Mariculture carbon sink efficiency in China: Measurements and driving factors

Xiuyi Shi
Southeast University
Yingzhi Xu (xuyingzhi315@163.com)
Southeast University https://orcid.org/0000-0002-7720-2714
Biying Dong
Southeast University
Nariaki Nishino
The University of Tokyo: Tokyo Daigaku

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Xiuyi Shi, a791521636@163.com

School of Economics and Management, Southeast University, Nanjing 211189, China

Yingzhi Xu* (Corresponding author), xuyingzhi@hotmail.com

School of Economics and Management, Southeast University, Nanjing 211189, China

Biying Dong, 514922818@qq.com

School of Economics and Management, Southeast University, Nanjing 211189, China

Nariaki Nishino, nishino@tmi.t.u-tokyo.ac.jp

Department of Technology Management for Innovation, School of Engineering, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan

Address: Jingguan Building, Dongnandaxue Road 2, Jiangning District, Nanjing 211189, China.

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Abstract

A measurements of China's mariculture carbon sink efficiency (MCSE) and its driving factors analysis are conducted in this paper. First, based on the Super-SBM model, the panel data from 9 Chinese coastal provinces (autonomous regions) during 2015-2019 are used to measure the MCSE in China. Second, the STRIPAT method and ridge regression method are used to explore the driving factors of China's MCSE. Third, a blueprint for China to achieve carbon neutrality is constructed, and the advantages of mariculture carbon sink are summarized. The results show that the mariculture carbon sink has a high carbon store and carbon flux, and it has a dual value of ecology and economy. Meanwhile, mariculture carbon sink has the less negative impacts on eco-environment. Further, the MCSE, on the whole, of the 9 coastal regions in China presents an upward trend in 2015-2019, and this trend is more significant in the Pan-Pearl River Delta (PPRD) and Circum-Bohai Sea (CBS) Economic Zone. In 2019, 66.67% of the regions in the sample is the SBM-efficient DMUs on technical efficiency (*TE*), and 88.89% of the regions in the sample is the BSM-efficient DMUs on pure technical efficiency (*PTE*). Finally, driving factors analysis shows that the affluence and service industry of a region may have a positive impact on the MCSE, while the population, urbanization and international trade may have a negative impact on the MCSE to a certain extent.

1. Introduction

Crossing over from an agricultural society to a modern industrial one usually at the expense of eco-environment, especially in developing countries. The over exploitation and utilization of natural resources has led to the climate change crisis, the major of which is global warming. It has gradually become a consensus that global warming is caused by human activities like excessive carbon emissions. Therefore, reducing carbon emissions, or even achieving net carbon emissions zero, is the key to mitigate global warming. For this purpose, a long-term temperature goal of holding the global average temperature increase to well below 2℃ and pursuing efforts to limit this to 1.5℃ above pre-industrial levels was set by the Paris Agreement in 2015 (Schleussner et al., 2016). China is a developing country with the largest economy and population in the current world, whose carbon emissions have reached around 27.92% of the whole world in 2019 (Friedlingstein et al., 2020). The past 20 years have witnessed not only the rapid growth of China's economy, but also the rapid increasing of carbon emissions. As one of the main carbon emissions country, China has the responsibility to contribute to the mitigation of global warming. Therefore, "China will strengthen intended nationally determined contributions (INDCs), adopt more powerful policies and measures, strive to achieve carbon peak by 2030, and achieve carbon neutrality by 2060." was declared by Chinese government at the 75th UN General Assembly. And also, "Carbon Peak" and "Carbon Neutrality" have become two significant national strategic goals (NDRC, 2015; Lv et al., 2021). Undoubtedly, the Chinese government will take a series of measures to meet the ultimate goal of carbon neutrality in the next 40 years.

Against this backdrop, how China can achieve those two goals has been widely concerned by most of scholars, especially whose research field related to climate change or environment protection, in the world nowadays. At the current stage, there are two main pathways towards carbon neutrality: carbon reduction and carbon fixation. On the one hand, measures on technological contribution, clean energy application, energy transition and energy conservation are being implemented to reduce carbon emissions in China, which is proved that they have significantly positive effects on carbon reduction by lots of studies (Hao et al., 2021; Su and Urban, 2021; Wang et al., 2021; Liu et al., 2021). These measures have also made a great contribution to meet the goal of carbon peak (Su et al., 2021; Yang et al., 2021); On the other hand, carbon sink is an effective way to fix the carbon in the atmosphere (Lin and Ge, 2019a). The carbon cycle is an important way in which living things interact with one another, and the carbon neutrality will be realized when carbon cycle becomes balanced and sustainable. Therefore, improving carbon sink biomass and carbon sink level is helpful for China to achieve the goal of carbon neutrality on schedule.

Land carbon sink, especially forestry carbon sink, usually occurred to our mind when carbon sink is mentioned, and there is also a truth that forest is the largest carbon store on the Earth, so the researches on forestry or land carbon sink are abundant in recent years (Daigneault and Favero, 2021; Heinrich et al., 2021; Wang et al., 2020). However, marine carbon sink is also an important part of carbon sink. Some related studies show that marine organisms have the unique advantages of high carbon fixation efficiency and long storage time (Nellemann et al., 2009), and the accurate valuation of marine carbon sink will help governments meet commitments to carbon neutrality goals (Wedding et al., 2021). In China, the mariculture carbon sink is the main part of manageable marine carbon sink. China's mariculture area was 20.4 thousand km^2. The mariculture carbon sink approximately accounts for around 77.28-81.09% of the whole marine carbon sink in China. The estimation of mariculture carbon sink capability in China is approximately 7.79-9.36 $TgC \cdot yr^{-1}$. These facts indicate that the mariculture, such as algae and shellfish, has a high carbon sink potential (Gao et al., 2016). Consequently, according to the analysis above, three questions addressed are put in place as follows: First, is China's mariculture carbon sink efficient? Second, how to evaluate mariculture carbon sink efficiency (MCSE) accurately? Third, what are the driving factors of MCSE in China? More adaptive pathways to neutralize carbon emissions in China can be therefore deployed once these questions are answered.

To resolve the above-mentioned questions, this paper empirically measures the MCSE in China by Super-SBM model, and analyzes the driving factors of MCSE in China by STIRPAT model and ridge regression method. The subsequent section of this paper is organized as follows: The related literature is reviewed in Section 2. Section 3 defines the concept of carbon sink efficiency, presents the construction of empirical model, and provides some corresponding formulas. Section 4 presents the data and variables. Section 5 shows and discusses the empirical results. According to the analysis above, the research conclusions are drawn in Section 6, and some further researches deserving study are also given based on these conclusions.

2. Literature review

Carbon sink is one of the essential pathways for China to realize carbon neutrality. Most studies related to China's carbon sink focus on land carbon sink (Yang et al., 2019). Lin and Ge (2019b) noticed a dual role of climate change mitigation and regional output increase in forestry carbon sink, and concluded that the ecological efficiency and productivity are greater than the economic development of forestry. Cui et al. (2018) studied the carbon sink capability of mangrove forests which distributed along the coast in tropical and subtropical zones, and found the mangrove forests have a greater carbon sink capability than that of terrestrial forests. Sha et al. (2020) found that grasslands played an important role in the global carbon cycle, and grasslands would act as potential carbon sink if degradation could be reversed. In recent years, the Natural Forest Protection Program (NFPP) and Carbon Emissions Trading (CET) in China are much effective in developing carbon sink, which can help to realize carbon neutrality (Jiang et al., 2017; Wu et al., 2020).

In addition to land carbon sink, marine carbon sink is also an important part of carbon sink in China, especially the mariculture carbon sink (Zhang et al., 2017). China is a large maritime country, with an area of 0.38 million km^2 of inland water and territorial sea clearly announced. In 2019, China's mariculture areas are over 1.99 million ha. The algae breeding area is around 0.14 million ha, shellfish culture area is around 1.20 million ha, and fishery area is around 75.35 thousand ha, accounting for 71.35% of the total area of mariculture (FBMARAC, 2020). China is rich in resources related to mariculture. Currently, the lack of understanding in mariculture carbon sink restrained the full utilization of it. According to a rough estimate, the production of marine-based seafood in China now accounts for over two-thirds of the world total, and the level of mariculture carbon sink each year is same as 5000 km^2 of forest. Although some studies have shown that mariculture also brings about a destruction of marine eco-environment called a double-edged sword, the mariculture carbon sink still has the potential for high efficiency carbon fixation (Meng and Feagin, 2019).

Some related literature is concentrating on the carbon fixation effect of mariculture carbon sink. Zhang et al. (2017) made a study on China's carbon sink processes and mechanisms in coastal mariculture environments, and concluded that the mariculture carbon sink, also called "blue carbon", is an important way to combat climate change and also has a dual value of ecology and economy. Further, the main types of it are shellfish and macro-algae mariculture. Jiang and Fang (2021) found that different mussel-kelp ratios in integrated mariculture will lead to the different carbon absorption capability, and concluded that the shellfish-seaweed mode of Integrated Multi-trophic Aquaculture (IMTA) is an advantageous system to create a net carbon sink with less negative effects on the environment. Ren (2021) made a study on the carbon sink capability and economic value of mariculture, and pointed out that the development of mariculture carbon sink in China is still in the primary stage, and the considerable ecological and economic value holds a significant development potential in the process of fighting climate change.

According to the literature above, it can be seen that the development of mariculture carbon sink should be evaluated by a series of scientific and reliable indicators. Compared with carbon sink scale, carbon sink efficiency is more suitable because of its comprehensiveness. On the one hand, efficiency is usually used in evaluating the relative effect from the perspective of input and output, and in recent years, the concept of mariculture efficiency is only used in the calculation of economic benefits (Onumah et al., 2010; Ji and Wang, 2015; Wang and Ji, 2017). However, the MCSE can measure the relative effect of mariculture in both carbon fixation capability and economic benefits based on a certain input. On that account, a comprehensive concept of MCSE should be proposed; On the other hand, there are two main types of methods to measure the efficiency in common, including parameter estimation method, such as Stochastic Frontier Analysis (SFA), and non-parametric estimation one, such as Data Envelopment Analysis (DEA) (Battese and Coeli, 1992; Charnes et al., 1978). Using the SFA model to measure an efficiency needs a more accurate construction of production function, and it is also usually used in the situation of single output. In contrast, the DEA model can be used without a production function setting, and it is more suitable for a multi-output situation as well as multi-input (Gang and Sickles, 1992). So far, it is not very easy to construct an accurate mariculture production function setting because of the smattering knowledge of mariculture carbon sink, meanwhile multi-output indicators as well as multi-input are expected to use for measuring its efficiency. Therefore, a Super-SBM model (an improved DEA model) will be used to measure the MCSE of China in this paper.

STIRPAT model is often used to explore the driving factors of the environment. In the early 1970s, Ehrlich and Holdren (1971) first established the IPAT model to explore the driving factors of environmental pressure. On this basis, Dietz and Rosa (1994) further generalized the STIRPAT model by decomposing, deleting or adding variables. Therefore, it is feasible to explore the driving factors of carbon sink efficiency by STIRPAT model. Le (2021) examined the driving factors of greenhouse gas emissions for 16 ASEAN + 6 countries during 1995-2014 by STIRPAT model. Results showed that trade openness and human capital have positive effects on reducing the major types of GHG emissions, and energy consumption, urbanization, industrialization, financial development and FDI have the opposite effects. Wen and Shao (2019) studied the factors of carbon emissions in commercial departments during 2001-2015 by STIRPAT model, concluding that economic growth, urbanization, population growth, energy intensity, and FDI increased carbon emissions, and the optimization of energy structure reduced carbon emissions. However, in the field of mariculture carbon sink, there are few studies using STIRPAT model to explore the driving factors.

Compared with the existing literature and based on the analysis above, the main contributions of this paper are as follows: (1) The concept of MCSE in this study is defined to measure the carbon sink effect on the basis of a certain cost in this study, which emphasizes both ecological and economic value; (2) Based on the panel data in China’s 9 coastal regions during 2015-2019, the Super-SBM model is used to measure and decompose the MCSE in China, and the potentials of mariculture carbon sink in different regions are evaluated and analyzed; (3) The STIRPAT model and ridge regression method are used to explore the driving factors of China's MCSE, and the development strategies and recommendations of mariculture carbon sink in different regions are given.

