ISSN 2286-4822
www.euacademic.org

EUROPEAN ACADEMIC RESEARCH
Vol. V, Issue 4/ July 2017

Impact Factor: 3.4546 (UIF)
DRJI Value: 5.9 (B+)

Time Series Analysis of Production and Price of Cattle and Milkfish in the Philippines

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Abstract:

The purpose of the study is to forecast quarterly production and farmgate prices of Cattle and Milkfish in the Philippines from 2017-2021. This paper takes into account the quarterly data of Cattle from 1980-2016 and Milkfish from 2002-2016; and quarterly farmgate prices of cattle and milkfish from 1990-2016 gathered from Philippine Statistics Authority which serve as the central statistical authority of the Philippine government on primary data collection. Autoregressive Integraded Moving Average (ARIMA) was used to forecast the quarterly production of Cattle and Milkfish in the Philippines while Autoregressive Moving Average was used for Farmgate prices. Models with lowest Akaike Information Critera (AIC) and Bayesian information criterion (BIC) was considered as best fitted model. Best fitted model obtained for Cattle production is ARIMA(4,1,2) and ARIMA(12,1,12) for Milkfish Production. ARMA(12,12) and ARMA(5,10) is the best fitted model respectively for cattle and milkfish farmgate prices.

Key words: ARIMA, Cattle Production, Milkfish Production Cattle Farmgate Price, Milkfish Farmgate Price, AIC, BIC

I. Introduction

Raising Cattle in the Philippines is mostly backyard type and traditionally led by the private sector Commercial feedlot fattening operation. It has been evaluated, however, that beef cattle raising in the country has a comparative advantage over other animal production ventures considering the increasing demand for beef; ability to transform low-quality and fibrous feed materials; availability of other forages and favorable climate for fodder production and adequate processing technologies and increased productivity (*source: pcarrd.dost.gov.ph*) Livestock raising is being recognized as a source of income for rural communities. In the citation of A.C. Castillo, the raising of farm animals is still on a small scale basis since it is intimately tied-in with farmers' activities and way of life. Cattle is raised for drought purposes and as source of cash in time of needs. Also, these animals offer a means whereby crop products and farm residues as well as native vegetation in uncultivated areas are converted into meat, milk, hides and other by-products. Aside from livestock products, the sustainability of fisheries and aquaculture is also relevant in an archipelago like the Philippines, where millions of families rely for their daily sustenance and income. According to Food and Agriculture Organization of the United Nations, aquaculture is making significant headway as the fastest-growing food sector. Among the sub-sectors in fisheries, it provides the most potential to reduce hunger and improve nutrition, alleviate poverty, generate economic growth, and ensure better use of natural resources.

Milkfish is one of the most important farmed fish species in the Philippines. Only a small volume out of the total production came from the wild (*source: pcarrd.dost.gov.ph*). Milkfish is an important commodity that is widely cultured in the Philippines. It is good to invest in Milkfish because of its high demand for food consumption in the Philippines.

Forecasting production and price of cattle and fish are important for potential users and policy makers by examining results and recommendations based on their trend and future values. This study will forecast the production and farmgate price of Cattle and Milkfish. In doing so, we have to review first the trend of the selected commodities in agriculture; investigate the model for forecasting selected commodities, forecast the future values of production and price; make recommendations based on the output.

The top 10 countries by forecast growth in beef, pork and chicken consumption from 2011 to 2021 include the Philippines. This was declared by United Kingdom-based think tank Chatham House based on projected consumption increases from Food and Agricultural Policy Research Institute-Iowa State University, 2012 (Plotnek, 2017). Relating this research to consumption is important because forecasting production can be based on consumption. Forecasting production or the capacity to produce can lead policy makers to look for agricultural commodity importation restriction and look for alternative products to produce to sustain consumption. Increasing Agricultural commodity production means increase employment rate and this will help the economy.

1.1 Objective of the Study

The main objective of study is to forecast the production and farmgate price of Cattle and Milkfish in the Philippines. More specifically, the study aims:

1. To present the trend in production and price of cattle and milkfish in the country;
2. To present the best fitted model in forecasting the production and price;
3. To compare the actual data and forecasted data; and
4. To forecast production and farmgate price of cattle and milkfish from 2017-2021.

1.2 Statement of the Problem

The study was conducted to formulate a model in forecasting production and farmgate prices of cattle and milkfish in the Philippines using Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA). Specifically, the study wants to answer the following questions:

1. What is the trend in production and price of cattle and milkfish in the country;
2. What model to use to forecast production and Farmgate price;
3. What is the difference between the actual data and forecasted data; and
4. What is the forecast and trend of the production and prices of cattle and milkfish from 2017 to 2021?

1.3 Significance of the Study

This research focuses on predicting future production and prices of Cattle and Milkfish in the Philippines through forecasting technique. By examining the result and recommendation of the study, policy makers and potential users can imposed necessary steps to improve the production and farmgate prices of cattle and milkfish. And also, this study can be helpful for new business growth related to cattle and milkfish.

1.4 Scope and Limitation

Data was collected from the Philippine Statistics Authority which serve as the central statistical authority of the Philippine government on primary data collection. This study used quarterly production data of Cattle from 1980-2016 and Milkfish from 2002-2016; and quarterly farmgate prices of cattle and milkfish from 1990-2016.

1.5 Research Paradigm

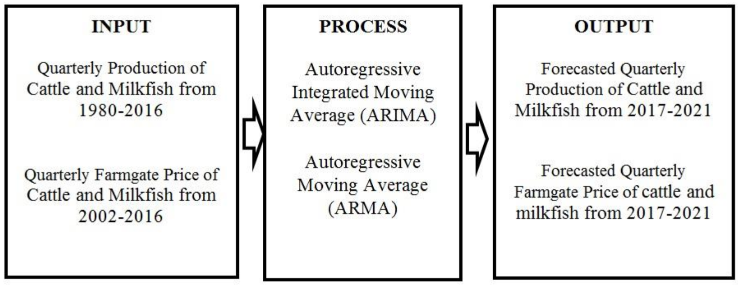


Figure 1. **Research Paradigm**

II. Review of Related Literature

2.1 Foreign Studies

T. Jai Sakar, et al (2010). Propose a technique using ARIMA model for cattle production in Tamilnadu. The estimated results indicate that there an increase in the cattle production which will improve the economy of the state. This provides evidence in favor of Box-Jenkins methodology as it applies to cattle production and future efficiency.

Jin, Power, & Elbakidze, 2008. Forecasting prices with structural econometric models requires forecasts of the relevant exogenous and lagged endogenous variables which are considered to be exogenous in estimation. While these forecasts can be obtained in a recursive manner, forecasts of exogenous variables often present problems for econometric model users Therefore, there was progressive on forecasting cattle prices from structural models to the univariate ARIMA models by Box and Jenkins that are based on current and past observations of the particular data series with no exogenous variables included.

Lazaro M. And Lazaro W. (2013) Fisheries forecasting is a very important tool for fisheries managers and scientists to enable them to decide on sustainable management issues Time series models have been used to forecast catches in fisheries sectors in different countries but to the contrary, Malaŵi has lagged behind in using time series model in forecasting. The study considered Autoregressive (AR), Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA) processes to select the appropriate stochastic model for forecasting annual commercial chambo catch from Lake Malawi. Based on ARIMA (p, d, q) and its components ACF, PACF, Normalized BIC, Box-Ljung Q statistics and residuals estimated, ARIMA (1, 1, 0) was selected. Based on the selected model, it could be forecasted that the commercial chambo catch would increase to 854 tonnes in 2020 from 437 tonnes in 2010

2.2 Local Studies

We want to know the future production of the said agricultural commodities based on past productions, this information to decision makers, it is important in many ways to the economy. ARMA (Autoregressive Moving Average) and Autoregressive Interated Moving Average model was use to forecast production and farmgate prices. It has been found that in terms of forecast ability ARMA models outperform AR models, when following for the same degrees of freedom. Also, the models with separate specification of a seasonal component do better than models where seasonal terms are modeled jointly with other components of the time series. Eventually, the models with a trend displaying the structural break in 1999 outperform other models. Interestingly enough, in the context of the sample examined, the standard in-sample model selection criteria provide rather poor guidance in identifying the best model for out-of-sample forecasting (Stovicek, 2007). A study found that ARMA models performed best for Crop yield prediction (Choudhury & Jones, 2014). Another study use ARMA for the prediction of Rainfall (Bugroho & Simanjuntak 2014).

III. Methodology

3.1 Statistical Tool

Statistical Software: Econometric Eviews used by researchers to investigate the data series, formulate ARMA or ARIMA model and forecast future values based on the selected model.

