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Structural dynamics of Sri Lankan artisanal tuna fisheries: Evidence from a 73 year time series and econometric analysis

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Abstract

This study employed advanced econometric methods to analyse 73 years (1950-2023) of catch data for skipjack (*Katsuwonus pelamis*) and yellowfin (*Thunnus albacares*) tuna from Indian Ocean Tuna Commission (IOTC) database. Bai-Perron tests identified four structural breaks at 1966, 1985, 2005 and 2014 ($p<0.01$), delineating five developmental phases. Regime switching models revealed differential volatility patterns, with skipjack showing higher volatility. Low volatility regime for skipjack showed mean returns of 0.084 (SD = 0.156, duration 8.7 years) while high volatility regime showed returns of -0.023 (SD = 0.387, duration 4.2 years). Johansen cointegration confirmed long-run equilibrium (trace=23.47, $p<0.01$) with error correction coefficient -0.31 (half-life 3.2 years). Non-linear ARIMA-GARCH models achieved 42% and 34% MAPE (Mean Absolute Percentage Error) reduction for skipjack and yellowfin respectively *versus* linear models. These findings demonstrate complex non-linear catch dynamics, providing robust frameworks for tropical tuna management under changing conditions.

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Introduction

Sri Lankan artisanal tuna fisheries represent a critical Indian Ocean component, contributing significantly to global production and local livelihoods (IOTC, 2023; Dayaratne *et al.*, 2014). The gillnet fishery targeting skipjack (*Katsuwonus pelamis*) and yellowfin (*Thunnus albacares*) evolved substantially over seven decades through technological advancement, market dynamics and environmental variability (Lehodey *et al.*, 1997; Fonteneau *et al.*, 2013). Understanding temporal dynamics is essential given increasing global pressures (Myers and Worm, 2003; Hampton *et al.*, 2005) and complex environmental-socioeconomic factors (Lehodey *et al.*, 2008).

Traditional linear models often fail to capture non-stationary nature and structural complexities in fisheries data (Stergiou *et al.*, 1997). Long term datasets present challenges including heteroscedasticity, structural breaks and regime shifts requiring advanced econometric methods (Hamilton, 1989; Bai and Perron, 1998). This study employed comprehensive analytical frameworks integrating structural break detection, non-linear modelling and forecasting to characterise temporal catch patterns, contributing to tropical tuna fisheries understanding (Pauly *et al.*, 1998). The primary challenge lies in complex, non-linear catch data spanning 73 years, exhibiting multiple structural breaks, regime shifts and heteroscedastic patterns (Hansen, 2001). Data shows discontinuities around 2014 when Indian Ocean Tuna Commission (IOTC) reporting expanded to both Western and Eastern Indian Ocean areas, requiring careful interpretation. Differential patterns between species suggest species-specific responses necessitating sophisticated approaches (Hare and Mantua, 2000; Lehodey *et al.*, 2008).

The primary objective of the study was to develop and apply advanced time series analytical methods to comprehensively characterise temporal dynamics of Sri Lankan artisanal tuna fisheries from 1950-2023. Specifically, this study aimed to identify and quantify structural breaks using econometric breakpoint detection methods (Zivot and Andrews, 1992; Bai and Perron, 2003); develop species-specific non-linear time series models accommodating heteroscedasticity and non-stationary characteristics (Bollerslev, 1986; Hamilton, 1990); quantify seasonal patterns using spectral analysis (Torrence and Compo, 1998); assess relative performance of linear *versus* non-linear modelling approaches (Teräsvirta, 1994); and develop robust forecasting models incorporating identified structural patterns (Diebold and Mariano, 1995).

Materials and methods

Data source

Annual catch data for *K. pelamis* and *T. albacares* obtained from IOTC Statistical Database (1950-2023) for Sri Lankan gillnet fisheries. Pre-2014 data covered Eastern Indian Ocean (F57) and post-2014 included Western areas (F51). Catches aggregated for 2014-2023 maintaining continuity. Box-Cox analysis indicated log transformation (λ≈0) appropriate for variance stabilisation (Box and Cox, 1964).

Catch-only data justification

This analysis relies exclusively on catch data without catch per unit effort (CPUE) or independent indices. IOTC provides longest available series (73 years) enabling long-term structural analysis impossible with shorter datasets. Historical effort data (pre-1990) are unavailable or unreliable due to inconsistent reporting (Dayaratne *et al.*, 2014). Observed patterns reflect combined influences of: (1) stock abundance changes; (2) effort dynamics; (3) technological improvements; (4) market/economic factors and (5) management interventions. Therefore, structural breaks cannot be attributed to stock dynamics alone without corroborating data. We interpret findings as characterising fishery systems integrating biological, technological, economic and social components rather than isolated stock trends. This systems-level perspective remains valuable as catch patterns directly impact communities and inform policy regardless of underlying drivers.

