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Research Article:

Price Behaviour of Selected Marine Fish Species in Colombo Market, Sri Lanka

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Abstract

In Sri Lanka, fish provide about 50% of the animal protein consumed, which is nearly three times the global average. The country's fisheries, including marine, inland, and aquaculture sectors, play an important role in food security and livelihoods. However, significant price fluctuations have impacted stakeholders such as fishers, traders, and consumers. This study analyses price trends and seasonal patterns of six selected fish species (large pelagic and small pelagic) consumed by Sri Lankans, which are commonly available in the Colombo market. Monthly retail prices from January 2014 to December 2025, obtained from the Hector Kobbekaduwa Agrarian Research and Training Institute, were used to develop forecasting models for better market insights. Real market prices were derived using the Colombo Consumer Price Index (CCPI), and time series techniques, including the Augmented Dickey-Fuller (ADF) test, Zivot–Andrews structural break test, Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving Average (SARIMA) models, were applied for analysis and forecasting. The results reveal a significant upward trend in nominal fish prices, while real prices remain relatively stable over time, indicating that inflation is the primary driver of observed price increases. A structural break was identified around 2020–2021, reflecting the impact of the COVID-19 pandemic and subsequent economic crisis in Sri Lanka. Seasonal price index values indicate variations in the monthly average real prices of different fish species. Model comparison results indicate that SARIMA models generally provide improved fit and forecasting performance for most fish species, particularly those exhibiting strong seasonal patterns, as evidenced by lower Akaike information criterion corrected (AICc) and Mean Absolute Percentage Error (MAPE) values. The residual analyses confirmed that most models adequately captured the data for forecasting purposes. The study highlights the significant roles of inflation, seasonality, and macroeconomic shocks in shaping fish price dynamics in Sri Lanka, emphasising the need for continuous market monitoring, price stabilisation mechanisms, and improved forecasting systems to support policy formulation, enhance affordability, and strengthen value chain efficiency in the fisheries sector.

Keywords: Marine fish; Price forecasting models; Real market price; Seasonality

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1. Introduction

Sri Lanka is endowed with vast ocean resources, both biological and non-biological, and has the opportunity to fully utilise them due to its location surrounded by the sea. Sri Lanka's economy depends on the marine fisheries sector, which drives export earnings, creates employment, and contributes to food security. Fish accounts for approximately fifty per cent of the animal protein consumed, which is three times the global average (World Bank, 2021). According to the Ministry of Fisheries, Aquatic and Ocean Resources progress report (2024), the fisheries sector in Sri Lanka employed over 2.7 million people in 2024, per capita fish consumption increased by 7.4% in 2024, and export earnings reached Rs. 86,241 million, and the government significantly increased capital allocation in the 2025 budget to strengthen the industry. The progress report of the Ministry of Fisheries, Aquatic and Ocean Resources indicates that a total fish harvest of 237,395 MT was recorded from the marine fishing sector for the period from January to September 2025. During the same period, per capita fish consumption was estimated at 34.03 grams per day.

Several socioeconomic and environmental aspects influence the price behaviour of marine fish in the Colombo market. The monsoon climate patterns in Sri Lanka significantly impact coastal fishing, necessitating seasonal migration between the main fishing grounds. Small-scale fishers make up most of the industry, with a few major commercial operators with state-of-the-art facilities (Perera et al., 2016). During monsoon seasons, unfavourable weather conditions make fishing challenging, thereby lowering supply and raising selling prices. Price-stabilisation mechanisms are essential to ensure affordability and maintain stable industry performance, as they help reduce the impact of seasonal price fluctuations. This is supported by a study conducted in Sri Lanka on dried fish varieties, which found clear seasonal price changes (Wickrama et al., 2021). Fish availability is significantly affected by seasonal fluctuations; during favourable seasons, higher catches lead to oversupply, lowering prices. Fish stocks may vary due to environmental anomalies, such as changes in sea temperature, which can affect prices (Rahim et al., 2022). Disruptions to the supply chain and the dynamics of the wholesale and retail markets are closely linked, and changes in wholesale market prices directly affect retail prices, indicating the degree of market integration. Fish supplies to markets such as Paliyagoda were restricted due to fuel shortages. As a result, wholesale prices for some species, such as Salaya, increased from LKR 230 to LKR 360 per kilogram (Central Bank of Sri Lanka [CBSL], 2022). The industry is dominated by cost-plus and competitive pricing strategies, which are influenced by the structure of the fish supply chain. The informal nature of pricing mechanisms is highlighted by the frequent dissemination of price information through intra-regional networks and personal contacts (Wickrama et al., 2023).

Climate change and related temperature shifts have affected fish populations, altering their distributions and catch rates. Migration of species is influenced by rising sea temperatures, which in turn affect market supply as well as availability (Dahms & Killen, 2023). Because shifting migration patterns are closely associated with changes in supply, climate change has become a significant factor in determining fish prices. Furthermore, marine fish mortality has been linked to harmful algal blooms (HABs), which disrupt the supply chain and increase price volatility (Oh et al., 2023). In addition to weather and climate changes, other factors that significantly impact fish prices include supply, the lack of long-term sales channels, consumer demand, market distance, fish quality, species, and size (Perera et al., 2016). Consumer demand, which is influenced by dietary preferences, income levels, and knowledge of fish's health benefits, has also been identified as a significant factor in determining fish prices. According to Hasan et al. (2023), there is a growing demand for fish which may influence market dynamics due to increased interest in sustainable aquaculture measures. Furthermore, macroeconomic factors such as inflation, trade policies, and fuel prices exacerbate price volatility. Market outcomes are further shaped by governance and institutional arrangements; small-scale fisheries operations are affected by cultural norms, regulatory frameworks, and private-sector involvement (Steenbergen et al., 2019). The COVID-19 pandemic had a significant impact on Sri Lanka's marine fisheries industry, with exports falling by 26% in 2020 and fish catches dropping by up to 20% (World Bank, 2021). While decreased demand from the food service industry led to price drops of 12.65% to 14.64% in Tokyo markets (Abe et al., 2022), disruptions like the temporary closure of the Paliyagoda fish market changed consumer behaviour and domestic price patterns (Amaralal et al., 2023).

