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Stagnation Amidst Growth in Odisha's Marine Fisheries: A District-Level Analysis of Trends, Instability and Forecasts

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Odisha's marine fisheries sector, though rich in resources, has experienced only modest growth over the past three decades. This study analyzes long-term trends (1990-91 to 2022-23), production instability, and future projections of marine fish output across the six coastal districts of Odisha. Using secondary data, the study applies compound growth rate analysis, exponential trend fitting, and time series forecasting models - ARIMA (0, 1, 1) and Holt's Linear Trend (HLT) to assess the sector's performance. Despite a 2.73 fold increase in total marine production during the study period, the overall compound growth rate remained low at 1.56%, indicating stagnation. Holt's model outperformed ARIMA in forecasting accuracy (93% vs. 84%), supported by a lower AIC value, making it the preferred model for short-term prediction. Instability was examined using the Coefficient of Variation (C.V.), Coppock's Instability Index (CII), and Cuddy-Della Valle Index (CDVI). Kendrapara emerged as the most unstable district, likely due to cyclone vulnerability, infrastructural gaps, regulatory constraints (e.g., turtle conservation bans), and limited mechanization. In contrast, districts like Balasore and Puri showed more stable but plateauing production. Findings also highlight how total catch alone can be misleading, as increases may reflect intensified fishing effort rather than healthier fish stocks. Catch per unit effort (CPUE) varies widely across gear types, with mechanized and multi-day trawlers showing much higher efficiency than traditional gears. To ensure sustainable marine fisheries growth in Odisha, policies must go beyond production targets to address district-specific vulnerabilities, improve disaster resilience, rationalize fishing effort, and strengthen local landing and market infrastructure.

(***Key words:*** *Coastal vulnerability, Instability analysis, Odisha, Production forecasting, Statistical modelling)*

Fish is a major source of high-quality animal protein, but the availability of fish has been at high risk for the past two decades due to a decline in fish production potential (FAO, 2020). The per capita fish consumption more than doubled from 9.1 kg in 1961 to 20.6 kg in 2021 (FAO, 2024). India's per capita yearly fish intake grew from 4.9 kg in 2005 to 8.89 kg in 2021 (Padiyar *et al.*, 2024). India is the 7th largest producer of marine capture fisheries in the world and occupied the second position in overall fisheries and aquaculture production during 2019-20 (FAO, 2022). In India, the marine fisheries sector supports almost 4.0 million people and provides for a sizable portion of the population's food and nutritional needs (Sathianandan, 2017). Odisha boasts the 6th longest coastal length in India, approximately 480 km (Kar *et al.*, 2021; Mishra *et al.*, 2019; Mishra *et al.*, 2023), with a continental shelf covering 23,830 km² (Mishra *et al.*, 2019). It hosts 55 landing centers and 739 fishing villages, contributing around 5.91% to India's coastal length (CMFRI-DoF, 2020).

The marine fishery sector in Odisha provides employment to approximately 5.96 lakh people, while the inland sector employs around 9.21 lakh people (Fisheries and Animal Resources Development Department, Government of Odisha, 2021). Odisha recorded a total fish production of 2.13 lakh tons during 2022-23, constituting 4.80% of India's marine fish production. In 2022, Odisha has observed a decrease in fish landing compared to other states of India except Gujarat (FRAEED-CMFRI, 2023). Marine fish production in Odisha has increased 2.73 times from 1990-91 to 2022-23. Although it has large marine resources and 5.91% of India's coastline, total fish production has increased 6.52 times (Department of Fisheries, Ministry of Fisheries, Animal Husbandry and Dairying, 2024). Odisha ranks 4th in disposition of

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fish catch in India during 2022-23 (10.52 lakh tonnes) and 5th in per capita fish consumption in India (17.73 kg person^{-1} year^{-1}) (DoF-MoFAHD, 2024). In 2022-23, Odisha's marine fish production contributed 16444.6 crores to the state's Gross State Value Added (GSVA), ranking 5th in India, but it has experienced very slow growth or stagnation over the last two decades (Fisheries and Animal Resources Development Department, Government of Odisha, 2021).

There are no recent studies that have looked at the trend analysis and instability analysis of marine fish production in Odisha. In Odisha, the trends and dynamics of marine fish production have not been extensively studied. Naik (2001) examined marine fish landings and marketing trends across various maritime districts in Odisha from 1980 to 1999, reporting an impressive average annual growth rate of 8.86% during this time. This underscores the sector's importance and its potential for ongoing growth. Raman *et al.* (2017) employed an Autoregressive Integrated Moving Average (ARIMA) model to predict marine fish production in Odisha based on time-series data from 1985 to 2012, and determined that ARIMA (0, 1, 1) was the best-fitting model, allowing for accurate forecasts of fish landings for the years 2013 to 2015. This approach highlights the value of time-series techniques in fisheries management and policy planning. Additionally, Raman *et al.* (2018) extended their modelling efforts to the Chilika Lagoon, a crucial aquatic ecosystem in Odisha. Using the Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) model, they analyzed fish production data from 2001 to 2015. Their findings indicated that SARIMAX (1, 0, 0) (2, 0, 0) offered the most reliable forecasts, predicting fish landings through 2018. Proper trend analysis and forecast of fish production are of immense value in an economic system. The proper forecast would pave the way for policymakers to formulate appropriate policy measures to enhance fish production and ensure profit for the fishers. The six coastal districts are Balasore, Bhadrak, Jagatsinghpur, Kendrapara, Puri, and Ganjam, which are the key contributors to the state's fisheries sector but have different trends in production over time (DoF-MoFAHD India, 2024; F&ARD Odisha, 2021). However, despite its vast marine resources and significant contributions to the fisheries sector, Odisha's marine fish production has grown slowly and stagnated over the last two decades (Nayak, 2022; Hoda *et al.*, 2021). This scenario calls for a detailed examination of production trends and instability across its coastal districts to uncover underlying factors and develop data-driven strategies for sustainable fisheries management.

MATERIALS AND METHODS

Data collection

The present study is limited by its reliance on secondary data. The time-series data of fish production of Odisha (1990-91 to 2022-23) were taken from the Handbook of Fisheries Statistics, Department of Fisheries, Ministry of Fisheries, Animal Husbandry & Dairying, Government of India (DAHD&F, 2009, 2014; DoF, 2019, 2022, 2024) for the analysis of growth rate and forecasting. District-wise marine fish production data for Odisha were taken from the Directorate of Fisheries, Govt. of Odisha, covering the six coastal districts of Balasore, Bhadrak, Jagatsinghpur, Kendrapara, Puri, and Ganjam (Fig. 1). The analysis has been done by using statistical programming-based open-source software named R version 4.3.1. MS - Excel 365 was also used for further analysis.

Estimation of compound growth rate (CGR) using log-linear model and trend line analysis

The CGR of fish production in Odisha was estimated by fitting a log-linear model (Salim and Biradar, 2009). The model is expressed as,

$$Y_t = (1 + r)^{t}$$

where,

Y_t is the fish production in the year t for which growth rate is estimated, A is constant, r rate of annual increment and,

Compound growth rate (CGR) was estimated as,

$$r = [\text{antilog (b)} - 1] * 100,$$

where,

the relative change in Y for a given absolute change in the value of the explanatory variable t is measured by the slope coefficient b.