3.2 Statistical Treatment

3.2.1 Data Preparation

Plot the series data to capture the possible trend and seasonality. Use Correlogram and examine ACF for stationarity. If the series is not stationary, take first differencing. Use Augmented Dickey-Fuller (ADF) Test for formal test. Once model is stationary proceed to model identification and estimation

3.2.1.1 Test for Stationarity: Augmented Dickey-Fuller (ADF) Test

The stationarity or otherwise of a series can strongly influence its behavior and properties. A series is said to be (weakly or covariance) stationary if the mean and autocovariances of the series do not depend on time. Any series that is not stationary is said to be nonstationary or has unit root. So having a unit root means:

$$\rho_1 = 1 \text{ in } y_t = \rho_1 y_{t-1} + \rho_2 \Delta y_{t-1} + \rho_3 \Delta y_{t-2} + \varepsilon_t \text{ or equivalently}$$

$$1-\rho 1 = 0 \text{ in } \Delta y_t = (\rho_1 - 1) y_{t-1} + \sum_{j=2}^{p} \rho_j (\Delta y_{t-j+1}) + \varepsilon_t$$

3.2.2. Model Identification and Estimation

Examine the ACF (for Moving average term) and PACF (for Autoregressive term) of the stationary series for possible ARIMA (Autoregressive Integrated Moving Average) model to estimate. Estimate the Models, if the parameters are significant proceed to Diagnostic Checking.

3.2.3 Residual diagnostic Checking

The model should past residual diagnostic checking to be considered as candidate model for forecasting.

3.2.3.1 Ljung–Box test

A type of statistical test of whether any of a group of autocorrelations of a time series are different from zero. Instead of testing randomness at each distinct lag, it tests the "overall" randomness based on a number of lags, and is therefore a portmanteau test.

The Ljung–Box test may be defined as: Ho: The data are independently distributed, Ha: The data are not independently distributed; they exhibit serial correlation.

The test statistic is: $$Q = n\,(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k}$$

where *n* is the sample size, $\hat{\rho}_k$ is the sample autocorrelation at lag *k*, and *h* is the number of lags being tested . Under H_o the statistic Q follows a $\chi^2_{(h)}$. For significance level α, the critical region for rejection of the hypothesis of randomness is.

$Q > \chi^2_{1-\alpha,h}$ where $\chi^2_{1-\alpha,h}$ is the α-quantile of the chi-squared distribution with h degrees of freedom.

The Ljung–Box test is rarely used in autoregressive integrated moving average (ARIMA) modeling. It is applied to the residuals of a fitted ARIMA model, not the original series, and in such applications the hypothesis actually being tested is that the residuals from the ARIMA model have no autocorrelation. When testing the residuals of an estimated ARIMA model, the degrees of freedom need to be adjusted to reflect the parameter estimation.

3.2.3.2 Correlogram

Correlogram is an aid to interpret a set of ACF and PACF where, sample autocorrelations are plotted against lag h. In addition, correlograms are used in the model identification stage for Box–Jenkins autoregressive moving average time series models. Autocorrelations should be near-zero for randomness; if the analyst does not check for randomness, then the validity of many of the statistical conclusions becomes suspect. The Correlogram is an excellent way of checking for such randomness.

3.2.3.3 Normality test

In statistics, the Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The test is named after Carlos Jarque and Anil K. Bera. A large p-value and hence failure to reject this null hypothesis is a good result. It means that it is reasonable to assume that the errors have a normal distribution. The residuals should be normally distributed so that the *t–statistics* used to evaluate the significance of AR and MA terms are valid. Jarque-Bera test have the formula:

$$JB = n\left(\frac{(k_3)^2}{6} + \frac{(k_4)^2}{24}\right), \quad k_3 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{ns^3}, \quad k_4 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^4}{ns^4} - 3$$

where x is each observation, n is the sample size, s is the standard deviation, k_3 is skewness, and k_4 is kurtosis.

3.2.3.4 Heteroskedasticity: White Test

Residuals from an ARIMA model should show a constant variance in order to support proper calculation of the unbiased standard errors that are part of the *t- statistics* and *F-statistics* required for hypothesis testing. White's test attempts to create whether or not the variance is changing.

Breusch–Pagan test is used to test for heteroskedasticity in a linear regression model.

Procedure:

Under the classical assumptions, ordinary least squares is the best linear unbiased estimator (BLUE), i.e., it is unbiased and efficient. It remains unbiased under heteroskedasticity, but efficiency is lost. Before deciding upon an estimation method, one may conduct the Breusch–Pagan test to examine the presence of heteroskedasticity. The Breusch–Pagan test is based on models of the type $\sigma_i^2 = h(z_i'\gamma)$ for the variances of the observations where $z_i = (1, z_{2i}, \ldots, z_{pi})$ explain the difference in the variances. The null hypothesis is equivalent to the (p-1) parameter restrictions: $\gamma_2 = \cdots = \gamma_p = 0$. The following Lagrange multiplier (LM) yields the test statistic for the Breusch–Pagan test:

$$\mathrm{LM} = \left(\frac{\partial \ell}{\partial \theta}\right)' \left(-E\left[\frac{\partial^2 \ell}{\partial \theta \, \partial \theta'}\right]\right)^{-1} \left(\frac{\partial \ell}{\partial \theta}\right)$$

This test is analogous to following the simple three-step procedure:

Step 1: Apply OLS in the model $y = X\beta + \varepsilon$ and compute the regression residuals.

Step 2: Perform the auxiliary regression $e_i^2 = \gamma_1 + \gamma_2 z_{2i} + \cdots + \gamma_p z_{pi} + \eta_i$ Always, *z* could be partly replaced by independent variables *x*

Step 3: The test statistic is the result of the coefficient of determination of the auxiliary regression in Step 2 and sample size n with: $\mathrm{LM} = nR^2$

The test statistic is asymptotically distributed as χ^2_{p-1} under the null hypothesis of homoscedasticity.

3.2.3.5 Serial Correlation

Testing for autocorrelation in a time series is a common task for researchers working with time-series data.

Breusch-Godfrey Serial Correlation LM test

Test used for AR (1) and higher orders of serial correlation. The Breusch-Godfrey Test regress the residuals on the original regressors and lagged residuals up to the specified lag order. (EViews User's Guide, p 338)

The Breusch–Godfrey serial correlation LM test is a test for autocorrelation in the errors in a regression model. It makes use of the residuals from the model being considered in a regression analysis, and a test statistic is derived from these. The null hypothesis is that there is no serial correlation of any order up to p.

Procedure:

Consider a linear regression of any form, for example

$$Y_t = \alpha_0 + \alpha_1 X_{t,1} + \alpha_2 X_{t,2} + u_t$$

where the errors might follow an AR(p) autoregressive scheme, as follows:

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \cdots + \rho_p u_{t-p} + \varepsilon_t.$$

The simple regression model is first fitted by ordinary least squares to obtain a set of sample residuals $\hat{u}_t$. Breusch and Godfrey proved that, if the following auxiliary regression model is fitted

$$\hat{u}_t = \alpha_0 + \alpha_1 X_{t,1} + \alpha_2 X_{t,2} + \rho_1 \hat{u}_{t-1} + \rho_2 \hat{u}_{t-2} + \cdots + \rho_p \hat{u}_{t-p} + \varepsilon_t$$

and if the usual $\mathbf{R^2}$ statistic is calculated for this model, then the following asymptotic approximation can be used for the distribution of the test statistic $nR^2 \sim \chi^2_p,$,when the null hypothesis $nR^2 \sim \chi^2_p$, holds (that is, there is no serial correlation of any order up to p). Here n is the number of data-points available for the second regression, that for $\hat{u}_t$,

$$n = T - p$$

where T is the number of observations in the basic series. Note that the value of n depends on the number of lags of the error term (p)

3.2.4 Forecasting and Forecast Evaluation Measures

Use the model to construct forecast, Graph the forecast against the actual values. Use AIC and BIC to choose the parsimonious model for forecasting.

3.2.4.1 Akaike Information Critera (AIC)

The **Akaike Information Critera (AIC)** is a generally used measure of a statistical model. It basically measures the goodness of fit, and the simplicity/parsimony, of the model into a single statistic. It can be written as

$$AIC = -2\log(L) + 2(p + q + k + 1)$$

where L is the likelihood of the data, k=1 if c≠0 and k=0 if c=0. Note that the last term in parentheses is the number of parameters in the model (including δ^2 the variance of the residuals).

3.2.4.2 Bayesian information criterion (BIC) or Schwarz criterion (also SBC, SBIC)

Bayesian information criterion (BIC) or Schwarz criterion (also SBC, SBIC) is a criterion for model selection among a finite set of models; the model with the lowest BIC is preferred. It is based, in part, on the likelihood function and it is closely related to the Akaike information criterion (AIC).

When fitting models, it is possible to increase the likelihood by adding parameters, but doing so may result in overfitting. Both BIC and AIC attempt to resolve this problem by introducing a penalty term for the number of parameters in the model; the penalty term is larger in BIC than in AIC.

The BIC is formally defined as

$$BIC = \ln(n)\, k - 2\ln(\widehat{L})$$

Where $\hat{L}$ is the maximized value of the likelihood function of the model, n = the number of data points, and k = the number of free parameters to be estimated.

