

Article

The Impact of Fishery Industry Agglomeration on the Green Development Efficiency of Aquaculture: Evidence from Provincial Panel Data in China

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Abstract

Promoting fishery industry agglomeration (AGG) is an important initiative to realize the green development efficiency of aquaculture (GEE) in the new era. This paper uses panel data from 30 provinces in China from 2008 to 2022. It employs the double fixed effect model and the mediating effect model to examine the impact of AGG on GEE. The results show that AGG has a positive effect on GEE. The green empowerment effect of homogeneous agglomeration is greater than that of heterogeneous agglomeration. In terms of specific agglomeration types, the positive effects of all types except the single tertiary industry agglomeration and the co-agglomeration of the primary and tertiary industries are statistically significant. There are obvious regional differences in the agglomeration effect, and the green dividend of agglomeration in the Yangtze River Basin and inland areas is more prominent. The agglomeration has the characteristics of diminishing marginal returns, and only the regions with a good green foundation can fully release the agglomeration advantages. Human capital and technological innovation play a partial intermediary role, and industrial structure upgrading has a masking effect. At this stage, the ecological orientation of industrial upgrading is insufficient to offset some of the positive effects of agglomeration. Based on this, it provides empirical support for differentiated cultivation of fishery green industrial clusters and smooth transmission channels of green elements.

Keywords: fishery industry agglomeration; aquaculture; green development efficiency; technology innovation; industrial structure upgrading

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1. Introduction

Against the backdrop of increasingly severe resource constraints and environmental pressures on the global agricultural and food systems, achieving sustainable productivity growth has become a central issue in development economics and resource management. This global challenge is particularly evident in the aquaculture sector, a crucial pillar of modern agriculture that provides a consistent supply of high-quality animal protein, thereby enhancing dietary nutrition, supporting public health, promoting economic growth, and generating employment[1–4]. But it also faces dual pressures from ecosystem degradation and greenhouse gas emissions. As the world's largest aquaculture producer, China's aquaculture output reached approximately 58.09 million tons in 2023, accounting

for over half of the global total [5], significantly contributing to global food and nutrition security. However, the rapid expansion of aquaculture has intensified environmental pressures, including the depletion of fishery resources, water pollution, eutrophication, and ecosystem degradation [6–8]. Additionally, structural imbalances in the supply of aquatic products have become increasingly pronounced [9]. In this context, China's pathway toward green transformation not only concerns domestic food security and ecological safety but also serves as a critical case in development economics for examining whether economic growth can be reconciled with environmental sustainability. Therefore, a thorough investigation into the mechanism between industrial agglomeration and green efficiency holds significant theoretical value and policy implications for understanding sustainable development pathways in the agricultural sectors of late-developing countries.

Referring to Chen et al. [10], fisheries industry agglomeration (AGG) refers to the spatial concentration of enterprises from identical or associated fishery sectors together with their supporting service systems within a fixed geographic scope. Current studies on AGG are still limited in quantity, yet existing case-based research has recognized agglomeration as an essential pathway to strengthen industrial competitiveness and achieve fishery sustainability.

Benefiting from agglomeration externalities, concentrated fishery clusters can raise production efficiency, optimize supply-chain operations, and improve trading performance [11,12]. At the international level, Norway's salmon-farming cluster gains export advantages via multi-dimensional knowledge spillover [13], while the United Kingdom's fish-processing cluster cuts energy consumption and carbon emissions with intelligent energy-management systems [14]. Outside the fishery field, Indonesian agricultural agglomeration also offers experience for coping with challenges brought by ASEAN economic integration [15]. Domestic empirical evidence identifies obvious spatial agglomeration characteristics and regional comparative advantages among China's coastal aquaculture industries. Scallop aquaculture is overwhelmingly concentrated in Hebei, Shandong, and Liaoning, whose combined market share exceeds 99% [16]. In Jiangsu Province, aquaculture activities are transferring from inland waters toward coastal zones; nevertheless, the inadequate agglomeration degree and unreasonable spatial layout call for targeted policy optimization [17].

In recent years, the green development of aquaculture has turned into a heated research theme. Previous studies interpret its connotation from resource utilization, ecological conservation, technical innovation, economic benefit, and food safety [18–21]. On that foundation, the present paper defines China's aquaculture green development (GEE) as an innovation-oriented development mode. Restricted by aquatic ecosystem bearing capacity, this mode relies on advanced theories and technologies to prioritize resource conservation and ecological protection, and finally achieves rational resource allocation, eco-friendly habitats, safe aquatic products, and coordinated economic gains through industrial green development planning.

Existing quantitative evaluations on the green development of aquaculture mainly adopt several mainstream approaches, including DEA-based assessment, stochastic frontier analysis, and total factor productivity measurement [22,23]. Most researchers select the Super-SBM model [24] or the SBM-GML model [25,26] for efficiency estimation. Several scholars have further constructed comprehensive evaluation systems covering environmental friendliness, economic efficiency, green technology innovation, and aquaculture scale [27,28]. Apart from measurement research, documented determinants of aquaculture green performance cover breeding patterns, marine ranching, the digital economy, and environmental regulation [29–32].

To sum up, the available literature predominantly concentrates on the measurement, evaluation and influencing-factor exploration of aquaculture green development. Research concerning AGG remains dominated by qualitative case analysis. The causal linkage and inner mechanism between AGG and GEE have not received sufficient attention.

Against this research gap, this paper investigates how AGG shapes GEE in China and explores its action channels to supply policy references for the sustainable and high-quality advancement of aquaculture. This study makes three principal contributions. First, it expands research on the agglomeration–green development nexus into the fishery domain and enriches fishery-economics theoretical frameworks. Second, it disentangles the influencing channels of AGG, focusing on technological innovation, industrial structure upgrading, and human capital accumulation. Third, it compares the heterogeneous impacts of specialized and diversified agglomeration modes, which facilitates the formulation of differentiated regional fishery policies.

2. Theoretical Analysis and Hypothesis

2.1. Analysis of the Influence of AGG on GEE

AGG affects GEE through scale, sharing, and learning effects. First, spatial agglomeration is a key competitive strategy for firms. This evolution from isolated points to integrated formations creates scale effects that cut unit costs and raise efficiency. These scale effects help reduce unit production costs and improve efficiency. Second, enterprises within agglomerated zones can achieve technical standardization and shared infrastructure [33]. This not only lowers the unit cost of environmental management but also improves environmental quality. Third, agglomeration facilitates information exchange and social learning. The inherent trust relationships within fishery clusters reduce learning costs, thereby lowering barriers to adopting cleaner technologies and enhancing innovation efficiency in green practices [34]. Based on these theoretical foundations, this paper proposes the following hypotheses:

H1. *AGG has a positive effect on GEE.*

2.2. Analysis of the Mechanism Through Which AGG Affects GEE

(1) Human capital

According to the push–pull theory [35], AGG creates abundant employment opportunities [7], attracts high-quality labor, and optimizes the structure of human capital. It also intensifies labor competition, compelling workers to continuously improve their professional skills, thereby enhancing overall human capital quality. Human capital enhancement plays a crucial role in promoting GEE. With the advancement of modern fisheries, highly skilled aquaculture personnel are better equipped to master intelligent technologies, enabling precision harvesting, optimized feeding regimes, and other refined operations. This liberates labor resources and facilitates sustainable aquaculture practices [36]. Based on this, this paper proposes the following hypothesis:

H2. *Human capital plays a positive mediating role in the effect of AGG on GEE.*

(2) Technology innovation

AGG can promote the concentration of technology, talent, resources, and other production factors, thereby reducing the cost of technology innovation and improving innovation efficiency. Technological exchange and sharing among enterprises within the agglomeration area can stimulate green technology innovation and drive both upstream and

downstream enterprises in the industrial chain [37]. In this way, it enhances green technology innovation through spillover effects [38], thereby enhancing the green innovation capacity of the entire industry. Technological innovation is a key pathway to promoting GEE. Technology innovations in the fishery can improve resource utilization efficiency and facilitate the development and application of green aquaculture techniques. This reduces energy consumption and aquatic environmental pollution [39], thereby fostering the sustainable development of aquaculture. Based on this, this paper defines the following hypothesis:

H3. Technological innovation partially mediates the positive effect of AGG on GEE.

(3) Industrial structure upgrading.

