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Original Research Article

AN ANALYSIS OF PAKISTAN'S CLIMATIC FACTORS AFFECTING MARINE FISH PRODUCTION

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Abstract *A lot of study has been done on how climate change impacts farming. But there aren't many studies in Pakistan that look at how climate change changes the number of fish that can be caught in the real world. This study's main goal is to look at the effects of climate change on fish in the sea around Pakistan from 1990 to 2020. It was given to us by the World Development Indicators. This study used the autoregressive distributed lag (ARDL) model to examine how the link between CO2 emissions, weather, rainfall, and sea fish production changes over time. Using the autoregressive distributed lag (ARDL) method to cointegration, a strong link was found between rains and the number of fish caught. To determine if rainfall has a statistically significant effect on sea fish production in the short term, we used the coefficient for rainfall (β = 5738.02) and found that it does. In the long run, it makes a difference at the 1% level of importance. Both changes in temperature and CO2 pollution hurt fish production a lot, according to the study. This is true in the short as well as in the long term. Researchers found that it would be helpful for lawmakers to make national policies that are better for adapting to climate change and supporting long-term control of marine fishing. Pakistan's fishing business should do a lot of research and development to find marine fish species that can live in places with a lot of CO2 and high temperatures*.

Keywords: *Marine Fish Production; Rainfall; Temperature; CO_2; ARDL model*

Introduction

Water is an important resource for the sustenance of all living organisms. A limited proportion of the earth's freshwater resources is accessible to humans, primarily due to unplanned urbanization, chemicals, and rapid industrialization. These factors contribute to significant pollution levels in aquatic organisms and the degradation of water quality, particularly affecting aquatic fauna, such as fish (Danylchuk et al., 2023). Water quality and availability directly impact the overall quality of life for any given population(Shah et al., 2019). The increase in population and industrial activities have significantly impacted the environment, particularly those concerning surface waters (Hanifa et al., 2022). Water quality variables encompass water characteristics that impact aquaculture species' growth, reproduction, survival, and production.

Fishing plays a significant role as a primary source of sustenance and economic growth for the nation while also serving as a means of livelihood for the coastal inhabitants of Pakistan. Fish is a cost-effective and crucial source of animal protein for the human population. The procurement of fish and fishery products can be traced back to two primary sources: wild catch from marine and freshwater environments and aquaculture practices (Lam et al., 2012) The exponential growth of the global human population has resulted in a corresponding surge in the demand for food resources. The fisheries sector is widely recognized as a crucial source of support for coastal societies and communities residing near inland water bodies, making it second only to agriculture in terms of its significance (Klein, 2011). As a result, the livelihoods of local inhabitants are heavily reliant on the fisheries sector, either directly or indirectly. The coastal, river, dam, lake, and reservoir areas are home to a significant population engaged in diverse occupations. Fish is considered one of the region's most extensively traded food commodities (Begum et al., 2022). The fish trade is crucial in facilitating economic growth through various means. Firstly, it serves as a significant source of cash revenue, which can be utilized to address international debt obligations. Additionally, the revenue generated from fish trade contributes to the financial resources required for the functioning of national governments. Moreover, importing fish for domestic consumption enhances national food security and promotes the diversification of diets within the country (Barange et al., 2018). Nevertheless, the advantages derived from this sector are frequently disregarded or downplayed in national economic planning. The significance of fisheries is frequently underestimated; however, the consequences of climate change on these industries and the communities residing along coastlines and riverbanks are challenging to disregard (Sumaila et al., 2011).

Fisheries and aquaculture rely on various aquatic ecosystems, including freshwater, coastal, and marine environments (Bellwood et al., 2003). The impact of climate change is already being observed in these ecosystems, as they exhibit a high degree of sensitivity to variations in temperature, salinity, and acidity. It is anticipated that livelihoods reliant on fisheries and aquaculture will be among (P. D. S. M. Shahzad, 2023; S. M. Shahzad, 2020, 2022, 2023) the initial sectors to experience substantial consequences due to climate change (Ali et al., 2009). The impact of climate change on natural resources has far-reaching implications for various aspects of society (Chandio, Jiang, et al., 2020; Thiault et al., 2019). The phenomenon of climate change presents a formidable peril to the production of marine fish (Pauly & Cheung, 2018). This environmental challenge hampers marine fish's developmental and reproductive capacities, diminishing their long-term viability prospects (Clarke et al., 2021). Climate change has led to the warming of ocean water, which has had direct and indirect implications for fish stocks. Various researchers have extensively studied and documented this relationship (Gamito et al., 2013; Sumaila et al., 2011). "The phenomenon of climate change has been identified as a significant factor in the decline of fish production (Lam et al., 2016), the reduction in fish species diversity (Brierley & Kingsford, 2009), and the decrease in fish size" (Begum, Masud, Alam, Mokhtar, & Amir, 2022).

