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Original Article

Forecasting monthly world tuna prices with a plausible approach

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Abstract

Skipjack, the most caught species of tuna globally, is a critical raw material for tuna industry in Thailand, the world's largest tuna-processing hub. However, tuna processors are finding it difficult to manage costs of these imported materials because of price fluctuations over time. Whereas most time series forecasting methods used in the literature model only three components: *trend*, *seasonality* and *error*, this study proposes a method to handle a fourth component as well: *cycle*. This method smooths monthly price data using a cubic spline that can detect cycles varying in both frequency and amplitude, and thus generates plausible forecasts by refitting the model after duplicating data from its most recent cycle. Results show that world tuna prices have a slightly upward trend in cyclical patterns with each cycle lasting approximately six years. Peak-to-peak amplitudes suggest that prices reached their peak at 2,350 US dollars per metric ton in 2017 and have started to fall, but will rebound after 2021.

Keywords: skipjack tuna prices, seasonal adjustment, cyclical pattern, spline interpolation, time series forecasting

1. Introduction

Skipjack, the most commonly caught species of tuna globally, is a critical raw material for tuna industry in Thailand, the world's largest tuna-processing hub. However, tuna processors have experienced high fluctuations in monthly skipjack prices over the past three decades, varying ±41%, from 380 to 2,350 US dollars (USD) per metric ton (MT) (Atuna, 2017). Economically, the world price of skipjack raw material for canning has a relatively high inverse correlation with the world catches of skipjack (Owen, 2001). The rapid increase of purse-seine fisheries (Hamilton, Lewis, McCoy, Havice, & Campling, 2011) using drifting fish aggregating devices (FAD) has resulted in the fast growth in skipjack catches (Davies, Mees, & Milner-Gulland, 2014; Fonteneau, Chassot, & Bodin, 2013), reaching two million MT in 2000, doubling the 1986 total catch (Food and Agriculture Organization [FAO], 2017) and causing the collapse in skipjack prices during 1999-2000. In the next year, 2001, prices were successfully stabilized just by reducing fishing efforts of members of the World Tuna Purse Seine Organization (Hamilton *et al*., 2011).

Currently tuna fisheries' targeted long-term sustainable tuna supplies are under-governed by tuna regional fishery management organizations. Several fishing regulations have been implemented, including limiting fishing efforts and closing for four months purse-seine fisheries in the tropical zone. In spite of the regulations, the capacity for global tuna stock renewal recently is being tested by observed rates of overfishing. For example, 39 percent of tuna stocks were

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overfished in 2014, and 4 percent more were exploited within one year, from year 2013 (International Seafood Sustainability Foundation [ISSF], 2015, 2016). In the most recent decade, the *volume* of world tuna catches has increased while the *rates* of catches have decelerated, and the tuna supply reached the optimal level of 5 million MT in 2014 (Lee, McNeil, & Lim, 2017). For the tuna trade, the monthly skipjack prices jumped to their highest levels in history with value of 2,350 USD/MT in 2013 and repeatedly through 2017 (Atuna, 2017). Even through specific cartels like the Forum Fisheries Agency have co-operated in setting catch levels in order to maintain desired prices, skipjack prices on purchase contracts have to be agreed on by all canners, traders and fishing companies because, for example, even a 1 percent increase in tuna prices results in a 1.55 percent decrease in demand from the canning industry (Miyake, Guillotreau, Sun & Ishimura, 2010). Thus, not only the uncertainties of global tuna supplies but also the dynamic preferences of world tuna consumers connect to variations in skipjack prices (World Bank and Nicholas Institute, 2016). Given the paucity of data on those changing demand and supply factors, this has led to the question of whether skipjack prices can be predicted based solely on the historical data of tuna prices.

