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Spatial differences and formation mechanisms of innovation ecosystem dynamic operational efficiency along the yellow river

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To scientifically evaluate the dynamic operational efficiency, spatial differences, as well as the formation mechanisms of the urban Innovation Ecosystem within the Yellow River Basin is highly important for the high-quality development of China. In the present research, both the economic circulation theory with the Innovation Ecosystem and the Data Envelopment Analysis – Malmquist Productivity Index (DEA-Malmquist) model were adopted to analysis the database from 59 cities along the Yellow River Basin. In parallel, the kernel density estimation, the Gini coefficient, and Panel Vector Autoregression (PVAR) model were applied for further comparison. The results revealed that the dynamic operational efficiency of the Innovation Ecosystem within the Yellow River Basin exhibited an obvious fluctuating downwards trend. The efficiency of spatial distribution in the upstream and midstream basins shows a left-skewed and polarized pattern, whereas the downstream basins exhibited a right-skewed distribution with less pronounced polarization. The results also revealed that the overall Gini coefficients for dynamic operational efficiency (TFP) and technical efficiency (EFF) in the Yellow River Basin tended to convergence, whereas those for technological change (TECH) are of an increasing trend. Moreover, the hypervariable density emerged as the primary factor driving disparities in TFP, TECH, and EFF within the basin. Furthermore, the relationships among TFP, TECH, and EFF were featured with the regional heterogeneity. In the midstream areas, there existed a self-improvement mechanism for the TFP, TECH, as well as the EFF. However, there was a stronger self-improvement mechanism for TECH but a self-weakening mechanism for TFP and EFF in the downstream regions.

Keywords Innovation ecosystem, Dynamic operational efficiency, Spatial differences, Mechanism research, PVAR model

The development of Innovation is the most important core for the knowledge economy, which is regarded as the primary driving force for progress. The Innovation development generally provides some new growth opportunities and essential support for societal advancement and high-quality development of the local economic[1]. With the deepening implementation of innovation-driven strategies, the Innovation Ecosystem, as a crucial platform that promotes knowledge creation, technology transfer, and industrial upgrading, has emerged as a new driving force for regional innovation development. The efficient Innovation Ecosystem is thus generally believed to be the cornerstone for achieving economic growth and societal progress. By facilitating the rapid exchange of knowledge and promoting open information sharing, the Ecosystem encourages the integration of innovation ideas. It also boosts entrepreneurial energy and enthusiasm through via the financial support, policy incentives, and technological services. An efficient Innovation Ecosystem serves as a critical driver for accelerating technological progress and fostering regional economic prosperity. It not only speeds up the development and application of new technologies but also pushes the boundaries of innovation. Furthermore, it elevates regional innovation capacity and competitiveness through attracting top talent and capital, which contributes to the achievement of the high-quality economic development and promotes the regional coordination[2].

The academic community has yet to reach a consensus on the definition of Innovation Ecosystem Dynamic operational efficiency. However, most scholars agree that it refers to the ability and effectiveness of an Innovation Ecosystem to transform innovation inputs into outputs over a specific period through the synergistic interactions

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among its various entities and elements[3–5]. This concept reflects a comprehensive evaluation of the Ecosystem's performance in resource allocation, collaborative innovation, and knowledge flow. For example, Liao Kaicheng[5] takes the social Ecosystem as a logical starting point, integrating, evolving, and advancing the operational characteristics of natural and social Ecosystems. On this basis, he analogizes the concept of Innovation Ecosystem dynamic operational efficiency. Chen Yizao[6] using the innovation value chain as a framework, constructs a regional Innovation Ecosystem encompassing four Innovation clusters: "policy Innovation environment, original Innovation R&D, technological Innovation application, and technological Innovation services," and measures its Innovation Ecosystem operational efficiency. Building on these conceptualizations, this study, grounded in economic circulation theory, constructs an Innovation Ecosystem framework that includes inputs (Innovation resources, Market environment, and Consumer demand) and outputs (Innovation patent outcomes and industrial value-added benefits). The DEA-Malmquist method is employed to assess the efficiency of value transformation within the Innovation elements.

The Yellow River Basin, recognized as the cradle of Chinese civilization, stands as a pivotal region of cultural heritage and economic significance in terms of the agriculture, energy, and other heavy industries. Spanning a vast area, this region is also famous for its abundant natural resources and diverse industrial structure, marked by distinct intraregional and interregional connectivity[7]. With the increasing attention given by the government to the development of the central and western regions and the application of the "14 th Five-Year Plan", the Yellow River Basin has ushered in new opportunities, particularly in promoting regional coordinated development and industrial transformation and upgrading associated with enormous potential. Nevertheless, the Basin faces challenges due to the uneven distribution of Innovation resources and underdeveloped mechanisms for technological Innovation[8]. These issues have historically impeded the region's capacity for Innovation development[9].

Traditional industries in the Yellow River Basin face significant pressure to transform and upgrade, with technological Innovation emerging as a critical driver for enhancing competitiveness and achieving high-quality development[10]. A thorough investigation into the Innovation Ecosystem operational efficiency of the Innovation Ecosystem in this region is of paramount importance. On one hand, it facilitates the optimization of resource allocation, improves resource utilization efficiency, and promotes industrial upgrading and economic transformation, thereby enhancing competitiveness[11]. On the other hand, it helps narrow regional disparities, fosters coordinated regional development, strengthens knowledge and technology exchange, and collectively addresses challenges[12]. Furthermore, the research outcomes can provide valuable support for government decision-making and optimize Innovation policies.

Given this context, this study focuses on the Yellow River Basin, employing the DEA-Malmquist index method to dynamically evaluate the Innovation Ecosystem operational efficiency of the Innovation Ecosystem across 59 prefecture-level cities from 2009 to 2023. The basin is divided into three regions: the upstream, midstream and the downstream (Table 1). The upper reach (e.g., Xining, Lanzhou) is characterized by abundant water resources and unique ecological environments, serving as a critical water conservation area with potential for clean energy development. The middle reach (e.g., Yinchuan, Hohhot, Xi'an) features diverse topography, including agriculturally rich areas like the Hetao Plain and ecologically fragile zones like the Loess Plateau, while also being a significant energy production base. The lower reach (e.g., Zhengzhou, Jinan) is relatively flat, densely populated, and economically advanced, with strong agricultural and industrial foundations, but faces challenges such as water scarcity and ecological pressures. Using kernel density estimation, this study assesses the spatiotemporal evolution characteristics of the Innovation Ecosystem operational efficiency in the Yellow River Basin. The Gini coefficient is applied to explore regional disparities in efficiency and their influencing factors. Finally, a PVAR model is utilized to analyze the intrinsic operational mechanisms of the Innovation Ecosystem in the Yellow River Basin.

Literature review

An Ecosystem is a unified entity formed through the interaction and interdependence of biological communities and their abiotic environment within a specific time and space. It performs critical functions, including material cycling, energy flow, information transfer, and ecological services[13]. Due to the analogous characteristics of Ecosystems and social systems, scholars have adapted the Ecosystem concept to the social sciences. In the 1990 s, the U.S. government, in its report Science in the National Interest, compared the science and technology enterprise to an Ecosystem rather than a production line. Concurrently, Moore introduced the "business Ecosystem" concept, framing enterprises as "species" within an Ecosystem and emphasizing co-evolution among participants[14]. As research advanced, the theory of Innovation Ecosystem expanded from business to broader Innovation contexts. This concept subsequently attracted significant academic attention. For example, scholars have defined and extended the Innovation Ecosystem from diverse perspectives. Huang Lucheng[15,16] proposed the "regional technological Innovation Ecosystem," describing it as a dynamic and complex system

Yellow River basin	Cities
Upstream	Ordos, Hohhot, Baotou, Yulin, Lanzhou, Baiyin, Dingxi, Xining, Yinchuan, Shizuishan, Wuzhong, Zhongwei
Midstream	Taiyuan, Datong, Yangquan, Changzhi, Shuozhou, Xinzhou, Jinzhong, Lvliang, Linfen, Yuncheng, Xi'an, Tongchuan, Baoji, Xianyang, Weinan, Shangluo, Tianshui, Pingliang, Qingyang
Downstream	Jincheng, Qingdao, Jinan, Zibo, Zaozhuang, Yantai, Weifang, Jining, Linyi, Tai'an, Liaocheng, Heze, Dezhou, Binzhou, Dongying, Weihai, Rizhao, Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Xinxiang, Jiaozuo, Hebi, Xuchang, Luohe, Shangqiu, Zhoukou

Table 1. Study area

formed by the interaction and interdependence of technological Innovation entities and their environments within a specific spatial scope. Wu Jinxi[17] further elaborated on the concept, defining an Innovation Ecosystem as a relatively stable and closed organizational structure shaped by the mutual dependence and collaboration of multiple Innovation entities and elements. Additionally, Etzkowitz and Leydesdorff[18] introduced the "Triple Helix" Innovation theory, emphasizing the role of interactions among universities, industries, and governments in shaping Innovation systems. Following the evolution of these core concepts, research has expanded to specific regions, with detailed explorations into the construction of indicator systems and the application of research methodologies.

