Economic Affairs, Vol. 70(02), pp. 199-217, June 2025
DOI: 10.46852/0424-2513.2.2025.4

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RESEARCH PAPER

Economic Impact of Climate Change on Fisheries: Evidence from Multi-country Using ARDL Approach

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Received: 14-03-2025 **Revised:** 27-05-2025 **Accepted:** 05-06-2025

ABSTRACT

Fish GDP has considerable impact from mean temperature, precipitation and CO_2 emission over a period of time. Here we use empirical findings from three South Asian countries namely Bangladesh, India and Thailand for period of 1991-2020 using an Autoregressive distributed lag (ARDL) model. There is a significant positive long-term relationship between CO_2 and fish GDP for Bangladesh and India, while temperature and precipitation show a non-significant negative association. In Thailand, precipitation has a significant positive impact on fish GDP, while temperature and CO_2 also have positive effects but are not statistically significant. The error correction term is highly significant, indicating a strong short run adjustment towards long run equilibrium. The fitted models were reliable and stable confirmed using econometric analysis. The positive influence of CO_2 emissions on fish GDP underscores the need for emissions reduction policies and sustainability efforts in India and Bangladesh. By leveraging insights from this model, these countries can develop both immediate and long-term strategies to sustain the health and productivity of the fisheries sector amidst environmental changes.

HIGHLIGHTS

- ARDL model quantifies long-term and short-term economic impacts of climate change on fisheries in India, Bangladesh, and Thailand
- CO_2 emissions positively influence fish GDP in Bangladesh and India, necessitating sustainability efforts.
- Temperature and precipitation exhibit a non-significant negative impact on fish GDP in Bangladesh and India.
- A strong short-run adjustment towards long-run equilibrium ensures model reliability.

Keywords: Economic impact, Climate change, GDP, Fisheries, CO_2 emission

Climate change refers to long term alteration in earth climate pattern including changes in the temperature, precipitation and other climate system that occurs naturally but recently which are primarily driven by human activities in particular burning of fossil fuels, deforestation and industrial development (khoshnevis Yazdi & Shakouri, 2010;

How to cite this article: Radhakrishnan, K., Maniselvam, J., Sri, K.K., Prakash, A., Velmurugan, R., Durai, V., Paulpandi, S. and Keerthana, S.R. (2025). Economic Impact of Climate Change on Fisheries: Evidence from Multi-country Using ARDL Approach. *Econ. Aff.*, **70**(02): 199-217.

Source of Support: None; **Conflict of Interest:** None

Lee *et al.* 2023). The escalation of average global temperature in atmosphere is largely instigated by emission of greenhouse gases such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) (Hussain *et al.* 2020; Lavell *et al.* 2012; Li, Cui, Zhang, & Zhang, 2024; Li *et al.* 2024; Murshed *et al.* 2022; Sovacool, Griffiths, Kim, & Bazilian, 2021; Trenberth, 2011; Usman & Balsalobre-Lorente, 2022; Xi-Liu & Qing-Xian, 2018). Changes in precipitation pattern mainly affect the ecosystem, agriculture and water resources which in turn directly affect the human communities (Lal, 2005; Mall, Gupta, Singh, Singh, & Rathore, 2006; Piao *et al.* 2010; Subba, Ma, Ma, & Han, 2024; H. Wang *et al.* 2024; Zhao, Su, Wang, Tao, & Jiang, 2021). These climate events heavily influence various production sectors, particularly the fisheries sector, which is a vital contributor to many developing economies that significantly augmenting GDP, improving food security and provides livelihoods for millions (Allison *et al.* 2009; Badjeck, Allison, Halls, & Dulvy, 2010; K. M. Brander, 2007; Do *et al.* 2021; Maulu *et al.* 2021) Guinea, Senegal, and Uganda. Fish consumption has amplified owing to increased awareness of its health benefit with fish serving as a primary source of animal protein for about 3 billion people globally (FAO, 2024).

Despite, capture fisheries in developing economies have reached their maximum sustainable yield and the majority of production now comes from culture fisheries. Fish production is affected by various aspects with growing threats form climate change being particularly concerning, leaving 3.3 to 3.6 billion people highly vulnerable (IPCC, 2022). Since 1850, global temperatures have increased by 1.1°C, altering fish metabolism rates, reducing survival rates, and increasing algal blooms (IPCC, 2023). Changes in precipitation patterns reduce water availability for aquaculture activities (Barange *et al.* 2018), disrupt the availability of fish seed (Siddique *et al.* 2022), and decrease water quality, potentially leading to higher disease prevalence due to lower oxygen levels (Maulu *et al.* 2021; Sharma *et al.* 2014). These climate events ultimately affect the distribution, abundance, and productivity of fish stocks and aquaculture, leading to a reduction in fish production (Burden & Fujita, 2019; Maulu *et al.* 2021; Rijnsdorp, Peck, Engelhard, Möllmann, & Pinnegar, 2009; Seggel & De Young, 2016). Additionally, disease management and the implementation of climate adaptation measures further escalate the production costs of fish (FAO, 2024; Maulu *et al.* 2021). The changes in climate significantly affect the fish production leads to reduce the fish availability and accessibility for economically vulnerable people and income generation also diminish (Barange *et al.* 2018; Maulu *et al.* 2024; Mohammed & Uraguchi, 2013). The economic consequences of climate changes are profound. While much of the research has focused on ecological impacts, economic losses in the fisheries and aquaculture sector due to climate variability have been relatively underexplored. We could infer from these studies that understanding the economic impact of climate change on fisheries is paramount which is subjected to countries intensity.

Of the Southeast Asian countries, India, Bangladesh and Thailand are significantly contributes to fisheries sector, and are also highly vulnerable to climate change. For instance, Bangladesh, a key player in global fishery production, has experienced significant economic losses—around 140 million US dollars in its aquaculture sector due to climate change (Islam *et al.* 2024). Similarly, India, frequently impacted by floods, cyclones, droughts, and rising temperatures, is projected to see a 24% decrease in agricultural production by 2080 due to climate change (Zhai & Zhuang, 2009). In Thailand, extreme weather conditions have negatively impacted short-run macroeconomic performance, with the great flood in 2011, triggered by the La Nina phenomenon, causing damage to the Thai economy amounting to approximately US$ 6.23 billion (Jatuporn & Takeuchi, 2023). Therefore, present study aims to examine the long-term and short-term economic impact of climate change on fisheries for India, Bangladesh and Thailand, Here, Autoregressive Distributed Lag (ARDL) model is employed to quantify the long-term and short-term impacts among the variables, offering robust results even in small sample sizes. It is essential for understanding the economic ramifications of climate change on fisheries and based on the long-term and short-term effect it guiding for effective policy intervention.

MATERIALS AND METHODS

Data source and variables selection

Historical annual mean temperature (in °C) and precipitation total (in mm) obtained for the period 1990-2020 from Climate change Knowledge portal, World Bank for India, Bangladesh and Thailand. The CO_2 emission (in MT) sourced from the World Development Indicators and the fisheries gross domestic product (GDP) was taken from Ministry of Fisheries with respective countries for the same period. Following recent literature, to assess economic impact of climate change on fisheries, fish GDP is considered as endogenous variable and temperature, precipitation and CO_2 emission are exogenous variable. Fish GDP capture overall economic value generated by the sector, reflecting its performance and productivity, quantifying economic loss and gain, provide essential insight for policy making and long term economic planning.

Temperature plays crucial role both marine and inland fish production. Temperature variations can influence fish physiology, distribution, and ecosystem dynamics, which can impact fish production and fisheries management ultimately affecting the return generate from fisheries. Changes in temperature can reduce the productivity and increased vulnerability, especially in low-latitude regions and inland fisheries. For instance, elevated temperatures can disturb fish reproduction, alter spawning periods, and impact on larval development and survival. These effects are regulated through the endocrine system and can be exacerbated by ocean acidification (Pankhurst & Munday, 2011). Long-term warming may support more productive food webs in subtropical pelagic ecosystems due to increased trophic transfer efficiency and primary production (Britten & Sibert, 2020). Which indirectly affects fish production through alterations in food availability and ecosystem dynamics (Brander, 2010; Gobler *et al.* 2018). Variations in precipitation affects marine fish production by altering habitats and primary production rates, which subsequently influence fishery catches and biodiversity (Brander, 2007). Heavy rainfall increases nutrient runoff, boosting some fish stocks while others decline due to complex food web interactions (Brown *et al.* 2010). Increased precipitation and water levels generally favor fish reproduction, recruitment, and immigration in inland reservoirs but, heavy rainfall can reduce fish catch and catch per unit effort (CPUE) due to fish migration to newly inundated areas and reduced fishing activities (Patrick, 2016). Thus, irregular precipitation patterns, driven by climate change, disrupt inland fisheries production and management, necessitating adaptive strategies for sustainable fisheries (Patrick, 2016).

