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A Pathway to Sustainable Development: The Relationship Between Fishery Digitalization and the Green Transformation of Fisheries

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Abstract

Using panel data from 30 Chinese provinces spanning 2011–2024, this study assesses the digitalization and green transformation of fisheries using the entropy-weighted TOPSIS method and the super-efficiency epsilon-based measure (EBM) model, respectively. A two-way fixed-effects model is then employed to examine the relationship between the digitalization and green transformation of fisheries. The results reveal a positive association that persists across a series of robustness and endogeneity checks. Analysis of potential mediating channels indicates positive indirect associations through aquaculture intensification, aquatic product processing efficiency, and fishery industrial structure upgrading, whereas the fishing efficiency channel is not statistically supported. Heterogeneity analysis shows that the positive association is stronger in Eastern China and becomes more pronounced as regional innovation and human capital levels increase. Spatial analysis further reveals spatial dependence in the green transformation of fisheries and a positive association between local fishery digitalization and the green transformation of fisheries in neighboring regions.

Keywords: fishery digitalization; green transformation of fisheries; aquaculture intensification; processing efficiency; fishery industrial structure upgrading

1. Introduction

The Food and Agriculture Organization clearly states in the "State of World Fisheries and Aquaculture" (Data source: https://openknowledge.fao.org/server/api/core/bitstreams/09d03e2f-7097-4d59-bf94-db65e95f44fd/content/cd8357en.html#gsc.tab=0) (accessed on 15 June 2026)report that fisheries are both a key driver of national economic development and the primary source of high-quality protein and other essential nutrients. Fisheries play a crucial role in improving global dietary structures and ensuring food security [1]. According to the "China Fisheries Economic Statistical Bulletin," (Data source: https://yyj.moa.gov.cn/gzdt/202507/t20250707_6475475.htm) (accessed on 20 July 2026)by 2024, the total output value of the fishery sector had reached 3417.2 billion yuan. Fishery product output and export volumes account for approximately 40% and 13% of the global total, respectively, solidifying China's leadership position and contributing significantly

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to the development of global fisheries. However, this rapid expansion of the industry and market has been accompanied by a significant increase in the exploitation of fishery resources, leading to crises such as environmental pollution, ecological degradation, and resource depletion, which severely constrain the sustainable development of the sector. In this context, transitioning fisheries from a high-consumption, high-pollution, and low-efficiency model to a new development paradigm that balances economic vitality with green ecology has become both an urgent strategic necessity and an inevitable path toward achieving the green transformation of fisheries (GTF).

The new generation of digital technologies is transforming dynamics, quality, and efficiency, accelerating their integration and reshaping the traditional industrial landscape [2]. This wave of digitization has revolutionized the global fishery sector, providing robust technological and data support for GTF [3] and establishing a new frontier for international competition. The European Green Deal, adopted by the European Commission (Data source: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/story-von-der-leyen-commission/european-green-deal_en) (accessed on 20 July 2026), aims to utilize digital technologies to optimize fishery operations and reduce pollutants and carbon emissions. China's "14th Five-Year Plan for National Fisheries Development" (Data source: https://yyj.moa.gov.cn/gzdt/202201/t20220107_6386443.htm) (accessed on 20 July 2026) emphasizes the use of digital transformation to guide fisheries toward greater efficiency and sustainability. These international experiences collectively highlight the vast potential and universal value of digitization in advancing GTF. Therefore, systematically elucidating the underlying mechanisms and external conditions has become a central concern for policymakers, industry practitioners, and academics.

The existing literature primarily examines the measurement of fishery digitalization (FD) and GTF, as well as the relationship between them. Representative studies are summarized in Table 1. Regarding digitalization measurement, previous studies mainly use regional digital economy indicators to characterize the digital context of fishery development. Jiang et al. (2024) [4] applied the entropy method using indicators such as the number of digital economy enterprises, employment in software and information services, and the number of internet domain names. Building on this approach, Wang et al. (2025a) [5] employed TOPSIS with indicators including mobile base station density, digital product manufacturing output, and total telecommunications business volume. Xia et al. (2025) [6] and Zhang et al. (2025) [7] incorporated indicators of telecommunications penetration, internet infrastructure, and digital finance into their respective measurement frameworks. Although these studies provide a basis for assessing digitalization, they offer limited insight into the penetration and application of digital technologies in fishery production and business operations. Regarding GTF measurement, existing studies primarily adopt green production efficiency and sustainable development perspectives. The former typically integrates production inputs, economic outputs, and environmental burdens into an efficiency assessment framework. Guo et al. (2022) [8] used an SBM model to estimate green production efficiency in aquaculture, incorporating indicators such as aquaculture area, the number of fish fry, output value, and pollution emissions. Chen et al. (2024) [9] further included carbon emissions as an undesirable output to assess the ecological efficiency of marine fisheries. The sustainable development perspective emphasizes overall development performance. For example, Zhang et al. (2024) [10] incorporated pollution losses, disaster losses, and the number of fishing vessels into an indicator system to assess the sustainable development of marine fisheries. These two approaches emphasize relative efficiency and multidimensional performance, respectively, reflecting distinct approaches to measuring green transformation. Regarding the relationship between the two, Ji and Li (2024) [11], using panel data from 30 Chinese provinces, identified a positive association between digitalization and sustainable fishery development, with technological progress and technical efficiency as potential transmission channels. Combining fully modified ordinary least squares with fuzzy-

set qualitative comparative analysis, Li and Ji (2024) [12] found that this relationship depends on contextual conditions and that no single factor constitutes a necessary condition for fishery sustainable development. Li et al. (2025b) [3] found that the positive association between the digital economy and fishery green total factor productivity may involve improved resource allocation and becomes stronger as environmental regulation increases. Overall, these studies primarily examine mechanisms such as technological progress and resource allocation, while paying limited attention to differences across subsectors and production stages within fisheries. The internal division of activities among aquaculture, capture fisheries, and processing remains insufficiently explored.

In fact, FD can facilitate GTF through fishery sectors (the primary sector), fishery industrial and construction sectors (the secondary sector), and fishery distribution and service sectors (the tertiary sector). In the primary fishery sector, aquaculture water quality monitoring systems based on narrowband Internet of Things technology enable remote collection of data from multiple sensors and intelligent control [13], corresponding to greater aquaculture intensification. Additionally, integrated vessel-shore networks built around maritime satellite communications and the BeiDou Navigation Satellite System facilitate access to real-time information on fish distribution [14] and are closely associated with fishing efficiency. However, improvements in fishing efficiency may have both positive consequences, such as reduced unproductive navigation and increased output, and negative consequences, including overfishing and greater pressure on fishery resources. In the secondary fishery sector, digital twin models and near-infrared spectroscopy have been used to upgrade aquatic product processing equipment [15], corresponding to higher aquatic product processing efficiency. In the tertiary fishery sector, digitalization has helped overcome traditional consumption constraints and trade barriers, giving rise to new service models such as direct-to-consumer e-commerce and smart cold chains [16]. These developments are associated with fishery industrial structure upgrading and higher levels of GTF.

Moreover, the relationship between FD and GTF is not uniform but exhibits considerable heterogeneity. Geographically, Eastern China benefits from accumulated technological expertise and well-developed supporting infrastructure compared with Central and Western China [17]. These conditions support FD and allow its potential benefits to materialize more fully and consistently, corresponding to a stronger positive association with GTF. Regarding regional innovation, greater innovation capacity reduces investment risks and the costs of trial and error in fishery digitalization [18] and curbs the overexploitation of aquatic organisms, showing an association with joint improvements in economic and ecological outcomes. Regarding regional human capital, a more highly skilled workforce is better equipped to assimilate and apply advanced digital technologies [19], corresponding to greater economic value creation and green development.

Against this background, this study addresses three central research questions. RQ1: What is the relationship between FD and GTF? RQ2: What potential mediating channels underlie this relationship? RQ3: Does the relationship between FD and GTF exhibit heterogeneity? To address these questions, this study uses provincial panel data from China spanning 2011–2024 and employs multi-way fixed-effects models, mediation models, and a spatial Durbin model to conduct a systematic analysis.

The marginal contributions are as follows: First, regarding the measurement of FD, this study develops an evaluation system based on the technology-organization-environment (TOE) framework, reflecting the reliance of digital technology adoption in Chinese fisheries on extension systems and the importance of public services and fiscal support for industry development. The framework integrates digital technology availability, the capacity of industry organizations to absorb and apply technologies, and market and policy support, aligning with the technological, organizational, and environmental requirements

of FD in China. Unlike studies that primarily use regional indicators of internet access, telecommunications, and digital finance [4–7], this study focuses on digital applications within fisheries and their supporting conditions. By incorporating key indicators of fishery information platforms, technology extension capacity, and external support, the evaluation system distinguishes regional digital resource provision from the capacity of fisheries to apply these resources. This approach better captures fishery-specific characteristics and provides a more targeted basis for measuring FD. Furthermore, recognizing that a single measurement method may not adequately assess uncertainty in index construction, this study uses entropy-weighted TOPSIS to construct the baseline index and employs CRITIC and principal component analysis to construct alternative indices. These methods enable cross-validation from the perspectives of indicator dispersion, information conflict, and shared variation, allowing the sensitivity of the measurement results to weighting and information aggregation methods to be assessed.

Second, regarding the assessment of GTF, this study incorporates fishery carbon sinks, carbon emissions, and pollutant emissions into a common evaluation framework, reflecting the importance of both aquaculture and capture fisheries in China's production structure. The large scale of these activities makes biological carbon fixation and carbon removal through harvesting important dimensions of fisheries' ecological functions in China. Continuing energy demand across production stages highlights the need to balance economic output and carbon emission burdens under China's carbon peaking and carbon neutrality goals. Meanwhile, extensive pond and fed aquaculture generates substantial environmental pressures from nutrients and organic matter associated with uneaten feed and excreta, which are captured through total nitrogen (TN), total phosphorus (TP), and chemical oxygen demand (COD) emissions. Compared with studies focusing on green productivity and ecological efficiency [8,9], this study further distinguishes relative efficiency from absolute environmental performance. The super-efficiency EBM model is used to measure the overall efficiency underlying GTF, while the quantities of carbon sequestered, carbon emitted, and pollutants discharged serve as supplementary absolute indicators. This approach examines whether the positive association between FD and relative efficiency also corresponds to greater carbon sinks and lower environmental burdens. Furthermore, GTF is recalculated under alternative returns-to-scale assumptions and model orientations, providing empirical support and a methodological reference for its assessment.

Third, regarding transmission mechanisms, this study examines activities within the primary fishery sector, the secondary fishery sector, and the tertiary fishery sector, separately investigating four potential channels: aquaculture intensification, fishing efficiency, aquatic product processing efficiency, and fishery industrial structure upgrading. Whereas previous studies focus on general mechanisms such as technological progress and technical efficiency [11], entrepreneurial activity [6], and resource allocation [3], this study examines potential mechanisms at specific production and service stages, identifying the resource use patterns and environmental constraints associated with each channel. Within the primary fishery sector, the aquaculture intensification channel concerns input allocation and production management within limited aquatic space, examining their associations with GTF in terms of feed utilization, water consumption, and pollution loads. The fishing efficiency channel distinguishes two potentially coexisting processes—operational savings and pressure on fishery resources—to examine the ambiguity of its relationship with GTF. Within the secondary fishery sector, the aquatic product processing efficiency channel focuses on raw material conversion and processing operations, examining the relationship between resource use in processing and GTF through raw material losses and processing energy consumption. Within the tertiary fishery sector, the fishery industrial structure upgrading channel examines the economic benefits and environmen-

tal burdens associated with the extension of value creation into trade, logistics, and professional services. These distinctions clarify the different environmental implications of intensive spatial use, natural resource extraction, raw material processing, and growth in service value, providing greater industry specificity to the potential channels linking FD and GTF. Furthermore, to reduce potential overlap between the components used to construct certain mediators and GTF, this study replaces GTF with absolute environmental performance indicators and re-examines the proposed channels. This approach helps mitigate mechanical associations and strengthens the rigor of the analysis.

Fourth, regarding heterogeneity, this study examines how the relationship between FD and GTF varies with regional location, innovation levels, and human capital, considering both regional context and the capacity to absorb digital technologies. Beyond comparing Eastern China with Central and Western China, it explores the complementarities between *FD* and regional innovation and human capital. Regional innovation reflects the knowledge base for adapting and applying digital technologies, while human capital captures the workforce capacity to absorb and use these technologies. This perspective provides new insights into regional differences in the relationship between FD and GTF. Empirically, this study interacts FD with continuous measures of regional innovation and human capital to examine how the strength of its association with GTF varies across these conditions, reducing the information loss and dependence on arbitrary thresholds associated with sample grouping. This analysis advances understanding of the conditions shaping the FD-GTF relationship and provides a theoretical and empirical basis for local governments to formulate targeted policies.

Table 1. Comparison of representative studies.

