THE IMPACT OF CLIMATE RISK ON THE OPERATIONAL EFFICIENCY OF FISHERY ENTERPRISES: EVIDENCE FROM CHINA

SUN, L. L. – LIU, H. Y. – QU, S. L.*

Qingdao University of Science and Technology, Qingdao 266061, China

**Corresponding author*
e-mail: jgxyqsl@126.com

(Received 15th Oct 2025; accepted 6th Jan 2026)

Abstract. The marine environment is facing numerous challenges, and consequently the development of fishery enterprises is subject to significant risks. To analyze how climate risks affect the operational performance of fisheries companies, this research uses seven listed Chinese fishery enterprises as empirical subjects, collects relevant data from 2012 to 2023, and employs data envelopment analysis (DEA) model and Malmquist index to perform both static and dynamic evaluations of operational efficiency of these seven fishery enterprises, deriving operational efficiency indices. Additionally, a Tobit regression model was employed to regress climate risks against operational performance. Results indicate that climate risks significantly reduce the operational efficiency of fisheries enterprises, with transformation risks serving as the primary reason. Moderating effect analysis reveals that companies actively advancing digital transformation or improving ESG performance can effectively mitigate this negative impact. Further economic consequence analysis shows that climate risks indirectly elevate carbon dioxide emissions in the cities where these enterprises operate by suppressing corporate efficiency, triggering cascading effects on ecosystems. This study deepens understanding of the micro-level transmission mechanisms of climate risks and their macro-level ecological effects, providing strategic references for global fisheries enterprises to address climate risks and balance operations with ecological conservation amid unstable marine environments.
Keywords: *ESG, digital transformation, DEA-Malmquist-Tobit model*

Introduction

The global fishing industry is facing systemic challenges due to climate change. As reported by the Food and Agriculture Organization of the United Nations (FAO, 2024) in "The State of World Fisheries and Aquaculture," more than 3.2 billion people worldwide obtain at least 20% of their animal protein from fish on a daily basis. However, climate change has already put global marine ecosystems at risk of declining productivity, due to extreme events, frequent disasters, and fluctuations in biological resources. Additionally, the El Niño phenomenon has caused abnormal sea temperatures, and these physical risks directly impact the distribution and abundance of fishery resources. Moreover, at the transformative level, climate-related disasters disrupt processing and transportation, leading to supply chain interruptions. Meanwhile, the United Nations Framework Convention on Climate Change requires fisheries to reduce carbon emissions and promote low-carbon technology transitions, but small-scale fisheries lack financial support and face significant policy and market pressures. In this context, exploring how fishery enterprises can address climate risks to maintain operational efficiency has become a critical concern for worldwide sustainable development efforts.

China leads the world in fishery supply, generating 28% of the global volume and being the largest exporter (FAO, 2022), with the livelihoods of 120 million people closely tied to the fishery industry chain. Additionally, the "ecological priority, innovation-

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

driven" strategy outlined in China's "14th Five-Year Plan for National Fishery Development" aligns strategically with the United Nations Sustainable Development Goals (SDGs) on "protecting and sustainably using the ocean and its resources." Especially against the setting of developing countries generally facing insufficient technological reserves and limited policy implementation capabilities, the practical experience of Chinese fishery enterprises in climate adaptation holds significant demonstration value—they not only face frequent physical risks such as typhoons and rising sea temperatures but also must address transformative pressures from international carbon regulations and green trade barriers. This dual challenge characteristic provides a unique case study for understanding global fisheries climate adaptation mechanisms.

Notably, in the wake of digital technology's swift advancement, the influence of digital transformation on enterprises is becoming increasingly widespread. In China's fishery sector, several listed companies have actively implemented digital transformation strategies. By updating digital technologies, fishery enterprises can more accurately monitor climate dynamics, make production adjustments in advance, and effectively mitigate the adverse impacts of climate risks, providing new approaches and tools for sustainable development. Additionally, in 2004, the United Nations Environment Programme (UNEP) took the initiative to introduce ESG, emphasizing the holistic assessment of a company's environmental stewardship, social commitment, and corporate oversight, all while aiming to achieve financial goals (Sun et al., 2025). Aligned with the 20th CPC National Congress directives, China introduced the "Enterprise Sustainable Disclosure Standards—Basic Standards (Trial)" in 2024 to institutionalize corporate sustainability reporting. This policy framework guides businesses in systematically improving their ESG metrics, with particular emphasis on environmental stewardship, social accountability, and governance excellence. The standards further facilitate corporate identification and management of both physical and transitional climate risks, enhancing resilience against ecological uncertainties.

Overall, prior research has primarily focused on how climatic physical factors affect fishery resource distribution or macro-level assessments of fishery economic losses, with insufficient attention to the micro-level transmission mechanisms of transition risks. Additionally, while some scholars have explored the independent effects of digitalization or ESG on corporate performance, no studies have yet revealed the interactive effects of their collaborative response to climate risks. Methodologically, existing studies mostly employ single regression models, lacking a complete analytical chain from efficiency measurement to impact mechanisms.

Given this, this paper uses seven listed Chinese fishery enterprises as research samples, innovatively applying the DEA-BCC method to measure static operational efficiency, the Malmquist index to evaluate dynamic evolution in operating performance, and Tobit regression to construct a "climate risk-corporate operational efficiency" impact model. The results indicate that transition risks are the core factor leading to operational efficiency losses in Chinese fisheries companies; digital transformation and ESG practices can synergistically mitigate the effects of climate risks on operational efficiency. This research utilizes a combined DEA-Malmquist-Tobit analytical model to examine the causal linkages between climate risks and operational efficiency in fishery enterprises, providing a new methodological paradigm for global climate adaptation research.

It is evident that climate change poses dual challenges to fisheries enterprises by impacting their resource base, production costs, and market environment. To address these challenges, proactively pursuing digital transformation to enhance production

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

resilience and management precision, alongside actively implementing ESG principles to build sustainable competitiveness, have emerged as critical adaptation strategies within the industry. However, systematic testing based on micro-enterprise data remains lacking regarding how these two strategies specifically influence the transmission mechanism between climate risks and business operational efficiency, and whether their moderating effects are significant. Given this, this study aims to explore how climate risks impact the operational efficiency of fishery enterprises and empirically test the moderating roles of digital transformation and ESG practices in this process, thereby clarifying the complete logical chain from climate challenges to corporate adaptation.

The contributions of this study are multifaceted. Theoretically, it breaks through the limitations of traditional climate economics, which focuses on macro-level impacts, and for the first time reveals the dominant role of transition risks in the operational efficiency of fishery enterprises based on micro-level enterprise data. Additionally, it constructs a theoretical structure for the synergistic effects of digital transition and ESG practices, elucidating non-technical adaptation pathways for enterprises to address climate risks. Practically, this study offers replicable risk mitigation solutions for fishery enterprises in developing countries, provides empirical evidence for international organizations to formulate differentiated climate policies, and offers micro-level data support for global fisheries carbon footprint calculations.

Literature review

Currently, most domestic and foreign researches on fishery production effectiveness use data envelopment analysis (DEA) or stochastic frontier analysis (SFA) models to carry out effectiveness assessment. Overseas scholars began researching fishery productivity earlier, with a wealth of empirical research methods, and the application of the DEA and SFA models is relatively widespread (Ma'arif et al., 2025). These studies focus on input-output efficiency analysis of fisheries production across different regions, providing theoretical foundations for the efficient utilization of fishing resources and sustainable development. Diana Tingley et al. (2005) utilized stochastic frontier analysis and data envelopment analysis models to investigate many causes influencing the production effectiveness of fishery in the British Channel and paralleled the above methods, reaching internally consistent conclusions. Sagheer et al. (2025) assessed the green cost efficiency of aquaculture in 18 Asian countries from 1990 to 2020 using DEA models and panel regression. Xu et al. (2022) employed the SBM-DEA model to measure the ecological efficiency of marine aquaculture in 10 coastal provinces and municipalities in China. They found that while the ecological efficiency of China's marine aquaculture remains at a relatively low level, it has shown an overall fluctuating upward trend. Idda et al. (2009) also used a DEA model to evaluate the economic effectiveness of small-sized fisheries in the Mediterranean region. Research results revealed fleets in this area faced both short-term and long-term overcapacity challenges, and suggested that fishermen could increase production by increasing effective fixed inputs at the current technological level. Elhendy's (2012) research measured TFP dynamics through the application of the Malmquist index for conventional fishing fleets in the Arabian Gulf between 2001 and 2006. The research results indicate that priority should be given to improving fishery technology and fishermen's fishing abilities.

As the issue of global climate change becomes increasingly prominent, some scholars have begun to concentrate on the influence of climate risks on fisheries. Currently, the mainstream approach to climate risk research involves categorizing climate risks into physical risks (containing severe risks and chronic risks) and transition risks (Tigchelaar et al., 2024). On the one hand, physical risks can cause significant economic losses, such as changes in the distribution and abundance of fishery resources due to rising sea temperatures and frequent extreme weather events (Yin et al., 2025). Thøgersen et al. (2015) found that climate change has a significant negative impact on cod stocks, with declining salinity leading to reduced reproductive success in cod. Research indicates that climate change-induced ocean acidification and temperature increases have already had profound impacts on marine ecosystems, thereby threatening the sustainability of fishery resources (Litzow et al., 2024). On the other hand, transition risks stem from the influence of low-carbon economic transition on the fisheries industry chain, including challenges posed by policy adjustments and technological innovations (Drexler et al., 2025). Existing literature indicates that physical risks caused by climate change not only reduce the biomass of fishery resources but also exacerbate the uncertainty of fisheries management (Feng et al., 2025; Akoglu et al., 2024). For example, the increased frequency and intensity of marine heatwaves have already had significant impacts on multiple fishery regions, further highlighting the urgency of climate adaptation strategies (Kajtar et al., 2024; Szymkowiak and Steinkruger, 2024). Furthermore, Islam et al. (2024) quantified for the first time the economic losses incurred by aquaculture due to climate-induced extreme events through the scraping and analysis of Bangladeshi newspaper data. They highlighted the significant potential of climate information services (CIS) in mitigating such losses, providing empirical evidence from a developing country to understand the economic impacts of physical climate risks on fisheries.

In contemporary research, the application of digital transformation in the fishery industry has gradually become a research hotspot. Scholars have explored the enabling effects of digital technology in promoting high-quality development in fisheries from various perspectives. For example, Xia et al. (2025) constructed a provincial panel data model for China to empirically analyze the positive influence of the digital economy on the qualitative development of the fishing economy, and validate the mediating role of technical innovation and entrepreneurship activities in the process. Li et al. (2025) focused on China’s coastal areas, studying how digital technology can improve green TFP in the fisheries sector, and revealed how digital transformation can help improve resource efficiency and environmental sustainability. Zhang et al. (2025) conducted more in-depth research to seek how the digital economy influences carbon emissions from marine fishing, finding that the digital economy development index can significantly reduce carbon emissions and revealing its spatial spillover effects through a spatial Dubin model. Additionally, Tilley et al. (2024) used the “Peskas” system in the Democratic Republic of Timor-Leste as an example to demonstrate the practical application value of real-time fishery monitoring data in policy-making and resource management, emphasizing the supportive role of digital technology in the sustainable development of small-scale fisheries. These studies provide theoretical foundations for the digital transformation of fisheries and offer scientific references for policymakers to optimize fisheries management strategies (Li and Ji, 2024; Ye et al., 2025).

Meanwhile, research on the connection between ESG and fisheries has also become a focal point in academic circles recently. Existing researches primarily analyze the influence of ESG on the operating efficiency of fisheries companies, sustainable utilization of fishing resources, and the high-value utilization of fishery waste. Sun et al. (2025) used DEA models and Tobit regression to analyze the relationship of ESG level and the operating performance of Chinese listed fishery firms, finding that ESG performance considerably improved the overall efficiency of enterprises. Additionally, the high-value utilization of fishery waste is another research hotspot. Moosavi-Nasab et al. (2020) studied an enzyme-assisted acid hydrolysis process for extracting gelatin from fish byproducts, finding that this method significantly improves gelatin yield and quality, offering new insights into the sustainable utilization of fishery waste. Taktak et al. (2021) further developed microfiber materials based on fish gelatin for encapsulating fish oil, demonstrating the application potential of fishery byproducts in the food and nutrition sectors. In terms of fishery resource management, Turgeon et al. (2021) conducted a life cycle assessment to study the impact of hydropower development on fish diversity, proposing biodiversity-based characteristic factors to provide quantitative tools for fishery ecological conservation under the ESG framework. Rusco et al. (2024) explored the role of integrated multi-trophic aquaculture systems in enhancing aquatic animal welfare and meat quality, emphasizing the importance of ESG in promoting sustainable fishery development. Additionally, fishery ESG research encompasses supply chain optimization and social responsibility. Ragni et al. (2024) assessed the impact of replacing fishmeal with seafood waste on the growth and meat quality of Japanese shrimp, and analyzed its economic and social benefits using ESG indicators, providing references for social responsibility practices in fisheries enterprises.

