International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 7, 2025
https://www.theaspd.com/ijes.php

Impact of Climate Variability on Marine Fisheries: Some Panel Evidence from Coastal Odisha

Biswajit Sarangi[1]
[1]Department of Economics, MSCB University, Baripada, Odisha, India, 757003.
sarangibiswajit36@gmail.com, 0009-0006-4117-8798

Abstract
The study aims to analyse how climate variability affects marine fish production in Odisha, a key coastal region of India. To substantiate the objective, data on annual marine fish production from all six coastal districts of Odisha, sourced from the Directorate of Fisheries, Govt. of Odisha. However, the explanatory variables for the study, representing climate variability, include annual average precipitation, temperature, relative humidity, surface pressure, wind speed, and wind direction, with data sourced from the NASA Power Data Access Viewer. The study spans from 2000 to 2022, covering the period for which data is available. Log transformation is applied to mitigate multicollinearity, and then the presence of unit root in the panel data is examined using both common and individual stationarity tests at the intercept and trend level. After confirming the stationarity of the variables at different levels, the Pooled Mean Group (PMG) model is employed. Following this, the first stage heteroscedastic Fully Modified Ordinary Least Squares (FMOLS) is used for robustness analysis. The study found that marine fishery production in Odisha is positively affected by relative humidity, temperature, surface pressure, and negatively affected by frost days, clear-sky days, precipitation, wind direction, and wind speed. Thus, to optimise production, a robust climate monitoring system should be established to forecast key climatic variables and integrate these insights into fishery management plans and fishing schedules.
Key Words: *Climate Variability, Coastal Odisha, FMOLS, Marine Fisheries, PMG.*

1. INTRODUCTION

The fisheries sector is a crucial component of India's primary economy at global, national, and regional levels, providing employment, sustaining livelihoods, contributing to food security through protein supply, earning foreign exchange, and fostering economic integration both at backward and forward stages (Nayak, 2022). The fisheries sector is generally classified into inland and marine fisheries, each with distinct ecological and economic characteristics. Among these, marine fisheries assume a particularly critical role at the global level, as they contribute significantly to food security, provide employment opportunities, support the livelihoods of millions of coastal communities, and drive economic growth (Xu et al., 2024; Teh & Sumaila, 2013). Despite their significance, these fisheries are highly vulnerable to climate variability (Banerjee & Mohapatra, 2023; Bahinipati & Sahu, 2012), given that the livelihoods of coastal communities are intimately dependent on stable and predictable climatic conditions.

Savitsky (2017) defines climatic variability as short-term fluctuations in climate occurring over periods ranging from one month to thirty years. The fishery sector faces mounting challenges due to climate variability, including high and changing temperatures (Sethi et al., 2025), fluctuating precipitation, and shifting wind patterns, which disrupt marine ecosystems (Kumar et al., 2017), alter fish migration and affect productivity. The marine fisheries sector is also affected by climate variability in many ways, including rising sea surface temperatures, shifting ocean circulation, acidification, and the increasing frequency and intensity of extreme weather events (Badjeck et al., 2010). These environmental changes directly affect critical biological functions in fish, including migration, breeding patterns, growth rates, mortality, and reproductive success (Brander, 2008). As a result, species distribution, abundance, and composition have been altered, leading to a decline in marine biodiversity (Vivekanandan, 2010). All these cause a reduction in fish harvests and compel fishers to seek alternative livelihoods, often in inland areas (Vivekanandan, 2010). These changes not only diminish the availability of marine resources but also threaten the income, livelihood security, and long-term resilience of fishing communities, thereby undermining the socioeconomic well-being of coastal populations (Priyadarshi et al., 2019). Therefore, climate variability exacerbates existing issues like overfishing, pollution, and habitat loss by

altering ocean conditions (Xu et al., 2024), especially in terms of temperature and biogeochemical properties (Barange et al., 2018; Sumaila et al., 2011).
The India Network for Climate Change Assessment (INCCA) report 2010, published by the Ministry of Environment and Forests, Government of India, identifies Odisha as one of 13 coastal states in the country highly vulnerable to sea level rise and cyclonic activity. The report emphasizes that a significant proportion of Odisha‘s coastal population depends on climate-sensitive sectors such as marine fisheries and agriculture for their livelihoods. In fact, Odisha is often described as the "cyclone capital of India", given the frequent occurrence of severe cyclonic events along its coastline (Kumar et al., 2010; Sharma & Patwardhan, 2008). Historically, such cyclones have caused widespread devastation, affecting not only agriculture and fisheries but also critical infrastructure sectors, including telecommunications and energy (Annual Report on Natural Calamities, 2019-20). In response to these recurring threats, the state government has adopted a range of adaptation measures, such as the development of advanced early warning systems and the construction of multipurpose cyclone shelters. Despite these interventions, the intensity and frequency of extreme climatic events have continued to disrupt the livelihoods of communities that depend heavily on fragile coastal economies (Bahinipati & Sahu, 2012). Consequently, the influence of climate variability on marine fisheries is particularly pronounced in Odisha. This underscores the urgent need to investigate the complex relationship between climate variability and marine fishery production in Odisha to develop resilient fisheries management strategies. The present study, therefore, seeks to examine the influence of various climate variability factors on marine fishery production in Odisha. In order to ensure a comprehensive and regionally representative assessment, the analysis encompasses all six coastal districts of Odisha, thereby capturing the spatial diversity of climatic conditions and their implications for marine fisheries across the state‘s coastline. To the best of my knowledge, there exist very few proper studies either in Odisha or in India that have specifically analyzed the influence of climate variability on marine fishery production through the application of econometric techniques. In the absence of such region-specific empirical studies, the present work draws substantially on insights and evidence available in the international body of literature, which provides the principal foundation for supporting and contextualizing its findings. Furthermore, this study incorporates a set of variables to capture climate variability that have either been rarely employed or, in some cases, scarcely explored in existing research. Since limited empirical investigations have been conducted on these dimensions, the findings of the present work are necessarily interpreted in light of theoretical considerations and conceptual frameworks rather than being strongly anchored in prior empirical or analytical evidence.

