Time series analysis of Arrivals and Prices of Groundnut and Sunflower in Sira and Challakere market

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CERTIFICATE

T**his is to certify that the thesis entitled** "Time series analysis of Arrivals and Prices of Groundnut and Sunflower in Sira and Challakere market" **submitted by** Ms PADMASHRI, H.S **for the degree of** MASTER OF SCIENCE **in** AGRICULTURAL STATISTICS, **to the University of Agricultural Sciences, Bangalore is a record of research work done by her during the period of her study in this university under my guidance and the thesis has not previously formed the basis for the award of any degree, diploma, associate ship, fellowship or other similar titles.**

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(MY PARENTS)

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Time series analysis of Arrivals and Price of Groundnut and Sunflower in Sira and Challakere market

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ABSTRACT

Indian vegetable oil economy is fourth largest in world, accounting around 14 per cent of the oilseeds area (26.51 million hectares in 2006-07) and 8.5 per cent of the world's oilseeds production (24.28 million tonnes in 2006-07). India ranks first in the world in production of groundnut and fourth in sunflower. Oilseeds sector occupies a distinct position in the Indian agriculture sector after cereals, sharing about 13 per cent of country's gross cropped area, accounting for 3 per cent of Gross National Product and 10 per cent of the value of agriculture product.

Karnataka has a spread of 7.635 lakh hectares of groundnut, producing 3.271 lakh tons and has productivity of 451 kilograms per hectare. It has spread of 12.305 lakh hectares of sunflower, producing 3.842 lakh tons and has productivity of 329 kilograms per hectare.

The present study was conducted using ten years data from Sira and for sixteen years from Challakere market. The secondary data pertaining to monthly arrivals (Quintal) and price (Rs /Quintal), of groundnut and sunflower were collected from respective Agriculture Produce Marketing Board (APMC).

Box-Jenkins procedure was used to fit ARIMA model and to forecast mean prices and arrival for next 12 months. Since, there was seasonality in the data seasonal ARIMA model were fit. Prices of groundnut and sunflower, of Sira and Challakere markets were non-stationary, differenced series were used.

The study shows that price and arrivals of both crops of Challakere market depends on previous one year's values and on two months back values (except for sunflower arrivals- it depends on one month back values). In Sira market the prices had its dependence on previous year's value and arrivals has its dependence on two years back values.

Volatility in prices and arrivals of both crops from both markets is modeled using ARCH model. These models forecasted the variance of prices and arrivals. Later, these variances were used in obtaining the forecasts of actual prices and arrivals. Lagrange-Multiplier (LM) test declared the presence of ARCH effect in all series except for Sunflower arrivals in both challakere and sira markets.

ARCH (1) model is found to be adequate in modeling the variance and same is used in forecasting the prices and arrivals of groundnut and sunflower at challakere and sira markets, for a duration of 12 months.

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INTRODUCTION

INTRODUCTION

Indian vegetable oil economy is the fourth largest in the world, next to the US, China and Brazil, accounting around 14 per cent of the oilseeds area (27.74 million hectares in 2005-06 and 26.51 million hectares in 2006-07) and 8.5 per cent of the world's oilseeds production (27.97 million tonnes in 2005-06 and 24.28 million tonnes in 2006-07). The oilseeds sector occupies a distinct position in the Indian agriculture sector after cereals, sharing about 13 per cent of country's gross cropped area, accounting for 3 per cent of Gross National Product and 10 per cent of the value of agriculture product.

India is also endowed with the diverse agro economical conditions suitable for production of nine important oilseed crops: groundnut, sesame, castor, linseed, safflower, rapeseed-mustard, sunflower, soybean and Niger. India also produces two perennial oilseeds crop– coconut and oil palm, besides the secondary oilseed crops such as maize and cotton. India ranks first in the world in production of groundnut, sesamum, castor and linseed and safflower. It is second in rapeseed production and fourth in the production of sunflower and soybean. The productivity of oilseeds (0.59 ton per hectare for groundnut and 0.62 ton per hectare for sunflower) has been less than 2/3rds of the world's average (1.02 ton per hectare for groundnut and 1.18 ton per hectare for sunflower) productivity.

India was self sufficient in vegetable oils in the 1950s; however, by the 1960s the domestic demand-supply equilibrium almost vanished. The turning point arrived in 1988, when the country faced shortfall of 2 million tonnes of oil, necessitating imports worth $1billion. At this situation, government made a concerted effort to make oilseeds more attractive to growers, through a combination of specialized extension campaign including the high-profile Technology Mission. As a result, the country became almost self-sufficient (maximum of 98% during 1992-93 and 1993-94) in edible oil. In early 90s, the high prices of oils

encouraged the entry of more firms into the business. The result was a substantial expansion of processing capacity and an unprecedented increase in oilseeds production, in particular soybeans, by over 70 per cent in six years. However, the liberalization of Indian economy at this point of time fundamentally changed the import regime of India's edible oil particularly in 1994 when as part of its obligations under World Trade Organization (WTO) rules; India eliminated the state monopoly on imports and placed the imports under a privatized Open General License (OGL) system. Under the new rules, India also agreed to eliminate import quotas and placed upper bound limits on tariff levels. These changes made the rules governing edible oil import more transparent and more responsive to market forces. Imports of edible oil that were 1.5 million tones in 1986-87 gradually declined to 0.1 million tones in 1992-93 but have now reached 4.3 million tones (2004-05). Population pressure coupled with better standard of living, low oilseeds production due to aberrant weather for several years and liberalization of import-export policy, are the causes behind such an import scenario. The corresponding export earnings however, have been much lower due to depressed prices in the international market.

Most of the area (70%) and production (75%) of groundnut are concentrated in the four states namely Gujarat, Andhra Pradesh, TamilNadu and Karnataka. Andhra Pradesh, Tamil Nadu, Karnataka and Orissa have irrigated area comprising about 6 per cent of the total groundnut area in India. Spread of 7.635 lakh hectares of groundnut, produces 3.271 lakh ton and has productivity of 451 kilograms per hectare in Karnataka. Generally, as a kharif crop, groundnut is grown year after year. In certain places, it is rotated with wheat, jowar, bajra, garden crops, such as potatoes, onions, chillies, garlic, ginger and turmeric. The yields of the cereal crops following groundnut are usually increased by about 25 per cent. Pulses, e.g. red gram (arhar), mash and moong are grown mixed with groundnut. In certain places, millets e.g.

jowar and bajra, and castor are grown mixed with groundnut. Varities S-206 (yield of 1,000-1,200 kg of pods/ha with 50 per cent oil) and S-230 (yield of 1,200-1,300 kg of pods/ha with 50 per cent oil) are cultivated in Karnataka.

Around 70 per cent of Sunflower is produced in the Rabi (November – March) season. The kharif (June – September) period accounts for less than 30 per cent of the crop currently. The major producers are Karnataka (35%), Andhra Pradesh (30%), and Maharashtra (15%). Spread of 12.305 lakh hectares of sunflower, produces 3.842 lakh ton and has productivity of 329 kilograms per hectare in Karnataka. Sunflower is grown as crop with redgram, groundnut, ragi and soybean. Mixed cropping of sunflower with cotton and Groundnut with sunflower (6:2) resulting with intercropping is more common.

At the same time, the issue of prices volatility has assumed critical importance today in the context of agricultural trade liberalization. One of the major arguments advanced against agricultural trade liberalization is that it would lead to transmission of international prices volatility into domestic markets. Thus, it is argued that, it will have serious implication for food security of the poor in a country where providing economic access to food is the biggest challenge. The merit of this argument can only be judged by a detailed empirical analysis of agricultural prices volatility in international and domestic markets.

