

The Evolution of Niche Fitness in China's Regional Digital Innovation Ecosystems: An Evaluation and Prediction Framework

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With the rapid expansion of digital innovation ecosystems (DIEs), the quantitative assessment of system adaptability and collaborative evolutionary capacity, as well as the forward-looking prediction of future development trajectories, has become increasingly important. Nevertheless, existing studies still lack an integrated analytical framework capable of simultaneously capturing multidimensional ecological elements and supporting reliable trend forecasting. To address this limitation, this study develops an ecology-inspired evaluation and prediction framework specifically designed for DIEs. The framework conceptualizes niche structure across four dimensions, including digital innovation communities, resources, environment, and demand, and applies the method based on the removal effects of criteria (MERECE) for objective weighting. This approach is combined with an improved measurement of alternatives and ranking according to compromise solution (MARCOS) method using the Heronian mean (HM) operator to derive composite measures of niche fitness. In addition, enhanced grey prediction models are introduced to strengthen the framework's capacity to forecast evolutionary trends under weak-information conditions. The framework is empirically applied to provincial-level DIEs data from China covering the period from 2015 to 2021. The results indicate that overall niche fitness exhibits a fluctuating upward trend, accompanied by pronounced regional differentiation. Persistent imbalances are observed across niche dimensions, with resources, communities, and demand niches emerging as the primary constraints on the evolutionary process of DIEs. Forecasting results further suggest that niche fitness is likely to continue improving in the coming years, although structural misalignments may remain difficult to fully resolve in the short term. Overall, the proposed evaluation and prediction framework enables the systematic identification of structural constraints and latent development potential within DIEs, while also facilitating the analysis of their future evolutionary trajectories. As such, it provides a generalizable and scalable methodological tool for comparative analysis, dynamic monitoring, and cross-regional research on DIEs.

Keywords: *Digital Innovation Ecosystems (DIEs); Niche Fitness; Evaluation Model; Method Based on Removal Effects of Criteria (MERECE); Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS); Grey Prediction Model.*

Introduction

In the digital era, the innovation landscape is undergoing profound transformation, with significant shifts in processes, key actors, and resource allocation mechanisms. The widespread adoption of digital technologies - such as big data, artificial intelligence, cloud computing, and blockchain - has not only redefined traditional innovation systems but has also catalyzed the digital reconfiguration of innovation ecosystems (Burstrom *et al.*, 2021; Ma *et al.*, 2024). Within this evolving context, digital innovation ecosystems (DIEs) have emerged as a dynamic, open, and highly interconnected paradigm, attracting considerable attention from both academia and industry (Beltagui, 2020; Wang, 2021; Secundo *et al.*, 2024). Powered by digital technologies, DIEs enable multiple innovation actors to collaborate efficiently, share resources, and continuously evolve through a delicate interplay of competition and cooperation. However, their inherent dynamism, complexity, and uncertainty (Pershina, 2019; Senyo, 2019; Burstrom *et al.*, 2021) pose substantial challenges to system

stability and sustainable development. Unlike traditional innovation ecosystems, which emphasize physical resources, linear innovation pathways, and stable collaborative relationships, DIEs require participants to exhibit a higher degree of digital adaptability and co-evolutionary capability to thrive in an increasingly volatile environment (Chen *et al.*, 2024; Zhang *et al.*, 2024).

In the existing literature, innovation ecosystems are most commonly examined from the perspectives of organizational architecture, role positioning, and value co-creation (Fauth *et al.*, 2024; Neto *et al.*, 2024). This line of research highlights collaborative boundaries, positional structures, and value networks within ecosystems, thereby elucidating interaction mechanisms among innovation actors and establishing a solid theoretical foundation for understanding the systemic nature of innovation ecosystems. However, such studies largely concentrate on structural relationships and coordination logic, while providing limited quantitative insight into heterogeneity in actor adaptability, the degree of resource alignment, and the

evolutionary capacity of the system as a whole. These limitations become particularly salient in DIEs, where rapid technological change and dense interdependencies generate highly complex and dynamic processes that existing frameworks struggle to capture.

Against this backdrop, niche theory offers a conceptually robust and operationally feasible perspective for analyzing the evolution of DIEs. By emphasizing the functional positioning of system elements with respect to resource utilization, environmental adaptation, and interaction patterns (Hutchinson, 1957; Coles *et al.*, 2018), niche theory provides a coherent basis for characterizing role differentiation, resource acquisition structures, and evolutionary pathways within DIEs. In highly networked and interconnected digital innovation environments, variations in niche positioning directly influence actors' adaptive capacity, systemic status, and collaborative efficiency. Consequently, niche fitness has emerged as a critical construct for assessing the alignment between actor capabilities and system requirements (Lemos *et al.*, 2023).

Empirical research on DIEs has generally followed two main strands. One strand adopts qualitative approaches to develop conceptual frameworks that describe system structures, constituent elements, and operating mechanisms (Secundo *et al.*, 2024). The other relies on historical data or simulation-based models to explore dynamic evolutionary patterns (Zhang *et al.*, 2024). Despite their contributions, both strands tend to focus on isolated system attributes, such as digital innovation resilience or innovation intensity, and construct evaluation schemes based on single dimensions (Du & Jian, 2024; Huang & Mao, 2024). As a result, existing studies remain limited in their ability to systematically capture the complex interactions among digital innovation actors and environments, and they offer only partial insights into the logic of collaborative evolution at the ecosystem level.

Within the broader innovation ecosystems literature, quantitative models are primarily employed to evaluate the effectiveness of value co-creation processes (Lee & Roh, 2023; Bakry *et al.*, 2024). Niche fitness theory has also been introduced to assess actor adaptability and relative positioning, leading to evaluation frameworks encompassing innovation communities, resources, environments, and capabilities (Xie *et al.*, 2023). However, these frameworks are largely designed for general innovation ecosystems and do not adequately account for the distinctive features of DIEs. In particular, DIEs are characterized by platform-based and highly networked actor structures, resource configurations dominated by data, algorithms, and digital infrastructure, environments shaped jointly by digital institutions, market mechanisms, and platform governance, and demand-side dynamics marked by immediacy and rapid feedback (Kolagar *et al.*, 2022). These features substantially heighten system complexity, adaptability, and uncertainty, thereby placing new demands on the measurement of niche fitness. Although recent studies have attempted to improve model precision by distinguishing between absolute and relative niche fitness or by applying heterogeneous weighting methods (Xie *et al.*, 2023; Zhu & Sun, 2023), such efforts have not fundamentally resolved how niche fitness theory can be systematically extended and adapted to the context of DIEs.

In summary, a comprehensive niche fitness evaluation framework that can systematically capture the multi-actor,

multi-resource, multi-environment, and multi-demand characteristics of DIEs, while also elucidating their patterns of collaborative evolution, remains absent. This theoretical and methodological gap not only constrains the precise assessment of actor adaptability, interaction intensity, and collaborative capacity, but also hampers a deeper understanding of the evolutionary trajectories and development dynamics of DIEs.

To bridge the existing gaps, this study adopts an ecological lens by introducing the concept of niche fitness to investigate the evolutionary dynamics of DIEs. Specifically, this research seeks to answer the following key questions:

(1) What are the structural components of DIEs, and how can their niche fitness be effectively measured?

(2) How has the niche fitness of DIEs evolved, and what are the anticipated future development trends?

To address these questions, this study establishes a comprehensive evaluation framework for the niche fitness of DIEs, encompassing the niches of digital innovation communities, resources, environment, and demand. A comprehensive niche fitness evaluation model is proposed by integrating the method based on removal effects of criteria (MERECE) for weighting, and an improved measurement of alternatives and ranking according to compromise solution (MARCOS) method using the Heronian mean (HM) operator. Additionally, various enhanced grey prediction models are employed to forecast the niche fitness of DIEs across 30 provinces in China. This provides critical insights and actionable guidance for the development and optimization of DIEs.

Compared to existing studies, this research offers several potential contributions:

(1) Adopting an ecological perspective, this study introduces niche theory to develop a comprehensive niche fitness evaluation framework specifically tailored to DIEs. The framework integrates four dimensions, namely digital innovation communities, resources, environment, and demand niches, enabling a systematic assessment of overall niche fitness and internal heterogeneity within DIEs. Compared with existing frameworks that primarily examine ecological relationships and value co-creation mechanisms in general innovation ecosystems (Lee & Roh, 2023; Bakry *et al.*, 2024), the proposed framework more effectively captures the distinctive digital characteristics of DIEs, thereby overcoming the limited applicability of traditional niche-based approaches in digital contexts. Furthermore, in contrast to prior studies that focus on isolated attributes of DIEs, such as system resilience or innovation intensity (Du & Jian, 2024; Huang & Mao, 2024), this study adopts a multidimensional niche perspective to provide a more integrated understanding of collaborative evolutionary mechanisms. Overall, the framework offers a systematic and context-sensitive analytical tool for evaluating the development of DIEs.

(2) In terms of the niche fitness evaluation model, this research adopts the MERECE, which determines objective standard weights from an exclusion perspective, along with an improved MARCOS method that incorporates the HM operator. Unlike previous studies that primarily integrate heterogeneous weighting methods with grey relational analysis models (Han *et al.*, 2021; Xie *et al.*, 2023), this approach not only extracts and represents the full extent of

information embedded within ecological indicators but also enhances evaluation accuracy by accounting for interdependencies among ecological indicators and applying a compromise ranking strategy. By providing a more precise assessment of the overall development level and internal disparities within DIES, this method serves as a rigorous and systematic analytical tool for advancing research on the evaluation of DIES.

(3) In contrast to existing studies that primarily focus on a singular analysis of the historical development trends of DIES (Rong *et al.*, 2024), this study adopts an extrapolative forecasting approach to explore the niche fitness of DIES, introducing a new analytical perspective. Building upon the basic GM (1,1) model, the study further incorporates the grey model with parameter optimization (OGM) and the grey model with parameter optimization and Fourier series modification (FOGM), to enhance forecasting accuracy. The results reveal that, over the next five years, regional DIES in China are expected to exhibit positive growth, though imbalanced development across ecological dimensions may continue to constrain the system's evolution. By forecasting these future trends, this study not only provides a theoretical foundation for improving the development of DIES but also offers valuable insights to guide decision-making in practice.

The remainder of this study is organized as follows. Section 2 reviews the related literature. Section 3 outlines the methodology. Section 4 conducts the results and discussion. Section 5 presents the conclusions, implications, and prospects.

Literature Review

DIES

The concept of DIES is derived from innovation ecosystems, which in turn originates from biological analogies (Adner, 2006). It highlights the interdependence of participants, activities, and artifacts, as well as the institutions and relationships that are crucial to innovation performance. With the development of digital technologies, such as big data, artificial intelligence, and blockchain, the structure and functions of innovation ecosystems have been significantly empowered, gradually evolving into DIES. While scholars have increasingly recognized the significant influence of digital technologies on innovation ecosystems, some continue to operate within the confines of traditional frameworks, without fully integrating these digital components to form a comprehensive DIES (Serrano-Ruiz *et al.*, 2024; Zhou *et al.*, 2024). Nonetheless, research into DIES has been expanding steadily. Broadly speaking, current studies on DIES are primarily focused on several key areas: conceptual frameworks, dynamic evolution, and governance.

Digital innovation has become an increasingly ubiquitous phenomenon, gradually penetrating a diverse range of fields (Burstrom *et al.*, 2021; Wolfert *et al.*, 2023). As part of ongoing exploratory research, scholars from various disciplines have actively worked to expand the theoretical framework of DIES, delving into its conceptual foundations, defining characteristics, and essential components. DIES refer to loosely coupled organizational systems with ecological characteristics, where autonomous actors leverage digital technologies to create products, optimize business processes, and innovate business models,

all while engaging in dynamic collaboration and competition (Beltagui, 2020; Wang, 2021). These systems retain key features of traditional innovation ecosystems, such as openness, symbiotic coupling, and nonlinear interactions commonly seen in complex systems (Robaczewska *et al.*, 2019). In addition, they introduce distinctive traits, including higher heterogeneity among innovation actors, increased complexity in resource flows, and more blurred system boundaries (Perschina *et al.*, 2019; Senyo *et al.*, 2019; Burstrom *et al.*, 2021). Viewed as complex networks of stakeholders and their collaborative relationships, DIES center around core symbiotic units, which include enterprises, research institutions, consumers, suppliers, and other key entities (Li *et al.*, 2022; Chen *et al.*, 2024). Based on this understanding, Li & Liu (2024) proposed a three-layer "core-periphery" structural framework for DIES.

Research on the dynamic evolution of DIES views these systems as evolving collectives comprising actors, institutions, and relationships. The symbiotic coupling and nonlinear interactions among diverse participants within the system play a crucial role in realizing value co-creation. Compared to traditional ecosystems, the value co-creation process in DIES is considerably more complex (Xu *et al.*, 2023). Chae (2019) explored this complexity by revealing the evolution mechanisms of big data ecosystems through complex network analysis. Several scholars have utilized evolutionary game models to investigate the symbiotic evolution and coordination mechanisms among multiple actors in these ecosystems (Chen *et al.*, 2024; Zhang *et al.*, 2024). Ning *et al.* (2022) developed Lotka-Volterra dynamic evolution models for both two-entity and three-entity configurations to explore the symbiotic evolution patterns within DIES. Additionally, some scholars have adopted an empirical approach, evaluating the evolutionary trends of these ecosystems by focusing on specific characteristics. For instance, evaluation frameworks have been created to assess system resilience (Chen & Cai, 2023; Du & Jian, 2024) and symbiosis (Liu, 2024), using various models to investigate these dimensions. Building on insights into the evolutionary mechanisms and characteristics of DIES, scholars have delved into the exploration of governance mechanisms. Numerous studies have employed exploratory case studies and simulations to highlight the effectiveness of governance strategies, particularly those centered on trust, knowledge sharing, and institutional structures (Li *et al.*, 2022; Ma *et al.*, 2024).

Niche Fitness in Complex Systems

The concept of niche fitness was developed in tandem with the notion of the niche itself. When Grinnell (1917) first introduced the idea of a niche, it inherently included the concept of environmental fitness, which refers to a species' ability to perform optimally within an environment conducive to its survival. Hutchinson (1957) later expanded on this by proposing the "niche hypervolume" theory, which conceptualized a species' environmental requirements as a multi-dimensional space. The environmental variables across these dimensions collectively determine a species' fitness. The fundamental niche represents the theoretical space where a species achieves optimal fitness across all dimensions, whereas the realized niche reflects the actual

conditions under which the species survives, capturing the dynamic equilibrium of niche fitness. Li & Lin (1997) further advanced this idea by developing a niche fitness model that quantifies the proximity between a species' realized niche and its ideal niche, providing a valuable quantitative tool for expanding niche applications.

The niche fitness model was initially employed in natural ecosystems, particularly in fields such as agriculture, forestry, land use, and environmental pollution (Chen *et al.*, 2022; Yin *et al.*, 2022; Lemos *et al.*, 2023). With the rapid development of niche fitness theory, its application has progressively expanded to encompass complex economic and social systems. Given that innovation is the fundamental driving force behind development, it has attracted considerable scholarly attention. Researchers have combined the innovation ecosystem framework with niche fitness theory, leading to a substantial body of research that primarily focuses on evaluation models, key influencing factors, and their broader impacts.

In terms of evaluation, much of the existing research draws on niche hypervolume theory, constructing multi-dimensional frameworks to assess niche fitness at various levels, including national, regional, urban, and industrial innovation ecosystems (Yin *et al.*, 2022; Xie *et al.*, 2023; Xiao *et al.*, 2024). Beyond expanding the scope of research subjects and corresponding evaluation systems, scholars have introduced substantial refinements to niche fitness models. For example, Zhu & Sun (2023) differentiated between absolute and relative niche fitness, thereby developing a more comprehensive evaluation model. Moreover, advancements in the weighting methodologies for niche fitness indicators have been a central focus. Objective approaches such as entropy and grey relational analysis, as well as subjective methods like the analytic hierarchy process (AHP) and fuzzy comprehensive evaluation, have been employed to more precisely capture the developmental trajectory of niche fitness within innovation ecosystems (Yao *et al.*, 2016; Han *et al.*, 2021; Xie *et al.*, 2023). In addition, scholars have investigated the causal mechanisms underpinning the enhancement of niche fitness in innovation ecosystems. Factors such as digitization, innovation costs, and return on investment have been identified as critical determinants (Rabelo Neto *et al.*, 2024). Furthermore, improvements in niche fitness have been demonstrated to positively influence high-quality economic development, industrial clustering, and the mitigation of environmental pollution (Cao *et al.*, 2023; Huang *et al.*, 2023).

