

Article

Impact of Extreme Climate Risk on Chinese Freshwater Aquaculture Production

Yingli Zhang ¹, Hang Qu ¹ and Shunxiang Yang ^{1,2,*} 

¹ College of Economics & Management, Shanghai Ocean University, Shanghai 201306, China; yl-zhang@shou.edu.cn (Y.Z.); m240501458@st.shou.edu.cn (H.Q.)

² College of Economics & Management, Tongren Polytechnic University, Tongren 554300, China

* Correspondence: shunxiangyang4@gmail.com

Abstract

Against the backdrop of global warming and an increase in extreme weather events, the freshwater aquaculture industry, which is highly dependent on environmental conditions, faces severe challenges. As the world's largest producer of freshwater aquaculture, the stability of China's production is crucial for ensuring national food security and rural livelihoods. This study utilizes provincial panel data from China (2007–2023) and employs the HP filter separately for each province to construct a “climate-induced output” indicator. A panel data model is then established to examine the impact and transmission mechanisms of extreme climate risks on freshwater aquaculture output. The findings reveal the following: (1) Climate risks exert a significant negative impact on freshwater aquaculture production, with extreme low temperatures, droughts, and extreme rainfall having particularly pronounced effects. (2) Natural disasters play a partial mediating role between extreme climate and output, accounting for approximately 26.35% of the total effect. (3) From an overall perspective, both increased labor productivity and greater operational scale can significantly mitigate the negative impacts of climate risks. This study provides empirical evidence to inform policies on optimizing regional aquaculture layouts, enhancing climate resilience, and formulating adaptive strategies.

Keywords: extreme climate; climate-induced output; freshwater aquaculture; natural disasters

Key Contribution: This study constructs a “climate-induced output” indicator to examine the impact of extreme climate shocks on freshwater aquaculture output, which is a significant negative impact on output.



Academic Editor: Pablo Arechavala-Lopez

Received: 6 December 2025

Revised: 10 January 2026

Accepted: 15 January 2026

Published: 22 January 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Under the ongoing trend of global climate warming, the frequency and intensity of extreme weather events continue to increase [1]. The IPCC Sixth Assessment Report highlights that any continued warming in the future will lead to more frequent and intense extreme events, further exacerbating risks associated with extreme weather and climate. Characterized by suddenness, locality, and high uncertainty, extreme climate events pose severe challenges to socioeconomic development and natural ecosystems—particularly for the aquaculture industry, which is highly dependent on environmental conditions [2]. Climate change significantly affects both the level and stability of aquaculture production through pathways such as fluctuations in water temperature, decreases in dissolved oxygen, disease outbreaks linked to stocking density, and reduced feed utilization efficiency [3].

As the world's largest freshwater aquaculture producer, China has long accounted for approximately 60% of global output, playing a critical role in supplying high-quality animal protein for its population, promoting rural employment and income growth, and safeguarding national food security. China's freshwater aquaculture primarily focuses on species such as grass carp, silver carp, and bighead carp, and relies mainly on production models including pond culture, reservoir and lake pen aquaculture, and integrated rice-fish farming. These systems typically involve shallow, enclosed or semi-enclosed water bodies with limited water exchange capacity and minimal scope for environmental regulation, making them highly sensitive to climatic anomalies and extreme events [4]. In recent years, many major aquaculture provinces in China have frequently experienced extreme climate events such as heatwaves, heavy rainfall, floods, and periodic droughts. This has led to a significant increase in the affected aquaculture area and economic losses, establishing extreme climate as a prominent factor threatening both the output security and sustainable development of the freshwater aquaculture industry [5].

Existing research on the relationship between climate change and aquaculture has primarily focused on the potential impacts of global warming on fishery resources, mariculture, and coastal ecosystems at global or regional scales, revealing changes in output, species composition, and spatial distribution [2,6]. Some studies have further proposed technical pathways for adaptation and mitigation from the perspectives of engineering facilities, breed improvement, adjustments in farming practices, and risk management [7,8].

However, limitations remain in the identification of output effects in existing research. On one hand, most studies are based on specific river basins or single species, focusing on case analyses of individual extreme climate events such as high temperatures, low temperatures, or extreme rainfall, or utilize average climate indicators to assess long-term trend impacts on output. There is a lack of identification of output fluctuations in freshwater aquaculture induced by extreme climate. First, this study does not rely on average climate measures. Instead, it constructs indicators for extreme high temperature, extreme low temperature, extreme drought, and extreme rainfall based on historical station observation data. By capturing extreme events that exceed specific thresholds, it more directly measures abnormal climate fluctuations. Second, this study integrates these four dimensions of extreme climate information through weighted aggregation to construct a composite "Climate Physical Risk Index." This comprehensive index aims to more fully capture the overall physical risk exposure a region faces due to multiple types of extreme climate events. On the other hand, when constructing output indicators at the regional level, existing studies have failed to effectively disentangle the contributions of non-climatic factors such as capital, labor, and technological inputs, thus making it difficult to accurately capture the "net impact" of climate variability on output.

Furthermore, the impact of extreme climate on output fluctuations in freshwater aquaculture is not unilaterally and directly determined by climatic factors alone, but is jointly influenced by systemic vulnerability and adaptive capacity. In terms of impact pathways, extreme climate often leads to output fluctuations through indirect channels such as exacerbating natural disasters, triggering water environment degradation, and disease outbreaks. However, the transmission mechanism of natural disasters as a key mediating variable lacks systematic empirical testing. Concurrently, labor productivity and the degree of scale operation, as indicators reflecting management capability and capital conditions of operating entities, may moderate the ultimate output effects of climate shocks by influencing technology adoption, facility allocation, and emergency response speed [9–11]. Nevertheless, the identification and quantitative testing of these moderating effects remain insufficient.

In this context, this paper focuses on provincial-level freshwater aquaculture in China to study the impact of extreme climate shocks on output fluctuations. The marginal contributions of this paper are threefold: first, it constructs a “climate-induced output” indicator that effectively disentangles the influence of non-climatic factors, providing a basis for more accurately identifying the net effect of climate shocks on aquaculture output (hereafter, unless otherwise specified, “freshwater aquaculture output” refers to this “climate-induced output”). Building on this, it systematically tests the mediating mechanism of natural disasters between climate shocks and output loss, revealing the key transmission pathway of “climate shock→natural disaster→output loss”. Simultaneously, it empirically verifies the moderating effects of labor productivity and scale operation on the negative impacts of extreme climate, uncovering the regulatory mechanisms for enhancing the climate resilience of freshwater aquaculture from the dimensions of operational capability and scale, thereby providing a scientific basis for formulating differentiated industrial policies.

The structure of this paper is as follows: Section 1 is the introduction, explaining the research background, significance, and shortcomings of existing studies, and presenting the research objectives and marginal contributions of this paper. Section 2 covers the theoretical foundation and research hypotheses, sorting out the theoretical mechanisms through which extreme climate affects freshwater aquaculture output and proposing research hypotheses. Section 3 details the research model and methodology, explaining variable construction, model specification, and descriptive statistics. Section 4 presents the empirical results of baseline regression. Section 5 conducts mechanism tests, and tests of moderating effects. Section 6 provides the research conclusions and outlines the next steps for the research.

2. Theoretical Mechanisms and Hypotheses

2.1. Theoretical Mechanisms

Extreme climate exerts influence on freshwater aquaculture output through multiple pathways. On one hand, events such as high temperatures, heavy rainfall, and droughts directly reduce output. On the other hand, they indirectly exacerbate output losses by increasing the frequency and intensity of disasters such as extreme rainfall and droughts. Concurrently, labor productivity and scale of operation, as concentrated representations of management level and risk resistance capacity, exert significant moderating effects on freshwater aquaculture.

