1. MEASURING EFFICIENCY OF OCEAN ECONOMY IN CHINA BASED ON A NOVEL LUENBERGER APPROACH

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Abstract

This paper proposes a novel Luenberger approach based on directive SBM method and Luenberger indicator to solve the intertemporal effect of dynamic factors. The new Luenberger indicator can be decomposed into dynamic pure efficiency change index, dynamic scale efficiency change index, technology progress index and dynamic effect index. The empirical application focuses on the growth performances of ocean economy in 11 coastal areas of China. The conclusions are as follows. First, the intertemporal effect of capital factor shows that the technical frontier is on the rise and the total factor productivity level is improved. The technical progress is the driving force of Chinese ocean economy growth performance. Second, the labor force, dynamic capital output and desirable output have positive relationships with the efficiency of ocean economy considering the environmental problem. However, the dynamic capital input, resource consumption and environmental pollution have negative effects, respectively.

Keywords: ocean economy, capital dynamic effect, green efficiency, Luenberger

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1 Introduction

China has achieved a significant improvement in the development of ocean economy since the implementation of the national maritime power strategy. In 2016, China's gross ocean product (GOP) has reached $ 1085 billion, which accounts for 9.5% of the gross domestic product (GDP). The data shows that the ocean economy has become a new driving force to the national economy. However, while the government is pleased with the achievements of China's ocean economy development, the overexploitation and the destruction issues have become inescapable. Currently acutely restricted by the marine resources and environment, the ocean economy development has been proved to be destructive in many places (Douvere, 2008). A key challenge is to investigate the trend of Chinese ocean economy growth performance and explore the factors, which are essential for the management of ocean economy to provide better policy tools.

From the point of view of sustainable economic growth, total factors productivity (TFP) analysis has become a key method to study the economic growth performance. The most widely used to analyze TFP is the Malmquist indicator. Namely, the Malmquist index based on traditional distance function can be decomposed into two parts, *i.e.,* technological progress and efficiency changes. However, this method neglects to take the bad outputs into account, such as the consumption of resources and environmental pollution and it is a static model. An intriguing aspect is to incorporate the properties of the dynamic production technology into the TFP analysis. Chambers *et al.* (1996) designed a Luenberger productivity indicator with additive structure, which offered the powerful advantage of focusing on changes in input and output bundles. In recent years, the Luenberger productivity indica3tor has been broadly used to evaluate the evolution in productivity and efficiency for many economic units (Epure *et al.,* 2011). For example, scholars have applied Luenberger index method to measure the efficiency of China's environment or productivity problems (Barros and Peypoch, 2007). For these two methods, Chung *et al*. (1997) proposed a Malmquist-Luenberger (ML) index, which introduced directional distance function (DDF)3 into the traditional DEA model. The advantage of the ML index is to take undesirable outputs into the TFP framework for measuring economic growth efficiency. Furthermore, environmental factors have been introduced into the productivity analysis framework and empirical research on the Chinese economy gradually (Chen *et al*., 2010; Hu *et al*., 2011; Li *et al*., 2014; Ding *et al*., 2016). In the above-mentioned literature, we may see that most of the scholars presented the radial or oriented DEA model to calculate the DDF. In the imperfect situation, such as over input, under output, non-zero slack in input or output, the radial method may overestimate the efficiency of the evaluation unit, and the oriented approach also has difficulty in getting the accurate result for the reason of neglecting some aspects of input or output. To solve the problem, the non-radial and non-oriented approach for efficiency measure, *i.e.,* the slack-based measure (SBM) was proposed by Tone (2001). Then Färe *et al*. (2010) and Fukuyama *et al*. (2010) constructed a generalized non-radial and non-oriented directional distance function, which had been applied to various types of productivity and efficiency studies (Boloori and Pourmahmoud, 2016).

In the case of the ocean economy growth performance, there are a few papers recently published for measuring efficiency. As was stated above, the DEA methods had become popular tools to access the efficiency of ocean economy considering the environment and resources factors. It suggests that producing more economic values on the fewer price of resources and environment impact is an urgent problem to be solved (Kang *et al*., 2016; Yu *et al*., 2016). For instance, considering carbon emission, Huang and Fu (2013) calculated the efficiency of low carbon ocean economy by using three-stage DEA method. Ding *et al*. (2017) assessed efficiency of ocean economy for 11 coastal areas with the help of the DEA-Malmquist index model. They found that the true productivity growth accounting for pollution and irrational use of marine resources would be underestimated if the changes in undesirable outputs were ignored. Recently, along with the study of efficiency estimation, the research began to focus on exploring the dynamic capital invested in the ocean economy. The investment not only directly plays an important role in economic development, but also indirectly promotes the technological progress. Li *et al*. (2014) pointed out that investment and economic growth related strongly and showed somewhat lagged effect on long term. The reason was that it took a long time to form the production capacity for the fixed investment, limited by stable industrial structure and supply capacity (Lee *et al*., 2016). However, among the previous studies, the technical difficulty with the existing index models is how to deal with the dynamic input factors directly. For the DEA model, Färe and Grosskopf (1997) took the dynamic factor into account firstly. Then, Nemoto and Goto (2003) considered the fixed capital investment as the dynamic factors in the two periods. Namely, the fixed factor was both the input factor of the current period and the output factor of the previous period. Furthermore, Tone and Tsutsui (2010) introduced the dynamic factors proposed by Färe and Grosskopf (1997) into the method. Although there is some literature concentrated on the dynamic capital problem, few researches focused on the intertemporal effect of capital factor on the efficiency evaluation from the non-radial and non-oriented view.

