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Do Climate Variables Influence Fish Production in Top Fishery Economies? Evidence from the ARDL Approach

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ABSTRACT

Climate change poses significant challenges to food security worldwide, particularly in the fisheries sector, where fish production is highly sensitive to climatic variables. This study investigates the long- and short-run impacts of climate change on fish production in four major fish-producing countries, China, India, Vietnam, and Bangladesh, using annual time-series data from 1990 to 2020. An Autoregressive Distributed Lag (ARDL) model was employed to examine long-run equilibrium relationships between climate factors (precipitation, minimum, mean, and maximum temperatures, and CO_2 emissions) and total fish production, as well as adjustments to short-run deviations. The findings revealed distinct patterns across countries: CO_2 emissions positively influenced long-term fish production in China, India, and Bangladesh, whereas precipitation boosted fish production in China and Bangladesh. In contrast, Vietnam showed no long-run equilibrium, indicating higher sensitivity to short-term climatic fluctuations. In the short run, CO_2 emissions significantly enhanced fish production in Bangladesh, with regional temperature effects varying. The minimum temperature positively impacted long-term fish production in China but negatively affected it in Bangladesh. In Vietnam, an increase in the maximum temperature enhanced short-run production, whereas a decrease in the minimum temperature reduced it. This study examined the critical role of CO_2 emissions, precipitation, and temperature in influencing fish production, offering key insights for policymakers to develop adaptive strategies for sustainable fish production amid climate change.

INTRODUCTION

Global fisheries and aquaculture are vital to economies worldwide, contributing significantly to GDP and supporting global food security (FAO 2024). Approximately 3 billion people worldwide depend on fish and fishery products to meet 20 percent of their animal protein intake (FAO 2024). However, these sectors are increasingly at risk due to changing climate patterns. According to the Intergovernmental Panel on Climate Change (IPCC), climate change is a statistically significant alteration in climate properties that persists for decades or longer, resulting from both natural variability and human activities. This phenomenon is widely acknowledged as an inevitable outcome of over 200 years of greenhouse gas emissions from various sources (Lee et al. 2023). The impacts of climate change are irreversible (Masson- Delmotte et al. 2021) and have led to significant declines in aquatic system diversity and productivity. Climate change poses significant risks to marine and freshwater species and the ecosystems they inhabit (Allan et al. 2005, FAO 2024). Tropical regions, particularly South Asia, are especially vulnerable to these effects (Pörtner et al. 2014). Key climate change impacts, such as rising temperatures, changes in precipitation, sea level rise, harmful algal blooms, increased disease, ocean acidification, and extreme weather events, directly influence fish production by altering the biological productivity of fish stocks, as evidenced by various studies (O' Reilly et al. 2003, Perry et al. 2005, Vollmer et al. 2005, Arnason 2007, Cochrane et al. 2009, Eboh 2009, Gamito et al. 2013, Muthoka et al. 2024). These changes pose risks not only to coastal regions that sustain fisheries and aquaculture but also to the livelihoods, productivity, and well-being of the communities that rely on them (Daw et al. 2009, Badjeck et al. 2010), and the consequent rise in prices is expected to have substantial impacts on food security (Agnishwaran et al. 2024). An estimated 3. 3.3–3. 6 billion people face high vulnerability to the effects of climate change, with the most severe risks concentrated in underdeveloped and developing regions. Climate change disrupts critical processes in fish species, such as feeding, migration, and breeding behaviors, further intensifying its impact on fisheries (Brander 2010). The effects of climate variables, such as temperature, precipitation, and CO_2 emissions, on fish production are complex and regionally variable, necessitating a detailed understanding of their effects across different contexts.

Climate change induces significant hydrological changes in aquatic ecosystems. Since 1850, global temperatures have risen by 1.1°C, primarily driven by human-induced global warming, with adverse effects on the environment (Lee et al. 2023). These shifts alter the physical and chemical properties of water bodies, including temperature, salinity, and pH, which in turn influence the physiological, biological, and genetic traits of aquatic species (Menon et al. 2023). Temperature fluctuations contribute to thermal stratification and the development of oxygen minimum zones in water bodies, posing challenges to the survival of various organisms (Ng'onga et al. 2019, Mugwanya et al. 2022). Elevated CO_2 levels alter ocean pH, leading to ocean acidification and coral bleaching, which can affect aquatic biodiversity (Thomas et al. 2022). Furthermore, the combination of climate change and overexploitation may exert additional pressure on fish populations (Perry et al. 2010, Planque et al. 2010). Water scarcity, exacerbated by rising temperatures and fluctuating rainfall patterns, presents further challenges to freshwater and marine ecosystems, potentially intensifying the impact of existing pollution (Alsaleh 2024).

Despite clear evidence of climate change's effects on aquatic ecosystems and fisheries, these impacts are often overlooked in climate adaptation policies (Badjeck et al. 2010). Analyzing long-run equilibrium relationships between climate variables and fish production, and understanding adjustments to short-run deviations, is critical for effective, evidence-based decision-making and resource allocation. Among the key fish-producing countries, China, India, Vietnam, and Bangladesh are pivotal to the global fisheries sector and are vulnerable to climate change impacts. Although substantial research has examined the relationship between climate change and fisheries globally (Cheung et al. 2009, Das et al. 2020, Doney et al. 2012,2009, Fernandes et al. 2016, Lam et al. 2012, Mohanty et al. 2017, Ninawe et al. 2018, Raubenheimer & Phiri, 2023, Suh & Pomeroy 2020, Vass et al. 2009), the application of advanced econometric techniques, such as the Autoregressive Distributed Lag (ARDL) approach, within the fisheries sector remains limited. Most empirical studies employing ARDL models have focused on the agricultural sector (Janjua et al. 2014, Zhai et al. 2017, Ahsan et al. 2020, Chandio et al. 2020, Demirhan 2020, Nasrullah et al. 2021, Warsame et al. 2021, Ramzan et al. 2022, Tagwi 2022, Waris et al. 2023). Addressing this gap, the present study uses the ARDL model to explore long-run cointegration relationships between climate variables and fish production in leading fish economies, thereby offering new insights into the fisheries sector's response to climate change. The ARDL model is particularly adept at analyzing long-run relationships and performs well with small sample sizes, providing reliable results in regression contexts (Bhuyan, Mohanty & Patra 2023).