Pakistan is undergoing a notable shift in its climatic conditions, characterized by a surge in temperatures, heightened fluctuations in precipitation patterns, escalating sea levels, and a surge in extreme weather phenomena (Md. R. Rahman & Lateh, 2017). According to the Global Climate Risk Index, Pakistan is seventh among the ten nations that have experienced the most significant negative impacts from extreme weather events and climate change. Furthermore, it is imperative to acknowledge that Pakistan is confronted with an unprecedented peril of economic depression within the forthcoming three decades, primarily attributable to the exacerbating global climate conditions (Caesar et al., 2015). The present condition may initially manifest within the nation as a deficiency in marine seafood productivity, consequently leading to food insecurity (Shahzadi et al., 2020). According to the Department of Fisheries, the fishing industry plays a crucial role in the nation by serving as the principal provider of "animal protein, generating employment opportunities, ensuring food and nutritional security, conserving aquatic biodiversity, and fostering socioeconomic development" (Begum, Masud, Alam, Mokhtar, & Amir, 2022). The marine fisheries sector exhibits relative underdevelopment when juxtaposed with other economic sectors, as highlighted by Hossain et al., (2020). Furthermore, it is worth noting that the accessibility and consumption of fish play a crucial role in population's overall well-being and food security maintenance (Toufique & Belton, 2014).

The ARDL model will be used in this study to look at the changing relationship between CO2 emissions, weather, rainfall, and marine fish production in Pakistan. Many studies examining how climate change affects marine fish production have used different correlation and regression models (Ho et al., 2016; Shah et al., 2019). However, using the ARDL bounds testing technique of cointegration, this study will give us a full picture of how climate conditions affect marine fish output. This study uses several econometric tools to test the ARDL method's reliability further. Pakistan's marine fish production was the topic of this study. However, the same method could be used to examine how climate change affects aquaculture and freshwater fish. The study's findings will help us understand how climate change is changing marine fisheries and the creation of plans to deal with these changes. Sustainable management of Pakistan's marine fisheries is a big problem, and this study could help with the fight against climate change. Finally, the study could help with better adaptable conservation and long-term control of marine fisheries in response to climate change.

Need for the project There have been several empirical investigations on how climate affects marine fish output from different parts of the world. Cheung et al., (2009) examined the anticipated trajectory of global fisheries production, and their findings converge on a concerning projection of a significant decline. These studies highlight the potential consequences the world's fisheries sector may face soon. In the last two centuries, high green quantities of greenhouse gases have become a part of the global atmosphere, including CO_2, CH_4, and N_2O.

Munday et al., (2013) have helped create a general picture of the adverse effect of CO2 on different biological processes. Frommel et al., (2014) assessed the possible effect of increasing carbon dioxide concentrations in the ocean on marine fish species. In other words, the researchers suspected that the developmental procedures for these organisms would be affected negatively by increased CO2 concentrations in the ocean water. Clarke et al. (2021) investigated the consequences of raised carbon dioxide concentration on fish populations. This research has revealed the effect of elevated CO2 environments on the growth of marine fish.

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Additionally, higher CO2 affects the auditory sensitivity of marine fishes. Ocean acidification and associated increases in carbon dioxide concentration in oceans may also contribute to acidosis, which poses a grave risk to the growth and development of marine fish in their very first stages of life (Lloret et al., 2004). Marine species moving too poleward or too high altitudes due to warm, acidic, and low-oxygen seawater have been widely reported in regions such as the North Sea and the Bering Sea. This is a pattern of migration that could either be a permanent or temporary response to the changing environmental conditions in these marine ecosystems. Marine species have been noted to migrate towards warm, acidic, and low-oxygen seawater presence. Alexander et al. (2006) noted a recent change in ocean water extremes. The effects of temperature on fisheries have been much concern and research. Specifically, the influence of air temperature on pelagic fish landings.