IV. Results and Discussion

4.1 TIME SERIES PLOT
4.1.1 CATTLE PRODUCTION

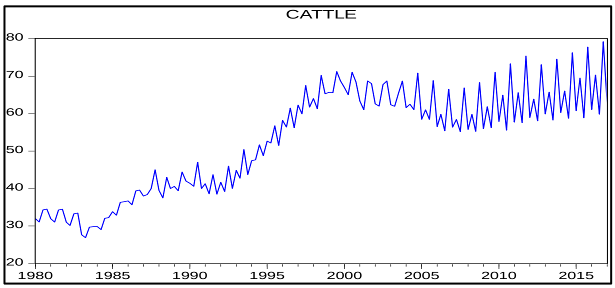


Figure 2. **Time Series plot of Cattle Production in the Philippines 1980Q1 – 2016Q4**

A perusal of Figure 2 reveals an increasing trend in the cattle production in the Philippines over the years. At the same time, the figure also shows that the production is highest during the first and third quarter and lowest during second and fourth quarter during the year.

Dickey fuller test was used to test if unit root exist for Cattle production. Actual series is not stationary but after first differencing the series become stationary (See Appendix A, Table 1) After the first differencing the time series data on the production became stationary. (See Appendix A, Table 2)

4.1.2 MILKFISH PRODUCTION

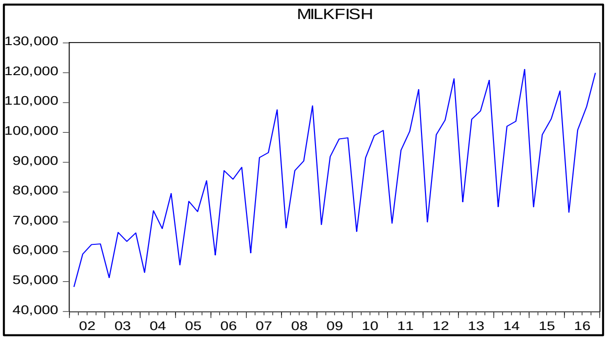


***Figure 3*. Time Series Plot Fish Production in the Philippines 1980Q1 – 2016Q4**

Analysis of Figure 3 reveals an increasing movement in the Milkfish production in the Philippines over the years. At the same time, the figure also shows that the production is highest during the second and fourth quarter and lowest during first and third quarter during the year.

Dickey fuller test was used to test if unit root exist for Milkfish production. Actual series is not stationary but after first differencing the series become stationary (See Appendix A, Table 1) After the first differencing the time series data on the production became stationary. (See Appendix A, Table 2)

4.1.3 Cattle Farmgate Price

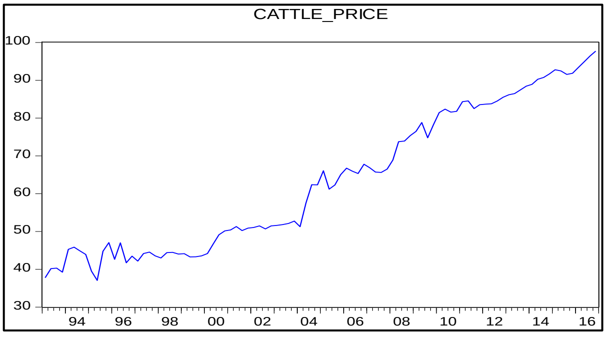


***Figure 4*. Time Series Plot of Cattle Farmgate Price in the Philippines from1980Q1 – 2016Q4**

Analysis of Figure 4 reveals an increasing movement in farmgate price of cattle in the Philippines over the years.

4.1.2 Milkfish Farmgate Price

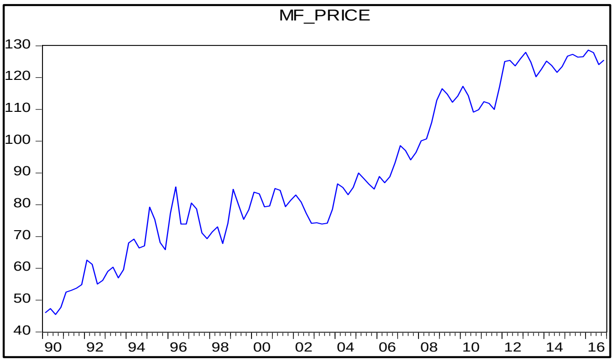


***Figure 5.* Time Series Plot of Milkfish Price in the Philippines from1980Q1 – 2016Q4**

Analysis of Figure 5 reveals an increasing movement in farmgate price of milkfish in the Philippines over the years.

4.2 Selecting the Candidate Forecasting Model

To select the best fitted model for forecasting out of three above, the researcher chose the model with lowest BIC (Bayesian Information Criterion) and AIC (Akaike Information Criterion) values. Table 1 summarizes the output of each of the fitted ARIMA model in the time series.

The candidate models for cattle production are: ARIMA(4,1,2); ARIMA(1,1,7); and ARIMA(12,1,4), for milkfish production are: ARIMA(12,1,4); ARIMA(4,1,8); and ARIMA (12,1,12), for cattle farmgate price are ARMA(12,12) and ARMA(6,8), and for milkfish farmgate price are ARMA(8,4) and ARMA(5,10) (see Appendix B).

Table 1
AIC AND BIC Values of fitted ARIMA Models

Series Data	ARIMA Model	AIC	BIC	R-squared	MAPE
Cattle Production	(4,1,2)	3.94	4.02	94.76	2.36
	(1,1,7)	3.95	4.01	94.63	2.54
	(12,1,4)	4.52	4.6	91.09	3.49
Milkfish Production	(12,1,4)	20.08	20.2	95.04	3.59
	(4,1,8)	19.58	19.73	96.75	2.63
	12,1,12	19.59	19.71	96.96	2.66
Cattle Farmgate Price	(12,12)	4.11	4.2	98.96	1.8
	(6,8)	4.12	4.26	99.04	1.91
Milkfish Farmgate Price	(8,4)	5.21	5.1	98.15	1.88
	(5,10)	5.19	5.08	98.23	2.75

The table shows that the lowest AIC and BIC values for cattle production is the ARIMA(4,1,2) model with (p=4, d=1 and q=2), for milkfish production is the ARIMA(12,1,12) model with (p=12, d=1 and q=12), for cattle farmgate price is the ARMA (12, 12) model with (p=12 d=1 q=12), for milkfish farmgate price is the ARMA (5,10) model with (p=5, d=0 and q=10), hence this model can be the best predictive model for making forecasts for future production and price of cattle and milkfish values.

4.3 Actual versus Forecast

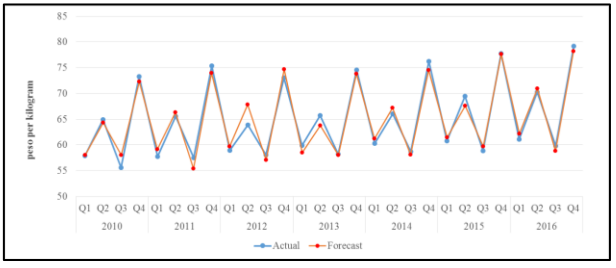


Figure 6. **Actual Cattle Production versus Forecasted Cattle Production**

Figure 6 above shows the forecasted cattle production follow the trend of the actual value. The forecast values follows the trend of the actual data on cattle production.

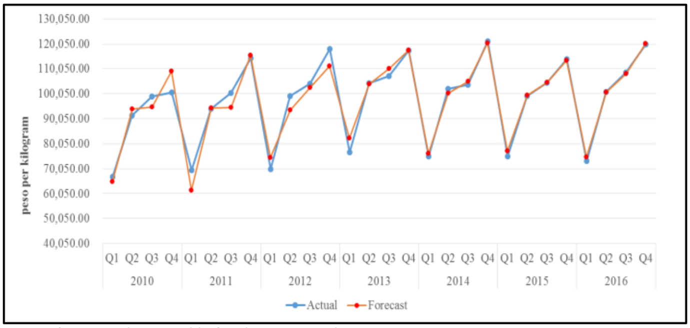


Figure 7. **Actual Milkfish Production versus Forecast Milkfish Production**

Figure 7 above shows the forecasted milkfish production follow the trend of the actual value.

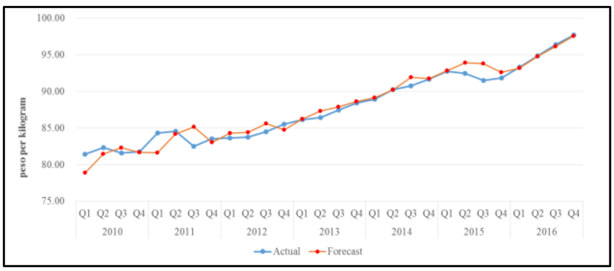


Figure 8. **Actual Cattle Farmgate Price versus Forecast Cattle Farmgate Price**

The figure 8 above shows the forecasted farmgate price of cattle follow the trend of the actual value.

