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Article

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Urban New-Energy Innovation in China: Spatiotemporal Dynamics, Collaboration Networks, and Associated Factors

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Abstract

New-energy technology innovation is an important driver of the low-carbon energy transition, with increasingly pronounced spatial clustering and intercity collaboration. Yet the co-evolution of innovation output and collaboration networks and the factors associated with network evolution remain unclear. Using city-level patent data from China for 2020–2024, we combine geospatial analysis, social network analysis, and zero-modified valued exponential random graph models to examine the spatiotemporal patterns, network evolution, and factors associated with collaboration. The results show that urban new-energy innovation output increased from 19,379 to 38,904 patent applications, remaining concentrated in the Yangtze River Delta, Pearl River Delta, and Beijing–Tianjin–Hebei region while gaining strength in central and western China. Intercity collaboration also expanded, with collaboration ties increasing from 502 to 1,227 and collaboration intensity rising, alongside persistent concentration in

eastern core cities and growing interregional linkages. Further analysis shows that endogenous network effects and collaboration persistence were consistently positively associated with intercity collaboration. Administrative proximity also showed a strong positive association: the conditional odds of collaboration for city pairs within the same province were 3.14–5.45 times those for cross-province pairs. Technological proximity and the innovation resource base showed significant positive associations in most years, whereas associations with geographical proximity and policy factors varied. These findings provide empirical evidence to inform the spatial configuration of regional innovation and support interregional collaborative innovation.

Keywords: new-energy innovation; intercity collaboration network; spatiotemporal patterns; multidimensional proximity; valued exponential random graph model

1 Introduction

New-energy technological innovation plays an important role in advancing clean-energy technologies and supporting the low-carbon energy transition (Markard 2018). Progress in this field depends not only on research and development (R&D) investment and technological advances (Gallagher et al. 2012), but also on interactions among innovators, institutional settings, and knowledge networks (Hekkert et al. 2007). Cities play a central role in this process by concentrating innovation resources and outputs while connecting knowledge across regions. Examining the spatial distribution of new-energy innovation and intercity collaboration can therefore provide important insights into how innovation is organized and evolves across China.

Patent-based studies have been widely used to measure energy technology innovation and characterize its underlying knowledge base (Johnstone et al. 2010; Hötte et al. 2021; Popp 2002). Particular attention has been given to the combined effects of demand pull, R&D support, and market conditions (Costantini et al. 2015; Noailly and Smeets 2015; Nesta et al. 2014), as well as to differences in policy effects across technology fields and policy mixes (Nicolli and Vona 2016; Rogge and Reichardt 2016; Lin and Chen 2023). Research on low-carbon technologies has further examined how

price incentives and environmental regulation influence the direction of innovation (Calel and Dechezleprêtre 2016; Aghion et al. 2016), while more recent work has incorporated digitalization and regional economic conditions into the analysis (Feng et al. 2026; Ma et al. 2023).

From a spatial perspective, research has examined regional disparities, spatial dependence, and convergence in new-energy innovation (Wang and Shi 2014; Bai et al. 2020; He et al. 2022), together with shifts in innovation centers and changes in local clustering (Zhang et al. 2021b; Duan and Du 2022). Research in innovation geography has long emphasized the localized nature of knowledge spillovers and the roles of skilled labor mobility and co-invention ties (Jaffe et al. 1993; Bottazzi and Peri 2003; Breschi and Lissoni 2009). Related studies of energy technologies have traced knowledge diffusion across both geographic and technological boundaries (Verdolini and Galeotti 2011; Noailly and Shestalova 2017). These findings highlight the importance of regional industrial and knowledge bases, as well as interregional linkages, in shaping the spatial organization of innovation (Tanner 2014; Grillitsch and Hansen 2019; Feng et al. 2021).

A growing body of work has also examined interregional innovation collaboration and its organization across spatial scales (Yang et al. 2022; Zhang et al. 2021a; Suo et al. 2024). Joint patent applications are commonly used to characterize the extent and intensity of collaboration, identify key actors, and reveal community structures (Liu and Yu 2019; Miao et al. 2026; Zhou et al. 2024). Subsequent studies have explored the spatial roles of network nodes and the environmental implications of collaboration networks (Jiang et al. 2026; Gao et al. 2026). More broadly, network research shows that prior ties and overall network connectivity can influence knowledge diffusion and innovation output (Singh 2005; Schilling and Phelps 2007). Multidimensional proximity theory provides a complementary explanation of partner selection through geographical, cognitive, organizational, social, and institutional proximity (Boschma

2005; Balland 2012; Broekel and Boschma 2012), while also emphasizing the importance of previous collaboration and shared partners in network evolution (Crescenzi et al. 2016; ter Wal 2014). Recent studies of intercity green innovation have begun to integrate proximity analysis with annual network dynamics, providing a more detailed understanding of how collaboration patterns vary across city pairs and over time (Gao and Di 2026; Zhu and Ye 2025).

Previous studies have provided an important basis for understanding the spatiotemporal organization of new-energy technological innovation, yet several limitations remain. First, innovation output and intercity collaboration networks have largely been examined in isolation, leaving an incomplete understanding of how urban innovation output and cross-regional knowledge linkages jointly shape the spatial organization of new-energy innovation. Second, the factors underlying network evolution have not been sufficiently examined. Conventional attribute-based regressions and static network analyses are limited in their ability to account simultaneously for collaboration intensity and temporal dependence, particularly the persistence of prior collaboration and the lagged effects of city characteristics. As a result, the processes underlying the evolution of new-energy innovation collaboration networks require further investigation.

To address these gaps, we analyze city-level new-energy patent applications and intercity joint patent applications in China from 2020 to 2024. We characterize the spatiotemporal distribution of innovation output and changes in the scale, intensity, and spatial organization of intercity collaboration networks. We then apply zero-modified valued exponential random graph models with lagged covariates to assess how network structure, multidimensional proximity, innovation resources, and policy conditions are associated with collaboration, while accounting for prior ties and network dependence. Together, these analyses provide a city-level perspective on the spatial organization and evolution of new-energy innovation and its interregional R&D connections.

2 Data sources and methods

2.1 Data sources and processing

The study uses new-energy patent data, city-level panel data, geospatial data, and policy pilot data. To improve comparability across cities, patent records underwent standardized cleaning, geocoding, and validation and correction of city assignments. Patent records, city-level statistical indicators, spatial coordinates, and policy pilot information were matched by city and year to construct a panel covering 2020–2024. Table 1 summarizes the data sources.

2.1.1 New-energy patent data

New-energy patent data were obtained from the Patent Search and Analysis System of the China National Intellectual Property Administration (CNIPA). The records include patent titles, types, applicants, filing dates, and technology categories. Patent records were assigned to cities through sequential matching. Place names were first extracted from company names and matched against a national list of prefecture-level cities. Where company names did not identify a city, registered business addresses were geocoded using the Amap Web API to determine the corresponding prefecture-level city. Point-of-interest (POI) searches were used to supplement city assignments for records that remained unresolved. After city name standardization, validation and correction of city assignments, and removal of anomalous records, 138,094 valid patent records remained for 2020–2024.

2.1.2 Other city-level data

Administrative boundary vector data and coordinates of municipal government seats were obtained from the standardized geographic information database of the Ministry of Natural Resources. Data on gross regional product and expenditure on science were obtained primarily from the China City Statistical Yearbook and municipal statistical

communiqués. These sources also provided enrollment data for regular higher education institutions and secondary vocational education. Lists of national innovative city pilots were compiled from official documents issued by the Ministry of Science and Technology. National low-carbon city pilot lists were obtained from the National Development and Reform Commission. Pilot information was matched by city and implementation year.

2.2 Methods

Figure 1 presents the research framework. Drawing on data on new-energy patents, city characteristics, spatial locations, and policy pilots, we examine the spatiotemporal patterns of innovation output, trace the evolution of intercity collaboration networks, and assess the factors associated with collaboration.

2.2.1 Spatiotemporal patterns of new-energy innovation output

Annual city-level new-energy patent application counts were used to measure innovation output, denoted by $q_{i,t}$. Patents were assigned to years according to their filing year, and each patent was counted only once within each city. Joint applications involving multiple cities were counted separately in each participating city. We analyzed spatiotemporal patterns in innovation output in terms of spatial clustering, shifts in the spatial center of gravity, and neighborhood spatial association.