Research Gaps

Overall, the existing literature reveals several notable limitations.

First, research on DIES has been dominated by qualitative analyses focusing on conceptual frameworks, system components, and operating mechanisms (Secundo *et al.*, 2024), while quantitative investigations remain relatively scarce. The limited empirical studies available tend to construct evaluation systems around single attributes, such as ecosystem resilience or innovation intensity (Du & Jian, 2024; Huang & Mao, 2024). As a result, they provide only partial insights and fail to systematically capture the

complex dynamic interactions and symbiotic relationships between digital innovation actors and their environments. This underscores the need for a niche fitness evaluation framework that can comprehensively reflect the collaborative evolutionary dynamics of DIES.

Second, in the broader innovation ecosystems literature, niche fitness has been widely applied to assess actor adaptability and relative positioning within systems, giving rise to multidimensional evaluation frameworks that incorporate communities, resources, environments, and capabilities (Coles *et al.*, 2018; Xie *et al.*, 2023). However, these frameworks are largely grounded in traditional innovation contexts and are ill suited to the distinctive characteristics of DIES. In particular, DIES are marked by networked and platform-based actor structures, resource configurations driven by data and algorithms, environments jointly shaped by digital institutions and platform governance, and demand-side dynamics characterized by high volatility and real-time feedback (Kolagar *et al.*, 2022). These features substantially increase system complexity and uncertainty, thereby placing new demands on the measurement of niche fitness for DIES.

Third, most existing studies emphasize the historical evolution of DIES (Rong *et al.*, 2024) and rely predominantly on static or retrospective analyses, offering limited insight into future development trajectories. Given the inherently dynamic and uncertain nature of DIES, analyses based solely on past trends are insufficient to uncover latent evolutionary mechanisms or anticipate potential structural shifts. There is therefore a clear need to incorporate predictive approaches that can trace future evolutionary pathways, thereby deepening understanding of ecosystem dynamics and supporting more forward-looking governance.

Methodology

Research Framework

This study initially deconstructs the components of DIES and, grounded in niche theory, formulates a comprehensive evaluation framework for the niche fitness of these ecosystems. Subsequently, a holistic evaluation model for niche fitness is employed, integrating MEREC-based weighting with the enhanced MARCOS method. Finally, advanced grey prediction models are utilized to conduct extrapolative forecasting and in-depth analysis of the niche fitness within DIES. The research framework is depicted in Figure 1.

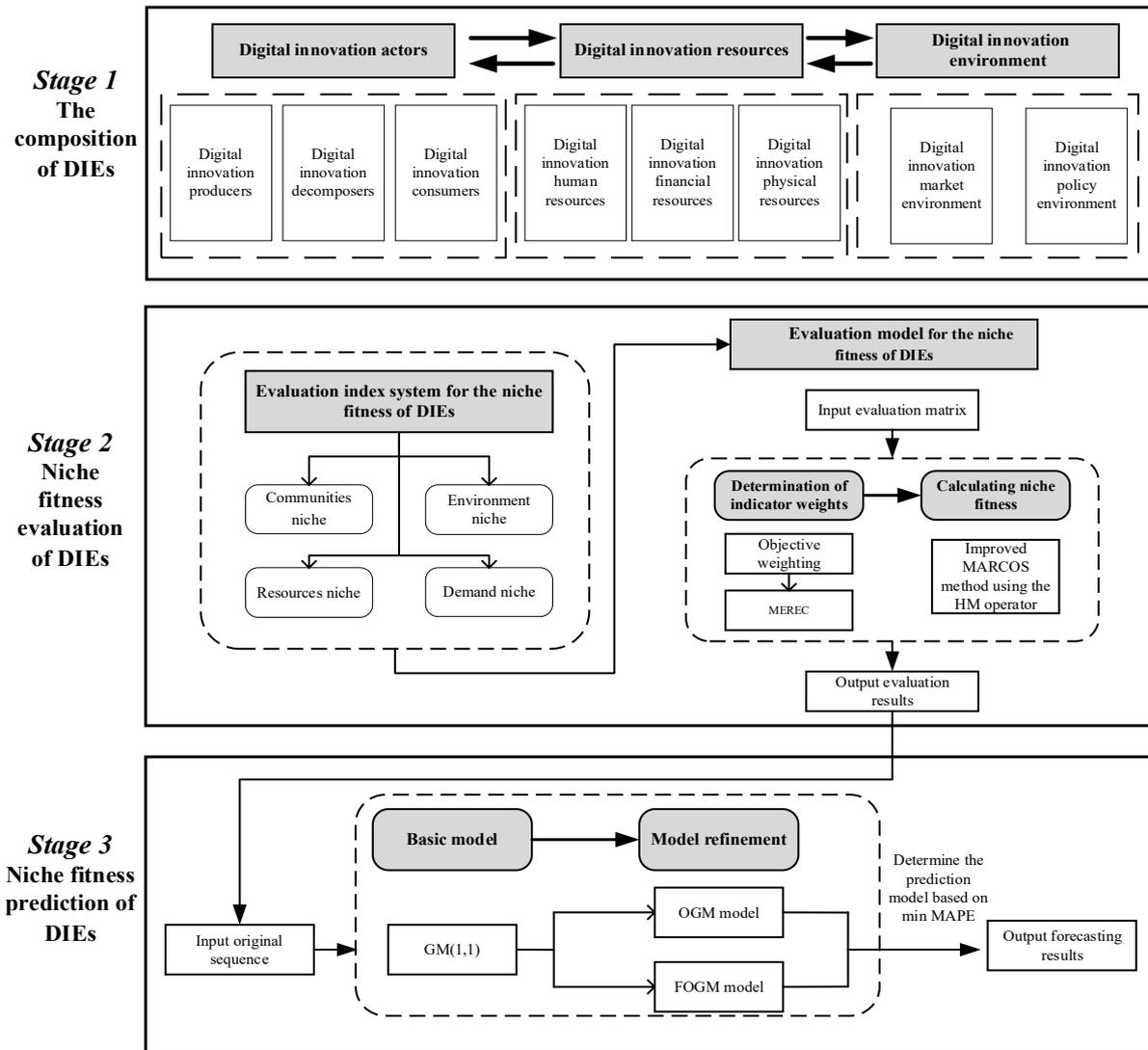


Figure 1. Research Framework

Niche Fitness Evaluation of DIES

The Composition of DIES

Innovation ecosystems, much like natural ecosystems, consist of actors, resources, and environment (Rabelo Neto *et al.*, 2024). With the rise of digital technologies, these components have adopted distinct digital attributes, resulting in a more open, collaborative, and efficient system for value co-creation, commonly referred to as the DIES (Zhang *et al.*, 2021). This evolving ecosystem is characterized by three key elements: digital innovation actors, digital innovation resources, and the digital innovation environment.

(1) Digital innovation actors are the primary drivers of innovation activities. Drawing from the classification of actors within traditional innovation ecosystems (Cao *et al.*, 2023; Zhou *et al.*, 2024), digital innovation actors can be divided into three categories based on their roles: digital innovation producers, decomposers, and consumers. Digital innovation producers, which include universities and research institutions, are responsible for pioneering foundational digital technologies (Chen *et al.*, 2024). Their

capacity for innovation not only fuels the sustainable growth of the digital innovation ecosystem but also serves as the foundation for value creation. Digital innovation decomposers facilitate the transformation of these foundational technologies into final products, and they typically consist of diverse enterprises that engage in both competition and collaboration (Xu *et al.*, 2023; Chi *et al.*, 2024). Digital innovation consumers, comprising organizations and individuals, purchase and utilize these innovations, contributing to value creation within the ecosystems (Zhang *et al.*, 2024).

(2) Digital innovation resources refer to elements that can be directly leveraged by digital innovation actors as primary inputs for value creation within the system. Traditional innovation resources remain crucial in DIES. However, with the integration of digital technologies, many of these resources have gradually been infused with digital attributes. Meanwhile, new digital resources originating from cyberspace have emerged, and together, these resources drive innovation within DIES. The key categories of digital innovation resources include human, financial, and physical resources. Digital innovation human resources

comprise individuals engaged in digital innovation activities. These individuals, as carriers of knowledge, information, and technology, possess both the innovative mindset and the capabilities required to mobilize material, energy, and information flows within the digital innovation ecosystem (Tekic & Fuller, 2023; Galanti & Fantinelli, 2024). Digital innovation financial resources refer to the capital investments that support the development of digital technologies, the production of digital products, and the execution of other innovation activities (Liu *et al.*, 2023). Physical resources encompass the material assets used throughout the innovation process. Digital infrastructure, in particular, forms the foundation for the research, development, and application of core digital technologies. Its level of advancement reflects the system's potential for digital growth and significantly influences the progress of DIEs (Hussain *et al.*, 2024).

(3) Digital innovation environment serves as a critical foundation, enabling innovation activities, with the government and market occupying central roles. The

government, through the formulation and execution of strategic policies, plays a vital role in steering and accelerating the development of digital innovation, thereby cultivating a robust policy framework for DIEs (Papyshev & Yarime, 2023). Concurrently, the market contributes by fostering a conducive and competitive digital business environment, which is essential for the ecosystem's dynamic operations (Chen & Wang, 2024).

Overall, DIEs refer to complex network systems wherein diverse digital innovation actors, under the influence of the digital innovation environment, engage in both competition and collaboration, fostering symbiotic relationships. These actors leverage both digital and non-digital resources to drive open innovation, enabling the development, transformation, and application of digital technologies that result in innovative products or services. This process ultimately culminates in value co-creation across the entire system. Figure 2 illustrates the fundamental structural model of DIEs.

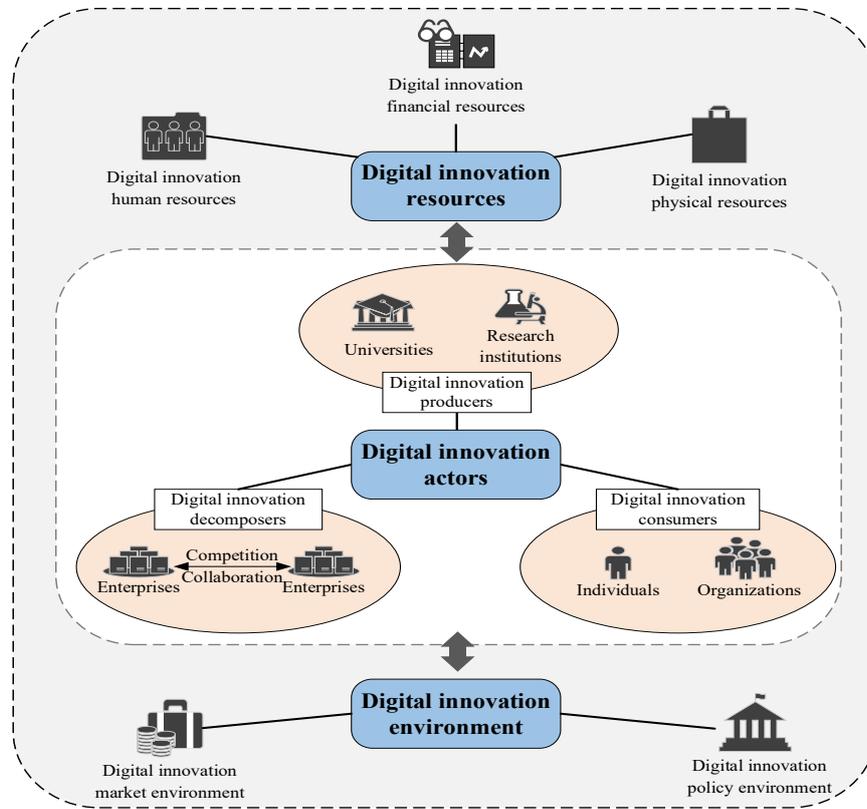


Figure 2. The Fundamental Structural Model of DIEs

Evaluation Metrics

In natural ecosystems, the niche describes the functional position of a species within the ecosystem, including its resource utilization, habitat, and interactions with other species. Ecological studies suggest that a niche encompasses both biotic and abiotic dimensions, with the complete niche being viewed as the collective niches of all species (Litvak & Hansell, 1990). Extending this concept to DIEs, a niche can be used to describe the roles, functions, and interrelationships of various digital innovation elements within the system. In DIEs, the niche of each digital innovation element determines

its ability to access resources, adapt to technologies, and maintain market competitiveness within the digital innovation network. Moreover, niche fitness measures the survival and development capabilities of digital innovation elements within the system, reflecting how well these elements align their capabilities with the ecosystem's requirements. Digital innovation elements with high niche fitness are better positioned to effectively integrate system resources, foster collaborative synergies, and sustain a competitive edge in a rapidly evolving market environment.

The niche of a DIEs can be conceptualized as the union of all ecological niches across both biotic and abiotic dimensions, reflecting the overall developmental context of the ecosystem. Building upon the previous analysis of the components of DIEs and drawing from research on the ecological niches of general innovation ecosystems (Cao *et al.*, 2023; Xie *et al.*, 2023), we further delineate the niche of DIEs. The biotic dimension refers to all the digital innovation entities within the ecosystem, with their corresponding niche termed the digital innovation communities niche. The abiotic dimension, on the other hand, includes elements external to the digital innovation entities, such as digital innovation resources and the broader environment. These correspond to the digital innovation resources niche and the digital innovation environment niche, respectively. Additionally, through the interactions between digital innovation entities, resources, and the

environment, various forms of digital innovation performance may emerge, such as stimulating digital innovation vitality, promoting the growth of the digital economy, and advancing the development of a digital society (Li *et al.*, 2024; Zhang & Chen, 2024). These performances embody the value creation capability of DIEs, which, in turn, meets diverse digital innovation needs. Therefore, in this study, the value creation function of DIEs is considered an independent niche, referred to as the digital innovation demand niche. In conclusion, the niche of DIEs comprises four key dimensions: the digital innovation communities niche, the digital innovation resources niche, the digital innovation environment niche, and the digital innovation demand niche. To evaluate the niche fitness of DIEs and gain insights into their developmental level, a niche fitness evaluation index system has been developed based on the preceding analysis (Table 1).

Table 1

Evaluation Index System for the Niche Fitness of DIEs

Decision level	Ecological dimensions	Ecological factors	Ecological indicators	Tendency	References
Niche fitness of DIEs	Biotic	Digital innovation producers	Number of universities C11	+	Zeng <i>et al.</i> , 2024
		Digital innovation decomposers	Number of R&D institutions C12	+	Xie <i>et al.</i> , 2023
		Digital innovation communities C1	Number of enterprises with R&D activities in the digital industry C13	+	Zhang <i>et al.</i> , 2024
		Digital innovation consumers	Number of industrial enterprises above scale C14	+	Zeng <i>et al.</i> , 2024
			Number of internet users C15	+	Du & Jian, 2024
	Digital innovation resources C2	Digital innovation human resources	R&D staff in the digital industry C21	+	Zeng <i>et al.</i> , 2024
		Digital innovation financial resources	Internal R&D expenditure in the digital industry C22	+	Du & Jian, 2024
		Digital innovation physical resources	New product development expenditure in the digital industry C23	+	Zeng <i>et al.</i> , 2024
			Optical cable length C24	+	Zeng <i>et al.</i> , 2024
			Number of broadband access ports C25	+	Du & Jian, 2024 Zeng <i>et al.</i> , 2024
	Abiotic	Digital innovation market environment C3	Business credit environment index C31	+	Liu <i>et al.</i> , 2024
		Digital innovation environment C3	Digital financial inclusion index C32	+	Li <i>et al.</i> , 2024
		Digital innovation policy environment	Intensity of fiscal expenditure on science and technology C33	+	Chen & Wang, 2024 Zeng <i>et al.</i> , 2024
		Digital innovation technological performance C4	Digital government service capacity C34	+	Li <i>et al.</i> , 2024
	Digital innovation demand C4	Digital innovation technological performance	Number of patent applications in the digital industry C41	+	Li <i>et al.</i> , 2024 Wang & Tang, 2024
		Digital innovation economic performance	Revenue from new product sales in the digital industry C42	+	Zhang <i>et al.</i> , 2024
Digital innovation social performance		The ratio of e-commerce transactions to GDP C43	+	Wei & Gu, 2022	
		Per capita mobile internet data usage C44	+	Li <i>et al.</i> , 2024	

Note: “+” indicates a benefit-type indicator

Evaluation Model

The niche fitness evaluation model presented in this paper is composed of two key components: determining ecological indicators weights using the MEREC and calculating niche fitness through an enhanced MARCOS method, which incorporates the HM operator.

(1) Determination of ecological indicator weights based on the MEREC.