Industrial agglomeration can reduce information asymmetry [10], promote the specialized division of labor in fishery-related economic activities, and enable enterprises to gain greater cost advantages in market competition. These advantages allow enterprises to allocate more resources toward upgrading the fishery industry. The market's survival-of-the-fittest mechanism drives resource concentration toward more competitive firms, thereby facilitating the green and high-end development of the fishery sector and advancing industrial structure upgrading. From the perspective of circular economic theory, associated enterprises can form symbiotic relationships involving the exchange of materials and resources, which promotes resource recycling [40], reduces environmental pollution, and alleviates environmental pressure. Additionally, industrial structure upgrading is often accompanied by technological innovation and progress. The application of new technologies can improve breeding efficiency, reduce aquaculture costs, and lower resource consumption, thereby achieving green and sustainable development. Based on this analysis, this paper introduces the following hypothesis:

H4. Industrial structure upgrading partially mediates the positive effect of AGG on GEE.

Drawing on the analysis above, the hypothetical framework of the study is illustrated in Figure 1.

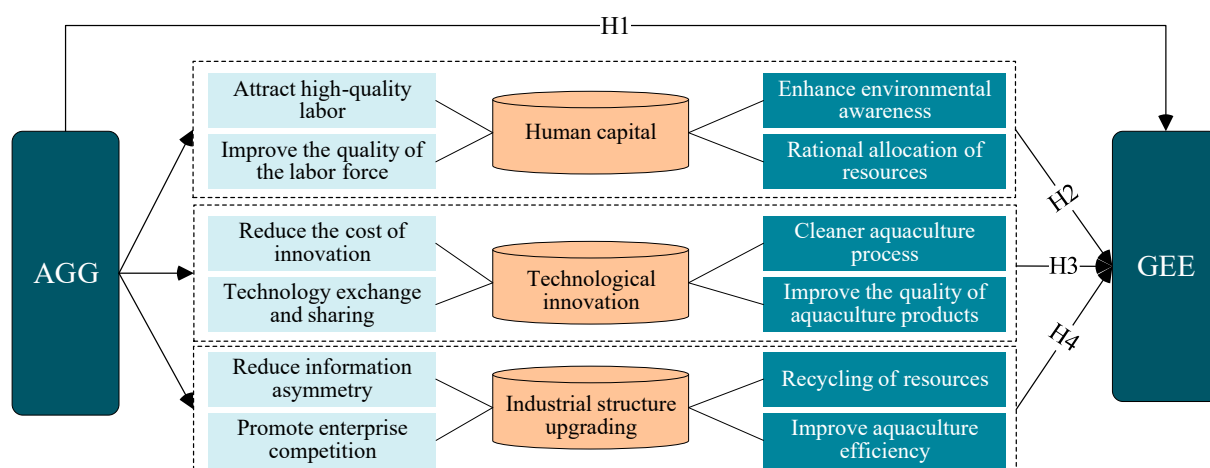


Figure 1. The conceptual framework of the AGG impact on GEE.

3. Research Design

3.1. Model Construction

3.1.1. Benchmark Regression Model

Based on the characteristics of panel data that encompass both individual and time dimensions, and considering the interference of time-invariant individual heterogeneity and common time trends in estimation, this paper adopts a fixed effects model for the benchmark regression. Through double-demeaning transformations across both individual and time dimensions, the model effectively controls for the unobserved u_i and λ_t , thereby identifying the net effect of industrial agglomeration on green development. Equation (1) represents the specified model:

$$GEE_{it} = \alpha_0 + \omega AGG + \sum_{m=1}^4 a_m X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where GEE represents the green development efficiency of aquaculture, AGG denotes fishery industry agglomeration, X signifies the set of control variables, α_0 shows the intercept, ω indicates the estimated coefficients of the core explanatory variables, and ε_{it} represents the random error term. u_i denotes the individual fixed effect and λ_t denotes the time fixed effect.

3.1.2. Mediating Effects Model

In order to further clarify the impact mechanism of AGG on GEE , this paper employs the stepwise regression method proposed by Baron and Kenny to test whether human capital, technological innovation, and industrial structure upgrading have intermediary effects between AGG and GEE . The regression equation is set as follows:

$$M_{it} = \alpha_0 + \omega AGG + \sum_{m=1}^4 a_m X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$GEE_{it} = \alpha_0 + \omega AGG + \delta M_{it} + \sum_{m=1}^4 a_m X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where M_{it} represents the mediating variable, mainly including human capital, technological innovation, and industrial structure upgrading. The remainder are identical to the uniform formula (1).

3.2. Data Sources and Variable Measurement

3.2.1. Data Sources

Due to significant data gaps for Hong Kong, Macao, Taiwan, and the Tibet Autonomous Region, this study focuses on the remaining 30 provincial-level administrative regions in China based on data availability. The data used in this paper mainly come from the *China Statistical Yearbook*, *China Fishery Statistical Yearbook*, *Provincial Statistical Yearbooks*, the *Handbook of Coefficients of Production and Discharge of Fishery Pollution Sources of the First National Pollution Source Census*, and various statistical yearbooks published by the National Bureau of Statistics from 2008 to 2022.

3.2.2. Variable Measurement

(1) Explained variable

This paper adopts the improved Super-SBM model proposed by Tone [41] to evaluate GEE . The super-efficient SBM model accounts for undesirable outputs and slack, enabling a more accurate assessment of the effective efficiency of decision-making units. Consequently, it provides a more precise measurement of GEE . Equations (4) and (5) show the specific model:

$$\rho = \min \frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{r_i^x}{x_{i0}}}{1 - \frac{1}{r_1 + r_2} \left(\sum_{k=1}^{r_1} \frac{r_k^y}{y_{k0}} + \sum_{l=1}^{r_2} \frac{r_l^z}{z_{l0}} \right)} \quad (4)$$

$$s.t. \left\{ \begin{array}{l} x_{i0} \geq \sum_{j=1, \neq 0}^n \mu_j x_j - r_i^x, \forall i; \\ y_{k0} \leq \sum_{j=1, \neq 0}^n \mu_j y_j + r_k^y, \forall k; \\ z_{l0} \geq \sum_{j=1, \neq 0}^n \mu_j z_j - r_l^z, \forall l; \\ r_i^x \geq 0; r_k^y \geq 0; r_l^z \geq 0, \lambda_j \geq 0, \forall i, j, k, l; \end{array} \right\} \quad (5)$$

where ρ represents the optimal value of efficiency; m , r_1 , and r_2 are the number of input, desired output, and non-desired output indicators; x , y , z denote input, desired output, and non-desired output, respectively; r_i^x , r_k^y , and r_l^z indicate the slack variables corresponding to the three indicators; and μ_j is the weight of the decision unit.

We refer to relevant research [24,42]. The input, expected output, and undesired output indicators of GEE are shown in Table 1. The specific calculation formula is shown in the Appendix A.

Table 1. Input–output index of GEE.

Category	Indicators	Unit
Input Indicators (see Appendix A.1.)	Aquaculture area	hectare
	Number of aquaculture employees	person
	Total power of aquaculture motorized fishing vessels	kilowatt
	Intermediate consumption of aquaculture	billion yuan
	Quantity of aquaculture seedlings stocked	consolidated indicators
Desirable Outputs	Total output value of aquaculture	100 million yuan
	Carbon sinks from aquaculture (calculated from the coefficients detailed in Appendix Tables A1 and A2)	tons
	Total nitrogen and total phosphorus production from aquaculture (Method: see Appendix Equation (A3))	tons
Undesirable Outputs	Carbon emissions from aquaculture (Method: see Appendix Equations (A4) and (A5))	tons

(2) Core explanatory variable

Drawing on Wang et al. [43], AGG is expressed as the locational entropy of the fishery industry in the region. A large value of locational entropy means a high degree of AGG. Equation (6) shows the specific measurement formula for AGG.

$$AGG_{it} = \frac{fa_i / gdp_i}{\sum_i fa_i / \sum_i gdp_i} \quad (6)$$

where i denotes the region, with AGG_{it} representing the degree of AGG in region i at time t . fa_i and gdp_i refer to the total fishery output value and gross domestic product (GDP) of region i , respectively; and fa and gdp characterize the total fishery output value and GDP of the whole study area, respectively.

