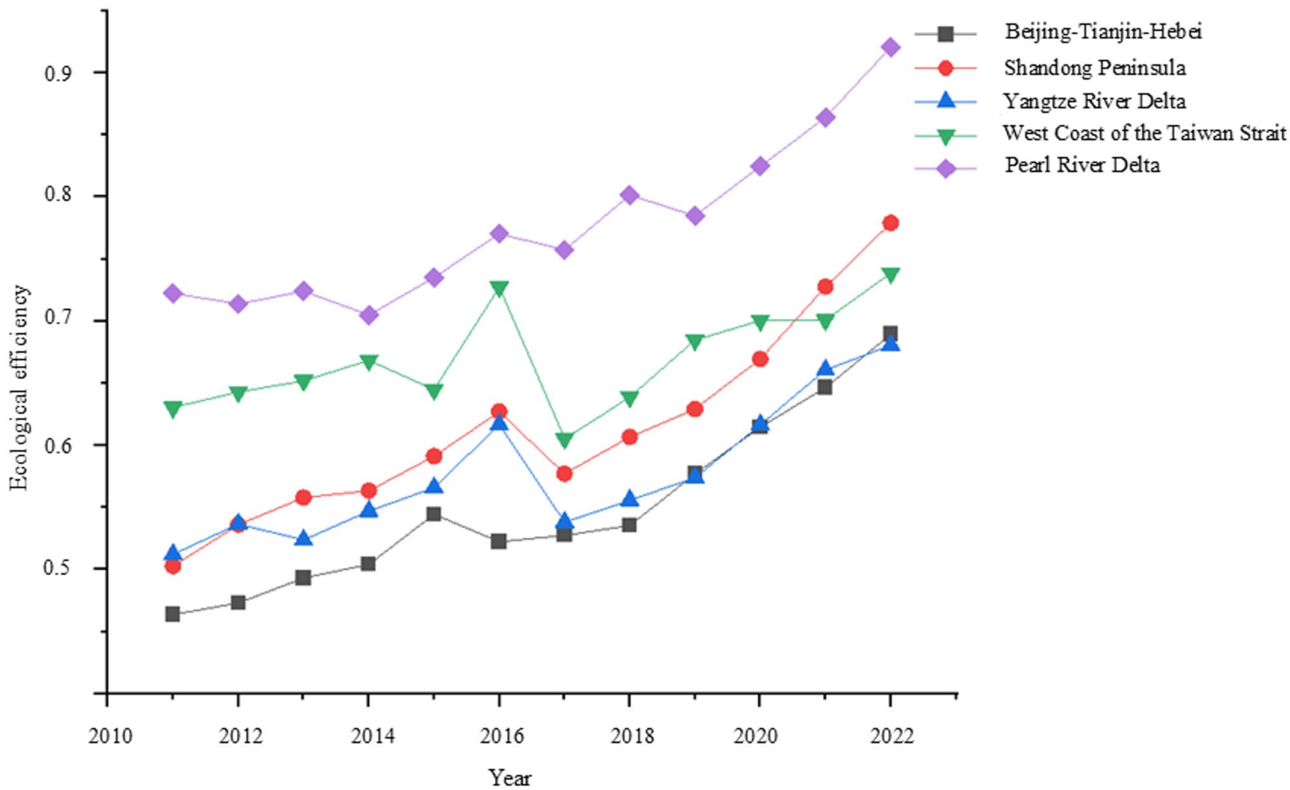

Fig. 3. Temporal trends in EE in five major coastal urban agglomerations.