Extreme volatility in commodity prices, particularly of food commodities, affects poor agricultural laborers and labour engaged in unorganized sector adversely because their wages are not index- linked. Small farmers in countries like India, with low propensity to save and poor access to efficient saving instruments can not cope with the revenue variability resulting from fluctuations in output prices. They do not possess the requisite knowledge for crop diversification and lack of access to appropriate technology. Commodity prices volatility poses

problems also for the governments and exporters of the primary commodity-producing developing countries. For governments, unforeseen variations in export prices can complicate budgetary planning and jeopardize attainment of the debt targets.

The nominal prices of agricultural commodities exhibit much more variability than those of non-agricultural commodities. Traditionally, volatility in agricultural prices has been attributed to

a) Low prices and income elasticities of agricultural products.

b) Inherently unstable agricultural production because of unforeseeable and unpreventable exogenous shocks like weather.

Volatility possess is a big challenge in modeling financial time series like Agricultural prices, stock prices, exchange rates, inflation. Characteristics of most of these financial time series are that in their level form they are random walks; that is they are non-stationary. On the other hand, in first difference form, they are generally stationary; therefore modeling for their first difference is more appropriate. But these differences often exhibit wide swings or volatility, suggesting that the variance of financial time series varies over time.

Study of time series data helps in deciding the appropriate time and place for disposing the surplus and prediction of future (arrivals and prices) of the crops. It also helps to provide guidelines to policy makers and planners in formulating national production and prices policies.

Thus the specific objectives of the study are,

1) Forecasting arrivals and prices of groundnut and sunflower by Autoregressive models,
2) To analyze the volatility in the arrivals and prices of groundnut and sunflower

REVIEW OF LITERATURE

II. REVIEW OF LITERATURE

In this chapter, studies on arrivals and prices of groundnut and sunflower are being reviewed. These articles illustrate the use of statistical methods in analyzing market arrival and prices.

The reviews presented below are grouped under two heads as listed here,

2.1. Autoregressive Models

2.2. Volatility analysis

2.1. Autoregressive Models

A class of models namely: Autoregressive (AR), Moving Average (MA) and Auto Regression Integrated Moving Average (ARIMA). Box and Jenkins popularized it during late sixties. The application of these models for predicting prices of agricultural commodities is very few. Some studies, which have used this model, reviewed below though they do not concern to vegetables. This has done as it illustrates the use of this model in food grain markets.

Lijung and Box (1978) proposed an alternate test to the Box-Pierce Q-statistic, because the value of the Q-statistic inflated for large values of n. Their modified test was,

$Q_r = n(n+2)^n (n-k)^{-1} r^2_k$

Where,

Q_r : Follows a χ^2 (n-q-p df) distribution

r_k : Sample auto correlation at time log k

Chatfield (1977) observed that the Box-Jenkins approach being a valuable addition in the forecasts tool bag, which have deeper understanding of time series behavior. Even though, it found to be more expensive yet the accuracy justified the cost.

Makridakis and Hibbon (1979) observed that accuracy of forecasts is negatively associated with the error term. Several tests to arrive at the accuracy of forecasts like Mean Square Error (MSE). Theil's-U coefficient and Mean Absolute Percentage Error (MAPE) suggested.

Chengappa (1980) applied the Box-Jenkins model to forecast pool sale and export auction prices of coffee. Monthly data used and due to the distinct seasonal variation in prices, the ARIMA seasonal model was applied. The pool sale prices forecasts were found to be accurate when compared to forecasts of export prices. This attributed to possible lack of stationary to the data. Hence, the adoption of differencing procedure or transformations to make the data stationary found necessary for a better estimate of export prices.

Achoth (1985) analyzed supply, prices and trend of Indian tea by fitting ARIMA models to data on prices and production. Moving average models found to be most suitable. Among the prices series particular months prices not related to the prices of the immediate previous month but significantly related to the prices of the same month in previous year. However, the production in a particular month was related both to production of the previous month as well as to the production of the same month in previous years. Forecasts yielded reasonably good results as judged from the tests of their efficiency. The forecasts of prices were superior when compared to the forecasts of quantities, which was attributing to the highly structured pattern of prices behavior.

Achoth (1985) fitted seasonal ARIMA model to prices data of tea at Calcutta and Cochin auctions to production data of Northern and Southern regions of the country and quantity of tea exports and their prices. He identified that the moving average model was most suitable. Forecasts from these models yielded reasonably good ex-post and ex-ante forecasts judging from the test of their efficiency. Further, some of the models fitted to the quantity series did reveal a certain degree of

inadequacy, which was not consider serious probably because certain cyclic pattern may not have been captured by the model.

Lanciotti (1990) established a paper that analyses time series data of monthly prices for a group of dairy products with the aim of obtaining reliable forecasts. The method of analysis employed is ARIMA as put forward by Box-Jenkins. The time series data covers both wholesale and retail prices for butter: Gorgonzola, Provolone, Grana Padano and Pasmigiano Reggiano. To estimate the reliability of the forecasts obtained, a comparison is made with those resulting from naïve models do not require any estimates. Indicators on the accuracy of the forecasts show that except for Grana Padana, Le ARIMA forecasts are better.

Min (1995) applied ARIMA models to forecast the changes in the number of hogs and hog farms in Korea by total and herd size. The ARIMA model, for pig production was identified and estimated using quarterly data for 1985(1) to 1994(4). The forecasting period was 3-year horizon, from 1995(1) to 1997(4). The number of pig farms in the fourth quarter of 1997 was predicted to decrease from 39.81 to 36.45 per cent (32,642 households), while the number of pigs predicted to increase from 7.44 to 8.23 per cent (6398 per head).

Alebrahiem (1996) employed time series data of retail prices of eggs in Saudi Arabia between January 1990 and December 1994 and constructed a model, which could be used to forecast future prices. Procedure involved two methods, that is, first constructs ARIMA models, while the second uses the multiple regression technique to account for trend and seasonality, followed by analysis of components of the regression error. The findings of the study indicated that the seasonality of prices, results also showed that egg prices start significantly decrease in April and continue to fall until August, then start to improve in September reached highest level in February. The regression model was used to forecast prices of the nine months of 1995. Forecasted prices were very accurate since percentage deviation from real values did not

exceed 3 per cent. Study recommended the erection of factories and manufacture of egg powder by utilizing the excess supply of eggs in the April-August period, and examination of the potential of export markets.

Srivastava and Brahmaprakash (1994) used ARIMA models for forecasting sugarcane productivity based on the time series data of fifty years (1940-41 to 1989-90) in Bihar. Their findings, therefore, ascertained that the time series data on sugarcane productivity for the state of Bihar was described by an ARIMA (0, 1, 1) model.

Yin-Runsheng and Min, R.S (1999) used univarate ARIMA model to forecast timber prices using quarterly prices series, Timber Mart South. The results showed that most of the selected pipe pulpwood and saw timber markets in six southern US states was be evaluated using ARIMA models, and that short-term forecasts, especially those of one lead forecasts, are fairly accurate. It is suggested that forecasting future prices could aid timber producers and consumers alike in timing harvests reducing uncertainty and enhancing efficiency.

Amin and Razzaque (2000) stated ARIMA model is a way of describing how a time series variable is related to its own past value. Mainly an ARIMA model is used to produce the best weighted average forecast for a single time series. Producing forecast from an ARIMA model is straight forward.

Mastny (2001) used ARIMA models, also called Box and Jenkins, models after their developers, is a group of models allowing the analysis of time series with various features. Article demonstrates the possible usage of the Box-Jenkins methodology for the analysis of time series for agricultural commodities. The paper contains a basic mathematical explanation of ARIMA models together with a practical illustration of a prices development forecast for a selected agricultural commodity.