Based on the above analysis, this paper constructs a theoretical framework—depicted in Figure 1—that extreme climate risks, such as heavy rainfall, drought, high temperatures, and low temperatures, collectively lead to aquaculture output losses by triggering natural disasters. Meanwhile, labor productivity and intensive aquaculture practices play key moderating roles in this process.

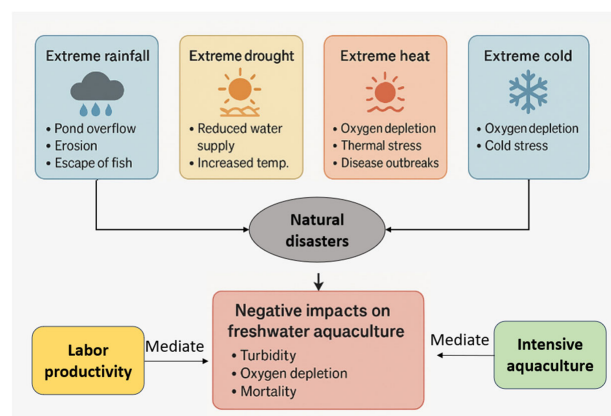


Figure 1. Theoretical Analytical Framework.

2.2. Research Hypotheses

Compared to mariculture net-pen or industrialized recirculating systems, China's freshwater aquaculture primarily relies on shallow water bodies such as ponds and reservoirs, which possess limited water exchange capacity and a limited capacity for environmental regulation. These systems are more susceptible to sudden water quality deterioration and ecological imbalance under extreme climate conditions [12–14]. Climate warming alters thermal stratification in water bodies, increases water temperature, and reduces dissolved oxygen levels, thereby impairing fish growth and immune function. Simultaneously, it accelerates pathogen reproduction and spread, significantly increasing the risk of disease outbreaks [3,15]. Extreme rainfall and flooding can cause pond overflow, embankment erosion, and the escape of cultured organisms. Furthermore, they introduce large amounts of sediment and nutrients into water bodies, leading to sharp increases in turbidity, ammonia, and organic load, which induce water quality degradation and abnormal algal fluctuations [16,17]. Conversely, droughts reduce water replenishment, intensify reliance on engineering measures such as water pumping and aeration, drive up production costs, and constrain output potential. When high temperatures coincide with extreme precipitation, the increase in feed conversion ratio and decreased feed utilization efficiency cause actual output to deviate significantly from expectations. This phenomenon is particularly pronounced in China's pond aquaculture systems, which are characterized by high stocking densities and heavy dependence on water exchange [4]. Therefore, the following hypothesis is proposed:

H1: *Extreme climate will have a negative impact on freshwater aquaculture output.*

In freshwater aquaculture, natural disasters serve as a critical mediating mechanism linking extreme climate shocks to output fluctuations. Extreme climate significantly increases the frequency and intensity of disasters such as extreme rainfall, droughts, and heatwaves [18], thereby amplifying their damaging effects on aquaculture infrastructure and the aquatic environment [12,15]. Studies from major freshwater aquaculture regions in Bangladesh, Vietnam, and China indicate that extreme climate, by inducing and intensifying disasters like extreme rainfall and droughts, significantly elevates risks including pond overflow, embankment breaches, and damage to production facilities. Furthermore, the intensity of these disasters shows a significant positive correlation with output loss per unit area, a phenomenon particularly pronounced in high-density farming areas or regions with low water body carrying capacity [19–21]. This evidence demonstrates the typical mediating role of natural disasters in the process through which extreme climate affects freshwater aquaculture output: extreme climate first increases the probability and intensity of disasters, damaging aquaculture infrastructure and the water environment, which in turn leads to a significant decline in output [22]. Therefore, this paper proposes the following hypothesis:

H2: *Extreme climate exerts a significant negative impact on aquaculture output by amplifying natural disasters.*

In freshwater aquaculture systems with limited self-buffering capacity of water bodies, management level is a key factor determining their ability to cope with extreme climate. Labor productivity can be viewed as a reflection of the comprehensive management capabilities of aquaculture operators in areas such as water quality regulation, disease prevention and control, precision feeding, emergency response, and facility maintenance [9].

Aquaculture operators with higher labor productivity typically possess stronger environmental monitoring and diagnostic capabilities, enabling them to identify water body

abnormalities more promptly and quickly implement measures such as aeration, water exchange, and feed adjustment. This helps mitigate sudden drops in dissolved oxygen and the accumulation of harmful substances under extreme climate conditions, reducing the risks of stress and mortality in cultured organisms.

Furthermore, higher labor productivity is often accompanied by the adoption of management-enhancing technologies such as automation and digitalization, including online water quality monitoring and data-driven management platforms, which help improve the efficiency and speed of environmental regulation, thereby attenuating the negative impact of extreme climate on output [23].

Therefore, labor productivity is expected to play a significant moderating role between extreme climate and freshwater aquaculture output. Based on this, Hypothesis 3 is proposed:

H3: *When regional labor productivity is higher, it can mitigate the negative impact of extreme climate on freshwater aquaculture output.*

The scale of operation is a core factor influencing capital accumulation capacity and the level of infrastructure configuration. Larger-scale operators can make systematic investments in fixed assets such as high-efficiency aeration and oxygenation equipment, pump drainage and circulation systems, backup power facilities, and standardized pond construction, thereby significantly enhancing environmental control capabilities and safety redundancy under extreme climate conditions [2].

Simultaneously, a larger operational scale helps amortize the high costs of resilience facilities like intelligent online water quality monitoring systems, standardized pond upgrades, and extreme rainfall control and drainage projects, improving the economic feasibility of such investments and strengthening the environmental stability and recovery speed of the aquaculture system during abnormal climate events. Furthermore, scale expansion increases the likelihood of adopting advanced technologies, such as water quality data analysis, IoT monitoring platforms, and precision management strategies based on ecological risk management. This enhances the capacity for early identification and intervention regarding abnormal water quality changes and potential disease risks, thereby reducing the impact of extreme climate events on output [24].

Therefore, scaled operations, through improved infrastructure, technology adoption, and management, enhance the ability to withstand extreme climate and are expected to play a significant moderating role in the relationship between extreme climate and freshwater aquaculture output. Based on this, the following hypothesis is proposed:

H4: *A higher scale of operation can mitigate the negative impact of extreme climate on freshwater aquaculture output.*

3. Methods and Data

3.1. Data

3.1.1. Dependent Variable

This study employs provincial-level panel data from mainland China for the period 2007–2023 based on data availability and statistical consistency to investigate the impact of extreme climate shocks on fluctuations in freshwater aquaculture output. The output of freshwater aquaculture is determined by both natural and non-natural factors. Therefore, the total freshwater aquaculture output Y_t is decomposed into three components: trend output Y_t^T , climate-induced output Y_t^C , and random ε_t , expressed as follows:

$$Y_t = Y_t^T + Y_t^C + \varepsilon_t \quad (1)$$

Here, the trend output Y_t^T primarily reflects the production level driven by technological progress, encompassing factors such as technological advancements, improvements in cultured species, and market demand. The climate-induced output Y_t^C refers to the output fluctuation influenced by variations in climatic factors. The random ε_t denotes the output affected by stochastic factors [25–27]. In empirical practice, the random output ε_t is typically treated as white noise and is not separately identified. Consequently, the climate-induced output is defined as follows:

$$Y_t^C = Y_t - Y_t^T \quad (2)$$

The trend output Y_t^T is derived using the Hodrick–Prescott (HP) filter method applied to the total output series Y_t^T . The HP filter effectively removes long-term trends while retaining medium-to-short-term fluctuations, which aligns well with the temporal scale of climate shocks that is the focus of this study. The results of the HP filter depend on the choice of the smoothing parameter λ . In line with the annual frequency of our data and established empirical practice, λ is set to 100 to compute a relatively smooth long-term trend component [28]. The difference between the original output series and this trend is then defined as the short-term fluctuation component, namely the climate-induced output Y_t^C [29]. The climate-induced output component Y_t^C serves as the key explained variable in this study, primarily reflects output fluctuations driven by climatic variations after controlling for long-term technological and economic trends.

