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Forecasting Price of Selected Agricultural Commodities In Bangladesh: An Empirical Study

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Abstract

This paper forecasts the future prices of three different agricultural commodities including Boro-hybrid, Aman-hybrid, and Flour from March 2010 to February 2012 based on secondary data from January 2001 to February 2010, as the forecasted commodity price plays an important role in taking any economic decision for a country. To forecast the commodity prices the ARIMA models are adopted based on model selection criteria and error statistics among the competing models. The modified Box-Pierce (Ljung-Box) LB statistic shows that the fitted models are well for respective commodities. The increasing trends are observed in forecasted prices of all the three commodities and the increase in prices of Aman-hybrid and Flour is observed to be very high compared to Boro-hybrid. The rate at which the prices of these commodities are increasing is alarming.

Key Words: Agricultural Commodity Price, Forecasting, Box-Jenkins Methodology, ARIMA Model, Multiplicative Model, LB Statistic.

JEL Classification Codes: C32, C51, C52, C53.

Introduction

Forecasting price of the important commodities is very essential for the policy makers of a country. Bangladesh as a developing country where approximately 40% of the people are living below the poverty line can take necessary action if it can form an idea about the future price of the selected commodities. For many countries, especially developing countries, primary commodities remain an important source of export earnings, and commodity price movements have a major impact on overall macroeconomic performance. Hence, commodity-price forecast is a key input to macroeconomic policy planning and formulation (Chakriya and Husain, 2004). Agricultural commodity prices increased sharply since 2002 and especially in the past two years when grains and oilseeds prices doubled. The IMF's index of internationally traded food commodity prices increased 130 percent from January 2002 to June 2008 and 56 percent from January 2007 to June 2008 (Mitchell, 2008). The increased price of the commodity has generated significant discussion on the causes and on making appropriate decision (Frankel and Rose, 2009, Timmer and Dawe, 2007, World Bank, 2008, Sugden, 2009).

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The main objective of this paper is to forecast the monthly average price of the selected agricultural commodities including *Boro-hybrid*, *Aman-hybrid*, and *Flour*. There are five approaches to economic forecast based on time series data such as exponential smoothing methods, single-equation regression models, simultaneous-equation regression models, autoregressive integrated moving average models (ARIMA), and vector autoregression. Among them, Autoregressive Integrated Moving Average (ARIMA), popularly known as Box-Jenkins methodology is extensively used in this study.

Organization of the paper is as follows: Section 2 gives the details description about the methodology and sources of data. The results obtained from the data are shown in section 3 and finally the comments and conclusion is highlighted on section 4.

Data and Methodology

The secondary time series data on the prices of *Boro-hybrid*, *Aman-hybrid*, and *Flour* per quintal over the period, January, 2001, through February, 2010, has been used to forecast the future prices separately for the respective food items. The time series data are collected from the Department of Agricultural Marketing (DAM) under the Ministry of Agriculture of the Government of Bangladesh.

In order to evaluate the forecasted prices for three different agricultural commodities, a variety of time series models such as Autoregressive (AR) model, Moving Average (MA) model, Autoregressive Integrated Moving Average (ARIMA) model, Seasonal Autoregressive Integrated Moving Average (SARIMA) model, Multiplicative Seasonal Model, is adopted to find the best suited model and to increase the accuracy of the forecast.

The autoregressive model of order p is denoted by $AR(p)$ and is defined as:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \tag{2.1}$$

where, $\varphi_1, \varphi_2, ..., \varphi_p$ are the parameters of the model, c is a constant and ε_t is white noise. The moving average model of order q is defined as:

$$x_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta_q \varepsilon_{t-q} \tag{2.2}$$

where, $\theta_1, \theta_2, ..., \theta_q$ are the coefficients of the model and ε_t is white noise. The $ARIMA(p, d, q)$ model in terms of the backward shift operator B can be written as:

$$\left(1 - \varphi_1 B - ... - \varphi_p B^p\right) W_t = \left(1 - \theta_1 B - ... - \theta_q B^q\right) A_t \tag{2.3}$$

where, $W_t = (1 - B)^d Z_t$, is the first regular difference of the original price series Z_t and A_t is the random shock which follows a white noise process with mean zero (O'Donovan 1983 and