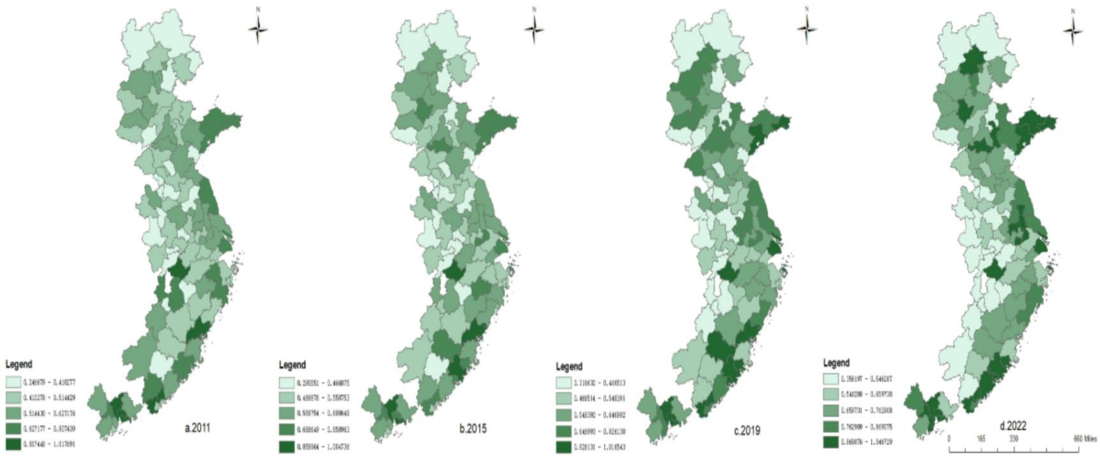

Fig. 4. Evolution of the spatial pattern of EE in coastal urban agglomerations. Software version: ArcMap 10.8, URL: https://www.esri.com/zh-cn/arcgis/products/index. This map is produced based on the standard map with the review number GS(2024)0650, downloaded from the National Geographic Information Public Service Platform (website: https://www.tianditu.gov.cn/). No modifications were made to the original base map.

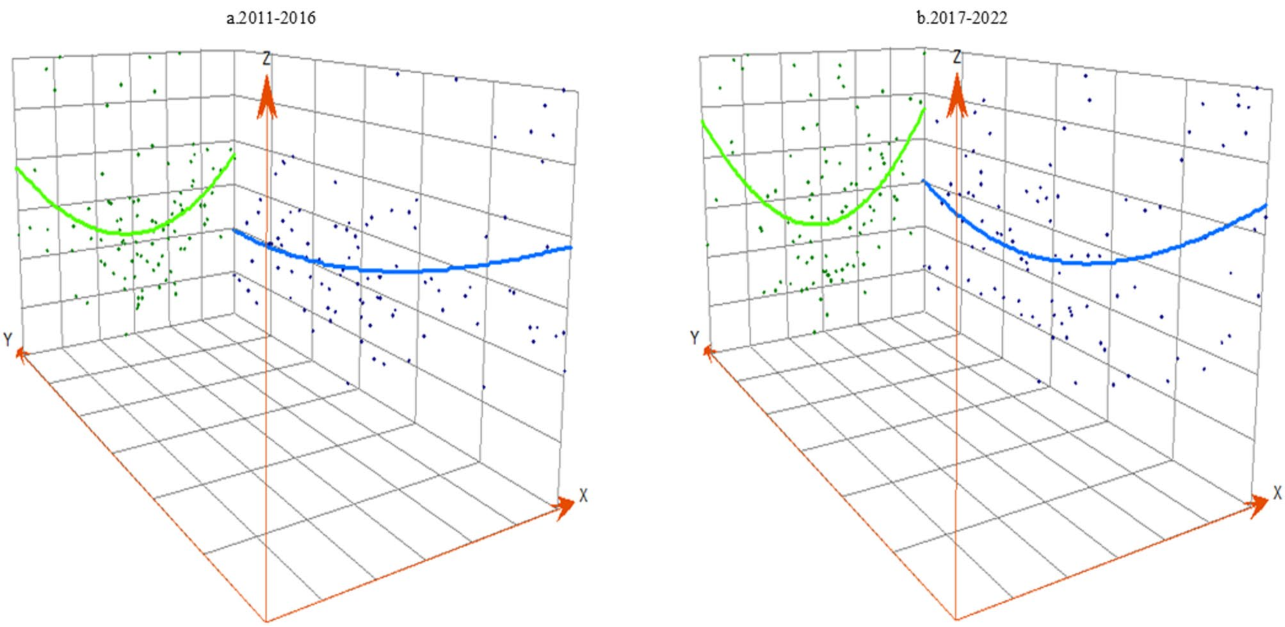

Fig. 5. Trend surface analysis of EE in coastal urban agglomerations.

analysis using ArcGIS 10.8. The study period was divided equally into two phases (2011–2016 and 2017–2022), with Fig. 5 revealing systematic directional variations in EE gradients. Along the north-south direction (blue fitted lines in Fig. 5a and b), both periods showed higher efficiency in southern regions, though the 2017–2022 phase exhibited an expanded north-south disparity as Beijing-Tianjin-Hebei and Shandong Peninsula improved while Pearl River Delta maintained its leading position, ultimately forming a central depression flanked by elevated northern and southern zones. The east-west analysis (green fitted lines in Fig. 5a and b) confirmed persistent U-shaped distributions during 2017–2022 with overall efficiency gains, yet demonstrated widening coastal-inland gaps and a more pronounced central depression, indicating southern and eastern coastal cities gradually consolidated their positions as EE leaders over time, while central regions lagged. These findings show that over time, southern coastal urban agglomerations and eastern coastal cities gradually occupied the high ground of EE.