A key research focus is the scope of investigation. He et al.[19] explored the impact of coordinated agglomeration between financial and manufacturing industries on manufacturing Innovation efficiency across 11 provinces along the Yangtze River Economic Belt. Sun et al.[20] utilized gravity-standard deviation ellipse and Dagum Gini coefficient methods to revel the spatiotemporal differentiation characteristics of green Innovation development in the Inner Mongolia Yellow River Ecological Economic Belt. Another research carried by Fan Yufeng Ma et al.[21] concentrated on the Beijing-Tianjin-Hebei urban agglomeration. They adopted the super-efficiency SBM model and ML index to analyse Innovation efficiency within this urban cluster. Similarly, Liu et al.[22] investigated the high-tech industries in the Pearl River Delta, employing the DEA-Malmquist index and ESDA model to measure Innovation efficiency and empirically analyse the in-behind driving factors. Li Ying et al.[23] analyzed the spatial evolution of industrial technology Innovation efficiency in the Guangdong-Hong Kong-Macao Greater Bay Area from a dynamic perspective, employing the Malmquist index. Similarly, Yuan Rong et al.[24] investigated the spatial differentiation and influencing factors of technological Innovation efficiency in the Yangtze River Delta region, utilizing a super-efficiency SBM model combined with the Malmquist index.

In terms of quantitative methods, initial research primarily focused on qualitative descriptions of various elements within Innovation Ecosystem. As studies progressed, scholars began to develop quantitative evaluation systems. Some studies on constructing evaluation index systems for Innovation Ecosystem dynamic operational efficiency are based on production function theory. For instance, Wang Yin and Sun Yi et al.[25] developed an evaluation framework for Innovation Ecosystem based on the dual characteristics classification and Innovation mechanisms. Ou Guangjun et al.[26] assessed the capabilities of Innovation Ecosystem through the design of indicators and evaluation systems, emphasizing the importance of openness and population structure dimensions. Yan Li[27] introduced Innovation environment variables into Innovation inputs, constructing a relatively comprehensive model for evaluating Innovation efficiency, and was the first to propose the combined use of principal component analysis and DEA methods to measure regional Innovation efficiency in China. Su Yaohua and Li Quan[28] divided the Innovation process into two stages—research and development, and achievement transformation—to build an indicator system, and employed stochastic frontier analysis to estimate the Innovation efficiency of high-tech industries. He et al.[29] constructed an industrial evaluation index system based on three stages: assimilation, growth, and utilization. This system was applied to measure the Innovation Ecosystem dynamic operational efficiency of 15 high-tech industries in China, identifying potential pathways for improvement. Liao et al.[5] created an evaluation index system with 87 indicators on the basis of Innovation input-output theory. Their study investigated regional disparities in dynamic operational efficiency and the formation mechanisms across China. In a related approach, Fan et al.[30] established an index system focusing on technological research and development, environmental support, and results transformation. This system was utilized to evaluate and analyse the determinants of green technological Innovation efficiency in 82 cities along the Yellow River Basin.

In terms of measurement of Innovation Ecosystem dynamic operational efficiency, data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are domestically and internationally applied. Liu et al.[31] employed a multiperiod network DEA model to evaluate enterprise-level efficiency in technological Innovation, R&D, and outcome transformation within enterprises. Lu et al.[32] applied a panel threshold model to analyze how foreign direct investment (FDI) and economic development levels influence agricultural technological Innovation in China. Fan et al.[33] employed a super-efficiency SBM model to assess the efficiency of green technological Innovation in Chinese industry. They highlighted how the misallocation of R&D resources affects this efficiency. Wang et al.[34] utilized SBM-DEA to study China's green Innovation efficiency, regional differences, and spatial convergence characteristics. Zhang et al.[35] implemented a three-stage DEA-Malmquist approach to evaluate the dynamic and static Innovation efficiency of listed CNC machine tool companies. Li et al.[36] measured green Innovation efficiency in the manufacturing sector across 11 provinces and cities along the Yangtze River Economic Belt using a super-efficiency SBM model that accounts for undesirable outputs. Zhao et al.[37] assessed the green Innovation efficiency across 30 provinces in China from 2000 to 2020, utilizing the SBM-DDF-GML model. Kang Xia et al.[38] applied the coefficient of variation method and the global Malmquist-GML index to evaluate the efficiency of science and technology development in China's coastal land-sea coordination plans between 2006 and 2015. Their analysis also highlighted regional variations among these plans.

There are several limitations in terms of regional Innovation Ecosystem dynamic operational efficiency. First, most studies related to regional Innovation Ecosystem dynamic operational efficiency focus on the provincial level, with insufficient exploration at the municipal level. Second, input indicators predominantly emphasize funding and manpower, overlooking the Innovation value generated during the Innovation chain development process. This narrow input-output perspective leads to an incomplete evaluation system. Third, the existing literature has mostly concentrated on the efficiency of Innovation systems in a single region or industry, with limited analyses of spatial structures and evolutionary patterns of regional Innovation efficiency. Finally, most studies emphasize the overall operational efficiency of the Innovation Ecosystem while inadequately addressing regional disparities. In particular, the roles of both intrinsic factors and dynamic relationships have not been comprehensively integrated into a unified framework for analysis. In light of these limitations, further research

System name	Dimension name
Input system	Innovation sources
	Market environment
	Consumer demand
Output system	Innovation patent achievements
	Industrial value-added benefits

Table 2. Indicator system for evaluation innovation ecosystem.

Stage	Primary indicator	Secondary indicator	Unite	Attribute	Weight
Innovation resources 0.65546	Participation of production entities 0.51196	Number of regular higher education institutions	Institutions	+	0.09560
		Full-time teachers in regular higher education institutions	persons	+	0.10895
		Students in regular higher education institutions	persons	+	0.10710
		Research and technical personnel	10,000 persons	+	0.10852
		Education personnel	10,000 persons	+	0.02943
		Number of enterprises above designated size	Entities	+	0.06236
	Research and development fiscal expenditure 0.14350	Education expenditure	10,000 CNY	+	0.03920
		Science expenditure	10,000 CNY	+	0.10430
Market environment0.22091	Market level 0.08270	Per capita GDP	CNY	+	0.03159
		Average number of employees on duty	10,000 persons	+	0.03983
		Proportion of tertiary industry added value	%	+	0.01128
	Marketization and internationalization level 0.13821	Marketization index	%	+	0.01132
		Foreign investment utilization amount	10,000 USD	+	0.12689
Consumer demand 0.12363	Public attention 0.06514	"Innovation" index	--	+	0.03404
		"Technology" index	--	+	0.03110
	Consumption capacity 0.05849	Resident consumption level	CNY	+	0.02818
		Government consumption level	CNY	+	0.03031

Table 3. Innovation ecosystem investment indicator system.

to develop a more comprehensive and detailed evaluation system for regional Innovation Ecosystem is thus requested.

The potential contributions of the present research are as follows: First, it integrates the concept of the Innovation Ecosystem is integrated with economic circular theory upon the municipal scale. This integration establishes a research framework called the "Innovation Ecosystem operation chain", which emphasizes the close connection and synergistic effects of various stages in the Innovation process is established; Second, it develops a comprehensive evaluation index system termed as "the Innovation chain", which consists of the Innovation research and development, the outcome promotion, and the application segment. By considering dynamic interactions within the system, it provides a novel perspective and method for assessing Innovation Ecosystem dynamic operational efficiency. Third, it employs the PVAR model to investigate the dynamic relationships and interactions between the Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem and its decomposed variables in the Yellow River Basin. The importance of understanding and utilizing these inherent mechanisms in practice is emphasized, aiming to promote the sustainable development of the Innovation Ecosystem in the Yellow River Basin and the comprehensive revitalization of the regional economy through data-driven decision support. Overall, this study not only expands the theoretical understanding of the intrinsic driving mechanisms of the Innovation Ecosystem, but also provides a powerful analytical tool closely linked to practical applications. It provides valuable guidance for Innovation practices in the Yellow River Basin and beyond, enhancing the understanding and utilization of Innovation Ecosystem dynamics for sustainable development and regional economic growth.

Research design
Theoretical mechanism of evaluation index system
Based on economic circular theory, we constructed an Innovation Ecosystem that encompasses input-output dynamics (Table 2). The input system comprises three dimensions: "Innovation sources", "Market environment" and "Consumer demand" (Table 3). The output system includes "Innovation patent achievements" and "industrial value-added benefits", measured by the number of patents granted and industrial added value, respectively. As can be seen from Table 2, "Innovation sources" refers to the origin or foundation of Innovation, serving as the initial driving force for Innovation activities. It is primarily realized through the active participation of production entities (e.g., enterprises, research institutions) and investments in R&D expenditures. As the core force of Innovation, production entities, combined with sufficient financial support, constitute the starting point

of Innovation; "Market environment" represents the ecological and contextual conditions in which Innovation occurs, determining whether Innovation can proceed smoothly and sustainably. Key factors such as market conditions, marketization level, and internationalization degree provide essential ecological support for Innovation activities; and "Consumer demand" emphasizes external driving forces in Innovation, particularly the role of public attention and consumer capacity in promoting Innovation. These factors provide stronger momentum for Innovation activities and reflect the extent to which Innovation outcomes are successfully integrated into markets and society.

