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MEASUREMENT AND SPATIOTEMPORAL EVOLUTION CHARACTERISTICS ANALYSIS FOR THE PROVINCIAL DEVELOPMENT LEVEL OF INTELLIGENT CONSTRUCTION IN CHINA

Yudan DOU, Xueya YAN, Xin GUO, Shengbin MA✉, Longzhu ZHONG

Department of Construction Management, Dalian University of Technology, Dalian 116024, China

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Abstract. Intelligent Construction (IC) is emerging as a transformative approach within the architecture, engineering, and construction (AEC) industry, garnering significant global attention. There exist considerable disparities in the development levels of IC across various provinces in China, leading to uneven advancement that complicates precise policy formulation and differential implementation. Previous studies have primarily evaluated IC at the project and enterprise levels, thus lacking a comprehensive measure of the provincial IC development level. To bridge this gap, this study introduces a quantitative method to assess provincial IC development levels in empirical data, analyzing their driving factors and spatiotemporal evolution. Initially, based on the Politics-Economy-Society-Technology (PEST) analysis model, 16 measurement indexes were identified through a combination of literature review and expert interviews. Original data for these indexes were acquired via policy and media news mining, along with literature and patent indexing, etc. Subsequently, a quantification method for each index was established. The "analytic network process (ANP), entropy weight, and game theory" integration method was used to calculate combination weights. Finally, the development level of IC was quantitatively measured based on the cloud matter-element model, and the spatiotemporal evolution characteristics of the provincial development level in China from 2012 to 2022 were analyzed. The results indicate that (1) the development level of IC in China is divided into four levels, and the overall development level is relatively low, with only Beijing, Shanghai, and Shandong ranking at level I. (2) The development level shows a trend of increasing from northwest to southeast, with policy and technological factors being the main driving forces. (3) There is a significant spatial positive correlation between the development levels of provinces, and their spatial agglomeration effects are gradually developing from coastal areas to inland areas. The research results provide a theoretical basis for stakeholders such as governments and enterprises to formulate differentiated development strategies for IC and also provide a reference for measuring the development level of IC and other fields in other countries.

Keywords: intelligent construction, development level, spatiotemporal evolution, measurement system, China.

✉Corresponding author. E-mail: *mshengbin@mail.dlut.edu.cn*

1. Introduction

The construction industry, as a pillar industry of the national economy, still faces many challenges such as labor shortage, environmental pollution, resource waste, low production efficiency, high safety risks, and low levels of informatization and automation (Ji et al., 2017). These challenges are common in the global architecture, engineering, and construction (AEC) industry (Dou et al., 2023). Therefore, many countries are committed to applying new-generation information technologies such as artificial intelligence (AI), big data, the Internet of Things (IoT), 5G, blockchain in the construction industry to address these challenges (You & Feng, 2020). The integrated application of these new technologies has led to the emergence of an innovative construction method in the construction industry-intelligent construction (IC), which has become an important way to promote the transformation, upgrading, and sustainable development of the construction industry (Yan et al., 2023). IC can effectively improve the efficiency of detailed design (Zhao et al., 2022), construction (Ren & Zhang, 2021), operation, and maintenance (Huang et al., 2022), and achieve high integration and informatization of the entire industry chain. The application of IC technology has greatly liberated labor and improved the safety level, environmental benefits, and resource value of construction sites (Bradley & Seward, 1990). Some developed countries have taken the lead in implementing strategic layouts in the field of IC, such as the "*Infrastructure Reconstruction Strategic Plan*" proposed by the United States, the

"*Japan Revitalization Strategy*" initiated by Japan, and the "*Digital-based Industrial Innovation Development Strategy*" proposed by South Korea (Forcael et al., 2020).

China is the largest developing country and has been actively following in the footsteps of developed countries to promote the development of IC (see Figure 1a). In China, the concept of IC was proposed by the Ministry of Housing and Urban Rural Development [MHURD] in May 2017. In July 2020, the government issued "*the guiding opinions of the MHURD and other departments on promoting the coordinated development of intelligent construction and industrialized industrialization*" (MHURD, 2020). Existing studies emphasize the integration of emerging technologies with engineering practices. For instance, the IoT enhances data collection and analysis (Li et al., 2018), Building Information Modeling (BIM) and cloud platforms improve project management (Bucchiarone et al., 2020), robotics and automation systems streamline construction processes (Davila Delgado et al., 2019), and blockchain technology promote collaboration across various projects (Abioye et al., 2021). The widespread adoption of digital technology has significantly boosted project efficiency and quality, driving innovation in the industry (Zhang et al., 2024). However, although the technological development of IC has made some progress, it still faces several practical challenges. First, the IC development is influenced not only by micro-level technological development but also by macro factors such as policies, economics, and social conditions, involving coordination among various stakeholders across different levels (Ma et al., 2022). Second, IC is still in its early developmental phase, characterized by low motivation from enterprises, with initiatives primarily driven from the top down by governments at various levels (Ma et al., 2022). In this context, the absorption and implementation of IC-related policies from higher-level governments vary significantly among provinces (Dejaco et al., 2017), influenced by resource allocation, economic status, and development strategies, resulting in notable disparities in IC promotion across provinces (see Figure 1b). These disparities may lead to distorted development of IC at the provincial level. Lastly, comprehensively understanding the development data of IC across different regions poses challenges, hindering accurate policy formulation and the implementation of differentiated strategies. Therefore, a macro-level provincial IC evaluation system is anticipated to address these challenges, with primary objectives that include: (1) How can the overall development level of provincial IC be assessed? (2) Which indexes should be used to measure the provincial IC development levels, and how can these indexes effectively identified, quantified, and the necessary data collected? (3) What are the spatiotemporal evolution characteristics of provincial IC development levels?

However, there is currently no systematic research that reveals these objectives. Specifically, the previous research has the following shortcomings: (1) Previous studies often rely on qualitative and static measurement methods focused on individual projects or enterprises, which do not effectively capture the trends and characteristics of IC development across different periods and regions (Ke et al., 2022). Existing data and evaluation systems inadequately account for regional differences, lacking a scientific and effective quantitative monitoring mechanism for IC development, particularly at the provincial level (Dejaco et al., 2017). (2) Existing research has not established a comprehensive evaluation index system for the regional development level of IC. There is an urgent need for a holistic framework to elucidate policy performance (Nasirian et al., 2019), economic benefits (Hong et al., 2018), social impacts (Tam et al., 2015), and technological advancements (Jedel & Antonowicz, 2018) in this field. More importantly, traditional methods that rely on expert interviews and statistical yearbooks to obtain indicators and related data are not suitable for this study (Wang et al., 2021). Macro-level IC data are fragmented and not incor-

a) Number of national-level policie

b) Number of provincial-level policies

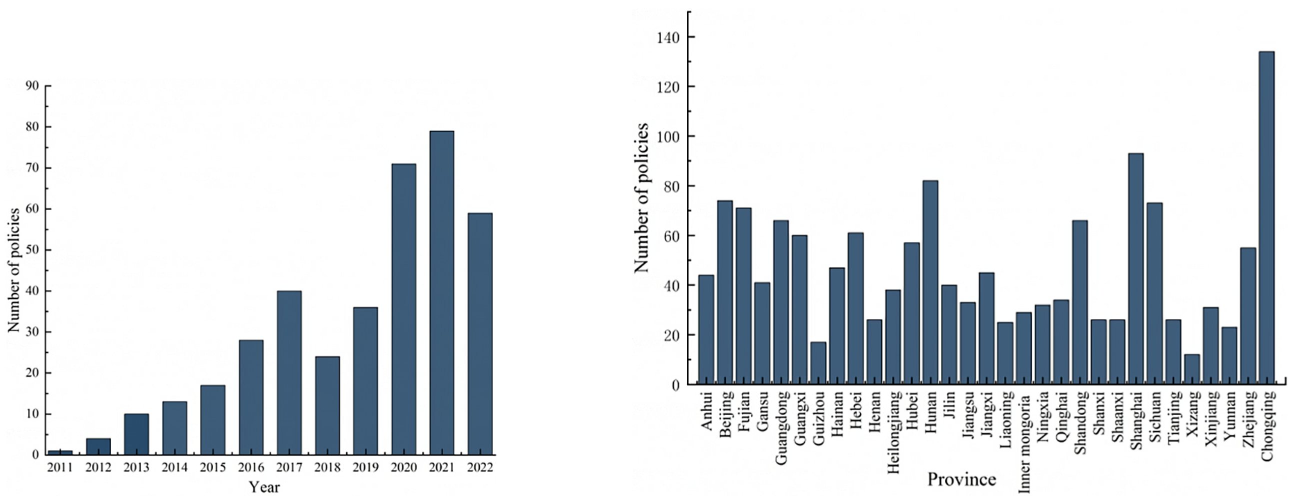

Figure 1. Number of national-level and provincial-level IC-related policies in China

porated into statistical yearbooks, while expert interviews are inherently subjective, making it difficult to objectively assess development levels across different regions. Consequently, data collection and quantification methods should move beyond expert interviews and surveys, incorporating multi-source online data mining, such as news articles and policy documents (Dou et al., 2019). (3) Previous studies on the spatiotemporal analysis of the construction industry have predominantly focused on regional disparities, often neglecting the development of quantitative models that integrate multidimensional data to uncover complex spatiotemporal interactions (Luo & He, 2021). The comprehensive evaluations combined with the spatial and temporal dimensions would optimize resource allocation, promote technological innovation, enhance talent cultivation, and solve the problems of opaque data and insufficient policy guidance in current management practices.

Accordingly, to address the aforementioned practical challenges and research gaps, this study introduces several key innovations: (1) A provincial evaluation model for the development of IC is established, considering regional disparities. This model addresses the limitations of previous studies in capturing provincial IC development differences and trends. (2) A comprehensive evaluation index system for provincial IC development levels is constructed. The study employs multi-source online data mining methods to collect and measure indicator data, effectively addressing the issues of missing IC-related indicators and challenges in data aggregation. (3) Spatiotemporal evolution analysis, based on Moran's Index, is conducted to reveal spatiotemporal development characteristics, highlighting regional interconnectivity and spatial agglomeration effects. In summary, this study contributes to the theoretical framework and quantitative methodology for evaluating IC development levels. The conclusions offer valuable references for IC planning and governance in regions similar to China, equipping governments and industries with effective assessment tools to improve decision-making and optimize policies. The retain of this paper is organized as follows. Section 2 reviews past literature. Section 3 discusses the construction of the research framework, research area, measurement system, and spatiotemporal evolution analysis method. Section 4 presents the holistic measurement results and discussion of the development level of intelligent construction. The final section summarizes the main findings.

