Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
Article in press
https://doi.org/10.3846/tede.2022.17913

THE RECENT ECOLOGICAL EFFICIENCY DEVELOPMENT IN CHINA: INTERACTIVE SYSTEMS OF ECONOMY, SOCIETY AND ENVIRONMENT

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Received 29 August 2021; accepted 19 September 2022; first published online 15 November 2022

Abstract. Ecological efficiency (EE) provides much reference for formulating appropriate regional economic, social and environmental policies to promote sustainable development. Interactive subsystems of economy, society and environment within EE system have been considered in this paper. By innovatively integrating the merits of two advanced economic research methods (global super efficiency network data envelopment analysis (GSE-NDEA) and panel vector autoregression (PVAR) and updating the EE evaluation indicator system by following the new features of sustainable development in the recent China, this paper comprehensively evaluates EE by drawing evidence from 3 regions in China during the period of 2011–2020, and further reveals how the three subsystems within EE system interact to achieve EE enhancement. The findings show EE and its three subsystems' trend, the major constrains of EE development, the regional discrepancies in EE progress, and the interactions among the subsystems of economy-society-environment within the EE system in different regions of China. The policy implications are proposed accordingly.

Keywords: ecological efficiency (EE), economy-society-environment, interactive subsystems, regional development, global super efficiency network data envelopment analysis (GSE-NDEA), panel vector autoregression (PVAR).

JEL Classification: O11, O20, Q56, R11.

Introduction

In the past long time, the extensive growth mode has created a miracle of China's economic growth, but caused huge resource consumption and serious environmental contamination. The primary energy consumption in China has reached 151.21 EJ in 2020, accounting for

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nearly 1/3 of the total primary energy consumption in the world (BP, 2021), and its CO_2 emissions has taken up 41% of the world's cumulative emissions, exceeding the total emissions of the United States and the European Union (Global Carbon Project, 2021). In addition, China is experiencing a period of accelerated urbanization, which further intensifies the pressure of environmental pollution and energy consumption (Yang et al., 2021a). According to the 2018 global environmental performance index report, China ranked 120th among 180 countries (Wendling et al., 2018), and is one of the most polluted countries in the world. To this end, the Chinese government has to actively take governance measures to reduce environmental contamination and CO_2 emissions, and improve ecological efficiency (EE) (Sun & Loh, 2019). EE can reflect the relationship between economic/social development and environmental quality (Zameer et al., 2020), and has been used by international organizations and research institutions as a core index to evaluate the level of regional sustainable development (Li et al., 2017a). Therefore, an objective and scientific evaluation of China's EE level plays a significant role in achieving its goal of sustainable development.

EE was proposed in 1990, initially referring to the efficiency of using ecological resources to satisfy human-being's demands (Beltrán-Esteve et al., 2017). The organization for economic cooperation and development (OECD) defined EE as the ratio of input to output, and the higher EE level suggests that the human achieves more economic value with less resources (Sun & Loh, 2019). The World Business Council for Sustainable Development (WBCSD) has further improved the concept of EE and believed that it can be used to achieve a balance between the quality of human life and sustainable development (De Simone & Popoff, 1997). On the one hand, with the deepening of EE research, the concept of EE has been expanded, covering the essence of the overall development of economy, society and environment. However, most of the existing studies focused on evaluating EE only from the economic and environmental aspects (e.g. Wang & Chen, 2020; Chen et al., 2020), ignoring the impact of social development of EE, resulting in incomplete EE evaluation results. On the other hand, in order to achieve sustainable development, China has successively formulated strategies for ecological civilization construction, green development, low-carbon economy and carbon neutrality in recent years. Under the new situation, there is no doubt that EE in China has different characteristics from that before. The existing EE evaluation indicator system is not applicable for the development of the times. Thereby, it will have important theoretical value to improve the EE evaluation indicator system in combination with the new characteristics of the times development. Additionally, due to its vast territory and uneven distribution of resources, China's regional development is obviously different (Liang et al., 2016), resulting in distinguished EE development levels in different regions. Moreover, unsatisfied level of EE in different regions of China may be caused by different reasons, like overpopulation, unreasonable industrial structure or weak resource endowment. Hence, scientifically evaluating the development level and evolution trend of EE in different regions, and digging out the reasons for the unsatisfied level of EE in different regions, will have important practical significance for better formulating different regional EE promotion countermeasures and promoting the overall sustainable development in China. Finally, most of the existing studies statically analyzed the reasons for the blocked development of EE from a single subsystem of economy, society or environment, such as economic growth mode (Wang et al., 2020), urbanization development level (Yao et al., 2021), natural resource endowment (Wang & Chen, 2020), and put forward corresponding policy suggestions to improve EE. However, the existing research lacked consideration of the dynamic relationship between economic subsystem (EcS), social subsystem (SS) and environmental subsystem (EnS) within the EE system. It is easy to result in deviation in the implementation of relevant policies, and block the improvement of EE. For instance, China issued a new environmental protection law in 2015, expecting to improve the effect of environmental governance through strict environmental regulations, but it led to the weak economic development (Yang et al., 2021b), which is not conducive to the improvement of EE eventually. Consequently, it is necessary to further explore the relationship among the EcS, SS and EnS, so as to ensure the comprehensiveness of EE related policy design and better improve China's EE level. Accordingly, this study will explore the evaluation process of EE development level in China's different regions under the new situation of China's environment governance (2011–2020), understand the crux (weak subsystem) that restricts the development of EE in different regions of China, reveal how the EcS, SS and EnS interact within the EE system, and then design appropriate policy implications for the development of EE in China.

The remainder of the research is arranged as follows. Section 1 conducts a literature review, which lays theoretical foundation for this research. Section 2 shows the research design, paving the way for the empirical research later. Section 3 presents the empirical analysis, including the evaluation of EE and the efficiency of its three subsystems, and explication of the interaction of the three subsystems within the EE. Section 4 proposes the policy implications on the basis of empirical research to improve EE. Lastly, the section of conclusions makes a summary of the research findings, contributions, as well as the limitations.

1. Literature review

1.1. EE and its evaluation in China

German scholars Schaltegger and Sturm (1990) first proposed the concept of EE to promote the balance between environmental protection and economic development. With practice development, different international organizations and scholars have redefined and gradually enriched the connotation of EE, making it take into account the unity of the benefits of economy, society and environment (Yu et al., 2019a).

Within the EE system, the endless development of EcS and SS demands for EnS and the relatively stable supply of EnS has led to contradictions throughout the development process of EE (Liu et al., 2020). Firstly, EcS provides financial support (such as infrastructure investment) for the SS with its features of product production (Yang et al., 2021a). In turn, SS can give the necessary human resources to EcS. However, when economic development reaches saturation, social development may stagnate and accompany with massive social problems, like growing unemployment rate and prices (Duan et al., 2020). Secondly, EnS provides necessary natural conditions (e.g. land) for social development (He et al., 2017). Meanwhile, the development of SS can continuously enhance human environmental awareness (Zhang et al., 2014), then effectively achieving the improvement of environmental quality (Walsh et al., 2020; Xu & Hu, 2020). While, the SS may decline if it exceeds the carrying capacity of EnS.

The de-urbanization is a case in point (Yang et al., 2021a). Finally, EcS can provide enough economic support for the enhancement of EnS (Cheng et al., 2019), and a region with high-quality EnS is more likely to attract more investments for EcS (Tian et al., 2016). Obviously, in the development process of EcS, a amount of waste is inevitably discharged into EnS. There is much possibility for capital and human to quit the operations when EnS becomes worse, causing for the recession in EcS (Zhang et al., 2014). Generally, the improvement of EE means that regional economic, social and environmental development is more balanced (Sun & Loh, 2019), which is a effective tool to evaluate the degree of regional sustainable development (Li et al., 2017a; Beltrán-Esteve et al., 2017).

With the growing claims for sustainable development in China, the importance of EE has been widely recognized. Since the premise of improving EE requires an objective understanding of the development status of EE, so how to evaluate EE scientifically and accurately has aroused great concern of scholars (see Table 1). Seen from Table 1, ecological footprint (EF), life cycle assessment (LCA), entropy weight method (EWM) and data envelopment analysis (DEA) are the common research methods for EE evaluation. In fact, these methods have their pros and cons. In terms of EF, it is an analysis method based on static indicators, that is, assuming that the population, technology and material consumption levels are unchanged (Helmut, 2001), but in fact these indicators change with the development of time, which leads to the inaccurate EE evaluation. LCA is utilized to explore the activities of EE throughout the whole life cycle from the perspective of environmental influence, and resource consumption and occupancy, but the issues of research boundaries, functional unit definitions as well as quality control of data are subjectively determined (Reap et al., 2008), leading to uncertain and subjective results. Employing EWM to evaluate the comprehensive level of the system can screen important indicators to the greatest extent and objectively compress the evaluation system, but it may lead to the loss and overlap of indicators, making the evaluation results deviate from the reality and reduce the accuracy of the evaluation (Zhang et al., 2014). Comparatively, DEA, a non-parametric method holds the superiority of objectivity, convenience and universality, which is successfully employed in the field of EE evaluation (Wang et al., 2021a). It is capable to directly obtain the efficiency result of each decision-making unit (DMU) through multiple inputs and outputs (Wang et al., 2018a), and the weights of different indicators are derived on the basis of the optimal principle instead of a pre-hypothesis (Yu et al., 2019a), thus avoiding the influence of subjective preference. In addition, the specific form of the production function and the unit of data in the model are not strictly limited, which make it easier to operate (Mardani et al., 2017). Given of comparative advantages of DEA, it is adapted to evaluate EE in this paper.