MATERIALS AND METHODS

Data and Variables

The annual dataset contains time-series statistics from 1990 to 2020 for four Asian countries, namely China, India, Vietnam, and Bangladesh. The key variables of interest were total fish production (TFP), which includes both marine and inland fish production, measured in million tons, climatic variables, such as precipitation, measured in mm, minimum temperature, mean temperature, and maximum temperature, expressed in degrees Celsius, and CO_2 emissions, measured in metric tons per capita. The dataset was compiled from FishStatJ, Food and Agriculture Organization (FAO 2021) for total fish production, Climate Change Knowledge Portal (CCKP), and World Development Indicators (WDI) for climate variables (see Table 1). This study used total fish production as the dependent variable, whereas precipitation, minimum temperature, mean temperature, maximum temperature, and CO_2 emissions were employed as explanatory variables. The selection of climate variables in this study was based on their critical influence on marine and inland ecosystems, particularly concerning fish production. Precipitation is a key variable owing to its direct impact on freshwater inputs into coastal and marine environments, altering salinity, nutrient levels, and habitat conditions, which are crucial for the distribution and productivity of fish populations (Nye et al. 2009). Minimum temperature is justified by its role in defining the lower thermal limit for fish, where sudden drops can cause thermal stress, reducing metabolic rates and impairing growth, reproduction, and survival, thereby revealing the species' vulnerability to cold extremes (Volkoff & Rønnestad 2020). Mean temperature is crucial for understanding the long-term thermal environment affecting metabolic functions, growth, and reproduction, with shifts potentially altering species distribution and ecosystem dynamics (Mugwanya et al. 2022). Maximum temperature was selected for its importance in assessing the impacts of extreme heat on fish, where exceeding thermal thresholds can lead to heat stress, habitat loss, and mortality, driving shifts in species distribution and community structure (Neubauer and Andersen, 2019). CO_2 emissions, a key driver of global warming and ocean acidification, were selected for their extensive impact on marine and inland ecosystems, as elevated CO_2 levels lead to rising surface temperatures that influence fish physiology, behavior, and habitat availability (Harley et al. 2006, Fabry et al. 2008). By including these variables, this study aimed to provide a comprehensive assessment of how various aspects of climate change collectively influence fish production. To address multicollinearity (Mansfield & Helms 1982) and heteroscedasticity (Engle 1982) in the annual time-series data, we applied natural logarithmic transformations to all variables. This logarithmic transformation stabilizes the data variance and produces more reliable and precise results (Dumrul & Kilicaslan 2017).

Econometric Methodology

Model Specification

The empirical framework for this study is outlined in the following implicit form:

$$TFP_t = f(PREC_t, MINTEM_t, MEANTEM_t, MAXTEM_t, CO_{2_t}) \quad \ldots(1)$$

The relationship in its fitted form can be expressed as follows:

$$LnTFP_t = \alpha_0 + \alpha_1 LnPREC_t + \alpha_2 LnMINTEM_t + \alpha_3 LnMEANTEM_t + \alpha_4 LnMAXTEM_t + \alpha_5 LnCO_{2_t} + \varepsilon_t \ldots(2)$$

where$LnTFP_t$ denotes the logarithm of total fish production, $LnPREC_t$ stands for the logarithm of precipitation, $LnMINTEM_t$ represents the logarithm of the minimum$LnMEANTEM_t$ temperature, indicates the logarithm of mean temperature, $LnMAXTEM_t$ signifies the logarithm of maximum temperature, and $LnCO_{2_t}$ refers to the logarithm of CO_2 emissions.

Auto Regressive Distributed Lag (ARDL)

We employed an Autoregressive Distributed Lag (ARDL) model to analyze the short-run and long-run relationships between total fish production and climatic variables (Pesaran & Shin 1995, Pesaran et al. 2001). The choice of the ARDL model is driven by its suitability for examining cointegration and short-term relationships and its effectiveness as an alternative to the more commonly employed Johansen test (Asumadu-Sarkodie & Owusu 2016, Abbas 2020, Chandio et al. 2020, Warsame et al. 2021). This model is particularly advantageous because it offers unbiased long-run estimates even when some endogenous variables are treated as regressors (Adom et al. 2012). The ARDL approach estimates both short- and long-run coefficients using Ordinary Least Squares (OLS) and accommodates regressors that may be either integrated at I(0), I(1), or mutually cointegrated. Unlike many other cointegration methods, the ARDL model delivers consistent results even with smaller sample sizes (Pesaran & Shin, 1995, Pesaran et al. 2001, Adom et al. 2012). In this context, the ARDL model is well-suited for estimating the impact of climate change on total fish production.

Unit Root Tests

To accurately assess the impact of climate change on total fish production in Asian countries, it is crucial to first verify the stationarity of the variables to prevent biased outcomes. To ensure stationarity in the time-series data, we applied unit-root tests, specifically the Augmented Dickey-Fuller "ADF" (1979) and Phillips-Perron "PP" (1988) tests. The ADF test was conducted using the following regression equation:

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \quad \ldots(3)$$

where, ΔY_t represents the first difference of the variable Y_t, α denotes a constant term, b_t is the coefficient associated with the time trend t, γ is the coefficient of the lagged level of the series, δ_i are the coefficients corresponding to the lagged first differences, p indicates the number of lagged terms, and ε_t represents the error term.

The Phillips-Perron (PP) test was also used to complement the ADF test. It addresses serial correlation and heteroscedasticity in the error terms through nonparametric adjustments to the test statistics (Vogelsang and Wagner, 2013). The PP test equation is expressed as:

$$Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \varepsilon_t \quad \ldots(4)$$

For both tests, the presence of a unit root in the time series is determined by examining whether the p-value is below 0.05. If the null hypothesis (H0), which suggests non-stationarity, is rejected, it favours the acceptance of the alternative hypothesis (H1), indicating that the series is stationary.

Estimation Procedure

The ARDL model was used to assess the relationships among variables by initially examining the presence of a long-run association. In this study, the long-term association between lnTFP, lnPREC, lnMINTEM, lnMEANTEM, lnMAXTEM, and $lnCO_2$ was evaluated through the bounds testing approach. The ARDL bounds testing model for our study can be described as:

$$\Delta LnTFP_t = \alpha_0 + \alpha_1 \sum_{i=1}^{p} \Delta LnTFP_{t-i} + \alpha_2 \sum_{i=1}^{q1} \Delta LnPREC_{t-i} + \alpha_3 \sum_{i=1}^{q2} \Delta LnMINTEM_{t-i} + \alpha_4 \sum_{i=1}^{q3} \Delta LnMEANTEM_{t-i} + \alpha_5 \sum_{i=1}^{q4} \Delta LnMAXTEM_{t-i} + \alpha_6 \sum_{i=1}^{q5} \Delta LnCO_{2_{t-i}} + \gamma_1 LnTFP_{t-i} + \gamma_1 LnPREC_{t-i} + \gamma_1 LnMINTEM_{t-i} + \gamma_1 LnMEANTEM_{t-i} + \gamma_1 LnMAXTEM_{t-i} + \gamma_1 LnCO_{2_{t-i}} + \varepsilon_t \quad \ldots(5)$$

Where, α_i and γ_i are short- and long-run coefficients, α_0 is the constant, p and q_i are optimal lag orders of regressand and regressors, Δ represents the first difference operator and ε_t is the white noise error term.

To assess the long-run relationship among the variables, we formulated the following hypotheses: the null hypothesis (H0) assumes no long-run association among the variables ($\alpha1 = \alpha2 = \alpha3 = \alpha4 = \alpha5 = \alpha6$), while the alternative hypothesis (H1) indicates differing parameters ($\alpha1 \neq \alpha2 \neq \alpha3 \neq \alpha4 \neq \alpha5 \neq \alpha6$). The ARDL bounds-testing method employs F-statistics to determine the long-term cointegration among the selected variables. According to Pesaran et al. (2001), the F-test statistics involve two key thresholds: the lower and upper limits. An F-statistic falling below the lower bound indicates no significant long-term relationship, whereas a statistic exceeding the upper bound suggests the presence of a long-term association. If the F-test statistic is between these bounds, the results are inconclusive.