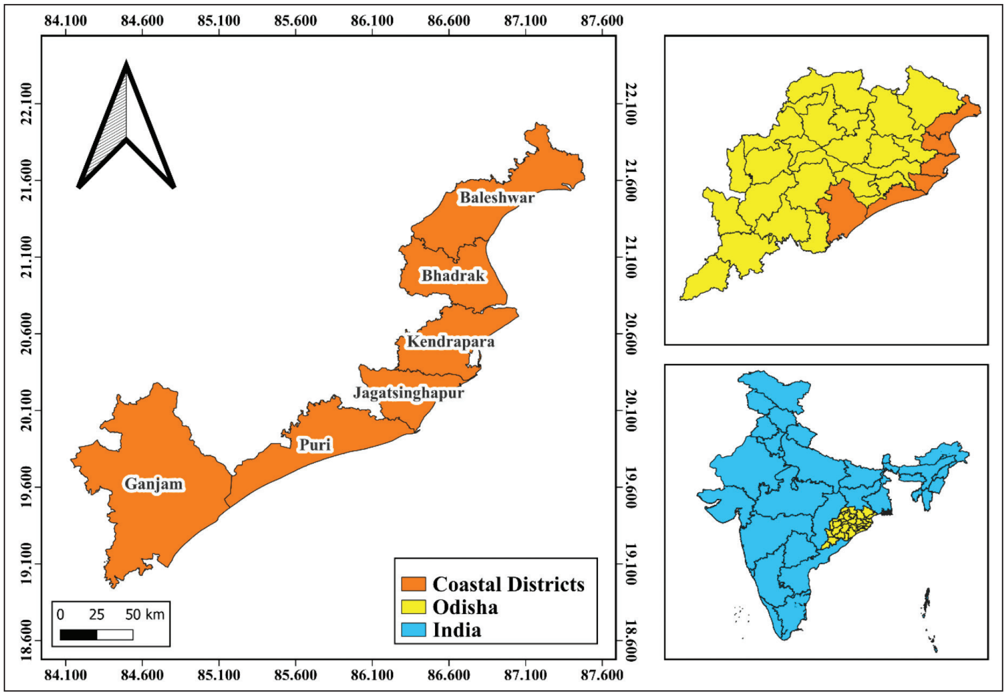


Fig. 1. *Coastal districts of Odisha*

The Compound Growth Rate (CGR) model was employed to capture long-term growth patterns using a log-linear approach (Salim and Biradar, 2009). Compound growth rate (CGR) has been widely used to estimate growth trends in the fisheries sector (Debroy *et al.*, 2016; Jeyanthi and Nikita, 2012; Sharma, 2017). Trendline estimation is often referred to as a technique for finding an underlying pattern of behavior of observed data in time-series data (Mudelsee, 2019; Sen, 2014). This pattern would be hidden partially or completely by noise (error). A simple description of these techniques is trend line estimation, which is widely used and nothing but a regression analysis (Gujarati *et al.*, 2012).

Autoregressive integrated moving average (ARIMA) model

ARIMA is a prediction model used for time series analysis and forecasting. A time series is a collection of observations of well-defined data items obtained through repeated measurements over time. The ARIMA model is extensively used due to its parsimoniousness and lowest forecast error. Authors used the ARIMA model to forecast fish production (Karunarathna *et al.*, 2017; Tsitsika *et al.*, 2007; Venugopalan and Srinath, 1998).

Autoregressive integrated moving average refers to the time series data's ability to differentiate between both Autoregressive (AR) and moving average (MA) models. The variables "p", "d", and "q" in ARIMA (p, d, q) time series stand for the number of autoregressive terms, integration, or the number of times the series must be changed before it becomes stationary, and moving average terms (MA), respectively.

The ARIMA (p, d, q) is,

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \mu_t + \Theta_1 \mu_{t-1} + \Theta_2 \mu_{t-2} + \ldots + \Theta_q \mu_{t-q}$$

where,

y_t is the production of fish at time t,

y_{t-1}, y_{t-2}, y_{t-3}..., y_{t-p} are the lag values at time t-1, t-2,.., t-p,

μ_t, μ_{t-1},......,μ_{t-q}, are the error terms and its lag values,

ϕ_1,....,ϕ_p are the coefficients of autoregressive model and

θ_1,….,θ_q are the coefficients of moving average model.

This model fitting process requires four steps:

Model Identification, Estimation, Diagnostic Checking, and Forecasting:

Model identification

Initially, the autocorrelation function (ACF) and partial autocorrelation function (PACF) were used to assess the data for stationarity. Finding the initial values for the orders of the non-seasonal parameters "p" and "q," which are acquired by searching for significant correlations in the ACF and PACF plots, was the next stage in the identification process.

Estimation

Simple least squares is typically used for this computation, but occasionally nonlinear (in parameter) estimation techniques must be used. Software R 4.3.1 was used for the estimation.

Diagnostic checking

The residuals from the fitted model were analysed to determine the model's adequacy, and other models were taken into consideration as needed. Other ARIMA models were tried until a model that fit the data satisfactorily was found if the first model that was identified seemed to be insufficient. For different combinations of AR and MA, different models were produced. The Akaike Information Criteria (AIC) minimum value, which is given by,

$$AIC= -2 \ln L + 2m,$$

where,

m = p + q and L is the likelihood function, was used to determine the best model both individually and collectively. The model that best fits the data is the one with the lowest AIC. The AIC has the benefit of not requiring model nesting for comparison, in addition to theoretical arguments.

Forecasting

The final stage of ARIMA modelling is forecasting. The accuracy of the model was first compared to all the competing models, and then a five-year forecast was made from 2023-2024 to 2027-2028. This was done because forecasting errors increase quickly if the forecast is made too far into the future (Meade, 2002; Nissi *et al.*, 2025).

Holt's linear trend method

Holt's two-parameter model, also known as linear exponential smoothing, is a popular smoothing model for forecasting data with trend which is an extension of simple exponential smoothing. This method involves a forecast equation and two smoothing equations (Holt, 1957).

$$F_{t+h} = L_t + b_t h \qquad \text{----- (1)}$$

$$L_t = \alpha Y_t + (1 - \alpha)(L_{t-1} + b_{t-1}) \qquad \text{----- (2)}$$

$$b_t = \beta (L_t - L_{t-1}) + 1 - \beta) b_{t-1} \qquad \text{----- (3)}$$

Where,

Eq. (1) represents the forecast equation

Eq. (2) denotes the level equation

Eq. (3) denotes the trend equation.

L_t denotes an estimate of the level of the series at time t,

b_t denotes an estimate of the trend (slope) of the series at time t,

α is the smoothing parameter for the level, $0 \le \alpha \le 1$

β is the smoothing parameter for the trend, $0 \le \beta \le 1$

h is the no. of forecasts.