In addition, it can be seen from Table 1 that scholars have evaluated the EE of different research samples in China according to research needs, including provinces, regions, cities, industries and sectors. These studies have indeed promoted the development of EE in China from different aspects. However, even for the latest EE evaluation study, its research periods have just been updated to 2017 (see Table 1), and the evaluation of China's provincial EE is even earlier. However, China has paid more attention to sustainable development and implemented a series of new measures from 2017. For example, in 2018, China restructured the its ministries and established the Ministry of Ecology and Environment to further strengthen

Table 1. The summary of EE related evaluation in China (part)

Authors	Scope	Period	Model
Bing et al. (2008)	30 provinces-China	2004	CCR-DEA
Teng and Wu (2014)	An exhibition hall in Wuhan-China	2012	LCA
Fan et al. (2017)	40 industrial parks-China	2012	MPI-DEA
Li et al. (2017b)	262 cities-China	2005–2012	SBM-DEA
Ren et al. (2018)	30 provinces-China	2000–2013	DDF-DEA
Zhou et al. (2018)	Guangdong province-China	2005–2014	SE-DEA
Yue et al. (2018a)	Yangtze River Economic Belt-China	2003–2014	EBM-DEA
Yue et al. (2018b)	273 cities-China	2003–2015	Undesirable SE-DEA
Xing et al. (2018)	26 economic sectors-China	2016	LCA & DEA
Lin and Zhu (2019)	114 cities-China	2005–2016	NDDF-DEA
Yu et al. (2019b)	191 cities-China	2003–2013	Meta-SBM-DEA
Yang and Yang (2019)	China	1978–2016	EF
Sun and Loh (2019)	30 provinces-China	1998–2015	Bootstrap-DEA
Wang et al. (2020)	13 cities in Jiangsu province-China	2007, 2012, 2017	Entropy-weighting TOPSIS method
Chen et al. (2020)	30 provinces-China	2002–2016	SE-DEA & Grey entropy weight method
Wang et al. (2021b)	29 provinces-China	2006–2015	EF

environmental protection from the top-level. In 2020, China put forward the major strategic decision to achieve carbon peak by 2030, and began to actively practice the strategy of low-carbon circular economy. All these undoubtedly show that the previous EE evaluation indicator system and research results are not appropriate for the new development anymore, and have to be improved to follow the demands of new times.

1.2. DEA model and its applications in EE

DEA has been paid booming attention since it was put forward by Charnes et al. (1978). After decades of continuous development, a series of improved DEA models, such as BCC model (Banker et al., 1984), fuzzy DEA model (Shermeh et al., 2016), stochastic DEA model (Sueyoshi, 2000), and network DEA model (Färe & Grosskopf, 2000) have been proposed successively. Noted that different models have different applied scope, and scholars selected, used and improved them according to research needs.

The earliest research on the application of DEA to EE evaluation can be traced back to Dyckhoff and Allen in 2001. They described the unique advantages of DEA in the study of EE (Dyckhoff & Allen, 2001). Subsequently, the research on EE based on DEA sharply increased. Most of the early studies regarded EE as a "black box" (i.e. only the input and output of the overall EE system were considered, and the interaction between EcS, SS and EnS within the EE system was not taken into account), then the traditional DEA model is used to evaluate EE (e.g. Picazo-Tadeo et al., 2011). Some scholars believed that the traditional DEA model is a radial model, which can not accurately reflect the invalidity of each indicator, and may also lead to inaccurate evaluation results (Adler & Volta, 2016; Roshdi et al., 2018). Therefore, the non-radial DEA models have been applied to EE evaluation (e.g. Chen & Delmas, 2012; Shen et al., 2020). Moreover, given the deficiency that the traditional DEA model can only divide DMUs into valid and invalid types, but cannot further distinguish valid DMUs. Some scholars used the super efficiency DEA (SE-DEA) model to evaluate the EE (e.g. Jiang & Tan, 2020). The salient idea of super efficiency DEA is that the evaluated DMU is removed from the reference set when measuring the efficiency result, which allows the effective DMU to have an efficiency greater than 1, and thus can realize the aim of further distinguishing valid DMUs (Song et al., 2022). Clearly, although the follow-up research has improved the accuracy of EE evaluation results by improving the traditional DEA model, it still regards EE as a "black box" in essence, which can not accurately reflect the connotation that EE takes into account the unity of economic, social and environmental performance. In order to solve this problems, some scholars began to use the NDEA model to study EE. For example, Hampf (2014) divided EE into two subsystems: economic production and terminal pollution control, and evaluated EE of 23 thermal power plants in the United States using NDEA model. Similar network structures were subsequently employed in EE studies in the semiconductor industry (Lin et al., 2019) and the industrial sector (Wang et al., 2021a). However, the EE evaluation under the above network structure only focuses on EcS and EnS, ignoring the important role played by SS in EE. To our best knowledge, only Yu et al. (2019a), Boussemart et al. (2020) and Shen et al. (2022) have taken into account EcS, SS and EnS in measuring EE or sustainable development level. Although the latter two built the indicator system from the three subsystems, they do not consider the interaction between different subsystems. Namely, they implied that the impact of the three subsystems is one-way, which is inconsistent with the reality. Although the research of Yu et al. (2019a) has taken into account the interaction between EcS, SS and EnS, there are still some deficiencies as follows: first, the adopted NDEA model in their study is only applicable to the horizontal comparison of regional differences of EE in a certain year (Wang & He, 2017; Ding et al., 2020), and it is unable to explore the changes of EE over time in different regions. Second, their study selected 23 evaluation indicators in the case of only 30 DMUs. Too many indicators will have an adverse impact on the evaluation results (Ruggiero, 2005; Han et al., 2015). If the efficiency of many DMUs is 1, they cannot be fully ranked. As mentioned above, the latter problem can be solved by the super efficiency DEA. As for the former, a common solution is to adopt the global technology put forward by Pastor and Lovell (2005). Since the production frontier based on global technology represents the best level of production for all periods, the resulting efficiency scores of different periods are comparable (Xu et al., 2021).

To meet the above challenges about EE research, the paper will evaluate the EE of 30 Chinese provinces by proposing a global super efficiency network DEA model (GSE-NDEA). In our proposed model, NDEA takes the interactions of EcS, SS and EnS of EE into account. And the idea of global technology makes the obtained efficiencies of different periods comparable. Meanwhile, the idea of global technology indirectly expands the number of DMUs, which is helpful to alleviate the adverse impact of excessive indicators on efficiency scores. Additionally, the idea of super efficiency model can achieve the full ranking for all DMUs.

1.3. Panel vector autoregression (PVAR) model and its applications

As outlined in section 2.1 the interaction between the three subsystems of EE is usually complex, dynamic, and non-linear. If only one subsystem is regulated without considering the dynamic relationship between it and other subsystems, it is likely to fall into the dilemma of fragmented governance, which may form a cycle of high investment but poor performance of EE. For example, the extensive economic development policies has result in serious environmental pollution, a wide gap between the rich and the poor, and fierce social contradictions (Duan et al., 2020). Moreover, relying only on strict environmental laws for environmental protection will hinder economic and social development (Yang et al., 2021b). Thereby, determining how the three subsystems interact with each will help to the decision makers better design the more comprehensive strategies to promote the improvement of EE. Although the GSE-NDEA model has indeed more accurately evaluated EE by considering the interaction between EcS, SS and EnS, it has not yet clarified how the three interact. The PVAR model is thus borrowed to fill up the problem in this paper since it has the merits in exploring the complex, dynamic and non-linear interactions of multiple systems (Abrigo & Love, 2016).

The PVAR model can be used to explore the dynamic influence of random variables on specific variables (Alsaedi & Tularam, 2020). It can support the panel data, and the individual heterogeneity is also taken into consideration (Wu et al., 2020). Additionally, data volume and data format are not strictly required in PVAR model (Jawadi et al., 2016). Because of China's vast territory and huge differences in natural resource endowments, the PVAR model can control the unobservable individual consistency caused by regional differences, which can make the model estimation results more accurate and reliable. In fact, the final effects of PVAR modeling is almost similar with multivariable regression equations (Tang et al., 2022), but it is more easy-operative than the multivariable regression equations (Acheampong, 2018; Kuang et al., 2020).

In view of the above advantages of PVAR model, it is often used to recognize the complex relationship among multiple systems (e.g. Shen & Li, 2020; Berdiev & Saunoris, 2016). This paper mainly uses the PVAR model to further reveal the interaction between EcS, SS and EnS within the EE system, so as to design a series of comprehensive EE promotion policies. As a result, the variables in the PVAR model of this paper are EcS, SS and EnS. Integrating the strengths of GSE-NDEA model and PVAR model can solve the problem of low efficiency of resources utilization, caused by inefficient management of the three-subsystem network structure (Gharaei et al., 2019), providing a new perspective and methodology for the exploration the in-depth causes of the unsatisfied EE.

2. Research design

2.1. Research scope and data resource

China can be divided into three main regions by convention: the east, the inner, and the west (Piao et al., 2019), which are shown in Figure 1. Owing to the data lacked, Tibet, Hong Kong, Taiwan and Macau did not be included, thus there are 30 provinces in this research.

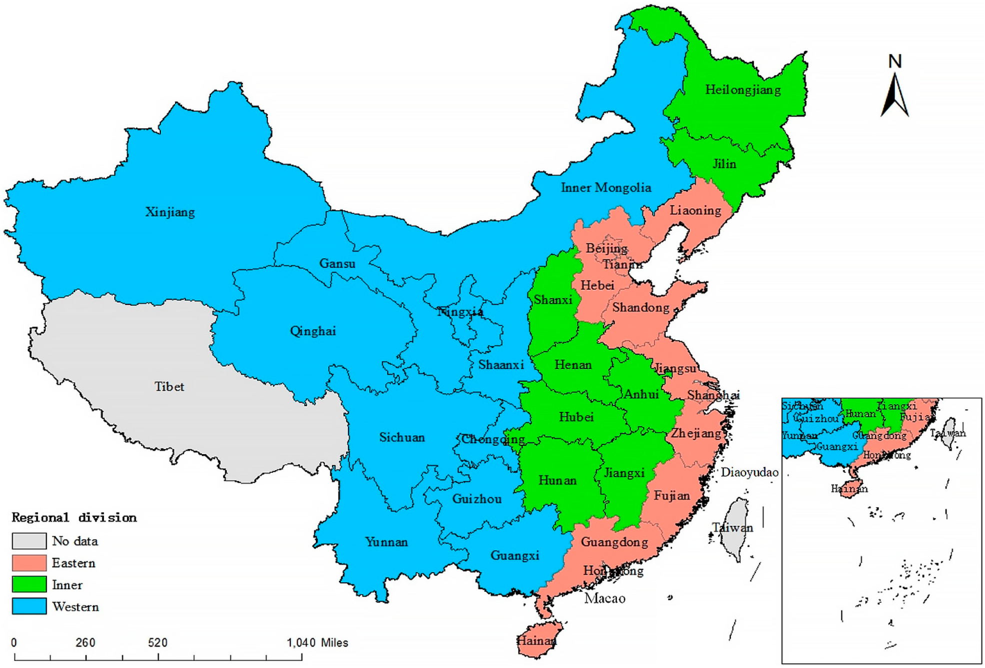


Figure 1. Three major regions of China

This study collected data from the year of 2011 to 2020. This periods is the implementation stage of China's environmental protection plan from the 12th Five Year Plan (2011–2015) to the 13th Five Year Plan (2016–2020). Under the new planning, China has introduced many new measures to promote sustainable development, mainly including resource cycle, pollution and carbon reduction, green development, etc. For example, in 2013, Shenzhen launched the first pilot of carbon emission trading rights, which is one of the symbols of China's in-depth implementation of energy conservation, emission reduction, pollution reduction and carbon reduction strategies. In 2015, the 18th CPC Central Committee formally proposed the concept of green development. In 2018, the construction of ecological civilization was officially incorporated into the constitution of China. Studying the development level of EE during the new period can reflect the latest characteristics of China's sustainable development, help to improve the relevant results of the existing EE evaluation research, and provide support for designing EE promotion policies that are more adaptable to the characteristics of the new times.