3. Methodologies

3.1. Super-SBM model

Data Envelopment Analysis (DEA) model is a non-parametric method using a linear program to solve the efficiency measure problem of multi-input and multi-output. The traditional DEA model includes the DEA-CCR and DEA-BCC models, which can measure the relative efficiency of a set of decision-making units (DMUs) (Charnes et al., 1978; Banker et al., 1984). However, considering that the traditional DEA model cannot account for the impact of the slacks, which causes a reduction in the reliability of efficiency measures when the undesirable output exists (Deng and Yan, 2019). To solve this problem, a non-angular and non-radial SBM model, which makes slacks be introduced into the objective function, was developed by Tone (2001). For measuring MCSE, carbon emissions from mariculture need to be taken into account as an undesirable output, and the SBM model is therefore used in this paper. The construction of the SBM model is as follows:

Firstly, an SBM model is constructed. Assume that there are n DMUs, p inputs, q_1 desirable outputs, and q_2 undesirable outputs in each DMU. The vectors $\mathbf{x} \in \mathbf{R}^p, \mathbf{y}_1 \in \mathbf{R}^{q_1}, \mathbf{y}_2 \in \mathbf{R}^{q2}$ represent these indicators, respectively, and the three matrices $\boldsymbol{X}$, $\boldsymbol{Y}_1$, $\boldsymbol{Y}_2$ can be defined as formula (1), (2), and (3):

$$\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \Lambda, \mathbf{x}_n]^{\mathrm{T}} \in \mathbf{R}^{p \times n} > \mathbf{0} \tag{1}$$

$$\mathbf{Y}_1 = [\mathbf{y}_{11}, \mathbf{y}_{12}, \Lambda, \mathbf{y}_{1n}]^{\mathrm{T}} \in \mathbf{R}^{q_1 \times n} > \mathbf{0} \tag{2}$$

$$\mathbf{Y}_2 = [\mathbf{y}_{21}, \mathbf{y}_{22} \Lambda\ , \mathbf{y}_{2n}]^{\mathrm{T}} \in \mathbf{R}^{q_2 \times n} > \mathbf{0} \tag{3}$$

And then, the set of production possibility set P can be defined as formula (4):

$$P(\mathbf{x}, \mathbf{y}_1, \mathbf{y}_2) = \left\{ (\mathbf{x}, \mathbf{y}_1, \mathbf{y}_2) \middle| \mathbf{x} \geq \mathbf{X}\boldsymbol{\lambda}, \mathbf{y}_1 \leq \mathbf{Y}_1\boldsymbol{\lambda}, \mathbf{y}_2 \geq \mathbf{Y}_2\boldsymbol{\lambda}, \boldsymbol{\lambda} \geq \mathbf{0} \right\} \tag{4}$$

where $\boldsymbol{\lambda}=[\lambda_1,\lambda_2,\cdots,\lambda_n]$ is a non-negative vector that indicates the weight of the efficiency measure. The technical efficiency (TE) under the SBM model can be defined as equation (5):

$$TE_{\mathrm{SBM}} = \min \frac{1 - \dfrac{1}{p}\displaystyle\sum_{i=1}^{p} \frac{s_{x_i}^-}{x_{io}}}{1 + \dfrac{1}{q_1+q_2}\left(\displaystyle\sum_{i=1}^{q_1} \frac{s_{y_{1i}}^+}{y_{1io}} + \sum_{i=1}^{q_2} \frac{s_{y_{2i}}^-}{y_{2io}}\right)}$$

$$\text{s.t.} \begin{cases} \mathbf{x}_o = \mathbf{X}\boldsymbol{\lambda} + \mathbf{s}_x^- \\ \mathbf{y}_{1o} = \mathbf{Y}_1\boldsymbol{\lambda} - \mathbf{s}_{y_1}^+ \\ \mathbf{y}_{2o} = \mathbf{Y}_2\boldsymbol{\lambda} + \mathbf{s}_{y_2}^- \\ \mathbf{s}_x^- \geq \mathbf{0}, \mathbf{s}_{y_1}^+ \geq \mathbf{0}, \mathbf{s}_{y_2}^- \geq \mathbf{0} \end{cases} \tag{5}$$

where vectors $\mathbf{s}_x^-, \mathbf{s}_{y_1}^+, \mathbf{s}_{y_2}^-$ respectively represent slacks in inputs, desirable outputs, and undesirable outputs; - means that the actual indicators are greater than the frontier ones; + means that the actual indicators are less than the frontier ones; the subscript o in the equation is the measured unit; TE_{SBM} represents the technical efficiency under the SBM model ranging from 0 to 1, and the DMU is efficient if the TE_{SBM} = 1. To further rank the SBM-efficient DMUs, the scholar Tone (2002) also improved the SBM model by combining the Super-efficiency DEA model, and then developed the Super-SBM model. The process of the Super-SBM model can be further constructed as follows:

In the Super-SBM model, a production possibility set $P'(\mathbf{x}_o, \mathbf{y}_{1o}, \mathbf{y}_{2o})$ spanned by $(\mathbf{X}, \mathbf{Y}_1, \mathbf{Y}_2)$ excluding the SBM-efficient DMUs $(\mathbf{x}_o, \mathbf{y}_{1o}, \mathbf{y}_{2o})$ can be defined as formula (6):

$$P'(\mathbf{x}_o, \mathbf{y}_{1o}, \mathbf{y}_{2o}) = \left\{ (\bar{\mathbf{x}}, \bar{\mathbf{y}}_1, \bar{\mathbf{y}}_2) \middle| \bar{\mathbf{x}} \geq \sum_{i=1,\neq o}^{n} \lambda_i \mathbf{x}_i, \bar{\mathbf{y}}_1 \leq \sum_{i=1,\neq o}^{n} \lambda_i \mathbf{y}_{1i}, \bar{\mathbf{y}}_2 \leq \sum_{i=1,\neq o}^{n} \lambda_i \mathbf{y}_{2i}, \bar{\mathbf{y}}_1 \geq \mathbf{0}, \boldsymbol{\lambda} \geq \mathbf{0} \right\} \tag{6}$$

where the vectors $\bar{\mathbf{x}}, \bar{\mathbf{y}}_1, \bar{\mathbf{y}}_2$ correspond to the above ones $\mathbf{x}, \mathbf{y}_1, \mathbf{y}_2$. Further, a subset

$\overline{P}'(\mathbf{x}_o, \mathbf{y}_{1o}, \mathbf{y}_{2o})$ of $P'(\mathbf{x}_o, \mathbf{y}_{1o}, \mathbf{y}_{2o})$ can be defined as formula (7):

$$\overline{P}'(\mathbf{x}_o, \mathbf{y}_{1o}, \mathbf{y}_{2o}) = P'(\mathbf{x}_o, \mathbf{y}_{1o}, \mathbf{y}_{2o}) \cap \{\overline{\mathbf{x}} \geq \mathbf{x}_o, \overline{\mathbf{y}}_1 \geq \mathbf{y}_{1o}, \overline{\mathbf{y}}_2 \geq \mathbf{y}_{2o}\} \tag{7}$$

In formula (7), $\overline{P}'(\mathbf{x}_o, \mathbf{y}_{1o}, \mathbf{y}_{2o})$ is not empty by the assumption $\mathbf{X} > \mathbf{0}, \mathbf{Y}_1 > \mathbf{0}, \mathbf{Y}_2 > \mathbf{0}$. According to the study made by Tone (2002), the *TE* under the Super-SBM model can be defined as equation (8):

$$TE_{\text{Super-SBM}} = \min \frac{\frac{1}{p}\sum_{i=1}^{p}\frac{\overline{x}_i}{x_{io}}}{\frac{1}{q_1+q_2}\left(\sum_{i=1}^{q_1}\frac{\overline{y}_{1i}}{y_{1io}} + \sum_{i=1}^{q_2}\frac{\overline{y}_{2i}}{y_{2io}}\right)}$$

$$\text{s.t.}\begin{cases} \overline{\mathbf{x}} \geq \sum_{i=1,\neq o}^{n}\lambda_i \mathbf{x}_i \\ \overline{\mathbf{y}}_1 \leq \sum_{i=1,\neq o}^{n}\lambda_i \mathbf{y}_{1i} \\ \overline{\mathbf{y}}_2 \geq \sum_{i=1,\neq o}^{n}\lambda_i \mathbf{y}_{2i} \\ \overline{\mathbf{x}} \geq \mathbf{x}_o, \overline{\mathbf{y}}_1 \leq \mathbf{y}_{1o}, \overline{\mathbf{y}}_2 \geq \mathbf{y}_{2o}, \overline{\mathbf{y}}_1 \geq \mathbf{0}, \boldsymbol{\lambda} \geq \mathbf{0} \end{cases} \tag{8}$$

The Super-SBM model constructed as equation (8) is a form of constant returns to scale, and it also has another variable returns to scale form, i.e., imposing the constraint $\sum_{i=1,\neq o}^{n}\lambda_i = 1$. Therefore, the $TE_{\text{Super-SBM}}$ can be decomposed into two parts called pure technical efficiency (*PTE*) and scale efficiency (*SE*), which can be indicated as equation (9):

$$TE = PTE \times SE \tag{9}$$

where the *PTE* indicates the ratio of distance between actual output and returns to scale, which reflects the technical progress, and the *SE* indicates the change of returns to scale.

3.2. STIRPAT model

STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model originates from IPAT model firstly put forward by Ehrlich and Holdren (1971), which is commonly applied to specify the driving factors that influence environmental pressure. IPAT model is depicted as equation (10):

$$I = P \times A \times T \quad (10)$$

where I indicates environmental pressure, P indicates population, A indicates affluence, and T indicates technology.

However, IPAT model is only a concise and simple accounting equation to examine the driving factors of environmental pressure, which is in conflict with the environmental Kuznets curve (EKC) hypothesis because of the same factor elasticity. On that account, STIRPAT model is developed by Dietz and Rosa (1994) to overcome the limitation of IPAT model. Maintaining the factors of population, affluence, and technology, STIRPAT model rejects the same elasticity assumption and adds a stochastic disturbance for facilitating empirical analysis. Due to its flexibility, STIRPAT model is used in this study to explore the driving factors of MCSE in China. STIRPAT model is depicted as equation (11), and it can be further transformed into equation (12) by taking the natural logarithm:

$$I = \beta P^a A^b T^c \delta \quad (11)$$

$$\ln I = \ln \beta + a \ln P + b \ln A + c \ln T + \ln \delta \quad (12)$$

where I, P, A, and T have the same meaning as in the IPAT framework, β, a, b, and c are the parameters to be estimated, δ is the stochastic disturbance, and $\ln(\cdot)$ indicates taking the natural logarithm. Here, a, b, and c are equivalent to the elasticity of driving factors, which refers to the change in environmental pressure caused by unit change of a driving factor, ceteris paribus.

In addition, some other variables can be added into STIRPAT model for exploring the driving factors of environmental pressure more comprehensively. Therefore, this study established an extended STIRPAT model including driving factors of population, affluence, technology, service industry, urbanization, and international trade. The extended STIRPAT model can be constructed as equation (13):

$$\ln I_{it} = \beta_0 + \beta_1 \ln P_{it} + \beta_2 \ln A_{it} + \beta_3 \ln T_{it} + \beta_4 \ln SI_{it} + \beta_5 \ln U_{it} + \beta_6 \ln IT_{it} + \delta_{it} \tag{13}$$

where i is the province code, t is the period code, I indicates MCSE, P, A, and T still indicates population, affluence, and technology, respectively, SI indicates service industry, U indicates urbanization, IT indicates international trade, β_j (j = 0, 1, ⋯, 6) are the parameters to be estimated, δ is the stochastic disturbance. Obviously, the driving factors of MCSE can be analyzed more comprehensively by the extended STIRPAT model.