In forecasting agriculture scenario in Tamil Nadu by Balamangala et al. (2001), ARIMA models were built for the data related to the

cultivable area, production and productivity of chosen crops over the period 1956-57 to 1994 -95 and to forecast for the subsequent five year, considering 1994-95 as the base year. With regard to production, finger millet and groundnut had a decreasing level of production with a decrease in the area of cultivation whereas; Sorghum, green gram and red gram the cultivable area decreased though increased production level. With regard to productivity of the crops, maize, black gram, green gram and cotton showed a decreasing trend during the forecasting period while other crops such as rice, sorghum, pearl millet, red gram, sugarcane and groundnut showed a mild increasing trend.

Ansari and Ahmed (2001) applied ARIMA modeling for time series analysis of world tea prices and industrialized countries export prices. The results of the estimated ARIMA equations imply that the information on the industrialized countries export prices can be forecasted from information on the prices of the previous two periods. Results concluded, from the fitted ARIMA models, that autoregressive processes generate both prices series and there is no influence of external factors.

Selvakumar (2003) forecasted the future demand for agriculture manpower In Government and Private sectors using ARIMA models. He revealed that the supply of agricultural graduates exceeds the demand and could lead to unemployment for agriculture manpower. By creating new jobs in agriculture by Government sector and investment in agriculture business by private sectors would be beneficial to boost the Indian agriculture sector.

Indira Rajaraman and Arindam Datta (2003) forecasted the Agriculture production of five states of India namely Punjab, Rajasthan, Karnataka, Andhra Pradesh and Uttar Pradesh using ARIMA models. They have used Index of Agricultural Production (IAP) rather than Gross State Domestic Product (GSDP) of the states. Models were fitted for the data from 1950-51 to 2000-2001 and forecasted for next three years. The forecast for 2002-2003 showed negative growth for Rajasthan (-

1.7%) and Andhra Pradesh (-3.5%). The forecast for Punjab and Karnataka were positive with 1.8 and 5.0 per cent, respectively.

2.2 Volatility Analysis

Diongue et al. (2006) investigated conditional mean and variance forecasts using a dynamic model following a k-factor GIGARCH process. They were particularly interested in calculating the conditional variance of the prediction error. They applied this method to electricity prices and test spot prices forecasts until one month ahead forecast. Results showed that the k-factor GIGARCH process is a suitable tool to forecast spot prices, using the classical RMSE criteria.

Traditional econometric models assume a constant one-period forecast variance. To generalize this implausible assumption, Engle (1982), gave a new class of stochastic processes called autoregressive conditional heteroscedastic (ARCH) processes. This process has features like, mean zero, serially uncorrelated processes with non-constant variances conditional on the past, but constant unconditional variances. For such processes, recent past would give information about one-period forecast variance. A regression model is then introduced with disturbances following an ARCH process. Maximum likelihood estimators are described and a simple scoring iteration was formulated. Ordinary least squares maintain its optimality properties in this set-up, but maximum likelihood was more efficient. The relative efficiency was calculated and found to be infinite. To test whether the disturbances follow an ARCH process, the Lagrange multiplier procedure was employed. The test is based simply on the autocorrelation of the squared OLS residuals. This model was used to estimate means and variances of inflation in the U.K. The ARCH effect was found to be significant and estimated variances increased substantially during chaotic seventies.

Han et al. (2006) had considered ARCH processes with persistent covariates and provide an asymptotic theory that explains how such

covariates affect various characteristics of volatility. Specifically, we propose and study a volatility model, named ARCH-NNH model, which is an ARCH (1) process with a nonlinear function of a persistent, integrated or nearly integrated, explanatory variable. Statistical properties of time series given by this model are investigated for various volatility functions. It is shown that the model generates time series that have two prominent characteristics: high degree of volatility persistence and leptokurtosis. Due to persistent covariates, the time series generated by the existing model had the long memory property in volatility that was commonly observed in high frequency speculative returns. On the other hand, the sample kurtosis of the time series generated by the model either diverges or has a well-defined limiting distribution with support truncated on the left by the kurtosis of the innovation, which successfully explains the empirical finding of leptokurtosis in financial time series. It is shown that the default premium (the yield spread between Baa and Aaa corporate bonds) predicts stock return volatility, and the interest rate differential between two countries accounts for exchange rate return volatility. The forecast evaluation shows that our model generally performs better than GARCH (1,1) and FIG-ARCH at relatively lower frequencies.

Kovacic and Zlatko (2007) investigated the behavior of stock returns in an emerging stock market namely, the Macedonian Stock Exchange, focusing on the relationships between returns and conditional volatility. The conditional mean followed a GARCH-M model, while for the conditional variance one symmetric (GARCH) and four asymmetric GARCH types of models (EGARCH, GJR, TARCH and PGARCH) were tested. They examined how accurately these GARCH models forecast volatility under various error distributions. Three distributions were assumed, i.e. Gaussian, Student-t and Generalized Error Distribution. The empirical results showed the following: (i) the Macedonian stock returns time series display stylized facts such as volatility clustering,

high kurtosis, and low starting and slow-decaying autocorrelation function of squared returns; (ii) the asymmetric models show a little evidence on the existence of leverage effect; (iii) the estimated mean equation provide only a weak evidence on the existence of risk premium; (iv) the results are quite robust across different error distributions; and (v) GARCH models with non-Gaussian error distributions are superior to their counterparts estimated under normality in terms of their in-sample and out-of-sample forecasting accuracy.

Nicholas and Anthony (2006) examined the process of relative food prices volatility and have investigated how short-run deviations from the relationships between relative food prices and particular macroeconomic fundamentals affect the volatility for the case of Greece. The methodology followed in this paper to measure relative food prices volatility was Generalized Autoregressive Conditional Heteroscedastic (GARCH) and GARCH-X models. The latter model allows the link between short-run deviations from a long-run co-integrated relationships and volatility. The results from a GARCH-X (1, 1) model showed that a significant and positive effect is imposed by the deviations on the volatility of relative food prices. These findings implied that the forecasting business of relative food prices is expected to become a harder task.

Nikolaos (2001) investigated that the determinants of agricultural prices formation emphasizes on the detection of possible impacts caused by inflation uncertainty. The empirical methodology employs the GARCH technique to model the Uncertainty variable, as well as VAR modeling and variance decomposition analysis to investigate possible causal effects among the involved variables.

Pagan and Schwert (1990) have compared several statistical models for monthly stock return volatility. The focus was on U.S. data from 1834-1925. Also, the Great Depression had levels of stock volatility that were inconsistent with stationary models for conditional

heteroskedasticity, they showed the importance of nonlinearities in stock return behavior that were not captured by conventional ARCH or GARCH models. They also showed the non stationarity of stock volatility, even over 1834-1925 periods.

Satheesh et al. (1988) applied the recent developments in time-series modeling to analyze the retail prices of beef, pork, and chicken. Specifically, generalized autoregressive conditional heteroscedasticity (GARCH) models were fit to these data to determine if, unlike more traditional time-series models, the conditional variances of the underlying stochastic processes are non constant. The estimation results rejected the constant conditional variance assumption. Furthermore, *ex post* forecast intervals generated from GARCH processes indicated that the forecasting accuracy of estimated models have varied widely over time with substantial volatility occurring during 1970s and early 1980s.

Wheat futures prices (Anonymous, 2007) have been playing an active role in China's agricultural prices system since the contract's debut at the China Zhengzhou Commodity Exchange (CZCE). Research paper analyzes CZCE wheat futures prices from 2000 to 2002 quantitatively. Results showed that the prices have unit root and time-varying variances. Alternative ARCH, GARCH, and ARMA models were fitted to the data resulting in the selection of AR (1), ARCH (2), and GARCH (1,1) models. Comparisons of these three models indicated that ARCH/GARCH described the prices better than ARMA model, and GARCH further improved upon ARCH. Out-of-sample prediction performance also confirmed the result.