Research Topic	Literature	Data and Sample	Key indicators and Measurement Methods	Identification Strategy	Main Findings
Digitalization	Jiang et al. (2024) [4]	China's coastal provinces from 2011 to 2022	Measured using the entropy weighting method based on indicators such as the number of digital economy-related enterprises, employment in the software and information services industry, and the number of internet domain names.	Fixed effects regression, mediating effect regression	The digital economy is positively associated with the quality of marine fishery economic development, with scientific and technological innovation serving as a linking channel and the relationship exhibiting regional heterogeneity.
	Wang et al. (2025a) [5]	China's coastal cities from 2008 to 2021	Measured using the entropy-weighted TOPSIS method based on indicators such as mobile base station density, digital product manufacturing output, and total telecommunications business volume.	Fixed effects regression, mediating effect regression	The digital economy is positively associated with marine fishery economic resilience. The mechanisms include human capital, technological innovation, and industrial structure upgrading.
	Xia et al. (2025) [6]	29 provinces from 2011 to 2021	Measured using the entropy weighting method based on indicators such as mobile phone penetration, the number of broadband internet connections, and the number of web pages.	Fixed effects regression, mediating effect regression	The digital economy is positively associated with high-quality fishery economic development, with technological innovation and entrepreneurial activity serving as linking channels. This

					association is more pronounced in coastal regions.
	Zhang et al. (2025) [7]	Coastal provinces from 2011 to 2022	Measured using the entropy weighting method based on indicators such as employment in the internet industry and digital finance.	Spatial Durbin regression	The digital economy exhibits a negative spatial effect on local marine fishery carbon emissions but a positive spillover effect on those in neighboring regions. These effects are more pronounced in southern coastal regions and regions with lower carbon emissions.
Green transformation of fisheries	Guo et al. (2022) [8]	30 provinces from 2003 to 2020	Measured using the SBM model, with aquaculture area and the number of fish juveniles among the input indicators, and output value and pollution quantities as output indicators.		Green total factor productivity in mariculture is highest in China's East China Sea region, followed by the South China Sea region. In freshwater aquaculture, green total factor productivity is highest in the western region and lowest in the eastern region.
	Chen et al. (2024) [9]	Coastal provinces from 2008 to 2021	Measured using the SBM model, with inputs including marine fishery employment and mariculture area, and outputs including marine fishery output value and carbon emissions.	Fixed effects regression, random effects regression	Marine fishery eco-efficiency exhibits an upward trend. Industrial structure and environmental regulation are positively associated with eco-efficiency, whereas openness to the outside world is negatively associated with it.
	Zhang et al. (2024) [10]	Coastal provinces from 2011 to 2020	Measured using the entropy-weighted TOPSIS method based on indicators such as marine economic losses caused by pollution, economic losses caused by typhoons and flooding, and the number of fishing vessels.		Marine fishery sustainability exhibits an upward trend, with resource and technological factors playing prominent roles.
The relationship between digitalization and the green transformation of fisheries	Ji and Li (2024) [11]	30 provinces from 2011 to 2021		Fixed effects regression, mediating effect regression	Digitalization is positively associated with sustainable fishery development, with technological progress and technical efficiency serving as potential linking channels.
	Li and Ji (2024) [12]	30 provinces from 2011 to 2021		Fully modified ordinary least squares, fsQCA	Digitalization is positively associated with sustainable fishery development, but no single factor constitutes a necessary condition. This

			association is weaker in less developed regions.
Li et al. (2025b) [3]	Coastal provinces from 2011 to 2022	Fixed effects regression, threshold effect regression	The digital economy is positively associated with fishery green total factor productivity, with resource allocation serving as a linking channel. This relationship strengthens as environmental regulation becomes more stringent.

2. Theoretical Analysis and Research Hypothesis

2.1. The Relationship Between FD and GTF

FD presents new opportunities for the development of traditional fisheries. First, FD can enhance the transmission and processing capabilities of fishery information. On one hand, FD provides efficient platforms for information exchange through digital technologies such as big data and IoT, breaking down information barriers in production processes [20]. It reduces search and management costs, while improving the coordination of labor, capital, and other resource allocation. On the other hand, due to the regional nature of fishery production and the perishable nature of its products, FD accelerates the dissemination of market information, allowing operators to access real-time market dynamics [1]. This enables them to promptly adjust production structures and processing technologies, ensuring a precise link between the consumer and production sides, thus optimizing resource allocation efficiency and supply quality. This is associated with greater economic benefits. Moreover, FD is a key strategy for transitioning from an extensive production model to green development. Digital platforms, by offering services such as training, guidance, and consulting, facilitate the sharing of production experiences and green technologies [11], reducing production losses, carbon emissions, and environmental pollution. At the same time, FD enables the dynamic monitoring of environmental indicators and provides timely feedback to producers and regulatory authorities, ensuring the implementation of green production.

Second, FD promotes technological progress. The technology collaboration and sharing platforms created by FD foster an interconnected innovation network among fishery enterprises, universities, local governments, and research institutions [21], establishing a knowledge and technology dissemination chain. This stimulates the enthusiasm of stakeholders to participate in technology research and development (R&D) and services by facilitating technological spillovers, and helps fishery practitioners master cutting-edge technologies and apply smart sensor devices. It alleviates the disconnect between technological supply and demand, and shortens the learning and application cycle for green technologies [22], driving the synergistic development of economic growth and green benefits. Additionally, digitalization strengthens fishery technology [4], driving comprehensive innovation in equipment. For example, the development of energy-efficient fishing vessels and gear reduces energy consumption and carbon emissions in aquaculture and fishing processes. Digital platforms also enable consumers to trace the green production, clean storage, and safe transportation of aquatic products, motivating operators to adopt green technologies [6].

Third, FD alleviates financing constraints. FD enables financial institutions to obtain information about fishery production, operations, and sales [23], increasing opportunities for operators to access green agricultural loans and providing financial support. This is closely associated with improvements in GTF. This study proposes:

Hypothesis 1. *FD is positively associated with GTF to some extent.*

2.2. The Potential Mechanism of FD and GTF

2.2.1. Fishery Sectors Perspective

From the perspective of the primary fishery sector, the key pathways to success include aquaculture intensification and improved fishing efficiency. In terms of aquaculture intensification, first, FD has facilitated the development of new intensive aquaculture systems. FD drives the development of more intensive and advanced aquaculture systems, leading to diverse models such as raft farming, deep-sea cage farming, and marine ranching [14]. In particular, marine ranching, a key form of carbon-sequestering fisheries, creates stable growth environments for fish, shrimp, shellfish, algae, and other organisms by implementing artificial propagation in confined waters. This not only increases aquaculture yields but also improves regional ecology [5], fully harnessing the scale effects of the green economy. Second, FD has enabled more efficient management across the entire aquaculture process. Intelligent systems, such as water quality sensors and underwater robots, monitor water quality and temperature in real-time [24], activating automatic purification mechanisms to maintain optimal aquaculture conditions. Additionally, the use of computer vision and automation equipment replaces traditional manual operations, enabling precise feeding and cross-tank species transfer [25]. This improves ecological carrying capacity and control levels, providing technical support for intensive aquaculture.

Furthermore, aquaculture intensification reduces the marginal cost of energy usage [26] and improves feed conversion efficiency [27], converting saved input factors into actual economic benefits and decoupling economic output from environmental pollution. Aquaculture intensification requires optimal resource allocation within confined spaces, making environmental capacity a critical constraint. The self-purification ability of water bodies shifts from being a public good to a scarce resource, with environmental negative externalities being internalized [9]. This compels aquaculture operators to adopt resource-saving and environmentally friendly production methods, reducing pollutants and carbon emissions at the source, which is associated with higher GTF. This study proposes:

Hypothesis 2a. *Aquaculture intensification may serve as a positive mediator in the relationship between FD and GTF.*

Regarding fishing efficiency, first, FD has transformed the information paradigm of fishery production, driving technological innovation and iterative upgrades of fishing vessels and supporting equipment. The increasing marginal returns of data elements have driven the demand for the intelligent upgrading of equipment. Multi-source information systems, such as underwater sonar and satellite remote sensing, combined with intelligent fishery prediction models, require fishing vessels to be equipped with hardware capable of real-time data acquisition and edge computing [14]. The ship-shore integrated network, centered on the BeiDou navigation system and maritime satellite communication, enables the sharing of fishery information and operational coordination among fleets [24], requiring traditional fishing vessels to undergo comprehensive upgrades to their communication and navigation systems. Furthermore, with the establishment of a full supply chain traceability system, fishing vessels must be equipped with standardized devices such as catch identification and electronic fishing logs [28] to meet transparent management requirements. These changes have not only upgraded traditional, inefficient fishing vessels but also created a new digitalized production model, both of which are associated with improvements in fishing efficiency. Second, FD optimizes fishing route planning. Fishing operators can use digital tools like IoT sensors and smart fishing nets to efficiently analyze

fish school distribution and movement patterns [22]. Simultaneously, fishing strategies are dynamically optimized based on market demand [3], enabling precise fishing.

Furthermore, fishing efficiency is also linked to GTF. Higher fishing efficiency is typically associated with optimized fishing routes, improved access to information, and more efficient equipment use. When catch volumes remain relatively stable, the operating time, travel distance, and fuel inputs required per unit of output decrease, alongside reductions in exploratory fishing, unproductive navigation, and bycatch of non-target species [10,29]. These changes reduce energy consumption and ecological disturbance per unit of output. Under these conditions, improvements in fishing efficiency may be associated with higher GTF. However, increased fishing efficiency may also undermine the sustainable management of fishery resources. Under limited resource carrying capacity and tightening ecological constraints, higher fishing efficiency may be accompanied by an expansion of fishing grounds and faster resource extraction, increasing the risks of overfishing, imbalances in population structure, and pressure on fishery resources [30]. Under these circumstances, improvements in fishing efficiency may be negatively associated with GTF. Accordingly, this study proposes the following hypothesis:

Hypothesis 2b. *Fishing efficiency may mediate the relationship between FD and GTF, but the direction of this mediation remains to be empirically examined.*

2.2.2. Fishery Industrial and Construction Sectors Perspective

From the perspective of the secondary fishery sector, FD is closely associated with aquatic product processing efficiency. In the raw material processing stage, intelligent perception systems based on hyperspectral imaging and deep learning algorithms [31] perform multi-dimensional quantitative analysis of the quality characteristics of aquatic raw materials, enabling precise grading and optimal use. In the processing stage, digitalization enables processing enterprises to collect data through distributed sensors and build dynamic correlation models between key process parameters and product quality indicators [32], shifting processing methods from traditional experiential judgments to data-driven models. In the quality control stage, Ma et al. (2025) [15] highlight that the deep integration of near-infrared spectroscopy technology and machine learning algorithms has established a quality monitoring and intervention mechanism throughout the entire process, shifting quality control from post-production inspection to process prevention. As a result, FD improves raw material utilization, preserves natural nutritional components, and is positively associated with aquatic product processing efficiency.

Furthermore, aquatic product processing efficiency is also associated with GTF. In terms of green benefits, Mondragon et al. (2021) [24] highlight that high levels of processing efficiency increase the marginal output of limited resource elements, alleviating the industry's dependence on natural fishery resources and providing space for the structural restoration and functional maintenance of aquatic ecosystems. At the same time, the improvement in processing efficiency reduces energy consumption intensity. With the promotion of clean production models, it curbs the expansion of carbon footprints and alleviates environmental pressure on coastal ecosystems by gradually utilizing and recycling processing by-products [7]. In terms of economic benefits, the improvement in processing efficiency optimizes the allocation of labor, capital, and technology, reducing marginal costs [9] and increasing market value through economies of scale. Moreover, higher processing efficiency enables processing enterprises to implement product differentiation strategies, overcoming the challenges of homogeneous competition [6], and capturing brand premiums and structural dividends from niche markets. This study proposes:

Hypothesis 3. *Aquatic product processing efficiency may serve as a positive mediator in the relationship between FD and GTF.*

2.2.3. Fishery Distribution and Service Sectors Perspective

From the perspective of the tertiary fishery sector, FD will gradually phase out the high-energy-consumption and high-emission primary and secondary sectors, guiding the industrial structure toward the transformation and upgrading of a low-pollution, high-value-added tertiary fishery sector. On the supply side, digitalization breaks traditional trade barriers and changes the nature of on-site consumption, giving rise to emerging service models like fishery e-commerce [33]. Digitalization deepens the social division of labor and expands social networks, increasing cross-regional and cross-industry employment opportunities, and accelerating labor transfer to high-value-added industries [34]. On the demand side, digital technologies support the digital and intelligent development of the tertiary fishery sector [24], accurately identifying consumer demand, optimizing service processes [35], and addressing market information asymmetry. These developments are associated with fishery industrial structure upgrading.

Furthermore, fishery industrial structure upgrading serves the dual functions of resource optimization and effective pollution control and is associated with GTF. On one hand, industrial structure upgrading promotes the shift from resource dependency to knowledge capital-driven growth [36], supporting the green development. For example, technological services enhance green innovation and low-carbon, clean capabilities [21], improving the resource utilization efficiency of operators. Smart logistics services optimize distribution paths to reduce pollution and carbon emissions [16]. On the other hand, industrial structure upgrading improves the modern governance system. Third-party certification has established a quality signal transmission mechanism, management consulting services provide specialized environmental governance solutions, and market information services guide green development, forming a multi-stakeholder collaborative governance model involving the government, market, and society [37], laying a foundational institutional framework for GTF. This study proposes:

Hypothesis 4. *Fishery industrial structure upgrading may serve as a positive mediator in the relationship between FD and GTF.*

The logical framework is presented in Figure 1.

