

Forecasting Farm-Gate Catfish Prices in Uganda Using SARIMA Model

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Abstract: Stabilization of prices of essential agricultural commodities continues to remain an area of major concern for policy makers; given that price instability affects both producers and consumers, and has macroeconomic implications. This paper examines farm-gate price behavior in the African catfish markets in Uganda, and develops a forecasting model that adjusts for the seasonal fluctuations in the price series. The analysis utilizes monthly catfish real price series for the period January 2006 to December 2013. The model provides good in-sample and out-of-sample forecasts for the eight-year time period. The out-sample predictions based on SARIMA (1, 1, 1) (0, 1, 1)₁₂ model suggest that the stochastic seasonal fluctuations depicted in the price series are successfully modeled, and that catfish real prices follow an upward trend. The findings can assist policy makers and major stakeholders to gain insight into more appropriate economic and sectorial policies that can lead to the development of reliable market information systems and up-to-date data on catfish supply, demand and stocks.

Keywords: SARIMA models; Box – Jenkins; Forecasting; catfish prices; Uganda

1. Introduction

Over the last decade, aquaculture has emerged as a vibrant subsector in Uganda, with its share in total fish production increasing substantially^[1]. With increasing market prices, government intervention for increased production, and stagnating supply from capture fisheries, aquaculture has attracted entrepreneur farmers seeking to exploit the business opportunity provided by the prevailing fish demand. The bulk of the increase in aquaculture production has been attributed to the African catfish (*Clarias gariepinus*) which accounts for more than 65% of aquaculture production in Uganda. African catfish farming is flourishing mostly due to its relatively developed production technology, emerging new markets in the region, and the growing middle class in Uganda. Its market is sustained by the relatively consistent supply from farms. Although production has increased over time, fish prices in general have remained highly unstable, a phenomenon that could potentially explain why fish producers are operating at narrow net margins. Basic economic theory suggests that the role which the price mechanism is expected to perform does not materialize in a highly unstable price situation. In such instances, price fluctuation translate into significant price risk, since the magnitude and the direction of the price changes are often unknown to producers; hence, making the timing of production extremely important. As an illustration, selling 5kg fish in November for UGX 2257 per kilogram will bring losses, whereas, selling the same fish in June for UGX 2410 per kilogram may be very profitable. Therefore, farmers have to frequently assess whether to harvest to capture a known price, or to continue to feed to deliver a larger fish at an unknown future price^[2]. This has increased the risk faced by fish producers in general, and catfish farmers in particular. The objective of this paper therefore, is to develop a forecasting model that would allow catfish farmers in Uganda to make better-informed decisions and to manage price risk.

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Price forecasting in fisheries and aquaculture has been the subject of a wide range of studies which have used a variety of approaches, ranging from simple to more complex forecasting models. Relevant studies include Curtis, Ligeon and Hishamunda ^[3] who used autoregressive conditional heteroscedastic (ARCH) models and the generalized autoregressive conditional heteroscedastic (GARCH) with ordinary least squares (OLS), unconditional least squares (ULS), and maximum likelihood (ML) models to forecast whole and frozen catfish prices in the U.S. Similarly, Guttormsen^[4] used classical additive decomposition (CAD), Holt-Winters exponential smoothing (HW), auto-regressive moving average (ARMA), vector auto-regression (VAR) and two different naïve models to forecast weekly producer prices for salmon in Norway. Gordon^[5] used ARMAX model to provide a parsimonious characterization of producer prices and simulated price effects from exchange rate shocks in Canada. Gu and Anderson^[6] used an approach that combines seasonality removal with a multivariate, state-space time series forecasting model to provide short-run forecasts for the U.S. salmon market. Prista et al.^[7] used seasonal autoregressive integrated moving average (SARIMA) models to fit, forecast, and monitor meagre landings in Portugal. This paper contributes to this body of knowledge by developing a SARIMA model to forecast farm-gate catfish prices in Uganda.