In summary, existing research has achieved significant results in areas such as fisheries production efficiency assessment, climate risk impacts, digital transformation, and ESG practices. However, the following research gaps remain: Firstly, although DEA and SFA models are widely applied in fishery efficiency analysis, few studies incorporate climate risk as an exogenous variable into the efficiency assessment framework, making it difficult to completely reveal dynamic impact mechanisms about climate change on operational efficiency of fishery enterprises; Secondly, research on the connection between climate risk and fishery efficiency has primarily concentrated on macro-level resource volatility analysis, lacking empirical testing of micro-level adaptation strategies at the enterprise level; finally, while existing ESG research has examined the promotional role of sustainable practices on fishery efficiency, it has not systematically investigated how ESG performance moderates the impact of climate risk on enterprise efficiency. This study constructs a climate risk indicator system and uses it as an explanatory variable. Through a Tobit two-stage model, it quantifies the direct influence of climate risk on the operating performance of listed fisheries firms in China. Additionally, it identifies moderating effects of digital transformation and ESG performance on this impact, thereby providing more targeted management insights and policy recommendations for fisheries enterprises to achieve sustainable development under the backdrop of climate change.

Methods

Scholars both domestically and internationally have extensively employed models such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to assess the operational efficiency of fishery enterprises (Ma'arif et al., 2025; Idda et al., 2009). Compared to SFA, which represents "parametric methods," DEA, as a "non-parametric method," focuses on data-driven approaches and avoids the subjective specification of production functions, thereby enhancing the objectivity of efficiency evaluations (Førsund and Sarafoglou, 2002). Therefore, this study follows established

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

practices in fishery efficiency research (Sagheer et al., 2025; Sun et al., 2025), and employs the DEA-BCC model and the Malmquist index method to conduct a comprehensive efficiency measurement of fishery enterprises' operational performance. Furthermore, since efficiency scores derived from the DEA-BCC model range between 0 and 1, exhibiting truncated data characteristics, this study adopts the Tobit regression method, referencing the research of Sun et al. (2025), to delve into the key factors influencing the operational performance of Chinese fishery companies.

DEA-BCC model

Data Envelopment Analysis (DEA) is a non-parametric efficiency evaluation method according to input-output indicators, primarily used to assess relative performance levels of similar decision-making units (DMU). This method employs linear programming techniques to address efficiency measurement issues involving multiple inputs and outputs. Its advantages include the absence of the need to predefine production function forms or determine indicator weights, and it is unaffected by units of measurement, making it widely applied in efficiency assessment research across various fields.

The DEA method was first put forward by operations researchers Charnes, Cooper, and Rhodes, who developed the CCR model underpinned by the "relative efficiency" theory to measure the technical performance of DMUs under conditions of constant returns to scale. Subsequently, Banker, Charnes, and Cooper further improved this method by adopting the VRS (variable returns to scale) postulate, proposing a more flexible BCC model, thereby expanding the application scope of the DEA method. For listed fishery enterprises, the heterogeneity of their resource endowments and management practices often exhibits variable returns to scale (Idda et al., 2009), making it difficult to define a constant decision unit. Therefore, drawing on Sun et al. (2025), this study employs a BCC model based on variable returns to scale to conduct a static analysis of the comprehensive performance of fishery companies. The BCC model primarily calculates the comprehensive efficiency value (Crste) of a company and decomposes it into pure technical efficiency (Vrste) and scale efficiency (Scale), i.e., Crste = Vrste ×Scale. The mean value ranges from 0 to 1, with values closer to 1 indicating higher efficiency.

The fundamental concepts and mathematical formulations of the DEA-BCC model can be summarized as follows:

The study involves n DMUs, with each representing a publicly traded fishing company that employs m inputs to generate s outputs. Let x_{ij} represent the j-th output of DMU_i, and let Y_{ir} represent the r-th output of DMU_i. DMU_i is expressed by vectors x_i andy_i. $x_i = (x_{i1}, x_{i2}, x_{i3}, \cdots\cdots x_{im})^T$ $y_i = (y_{i1}, y_{i2}, y_{i3}, \cdots\cdots y_{is})^T$. Then, within its production possibility set, the DMU's efficiency value is represented linearly using *Equation 1*:

$$\begin{gathered} \mathrm{Min}\{\theta-\beta(\sum_{j=1}^{m} s_j^- + \sum_{r=1}^{s} s_r^+)\} \\ \text{s.t.} \sum_{i=1}^{n} \gamma_i x_{ij} + s_r^- = \theta x_{ij0}, j\in(1,2,3,\cdots, m) \\ \textstyle\sum_{j=1}^{n} \gamma_i y_{ir} - s_j^+ = y_{ir0}, r\in(1,2,3,\cdots, s) \\ \sum_{i=1}^{n} \gamma_i = 1 \\ \theta, \gamma_i, s_r^-, s_j^+ \geq 0, i=1,2,\cdots, n \end{gathered} \tag{Eq.1}$$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

In the equation, s_i^- and s_r^+ are slack variables; γ illustrates the weight corresponding to the i-th DMU; β belongs to a non-Archimedean infinitesimal quantity; As an efficiency metric, θ reflects the minimum value for all inputs that a DMU can potentially achieve while maintaining its current output level. If $\theta = 1$, DMU is effective, if $0 < \theta < 1$, DMU is ineffective.

DEA-Malmquist index model

The DEA-BCC model is primarily used for static analysis and can calculate the efficiency level of the DMUs in a specific year, but it is difficult to reflect dynamic evolution of efficiency over time. To address the issue, Färe et al. (1994) proposed the DEA-Malmquist exponential model. This model compares the relative distance changes between decision-making units and the production frontier across different periods, enabling not only the analysis of the dynamic evolution of efficiency but also the decomposition of the total factor productivity change index (Tfpch). In this way, we can have a more in-depth understanding of the root causes and trends behind the fluctuations in the efficiency of fishery enterprises. Considering that climate risks, such as rising sea temperatures and extreme weather events, exert time-varying pressures on fishery production and resource availability (Yin et al., 2025; Tigchelaar et al., 2024), analyzing the dynamic evolution of efficiency is essential. The Malmquist index allows for the decomposition of total factor productivity changes, helping to discern whether efficiency fluctuations are driven by technological progress, scale adjustments, or pure technical efficiency changes. This approach has been utilized to study productivity dynamics in fisheries under changing environmental conditions (Elhendy et al., 2012). Therefore, this paper adopts the Malmquist index to analyze changes in the dynamic operational efficiency of fishery enterprises, drawing upon the research of Elhendy et al. (2012).

The Malmquist index between period t and period t + 1 can be formulated as:

$$\begin{aligned} \text{Tpfch} &= M_0\left(x_{t+1}, y_{t+1}, x_t, y_t\right) \\ &= \frac{D_0^{t+1}\left(x_{t+1}, y_{t+1}\right)}{D_0^t\left(x_t, y_t\right)} \times \sqrt{\frac{D_0^t\left(x_{t+1}, y_{t+1}\right)}{D_0^{t+1}\left(x_{t+1}, y_{t+1}\right)} \times \frac{D_0^t\left(x_t, y_t\right)}{D_0^{t+1}\left(x_t, y_t\right)}} \end{aligned} \quad \text{(Eq.2)}$$

The total factor productivity change index acts as a key metric for measuring changes in the operational efficiency of fishery enterprises between period t and t + 1. Changes in its value have clear implications for efficiency. If Tfpch > 1, it demonstrates that the operating efficiency of fisheries enterprises has improved compared to the preceding period. If Tfpch = 1, it demonstrates that the operational efficiency of fishery enterprises remains stable. If Tfpch < 1, it demonstrates that the operating performance of fisheries companies has declined.

In the above equation, x denotes the input quantity of decision-making units, y denotes the output quantity of decision-making units, $D_0^t(x_t,y_t)$ denotes the technical performance value of the DMU during period t, $D_0^{t+1}(x_{t+1},y_{t+1})$ represents the technical performance value of the DMU during period t+1, and $\frac{D_0^{t+1}(x_{t+1},y_{t+1})}{D_0^t(x_t,y_t)}$ represents the technical efficiency change index (Effch) quantifying technical efficiency variation across periods t and t + 1. If Effch > 1, it demonstrates an advancement in technical efficiency; otherwise, it

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

indicates a deterioration. $\sqrt{\frac{D_0^t(x_{t+1},y_{t+1})}{D_0^{t+1}(x_{t+1},y_{t+1})}\times\frac{D_0^t(x_t,y_t)}{D_0^{t+1}(x_t,y_t)}}$ is the technological progress change index (Techch), reflecting the extent of technological innovation or progress between period t and t + 1. When Techch > 1, it demonstrates that the enterprise has made substantial progress in industrial technological innovation; otherwise, it reflects a decline in industrial technological development. Additionally, assuming variable returns to scale, Effch is constituted by changes in pure technical efficiency and scale efficiency. Therefore, the Malmquist index can be represented as: Tfpch = Effch×Techch = Pech×Sech×Techch.

Tobit model

The research employs the DEA-BCC model to measure and evaluate the operating efficiency of listed fisheries enterprises in China. Each enterprise's efficiency value falls within the range of 0 to 1, with observations exceeding 1 truncated to form cross-sectional data characteristics. During the model selection process, the study found that the fixed-effects Tobit model struggles to capture sufficient individual heterogeneity due to the limitations of conditional maximum likelihood estimation. Introducing panel dummy variables into a mixed Tobit regression would lead to biased parameter estimates. The likelihood ratio test (LR test) results showed a p-value of 0.00015, which is less than 0.01, significantly rejecting random effects hypothesis. This empirical evidence indicates that the model exhibits significant individual effects, making the random effects panel Tobit model more appropriate (Chen, 2014). Therefore, this paper, building upon the work of Sun et al. (2025), selects the Tobit random panel regression model to examine further key components affecting corporate operational efficiency. The fundamental formulation of the model can be expressed as:

$$Y_i^* = \beta_i X_i + \varepsilon_i$$
$$Y_i^* = \begin{cases} Y_i^*, Y_i^* > 0 \\ 0, Y_i^* \le 0 \end{cases} \quad \text{(Eq.3)}$$

In this model, Y_i^* represents the explained variable, X_i represents the explanatory variable, β_i represents the coefficient term, and ε_i is the random error term, and $\varepsilon_i \sim N(0,\delta_\varepsilon^2)$. This study built Tobit models like the following:

$$\begin{aligned} Crste_{it} &= \beta_0+\beta_1 Climate\ risk_{it}+\beta_2 Mshare_{it} \\ &+\beta_3 Em_{it}+\beta_4 Board_{it}+\beta_5 Cashflow_{it}+\beta_6 Top1_{it}+\delta_t+\varepsilon_{it} \end{aligned} \quad \text{(Eq.4)}$$

Among them, $Crste_{it}$ is the operating performance of the i-th company among the listed fishing enterprises in China in the t-th year (in which operational performance is measured by the comprehensive efficiency calculated by the BCC model); the subscript "i" ranges from 1 to 7, and "t" covers the years from 2012 to 2023.; δ_t represents control time fixed effect; ε_{it} is a random disturbance term.

Variable selection and data sources

The research subjects were selected based on the 2012 China Securities Regulatory Commission's benchmark industry classification system, with a primary focus on listed

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

fishery enterprises. After excluding enterprises with ST status and those with missing key variables, 7 listed fishing enterprises with relevant data from 2012 to 2023 were ultimately chosen as the research subjects for this research, as presented in *Table 1*. The data utilized in the study were sourced from the China Stock Market and Accounting Research Database (CSMAR) and the China Research Data Service Platform (CNRDS), with measurement software including DEAP 2.1 and STATA 17.

