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Hanumanthaiah R
Research Scholar, Department. Of Farm Engineering, Institute of agricultural sciences, Banaras Hindu University, Varanasi, Uttar Pradesh, India

Abhishek Singh
Assistant. Professor, Department. Of Farm Engineering, Institute of agricultural sciences, BHU, Varanasi, Uttar Pradesh, India

Corresponding Author:
Hanumanthaiah R
Research Scholar, Department. Of Farm Engineering, Institute of agricultural sciences, Banaras Hindu University, Varanasi, Uttar Pradesh, India

Garch nonlinear modelling and forecasting of prices and arrivals of black pepper in Karnataka

Hanumanthaiah R and Abhishek Singh

Abstract
An attempt is made to compare the Linear and Non linear time series models.The Box Jenkins Auto regressive integrated moving average (ARIMA) and Generalized auto regressive conditional heteroscedastic (GARCH) models are studied and applied for modeling and forecasting of Prices and Arrivals of Black pepper in Bengaluru Market. Augmented Dickey Fuller (ADF) test is used for testing the stationarity of the series. ARCH-LM test is used for testing the volatility. It is found that ARIMA model cannot capture the volatility present in the data set whereas GARCH model has successfully captured the volatility. Root Mean square error (RMSE), Mean absolute error (MAE) and Mean absolute prediction error (MAPE) were computed. The GARCH (2, 1) and GARCH (1, 3) were found to be better models in forecasting prices and Arrivals of Black pepper in Bengaluru Market. The values for RMSE, MAE and MAPE obtained were smaller than those in ARIMA (1, 1, 1) and ARIMA (1 0 2) models respectively for Prices and Arrivals. The AIC and SIC values from GARCH models were smaller than that from ARIMA model. Therefore, it shows that GARCH is a better model than ARIMA for estimating Monthly Prices and Arrivals of Black Pepper in Bengaluru Market.

Keywords: Modeling, ARIMA, Forecasting, Accuracy, Volatility, GARCH, Differencing

1. Introduction
Price forecasting is an integral part of commodity trading and price analysis. Quantitative accuracy with small errors, along with turning point forecasting power is important for evaluating forecasting models. Agricultural commodity production and prices are often random as they are largely influenced by eventualities and are highly unpredictable in case of natural calamities like droughts, floods, and attacks by pests and diseases. This leads to a considerable risk and uncertainty in the process of price modelling and forecasting.
Forecasting prices and arrivals of agricultural commodities is of utmost importance for planning in advance to resist any abnormalities. Forecasting methods anticipate the future purchasing actions of consumers by evaluating past revenue and consumer behaviour over the previous months or year to discern patterns and develop forecasts for the upcoming months. So Forecast of pepper prices are intended to be useful for farmers, policy makers and agribusiness industries. In the present era of globalization, management of food security in the agriculture dominated developing countries like India needs efficient and reliable food price forecasting models more than ever. Sparse and time lag in the data availability in developing economies, however, generally necessitate reliance on time series forecasting models.
The presence of increased volatility in the agricultural commodity prices has become a common feature mainly due to globalization. Volatility is of much concern as its presence disrupts the normal behaviour of any time-series data and agricultural commodity price series is no exception to it. Understanding the nature of agricultural commodity price volatility is required for improving agricultural market analysis and policy development. This has led to the development and application of many time series models. As a result, modelling and forecasting of volatility by nonlinear models has emerged as an important tool for time-series analysis. The most commonly used statistical models are the Autoregressive Conditional Heteroscedastic (ARCH) models (Engle 1982) [3], Generalized ARCH (GARCH) model (Bollerslev1986) [1], Bi linear (BL) time-series models (Granger and Anderson 1978) [5].
This study is undertaken with the hypothesis that ARIMA model for forecasting is suitable for non-volatile data, as its inability to capture the volatility component more precisely. Whereas GARCH models are more versatile in capturing the persistent volatility in the time series data. The prices of Black Pepper are more volatile than cereal commodities in India as evident from

The time series data. Therefore, in the present study, univariate ARIMA and GARCH models were fitted to identify better forecast for prices and Arrivals of Black Pepper in Bengaluru Market. To this end, the forecast performance was compared on the basis of Mean square prediction error (MAPE), mean absolute prediction error (MAE) and Root mean square errors (RMSE).