3.3. Ridge regression

To alleviate the multicollinearity between explanatory variables, this paper uses ridge regression for STIRPAT model. Ridge regression is one of the most effective solutions to deal with multicollinearity. It can obtain acceptable biased estimates with small mean square errors in the independent variables through the trade-offs between bias and variance (Hoerl and Kennard, 1970). Consider the standard model for multiple linear regression:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\delta} \tag{14}$$

where it is assumed that $\mathbf{X}$ is an $n \times p$ matrix of explanatory variables and of rank p, $\boldsymbol{\beta}$ is a $p \times 1$ vector of parameters to be estimated, $\boldsymbol{\delta}$ is an $n \times 1$ vector of the errors with $E(\boldsymbol{\delta}) = \mathbf{0}$ and $E(\boldsymbol{\delta}\boldsymbol{\delta}^{\mathrm{T}}) = \sigma^2 \mathbf{I}_n$. Here, σ is the standard deviation, $\mathbf{I}_n$ is an identity matrix of order n. The unbiased β estimate is normally given by:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{Y} \tag{15}$$

where $\hat{\boldsymbol{\beta}}$ is the estimate of $\boldsymbol{\beta}$, the matrix $\mathbf{X}^{\mathrm{T}}\mathbf{X}$ is ill-conditioned, i.e., the value of determinant

$\left|\mathbf{X}^{\mathrm{T}}\mathbf{X}\right|=0$, when the variables in matrix $\mathbf{X}$ are highly multicollinear. This may lead to a highly sensitivity to the slight variations in data when attempting to estimate matrix $(\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}$. For solving this problem, the ridge regression estimation is therefore given by:

$$\hat{\boldsymbol{\beta}}^{*}=(\mathbf{X}^{\mathrm{T}}\mathbf{X}+k\mathbf{I}_{p})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{Y}, k\geq 0 \tag{16}$$

where $\hat{\boldsymbol{\beta}}^{*}$ is the ridge regression estimate of $\boldsymbol{\beta}$, k indicates ridge parameter. Generally, ridge regression determines the optimal value of k by increasing the value of k from 0 until all regression coefficients appear to have stabilized, thereby the results of ridge regression are obtained.

4. Study areas, variables and data

4.1. Profile of study areas

China is a large country with vast coastal areas, and has three coastal economic zones: Circum-Bohai Sea (CBS) Economic Zone, Yangtze River Delta (YRD) Economic Zone and Pan-Pearl River Delta (PPRD) Economic Zone (Fig. 1). Specifically, the Circum-Bohai Sea Economic Zone includes Liaoning, Hebei and Shandong, the Yangtze River Delta Economic Zone includes Jiangsu and Zhejiang, and the Pan-Pearl River Delta Economic Zone includes Guangdong, Guangxi, Hainan and Fujian. These are the main mariculture industry areas in China and is over 1.99 million ha in 2019. Therefore, these areas are selected as the study objects in this paper. Specifically, in 2018, the algae breeding area is around 0.14 million ha, shellfish culture area is around 1.24 million ha, accounting for 67.80% of the total area of mariculture. The mariculture output is around 20.30 million t. The output of algae and shellfish are 2.34 million t and 14.40 million t, respectively, accounting for 82.63% of the total mariculture output. In 2019, there are approximately 1.20 million ha of shellfish, 0.14 million ha of algae and 75.35 thousand ha of fish, accounting for 71.35% of the total mariculture organisms (FBMARAC, 2020). Some studies have shown that the estimation of marine carbon sink capability in China is approximately 7.79-9.36 TgC·yr-1, and the mariculture carbon sink approximately accounts for around 77.28-81.09% of the whole marine carbon sink in China (Gao et al., 2016).

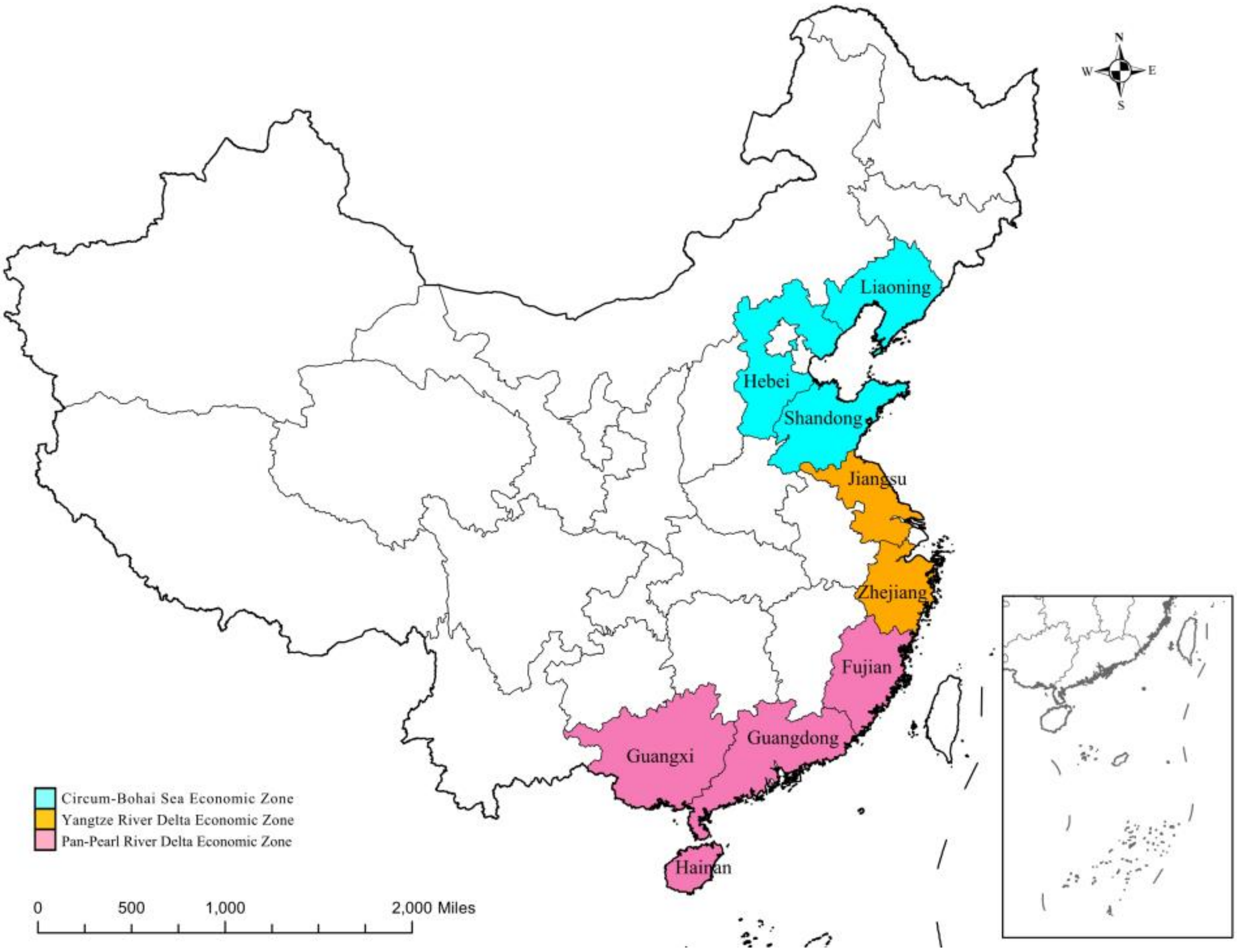


Fig. 1. Distribution of study areas.

Moreover, it is noted that in this paper: (1) Tianjin and Shanghai are not included because of their small mariculture scale and the lack of statistical data related to mariculture in China Fishery Statistical Yearbook; (2) Hong Kong, Macao and Taiwan are not included owing to the inconsistency of statistical standards.

4.2. Variables and data

In this paper, the MCSE is defined as the net positive effect of carbon sink in mariculture based on a certain input, and it is illustrated in Fig. 2, which includes the input and output of MCSE as well as the impact mechanism on carbon neutrality. Note that the selection of indicators in the Super-SBM model used in the following sections will also conform to this illustration.

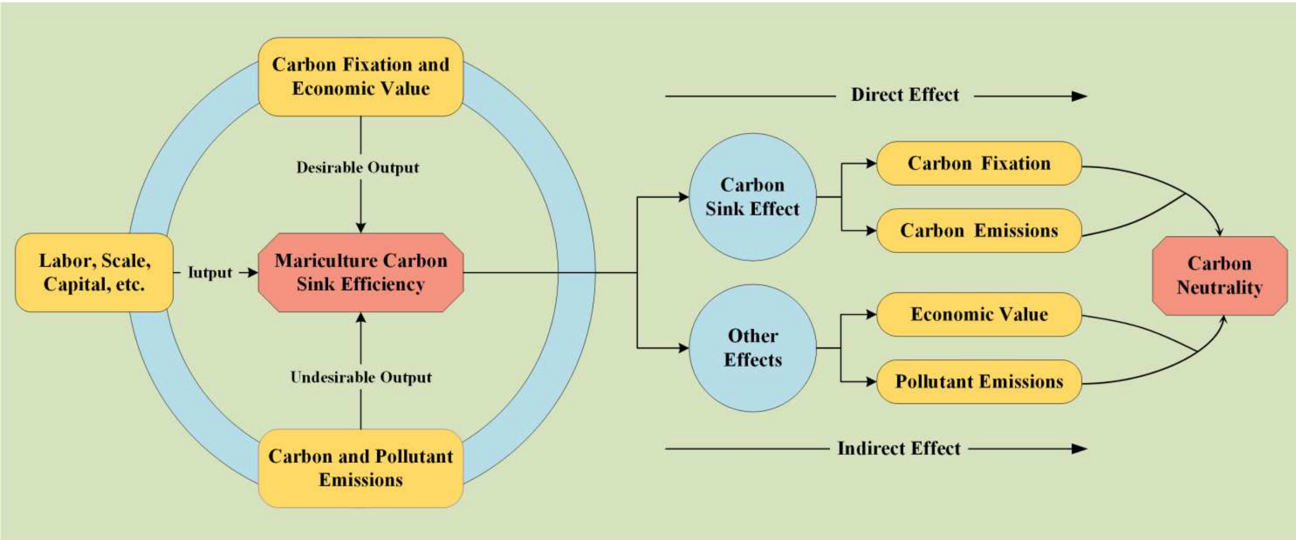


Fig. 2. The graphic illustration of MCSE.

Specifically, from Fig. 2, the input mainly includes labor, scale, capital and any other intermediate consumption, and the output is divided into desirable one (including carbon fixation and economic value) and undesirable one (including carbon and pollutant emissions). Further, the net carbon sink which equals carbon fixation minus carbon emissions has a direct effect on carbon neutrality, while the economic value and pollutant emissions have a indirect effect on that. It can be inferred that the economic value and pollutant emissions reduction in mariculture may exert a sustainable effect on carbon sink, which is conducive to steadily achieving net carbon emissions zero in a long time for China.

First, the selection of variables in Super-SBM model is as follows: (1) Variables of inputs. In general, mariculture belongs to agriculture. Therefore, referring to the main inputs in agriculture, labor force, mariculture labor force, mariculture area, and other cultivation capital are selected as the input variables; (2) Variables of desirable outputs. Desirable outputs are positive output variables. For measuring the dual value of ecology and economy in mariculture carbon sink, carbon fixation amounts and economic output value in mariculture industry are selected as the desirable output variables; (3) Variables of undesirable outputs. Undesirable outputs are negative output variables. Most of the mariculture organisms are heterotrophs whose physiological activity cannot avoid producing nitrogen and phosphorus pollutants. In addition, the mariculture industry has a large scale of diesel and electricity consumption, which causes large amounts of additional carbon emissions. Therefore, pollutant emissions amounts and additional carbon emissions amounts can be selected as the undesirable outputs. The specific indicators of these variables and their data sources are shown in Table 1.

Some indicators in Table 1 need a further clarification. (1) Carbon fixation amounts (*Fixation*). Shellfish and algae culture are the main components of mariculture carbon sink, so this paper sets them as the study objects. Carbon Comprehensive Coefficient Method (CCCM) is used in this study to calculate this indicator. According to the study by Shao et al. (2015), the carbon comprehensive coefficient of shellfish is 0.0888 t/t, and the carbon comprehensive coefficient of algae is 0.3415 t/t; (2) Pollutant emissions (*Pollutant*). Shellfish is the main source of nitrogen and phosphorus pollutants. According to the study by Zong et al. (2017), the calculation formula of nitrogen and phosphorus pollutants is as formula (17), (18) and (19):

$$NI_p = \sum_{i=1}^{n} P_i \alpha_i \tag{17}$$

$$PH_p = \sum_{i=1}^{n} P_i \beta_i \tag{18}$$

$$Pollutant = NI_p + PH_p \tag{19}$$

where NI_p and PH_p are the nitrogen pollutants and phosphorus pollutants respectively, P_i is the production of shellfish i, α_i and β_i are the pollutants producing coefficient of nitrogen and phosphorus respectively; (3) Additional carbon emissions amounts (*Emissions*). Agricultural consumption of diesel and electricity multiplies by the proportion of mariculture output value in the total agriculture.