Table 1. *Basic information on seven listed fisheries enterprises*

Company abbreviation	Stock Code	Year-to-market	Industry	Business scope
CNFC	000798	1998	Marine fishery	Multiple sectors including the fishing of deep-sea seafood such as tuna and squid, seafood processing and trade, and offshore fishing services
ZONECO	002069	2006	Marine fishery	Primarily engaged in marine delicacy breeding and seedling cultivation, marine aquaculture enhancement, marine food research and development, processing and sales, cold chain logistics, and fishery equipment industries
ORIENTAL OCEAN	002086	2006	Marine fishery	Primarily engaged in marine seedling breeding and aquaculture, aquatic product processing, biotechnology, bonded warehousing and logistics, as well as the research, development, production, sales, and testing services of in vitro diagnostic reagents
BAIYANG	002696	2012	Freshwater fishery	Feed and Feed Ingredients Business, Aquatic Products Processing and Bioproducts Business, Deep-sea Fishing and Processing Business
SKMIC	600097	1997	Marine fishery	Engaged in offshore fishing operations, aquatic product processing and sales, and related trade activities
DHGF	600257	2000	Fishery service industry	Engaged in the production and sales of health products, including the farming, processing, and sales of freshwater fish and related aquatic products
HOMEY	600467	2004	Marine fishery	Coordinated development of the four major industries: marine aquaculture, food processing, offshore fishing, and pharmaceuticals and healthcare

Indicator settings

Input-output indicators

Based on DEA model indicator selection principles and data accessibility principles, this paper assesses the operational performance of the fisheries companies. As shown in *Table 2*, the evaluation system is classified into two main parts: input indicators and output indicators.

(1) Input indicators

Asset investment is crucial to a company's operations and development, and it is also critical to improving fiscal condition and competitive advantage. The research classifies asset investment depending on the character and use of assets, and selects three important index: company size (X1), operating cost (X2), and number of employees (X3). These represent the three components of total asset investment, material investment, and personnel investment, respectively. When using these indicators, logarithmic transformations are applied to company size, operating costs, and employee count to address differences in scale among the three variables, thereby eliminating potential heteroskedasticity issues.

Additionally, corporate operational performance can be assessed using multiple financial indicators, including total asset turnover rate (X5), accounts receivable turnover rate, inventory turnover rate, fixed asset turnover rate, and current asset turnover rate (X4). The total asset turnover rate measures the efficiency of asset utilization and reflects the capacity of total assets to generate revenue. A higher total asset turnover rate suggests greater asset utilization and stronger revenue-generating capacity. The accounts receivable turnover rate reflects efficiency of accounts receivable management and speed of conversion into cash, measuring the speed at which accounts receivable are recovered; The inventory turnover rate measures the level of inventory management and liquidity, reflecting the speed of inventory turnover and its ability to be converted into cash; The fixed asset turnover ratio reflects efficiency of use of company fixed assets and indicates the revenue-generating capacity of fixed asset investments. The current asset turnover ratio assesses the operational efficiency of a company’s current assets and reflects the revenue-generating capacity and turnover speed of current assets. This paper selects turnover ratios for total assets and current assets as indicators for assessing an enterprise’s operational status because these two ratios reflect the company’s overall asset usage rate and short-term effectiveness.

When assessing risks, companies encounter multiple operational challenges, notably liquidity shortages and asset illiquidity. These risks can impair an enterprise’s debt-repayment capacity and negatively impact its creditworthiness and reputation. Therefore, this paper considers using the current ratio (X6) and quick ratio (X7) to assess an enterprise’s risk profile, measuring its short-term debt-repayment capacity, and the debt-to-equity ratio (X8) to measure its long-term debt-repayment capacity.

Table 2. *Input-output indicators of the DEA model*

Indicators			Formula
Input indicators	Company size	X1	Ln(total assets)
	Operating cost	X2	Ln(operating cost)
	Number of employees	X3	Ln(number of employees + 1)
	Current asset turnover rate	X4	Operating revenue/average current asset occupancy
	Total asset turnover rate	X5	Operating revenue / Average total assets
	Current ratio	X6	Current assets/current liabilities
	Quick ratio	X7	(Current assets-inventory) / Current liabilities
	Debt-to-equity ratio	X8	Total liabilities/total assets
Output indicators	Operating profit margin	Y1	Operating profit/operating revenue
	Return on equity	Y2	Net income/average balance of shareholders’ equity
	Earnings per share	Y3	Net profit for the current period / Paid-in capital at the end of the current period

(2) Output indicators

The operational efficiency of a business can be assessed through its post-production profit and revenue metrics, including gross profit margin, return on equity, operating

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

profit margin, return on assets, basic earnings per share, and net asset value per share. To assess a firm's profitability per share from its core business, this study focuses on operating profit margin, return on equity, and basic earnings per share.

Operating profit margin (Y1) reflects an enterprise's ability to generate profits through operations without considering non-operating costs, thereby showcasing the profitability of its core business. Return on equity (ROE)(Y2) highlights the relationship between investment and returns, reflecting a company's overall ability to generate returns using its capital. It is a comprehensive indicator for evaluating the return level of a company's assets and their accumulation. Earnings per share (EPS) (Y3) is typically used to reflect a company's operating results, measuring the profitability and potential investment risks for common shareholders. It helps stakeholders such as investors and creditors evaluate a company's profitability and predict its growth potential.

(3) Data preprocessing

In order to use the DEA model smoothly, the sample data must be guaranteed to be positive. Due to the existence of negative and zero values in raw data, preprocessing of the panel dataset is required prior to model estimation. The processing method is minimum-maximum normalization, which linearly compresses the data to the range [0,1]. The calculation follows this formal expression:

$$X_{ij}=\frac{X_{ij}\text{-}\min(X_j)}{\max(X_j)\text{-}\min(X_j)} \tag{Eq.5}$$

At the same time, to avoid 0 values, normalized data is adjusted to range (0.001, 0.999).

Regression indicators

The core variables of this paper are shown in *Table 3*.

Table 3. *Selection and definition of Tobit model variables*

Variable type	Variable name	Sign	Variable definition
Explained variable	Operational efficiency	Crste	Calculated by the DEA-BCC model
Explanatory variable	Climate risks	Climate risk	Text analysis method for analyzing the frequency of relevant words in annual reports
Control variables	Management shareholding ratio	Mshare	Number of shares held by directors, supervisors, and senior management / Total number of shares issued
	Cash flow ratio	Cashflow	Net cash flow from operating activities/total assets
	Equity multiplier	EM	Year-end total assets/year-end shareholders' equity
	Largest shareholder shareholding ratio	Top1	Number of shares held by the largest shareholder/total number of shares

(1) Explained variable

Operational efficiency of Chinese listed fisheries companies. To achieve a comprehensive evaluation of the operating efficiency of fisheries companies, this

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

research applies the DEA-BCC analysis to conduct a quantitative analysis of the performance of these enterprises from 2012 to 2023.

(2) Explanatory variable

Climate risks of listed Chinese fishery enterprises were selected as explanatory variables. Li et al. (2020) constructed a lexicon through text analysis of earnings conference call transcripts from U.S. listed companies and measured climate risk by calculating the frequency of the keyword “climate risk,” representing existing research on corporate-level climate risk. Therefore, building upon the research of Li et al. (2020) and referencing existing literature (Du et al., 2023), this paper establishes a “climate risk” lexicon and employs a combined approach of text mining and machine learning techniques to identify keywords related to climate risk. Subsequently, the standardized ratio of frequency of these keywords in company yearly reports to the words in the reports was calculated to construct a comparable quantitative indicator of climate risk. This metric design has clear economic implications, with its numerical changes maintaining a positive correlation with the firm’s true climate risk exposure levels. That is, when the metric value increases, it indicates that the company is more significantly affected by the potential threats and uncertainties of climate change in its production and operations, while a decrease suggests that climate risks are relatively manageable.

(3) Control variables

Considering existing literature and data availability, the concepts of scale efficiency and technical efficiency encompass three interrelated aspects: production processes, operational systems, and managerial practices (Wang and Liu, 2023). Therefore, cash flow ratio, equity multiplier, management shareholding ratio, and largest shareholder shareholding ratio are selected as control variables.

DEA results and Tobit regression results

The empirical process consists of three parts. The first part starts from a static perspective and uses the DEA-BCC model to analyze transformations in comprehensive efficiency, technical efficiency and scale efficiency of 7 publicly traded Chinese fishery companies between 2012 and 2023. The second part uses the Malmquist index to examine changes in the operating performance of fishing companies through dynamic changes. Section three employs a Tobit model with random effects to analyze climate risk’s influence on the operational performance of fisheries enterprises and performs robustness tests. Additionally, through moderation effect analysis, it is found that the extent of digital advancement and ESG performance moderate the influence of climate-related risks on the operating efficiency of listed fishing firms.

Static analysis of the DEA-BCC model

This paper conducts static analysis about the operational performance of Chinese listed fishing companies between 2012 and 2023, determining their Crste, Vrste and Scale. The results are shown in *Table 4*.

Between 2012 and 2023, the average comprehensive efficiency value of listed fishing companies in China was 0.9798. The data shows that the average technical efficiency (0.9875) and scale efficiency (0.9917) values did not reach the efficient frontier,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

indicating a slightly inefficient state. Additionally, it was found that the average scale efficiency was greater than average technical efficiency, indicating that operational performance losses of Chinese listed fishing companies stem more from deficiencies in technology and management rather than issues related to production scale. Therefore, companies should prioritize optimizing production technology or management capabilities rather than simply pursuing scale expansion.

Table 4. *Average operating efficiency of listed fishery enterprises in China, 2012-2023*

FIRM	Crste	Vrste	Scale
CNFC	0.9840	0.9840	1.0000
ZONECO	0.9311	0.9464	0.9827
ORIENTAL OCEAN	1.0000	1.0000	1.0000
BAIYANG	0.9474	0.9854	0.9600
SKMIC	1.0000	1.0000	1.0000
DHGF	0.9958	0.9968	0.9991
HOMEY	1.0000	1.0000	1.0000
Mean	0.9798	0.9875	0.9917

From the corporate perspective, among the seven companies, ORIENTAL OCEAN, SKMIC and HOMEY achieved a comprehensive efficiency value of 1, indicating that they are in a DEA-efficient state, meaning these three companies have maximized their efficiency. However, between 2012 and 2023, CNFC, ZONECO, BAIYANG and DHGF all had comprehensive efficiency scores below 1, indicating they were in an inefficient state with resource wastage. Among these seven listed fishery enterprises, ZONECO had the lowest comprehensive efficiency score at 0.9311. The core issue underlying ZONECO's low comprehensive efficiency lies in its exploitation of the difficult-to-verify nature of scallop farming, frequently fabricating "natural disasters" to justify abnormal inventory write-downs (such as the three instances of "scallops disappearing" in 2014, 2017, and 2019), thereby concealing management chaos and financial fraud. In 2020, the China Securities Regulatory Commission (CSRC) confirmed the company's inflated profits.

Additionally, the company blindly expanded its single-species farming operations without adjusting its model despite deteriorating ecological conditions in its farming waters. Compounded by major shareholder fund misappropriation and frequent internal conflicts, this led to a sharp decline in asset turnover rates and consistently negative return on equity (ROE). Ultimately, regulatory penalties and credit bankruptcy hindered its financing capabilities, further deteriorating efficiency, making it a textbook case of governance failure in the A-share market. Additionally, among these seven companies, the three mentioned above also achieved pure technical efficiency scores and scale efficiency scores of 1, indicating that decision-making units have achieved the efficiency frontier of technical efficiency given the existing size and resource deployment, maximizing output or minimizing input within existing technical constraints. Meanwhile, although CNFC has not reached a score of 1 in respect of comprehensive efficiency and pure technical efficiency, its scale efficiency has reached a score of 1, indicating that the main factor affecting CNFC's overall efficiency is pure technical efficiency, and advancements are needed in the technological aspect.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

Further analysis reveals that four companies have overall efficiency values lower than their scale efficiency values, suggesting the existence of diseconomies of scale. These companies should reassess their input-output balance to reduce their scale and optimize resource allocation.

Dynamic analysis of the DEA-Malmquist index

The conventional DEA approach fails to account for industry-wide technological advancements affecting decision-making units. Therefore, this research employs the Malmquist productivity index to study the alterations of total factor productivity in Chinese listed fishery companies, assessing their dynamic operational efficiency. The findings are presented in *Table 5*.