This paper aims to evaluate the efficiency of Chinese ocean economy growth under the environment and energy constraints. The contributions are as follows. Firstly, the paper introduces dynamic factors into the traditional Luenberger index model and proposes a new dynamic productivity index construction and decomposition method. Specifically, we combine the DDF with the SBM model to deal with the intertemporal effect of dynamic factors, which is called DSBI (directional slack-based index)-Luenberger model based on both desirable and undesirable outputs. Secondly, this new dynamic productivity index decomposition method is used to analyze the impact of input and output factors on the TFP of China's ocean economy. The capital factors are presented to describe the intertemporal effect on ocean economy growth. The empirical studies show that labor force, dynamic capital output and desirable output have positive relationships to the performance of ocean economy growth. On the contrary, dynamic capital input, resource consumption and environmental pollution have negative relationships to performance. Among the resource and environmental factors, the fishing, waste water and solid waste have significant negative impacts. The energy consumption and COD have positive impacts, which can help the government manage the ocean economy as regards these aspects.

The remainder of this paper is structured as follows. Section 2 presents a new Luenberger indicator, *i.e.,* the DSBI-Luenberger model. In section 3 the analysis of empirical results is given. There are some discussions about empirical analysis in section 4. Section 5 concludes this paper.

2. Model

In this section, a dynamic DSBI-Luenberger model was set up. For that, this paper established a dynamic Luenberger indicator and gave analysis firstly. Then, the construction of a DSBI directional distance function was proposed.

2.1 The Dynamic Luenberger Indicator

This paper incorporates dynamic factors in a Luenberger productivity indicator. This indicator does not require a selection from the perspective of measure, facilitates simultaneous consideration of decreased inputs and increased outputs, and supports cost minimization and income maximization. If we assume that there are N production decision-making units during period T, then, each decision-making unit uses input factor x to produce M types of expected output factor y and I types of undesirable output factor b. In addition, there are R types of dynamic factor z (i.e., the outputs during period t constitute the inputs during period $t+1$). Accordingly, we define the dynamic Luenberger indicator from period t to period t+1 as follows:

$$DL_t^{t+1} = \frac{1}{2}\left\{\begin{array}{l}\left[S^t\left(x^t, z^{t-1}, y^t, z^t, b^t; g\right) - S^t\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}; g\right)\right] \\ +\left[S^{t+1}\left(x^t, z^{t-1}, y^t, z^t, b^t; g\right) - S^{t+1}\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}; g\right)\right]\end{array}\right\} \quad (1)$$

In equation (1), g is a direction vector that encompasses the undesirable output and the expected output, and S^t is the directional distance function during period t. When $S^t(t+1)$ and $S^{t+1}(t)$ are derived, an infeasible solution results in outcome error. This paper uses all data throughout the analysis period to establish technical boundaries and then assesses the efficiency of all observed values within unified boundaries. Our method enables the difference in technical efficiency to be obtained from the observed values during adjacent periods. In addition, it facilitates the inclusion of unassessed sample points within the technical boundary, which effectively prevents problems with infeasible solutions. The specific calculation process is as follows.

First, we use the following formula to derive the environmental inefficiency value GS under the unified boundary (intertemporal DEA) and environmental inefficiency value CS under the current technical boundary (current period DEA) based on the directional distance function, where the "*c*" and "*v*" subscripts represent constant returns to scale (CRS) and variable returns to scale (VRS):

$$GS_C(t) - CS_C(t) = TG_C(t) \quad (2)$$

In equation (2), TG is the technical gap, which indicates the measured efficiency gap within two different technical boundaries. We can now express the dynamic Luenberger productivity indicator by employing formula (3):

$$DL_t^{t+1} = GS_C(t) - GS_C(t+1) \quad (3)$$

Analogously, the dynamic Luenberger productivity indicator can be decomposed into dynamic Luenberger efficiency change (DLEC) and dynamic Luenberger technical progress (DLTP) as follows:

$$DLEC_t^{t+1} = CS_C(t) - CS_C(t+1) \quad (4)$$

$$DLTP_t^{t+1} = TG_C(t) - TG_C(t+1) \quad (5)$$

After considering scale efficiency factors, the DLEC decomposition results and the conventional productivity index results do not differ greatly. DLEC can be decomposed into dynamic Luenberger pure efficiency change (DLPEC) and dynamic Luenberger scale efficiency change (DLSEC), as shown in the following equations:

$$\begin{aligned} DLPEC_t^{t+1} &= S_V^t\left(x^t, z^{t-1}, y^t, z^t, b^t; \mathrm{g}\right) - S_V^{t+1}\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}; g\right) \\ DLSEC_t^{t+1} &= \left[S_C^t\left(x^t, z^{t-1}, y^t, z^t, b^t; \mathrm{g}\right) - S_V^t\left(x^t, z^{t-1}, y^t, z^t, b^t; \mathrm{g}\right)\right] - \\ &\quad \left[S_C^{t+1}\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}; g\right) - S_V^{t+1}\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}; g\right)\right] \end{aligned} \tag{6}$$

In equation (6), DLPEC is the change in dynamic pure efficiency from the *t* th period to period *t+1*, and DLSEC is the change in dynamic scale efficiency from period *t* to period *t+1*. These two indicators take the intertemporal effect of dynamic factors on overall efficiency changes into consideration, and both assess productivity changes induced by management, accumulation of experience, and scale.