To capture the short-term dynamics between variables, an ARDL-based Error Correction Model (ECM) was employed, as detailed below.

$$\Delta LnTFP_t = \emptyset_0 + \emptyset_1 \sum_{i=1}^{p} \Delta LnTFP_{t-i} + \emptyset_2 \sum_{i=1}^{q-1} \Delta LnPREC_{t-i} + \emptyset_3 \sum_{i=1}^{q-1} \Delta LnMINTEM_{t-i} + \emptyset_4 \sum_{i=1}^{q-1} \Delta LnMEANTEM_{t-i} + \emptyset_5 \sum_{i=1}^{q-1} \Delta LnMAXTEM_{t-i} + \emptyset_6 \sum_{i=1}^{q-1} \Delta LnCO_{2_{t-i}} + \emptyset\, ECT_{t-1} + \epsilon_t \quad \ldots(6)$$

Where, $\emptyset_0$ represents the intercept, $\emptyset_i$ denotes the short-run coefficient, $\in_t$ is the error term, and ECT_{t-1} indicates the lagged residual from the model that determines the long-term relationship. The error correction method describes the speed at which adjustment occurs to restore long-term equilibrium after a short-term shock.

Equation (6) illustrates that total fish production is influenced by its past values, the current and lagged values of the regressors, and the lagged error term. Parameter $\emptyset$ is anticipated to be negative (between 0 and -1), as this indicates the extent to which equilibrium is restored in absolute terms. A positive $\emptyset$ indicates that the model is out of equilibrium and unstable, with no tendency to return to long-run equilibrium. The optimal lag lengths for each variable were established using the Akaike Information Criterion (AIC).

Diagnostic and Stability Tests

This study conducted a series of diagnostic tests to evaluate the model's reliability and validity, following the methodology outlined by Pesaran et al. (2001). To detect serial correlation, the Breusch-Godfrey Serial Correlation LM Test was applied, which is recognized for its ability to accommodate lagged dependent variables, thus enhancing the model's reliability (Breusch 1978, Godfrey 1978). Heteroscedasticity was assessed using the Breusch-Pagan-Godfrey (BPG) test, which ensures accurate variance in the residuals and robustness of the model's estimates (Breusch & Pagan 1979). The normality of the residuals was assessed using the Jarque-Bera (JB) test, which evaluates the skewness and kurtosis of the residuals to determine whether they follow a normal distribution, thereby confirming the appropriateness of the model (Jarque & Bera 1987). To examine the stability of both long and short-run coefficients, the cumulative sum of recursive residuals (CUSUM) test was conducted, as proposed by Brown et al. (1975)

RESULTS AND DISCUSSION

Descriptive Statistics

Table 2 reports the descriptive statistics for the study variables for each country from 1990 to 2020. Total fish production revealed significant disparities, with China exhibiting the highest mean production at 53.19 million metric tons (MT), followed by India (7.48 MT), Vietnam (3.83 MT), and Bangladesh (2.40 MT). The skewness values indicate that China's production distribution is slightly left-skewed (-0.20), whereas India, Vietnam, and Bangladesh display right-skewed distributions, indicating the presence of occasional high production figures. Annual precipitation was highest in Bangladesh, averaging 2185.55 mm, followed by Vietnam (1769.98 mm), India (1114.37 mm), and China (610.70 mm). The distribution of precipitation data was nearly symmetric in all countries, with minimal skewness, reflecting stable precipitation patterns. However, Bangladesh showed the highest variability in precipitation, as indicated by a standard deviation of 275.91 mm, whereas China exhibited the lowest variability (32.53 mm). Temperature variables (annual minimum, mean, and maximum temperatures) presented distinct climatic profiles across the countries. Bangladesh and Vietnam experience the highest temperatures, with mean temperatures of 25.71˚C and 24.80˚C, respectively, whereas China has the lowest mean temperature at 7.59˚C. The temperature distributions across all countries were generally near-normal, with skewness values close to zero, indicating stable and consistent temperature trends. CO_2 emissions are significantly higher in China, with a mean of 4.66 metric tons per capita, compared with India (1.13 MT), Vietnam (1.32 MT), and Bangladesh (0.28 MT). The distribution of CO2 emissions was slightly positively skewed in all countries, with China showing modest skewness (0.15) and lower kurtosis (1.34), suggesting a relatively normal distribution with occasional periods of higher emissions. Vietnam exhibited the highest variability in emissions (standard deviation of 0.96 MT), whereas Bangladesh showed the least variability (0.15 MT). Fig. 1 (a, b, c, d) reveals a consistent upward trajectory in total fish production and CO_2 emissions in China, India, Vietnam, and Bangladesh from 1990 to 2020. Temperature and precipitation trends exhibited considerable variability, with distinct fluctuations in each country, reflecting the complex interplay between climatic conditions and fish production over time.

Unit Root Tests

The results of the unit root tests shown in Tables 3a and 3b for China, India, Vietnam, and Bangladesh indicate that the variables under study predominantly exhibit stationarity at the first difference, as evidenced by both the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) tests. Specifically, for China and India, all variables, including total fish production (TFP), precipitation, temperature-related variables, and CO_2 emissions, are non-stationary at the level but become stationary after differencing, implying an order of integration of I(1). In Vietnam and Bangladesh, most variables also follow a similar pattern, with the exception of minimum temperature and precipitation variables that exhibit stationarity at both levels and the first difference, indicating that they are integrated of order I(0) or I(1). The stationarity of these variables at mixed levels of integration, I(0) and I(1), makes it suitable for the ARDL approach. Furthermore, it allows for a comprehensive analysis of the long-run relationships between fish production and climate indicators in these countries.

Co-integration Testing

The ARDL bounds test was employed to confirm the existence of a long-run relationship between total fish production and the selected climatic factors. The results are presented in Table 4 for the four countries. For China and Bangladesh, the F-statistic values of 6.99 and 6.50, respectively, exceed the upper critical bounds at both the 5% and 1% significance levels, indicating the existence of a long-run relationship or cointegration among the variables. In India, the F-statistic of 5.46 surpasses the upper bound at the 5% significance level, further supporting the presence of a long-term relationship. However, in Vietnam, the F-statistic of 1.26 falls below the lower critical bound, suggesting the absence of a long-run relationship or cointegration among the variables in this case. These findings indicate long-run relationships between total fish production (lnTFP) and precipitation (lnPREC), minimum temperature (lnMINTEM), mean temperature (lnMEANTEM), maximum temperature (lnMAXTEM), and CO_2 emission ($lnCO_2$) in China, India, and Bangladesh, while Vietnam shows no evidence of cointegration. Fig. 2 (a, b, c, d) shows the model selection process based on the Akaike Information Criterion (AIC). The optimal ARDL model for each country was determined by identifying the model with the lowest Akaike information criterion (AIC) value. Specifically, the selected models are ARDL (1, 2, 1, 1, 1, 2) for China, ARDL (1, 0, 0, 0, 0, 0) for India, ARDL (1, 0, 1, 0, 2, 0) for Vietnam, and ARDL (1, 2, 2, 2, 2, 2) for Bangladesh.

ARDL Long-Run and Short-Run Estimation

After confirming cointegration among the variables, the ARDL model was employed to assess the long- and short-run impacts of climatic variables on total fish production across each country.

China: Table 5 highlights the long-run and short-run relationships between climatic variables and total fish production in China over time. In contrast to the mean temperature, we observed a significant positive long-run impact of precipitation, minimum temperature, and CO_2 emissions on fish production. Specifically, the long-run coefficient for precipitation (2.44) was highly significant ($p < 0.001$), indicating a strong positive influence on fish production. The relationship between CO_2 emissions and fish production was positive, with a coefficient of 0.45, and was significant at the 1% level ($p < 0.001$). The minimum temperature also showed a positive effect (1.38, $p = 0.063$), although it was marginally significant at the 10% level. Meanwhile, the long-run coefficients for mean and maximum temperatures are not statistically significant, with the former showing a negative effect (-13.12, $p = 0.139$) and the latter showing a positive effect (11.36, $p = 0.241$). The stability of the long-run coefficients is assessed using short-run dynamics. This analysis involved estimating an error correction model (ECM) in conjunction with long-run estimates. The error correction term (ECT) represents the speed at which the regressand, total fish production, returns to its long-run equilibrium after a change in regressors. The speed of adjustment in this case is 0.24, indicating a 24%

correction towards equilibrium within a period. In the short run, total fish production was significantly influenced by current precipitation, which had a positive impact with a coefficient of 0.26 ($p < 0.001$), and lagged CO_2 emissions, which also showed a significant positive effect with a coefficient of 0.16 ($p = 0.010$). In contrast, immediate CO2 emissions, as well as minimum, mean, and maximum temperatures, did not have statistically significant effects on fish production in the short run, as indicated by their high p-values ($P > 0.05$).