2. Materials and Methods

Forecasting Framework

During the past few decades, much effort has been devoted to the development and improvement of time series forecasting models^[3-7]. One of the most important and widely used time series models is the Auto-Regressive Integrated Moving Average (ARIMA) model. The popularity of the ARIMA model is due to its statistical properties, as well as, use of well-known Box-Jenkins methodology in the model building process. In general, an ARIMA model is characterized by the notation ARIMA (p, d, q), where p, d and q denote orders of Auto-Regression (AR), Integration (differencing) and Moving Average (MA), respectively. An ARMA (p, q) process can be defined as:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \quad (1)$$

Where, y_t and ε_t are the actual value and random error at time period t, respectively, ϕ_i (i=1, 2, p) and θ_j (j=1, 2... q) are the model parameters. The random errors, ε_t are assumed to be independently and identically distributed with a mean of zero and a constant variance of σ^2 . The Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model is an extension of the ARIMA model, which not only captures regular difference, autoregressive, and moving average components as the ARIMA model, but also handles seasonal behavior of the time series. In the SARIMA model, both seasonal and regular differences are performed to achieve stationarity prior to fitting the model.

To solve the problem of the seasonal character of catfish price series, SARIMA model is proposed here, which includes trend, seasonal component, and short-time adjustments. The model is derived from the standard Box-Jenkins model ^[8, 9]. SARIMA models include seasonal and non-seasonal factors in the multiplicative model according to the following formula:

$$\Phi_p (B^s) Z_t = \Theta_q (B^s) a_t \quad (2)$$

Where “s” represents the number of periods per season \mathbf{a}_t is the usual Gaussian white noise process and B is

the backshift operator. Seasonal differencing may be in order if the seasonal component follows a random walk, as in:

$$\nabla Z_t = Z_t - Z_{t-s} = (1 - B^s)Z_t \quad (3)$$

The seasonal difference of order D is defined as:

$$\nabla_s^D Z_t = (1 - B^s)^D Z_t \quad (4)$$

So the final form of SARIMA (p, d, q) x (P, D, Q)_s can be formed as:

$$\Phi_p(B^s)\phi_p(B)\nabla_s^D\nabla^d Z_t = \Theta_q(B^s)\theta_q(B)a_t \quad (5)$$

Where

$$\Phi_p(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \dots - \Phi_p B^{ps}$$

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$$

$$\Theta_q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \dots - \Theta_q B^{qs}$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q$$

In the current study, the focus is on monthly catfish price series and since the seasonal period of the series $s = 12$, equation (5) can be rewritten as:

$$\Phi_p(B^{12})\phi_p(B)\nabla_{12}^D\nabla^d Z_t = \Theta_q(B^{12})\theta_q(B)a_t \quad (6)$$

where $\phi_p(B)$ is the autoregressive stationary operator (non-seasonal) of order p; $\Phi_p(B^{12})$ is the autoregressive stationary operator of order P and seasonal station 12; $\theta_q(B)$ is the operator of invertible moving average (non-seasonal) of order q; $\Theta_q(B^{12})$ is the seasonal invertible of moving average operator of order Q and seasonal station 12; ∇^d is the part of non-seasonal integration order d; ∇_{12}^D is the part of seasonal integration order D and seasonal station 12.

3. Data Description

The analysis utilizes an updated data sample^[10-12] of monthly average catfish prices covering the period January 2006 through December 2013. The data are taken from secondary source recorded data by the Aquaculture Management Consultant^[13]. To adjust for inflation, catfish prices, expressed in Uganda Shillings (UGX) per kilogram (kg), were deflated using a consumer price index (CPI) deflator from the Uganda Bureau of Statistics^[14]. The deflated series is plotted in Figure 1, showing consistent pattern of short-term changes, which is an indication of non-stationarity of the time series. The sharp decreases observed annually during the months of February, August and December suggests the possibility of some seasonal component that could also make catfish price series non-stationary. For further testing of the stationarity of the price series, Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) unit root test statistics are

applied. The optimal number of lags is determined using the Schwarz information criteria. The unit root test results are reported in Table 2, confirming that the hypothesis of non-stationarity cannot be rejected at the 5% significance level.