Spatial transition patterns

This study analyzes EE transition patterns in China's five coastal megaregions using conventional and spatial Markov chains. Key findings include: (1) Diagonal probabilities in the transition matrix all exceed non-diagonal

	Type of spatial lag	t/(t+1)	I	II	III	IV	Observations
Traditional	lag-free	I	0.7806	0.2122	0.0072	0.0000	278
		II	0.1007	0.6381	0.2351	0.0261	268
		III	0.0147	0.0989	0.6703	0.2161	273
		IV	0.0000	0.0211	0.0928	0.8861	237
Spatial	I	I	0.8182	0.1818	0.0000	0.0000	88
		II	0.1091	0.6909	0.2000	0.0000	55
		III	0.0667	0.0000	0.9333	0.0000	15
		IV	0.0000	0.0000	0.0000	1.0000	6
	II	I	0.7885	0.1923	0.0192	0.0000	104
		II	0.1412	0.5882	0.2588	0.0118	85
		III	0.0198	0.1089	0.7426	0.1287	101
		IV	0.0000	0.0323	0.0968	0.8710	31
	III	I	0.7595	0.2405	0.0000	0.0000	79
		II	0.0842	0.6632	0.2316	0.0211	95
		III	0.0097	0.0971	0.5825	0.3107	103
		IV	0.0000	0.0225	0.1573	0.8202	89
	IV	I	0.5000	0.5000	0.0000	0.0000	6
		II	0.0313	0.6250	0.2500	0.0938	32
		III	0.0000	0.1111	0.6296	0.2593	54
		IV	0.0000	0.0196	0.0490	0.9314	102

Table 3. Spatial Markov chain transfer probability matrix for coastal urban agglomerations.

elements (minimum diagonal probability: 63.81%; maximum non-diagonal probability: 23.51%), indicating a minimum 63.81% probability of maintaining original efficiency states and confirming "status quo inertia". (2) Extreme quartiles (I and IV) show higher stability (78.06% and 88.61% respectively) than intermediate quartiles (II: 63.81%; III: 67.03%), demonstrating "club convergence". (3) Upward transition probabilities (21.22% for I→II, 23.51% for II→III, 21.62% for III→IV) significantly exceed downward probabilities (10.07% for II→I, 9.89% for III→II, 9.28% for IV→III), particularly for quartiles II and III. (4) Adjacent-quartile transitions (maximum probability: 23.51%) dominate non-adjacent transitions (maximum: 2.61%), aligning with lifecycle theory. Spatial effects testing (Eq. 4: Qb = 89.338658, $p = 0.000002$) confirms significant spatial spillovers, necessitating spatial Markov matrices with a 1-year lag. Results show: (1) Efficiency types demonstrate spatial synergy - regions with type I neighbors contain more type I observations (t period) than other types, and similarly for type IV. (2) Neighborhood types critically influence transitions: adjacency to high-efficiency cities elevates upward transition probabilities ($P_{12}|_3$= 24.05%> P_{12} =21.22%; $P_{12}|_4$ =50%>21.22%; $P_{23}|_4$ =25%>23.51%; $P_{34}|_4$ =25.93%>21.61%), indicating spatial spillovers facilitate path-breaking upgrades.

Configuration analysis of EE improvement pathways in urban agglomerations

Calibration

Using EE as the outcome variable, this study examines differentiated configuration pathways of seven antecedent conditions under government, market, and technology institutional logics. Following Fiss (2011), in the absence of strong theoretical priors, mechanically applying fixed thresholds to set calibration anchors can introduce significant bias due to outliers[52]. Therefore, setting anchors based on percentiles in alignment with the data distribution characteristics can identify relatively high, medium, and low levels within the sample. This approach is regarded as the most objective and equitable calibration method[53]. Given the numerical characteristics of the selected variables, continuous variables were calibrated into fuzzy sets (0–1) using direct calibration, with the 90th, 50th, and 10th percentiles as full membership, crossover, and full non-membership anchors, respectively. Cases with exact 0.5 membership scores were recoded as 0.499 to minimize data exclusion.