Pankratz 1984). Similarly, the seasonal autoregressive integrated moving average $SARAIMA(P,D,Q)_s$ model in terms of backward shift operator B can be expressed as:

$$\left(1-\varphi_s B^s-\ldots-\varphi_{sP}B^{sP}\right)W_t=\left(1-\theta_s B^s-\ldots-\theta_{sQ}B^{sQ}\right)A_t \quad (2.4)$$

where, $W_t=\left(1-B^s\right)^d Z_t$, $s=12$ for monthly data and $s=4$ for quarterly data and the random shocks A_t does not follow the white noise process as like equation (2.3). Combining (2.3) and (2.4) we obtain:

$$\left(1-\varphi_1 B-\ldots-\varphi_p B^p\right)\left(1-\varphi_s B^s-\ldots-\varphi_{sP}B^{sP}\right)W_t=\left(1-\theta_1 B-\ldots-\theta_q B^q\right)\left(1-\theta_s B^s-\ldots-\theta_{sQ}B^{sQ}\right)A_t$$

(2.5)

A constant term θ_0 is added to the model (2.5) to accommodate the possibility that the variables W_t may have a non-zero mean. Thus the model can be written as:

$$\left(1-\varphi_1 B-\ldots-\varphi_p B^p\right)\left(1-\varphi_s B^s-\ldots-\varphi_{sP}B^{sP}\right)W_t=\theta_0+\left(1-\theta_1 B-\ldots-\theta_q B^q\right)\left(1-\theta_s B^s-\ldots-\theta_{sQ}B^{sQ}\right)A_t$$

(2.6)

Since, we consider the monthly price data series, finally the model (2.6) can be written as:

$$\left(1-\varphi_1 B-\ldots-\varphi_p B^p\right)\left(1-\varphi_{12} B^{12}-\ldots-\varphi_{12P}B^{12P}\right)W_t=\theta_0+\left(1-\theta_1 B-\ldots-\theta_q B^q\right)\left(1-\theta_{12} B^{12}-\ldots-\theta_{12Q}B^{12Q}\right)A_t$$

(2.7)

Model (2.7) is the multiplicative seasonal model of order $(p,d,q)(P,D,Q)_{12}$. Here the term $\left(1-\varphi_1 B-\ldots-\varphi_p B^p\right)$ is known as the regular autoregressive operator of order p, the term $\left(1-\varphi_{12}B^{12}-\ldots-\varphi_{12P}B^{12P}\right)$ is the seasonal autoregressive operator of order P, the term $\left(1-\theta_1 B-\ldots-\theta_q B^q\right)$ is called the regular moving average operator of order q and the last term $\left(1-\theta_s B^s-\ldots-\theta_{sQ}B^{sQ}\right)$ is the seasonal moving average operator of order Q.

The autocorrelation function (ACF) and the partial autocorrelation function (PACF) are used to determine the order of regular and seasonal autoregressive and moving average operators and the number of difference(s) after which the series of selected agriculture commodities achieve stationarity.

The diagnostic check about the models identified for forecasting *Boro-hybrid*, *Aman-hybrid*, and *Flour* is carried out by modified Box-Pierce (Ljung-Box) LB statistic (Ljung and Box, 1978) which is defined as:

$$LB=n(n+2)\sum_{k=1}^{m}\left(\frac{\hat{\rho}_k^2}{n-k}\right) \quad (2.8)$$

where, n is the sample size and k represents the number of lag and for large sample the LB statistic follows the chi-square distribution with m degrees of freedom.

Results

The time series plot represents the basic idea about the time series data on three different agricultural commodities form January 2001 to February 2010. After examining the correlogram, it is revealed that all the three commodities are integrated of order one. That means, though all the considered time series are non-stationary, yet their first difference becomes stationary.

