FORECASTING COCOA BEAN PRICES USING UNIVARIATE TIME SERIES MODELS

***Assis, K.*[1] *, Amran, A.*[2] *, & Remali, Y.*[3]**
[1]School of Sustainable Agriculture, [2]School of Science and Technology,
[3]School of Business and Economics
Universiti Malaysia Sabah, Locked Bag 2073
88999 Kota Kinabalu Sabah, Malaysia
assis@ums.edu.my

ABSTRACT

The purpose of this study is to compare the forecasting performances of different time series methods for forecasting cocoa bean prices. The monthly average data of Bagan Datoh cocoa bean prices graded SMC 1B for the period of January 1992 - December 2006 was used. Four different types of univariate time series methods or models were compared, namely the exponential smoothing, autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity (GARCH) and the mixed ARIMA/GARCH models. Root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and Theil's inequality coefficient (U-STATISTICS) were used as the selection criteria to determine the best forecasting model. This study revealed that the time series data were influenced by a positive linear trend factor while a regression test result showed the non-existence of seasonal factors. Moreover, the Autocorrelation function (ACF) and the Augmented Dickey-Fuller (ADF) tests have shown that the time series data was not stationary but became stationary after the first order of the differentiating process was carried out. Based on the results of the ex-post forecasting (starting from January until December 2006), the mixed ARIMA/GARCH model outperformed the exponential smoothing, ARIMA, and GARCH models.

Keywords: Univariate time series models, Exponential Smoothing, ARIMA, GARCH, ARIMA/GARCH, model selection criteria

Introduction

Cocoa, scientifically known as *Theobroma cacao L.* is the third-largest agricultural commodity in Malaysia after oil palms and rubber. Malaysia now exports cocoa products to sixty-six countries (Ministry of Plantation Industries, and Commodities, 2006). Bagan Datoh is situated in the state of Perak, Malaysia and Bagan Datoh cocoa bean price was one of the most important indicators in representing the Malaysia cocoa bean prices in early 2000s. Domestic cocoa bean prices are changing from time to time and very volatile (Yusoff and Salleh, 1987 and Arshad and Zainalabidin, 1994). Instability of cocoa prices creates significant risks to producers, suppliers, consumers, and other parties that are involved in the marketing and production of cocoa beans, particularly in Malaysia. In risky conditions and amidst price instability, forecasting is very important in helping to make decisions. Accurate price forecasts are particularly important to facilitate efficient decision making as there is time lag intervenes between making decisions and the actual output of the commodity in the market.

Modelling or forecasting of agricultural price series, like that of other economic time series, has traditionally been carried out either by building an econometric model or by applying techniques developed for analyzing stationary time series. Time series forecasting is a major challenge in many real world applications such as stock price analysis, palm oil prices, natural rubber prices, electricity prices, and flood forecasting. This type of forecasting is to predict the values of a continuous variable (called as response variable or output variable) with a forecasting model based on historical data. There are two types of time series forecasting modeling methods; univariate and multivariate. Univariate modeling methods generally used time only as an input variable with no other outside explanatory variables (Celia et al., 2003). This forecasting method is often called univariate time series modeling. A few commonly employed methods in univariate time series models are exponential smoothing, autoregressive-integrated-moving average (ARIMA), and Autoregressive Conditional Heteroscedastic (ARCH) (Elham et al., 2010).

The last few decades have witnessed significant advances in the topic of exponential smoothing. It has established itself as one of the leading forecasting strategies (Robert and Amir, 2009). Fatimah and Roslan (1986) confirmed the suitability of univariate ARIMA models in agricultural prices forecasting. Mad Nasir (1992) has noted that ARIMA models have the advantage of relatively low research costs when compared with econometric models, as well as efficiency in short term forecasting. One of the earliest time series models allowing for heteroscedasticity is the Autoregressive Conditional Heteroscedastic (ARCH) model introduced by Engle (1982). Bollerslev (1986) extended this idea into Generalized Autoregressive Conditional Heteroscedastic (GARCH) models which give more parsimonious results than ARCH models, similar to the situation where ARMA models are preferred over AR models. Kamil and Noor (2006) have developed a time series model of Malaysian palm oil prices by using ARCH models. Zhou et al. (2006) have proposed a new network traffic prediction model based on non-linear time series ARIMA/GARCH. They found that the proposed ARIMA/GARCH outperformed the existing Fractional Autoregressive Integrated Moving Average (FARIMA) model in terms of prediction accuracy. Therefore, the objective of this research is to compare the forecasting performances of four different univariate time series methods or models for forecasting cocoa bean prices (i.e. Bagan Datoh cocoa bean prices), namely exponential smoothing, ARIMA, GARCH, and the mixed ARIMA/GARCH models.

