Front. Eng. Manag. 2022, 9(3): 425–438
https://doi.org/10.1007/s42524-022-0205-5

RESEARCH ARTICLE

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Sustainability performance analysis of environment innovation systems using a two-stage network DEA model with shared resources

Abstract The term environmental innovation system refers to an innovation network composed of enterprises, universities, and research institutions involved in the development and diffusion of environmental technology, with the participation of a government. An environmental innovation system not only exerts important impact on the achievement of carbon neutrality but also affects social and economic activities. Investigations on environmental innovation system performance constantly assume a single-stage independent system while ignoring its internal structure. However, such systems are composed of environmental innovation research and development (R&D) and environmental innovation conversion subsystems. A two-stage data envelopment analysis (DEA) model is developed in this study to analyze the efficiency of Chinese regional environmental innovation system by opening the "black box" and considering shared resources. Empirical results indicated that China presents high overall environmental innovation efficiency although some regions need to improve. Regions with low efficiencies in both environmental innovation R&D (EIR) and environmental innovation conversion (EIC) subsystems should expand their investment in and strengthen the management of environmental innovation resources. Regions with low EIR efficiency should improve the absorption and transformation of environmental innovation achievements. Regions with low EIC efficiency should increase investment in the commercialization of environmental innovation achievements and encourage green economy industries, such as new energy, art, tourism, and environmental protection.

Keywords data envelopment analysis, environmental efficiency, environmental innovation system, shared resources, two-stage structure

Received August 26, 2021; accepted April 28, 2022

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This research was financially supported by the National Natural Science Foundation of China (Grant Nos. 71904084, 71971203, 71571173, and 71921001), the Philosophy and Social Science Foundation in Colleges and Universities in Jiangsu Province (Grant No. 2020SJA0340), the Major Programme of National Social Science Foundation of China (Grant No. 21&ZD110), Postdoctoral Science Foundation of China (Grant No. 2020TQ0145), the Natural Science Foundation for Jiangsu Province (Grant No. BK20190427), the Innovation and Entrepreneurship Foundation for Doctor of Jiangsu Province, the Four Batch Talent Programs of China, and the Fundamental Research Funds for the Central Universities (Grant No. WK2040160028).

1 Introduction

Problems of carbon emission and energy shortage have attracted considerable research attention in recent years (Zhou et al., 2010; Satterthwaite, 2011; Zhu et al., 2020). Carbon emission caused by economic activities has become a serious barrier to sustainable development (Yang et al., 2015). China has pledged to achieve the peak of its CO_2 emissions by 2030 and carbon neutrality by 2060 (Chen et al., 2021). Such ambitious goals lead to requirements for sustainable development. Energy shortage caused by an imbalance between limited supplies and increasing energy consumption has also become a serious challenge in sustainable development (Zhao et al., 2019).

Environmental regulation and innovation are two important concepts in the field of sustainable development that have been extensively investigated by many scholars and policymakers to alleviate problems of carbon emission and energy shortage (Meyer, 1995; Bressers and Rosenbaum, 2000; Chen, 2008). Yew and Zhu et al. (2019) indicate that innovative practices beyond the government provision addressing environmental problems are usually adopted by social sectors in addition to environmental regulation implemented by official authorities. Therefore, environmental innovation can be viewed as a proactive measure to address current regulatory inadequacies and eliminate energy shortage and environmental issues (Yew and Zhu, 2019). Impacts of environmental innovation addressing environmental issues have been empirically investigated. For example, Brunnermeier and Cohen (2003) propose that pressures of both pollution abatement and international competitiveness of an industry positively activate environmental innovation. Hemmelskamp et al. (2000) indicate that innovation-oriented policies are more effective than the diffusion of environmental innovation. On the basis of a study on South Korean-owned firms in China, Long et al. (2017) reveal that environmental innovation positively impacts both economic and environmental performance.

Studies on the impact of environmental innovation on energy and environmental performance typically use three main perspectives: Pollution reduction, industrial environment performance, and regional sustainable development. First, environmental innovation is an efficient way to curb pollution emissions. For instance, the empirical study of Zhang et al. (2017) indicates that environmental innovation measures effectively promote the reduction of carbon emissions in China. Mensah et al. (2018) apply three models to analyze the impact of innovation on carbon emissions in Organization for Economic Cooperation and Development (OECD) countries. The finding of the authors reveals that innovation is necessary to reduce carbon emissions. Sterner and Turnheim (2009) investigate the effect of technical change on abatement in Sweden and demonstrate that both innovation and technology dispersion play an important role in emission reduction.

Second, empirical evidence indicated that environmental innovation may improve the environmental performance of industries. For example, Brunnermeier and Cohen (2003) analyze the determinants of environmental innovation in American manufacturing industries and show that environmental innovation will likely occur in industries with high levels of international competition. Lin et al. (2013) investigate the relationship among market demand, green product innovation, and firm performance in the Vietnamese motorcycle industry. The evidence in this study indicates that green product innovation exerts a positive impact on firm performance. Fraj et al. (2015) examine environmental strategies and competitiveness in the hotel industry and indicate that innovativeness directly impacts organizational competitiveness.

Third, environmental innovation is the key driver for sustainable development at the regional level. On the basis of these observations, some studies investigate the inner mechanism between environmental innovation and performance. For example, Costantini et al. (2013) examine the links between environmental performance and innovation in 20 Italian regions and empirically demonstrate that innovation plays a major role in influencing environmental performance. Ghisetti and Quatraro (2017) investigate how environmental innovation affects environmental performance in Italian regions and show that environmental innovation positively affects environmental performance in regions and sectors. Zhang et al. (2018) analyze whether technological innovation can promote green development in 105 cities in China and reveal that technology innovation exerts a positive effect on eco-efficiency, in which the effect is greater in eastern cities than that in central and western cities.

Shephard (1971) first introduces the concept of environmental efficiency. Indexes for measuring environmental efficiency can be divided into two categories: Nonparametric and parametric methods (Reinhard et al., 2000). The data envelopment analysis (DEA) method proposed by Charnes et al. (1978) is a nonparametric method for evaluating the relative efficiency of a set of decision-making units (DMUs) (Zhu et al., 2022). For example, Zhou et al. (2008) consider different environmental technologies and discuss DEA techniques for evaluating the performance of carbon emission in eight world regions. Kortelainen (2008) proposes a Malmquist index approach for measuring the dynamic environmental performance of 20 European Union member states. Wang et al. (2013) measure the regional energy and environmental efficiency of three areas in China.

Song et al. (2014) extend the DEA to a two-stage model considering undesirable outputs to measure environmental performance. Chen and Jia (2017) develop a set of DEA models to evaluate the performance of a two-stage network process with shared inputs. The comprehensive evaluation of environmental efficiency originated from a study on carbon dioxide emissions treated as undesirable outputs (Song et al., 2012). DEA uses four perspectives to evaluate environmental factors properly and model undesirable outputs (Halkos and Petrou, 2019). First, the traditional measure simply ignores undesirable production output (He et al., 2013). However, disregarding undesirable outputs may lead to misleading results (Chung et al., 1997). For example, Pathomsiri et al. (2008) investigate the productivity of airports, compare the results with those obtained by models without undesirable outputs, and demonstrate that both desirable and undesirable outputs should be included in the evaluation. Second, some studies regard undesirable outputs as inputs in production (Chen and Jia, 2017). For example, Hailu and Veeman (2001) incorporate undesirable outputs into their models to provide a comprehensive representation of the production technology. Third, one can assume that undesirable outputs are weakly disposable whereas desirable outputs are strongly disposable. For example, Färe et al. (1996) develop an environmental performance indicator decomposed into pollution and input–output indexes on the basis of the DEA method under the assumption that undesirable outputs are weakly disposable (Yang and Pollitt, 2009). Fourth, transformation can be applied to undesirable outputs (Halkos and Petrou, 2019) (e.g., subtracting the amount from the maximum value) to evaluate efficiency on the basis of transformed data (Song et al., 2012). For example, Amado et al. (2012) combine DEA and the transformation method for enhanced performance assessment (Halkos and Petrou, 2019).