2. LITERATURE REVIEW

A growing body of literature has explored how climatic and environmental variables influence marine fish catch and production across different regions. Ajibade et al. (2024) conducted a long-term empirical investigation in Nigeria covering the period from 1980 to 2019, aiming to assess the impacts of marine pollution and climate factors on small-scale fisheries. Utilizing the Engle-Granger Cointegration Test and an Error Correction Model, the study revealed that strong winds, elevated sea temperatures, and plastic waste, both current and lagged, significantly reduced small-scale fish catch. This suggests a combined effect of climate dynamics and anthropogenic pollution on deteriorating marine resource availability.
Focusing on Saudi Arabia's natural fisheries, Alnafissa et al. (2021) applied a Multiple Regression model to analyze data from 2000 to 2019. Their findings underscore that an increase in industrial fishing boats and labour force contributed positively to fish output, whereas strong winds negatively impacted production. Moreover, the low output elasticity of 0.10 (<1) indicates that the fisheries sector operated under diminishing returns, implying inefficiencies in input utilization.
The Korean coastline offers another perspective, as explored by Cho et al. (2025), who employed the ARDL Cointegration Test over 30 years (1993–2023) to examine the effects of sea surface temperature, CO_2 emissions, and rainfall variability on coastal and offshore fish production (COFP). The results were alarming: a 1 per cent increase in each of these variables led to respective declines in fish production by 3.52 per cent, 0.82 per cent, and 0.34 per cent, indicating severe consequences from ocean warming, acidification, and hydrological instability.

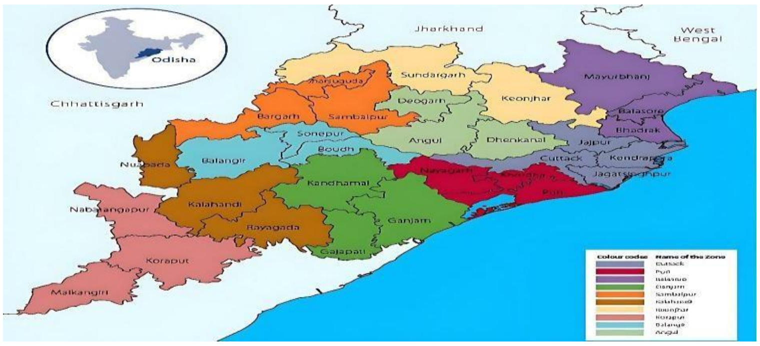
A more localized study by Demirci (2025) in Iskenderun Bay for the period 2017–2023 used Multiple Linear Regression to analyze the effects of wind dynamics on trawl fishing. The findings highlighted a direct negative relationship, where stronger winds reduced fishing effort by approximately 0.367 hours, underlining how even moderate environmental fluctuations can limit fishing operations. Similarly, Farquhar et al. (2022) looked at the impact of weather changes on small-scale fisheries in Madagascar, analysing data from 1979 to 2020. Using mean and linear regression techniques, they identified a gradual loss of 21.7 fishing hours annually, with seasonal variations showing more favourable conditions during the rainy season (November-April) compared to the dry season (May-October), which illustrates how seasonal climate cycles can shape local fishing economies and access.
An ecological dimension is added by Hu et al. (2021), who applied Empirical Dynamic Modelling (EDM) to determine the environmental drivers of hairtail catch in the East China Sea. Their analysis showed that monsoon winds, sea salt levels, rainfall, sea temperature, and cyclone strength influence nutrient dynamics, which in turn regulate fish availability, indicating a complex biophysical feedback loop in the marine ecosystem.
Looking further back, Sutcliffe et al. (1977) investigated commercial fish catch data from the Gulf of Maine (1940-1959). Using correlation analysis, they found that sea temperature positively influenced the catch levels of 10 out of 17 species. Interestingly, despite species-specific changes, the total commercial catch remained stable, suggesting a form of ecological equilibrium or species compensation.
Across these studies, a consistent theme emerges, i.e., climatic and oceanographic variables, particularly temperature, wind, rainfall, and pollution, significantly impact marine fishery yields, although the direction and magnitude of these effects vary by region. Therefore, the inclusion of relative humidity, number of frost days and clear sky days will provide new insights into the nexus between climate variability and marine fisheries. Methodologies range from time-series econometrics (cointegration) to regression and correlation techniques, showcasing the scarcity of panel data-related literature to uncover these relationships.

3. MATERIALS & METHODS

3.1 Fishery Profile of Odisha

Odisha is one of India‘s coastal states and has rich marine water resources. Its coastline spans 480 kilometres along the Bay of Bengal, making up 8 per cent of India‘s total shoreline. The state‘s continental shelf up to 200 meters depth covers 24,000 square kilometres or 4.5 per cent of India‘s continental shelf area, stretches up to 120 km in the north and 40 km in the south from the coast, offering considerable potential for marine fisheries (Nayak, 2022). According to the Annual Activity Report 2021-22 of the Fisheries & Animal Resources Development Department, Government of Odisha, Odisha ranked as India‘s fourth-largest fish-producing state in 2021-22, with a total output of 9.91 lakh metric tons, contributing 6 per cent to the country‘s overall fish production. The fishery sector contributes 2.43 per cent to Odisha‘s Gross State Domestic Product (GSDP), with an estimated fisher population of 15.18 lakh, comprising 5.96 lakh marine and 9.21 lakh inland fishers. Odisha also has one of the highest fish consumption rates in the country. As per NFHS-5 (2019-21), 94.75 per cent of its population consumes fish, resulting in a notable per capita fish consumption of 16.34 kg.