The theory of Innovation Ecosystem is inspired by ecological studies, which employ biological metaphors to illustrate the structure, dynamics, and interactions among participants. In particular, their connection to the external environment in Innovation activities. Correspondingly, the Innovation activities of the Innovation Ecosystem are divided into three stages (i.e., the Innovation sources, Market environment and Consumer demand), and the operational framework of which is illustrated in Fig. 1 for reference.

Research methods

Measurement of the innovation ecosystem dynamic operational efficiency of the innovation ecosystem

This study employs the DEA-Malmquist index to assess the Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem in the Yellow River Basin. The Malmquist index method, grounded in Data Envelopment Analysis (DEA), is a non-parametric approach for evaluating dynamic performance. It captures the efficiency evolution of decision-making units over time[39]. Its fundamental principle is as follows: Assume there are n decision-making units over t production periods, with (X_r^{t+1}, Y_r^{t+1}) representing the inputs and outputs for the r^{th} decision-making unit in period $t+1$. Let $D_r^t(X_r^{t+1}, Y_r^{t+1})$ denote the Innovation Ecosystem dynamic operational efficiency change of decision-making unit r in period $t+1$ based on the production frontier at time t. The Malmquist total factor productivity index for the r^{th} decision-making unit from time t to $t+1$ is calculated as follows:

$$M_r = \left[M_r^t * M_r^{t+1}\right]^{\frac{1}{2}} = \left[\frac{D_r^t\left(X_r^{t+1}, Y_r^{t+1}\right)}{D_r^t\left(X_r^t, Y_r^t\right)} * \frac{D_r^{t+1}\left(X_r^{t+1}, Y_r^{t+1}\right)}{D_r^{t+1}\left(X_r^t, Y_r^t\right)}\right]^{\frac{1}{2}} \tag{1}$$

A value of $M_r>1$ indicates an increase in Innovation Ecosystem dynamic operational efficiency from period t to $t+1$, while a value less than 1 suggests a decrease. TFP can be further decomposed into two parts: EFF and TECH, with the formula:

$$M_r = \mathrm{EFF} * \mathrm{TECH} = \frac{D_r^{t+1}\left(X_r^{t+1}, Y_r^{t+1}\right)}{D_r^t\left(X_r^t, Y_r^t\right)} * \left[\frac{D_r^t\left(X_r^t, Y_r^t\right)}{D_r^{t+1}\left(X_r^t, Y_r^t\right)} * \frac{D_r^t\left(X_r^{t+1}, Y_r^{t+1}\right)}{D_r^{t+1}\left(X_r^{t+1}, Y_r^{t+1}\right)}\right]^{\frac{1}{2}} \tag{2}$$

Herein, EFF >1 implies an improvement in technical efficiency, whereas a value less than 1 indicates a decline. Similarly, TECH >1 signifies technological advancement, while a value less than 1 indicates technological regression.

Spatial distribution of the innovation ecosystem dynamic operational efficiency

Kernel density estimation is a non-parametric statistical technique to estimate the probability density function of a set of data. By generating a continuous probability density curve, it visualizes the distribution of a random variable. This method effectively reveals the temporal evolution patterns of TFP, TECH, and EFF in the upper, middle, and downstream of the Yellow River Basin. The mathematical formulations are as follows:

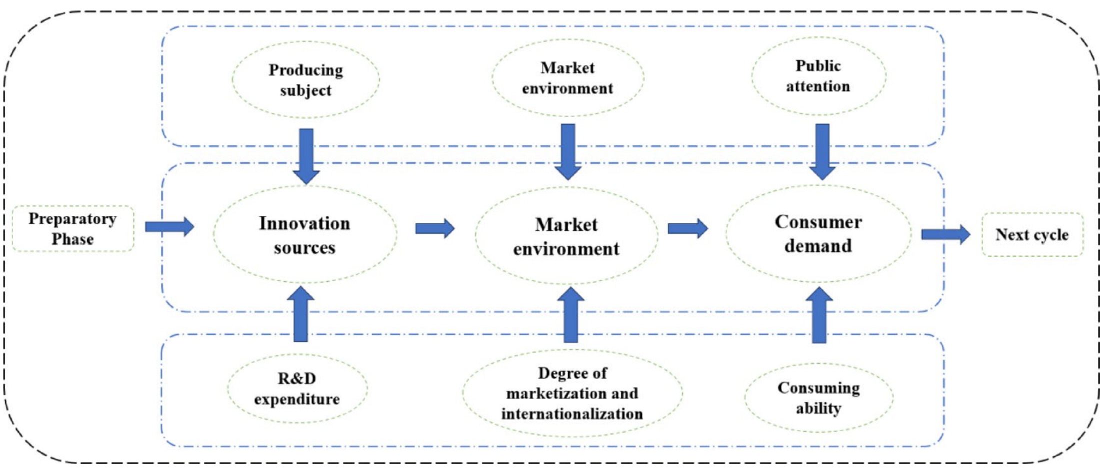

Fig. 1. Operational structure of the Innovation Ecosystem's innovation activities.

$$\mathrm{f(y)}=\frac{1}{N\mathrm{h}}\sum{}_{j=1}^{N}K\left(\frac{y_j-\bar{y}}{h}\right) \tag{3}$$

$$\mathrm{K(y)}\ \frac{1}{\sqrt{(2\Pi)}}\exp(-\frac{y^2}{2}) \tag{4}$$

Where (f(y)) represents the density function of the random variable y, N and j denote the number of sample points and basin units, K(·) is the kernel function, and h is the bandwidth[40]. The kernel function value, (K(y; h)), decreases as the distance between the point to be estimated, y, and the sample points increases. This means that the probability density estimate of a point is larger when there are more sample points near it, and vice versa.

Measurement of Spatial differences

This study utilizes the Dagum Gini coefficient decomposition method[41] to analyze the spatial heterogeneity of TFP, TECH, and EFF in the upper, middle, and downstream of the Yellow River Basin. This approach decomposes the overall difference into three components: intraregional differences, interregional differences, and trans-variation density. The mathematical expression for this decomposition is as follows:

$$\mathrm{G}=G_w+G_{nb}+G_t \tag{5}$$

$$\mathrm{G}=\frac{\sum{}_{j=1}^{k}\sum{}_{\mathrm{h}=1}^{k}\sum{}_{i=1}^{n_j}\sum{}_{r=1}^{n_h}|m_{ji}-m_{hr}|}{2\mu\, n^2} \tag{6}$$

$$G_w=\sum{}_{j=1}^{k}G_{jj}p_js_j \tag{7}$$

$$G_{jj}=\frac{\sum{}_{i=1}^{n_j}\sum{}_{r=1}^{n_h}|m_{ji}-m_{jr}|}{n_jn_h(\mu_{\ j}+\mu_{\ h})} \tag{8}$$

$$G_{nb}=\sum{}_{j=2}^{k}\sum{}_{\mathrm{h}=1}^{j-1}G_{jh}(p_js_h+p_hs_j)D_{jh} \tag{9}$$

$$G_t=\sum{}_{j=2}^{k}\sum{}_{\mathrm{h}=1}^{j-1}G_{jh}(p_js_h+p_hs_j)(1-D_{jh}) \tag{10}$$

$$G_{jh}=\frac{d_{jh}-p_{jh}}{d_{jh}+p_{jh}} \tag{11}$$

$$d_{jh}=\int_0^{\infty}dF_j\,(m)\int_0^{m}(m-x)\,dF_h\,(x) \tag{12}$$

$$p_{jh}=\int_0^{\infty}dF_h\,(m)\int_0^{m}(m-x)\,dF_j\,(x) \tag{13}$$

Here, k represents the number of basins, $n_j(\,n_h)$ denotes the number of cities within the $\mathrm{j}^{\mathrm{th}}(\mathrm{h}^{\mathrm{th}})$ basin, and $m_{ji}(\,m_{hr})$ represents the Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem in the $\mathrm{i}^{\mathrm{th}}(\mathrm{r}^{\mathrm{th}})$ city within the $\mathrm{j}^{\mathrm{th}}(\mathrm{h}^{\mathrm{th}})$ basin. μ indicates the average Innovation Ecosystem dynamic operational efficiency of the Yellow River Basin. G_w represents the contribution of within-basin differences, G_{nb} represents the contribution of between-basin differences, and G_t represents the contribution of super-dense density. $p_j{=}\,n_j$/n, $s_j{=}\,n_j\mu_{\ j}$/n μ, where G_{jj} represents the intra-group Gini coefficient for the j^{th} city group, G_{jh} represents the interregional Gini coefficient between the j^{th} and h^{th} city groups, and D_{jh} represents the relative impact of Innovation Ecosystem dynamic operational efficiency between the j^{th} and h^{th} city groups.