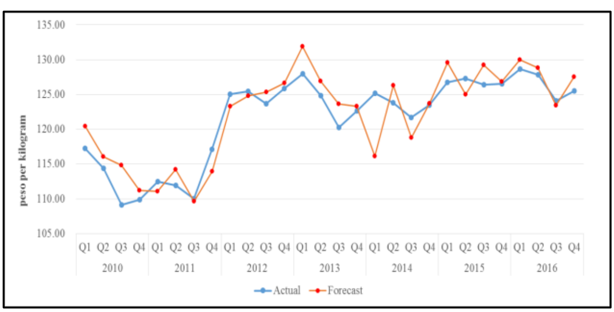


Figure 9. **Actual Milkfish Farmgate Price versus Forecast Milkfish Farmgate Price**

The figure 9 above shows the forecasted farmgate price of milkfish follow the trend of the actual value.

4.1.3 Forecast from the Best Model

The production model for cattle is a function of the past values of cattle production with autoregressive of order four and moving average of order two.

The forecasting model for cattle production is statistically significant as shown by the computed p-value of the F-statistics, 0.00. The coefficient of determination suggests that the independent variable explain 94 percent of the total variation in cattle production. On the average, the model's forecast is off by 2.36 percent of the actual production. (Appendix B, Table 1)

Table 2
ARIMA (4,1,2) Forecasted Cattle Production from 2017Q1-2021Q4

Quarter	Production in '000 metric ton						Percent change				
	2016	2017F	2018F	2019F	2020F	2021F	17F/16	18F/17F	19F/18F	20F/19F	21F/20F
Q1	61.09	62.37	63.63	64.67	65.50	66.16	*2.10*	*2.02*	*1.62*	*1.29*	*1.00*
Q2	70.28	72.14	73.81	75.31	76.68	77.92	*2.64*	*2.31*	*2.04*	*1.81*	*1.62*
Q3	59.86	60.65	61.30	61.82	62.25	62.59	*1.32*	*1.07*	*0.86*	*0.69*	*0.55*
Q4	79.18	80.25	81.14	81.88	82.50	83.02	*1.35*	*1.11*	*0.91*	*0.76*	*0.63*

The estimated cattle production for 2016 Q4 is 79.18 thousand metric tons which is 1.83 percent higher as compared to the same period last year. Based on the prediction result that there is a positive increase in cattle production in all quarters up to 2021.

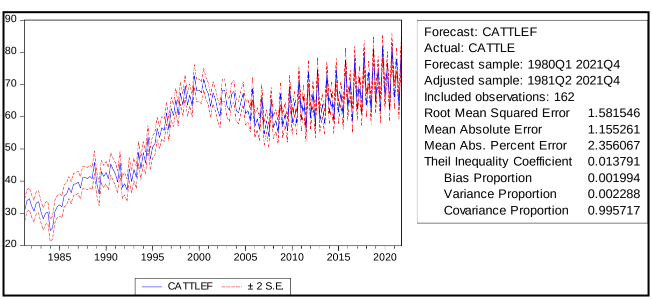


Figure 10. **Graph of ARIMA (4,1,2) Forecasted Cattle Production from 2017Q1-2021Q4**

The production model for milkfish is a function of the past values of milkfish production with autoregressive of order twelve and moving average of order twelve. Below is the estimated equation:

The forecasting model for milkfish production is statistically significant as shown by the computed p-value of the F-statistics, 0.00. The coefficient of determination suggests that the independent variable explain 99 percent of the total variation in milkfish production. On the average, the model's forecast is off by 2.66 percent of the actual production. (Appendix C).

Table 3

ARIMA (12,1,12) Forecasted Milkfish Production from 2017Q1-2021Q4

Quarter	Production in metric ton						Percent change				
	2016	2017F	2018F	2019F	2020F	2021F	17F/16	18F/17F	19F/18F	20F/19F	21F/20F
Q1	73,251	74,790	75,850	75,307	76,347	77,942	*2.10*	*1.42*	*(0.72)*	*1.38*	*2.09*
Q2	100,827	100,526	100,402	103,057	102,424	102,342	*(0.30)*	*(0.12)*	*2.64*	*(0.61)*	*(0.08)*
Q3	108,599	105,102	107,575	112,429	108,952	111,643	*(3.22)*	*2.35*	*4.51*	*(3.09)*	*2.47*
Q4	119,978	123,981	117,610	125,580	130,250	123,046	*3.34*	*(5.14)*	*6.78*	*3.72*	*(5.53)*

The estimated milkfish production for 2016Q4 is 73,251.41 metric tons which is 5.37 percent higher as compared to the same period last year.

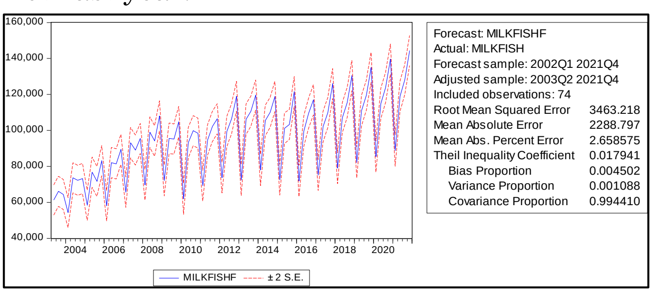


***Figure 11*. Graph of ARIMA(12,1,12) Forecasted Milkfish Production from 2017Q1-2021Q4**

The price model for cattle is a function of the time with autoregressive of order twelve and moving average of twelve.

The forecasting model for farmgate price of cattle is statistically significant as shown by the computed p-value of the F-statistics, 0.00. The coefficient of determination suggests that the independent variable explain 99 percent of the total variation in milkfish production. On the average, the model's forecast is off by 1.78 percent of the actual price. (Appendix D)

Table 4
ARMA (12,12) Forecasted Cattle Farmgate Price from 2017Q1-2021Q4

Quarter	Peso per kilogram						Percent change				
	2016	2017F	2018F	2019F	2020F	2021F	17F/16	18F/17F	19F/18F	20F/19F	21F/20F
Q1	93.35	98.86	103.55	107.71	111.46	114.94	*5.90*	*4.74*	*4.03*	*3.48*	*3.13*
Q2	94.88	99.98	104.86	108.54	112.54	116.24	*5.37*	*4.88*	*3.51*	*3.68*	*3.29*
Q3	96.40	101.35	106.16	109.43	113.67	117.57	*5.14*	*4.74*	*3.08*	*3.88*	*3.43*
Q4	97.72	102.43	107.00	110.41	114.82	118.88	*4.82*	*4.46*	*3.18*	*4.00*	*3.53*

The estimated price for 2016Q4 is 6.38 percent higher as compared to the same period last year. The table shows that there will be an increase up to 2021.

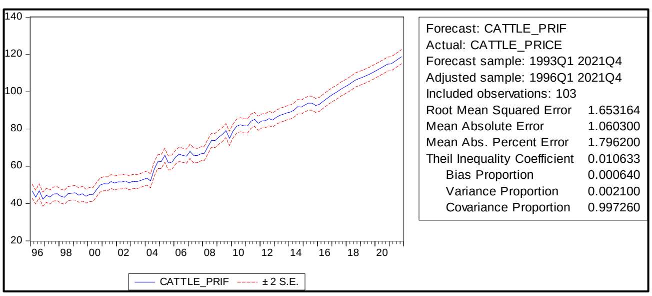


***Figure 12.* Graph of ARMA(12,12) Forecasted Cattle Farmgate Price from 2017Q1-2021Q4**

The model for milkfish farmgate is a function of the time with autoregressive of order five and moving average of order 10

The forecasting model for milkfish farmgate price is statistically significant as shown by the computed p-value of the F-statistics, 0.00. The coefficient of determination suggests that the independent variable explain 98 percent of the total variation in milkfish farmgate. On the average, the model's forecast is off by 2.63 percent of the actual production. (Appendix E).

Table 5
ARMA (5,10) Forecasted Fish Farmgate Price from 2017Q1-2021Q4

Quarter	Peso per kilogram						Percent change				
	2016	2017F	2018F	2019F	2020F	2021F	17F/16	18F/17F	19F/18F	20F/19F	21F/20F
Q1	128.65	125.73	131.27	136.17	139.33	142.42	*(2.27)*	*4.40*	*3.73*	*2.32*	*2.22*
Q2	127.83	127.35	132.70	138.07	140.52	143.37	*(0.37)*	*4.20*	*4.05*	*1.77*	*2.02*
Q3	124.07	128.26	134.17	138.82	141.15	144.03	*3.38*	*4.61*	*3.47*	*1.68*	*2.04*
Q4	125.50	128.81	135.11	139.40	141.73	144.69	*2.64*	*4.89*	*3.18*	*1.68*	*2.08*

The estimated price for 2016Q4 is 0.83 percent lower as compared to the same period last year. The table shows that there will be an increase up to 2021.