Figure 1. Monthly catfish farm-gate real prices

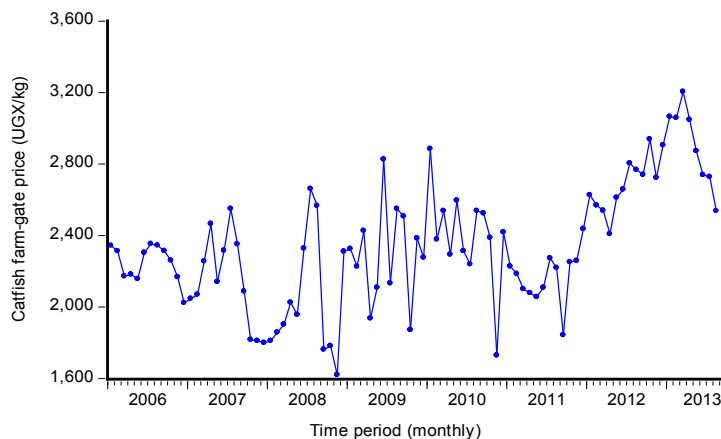


Table 1 Stationarity Test for Real Prices		
	ADF	PP
Levels	-0.29[1]	0.34 (13)
1st Difference	-11.40**[0]	-71.14**(1)

[] represents lags while () represents bandwidth

0.05 critical values: -2.89

Lag Length- based on SIC, maxlag=11.

Investigation is also done by examining the autocorrelation (ACF) and partial autocorrelation (PACF) functions (Figure 2). As shown in the figure, the ACF dies down extremely slowly, while the PACF cuts off after the first lag. Overall, the unit root test results and plots of the correlogram confirm that the time series price data are not stationary, and thus need some treatments to be transformed to a stationary series. Accordingly, the first difference of the series is examined (Table 2), and the test results confirm that catfish real price series is integrated of order 1 or I(1). The plot of the first differenced series is displayed in Figure 3, showing that the differenced series is stationary but shows some seasonal patterns. The next step was to examine the behavior of the seasonal patterns in the data using the seasonal unit root test.

Figure 3. Time Series Plot of First Differences of Monthly Catfish Real Price Series

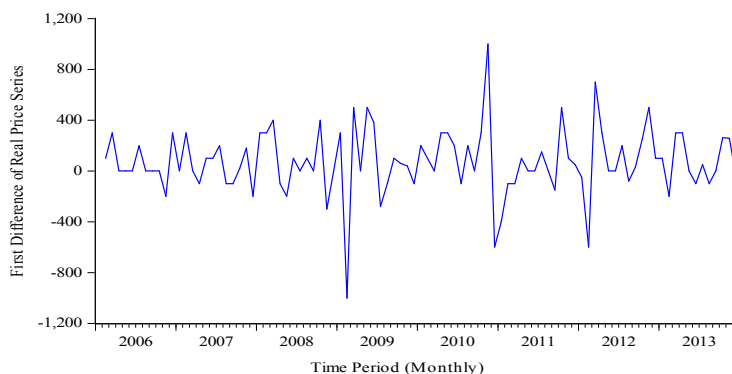
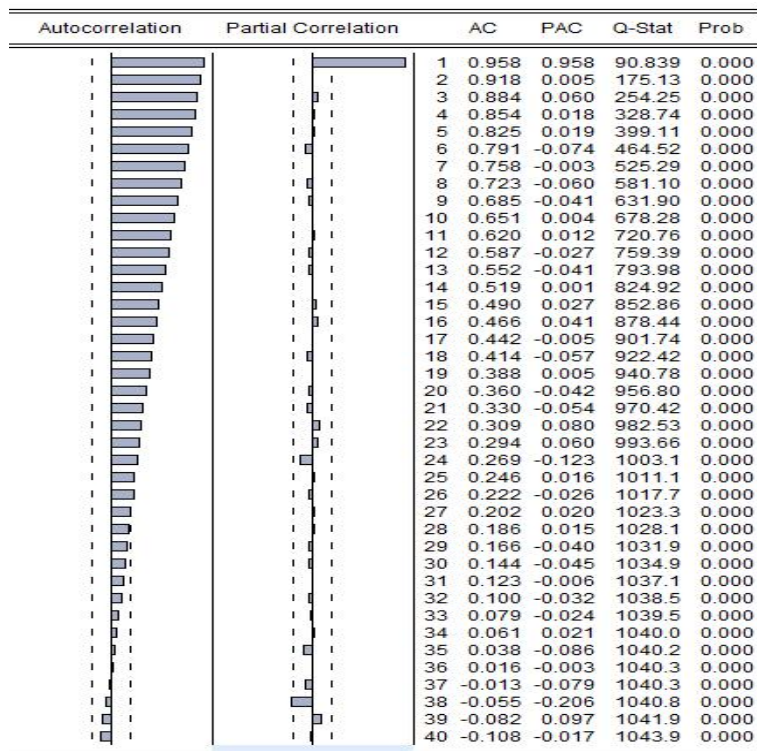


