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Original Article

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Environmental management efficiency evaluation based on indicator information integration and DEA-Malmquist index

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Abstract

Aim: Completeness of indicator information is an important problem that needs to be further studied in environmental management efficiency evaluation (EMEE). However, this problem has not attracted sufficient attention in existing studies and there is lack of the total factor productivity analysis, which is an effective method to evaluate the environmental management efficiency change that has been applied in different fields.

Methods: A novel EMEE model is proposed based on indicator information integration and DEA-Malmquist index, in which the kernel of the indicator information integration is the evidential reasoning approach with an indicator weight calculation.

Results: The DEA-Malmquist index is introduced to evaluate the efficiency of environmental management and also analyzes its efficiency change based on the integrated indicator information. A case study of 30 provinces (except Tibet) in mainland China from 2005-2017 is provided to illustrate the analysis of regional efficiency distribution, efficiency change and improvement strategy of environmental management.

Conclusion: The proposed model can provide a reference for the improving regional environmental protection



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Keywords: Evidential reasoning, indicator information integration, environmental management, efficiency evaluation, improvement strategy

INTRODUCTION

With the rapid development of the economy, the dilemma of environmental protection *vs.* economic development has gradually emerged. Once the emission of pollution has exceeded the capacity of the environment, it not only increases the difficulty of environmental recovery and management but also makes economic development unsustainable. Therefore, the improvement of environmental management for controlling serious pollution emission and ecological damage has become an important issue for sustainable development.

The efficiency evaluation of environmental management is a concern in academia. In recent years, studies on environmental management efficiency evaluation (EMEE) have emerged, and the main study of environmental management has been focused on empirical analysis and practical research^[1-3]. At the same time, the impact of various indicators on EMEE is also different^[4,5]. Due to the limited data available and incompleteness of knowledge, only a few (insufficient) output indicators have been selected for efficiency evaluation^[6,7]. The disadvantage of this indicator selection method is that the soundness of the output indicators must be ignored in environmental treatment. For example, Chen *et al.*^[5] selected chemical oxygen demand (COD) as an output indicator to represent wastewater discharge, thus ignoring other indicators related to wastewater discharge, such as wastewater discharge, NO_x emission, *etc.* Furthermore, most previous studies have treated the importance of different input and output indicators equally during the system modeling of environmental management, but it is clear that different indicators always play different roles in the system modeling. Although some existing studies involved weight calculation^[8], these weight calculation methods have been rarely used in the field of environmental management. Therefore, many challenges should be solved in future studies about environmental management:

- (1) The previous studies on regional EMEE are still inconsistent because different indicator selection methods will result in the selection of different indicators. Indicator selection usually plays an important role in EMEE. However, existing studies on environmental management indicator selection have been mainly based on expert experience or empirical judgment^[5], which has a great impact on the accuracy and objectivity of environmental management efficiency evaluation.
- (2) The integrity of indicator information has been ignored in previous studies of EMEE. This is because indicator selection may result in the loss of indicator information and affect evaluation results. At the same time, there is a rule of thumb in DEA theory^[9] that the number of decision-making units (DMUs) must be at least 2-3 times the number of evaluation indicators. Too many indicators applied in a DEA model^[10] will make the efficiency of all DMUs approach 1 and reduce the differentiation among them.
- (3) Most previous studies on EMEE are based on the statistical analysis of environmental management efficiencies; the change of these efficiencies has been rarely analyzed for regional environmental management. It is clear from a previous study^[11] that the analysis of efficiency changes can clearly provide the change rate of environmental management efficiency and help investigate the problem of input-output structure by the change of efficiency.

To solve the above-mentioned challenges of environmental management efficiency evaluation, a novel efficiency evaluation model is proposed in this study and its main components include: (1) calculating the relative weights of different undesirable and desirable output indicators for environmental management;

(2) integrating the set of undesirable output indicators and desirable output indicators, respectively, by evidential reasoning (ER) approach based on the obtained indicator weights to obtain a new indicator of undesirable output and desirable output; and (3) using the DEA model and Malmquist index for the efficiency evaluation of environmental management based on the integrated indicators.

To validate the effectiveness of the proposed model, input, desirable output, and undesirable output indicators and data on environmental management of 30 provinces (except Tibet) in China from 2005 to 2017 are applied to provide a case study. Multiple kinds of efficiency-related outcomes are calculated to put forward the research scheme of environmental management of China. Additionally, the results of EMEE show that the comprehensive efficiency of environmental management is significantly different to pure technical efficiency in different management periods. The overall environmental efficiency and pure technical efficiency reveal an upward trend in China. In other words, the positive effect of the current input-output structure and technique on the comprehensive efficiency of environmental management becomes more significant over time.

ER-BASED INDICATOR INFORMATION INTEGRATION

Indicator weight calculation reviews the weight calculation for environmental indicators, while Indicator information integration reviews the ER approach^[12] for indicator information integration.

Indicator weight calculation

In environmental management, there are various kinds of environmental indicators, and all of them usually have different importance. To quantify the importance of different indicators, a well-known weight calculation method, called correlation coefficient and standard deviation method^[13], is introduced to calculate the weight of indicators based on collected environmental data.

Assumes that environmental management contains T environmental indicators C_t ($t = 1, \dots, T$) and each indicator has S collected environmental data $v_{s,t}$ ($s = 1, \dots, S$). Since environmental data are in a dimensional representation, they need to be dimensionless standardized. According to the different characteristics of indicators, the specific standardization is as follows:

$$e_{s,t} = \begin{cases} \frac{v_{s,t} - \min_{i=1,\dots,S} \{v_{i,t}\}}{\max_{i=1,\dots,S} \{v_{i,t}\} - \min_{i=1,\dots,S} \{v_{i,t}\}}, & \text{if } C_t \in \Omega_{benefit} \\ \frac{\max_{i=1,\dots,S} \{v_{i,t}\} - v_{s,t}}{\max_{i=1,\dots,S} \{v_{i,t}\} - \min_{i=1,\dots,S} \{v_{i,t}\}}, & \text{if } C_t \in \Omega_{cost} \end{cases} \quad (1)$$

where $\Omega_{benefit}$ denotes the set of benefit indicators, whose values are always the larger the better; Ω_{cost} denotes the set of cost indicators, whose values are always the smaller the better; and $e_{s,t}$ denotes the t th normalized value of the s th indicator.