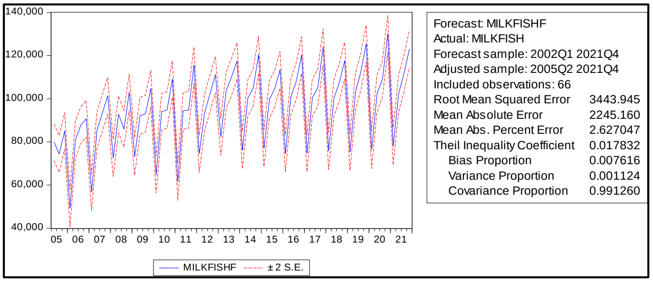


***Figure 13.* Graph of ARMA(5,10) Forecasted Milkfish Production from 2017Q1-2021Q4**

V. Summary, Conclusion and Recommendation

5.1 Summary and Conclusion

This study forecasted the production and farmgate price of Cattle and Milkfish in the Philippines Using Autoregressinve Integrated Moving Average (ARIMA) and Autoregressive Moving Average (ARMA). Models with lowest Akaike Information Critera (AIC) and Bayesian information criterion (BIC) was considered as best fitted model. Best fitted model obtained for Cattle production is ARIMA(4,1,2) and ARIMA(12,1,12) for Milkfish Production. ARMA(12,12) and ARMA(5,10) is the best fitted model respectively for cattle and milkfish farmgate prices. The results from these models are then used to make predictions of the future values of the production and price of Cattle and Milkfish from 2017-2021.

The trend in the production and price of cattle and milkfish in the country has an increasing movement over the years. The trend of the forecast follows the trend of the actual value. The forecasting ability of the model for a five year forecast is shown to be relatively good.

5.2 Recommendation

Policy makers can use the forecasted production and farmgate prices to impost acts that would benefit both producers and consumers. And also, this study can be relate to further studies where in production is related like consumption, import and exports of milkfish and cattle in the Philippines. Forecasting production and price can be done along with other variables like consumption, imports, exports through Vector Autoregressive Analysis; and also, Granger causality to know if the variables can granger cause each other.

APPENDIX A

Table 1

Testing for stationary of the time series data

Variable	ADF-test	Critical Value	Prob*	hypothesis (H_a)	Decision
Cattle Production	(1.34)	(2.88)	0.61	Stationary	Fail to reject H_o
Milkfish Production	(2.70)	(2.91)	0.08	Stationary	Fail to reject H_o
Cattle Farmgate Price	(11.11)	(2.89)	0.00	Stationary	Reject H_o
Milkfish Farmgate Price	(6.40)	(2.89)	0.00	Stationary	Reject H_o

*Mackinnon (1196) one-sided p-values

Table 2.

Testing for stationary of the time series data after first differencing

Variable	ADF-test	Critical Value	Prob*	hypothesis (H_a)	Decision
Cattle Production	(2.84)	(1.94)	0.00	Stationary	Reject H_o
Milkfish Productio	(5.00)	(2.92)	0.00	Stationary	Reject H_o

*Mackinnon (1196) one-sided p-values

APPENDIX B
DIAGNOSTIC CHECKING
Cattle Production Forecasting Model
ARIMA (4,1,2)

Table 3
Significance of the variable in ARIMA (4,1,2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(3)	-0.0894	0.03391	-2.6374	0.0093
AR(4)	0.93655	0.03374	27.7575	0
MA(1)	-0.6417	0.083134	-7.7183	0
MA(2)	0.23541	0.083767	2.81031	0.0057
R-squared	0.94756	Mean dependent var		0.33035
Adjusted R-squared	0.94642	S.D. dependent var		7.37643
S.E. of regression	1.70739	Akaike info criterion		3.93538
Sum squared resid	405.209	Schwarz criterion		4.01826
Log likelihood	-277.38	Hannan-Quinn criter.		3.96906
Durbin-Watson stat	2.0564			

Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.032	-0.032	0.1449	
		2	0.045	0.044	0.4398	
		3	-0.046	-0.043	0.7496	
		4	-0.132	-0.137	3.3471	
		5	-0.030	-0.036	3.4860	0.062
		6	-0.022	-0.014	3.5574	0.169
		7	-0.059	-0.071	4.0865	0.252
		8	0.005	-0.020	4.0905	0.394
		9	-0.072	-0.080	4.8893	0.430
		10	0.003	-0.016	4.8911	0.558
		11	0.091	0.079	6.1784	0.519
		12	0.017	0.010	6.2240	0.622

Figure 1 **Correlogram for ARIMA (4,1,2)**

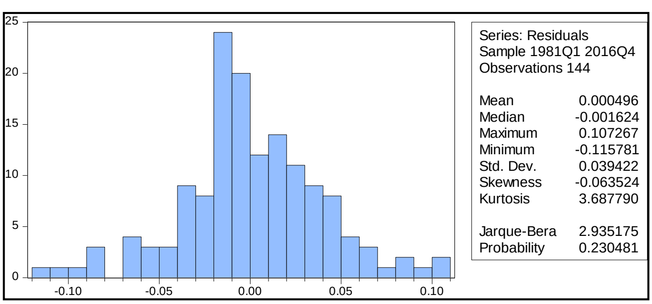


Figure 2. **Normality Test for ARIMA(4,1,2)**

Table 3

Breusch-Godfrey Serial Correlation LM Test for ARIMA(4,1,2)

F-statistic	1.03372	Prob. F(4,135)	0.3923
Obs*R-squared	3.93553	Prob. Chi-Square(4)	0.4148

Table 4

Heteroskedasticity Test for ARIMA(4,1,2)

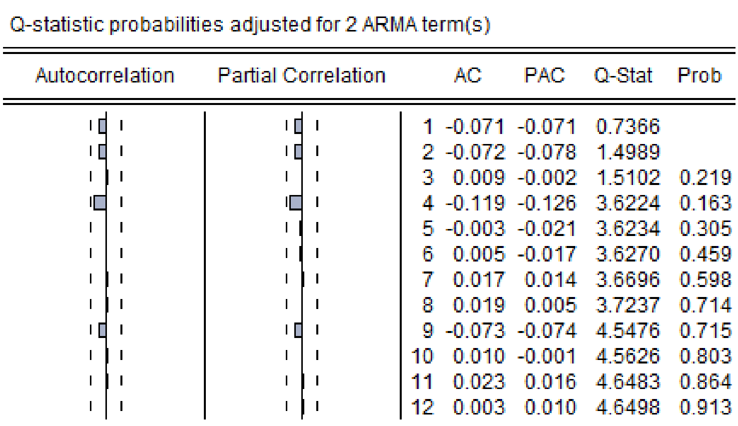
F-statistic	1.87666	Prob. F(10,132)	0.0538
Obs*R-squared	17.7999	Prob. Chi-Square(10)	0.0584
Scaled explained SS	24.0153	Prob. Chi-Square(10)	0.0076

ARIMA (1,1,7)

Table 5

Significance of the Variable in ARIMA (1,1,7)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CATTLE(-4))	0.95467	0.033189	28.7648	0
AR(1)	-0.5995	0.068972	-8.6914	0
MA(7)	-0.1536	0.084647	-1.8142	0.0718
R-squared	0.94631	Mean dependent var		0.33894
Adjusted R-squared	0.94553	S.D. dependent var		7.40183
S.E. of regression	1.72743	Akaike info criterion		3.95205
Sum squared resid	414.78	Schwarz criterion		4.0145
Log likelihood	-277.6	Hannan-Quinn criter.		3.97743
Durbin-Watson stat	2.13873			


Q-statistic probabilities adjusted for 2 ARMA term(s)

	AC	PAC	Q-Stat	Prob
1	-0.071	-0.071	0.7366	
2	-0.072	-0.078	1.4989	
3	0.009	-0.002	1.5102	0.219
4	-0.119	-0.126	3.6224	0.163
5	-0.003	-0.021	3.6234	0.305
6	0.005	-0.017	3.6270	0.459
7	0.017	0.014	3.6696	0.598
8	0.019	0.005	3.7237	0.714
9	-0.073	-0.074	4.5476	0.715
10	0.010	-0.001	4.5626	0.803
11	0.023	0.016	4.6483	0.864
12	0.003	0.010	4.6498	0.913

Figure 3. **Correlogram for ARIMA(1,1,7)**

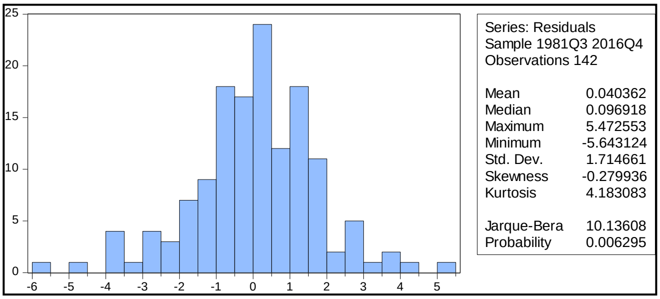


Figure 4 **Normality Test for ARIMA(1,1,7)**

Table 6

Breusch-Godfrey Serial Correlation LM Test for ARIMA (1,1,7)