DLTP is obtained from changes in the technical gap (TG) during adjacent periods while considering the intertemporal effect of dynamic factors and can be decomposed into conventional Luenberger technical progress (LTP) and a Luenberger dynamic effect (LDE):

$$LTP_t^{t+1} = \frac{1}{2}\left\{\left[S_V^{t+1}\left(x^t, z^t, y^t, b^t; g\right) - S_V^t\left(x^t, z^t, y^t, b^t; g\right)\right] + \left[S_V^{t+1}\left(x^{t+1}, z^{t+1}, y^{t+1}, b^{t+1}; g\right) - S_V^t\left(x^{t+1}, z^{t+1}, y^{t+1}, b^{t+1}; g\right)\right]\right\}$$

$$LDE_t^{t+1} = \frac{1}{2}\left\{\begin{array}{l} \left[\begin{array}{l} \left(S_C^{t+1}\left(x^t, z^{t-1}, y^t, z^t, b^t; g\right) - S_V^{t+1}\left(x^t, z^{t-1}, y^t, z^t, b^t; g\right)\right) - \\ \left(S_C^t\left(x^t, z^{t-1}, y^t, z^t, b^t; g\right) - S_V^t\left(x^t, z^{t-1}, y^t, z^t, b^t; g\right)\right) \end{array}\right] + \\ \left[\begin{array}{l} \left(S_C^{t+1}\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}; g\right) - S_V^{t+1}\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}; g\right)\right) - \\ \left(S_C^t\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}; g\right) - S_V^t\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}; g\right)\right) \end{array}\right] \end{array}\right\} \tag{7}$$

In summary, the dynamic Luenberger indicator from the period *t* to the period *t+1* can be decomposed as follows:

$$\begin{aligned} DL^{t,t+1} &= DLPEC\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}, x^t, z^{t-1}, y^t, z^t, b^t\right) \\ &\quad + DLSEC\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}, x^t, z^{t-1}, y^t, z^t, b^t\right) \\ &\quad + LTP\left(x^{t+1}, z^{t+1}, y^{t+1}, b^{t+1}, x^t, z^t, y^t, b^t\right) \\ &\quad + LDE\left(x^{t+1}, z^t, y^{t+1}, z^{t+1}, b^{t+1}, x^t, z^{t-1}, y^t, z^t, b^t\right) \end{aligned} \tag{8}$$

Although this paper provides a detailed decomposition of the dynamic Luenberger productivity indicator, it only analyzes total factor productivity from the perspective of whether efficiency has increased and technology has advanced. However, we do not know which of the many input and output factors causes total factor productivity to increase, production technology to advance or decline, or production efficiency to increase. This paper uses the advantages of the Luenberger indicator to construct an analytical model of influencing factors as follows:

$$\begin{aligned} DL_t^{t+1} &= GS_C^x(t) - GS_C^x(t+1) + GS_C^{zi}(t) - GS_C^{zi}(t+1) + GS_C^y(t) - GS_C^y(t+1) \\ &\quad + GS_C^{zo}(t) - GS_C^{zo}(t+1) + GS_C^b(t) - GS_C^b(t+1) \end{aligned} \tag{9}$$

Equation (9) decomposes productivity DL into the five parts $DL^x, DL^{zi}, DL^y, DL^{zo}, DL^b$. For example, $DL^x = GS_C^x(t) - GS_C^x(t+1)$. These decompositions express the effect of inputs, dynamic factor inputs, expected outputs, dynamic factor outputs, and undesirable outputs, respectively, on total factor productivity. We now use the dynamic Luenberger indicator to decompose the increase in total factor productivity into dynamic efficiency change and dynamic technical progress, where the change in dynamic efficiency indicates the distance between the technical boundaries at the sample point, and dynamic technical progress indicates the degree to which the technical boundaries have expanded outward. Hence, The DLEC can be decomposed into the following factors.

$$\begin{aligned} DLEC_t^{t+1} &= CS_C^x(t) - CS_C^x(t+1) + CS_C^{zi}(t) - CS_C^{zi}(t+1) + CS_C^y(t) - CS_C^y(t+1) \\ &\quad + CS_C^{zo}(t) - CS_C^{zo}(t+1) + CS_C^b(t) - CS_C^b(t+1) \end{aligned} \tag{10}$$

$$\begin{aligned} DLTP_t^{t+1} &= TG_C^x(t) - TG_C^x(t+1) + TG_C^{zi}(t) - TG_C^{zi}(t+1) + TG_C^y(t) - TG_C^y(t+1) \\ &\quad + TG_C^{zo}(t) - TG_C^{zo}(t+1) + TG_C^b(t) - TG_C^b(t+1) \end{aligned} \tag{11}$$

In equations (10) and (11), the DLEC indicator is decomposed to $DLEC^x, DLEC^{zi}, DLEC^y$, $DLEC^{zo}, DLEC^b$. For example, $DLEC^x = CS_C^x(t) - CS_C^x(t+1)$. The corresponding DLTP indicator is decomposed to $DLTP^x, DLTP^{zi}, DLTP^y, DLTP^{zo}, DLTP^b$. For example, $DLTP^x = TG_C^x(t) - TG_C^x(t+1)$. These decompositions indicate the contribution of inputs, dynamic factor inputs, outputs, dynamic factor outputs, and the environment, respectively, on efficiency and technical progress. The new dynamic Luenberger productivity index decomposition method proposed in this paper can link total factor productivity, changes in efficiency, and technical progress with dynamic factors and input/output factors, thus revealing the laws that govern changes in the ocean economy's total factor productivity.