Forecasting agricultural prices is considered essential for maintaining market stability and guaranteeing food security. It provides stakeholders with information that makes it possible to minimise possible risks, allocate resources effectively, and optimise planting choices. However, predicting prices during food safety incidents poses special difficulties because unforeseen disruptions can have a significant impact on consumer behaviour and market dynamics (Jin et al., 2024). In recent years, significant fluctuations in wholesale and retail fish prices have highlighted the importance of modelling price dynamics to understand historical movements and predict future trends.

A range of univariate forecasting methods, including Autoregressive Integrated Moving Average (ARIMA), exponential smoothing techniques, and machine learning approaches such as neural networks, are commonly applied in time series analysis depending on data characteristics such as trend, seasonality, and autocorrelation (Miller & Kim, 2021). In addition, both Seasonal Autoregressive Integrated Moving Average (SARIMA) and classical linear regression approaches such as Ordinary Least Squares (OLS) have been widely used in forecasting applications. Empirical evidence from Sri Lanka and other countries suggests that traditional linear models such as ARIMA and SARIMA perform well in contexts where the data exhibit linear patterns and seasonal stationarity, including applications in GDP growth, agricultural prices, and financial time series (Tampouris & Dritsaki, 2026; Perera et al., 2016; Wickrama et al., 2021; Miller & Kim, 2021). However, when structural breaks, business cycle fluctuations, or regime-dependent volatility are present, non-linear regime-switching models, such as Markov-switching models and threshold autoregressive models, have been found to perform better than simple linear models (Garcia, 1998; Hamilton, 1989).

Supporting this, Perera et al. (2016) studied the price behaviour of important marine fish species in the Colombo fish market, while Floros & Failler (2006) used SARIMA models to predict monthly fisheries prices in the United Kingdom. Real prices remained relatively stable, with seasonal peaks in the middle months, despite nominal prices rising over time, according to their analysis. It was discovered that higher-order SARIMA models could accurately forecast and capture the dynamic behaviours of actual fish prices. Econometric models like ARCH and GARCH have also been used to address price volatility (Odah, 2025). Significant fluctuations in Sri Lankan seafood prices were noted by Gunawardena et al. (2023), underscoring the need for accurate forecasting to mitigate negative effects on producers and consumers. Research on dynamic price analysis and forecasting in the local context is still limited, even though many studies have examined the economic, marketing, and policy aspects of the marine and ornamental fisheries sectors (Priyashadi et al., 2024; Herath & Radampola, 2016; Wickrama et al., 2021; Perera et al., 2016). Since there are not many updated studies in the last ten years, current data must be used to improve existing models. Thus, the objective of this study is to analyse price trends of selected fish species in the Colombo market, examine their seasonal patterns, and develop reliable forecasting models to support market planning and decision-making.

2. Methodology and Data

2.1. Data and Fish Type Selection

Six different fish species were used in the analysis, including the most popular large pelagic species, such as *Katsuwonus pelamis* (also known as "Balaya" or "Skipjack tuna), *Istiophorus platypterus* (also known as "Thalapath" or "Sailfish"), *Thunnus albacares* (also known as "Kelawalla" or "Yellowfin tuna), and *Scomberomorus commerson* (also known as "Thora"). *Sardinella gibbosa* [‘Salaya’ (sardine)] and *Amblygaster sirm* [‘Hurulla’ (trenched sardinella)] are two of the small pelagics. For this study, the average monthly retail prices of fish in Colombo, as reported by the Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI), were used from January 2014 to December 2025.

2.2. Analytical procedure

2.2.1. Nominal Price Calculation

The nominal market prices (NMP) of fish were converted into real market prices (RMP) to avoid inflation in the analysis. For this, the price deflator of the Colombo Consumer Price Index (CCPI) in the food and non-alcoholic beverages group was used. The CCPI is a socioeconomic indicator constructed to measure changes over time in the general level of prices of consumer goods and services that a representative group of households pays. The CCPI is compiled and published by the Department of Census and Statistics of Sri Lanka and is considered the official indicator of changes in the country's consumer price level. It measures the change over time in the cost of a fixed basket of goods and services commonly purchased by most households.

For this analysis, the CCPI of 2013 and 2021 were considered. Since the CCPI was constructed using two different base years, a conversion was required to ensure consistency and comparability of the data. Accordingly, the CCPI series based on the 2013 base year was converted into the 2021 base year using a conversion factor (γ) calculated using a set of CCPIs computed using both base years. It can be shown as depicted in equation (1) below (Perera et al., 2016).

$$\gamma = \frac{1}{n}\sum_{j=1}^{n}\frac{\mathrm{CCPI}_{j,2013=100}}{\mathrm{CCPI}_{j,2021=100}} \qquad (1)$$

RMP is calculated as given in the following equation (2).

$$\mathrm{RMP} = \frac{\mathrm{NMP}}{CCPI_{2021=100}} \times 100 \qquad (2)$$

Descriptive statistics were computed for both NMP and RMPs to provide an initial understanding of the data. The measures of central tendency and dispersion were calculated, and the NMP and RMPs were plotted over time. Moving averages were also used to smooth the time series and identify underlying trends in both RMP and NMP.