Based on the $S \times T$ normalized values, the correlation coefficient of the t th indicator, denoted as R_t , can be calculated when assuming that the weights of T indicators are w_t ($t = 1, \dots, T$). The specific formula of calculating R_t is as follows:

$$R_t = \frac{\sum_{s=1}^S (e_{s,t} - \bar{e}_t)(d_{s,t} - \bar{d}_t)}{\sqrt{\sum_{s=1}^S (e_{s,t} - \bar{e}_t)^2 \cdot (d_{s,t} - \bar{d}_t)^2}} \quad (2)$$

where $d_{s,t}$ denotes the overall assessment value of the s th datum in the t th indicator when the t th indicator does not consider the overall assessment. \bar{e}_t and \bar{d}_t denote the mean of normalized values and overall assessment values at the t th indicator. The specific formulae for calculating $d_{s,t}$, \bar{e}_t and \bar{d}_t are as follows:

$$d_{s,t} = \sum_{i=1, i \neq s}^S e_{i,t} w_t \quad (3)$$

$$\bar{d}_t = \frac{\sum_{s=1}^S d_{s,t}}{S} \quad (4)$$

$$\bar{e}_t = \frac{\sum_{s=1}^S e_{s,t}}{S} \quad (5)$$

Here, it is worth noting that, if R_t is close to 1, then the t th indicator has a little influence on environmental management and can be assigned a small weight; otherwise, the weight of the t th indicator should be large. Additionally, the standard deviation of the t th indicator, denoted as σ_t , can be calculated using the following formula:

$$\sigma_t = \sqrt{\frac{\sum_{s=1}^S (e_{s,t} - \bar{e}_t)^2}{S}} \quad (6)$$

According to the T correlation coefficients and T standard deviations, a new weight of each indicator, denoted as \bar{w}_t , can be obtained using Equation (7):

$$\bar{w}_t = \frac{\sigma_t \sqrt{1 - R_t}}{\sum_{k=1}^T \sigma_k \sqrt{1 - R_k}} \quad (7)$$

Finally, because the T initial weights w_t are provided by the assumption and they are equal to the T new weights \bar{w}_t , the weight of T indicators can be calculated by the optimization model below:

$$\begin{aligned} \text{Min } J &= \sum_{t=1}^T (w_t - \bar{w}_t)^2 \\ \text{s.t. } \sum_{t=1}^T w_t &= 1 \\ w_t &\geq 0; t = 1, \dots, T \end{aligned} \quad (8)$$

Indicator information integration

In EMEE, the number of inputs, outputs, and DMUs must satisfy a numerical condition, e.g., the number of DMUs should be greater than twice the sum of the number of inputs and outputs^[14]. For this reason, the ER approach^[12], which has been sourced from the Dempster-Shafer theory of evidence^[15,16] and has a powerful ability in information fusion, is introduced to integrate indicator information.

Assume that environmental management contains T environmental indicators C_t ($t = 1, \dots, T$), each indicator has a weight w_t ($t = 1, \dots, T$) obtained from Indicator weight calculation, and there is a shared set of mutually exclusive and collectively exhaustive evaluation grades, denoted as $H = \{H_1, \dots, H_N\}$. Based on the N grades, the distributed assessment of each indicator, denoted as $S(C_t)$, can be defined as

$$S(C_t) = \{(H_n, \beta_{n,t}), n = 1, \dots, N\} \quad (9)$$

in which, $\beta_{n,t}$ denotes the belief degree assigned to the n th grade for the t th indicator, which satisfies:

$$\sum_{n=1}^N \beta_{n,t} \leq 1 \quad (10)$$

$$\beta_{n,t} \geq 0; n = 1, \dots, N \quad (11)$$

Based on the distributed assessments and T weights, the basic probability assignments (BPAs) for each indicator can be calculated as

$$m_{n,t} = m(H_n) = w_t \beta_{n,t}, n = 1, \dots, N; t = 1, \dots, T \quad (12)$$

$$\bar{m}_{H,t} = \bar{m}_t(H) = 1 - w_t, t = 1, \dots, T \quad (13)$$

$$\tilde{m}_{H,t} = \tilde{m}_t(H) = w_t (1 - \sum_{n=1}^N \beta_{n,t}), t = 1, \dots, T \quad (14)$$

where $m_{n,t}$ is the BPA of the n th grade on the t th indicator; $\tilde{m}_{H,t}$ is the uncertain BPA caused by the relative weight of the t th indicator; and $\tilde{m}_{H,t}$ is the uncertain BPA caused by the incompleteness of the distributed assessment.

According to the analytical ER algorithm^[10], the BPAs of T indicators can be integrated as the BPAs of a new integrated indicator, namely indicator information integration. The corresponding formulas are as follows:

$$m_n = k \left[\prod_{t=1}^T (m_{n,t} + \bar{m}_{H,t} + \tilde{m}_{H,t}) - \prod_{t=1}^T (\bar{m}_{H,t} + \tilde{m}_{H,t}) \right], n = 1, \dots, N \quad (15)$$

$$\tilde{m}_H = k \left[\prod_{t=1}^T (\bar{m}_{H,t} + \tilde{m}_{H,t}) - \prod_{t=1}^T \bar{m}_{H,t} \right] \quad (16)$$

$$k = \left[\sum_{n=1}^N \prod_{t=1}^T (m_{n,t} + \bar{m}_{H,t} + \tilde{m}_{H,t}) - (N-1) \prod_{t=1}^T (\bar{m}_{H,t} + \tilde{m}_{H,t}) \right]^{-1} \quad (17)$$

$$k = \left[\sum_{n=1}^N \prod_{t=1}^T (m_{n,t} + \bar{m}_{H,t} + \tilde{m}_{H,t}) - (N-1) \prod_{t=1}^T (\bar{m}_{H,t} + \tilde{m}_{H,t}) \right]^{-1} \quad (18)$$