Engle (2001) has presented a research paper on ARCH and GARCH models using an example of risk measurement in a portfolio with three sections: NASDAQ, Dow-jones and Long bonds. GARCH (1, 1) was found to be the best fit. Box-Lijung Q-statistic was used to check the residual ARCH effect rejects the null hypothesis.

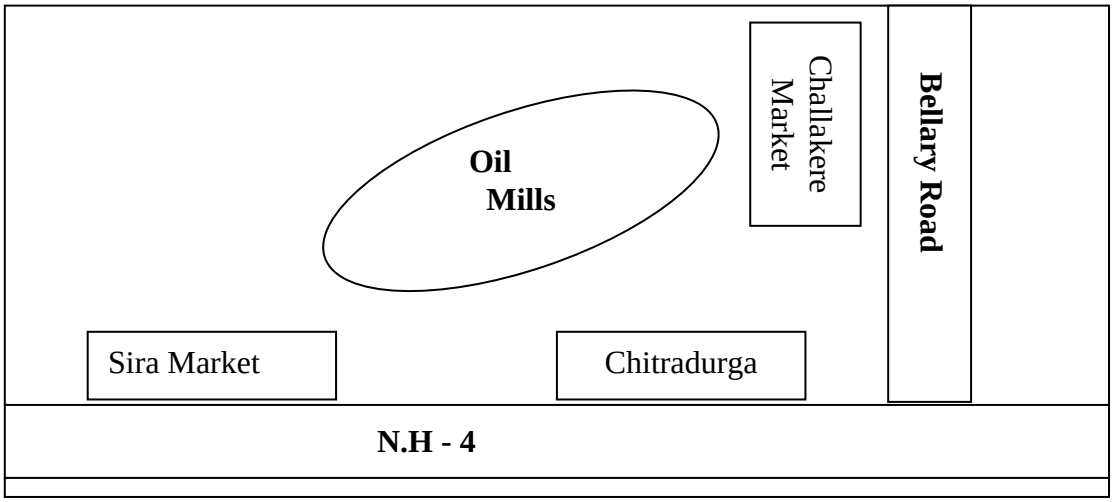
METHODOLOGY

III. MATERIALS AND METHODS

The study was undertaken with an overall objective of analyzing the arrivals and prices of Groundnut and Sunflower in Challakere and Sira markets of Karnataka state. This chapter provides a brief description of materials and methods of statistical analysis employed in the present study.

3.1. Selection of Sample Area

In Karnataka, out of 143 regulated markets the Challakere and Sira regulated market have been selected for the study. A brief description about the location of the selected markets is presented below.



3.2 Database

The data collected for the study were monthly prices and monthly arrivals of oilseeds from Challakere APMC for sixteen years and from Sira for ten years. Data on monthly arrivals is recorded in quintals and monthly prices in Rupees per quintal.

Monthly arrival is the total arrival of the produce in the month. The monthly price is the maximum of the modal prices in the month. A modal price is the prices of the mid 60 percent of the produce.

3.3 Methods of Statistical Analysis

In this section, a brief description of statistical methods employed is presented. Time series analysis employed for studying the long-term, short-term and other periodic fluctuations in prices and arrivals of groundnut and sunflower for each market

3.3.1 Auto-Regressive Models :

The Box-Jenkins procedure is concerned with fitting a mixed Auto regressive Integrated Moving Average (ARIMA) model to a given set of data. The main objective in fitting this ARIMA model is to identify the stochastic process of the time series and predict the future values accurately. The Box-Jenkins model fulfills these two conditions.

George Box and Jenkins have studied ARIMA models extensively. Their name is frequently used synonymously with general ARIMA process applied to time series analysis and forecasting. However, the optimal forecast of future values of a time-series are determined by the stochastic model for that series. Main stages in fitting box-Jenkins forecasting model are as follows:

1. Identification
2. Estimating the parameters
3. Diagnostic checking and
4. Modification

This model involves purely a random process. The co-variance stationary condition is prerequisite for fitting Box-Jenkins model.

3.3.2 Stationarity :

A common assumption in many time series technique is that the data are stationary. A stationary process has property that the mean and

variance do not change over time. In mathematical terms, stationarity series is defined as a flat looking series, without trend, constant over time and no periodic fluctuations. If mean changes over time (with some trend or cyclic pattern) and variance is not reasonably constant then series is non-stationary in both mean and variance.

It is very difficult to find a stationary series, in practice either mean shift with time because of several factors like technology, demand, population, etc., or the variance changes over time. However, the method of differencing is used to make series stationary. Conversely, a stationary series may be summed or integrated to give a non-stationary one.

Since the ARIMA model refer only to a stationary time series, the first stage of Box-Jenkins model is reducing non-stationary series X_t to a stationary series Y_t by taking first differences as follows

$$Y_t = \nabla X_t = X_t - X_{t-1} = X_t - LX_t = (1-L)\, Xt$$

Where, L = Backward shift operator

The backward shift operator is convenient of describing the process of differencing. L is defined as, $L^i X_t = X_{t-i}$ for i = 1, 2……

Suppose the first difference of the series does not become stationary then second order differencing is done as follows;

$$\begin{aligned} Y_t &= \nabla (\nabla X_t) = \nabla (X_t - X_{t-1}) = \nabla (X_t) - \nabla (X_{t-1}) \\ &= (X_t - X_{t-1}) - (Xt_{-1} - X_{t-2}) \\ &= X_t - 2X_{t-1} + X_{t-2} \\ &= X_t - 2LX_t + L^2X_t = (1 - 2L + L^2)\, X_t \\ &= (1 - L)^2\, X_t \end{aligned}$$

In general, if it takes d^{th} order difference to achieve stationary, it is written as: d^{th} order difference = $(1-L)^d\, X_t$

In order to test the stationarity, autocorrelation function (ACF) of difference series (Y_t) is computed up to 24 lags. If the ACF for first and

higher differences (after 2-3 lags) drop abruptly to zero then it indicates the series is stationary.

3.3.3 Stationary time series model :

3.3.3.1 Auto Regressive process (p, o, o)

The observation Y_t depends on previous observation and error term e_t so it is called as auto regressive process (AR process)

$$Y_t = \mu + \varnothing_1 Y_{t-1} + \varnothing_2 Y_{t-2} + \ldots + \varnothing_p Y_{t-p} + e_t \qquad (3.1)$$
$$= \varnothing_p (L) (Y_t - \mu) + e_t$$

Note the term μ in equation (3.1) is not quite the same as the "Mean" of the Y series. Rather, the development is as follows:

$$(Y_t - \mu) = \phi_t (Y_t - \mu) + e_t$$
$$= \phi_1 (Y_{t-1} - \mu) + \phi_2 (Y_{t-2} - \mu) + \ldots + \phi_p (Y_{t-p} - \mu) + e_t$$
$$= (\phi_1 Y_{t-1} - \phi_1 \mu) + (\phi_2 Y_{t-2} - \phi_2 \mu) + \ldots + (\phi_p Y_{t-p} - \phi \mu) + e_t$$
$$Y_t = (\mu - \phi_1 \mu - \ldots - \phi \mu) + \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + e_t$$
$$= \mu_1 + \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + e_t$$

In addition, the values of auto regressive coefficient is restricted to lie between – 1 and + 1.

3.3.3.2 Moving Average Process (o, o, q)

If the observation Y_t depends on one or more previous error terms (e_t's) then we have Moving Average (MA) process.

$$Y_t = (\mu_1 + e_t - \theta_1 e_{t-1} + \theta_2 e_{t-2} - \ldots + (-1)^q \theta_q e_{t-q})$$

Where, θ_i = i^{th} moving average parameter, i = 1, 2…q, q = order moving average. Values of the coefficient are restricted to lies between –1 to +1.