2.2 The New Directional Distance Function

Based on the slack variable method of Tone (2001), Fukuyama *et al.* (2010) incorporated slack variables in a directional distance function and proposed the slack-based model (SBM) for the measurement of efficiency losses. This model overcomes the technical issue of error caused by radial and orientation selection. This paper presents a new directional slack-based index (DSBI), which incorporates dynamic factors in the SBM model. It defines the dynamic directional distance function of *k* decision-making units during the period *t* as follows:

$$\begin{aligned} & \overline{S_v^t}\left(x_{kt}, z_{kt-1}^i, y_{kt}, z_{kt}^o, b_{kt}, g^x, g^{zi}, g^y, g^{zo}, g^b\right) \\ &= \max_{s^x, s_{t-1}^{zi}, s^y, s_t^{zo}, s^b, \lambda} \frac{1}{3}\left[\frac{1}{N+R}\left(\sum_{n=1}^{N}\frac{S_{nt}^x}{g_{nt}^x} + \sum_{r=1}^{R}\frac{S_{rt-1}^{zi}}{g_{rt-1}^{zi}}\right) + \frac{1}{M+R}\left(\sum_{m=1}^{M}\frac{S_{mt}^y}{g_{mt}^y} + \sum_{r=1}^{R}\frac{S_{rt}^{zo}}{g_{rt}^{zo}}\right) + \frac{1}{I}\sum_{i=1}^{I}\frac{S_{it}^b}{g_{it}^b}\right] \\ & s.t. x_{nk't} = \sum_{k=1}^{K} x_{nkt}\lambda_{kt} + s_{nt}^x \left(n = 1,\ldots,N, t = 1,\ldots,T\right) \\ & z_{rk't-1}^i = \sum_{k=1}^{K} z_{rkt-1}^i \lambda_{kt-1} + s_{rt-1}^{zi} \left(r = 1,\ldots,R, t = 1,\ldots,T\right) \\ & y_{mk't} = \sum_{k=1}^{K} y_{mkt}\lambda_{kt} - s_{mt}^y \left(m = 1,\ldots,M, t = 1,\ldots,\mathrm{T}\right) \\ & z_{rk't}^o = \sum_{k=1}^{K} z_{rkt}^o \lambda_{kt} - s_{rt}^{zo} \left(r = 1,\ldots,R, t = 1,\ldots,T\right) \\ & b_{ik't} = \sum_{k=1}^{K} b_{ikt}\lambda_{kt} + s_{it}^b \left(i = 1,\ldots,I, t = 1,\ldots,T\right) \\ & \sum_{k=1}^{K} \lambda_{kt-1} z_{rkt-1}^o = \sum_{k=1}^{K} \lambda_{kt} z_{rkt}^i \,\forall r \left(t = 1,\ldots,T\right) \\ & \sum_{k=1}^{K} \lambda_{kt} = 1, s_{nt}^x \ge 0, s_{rt-1}^{zi} \ge 0, s_{mt}^y \ge 0, s_{rt}^{zo} \ge 0, s_{it}^b \ge 0, \lambda_{kt} \ge 0 \end{aligned} \tag{12}$$

In equation (12), $\left(x_{nk't}, z^{i}_{rk't-1}, y_{mk't}, z^{o}_{rk't}, b_{ik't}\right)$ represent the *N*-dimensional inputs, *R*-dimensional dynamic input factors, *M*-dimensional expected outputs, *R*-dimensional dynamic output factors, and the *I*-dimensional undesirable output vector of decision-making unit *k*, respectively, and express the directional vectors of reduced inputs, reduced dynamic inputs, increased expected outputs, increased dynamic outputs, and reduced undesirable outputs, respectively, where $\left(s^{x}, s^{zi}, s^{y}, s^{zo}, s^{b}\right)$ express the vectors of input redundancy, dynamic factor input redundancy, expected output gap, dynamic factors output gap, and undesirable output redundancy, respectively. In equation (12), the objective function maximizes the sum of the mean input inefficiencies and output inefficiencies, and the calculated distance function value represents the inefficiency level of that decision-making unit, where the larger that the value is, the lower the efficiency. To determine the specific sources of inefficiency, the inefficiency value can be decomposed as follows:

$$IE = \vec{S}_{v}^{t} = IE_{v}^{x} + IE_{v}^{zi} + IE_{v}^{y} + IE_{v}^{zo} + IE_{v}^{b} \qquad (13)$$

To estimate the distance function value, we selected the following direction vector to standardize the input and output slack variables:

$$g_{n}^{x} = x_{n}^{\max} - x_{n}^{\min}, g_{r}^{zi} = z_{r}^{i\max} - z_{r}^{i\min}, g_{m}^{y} = y_{m}^{\max} - y_{m}^{\min}, g_{r}^{zo} = z_{r}^{o\max} - z_{r}^{o\min}, g_{i}^{b} = b_{i}^{\max} - b_{i}^{\min} \qquad (14)$$

This approach is adopted because the distance function that underlies this direction vector exhibits several excellent characteristics, such as being non-negative, being zero, Pareto-Koopman efficiency, transitive invariance, and unit invariance.

3. Empirical Results

3.1 Data and Descriptions

The analysis relies on a panel data of China's 11 coastal regions over the period 2002–2012, which are collected from China Marine Statistical Yearbook (CMSY), China Statistical Yearbook (CSY), and China Marine Usage Management Declaration (CMUMD).

The input indicators are as follows. In the sample, each coastal region has two inputs, that is, marine capital stock and marine labor force. For the labor force, it chooses the annual average ocean-related employment as a proxy. The marine capital stock is selected as the dynamic factor. Firstly, it estimates the capital stock of 11 coastal regions by referring to Zhang (2004), because there are no official statistics on it. It adopts the results from Zhang (2004) to set the original capital stock in 2000 and then estimates the current capital stock of 11 coastal regions as $k_t = (1-\delta)k + I_t$, where k_t represents the fixed capital stock and I_t denotes annual physical capital investment. Here, δ is the capital depreciation rate, denoted by $\delta = 10.96\%$ (see details in the previous study of Ding *et al.*, 2017). Furthermore, the former marine capital stock is used as the input variables and the current marine capital stock is considered as the output variable.

The output indicators include one desirable output and three undesirable outputs. The paper details the data sources and calculation methods of each variable as follows. The desirable output is chosen from the perspective of economic efficiency. GOP is used as a proxy for economic efficiency and it is a sensitive indicator for measuring ocean economy efficiency. The undesirable outputs include two types of activities, *i.e.,* resource depletion and environmental pollution. Hence, from the resource depletion point of view, the marine fishery production is chosen, which has been the biggest threat to ocean health. The energy consumption is used as a proxy for the consumption of marine minerals, gas and petroleum. Then, from an environmental perspective, the undesirable outputs include marine industrial wastewater, marine industrial solid waste, and the removal rate of chemical oxygen demand (COD) in marine industrial wastewater.