The influence of CO_2 emissions on both marine and inland fish production is a critical area of study, given the significant role of fisheries in global food security and the environment. CO_2 emissions from marine fisheries are substantial, significantly impacting on marine ecology and fish production (Greer *et al.* 2019; Mariani *et al.* 2020; Parker *et al.* 2018; Zhang *et al.* 2023). The increase in emissions is primarily driven by fuel-intensive fishing practices (Kristofersson, Gunnlaugsson, & Valtysson, 2021) and the removal of large fish, which limits blue carbon sequestration (Mariani *et al.* 2020). The development of the marine fishery economy and trade increases CO_2 emissions, while technical advancements and income growth of fishermen are negatively related to carbon emissions (Zhang *et al.* 2023). To capture the climate variable influence on fish GDP, data transformed by taking natural logarithmic to avoid the Multicollinearity (Mansfield and Helms, 1982) and Heteroscedasticity (Engle, 1982) that produce more reliable and precise results (Kılıçarslan & Dumrul, 2017).

Econometric Methodology

1. Model specification

The Autoregressive Distributed Lag (ARDL) is, an econometric, model testing the existence of a level relationship between an endogenous variable and set of regressor (Pesaran, Shin, & Smith, 2001). This is developed and applied by (Pesaran *et al.* 2001) and the main approach taken from Engle and Granger (1987). The ARDL model is developed with eight assumptions namely (i) variables are integrated of order zero (I(0)) or order one (I(1)), but not of order two (I(2)) or higher; (ii) dependent variable and independent variables is linear; (iii) correctly specified with appropriate lag lengths for both dependent and independent variable; (iv) no simultaneity bias; (v) homoscedastic and no serial correlation; (vi) residuals are normally distributed; (vii) stability of relationships; (viii) error correction term is stationary. Widely adopted in recent times resulting suitability for small sample sizes, robustness to model specification, and ease of estimation (Adom, Bekoe, & Akoena, 2012; Pesaran *et al.* 2001). Globally studies performed to appraise economic impact of climate change on Agriculture in India, Bangladesh, and Nepal (Ahmed & Saha, 2023), on rice production in South Korea (Nasrullah *et al.* 2021), on rice productivity in Malaysia (Zhang *et al.* 2023), on cereal production in Pakistan (Chandio *et al.* 2021), on marine fisheries in Bangladesh (Begum, Masud, Alam, Mokhtar, & Amir, 2022) but paucity studies noticed with respect to fisheries. The coefficient estimate in ARDL model uses Ordinary Least Squares (OLS) model and is well suited to study economic impact of climate change on fisheries that specified in the present study as below:

$$FGDP_t = f(PREC_t, MEANTEM_t, CO_{2t})$$

The relationship is expressed in logarithmic form as follows:

$$LnFGDP_t = \alpha_0 + \alpha_1 LnPREC_t + \alpha_2 LnMEANTEM_t + \alpha_3 LnCO_{2t} + \varepsilon_t$$

Where $LnFGDP_t$ indicate logarithm of fish GDP, $LnPREC_t$ denotes logarithm of precipitation, $LnMEANTEM_t$ represent logarithm of mean temperature and $LnCO_{2t}$ signifies logarithm of CO_2 emissions.

2. Unit root tests

To avoid spurious regression, it is essential to conduct a unit root test. A unit root test is a fundamental statistical procedure in time series analysis, used to determine whether a series is non-stationary and contains a unit root. This step is crucial for applying the correct transformations and selecting an appropriate model. Stationarity is a key assumption in time series modeling, as non-stationarity can lead to biased or unreliable inferences. There are three unit root test namely (i) Augmented Dickey-Fuller (ADF), (ii) Phillips-Perron (PP) and (iii) Kwiatkowski-Phillips-Schmidt-Shin (KPSS). It is crucial to apply multiple unit root tests to determine the integration order of a series, as the power of these tests can vary depending on the sample size (Raihan & Tuspekova, 2022). In the present study, first two methods used to check the stationarity of the data. The ADF test refines the Dickey-Fuller test by introducing lagged differences of the time series, effectively accounting for higher-order serial correlation in the data (Dickey & Fuller, 1979). The ADF test was conducted based on the following regression equation:

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

where, ΔY_t is the first difference of the variable Y_t represent a constant term, β_t represent 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 proposed (Phillips, 1988) and utilized alongside the ADF test to account for serial correlation and heteroskedasticity in the error terms through non-parametric adjustments to the test statistics (Vogelsang & Wagner, 2013). The PP test equation is expressed as follows:

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \varepsilon_t$$

The presence of a unit root is indicated by a p-value greater than 0.05, which suggests that we fail to reject the null hypothesis. The null hypothesis posits that the time series has a unit root and is non-stationary, while the alternative hypothesis asserts that the time series does not have a unit root and is stationary.

3. Cointegration test

The ARDL bounds test, as outlined by (Pesaran *et al.* 2001), was employed to identify cointegration among the variables. In this study, the long-term relationship between LnFGDP, LnPREC, LnMEANTEM, and Ln CO_2 was assessed using the bounds testing approach. The ARDL bounds testing model for this analysis is formulated as follows:

$$\begin{aligned}\Delta \mathrm{LnTFP_t} = {} & \alpha_0 + \alpha_1 \sum_{i=1}^{p} \Delta \mathrm{LnFGDP_{t-i}} + \alpha_2 \sum_{i=1}^{q1} \Delta \mathrm{LnPREC_{t-i}} \\ & + \alpha_3 \sum_{i=1}^{q2} \Delta \mathrm{LnMEANTEM_{t-i}} + \alpha_6 \sum_{i=1}^{q3} \Delta \mathrm{LnCO_{2_{t-i}}} \\ & + \gamma_1 \mathrm{Lnfgdp_{t-i}} + \gamma_1 \mathrm{LnPREC_{t-i}} \\ & + \gamma_1 \mathrm{LnMEANTEM_{t-i}} + \gamma_1 \mathrm{LnCO_{2_{t-i}}} + \varepsilon_t\end{aligned}$$

Where, and represents the short and long-run coefficients, denotes the constant, and signifies optimal lag orders of regress and regressors, represents the first difference operator and is the white noise error term.

To evaluate the long-run relationship among the variables, we established the following hypotheses: the null hypothesis (H0) posits no long-run association among the variables ($\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6$), while the alternative hypothesis (H1) suggests that the parameters ($\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq \alpha_6$). The ARDL bounds-testing approach utilizes F-statistics to test for long-term cointegration among the variables. The F-test statistic is compared against two critical thresholds: the lower bound and the upper bound. An F-statistic below the lower bound indicates no significant long-run relationship, while a statistic above the upper bound confirms the existence of a long-run relationship. If the F-statistic lies between these bounds, the results are considered inconclusive (Pesaran *et al.* 2001).

The ARDL-based Error Correction Model (ECM) is employed to capture the short-term dynamics among variables, as detailed below:

$$\begin{aligned}\Delta \mathrm{LnTFP_t} = {} & \emptyset_0 + \emptyset_1 \sum_{i=1}^{p} \Delta \mathrm{LnTFP_{t-i}} + \emptyset_2 \sum_{i=1}^{q-1} \Delta \mathrm{LnPREC_{t-i}} \\ & + \emptyset_3 \sum_{i=1}^{q-1} \Delta \mathrm{LnMEANTEM_{t-i}} + \emptyset_4 \sum_{i=1}^{q-1} \Delta \mathrm{LnCO_{2_{t-i}}} \\ & + \emptyset\, \mathrm{ECT_{t-1}} + \epsilon_t\end{aligned}$$

Where, $\emptyset_0$ is intercept, $\emptyset_i$ *signifies short-run coefficient,* ϵ_t *represent error term, and* ECT_{t-1} shows lagged residual from the model that determines the long-term relationship. The error correction method explains the speed at which the adjustment takes place to long-term equilibrium following a short-term shock.

The equation demonstrates that fish GDP is affected by its own past values, the current and lagged values of the regressors, and the lagged error term. The parameter $\emptyset$ is expected to be negative (between 0 and -1), reflecting the rate at which equilibrium is restored in absolute terms A positive $\emptyset$ would suggest that the model is out of equilibrium and unstable, showing no tendency to revert to the long-run equilibrium. The optimal lag lengths for each variable were determined using the Akaike Information Criterion (AIC).

