



# Can environmental regulation promote the green output bias in China's mariculture?

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## Abstract

The green output bias of technological progress is the key factor driving the green transformation of mariculture. This study considers whether environmental regulation can promote the green output bias. Utilizing data envelopment analysis (DEA), we decomposed the green output biased technological progress index (OBTC) and constructed the index to measure the output bias between output value and pollutant emissions. The results show spatial and temporal differences in the green output bias, with different bias values for three major Chinese coastal regions during the study period. As the bias value mainly fluctuates around the zero value, the degree of green output bias must be enhanced. Considering the heterogeneity of environmental regulation, we empirically study the relation that exists between environmental regulation and green output bias. Our findings indicate a *U*-shaped relation between two categories of environmental regulation and the green output bias. Green technology partially intermediates the mechanisms by which these environmental regulations influence green output bias. Our results have implications for policymakers and other stakeholders for strengthening environmental regulation, promoting green technological innovation, and the scientific planning of the species and scale of mariculture to promote sustainable development.

**Keywords** Environmental regulation · Green output bias · Biased technological progress · Mariculture · Data envelopment analysis · Marine economy

## Introduction

Since the twenty-first century, the development speed and scale of mariculture has been expanding, which has become a significant support for China's marine economy, but has also brought serious environmental problems. The rapid expansion of the scale of mariculture has resulted in the overexploitation of mariculture areas. For example, the deposition of mariculture biological excretion, nitrogen, phosphorus, and other nutrient accumulation poses severe ecological threats to these areas. Therefore, it is necessary to change the mode of economic growth and improve the contribution of technological progress to total factor productivity. In general, technological progress will not increase

the input and output efficiency of factors in an equal proportion; that is, technological progress has factor bias. In the development process of mariculture, expected output and non-expected output coexist. Whether green output bias can be achieved is the critical element driving the green transformation of mariculture (Li et al. 2019; Ji et al. 2022). Environmental regulation is an important factor driving green output bias. When the government implements environmental regulation policies, enterprises' green technology R&D decisions will be affected, and the bias of technological progress will change. Based on this, we empirically explored the level of green output bias in mariculture, and considering the heterogeneity of environmental regulation, the relation between environmental regulation and green output bias, and the influence path between the two. The purpose of this paper is to reveal the relative problems between mariculture development and ecological environment, to provide guidance for formulating effective environmental regulation policies, and to put forward measures to promote green output bias, so as to realize the green development of mariculture.

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To study the relationship between environmental regulation and green output bias, it is necessary to explore the related concepts of green output bias, environmental regulation, and the existing research on environmental regulation and green output bias. The concept of green output bias can be traced back to the concept of technological progress bias (Hicks 1932), which mainly focused on two basic factors of production: labor and capital (Klump et al. 2007; Sato and Morita 2009). It is now increasingly being applied to environmental economics, and the technological progress bias model is being extended to a wider range of factors. Energy factors and undesired outputs have been included in the measurement system. Economic growth is constantly increasing under the dual constraints of resources and environment. Green biased technological progress has become the focus of many scholars. Acemoglu et al. (2012) analyzed biased technological progress under environmental constraints based on the framework of endogenous economic growth model, and found that the bias of technological progress between clean technology and polluting technology depends on three key effects: price, market size, and productivity. The government can guide the development of clean technology through temporary environmental policies, thus changing the bias of technological progress. Based on the research of Acemoglu et al. (2012), Acemoglu et al. (2016) removed the assumption of constant elasticity of substitution for contaminants and cleaning products, and used the data of the US energy sector for parameter calibration. The results of the simulation calculation show that environmental taxes and green R&D subsidies can make the transition from polluting technology to clean technology. The optimal environmental regulation strategy is to carry out R&D subsidies substantially first, and then continue to collect environmental taxes. Aghion et al. (2016) divided production technology into clean technology and pollution technology. The results show that when energy prices rise, enterprises tend to develop clean technology, and the government can use tax tools to promote technological progress biased toward clean technology. Song and Wang (2016) argued that labor structure has a significant impact on green technological progress bias, and that an increase in the aging population will facilitate the use of polluting technologies. Li et al. (2019) considered water resources and pollution emissions, and discussed green technological progress bias in China's industry from the perspective of input and output. When the proportion of technological progress biased towards expected output is higher than that of undesired output, green output bias is presented.

Environmental regulation was initially administered by governments and focused on acts of environmental pollution. Tietenberg (1998) pointed out that there are three general categories of environmental regulation instruments. According to the order of development time, the first is the

command type, the second is the incentive type, and the last is the voluntary type. There are various choices of environmental regulation tools in existing studies: command-and-control environmental regulations include environmental pollution emission standards, measures such as limiting the concentration and volume of corporate pollutant emissions (Macho-Stadler 2008); market-based incentive environmental regulation include emission fees (Testa et al. 2014); and voluntary regulation tools include environmental petitions, resource agreements, and ecological labels (Khanna et al. 1998). Studies of environmental regulation from the perspective of enterprise performance have posited that businesses perform a cost–benefit analysis of economic regulation to determine whether the benefits are large enough to justify the costs by computing cost–benefit indicators to support their decision making process. Cost indicators include environmental taxes (Kim 2010), and benefit indicators include financial expenditure related to environmental protection and environmental pollution control investment (Leiter et al. 2011; Naso and Yi 2017). Environmental regulation tools gradually develop towards diversification.

Can environmental regulation promote green output bias? The existing studies rarely involve this aspect. They mostly focus on the relation between environmental regulation and technological progress, and there are three main viewpoints. The first viewpoint, which involves the *compliance cost* effect, proposes that environmental regulation inhibits technological progress. Kneller and Manderson (2012) empirically studied the British manufacturing industry during 2000–2006 utilizing the system GMM model and concluded that environmental regulation inhibited technological progress. Zárate-Marco and Vallés-Giménez (2012) empirical study of 450 manufactured industries in Spain during 1989–2001 found that when the government strengthened the implementation of environmental policies the level of technological progress declined. Granderson and Prior (2013) studied the traditional energy power generation industry in America. Their empirical results demonstrated that environmental regulation hindered the technological progress, and there was a negative relationship between the two. Aklin (2016) posited that environmental regulation increased production and management costs, and that excessive environmental regulation motivated enterprises to sacrifice long-term interests and commit errors in strategic decision making to meet environmental standards—which was not conducive to technological innovation and technological progress. The second viewpoint, which involves the *innovation compensation* effect, proposes that the appropriate level of environmental regulation motivates companies to acquire green technology and promote technological progress. Domazlicky and Weber's (2004) tested the Porter hypothesis with a study of American chemical enterprises. The findings showed a positive relationship between the two.