Measurement of the operational mechanism of innovation ecosystem dynamic operational efficiency

The Panel Vector Autoregression (PVAR) model is a multivariate time series analysis method based on the Vector Autoregression (VAR) model, which was firstly introduced by Holtz Eakin et al. (1988)[42]. This model integrates time series data from multiple variables into a unified panel dataset, facilitating the exploration of causal relationships and the prediction of future trends. Unlike conventional VAR models, the PVAR model treats all variables as endogenous, eliminating the need for predefined causal assumptions. It examines the influence of each variable and its lagged terms on other variables within the system. The PVAR model overcomes two significant limitations of traditional VAR models: the necessity for extensive time series data and the inability to account for individual heterogeneity. By utilizing panel data, it incorporates both individual and time effects, thereby enhancing its analytical rigor. in the present research, a PVAR model[43] was constructed to investigate the dynamic relationships between TFP, TECH, and EFF, with the specific formula listed in below:

$$y_{i,t}=\beta_{\ 0}+\sum{}_{m=1}^{p}\alpha_{\ m}y_{i,t-m}+f_i+d_i+\mu_{\ i,t} \tag{14}$$

The PVAR model captures the dynamic relationships between TFP, TECH, and EFF. In the model, the vector $y_{i,t}$ represents the combination of TFP, TECH, and EFF, $\beta_{\ 0}$ represents the intercept, $\alpha_{\ p}$ represents the coefficient matrix, $y_{i,t-m}$ represents the lag of all endogenous variables up to order m, f_i and d_i represent the fixed effects and time effects respectively, and $\mu_{i,t}$ represents the random disturbance term.

Index selection and data source

Following the research carried by Kang and Li[44], this study utilizes the range transformation method to normalize individual indicator. The entropy method is subsequently applied to determine the weights of these indicators. The normalization values of corresponding tertiary indicators fare weighted and aggregated to compute the results for primary and secondary indicators, as summarized in Table 3.

This study evaluates the dynamic operational efficiency of the Innovation Ecosystem across 59 prefecture-level cities within the Yellow River Basin. The data utilized in this research, such as: "Innovation" index and "Technology" index are sourced from the official website of Baidu Index Query(https://index.baidu.com*);* Marketization index, Foreign investment utilization amount are sourced from the EPS database (https://www.epsnet.com.cn*)*. Number of regular higher education institutions, Full-time teachers in regular higher education institutions, Students in regular higher education institutions, Research and technical personnel, Education personnel, Number of enterprises above designated size, Average number of employees on duty, Marketization index, Foreign investment utilization amount, Resident consumption level, Government consumption level are sourced from the *City Statistical Yearbooks*; Per capita GDP, Education expenditure, Science expenditure, Proportion of tertiary industry added value are sourced from the *Urban Statistical Bulletins*. Where data for specific city indicators are missing, they are filled using either exponential smoothing or interpolation methods.

Empirical analysis

Measurement and analysis of the Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem in cities along the Yellow River Basin.

Overview description

The Malmquist index method was adopted in this section to calculate TFP, TECH, and EFF of the Innovation Ecosystem in cities along the Yellow River Basin from 2009 to 2023. Owing to space constraints, only the efficiency values for the years 2009, 2014, 2019, and 2023 are presented here. The specific results are provided in Table 4; Fig. 2.

From 2009 to 2023, the TFP in the Yellow River Basin decreased from 0.945 to 0.898, representing a notable decline. During the same period, the TECH and EFF remained relative stability. This divergence indicates stagnant technological advancement and efficiency improvements have constrained productivity growth, reflecting reduced Innovation-driven production efficiency and suboptimal resource allocation. Meanwhile, the policymakers may need to prioritize both the resource management and technological Innovation strategies to drive sustainable regional development.

It is in 2009 that the effective rate of TFP, defined as the proportion of areas with efficiency values greater than 1, stood at 37%. This metric revealed a distinct spatial efficiency gradient, with the upper basin demonstrating superior performance compared to the middle and lower reaches, reflecting significant regional disparities in Innovation capacity. By 2014, the effective rate had declined to 24%, indicating a substantial decline in the dynamic operational efficiency. This downward trend highlights the urgent need to optimize the Innovation environment and boost the vitality of Innovation efforts. The period from 2019 to 2023 witnessed the development pattern in the Yellow River Basin evolved. Initially, the middle reaches had efficiency advantages, whereas the upper and lower reaches struggled. Over time, the development became more balanced across the upper, middle, and lower reaches. However, this shift also highlighted ongoing challenges in resource allocation and technological Innovation. These findings suggest that achieving coordinated basin-wide development will require targeted policy interventions and structural reforms to strengthen Innovation Ecosystem and optimize resource distribution.

The effective rates of TECH in 2009 and 2014 remained consistently low at 14% and 15%, respectively. By 2019, TECH in the upstream region had increased, reflecting significant progress in technological Innovation that positively impacted the region's economic development and competitiveness. By 2023, TECH experienced basin-wide enhancement, indicating that Innovation entities actively developed new models and technologies to strengthen regional Innovation capabilities. This progress underscores the growth adaptability and technology absorption capacity of Innovation entities, as well as the positive impact of policy guidance in driving regional Innovation Ecosystem dynamic operational efficiency.

It should be noted that the effective rate of EFF's Innovation Ecosystem dynamic operational efficiency in 2009 reached 49%, demonstrating widespread improvement across all streams of the basin. Between 2014 and 2019, this rate increased from 27 to 42%, accompanied by a spatial transformation from an "upper-middle stream dominance" pattern to a "middle-lower stream leadership" structure in the Yellow River Basin. This shift

	TFP				TECH				EFF			
Basin	2009	2014	2019	2023	2009	2014	2019	2023	2009	2014	2019	2023
Yellow River Basin	0.945	1.155	1.084	0.898	0.91	1.14	1.057	0.946	1.039	1.013	1.026	0.949
Upper basin	1.092	1.010	0.964	0.941	0.907	0.937	1.023	1.090	1.206	1.079	0.951	0.870
Middle basin	0.897	1.054	1.025	0.892	0.884	0.959	0.970	1.085	1.024	1.101	1.075	0.826
Lower basin	0.966	0.860	0.929	0.915	0.937	0.918	0.927	1.033	1.033	0.937	1.007	0.886

Table 4. Dynamic operational efficiency of the innovation ecosystem in the yellow river basin.

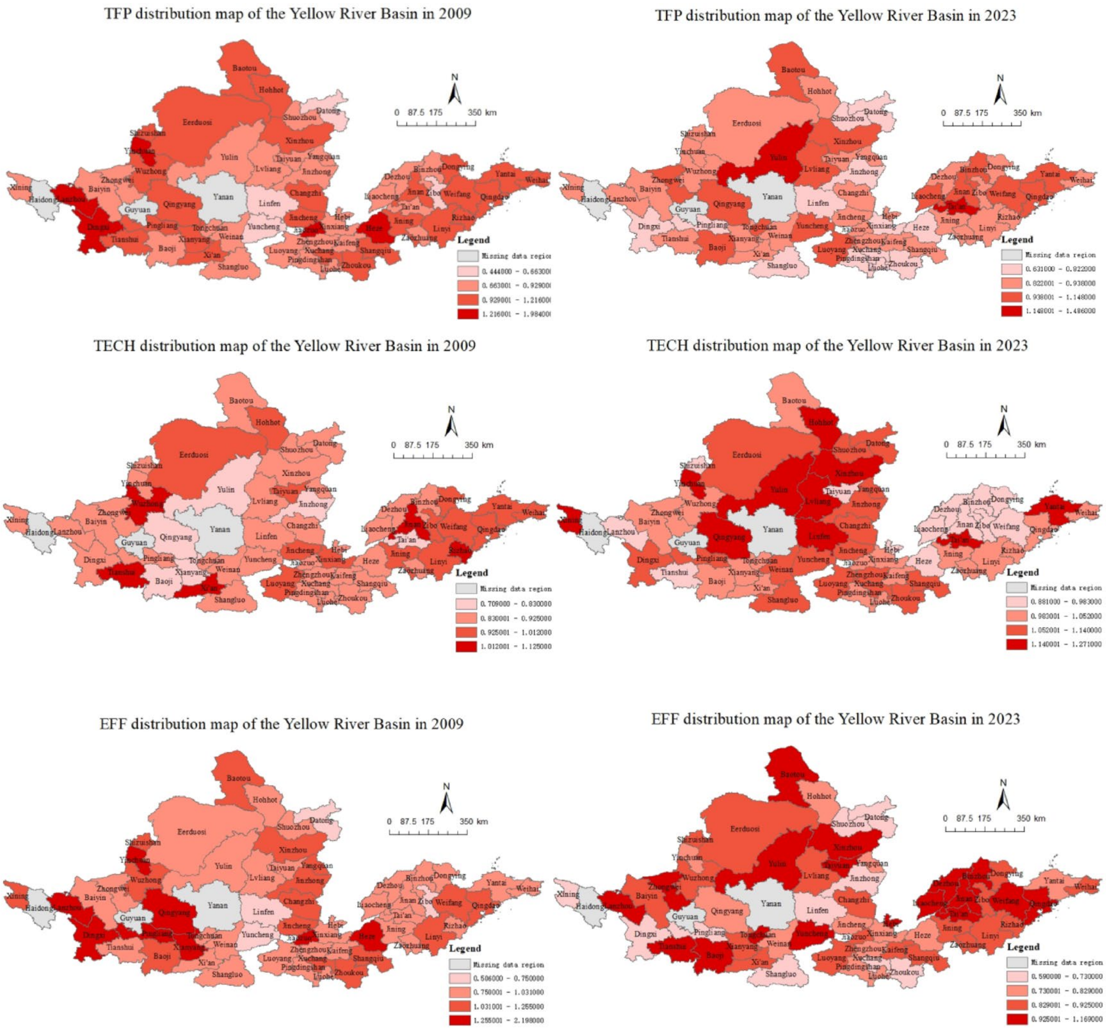

Fig. 2. Spatial distribution map of Innovation Ecosystem Dynamic Operational Efficiency in Cities of the Yellow River Basin. (The map in Fig. 2 is created based on the standard map with the review number GS(2022)1873, downloaded from the Standard Map Service System of the Map Technology Review Center of the Ministry of Natural Resources of the People's Republic of China. The base map has not been modified. The software used is ArcMap (version 10.8), which can be accessed at [https://www.esri.com/en-us/home].).

revealed the growth from the upper and middle reaches to the middle and lower reaches, demonstrating the potential and advantages of the middle and lower reaches in Innovation and efficiency increase. By 2023, the development of EFF in the Yellow River Basin faced significant challenges. Inefficiencies were prevalent across the upstream, middle stream, and downstream. These issues highlighted deficiencies in management practices and institutional frameworks. This revealed a disconnection between technological Innovation and practical application within the basin. Optimizing the Innovation management system is now crucial. Enhancing technical efficiency is essential for promoting an efficient and sustainable development of the Innovation Ecosystem.