3.3.3.3 Mixtures: ARIMA Process

If the non-stationary is added to a mixed ARMA process, then the general ARIMA (p, d, q) is implied. Here the word I: Integrated, refers to the differencing of the data series. In its general form, the ARIMA model is expressed as follows:

ARIMA (p, d, q) $(P, D, Q)_s$

p = order of non-seasonal auto regressive (AR)

d = order of non-seasonal difference

q = order of non-seasonal moving average (MA)

P = order of seasonal auto regressive (SAR)

D = order of seasonal difference

Q = order of seasonal moving average (SMA)

S = length of the season

3.3.3.4 Identification of models:

The purpose of the identification phase is to select a specific ARIMA Model from the general class of ARIMA (p, d, q) $(P, D, Q)_s$ process. Before estimating the parameter (p, q, P and Q) of model, the data are examined to decide about the model which best explains the data. Appropriate p, q, P and Q values are obtained by examining the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of differenced series Y_t. Usually ACF and PACF are calculated up to maximum of 25 lags (k). The sample auto correlation for time lag k is defined as,

$$P_k(Y_t) = r_k(Y_t)$$

$$= \frac{e_k(Y_t)}{e_0(Y_t)}$$

Where, $e_k(Y_t) = \frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \bar{Y}\right)\left(Y_{t+k} - \bar{Y}\right)$, k = 0,1,2…24, t =1,2…n-k,

n = Length of time period

The order will simply be equal to the number of partial autocorrelation significantly different from zero. The partial autocorrelation up to p time lags will be significant while the remaining will be closer to zero. This cut off p will be the order of the AR process. On the other hand, the order of MA can be identified by examining the

autocorrelation function. When the first q autocorrelation are significantly different from zero and if the others are not, then q is the order of the MA process.

Yet another application of the autocorrelation function is to determine whether the data contains a strong seasonal component. This phenomenon is established if the autocorrelation coefficients at lags between t and t-12 are significant. If not, these, coefficients will not be significantly different from zero.

3.3.3.5 Estimation of parameters:

After tentatively identifying the suitable model, next step is to estimate θ and ∅. It is first necessary to work out the moving average process to estimate θ and then perform analytical least squares to estimate the autoregressive parameters ∅, such that the error sum of squares is minimum.

The sum of the squares are obtained as,

$$S(\theta, \varnothing) = \sum_{t=1} e_t^2 (\theta, \varnothing) \qquad \text{where, } t = 1, 2, 3 \ldots n.$$

The preliminary value of the tentatively identified model are obtained by using the sample ACF as proxy for Y (k) and solved for ∅ and θ. Then, by an iterative process, we obtained the maximum likelihood estimate of θ and ∅ for actual series by minimizing the sum of square of residuals.

There are fundamentally two ways of getting estimates for such parameters:

- Trial and error: Examine many different values and choose set of values that minimizes the residual sum of squares
- Iterative method: Choose a preliminary estimate and let a computer program refine the estimate iteratively

The latter method is used in our analysis for estimating the parameters.

3.3.3.6 Diagnostic checking of the model:

After having estimated the parameters of a tentatively identified ARIMA model, it is necessary to verify if the model is adequate.

Examining ACF and PACF of residuals may show up an adequacy or inadequacy of the model. If it shows random residuals, then it indicates that the tentatively identified model was adequate. When an inadequacy is detected, the checks should give an indication of how the model need to be modified, after which further fitting and checking takes place. Some of the diagnostic checks are mentioned below:

1) Over fitting method: The method is given by Box-Jenkins. It uses more parameters than necessary. Over fitting involves fitting a more elaborate model than that is indicated by the identification procedure. If the model to be fitted is identified as ARIMA (p, d, q) and instead we fit a ARIMA (p, d, q+1). However, the main difficulty in the correct identification is not getting enough clues from the ACF because of inappropriate level of differencing.

2) ACF and **PACF** of the **residuals** are considered as random when all their ACF are within the limits.

$$\pm 1.96\sqrt{\frac{1}{(n-12)}}$$

3) Box and Ljung (1978) 'Q' statistic checks whether the auto correlation for those residuals are significantly different from zero. It is computed as follows,

$$Q = n(n+2)\sum_{k=1}^{m}(n-k)^{-1}r_k^2$$

Here, Q is distributed approximately as a Chi-square with (m-h) degree of freedom. Here, h = Number of parameters estimated; n = N – D; D= Differencing. m = Maximum lag considered; N= Total number of observations; r_k= ACF for lag k

4) The Akike Information Coefficient (AIC): Minimum AIC certains the differencing order (d, D) required to attain stationarity so the appropriate number of AR and MA parameters is obtained. It is computed as follows;

$$AIC_{(p+q)} = N\,\sigma^2 + 2\,(p+q)$$

Where, σ^2 = Estimated MSE; N= Number of observation;

(p + q) = Number of parameters to be estimated

This diagnostic checking helps us to identify the differences in the model, so that the model could be subjected to modification, if needed.

3.3.3.7 Forecasting :

The principle objective of developing ARIMA model for a variable is to generate post sample period forecast for the same variable. The ultimate test for any model is whether it is capable of predicting future events accurately or not. If the model is

$(1-\phi\,L)\,Y_t = (1-\theta L)\,e_t$ Here, θ : moving average coefficients and ϕ : Autoregressive coefficients.

To know the accuracy in prediction, series is reduced by some m units. Reduced series is known as Ex-ante series and m is the lag value by which we reduce the series. Best identified model is fit and forecasts are obtained for m time units. Accuracy of forecasts from Ex-ante series is tested using following tests (Makridakis and Hibbon, 1979).

1) Mean average percentage error (MAPE): The formula for this is

$$MAPE = \frac{1}{n}\frac{\sum_{t=1}^{n}\left|X_t - \hat{X}_t\right|}{X_t} X\,100$$

Where, X_t = Actual values and $\hat{X}_t$ = Predicted values

2) Theil's-U coefficient: Theil's-U coefficient of inequality is a measure of the degree to which one time series (X) differs from another (Y). The score turned by Theil's test is 1-U for consistency. U varies from 0 to 1 meaning maximum disagreement,

$$U = \sqrt{\frac{\sum_{t=1}^{n} \left(X_t - \hat{X}_t\right)^2}{\sum_{t=1}^{n-1} \left(X_t - X_{t-1}\right)^2}}$$

Where, X_t = Actual values and $\hat{X}_t$ = Predicted values

When both MAPE and Theil's-U coefficient say that model is accurate i.e., nearer to the actual series then same model can be used to obtain the Ex-post forecasts. However, using these methods, Ex-post forecasts can also do for comparing with the value actually realized.

3.4.1 VOLATITLITY ANALYSIS

Volatility poses a big challenge in modeling financial time series like Agricultural prices, stock prices, exchange rates, inflation. Characteristics of most of these financial time series are that in their level form they are random walks; that is they are non-stationary. On the other hand, in the first difference form, they are generally stationary, therefore modeling for their first difference is more appropriate, instead modeling the level of financial time series, but these differences often exhibit wide swings or volatility, suggesting that the variance of financial time series varies over time. The expected value of all error terms, in absolute value, is the same at any given point. Thus, the expected value of any given error term, squared, is equal to the variance of all the error terms taken together. This assumption is called homoskedasticity. Conversely, data in which the expected value of the error terms is not equal, in which the error terms may reasonably be expected to be larger for some points or ranges of the data than for others, is said to suffer from heteroskedasticity. Such a time series with varying variance are modeled by autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models. The goal of such models is to provide a volatility measure – like a standard deviation - that can be used in financial decision concerning risk analysis, portfolio selection and derivative pricing.