Table 1. Summary of IC definitions

References	Definitions
Chen and Ding (2021)	IC is an innovative engineering paradigm resulting from the convergence of novel information technology and engineering practices. It facilitates comprehensive integration and efficient synergy across project planning, design, construction, and maintenance services through standardized modeling, networked interaction, visualization, cognition, high-performance computation, and intelligent decision support.
Mao (2019)	The utilization of advanced technologies during the design and construction phases enhances overall project quality by incorporating augmented reality, perception, decision-making, execution, and feedback mechanisms.
Wang and Yang (2018)	The advent of IC aims to fulfill specific functional requirements and user needs by leveraging advanced technology to imbue the entire construction process and operational environment of a project with intelligence, thereby enabling effective project management.
Zeng and Wang (2020)	Stakeholders involved in the project construction process strive to optimize the construction program, enhance construction methods, and leverage new technologies to promote resource conservation and productivity improvements. This is aimed at achieving comprehensive information control of the entire project and fostering sustainable development within the construction industry.
Kong and Ma (2020)	IC represents the integration of the entire construction process with physical systems through the amalgamation of intelligent computing, information and communication technologies, and other integrated technologies. This integration facilitates the management and control of construction process elements such as personnel, mechanical equipment, and facilities.
Wu et al. (2022)	The essence of IC lies in (1) generating a digital twin of a project through real-time data collection and integration; (2) simulating all life cycle activities, including planning, design, construction, and operation and maintenance; (3) optimizing decision-making in these activities; and (4) executing the physical project based on optimized decisions.
Fan et al. (2021)	IC encompasses the theory, method, process, and technology that integrates and fuses sensing technology, communication technology, data technology, construction technology, and project management to sense, analyze, control, and optimize the safety, quality, environmental impact, schedule, and cost of buildings and their construction activities.
Rossi et al. (2019)	IC represents a new generation of information technology, including cloud computing, Building the BIM, IoT, Geographic Information System (GIS), and AI, at its core, deeply integrated within the engineering construction system to form an innovative engineering construction model.
Mao and Peng (2020)	IC constitutes a novel construction approach founded on a high degree of information technology integration and industrialization. It leverages new technologies to empower the construction process, driving the enhancement of the three production elements in engineering construction activities, facilitating the seamless flow of construction data, integrating the entire construction activity process, achieving information integration and business synergy across the industry chain, enhancing energy efficiency during construction, and optimizing resource utilization.

2. Literature review

2.1. Intelligent construction

In the era of Industry 4.0, the application of new-generation information and artificial intelligence technologies, such as the IoT, big data, and cloud computing (Liu et al., 2016), in engineering project construction is becoming increasingly widespread (Han & Wang, 2018). This has given rise to the concept of IC, which has rapidly developed from an emerging concept to a hot research field. However, a unified understanding of the definition and scope of IC has not yet been formed worldwide. Representative definitions of IC are provided in Table 1.

This study defines IC as a novel construction and management method that utilizes emerging information technologies such as BIM technology, the IoT, and AI to enhance the production factors, productivity, and production relations of the entire engineering and construction activities. It aims to maximize the sharing of construction information, fuse the various stages of the entire construction lifecycle, and achieve a high level of integration and informatization across the entire industry chain. Additionally, it seeks to improve the energy efficiency of the construction process and maximize the value of resources.

The future trajectory of IC can be delineated based on the level of automation, encompassing the stages of mechanization, automation, and robotization (Sobotka & Pacewicz, 2017). Moreover, the degree of IC automation can be delineated into 10 levels, reflecting the human-machine interaction continuum, ranging from human responsibility for complete operation and control to automated operation and control by machines (Sheridan & Verplank, 1978). Currently, the construction industry in various nations is advancing towards higher levels of IC, with widespread application in residential construction (Štefanič & Stankovski, 2019), commercial buildings (Huang et al., 2024) and various infrastructure projects, including water conservancy (Zhong et al., 2019), bridges (Dunn et al., 1999), and transportation (Feng, 2019), spanning the entire life cycle of engineering design, construction, and operation and maintenance. Research by domestic and international scholars predominantly concentrates on the development, application, and promotion of individual technologies such as BIM (Son et al., 2015), AI (Aguilar & Hewage, 2013), cloud computing (Chancellor & Lu, 2016), and robotics (Cai et al., 2020), primarily at the micro level. Limited research has been conducted on comprehending the industrial development level of IC at the macro level and elucidating regional developmental disparities.

2.2. Measurement of development level

A scientifically effective measurement of development levels serves as a crucial tool for understanding the scale and dynamics of socio-economic phenomena across different periods, particularly within the construction industry. This enables stakeholders, such as government agencies and enterprises, to gain in-depth insights into local developmental foundations, thereby facilitating the formulation of targeted plans or strategic decisions (Huang et al., 2021). While evaluation studies in the construction sector are not a new field, previous research has yielded positive results in areas such as sustainability (Kucukvar & Tatari, 2013; Tatari & Kucukvar, 2012), development potential (Ozkan et al., 2012), regional competitiveness (Qinghua & Yanping, 2015), and productivity (Chancellor & Lu, 2016). With the sustainable development of digitalization, intelligence, and industrialization in the construction industry, establishing an evaluation system specifically for IC has become a pressing need. Existing evaluation on IC are often limited to specific technologies, such as assessing BIM maturity (Kam et al., 2017), evaluating the application of IoT (Oke & Arowoiya, 2021), and examining blockchain performance (Cong & Zi, 2020). However, previous research on IC evaluation lacked a macro perspective on reglonal development, which could not effectively guide the differentiated formulation and guidance of policles in different reglons.

Drawing insights from evaluation research in other areas of the construction industry, such as static and dynamic analyses to assess the development levels of prefabricated construction (PC) (Ji et al., 2019), qualitative evaluations based on industrial policy performance (Park et al., 2011), and cloud model assessments of construction industrialization (Wang et al., 2021), offers valuable implications for IC evaluation. These studies have developed macro-regional PC evaluation index systems through expert interviews and literature surveys, emphasizing the importance of technological, policy, economic, and social factors (Dou et al., 2019). They provide valuable insights for the evaluation of IC. However, due to the lack of relevant statistical data, these studies predominantly rely on small-scale case analyses of specific projects or regions (Liu et al., 2017), making it difficult to comprehensively capture the overall development of the industry, especially at the national level, where macro-regulatory goals are challenging to achieve. Moreover, the existing foundational data and evaluation systems have not fully considered regional differences, lacking a scientific and effective quantitative monitoring mechanism for IC development, particularly at the provincial level (Dejaco et al., 2017). Multi-source data driven by new media can effectively supplement traditional statistical data, providing more multidimensional information to support IC evaluation, particularly in situations where regional data is dispersed and challenging to unify (Brossard, 2013). Existing studies often utilize the entropy-weighted TOPSIS method (Gu et al., 2021) or statistical analysis following text mining to explore spatiotemporal evolution (Luo & He, 2021). However, they lack rigorous quantitative models capable of integrating multidimensional data and uncovering complex spatiotemporal interaction characteristics. Establishing a comprehensive IC evaluation framework based on quantitative data is critical to identifying provincial development statuses and disparities, enabling the formulation of targeted development strategies, and facilitating the industry's intelligent upgrade from local to national scales.

3. Methodology

3.1. Research framework

This study measures the overall development level of IC and analyzes the spatiotemporal evolution characteristics of each province's development level. Firstly, 16 indexes for measuring the development level of IC are identified based on the PEST analysis model. Then, corresponding quantitative methods are designed for each index, and an integrated approach combining entropy weight, Analytic Network Process (ANP), and game theory is used to calculate indexes weights. Furthermore, the cloud matter-element model is employed to measure the development level of IC. Finally, Moran's Index is used to analyze the temporal dynamics and spatial autocorrelation of the measurement results, exploring the spatiotemporal evolution characteristics of IC development. Figure 2 presents the research framework.

3.2. Study area

The geographical characteristics, cultural characteristics, and economic foundation will all affect the regional development level of the industry. The division of provinces in China meets the convergence of the above characteristics, and the regional statistical system is also based on provinces, municipalities directly under the central government, and autonomous regions. Due to the inability to obtain complete information in regions such as Taiwan, Hong Kong, and Macau, this paper selects 22 provinces, 4 municipalities directly under the central government, and 5 autonomous regions in mainland China as the measurement objects, collectively referred to as "provinces" in the following text.

3.3. Measurement system for the development level of IC

3.3.1. Determination of measurement indexes

The measurement index system for the IC development level has not formed a unified standard, especially with few studies focusing on the measurement of the provincial development level. The PEST analysis model provides ideas for establishing a comprehensive index system for measuring the development level of IC. This model is often used for macro analysis of the external strategic environment of enterprises or industries, including political, economic, social, and technological dimensions. The measurement index system constructed with the PEST model can take into account various aspects of industry development and select targeted indexes that can reflect provincial development characteristics.

Due to the limited literature directly related to the measurement indexes of IC development level, this study referred to relevant achievements in the field of industrialized construction. This is because the external environment of industrialized construction and IC development is similar. Therefore, based on the PEST model, this study used literature analysis and expert interviews to identify indexes, and further tested the rationality and representativeness of the indexes through expert interviews. The author invited 10 experts engaged in IC-related work, including construction enterprises (3 people, 30%), research institutions (2 people, 20%), industry associations (2 people, 20%), and government agencies (3 people, 30%), for interviews. When at least half of the experts believe that the index is unreasonable or atypical, it will be deleted. In addition, this study also tested the usability of index data. Finally, 16 indexes were determined to measure the development level of IC. The measurement index system is shown in Table 2.