It is important to emphasize that the resulting “climate-induced output” is essentially an approximate indicator constructed through statistical methods. The underlying logic is based on the assumption that short-term output fluctuations are primarily driven by exogenous shocks such as climate factors, and thus, the filtered cyclical component is approximated as the “climate-induced” portion for analysis. However, this is not a purely physical measure of climate, as the fluctuation component may statistically include contributions from other unobserved short-term factors (such as policy changes or temporary market fluctuations). Our analysis is grounded in the reasonable statistical assumption that climate risk is the dominant and systematic factor driving these short-term fluctuations, and we estimate its impact elasticity and economic losses based on this premise.

In the subsequent models, the climate-induced output Y_t^C replaces the total output Y_t as the explained variable, used to identify the impact of extreme climate shocks on freshwater aquaculture output. Compared to using total aquaculture output, the “climate-induced output” more effectively reflects the shock of extreme climate on production [25,27]. Furthermore, this detrending process reduces the risk of spurious regression caused by common long-term trends, thereby enhancing the validity and robustness of the estimation results [30,31].

For robustness checks, this study applies the same HP filter specification to the output value of freshwater aquaculture to construct a corresponding “climate-induced output value,” which is then used to replace the baseline explained variable. This tests the sensitivity of the main findings to changes in the output measurement metric.

3.1.2. Explanatory Variable

Climate Physical Risk Index refers to the potential impacts or uncertainties imposed by climate change and related factors on economic, social, and environmental systems. For the freshwater aquaculture industry, while both physical risks and transition risks exist, the main impact on production processes primarily comes from physical risks [32]. This study refers to the method of Guo et al. [33] to construct a Climate Physical Risk Index based on the number of days of four types of extreme weather events: extreme high temperature, extreme low temperature, extreme precipitation, and extreme drought. The raw data are

sourced from the National Oceanic and Atmospheric Administration (NOAA) of the United States. Taking the Extreme Drought Days (EDD) index as an example, data from each station is first collected and missing values are removed, then calculated according to the following formula:

$$\tau_{i,n} = \sum_{t=1}^{365} \tau_{i,n,t} \quad (3)$$

$$\tau_{i,n,t} = \begin{cases} 1, & \text{if } \tau_{i,n,t} < \tau_i^5 \\ 0, & \text{if } \tau_{i,n,t} \geq \tau_i^5 \end{cases} \quad (4)$$

where τ_i^5 is the fifth percentile of the historical daily humidity at station i , representing the threshold for extreme drought conditions. $\tau_{i,n,t}$ denotes the humidity at station i on day t of year n . If the daily humidity is below this station-specific threshold, it is counted as an extreme drought day; if the daily humidity is equal to or above the threshold, the day is considered to have no extreme drought. Similarly, for other extreme climate events: the tenth percentile of the station's historical daily average temperature represents the threshold for extreme low temperature; the ninetieth percentile of the station's historical daily average temperature represents the threshold for extreme high temperature; the ninety-fifth percentile of the station's historical daily rainfall represents the threshold for extreme rainfall.

After calculating the extreme drought index for each station, the regional extreme drought index is further computed to characterize the overall situation of the province.

$$\tau_n = \frac{1}{m} \sum_{i=1}^m \tau_{i,n} \quad (5)$$

In Equation (5), τ_n represents the average extreme drought index across all stations (a total of m stations) in year n .

Considering that the four extreme climate indicators cannot be directly compared, this study applies min-max normalization to the original data. Taking the Extreme Drought Days (EDD) index as an example, the normalization formula is as follows:

$$\overline{EDD}_{m,n} = \frac{EDD_{m,n} - \min_{k=1,\dots,K; l=1,\dots,L} \{EDD_{k,l}\}}{\max_{k=1,\dots,K; l=1,\dots,L} \{EDD_{k,l}\} - \min_{k=1,\dots,K; l=1,\dots,L} \{EDD_{k,l}\}} \quad (6)$$

where K represents the number of regions and L represents the total number of years. Due to regular differences across regions, such as seasonal variations, and particularly the changing proportion of each climatic factor in disaster impacts, after calculating the four indicators—LTD, HTD, EDD, and EED—weight allocation must be applied to these four indicators.

$$CPRI_{m,n} = \omega_1 \overline{LTD}_{m,n} + \omega_2 \overline{HTD}_{m,n} + \omega_3 \overline{EDD}_{m,n} + \omega_4 \overline{EED}_{m,n} \quad (7)$$

Following the benchmark framework for climate disaster assessment proposed by Kun Guo [33] and in accordance with the specifications in Appendix C of the national standard "Meteorological Drought Grade" (GB/T 20481-2017) [34], this study adopts the principle of equal weight allocation, uniformly setting the weights of the four indices at 0.25 each. This approach aligns with the internationally recognized criterion of Equal Weighting without Prior knowledge. Its theoretical basis lies in the fact that when the contribution of multiple indicators is uncertain, equal weight allocation can effectively avoid subjective bias while satisfying the principle of minimum information loss [35]. This method has been validated through 30 global climate risk assessment studies, demonstrating significant

methodological universality. Furthermore, this weight allocation strategy complies with the guidance of the national standard “Meteorological Drought Grade” (GB/T 20481-2017), which states: “when prior knowledge on the contribution of multiple indicators is lacking, equal weight allocation should be adopted as the baseline reference scheme [36].”

3.1.3. Mediating Variable

Natural Disaster (Disaster). This study uses the disaster-affected area to measure the degree of risk loss. This variable is estimated from provincial yearbook data on aquaculture disaster area, adjusted by the share of freshwater output in total aquaculture.

3.1.4. Moderating Variables

Production Efficiency (Eff) and Scale of Operation (Scale). Production efficiency in freshwater aquaculture is measured by the ratio of freshwater aquaculture output to the number of freshwater aquaculture practitioners [37]. The scale of operation is measured by the aquaculture area per labor, i.e., the farming area per laborer.

3.1.5. Control Variables

The control variables introduced in this study, categorized within the Cobb–Douglas production function framework, include the following: land input: freshwater aquaculture area (area); labor input: number of freshwater aquaculture practitioners (labor); capital input: power of freshwater aquaculture motorized fishing vessels (boat); resource input: surface water resources (water); and the macroeconomic control variable GDP per capita (GDP), characterizing regional economic development levels, thereby isolating the impact of infrastructure and factor inputs on climate-induced output. and government expenditure on agriculture, forestry, animal husbandry, and fishery (finance), controlling for the influence of government support for climate-induced outputs through public goods [38,39].

The description of variables and data sources involved in this study are presented in Table 1.

Table 1. Variable Definitions and Measurements.