3.4.2 THE ARCH MODEL

Engle (1982) showed that it is possible to simultaneously model the mean and variance of a series. As preliminary step to understanding Engle's methodology, it should be noted that the conditional forecasts are vastly superior to unconditional forecasts. To elaborate, suppose we estimate the stationary model

$$y_t = a_0 + a_1 y_{t-1} + u_t$$

To forecast y_{t+1}, the conditional forecast of y_{t+1} is:

$$E_t y_{t+1} = a_0 + a_1 y_t$$

If we use this conditional mean to forecast y_{t+1}, the forecast error variance is $E_t (y_{t+1} - a_0 - a_1 y_t)^2 = \sigma^2$. Instead, if unconditional forecasts are used, the unconditional forecast is always the long- run mean of the (y_t) sequence that is equal to $a_1/(1-a_0)$.The unconditional forecast error variance is

$$E((y_{t+1} - a_0/(1-a_1))^2) = E((u_{t+1} + a_1 u_t + a_1^2 u_{t-1} + a_1^3 u_{t-2} + \ldots.)^2)$$
$$= \sigma^2/(1-a_1^2)$$

Since $\{1/(1-a_1)\} > 1$, the unconditional forecast has a greater variance than the conditional forecasts (since they take into account the known current and past realization of series) are preferable. Similarly, if the variance of (u_t) is not constant, we can estimate any tendency for sustained movements in the variance using ARMA model. For example, let (u_t) denote the estimated residuals from the model

$$y_t = a_0 + a_1 y_{t-1} + u_t$$

$$\text{Var}(y_{t+1}/y_t) = E_t((y_{t+1} - a_0 - a_1 y_t)^2) = E_t \hat{u}^2_{t+1} = \sigma^2$$

Thus for, we have set $E_t \hat{u}^2_{t+1}$ equal to σ^2 now suppose that the conditional variance is not constant. One simple strategy is to model the

conditional variance of y_t, evolves according to the autoregressive process given

$$\sigma^2{}_t = a_0 + a_1 \hat{u}^2{}_{t-1} \ldots\ldots\ldots\ldots\ldots \quad (3.2)$$

If the values of $a_1, \ldots\ldots, a_n$ are all equal to zero. The estimated variance is simply the constant a_0. Otherwise, the conditional variance of y_t evolves according to the autoregressive process given by (3.2) can come from an auto regression, an ARMA model, or a standard regression model.

This linear specification of (3.2) is known as the ARCH (1) model. The full model would be

$$y_t = \beta_0 + \beta_1 y_{t-1} + \ldots\ldots + \beta_k y_{t-k} + u_t \qquad \text{Where } u_t \sim N(0, \sigma^2)$$

Where $\sigma^2{}_t = \alpha_0 + \alpha_1 \hat{u}^2{}_{t-1}$

This can be extended to the general case where the error variance depends on q lags of squared error terms.

$$\sigma^2{}_t = \alpha_0 + \alpha_1 \hat{u}^2{}_{t-1} + \alpha_2 \hat{u}^2{}_{t-2} + \ldots + \alpha_q \hat{u}^2{}_{t-q}$$

This is an ARCH model extended up to q lags that is ARCH (q) model. Instead of calling the variance $\sigma^2{}_t$ in the literature it is usually called h_t, so the model is

$$y_t = \beta_0 + \beta_1 y_{t-1} + \ldots\ldots + \beta_k y_{t-k} + u_t \qquad u_t \sim N(0, h_t)$$

where; $h_t = \alpha_0 + \alpha_1 \hat{u}^2{}_{t-1} + \alpha_2 \hat{u}^2{}_{t-2} + \ldots + \alpha_q \hat{u}^2{}_{t-q}$ and k = no of lags.

The simplest example from the class of multiplicative conditionally heteroscedastic models proposed by Engle (1982) is

$$\sigma_t = \sqrt{\alpha_0 + \alpha_1 u_{t-1}^2}\, v_t \qquad \ldots\ldots\ldots\ldots \quad (3.3)$$

Where; v_t = white noise process such that $\sigma_v^2 = 1$, v_t and u_{t-1} are independent of each other, and a_0, a_1 are constant such that $a_0 > 0$ and $0 < a_1 < 1$. This is similar to earlier process but in multiplicative forms.

Properties of the (u_t) sequence are not affected by (3.3) since the elements of the (u_t) sequence have a mean zero and are uncorrelated. The variance is constant and all auto covariance's are zero. However, the influence of (3.3) falls entirely on the conditional variance. Since σ_v^2=1, the variance of u_t conditioned on the past history of u_{t-1}, u_{t-2} ... is

$$E\,(u_t^{\,2} / u_{t-1}, u_{t-2}, ...) \;=\; a_0 + a_1\, u_{t-1}^{\,2} \qquad \text{(3.4)}$$

The conditional variance of u_t is dependent on the realized value of $u_t^{\,2}$. If the realized value of $u_{t-1}^{\,2}$ is large, the conditional variance in t will be large as well the conditional variance fallows of first-order autoregressive process denoted by ARCH (1). As opposed to usual auto regression, the coefficients a_0 and a_1 have to be restricted. In order to ensure that the conditional variance is never negative; it is necessary to assume that both a_0 and a_1 are positive. After all, if a_0 is negative, a sufficiently small realization of the u_{t-1} will mean that (3.4) is negative. Similarly, if a_1 is negative, a sufficiently large realization of the u_{t-1} can render a negative value for the conditional variance. Moreover, to ensure the stability of the autoregressive process, it is necessary to restrict to a_1 such that $0<a_1<1$.

In an ARCH model, the error structure is such that the conditional and unconditional mean are equal to zero and v_t, errors are not independent. When the realized value of the u_{t-1} is far from zero, so that $a_1\ (u_{t-1})^2$ is relatively large, the variance of u_t will tend to be large. The conditionally heteroscedasticity in (u_t) will result in (y_t) being an ARCH process. Thus, the ARCH models are able to capture periods of tranquility and volatility in the (y_t) series.

To formally examine the properties of the (y_t) sequence, the conditional mean and variance are given by

$$E_{t-1}\, y_t = a_0 + a_1\, y_{t-1}$$

And Var $(y_t / y_{t-1}\, y_{t-2}....) = E_{t-1}(y_t - a_0 - a_1\, y_{t-1})^2$

$$= E_{t-1}(u_t)^2 \quad = \quad a_0 + a_1 (u_{t-1})^2$$

Since a_1 and u_{t-1}^2 cannot be negative, the minimum value for conditional variance is a_0. For any nonzero realization of u_{t-1}, the conditional variance of y_t is positively related to a_1. The unconditional mean and variance of y_t can be obtained by solving the difference equation for y_t and then taking expectation. If the process began sufficiently far in the past (so that the arbitrary constant A can safely be ignored), the solution for y_t is

$$y_t = a_0 / (1 - a_1) + \sum_{i=0}^{\infty} a_1^i u_{t-i} \quad ..... \qquad (3.5)$$

Since $E u_t = 0$ for all t, the unconditional expectation of (3.5) is $E\, y_t = \{a_0 / (1 - a_1)\}$. The unconditional variance can be obtained in similar fashion using (3.4). Given that $E u_t\, u_{t-1}$ is zero for all $i \neq 0$, the unconditional variance of y_t follows directly from (3.5) as

$$\text{Var}\,(y_t) = \sum_{i=0}^{\infty} a_1^{2i}\, \text{var}(u_{t-i})$$

From the result that the unconditional variance of u_t is constant (i.e., var (u_t)= var (u_{t-1}) = ...= $a_0/(1 - a_1)$, it follows that

$$\text{Var}\,(y_t) = (a_0 / (1 - a_1))(1 / (1 - a_1^2))$$

Clearly, the variance of y_t sequence is increasing in both a_1 and absolute value of a_1. Although the algebra can be bit tedious, the essential point is that the ARCH error process can be used to model periods of volatility within the univariate framework.