2. Materials and Methods

Monthly secondary data for prices and arrivals of Black pepper (2003-2017) will be collected from the Karnataka State Agricultural Marketing Board, Yeshwanthpur Bangalore Karnataka.

2.1 Description of Models

ARIMA models are capable of representing stationary as well as non-stationary time series (Box *et al.*, 2007) [2]. GARCH) model is capable to capture volatility in time series data. Thus, both models were fitted to the Gram prices and their performances were compared.

2.1.1 The ARIMA Model

The Autoregressive moving average (ARMA) model, denoted as ARMA (p, q), is given by

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p w_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}$$

Or equivalently by $\phi(B) y^t = \theta_0 + \theta(B)\varepsilon_t$

Where $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots\ldots - \varphi_p B^p$ and

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

In the above, B is the backshift operator defined by $By_t = y_{t-1}$.

A generalization of ARMA models, which incorporates a wide class of non-stationary time-series, is obtained by introducing "differencing" in the model. The simplest example of a non-stationary process which reduces to a stationary one after differencing is "Random Walk". A process { y_t } is said to follow Autoregressive integrated moving average (ARIMA), denoted by ARIMA (p, d, q), if $\nabla^d y_t = (1-B)^d \varepsilon_t$ is ARMA (p, q). The model is written as

$\varphi(B)(1-B)^d y_t = \theta(B)\varepsilon_t$ where ε_t are identically and independently distributed as $N(0,\sigma^2)$. The integration parameter d is a non-negative integer. When d = 0, the ARIMA (p, d, q) model reduces to ARMA (p, q) model.

2.1.2 The GARCH Model

Autoregressive conditional heteroscedastic (ARCH) models are used whenever there is reason to believe that, at any point in a series, the terms will have a characteristic size, or variance. In particular ARCH models assume the variance of the current error term to be a function of the actual sizes of the previous time periods' error terms. Often, the variance is related to the squares of the previous innovations. ARCH models are generally employed in modeling financial time series that exhibit time-varying volatility clustering. If an ARMA model is assumed for the error variance, the model is called a generalized auto regressive conditional heteroscedasticity (GARCH) model (Bollerslev, 1986) [1].

The ARCH (q) model for the series $\{\varepsilon_t\}$ is defined by specifying the conditional distribution of ε_t given the information available up to time $t-1$. Let ψ_{t-1} denote this information. ARCH (q) model for the series ε_t is given by

$$\varepsilon_t / \psi_{t-1} \sim N(0, h_t) \quad \ldots\ldots (3.16)$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \quad \ldots\ldots (3.17)$$

Where $a_0 >$ $a_i \geq 0$, for all i and $\sum_{i=1}^{q} a_i < 1$ are required to be satisfied to ensure non-negative and finite unconditional variance of stationary $\{\varepsilon_t\}$ series.

Bollerslev (1986) [1] proposed Generalized ARCH model (GARCH) model, in which conditional variance is also a linear function of its own lags and has the form.

$$h_t = a_0 + \sum_{i=1}^{q} a_i y_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j} \quad \ldots\ldots (3.27)$$

A sufficient condition for the conditional variance to be positive with probability one is $a_{0.}>0$, $a_i \geq 0, i = 1,2,\ldots\ldots q.$ $b_j \geq 0$, $j = 1,2,\ldots\ldots p$. The GARCH (p, q) process is weakly stationary if and only if $\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} b_j \leq 1$.