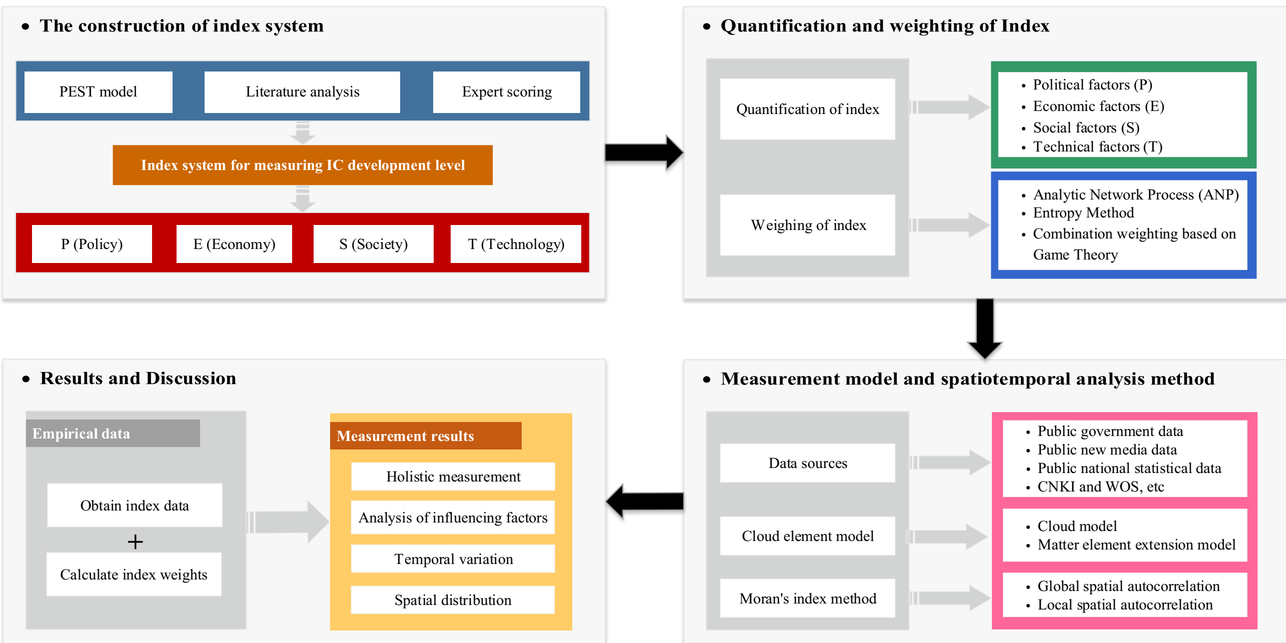

Figure 2. Research framework

Table 2. Measurement index system of IC development level

Primary index	Sub-index	Justification
Political index (P)	Policy tools (P1)	Gan et al. (2023)
	Policy intensity (P2)	Gan et al. (2023); Luo et al. (2021)
	Policy objectives (P3)	Dou et al. (2019)
	Technical standard specification level (P4)	Borrás and Laatsit (2019); Ma et al. (2019)
Economic index (E)	Number of IC-related enterprises (E1)	Liu et al. (2017)
	Number of demonstration cities, bases and projects (E2)	Xu et al. (2024)
	Labor productivity (E3)	Liu et al. (2017)
	Contribution to regional economy (E4)	Dou et al. (2019)
Social index (S)	Appearing frequency of IC-related news (S1)	Dou et al. (2019); Expert interviews; New media information
	The keyword search popularity (S2)	Dou et al. (2019)
	Clicks of IC-related news (S3)	Dou et al. (2019); Expert interviews; New media information
	Forwarding quantity of IC-related news (S4)	Dou et al. (2019)
Technical index (T)	Number of IC-related research institutions and associations (T1)	Lu et al. (2018)
	Technical equipment rate (T2)	Wang and Wu (2022)
	Number of IC-related patents (T3)	Xue et al. (2024)
	Number of published papers (T4)	Xue et al. (2024)

3.3.2. Index quantification methods

(1) Political Indexes

Policy tools (P1). This refers to the number of IC-related policies issued by the government. Using Eqn (1) to unify the dimensions of P1 data, where C_{1j} represents the cumulative number of IC-related policies in province j, and P_{1j} represents the index score of province j.

$$P_{1j} = 10\left(1 - \frac{\max C_{1r} - C_{1j}}{\max C_{1r} - \min C_{1r}}\right),\ j, r = 1, 2, \ldots, n. \quad (1)$$

Policy intensity (P2). P2 represents the degree of compulsion in the implementation process of IC-related policies. Generally, the higher the administrative level of policy issuers, the wider the scope of policy application, the stronger the policy intensity, and the higher the quantitative score. Based on the scoring criteria of policy intensity in Table 3, the i-th policy of province j was scored to obtain C_{2ji}, where P_{2j} represents the index score of province j.

$$P_{2j} = 2\frac{\sum_{i=1}^{m} C_{2ji}}{m},\ j = 1, 2\ldots, n, i = 1, 2\ldots m. \quad (2)$$

Policy objectives (P3). This mainly evaluates the level of IC development goals set by local governments in policy documents, especially the comparison with the IC's goals pointed out in the State Council documents in 2025 and 2035. The quantification of policy goals is mainly achieved by comparing the consistency of goals set by local and national governments. If the two are consistent, a score of 3 will be given. If the local goals are higher than the national goals, a score of 5 or 4 will be given. Otherwise, a score of 2 or 1 will be given. The scoring criteria for P4 are shown in Table 4, and the quantification method is similar to P2.

Table 3. Quantitative scoring criteria for policy intensity

Score	Quantitative scoring criteria
5	Regulations, regulations, decisions, opinions, methods, and standards issued by provincial people's congresses, provincial governments, departments, and bureaus.
3	Plans, guidelines, temporary regulations, detailed rules, and conditions.
1	Notification, announcement, evaluation method, trial implementation method.

Table 4. Quantitative scoring criteria for policy objectives

Score	Quantitative scoring criteria
5	The local government has set IC development goals, clearly defining timelines and target outcomes, and the goal setting is higher than national requirements.
3	The local government has set IC development goals that are consistent with national requirements.
1	The local government has not set goals or the goals are lower than national requirements.

Technical standard specification level (P4). P4 is mainly represented by the number of IC-related technical standards issued by local authorities. These technical standards have a promoting and regulating effect on the provincial development of IC. The quantification method is similar to P1.

(2) Economic indexes

Number of IC-related enterprises (E1). The data for this index is obtained through publicly available online information such as listed company information, industry-related exhibition exhibitor directories, and self-built website registration companies. The quantification method is similar to P1.

Number of demonstration cities, bases and projects (E2). This is mainly represented by the number of IC demonstration cities, industrial bases, and technology demonstration projects announced by the MHURD. The quantification method is similar to P1.

Labor productivity (E3). This refers to the labor productivity of the construction industry in each province released by the National Bureau of Statistics. The quantification method is similar to P1.

Contribution to regional economy (E4). E4 is mainly represented by the ratio of the construction industry output value to the GDP of each province released by the National Bureau of Statistics, and the quantification method is similar to P1.

(3) Social indexes

Appearing frequency of IC-related news (S1). IC-related news is mainly obtained through crawling on some news websites and classified by the province through text analysis. To ensure the objectivity of the data, the news in t is average and recorded as Q_{1j}. The quantitative method is shown in Eqns (3)–(4). Where q_{1ja} represents the number of IC-related news; S_{1j} represents the index score of province j; t represents the time of news searching.

$$Q_{1j}=\frac{\sum_{a=t_1-t}^{t} q_{1ja}}{t},\ a=t_1-t, t_1-t+1\ldots,t_1; \tag{3}$$

$$S_{1j}=10\left(1-\frac{\max Q_{1r}-Q_{1j}}{\max Q_{1r}-\min Q_{1r}}\right),\ j,r=1,2,\ldots,n. \tag{4}$$

Appearing frequency of IC-related news (S2). This reflects the population's attention to IC-related keywords within a province. Determine the search popularity value S_{2j} based on the search ranking obtained through a crowd portrait analysis of the Baidu Index. Assuming that the search ranking of keyword i in province j within a certain interval is P_{ij}. Then, the average ranking S_{2j} of IC-related keywords in province j and the unified dimension value S_{2j} can be obtained:

$$s_{2j}=\frac{\sum_{i=1}^{I} p_{ij}}{I},\ \ i=1,2,\ldots I,\ j=1,2,\ldots,n; \tag{5}$$

$$S_{2j}=\frac{10}{n}\left(\max S_{2r}-S_{2j}+1\right),\ \ j,r=1,2\ldots,n. \tag{6}$$

Clicks of IC-related news (S3). This reflects the concerns of IC-related news. This study uses the traffic of official websites such as WeChat, Sina, Sohu, and Baidu as the data source, and calculates the average click in t to obtain S_{3j}. The quantification method is similar to S1.

Forwarding quantity of IC-related news (S4). This refers to the number of reposts of IC-related news on new media channels (WeChat, Weibo, etc.). The quantification method is similar to S1.

(4) Technological indexes

Number of IC-related research institutions and associations (T1). The research institutions and associations in T1 are at or above the municipal level. The quantification method is similar to P1.

Technical equipment rate (T2). This refers to the technical equipment rate of the construction industry in each province released by the National Bureau of Statistics. The quantification method is similar to P1.

Number of IC-related patents (T3). This is an important index reflecting the technological innovation achievements of construction enterprises in a province. The statistical object of this index is enterprises within the IC industry demonstration base recognized by the MHURD. The quantification method is similar to P1.

Number of published papers (T4). The data for this index was obtained through statistical analysis of IC-related papers in the China National Knowledge Infrastructure (CNKI) and Web of Science core database (WOS). The quantification method is similar to P1.

3.3.3. Indexes weights calculation

To ensure the rationality of the measurement results, this study adopts the combination weighting method to calculate indexes weights, namely the "ANP – entropy weight – game theory" integration method. Firstly, use ANP to determine the subjective weights of the indexes. ANP overcomes the shortcomings of AHP and is more in line with practical decision-making problems, theoretically solving complex dynamic feedback system problems (Shyur, 2006). However, due to differences in the knowledge reserves and understanding of IC among different experts, ANP can lead to subjective bias in the evaluation results. Therefore, this study introduces the entropy weight method to determine objective weights based on the objective laws exhibited by index data. Finally, game theory is used to fuse the subjective and objective weights to obtain the combined weights. The determination of combination weights is mainly aimed at Nash equilibrium, with the minimum deviation between the two sets of weights as the final game result. Using this method can reduce the degree of deviation between the subjective and objective weighting results, making the measurement results more accurately reflect the real situation (Kordos & Lapa, 2018). The steps for calculating combination weights using game theory are as follows.