Fernandes et al. (2016) devised methods for forecasting the long-term productive potential of Bangladeshi maritime fisheries under various climatic scenarios. They discovered that climate change effects (as a result of elevated emissions) are projected to reduce Bangladesh's EEZ's prospective fish yield. Fernandes et al. (2020) delved into examining aspects of climate change and the possible impacts on four important pelagic commercial species of the NEA. The following literature review investigates the anticipated changes in potential capture in the NEA's northern and southern regions. As the analysis goes, the capture potential will increase in the northern part while decreasing in the southern part. These divergent trends can be primarily attributed to variations in temperature and primary production. Shahzadi et al. (2020) aimed to investigate the potential impact of temperature on the productivity of estuarine fish and crustaceans in Pakistan. The authors concluded that no statistically significant correlation was observed between fish species and the overall temperature. This finding suggests that temperature may not be a significant factor influencing the productivity of estuarine fish and crustaceans in the studied region.

Warm-blooded and cold-blooded fish have been impacted by the shift in ocean temperatures in three sections of the Portuguese coast's fisheries (Leitao et al., 2018). Cheung et al., (2009) used a dynamic bioclimate envelope model to calculate the maximum exploitation of species over various climates. They predict that animals will move away from these areas when ocean temperatures increase, reducing capture potential in several coastal locales, especially in the tropics and along the southern boundaries of semi-enclosed seas. Raising temperatures alters the pattern and distribution of precipitation by increasing evapotranspiration and air moisture (Hossain et al., 2018). Storms, cyclones, tornadoes, and heavy precipitation are some severe weather phenomena linked to increasing global temperatures. Moreton Bay and Cairns, Australia were studied (1988-2004) by Meynecke et al. (2006), and they found that yearly rainfall was positively correlated with the number of fish caught. Precipitation swings are very closely linked to seasonality.

According to Ho et al. (2016), the catch of winter and/or spring species in Taiwan's coastal-capture fisheries went down every year from 1963 to 2010, while the catch of summer and/or fall species went up. However, a look at limited time series data on weather and fish arrivals for three different places in Sabah, Malaysia According to Jafar-Sidik et al. (2010), big changes in the number of fish caught were caused by weather conditions. They also found a strong link between heavy rain and more fish being caught. In marine and coastal environments, phytoplankton growth depends on the supply of nutrients, radiation, and stability. Light is needed for photosynthesis, which is done by micro (phytoplankton) and macro (seaweed) algae, green plants, and photosynthetic microbes (Bakun & Weeks, 2004). Rising phytoplankton levels in the Ganga-Brahmaputra-Meghna basin have been linked to more Hilsa being caught in the northern Bay of Bengal (BoB), which is off the coast of Bangladesh (Hossain et al., 2020). Mixing surface and groundwater by the wind may cause the coastal zone to rise and saltwater fisheries to produce more fish (Pitchaikani & Lipton, 2012).

A machine learning method was used along with the highest and lowest air temperatures, SST, rainfall, the length and frequency of rain, and humidity to predict fish production in Malaysia's five most popular states (Rahman et al., 2021). Even though they couldn't find a statistically significant link between climate and geography, they did find that climate factors could affect fish output when the feature significance score was considered. A significant quantile regression study (Zink et al., 2018) suggests that water temperature, salinity, depth, and the presence of submerged aquatic plants may limit the number of pink prawns.

Materials and Techniques for Research

This investigation utilized annual time series data from 1990 to 2020. The World Development Indicator (WDI) is the source of time series data shown in table 1. This data includes fish productivity, CO2 levels, temperatures, and rainfall. The linear function displayed below may be used to explain the link between the production of marine fish and the various meteorological factors.

$$\boldsymbol{FP_t = \beta_o + \beta_1 CO2_t\, t + \beta_2\, TMP_t + \beta_3\, RF_t + \varepsilon_t} \qquad (\mathbf{1})$$

Table 1: Sources and description of variables

Indicators	Code	Unit	Data Source
Fish Production	FP.	Tons	WDI
Carbon Dioxide	CO_2	Metric tons per capita	WDI
Temperature (C°)	TMP	Celsius (C°)	WDI
Rainfall (mm)	RF	Millimeter (mm)	WDI