To further explore the agglomeration effect of GEE, this paper divides the AGG into homogeneous agglomeration (HOAGG) and heterogeneous agglomeration (HEAGG) (homogeneous and heterogeneous industries are mainly divided into three industries according to the *China Fisheries Statistical Yearbook*, including production industry, processing/manufacturing industry, and service industry) based on industry characteristics. Due to the absence of fishery processing and service industry output values in Qinghai, the sample is excluded from the analysis when measuring homogeneous and heterogeneous agglomeration. The homogeneous agglomeration (homogeneous agglomeration is calculated using the mean value of AGG_1 , AGG_2 and AGG_3) is further divided into three

types—AGG₁ (AGG₁ represents the agglomeration of production sectors including aquaculture, fishing and aquaculture nurseries), AGG₂ (AGG₂ represents the agglomeration of processing/manufacturing sectors including aquatic product processing, fishery feed, fishery drugs, etc.) and AGG₃ (AGG₃ represents the agglomeration of service sector including aquatic circulation, aquatic transportation, and leisure fisheries)—measured using the location entropy method described in the previous section. Heterogeneous agglomeration (heterogeneous agglomeration is calculated using the mean value of AGG₁₂, AGG₁₃, AGG₂₃ and AGG₁₂₃) is categorized into four types: AGG₁₂, AGG₁₃, AGG₂₃ and AGG₁₂₃ [30,44]. The specific calculation formula is as follows:

$$AGG_m = \left(1 + \frac{|AGG_m - AGG_n|}{AGG_m + AGG_n}\right) + AGG_m + AGG_n \quad (7)$$

where AGG_m denotes the index of m industry agglomeration, AGG_n denotes the index of n industry agglomeration, and both the AGG_m and AGG_n are calculated by the location entropy index.

Specifically, the AGG_{123} within heterogeneous agglomeration is measured by the chain-coagglomeration index. The specific formula is as follows:

$$AGG_{123} = \sqrt[3]{AGG_1 * AGG_2 * AGG_3} \quad (8)$$

(3) Mediating variables

Based on the analysis of the mechanisms in Section 2, human capital, technological innovation, and industrial structure upgrading are used as the mechanism variables in this study to examine the impact pathways of fishery industry agglomeration on the green development of China's aquaculture industry. Given the availability of aquaculture industry data, the specific indicators are calculated as follows:

(1) Human capital (HUM). Professionally trained fish farmers are more likely to adopt innovative practices such as low-pollution feed and precision feeding techniques, thereby indirectly reducing aquaculture pollution and promoting the sustainability of aquaculture. Human capital is measured as the ratio of fishery output value to the number of aquaculture practitioners.

(2) Technology innovation (TEC). Innovations in aquaculture technology are transforming conventional farming practices into environmentally sustainable production systems through resource recycling, pollution reduction, and efficiency enhancement, thereby propelling the aquaculture industry towards green development. Referring to the study [45], technological innovation is expressed by the number of green patent licenses multiplied by the proportion of fisheries in GDP.

(3) Industrial structure upgrading (ISU). This paper adopts the spatial angle vector method proposed by Fu [46] to construct an industrial structure upgrading index. First, a set of three-dimensional vectors is formed using the proportion of output value from the three sectors within the overall fisheries industry $X_0 = (x_{1,0}, x_{2,0}, x_{3,0})$. Secondly, the angles θ_1 , θ_2 , and θ_3 are between vectors $X_1 = (1 \ 0 \ 0)$, $X_2 = (0 \ 1 \ 0)$, and $X_3 = (0 \ 0 \ 1)$ in the computational industry from lower to higher levels. Finally, the industrial structure upgrading index (ISU) is calculated using the following formula:

$$\theta_j = \arccos \left\{ \frac{\sum_{i=1}^3 (x_{ij} \times x_{i0})}{\left(\sum_{i=1}^3 (x_{i,j}^2)^{1/2} \times \sum_{i=1}^3 (x_{i,0}^2)^{1/2} \right)} \right\}, j = 1, 2, 3 \quad (9)$$

$$ISU = \sum_{k=1}^3 \sum_{j=1}^3 \theta_j \quad (10)$$

(4) Control variables

To more accurately assess the impact of AGG on GEE and address endogeneity issues arising from omitted variables in the model estimation results, this study introduces the following control variables based on prior research [47].

(1) Education level (EDU). Regional education level can influence technological innovation, management efficiency, and green production awareness in the aquaculture industry and further regulate the green development process of aquaculture. The specific calculation method is as follows: the number of students enrolled in higher education divided by the year-end permanent population.

(2) Aquaculture level (AL). Aquaculture level effectively reflects the developmental scale and industrial foundation of regional aquaculture, which optimizes the industrial structure of fisheries and facilitates the steady advancement of green transformation in the aquaculture industry. The specific calculation method is as follows: the output value of aquaculture divided by the total output value of fisheries.

(3) Technical facility (TF). Fishery technical facilities effectively improve the regional aquaculture technical service capacity and popularization level of green breeding technologies, thereby supporting the technological upgrading and sustainable green development of the aquaculture industry. The specific calculation method is as follows: the number of aquatic technology promotion institutions divided by the aquaculture area.

(4) Income levels of fishermen (INC). Increased income levels among fishermen can enhance their economic capacity to adopt ecological aquaculture techniques and environmentally friendly equipment, thereby proactively driving the transformation of the aquaculture industry towards a green and sustainable model. The specific calculation method is as follows: the logarithm of the per capita income of fishermen.

Table 2 reports the descriptive statistics of the core variables.

Table 2. Descriptive statistics for the main variables.

Variable Name	Observations	Mean	SD	Min	Max
GEE	450	0.5266	0.1989	0.3123	1.0671
AGG	450	0.8318	0.9933	0.003	4.3129
ISU	450	5.0988	0.304	4.7124	7.0316
TEC	450	36.8429	78.9362	0.0011	585.2142
HUM	450	11.9158	1.9254	6.4232	14.4448
EDU	450	0.0201	0.006	0.0074	0.0436
AL	450	0.5227	0.1856	0.0449	1
TF	450	0.0027	0.0026	0.00004	0.0139
INC	450	9.4621	0.5206	7.4321	10.3729

4. Temporal and Spatial Evolution of GEE

4.1. Temporal Evolution

To examine the temporal evolution of GEE in China, this paper uses the average GEE values across 30 provinces from 2008 to 2022. As shown in Figure 2, the average level of GEE in China during the study period is between 0.46 and 0.66, with some fluctuations but an overall upward trend. This trend encompasses two stages. In the first stage (2008–2011), GEE showed a decreasing trend, which can be attributed to the global financial crisis in 2008 and the ongoing transition from an extensive to a more refined development model in China's aquaculture sector. In the second stage (after 2012), GEE demonstrated an upward trend with some fluctuations, largely influenced by policy initiatives such as the issuance of the No. 1 Central Document in 2012 and related policies, such as Several Opinions on Accelerating the GEE, issued in 2009.

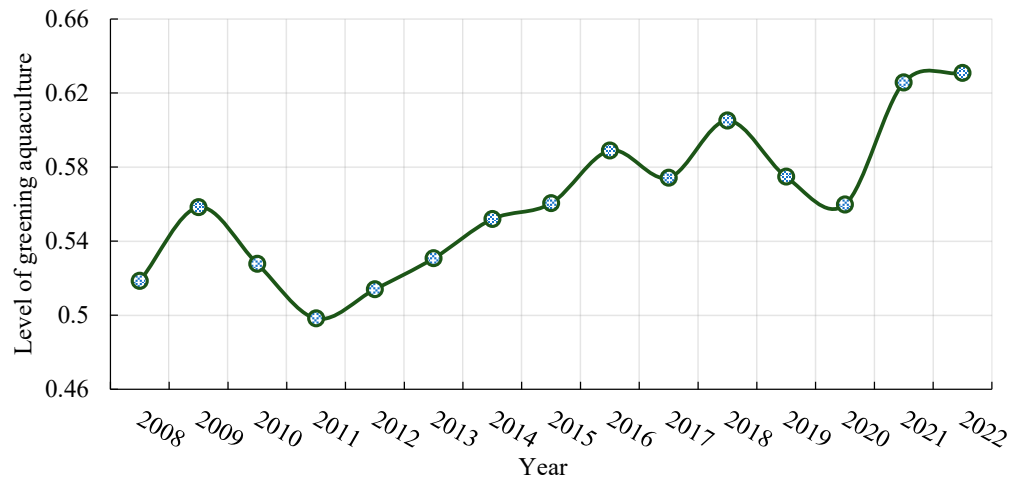


Figure 2. Temporal evolution of GEE in 2008–2022.