Figure 2. Correlogram of Original Catfish Real Price Series



4. Seasonal Unit Root Test

The most common approach used to determine if the seasonal behavior in the data series is deterministic, stochastic or stationary under seasonal frequencies is the HEGY approach [15]. As extended by Franses [16], the seasonal frequencies in the data series are π , $\pi/2$, $2\pi/3$, $\pi/3$, $5\pi/3$ and $\pi/6$. Testing for both seasonal and non-seasonal unit roots is also implied in testing for the significance of π_i . The t-test is used to test the separate π 's of the null hypothesis. It is a one sided t-test that $\pi_1 = 0$ and $\pi_2 = 0$ of the null hypothesis, respectively. The two sided t-test are used in testing for the null hypothesis of $\pi_i = 0$, $i = 3, \dots, 12$. The F-statistic is used to test for the joint null hypothesis that π_2 , π_3 , and π_4 are all zero and that all four π 's are jointly zero ($\pi_1 = \pi_2 = \pi_3 = \pi_4 = 0$). The asymptotic distribution of the test statistics under the respective null hypothesis depend on the deterministic terms in the model. There is no seasonal unit root if π_2 through π_{12} are significantly different from zero. If $\pi_1 = 0$, then the presence of non-seasonal unit root cannot be rejected. Table 2 presents the results from the HEGY test, suggesting that, the null hypothesis of unit root at the non-seasonal frequency cannot be rejected while the presence of unit root at the seasonal frequency can be rejected at the 5% level only for three seasonal frequencies (π , $2\pi/3$ and $5\pi/3$). The failure to reject the null hypothesis of unit root at the rest of the seasonal frequencies implies the presence of some seasonal components in the catfish real price series, thus raising the need to perform seasonal differencing on the price series.

Auxiliary Regression	Seasonal Frequency	Test Statistics	Simulated P-value*	5% Critical values^
t-test: $\pi_1=0$	0	-2.34	0.32	-3.19
t-test: $\pi_2=0$	π	-4.10	0.01	-2.65
F-test: $\pi_3=\pi_4=0$	$\pi/2$	4.20	0.13	5.77

F-test: $\pi_5=\pi_6=0$	$2\pi/3$	8.81	0.00	5.77
F-test: $\pi_7=\pi_8=0$	$\pi/3$	5.17	0.06	5.77
F-test: $\pi_9=\pi_{10}=0$	$5\pi/3$	5.73	0.03	5.84
F-test: $\pi_{11}=\pi_{12}=0$	$\pi/6$	4.96	0.07	5.82

*Monte Carlo Simulations: 1000

Selected lag using aic criteria: 2

^Franses and Hobijn^[17]