Structural break detection

Bai-Perron sequential procedure determined break points endogenously (Bai and Perron, 2003). Maximum breaks (*m*) = 5, minimum segment 10 years and Bayesian Information Criterion (BIC) selected break dates. Zivot-Andrews unit root test identified breaks while testing stationarity (Zivot and Andrews, 1992). Chow tests validated breakpoint significance (Chow, 1960).

Regime switching models

Markov models captured state dependent dynamics (Hamilton, 1989). For two-regime specification, the model is defined as: y_t = μ_S+φ_S·y_(t-1) + σ_S·ε_t where $S_t \in \{1,2\}$ represents unobserved regime. The optimal number of regimes was selected based on the Akaike Information Criterion (AIC), BIC and likelihood ratio tests. Model parameters were estimated using the Expectation-Maximisation (EM) algorithm (Kim and Nelson, 1999) implemented in the R package 'MSwM'. Model diagnostics included tests for normality (Jarque-Bera), autocorrelation (ACF), classification accuracy and regime persistence.

Heteroscedasticity modeling

Volatility clustering in the time series was assessed using the Autoregressive Conditional Heteroskedasticity-Lagrange Multiplier (ARCH-LM) test (Engle, 2002). To model conditional heteroscedasticity, Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models were applied following a systematic approach. First, the mean equation was specified using an AutoRegressive Integrated Moving Average (ARIMA) model selected *via* auto.arima function based on the AIC. Secondly, the presence of ARCH effects in the residuals was tested using the ARCH-LM test. Susequently, (a GARCH (1,1) model was initially fitted and higher order GARCH models were considered where necessary. Final model selection was based on AIC, BIC and diagnostic checks. The selected models were: ARIMA(2,1,1)-GARCH(1,1) for Skipjack tuna and ARIMA(1,1,2)-GARCH(1,1) for yellowfin tuna.

Cointegration analysis

Long-run equilibrium relationships were examined using the Johansen framework (Johansen, 1991). Prior to this, Augmented Dickey-Fuller (ADF) tests were conducted to confirm that the time series were integrated of order one, I(1). The optimal lag length was determined as 3 based on the AIC, BIC and Hannan-Quinn criterion. Johansen's trace and maximum eigenvalue tests were applied to identify the presence and number of cointegrating relationships. When cointegration was detected, a Vector Error Correction Model (VECM), captured both short-run dynamics and long-run equilibrium adjustments. The results were validated using the Engle-Granger two-step approach (Engle and Granger, 1987).

Model evaluation

Teräsvirta test examined non-linearity (Teräsvirta, 1994). Forecasting performance was evaluated using standard accuracy metrics, including "Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Model forecast accuracy was further compared using the Diebold-Mariano test (Diebold and Mariano, 1995). All analyses were conducted using R Software (version 4.3.1) with packages including 'strucchange', 'MSwM', 'urca', 'rugarch', 'forecast' and 'tseries'.

Results and discussion

Temporal patterns and developmental phases

Analysis identified five distinct phases in the time series (Table 1). These phases represent data-driven catch patterns rather than confirmed biological trends given the absence of fishing effort data. Initial Development (1950-1965) phase was characterised by modest catches (skipjack: 317.8 t, yellowfin: 136.5 t) with low variability (CV = 0.24), consistent with traditional small-scale fisheries though potentially reflecting incomplete reporting. The Expansion Phase (1966-1985) demonstrated a dramatic increase in catches with an average annual growth rate of 12.4%. However, in the absence of effort data, it is not possible to elucidate whether growth reflects increase in stock abundance, fleet expansion, or improved catchability. The concurrent rise in both species suggests the

Table 1. Descriptive statistics and structural break analysis across developmental phases

Period	Years	Skipjack			Yellowfin			Chow F
		Mean (t)	CV	Growth (%)	Mean (t)	CV	Growth (%)	
Initial development	1950-1965	317.8	0.24	-2.1	136.5	0.24	-2.1	-
Expansion phase	1966-1985	3,847.2	0.43	12.4	1,719.8	0.43	12.4	18.7***
Peak production	1986-2005	8,562.1	0.28	3.8	3,686.4	0.28	3.8	12.3***
Decline period	2006-2013	9,471.3	0.23	-4.2	4,076.5	0.23	-4.2	8.9**
Spatial expansion	2014-2023	19,784.8	0.40	5.1	3,321.4	0.86	-2.3	15.4***

CV = Coefficient of variation; *** $p<0.01$, ** $p<0.05$

influence of common drivers including both biological and fishing related factors. During the Peak Production (1986-2005) phase, catches remained consistently high, potentially indicating stock maturation or alternatively saturation of fleet capacity. Decline Period (2006-2013) showed a negative growth rate (-4.2%), suggesting either stock limitations or reduced fishing effort due to economic factors or security related concerns. Finally the Spatial Expansion phase (2014-2023) appears to be primarily driven by changes in data coverage (*e.g.* inclusion of Western fishing areas) rather than biological expansion, although species specific differences in spatial response were evident.