3.2 Analysis at the Level of Overall Ocean Economy

At the level of geography, the average increase in the green total factor productivity of China's ocean economy was 0.27%. However, although this increase reveals a growing trend, the growth rate remained at a relatively low level. Variations in the ocean economy green total factor productivity originate in dynamic efficiency changes and dynamic technical progress. The former reflects the intertemporal effect of dynamic factors (*e.g.*, marine capital stock) on overall efficiency and assesses green productivity (DLEC) connected with efficiency improvements. That green energy productivity increased at an average rate of -0.04% indicates that it has diverged from the technical boundary constructed using current-period data and that China's ocean economy green efficiency has not improved. The latter examines the intertemporal effect of dynamic factors on overall efficiency and assesses green productivity (DLTP) connected with technical progress. That green productivity increased at an average rate of 0.31% indicates that the technical boundary constructed using intertemporal data exhibits an increasing trend and that the level of green technology in China's ocean economy has risen. Thus, it is evident that technological progress has been the primary driving force of China's ocean economy green total factor productivity and that straightforwardly improving production technology will be an effective route to increasing China's ocean economy green total factor growth.

Based on formulas (3)-(5), this paper measures the dynamic Luenberger productivity indicators for various locations in coastal China and decomposes these indicators into DLPEC, DLSEC, conventional LTP, and Luenberger dynamic efficiency (LDE) (Table 1).

3.3 Analysis from the Dynamic Perspective

Dynamic efficiency changes represent the combined effect of changes in dynamic pure technical efficiency and changes in dynamic scale efficiency. The former represent changes in productivity attributable to management, technology, and accumulation of experience and exhibited an average growth rate of 0.05%. The latter represent changes in productivity attributable to scale factors and exhibited an average growth rate of -0.09%. The negative growth rate of dynamic scale efficiency implies that the ocean economy green technical boundary under the current-period DEA is shifting towards unvarying returns to scale technology. In conclusion, changes in dynamic pure technical efficiency constitute the primary source of variation in China's ocean economy green efficiency. Therefore, changes in conventional technical progress and the capital dynamic technology effect are jointly creating growth in the green total factor productivity of China's ocean economy. The former is in the dominant position, and the growth rate of the capital dynamic effect is relatively low in comparison, which reflects that China's ocean economy has not emphasized dynamic development and has neglected continuing economic development based on the input of marine capital.

Table 1

Ocean Economy Green Total Factor Productivity Indicators and Their Decomposition

Region	DLTFP	DLEC	Decomposed indicators		DLTP	Decomposed indicators	
			DLPEC	DLSEC		LTP	LDE
Tianjin	0.0094	0.0048	0.0069	-0.0021	0.0046	0.0025	0.0021
Hebei	0.0062	0.0054	0.0025	0.0029	0.0008	0.0035	-0.0027
Liaoning	-0.0021	-0.0051	-0.0034	-0.0017	0.0030	0.0014	0.0016
Shanghai	0.0164	0.0087	0.0059	0.0028	0.0077	0.0058	0.0019
Jiangsu	-0.0026	-0.0008	0.0025	-0.0034	-0.0017	0.0034	-0.0051
Zhejiang	0.0039	0.0017	0.0012	0.0005	0.0022	0.0007	0.0015
Fujian	0.0011	-0.0053	-0.0031	-0.0022	0.0064	0.0042	0.0022
Shandong	0.0083	0.0073	0.0058	0.0015	0.0010	0.0016	-0.0005
Guangdong	-0.0076	-0.0068	-0.0074	0.0006	-0.0008	-0.0001	-0.0007
Guangxi	-0.0039	-0.0107	-0.0087	-0.0019	0.0067	0.0064	0.0003
Hainan	0.0010	-0.0033	0.0035	-0.0067	0.0043	-0.0017	0.0059
Mean	0.0027	-0.0004	0.0005	-0.0009	0.0031	0.0025	0.0006

3.4 Analysis at the Level of Regions

Although the overall ocean economy green total factor productivity of coastal areas has been in a state of relatively slow growth, there were large differences between various coastal areas, and several provinces (Liaoning, Jiangsu, Guangdong, and Guangxi) have displayed decreasing performance. The increase in the ocean economy green total factor productivity of Liaoning and Guangxi has been constrained by decreasing dynamic pure technical efficiency and dynamic scale efficiency. Jiangsu's 0.26% ocean economy green total factor productivity decrease is primarily attributable to the constraining effect of decreases in dynamic efficiency and dynamic technical progress (by 0.08% and 0.17%, respectively). In this case, decreasing dynamic efficiency and dynamic technical progress were attributable to low dynamic scale efficiency and capital dynamic effect. The decrease in Guangdong's ocean economy green total factor productivity is attributable to three factors: changing dynamic pure efficiency, conventional technical progress, and capital dynamic effect. These results indicate that the harmful nature of developing the ocean economy at the expense of resource consumption and environmental pollution has begun to become apparent. In contrast, Shanghai, Tianjin, and Shandong had the highest ocean economy green productivity. Shanghai and Tianjin benefited from the early accumulation of capital and superior geographic conditions, while Shandong took advantage of its status as a leading maritime province and central and local government policies aimed at making it a "blue" economic zone to avoid any decline in ocean economy green productivity. While Zhejiang and Fujian are leading maritime provinces, their green total factor productivity values have been lower than that of Shandong, which is attributable in both cases to a low dynamic efficiency growth rate. The combined effect of a relatively low dynamic efficiency growth rate and decreasing technical efficiency due to the excessive resource dependence of the ocean economy and excessive environmental pollution has prevented these provinces from realizing the intensive use efficiency of various marine production factors.