In time-series analyses, various disciplines have methods and techniques to assess patterns and trends. These disciplines include demography, climate sciences, fisheries practices and finance. Statistical methods in these disciplines include multiple linear regression models (Chesoh & Lim, 2008; Komontree, Tongkumchum, & Karntanut, 2006), vector auto regression (Guttormsen, 1999), exponential smoothing (Suwanvijit, Lumley, Choonpradubm, & McNeil, 2011), a combination of ARIMA models and neural networks (Georgakarakos, Koutsoubas, & Valavanis, 2006; Gutiérrez-Estrada, Silva, Yáñez, Rodrıguez, & Pulido-Calvo, 2007; Naranjo, Plaza, Yanez, Barbieri, & Sanchez, 2015), polynomial regression (Wanishsakpong & McNeil, 2016), and spline smoothing (Lee *et al*., 2017; McNeil & Chooprateep, 2014; McNeil, Odton, & Ueranantasun, 2011; McNeil, Trussell, & Turner,1977; Sharma, Ueranantasun, & Tongkumchum, 2018; Watanabe, 2016; Wongsai, Wongsai, & Huete, 2017).

Most statistical methods used in the literature model *trend*, *seasonal*, and *error* components in time-series forecasting. For greater plausibility and accuracy an approach was needed to handle a fourth component as well: *cycle*. Our approach fits a smooth trend to the seasonally adjusted time series data, detects cycles varying in both frequency and amplitude and thus creates forecasts by refitting the cubic spline model after duplicating data from its most recent cycle. This enables us to produce more plausible forecasts than other methods that have been used in the literature.

2. Materials and Methods

The data used in this study are monthly skipjack tuna prices paid by processors in Thailand for supplies of tuna. They are Bangkok prices at cost and freight terms in USD/MT for the most commonly traded size, 1.8 kilograms and up, of frozen skipjack. The time-series dataset that includes a 32-year documentation of skipjack prices, monthly, from 1986 to 2017 shown in Figure 1 was obtained from two sources: FAO (2014) and Atuna (2017).

These monthly tuna prices were log-transformed to satisfy statistical assumptions of normality and homogeneity of variance as illustrated in Figure 2, in which (a) the Box-Cox transformation shows that the optimal λ, an estimate of power transformation is close to zero, meaning that a log transformation is needed (Sakia, 1992) and (b) the normal

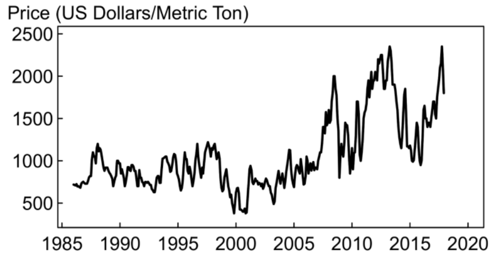

Figure 1. Monthly skipjack tuna prices from 1986 to 2017

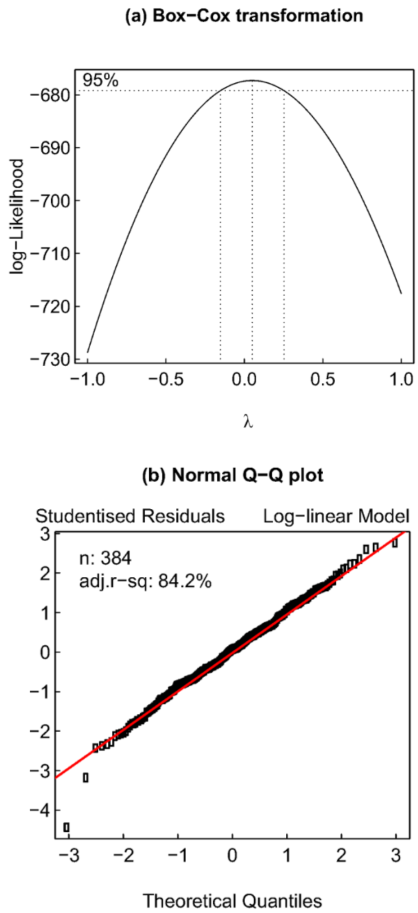

Figure 2. (a) A Box-Cox transformation of tuna prices time-series showing that the 95% confidence interval for λ does not include 1, meaning that a transformation is needed and the optimal λ is close to zero, suggesting that a natural log is the most appropriate power transformation. (b) A normal quantile-quantile plot of studentised residuals of the linear model after fitting log-transformed tuna prices, resulting in an adjusted r-squared of 84.2%.

quantile-quantile plot also confirms that the studentized residuals from the log-linear model are normally distributed. A linear regression model then was fitted to the logged tuna prices with year and month as predictors. By using weighted-sum contrasts in the fitted linear model (Tongkumchum & McNeil, 2009), the individual 95% confidence intervals confirm that both year and month are significant factors in the fluctuating prices. The data were seasonally adjusted before used as outcome variables for the proposed model. Moreover, residuals of this first additive model were used to explore the autocorrelation of the time series in order for developing appropriate methods to handle the case study of tuna prices.