Table 5. *Average Malmquist index and decomposition of Chinese listed fishery enterprises, 2012-2023*

Year	Effch (Technical efficiency change index)	Techch (Technological progress index)	Pech (Pure technical efficiency change index)	Sech (Scale efficiency change index)	Tfpch (Total factor productivity)
2012-2013	0.992	1.300	0.990	1.003	1.290
2013-2014	1.008	0.915	1.027	0.982	0.922
2014-2015	0.995	0.707	0.985	1.010	0.704
2015-2016	1.035	0.884	1.026	1.009	0.915
2016-2017	1.000	0.904	1.000	1.000	0.904
2017-2018	1.000	0.945	1.000	1.000	0.945
2018-2019	0.982	1.006	0.994	0.988	0.988
2019-2020	0.998	1.545	1.002	0.996	1.541
2020-2021	0.998	0.670	0.996	1.002	0.668
2021-2022	1.023	1.201	1.009	1.014	1.228
2022-2023	0.927	1.189	0.959	0.967	1.102
Mean	0.996	0.995	0.999	0.997	0.991

Table 5 reveals that Chinese listed fishery companies experienced an average total factor productivity (TFP) index of 0.991 during 2012-2023, reflecting a 0.9% annual decline. This downward trend indicates deteriorating production efficiency across the sector. The pure technical efficiency change index was 0.999, and the scale efficiency change index was 0.997. The reduction in technical efficiency is primarily influenced by the shift in scale efficiency metrics. It turns out from the results that Malmquist indices (Tfpch) for the periods 2013-2014, 2014-2015, 2015-2016, 2016-2017, 2017-2018, 2018-2019, and 2020-2021, the Malmquist index (Tfpch) was less than 1.000, indicating that total factor productivity level in this period was lower than the previous year. The table data reveal that the drop in TFP is primarily attributable to the deterioration in the technological advancement index, suggesting that the reduced productivity of listed fishing companies in China stems primarily from their technological regression.

As illustrated in *Figure 1*, the annualized Malmquist indicator and its disintegration for fishing enterprises in China exhibit varying degrees of fluctuation. Among these, the variations in technical efficiency are minimal, with its breakdown into pure technical and scale efficiency showing negligible fluctuations. However, the variations of total factor productivity and the technical progress indicator are very large, and trends in their fluctuations are largely consistent. This indicates that technological progress has had an important influence on the enhancement of TFP for listed fishing firms in China from 2012 to 2023. Therefore, to enhance overall efficiency, it is necessary to increase R&D investment, support innovation in technology and novel product creation, and improve operational processes to align productivity with technological progress, thereby enhancing the company's overall efficiency. Technological progress is the main driving force for promoting Sustainable transition and advancement in fishing enterprises.

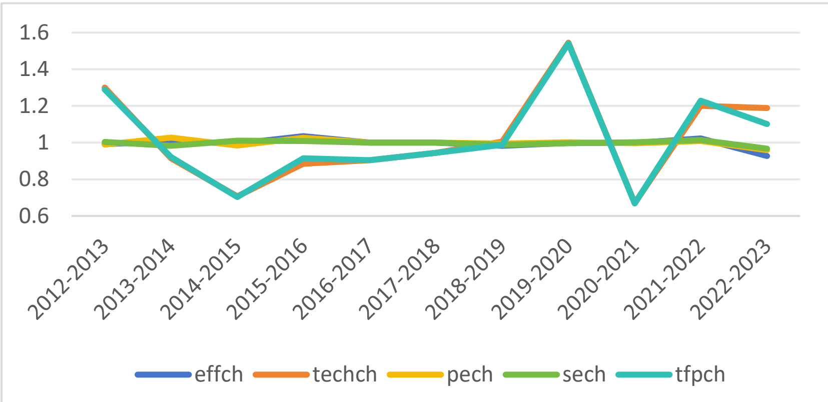

Figure 1. *Calculation and decomposition of the annualized Malmquist productivity index for listed fishery companies in China (2012-2023)*

Table 6 shows the breakdown of operational efficiency for listed Chinese fishery enterprises. As shown in the table, from 2012 to 2023, three companies had total factor productivity ratios exceeding 1: ZONECO, ORIENTAL OCEAN and HOMEY. The remaining companies all had indicators below 1, indicating that under dynamic analysis, the operational performance of Chinese fisheries enterprises has been constantly declining and requires additional improvement. Among the entities, CNFC witnessed the largest decline in TFP, experiencing a reduction of 20.2% over 12 years, followed by DHGF, which decreased by 6.8% over 12 years. Through overall observation, it was found decline in the technological progress indicator explained the mean total factor productivity reduction.

Table 6. *Breakdown of operating efficiency of listed Chinese fisheries companies*

Firm	Effch	Techch	Pech	Sech
798	0.981	0.814	0.981	1
2069	1.019	1.047	1.017	1.002
2086	1	1.233	1	1
2696	0.972	0.98	0.993	0.979
600097	1	0.98	1	1
600257	1	0.932	1	1
600467	1	1.023	1	1
Mean	0.996	0.995	0.999	0.997

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

Tobit regression results

Descriptive statistics of variables

The study sample covers seven Chinese listed fishery companies from 2012 to 2023. Due to incomplete financial data disclosure in certain company-year combinations, we obtained an unbalanced panel dataset comprising 74 valid observations after excluding these outliers. *Table 7* presents descriptive statistics for the key variables.

Table 7. *Descriptive statistics for variables*

VarName	Obs	Mean	SD	Min	Median	Max
Climate risk	74	0.0030	0.0017	0.0008	0.0026	0.0111
Crste	74	0.9798	0.0594	0.7310	1.0000	1.0000
Digital	74	0.0046	0.0042	0.0000	0.0038	0.0253
ESG	74	25.4434	10.9778	7.0471	22.2101	65.4486
Mshare	74	0.0592	0.1501	0.0000	0.0002	0.5496
EM	74	3.6848	7.4381	-1.7350	1.7496	50.1775
Cashflow	74	0.0436	0.0580	-.2225	0.0411	0.2443
Top1	74	0.3194	0.1049	0.1322	0.3076	0.6139

As illustrated in *Table 7*, the maximum value of climate risk for listed fishing enterprises in China obtained through text analysis is 0.0111, the minimum value is 0.0008, and the average is 0.0030. Variation's degree is relatively large, suggesting that there are substantial differences in climate risks among Chinese listed fishery enterprises. Chinese listed fisheries companies exhibited operational efficiency scores ranging from 0.7310 to 1.0000, with a mean value of 0.9798 during the study period. The degree of variation is small, suggesting that the operating effectiveness of most fishery companies is near optimal and developing effectively. Based on the ESG index from the CNRDS database to assess corporate ESG levels, the mean value of 25.4434, the median of 22.2101, and the maximum value of 65.4486, it is evident that ESG levels of listed fishing companies in China are relatively low, indicating that it is important to strengthen their ESG performance.

Additionally, ESG standard deviation is 10.9778, suggesting that there are notable disparities in ESG levels of listed fisheries enterprises in China. Digital transformation level was obtained using machine learning methods and text analysis, with a standard deviation of 0.0042. This signifies that the extent of digitalization in Chinese listed fishery companies has changed very little. In terms of control variables, the median and average values for cash flow ratio, and the largest shareholder's equity ratio are nearly identical, suggesting that there are commonalities in corporate governance structures, financial strategies, and equity models. The mean and median values for the management shareholding ratio and equity multiplier differ significantly, indicating there are notable differences in equity incentive levels across various listed fishery companies. This also reflects significant differentiation among Chinese listed fishery enterprises in terms of capital strategies, business models, risk preferences, and resource acquisition capabilities.

Correlation analysis

Perform VIF testing on the model before regression. The VIF testing outcomes are tabulated in *Table 8*.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

Table 8. *VIF test results*

	VIF	1/VIF
top1	1.370	0.730
cashflow	1.235	0.810
Climate risk	1.203	0.831
mshare	1.183	0.845
em	1.119	0.894
Mean VIF	1.222	0.894

As *Table 8*'s VIF analysis indicates, the maximum variance inflation factor (VIF) for each variable is 1.370, which is less than 5, and the mean VIF is less than 2. This suggests that there is no severe multicollinearity among selected control variables. Further regression analysis can be conducted on the dependent variable without affecting the outcomes of empirical analysis. Therefore, this study primarily employs a random-effects Tobit regression model to regress the connection between explanatory variables and the dependent variable, effectively controlling for the influence of time-related factors.

Regression results and analysis

By examining *Table 9*, it is observed that the p-value for the influence of climate risk on the operating efficiency of listed fisheries companies in China is 0.008, indicating a substantial negative correlation between climate risk and operational efficiency of fishing companies at 1% significance level. This suggests that climate risk can substantially reduce the operating efficiency of fishing companies.

Table 9. *Tobit benchmark regression results*

Variable	Crste			
	Coefficient	Standard error	t	p
Climate risk	-98.008***	36.824	-2.660	0.008
Mshare	0.648*	0.369	1.750	0.079
EM	0.020*	0.012	1.700	0.089
Cashflow	0.135	0.417	0.320	0.746
Top1	-0.882	0.565	-1.56	0.118
Constant	1.752***	0.312	5.62	0.000
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Meanwhile, the regression results indicate that both the proportion of management shareholding and the equity multiplier exert a significant positive impact at the 10% level on the operational efficiency of listed Chinese fisheries enterprises. When management holds company shares, their interests align to a certain extent with those of shareholders, and their interests become tied to risk-bearing, thereby reducing agency costs, optimizing governance structures, and enhancing operational efficiency. A higher equity multiplier enables enterprises to leverage financial instruments to expand their operational scale and improve capital utilization efficiency. When the return on investment exceeds the cost of debt, it generates higher returns for shareholders, thereby positively influencing operational efficiency.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

Although the cash flow ratio and the largest shareholder's ownership ratio have no significant impact on the operating performance of listed Chinese fishery companies, analyzing the direction of their coefficients reveals the overall influence of these factors on corporate operational efficiency. The cash flow ratio exerts a positive effect on operational efficiency: ample cash flow safeguards short-term debt repayment capacity, reduces liquidity risk, supports efficient operations and investments, and consequently enhances operational efficiency. The largest shareholder's ownership ratio exerts a negative influence on operational efficiency. An excessively high ownership concentration may trigger "controlling shareholder issues," leading to excessive interference in management, suppression of other shareholders' governance functions, or even self-dealing through related-party transactions. These dynamics ultimately diminish decision-making quality and resource allocation efficiency.

Robust test

(1) Two-period lag test

In the study above, this paper argues that climate risk affects the operational efficiency of fisheries companies. Since the climate risk's influence on enterprises is not instantaneous and may involve a certain time lag, this paper further tests the stability of the results by comparing the results of the benchmark model with those obtained by lagging the climate risk variable by two periods. As shown in *Table 10*, the findings indicate that the regression coefficient of climate risk lagged by two periods on the operational efficiency of fishery enterprises is -76.775, with a P-value of 0.035. At the 5% confidence level, the finding proves statistically significant. This indicates that climate risks lagging by two periods are significantly negatively correlated with the operational performance of listed fishing firms in China. This further indicates that the influence of climate risks is not immediately apparent, but rather exhibits a certain degree of lag, primarily due to the cumulative damage caused by extreme weather or changes in the marine environment to fishery resources. This, in turn, exerts a sustained drag on subsequent years' aquaculture costs, output stability, and other factors, thereby reducing operational efficiency.

Table 10. *Robustness of the two-period lag test*

Variable	Crste			
	Coefficient	**Standard error**	**t**	**p**
Climate risk$_{t\text{-}2}$	-76.775**	36.488	-2.100	0.035
Mshare	0.591	0.433	1.370	0.172
EM	0.021	0.014	1.520	0.129
Cashflow	0.347	0.550	0.630	0.528
Top1_w	-0.774	0.523	-1.480	0.139
Constant	1.724***	0.330	5.220	0.000
Year	Control	Control	Control	Control

*** p < 0.01, ** p < 0.05, * p < 0.1

(2) Add market conditions as control variables

Adopting a methodology of Tang (2021), the Fan Gang marketization indicator served as a representative for marketization levels, and control variables were integrated into the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

model. *Table 11* displays regression analysis findings. It indicates that after incorporating market condition control variables, the p-value is 0.005, which is statistically significant at 1% confidence level. The conclusion regarding the climate risk's influence on the operating efficiency of fisheries firms remains unchanged, with the climate risk coefficient still significantly positive, confirming the robustness of the original conclusion.