2.2.2. Seasonal Price Index Calculation

To analyse seasonal fluctuations in fish prices, the Seasonal Price Index (SP Index) was calculated for each month from 2014 to 2025 using the following equation (3).

$$SP\ Index_m = \frac{Mean\ Price\ for\ Month\ m}{Overall\ Mean\ Price} \times 100 \qquad (3)$$

2.2.3. Stationarity Tests (ADF and KPSS)

The Zivot-Andrews test was applied to the RMP dataset in order to detect the presence of an endogenous structural break in the series (Zivot & Andrews, 1992). Based on the identified break-point, the dataset was subsequently divided into pre-break and post-break periods. Stationarity of each sub-sample was examined separately.

To ensure the validity of time series models, the stationarity of the RMP data across different fish species was tested using the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The ADF test was used to examine the null hypothesis of a unit root (H_0: non-stationarity), indicating non-stationarity, whereas the KPSS test evaluated the null hypothesis of stationarity around a deterministic trend (H_0: stationarity). Where non-stationarity was detected, first-order differencing was applied to the series to achieve stationarity. These procedures ensured that all-time series met the assumptions required for ARIMA and SARIMA modelling.

2.2.4. Time Series Modelling and Forecasting

For forecasting fish prices, several time-series models were considered, including ARIMA and SARIMA models. The 'auto.arima()' function was applied to automatically select the best ARIMA and SARIMA models based on their Akaike information criterion corrected (AICc) values. Model fitting was carried out using the 'forecast' package, by which Maximum Likelihood Estimates of the model parameters can be obtained. Outliers in the time series data were identified and removed using the 'tsclean' function in R software, and Seasonal and Trend decomposition using LOESS (STL) was applied to decompose the time series data into seasonal, trend, and remainder components. The ARIMA model was fitted without seasonal components, whereas the SARIMA model included seasonal adjustments, with a cycle of 12 months. Each model was evaluated based on the AICc, a measure of model fit that penalises models with more parameters. Additionally, the Mean Absolute Percentage Error (MAPE) was calculated to assess each model's forecasting accuracy. The best model for each fish species was selected based on the lowest AICc value and the best forecast accuracy (Hyndman et al., 2018).

Diagnostic checks of the selected models were completed through residual plots, normal probability plots of residuals, ACF and PACF plots (autocorrelation and partial autocorrelation functions) of residuals and squared residuals, and the Ljung-Box test (Ljung & Box, 1978) to assess serial dependence. Forecasting accuracy was evaluated using the Mean Absolute Percentage Error (MAPE), which compares predicted and actual values to assess predictive performance. All statistical analyses and modelling procedures were conducted using the R programming language.

3. Results and Discussion

3.1. Descriptive Statistics of Fish Prices

The analysis of nominal and real fish prices from 2014 to 2025 reveals key variations across different fish species. Table 1 presents the descriptive statistics for nominal fish prices (NMP), while Table 2 presents the real prices (RMP), adjusted for inflation. Converting nominal prices to real prices allows for a clearer understanding of actual price behaviour over time, eliminating the effects of inflationary fluctuations (Fackler & Goodwin, 2001). The analysis of NMP shows significant variability, with higher mean values for high-value species such as Thora (LKR 1,995.32) and Thalapath (LKR 1,410.77), while lower values for Salaya (LKR 341.35) and Hurulla (LKR 606.34). The standard deviation values indicate substantial price dispersion, particularly for Thora (LKR 815.82) and Kelawalla (LKR 630.21), suggesting high price volatility. The skewness values for all fish species are positive, ranging from 0.75 to 1.29, indicating a right skew, with extremely high prices more frequent than low ones. The kurtosis values suggest that the distributions of most fish prices are light-tailed, indicating relatively fewer extreme price variations across the series.

Table 1. Descriptive Statistics of the Nominal Prices of Fish (LKR/kg)

Fish Type	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Salaya	341.35	283.45	192.30	122.07	878.67	1.03	0.01
Hurulla	606.34	525.18	285.72	245.61	1,403.41	0.79	-0.57
Balaya	801.47	671.13	370.69	327.71	1,801.47	0.89	-0.24
Kelawalla	1,304.19	1,019.92	630.21	617.78	2,679.33	0.75	-1.02
Thora	1,995.32	1,641.42	815.82	1,025.02	4,142.63	0.84	-0.76
Thalapath	1,410.77	1,183.86	563.20	797.44	3,083.68	1.29	0.71

Source: Authors' calculations based on monthly fish price series obtained from HARTI (2014–2025).

The descriptive statistics for RMP show lower mean values across all fish species compared to nominal prices. This adjustment accounts for inflationary effects, providing a clearer picture of price trends. Thora continues to exhibit the highest RMP (LKR 1,792.92), whereas Salaya remains the lowest (LKR 287.41). Standard deviations of RMPs are significantly lower compared to nominal prices, suggesting that inflation-adjusted price fluctuations are more stable over time.

Skewness values in real prices are relatively low, indicating a near symmetrical distribution for most fish species, with Balaya (0.04) and Kelawalla (0.15) showing balanced distributions, while Thora (-0.40) and Thalapath (-0.46) exhibit slight negative skewness. The kurtosis values remain negative across all fish species, further confirming a flatter distribution compared to the normal distribution.