Methodology

The monthly Bagan Datoh cocoa bean prices graded SMC 1B was used for this study which was collected from the official website of The Malaysian Cocoa Board (http://www.koko.gov.my/lkmbm/loader.cfm?page=statisticsFrm.cfm). The time series data was measured in Ringgit Malaysia per tonne (RM/tonne). The time series data ranged from January 1992 until December 2006. The coefficient of variation (V) was used to measure the index of instability of the time series data. The coefficient of variation (V) is defined as

$$V = \frac{\sigma}{\overline{Y}}$$

where σ is the standard deviation

and $\overline{Y} = \frac{\sum_{t=1}^{n} Y_t}{n}$ is the mean of Bagan Datoh cocoa bean prices changes.

A completely stable data has $V = 1$, but unstable data are characterized by a $V > 1$ (Telesca et al., 2008). Regression analysis was used to test whether trends and seasonal factors exist in the time series data. The existence of linear trend factors was tested through this regression equation

$$Y = \beta_0 + \beta_1 Trend + \varepsilon \qquad \varepsilon \sim WN(0, \sigma^2)$$

with Y is the time series data of the study, $Trend$ is the linear trend factor, β_0 & β_1 are parameters and ε is the error of the model with an assumption of white noise (WN). The hypothesis of the model was

$H_0 : \beta_1 = 0$ (Non-existence of linear trend factor)

$H_1 : \beta_1 \neq 0$ (Linear trend factor exists)

With the month of January as the base month, the existence of seasonal factor was detected by using regression as shown below

$$Y = \beta_0 + \beta_1 Trend + \beta_2 Feb + \beta_3 Mar + \beta_4 Apr + \beta_5 May + \beta_6 Jun + \beta_7 Jul$$
$$+ \beta_8 Aug + \beta_9 Sep + \beta_{10} Oct + \beta_{11} Nov + \beta_{12} Dec + \varepsilon$$

and hypothesis was defined as

$H_0 : \beta_2 = \beta_3 = \beta_4 = ... = \beta_{12} = 0$ (Non-existence of seasonal factor)

$H_1 :$ At least one of $\beta_2, \beta_3, ..., \beta_{12} \neq 0$ (Seasonal factor exists)

The correlogram and Augmented Dickey-Fuller (ADF) test were chosen to test the stationary of the time series data.

Exponential smoothing

The h-periods-ahead forecast is given by:

$$\hat{Y}_{t+h} = a + bh$$

with a and b are permanent components. Both of these parameters are counted by the following equations

$$a_t = \alpha Y_t + (1-\alpha)(a_{t-1} + b_{t-1})$$
$$b_t = \beta(a_t - a_{t-1}) + (1-\beta) b_{t-1}$$

with $0 < \alpha, \beta < 1$.

ARIMA

This study followed the Box-Jenkins methodology which involves four steps. These are identification, estimation, model checking, and forecasting. ARMA(p,q) processes can be simply expressed as the following two equations

$$Y_t = x_t \gamma + e_t \qquad (1)$$

$$e_t = \sum_{i=1}^{p} \phi_i \mu_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (2)$$

where, x_t : the explanatory variables, e_t: the disturbance term, ε_t: the innovation in the disturbance, p: the order of AR term, q: the order of MA term. In equation (2), the disturbance term (μ_t) again consists of three parts. The first part is AR terms and the second part is MA terms. The last one is just a white-noise innovation term. If we replace the data (Y) with the difference data ($\Delta Y_t = Y_t - Y_{t-1}$), then the ARMA models become ARIMA(p,d,q) models.