Thus, the BPAs of the integrated indicator is then transformed into the distributed assessment $S(C) = \{(H_n, \beta_n), n = 1, \dots, N\}$, in which the belief degree of the n th grade is calculated as follows:

$$\beta_n = \frac{m_n}{1 - \bar{m}_H}, n = 1, \dots, N \quad (19)$$

Meanwhile, the belief degree of uncertainty is calculated as

$$\beta_H = \frac{\tilde{m}_H}{1 - \bar{m}_H} \quad (20)$$

Finally, to effectively show integrated indicator information, the distributed assessment should be transformed into a numerical value. Hence, when $u(H_n)$ is the utility of the n th grade, the minimum, maximum, and average utility values of the integrated distributed assessment are calculated as follows:

$$u(S(C))_{\min} = \sum_{n=1}^N \beta_n u(H_n) + u(H_1) \beta_H \quad (21)$$

$$u(S(C))_{\max} = \sum_{n=1}^N \beta_n u(H_n) + u(H_N) \beta_H \quad (22)$$

$$u(S(C)) = \sum_{n=1}^N \beta_n u(H_n) + \frac{u(H_1) + u(H_N)}{2} \beta_H \quad (23)$$

DEA-MALMQUIST INDEX-BASED EFFICIENCY EVALUATION

Efficiency measure with undesirable outputs introduces the efficiency evaluation with undesirable outputs, while DEA-Malmquist index for efficiency evaluation proposes the dynamic efficiency evaluation based on Malmquist index.

Efficiency measure with undesirable outputs

In environmental management, undesirable outputs are inevitable factors, e.g., SO₂ and CO₂ in waste gas emission, and they have important influences on efficiency evaluation. To achieve environmental management more scientifically, a DEA undesirable output model^[17] is applied to evaluate the efficiency of environmental management with undesirable outputs, in which the DEA undesirable output model is a DEA model for efficiency evaluation and has the same advantages as other DEA models^[18-20], e.g., the feasibility of efficiency evaluation for multiple inputs and outputs and no need for dimensionless data processing and weight assumption.

In the DEA undesirable output model, suppose that there are n DMUs with m input indicators, s desirable output indicators, and h undesirable output indicators. Accordingly, the input data, desirable output data, and undesirable output data of n DMUs can be denoted as X , Y , and Z , respectively.

$$X = \begin{bmatrix} x_{11} & \dots & x_{1j} & \dots & x_{1n} \\ \dots & \dots & \dots & \dots & \dots \\ x_{i1} & \dots & x_{ij} & \dots & x_{in} \\ \dots & \dots & \dots & \dots & \dots \\ x_{m1} & \dots & x_{mj} & \dots & x_{mn} \end{bmatrix}_{m \times n} \quad (24)$$

$$Y = \begin{bmatrix} y_{11} & \dots & y_{1j} & \dots & y_{1n} \\ \dots & \dots & \dots & \dots & \dots \\ y_{r1} & \dots & y_{rj} & \dots & y_{rn} \\ \dots & \dots & \dots & \dots & \dots \\ y_{s1} & \dots & y_{sj} & \dots & y_{sn} \end{bmatrix}_{s \times n} \quad (25)$$

$$Z = \begin{bmatrix} z_{11} & \dots & z_{1j} & \dots & z_{1n} \\ \dots & \dots & \dots & \dots & \dots \\ z_{f1} & \dots & z_{fj} & \dots & z_{fn} \\ \dots & \dots & \dots & \dots & \dots \\ z_{h1} & \dots & z_{hj} & \dots & z_{hn} \end{bmatrix}_{h \times n} \quad (26)$$

Next, according to the input data X , desirable output data Y , and undesirable output data Z shown in Equations (24)-(26), the following optimization model, which was proposed by Seiford and Zhu^[17], can be used to evaluate the efficiency of each DMU with consideration of undesirable outputs and the condition of constant returns to scale:

$$\begin{aligned}
 \theta_0^* &= \min \theta_0 \\
 \text{s.t. } \sum_{j=1}^n \lambda_j x_{ij} &\leq \theta_0 x_{i0}; i = 1, \dots, m \\
 \sum_{j=1}^n \lambda_j y_{rj} &\geq y_{r0}; r = 1, \dots, s \\
 \sum_{j=1}^n \lambda_j b_{fj} &\geq b_{f0}; f = 1, \dots, h
 \end{aligned} \tag{27}$$

where

$$b_{fj} = -z_{fj} + \max_{j=1, \dots, n} \{z_{fj}\} + \min_{j=1, \dots, n} \{z_{fj}\} \tag{28}$$

Finally, the efficiency value θ_j^* ($j = 1, \dots, n$) of n DMUs can be obtained. When $\theta_j^* = 1$, it means that the input-output structure of the j th DMU is effective; otherwise, it means that the input-output structure of the j th DMU still needs to be improved.

It is worth noting that the optimization model shown in Equation (27) is a minimum optimization problem, so it can be solved by using the optimization toolbox in MATLAB, e.g., linprog function, or some swarm intelligence algorithms.

Additionally, when an increase or decrease in inputs or outputs will result in a proportional change in the outputs or the inputs, namely variable returns to scale, the following constraint condition should be added in the optimization model shown in Equation (27) to evaluate the efficiency of each DMU with consideration of undesirable outputs.

$$\sum_{j=1}^n \lambda_j = 1 \tag{29}$$

DEA-Malmquist index for efficiency evaluation

Since the efficiencies obtained in Efficiency measure with undesirable outputs are static and usually fail to reflect the change of comprehensive efficiency and technical efficiency, dynamic efficiencies should be considered to effectively perform environmental management. For this reason, the Malmquist index^[21] is used to enhance the efficiency evaluation of environmental management.