India: The ARDL model results (Table 6) revealed that in the long run, only CO_2 emissions had a significant and positive impact on total fish production, with a coefficient of 1.08 ($p < 0.001$), whereas precipitation and temperature variables (minimum, mean, and maximum temperatures) did not exhibit significant relationships with fish production. Precipitation showed a coefficient of 0.09 ($p = 0.833$), whereas the minimum, mean, and maximum temperatures presented coefficients of 26.30, -42.97, and 10.35, respectively, with corresponding high p-values (0.777, 0.856,

Fig. 1a: Trends in fish production and climate indicators for China during 1990–2020.

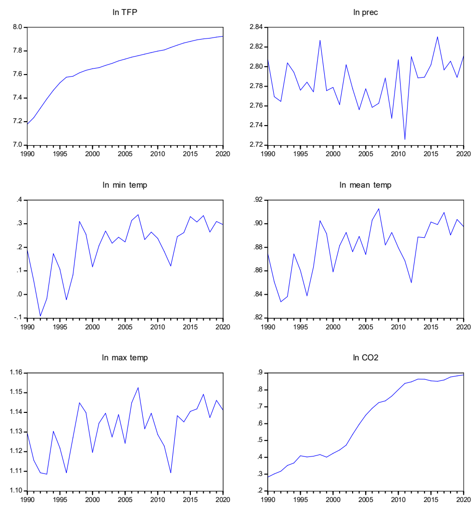

Fig. 1b: Trends in fish production and climate indicators for India during 1990–2020.

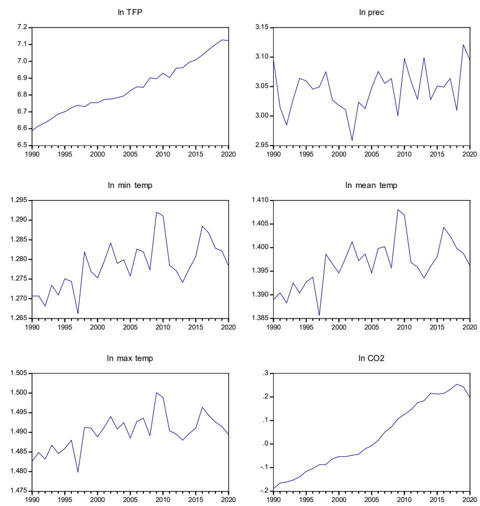

Fig. 1c: Trends in fish production and climate indicators for Vietnam during 1990–2020.

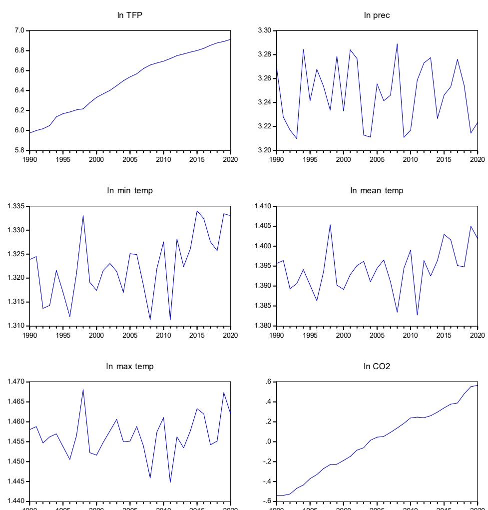

Fig. 1d: Trends in fish production and climate indicators for Bangladesh during 1990–2020.

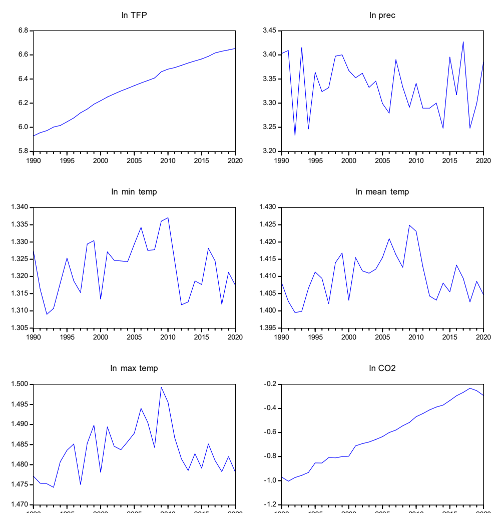

Fig. 1: Trends in fish production and climate indicators for different countries.

Fig. 2a: AIC model selection for China.

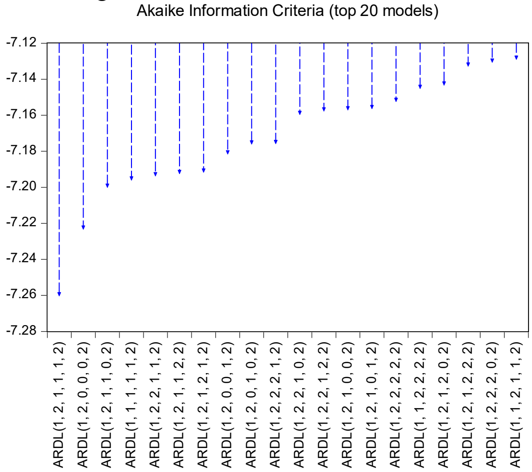

Fig. 2b: AIC model selection for India.

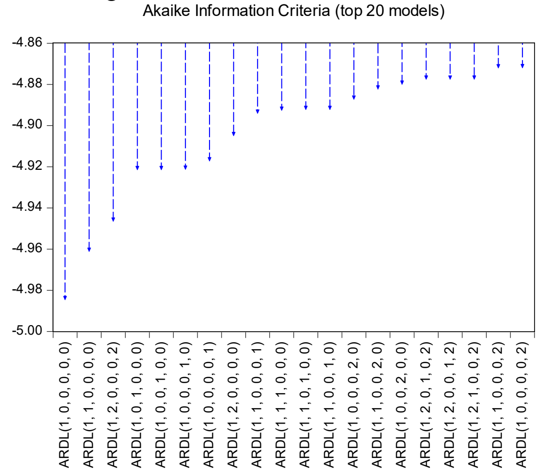

Fig. 2c: AIC model selection for Vietnam.

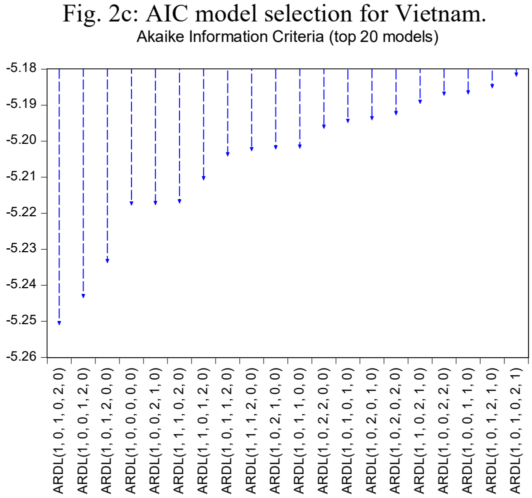

Fig. 2d: AIC model selection for Bangladesh.