Previous studies seldom investigate the impact of environmental innovation on environmental efficiency while considering the inner structure of the innovation system. According to Gopalakrishnan and Damanpour (1997), we can recognize the inner structure of an innovation system as a composition of multiple stages. Guan and Chen (2010) and Wang et al. (2016) divide the progress of innovation into research and development (R&D) and innovation marketing stages, but both studies are based on the standard two-stage model and ignore shared inputs. Some input resources are proportionally shared by two stages in many practical cases (Chen et al., 2010). For example, Wu et al. (2017) propose that two nonenergy factors, namely, industrial labor force and capital, can be used in both energy utilization and pollution treatment stages in the system modeling Chinese industry.

We investigate the impact of environmental innovation on environmental performance by constructing an environmental innovation system with two substages of environmental innovation R&D (EIR) and environmental innovation conversion (EIC) in this study. Compared with the traditional DEA model, the linear programming model adopted in this study considers the impact of different stages of environmental innovation and the allocation of R&D resources in different stages on the overall efficiency. We first investigate overall efficiencies of the environmental innovation system to evaluate the efficiencies of Chinese provincial-level regions. We then further obtain the efficiency of the two stages in a practical real-world linkage. We treat environmental investment as a shared input used in both EIR and EIC stages in this linkage. Moreover, some outputs from EIR are viewed as inputs of EIC. We evaluate environmental innovation systems of Chinese provincial-level regions to obtain helpful insights and practical advice for decision makers. The ecological efficiency of environmental innovation systems is evaluated in this study using DEA. It expands the theoretical connotation of ecological efficiency. The proposed two-stage system of environmental innovation in this study can thoroughly analyze the role of innovation in energy conservation and carbon dioxide emission control.

The rest of this paper is organized as follows. Our two-stage model for measuring efficiencies of the environmental innovation system in a linkage setting is introduced in Section 2. The empirical results of the model for evaluating environmental innovation systems in China from 2015 to 2019 are discussed in Section 3. Policy recommendations and conclusions for Chinese provincial-level regions to improve their environmental innovation system efficiencies are presented in Section 4.

2 Proposed model

A two-stage network DEA model that considers shared inputs and undesirable environment outputs is proposed in this section to investigate the efficiency of the environmental innovation system. The economic implication of the following linear programming models determines whether minimal R&D resources can be invested to achieve the current output level of environmental innovation under the existing technology level, policy, and industrial structure. R&D resources are generally considered underutilized. Meanwhile, environmental innovation efficiency is considered effective. Suppose that n DMUs exist, and each DMU_j ($j = 1, \ldots, n$) consists of two stages (EIR and EIC stages) in the environmental innovation system. Figure 1 shows the two-stage network process of the environmental innovation system.

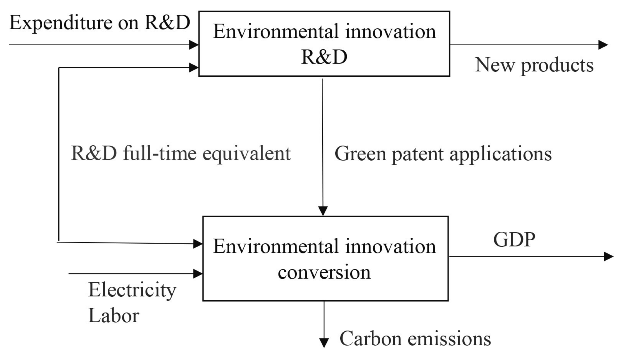

Fig. 1 The two-stage environmental innovation system with shared inputs.

Both stages of EIR and EIC consume general and shared inputs. General inputs are used in only one stage (EIR or EIC), but shared inputs are used by both stages. Let parameter α_j ($0 < \alpha_j < 1$) denote the proportion of shared inputs to be used in the EIR stage. Specifically, EIR uses inputs X_{ij}^1 and $\alpha_j K_{pj}$ to generate outputs Y_{ij}^1 and intermediate outputs Z_j. EIC uses inputs X_{ij}^2, $(1-\alpha_j) K_{pj}$ and intermediate outputs Z_j to generate desirable Y_{ij}^2 and undesirable F_j outputs.

On the basis of the traditional CCR (Charnes–Cooper–Rhodes) model (Charnes et al., 1978), we can measure the efficiency of a focal DMU (DMU_0) in EIR as follows:

$$e_{j_0}^1=\frac{\mu^{\mathrm{T}}Y_{j_0}^1+\delta^{\mathrm{T}}Z_{j_0}}{\nu^{\mathrm{T}}X_{j_0}^1+\pi^{\mathrm{T}}(\alpha_{j_0}K_{j_0})}\ \ (\mu,\ \nu,\ \pi,\ \delta\geqslant 0),\tag{1}$$

where $e_{j_0}^1$ is the ratio of the weighted sum of outputs to the weighted sum of inputs in EIR, and μ, ν, π, δ represent the weights of relevant inputs and outputs respectively.

The efficiency of EIC can be measured as follows:

$$e_{j_0}^2=\frac{\omega^{\mathrm{T}}Y_{j_0}^2-\xi^{\mathrm{T}}F_{j_0}}{\rho^{\mathrm{T}}X_{j_0}^2+\pi^{\mathrm{T}}(1-\alpha_{j_0})K_{j_0}+\delta^{\mathrm{T}}Z_{j_0}}\ \ (\omega,\ \pi,\ \rho,\ \delta,\ \xi\geqslant 0).\tag{2}$$

The negative sign of the second term in the numerator of model (2) is due to the vector ξ that represents the weights of undesirable outputs, which is a small positive number (Korhonen and Luptacik, 2004; Amirteimoori, 2013; Wu et al., 2016a). ω and ρ represent the weights of relevant outputs and inputs respectively.

We define the overall efficiency of DMU_0 as the combination of the two stages in a weighted sum of efficiency scores:

$$E_{j_0}=\lambda_1e_{j_0}^1+\lambda_2e_{j_0}^2,\tag{3}$$

where λ_1 and λ_2 reflect the relative importance of EIR and EIC stages, respectively. On the basis of previous studies (Chen et al., 2010; Amirteimoori, 2013; Lei et al., 2015; Wu et al., 2016a), we assume that λ_1 and λ_2 are externally determined and satisfy the condition $\lambda_1+\lambda_2=1$. The overall efficiency of the whole process can then be calculated as follows:

$$\begin{aligned}&\text{Max } E_{j_0}=\lambda_1e_{j_0}^1+\lambda_2e_{j_0}^2\\ &\textit{subject to}\quad e_j^1\leqslant 1\ (j=1,\ ...,\ n),\\ &\qquad e_j^2\leqslant 1\ (j=1,\ ...,\ n),\\ &\qquad \lambda_1+\lambda_2=1,\\ &\qquad L_j\leqslant\alpha_j\leqslant U_j,\\ &\qquad \mu,\ \omega,\ \nu,\ \pi,\ \rho,\ \delta,\ \xi,\ \lambda_1,\ \lambda_2\geqslant 0,\end{aligned}\tag{4}$$

where L_j and U_j are the lower and upper proportion bounds of a shared resource, respectively (Wu et al., 2016a). Similar to previous studies (e.g., Amirteimoori, 2013; Wu et al., 2016a), we define the following:

$$\lambda_1=\frac{\nu^{\mathrm{T}}X_{j_0}^1+\pi^{\mathrm{T}}(\alpha_{j_0}K_{j_0})}{\nu^{\mathrm{T}}X_{j_0}^1+\pi^{\mathrm{T}}K_{j_0}+\rho^{\mathrm{T}}X_{j_0}^2+\delta^{\mathrm{T}}Z_{j_0}},$$

$$\lambda_2=\frac{\rho^{\mathrm{T}}X_{j_0}^2+\pi^{\mathrm{T}}(1-\alpha_{j_0})K_{j_0}+\delta^{\mathrm{T}}Z_{j_0}}{\nu^{\mathrm{T}}X_{j_0}^1+\pi^{\mathrm{T}}K_{j_0}+\rho^{\mathrm{T}}X_{j_0}^2+\delta^{\mathrm{T}}Z_{j_0}},\tag{5}$$

where $\nu^{\mathrm{T}}X_{j_0}^1+\pi^{\mathrm{T}}K_{j_0}+\rho^{\mathrm{T}}X_{j_0}^2+\delta^{\mathrm{T}}Z_{j_0}$ is the total amount of input resources used in the whole system of DMU_0. Hence, the following formula is obtained: $E_{j_0}=\lambda_1e_{j_0}^1+\lambda_2e_{j_0}^2=\frac{\mu^{\mathrm{T}}Y_{j_0}^1+\delta^{\mathrm{T}}Z_{j_0}+\omega^{\mathrm{T}}Y_{j_0}^2-\xi^{\mathrm{T}}F_{j_0}}{\nu^{\mathrm{T}}X_{j_0}^1+\pi^{\mathrm{T}}K_{j_0}+\rho^{\mathrm{T}}X_{j_0}^2+\delta^{\mathrm{T}}Z_{j_0}}$.

The efficiency of the entire system can be modeled as follows:

$$\begin{aligned}&\text{Max } E_{j_0}=\frac{\mu^{\mathrm{T}}Y_{j_0}^1+\delta^{\mathrm{T}}Z_{j_0}+\omega^{\mathrm{T}}Y_{j_0}^2-\xi^{\mathrm{T}}F_{j_0}}{\nu^{\mathrm{T}}X_{j_0}^1+\pi^{\mathrm{T}}K_{j_0}+\rho^{\mathrm{T}}X_{j_0}^2+\delta^{\mathrm{T}}Z_{j_0}}\\ &\textit{subject to}\quad e_j^1=\frac{\mu^{\mathrm{T}}Y_j^1+\delta^{\mathrm{T}}Z_j}{\nu^{\mathrm{T}}X_j^1+\pi^{\mathrm{T}}(\alpha_jK_j)}\leqslant 1,\\ &\qquad e_j^2=\frac{\omega^{\mathrm{T}}Y_j^2-\xi^{\mathrm{T}}F_j}{\rho^{\mathrm{T}}X_j^2+\pi^{\mathrm{T}}(1-\alpha_j)K_j+\delta^{\mathrm{T}}Z_j}\leqslant 1,\\ &\qquad L_j\leqslant\alpha_j\leqslant U_j,\\ &\qquad \mu,\ \omega,\ \nu,\ \pi,\ \rho,\ \delta,\ \xi\geqslant 0.\end{aligned}\tag{6}$$

Although model (6) is a nonlinear program, we can transform it into a standard linear program by following the technique of Charnes and Cooper (1962). The transformation is shown in the following steps.

Step 1: Charnes–Cooper transformation

Let $t=\frac{1}{\nu^{\mathrm{T}}X_{j_0}^1+\pi^{\mathrm{T}}K_{j_0}+\rho^{\mathrm{T}}X_{j_0}^2+\delta^{\mathrm{T}}Z_{j_0}}$ and $\mu'=t\mu$, $\omega'=t\omega$, $\nu'=t\nu$, $\pi'=t\pi$, $\rho'=t\rho$, $\delta'=t\delta$, $\xi'=t\xi$. Program (6) can be transformed into the following:

$$\begin{aligned}&\text{Max } E_{j_0}=\mu'^{\mathrm{T}}Y_{j_0}^1+\omega'^{\mathrm{T}}Y_{j_0}^2+\delta'^{\mathrm{T}}Z_{j_0}-\xi'^{\mathrm{T}}F_{j_0}\\ &\textit{subject to}\quad \mu'^{\mathrm{T}}Y_j^1+\delta'^{\mathrm{T}}Z_j-\left(\nu'^{\mathrm{T}}X_j^1+\pi'^{\mathrm{T}}(\alpha_jK_j)\right)\leqslant 0,\\ &\qquad \omega'^{\mathrm{T}}Y_j^2-\xi'^{\mathrm{T}}F_j-\left(\rho'^{\mathrm{T}}X_j^2+\pi'^{\mathrm{T}}(1-\alpha_j)K_j+\delta'^{\mathrm{T}}Z_j\right)\leqslant 0,\\ &\qquad \nu'^{\mathrm{T}}X_{j_0}^1+\pi'^{\mathrm{T}}K_{j_0}+\rho'^{\mathrm{T}}X_{j_0}^2+\delta'^{\mathrm{T}}Z_{j_0}=1,\\ &\qquad L_j\leqslant\alpha_j\leqslant U_j,\\ &\qquad \mu',\ \omega',\ \nu',\ \pi',\ \rho',\ \delta',\ \xi'\geqslant 0.\end{aligned}\tag{7}$$

Step 2: Variable alteration

Program (7) is still a nonlinear program because of the presence of $\pi'^{\mathrm{T}}(\alpha_jK_j)$ and $\pi'^{\mathrm{T}}(1-\alpha_j)K_j$ in some constraints. Let $\gamma_j^{\mathrm{T}}K_j=\pi'^{\mathrm{T}}(\alpha_jK_j)$. Then we can convert program (7) into program (8). Hence, $\alpha_j=\frac{\gamma_j}{\pi'}$ $(j=1,\ ...,\ n)$, given that $\gamma_j=\alpha_j\pi'$.

$$\text{Max } E_{j_0} = \mu'^{\mathrm{T}} Y_{j_0}^1 + \omega'^{\mathrm{T}} Y_{j_0}^2 + \delta'^{\mathrm{T}} Z_{j_0} - \xi'^{\mathrm{T}} F_{j_0}$$

$$\textit{subject to} \quad \mu'^{\mathrm{T}} Y_j^1 + \delta'^{\mathrm{T}} Z_j - \nu'^{\mathrm{T}} X_j^1 - \gamma_j^{\mathrm{T}} K_j \leqslant 0,$$

$$\omega'^{\mathrm{T}} Y_j^2 - \xi'^{\mathrm{T}} F_j - \rho'^{\mathrm{T}} X_j^2 - \pi'^{\mathrm{T}} K_j + \gamma_j^{\mathrm{T}} K_j - \delta'^{\mathrm{T}} Z_j \leqslant 0,$$

$$\nu'^{\mathrm{T}} X_{j_0}^1 + \pi'^{\mathrm{T}} K_{j_0} + \rho'^{\mathrm{T}} X_{j_0}^2 + \delta'^{\mathrm{T}} Z_{j_0} = 1,$$

$$L_j \leqslant \alpha_j \leqslant U_j,$$

$$\mu',\ \omega',\ \nu',\ \pi',\ \rho',\ \delta',\ \xi' \geqslant 0. \tag{8}$$

Efficiency decomposition

We further investigate the efficiency decomposition of the whole system to examine the inefficiency and potential of each of the two stages (Lei et al., 2015). Kao and Hwang (2008), Liang et al. (2008) and Chen et al. (2009) explore the details of related issues of efficiency decomposition in a two-stage network DEA. Chen et al. (2009) propose that the overall efficiency of the whole system should be a weighted sum of individual stages rather than a simple combination of efficiencies. Independently evaluating the two stages can identify the sources of inefficiency in the entire system (Kao and Hwang, 2008). Lei et al. (2015) extend efficiency decomposition to a parallel system in a two-stage network DEA method to measure the performance of nations in the Summer Olympic Games. A barrier of decomposition efficiency in a two-stage system appears because the individual stage's efficiency may not be unique given that model (8) may present multiple solutions. We can measure the optimal efficiency of one stage while maintaining the overall efficiency to solve this problem (Wu et al., 2016a).