$\omega_k=\left[\omega_{k1},\omega_{k2},\ldots,\omega_{kn}\right]$ is the set of weight vectors, where k (k = 1,2 , ..., P) is the number of weight calculation methods used. In this paper, P = 2 and n = 16, which means that the weight vectors determined by ANP and entropy weight method are ω_1 and ω_2, respectively.

(1) The minimum deviation strategy based on game theory can be represented by Eqn (7):

$$\min\left\|\sum_{k=1}^{P}\lambda_k\omega_k^T-\omega_k\right\|,\ k=1,2. \tag{7}$$

(2) Let $\lambda=\{\lambda_1,\lambda_2\}$ be a linear combination coefficient and convert Eqn (8) into an optimal first-order derivative:

$$\begin{pmatrix}\omega_1\omega_1^T & \omega_1\omega_2^T\\ \omega_2\omega_1^T & \omega_2\omega_2^T\end{pmatrix}\begin{pmatrix}\lambda_1\\ \lambda_2\end{pmatrix}=\begin{pmatrix}\omega_1\omega_1^T\\ \omega_2\omega_2^T\end{pmatrix}. \tag{8}$$

(3) Then, normalize coefficient λ to obtain the combination coefficient:

$$\lambda_1^*=\frac{\lambda_1}{\lambda_1+\lambda_2},\ \lambda_2^*=\frac{\lambda_2}{\lambda_1+\lambda_2}. \tag{9}$$

(4) Obtain the combination weights based on Eqn (10):

$$\omega=\lambda_1^*\omega_1^T+\lambda_2^*\omega_2^T. \tag{10}$$

3.3.4. Development level measurement method: Cloud matter-element model

(1) Cloud model. Cloud model can reflect the correlation between randomness and fuzziness in different dimensions of the same event, and form mapping relationships between qualitative and quantitative things. The model has numerical features such as expectation (*Ex*), entropy (*En*), and hyper entropy (*He*). *Ex* represents the average value in the studied sample data. *En* mainly measures the randomness and degree of confusion in qualitative descriptions. *He* describes the randomness and chaos degree of entropy, and the larger *He*, the greater the degree of dispersion of the assessment samples.

(2) Matter element analysis method. This method was proposed by Chinese scholar Cai (1999) in the 1980s and can effectively solve incompatible problems in the real world. Usually, things are represented as R = (N, C, V), where R represents the basic element of things composed of these three factors. N represents the name of the object, C represents the feature to which the object belongs, and V represents the numerical value of the feature to which it belongs.

(3) Cloud matter-element model. Cloud model can effectively express the fuzziness and irregularity of things, matter element analysis method can solve incompatible problems. Therefore, this paper combines the two to measure the development level of IC. According to the IC development level measurement index system constructed in Section 3.3.1, the IC development level is taken as the overall measurement index element, including four primary measurement indexes of policy, economy, society, and technology, and 16 subindexes as the index layer element. The expression of the cloud matter-element model is shown in Eqn (11):

$$R=\begin{bmatrix}N & C_1 & (Ex_1,En_1,He_1)\\ & C_2 & (Ex_2,En_2,He_2)\\ & C_3 & (Ex_3,En_3,He_3)\\ & \vdots & \vdots\\ & C_n & (Ex_n,En_n,He_n)\end{bmatrix}, \tag{11}$$

where R represents the standard cloud element for measuring the development level of IC; C represents the index to be evaluated; (*Ex*, *En*, *He*) represents the standard cloud corresponding to the indexes to be evaluated.

The calculation steps for the cloud matter-element model are as follows.

Step 1: Determine standard cloud parameters

According to the index quantification method in Section 3.3.2, all index data will be uniformly processed into interval data of [0,10]. Referring to the research of relevant researchers (Liu et al., 2017; Wang et al., 2021), the development level of IC is divided into four levels from low to high: I, II, III, and IV. The corresponding standard cloud parameters are (0,2], (2,4], (4,7], and (7,10].

Step 2: Determine indexes weights

Use the combination weighting method proposed in Section 3.3.3 to determine the combination weights of indexes.

Step 3: Determine membership degree

Consider the sample data as a cloud droplet xi, and calculate the membership degree of x_i (i.e., the values of various indexes) following *En* based on the determined numerical characteristics of the cloud (*Ex*, *En*, *He*):

$$k_{jh}\left(x_i\right)=\exp\left[-\frac{(x_i-Ex)^2}{2(En^{'})^2}\right], \tag{12}$$

where $k_{jh}(x_i)$ is the membership degree between the *i-th* index value x_i and the h-th level; *Ex* is the expectation of the normal cloud model for the measurement level.

Calculate the cloud correlation degree between the IC development level measurement index and each index level using Eqn (13), and form a cloud correlation value matrix **K**:

$$\mathbf{K}=(k_{j\times h})_{n\times L}=\begin{bmatrix}k_{11} & k_{12} & \cdots & k_{1L}\\ k_{21} & k_{22} & \cdots & k_{2L}\\ \vdots & \vdots & \ddots & \vdots\\ k_{n1} & k_{n2} & \cdots & k_{nL}\end{bmatrix}, \tag{13}$$

where n is the number of indexes and L is the number of measurement levels of indexes.

Step 4: Calculate the cloud correlation degree

Calculate the cloud correlation degree between the IC development level measurement index and the corresponding level using Eqn (14):

$$k_j(N_j)=\sum_{j=1}^{n}\omega_i k_{jh}(x_i), \tag{14}$$

where $k_j(N_j)$ is the correlation degree of the corresponding level j, and ω_i is its corresponding index weight.

Step 5: Determine the development level

According to the principle of maximum membership degree, determine the membership level of provincial IC development level:

$$k_j = \max\left\{j = 1, 2, \cdots, n\right\} K_j(N_j). \quad (15)$$

3.4. Spatiotemporal evolution analysis method

This study analyzes the spatiotemporal evolution of the measurement results of the provincial development level of IC from 2013 to 2022 and explores the overall development trend and dynamic changes in the driving factors (PEST) of provincial IC from a temporal perspective. Using Moran's index (Moran's I) to explore the spatial correlation of provincial IC development from a spatial perspective, in-depth analysis of the spatial agglomeration phenomenon at the provincial level.

Spatial correlation refers to the similarity of variable values between adjacent regions, and Moran's I is the most commonly used analytical method (Srejić et al., 2023). The Moran's I is divided into global and local Moran's I. The former can only reflect whether the national IC development level has spatial correlation, while the latter can more accurately reflect the correlation and agglomeration of IC development levels between each province and neighboring provinces. The research object of spatial correlation analysis does not include Xizang, because Xizang's geographical location, climate conditions, and economic structure are very different from other provinces.

(1) Global spatial correlation

The global Moran' I is a key index for analyzing global spatial correlation:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}; \quad (16)$$

$$S^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}, \quad (17)$$

where I ($-1 \le I \le 1$) is the global Moran' I, where $I > 0$, $I < 0$, and $I = 0$ respectively indicate that the research object has positive, negative, and uncorrelated spatial correlations. N represents the number of provinces, x_i and w_{ij} represent the IC development level scores of provinces i and j, $\bar{x}$ is the average of the IC development level scores of 30 provinces, and S2 represents the variance. w_{ij} is a spatial weight matrix, divided into geographic and economic distance weight matrices, this paper uses an economic distance matrix. Based on the IC development level scores of 30 provinces in China from 2013 to 2022, the global Moran' I was calculated using Stata software.

(2) Local spatial correlation

The local Moran' I is a key index for observing the spatial agglomeration phenomenon of a specific region:

$$I_i = \frac{x_i - \bar{x}}{S^2}\sum_{j \ne i} w_{ij}\left(x_j - \bar{x}\right). \quad (18)$$

4. Results and discussion

4.1. Index data acquisition

Taking into account the timeliness of research and information consistency, this study sets the deadline for data acquisition as December 31st, 2022, and the data collection for all indexes will be restricted before this point. As shown in Table 5, the data is divided into fixed-time interval data and historical data, which is determined according to different attributes of the information.

Table 5. Time data for corresponding indexes

Date type	Time	Corresponding indexes
Fixed-time interval data	1/1, 2022 to 31/12, 2022	E3/E4/S1/S2/S3/S4/T2
Historical data	Up to 31/12, 2022	P1/P2/P3/P4/E1/E2/T1/T3/T4

(1) Political indexes data

Using keywords such as "intelligent construction", "smart construction", "smart construction sites", "digital construction", as well as related keywords such as "BIM", "artificial intelligence", "Internet of Things", "mobile communication technology", and "big data", the search was conducted on the official websites of 31 provincial governments, the State Council, the MHURD, and the PKULAW (https://www.pkulaw.com/). Through manual screening, duplicate, expired, low relevance, and informal policy texts were excluded, and 741 policy texts were ultimately determined. Based on data, quantify policy tool (P1), policy intensity (P2), and policy objective (P3). The technical standard specification level (P4) is determined by the number of technical standards issued by local governments, and the data is sourced from the websites of housing and construction bureaus in various provinces, CNKI (https://www.cnki.net/), and CSSN (https://www.cssn.net.cn/cssn/index). The data on the political index of each province is summarized in Table 6.

(2) Economic indexes data

The number of IC-related enterprises (E1) is determined based on the place of registration of the enterprise. The demonstration efficiency level (E2) is expressed by the number of intelligent construction pilot cities and demonstration projects. The number of pilot cities is derived from "the Notice of the MHURD on Publishing Intelligent Construction Pilot Cities" (2022, No. 82). In the notice, 24 cities were identified as the first batch of IC demonstration cities. The number of demonstration projects comes from the first batch of typical case lists of IC new technologies, new products, and innovative services released by the MHURD. The data on labor productivity (E3) and contribution to regional economy (E4) are sourced from the National Bureau of Statistics, the China Statistical Yearbook, and the construction industry statistical yearbooks of provinces. The data on the economic index of each province is summarized in Table 6.