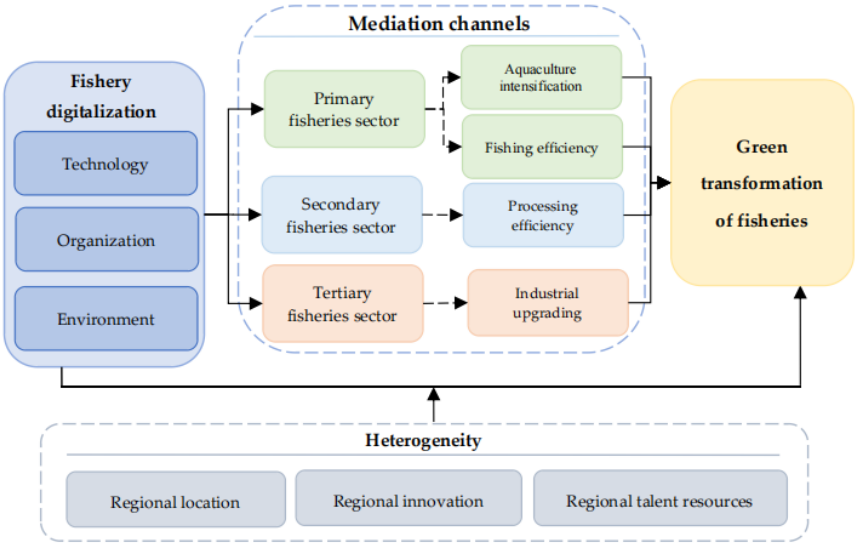


Figure 1. The theoretical framework of FD and GTF.

3. Study Design and Methods

3.1. Methodologies and Models

3.1.1. Methodology for Measuring FD

Drawing on the work of Jiang et al. (2024) [4] and Zhang et al. (2024) [10], this study uses the entropy-weighted TOPSIS method to measure the level of FD. In the first step, assume there are m evaluation objects, each with n evaluation indicators, and construct a judgment matrix:

$$X = (x_{ij})_{m\times n}(i = 1,2,\cdots,m; j = 1,2,\cdots,n) \tag{1}$$

In the second step, perform range normalization on the matrix, scaling the original indicator values to a uniform range (between 0 and 1):

$$Y_{ij} = \frac{X_{ij} - \min X_j}{\max X_j - \min X_j}, \text{ for positive indicators} \tag{2}$$

$$Y_{ij} = \frac{\max X_j - X_{ij}}{\max X_j - \min X_j}, \text{ for negative indicators} \tag{3}$$

X_{ij} represents the original indicator, $\max X_j$ denotes the maximum value of the j-th indicator, $\min X_j$ denotes the minimum value of the j-th indicator, and Y_{ij} is the normalized indicator.

In the third step, calculate the information entropy and the weights of each indicator:

$$E_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij}\ln p_{ij} \tag{4}$$

$$W_j = \frac{1 - E_j}{\sum_{l=1}^{n}(1 - E_l)} \tag{5}$$

Here, $P_{ij} = \dfrac{Y_{ij}}{\sum_{h=1}^{m} Y_{hj}}$; $W_j \in [0,1]$, and $\sum_{j=1}^{n}(w_j) = 1$.

In the fourth step, calculate the weighted matrix and determine the optimal and worst solutions:

$$R = (r_{ij})_{m\times n}, r_{ij} = W_j \times Y_{ij}(i = 1,2,\cdots,m; j = 1,2,\cdots,n) \tag{6}$$

$$S_j^+ = \max(r_{1j}, r_{2j},\cdots, r_{mj}), S_j^- = \min(r_{1j}, r_{2j},\cdots, r_{mj}) \tag{7}$$

In the fifth step, the Euclidean distances of each evaluation unit from the positive and negative ideal solutions are calculated, and the relative closeness coefficient is then computed to measure FD:

$$sep_i^+ = \sqrt{\sum_{j=1}^{n}(s_j^+ - r_{ij})^2} \tag{8}$$

$$sep_i^- = \sqrt{\sum_{j=1}^{n}(s_j^- - r_{ij})^2} \tag{9}$$

$$C_i = \frac{sep_i^-}{sep_i^+ + sep_i^-}, C_i \in [0,1] \tag{10}$$

3.1.2. Methodology for Measuring GTF

Following Ji and Li (2024) [11] and Li and Ji (2024) [12], this study employs the super-efficiency EBM model to estimate GTF. Compared with the conventional DEA model, the super-efficiency EBM model not only provides a more detailed characterization of the slacks associated with individual inputs, desirable outputs, and undesirable outputs, but also overcomes the inability of conventional DEA models to discriminate among efficient decision-making units on the efficiency frontier through its super-efficiency structure. This enables effective ranking among highly efficient regions, thereby enhancing the model's discriminatory power and practical applicability. Therefore, the super-efficiency EBM model is well suited to the measurement context of this study. The specific model is formulated as follows:

$$\min \rho = \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \rho x_{io}, i = 1,2,\cdots,m \\ \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, r = 1,2,\cdots,s_1 \\ \sum_{j=1}^{n} \lambda_j b_{rj} + s_r^b = b_{ro}, r = 1,2,\cdots,s_2 \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0, s_r^b \geq 0, \end{cases} \tag{11}$$

where ρ denotes the final overall score for the green transformation of fisheries (i.e., the objective function); λ_j denotes the weight assigned to the linear combination; x, y, and b represent the input, desirable output, and undesirable output variables, respectively; s^-, s^+, and s^b are the corresponding slack variables used to capture input/output excesses or shortfalls; i denotes the index of input factors; r denotes the index of output factors; j denotes the index of decision-making units (DMUs), namely, the provinces; m denotes the total number of input factors; n denotes the total number of decision-making units; and s_1 and s_2 denote the total numbers of desirable and undesirable output categories, respectively.

MaxDEA 9 software was employed for model estimation and computation. The resulting super-efficiency scores were used to characterize the efficiency and level of GTF across the sample provinces, thereby providing a solid foundation for the subsequent empirical analysis.

3.1.3. Benchmark Model

This study examines the relationship between FD and GTF using the following regression model:

$$GTF_{i,t} = \alpha_0 + \alpha_1 FD_{i,t} + \alpha_2 \sum Controls_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{12}$$

Here, $GTF_{i,t}$ represents the level of green transformation of fisheries in province i at time t; $FD_{i,t}$ represents the level of fishery digitalization in province i at time t; $Controls_{i,t}$ is a set of control variables; μ_i is the provincial fixed effect, used to control for factors at the provincial level that do not change over time; δ_t is the time fixed effect, used to control for changes in factors that have a common impact on the sample during the study period; $\varepsilon_{i,t}$ is the random disturbance term.

Furthermore, to account for potential heteroskedasticity and serial correlation within provinces, this study uses standard errors clustered at the provincial level. The sample comprises 30 provincial clusters, providing a basis for cluster-robust inference. This approach allows disturbances to be correlated across years within the same province and does not impose homoskedasticity, making it suitable for the panel structure of this study.

3.1.4. Mechanism Test Model

To further investigate the potential mechanisms underlying the relationship between FD and GTF, this study constructs the following mediation models and validates them using the Sobel and Bootstrap tests:

$$MED_{i,t} = \beta_0 + \beta_1 FD_{i,t} + \beta_2 \sum Controls_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (13)$$

$$GTF_{i,t} = \gamma_0 + \gamma_1 FD_{i,t} + \gamma_2 MED_{i,t} + \gamma_3 \sum Controls_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (14)$$

Here, $MED_{i,t}$ represents the mediator variable, which includes aquaculture intensification (AQU), fishing efficiency (CAP), processing efficiency (PRO), and industrial structure upgrading (UPG). The meanings of the other symbols remain unchanged.

The Sobel and Bootstrap tests assess the statistical significance of the indirect effect using the product of the mediation path coefficients and its standard error. The Bootstrap procedure resamples provinces to preserve the within-province dependence structure of the panel data. A total of 1000 bootstrap replications are performed, and inference is based on the 95% confidence interval for the indirect effect.

3.1.5. Spatial Durbin Model

This study extends the conventional panel model by incorporating spatially lagged dependent and explanatory variables to construct a spatial Durbin model, which examines spatial spillovers in the relationship between FD and GTF. The model is specified as follows:

$$GTF_{i,t} = \alpha_0 + \rho WGTF_{i,t} + \alpha_1 FD_{i,t} + \xi WFD_{i,t} + \alpha_2 \sum Controls_{i,t} + \omega \sum WControls_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (15)$$

Here, ρ denotes the spatial autoregressive coefficient to be estimated; ξ is the coefficient on the spatially lagged FD; and ω denotes the coefficients on the spatially lagged control variables. W represents the spatial weights matrix. This study uses an inverse-distance weights matrix constructed from the Euclidean distances between the geometric centers of grid cells. The matrix is standardized to eliminate the influence of measurement units and ensure the statistical interpretability of the spatial lag terms.

3.2. Variable Selection and Data Description

3.2.1. Explanatory Variable

Owing to its strong applicability and extensibility, the technology-organization-environment (TOE) framework has been widely applied in research on the digital economy [12]. Meanwhile, the penetration and application of digital technologies in the fishery sector can also be reflected across the technological, organizational, and environmental dimensions. Therefore, considering the practical context, this study incorporates FD into the TOE theoretical framework to construct a comprehensive evaluation index system and employs the entropy-weighted TOPSIS method for measurement.

The Technology (T) dimension captures the availability of resources, information infrastructure, and technological application capacity supporting FD. FD encompasses not only the development of digital technologies and online platforms but also their practical application in information dissemination, technical services, and knowledge diffusion. Accordingly, this study selects indicators covering fishery websites, mobile platforms, technical consultation hotlines, and technical bulletins to measure the technological foundations and application conditions of FD.

Among them, fishery websites and mobile platforms serve as important channels for disseminating digital information in fisheries [11]. Websites provide policy, technical, and market information, while mobile platforms further improve the convenience and accessibility of digital services. Greater numbers of these platforms indicate more developed

digital information infrastructure and deeper integration of digital technologies into fishery production and business operations. These two indicators are measured by the numbers of fishery-related websites and mobile platforms, respectively. Fishery technical consultation hotlines enable feedback on technical needs, remote consultation, and service follow-up, reflecting the application of digital technologies in fishery technical services. Fishery technical bulletins facilitate the dissemination of production technologies and risk warnings through digital information collection and distribution, reflecting the capacity to disseminate digital knowledge in fisheries [12]. Higher indicator values signify greater capacity for the digital provision, transmission, and application of fishery technical information. These indicators are measured by the numbers of fishery technical consultation hotlines and technical bulletins, respectively.

The Organization (O) dimension captures the organizational foundations of digital technology adoption in fisheries, including organizational structures, human capital, and management capacity. Fishery digitalization depends not only on technology provision but also on organizational actors, skilled personnel, and management mechanisms that support the implementation of digital technologies in production and business operations. Accordingly, this study selects indicators related to fishery technology extension institutions, training activities, and fishery administration agencies to assess organizational support for FD.

Specifically, fishery technology extension institutions undertake digital technology extension, technical demonstrations, and information dissemination. A larger number of these institutions indicates a more developed organizational system and more accessible channels for disseminating digital technologies to local producers [38]. Higher educational attainment among fishery technology extension personnel enhances their ability to understand, apply, and disseminate digital technologies, including big data, the Internet of Things, and smart equipment, thereby advancing FD. This indicator is measured by the number of extension personnel holding a bachelor's degree or higher. Professional training for extension personnel and technical training for fishers reflect knowledge renewal within extension organizations and skills development among producers, respectively. Continuous training improves extension personnel's and fishers' ability to access and use digital tools, lowers barriers to digital technology adoption, and facilitates the transition from technology extension to practical application in production [25]. These indicators are measured by the numbers of professional training sessions for fishery technology extension personnel and technical training sessions for fishers, respectively. The number of fishery administration agencies reflects the governance and management foundations of FD. Well-developed fishery administration structures support the digitalization of information collection, resource monitoring, and public services, increasing the application of digital technologies in industry governance.

The Environment (E) dimension captures the influence of market demand, government investment, and resource support on FD. Accordingly, this study selects fishery e-commerce, fiscal support for fisheries, and fishery technology extension funding to characterize the external environment for FD. Fishery e-commerce sales reflect the practical application of digital technologies in aquatic product trading, distribution, and marketing. A larger e-commerce market indicates greater participation by fishery operators in online transactions, digital marketing, and digital supply chains, as well as a stronger role of market demand in advancing FD [28]. Fiscal support for fisheries reflects government support for digital infrastructure, digital technology adoption, and industrial transformation. It also reduces the initial costs of digital transformation for fishery operators and provides essential financial support. This indicator is measured by expenditure allocated to fisheries within general government expenditure. Fishery technology extension funding captures the resources available to support technology extension and public service systems, facilitating the diffusion of digital research and development outcomes, smart

equipment, and information services into fishery production and business operations. This indicator is measured by funding allocated to fishery technology extension projects. Detailed indicators are presented in Table 2.

To construct the FD index, this study normalizes the indicators and estimates their weights using all observations pooled across the full study period, rather than separately for each year. This approach offers three advantages. First, it ensures comparability across years by applying a common normalization benchmark. Second, it captures the overall variability and information contribution of each indicator throughout the study period, avoiding substantial fluctuations in normalization parameters and weights arising from annual sample variation. Third, it maintains a consistent indicator framework and evaluation criteria, allowing changes in the index to reflect the evolution of FD across provinces rather than mechanical changes induced by adjustments to indicator weights.

Table 2. Indicator system for *FD*.