If the overall system is efficient, then each stage must also be efficient. If the overall system is inefficient, then we can decompose the efficiency of the whole system into efficiencies for each stage (Lei et al., 2015). $E_{j_0}^*$ denotes the overall efficiency of DMU_0. EIR's maximum efficiency $e_{1j_0}^*$ can be measured while maintaining the overall efficiency $E_{j_0}^*$ as follows:

$$\text{Max } e_{1j_0}^* = \frac{\mu^{\mathrm{T}} Y_{j_0}^1 + \delta^{\mathrm{T}} Z_{j_0}}{\nu^{\mathrm{T}} X_{j_0}^1 + \pi^{\mathrm{T}} (\alpha_{j_0} K_{j_0})}$$

$$\textit{subject to} \quad \frac{\mu^{\mathrm{T}} Y_j^1 + \delta^{\mathrm{T}} Z_j}{\nu^{\mathrm{T}} X_j^1 + \pi^{\mathrm{T}} (\alpha_j K_j)} \leqslant 1,$$

$$\frac{\omega^{\mathrm{T}} Y_j^2 - \xi^{\mathrm{T}} F_j}{\rho^{\mathrm{T}} X_j^2 + \pi^{\mathrm{T}} (1 - \alpha_j) K_j + \delta^{\mathrm{T}} Z_j} \leqslant 1,$$

$$\frac{\mu^{\mathrm{T}} Y_{j_0}^1 + \delta^{\mathrm{T}} Z_{j_0} + \omega^{\mathrm{T}} Y_{j_0}^2 - \xi^{\mathrm{T}} F_{j_0}}{\nu^{\mathrm{T}} X_{j_0}^1 + \pi^{\mathrm{T}} K_{j_0} + \rho^{\mathrm{T}} X_{j_0}^2 + \delta^{\mathrm{T}} Z_{j_0}} = E_{j_0}^*,$$

$$L_j \leqslant \alpha_j \leqslant U_j,$$

$$\mu,\ \omega,\ \nu,\ \pi,\ \rho,\ \delta,\ \xi \geqslant 0. \tag{9}$$

Model (9) can be converted into the following program on the basis of the Charnes–Cooper transformation:

$$\text{Max } e_{1j_0}^* = \mu'^{\mathrm{T}} Y_{j_0}^1 + \delta'^{\mathrm{T}} Z_{j_0}$$

$$\textit{subject to} \quad \mu'^{\mathrm{T}} Y_j^1 + \delta'^{\mathrm{T}} Z_j - \nu'^{\mathrm{T}} X_j^1 - \gamma_j^{\mathrm{T}} K_j \leqslant 0,$$

$$\omega'^{\mathrm{T}} Y_j^2 - \xi'^{\mathrm{T}} F_j - \rho'^{\mathrm{T}} X_j^2 - \pi'^{\mathrm{T}} K_j + \gamma_j^{\mathrm{T}} K_j - \delta'^{\mathrm{T}} Z_j \leqslant 0,$$

$$\mu'^{\mathrm{T}} Y_{j_0}^1 + \delta'^{\mathrm{T}} Z_{j_0} + \omega'^{\mathrm{T}} Y_{j_0}^2 - \xi'^{\mathrm{T}} F_{j_0} = E_{j_0}^*,$$

$$\nu'^{\mathrm{T}} X_{j_0}^1 + \gamma_{j_0}^{\mathrm{T}} K_{j_0} = 1,$$

$$L_j \leqslant \alpha_j \leqslant U_j,$$

$$\mu',\ \omega',\ \nu',\ \pi',\ \rho',\ \delta',\ \xi' \geqslant 0. \tag{10}$$

According to Lei et al. (2015) and Wu et al. (2016a), the EIC's efficiency score for DMU_0 can be measured using $e'_{2j_0} = \frac{E_{j_0}^* - \lambda_1^* e_{1j_0}^*}{\lambda_2^*}$. Here, λ_1^* and λ_2^* are optimal weights based on model (10). However, the optimal value of e'_{2j_0} in this formula cannot be guaranteed. Therefore, we calculate the optimal efficiency of EIC as follows:

$$\text{Max } e_{2j_0}^* = \omega'^{\mathrm{T}} Y_{j_0}^2 - \xi'^{\mathrm{T}} F_{j_0}$$

$$\textit{subject to} \quad \mu'^{\mathrm{T}} Y_j^1 + \delta'^{\mathrm{T}} Z_j - \nu'^{\mathrm{T}} X_j^1 - \gamma_j^{\mathrm{T}} K_j \leqslant 0,$$

$$\omega'^{\mathrm{T}} Y_j^2 - \xi'^{\mathrm{T}} F_j - \rho'^{\mathrm{T}} X_j^2 - \pi'^{\mathrm{T}} K_j + \gamma_j^{\mathrm{T}} K_j - \delta'^{\mathrm{T}} Z_j \leqslant 0,$$

$$\mu'^{\mathrm{T}} Y_{j_0}^1 + \delta'^{\mathrm{T}} Z_{j_0} + \omega'^{\mathrm{T}} Y_{j_0}^2 - \xi'^{\mathrm{T}} F_{j_0} = E_{j_0}^*,$$

$$\rho'^{\mathrm{T}} X_{j_0}^2 + \pi'^{\mathrm{T}} K_{j_0} - \gamma_{j_0}^{\mathrm{T}} K_{j_0} + \delta'^{\mathrm{T}} Z_{j_0} = 1,$$

$$L_j \leqslant \alpha_j \leqslant U_j,$$

$$\mu',\ \omega',\ \nu',\ \pi',\ \rho',\ \delta',\ \xi' \geqslant 0. \tag{11}$$

We can obtain the EIC's optimal efficiency $e_{2j_0}^*$ while maintaining the optimal efficiency of the entire system by solving model (11). Similarly, we can calculate the EIR's efficiency score using $e'_{1j_0} = \frac{E_{j_0}^* - \lambda_2^* e_{2j_0}^*}{\lambda_1^*}$. If $e_{1j_0}^* = e'_{1j_0}$ and $e_{2j_0}^* = e'_{2j_0}$, then we obtain a unique result of efficiency decomposition.

3 Application

The impact of environmental innovation on environmental performance is investigated using the constructed framework with two stages and shared inputs by considering the inner mechanism of environmental innovation according to the data of 30 provincial-level administrative regions of China. Notably, Tibet, Taiwan, Hong Kong, and Macao are excluded from the analysis due to lacking data. The statistical information is obtained from the *China Statistical Yearbook on Science and Technology*, State Intellectual Property Office of China, *China Energy Statistical Yearbook*, *China Statistical Yearbook*, and *China Environment Yearbook*. Empirical data of variables covers the period from 2015 to 2019. Statistical descriptions of the dataset are listed in Table 1.

We use the two-stage network model for evaluating the efficiency of the environmental innovation system in China. The whole system in our model is divided into two subsystems: EIR and EIC. Multiple input–output variables should be available and appropriate in the empirical data to evaluate systems and their subsystems properly (Guan and Chen, 2010). Hence, we demonstrate the appropriateness and feasibility of input–output variables in this section.