Structural break analysis

Structural break analysis using the Bai-Perron method identified four significant breakpoints in the time series at 1966, 1985, 2005 and 2014 (all $p<0.01$) (Table 2). Sequential F-statistics exceeded the corresponding critical values and the BIC supported a model with 4 breaks over alternative specifications. The breakpoints in 2014 clearly reflects a methodological change (*e.g.*, expanded spatial coverage) rather than a biological shift. The Zivot-Andrews test further identified 2005 as the most significant structural break with test statistics of -5.84 and -5.62 ($p<0.01$). Augmented Dickey–Fuller (ADF) tests confirmed that both series are non-stationary in levels but achieved stationarity after first differencing (ADF: -7.82 and -7.54, $p<0.01$), thereby validating their integration of order one, I (1).

Regime switching models

Two-regime Markov-switching models were identified as optimal for both species (Table 3) . Skipjack tuna exhibited higher volatility than yellowfin. For skipjack, low volatility regime was characterised by $\mu_1 = 0.084$ and $\sigma_1 = 0.156$, with an average duration of 8.7 years; whereas the high volatility regime showed, $\mu_2 = -0.023$ and $\sigma_2 = 0.387$, with a shorter duration of 4.2 years. Yellowfin tuna showed more stable dynamics, with a classification accuracy of 91.7%, compared to 89.2% for skipjack. High regime persistence ($p>0.73$) for both species indicates that once a regime is entered, it tends to persist for an extended period. The negative mean returns observed during high volatility regimes suggest an association with periods of declining catches, however, the underlying drivers remain ambiguous in the absence of fishing effort data. Residual diagnostics confirmed good model fit and adequacy, with no evidence of non-normality (Jarque-Bera, $p>0.05$), or autocorrelation (Ljung-Box, $p>0.05$).

Table 2. Results of structural break tests and integration order of variables

Test	Skipjack	Yellowfin
Bai-Perron breaks	1966, 1985, 2005, 2014	1966, 1985, 2005, 2014
F(1 *vs* 0)	42.7***	38.4***
F(4 *vs* 3)	12.5***	11.9***
BIC optimal	4	4
Zivot-Andrews break	2005	2005
Test statistic	-5.84***	-5.62***
ADF (first difference)	-7.82***	-7.54***

*** $p<0.01$

Cointegration analysis

Strong evidence of a long-run equilibrium relationship between the two species was observed. Strong evidence of a long-run equilibrium relationship between the two species was observed (trace statistic = 23.47, $p<0.01$; Table 4). This finding was further supported by the Engle-Granger test (ADF=-4.23, $p<0.01$). The estimated Error correction coefficient (α=-0.31; SE = 0.087, t = -3.56, $p<0.01$) indicates that approximately 31% of deviations from long-run equilibrium are corrected annually, corresponding to a half-life of about 3.2 years. These results suggest the presence of system-level linkages between the species rather than direct biological interactions, particularly in the absence of effort data. Potential shared drivers amy include environmental variability, correlated fishing effort, technological changes, or synchronised management practices. Diagnostic tests of the Vector Error Correction Model

Table 3. Estimated parameters and diagnostics of regime switching models

Parameter	Skipjack	Yellowfin
Model selection		
AIC (2 regimes)	128.3	121.9
BIC (2 regimes)	142.7	136.4
Low volatility regime		
Mean return (μ_1)	0.084	0.076
Std. deviation (σ_1)	0.156	0.142
Duration (years)	8.7	9.1
High volatility regime		
Mean return (μ_2)	-0.023	-0.031
Std. deviation (σ_2)	0.387	0.421
Duration (years)	4.2	3.8
Diagnostics		
Classification accuracy	89.2%	91.7%
Jarque-Bera	2.84	2.12

Table 4. Cointegration analysis results

Test/Parameter	Results
Johansen trace (r = 0)	23.47***
Johansen max eigen value	18.64***
Engle-Granger ADF	-4.23***
Error correction (α)	-0.31***
Half-life (years)	3.2
VECM lag order	3
Portmanteau Q (20)	42.8 (p=0.31)

*** p<0.01

(VECM) confirmed model adequacy, with no evidence of non-normality (p = 0.37), or autocorrelation (p = 0.31), and stable eigenvalues, indicating system stability.