Specification of econometric Model

The ARDL model is used to examine the short-term and long-term relationships between the factors being studied. Asumadu-Sarkodie & Owusu (2016); CHANDIO et al., 2020; Chandio, Jiang, et al., 2020; Chandio, Ozturk, et al., 2020; Warsame et al., 2021). This empirical research uses ARDL to examine cointegration and short- and long-run interactions because it has been used extensively in academic literature. In addition, it has some advantages over other statistical tools. Adom et al. (2012) say that the ARDL method gives a fair long-run estimate when certain endogenous factors are used as regressors. Cointegration of factors is done with the Ordinary Least Squares (OLS) method, and both the short-run and long-run coefficients are found at the same time. And finally, "ARDL can be used whether the model's regressors are fully I (0), I (1), or mutually cointegrated" (Begum, Masud, Alam, Mokhtar, & Amir, 2022). Finally, the ARDL test doesn't have residual correlation, so it can deal with situations where factors differ (Marques et al., 2016). Finally, the ARDL method gives strong and reliable results even when the sample size is small. Other cointegration methods change depending on the sample size (Pesaran et al., 2001a). The extended ARDL equation (1) below can be used to describe the ARDL model for this study:

$$\Delta FP_{t-1} = \theta_o + \alpha_1 FP_{t-1} + \alpha_2 CO2_{t-1} + \alpha_3 TEM_{t-1} + \alpha_4 RF_{t-1} + \sum_{i=t}^{\rho} \gamma_1 j \Delta FP_{t-1} + \sum_{i=t}^{\rho} \gamma_2 j \Delta CO2_{t-1} + \sum_{i=t}^{\rho} \gamma_3 j \Delta TMP_{t-1} + \sum_{i=t}^{\rho} \gamma_4 j \Delta RF_{t-1} + \varepsilon_t \qquad (2)$$

This study uses a set of symbols to represent various model components. Specifically, $\boldsymbol{\theta}$ uses to denote the intercept, **Δ** is utilized to represent the first difference, $\boldsymbol{\rho}$ is used to signify the number of lags, **t** is employed to "predict the time trend, $\boldsymbol{\alpha}$ indicates the coefficient of the short run, $\boldsymbol{\gamma}$ represents the coefficient of the long run, and $\boldsymbol{\varepsilon_t}$ is utilized to represent the error term" (Begum, Masud, Alam, Mokhtar, & Amir, 2022).

Estimation Procedure

There are two main ways that the ARDL model checks the link. In the first step, you check to see if the study factors have a long-term relationship. The goal of this study was to use the bound test method to investigate the long-term connection between FP (fiscal policy), CO2 (carbon dioxide emissions), TEM (temperature), and RF (rainfall). Pesaran and Shin (1999) say that the bound test depends on using lower and upper limits, which are important numbers in this case. The lower-bound critical values are used for I (0) variables, and the upper-bound critical values are used for I (1). The calculated F-statistic will be compared with the upper limits. If it exceeds, such null hypothesis that nothing is integrated will be rejected. Sustained cointegration is the term used here to describe the results of this study, indicating that these factors are linked. The lower limit of F-statistic should be exceeded to nullify the hypothesis of cointegration. Hence, the variables are not related to one another over time. The following is how the ideas are put together:

H0 denotes no difference associated with γ_1, ³_2, ³_3, and γ_4. Hypothesis 0 is that the factors are independent of each other. This, therefore, means that the no cointegration argument cannot be defended. The idea is that the coefficients of γ1, ³2, ³3, and γ4 are not all zero. The second hypothesis (Ha) is that they are separate. In this case, however, it could not be refuted that a theory of cointegration exists.

The given equation can serve as a rough idea of the long-term variable of the ARDL model.

$$FP_{t-1} = \beta_o + \sum_{i=t}^{\rho} \beta_1 j\, FP_{t-1} + \sum_{i=t}^{\rho} \beta_2 j\, CO2_{t-1} + \sum_{i=t}^{\rho} \beta_3 j\, TMP_{t-1} + \sum_{i=t}^{\rho} \beta_4 j\, RF_{t-1} + \varepsilon_t \qquad (3)$$