Owing to the lag feature of statistical yearbook, all the data was extracted from *China Energy Statistical Yearbook* (2012–2021), *China Statistical Yearbook* (2012–2021), *China Industry Statistical Yearbook* (2012–2021), *China Statistical Yearbook on Science and Technology* (2012–2021), *China Statistics Yearbook on Environment* (2012–2021), *China Civil Affairs' Statistical Yearbook* (2012–2021) and *Statistical Communique on the National Economic and Social Development* (2012–2021) of each province. The methods of average annual growth rate and interpolation are employed to estimate the missing data.

2.2. Indicator selection for EE system

According to the previous experience (Liu et al., 2011), the research selects the indicators of EcS, SS and EnS by following the principles of representativeness, availability, adaptability and systematization. To meet the principle of the representativeness, the most cited indicators in this field are selected. To meet the principle of the availability, the easily collecting and understanding indicators are selected. To meet the principle of the adaptability, the indicators in line with relevant policies of EE are selected. As one of the research purposes of this paper is to improve the existing EE evaluation indicator system on the basis of the new characteristics of China's sustainable development, the indicator selection needs to be based on the EE related policies in the latest periods. To meet the principle of the systematization, the selected indicators should cover the significant sectors of the EE system. Eventually, the following indicators were selected to evaluate the EE (see Figure 2), and their introduction is shown in Table 2.

(a) For the external input indicator of this subsystem, TEC can reflect the energy consumption status of a region in the process of economic development. It directly reflects the status of industrial structure, equipment and technical level and efficiency of energy utilization, and indirectly reflects the effect of various energy-saving policies issued by China after the 12th Five Year Plan (Wang et al., 2020). Additionally, in recent years, China has repeatedly stressed the need to optimize the investment structure to build a green low-carbon circular economy system. For example, the State Council issued *the Notice on Adjusting and Improving the Capital System for Fixed Asset Investment Projects* in 2015. It can be seen that TFAI can show the efforts of the Chinese government to promote the overall economic, social and environmental development by optimizing the investment structure of fixed assets and increasing effective investment (Rashidi & Saen, 2015). So it is also taken as the external input indicator of EcS. PETI is the internal input indicator from SS to EcS. It enables to show the transformation degree of economic structure and social activities to sustainable development (Cheng et al., 2019).

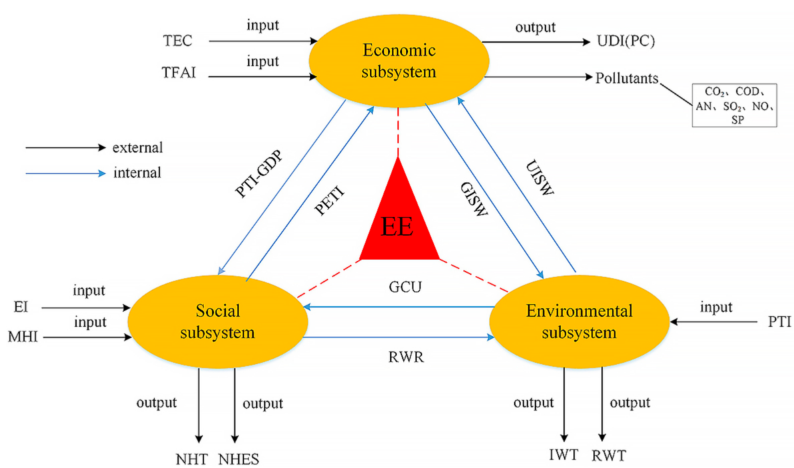


Figure 2. Indicator selection

Table 2. The introduction of EE's indicators

Input			Output		
Economic subsystem					
External	TEC	Total Energy consumption	External	UDI (PC)	Disposable income of urban residents (per capita)
	TFAI	Total fixed asset investment		CO_2	Carbon dioxide emissions
Internal	PETI	Proportion of employees in the tertiary industry		COD	Chemical Oxygen demand emissions
	UISW	The utilization amount of industrial solid waste		AN	Ammonia Nitrogen emissions
				SO_2	Sulphur dioxide emissions
				NO	Nitrogen Oxide emissions
				SP	Particulate matter emissions
				PTI-GDP	Proportion of added value of tertiary industry in gross domestic product
			Internal	GISW	The generation amount of industrial solid waste
Social subsystem					
External	EI	Education investment	External	NHES	Number of higher education students
	MHI	Medical and health investment		NHT	Number of health technicians
Internal	PTI-GDP	Proportion of added value of tertiary industry in gross domestic product	Internal	PETI	Proportion of employees in the tertiary industry
	GCU	Green coverage rate of urban built-up area (%)		RWR	Residential waste removal amount
Environmental subsystem					
External	PTI	Pollutant treatment investment	External	IWT	Industrial solid waste treated
Internal	GISW	The generation amount of industrial solid waste		RWT	Residential waste treated
			Internal	GCU	Green coverage rate of urban built-up area (%)
				UISW	The utilization amount of industrial solid waste

For the external output indicators of EcS, UDI (PC) is one of the main indicators to reflect the results of economic development, so it is included in this study. CO_2, COD, AN, SO_2, NO and SP are inevitable pollutants in economic production activities. In this study, they are regarded as undesirable output (external output) indicators in economic production activities to show China's efforts in reducing pollution and carbon in recent years. The PTI-GDP of each province is selected as the internal output indicator of EcS flowing into SS, because it is not only a significant indicator to evaluate the status of economic green development (Wang et al., 2018b), but also reflects the added value of products and services in economic activities (Sun & Loh, 2019). The internal indicators of EcS and EnS are explained in detail below.

(b) To fully reflect the connotation of SS and consider the data availability, the indicators are selected from the important aspects closely related to people's lives: education and medical care. Accordingly, SS includes 2 external input indicators, including EI and MHI, and 2 external output indicators: NHT and NHES. As for the internal indicators of SS, the internal indicators between SS and EcS have been described in detail above and will not be repeated here. The internal indicators of SS and EnS will be supplemented below.

(c) The external input indicator of the system is PTI, which can reflect the investment degree of a region in EnS activities (Yu et al., 2019a). In consideration of the systematization and representativeness of the data, RWT and IWT are selected as the embodiment of EnS governance effectiveness (external output) from the two levels of industrial production and residents' lives, which is in line with the characteristics of resource reuse advocated by Chinese government. In the process of economic production, it is inevitable to produce solid waste and flow into EnS. Therefore, this paper selects GISW as the internal input indicator flowing from EcS to EnS. In order to make the input and output indicators coordinated, this paper selects UISW as the internal output indicator of EnS flowing into EcS. It is because EnS will return the resources that can be reused to EcS to bring greater economic benefits, which is one of the connotations of sustainable development. UISW represents the reuse of waste resources (Yang et al., 2021a), which can effectively reflect the effect of China's active resource conservation and circular economy policies after the 12^{th} Five Year Plan. Good social administration can bring benefits to EnS. As a result, RWR is selected as the internal input indicator of SS flowing into EnS in this study. As for the internal output indicator of EnS flowing into SS, it means that the enhancement of environmental governance enables to enhance people's quality of life. GCU can well reflect this feature and is a representative indicator in this field (Cheng et al., 2019), so this study chose it.

The existed studies showed that the more the number of indicators, the more vulnerable the model results are (Li et al., 2017b). To this end, the entropy weight method is used in this study to emerge the undesirable outputs (CO_2, COD, AN, SO_2, NO, SP) together. Therefore, this paper selects 17 indicators in total to evaluate EE.

2.3. Modeling

The steps to construct the GSE-NDEA and PVAR models are discussed in detail below.

2.3.1. GSE-NDEA model

To facilitate modeling, the three interactive subsystems of economy, society and environment under the EE in Figure 2 can be simplified into the network structure shown in Figure 3. Assuming that the three subsystems can be expressed as p (p = 1,2,3), the external input indicator of the subsystem of the j^{th} DMU is expressed as $x_{ij}^{p}(i=1,\ldots,m;p=1,2,3)$, and the external output indicator is divided into two parts: the desirable output $\left(y_{rj}^{p}(r=1,\ldots,s;p=1,2,3)\right)$ and the undesirable output $\left(c_{dj}^{p}(d=1,\ldots,D;p=1,2,3)\right)$. In addition, there is a internal indicator Z between different subsystems, where $z_{hj}^{k,p}(h=1,\ldots,H;k=1,2,3;p=1,2,3)$ represents the h^{th} internal indicator from subsystem k to subsystem p, which is both the output of subsystem k and the input of subsystem p.