First-Level Indicators	Secondary Indicators	Indicator Description (Unit)	Attribute	Data Sources	Entropy Weights	Critic Weights	PCA Weights
Technology (T)	Fishery websites	Number of fishery-related websites (count)	+	*China Fishery Statistical Yearbook*, EPS Database.	0.1051	0.1327	0.0536
	Fisheries mobile platforms	Number of fisheries-related mobile platforms (count)	+	*China Fishery Statistical Yearbook*, Provincial Fisheries Statistical Yearbooks.	0.0247	0.0311	0.0781
	Fisheries technical consultation hotlines	Number of fisheries technical consultation hotlines (count)	+	*China Fishery Statistical Yearbook*, EPS Database.	0.0812	0.1187	0.0721
	Fishery technical bulletins	Number of fishery technical bulletins (count)	+	*China Fishery Statistical Yearbook*, Provincial Fisheries Statistical Yearbooks.	0.1298	0.0661	0.0879
Organization (O)	Aquaculture technology extension institutions	Number of aquaculture technology extension institutions (count)	+	*China Fishery Statistical Yearbook*, EPS Database.	0.0589	0.1025	0.0952
	Educational attainment of aquaculture technology extension personnel	Number of aquaculture technology extension personnel with a bachelor's degree or higher (persons)	+	*China Fishery Statistical Yearbook*, EPS Database	0.0841	0.0715	0.0889
	Training for aquaculture technology extension personnel	Participation in professional training for aquaculture technology extension personnel (person-times)	+	*China Fishery Statistical Yearbook*, Provincial Fisheries Statistical Yearbooks.	0.0651	0.0728	0.0873
	Technical training for fishers	Participation in technical training for fishers (person-times)	+	*China Fishery Statistical Yearbook*, EPS Database.	0.1314	0.0532	0.0813
	Fishery administration agencies	Number of fishery administration agencies (count)	+	*China Fishery Statistical Yearbook*.	0.0278	0.1163	0.0906
Environment (E)	Fishery e-commerce	Fishery-related e-commerce sales (10,000 yuan)	+	*China Fishery Statistical Yearbook*, EPS Database.	0.1463	0.0567	0.0954

	Fiscal support for fisheries	Expenditure on fisheries within general government expenditure (10,000 yuan)	+	*China Fishery Statistical Yearbook*, EPS Database.	0.0868	0.1036	0.0846
	Funding for fishery technology extension	Funding for fishery technology extension projects (10,000 yuan)	+	*China Fishery Statistical Yearbook*, Provincial Fisheries Statistical Yearbooks.	0.0589	0.0748	0.0849

3.2.2. Explained Variable

This study selects the following input–output indicators. The input indicators consist of three main factors: resources, labor, and capital. Regarding resource inputs, this study follows Guo et al. (2022) [8] and uses aquaculture area and the number of aquatic juveniles stocked. Aquaculture area determines production scale and output potential and is closely related to environmental and ecological carrying capacity, making it a key indicator of resource inputs in fisheries. Aquatic juveniles constitute a fundamental input in aquaculture, representing the initial stage of production and future output potential. Labor input is measured by the number of fishery workers [9]. Workforce size directly affects fishery output and resource use efficiency through production, management, and technical operations. Following Li et al. (2025a) [39], capital input is measured by year-end fishing vessel tonnage. Fishing vessels reflect the scale of capital and the level of equipment used in fishery production, directly influencing the volume, efficiency, and geographical scope of fishing operations.

Expected outputs include the total output value of the fishery economy [40] and fishery carbon sinks. The total output value of the fishery economy encompasses the entire fishery value chain, including the primary sector, centered on aquaculture and capture fisheries; the secondary sector, represented by aquatic product processing; and the tertiary sector, covering fishery distribution, warehousing, and recreational fisheries. It serves as a key indicator for assessing the overall scale and economic contribution of fisheries.

Regarding fishery carbon sinks, this study comprehensively estimates their magnitude for fish, crustaceans, shellfish, and algae across four production activities: freshwater aquaculture, freshwater capture fisheries, marine aquaculture, and marine capture fisheries. Drawing on Gan et al. (2025) [41] for estimates of carbon removal through freshwater aquatic production, Table 3 summarizes the carbon sink coefficients for 12 freshwater species, comprising seven fish species, two crustacean species, and three shellfish species. Because species-specific catch data are unavailable for freshwater capture fisheries, the calculations use the mean carbon sink coefficient within each of the fish, crustacean, and shellfish groups. Given the diversity of marine algae, this study follows Wang et al. (2025c) [42] in assigning carbon sink coefficients to eight marine algal species, with a dry-to-wet weight ratio of 0.2. As freshwater algal production is relatively low and research on its carbon sink capacity is limited, the mean carbon sink coefficient for marine algae is used as a proxy.

Table 3. Carbon sink parameters for aquatic organisms.

Category	Species	Carbon Sink Coefficient
Freshwater fish	Grass carp	0.1281
	Silver carp	0.1679
	Common carp	0.1136
	Crucian carp	0.1422
	Bighead carp	0.1340
	Mandarin fish	0.1273
	Blunt Snout bream	0.1687
Freshwater crustaceans	Shrimp	0.1108

	Crabs	0.1110
Freshwater shellfish	Freshwater mussels	0.0890
	Freshwater clams	0.1106
	Freshwater snails	0.0793
Marine algae	Kelp	0.3120
	Laver	0.2740
	Green laver	0.2780
	Gelidium	0.3070
	Gracilaria	0.2060
	Wakame	0.2640
	Eucheuma	0.2430
	Hijiki	0.2390

Biological parameters are essential for estimating the magnitude of carbon sinks associated with marine shellfish. Following Chen et al. (2024) [9], Table 4 presents key parameters for marine shellfish species, including scallops, oysters, and razor clams, such as dry-to-wet weight ratios, the proportions of different tissues, and carbon contents.

Table 4. Carbon sink parameters for marine shellfish.

Species	Dry-to-Wet Weight Ratio	Soft Tissue Proportion of Total Dry Weight	Shell Proportion of Total Dry Weight	Soft Tissue Carbon Content	Shell Carbon Content
Scallops	0.640	0.140	0.860	0.439	0.114
Oysters	0.650	0.060	0.940	0.460	0.127
Razor Clams	0.710	0.030	0.970	0.450	0.132
Clams	0.530	0.020	0.980	0.449	0.115
Mussels	0.750	0.080	0.920	0.444	0.118
Others	0.640	0.110	0.890	0.439	0.114

The formulas used to calculate carbon sinks for each species under each production activity are as follows:

$$C_e = C_a + C_b + C_c + C_d \tag{16}$$

$$C_a = \sum_m \sum_n (P_{mn} \times \lambda_{mn}) + (P_f \times \lambda_f \times 0.2) \tag{17}$$

$$C_c = C_g + C_h + (P_i \times \lambda_i) + (P_l \times \lambda_l) \tag{18}$$

$$C_g = C_o + C_r = \sum_k P_k \times \mu_k \times (M_s \times \omega_1 + M_t \times \omega_2) \tag{19}$$

$$C_h = \sum_j (P_j \times \lambda_j \times 0.2) \tag{20}$$

Here, a denotes carbon fixation from freshwater aquaculture; b denotes carbon fixation from freshwater capture fisheries; c denotes carbon fixation from mariculture; d denotes carbon fixation from marine capture fisheries; e denotes the total magnitude of carbon sinks; m represents farmed freshwater fish, crustaceans, and shellfish; f represents freshwater algae; n denotes the corresponding species; p denotes production; λ is the carbon sink coefficient; g denotes carbon fixation by shellfish; h denotes carbon fixation by algae; i represents fish; l represents crustaceans; o denotes shell carbon content; r denotes soft tissue carbon content; s denotes the shell proportion; t denotes the soft tissue proportion; k and j represent different species of marine shellfish and marine algae, respectively; μ is the dry-to-wet weight ratio; and ω_1 and ω_2 denote shell and soft tissue carbon content, respectively. The carbon sink coefficient for marine fish is approximated using that of

freshwater mandarin fish, which have similar living habits and edible tissue composition. For marine crustaceans, the mean carbon sink coefficient of freshwater crustaceans is used. Carbon fixation from freshwater and marine capture fisheries is calculated by multiplying the catches of fish, crustaceans, shellfish, and algae by their corresponding carbon sink coefficients and summing the resulting values.

Unexpected outputs include fishery carbon emissions, TN, TP, COD emissions, and economic losses in aquatic products due to pollution [39]. Specifically, following Zhang et al. (2025) [7], fishery carbon emissions are calculated across three main stages. For the capture stage, fuel consumption coefficients for motorized marine fishing vessels by fishing method are obtained from the Reference Standards for Estimating Fuel Consumption for Domestic Motorized Fishing Vessel Fuel Subsidies (Data source: https://www.moa.gov.cn/gk/tzgg_1/tfw/201006/t20100606_1538704.htm) (accessed on 9 March 2026). In addition to these vessels, motorized vessels used in inland capture fisheries and aquaculture also generate carbon emissions. Following Zeng and Chen (2026) [43], motorized vessels other than those used in marine capture fisheries are assumed to operate for an average of 1200 h annually. The average fuel consumption rates for different years are presented in Table 5.

Table 5. Average fuel consumption rates of motorized fishing vessels other than marine capture vessels.

Year	Fuel Consumption Rate (g/kW·h)	Year	Fuel Consumption Rate (g/kW·h)
2011	248.1	2018	235.1
2012	246.3	2019	233.3
2013	244.4	2020	231.4
2014	242.6	2021	229.5
2015	240.7	2022	227.7
2016	238.8	2023	225.9
2017	237.0	2024	224.1

Fuel consumption by non-marine motorized fishing vessels is calculated using the following formula:

$$F_{it} = P_{it} \times S_{it} \times T \tag{21}$$

Here, i denotes motorized vessels used in inland capture fisheries or aquaculture, and t denotes the year. F represents fuel consumption, P is vessel engine power, T denotes annual operating hours, and S is the fuel consumption rate.

After estimating fuel consumption for each vessel category, carbon emissions are calculated using the Oak Ridge National Laboratory (ORNL) fossil fuel combustion method, as follows:

$$Q_{CO_2} = F \times \mu \times K \times n \times \xi \times \omega \tag{22}$$

Here, F denotes fuel consumption by motorized fishing vessels; μ is the coefficient for converting fuel consumption into standard coal equivalent; K represents the effective oxidation fraction; n is the carbon content per tonne of standard coal equivalent; and ξ is the ratio of CO_2 emissions from fuel oil to those from coal at the same calorific value. ω is the conversion factor from carbon to CO_2 based on relative atomic masses, with a value of 3.67.

For the aquaculture stage, electricity consumption is estimated using the equipment electricity consumption parameters provided by Song et al. (2024) [44], as detailed in Table 6. Carbon emissions are then calculated using the national electricity grid carbon emission factors published by China's Ministry of Ecology and Environment (Data source: https://www.mee.gov.cn/xxgk2018/xxgk/xxgk01/202512/t20251231_1139517.html) (accessed on 25 March 2026), with the corresponding values reported in Table 7.

Table 6. Equipment energy consumption parameters for aquaculture systems.

Aquaculture Stage	Aquaculture Method	Category	Freshwater	Marine
Aeration process	Pond aquaculture	Proportion of area aerated	0.8	0.8
		Electricity consumption per unit area (kW·h/hm²)	2.25	2.25
		Annual operating time (h)	800	800
	Industrial aquaculture	Feeding rate	0.03	0.03
		Oxygen consumption per unit of feed (kg/kg)	0.5	0.5
		Roots blower aeration efficiency (kg/kW·h)	0.8	0.8
		Annual operating time (d)	200	200
Water exchange process	Pond aquaculture	Average water depth (m)	1.5	1
		Water replenishment rate	0.02	0.02
		Pump water delivery per unit of electricity (m³/kW·h)	60	60
		Annual operating time (d)	200	200
	Industrial aquaculture	Water exchange frequency (times/d)	4	4
		Pump water delivery per unit of electricity (m³/kW·h)	30	20
		Annual operating time (d)	200	200

Table 7. National electricity grid carbon emission factors.

Year	Carbon Emission Factor (kg/kW·h)	Year	Carbon Emission Factor (kg/kW·h)
2011	0.764	2018	0.599
2012	0.718	2019	0.580
2013	0.707	2020	0.566
2014	0.672	2021	0.558
2015	0.643	2022	0.552
2016	0.618	2023	0.546
2017	0.606	2024	0.540

The processing stage includes electricity and steam consumption during processing, as well as electricity used for refrigeration, freezing, and ice production [45]. The energy consumption parameters for each operation are presented in Table 8. CO_2 emissions from electricity consumption are calculated using the emission factors reported in Table 7, while emissions from steam consumption are estimated by converting each tonne of steam into 100 kg of standard coal equivalent. Finally, emissions from the capture, aquaculture, and processing stages are summed to obtain total fishery carbon emissions.

Table 8. Energy consumption coefficients for cold storage and processing.

Stage	Category	Electricity Consumption	Steam Consumption
Cold storage facility	Refrigerated storage	1.25 kW·h/t·d	/
	Ice production	62 kW·h/t	/
	Frozen products	350 kW·h/t	/
Processing	Surimi Production (60% Surimi Content)	38 kW·h/t	/
	Surimi Product Processing	29.5 kW·h/t	500 kg/t
	Dried and Salted Products (30% Mechanized Processing)	29.5 kW·h/t	1200 kg/t

Following Zhou et al. (2023) [40], this study estimates fishery emissions of TN, TP, and COD using pollutant discharge coefficients from the Manual of Pollution Generation and Discharge Coefficients for Aquaculture in the First National Census of Pollution Sources (Data source: https://max.book118.com/html/2025/0308/5322040212012112.shtm) (accessed on 17 March 2026) and production data from the *China Fishery Statistical Yearbook*.

The calculation proceeds in four steps. First, province-specific TN, TP, and COD discharge coefficients are obtained from the manual for more than 20 freshwater fish species, including sturgeon and eel, across four aquaculture systems, and for multiple marine fish species, including pufferfish and sea bass, across five aquaculture systems. Species-specific freshwater and marine aquaculture production data are obtained from the *China Fishery Statistical Yearbook* and the EPS database. Second, the discharge coefficients for each pollutant are averaged across the relevant aquaculture systems for each freshwater and marine fish species. Third, freshwater aquaculture production in each province is matched with the corresponding species-specific discharge coefficients to estimate TN, TP, and COD emissions by species. These estimates are then aggregated to obtain total freshwater aquaculture emissions of each pollutant. The same procedure is applied to marine aquaculture. Finally, freshwater and marine aquaculture emissions are summed to obtain total fishery emissions of TN, TP, and COD.