4. Dynamic Factors Decomposition

4.1 Results of Decomposition the Changes in the Green Total Productivity

According to formula (9), total factor productivity can be obtained by comparing the green inefficiency value during adjacent periods within a unified boundary. If the productivity index associated with a certain input or output factor is positive, this indicates that the green inefficiency value connected with that factor has decreased, and the factor has a positive effect on green total factor productivity (and vice versa).

Table 2

Decomposition of Changes in Green Total Factor Productivity of China's Ocean Economy Based on Different Input and Output Factors

Region	Total efficiency value	Input	Dynamic factors		Output	Total efficiency of resource and environment	Resource consumption		Environmental pollution		
		labor	Capital Dynamic inputs	Capital dynamic outputs			Energy	fishing	wasted water	COD	Solid waste
Tianjin	0.0094	0.0085	-0.0019	0.0015	0.0082	-0.0070	0.0072	-0.0074	-0.0040	0.0029	-0.0057
Hebei	0.0062	0.0041	-0.0019	0.0016	0.0079	-0.0056	0.0070	-0.0063	-0.0069	0.0061	-0.0055
Liaoning	-0.0021	-0.0019	-0.0017	0.0018	0.0062	-0.0065	0.0058	-0.0060	-0.0053	0.0037	-0.0047
Shanghai	0.0164	0.0113	-0.0020	0.0021	0.0079	-0.0029	0.0047	-0.0068	-0.0027	0.0059	-0.0040
Jiangsu	-0.0026	-0.0018	-0.0019	0.0017	0.0053	-0.0058	0.0020	-0.0053	-0.0038	0.0035	-0.0021
Zhejiang	0.0039	0.0089	-0.0017	0.0016	0.0088	-0.0137	-0.0002	-0.0074	-0.0057	0.0050	-0.0054
Fujian	0.0011	0.0095	-0.0020	0.0017	0.0049	-0.0130	0.0065	-0.0072	-0.0031	-0.0036	-0.0055
Shandong	0.0083	0.0057	-0.0018	0.0017	0.0075	-0.0047	0.0067	-0.0074	-0.0065	0.0074	-0.0050
Guangdong	-0.0076	-0.0019	-0.0018	0.0017	0.0087	-0.0143	0.0059	-0.0071	-0.0048	-0.0021	-0.0061
Guangxi	-0.0039	-0.0085	-0.0016	0.0015	0.0070	-0.0023	0.0073	-0.0074	-0.0039	0.0064	-0.0047
Hainan	0.0010	0.0039	-0.0017	0.0014	0.0055	-0.0080	0.0059	-0.0074	-0.0003	0.0007	-0.0069
Mean	0.0027	0.0034	-0.0018	0.0017	0.0071	-0.0076	0.0053	-0.0069	-0.0043	0.0033	-0.0050

Table 2 displays a breakdown of ocean economy green total factor productivity according to various input and output factors during the period 2003-2012. The table reveals that labor input, capital dynamic output, and expected output have a positive effect on the green growth performance of China's ocean economy. In particular, the 0.71% increase in green total factor productivity attributable to growth in the ocean economy indicates that the rapid growth of China's ocean economy during the sampling period was the chief reason for increased productivity. Labor input was the second-most important cause of increased productivity and accounted for 0.34% of productivity. Compared with labor input, capital dynamic output accounted for relatively little productivity (only 0.17%). Factors with a negative influence on ocean economy green growth included capital dynamic input, resource consumption, and environmental pollution. If resource consumption and pollution emissions are combined, the total productivity value attributable to these factors is approximately -0.76%. This outcome indicates that resource consumption and pollution emissions are in fact the primary source of green inefficiency in China's ocean economy and have a significant negative effect on the green growth performance of the ocean economy. Among indicators associated with resource consumption and pollution emissions, fishing, wastewater discharges, and solid waste disposal have negative impacts on the green productivity. Fishing has the most significant negative impact, followed by solid waste disposal. Conversely, energy and COD emissions have a positive effect on green productivity, which indicates that energy conservation and reduced COD emissions can contribute considerably to improving the green growth of the ocean economy. However, we may notice an interesting issue in this regard: In the foregoing static analysis of the green efficiency of the ocean economy, we observed out that fisheries depletion and COD emissions make relatively large contributions to resource and environmental inefficiency and have the largest negative impacts on the productivity of the ocean economy. However, we also find that COD emissions have a positive influence on the green total factor productivity of the ocean economy. How can this phenomenon be best explained? Referring to formula (3), we may notice that total factor productivity is derived by comparing inefficiency values during adjacent periods of time within a unified boundary. Although the inefficiency value of COD emissions is relatively high, which indicates that in fact it constitutes the chief cause of resource and environmental inefficiency, the decreasing trend in inefficiency during the analysis period indicates that the inefficiency of COD emissions improved somewhat. Therefore, it has a positive influence on the green total factor productivity.