As mentioned in Section 2.2, the traditional DEA model only takes the initial input and final output into account, ignoring the connections between different internal subsystems. At this time, the EE can be obtained through model (1):

$$\begin{aligned}
&E^{b}=\min\frac{(\phi+\varphi)}{2}\\
&\text{s.t.}\\
&\quad \textstyle\sum_{j=1}^{n}\lambda_j x_{ij}^{p}\le \phi x_{i0}^{p}\quad (i=1,\ldots,m;p=1,2,3),\\
&\quad \textstyle\sum_{j=1}^{n}\lambda_j y_{rj}^{p}\ge y_{r0}^{p}\quad (r=1,\ldots,s;p=1,2,3),\\
&\quad \textstyle\sum_{j=1}^{n}\lambda_j c_{dj}^{p}= \varphi c_{d0}^{p}\quad (d=1,\ldots,D;p=1,2,3),\\
&\quad \textstyle\sum_{j=1}^{n}\lambda_j=1,\\
&\quad \lambda_j\ge 0, 0\le\phi\le 1, 0\le\varphi\le 1, \forall j.
\end{aligned} \tag{1}$$

In model (1), λ_j indicates the role of the j^{th} DMU in the formation of production frontier (Bostian et al., 2018). Where, ($\sum_{j=1}^{n}\lambda_j x_{ij}^{p}$, $\sum_{j=1}^{n}\lambda_j y_{rj}^{p}$, $\sum_{j=1}^{n}\lambda_j c_{dj}^{p}$) constitute a group of

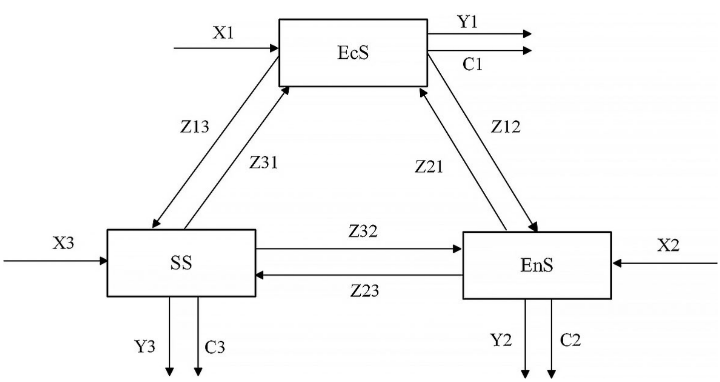


Figure 3. The network structure of EcS, SS and EnS

virtual optimal DMUs (Chen et al., 2022). Apparently, compared with the evaluated DMU_0 on the right side of the constraints, the optimal DMU consumes less inputs, produces more desirable outputs, and emits fewer undesirable outputs. The key idea of DEA model is to explore the gap between the evaluated DMU and the optimal DMU, which can be measured from the two dimensions of input and output. Given that decision makers have greater control over input than output (Vaezi et al., 2021), this paper selects the input-oriented model for efficiency solution. Variable ϕ indicates the potential reduction degree of input indicator. Additionally, we also allow for the potential reduction of undesirable output, denoting as φ. When $\phi = \varphi = 1$, it indicates that the evaluated DMU_0 is equivalent to the optimal DMU, indicating that it is effective. Otherwise, the evaluated DMU_0 is ineffective. It should be pointed out that the model uses equality constraints to deal with undesirable outputs, which reflects the weak disposability (Färe et al., 1989), which is one of the mainstream methods for modeling undesirable output in DEA (Adler & Volta, 2016; Chen et al., 2021b). Equality constraint $\sum_{j=1}^{n}\lambda_j = 1$ indicates that the assumption of variable return to scale is employed in the model, which can better reflect the situation that there are significant differences in resource endowments, technological level and so on in different regions of China.

Model (1) ignores the internal structure of EE and potential conflicts of the internal indicator (Z) between subsystems (Ma et al., 2018; Hatami-Marbini & Saati, 2020). Specifically, the internal indicator often has a dual role, which is both the output of the former subsystem and the input of the latter subsystem. To maximize efficiency result, the former subsystem hopes that the more internal indicator the better, while the latter subsystem hopes that the less internal indicator the better. In order to solve the above dilemma, a great part of scholars measure the efficiency of DMU from the perspective of network. Referring to Sun et al. (2019) and Pereira et al. (2021), the NDEA model under the above economic, social and environmental interaction can be expressed as:

$$\begin{aligned}
& E^n = w^p * E^p = \min w^p * \left(\frac{1}{m+D}\left(\sum_{i=1}^{m}\phi_i^p + \sum_{d=1}^{D}\varphi_d^p\right)\right) \\
& \text{s.t.} \\
& \quad \sum_{j=1}^{n}\lambda_j^p x_{ij}^p \le \phi_i^p x_{i0}^p && (i=1,\dots,m; p=1,2,3), \\
& \quad \sum_{j=1}^{n}\lambda_j^p y_{rj}^p \ge y_{r0}^p && (r=1,\dots,s; p=1,2,3), \\
& \quad \sum_{j=1}^{n}\lambda_j^p c_{dj}^p = \varphi_d^p c_{d0}^p && (d=1,\dots,D; p=1,2,3), \\
& \quad \sum_{j=1}^{n}\lambda_j^k z_{hj}^{k,p} = \sum_{j=1}^{n}\lambda_j^p z_{hj}^{k,p} && (h=1,\dots,H; k=1,2,3; p=1,2,3), \\
& \quad \sum_{j=1}^{n}\lambda_j^p = 1, && \forall p, \\
& \quad \lambda_j^p \ge 0, \lambda_j^k \ge 0, 0 \le \phi_i^p \le 1, 0 \le \varphi_d^p \le 1, \quad \forall j,k,p,i,d.
\end{aligned} \tag{2}$$

Different from model (1), model (2) introduces three different intensity vectors $\left(\lambda_j^p, p=1,2,3\right)$, corresponding to three subsystems respectively. In addition, model (2) considers the characteristics of internal indicator $\left(z_{hj}^{k,p}\right)$. In model, the idea of free-links from Tone and Tsutsui (2009) is adopted, indicating that the optimal value of the internal indicator can be determined by maximizing the overall efficiency result of the system. Moreover, model (2) allows different inputs and undesirable outputs to be reduced by different proportions.

Thus, it can be regarded as a non-radial DEA model, which is more in line with the reality (Zhou et al., 2007; Cui & Li, 2018). Another difference from model (1) is that the objective function of model (2) simultaneously considers the reduction of input and undesirable output of the three subsystems, and the importance of different subsystems can be reflected by weight w^p. The meaning of other constraints is similar to that of model (1), which will not be repeated here. Only when $E^n = 1$, the DMU has reached the optimal level where the input and undesirable output do not need to improve, and vice versa. Although the model (2) considers the different subsystems of EE, in order to accurately describe the functions of each subsystem, the network DEA model often contains many input-output indicators, which may cause the dilemma that the efficiency result of many DMUs' value is 1, and it is impossible to fully rank all DMUs. Therefore, the super efficiency idea of Anderson and Petersen (1993) is introduced into the above network DEA model.

$$
\begin{aligned}
& E^{sn} = \min w^{p} * \left(\frac{1}{m+D}\left(\sum_{i=1}^{m}\phi_i^p + \sum_{d=1}^{D}\varphi_d^p\right)\right) \\
& \text{s.t.} \\
& \quad \sum_{j=1,\neq 0}^{n}\lambda_j^p x_{ij}^p \le \phi_i^p x_{i0}^p \qquad (i=1,\ldots,m; p=1,2,3), \\
& \quad \sum_{j=1,\neq 0}^{n}\lambda_j^p y_{rj}^p \ge y_{r0}^p \qquad (r=1,\ldots,s; p=1,2,3), \\
& \quad \sum_{j=1,\neq 0}^{n}\lambda_j^p c_{dj}^p \le \varphi_d^p c_{d0}^p \qquad (d=1,\ldots,D; p=1,2,3), \\
& \quad \sum_{j=1,\neq 0}^{n}\lambda_j^k z_{hj}^{k,p} = \sum_{j=1,\neq 0}^{n}\lambda_j^p z_{hj}^{k,p} \qquad (h=1,\ldots,H; k=1,2,3; p=1,2,3), \\
& \quad \sum_{j=1,\neq 0}^{n}\lambda_j^p = 1, \quad \forall p \\
& \quad \lambda_j^p \ge 0, \lambda_j^k \ge 0, 0 \le \phi_i^p \le 1, 0 \le \varphi_d^p \le 1, \quad \forall j,k,p,i,d.
\end{aligned} \tag{3}
$$

Different from the model (2), the evaluated DMU_0 is excluded from the production frontier in model (3), which can be seen from the left of the constraints. In this way, the efficiency score of effective DMU is allowed to be greater than 1, so that all DMUs can be fully ranked. In fact, the super efficiency DEA model under the network structure has been proposed by some scholars, such as the series two-stage super efficiency DEA model (Golshani et al., 2019), the series three-stage super efficiency DEA model (Chen et al., 2021a), the hybrid network DEA model including both series and parallel structures (Wang & Feng, 2020) and so on. However, the idea of super efficiency has not been incorporated into the three-stage network structure including interaction. This paper makes up for this deficiency.

In addition, the traditional/classical DEA model is mainly used to evaluate the performance of different DMUs in a certain year. The efficiency result of the same DMU in different years is not comparable (Choi et al., 2012). However, the change of DMU efficiency over time is often one of the focuses of decision makers. In order to achieve the efficiency comparability over research period, Pastor and Lovell (2005) proposed global technology by incorporating DMU of different periods into the construction of production frontier. Similar treatment has been adopted by many researches, such as Sueyoshi and Yuan (2017) and Kourtzidis et al. (2021). The global super efficiency network DEA model considering the interaction between subsystems can be constructed as follow:

$$
\begin{aligned}
& E^{gsn} = \min w^{t,p} * (\frac{1}{m+D}(\sum_{i=1}^{m}\phi_i^{t,p} + \sum_{t=1}^{T}\varphi_d^{t,p})) \\
& s.t. \\
& \quad \sum_{t=1}^{T}\sum_{j=1,\neq 0}^{n}\lambda_j^{t,p}x_{ij}^{t,p} \le \phi_i^{t,p}x_{i0}^{t,p} \qquad (i=1,...,m; p=1,2,3; t=1,...,T), \\
& \quad \sum_{t=1}^{T}\sum_{j=1,\neq 0}^{n}\lambda_j^{t,p}y_{rj}^{t,p} \ge y_{r0}^{t,p} \qquad (r=1,...,s; p=1,2,3; t=1,...,T), \\
& \quad \sum_{t=1}^{T}\sum_{j=1,\neq 0}^{n}\lambda_j^{t,p}c_{dj}^{t,p} \le \varphi_t^{t,p}c_{d0}^{t,p} \qquad (d=1,...,D; p=1,2,3; t=1,...,T), \\
& \quad \sum_{t=1}^{T}\sum_{j=1,\neq 0}^{n}\lambda_j^{t,k}z_{hj}^{t,k,p} = \sum_{j=1,\neq 0}^{n}\lambda_j^{t,p}z_{hj}^{t,k,p} \quad (h=1,...,H; k=1,2,3; p=1,2,3; t=1,...,T), \\
& \quad \sum_{t=1}^{T}\sum_{j=1,\neq 0}^{n}\lambda_j^{t,p} = 1, \quad \forall p,t \\
& \quad \lambda_j^{t,p} \ge 0, \lambda_j^{t,k} \ge 0, 0 \le \phi_i^{t,p} \le 1, 0 \le \varphi_d^{t,p} \le 1, \ \forall j,k,p,i,d,t.
\end{aligned}
\tag{4}
$$

Model (4) considers the time dimension on the basis of model (3), which can achieve the purpose of efficiency comparability during the research period. It is easy to find that, compared with the horizontal comparison between DMUs, the DEA model under global technology indirectly increasing the number of DMUs, which can alleviate the adverse impact of too many indicators to a certain extent.