Measures of instability

Coefficient of variation

Coefficient of Variation was used to examine the instability in the time series production data of various produces (Sharma, 2017; Siby and Arunachalam, 2020; Rajani *et al.*, 2023) have used Coefficient of Variation to examine instability. A higher numerical value for the index represents greater instability.

$$\text{Coefficient of Variation (C.V.)} = \frac{\text{Standard Deviation (S. D.)}}{\text{Mean}} \times 100$$

Coppock instability index (CII)

CII, which is calculated as the antilog of the square root of the logarithmic variance using the following function (Coppock, 1962). CII was used by many researchers to examine the instability in production data over time for various products (Fauzi and Anna, 2012; Radhakrishnan *et al.*, 2016 & 2018; Wasim, 2007) have used CII to examine instability. Coppock instability index is a close approximation of the average year-to-year percentage variation adjusted for trend and the advantage is that it measures instability in relation to the trend in production. A higher numerical value for the index represents greater instability, like what is in the coefficient of variation.

$$CII = \text{Antilog}\ (\sqrt{V \log} - 1) * 100$$

Where, V log is the logarithmic difference of log X_{t+1} and log X_t

$$V\ log = \frac{\Sigma \left(log \frac{x_{t+1}}{x_t} - m\right)^2}{n}$$

'X_t' is Production in m_t, t' is number of years; 'm' is mean of the difference between logs of X_{t+1} and X_t.

Cuddy and della valle index (CDVI)

CDVI was originally developed by Cuddy and Della Valle (1978) for measuring the instability in time series data that is characterized by trend. CDVI is considered the best measure in determining the instability in the production sector, as it has an apparent scale of measure (Rajani *et al.*, 2023). Instability is classified into three levels based on its value: low instability is defined as being between 0 and 15, medium instability is exceeds 15 but less than 30, and high instability is greater than 30.

$$CDVI = C.V. * \sqrt{(1-R^2)}$$

where, C.V. is the simple Coefficient of Variation in percent, R^2 is the coefficient of determination from time trend regression adjusted by the number of degrees of freedom.

To comprehensively assess the production instability across time, both Coefficient of Variation (C.V.) and Coppock Instability Index (CII) were employed in this study. The C.V. provides a basic and intuitive measure of relative variability by comparing standard deviation to the mean, making it a simple yet effective tool to quantify fluctuations. However, it does not account for the underlying trend in the time series data. In contrast, the CII offers a more refined estimate by adjusting for trend, capturing the average year-to-year percentage variation in a logarithmic scale. The use of both indices allows for a more robust and complementary evaluation of instability C.V. captures absolute variability, while CII addresses trend-adjusted relative changes. This dual approach ensures a more accurate and comprehensive analysis, particularly in datasets where production trends.

RESULTS AND DISCUSSION

Growth trends of fish production in Odisha

A decadal analysis of Odisha's marine fish production from 1990 to 2023 (Table 1) demonstrates a general rise with notable expansion in recent years. In social science research, an R-squared of 0.50 to 0.99 is considered appropriate, particularly when most of the explanatory factors are statistically significant (Ozili, 2023), which is also seen in the present study (Table 1). In Odisha, the percentage of marine fish production accounted for by the mechanized sector grew from 40% in 1980 to 68% in 1997 (Raman et al., 2017; Sathiadas and Salim, 2012). At the 1997

Table 1. *Descriptive statistics and decadal growth rate of marine fish production (in MT) in Odisha*

Decadal period	Mean	SD	CV (%)	CGR (%)	R^2
Period 1 (1990-1991 to 1999-2000)	117509.00	22479.21	19.13	5.50	0.61
Period 2 (2000-2001 to 2009-2010)	123474.00	7228.94	5.85	1.67	0.74
Period 3 (2010-2011 to 2019-2020)	138511.00	16995.05	12.27	3.62	0.76
Period 4 (2020-2021 to 2022-2023)	195333.33	21079.22	10.79	11.28	0.95
Entire period	132755.76	27255.47	20.53	1.56	0.56

pricing level, the anticipated total capital investment for fishing equipment alone comes to Rs. 4,117 crores (Sathiadhas and Salim, 2012). As a result, the marine fisheries sector saw a huge growth in Period-I (1990-1991 to 1999-2000). Marine fish production in Odisha was highest during Period-I, whereas in Period-II (2000-2001 to 2009-2010) it was minimum (Table 1) and for the entire period, CGR was 1.56%, which indicates stagnant condition in the marine fish sector of Odisha. Odisha faced several cyclones during the period 2000-01 to 2019-20 period such as Phailin (2013), Hudhud (2014), Titli (2018), Fani and Bulbul (2019), Amphan (2020), etc., which has resulted in a reduction in marine fish production in Period-II (2000-2001 to 2009-2010) and Period-III (2010-11 to 2019-2020). Coastal Odisha remains highly vulnerable to cyclones, with 33% of storms in the Bay of Bengal making landfall here between 1891 and 2011, resulting in recurrent livelihood disruptions for climate-sensitive sectors such as fisheries (Pradhan, 2025a). The National Institute of Disaster Management (NIDM) has emphasized the revival of littoral zones, mangrove restoration, and diversification of livelihoods as key strategies for enhancing resilience (Pradhan, 2025a). The data also shows that the annual growth rate varied and decreased from the preceding year in the years (Fig. 2) when a natural catastrophe struck (usually a major cyclonic storm: Super Cyclone in 1999-2000, Cyclone Jal in 2010-11, Cyclone Phailin in 2013-14). The year 2019-20, with an annual growth rate of - 0.64%, follows the same pattern of observations (Banerjee and Mohapatra, 2023).

In Phailin, only in the Puri and Ganjam districts, 10,937 marine fishers were affected, 3,429 fishing crafts were damaged and 8,039 fishing gears were distorted, along with a 10% drop in fish catch (ADB, Govt. of Odisha, and The World Bank, 2013), whereas due to Amphan only, Odisha marine fisheries sector sustained a loss of 10,49,57,000/- (Raju *et al.*, 2020).