Necessity analysis

Before configuration analysis, individual condition consistency scores determine necessary conditions: (1) Conditions with ≥ 0.9 consistency are considered necessary for the outcome. (2) Unlike conventional QCA, dynamic QCA enhances reliability by evaluating between-group and within-group consistency adjusted distances to assess temporal and case effects. Smaller adjusted distances (closer to 0) indicate a more precise measurement. Table 4 shows all antecedent conditions' consistency scores < 0.9 (non-necessary individually), with adjusted distances < 0.2 threshold, confirming the absence of temporal/case effects[54]. Further analysis of condition configurations is required to examine synergistic effects under different institutional logics.

Configuration analysis

The configuration pathway analysis requires four parameter specifications. First, configuration consistency exceeding 0.75 indicates sufficient conditions for the outcome variable[55]; thus, this study sets the consistency threshold at 0.8. Second, given that the sample size exceeds 150 cases, the case frequency threshold is set at

Antecedent variables	High EE			
	Consistency of aggregation	Coverage of aggregation	Between-group consistency adjustment distance	Within-group consistency adjustment distance
X1	0.617	0.605	0.055	0.031
~ X1	0.637	0.589	0.058	0.031
X2	0.542	0.543	0.032	0.053
~ X2	0.709	0.643	0.019	0.044
X3	0.686	0.704	0.019	0.044
~ X3	0.588	0.522	0.015	0.049
X4	0.78	0.721	0.057	0.034
~ X4	0.508	0.498	0.132	0.043
X5	0.675	0.667	0.064	0.038
~ X5	0.6	0.551	0.079	0.043
X6	0.666	0.721	0.055	0.042
~ X6	0.615	0.523	0.063	0.047
X7	0.667	0.715	0.06	0.042
~ X7	0.615	0.526	0.067	0.046

Table 4. Consistency analysis of antecedent variables.

Antecedent variables	Market-dominated	Government-market dual-driven type	Market- technology dual-driven type			
	M1 Openness-Green finance-Industrial structure driven	H1 Environmental regulation-Openness-Green finance driven	S1 Green finance-Digital technology innovation synergy		S2 Openness-Green finance-Green technology innovation driven	S3 Openness-Green finance-Industrial structure-Digital technology innovation synergy
	M1	H1	S1a	S1b	S2	S3
X1		A		u	u	
X2	U	U	U	U	U	
X3	A	A		a	A	A
X4	A	A	A	A	A	A
X5	A			u	u	A
X6	u	u	A	A		A
X7	u	u	a		A	a
Consistency	0.904	0.894	0.874	0.938	0.931	0.897
Coverage	0.23	0.24	0.478	0.239	0.236	0.419
Unique coverage	0.005	0.023	0.082	0.001	0.001	0.069
PRI	0.611	0.617	0.738	0.762	0.729	0.781
Between-group consistency adjustment distance	0.008	0.021	0.016	0.011	0.012	0.01
Within-group consistency adjustment distance	0.02	0.021	0.021	0.014	0.015	0.019
Overall consistency	0.85					
Overall coverage	0.605					

Table 5. Configuration pathways for high EE in coastal urban agglomerations.

2 to ensure 75% case coverage. Third, the proportional reduction in inconsistency (PRI) should exceed 0.5[56]; through parameter testing and considering required solution coverage, this study sets PRI at 0.6. Fourth, due to inconclusive evidence regarding antecedent conditions' directional effects on EE, the counterfactual analysis makes no directional assumptions - both presence and absence of single conditions may contribute to high efficiency.

The intermediate solution was derived, with core/ peripheral conditions determined by nesting parsimonious and intermediate solutions (conditions appearing in both solutions are marked as core presence A; those appearing only in the intermediate solution as peripheral presence a; absent in both as core absence U; absent in only one as peripheral absence u). As Table 5 shows, each high-efficiency configuration type across the five megaregions is analyzed separately.

Table 5 demonstrates an overall solution consistency of 0.85, indicating that 85% of cases following these six configurations achieved high EE. The solution coverage reaches 0.605, explaining approximately 60% of high-efficiency cases. These six configurations can be categorized into three types: market-dominated (M1: Openness-Green finance-Industrial structure driven), government-market dual-driven (H1: Environmental regulation-Openness-Green finance driven), and market-technology dual-driven (S1a-S1b: Green finance-Digital technology innovation synergy; S2: Openness-Green finance-Green technology innovation driven; S3: Openness-Green finance-Industrial structure-Digital technology innovation synergy).