A cubic spline model was chosen to fit seasonally adjusted logged tuna prices. This is because spline functions (Rice, 1969; Wold, 1974) are piecewise polynomials connected by knots located along the range of the time series, and cubic splines have desirable optimality with respect to fitting and forecasting (Lukas, Hoog & Anderssen, 2010). They minimize the integrated squared second derivative and provide plausible linear forecasts that can be controlled by a judicious placement of the knots. The final integrated spline log-linear models developed in this study were constructed as following equations:

$$Y_t = S(t) + z_t \tag{1}$$

where *t* represents a period of observations (1-384), Y_t is the seasonally adjusted logged skipjack prices for period *t*, $S(t)$ is a cubic spline function for period *t* and z_t is the random error. A cubic spline function *S(t)* is expressed as below mathematical form:

$$S(t) = a + bt + \sum_{k=1}^{p-2} c_k \left[(t-t_k)_+^3 - \frac{(t_p - t_k)}{(t_p - t_{p-1})}(t - t_{p-1})_+^3 + \frac{(t_{p-1} - t_k)}{(t_p - t_{p-1})}(t - t_p)_+^3 \right]$$

where p is number of knots, $t_1 < t_2 < ... < t_p$ are specified time knots and $(t - t_k)_+$ is $t - t_k$ for $t > t_k$ and 0 otherwise, and a, b and $c_1, c_2, ..., c_{p-2}$ are parameters to be estimated. Importantly, the key outcome variable of the model (Y_t) is derived from the sub-equation following:

$$\boldsymbol{Y_t = Y_{ij} = P_{ij} - \bar{Y}_j + \bar{P}} \tag{2}$$

where Y_{ij} is the seasonally adjusted of logarithm of skipjack tuna prices for month *j* in year *i*, P_{ij} is the logarithm of skipjack tuna prices of month *j* in year *i*, $\bar{Y}_j$ is the adjusted means of logarithm of skipjack tuna prices for month *j*, $\bar{P}$ is the overall mean of logarithm of skipjack tuna prices. All data analyses and statistical modeling were carried out by using R program (R Core Team, 2017).

The first spline model was fitted to the seasonally adjusted logged data with nine knots along the observations in which one at the beginning, one at the end, and the rest placed at 4-year equally spaced intervals to provide the most plausible *trend* analysis of tuna prices. Fitting the natural spline, it includes a number of linear terms corresponding to a number of knots in the function and the more knots are placed the smoother curve will be but the more parameters need to be estimated. For this case of tuna prices, the seasonal adjustment only accounts for a very small percentage of the coefficient of determination. Then, the second spline model was fitted to the same outcome variables but with more knots, 17 of 2-year equispaced knots, to obtain the best goodness of fit to the data and, importantly, detected *cycles* varying in both frequency and amplitude within the fluctuations of tuna prices. Along those cyclical patterns of price fluctuations, the last four data points making the peak-to-peak amplitude were pinned and a wave period on these curves was spotted as the most recent cycle. Data duplication (Dureh, Choonpradub, & Green, 2017; Lunn & McNeil, 1995) was then deployed to create future cycles by duplicating data from the most recent cycle detected in tuna prices where the starting point of the duplicated data is the point that most perfectly corresponds to the last observation and accommodates the same wave. Additionally, the method offers an optional parameter for making duplicated data adjustable. Then, we generated plausible forecasts by refitting the second spline model to the entire time series plus a duplicated future cycle. For the method validation, we also did a test by applying the method to a certain years backward of data in order to evaluate its ability to detect cyclical patterns and to forecast plausible tuna prices.