	Variable	Description	Data Source
Dependent Variable	γ^C	Freshwater aquaculture output (hundred thousand tons)	China Fishery Yearbook
Explanatory Variables	CPRI	Climate Physical Risk Index	National Oceanic and Atmospheric Administration (NOAA)
	HTD	extreme high temperature	
	LTD	extreme low temperature	
	EDD	extreme drought	
	ERD	extreme rainfall	
Control Variables	area	Freshwater aquaculture area (million hectares)	China Fishery Yearbook
	labor	Practitioners in freshwater aquaculture (million persons)	
	boat	Power of mechanized fishing vessels (million kilowatts)	
	water	Surface water resources (trillion cubic meters)	
	GDP	Per capita GDP (ten thousand yuan)	China Statistical Yearbook
	finance	Fiscal expenditure on agriculture, forestry, animal husbandry, and fishery (billion yuan)	
Mediating Variable	Disaster	Disaster-affected area (million hectares)	
Moderating Variables	Eff	Labor productivity = Freshwater aquaculture output/Practitioners in freshwater aquaculture	China Fishery Yearbook
	scale	Scale of aquaculture = Freshwater aquaculture area/Practitioners in freshwater aquaculture	

3.2. Model Specification

This study employs provincial-level panel data from mainland China for the period 2007–2023 based on data availability and statistical consistency to investigate the impact of extreme climate shocks on fluctuations in freshwater aquaculture output. Based on the results of the Hausman test ($p < 0.05$, rejecting the null hypothesis), a fixed-effects model is selected for regression. Furthermore, the model controls for both entity and year fixed effects and utilizes robust standard errors. The final two-way fixed effects regression model is specified as follows:

$$Y_{it}^C = \alpha_0 + \beta_0 CPRI_{it} + \beta_1 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

Here, Y_{it} represents the climate-induced aquaculture output in region i during period t , $CPRI_{it}$ denotes the climate risk in region i during period t , $Control_{it}$ represents a set of control variables, μ_i indicates province fixed effects, λ_t indicates time fixed effects, and ε_{it} is the disturbance term.

To further investigate the pathways and mechanisms through which climate risk affects freshwater aquaculture output, this study employs the following models to test for mediating and moderating effects:

$$Disaster_{it} = \alpha_0 + \beta_0 CPRI_{it} + \beta_1 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (9)$$

$$Y_{it}^C = \alpha_0 + \beta_0 CPRI_{it} + \beta_1 Damage_{it} + \beta_2 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (10)$$

$$Y_{it}^C = \alpha_0 + \beta_0 CPRI_{it} + \beta_1 Eff_{it} + \beta_2 CPRI_{it} \times Eff_{it} + \beta_3 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (11)$$

$$Y_{it}^C = \alpha_0 + \beta_0 CPRI_{it} + \beta_1 scale_{it} + \beta_2 CPRI_{it} \times scale_{it} + \beta_3 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (12)$$

In models (9) and (10), $Disaster_{it}$ is the mediating variable, representing the disaster-affected area in region i during period t . If β_0 is significantly positive and β_1 is significantly negative, it indicates that increased climate risk reduces freshwater aquaculture output by expanding the disaster-affected area. μ_i indicates province fixed effects and λ_t indicates time fixed effects, and ε_{it} is the disturbance term.

Models (11) and (12) are for testing the moderating effect. Eff_{it} represents output per worker, measuring production efficiency; $Scale_{it}$ denotes the aquaculture area per worker, measuring the scale of operation. If the signs of β_1 and β_2 are opposite, it indicates that improvements in production efficiency and scale of operation can mitigate the impact of climate risk on freshwater aquaculture output. μ_i indicates province fixed effects and λ_t indicates time fixed effects, and ε_{it} is the disturbance term.

3.3. Descriptive Statistics

Figure 2 visually presents the trends in the overall Climate Physical Risk Index (CPRI) and its four components—extreme low temperature, extreme high temperature, extreme drought, and extreme rainfall—across Chinese provinces from 2007 to 2023. This set of heatmaps is designed to visually present the spatiotemporal patterns of CPRI and its components. The color intensity in all heatmaps represents the standardized relative intensity, with colors ranging from light (blue/green, indicating lower risk) to dark (red/brown, indicating higher risk). The heat map reveals that climate risks associated with extreme low temperatures occurred more frequently prior to 2013. This set of heatmaps is designed to visually present the spatiotemporal patterns of CPRI and its components across Chinese provinces from 2007 to 2023. The color intensity in all heatmaps represents the standardized relative intensity, with colors ranging from light (blue/green, indicating lower risk) to dark (red/brown, indicating higher risk). As shown in the legend on the right, the overall CPRI

ranges from 22.5 to 120, LTD ranges from 0 to 100, HTD ranges from 22.5 to 120, ERD ranges from 4.2 to 87.4, and EDD ranges from 0 to 191. Specifically, with global warming, the risk of extreme high temperature events has shown an increasing trend in subsequent years. Meanwhile, extreme drought risks are primarily observed in inland regions such as Qinghai, Xinjiang, and Inner Mongolia, while coastal areas like Shanghai and Jiangsu experience relatively higher frequencies of extreme precipitation.

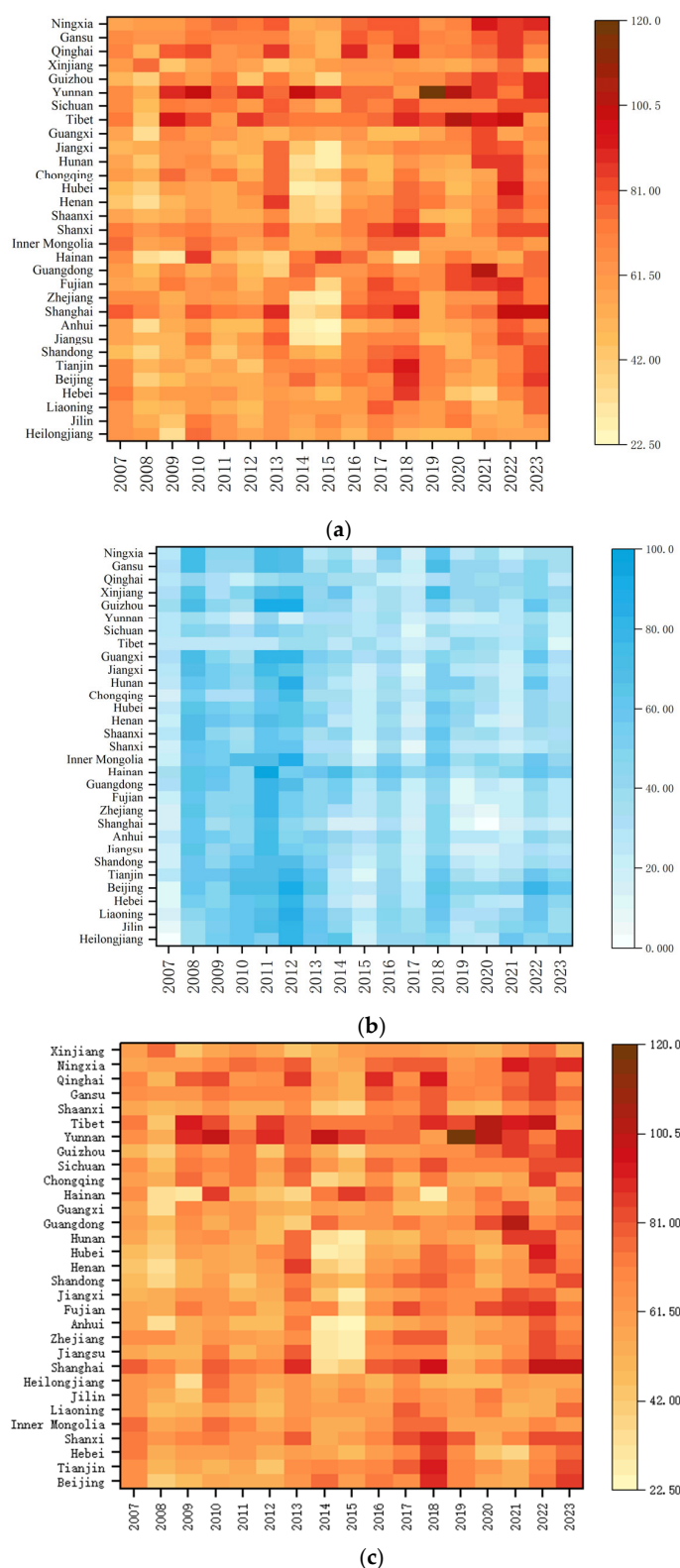


Figure 2. Cont.