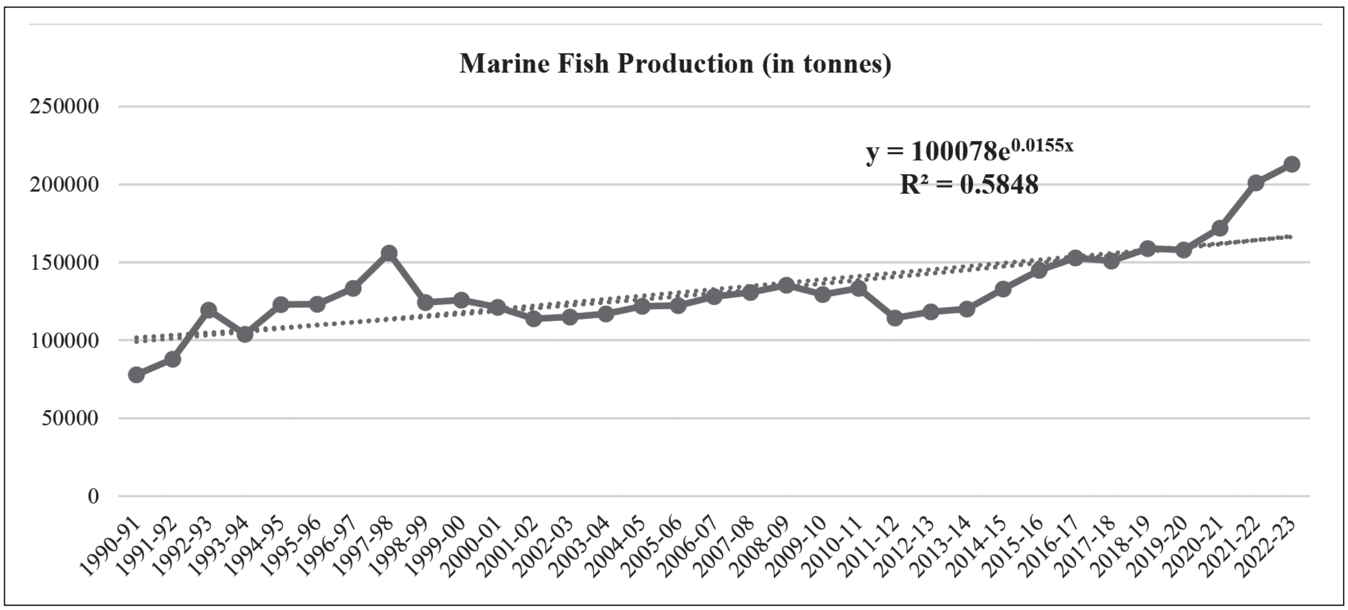


Fig. 2. *Year-wise marine fish production in Odisha (1990-1991 to 2022-2023)*

However, these ecological vulnerabilities are now compounded by external trade shocks; the recent 50% tariff imposed by the US on Indian seafood has drastically reduced exports, leading to production cuts and threatening the livelihoods of over 16 lakh workers in Odisha's seafood sector (Pradhan, 2025b).

The year-wise marine fish production in Odisha from 1990-91 to 2022-23 (Fig. 2) shows that the 1980s and 1990s saw a significant rise in mechanized vessels in Odisha (Sathiadhas, 2009). Due to diversification and an expanded region of activity, the growth rate in

1997 was 147% (Sathiadas and Salim, 2012). In India, the yearly per capita production of active fishermen decreased from 8130 kg in 1997-1998 to 4175 kg in 2003–2004, indicating a sharp fall (Sathiadhas, 2005). The multi-day trawl has the highest capture per unit of effort (CPUE), followed by the mechanized gillnetter (F&ARD Odisha, 2021), which indicates that the introduction of mechanized and motorized vessels has significantly affected the marine fisheries sector of Odisha. At the 1997 pricing level, the projected gross capital investment in fishing equipment alone came to Rs. 4,117 crores; of this, 58% was invested in the small-scale mechanized sector, 9% in deep-sea boats, 12% in the motorized sector, and 22% in the non-mechanized sector (Sathiadhas, 2006), which demonstrates unequivocally how commonplace disguised unemployment is in the mechanized fishing industry of India.

Marine fisheries in Odisha reflect a paradox of stagnation amidst growth. Despite rapid mechanization and fleet expansion, production declined due to overcapacity, overfishing nearing maximum sustainable yield, and resource stress. Rising operational costs, restrictive policies, and mechanized encroachment further deepened socioeconomic vulnerability, with fishers facing low incomes, poor health, and migration pressures. Infrastructural gaps, including inadequate harbours and unhygienic, intermediary-driven markets, compounded inefficiencies. Thus, stagnation stems primarily from ecological overexploitation, institutional shortcomings, and weak market infrastructure, highlighting the unsustainability of growth driven solely by mechanization rather than balanced resource and livelihood management (Anon., 2007). Raju *et al.* (2021) also observed disguised unemployment in the marine fisheries sector of Odisha.

Table 2. *Summary of ARIMA Model Fit*

Component	Value
ARIMA Order (p, d, q)	(0, 1, 1)
MA Coefficient (ma1)	-0.0214
Standard Error (s.e.)	0.1502
AIC	701.90
Log Likelihood	-348.95
Estimated σ^2	173,459,034
Mean Error (ME)	4,174.28
Root Mean Squared Error (RMSE)	12,969.31
Mean Absolute Error (MAE)	9,384.62
Mean Absolute Percentage Error (MAPE)	7.02%
First Autocorrelation of Residuals (ACF1)	-0.113