2.3.2. PVAR model

In order to identify how the three subsystems interact, the PVAR model is presented as follows (Holtz-Eakin et al., 1988):

$$
Y_{it} = \gamma_0 + \sum_{j=1}^{p}\gamma_j Y_{i,t-j} + \alpha_i + \beta_t + \varepsilon_{it}\,(i=1,2,\cdots,n,t=1,2,\cdots,k), \tag{4}
$$

where Y_{it} is the endogenous variable identified by temporal and regional factors, which can reflect the conditions in EcS, SS and EnS. γ_0 represents the estimated coefficient of the constant term, γ_j suggests the lagged endogenous variable, p stands for the lag period, j refers to the lag order, and α_i in the formula embodies the individual effects and can be used to explicate the otherness of the cross-sectional. Similarly, β_t indicates a time effect vector that can exhibit the temporal characteristics of variables. Lastly, ε_{it} is utilized to express the random disturbance.

3. Empirical analysis

The part majorly includes two steps: the studies on evaluating EE system and the efficiency of its subsystems from the perspectives of the whole China and its three regions, and then the studies of revealing the specific interaction between subsystems within the EE system.

3.1. Evaluation EE system and the efficiency of its subsystems

3.1.1. Evaluation EE system and the efficiency of its subsystems in China

Based on model (4), the efficiency of EE and its three subsystems in China from 2011 to 2020 can be evaluated. Among them, the results of EE are shown in Figure 4.

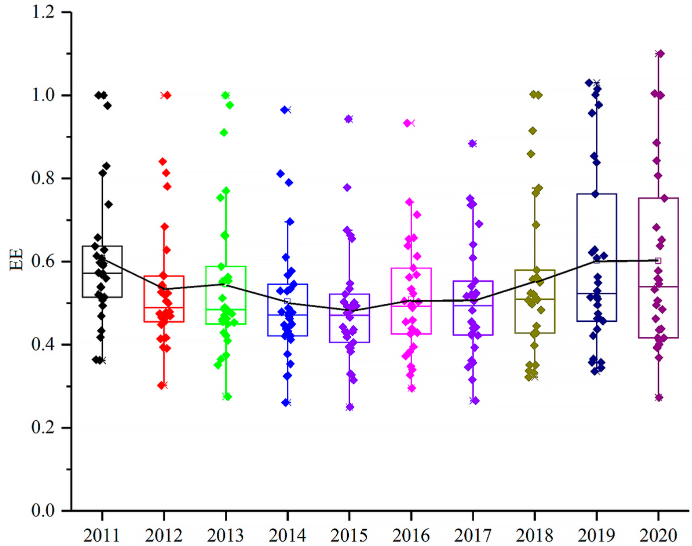


Figure 4. The EE of China from 2011 to 2020

Figure 4 shows the EE distribution of 30 provinces in different years during the study period. The line between the box-plot represents the average EE level of each year. It can be seen that China's EE generally showed a U-shaped change trend from 2011 to 2020. It shows the fluctuation and decline trend before 2015, and rose slowly from 2015 to 2019. The EE in 2020 was basically the same as that in 2019. The above trends are basically consistent with China's development status. During the 12th Five Year Plan period (since 2011), the Chinese government attached great importance to the construction of ecological civilization (Lin & Chen, 2020), and vigorously promoted the coordinated development of economic development, environmental protection and social prosperity. During this period, the Chinese government has successively promulgated massive environmental protection policies, such as the *Air Pollution Prevention and Control Action Plan* in 2013, and the *Water Pollution Prevention and Control Action Plan* in 2015, to change the past extensive mode of economic development and improve people's quality of life. However, at the initial stage of economic structure transformation, various social contradictions emerged one after another (Zhan & Jong, 2018), which led to a short-term decline in EE. With the various measures to promote the transformation of industrial structure taken effects, China's EE has been gradually improved. Unfortunately, the COVID-19, which began to prevail at the end of 2019, has had a serious influence on the development of China and even the world (Zhong & Zeng, 2022), and also affected the improvement of EE in China.

From the distribution of EE in different provinces in each year, the average level of EE in each year during the study period was higher than the median. It is able to infer from the occurrence of outliers in the box-plot (especially from 2011 to 2018), the main reason for the above phenomenon is that the high level of EE in individual provinces has raised the average level, reflecting the uneven development of EE in different provinces and cities in China. It is worth mentioning that, China's EE seems to have shown a good development trend in terms of both the average and median of EE after 2017, but the length of the box-plot has increased significantly during this period, reflecting the Matthew effect of "the stronger the stronger, the weaker the weaker" in China's EE in recent years, which should be paid attention to by the government.

To further analyze the internal causes of EE changes in China, Figure 5 shows the efficiency changes of the three subsystems during the study period. On the whole, SS performs best, followed by EcS and EnS. Since the reform and opening up, the levels of economy and society in China have continuously improved. However, the cost paid is the serious damage to resources and environment (Qu et al., 2020). For a long time, the unscientific development model has resulted in the continuous low efficiency of EnS. From the perspective of time dimension, EcS and EnS show similar change trends, and are basically in line with the change trend of EE in Figure 4, which reflects the importance of these two subsystems to EE to a certain extent. The efficiency of SS showed a slow downward trend before 2017, and then increased slightly. The report of the 19th National Congress of the Communist Party of China (in 2017) clearly pointed out that the main contradiction in China's society has been transformed into the contradiction between the people's growing needs for a better life and unbalanced and inadequate development. This shows that there are many problems in China's social development, such as large regional differences and imperfect coverage of social development. This research results show that the overall efficiency of SS in China is poor in recent years, which supports the above view to some extent. It can also be seen from Figure 5 that the efficiency gap of the three subsystems has narrowed significantly, reflecting that the coordinated development of EnS, SS and EcS in China is gradually being realized.

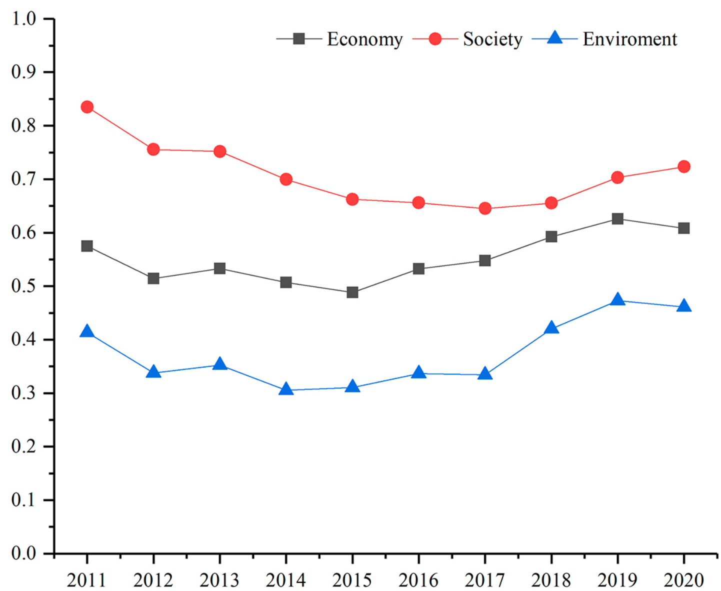


Figure 5. The efficiencies of three subsystems

3.1.2. Efficiency of EE and its subsystems in China's three major regions

As the above outlined, different regions in China have different EE development level. Figure 6 shows the efficiency changes of EE and three subsystems in the eastern, inner and western regions during the study period. It can be found that the EE in eastern China was always higher than that in inner and western China. In the past decades, the eastern region of China has been a priority development region of the state based on its comparative strengths (Chen et al., 2021a). It has always been better than the inner and western regions in terms of high-quality talents, scientific and technological level, infrastructure construction and economic strength (Lin & Zhu, 2021). In addition, owing to the continuous optimization of the industrial structure in the eastern region in recent years, the original resources and labor-intensive enterprises in the eastern region have been transferred to the inner and western regions (Xue et al., 2022), which will undoubtedly have a certain impact on the EE of the inner and western regions. It is clear to see from Figure 6 that the EE of the western region fluctuated before, but grew in the later period and even has surpassed that of the inner region after 2018. It is probably because the western region of China has a weak industrial foundation, a single industrial structure and lagged high-tech industries (Zhang et al., 2020; Chen et al., 2021a). Moreover, the ecological environment in the western region is fragile (Xia et al., 2020). These objective factors make the EE in the western region vulnerable to external shocks (such as environmental regulation), resulting in a significant decline of EE in this region in the early stage of this research. At the same time, these objective factors have

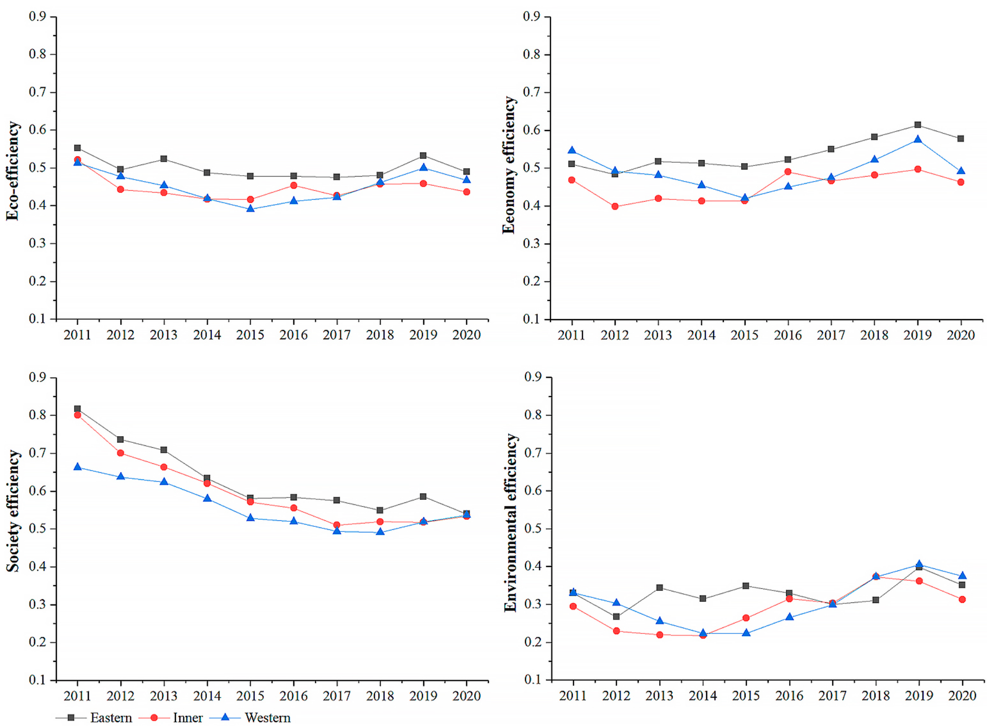


Figure 6. The efficiencies of three regions

restrained the rapid development of their own heavily polluting enterprises and the transfer of polluting enterprises in the eastern region to the region to a certain extent, making this region recover from the impact of external shocks and then EE growing fast.