In the process of dynamic efficiency evaluation, let us suppose that the input data, desirable output data, and undesirable output data at the t th period are denoted as X^t , Y^t , and Z^t , respectively. The Malmquist index formula from the t th period to the $(t + 1)$ th period is defined as follows, in which the Malmquist index is a useful approach for productivity measurement in DEA and can calculate the relative performance of a DMU at different periods of time using the technology of a base period.

$$M(X^{t+1}, Y^{t+1}, Z^{t+1}, X^t, Y^t, Z^t) = \left[\frac{D_c^t(X^{t+1}, Y^{t+1}, Z^{t+1})}{D_c^t(X^t, Y^t, Z^t)} \times \frac{D_c^{t+1}(X^{t+1}, Y^{t+1}, Z^{t+1})}{D_c^{t+1}(X^t, Y^t, Z^t)} \right]^{1/2} \tag{30}$$

Where D_c^t and D_c^{t+1} denote the distance function estimated with the t th period and the $(t+1)$ th period under the condition of constant returns to scale, respectively, and their values can be obtained by using the optimization model shown in Equation (27) to evaluate the efficiency of the DMUs constructed by X^t , Y^t , and Z^t or X^{t+1} , Y^{t+1} , and Z^{t+1} . It is worth noting that the distance should satisfy convexity, ineffectivity, and minimality because it is related to DEA. Additionally, $M > 1$ indicates that the comprehensive efficiency level of environmental management is improved; $M = 1$ indicates that the comprehensive efficiency level of environmental management remains unchanged; and $M < 1$ indicates that the level of environmental management efficiency decreases. According to the authors of^[21], Equation (30) can be decomposed into the following two components:

$$TFPC(X^{t+1}, Y^{t+1}, Z^{t+1}, X^t, Y^t, Z^t) = \frac{D_c^{t+1}(X^{t+1}, Y^{t+1}, Z^{t+1})}{D_c^t(X^t, Y^t, Z^t)} \times \left[\frac{D_c^t(X^t, Y^t, Z^t)}{D_c^{t+1}(X^t, Y^t, Z^t)} \times \frac{D_c^t(X^{t+1}, Y^{t+1}, Z^{t+1})}{D_c^{t+1}(X^{t+1}, Y^{t+1}, Z^{t+1})} \right]^{1/2} \quad (31)$$

$$= EC \times TC$$

where EC and TC denote the efficiency change and the technical change, respectively. $EC > 1$ indicates that the efficiency of environmental management is improved; $EC = 1$ indicates that the efficiency of environmental management has not changed; and $EC < 1$ indicates that the efficiency of environmental management is reduced.

When the EMEE is assumed to have variable returns to scale, EC can be further decomposed into the following two components:

$$EC = \frac{D_c^{t+1}(X^{t+1}, Y^{t+1}, Z^{t+1})}{D_c^t(X^t, Y^t, Z^t)}$$

$$= \frac{D_v^{t+1}(X^{t+1}, Y^{t+1}, Z^{t+1})}{D_v^t(X^t, Y^t, Z^t)} \times \left(\frac{D_v^t(X^t, Y^t, Z^t)}{D_c^t(X^t, Y^t, Z^t)} \times \frac{D_c^{t+1}(X^{t+1}, Y^{t+1}, Z^{t+1})}{D_v^{t+1}(X^{t+1}, Y^{t+1}, Z^{t+1})} \right) \quad (32)$$

$$= PTEC \times SEC$$

where $PTEC$ and SEC denote the pure technical efficiency change and the scale efficiency change. D_v^t and D_v^{t+1} denote the distance function estimated with the t th period and the $(t+1)$ th period under the variable of constant returns to scale, respectively, and their values can be obtained by using the optimization model shown in Equation (27) together with Equation (29) to evaluate the efficiency of the DMUs constructed by X^t , Y^t , and Z^t or X^{t+1} , Y^{t+1} , and Z^{t+1} .

FRAMEWORK OF EFFICIENCY EVALUATION MODEL FOR ENVIRONMENTAL MANAGEMENT

Based on the ER-based indicator information integration shown in ER-BASED INDICATOR INFORMATION INTEGRATION and the DEA-Malmquist index-based efficiency evaluation shown in DEA-MALMQUIST INDEX-BASED EFFICIENCY EVALUATION, in this section, the framework of the EMEE model is proposed. Its main processes are depicted in Figure 1.

As shown in Figure 1, the detailed steps for EMEE are as follows.

Step 1. ER-based indicator information integration for desirable and undesirable output indicators. Suppose that there are s desirable output indicators and h undesirable output indicators and their data are collected from n regions and T years, namely, $y_{r,j}^t$ ($t = 1, \dots, T; j = 1, \dots, n; r = 1, \dots, s$) and $z_{f,j}^t$ ($f = 1, \dots, h$). Hence, based on the indicator weight calculation shown in Indicator weight calculation and the indicator formation integration shown in Indicator information integration, all these data of s desirable output indicators and h undesirable output indicators should be integrated into $T \times n$ new data y_j^t and z_j^t .

Step 2. DEA-Malmquist index-based efficiency evaluation based on the integrated desirable and undesirable output data. Suppose that there are m input indicators and their data collected from n regions and T years are $x_{i,j}^t$ ($i = 1, \dots, m$). Hence, based on $T \times n$ integrated desirable and undesirable output data, the corresponding data matrix used for efficiency evaluation can be generated and denoted as $X^{(t)} = (x_{i,j}^t)_{m \times n}$, $Y^{(t)} = (y_j^t)_{1 \times n}$, and $Z^{(t)} = (z_j^t)_{1 \times n}$. Furthermore, efficiency, TFPC, EC, PTEC, and SEC can be calculated based on the efficiency measure shown in Efficiency measure with undesirable outputs and the efficiency evaluation shown in DEA-Malmquist index for efficiency evaluation.