Table 2. Descriptive Statistics of the Real Prices of Fish (LKR/kg)

Fish Type	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Salaya	287.41	279.45	65.11	172.24	462.75	0.54	-0.32
Hurulla	530.46	523.68	117.61	270.07	796.76	0.23	-0.72
Balaya	708.78	715.40	168.17	361.50	1,093.66	0.04	-0.49
Kelawalla	1,123.89	1,119.27	182.01	748.02	1,622.15	0.15	-0.20
Thora	1,792.92	1,902.03	365.12	1,068.90	2,377.21	-0.40	-1.20
Thalapath	1,294.37	1,361.25	318.24	641.20	1,949.69	-0.46	-0.95

Source: Authors' calculations based on HARTI data (2014–2025), converted to real prices.

3.2 Time Series Plots of Fish Prices

Time series plots of the real and nominal prices for Salaya, Hurulla, Balaya, Kelawalla, Thora and Thalapath are presented in Figures 1-6. The NMP represents actual market prices over time, while the RMP has been adjusted for inflation using the 2021 base-year CCPI. The prices of fish species like Salaya, Hurulla, Balaya, Kelawalla, Thora and Thalapath show distinct trends, with nominal prices remaining relatively stable or growing gradually until late 2021, then exploding upward with high volatility and multiple sharp peaks from 2022 onward, while RMPs, adjusted for inflation, remained relatively stable with a mild downward tendency in most cases after 2022.

Inflation, supply chain disruptions, fuel price increases, and rising operational costs have contributed to the observed price changes, together with seasonal fluctuations and shifting consumer demand. Periodic price spikes are associated with reduced fish stocks, export demand, and adverse weather conditions, while a notable surge in nominal prices after 2020 is linked to the COVID-19 pandemic and the 2022 economic crisis in Sri Lanka (Food and Agriculture Organization of the United Nations, 2022; CBSL, 2023). The relative stability of RMPs indicates that inflation plays a dominant role in driving nominal price increases, suggesting that external macroeconomic pressures, rather than intrinsic changes in fish value, largely determine price movements (White et al., 2020). Inflation, measured by the Consumer Price Index, reflects changes in the cost of a representative basket of goods and services, thereby influencing consumer purchasing power. In Sri Lanka, inflation showed notable fluctuations, increasing from 3.2% in 2014 to 7.7% in 2017, then declining to 2.1% in 2018, and sharply rising to 49.7% in 2022 before moderating to 16.5% in 2023 (World Bank, 2024), underscoring its significant impact on price dynamics. Overall, the time-series plots in Figures 1 to 6 revealed that the marked rise in nominal prices of Salaya, Hurulla, Balaya, Kelawalla, Thora, and Thalapath from 2022 onwards was predominantly driven by macroeconomic factors, while real prices remained relatively stable. This divergence was mainly attributed to high inflation and fuel shortages during Sri Lanka's 2022 economic crisis.