Given that the ecological indicators within the constructed niche fitness evaluation system for DIEs (Table 1) are objective metrics, which can be directly obtained from statistical data, an objective weighting method is employed to maximize the extraction and reflection of the information contained in the data itself. Common objective weighting methods include the entropy method, criteria importance through inter-criteria correlation (CRITIC), and

MEREC. Notably, the MEREC, introduced by Keshavarz-Ghorabae *et al.* (2021), represents a novel approach to determining indicator weights. Distinct from other methods, MEREC derives objective weights from the perspective of exclusion rather than inclusion. By assessing the absolute deviation between the overall performance of alternatives and their performance after the exclusion of specific indicators, the method assigns greater weight to indicators that exert a more substantial influence on performance. Furthermore, this approach allows decision-makers to disregard certain indicators during the decision process, thereby enhancing the robustness of the weight allocation. This method has found widespread application across numerous domains (Zorlu *et al.*, 2023; Najafi *et al.*, 2023). Consequently, the MEREC is employed to determine the weighting of ecological indicators within the niche fitness evaluation framework for DIES.

Assuming that the number of DIES under evaluation is m and the number of ecological indicators is n , the observed value of the j -th ecological indicators for the i -th DIE is denoted as x_{ij} ($i = 1, 2, \dots, m; j = 1, 2, \dots, n$). These values collectively form the original data matrix for the niche fitness evaluation of DIES, represented as $X = [x_{ij}]_{m \times n}$. The following outlines the fundamental steps for determining ecological indicators weights using the MEREC method. The detailed computational process is provided in Appendix A (1).

Step 1. Normalize the original data matrix.

Since all ecological indicators in the niche fitness evaluation system (Table 1) are benefit-type indicators, normalization is performed using Eq. (A1) to transform the original data matrix $X = [x_{ij}]_{m \times n}$ into the normalized matrix $N = [n_{ij}^x]_{m \times n}$.

Step 2. Calculate the removal effect for the j -th ecological indicator.

First, the overall performance of the i -th DIE, including all ecological indicators, is computed using Eq. (A2) and denoted as S_i . Next, the performance of the i -th DIE after removing the j -th ecological indicator is calculated using Eq. (A3) and denoted as S_{ij}^- . Then, the absolute deviation sum of the j -th ecological indicator, representing its removal effect, is obtained using Eq. (A4) and denoted as E_j . This step identifies the contribution of each ecological indicator to the overall system performance.

Step 3. Determine the j -th ecological indicator weight.

Based on the contribution level of each ecological indicator, the objective weight of the j -th ecological indicator, denoted as w_j , is derived using Eq. (A5).

(2) Niche fitness evaluation based on the enhanced MARCOS method.

The MARCOS method is a comprehensive evaluation approach that focuses on assessing and ranking alternatives through a compromise solution. This method first establishes the relationship between the observed values and reference values of the evaluation objects and, based on this, determines the utility function of the evaluation objects. It simultaneously conducts a compromise ranking of the ideal and anti-ideal solutions (Stevic *et al.*, 2020). In this study, we apply the MARCOS method to niche fitness evaluation,

analyzing the relationship between the current niche and the ideal and anti-ideal niches to determine the niche fitness. Compared to other methods, MARCOS offers greater stability during the calculation process while providing more comprehensive and holistic evaluation results (Haq *et al.*, 2022). Furthermore, to further optimize the niche fitness evaluation model and address the interrelationships among the ecological indicators within the niche fitness evaluation system of DIES, we enhance the basic MARCOS method by incorporating the HM operator. This modification improves both the accuracy and rationality of the evaluation. The following outlines the basic steps of the improved MARCOS niche fitness evaluation method, with the detailed calculation process provided in Appendix A (2).

Step 1. Determine the extended evaluation matrix. Based on the original data matrix $X = [x_{ij}]_{m \times n}$, the ideal niche (denoted as AI) and the anti-ideal niche (denoted as AAI) are incorporated according to Eqs. (A6) and (A7), respectively. The ideal niche represents the optimal niche fitness of DIES, while the anti-ideal niche reflects the worst-case niche fitness scenario. This process results in the formation of the extended evaluation matrix $X^e = [x_{ij}]_{(m+2) \times n}$ for niche fitness of DIES, as defined in Eq. (A8).

Step 2. Normalize the extended evaluation matrix. The extended evaluation matrix $X^e = [x_{ij}]_{(m+2) \times n}$ is then normalized to yield a new matrix, denoted as $U = [u_{ij}]_{(m+2) \times n}$, as per the normalization process outlined in Eq. (A9).

Step 3. Determine the weighted extended evaluation matrix. The ecological indicator weights w_j are applied to the normalized matrix $U = [u_{ij}]_{(m+2) \times n}$ through multiplication to derive the weighted extended evaluation matrix $Z = [z_{ij}]_{(m+2) \times n}$ (Eq. A10).

Step 4. Determine the relative utility function of the i -th DIE's niche. Initially, the utility degrees K_i^+ and K_i^- of the i -th DIE's niche are calculated in relation to the ideal and anti-ideal niches, respectively, as outlined in Eqs. (A11) and (A12). Subsequently, the utility functions $f(K_i^+)$ and $f(K_i^-)$ for the i -th DIE's niche are derived relative to the ideal and anti-ideal niches, represented by Eqs. (A16) and (A17), respectively.

Step 5. Determine the niche fitness of the i -th DIE. Based on the compromise between the i -th DIE's niche relative to the ideal and anti-ideal niches, the niche fitness of the i -th DIE, denoted as $f(K_i)$, is determined according to Eq. (A18).

Step 6. Assess the evolutionary potential of the niche fitness for the i -th DIE. In this step, the evolutionary potential of niche fitness for the i -th DIE is assessed. Evolutionary potential is defined as the development capacity embedded in the current level of niche fitness of a DIE. It reflects the extent to which the ecosystem retains the ability to further enhance its niche fitness under existing structural and environmental conditions. The evolutionary potential is calculated according to Eq. (A19). A lower value of evolutionary potential indicates limited room for improvement in niche fitness. By contrast, a higher value implies that the ecosystem possesses greater scope for niche

fitness enhancement and exhibits stronger development capacity and evolutionary potential.

Niche Fitness Prediction of DIEs

When predicting niche fitness trends of DIEs, careful model selection is essential. The use of grey prediction models in this study is justified by two key considerations. First, niche fitness data for DIEs typically exhibit small sample sizes, short time horizons, and incomplete system information. Such characteristics do not align with the assumptions of conventional time-series models, including the auto regressive integrated moving average (ARIMA) and vector auto regression (VAR) models, which generally require stationarity and relatively long observation periods. They also limit the feasibility of data-intensive machine learning approaches, such as long short-term memory networks (LSTM) and extreme gradient boosting (XGBoost), whose predictive performance depends heavily on large training samples and rich feature sets. By contrast, grey prediction models are explicitly designed for weak-information environments. Their ability to operate effectively with limited data, combined with strong robustness under uncertainty, makes them particularly well suited to the characteristics of DIE niche fitness data. Accordingly, the adoption of grey models provides a methodologically appropriate and theoretically grounded approach for predicting niche fitness trends in this study.

Building on the work of Ene & Öztürk (2017), the predicting framework in this study is structured in two phases: the construction of a basic model and subsequent model refinement. Initially, the GM (1,1) basic model is developed. This is followed by two improved models: OGM model and FOGM model. The model with the lower prediction error is then selected for further forecasting.

Basic Model

The niche fitness evaluation results of the DIEs are used as the original data sequence. Assuming the original data sequence is $F^{(0)} = \{f^{(0)}(1), f^{(0)}(2), \dots, f^{(0)}(t)\}$. The following are the basic steps for constructing the GM (1,1) model based on the original data sequence. The detailed calculation process is provided in Appendix B (1).

Step 1. Feasibility analysis for modeling.

Perform the level ratio test (Eq. B1) on the original data sequence $F^{(0)}$. If the test is passed, it proves that the GM (1,1) model is suitable for the data.

Step 2. Compute the one-time accumulating sequence.

Perform the accumulating generation operator (Eq. B2) on the original data sequence $F^{(0)}$ to generate one-time accumulating sequence, denoted as

$$F^{(1)} = \{f^{(1)}(1), f^{(1)}(2), \dots, f^{(1)}(t)\} .$$

This step helps reduce the randomness in the original data and highlights its underlying trend.

Step 3. Establish the differential equation and solve.

Assume that the accumulating sequence satisfies an exponential change trend, and describe its evolution using a first-order differential equation (Eqs. B3–B5). Then, apply the least-squares estimation to solve for the model parameters (Eqs. B6 – B8).

Step 4. Establish the prediction model.

First, substitute the solved parameters into the cumulative prediction formula (Eq. B10). Then, apply inverse accumulating generation operator to obtain the prediction model for DIE's niche fitness original data sequence (Eq. B11).

Step 5. Accuracy testing.

Following the methods of previous studies (Ene and Ozturk, 2017; Chaturvedi, 2022; Moreno, 2024), we use the Mean Absolute Percentage Error (MAPE) method for accuracy testing (Eq. B14). Typically, a MAPE value less than 10 % is considered an excellent prediction accuracy.

Model Refinement

(1) Grey model with parameter optimization (OGM)

The OGM is built upon the basic GM (1,1) by adjusting the coefficient α in Eq. (B3) to achieve optimal prediction accuracy. Below are the basic steps of this method, with the detailed computation process provided in Appendix B (2).

Step 1. Develop the GM (1,1) model for the niche fitness of DIEs with $\alpha = 0.1$.

Step 2. Calculate the MAPE for the OGM model at $\alpha = 0.1$.

Step 3. If $\alpha < 0.9$, update $\alpha^{new} = \alpha + 0.1$, and compute the corresponding MAPE*. Then, compare MAPE* with MAPE.

Step 4. Output the predicted value corresponding to the minimum of $\{MAPE, MAPE^*\}$.

(2) Grey model with parameter optimization and Fourier series modification (FOGM)

The FOGM model is derived from the OGM model by integrating Fourier series to adjust the residuals. These corrected residuals are subsequently incorporated into the OGM model's output, yielding the final refined prediction values. Below are the basic steps of this method, with the detailed computation process provided in Appendix B (2).

Step 1. Calculate the residual sequence $\varepsilon_{OGM}^{(0)}$ for the DIE's niche fitness based on the OGM model (Eq. B15).

Step 2. Represent the residual sequence $\varepsilon_{OGM}^{(0)}$ using Fourier series (Eq. B16), and convert it into matrix form $\varepsilon_{OGM}^{(0)} \approx LC$ (Eqs. B17-B19). Then, use the least-squares estimation method to determine the coefficient matrix C (Eq. B20).

Step 3. Compute the modified residual sequence $\varepsilon_{FOGM}^{(0)}$, and add it back to the predicted values of the OGM model to achieve the final correction (Eq. B21).

Sample and Data

To ensure both data integrity and accessibility, this study focuses on 30 provinces in China (excluding Hong Kong, Macau, Taiwan, and Tibet) as the foundational units for analysis. Since China does not currently maintain independent statistical records for the digital industry, and given that digital innovation is predominantly concentrated within high-tech sectors, this study draws upon prior research (Hong *et al.*, 2024; Zhang *et al.*, 2024) and selects the " manufacture of communication equipment, computers, and other electronic equipment " and " information transfer, software, and information technology services " industries as proxies for the digital sector. Moreover, the concept of

digital transformation was first introduced in China's 2015 *Made in China 2025* initiative and later reinforced in the State Council's *Guiding Opinions on Actively Promoting the 'Internet+' Action*, where digital transformation was positioned as one of the seven key strategic priorities. Since then, digital transformation has not only become a cornerstone of national policy but has also ushered in a phase of accelerated development across multiple sectors. Accordingly, this study undertakes a comprehensive evaluation and forecast of the DIES in 30 provinces across China for the periods 2015–2021 and 2022–2026, aiming to systematically elucidate the evolutionary trends and development trajectory of DIES in China.

With the exception of the "business credit environment index", sourced from the *China Urban Business Credit Environment Index*, the "digital government service capacity" from the *Survey and Evaluation Report on Provincial and Key Cities' Integrated Government Service Capacity*, and the "digital financial inclusion index" from the *Peking University Digital Financial Inclusion Research Center*, all other data are derived from the *China Statistical Yearbook*, the *China High-Tech Industry Statistical Yearbook*, provincial and municipal statistical yearbooks, and the EPS database. Monetary indicators have been adjusted using the price deflator to account for inflation. Missing data points were filled using interpolation methods.

Results and Discussion

Evaluation Results of Niche Fitness of DIES

Analysis of Niche Fitness and Evolutionary Potential

Table 2 presents the weight distribution of ecological indicators within China's DIES niche fitness evaluation framework from 2015 to 2021, as determined by the MEREC method. The findings reveal notable variations in the weight distribution of indicators over the study period. Among them, revenue from new product sales in the digital industry (C42) exhibits the highest average weight (0.1331), indicating its paramount significance in shaping DIES' niche fitness. This

underscores the critical role of marketization efficiency in translating digital innovation outputs into tangible ecosystem adaptability. Additionally, substantial weights have been assigned to the number of enterprises engaged in R&D activities in the digital industry (C13), internal R&D expenditure in the digital industry (C22), and new product development expenditure in the digital industry (C23). This underscores the indispensable role of enterprises as primary innovation entities, whose investment in research and development, strategic resource allocation, and financial commitments significantly propel the evolution of DIES. Collectively, the analysis underscores that technological innovation and its commercialization, investment in digital innovation resources, and innovation-driven performance outputs are foundational determinants of DIES' niche fitness. These findings not only reinforce the indispensability of innovation in ensuring the long-term sustainability of the digital economy but also provide strategic insights for evidence-based policymaking. Accordingly, greater emphasis should be placed on strengthening support for corporate R&D initiatives, optimizing innovation resource allocation, enhancing R&D efficiency, and fostering the seamless commercialization of technological advancements, thereby reinforcing the adaptive capacity of DIES.

The final evaluation results were determined by applying the MARCOS method, enhanced with the HM operator. Figure 3 depicts the evolutionary trends of niche fitness and evolutionary potential within China's digital innovation ecosystem over the study period. The findings indicate a fluctuating upward trend in niche fitness from 2015 to 2021, with an average annual growth rate of 1.77%. Nevertheless, the maximum value reached was only 0.1280, significantly below the threshold of 1. Although the corresponding evolutionary potential of niche fitness exhibits a fluctuating downward trend, it still retains substantial room for further evolution. These results underscore that China's digital innovation ecosystem remains in its early developmental stages, requiring sustained and strategic guidance to close the evolutionary gap and improve niche fitness.

Table 2

Weights of Ecological Indicators									
Ecological dimensions	Ecological indicators	2015	2016	2017	2018	2019	2020	2021	Average
Digital innovation communities	C11	0.0578	0.0509	0.0609	0.0621	0.0549	0.0636	0.0603	0.0586
	C12	0.0754	0.0670	0.0834	0.0833	0.0801	0.0881	0.0899	0.0810
	C13	0.0863	0.0851	0.0974	0.0949	0.0983	0.0929	0.0995	0.0935
	C14	0.0698	0.0602	0.0717	0.0722	0.0635	0.0743	0.0707	0.0689
Digital innovation resources	C15	0.0618	0.0533	0.0634	0.0630	0.0552	0.0642	0.0605	0.0602
	C21	0.0908	0.0975	0.0701	0.0649	0.1124	0.0689	0.0964	0.0859
	C22	0.1022	0.1379	0.0805	0.0707	0.0847	0.0668	0.0694	0.0875
	C23	0.1003	0.0961	0.0863	0.0792	0.1050	0.0774	0.0689	0.0876
Digital innovation environment	C24	0.0519	0.0454	0.0553	0.0530	0.0462	0.0522	0.0507	0.0507
	C25	0.0602	0.0530	0.0614	0.0617	0.0543	0.0617	0.0592	0.0588
	C31	0.0010	0.0008	0.0012	0.0012	0.0012	0.0015	0.0015	0.0012
	C32	0.0022	0.0020	0.0021	0.0022	0.0020	0.0022	0.0019	0.0021
Digital innovation demand	C33	0.0128	0.0120	0.0140	0.0211	0.0184	0.0212	0.0185	0.0169
	C34	0.0036	0.0036	0.0045	0.0055	0.0019	0.0029	0.0033	0.0036
Digital innovation demand	C41	0.0646	0.0752	0.0579	0.0758	0.0940	0.1089	0.0974	0.0820
	C42	0.1279	0.1313	0.1607	0.1632	0.1036	0.1239	0.1214	0.1331
	C43	0.0213	0.0201	0.0149	0.0174	0.0170	0.0196	0.0209	0.0187
	C44	0.0100	0.0086	0.0141	0.0087	0.0073	0.0096	0.0096	0.0097

Note: The values in bold represent the weights of the ecological indicators that rank within the top 25 % for that year.