In this context, β_o represents the intercept term, β designates the "coefficient of the long-run relationship, ρ and represents the order of lags, Δ represents the first difference operator, and ε_t represents the error term. The next phase of the model entails finding the short-term dynamic coefficients by computing the error correction model that aligns with the long-term estimates. The representation of the Error Correction Model (ECM) inside the Autoregressive Distributed Lag (ARDL) model may be expressed as under" (Begum, Masud, Alam, Mokhtar, & Amir, 2022):

$$\Delta FP_{t-1} = \beta_o + \sum_{i=t}^{\rho} \beta_1 j \Delta FP_{t-1} + \sum_{i=t}^{\rho} \beta_2 j \Delta CO2_{t-1} + \sum_{i=t}^{\rho} \beta_3 j \Delta TMP_{t-1} + \sum_{i=t}^{\rho} \beta_4 j \Delta RF_{t-1} + \beta ECM_{t-1} + \varepsilon_t \quad \textbf{(4)}$$

The symbol β_o represents the intercept in the equation, while β denotes the coefficient of the short run. The error term, ε_t, is denoted using the same symbol. In addition, the lagged residual value, ECM_{t-1}, is obtained from the model that captures the long-term connection.

The diagnostic and stability tests are very important to the research process. The purpose of these tests is to check the data's accuracy and dependability, and ensure that the study results are consistent and strong. To see how reliable the model was, this "study used several diagnostic tests, such as serial correlation, heteroscedasticity, and normality in the residuals" (Begum, Masud, Alam, Mokhtar, & Amir, 2022), as described by Pesaran et al. (2001). The researchers also used the CUSUM and CUSUMSQ tests, first suggested by Brown et al. (1975), to check how stable the long- and short-run coefficients were.

Findings from empirical research/ Empirical analysis

Before engaging in any regression analysis, data analysis performs a crucial role in the understanding of the research (Danylchuk et al., 2023). Data analysis has different statistics tools to analyze data. It further helps explain the econometric analysis of the specified study model. For quantitative data analysis, Descriptive statistics are used to summarize data (Kaliyadan & Kulkarni, 2019). It provides information on whether the data is normally distributed, there is any outlier in data, measures of central tendency, and dispersion of data (Mishra, Pandey, Singh, Gupta, Sahu, & Keshri, 2019). The summary statistics shown in Table 2 are derived from a dataset of 31 yearly observations from 1990 to 2020. This table comprehensively describes the qualities and attributes of the variables under investigation used in the present research. Additionally, it can be shown from Table 2 that "marine fish production exhibits the greatest mean value, while CO2 emission has the lowest mean value" (Begum, Masud, Alam, Mokhtar, & Amir, 2022). The study revealed that marine fish production exhibited the greatest maximum value, whereas CO2 emissions had the lowest minimum value. Most variables had standard deviations lower than their respective mean values, indicating favorable performance across all variables. Based on the observed kurtosis values, it can be concluded that all variables exhibit a platykurtic distribution, suggesting that the estimated parameters possess positive kurtosis values that are smaller than three. The analysis of skewness revealed that CO_2 shows right tails, indicating positive skewness. Conversely, the other variables display distributions with elongated left tails, indicating negative skewness. Based on the Jarque-Bera statistic, it may be inferred that all variables exhibited a normal distribution characterized by a consistent variance and a covariance of zero. This indicates that the variables are appropriate for estimating purposes. Figure 1 shows the trend of variables used in the study.

Table 2 Analysis of descriptive statistics

	FP	CO2	TMP	RF
Mean	597405.6	0.693874	20.61737	25.78781
Median	599674.0	0.697409	20.65272	25.90000
Maximum	694395.0	0.918473	22.00000	35.27298
Minimum	463828.0	0.505906	19.44474	15.98308
Std. Dev.	54265.93	0.101950	0.559011	4.807761
Skewness	-0.441913	0.152987	-0.060953	-0.010679
Kurtosis	2.749521	2.437730	2.119012	2.249545
Jarque-Bera	1.090024	0.529283	0.037491	0.728034
Probability	0.579835	0.767481	0.981429	0.694879
Sum	18519574	21.51010	639.1386	799.4222
Sum Sq. Dev.	8.83E+10	0.311817	9.374800	693.4370
Observations	31	31	31	31