The three-dimensional kernel density estimation (Figure 3) demonstrates a discernible upward trajectory in GEE. This progression exhibits an evolution characterized by a transition from multi-peaked to single-peaked distributions with concurrent attenuation of polarization phenomena. This trend reflects progression toward greater equilibrium, coordination, and sustainability in aquaculture green development. The observed transition signifies markedly diminished spatial disparities among aquaculture zones, enhanced resource allocation efficiency, and a strategic shift from extensive expansion to quality-oriented advancement.

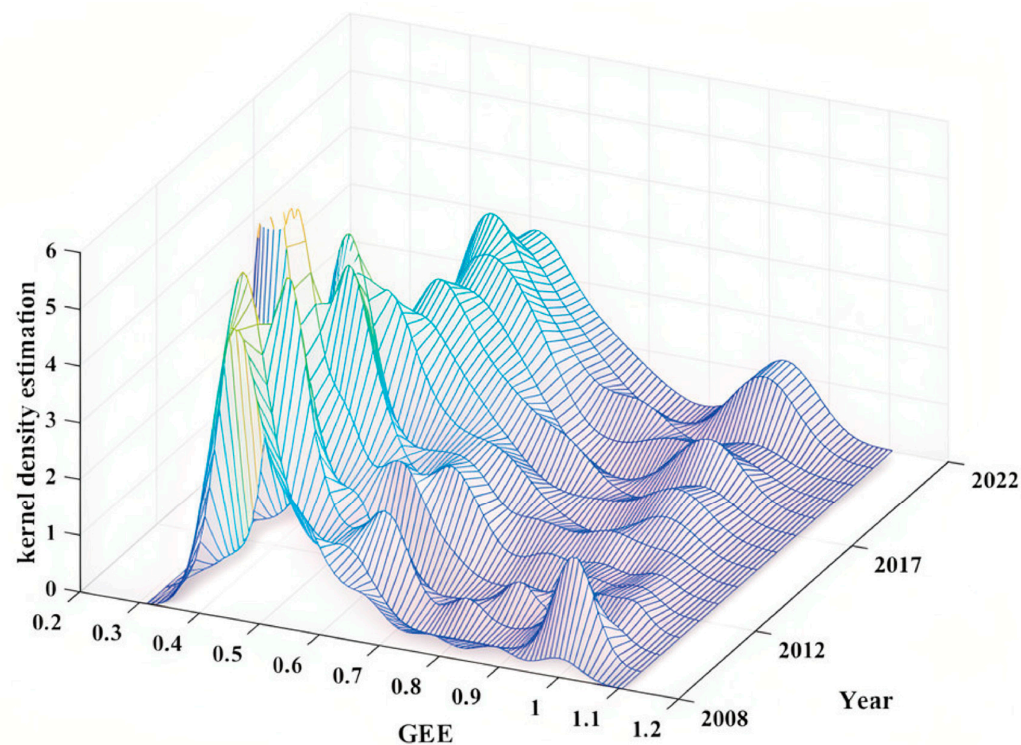


Figure 3. Kernel density estimation of GEE in 2008–2022. Color indicates the estimated density; warmer colors denote higher values.

4.2. Spatial Evolution

To analyze the spatial evolution of GEE, this paper utilizes ArcGIS 10.8 software and the natural break point method to divide the GEE into four categories: low, medium, high, and very high levels. Using the benchmark years of China's Five-Year Plans, this study examines the spatial distribution of China's GEE in 2011, 2016, and 2021. Regarding Figure 4, the overall trend of GEE has improved from 2011 to 2021, exhibiting a pattern of concentration towards the east. The core areas of the GEE, initially located in the Pearl River Delta and the Bohai Rim, have gradually expanded to encompass the entire southeastern coastal region. In particular, East China has maintained the most prominent upward trend in GEE. Several concrete contributing factors account for this favorable tendency. First, superior economic foundations and mature coastal aquaculture industries facilitate industrial upgrading and eco-friendly farming transformation. Second, abundant skilled labor resources provide human capital support for updated breeding technology and environmental management. Third, stringent marine environment regulation, convenient coastal logistics and frequent inter-city technology spillover accelerate the popularization of low-pollution aquaculture modes. In general, nearly all areas with outstanding aquaculture green performance lie to the east of the Hu Huanyong Line, which verifies that regional economic level, labor stock, industrial foundation, and environmental governance together determine the spatial disparity of GEE.

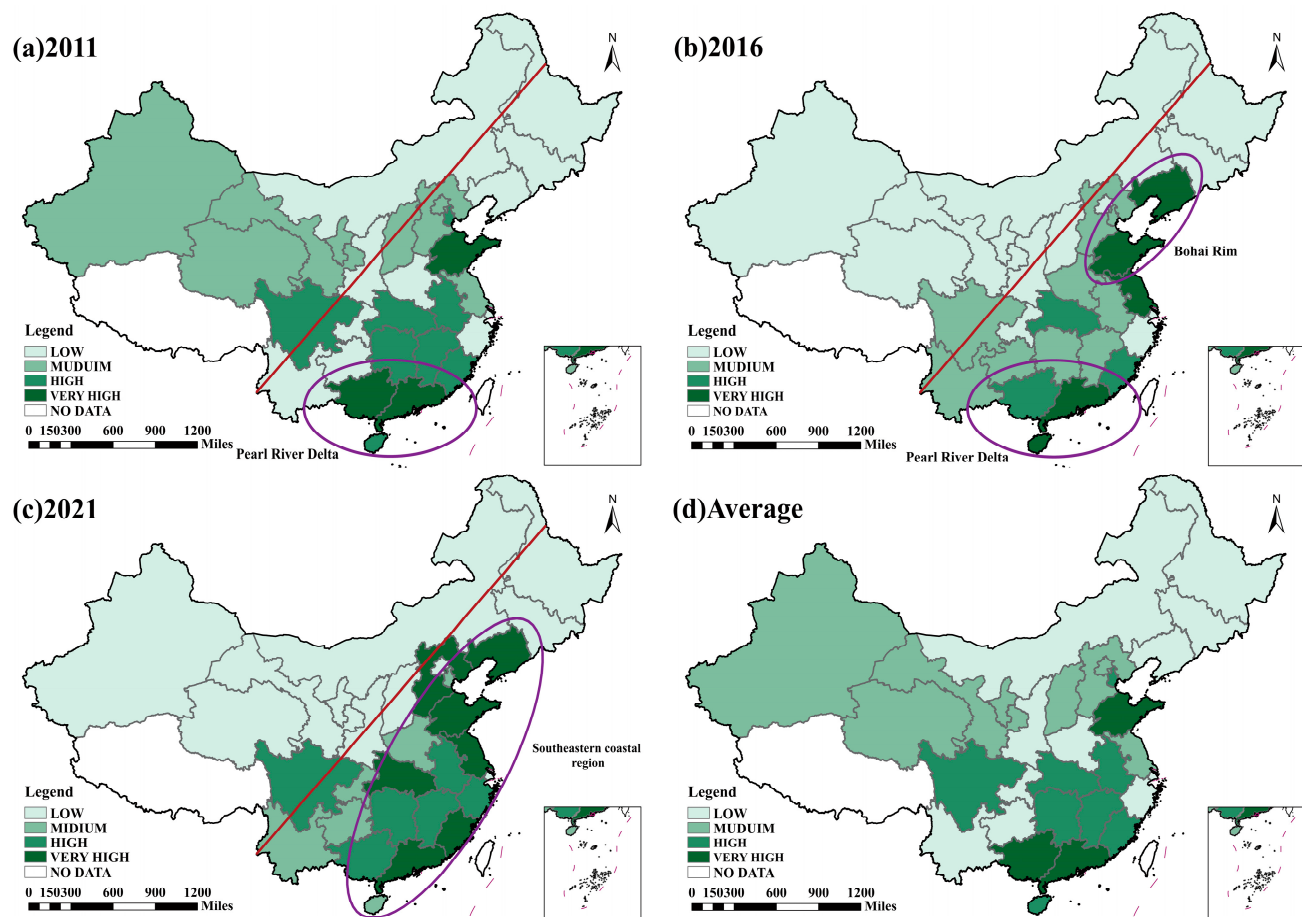


Figure 4. Spatial distribution of GEE. Red line: the Hu Huanyong Line. Purple-red circles: areas of high GEE concentration.