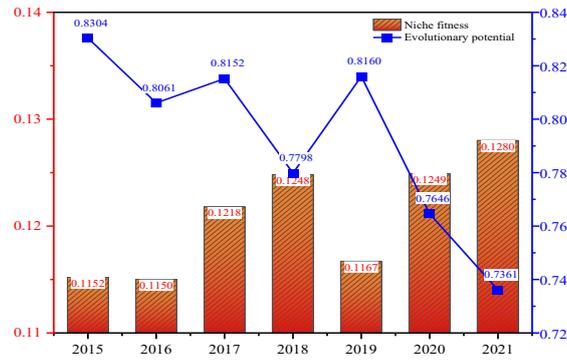


Figure 3. Evolutionary Trends of Niche Fitness and Evolutionary Potential within China's Overall Digital Innovation Ecosystem from 2015 to 2021

At the regional level, heat maps were utilized to illustrate the evolutionary trends in niche fitness and evolutionary potential across Chinese provinces from 2015 to 2021 (Figures 4 and 5). The findings indicate that Shanghai, Guangdong, Jiangsu, Beijing, Zhejiang, and Tianjin consistently ranked at the top in terms of niche fitness, demonstrating a considerable advantage over other regions. Notably, Shanghai and Guangdong emerged as leaders in China's digital innovation landscape. However, the average annual growth rate in these regions was only 0.40%, falling short of the national average of 1.77%. This suggests that despite their advanced development, these regions face the risk of stagnation and must address potential phase lock-in. In contrast, regions such as Xinjiang, Qinghai, Heilongjiang, Inner Mongolia, and Gansu, which ranked lower in niche fitness, exhibit substantial potential for growth. These provinces, primarily located in the northwest and northeast, achieved a higher average growth rate of 3.06%, surpassing the national average. Nonetheless, they continue to grapple with significant challenges such as geographic isolation, economic underdevelopment, talent drain, and weaker digital infrastructure (Zeng *et al.*, 2024).

To offer a more intuitive understanding of the evolutionary trends in DIEs across China's provinces, ArcGIS was employed to generate spatial distribution maps of niche fitness and evolutionary potential for four key time points: 2015, 2017, 2019, and 2021 (Figures 6 and 7). The analysis reveals that, from 2015 to 2021, China's DIEs exhibited relative stability, with pronounced regional clustering. Niche fitness generally followed a pattern of higher values in the east and lower values in the west, with coastal regions outperforming inland areas. Conversely, due to the inverse relationship between evolutionary potential and niche fitness, evolutionary potential displayed the opposite trend, with higher values in the west and lower values in the east. During the study period, eastern and central provinces demonstrated robust progress in their DIEs, while some central and western provinces entered phases of accelerated digital innovation growth. In contrast, most provinces in the northwest and northeast remained at lower stages of development, highlighting the need for these regions to intensify efforts in building their DIEs and expedite progress.



Figure 4. Niche Fitness of DIEs Across Chinese Provinces from 2015 to 2021

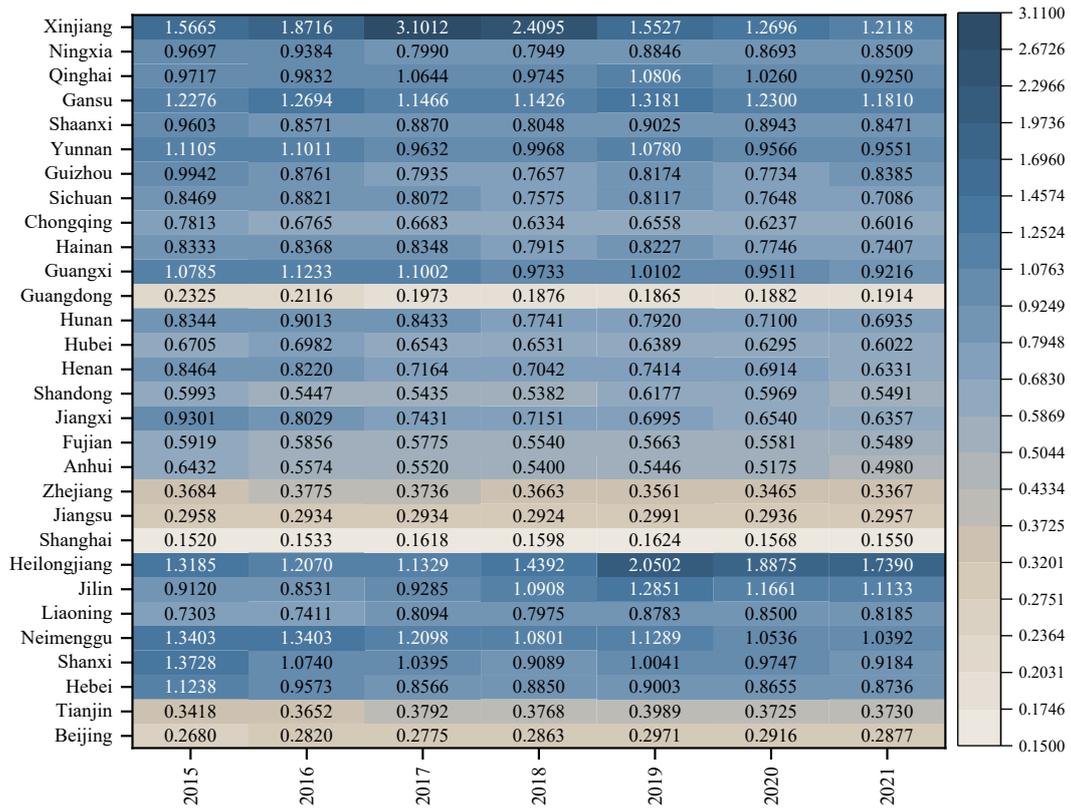


Figure 5. Evolutionary Potential of DIES Across Chinese Provinces from 2015 to 2021

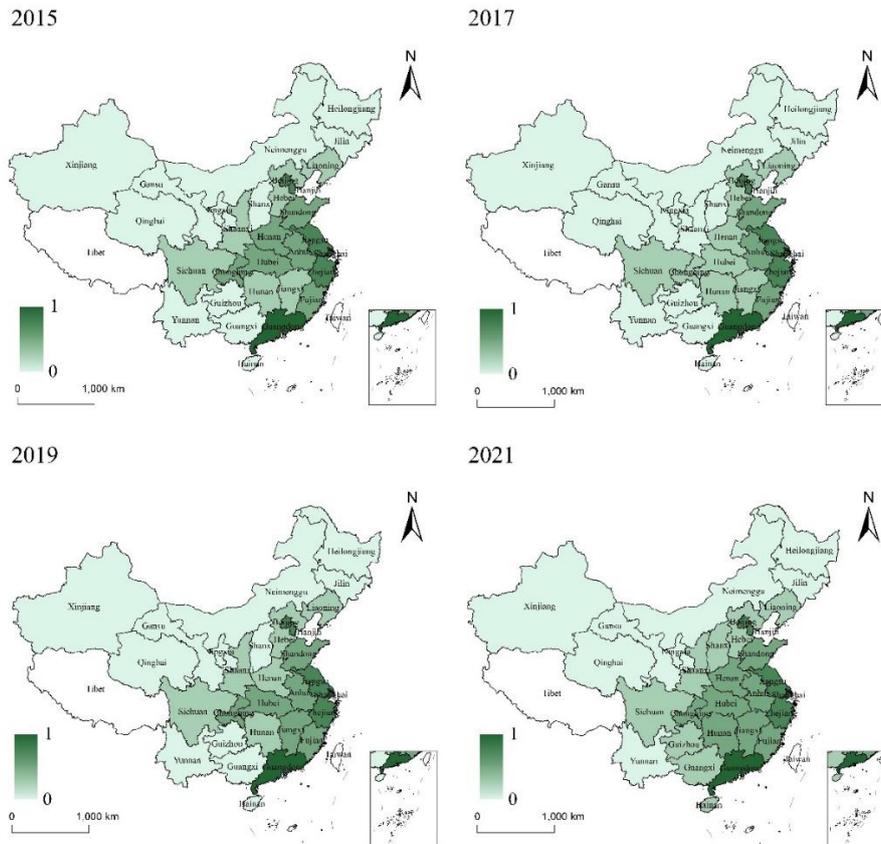


Figure 6. Spatial Distribution of Niche Fitness of DIES Across Chinese Provinces

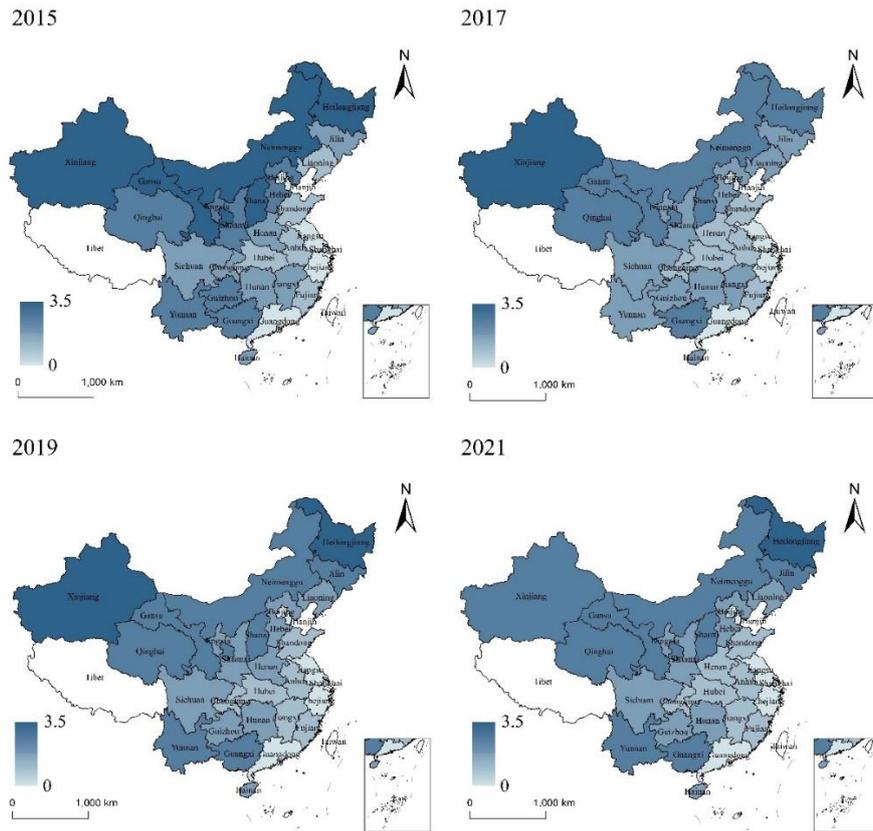


Figure 7. Spatial Distribution of Evolutionary Potential of DIEs Across Chinese Provinces

To more precisely identify the categorical characteristics of DIEs across Chinese provinces, we conducted a systematic cluster analysis using SPSS, based on the key variables of niche fitness and evolutionary potential from 2015 to 2021. The analysis revealed that when the clustering coefficient surpassed 4, certain clusters comprised only a single province. Consequently, we classified the DIEs of the 30 provinces into four distinct categories, with an optimal clustering coefficient of 0.102. The final clustering results for DIEs across China's provinces are depicted in Figure 8.

The findings reveal that Shanghai, Guangdong, Jiangsu, Beijing, Zhejiang, and Tianjin constitute the top tier of DIEs, classified as "digital innovation leaders". In these regions, the average niche fitness exceeds 0.2, positioning them at the heart of key economic zones, namely the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei. With superior geographic advantages, advanced infrastructure, and a concentration of highly skilled innovation talent, these areas provide optimal conditions for the rapid development of DIEs.

The second tier, termed "digital innovation developers", includes 15 provinces such as Shandong, Fujian, Anhui, Hebei, Henan, Chongqing, and Jiangxi. These regions are primarily located in eastern and central China. Provinces like Anhui, Shandong, Fujian, and Hebei either lie within or

adjacent to the core economic zones mentioned earlier, benefiting from the spillover effects of the leading innovation regions. Meanwhile, provinces such as Chongqing, Sichuan, Hunan, and Hubei, situated in central China's economic heartland, have robust foundations in industry-academia-research integration, giving them a competitive edge in fostering digital innovation.

The third tier, labeled "digital innovation starters", comprises seven provinces, including Shanxi, Jilin, Guangxi, Yunnan, Qinghai, Inner Mongolia, and Gansu. These provinces are predominantly located in the western regions, where agriculture and heavy industry dominate the economic landscape. Although these areas have relatively low levels of economic development, initiatives such as the "Eastern Data, Western Computing" project have provided a certain degree of potential for digital innovation growth in these regions (Zhang *et al.*, 2022).

At the bottom, the fourth tier, referred to as "digital innovation laggards", consists of Heilongjiang and Xinjiang. Located at the northeastern and northwestern edges of China, respectively, these provinces face significant limitations due to geographic isolation, resource constraints, and challenging climatic conditions, which have stifled economic growth and created less favorable environments for the advancement of digital innovation.

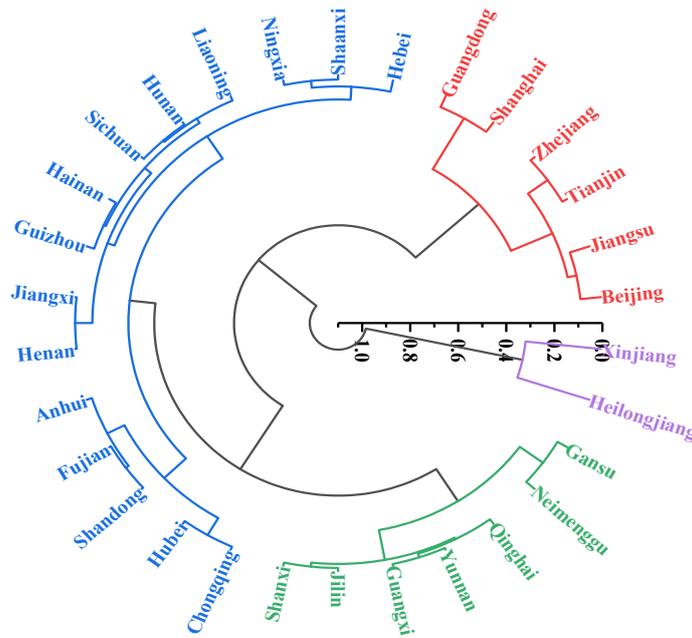


Figure 8. The Clustering Results for DIEs Across China's Provinces

Analysis of Niche Fitness for Ecological Dimensions of DIEs

To delve into the underlying causes of the low-level development in niche fitness within DIEs, we conducted a detailed calculation of the niche fitness across various ecological dimensions for 30 Chinese provinces from 2015 to 2021. Building on the previous analysis, the digital innovation ecosystem comprises 18 ecological indicators

($n=18$), distributed as follows: five indicators each for the niches of digital innovation communities and digital innovation resources, and four indicators each for the niches of digital innovation environment and digital innovation demand. These indicators resulted in 14 data matrices, consisting of 30×5 and 30×4 matrices, respectively. The data for each dimension were sequentially input into the evaluation model for further analysis. The results are summarized in Table 3 and depicted in Figure 9.

Table 3

Niche Fitness for Ecological Dimensions of DIEs in China from 2015 to 2021

Ecological dimensions	2015	2016	2017	2018	2019	2020	2021
Digital innovation communities	0.1102	0.1129	0.1172	0.1189	0.1204	0.1221	0.1219
Digital innovation resources	0.0797	0.0807	0.0825	0.0845	0.0821	0.0847	0.0898
Digital innovation environment	0.5217	0.5181	0.5323	0.5067	0.4871	0.5289	0.5410
Digital innovation demand	0.1383	0.1331	0.1371	0.1333	0.1191	0.1257	0.1333

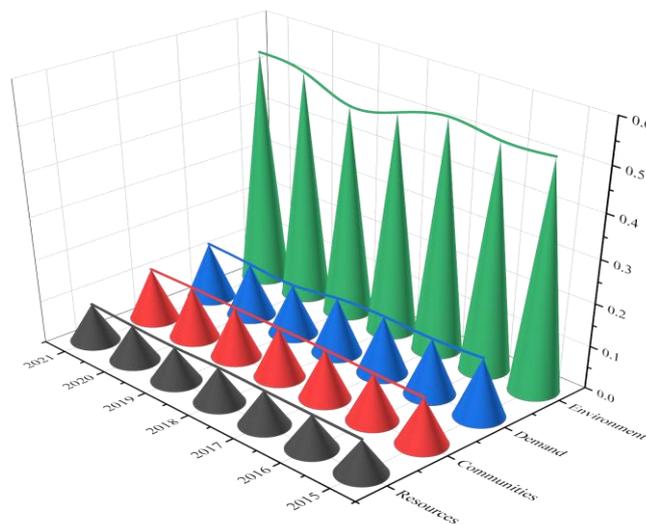


Figure 9. Evolutionary Trends of Niche Fitness for Ecological Dimensions of DIEs in China from 2015 to 2021

The data from 2015 to 2021 reveal significant heterogeneity in the development of various ecological dimensions within China's digital innovation ecosystem. The average niche fitness for the digital innovation environment was 0.5194, noticeably higher than the other dimensions, with a slight increase of 0.61 %. This indicates that China's digital innovation environment is well-developed, offering a favorable market and strong policy support. In contrast, the niche fitness of digital innovation communities (0.1177) and digital innovation demand (0.1314) were similar, while digital innovation resources, despite an annual growth rate of 2.01 %, had a lower average of 0.0834. This gap explains why China's digital innovation ecosystem remains in its early stages, with ample room for evolution. To enhance the overall niche fitness, increased investment in digital innovation

resources is crucial, alongside fostering community diversity and improving innovation performance.