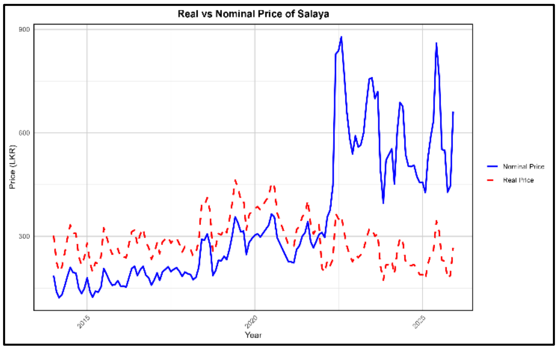

Figure 1. Time Series Plot of Nominal and Real Prices of Salaya

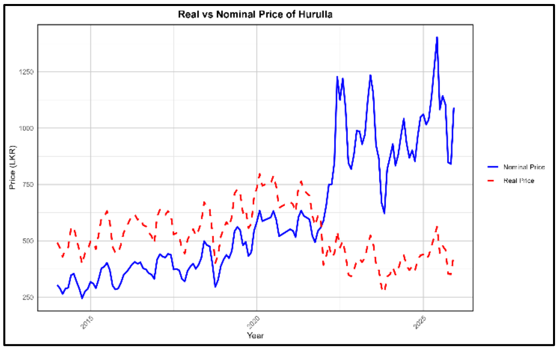

Figure 2. Time Series Plot of Nominal and Real Prices of Hurulla

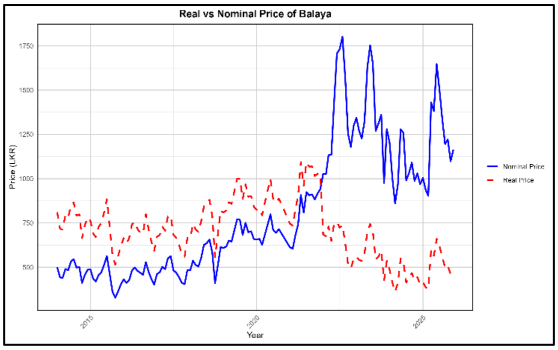

Figure 3. Time Series Plot of Nominal and Real Prices of Balaya

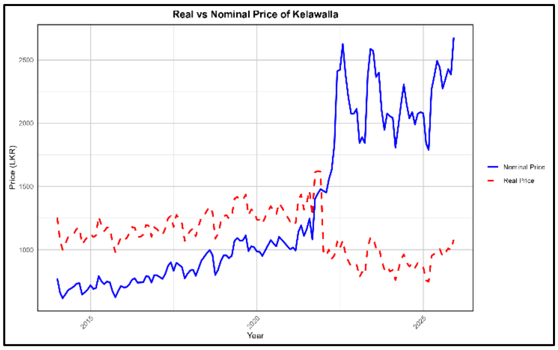

Figure 4. Time Series Plot of Nominal and Real Prices of Kelawalla

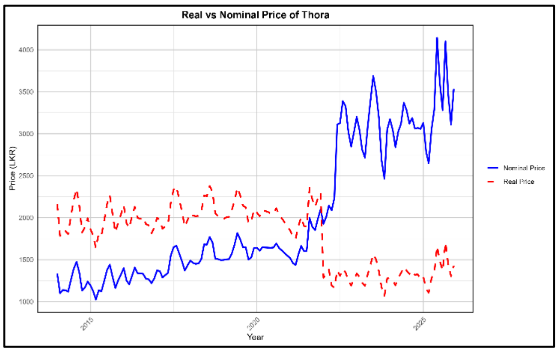

Figure 5. Time Series Plot of Nominal and Real Prices of Thora

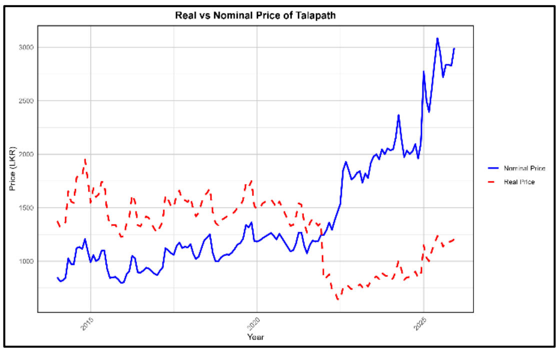

Figure 6. Time Series Plot of Nominal and Real Prices of Thalapath

3.3. Seasonal Price Index of Fish Real Prices

Figures 7 to 12 illustrate the seasonal price index (SP index) variations of six fish species based on their monthly average RMP from 2014 to 2025. In Figure 7, the SP index for Salaya is observed to be greater than 100 from late April to September, while lower values are recorded in October, November, and December. In Figure 8, the SP index of Hurulla remains above 100 in February, April, and June to August, with the highest value recorded in June and the lowest in October. This pattern indicates that peak demand and limited supply during certain months influence price fluctuations. For Balaya (Figure 9), the highest SP index is observed in June, whereas the lowest is in November. The SP index remains above 100 from April to September, reflecting the impact of seasonal fish availability and fishing conditions. In Figure 10, the SP index of Kelawalla is lowest in March, while values remain above 100 between April and October. This indicates that price increases are linked to fishing constraints in monsoon periods. Figure 11 shows that the SP index remains below 100 from January to May, with the highest value recorded in August and the lowest in March. Finally, in Figure 12, the SP index for Thalapath is observed to be lower than 100 from January to March, with the highest value in May and the lowest in January. These fluctuations indicate that fish supply shortages caused by monsoon seasons directly impact market prices.

Overall, the observed price variations align with previous studies, indicating that fish production in Sri Lanka is significantly affected by the Southwest Monsoon (May-September) and the Northeast Monsoon (December-February). This decline is mainly due to adverse weather conditions and reduced community participation in fishing activities (Dayalatha, 2020; Murray & Little, 2000; Wickrama et al., 2021).

Fish production is reduced during the Southwest and Northeast monsoons along the northern, eastern, western, and southern coasts. As a result, it has been observed that large pelagic raw fish are produced at lower levels during the Southwest Monsoon, while small pelagic fish production is reduced during both monsoon seasons in Sri Lanka (Koralagama, 2009; Wickrama et al., 2021). Comparable seasonal price fluctuations have also been reported in the fisheries sectors of India and Bangladesh, where monsoon-related variations in fish supply have been associated with changes in fish prices (Viswanatha et al., 2018).