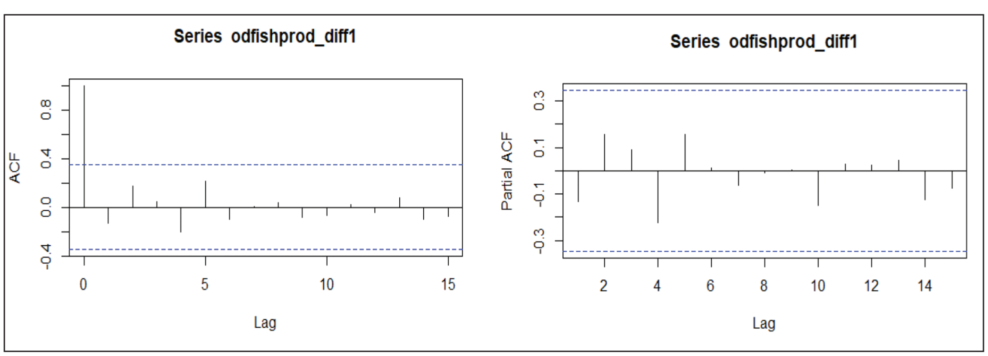


Fig. 3. *ACF, PACF from ARIMA (0, 1, 1) – Marine fish production in Odisha*

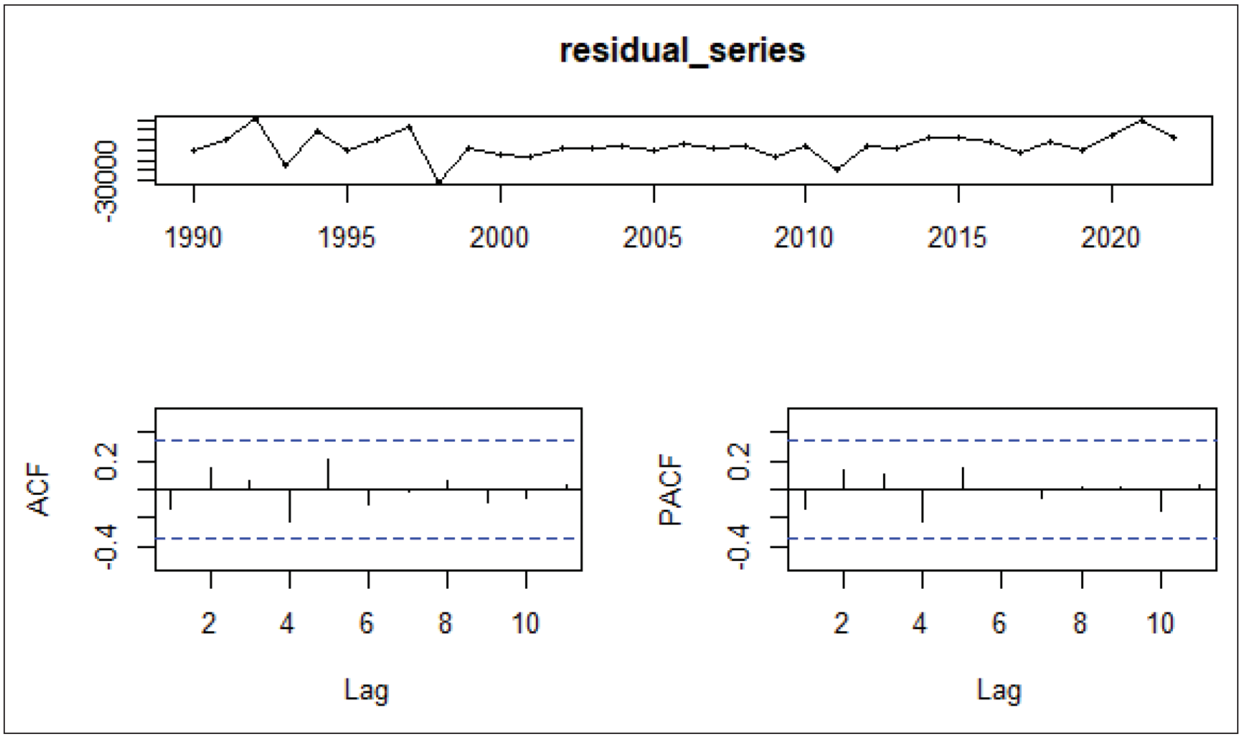


Fig. 4. *Residuals from ARIMA (0, 1, 1) – Marine fish production in Odisha*

Table 3. *Holt's linear trend model in marine fish production in Odisha*

Holt's linear trend model	Smoothing parameters		AIC
	Alpha (α)	Beta (β)	
Marine fish production in Odisha	0.7794	0.1951	567.7966

Forecasting marine fish production in Odisha using time series modelling

In the present study, ARIMA (0, 1, 1) is the model that fits marine fish production the best. Out of all the models that were tested, ARIMA (0, 1, 1) model was with the lowest AIC (Akaike Information Criterion) value of 701.9 and was chosen as the best-fit model (Aho *et al.*, 2014; Table 2), for Odisha's marine fish production during the period of 1990-1991 to 2022-2023. ACF (Autocorrelation Function) and PACF

Table 4. *Accuracy of ARIMA (0,1,0) model and Holt's linear trend model*

Year	ARIMA (0, 1, 1)			Holt's linear trend		
	Actual production (MT)	Forecasted production (MT)	Difference (%)	Actual production (MT)	Forecasted production (MT)	Difference (%)
2020-21	172000	160758.62	-6.54	172000	162615.97	-5.455833
2021-22	201000	162517.24	-19.15	201000	174954.46	-12.95798
2022-23	213000	166275.86	-21.94	213000	204239.73	-4.112804
		Average	-15.87		Average	-7.51
		Accuracy	≈ 84%		Accuracy	≈ 93%

(Partial Autocorrelation Function) are used to verify the data's stationarity (Fig. 3).

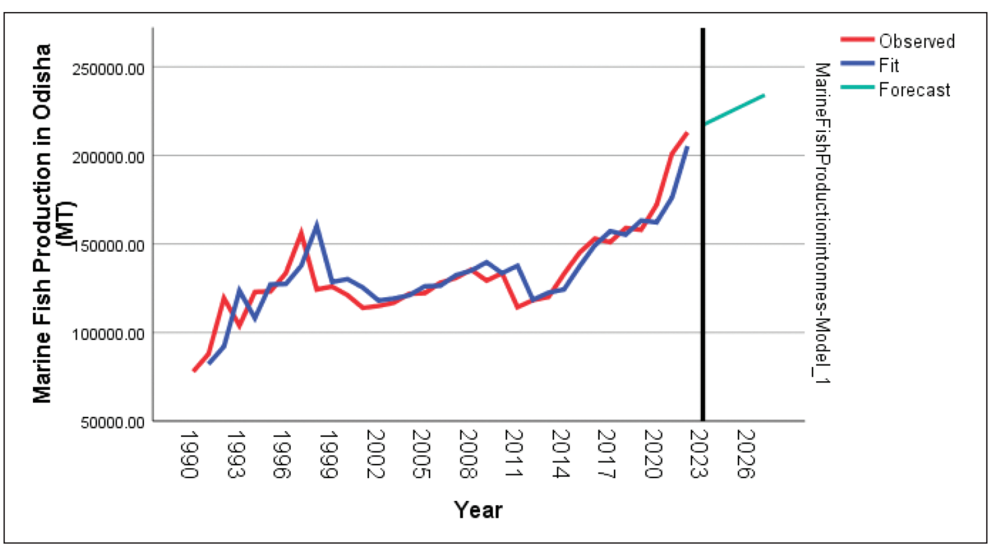
In Holt's Linear Trend model, the trend component's contribution is reflected in the Beta value, a higher Alpha value indicates that recent observations have a significant impact on the forecast (Konstantinovsky, 2024). The HLT model's AIC value of 567.7966 (Table 3) is lower than that of the ARIMA (0, 1, 1) model (701.9) (Table 2).

The accuracy of two forecasting models (Holt's Linear Trend model and the ARIMA (0, 1, 1) model) in estimating marine fish production over three years (2020-21, 2021-22, and 2022-23) in metric tons (MT) was compared and the accuracy of Holt's Linear Trend Model is higher (≈93%) than that of the ARIMA model (≈84%) when both models are evaluated using the percentage difference between actual and predicted values (Table 4).