Figure 10 highlights the variation in niche fitness across different ecological dimensions within the four tiers of DIEs. The results show clear differentiation within each tier, following the overall trend. The development pattern generally follows the hierarchy of "first tier > second tier > third tier > fourth tier". As the "digital innovation leaders", the first tier significantly outperforms the others across all dimensions, demonstrating a clear advantage. Apart from the digital innovation environment, the remaining tiers exhibit substantial gaps in communities, resources, and demand fitness compared to the first tier, with the largest gap reaching 0.4458. This suggests that lower tiers should focus on collaboration and knowledge sharing to strengthen spillover effects and enhance their performance in these areas.

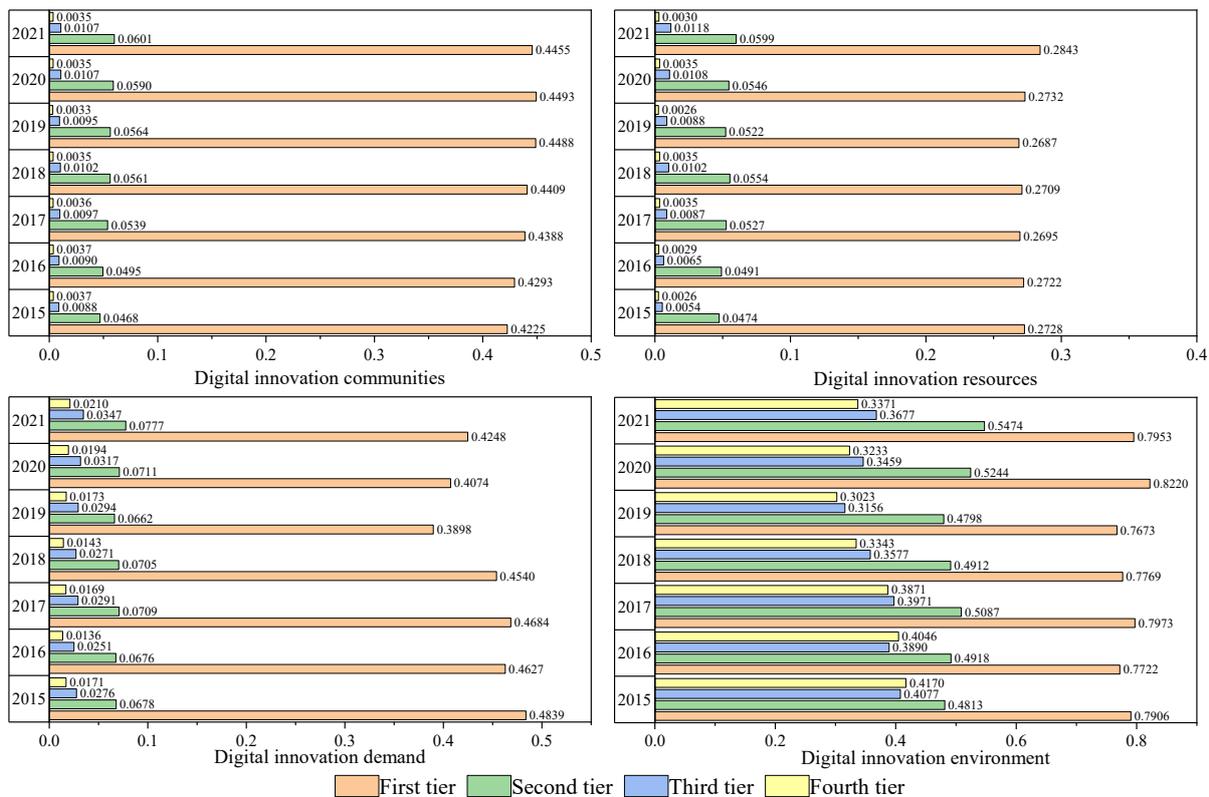


Figure 10. Niche Fitness Across Different Ecological Dimensions Within the Four Tiers of DIEs

As the weights of ecological indicators derived in this study fluctuate only over time, regional disparities in the niche fitness of DIEs within the same year are primarily shaped by the actual performance of these indicators rather than by variations in their assigned weights. Such disparities underscore the uneven development of DIEs across regions in terms of digital innovation communities, resources, environments, and demand. Due to space constraints in the main text, Table 4 presents the average niche fitness scores of DIEs across different regions from 2015 to 2021, including both overall scores and scores for each individual dimension. Detailed annual data are provided in Appendix C.

As shown in Table 4, the first tier exhibits a notably low average score of 0.2731 in the digital innovation resources dimension, significantly lagging behind other dimensions. Consequently, deficiencies in digital innovation resources

have emerged as the principal bottleneck constraining improvements in niche fitness for DIEs in the first tier. In the second tier, despite an average score of 0.5035 in the digital innovation environment dimension, severe deficiencies are evident in the digital innovation community, resources, and demand dimensions, where the highest recorded score is merely 0.0777 (see Appendix C). The fragility of these three ecological dimensions presents a formidable barrier to the advancement of DIEs within this tier. A similar pattern is observed in the third and fourth tiers, where the highest niche fitness scores are recorded in the digital innovation environment dimension, with averages of 0.3687 and 0.3580, respectively. However, the highest scores across other dimensions remain significantly lower—merely 0.0347 for the third tier and 0.0210 for the fourth tier—indicating a pronounced imbalance in ecological

dimension development (see Appendix C). This pronounced disparity has significantly hindered the overall progression of DIES within these two tiers.

The variations in niche fitness observed among different regional DIES suggest that their development is fundamentally constrained by the degree of coordination among ecological dimensions. For first tier, strengthening the supply of digital innovation resources is imperative. The

second tier necessitates the revitalization of innovation entities and the promotion of more effective resource utilization. Meanwhile, in the third and fourth tiers, an emphasis should be placed on optimizing the innovation environment while simultaneously fostering the synergistic development of digital innovation communities, resources, and demand to enhance overall niche fitness levels.

Table 4

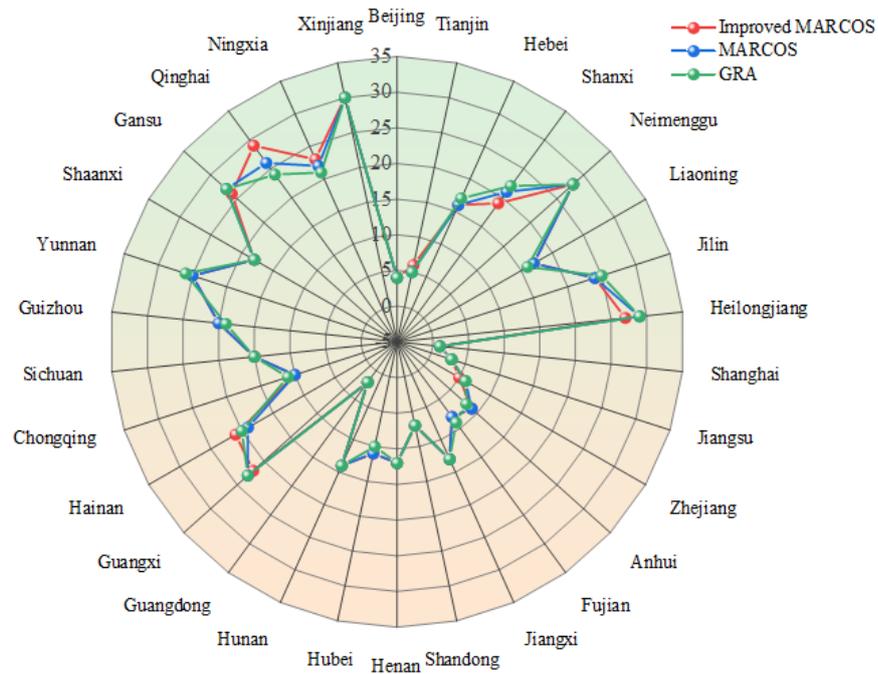
The Average Scores for Overall and Sub-Dimension Niche Fitness of DIES Across Different Regions Over the Period 2015–2021

	Average scores				
	Overall niche fitness	Sub-dimensional niche fitness			
	Overall	Communities	Resources	Environment	Demand
Beijing	0.2957	0.3190	0.1265	0.8699	0.4568
Tianjin	0.2394	0.3334	0.0891	0.6479	0.3160
Shanghai	0.5813	0.9335	0.2996	0.8234	0.5722
Jiangsu	0.3813	0.4320	0.2951	0.7449	0.3606
Zhejiang	0.2579	0.2710	0.1929	0.7773	0.2170
Guangdong	0.5513	0.3470	0.6352	0.8692	0.7270
First Tier	0.3845	0.4393	0.2731	0.7888	0.4416
Hebei	0.0540	0.0456	0.0354	0.3882	0.0366
Liaoning	0.0530	0.0382	0.0327	0.4249	0.0444
Anhui	0.1245	0.1017	0.0826	0.7517	0.1088
Fujian	0.1304	0.0930	0.1115	0.5600	0.1241
Jiangxi	0.0821	0.0661	0.0525	0.5447	0.0689
Shandong	0.1380	0.1143	0.1081	0.5435	0.1261
Henan	0.0857	0.0685	0.0516	0.4878	0.0931
Hubei	0.0924	0.0553	0.0750	0.6484	0.0792
Hunan	0.0754	0.0539	0.0564	0.4764	0.0617
Hainan	0.0320	0.0220	0.0135	0.4304	0.0290
Chongqing	0.0929	0.0763	0.0549	0.4513	0.1055
Sichuan	0.0650	0.0234	0.0645	0.4618	0.0671
Guizhou	0.0352	0.0203	0.0144	0.4835	0.0347
Shaanxi	0.0472	0.0267	0.0341	0.4222	0.0387
Ningxia	0.0280	0.0128	0.0081	0.4780	0.0364
Second Tier	0.0757	0.0545	0.0530	0.5035	0.0703
Shanxi	0.0356	0.0228	0.0194	0.4075	0.0288
Inner Mongolia	0.0145	0.0017	0.0035	0.3309	0.0302
Jilin	0.0246	0.0140	0.0083	0.3883	0.0256
Guangxi	0.0306	0.0169	0.0147	0.4062	0.0281
Yunnan	0.0230	0.0087	0.0093	0.3690	0.0296
Gansu	0.0173	0.0039	0.0057	0.3536	0.0260
Qinghai	0.0127	0.0007	0.0014	0.3253	0.0365
Third Tier	0.0226	0.0098	0.0089	0.3687	0.0292
Heilongjiang	0.0161	0.0060	0.0050	0.3712	0.0159
Xinjiang	0.0100	0.0011	0.0012	0.3447	0.0183
Fourth Tier	0.0130	0.0035	0.0031	0.3580	0.0171

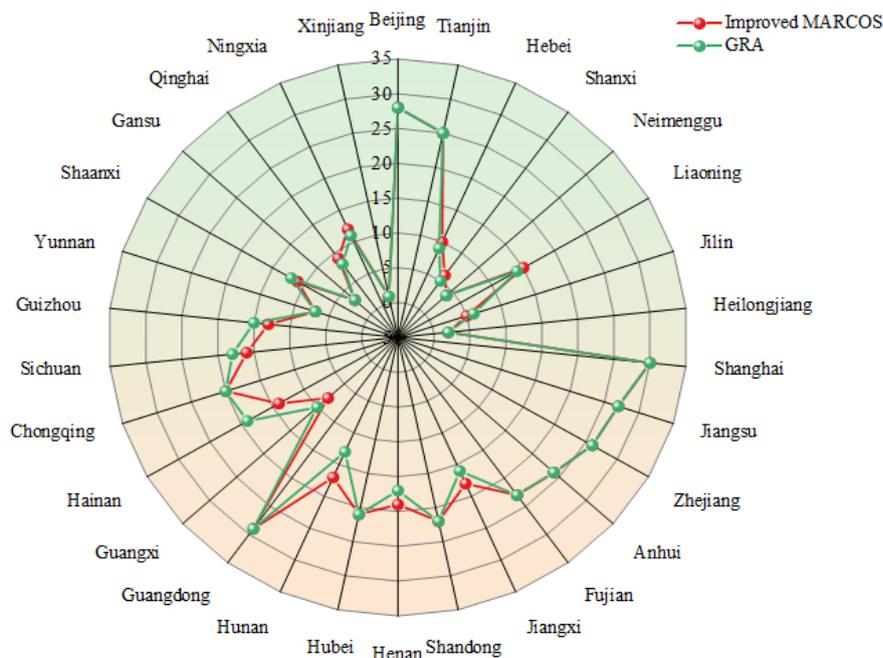
Comparative Analysis

To verify the feasibility of the proposed niche fitness evaluation model based on the improved MARCOS method, we compared it with the basic MARCOS method and the traditional niche fitness model, which typically employs the grey relation analysis (GRA) approach (Cao *et al.*, 2023; Xie *et al.*, 2023). We used these methods to calculate the niche fitness and evolutionary potential of DIES across 30 provinces from 2015 to 2021. Since the evolutionary potential calculation is the same for both the improved and basic MARCOS methods, it is not repeated here. Figure 11 compares the average results from all three models for the same period.

The analysis shows that the rankings for average niche fitness and evolutionary potential are largely consistent across the three models, with only minor variations in a few provinces. This consistency confirms that the proposed niche fitness evaluation model based on the improved MARCOS method is both valid and feasible. By incorporating the HM operator to account for correlations between ecological indicators, the improved model demonstrates the impact of these relationships on niche fitness. In conclusion, the proposed model provides a solid framework for evaluating niche fitness in China's DIES.



(a) Rankings for niche fitness



(b) Rankings for evolutionary potential

Figure 11. Comparison of Evaluation Results of DIES from Different Methods

Forecasting Results of Niche Fitness of DIES

Comparison of Forecasting Results from Different Models

Before constructing the grey prediction model, we confirmed that all original data sequences passed the level ratio test, ensuring they met the modeling requirements. Table 5 shows the niche fitness predictions and accuracy results for China’s overall digital innovation ecosystem across different models. Both the OGM and FOGM models have a MAPE below 10 %, with the FOGM model demonstrating greater accuracy ($0.5831 < 2.2417$). Table 6 presents the prediction

accuracy for each ecological dimension, where all MAPE values for digital innovation communities, resources, environment, and demand are below 10%, confirming strong predictive performance. The FOGM model consistently outperforms the OGM model, with MAPE values below 1 %, indicating higher precision. Figure 12 compares the original niche fitness values with those predicted by the FOGM model, showing minimal differences. Based on these results, the FOGM model will be used to forecast niche fitness and its ecological dimensions for 2022–2026.