4. Diagnostic and stability tests

This study employed a series of diagnostic tests to assess the model's reliability and validity (Pesaran *et al.* 2001). To identify serial correlation, we applied the Breusch-Godfrey Serial Correlation LM Test, which is effective for models with lagged dependent variables, thereby enhancing the robustness of the model (Breusch, 1978; Godfrey, 1978). Heteroscedasticity was evaluated using the Breusch-Pagan-Godfrey (BPG) test, which helps ensure that the variance of residuals is accurately estimated and that the model's estimates remain robust (Breusch & Pagan, 1979). The normality of residuals was tested with the Jarque-Bera (JB) test, which examines the skewness and kurtosis of the residuals to confirm whether they follow a normal distribution, thus validating the model's appropriateness (Jarque & Bera, 1987). To assess the stability of both long- and short-run coefficients, we performed the cumulative sum of recursive residuals (CUSUM) test (Brown *et al.* 1975).

5. Granger Causality test

This study also aims to examine the causal relationship between the variables under consideration. The Granger causality test, as introduced by Granger (1969), is used to assess causality between variables. According to this test, if past values of a variable '*y*' significantly enhance the prediction of future values of another variable '*x*', then '*y*' is said to Granger cause '*x*'. A key prerequisite for applying the Granger causality test is that the time series must be stationary. The same has been applied in the present study to determine the relationship among the variables of fish GDP and climate variables (temperature, precipitation and CO_2 emission).

RESULTS

Descriptive statistics

Table 1 presents the summary statistics for fish GDP, precipitation, temperature, and CO_2 emissions across India, Bangladesh, and Thailand. In India, the average fish GDP is 74,736.61, with a substantial standard deviation of 82,324.55,

Table 1: Descriptive statistics

	India				Bangladesh				Thailand			
	FGDP	PREC	TEMP	CO_2	FGDP	PREC	TEMP	CO_2	FGDP	PREC	TEMP	CO_2
Mean	74736.61	1203.87	24.50	1.13	29305.50	2264.27	25.69	0.28	100212.36	1663.11	26.85	3.10
Standard Error	14785.93	29.30	0.07	0.07	4390.05	55.05	0.06	0.03	3241.08	27.89	0.08	0.12
Median	35182.00	1182.68	24.50	0.98	18890.00	2225.55	25.68	0.23	106091.00	1665.58	26.95	3.32
Standard Deviation	82324.55	163.11	0.38	0.38	24442.78	306.50	0.34	0.15	18045.58	155.30	0.42	0.66
Kurtosis	0.71	2.39	-0.21	-1.38	0.65	-0.01	-0.35	-0.93	3.10	0.96	-0.39	-0.20
Skewness	1.37	1.09	-0.02	0.42	1.28	0.56	0.10	0.62	-1.77	-0.29	-0.15	-0.84
Range	283365.00	819.86	1.49	1.15	85815.50	1244.22	1.38	0.49	79946.54	743.63	1.74	2.26
Minimum	5161.00	911.52	23.77	0.65	6006.00	1782.18	24.98	0.10	43128.00	1293.58	25.85	1.59
Maximum	288526.00	1731.38	25.26	1.80	91821.50	3026.40	26.36	0.59	123074.54	2037.21	27.59	3.85
Sum	2316835.00	37319.82	759.46	35.14	908470.41	70192.31	796.27	8.71	3106583.24	51556.29	832.50	96.19
Count	31.00	31.00	31.00	31.00	31.00	31.00	31.00	31.00	31.00	31.00	31.00	31.00

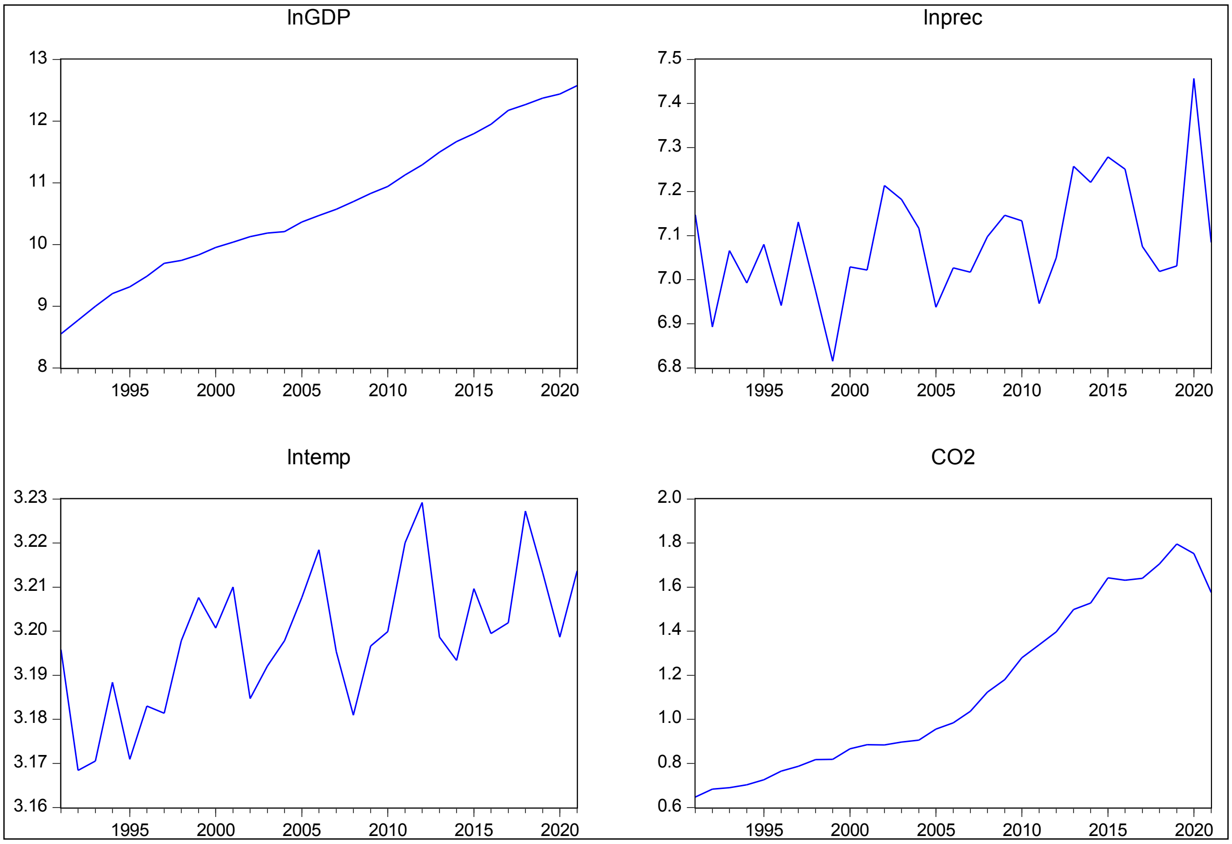

Fig. 1: Time plot for fish GDP and climate variables (precipitation, temperature and CO_2) for India

indicating considerable variability. The mean precipitation and temperature are 1,203.87 mm and 24.50°C, respectively, with standard deviations of 163.11 mm and 0.38°C. The average CO_2 emissions in India are 1.13 kg, with a standard deviation of 0.38 kg. Bangladesh displays a mean fish GDP of 29,305.50 and a standard deviation of 24,442.78, signifying moderate variability. The average precipitation in Bangladesh is 2,264.27 mm, and the mean temperature is 25.69°C. CO_2 emissions average 0.28 kg, with a standard deviation of 0.15 kg. In Thailand, the average fish GDP is 100,212.36, accompanied by a moderate standard deviation of 18,045.58. The country experiences an average precipitation of 1,663.11 mm and a mean temperature of 26.85°C. CO_2 emissions average 3.10 kg for the period from 1991 to 2021. However, the logarithmic value of fish GDP and climate variables (temperature, precipitation and CO_2 emission) for India, Bangladesh and Thailand are given in Fig. 1-3 respectively.