(1) Market-dominated type (M1). Configuration M1 demonstrates that high openness, developed green finance, and an advanced industrial structure serve as core conditions enabling high EE even without government intervention, digital technology innovation, or green technology innovation. This pathway covers 23% of cases. Characterized by market dimension variables, it is designated "M1: Openness-Green finance-Industrial structure driven". High openness facilitates international resource flows and technology exchange28, green finance provides capital support for clean technology R&D while reducing financing constraints for environmentally friendly enterprises and undesirable outputs42, and industrial upgrading enhances ecological benefits by eliminating high pollution firms and optimizing resource allocation33. This pathway's success relies on the virtuous interaction among open economy vitality, mature green finance systems, and continuous industrial structure optimization. Within M1, high openness introduces technology diffusion and green investments that generate investable projects for green finance development; simultaneously, green finance reduces industrial upgrading financing barriers through optimized capital allocation; industrial upgrading further enhances openness quality by promoting agglomeration of high-value-added green industries. This configuration reveals the endogenous mechanism of ecological efficiency improvement under market-dominated paradigms.

(2) Government-market dual-driven type (H1). Configuration H1 indicates that stringent environmental regulation, high openness, and developed green finance constitute core conditions for high efficiency, covering 24% of cases. Termed "H1: Environmental regulation-Openness-Green finance driven", this pathway combines governmental and market dimensions. High environmental regulation forces production optimization and pollution reduction through strict policies, providing institutional safeguards for green development38; high openness introduces advanced environmental technologies and management experience, enhancing market vitality and competition efficiency57; developed green finance accelerates green transition by funding low-carbon industries and sustainable projects58. Under their synergy, environmental regulation establishes mandatory standards that screen imported green technologies while guiding green finance investments; openness reinforces regulatory implementation through international competition and creates cross-border green investment opportunities. This pathway's success depends on effective environmental policy enforcement, deep engagement of open economies, and perfected green finance systems, reflecting complementarity and synergy in EE improvement under government market dual-driven models.

(3) Market-technology dual-driven type (S1-S3). Configurations S1a (47.8% coverage) and S1b (23.9% coverage), collectively designated "S1: Green finance-Digital technology innovation synergy", share core conditions of developed green finance, advanced digital technology innovation, and low government intervention, supplemented by either high openness (S1a) or high green innovation (S1b). Developed green finance constrains polluting firms' financing while expanding funding channels for green enterprises, improving investment efficiency, and enabling green transition59; advanced digital technology innovation optimizes resource utilization through intelligent data-driven management35; low government intervention indicates market self-regulation dominance. S1a leverages openness for international technology and capital inflows, while S1b utilizes green innovation to enhance clean production capabilities. Within S1, green finance and digital technology innovation establish mutual reinforcement: Digital technologies improve environmental monitoring precision that guides green finance toward clean industries, while green finance provides dedicated funding for environmental applications of digital technologies.

Configurations S2 " Openness-Green finance-Green technology innovation driven" (23.6% coverage) and S3 "Openness-Green finance-Industrial structure-Digital technology innovation synergy" (41.9% coverage) confirm the market technology collaborative paradigm. High openness promotes transnational flows of green technologies through international spillovers and market competition; developed green finance establishes diversified investment systems (e.g., green credit, green funds) that precisely allocate resources to low-carbon industries and R&D. While openness and green finance remain essential, the core presence of digital and green technology innovation further validates the effectiveness of market technology synergistic frameworks.

Configuration Spatiotemporal heterogeneity analysis
Dynamic QCA addresses the limitation of traditional static approaches by incorporating temporal dimensions, revealing temporal variations in within-group consistency levels and identifying dynamic transitions among different patterns. Drawing on the theoretical and methodological framework of panel QCA proposed by Castro and Ariño[54], this study further examines the between-group and within-group consistency, as well as consistency adjustment distance for each configuration across five urban agglomerations[54]. As shown in Table 5, both between-group and within-group consistency adjustment distances for individual configurations remain below 0.2, indicating no significant temporal or case effects during the study period. The aggregated consistency results demonstrate robust stability and explanatory power.