4.2 Analysis of Factors at Regional Level

At the level of regions, the factors that influence the green total factor productivity of the ocean economy in various coastal areas display the following characteristics: (1) The association between productivity and labor input reveals that the labor inputs of Shanghai, Fujian, Zhejiang, and Tianjin had a significant positive influence on their ocean economy green productivity, while the labor inputs of Guangdong, Guangxi, Liaoning and Jiangsu had a significant negative influence on their green productivity, and the labor input efficiency of these regions exhibited a decreasing trend. (2) The association between productivity and capital dynamic input factors (dynamic inputs and dynamic outputs are combined for the purpose of analysis) reveals that capital dynamic factors had a weakly negative, fluctuating influence (ranging from -0.01% to -0.03%) on ocean economy green productivity in the various coastal areas. Capital dynamic output had a 0.17% positive influence. When taking capital as the only input factor, a relatively large lag effect on the green total factor productivity of the ocean economy appears. Because the dynamic effect of marine capital stock more objectively reflects the effect of capital in the dynamic production process, using this factor not only helps avoid overestimating the improved efficiency of marine capital stock but also underestimating productivity associated with marine capital. Thus, the effect of marine capital stock on marine green total factor productivity can be objectively and accurately assessed. (3) Productivity results associated with outputs reveal that the outputs of the coastal areas had a positive influence on ocean economy green total factor productivity. This was most evident in the case of Zhejiang and Shanghai, which confirms that the GOP of the rapid growth of the ocean economy is the main path to the effective green growth of China's ocean economy. However, why has the green total factor productivity of China's ocean economy increased so slow, and why has it had negative growth in certain provinces? (4) Productivity results associated with resources and the environment reveal that resource consumption and pollution emissions have significant negative effects on the green total factor productivity of the ocean economy in the various coastal areas. In particular, Guangdong, Zhejiang, and Fujian have the highest negative productivity associated with resources and the environment. This phenomenon answers the foregoing question. While the ocean economy has grown rapidly, overall resource use efficiency and environmental administration experienced notable, persistent problems during the sampling period. For instance, fishing, wastewater discharges, and waste disposal did not exhibit significant improvement, and all of these factors represent important constraints on the improvement of the green total factor productivity of the ocean economy.

4.3 Dynamic Trends in Individual Periods

The foregoing analysis addresses the influence of various input and output factors on green total factor productivity in various coastal areas during the period 2003-2012. However, we were unable to determine dynamic trends within individual periods. Because DLTFP, DLEC, and DLTP are derived from differences in the three variables defined in the second section of this paper during adjacent periods, they are based on the environmental inefficiency value GIE measured within a unified boundary, the environmental inefficiency value CIE, and TG measured within the current-period boundary. Therefore, by finding the changes in these three variables during the sampling period, we can obtain reasonable explanations for China's ocean economy green growth performance, changes in efficiency, and changes in technical progress.

Figure 1 shows the changes in the ocean economy green inefficiency GIE and the inefficiency GIE value of inputs, outputs, dynamic factors, resources, and pollution within a unified boundary during the period 2003-2012. According to formula (3), because productivity equals the GIE differences between the coastal areas during adjacent periods, if the inefficiency value during the period *t+1* is greater than that during the period *t*, the productivity index will be positive (and vice versa). Figure 1 reveals that while the GIE value associated with resource consumption and pollution emissions during the period 2003-2006 was higher than the GIE value during other periods, there was a monotonic decreasing trend, and the GIE value associated with inputs had a steadily increasing trend during this period. The inefficiency curves of other factors were relatively flat, which indicates that labor input, resource consumption, and pollution emissions were the main factors responsible for the negative growth in ocean economy green total factor productivity during the period 2003-2006. For its part, the decrease in input efficiency was the primary cause of decrease in the green total factor productivity. During the period 2006-2008, the GIE value associated with inputs decreased from 0.2675 in 2005 to 0.2372 in 2006, while the GIE associated with resource consumption and pollution emissions decreased from 0.3633 in 2003 to 0.2556 in 2006. Compared with earlier periods, the inefficiency values of input, resource, and environmental factors decreased during this period, which was the primary cause of the increase in the ocean economy green growth performance during this period. During the period 2008-2010, the ocean economy green inefficiency GIE value reached a peak. During this period, the GIE values associated with labor input, resource consumption, and environmental pollution emissions remained high and relatively flat. However, the GIE values associated with outputs and dynamic factors rose, and the GIE value associated with dynamic factors reached 0.1097 in 2009. The inadequate efficiency of dynamic factors in the ocean economy constituted the primary constraint on green growth in the ocean economy during this period. During the period 2010-2012, the GIE values associated with labor input, resource consumption, and pollution emissions displayed decreasing trends. However, the inefficiency curve associated with output displayed an increasing trend and reached 0.1335 in 2012, which was primarily associated with the growth in the ocean economy during the most recent two years. During this period, the increasing efficiency of resource consumption and the pollution emissions were the main factors driving the green total factor productivity increase in the ocean economy. Labor input efficiency was the second-most important factor during this period. In addition, the decrease in output efficiency cannot be neglected.