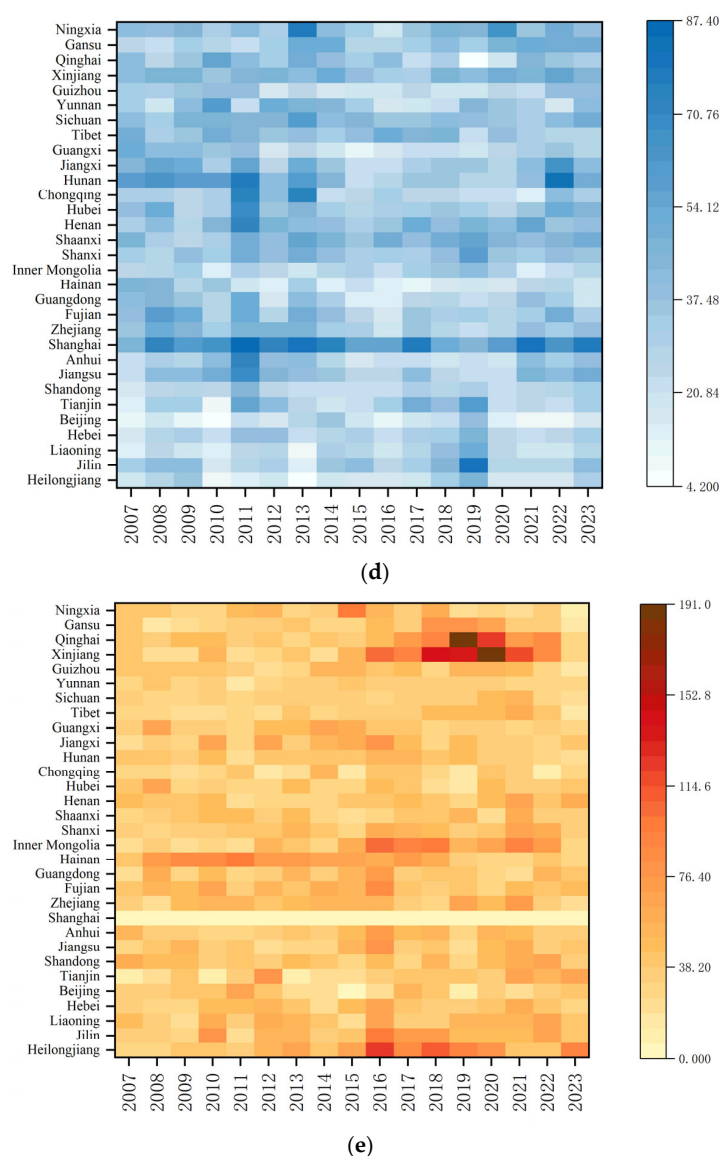


Figure 2. Heat Maps of (a) CPRI; (b) extreme low temperature; (c) extreme high temperature; (d) extreme rainfall; (e) droughts.

Table 2 presents the descriptive statistics of the variables. The results show considerable variability across all variables. The mean value of freshwater aquaculture output is 9.01 with a standard deviation of 11.19, and a notable wide gap exists between the maximum and minimum values, indicating substantial disparities in production scale across the sample. Regarding factor inputs, the mean values for labor and water area are 5.25 and 8.67, respectively, with standard deviations close to or exceeding their means, reflecting significant disparities in the allocation of production factors. The Variance Inflation Factor (VIF) test results are shown in the table below. The maximum VIF among the variables is 2.03, indicating no significant multicollinearity issues, thus satisfying the basic requirements for subsequent regression analysis.

Table 2. Results of Descriptive Statistical Analysis and VIF Test.

Var. Name	Obs	Mean	SD	Median	Max	Min	VIF
γ^C	517	9.0057	11.1873	3.8789	52.1493	−0.0019	-
CPRI	517	45.6984	8.1471	45.5084	84.3409	25.8066	1.05
GDP	517	2.3994	2.3202	1.6588	13.7905	0.0350	2.03
area	517	17.5557	17.6797	10.7791	88.6963	0.0003	1.21
boat	517	0.00000593	0.00001030	0.00000077	0.00004697	0.000000005	1.18
labor	517	0.00004376	0.00004607	0.00002435	0.00018763	0.000000006	1.24
water	517	866.8032	952.0111	556.9000	4749.9000	5.1000	1.10
finance	517	484.8901	313.4948	430.3900	1455.2000	22.9600	2.01

4. Results

4.1. Baseline Regression

Prior to regression, a Hausman test was conducted. The result showed a p -value of 0.0000, significantly rejecting the null hypothesis; therefore, the fixed-effects model was selected for regression. Table 3 presents the baseline regression results of this study. Column (1), which includes neither control variables nor fixed effects, shows that an increase in the Climate Physical Risk Index significantly reduces freshwater aquaculture output, providing preliminary support for our hypothesis. Column (2) includes control variables, and the result similarly indicates that heightened climate risk decreases output. The final column incorporates both entity and year two-way fixed effects. The results continue to show a significant negative relationship between climate risk factors and freshwater aquaculture output, with a regression coefficient of -3.111 , significant at the 1% level. For each one-unit increase in the Climate Physical Risk Index, freshwater aquaculture output will decrease by an average of 3.111 hundred thousand tons. These regression results collectively indicate that a higher Climate Physical Risk Index is associated with lower freshwater aquaculture output, meaning climate risk significantly reduces output, which is consistent with the research hypothesis.

Regarding the control variables, the regression coefficient for GDP per capita is significantly positive. An increase in GDP per capita may imply greater capital investment and a more advanced level of economic development, factors which can enhance freshwater aquaculture output [40]. The loss of significance of the boat variable under the fixed effects specification occurs because its time-invariant nature across panels leads the model to absorb most of its explanatory power, leaving limited within-unit variation for precise estimation.

The regression coefficients for freshwater aquaculture area and total water resources are also significantly positive, suggesting that regions with larger aquaculture areas and more abundant water resources tend to have higher output. The coefficient for government expenditure is significantly positive as well. Increased fiscal expenditure can provide robust support for increasing output and efficiency in freshwater aquaculture through channels such as subsidized policies, infrastructure development, ecological protection, and market system construction [41].

Furthermore, this study disaggregates climate risk into four distinct extreme climate events: low temperature, high temperature, drought, and extreme rainfall. The regression results are presented in Table 4. Column (1) shows that the coefficient for extreme low temperature is -1.969 , significant at the 5% level, indicating that low temperature shocks significantly suppress freshwater aquaculture output. Freshwater aquaculture species are poikilothermic animals, meaning their metabolism and behavior are highly dependent on water temperature. A sharp drop in water temperature can inhibit activity and feeding, accelerate energy consumption, weaken immune function, and increase mortality rates,

ultimately leading to decreased output [42]. Column (3) reveals that the coefficient for extreme drought is -1.731 , also significant at the 5% level. This suggests that drought reduces output significantly by diminishing water volume and lowering water levels, which compresses farming space, affects fish stocking, and exacerbates water pollution. Column (4) indicates that the coefficient for extreme rainfall is -2.006 , significant at the 1% level. Heavy rainfall cause drastic fluctuations in water pH, dissolved oxygen, and temperature, inducing stress responses in fish and increasing mortality risk, ultimately resulting in a notable decline in freshwater aquaculture output.

Table 3. Benchmark Regression Results.