Fig. 1: Coastal Map of Odisha



Source: Annual Activity Report 2021-22, pp. 08

The present study employs a diagnostic research design to investigate the impact of climate variability on marine fishery production across all six coastal districts of Odisha—Balasore, Bhadrak, Jagatsinghpur, Puri, Ganjam, and Kendrapara—as illustrated in Figure 1, spanning the period from 2000 to 2022. The period of study is chosen based on data availability.

3.2 Variables & Data Source

The study is purely based on secondary data, with marine fish production data collected from the Directorate of Fisheries, Government of Odisha, and climate-related variables including Precipitation, Relative Humidity, Wind Speed, Wind Direction, Earth Skin Temperature, Surface Pressure, Number of Frost and Sky Clear Days, sourced from the NASA Power Data Access Viewer. The description of all variables, along with the rationale for their selection, is presented in Table 1.

Table 1: Variables of the Study

Variables	Description	Relation to Climate Variability	Relation to Fish Production
Precipitation (mm)	Total annual rainfall measured in millimetres.	It fluctuates with climate patterns like monsoons, cyclones, and seasonal variability.	It affects salinity, nutrient runoff, and habitat conditions; it also impacts phytoplankton growth, which forms the base of the marine food web.
Relative Humidity (per cent)	Measure of atmospheric moisture as a percentage.	Varies with temperature and air circulation patterns, thereby influencing evaporation rates and cloud cover.	Influences water temperature stability and light penetration, both crucial for photosynthesis, habitat suitability and thus, plankton growth.
Wind Speed (at 2m) (m/s)	The speed of wind is measured at 2 meters above ground level.	Changes in atmospheric pressure systems, such as monsoons and storms, influence upwelling and ocean currents.	Drives upwelling of nutrient-rich waters, enhancing fish productivity; strong winds can disrupt fishing activities.
Wind Direction (at 2m)	Direction from which the wind originates, measured at 2 meters above	Shifts are due to seasonal and regional atmospheric pressure changes.	Alters the direction of ocean currents and nutrient distribution, influencing fish migration and availability in fishing zones.

	ground level.		
Earth Skin Temperature/ Temperature (°C)	Surface temperature of the Earth, including land and sea.	Directly influenced by global warming, seasonal variations, and atmospheric conditions.	Affects fish metabolism, growth, and reproduction; drives species to migrate to optimal temperature zones, altering their distribution.
Number of Frost Days	Annual count of days with minimum temperature below freezing (0°C).	Represents extreme cold events linked to seasonal and regional climatic patterns.	Sudden temperature drops can stress warm-water species and suppress plankton growth, reducing the food supply for fish.
Number of Clear Sky Days	Annual count of days with little or no cloud cover.	Affected by atmospheric moisture levels, cloud formation, and climatic oscillations.	Enhances light penetration, promoting photosynthesis and phytoplankton growth; prolonged clear skies can overheat water, driving fish to cooler depths.
Surface Pressure (hPa)	Atmospheric pressure at the Earth's surface.	Reflects weather systems like cyclones (low pressure) & anticyclones (high pressure), which are influenced by climate variability.	Affects water mixing and stratification; low pressure can bring storms that disrupt fishing activities, while high pressure stabilises ecosystems.
Marine Fishery Production (tons)	Quantity of fish harvested annually, measured in tons.	Influenced by climate variability through changes in habitat, food availability, and species migration.	Dependent variable, indicating the total output of marine fisheries.

Source: Author‘s Own

3.3 METHODS

Panel data is well-suited for this study for the spatial and temporal dimensions of the research. Panel data offers a methodological advantage by allowing the simultaneous observation of multiple cross-sections (districts) over time, thereby improving the robustness and reliability of the estimations through the inclusion of both temporal dynamics and district-level heterogeneity. In addition, as there are eight independent variables in the study, all the variables are first transformed into logarithmic form to reduce the issue of multicollinearity **(**Jena, 2021**)**.

To ensure the appropriate modelling of the data, the study begins with panel unit root testing to determine the stationarity properties of the variables involved. Stationarity is a crucial requirement in time series and panel data analysis because the presence of unit roots (non-stationarity) can lead to spurious regression results. Therefore, both individual and common unit root tests are conducted. For individual unit root tests, the Im, Pesaran and Shin (IPS) test, and Fisher-type tests such as the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test are employed. These tests allow for heterogeneous autoregressive roots across cross-sections, accommodating the differences in climatic and economic conditions among the six districts by separately testing the case of a unit root for each variable in each cross-section. Additionally, common unit root tests such as the Levin, Lin & Chu (LLC) test and the Breitung test are used. These tests assume a common unit root process across districts and provide an alternative robustness check to validate the stationarity findings from the individual tests. The combination of these tests ensures a thorough understanding of the order of integration of each variable and helps in deciding the appropriate econometric modelling strategy.