Table 6. Data summary of political, economic, social, and technological indexes

Province	Political indexes				Economic indexes				Social indexes				Technical indexes			
	P1	P2	P3	P4	E1	E2	E3	E4	S1	S2	S3	S4	T1	T2	T3	T4
Anhui	44	3	116	0	210	1	533025	0.30	145	231.37	0	646	8	12693.7	51	37
Beijing	74	5	73	7	101	11	640306	0.23	279	290.34	315	866	7	22362.8	97	440
Fujian	71	3	86	0	78	7	322044	0.29	85	393.65	2	632	0	11530	24	60
Gansu	41	1	28	0	101	0	460221	0.20	19	760.80	4	375	1	15139.1	5	16
Guangdong	66	5	56	4	397	13	543078	0.15	150	314.13	19	1360	28	6378.2	120	195
Guangxi	60	3	36	0	20	2	533283	0.24	139	216.60	4	520	2	6372.4	10	41
Guizhou	17	1	35	0	77	0	541463	0.21	65	34.90	0	424	2	7127.4	2	26
Hainan	47	3	61	0	42	0	674177	0.06	57	2.70	25	297	1	6180.7	0	4
Hebei	61	5	75	3	92	6	645244	0.15	60	996.83	196	721	3	21453.7	17	78
Henan	26	1	33	2	77	4	460776	0.22	54	234.22	5	823	4	7478.9	19	83
Heilongjiang	38	5	119	0	25	1	427535	0.08	29	79.80	0	424	1	14699.9	3	39
Hubei	57	5	151	2	158	5	761375	0.32	85	157.28	425	713	2	7841.7	35	213
Hunan	82	3	180	0	72	4	440835	0.26	96	260.95	0	653	2	4411.3	22	47
Jilin	40	3	99	2	42	1	598758	0.15	37	0.00	0	391	3	19245.5	4	27
Jiangsu	33	5	148	0	138	11	369394	0.30	81	277.93	139	1069	6	26874.7	125	311
Jiangxi	45	3	58	5	48	1	537197	0.29	98	715.60	22	530	2	19160	7	26
Liaoning	25	5	44	4	47	2	578784	0.14	58	395.85	0	578	7	7048.9	23	68
Inner Mongolia	29	3	26	0	113	0	521443	0.06	30	55.90	0	387	2	4358.6	1	22
Ningxia	32	1	9	1	28	0	388376	0.14	20	11.90	0	247	0	5440.5	0	0
Qinghai	34	3	9	0	6	1	713397	0.15	9	0.00	1	182	1	9964.8	0	1
Shandong	66	5	162	7	17	9	534832	0.18	141	365.28	17	970	11	13192.3	38	92
Shanxi	26	5	37	1	59	1	461711	0.23	32	85.55	0	483	1	10624.2	6	25
Shaanxi	26	5	83	0	5	2	553359	0.29	41	365.70	2	605	1	4207	28	119
Shanghai	93	3	117	0	77	5	760651	0.19	258	240.42	10	699	5	16678.5	95	354
Sichuan	73	5	54	0	68	10	420179	0.29	162	427.25	43	865	7	19638.8	44	92
Tianjin	26	3	58	0	30	2	526910	0.28	264	526.37	1	435	1	5189.2	18	99
Xizang	12	1	32	0	21	0	586263	0.14	8	0.00	0	116	0	6235.8	1	1
Xinjiang	31	1	23	0	39	2	497108	0.17	17	28.60	1	369	1	12225.8	4	7
Yunnan	23	3	52	0	86	0	452075	0.25	33	263.40	3	478	3	11718	3	20
Zhejiang	55	3	74	2	107	11	393185	0.28	120	246.41	6	942	5	48358.8	70	105
Chongqing	134	5	47	4	64	1	436359	0.32	209	336.95	2	553	3	8544.7	37	111

(3) Social indexes data

S1, S3, and S4 are indexes related to news, with data sourced from Baidu, Sina, and Sohu (three large news clients with a big influence in China), Weibo, Subscription number of WeChat, and information from the State Council, Ministry of Housing and UrbanRural Development, National Construction Information Network, and Science and Industrialization Development Center of the Ministry of Housing and Urban-Rural Development. Firstly, this study utilized Octopus software to collect news information from the internet, and a total of 8547 IC-related news items were collected. Then, delete duplicate news and some low-relevance advertising information, keeping 4886 items (Huang et al., 2025). Finally, using the stuttering word segmentation package in Python language, the text was segmented to match news with provinces, resulting in 1310 provincial news. The process of news cleaning and classification is shown in Figure 3. In addition, the keyword search popularity (S2) within the region is obtained through Baidu Index. Baidu Index is a data-sharing platform based on uninterrupted user behavior data, and its character portrait module can reflect the ranking of regional popularity. The data on the social index of each province is summarized in Table 6.

(4) Technical indexes data

The number of IC-related research institutions and associations (T1) was obtained from publicly available information on the Internet, with a total of 121 collected. The technical equipment rate (T2) is derived from the statistical yearbooks of the construction industry in each province. The number of IC-related papers published (T3) comes from CNKI and Baiten (https://www.baiten.cn/). Screen patents based on their names and abstracts, and classify them by province based on their registration attribution, author organization attribution, and patent attribution. The number of IC-related papers published (T4) comes from CNKI and WOS (https://clarivate.com.cn/). The data on the technical index of each province is summarized in Table 6.

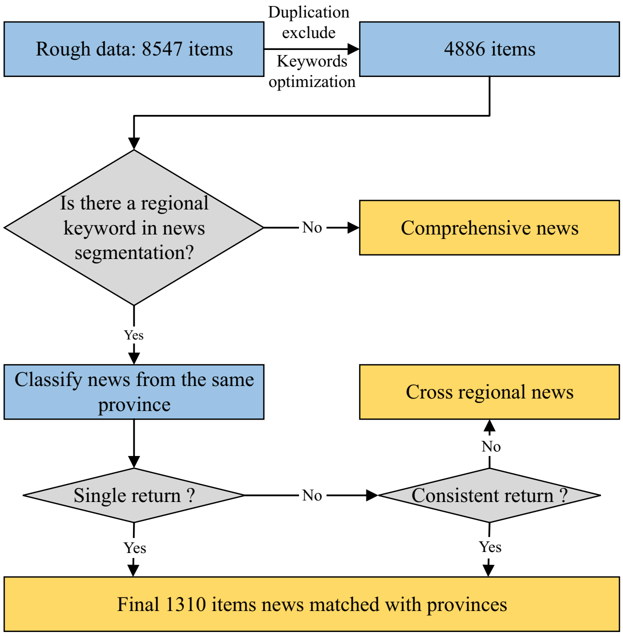

Figure 3. News cleaning and classification process

4.2. Determination of indexes weights

This paper uses ANP and entropy weighting methods to calculate subjective and objective weights respectively, and combines the two weights using game theory to obtain the combined weights of 16 indexes, as shown in Table 7.

Table 7. Combination weight of index

Index	Subjective weight	Objective weight	Combination weight
P1	0.0883	0.0301	0.0611
P2	0.1900	0.0342	0.1169
P3	0.1929	0.0339	0.1184
P4	0.0260	0.1281	0.0739
E1	0.0387	0.0470	0.0426
E2	0.0570	0.0744	0.0651
E3	0.0470	0.0191	0.0340
E4	0.0710	0.0184	0.0463
S1	0.0174	0.0642	0.0394
S2	0.0127	0.0497	0.0301
S3	0.0050	0.1998	0.0963
S4	0.0449	0.0224	0.0343
T1	0.0630	0.0711	0.0668
T2	0.0602	0.0567	0.0585
T3	0.0814	0.0800	0.0807
T4	0.0045	0.0709	0.0356

4.3. Holistic measurement for the development level of IC

To ensure the dimension uniformity and comparability of the index data, and the reliability of the conclusions, all the indexes need to be processed according to the quantitative method in Section 3.3.2. Then, based on the calculation steps of the cloud matter-element model in Section 3.3.4, the development level of IC in 31 provinces of China is obtained, as shown in Table 8.

ArcGIS 10.7 was used to link development levels with spatial analysis units in vector form, and to plot the spatial distribution of IC's development levels in 31 provinces of China (see Figure 4).

Table 8. The development level of IC

Province	Level	Province	Level	Province	Level
Anhui	II	Hubei	IV	Shanxi	IV
Beijing	I	Hunan	III	Shaanxi	IV
Fujian	II	Jilin	IV	Shanghai	I
Gansu	III	Jiangsu	III	Sichuan	IV
Guangdong	II	Jiangxi	III	Tianjin	IV
Guangxi	IV	Liaoning	IV	Xizang	IV
Guizhou	IV	Inner Mongolia	IV	Xinjiang	IV
Hainan	IV	Ningxia	III	Yunnan	IV
Hebei	IV	Qinghai	IV	Zhejiang	II
Henan	III	Shandong	I	Chongqing	IV
Heilongjiang	IV	–	–	–	–

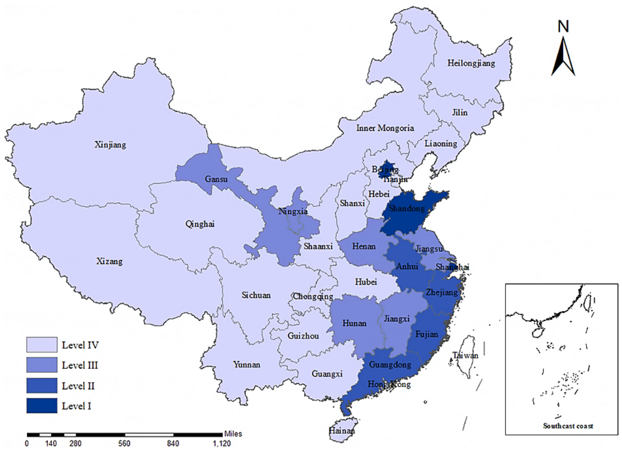

Figure 4. Provincial development level of IC in China

Level I: Beijing, Shanghai, and Shandong. Beijing and Shanghai are the political, economic, cultural, and educational centers in northern and southern China, respectively, gathering numerous research institutions related to the construction industry. The development of IC has strong momentum and abundant resources. As a hub for technological innovation, Beijing leverages its high level of technological equipment and research output (e.g., number of patent grants and paper publications) as primary advantages. Additionally, the city drives the efficient implementation of IC technologies by establishing industry standards through mandatory government policies and technical specifications. Shanghai, on the other hand, has developed a comprehensive approach to IC by utilizing its well-structured policy toolkit. This includes strategic planning, talent development, and technological support, complemented by its ability to integrate international resources. Together, these factors contribute to Shanghai's holistic advancement in IC. Both Beijing and Shanghai have introduced numerous policies to support the development of IC. For example, Beijing provides area incentives, and financial incentives, as well as tax refunds, fee reductions, and credit support measures for eligible projects. Shanghai provides a reward of no more than 10 million yuan or a 3% plot ratio for eligible projects. Moreover, the scale of the construction industry is closely related to population and economic conditions. Shandong has a large population and a relatively high economic level, so the scale of the construction industry continues to expand, achieving a relatively high level of modernization and informatization. In the field of IC, the Shandong government attaches great importance to the development of IC and has also provided a lot of policy support, continuously improving the technology level of IC. In addition, the development of the construction industry in Beijing, Shanghai, and Shandong has always received social attention, with more news reports related to IC, and relatively high click-through rates and reposts. Policies and technologies serve as the primary driving forces, while multidimensional drivers, including economic factors and social attention, collectively shape the leading positions of these three regions in the field of IC.