Bauman et al. (2008) studied South Korea's fossil fuel power industry and, utilizing ordinary least squares (OLS) regression, found that an improvement in the strength of environmental regulations lead to higher marginal abatement costs in the power industry, thereby contributing to technological progress in the industry. Guo et al. (2017) empirically studied a refinery in Los Angeles, California, and found that environmental regulation plays a contributing function in technological progress. The third viewpoint is the *nonlinear* viewpoint. Lanoie et al. (2008) conducted a study utilizing 1996–2008 data for the manufacturing sector in Eastern Canada. Their empirical results showed that environmental regulation hindered technological progress. However, if the lag effect of environmental regulation was taken into account in the empirical analysis, the relationship between the two changed from a significant negative correlation to a significant positive correlation.

Green technological progress is the critical element to the sustainable development of mariculture (Sun and Ji 2021) and an important source of productivity growth in mariculture (Hassanpour et al. 2010). Mariculture not only brings expected output—such as economic benefits—but also brings unexpected output—such as environmental pollution. For example, Martinez-Cordero and Leung (2004) showed that wastewater emissions containing nitrogen and phosphorus were unexpected outputs for mariculture in Mexican shrimp farms. Bennett et al. (2001) evaluated the mariculture environment in tropical fisheries and found that mariculture caused severe pollution. They proposed the strengthening of all aspects of national environmental protection supervision policies to achieve the sustainable development of mariculture. Feng et al. (2004) analyzed the existing production mode of mariculture in China. They argued that it was not suitable for the sustainable development of mariculture, and advocated new breeding modes and reduced pollution technologies to maintain the long-term health of the marine environment and achieve sustainable growth in mariculture. Bosch-Belmar et al. (2017) quantitatively analyzed the pollution caused by salmon aquaculture, and showed that the resultant pollution of nearby waters affected the ability of salmon aquaculture to realize long-term development. Nielsen et al. (2014) considered resource and environmental constraints in their study of green technological progress, and proposed that scaling up could help realize green technological progress. With the advancement of the theory of technological progress bias, academics have explored the input bias between different input factors of capital, labor, and mariculture area from the input viewpoint (Sun and Ji 2021), and have analyzed the output bias between output value and pollution emission from the output viewpoint (Ji et al. 2022).

Our study is an extension of the existing research. First, we took the pollutants of mariculture as unexpected output

into the analysis framework of traditional input–output factors such as capital, labor, mariculture area, and output value. Next, we applied the data envelopment analysis model to calculate the green total factor productivity index (GTFP), and we further decomposed it into a green output biased technological progress index (OBTC). Then, on the basis of this index, we constructed a composite index to gauge the output bias between output value and pollution emissions, and empirically studied the effect and influence path of environmental regulation on green output bias. Finally, combined with the empirical analysis results, we took measures to promote the green output bias.

Our study contributes to the literature as follows. First, we built a composite index to measure the green output bias of mariculture, and thus broaden the understanding of green output bias. Most studies have relied on the traditional judgment criteria to determine whether technological progress is biased towards a certain factor, but the degree of green output bias and empirical analysis are also important research considerations. Second, our exploration of the relation between environmental regulation and the green output bias from the viewpoint of green development enriches the literature on green output bias. Third, the intermediary effect model is applied to analyze the indirect transmission mechanism of environmental regulation influencing green output bias through green technology, so as to provide useful policy implications for the green development and long-term development of China's mariculture.

The “**Methods**” section addresses our study's methods including a discussion of the mechanism analysis of environmental regulation affecting green output bias, and the measurement and analysis of green output bias. The “**Analysis of green output bias results**” section presents and discusses our study's results. The “**Discussion of the empirical study of environmental regulation affecting green output bias**” section is a discussion of the empirical study of environmental regulation affecting green output bias. In the “**Conclusion and policy recommendations**” section, we conclude and provide policy recommendations.

## Methods

### Mechanism analysis of environmental regulation affecting green output bias

Environmental regulation is the restraint or motivation of enterprises in the manufacturing process, which influences the R&D behavior of enterprises. In response to environmental regulations, enterprises adopt coping strategies that determine production methods, and the impact on output value and pollutant emissions will change the output bias. The strategy of these enterprises is summed up as the green

output bias in the industry. Considering that environmental regulation can be classified into two categories—command-and-control environmental regulation and market-based incentive environmental regulation, this paper discusses the impact mechanism of these two categories of environmental regulation, and puts forward relevant hypotheses, as shown in Fig. 1.

Command-and-control environmental regulation mainly means that the government restricts the production behavior of enterprises through laws and regulations, and reduces the negative external impact of the economic entity on the environment in production activities. This regulatory means is strongly binding, and enterprises can only passively accept environmental regulation policies. For example, the government will set mandatory market emission access standards; that is, not meeting certain cleaning standards or pollution emission standards are not allowed to enter the market. In order to meet the emission standards, enterprises may purchase pollution treatment equipment in the short term, which will increase the cost of enterprises and adversely affect the expected output of enterprises. In order to pursue long-term interests, enterprises will prevent and control pollution from the source, implement clean technology and other measures to reduce pollution rate, and reduce undesirable output. In the early stage of implementation, enterprises generally face higher pollution control costs. At this time, the *compliance cost* effect occupies a dominant position—which is not conducive to the green output bias. With the continuous advancement of environmental regulation policies, enterprises gradually realize the importance of green production, and conduct innovation activities. When innovation income is greater than the pollution control cost, the *innovation compensation* effect plays a major role—which is conducive to the green output bias. Based on this, this paper proposes the following hypothesis:

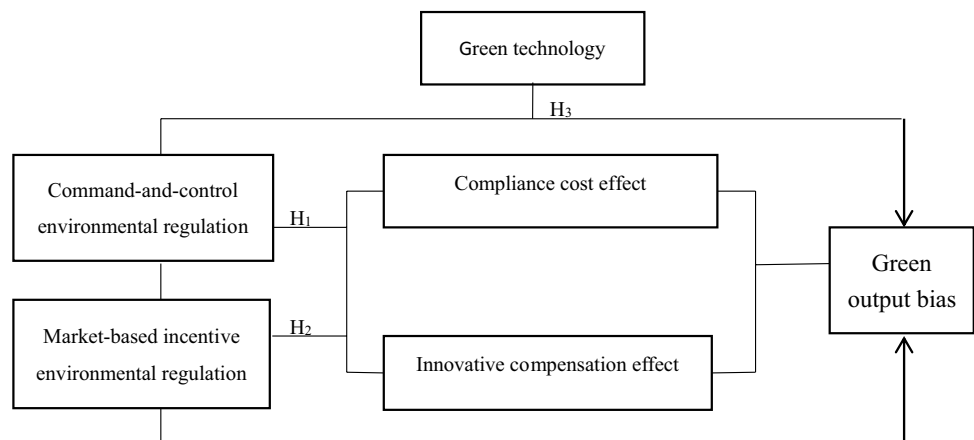
**H1:** Command-and-control environmental regulation has a U-shaped relationship with green output bias.