Table 11. *Adding market conditions as control variables*

Variable	**Crste**			
	Coefficient	**Standard error**	**t**	**p**
Climate risk	-94.823***	33.383	-2.84	0.005
Mshare	0.494	0.312	1.58	0.114
EM	0.010	0.009	1.03	0.303
Cashflow	0.120	0.418	0.29	0.773
Top1_w	-0.979**	0.418	-2.34	0.019
Market	0.176***	0.059	2.99	0.003
Constant	0.209	0.387	0.54	0.589
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(3) Replace explanatory variables

To ensure the reliability of the conclusions regarding the impact of baseline regression climate risks on the operational efficiency of fishery enterprises, this study references the research approach and methodology of Guo et al. (2024) in constructing a climate physical risk index. By incorporating the regional attributes of the provinces where fishery enterprises are located and replacing core explanatory variables, robustness tests are conducted. Given the multidimensional nature of climate risk, this study constructs provincial-level proxy indicators for climate risk across three dimensions: comprehensive dimension, physical impact dimension, and system vulnerability dimension, as shown in *Table 12*. After matching these indicators to the provinces where the enterprises are located, the baseline model is regressed again, as detailed below.

(a) Development and regression of the comprehensive climate risk index

First, comprehensively considering the dual attributes of meteorological physical impacts and systemic vulnerability in climate risk, a comprehensive climate risk index at the provincial level was developed. This index system comprises two core dimensions with 18 foundational indicators, all calculated based on relevant data from all provinces in China:

In the meteorological factors dimension, referencing the methodology of Guo et al. (2024), the following indicators were selected: extreme low temperature days (LTD), extreme high temperature days (HTD), extreme rainfall days (ERD), and extreme drought days (EED). Specifically, based on daily average observational data from national meteorological stations, extreme climate events were defined using a quantile threshold method and then weighted and synthesized to accurately reflect the intensity of physical climate impacts across provinces. The remaining four indicators were also aggregated and calculated based on provincial meteorological observation data.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

Table 12. *Indicator name and definition*

Climate risk		Variable	Variable name	Variable description
Meteorological factors		LTD	Extreme cold days (days)	
		HTD	Extreme heat days (days)	
		ERD	Extreme rainfall days (days)	
		EED	Extreme drought days (days)	
Vulnerability factors	Social vulnerability	PopVulIndex	Population vulnerability index (%)	Population under 15 and over 65 / Total Population × 100
		LivVulIndex	Livelihood vulnerability index (%)	Household dependency ratio
		PopEduIndex	Population education index (%)	Illiteracy rate
		PubHealAdapIndex	Public health adaptability index (per capita)	Physicians per 1000 people
		SocialEquityIndex	Social equity index (%)	Urban per capita disposable income / Rural per capita disposable income × 100
		DisSenIndex	Disaster vulnerability index (%)	Affected population / Total population × 100
	Economic vulnerability	EconSenIndex	Economic vulnerability index (%)	Direct economic losses from natural disasters / Regional GDP × 100
		ClimSenInduIndex	Climate-sensitive industries index (%)	Share of primary industry in GDP
		EconAdapIndex	Economic adaptability index (yuan)	Per capita GDP
		ClimProtCapIndex	Climate resilience index (%)	Adaptation investment / Regional fiscal expenditure × 100. “Adaptation investment” is defined as “public expenditure in areas such as environmental protection, healthcare, agriculture, forestry, water conservancy, land resources, and meteorology”
	Environmental vulnerability	ClimateSecurityIndex	Climate security index (billion yuan/hectare)	Direct economic losses from natural disasters / Arable land area
		NatResEndIndex	Natural resource endowment index (%)	Forest coverage rate
		WaterSecurityIndex	Water security index (%)	Per capita water consumption / Per capita water resources × 100

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

The vulnerability dimension is subdivided into three sub-dimensions: social vulnerability, economic vulnerability, and environmental vulnerability. It encompasses 13 indicators, including the Population Vulnerability Index (PopVulIndex), Economic Sensitivity Index (EconSenIndex), and Climate Security Index (ClimateSecurityIndex). All indicators are calculated using provincial statistical data, comprehensively characterizing the systemic resilience level of provinces where fishery enterprises are located in coping with climate impacts.

For these provincial-level foundational indicators, this study adopts the entropy weighting method to determine objective weights for each indicator, referencing the research of Wang et al. (2025). The weighted calculation yields the comprehensive climate risk score (CR_All) for each province. In regression analysis, the core explanatory variable is matched to the corresponding provincial score based on the registered location of the sample enterprises, replacing the climate risk word frequency indicator in the baseline regression. As shown in *Table 13*, the estimated coefficients for CR_All maintain consistent signs with the benchmark regression and are statistically significant in the negative direction. This indicates that the impact of climate risk on the operational efficiency of fishery enterprises remains stable regardless of whether text word frequency proxies or composite provincial multidimensional objective indicators are used.

Table 13. *Comprehensive climate risk indicator*

Variable	**Crste**			
	Coefficient	**Standard error**	**t**	**p**
CR_All	-4.121***	0.315	-13.06	0.000
Mshare	0.558	0.379	1.47	0.141
EM	0.030***	0.002	16.09	0.000
Cashflow	-3.441***	0.524	-6.56	0.000
Top1_w	0.362***	0.115	3.16	0.002
Constant	1.677***	0.131	12.82	0.000
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(b) Development and regression analysis of climate-physical risk indicators at the meteorological factor level

Focusing on the core drivers of climate risk—meteorological physical impacts—we construct provincial-level climate physical risk indicators. Referencing the criteria of Guo et al. (2024) for defining extreme climate events, we select four key indicators: extreme rainfall days (ERD), and extreme drought days (EED). Raw values were aggregated from provincial meteorological observation data, standardized, and then synthesized using simple arithmetic averaging to form the provincial climate physical risk index (CPRI). This index reflects the intensity of regional extreme climate events based on actual meteorological station data, enabling the pure capture of direct impacts from provincial climate physical shocks on local fishery enterprises.

In the regression analysis, the scores corresponding to the provinces where the enterprises are located were matched as core explanatory variables and substituted into the baseline model for re-regression. As shown in *Table 14*, the coefficient for climate physical risk at the meteorological factor level is significantly negative. This result

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

validates that climate physical risk at the meteorological factor level, as a core component of climate risk, exerts a direct impact on the operational efficiency of fisheries enterprises in the province where the enterprise is located. It also aligns with the conclusion emphasized by Guo et al. (2024) that "regional physical risk indicators constructed based on meteorological observation data exhibit higher accuracy and consistency."

Table 14. *Climate-related physical risks at the meteorological factor level*

Variable	Crste			
	Coefficient	**Standard error**	**t**	**p**
CR_All	-0.037***	0.009	-4.18	0.000
Mshare	0.664	0.426	1.56	0.119
EM	0.052***	0.011	4.56	0.000
Cashflow	-2.430***	0.772	-3.15	0.002
Top1_w	0.018	0.543	0.03	0.973
Constant	3.473***	0.604	5.75	0.000
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(c) Construction and regression of the comprehensive climate vulnerability index

Focusing on the transmission pathway of climate risks—systemic vulnerability—this study constructs a comprehensive climate vulnerability index at the provincial level. After excluding meteorological factors, 13 foundational indicators across three categories—social vulnerability, economic vulnerability, and environmental vulnerability—were selected. All indicators were calculated using provincial statistical data. Following Wang et al.'s (2025) methodology, entropy weighting was applied to determine indicator weights, yielding weighted composite climate vulnerability scores (CR_Vul) for each province. This indicator reflects each province's sensitivity and adaptive capacity to climate shocks in terms of population structure, economic foundation, and environmental carrying capacity. It serves as a crucial moderator and transmission channel for climate risk impacts on fishery enterprises within the region.

During regression analysis, the corresponding provincial score was matched to the enterprise's location and used as the core explanatory variable to re-estimate the baseline model. As shown in *Table 15*, the estimated coefficient for CR_Vul is significant and maintains the same sign as in the baseline regression. This indicates that climate vulnerability, as a key dimension of climate risk, exerts a stable effect on the operational efficiency of fisheries enterprises in the respective provinces by amplifying or mitigating the impacts of physical shocks. This further corroborates the multiple pathways and robustness through which climate risk influences the operational efficiency of fisheries enterprises.

In summary, regression analyses conducted after matching enterprises to their provincial locations yield results highly consistent with the benchmark regression conclusions—whether using the integrated climate risk index combining provincial meteorological and vulnerability factors, the climate physical risk index based on provincial meteorological observations, or the climate vulnerability index reflecting provincial systemic resilience. Combined with the scientific methodology for constructing provincial climate physical risk indices proposed by Guo et al. (2024), this

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

study's robustness tests not only validate the reliability of core conclusions but also precisely capture the regional transmission effects of climate risks on fishery enterprise operational efficiency through provincial multidimensional indicator decomposition and enterprise-region matching design, thereby enhancing the persuasiveness of the research findings.

Table 15. *Composite climate vulnerability index*

Variable	Crste			
	Coefficient	Standard error	t	p
CR_All	-4.100***	0.092	-44.55	0.000
Mshare	0.762	0.058	13.20	0.000
EM	0.021***	0.001	15.10	0.000
Cashflow	-3.370***	0.154	-21.92	0.000
Top1_w	0.068	0.068	1.00	0.317
Constant	1.566***	0.046	34.06	0.000
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Moderation effect analysis

(1) The moderating effect of digital transformation

To measure the degree of digital transformation in fishery enterprises, this research referenced a research framework proposed by Zhao (2021), focusing on four core components: digital technology application, internet business models, smart manufacturing, and modern information systems. This study counted the frequency of relevant keywords in annual reports to quantify degree of transformation in each area. Based on this, word frequency data was standardized to eliminate unit effects, and the entropy method was applied to ascertain the weights of each dimension's indicators. Ultimately, a comprehensive DIGI_text index was constructed to stand for the digital transformation's degree of fishery firms. To examine whether the digital transformation of fishery companies affects the influence of climate risk on their operational efficiency, this paper presents the following model:

$$\begin{aligned} Crste_{it} = \beta_0 + \beta_1 \text{Climate risk}_{it} + \beta_2 digtal + \beta_3 \text{Climate risk}_{it} \times digtal \\ + \beta_4 Mshare_{it} + \beta_5 Em_{it} + \beta_6 Cashflow_{it} + \beta_7 Top1_{it} + \delta_t + \varepsilon_{it} \end{aligned} \quad \text{(Eq.6)}$$

Among these variables, digital is the variable used to evaluate the extent of a company's digital transformation, while the remaining variables remain consistent with the baseline regression model. Based on the analysis above, climate risks can significantly reduce the operating performance of Chinese listed fishing companies. Technological developments and an increasing degree of digital transformation within companies will have an impact on the effect of climate risk on operational efficiency. Enterprises with a higher degree of digital transformation leverage digital technologies to achieve precise monitoring and control of aquaculture environments, overcoming natural constraints to increase output. Additionally, they utilize smart devices to optimize processes such as feed distribution and disease prevention, reducing labor costs and operational errors.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

Furthermore, they employ data-driven approaches to optimize supply chain management, enhancing logistics and sales efficiency. The regression outcomes are demonstrated in *Table 16*. The estimated coefficient of interaction term "Climate Risk × digital" is considerably positive at 1% degree, revealing that the negative influence of climate risk on the operational performance of Chinese fishing firms weakens with the rising level of digital transformation.

Table 16. *Digital transformation as a moderating effect*

Variable	Crste			
	Coefficient	**Standard error**	**t**	**p**
Climate risk	-0.008	0.010	-0.86	0.391
Dig	-0.030***	0.009	-3.35	0.001
Climate risk*dig	0.022***	0.008	2.80	0.005
Mshare	0.227***	0.060	3.77	0.000
EM	0.003***	0.001	2.77	0.006
Cashflow	0.072	0.104	0.69	0.487
Top1_w	0.011	0.087	0.12	0.902
Constant	0.905***	0.040	22.36	0.000
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(2) The moderating effect of ESG

In order to examine whether fishery enterprises with high ESG ratings are affected by climate risks in terms of their operational efficiency, this paper constructs the following model:

$$\begin{aligned} Crste_{it} &= \beta_0+\beta_1 Climate\ risk_{it}+\beta_2 ESG+\beta_3 Climate\ risk_{it}\times ESG \\ &+\beta_4 Mshare_{it}+\beta_5 Em_{it}+\beta_6 Cashflow_{it}+\beta_7 Top1_{it}+\delta_t+\varepsilon_{it} \end{aligned} \quad \text{(Eq.7)}$$

Among these, ESG serves as the variable for measuring a company's ESG performance, while the remaining variables align with those of the benchmark regression model.