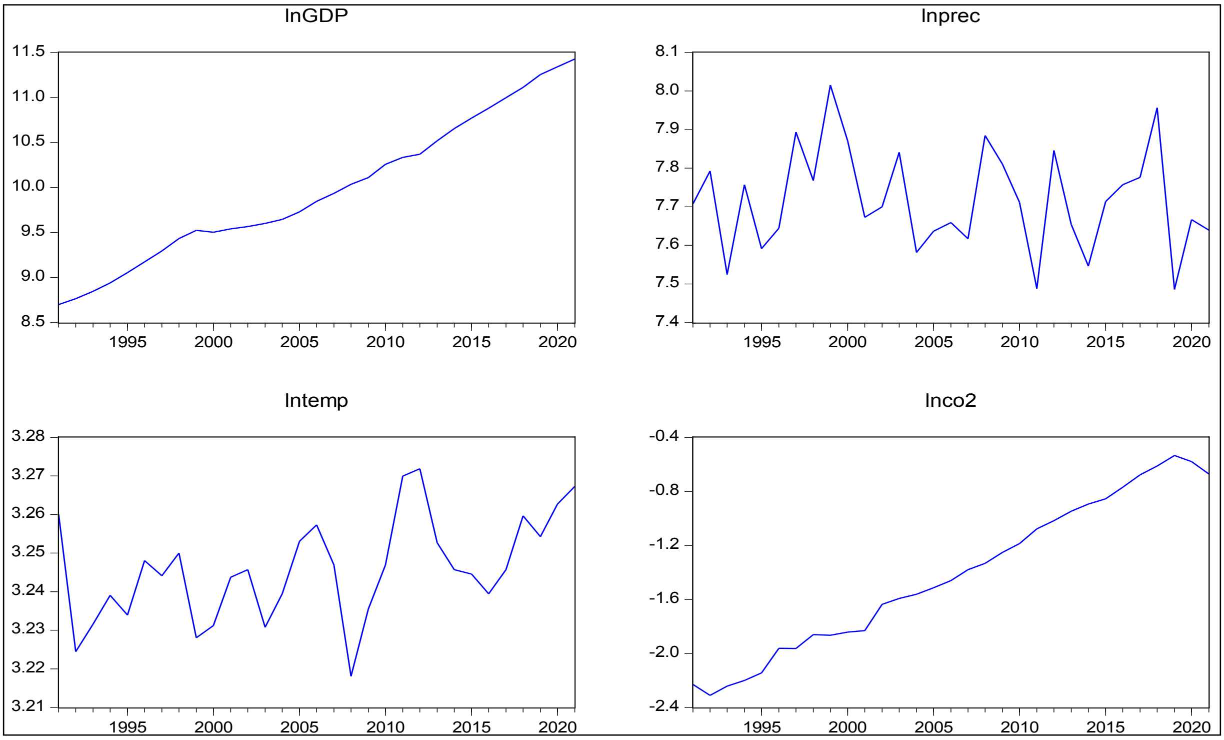

Fig. 2: Time plot for fish GDP and climate variables (precipitation, temperature and CO_2) for Bangladesh

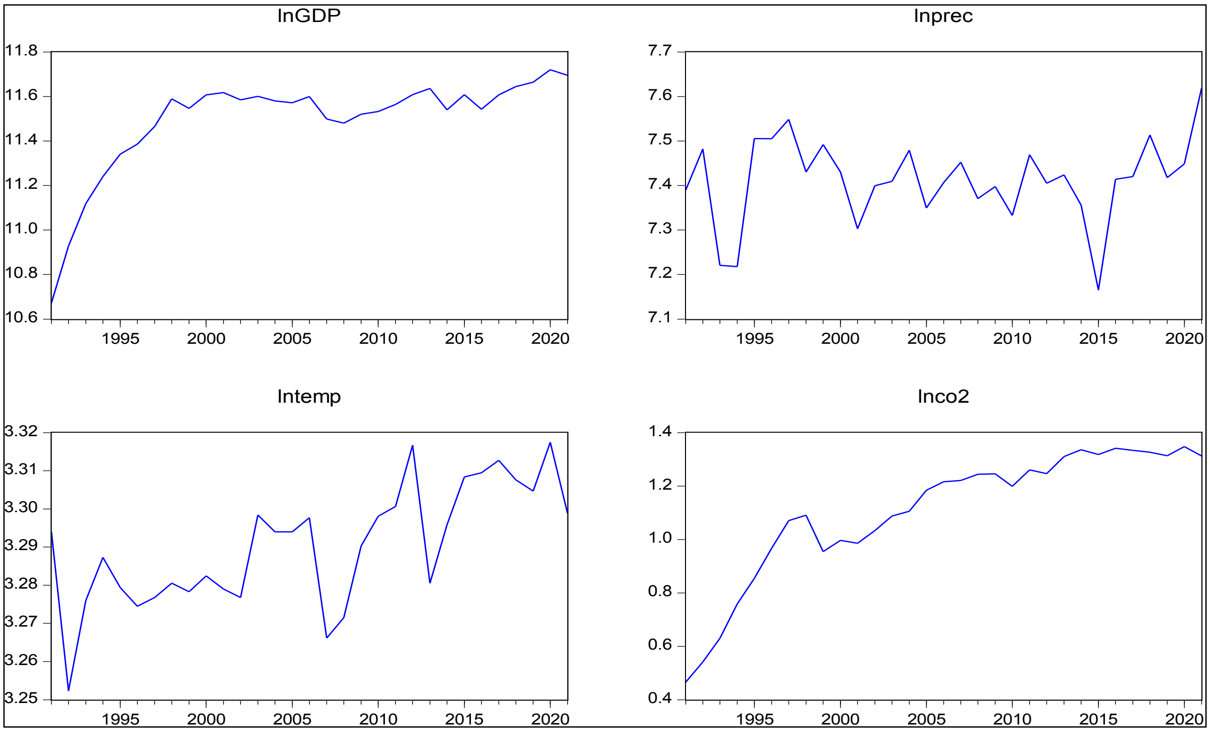

Fig. 3: Time plot for fish GDP and climate variables (precipitation, temperature and CO_2) for Thailand

Unit root test

The Augmented Dickey-Fuller (ADF) test results for India demonstrate that the test statistic values for fish GDP, precipitation, temperature, and CO_2 emissions are below the 5% critical value, and the p-values are less than 0.05 at I(0), leading to the rejection of the null hypothesis and confirming that the time series data is stationary (Table 2). In Bangladesh, both the Phillips-Perron (PP) test and ADF test reveal that the test statistic values for precipitation, temperature, and CO_2 emissions exhibit p-values below 0.05 at I(0) and I(1), indicating stationarity in the time series data, while the fish GDP shows moderate significance. For Thailand, both the PP and ADF tests yield significant p-values for fish GDP, precipitation, temperature, and CO_2 emissions at I(1), confirming the rejection of the null hypothesis and establishing that the time series data is stationary.

ARDL bound for cointegration

The ARDL bounds test was employed to ascertain the existence of a long-run relationship between climate variables and fish GDP in India, Bangladesh, and Thailand (Table 3). For India, the F-statistic value of 7.447 exceeds the upper critical value of 5.23, indicating a statistically significant long-run relationship ($p < 0.001$). In Bangladesh, the F-statistic of 32.386 surpasses the upper critical value of 4.66, robustly suggesting a statistically significant long-run relationship ($p < 0.001$). Similarly, Thailand's F-statistic also exceeds the critical value, demonstrating a statistically significant long-run relationship ($p < 0.001$). These findings collectively indicate a significant long-run relationship between fish GDP and climate variables (mean temperature, annual precipitation, and CO_2 emissions) for all three countries. The optimal ARDL model for each country was selected based on the

Table 2: Unit root tests results.

		PP				ADF			
		At level	**Prob.**	**1st Diff**	**Prob.**	**At level**	**Prob.**	**1st Diff**	**Prob.**
India	*LNGDP*	-2.089	0.531	-3.607	0.047	-5.061	0.002	-2.443	0.350
	LNPREC	-11.490	0.000	-20.471	0.000	-5.440	0.001	-7.651	0.000
	LNTEMP	-4.357	0.009	-18.709	0.000	-4.078	0.018	-4.683	0.005
	CO_2	-1.519	0.800	-1.347	0.855	-4.010	0.022	-0.862	0.944
Bangladesh	*LNGDP*	-1.057	0.920	-3.330	0.081	-1.395	0.841	-3.305	0.085
	LNPREC	-5.402	0.001	-13.417	0.000	-5.402	0.001	-8.968	0.000
	LNTEMP	-7.227	0.000	-11.033	0.000	-4.334	0.010	-4.663	0.005
	$LNCO_2$	-3.053	0.135	-5.373	0.001	-3.153	0.113	-5.301	0.001
Thailand	*LNGDP*	-6.284	0.000	-4.776	0.003	-6.210	0.000	-4.766	0.003
	LNPREC	-3.767	0.033	-15.859	0.000	-3.955	0.022	-4.374	0.010
	LNTEMP	-7.428	0.000	-17.171	0.000	-5.786	0.000	-4.720	0.005
	$LNCO_2$	-2.578	0.292	-4.566	0.006	-2.579	0.292	-9.736	0.000

Table 3: Results of the ARDL Bounds cointegration test

			Critical value	
	F-statistic Value	**Significance level**	**Lower bound**	**Upper bound**
India	7.447	5%	3.38	4.23
		1%	4.30	5.23
Bangladesh	32.386	5%	2.79	3.67
		1%	3.65	4.66
Thailand	12.344	5%	2.79	3.67
		1%	3.65	4.66

lowest AIC value: ARDL (1, 0, 0, 2) for India (Fig. 4), ARDL (1, 0, 0, 0) for Bangladesh (Fig. 5), and ARDL (1, 2, 2, 0) for Thailand (Fig. 6).