Economic losses in aquatic products caused by pollution quantify the adverse effects of anthropogenic pollution, including industrial discharges, agricultural nonpoint source pollution, and domestic sewage, on aquatic ecosystems and their socioeconomic value. The detailed indicator system is presented in Table 9.

Table 9. Indicator system for GTF.

Indicator Type	Indicator Name	Indicator Description	Unit	Data Source
Input	Resource	Aquaculture area	Hectares	*China Fishery Statistical Yearbook*, EPS Database.
		Number of seedlings	100 Million Individuals	*China Fishery Statistical Yearbook*, Provincial Fisheries Statistical Yearbooks.
	Labor	Number of fisheries workers	Persons	*China Fishery Statistical Yearbook*, Provincial Fisheries Statistical Yearbooks.
	Capital	Tonnage of fishing vessels	Gross Tonnage	*China Fishery Statistical Yearbook*, EPS Database.
Output	Expected output	Total output value of the fisheries economy	10,000 yuan	*China Fishery Statistical Yearbook*, EPS Database.
		Fisheries carbon sinks	Tons	Chen et al. (2024) [9], Gan et al. (2025) [41], Wang et al. (2025c) [42].
	Unexpected output	Fisheries carbon emissions	Tons	*China Fishery Statistical Yearbook*, EPS Database, Reference Standards for Estimating Fuel Consumption for Domestic Motorized Fishing Vessel Fuel Subsidies.
		TN, TP, and COD emissions in fisheries	Tons	*China Fishery Statistical Yearbook*, EPS Database, Manual of Pollutant Generation and Discharge Coefficients for Aquaculture in the First National Census of Pollution Sources.
		Economic losses in aquatic products caused by pollution	10,000 yuan	*China Fishery Statistical Yearbook*, Provincial Fisheries Statistical Yearbooks.

3.2.3. Control Variables

This study, drawing on the works of Wu et al. (2025) [46], Xia et al. (2025) [6], and Zhang et al. (2025) [7], incorporates the following control variables: (1) Trade dependence (TRA), represented by the ratio of regional aquatic product import and export value to regional GDP. (2) Environmental regulation (ENV), represented by the ratio of regional environmental governance investment to regional GDP. (3) Foreign direct investment (FDI), represented by the ratio of foreign direct investment to regional GDP. (4) Financial development level (FIN), represented by the ratio of total deposits and loans from financial institutions to regional GDP. (5) Industrial structure (STR), represented by the ratio of the output value of the tertiary industry to regional GDP. (6) Industrial agglomeration (AGG), represented by the ratio of employed individuals to the administrative area of the region. The descriptive statistics results are presented in Table 10.

Table 10. Descriptive statistics results.

Variable Type	Variable Name	Obs	Mean	Std. Dev.	Min	Max	Unit	Data Source
Explanatory variable	FD	420	0.1223	0.0843	0.0122	0.5183		*China Fishery Statistical Yearbook*, EPS Database, Provincial Fisheries Statistical Yearbooks.
Explained variable	GTF	420	0.7184	0.2417	0.0357	1.4668		*China Fishery Statistical Yearbook*, EPS Database, Reference Standards for Estimating Fuel Consumption for Domestic Motorized Fishing Vessel Fuel Subsidies, Manual of Pollutant Generation and Discharge Coefficients for Aquaculture in the First National Census of Pollution Sources.
Control variables	TRA	420	0.2163	0.7219	0.0000	7.7153	Ratio	*China Fishery Statistical Yearbook*, *China Statistical Yearbook*, the National Bureau of Statistics
	ENV	420	0.0108	0.0073	0.0016	0.0423	Ratio	*China Statistical Yearbook*, the National Bureau of Statistics
	FDI	420	0.0197	0.0201	0.0000	0.1210	Ratio	*China Statistical Yearbook*, the National Bureau of Statistics
	FIN	420	3.3354	1.2025	1.2791	8.1641	Ratio	*China Statistical Yearbook*, the National Bureau of Statistics
	STR	420	0.4857	0.1089	0.2641	0.9073	Ratio	*China Statistical Yearbook*, the National Bureau of Statistics
	AGG	420	0.0256	0.0381	0.0004	0.2171	Ratio	*China Statistical Yearbook*, the National Bureau of Statistics

3.3. Data Source

This study uses data from 30 provinces of China between 2011 and 2024, excluding Hong Kong, Macau, Taiwan, and Tibet, for the following reasons: First, since 2011, the global wave of digitalization has accelerated, and China has implemented a series of strategies, such as "Internet Plus," to promote the digital transformation of various industries, particularly the development of digital fisheries [12]. Additionally, data for 2025 is largely unavailable, so the study uses data from 2011 to 2024. Second, based on data availability, the measurement of FD and GTF primarily relies on provincial-level data. Due to significant data gaps in Hong Kong, Macau, Taiwan, and Tibet, the study selects the 30 provinces

of mainland China as the valid sample. Data sources include the *China Fishery Statistical Yearbook*, *China Statistical Yearbook*, the EPS database, provincial fisheries statistical yearbooks, and the National Bureau of Statistics. For indicators involving monetary values, this study applies deflation using the regional gross domestic product indices (previous year = 100) published in the *China Statistical Yearbook*. Taking 2010 as the base year, the annual indices, divided by 100, are multiplied sequentially to construct a fixed-base price index, which is then used to convert nominal values into real values. To limit the influence of extreme values, continuous variables are winsorized at the 1st and 99th percentiles without removing any observations. A small number of missing observations are imputed using linear interpolation, and the imputation results are reported in Table 11.

Table 11. Missing value imputation results.

Variable Type	Variable Name	Original Sample Size	Missing Rate	Imputed Sample Size	Final Sample Size
Explanatory variable	Fishery Websites	396	5.71%	24	420
	Fishery Mobile Platforms	411	2.14%	9	420
	Fishery Technical Consultation Hotlines	415	1.19%	5	420
	Fishery Technical Bulletins	407	3.10%	13	420
	Fishery Administration Agencies	397	5.48%	23	420
	Fishery E-commerce	393	6.43%	27	420
Explained variable	Fishery carbon sinks	408	2.86%	12	420
	Fishery carbon emissions	401	4.52%	19	420
	TN, TP, and COD emissions in fisheries	412	1.90%	8	420
	Economic losses in aquatic products caused by pollution	416	0.95%	4	420
Control variables	TRA	413	1.67%	7	420
	ENV	402	4.29%	18	420
	FDI	417	0.71%	3	420

4. Empirical Results

4.1. Benchmark Regression

Table 12 presents the baseline regression results for the relationship between FD and GTF. Column (1) excludes control variables and fixed effects. The estimated coefficient on FD is 0.6407 and is statistically significant, with a 95% confidence interval of [0.3412, 0.9401]. After control variables are included in Column (2), the coefficient increases to 0.9393, with a 95% confidence interval of [0.4277, 1.4510], and is significant at the 1% level. The within R-squared increases to 0.2026. Column (3) further includes province and year fixed effects. The coefficient on FD is 0.9781, with a 95% confidence interval of [0.4185, 1.5378], and remains significant at the 1% level. As control variables and fixed effects are introduced, the R-squared increases from 0.0475 to 0.2168, indicating improved model fit. In economic terms, a one-standard-deviation increase in FD is associated with a 0.0825-unit increase in GTF. These results indicate a positive association between FD and GTF, supporting Hypothesis 1.

Table 12. Benchmark regression results.

	(1) GTF	(2) GTF	(3) GTF
FD	0.6407 ***	0.9393 ***	0.9781 ***
	(0.1523)	(0.2502)	(0.2736)
TRA		0.0118	0.0027
		(0.0220)	(0.0272)
ENV		−1.3972	1.0114
		(2.4865)	(3.6429)
FDI		−3.8144 ***	−3.7646 ***
		(0.8587)	(1.0385)
FIN		0.0890 **	0.0906 *
		(0.0413)	(0.0471)
STR		−0.7930 **	−0.8157 *
		(0.3229)	(0.4328)
AGG		1.4123 ***	1.6176 ***
		(0.4204)	(0.4663)
_cons	0.5779 ***	0.6810 ***	0.6515 ***
	(0.0222)	(0.1028)	(0.0990)
Province F.E.	NO	NO	YES
Year F.E.	NO	NO	YES
Observations	420	420	420
Within R-squared	0.0475	0.2026	0.2168

Note: ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses.

4.2. Robustness Test

4.2.1. Variable Sensitivity Analysis

(1) Replace the core explanatory variable. First, although the FD in the baseline analysis was constructed using the entropy-weighted TOPSIS approach, the possibility of measurement uncertainty cannot be completely excluded. Entropy weighting limits the role of researcher discretion; however, the weights it generates are conditional on the characteristics of the sample and may therefore change with the observation period, geographical coverage, or distribution of the underlying data. In addition, a higher degree of statistical variation in an indicator does not necessarily imply that the indicator is substantively more important for fishery digitalization. To address this concern, the index was reconstructed using the CRITIC approach, yielding an alternative measure denoted by FD_cri, which was subsequently substituted into the regression specification. The CRITIC method derives weights from two dimensions: the extent of variation in each indicator and its correlation with the remaining indicators. It consequently reflects both an indicator's discriminatory capacity across observational units and the extent to which it contains information distinct from that of other indicators, thereby limiting the repeated allocation of weight to highly correlated variables. As shown in Column (1) of Table 13, the coefficient on FD_cri is 0.7374 and is significant at the 1% level, with a confidence interval of [0.2612, 1.2136]. This result is broadly consistent with the baseline estimates.

Second, because entropy weights may primarily reflect statistical variation in the sample rather than adequately capture economic importance, this study also uses principal component analysis (PCA) to construct an alternative index (FD_pca). PCA extracts the principal components of the original indicators and weights them according to their shares of explained variance, retaining as much information as possible. The regression model is then re-estimated using FD_pca. As shown in Column (2), the coefficient on FD_pca is positive at 0.4691 and significant at the 1% level, with a confidence interval of [0.1946, 0.7436].

Third, FD is lagged by one period (L.FD) to examine the relationship between current FD and subsequent GTF (Ji and Li, 2021) [38]. As shown in Column (3), the coefficient on L.FD is 1.0158 and is statistically significant, with a confidence interval of [0.4271, 1.6046].

(2) Replacing the dependent variable. First, the baseline GTF measure is estimated using an output-oriented production frontier under variable returns to scale. To assess robustness, this study changes the returns-to-scale assumption to constant returns to scale and adopts an input-oriented specification to recalculate GTF. This examines the sensitivity of GTF scores to assumptions about returns to scale and model orientation.

As reported in Column (4), the coefficient on FD is 0.9850 and is statistically significant, with a 95% confidence interval of [0.4253, 1.5448]. This finding indicates that the positive association between FD and GTF remains robust to the alternative frontier specification.

Second, GTF scores estimated using the super-efficiency EBM model primarily reflect provincial efficiency relative to the green production frontier and do not directly indicate absolute improvements in environmental conditions. Accordingly, this study constructs alternative dependent variables using the magnitude of fishery carbon sinks, carbon emissions, and TN, TP, and COD emissions. These indicators provide a comprehensive assessment of fishery environmental performance. Specifically, carbon sinks reflect the capacity of fishery ecosystems to absorb and fix carbon dioxide [42]; carbon emissions capture greenhouse gas emissions from fishery production and business operations [9]; and TN, TP, and COD reflect nutrient loads and organic pollution in water bodies [3]. The natural logarithm of the magnitude of fishery carbon sinks is denoted by SIN, while the natural logarithm of the sum of carbon, TN, TP, and COD emissions is denoted by FEL. Both variables are subsequently used as dependent variables in the regression models.

As shown in Columns (5)–(6), the coefficient on FD is 1.0006 in the SIN regression, with a confidence interval of [0.6807, 1.3206], and −0.9433 in the FEL regression, with a confidence interval of [−1.5449, −0.3418]. Both coefficients are significant at the 1% level. These findings indicate that FD is positively associated with fishery carbon sinks and negatively associated with the aggregate environmental load comprising carbon, TN, TP, and COD emissions.

Table 13. Variable sensitivity test results.

	(1) GTF	(2) GTF	(3) GTF	(4) GTF	(5) SIN	(6) FEL
FD_cri	0.7374 ***					
	(0.2328)					
FD_pca		0.4691 ***				
		(0.1342)				
L.FD			1.0158 ***			
			(0.2879)			
FD				0.9850 ***	1.0006 ***	−0.9433 ***
				(0.2737)	(0.1564)	(0.3058)
_cons	0.5344 ***	0.6041 ***	0.6536 ***	0.6496 ***	0.8199 ***	1.1125 ***
	(0.1167)	(0.1061)	(0.0971)	(0.0990)	(0.0944)	(0.1753)
Controls	YES	YES	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
Observations	420	420	390	420	420	420
Within R-squared	0.2102	0.2122	0.2161	0.1905	0.6267	0.1673

Note: *** indicates $p < 0.01$; Robust standard errors clustered at the provincial level are reported in parentheses.

4.2.2. Adjusting the Study Sample and Standard Errors

(1) Adjusting the time window. On one hand, the Yangtze River Basin is resource-rich, accounting for approximately 60% of the total freshwater fishery output. In 2020, China issued the "Notice on the Scope and Duration of the Fishing Ban in Key Waters of the Yangtze River Basin" and implemented a ten-year fishing ban in the Yangtze River, significantly disrupting both fishery production and ecology. On the other hand, to avoid exogenous shocks from the COVID-19 pandemic, which fully erupted after 2020, affecting digital infrastructure development and fishery operations and potentially distorting the research results. This study readjusts the observation period to 2011–2019.