Temporal evolution patterns and spatial distribution characteristics of the dynamic operational efficiency of the Innovation Ecosystem in the Yellow River Basin

Kernel density functions visually depict the temporal evolution patterns and spatial distribution characteristics of variables. Therefore, this study utilizes Gaussian kernel density estimation to analyse the Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem in the Yellow River Basin. Three-dimensional kernel density evolution maps of the overall Yellow River Basin (Fig. 3) and the upstream (Fig. 4), midstream (Fig. 5), and downstream (Fig. 6) of the Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem were generated via MATLAB 2023.

From the perspective of TFP, the Yellow River Basin, including its upstream and midstream, displays a left-skewed kernel density curve during the study period. Peak characteristics alternate between unimodal and bimodal patterns, indicating TFP decline and increasing polarization. However, the downstream region shows the opposite trend, with no significant polarization. The peak states of the Yellow River Basin and the upper,

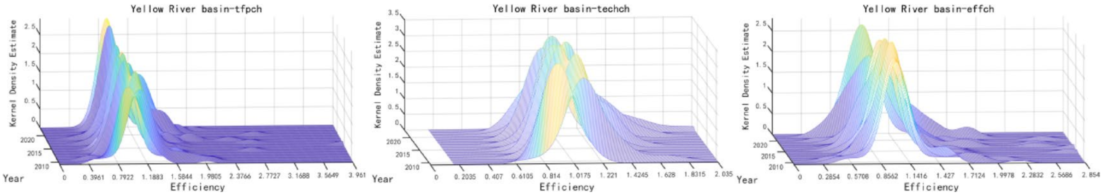

Fig. 3. Kernel density plot of TFP, TECH, and EFF in the Yellow River Basin.

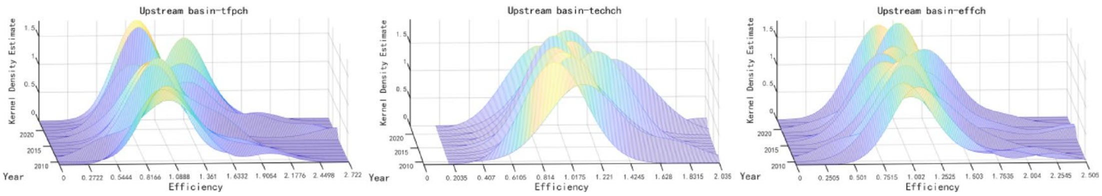

Fig. 4. Kernel density plot of TFP, TECH, and EFF in the upstream of the Yellow River Basin.

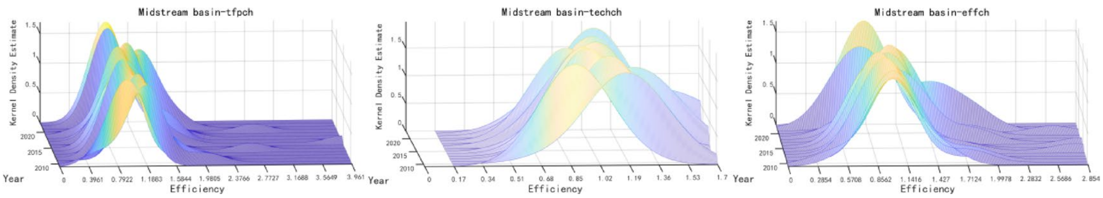

Fig. 5. Kernel density plot of TFP, TECH, and EFF in the midstream of the Yellow River Basin.

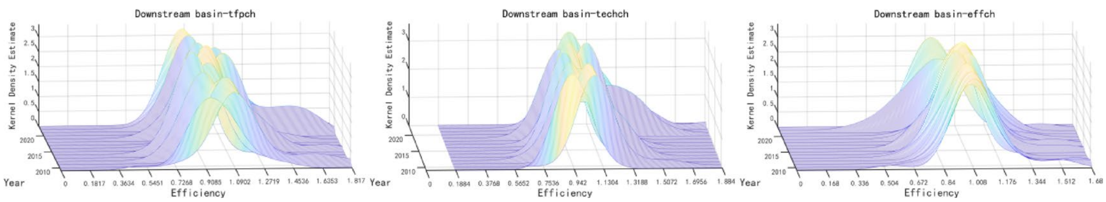

Fig. 6. Kernel density plot of TFP, TECH, and EFF in the downstream of the Yellow River Basin.

middle, and downstream transitions from "low and flat" or "low and sharp" to "high and sharp". This transition suggests reduced regional disparities and a convergence trend in TFP.

In terms of TECH, the Yellow River Basin and its middle to downstream regions display right-skewed kernel density curves, primarily unimodal. This indicates a rising trend in TECH with no significant polarization. All three regions exhibit similar shifts in peak distribution shifts, pointing to increasing regional disparities in TECH. The upstream, however, shows the opposite development trend with distinct peak states and characteristics. Specifically, the regional differences in TECH in the upstream initially narrow but later widen, accompanied by emerging polarization.

During the study period, both the entire basin and the downstream show a trend of rightward movement in the distribution of EFF. However, their peak states displayed spatially opposite evolutionary patterns. This indicates the increased EFF within these regions, their regional differences are developing in opposite directions. Specifically, the regional differences decreased across the basin but increased in the downstream. A polarization emerged gradually in the basin but declined downstream. Both the upstream and midstream experienced the declined EFF trend with polarization signs. The spatial distribution narrowed progressively in the upstream, while the midstream differences weakened initially before intensifying.

Regional difference evolution characteristics of the dynamic operational efficiency of the urban Innovation Ecosystem in the Yellow River Basin

This study applied the Dagum Gini coefficient decomposition method to examine the spatial difference evolution characteristics of the Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem across

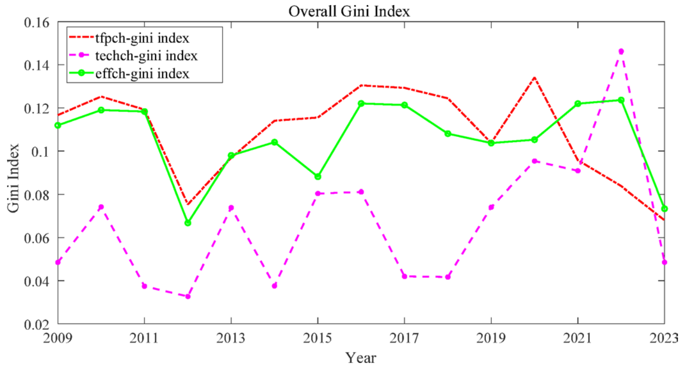

Fig. 7. Changes in G_{TFP}, G_{TECH} and G_{EFF}.

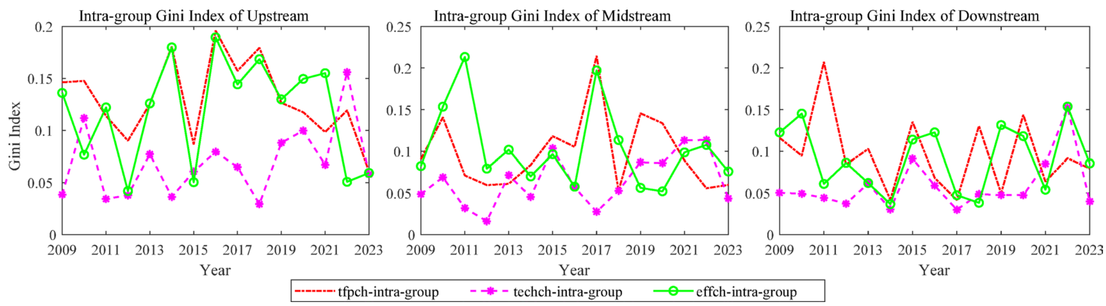

Fig. 8. Changes in G_{TFP}, G_{TECH} and G_{EFF} in the upper, middle and downstream of the Yellow River Basin.

the Yellow River Basin. Figures 7 and 8 present the temporal trends of the Gini coefficients (G_{TFP}, G_{TECH}, G_{EFF}) for TFP, TECH, and EFF from 2009 to 2023. These figures compare patterns in the entire basin with those in its upper, middle, and downstream regions.