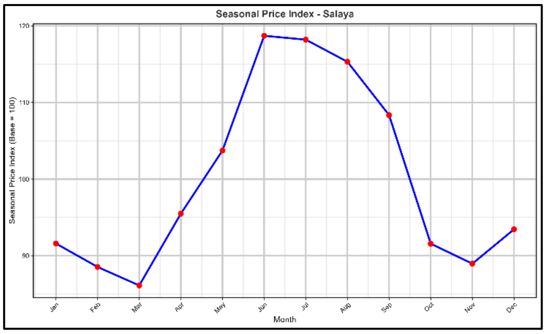

Figure 7: Seasonal price index plot of each month of Salaya

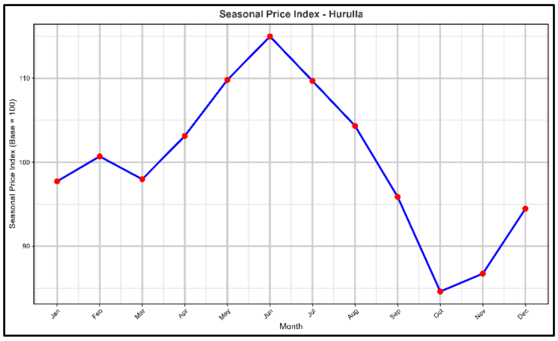

Figure 8: Seasonal price index plot of each month of Hurulla

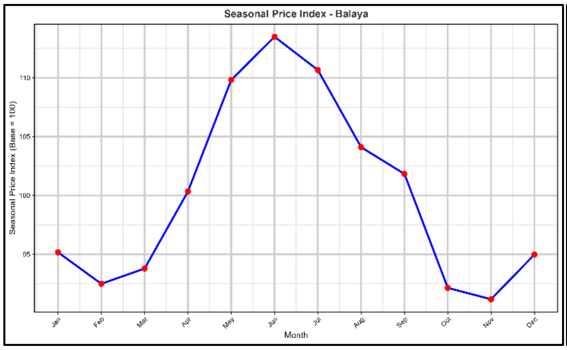

Figure 9: Seasonal price index plot of each month of Balaya

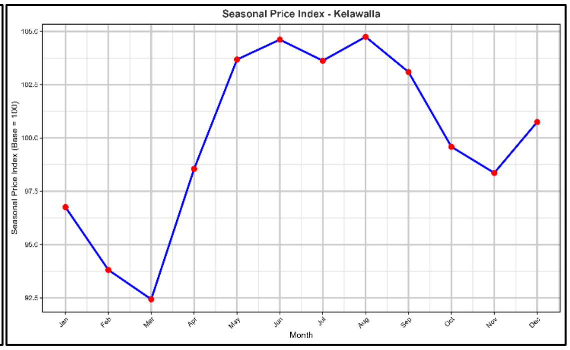

Figure 10: Seasonal price index plot of each month of Kelawalla

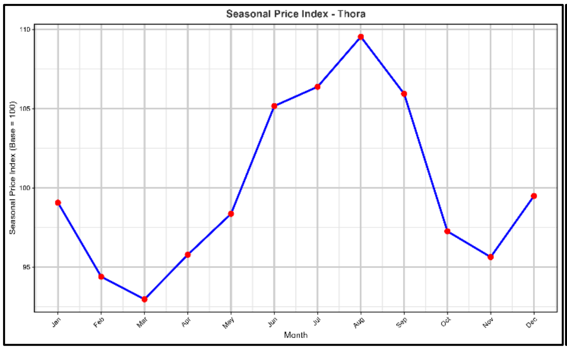

Figure 11: Seasonal price index plot of each month of Thora

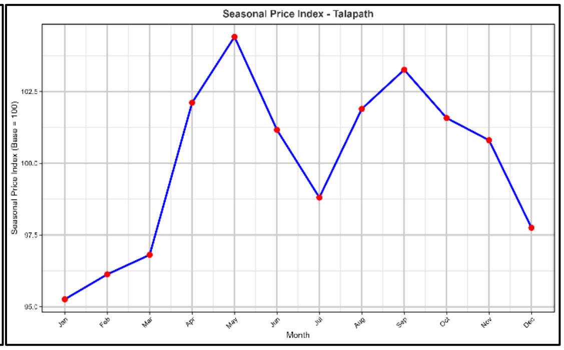

Figure 12: Seasonal price index plot of each month of Thalapath

3.4. Identification of Structural Breaks in Fish Price Series

The Zivot–Andrews test was applied to identify structural breaks in the fish price series, with critical values (CV) representing threshold values used to determine the statistical significance of the test statistic at 1%, 5%, and 10% levels. The results (Table 3) indicate a significant structural break in each series, with Salaya showing an earlier break in August 2020, while all other fish types exhibit breaks in December 2021. These breakpoints suggest a notable shift in price behaviour, likely associated with major economic disruptions such as the COVID-19 pandemic and subsequent macroeconomic instability in Sri Lanka. Although different break dates were identified across fish types, a common structural division was applied as 2014–2021 (pre-period) and 2022–2025 (post-period) for consistency and comparability.

3.4.1. Comparison of Mean Fish Prices Before and After the Structural Break

A decline in real fish prices was observed in the post-period (2022–2025) compared to the pre-period (2014–2021) across all fish types. Based on the results presented in Table 4, the Welch two-sample t-test was applied in R using the ‘t.test()’ function to compare mean real fish prices between the pre-period (2014–2021) and post-period (2022–2025). A statistically significant difference was observed across all fish types, with p-values below 0.001. Mean prices were significantly higher in the pre-period than in the post-period. The largest differences were identified for Thora and Thalapath, while relatively smaller but still significant differences were observed for Salaya. Overall, a significant downward shift in real fish prices was confirmed after the structural break, as shown in Table 4.

Table 3. Zivot–Andrews Structural Break Test Results for Fish RMP Series

Fish Type	Test Statistic	1% CV	5% CV	10% CV	Break Year and Month
Salaya	-5.6221	-5.57	-5.08	-4.82	2020-08
Hurulla	-5.1768	-5.57	-5.08	-4.82	2021-12
Balaya	-5.6186	-5.57	-5.08	-4.82	2021-12
Kelawalla	-8.8583	-5.57	-5.08	-4.82	2021-12
Thora	-8.5891	-5.57	-5.08	-4.82	2021-12
Thalapath	-6.1830	-5.57	-5.08	-4.82	2021-12

Source: Authors' calculations based on HARTI data (2014–2025), converted to real prices.

Table 4. Pre- and Post-Break Mean Comparison of Fish Prices (Welch t-test)

Fish Type	Mean (Pre)	Mean (Post)	t-value	p-value
Salaya	306.82	248.59	5.93	<0.001
Hurulla	586.54	418.29	12.62	<0.001
Balaya	788.60	549.15	11.33	<0.001
Kelawalla	1222.18	927.31	15.88	<0.001
Thora	2027.49	1323.80	28.72	<0.001
Thalapath	1491.23	900.65	21.17	<0.001

Source: Authors' calculations based on HARTI data (2014–2025), converted to real prices.

3.5 Stationarity Test Results of Fish Price Series

Table 5 presents the results of the ADF and KPSS tests conducted to assess the stationarity of real fish price series across pre- and post-periods. In the ADF test, the null hypothesis of a unit root was not rejected for the original series in several cases, as some p-values exceeded the 0.05 significance level, indicating non-stationarity. Similarly, the KPSS test, which evaluates stationarity around a trend, showed mixed results, with several p-values below 0.05, further suggesting non-stationarity in the level data. To address this issue, first-order differencing was applied. After differencing, the ADF test results showed p-values below 0.05 for all fish species in both periods, indicating rejection of the unit root hypothesis. At the same time, the KPSS test results showed p-values above 0.05, supporting stationarity. Therefore, the series is considered non-stationary in levels but stationary after first differencing, indicating an integration order of I(1). These results justified the use of differenced data for subsequent time series analysis and model estimation.