Municipal government seats were used as point locations, with annual patent application counts as weights. Kernel density estimation with a quartic kernel identified clusters of high innovation output and their regional expansion (Silverman 1986):

$$f_t(\boldsymbol{u}) = \frac{3}{\pi h^2} \sum_{i=1}^{n} q_{i,t} \left(1 - \frac{\|\boldsymbol{u} - \boldsymbol{u}_i\|^2}{h^2}\right)^2 \mathrm{I}(\|\boldsymbol{u} - \boldsymbol{u}_i\| < h). \tag{1}$$

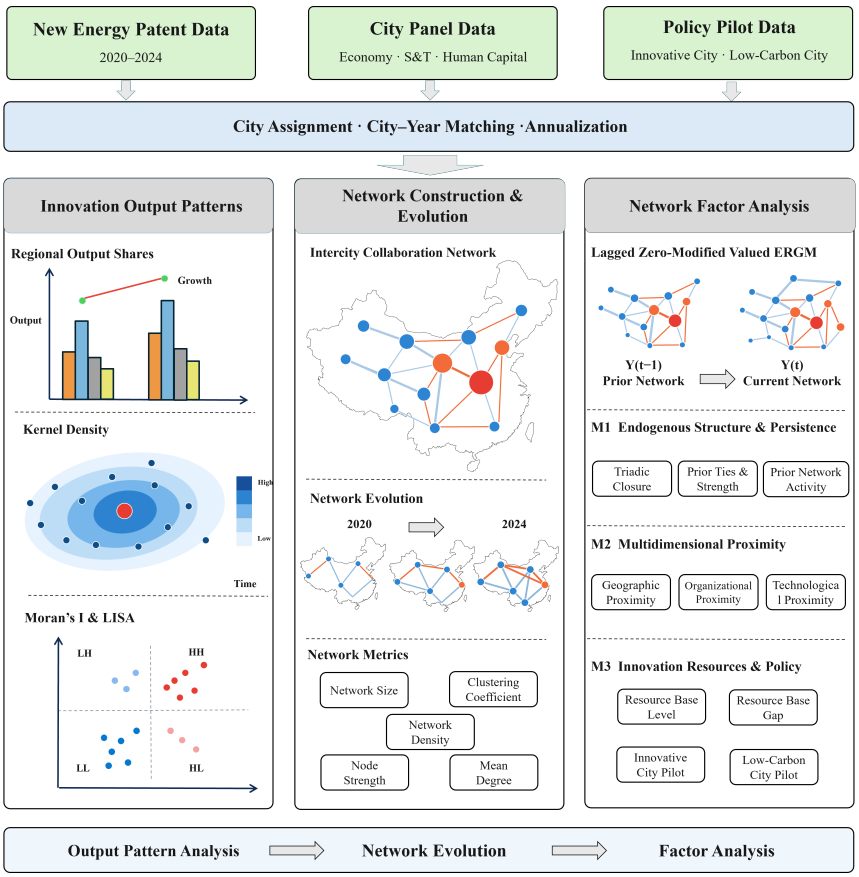


Fig. 1 Research framework

Here, $f_t(\boldsymbol{u})$ is the kernel density of innovation output at location $\boldsymbol{u}$, and $\boldsymbol{u}_i$ denotes the planar coordinates of a municipal government seat. $q_{i,t}$ is the annual patent application count for a city, h is the search radius, and n is the number of sample cities. $\mathrm{I}(\cdot)$ is an indicator function. Identical kernel density parameters were used in all years to ensure comparability over time.

Global Moran's I was used to test overall spatial autocorrelation (Moran 1950). Local indicators of spatial association (LISA) were used to identify local patterns of spatial association (Anselin 1995):

Table 1 Data sources

Data category	Data description	Period	Spatial scale	Source
New-energy patent data	Patent title, type, applicant, filing date, technology category, and applicant city	2020–2024	City	CNIPA Patent Search and Analysis System
Geospatial data	Administrative boundary vector data and coordinates of municipal government seats	2024	City	Standardized geographic information database of the Ministry of Natural Resources
City-level panel data	Gross regional product, expenditure on science, and enrollment in regular higher education institutions and secondary vocational education	2020–2024	City	China City Statistical Yearbook and municipal statistical communiqués
Policy pilot data	National innovative city pilots and national low-carbon city pilots	2020–2024	City	Official documents of the Ministry of Science and Technology (2016, 2018, 2022) and the National Development and Reform Commission (2010, 2012, 2017)

$$
\begin{aligned}
I_t &= \frac{n}{S_0} \frac{\sum_i \sum_j v_{ij}(q_{i,t} - \overline{q}_t)(q_{j,t} - \overline{q}_t)}{\sum_i (q_{i,t} - \overline{q}_t)^2}, \\
I_{i,t} &= \frac{q_{i,t} - \overline{q}_t}{m_{2,t}} \sum_j v_{ij}(q_{j,t} - \overline{q}_t).
\end{aligned}
\tag{2}
$$

Here, n is the number of sample cities, and $\overline{q}_t$ is the annual mean of city-level innovation output. v_{ij} denotes inverse-squared-distance spatial weights, S_0 is the sum of all spatial weights, and $m_{2,t}$ is the population variance of city-level innovation output. Statistical significance was assessed using a two-sided random permutation test, with $p < 0.05$ as the threshold for identifying local associations. Significant cities were classified according to whether their innovation output and neighborhood spatial

lag were above or below the respective means. The resulting categories were high–high (HH), high–low (HL), low–high (LH), and low–low (LL).

2.2.2 Analysis of new-energy innovation collaboration networks

Intercity joint patent applications were defined as applications with applicants located in two or more cities, yielding 10,967 valid applications. Annual intercity new-energy innovation collaboration networks were constructed for 2020–2024. Cities served as nodes, intercity joint application relationships as undirected edges, and the number of joint applications as edge weights. These undirected edges represented collaboration ties between cities jointly involved in patent applications. They were used to analyze the spatial configuration and network structure of collaboration.

Let P_t denote the set of intercity joint patent applications in year t, and let N denote the total number of cities. For patent p, if applicants are located in both cities i and j, then $I_{ijp,t} = 1$; otherwise, the indicator equals 0. The weighted and binary adjacency matrices of the intercity new-energy innovation collaboration network are defined as follows:

$$W_t = \begin{bmatrix} 0 & w_{12,t} & \cdots & w_{1N,t} \\ w_{21,t} & 0 & \cdots & w_{2N,t} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1,t} & w_{N2,t} & \cdots & 0 \end{bmatrix} \tag{3}$$

$$A_t = \begin{bmatrix} 0 & a_{12,t} & \cdots & a_{1N,t} \\ a_{21,t} & 0 & \cdots & a_{2N,t} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1,t} & a_{N2,t} & \cdots & 0 \end{bmatrix} \tag{4}$$

The matrix elements $w_{ij,t}$ and $a_{ij,t}$ represent the intercity collaboration weight and binary collaboration tie, respectively, and are calculated as follows:

$$w_{ij,t} = \begin{cases} \sum_{p \in P_t} I_{ijp,t}, & i \neq j, \\ 0, & i = j. \end{cases} \tag{5}$$

$$a_{ij,t} = \begin{cases} 1, & w_{ij,t} > 0, \\ 0, & w_{ij,t} = 0. \end{cases} \tag{6}$$

These definitions yield the annual weighted network W_t and binary network A_t. Both adjacency matrices are symmetric, with zeros on the main diagonal. Full counting was applied to patents involving three or more cities, adding 1 to the edge weight of every pair of participating cities. A common node set was used across years, retaining isolates with no collaboration ties to ensure comparability over time. Descriptive analyses treated cities that actually participated in collaboration in a given year as active nodes.

Network evolution was analyzed in terms of collaboration scale, collaboration intensity, and their distribution across cities. Network size was measured by the number of active cities and collaboration edges. Collaboration intensity was characterized by total edge weight and mean edge weight among collaborating city pairs. Total edge weight is the sum of all collaboration edge weights. Mean edge weight among collaborating city pairs equals total edge weight divided by the number of collaboration edges. Node strength is the sum of weights on all collaboration edges incident to a city. The share of total node strength accounted for by the top 10 cities was used to measure the concentration of collaboration intensity. Together with each city's number of collaboration partners, these measures characterized differences in the breadth and intensity of collaboration.