Variable	(1) γ^C	(2) γ^C	(3) γ^C
CPRI	-1.445^* (0.818)	-1.950^{***} (0.495)	-3.111^{***} (1.017)
GDP		0.908^{***} (0.235)	0.922^{***} (0.251)
area		0.066^{**} (0.029)	0.078^{**} (0.035)
boat		0.186^* (0.109)	0.178 (0.144)
labor		0.164 (0.143)	0.169 (0.163)
water		0.031^{**} (0.015)	0.040^{**} (0.016)
finance		0.195 (0.118)	0.346^{**} (0.151)
Constant	9.666^{***} (0.374)	5.448^{***} (0.622)	5.561^{***} (0.651)
Year Fixed	NO	NO	YES
Province Fixed	NO	NO	YES
Number of id	31	31	31
Observations	517	517	517
R-squared	0.003	0.543	0.553

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results in Column (2) show that the coefficient for extreme high temperature is statistically insignificant, suggesting no clear net effect of high temperature shocks on freshwater aquaculture output. The potential reasons are twofold. On one hand, moderate warming within a certain range can promote fish digestion and feeding, thereby enhancing growth rates, and increased ultraviolet radiation can suppress pathogenic microorganisms in the water and on fish surfaces [43]. On the other hand, high temperatures can easily lead to increased organic load, water quality deterioration, and metabolic disorders, which are detrimental to fish growth and survival. These opposing positive and negative effects might offset each other, resulting in the lack of a statistically significant impact in the regression results. Additionally, from the perspective of data characteristics, significant geographic heterogeneity exists in the species composition and spatial distribution of aquaculture across different provinces in China. As a result, the impacts of rising temperatures exhibit distinct regional variations: in northern regions, moderate warming may shorten the aquaculture cycle and enhance production efficiency, whereas in southern regions, high temperatures are likely to intensify pressure on freshwater aquaculture production. To some extent, these opposing effects between the north and south may offset each other, which could explain why the regression results for the indicator of high-temperature days are not statistically significant in the model.

Table 4. Regression Results for Different Risk Types.

Variable	(1) γ^C	(2) γ^C	(3) γ^C	(4) γ^C
LTD	−1.969 ** (0.809)			
HTD		1.350 (0.869)		
EDD			−1.731 ** (0.653)	
ERD				−2.006 *** (0.655)
Constant	6.204 *** (1.262)	4.824 ** (1.774)	6.008 *** (1.267)	6.763 *** (1.396)
Control Variables	YES	YES	YES	YES
province fixed	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES
Observations	517	517	517	517
R-squared	0.466	0.463	0.477	0.468
Number of id	31	31	31	31

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$.

4.2. Robustness Check: Replacing the Explained Variable

To verify the reliability of the aforementioned regression results, this study selects the output value of freshwater aquaculture as an alternative explained variable for re-estimation. The results are presented in Table 5. The reduction in sample size is because data on output values for certain earlier years and specific provinces are missing. To ensure analytical accuracy and avoid potential biases introduced by data imputation, the robustness check section uses a sample of 366 observations based on actually available data. As shown, the regression coefficients for the overall Climate Physical Risk Index, extreme low temperature, extreme drought, and extreme rainfall on the aquaculture output value remain significantly negative. This confirms that the main conclusions of this study hold.

Table 5. Regression Results with Alternative Dependent Variable.

Variables	(1) Value	(2) Value	(3) Value	(4) Value	(5) Value
CPRI	−16.56 ** (8.029)				
LTD		−7.794 * (4.198)			
HTD			4.178 (3.434)		
EDD				−7.775 * (4.199)	
ERD					−5.801 * (3.169)
Constant	12.04 * (6.741)	19.72 *** (5.504)	0.701 (4.539)	4.846 (4.324)	7.140 (4.324)
Control Variables	YES	YES	YES	YES	YES
Fixed Effects	YES	YES	YES	YES	YES
Number of id	31	31	31	31	31
Observations	366	366	366	366	366
R-squared	0.516	0.433	0.512	0.519	0.513

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5. Further Discussion

To verify the mechanism through which extreme climate affects freshwater aquaculture output, this study employs natural disasters (Disaster) as a mediating variable for analysis, with significance tested using the Sobel test. The results are presented in Table 6.

Table 6. Mechanism Test for Disaster-Affected Area.

Variables	(1) γ^C	(2) Disaster	(3) γ^C
CPRI	−3.111 *** (1.017)	5.999 *** (2.163)	−2.412 ** (0.894)
Disaster			−0.144 *** (0.031)
Constant	5.561 *** (0.651)	2.712 (2.309)	6.913 *** (0.790)
Control Variables	YES	YES	YES
Province Fixed	YES	YES	YES
Year Fixed	YES	YES	YES
Sobel Test		−0.863 ** (z = −2.293)	
Mediation Effect Coefficient		−0.863 ** (z = −2.293)	
Direct Effect Coefficient		−2.412 ** (z = −2.081)	
Total Effect Coefficient		−3.276 *** (z = −2.727)	
Proportion of Mediation Effect		0.2635	
Number of id	31	31	31
R-squared	0.599	0.299	0.617

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$.

Column (1) reports the total effect of extreme climate on freshwater aquaculture output, with a coefficient of −3.111, significant at the 1% level, suggesting that extreme climate overall significantly suppresses output. Columns (2) and (3) present the decomposition of the mediating effect: the impact of climate risk on natural disasters shows a coefficient of 5.999, significantly positive at the 1% level, implying that increased extreme climate significantly associated with a higher incidence of natural disasters. After controlling for extreme climate, the effect of natural disasters on output remains significantly negative with a coefficient of −1.169, while the direct effect of climate risk is −2.412. The Sobel test confirms that the mediating effect is statistically significant. The results are consistent with natural disasters play a partial mediating role between extreme climate and freshwater aquaculture output, with the indirect effect transmitted through this channel accounting for approximately 26.35% of the total effect. This indicates that a notable portion of the reduction in output associated with extreme climate appears to operate through the intensification of natural disaster impacts.

Building upon the baseline regression, interaction terms between the Climate Physical Risk Index (CPRI) and both production efficiency (eff) and scale of operation (scale) are introduced to test for moderating effects. The results are presented in Table 7.

This study employed the control function approach to test for potential endogeneity issues in the model [44]. Specifically, we used the one-period lagged values of key explanatory variables Eff and scale as instrumental variables. Endogeneity was assessed by examining the significance of the control function term (the residuals from the first-stage regression). The results in Table A1 of Appendix A show that the coefficient of this residual term is statistically insignificant ($p > 0.1$), indicating that the model is not substantially affected by omitted variable bias and supporting the reliability of the baseline estimation results.

Table 7. Moderating Effect Test.

Variable	(1) γ^C	(2) γ^C	(3) γ^C
CPRI	−3.111 *** (1.017)	−4.694 *** (1.458)	−3.605 *** (0.885)
eff		−23.50 * (13.51)	
CPRI * eff		0.358 ** (0.170)	
scale			−12.60 ** (5.980)
CPRI * scale			0.212 * (0.116)
Constant	5.561 *** (0.651)	6.518 *** (0.792)	5.740 *** (0.637)
Control Variables	YES	YES	YES
Fixed Effects	YES	YES	YES
Number of id	31	31	31
Observations	517	517	517
R-squared	0.553	0.558	0.553

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In Column (2), the coefficients for the main effect of CPRI and the interaction term CPRI*eff are opposite in signs and both are statistically significant. This indicates that, all else being equal, a higher level of labor productivity can mitigate the suppressive effect of increasing climate risk on freshwater aquaculture output.

Similarly, in Column (3), the coefficients for the main effect of CPRI and the interaction term CPRI*scale are also opposite in sign and statistically significant. This suggests that a larger farming area per laborer, representing a higher degree of scale operation, weakens the output-reducing effect associated with increased climate risk.

The results for the moderating effects of these two variables are consistent with the hypotheses proposed in this study. It is important to explicitly note that the moderating effects of productivity and scale on climate risk shocks revealed in this study are average effects identified at the aggregate level based on nationwide provincial panel data. These finding highlights important moderating patterns at the macro level. However, regional disparities in China's freshwater aquaculture industry are significant, with systematic differences across regions in terms of resource endowments, dominant aquaculture species, technology adoption levels, and marketization. Therefore, the specific strength—or even direction—of these moderating effects may exhibit heterogeneity across different regions. The universal patterns identified at the aggregate level in this study provide a foundation for understanding macro-level dynamics.