Long-run and short-run estimation

India: In the long run, the coefficients for precipitation and temperature in India were -0.291 and -1.551, respectively; however, these coefficients were not statistically significant ($p > 0.05$) (Table 4). In contrast, the coefficient for CO_2 emissions was 1.588 and was statistically significant ($p < 0.01$), indicating a robust long-term relationship with fish GDP. In the short run, the first difference of CO_2 emissions exhibited a positive coefficient of 0.155, while the lagged difference of CO_2 emissions showed a negative coefficient of -0.352, though neither was statistically significant ($p > 0.05$). The error correction term was significantly negative (-0.410;

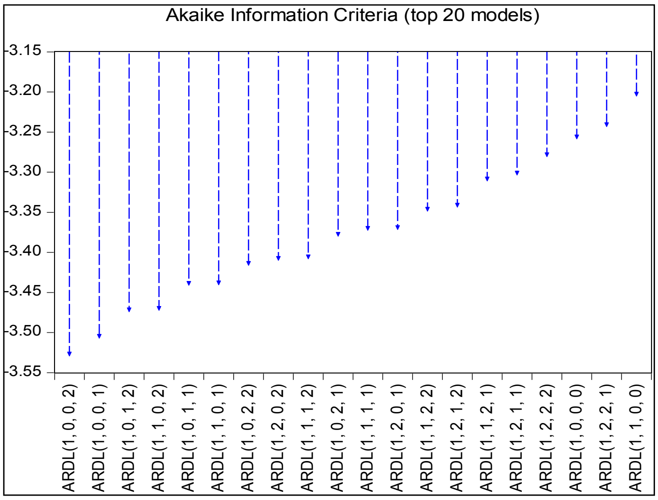

Fig. 4: AIC model selection for India

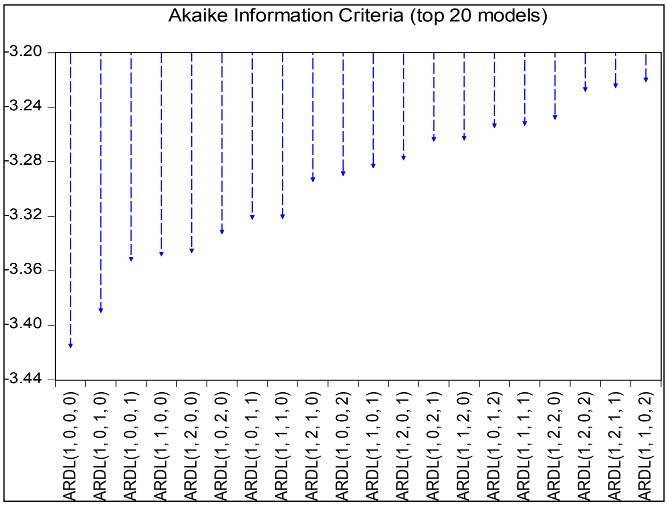

Fig. 5: AIC model selection for Bangladesh

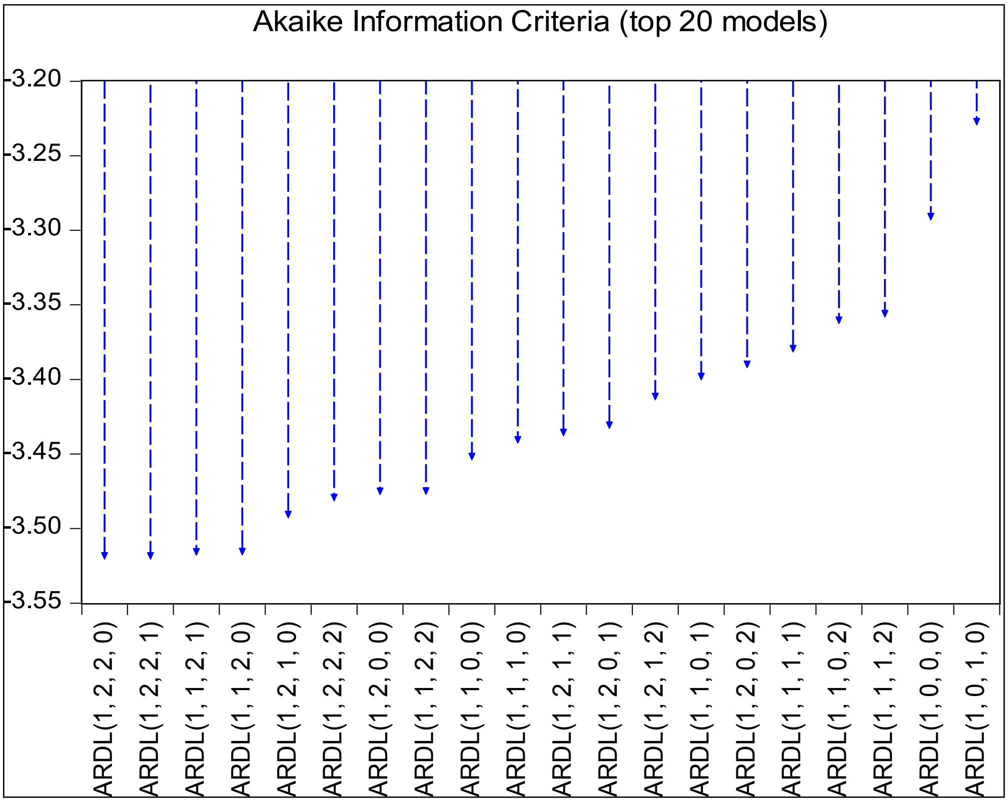

Fig. 6: AIC model selection for Thailand

Table 4: ARDL and ECM results for India

Long Run				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LNPREC	-0.291	0.218	-1.334	0.197
LNTEMP	-1.551	2.046	-0.758	0.457
CO_2	1.588	0.252	6.292	0.000
@TREND	0.062	0.011	5.681	0.000
Short run				
D(CO_2)	0.155	0.126	1.229	0.233
D(CO_2(-1))	-0.352	0.200	-1.760	0.093
ECM(-1)	-0.410	0.062	-6.658	0.000
R-squared	0.646			
Adjusted R-squared	0.603			
ARDL(1, 0, 0, 2)				

Table 5: ARDL and ECM results for Bangladesh

Long Run				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LNPREC	-0.581	1.007	-0.577	0.569
LNTEMP	-1.885	10.219	-0.184	0.855
$LNCO_2$	1.686	0.347	4.858	0.000
C	24.126	37.584	0.642	0.527
Short run				
ECM(-1)	-0.073	0.005	-13.706	0.000
R-squared	0.173			
Adjusted R-squared	0.173			
ARDL(1, 0, 0, 0)				

$p < 0.001$), demonstrating a strong adjustment mechanism towards long-run equilibrium. The model's R-squared and adjusted R-squared values were 0.646 and 0.603, respectively, suggesting a good fit. The ARDL model specification (1, 0, 0, 2) reflects the lag structure used in the analysis. These results underscore that CO_2 emissions exert a significant long-term impact on fish GDP in India, with a robust adjustment process to equilibrium in the short run

Bangladesh: In long run, the precipitation and temperature had negative coefficient value of -0.581 and -1.885, respectively, statistically not significant (P>0.005). The CO_2 coefficient (1.686) was found to be positive and statistically significant (P<0.05), suggesting a strong long term relationship with fish GDP (Table 5). In the case of short run, error correction term was found negative of -0.073 (P<0.001), indicating a significant and relatively moderate speed of adjustment towards the long-run equilibrium. The R-squared value (0.173) and adjusted R-squared (0.173) showed relatively modest fit of the data points. The ARDL model specification was (1, 0, 0, 0), reflecting the chosen lag structure. Results highlight the significant long-term impact of CO_2 levels on fish GDP in Bangladesh, with a clear mechanism for returning to equilibrium in the short run.