Since the variables exhibit a mix of integration orders, the log of marine fishery production is stationary at first difference, I(1) and others at level I(0), the Panel Autoregressive Distributed Lag (Panel ARDL) model is selected for further analysis. The Panel ARDL framework is particularly useful in such scenarios because it accommodates different orders of integration [I(0) or I(1)] among the variables, unlike traditional cointegration models that require all variables to be integrated of the same order. In this study, the Panel ARDL model is estimated using the Pooled Mean Group (PMG) method under the assumption of unrestricted trend and constant. The PMG approach allows for the short-run coefficients and error variances to differ across districts while constraining the long-run coefficients to be homogeneous (Pesaran et al., 1999). This is a reasonable assumption in the present context, as short-term fluctuations in fishery production due to climate variability may vary widely among districts depending on local adaptation strategies, fishing infrastructure, and socio-economic factors. However, the long-run relationship between climate variables and marine fisheries is expected to follow a common pattern across the state. The long and short-run equations of this model are shown in equations 1 and 2, respectively.

$$LMFP_{it} = \alpha_{0i} + \sum_{j=1}^{p} \alpha_{1ij} LMFP_{it-1} + \sum_{j=1}^{p} \alpha_{2ij} LPre_{it-1} + \sum_{j=1}^{p} \alpha_{3ij} LT_{it-1} + \sum_{j=1}^{p} \alpha_{4ij} LRH_{it-1} + \sum_{j=1}^{p} \alpha_{5ij} LSP_{it-1} + \sum_{j=1}^{p} \alpha_{6ij} LWS_{it-1} + \sum_{j=1}^{p} \alpha_{7ij} LWD_{it-1} + \sum_{j=1}^{p} \alpha_{8ij} LFD_{it-1} + \sum_{j=1}^{p} \alpha_{9ij} LSCD_{it-1} + \mu_{it} \quad \ldots\ldots (\mathbf{1})$$

$$\Delta LMFP_{it} = \beta_{0i} + \sum_{j=1}^{p} \beta_{1ij}\, \Delta LMFP_{it-1} + \sum_{j=1}^{p} \beta_{2ij}\, \Delta Pre_{it-1} + \sum_{j=1}^{p} \beta_{3ij}\, \Delta LT_{it-1} + \sum_{j=1}^{p} \beta_{4ij}\, \Delta LRH_{it-1} + \sum_{j=1}^{p} \beta_{5ij}\, \Delta LSP_{it-1} + \sum_{j=1}^{p} \beta_{6ij}\, \Delta LWS_{it-1} + \sum_{j=1}^{p} \beta_{7ij}\, \Delta LWD_{it-1} + \sum_{j=1}^{p} \beta_{8ij}\, \Delta LFD_{it-1} + \sum_{j=1}^{p} \beta_{9ij}\, \Delta LSCD_{it-1} + \beta_{10ij} ECC_{t-1} + \delta_i \Delta T_t + \mu_{it} \quad \ldots\ldots\ldots\ldots\ldots (\mathbf{2})$$

In the equations, LMFP = Log of marine fishery production for panel unit ‗i' at time ‗t', j = number of lags (which is 1 in the model, selected as per Standard VAR), LPre = Log of Precipitation, LT = Log of Temperature, LRH = Log of Relative Humidity, LSP = Log of Surface Pressure, LWS = Log of Wind Speed, LWD = Log of Wind Direction, LFD = Log of no. of Frost Days, LSCD = Log of no. of Sky Clear Days, μ = error term, ECC = error correction coefficient, T = time and Δ = first difference operator of the variables. α and β are the long and short-run coefficients, respectively.

To further validate the findings of the Panel ARDL estimates, a robustness check is conducted by estimating the heterogeneous first-stage long run coefficients through the Fully Modified Ordinary Least Squares (FMOLS) method. FMOLS was developed by Phillips and Hansen (1990) to provide an efficient estimation of cointegrating regressions, especially if the variables are I(1). However, in this study, the Pedroni (2001) heterogeneous FMOLS estimator is applied for panel cointegration analysis, as it effectively addresses issues of endogeneity and serial correlation (Khan et al., 2019; Ozcan, 2013), which are common in panel data. Pedroni's version of FMOLS is a non-parametric estimator that accounts for individual-specific intercepts and incorporates heterogeneity across panel units (Leng et al., 2024). It is thus the most appropriate technique for panels involving heterogeneous cointegration (Hamit-Haggar, 2012). Therefore, in this study, to counter the mixed order of the variables [I(0) & I(1)], non-normality, endogeneity, serial correlation and heteroscedasticity, the heterogeneous first-stage FMOLS is used to ensure whether the long-run relationships established through the Panel ARDL model are statistically significant.

In addition to the estimations, a series of diagnostic tests has been conducted to ensure the robustness of the model. The Jarque-Bera test is applied to assess whether the residuals are normally distributed, indicating the validity of standard statistical inferences. To detect any presence of heteroscedasticity, i.e., unequal variances across cross-sectional units, the Likelihood Ratio test for panel heteroscedasticity is employed. Furthermore, the Wald Chi-Square test is used to determine whether the set of independent variables, when considered together, has a statistically significant impact on marine fishery production.

4. RESULTS AND DISCUSSION

The panel unit root test results in Table 2 indicate that most variables in the study are stationary at level or integrated of order zero or I(0), while only one variable, LMFP (Log of Marine Fishery Production), is non-stationary at level but becomes stationary after first differencing, indicating it is integrated of order one or I(1). This conclusion is based on the significance of various common (LLC & Breitung) and individual (IPS, ADF & PP) unit root test statistics. Variables such as LPre, LRH, LT, LSP, LWS, LWD, LFD, and LSCD reject the null hypothesis of ―presence of a unit root‖ in most of the tests, confirming their stationarity at the level. Hence, the coexistence of both I(0) and I(1) variables indicates that the Panel ARDL model is the most appropriate analytical approach for the study.