As shown in Column (1) of Table 14, the estimated coefficient on FD is positive and statistically significant, with a confidence interval of [0.3321, 1.7345], consistent with the baseline results.

(2) Excluding the municipal sample. Due to their special administrative status and policy preferences, municipalities directly under the central government have inherent advantages in areas such as digital economy infrastructure and human capital [47], potentially affecting the applicability of the results. Therefore, this study excludes the samples from Beijing, Shanghai, Chongqing, and Tianjin.

As reported in Column (2) of Table 14, the coefficient on FD is 1.1085 and is significant at the 5% level, with a confidence interval of [0.2138, 2.0032].

(3) To examine the sensitivity of the estimates to interpolation, this study excludes interpolated observations and re-estimates the baseline model. Because the procedures used to construct FD and GTF involve indicator normalization and weight estimation and require a complete balanced panel, the full sample used to construct these two core variables is retained. Only observations with interpolated control-variable values are excluded from the regression sample. This approach preserves consistency in the measurement of FD and GTF while assessing the sensitivity of the findings to interpolation in the control variables.

As shown in Column (3) of Table 14, the coefficient on FD remains positive and statistically significant, with a confidence interval of [0.4064, 1.5274]. This result provides further support for the robustness and reliability of the findings.

(4) Wild Cluster Bootstrap Method. Correlation among observations can give rise to differences in cluster structure. Conventional cluster-robust inference relies on asymptotic conditions requiring a sufficiently large number of clusters; with a limited number of clusters, standard error estimates and significance tests may be distorted. Accordingly, this study applies the wild cluster bootstrap to adjust inference based on standard errors clustered across 30 provinces. Specifically, a restricted model is estimated under the null hypothesis that the coefficient on FD is zero. All residuals within the same province are assigned a common random weight, taking values of −1 or 1 with equal probability, to preserve the within-province error correlation structure. The empirical distribution of the t-statistic is constructed using 9999 bootstrap replications to calculate a two-sided p-value, and a 95% confidence interval is obtained by inverting the test. The resulting wild cluster bootstrap p-value is 0.0036, with a 95% confidence interval of [0.3340, 1.5954]. Thus, the coefficient on FD remains positive and statistically significant at the 1% level under the adjusted inference, supporting the robustness of the main findings.

Table 14. Robustness test results using alternative samples.

	(1) GTF	(2) GTF	(3) GTF
FD	1.0333 ***	1.1085 **	0.9669 ***
	(0.3429)	(0.4344)	(0.2741)
_cons	0.6200 ***	0.7400 ***	0.6518 ***
	(0.1095)	(0.2198)	(0.1120)
Controls	YES	YES	YES
Province F.E.	YES	YES	YES
Year F.E.	YES	YES	YES
Observations	270	364	397
Within R-squared	0.1856	0.1704	0.2136

Note: ***, ** indicate $p < 0.01$, $p < 0.05$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses.

4.2.3. Omitted Variable Test

To examine potential estimation bias arising from unobservable factors, this study further conducted a robustness test using the method proposed by Oster (2019) [48]. First, with the ratio of the correlation between unobservable variables and the dependent variable to that between observable variables and the dependent variable specified as δ (typically set to 1), and the maximum goodness of fit R_{max} attainable when all potentially relevant variables are included given, the adjusted coefficient of the key explanatory variable, β_1^*, was calculated. If this coefficient falls within the 95% confidence interval of the baseline estimate α_1, the findings are considered unlikely to be substantially affected by omitted variables. Second, assuming that the true coefficient $\alpha_1 = 0$, the value of δ was inferred based on the specified R_{max}. In general, a value of $\delta > 1$ indicates that unobservable factors would need to possess greater explanatory power than observable factors for the main conclusion to be invalidated; this criterion can therefore be used to assess the severity of omitted-variable bias.

Table 15 reports the test results. In Row 1, the estimated β_1* under the assumption of $\delta = 1$ falls within the 95% confidence interval of the baseline regression coefficient. In Row 2, the value of δ calculated under the assumption that $\alpha_1 = 0$ is significantly greater than 1. These results indicate that the baseline regression findings are not seriously affected by omitted-variable bias.

Table 15. Oster's omitted variable test results.

R_{max}	Testing Method	Judgment Standard	Actual Estimated Result	Whether to Pass
0.3656	First procedure	[0.4418, 1.5144]	β_1* = 1.1525	YES
	Second procedure	$\delta > 1$	δ = 10.6637	YES

Note: Here, * indicates that the coefficient has been adjusted for potential omitted-variable bias using the Oster method under the specified assumptions; it does not denote statistical significance.

4.3. Endogeneity Test

This study employs instrumental variable two-stage least squares (IV-2SLS) estimation to mitigate potential endogeneity concerns. First, following Li et al. (2026a) [49], this study uses the logarithm of manufacturing fixed asset investment in each province as the first instrumental variable (IV_1). On the one hand, FD relies heavily on hardware such as intelligent aquaculture equipment, automated control equipment, and data processing

equipment [28]. Such equipment is primarily supplied by manufacturing industries, including metal products and polymer materials. Increased manufacturing fixed asset investment helps expand the production capacity of relevant equipment, strengthen digital technology supply chains, and reduce the costs incurred by fishery operators in acquiring and adopting digital facilities. This facilitates the integration of digital technologies into fishery production, management, and services, thereby promoting FD. Thus, IV_1 is strongly correlated with FD. On the other hand, according to the Industrial Classification for National Economic Activities, manufacturing fixed asset investment constitutes capital formation within the manufacturing sector and primarily aims to expand production scale and manufacturing capacity [49]. It falls outside the agricultural sector and is relatively unlikely to directly affect GTF, providing preliminary support for the exogeneity assumption, which nevertheless requires careful assessment.

Second, following Wu et al. (2025) [46], this study uses the interaction between terrain ruggedness and a time trend as the second instrumental variable (IV_2). The rationale is that terrain conditions affect the installation costs and spatial deployment efficiency of digital equipment in fisheries. Compared with flatter areas, regions with greater terrain ruggedness face higher costs for base station construction and equipment maintenance, which also constrain the diffusion of digital technologies and the adoption of digital equipment in fisheries. Accordingly, IV_2 is negatively correlated with FD, satisfying the relevance requirement. Moreover, terrain ruggedness is a relatively stable natural geographic characteristic that remains largely unchanged during the sample period. Therefore, its direct effect on GTF may be limited, lending some support to the exogeneity assumption, although this assumption still requires careful assessment.

The results are reported in columns (1)–(2) of Table 16. In the first stage, the coefficient of IV_1 on FD is 0.0169, with a confidence interval of [0.0025, 0.0313], while that of IV_2 is −0.0468, with a confidence interval of [−0.0642, −0.0294]. Both coefficients are statistically significant and consistent with expectations. The Kleibergen–Paap rk LM statistic for the underidentification test is 8.6540 and is significant at the 5% level, indicating that the instruments are correlated with the endogenous explanatory variable and that the model is identified. The Kleibergen-Paap rk Wald F statistic for the weak instrument test is 23.9770, exceeding the Stock–Yogo critical value at the 10% significance level and suggesting that weak-instrument concerns may be relatively limited. The Hansen J statistic for the overidentification test is 1.4970, with a *p*-value greater than 0.1, indicating insufficient statistical evidence to reject the overidentifying restrictions. In the second stage, after introducing IV_1 and IV_2, the coefficient of FD on GTF is 1.0504, with a confidence interval of [0.0252, 2.0755], and is significant at the 5% level.

Furthermore, this study replaces the explanatory variable with FD_cri to assess the sensitivity of the instrumental variable results. As reported in columns (3)–(4) of Table 16, the first-stage coefficient of IV_1 is 0.0369, with a confidence interval of [0.0170, 0.0568], while that of IV_2 is −0.0546, with a confidence interval of [−0.0736, −0.0357]. Both coefficients are statistically significant. The underidentification and weak instrument tests yield statistics of 8.9580 and 26.9410, respectively. These results provide statistical support for model identification and instrument relevance, alleviating concerns about weak identification to some extent. The overidentification test statistic is 1.1690, with a *p*-value greater than 0.1; thus, the null hypothesis that the overidentifying restrictions hold is not rejected. In the second stage, the estimated coefficient of FD_cri on GTF is 0.6632 and is significant at the 10% level, further supporting the reliability of the findings.

However, this study acknowledges that the IV strategy cannot fully eliminate potential endogeneity concerns, as the instruments may be associated with GTF through channels other than FD, including industrial pollution, transport accessibility, and regional in-

dustrial restructuring. Accordingly, this study interprets the IV-2SLS results as complementary evidence supporting the robustness of the baseline relationship, rather than definitive proof that endogeneity concerns have been fully resolved. The relationship between FD and GTF is therefore interpreted as an association rather than a causal effect.

Table 16. Endogeneity test results.

	(1) FD	(2) GTF	(3) FD_cri	(4) GTF
IV_1	0.0169 ** (0.0073)		0.0369 *** (0.0101)	
IV_2	−0.0468 *** (0.0089)		−0.0546 *** (0.0096)	
FD		1.0504 ** (0.5012)		
FD_cri				0.6632 * (0.3458)
Controls	Yes	Yes	Yes	Yes
Province F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Observations	420		420	
R-squared	0.1935		0.1864	
Kleibergen-Paap rk LM statistic	8.6540 **		8.9580 **	
Kleibergen-Paap rk Wald F statistic	23.9770 [19.9300]		26.9410 [19.9300]	
Hansen J statistic	1.4970		1.1690	

Note: ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses; The values in [] represent the critical values of the Stock–Yogo weak instrument identification F-test at the 10% significance level.

5. Further Analysis

5.1. Mechanism Test

5.1.1. Mechanism Test from the Fishery Sectors Perspective

Following Ha (2024) [14], this study measures aquaculture output per unit area (AQU) as the ratio of aquaculture output to aquaculture area and uses it as a proxy for aquaculture intensification. The rationale is that, from a productivity perspective, aquaculture output represents the output generated by aquaculture activities, while aquaculture area represents the water resources occupied during production. Higher output per unit area indicates greater production within a given aquaculture area. Aquaculture operators can improve spatial resource utilization efficiency by increasing stocking density, improving production technologies, and optimizing resource allocation. Accordingly, aquaculture output per unit area can, to some extent, reflect the transition from extensive to intensive resource use and serve as a reasonable proxy for aquaculture intensification.

Columns (1)–(2) of Table 17 present the mechanism test results for AQU. In column (1), the coefficient of *FD* on AQU is 1.3075 and is statistically significant at the 1% level, indicating a positive association between FD and AQU. In column (2), the estimated coefficient of AQU on GTF remains positive at 0.0867. The Sobel test yields a statistically significant mediation effect of 0.1133, while the Bootstrap test reports a confidence interval of [−0.0171, 0.2437]. Although statistical significance decreases, the effect remains statistically significant. These results indicate that AQU plays a positive mediating role in the

relationship between FD and GTF: FD is positively associated with AQU, which is, in turn, positively associated with GTF, supporting Hypothesis 2a.

However, because aquaculture area is also used to calculate GTF, the mechanism tests may be affected by mechanical overlap. To assess the robustness of the results, this study replaces GTF with absolute environmental indicators, including SIN and FEL, and repeats the mediation tests. These environmental variables do not directly incorporate the components of the mediator, thereby reducing the interference of mechanical overlap in mechanism identification. The results are reported in columns (3)–(4). In column (3), the coefficient of AQU on SIN is 0.1011 and is statistically significant, indicating a positive association between AQU and SIN to some extent. The Sobel and Bootstrap tests yield a mediation effect of 0.1322, with a Bootstrap confidence interval of [0.0660, 0.1984], indicating statistical significance in both tests. In column (4), the coefficient of AQU on FEL is negative at −0.1673. The Sobel test yields a mediation effect of −0.2187, while the Bootstrap test reports a 95% confidence interval of [−0.3087, −0.1287], indicating statistical significance. These findings suggest that FD is positively associated with AQU, while higher AQU is associated with higher SIN and lower FEL. Thus, replacing the outcome with absolute environmental performance indicators confirms the mediating role of AQU.

Table 17. Mechanism test results for AQU.

	(1) AQU	(2) GTF	(3) SIN	(4) FEL
FD	1.3075 ***	0.8648 ***	0.8684 ***	−0.7246 ***
	(0.2655)	(0.1576)	(0.0750)	(0.2776)
AQU		0.0867 ***	0.1011 ***	−0.1673 ***
		(0.0299)	(0.0142)	(0.0527)
_cons	−0.4725 ***	0.7293 ***	0.8330 ***	1.1416 ***
	(0.1360)	(0.0901)	(0.0429)	(0.1604)
Controls	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Observations	420	420	420	420
R-squared	0.3876	0.2476	0.6427	0.6476
Sobel test		0.1133 **	0.1322 ***	−0.2187 ***
Bootstrap test		0.1133 *	0.1322 ***	−0.2187 ***

Note: ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses.

To examine whether fishing efficiency mediates the relationship between FD and GTF, this study follows Wang and Wang (2022) [26] and uses the ratio of capture fishery output to the number of professional fishing workers as a proxy for fishing efficiency. This indicator reflects fishing output per unit of labor input. A higher value may indicate improvements in operational scheduling, route planning, and resource allocation, which may also reduce disturbances to aquatic ecosystems from unproductive fishing activities. Thus, from a productivity perspective, this indicator can, to some extent, be linked to ecological and environmental impacts.