GARCH

The standard form of GARCH(p,q) models can be specified as following three equations:

$$Y_t = x_t\gamma + \varepsilon_t \quad (3)$$

$$\varepsilon_t = v_t\sqrt{\sigma_t^2} \quad (4)$$

$$\sigma_t^2 = \delta + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \quad (5)$$

Where, p: the order of GARCH term, q: the order of ARCH term, and $\sigma_v^2 = 1$. Equation (3) and (5) are respectively called mean equation and conditional variance equation. The mean equation is written as a function of exogenous variables (x_t) with an error term (μ_t). The variance equation is a function of mean (δ), ARCH (μ_{t-i}^2) and GARCH term (σ_{t-j}^2).

ARIMA/GARCH

Combination of ARIMA(p,d,q) and GARCH(p,q) are written as below:

$$(\Delta Y_t)^d = \sum_{i=1}^{p}\phi_i(\Delta Y_{t-i})^d + \varepsilon_t + \sum_{j=1}^{q}\theta_j\varepsilon_{t-j} \qquad \varepsilon_t \sim WN(0,\sigma_t^2) \quad (6)$$

$$\sigma_t^2 = \delta + \sum_{j=1}^{q}\beta_j\varepsilon_{t-j}^2 + \sum_{i=1}^{p}\alpha_i\sigma_{t-i}^2 \quad (7)$$

Eight model selection criteria as suggested by Ramanathan (2002) were used to chose the best forecasting models among ARIMA and GARCH models (see Table 1). While, the best time series methods for forecasting Tawau cocoa bean prices was chosen based on the values of four criteria, namely RMSE, MAE, MAPE, and U-statistics (see Table 2). Finally, the selected model was used to perform short-term forecasting for the next twelve months for Tawau cocoa bean prices starting from January 2007 until December 2007.

Table 1: Model Selection Criteria (Ramanathan, 2002)

No.	Criteria	Formula
1	AIC	$\left(\frac{ESS}{n}\right)e^{2f/n}$
2	FPE	$\left(\frac{ESS}{n}\right)\frac{n+f}{n-f}$
3	GCV	$\left(\frac{ESS}{n}\right)\left[1-\left(\frac{f}{n}\right)\right]^{-2}$
4	HQ	$\left(\frac{ESS}{n}\right)(\ln n)^{2f/n}$
5	RICE	$\left(\frac{ESS}{n}\right)\left[1-\left(\frac{2f}{n}\right)\right]^{-1}$
6	SCHWARZ	$\left(\frac{ESS}{n}\right)n^{f/n}$
7	SGMASQ	$\left(\frac{ESS}{n}\right)\left[1-\left(\frac{f}{n}\right)\right]^{-1}$
8	SHIBATA	$\left(\frac{ESS}{n}\right)\frac{n+2f}{n}$

Note: n = Number of observations; f = Number of parameters; ESS = Error sum of square

Table 2: Forecast Accuracy Criteria

No.	Criteria	Formula
1	RMSE	$\sqrt{\frac{ESS}{n}}$
2	MAE	$\frac{\sum_{t=1}^{n} \lvert Y_t - \hat{Y}_t \rvert}{n}$
3	MAPE	$\frac{\sum_{t=1}^{n} \left\lvert \frac{Y_t - \hat{Y}_t}{Y_t} \right\rvert}{n} \times 100\%$
4	U-statistics	$\frac{RMSE}{\sqrt{\sum_{t=1}^{n} \hat{Y}^2 / n} + \sqrt{\sum_{t=1}^{n} Y^2 / n}}$

Note: Y_t = The actual value at time t; $\hat{Y}_t$ = The forecast value at time t; n = The number of observations; ESS = The error sum of square

Results

The results showed that the coefficient of variation (V) of the time series data was 0.998. Because of the V value was closed to 1, so this study was concluded that the time series data was stable (Telesca et al., 2008). The results of the regression analysis have shown that positive linear trend factor exists in the time series data but seasonal factor was not. With referring to the correlogram and the Augmented Dickey-Fuller tests results, the time series data of the study was not stationary. But after the first order of differencing was carried out, the time series data became stationary (see Figure 1).