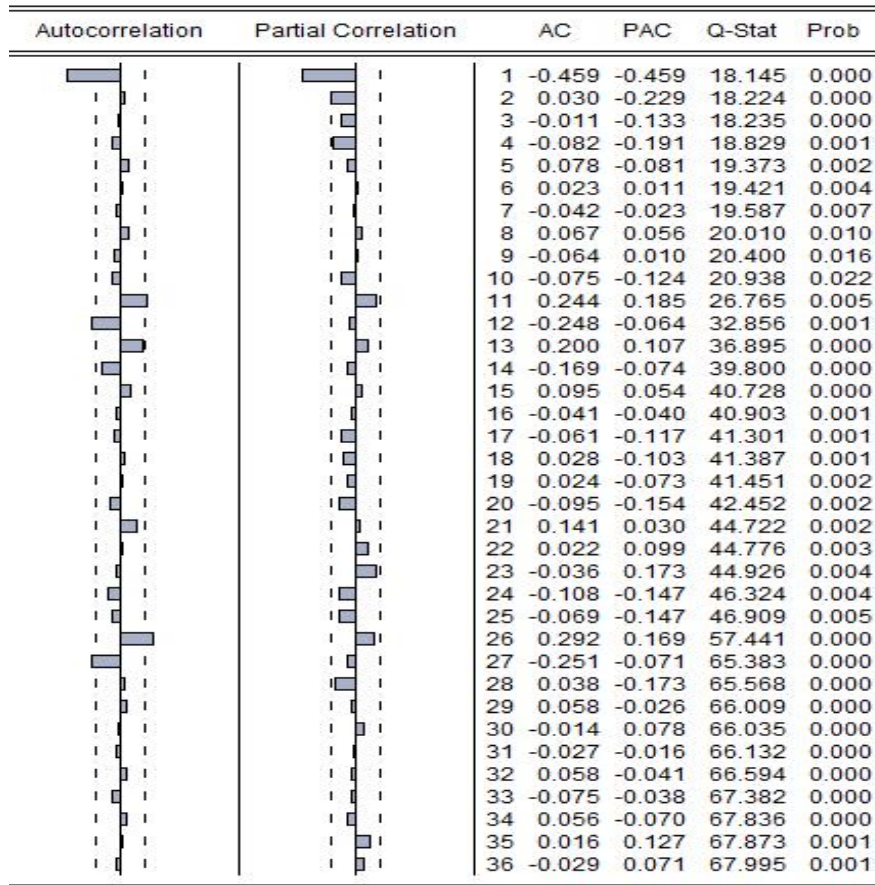
The next step in the Box and Jenkins procedure is to determine the order of the AR and MA for seasonal and non-seasonal components. This is accomplished using the sample ACF and PACF plots of the price series. Earlier examination of the ACF plot in Figure 2 revealed that the ACF declines very slowly while the PACF showed a single spike at the first lag. These observations suggest $p=1$ and $q=1$ as starting points in describing the catfish real price series as coming from a non-seasonal AR and MA process, respectively. Hence, the model that gives rise to these observations is an ARIMA (1, 1, 1) model, since the data series was differenced (*i.e.* $d=1$) to attain stationarity. Similarly, the plot of the ACF and PACF of the seasonally differenced series is presented in Figure 4. A critical look at the seasonal lags shows that the ACF spikes at seasonal lag 12 dies down to zero for other seasonal lags, while the PACF shows no spike at any of the seasonal lags, suggesting that $p=0$ and $q=1$ would be needed to describe these data as coming from a seasonal autoregressive and moving average process. Hence, the time series model that gives rise to these observations is an ARIMA (0, 1, 1) model, since the data are seasonally differenced once (*i.e.* $d=1$) to address the presence of seasonal frequencies as indicated by the HEGY seasonality test in Table 2. Overall, the first guess model based on these observations is SARIMA (1, 1, 1) (0, 1, 1)₁₂. The model is estimated along with other possible models and the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (BIC) are used to select the best model.

5. Identification of the SARIMA Model

In the identification phase, six tentative SARIMA models are tested and the corresponding AIC, AICC and BIC values for each of the models are presented in Table 3. The results show that SARIMA (1, 1, 1) (0, 1, 1)₁₂ has the least AIC, AICC and BIC values, and thus presented as the best model. The next stage of the Box-Jenkins approach is the estimation of parameters of the selected model.

SARIMA Model	# of estimated parameters	AIC	AICC (F-corrected-AIC)	BIC
(0,1,0) (0,1,1)	2	1182.57	1182.72	1187.41
(0,1,0) (1,1,0)	2	1199.47	1199.62	1204.31
(0,1,1) (0,1,1)	3	1180.70	1181.01	1187.96
(0,1,1) (1,1,0)	3	1192.63	1192.93	1199.89
(1,1,0) (0,1,1)	3	1181.97	1182.28	1189.23
(1,1,0) (1,1,0)	3	1195.13	1195.43	1202.39
(1,1,1) (0,1,1)	4	1178.74	1179.26	1187.42
(1,1,1) (1,1,0)	4	1192.72	1193.23	1202.39

Figure 4. Correlogram of the Seasonally Differenced Monthly Catfish Prices



6. Parameter Estimation

The parameters of SARIMA (1, 1, 1) (0, 1, 1)₁₂ are estimated using the maximum likelihood estimator in Eviews Version 7.2. As reported in Table 4, the coefficient of the estimated ARIMA and the seasonal MA parameters are 0.6532, 0.9012 and 0.8095, respectively. Based on 95% confidence level, it can be concluded that all the coefficients of the SARIMA (1, 1, 1) (0, 1, 1)₁₂ model are significantly different from zero.