2.2.3 Factors associated with new-energy innovation collaboration networks

Counts of intercity joint patent applications are nonnegative integers with many zeros and interdependent ties. We used a zero-modified valued exponential random graph model (ERGM) with lagged covariates (Krivitsky 2012). The model retains collaboration counts while separately representing the distribution of edge weights and the number of nonzero ties. Network statistics account for structural dependence among collaboration ties. Let Y_t denote the current random valued network, with observed realization W_t, candidate realization y_t, and corresponding binary network b_t. Using a geometric reference measure, $h(y_t) = 1$, the model is specified as follows:

$$\begin{aligned} &\Pr_{\boldsymbol{\Theta}_t}(Y_t = y_t \mid W_{t-1}, X_{t-1}) \\ &\quad = \frac{1}{\kappa_t(\boldsymbol{\Theta}_t)} \exp\Bigg\{ \theta_{s,t} S(y_t) + \theta_{0,t} N(b_t) \\ &\qquad + \theta_{g,t} G(b_t; 0.5) + \sum_{i<j} b_{ij,t} \boldsymbol{\beta}_t^{\mathrm{T}} \boldsymbol{x}_{ij,t-1} \Bigg\}. \end{aligned} \tag{7}$$

Here, $b_{ij,t} = \mathrm{I}(y_{ij,t} > 0)$, and κ_t is the normalizing constant ensuring that probabilities sum to 1 over all possible networks. W_{t-1} and X_{t-1} denote the previous year's network and city attributes, respectively. $\boldsymbol{x}_{ij,t-1}$ denotes dyadic covariates constructed from prior network information, city attributes, and fixed geographical and provincial information. G is the triadic closure statistic for the current binary network. The parameter vector $\boldsymbol{\Theta}_t$ contains $\theta_{s,t}$, $\theta_{0,t}$, $\theta_{g,t}$, and the covariate coefficients $\boldsymbol{\beta}_t$, all of which are estimated. The two baseline statistics are defined as follows:

$$S(y_t) = \sum_{i<j} y_{ij,t} \quad (\text{sum}), \qquad N(b_t) = \sum_{i<j} b_{ij,t} \quad (\text{nonzero}). \tag{8}$$

The sum statistic is the total edge weight of the network, and its coefficient characterizes the distribution of positive edge weights. The nonzero statistic counts city

pairs with at least one collaboration and adjusts the overall propensity for ties to exist. Together, these terms accommodate a network containing many zeros and varying collaboration counts. Under the geometric reference measure, $\theta_{s,t} < 0$ is required. Apart from sum, the triadic closure term and dyadic covariates act on the nonzero tie process, explaining whether a city pair collaborates at least once.

Three groups of explanatory factors were specified to examine associations of collaboration ties with network characteristics, intercity proximity, city resources, and policy conditions.

The first group captures endogenous network structure and collaboration persistence. Triadic closure was represented by the geometrically weighted edgewise shared partner (GWESP) statistic, gwesp. Its decay parameter was fixed at 0.5, assigning diminishing marginal weights to additional shared partners. Prior collaboration partner count, lagact, was calculated by summing the two cities' degrees in the previous year, adding 1, and taking the natural logarithm. The result was standardized across city pairs. Prior collaboration status, lagtie, was coded 1 if the pair collaborated in the previous year and 0 otherwise. Prior collaboration intensity, lagstr, was calculated by applying the $\ln(1 + w)$ transformation to previous-year edge weights and standardizing the transformed values among previously collaborating pairs. Pairs with no prior collaboration were assigned 0. Accordingly, the lagtie coefficient represents an existing tie at the mean level of prior log-transformed collaboration intensity.

The second group captures multidimensional proximity. To calculate geographical proximity, geo, we added 1 to the great-circle distance between municipal government seats, measured in km. We then took the reciprocal and standardized the resulting values across city pairs. Administrative proximity, org, was coded 1 for cities in the same province and 0 otherwise. For technological proximity, tech, each city's technology vector comprised previous-year patent counts in four categories: lithium batteries,

silicon photovoltaics, new-type energy storage, and hydrogen energy. Cosine similarity was calculated for each city pair and then standardized. Similarity was set to 0 if either city had a zero technology vector.

The third group captures city-level innovation resources and the policy environment. Gross regional product, expenditure on science, new-energy patent application counts, and human capital jointly represented each city's innovation resource base. Human capital was measured as total enrollment in regular higher education institutions and secondary vocational education. The four indicators underwent the $\ln(x+1)$ transformation and were standardized across cities within each year. The first principal component was extracted, and its sign was adjusted so that higher scores indicated a stronger overall resource base. The scores were then standardized again. The sum of the two cities' indices defined their combined innovation resource base, irf. Their absolute difference defined the difference in innovation resource bases, ird. National innovative city pilot and national low-carbon city pilot status were coded 0 or 1 using official lists and implementation dates. Summing the two cities' statuses yielded the respective numbers of pilot cities in each pair, icp and lcp, each taking values of 0, 1, or 2.

Networks for 2021–2024 were estimated separately. Prior network variables, technology structure, city resources, and pilot status were lagged by one year. Triadic closure was measured using the current network, while geographical distance and provincial affiliation were treated as fixed attributes. Model specifications were expanded sequentially. M1 included baseline network terms, triadic closure, and prior network variables. M2 added multidimensional proximity, and M3 further included city-level innovation resources and the policy environment. This sequence allowed comparison of associations after controlling for additional factors. Markov chain Monte Carlo maximum likelihood estimation (MCMC-MLE) was performed using the ergm

and ergm.count packages in R. Coefficients and standard errors were reported, and statistical significance was assessed using two-sided Wald tests.

3 Spatiotemporal patterns of new-energy innovation output

3.1 Spatial clustering and expansion of innovation output

From 2020 to 2024, city-level new-energy innovation output in China increased overall. Eastern China continued to lead in innovation output, while the relative shares of central and western China increased (Figure 2). The annual national sum of city-level patent application counts rose from 19,379 to 38,904, with eastern China consistently contributing approximately two-thirds of the total. National year-on-year growth exceeded 10% in each year from 2021 to 2023. Eastern, central, and western China all recorded their highest growth rates in 2022, with each peak exceeding 20%; northeastern China followed a different pattern. National innovation output declined in 2024, whereas western China maintained growth of 7.57%, showing continued expansion compared with the other regions.

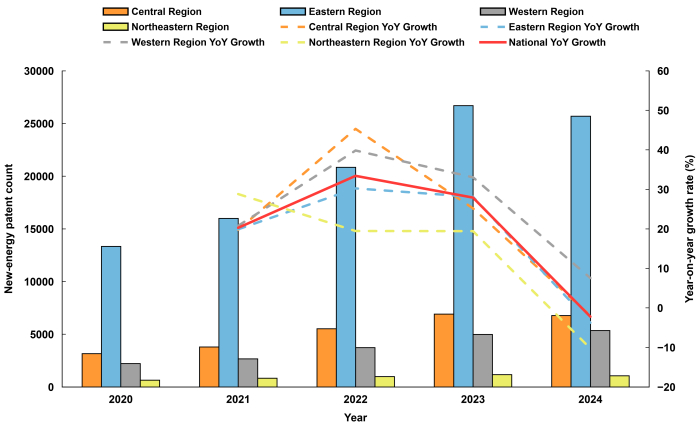
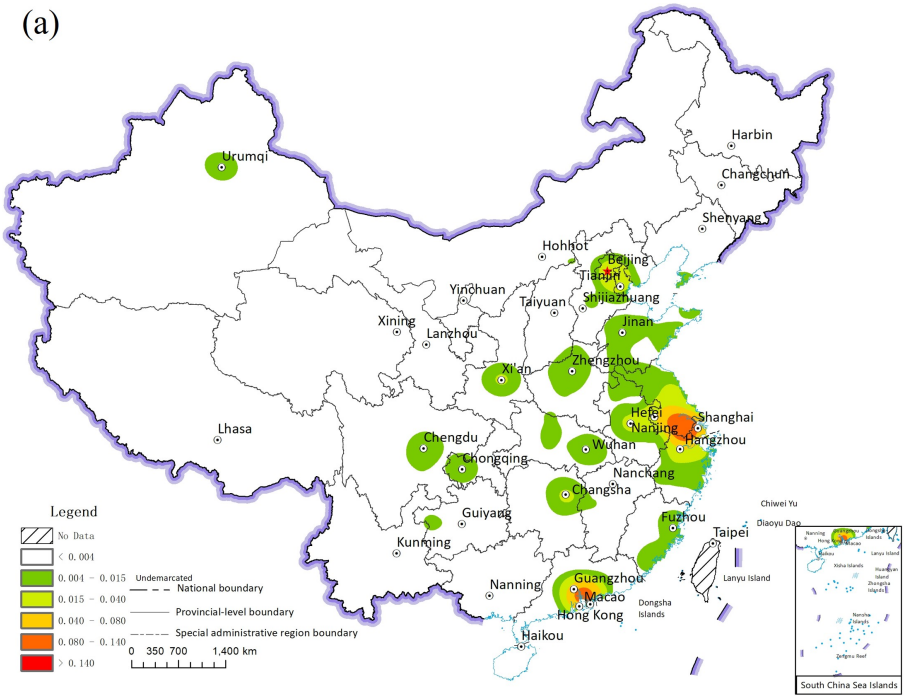


Fig. 2 New-energy innovation output and year-on-year growth rates in China's four major regions from 2020 to 2024

Weighted point kernel density estimates revealed stronger core clustering in eastern China, increasing connections among peripheral patches, and the growth of inland innovation nodes (Figure 3). The Yangtze River Delta and Pearl River Delta remained the principal clusters of high innovation output. Beijing and Tianjin anchored an important northern innovation cluster in the Beijing–Tianjin–Hebei region. After 2022, clustering intensified within the core high-output areas, with a tendency toward contiguous north–south expansion between Beijing–Tianjin–Hebei and the Yangtze River Delta. Clusters expanded around central nodes such as Hefei and Wuhan, whereas western nodes such as Xi'an and Chengdu largely retained localized clusters. Overall, spatial expansion combined contiguous clustering in eastern China, connections among patches in central China, and growth around individual nodes in western China.