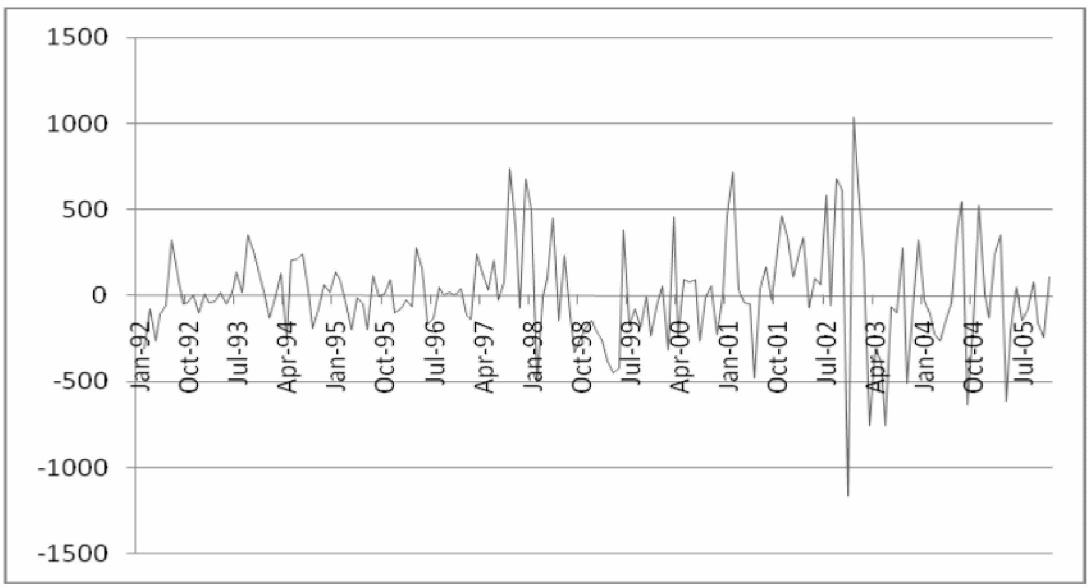

Figure 1: Time Series Data (After first order of differencing)

Exponential Smoothing

The double exponential smoothing method was used as the regression result has showed the positive linear trend factor exists in the time series data. Double exponential smoothing models consist with two parameters which symbolized as α for mean and β for trend. The best model of the double exponential smoothing has been selected based on the lowest value of MSE (Mean Square Error) from combination of α and β with condition $0<\alpha,\beta<1$. The result showed that combination $\alpha=0.9$ and $\beta=0.1$ was the best forecasting model of double exponential smoothing method (see Table 3). The double exponential smoothing model was written in equation form as (see Table 4)

$$F_{T+h} = a + bh = 4337.292 + (h) * (-49.11296)$$

Table 3: Error Sum of Square (ESS) According to α and β Values

β	α								
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.1	148574494	60780095	35967343	26067863	21171464	18416856	16768235	15782220	15241640
0.2	148089497	53009132	31511913	23584886	19811357	17698855	16458187	15770767	15480149
0.3	119506562	46290637	28206803	22285672	19352556	17631819	16634131	16145314	16047802
0.4	111432010	40011203	26500856	22044141	19491565	17928248	17065146	16727264	16807669
0.5	110413625	35644209	26183982	22388117	19867461	18359472	17604439	17418829	17693899
0.6	99118908	33322485	26752761	22906942	20285055	18833953	18201394	18191436	18692544
0.7	82089304	32620680	27706387	27706387	20691928	19333711	18846891	19044923	19810004
0.8	69046203	33216629	28645428	23736262	21099517	19860841	19543802	19989248	21059009
0.9	61520834	34765722	29338707	24034747	21526024	20417178	20299223	21038783	22452919

Table 4: EViews Output of the Double Exponential Smoothing Model

Sample: 1992M01 2005M12			
Included observations: 168			
Method: Holt-Winters No Seasonal			
Original Series: BAGANDATOH			
Forecast Series: BAGANDATOHSM			
Parameters:	Alpha		0.9000
	Beta		0.1000
Sum of Squared Residuals			15241640
Root Mean Squared Error			301.2043
End of Period Levels:		Mean	4337.292
		Trend	-49.11296