Level II: Guangdong, Fujian, Zhejiang, and Anhui. Guangdong, Fujian, and Zhejiang are all located in the eastern coastal region and are provinces with relatively concentrated enterprises related to the construction industry. These regions are at the forefront of China's reform and opening up, with rapid economic development, large population inflows, and a high demand for housing and infrastructure. Therefore, the construction industry in these provinces has a large scale of development, a high level of technological innovation, and the economic foundation and resource conditions to develop IC. Guangdong is significantly driven by technological indexes. Its numerous IC-related research institutions and associations provide strong support for technological innovation, the formulation of industry standards, and the cultivation of professional talent, thereby greatly advancing the development of IC in the region. The concentration of research institutions not only fosters technological innovation but also offers scientific foundations for the development and implementation of government policies. Meanwhile, industry associations play a critical role in resource integration, industrial coordination, and market promotion, further accelerating the Guangdong's IC developmen. In addition, In addition, Anhui is landlocked but geographically advantaged, so policy factors play a key role. Anhui connects the east and the west, with a north-south connection and the Yangtze River transportation waterway, highways, and a complete railway transportation system. Meanwhile, Anhui actively participates in the integrated development of the Yangtze River Delta. Therefore, the construction industry in Anhui has also achieved good development, and the local government has invested a lot of policy support in IC, resulting in a relatively high development level of IC.

Level III: Many inland provinces, particularly in the northeast, northwest, and southwest, do not consider construction a pillar industry, leading to low output value and weak technological innovation, which hampers IC development. For example, provinces like Jiangxi and Henan have dense populations but face slow IC progress due to weaker economic foundations. However, this does not imply that these regions lack potential for IC; rather, the challenges they face and the considerable room for development present opportunities for the future of IC. It is noteworthy that Jiangsu, as a relatively developed coastal region in terms of economic and technological progress, is categorized in the Level III. Data and research indicate that the province is in a critical phase of transformation and upgrading, requiring time for returns on technology investments, which has probably led to a relatively low labor productivity. Additionally, the province's economic focus is on traditional manufacturing, high-tech industries, and services, resulting in insufficient attention from provincial government departments toward the construction industry, and a cautious approach to policy document issuance. This suggests that the key driving role of policy factors should be strengthened in such provinces.

Level IV: China's vast territory results in imbalanced development of IC across provinces. This imbalance stems partly from limited resources and government policies that prioritize certain provinces, allowing them to achieve advanced IC development and drive progress in neighboring areas. In provinces such as Heilongjiang, Xinjiang, Yunnan, and Guangxi in level IV, inadequate government support, lagging economic resources, limited outreach, and diminished technological innovation exacerbate development difficulties. These regions need enhanced policy support, resource allocation, and innovation guidance to effectively raise their IC levels and close the gap with more developed areas.

This research is conducted within the context of China; however, the transition towards industrialization and intelligence in the construction industry is a global trend that holds relevance for various countries and regions. While some nations focus on establishing project-level standards for IC assessment, they often fall short in guiding regional evaluations of IC development levels. This study presents a practical framework for assessing regional development levels in intelligent construction, which, with minor adjustments, can be applicable to other countries, aiding them in identifying regional disparities in IC advancement. Notably, expansive countries and regions can benefit from China's experiences and insights in regional IC development, enabling them to formulate differentiated strategies for IC growth tailored to specific areas and to optimize regional resource allocation amidst uneven economic development.

4.4. The spatiotemporal evolution of the development level of IC

4.4.1. Temporal variation analysis

This study selected 2013, 2016, 2019, and 2022 as four observation years and used ArcGIS to draw spatiotemporal distribution maps of IC development levels in 31 provinces in China. As shown in Figure 5, the development level of China's IC shows a trend of increasing from northwest to southeast.

As shown in Figure 5a, the overall development level of IC in China's provinces was relatively low in 2013, with scores generally below 2. By 2016, some provinces such as Beijing, Jiangsu, Shanghai, and Zhejiang had significantly improved their IC development scores. They have increased the promotion and application of BIM technology, significantly improving the level of IC through measures such as introducing advanced construction technologies, strengthening talent cultivation, and providing policy support. However, the development level of IC in most provinces is still relatively low. By 2019, provinces with higher scores had begun to form agglomeration effects, mainly concentrated in areas centered around Beijing and Chongqing. This is because Beijing and Chongqing have actively responded to IC-related policies, vigorously promoted the improvement of IC level, and synchronously driven the development of surrounding cities. In August 2020, the MHURD and nine other departments issued "several opinions on accelerating the development of new building industrialization", aiming to promote the comprehensive transformation and upgrading of the construction industry through IC. IC has been further identified as a national strategy. Therefore, by 2022, the overall development level of IC in China has significantly improved, especially in the eastern and central provinces. In addition, Shaanxi, Chongqing, and Sichuan also scored higher. Overall, the development of provincial IC in China is gradually converging from low-development-level areas to high-development-level areas.

To explore the impacts of different indexes (P, E, S, and T) on the overall development level of IC, this study analyzed the scores of different indexes from 2013 to 2022, as shown in Figure 6. It is found that the performance of four indexes (P, E, S, and T) varies dynamically in different years.

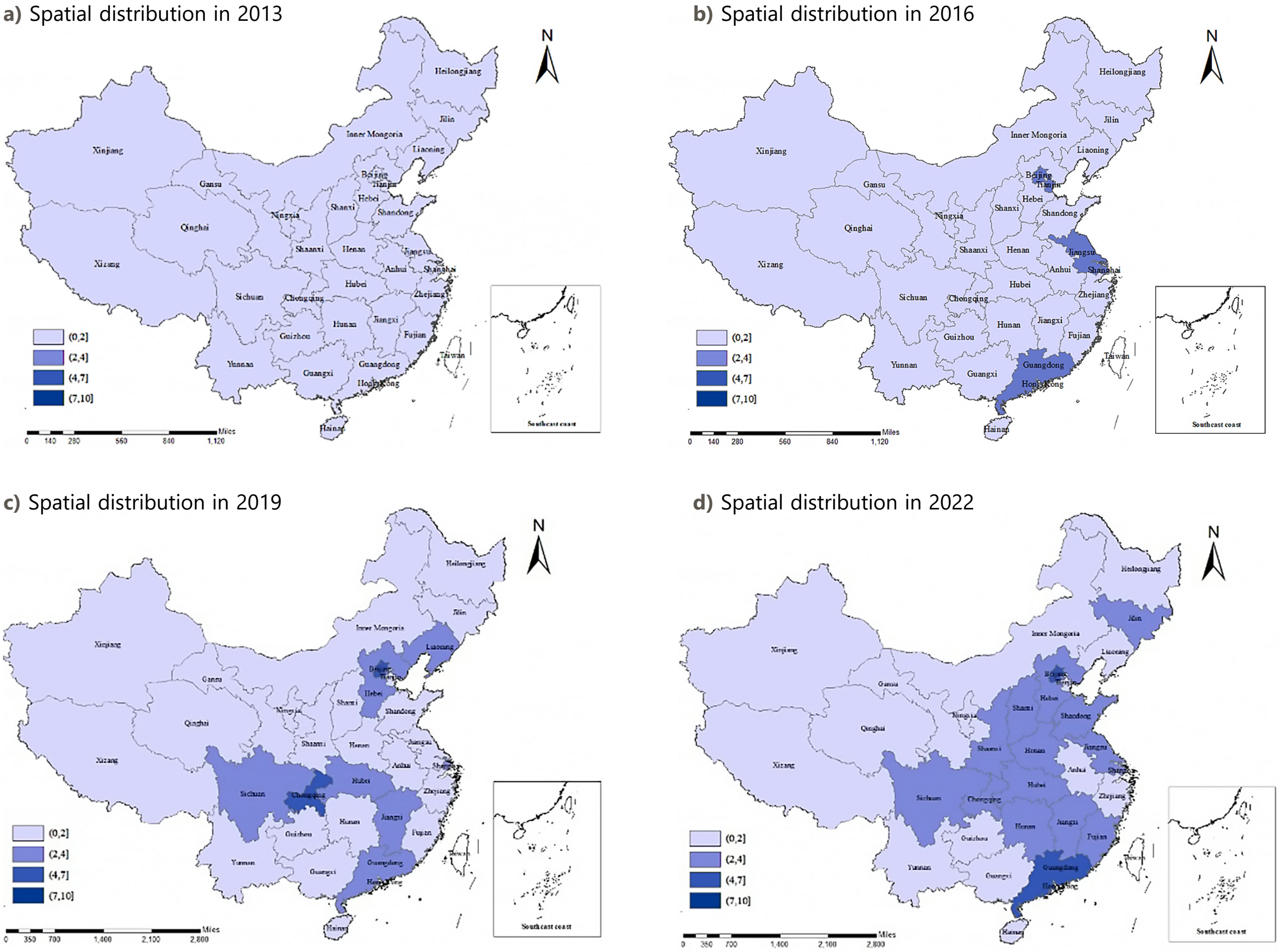

Figure 5. The spatial distribution of IC development level scores from 2013 to 2022