Market-based incentive environmental regulation is to use the market mechanism to guide and regulate the behavior of economic entities. This means of regulation is based on the “polluter pays” principle, such as environmental taxes, emission trading, and other ways, which is generally not subject to government constraints. In the short term, enterprises generally choose to pay pollution charges, which will squeeze the productive funds of enterprises, increase the cost of enterprises, and is not conducive to green output bias. In the long run, market-based incentive environmental regulation gives enterprises more subjective initiative, which can promote enterprises to carry out green technology innovation, and force polluting enterprises to withdraw from production and eliminate backward production capacity. Enterprises can choose the most suitable green development path according to their own development ability, and make decisions on the optimal production technology level, production factor input, and pollution emission in the production process based on the principle of profit maximization, so as to achieve the optimal value of green production efficiency. In the process of market-based incentive environmental regulation intensity from weak to strong, enterprises tend to divert funds from pollution emissions to technology import, absorption, and innovation. The *innovation compensation* effect caused by environmental regulation is greater than the *compliance cost* effect, and the promotion effect of environmental regulation on green output bias appears. Based on this, this paper proposes the following hypothesis:

**H2:** Market-based incentive environmental regulation has a U-shaped relationship with green output bias.

According to the above mechanism analysis, both categories of environmental regulation will have an impact on green output bias. When governments implement environmental regulation policies, enterprises will conduct technological innovation activities to improve their competitive market advantage. As a key factor in technological

**Fig. 1** Influence mechanism analysis chart



innovation activities, green technology is inevitably affected by environmental regulation. In addition, green technology is also an important indicator driving green output bias. Consequently, environmental regulation not only has a direct impact through the environmental regulation–green output bias, but also has an indirect impact through green technology. The effects of two categories of environmental regulation are discussed separately. Command-and-control environmental regulation mainly depends on the implementation of government enforcement, which has the advantage of quick effect and has a strong effect on green technology. Market-based incentive environmental regulation mainly induces enterprises to develop, use, and promote green technology through market means, which has the characteristics of strong flexibility. With the further improvement of market mechanism, the effect of this regulation on green technology will be more and more significant. When the intensity of the above two categories of environmental regulation is in a moderate range, this will lead enterprises to carry out green technology innovation activities independently, reduce pollutant emissions in the production process, and the benefits of green technology are greater than the cost of pollution control, promoting green output bias. Based on this, this paper proposes the following hypothesis:

**H3:** Green technology plays a role in the path of heterogeneous environmental regulation affecting green output bias.

**Measurement method of green output bias**

The RDM model based on the directional distance function (Portela et al., 2004) is adopted, and the improvement of the invalid unit by the RDM model is closer to the effective frontier. The direction vector of the RDM is the possible improvement range of the decision-making unit, which corrects the unexpected output data and improves the scientificity of the estimation results. Assuming that the input vector and output vector in the production process are  $x = (x_1, x_2, \dots, x_n) \in R_+^N$  and  $y = (y_g, y_b)$ , respectively, where the expected output vector is  $y_g = (y_{g1}, y_{g2}, \dots, y_{gm}) \in R_+^N$ , the unexpected output vector is  $y_b = (y_{b1}, y_{b2}, \dots, y_{bl}) \in R_+^N$ , and the corresponding output set is  $P(x) = \{(y_g, y_b) : x \text{ can produce } (y_g, y_b)\}$ . Define the direction vector as  $g = (g_x, g_y) = (R_x, R_{y_g}, -R_{y_b})$ , where  $R_x = x_n - \min\{x\}$ ,  $R_{y_g} = \max\{y_g\} - y_{gm}$ , and  $R_{y_b} = y_b - \min\{y_b\}$ . RDM directional distance function can be defined as  $\bar{D}_0(x, y_g, y_b; g) = \sup\{\beta : x_n - \beta R_x, y_g + \beta R_{y_g}, y_b - \beta R_{y_b}\}$ . The RDM output distance function is  $\bar{D}_0(x, y_g, y_b; g) = \sup\{\beta : y_g + \beta R_{y_g} \in P(x), y_b - \beta R_{y_b} \in P(x)\}$ .

The Malmquist total factor productivity index (TFP) is used to measure the radial distance between the

combination of input–output factors and the production front. We referred to Färe et al. (1997) to decompose the Malmquist TFP index, and to further decompose the technological progress index to obtain the output biased technological progress index (*OBTECH*), the input biased technological progress index (*IBTECH*), and the technological change scale index (*MATECH*). The specific formula is

$$OBTECH = \sqrt{\frac{(1 + \bar{D}_0^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1} - b^{t+1})) (1 + \bar{D}_0^{t+1}(x^{t+1}, y^t, b^t; y^t - b^t))}{(1 + \bar{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1} - b^{t+1})) (1 + \bar{D}_0^t(x^{t+1}, y^t, b^t; y^t - b^t))}} \tag{1}$$

$$IBTECH = \sqrt{\frac{(1 + \bar{D}_0^{t+1}(x^t, y^t, b^t; y^t - b^t)) (1 + \bar{D}_0^t(x^{t+1}, y^t, b^t; y^t - b^t))}{(1 + \bar{D}_0^t(x^t, y^t, b^t; y^t - b^t)) (1 + \bar{D}_0^{t+1}(x^{t+1}, y^t, b^t; y^t - b^t))}} \tag{2}$$

$$MATECH = \sqrt{\frac{(1 + \bar{D}_0^t(x^t, y^t, b^t; y^t - b^t))}{(1 + \bar{D}_0^{t+1}(x^t, y^t, b^t; y^t - b^t))}} \tag{3}$$

Our study explored the green output bias, so it mainly involved the calculation of the *OBTECH*, but this index mainly measures the promoting or inhibiting of *OBTECH* on TFP, and cannot give the output bias between different factors. Based on Weber and Domazlicky (1999) and Yang et al. (2019), our study constructed a green output bias index to measure the output bias between increasing output value and increasing pollutant emissions:

$$BIAS = (1 - OBTECH) \left( \frac{y_1^{t+1}/y_1^t}{y_2^{t+1}/y_2^t} - 1 \right) \tag{4}$$

where  $y_1$  and  $y_2$  represent the expected output and unexpected output, respectively. Specifically,  $y_1$  refers to the total output of mariculture and  $y_2$  refers to the pollutants from mariculture.  $\frac{y_1^{t+1}/y_1^t}{y_2^{t+1}/y_2^t}$  is the change rate of marginal substitution rate of output factors. If *BIAS* > 0, technological progress is inclined to produce  $y_1$ ; if *BIAS* < 0, technological progress is inclined to produce  $y_2$ ; and if *BIAS* = 0, there is no technological progress bias. Table 1 shows the corresponding rules, which are not included in the table when there is no technological progress bias.