Thailand: A significant positive confident of 1.021 (P<0.01) was observed for the precipitation in long run. Contrarily, the coefficients for temperature and CO_2 coefficients at 5.352 and 0.047, respectively and did not differ significantly (P>0.005) (Table 6). In short run, the first difference of precipitation and its lagged term were not significant (P>0.05), with coefficients of 0.019 and -0.104, respectively. Conversely, significant first difference of temperature and its lagged term coefficients of 1.971 and 1.036,

Table 6: ARDL and ECM results for Thailand

Long Run				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LNPREC	1.021	0.348	2.937	0.009
LNTEMP	5.352	3.557	1.504	0.149
$LNCO_2$	0.047	0.276	0.171	0.866
@TREND	-0.002	0.008	-0.302	0.766
Short run				
C	-5.270	0.692	-7.619	0.000
D(LNPREC)	0.019	0.065	0.299	0.768
D(LNPREC(-1))	-0.104	0.063	-1.632	0.119
D(LNTEMP)	1.971	0.527	3.740	0.001
D(LNTEMP(-1))	1.036	0.492	2.105	0.049
CointEq (-1)*	-0.387	0.051	-7.652	0.000
R-squared	0.782692			
Adjusted R-squared	0.735451			
ARDL(1, 2, 2, 0)				

Table 7: Granger Causality

	India		Bangladesh		Thailand	
Null Hypothesis:	**F-Statistic**	**Prob.**	**F-Statistic**	**Prob.**	**F-Statistic**	**Prob.**
LNPREC does not Granger Cause LNFGDP	0.326	0.725	0.936	0.406	1.588	0.225
LNFGDP does not Granger Cause LNPREC	2.960	0.071	0.143	0.867	4.835	0.017
LNTEMP does not Granger Cause LNFGDP	0.101	0.904	0.631	0.541	1.442	0.256
LNFGDP does not Granger Cause LNTEMP	3.867	**0.035**	2.901	0.074	0.701	0.506
CO_2 does not Granger Cause LNFGDP	5.444	0.011	1.928	0.167	0.177	0.839
LNFGDP does not Granger Cause CO_2	3.004	0.069	0.516	0.604	1.647	0.214
LNTEMP does not Granger Cause LNPREC	3.024	0.067	0.210	0.812	2.426	0.110
LNPREC does not Granger Cause LNTEMP	1.889	0.173	0.388	0.682	0.267	0.768
CO_2 does not Granger Cause LNPREC	4.097	0.030	3.657	0.041	0.766	0.476
LNPREC does not Granger Cause CO_2	1.938	0.166	0.059	0.943	0.779	0.470
CO_2 does not Granger Cause LNTEMP	2.780	0.082	5.761	0.009	1.053	0.364
LNTEMP does not Granger Cause CO_2	0.825	0.450	0.202	0.818	1.370	0.273

respectively, indicating a strong short-term impact of temperature changes. The error correction term of -0.387 (P<0.001) was observed, suggesting significant and relatively rapid adjustment back to long-run equilibrium. The model's R-squared and adjusted R-squared of 0.783, and 0.735 was noticed respectively, demonstrating a good fit of the model. The ARDL model specification was (1, 2, 2, 0), reflecting the lag structure used in the analysis. The precipitation and temperature significantly influenced the fish GDP in Thailand in long run and in short run respectively, with a robust mechanism for adjustment to equilibrium.

Granger causality tests

The CO_2 emissions significantly (F = 5.444; P < 0.05) influenced the GDP and precipitation (4.097 P = 0.030) but the GDP influences both precipitation (F = 2.960; P = 0.071) and temperature (F = 3.867; P = 0.035) with moderate significant for India (Table 7). Additionally, CO_2 levels impact precipitation with an F-statistic of 4.097 (p = 0.030). Similarly, in Bangladesh, CO_2 emissions influenced the precipitation (F = 3.657; P = 0.041) and temperature (F = 5.761 P = 0.009). The Granger causality analysis reveals several unidirectional relationships between environmental and economic variables in India, Bangladesh, and Thailand. In India, CO_2 emissions significantly influence GDP (LNGDP), with an F-statistic of 5.444 (p = 0.011), and GDP influences both precipitation (LNPREC) with an F-statistic of 2.960 (p = 0.071) and temperature (LNTEMP) with an F-statistic of 3.867 (p = 0.035). Additionally, CO_2 levels impact precipitation with an F-statistic of 4.097 (p = 0.030). The fish GDP in Thailand impacts precipitation, as indicated by an F-statistic of 4.835 (p = 0.017). No bidirectional relationships were identified, but near-significant bidirectional relationships include the influence of GDP on CO_2 in India and the reciprocal influence between GDP and temperature in Bangladesh,

Diagnostic and structural stability test

The Breusch-Godfrey test indicates the absence of serial correlation for India (F = 2.648; P = 0.097), Bangladesh (F = 2.905; P = 0.075), and Thailand (F = 2.845; P = 0.086), as the P values exceed the 0.05 threshold. Fig. 7 further demonstrates that there is no evidence of heteroscedasticity, and the residuals are normally distributed for India, Bangladesh, and Thailand, as suggested by the P values, all of which are greater than 0.05. The CUSUM (Fig. 8 for India, Fig. 9 for Bangladesh and Fig 10 for Thailand) and CUSUM square (Fig. 11 for India, Fig. 12 for Bangladesh and Fig. 13 for Thailand) tests were administered to verify the parameter consistency of the equation underpinning the ARDL model.

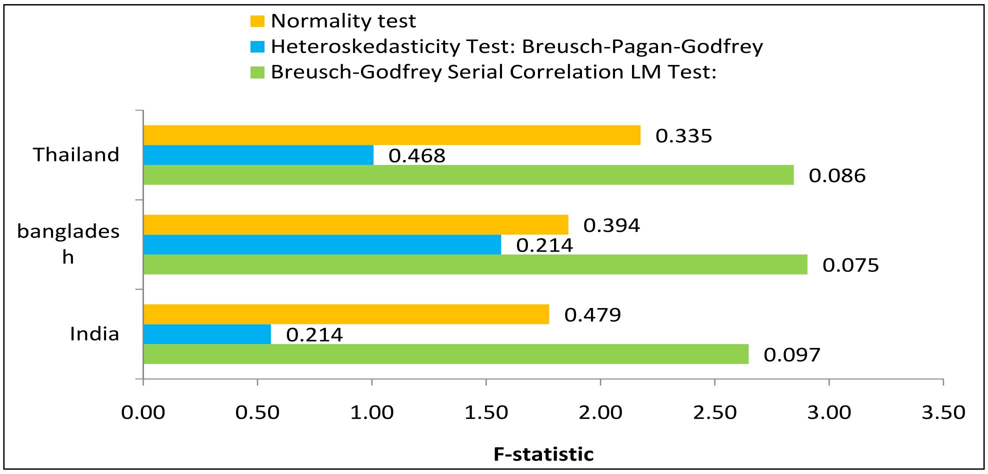

Fig.7: The clustered bar shows the F statistic of different ARDL model diagnostic tests and values presented in the data label is the p value of the respective test. All there test were not statistically significant because the observed p value greater than 0.05