3. Results

Figure 3 illustrates that seasonal patterns of monthly skipjack tuna prices start rising in June and reach the highest level in August before falling to the lowest in December, then bouncing back and staying stable till May. After eliminating these patterns, the seasonally adjusted log-transformed skipjack prices are aligned closely along the 95% confidence intervals of annual prices. The first cubic spline (Model 1) with nine of 4-year equispaced knots fitted to these outcomes shows a slightly downward trend in tuna prices starting in 2018.

The second cubic spline (Model 2) with 17 of 2-year equispaced knots fitting offers the best curve fitting existing patterns with high adjusted r-squared, 83% as demonstrated in Figure 4. The spline model obviously captures cyclical patterns during the past decade within the rises and falls of skipjack tuna prices. Over the 32 years, the peak-to-peak of prices was noticeable and repeated almost the same amplitude and frequency during 2009 and through to 2017. It started from the lowest price (1,145 USD/MT) in October, 2009 to the highest price (2,096 USD/MT) in June, 2012, and then was down to its lowest, 1,189 USD/MT, in September 2015 before climbing up to its ultimate highest at 2,308 USD/MT in December 2017. These four data points of the peaks were pinned and identified a wave period as the most recent cycle. The cycle detected along this spline fitting covers approximately six years, from March 2011 to March 2017 with 1,640 USD/MT on average. This means that the next cycle started in April 2017 and the price of 2,350 USD/MT in November 2017 probably was a rising peak of the next cycle.

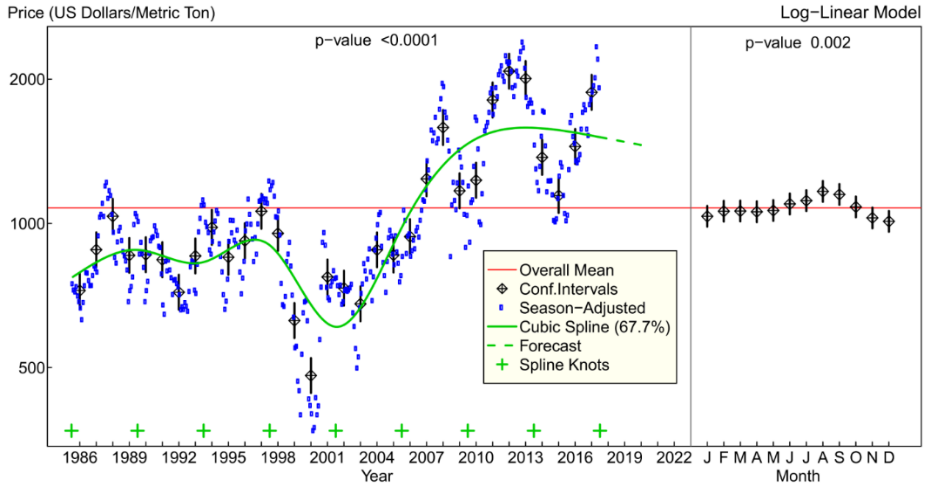

Figure 3. The plot of 95% confidence intervals of individual independent variables – year (left panel) and month (right panel) by using weighted-sum contrasts in the fitted log-linear model. The blue dots are seasonally adjusted skipjack prices and the horizontal line represents the overall mean of all 384 observations. The p-values above the graph indicate statistically significant individual predictors. The first cubic spline fitting (solid curve) contains 4-year equispaced knots (plus sign) in which the first and last knots are the first and last observations and the model's adjusted r-squared is 67.7%. The predicted trend of next two-years is represented by the dashed line.