Table 5

Niche Fitness Predictions and Accuracy Results for China's Overall Digital Innovation Ecosystem Across Different Models

Region	Years	Original data	OGM		FOGM	
			Forecasting result	APE (%)	Forecasting result	APE (%)
Overall	2016	0.1150	0.1174	2.0636	0.1142	0.7054
	2017	0.1218	0.1192	2.1264	0.1226	0.6660
	2018	0.1248	0.1211	2.9842	0.1240	0.6500
	2019	0.1167	0.1230	5.3733	0.1175	0.6951
	2020	0.1249	0.1249	0.0039	0.1241	0.6495
	2021	0.1280	0.1268	0.8986	0.1278	0.1325
	MAPE (%)			2.2417		0.5831

Table 6

Niche Fitness Predictions and Accuracy Results for Ecological Dimensions of China's Overall Digital Innovation Ecosystem Across Different Models

Ecological dimensions	Years	Original data	OGM		FOGM	
			Forecasting result	APE (%)	Forecasting result	APE (%)
Digital innovation communities	2016	0.1129	0.1151	1.9589	0.1131	0.2142
	2017	0.1172	0.1168	0.3320	0.1170	0.2064
	2018	0.1189	0.1185	0.3067	0.1191	0.2034
	2019	0.1204	0.1203	0.0954	0.1202	0.2009
	2020	0.1221	0.1221	0.0320	0.1223	0.1981
	2021	0.1219	0.1239	1.6102	0.1228	0.7059
	MAPE (%)			0.7225		0.2882
Digital innovation resources	2016	0.0807	0.0808	0.1124	0.0806	0.1633
	2017	0.0825	0.0822	0.3857	0.0826	0.1598
	2018	0.0845	0.0836	1.0689	0.0844	0.1560
	2019	0.0821	0.0850	3.5764	0.0822	0.1605
	2020	0.0847	0.0865	2.1256	0.0846	0.1556
	2021	0.0898	0.0880	2.0159	0.0890	0.9346
	MAPE (%)			1.5475		0.2883
Digital innovation environment	2016	0.5181	0.5140	0.7874	0.5166	0.2803
	2017	0.5323	0.5164	2.9886	0.5338	0.2728
	2018	0.5067	0.5188	2.3828	0.5052	0.2866
	2019	0.4871	0.5212	6.9938	0.4886	0.2981
	2020	0.5289	0.5236	1.0075	0.5274	0.2746
	2021	0.5410	0.5260	2.7751	0.5342	1.2534
	MAPE (%)			2.8226		0.4443
Digital innovation demand	2016	0.1331	0.1332	0.1065	0.1327	0.2636
	2017	0.1371	0.1318	3.8565	0.1375	0.2559
	2018	0.1333	0.1304	2.1763	0.1329	0.2632
	2019	0.1191	0.1290	8.3127	0.1195	0.2946
	2020	0.1257	0.1276	1.5250	0.1253	0.2791
	2021	0.1333	0.1262	5.2902	0.1299	2.5135
	MAPE (%)			3.5445		0.6450

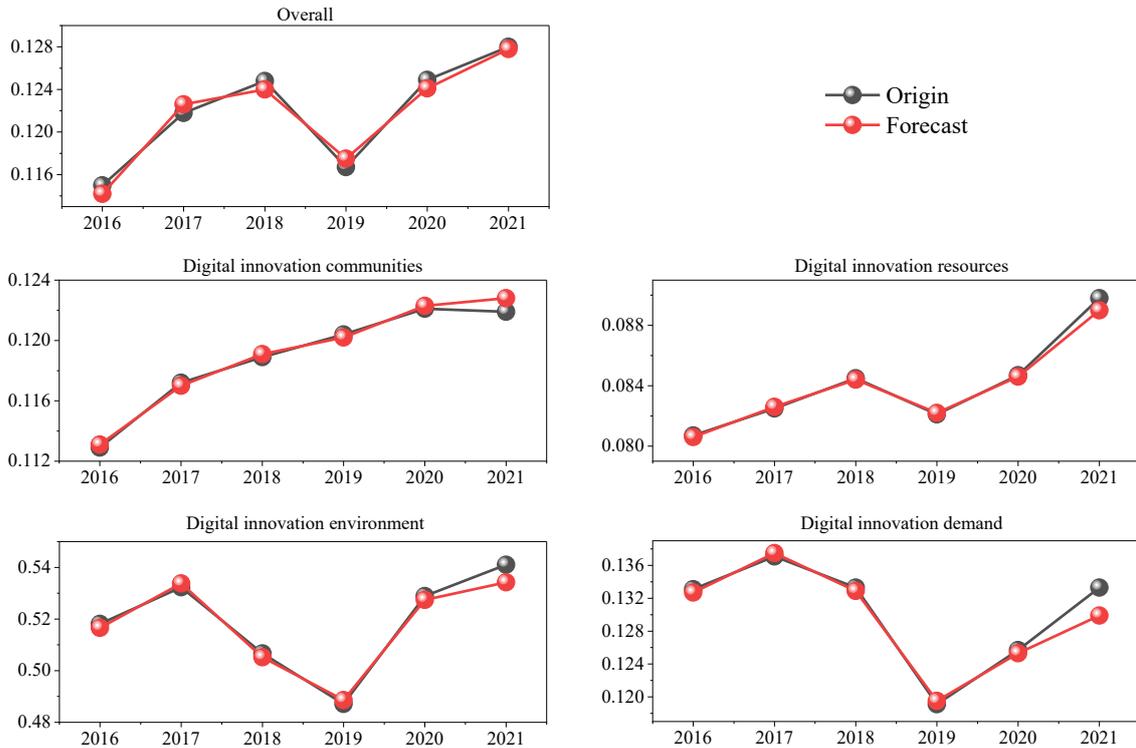


Figure 12. Comparison of the Original Data and Forecasting Results of FOGM for the Niche Fitness of Overall DIEs and Ecological Dimensions in China

Forecasting Results of Niche Fitness of DIEs Based on FOGM

Figure 13 shows the predicted trends in niche fitness across China's digital innovation ecosystem for 2022–2026, based on the FOGM model. Over the next five years, overall niche fitness is expected to rise, with an average annual growth rate of 2.04 %, surpassing the 1.77 % growth rate from 2015–2021, indicating positive development. Growth rates will vary across tiers: 6.47 % for the third tier, 3.84 %

for the fourth, 3.79 % for the second, and 0.88 % for the first. Despite these differences, the hierarchy of "first tier > second tier > third tier > fourth tier" remains stable. The first tier, primarily composed of provinces in the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei regions, will maintain niche fitness levels slightly above the national average, while other tiers will lag significantly behind. These results highlight the need to reduce regional disparities to further accelerate the ecosystem's overall development.

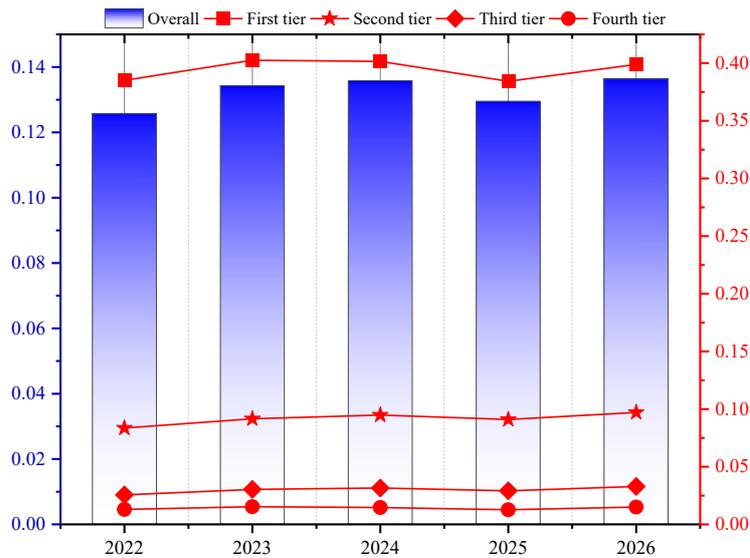


Figure 13. Predicted Evolutionary Trends in Niche Fitness Across China's Overall and Four Tiers of DIEs from 2022 to 2026

Forecasting Results of Niche Fitness for Ecological Dimensions of DIES Based on FOGM

Figure 14 shows the projected trends in niche fitness across various ecological dimensions for China and its regions from 2022 to 2026, based on the FOGM model. On the whole, the average difference between ecological dimensions over the next five years is anticipated to be 0.2198, slightly below the 2015–2021 level ($0.2198 < 0.2203$), indicating a modest convergence. The digital innovation environment niche remains the strongest, providing essential support to the ecosystem, while digital innovation communities, resources, and demand continue to lag, hindering balanced development. The digital innovation demand niche is expected to decline, highlighting the need for greater focus on practical implementation to unlock its value-creation potential in technology, economy, and society.

Regionally, the first tier, encompassing the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei regions, leads across all dimensions. However, its internal variance of 0.5348 is higher than other tiers, potentially limiting its growth. The second tier, located in eastern and central China, benefits from proximity to the first tier, amplifying spillover effects and enabling stronger development than the third and fourth tiers. In contrast, the third and fourth tiers, primarily in western and northeastern China, are expected to see declines in the digital innovation environment niche, driven by a focus on economic growth and political advancement, with reduced support for high-risk, high-investment digital innovation. These tiers will continue to show the weakest performance in digital innovation communities, resources, and demand.

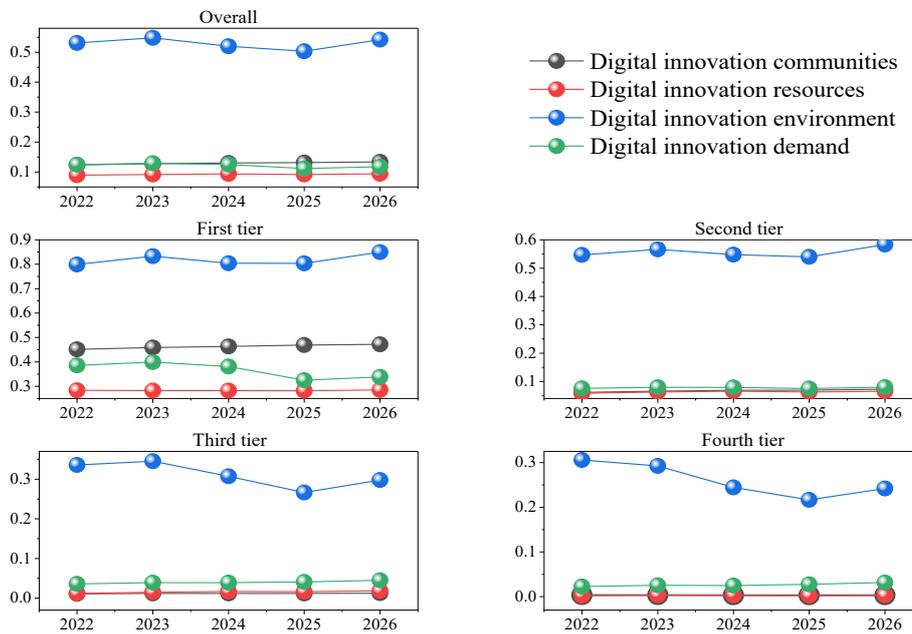


Figure 14. Predicted Evolutionary Trends of Niche Fitness for Ecological Dimensions Across China's Overall and Four Tiers of DIES from 2022 to 2026

Conclusions and Implications

Conclusions

This study addresses key challenges in evaluating DIES and the uncertainty surrounding their evolutionary dynamics by developing an integrated evaluation–prediction framework grounded in niche theory. The framework comprises a four-dimensional niche fitness evaluation system covering digital innovation communities, resources, environment, and demand, a composite assessment model that combines MEREK-based weighting with an improved MARCOS approach, and enhanced grey prediction models. Together, these components enable a systematic examination of the development level, structural heterogeneity, and prospective evolutionary trajectories of niche fitness across multi-regional DIES. Owing to its strong replicability, low data requirements, and suitability for weak-information contexts, the proposed framework offers a transferable analytical toolkit for quantitative research on DIES.

Based on this framework, the study conducts an empirical analysis of niche fitness evolution across 30 Chinese provinces from 2015 to 2021, followed by trend forecasting for the subsequent five years. The findings indicate that: (1) the overall niche fitness of China’s DIES has steadily improved but remains at an early stage of structural consolidation, with regional differentiation persistently following a four-tier pattern that reflects cumulative advantage and path dependence; (2) deficiencies in resources, communities, and demand niches represent the primary constraints on ecosystem upgrading, indicating that niche fitness evolution is limited by insufficient multidimensional coupling rather than by the absence of any single element; and (3) forecast results suggest that overall niche fitness will continue to increase in the medium term, while regional stratification is likely to persist. Leading regions, concentrated in the Yangtze River Delta, the Pearl River Delta, and the Beijing–Tianjin–Hebei urban agglomeration, are expected to experience a gradual slowdown in growth, whereas some central and western

regions may encounter temporary weakening in environmental and demand niches. This pattern points to an “uneven convergence” trajectory in the future evolution of China’s DIES.

Overall, the proposed niche fitness evaluation and prediction framework not only captures the current state of DIES but also facilitates the identification of evolutionary trends and structural bottlenecks. It provides a systematic and operational analytical tool for monitoring, governing, and optimizing DIES, and contributes to the further theoretical refinement and methodological advancement of research in this field.

Managerial Implications

(1) To mitigate the low niche fitness of China’s digital innovation ecosystem and the pronounced regional disparities, the government should actively foster open and collaborative innovation across regions, while implementing region-specific strategies that encourage tailored digital innovation ecosystem development. It is crucial to harness the clustering and spillover effects of ecosystem growth by accelerating the development of cutting-edge digital technologies in eastern provinces, thereby avoiding innovation lock-in and consolidating the region’s leadership in digital innovation. Concurrently, efforts must focus on strengthening the digital infrastructure in central and western regions, with an emphasis on increasing resource allocation and enhancing the capacity for digital innovation learning and absorption in these areas. Through enhanced regional collaboration and integration, the disparities between regions can be reduced, enabling systemic evolution and sustainable upgrades.

(2) To mitigate the imbalance in the development of various ecological dimensions within DIES, which hampers systemic evolution and progression, it is imperative to not only strengthen the digital innovation environment but also to enhance the diversity of innovation actors, aggregate premium digital resources, and meet a broad spectrum of innovation demands. The government must sustain its strategic guidance on digital innovation by refining both the market infrastructure and policy landscape, while advancing an integrated approach that encompasses universities, research institutions, and digital enterprises. Priority should be given to attracting and cultivating leading digital innovation enterprises that possess significant spillover effects, thereby accelerating capabilities in the development and commercialization of digital technologies. In parallel, it is essential to establish a robust mechanism for cultivating digital innovation talent, supported by dedicated innovation funds that encourage universities, enterprises, and research institutions to drive digital technology breakthroughs and foster new product development within the digital industry. Enhancing the depth of collaboration between academia, industry, and research institutions will optimize synergies among innovation actors, resources, and environmental factors. Ultimately, enhancing the alignment between digital innovation research and market demand, while continuously expanding the application landscape for digital technologies, is essential. Accelerating the implementation of digital innovation projects will, in turn, significantly enhance the ecosystem’s value creation capacity.

Limitations and Prospects

Despite its contributions, this study has certain limitations. First, the standardization and precision of the selected indicators for assessing the niche fitness of DIES require further refinement. Future research should integrate a broader set of nuanced indicators, grounded in enriched data and real-world digital innovation practices, to enhance the rigor and comprehensiveness of the evaluation framework. Second, in-depth case studies of representative regions could be undertaken to analyze specific strategies, best practices, and challenges across key dimensions such as digital innovation communities, resources, environment, and demand. These case studies would facilitate the development of more targeted policy recommendations and practical guidelines, thereby increasing the applicability and strategic relevance of the findings. Lastly, building upon an understanding of the evolutionary dynamics of DIES, future research should further investigate the underlying drivers of system evolution and their corresponding economic and societal implications. Such an inquiry would provide valuable, evidence-based insights to inform policy and strategic decision-making for the sustainable advancement of the digital economy.

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Appendix

Appendix A: Evaluation model for the niche fitness of DIES

(1) *Determination of ecological indicator weights based on the MEREC*

Assuming that the number of DIES under evaluation is m and the number of ecological indicators is n , the observed value of the j -th ecological indicators for the i -th DIE is denoted as x_{ij} ($i = 1, 2, \dots, m; j = 1, 2, \dots, n$). These values collectively form the original data matrix for the niche fitness evaluation of DIES, represented as $X = [x_{ij}]_{m \times n}$.

Step 1. Normalize the original data matrix.

The original data matrix $X = [x_{ij}]_{m \times n}$ is normalized using Eq. (A1) and denoted as $N = [n_{ij}^x]_{m \times n}$.

$$n_{ij}^x = \frac{\min_i x_{ij}}{x_{ij}} \text{ if } j \in B \tag{A1}$$

where n_{ij}^x represents the elements in the normalized matrix $N = [n_{ij}^x]_{m \times n}$, B denoting the set of benefit-type indicators.

Step 2. Calculate the removal effect for the j -th ecological indicator.