Parameter	Estimate	Standard Errors	t-Value
Nonseasonal AR			
Lag 1	0.6532*	0.12170	5.3767
Nonseasonal MA			
Lag 1	0.9012*	0.07270	12.3962
Seasonal MA			
Lag 12	0.8095*	0.07984	10.1390
Variance	0.66652E+05		
Likelihood Statistics			
Effective number of observations (nefobs)			83
Log likelihood (L)			-585.3719
AIC			1178.7438
AICC (F-corrected-AIC)			1179.2566
Hannan Quinn			1182.6308
BIC			1187.4192
Number of parameters estimated (np)			4

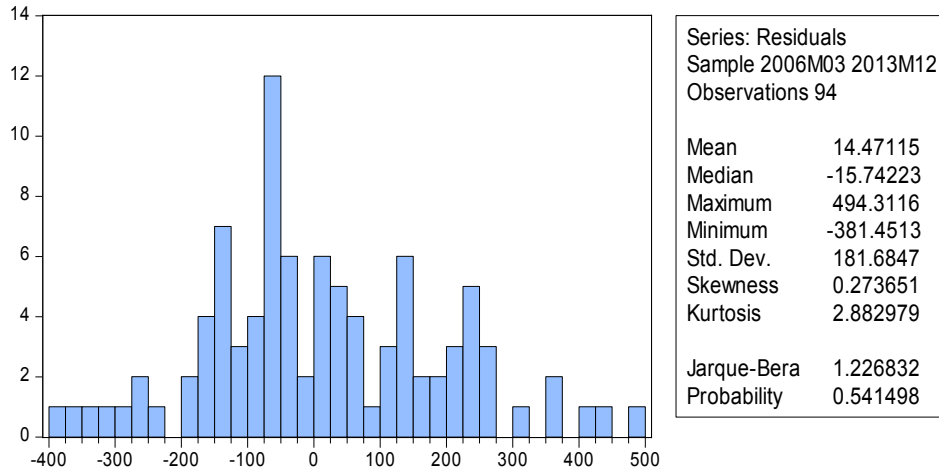
7. Model Validation

Model verification stage of the Box-Jenkins approach is concerned with checking the residuals of the estimated model to determine if the model contains any systematic pattern, which can be removed to improve on the selected SARIMA model. Verification is tested by verifying the PACF of the residuals and the normal probability plot of the residuals. Figure 5 presents the correlogram of residual of the series, indicating that there is no significant spike of PACF. This means that the residual of SARIMA (1, 1, 1) (0, 1, 1)₁₂ model are white noise. That is, the residuals have zero mean, constant variance and also uncorrelated. The p-values for the Ljung-Box statistic clearly all exceed 5% for all lag orders, implying that there is no significant departure from white noise for the estimated residuals. Furthermore, Figure 6 presents the histogram of the estimated residuals and the associated statistics. The reported Jarque–Bera test for normality of the residuals is estimated to be 1.227, which is less than the critical value of chi–square distribution at 5% level of significance. Based on the Jarque–Beratest, the null hypothesis of normality cannot be rejected. Once the model diagnostic tests showed that all the estimated parameters are significant and the residual series are random, it was concluded that SARIMA (1, 1, 1) (0, 1, 1)₁₂ model is adequate for forecasting catfish real prices.