5. Empirical Analysis

5.1. Analysis of Benchmark Regression Results

Before the benchmark regression, this paper uses the Pearson correlation test to explore the linear correlation characteristics of each variable. The test results are shown in Table 3. The results show that AGG is significantly positively correlated with GEE, which is basically consistent with the expected theoretical direction, so subsequent empirical regression can be carried out.

In this paper, a fixed effect model is used as the benchmark specification to reduce the omitted variable bias caused by unobserved time-invariant regional features. In order to solve the potential heteroscedasticity and sequence correlation, the feasible generalized least squares (FGLS) method is used for supplementary estimation. Considering the inherent spatial correlation of aquaculture economic activities, the spatial Durbin model (SDM) is further used to identify regional spatial spillover effects. As shown in Table 4, in the benchmark regression, the coefficient of AGG is significantly positive. In the FGLS and SDM estimates, the coefficient of AGG is still positive and significant, indicating that the results of the article have certain robustness. AGG leverages supply chain coordination to promote resource sharing and green technology innovation, internalize the positive externalities of pollution control, lower firms' regulatory compliance costs, and further improve resource utilization efficiency and mitigate aquaculture water pollution. These empirical results support H1.

Table 3. Correlation analysis.

Variable	GEE	AGG	ISU	TEC	HUM	EDU	AL	TF	INC
GEE	1								
AGG	0.4882 ***	1							
ISU	0.1383 ***	0.0911 *	1						
TEC	0.6406 ***	0.3198 ***	0.1449 ***	1					
HUM	0.5067 ***	0.5805 ***	0.1285 ***	0.4145 ***	1				
EDU	0.0500	0.0116	0.1238 ***	0.1341 ***	−0.0244	1			
AL	−0.3476 ***	−0.6045 ***	−0.6122 ***	−0.3054 ***	−0.5050 ***	−0.1491 ***	1		
TF	−0.0937 **	−0.2817 ***	0.0523	−0.1807 ***	−0.1829 ***	−0.0158	0.1855 ***	1	
INC	0.3735 ***	0.2042 ***	−0.1028 **	0.4218 ***	0.1777 ***	0.4865 ***	−0.2336 ***	−0.2223 ***	1

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Benchmark regression results.

Variable	(1)	(2)	(3)
	FE	FGLS	SDM
AGG	0.0920 ** (0.0414)	0.0929 *** (0.0133)	0.0882 *** (0.0315)
EDU	−8.6343 *** (3.0961)	−6.1955 *** (2.0871)	−4.9731 * (2.6418)
AL	0.1645 *** (0.0593)	0.1376 *** (0.0319)	0.1656 *** (0.0604)
TF	−0.7102 (2.3143)	0.2803 (3.8133)	0.7682 (2.8854)
INC	0.0168 (0.0163)	0.0050 (0.0066)	0.0120 (0.0171)
Province FE	YES	YES	YES
Year FE	YES	YES	YES
Constant	0.3806 **	0.5769 ***	

	(0.1476)	(0.1169)	
N	450	450	450
R ²	0.8704		0.0015

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors.

This study decomposes AGG into HOAGG and HEAGG, and incorporates both categories into the baseline regression model for empirical analysis. As shown in Table 5, the coefficients of HOAGG and HEAGG are significantly positive, implying that both agglomeration patterns have a positive impact on GEE. The coefficient of HOAGG is greater than that of HEAGG, which indicates that the agglomeration dividend formed by the current industry is dominant. HOAGG is convenient for aquaculture practitioners to carry out technical exchanges, centralized pollution control, and integration of production factors. However, there are running-in costs and industrial adaptation thresholds between heterogeneous industries, so its green driving effect is relatively weak.

This paper further examines the effects of different types of agglomeration sub-types, and the specific results are shown in Table 6. In homogeneous agglomeration, AGG₁ and AGG₂ show significant positive coefficients, while AGG₃ has no statistical significance. This is because the correlation between homogeneous business entities in this type of industry is weak, and the homogeneous competition of production mode is strong, which easily causes resource crowding out. It is difficult to achieve the agglomeration advantage of sharing green aquaculture experience and sharing environmental protection facilities. For heterogeneous agglomeration, AGG₁₂, AGG₂₃ and AGG₁₂₃ have a positive impact on GEE, and the coefficient of AGG₁₂₃ is the largest. This evidence confirms the necessity of promoting the integrated development of fishery-related primary, secondary and tertiary industries. However, AGG₁₃ has no statistical significance, which is due to the weak industrial chain linkage between the aquaculture industry and the service industry, the lack of green technology spillover channels between industries, and the difficulty in releasing the synergistic benefits of spatial agglomeration.

Table 5. Regression results for different agglomeration patterns.

Variable	(1)	(2)
HOAGG	0.0351 *** (0.0076)	
HEAGG		0.0211 *** (0.0044)
Control	YES	YES
Province FE	YES	YES
Year FE	YES	YES
Constant	0.3944 *** (0.1419)	0.3650 ** (0.1427)
N	450	450
R ²	0.8717	0.8715

Note: ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors.

Table 6. Regression results for different agglomeration types.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGG ₁	0.1429 *** (0.0519)						
AGG ₂		0.0106 *** (0.0020)					
AGG ₃			0.0090				

			(0.0130)				
AGG ₁₂				0.0105 ***			
				(0.0020)			
AGG ₁₃					0.0118		
					(0.0110)		
AGG ₂₃						0.0105 ***	
						(0.0021)	
AGG ₁₂₃							0.0960 ***
							(0.0221)
Control	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Constant	0.3182 **	0.4026 ***	0.3792 **	0.3876 ***	0.3426 **	0.3791 ***	0.3782 ***
	(0.1469)	(0.1412)	(0.1469)	(0.1422)	(0.1564)	(0.1411)	(0.1436)
N	450	450	450	450	450	450	450
R ²	0.8722	0.8708	0.8677	0.8708	0.8679	0.8711	0.8746

Note: ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors.

5.2. Heterogeneity Analysis

5.2.1. Regional Heterogeneity: River Basins and Coastal–Inland Zones

We first divide the sample into the Pearl River Basin, Yellow River Basin, Yangtze River Basin, the coastal regions and the inland regions to identify geographic heterogeneity. The specific results are shown in Table 7. The results indicate that the impact of AGG on GEE may exhibit marked regional heterogeneity, with a significant positive effect observed in the Yangtze River Basin, while the coefficients in the Pearl River Basin and the Yellow River Basin are statistically insignificant. These regional disparities may originate from differences in fishery industrial foundation, aquatic resource endowments, and ecological carrying capacities across the basins. The Yangtze River Basin possesses a relatively complete fishery supporting chain, abundant freshwater resources and a comparatively mature market system. AGG may facilitate the exchange of low-carbon breeding technologies, centralized pollution treatment and shared infrastructure, thereby partially unlocking the green spillover effect of agglomeration. By comparison, the Pearl River Basin features relatively scattered aquaculture operations and cross-regional water pollution, which possibly weakens the scale advantages of agglomeration. The Yellow River Basin faces water scarcity and a fragile aquatic ecosystem; fishery production is constrained by rigid water resource limits, so agglomeration fails to generate evident green dividends.

When classified by coastal and inland attributes, AGG yields significant effects in both subgroups, and this effect in inland areas is slightly stronger than that in coastal regions. The inland waters have strong regional closure, and the water environment problems are more easily controlled by local environmental supervision. After the fishery agglomeration, the space of similar breeding subjects is concentrated, the pollution risk is concentrated, and the constraint of environmental regulation is greater, which forces the cluster to upgrade the environmental protection breeding mode. The coastal waters are highly mobile, and pollution has the characteristics of cross-regional diffusion, and territorial supervision is difficult. Coastal fishery agglomeration mainly brings business convenience, labor pooling and supply chain advantages. Enterprises give priority to expanding production capacity, and the willingness for environmental protection transformation remains weak. The green effect of agglomeration is relatively limited.