<u>Analysis of intraregional disparities</u> Regional disparity analysis in Fig. 7 reveals three key patterns. Both the G_{TFP} and G_{EFF} exhibit a "decrease-increase-decrease" trend, with annualized rates of −3.532% and −2.775%, respectively. This pattern suggests progressive narrowing of TFP and EFF gaps among basin cities. Conversely, G_{TECH} shows fluctuating growth (0.0078% annual rate) from 2009 to 2023, indicating widening TECH disparities. Mean values further clarify these trends: G_{TFP} (0.108) closely approximates G_{EFF} (0.106), demonstrating aligned spatial divergence patterns for these metrics. Notably, G_{EFF} changes emerge as the dominant factor in G_{TFP} variation, while G_{TECH} changes exert comparatively minor influence.

Figure 8 illustrates the evolution of intraregional disparities in TFP, TECH, and EFF within the Innovation Ecosystem of the Yellow River Basin from 2009 to 2023. The upstream region shows declining disparities, with G_{TFP} and G_{EFF} decreasing at annual average rates, respectively. Conversely, G_{TECH} increases at an annualized rate of 0.028%, indicating widening TECH disparities. Mean disparity values reveal a clear hierarchy: G_{TFP} (0.1297) > G_{EFF} (0.1186) > G_{TECH} (0.0692). The parallel trends observed between TFP and EFF suggest that G_{EFF} fluctuations predominantly drive G_{TFP} variations. This pattern highlights Innovation Ecosystem dynamic operational efficiency as a critical determinant of total factor productivity dynamics in the upstream region.

During the fourteen years, the midstream region of the Yellow River Basin showed decreasing disparities in TFP, TECH and EFF. The observed average annual decline rates reached −0.02497%, −0.01537% and −0.02374%, respectively. It indicates gradual improvement in balanced development across these three indicators. Mean values of G_{TFP}, G_{TECH}, and G_{EFF} measured 0.0986,0.0644 and 0.1036 respectively. Disparity magnitudes followed the order: EFF > TFP > TECH. The parallel evolution of TFP and EFF metrics suggest that fluctuations in G_{EFF} predominantly drive variations in G_{TFP}.

The downstream region exhibited negative annual growth rates in green total factor productivity (G_{TFP}) components, with mean declines of −0.02497% (TFP), −0.01537% (TECH), and −0.02374% (EFF), signaling progressive convergence among these metrics. Notably, synchronicity emerged between intraregional G_{TFP} and G_{EFF} fluctuation patterns, revealing coordinated spatial dynamics of TFP and EFF. This covariation strongly implies G_{EFF} variations constitute the principal driver of G_{TFP} fluctuations in the basin's lower reaches.

In conclusion, the TFP, TECH, and EFF in the upstream, midstream, and downstream of the Yellow River Basin exhibit spatial heterogeneity. Critically, metrics exhibit the spatial convergence, with EFF variations serving as the primary driver of TFP divergence dynamics. This causal asymmetry establishes a cascade-type interdependency between the two factors, wherein localized EFF fluctuations propagate disproportionately through the productivity system—a phenomenon analogous to a "butterfly effect" in regional economic-environmental linkages.

Interregional difference analysis Table 5 delineates divergence dynamics in TFP, TECH, and EFF of the across urban Innovation Ecosystem in the Yellow River Basin. It is from 2009 to 2023 that TFP's annual average growth rate was negative across the regions, signaling a convergence in disparities. Spatial decomposition highlights elevated disparity coefficients between upper-middle (0.1262) and upper-lower (0.1296) strata, surpassing middle-lower differentials (0.1098). This tiered disparity structure underscores systemic productivity gaps isolating upstream regions, attributable to compounded deficits in technological Innovation infrastructure and resource mobility efficiency.

The annual average growth rates of TECH between the upper-middle and upper-lower streams were positive, indicating an expansion in their degrees of differentiation. Conversely, the degree of differentiation between the middle and lower reaches exhibited a narrowing trend. The dynamic evolution trends and mean values between the upper-middle, upper-lower, and middle-downstream are approximately equal, showing a similar convergence in TECH disparities between regions.

EFF disparities displayed accelerated convergence, with upper-middle, upper-lower, and middle-lower strata recording annualized decline rates of −3.741%, −3.879%, and − 1.505%, respectively. This indicates that the convergence rate between the upper-middle and upper-lower streams was faster than that between the middle-lower streams. Analysis of the mean values revealed that the interregional differences between the upper-middle and upper-lower streams were greater than those between the middle-lower streams.

In summary, the degree of differentiation in TFP between the upper-middle and upper-lower reaches displayed a converging trend, whereas TECH demonstrated countervailing divergence. The differences in TFP and EFF were similar between the upper-middle and upper-lower reaches and were greater than those between the middle-lower streams. Crucially, the convergence rate between the upper-middle and upper-lower stream was more significant than that between the middle-lower streams.

Disparity sources and contribution analysis As quantified in Table 6 and visualized in Fig. 9, the sources and contributions of regional differences in TFP, TECH, and EFF within the Innovation Ecosystem of the Yellow River Basin exhibits distinct drivers of regional productivity disparities. The hyper density (HD) contributed 43.757% to overall TFP differences, making it the primary source of variation. intraregional differences (IN) contributed 31.428%, while interregional differences (BT) had an average contribution of 24.816%.

Significant variability was observed in the contribution rates of HD and BT during the study period. HD's contribution to TECH differences fluctuated between 22% and 61%, whereas BT's contribution ranged from 4 to 48%. In contrast, IN's contribution to TECH differences remained stable at approximately 32.831%.

With respect to the dynamic changes in contribution rates, BT had the largest average contribution to overall EFF differences but showed a decreasing trend. IN's contribution to EFF differences exhibited minor changes, whereas HD's contribution to EFF differences displayed an oscillating upwards trend. HD's contribution decreased from 42.07% in 2009 to 32.492% in 2014, then increased to 33.081% in 2018, and finally reached 43.871% in 2023.

It has been well identified that the HD is the principal factor affecting the fluctuations in TFP, TECH, and EFF differences in the Yellow River Basin. This observation indicates a high degree of overlap and interaction among the upper, middle, and down streams. IN maintained stable contributions (29–33%), demonstrating persistent

Year	TFP			TECH			EFF		
	Upper-middle	Upper-lower	Middle-lower	Upper-middle	Upper-lower	Middle-lower	Upper-middle	Upper-lower	Middle-lower
2009	0.1293	0.1497	0.1081	0.0467	0.0548	0.0529	0.1231	0.1412	0.1051
2010	0.1518	0.1277	0.1233	0.0965	0.0909	0.0681	0.1198	0.1201	0.1547
2011	0.1009	0.1701	0.1545	0.0368	0.0453	0.0399	0.1747	0.0996	0.1530
2012	0.0784	0.0895	0.0743	0.0303	0.0420	0.0296	0.0659	0.0708	0.0848
2013	0.1145	0.1352	0.0875	0.0773	0.0761	0.0680	0.1306	0.1195	0.0884
2014	0.1414	0.1392	0.0968	0.0427	0.0379	0.0409	0.1363	0.1296	0.0762
2015	0.1146	0.1261	0.1312	0.0851	0.0778	0.0984	0.0832	0.1025	0.1093
2016	0.1646	0.1562	0.0913	0.0715	0.1006	0.0880	0.1359	0.1670	0.1039
2017	0.1970	0.1268	0.1464	0.0494	0.0521	0.0307	0.1795	0.1170	0.1388
2018	0.1709	0.1920	0.0993	0.0434	0.0420	0.0516	0.1705	0.1533	0.0839
2019	0.1477	0.0996	0.1191	0.0979	0.0795	0.0725	0.1012	0.1499	0.1112
2020	0.1288	0.1394	0.1523	0.1029	0.1364	0.0937	0.1146	0.1496	0.0912
2021	0.0972	0.1057	0.1137	0.1005	0.0843	0.1047	0.1357	0.1524	0.1197
2022	0.0931	0.1125	0.0775	0.1484	0.1840	0.1495	0.1116	0.1446	0.1367
2023	0.0627	0.0744	0.0721	0.0537	0.0551	0.0489	0.0695	0.0780	0.0838
Average	0.1262	0.1296	0.1098	0.0722	0.0772	0.0692	0.1235	0.1263	0.1094
Annual growth rate	−0.047%	−0.046%	−0.027%	0.009%	0.0003%	−0.005%	−3.741%	−3.879%	−1.505%

Table 5. Gini coefficient table of TFP, TECH, and EFF across regions.