F-statistic	0.53908	Prob. F(12,127)	0.8856
Obs*R-squared	6.80698	Prob. Chi-Square(12)	0.8701

Table 7

Heteroskedasticity Tes t for ARIMA (1,1,7)

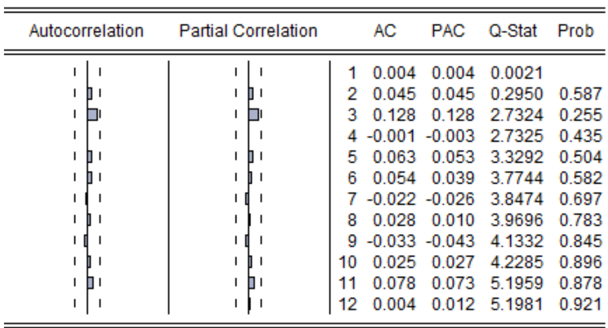
F-statistic	1.62366	Prob. F(6,135)	0.1452
Obs*R-squared	9.55739	Prob. Chi-Square(6)	0.1446
Scaled explained SS	14.448	Prob. Chi-Square(6)	0.025

ARIMA (12,1,4)

Table 8

Significance of the Variable for ARIMA(12,1,4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(3)	-0.3076	0.056661	-5.4288	0
AR(12)	0.75097	0.063713	11.7869	0
MA(4)	0.46079	0.059007	7.80907	0
MA(1)	-0.539	0.058311	-9.2433	0
R-squared	0.91093	Mean dependent var		0.3817
Adjusted R-squared	0.90889	S.D. dependent var		7.55824
S.E. of regression	2.28137	Akaike info criterion		4.51661
Sum squared resid	681.806	Schwarz criterion		4.60269
Log likelihood	-300.87	Hannan-Quinn criter.		4.55159
Durbin-Watson stat	2.37758			



Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.004	0.004	0.0021	
		2	0.045	0.045	0.2950	0.587
		3	0.128	0.128	2.7324	0.255
		4	-0.001	-0.003	2.7325	0.435
		5	0.063	0.053	3.3292	0.504
		6	0.054	0.039	3.7744	0.582
		7	-0.022	-0.026	3.8474	0.697
		8	0.028	0.010	3.9696	0.783
		9	-0.033	-0.043	4.1332	0.845
		10	0.025	0.027	4.2285	0.896
		11	0.078	0.073	5.1959	0.878
		12	0.004	0.012	5.1981	0.921

Figure 5 Correlogram for ARIMA(12,1,4)

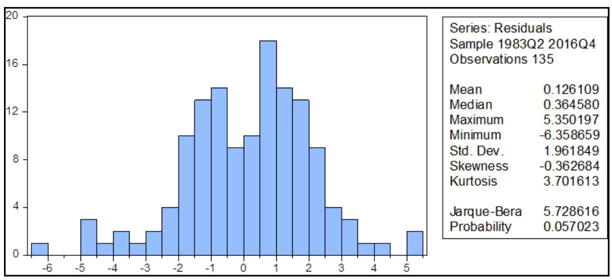


***Figure 6.* Normality Test for ARIMA(12,1,4)**

Table 9

Breusch-Godfrey Serial Correlation LM Test for ARIMA(12,1,4)

F-statistic	2.35692	Prob. F(3,128)	0.0749
Obs*R-squared	5.7068	Prob. Chi-Square(3)	0.1268

Table 10

Heteroskedasticity Test for ARIMA(12,1,4)

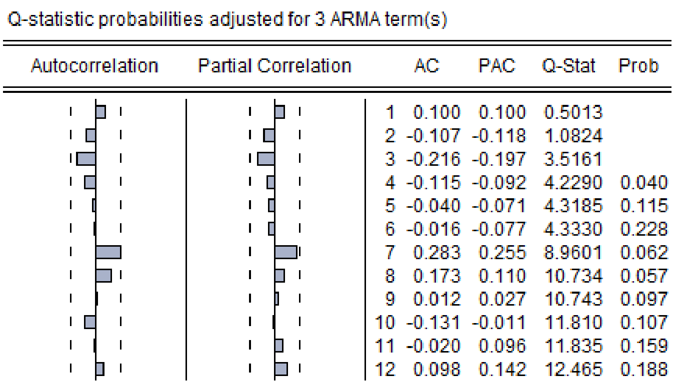
F-statistic	0.23273	Prob. F(10,124)	0.9925
Obs*R-squared	2.48703	Prob. Chi-Square(10)	0.9911
Scaled explained SS	3.21805	Prob. Chi-Square(10)	0.9758

APPENDIX C
DIAGNOSTIC CHECKING
Milkfish Production Forecasting Model
ARIMA(12,1,4)

Table 11
Significance of the Variable for ARIMA(12,1,4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(12)	1.0644	0.068533	15.5312	0
MA(4)	0.726604	0.075313	9.64779	0
MA(3)	-0.27331	0.092037	-2.9696	0.0048
R-squared	0.950412	Mean dependent var		1369.9
Adjusted R-squared	0.948158	S.D. dependent var		23655.5
S.E. of regression	5386.08	Akaike info criterion		20.0827
Sum squared resid	1.28E+09	Schwarz criterion		20.2008
Log likelihood	-468.944	Hannan-Quinn criter.		20.1272
Durbin-Watson stat	2.539958			

Correlogram


Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.100	0.100	0.5013	
		2	-0.107	-0.118	1.0824	
		3	-0.216	-0.197	3.5161	
		4	-0.115	-0.092	4.2290	0.040
		5	-0.040	-0.071	4.3185	0.115
		6	-0.016	-0.077	4.3330	0.228
		7	0.283	0.255	8.9601	0.062
		8	0.173	0.110	10.734	0.057
		9	0.012	0.027	10.743	0.097
		10	-0.131	-0.011	11.810	0.107
		11	-0.020	0.096	11.835	0.159
		12	0.098	0.142	12.465	0.188

Figure 7 **Correlogram for ARIMA(12,1,4)**

Normality

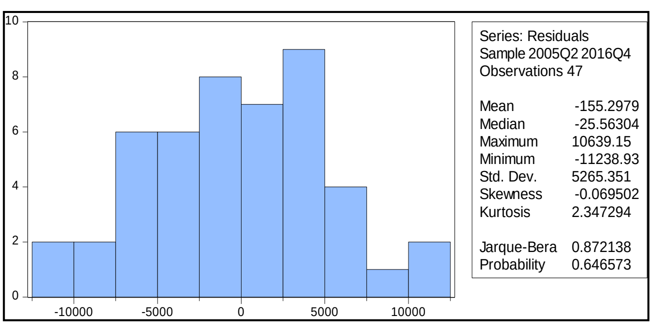


Figure 8 Normality Test for ARIMA(12,1,4)

Table 12

Breusch-Godfrey Serial Correlation LM Test for ARIMA(12,1,4)

F-statistic	1.26381	Prob. F(12,32)	0.2863
Obs*R-squared	15.0841	Prob. Chi-Square(12)	0.2369

Table 13

Heteroskedasticity Test for ARIMA(12,1,4)

F-statistic	1.07118	Prob. F(5,41)	0.3904
Obs*R-squared	5.43034	Prob. Chi-Square(5)	0.3656
Scaled explained SS	3.22848	Prob. Chi-Square(5)	0.6648

ARIMA(4,1,8)

Table 14

Significance of the Variable for ARIMA(4,1,8)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(4)	1.026566	0.02506	40.9605	0
MA(8)	-0.53395	0.03732	-14.306	0
MA(1)	-0.73575	0.05509	-13.356	0
MA(6)	0.306916	0.05741	5.34623	0
R-squared	0.967535	Mean dependent var		1247.86
Adjusted R-squared	0.965626	S.D. dependent var		22500.6
S.E. of regression	4.17E+03	Akaike info criterion		19.58
Sum squared resid	8.88E+08	Schwarz criterion		19.726
Log likelihood	-534.449	Hannan-Quinn criter.		19.6364
Durbin-Watson stat	2.06812			

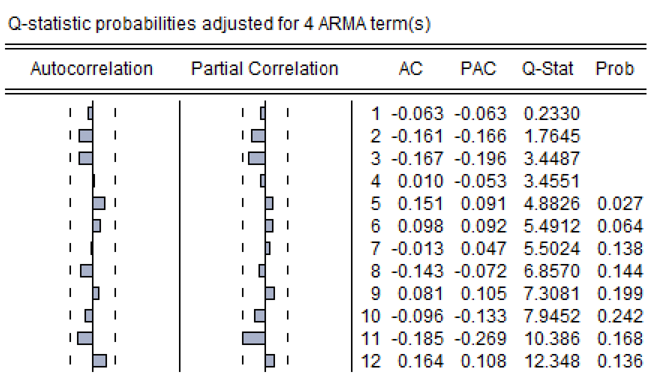


Figure 9 Correlogram for ARIMA(4,1,8)