ARIMA

All models which fulfilled the criteria of $p+q\leq 5$ have been considered and compared in this study and there were twenty ARIMA(p,d,q) models which fulfilled the criteria. Parameters of the models were estimated with the least square method. Parameters which were not significant at 5% confidence level were dropped from the model. Using the eight model selection criteria suggested by Ramanathan (2002), the ARIMA(3,1,2) model was selected as the best model among the other ARIMA models. However, the parameters of AR(1) and MA(1) were found not significant and thus dropped from the model. The ARIMA(3,1,2) model was written in equation form as (see Table 5)

$$\hat{z}_t = 16.53833 - 0.936073 z_{t-2} + 0.188524 z_{t-3} + 0.105330 \varepsilon_{t-1} + 0.972281 \varepsilon_{t-2}$$

Table 5: Estimation of ARIMA(3,1,2)

Variables	Coefficient	Standard error	Z-statistic	p-value
Constant	16.53833	26.37156	0.627128	0.5315
AR(2)	-0.936073	0.022439	-41.71719	<0.0001*
AR(3)	0.188524	0.023478	8.029818	<0.0001*
MA(1)	0.105330	0.020494	5.139572	<0.0001*
MA(2)	0.972281	0.015673	62.03491	<0.0001*

Note: *$p<0.05$

GARCH

Identification and estimation of GARCH(p,q) models in this study were done by following the four steps that were ARCH effect checking, estimation, model checking, and forecasting. Four GARCH(p,q) models were selected and compared, namely GARCH(1,1), GARCH(1,2), GARCH(2,1), and GARCH(2,2). Using the eight model selection criteria suggested by Ramanathan (2002), the GARCH(1,1) model has been selected as the best model among the other three GARCH models.

Table 6: Estimation of GARCH(1,1)

Variables	Mean equation			
	Coefficient	**Standard error**	**Z-statistic**	**p-value**
Constant	-0.4290	18.7540	-0.0229	0.9818
	Conditional variance equation			
Constant	8467.87	4029.91	2.1013	0.0356*
ε_{t-1}^2	0.2838	0.1000	2.8383	0.0045*
σ_{t-1}^2	0.6244	0.1195	5.2238	<0.0001*

Nota: *$p<0.05$

The GARCH(1,1) model was written in equation form as (see Table 6)

$$\hat{z}_t = -0.4290 \qquad \text{(Mean equation)}$$

$$\hat{\sigma}_t^2 = 8467.87 + 0.2838\varepsilon_{t-1}^2 + 0.6244\sigma_{t-1}^2 \qquad \text{(Conditional variance equation)}$$

ARIMA/GARCH

ARCH effect which was tested by using a regression analysis exists in the ARIMA(3,1,2) model. That means the ARIMA(3,1,2) model could be mixed with the best GARCH model (i.e. GARCH(1,1)).

Table 7: Estimation of ARIMA(3,1,2)/GARCH(1,1)

Variables	Coefficient	Standard error	Z-statistic	p-value
ARIMA(3,1,2)				
Constant	16.53833	26.37156	0.627128	0.5315
AR(2)	-0.936073	0.022439	-41.71719	<0.0001*
AR(3)	0.188524	0.023478	8.029818	<0.0001*
MA(1)	0.105330	0.020494	5.139572	<0.0001*
MA(2)	0.972281	0.015673	62.03491	<0.0001*
GARCH(1,1)				
C	3303.235	1427.419	2.31413	0.0207*
ε_{t-1}^2	0.143294	0.048339	2.964356	0.003*
σ_{t-1}^2	0.821894	0.05859	14.02778	<0.0001*

Nota: *$p<0.05$

The ARIMA(3,1,2)/GARCH(1,1) model was written in equation form as (see Table 7)

$$\hat{z}_t = 16.53833 - 0.936073 z_{t-2} + 0.188524 z_{t-3} + 0.105330 \varepsilon_{t-1} + 0.972281 \varepsilon_{t-2}$$

$$\hat{\sigma}_t^2 = 3303.235 + 0.143294 \varepsilon_{t-1}^2 + 0.821894 \sigma_{t-1}^2$$

Model selection

Four model selection criteria were used to select the best forecasting model from four different types of models, that is the exponential smoothing model, ARIMA(3,1,2), GARCH(1,1), and ARIMA(3,1,2)/GARCH(1,1). Based on the results of the ex-post forecasting (starting from January until December 2006), the GARCH(1,1) model was selected as the best short-term forecasting model of Bagan Datoh cocoa bean price graded SMC 1B (see Table 8).