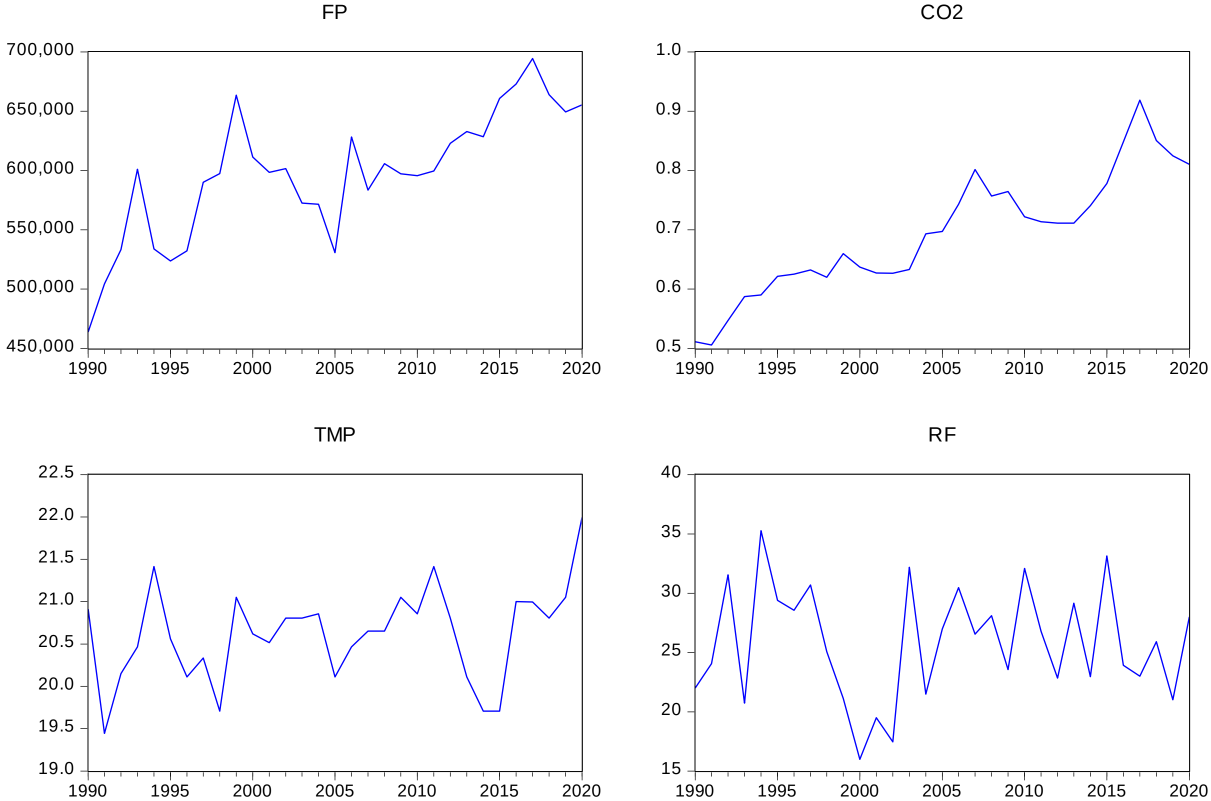

Figure 1 Trent of Variables

The unit root test can determine whether time series variables are stationary (Kim & Choi, 2017). Two different unit root tests, the Augmented Dickey-Fuller (Dickey & Fuller, 1979) and the Phillips-Perron (Phillips & Perron, 1988), were employed to determine the variables' integration order. This paradigm is implemented when everything remains in the initial, non-changing state (level I (0)). "Vector Autoregressive Model" (Shrestha & Bhatta, 2018) also refers to this technique. If the variables are stable at the initial difference I(1), then the Engel-Ganger or the Johansen cointegration test can be applied (Engle & Granger, 1987; Johansen, 1988). Alternative: a model of autoregressive distributed lags where I(0) and I(1) have bound co-integration (Pesaran and Shin, 1999b). According to the results of the two-unit root tests, the variables are integrated not at the I(2) level but at the I(0) or I(1) level. This shows that the dataset chosen in this study is unit root-free and can be subjected to ARDL regression analysis.

Table 3. Augmented Dickey-Fuller Unit Root Test

	Level	**First difference**	
Variable	**Prob. Value**	**Prob. Value**	**Order**
FP	0.0677	0.0000	1(1)
CO2	0.5258	0.0010	1(1)
TM	0.0595	0.0184	1(1)
RF	0.0008	0.0000	1(0)
PP Unit Root Test			
FP	0.0712	0.0000	1(1)
CO2	0.5258	0.0009	1(1)
TM	0.0697	0.0000	1(1)
RF	0.0000	0.0000	1(0)

Following a study on the "unit root and the order of integration for ARDL mode, determining the best lag length depending on the number of lags" (Begum, Masud, Alam, Mokhtar, & Amir, 2022), selected. The results of a variety of selection criteria are shown in Table 4. The Akaike information criterion, or AIC, determines the order of appropriate pause duration.