2.1.2.1 Estimation of Parameters

Estimation of parameters for ARIMA model is generally done through nonlinear least squares method. Fortunately, several software packages are available for fitting of ARIMA models. In this paper, SPSS and R software package is used. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) values for ARIMA model are computed by

$$AIC = T' \log(\sigma^2) + 2(p+q+1) \quad \text{And}$$
$$BIC = T' \log(\sigma^2) + (p+q+1)\log T'$$

Where T' denotes the number of observations used for estimation of parameters and σ^2 denotes the Mean square error.

In order to estimate the parameters of GARCH model, Method of maximum likelihood is used. The log likelihood function of a sample of T observations, apart from constant, is

$$L_T(\theta) = T^{-1} \sum_{t=1}^{T} (\log h_t + \varepsilon_t^2 h_t^{-1})$$

Where

$$h_t = a_0 + \sum_{i=1}^{q} a_i y_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j}$$

If $f(.)$ denotes the probability density function of ε_t, generally, maximum likelihood estimators are derived by minimizing

$$L_T(\theta) = T^{-1}\sum_{t=v}^{T}(\log\sqrt{\widetilde{h}_t} - \log f(\varepsilon_t/\sqrt{\widetilde{h}_t}))$$

Where $\widetilde{h}_t$ is the truncated version of h_t (Fan and Yao 2003) [4]. For heavy tailed error distribution, Peng and Yao (2003) [6] proposed least absolute deviations estimation (LADE) which minimizes the $\sum_{t=v}^{T}\left|\log\varepsilon_t^2 - \log(h_t)\right|$ where $v = p+1$, if $q = 0$ and $v > p+1$ if $q > 0$. Fan and Yao (2003) [4] and Straumann (2005) [7] have given a good description of various estimation procedures for conditionally heteroscedastic time-series models.

The Akaike information criterion (AIC) and Bayesian information criterion (BIC) values for GARCH model with Gaussian distributed errors are computed by

$$AIC = \sum_{t=1}^{T}(\log h_t + \varepsilon_t^2\widetilde{h}_t^{-1}) + 2(p+q+1)$$

$$BIC = \sum_{t=1}^{T}(\log h_t + \varepsilon_t^2\widetilde{h}_t^{-1}) + 2(p+q+1)\log(T-v+1)$$

Where T is the total number of observations.

Evidently, the likelihood equations are extremely complicated. Fortunately, the estimates can be obtained by using a software package, like E Views, SAS, SPLUS GARCH, GAUSS, TSP, MATLAB, and RATS. In the present investigation, the Gaussian maximum likelihood estimation procedure available in E Views software package, Ver. 8 is used for data analysis

2.1.2.2 Testing for ARCH Effects

Let $\varepsilon_t = y_t - \mu_t$ be the residuals of the mean equation the squared series $\{\varepsilon_t^2\}$ is then used to check for conditional heteroscedasticity, which is also known as the ARCH effects. The test for conditional heteroscedasticity is the Lagrange multiplier test of Engle (1982) [3]. This test is equivalent to usual F statistic for testing $a_i = 0$ (q=1, 2…q) in the linear

Regression $\varepsilon_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + ... + a_q\varepsilon_{t-q}^2 + e_t$, t= q+1… T where e_t denotes the error term, q is the pre specified positive integer, and T is the sample size. Specifically the null hypothesis is $H_0 : a_1 = a_2 = ... = a_q = 0$.

Let $SSR_0 = \sum_{t=q+1}^{T}(\varepsilon_t^2 - \varpi)^2$,

Where $\varpi = (\frac{1}{T})\sum_{t=q+1}^{T}(\varepsilon_t^2)$ is the sample mean of $\{\varepsilon_t^2\}$, and

$SSR_1 = \sum_{t=q+1}^{T}(\hat{e}_t)^2$ where $\hat{e}_t$ the least square residual of prior regression. Then we have $F = \frac{(SSR_0 - SSR_1)/q}{SSR_1(T-2q-1)}$ which is asymptotically distributed as chi squared distribution with q degrees of freedom under the null hypothesis. The decision rule is to reject the null hypothesis if $F > \chi_q^2(\alpha)$ where $\chi_q^2(\alpha)$ is the upper $100(1-\alpha)^{th}$ percentile of χ_q^2 or the p value of F is less than α.