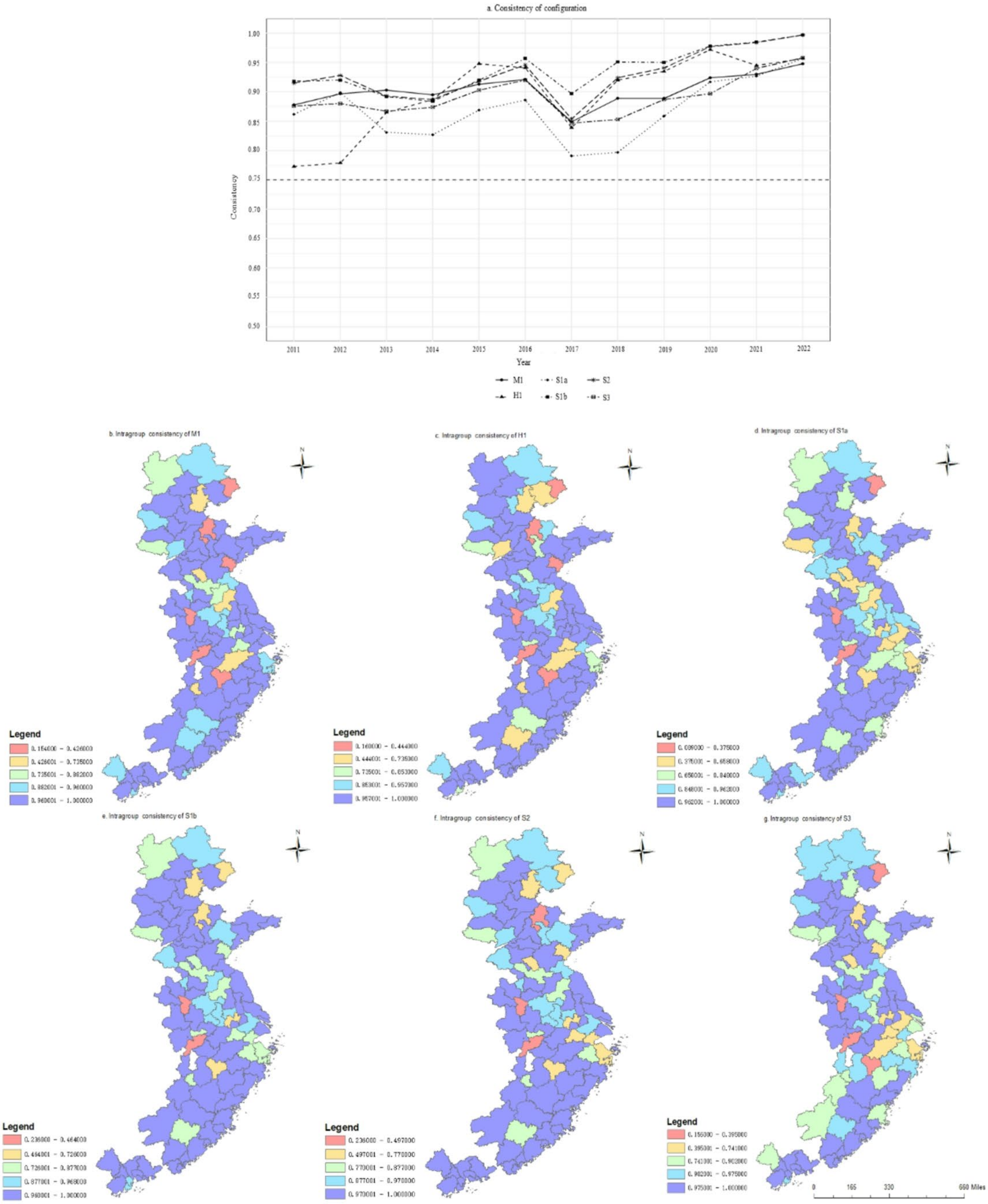

Fig. 6. Spatial and temporal variability of configuration paths. Software version: ArcMap 10.8, URL: https://www.esri.com/zh-cn/arcgis/products/index. This map is produced based on the standard map with the review number GS(2024)0650, downloaded from the National Geographic Information Public Service Platform (website: https://www.tianditu.gov.cn/). No modifications were made to the original base map.

Temporal heterogeneity Between-group consistency evaluates whether each conditional configuration serves as a sufficient condition for the outcome in every year of the sample period. Figure 6a illustrates the temporal trends of between-group consistency for the five urban agglomerations, with the horizontal axis representing years and the vertical axis indicating consistency levels.

Across the five major urban agglomerations from 2011 to 2022, all six configurations exhibit consistency levels above 0.75, confirming strong explanatory power. Further analysis of the temporal trends reveals fluctuating but generally rising consistency levels. Notably, configuration H1 (government-market driven) shows a rapid increase after 2012, highlighting how the synergistic interaction between government intervention and market mechanisms under China's political system can swiftly enhance urban sustainable development. Dynamic QCA effectively compensates for the absence of temporal dimensions in traditional static analyses by tracking temporal trends in within-group consistency. Simultaneously, the between-group consistency results elucidate the dynamic evolution of high EE driving modes in China's coastal urban agglomerations.