The ARCH process given by (3.3) has been extended in several interesting ways. Engle's (1982) original contribution considered the entire class of higher order ARCH (q) processes:

$$u_t = v_t \sqrt{a_0 + \sum_{i=0}^{q} a_i u_{t-i}^2}$$

In the above equation all shocks from u_{t-1} to u_{t-q} have a direct effect on u_t so that the conditional variance acts like an autoregressive process of order q.

3.4.3 GARCH Model

GARCH models are important in finance because they enable modeling of volatility clustering. Volatility clustering occurs because periods of high volatility in trading financial assets are interspersed with periods of low volatility. GARCH models enable clustering to be captured without implementing full chaos models. Full chaos finance models often develop incomplete markets, i.e. replicating strategies will not exist.

Bollerslev (1986) extended the Engle's original work by developing a technique that allows the conditional variance to be dependent on previous own lags like an ARMA process. Now let the error process be such that

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad \ldots\ldots\ldots\ldots \quad (3.6)$$

This is a GARCH (1,1) model, which is like an ARMA (1,1) model for the variance equation

We can also write

$$\sigma_{t-1}^2 = \alpha_0 + \alpha_1 u_{t-2}^2 + \beta \sigma_{t-2}^2 \quad \ldots\ldots\ldots\ldots\ldots \quad (3.7)$$

$$\sigma_{t-2}^2 = \alpha_0 + \alpha_1 u_{t-3}^2 + \beta \sigma_{t-3}^2 \quad \ldots\ldots\ldots\ldots\ldots \quad (3.8)$$

Substituting (3.7), in (3.6) for σ_{t-1}^2 and σ_{t-2}^2 in the above equation we get

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta(\alpha_0 + \alpha_1 u_{t-2}^2 + \beta \sigma_{t-2}^2)$$

$$= a_0 + a_1 u_{t-1}^2 + a_0 \beta + a_1 \beta u_{t-2}^2 + \beta^2 \sigma_{t-2}^2 \ldots\ldots\ldots \quad (3.9)$$

Substituting (3.8) in to (3.9) for σ_{t-2}^2 in the above equation we get

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_0\beta + \alpha_1\beta u_{t-2}^2 + \beta^2(\alpha_0 + \alpha_1 u_{t-3}^2 + \beta\sigma_{t-3}^2)$$

$$\sigma_t^2 = \alpha_0 (1+\beta+\beta^2) + \alpha_1 u_{t-1}^2 (1+\beta L+\beta^2 L^2) + \beta^3 \sigma_{t-3}^2$$

An infinite number of successive substitutions would yield

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_0\beta + \alpha_1\beta u_{t-2}^2 + \alpha_0\beta^2 + \alpha_1\beta^2 u_{t-3}^2 + \beta^3\sigma_{t-3}^2$$

$$\sigma_t^2 = \alpha_0 (1+\beta+\beta^2+...) + \alpha_1 u_{t-1}^2 (1+\beta L+\beta^2 L^2+...) + \beta^\infty \sigma_0^2$$

So GARCH (1,1) model can be written as an infinite order of ARCH model.

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + ... + \alpha_q u_{t-q}^2 + \beta_1\sigma_{t-1}^2 + \beta_2\sigma_{t-2}^2 + ... + \beta_p\sigma_{t-p}^2$$

The GARCH (1,1) model can be extended to GARCH (p, q)

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad \text{.....} \quad (3.10)$$

This generalized ARCH (p, q) model – called GARCH (p, q) – allows for both autoregressive and moving average components in the heteroscedastic variance. If we set p=0 and q=1, it is clear that the first order ARCH (1) model is simply a GARCH (0, 1) model. If all β_1 equal zero, the GARCH (p, q) model is equivalent to an ARCH (q) model. The benefits of the GARCH model should be clear; a high order ARCH model may have more parsimonious GARCH representation that is much easier to identify and estimate. This is particularly true since all coefficients in (3.10) must be positive. Moreover, to ensure that the conditional variance is finite, all characteristic roots of (3.10) must be lie inside the unit circle. Clearly, the more parsimonious model will entail fewer coefficient restrictions.

The key feature of GARCH models is that the conditional variance of the disturbance of the (y_t) sequence constitutes an ARMA process. Hence, it is to be expected that the residuals from a fitted ARMA model should display this characteristic pattern. To explains, suppose we estimate (y_t) as an ARMA process. If our model of (y_t) is adequate, the

ACF and PACF of the residuals should be indicative of white noise process. However, the ACF of squared residuals can help in identifying the order of the GARCH process.

3.4.4 Testing for ARCH/ GARCH effect.

Lagrange-Multiplier test is used to test the effect. The procedure is listed below:

STEP 1: Estimate the (y_t) sequence using the best –fitting ARMA model

$$y_t = \beta_1 + \beta_2 x_{2t} + \ldots + \beta_k x_{kt} + u_t$$

STEP 2: Then square the residuals, and regress them on q own lags to test for ARCH of order q, i.e. run the regression

$$\hat{u}_t^2 = \gamma_0 + \gamma_1 \hat{u}_{t-1}^2 + \gamma_2 \hat{u}_{t-2}^2 + \ldots + \gamma_q \hat{u}_{t-q}^2 + v_t$$

Obtained R^2 from this regression

STEP 3: The test statistic is defined as $T.R^2$ (the number of observation multiplied by the coefficient of multiple correlation) from the last regression, and is distributed as a $\chi 2(q)$.

STEP 4: The null and alternative hypotheses are

H_0: $\gamma_1 = 0$ and $\gamma_2 = 0$ and $\gamma_3 = 0$ and ... and $\gamma_q = 0$

H_1: $\gamma_1 \neq 0$ or $\gamma_2 \neq 0$ or $\gamma_3 \neq 0$ or ... or $\gamma_q \neq 0$.

STEP 5: If the value of the test statistic is greater than the critical value from the $\chi 2$ distribution, then reject the null hypothesis.

3.4.5 Generalized Least Square Estimation (GLS)

In the presence of heteroscedasticity OLS estimators are still best linear unbiased estimators (BLUE) if the assumption of homoskedasticity of the classical model is violated. In fact, the variance of u_i, Homoskedastic or heteroscedastic, plays no part on the determination of the unbiasedness property. $\hat{\beta}_2$ is consistent estimator despite

heteroscedasticity but it is no longer efficient estimator as there is no minimum variance and results in giving a false sense of precision. Thus OLS method is not appropriate in presence of heteroscedasticity to overcome this Generalized least square (GLS) models are used. GLS are nothing but OLS method on transformed data. If ARCH or GARCH effect is found we will have to use GLS. Consider the OLS model

$$y_t = \beta_1 + \beta_2 y_{t-1} + u_i$$

For ease of algebraic manipulation we write as

$$y_t = \beta_i y_{0i} + \beta_2 y_{t-1} + u_i \qquad \ldots\ldots \qquad (3.11)$$

Where $y_{0i} = 1$ for each i.

Now assume that the heteroscedastic variance σ_i^2 is known from ARCH/GARCH models. Divide (3.11) by σ_i to obtain

$$\frac{y_i}{\sigma_i} = \beta_1\left(\frac{y_{0i}}{\sigma_i}\right) + \beta_2\left(\frac{y_{t-1}}{\sigma_i}\right) + \left(\frac{u_i}{\sigma_i}\right)$$

This for ease of expansion is represented as,

$$y_i^* = \beta_1^* y_{0i}^* + \beta_2^* y_{t-1}^* + u_i^*$$

Where the transformed variable are original variables divided by the (known σ_i). β_0^* and β_1^* , the parameters of the transformed model,

The purpose of transforming the original variable in such a way the transformed variables satisfy the assumption of homoskedasticity of the classical OLS. The feature of transformed model is

$$Var(u_i^*) = E(u_i^*)^2 = E\left(\frac{u_i}{\sigma_i}\right)^2 = \frac{1}{\sigma_i^2}E(u_i^2) = \frac{1}{\sigma_i^2}(\sigma_i^2) = 1$$

Since σ_i^2 is known

3.4.6 Forecasting Variances using GARCH Models

Producing conditional variance forecasts from GARCH models uses a very similar approach to producing forecasts from ARMA models.