3. Results and Discussion

The price and Arrivals series on Black Pepper roofed monthly data from 2003 January, to October, 2017(5 month data set used for validation of the result). An ARIMA model was attempted using the SPSS 23.0 and R statistical packages, Whereas GARCH model was fitted using E-Views software version 8. These models were then used to forecast five month out-of-sample set.

Augmented Dickey Fuller test was applied to the Black pepper price series of Bengaluru Market to test the null hypothesis that the series has unit root or non-stationary. The results are given in Table 1. The result shows that the series has unit root. The alternative hypothesis is true. Thus, data series was subjected to first differencing to make the data stationary. The results of differenced series indicated that the't -Statistic' obtained for price series is not significant, we are bound to reject the null hypothesis and the alternative hypothesis of stationary series is true. The Black pepper price series became stationary at one differencing and the data is now ready for further econometric analysis.

Table 1: Augmented Dickey-Fuller Stationarity Test for Black Pepper prices of Bengaluru Market

	Level data		At First Difference	
	t-Statistic	**Prob***	**t-Statistic**	**Prob***
ADF Test value	-1.072	0.726	-15.220	0.000*
1% Level	-3.466		-3.467	
5% Level	-2.877		-2.877	
10% Level	-2.575		-2.575	

*MacKinnon (1996) one-sided p-values.

3.1 Estimation of ARIMA model

Estimated parameters for a tentative model were selected on the basis of significance level of AR and MA terms given in Table 2. In this particular case one Auto Regressive and moving average terms were found to be statistically significant i.e. ARIMA (1, 1, 1). The estimates equation obtained in the model as follows:

Table 2: Estimate of the ARIMA Model parameters for Black Pepper prices of Bengaluru Market

	Estimate	SE	Test stat.	Sig.
Difference	1			
AR Lag 1	-0.932	0.068	-13.804	0.000
MA Lag1	-0.847	0.099	-8.524	0.000

ARCH Lagrange Multiplier (LM) test, a heteroscedastic test developed by Engle (1982) [3], was used to determine the presence of ARCH effect in the residuals. From Figure.1 we can observed that there are periods where the residuals fluctuate heavily, means it has periods of high volatility followed with periods of low volatility, so we can expect ARCH/GARCH effect for this series. This ARCH/GARCH effect confirmed through Lagrange Multiplier (LM) test. From table3 we can observe significance of Lagrange Multiplier (LM) test at 1 per cent level of significance. So, overall we say that there is ARCH/GARCH effect for this series.

Table 3: Heteroscedasticity Test for Black Pepper Prices of Bengaluru Market

Lagrange Multiplier (LM) Test	
Obs* R^2	
44.58	0.000*

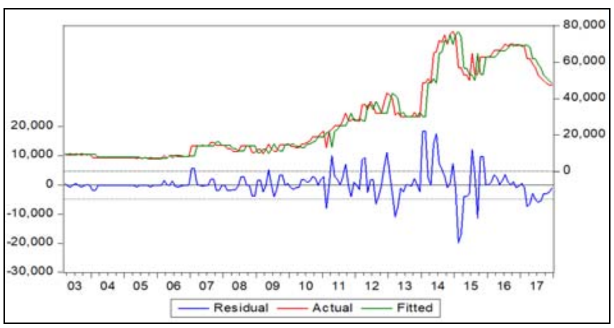

Fig 1: Residual plot of AR (1) process for Black Pepper price of Bengaluru Market

3.2 Specifying a Mean Equation

In this study both AIC and Schwartz Criterion were employed to select an appropriate Mean model for the sample of the data available. Table 4 displays the summaries of the AIC and Schwartz Criterion of different AR models. AR (1) model exhibits lesser AIC and Schwartz criterion, so it is selected as the best order among different AR orders.