5.2.2. Conditional Heterogeneity: Environmental Regulation, Agglomeration Level and Green Development Level

To further uncover the boundary conditions of agglomeration's green effect, we conduct group regression based on the median of the aquaculture environmental regulation (the aquaculture environmental regulation is constructed as the multiplication of the environmental pollution abatement expenditure by the proportion of aquaculture gross output value to regional GDP), AGG and GEE. The specific results are shown in Table 8. Columns (1)–(2) of Table 8 reveal that AGG in regions with stringent environmental regulations exerts a weaker effect on the GEE than in regions with lax regulations. This study contends that the elevated environmental thresholds in strictly regulated areas compel firms to accomplish green transformation prematurely, thereby narrowing the marginal room for further improvement through agglomeration. Conversely, regions with lax regulations suffer from a weaker green foundation; thus, the technology diffusion and scale effects induced by agglomeration can more readily unlock emission-reduction dividends, rendering the impact more pronounced. Columns (3)–(4) of Table 8 reveal that the positive impact coefficient is larger in low-AGG areas than in high-AGG areas. This discrepancy arises because low-AGG areas remain in a scale-dividend phase, where technology diffusion and collaborative pollution control offer considerable room for improvement. Conversely, high-AGG areas have approached optimal scale; excessive enterprise concentration triggers crowding effects and elevates pollution loads, offsetting marginal gains through internal inefficiencies and resulting in a lower coefficient. Columns (5)–(6) of Table 8 reveal that the positive impact coefficient in areas with high GEE is greater than that in low-GEE areas. In high-GEE areas, strict environmental regulations, advanced technologies, and mature industrial chains enable agglomeration to cut pollution per unit via shared facilities, technology spillovers, and scale effects. In low-GEE areas, agglomeration tends toward extensive expansion with weak resource constraints, worsening pollution. Hence, the impact gap is significant.

Table 7. The regional heterogeneity effects of AGG on GEE.

Variable	(1)	(2)	(3)	(4)	(5)
	Pearl River	Yellow River	Yangtze River	Coastal areas	Inland Areas
AGG	0.0126 (0.0488)	−0.2781 (0.1984)	0.2911 *** (0.0771)	0.1349 ** (0.0679)	0.1429 ** (0.0655)
Control	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Constant	−0.1011 (0.2949)	0.4764 * (0.2415)	0.6618 (0.7419)	−0.5865 (0.7294)	0.2871 *** (0.0765)
N	90	135	105	165	285
R ²	0.9483	0.8841	0.9021	0.8433	0.7933

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors.

Table 8. The conditional heterogeneity effects of AGG on GEE.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Stringent Regulation	Lax Regulation	High-AGG	Low-AGG	High-GEE	Low-GEE
AGG	0.0955 * (0.0518)	0.1284 * (0.0739)	0.1373 *** (0.0426)	0.5298 ** (0.2097)	0.1190 ** (0.0504)	0.0014 (0.0127)
Control	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Constant	0.3415 (0.2862)	0.0740 (0.1881)	0.6579 (0.4421)	0.4279 *** (0.0821)	0.2447 (0.4736)	0.2902 *** (0.0427)
N	225	225	225	225	225	225

R ²	0.8859	0.8897	0.8843	0.7043	0.8514	0.8253
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Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors.

5.3. Robustness Test

To ensure the reliability of the benchmark regression and mechanism analysis, this study conducted multidimensional robustness tests. These tests included reducing the sample size, winsorizing variables, and adding control variables. As shown in column (1) of Table 9, we first excluded the pandemic years (2020–2022). The COVID-19 outbreak disrupted markets, caused stocking backlogs, and affected green efficiency. The results remain consistent with the baseline regression. Column (2) of Table 9 presents results after winsorizing the variables. The findings are largely consistent with earlier regressions, supporting robustness. Considering that omitted variables may lead to estimation bias, we further supplement control variables in column (3) of Table 9. We add GDP and factory-based aquaculture level (FA) to the regression model to capture the impacts of economic development level and aquaculture production mode. The coefficient of AGG is still positive and significant at the 10% level.

Table 9. Robustness results.

Variable	(1)	(2)	(3)
AGG	0.0844 * (0.0465)	0.0920 ** (0.0414)	0.0718 * (0.0392)
FA			0.1236 (0.1893)
GDP			0.0353 *** (0.0080)
Control	YES	YES	YES
Province FE	YES	YES	YES
Year FE	YES	YES	YES
Constant	0.4951 *** (0.1257)	0.3806 ** (0.1476)	0.3348 *** (0.1282)
N	360	450	450
R ²	0.9010	0.8704	0.8843

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors.

5.4. Endogeneity Test Results

Potential endogeneity problems exist between fishery industrial agglomeration and the green development of aquaculture. On the one hand, industrial agglomeration can positively affect aquaculture green transformation; on the other hand, regions with higher aquaculture green efficiency may attract fishery enterprises to cluster, leading to reverse causality. To address such concerns, this study employs two instrumental variables for AGG: the interaction between 2008 road network density and terrain relief (IV1), and the interaction between aquatic product trade volume and 2008 terrain relief (IV2). The 2008 road network and terrain relief represent historical geographic characteristics predetermined relative to current green economic efficiency, satisfying the exogeneity requirement. Meanwhile, aquatic product trade serves as an external shock that influences agglomeration through historical resource endowment differentials, meeting the exclusion restriction. To address the issue that the selected instrumental variables exhibit minimal within-individual variation, simultaneously incorporating both individual and time two-way fixed effects would result in the complete absorption of the instruments, rendering the model unidentifiable. Consequently, this study adopts a specification that controls solely for year fixed effects. Table 10 reports the two-stage least squares estimation results.

Results show that the Kleibergen–Paap rk LM statistic yields a p -value of 0.000, and the Cragg–Donald Wald F statistic is 29.33, exceeding the conventional threshold of 10. The Hansen J statistic produces a p -value of 0.194. These test outcomes suggest that the selected instrumental variables are free from weak instrument issues and satisfy the joint exogeneity assumption, providing supportive and suggestive evidence for the present research. The second-stage estimation reveals that the coefficient on AGG is 0.192, which is significantly positive at the 1% level. This suggests that AGG exerts a beneficial effect on GEE.

Table 10. Endogenous results.

Variable	2SLS	
	First Stage	Second Stage
AGG		0.1918 * (0.0597)
IV1	0.0183 *** (0.0032)	
IV2	−0.3239 *** (0.0655)	
Control	YES	YES
Constant	1.2707 (1.0217)	
Year FE	YES	YES
Kleibergen–Paap rk LM statistic		27.757 ***
Cragg–Donald Wald F statistic		29.329
Kleibergen–Paap rk Wald F statistic		31.411
Stock–Yogo 10% maximal IV size		19.93
Hansen J statistic P-val		0.1040
Endogeneity test P-val		0.0596
N	450	450

Note: * $p < 0.1$, *** $p < 0.01$; figures in parentheses are robust standard errors.

5.5. Mechanism Test

In this paper, the stepwise regression method is used to test the mediating effect, and the Bootstrap method is used to sample 1000 times to test the indirect effect. The regression results are shown in Table 11. First, according to Table 11, columns 1–2, the coefficient of AGG to HUM is significantly positive at the 1% level. After incorporating the mediating variables, the AGG and HUM coefficients are significantly positive. The Bootstrap test showed that the bias-corrected (BC) 95% confidence intervals for both the indirect and direct effects excluded 0, which proved that there was a partial mediation effect. AGG may attract fishery practitioners and promote human capital accumulation in aquaculture, thereby exerting a positive effect on GEE. H2 is established.

Secondly, according to Table 11, columns 3–4, the coefficient of AGG on TEC is significantly positive at the 1% level. After incorporating the intermediary variable, the coefficients of AGG and TEC are significantly positive. The Bootstrap test showed that the BC 95% confidence intervals for both the indirect and direct effects excluded 0, and there is a partial mediating effect. AGG might promote technological progress via factor agglomeration and knowledge spillovers, which causes a positive influence on green development in aquaculture. H3 is established.

Thirdly, according to Table 11, columns 5–6, it can be seen that the coefficient of AGG to the ISU is significantly positive at the 1% level. After the mediating variables are included, the coefficients of AGG and ISU are significantly negative. The Bootstrap results

showed that the BC 95% confidence interval for the indirect effect was $[-0.0322, -0.0110]$, which excluded zero, indicating that the indirect effect was significantly negative, and there is a masking effect. AGG is conducive to fishery industrial upgrading, yet such upgrading at this stage does not sufficiently integrate ecological objectives. This omission is likely to restrain GEE and neutralize part of the positive influence of agglomeration. H4 is partially established.