Based on the preceding analysis, climate risks can considerably reduce operational performance of Chinese listed fishing companies, while enterprises with higher ESG levels not only focus on sustainable fishing and aquaculture in environmental aspects, reasonably utilize resources, reduce negative impacts on the environment, and ensure long-term stable fishery production, but also prioritize employee welfare and training in social aspects, enhance employee satisfaction and loyalty, and improve work efficiency. Additionally, in governance aspects, they improve corporate governance structures and risk management systems to ensure scientific decision-making, standardized operations, effectively reduce operational risks, and promote the overall improvement of corporate operational efficiency. This study utilizes ESG rating data from the CNRDS database, where higher values indicate higher ESG ratings, stronger ESG levels, and better ESG performance. These are treated as moderating variables, and regression outcomes are listed in *Table 17*. The interaction term "Climate Risk × ESG" reveals a notably positive coefficient, with statistical significance at

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

the 1% level. This indicates that as a company's ESG level improves, the climate risk's negative influence on the operating performance of fishing firms is mitigated. This suggests that fishery enterprises with good ESG performance have effectively enhanced their resilience to climate risks through environmental governance, fulfillment of social responsibilities, and improved corporate governance, thereby mitigating the climate risk's impact on their operations. Although the individual impact of ESG on corporate operational efficiency does not reach a significant level, its interaction with climate risk highlights the strategic value of ESG in risk management.

Table 17. *ESG as a moderating effect*

Variable	Crste			
	Coefficient	Standard error	t	p
Climate risk	0.002	0.009	0.26	0.796
ESG	0.006	0.009	0.62	0.533
Climate risk*ESG	0.024***	0.008	3.02	0.003
Mshare	0.220***	0.060	3.67	0.000
EM	0.003***	0.001	3.01	0.003
Cashflow	0.070	0.106	0.67	0.504
Top1_w	-0.016	0.086	-0.19	0.852
Constant	0.943***	0.040	23.61	0.000
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Further analysis

The aforementioned benchmark regression and moderation effect analysis confirms that climate risk exerts a significant direct impact on corporate operational efficiency. However, this conclusion does not yet reveal its underlying mechanism: climate risk is a multidimensional concept, and its various components may exhibit systematic differences in the pathways through which they affect enterprises and in the intensity of their impacts. Based on the mainstream classification framework in current climate risk research, this study categorizes climate risk into two major types: physical risk and transition risk. Physical risk involves the physical impacts of extreme weather events or chronic conditions; Transition risks refer to the financial and operational risks enterprises face during the transition to a low-carbon economy due to policy and regulatory adjustments, technological shifts, changing market preferences, and reputational pressures (TCFD, 2017). These risks stem from the transition process itself and are primarily driven by policy regulations, societal expectations, and pressures. Additionally, drawing on the research of Li et al. (2020), physical risks are further subdivided into acute risks and chronic risks. Acute risks denote direct impacts on corporate assets and supply chains caused by sudden, high-intensity extreme weather events (typhoons, floods, storm surges). Chronic risks represent systemic threats to operational environments and resource foundations stemming from long-term, gradual climate change trends (persistent sea temperature rise, ocean acidification, sea level elevation).

The lexicon construction and classification methodology in this paper primarily references the established paradigm developed by Du et al. (2023) for analyzing annual reports of Chinese listed companies. First, based on the TCFD framework and the Chinese

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

context, a preliminary set of seed keywords related to the three risk categories was identified. For example, transition risks focus on terms like “low-carbon,” “emission reduction,” “green transition,” and “carbon emission rights”; severe risks focus on “typhoons,” “flooding,” “extreme weather,” and ‘disasters’; chronic risks center on “water temperature,” “acidification,” “sea level,” and “long-term changes.” Second, drawing from the combined text analysis and machine learning approach used in that literature, the seed sets were expanded and optimized to ensure the dictionary’s completeness and contextual adaptability. Finally, three independent keyword libraries were formed. Through full-text analysis of sample companies’ annual reports, the total frequency of each keyword in the sub-libraries was calculated. Quantitative indicators for transition risks, acute risks, and chronic risks were constructed based on the proportion of each keyword’s frequency relative to the total word count in the annual reports. Higher values indicate greater risk exposure in that dimension. Based on this, we conducted regression analyses on equations (8), (9), and (10) to systematically examine the differential impacts of various climate risks on the operational performance of Chinese listed fishery companies.

$$\begin{aligned}Crste_{it}=\beta_0+\beta_1 Severe\ risk_{it}+\beta_3 Mshare_{it}+\beta_4 Em_{it}\\ +\beta_5 Cashflow_{it}+\beta_6 Top1_{it}+\delta_t+\varepsilon_{it}\end{aligned} \quad \text{(Eq.8)}$$

$$\begin{aligned}Crste_{it}=\beta_0+\beta_1 Chronic\ risk_{it}+\beta_3 Mshare_{it}+\beta_4 Em_{it}\\ +\beta_5 Cashflow_{it}+\beta_6 Top1_{it}+\delta_t+\varepsilon_{it}\end{aligned} \quad \text{(Eq.9)}$$

$$\begin{aligned}Crste_{it}=\beta_0+\beta_1 Transition\ risk_{it}+\beta_3 Mshare_{it}+\beta_4 Em_{it}\\ +\beta_5 Cashflow_{it}+\beta_6 Top1_{it}+\delta_t+\varepsilon_{it}\end{aligned} \quad \text{(Eq.10)}$$

Tables 18–20 present regression results of the influence of transition risks, chronic risks, and severe risks on the operating performance of listed Chinese fisheries enterprises. The findings indicate a positive coefficient for transition risks, statistically significant at 5% level, implying that transition risks are an important factor influencing the operating performance of listed Chinese fishing companies. The coefficients for severe risks and chronic risks are not significant, suggesting that physical risks within climate risks do not significantly impact operational performance of listed Chinese fishery enterprises. The reason lies in the important negative influence of transition risks on the operational effectiveness of listed fishing companies in China, which stems from direct compliance cost pressures and changes in market demand. For example, the short-term increase in corporate burdens resulting from technological upgrades and green certification requirements under the “dual carbon” goals, coupled with consumers’ and investors’ preferences for sustainable fisheries, further amplifies the pressure for transition.

In contrast, the influence of physical risks (involving severe risks and chronic risks) is not significant. On the one hand, this is because fishery enterprises have adapted to gradual climate change or sudden disasters by adjusting their operational areas, relying on insurance and government subsidies. On the other hand, the long-term and dispersed nature of physical risks smooths out their impacts, while policy buffers (such as fuel subsidies and disaster compensation) further weaken their short-term effects. Additionally, the influence of physical climate risks on corporate operational efficiency may be lagged and long-term rather than directly affecting current operational efficiency. For example, abnormal weather

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

conditions in ZONECO occurred early on (such as in 2014), but their significant negative impact on the company's financial indicators was not fully reflected until subsequent years (such as 2016-2018). This reflects how physical climate risks exert a long-term influence on business efficiency, with a lag of 3-5 years, through channels such as destroying aquaculture resources and increasing remediation costs.

Table 18. *Impact of transformation risks on the operational efficiency of listed Chinese fisheries companies*

Variable	**Crste**			
	Coefficient	**Standard error**	**t**	**p**
Transit Risk	-88.799**	39.131	-2.27	0.023
Mshare	0.712*	0.416	1.71	0.087
EM	0.022*	0.014	1.61	0.107
Cashflow	0.159	0.490	0.32	0.746
Top1_w	-1.000	0.688	-1.45	0.146
Constant	1.824***	0.368	4.96	0.000
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 19. *Impact of chronic risks on the operational efficiency of listed Chinese fishing companies*

Variable	**Crste**			
	Coefficient	**Standard error**	**t**	**p**
Chronic Risk	-227.326	266.619	-0.85	0.394
Mshare	0.432	0.447	0.97	0.333
EM	0.031**	0.014	2.24	0.025
Cashflow	0.426	0.639	0.67	0.505
Top1_w	-0.189	0.650	-0.29	0.771
Constant	1.253***	0.294	4.26	0.000
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 20. *Impact of severe risks on the operational efficiency of listed Chinese fisheries companies*

Variable	**Crste**			
	Coefficient	**Standard error**	**t**	**p**
Severe Risk	-280.572	400.279	-0.70	0.483
Mshare	0.640	0.491	1.30	0.192
EM	0.025*	0.013	1.95	0.051
Cashflow	0.777	0.680	1.14	0.253
Top1_w	-0.334	0.637	-0.52	0.600
Constant	1.282***	0.297	4.32	0.000
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

Analysis of economic consequences

The preceding discussion reveals that transition risks are the core direct factor suppressing corporate efficiency. Does this micro-level efficiency loss induced by climate risks also generate broader macro-level consequences? This section explores how the aforementioned direct impacts can further produce indirect negative spillover effects on local ecosystems by altering firms' production behaviors. As production entities reliant on natural resources, fishery enterprises exhibit a close correlation between fluctuations in their operational efficiency and the quality of the ecological environment. To reveal the extended effects of this impact, this study adopts the research approach of Reich et al. (2024), which measures ecosystem impacts using CO_2 emissions. It employs the CO_2 emissions of the city where the enterprise is located as a core proxy indicator for ecosystem status, empirically testing the indirect economic consequences of climate risks on ecosystems through the suppression of fishery enterprise operational efficiency.

On one hand, climate risks significantly reduce the operational efficiency of fishery enterprises by damaging fishery resource endowments through extreme weather events and increasing input costs for production factors. To alleviate the profitability pressure caused by declining efficiency, enterprises may tend to adopt extensive production strategies, such as expanding fishing scale, increasing the frequency of energy-consuming equipment use, and reducing environmental protection investment intensity, thereby compensating for operational losses at the expense of the ecological environment. On the other hand, diminished operational efficiency weakens enterprises' capacity for sustainable development, leaving them with insufficient funds and motivation to pursue green production technology R&D or ecological conservation investments, thereby further exacerbating ecological burdens. As a direct emission resulting from energy consumption and extensive operations in enterprise production activities, CO_2 emissions serve as a tangible indicator of the impact of enterprise operations on ecosystems. Therefore, this study selects this metric as the benchmark for measuring ecosystem status.

To precisely identify the transmission pathway "climate risk → fishery enterprise operational efficiency → CO_2 emissions," this study adopts a two-stage regression method, referencing the research by Yongtae et al. (2020). In the first stage, a core Tobit regression model is used to estimate the impact of climate risk on fishery enterprise operational efficiency. The model's predicted value—the operational efficiency forecast (Crste_hat)—is extracted. This forecast value purely reflects the direct inhibitory effect of climate risk on enterprise operational efficiency. In the second stage, the predicted value of operational efficiency is regressed against a proxy variable for ecosystem health (CO_2 emissions) to examine the indirect impact of climate risk on ecosystems after suppressing fishery enterprise operational efficiency.

Table 21 shows that the coefficient for Crste_hat is significantly positive at the 1% level, indicating that climate risks significantly increase CO_2 emissions in the cities where fishing enterprises are located by suppressing their operational efficiency. In other words, the lower the operational efficiency of fishing enterprises, the higher the CO_2 emission intensity in their respective cities. This finding validates that the negative impact of climate risk on enterprise operational efficiency transmits to ecosystems through extensive production practices and insufficient environmental investments, ultimately exacerbating CO_2 emissions and causing adverse ecological consequences.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

Table 21. *Analysis of economic consequences*

Variable	CO_2			
	Coefficient	**Standard error**	**t**	**p**
Crste_hat	1.417***	0.417	3.40	0.001
Mshare	-0.503	0.487	-1.03	0.305
EM	-0.027***	0.009	-2.85	0.006
Cashflow	0.020	0.983	0.02	0.984
Top1_w	0.723	0.624	1.16	0.251
Year	Control	Control	Control	Control

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Discussion

This study employs Data Envelopment Analysis (DEA-BCC) and Malmquist efficiency indicators to conduct static and dynamic evaluations of fishery enterprises' operational efficiency. It further utilizes a Tobit random effects model to empirically analyze the relationship between climate risk and the operational efficiency of seven listed Chinese fishery enterprises from 2012 to 2023, while exploring its transmission mechanisms and economic consequences. The findings hold significant theoretical and practical implications:

First, regarding the efficiency status of fishery enterprises, both static and dynamic analyses indicate that the comprehensive efficiency, pure technical efficiency, and scale efficiency of China's listed fishery companies all fall below the efficient frontier, with total factor productivity (TFP) exhibiting a declining trend. Malmquist index decomposition reveals that the decline in TFP primarily stems from the recession of technical progress rather than scale inefficiency. This finding aligns with existing research emphasizing the critical role of technological capabilities in enhancing fishery productivity (Idda et al., 2009; Elhendy, 2012). It indicates that operational inefficiency in Chinese fishery enterprises stems more from deficiencies in production technology and management practices than from inappropriate business scale. Therefore, expanding scale without concurrent technological upgrading and management optimization cannot achieve sustainable efficiency gains. This indicates that fisheries enterprises need to increase R&D investment to promote the application and innovation of aquaculture technologies, intelligent equipment, and digital management systems in fishery production, thereby reversing the trend of technological decline.