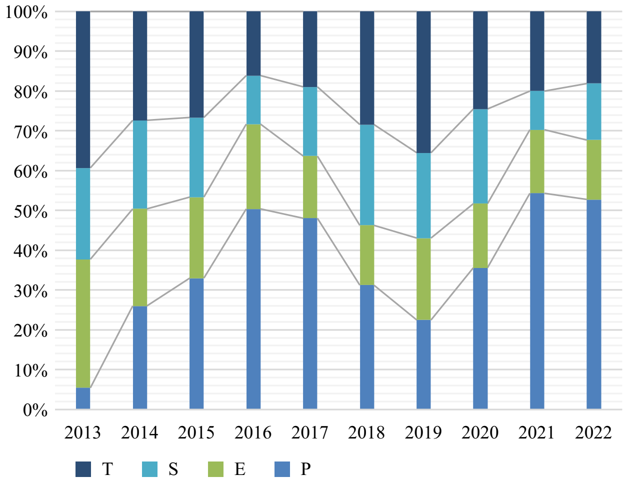

Figure 6. Measurement of development levels of different indexes from 2013 to 2022

Figure 6 shows that policy indexes and technical indexes have the highest contribution to the development level of IC in China. Policy factors play a significant leading role in the development of IC and are the main driving force. As time goes by, the scores of policy indexes gradually increase, indicating that the government's emphasis on IC is constantly increasing. Various policies have been formulated to guide and promote the development of IC, such as providing financial support, tax incentives, and market access. Effective policies help regulate industry operations and promote standardization and compliance. Technical factors also play an important supporting and driving role in the development of intelligent construction. IC has broken the traditional development model of the construction industry, relying on advanced information technology and the application of intelligent equipment. IC is a highly integrated field of architecture, artificial intelligence, computer science, and management, which urgently requires integrated innovation in construction, sensing, information technology, and management models. Technological progress plays an important role in improving building quality, enhancing construction efficiency, and reducing costs. From 2013 to 2022, the contribution of social and economic indexes to the development level of IC was significantly smaller, with a decreasing trend of fluctuations. This indicates that social and economic factors have a significantly smaller driving force on IC than policy factors, playing a supporting and balancing role. Overall, from 2013 to 2022, the scores of policy indexes have remained at a high level, and the current demand for policy-driving forces in IC development is sustained. Although there is a decreasing trend in the scores of other indexes, they cannot be ignored.

4.4.2. Spatial agglomeration analysis

(1) Global spatial correlation

To explore whether provincial IC development in China is spatially correlated, this study uses the Moran index method for spatial correlation analysis. The research object of spatial correlation analysis does not include Xizang, because Xizang's geographical location, climate conditions, and economic structure are very different from other provinces, and the public data from 2013 to 2022 is missing, which is difficult to obtain. Based on the comprehensive measurement of IC development level in 30 provinces of China from 2013 to 2022, the global Moran index value was calculated using Stata software, as shown in Table 9. The global Moran index of the development level of IC in China's provinces has fluctuated, but it remains between 0.157 and 0.275 and has passed the 10% significance level test. This indicates that there is a significant spatial correlation in the development level of IC among different provinces in China, which means that the development level of IC has spatial agglomeration (high-high adjacency and low-low adjacency).

Table 9. Global Moran index value

Years	Moran's I	Z	P-value
2013	0.226	3.312	0.001
2014	0.170	0.854	0.064
2015	0.190	1.956	0.050
2016	0.164	1.850	0.064
2017	0.275	2.734	0.006
2018	0.157	1.657	0.098
2019	0.260	2.554	0.011
2020	0.232	2.551	0.011
2021	0.163	1.729	0.084
2022	0.163	1.711	0.087

(2) Local spatial correlation

The global Moran index characterizes the dependence of the overall space, but cannot indicate the category of spatial agglomeration. The local Moran index can be used to observe the agglomeration characteristics of a specific region. Figure 7 is a scatter plot drawn based on the local Moran index, representing the local spatial distribution of different provinces in China. The first quadrant represents a high-high (H-H) cluster, indicating that the corresponding provinces and neighboring provinces have a relatively high development level of IC. The third quadrant represents a low-low (L-L) cluster, indicating that the corresponding provinces and neighboring provinces have relatively low development level of IC. The provinces in the first and third quadrants exhibit positive spatial correlation. The second quadrant represents a low-high (L-H) cluster, indicating that the corresponding province has a lower development level of IC while neighboring provinces have a higher development level of IC. The fourth quadrant represents a high-low (H-L) cluster, indicating that the corresponding province has a higher development level of IC while neighboring provinces have a lower development level of IC. The provinces in the second and fourth quadrants exhibit negative spatial correlation.

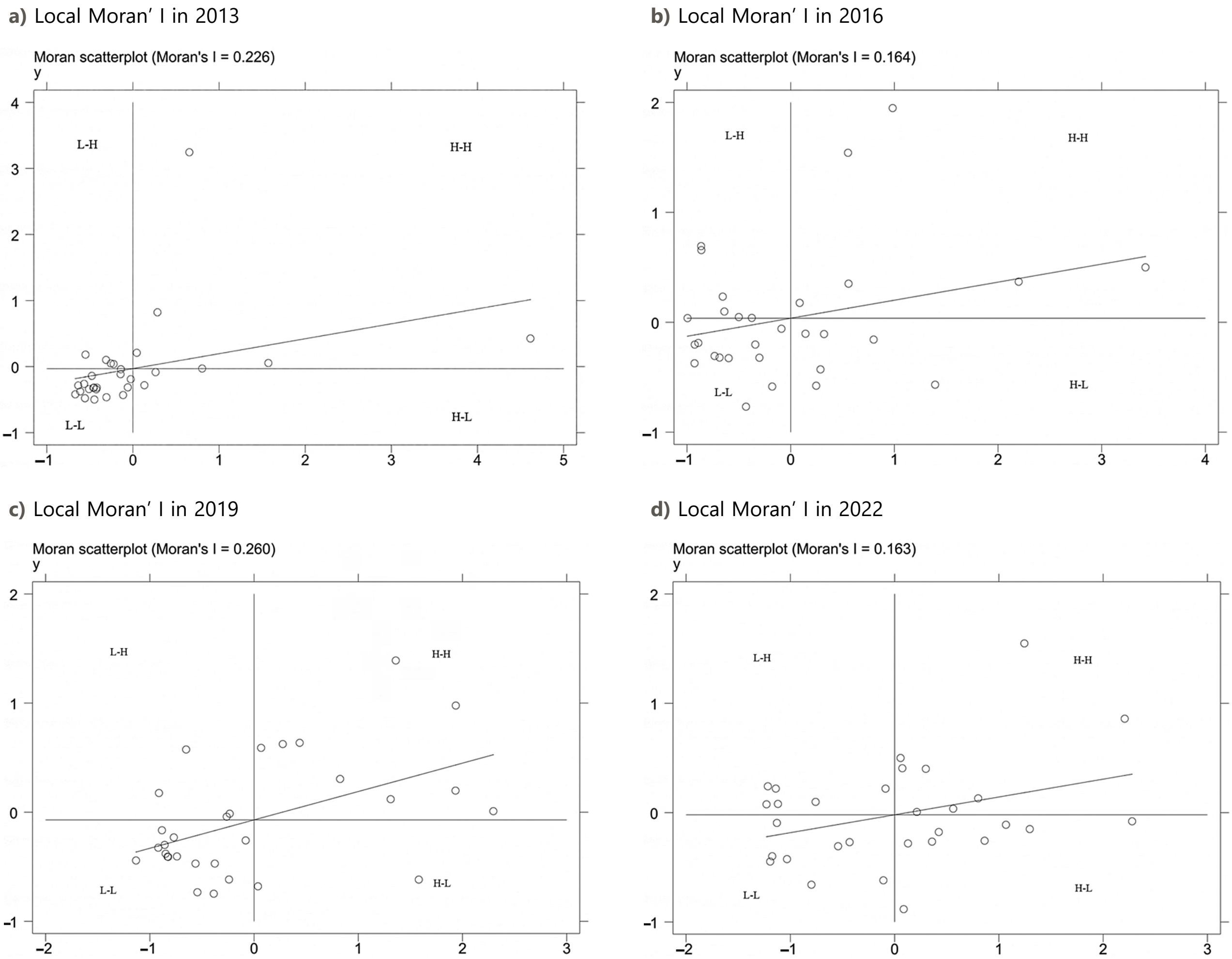

Figure 7. Scatter plot of local Moran index in different provinces of China

Based on Figure 7, the spatial distribution of provinces in different quadrants for 2013, 2016, 2019, and 2022 can be obtained. Most provinces are located in the first quadrant (H-H) and third quadrant (L-L), indicating a positive correlation between the IC development level of most provinces in China and neighboring provinces. Different provinces have a high degree of spatial dependence and significant spatial agglomeration characteristics. Specifically, the number of provinces in the third quadrant is less than that in the first quadrant, indicating that the agglomeration of low-development-level provinces is greater than that of high-development-level provinces. It shows that China's IC development is still in a backward state. However, the number of spatial clusters showed a downward trend from 2013 to 2022, which may be due to the optimization of industrial structure by the government and the market. In addition, small number of provinces in the second quadrant (L-H) and fourth quadrant (H-L) indicates that only a few neighboring provinces have significant spatial differences in IC development levels, which may be caused by their different economic development and technological progress. From a temporal perspective, the number of provinces in the first quadrant (H-H) has increased. Shanghai, Beijing, Hubei, Chongqing, and others have always been in this quadrant and have a sustained driving effect on neighboring provinces. The number of provinces in the third quadrant (L-L) decreases, such as Hebei, Henan, and Shanxi gradually disappearing in the third quadrant. From a spatial perspective, these inland provinces promote technological innovation and economic restructuring by learning from the advanced IC experience of surrounding provinces, and the IC development level of these provinces is gradually improving. The spatial agglomeration effect is gradually developing from coastal areas to inland areas. However, provinces such as Guangxi, Qinghai, Yunnan, and Anhui have always been in the third quadrant (L-L). This means that the development of IC in these provinces still faces certain challenges and room for improvement.