From the three subsystems of EE, the efficiency of EnS in the three regions is significantly lower than that of the other two subsystems. Additionally, the environmental efficiency of the three regions showed obvious fluctuations, but the fluctuation range of each region was different, which reflects that environmental regulation issued by Chinese government indeed had a significant impact on the EnS of each region, but the impact was different for different regions. Comparatively, the efficiency change trend of EcS and SS in the three regions is more obvious. On the whole, the efficiency of EcS has the highest level in the east, then is the west, and the last one is the inner. Also, the efficiency of EcS of the three regions decreased to some extent during the period of 12th Five Year Plan, then began to rise slowly, and finally fell again due to the impact of COVID-19. Different from EcS, the efficiency of SS in the three regions is the highest in the east, the second in the inner and the lowest in the west. The possible reason for this regional difference is that the improvement of social security needs the economic support (He et al., 2020). Although the tilt strategies to the inner and western regions have been deeply promoted in recent years and have achieved remarkable results, the progressive decreasing trend of economic development capacity from the east, the inner and the west has not been fundamentally changed.

3.2. Interaction between the three subsystems within EE

Based on the results of section 4.1, the PVAR model is used to further reveal how the three subsystems interact, so as to better promote the coordinated development of the three, and ultimately achieve the high-quality EE. There are five steps included in the PVAR model testing.

3.2.1. Unit root test

The stability of the data is the basis for determining whether the PVAR model can be implemented. That is, the unit root is banned in the model to avoid "spurious regression" (Liao et al., 2018). Consequently, unit root test on each variable should be performed first. According to the previous experience (Tang et al., 2022), the four tests of Levine-Lin-Chu (LLC) test, Im, Pesaran, and Shin (IPS) tests, Fisher-Augmented Dickey-Fuller (Fisher-ADF) tests, and Fisher-Phillips-Perron (Fisher-PP) test are comprehensively employed in the paper. The results can be found in Table 3.

Basically, the first-order difference sequence of the variables should be used to see if can be stable when the original sequence of them is a non-stability sequence (Kuang et al., 2020). If they can pass all the above tests, the variables are deemed as stable, and vice versa (Feng et al., 2020). Seen from Table 3 that the first-order difference sequence of these three variables are all stable, which indicates these variables can be further analyzed (Jouida, 2018). In the subsequent calculation process, the data after the first-order difference are used to carry out the research.

Table 3. The results of unit root test of EcS, SS, EnS

Variables	Region	LLC	IPS	ADF	PP	Conclusion
economic	Eastern	−2.7e+13***	−2.6448***	1.9862**	9.2019***	Stable
		(0.0000)	(0.0041)	(0.0235)	(0.0000)	
Δeconomic		−1.0e+14 ***	−5.0189 ***	165.7750 ***	170.2971 ***	Stable
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	
society		−4.1e+13 ***	−0.4295	4.0394***	1.5006*	Unstable
		(0.0000)	(0.3338)	(0.0000)	(0.0667)	
Δsociety		−7.6e+13 ***	−4.0141 ***	137.3763 ***	165.9238 ***	Stable
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	
environmental		−4.1e+13 ***	−1.2552	0.9412	9.4496***	Unstable
		(0.0000)	(0.1047)	(0.1733)	(0.0000)	
Δenvironmental		−1.4e+14 ***	−3.2521 ***	91.7580 ***	127.2656 ***	Stable
		(0.0000)	(0.0006)	(0.0000)	(0.0000)	
economic	Western	−4.4e+13 ***	−0.9130	3.1627***	3.1611***	Unstable
		(0.0000)	(0.1806)	(0.0008)	(0.0008)	
Δeconomic		−3.0e+13 ***	−4.3151 ***	9.6877***	19.6552***	Stable
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	
society		−2.0e+13 ***	−2.1975**	2.3033**	25.7791***	Stable
		(0.0000)	(0.0140)	(0.0106)	(0.0000)	
Δsociety		−5.4e+13***	−3.5745 ***	19.0671 ***	225.1139***	Stable
		(0.0000)	(0.0002)	(0.0000)	(0.0000)	
environmental		−2.0e+13 ***	−0.0987	0.9953	2.2642**	Unstable
		(0.0000)	(0.4607)	(0.1598)	(0.0118)	
Δenvironmental		−3.5e+13 ***	−4.3410 ***	102.1396 ***	154.7896***	Stable
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	
economic	Inner	−2.6e+13***	−0.9657	0.5333	1.7999**	Unstable
		(0.0000)	(0.1671)	(0.2969)	(0.0359)	
Δeconomic		−1.1e+14 ***	−4.0397 ***	3.1139 ***	27.8182***	Stable
		(0.0000)	(0.0000)	(0.0009)	(0.0000)	
society		−2.6e+13***	−0.3749	1.8346**	1.2004	Unstable
		(0.0000)	(0.3539)	(0.0333)	(0.1150)	
Δsociety		−6.0e+13 ***	−2.2649 **	29.5127 ***	6.0937***	Stable
		(0.0000)	(0.0118)	(0.0000)	(0.0000)	
environmental		−1.6e+13***	−0.6642	0.9796	1.8001**	Unstable
		(0.0000)	(0.2533)	(0.1636)	(0.0359)	
Δenvironmental		−8.9e+13 ***	−1.9112 **	1.6641 **	4.1627***	Stable
		(0.0000)	(0.0280)	(0.0480)	(0.0000)	

3.2.2. Co-integration test

The co-integration test is employed to confirm if the variables have a long-term equilibrium relationship with each other. By following the previous experience (e.g. Liao et al., 2018), the Augmented Dickey-Fuller (ADF) test is used for determination. The ADF values of China's eastern, inner and western regions all have passed the 1% significance level test, and their t values are respectively –5.4322, –2.1655 and –2.9161. This result suggests that the relationship between EcS, SS and EnS is the long-term equilibrium in all regions of China.

3.2.3. Optimal lag order selection

To conduct the PVAR model, the optimal lag period should be determined first. Referring to the existing experience (Kuang et al., 2020; Carrasco et al., 2009), Akaike's Information Criteria (AIC), Baysian Information Criteria (BIC), Hannan & Quinn Information Criteria (HQIC) are adopted to measure the performance of the model. The evaluation results of optimal lag order of the study are shown in Table 4. These criteria regard the period with the smallest statistical value as the optimal lag period.

Table 4. The results of optimal lag order test of EcS, SS, EnS

	Optimal lag order in the eastern region			Optimal lag order in the western region			Optimal lag order in the inner region		
lag	AIC	BIC	HQIC	AIC	BIC	HQIC	AIC	BIC	HQIC
1	–4.31139	–3.03295*	–3.90554*	–5.49992	–4.22148*	–4.98855*	–6.72904*	–5.53553*	–6.26632*
2	–4.57413	–2.88212	–3.80003	–5.50879*	–3.81678	–4.84020	–6.28012	–4.64282	–5.66138
3	–4.63028*	–2.44046	–3.78346	–4.89763	–2.70781	–4.05081	–5.65128	–3.49796	–4.8727
4	–3.97147	–1.17354	–2.93386	–3.90270	–1.10476	–2.86509	–4.4735	–3.2217	–3.3844

In terms of the eastern region, the statistical values of BIC and HQIC suggest that the optimal order is the 1^{rd} order, and the value of AIC recommends that the optimal order is the 3^{st} order. While, the judgment of the optimal lag period is determined by the detection value with the most passes (Tang et al., 2022). Therefore, the research sets the optimal lag order in the eastern region as the 1^{rd} order. Similarly, the optimal order in the western region is 1^{st}. Regarding the inner region, the statistical values of AIC, BIC and HQIC are the smallest in the 1^{st}, so the optimal lag order is set as 1^{st}.

3.2.4. Impulse response analysis

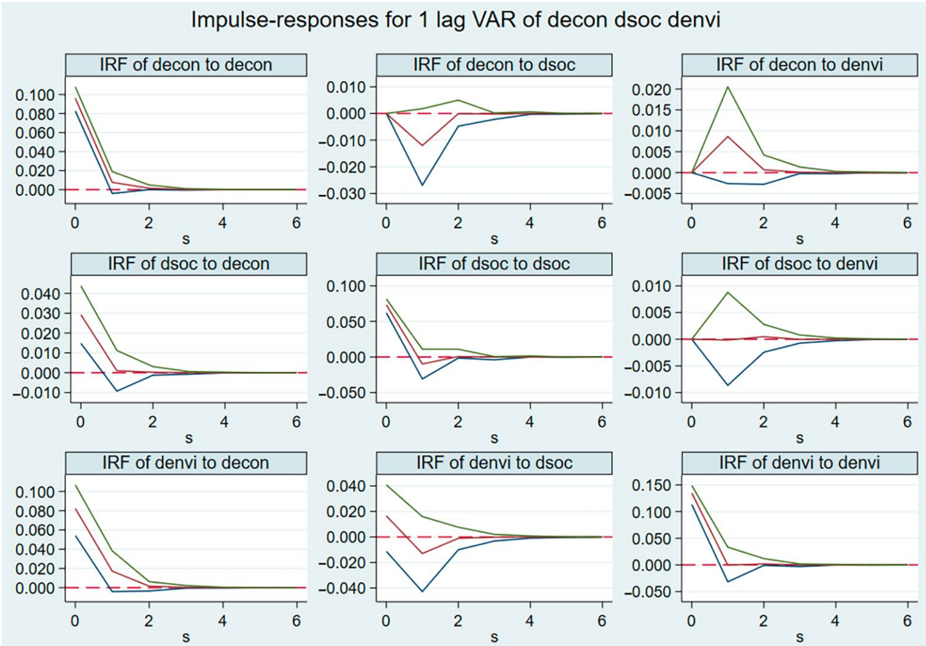
The impulse response describes the response of a standard deviation shock brought from a variable to another under the maintenance of other variables (Lin & Wang, 2019). The purpose of impulse response analysis is to visualize the interaction process between EcS, SS and EnS, so that the target audiences can easily catch the crux of the unsatisfied EE in different regions and formulate insightful policy and managerial implications accordingly. Referring to the existed research experience (Yang et al., 2021b), the Monte Carlo experiment is adopted to simulate the interaction of the three for 1,000 times, and the results are shown in Figures 7–9.