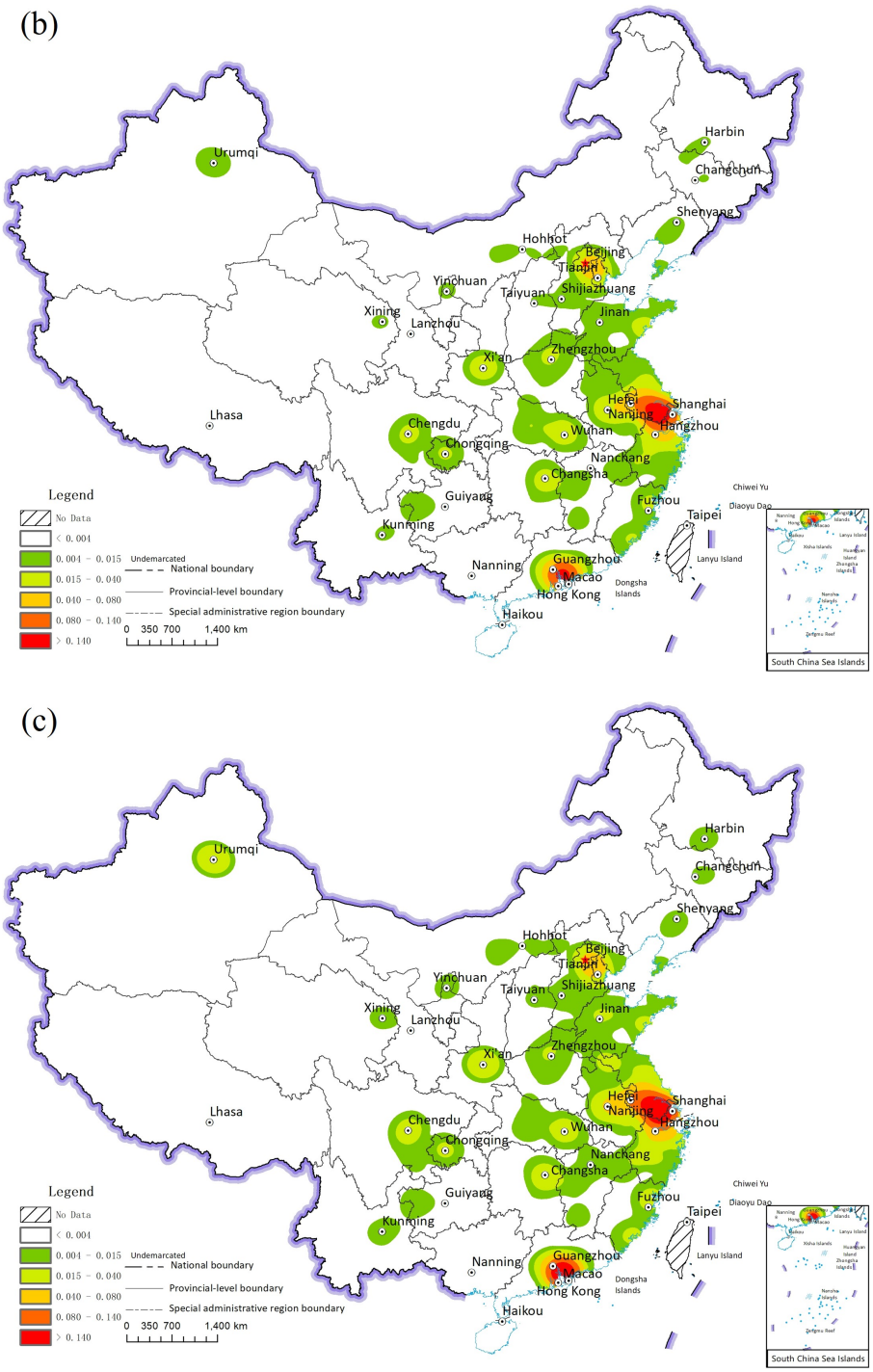


Fig. 3 Evolution of the kernel density of city-level new-energy innovation output in China from 2020 to 2024: (a) 2020, (b) 2022, (c) 2024

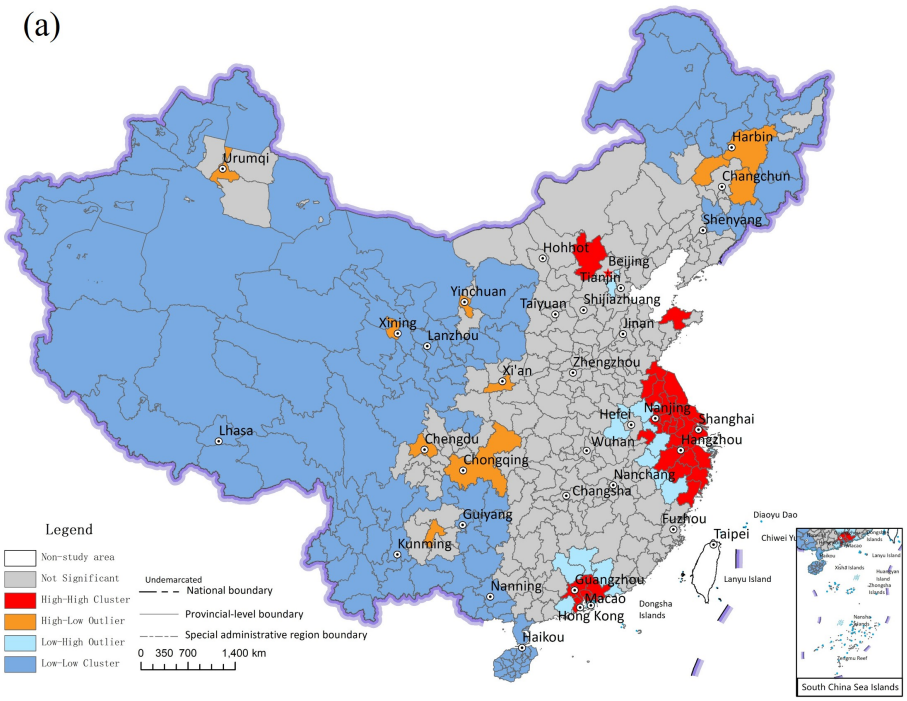
3.2 Local spatial clustering and its evolution

Global Moran's I ranged from 0.409 to 0.462 during 2020–2024, indicating consistently significant positive spatial autocorrelation in city-level new-energy innovation output. Regional clustering was therefore a stable feature throughout the study period. The LISA results further characterized local spatial associations in innovation output (Figure 4). High–high (HH) clusters were concentrated in the Yangtze River Delta and Pearl River Delta. These regions contained cities with high levels of innovation output in China, and their technological innovation activities showed significant positive local spatial association. The extent of clustering in the Yangtze River Delta expanded throughout the study period.

High–low (HL) spatial outliers mainly occurred in some regional centers in central and western China. These cities had high innovation output but were surrounded by cities with low output. This pattern reflected weak innovation linkages between core nodes and surrounding cities and a limited role in stimulating innovation in surrounding areas. Low–high (LH) spatial outliers mainly occurred along the peripheries of high-output areas in the Yangtze River Delta and Pearl River Delta. Their own innovation output was low despite high output in neighboring cities. These cities had yet to fully translate proximity advantages into local innovation growth because of limited capacities to absorb innovation and put it into practice.

Low–low (LL) clusters were concentrated in northwestern and southwestern China, forming contiguous areas with low innovation output in both focal and neighboring cities. This pattern was associated with relatively weak economic foundations, insufficient industrial support, and limited innovation investment.