Table 1. Specific indicators and data sources in Super-SBM model.

Variable types	Variables	Indicators	Data sources
Inputs	Mariculture labor force (*Labor*)	Annual number of employees in mariculture industry (thousand people)	China Fishery Statistical Yearbook (2016-2020)
	Mariculture area (*Area*)	Annual cultivation area in mariculture industry per year (thousand ha)	China Fishery Statistical Yearbook (2016-2020)
	Other cultivation capital (*Capital1*; *Capital2*)	Annual Output value of seedlings in mariculture industry (million Chinese Yuan, CNY)	China Fishery Statistical Yearbook (2016-2020)
		Annual quantity of marine fishing motor vessels (thousand t)	China Fishery Statistical Yearbook (2016-2020)
Desirable outputs	Carbon fixation amounts (*Fixation*)	Annual carbon fixation amounts of mariculture (thousand t)	China Fishery Statistical Yearbook (2016-2020)
	Economic output value (*Economy*)	Annual total output value of mariculture industry (billion CNY)	China Fishery Statistical Yearbook (2016-2020)
Undesirable outputs	Pollutant emissions (*Pollutant*)	Annual quantity of phosphorus and nitrogen pollutants produced in mariculture industry (thousand t)	China Fishery Statistical Yearbook (2016-2020)
	Additional carbon emissions amounts (*Emissions*)	Annual carbon emissions from diesel and electricity in mariculture industry (thousand t)	China Rural Statistical Yearbook (2016-2020), China Statistical Yearbook (2016-2020) and China Fishery Statistical Yearbook (2016-2020)

Second, based on the model constructed in the previous section, the variables in extended STRIPAT model include MCSE(*I*), Population(*P*), Affluence(*A*), Technology(*T*), Service industry(*SI*), Urbanization(*U*), and International trade(*IT*). Referring to some related researches (Zhou et al., 2022; Ren, 2021; Meng and Feagin, 2019), the specific indicators of these variables and their data sources are shown in Table 2. In addition, considering that the variable *I* may be less than 1, it is therefore addressed by positive translation.

Table 2. Specific indicators and data sources in STIRPAT model.

Variables	Indicators	Data sources
MCSE (*I*)	*PE* measured by Super-SBM model	China Rural Statistical Yearbook (2016-2020), China Statistical Yearbook (2016-2020) and China Fishery Statistical Yearbook (2016-2020)
Population (*P*)	Population at the end of each year (million people)	China Statistical Yearbook (2016-2020)
Affluence (*A*)	Annual GDP (billion CNY)	China Statistical Yearbook (2016-2020)
Technology (*T*)	Annual expenditure on R&D of industrial enterprises above designated size (billion CNY)	China Statistical Yearbook (2016-2020)
Service industry (*SI*)	Annual GDP of Service industry (billion CNY)	China Statistical Yearbook (2016-2020)
Urbanization (*U*)	Proportion of urban population at the end of each year (%)	China Statistical Yearbook (2016-2020)
International trade (*IT*)	Annual value of international trade (billion United States Dollar, USD)	China Statistical Yearbook (2016-2020)

Finally, the data used in this paper are all from China Fishery Statistical Yearbook (2016-2020), China Rural Statistical Yearbook (2016-2020) and China Statistical Yearbook (2016-2020), and the monetary indicators above are deflated at the constant price of 2015.

5. Results and discussion

5.1. Descriptive statistics of data

Table 3 shows the descriptive statistics of variables in this paper, and Fig. 3 further shows their regional proportional distribution. For the mariculture area (*Area*), the top two are Liaoning and Shandong (751.156 and 573.496 thousand ha, respectively). These two provinces account for 35.45% and 27.06% of the total, respectively. More than half scale of the total mariculture area is in Liaoning and Shandong provinces; for the carbon fixation amounts (*Fixation*), the top two are Fujian and Shandong (612.508 and 585.072 thousand t, respectively), accounting for 30.07% and 28.72% of the total, respectively; for the economic output value (*Economy*), the top two are Shandong and Fujian

(88.000 and 70.598 billion CNY, respectively), accounting for 26.68% and 21.40% of the total, respectively. In addition, the economic value may have a positive correlation with mariculture carbon sink. For example, the mariculture area of Fujian is only 164.509 thousand ha which is far less than that of Liaoning (751.156 thousand ha), while the carbon fixation amounts is more than that of Liaoning (612.508 thousand t > 335.146 thousand t). The probable reason for this maybe the economic output value of Fujian in mariculture is more than that of Liaoning (70.598 billion CNY > 37.358 billion CNY), indicating that the economic value should be taken into account when studying the effect of mariculture carbon sink. In summary, it can be seen that China has a large scale of total economic output value in mariculture, meaning that mariculture carbon sink in China's 9 coastal regions may efficient and sustainable from the index of MCSE.

Table 3. Descriptive statistics of variables.

Variables	Units	Hainan	Guangdong	Guangxi	Fujian	Zhejiang
Labor	thousand people	39.124	119.361	127.915	224.582	58.591
Area	thousand ha	22.626	176.644	50.885	164.509	82.719
Capital1	million CNY	2404.150	3110.160	2666.939	4582.471	2010.884
Capital2	thousand t	528.912	981.576	460.826	1283.141	2657.862
Fixation	thousand t	9.044	197.236	82.839	612.508	104.180
Economy	billion CNY	10.867	52.606	18.385	70.598	18.989
Emissions	thousand t	71.663	2116.860	137.853	1206.667	3080.541
Pollutant	thousand t	0.646	41.225	20.564	58.749	21.343
P	million people	9.266	111.768	48.810	39.076	56.746
A	billion CNY	4.472	89.664	19.047	33.034	52.091
T	billion CNY	0.977	189.678	8.936	46.150	104.822
SI	billion CNY	250.803	4790.293	839.872	1463.447	2748.955
U	%	57.646	69.972	49.132	64.664	67.940
IT	billion USD	12.313	1021.113	57.424	175.442	388.170

Variables	Units	Jiangsu	Shandong	Hebei	Liaoning	Total sample
Labor	thousand people	38.251	168.365	25.654	106.647	100.943
Area	thousand ha	185.218	573.496	111.795	751.156	235.450
Capital1	million CNY	6714.050	7859.494	1288.548	6857.458	4166.017
Capital2	thousand t	389.664	1106.903	257.806	743.551	934.471
Fixation	thousand t	71.815	585.072	38.988	335.146	226.314
Economy	billion CNY	23.452	88.000	9.629	37.358	36.654

Emissions	thousand t	3814.790	808.738	236.209	578.220	1339.060
Pollutant	thousand t	18.740	121.984	17.880	70.638	41.308
P	million people	80.250	99.834	75.126	43.680	62.728
A	billion CNY	85.120	70.240	33.402	24.910	45.776
T	billion CNY	184.572	137.998	35.320	27.395	81.761
SI	billion CNY	4284.342	3413.305	1499.233	1269.497	2284.416
U	%	68.644	59.860	54.742	67.684	62.254
IT	billion USD	587.813	265.783	51.998	100.405	295.607

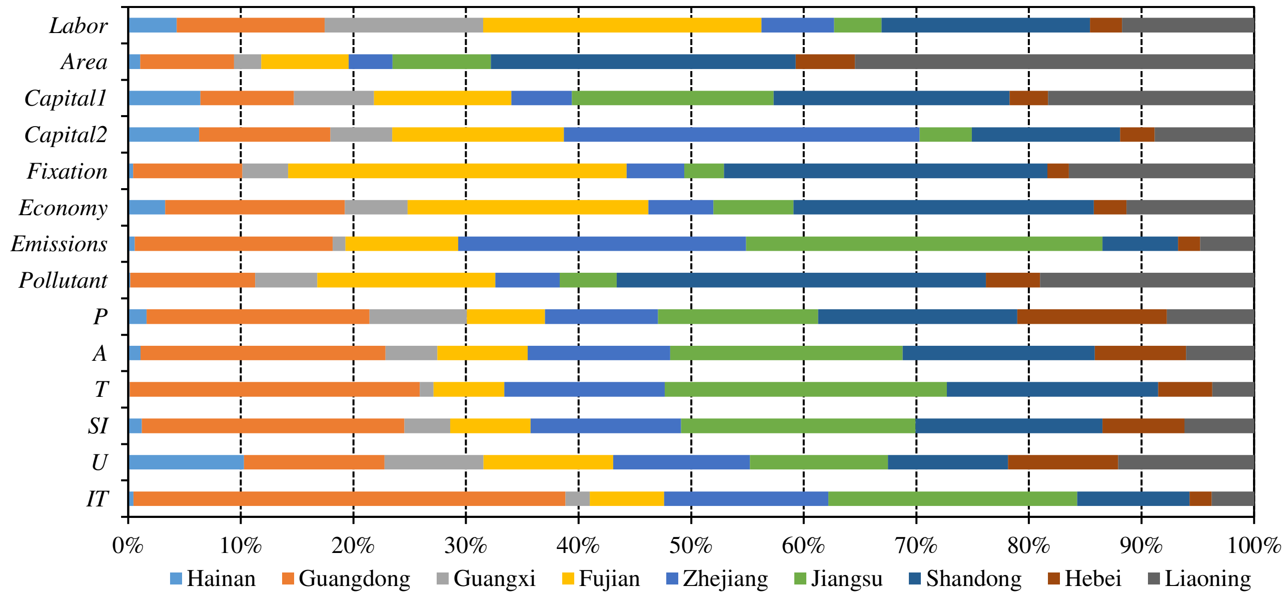


Fig. 3. Regional proportional distribution of variables.

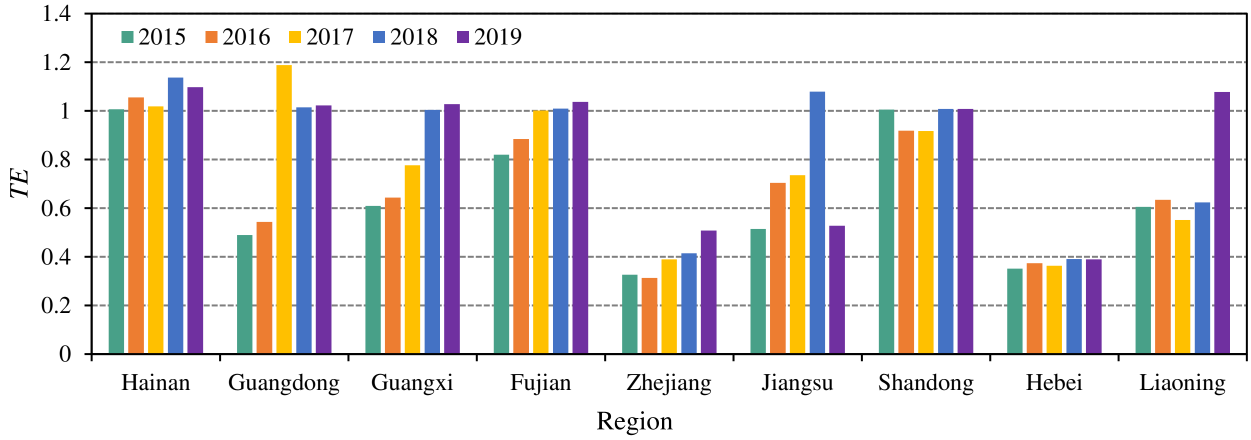
5.2. Results of MCSE

Based on the panel data of China's 9 coastal provinces (autonomous regions) during 2015-2019, the Super-SBM model constructed above is used to measure their MCSE. The results of MCSE are shown in Table 4 and Fig. 4. Two points need to be noted that: (1) the efficiency results have been shown in three forms *TE* (based on constant returns to scale model), *PTE* (based on variable returns to scale model) and *SE*; (2) the non-oriented method has been selected in this paper.