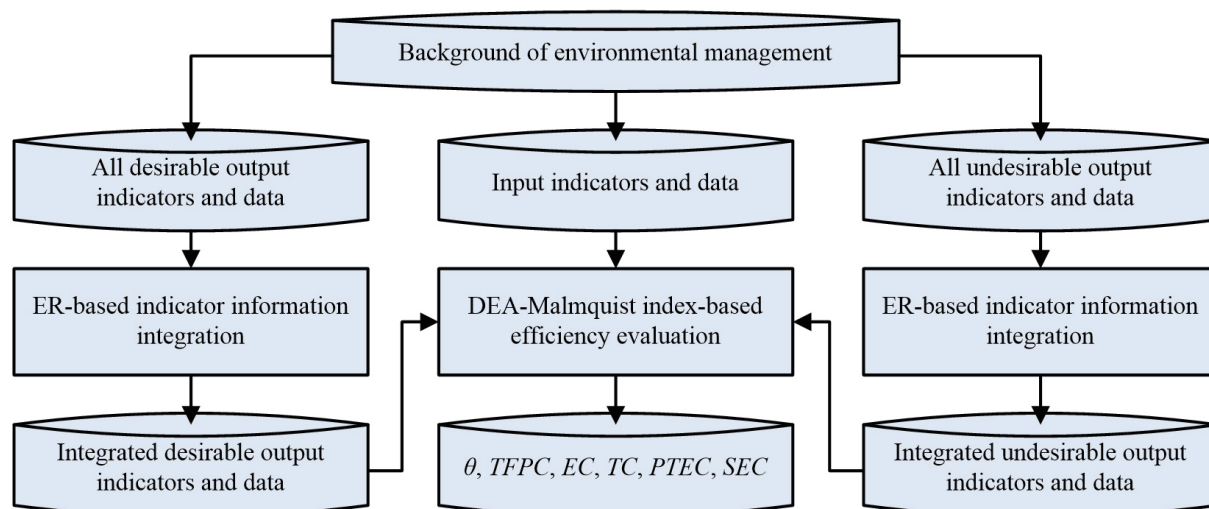


Figure 1. Framework of environmental management efficiency evaluation. TFPC: Total factor productivity change; EC: efficiency change; TC: technical change; PTEC: pure technical efficiency change; SEC: scale efficiency change; ER: evidential reasoning.

CASE STUDY

In this section, the environmental management data of 30 provinces in China from 2005 to 2017 are preprocessed. According to the specific steps shown in FRAMEWORK OF EFFICIENCY EVALUATION MODEL FOR ENVIRONMENTAL MANAGEMENT, the efficiency of regional environmental management and its technical change efficiency are analyzed based on integrated indicators. Finally, the improvement strategy of regional environmental management is discussed.

Data resource and variable determination

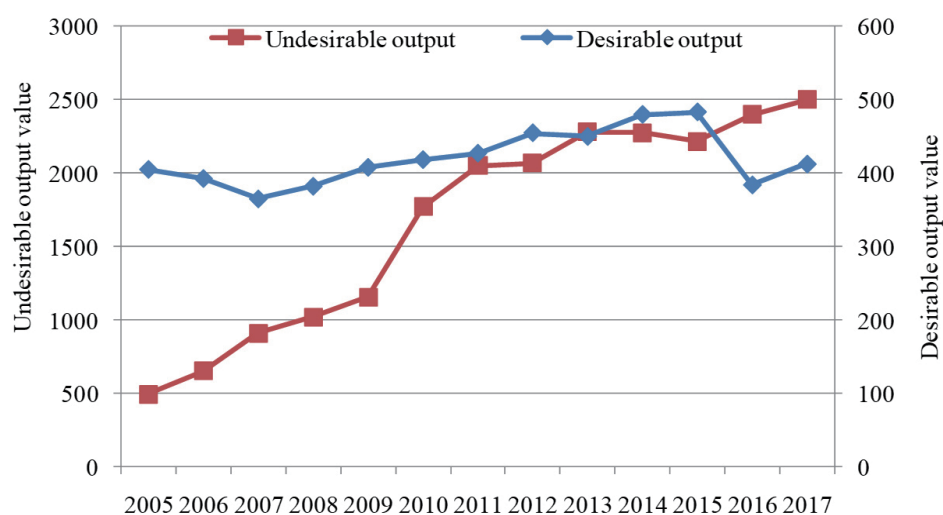
This paper selects the general rule of environmental indicators and takes undesirable outputs and desirable outputs as the output indicators of environmental management. Therefore, based on the previous studies^[22,23], GDP and profit of enterprises above scale (unit: 100 million yuan) are selected as desirable outputs, and waste gas emission, waste water emission, and solid waste emission are selected as undesirable output for efficiency evaluation, in which waste gas emission includes SO₂ (unit: 10,000 ton), CO₂ (unit: 10,000 ton), and smoke and dust emission (unit: 10,000 ton); waste water emission includes the total amount of wastewater (unit: 10,000 ton), COD (unit: 10,000 ton), and NO_x emission (unit: 10,000 ton); and solid waste emission includes solid emission (unit: 10,000 ton).

Input indicators include labor input, capital input, and energy input, in which labor input (unit: 10,000 people) is measured by the number of employees, capital investment (unit: 100 million yuan) is measured by regional fixed assets investment, and energy input (unit: 100 million ton) is obtained by the total regional power consumption. It is worth noting that all the above indicators and their historical data can be derived from the China Environmental Statistical Yearbook, the China Energy Statistical Yearbook, and the China Statistical Yearbook. Table 1 shows the statistical analysis of the integrated desirable output and undesirable output obtained from the ER-based indicator information integration, as well as three inputs.

To provide the details of the integrated undesirable and desirable outputs, Figure 2 shows the average value of the integrated desirable output and undesirable output in each year of China. Figure 2 clearly shows that the emission of undesirable output increased rapidly from 2005 to 2017, and there was obvious change during 2005-2011. From the perspective of time change, the emission of desirable output is relatively stable. The desirable output shows a significant upward trend after 2015. In the process of the rapid development of China's economy, while increasing the economic output value, governments are also trying their best

Table 1. Statistical analysis of input-output indicators

Indicator	Average	Standard	Minimum	Maximum
Integrated desirable output	1673	1939	21	10574
Integrated undesirable output	420	274	29	1360
Labor input	493	338	43	1973
Capital input	9765	11262	416	88711
Energy input	1496	1160	82	5959

**Figure 2.** Integrated desirable and undesirable output from 2005 to 2017.

to control the emission of pollutants to ensure the win-win situation of economy and environmental protection, as indicated by the undesirable emission rate of environmental pollution slowing down after 2011.

Regional distribution of environmental management efficiency

To study the changes of environmental management efficiency in each province and find the internal reasons for efficiency changes, the annual change of environmental management efficiency in each province is calculated according to the proposed model. For the sake of simplicity, the environmental management in China is divided into two stages: 2005-2010 and 2011-2017. In terms of space, this paper studies the differing efficiency of regional environmental management according to the division of provinces.