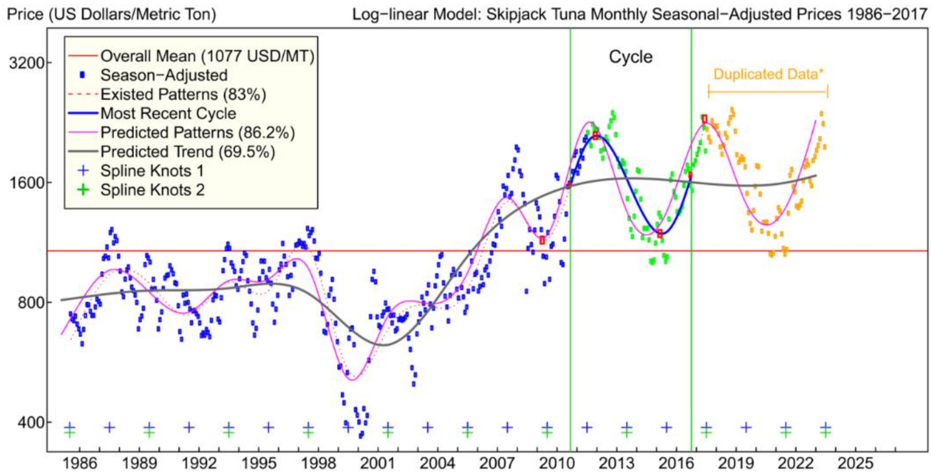

Figure 4. The plot shows cyclical patterns and forecasts for skipjack tuna prices. The blue dotted line demonstrates existing patterns from fitting the second spline model with 2-year equispaced knots (blue plus). The solid blue line is the most recent cycle of price fluctuations detected from the repeated peak-to-peak data points, the four small red circles. The green dots are seasonally adjusted observations used for duplicating data for creating a future cycle (orange dots). In the graph, the pink curve is forecasts derived from refitting the second spline model to the entire time series plus a duplicated future cycle and the solid black line is the trend from the first spline model with 4-year equispaced knots (green plus). The values in parenthesis in the legend are adjusted r-squared of each spline fitted model except the one after overall mean (1077 USD/MT) is the average prices of observations from 1986-2017 used in this fitting.

To create a future cycle, we duplicated data from the most recent cycle, starting from January 2012 in order to completely connect the last period (December 2017) of observations. Moreover, to smoothly accommodate the data representing the future cycle of the trend in tuna prices, the small but noticeably upward slope between the two bottom peaks (1,189 -1,145 = 44 USD/MT) was added to the duplicated cycle. Then, the second spline model with 2-year equispaced knots was fitted again, but to the entire time series plus the additional data of the duplicated cycle to generate forecasts of tuna prices and its resulting higher adjusted r-squared, 86.2%. In this predicted cycle, the skipjack prices would start dropping slightly in 2018, about 20 USD/MT monthly to the lowest point, 1,250 USD/MT in the middle of 2021 then bouncing back. The predicted trend from the first spline model in Figure 4 also illustrates a marginally upward trend of cyclical patterns for skipjack tuna prices in the long-term forecasts after a short-term slightly downward trend with the annual average prices range from 1,570 to 1,641 USD/MT for the forecast periods of 2018-2023.

By running rigorous testing, the method was applied to the data from 1986-2014. As demonstrated in Figure 5, the second cubic spline model (Model 2) also detected the peak-to-peak amplitude of price variations covering the six-year cycle, from 2008 to 2014. Its prediction of 3-year prices during 2015-2017 compared with the actual values resulted in errors with mean absolute percentage errors (MAPE) 12.01% as exhibited in Table 1. The average forecasts in 2015 were higher than the average actual prices 4.2% but lower in 2016 and 2017 with -8.6% and -5.8 respectively. This indicates high price fluctuations within months but in the same rises and falls as direction the method captures. When applying the method to data from 1986-2012 in order to forecast 5-year further backward from the latest year of dataset, the forecasting performance dropped significantly. Figure 6 shows that the prices started forming the wave of cycle in 2007, straightly climbed to the peak in the mid of 2008, the first time hit 2000 USD/MT in history and continually fell to the end of 2009 before bouncing upward to another peak in 2012. But, this starting cycle did not have peak amplitudes in the same frequency and consequently the forecasts of 2013-2017 from this test obtain high MAPE, 21.71%. The forecasts this method generates are at least in the right direction of price fluctuations through not exactly in the same timeframe because the cycles that the spline model detects have variable periods.