Table 2: Panel Unit Root Test

Variables	Common Unit Root Test	Individual Unit Root Test	Level of

	LLC	Breitung	IPS	ADF	PP	Stationarity
LMFP	3.49420	2.90092	2.57644	4.03226	7.48922	**At 1st Difference**
ΔLMFP	-0.14417	-1.87403**	-2.27456**	24.5851**	105.051***	
LPre	3.23626	-4.12570***	-2.47859***	24.3568**	95.4557***	**At level**
LRH	-1.86729**	-2.24714**	-0.03890	9.66405	32.3436***	**At level**
LT	-5.58496***	-4.33076***	-3.06771***	28.9223***	57.7001***	**At level**
LSP	-1.69795**	-1.30426*	-3.17871***	29.6137***	16.4012	**At level**
LWS	5.90638	-2.59555***	-1.37289*	16.6006	76.3681***	**At level**
LWD	-1.68457**	0.84075	-2.20055**	22.8188**	65.1434***	**At level**
LFD	-1.90584**	-4.42810***	-1.59356*	18.9024*	51.9544***	**At level**
LSCD	4.33326	-4.35238***	-3.69764***	34.6035***	144.200***	**At level**

Note: (***), (**), (*) represent statistically significant at 1, 5 & 10 per cent levels.
Source: Author‘s Compilation

Table 3 presents the PMG long-run and short-run results. In the short-run equation, the negative and statistically significant lagged error correction coefficient (ECC) confirms a stable long-run relationship, with about 18 per cent of the short-term deviations correcting each year. In the long run, the results show that a 1 per cent increase in precipitation (LPre) leads to a 0.38 per cent decline in marine fishery production for the sample period, possibly because excessive rainfall alters salinity and disrupts marine habitat conditions. This finding is corroborated by Cho et al. (2025). Their article explains that heavy rainfall reduces the salinity of seawater as large volumes of freshwater enter coastal and estuarine areas, which can stress marine species adapted to stable salt levels. Additionally, rainwater carries sediments and pollutants into the sea, increasing turbidity or water cloudiness. This murkiness blocks sunlight, which in turn hampers the growth of phytoplankton, tiny algae that form the foundation of the marine food chain. With reduced phytoplankton availability, the entire ecosystem is affected, leading to lower fish availability and thus reduced fishery production.

A 1 per cent rise in wind speed (LWS) reduces fishery output by 4.54 per cent, since strong winds disturb sea conditions and hinder fishing operations. This finding is backed by Alnafissa et al. (2021), who observed that in Saudi Arabia‘s coastal fisheries, a 10 per cent rise in wind speed caused a 6.8 per cent drop in fish production. This mainly happened because strong winds created rough sea conditions, making it harder for fishers to go out and operate their boats effectively. Similarly, Demirci (2025) showed that in Turkey‘s Iskenderun Bay, each unit rise in wind speed reduced daily fishing time by approximately 0.367 hours, as strong winds made it difficult for trawl boats to operate effectively. Therefore, fishermen are averse to high winds and waves (Sainsbury et al., 2021). Ajibade (2024) also concluded the inverse relationship between the two in the context of Nigeria.

Surface pressure (LSP) has a strong positive effect, where a 1 per cent increase corresponds to a 222.88 per cent rise in fishery production (LMFP), suggesting that stable atmospheric conditions create favourable environments for fishing. Though there is no proper study claiming that surface or atmospheric pressure has a positive impact on marine fishery, but a study conducted in the Aransas Channel Inlet of the Gulf of Mexico by Bolser et al. (2023) found that increases in barometric (air) pressure were positively associated with higher fish acoustic backscatter, which is used as a proxy for fish density. Specifically, a rise in atmospheric pressure of +2 mb, typically following winter cold fronts, was identified as the second most important factor influencing fish presence after temperature. This suggests that higher air pressure may indirectly enhance marine fish availability during certain seasonal conditions by influencing water temperature and movement patterns.

Likewise, a 1 per cent increase in temperature (LT) results in a 25.68 per cent increase in production, as warmer waters may support greater biological activity and expanded fish habitats. The result is supported by Sutcliffe et al. (1977), who found that in the Gulf of Maine, sea temperature was positively correlated with fish catch in 10 out of 17 species, suggesting that seasonal warming could enhance fish availability and catch rates. Moreover, a study on the East China Sea by Hu et al. (2021) demonstrated that sea surface temperature contributed to improved fish catch by enhancing nutrient availability and primary productivity, which in turn supported the growth of fish stocks, unlike Ajibade et al. (2024). In contrast, the number of frost days (LFD) and sky clear days (LSCD) negatively impact fishery production by 38.04 per cent and 8.24 per cent, respectively. Though there is no proper study concluded that clear-

sky days (i.e., periods with no cloud cover) have a negative impact on marine fishery production, yet a study on small-scale fisheries in Madagascar by Farquhar et al. (2022) noted that fishing effort was actually higher during the rainy season compared to dry, clearer periods, but this was attributed to socio-economic and seasonal factors rather than the presence or absence of clouds. Also, there is no existing literature supporting the impact of frost days on fisheries.
Additionally, the results reveal that a 1 per cent increase in relative humidity (LRH) leads to a substantial 36.55 per cent rise in fishery output, likely because higher humidity enhances marine ecosystems by promoting plankton growth, which supports fish breeding and survival, but no direct literature evidence is available to support the effect of humidity on fishery output. Finally, the impact of wind direction (LWD) in the long run is not statistically significant. However, in the short run, except for wind direction, which has an adverse impact on MFP, all other variables are found to be statistically insignificant. A study on the California coast by Scientists at UC San Diego (2008) showed that changes in wind-driven upwelling affected the availability of plankton, sardines, and anchovies, leading to a drop in fishery productivity, supporting the result of this study.
The Wald Chi-square test shows strong statistical significance ($p < 0.01$), confirming that the explanatory variables jointly influence marine fishery production in Odisha for the sample period. However, the significance of the Jarque-Bera test suggests that the residuals deviate from normality, while the significant Likelihood Ratio test for panel heteroscedasticity indicates that the variance of residuals is not consistent across cross-sectional units. In light of these issues, the study employs the first-stage heterogeneous FMOLS approach as a robustness check, effectively addressing the problems of non-normal residuals, as it is a non-parametric tool, and heteroscedasticity to ensure more reliable and consistent estimates.