Table 4: Autoregressive Model selection for the Black Pepper prices of Bengaluru Market Using AIC and SBC

	Akaike Info. Criterion	Schwartz Criterion
AR (1)	22.495	22.548
AR (2)	22.537	22.608
AR (3)	22.571	22.659
AR (4)	22.599	22.705
AR (5)	22.623	22.747

3.3 Specifying a Volatility Model

In this study both AIC and Schwartz criterion were employed to select an appropriate GARCH model for the Sample of the data available. Table 5 displays the summaries of the AIC and Schwartz Criterion of different GARCH models. GARCH (2, 1) model exhibits lesser AIC and Schwartz Criterion. So, we selected it as the best model among different GARCH models.

Table 5: GARCH Model selection for the Black Pepper Price of Bengaluru Market Using AIC and SBC

	Akaike Info. Criterion	Schwartz Criterion
GARCH (0,1)	22.884	22.937
GARCH (1.1)	22.294	22.365
GARCH (1,2)	22.220	22.308
GARCH (2,1)	21.883	21.971
GARCH (2,2)	22.095	22.201

3.4 Simultaneous Estimation of the Mean and Volatility Equations

Simultaneously model the mean and variance of Somwarpet Arrivals GARCH models for conditional variance was considered. Table 6 shows result of the estimated parameters of both the mean and volatility equations.

The estimates of GARCH (2, 1) model shows that all the coefficients of mean and variance equation are statistically significant at both 1% and 5% level of significance. $\alpha_2>0$ and $\beta_1>0$ so, this model satisfied sufficient condition for the conditional variance. This model satisfied sufficient condition for the conditional variance as given in equation 4.1.

Table 6: AR-GARCH Model selection for the Black Pepper Price for Bengaluru Market Using AIC and SBC

	Coefficient	Std. Error	Z-Statistics	Prob.
Mean Equation				
θ_0	28670.01	202099.70	0.1418	0.387
θ_1	0.9840	0.120	8.177	0.000*
Variance Equation				
α_0	3.40	0.603	5.557	0.000*
α_1	0.304	0.3418	0.8909	0.373
α_2	0.666	0.5482	1.2161	0.223
β_1	0.651	0.296	2.003	0.027*
R^2	0.9743			
Akaike info criterion	21.059			
Schwartz criterion	21.167			
Durbin-Watson stat	2.242			

$$\sigma_t^2 = 3.40 + 0.304\varepsilon_{t-1}^2 + 0.666\varepsilon_{t-2}^2 + 0.651\sigma_{t-1}^2 \quad \ldots\ldots (1)$$

Similarly Augmented Dickey Fuller test was applied to the Black pepper Arrivals series of Bengaluru Market to test the null hypothesis that the series has unit root or non-stationary. The results are given in Table 7. The result shows that the series has no unit root. The Black pepper Arrivals original series is in Stationary so differencing is not required and the data is ready for further econometric analysis.

Table 7: Augmented Dickey-Fuller Stationarity Test for Black Pepper Arrivals of Bengaluru Market.

	Level data		At First Difference	
	t-Statistic	Prob*	t-Statistic	Prob*
ADF Test value	-8.865	0.000*		
1% Level	-3.467			
5% Level	-2.877			
10% Level	-2.575			

3.5 Estimation of ARIMA model

Estimated parameters for a tentative model were selected on the basis of significance level of AR and MA terms given in Table 8. In this particular case one Auto Regressive, two nonseasonal moving average terms were found to be statistically significant. The estimates equation obtained in the model as follows:

Table 8: Estimate of the ARIMA Model parameters for Black Pepper Arrivals of Bengaluru Market

	Estimate	SE	Test stat.	Sig.
AR Lag1	0.920	0.075	12.322	0.000
MA Lag 1	0.580	0.111	5.245	0.000
MA Lag2	0.189	0.091	2.083	0.039

we check for the ARCH effect for Arrivals, From Figure 2, we can observed that there are periods where the residuals fluctuate heavily, means it has periods of high volatility followed with periods of low volatility, so we can expect ARCH/GARCH effect for this series. This ARCH/GARCH effect confirmed through Lagrange Multiplier (LM) test. From table 9 we can observe significance of Lagrange Multiplier (LM) test at 1 per cent level of significance. So, overall we say that there is ARCH/GARCH effect for this series.