Figure 5. Correlogram of SARIMA (1, 1, 1) (0, 1, 1)₁₂ Model Residuals

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	-0.017	-0.017	0.0267	0.870
		2	0.011	0.011	0.0386	0.981
		3	-0.014	-0.013	0.0574	0.996
		4	-0.042	-0.043	0.2365	0.994
		5	0.169	0.168	3.1369	0.679
		6	0.029	0.035	3.2226	0.780
		7	-0.024	-0.030	3.2839	0.858
		8	-0.052	-0.052	3.5642	0.894
		9	-0.074	-0.062	4.1516	0.901
		10	-0.118	-0.151	5.6537	0.843
		11	-0.075	-0.100	6.2726	0.855
		12	0.123	0.133	7.9490	0.789
		13	0.039	0.068	8.1222	0.836
		14	0.003	0.020	8.1233	0.883
		15	-0.104	-0.065	9.3599	0.858
		16	-0.088	-0.060	10.266	0.852
		17	0.063	0.007	10.737	0.870
		18	-0.008	-0.061	10.745	0.905
		19	-0.018	-0.056	10.784	0.931
		20	-0.131	-0.128	12.883	0.882
		21	-0.190	-0.183	17.360	0.689
		22	0.023	0.031	17.425	0.739
		23	0.042	0.098	17.649	0.776
		24	-0.023	-0.027	17.718	0.816
		25	0.118	0.128	19.538	0.771
		26	0.003	0.062	19.539	0.813
		27	0.142	0.170	22.262	0.724
		28	0.010	-0.009	22.275	0.768
		29	0.086	0.049	23.313	0.762
		30	0.130	0.043	25.692	0.691
		31	0.158	0.099	29.253	0.556
		32	-0.120	-0.180	31.364	0.499
		33	-0.018	0.043	31.411	0.546
		34	0.013	0.038	31.436	0.594
		35	-0.089	-0.133	32.661	0.582
		36	0.097	0.051	34.130	0.558

Figure 6. Histogram of the Residuals of Fitted SARIMA Model



8. Model Forecasting

The selected SARIMA (1, 1, 1) (0, 1, 1)₁₂ model is used to conduct both in-sample and out-sample forecasts for catfish prices in Uganda. Thus, the first forecast (for January to December 2012) is constructed based on in-sample estimation using the period January 2006 to December 2012. The one-year in-sample size is chosen arbitrarily. The predicted catfish prices are then compared with the observed catfish prices (Table 5). From the table, it can be noticed that most of the predicted catfish real prices are close to the observed prices. Moreover, all the actual prices fall within the 95% confidence intervals of the forecasts, which confirms that the model provides an acceptable fit to predict monthly catfish real prices.

The out-sample forecast is conducted using the full data sample from January 2006 to December 2013. Table 6 presents the forecasts for January to December 2014, and Figure 7 plots the forecasted prices. As depicted in Figure 7, SARIMA (1, 1, 1,) (0, 1, 1)₁₂ model predicts a continued upward trend observed in the historical price series. The accuracy of the model is evaluated based on the mean absolute percentage error (MAPE), the root-mean-square error (RMSE), and the mean absolute error (MAE). A mere glance at the results in Table 7 clearly indicates that the model is correctly specified for the purpose of forecasting. For instance, MAPE results suggest that the model can forecast catfish real prices within an accuracy of 4.9%, meaning that the forecast are off by about 5% on average.

Table 5
Actual and In-sample Predicted Prices (UGX/kg)for SARIMA (1,1,1) (0,1,1)₁₂Model

Month	Actual (UGX/kg)	Forecast (UGX/kg)	LCL	UCL	Month	Actual (UGX/kg)	Forecast (UGX/kg)	LCL	UCL
2013.Jan	7100	6941	6361	7521	2013.Jul	7450	7426	6854	7997
2013.Feb	6900	6965	6371	7560	2013.Aug	7350	7435	6867	8002
2013.Mar	7200	7000	6404	7595	2013.Sep	7352	7369	6802	7936
2013.Apr	7500	7211	6635	7788	2013.Oct	7614	7386	6819	7953
2013.May	7500	7446	6872	8019	2013.Nov	7871	7660	7075	8245
2013.Jun	7400	7471	6899	8043	2013.Dec	7827	7840	7270	8410