Figure 1

Changes in Ocean Economy Green Inefficiency GIE and Related Factors, 2003-2012

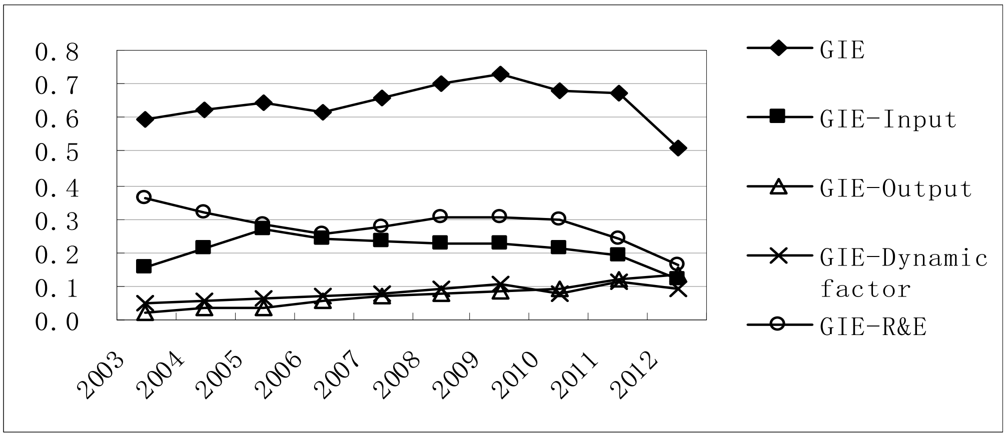


Figure 2 shows ocean economy green inefficiency CIE trends within the technical boundary during the current period. According to formula (4), changes in dynamic efficiency represent differences in CIE during adjacent periods in the coastal areas. The change in dynamic efficiency is positive when the CIE value for the period *t+1* is larger than the value for the period *t*, which implies efficiency has increased, and negative when the CIE value decreases, which implies that efficiency has decreased. The trend of CIE change associated with resource consumption and pollution emissions during the entire period was similar to that of CIE change associated with green inefficiency in the ocean economy. The CIE value associated with inputs rose to 0.1836 during 2003 and 2004, which was a direct result of the change in dynamic efficiency shifting to negative during this period. Apart from dynamic factors, the CIE values associated with labor input, output, and resources/environment increased during the period 2008-2011, which accounts for the primary factors that explain the decrease in efficiency during this period.

Figure 2
Changes in Ocean Economy Green Inefficiency CIE and Related Factors, 2003-2012

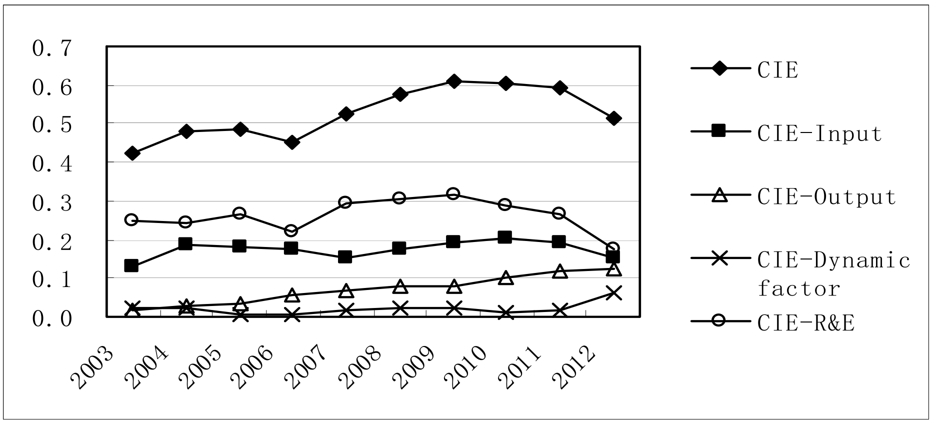
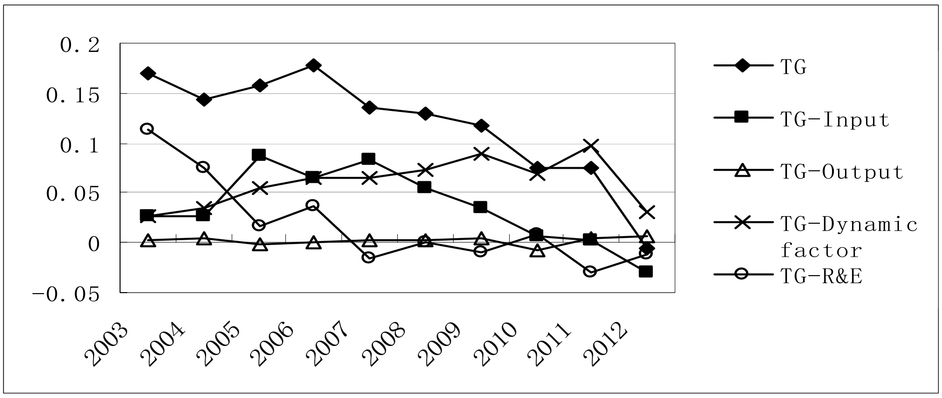


Figure 3 shows the trend of the ocean economy TG value in the coastal areas during the sampling period. According to formula (5), the dynamic technical progress rate is the difference in TG during adjacent periods, and the changes in the values obtained under different technical boundaries express technical progress trends. A comparison of Figure 1 with Figures 2 and 3 reveals that while the trends in the ocean economy green inefficiency value GIE are largely similar, TG has the opposite trend. This indicates that changes in efficiency, not changes in technical progress, were the primary drivers of the downward trend in the green growth performance of China's ocean economy during certain periods. We can observe from the effect of the various input and output factors on technical progress that resource consumption and pollution emissions were associated with a significant decrease in TG during the sampling period, followed by TG associated with labor input. In an opposite trend, TG associated with capital dynamic factors displayed a significant increasing trend, which indicates that capital dynamic factors have a significant positive effect on technical progress. Finally, output factors have the smallest effect on technical progress.

Figure 3
Changes in Ocean Economy TG and Related Factors, 2003-2012



5. Conclusions

Taking the advantage of the dynamic Luenberger index, this paper analyzes the specific factors that influence the trend of total factor productivity, efficiency change and technological progress of the Chinese ocean economy. There are some comprehensive policy recommendations. For example, in Guangdong, Guangxi, Liaoning and Jiangsu regions, productivity declines related to labor input. Hence, the measures are provided to improve the growth performance of Chinese ocean economy, *i.e.,* optimizing human resource allocation and increasing human capital investment. The ocean economy growth in Shanghai, Jiangsu and Zhejiang shows high resource dependence. Therefore, in order to develop ocean economy in these areas, the government should pay more attention to resources unified management to adjust and optimize structure of ocean economy. At the same time, the government should limit energy-intensive, high-emission projects strictly and improve project size and quality. In Fujian and Guangdong, environmental problems are most prominent for the growth of the ocean economy. Hence, ocean ecological reserve needs to be set up, which needs to balance the development and environmental protection. By controlling the discharge of pollutants into the sea strictly, improving the environment of the sea and strengthening the restoration and protecting ocean ecological environment, we can truly realize the green development of ocean economy in these areas.

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