6. Conclusions

Based on provincial panel data from 2007 to 2023, this study systematically evaluates the impact of extreme climate events on China's freshwater aquaculture output. The regression results provide direct empirical support for Hypothesis H1, revealing that overall extreme climate risk exerts a significant suppressing effect on output. Decomposing this aggregate effect shows that extreme low temperatures, drought, and rainfall are significant drivers of output reduction, while extreme high temperatures show no statistically significant impact. The mechanism analysis offers nuanced support for Hypothesis H2. The findings establish a significant partial mediating role for natural disasters, confirming that amplifying disaster impacts is one critical pathway—though not the exclusive

one—through which climate risk curtails output. Furthermore, the investigation into mitigating factors validates Hypotheses H3 and H4. The evidence demonstrates that both higher regional labor productivity and a larger scale of operation serve as effective buffers, significantly attenuating the negative climatic impact on output.

Our findings indicate that improving per-unit labor productivity and resource scale can significantly enhance a system's resilience against climate change. On the one hand, regions should focus on improving the labor productivity of aquaculture operators by refining supporting policies and service provision. This can be achieved through the promotion of aquaculture technologies, vocational skill training, and demonstration farm development to strengthen farmers' professional capabilities in areas such as breeding management, disease prevention, and risk identification. Furthermore, the application of digital technologies—such as intelligent environmental control, automated feeding, and online monitoring—should be encouraged. These measures can increase output per labor unit and enhance the precision of production management without significantly raising labor input, thereby strengthening the aquaculture system's capacity to adapt to and recover from extreme climate shocks. On the other hand, steady progress should be made toward appropriately scaled operations. Leveraging organizational forms such as cooperatives, family farms, and leading enterprises, the scale structure of aquaculture can be optimized through measures like land transfer, unified technical standards, and joint procurement. Scaling up can drive facility upgrades and improve risk diversification capabilities, increasing capital investment in critical infrastructure such as aerators, anti-escape nets, pond embankments, and drainage systems. Simultaneously, greater efforts should be made to coordinate the construction of regional water conservancy and aquaculture infrastructure, and to improve monitoring, early warning, and emergency response systems for events such as extreme low temperature, droughts, and extreme rainfall. This will help reduce output volatility and disaster losses, thereby reinforcing the risk mitigation effects achieved through enhanced labor productivity and scaled operations.

Given that global aquaculture faces the common challenge of increasingly frequent extreme weather events, the evidence and policy recommendations presented in this paper are not only applicable to emerging aquaculture nations like China but can also offer valuable insights for other developing countries in designing adaptive aquaculture policies, optimizing production organizational forms, and guiding infrastructure investment.

This study has limitations in data and methodology. First, the national-level analysis masks regional heterogeneity in climate conditions, aquaculture models, and species composition, which limits its guidance value for local policies. Second, although the HP filter method is employed to separate output fluctuations, non-climatic shocks such as disease outbreaks and seed supply issues may cause interference and cannot be fully isolated, leading to measurement errors. Third, the “climate-induced output” indicator lacks biological efficiency measures such as survival rates, making the pathways of impact insufficiently clear. Future research should: employ non-linear models to capture complex climate effects; conduct subgroup analyses by species, mode, and entity to reveal resilience differences; and refine data with metrics like survival rates to better trace impact mechanisms.

Author Contributions: Y.Z.: Conceptualization, Methodology, Project Administration, Formal Analysis, Writing—Original Draft; H.Q.: Software, Investigation, Data Curation, Formal Analysis, Visualization, Writing—Original Draft; S.Y.: Validation, Supervision, Writing—Review and Editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Shanghai Fisheries Economic Research Association Shanghai Municipal Government Social Survey Center (Shanghai Ocean University Branch) grant number [SHYJYJH-B-252601].

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Endogeneity Test Results.

Variables	(1) n1 Output	(2) n2 Output
eff	−0.0770 (0.0598)	
GDP	0.953 *** (0.247)	0.936 *** (0.244)
area	0.0583 (0.0426)	0.0576 (0.0423)
boat	0.000508 (0.179)	−0.0474 (0.168)
labor	0.183 (0.164)	0.224 (0.155)
water	0.000241 (0.000253)	0.000226 (0.000249)
finance	0.00286 * (0.00140)	0.00338 ** (0.00152)
res_eff	−0.155 (0.113)	
scale		−0.0181 (0.0256)
res_scale		0.108 (0.0992)
Constant	4.963 *** (0.679)	4.690 *** (0.699)
Observations	486	486
R-squared	0.547	0.541
Number of id	31	31

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

1. Wang, Y.; Chen, W. Extreme Climate, Agricultural Machinery Operation Service Market and Food Production: An Empirical Analysis Based on Panel Data from 13 Major Grain-Producing Areas. *J. Agrotech. Econ.* **2024**, *10*, 70–90. [\[CrossRef\]](#)
2. Cochrane, M.A.; Barber, C.P. Climate Change, Human Land Use and Future Fires in the Amazon. *Glob. Change Biol.* **2009**, *15*, 601–612. [\[CrossRef\]](#)
3. Ficke, A.D.; Myrick, C.A.; Lara, J. Hansen Potential Impacts of Global Climate Change on Freshwater Fisheries. *Rev. Fish Biol. Fish.* **2007**, *17*, 581–683. [\[CrossRef\]](#)
4. Tye, S.P.; Siepielski, A.M.; Bray, A.; Rypel, A.L.; Phelps, N.B.D.; Fey, S.B. Climate Warming Amplifies the Frequency of Fish Mass Mortality Events across North Temperate Lakes. *Limnol. Oceanogr. Lett.* **2022**, *7*, 510–519. [\[CrossRef\]](#)
5. China Meteorological Administration. *Blue Book on Climate Change of China 2024*, 1st ed.; Science Press: Beijing, China, 2024; ISBN 978-7-03-079018-7.
6. Lam, V.W.Y.; Cheung, W.W.L.; Reygondeau, G.; Sumaila, U.R. Projected Change in Global Fisheries Revenues under Climate Change. *Sci. Rep.* **2016**, *6*, 32607. [\[CrossRef\]](#)
7. Handisyde, N.; Telfer, T.C.; Ross, L.G. Vulnerability of Aquaculture-Related Livelihoods to Changing Climate at the Global Scale. *Fish Fish.* **2017**, *18*, 466–488. [\[CrossRef\]](#)