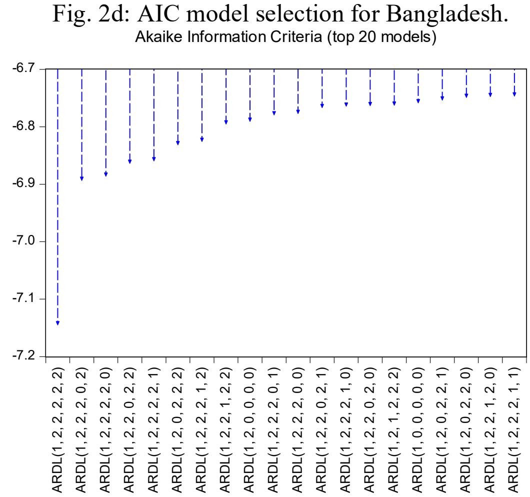

Fig. 2: AIC model selection for different countries.

and 0.944, respectively), indicating a lack of significant impact. After long-run cointegration was established, the short-run dynamics among the variables were subsequently calculated. The climatic variables, including precipitation, minimum temperature, mean temperature, maximum temperature, and CO_2 emissions, exhibited a lag of 0, indicating that changes in these variables do not immediately affect fish production in the short term. The error correction term (ECT) of -0.24 suggests that approximately 24% of any deviation from the long-run equilibrium is adjusted in each period. This implies that fish production is more influenced by long-term climate patterns than by immediate fluctuations.

Vietnam: The ARDL model, as indicated by the F-statistic from the bounds test, suggests that there is no long-run equilibrium in Vietnam, implying that only short-run relationships exist. The results of the short-run coefficients are shown in Table 7. Precipitation, mean temperature, maximum temperature, and CO_2 emissions do not exhibit significant relationships with total fish production in the short run, as reflected by their high p-values. However, the first lag of the minimum and the first lag of maximum temperatures affected the total fish production at the 10% significance level. The outcome of short-run coefficients revealed that a 1% increase in minimum temperature leads to a 2.19% decrease in total fish production, whereas a 1% increase in maximum temperature leads to a 3.02% increase in total fish production. Although precipitation and mean temperature were positively correlated with fish production and CO2 emissions were negatively correlated, these effects were not statistically significant ($P > 0.05$).

Bangladesh: In the long run, CO_2 emissions exerted a strong positive influence on fish production, with a coefficient of

Fig. 3a: Plot of CUSUM test for China.

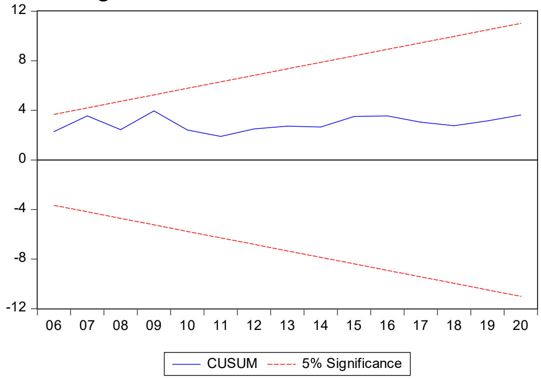

Fig. 3b: Plot of CUSUM test for India.

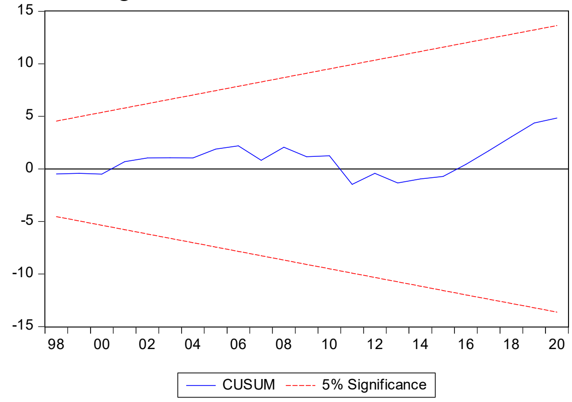

Fig. 3c: Plot of CUSUM test for Vietnam.

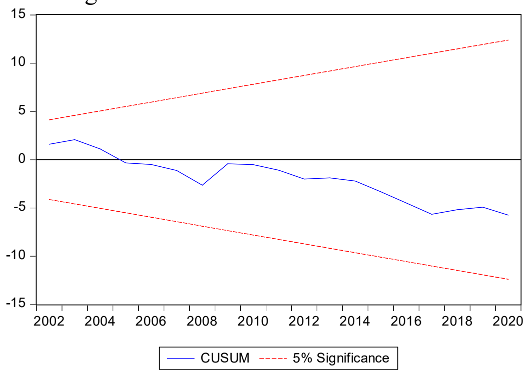

Fig. 3d: Plot of CUSUM test for Bangladesh.

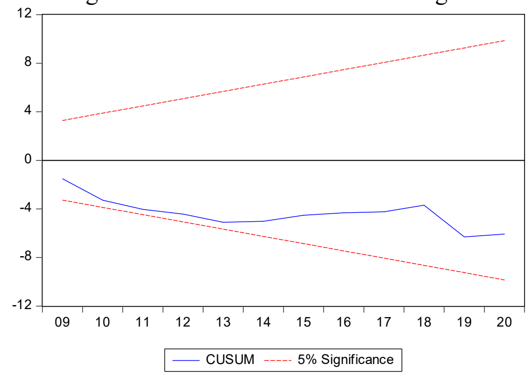

Fig. 3: Plot of the CUSUM test for different countries.

0.87 ($p < 0.001$), while precipitation also showed a significant positive impact, with a coefficient of 1.39 ($p = 0.001$) (Table 8). Temperature variables showed mixed results, with the minimum temperature showing a negative effect at -158.96 ($p = 0.083$), indicating marginal significance, whereas the mean and maximum temperatures did not exhibit a statistically significant impact on total fish production. In the short run, precipitation continues to play a critical role, with its immediate effect showing a significant positive coefficient of 0.14 ($p < 0.001$). However, the lagged effect of precipitation was negative and significant, with a coefficient of -0.12 ($p = 0.001$), indicating that an increase in precipitation may have a delayed adverse impact on total fish production. Furthermore, the first lags of the minimum and maximum temperatures were also significant, with coefficients of 27.14 ($p = 0.001$) and 35.26 ($p = 0.002$), respectively, suggesting that past temperature variations influence current production levels. Meanwhile, the immediate effect of CO_2 emissions was not statistically significant (0.03, $p = 0.576$), and the lagged effect was significant and negative, with a coefficient of -0.23 ($p = 0.002$), indicating that previous increases in CO_2 emissions may lead to a reduction in fish production over time.

In addition, the ECM coefficient is -0.31 and is significant at the 1% level. This suggests that deviations from equilibrium in the short run were adjusted at a rate of approximately 31% annually, progressively aligning towards the long-run equilibrium.