(a)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Haikou
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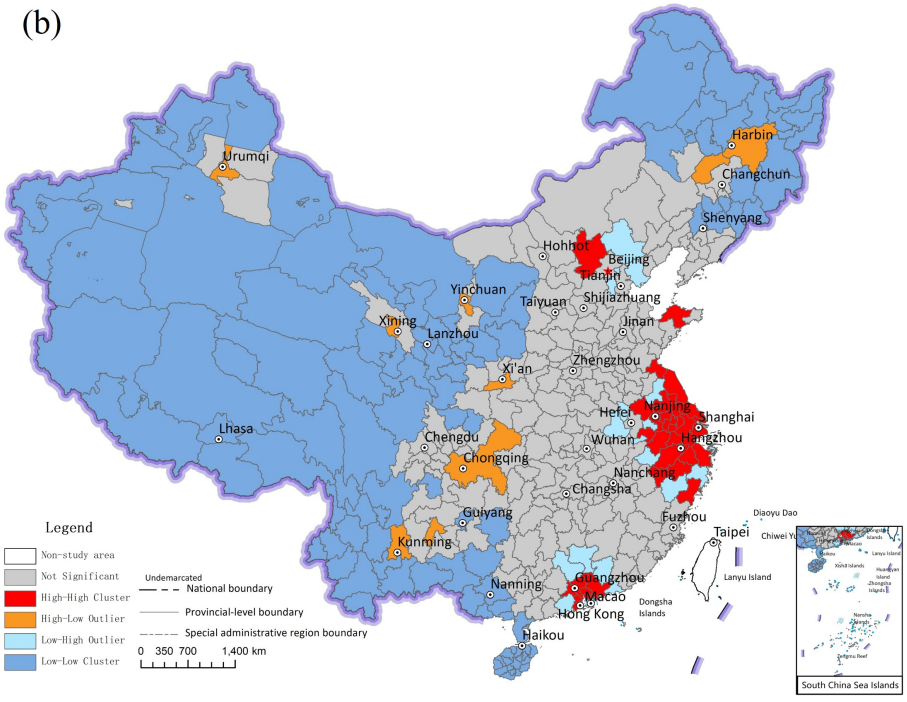
(b)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Hong Kong
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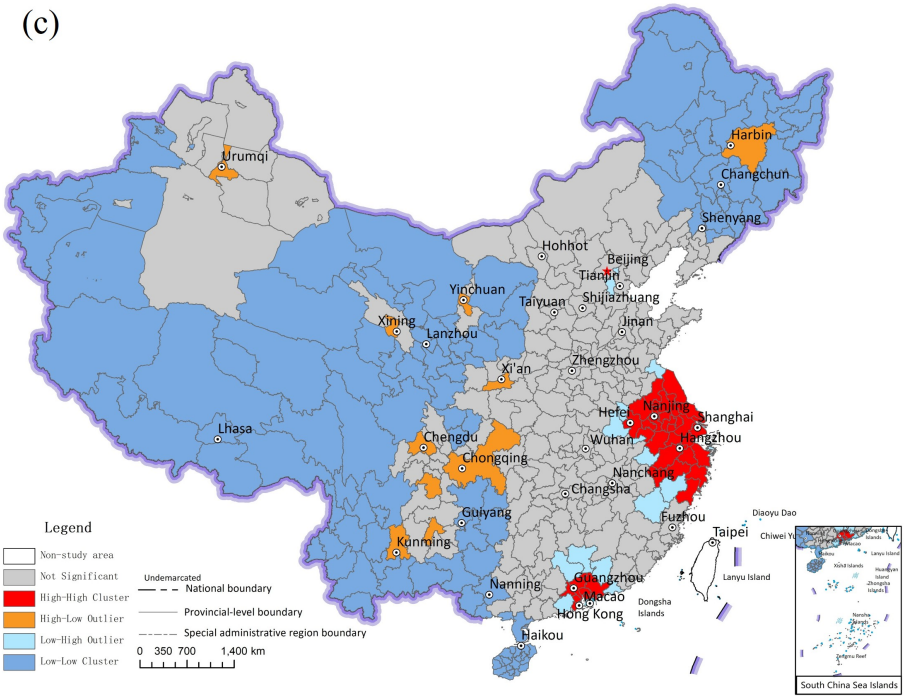


Fig. 4 LISA clustering patterns of city-level new-energy innovation output in China from 2020 to 2024: (a) 2020, (b) 2022, (c) 2024

4 Spatiotemporal evolution of new-energy innovation collaboration networks

4.1 Evolution of network size and structure

The intercity new-energy innovation collaboration network expanded steadily from 2020 to 2024, with a marked increase in collaboration intensity (Table 2). As more cities and collaboration ties entered the network, both the breadth and intensity of intercity collaboration increased. Collaboration intensity nevertheless remained concentrated in a subset of core cities.

Participation in intercity new-energy innovation collaboration broadened, while collaboration among cities intensified. From 2020 to 2024, the number of active cities

increased from 177 to 244, and collaboration edges increased from 502 to 1,227. These changes indicate a widening geographical scope of participation. Total edge weight increased from 1,622 to 7,358, substantially outpacing growth in the number of collaboration edges. Mean edge weight among collaborating city pairs rose from 3.23 to 6.00, indicating more frequent collaboration per pair on average. The network thus expanded in both collaboration scale and intensity.

Collaboration intensity was unevenly distributed across cities, which differed in both the breadth and frequency of collaboration. The top 10 cities' share of total node strength fluctuated but increased overall from 41.89% in 2020 to 53.33% in 2024. This increase indicates greater concentration of collaboration intensity in a small number of cities. Beijing consistently had the largest number of collaboration partners, with the count rising from 62 to 110. In 2024, node strengths reached 1,136 in Foshan, 1,116 in Zhuhai, 1,045 in Tianjin, and 959 in Jinhua, reflecting frequent collaboration. However, the number of partners did not correspond fully to node strength, indicating differences between the breadth and intensity of collaboration across cities.

Table 2 Annual indicators of the intercity new-energy innovation collaboration network from 2020 to 2024

Indicator	**2020**	**2021**	**2022**	**2023**	**2024**
Number of active cities	177	195	229	242	244
Number of collaboration edges	502	654	856	1,071	1,227
Total edge weight	1,622	2,489	3,382	4,880	7,358
Mean edge weight among collaborating city pairs	3.23	3.81	3.95	4.56	6.00
Top 10 cities' share of total node strength (%)	41.89	48.15	42.96	42.06	53.33

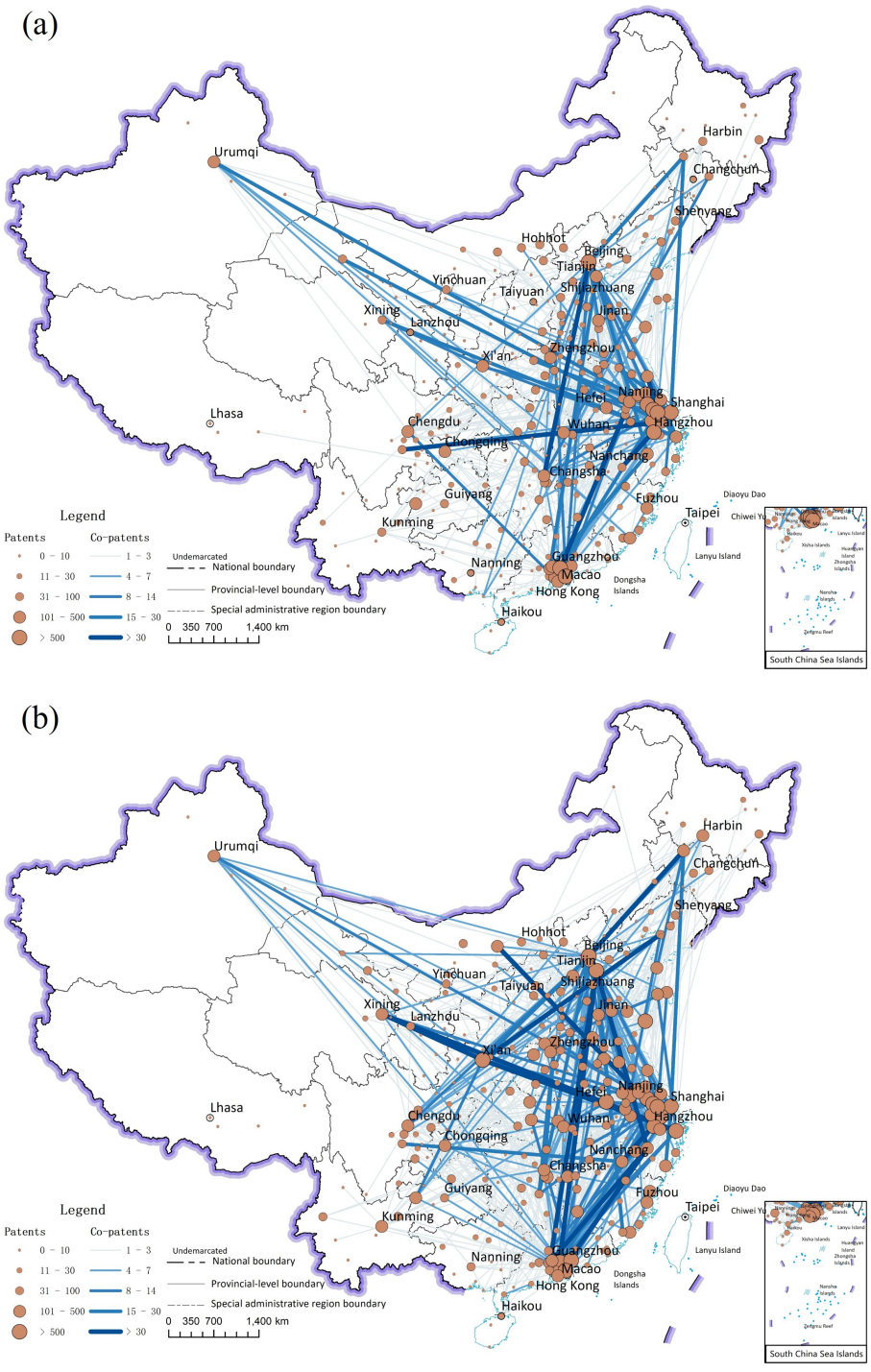
Note: Active cities participated in at least one new-energy innovation collaboration in the relevant year. Total edge weight is the sum of all collaboration edge weights. Mean edge weight among collaborating city pairs equals total edge weight divided by the number of collaboration edges. Node strength is the sum of all collaboration edge weights incident to a city. The top 10 cities' share is their combined node strength divided by total node strength across the network, with cities ranked by node strength.