Second, regarding the impact of climate risk, both baseline regression analysis and robustness tests indicate that climate risk significantly weakens the operational efficiency of fisheries enterprises. By decomposing climate risk, we find that the negative impact primarily stems from transition risk, while the effect of physical risk is not statistically significant. This finding contrasts sharply with numerous existing studies focusing on physical risks (Yin et al., 2025; Islam et al., 2024). The dominance of transition risks can be attributed to their more direct and pervasive impact channels. Policies such as carbon emission regulations and international green trade barriers directly elevate compliance costs and alter market access, exerting uniform pressure on corporate management efficiency. In contrast, the effects of physical risks are mitigated through ex-post measures or exhibit longer lag effects, obscuring their immediate impact on annual efficiency metrics. This elucidates the core transmission pathways through which climate

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

risks affect business operations, indicating that the transition pressures currently represent the central challenge for fisheries enterprises.

Third, this study finds that both digital transformation and enhanced ESG performance significantly mitigate the negative impact of climate risks on the operational efficiency of fisheries enterprises. Digital technologies enhance resilience by enabling real-time monitoring of aquaculture environments for physical risk early warning and optimizing supply chains to mitigate policy-induced disruptions. Concurrently, strong ESG performance helps enterprises gain policy preferences, ease financing constraints, and improve resource allocation efficiency through standardized environmental management and sustainable practices, thereby strengthening overall risk buffering capacity. Collectively, technological reinforcement and ESG performance enhancement constitute vital strategies for fisheries enterprises to address climate risks and enhance climate resilience.

Fourth, further economic consequence analysis indicates that the negative impact of climate risks on fishery enterprises' operational performance will indirectly elevate carbon dioxide emissions in their host cities. Specifically, by extracting operational efficiency projections under climate risk impacts and regressing them against urban CO_2 emissions, we find that efficiency losses caused by climate risks induce enterprises to adopt extensive production behaviors (such as expanding fishing scale and increasing energy consumption), ultimately harming ecosystems. This finding reveals the transmission pathway of climate risks from micro-level enterprise operations to macro-level ecological environments, enriching the practical significance of this study in the field of ecological conservation.

This research shifts the perspective of climate risk studies from the macro-level resource dimension to the micro-level enterprise efficiency dimension. It empirically validates the dominant role of transition risks while revealing the role of digital transformation and enhanced ESG performance in helping fishery enterprises cope with climate risks. However, this study still has several limitations, pointing the way for future research. Specifically: First, the sample comprises only seven listed fishery companies. While representative, the small sample size may limit the observation of specific effects. Future research could expand to include unlisted or small-scale fishery enterprises to enhance the generalizability of findings. Second, digital transformation is treated as a composite indicator. Subsequent studies could differentiate between various digitalization modes (production digitalization and management digitalization) to examine heterogeneous impacts. Finally, the transmission mechanisms explored here remain incomplete. Other potential mediating variables—such as corporate innovation capabilities or supply chain collaboration—warrant further investigation.

Conclusion and policy recommendations

Conclusion

This research utilizes DEA-BCC and Malmquist index analysis to conduct static and dynamic assessments of the operating performance of fishing companies, and utilizes the Tobit random effects model to empirically analyze the relationship between climate risks from 2012 to 2023 and the operating performance of seven listed Chinese fishing companies. The details are as follows:

(1) The comprehensive, average technical, and scale efficiencies of Chinese fisheries companies from 2012 to 2023 were all less than 1, with average scale efficiency exceeding average technical efficiency. This suggests that operating performance losses

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

of Chinese listed fishery companies are primarily attributed to deficiencies in technology and management. If these companies rely solely on scale expansion while neglecting technological upgrades and management optimization, they may struggle to improve operational efficiency significantly. Therefore, companies should prioritize optimizing production processes, introducing advanced aquaculture or fishing technologies, and strengthening supply chain management to improve resource utilization efficiency.

(2) The average TFP index of Chinese listed fishing firms between 2012 and 2023 was less than 1, suggesting that the production efficiency of fisheries firms shows a decreasing trend. Through Malmquist index decomposition, it was found that a decrease in total factor efficiency is mainly due to a diminish in the technological progress indicator, indicating that while some companies have optimized the application of existing technologies, the industry as a whole lacks sufficient technological innovation capabilities. Therefore, fishery enterprises need to increase R&D investments and promote the adoption of digital technologies such as automation, Internet of Things, and artificial intelligence in fishery production to reverse the trend of technological decline.

(3) Climate risks can considerably reduce the operating performance of Chinese listed fishing enterprises, and this negative impact remains robust after a series of robustness tests (including replacing core explanatory variables with a comprehensive climate risk index constructed by entropy weight method, and adding control variables). Additionally, climate risks are categorized into physical risks and transition risks. Empirical tests reveal that the negative influence of climate risks on the operational performance of fisheries companies is caused by transition risks, which stem from direct compliance cost pressures and changes in market demand.

(4) Implementing a digital transformation strategy can significantly mitigate the climate risk's influence on operating performance of Chinese fisheries companies. This indicates that digital technologies not only enhance production efficiency but also strengthen companies' resilience to climate uncertainties, thereby promoting overall efficiency improvements. Therefore, policymakers may consider providing subsidies or tax incentives to encourage fishery enterprises to accelerate their digital transformation.

(5) Strong ESG performance can also significantly mitigate the climate risk's influence on the operating performance of listed Chinese fisheries companies. This finding supports the notion that "sustainability equals competitiveness," indicating that fishery enterprises can reduce operational risks and attract long-term investors through ESG practices such as ecological farming.

(6) Further economic consequence analysis shows that the negative impact of climate risks on the operating performance of fishery enterprises will indirectly promote the increase of CO_2 emissions in the cities where the enterprises are located. Specifically, by extracting the predicted value of operating efficiency affected by climate risks and regressing it on urban CO_2 emissions, it is found that the efficiency loss caused by climate risks will induce enterprises to adopt extensive production behaviors (such as expanding fishing scale and increasing energy consumption), which ultimately imposes a negative impact on the ecosystem. This result reveals the transmission path of climate risks from micro-enterprise operations to the macro-ecological environment, enriching the practical implications of this research in the field of ecological protection.

Policy recommendations and global implications

In view of the research conclusions mentioned above, we have put forward the following policy recommendations:

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

(1) In terms of technological innovation and digital transformation, it is important to establish a government-enterprise collaborative technological innovation system and promote industrial upgrading through a dual-pronged approach of "bringing in" and "independent innovation." On the one hand, we should introduce advanced production technologies and equipment from both domestic and international sources. On the other hand, we should encourage internal R&D efforts by establishing a fisheries science and technology innovation alliance led by the government, integrating the R&D capabilities of universities, research institutions, and enterprises to focus on breakthroughs in key areas such as intelligent aquaculture equipment and precision fishing technology. Additionally, we should provide subsidies to enterprises adopting digital technologies, establish fisheries digitalization demonstration bases, and promote the application of mature technologies. Notably, digital transformation should also focus on reducing carbon emissions—for example, promoting energy-saving intelligent equipment and optimizing production processes to curb the extensive production behaviors induced by efficiency losses, thereby aligning technological upgrading with ecological protection.

(2) In response to climate risks, enterprises need to establish a multi-tiered risk management system, combining technological innovation, financial support, and policy guidance to enhance risk-resilience comprehensively. Research indicates that a well-established risk management mechanism can significantly reduce efficiency losses caused by climate anomalies. In terms of financial tool innovation, efforts should be focused on developing climate insurance products, creating index-based insurance products based on objective parameters such as water temperature, typhoon paths, and wave heights, and establishing a rapid claims settlement mechanism. Additionally, the national government should provide a 30%-50% subsidy on premiums to reduce the cost of insurance participation for enterprises. In terms of technical prevention, it is recommended to integrate monitoring methods such as satellite remote sensing, ocean buoys, and shore-based radar to establish a national fishery disaster warning platform, achieving 72-hour precise warnings for disasters such as typhoons, red tides, and oxygen depletion, and pushing real-time alerts to aquaculture enterprises through multiple channels such as mobile apps and SMS. The relevant government authorities should take the lead in formulating the "Technical Specifications for Climate-Adaptive Aquaculture," imposing mandatory technical standards on aquaculture enterprises in high-risk areas, including the installation of emergency aeration equipment, the construction of deep-water net pens capable of withstanding winds and waves exceeding 12 on the Beaufort scale, and the establishment of real-time monitoring systems for aquaculture environments. Compliance with these technical standards should be linked to policies such as marine area usage approvals and fiscal subsidies to create an incentive and constraint mechanism. Furthermore, climate resilience demonstration zones should be established in key aquaculture areas to promote adaptive technologies such as deep-water net pens resistant to wind and waves and ecological breakwaters, providing replicable models for the entire country.

(3) In terms of ESG, improving the ESG performance of listed fishing enterprises is very important. Firstly, the China Securities Regulatory Commission (CSRC) should establish a dedicated "Guidelines for ESG Information Disclosure by Listed Fisheries Companies," mandating disclosure of core indicators such as carbon emissions intensity and aquaculture wastewater treatment rates, and establishing a third-party verification mechanism; Secondly, implement differentiated incentive policies, providing green approval channels and corporate income tax reductions for companies with ESG ratings

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

of AA or above, and incorporating ESG indicators into executive performance evaluations with a weighting of no less than 20%; Thirdly, promote green financial innovation, support the issuance of blue bonds for ecological aquaculture upgrades, develop ESG-linked loan products, and establish a fisheries green development fund; Fourthly, strengthen ecological protection by formulating the "Technical Specifications for Ecological Aquaculture," establishing an ecological compensation mechanism, and conducting pilot projects for fisheries carbon sink calculations; Fifthly, enhance social responsibility by implementing a fisherman training program, establishing a full-process traceability system, and regularly publishing social responsibility reports; Finally, strengthen alignment with international standards by encouraging the acquisition of MSC/ASC certifications, participating in the formulation of international ESG standards, and collaborating with multinational retailers to build green supply chains. Through a combination of institutional constraints, market incentives, and technological innovation, the ESG performance of fishery enterprises can be comprehensively improved, driving sustainable advancement of the industry.

The empirical analysis of research explores the influence of climate risks on the operating efficiency of listed fishing companies in China, not only providing a scientific basis for the superior advancement of the Chinese fishery industry but also contributing important knowledge reserves for the global blue economy transition through its research framework and methodology.

From an international comparative perspective, the study reveals significant cross-border implications: For developed countries like Norway and Canada, China's innovative practices in climate-adaptive aquaculture technologies and low-cost digital solutions can complement their advanced manufacturing advantages, jointly improving the global fisheries climate risk management system; For developing countries like Vietnam and Indonesia, China's experience in establishing a collaborative innovation mechanism featuring "government guidance, enterprise leadership, and research support," as well as promoting "digital demonstration bases," is particularly worth learning from. These countries can adapt to local conditions by prioritizing the introduction of low-cost water quality monitoring equipment and wave-resistant aquaculture facilities developed in China, while also referencing China's disaster warning and response mechanisms. Notably, our findings on the "climate risk → enterprise efficiency loss → CO_2 emission increase" transmission path provide a critical reference for global fisheries to balance economic development and ecological protection—developing countries can avoid repeating the "extensive production at the cost of ecology" model by learning from China's integrated policies of technological upgrading, ESG enhancement, and carbon emission control. In the future, they can leverage international platforms such as World Bank technical assistance projects and the Global Environment Facility (GEF) to transform China's climate resilience-building solutions into international public goods. Three specific pathways can be adopted: Firstly, compile a "Fisheries Climate Adaptation Technology Guide" to systematically summarize China's experience; Secondly, establish a "South-South Cooperation Fisheries Transformation Fund" to support technology introduction in developing countries; Thirdly, establish a transnational fisheries technology innovation alliance to promote global knowledge sharing and technical collaboration in addressing climate change. This knowledge transformation process will effectively advance the achievement of the United Nations Sustainable Development Goal (SDG 14) and provide Chinese wisdom and solutions for the global blue economy transition.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852

Acknowledgements. We acknowledge the support from: The National Social Science Fund of China; Humanities and Social Science Fund Project of the Ministry of Education of China (Grant No. 24YJC630185); Shandong Provincial Natural Science Foundation (Grant No. ZR2022QG020); Key R&D Program (Soft Science Project) of Shandong Province (Grant No. 2024RKY0304). Their funding has been essential to our research.