Spatial heterogeneity Within-group consistency is analyzed at the city level, assessing whether each configuration serves as a sufficient condition for the outcome across the study period. As illustrated in Fig. 6b–g, the legend (from top to bottom) denotes consistency levels as low, moderately low, moderately high, high, and very high. (The data corresponding to Fig. 6 can be found in Table 3 of Online Appendix A) The results demonstrate that most cities exhibit consistency levels exceeding 0.8 across the six configurations. The findings reveal that from 2011 to 2022, cities did not adhere to uniform configurations, with some achieving high EE through multiple pathways. For instance, the Pearl River Delta urban agglomeration displayed consistently high alignment across all six paths. In contrast, the West Taiwan Strait urban agglomeration showed stronger consistency in M1, S1, and S2 compared to H1 and S3. Within the same configuration type, cities in the Yangtze River Delta exhibited higher consistency in S1b and S2 than in S1a. At the individual city level, Zhangjiakou (Beijing-Tianjin-Hebei agglomeration) demonstrated very high consistency in H2 despite limited explanatory power in other paths. Similarly, most cities in Zhejiang Province (Yangtze River Delta) had weaker consistency in S3 but stronger alignment with M1, H1, S1b, and S2. These findings highlight how dynamic QCA, unlike conventional single-factor regression analyses, enables the identification of region- and year-specific pathways, yielding more targeted and valid conclusions.

Robustness checks

This study employs two approaches to verify robustness. First, raising the consistency threshold from 0.8 to 0.85 yields identical configurations across all six paths. Second, increasing the case frequency threshold by one unit (adjusting to 3) reduces the number of paths from six to four while preserving the fundamental configuration types. These results confirm the robustness of our findings. Due to space constraints, detailed robustness check results are presented in Online Appendix A, Tables 4 and 5.

Discussion

Research findings

First, while previous studies have extensively analyzed the spatiotemporal evolution of EE, this study reveals a distinct ranking: Pearl River Delta > West Taiwan Strait > Shandong Peninsula > Yangtze River Delta > Beijing-Tianjin-Hebei urban agglomerations. This contrasts with Zhang et al. (2022) conclusion (Yangtze River Delta > Pearl River Delta > Beijing-Tianjin-Hebei). The lower EE observed in the Yangtze River Delta may stem from our inclusion of an expanded urban agglomeration boundary. Although broader in scope, the expanded region exhibits pronounced internal development disparities, where lower-efficiency areas dilute the overall performance. This underscores the need for enhanced regional ecological coordination mechanisms under the Yangtze River Delta integration strategy, leveraging spillover effects from core high-efficiency zones.

Second, human activities operate within spatially constrained contexts where distance decay effects significantly influence the spatial redistribution of economic factors - a critical yet often overlooked driver in shaping economic geography patterns. As a key indicator of regional sustainable development potential, EE research has notably lacked investigation into its spatial dynamic transfer mechanisms, particularly in specialized elongated regions like river basin economic belts and coastal urban agglomerations extending north-south or east-west. This study reveals that while coastal urban agglomerations exhibit inertia in EE transfer, proximity to high-efficiency cities can enhance upward transition probabilities through neighborhood spillover effects, thereby enabling path breakthroughs. Consequently, prioritizing high-efficiency spillover effects, establishing cross-administrative eco-environmental collaborative governance platforms, and implementing institutional innovations to eliminate factor mobility barriers would significantly contribute to improving EE and reshaping sustainable development frameworks.

Third, previous studies have employed methods such as difference-in-differences[20], spatial econometric models[18], and geographically weighted regression[2]to investigate the driving factors of EE, revealing the net effects of individual variables on EE improvement. However, the selection of factors tends to be fragmented, lacking a systematic analytical framework to integrate the rationale behind factor selection and failing to uncover the interactions among multiple factors. This limitation is particularly significant given China's unique political system and market economy conditions. This study comprehensively constructs a "government-market-technology" antecedent condition analysis framework based on institutional logic. Innovatively applying the QCA method, we explore the multiple pathways through which these antecedent conditions interact to generate high EE from both temporal and spatial dimensions. The research identifies three types of configuration pathways leading to high EE: market-driven (M1: Openness-Green finance-Industrial structure driven), government-market dual-driven (H1: Environmental regulation-Openness-Green finance driven), and market-technology dual-driven (S1: Green finance-Digital technology innovation synergy, S2: Openness-Green finance-Green technology innovation driven, S3: Openness-Green finance-Industrial structure-Digital technology innovation synergy). Notably, green finance development serves as a core condition present in all pathways, which supports and extends existing findings (Zhu Jingyu and Cui Ran 2024).