4.2 Evolution of spatial organization and regional ties

During 2020–2024, the intercity new-energy innovation collaboration network evolved from a network anchored by a few hubs toward connections spanning multiple regions and directions (Figure 5). Early collaboration ties were concentrated in eastern cities. As ties among central cities became denser and the network extended into northeastern and western China, its spatial configuration became approximately diamond-shaped. Regional hubs in Beijing–Tianjin–Hebei, the Yangtze River Delta, Pearl River Delta, and Chengdu–Chongqing region outlined this configuration. Wuhan, Hefei, and Changsha further strengthened connections within the diamond.

Collaboration intensity was concentrated in eastern cities and their interregional ties, making eastern China a major hub of the national new-energy innovation collaboration network. In 2024, collaboration within eastern China accounted for 51.3% of national total edge weight, while collaboration involving eastern cities accounted for 87.4%. Ties linking eastern China with central, western, and northeastern China accounted for 20.7%, 12.5%, and 2.9% of national total edge weight, respectively.

Interregional collaboration ties continued to expand, and cities outside eastern China became more involved in the network. The number of active cities outside eastern China increased from 107 in 2020 to 161 in 2024. Chengdu, Xi'an, and Urumqi extended the network westward. Harbin strengthened northeastern China's interregional ties through collaboration with cities such as Beijing and Shanghai. In 2024, the edge weight of northeastern China's interregional collaboration reached 398, substantially exceeding its intraregional edge weight of 20. Nationally, intraregional collaboration accounted for 50.6%–58.7% of total edge weight, remaining an important form of collaboration. Growing interregional ties further strengthened innovation connections across regions.


(a)
Urumqi
Harbin
Changchun
Shenyang
Hohhot
Beijing
Tianjin
Yinchuan
Taiyuan
Shijiazhuang
Xining
Lanzhou
Jinan
Zhengzhou
Xi'an
Nanjing
Hefei
Shanghai
Lhasa
Chengdu
Wuhan
Hangzhou
Chongqing
Nanchang
Changsha
Guiyang
Fuzhou
Diaoyu Dao
Chiwei Yu
Taipei
Kunming
Lanyu Island
Nanning
Guangzhou
Macao
Hong Kong
Dongsha Islands
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Legend
Patents
0 - 10
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101 - 500
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Co-patents
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National boundary
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Special administrative region boundary
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Urumqi
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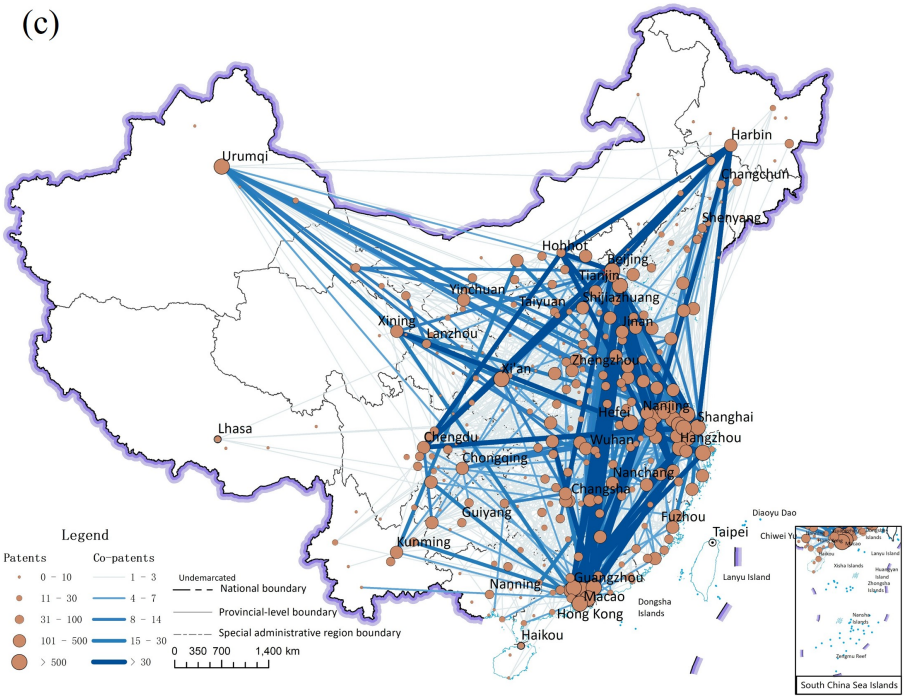

Fig. 5 Intercity new-energy innovation collaboration networks in China from 2020 to 2024: (a) 2020, (b) 2022, (c) 2024. Note: Node size represents the number of new-energy patent applications in each city. Line width represents the number of intercity joint patent applications. Consistent classification thresholds were used for node sizes and line widths across years

5 Factors associated with new-energy innovation collaboration networks

We estimated M1 with endogenous network structure and collaboration persistence, M2 with additional multidimensional proximity variables, and M3 with innovation resources and the policy environment. Full estimation results are reported in Table A1. Figures 6–8 present the coefficients and 95% confidence intervals for the three groups of factors in M3 for 2021–2024. The following analysis uses the full model to examine conditional associations between these factors and nonzero collaboration ties.

Conditional odds are the ratio of the probability that a city pair collaborates to the probability that it does not, holding other factors and all remaining network ties constant. A one-unit increase in a dyadic attribute multiplies the conditional odds of collaboration by e^{β}, the conditional odds ratio. Here, β is the estimated coefficient for that attribute. A ratio above 1 indicates a greater propensity to collaborate, whereas a ratio below 1 indicates a lower propensity. These ratios do not imply equivalent multiplicative changes in collaboration probabilities. Interpreting triadic closure additionally requires accounting for the change in network statistics induced by adding a collaboration tie.

5.1 Endogenous network structure and collaboration persistence

Triadic closure (gwesp) and prior collaboration partner count (lagact) had significant positive coefficients in all four years (Figure 6). Collaboration thus tended to concentrate around previously active nodes, and cities with shared partners showed a greater propensity to collaborate. After controlling for other included factors, triadic closure coefficients ranged from 0.603 to 0.849. These coefficients reflect local groupings in which collaboration partners are connected to one another. Prior collaboration partner count captured the continuing association with the breadth of prior collaboration. Holding other included factors constant, a one-standard-deviation increase in this variable was associated with 1.79–3.42 times the conditional odds of collaboration in the following year.

Prior collaboration status (lagtie) and prior collaboration intensity (lagstr) also had significant positive coefficients in all four years (Figure 6). These results indicate persistent collaboration ties. Both previous collaboration and greater prior collaboration intensity were associated with a stronger propensity for continued collaboration. At the mean log-transformed prior collaboration intensity, previously collaborating pairs

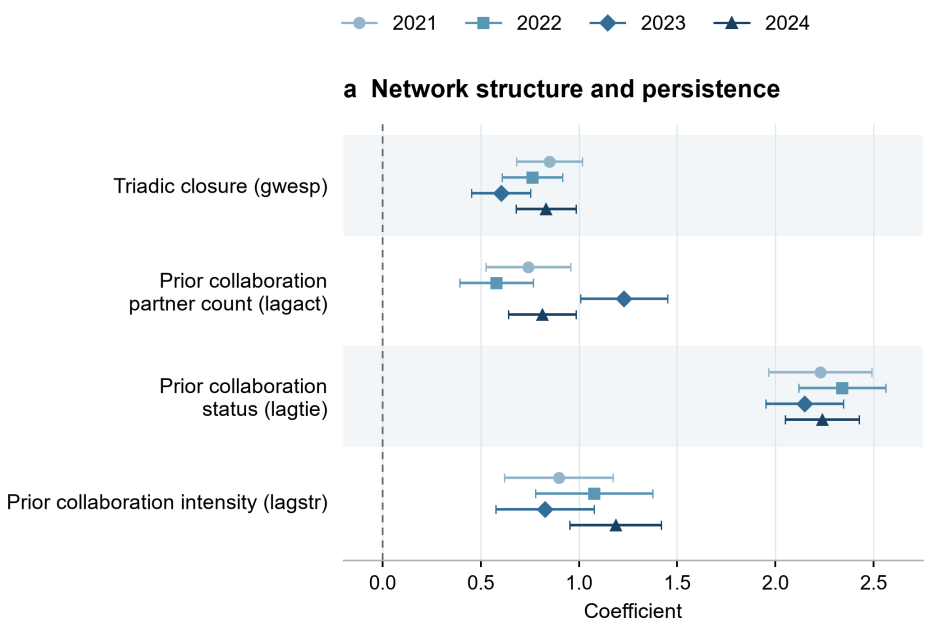

Fig. 6 Estimated coefficients for endogenous network structure and collaboration persistence from 2021 to 2024

had 8.58–10.38 times the conditional odds of next-year collaboration compared with previously noncollaborating pairs, holding other factors constant. Among previously collaborating pairs, a one-standard-deviation increase in log-transformed prior collaboration intensity corresponded to 2.29–3.27 times the conditional odds of continued collaboration in the following year.