As shown in Fig. 1, EIR's unique input is the expenditure on R&D and the output is new products and green patent applications. The R&D full-time equivalent is a type of shared input modeling labor used in both EIR and EIC. Expenditure on R&D and R&D full-time equivalent are selected to measure the economic and labor investments

Table 1 Statistical descriptions of the dataset

Variables		2015	2016	2017	2018	2019
Expenditure on R&D	Min	115842.70	139976.70	179108.60	172951.10	205680.10
	Max	18012271.00	20351439.90	23436283.20	27046969.00	30984890.00
	Mean	4722253.49	5224843.35	5867754.90	6558074.18	7379747.62
	SD	5182068.27	5778686.80	6492727.04	7234770.81	8117404.69
New products	Min	24.00	37.00	36.00	49.00	72.00
	Max	15127.00	22541.00	32392.00	38526.00	46263.00
	Mean	2571.93	3104.27	3795.80	4387.10	5223.87
	SD	3717.68	4865.39	6462.94	7550.92	8997.01
Green patent applications	Min	124.00	145.00	155.00	256.00	342.00
	Max	13554.00	15575.00	18693.00	28621.00	26176.00
	Mean	3282.57	3890.50	4175.03	5923.47	5534.67
	SD	3720.31	4292.47	4770.06	6901.04	6484.31
Electricity	Min	272.36	287.31	304.95	327.00	354.89
	Max	5310.69	5610.13	5958.97	6323.00	6695.85
	Mean	1896.42	1989.93	2118.90	2279.30	2413.60
	SD	1346.39	1433.11	1502.58	1604.27	1676.25
Labor	Min	321.41	324.28	326.97	329.26	330.20
	Max	6723.30	6726.39	6766.86	7132.99	7150.25
	Mean	2777.57	2766.12	2766.24	2770.74	2750.14
	SD	1809.62	1804.02	1801.15	1830.15	1812.12
R&D full-time equivalent	Min	4007.70	4165.60	5655.80	4301.10	5476.00
	Max	520302.50	543437.70	565287.30	762733.30	803207.80
	Mean	125257.25	129231.05	134411.64	145995.87	159967.29
	SD	135187.98	139860.03	148161.03	174246.07	189819.45
Gross domestic product (GDP)	Min	2417.05	2572.49	2624.83	2865.23	2965.95
	Max	72812.55	80854.91	89705.23	97277.77	107671.07
	Mean	24058.05	25963.95	28194.31	30440.99	32787.84
	SD	18046.47	19937.99	22025.35	23731.16	25774.58
Carbon emissions	Min	3647.83	4518.03	4231.69	6326.27	3953.70
	Max	105702.99	110811.29	110615.20	121494.22	125030.31
	Mean	34186.58	34440.09	35424.97	37264.38	37904.16
	SD	23181.53	23852.49	24527.65	26589.50	28425.38

in the EIR stage, respectively. The majority of R&D activities geared toward environmental innovation are indirectly market-oriented; hence, we define this variable as an intermediate output of EIR, which would be used in the EIC stage as an input. The innovation activity related to environmental improvement is analyzed in this study. However, specific statistical information on EIR is lacking. Therefore, we use expenditure on R&D, R&D full-time equivalent, and new products as appropriate proxies for environmental innovation. Our data for green patent applications are based on the green inventory defined by the World Intellectual Property Organization (WIPO). The input/output variables are defined as shown in Table 2.

Expenditure on R&D: This proxy for environmental innovation is the intramural expenditure on R&D of the provincial region (Chen et al., 2018) that refers to the actual internal expenditure of the R&D institution in the current year. Expenditure on R&D is a technological innovation indicator in China's high-technology industries at the provincial level (Guan and Chen, 2010). Expenditure on R&D is selected as the capital input of the EIR stage in this study.

New products: This proxy for environmental innovation is the number of new product projects with new technical principles, new design, and production, as specified in the relevant yearbook. R&D activities can be directly generated in the form of projects. A new product project begins as an idea and then proceeds to the steps of screening, project definition, and business analysis before finally completing product development (Pujari, 2006). The number of new products developed is the indicator of the output of science and technology (Tomkovick and Miller, 2000). We select this indicator to reflect the effect of R&D on economic development and achievements of basic and applied research in a provincial region.

Green patent applications: The number of patents is the suitable indicator for measuring invention output (Guan and Chen, 2012). Patents are also an input of science and technology resources needed in the conversion stage of technology innovation. However, the categorization of green patent application in China's patent classification system is unclear. Data on green patent applications are collected from the website of the State Intellectual Property Office of China and searched using the International Patent Classification (IPC) number related to "green technology" (Fujii and Managi, 2019). "Green technology" is an environmental technology selection standard corresponding to IPC (Cho and Sohn, 2018) that analyzes the field of green technology according to officially recognized number of invention and utility model patents. The corresponding relationship between the environmental technology field and IPC classification is established by comparing the technical field with the IPC classification number. The number of green patent applications in this study is selected as the indicator of an intermediate output.

R&D full-time equivalent: This measure refers to the total number of full-time and part-time personnel converted into full-time personnel according to workload (Li et al., 2020). The expenditure on R&D and R&D full-time equivalent inputs fully show the innovation strength and potential of a region, respectively, which comprehensively represent the regional innovation capacity. The two-stage environmental innovation of a provincial region, including both stages of technological innovation and application, is a continuous process; hence, the R&D full-time equivalent is split between the two stages. R&D full-time equivalent is treated as a shared input and the proportion of R&D full-time equivalent α_{j_0} is considered a parameter in this study. The R&D full-time equivalent portion $\alpha_{j_0}K_{j_0}$ is allocated to the EIR stage, and the remaining part $(1-\alpha_{j_0})K_{j_0}$ is assigned to the EIC stage.

Electricity: This basic indicator can quantitatively measure the electric power consumption at the provincial level. The annual electric power consumption of each provincial region is used to represent the energy input. Although energy consumption can promote economic growth by increasing productivity, it can also aggravate environmental damage by increasing pollutant emissions (Tiba and Omri, 2017). Developments in science and technology are transformed into economic and environmental benefits using resources, such as labor and energy, through the conversion of environmental innovation.

Table 2 Variables and definitions

Indicator	Variable	Units	Definition
Input in EIR	Expenditure on R&D	10000 yuan	Intramural expenditure on R&D by provincial region
Output in EIR	New products	Unit	Number of new product development projects
Intermediate output in EIR (Input in EIC)	Green patent applications	Piece	Number of green patent applications
Shared input	R&D full-time equivalent	Person-year	Total workload of full-time and part-time personnel
Input in EIC	Electricity	100 million kWh	Regional consumption of electricity
	Labor	10000 persons	Number of full-time employees of a specific region in China
Desirable outputs in EIC	GDP	100 million yuan	Gross domestic product
Undesirable outputs in EIC	Carbon emissions	10 thousand tons	Annual regional carbon emissions

Electric power is an efficient, clean, and convenient form of energy utilization and widely used in all aspects of economy and society. Therefore, electricity is selected as the energy input in the conversion stage of environmental innovation in this work.

Labor: Labor is the number of employed people in the population of the region. According to the yearbooks, the employed population refers to the people aged 16 or above who engage in certain social labor or business activities and obtain labor remuneration or business income. Hence, the number of employees in different regions is used as the input of labor in the EIC stage in this study.

Gross domestic product (GDP): The GDP is utilized to measure the value of all final products and services produced by each provincial region's economy in a year (Wu et al., 2010) and the optimal indicator for measuring the condition of a region's economy. Enhancing the regional environmental innovation capacity aims to increase the economic benefit and potential. Hence, GDP is chosen as the economic output of the EIC stage.