Table 4 outcomes of Lag Length Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-418.2049	NA	51970115	29.11758	29.30617	29.17664
1	-370.9856	78.15600*	6119157.*	26.96453*	27.90749*	27.25985*
2	-361.1997	13.49785	10081688	27.39308	29.09042	27.92467

* Indicates lag order selected by the criterion,

Table 5 provides an overview of the findings of the ARDL bound test, which shows a long-term link between the productivity of marine fisheries and certain climatic conditions. This page contains Table 5. The results showed that the upper-bound values at 1%, 5%, and 10%, respectively, are lower than the calculated F-statistics value of 5.2323, which is higher than that. As a result, the cointegration alternative hypothesis, a long-term association between marine fish output, CO2 emissions, temperature, and rainfall from 1990 to 2020, is verified. The best model should be used to calculate the long-term equilibrium connection once the cointegration stage is finished.

Table 5 ARDL bounds test for cointegration

Test Statistic	Value	k
F-statistic	5.232351	3
Critical Value Bounds		
Significance	**I(0) Bound**	**I(1) Bound**
10%	2.72	3.77
5%	3.23	4.35
2.5%	3.69	4.89
1%	4.29	5.61

Using the ARDL bounds test to show that variables are integrated over the long term, this study found both short-term and long-term results. Table 6 shows the short- and long-term outcomes. It gives an overall picture of how the variables change over time, both in the short and long run.

The findings show that CO_2 emissions and the growth of marine fish are not related in a good way. The long-term CO_2 negative coefficient (-4596.29) and the chance value (0.0036) that goes with it led to this conclusion. A bad connection is found because the long-term temperature coefficient is -888.85, and the chance value is only 0.026. It has been shown statistically that rainfall and sea fish production are linked well. The long-run coefficient is 5943, and the probability value is 0.032. The short-run effects of variables are found after the long-run cointegration is done. Based on Table 6, it was found that CO_2 pollution and temperature had a strong and negative effect on the production of marine fish. Table 6 shows even more ways rain is good for producing seafish. It is also important to note that the "calculated ECM coefficient shows a negative and statistically significant link at the 1% level" (Begum, Masud, Alam, Mokhtar, & Amir, 2022). This shows that the model's variables are cointegrated. One way to determine how fast balance is reached is using the Error Correction Model (ECM). In this case, the ECM value is -0.396, which means that the production of seafish is out of balance by 40% in the short term. In the long term, regressors bring production back into balance every year.

Table 6. Regression analysis for fish growth and abiotic factors

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long Run Results				
CO2	-4596.29	1384.57	-3.319	0.0036
TEMP	-888.85	385.22	-2.307	0.0026
RF	5943.48	938.88	6.330	0.0049
C	1540.21	658.32	2.339	0.0032
Short Run Results				
D(CO2)	-3922.07	1635.38	-2.398	0.031
D(TEMP)	3796.56	1652.35	2.281	0.0019
D(RF)	5738.02	1002.39	5.724	0.0045
CointEq(-1)	-0.396976	0.325944	-1.217926	0.2467

This study used several "diagnostic tests to examine the ARDL model's reliability and stability. The diagnostic tests did not exhibit serial correlation, non-normality, or heteroscedasticity in the ARDL model" (Begum, Masud, Alam, Mokhtar, & Amir, 2022), according to Table 7. CUSUM and CUSUM square tests are used to examine the stability of the model (Caporale & Pittis, 2004). Figures 2 and 3 show that the ARDL model is stable, as the marine fish production lines for both experiments remain below the significance threshold of 5% over time.

Table 7. CUSUM and CUSUM square tests are used to examine the stability of the model

Diagnostic Test	F value	P value
Serial Correlation Test	0.666109	0.5400
Glejser test (Heteroscedasticity)	0.821657	0.652
Normality Test	0.624802	0.449