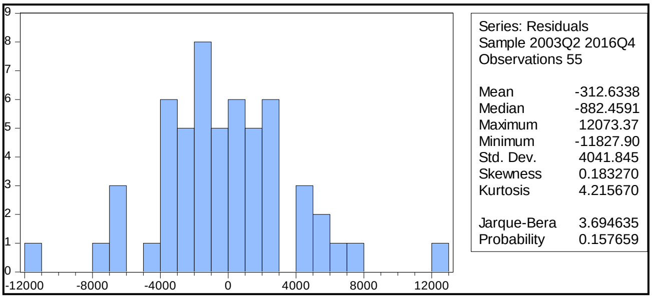


Figure 10. Normality Test for ARIMA(4,1,8)

Table 15

Breusch-Godfrey Serial Correlation LM Test for ARIMA(4,1,8)

F-statistic	0.63984	Prob. F(8,43)	0.7399
Obs*R-squared	5.55119	Prob. Chi-Square(8)	0.6974

Table 16

Heteroskedasticity Test for ARIMA(4,1,8)

F-statistic	0.42891	Prob. F(10,44)	0.9245
Obs*R-squared	4.88512	Prob. Chi-Square(10)	0.8987
Scaled explained SS	6.60382	Prob. Chi-Square(10)	0.7622

ARIMA(12,1,12)

Table 17

Significance of the Variable for ARIMA(12,1,12)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(12)	1.101436	0.02624	41.9775	0
AR(5)	0.053676	0.02038	2.63368	0.0116
MA(12)	-0.96346	0.02727	-35.325	0
R-squared	0.969589	Mean dependent var		1369.9
Adjusted R-squared	0.968206	S.D. dependent var		23655.5
S.E. of regression	4217.955	Akaike info criterion		19.5938
Sum squared resid	7.83E+08	Schwarz criterion		19.7119
Log likelihood	-457.454	Hannan-Quinn criter.		19.6382
Durbin-Watson stat	2.508435			

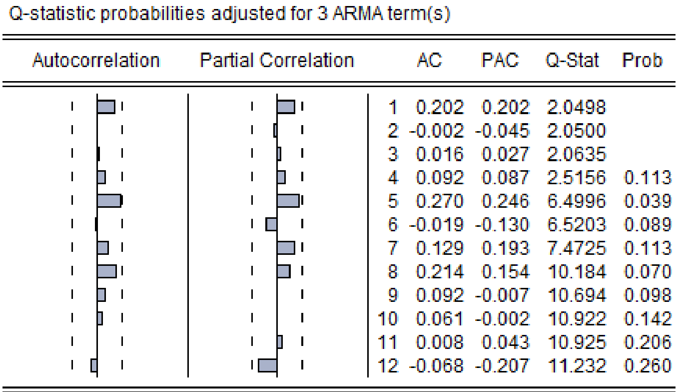


Figure 11. Correlogram for ARIMA(12,1,12)

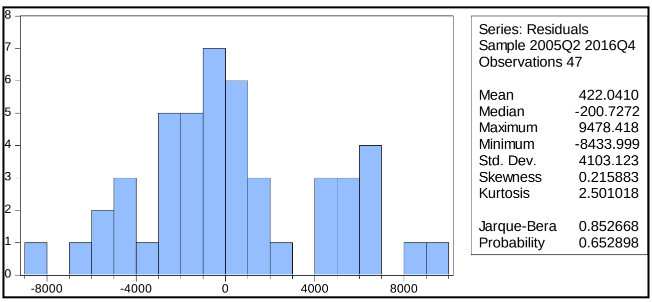


Figure 12. Normality Test for ARIMA(12,1,12)

Table 18

Breusch-Godfrey Serial Correlation LM Test for ARIMA(12,1,12)

F-statistic	1.55545	Prob. F(12,32)	0.1557
Obs*R-squared	16.9941	Prob. Chi-Square(12)	0.1498

Table 19

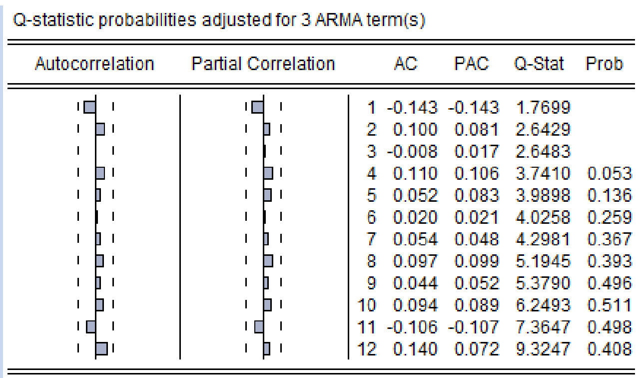
Heteroskedasticity Test for ARIMA(12,1,12)

F-statistic	1.14646	Prob. F(6,40)	0.3539
Obs*R-squared	6.89653	Prob. Chi-Square(6)	0.3305
Scaled explained SS	4.83319	Prob. Chi-Square(6)	0.5654

APPENDIX D
DIAGNOSTIC CHECKING
Cattle Farmgate Forecasting Model
ARMA(12,12)

Table 20
Significance of the variables for ARMA(12,12)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.912911	0.045447	20.08732	0
AR(12)	0.107883	0.050763	2.125219	0.0366
MA(12)	-0.245729	0.109326	-2.247674	0.0273
R-squared	0.989641	Mean dependent var		66.4812
Adjusted R-squared	0.989385	S.D. dependent var		18.0514
S.E. of regression	1.859803	Akaike info criterion		4.11388
Sum squared resid	280.1683	Schwarz criterion		4.20069
Log likelihood	-169.7829	Hannan-Quinn criter.		4.14878
Durbin-Watson stat	2.2249			


Q-statistic probabilities adjusted for 3 ARMA term(s)

	AC	PAC	Q-Stat	Prob
1	-0.143	-0.143	1.7699	
2	0.100	0.081	2.6429	
3	-0.008	0.017	2.6483	
4	0.110	0.106	3.7410	0.053
5	0.052	0.083	3.9898	0.136
6	0.020	0.021	4.0258	0.259
7	0.054	0.048	4.2981	0.367
8	0.097	0.099	5.1945	0.393
9	0.044	0.052	5.3790	0.496
10	0.094	0.089	6.2493	0.511
11	-0.106	-0.107	7.3647	0.498
12	0.140	0.072	9.3247	0.408

Figure 13. Correlogram for ARMA(12,12)

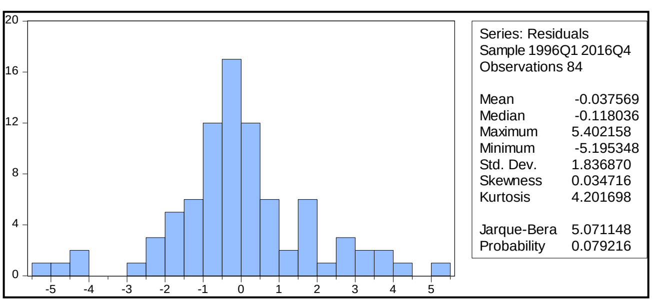


Figure 14. Normality Test for ARMA(12,12)

Table 21

Breusch-Godfrey Serial Correlation LM Test for ARMA(12,12)

F-statistic	1.514734	Prob. F(12,69)	0.14
Obs*R-squared	17.48628	Prob. Chi-Square(12)	0.1322

Table 22

Heteroskedasticity Test ARMA(12,12)

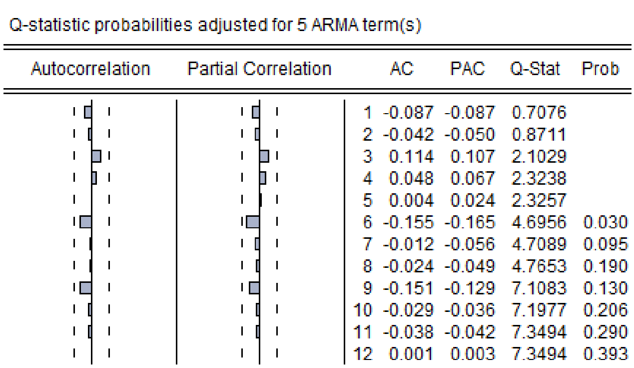
F-statistic	1.19165	Prob. F(6,77)	0.3197
Obs*R-squared	7.13719	Prob. Chi-Square(6)	0.3083
Scaled explained SS	10.6112	Prob. Chi-Square(6)	0.1012

ARMA(6,8)

Table 23

Significance of the Variables for ARMA(6,8)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.852597	0.055499	15.36251	0
AR(6)	0.677031	0.084893	7.97515	0
AR(5)	-0.50793	0.105513	-4.813908	0
MA(5)	0.797081	0.056214	14.17938	0
MA(8)	-0.17508	0.061314	-2.855386	0.0054
R-squared	0.990411	Mean dependent var		64.90578
Adjusted R-squared	0.989959	S.D. dependent var		18.43432
S.E. of regression	1.847167	Akaike info criterion		4.119136
Sum squared resid	290.0222	Schwarz criterion		4.258014
Log likelihood	-180.361	Hannan-Quinn criter.		4.17514
Durbin-Watson stat	2.161403			