Diagnostic Inspection

The diagnostic tests for the model, as shown in Table 9, revealed no significant issues of serial correlation, heteroskedasticity, or non-normality of residuals across the different countries under study. The Breusch-Godfrey Serial correlation LM test indicates no significant evidence of serial correlation in the residuals, with F-statistics of 0.23 ($p = 0.79$) for China, 1.32 ($p = 0.36$) for India, 2.62 ($p = 0.12$) for Bangladesh, and 1.63 ($p = 0.22$) for Vietnam. The Breusch-Pagan-Godfrey Heteroskedasticity Test further supports the model's validity by showing no significant presence of heteroskedasticity, as evidenced by the p-values for all countries, which are greater than 0.05. Additionally, the Jarque-Bera Normality test confirms that the residuals are normally distributed, with χ^2 values of 0.25 ($p = 0.87$) for

China, 0.78 (p = 0.67) for India, 0.55 (p = 0.75) for Bangladesh, and 0.31 (p = 0.85) for Vietnam. Furthermore, the stability of the model was assessed using the cumulative sum of recursive residuals (CUSUM) test. As illustrated in Figs. 3 (a, b, c, d), the trajectories of total fish production remain within the 5% significance level throughout the period, thereby validating the stability of the ARDL model in all the countries studied.

DISCUSSION

Globally, climate change affects marine and freshwater fish species by shifting their distribution and altering their habitats, which in turn reduces their productivity (Allan et al. 2005, FAO 2024). Tropical ecosystems, particularly in Asia, are particularly vulnerable to these changes (Pörtner et al. 2014). This study examined the impact of climate change on fisheries in the top fish-producing countries.

China

Based on this study, precipitation has a long-term impact on the total fish production in China. We observed that a

Table 1: Variable description and data sources. Source: Author's collection from various databases.

	Variable	Code	Measurement Unit	Source
Dependent Variable	Total Fish Production	TFP	Million tons	FishStatJ, FAO
Independent Variables	Annual Precipitation	PREC	Millimeter	CCKP
	Annual Minimum Temperature	MINTEM	Degree Celcius	CCKP
	Annual Mean Temperature	MEANTEM	Degree Celcius	CCKP
	Annual Maximum Temperature	MAXTEM	Degree Celcius	CCKP
	CO_2 emission	CO_2	Metric Tons per capita	WDI

Table 2: Descriptive Statistics.

Country	Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
China	Total Fish production	53.19	53.79	83.93	15.11	20.14	-0.20	2.08
	Annual Precipitation	610.70	614.41	676.47	531.98	32.53	-0.14	2.84
	Annual Minimum Temperature	1.65	1.73	2.18	0.81	0.38	-0.59	2.47
	Annual Mean Temperature	7.59	7.62	8.18	6.82	0.37	-0.49	2.32
	Annual Maximum Temperature	13.54	13.63	14.21	12.84	0.39	-0.41	2.24
	CO_2 emission	4.66	4.47	7.76	1.91	2.18	0.15	1.34
India	Total Fish production	7.48	6.70	13.41	3.88	2.77	0.76	2.51
	Annual Precipitation	1114.37	1120.49	1322.44	908.97	93.05	0.12	2.74
	Annual Minimum Temperature	18.99	18.98	19.59	18.46	0.27	0.28	2.84
	Annual Mean Temperature	24.92	24.92	25.59	24.30	0.29	0.16	3.04
	Annual Maximum Temperature	30.91	30.93	31.63	30.19	0.32	0.03	3.20
	CO_2 emission	1.13	0.98	1.80	0.65	0.38	0.40	1.64
Vietnam	Total Fish production	3.83	3.44	8.19	0.94	2.32	0.37	1.80
	Annual Precipitation	1769.98	1762.83	1945.05	1621.31	104.95	0.07	1.67
	Annual Minimum Temperature	21.03	21.01	21.58	20.48	0.32	0.04	2.23
	Annual Mean Temperature	24.80	24.80	25.43	24.14	0.31	0.08	2.94
	Annual Maximum Temperature	28.62	28.59	29.38	27.85	0.34	0.09	3.58
	CO_2 emission	1.32	1.11	3.68	0.29	0.96	0.95	3.09
Bangladesh	Total Fish production	2.40	2.22	4.50	0.85	1.17	0.32	1.82
	Annual Precipitation	2185.55	2156.07	2674.16	1710.40	275.91	0.01	1.92
	Annual Minimum Temperature	21.01	21.11	21.73	20.37	0.37	0.04	2.11
	Annual Mean Temperature	25.71	25.67	26.60	25.09	0.39	0.43	2.62
	Annual Maximum Temperature	30.45	30.45	31.57	29.81	0.44	0.66	3.04
	CO_2 emission	0.28	0.23	0.59	0.10	0.15	0.59	2.03

Table 3a: Unit Root Tests.

		PP			ADF		
		At level	1st Diff	Implied order of integration	At level	1st Diff	Implied order of integration
China	LN_TFP	3.07	-1.68*	I (1)	1.41	-1.67*	I (1)
	LN_PREC	0.06	-30.69***	I (1)	0.20	-12.66***	I (1)
	LN_MIN_TEMP	-0.81	-7.30***	I (1)	0.39	-8.59***	I (1)
	LN_MEAN_TEMP	0.69	-9.60***	I (1)	0.14	-6.55***	I (1)
	LN_MAX_TEMP	0.69	-12.61***	I (1)	0.13	-7.44***	I (1)
	LN_CO2	2.46	-1.84*	I (1)	1.20	-1.90*	I (1)
India	LN_TFP	11.25	-4.50***	I (1)	6.82	-9.79***	I (1)
	LN_PREC	-0.02	-9.82***	I (1)	0.40	-9.19***	I (1)
	LN_MIN_TEMP	0.40	-10.69***	I (1)	0.22	-7.13***	I (1)
	LN_MEAN_TEMP	0.39	-9.81***	I (1)	0.26	-7.48***	I (1)
	LN_MAX_TEMP	0.28	-8.70***	I (1)	0.28	-7.83***	I (1)
	LN_CO2	-0.62	-2.03**	I (1)	-0.98	-2.03**	I (1)

Table 3b: Unit Root Tests.

		PP			ADF		
		At level	1st Diff	Implied order of integration	At level	1st Diff	Implied order of integration
Vietnam	LN_TFP	-0.22	-4.44***	I (1)	-0.77	-4.37***	I (1)
	LN_PREC	-6.81***	-21.29***	I (0), I (1)	-4.69***	-5.38***	I (0), I (1)
	LN_MIN_TEMP	-4.92***	-22.32***	I (0), I (1)	-4.92***	-5.93***	I (0), I (1)
	LN_MEAN_TEMP	-4.99***	-18.75***	I (0), I (1)	-5.00***	-8.03***	I (0), I (1)
	LN_MAX_TEMP	-5.04***	-17.90***	I (0), I (1)	-5.19***	-7.88***	I (0), I (1)
	LN_CO_2	-2.30	-5.32***	I (1)	-2.30	-4.92***	I (1)
Bangladesh	LN_TFP	0.04	-4.28***	I (1)	0.24	-4.35***	I (1)
	LN_PREC	-7.19***	-19.28***	I (0), I (1)	-7.19***	-6.91***	I (0), I (1)
	LN_MIN_TEMP	-3.24*	-14.81***	I (0), I (1)	-3.24*	-6.50***	I (0), I (1)
	LN_MEAN_TEMP	-2.87	-16.82***	I (1)	-2.94	-6.46***	I (1)
	LN_MAX_TEMP	-2.94	-16.06***	I (1)	-3.00	-6.54***	I (1)
	LN_CO_2	-3.05	-5.37***	I (1)	-3.15	-5.30***	I (1)

Note: (*) Significant at the 10%, (**) Significant at the 5%, (***) Significant at the 1% level

Table 4: Bounds Cointegration Test.