5.2 Multidimensional proximity

Administrative proximity (org) had a significant positive coefficient in all four years (Figure 7), indicating a persistent collaboration advantage for cities within the same province. Shared provincial affiliation was therefore a stable feature of the spatial organization of collaboration. Holding other included factors constant, city pairs within the same province had 3.14–5.45 times the conditional odds of collaboration compared with pairs in different provinces. This finding reflects a consistent association between

shared provincial affiliation and collaboration ties. Geographical proximity (geo), by contrast, was significantly positive only in 2021 and 2024, indicating variation in its association with collaboration across years. This pattern may reflect the relative ease of interregional knowledge diffusion in new-energy technologies. Innovation in photovoltaics, fuel cells, and energy storage is not restricted to neighboring locations (Persoon et al. 2022). National policies also encourage innovation actors to establish joint R&D platforms and share scientific and technological resources (National Development and Reform Commission and National Energy Administration 2022), providing organizational support for interregional collaboration.

Technological proximity (tech) had significant positive coefficients in 2021, 2023, and 2024 (Figure 7), indicating a positive association between technological matching and collaboration in most years. Comparing M2 and M3 shows that its coefficients declined in all four years after innovation resources and the policy environment were included. For 2022, the coefficient was statistically significant in M2 but nonsignificant in M3. Partner selection therefore reflected technological matching as well as the resource bases and policy environments of both collaborating cities.

5.3 City-level innovation resources and the policy environment

A stronger combined resource base corresponded to a greater propensity to collaborate in most years (Figure 8). The advantage associated with similar resource bases was significant only in 2023 and 2024. The combined innovation resource base (irf) had positive coefficients in all four years, with statistical significance in 2021, 2022, and 2024. Holding other included factors constant, a one-unit increase corresponded to 1.25–1.50 times the conditional odds of collaboration in those three years. The difference in innovation resource bases (ird) had negative coefficients in all four years, but was significant only in 2023 and 2024. Differences between the two cities' resource bases had a relatively small association with the conditional odds of collaboration.

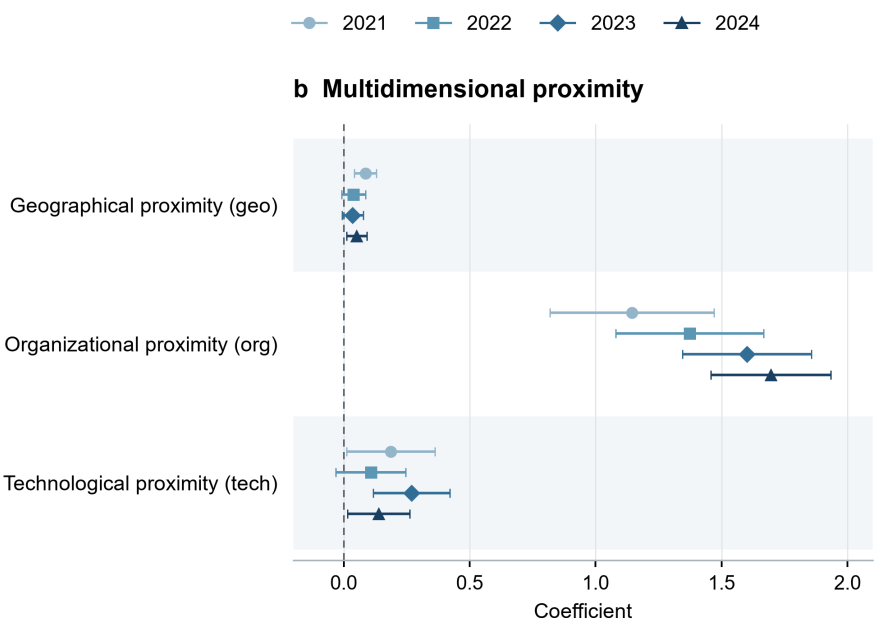

Fig. 7 Estimated coefficients for multidimensional proximity from 2021 to 2024

Variation in statistical significance across years may be related to collaboration needs. R&D collaboration involves acquiring complementary resources but is also constrained by both partners' capacities to absorb knowledge and invest in R&D (Audretsch et al. 2025).

Associations with the policy environment also varied across years. The number of innovative city pilots in a city pair (icp) had significant positive coefficients only in 2023 and 2024. This variation may reflect differences in local conditions for innovation and policy implementation. The innovative city pilot program's effects on industry–university–research collaborative innovation vary across regions and between provincial capitals and other cities (Zeng et al. 2023). Whether pilot status translates into collaboration advantages also depends on how local innovation resources are organized and used. The coefficient for the number of low-carbon city pilots in a city pair (lcp) was not statistically significant in any of the four years. The low-carbon pilot

program covers energy mix restructuring, energy conservation and reduced energy consumption, carbon emissions management, and the application of low-carbon technologies. It also requires localities to determine development pathways suited to their conditions (National Development and Reform Commission 2017). Its policy outcomes may therefore be more evident in local technology applications and emissions reduction practices.

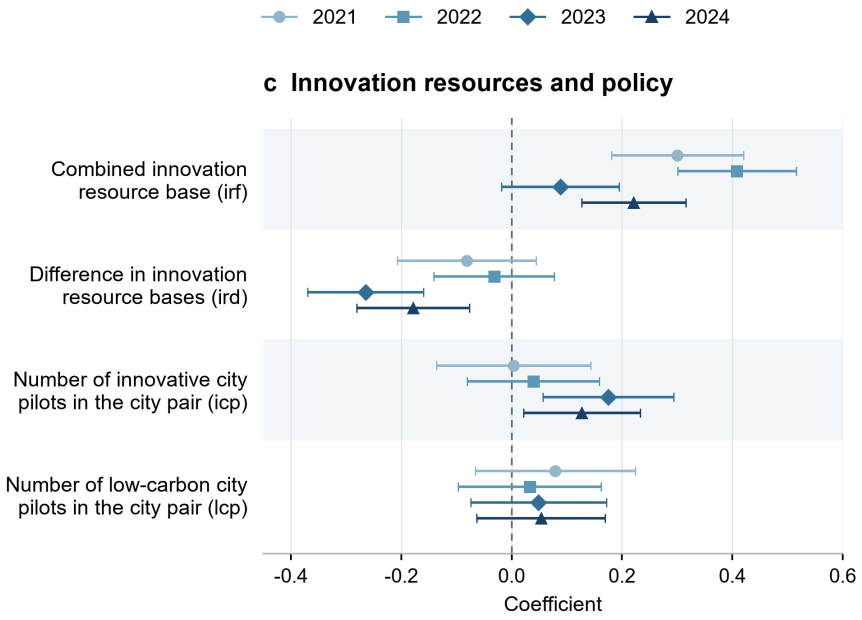

Fig. 8 Estimated coefficients for city-level innovation resources and the policy environment from 2021 to 2024

6 Conclusions and discussion

6.1 Conclusions

Using city-level new-energy patent data in China from 2020 to 2024, this study combines spatial analysis, social network analysis, and ERGMs. It examines spatiotemporal patterns of innovation output, the evolution of collaboration networks, and associated factors. The main findings are as follows.

City-level new-energy innovation output increased over 2020–2024 and exhibited significant spatial clustering. Intercity collaboration networks expanded over the same period, with increasing collaboration intensity. Spatial clustering of innovation output aligned with the concentration of collaboration around core cities. Interregional network expansion nevertheless coexisted with regional disparities in innovation output. Innovation output was concentrated in eastern areas, particularly the Yangtze River Delta, Pearl River Delta, and Beijing–Tianjin–Hebei region. Strong collaboration ties were also concentrated among eastern cities and in their interregional connections. This alignment indicates close correspondence between the spatial distribution of innovation output and intercity collaboration ties. Innovation nodes in central and western China gradually strengthened, and interregional collaboration ties increased. However, clusters of high innovation output remained concentrated in eastern China. Differences in innovation levels between some central and western cities and their surrounding areas also remained pronounced.