Columns (1)–(2) of Table 18 present the mechanism test results for CAP. In column (1), the coefficient of FD on CAP is 0.9995 and is statistically significant, indicating a positive association between FD and CAP. After the mediator is introduced in column (2), the coefficient of FD decreases, whereas the coefficient of CAP is statistically insignificant. The Sobel and Bootstrap tests yield a mediation effect of 0.0196, which is insignificant in both tests. The Bootstrap confidence interval is [−0.0413, 0.0805].

To eliminate the influence of mechanical overlap in indicator construction on the estimates, this study uses SIN and FEL as dependent variables. As reported in columns (3)–(4), the coefficients of CAP on SIN and FEL are 0.0510 and 0.0213, respectively, neither of which is statistically significant. The Sobel and Bootstrap tests yield mediation effects of 0.0509 and 0.0213, with Bootstrap confidence intervals of [−0.0406, 0.1424] and [−0.0349, 0.0774], respectively. Neither effect is statistically significant. These results indicate that although FD is positively associated with CAP, the associations of CAP with GTF and the environmental performance indicators SIN and FEL are limited, suggesting that Hypothesis 2b is not supported.

The reasons for these findings are as follows. First, existing digital equipment may be insufficiently adapted to fishing operations. The dynamic nature and environmental uncertainty of fishing activities place considerable demands on the corrosion resistance, continuous power supply, and operational stability of digital equipment. However, existing equipment may still have limitations in these respects and may be inadequately suited to complex aquatic environments and changing operational conditions [22]. Second, capture fisheries remain characterized by fragmented, small-scale operations [28]. In this context, some fishers may have limited digital literacy, equipment operating skills, and financial resources. These limitations may constrain digital adoption in fishing operations, leaving the positive association between CAP and GTF less apparent. Third, under resource carrying capacity limits and environmental constraints, improvements in fishing efficiency may coincide with greater fishing intensity, expanded operating areas, and increased pressure on resource extraction [30]. These changes increase the risk of overfishing and exacerbate fishery carbon emissions and pollutant discharges, including TN, TP, and COD. This is reflected in the estimated coefficient of CAP on FEL. Overall, the relationships among FD, CAP, and GTF are not necessarily consistent in direction.

Table 18. Mechanism test results for CAP.

	(1) CAP	(2) GTF	(3) SIN	(4) FEL
FD	0.9995 ***	0.9585 ***	0.9497 ***	−0.9646 ***
	(0.3494)	(0.1559)	(0.0716)	(0.3017)
CAP		0.0196	0.0510	0.0213
		(0.0229)	(0.1965)	(0.0348)
_cons	0.5634 ***	0.7225 ***	0.7604 ***	1.8849 ***
	(0.1790)	(0.0800)	(0.0368)	(0.3398)
Controls	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Observations	420	420	420	420
R-squared	0.0616	0.2320	0.6605	0.6794
Sobel test		0.0196	0.0509	0.0213
Bootstrap test		0.0196	0.0509	0.0213

Note: *** indicates $p < 0.01$; Robust standard errors clustered at the provincial level are reported in parentheses.

5.1.2. Mechanism Test from the Fishery Industrial and Construction Sectors Perspective

Following Xia et al. (2025) [6], this study uses the ratio of total aquatic product processing output to the number of professional fishery workers as a proxy for aquatic product processing efficiency (PRO). This indicator reflects processing output per unit of labor input. Its suitability as a proxy for an environmental mechanism lies in the close relation-

ship between processing efficiency, resource utilization, and pollution control during processing. Higher aquatic product processing efficiency is typically associated with equipment digitalization and process modernization and may correspond to lower resource consumption and pollutant emission intensities. Thus, this indicator can, to some extent, capture environmental associations from a productivity perspective.

The test results are presented in columns (1)–(2) of Table 19. In column (1), the estimated coefficient of FD on PRO is 5.7024 and is statistically significant, indicating a clear positive relationship between FD and PRO. In column (2), the coefficient of PRO on GTF is 0.0311. The Sobel and Bootstrap tests yield a mediation effect of 0.1776, significant at the 1% and 5% levels, respectively, with a Bootstrap confidence interval of [0.0362, 0.3189]. These results indicate that PRO plays a positive mediating role in the relationship between FD and GTF. The associations among FD, PRO, and GTF are therefore consistent in direction, supporting Hypothesis 3.

To further examine whether the mediating role of PRO is affected by mechanical overlap with GTF arising from their indicator composition, this study incorporates absolute environmental indicators, including SIN and FEL, into the model and re-estimates the regressions. The results are reported in columns (3)–(4). In column (3), the coefficient of PRO on SIN is 0.0120 and is statistically significant, indicating a positive association between PRO and SIN. The Sobel and Bootstrap tests yield a mediation effect of 0.0683, significant at least at the 5% level in both tests, with a Bootstrap confidence interval of [0.0053, 0.1312]. In column (4), the coefficient of PRO on FEL is negative at −0.1438. The Sobel test yields a mediation effect of −0.8200, while the Bootstrap test reports a confidence interval of [−1.5212, −0.1188], indicating statistical significance. These findings indicate that FD is positively associated with PRO, while higher PRO is associated with higher SIN and lower FEL. By substituting absolute environmental performance indicators for the outcome variable, this study confirms the mediating role of PRO.

Table 19. Mechanism test results for PRO.

	(1) PRO	(2) GTF	(3) SIN	(4) FEL
FD	5.7024 ***	0.8005 ***	0.9323 ***	−0.1233
	(0.9602)	(0.1594)	(0.0747)	(0.0965)
PRO		0.0311 ***	0.0120 ***	−0.1438 ***
		(0.0085)	(0.0040)	(0.0411)
_cons	2.1207 ***	0.6328 ***	0.8682 ***	1.9055 ***
	(0.5683)	(0.0917)	(0.0429)	(0.4415)
Controls	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Observations	420	420	420	420
R-squared	0.1889	0.2667	0.5907	0.6063
Sobel test		0.1776 ***	0.0683 ***	−0.8200 ***
Bootstrap test		0.1776 **	0.0683 **	−0.8200 **

Note: ***, ** indicate $p < 0.01$, $p < 0.05$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses.

5.1.3. Mechanism Test from the Fishery Distribution and Service Sectors Perspective

Based on Wang et al. (2025a) [5], this study measures fishery industrial structure upgrading (UPG) by dividing the output of the fishery distribution and services sector by the total fishery economy output. The results are reported in columns (1)–(2) of Table 20. In column (1), the coefficient of FD on UPG is 0.8252 and is significant at the 1% level, indicating a positive association between FD and UPG. After UPG is introduced in column (2), the

coefficient of FD on GTF decreases relative to the baseline estimate. The Sobel and Bootstrap tests yield a mediation effect of 0.3068, which is statistically significant in both tests, with a Bootstrap confidence interval of [0.1343, 0.4793]. These results demonstrate a partial mediating association through UPG: FD is positively associated with UPG, which, in turn, is positively associated with GTF.

Because UPG is constructed using output value indicators, it may share components with GTF, potentially creating mechanical overlap. This study therefore uses SIN and FEL as alternative dependent variables to capture absolute changes in environmental performance and reduce overlap between the mediator and the outcome. The results are reported in columns (3)–(4). In column (3), the coefficient of UPG on SIN is positive and significant at the 5% level, indicating a positive association between UPG and SIN. The mediation effect is 0.1286, with a Bootstrap confidence interval of [0.0014, 0.2558], indicating statistical significance. In column (4), the coefficient of UPG on FEL is −0.5016 and is statistically significant, indicating a negative association between UPG and FEL. The Sobel and Bootstrap tests yield a statistically significant mediation effect of −0.4139, with a Bootstrap confidence interval of [−0.6889, −0.1389]. These findings indicate that UPG is positively associated with SIN and negatively associated with FEL, suggesting that UPG also mediates the associations between FD and the absolute environmental performance indicators. Taken together, these results support Hypothesis 4.

It should be emphasized that the mediation models rely on the strong assumption of sequential ignorability and are subject to the limitations of observational panel data. Accordingly, these mediation results should be interpreted as evidence of statistical associations rather than definitive causal mechanisms. This study therefore maintains a cautious interpretation of these mediating relationships.

Table 20. Mechanism test results for UPG.

	(1) UPG	(2) GTF	(3) SIN	(4) FEL
FD	0.8252 *** (0.0768)	0.6713 *** (0.1737)	0.8720 *** (0.0887)	−0.5294 ** (0.2126)
UPG		0.3718 *** (0.1027)	0.1559 ** (0.0776)	−0.5016 *** (0.1668)
_cons	−0.1294 *** (0.0393)	0.7817 *** (0.0788)	0.8130 *** (0.0403)	1.1613 *** (0.2523)
Controls	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Observations	420	420	420	420
R-squared	0.4249	0.2951	0.5939	0.6168
Sobel test		0.3068 ***	0.1286 **	−0.4139 ***
Bootstrap test		0.3068 ***	0.1286 **	−0.4139 ***

Note: ***, ** indicate $p < 0.01$, $p < 0.05$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses.

5.2. Heterogeneity Effect Analysis

5.2.1. Heterogeneity by Regional Location

This study divides the sample into eastern and central–western regions based on the "Opinions on Defining the Division of Eastern, Central, and Western Regions" and conducts grouped regression. The results are reported in columns (1)–(2) of Table 21. In the eastern region, the coefficient of FD is 1.1159 and is significant at the 1% level, whereas the estimated coefficient in the central and western regions is 0.8672 and is statistically insignificant. To ensure the credibility of the findings, this study also employs Fisher's combined test to examine coefficient differences between groups. Specifically, provinces are sampled with replacement

separately within each group in every resampling iteration, retaining all annual observations for each selected province. The group-specific regression models are then re-estimated, and Fisher's combined statistic is calculated. This procedure is repeated 1000 times, and the *p*-value for the between-group difference is calculated from the empirical distribution of the Bootstrap statistics. The resulting *p*-value is 0.0000, demonstrating a significant difference in coefficients between the groups.

Furthermore, this study replaces the explanatory variable with FD_cri to conduct a sensitivity analysis. As reported in columns (3)–(4), the coefficient of FD_cri in the eastern region is 0.7640 and is significant at the 5% level, whereas the coefficient in the central and western regions is 0.4356 and is statistically insignificant. Fisher's test of between-group coefficient differences also yields a *p*-value of 0.0000. These findings indicate that the positive association between FD and GTF is more pronounced in the eastern region.

On the one hand, the eastern region consists largely of coastal provinces with well-developed fishing ports and aquatic product trading networks. Marine capture fisheries, mariculture, and aquatic product processing have substantial demand for digital technologies, facilitating their adoption across these activities. Regarding fishery composition, the eastern region exhibits greater operational scale and specialization, allowing digital technologies to operate through multiple pathways, including intelligent production and lean management [26]. By contrast, fisheries in the central and western regions are generally dominated by freshwater production and fragmented operators, limiting the depth and breadth of digital technology adoption.

On the other hand, the diffusion and application of digital technologies depend on regional technological capabilities and supporting infrastructure. The eastern region benefits from well-developed infrastructure, human resources, and application settings [47], facilitating the effective integration of digital technologies into fisheries and corresponding to a pronounced positive association between FD and GTF. In the central and western regions, constraints in digital infrastructure and factor endowments weaken this positive relationship [17]. Moreover, substantial seasonal temperature variations and frequent weather events, such as extreme cold, in these regions can cause failures in essential digital equipment, including automated water supply systems and water quality sensors [38], making the positive association between FD and GTF less pronounced.

Table 21. Heterogeneity test results by regional location.

	(1) **Eastern**	**(2)** **Central–Western**	**(3)** **Eastern**	**(4)** **Central–Western**
FD	1.1159 ***	0.8672		
	(0.3952)	(0.8218)		
FD_cri			0.7640 **	0.4356
			(0.3146)	(0.8110)
_cons	0.6694 ***	0.7134 **	0.4675 **	0.6709 **
	(0.2125)	(0.2870)	(0.2261)	(0.3112)
Controls	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Observations	154	266	154	266
Within R-squared	0.3973	0.2307	0.4350	0.1895
Between-Group Coefficient Difference Test p-value	0.0000		0.0000	

Note: ***, ** indicate $p < 0.01$, $p < 0.05$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses.

5.2.2. Heterogeneity by Regional Innovation Level

Regional innovation plays an important role in the capacity to absorb knowledge and translate it into new technologies during fishery development. Following Thann et al. (2025) [36], this study measures regional innovation using the logarithms of regional patent applications (INN_app) and patent grants (INN_gra). Given the continuous nature of these variables, an interaction specification is more appropriate than subgroup regressions. Grouping continuous variables relies on arbitrarily defined thresholds, which can result in information loss, reduce statistical power, and make the findings sensitive to threshold selection. Accordingly, this study introduces interaction terms (FD × INN_app and FD × INN_gra) to examine heterogeneity.

The results are reported in columns (1)–(2) of Table 22. The coefficients of INN_app and INN_gra are 0.0684 and 0.0651, respectively, both significant at the 5% level, indicating a positive association between regional innovation and *GTF*. The estimated coefficients of FD × INN_app and FD × INN_gra on GTF are 0.1528 and 0.1329, respectively, and both are statistically significant. These findings indicate that the positive association between FD and GTF becomes more pronounced as regional innovation increases.

According to absorptive capacity theory, regional innovation is a key determinant of the ability to identify, assimilate, and apply digital technologies [36]. Higher regional innovation helps reduce the investment costs and risks associated with FD and accelerates the implementation of digital applications in fisheries [4], strengthening the integration of digital technologies into the real economy of fisheries. This enhances operators' capacity to acquire information and respond to feedback, enabling them to identify target customers' needs promptly [16] and increase market profits. It can also alleviate the overexploitation of natural fishery resources and reduce environmental pollution and carbon emissions [28]. Thus, regional innovation strengthens the positive association between FD and GTF.