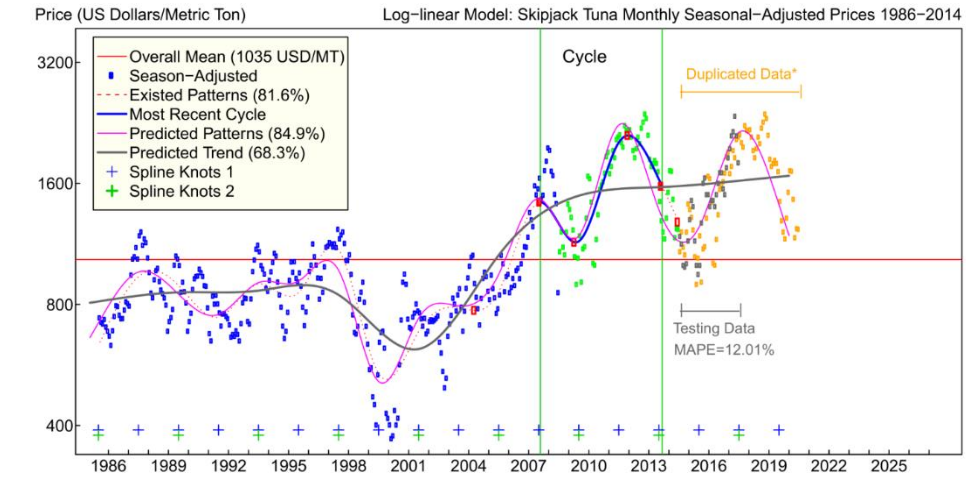

Figure 5. The plot shows testing results by applying the method to data from 1986-2014 having the overall mean at 1035 USD/MT. It detected the peak-to-peak amplitude of price variations covering the six-year cycle, from 2008 to 2014. The black dots are actual tuna prices of 2015-2017 and the forecasting errors, MAPE from the second cubic spline model (pink curve) are, 12.01%.

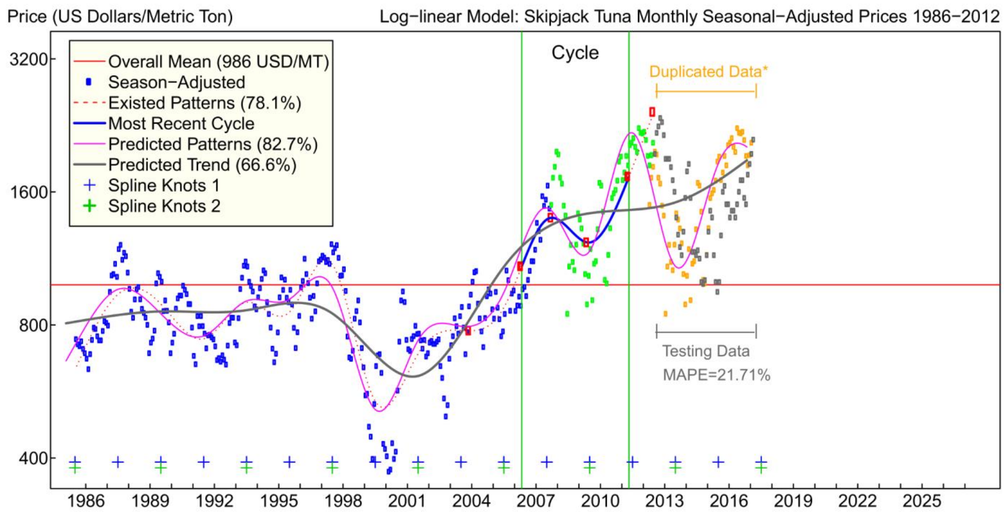

Figure 6. The plot shows results when applying the method to data from 1986-2012 to test forecasts 5-year further backward. In these data, having much lower overall mean at 986 USD/MT, it spoted the starting point of cyclical patterns from 2007 to 2012, covering five-year period under changes in tuna fishery management. The black dots are actual tuna prices of 2013-2017 and its results high MAPE, 21.71%.

At the time of writing, the data of skipjack tuna prices during January-November, 2018 from the Thai Union Group Public Company Limited (2018) was only publicly available. Even through these purchasing contract prices of a specific company were obtained from different data source to the one we used for data modeling, they are useful to test our model since the company is the world's largest producer of canned tuna and procured the largest volume of tuna landings in Thailand. By comparing these actual prices to our forecasts of 2018, the skipjack prices had a downward trend like the cycle we detected but it dropped much faster than the second spline model (Model 2) predicts with the large MAPE, 44%, as compared in Table 1. Nevertheless, it is interesting to learn that these true prices were close to the predicted values from the first spline model (Model 1) with much smaller MAPE, 7.5%. Furthermore, the average prices of these 11 months (January-November, 2018) from the forecasts (1,589 USD/MT) were just 2.5% higher than the actual average prices (1,550 USD/MT).