**Variable selection**

**Output variables**

The total output value of the mariculture was selected as the expected output in accordance with existing studies. To avoid the influence of price factors, the values of the variable were processed in this study with 2008 as the baseline

**Table 1** Corresponding rules between the green output bias and the output biased technological progress index

BIAS	OBTECH	$\frac{y_1^{t+1}}{y_2^{t+1}} / \frac{y_1^t}{y_2^t}$	Criteria
> 0	> 1	< 1	$y_1$ -producing
	< 1	> 1	
< 0	> 1	> 1	$y_2$ -producing
	< 1	< 1	

period. The data of this variable were obtained from the China Fishery Statistical Yearbook.

In terms of unexpected output variable, the main pollutants in mariculture are total nitrogen, total phosphorus, and chemical oxygen demand. The current China Fishery Statistical Yearbook did not involve the production of these pollutants. Therefore, this study drew on Chen et al. (2016), and the specific calculation formula follows:

$$E_{u,n} = \sum_{i,j} Y_{i,n} w_{i,j,n} e_{u,i,j,n} \tag{5}$$

$$w_{i,j,n} = w_{j,n} r_{i,j} / \sum_j w_{j,n} r_{i,j} \tag{6}$$

$$E_n = \sum_u E_{u,n} / K_u \tag{7}$$

where  $E_{u,n}$  means the sum of pollutants  $u$  ( $u = N, P, COD$ ) produced by  $n$  coastal areas engaged in mariculture;  $Y_{i,n}$  means the yield of seafood  $i$  in  $n$  coastal areas;  $w_{i,j,n}$  means the share of yield derived using culture method  $j$  in the production of seafood  $i$  in  $n$  coastal areas;  $e_{u,i,j,n}$  means the pollution generation coefficient of pollutant  $u$  produced by seafood  $i$  cultured by method  $j$  in  $n$  coastal areas;  $w_{j,n}$  means the share of total production by various culture methods in  $n$  coastal areas; set  $r_{i,j}$  as a virtual variable, when the seafood  $i$  can be bred in the way  $j$ , take 1, otherwise take 0;  $E_n$  represents the total equivalent pollution of mariculture in  $n$  coastal areas; and  $K_u$  is the standard pollution concentration of type III water quality in GB3838-2002 (nitrogen is 1 mg/L, phosphorus is 0.2 mg/L, and COD is 20 mg/L). Fish (10 species), crustaceans (6 species), and other species (4 species) are selected as the breeding species. Pond breeding, factory breeding, net box breeding, raft breeding, and beach breeding were selected as the breeding methods. The relevant data on the production and discharge coefficient of pollution sources in the aquaculture industry were from the First National Census on Pollution Sources and the China Fishery Statistical Yearbook. The pollution coefficient in the census was derived from the methods of material balance and direct water quality monitoring. However, according to Zong et al. (2017), it is not appropriate to calculate

the pollution generation coefficient of acquired creatures as representative of filter-feeding shellfish by this approach. Therefore, this study does not calculate the aquaculture pollutants of shellfish.

**Input variables**

**Mariculture area input** The development of mariculture depends heavily on the mariculture area (e.g., locations suitable for species and culture systems), and limited mariculture area resources play a vital part in the growth of mariculture. Therefore, it was necessary to incorporate the mariculture area elements into the input–output analysis framework. We selected the area of mariculture to measure the input of marine resources. The data of this variable were acquired from the China Fishery Statistical Yearbook.

**Labor input** The amount of professional employees in the marine fishery aquaculture was chosen as labor input, the variable is the number of workers directly engaged in mariculture production activities, and has an important impact on mariculture production activities. The data of this variable were acquired from the China Fishery Statistical Yearbook.

**Capital input** Scholars typically choose capital stock index to measure capital investment, but we found no clear statistics about the capital stock of mariculture. Therefore, this study referred to the research of Wang et al. (2007) to estimate the capital stock data of mariculture. First, the perpetual inventory approach was applied to the estimation of agricultural capital stock in 2008–2019, as shown in formula (8). Second, the capital stock of mariculture was estimated by assuming that mariculture has the same capital–output ratio as agriculture, as shown in formula (9).

$$K_{At} = I_{At} + (1 - \delta)K_{At-1} \tag{8}$$

$$K_t = \frac{Y_t}{Y_{At}} K_{At} \tag{9}$$

In the formula,  $K_{At}$  and  $K_{At-1}$  mean the capital stock of the current period and the previous period, respectively;  $\delta$  means a depreciation rate of 4.24%;  $I_{At}$  means the current increase in agricultural fixed assets;  $Y_{At}$  means the agricultural added value;  $Y_t$  means the value added of mariculture; and  $K_t$  means the capital stock to be estimated.

In this study, we selected the relevant 2008–2019 data of 10 coastal areas in the South China Sea area (Guangdong, Guangxi, and Hainan provinces), East China Sea area (Jiangsu, Zhejiang, and Fujian provinces), and the Bohai Sea area (Tianjin, Hebei, Liaoning, and Shandong provinces).

For data integrity, we did not consider Shanghai, as significant data were missing. The descriptive statistical analysis of variables is shown in Table 2.

## Analysis of green output bias results

In our study, the green output bias index of mariculture in coastal areas was measured according to the previous measurement method. Limited by the length of this article, we mapped the green output bias index for 2009–2019 by grouping coastal areas into three major areas, as shown in Fig. 2, which replaces the calculation results. The starting year of this study is 2008, and the 2008–2009 green out bias is the value of 2009, which is similar to that in other years.