To more intuitively represent the spatial distribution and temporal changes of different clusters, ArcGIS 10.7 was used to connect different clusters with spatial analysis units in vector form, as shown in Figure 8.

From a geographical distribution perspective, between 2013 to 2019, driven by both economic and technological indexes, coastal regions gradually formed H-H clusters, becoming the core areas for IC development in China. These regions benefited from high economic levels, numerous pilot cities, and elevated labor productivity, which provided a solid economic foundation for the advancement of IC.

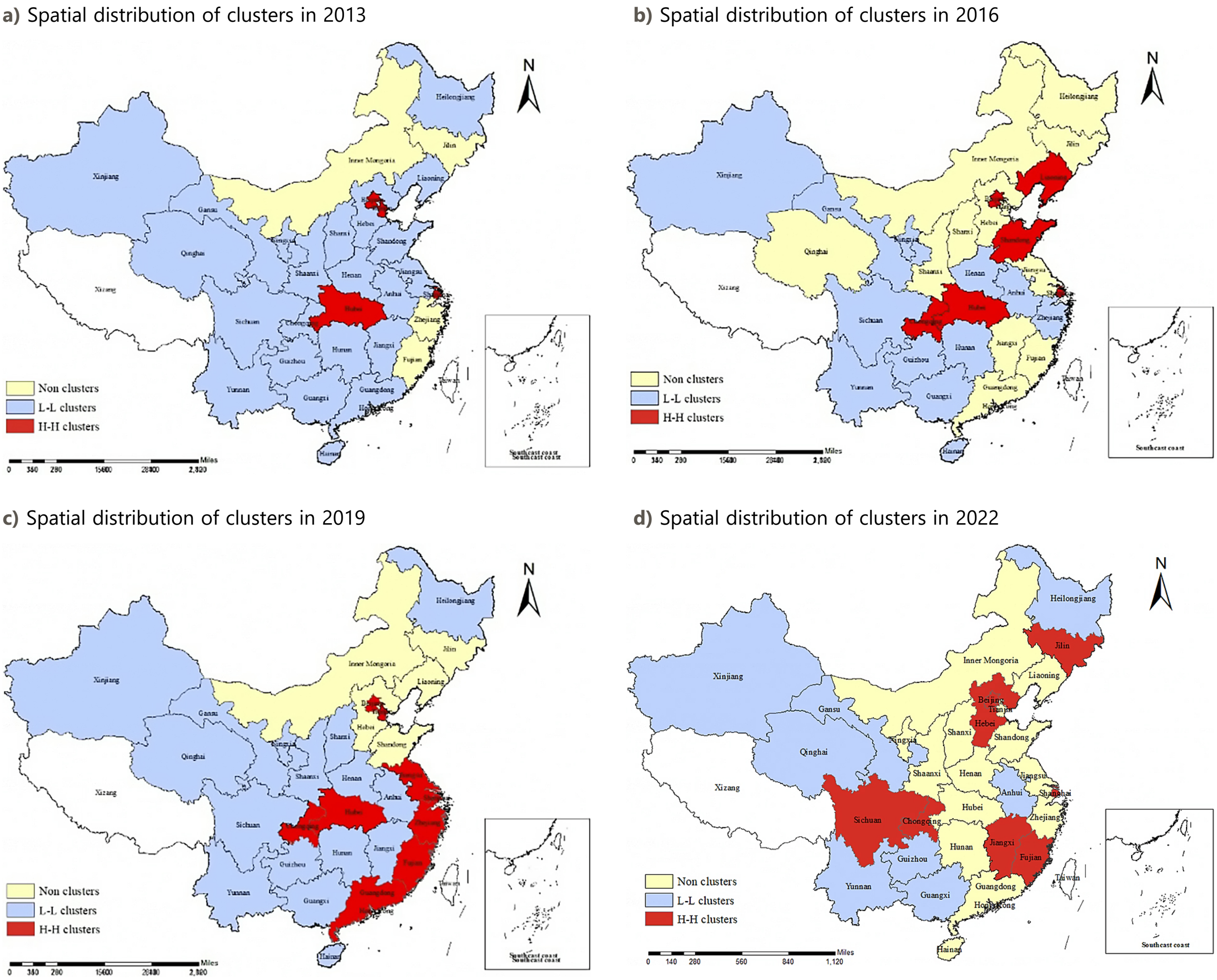

Figure 8. Spatial distribution of IC clusters in different years

Additionally, their dense populations, abundant resources, and well-developed transportation networks attract substantial inflows of population and enterprises. The concentration of IC enterprises, coupled with the promotion of pilot cities and projects, not only reinforced IC development within these regions but also facilitated the growth of neighboring areas through demonstration effects. These synergistic factors have enabled coastal regions to lead in both the research and application of IC technologies, while simultaneously establishing them as benchmarks for modernization and the intelligent transformation of the construction industry. After 2019, some provinces began overcoming the challenges associated with L-L clusters by advancing technological innovation and restructuring their economic systems. This shift enhanced their competitiveness in the construction sector and elevated IC development levels. Notably, the release of the "Guiding Opinions on Promoting the Coordinated Development of Intelligent Construction and Construction Industrialization" in 2020 (MHURD, 2020) marked the beginning of a policy dividend period for IC. The strong support at the national level was met with proactive responses from provinces and cities, which introduced corresponding standards, regulations, and measures to boost local IC development, significantly improving IC levels. Policy incentives and technological advancements facilitated the widespread promotion and application of IC technologies. Inland regions, in particular, invested heavily in the construction of intelligent industrial parks and innovation hubs, attracting high-tech industries and knowledge-intensive enterprises. Therefore, inland areas have gradually developed the conditions for H-H clusters, and H-H clusters have also begun to shift towards inland areas.

In addition, the provinces with the highest number of L-L clusters are mainly concentrated in the central and western regions of China. The region should fully tap into its geographical advantages, formulate IC development strategies tailored to local conditions, actively strengthen cooperation with high-level regions, and seek IC linkage development between provinces. The distribution of provinces in non-clusters (H-L and L-H) has undergone significant changes from 2013 to 2022, because the development of IC in each province is still in the exploratory stage, and the development level lacks stability. Furthermore, provinces located in non-clusters do not necessarily indicate the development level of IC in these areas. For example, the development level of IC in Shandong is relatively high, but it is not located in the cluster, which indicates that Shandong lacks cooperation with neighboring provinces and has not fully driven the development of IC in neighboring provinces. This type of province should actively play a leading role, strengthen cooperation between provinces, and develop towards scale and regionalization. The development level of IC in Hebei is relatively low, and it was not in the cluster in the early stage. However, Hebei is adjacent to Beijing and Tianjin, which have higher development levels of IC and have gradually joined the H-H cluster. This type of province should actively seek help from neighboring high-level provinces in terms of resources and knowledge to improve its development level of IC.

5. Conclusions and implications

This study quantitatively measured the development level of IC in 31 provinces of China and conducted temporal changes and spatial agglomeration analysis. The findings contribute to the tailored development and coordinated coupling of IC at the provincial level, facilitating structural adjustments and upgrades in the construction industry, and providing a basis for differentiated policy formulation. The specific conclusions are as follows: (1) This study used the PEST model to construct a provincial IC development level measurement index system from four dimensions: policy, economy, society, and technology. A multi-source data collection approach is utilized, along with the design of index quantification and composite weighting methods. (2) The cloud matter-element model is used to measure the development level of IC in 31 provinces of China. The development level of IC in these provinces is divided into four levels, with Beijing, Shanghai, and Shandong ranking at the highest level, followed by Guangdong, Fujian, Zhejiang, and Anhui. The development level of most other provinces is relatively low. (3) The results of spatiotemporal evolution analysis indicate that IC in China is in its early stages, with an overall low development level and a trend of increasing from northwest to southeast. Policy and technological factors have been identified as the dominant factors driving the development level of IC in China. There is a significant spatial positive correlation in the development level of IC between provinces in China, and its spatial agglomeration effect is gradually developing from coastal areas to inland areas.

Theoretically, this study enhances the understanding of the intrinsic patterns and influencing factors of IC development, providing a solid theoretical foundation for the differentiated and dynamic evolution of IC in China. It also serves as a reference for measuring IC and development levels in other countries and sectors. Practically, (1) this research offers a scientific measurement method for countries or regions developing IC. Government can define the overall development direction for IC, formulate regional development policies, and optimize resource allocation. It is essential to actively cultivate and establish collaborative networks across provinces and cities, enhancing cooperation between local markets and surrounding areas. This can stimulate the development of lower-level regions by leveraging higher-level ones, fostering broader industrial agglomeration in IC, thereby improving the efficient allocation and circulation of resources and promoting economies of scale in IC across provinces and enterprises. (2) Stakeholders can develop and select appropriate strategies based on local development levels to achieve differentiated enhancement and promotion of IC. Enterprises can utilize the four dimensions of the PEST model to elevate IC development levels. For instance, at the policy level, governments can formulate incentive measures that combine mandatory policies with incentives to promote IC. Economically, fostering and increasing market demand for IC, expanding market share, and accelerating the construction of IC industry bases are crucial. Socially, enhancing media outreach can raise awareness of IC among stakeholders and the public. Technologically, accelerating integrated innovation can advance the IC industry's ecosystem towards a complete, rational structure with mature technological processes.

However, there are still certain limitations to the research. The PEST model can provide sufficient analysis of the external environment for the IC's development, but cannot analyze internal factors in the industry, such as supply chain levels. This is also related to the fact that the IC's development is still in its early stages, and many internal factors in the industry cannot be obtained. In the future, with the continuous development of IC, a more comprehensive measurement index system will be established.

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Author contributions

Yudan Dou designed the overall research and framework of the paper, and was responsible for the core content of the paper. Xueya Yan is responsible for the main research work and thesis writing. Xin Guo was responsible for data collection, questionnaire survey and other related research. Shengbin Ma controlled the overall thinking of the study, and made an excellent contribution to literature review and conceptual model building. Longzhu Zhong provided assistance in collecting references and polishing the paper.

Disclosure statement

The authors declare no conflicts of interest.

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