Table 8: Four Model Selection Criteria

Criteria	Double Exponential Smoothing	ARIMA(3,1,2)	GARCH(1,1)	ARIMA(3,1,2)/ GARCH(1,1)
RMSE	515.1244909	238.5100782	219.0348756	236.426303
MAE	433.8590833	198.9448333	142.3456667	195.6330833
MAPE	9.556988755	4.510056702	3.054184854	4.437227514
U-Statistics	0.060762006	0.02643127	0.024875292	0.026185129

Ex-ante forecasting

Based on ex-ante forecasting by using the GARCH(1,1) model, Figure 2 shows that the short-term forecasting indicated an upward trend of Bagan Datoh cocoa bean price for the period January – December 2007.

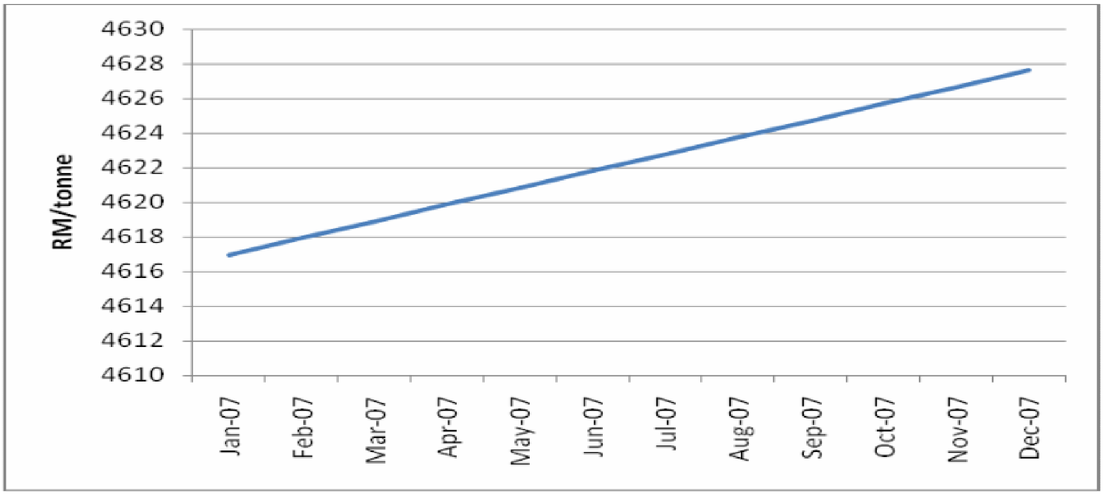

Figure 2: Short-term Forecasting of Tawau Cocoa Bean Prices

Discussion

The result showed that the time series data (starting January 1992 until December 2006) was stable. This is contradict with the previous researches (Yusoff and Salleh, 1987 and Arshad and Zainalabidin, 1994) which stated that domestic cocoa bean prices are changing from time to time and very volatile. The results of the regression analysis have shown that positive linear trend factor exists in the time series data but seasonal factor was not. That means the cocoa bean prices of Bagan Datoh have increased in the period of 1992-2006 but seasonal factor which is usually related to climate change has not given any significant influence on the monthly changes of cocoa bean prices. The GARCH model outperformed the exponential smoothing, ARIMA and the mixed ARIMA/GARCH for the case of forecasting monthly Bagan Datoh cocoa bean prices. This is in disagreement with the findings in the literature (Zhou et al., 2006). Some of previous research have found that ARIMA models (Fatimah and Roslan, 1986; Mad Nasir, 1992; Elham et al., 2010) and also GARCH-type models (Kamil and Noor, 2006) were the best or suitable price forecasting models in terms of prediction accuracy, but the accuracy of the mixed ARIMA/GARCH should also be considered in price forecasting for the future researches.