Country	F-statistic Value	Significance level	Critical value	
			Lower bound	Upper bound
China	6.99	5%	2.62	3.79
		1%	3.41	4.68
India	5.46	5%	2.39	3.38
		1%	3.06	4.15
Vietnam	1.26	5%	2.62	3.79
		1%	3.41	4.68
Bangladesh	6.50	5%	2.62	3.79
		1%	3.41	4.68

Table 5: Results of long and short-run coefficients using the ARDL model for China.

Long run				
	Coefficient	Std. Error	t-Statistic	Prob.
LN_PREC	2.44	0.53	4.57	0.000
LN_MIN_TEMP	1.38	0.68	2.01	0.063
LN_MEAN_TEMP	-13.12	8.40	-1.56	0.139
LN_MAX_TEMP	11.36	9.30	1.22	0.241
LN_CO_2	0.45	0.04	10.35	0.000
Short run				
	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.21	0.01	-21.34	0.000
D(LN_PREC)	0.26	0.05	5.46	0.000
D(LN_PREC(-1))	-0.09	0.05	-2.03	0.061
D(LN_MIN_TEMP)	0.10	0.08	1.29	0.216
D(LN_MEAN_TEMP)	-0.80	0.82	-0.98	0.343
D(LN_MAX_TEMP)	0.61	0.83	0.74	0.469
D(LN_CO_2)	0.06	0.06	1.09	0.294
D(LN_CO_2 (-1))	0.16	0.06	2.97	0.010
ECM(-1)*	-0.24	0.01	-23.65	0.000
ARDL (1, 2, 1, 1, 1, 2)				

Table 6: Results of long and short-run coefficients using the ARDL model for India.

Long Run				
	Coefficient	Std. Error	t-Statistic	Prob.
LN_PREC	0.09	0.43	0.21	0.833
LN_MIN_TEMP	26.30	91.88	0.29	0.777
LN_MEAN_TEMP	-42.97	234.62	-0.18	0.856
LN_MAX_TEMP	10.35	144.33	0.07	0.944
LN_CO_2	1.08	0.13	8.07	0.000
C	17.56	11.28	1.56	0.133
Short run				
	Coefficient	Std. Error	t-Statistic	Prob.
CointEq(-1)*	-0.24884	0.035857	-6.93995	0
ARDL (1, 0, 0, 0, 0, 0)				

Table 7: Results of Short run ARDL model for Vietnam.

Short run				
	Coefficient	Std. Error	t-Statistic	Prob.*
LN_TFP(-1)	1.05	0.12	8.40	0.000
LN_PREC	0.30	0.23	1.34	0.197
LN_MIN_TEMP	-3.63	22.29	-0.16	0.872
LN_MIN_TEMP(-1)	-2.19	1.21	-1.80	0.088
LN_MEAN_TEMP	6.01	54.62	0.11	0.914
LN_MAX_TEMP	-1.83	32.68	-0.06	0.956
LN_MAX_TEMP(-1)	3.03	1.55	1.96	0.065
LN_MAX_TEMP(-2)	1.34	0.84	1.59	0.128
LN_CO_2	-0.04	0.11	-0.35	0.732
C	-5.62	4.39	-1.28	0.216
ARDL (1, 0, 1, 0, 2, 0)				

Table 8: Results of long and short-run coefficients using the ARDL model for Bangladesh.

Long run				
	Coefficient	Std. Error	t-Statistic	Prob.
LN_PREC	1.39	0.33	4.15	0.001
LN_MIN_TEMP	-158.96	84.01	-1.89	0.083
LN_MEAN_TEMP	351.15	201.62	1.74	0.107
LN_MAX_TEMP	-183.29	117.26	-1.56	0.144
LN_CO_2	0.87	0.02	40.16	0.000
Short run				
	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.34	0.45	-7.39	0.000
D(LN_PREC)	0.14	0.03	5.17	0.000
D(LN_PREC(-1))	-0.12	0.03	-4.57	0.001
D(LN_MIN_TEMP)	-8.26	6.14	-1.35	0.203
D(LN_MIN_TEMP(-1))	27.14	6.07	4.48	0.001
D(LN_MEAN_TEMP)	16.60	14.75	1.13	0.282
D(LN_MEAN_TEMP(-1))	-62.85	14.70	-4.27	0.001
D(LN_MAX_TEMP)	-6.60	8.57	-0.77	0.456
D(LN_MAX_TEMP(-1))	35.26	8.61	4.09	0.002
D(LN_CO_2)	0.03	0.05	0.57	0.576
D(LN_CO_2 (-1))	-0.23	0.06	-3.99	0.002
CointEq(-1)*	-0.31	0.04	-7.43	0.000
ARDL (1, 2, 2, 2, 2, 2)				

Table 9: Diagnostic tests of the model.

	China		India				Bangladesh	
	F - Statistics	P - value	F - Statistics	P - value	Vietnam	P - value	F - Statistics	P - value
Breusch-Godfrey Serial Correlation LM Test	0.23	0.79	1.32	0.36	1.63	0.22	2.62	0.12
Heteroskedasticity Test: Breusch-Pagan-Godfrey	1.01	0.47	1.33	0.28	1.78	0.13	0.67	0.77
Normality test: Jarque-Bera	0.25	0.87	0.78	0.67	0.31	0.85	0.55	0.75

1% increase in annual precipitation could increase total fish production by 2.44%. Several studies have provided insights into these relationships. For instance, Holst and Yu (2010) found that precipitation positively impacts aquaculture outputs, whereas a 1°C increase in annual average temperature was associated with a rise in national mean output of 1.47 million tons. Similarly, Meynecke et al. (2006) identified a significant positive correlation between annual rainfall and total fish production in Australia, highlighting the importance of precipitation for fishery yields. The study indicated seasonality with a trend in annual temperature over time, ranging from 1.6°C to 13.5°C. China's seas have generally warmed over the past few decades, with the East China Sea experiencing the most significant rise and the South China Sea the least, leading to varying impacts on fisheries (Belkin 2009, Liang et al. 2018). Consistent with these findings, our analysis demonstrated that mean temperature negatively impacts fish production, suggesting that rising temperatures may pose challenges to sustaining fisheries in the region. China's national climate commitment, which aims for carbon neutrality by 2060 and an emissions peak by 2030, highlights the significance of understanding the impact of climatic factors on fishery outputs. Chandio et al. (2020) revealed that CO_2 emissions have a significant positive effect on agricultural output in China in both long-run and short-run analyses. However, they also found that temperature exerts a negative effect on agricultural output in the long run, suggesting that the benefits of CO2 fertilization may be offset by the adverse impacts of rising temperatures. This complexity is echoed in Janjua et al. (2014), who reported that CO_2 and precipitation positively influenced wheat production in Pakistan over the long run, reinforcing the notion that different climatic variables can have varied effects on agricultural productivity depending on the context and timescale.