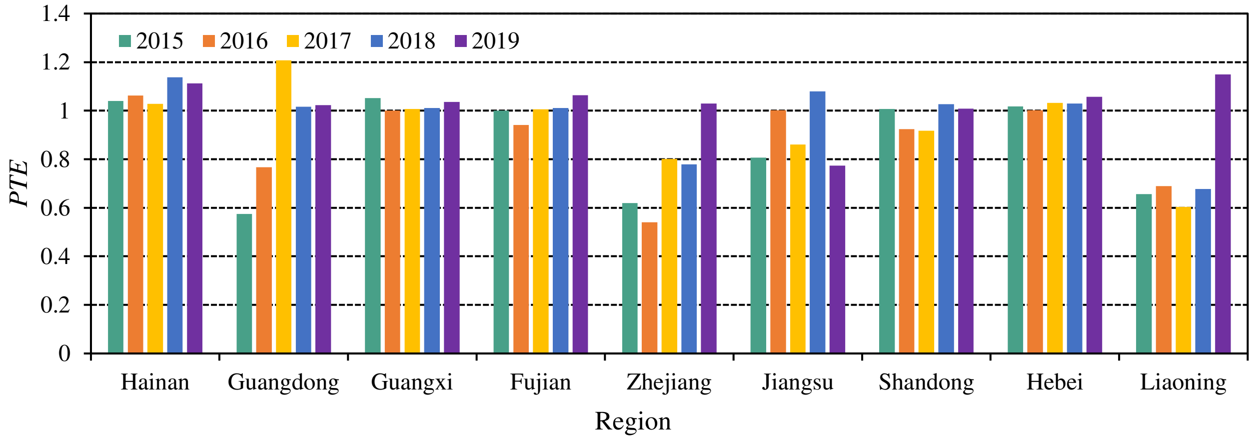
As shown in Table 4 and Fig. 4, in 2019, 66.67% of the regions in the sample is the SBM-efficient DMUs on *TE*, and 88.89% of the regions in the sample is the SBM-efficient DMUs on *PTE*. This result shows that the mariculture carbon sink is efficient in China's 9 coastal regions generally. Further, the MCSE in all regions has an upward trend from 2015 to 2019. In 2015, most of the *TE*s of these regions are not the SBM-efficient DMUs, whereas the situation has reversed in 2019, i.e., most of the *TE*s are reaching the SBM-efficient (Fig. 4a). This situation also holds true for *PTE*. Specifically, there are four regions (Hainan, Guangxi, Shandong, and Hebei) that are not the SBM-efficient DMUs in 2015, while there is just only one region (Jiangsu) in 2019 (Fig. 4b). For *SE*, most of the regions are close to 1, especially in 2018 and 2019 (Fig. 4c), which means the scale efficiency of mariculture carbon sink in China is basically SBM-efficient. The analyses above indicate that the overall MCSE in China in recent years is high, especially in *PTE*, which confirms the advantages of mariculture carbon sink in China. In other words, developing mariculture carbon sink will help these coastal regions to improve carbon sink capability. However, the MCSE varies greatly in different regions on the whole, whether from the perspective of *TE* or *PTE*. This shows that different regions have different characteristics in mariculture. The following will further analyze from the perspective of different economic zones and provinces (autonomous regions).

Table 4. Results of MCSE during 2015-2019.

Period	Index	Hainan	Guangdong	Guangxi	Fujian	Zhejiang	Jiangsu	Shandong	Hebei	Liaoning
	TE	1.007	0.489	0.609	0.820	0.326	0.515	1.006	0.351	0.606
2015	*PTE*	1.040	0.574	1.052	1.000	0.619	0.806	1.007	1.017	0.657
	SE	0.968	0.852	0.579	0.820	0.527	0.639	0.999	0.345	0.922
	TE	1.055	0.543	0.644	0.884	0.313	0.704	0.919	0.374	0.634
2016	*PTE*	1.062	0.767	1.001	0.941	0.540	1.002	0.924	1.002	0.689
	SE	0.993	0.708	0.643	0.939	0.580	0.703	0.995	0.373	0.920
	TE	1.019	1.188	0.776	1.001	0.389	0.735	0.917	0.363	0.552
2017	*PTE*	1.028	1.208	1.007	1.006	0.801	0.861	0.917	1.032	0.603
	SE	0.991	0.983	0.771	0.995	0.486	0.854	1.000	0.352	0.915
	TE	1.137	1.015	1.004	1.009	0.415	1.079	1.008	0.391	0.624
2018	*PTE*	1.137	1.016	1.011	1.011	0.779	1.080	1.027	1.029	0.677
	SE	1.000	0.999	0.993	0.998	0.533	0.999	0.981	0.380	0.922
	TE	1.097	1.023	1.028	1.037	0.508	0.528	1.008	0.390	1.078
2019	*PTE*	1.112	1.023	1.036	1.064	1.029	0.774	1.008	1.057	1.149
	SE	0.987	1.000	0.992	0.975	0.494	0.682	1.000	0.369	0.938



(a)



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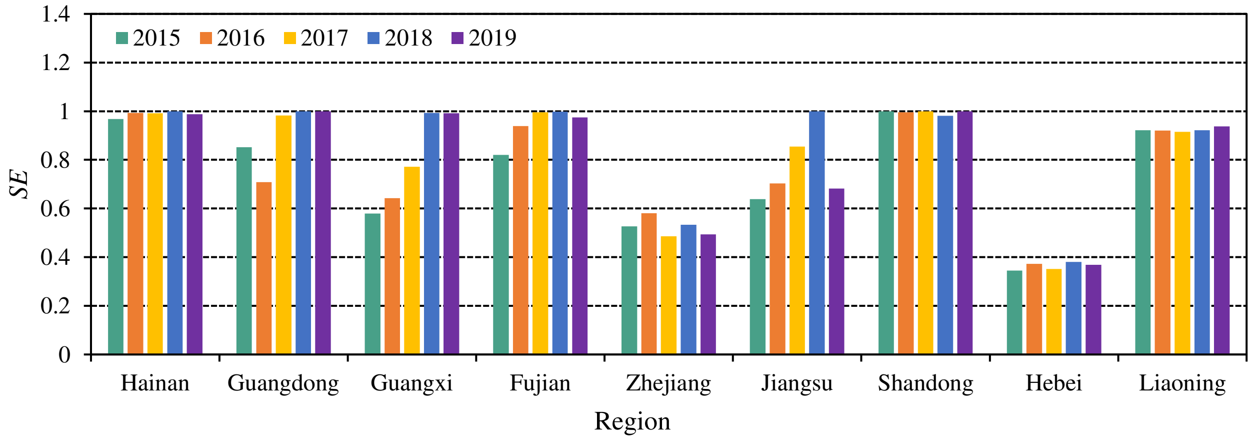


(c)

Fig. 4. Results of MCSE during 2015-2019.

Note: (a) Results of *TE*; (b) Results of *PTE*; (c) Results of *SE*.

Fig. 5, Fig. 6, and Fig. 7 present the regional distribution of *TE*, *PTE*, and *SE* during 2015-2019, respectively. First of all, the MCSE of PPRD Economic Zone is the highest one in China, and it shows an obvious upward trend. In 2018 and 2019, all regions in PPRD Economic Zone are the SBM-efficient DMUs in *TE* and *PTE*, and the *SE*s of PPRD Economic Zone are all close to 1 (Table 4). An example is Guangdong province, it can be seen that the MCSE of Guangdong province has an obvious increase (TE_{2019} = 1.023 > TE_{2015} = 0.489, PTE_{2019} = 1.023 > PTE_{2015} = 0.574) (Table 4). In recent years, Guangdong province has consolidated its position in the national fishery development by adjusting the industrial structure, improving supporting facilities in mariculture, and developing green and efficient mariculture. To sum up, the regions in the PPRD Economic Zone should continuously focus on the development of mariculture carbon sink, further implement the scale expansion strategy, and keep the current development trend.

Secondly, for YRD Economic Zone, although the MCSE is not high, the *PTE*s is much higher than the *TE*s, which also means the mariculture carbon sink in YRD Economic Zone has a bad performance on *SE*. The main reason of this probably is the huge consumption of diesel and electricity ($Emissions_{\text{Zhejiang}}$ = 3080.541 and $Emissions_{\text{Jiangsu}}$ = 3814.790) (Table 3). In despite of this, the *PTE* of Zhejiang and Jiangsu are by and large increasing, e.g., Zhejiang (TE_{2019} = 0.508 > TE_{2015} = 0.326, PTE_{2019} = 1.029 > PTE_{2015} = 0.619) and Jiangsu (TE_{2018} = 1.079 > TE_{2015} = 0.515, PTE_{2018} = 1.080 > PTE_{2015} = 0.806) (Table 3). As a result, from 2015 to 2019, the most obvious problem in YRD Economic Zone is that the *SE* is not very high and represents a downward trend, implying that the input scale of different production factors needs to be adjusted accordingly and the over-consumption of diesel and electricity in mariculture industry needs to be effectively reduced.

Finally, the situation in CBS Economic Zone is more complex, with different situations in Shandong, Hebei, and Liaoning. Shandong is the most SBM-efficient regions in CBS Economic Zone, which has continuous high *TE*, *PTE* and *SE* during 2015-2019 (Table 4). Shandong province has the largest mariculture output value in China, and the production of seafood also ranks first in the whole country all the year round (*Economy* = 88.000) (Table 3). The development of mariculture carbon sink in Shandong is superior and efficient; Liaoning has the high *SE* (e.g., SE_{2018} = 0.922), however its *TE* is not very high (e.g., TE_{2018} = 0.624), indicating that the *PTE* of Liaoning is low (e.g., PTE_{2018} = 0.677). The mariculture area of Liaoning is larger than Shandong ($Area_{\text{Liaoning}}$ = 751.156 > $Area_{\text{Shandong}}$ = 573.496), whereas the carbon fixation amounts ($Fixation_{\text{Liaoning}}$ = 335.146 < $Fixation_{\text{Shandong}}$ = 585.072) and economic output value ($Economy_{\text{Liaoning}}$ = 37.358 < $Economy_{\text{Shandong}}$ = 88.000) in mariculture industry are exactly the opposite (Table 3). Liaoning needs to increase the utilization efficiency of inputs in mariculture carbon sink to solve this problem. For all that, the MCSE of Liaoning is still increasing (e.g., TE_{2019} = 1.078 > TE_{2015} = 0.606, PTE_{2019} = 1.149 > PTE_{2015} = 0.657) (Table 4); Hebei has a continuous high *PTE* (e.g., PTE_{2015} = 1.017, PTE_{2019} = 1.057) while has a low *SE* (e.g., SE_{2015} = 0.345, SE_{2019} = 0.369) (Table 4), which means the input scale of production factors is far away from the frontier, i.e., it is essential for Hebei to adjust the scale to improve the MCSE. From Table 3, the input scale of Hebei is much smaller than other regions (e.g., *Labor*, *Capital1*, *Capital2* are the smallest one in all regions), indicating that reasonably increasing the investment in mariculture is an effective strategy to improve the MCSE of Hebei. In recent years, CBS Economic Zone is the largest mariculture industrial base in China, especially in Liaoning Peninsula and Jiaodong Peninsula. The key to improve the MCSE of CBS Economic Zone is to further increase the economic output value in mariculture. For each province, Shandong is at the leading position of the MCSE in China, Liaoning and Hebei, however, still have room for improvement.