According to the statistical data of China Statistical Yearbook in the recent five years, the relative efficiency of environmental management for each province can be calculated, as shown in Figure 3. From the perspective of environmental management efficiency from 2013 to 2017, Heilongjiang, Shanghai, and Shandong achieve the desired environmental management, namely the efficiency of these three provinces is 1. However, the other 27 provinces did not reach relative effective value of efficiency in a certain year, and the management efficiency of most provinces in the western region continues to decline; the relative efficiency of each year is quite different from that of other regions.

From the perspective of the returns to scale, Figure 4 shows that the environmental management income of each province has an increasing trend from 2013 to 2017, indicating that input factors still have a large driving space for output, so the inputs should be increased to improve the management efficiency. However, a few provinces are characterized by diminishing returns to scale, that is, excessive investments in environmental management lead to redundant outputs, and optimizing input resource is an important

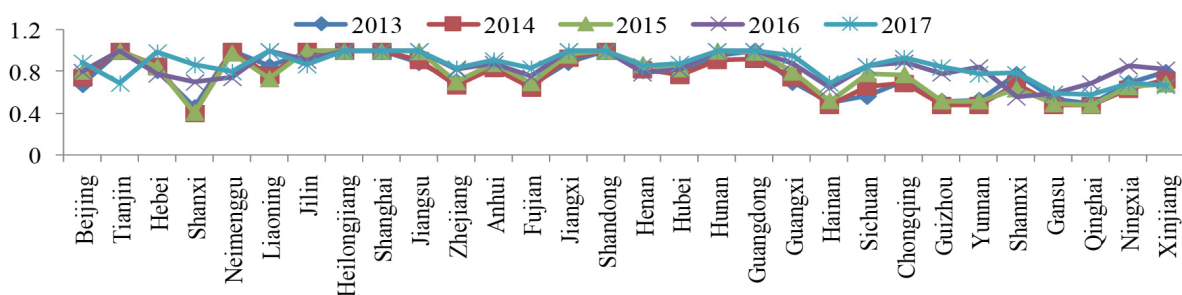


Figure 3. Comprehensive efficiency of different provinces from 2013 to 2017.

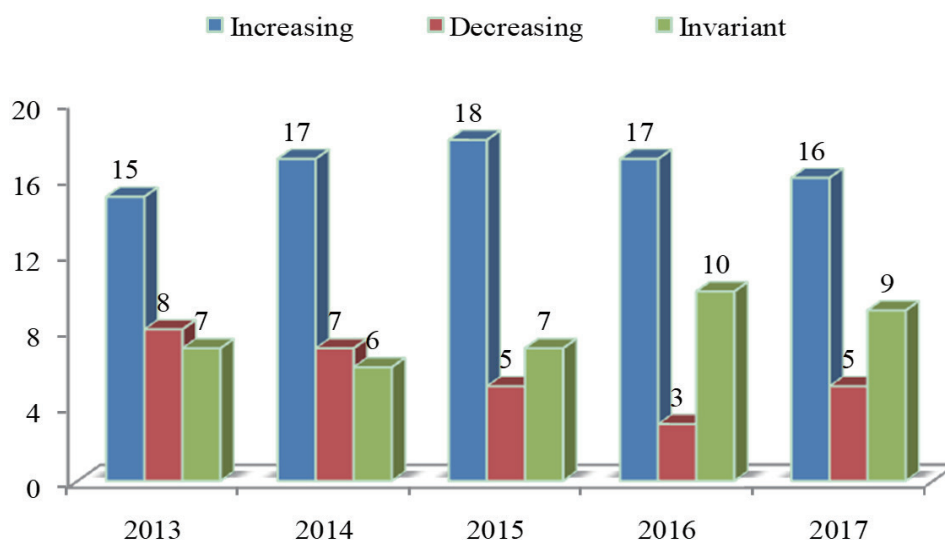


Figure 4. Number of provinces showing different returns to scale from 2013 to 2017.

issue for those provinces. Overall, the environmental management efficiency in China's provinces is quite different, and the management capacity is uneven, which also results in the environmental management efficiency of each province not being effectively improved over time. It shows that reasonable allocation of input-output structure and development of environmental management policies are still the keys to solving the current environmental management problems in China.

To present the efficiency regional environmental management, Figure 5 shows the regional average environmental efficiency in 2017 of seven regions in China. Through comprehensive analysis, it is obvious that the environmental management efficiency in eastern and southern China is higher than that in other regions, while it is lower in southwest China. In addition to the influence of natural environment and resources endowment, there are significant differences in pure technical efficiency of environmental management in different regions of China due to the difference of economic development level and local policies. The pure technical efficiency of eastern, central, and northeastern China is relatively high. The economic development, population density, and technical level are relatively developed in northern and eastern China. However, the industrial pollution in northwest China is less than that in other regions. Due to the relatively backward economic development in southwest China, it is often characterized by insufficient investment. How to both control the economic development and environmental protection sustainability is a major problem in the northern and northwestern regions of China.

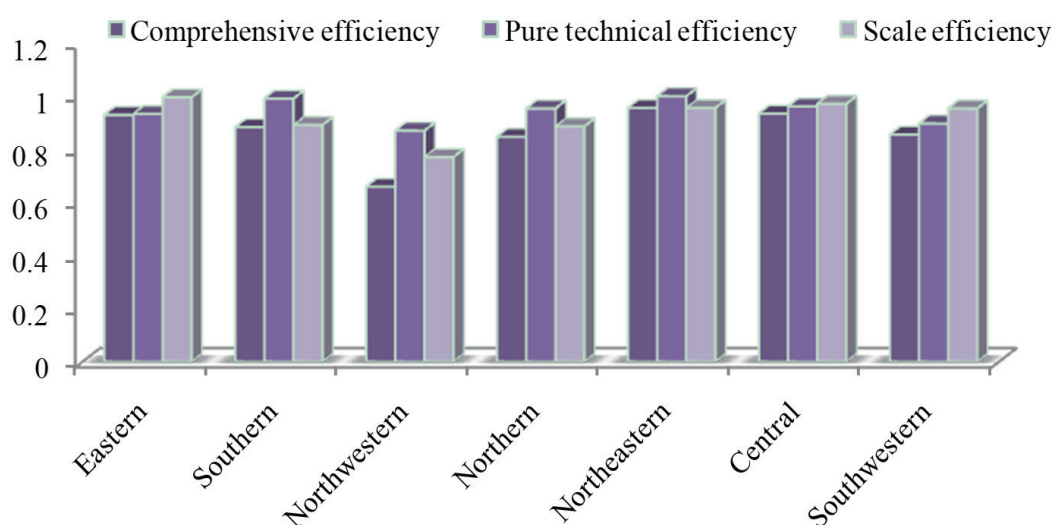


Figure 5. Efficiency distribution of different regions in China.