Table 3: PMG Results

Long-run Estimation			**Short-run Estimation**		
Variables	**Coefficient**	**P-Value**	**Variables**	**Coefficient**	**P-Value**
LPRE	-0.376427*	0.0916	**ΔLPRE**	0.002123	0.9636
LRH	36.55395***	0.0029	**ΔLRH**	-0.993213	0.8664
LSCD	-8.245364***	0.0001	**ΔLSCD**	-0.071911	0.9472
LSP	222.8782***	0.0000	**ΔLSP**	-14.48257	0.7476
LT	25.67523**	0.0109	**ΔLT**	-1.462807	0.7323
LWD	1.191070	0.3239	**ΔLWD**	-0.855700***	0.0064
LWS	-4.539877***	0.0002	**ΔLWS**	-0.023304	0.9571
LFD	-38.04350***	0.0035	**ΔLFD**	1.137175	0.8515
			Intercept	-89.21302*	0.0584
			TREND	0.001339	0.3577
			ECC(-1)	-0.183974*	0.0586
Log-Likelihood	296.1421				
Jarque – Bera	28.30101 (0.000001)				
LR Test [6]	78.26975 (0.0000)				
Wald Chi [8]	60.69887 (0.0000)				

Note: (***), (**), (*) represent statistically significant at 1, 5 & 10 per cent levels.
The values in the brackets [] show the degrees of freedom for the respective test.
Source: Author‘s Compilation

The heterogeneous first-stage FMOLS results in Table 4 provide robust evidence for the long-run relationships between various climatic factors and marine fishery production. The results show that LRH, LSP, LWD, and LSCD have statistically significant effects on marine fishery production. Specifically, LRH has a positive coefficient of 4.76 and is significant at the 10 per cent level, while LSP has a large positive effect of 134.47, with statistically significant at the 1 per cent level. LWD and LSCD have negative coefficients of -1.91 and -4.38, respectively, and both are significant at the 1 per cent level. The consistency of the signs of the statistically significant coefficients with those of the PMG long-run results further validates the reliability for relative humidity, sky clear days and surface pressure. The model has an R2 of 0.926 and an adjusted R2 of 0.918, along with a minimal standard error of regression at 0.079126, indicating a good fit.

Table 4: Heterogeneous First-Stage FMOLS Results

Variable	Coefficient	P-Value
LPRE	0.057357	0.5588
LRH	4.756332*	0.0975
LSP	134.4736***	0.0003
LT	-1.248054	0.6331
LWD	-1.909129***	0.0000
LWS	-0.494447	0.2328
LSCD	-4.376755***	0.0000
LFD	-2.386245	0.4083
R^2	0.926595	
Adj. R^2	0.918507	
S.E. Regression	0.079126	

Note: (***), (**), (*) represent statistically significant at 1, 5 & 10 per cent levels.
Source: Author's Compilation

5. CONCLUSION

The present study empirically investigates the impact of climate variability on marine fishery production in Odisha, a prominent coastal state of India, over the period 2000–2022. Recognising the increasing vulnerability of fisheries to changing climatic conditions, such as rising sea temperatures, erratic rainfall, shifting wind patterns, and extreme weather events, the study aims to identify the influence of specific climate variables on marine fish production across all six coastal districts of Odisha, namely Balasore, Bhadrak, Jagatsinghpur, Puri, Kendrapara, and Ganjam. Using annual panel data for marine fish production from the Directorate of Fisheries, Government of Odisha, and climate data from the NASA Power Data Access Viewer, the research employs a rigorous econometric approach. After ensuring the stationarity of the data through both common and individual panel unit root tests, the PMG model is used to estimate both long-run and short-run relationships, with robustness tested through the heterogeneous first-stage FMOLS model.

The study reveals a nuanced relationship between climatic variables and marine fishery production in Odisha. Specifically, the long-run estimates suggest that temperature, surface pressure, and relative humidity have statistically significant positive effects on marine fish production in Odisha. Conversely, precipitation, wind speed, number of frost days, and clear sky days exert a negative influence on fish production. The short-run dynamics, however, are statistically insignificant except for wind direction, indicating that fishery responses to climate variability are more pronounced over the long term. The FMOLS results also validate the long-run results for relative humidity, surface pressure and frost days. However, a limitation of the study is that climate variability data are available only in calendar year format and limited to district headquarters, while data on marine fishery production follow the financial year format, leaving the researcher constrained to use the available dataset due to a lack of control over data accessibility. To avoid potential data inaccuracies and significant information loss, no method has been applied to convert data between calendar and financial year formats or to generalise the district headquarters data to the entire district level. Therefore, the study leaves the scope for future research to convert the available data to appropriate formats by changing calendar year data to financial year format and generalising headquarters-level data to the district level, enabling comparison with the present findings to derive more meaningful and robust conclusions, even though headquarters-level climate data are often considered as the best available proxy given the constraints in data availability and infrastructure, as district headquarters typically serve as the administrative and economic centres, where reliable and continuous climate monitoring stations are typically located, and generally exhibit climatic conditions that are broadly indicative of the district as a whole.

The findings of the study underscore the critical need to integrate climate sensitivity into marine fishery policy frameworks. One of the foremost policy implications is the establishment of a robust climate and ocean monitoring system to generate real-time data on key environmental indicators such as sea surface temperature, wind conditions, and precipitation trends. This system should be linked with the existing early warning systems in Odisha for more accurate prediction of extreme weather events like cyclones and erratic monsoons, which often disrupt fishing cycles and endanger livelihoods. Second, adaptive fishery management strategies must be adopted. These include adjusting fishing schedules based on seasonal climate forecasts, identifying climate-resilient species for sustainable harvesting, and developing marine spatial plans that recognise shifting fish habitats due to ocean warming. Finally, the study recommends targeted capacity-building programs for fishers to interpret weather and oceanographic data effectively. Training workshops and mobile-based advisories can play a pivotal role in making climate information more accessible and actionable for local fishing communities in Odisha.