Mechanism tests show that AGG drives human capital upgrading, green technology diffusion and industrial chain integration via supply chain coordination and knowledge spillovers. They help strengthen environmental management, optimize input structures and reduce fixed pollution control costs. The coordinated advantages boost resource allocation efficiency and are positively linked to green development in aquaculture.

Table 11. Results of the mechanism test.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	HUM	GEE	TEC	GEE	ISU	GEE
AGG	0.3926 *** (0.0746)	0.0773 *** (0.0194)	0.5846 *** (14.5919)	0.0529 ** (0.0196)	0.2409 * (0.0969)	0.1066 *** (0.0211)
HUM		0.0374 *** (0.0103)				
TEC				0.0670 *** (0.0077)		
ISU						−0.0608 *** (0.00093)
Control	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Constant	−9.5643 *** (0.4713)	0.7380 *** (0.1039)	−24.4822 (86.0981)	0.3970 *** (0.1210)	6.2823 *** (0.3177)	0.7624 *** (0.1442)
R ²	0.9042	0.8727	0.6877	0.8925	0.8428	0.8718
Indirect Effect	[0.0002, 0.0059]		[0.0063, 0.0267]		[−0.0322, −0.0110]	
BC 95% Confidence Interval						
Direct Effect	[0.0548, 0.1169]		[0.0471, 0.0967]		[0.0783, 0.1346]	
BC 95% Confidence Interval						
Mediation Pattern	partial mediation		partial mediation		masking effect	
N	450		450		450	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. To mitigate unobserved regional heterogeneity and time-varying trends, the regression model incorporates a full set of regional and year dummy variables. Given the potential for common macroeconomic shocks and cross-sectional dependence across provinces, Driscoll–Kraay (DK) standard errors (with a default bandwidth of two) are employed to ensure robust inference against heteroskedasticity, serial correlation, and cross-sectional dependence.

6. Conclusions, Implications and Limitations

6.1. Conclusions

Based on the panel data of 30 provinces in China from 2008 to 2022, this paper examines the impact of AGG on GEE by using fixed effects and further examines the transmission mechanism and heterogeneity effect. The main findings are summarized as follows.

First, AGG is significantly and positively associated with GEE. Industrial agglomeration facilitates resource sharing, green technology innovation, cost reduction and collaborative water pollution control, which jointly advance the sustainable green development of aquaculture.

Second, both homogeneous fishery agglomeration and heterogeneous fishery agglomeration show significant positive relationships with GEE. But the green dividend brought by homogeneous agglomeration is stronger. Single aquaculture and processing industry agglomeration has a positive effect, while independent service industry agglomeration is not significant. Breeding-processing, processing-service and tertiary industry integration all promote green performance, while breeding-service integration fails to produce agglomeration synergy effects due to weak industrial linkage and blocked green technology spillover.

Third, AGG's green effect exhibits obvious geographic and conditional heterogeneity. Geographically, AGG has a significant positive effect on GEE only in the Yangtze River Basin; both coastal and inland regions see positive effects, with inland areas showing stronger gains. Conditionally, AGG follows diminishing marginal returns and only works well in regions with high initial aquaculture green development levels.

Fourth, human capital and green technology innovation play a partial intermediary role in the relationship between fishery industry agglomeration and aquaculture green development. The industrial structure upgrading has a masking effect. While agglomeration promotes industrial upgrading, the existing structural adjustment puts economic benefits above ecological protection, which hinders the green development of aquaculture.

6.2. Implications

Based on these empirical results, we propose a set of policy implications.

- (1) Local governments should prioritize fostering homogeneous aquaculture and aquatic product processing clusters, build shared pollution treatment facilities and technical exchange platforms to amplify centralized governance advantages. They should strictly control the scale of single fishery service agglomeration and avoid resource crowding without industrial support. They should accelerate the integrated development of primary, secondary and tertiary fishery industries, focus on cultivating aquaculture-processing-service full-chain parks, and limit low-efficiency simple coupling between breeding and service sectors lacking technical spillover links. Meanwhile, they should establish dynamic monitoring mechanisms for agglomeration scale; for areas with excessive industrial concentration, they should introduce entry thresholds to alleviate resource competition and pollution overload, and comply with the diminishing marginal return rule of agglomeration.
- (2) For the Yangtze River Basin, continue to expand fishery cluster construction, improve supporting industry chains and low-carbon technology systems to fully release agglomeration green dividends. In the Pearl River and Yellow River Basins, postpone large-scale agglomeration planning; first, carry out water environment joint prevention and control, optimize water resource allocation, and lay ecological and industrial foundations for cluster development. In inland regions, support large-scale concentrated breeding zones and rely on closed water bodies to implement unified environmental supervision to strengthen green upgrading incentives. For coastal areas, establish cross-regional marine pollution joint governance mechanisms, add ecological assessment indicators to fishery cluster policies, and force coastal breeding enterprises to increase investment in green transformation rather than blind capacity expansion. In addition, tilt financial and technical support to regions with low initial aquaculture green efficiency, complete pollution control infrastructure, and improve local technology absorption capacity to activate agglomeration green potential.
- (3) Rely on fishery industrial clusters to set up special training bases for aquaculture technicians, introduce talent subsidy policies for professional breeding and environmental protection practitioners, and expand the human capital accumulation effect of agglomeration. Build cluster-level green fishery technology innovation platforms,

encourage knowledge exchange and technical sharing among adjacent operating entities, subsidize enterprises' research and development of low-pollution breeding equipment, and expand the transmission contribution of technological innovation. Local authorities should take fishery clusters as carriers to regularly organize technical promotion activities and break internal information barriers within industrial agglomerations.

- (4) Revise the performance evaluation standard of fishery industrial upgrading, incorporate water resource utilization rate, aquaculture pollution emission and other ecological indicators into industrial development assessment, and reverse the single economic-oriented restructuring tendency. When promoting fishery industrial chain extension, formulate matching ecological access standards, set pollution reduction targets for new processing and service links, and coordinate economic output and water ecological protection. Carry out regular ecological audits for industrial upgrading projects within clusters, rectify projects that damage the water environment, and weaken the offsetting impact of industrial restructuring on agglomeration's green promotion effect.

6.3. Limitations

Despite its contributions, this study has several limitations that should be acknowledged. First, the measurement of GEE, while comprehensive, is constrained by the availability of provincial-level data. The aggregation of aquaculture activities across diverse species and farming systems may mask finer-grained heterogeneities. For example, the environmental footprint of intensive shrimp farming differs markedly from that of extensive bivalve cultivation, yet our provincial-level GEE indicator treats them within the same framework. Future research could benefit from using more disaggregated data at the farm or species level to explore these internal heterogeneities.

Second, the study's focus on provincial-level agglomeration may overlook intra-regional spatial variations. The location entropy index captures the concentration of fisheries' activity within a province relative to the national average, but it does not capture the spatial distribution within the province. A firm located in a dense cluster within the same province could experience different agglomeration effects than one located in a less concentrated area. A more granular spatial analysis, perhaps using Geographic Information Systems (GIS) and micro-level firm data, would provide a more precise understanding of the spatial mechanisms at play. Third, the study is limited to China's aquaculture sector. The generalizability of our findings to other countries, particularly those at different stages of economic development and with varying institutional frameworks, remains an open question. Comparative studies across different cultural and policy contexts would be valuable for establishing the universality of our findings.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su181910064/s1>. Data S1: paper stata; Code S1: Stata code; Model S1: SDM.

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Appendix A

This section primarily describes the measurement method of GEE.

Appendix A.1. Fishery Inputs

Aquaculture area, aquaculture employees, power of aquaculture fishing vessels, intermediate consumption and number of seedlings were selected as fishery production input indicators. Among them, the intermediate consumption of aquaculture was converted based on the intermediate consumption of fishery; aquaculture's intermediate consumption is calculated as (Intermediate Consumption of Fishery) $\times$ (Aquaculture Output Value/Primary sector fishery Output Value). The other data were taken from the China Fishery Statistical Yearbook. In the statistical yearbook, the data of small consumption in the middle of the fishery is only counted until 2018, so the linear interpolation method is used to account for the data lagging in 2018.

Appendix A.2. Desired Output

Desired output is measured by the total output value of the aquaculture and carbon sinks.