Carbon emissions: Carbon emission refers to the average greenhouse gas emissions produced in processes of production, transportation, utilization, and recovery, which is an undesirable output negatively correlated with the impact of innovation on the environment. On the basis of the carbon footprint model, the measurement of carbon emission is successfully used in Chang et al. (2013) and Wu et al. (2016b). We calculate carbon emissions from the consumption of fossil fuels according to guidelines from the International Panel on Climate Change (IPCC) for measuring carbon emission (Eq. (12)). We can use the consumption of fossil fuels of each provincial region over the years to calculate its carbon dioxide emissions. Accordingly, fossil fuels are divided into six categories: Coal, petrol, diesel, kerosene, fuel oil, and natural gas (Wu et al., 2020).

$$Carbon\ emissions = \sum_{i=1}^{n} (A \times CCF_i \times HE_i \times COF_i) \times \frac{44}{12}, \tag{12}$$

where A represents all fossil fuels, CCF is the carbon content factor, HE is the heat equivalent, and COF is the carbon oxidation factor of fossil fuels. Additional information on carbon emission factors is listed in Table 3. The subscript i represents different kinds of fossil fuels (Chang et al., 2013).

4 Results and analysis

Efficiencies of environmental innovation systems of 30 provincial-level regions in China are measured using our model. On the basis of Wu et al. (2016a), we set the bounds to $L_j = 0.25$ and $U_j = 0.75$ on the proportional use of the shared resource. Note that we have used different bounds (i.e., $L_j = 0.1$ and $U_j = 0.9$, $L_j = 0.2$ and $U_j = 0.8$) and further revealed that the results are insensitive to the bound setting. We then obtain the empirical results from 2015 to 2019 using these bounds in the model. Efficiencies of environmental innovation systems of different regions in 2019 are listed in Table 4. The $E_{j_0}^*$ column shows the overall efficiency of environmental innovation systems. $e_{1j_0}^*$ and $e_{2j_0}^*$ columns present the maximum efficiency scores of EIR and EIC subsystems, respectively, while maintaining the overall system efficiency $E_{j_0}^*$. α_{j_0} and $1-\alpha_{j_0}$ columns present the optimal proportions of a shared resource for the two stages. The last row shows the average efficiency scores and regional optimal proportions.

The following conclusions can be drawn from Table 4. First, Beijing, Inner Mongolia, Shanghai, Jiangxi, Fujian, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Yunnan, Qinghai, and Xinjiang are overall efficient in their environmental innovation systems. Therefore, each subsystem of these 15 regions is also efficient. Other regions, such as Hebei (0.7856), Zhejiang (0.7356), Gansu (0.6787), and Ningxia (0.7319), demonstrate low overall efficiency. The average overall environmental innovation efficiency is high at 0.9012, which indicated that China presents a relatively high overall environmental innovation efficiency although some regions need to improve their overall efficiency.

Second, 13 provinces (Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Shandong, Henan, Guizhou, Shaanxi, and Gansu) present low efficiency in the EIR subsystem while 3 provinces (Zhejiang, Gansu, and Ningxia) show low efficiency in the EIC subsystem. However, the average efficiencies of EIR and EIC stages are 0.8363 and 0.9208, respectively, while maintaining the overall efficiency. These results indicated that the EIC performs better than EIR in China's environmental innovation system.

Third, we consider the optimal proportion of the resource shared between EIR and EIC subsystems from the perspective of the optimal proportion of shared resources in the environmental innovation system. For

Table 3 Carbon emission factors of major fossil fuel types in China

Fossil fuels	Coal	Petrol	Kerosene	Diesel	Fuel oil	Natural gas
CCF	27.28	18.90	19.60	20.17	21.09	15.32
HE	192.14	448.00	447.50	433.30	401.90	0.38
COF (%)	92.3	98.0	98.6	98.2	98.5	99.0

Table 4 Efficiencies of environmental innovation systems of 30 Chinese provincial-level regions in 2019

Region	E^*_{j0}	e^*_{1j0}	e^*_{2j0}	α_{j0}	$1-\alpha_{j0}$
Beijing	0.9690	0.9095	1.0000	0.25	0.75
Tianjin	0.8368	0.8433	0.8334	0.57	0.43
Hebei	0.7856	0.7174	0.8015	0.53	0.47
Shanxi	0.8216	0.6152	0.8595	0.53	0.47
Inner Mongolia	1.0000	1.0000	1.0000	0.56	0.44
Liaoning	0.8453	0.6524	0.9011	0.53	0.47
Jilin	0.8521	0.6202	0.9003	0.57	0.43
Heilongjiang	0.8237	0.6000	0.8667	0.63	0.37
Shanghai	0.9935	0.9751	1.0000	0.53	0.47
Jiangsu	0.8044	0.6890	0.8858	0.51	0.49
Zhejiang	0.7356	0.6906	0.7787	0.35	0.65
Anhui	0.8087	0.6012	0.8799	0.34	0.66
Fujian	1.0000	1.0000	1.0000	0.51	0.49
Jiangxi	0.9530	0.9413	0.9610	0.38	0.62
Shandong	0.8457	0.6814	0.9082	0.48	0.52
Henan	0.8998	0.7714	0.9459	0.55	0.45
Hubei	0.9771	0.8602	1.0000	0.51	0.49
Hunan	0.9941	0.9672	1.0000	0.36	0.64
Guangdong	1.0000	1.0000	1.0000	0.26	0.74
Guangxi	0.9847	0.9538	1.0000	0.60	0.40
Hainan	1.0000	1.0000	1.0000	0.55	0.45
Chongqing	1.0000	1.0000	1.0000	0.26	0.74
Sichuan	1.0000	1.0000	1.0000	0.26	0.74
Guizhou	0.8613	0.7430	0.8828	0.61	0.39
Yunnan	1.0000	1.0000	1.0000	0.51	0.49
Shaanxi	0.8662	0.6308	0.9337	0.57	0.43
Gansu	0.6787	0.7829	0.6139	0.62	0.38
Qinghai	0.9679	1.0000	0.9616	0.61	0.39
Ningxia	0.7319	0.8424	0.7085	0.57	0.43
Xinjiang	1.0000	1.0000	1.0000	0.57	0.43
Average	**0.9012**	**0.8363**	**0.9208**	**0.49**	**0.51**

example, the optimal proportions of R&D full-time equivalent for EIR and EIC in Gansu are 0.62 and 0.38, respectively. Hence, Gansu should invest more of its shared input in EIR than EIC to achieve an optimal division of shared resources. The average optimal proportion of shared resources of 30 regions for EIR to consume is 0.49. We can conclude that the Chinese government should allocate more shared resources to EIC than EIR to improve the overall efficiency of the national environmental innovation system.

Figure 2 shows the overall efficiency of 30 Chinese regions from 2015 to 2019. Three regions (Chongqing, Guangdong, and Hainan) are at the frontier of environmental innovation efficiency. Chongqing and Guangdong present high economic strength and strong environmental technical foundations. The large investment of regional government and enterprises in human and innovation resources have attracted many innovative talents and businesses. Hainan demonstrates an excellent tourism industry and environmental quality. Moreover, Hainan has took the lead in building a sustainable ecological province in China since 1999. Although the overall efficiencies of the environmental innovation system in Beijing, Fujian, Guangxi, Hunan, Inner Mongolia, and Shanghai are less than 1, their values have reached a high level. The above mentioned nine regions need to play a demonstration role using their environmental technology advantages and actively help other regions with low innovation efficiency values to progress and improve the overall efficiency of the national environmental innovation system. Anhui, Gansu, Hebei, Ningxia, Shanxi, and Zhejiang present low overall efficiency values. These provinces should first expand their investment in environmental innovation resources to close the regional gap, strengthen their management, and use an optimal allocation of environmental innovation resources to improve their efficiency in utilizing environmental innovation resources.