In the figures, the X-axis represents the lag period, which is set to 6 in the research by referring the previous study (Lin & Wang, 2019), representing the forecast of 6 periods. The Y-axis stands for the degree of impulse response. The dotted line indicates that the response is 0, and the red solid line refers to the impulse response value, and the blue and green solid lines respectively signify the estimated values of the 5% quantile and 95% quantile. It is clear to see from Figures 7–9 that the development of EcS, SS, and EnS in the three major regions depends on themselves, but the interactions between the three are significantly different. The results will be discussed in detail as follows:

(1) The first is the interaction between EcS and SS in the eastern region. According to Figure 7, the influence of EcS on SS has not changed under a standard deviation pulse in current period, which suggests that the EcS has a lagging impact on SS. With the passage of time, the impact of the pulse becomes weak, and the influence approaches 0 in the 6^{th} period, which suggests that the impact of EcS on SS is long-standing. Comparatively, the impact of SS on EcS presents a positive impact in the current period, implying that the impact of SS on EcS is timely. The pulse value also approaches 0 in the 1^{th} period. This shows that the impact of SS on EcS is short-term. So do the interaction between EcS and EnS. As for the influence of EnS on SS, it is timely and long-term. While, the influence of SS on EnS has not changed under a standard deviation pulse in current period, and shows very slight change in the later periods, suggesting the impact of SS on EnS is lagging and weak. This is because the social development in the eastern region has reached a high level, and various infrastructures tend to complete, so there is little potential improvement of SS contributes to slight effect on the enhancement of EnS.

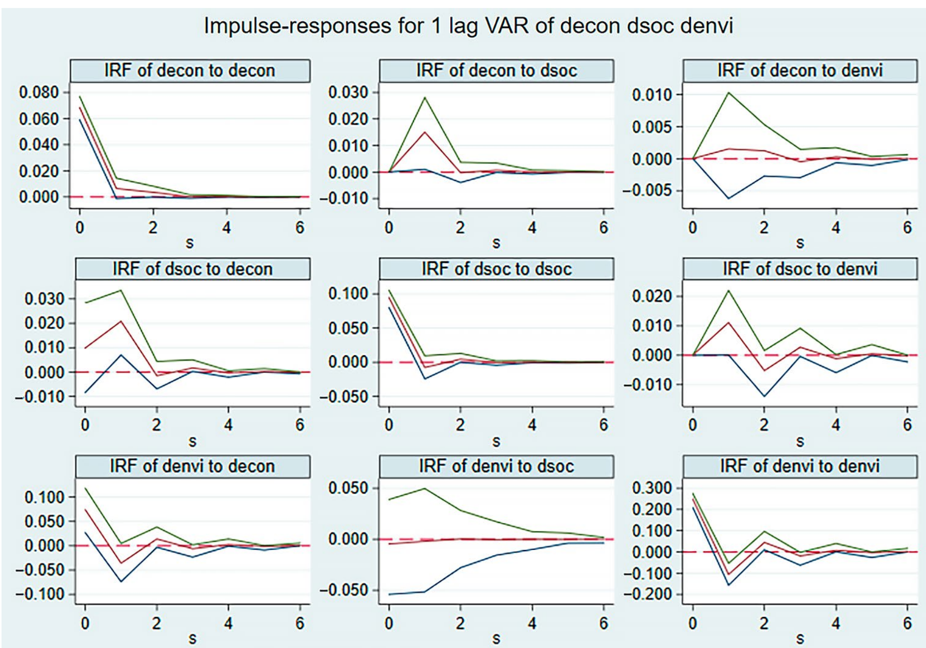
(2) As shown in Figure 8, the influence of EcS on SS is lagging and long-term, and the influence of SS on EcS is timely and long-term in the western region. The interaction between EcS and EnS, as well as SS and EnS in the western region is similar with that of EcS and SS. It should be pointed out that EnS first exerts a negative effect on SS, but it surpasses 0 (positive effect) in the subsequent periods, and finally approaches 0. This shows that the improvement of economy in the western region in the infancy period may have a negative impact on the regional social development. This is because the economic development in the western region has been lagging behind for a long time, and social governance was neglected in the early stage of vigorously promoting economic development, resulting in worrying social conditions such as, the gap between the rich and the poor and money worship. Interestingly, the development of SS in this region may sometimes bring negative effects on the EnS (see Figure 8). It is understandable that the lower utilization rate of resources than the eastern region lead to much resource consumption in social development, negatively affecting EnS. Similarly, the development of EnS also exerts negative effects on SS in some time. It is because the blindly prohibition of industries development in the western region for the sake of environmental quality improvement will lead to the decline of employment rate, the loss of Infrastructure investment, and other social issues in this region.

(3) EcS in the inner region has weak impact on SS. Although SS shows a slight positive impact on EcS, it returns to and maintains negative effect in the subsequent periods until the impulse value approaches 0. It is assumed that the reason for this result is same with that in western region. In general, the impact of EcS on SS is lagging and long-term.



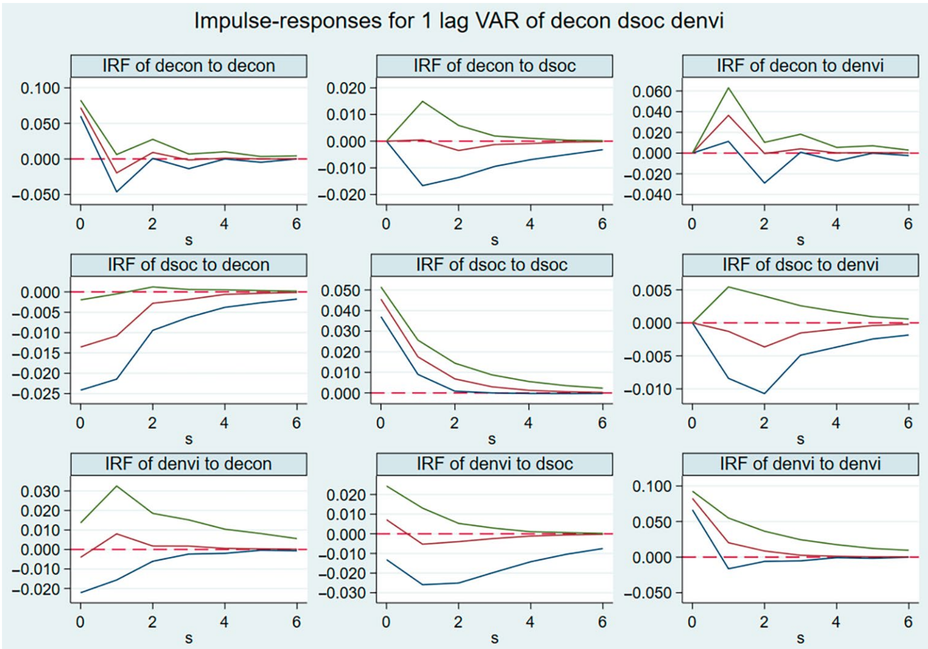
Note: Errors are 5% on each side generated by Monte-Carlo with 1000 reps.

Figure 7. The results of impulse response of EcS, SS, EnS in the eastern region



Note: Errors are 5% on each side generated by Monte-Carlo with 1000 reps.

Figure 8. The results of impulse response of EcS, SS, EnS in the western region



Note: Errors are 5% on each side generated by Monte-Carlo with 1000 reps.

Figure 9. The results of impulse response of EcS, SS, EnS in the inner region

While, the impact of SS on EnS shows the lagging, negative and long-term features. This may be because a large number of immigrants have migrated to the inner region in recent years. The rapid expansion of the population in a short period of time has brought challenges to the local economic development, and it should take a amount of time for the demographic pressure to change into a demographic dividend. The above two results indicate that the interaction between EcS and SS Is not collaborative, which should be attached great importance by the government. Second, the impact of EcS on EnS of the inner region is also lagging and long-term, but keeps the positive impact all the time. The impact of EnS on EcS is timely and long-term, but fluctuates. Third, SS has a weak impact on EnS. The impact of EnS on SS is timely and long-term, but fluctuates around 0 throughout the period, which implies that the influence of EnS on SS in this region is unstable. The above results indicate that the interaction relationships among EcS, SS and EnS varies in different regions, and the mutual promotion mechanism between the inner region is urgent to be formed.

3.2.5. Variance decomposition

Variance decomposition is to decompose the estimated mean square error of all endogenous variables into the contribution of each variable in the system to random shocks. It can be used to analyze the contribution of each variable in leading to the fluctuations of the three subsystems, thereby further digging out the results of impulse response (Lin & Zhu, 2017).