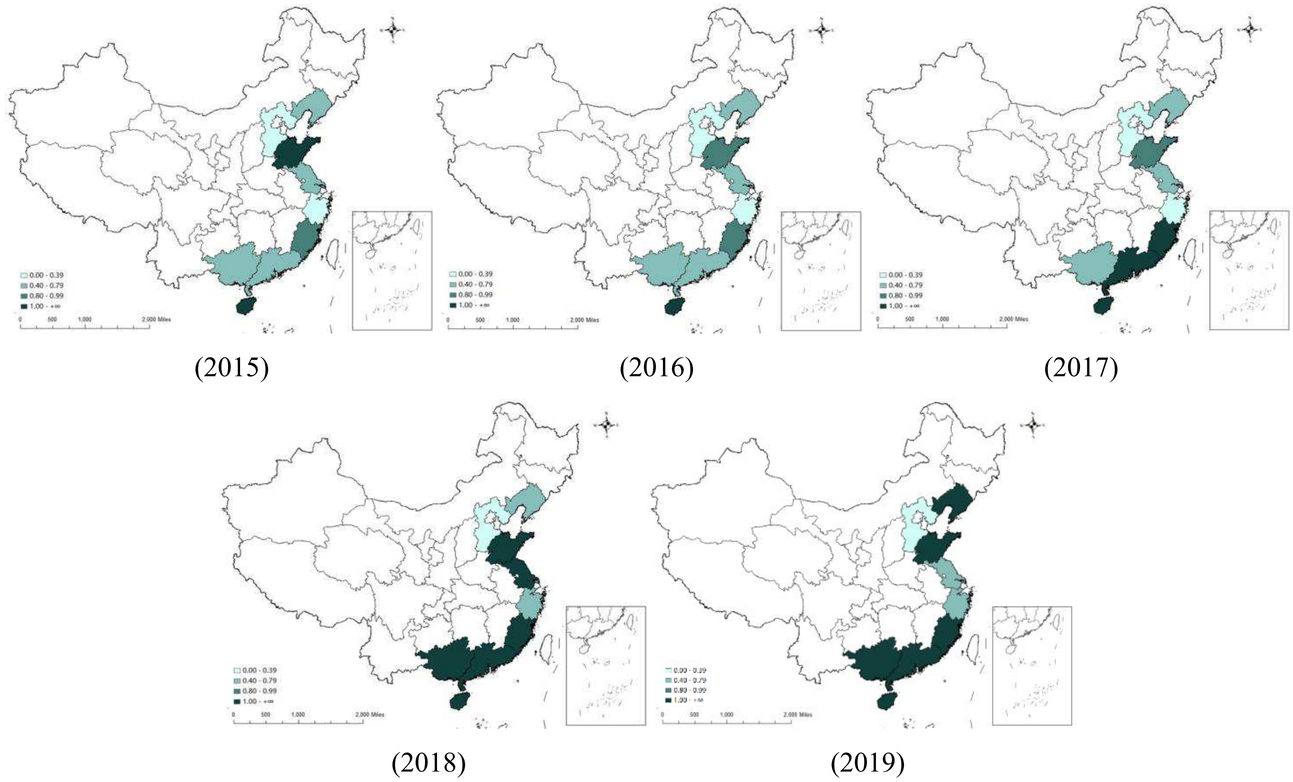


Fig. 5. Regional distribution of *TE* results during 2015-2019.

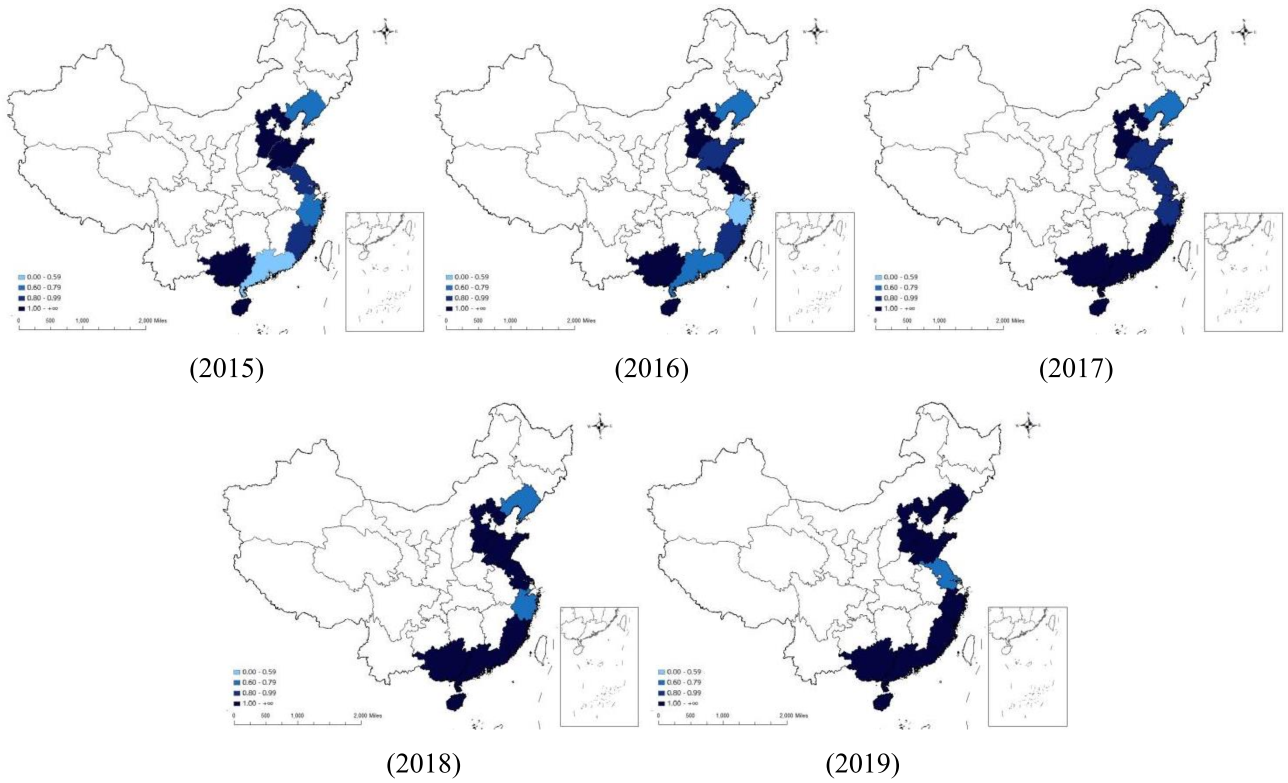
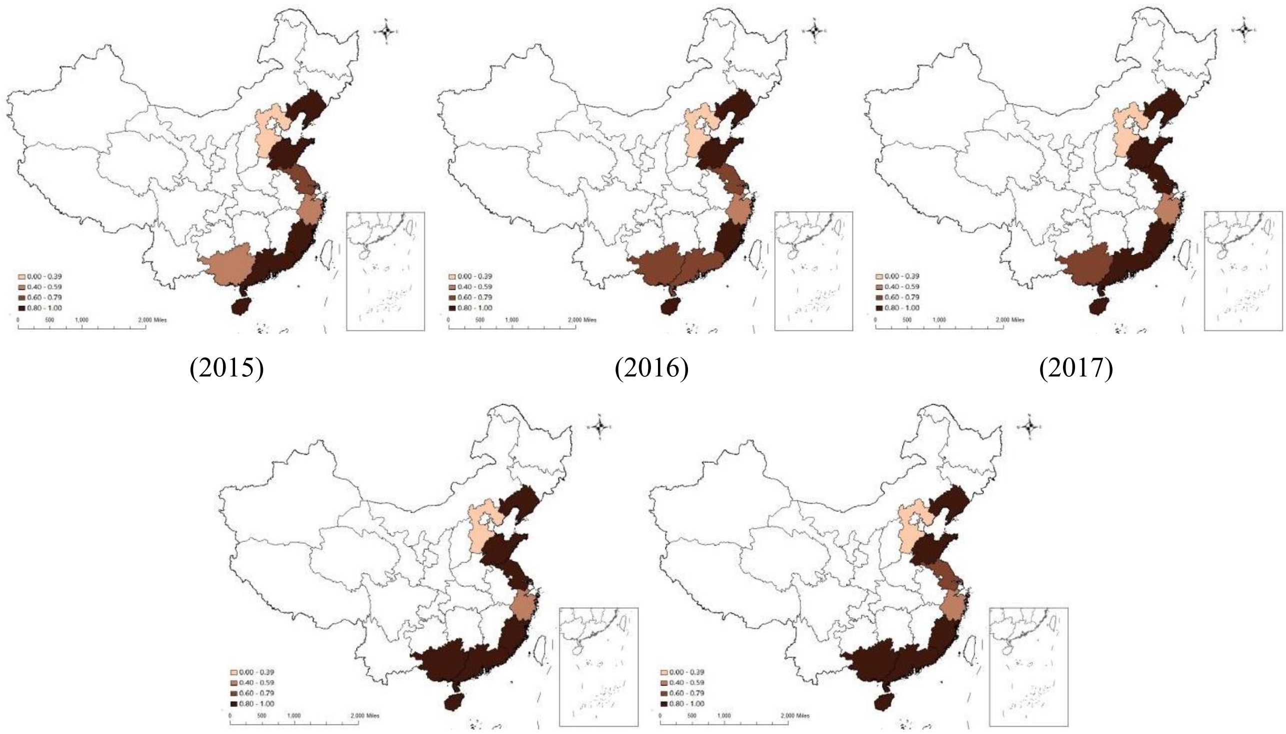


Fig. 6. Regional distribution of *PTE* results during 2015-2019.



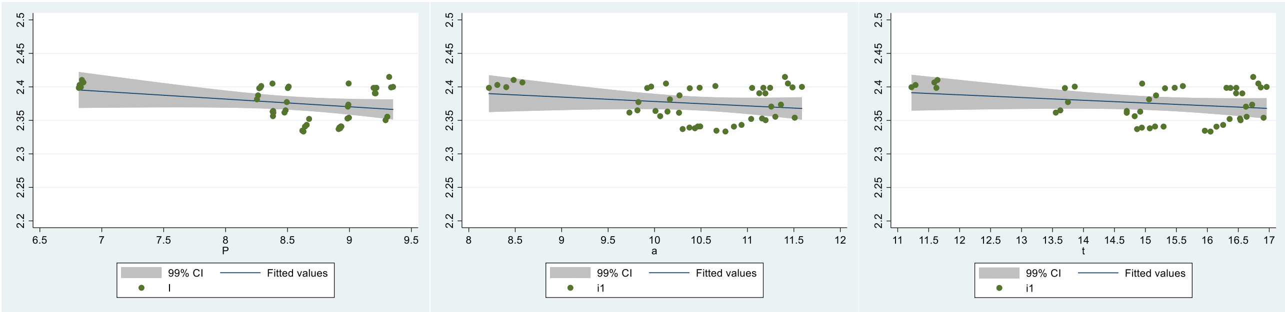
(2015) (2016) (2017)

(2018) (2019)

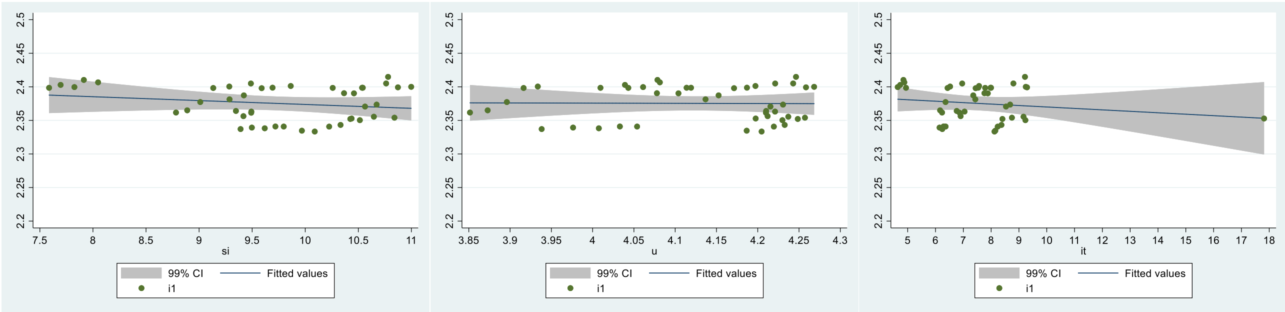
Fig. 7. Regional distribution of SE results during 2015-2019.

5.3. Results of driving factors regression

Initially, correlation analysis between outcome variable and explanatory variables are conducted. The results of correlation analysis are shown in Fig. 8. On the whole, the MCSE is negatively correlated with each explanatory variable in the sample during 2015-2019. This preliminary indicates that the improvement of population, affluence, technology, service industry, urbanization and international trade level may not increase the MCSE of China, indicating that the input of factors may need to concentrate more on mariculture. Based on this, a further regression of driving factors is necessary. Considering that the problem of multicollinearity may exist between explanatory variables, the Pearson correlation coefficients among explanatory variables and the VIF test are therefore carried out to examine the degree of multicollinearity between explanatory variables, and the results are presented in Table 5 and Table 6.