As shown in Figs. 3 and 4, the environmental innovation efficiency of eleven provinces (Anhui, Gansu, Guizhou, Henan, Hebei, Heilongjiang, Liaoning, Shaanxi, Shandong, Shanxi, and Zhejiang) is low in the EIR subsystem while that of six provinces (Anhui, Gansu, Hebei, Ningxia, Shanxi, and Zhejiang) is low in the EIC subsystem. Anhui, Gansu, Hebei, Shanxi, and Zhejiang present low efficiencies in both EIR and EIC subsystems. For example, the poor scientific research infrastructure and insufficient government investment in Gansu directly lead to minimal environmental innovation achievements and a backward environmental industry. Although Zhejiang boasts of rich R&D resources and high economic strength, it has not achieved a corresponding level of efficiency in the environmental innovation system. Zhejiang is competitive in the fields of internet service, chemical industry, and medical and communication equipment. We can combine our own scientific research resource advantages with industrial competitiveness and vigorously develop the new energy industry under the background of carbon neutralization. Some provinces with low EIR efficiency (Guizhou, Henan, Shaanxi, and Shandong) demonstrate acceptable capacity for environmental innovation absorption and transformation, as reflected in their relatively high EIC score, although their independent EIR should be improved. These provinces can potentially optimize their absorption and transformation of environmental innovation achievements according to their capacity of independent EIC. However, their lack of independent R&D capability, as reflected in their low EIR score, is not conducive to improving the overall efficiency of their environmental

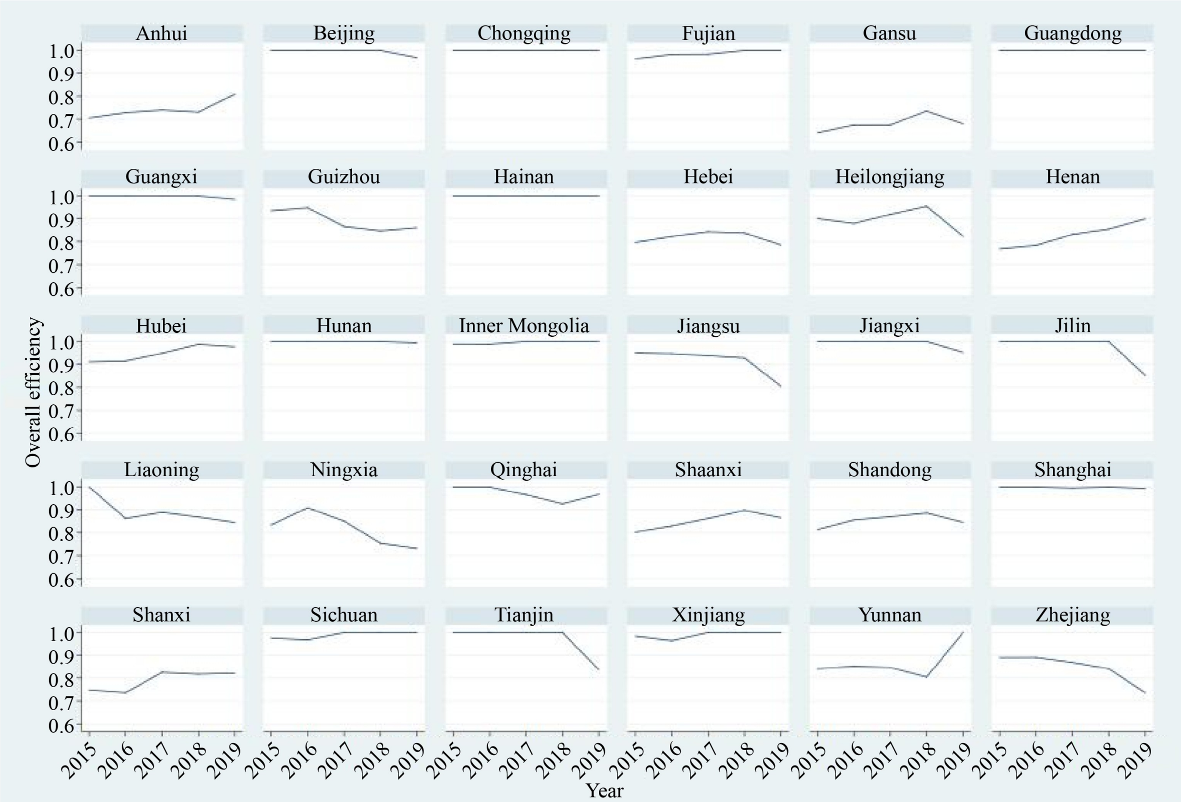

Fig. 2 Overall efficiency of 30 Chinese regions from 2015 to 2019.

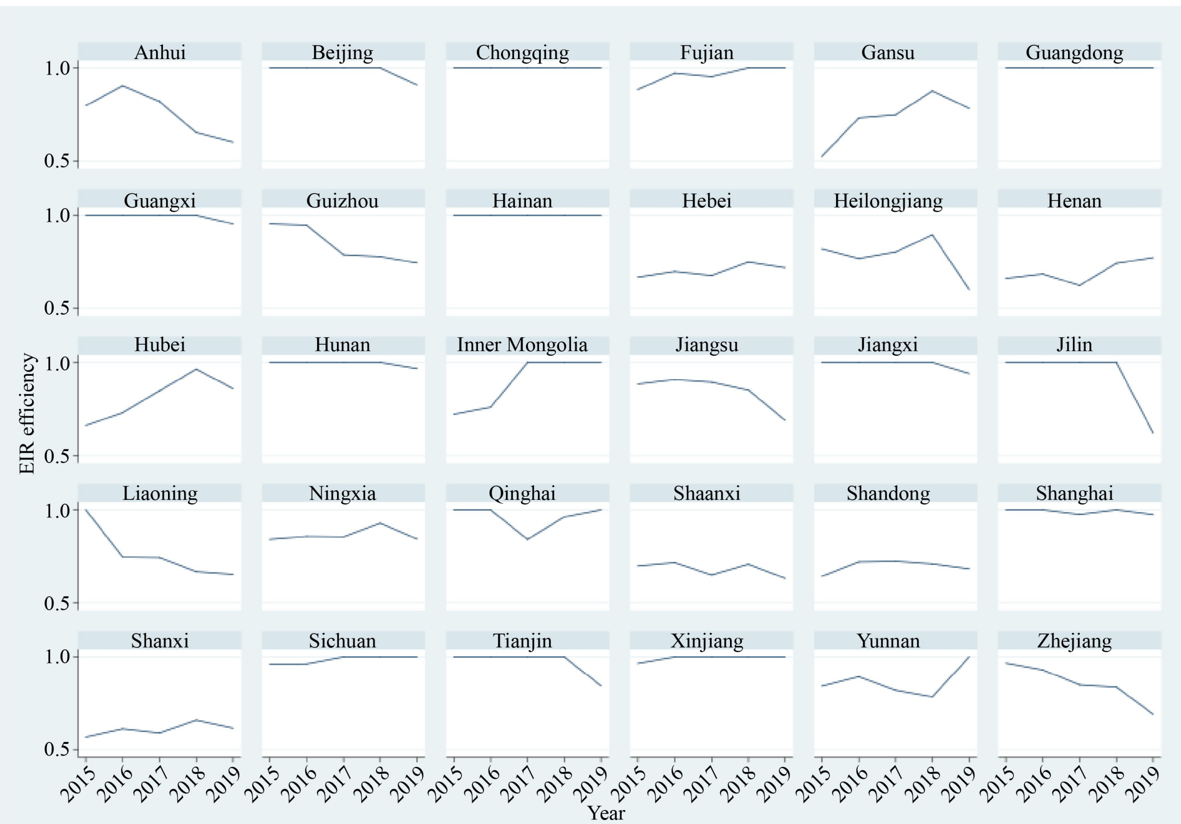

Fig. 3 EIR efficiency of 30 Chinese regions from 2015 to 2019.