Table 2. Environmental management efficiency changes from 2005 to 2017

Year	EC	TC	PTEC	SEC	TFPC
2005	1	1	1	1	1
2006	1.059	1.024	1.045	1.014	1.084
2007	1.087	1.011	1.038	1.047	1.099
2008	0.912	1.054	0.943	0.967	0.962
2009	1.154	0.859	1.132	1.02	0.991
2010	0.997	1.166	0.993	1.005	1.163
2011	1.05	0.94	1.011	1.039	0.987
2012	0.967	0.97	1	0.967	0.938
2013	0.977	0.927	0.984	0.994	0.906
2014	0.976	1.023	0.98	0.996	0.999
2015	1.036	0.938	1.027	1.009	0.972
2016	1.101	0.781	1.063	1.036	0.859
2017	1.016	1.002	1.045	0.973	1.018

EC: Efficiency change; TC: technical change; PTEC: pure technical efficiency change; SEC: scale efficiency change; TFPC: total factor productivity change.

Time changes of environmental management efficiency

In this section, time changes of environmental management efficiency are analyzed. Table 2 shows the results obtained from the DEA-Malmquist index-based efficiency evaluation. In Table 2, EC, TC, PTEC, EC, and TFPC indicate that the efficiency of environmental management has increased rapidly. It can be seen that the overall efficiency of China's environmental management has improved over time. In addition to large floating, there is an obvious upward trend. With the rapid development of China's economy, environmental problems have been alleviated and improved.

Figure 6 shows Environmental management efficiency change in different provinces. Figure 6 clearly shows that the efficiency of environmental management in most provinces is not stable, as the efficiency fluctuates greatly, especially in the eastern and central provinces of China, e.g., Beijing and Shandong in the eastern region and Hubei, Hunan, and Jiangxi in the central region, indicating that the efficiency of environmental management in most provinces has been significantly improved. There are still many imperfections in the current environmental management in China, such as the lack of institutional standardization in the process of environmental management, which affects the regional coordination and stability of environmental management. However, from the overall time change, China's environmental management

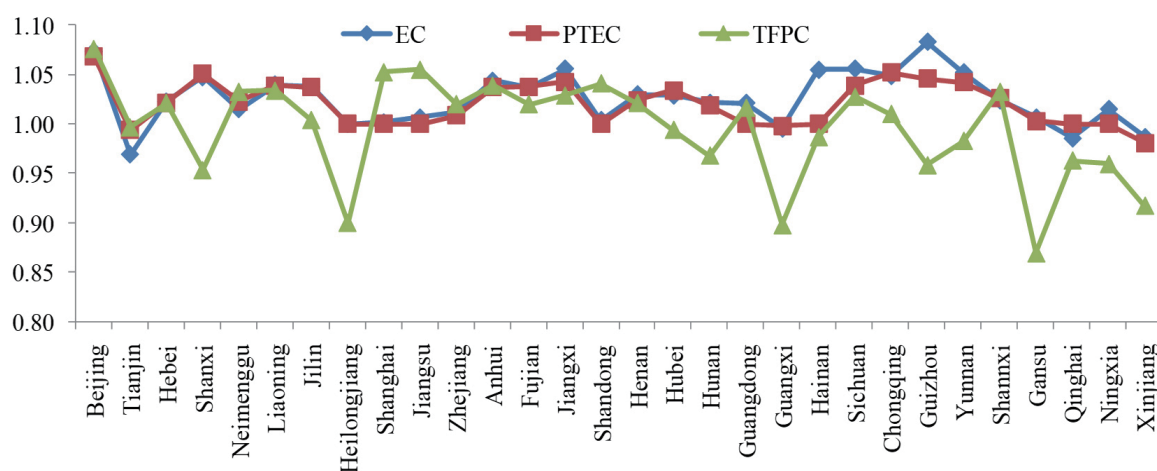


Figure 6. Environmental management efficiency changes in different provinces.

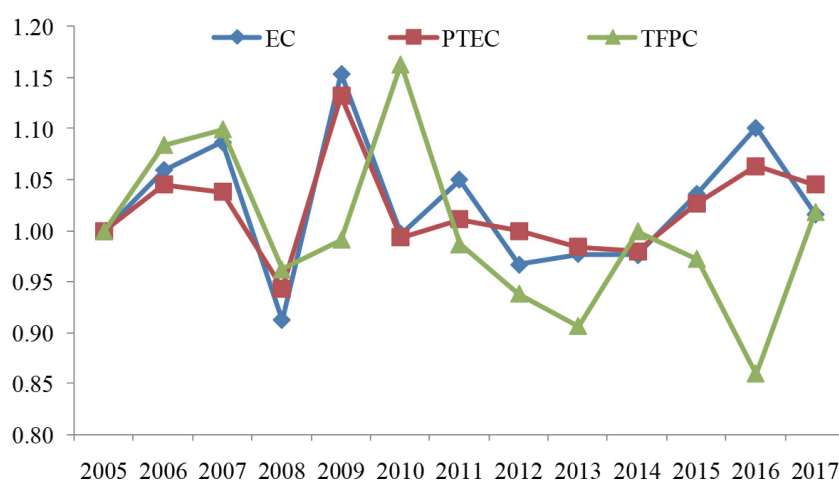


Figure 7. Environmental management efficiency change rate from 2005 to 2017.

efficiency shows a gradual upward trend, indicating that current environmental management is relatively reasonable.