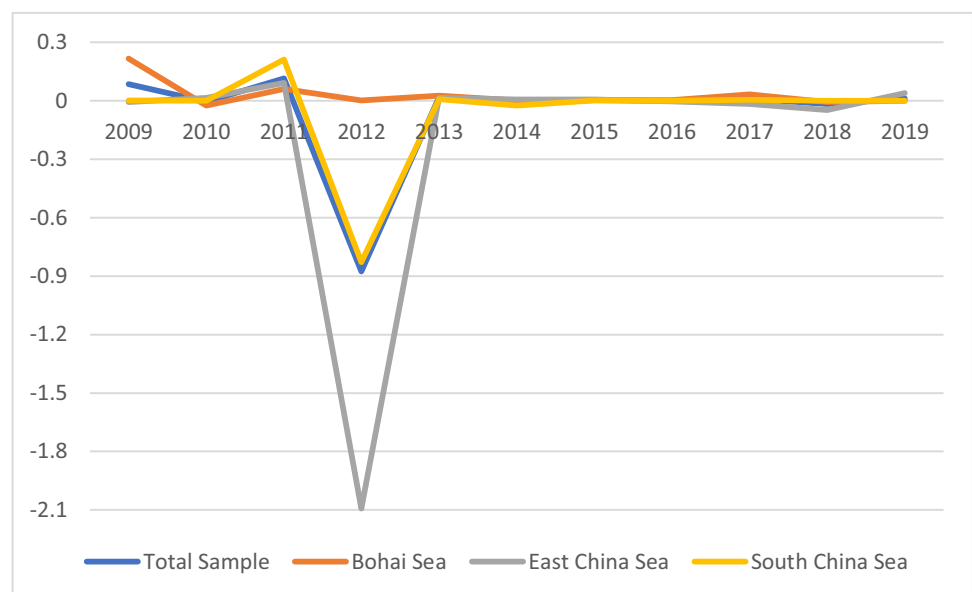
From the perspective of time dimension, except for the cliff-like decline in 2012, the fluctuation of green output bias index in other years is relatively small and the overall is relatively stable. In the early stage of the study (2009–2011), the green output bias shows a slight upward trend, which indicates that the green output bias of mariculture is resisted by the original extensive production mode, but the green

development policy of mariculture makes technological progress biased towards green output. However, in 2012, the green output bias index became negative and reached the lowest point, mainly due to the serious fishery disaster in that year, which had a negative impact on the green development of mariculture. According to the “2012 Statistical Bulletin of the National Fisheries Economy,” due to fishery disasters throughout the year, the affected aquaculture area was 1087.78 thousand hectares, the loss of aquatic products was 1.3854 million tons, 874 ships were sunk, and the direct economic loss was 23.739 billion yuan. Since then, under the guidance of policy documents such as the “Twelfth Five-Year Plan for National Fisheries Development” and “Several Opinions on Promoting the Sustainable and Healthy Development of Marine Fisheries,” the green development of mariculture has achieved remarkable results. The national favorable policies have formed a good orientation for the growth of green total factor productivity, and the degree of green output bias has increased significantly in 2013. In the later period of the study (2014–2019), the green output bias showed a fluctuating upward trend. In 2016, China’s fisheries first proposed “ecological priority and green development.” In 2019, the “Opinions on Accelerating the Green

**Table 2** Description statistics of input–output variables

Variables	Symbol	Unit	Mean	Standard deviation	Minimum	Median	Maximum
Total output value of mariculture	<i>Y</i>	Ten thousand yuan	1.400e+06	1.200e+06	15,648	910,000	4.700e+06
Equal standard pollutants	<i>P</i>	Tons	4878	6814	37.89	2073	34,388
Mariculture capital	<i>K</i>	Ten thousand yuan	2.400e+06	3.000e+06	53,221	1.300e+06	1.200e+07
Mariculture employees	<i>L</i>	Millions	88,598	66,447	621	61,106	230,000
Mariculture area	<i>S</i>	Hectare	210,000	240,000	813	130,000	940,000

**Fig. 2** Green output bias index trend for mariculture by region 2009–2019



Development of Aquaculture Industry” pointed out that it is necessary to “integrate the concept of green development into the whole process of aquaculture production and implement an ecologically healthy aquaculture system.” These policy guidelines have effectively promoted the green development of mariculture industry.

From the regional dimension, the trend of green output bias in the three regions of Bohai Sea, East China Sea, and South China Sea is consistent, and the degree of green output bias from high to low is Bohai Sea > South China Sea > East China Sea. According to the development of China’s mariculture industry, Tianjin, Hebei, and Liaoning, located in the Bohai Sea region, are the key areas of China’s mariculture industrialization, and have developed into large-scale and standardized industrial clusters. The data obtained from the China Fishery Statistics Yearbook shows that the proportion of industrialized mariculture production in the Bohai Sea region was the highest from 2009 to 2019, with an average value of 0.0695, while the average value of the East China Sea and the South China Sea was only 0.0066. Sustainable industrialized mariculture methods have promoted the green output bias in the Bohai Sea region. The trend chart of the South China Sea region is consistent with the full sample trend chart, indicating that the South China Sea region has a more obvious influence on the development of the whole coastal area. The South China Sea region is vast and rich in resources, and the green development of mariculture has great potential. The East China Sea region may have certain difficulties in the application of green technology, which limits the green output bias. From the low degree of green output bias, it can be inferred that the coastal areas mostly adopt the traditional methods of mariculture development, sacrificing the marine environment to development. In the future, these coastal areas should be transformed into a green mariculture mode, taking into account the economy and ecology in the process of mariculture development.

## Discussion of the empirical study of environmental regulation affecting green output bias

### Variable selection

To our knowledge, the influencing factors of green output bias in mariculture have not yet been studied. Referring to Li et al. (2019), factors influencing green output bias in mariculture are identified by analyzing the factors influencing the OBTC index. The technological progress accounting system contains production factor inputs, desired outputs, and non-desired outputs. The green output bias is mainly to distinguish the output bias between desired outputs and non-desired outputs, so the factors

affecting the output value and pollution of mariculture industry can influence the technological progress bias. The explanatory variable in this study is environmental regulation. The means of environmental regulation are diverse. As far as the mariculture industry is concerned, it mainly includes two categories of environmental regulation. Command-and-control environmental regulation is usually measured by environmental pollution control investment per unit of output value, and is represented by the abbreviation *CER*. Market-based incentive environmental regulation is measured by the sea area usage fee per unit of authorized sea area, and is represented by the abbreviation *MER*. This study considered the influence of these two categories of environmental regulation on the green output bias.

Combined with the actual conditions, we selected several control variables. The first variable is the resource endowment of mariculture, which measures the structure and scale of mariculture. The resource endowment will affect the production efficiency of mariculture, and make the output value different from the increase of pollutants, which affects the green output bias. The second variable, in terms of human capital and technology promotion, are the educational level of promotion personnel, promotion facilities, and fishermen training intensity. Human capital and technology promotion will affect the green production concept and practical ability of relevant practitioners, and then affect the green output bias. The third variable is the level of economic development, and the selected index is the level of fishery economic development. The external environmental conditions of mariculture development will affect the green output bias. The specific explanations of each variable are shown in Table 3.