(*P*) (*A*) (*T*)



(*SI*) (*U*) (*IT*)

Fig. 8. Results of correlation analysis.

As shown in Table 5, the Pearson correlation coefficients among explanatory variables are all highly significant. Only the significance between ln*P* and ln*U* is 0.10, and the others are all 0.01. Further, it can be seen from Table 6 that the VIFs of ln*P*, ln*A*, ln*T*, and ln*SI* are 320.43, 179.71, 77.84, and 20.40, respectively, which are all higher than 10. These results demonstrate that serious multicollinearity exists between explanatory variables. In summary, the regression coefficients obtained by OLS fit are not reliable. For obtaining a reliable regression result, the multicollinearity between explanatory variables needs to be eliminated. Therefore, the ridge regression method is used in this study instead of OLS method.

Table 5. Results of Pearson correlation coefficients among explanatory variables.

Variables	ln*P*	ln*A*	ln*T*	ln*SI*	ln*U*	ln*IT*
ln*P*	1					
ln*A*	0.934^{***} (0.000)	1				
ln*T*	0.904^{***}	0.989^{***}	1			

	(0.000)	(0.000)				
ln*SI*	0.907^{***}	0.994^{***}	0.984^{***}	1		
	(0.000)	(0.000)	(0.000)			
ln*U*	0.257^{*}	0.529^{***}	0.592^{***}	0.591^{***}	1	
	(0.088)	(0.000)	(0.000)	(0.000)		
ln*IT*	0.573^{***}	0.684^{***}	0.691^{***}	0.691^{***}	0.512^{***}	1
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Notes: P-statistics are in parentheses. Significance levels are: *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 6. Results of VIF test.

Variables	VIF	1/VIF
ln*P*	320.43	0.005565
ln*A*	179.71	0.012847
ln*T*	77.84	0.049013
ln*SI*	20.40	0.132668
ln*U*	7.54	0.495754
ln*IT*	2.02	0.005565
Mean VIF	101.32	

As mentioned above, ridge regression needs to select an optimal ridge parameter k. The relationship between R-square and k is shown in Fig. 9. It can be seen from Fig. 9 that the R-square has a high change rate before k = 0.240, while it turns to be stable after k = 0.240. As a result, the ridge parameter k is selected as 0.240. Based on this, the ridge regression is conducted on the variables above, and the results of ridge regression are reported in Table 7. The validity of the ridge regression can be examined with the statistics of R-square, F test, and t test. As shown in Table 7, the R-square is 0.419, the F-statistic is 2.187, and the P-statistic of F test is 0.066, basically meaning that the ridge regression is significant and the fitting degree is good. Specifically, for each explanatory variable, ln$P$, lnSI, and ln$U$ are significant at the significance level of 0.01, ln$A$ and lnIT are significant at the significance level of 0.05, and only ln$T$ is not significant, further indicating that the ridge regression is well fitted. Eventually, the fitted ridge regression equation is as follows:

$$\ln I = -0.088 \ln P + 0.089 \ln A + 0.006 \ln T + 0.161 \ln SI - 0.306 \ln U - 0.001 \ln IT + 3.671 \tag{20}$$

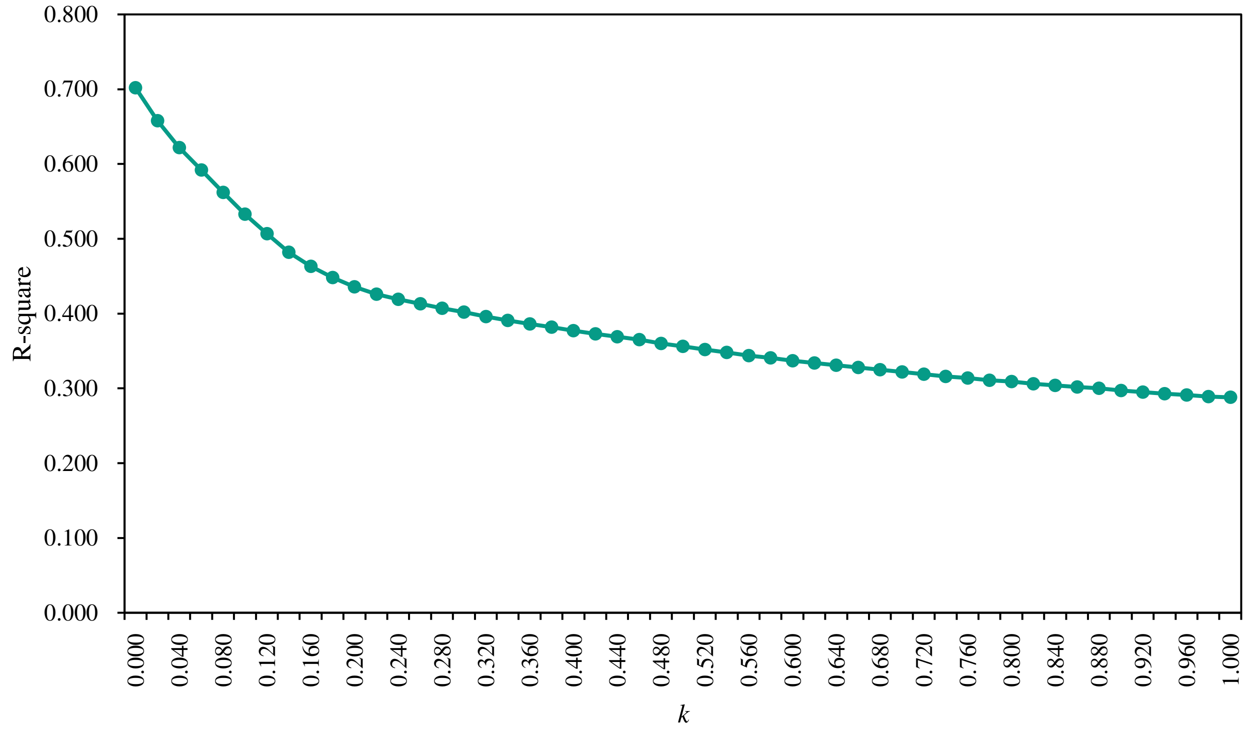


Fig. 9. Relationship between R-square and *k*.

According to the results of ridge regression from equation (20) and Table 7, ln*P*, ln*A*, ln*U*, and ln*IT* have significant negative impacts on MCSE in China during 2015-2019, while ln*SI* has a significant positive impact. The importance of these driving factors can be indicated by the absolute values of their elastic coefficients, the driving factors are therefore listed in descending order by their elastic coefficients as: urbanization (-0.306), service industry (0.161), affluence (0.089), population (-0.088), and international trade (-0.001).

Urbanization has a significant negative impact on MCSE in China. The elastic coefficient of ln*U* is -0.306, meaning that an increase of 1% in urbanization produces a decrease of approximately 30.6% in MCSE. As the urbanization moves on, the capital inputs such as labor force may move from rural areas to cities and towns. This may weaken the factor input effect in the mariculture, and the MCSE is thereby reduced; Service industry has a significant positive impact on MCSE in China. The elastic coefficient of ln*SI* is 0.161, indicating that an increase of 1% in urbanization produces an increase of about 16.1% in MCSE. The upgrade of service industry has provided more convenience for the development of mariculture carbon sink, such as the continuous optimization of cold chain transportation, e-commerce platforms, and financing business in mariculture. Therefore, the MCSE maybe increased; Affluence has a significant negative impact on MCSE in China. The elastic coefficient of ln*A* is 0.089, meaning that an increase of 1% in urbanization produces an increase of around 8.9% in MCSE. The increase of affluence may stimulate the consumption of seafood, and improve the management level of mariculture, thereby increasing the MCSE; Population has a significant negative impact on MCSE in China. The elastic coefficient of ln*P* is -0.088, which means that an increase of 1% in urbanization produces a decrease of about 8.8% in MCSE. The increase of population may lead to an increase of factor prices in mariculture, thereby reducing the MCSE; International trade has a significant negative impact on MCSE in China. The elastic coefficient of ln*IT* is -0.001, which indicates that an increase of 1% in urbanization produces a decrease of around 0.1% in MCSE. The increase of international trade may have a certain impact on the local mariculture, thereby reducing the economic outputs of mariculture. As a result, the MCSE is decreased.

Table 7. Results of ridge regression.

Variables	Coefficients	Standard errors	t-statistics	P-statistics
ln*P*	-0.088^{***}	0.024	-3.685	0.001
ln*A*	0.089^{**}	0.035	2.536	0.015
ln*T*	0.006	0.009	0.602	0.551
ln*SI*	0.161^{***}	0.040	3.994	0.000
ln*U*	-0.306^{***}	0.919	-3.327	0.002
ln*IT*	-0.001^{**}	0.004E-1	-2.677	0.011
Constant	3.671^{***}	0.301	12.187	0.000
R-square	0.419			
F-statistic	2.187			
Prob > F	0.066			

Notes: Significance levels are: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.4. Further discussion

At present, land carbon sink has more advantages than marine carbon sink in scale. Some studies have shown that the estimation of marine carbon sink capability in China is approximately

7.79-9.36 TgC·yr-1, which significantly less than the land carbon sink estimation of 1.11±0.38 PgC·yr-1 in recent years (Gao et al., 2016; Wang et al., 2020). However, available data show that the marine products of China accounts for over two-thirds of the world total (Meng and Feagin, 2019), which means China is the largest producer of marine-based seafood all over the world. The mariculture carbon sink approximately accounts for around 77.28-81.09% of the whole marine carbon sink in China (Gao et al., 2016), that is to say, the mariculture carbon sink is also the largest and most manageable type of marine carbon sink. More importantly, compared with land carbon sink, the mariculture carbon sink is at an advantage in carbon sink effect and economic value. Exactly as the research made by Ren (2021) shows that the mariculture carbon sink not only has a higher potential carbon fixation capability, but also has a higher potential economic value. In other words, the mariculture carbon sink has a higher potential efficiency than the land one in China (Zhang et al., 2017). The probable reasons are that, on the one hand, the mariculture carbon sink in China mainly includes the culture of shellfish and algae, which accounts for at least 85% of the total. The carbon can be fixed by shellfish's calcification and algae's photosynthesis, and the shellfish as well as fish consumes algae and then excretes to sink carbon. This type of carbon sink has been considered to be a more efficient and steadier carbon sink way (Meng and Feagin, 2019; Gao et al., 2016); on the other hand, as shown in Fig. 10, the output value of China's aquatic product industry has increased from 401.61 billion CNY in 2005 to 1257.24 billion CNY in 2019 and now the annual growth rates are fluctuating at around 5% (NBSC, 2020), which shows a high economic value of China's mariculture in recent years. In addition, the mariculture production of China in 2016 has reached 19.6 million t, which is 42% higher than in 2005. The mariculture production of China accounted for 62% of the world total in 2014, and now this proportion has reached around 70-80% (Zhang et al., 2017; Gao et al., 2016). In conclusion, in China, mariculture carbon sink is efficient, and developing mariculture carbon sink in China is more capable than other regions around the world.