Conflict of Interest: The author declares no potential conflict of interest.
Data Availability: The data used in this study are available upon request.

REFERENCES

1) Ajibade, T.B., Yusuf, M.A., Adebayo, S.A., Adeyemi, U.T., & Omotesho, O.A. (2024). Impact of marine pollution and climatic factors on artisanal fish capture in Nigeria. *Sarhad Journal of Agriculture, 40*(2), 646–658. DOI: https://dx.doi.org/10.17582/journal.sja/2024/40.2.646.658
2) Alnafissa, M., Kotb, A., Alamri, Y., Alagsam, F., & Alhashim, J. (2021). The impact of climatic and environmental changes on the sustainable yield of the Saudi‘s capture fisheries. *Journal of King Saud University – Science,* 33:101458. DOI: https://doi.org/10.1016/j.jksus.2021.101458
3) Badjeck, M.C., Allison, E.H., Halls, A.S., & Dulvy, N.K. (2010). Impacts of climate variability and change on fishery-based livelihoods. *Marine Policy*, *34*(3), 375–383. DOI: https://doi.org/10.1016/j.marpol.2009.08.007
4) Bahinipati, C.S., & Sahu, N.C. (2012). Mangrove conservation as sustainable adaptation to cyclonic risk in Kendrapada District of Odisha, India. *Asian Journal of Environment and Disaster Management*, *4*(2), 183–202. DOI: https://doi.org/10.3850/S1793924012001137
5) Banerjee, S., & Mohapatra, D. (2023). Climate Change and Marine Fisheries: Stakeholders‘ Perspective from Coastal District of Odisha, India. *Asian Journal of Agricultural Extension, Economics & Sociology*, *41*(7), 172–182. Retrieved from: https://www.journalajaees.com/index.php/AJAEES/article/view/1960
6) Barange, M., Bahri, T., Beveridge, M., Cochrane, K.L., Funge-Smith, S., & Poulain, F., eds. (2018). Impacts of Climate Change on Fisheries and Aquaculture: Synthesis of Current Knowledge, Adaptation and Mitigation Options. *United Nations' Food and Agriculture Organization*, Fisheries and Aquaculture Technical Paper No. 627, 628–635.
7) Brander, K. (2008). Impacts of climate change on fisheries. *Journal of Marine Systems*, *79*(3-4), 389–402. DOI: https://doi.org/10.1016/j.jmarsys.2008.12.015
8) Bolser, D.G., Souza Jr., P.M., Egerton, J.P., Diaz, L., Richard, A., Olsen, Z., & Erisman, B.E. (2023). Variation in Temperature, Change in Barometric Pressure, and Salinity Explain Trends in the Acoustic Backscatter of Fishes Within a Large Ship Channel Inlet in the Gulf of Mexico. *Estuaries and Coasts*. DOI:
9) Cho, H., Jung, P., & Jeong, M. (2025). Effects of Climate Change on Korea‘s Fisheries Production: An ARDL Approach. *Fishes* 2025, *10*, 186. DOI: https://doi.org/10.3390/fishes10040186
10) Demirci, S. (2025). Impact of Regional Wind Changes on Trawl Fishing Effort Under the Pressure of Overfishing in the Iskenderun Bay. *Sustainability*, *17*(5), 2055. DOI: https://doi.org/10.3390/su17052055
11) Farquhar, S., Nirindrainy, A.F., Heck, N., Saldarriaga, M.G., and Xu, Y. (2022). The impacts of long-term changes in weather on small-scale fishers‘ available fishing hours in Nosy Barren, Madagascar. *Frontiers in Marine Science*, 9:841048. DOI: https://doi.org/10.3389/fmars.2022.841048
12) Fisheries & Animal Resources Development Department. Annual Activity Report. (2021-22). *Government of Odisha*. Retrieved from: https://fard.odisha.gov.in/sites/default/files/2023-11/Annual per cent20Activity per cent20Report per cent20F per cent26ARD per cent202021-22.pdf
13) Hamit-Haggar, M. (2011). Greenhouse gas emissions, energy consumption and economic growth: A panel cointegration analysis from Canadian industrial sector perspective. *Energy Economics*, *34*(1), 358–364. DOI: https://doi.org/10.1016/j.eneco.2011.06.005
14) Hu, J., Wang, P., & Zhang, H. (2021). The Relationship between Environmental Factors and Catch Abundance of Hairtail in the East China Sea Using Empirical Dynamic Modeling. *Fishes*, *6*(4), 80. DOI: https://doi.org/10.3390/fishes6040080
15) Jena, P.K. (2021). Nexus between Climate Change and Agricultural Production in Odisha, India: An ARDL Approach. *International Journal of Environment, Agriculture and Biotechnology, 6*(2), 136–144. DOI: https://dx.doi.org/10.22161/ijeab.62.15.
16) Khan, M.W., Panigrahi, S.K., Almuniri, K.S., Soomro, M.I., Mirjat, N.H., & Alqaydi, E.S. (2019). Investigating the Dynamic Impact of CO2 Emissions and Economic Growth on Renewable Energy Production: Evidence from FMOLS and DOLS Tests. *Processes*, *7*(8), 496. DOI: https://doi.org/10.3390/pr7080496
17) Kumar, B., Bhagyalekshmi, V., & Riyas, A. (2017). Climate Change, Fisheries and Coastal Ecosystem in India. *Journal of Aquatic Biology & Fisheries*, *5*(1), 07–17. Retrieved from: https://www.researchgate.net/publication/323987596_CLIMATE_CHANGE_FISHERIES_AND_COASTAL_ECOSYSTEMS_IN_INDIA