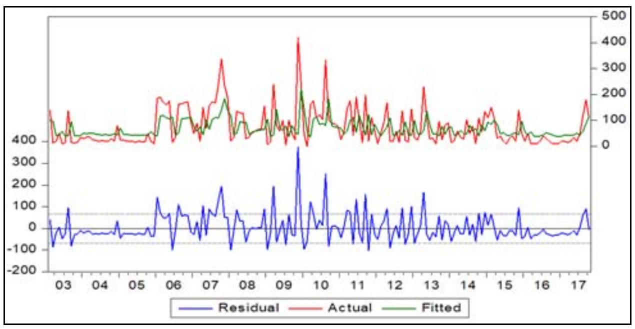

Fig 2: Residual plot of AR (1) process for Black Pepper Arrivals

Table 9: Heteroscedasticity Test for Black Pepper Arrivals in Bengaluru Market

Lagrange Multiplier (LM) Test	
Obs* R-Squared	
7.882	0.005*

3.6 Specifying a Mean Equation

In this study both AIC and Schwartz Criterion were employed to select an appropriate Mean model for the sample of the data available. Table 10 displays the summaries of the AIC and Schwartz Criterion of different AR models. AR (1) model exhibits lesser AIC and Schwartz criterion, so it is selected as the best order among different AR orders.

Table 10: Autoregressive Model selection for the Black Pepper Arrivals Using AIC and SBC

	Akaike Info. Criterion	Schwartz Criterion
AR (1)	11.378	11.435
AR (2)	11.380	11.449
AR (3)	11.389	11.478
AR (4)	11.395	11.502
AR (5)	11.403	11.528

By examining ACF of Residual Square in fig 3, we can observe sudden decay of auto correlation after first order. So it can be removed by adopting GARCH, one series.

3.7 Specifying a Volatility Model

In this study both AIC and Schwartz criterion were employed to select an appropriate GARCH model for the Sample of the data available. Table 11 displays the summaries of the AIC and Schwartz Criterion of different GARCH models. GARCH (1, 3) model exhibits lesser AIC and Schwartz Criterion. So, we selected it as the best model among different GARCH models.

Table 11: GARCH Model selection for the Black Pepper Arrivals Using AIC and SBC

	Akaike Info. Criterion	Schwartz Criterion
GARCH (0,1)	11.435	11.488
GARCH (0,3)	11.445	11.534
GARCH (1.1)	11.378	11.450
GARCH (1,2)	11.388	11.478
GARCH (1,3)	11.320	11.427
GARCH (2,1)	11.389	11.478
GARCH (2,2)	11.412	11.519

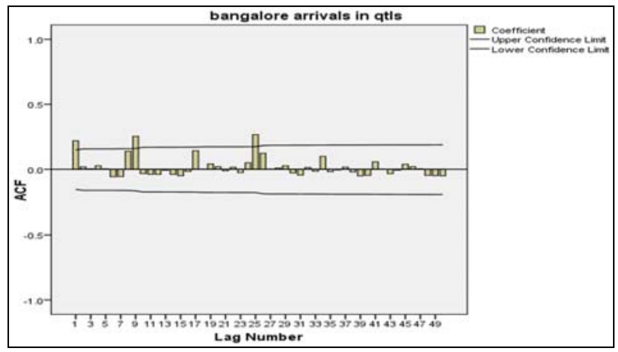

Fig 3: Auto correlations at different lags of Residuals squared Black Pepper Arrivals