Year	TFP			TECH			EFF		
	IN	BT	HD	IN	BT	HD	IN	BT	HD
2009	32.819	31.308	35.874	32.821	27.891	39.288	32.668	25.262	42.070
2010	33.865	3.749	62.386	30.762	22.450	46.788	32.944	6.630	60.426
2011	30.526	20.384	49.090	33.547	28.359	38.094	29.856	13.121	57.023
2012	34.264	9.980	55.756	35.117	36.318	28.565	32.284	23.557	44.159
2013	30.382	32.165	37.453	36.448	18.602	44.950	30.204	30.883	38.912
2014	28.862	43.338	27.801	33.129	27.204	39.667	29.603	37.906	32.492
2015	33.302	28.533	38.164	34.010	4.573	61.417	30.573	30.791	38.637
2016	32.038	42.650	25.312	29.056	48.801	22.143	31.584	26.394	42.022
2017	27.344	22.193	50.463	33.698	7.134	59.169	28.296	21.774	49.930
2018	26.504	36.552	36.944	33.069	11.627	55.304	25.666	41.253	33.081
2019	29.530	22.093	48.377	31.455	26.991	41.554	30.689	22.673	46.638
2020	35.007	6.838	58.155	30.213	45.704	24.083	31.190	35.192	33.619
2021	29.355	36.873	33.772	33.502	17.082	49.416	27.078	45.131	27.791
2022	32.146	20.769	47.085	33.099	21.246	45.655	33.102	32.731	34.166
2023	35.472	14.812	49.716	32.540	26.819	40.641	34.525	21.604	43.871
Average	31.428	24.816	43.757	32.831	24.720	42.449	30.684	27.660	41.656

Table 6. Regional differences and contributions of TFP, TECH, and EFF in the innovation ecosystem of the yellow river basin.

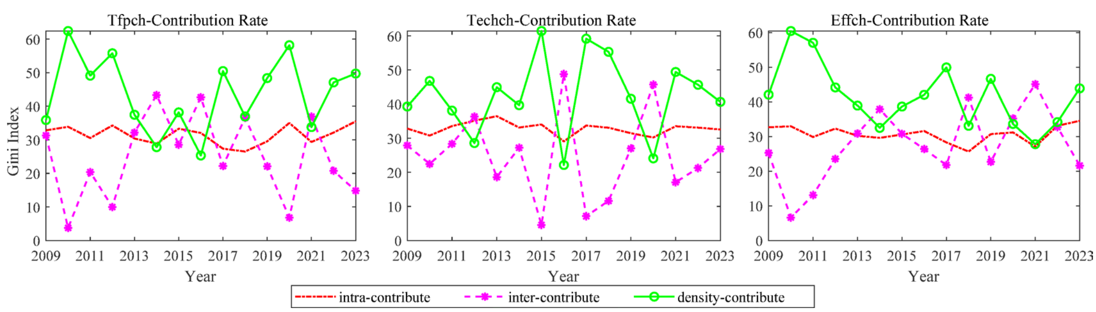

Fig. 9. Changes in the contribution rates of TFP, TECH, and EFF in the Yellow River Basin.

subregional Innovation inertia. Considering that the smallest impact of BT, reducing HD differences within the upper, middle, and lower regions is believed to be crucial to improve the Innovation Ecosystem dynamic operational efficiency of the Yellow River Basin.

Analysis of the formation mechanism of regional differences in the dynamic operation efficiency of the Innovation Ecosystem in the Yellow River Basin To further explore the systemic inter-dependencies of the Innovation Ecosystem within the Yellow River Basin, it is important to understand that TECH and EFF are derived from the decomposition of the TFP index, indicating a certain level of interdependence among them. The logical relationship among TFP, TECH, and EFF is depicted in Fig. 10. Given that the PVAR model allows each component to be an endogenous variable, the vector autoregression (PVAR) model was adopted in the present research to empirically test the interaction mechanisms among TFP, TECH, and EFF.

Assessing variable stationarity and Granger causality To validate the PVAR model's parameter estimation, stationarity testing was conducted with the application of five different methods—LLC, IPS, HT, ADF-Fisher, and PP-Fisher. These tests were systematically applied to TFP, TECH, and EFF across the upper, middle, and downstream reaches of the Yellow River Basin. As shown in Table 7, all variables satisfy the stationarity requirement at the 1% significance level across all five methods. This robust confirmation of data stationarity ensures the reliability of subsequent model estimations and statistical inferences.

To improve model specification and predictive performance, this study employs Granger causality test to examine the causal relationships between TFP, TECH, and EFF. The model framework incorporates optimal lag selection based on three established information criteria, such as the Bayesian information criterion (BIC), Akaike information criterion (AIC), and Hannan-Quinn information criterion (HQIC) for each reaches of the Yellow River Basin. The empirical results, including lag order selection and causality analysis, are systematically presented in Tables 8 and 9.

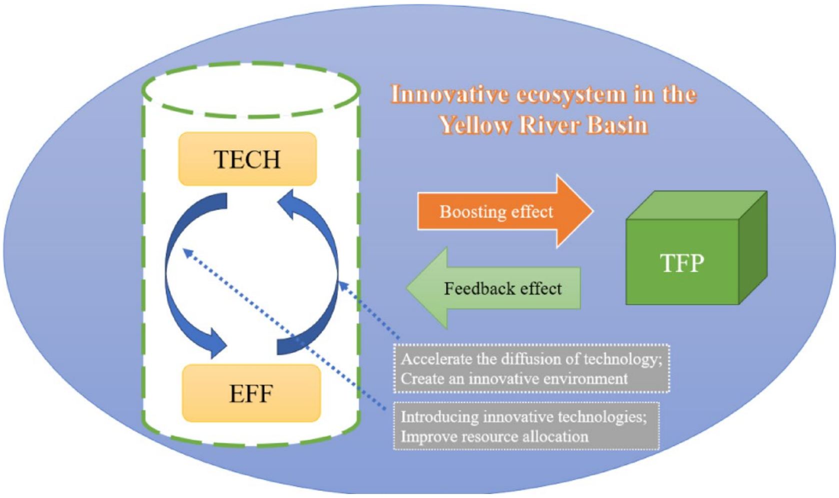

Fig. 10. Logical relationship among TFP, TECH, and EFF.

Region	Variable	LLC test	IPS test	HT test	ADF test	PP test	Result
Upper	TFP	−4.8101***	−6.3934***	−0.2523***	54.4748***	143.1621***	Stable
	TECH	−5.0069***	−6.6653***	−0.1932***	69.1529***	133.1355***	Stable
	EFF	−6.3273***	−7.1513***	−0.3149***	94.5792***	216.6133***	Stable
Middle	TFP	−5.5956***	−7.8824***	−0.1300***	88.0878***	229.5781***	Stable
	TECH	−3.5675***	−8.1129***	−0.1778***	72.0931***	202.9447***	Stable
	EFF	−6.0855***	−8.3965***	−0.2291***	107.3478***	250.8372***	Stable
Lower	TFP	−5.9112***	−9.6986***	−0.1816***	113.1249***	322.5222***	Stable
	TECH	−7.4623***	−9.5422***	−0.1457***	149.1068***	319.7177***	Stable
	EFF	−4.0443***	−9.6315***	−0.1546***	101.5222***	338.8066***	Stable

Table 7. Unit root test. **Notes**: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively.

Region	Lag order	AIC	BIC	HQIC
Upper	first-order	−1.6882*	−0.808432*	−1.33088*
	second-order	−0.445603	0.668077	0.006934
	third-order	3.37149	4.74737	3.93058
Middle	first-order	−0.688039	0.249693	−0.310501
	second-order	−1.66814*	−0.540062*	−1.21299*
	third-order	−1.62008	−0.276753	−1.07697
Lower	first-order	−0.796922	0.19878	−0.401176
	second-order	−5.16243*	−3.81814*	−4.62492*
	third-order	−4.97341	−3.81465	−4.5115

Table 8. Lag order determination. **Notes**: * represents the significance of the lag order.

Table 8 presents the optimal lag order determined by three information criteria across regions. The analysis identifies a first-order lag for upstream regions, while midstream and downstream regions show second-order lags as optimal.

The Granger causality test results reveal varied interactions among TFP, TECH, and EFF across different basins. Upstream regions demonstrate no detectable Granger causality among the three variables (i.e., TFP, TECH, and EFF). In contrast, midstream region shows bidirectional Granger causality between TECH and EFF, with unidirectional causality from TFP to TECH. Downstream regions also show comprehensive bidirectional causality among TFP, TECH, and EFF.

PVAR model analysis of the operational efficiency of the Innovation Ecosystem in the Yellow River Basin Because the absence of significant Granger causality relationships between TFP and TECH or EFF in the

Equation	Excluded	Upper		Middle		Lower	
		Chi2	Prob	Chi2	Prob	Chi2	Prob
H_TFP	H_TECH	0.1674	0.920	2.1343	0.344	9.6355	0.022**
H_TFP	H_EFF	0.1586	0.924	0.8983	0.638	6.5641	0.087*
H_TECH	H_TFP	0.4014	0.818	7.8278	0.020**	9.1069	0.028**
H_TECH	H_EFF	0.4589	0.795	8.6266	0.013**	8.4286	0.038**
H_EFF	H_TFP	0.2950	0.863	3.3470	0.188	9.6899	0.021**
H_EFF	H_TECH	0.3031	0.859	4.6738	0.097**	10.584	0.014**

Table 9. Granger causality test. **Notes**: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively.