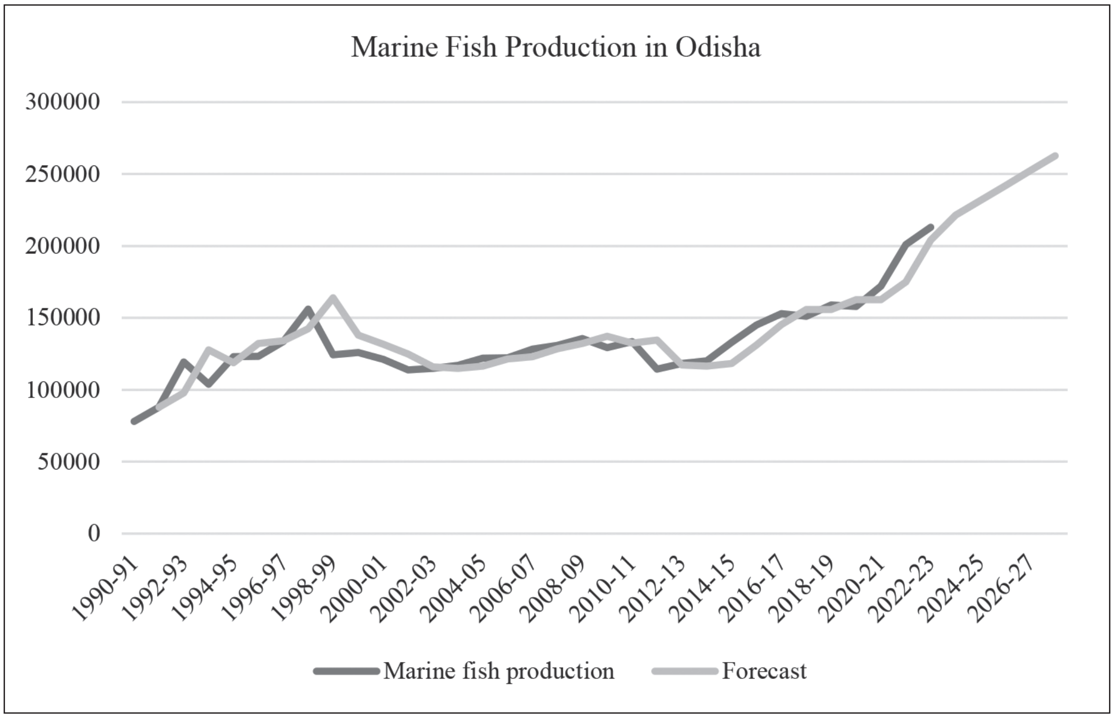
The AIC value of HLT model is also found to be lesser than the ARIMA (0, 1, 1) Model (Table 2, 3). A lower AIC value indicates a better model (Aho *et al.*, 2014; Wagenmakers *et al.*, 2004), and the HLT model is found to be more accurate in forecasting marine fish production in Odisha. Similar other studies have also reported that the HLT model was found to be

Table 5. *Forecasting of marine fish production of Odisha using ARIMA (0, 1, 1) model and Holt's linear trend model*

Year	Point forecast (In MT)	
	ARIMA (0, 1, 1)	Holt's linear trend
2023-24	217218.75	221384.95
2024-25	221437.50	231702.38
2025-26	225656.25	242019.80
2026-27	229875.00	252337.23
2027-28	234093.75	262654.66



5a. *Forecasted marine fish production of Odisha: ARIMA (0,1,0) model*



5b. *Forecasted marine fish production of Odisha: Holt's Linear Trend model*

Fig. 5. *Graphical comparison of ARIMA (0, 1, 0) model and Holt's Linear Trend model: forecast of marine fish production of Odisha*

more accurate compared to the ARIMA time series modeling (Ariffin *et al.*, 2024; Rahman and Ahmar, 2017; Rosenblad, 2021).

The forecasts for marine fish production in Odisha (in metric tons) from 2023-24 to 2027-28 (Table 5) show an increasing trend using both ARIMA (0, 1, 1) and Holt's Linear Trend models. While ARIMA (0, 1, 1) predicts a steady increase from 217,218.75 MT in 2023-24 to 234,093.75 MT in 2027-28 (Table 5, Fig. 5a); Holt's Linear Trend estimates higher values, starting at 221,384.95 MT in 2023-24 and reaching 262,654.66 MT by 2027-28 (Table 5, Fig. 5b), reflecting faster growth.

Table 6. *District-wise fish production of Odisha (2000-01 and 2020-21)*

District	2000-01 Production (MT)	2000-01 Share (%)	2020-21 Production (MT)	2020-21 Share (%)
Balasore	34,915	28.83	45,085	26.14
Bhadrak	9,350	7.72	15,583	9.04
Jagatsinghpur	33,899	28.00	43,634	25.30
Kendrapara	13,206	10.91	11,076	6.42
Puri	22,939	18.94	42,000	24.35
Ganjam	6,777	5.60	15,091	8.75
Total	121,086	100.00	172,469	100.00

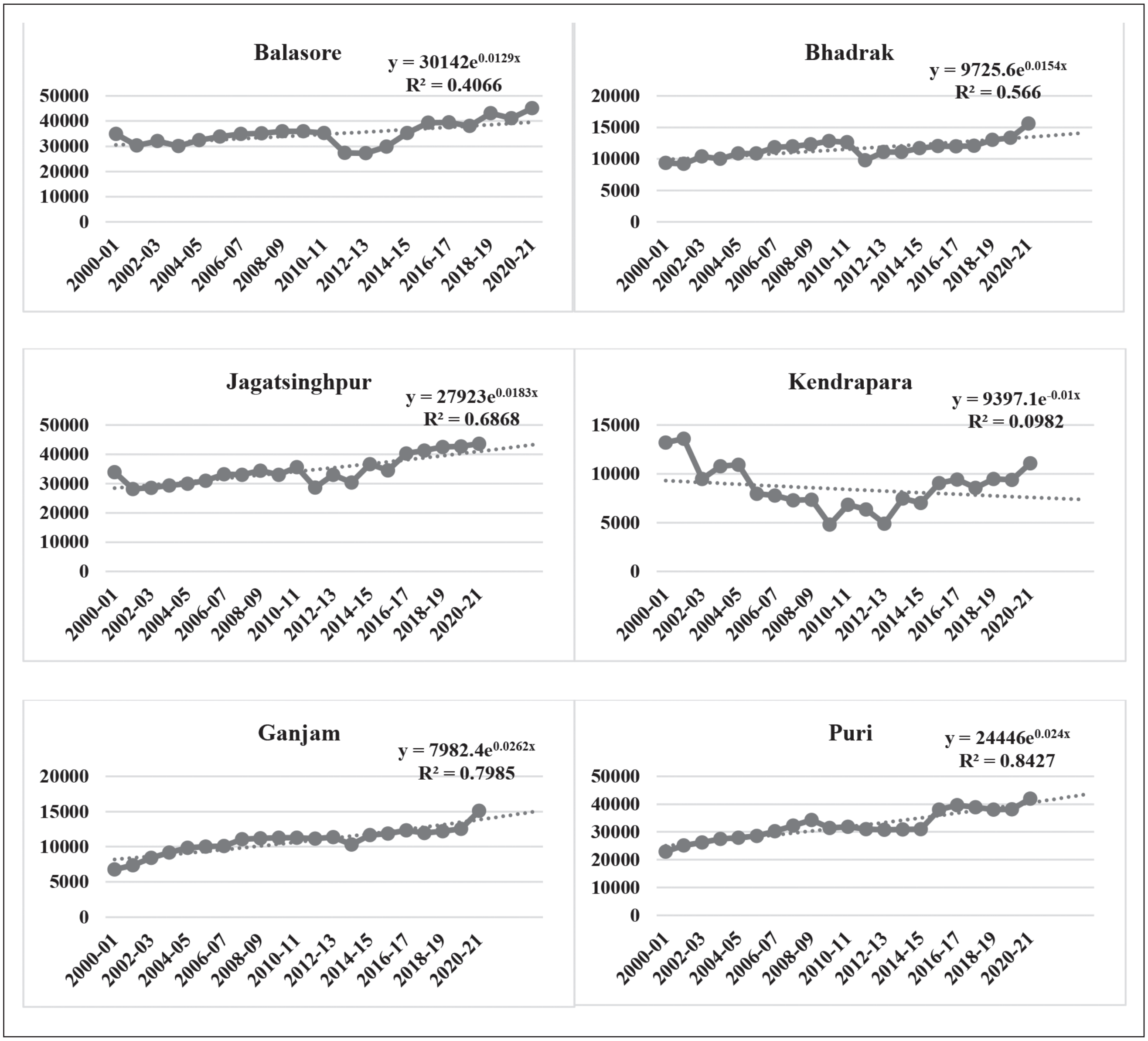


Fig. 6. *Growth trend of coastal district-wise marine fish production (2000-2001 to 2020-2021)*