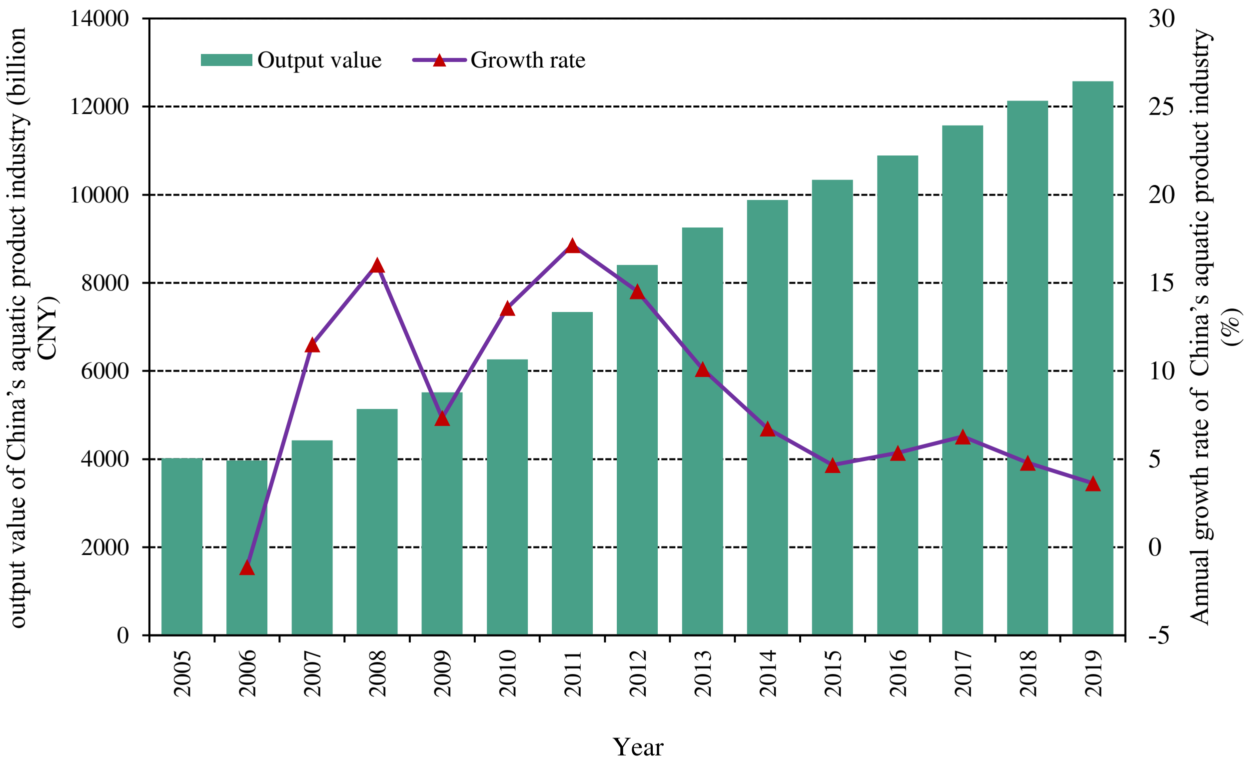


Fig. 10. Output value of China's aquatic product industry during 2005-2019.

Data source: China Statistical Yearbook 2020.

Finally, in terms of the above analyses, this paper summarized the pathways to carbon neutrality in China and clarified the role of mariculture carbon sink (Fig. 11). Specifically, the upper part of Fig. 11 shows the current carbon cycle situation in China. At current stage, on the one hand, manageable carbon emissions (carbon emissions deducting those basically necessary for respiration and survival of living things), are mainly from the secondary industry in China, which account for around 70% of the total emissions. These secondary industries include power generation, petrochemical, building materials, steel, nonferrous metals, paper making, etc. And also, primary industry (breeding, animal husbandry, etc.) and tertiary industry (transportation, etc.) have emitted manageable carbon respectively accounting for around 20% and 10%; On the other hand, around 57% of the manageable carbon has been emitted into atmospheric carbon store, and around 40% and 3% of the manageable carbon has been fixed respectively by natural carbon sink and CCS. Therefore, what can be imagined are that the proportion of natural carbon sink will become much higher with the continuous reduction of carbon emissions, and the efficient development of carbon sink is of great importance to achieve carbon neutrality for China as well as the goals set in the Paris Agreement.

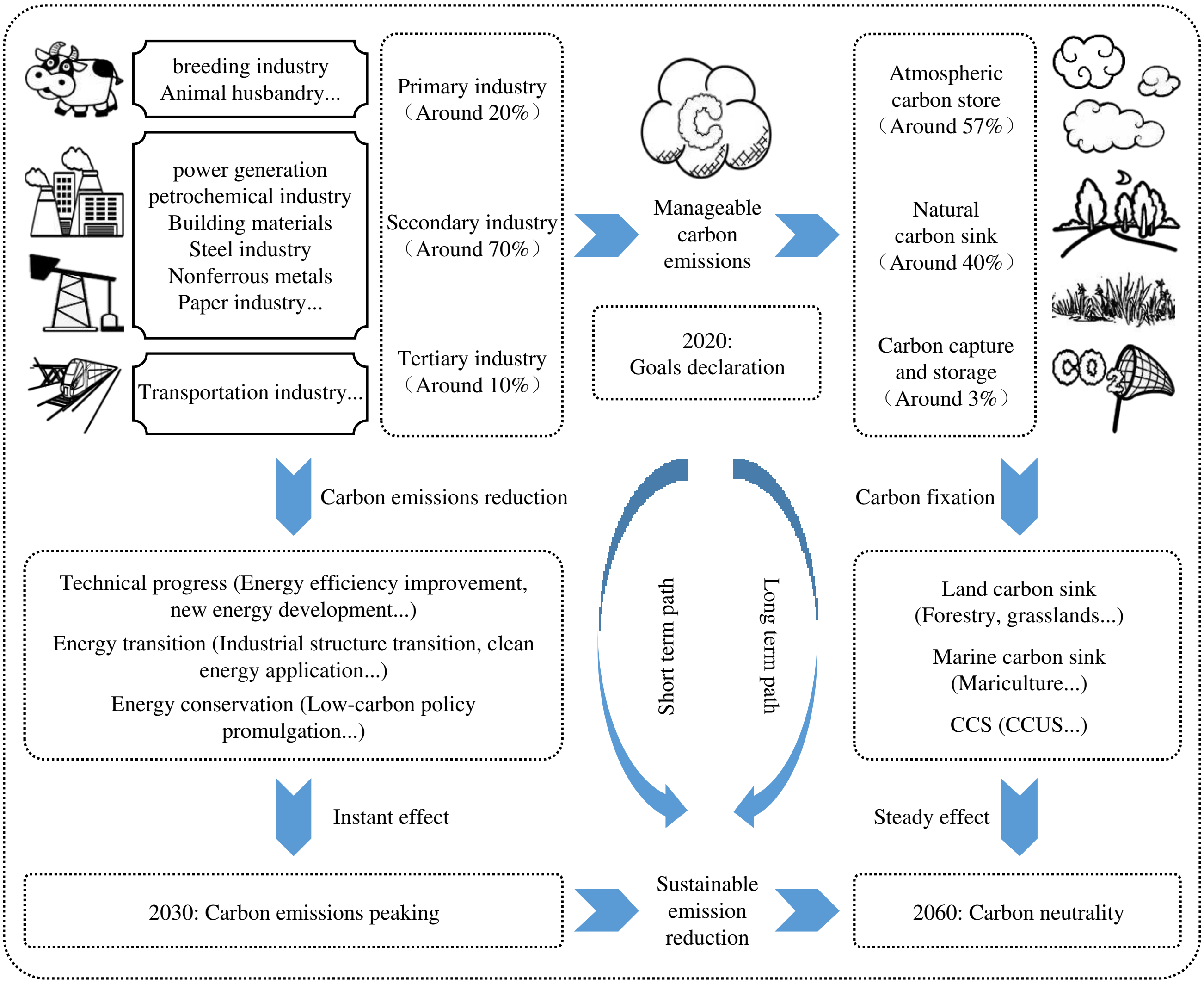


Fig. 11. The pathways to carbon neutrality in China and their roles

Data source: collected manually by the authors.

The explicit summary of the pathways to carbon neutrality in China and their roles are shown in the lower part of Fig. 11. Combined with the above analyses, what can be found are that: (1) carbon neutrality is the ultimate aim for carbon emissions peaking; (2) the pathway named carbon emissions reduction is expected to have a relatively instant effect while the other pathway named carbon fixation is expected to have a relatively steady effect; (3) due to the obvious diminishing marginal utility of carbon emissions reduction policies (technical progress, energy transition, energy conservation, etc.), carbon fixation will play a more decisive role in long term when comparing with carbon emissions reduction. Therefore, carbon fixation (land carbon sink, marine carbon sink, CCS, etc.) is a pathway to carbon neutrality which needs to be emphasized for China, especially in a long-term scenario. Currently, the mariculture carbon sink is relatively more efficient in China's 9 coastal regions, and three advantages of mariculture carbon sink are summarized. The first one is the high carbon store and carbon flux, which means the mariculture carbon sink holds a better carbon sink effect; the second one is the inherent economic value is high, which confers a long-term sustainability on mariculture carbon sink; the last one is the less negative impacts on eco-environment, indicating that developing mariculture carbon sink is more environmentally friendly. In summary, different regions should have different development strategies. For China's 9 coastal regions, mariculture carbon sink is an indispensable part of natural carbon sink. The in-depth development of mariculture carbon sink is suitable for improving the level of carbon fixation, thereby helping China achieve carbon neutrality by 2060.

6. Conclusions and implications

6.1. Conclusions

This study illustrates the goal of China to achieve carbon neutrality by 2060, analyzes the advantages of mariculture carbon sink on fixing carbon, defines the concept of the MCSE, uses the

Super-SBM model to measure the MCSE of the 9 coastal provinces (autonomous regions) in China during 2015-2019, and uses the STIRPAT model to explore the driving factors of MCSE. Based on this, the essential role of mariculture carbon sink for China to achieve the goal of carbon neutrality by 2060 is emphasized in this paper, and some conclusions have been drawn as follows:

First, the MCSE has been defined as the net positive effect of mariculture carbon sink based on a certain input. It has been revealed that the mariculture carbon sink has a high carbon store and carbon flux, and it has a dual value of ecology and economy. The mariculture area of 9 coastal regions in China is around 2.1181 million ha, the amounts of carbon fixation is around 2.0367 million tons, and the economic output is around 329.884 billion CNY, which indicates the mariculture carbon sink of China has a great development value. Furthermore, mariculture carbon sink has the less negative impacts on eco-environment. Second, the results of Super-SBM model have revealed that the MCSE, on the whole, of the 9 coastal regions in China presents an upward trend in 2015-2019, and this trend is more significant in the PPRD and CBS Economic Zone. The most obvious problem in the YRD Economic Zone and Hebei is that the scale efficiency (*SE*) is not very high. In 2019, 66.67% of the regions in the sample is the SBM-efficient DMUs on technical efficiency (*TE*), and 88.89% of the regions in the sample is the BSM-efficient DMUs on pure technical efficiency (*PTE*). Finally, the analysis of the driving factors shows that the affluence and service industry of a region may have a positive impact on the MCSE, while the population, urbanization and international trade may have a negative impact on the MCSE to a certain extent. All in all, the scale and efficiency of mariculture carbon sink in China is great all over the world, indicating that developing mariculture carbon sink is much crucial for China to achieve the goal of carbon neutrality by 2060.

6.2. Implications

In recent years, the Chinese government has employed a variety of administrative means and market regulations to fulfill carbon neutrality commitments. This study results show that the mariculture carbon sink can further help China achieve the goal of carbon neutrality, some implications are therefore provided to contribute to improving the level of China's mariculture carbon sink.

Considering the high efficiency of mariculture carbon sink in China, policymakers should focus on increasing the scale of mariculture carbon sink appropriately. First of all, Chinese government should clarify the resource characteristics and advantages of the three economic regions, form the scale advantage of characteristic mariculture industry, and pay attention to the rational layout of mariculture carbon sink density and structure; Second, Chinese government should cultivate and expand the new kinetic energy of mariculture carbon sink development, accelerate the use of new technologies, new equipment, and new models, and realize ecological mariculture carbon sink with high quality, high yield and high efficiency; Third, Chinese government should promote the development of mariculture carbon sink market economy, enhance the economic value of mariculture carbon sink, establish a pilot project for mariculture carbon sink trading, and build a modern mariculture carbon sink development system of China; Finally, the carrying capacity of resources and environment should be taken into account. Chinese government should control the total amounts of mariculture carbon sink within certain limits, and develop the sustainable mariculture carbon sink patterns.

Future research should also evaluate the effect of mariculture carbon sink, and continue to focus on how China can achieve the goal of carbon neutrality. It would be interesting to explore some other driving factors of MCSE (such as variety differences, regional climate, supporting industrial structure, etc.). In addition, the policy of mariculture carbon sink also deserves further attention.

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Author contribution

Xiuyi Shi: Writing - original draft, Conceptualization, Methodology, Data curation, Software. Yingzhi Xu: Resources, Project administration, Funding acquisition, Writing – review & editing. Biying Dong: Visualization, Validation. Nariaki Nishino: Supervision.

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