India

India is increasingly grappling with the impacts of climate change, which have intensified in both frequency and severity, affecting its natural environment, economy, and society (Mall et al. 2011, Kushawaha et al. 2021, Picciariello et al. 2021). The country is facing a range of extreme climate-related challenges, including heatwaves, floods, unpredictable monsoons, and declining groundwater reserves (Misra 2013, Dhara & Kolls 2021, Charak et al. 2024). Ranked as the 7th most affected nation by climate change according to the Global Climate Risk Index 2021 (Eckstein et al. 2021). India has committed to achieving net-zero emissions by 2070 and has made notable progress in decoupling its economic growth from emissions. According to the (IPCC 2022) report, India maintains a relatively low level of emissions per capita compared to other major global economies, demonstrating its commitment to sustainable development. Our study revealed a significant positive impact of CO_2 emissions on long-term fish production. CO_2 may enhance primary productivity by promoting the growth of aquatic vegetation and phytoplankton, which are key components of the food web, and the short-term effects appear less pronounced (Geider et al. 2001, Tremblay et al. 2015). These findings are consistent with the trends observed in the agricultural sector, where CO_2 emissions have also been found to positively influence long-term productivity. Ahmed & Saha (2023) reported a positive association between per capita CO_2 emissions and agricultural GDP in India over the long term, although no significant short-term effect was detected. This parallel between fisheries and agriculture highlights the complex nature of CO_2's role in enhancing productivity over extended periods. Moreover, climate change-induced physical changes, such as increased water temperature and altered dissolved oxygen levels, have been linked to a higher risk of disease outbreaks in aquatic systems (Harvell et al. 2002, Vilchis et al. 2005). These changes, driven by warming waters, could further exacerbate the challenges faced by India's fisheries and aquaculture sectors, which are critical to food security and livelihoods.

Vietnam

The results from the ARDL model for Vietnam reveal that no long-run equilibrium exists between climatic variables and total fish production, suggesting that only short-run relationships are significant. This aligns with the findings of Pham (2012), who similarly reported no significant relationship between temperature and shrimp productivity across multiple ecological regions in Vietnam. However, regional differences were noted, with temperature affecting shrimp production in the North-Central Coastal region, whereas rainfall had no notable impact. Cao et al. (2013) identified an inverse correlation between temperature and shrimp production, further supporting the complex relationship between climate and fisheries in Vietnam. The absence of long-run effects could be attributed to Vietnam's vulnerability to extreme climate events, which disrupt the consistency of the relationships between climatic variables and fish production. Vietnam is among the nations most severely impacted by climate change, as reported by the Ministry of Natural Resources and Environment (MoNRE, 2016). Frequent and extreme climate occurrences, such as typhoons, floods, and rising sea levels, have a profound effect on the fisheries sector, disrupting long-term trends and making it difficult to establish stable and long-run relationships between climate factors and production outputs. This unpredictable nature of extreme climate events may obscure long-run trends, as fish production systems adapt to short-term fluctuations rather than establishing long-term equilibrium. In response to these challenges, the Vietnamese government has implemented meticulously designed policies aimed at mitigating the impact of climate change. Vietnam's comprehensive strategies, such as the National Target Program to Respond to Climate Change (NTP-RCC), Vietnam Green Growth Strategy (VGGS), Law on Environmental Protection (2020), and National Action Plan on Climate Change (NAPCC), have been instrumental in mitigating the impacts of climate change on various sectors, including fisheries. These policies align with Vietnam's commitment to the Sustainable Development Goals (SDGs), which emphasize responsible production practices, protection of coastal and marine ecosystems, and climate resilience (Ministry of Planning and Investment 2018). Wilbanks (2003) highlights that climate change serves as both a challenge and a catalyst for advancing sustainable development, and this duality is evident in Vietnam's proactive approach. Through carefully designed government interventions, the country is managing the short-term impacts of climate change and helping to maintain the resilience of its fisheries sector.

Bangladesh

The ARDL model results for this country highlight a relationship between climatic variables and total fish production, with significant impacts observed in both the short and long runs. Bangladesh ranked 7th in long-term climate vulnerability from 2000 to 2019 (Global Carbon Atlas, 2022), reflecting its susceptibility to climate change, which appears to influence the fisheries sector in both time frames. The long-run analysis showed that CO_2 emissions have a strong positive influence on fish production, which is explained by the rise in per capita carbon emissions from 0.107 metric tons in 1990 to 0.510 metric tons in 2020. Although Bangladesh ranks 39th in per capita CO_2 emissions globally (Global Carbon Atlas 2022), its relatively low industrial greenhouse gas (GHG) emissions (Islam et al. 2020) suggest that this positive long-run association could be linked to the ecological dynamics of CO_2, enhancing primary productivity. This is consistent with the findings of Begum et al. (2022), who also reported a positive relationship between CO_2 emissions and marine fish production in Bangladesh over the long term. Precipitation also had a significant positive impact on fish production in both the long and short runs, reinforcing the notion that rainfall plays a vital role in Bangladesh's fisheries sector. Begum et al. (2022) found that a 1% increase in average rainfall could increase marine fish production by 1.65%, a result consistent with our study where precipitation had a sustained positive influence on fish output. This relationship aligns with research showing that increased rainfall often coincides with upwelling events that bring nutrient-rich waters to the surface, significantly boosting fish catch (Atindana et al. 2019). Similar positive associations between rainfall and fish productivity have been observed in other regions, such as Malaysia (Madihah Jafar-Sidik et al. 2010) and Pakistan (Ayub 2010), further substantiating the critical role of precipitation in driving marine fish production. The short-run results reveal a more nuanced picture. While precipitation continues to be a significant factor, its lagged effect turns negative, suggesting that excessive rainfall may initially benefit fish production but may have adverse delayed effects. This phenomenon may be attributed to ecological disruptions, such as the increased risk of undesirable phytoplankton blooms during periods of high atmospheric CO_2, which can negatively affect marine ecosystems (Schippers et al. 2004). Temperature variables also had significant short-run effects on fish production. Ho et al. (2013) observed that fish landings increase with rising temperatures. However, as temperatures continue to rise, increased stratification is expected to restrict the flow of nutrients to the surface, potentially reducing productivity (Kay et al. 2018). Bangladesh's proactive climate policies, including the Bangladesh Climate Change Strategy and Action Plan (BCCSAP 2009), the National Adaptation Program of Action (NAPA 2005), and the National Fisheries Policy (NFP), reflect the country's commitment to addressing the multifaceted challenges posed by climate change. These frameworks, alongside the Bangladesh Delta Plan 2100, aim to mitigate the long-term impacts of climate change on the fisheries sector, ensuring sustainability amidst increasing climate variability.

CONCLUSIONS

This study provides a fresh perspective on the impact of climate change on fisheries in four leading fish-producing countries: China, India, Vietnam, and Bangladesh. The results reveal long-run associations for all countries except Vietnam, where only short-run relationships are identified. In China and Bangladesh, precipitation and CO_2 emissions exhibited significant positive long-run impacts on fish production, highlighting the role of favorable weather patterns and carbon availability in supporting the aquatic ecosystem. The results for India, however, showed that only CO_2 emissions have a significant long-run effect, whereas temperature and precipitation do not display any significant impacts. In Vietnam, the absence of a long-run equilibrium suggests that fish production is influenced only by short-term climatic changes, particularly the lagged effects of the minimum and maximum temperatures. Diagnostic tests confirmed the robustness of the model, with no evidence of serial correlation, heteroskedasticity, or non-normality in the residuals. The policy implications of this study are significant. In China, promoting green aquaculture and reducing emissions through innovative technologies can enhance resilience to climate change effects. India should focus on low-carbon fishing practices and adaptive aquaculture systems to mitigate the adverse effects of rising temperatures, while improving water resource management to benefit from precipitation changes. Vietnam requires enhanced flood management strategies and the development of climate-resilient aquaculture to cope with precipitation variability. Given its vulnerability to climate-induced floods, Bangladesh must prioritize sustainable water practices and species diversification to safeguard fish production. Each country should integrate climate resilience into fisheries policies to ensure sustainable development and food security and mitigate the risks posed by rising temperatures and shifting precipitation patterns.

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