Table 5. Results ADF and KPSS Tests

Species	For Original Real Prices				For 1st Differenced Prices			
	Pre		Post		Pre		Post	
	ADF Test	KPSS Test	ADF Test	KPSS Test	ADF Test	KPSS Test	ADF Test	KPSS Test
Salaya	0.0566	0.01	0.0100	0.1000	0.01	0.1	0.01	0.1
Hurulla	0.0430	0.01	0.0962	0.1000	0.01	0.1	0.01	0.1
Balaya	0.1958	0.01	0.3245	0.0158	0.01	0.1	0.01	0.1
Kelawalla	0.0461	0.01	0.3720	0.1000	0.01	0.1	0.01	0.1
Thora	0.0100	0.10	0.0218	0.1000	0.01	0.1	0.01	0.1
Thalapath	0.2478	0.10	0.3780	0.0100	0.01	0.1	0.01	0.1

Source: Authors' calculations based on HARTI data (2014–2025), converted to real prices.

3.6 Price Forecasting Models for Each Fish Species

To identify the most suitable models for forecasting fish prices, the post-period data (2022–2025) were analysed using the ‘auto.arima()’ function in R, which evaluates a range of possible ARIMA and SARIMA model combinations. The selection of optimal models was based on the AICc and Mean Absolute Percentage Error (MAPE), while the adequacy of residuals was assessed using the Ljung–Box test. Table 6 presents the results, which indicate that SARIMA models generally provided a better fit compared to non-seasonal ARIMA models across most fish species, as evidenced by lower AICc values. For Salaya, the SARIMA (0,1,2) (0,1,1) $^{[12]}$ model substantially reduced AICc (1014.07) and MAPE (18.07%) compared to the ARIMA (2,1,2) model. A similar improvement was observed for Hurulla and Balaya, where SARIMA models showed lower AICc and improved forecasting accuracy, although MAPE remained relatively high for Balaya due to greater price variability. For Kelawalla and Thora, SARIMA models also outperformed ARIMA models, with noticeable reductions in both AICc and MAPE. However, for Thalapath, although the SARIMA model had a lower AICc, the ARIMA model had a lower MAPE, indicating mixed performance.

The Ljung–Box test results for all selected models yielded p-values greater than 0.05, suggesting that residuals are free from autocorrelation and that the models are adequately specified. Overall, SARIMA models were selected as the most appropriate for forecasting, particularly for species exhibiting seasonal patterns, while acknowledging that forecasting accuracy varies across species due to differences in price volatility.

The diagnostic checks of the selected SARIMA models indicate that the residuals are generally well-behaved, and the models are appropriately specified for forecasting purposes. The Ljung–Box test results show p-values greater than 0.05 for all fish species, including Balaya (0.9689), Hurulla (0.7761), Kelawalla (0.8416), Salaya (0.8205), Thalapath (0.8922), and Thora (0.8843), suggesting that no significant autocorrelation remains in the residuals. This confirms that the time dependence in the data has been adequately captured by the models.

In addition, the residual means are close to zero across all series, with values ranging from -2.4036 (Hurulla) to 1.0699 (Thora), indicating that the models are unbiased. The residual variances also remain stable within each model, although they differ across species depending on price volatility, with higher variability observed for Kelawalla (6,596.67) and Thora (16,867.79), while lower variability is seen for Salaya (918.23). Overall, these diagnostic results confirm that the selected SARIMA models are statistically adequate and suitable for forecasting monthly fish prices.

Table 6. Price forecasting models of each fish species

Fish Species	Model	AICc	MAPE	Ljung -Box_p
Salaya	ARIMA (2,1,2)	1129.76	31.19	0.8052
Salaya	*SARIMA (0,1,2) (0,1,1)$^{[12]}$	1014.07	18.07	0.9306
Hurulla	ARIMA (1,1,2)	1226.34	19.64	0.9998
Hurulla	*SARIMA (0,1,2) (0,1,1)$^{[12]}$	1093.96	12.44	0.7672
Balaya	ARIMA (1,1,2)	1314.35	58.99	0.9665
Balaya	*SARIMA (0,1,2)(0,1,1)$^{[12]}$	1186.05	23.19	0.9470
Kelawalla	ARIMA (1,1,1)	1366.38	17.37	0.6320
Kelawalla	*SARIMA (1,1,1)(0,1,1)$^{[12]}$	1246.87	8.49	0.8525
Thora	ARIMA (1,1,2)	1473.08	11.08	0.8037
Thora	*SARIMA (2,1,0)(0,1,1)$^{[12]}$	1326.15	9.01	0.8544
Thalapath	ARIMA (0,1,2)	1383.54	14.75	0.9808
Thalapath	*SARIMA (0,1,0)(0,1,1)$^{[12]}$	1256.71	19.39	0.6976

*Note: *The best-fitted models*

Source: Authors’ calculations based on HARTI data (2022–2025), converted to real prices.

Compared with Perera et al. (2016), differences in AICc and MAPE values are observed in the present study. These variations are likely due to differences in data structure and sampling frequency: Perera et al. (2016) used weekly data with a 52-week seasonal pattern, whereas the current study is based on monthly data with a 12-month seasonal period, which is more suitable for capturing intra-annual fluctuations in fish prices.