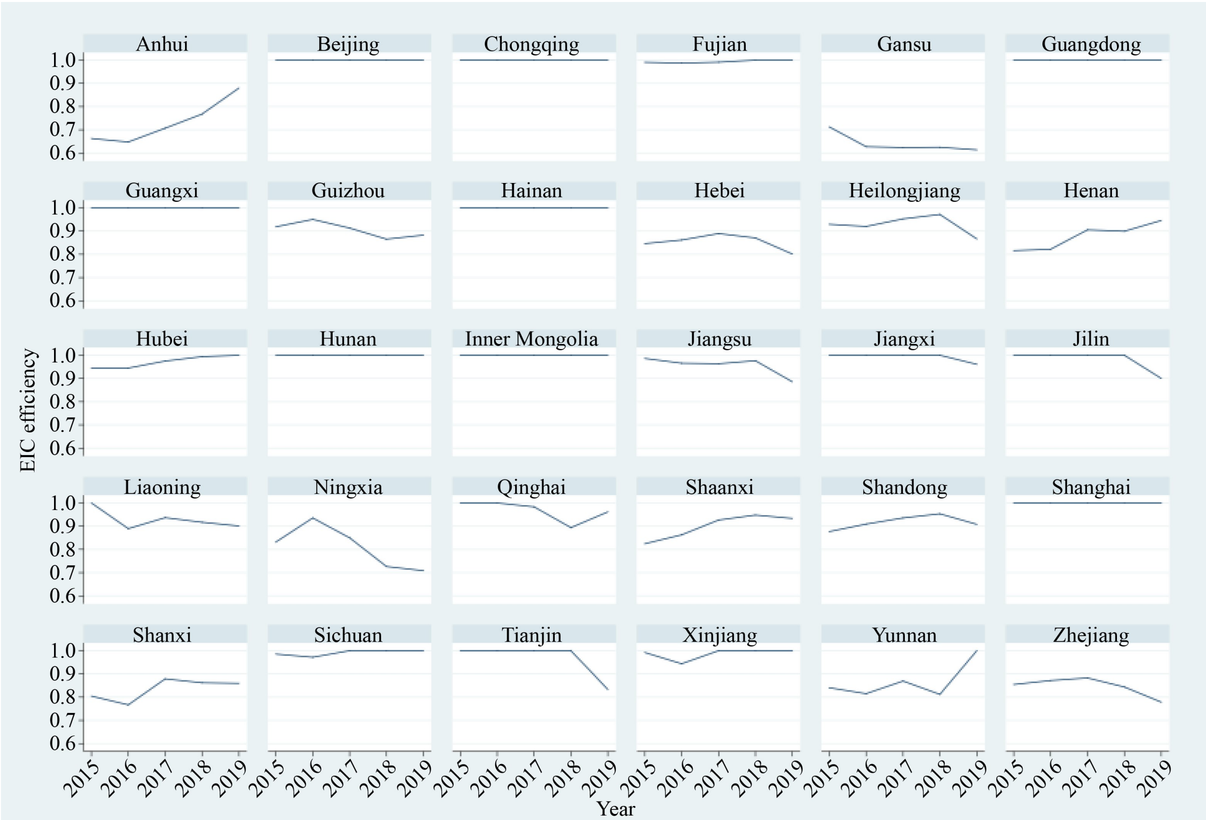

Fig. 4 EIC efficiency of 30 Chinese regions from 2015 to 2019.

innovation systems. Ningxia presents a low EIC efficiency and acceptable performance in EIR. However, its implementation of environmental innovation must be enhanced. On the one hand, Ningxia should increase investment support for the commercialization of environmental innovation achievements to enhance its capability to convert and absorb environmental technology. On the other hand, it should encourage the development of green economy industries, such as new energy, art, tourism, and environmental protection.

5 Conclusions and policy implications

Environmental protection has become a serious concern to society because of large emissions of industrial pollutants with the development of China's economy. The government formulates corresponding regulatory policies to address environmental pollution by promoting environmental protection and reducing emissions. Enterprises may choose to reduce production or implement green technology innovation measures to comply with environmental policies. However, production reduction will harm economic development. Hence, China can realize the win–win situation of economic development and environmental protection through environmental innovation. The efficiency of a region's environmental innovation system reflects its ability to create and transfer knowledge and deploy new products related to environmental protection.

5.1 Conclusions

The efficiency of environmental innovation systems is investigated at the Chinese provincial level in this study. A two-stage network DEA model with a shared resource is constructed on the basis of a two-stage system involved in environmental innovation. The proposed model measures the efficiencies of EIR and EIC subsystems. We empirically evaluate the environmental innovation system of 30 provincial-level administrative regions in China using the proposed model. The results indicated that China presents high overall environmental innovation efficiency. Although Chongqing and Guangdong demonstrate high economic strength and environmental technical foundation, they must use their advantages in environmental innovation and help other areas with low innovation efficiency to enhance the overall efficiency of the national environmental innovation system.

Some regions need to improve their overall environmental innovation system efficiency. Four provinces (Anhui, Gansu, Shaanxi, and Zhejiang) should expand investment in and strengthen the management of environmental innovation resources to improve the utilization of environmental innovation resources and enhance their low overall efficiency. Guizhou, Henan, Shaanxi, and Shandong show low EIR efficiency but demonstrate an acceptable capacity for EIC (i.e., with satisfactory EIC score). These provinces should enhance their independent R&D capability to improve their overall efficiency because their ability to perform independent innovation R&D is low (i.e., with low EIR score). Ningxia has low efficiency in the EIC subsystem, but performs better in the EIR subsystem, and the application of its environmental innovation achievements needs to be strengthened. It is necessary to increase investment support for the commercialization of environmental innovation achievements and develop green economy industries, such as new energy, art, tourism, and environmental protection.

5.2 Policy implications

The following suggestions are presented on the basis of the discussion in this study.

(1) Central and local governments should increase the investment in environmental innovation and promote environmental innovation R&D and conversion. However, relying on their own strength is difficult because a shortage of environmental innovation funds exists in some areas. The central government should increase the financial support for R&D and conversion of environmental innovation through financial allocation and environmental innovation awards. Local governments should prioritize projects related to environmental innovation and stop those that fail to meet environmental protection technical standards in time. We can accelerate the diffusion and absorption of environmental innovation among regions and promote the overall improvement on environmental innovation efficiency by dispatching and introducing environmental technological talents.

(2) We should improve the regional environmental innovation system and narrow the gap between regional environmental innovation ability. We should encourage scientific research institutions, colleges, universities, social organizations, and enterprises to become actively involved in the process of environmental innovation; build an environmental innovation network using a combination of production, study, and research; and establish an environmental innovation ecosystem in line with regional characteristics.

(3) Enterprises must be encouraged to increase their expenditure on environmental innovation R&D and conversion. First, the government should arrange the corresponding special funds and preferential tax policies to support environmental innovation R&D and conversion plans formulated by enterprises and alleviate the financing difficulties of enterprises. Second, central and local governments should actively build a cross-regional platform for environmental innovation investment and trading to guide the flow of social funds to enterprise environmental innovation R&D and conversion.

Note that we only consider the two basic aspects of social impact of environmental innovation, namely, economic development and environmental protection, while ignoring other factors in this study. We can expand the scope of research and establish an increasingly comprehensive evaluation framework by incorporating other aspects, such as social welfare and international trade. In addition, although the operational relationship between the two subsystems is discussed, this study ignores regional heterogeneity. These limitations of the proposed model may be regarded as the focus of future investigations.

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