The overall performance of the i -th DIE, including all ecological indicators, is computed using Eq. (A2) and denoted as S_i .

$$S_i = \ln \left(1 + \left(\frac{1}{n} \sum_j^n \left| \ln(n_{ij}^x) \right| \right) \right) \quad (A2)$$

Similarly, the performance of the i -th DIE after removing the j -th ecological indicator is calculated using Eq. (A3) and denoted as S'_{ij} .

$$S'_{ij} = \ln \left(1 + \left(\frac{1}{n} \sum_{k, k \neq j}^n \left| \ln(n_{ik}^x) \right| \right) \right) \quad (A3)$$

The sum of the absolute deviations for the j -th ecological indicator is calculated using Eq. (A4), yielding the removal effect of the j -th ecological indicator, denoted as E_j .

$$E_j = \sum_i^m |S'_{ij} - S_i| \quad (A4)$$

Step 3. Determine the j -th ecological indicator weight. The objective weight of the j -th ecological indicator is calculated through Eq. (A5) and is represented as w_j .

$$w_j = \frac{E_j}{\sum_j E_j} \quad (A5)$$

(2) Niche fitness evaluation based on the enhanced MARCOS method

Step 1. Determine the extended evaluation matrix.

Based on the original data matrix $X = [x_{ij}]_{m \times n}$ constructed for evaluating niche fitness of DIEs, both the ideal niche (denoted as AI) and the anti-ideal niche (denoted as AAI) are introduced. As all ecological indicators in this study are categorized as benefit-type indicators, the values of AI and AAI are determined according to Eq. (A6) and (A7), respectively.

$$AI = (x_{a1}, x_{a2}, \dots, x_{an}), \quad x_{aj} = \max_i x_{ij} \quad \text{if } j \in B \quad (A6)$$

$$AAI = (x_{aa1}, x_{aa2}, \dots, x_{aan}), \quad x_{aaj} = \min_i x_{ij} \quad \text{if } j \in B \quad (A7)$$

On this basis, an extended matrix $X^e = [x_{ij}]_{(m+2) \times n}$ is constructed to evaluate niche fitness of DIEs (Eq. (A8)).

$$X^e = \begin{matrix} & \begin{matrix} AAI \\ A_1 \\ A_2 \\ \vdots \\ A_l \\ \vdots \\ A_m \\ AI \end{matrix} & \begin{pmatrix} x_{aa1} & x_{aa2} & \cdots & x_{aaj} & \cdots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{l1} & x_{l2} & \cdots & x_{lj} & \cdots & x_{ln} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \\ x_{a1} & x_{a2} & \cdots & x_{aj} & \cdots & x_{an} \end{pmatrix} \end{matrix} \quad (A8)$$

Step 2. Normalize the extended evaluation matrix.

The extended evaluation matrix X^e is normalized using Eq. (A9), resulting in a matrix denoted as $U = [u_{ij}]_{(m+2) \times n}$.

$$u_{ij} = \frac{x_{ij}}{x_{aj}}, \text{ if } j \in B \quad (A9)$$

Step 3. Determine the weighted extended evaluation matrix.

The weighted extended evaluation matrix $Z = [z_{ij}]_{(m+2) \times n}$ is calculated according to Eq. (A10).

$$z_{ij} = w_j \cdot u_{ij} \quad (A10)$$

Here, w_j represents the weight of the j -th ecological indicator.

Step 4. Determine the relative utility function of the i -th DIE's niche.

The utility degrees K_i^+ and K_i^- of the realistic ecological niche of the i -th DIE relative to the ideal ecological niche and the anti-ideal niche are calculated according to Eqs. (A11) and (A12), respectively.

$$K_i^+ = \frac{T_i}{T_{AI}} \quad (A11)$$

$$K_i^- = \frac{T_i}{T_{AAI}} \quad (A12)$$

where the calculations of T_i , T_{AI} , and T_{AAI} incorporate the correlations between ecological indicators, with refinements introduced through the HM operator. The relevant formulas are provided in Eqs. (A13) to (A15).

$$T_i = \frac{2}{n(n+1)} \sum_{s=1}^n \sum_{j=s}^n \sqrt{z_{is} z_{ij}} \quad (i=1, 2, \dots, m) \quad (A13)$$

$$T_{AI} = \frac{2}{n(n+1)} \sum_{s=1}^n \sum_{j=s}^n \sqrt{z_{as} z_{aj}} \quad (A14)$$

$$T_{AAI} = \frac{2}{n(n+1)} \sum_{s=1}^n \sum_{j=s}^n \sqrt{z_{aas} z_{aaj}} \quad (A15)$$

The utility functions $f(K_i^+)$ and $f(K_i^-)$ of the i -th DIE's niche, relative to the ideal and the anti-ideal niche, are calculated using Eqs. (A16) and (A17), respectively.

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \quad (A16)$$

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \quad (A17)$$

Step 5. Determine the niche fitness of the i -th DIE.

The niche fitness $f(K_i)$ of the i -th DIE is determined based on the ideal and the anti-ideal niches, using Eq. (A18).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \quad (A18)$$

Step 6. Assess the evolutionary potential of the niche fitness for the i -th DIE.

The evolutionary potential EP_i of the niche fitness for the i -th DIE is calculated using Eq. (A19).

$$EP_i = \sqrt{\frac{1}{n} \cdot \frac{\sum_{j=1}^n |u_{ij} - u_{aj}|}{\sum_{j=1}^n |u_{ij} - u_{aaj}|}} \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (A19)$$

Here, u_{ij} represents the element in the normalized extended evaluation matrix $U = [u_{ij}]_{(m+2) \times n}$, while u_{aj} and u_{aaj} are the normalized values of the ideal and the anti-ideal niche, respectively. For any ecological indicator, the values of u_{aj} and u_{aaj} remain constant. Thus, the larger the value of u_{ij} , the smaller the value of $\frac{|u_{ij} - u_{aj}|}{|u_{ij} - u_{aaj}|}$, and consequently, the smaller the value of EP_i , indicating a more limited evolutionary space for the niche fitness of i -th DIE.

Appendix B: Niche fitness prediction model of DIES

(1) Basic prediction model

The niche fitness evaluation results of the DIES are used as the original data sequence. Assuming the original data sequence is $F^{(0)} = \{f^{(0)}(1), f^{(0)}(2), \dots, f^{(0)}(t)\}$.

Step 1. Feasibility analysis for modeling.

Perform the level ratio test on the original sequence $F^{(0)}$ using Eq. (B1) to verify the feasibility of the model. If $\lambda(t)$ falls within the interval $\left(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}}\right)$ (where e represents the natural logarithm), the test is passed.

$$\lambda(t) = \frac{f^{(0)}(t-1)}{f^{(0)}(t)}, t = 2, 3, \dots, T \quad (B1)$$

Step 2. Compute the one-time accumulating sequence.

Generate one-time accumulating sequence of the original sequence $F^{(0)}$, denoted as $F^{(1)} = \{f^{(1)}(1), f^{(1)}(2), \dots, f^{(1)}(t)\}$, where

$$f^{(1)}(t) = \sum_{k=1}^t f^{(0)}(k), t = 1, 2, \dots, T \quad (B2)$$

Step 3. Establish the differential equation and solve.

Define the grey derivative of one-time accumulating sequence $f^{(1)}$ as $d(t) = f^{(0)}(t) = f^{(1)}(t) - f^{(1)}(t-1)$. Let $z^{(1)}(t)$ represent the adjacent mean sequence of $f^{(1)}$, as follows:

$$z^{(1)}(t) = \alpha f^{(1)}(t) + (1 - \alpha) f^{(1)}(t-1) \quad (B3)$$

where $0 \leq \alpha \leq 1$, and α is typically set to 0.5. Thus, the grey differential equation of the niche fitness for DIES in the GM (1,1) model is as follows:

$$f^{(0)}(t) + az^{(1)}(t) = b, t = 2, 3, \dots, T \quad (B4)$$

The corresponding GM (1,1) whitening differential equations are

$$\frac{df^{(1)}(t)}{dt} + af^{(1)}(t) = b \quad (B5)$$

where a is the developing coefficient, and b is the gray input. Eq. (B4) is rearranged and transformed as follows:

$$-az^{(1)}(t) + b = f^{(0)}(t), t = 2, 3, \dots, T \quad (B6)$$

Eq. (B6) is converted into the following vector matrix form.

$$\begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(t) & 1 \end{bmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} f^{(0)}(2) \\ f^{(0)}(3) \\ \vdots \\ f^{(0)}(t) \end{pmatrix} \quad (B7)$$

That is, $Hu = Y$. The parameter matrix u is determined using the least-squares estimation.

$$\hat{u} = (a, b)^T = (H^T H)^{-1} H^T Y \quad (B8)$$

Step 4. Establish the prediction model.

Substitute the values of parameters a and b into Eq. (B5) to obtain the general solution of the sequence $f^{(1)}(t)$.

$$f^{(1)}(t) = \left[f^{(0)}(1) - \frac{b}{a} \right] e^{-a(t-1)} + \frac{b}{a}, t = 2, 3, \dots, T \quad (B9)$$

Accordingly, the time response function of the GM(1,1) model is derived as follows:

$$\hat{f}^{(1)}(t+1) = \left[f^{(0)}(1) - \frac{b}{a} \right] e^{-at} + \frac{b}{a}, t = 1, 2, \dots, T \quad (B10)$$

By applying inverse accumulating generation operator, the forecast model for the niche fitness of DIES' original sequence can be obtained:

$$\begin{aligned} \hat{f}^{(0)}(t+1) &= \hat{f}^{(1)}(t+1) - \hat{f}^{(1)}(t) \\ &= \left[f^{(0)}(1) - \frac{b}{a} \right] e^{-at} (1 - e^a), t = 1, 2, \dots, T \end{aligned} \quad (B11)$$

Step 5. Accuracy testing.

Let $f^{(0)}(t)$ represent the original sequence of niche fitness for DIES, with $\hat{f}^{(0)}(t)$ as the corresponding predicted sequence. The residual sequence can then be expressed as:

$$\varepsilon^{(0)}(t) = f^{(0)}(t) - \hat{f}^{(0)}(t), t = 2, 3, \dots, T \quad (B12)$$

The absolute percentage error (APE) and the mean absolute percentage error (MAPE) are defined as follows:

$$APE = \left| \frac{\varepsilon^{(0)}(t)}{f^{(0)}(t)} \right| \times 100\% \quad (B13)$$

$$MAPE = \frac{1}{T} \sum_{t=1}^T \left| \frac{\varepsilon^{(0)}(t)}{f^{(0)}(t)} \right| \quad (B14)$$

(2) Model refinement

Grey Model with Parameter Optimization (OGM)

The OGM is built upon the basic GM (1,1) by adjusting the coefficient α in Eq. (B3) to achieve optimal prediction accuracy. The specific process is as follows:

Step 1. Develop the GM (1,1) model for the niche fitness of DIEs with $\alpha = 0.1$.

Step 2. Calculate the MAPE for the OGM model at $\alpha = 0.1$.

Step 3. If $\alpha < 0.9$, update $\alpha^{new} = \alpha + 0.1$, and compute the corresponding MAPE*. Then, compare MAPE* with MAPE.

Step 4. Output the predicted value corresponding to the minimum of {MAPE, MAPE*}.

Grey Model with Parameter Optimization and Fourier Series Modification (FOGM)

Step 1. Calculate the residual sequence for the niche fitness of DIEs based on the OGM model, denoted as $\varepsilon_{OGM}^{(0)} = \{\varepsilon_{OGM}^{(0)}(2), \varepsilon_{OGM}^{(0)}(3), \dots, \varepsilon_{OGM}^{(0)}(t)\}$, where

$$\varepsilon_{OGM}^{(0)}(t) = f^{(0)}(t) - \hat{f}_{OGM}^{(0)}(t), t = 2, 3, \dots, T \quad (B15)$$

Here, $f^{(0)}(t)$ and $\hat{f}_{OGM}^{(0)}(t)$ represent the actual values and the predicted values based on the OGM model, respectively.

Step 2. Express the residual sequence using the Fourier series.

$$\varepsilon_{OGM}^{(0)}(t) \approx \frac{1}{2}a_0 + \sum_{i=1}^z \left[a_i \cos\left(\frac{2\pi it}{U}\right) + b_i \sin\left(\frac{2\pi it}{U}\right) \right] \quad (B16)$$

where $U = n - 1$ represents the period length, and z denotes the minimum deployment frequency of the Fourier series.

Transform Eq. (B16) into the following matrix form:

$$\varepsilon_{OGM}^{(0)} \approx LC \quad (B17)$$

where

$$L = \begin{bmatrix} \frac{1}{2} & \cos\left(2\frac{2\pi}{U}\right) & \sin\left(2\frac{2\pi}{U}\right) & \cos\left(2\frac{2\pi 2}{U}\right) & \sin\left(2\frac{2\pi 2}{U}\right) & \dots & \cos\left(2\frac{2\pi z}{U}\right) & \sin\left(2\frac{2\pi z}{U}\right) \\ \frac{1}{2} & \cos\left(3\frac{2\pi}{U}\right) & \sin\left(3\frac{2\pi}{U}\right) & \cos\left(3\frac{2\pi 2}{U}\right) & \sin\left(3\frac{2\pi 2}{U}\right) & \dots & \cos\left(3\frac{2\pi z}{U}\right) & \sin\left(3\frac{2\pi z}{U}\right) \\ \dots & \dots \\ \frac{1}{2} & \cos\left(t\frac{2\pi}{U}\right) & \sin\left(t\frac{2\pi}{U}\right) & \cos\left(t\frac{2\pi 2}{U}\right) & \sin\left(t\frac{2\pi 2}{U}\right) & \dots & \cos\left(t\frac{2\pi z}{U}\right) & \sin\left(t\frac{2\pi z}{U}\right) \end{bmatrix} \quad (B18)$$

$$C = [a_0, a_1, b_1, a_2, b_2, \dots, a_z, b_z]^T \quad (B19)$$

The coefficient matrix C is estimated using the least-squares method.

$$C = [a_0, a_1, b_1, a_2, b_2, \dots, a_z, b_z]^T \approx (L^T L)^{-1} L^T \varepsilon_{OGM}^{(0)} \quad (B20)$$

Step 3. By substituting the estimated Fourier coefficients from Eq. (B20) into Eq. (B16), the corrected residual sequence $\varepsilon_{FOGM}^{(0)}$ is computed. Consequently, the final refined prediction value is:

$$\hat{f}_{FOGM}^{(0)}(t) = \hat{f}_{OGM}^{(0)}(t) + \varepsilon_{FOGM}^{(0)}(t), t = 1, 2, \dots, T + 1 \quad (B21)$$

Appendix C

Table C1

The Overall and Sub-Dimension Niche Fitness of DIEs Across Different Regions from 2015 to 2018

	2015					2016					2017					2018				
	Over all niche fitness	Sub-dimensional niche fitness				Over all niche fitness	Sub-dimensional niche fitness				Over all niche fitness	Sub-dimensional niche fitness				Over all niche fitness	Sub-dimensional niche fitness			
		Over all	Communities	Resources	Environment		Demand	Over all	Communities	Resources		Environment	Demand	Over all	Communities		Resources	Environment	Demand	Over all
Beijing	0.3234	0.3559	0.1419	0.8828	0.523	0.2949	0.3346	0.1292	0.7910	0.4777	0.3107	0.3317	0.1304	0.8725	0.5013	0.3039	0.3224	0.1305	0.8467	0.4557
Tianjin	0.2671	0.3516	0.0799	0.7121	0.4921	0.2396	0.3453	0.0783	0.6586	0.3788	0.2482	0.3264	0.0882	0.6728	0.3668	0.2466	0.3222	0.0958	0.6218	0.3213
Shanghai	0.6049	0.9708	0.3098	0.8163	0.6321	0.5643	0.9322	0.2750	0.8469	0.609	0.5984	0.9329	0.3101	0.8496	0.6202	0.5943	0.9300	0.3067	0.8112	0.5999
Jiangsu	0.3723	0.4098	0.2825	0.7621	0.3863	0.3787	0.4456	0.2851	0.7311	0.3802	0.3874	0.4475	0.2857	0.7504	0.3791	0.3861	0.4417	0.2894	0.7290	0.3603
Zhejiang	0.2421	0.2420	0.1882	0.7681	0.2084	0.2385	0.2466	0.1857	0.7433	0.2043	0.2506	0.2585	0.1908	0.7594	0.2096	0.2572	0.2663	0.1930	0.7396	0.2107
Guangdong	0.4726	0.2050	0.6347	0.8018	0.6613	0.5396	0.2715	0.6795	0.8624	0.7265	0.5403	0.3360	0.6116	0.8789	0.7336	0.5652	0.3630	0.6103	0.9130	0.7759