Limitations

While this study provides theoretical insights for enhancing EE in coastal urban agglomerations and promoting sustainable development, several limitations should be acknowledged. Due to data unavailability at the county and township levels, the analysis was constrained to urban agglomerations. Future research could mitigate the measurement bias inherent in multi-source heterogeneous data by collecting more granular urban data, which would enhance the reliability and depth of the findings. Furthermore, we cannot exhaustively incorporate all factors into the institutional logics framework. Future research may further develop and continually refine this framework on the existing foundation.

Conclusions and policy implications

Research conclusions

This study employs the Super-EBM model to measure EE across five coastal urban agglomerations, investigates spatiotemporal dynamic transfer patterns through trend surface analysis and spatial Markov chains, and applies dynamic QCA to identify differentiated EE enhancement pathways from an institutional logic perspective. The primary findings are as follows:

(1) During the study period, EE across the five urban agglomerations exhibited fluctuating upward trends. The efficiency ranking is: Pearl River Delta > West Taiwan Strait > Shandong Peninsula > Yangtze River Delta > Beijing-Tianjin-Hebei. Efficiency disparities between agglomerations narrowed, with high-efficiency zones evolving from scattered distributions to contiguous clusters. Trend surface analysis reveals a north-south gradient with higher efficiency in southern regions and a U-shaped east-west gradient, showing widening overall gradient disparities.

(2) The traditional Markov chain analysis reveals that the transition patterns of EE exhibit a pronounced self-locking effect and inertia in transition. After incorporating the spatial weight matrix, further calculations using the spatial Markov chain indicate that the state of neighboring regions significantly influences local transition probabilities: low-efficiency cities adjacent to high-efficiency ones show a notably higher probability of upward transition. The spatial spillover effect helps regions break through their original path dependency and achieve a gradient leap in EE.

(3) From the perspective of the three-dimensional institutional logic encompassing "government-market-technology," dynamic QCA identifies three distinct synergistic pathways that drive high EE: market-driven (M1: Openness-Green finance-Industrial structure driven), government-market dual-driven (H1: Environmental regulation-Openness-Green finance driven), and market-technology dual-driven (S1: Green finance-Digital technology innovation synergy; S2: Openness-Green finance-Green technology innovation driven; S3: Openness-Green finance-Industrial structure-Digital technology innovation synergy). The three configurational pathways exhibit spatiotemporal heterogeneity.

Policy implications

Based on the research findings, the following policy implications are proposed:

(1) Strengthen collaborative ecological governance networks in high-efficiency zones to establish regional green growth poles. Leading agglomerations such as the Pearl River Delta and West Taiwan Strait with clustered high EE should transcend administrative boundaries to institutionalize cross-city green governance platforms. Key priorities include coordinated planning of shared environmental infrastructure (e.g., transboundary pollution prevention systems) and optimized green industrial chain layouts to avoid homogeneous competition, thereby transforming EE advantages into sustainable green competitiveness and developing internationally influential coastal green growth poles.

(2) Disrupt lock-in effects by amplifying spatial spillovers from high-efficiency cities. Addressing the north-south efficiency gradient requires establishing vertical ecological compensation mechanisms. Create dedicated funds with central government guidance, local matching, and private capital participation. Long-range interventions involve targeted support from southern high-efficiency cities to efficiency-deficient areas like Beijing-Tianjin-Hebei and the Yangtze River Delta for clean energy transitions, industrial green retrofits, and joint green projects. Short-range solutions implement city-pairing mechanisms between high and low-efficiency neighbors to activate transition inertia and leverage spatial spillovers.

(3) Coordinate multi-institutional logic synergies for context-specific pathways. Findings demonstrate regionally diverse drivers where distinct institutional combinations achieve high EE equivalently. Market-dominated regions (M1) should deepen openness and green finance innovation through green bond expansion, foreign investment steering toward low-carbon industries, and industrial restructuring. Government-market dual-driven areas (H1) must leverage political authority to strengthen environmental regulation-market incentive coordination. Market-technology dual-driven zones (S1-S3) require prioritized support for digital-green technology innovation and synergistic linkages among green finance, openness, and clean technologies.

Data availability

The derived panel dataset, as well as the code implementing spatial Markov and dynamic QCA analyses, can be accessed via the Open Science Framework (OSF) repository. DOI:10.17605/OSF.IO/6JSV8.

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