Assessment of the district-wise instability of the marine fisheries sector of Odisha

The major contribution to Odisha's overall marine fish production is in Balasore, Jagatsinghpur, and Puri districts (in 2020–21, 26.14%, 25.30%, and 24.35%, respectively, *i.e.*, collectively 75.8%) (Table 6). It can be observed that during the period 2000-01 to 2020-21 (Fig. 6, Table 6), marine fish production increased district-wise, such as in Balasore (1.29 times), Bhadrak (1.67 times), Jagatsinghpur (1.29 times), Puri (1.83 times), and Ganjam (2.23 times), except in Kendrapara (0.83 times). Overall marine fish production in Odisha during this period increased 1.42 times. Fig. 6 shows a high fluctuation in production in Kendrapara district, with a very low R-value of 0.0982.

In the past twenty years, marine fish production in Odisha has steadily increased across all districts (Table 6), along with an increase in the catch per unit effort (CPUE) (F&ARD Odisha, 2024) across all the coastal districts of Odisha. Ganjam and Puri

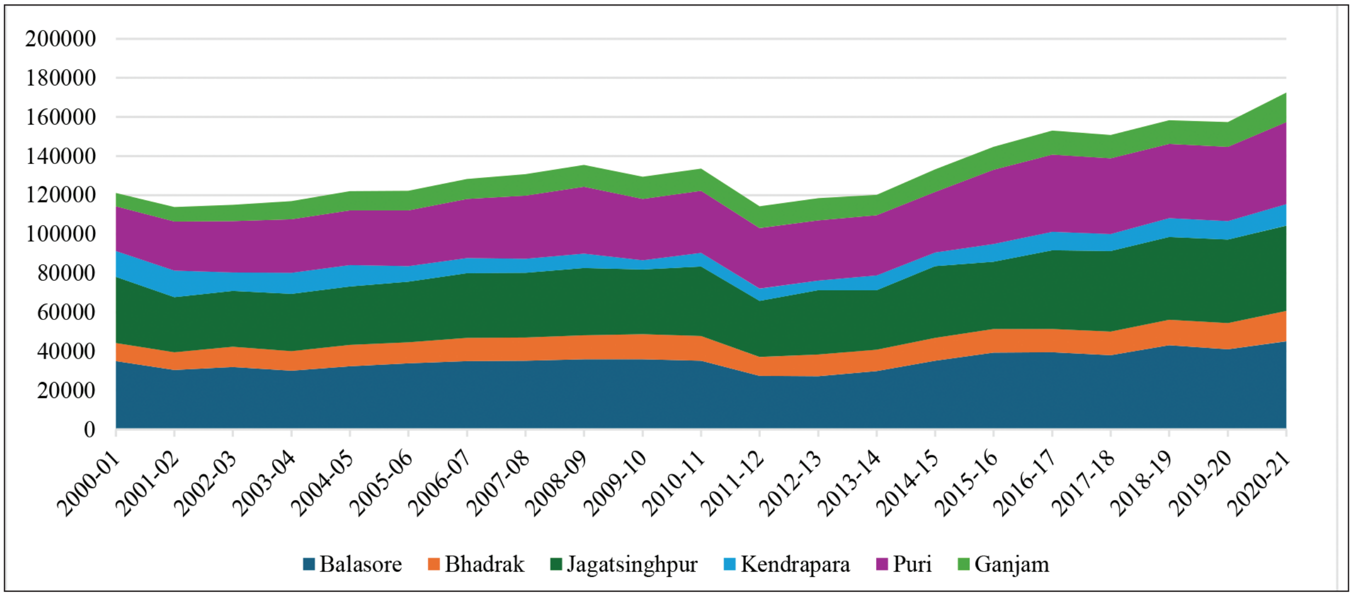


Fig. 7. *District-wise share in marine fish production of Odisha (2000-01 to 2020-21)*

Table 7. *District-wise instability of marine fish production of Odisha using C.V., CII, and CDVI measurement*

Total Period (2000-01 to 2020-21)	Balasore	Bhadrak	Jagatsinghpur	Kendrapara	Puri	Ganjam	Total
Coefficient Of Variation (C.V.)	13.40	12.52	14.08	26.27	15.73	16.71	12.46
Coppock's Instability Index	42.07	41.63	42.20	48.16	43.09	43.98	41.49
Cuddy-Delle Valle Instability Index	11.22	8.78	8.82	23.89	6.74	7.32	7.60