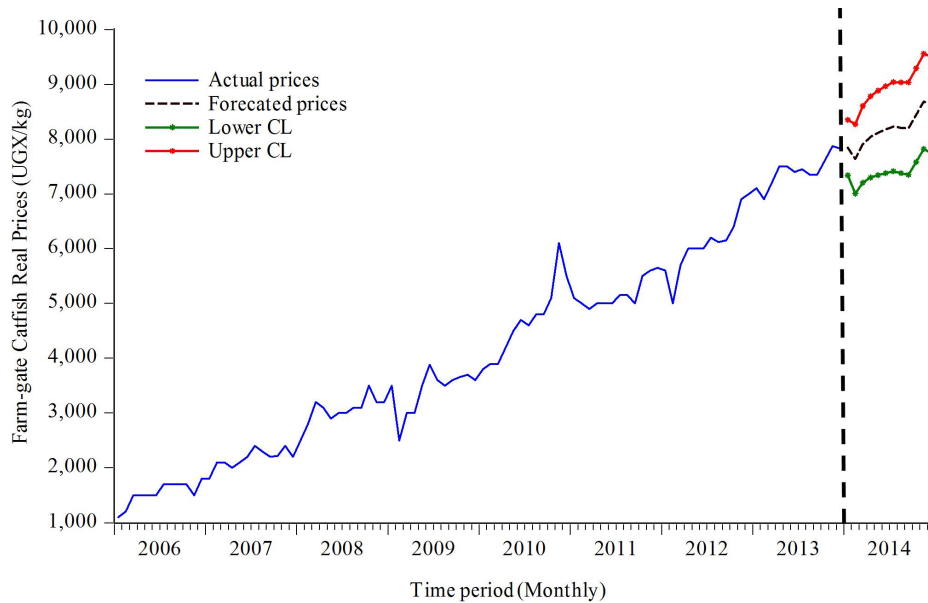
Table 6
Out-sample Predicted Real Prices [SARIMA (1,1,1) (0,1,1)₁₂]

Month	Forecast(UGX/kg)	LCL	UCL
2014.Jan	7844.20	7338.20	8350.21
2014.Feb	7636.82	7003.70	8269.93
2014.Mar	7903.72	7203.75	8603.69
2014.Apr	8040.49	7298.88	8782.11
2014.May	8113.11	7342.33	8883.90
2014.Jun	8170.29	7377.10	8963.48
2014.Jul	8225.60	7413.92	9037.28
2014.Aug	8204.34	7376.54	9032.13
2014.Sep	8189.48	7347.08	9031.87
2014.Oct	8437.01	7581.02	9293.01
2014.Nov	8684.21	7815.29	9553.13
2014.Dec	8623.84	7742.49	9505.19

Table 7
Forecast Performance for SARIMA (1,1,1) (0,1,1)₁₂Model

Root Mean Square Error	264.02
Mean Absolute Error	180.55
Mean Absolute Percent Error	4.909
Theil Inequality Coefficient	0.029
Bias Proportion	0.076
Variance Proportion	0.003
Covariance Proportion	0.922

Figure 7. Out-Sample Forecast for Catfish Prices in Uganda



9. Conclusions

Basic economic theory suggests that the behavior of agricultural commodity prices over time is governed by shifts in supply and demand. In particular, deviations of actual production from expected supplies can have a pronounced impact

on price patterns. This is particularly true for emerging agricultural sectors in developing countries like the aquaculture subsector in Uganda. The objective here was to develop a forecasting model to examine the behavior of farm-gate real prices in the catfish markets and to predict future prices using historical time series data from January 2006 to December 2013. To this end, a SARIMA (1, 1, 1) (0, 1, 1)₁₂ model that incorporate the seasonality of the time series was developed and tested. The results indicated that the model fitted the data well and that the stochastic seasonal fluctuations manifest in the data series were successfully modeled. Model predictions indicated that catfish real prices in Uganda continues to follow an increasing trend with stochastic seasonal effects. The mean absolute percentage error suggested that the estimated model can predict catfish real prices with an accuracy of 4.9%. As a way forward, these findings can help policy makers and other major stakeholders gain insights into more appropriate economic and sectorial policies that can lead to reliable market information system and up-to-date information on supply, demand and stocks. As others have noted, an adequate fish stock is a necessary component of a well-functioning market, in particular, to smooth out seasonal fluctuations and time lags in fish trade.

Limitation: The data used in this analysis are for a period of eight years, which is limited for complex time series models. Furthermore, the subsector examined is prevalent with market imperfections at the production, harvesting, and marketing levels, hence, caution should be exercised when drawing broader conclusions from the results. Despite the limitations, it is undeniable that price forecast is essential, even in such highly imperfect markets.

10. Acknowledgments

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