Heteroscedasticity and model performance

The ARCH-LM strongly rejected the null hypothesis of homoscedasticity (F=8.94, 8.72, p<0.001), indicating the presence of conditional heteroscedasticity. The Ljung-Box test further confirmed volatility clustering in the residuals (Q_{10} = 28.3, 26.7, p<0.01). High GARCH persistence values were observed for both species (skipjack: 0.89, yellowfin: 0.84), suggesting prolonged volatility effects. The Teräsvirta test decisively rejected linearity (F=12.7, 11.4, p<0.001), validating the use of non-linear modeling approaches. Incorporating ARIMA-GARCH models resulted in improved forecasting performance, reducing Mean Absolute Percentage Error (MAPE) by 42% for skipjack tuna and 34% for yellowfin, compared to linear ARIMA models (Table 5). Cross-validation results also indicated strong predictive performance (R^2=0.78 and 0.76 respectively). Diebold-Mariano test confirmed that these improvements were significant (p<0.001). Post-estimation diagnostics showed no remaining ARCH effects, autocorrelation, or normality violations, confirming the adequacy of the final models.

Species specific patterns

The observed differences between species suggest contrasting ecological and fishery dynamics, although alternative explanations cannot be ruled out. Skipjack tuna demonstrated rapid growth followed by sharp declines, which may reflect r-selected life history characteristics or alternatively reflecting fleet expansion-contraction cycles. In contrast, yellowfin tuna exhibited more gradual trends possibly indicating K-selected characteristics or differing market-driven dynamics. The spatial expansion observed after 2014 suggests that skipjack has a wider distribution extending into western waters, while yellowfin appears more concentrates in the eastern coastal regions. The higher volatility of skipjack suggests greater vulnerability to environmental and economic fluctuations, supporting the need for adaptive management approaches. However, the underlying drivers of these regime shifts (biological, fishing related or environmental) remain uncertain due to the lack of effort data. The presence of cointegration between the species highlights system-level interactions, emphasising the importance of integrated management approaches. The relatively slow error correction process (half-life of 3.2 years) indicates that the effects of management interventions may persist over extended periods, underscoring the need for consistent and stable policy frameworks.

Table 5. Out-of-sample forecasting performance of competing models

Model	Skipjack		Yellowfin	
	MAPE (%)	RMSE	MAPE (%)	RMSE
ARIMA	24.8	1847	28.2	1236
ARIMA-GARCH	14.4	1124	18.6	892
Cross-validation R^2	0.78	-	0.76	-
Diebold-Mariano	-4.23***	-	-3.89***	-

*** p<0.001

Study limitations and future directions

A primary limitation of this study is the absence of fishing effort data, which restricts the ability to directly infer stock abundance. Consequently, the observed patterns likely reflect a combination of biological, technological, economic, and social drivers, rather than purely ecological processes. Future research priorities include the development of standardised CPUE indices for recent decades; the integration of key environmental variables such as sea surface temperature (SST), chlorophyll-a, and Indian Ocean Dipole (IOD) indices; the compilation of spatially consistent historical datasets; the application of multivariate models that incorporate ecosystem-level components and the integration of climate projections to support long-term fisheries management and planning.

Management implications

The findings suggest that fisheries management should adopt regime-dependent reference points, with precautionary approaches during high volatility periods. However in the absence of effort data, it is not possible to determine whether such volatility reflects biological stress, changes in fishing practices or other external drivers. Therefore, management decisions should be supported by complementary data sources and monitoring frameworks The estimated adjustment half-life of approximately 3.2 years, indicates that management interventions may have persistent effects, highlighting the importance of consistency and long-term planning. For skipjack tuna, higher volatility and rapid regime transitions suggest the need for frequent monitoring and adaptive management strategies. In contrast, the relatively stable dynamics of yellowfin tuna may permit longer planning horizons while maintaining vigilance. CPUE standardisation is essential for both fisheries to better distinguish between changes in stock abundance and variations in catchability, thereby supporting more accurate stock assessments and effective management decisions.

This analysis demonstrates that Sri Lankan tuna fisheries exhibit complex, non-linear dynamics that require sophisticated analytical approaches beyond traditional methods. Although the absence of fishing effort data limits direct inference of stock abundance, the study successfully characterised system-level dynamics with important management implications. Five developmental phases (1950-1965; 1966-1985; 1986-2005; 2006-2013 and 2014-2023) provide a data-driven framework for understanding the temporal evolution of the fishery, although the underlying transition require further investigations. Regime-switching models revealed clear species-specific differences in catch volatility, while strong cointegration indicates long-run linkages between species, supporting the need for integrated management approaches that consider system-level interactions. The application of non-linear models improved forecasting accuracy, by 35-42%, demonstrating their practical value for fisheries planning and decision-making. Moreover, the methodological framework developed in this study offers a useful template for analysing other tropical tuna fisheries facing similar data challenges. In the context of increasing pressures from climate change, overfishing, and economic development pressures, the adoption of advanced analytical tools become increasingly essential for ensuring sustainable fisheries management and safeguarding the livelihoods as well as food security of coastal communities dependent on tuna resources.

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