Table 22. Heterogeneity test results by regional innovation level.

	(1) **GTF**	**(2)** **GTF**
FD	1.1337 *** (0.2832)	1.1219 *** (0.2812)
INN_app	0.0684 ** (0.0312)	
INN_gra		0.0651 ** (0.0306)
FD × INN_app	0.1528 ** (0.0745)	
FD × INN_gra		0.1329 ** (0.0601)
_cons	0.8765 *** (0.1538)	0.8756 *** (0.1499)
Controls	YES	YES
Province F.E.	YES	YES
Year F.E.	YES	YES
Observations	420	420
Within R-squared	0.2770	0.2803

Note: ***, ** indicate $p < 0.01$, $p < 0.05$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses.

5.2.3. Heterogeneity by Regional Talent Resources

Following Wang et al. (2025a) [5] and Wu et al. (2025) [46], this study measures regional talent resources using average years of schooling (TAL_edu) and the logarithm of

the number of individuals with a bachelor's degree or higher (TAL_deg). Table 23 presents the results. The coefficients of TAL_edu and TAL_deg on GTF are 0.1444 and 0.8717, respectively, and both are statistically significant, indicating a positive relationship between regional talent resources and GTF. The coefficients of the interaction terms FD × TAL_edu and FD × TAL_deg are positive at 0.6828 and 0.9405, significant at the 10% and 1% levels, respectively. These findings indicate that the positive association between FD and GTF becomes stronger as regional talent resources increase.

First, FD intensifies technological competition and creates a complex market environment, making technological adaptability a key factor in GTF [12]. High-quality talent possesses extensive digital knowledge, enabling them to quickly master cutting-edge tools such as big data analysis and cloud computing [19] and integrate these tools into fishery production and management systems. Moreover, high-quality talent helps fishery enterprises quickly respond to technological changes, completing system iterations and upgrades by optimizing technical solutions [47], ensuring that enterprises improve both economic and green performance under digitalization. However, regions lacking talent resources generally lack the understanding and ability to apply advanced technologies [36], making it difficult to fully unlock the technological potential of FD. Second, due to spatial agglomeration effects, regions rich in talent resources can generate knowledge spillovers [22], using technological advancements to develop environmentally friendly aquaculture and fishing systems as well as smart pollution control systems. This drives the transition of fishery production models from end-of-pipe governance to a full-process green transformation, providing a solid foundation for GTF. Thus, regional talent resources help strengthen the positive association between FD and GTF.

Table 23. Heterogeneity test results by regional talent resources.

	(1)	**(2)**
	GTF	**GTF**
FD	0.9377 ***	1.0004 ***
	(0.1344)	(0.1290)
TAL_edu	0.1444 **	
	(0.0591)	
TAL_deg		0.8717 ***
		(0.3050)
FD × TAL_edu	0.6828 *	
	(0.3632)	
FD × TAL_deg		0.9405 ***
		(0.2145)
_cons	−0.4246	0.6619 ***
	(0.4513)	(0.0721)
Controls	YES	YES
Province F.E.	YES	YES
Year F.E.	YES	YES
Observations	420	420
Within R-squared	0.2246	0.2301

Note: ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses.

5.3. Spatial Effect Test

5.3.1. Spatial Autocorrelation Test

Before estimating the spatial panel model, this study tests for spatial autocorrelation in FD and GTF. Most Moran's I statistics for both variables are significant at the 10% level, indicating pronounced spatial autocorrelation, as shown in Figure 2. These results suggest that FD and GTF exhibit spatial clustering owing to externalities associated with digital infrastructure, ecological conditions, and other factors. Omitting spatial interactions from the model may therefore yield biased estimates. Accordingly, a spatial model is needed to estimate both the local relationship and spatial spillover relationship between FD and GTF.

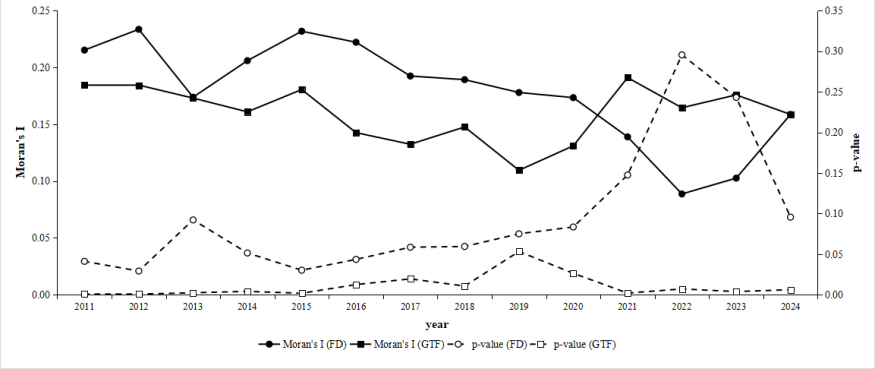


Figure 2. Spatial autocorrelation test results.

5.3.2. Spatial Panel Model Selection and Effect Decomposition

To ensure that the model specification aligns with the data structure, this study conducts spatial regression specification tests, with the results reported in Table 24. First, LM tests are used to identify the forms of spatial dependence. The LM error and robust LM error statistics are 11.5640 and 7.0190, respectively, and both are statistically significant, indicating the presence of spatial error effects. The LM lag and robust LM lag statistics are 6.6530 and 2.1070, respectively, and both are significant at least at the 10% level, indicating the presence of spatial lag effects. Therefore, neither the spatial error model (SEM) nor the spatial lag model (SLM) alone adequately captures the full structure of spatial dependence, making the spatial Durbin model (SDM) more appropriate. Next, LR and Wald tests are conducted to determine whether the SDM can be reduced to the SEM or SLM. The LR sem and LR sar statistics are 16.7700 and 14.1800, respectively, both significant at the 5% level. The Wald sem and Wald sar statistics are 40.7100 and 42.1400, respectively, and both are statistically significant. These results indicate that the SDM provides a statistically better fit and reject the hypotheses that it can be reduced to either model. Finally, LR tests are used to compare specifications with regional, time, and two-way fixed effects. The LR time and LR ind statistics are 387.7100 and 84.2900, respectively, rejecting the null hypotheses at the 1% level and indicating that the SDM with both time and regional fixed effects is the most appropriate specification.

The regression results are presented in Table 25. In column (1), the spatial autoregressive coefficient, rho, is 0.0578 and is significant at the 5% level, indicating interdependence in GTF across provinces: an increase in GTF in one province is accompanied by corresponding increases in neighboring regions. In columns (2)–(4), the direct effect of FD is 0.9970 and is significant at the 1% level, indicating a significant positive association between local FD and local GTF. This is consistent with the baseline regression results and further supports the robustness of Hypothesis 1. More importantly, the indirect effect, or spatial spillover effect, is also significantly positive, with a coefficient of 0.0989, indicating a positive relationship between FD in one province and GTF in neighboring provinces.

Spatially, FD is not a "zero-sum game": its positive environmental externalities can extend beyond administrative boundaries and are associated with coordinated improvements in GTF across a wider geographic area. The total effect of FD is 1.0959 and is statistically significant, indicating an overall positive association between FD and GTF when both local relationships and interregional spillovers are considered.

Table 24. Spatial regression model selection results.

Test Name		Test Statistic
LM test	LM error	11.5640 ***
	Robust LM error	7.0190 ***
	LM lag	6.6530 **
	Robust LM lag	2.1070 *
LR test	LR sem	16.7700 **
	LR sar	14.1800 **
	LR time	387.7100 ***
	LR ind	84.2900 ***
Wald test	Wald sem	40.7100 ***
	Wald sar	42.1400 ***

Note: ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

Table 25. Spatial Durbin regression results.

	(1) GTF	(2) Direct Effect	(3) Indirect Effect	(4) Total Effect
FD	0.9895 ***	0.9970 ***	0.0989 *	1.0959 ***
	(0.1731)	(0.1787)	(0.0529)	(0.3914)
Controls	YES	YES	YES	YES
Province F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Observations	420	420	420	420
rho	0.0578 **			
	(0.0288)			
sigma2_e	0.0382 ***			
	(0.0027)			
R-squared	0.1702			

Note: ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively; Robust standard errors clustered at the provincial level are reported in parentheses.

6. Conclusions and Policy Implications

6.1. Conclusions

GTF is essential to achieving economic growth and environmental protection. Using panel data from 30 Chinese provinces, municipalities, and autonomous regions from 2011 to 2024, this study first measures FD and GTF and then employs fixed-effects models, three-step mediation models, and a spatial Durbin model to empirically examine their relationship and potential mediating channels. The main conclusions are as follows.

First, FD is positively associated with GTF. This finding remains robust to alternative measures of the core variables, sample adjustments, the exclusion of interpolated observations, and Oster's omitted-variable sensitivity analysis, as well as endogeneity tests using instrumental variable two-stage least squares estimation. Second, aquaculture intensification, aquatic product processing efficiency, and fishery industrial structure upgrading exhibit potential positive mediating relationships between FD and GTF. However, the

fishing efficiency channel is not statistically significant, potentially reflecting practical constraints such as inadequate technological adaptation, limited digital capabilities among fishers, and restricted resource carrying capacity. Given the limitations of the available data and identification strategies, these potential mechanisms should be interpreted as statistical evidence of transmission channels rather than definitive causal pathways. Third, the relationship between FD and GTF exhibits heterogeneity. Their positive association is more pronounced in the eastern region than in the central and western regions. Moreover, this association strengthens as regional innovation and regional talent resources increase. Fourth, GTF is interrelated across regions, and local FD is positively associated with GTF in neighboring regions.

6.2. Policy Implications

This study offers the following recommendations: First, establish a "government-business" collaboration mechanism. The government should take the lead in developing digital infrastructure and public service platforms that cover the entire fishery value chain, strengthening the public provision of core elements such as data resources, underlying technologies, and software applications [1]. Simultaneously, by establishing special funds, providing fiscal and tax incentives, and other support measures, the government can reduce the initial costs of digital transformation for business operators and guide the formation of integrated digital fishery industry clusters, combining research and development, production, processing, and sales. Business operators should increase investment in digital hardware and software, actively adopt cutting-edge technologies such as artificial intelligence and the IoT, and enhance the technological foundation for digital transformation.

Second, leverage digitalization to enhance the efficiency of the entire industry chain. In the primary fishery sector, intelligent feeding, smart monitoring, and other systems should be standardized and applied in aquaculture [14], aiming to standardize data collection throughout the aquaculture process and achieve intensification. In the secondary fishery sector, priority should be given to the deployment of digital equipment, such as machine vision sorting and intelligent sterilization, and the establishment of a full-process quality traceability system, from raw material inspection to finished product shipment. This will drive the shift in processing models toward technology-intensive methods, thereby optimizing the processing efficiency of aquatic products. In the tertiary fishery sector, there should be robust development of intelligent supply-demand matching platforms and smart cold chain logistics, as well as active cultivation of emerging industries, such as recreational fisheries [16]. Through value chain restructuring and service model innovation, this will facilitate the upgrading of the fishery industrial structure.

Third, establish a regional cooperation mechanism to foster coordinated development. In response to the limited role of FD in central–western regions, local governments should leverage the "fisheries + internet" model to create a nationwide fishery resource and digital service platform [38], breaking down information barriers and facilitating cross-regional information sharing. Business operators should also utilize digital platforms to engage in cross-regional communication and cooperation, drawing on the experiences of advanced regions and exploring digital development paths tailored to their specific circumstances.

Fourth, implement differentiated governance strategies based on regional innovation levels. In regions with higher innovation levels, the government should prioritize establishing core technology research and development centers for FD, creating technology hubs. In regions with limited innovation capacity, the government should facilitate technology diffusion by establishing special funds and forming innovation alliances, thereby promoting the efficient cross-regional allocation of digital resources.

Fifth, strengthen the development of the talent pool. The government should actively implement a digital talent-driven strategy and introduce targeted talent development policies

[19], attracting high-quality, interdisciplinary talent to the fishery sector by enhancing the talent incentive system and development environment. Moreover, the government should foster industry–academia–research cooperation, establish training bases and industry research institutes, encourage university students to participate in FD practices, and cultivate professionals with both digital literacy and industry experience. Fishery enterprises should also strengthen employee training by regularly organizing "online + offline" dual-channel digital skills training through online platforms. Simultaneously, they should actively recruit high-quality talent to support the implementation of digital applications.

6.3. Limitations and Future Research

There exist some limitations. First, data availability constraints limit the empirical analysis to the provincial level. Although provincial statistics provide an overall picture of regional development, aggregated data may obscure local ecological differences across prefecture-level cities and counties. In addition, the extent to which these findings can be transferred to other national contexts is uncertain, given cross-country differences in institutional arrangements and socioeconomic conditions. As statistical systems continue to improve and more detailed information becomes available, subsequent studies should employ finer-scale data and incorporate international comparisons to derive conclusions that are both more precise and more broadly applicable.

Second, some interpolated values used to construct FD and GTF may deviate from actual observations, introducing measurement error. Moreover, mechanical links may remain between the mediating variables and GTF because of overlapping indicator components. Future research could explore alternative interpolation methods and use variables with greater independence in their construction to improve the accuracy of the findings.

Third, policies directly targeting fishery digitalization remain relatively scarce. Future research could exploit policies such as digital fishery pilot programs and fishery digital infrastructure initiatives as quasi-natural experiments and apply difference-in-differences methods to assess the causal effects of FD, thereby strengthening identification and addressing endogeneity.

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