Detection domain and variables	Middle reach			Lower reach		
	TFP	TECH	EFF	TFP	TECH	EFF
H_TFP L1	0.7943 (1.1261)	−1.4978** (0.6567)	1.5784 (1.1658)	2.3307* (1.3368)	−2.4872** (1.1183)	3.9998*** (1.3000)
H_TECH L1	−0.7567 (1.1641)	1.4778** (0.6793)	−1.5107 (1.2119)	−2.3757* (1.2929)	2.3760** (1.0537)	−3.9450*** (1.2603)
H_EFF L1	−0.8831 (1.2612)	1.7553** (0.7315)	−1.8407 (1.3066)	−2.6444* (1.5105)	2.7917** (1.2838)	−4.4856*** (1.5063)
H_TFP L2	0.8482 (0.8637)	−1.2378** (0.5250)	1.6556* (0.9228)	2.0649 (1.5214)	−2.6677** (1.2107)	3.8738*** (1.4996)
H_TECH L2	−1.2791 (0.9868)	1.4016** (0.5446)	−2.1823** (1.0222)	−2.0273** (1.5207)	2.7803** (1.2122)	−3.9238*** (1.5003)
H_EFF L2	−0.9153 (0.9663)	1.4553*** (0.5558)	−1.9051* (1.0162)	−2.1669 (1.6105)	2.7166** (1.2914)	−3.9709*** (1.6165)

Table 10. Regression results of the PVAR model. **Notes**: The values in parentheses are the standard deviations.

upstream, there are no significant interactions or mechanisms among TFP, TECH, and EFF in the upper region. Based on these findings the analysis focuses on the PVAR model results for the interactions among TFP, TECH, and EFF in the middle and downstream. The results are presented in Table 10.

The analysis identifies distinct temporal dynamics in regional productivity drivers. When TFP serves as the dependent variable, significant second-period lag effects from TECH and first-period lag effects from TFP, TECH, and EFF emerge in downstream regions ($p< 0.10$ and $p< 0.05$, respectively). These temporal dependencies are not observed in midstream regions. When TECH is the dependent variable, the development of TECH demonstrates consistent sensitivity to historical TFP levels. Both first and second-period lagged TFP significantly influence current TECH in midstream and downstream regions. Lagged TECH and EFF, significant at the 5% and 1% levels, respectively, positively influence the current TECH, TFP contributing further positive impacts. When EFF is the dependent variable, lagged TECH and EFF (two periods) in the midstream regions show weak negative correlations with current EFF, while TFP maintains a significant positive relationship. Downstream regions reveal more complex dynamics, with both first and second-period lagged TFP, TECH, and EFF demonstrating significant positive and negative effects on EFF improvement ($p< 0.01$).

In the midstream region, TFP, TECH, and EFF demonstrate self-enhancing mechanisms. Throughout the development of TFP, technological progress and economies of scale exhibit counteracting effects on TFP development. The advancement of TFP is driven by opposing forces: positive contributions from TECH and negative influences from EFF. Furthermore, TECH development promotes EFF improvement, whereas EFF growth exerts a suppressive effect on TECH, indicating that TECH plays a core strengthening role in the development of TFP.

Discussion

This study assesses the Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem in the Yellow River Basin, aiming to identify strategies for boosting regional Innovation competitiveness and achieving equitable resource allocation. Using city-level data, we analyzed the Ecosystem's efficiency, spatiotemporal patterns, regional disparities, and underlying mechanisms. Results show a fluctuating decline in the Innovation Ecosystem dynamic operational efficiency of the region's Innovation Ecosystem. Compared to the Yangtze River Economic Belt, the Yellow River Basin lags in Innovation resource aggregation and allocation efficiency, with weaker Ecosystem synergy[45]. Specifically, the Yangtze River Economic Belt outperforms in transforming scientific achievements and fostering Innovation-driven entrepreneurship, supported by robust Innovation platforms and higher input-output efficiency[46]. Relative to the Beijing-Tianjin-Hebei region, the Yellow River Basin operates at a lower Innovation level[47], with notable gaps in R&D investment intensity[48]. Meanwhile, the Guangdong-Hong Kong-Macao Greater Bay Area surpasses the Yellow River Basin in Innovation infrastructure and resource availability[49], leveraging its internationalized, market-driven, and collaborative Ecosystem to achieve greater Innovation efficiency and vitality.

Although the Innovation Ecosystem dynamic operational efficiency of Innovation Ecosystem has been extensively discussed, limited research has been carried out in specific geographical regions, such as at the municipal level in the Yellow River Basin. Moreover, the existing literature predominantly focuses on static analyses of Innovation Ecosystem dynamic operational efficiency, which generally neglects the dynamic interactions that underpin these systems. This study addresses these gaps by introducing the DEA-Malmquist model to dynamically assess the Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem in the Yellow River Basin. Different from previous research, this work expands the scope of Innovation efficiency measurement from a narrow "input-output" framework to a comprehensive "Innovation Ecosystem operation chain." This chain spans the entire Innovation process, including innovation sources, market environment, consumer demand. Through kernel density estimation and the Gini coefficient, this study further reveals spatial patterns and regional disparities in Innovation Ecosystem dynamic operational efficiency. The application of the PVAR model deepens the understanding of the dynamic relationships among TFP, TECH, and EFF, as well as regional heterogeneity. By integrating these approaches, this study not only advances the theoretical understanding of Innovation Ecosystem but also provides actionable insights and policy recommendations for enhancing Innovation capabilities and promoting high-quality development of regional Innovation competitiveness in the Yellow River Basin.

It should also be noted that there are still some certain limitations of this research. The analysis of 59 cities in the Yellow River Basin may not fully capture the diverse characteristics of Innovation Ecosystem across China. A more extensive and representative dataset would be required for broader and deeper investigations. Additionally, this research did not thoroughly examine other potential factors influencing Innovation Ecosystem dynamic operational efficiency, such as social and cultural elements, shifts in policy environments, and external drivers like education, talent development, and digital infrastructure. Future studies should explore the relationships between these variables and the Innovation Ecosystem dynamic operational efficiency of Innovation Ecosystem to provide a more comprehensive understanding.

Conclusion and policy recommendations

In the present research, the Innovation Ecosystem dynamic operational efficiency of Innovation Ecosystem in 59 cities within the Yellow River Basin from 2009 to 2023 was initially evaluated via the utilization of the DEA-Malmquist model. Subsequently, the efficiency distributions, regional disparities, and operational mechanisms of these Ecosystems were further investigated with the application of the kernel density estimation, the Gini coefficient, as well as the PVAR model. This analysis yielded the following research findings:

(1) The Innovation Ecosystem dynamic operational efficiency of the Innovation Ecosystem in the Yellow River Basin within the study period exhibited a fluctuating decline, primarily driven by a decrease in technological efficiency. Spatial analysis revealed distinct regional patterns: the upstream and midstream regions displayed a left-skewed distribution with significant polarization, while the downstream region showed a right-skewed distribution with less polarization.

(2) The Gini coefficients for Innovation Ecosystem dynamic operational efficiency and technical efficiency in the Yellow River Basin's Innovation Ecosystem shows convergence, whereas the coefficient for technological change increases. TFP and EFF exhibit spatial convergence across upstream, middle, and downstream regions. The convergence rates of TFP, TECH, and EFF were higher between upstream-midstream and upstream-downstream regions compared to midstream-downstream regions. Hypervariable density emerged as a key factor influencing disparities in TFP, TECH, and EFF.

(3) Technical efficiency, technological change, and dynamic efficiency interacted with significant regional heterogeneity. In the upstream region, no significant relationships were observed among TFP, TECH, and EFF. The midstream region displays a self-reinforcing mechanism for TFP, TECH, and EFF, with mutual reinforcement between EFF and TECH. In the downstream region, TECH exhibited a strong self-reinforcing mechanism, whereas TFP and EFF exhibit self-weakening mechanisms.

On the basis of these research findings, the following policy recommendations are proposed:

(1) Efforts should be given to integrate advanced management methods and Innovation technologies to improve EFF, while simultaneously developing suitable application frameworks to maximize the potential of new technologies. This approach will drive the advancement of TECH and foster an organic synergy, resonance, and mutual reinforcement between TECH and EFF, ultimately promoting the growth of total factor productivity (TFP).

(2) Cities such as Qingdao, Dingxi, and Jining, which are near the efficiency frontier, should serve as benchmarks to inspire regions with lower dynamic operational efficiency. Conversely, cities like Ordos, Yantai, and Yulin, which exhibit weak technological progress efficiency, can improve by optimizing the application of Innovation technologies and scientific management methods, fostering positive interactions between the two. Meanwhile, cities such as Hebi, Luohe, and Shizuishan, where technical efficiency lags, can enhance their performance by scaling up industrial operations and implementing Innovation resource policies. These measures would significantly bolster the overall Innovation Ecosystem dynamic operational efficiency in the Yellow River Basin.

(3) Regions within the Yellow River Basin should capitalize on their unique advantages and engage in cooperative initiatives with neighboring areas. Establishing a comprehensive system for technological Innovation and application can enhance information-sharing mechanisms and improve the efficient utilization of Innovation ideas and resources. This approach optimizes resource allocation across regions, strengthens the Innovation mindset and motivation of key stakeholders, and fosters positive interactions between Innovation

entities and their environments. Such efforts will effectively drive the high-quality development of Innovation Ecosystem dynamic operational efficiency.

Data availability

The dataset used and/or analyzed in this study is uploaded as supplementary material or obtained from the corresponding author upon reasonable request.

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Author contributions
Kong Xiaoni's contributions lie in the establishment of the theoretical foundation, research design, and manuscript review; Jin Shuliang's contributions are in drafting the initial manuscript, conducting data analysis, and creating figures and charts; Zhao Hongchao's contributions involve proofreading the manuscript and solving technical issues.

Declarations

Competing interests
The authors declare no competing interests.

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