## Model construction

### Basic regression models

When setting the econometric model, we utilized Ramsey’s regression equation specification error test (RESET) to determine whether there is a quadratic term in the explanatory variables. The results showed that there is a quadratic term of environmental regulation. Considering that the simultaneous introduction of two categories of environmental regulation may have multiple collinearity problems, we made regressions on the two categories of environmental regulation, and constructed the basic econometric model as follows:

$$BIAS = \alpha_0 + \alpha_1 ER + \alpha_2 ER^2 + \alpha_3 STR + \alpha_4 SCA + \alpha_5 EDU + \alpha_6 FAC + \alpha_7 TRA + \alpha_8 ECO + \varepsilon_{it} \quad (10)$$



**Table 3** Variable definition table

Variables	Symbol	Method of calculation
Green output bias	<i>BIAS</i>	Obtained through the calculation above
Command-and-control environmental regulation	<i>CER</i>	Environmental pollution control investment per unit of output value
Market-based incentive environmental regulation	<i>MER</i>	Sea area use fee per unit of authorized sea area
Mariculture structure	<i>STR</i>	Fish yield/total yield of mariculture
Mariculture scale	<i>SCA</i>	Mariculture area/total fishery aquaculture area
Educational level of extension personnel	<i>EDU</i>	Proportion of promoters with college degree or above
Promotion facility factors	<i>FAC</i>	Number of extension institutions/mariculture area
Training intensity of fishermen	<i>TRA</i>	Number of fishermen trained/number of fishery practitioners
Fishery economy development	<i>ECO</i>	Total output value of fishery economy/number of fishery employees

Among them, *BIAS* represents the green output bias; *ER* represents the two categories of environmental regulation, including *CER* and *MER*; and *STR*, *SCA*, *EDU*, *FAC*, *TRA*, and *ECO* as control variables represent the mariculture structure, mariculture scale, educational level of extension personnel, promotion facility factors, training intensity of fishermen, and fishery economy development, respectively. The explanation of each variable is as described above, and  $\varepsilon_{it}$  is the residual term.

### Intermediary effect model

In this study, we constructed an intermediary effect model to test. First, the effect of environmental regulation on the green output bias was examined. If  $\alpha_1$  and  $\alpha_2$  are significant in formula (11), it indicates that the total effect is established. Next we tested the effect of environmental regulation on green technology. If  $\gamma_1$  and  $\gamma_2$  in formula (12) are significant, it shows that environmental regulation has a significantly greater effect on green technology. Finally, green technology was introduced into the basic regression model to obtain formula (13). If  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  are significant, it indicates that green technology plays a partial intermediary role. If  $\beta_3$  is significant, but  $\beta_1$  and  $\beta_2$  are not significant, green technology plays a complete intermediary role.

$$BIAS = \alpha_0 + \alpha_1 ER + \alpha_2 ER^2 + \alpha_3 STR + \alpha_4 SCA + \alpha_5 EDU + \alpha_6 FAC + \alpha_7 TRA + \alpha_8 ECO + \varepsilon_{it} \quad (11)$$

$$TEC = \gamma_0 + \gamma_1 ER + \gamma_2 ER^2 + \gamma_3 STR + \gamma_4 SCA + \gamma_5 EDU + \gamma_6 FAC + \gamma_7 TRA + \gamma_8 ECO + \varepsilon_{it} \quad (12)$$

$$BIAS = \beta_0 + \beta_1 ER + \beta_2 ER^2 + \beta_3 TEC + \beta_4 STR + \beta_5 SCA + \beta_6 EDU + \beta_7 FAC + \beta_8 TRA + \beta_9 ECO + \varepsilon_{it} \quad (13)$$

In the formula, *ER* represents the two categories of environmental regulation—*CER* and *MER*—and the meaning of other variables is the same as that of the basic regression model; *TEC* represents the green technology; and the selection of green technology indicators is described in the “Impact mechanism analysis” section.

### Basic regression analysis

Considering that there are differences and mutual influence in the development of mariculture among regions, the model was tested, and the findings indicated the existence of between-group heteroskedasticity and within-group autocorrelation. Therefore, the generalized least squares (GLS) method was selected for analysis in this study. The monomial and quadratic terms of the two categories of environmental regulation were regressed in turn, and basic regression results are shown in Table 4.

The regression findings indicated that the monomial coefficient of the two categories of environmental regulation is negative, and the quadratic coefficient is positive, and it is significant at the level of 1%. This indicates that the impact of *CER* and *MER* on green output bias is consistent, and presents a *U*-shaped relationship. Thus, environmental regulation first inhibits green output bias and then promotes it. This verifies hypothesis 1 and hypothesis 2. This result is in accordance with the Porter hypothesis. When environmental regulation is at an appropriate degree, environmental regulation can contribute to green output bias and show innovative compensation effect. When the strength of environmental regulation grows to cross the inflection point of the *U* curve, environmental regulation can motivate companies to engage in environmental protection R&D activities, increase output

**Table 4** Basic regression results

Variables	(1)	(2)	(3)	(4)
<i>CER</i>	−7.6093*** (−24.46)	−30.0520*** (−22.66)		
<i>CER</i> <sup>2</sup>		696.9577*** (23.75)		
<i>MER</i>			−0.0260*** (−11.33)	−0.0784*** (−15.16)
<i>MER</i> <sup>2</sup>				0.0048*** (8.65)
<i>STR</i>	1.1254*** (14.00)	1.2332*** (26.13)	1.3523*** (15.57)	1.4046*** (17.91)
<i>SCA</i>	1.0076*** (19.37)	1.0780*** (29.12)	0.8203*** (23.99)	0.7117*** (19.13)
<i>EDU</i>	0.0012 (0.12)	−0.0333** (−2.15)	0.0262** (2.04)	0.0336*** (3.89)
<i>FAC</i>	9.1979*** (10.24)	9.6824*** (15.63)	9.4862*** (7.12)	7.3439*** (5.71)
<i>TRA</i>	1.4646*** (20.09)	1.6365*** (21.05)	1.1513*** (15.48)	0.9911*** (16.58)
<i>ECO</i>	−0.0183*** (−20.80)	−0.0206*** (−21.47)	−0.0124*** (−19.27)	−0.0111*** (−17.63)
Constant	−0.5215*** (−15.57)	−0.4069*** (−19.29)	−0.5532*** (−17.54)	−0.4549*** (−13.93)

\*\*\*, \*\*, and \* indicate that the results are significant at the confidence levels of 1%, 5%, and 10%, respectively, and the Z value of the variable estimation coefficient is in parentheses

value, reduce pollutant emissions, and promote green output bias.