[redacted]

Several time series models are employed to forecast the price of *Boro-Hybrid* for the month of March 2010 to March 2011 and the value of the model selection criteria and the different measures of forecasting error of the respective models are presented in Table-3 (See Appendix A). After examining the model selection criteria and error statistics, it is seen that the $ARIMA(3,1,3)$ is the best model for forecasting the price of *Boro-Hybrid.*

On the basis of the model selection criteria and the error statistics presented in Appendix A(see Table-4), it is seen that the multiplicative model $ARIMA(3,1,0)$ is the best fitted model for the future forecasting price of *Aman-Hybrid.*

Similarly, comparing the model selection criteria and the error statistics of different models applied for forecasting the future price of *Flour* given in Table- 5 in Appendix A, it is observed that the multiplicative model of order $ARIMA(3,1,3)$ is the best one.

Figure 2 represents the time series plot of actual and forecasted price of *Boro-hybrid, Aman-hybrid and Flour* for one year from March 2009 to February 2010 to check the validity of the estimated model and the additional forecasted price for two years from March 2010 for all the three commodities to show the future trends.

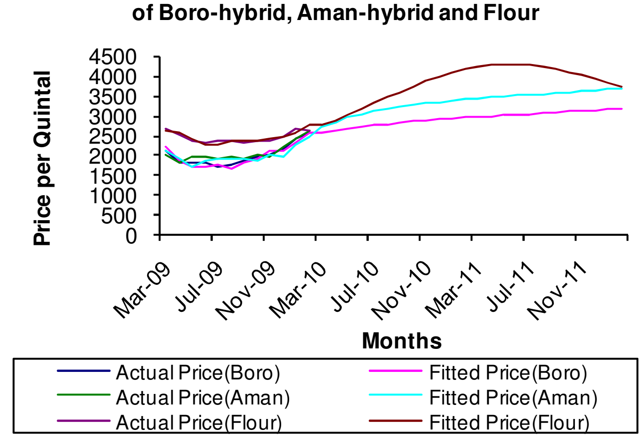

Figure 2: Actual and Forecasted Time Series Plot of Boro-hybrid, Aman-hybrid and Flour

The modified Box-Pierce (Ljung-Box) LB statistic shows that the sum of squared autocorrelation for the lags of 12, 24, 36 and 48 of the estimated residuals are not statistically significant for all the three models. In other words, the correlograms (see Appendix B, Figure 2 through Figure 7) of both autocorrelation and partial autocorrelation shows the residuals of the models are purely random. The LB statistic and the correlograms unveil that the fitted models are all right for the respective commodities.

The actual and fitted prices by using the best fitted model of the respective commodities are presented below for one year (March 2009 – February 2010) to check the validity of the models that are employed:

Table 1: Comparison of Actual and Fitted Price of the Commodities per Quintal

Month	*Boro-Hybrid*		*Aman-Hybrid*		Flour	
	Actual Price	Fitted Price	Actual Price	Fitted Price	Actual Price	Fitted Price
Mar 2009	2085	2213	2006	2115	2664	2590
Apr 2009	1817	1893	1815	1909	2504	2569
May 2009	1828	1713	1946	1733	2344	2418
Jun 2009	1814	1709	1972	1892	2313	2255
Jul 2009	1717	1766	1907	1957	2380	2265
Aug 2009	1762	1667	1939	1946	2358	2364
Sep 2009	1863	1817	1909	1946	2325	2366
Oct 2009	1971	1918	1993	1901	2351	2343
Nov 2009	2001	2118	1971	2016	2387	2399
Dec 2009	2138	2128	2207	1983	2465	2448
Jan 2010	2413	2351	2385	2267	2641	2556
Feb 2010	2548	2598	2599	2456	2635	2760

The forecasted price of the commodities including *Boro-Hybrid*, *Aman-Hybrid* and *Flour* for the next two years is given in the following table:

Table 2: Forecasted Price per Quintal for Three Different Agricultural Commodities