Figure 7 shows the results from the perspective of pure technical efficiency. It is clear that the change trend of technical efficiency level is basically consistent with that of comprehensive efficiency, and the technical level is relatively stable. With the progress of China's environmental management technology, the overall environmental efficiency shows a significant upward trend, indicating that the input of technical elements plays a role in the current process of environmental management. Therefore, to maintain the balance between environmental inputs and outputs, more attention should be paid to the inputs of technological progress and the innovation of environmental management tools, which is a key factor to maintain steady economic growth and environmental improvement.

Improvement strategy of regional environmental management efficiency

In this section, we analyze the comprehensive efficiency of environmental management of 30 provinces in China in 2017, which forms 30 analysis samples. We then analyze the input and output indicators of the samples that fail to reach the effective efficiency according to these data and obtain the number of provinces with unreasonable input-output indicators, which provides reference for the design of

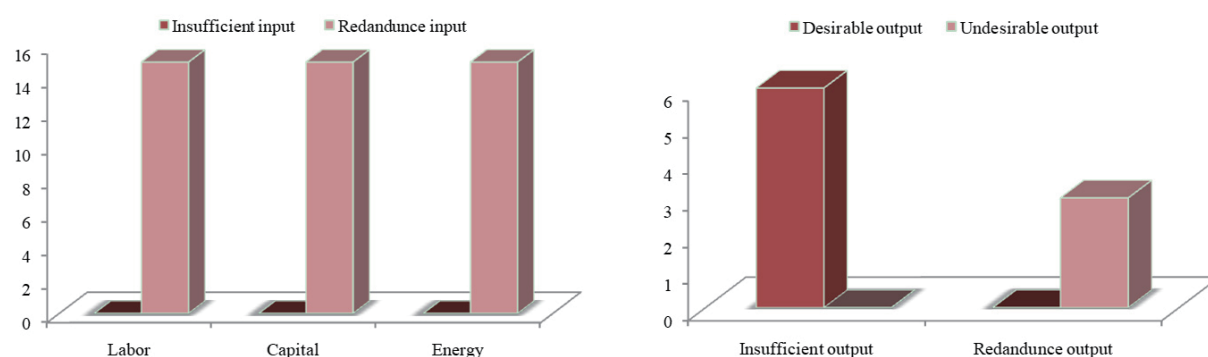


Figure 8. Number of provinces with redundant input and insufficient output.

Table 3. Values of input-output adjustments in different regions

	Environmental management input			Environmental management output	
	Labor	Capital	Energy	Desirable output	Undesirable output
Eastern	-319.726	-17469.4	-2347.01	0	0
Southern	-10.276	-529.238	-151.681	0	0
Northwestern	-253.79	-18834.4	-1219.74	162.496	-26.952
Northern	-479.949	-8726.58	-1679.79	0	-71.425
Northeastern	0	0	0	0	0
Central	-643.474	-41369.3	-2745.81	0	0
Southwestern	-207.468	-7642.71	-663.762	1247	0

environmental management efficiency improvement scheme, as shown in Figure 8. From the perspective of input redundancy, the situation of investment redundancy in environmental pollution control is more serious, which indicates that there are unreasonable investment resources and excessive investment in the implementation process of environmental management in China. The redundancy degree of the three input indicators is basically similar, and the number of provinces occupied by the three excessive investments is relatively large. However, from the perspective of output in 2017, it can be found that the output is not reasonable.

At the same time, to analyze the structural differences of regional environmental management inputs and outputs (see in Figure 8), the environmental management efficiency assessment of each province in 2017 is taken as an example, and the scheme for the adjustment of input-output structure of each region is also provided. The improvement results are shown in Table 3. As shown in Table 3, the key to improve the efficiency of environmental management lies in solving the situation of input redundancy and desirable output insufficient. Among the regions, the northeastern region does not need to adjust its inputs and outputs in 2017, while the other regions in China must focus on reducing input in environmental management. Northern and northwestern China mainly need to solve the problem of excessive emission of undesirable output. In terms of the redundancy of the three input indicators, the capital investment redundancy is the most serious. The capital investment in central China needs to be reduced by 41,369.4 billion yuan. In addition to excessive input and consumption of resources, which will result in the waste of resources due to the unreasonable input structure, the environmental pollution did not decrease due to the increase of environmental input, resulting in serious redundancy of environmental outputs.

CONCLUSIONS

Based on the environmental management data from 2005 to 2017, the EMEE in 30 provinces of China was performed on the basis of indicator information integration by the ER approach with weight calculation method and DEA-Malmquist index. Additionally, the efficiency of regional environmental management

was further evaluated from the two dimensions of regional efficiency distribution and dynamic efficiency change. The main conclusions are summarized as follows:

Firstly, from the sample analysis of environmental management in each province of China, it can be found that the comprehensive efficiency of environmental management in east China and south China is higher than that in other regions, and the environmental management efficiency in southwest China is the worst. According to the national data analysis, the results show that the comprehensive efficiency of environmental management in China's provinces has changed greatly, and the environmental management capacity is not stable. The change trend of pure technical efficiency is basically consistent with the comprehensive efficiency, and the fluctuation of comprehensive efficiency of environmental management is related to the fluctuation of technical efficiency. From the perspective of the change trend of scale benefit, there is still an unreasonable environmental input-output structure in every province, which is mainly due to the increase of scale benefit, that is, too little investment in environmental management leads to insufficient output.

Secondly, from the perspective of input-output structure, it can be found that there is redundancy in most regions, especially in capital input of environmental management. From the perspective of environmental output, it can be found that the structure of desirable output is basically reasonable, while there is significant redundancy in undesirable output. In addition to the effective allocation of input, it is necessary to reasonably reduce the emission of undesirable pollution output.

Thirdly, to effectively distinguish the changes of comprehensive efficiency and pure technical efficiency of environmental management over time, the results show that there are significant differences between the comprehensive efficiency of environmental management and pure technical efficiency in different management periods. However, the overall environmental efficiency and pure technical efficiency show a significant upward trend in China, that is, the positive effect of the current input-output structure and technique on the comprehensive efficiency of environmental management becomes more significant over time.

DECLARATIONS

Authors' contributions

Made substantial contributions to conception and design of the study and performed data analysis and interpretation: Li C, McHugh O

Performed supervision, as well as provided administrative, technical, and material support: Liu J, Martínez L

Availability of data and materials

Not applicable.

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Conflicts of interest

All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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