4. Discussion and Conclusions

The results of this tuna-prices analysis provide informative answers to the research questions. With our method, Skipjack tuna prices are statistically and plausibly predictable. We can extract a certain seasonal pattern and detect a cycle of price fluctuations from the 32-year tuna prices traded in Thailand, the largest marketplace for cannery-grade tuna. Possibly, this seasonal pattern of skipjack prices relates to the duration of FAD closures for purse-seine fisheries, introduced in 2009, starting with three months (July, August and September) and extending to four months (July, August, September, and October) in 2014. This FAD provision evidently has affected tuna catches – there has been observed some decreases of skipjack catches during the FAD closures and often increases in the months immediately following the FAD closures (Western and Central Pacific Fisheries Commission [WCPFC], 2014). These regulations, intended to help sustain tuna stocks, consequently contribute to seasonal patterns in tuna prices.

However, this statistical model development for forecasting monthly world tuna prices is a first step. We did not compare forecasting performance between our method and existing methods but by exploring classical methods like autoregressive models in the development stage, the autocorrelation diagnosis plots in Figure 7 clearly show that there is a strong autocorrelation within monthly tuna prices over time shown in Figure 7 (a) and residuals autocorrelation of either the first spline model in Figure 7 (b) or the second spline model in Figure 7 (c) identify many lagged terms significantly correlated. The existing autoregressive models cannot totally remove those correlated terms to satisfy an assumption of linearly unrelated errors for prediction. The highly fluctuated time-series data like this tuna prices data obviously needs a new approach for forecasting.

Unlike most statistical methods used in the literature, this study offers an approach to model all four time-series components - *trend*, *seasonality*, *error* and *cycle*, resulting in greater plausibility of forecasts, since it could draw more scientific and useful information out of the historical data. Given our world's complex, global dynamics forecasting future tuna prices based on past fluctuations is not a simple task. Skijpack tuna prices greatly tie to market demand of canned tuna, a global commodity product, which strongly affected by many elements such as substitute products, consumer preferences, trade barriers, environmental concerns and

Table 1. A comparison between predicted values and actual prices

Month	Forecasts of modeling data from 1986-2014									Forecasts of modeling data from 1986-2018					
	2015			2016			2017			2018					
	Actual price	Predicted value (M2)	% Error	Actual price	Predicted value (M2)	% Error	Actual price	Predicted value (M2)	% Error	Actual price*	Predicted value (M2)	% Error	Predicted value (M1)	% Error
1	1180	1225	3.8	1000	1205	20.5	1700	1522	-10.5	1550	2160	39.4	1596	2.9
2	1130	1212	7.2	1275	1218	-4.5	1700	1563	-8.0	1480	2191	48.0	1594	7.7
3	1000	1201	20.1	1600	1232	-23.0	1550	1607	3.6	1700	2216	30.4	1593	-6.3
4	990	1192	20.4	1650	1250	-24.3	1500	1651	10.1	1800	2236	24.2	1591	-11.6
5	1010	1185	17.3	1500	1269	-15.4	1750	1696	-3.1	1600	2250	40.6	1590	-0.6
6	1150	1180	2.6	1500	1292	-13.9	1850	1742	-5.8	1600	2256	41.0	1589	-0.7
7	1300	1177	-9.5	1400	1317	-5.9	1950	1789	-8.3	1300	2254	73.4	1587	22.1
8	1450	1176	-18.9	1450	1345	-7.2	2100	1835	-12.6	1450	2246	54.9	1586	9.4
9	1400	1178	-15.9	1450	1376	-5.1	2150	1881	-12.5	1650	2231	35.2	1585	-4.0
10	1150	1181	2.7	1400	1409	0.7	2350	1926	-18.0	1525	2210	44.9	1584	3.8
11	1000	1187	18.7	1500	1445	-3.7	2100	1970	-6.2	1400	2183	56.0	1582	13.0
12	950	1195	25.8	1600	1482	-7.4	1800	2011	11.7					
Average in year	1143	1191	4.2	1444	1320	-8.6	1875	1766	-5.8	1550	2221	43.3	1589	2.5
MAPE			13.6			11.0			9.2			44.4		7.5

Notes: M1 is the first cubic spline model (Model 1) with nine of 4-year equispaced knots for trend analysis. M2 is the second cubic spline model (Model 2) with 17 of 2-year equispaced knots for pattern analysis.
*retrieved from publicly available source on the website of Thai Union Group Public Company Limited (2018).