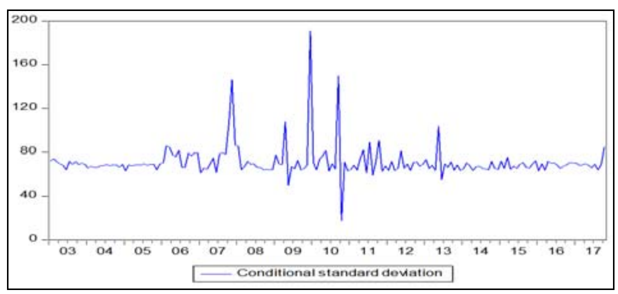

Fig 4: estimated conditional standard deviation from a GARCH (1, 3) model

3.8 Simultaneous Estimation of the Mean and Volatility Equations

Simultaneously model the mean and variance of Somwarpet Arrivals GARCH models for conditional variance was considered. Table 12 shows result of the estimated parameters of both the mean and volatility equations.

The estimates of GARCH (1, 3) model shows that all the coefficients of mean and variance equation are statistically significant at both 1% and 5% level of significance. $\alpha_1>0$ and $\beta_3>0$ so, this model satisfied sufficient condition for the conditional variance as given in equation 4.2.

Table 12: Parameter Estimates of AR-GARCH (1, 3) model for Black Pepper arrivals in Bengaluru Market

	Coefficient	Std. Error	Z-Statistics	Prob.
Mean Equation				
θ_0	70.060	8.943	7.833	0.000
θ_1	0.355	0.083	4.245	0.000
Variance Equation				
α_0	3347.136	416.698	8.032	0.000
α_1	0.102	0.037	2.690	0.007
β_1	0.363	0.068	5.342	0.000
β_2	0.441	0.0723	6.103	0.000
β_3	0.721	0.110	6.517	0.000
R^2	0.594			
Akaike info criterion	11.151			
Schwartz criterion	11.277			
Dubbin-Watson stat	1.960			

$$\sigma_t^2 = 3347.136 + 0.102\varepsilon_{t-1}^2 + 0.363\sigma_{t-1}^2 + 0.441\sigma_{t-2}^2 + 0.721\sigma_{t-3}^2 \quad (2)$$

4. Evaluation of forecast performances of ARIMA and GARCH models

The RMSE, MAPE and MAE values were obtained from estimated equations for both ARIMA and GARCH models presented in Table 12. All the Accuracy statistics values from GARCH model were smaller than that of ARIMA model. Therefore, it is concluded GARCH model performed better than ARIMA model in case of volatile data so, GARCH model performed better than ARIMA for modeling and forecasting of monthly prices and Arrivals of black pepper in Bengaluru market.

Table 12: Forecast Accuracy of Bengaluru Market Prices and Arrivals using ARIMA and GARCH

Month	Bengaluru Prices			Bengaluru Arrivals		
	Actual	ARIMA	GARCH	Actual	ARIMA	GARCH
June-17	57000	54097.69	52610.9	20	36.68	57.598
July -17	53000	54108.69	51134.9	50	39.81	52.267
Aug -17	51500	55289.88	49658.9	120	43.95	62.930
Sep -17	50000	55533.89	48182.9	180	48.02	87.811
Oct -17	48500	56799.88	47198.9	110	52.02	109.137
Accuracy statistics	RMSE	6643.72	940.44	RMSE	73.411	51.33
	MAPE	6165.00	877.74	MAPE	58.637	58.41
	MAE	12.748	1.77	MAE	58.576	37.99

5. Conclusion

ARIMA model was applied for forecasting Black pepper prices and Arrivals gives reasonable and acceptable forecasts. But, it did not perform very well when there exist volatility in the data series. GARCH model was also fitted to forecast Black pepper prices and Arrivals. The GARCH model performs better on account of its ability to capture the volatility by the time varying conditional variance. The GARCH was found to be a better model than ARIMA in forecasting Black pepper prices and Arrivals because the values for RMSE, MAE and MAPE calculated using GARCH model were lesser than ARIMA model. The deviations between actual and forecasted Gram prices were little in GARCH model. Therefore, it is suggested that GARCH model is a better model than ARIMA for forecasting volatile prices.

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