However, the specific effects of *CER* and *MER* on green output bias are different, mainly in the following aspects. On the one hand, the quadratic coefficient of *CER* is much larger than that of *MER*, indicating that the *U*-shaped curve of *CER* on green output bias is steeper. *CER* relies on government enforcement and has strong binding force. Compared with *MER*, it can play a greater instrumental role. Therefore, the green output bias shows a high sensitivity to the *CER*. On the other hand, the *U*-shaped curve inflection point of the two categories of environmental regulations on the green output bias is different. Through calculation, it can be obtained that the *U*-shaped curve inflection point of *CER* is 0.02, and the average level of this category of environmental regulation is 0.01, which is located on the left side of the *U*-shaped curve, indicating that the current level of environmental regulation has an inhibitory effect on the green output bias. The level of investment in environmental pollution control is low, which is not enough for enterprises to choose green production. We should further strengthen the intensity of environmental regulation, reduce the pressure of green R&D, and achieve green output bias. The inflection point of the *U*-shaped curve of *MER* is 8.17, and the average level of this category of environmental regulation is 1.82, which is on the left side of the *U*-shaped curve, indicating that the lower sea use fee makes the cost of enterprises lower and lacks the motivation for technological innovation. When the levy intensity of sea area use fee is increasing, crossing the inflection point of the *U*-shaped curve will stimulate enterprises to increase green R&D investment, introduce green technologies and processes, and achieve green output bias. In comparison, the average level of *CER* is closer to the inflection point of the *U*-shaped curve, and it is easier to cross the inflection point and play a positive policy effect.

In terms of control variables, mariculture structure (*STR*) is significantly and positively associated with the green output bias—that is, when the proportion of fish production increases, the degree of green output bias will increase. Under the condition of not exceeding the ecological carrying capacity of the mariculture area, a scientific and reasonable mariculture structure and a reasonable distribution of the proportion between fish and other species will help improve the green output bias. The coefficient of educational level of extension personnel (*EDU*) is significantly negative in column (2), while it is significantly positive in columns (3) and (4). The greater the educational level of extension personnel, the better their concept of green production, and the higher their ability to accept and apply green technology and promote technological progress in favor of increasing green output. The coefficient of extension facility factors (*FAC*) is significantly positive. It shows that the more technology promotion agencies per unit of mariculture area, it can help fishermen timely understand and obtain green aquaculture technologies and methods, and has a favorable influence on green output bias. The coefficient of fishermen's training intensity (*TRA*) is significantly positive. When the fishermen's training intensity increases, the application and promotion of green technology in mariculture will be more perfect, and the degree of green output bias will increase. The coefficient of fishery economic development level (*ECO*) is significantly negative, suggesting that when the economy develops at a higher level, the green output bias decreases.

### Regional heterogeneity test

In this study, the coastal areas were divided into three areas: the Bohai Sea, the East China Sea, and the South China Sea. The effects of *CER* and *MER* on the green output bias

**Table 5** Regional heterogeneity test results

Variables	Bohai Sea		East China Sea		South China Sea	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>CER</i>	−2.9649 (−1.13)		7.1813 (0.27)		−36.1449*** (−2.88)	
<i>CER</i> <sup>2</sup>	99.9883 (1.60)				901.9974** (2.34)	
<i>MER</i>		−0.0175* (−1.84)		−0.1250 (−0.88)		−0.0304 (−0.93)
<i>MER</i> <sup>2</sup>		0.0008 (1.20)				0.0034 (0.77)
<i>STR</i>	−0.1246 (−0.33)	0.4454 (1.00)	4.8541 (0.82)	3.5823 (0.47)	0.5405 (1.63)	−0.1006 (−0.23)
<i>SCA</i>	0.0263 (0.22)	0.1017 (0.76)	0.6273 (0.75)	0.7438 (0.72)	0.3539 (1.17)	0.0748 (0.15)
<i>EDU</i>	0.0149 (0.33)	−0.0002 (−0.01)	−0.0399 (−0.08)	−0.0582 (−0.08)	−0.0077 (−0.04)	−0.0566 (−0.17)
<i>FAC</i>	0.1571 (0.05)	−3.0692 (−0.92)	73.0351 (0.32)	59.1538 (0.20)	6.9349 (0.53)	−10.3985 (−0.65)
<i>TRA</i>	0.4310* (1.71)	0.6496** (2.51)	0.6239 (0.46)	0.4005 (0.24)	0.3170 (0.70)	0.0603 (0.08)
<i>ECO</i>	0.0040 (1.55)	0.0032 (1.48)	−0.0139 (−0.72)	−0.0157 (−0.65)	−0.0205 (−1.44)	0.0010 (0.06)
Constant	−0.0732 (−0.69)	−0.1445 (−1.21)	−1.0231 (−0.51)	−0.6944 (−0.25)	0.1360 (0.71)	0.0813 (0.27)

\*\*\*, \*\*, \* indicate that the results are significant at the confidence levels of 1%, 5%, and 10%, respectively

were studied, and the regional heterogeneity was tested. The regression findings are presented in Table 5. It can be found that there are great differences in the regression results of the three regions.

In Bohai Sea region, the regression result of *CER* to green output bias is not significant. The possible reason is that *CER* is mandatory, and the high implementation cost (Xie et al., 2017) cannot provide long-term dynamic supervision, resulting in the effect of command-and-control environmental regulation that is not significant. The monomial coefficient of *MER* is significantly negative, indicating that the effect of this category of environmental regulation on green output bias is negative. The possible reason is that *MER* is a criterion formulated on the whole, ignoring the individual differences of economic entities and the differences in ownership of economic entities, which will affect the effect (Ma and Li 2021). This leads to the production units with higher marginal cost of environmental pollution reduction bear a greater economic burden, and the production units with lower marginal cost of environmental pollution reduction do not get the greatest incentive effect to reduce pollution emissions. This is not conducive to the overall increase in green output bias. In the East China Sea region, the regression results show that the coefficients of two categories of environmental regulation are not significant. This result is similar to that of Becker (2011) and Liu and Chen (2022). Environmental regulation affects the action remuneration of economic entities by setting market access, technology, and environmental standards, which easily leads to rent-seeking phenomena. Moreover, the current market mechanism is not perfect, and environmental regulation policies have not played their due role. In the South China Sea region, the effect of *CER* on green output bias shows a significant *U*-shaped relationship. The monomial coefficient is significantly negative, and the quadratic coefficient is significantly

positive, which is consistent with Li et al. (2022) and Ma et al. (2022). The results are also consistent with the total sample regression results. The effect of *MER* on green output bias is not significant. The possible reason is that the collection mechanism of sea area use fee is not perfect (Sun and Ji 2021), which leads to the lack of policy role of environmental regulation.

### Impact mechanism analysis

As analyzed, the effect of environmental regulation on the green output bias presents a *U*-shaped relationship. To test this mechanism, we selected green technology (*TEC*) as the intermediary variable of environmental regulation on the green output bias (Table 6). The specific measurement method is to measure the ratio of industrialized mariculture output to mariculture output. We selected this intermediary variable considering that the development and application of green technology plays a significant function in the mechanism of environmental regulation affecting green output bias, and industrialized mariculture is currently recognized as a green mariculture method, which has the advantages of saving resources and protecting the environment, and represents the future direction of mariculture in the future. Aguilar-Manjarrez et al. (2013) analyzed mariculture activities and proposed that industrialized mariculture is a green development trend. The data of green technology variable comes from China Fishery Statistical Yearbook.