3.7 Forecasted Prices

The monthly forecasts for real fish prices for the period January to June 2026 were estimated using the selected SARIMA models, and the results are presented along with 95% confidence intervals to account for forecast uncertainty (Table 7).

For Salaya, the point forecasts gradually increased from LKR 240.57 in January to LKR 366.68 in June, while the corresponding confidence intervals widened over time, indicating increasing uncertainty in longer-term predictions. A similar upward trend was observed for Hurulla, where forecasts increased from LKR 458.37 in January to LKR 570.23 in June. In the case of Balaya, more pronounced fluctuations were observed, with forecasts ranging from LKR 441.26 to LKR 724.53 and relatively wider confidence intervals, reflecting higher price variability. Kelawalla, Thora, and Thalapath also showed increasing forecasted values over time, with Thora exhibiting the highest predicted prices among all species, reaching LKR 1,796.58 in June.

The confidence intervals for all species widened over the forecast horizon, indicating increased uncertainty in longer-term projections. The forecasted prices from the selected models for both January and February closely aligned with the actual RMP, providing further evidence that the models can produce reliable RMP forecasts.

Table 7. Forecast Values of Real Prices

Species	Month (2026)	Point Forecast (LKR)	95% Confidence Interval	
			Lower_95	Upper_95
Salaya	January	240.57	160.41	320.72
	February	199.12	101.50	296.73
	March	242.63	141.89	343.35
	April	268.65	165.00	372.29
	May	281.49	175.21	387.75
	June	366.68	257.84	475.51
Hurulla	January	458.37	341.75	574.98
	February	425.01	272.22	577.78
	March	441.34	275.44	607.23
	April	484.22	304.70	663.74
	May	525.35	333.33	717.38
	June	570.23	366.46	774.01
Balaya	January	485.11	289.88	680.34
	February	449.81	201.58	698.03
	March	441.26	163.54	718.98
	April	663.58	359.32	967.85
	May	628.39	299.72	957.06
	June	724.53	373.15	1,075.92
Kelawalla	January	1,020.25	790.55	1,249.95
	February	876.99	587.30	1,166.67
	March	835.40	515.38	1,155.41
	April	1,014.17	677.32	1,351.01
	May	1,014.04	667.46	1,360.63
	June	1,031.10	678.72	1,383.49
Thora	January	1,457.48	1,098.78	1,816.18
	February	1,280.89	808.36	1,753.43
	March	1,242.74	719.67	1,765.81
	April	1,414.55	842.47	1,986.62

	May	1,477.80	860.84	2,094.75
	June	1,796.58	1,137.77	2,455.39
Thalapath	January	1,472.02	1,219.08	1,724.95
	February	1,356.52	988.06	1,724.98
	March	1,325.85	890.06	1,761.65
	April	1,425.01	930.97	1,919.05
	May	1,493.48	947.38	2,039.59
	June	1,562.19	968.58	2,155.81

Source: Authors' calculations based on HARTI data (2022–2025), converted to real prices

4. Conclusions

This study provides a comprehensive analysis of price behaviour and forecasting of selected marine fish species in the Colombo market using monthly data from 2014 to 2025. The findings clearly demonstrate that fish prices are influenced by a combination of inflationary pressures, seasonal supply fluctuations, structural economic shocks, and environmental factors, including monsoons and climate variability. While nominal prices show strong upward trends, real prices remain relatively stable over time, confirming that inflation is the main driver of observed price increases.

Seasonal price indices indicate that fish prices fluctuate due to seasonal availability, weather conditions, and monsoon impacts, with significant price peaks observed during periods of limited supply. SARIMA models provided a better fit for species with seasonal patterns, while ARIMA models were sufficient for non-seasonal species, and residual analyses confirmed that most models adequately captured the data for forecasting purposes. The findings underscore the role of external economic and environmental factors such as inflation, supply chain disruptions, and weather patterns in shaping fish prices. It is recommended that policies focusing on price stabilisation be introduced, particularly during the peak seasons of the Southwest and Northeast monsoons and that forecasting models be further refined for future market decision-making.

These insights provide valuable guidance for policymakers, fisheries stakeholders, and market analysts in developing strategies to stabilise fish prices, improve market efficiency, and enhance the resilience of the fish value chain in Sri Lanka.

Limitations

Several limitations are identified in this study. First, the analysis is restricted to the Colombo fish market; therefore, the findings may not fully capture national-level fish price dynamics across regional markets in Sri Lanka. Market heterogeneity, including differences in supply chains, consumer demand, and distribution systems across districts, may lead to variations that are not reflected in this study.

Second, the econometric modelling is primarily based on ARIMA and SARIMA approaches, which are univariate in nature and rely heavily on historical price patterns. Although these models are effective in capturing trend and seasonal structures, they do not explicitly incorporate external explanatory variables or account for non-linear dynamics and structural breaks in the data. As such, important determinants of fish prices, such as income levels, consumer demand shifts, fuel prices, policy changes, and preference variations, are not directly included in the modelling framework, which may limit the explanatory power of the results and the ability of the models to fully capture price volatility and regime-dependent changes in the market.

Finally, the structural break identified in the series and the relatively short post-break period (2022–2025) may further constrain the robustness of parameter estimation and long-term forecasting performance, particularly under highly volatile market conditions.

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Author Contributions

M.A.E.K. Jayasinghe: Data curation, Formal analysis, Methodology, Investigation, Writing – original draft. C.S. Wijetunga: Methodology, Supervision, Validation, Writing – review & editing. Both authors read and approved the final version.

Data Accessibility

The data used in this study were obtained from the Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI).

Declaration of Conflict of Interest

The authors declare no conflicts of interest.

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