Month	*Forecasted Price Per Quintal*						
	Boro-Hybrid	*Aman-Hybrid*	Flour	Month	*Boro-Hybrid*	*Aman-Hybrid*	Flour
Mar 2010	2575	2734	2743	Mar 2011	2989	3431	4206
Apr 2010	2636	2849	2874	Apr 2011	3007	3458	4249
May 2010	2682	2955	3006	May 2011	3030	3483	4269
Jun 2010	2750	3036	3154	Jun 2011	3047	3506	4271
Jul 2010	2776	3106	3297	Jul 2011	3067	3529	4250
Aug 2010	2813	3168	3447	Aug 2011	3087	3551	4214
Sep 2010	2852	3219	3587	Sep 2011	3104	3573	4157
Oct 2010	2870	3264	3727	Oct 2011	3124	3594	4088
Nov 2010	2902	3305	3851	Nov 2011	3142	3615	4005
Dec 2010	2926	3341	3967	Dec 2011	3160	3636	3915
Jan 2011	2943	3373	4063	Jan 2012	3179	3656	3816
Feb 2011	2970	3404	4146	Feb 2012	3197	3677	3716

Conclusion

This paper considers two years from March 2010 to January 2012 for forecasting the price of three different commodities based on previous data from January 2001 to February 2010 and one year validation period from March 2009 to February 2010. It is revealed from Table 2 that the forecasted price for *Boro-Hybrid* will rise from Tk.2575 per quintal in March 2010 to Tk.2926 by the end of the year 2010. For the next year per quintal price for *Boro-Hybrid* will be between Tk. 2943 to Tk. 3197.

For *Aman-Hybrid,* a monotonic increasing trend is observed through 2010 to the first quarter of 2012. The forecasted price will lift up to Tk. 3373 per quintal in December 2010 from Tk. 2734 in March 2010. Then the price will be followed by the same increasing pattern and will lie between Tk. 3373 to Tk. 3677 per quintal from January 2011 to February 2012.

A huge increase is observed on the forecasted price of *Flour.* The price will rise from Tk. 3967 per quintal in December 2010 to Tk. 2743 in March 2010 and will rise to about Tk. 4200 in March 2011 and continue the same price up to August 2011. After that a slow decreasing pattern is observed and showed a price of Tk. 3716 per quintal in January 2012 which is still about Tk. 10 higher from March 2010. Figure 2 also visually shows the same pattern on the prices of the three agricultural commodities.

Finally, we may conclude that the overall price for the considered commodities will increase in the next two years and it will be helpful to the policy makers to take significant economic decision regarding these types of commodities.

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Appendix A

Table 3: Model Selection Criteria and Error Statistics for the Competing Models Applied to Forecast the Price of *Boro-Hybrid*

Model	Model Selection Criteria & Error Statistics				
	AIC	BIC	MAE	MAPE	RMSPE
ARIMA(3,1,0)	10328.5308	11400.7	63.74	3.68	0.0532
ARIMA(0,1,3)	10420.4384	11502.15	65.25	3.75	0.0529
ARIMA(3,1,3)	9532.49418	11331.03	61.37	3.61	0.0509
ARIMA(3,1,3)(1,0,1)	10332.8948	12904.21	66.17	3.94	0.0532
ARIMA(3,1,3)(2,0,1)	9795.15573	12538.46	63.12	3.75	0.0514
ARIMA(3,1,3)(1,0,2)	9776.06562	12514.02	63.30	3.76	0.0507

Table 4: Model Selection Criteria and Error Statistics for the Competing Models Applied to Forecast the Price of *Aman-Hybrid*

Model	Model Selection Criteria & Error Statistics				
	AIC	BIC	MAE	MAPE	RMSPE
ARIMA(3,1,0)	9363.22	10335.19	62.34	3.53	0.0506
ARIMA(0,1,3)	9541.536	10532.01	64.18	3.61	0.0510
ARIMA(3,1,3)	9606.538	11419.05	61.55	3.50	0.0505
ARIMA(3,1,3)(1,0,1)	9909.488	12375.44	61.02	3.47	0.0506
ARIMA(3,1,3)(2,0,1)	9943.038	12727.76	62.21	3.61	0.0520
ARIMA(3,1,3)(1,0,2)	10075.25	12896.99	61.32	3.50	0.0505