(1) Freshwater aquaculture carbon sinks were measured with reference to the method of Yang et al. [42], in which the carbon sink parameters of freshwater fishes, crustaceans, and shellfish were set with reference to Xie et al. [48]. Due to the lack of carbon sink coefficient parameter of freshwater algae with smaller production, the carbon sink coefficients of the seawater algae were calculated with reference to the average carbon sink coefficients of the various seawater algae. The specific formulas are as follows:

$$FC = \sum P_i \times C_i \quad (A1)$$

where FC denotes the freshwater aquaculture carbon sink, P_i is freshwater aquaculture species production, and C_i denotes the freshwater aquaculture species carbon sink coefficient. The carbon content coefficient of the main freshwater aquaculture species with the carbon sink function is detailed in Table A1.

Table A1. Carbon content of major freshwater cultivar (unit: %).

Species	Carbon Content (%)
Silver Carp	16.19
Bighead Carp	13.40
Grass Carp	12.81
Crucian Carp	14.22
Common Carp	11.36
Bluntnose Black Bream	16.87
Mandarin Fish	12.73
Freshwater Shrimp	11.08
Freshwater Mussel	8.90
River Snail	7.93
Freshwater Clam	11.06
Chinese Mitten Crab	11.10

(2) Carbon sinks in marine aquaculture primarily originate from algae and shellfish. With reference to the research methods of scholars such as Xiang et al., Yue and Wang et al., and Sun et al. [49–51], the specific formulas are as follows:

$$\begin{aligned}
 MC &= \sum C_r + \sum C_s \\
 \sum C_r &= P_m \times \beta \times \gamma_r \times \mu_r \\
 \sum C_s &= P_m \times \beta \times \alpha_s \times \delta_s \\
 C_z &= \sum P_z \times \beta_z \times \eta_z
 \end{aligned} \tag{A2}$$

where MC is the shellfish carbon sink, C_r is the soft tissue carbon sink, C_s is the shell carbon sink, P_m is total shellfish production, β is the dry–wet coefficient, γ_r is the soft tissue share, μ_r is the soft tissue carbon content, α_s is the shell share, δ_s is the shell carbon content, C_z is the algal carbon sink, C_r is algal production, β_z is the algal dry–wet coefficient and η_z is the algal carbon content. The dry–wet coefficient, mass proportion and content of shellfish and algae species in mariculture in China, and the data of the carbon ratio are shown in Table A2.

Table A2. Calculation coefficient of carbon sink in mariculture (unit: %).

Category	Species	Wet–Dry Coefficient (%)	Mass Proportion (%)		Carbon Ratio (%)	
			Soft Tissue	Shell	Soft Tissue	Shell
Marine Shellfish	Oyster	65.10	6.14	93.86	45.98	12.68
	Mussel	75.28	8.47	91.53	44.40	11.76
	Scallop	63.89	14.35	85.65	42.84	11.40
	Clam	52.55	1.98	98.02	44.90	11.52
	Razor Clam	70.48	3.26	96.74	44.99	13.24
	Other Shellfish	64.21	11.41	88.59	42.82	11.45
Marine Algae	Kelp	20.00	100.00	0.00	31.20	0.00
	Nori	20.00	100.00	0.00	41.96	0.00
	Gracilaria	20.00	100.00	0.00	20.60	0.00
	Wakame	20.00	100.00	0.00	28.81	0.00
	Gelidium	20.00	100.00	0.00	26.37	0.00
	Other Algae	20.00	100.00	0.00	30.36	0.00

Appendix A.3. Undesired Output

Aquaculture non-desired output is measured in this paper by the nitrogen and phosphorus production and carbon emissions from aquaculture.

(1) Total Nitrogen(TN) and Total Phosphorus (TP) Production from Aquaculture: The TN and TP production coefficients for each type of aquaculture species are derived from the “Manual of Production and Discharge Coefficients for Pollution Sources in Aquaculture Industry of the First National Pollution Source Census”, and the calculation formula is as follows:

$$E_{u,n} = \sum_{i,j} Y_{i,n} \omega_{i,j,n} q_{i,j,n} y_{i,j} \tag{A3}$$

$E_{u,n}$ denotes the level of aquaculture pollution production $u(u = N/P)$ in province n ; $Y_{i,n}$ denotes the production of culture species of category i in province n ; $\omega_{i,j,n}$ denotes the percentage of the production obtained by culture species of category i using the culture method of category j in province n ; and $q_{i,j,n}$ denotes the coefficient of the production of pollution by culture species of category i using the culture method of category j in province n . Since there is no specific value for the proportion of production obtained by adopting each farming method for different farming species in different provinces, this paper refers to the research method of Chen et al. [52] and estimates the proportion of the production of each farming method in each province to the total production of farming

based on the proportion of the production of each farming method to the total production of each province in the “China Fishery Statistical Yearbook” of previous years. In addition, $Y_{i,j}$ denotes dummy variables, which take the value of 1 when i type of aquaculture species can be cultured by j type of aquaculture method, and vice versa; they take a value of 0. Moreover, because the different modes of seawater aquaculture will lead to different pollution mechanisms of the aquaculture system itself, to calculate the nitrogen and phosphorus production of non-baiting farmed organisms in seawater aquaculture, we refer to Zong et al.’s research method [53].

(2) Carbon Emissions from Aquaculture: Carbon emissions from aquaculture can be divided into two parts: carbon emissions from energy combustion and indirect carbon emissions from electricity use. Carbon emissions from marine aquaculture are calculated using Shao et al.’s research method [54] with the following formula:

$$C_m = P \cdot \alpha \cdot \omega_1 \cdot \eta + (P_n \cdot \varepsilon + P_r \cdot \rho + L_n \cdot \delta + L_r \cdot \varphi) \cdot \omega_2 \beta \quad (\text{A4})$$

where C_m denotes the total carbon emissions from marine aquaculture; P is the total power of marine aquaculture vessels. α is the fuel consumption coefficient of marine aquaculture vessels. Referencing the “Reference Standard for Fuel Consumption Calculation of Domestic Motor Fishing Vessels Receiving Fuel Subsidies”, it is determined to be 0.225 tons per kilowatt. P_n and P_r represent the yields of marine pond aquaculture and marine factory aquaculture, respectively. ε and ρ represent the unit electricity consumption coefficients for marine pond aquaculture and marine intensive aquaculture, respectively, determined according to the research findings of Xu et al. [55], as 0.37 kilowatts per kilogram and 8.66 kilowatts per kilogram, respectively. ω_1 and ω_2 denote the coefficients of diesel fuel and electricity converted to standard coal, according to the “China Energy Statistical Yearbook”, which are 1.46 kg of standard coal per kilogram and 0.12 kg of standard coal per kilowatt, respectively. L_n and L_r represent the area (volume) of marine pond aquaculture and factory farming, respectively. δ and φ denote the oxidation electricity consumption coefficients per unit area (volume) for marine pond culture and intensive aquaculture, which are determined according to the research findings of Xu et al. [55], as 1440.17 kilowatts per hectare and 37.76 kilowatts per cubic meter, respectively. β is the carbon emission coefficient, according to research findings, which is 0.68 kg per kilogram of standard coal [56]. The formula for calculating carbon emissions from freshwater aquaculture is as follows:

$$C = P \cdot \alpha \cdot \omega_1 \cdot \eta + (L \cdot \delta + S \cdot \varphi) \cdot \omega_2 \beta \quad (\text{A5})$$

where C denotes the carbon emissions from freshwater aquaculture; P denotes the power of freshwater aquaculture fishing vessels. α denotes the fuel consumption coefficient of aquaculture fishing vessels. The coefficient was determined to be 0.225 tons per kilowatt with reference to the “Reference Standard for Measurement of Fuel Consumption for Oil Price Subsidy for Domestic Motorized Fishing Vessels”. L and S denote the production of freshwater pond aquaculture and freshwater factory aquaculture, respectively. δ and φ denote the coefficients of power consumption of pond aquaculture and factory aquaculture per unit of production, respectively, and were drawn from the results of the study by Xu et al. [55], which were determined as 0.377 kilowatts per kilogram and 8.667 kilowatts per kilogram. ω_1 and ω_2 denote the energy conversion coefficients of diesel and electricity, and the coefficients were determined as 1.4571 kg of standard coal per kilogram and 0.1229 kg of standard coal per kilowatt, respectively, by referring to the China Energy Statistical Yearbook. β is the carbon emission coefficient, which is 2.493 kg per kilogram of standard coal [57].

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