REFERENCES

[1] Akoglu, E., Saygu, I., Demirel, N. (2024): Decadal changes in the Sea of Marmara indicate degraded ecosystem conditions and unsustainable fisheries. – Frontiers in Marine Science 11: 1412656. https://doi.org/10.3389/FMARS.2024.1412656.

[2] Chen, Q. (2014): Advanced Econometrics and Stata Application. 2nd Ed. – Higher Education Press, Beijing.

[3] Drexler, M., Cerny-Chipman, E. B., Peterson Williams, M. J., Moore, M., Ridings, C. (2025): Harnessing the value of near-term actions for achieving climate-ready fishery management. – Frontiers in Marine Science 12: 1558251. https://doi.org/10.3389/FMARS.2025.1558251.

[4] Du, J., Xu, X. Y., et al. (2023): Does climate risk affect equity capital costs? Empirical evidence from text analysis of annual reports of Chinese listed companies. – Financial Review 15(3): 19-46 + 125 (in Chinese).

[5] Elhendy, A. M., Alkahtani, S. H. (2012): Efficiency and productivity change estimation of traditional fishery sector at the Arabian Gulf: the Malmquist productivity index approach. – Journal of Animal and Plant Sciences 22(2).

[6] FAO (2022): The State of World Fisheries and Aquaculture 2022. Towards Blue Transformation. – FAO, Rome. https://doi.org/10.4060/cc0461en.

[7] FAO (2024): The State of World Fisheries and Aquaculture 2024. Blue Transformation in action. – FAO, Rome. https://doi.org/10.4060/cd0683en.

[8] Färe, R., Grosskopf, S., Lindgren, B., Roos, P. (1994): Productivity Developments in Swedish Hospitals: A Malmquist Output Index Approach. – In: Data Envelopment Analysis: Theory, Methodology, and Applications. Springer, Dordrecht, pp. 253-272. https://doi.org/10.1007/978-94-011-0637-5_13.

[9] Feng, J., Zhang, F., Sun, M., Chen, Y., Zhu, J. (2025): Impacts of temporal growth variability on fisheries stock assessment in changing oceans: a case study of Eastern Atlantic skipjack. – Frontiers in Marine Science 12: 1555106. https://doi.org/10.3389/FMARS.2025.1555106.

[10] Førsund, F. R., Sarafoglou, N. (2002): On the origins of data envelopment analysis. – Journal of Productivity Analysis 17(1): 23-40.

[11] Guo, K., Ji, Q., Zhang, D. (2024): A dataset to measure global climate physical risk. – Data in Brief 54: 110502. https://doi.org/10.1016/j.dib.2024.110502.

[12] Idda, L., Madau, F. A., Pulina, P. (2009): Capacity and economic efficiency in small-scale fisheries: evidence from the Mediterranean Sea. – Marine Policy 33(5): 860-867. https://doi.org/10.1016/j.marpol.2009.03.006.

[13] Islam, S., Hossain, P. R., Braun, M., Amjath-Babu, T. S., Mohammed, E. Y., Krupnik, T. J., Chowdhury, A. H., Thomas, M., Mauerman, M. (2024): Economic valuation of climate induced losses to aquaculture for evaluating climate information services in Bangladesh. – Climate Risk Management 43: 100582. https://doi.org/10.1016/J.CRM.2023.100582.

[14] Kajtar, J. B., Holbrook, N. J., Lyth, A., Hobday, A. J., Mundy, C. N., Ugalde, S. C. (2024): A stakeholder-guided marine heatwave hazard index for fisheries and aquaculture. – Climatic Change 177(2): 26. https://doi.org/10.1007/S10584-024-03684-8.

[15] Li, L., Jiang, S., Lin, Y. (2025): The impact of the digital economy on sustainable fisheries: insights from green total factor productivity in China's coastal regions. – Sustainability 17(6): 2673. https://doi.org/10.3390/SU17062673.

[16] Li, Q., Shan, H., Tang, Y., Yao, V. (2020): Corporate climate risk: measurements and responses. – The Review of Financial Studies 37(6): 1778-1830. https://doi.org/10.2139/ssrn.3508497.

[17] Li, Y., Ji, J. (2024): The digitalization of Chinese fisheries and its configuration path to empower fishery sustainable development. – Journal of Cleaner Production 466: 142807. https://doi.org/10.1016/j.jclepro.2024.142807.

[18] Litzow, M. A., Malick, M. J., Kristiansen, T., Connors, B. M., Ruggerone, G. T. (2024): Climate attribution time series track the evolution of human influence on North Pacific Sea surface temperature. – Environmental Research Letters 19(1): 014014. https://doi.org/10.1088/1748-9326/ad0c88.

[19] Ma'arif, S., Budiyanto, M. A., Theotokatos, G. (2025): Progress in hybrid and electric propulsion technologies for fishing vessels: an extensive review and prospects. – Ocean Engineering 316: 120017. https://doi.org/10.1016/j.oceaneng.2024.120017.

[20] Moosavi-Nasab, M., Yazdani-Dehnavi, M., Mirzapour-Kouhdasht, A. (2020): The effects of enzymatically aided acid-swelling process on gelatin extracted from fish by-products. – Food Science & Nutrition 8(9): 5017-5025. https://doi.org/10.1002/fsn3.1799.

[21] Ragni, M., Colonna, M. A., Di Turi, L., Carbonara, C., Giannico, F., Cariglia, M., Palma, G., Tarricone, S. (2024): Partial replacement of fishmeal with seafood discards for Juvenile Penaeus japonicus: effects on growth, flesh quality, chemical and fatty acid composition. – Fishes 9(6): 195. https://doi.org/10.3390/fishes9060195.

[22] Reich, B. P., Mohanbabu, N., Isbell, F., et al. (2024): High CO_2 dampens then amplifies N-induced diversity loss over 24 years. – Nature 635: 370-375. https://doi.org/10.1038/S41586-024-08066-9.

[23] Rusco, G., Roncarati, A., Di Iorio, M., Cariglia, M., Longo, C., Iaffaldano, N. (2024): Can IMTA System improve the productivity and quality traits of aquatic organisms produced at different trophic levels? The benefits of IMTA—not only for the ecosystem. – Biology 13(11): 946. https://doi.org/10.3390/biology13110946.

[24] Sagheer, M., Yang, Z., Alsaleh, M. (2025): Determinants influencing green cost efficiency in the aquaculture sector: new insights from Asian countries. – Marine Policy 180: 106783. https://doi.org/10.1016/J.MARPOL.2025.106783.

[25] Sun, L., Zhang, X., Zhao, Z., Zhang, J. (2025): ESG is conducive to improving the operating efficiency of fishery enterprises—based on DEA model and Tobit regression analysis. – Regional Studies in Marine Science 85: 104158. https://doi.org/10.1016/J.RSMA.2025.104158.

[26] Szymkowiak, M., Steinkruger, A. (2024): Climate change attribution, appraisal, and adaptive capacity for fishermen in the Gulf of Alaska. – Climatic Change 177(6): 97. https://doi.org/10.1007/S10584-024-03753-Y.

[27] Taktak, W., Nasri, R., López-Rubio, A., Chentir, I., Gómez-Mascaraque, L. G., Boughriba, S., Nasri, M., Karra-Chaâbouni, M. (2021): Design and characterization of novel ecofriendly European fish eel gelatin-based electrospun microfibers applied for fish oil encapsulation. – Process Biochemistry 106: 10-19. https://doi.org/10.1016/J.PROCBIO.2021.03.031.

[28] Tang, M., Li, Z., Hu, F., Wu, B., Zhang, R. (2021): Market failure, tradable discharge permit, and pollution reduction: evidence from industrial firms in China. – Ecological Economics 189: 107180. https://doi.org/10.1016/J.ECOLECON.2021.107180.

[29] TCFD (2017): Final report: recommendations of the task force on climate-related financial disclosures. – TCFD Report 11. https://www.fsb-tcfd.org/.

[30] Thøgersen, T., Hoff, A., Frost, H. S. (2015): Fisheries management responses to climate change in the Baltic Sea. – Climate Risk Management 10: 51-62. https://doi.org/10.1016/j.crm.2015.09.001.

[31] Tigchelaar, M., Selig, E. R., Sarhadi, A., Bruce, J., Allison, E. H., Battista, W., Fanzo, J., Kleisner, K. M., Mehrabi, Z., Naylor, R. L., Schmidhuber, J. (2024): Nutrition-sensitive

climate risk across food production systems. – Environmental Research Letters 20(1): 014046. https://doi.org/10.1088/1748-9326/AD9B3A.
[32] Tilley, A., Lam, R. D., Lazo, D. L., Lopes, J. D. R., Da Costa, D. F., Belo, M. D. F., Da Silva, J., Da Cruz, G., Rossignoli, C. (2024): The impacts of digital transformation on fisheries policy and sustainability: lessons from Timor-Leste. – Environmental Science & Policy 153: 103684. https://doi.org/10.1016/J.ENVSCI.2024.103684.
[33] Tingley, D., Pascoe, S., Coglan, L. (2005): Factors affecting technical efficiency in fisheries: stochastic production frontier versus data envelopment analysis approaches. – Fisheries Research 73(3): 363-376. https://doi.org/10.1016/j.fishres.2005.01.008.
[34] Turgeon, K., Trottier, G., Turpin, C., Bulle, C., Margni, M. (2021): Empirical characterization factors to be used in LCA and assessing the effects of hydropower on fish richness. – Ecological Indicators 121: 107047. https://doi.org/10.1016/j.ecolind.2020.107047.
[35] Wang, F., Guan, G., Wang, Q. (2025): Green financing the future: how smart cities transform China's carbon emissions landscape. – International Review of Economics & Finance 104823. https://doi.org/10.1016/j.iref.2025.104823.
[36] Wang, J. Y., C., Liu. (2023): Measurement of operating efficiency of agricultural listed companies and analysis of influencing factors. – Hebei Agric. Univ. 25(3): 14-24. https://doi.org/10.13320/j.cnki.jauhe.2023.0028.
[37] Xia, Z., Zeng, H., Chen, X. (2025): Digital economy and high-quality development of fishery economy: evidence from China. – Sustainability 17(10): 4338. https://doi.org/10.3390/SU17104338.
[38] Xu, J., Han, L., Yin, W. (2022): Research on the ecologicalization efficiency of mariculture industry in China and its influencing factors. – Marine Policy 137: 104935. https://doi.org/10.1016/J.MARPOL.2021.104935.
[39] Ye, T., Xie, J., Feifei, C. (2025): China's blue carbon plan and carbon reduction along the Belt and Road and Asia Pacific Region. – Aquatic Conservation: Marine and Freshwater Ecosystems 35(4): e70136. https://doi.org/10.1002/AQC.70136.
[40] Yin, J., Xue, Y., Li, Y., Zhang, C., Xu, B., Ren, Y., Chen, Y. (2025): Efficacy of fisheries management strategies in mitigating ecological, social, and economic risks of climate warming in China. – Journal of Environmental Management 373: 123859. https://doi.org/10.1016/J.JENVMAN.2024.123859.
[41] Yongtae K., Lixin, (Nancy) S., Zheng W., et al. (2020): The effect of trade secrets law on stock price synchronicity: evidence from the inevitable disclosure doctrine. – The Accounting Review. https://doi.org/10.2308/tar-2017-0425.
[42] Zhang, Y., Khan, S. U., Wang, Y. (2025): The future is digital: Can the digital economy drive marine sustainability? Exploring regional impacts on fisheries' carbon emissions in coastal China. – Journal of Cleaner Production 506: 145518. https://doi.org/10.1016/J.JCLEPRO.2025.145518.
[43] Zhao, C., Wang, W., Li, X. (2021): How digital transformation affects enterprise total factor productivity. – Finance and Trade Economics 42(7): 114-129. https://doi.org/10.19795/j.cnki.cn11-1166/f.20210705.001.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_18171852