	2015					2016					2017					2018				
	Over all niche fitne ss	Sub-dimensional niche fitness				Over all niche fitne ss	Sub-dimensional niche fitness				Over all niche fitne ss	Sub-dimensional niche fitness				Over all niche fitne ss	Sub-dimensional niche fitness			
		Over all	Communi ties	Resour ces	Environ ment		Dema nd	Over all	Communi ties	Resour ces		Environ ment	Dema nd	Over all	Communi ties		Resour ces	Environ ment	Dema nd	Over all
First Tier	0.3804	0.4225	0.2728	0.7906	0.4839	0.3759	0.4293	0.2722	0.7722	0.4627	0.3893	0.4388	0.2695	0.7973	0.4684	0.3922	0.4409	0.2709	0.7769	0.454
Hebei	0.0468	0.0410	0.0328	0.3751	0.0255	0.0497	0.0436	0.0313	0.4137	0.0332	0.0558	0.0458	0.0366	0.4159	0.0378	0.0554	0.0449	0.0386	0.3690	0.0335
Liaoning	0.0573	0.0422	0.0330	0.4807	0.0526	0.0499	0.0370	0.0274	0.4542	0.0466	0.0531	0.0377	0.0321	0.4307	0.0456	0.0558	0.0385	0.0349	0.4208	0.0435
Anhui	0.1018	0.0836	0.0658	0.6264	0.0951	0.1113	0.0922	0.0706	0.7690	0.1013	0.1203	0.1008	0.0786	0.7470	0.0999	0.1293	0.1050	0.0856	0.7251	0.1056
Fujian	0.1187	0.0822	0.0998	0.5478	0.1183	0.1220	0.0856	0.1055	0.5348	0.1213	0.1302	0.0936	0.1112	0.5513	0.1254	0.1374	0.0990	0.1198	0.5427	0.1229
Jiangxi	0.0531	0.0386	0.0301	0.4795	0.0478	0.0588	0.0468	0.0338	0.5101	0.0493	0.0742	0.0571	0.0464	0.5551	0.0594	0.0847	0.0697	0.0518	0.5381	0.0638
Shandong	0.1453	0.1124	0.1248	0.5072	0.1465	0.1521	0.1185	0.1260	0.5258	0.1606	0.1498	0.1233	0.1186	0.5372	0.1426	0.1468	0.1162	0.1147	0.5142	0.1391
Henan	0.0782	0.0632	0.0431	0.4207	0.1059	0.0791	0.0657	0.0476	0.4121	0.0966	0.0898	0.0694	0.0514	0.4882	0.1123	0.0924	0.0689	0.0534	0.4478	0.1134
Hubei	0.0818	0.0486	0.0705	0.6194	0.0629	0.0819	0.0493	0.0713	0.6071	0.0639	0.0872	0.0508	0.0710	0.6627	0.0717	0.0931	0.0552	0.0733	0.6428	0.0746
Hunan	0.0681	0.0430	0.0548	0.4498	0.0604	0.0654	0.0448	0.0519	0.4170	0.0565	0.0710	0.0509	0.0546	0.4452	0.0558	0.0764	0.0552	0.0554	0.4548	0.0584
Hainan	0.0309	0.0208	0.0116	0.4306	0.0328	0.0272	0.0183	0.0101	0.4342	0.0273	0.0313	0.0208	0.0134	0.3930	0.0311	0.0330	0.0228	0.0153	0.3695	0.0262
Chongqing	0.0777	0.0588	0.0400	0.4213	0.1141	0.0820	0.0662	0.0463	0.4578	0.0998	0.0926	0.0761	0.0526	0.4647	0.1066	0.0990	0.0804	0.0570	0.4406	0.1097
Sichuan	0.0579	0.0183	0.0583	0.4718	0.0611	0.0618	0.0206	0.0674	0.4370	0.0605	0.0635	0.0225	0.0690	0.4476	0.0585	0.0672	0.0240	0.0715	0.4460	0.059
Guizhou	0.0293	0.0152	0.0124	0.4800	0.0287	0.0305	0.0175	0.0115	0.4968	0.0319	0.0370	0.0206	0.0143	0.5279	0.0379	0.0403	0.0227	0.0166	0.5006	0.0354
Shaanxi	0.0436	0.0235	0.0305	0.4334	0.0384	0.0442	0.0257	0.0319	0.4598	0.0335	0.0466	0.0269	0.0321	0.4627	0.0367	0.0476	0.0263	0.0328	0.4435	0.034
Ningxia	0.0210	0.0103	0.0036	0.4756	0.0294	0.0207	0.0102	0.0039	0.4469	0.0311	0.0290	0.0117	0.0079	0.5020	0.0432	0.0326	0.0133	0.0098	0.5119	0.0384
Second Tier	0.0674	0.0468	0.0474	0.4813	0.0678	0.0691	0.0495	0.0491	0.4918	0.0676	0.0754	0.0539	0.0527	0.5087	0.0709	0.0794	0.0561	0.0554	0.4912	0.0705
Shanxi	0.0257	0.0196	0.0107	0.3994	0.0181	0.0277	0.0200	0.0142	0.4088	0.0179	0.0350	0.0215	0.0208	0.4314	0.0248	0.0403	0.0227	0.0241	0.4144	0.0309
Inner Mongolia	0.0114	0.0018	0.0011	0.3832	0.0233	0.0121	0.0017	0.0027	0.3555	0.0221	0.0152	0.0016	0.0042	0.3558	0.0298	0.0164	0.0017	0.0048	0.3063	0.0305
Jilin	0.0248	0.0144	0.0067	0.4430	0.0297	0.0246	0.0152	0.0072	0.4123	0.0298	0.0272	0.0154	0.0083	0.4310	0.0309	0.0264	0.0156	0.0098	0.3685	0.0212
Guangxi	0.0258	0.0151	0.0100	0.4526	0.0228	0.0248	0.0145	0.0109	0.4145	0.0212	0.0290	0.0160	0.0130	0.4291	0.0249	0.0322	0.0170	0.0150	0.4024	0.027
Yunnan	0.0196	0.0071	0.0048	0.3918	0.0327	0.0180	0.0077	0.0052	0.3918	0.0224	0.0227	0.0088	0.0070	0.3988	0.0311	0.0235	0.0094	0.0090	0.3631	0.0239
Gansu	0.0156	0.0033	0.0042	0.4168	0.0236	0.0143	0.0035	0.0040	0.3929	0.0192	0.0181	0.0040	0.0057	0.3804	0.0274	0.0190	0.0043	0.0066	0.3249	0.0261
Qinghai	0.0125	0.0006	0.0007	0.3673	0.0439	0.0128	0.0008	0.0011	0.3473	0.0429	0.0130	0.0007	0.0016	0.3535	0.0353	0.0138	0.0008	0.0021	0.3247	0.03
Third Tier	0.0193	0.0088	0.0054	0.4077	0.0276	0.0192	0.0090	0.0065	0.3890	0.0251	0.0229	0.0097	0.0087	0.3971	0.0291	0.0245	0.0102	0.0102	0.3577	0.0271
Heilongjiang	0.0159	0.0064	0.0046	0.4324	0.0146	0.0160	0.0064	0.0052	0.4190	0.0147	0.0186	0.0061	0.0059	0.4115	0.0215	0.0166	0.0059	0.0053	0.3507	0.0139
Xinjiang	0.0099	0.0010	0.0007	0.4016	0.0201	0.0080	0.0010	0.0006	0.3901	0.0125	0.0091	0.0011	0.0011	0.3628	0.0124	0.0106	0.0011	0.0016	0.3178	0.0147
Fourth Tier	0.0129	0.0037	0.0026	0.4170	0.0171	0.0120	0.0037	0.0029	0.4046	0.0136	0.0138	0.0036	0.0035	0.3871	0.0169	0.0136	0.0035	0.0035	0.3343	0.0143

Table C2

The Overall and Sub-Dimension Niche Fitness of DIES Across Different Regions from 2019 to 2021

	2019					2020					2021					Average				
	Overall niche fitness	Sub-dimensional niche fitness				Overall niche fitness	Sub-dimensional niche fitness				Overall niche fitness	Sub-dimensional niche fitness				Overall niche fitness	Sub-dimensional niche fitness			
		Overall	Communities	Resources	Environment		Demand	Overall	Communities	Resources		Environment	Demand	Overall	Communities		Resources	Environment	Demand	Overall
Beijing	0.2617	0.3003	0.1099	0.8532	0.3804	0.2846	0.3005	0.1207	0.9262	0.3966	0.2908	0.2875	0.1231	0.9171	0.4626	0.2957	0.3190	0.1265	0.8699	0.4568
Tianjin	0.2026	0.3149	0.0851	0.5664	0.1905	0.2361	0.3384	0.1009	0.6858	0.2145	0.2357	0.3353	0.0958	0.6180	0.2489	0.2394	0.3334	0.0891	0.6479	0.3160
Shanghai	0.5351	0.9354	0.2527	0.7625	0.499	0.5847	0.9234	0.3175	0.8591	0.5102	0.5875	0.9097	0.3252	0.8185	0.5349	0.5813	0.9335	0.2996	0.8234	0.5722
Jiangsu	0.3746	0.4456	0.3018	0.7180	0.3133	0.3858	0.4265	0.2970	0.7613	0.3598	0.3840	0.4073	0.3244	0.7623	0.3449	0.3813	0.4320	0.2951	0.7449	0.3606
Zhejiang	0.2564	0.2824	0.1912	0.7859	0.2063	0.2736	0.2957	0.1951	0.8159	0.2258	0.2872	0.3055	0.2063	0.8286	0.2538	0.2579	0.2710	0.1929	0.7773	0.2170
Guangdong	0.5950	0.4144	0.6716	0.9176	0.7495	0.5715	0.4111	0.6078	0.8835	0.7374	0.5747	0.4277	0.6310	0.8273	0.7046	0.5513	0.3470	0.6352	0.8692	0.7270
First Tier	0.3709	0.4488	0.2687	0.7673	0.3898	0.3894	0.4493	0.2732	0.8220	0.4074	0.3933	0.4455	0.2843	0.7953	0.4248	0.3845	0.4393	0.2731	0.7888	0.4416
Hebei	0.0534	0.0459	0.0328	0.3511	0.0441	0.0596	0.0490	0.0406	0.3871	0.0403	0.0574	0.0489	0.0348	0.4054	0.0415	0.0540	0.0456	0.0354	0.3882	0.0366
Liaoning	0.0485	0.0365	0.0310	0.3712	0.0406	0.0528	0.0382	0.0349	0.3983	0.0396	0.0537	0.0372	0.0358	0.4185	0.0424	0.0530	0.0382	0.0327	0.4249	0.0444
Anhui	0.1236	0.1063	0.0846	0.7549	0.102	0.1376	0.1116	0.0894	0.8144	0.1197	0.1474	0.1123	0.1033	0.8250	0.1384	0.1245	0.1017	0.0826	0.7517	0.1088
Fujian	0.1320	0.1012	0.1152	0.5347	0.1191	0.1330	0.0967	0.1071	0.6083	0.1229	0.1395	0.0928	0.1222	0.6003	0.1385	0.1304	0.0930	0.1115	0.5600	0.1241
Jiangxi	0.0930	0.0789	0.0645	0.5341	0.0792	0.1033	0.0832	0.0682	0.5963	0.0887	0.1078	0.0884	0.0729	0.6000	0.0941	0.0821	0.0661	0.0525	0.5447	0.0689
Shandong	0.1141	0.1003	0.0881	0.5340	0.0884	0.1217	0.1097	0.0880	0.5713	0.0908	0.1359	0.1197	0.0968	0.6146	0.1144	0.1380	0.1143	0.1081	0.5435	0.1261
Henan	0.0788	0.0676	0.0511	0.4653	0.0696	0.0879	0.0701	0.0546	0.5514	0.0762	0.0940	0.0745	0.0601	0.6289	0.0788	0.0857	0.0685	0.0516	0.4878	0.0931
Hubei	0.0963	0.0585	0.0765	0.6580	0.0919	0.1008	0.0616	0.0765	0.6594	0.094	0.1056	0.0632	0.0858	0.6894	0.0957	0.0924	0.0553	0.0750	0.6484	0.0792
Hunan	0.0742	0.0589	0.0534	0.4622	0.0596	0.0838	0.0601	0.0582	0.5602	0.0678	0.0892	0.0643	0.0668	0.5454	0.0734	0.0754	0.0539	0.0564	0.4764	0.0617
Hainan	0.0294	0.0222	0.0117	0.4129	0.0267	0.0355	0.0243	0.0157	0.4745	0.0279	0.0370	0.0251	0.0168	0.4979	0.0308	0.0320	0.0220	0.0135	0.4304	0.0290
Chongqing	0.0913	0.0812	0.0574	0.4177	0.0944	0.1036	0.0883	0.0626	0.4667	0.106	0.1043	0.0832	0.0685	0.4901	0.1076	0.0929	0.0763	0.0549	0.4513	0.1055
Sichuan	0.0634	0.0250	0.0603	0.4356	0.0694	0.0679	0.0264	0.0596	0.4567	0.0779	0.0730	0.0269	0.0655	0.5378	0.0833	0.0650	0.0234	0.0645	0.4618	0.0671
Guizhou	0.0339	0.0217	0.0141	0.4433	0.0347	0.0395	0.0228	0.0164	0.4911	0.0381	0.0362	0.0216	0.0153	0.4446	0.0359	0.0352	0.0203	0.0144	0.4835	0.0347
Shaanxi	0.0453	0.0271	0.0338	0.3652	0.0386	0.0487	0.0292	0.0368	0.3602	0.0393	0.0543	0.0279	0.0411	0.4306	0.0508	0.0472	0.0267	0.0341	0.4222	0.0387
Ningxia	0.0277	0.0144	0.0086	0.4566	0.0353	0.0315	0.0146	0.0105	0.4702	0.037	0.0334	0.0148	0.0127	0.4829	0.0403	0.0280	0.0128	0.0081	0.4780	0.0364
Second Tier	0.0737	0.0564	0.0522	0.4798	0.0662	0.0805	0.0590	0.0546	0.5244	0.0711	0.0846	0.0601	0.0599	0.5474	0.0777	0.0757	0.0545	0.0530	0.5035	0.0703
Shanxi	0.0357	0.0222	0.0204	0.3599	0.0345	0.0415	0.0268	0.0227	0.3999	0.0353	0.0431	0.0270	0.0226	0.4388	0.0398	0.0356	0.0228	0.0194	0.4075	0.0288
Inner Mongolia	0.0132	0.0015	0.0030	0.2756	0.0339	0.0161	0.0018	0.0038	0.3102	0.0352	0.0170	0.0018	0.0048	0.3299	0.0369	0.0145	0.0017	0.0035	0.3309	0.0302
Jilin	0.0208	0.0123	0.0075	0.3251	0.022	0.0241	0.0128	0.0090	0.3583	0.0229	0.0242	0.0122	0.0097	0.3800	0.0228	0.0246	0.0140	0.0083	0.3883	0.0256
Guangxi	0.0291	0.0166	0.0135	0.3662	0.0314	0.0351	0.0192	0.0192	0.3786	0.0324	0.0379	0.0200	0.0214	0.3998	0.0375	0.0306	0.0169	0.0147	0.4062	0.0281
Yunnan	0.0216	0.0090	0.0099	0.3171	0.0268	0.0279	0.0094	0.0135	0.3563	0.0363	0.0279	0.0093	0.0157	0.3639	0.0337	0.0230	0.0087	0.0093	0.3690	0.0296
Gansu	0.0160	0.0039	0.0059	0.2944	0.0266	0.0185	0.0043	0.0063	0.3237	0.0281	0.0193	0.0042	0.0069	0.3419	0.0311	0.0173	0.0039	0.0057	0.3536	0.0260
Qinghai	0.0106	0.0008	0.0015	0.2707	0.0308	0.0123	0.0008	0.0013	0.2941	0.0319	0.0141	0.0007	0.0018	0.3194	0.0413	0.0127	0.0007	0.0014	0.3253	0.0365
Third Tier	0.0210	0.0095	0.0088	0.3156	0.0294	0.0251	0.0107	0.0108	0.3459	0.0317	0.0262	0.0107	0.0118	0.3677	0.0347	0.0226	0.0098	0.0089	0.3687	0.0292
Heilongjiang	0.0138	0.0055	0.0044	0.3083	0.015	0.0159	0.0058	0.0052	0.3297	0.0151	0.0160	0.0059	0.0045	0.3465	0.0169	0.0161	0.0060	0.0050	0.3712	0.0159
Xinjiang	0.0086	0.0010	0.0008	0.2962	0.0196	0.0121	0.0013	0.0019	0.3170	0.0237	0.0116	0.0012	0.0015	0.3276	0.0259	0.0100	0.0011	0.0012	0.3447	0.0183
Fourth Tier	0.0112	0.0033	0.0026	0.3023	0.0173	0.0140	0.0035	0.0035	0.3233	0.0194	0.0138	0.0035	0.0030	0.3371	0.02130	0.0130	0.0035	0.0031	0.3580	0.0171

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