18) Kumar, T., Mahendra, R.S., Nayak, S., Radhakrishnan, K., & Sahu, K. (2010). Coastal vulnerability assessment for Orissa State, East Coast of India. *Journal of Coastal Research*, *26*(3), 523–534. Retrieved from: https://www.researchgate.net/publication/215730022_Coastal_Vulnerability_Assessment_for_Orissa_State_East_Coast_of_India
19) Leng, C., Wei, S., Al-Abyadh, M.H.A., Halteh, K., Bauetdinov, M., Le, L.T., & Alzoubi, H.M. (2024). An empirical assessment of the effect of natural resources and financial technologies on sustainable development in resource abundant developing countries: Evidence using MMQR estimation. *Resources Policy*, *89*, 104555. DOI: https://doi.org/10.1016/j.resourpol.2023.104555
20) Ministry of Environment and Forests. 2010. India Network for Climate Change Assessment (INCCA) Report 2010. *Government of India.*
21) NASA Power Data Access Viewer. https://powerlarcnasagov/data-access-viewer/
22) Nayak, M. (2022). Production and export of marine fishery in Odisha. *International Journal of Financial Management and Economics*, *5*(2), 93–99. Retrieved from: https://www.theeconomicsjournal.com/article/view/153/5-2-20
23) Ozcan, B. (2013). The nexus between carbon emissions, energy consumption and economic growth in Middle East countries: A panel data analysis. *Energy Policy*, *62*, 1138–1147. DOI: https://doi.org/10.1016/j.enpol.2013.07.016
24) Pesaran, M.H., Shin, Y., & Smith, R.P. (1999). Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association, 94*(446), 621–634. DOI: https://doi.org/10.2307/2670182
25) Phillips, P.C.B., and Hansen, B.E. (1990). Statistical inference in instrumental variables regression with I(1) processes. *Review of Economic Studies, 57*(1), 99–125.
26) Pedroni, P. (2001). Fully modified OLS for heterogeneous cointegrated panels. In *Advances in Econometrics: Nonstationary Panels, Panel Cointegration, and Dynamic Panels*; Emerald Group Publishing Limited, Bingley, UK, pp. 93–130. DOI: https://doi.org/10.1016/S0731-9053(00)15004-2
27) Priyadarshi, S., Ojha, S.N., & Sharma, A. (2019). An Assessment of Vulnerability of Fisher‘s Livelihood to Climate Change in the Coastal Odisha, India. *Current World Environment*, *14*(1), 60–67. DOI: http.//dx.doi.org/10.12944/CWE.14.1.08
28) Sainsbury, N.C., Schuhmann, P.W., Turner, R.A., Grilli, G., Pinnegar, J.K., Genner, M.J., & Simpson, S.D. (2021). Trade-offs between physical risk and economic reward affect fishers‘ vulnerability to changing storminess. *Global Environmental Change*, 69:102228. DOI: https://doi.org/10.1016/j.gloenvcha.2021.102228
29) Savitsky, R. (2017). Climate Variability Vs Climate Change: What‘s the Difference? *Visualize*. Retrieved from: https://www.verisk.com/insurance/visualize/climate-variability-vs-climate-change-what-s-the-difference/.
30) Sethi, B., Sahu, S.C., Gouda, K.C., Beuria, R., Mallick, M.K., Samal, S.K., Panigrahi, A., & Pati, A. (2025). Climate variability and warming in Coastal Odisha: Assessing interannual temperature trends and impacts. *Scientific Reports, 15* (2025), 11111. DOI: https://doi.org/10.1038/s41598-025-95035-5
31) Sharma, U., & Patwardhan, A. (2008). Methodology for identifying vulnerability hotspots to tropical cyclone hazard in India. *Mitigation and Adaptation Strategies for Global Change*, *13*(7), 703–717. DOI: https://doi.org/10.1007/s11027-007-9123-4
32) Special Relief Commissioner. (2019-20). Annual Report on Natural Calamities. *Revenue and Disaster Management Department*, *Government of Odisha*.
33) Sumaila, U.R., Cheung, W.W., Lam, V.W., Pauly, D., & Herrick, S. (2011). Climate change impacts on the biophysics and economics of world fisheries. *Nature Climate Change*, *1*, 449–456. DOI: https://doi.org/10.1038/nclimate1301
34) Sutcliffe, W.H., Drinkwater, K., & Muir, B.S. (1977). Correlations of fish catch and environmental factors in the Gulf of Maine. *Journal of the Fisheries Research Board of Canada*, *34*, 19–30.
35) Teh, L.C., & Sumaila, U.R. (2013). Contribution of marine fisheries to worldwide employment. *Fish and Fisheries*, *14*(1), 77–88. DOI: https://doi.org/10.1111/j.1467-2979.2011.00450.x
36) UC San Diego. (2008). Is California fish catch linked to wind patterns? Retrieved from: https://news.mongabay.com/2008/02/is-california-fish-catch-linked-to-wind-patterns/
37) Vivekanandan, E. (2010). Impact of climate change on Indian marine fisheries and options for adaptation. *Souvenir: lobster research in India*, 65–71. Retrieved from: https://eprints.cmfri.org.in/8432/
38) Xu, Y., Krafft, T., & Martens, P. (2024). The interaction between climate change and marine fisheries: Review, challenges, and gaps. *Ocean and Coastal Management*, *259*, 107479. DOI: https://doi.org/10.1016/j.ocecoaman.2024.107479