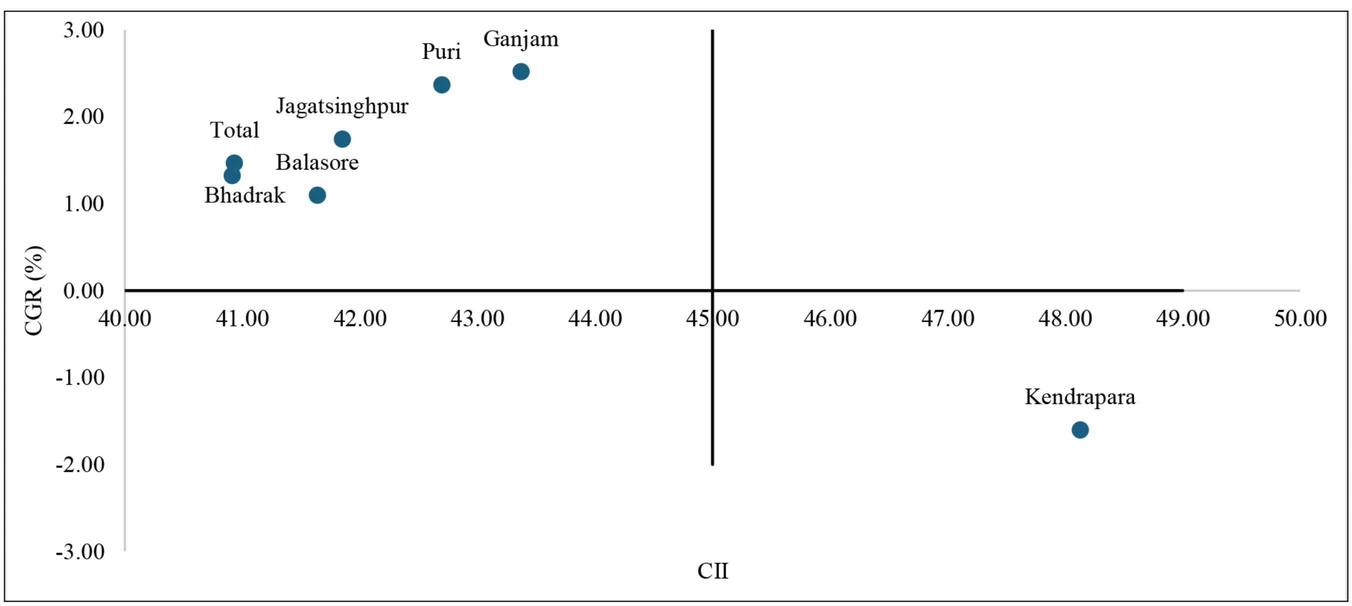


Fig. 8. *District-wise CII vs CGR (%) of Odisha (2000-01 to 2020-21)*

stand out as major contributors, evident from their substantial shares in the production graph (Table 6, Fig. 7). Balasore and Bhadrak also show moderate contributions, with production trends remaining relatively stable over time, and districts like Kendrapara and Jagatsinghpur have smaller shares, with consistent contributions that suggest little growth or decline over the years (Fig. 7, Table 6).

In the present study, it was found that there is a generally positive relationship between CII and CGR in most districts, where higher CII values tend to align with higher CGR (Fig. 8). This pattern is particularly noticeable in the cluster of points located in the top left. However, Kendrapara district is a notable exception, exhibiting a high CII (>45) alongside a negative CGR (≈ -1.5), which suggests a decline in the growth of marine fisheries despite significant instability (Fig. 8, Table 7). Among the districts, Puri and Ganjam stand out as top performers, boasting the highest CGR and relatively high CII values, and in contrast, districts such as Bhadrak, Balasore, Jagatsinghpur, and the overall state average display lower CGR values and moderate CII levels, indicating their comparatively weaker performance (Fig. 8, Table 7).

Kendrapara district shows the most significant fluctuations in marine fisheries production, as revealed by both the CDVI and CII (Table 7). The higher numerical values of these indices highlight the considerable variability in the district (Kumar *et al.*, 2017; Thomas *et al.*, 2020), with a clear trend towards medium instability levels throughout the study period.

Kendrapara district in Odisha ranks second among coastal districts in terms of exposure and sensitivity to cyclones (Bahinipati, 2014). Due to its significant vulnerability score, the district faces heightened risks from cyclones that can impact fishing activities, infrastructure, and marine fish production.

Since 2005, the Odisha government has imposed a seven-month fishing ban along the coast during the nesting and breeding season of olive ridley turtles (Panda *et al.*, 2014; Tripathy *et al.*, 2019). This measure aims to reduce turtle mortality but restricts fishing within specific radii from nesting sites, notably affecting fish production in the Gahirmatha sanctuary region of Kendrapara District (Panda *et al.*, 2014). Kendrapara District in Odisha has the highest poverty rate among coastal districts, with 52.6% of fishermen families below the poverty line (Ramesh *et al.*, 2024), which limits capacity building and investment in fishing infrastructure and technology. The district also lacks fisheries cooperatives, with only 1638 compared to other coastal areas, indicating challenges in collective resource management (CMFRI-DoF, 2020). Additionally, Kendrapara has a shortage of registered mechanized fishing vessels, with only 1027 inboard motorized vessels and 90 non-motorized vessels, considerably fewer than in other districts (CMFRI-DoF, 2020), which results in a reduced catch. In contrast, the rest of the other districts in Odisha have low CDVI scores (Table 7), indicating stable but stagnant marine fish production, consistent with the findings of the Fisheries and Animal Resources Development Department, Government of Odisha (2021), Hoda *et al.* (2021) and Nayak (2022).

CONCLUSION

Marine fish production in Odisha increased gradually over the years and recently a sharp increase in production has been observed in the state (CGR 11.28% during 2020-21 to 2022-23). Actual fish production in Odisha waters is higher than reported in the figures, evident in that while trawlers from West Bengal and Andhra Pradesh fish in Odisha, they land their catches in their home states (Bhanja *et al.*, 2023; BoBP, 1990; Raju *et al.*, 2021). In Odisha, an extensive network of intermediaries (long chain of market channels) facilitates the marketing of marine fish (Anon., 2007). These are constraints against the boom of marine fish production in the state resulting in reduced figures. Being a natural disaster-prone state, it significantly affects the marine fish production of the state as infrastructural and financial damage takes place in the districts due to disasters. Considering the stagnation observed in Odisha's marine fisheries, strengthening marine spatial planning (MSP) is essential to regulate fishing effort, protect spawning grounds, and reduce over-concentration in inshore waters, as demonstrated in other coastal contexts (Tailor *et al.*, 2021). The promotion of co-management models that bring together local fishers, cooperatives, and state agencies is equally effective to enhance compliance and reduce conflict, a strategy successfully applied in community-based coastal resource management initiatives elsewhere (IIRR, 1998). A higher fishing population compared to other states and lesser coastal length also may have contributed to depletion of marine resources along Odisha, hence lesser production may have been observed. The investment in local fish landing centers and open market spaces within Odisha shall reduce reliance on external markets, with improved cold storage and distribution facilities. The simplification of the extensive network of intermediaries and establishing direct market linkages with larger markets in the nearby states would help improve price realization by the fishers. For coastal districts of Odisha, setting up disaster-resilient infrastructure, with provision for financial support will pave the way for disaster mitigation and recovery. The forecasting analysis highlights varying degrees of production stability and growth potential across Odisha's marine districts. Ganjam and Balasore show relatively stable trends, presenting opportunities to strengthen value chain infrastructure, such as cold storage facilities and fish processing units, to reduce post-harvest losses and improve market access. In contrast, Jagatsinghpur and Kendrapara, which are more prone to cyclones and show stagnating production, would benefit from climate-resilient infrastructure, early warning systems, and the promotion of diversified, low-risk livelihoods like brackish water aquaculture or seaweed farming. The overall stagnant growth rate (CGR of 1.56%) underscores the need to shift from a volume-based approach to a value-driven model, emphasizing product quality, certification, and better market integration. Developing district-specific fisheries action plans, grounded in forecasting data and climate risk assessments, can enhance disaster resilience and long-term sustainability of the sector. Given Odisha's recurrent cyclone risks, the expansion of insurance and risk-transfer mechanisms, such as boat and gear insurance or parametric disaster insurance would help cushion losses and safeguard livelihoods, an approach that has proven effective in other parts of South Asia (BOBP-IGO, 2022). Building on this foundational analysis, future research can focus on integrating advanced forecasting techniques, such as machine learning models, to capture non-linear trends and improve accuracy. Incorporating environmental indicators like sea surface temperature, wind patterns, and cyclone frequency can enhance the predictive value of these models in a changing climate. Extending the district-level analysis to include socio-economic and fishing effort data will support more targeted and inclusive policy responses. Finally, establishing a real-time forecasting and advisory system, in collaboration with fisheries and disaster management agencies, can enable timely decision-making, reduce risks, and foster sustainable and climate-resilient marine fisheries in Odisha.

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CONFLICTS OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

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