The results in columns (1)–(3) in the table are the regression results of *CER*, green technology, and green output bias. The results in column (1) are the same as the basic regression results, so no longer repeat here. Column (2) in the table shows the regression findings of *CER* on green technology. There is an obvious inverted *U*-shaped relationship between them, which shows a tendency to increase and then decrease.

**Table 6** Test results of intermediary effect of green technology

Variables	(1)	(2)	(3)	(4)	(5)	(6)
<i>CER</i>	−30.0520*** (−22.66)	1.7793*** (6.14)	−31.8362*** (−23.64)			
<i>CER</i> <sup>2</sup>	696.9577*** (23.75)	−20.1935** (−2.34)	712.6587*** (23.56)			
<i>MER</i>				−0.0784*** (−15.16)	0.0024*** (3.10)	−0.0915*** (−45.05)
<i>MER</i> <sup>2</sup>				0.0048*** (8.65)	0.0002* (1.88)	0.0052*** (21.23)
<i>TEC</i>			0.7338*** (7.45)			0.8595*** (6.68)
<i>STR</i>	1.2332*** (26.13)	0.2259*** (17.37)	1.0421*** (24.53)	1.4046*** (17.91)	0.1650*** (10.97)	1.2929*** (40.55)
<i>SCA</i>	1.0780*** (29.12)	0.0648*** (7.76)	1.0074*** (34.32)	0.7117*** (19.13)	0.0842*** (9.22)	0.6241*** (31.72)
<i>EDU</i>	−0.0333** (−2.15)	0.0908*** (12.48)	−0.1161*** (−8.64)	0.0336*** (3.89)	0.0716*** (11.55)	−0.0573*** (−18.48)
<i>FAC</i>	9.6824*** (15.63)	5.3534*** (15.12)	4.7753*** (10.44)	7.3439*** (5.71)	5.0296*** (13.70)	2.1563** (2.08)
<i>TRA</i>	1.6365*** (21.05)	0.1797*** (6.94)	1.4095*** (22.09)	0.9911*** (16.58)	0.1984*** (8.78)	0.8071*** (17.95)
<i>ECO</i>	−0.0206*** (−21.47)	0.0026*** (6.86)	−0.0236*** (−26.42)	−0.0111*** (−17.63)	0.0018*** (9.25)	−0.0141*** (−51.17)
Constant	−0.4069*** (−19.29)	−0.1512*** (−11.40)	−0.2442*** (−12.60)	−0.4549*** (−13.93)	−0.1278*** (−10.11)	−0.2999*** (−21.55)

\*\*\*, \*\*, \* indicate that the results are significant at the confidence levels of 1%, 5%, and 10%, respectively

Before the intensity of *CER* is at the inflection point of the inverted *U* curve, *CER* promotes green technology. Under the incentive of environmental regulation, enterprises will conduct green R&D and other behaviors, and develop and apply green technology of mariculture. Column (3) is the regression findings of *CER* and green technology on green output bias. *CER* presents a *U*-shaped relationship on green output bias, and green technology promotes green output bias. The coefficients of all variables are significant; that is, they verify the intermediary effect of green technology. *CER* acts on the green output bias by influencing green technology. The results in columns (4)–(6) in the table are the regression findings of *MER*, green technology, and green output bias, which are basically similar to the results in columns (1)–(3). *MER* and green output bias are in a *U*-shaped relationship, *MER* and green technology are in a *U*-shaped relationship, and green technology promotes green output bias. The coefficients of all variables are significant, green technology plays an intermediary role, and *MER* affects the green output bias by affecting green technology. The above regression results verify hypothesis 3.

### Conclusion and policy recommendations

Under the background of increasingly serious environmental problems of mariculture, this paper incorporates undesired output and traditional input–output indicators into the analysis framework, and uses the DEA model based on the RDM directional distance function to measure the green total

factor productivity index. The green technological progress index is decomposed from the index, and then the green output biased technological progress index is decomposed. The green output biased technological progress index is combined with the inter-temporal changes of the output factor combination to construct a comprehensive index to measure the green output bias. The results show that the green output bias shows a fluctuating upward trend during the study period, and the level of green output bias needs to be further improved. There are regional differences in green output bias, and the level of green output bias in the three regions from high to low is Bohai Sea > South China Sea > East China Sea. Considering the heterogeneity of environmental regulation, this paper empirically tests the relationship between two categories of environmental regulation—*CER* and *MER*—and green output bias, and both show a *U*-shaped relationship. At present, the average level of the two categories of environmental regulation is located on the left side of the inflection point of the *U*-shaped curve, and the green output bias is more sensitive to *CER*. Considering the regional heterogeneity, the coastal areas are divided into the Bohai Sea, the East China Sea, and the South China Sea, and the regression results of the three regions are different. From the intermediary effect test, it can be concluded that green technology partially intermediates the mechanisms by which these two categories of environmental regulation influence green output bias—that is, these categories of environmental regulation affect green output bias by affecting green technology. According to our study’s results, we propose the following policy recommendations.

- Policymakers should enhance environmental regulation policies and reinforce two categories of environmental regulation—*CER* and *MER*, so that the intensity of environmental regulation is on the right side of the *U* curve. The implementation of environmental regulation policies should be in accordance with the principle of adapting to local circumstances. For mariculture areas with severe damage, stringent environmental regulation policies should be implemented to strictly control the number of unexpected outputs. For mariculture areas with less damage, long-term planning should be conducted with the goal of win–win for both the economy and the environment.
- Policymakers and other stakeholders—including industry representatives, farmers, organizations, nonprofits, and researchers—should strengthen green technology innovation and promote the function of green technology in the production of mariculture. The government, in particular, should establish special scientific research funding to encourage technology R&D and innovation; increase financial support for the building of technology promotion facilities; improve the coverage of technological extension institutions in mariculture; increase the training funds for extension personnel; and actively promote green mariculture methods, such as industrialized mariculture.
- Policymakers and other stakeholders should scientifically plan the varieties of mariculture species and the scale of mariculture to achieve both sustainable food production and the economic development of local communities. They should comprehensively consider the differences of pollution levels of different mariculture organisms, optimize the cultivated modes and varieties of mariculture, and strictly control the pollutant emissions of the mariculture industry. The density and feeding quantity of mariculture should be scientifically planned, with consideration to both economy and ecology, by taking multiple measures simultaneously to promote the green output bias of mariculture.

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