Table 5: Model Selection Criteria and Error Statistics for the Competing Models Applied to Forecast the Price of *Aman-Hybrid*

Model	Model Selection Criteria & Error Statistics				
	AIC	BIC	MAE	MAPE	RMSPE
ARIMA(3,1,0)	6195.40	6838.53	48.32	2.69	0.0381
ARIMA(0,1,3)	6496.87	7171.29	50.21	2.77	0.0389
ARIMA(3,1,3)	5942.48	7063.68	47.35	2.68	0.0373
ARIMA(3,1,3)(1,0,1)	6172.84	7708.94	48.00	2.73	0.0378
ARIMA(3,1,3)(2,0,1)	6017.42	7702.70	47.87	2.72	0.0363
ARIMA(3,1,3)(1,0,2)	6129.83	7846.60	48.75	2.80	0.0364

Appendix B

Figure 2:Autocorrelation Function for Residual-Boro Hybrid

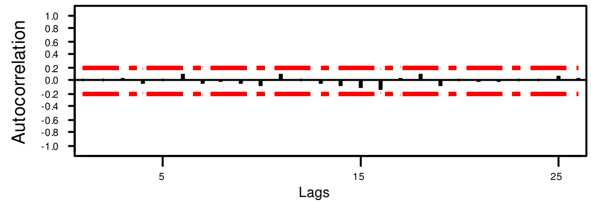

Figure 3: Partial Autocorrelation Function for Residual-Boro Hybrid

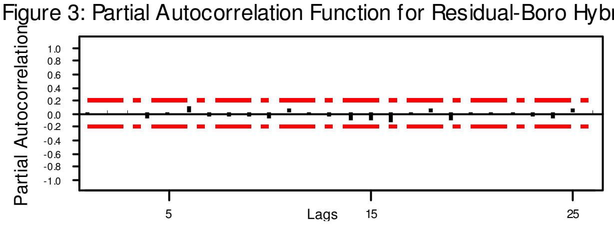

Figure 4: Autocorrelation Function for Residuals-Aman Hybrid

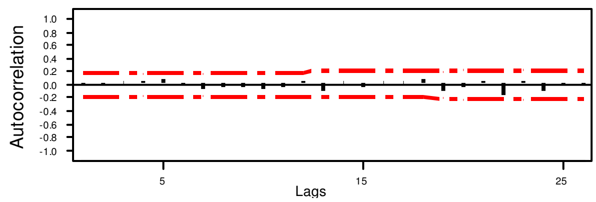

Figure 5: Partial Autocorrelation Function for Residuals-Aman Hybrid

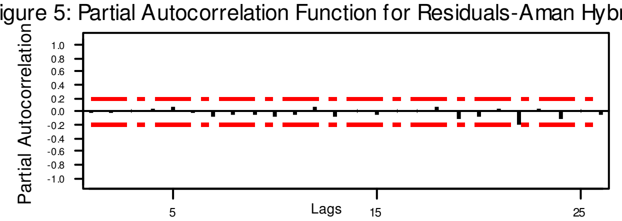

Figure 6: Autocorrelation Function for Residuals-Flour

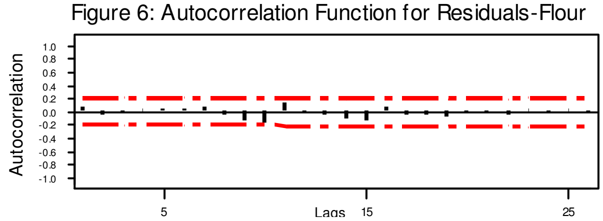

Figure 7: Partial Autocorrelation Function for Residuals-Flour