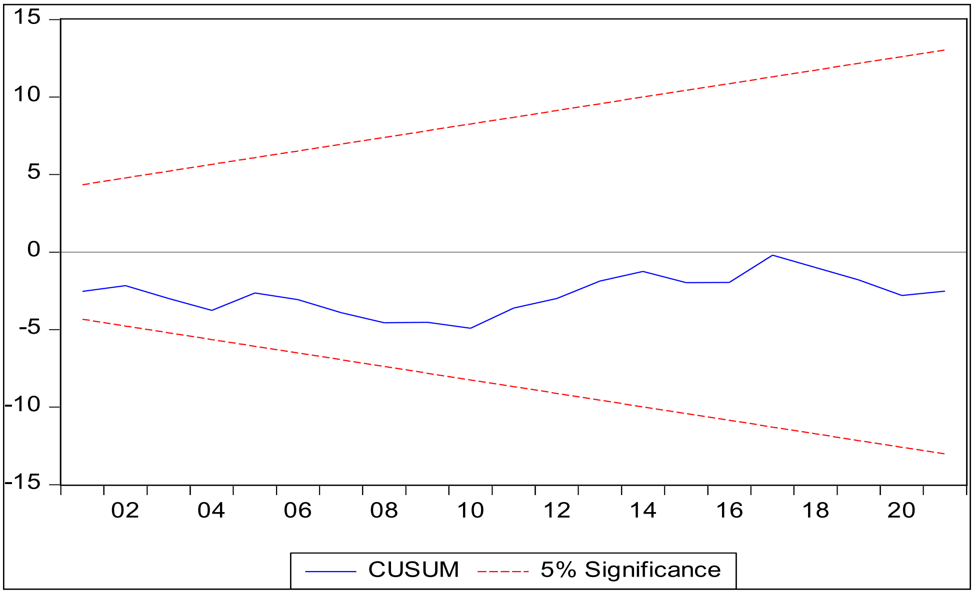

Fig. 8: Plot of CUSUM test for ARDL model stability for India

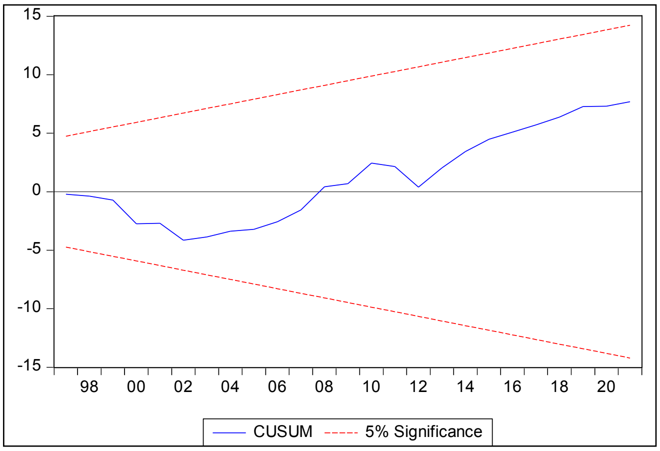

Fig. 9: Plot of CUSUM test for ARDL model stability for Bangladesh

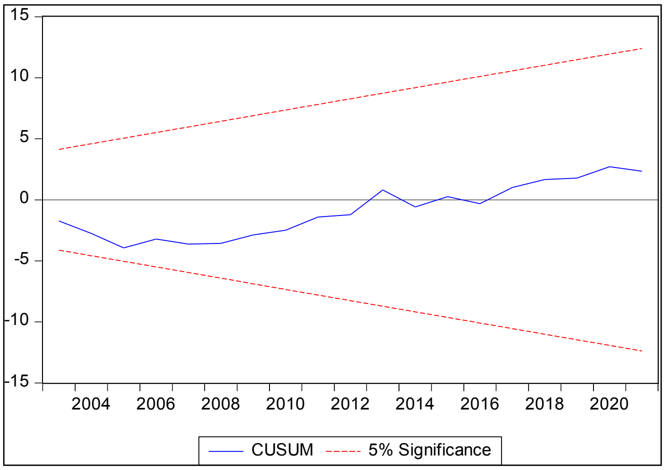

Fig. 10: Plot of CUSUM test for ARDL model stability for Thailand

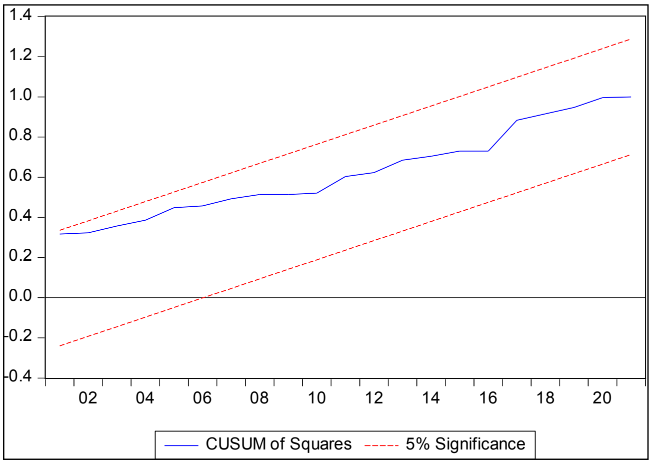

Fig. 11: Plot of CUSUM of square test for ARDL model stability for India

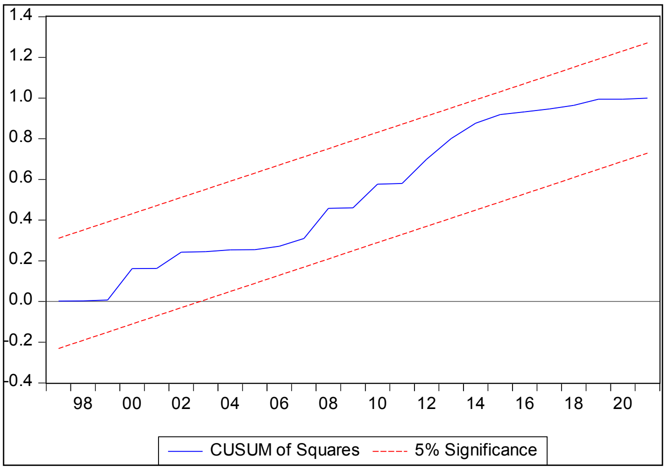

Fig. 12: Plot of CUSUM of square test for ARDL model stability for Bangladesh

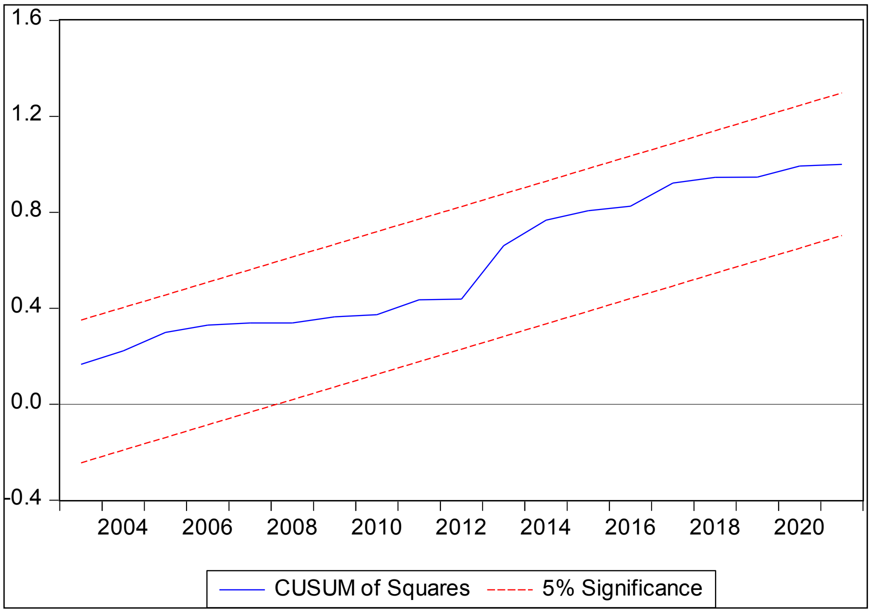

Fig. 13: Plot of CUSUM of square test for ARDL model stability for Thailand

The results for fish GDP for India, Bangladesh and Thailand in both tests consistently fell within the 5% significance threshold over time, thereby affirming the robustness and stability of the ARDL model.

DISCUSSION

Climate change significantly affects the fisheries sector, with potential impact on both local and global economies by reducing the productivity, altering species distribution, and decreasing potential yields. Many studies have examined the effect of climate change on fisheries globally, the present sturdy discuss the economic impact of climate change on fisheries reference to three highly populated Asian Countries.

Temperature

Temperature plays a crucial role in shaping aquatic habitats, directly influencing fish production and the species that thrive in them. India and Bangladesh experience more significant temperature variations compared to Thailand, resulting in a negative impact on fish GDP for India and Bangladesh, whereas Thailand shows a positive impact. The average temperature of 26.85°C in Thailand has been favorable for fish production, enhancing the metabolism and growth rates in species like shrimp (421,052 MT), tilapia (206,050 MT), and catfish (112,525 MT), which together contribute to about three-fourths of the total aquaculture production. The hardy nature of tilapia and catfish, along with their ability to tolerate a wide range of water parameters, supports increased production and income generation under warmer conditions. In Thailand, a 1% increase in temperature is projected to boost fish GDP by 5.35% in the long run. Similarly, temperature has also shown a positive correlation with the catch of Mullet, Sardinella, and Anchovies in Pakistan (Ayub, 2010), and increased pelagic fish landings in Malaysia (Ho, Maryam, Jafar-Sidik, & Aung, 2013). However, the rising temperature has adversely impacted the fisheries economics of India and Bangladesh. For instance, a 1% increase in temperature could reduce fish GDP by 1.55% in India and 1.88% in Bangladesh, though not significantly. Indian major carps, such as Rohu Catla, and certain shrimp species are more vulnerable to heat stress, which could lead to reduced fish GDP in the long term, especially since most of the major production comes from semi-intensive farming, which is susceptible to temperature fluctuations.