Intercity new-energy innovation collaboration was associated with endogenous network structure, multidimensional proximity, city-level innovation resources, and the policy environment, with varying strengths of association. Endogenous network structure and collaboration persistence showed consistently significant associations. Triadic closure, prior collaboration partner count, prior collaboration status, and prior collaboration intensity had significant positive coefficients in every year. Existing collaboration foundations and local network structure were thus closely associated

with tie formation and persistence. Among the proximity dimensions, administrative proximity was consistently significant and positive, while technological proximity was significant in most years. The significance of geographical proximity varied across years. Intercity collaboration was therefore associated with provincial affiliation and technological matching as well as geographical distance. A stronger combined innovation resource base generally corresponded to a greater propensity to collaborate, while negative associations with resource differences became significant in later years. The number of innovative city pilots in a city pair showed significant positive associations only in 2023 and 2024. The corresponding low-carbon city pilot count showed no significant associations.

6.2 Discussion

New-energy innovation output and strong collaboration ties remained concentrated in eastern China, while central and western cities became more involved in interregional networks. This uneven expansion highlights the need to coordinate established innovation hubs with emerging regional participants. In the context of clean-energy technology development, intercity patent collaboration provides an observable form of joint R&D across administrative boundaries. Our results suggest that these relationships are associated not only with the innovation resources available to cities but also with their existing network positions and prior ties. Triadic closure and collaboration persistence were consistently significant, while administrative proximity showed a strong positive association. Technological proximity and the combined innovation resource base were also positively associated with collaboration in most years. These patterns suggest that efforts to broaden cross-provincial R&D collaboration could consider technological matching, research capacity, and existing partnership networks. Policy associations were less consistent: the number of innovative city pilots in a city pair was positively associated with collaboration only in 2023 and 2024, whereas the

corresponding low-carbon city pilot count showed no significant association. Accordingly, policy designation alone should not be taken as evidence of stronger intercity collaboration. These findings provide insights for coordinating regional innovation resources and R&D partnerships in clean-energy technology development.

This study examines the spatial distribution, collaboration patterns, and evolution of new-energy innovation across Chinese cities. It also analyzes the main factors associated with intercity collaboration. The results capture the recent structure and changing patterns of new-energy innovation collaboration. However, the analysis relies mainly on patent application data. It therefore focuses on technological output and formal collaboration ties, while other forms of interaction are less well represented. In addition, the 2020–2024 observation period is better suited to identifying short-term changes than long-term trends. Differences across new-energy technology fields also warrant further investigation. Further analysis could incorporate information on joint R&D, technology transfer, and other forms of knowledge interaction. A longer observation period would also help assess whether the current network patterns persist over time. In addition, separate collaboration networks could be constructed for different new-energy technology fields. This would allow comparisons of collaboration scope, partner selection, and evolutionary paths across technologies, and provide a deeper understanding of how new-energy innovation collaboration develops.

Appendix A

Table A1 Full estimation results for zero-modified valued ERGMs with lagged covariates: (A) 2021–2022.

Model term	2021 M1	2021 M2	2021 M3	2022 M1	2022 M2	2022 M3
Baseline network terms						
sum	-0.302^{***}	-0.306^{***}	-0.306^{***}	-0.293^{***}	-0.292^{***}	-0.290^{***}
	(0.013)	(0.012)	(0.012)	(0.010)	(0.011)	(0.010)
nonzero	-7.264^{***}	-7.440^{***}	-7.302^{***}	-7.002^{***}	-7.187^{***}	-7.091^{***}
	(0.119)	(0.119)	(0.159)	(0.101)	(0.109)	(0.140)
Endogenous network structure and collaboration persistence						
gwesp	1.107^{***}	1.002^{***}	0.849^{***}	1.025^{***}	0.936^{***}	0.762^{***}
	(0.082)	(0.082)	(0.086)	(0.075)	(0.076)	(0.079)
lagact	0.919^{***}	0.979^{***}	0.742^{***}	0.875^{***}	0.939^{***}	0.580^{***}
	(0.076)	(0.074)	(0.110)	(0.068)	(0.069)	(0.096)
lagtie	2.599^{***}	2.316^{***}	2.228^{***}	2.603^{***}	2.368^{***}	2.340^{***}
	(0.124)	(0.131)	(0.134)	(0.113)	(0.112)	(0.113)
lagstr	0.907^{***}	0.898^{***}	0.897^{***}	1.020^{***}	1.036^{***}	1.077^{***}
	(0.145)	(0.145)	(0.142)	(0.148)	(0.154)	(0.152)
Multidimensional proximity						
geo		0.090^{***}	0.086^{***}		0.045^{*}	0.039
		(0.022)	(0.023)		(0.020)	(0.024)
org		1.106^{***}	1.144^{***}		1.344^{***}	1.373^{***}
		(0.153)	(0.166)		(0.142)	(0.150)
tech		0.359^{***}	0.187^{*}		0.303^{***}	0.107
		(0.085)	(0.089)		(0.066)	(0.071)
City-level innovation resources and policy environment						
irf			0.301^{***}			0.408^{***}
			(0.061)			(0.055)
ird			-0.081			-0.032
			(0.064)			(0.056)
icp			0.004			0.039
			(0.071)			(0.061)
lcp			0.079			0.033
			(0.074)			(0.066)

Table A1 Full estimation results for zero-modified valued ERGMs with lagged covariates (continued): (B) 2023–2024.

Model term	2023 M1	2023 M2	2023 M3	2024 M1	2024 M2	2024 M3
Baseline network terms						
sum	−0.248***	−0.248***	−0.248***	−0.181***	−0.182***	−0.183***
	(0.008)	(0.008)	(0.008)	(0.005)	(0.006)	(0.005)
nonzero	−7.029***	−7.250***	−7.015***	−7.478***	−7.633***	−7.434***
	(0.103)	(0.109)	(0.128)	(0.108)	(0.109)	(0.146)
Endogenous network structure and collaboration persistence						
gwesp	0.878***	0.742***	0.603***	1.148***	0.984***	0.832***
	(0.076)	(0.074)	(0.077)	(0.078)	(0.079)	(0.078)
lagact	0.989***	1.117***	1.229***	0.736***	0.905***	0.813***
	(0.064)	(0.066)	(0.113)	(0.058)	(0.063)	(0.088)
lagtie	2.545***	2.291***	2.149***	2.661***	2.387***	2.238***
	(0.098)	(0.104)	(0.101)	(0.096)	(0.092)	(0.096)
lagstr	0.812***	0.833***	0.827***	1.176***	1.186***	1.186***
	(0.124)	(0.109)	(0.128)	(0.123)	(0.106)	(0.119)
Multidimensional proximity						
geo		0.044*	0.035		0.063**	0.051*
		(0.020)	(0.021)		(0.022)	(0.020)
org		1.559***	1.600***		1.580***	1.696***
		(0.128)	(0.131)		(0.127)	(0.121)
tech		0.440***	0.269***		0.339***	0.139*
		(0.079)	(0.078)		(0.064)	(0.063)
City-level innovation resources and policy environment						
irf			0.088			0.221***
			(0.055)			(0.048)
ird			−0.265***			−0.178***
			(0.054)			(0.052)
icp			0.175**			0.127*
			(0.060)			(0.054)
lcp			0.049			0.053
			(0.063)			(0.059)

Note: Standard errors are reported in parentheses. *, **, and *** indicate significance at the 5%, 1%, and 0.1% levels, respectively. Blank cells indicate variables excluded from the relevant model. sum is the baseline total edge weight term; nonzero is the baseline nonzero tie term; and gwesp represents triadic closure. lagact is prior collaboration partner count; lagtie is prior collaboration status; and lagstr is prior collaboration intensity. geo, org, and tech denote geographical, administrative, and technological proximity, respectively. irf is the combined innovation resource base, incorporating economic scale, expenditure on science, the patent base, and human capital. ird is the difference in innovation resource bases. icp and lcp are the numbers of innovative city pilots and low-carbon city pilots in each city pair, respectively. M1 includes endogenous network structure and collaboration persistence. M2 adds multidimensional proximity to M1, and M3 adds city-level innovation resources and the policy environment to M2. All time-varying explanatory variables are lagged by one period.

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Statements and Declarations

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Competing Interests. The authors declare no conflicts of interest.

Data Availability. The data and core analysis code accompanying this study are available on Harvard Dataverse for peer review at https://dataverse.harvard.edu/previewurl.xhtml?token=313649fe-382b-4d9f-bc31-13648a91819c. The original data sources are described in Section 2.1 and Table 1.

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