Q-statistic probabilities adjusted for 5 ARMA term(s)

	AC	PAC	Q-Stat	Prob
1	-0.087	-0.087	0.7076	
2	-0.042	-0.050	0.8711	
3	0.114	0.107	2.1029	
4	0.048	0.067	2.3238	
5	0.004	0.024	2.3257	
6	-0.155	-0.165	4.6956	0.030
7	-0.012	-0.056	4.7089	0.095
8	-0.024	-0.049	4.7653	0.190
9	-0.151	-0.129	7.1083	0.130
10	-0.029	-0.036	7.1977	0.206
11	-0.038	-0.042	7.3494	0.290
12	0.001	0.003	7.3494	0.393

Figure 15. Correlogram for ARMA(6,8)

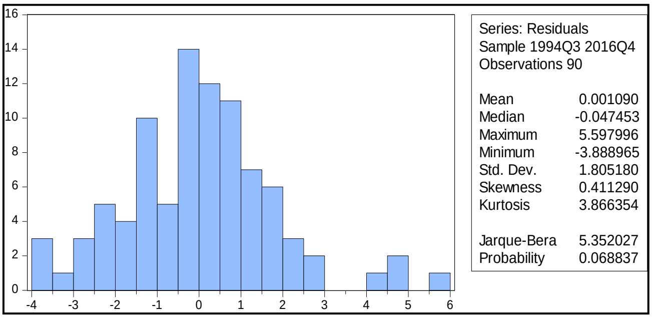


Figure 16. Normality Test for ARMA(6,8)

Table 24

Breusch-Godfrey Serial Correlation LM Test for ARIMA(6,8)

F-statistic	0.769411	Prob. F(8,77)	0.6306
Obs*R-squared	6.661916	Prob. Chi-Square(8)	0.5735

Table 25

Heteroskedasticity Test for ARIMA(6,8)

F-statistic	0.80325	Prob. F(15,74)	0.6704
Obs*R-squared	12.602	Prob. Chi-Square(15)	0.633
Scaled explained SS	16.1155	Prob. Chi-Square(15)	0.3744

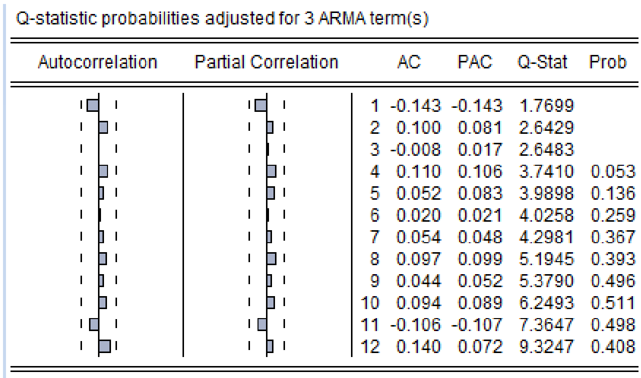
APPENDIX E
DIAGNOSTIC CHECKING
Milkfish Farmgate Forecasting Model
ARMA(8,4)

Table 26

Significance of the Variables for ARMA(8,4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	51.66866	8.802976	5.86945	0
TIME	0.818076	0.12088	6.76769	0
AR(1)	0.34181	0.134803	2.53562	0.0131
AR(8)	0.376329	0.085017	4.42654	0
MA(4)	0.36461	0.089103	4.09202	0.0001
MA(1)	0.99559	0.14689	6.7778	0
MA(2)	0.374261	0.152247	2.45826	0.0161
R-squared	0.981506	Mean dependent var		96.5238
Adjusted R-squared	0.980136	S.D. dependent var		20.3128
S.E. of regression	2.862895	Akaike info criterion		5.01775
Sum squared resid	663.8897	Schwarz criterion		5.21481

Log likelihood	-213.7809	Hannan-Quinn criter.	5.09714
F-statistic	716.4528	Durbin-Watson stat	1.83214
Prob(F-statistic)	0		


Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.143	-0.143	1.7699	
		2	0.100	0.081	2.6429	
		3	-0.008	0.017	2.6483	
		4	0.110	0.106	3.7410	0.053
		5	0.052	0.083	3.9898	0.136
		6	0.020	0.021	4.0258	0.259
		7	0.054	0.048	4.2981	0.367
		8	0.097	0.099	5.1945	0.393
		9	0.044	0.052	5.3790	0.496
		10	0.094	0.089	6.2493	0.511
		11	-0.106	-0.107	7.3647	0.498
		12	0.140	0.072	9.3247	0.408

Figure 17. Correlogram for ARMA(8,4)

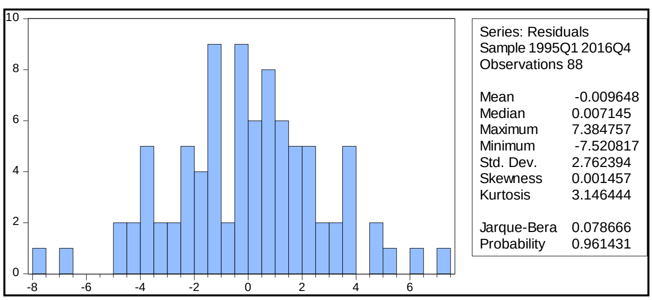


Figure 18. Normality Test for ARMA(8,4)

Table 27

Breusch-Godfrey Serial Correlation LM Test for ARMA(8,4)

F-statistic	1.36604	Prob. F(8,73)	0.2259
Obs*R-squared	11.4575	Prob. Chi-Square(8)	0.1771

Table 28

Heteroskedasticity Test for ARMA(8,4)

F-statistic	1.38535	Prob. F(35,52)	0.1407
Obs*R-squared	42.462	Prob. Chi-Square(35)	0.1804
Scaled explained SS	38.6091	Prob. Chi-Square(35)	0.3098

ARMA(5,10)

Table 29

Significance of the Variables for ARMA(5,10)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	54.3969	5.17394	10.5136	0
TIME	0.78336	0.08335	9.39885	0
AR(1)	0.71	0.07868	9.02438	0
AR(4)	0.50146	0.09646	5.19839	0
AR(5)	-0.3814	0.09728	-3.9212	0.0002
MA(1)	0.53556	0.04955	10.8082	0
MA(10)	-0.4641	0.04779	-9.711	0
R-squared	0.98233	Mean dependent var		95.5685
Adjusted R-squared	0.98107	S.D. dependent var		20.639
S.E. of regression	2.83991	Akaike info criterion		4.99923
Sum squared resid	677.469	Schwarz criterion		5.19237
Log likelihood	-220.46	Hannan-Quinn criter.		5.07715
F-statistic	778.243	Durbin-Watson stat		1.91955
Prob(F-statistic)	0			

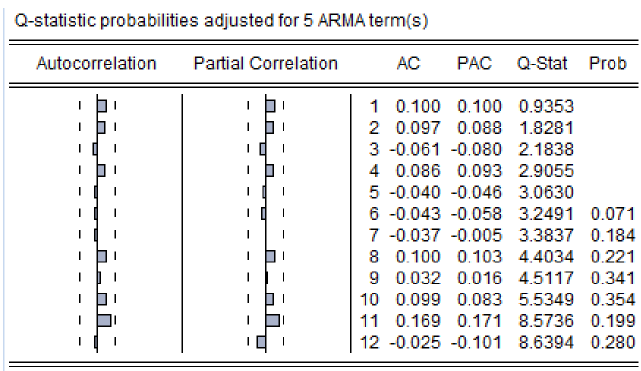


Figure 19. Correlogram of ARMA(5,10)

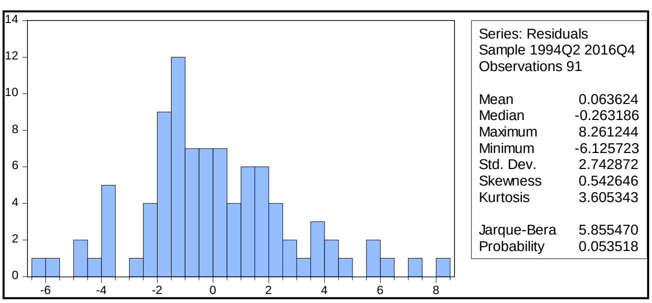


Figure 20. Normality Test of ARMA(5,10)

Table 30
Breusch-Godfrey Serial Correlation LM Test for ARMA(5,10)

F-statistic	0.55536	Prob. F(2,96)	0.5757
Obs*R-squared	1.17536	Prob. Chi-Square(2)	0.5556

Table 31
Heteroskedasticity Test for ARMA(5,10)

F-statistic	1.63955	Prob. F(34,56)	0.0496
Obs*R-squared	45.3961	Prob. Chi-Square(34)	0.0916
Scaled explained SS	51.3536	Prob. Chi-Square(34)	0.0285

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