In Bangladesh, species like pangasius and tilapia, mainly reared in semi-intensive systems, experience a decrease in growth rates due to lower average temperatures, which slows their metabolism. Notably, Bangladesh's shrimp production has recently declined by around 6-8% per year. An increase in temperature could significantly reduce marine fish production by 5.13% in Bangladesh (Begum *et al.* 2022), aligning with current observations. Moreover, higher temperatures create favorable conditions for pathogens, leading to more frequent disease outbreaks in aquaculture systems, which increases costs for disease management and results in production losses. In marine capture fisheries, rising temperatures affect species distribution, as seen with oil sardine and Indian mackerel catches in Gujarat, India, which are traditionally native to Kerala. Additionally, Indian mackerel is now being found at greater depths, with the percentage of the catch from bottom trawling increasing from 2% to 15% (CMFRI, 2023). Temperature also significantly impacts fish reproduction, with a major shift in spawning months from warmer (April-September) to cooler months (October-March) observed in western India's Arabian Sea (Vivekanandan, 2010). These shifts in fish populations and changes in productivity due to temperature fluctuations lead to economic losses for local fishing communities. Reduced fish stocks and migration, increase the operating costs of fishing, impacting seafood availability and the supply chain. Overall, these studies suggest that rising temperatures will generally have a negative economic impact on fisheries, with significant reductions in fish yields, revenues, and productivity, particularly in tropical and low-latitude regions.

Precipitation

The relationship between precipitation and fisheries is intricate, involving both direct and indirect impacts on fish populations, their habitats, and the communities that rely on them. Climate change is anticipated to increase rainfall variability, leading to more extreme weather events. This variability can disrupt fish habitats and affect fish productivity, posing significant challenges for fisheries management (Mendenhall *et al.* 2020; Muringai, Mafongoya, & Lottering, 2021). Shifts in precipitation patterns due to climate change can alter hydrological regimes, impacting fish habitats and potentially leading to changes in fish community structures (Brander, 2010; Ficke *et al.* 2007).

In India and Bangladesh, precipitation has shown a negative long-term relationship with fish GDP, indicating that a 1% increase in precipitation could reduce fish GDP by 0.295% and 0.58%, respectively. This contrasts with findings that a 1% increase in average precipitation can enhance marine fish production in Bangladesh. However, the larger variation in precipitation observed in Bangladesh, due to geographical disparities within the country, has led to a negative relationship (Hossain *et al.* 2014). Decreased precipitation and water levels can result in reduced fish yields and lower catch per unit effort (CPUE), as less favorable conditions emerge for fish reproduction and growth (Ng'onga, Kalaba, Mwitwa, & Nyimbiri, 2019; Patrick, 2016). Climate change projections indicating reduced precipitation and water levels are associated with significant declines in fish productivity and increased challenges for fisheries management (Muringai *et al.* 2021; Ng'onga *et al.* 2019; Patrick, 2016). In contrast, in Thailand, a 1% increase in precipitation could significantly boost fish GDP by 1.02%. Increased precipitation can enhance fish recruitment and growth by improving freshwater inflows into estuaries, positively affecting fish populations and commercial catches (Patrick, 2016; Stewart, Hughes, Stanley, & Fowler, 2020). Precipitation within estuarine catchments is positively related to the year-class strength of certain fish species, underscoring the importance of freshwater input for recruitment success (Stewart *et al.* 2020).

CO_2 emissions

CO_2 emissions play a crucial role in shaping fisheries' GDP, with both direct and indirect effects on the sector. Increased CO_2 emissions contribute to rising temperatures and ocean acidification, which in turn weaken marine ecosystems by disrupting food chains, reducing biodiversity, and diminishing productivity. These environmental changes lead to higher production costs per kilogram of fish and reduced fish catches, further exacerbating poverty in vulnerable coastal communities by threatening their livelihoods and local economies.

Interestingly, a 1% increase in CO_2 emissions is associated with a significant rise in fish GDP: 1.588% for India and 1.686% for Bangladesh, whereas the effect in Thailand is marginal at 0.047%. However, this relationship is not straightforward. From 1991 to 2021, CO_2 emissions per capita surged from 0.65 to 1.58 metric tons in India, from 0.10 to 0.51 metric tons in Bangladesh, and from 1.59 to 3.71 metric tons in Thailand. While no direct studies have examined CO_2 emissions' impact on fisheries, analogous research in agriculture provides some insights. For example, a study in South Korea found that increased CO_2 emissions could boost rice production by up to 0.15% (Nasrullah *et al.* 2021). Similarly, elevated CO_2 levels are projected to enhance rice production through accelerated photosynthesis, potentially increasing yields by 20% (Lv, Huang, Sun, Yu, & Zhu, 2020; J. Wang *et al.* 2015). In Bangladesh, the second lag of carbon emissions has been shown to positively impact agricultural production (Ghosh, Eyasmin, & Adeleye, 2023).

In India, over 80% of marine fish are caught using mechanized fishing fleets, which are significant sources of CO_2 emissions due to their high fuel consumption. For instance, trawlers in Palk Bay, India, emit the most CO_2 (1.823 tonnes of CO_2 per tonne of fish), followed by gillnetters (0.684 tonnes) and longliners (0.520 tonnes) (Infantina *et al.* 2023). Marine fisheries, particularly trawling operations, are major contributors to CO_2 emissions. For example, China's marine fisheries exhibited a rising and then declining trend in emissions from 2005 to 2020 (Ng'onga *et al.* 2019). Globally, marine fisheries consumed 40 billion liters of fuel in 2011, generating 179 million tonnes of CO_2-equivalent greenhouse gases, accounting for 4% of global food production emissions. Emissions grew by 28% between 1990 and 2011, driven by fuel-intensive crustacean fisheries (Stewart *et al.* 2020).

Industrial fishing has seen a significant increase in CO_2 emissions from 1950 to 2016, with industrial emissions intensity surpassing that of small-scale fisheries (Mendenhall *et al.* 2020). The development of the marine fishery economy and trade positively influences CO_2 emissions, while technological advancements and income growth among fishermen are associated with lower emissions (Ng'onga *et al.* 2019). Moreover, fishing subsidies, particularly those that enhance capacity, are linked to higher CO_2 emissions, whereas beneficial subsidies have the opposite effect (Gamito, Teixeira, Costa, & Cabral, 2015). In Iceland, overall catches and fish stock abundance are critical factors determining emissions, with larger catches and greater abundance leading to lower emissions per unit of output (Patrick, 2016). Under high CO_2 emission scenarios, global fisheries revenues could drop by 35% more than the projected decrease in catches by the 2050s, with developing countries being the hardest hit (Muringai *et al.* 2021). This highlights the urgent need for sustainable management practices to mitigate the impacts of CO_2 emissions on fisheries and ensure the long-term viability of this vital sector.

CONCLUSION

The study examined the economic impact of climate change on fisheries for three Asian countries namely India, Bangladesh and Thailand using the data from 1991 to 2020. In this study, fish GDP is endogenous variable while mean temperature, precipitation and CO_2 emission are exogenous variable. The ADF and PP test were applied to check stationarity of underlying variables. The ARDL found test employed to reconnoitre the long run cointegration connection among the studied variables. A series of diagnostic tests such as Breusch-Godfrey Serial Correlation LM, Breusch-Pagan-Godfrey and Jarque-Bera were employed to assess the model's reliability and the stability of model was assessed through CUSUM test. The ARDL model's findings of India underscore the significant long-term influence of CO_2 on fish GDP. This highlights the importance of emissions reduction policies and sustainability efforts. While the fisheries sector shows short-term resilience to CO_2 fluctuations, policymakers should avoid complacency. Leveraging insights from this model, they can develop both immediate and long-term strategies to maintain sector health and productivity in the face of environmental changes.

The ARDL model for Bangladesh indicates that CO_2 has a significant positive long-term impact on the dependent variable. However, temperature and precipitation do not exhibit clear long-term effects within this model. The strong short-run adjustment to equilibrium suggests resilience to shocks. Nevertheless, the weak overall model fit raises concerns about its explanatory power. Policymakers should consider these findings as part of a broader analysis, emphasizing improved accuracy and a wider range of variables for effective policy development. The ARDL model for Thailand underscores the crucial impact of precipitation on long-term outcomes, while also emphasizing the need to address short-term temperature fluctuations. The sector's resilience, signalled by a robust adjustment mechanism, is positive. However, policymakers must avoid prioritizing short-term gains over long-term sustainability. Comprehensive water management strategies should consider both immediate and delayed effects to ensure the sector's continued health and productivity amid changing environmental conditions.

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