8. Nobre, A.M.; Robertson-Andersson, D.; Neori, A.; Sankar, K. Ecological-Economic Assessment of Aquaculture Options: Comparison between Abalone Monoculture and Integrated Multi-Trophic Aquaculture of Abalone and Seaweeds. *Aquaculture* **2010**, *306*, 116–126, Erratum to *Aquaculture* **2010**, *308*, 199. [[CrossRef](#)]
9. Engle, C.R.; Stone, N.M. Competitiveness of U.S. Aquaculture within the Current U.S. Regulatory Framework. *Aquac. Econ. Manag.* **2013**, *17*, 251–280. [[CrossRef](#)]
10. Fossberg, J.; Forbord, S.; Broch, O.J.; Malzahn, A.M.; Jansen, H.; Handå, A.; Førde, H.; Bergvik, M.; Fleddum, A.L.; Skjermo, J.; et al. The Potential for Upscaling Kelp (*Saccharina latissima*) Cultivation in Salmon-Driven Integrated Multi-Trophic Aquaculture (IMTA). *Front. Mar. Sci.* **2018**, *5*, 418. [[CrossRef](#)]
11. Zdeněk, R.; Lososová, J.; Mráz, J. Long-Term Trends in the Economic Viability of Pond Aquaculture in Central Europe—The Example of Czechia. *Aquaculture* **2025**, *598*, 742069. [[CrossRef](#)]
12. Cao, L.; Wang, W.; Yang, Y.; Yang, C.; Yuan, Z.; Xiong, S.; Diana, J. Environmental Impact of Aquaculture and Countermeasures to Aquaculture Pollution in China. *Environ. Sci. Pollut. Res. Int.* **2007**, *14*, 452–462. [[CrossRef](#)]
13. Song, C.; Chen, J.; Qiu, L.; Meng, S.; Fan, L.; Hu, G. Ecological remediation technologies for China's freshwater aquaculture pond environment: A review. *Chin. J. Ecol.* **2012**, *31*, 2425–2430. [[CrossRef](#)]
14. Zhou, L.; Chen, Z.; Xu, X. Analysis of Space Change Influence Factors for Freshwater Aquaculture Development in China. *J. Agric. Sci. Technol.* **2017**, *19*, 110–118. [[CrossRef](#)]
15. Wind, T.; Ros, A.; Chucholl, C.; Roch, S.; Schumann, M.; Schulz, C.; Brinker, A. Inland Freshwater Aquaculture in a Warming World. *Sci. Total Environ.* **2024**, *934*, 173275. [[CrossRef](#)]
16. Eekhout, J.P.C.; De Vente, J. Global Impact of Climate Change on Soil Erosion and Potential for Adaptation through Soil Conservation. *Earth-Sci. Rev.* **2022**, *226*, 103921. [[CrossRef](#)]
17. Ramos, M.C.; Lizaga, I.; Gaspar, L.; Quijano, L.; Navas, A. Effects of Rainfall Intensity and Slope on Sediment, Nitrogen and Phosphorous Losses in Soils with Different Use and Soil Hydrological Properties. *Agric. Water Manag.* **2019**, *226*, 105789. [[CrossRef](#)]
18. Bellprat, O.; Guemas, V.; Doblas-Reyes, F.; Donat, M.G. Towards Reliable Extreme Weather and Climate Event Attribution. *Nat. Commun.* **2019**, *10*, 1732. [[CrossRef](#)] [[PubMed](#)]
19. Chandrabalan, A.; Ramachandran, R. Molecular Mechanisms Regulating Proteinase-Activated Receptors (PARs). *FEBS J.* **2021**, *288*, 2697–2726. [[CrossRef](#)]
20. Hossain, M.Z.; Kalam Azad, M.A.; Karmakar, S.; Islam Mondal, M.N.; Das, M.; Rahman, M.M.; Haque, M.A. Assessment of Better Prediction of Seasonal Rainfall by Climate Predictability Tool Using Global Sea Surface Temperature in Bangladesh. *Asian J. Adv. Res. Rep.* **2019**, *4*, 1–13. [[CrossRef](#)]
21. Joffre, O.M.; Castine, S.A.; Phillips, M.J.; Senaratna Sellamuttu, S.; Chandrabalan, D.; Cohen, P. Erratum to: Increasing Productivity and Improving Livelihoods in Aquatic Agricultural Systems: A Review of Interventions. *Food Secur.* **2017**, *9*, 61–62. [[CrossRef](#)]
22. Posadas, B.C. Economic Impacts of Disasters and Economic Events on Commercial Fishery—The Case of Mississippi Blue Crabs. *Oceans* **2025**, *6*, 3. [[CrossRef](#)]
23. Gee, J.; Pinello, D.; Polymeros, K. Drivers of Labor-Related Indicators across Diverse Mediterranean Fisheries. *Sustainability* **2017**, *9*, 2000. [[CrossRef](#)]
24. Rowan, N.J. The Role of Digital Technologies in Supporting and Improving Fishery and Aquaculture across the Supply Chain—Quo Vadis? *Aquac. Fish.* **2023**, *8*, 365–374. [[CrossRef](#)]
25. Lobell, D.B.; Schlenker, W.; Costa-Roberts, J. Climate Trends and Global Crop Production since. *Science* **2011**, *333*, 616–620. [[CrossRef](#)] [[PubMed](#)]
26. Lobell, D.B.; Field, C.B. Global Scale Climate–Crop Yield Relationships and the Impacts of Recent Warming. *Environ. Res. Lett.* **2007**, *2*, 14002. [[CrossRef](#)]
27. Schlenker, W.; Roberts, M.J. Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. *Proc. Natl. Acad. Sci. USA* **2009**, *106*, 15594–15598. [[CrossRef](#)]
28. Hodrick, R.J.; Prescott, E.C. Postwar U.S. Business Cycles: An Empirical Investigation. *J. Money Credit Bank.* **1997**, *29*, 1–16. [[CrossRef](#)]
29. Wang, G.; Lu, J.; Chen, K. Exploration of Method in Separating Climatic Output Based on HP Filter. *Chin. J. Agrometeorol.* **2014**, *35*, 195–199.
30. Granger, C.W.J.; Newbold, P. Spurious Regressions in Econometrics. *J. Econom.* **1974**, *2*, 111–120. [[CrossRef](#)]
31. Phillips, P.C.B. Understanding Spurious Regressions in Econometrics. *J. Econom.* **1986**, *33*, 311–340. [[CrossRef](#)]
32. Liu, B.; Li, Y.; Jiang, Y. Climate Changes and the Total Factor Productivity of Manufacturing Enterprises: Mechanism Analysis and Empirical Tests. *J. Hunan Univ. Soc. Sci.* **2023**, *37*, 78–87. [[CrossRef](#)]
33. Guo, K.; Ji, Q.; Zhang, D. A Dataset to Measure Global Climate Physical Risk. *Data Brief* **2024**, *54*, 110502. [[CrossRef](#)]

34. GB/T 20481-2017; Grades of Meteorological Drought; Standard. General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China. Standardization Administration of the People's Republic of China: Beijing, China, 2017.
35. Rubinstein, A. *Modeling Bounded Rationality*; The MIT Press: Cambridge, MA, USA, 1998; ISBN 978-0-262-28275-8.
36. Yang, S.; Liao, Z.; Zhang, Y.; Ren, Y.; Qu, H. Climate Risk in Intermediate Goods Trade: Impacts on China's Fisheries Production. *Fishes* **2025**, *10*, 210. [[CrossRef](#)]
37. Gao, F. Evolution Trend and Internal Mechanism of Regional Total Factor Productivity in Chinese Agriculture. *J. Quant. Tech. Econ.* **2015**, *32*, 3–19+53. [[CrossRef](#)]
38. Ma, Y.; Liu, Y.; Yu, S. The Impact of Climate Change on Agricultural Economic Resilience: Moderating Effect of Fiscal Support for Agriculture. *Chin. J. Eco-Agric.* **2025**, *33*, 166–177.
39. Gong, B.; Wang, S. The Multichannel Effects of Fiscal Expenditure on China's Agricultural Growth. *Agric. Econ. Issues* **2021**, *1*, 54–68. [[CrossRef](#)]
40. Zhang, L.; Han, L.; Yang, Y. Effect of fishery technology progress on fishermen's income: Based on tests of provincial panel data in China. *Resour. Sci.* **2019**, *41*, 655–668.
41. Baoteregen, B. The Development Status and Promotion Strategies of Modern Fisheries in Liaoning Province. *J. Dalian Marit. Univ. Soc. Sci. Ed.* **2012**, *11*, 23–27.
42. Soyano, K.; Mushirobira, Y. The Mechanism of Low-Temperature Tolerance in Fish. *Adv. Exp. Med. Biol.* **2018**, *1081*, 149–164. [[CrossRef](#)] [[PubMed](#)]
43. Porter, C.B.; Krom, M.D.; Robbins, M.G.; Brickell, L.; Davidson, A. Ammonia Excretion and Total N Budget for Gilthead Seabream (*Sparus aurata*) and Its Effect on Water Quality Conditions. *Aquaculture* **1987**, *66*, 287. [[CrossRef](#)]
44. Wooldridge, J. *Introductory Econometrics: A Modern Approach*; South-Western Cengage Learning: Singapore, 1999.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.