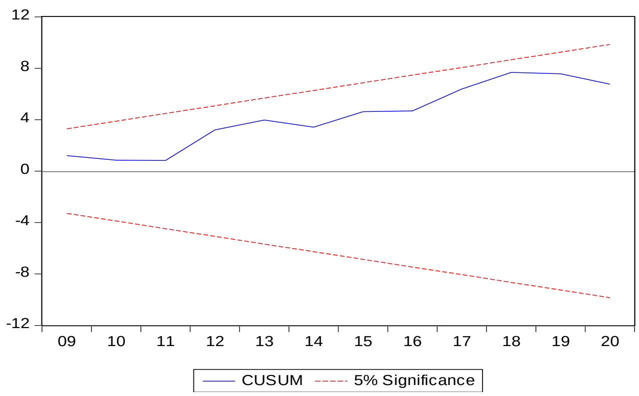

Figure 2 graph of CUSUM Test

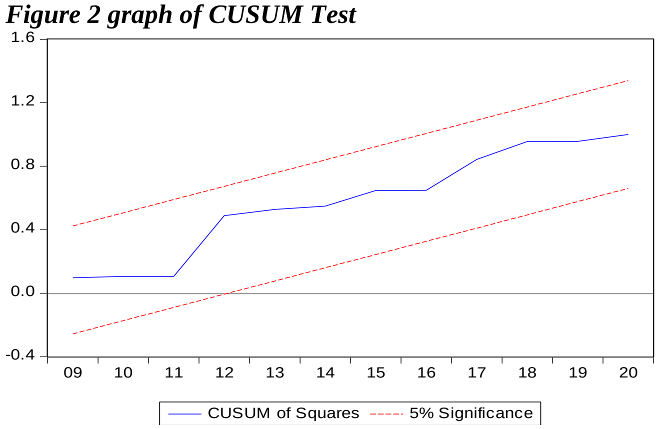

Figure 3 Graph of CUSUM of Square Test

Policy Implications

This study looks at the real-world link between climate factors like CO2 pollution, temperature, and rainfall and how these factors affect the growth of marine fish. The ARDL model found a statistically significant negative relationship between CO2 emissions and the output of coastal fish in both the short and long term. For both lengths of time, this is true. It has been shown that Pakistan's marine fish production decreases when carbon dioxide (CO2) levels go up over time. Temperature changes hurt marine fish populations' short- and long-term productivity. On the other hand, rain or snow causes coastal fish populations to be more productive in the short and long term.

The study's results have several social implications. This study looks at how changes in weather and oceanography affect the number of fish that live in Pakistan's seas. Policymakers need to quickly develop a complete marine fisheries strategy that includes short-term plans to change people's ways of making a living and how people fish. Pakistan should do a lot of study and development in its fisheries on fish species that can handle changing temperatures well. The government of Pakistan set up a broad policy system that includes a lot of different groups to deal with the "effects of climate change on marine fisheries. Donor agencies, businesses, small-scale marine fishers, members of civil society, and fisheries workers should all be on this list of stakeholders" (Begum, Masud, Alam, Mokhtar, & Amir, 2022). The study could help the government improve how it manages marine fisheries by discovering new and useful information. So, this study can make a big difference in achieving the Sustainable Development Goals (SDGs), especially when ensuring enough food for everyone. Although this work makes a big contribution, it is important to recognize that it has some problems. These problems could be used as topics for future study. There are some things that this study doesn't look at that might impact the production of sea fish. Some of these factors are salinity, pH, the "availability of habitat, dissolved oxygen levels, primary production, current speed, plankton biomass, water depth, wind direction, species composition, river flows, the number of fishermen, and the size of fishing fleets" (Begum, Masud, Alam, Mokhtar, & Amir, 2022). It would be best to think about these things because they could greatly affect the overall production of sea fish. Human-made factors, like overfishing, pollution, and other similar variables, might be investigated in later studies. Some parts are left out because of the limited amount of material available. The study also used national climate data, which might not properly show how climate change affects different coastal fishery regions. As soon as it becomes possible to make better environmental databases, more study needs to be done on how climate change affects the production of marine salmon.

Conclusion

In conclusion, this investigation concentrates exclusively on the total marine output. However, future research may investigate the effect of climate on economically important marine fish species in Pakistan. In addition, the estimated model underwent a comprehensive set of diagnostic and model stability tests to ascertain the accuracy and integrity of the study's results while ensuring the absence of any potential biases or misleading interpretations. "This ensures that both the functional shape and the model are accurate. In addition, it affirms the model's lack of heteroscedasticity and serial correlation concerns" (Begum, Masud, Alam, Mokhtar, & Amir, 2022). Numerous diagnostic and stability tests were conducted throughout the study to validate the model's consistency.

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Declarations

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Authors Contribution

MSS wrote and completed manuscript.

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