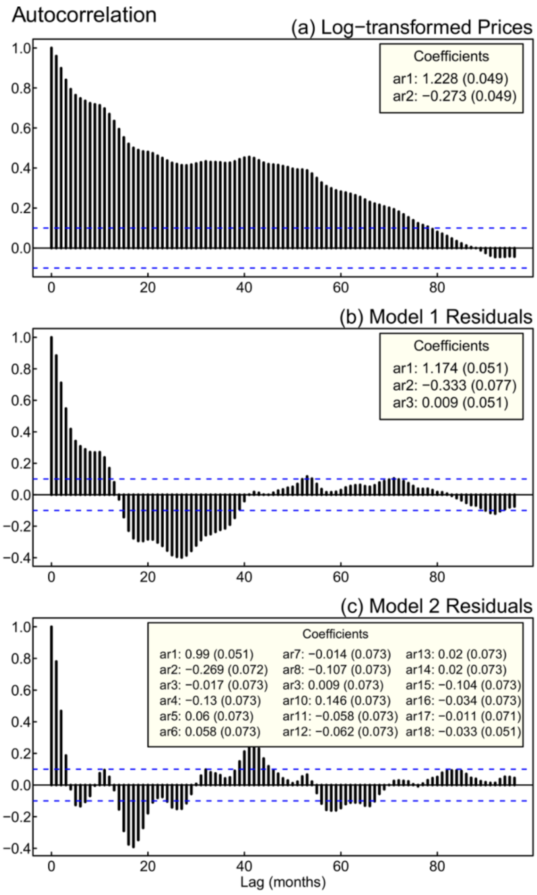

Figure 7. The autocorelation plots showing significant autocorrelation within data (a) and residuals of both the first spline model (b) and the second spline model (c). The legend exhibits coefficients of significant correlated lagged terms and its standard errors in brackets.

even the global economy (Miyake, Guillotreau, Sun, & Ishimura, 2010). Thus, the model development, validation and interpretation were carefully preceded by principal criteria, not only *how well the model statistically fits past data* but also, importantly, *how plausibly the model will forecast future data* corresponding to the realities of the world tuna industry.

From the model testing, our method may fail to consistently give high accurate estimates of future prices of market demand-driven tuna because its price fluctuations have variable periods involved in the cycles. However, its forecasts provide at least plausible long-term price trends and cycles economically corresponding to demand and supply in world tuna trade. Tuna canneries can use these scientific results for material requirement planning and to be a reference when negotiating contract prices with tuna suppliers and traders. Since the six-year cycles detected in this study also illustrate that the peak-to-peak of skipjack price variations was quite wide, -900 to +1,120 USD/MT, changes from -43 to +94 percent, such variation may become a topic for future discussion in a forum like the annual world tuna trade conference attended by tuna supply-chain stakeholders. Seeking an agreement to narrow such price fluctuations would help reduce business risks among related stakeholders not only tuna processors, but also fishers and traders.

This forecasting method should be broadly applicable to other similar time-series data, not just records of tuna prices. Moreover, our duplication method could be also extended further by using Efron's bootstrap resampling technique (Efron & Tibshirani, 1998) to provide a range for plausible forecasts. The cycles that the spline detects have variable periods and if we could get a better estimate of the next period they would be spot-on. Given that we have several cycles, we could then get different sets of forecasts based on different duration of the next cycle. Such further innovative aspect would make the model more dynamically correspond to real economic cycles, which have a chance to repeat in the future but not be the exact same duration as in the past. For those further improvement, to evaluate forecasting performance of the methods will require a fully-fledged Monte Carlo simulation study which beyond the scope of the present study.

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