Conclusion

This study investigates four different types of univariate time series methods, namely exponential smoothing, ARIMA, GARCH, and the mixed ARIMA/GARCH. The results showed that GARCH model outperformed the exponential smoothing, ARIMA and the mixed ARIMA/GARCH model for forecasting Bagan Datoh cocoa bean prices. Forecasting the future prices of cocoa bean through the most accurate univariate time series model can help the Malaysian government as well as the buyers (e.g. exporters and millers) and sellers (e.g. farmers and dealers) in cocoa bean industry to perform better strategic planning and also to help them in maximizing revenue and minimizing the cost of price.

References.

1. Arshad, F.A. and M. Zainalabidin, 1994. Price discovery through crude palm oil futures market: An economic evaluation. *Proceedings of the 3rd Annual Congress on Capitalising the Potentials of Globalisation-Strategies and Dynamics of Business,* (CPGSDB'94), IMDA, Malaysia, pp: 73-92.
2. Bollerslev, T. 1986. Generalized Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics*, **31**(3): 307-327.
3. Celia, F., Ashish, G., Amar, R., and Les, S. 2003. Forecasting women's apparel sales using mathematical modeling. *International Journal of Clothing, Science and Technology*, **15**(2): 107-125
4. Elham, K., Masoumeh, Z. and Ebrahim, B. M. 2010. Prediction of added value of agricultural subsections using artificial neural networks: Box-Jenkins and Holt-Winters methods. *Journal of Development and Agricultural Economics*, **2**(4): 115-121. URL: http://www.academicjournals.org/JDAE/PDF/Pdf2010/Apr/Kahforoushan%20et%20al.pdf
5. Engle, R. F. 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, **50**(4): 987-1008.
6. Fatimah, M.A. and Roslan, A.G. 1986. Univariate approach towards cocoa price forecasting. *The Malaysian Journal of Agricultural Economics*, **3**: 1-11.
7. Kamil, A.A. and A. Md. Noor, 2006. Time series modeling of malaysian raw palm oil price: Autoregressive conditional heteroskedasticity (ARCH) model approach. *Discov. Math.*, **28**: 19-32.
8. Mad Nasir, S., Mat Lani, R. and Chew, T. A. 1992. An Econometric Analysis of Cocoa Prices: A Structural Approach. *Jurnal Ekonomi Malaysia*, **25**(2): 3-17. ISSN 01261962
9. Ministry of Plantation Industries and Commodities (MPIC). 2006. *Report On Malaysia Plantation Industries and Commodities (2001-2005)*. Putrajaya. ISSN: 1823-7770
10. Official website of Malaysian Cocoa Board. 2009. *Monthly Cocoa Prices*. [On-line]. Available: http://www.koko.gov.my/lkm/loader.cfm?page=statisticsFrm.cfm (Access on 05-06-2009)
11. Ramanathan, R., 2002. *Introductory Econometric with Applications*. 5th Edn., Thomson Learning, *South* Carolina, pp: 688.
12. Robert, R. A. and Amir, F. A. 2009. A New Bayesian Formulation for Holt's Exponential Smoothing. *Journal of Forecasting*, **28**: 218–234.
13. Stock, J. H. and M. W. Watson (2007). Why has U.S. inflation become harder to forecast? *Journal of Money, Credit and Banking*, 39(3).
14. Telesca, L., M. Bernardi and C. Rovelli, 2008. Time-scaling analysis of lightning in Italy. *Commun. Nonlinear Sci. Numer. Simulation,* **13**: 1384-1396.
15. Yusoff, M. and M. Salleh, 1987. The elasticities of supply and demand for malaysian primary commodity exports. *Malaysian J. Agric. Econ.*, **4**: 59-72.
16. Zhou, B., He, D., and Sun, Z. 2006. *Modeling and Simulation Tools for Emerging Telecommunication Networks*. Springer US: 101-121. ISBN 978-0-387-32921-5 (Print) 978-0-387-34167-5 (Online)