Table 5. The results of variance decomposition of EcS, SS, EnS in China's three major regions

Eastern	Lag order	decon	dsoc	denvi	Western	Lag order	decon	dsoc	denvi	Inner	Lag order	decon	dsoc	denvi
decon	1	1.000	0.000	0.000	decon	1	1.000	0.000	0.000	decon	1	1.000	0.000	0.000
dsoc	1	0.137	0.863	0.000	dsoc	1	0.136	0.864	0.000	dsoc	1	0.081	0.919	0.000
denvi	1	0.269	0.011	0.720	denvi	1	0.495	0.007	0.498	denvi	1	0.002	0.007	0.990
decon	2	0.977	0.015	0.008	decon	2	0.967	0.006	0.028	decon	2	0.808	0.000	0.192
dsoc	2	0.135	0.864	0.001	dsoc	2	0.133	0.845	0.022	dsoc	2	0.112	0.888	0.001
denvi	2	0.276	0.017	0.707	denvi	2	0.517	0.012	0.472	denvi	2	0.011	0.011	0.978
decon	3	0.975	0.016	0.009	decon	3	0.953	0.008	0.039	decon	3	0.809	0.002	0.189
dsoc	3	0.131	0.867	0.002	dsoc	3	0.129	0.829	0.042	dsoc	3	0.112	0.883	0.005
denvi	3	0.278	0.019	0.703	denvi	3	0.531	0.021	0.448	denvi	3	0.011	0.013	0.976
decon	4	0.975	0.016	0.009	decon	4	0.953	0.008	0.039	decon	4	0.807	0.002	0.191
dsoc	4	0.131	0.867	0.002	dsoc	4	0.129	0.829	0.042	dsoc	4	0.112	0.881	0.006
denvi	4	0.278	0.019	0.703	denvi	4	0.531	0.021	0.448	denvi	4	0.012	0.013	0.975
decon	5	0.975	0.016	0.009	decon	5	0.953	0.008	0.039	decon	5	0.807	0.002	0.191
dsoc	5	0.131	0.867	0.002	dsoc	5	0.129	0.829	0.042	dsoc	5	0.112	0.881	0.007
denvi	5	0.278	0.019	0.703	denvi	5	0.531	0.021	0.448	denvi	5	0.012	0.014	0.975
decon	6	0.975	0.016	0.009	decon	6	0.953	0.008	0.039	decon	6	0.807	0.002	0.191
dsoc	6	0.131	0.867	0.002	dsoc	6	0.129	0.829	0.042	dsoc	6	0.112	0.881	0.007
denvi	6	0.278	0.019	0.703	denvi	6	0.531	0.021	0.448	denvi	6	0.012	0.014	0.975

Similarly, this research still employs Monte Carlo experiments to perform 1,000 simulations and predict 6 periods. Table 5 exhibits the results.

It is clear to see from Table 5 that the interaction of the three variables tends to be stable in the later few periods, indicating that the contribution value of each variable is explanatory at this time. In the short term (the first period), 100% of the changes in EcS in each region are contributed by themselves. As time goes by, the contribution rate relying on themselves gradually decrease. By the 6th period, the contribution rate of EcS in the three major regions to their own development has respectively dropped to 97.5%, 95.3% and 80.7%. This shows that the development of EcS will also be promoted by the other two systems in the long run, but the result is not significant. Thereby, EcS in all regions is largely dependent on its own development, and the promotion mechanism of EcS by other systems has not yet been formed, supporting the results of impulse response. Similarly, SS and EnS in all regions are also most affected by themselves in the short term, and gradually weaken in the later periods. However, the contribute rate to their own development are still the highest in the 6th period. These results once again remind decision-makers that it is exceedingly urgent to promote the formation of mutual promotion mechanisms between the three subsystems.

4. Discussion and implications

First of all, given EnS is the main limitation of EE improvement, so this subsystem should be much enhanced. On the one hand, improvements can be made from the input of EnS. It can be seen from Figure 2 that the input indicator of EnS refers to PTI. China's long-standing one-dimensional government regulation model makes environmental governance fall into the low efficiency dilemma of high investment and low return. China has increased its financial investment in environmental protection year by year. The amount of expenditure has increased from 99.58 billion yuan in 2007 to 793.02 billion yuan in 2019. However, the high financial investment has failed to achieve the expected effect of environmental governance. In the face of the long-term low efficiency governance dilemma under the government's one-dimensional control, and the requirements for the holistic development of the economy, society and environment under the sustainable development strategy, it is urgent to advocate the transformation from the current mode to the multi-agent collaborative governance mode, so as to improve the environmental governance performance and make more effective use of environmental investment. On the other hand, the improvement of EnS's output cannot be ignored. According to the Figure 2, the output of EnS majorly refers to pollutants emission, which can be reduced from two aspects: external pressure and internal motivation. First, the further spread of environmental pollution can be curbed from the perspective of external pressure by further improving environmental laws, improving the supervision and accountability system for environmental violations, and the accountability system for poor environmental governance. Second, the types of market regulatory instruments such as green financial instruments, market access threshold setting, and emission trading should be further expanded, to enhance the willingness of polluters to take the initiative in environmental governance from the perspective of internal motivation.

Second, as the development of the EE system in the three regions is limited by different weak subsystems, the improving policies of EE should be formulated based on local conditions. For the eastern region, it is urgent to further improve environmental performance. In addition to optimizing the mode of economic development and developing green industries, relying on technology support to play the role of intellectual governance is another outlet for the eastern region to improve environmental efficiency. The eastern region has gathered the most developed big data, artificial intelligence, and blockchain in China, which can be used to build the pilot of environmental governance platform, improve the construction of intelligent pollution prevention and control system, enhance the ability of pollution prediction, early warning and prevention, and then improve regional environmental efficiency. For the inner region, how to promote regional economic development with high quality deserves attention. Firstly, it is urgent to further upgrade the industrial structure and introduce high-tech enterprises. Secondly, increasing innovation investment, and actively constructing the integration platform of industry-university-research is also recommended. This will help to combine the capital and technological achievements promotion ability of enterprises, the theoretical achievements of universities or scientific research institutions with the scientific research foundation within a region, to grasp the initiative of industrial transformation, to reap technology spillover benefits, and to enhance the sustainable development potential of economy. For the western region, enhancing its social efficiency needs to be paid special attention. Since the development endowment of this region is obviously inferior to that of other regions, the necessary tilt policy and support are desirable. Furthermore, it is necessary to improve the ecological compensation system in the western region, which can help the western region optimize resource exploitation tools, improve infrastructure, stimulate employment, upgrade of industrial structure in the region, and promote the overall development of EcS, SS and EnS in the western region.

Ultimately, in view of the weak mutual promotion between EcS, SS and EnS in various regions, it is imperative to form the mutual promotion mechanisms between the three systems. Considering that the interaction between some subsystems may be lagging and long-term, deepening and broadening international cooperation with foreign countries is recommended. It will help to improve the use rate of regional natural resources, innovations and human resources to maximize the reward of economic and social input, and then the formation of a mutual promotion mechanisms for EcS, SS and EnS is ultimately promoted. Moreover, deeply rooted in the concept of green development, further promoting the green transformation of industry and promoting a green lifestyle are also one of the outlets to improve the interaction mechanism of EcS, SS and EnS. Driven by the dual transformation of production and lifestyle to green economy, traditional industries are either eliminated by the market or forced to transform, and then the target of improving the high-quality development of the economy, society and environment can be achieved eventually. On the one hand, the government can regulate the use of green financial instruments and strengthen the construction of industry-university-research integration platform, so as to enhance its support for the green industry. On the other hand, the government can guide the green lifestyle by popularizing the advantages of green products, strengthening the publicity and policy incentives of green lifestyle, and increasing the construction of public transport and other public infrastructure.

Conclusions

Since 12th Five Year Plan (in 2011), China has entered a new stage with increasing attention attached to sustainable development, and a series of new measures have been introduced to promote sustainable development. Given the fact that EE enables to reflect the degree of regional sustainable development, the GSE-NDEA model and the PVAR model were integrated to evaluate the EE system and its three subsystems of China as the whole and its three major regions from 2011 to 2020. The paper aims to explore the recent development process and recognize the development problems of EE in China during this new stage, and attempt to propose the insightful and appropriate implications to promote the enhancement of sustainable development in China on the basis of the results. The results confirm that EE in China has improved significantly. EnS is the lagging subsystem for the improvement of China's EE. This shows that China should pay more attention to environmental governance in order to better promote the process of sustainable development. Although the efficiency of EcS, SS, EnS are on the rise in all regions, the improvement of EE in different regions is constricted by different weak subsystems, and the restricted subsystem in different regions is identified. In addition, the interaction between different subsystems varies from different regions, and the research further reveals how they work. The above conclusions provide support for the design of regional sustainable development strategy according to local conditions, so as to better promote the sustainable development strategy in the whole country. Lastly, the development of the three subsystems actually depends more on themselves, and the mutual promotion mechanism between systems remains to be formed. This conclusion shows that it is necessary to design policies to enhance the holistic development of the economy, society and environment, instead of one aspect only, so as to avoid falling into the dilemma of fragmented governance.

The study has both theoretical and practical significance. In view of its theoretical significance. First of all, the evaluation indicator system in China is optimized. On the one hand, the research fully considered the EE system consisting of three interacting subsystems (EcS, SS and EnS), which makes up for the deficiency of regarding EE as a "black box" (neglecting the interaction of the subsystems within EE) or ignored the SS in previous studies. On the other hand, the existing EE evaluation indicator system is updated based on the latest characteristics of China's sustainable development, to let the evaluation results more consistent with the practical situation in recent China. Secondly, the application of PVAR model in the research made it possible to further clarify the interaction between EcS, SS and EnS within EE in different regions of China, and also to provide a reference for other studies in the field of interaction exploring. In terms of the practical significance, the integrative application of GSE-NDEA and PVAR models helps to deepen the understanding of China's EE development process, and more practical policy implications for the EE improvement can be proposed accordingly. Additionally, the exact interaction and actual development level of the three subsystems within EE in different regions have been clarified, so as to better promote the sustainable development in China.

This paper was an exploratory study, which has the following three limitations. Firstly, due to the space limitation, although the regional difference of EE development is considered, the spatial correlation is not further discussed in this paper. In order to verify and improve the research results, the spatial econometrics can be employed to further analyze this issue, so that it may be able to recognize clearer interaction between different subsystems across the regions with time going by. Secondly, the research does not particularly consider the lag characteristics of some economic indicators, which can be optimized in the future through the equivalence statistical method based on variance and covariance. Ultimately, the PVAR model may lead to the problem of totally misleading inferences. In this paper, 30 provinces in China are taken as samples. The bootstrap regression model and other error verification methods are not suitable for such a small sample. Therefore, future research can be carried out by expanding research samples (e.g. 114 key cities in China) and using the bootstrap regression model for potential improvement.

Funding

This work is supported by the Chunhui Plan Cooperative Research Project Foundation of Ministry of Education of China (Grant No. HLJ2019002).

Author contributions

R.Y., Y.T. and X.M. conceived the study and were responsible for the design and development of this paper. Y.C., R.Y. and S.W. were responsible for data collection and analysis. R.Y. and S.W. were responsible for data interpretation. R.Y. and Y.T. wrote the first draft of the article. S.W., C.W., Y.T. and K.L. were responsible for reviewing and editing.

Disclosure statement

The authors declare no conflict of interest.

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