Consider the following GARCH (1,1) model: ,

$$y_t = \mu + u_t \qquad u_t \sim N(0,\sigma_t^2), \qquad \sigma_t^2 = a_0 + a_1 u_{t-1}^2 + \beta\sigma_{t-1}^2$$

It is needed is to generate forecasts of $\sigma_{T+1}^2 \mid T$, $\sigma_{T+2}^2\ \Omega \mid T$, ..., $\sigma_{T+s}^2\ \Omega \mid T$ where Ω_T denotes all information available up to and including observation T.

Adding one to each of the time subscripts of the above conditional variance equation, and then two, and then three would yield the following equation

$\sigma_{T+1}^2 = \alpha_0 + \alpha_1 + \beta\sigma_T^2$,

$\sigma_{T+2}^2 = \alpha_0 + \alpha_1 + \beta\sigma_{T+1}^2$,

$\sigma_{T+3}^2 = \alpha_0 + \alpha_1 + \beta\sigma_{T+2}^2$

Let $\sigma_{1,T}^{f\ 2}$ be the one step ahead forecast for σ^2 made at time T. This is easy to calculate since, at time T, the values of all the terms on the RHS are known.

$\sigma_{1,T}^{f\ 2}$ Would be obtained by taking the conditional expectation of the first equation:

$$\sigma_{1,T}^{f\ 2} = \alpha_0 + \alpha_1 u_T^2 + \beta\sigma_T^2$$

Given, $\sigma_{1,T}^{f\ 2}$ how is $\sigma_{2,T}^{f\ 2}$, the 2-step ahead forecast for σ^2 made at time T, Taking the conditional expectation of the second equation:

$$\sigma_{2,T}^{f\ 2} = \alpha_0 + \alpha_1 E(u_{T+1}^2 \mid \Omega_T) + \beta\ \sigma_{1,T}^{f\ 2}$$

Where $E(u_{T+1}^2 \mid \Omega_T)$ is the expectation, made at time T, of u_{T+1}^2, which is the squared disturbance term. We can write

$$E\left(u^2_{T+1} \mid \Omega_T\right) = \sigma^2_{T+1}$$

But σ^2_{T+1} is not known at time T, so it is replaced with the forecast for it, $\sigma^{f\ 2}_{1,T}$, so that the 2-step ahead forecast is given by

$$\sigma^{f\ 2}_{2,T} = \alpha_0 + \alpha_1 \sigma^{f\ 2}_{1,T} + \beta\ \sigma^{f\ 2}_{1,T}$$

$$\sigma^{f\ 2}_{2,T} = \alpha_0 + \{\alpha_1 + \beta\}\ \sigma^{f\ 2}_{1,T}$$

Any s-step ahead forecast ($s \geq 2$) would be produced by

$$h^f_{s,T} = \alpha_0 \sum_{i=1}^{s-1} (\alpha_1 + \beta)^{i-1} + (\alpha_1 + \beta)^{s-1} h^f_{1,T}$$

3.4.7 Practical steps in fitting ARCH models

1. Data is converted as log (lag (y_t/y_{t-1}))
2. Based on ACF and PACF ARIMA models are fit
3. Test for Arch effects in residuals obtained from autoregressive models

   → Using Lagrange's-Multiplier test

4. Fit ARCH/GARCH model for the modified series

   → Among all identified models, model with High R2 and low AIC value is considered to be the best.

   → Initially variance is modeled; using this variance, by generalized least square technique actual series is modeled

5. Obtain the residuals and check for ARCH effect in residuals,

   → Using Lagrange's-Multiplier test

RESULTS

IV. RESULTS

Keeping in view, the specific objectives of the present study, data collected on prices and arrivals of Groundnut and Sunflower from Sira and Challakere markets were subjected to statistical analysis using technique outlined in the methodology chapter. The result of analysis is presented, market and crop wise under two heads as follows.

4.1 AUTOREGRESSIVE MODELS

Box-Jenkins procedure was preferred to fit autoregressive model and to forecast. The results are presented below in the Table 4.1 to 4.10. Forecasts are listed in Tables from 4.14 to 4.21.

4.2 VOLATILITY MODELS

An ARCH-GARCH model was used to capture the volatility in the series. The result is presented below in the Table 4.11 to 4.13. Forecasts are listed in Tables from 4.14 to 4.21.

4.1 AUTOREGRESSIVE MODELS

4.1.1 CHALLAKERE MARKET

4.1.1.1 Groundnut Arrivals:

4.1.1.1.1 Identification

Each individual coefficient of ACF (Autocorrelation Function) was tested for its significance using 'Box-Ljung' test. The ACF and PACF, values and plots listed in Fig-1(a), Fig-3(a) and Appendix-I, gives a hint that values of p, P, q, Q could be 1 or 2 or 3. The ACF plot indicates seasonality effect so, D=1. Thus, the tentatively identified models (p, d, q)(P, D, Q), are as follows $(2,1,1)(1,1,2)_{12}$; $(2,1,1)(2,1,1)_{12}$; $(2,1,2)(2,1,1)_{12}$; $(2,1,2)(1,1,1)_{12}$ and $(2,1,1)(1,1,1)_{12}$.

4.1.1.1.2 Estimation of parameters

After identifying the models tentatively, next step is to obtain the estimate using method of least square estimation of the parameters such

that error sums of square are to be minimum. *i.e.,* $s_{(\phi,\theta)} = \sum_{t=1}^{n} e_t^2(\phi,\theta)$

Parameters of the tentatively identified models were estimated by an iterative process and then residuals of each of the model are obtained.

4.1.1.1.3 Diagnostic checking

The tentatively identified models, its Akaike Information Coefficient (AIC) and Box-Ljung 'Q' statistics, is listed in Table 4.1. Model: $(2, 1, 1)(1, 1, 1)_{12,}$ having the least AIC and Q-value, becomes the best model. The values and plots of ACF, its Q-value and PACF of residuals are shown in Appendix-II and Fig-4(a) and Fig-5(a). Model with its parameters, MAPE, Theil's-U value are listed in Table 4.9. The model is:

$Y_t = -10.207 + 0.712Y_{t-1} - 0.331Y_{t-2} + 0.238Y_{t-12} + 0.993e_{t-1} - 0.827e_{t-12}$

Table 4.1: Tentatively identified models for groundnut arrivals: Challakere market

Model	AIC	Q-VALUE
(2,1,1) (1,1,2)	4296.787	26.39
(2,1,2) (2,1,1)	4297.698	32.74
(2,1,1) (2,1,1)	4292.919	21.55
(2,1,2)(1,1,1)	4297.996	23.48
(2,1,1)(1,1,1)	4291.169	18.11

4.1.1.1.4 Forecasting

Forecasted monthly arrivals for the year 2009 are listed in Table-4.14 and Fig -6.

4.1.1.2 Groundnut Prices:

4.1.1.2.1 Identification

The plot and values of Auto Correlation Function (ACF) listed in Fig-1(b) and Appendix-I, clearly indicate nonstationarity. So the series is differenced with d=1, the plots and values of ACF and PACF of differenced series are presented in Fig-1(c), Fig-3(b) and Appendix-I.

Further, the presence of peak at first values clearly indicate suitability of the choice of seasonal difference D=1, to accomplish stationary series. Based on ACF and PACF of differenced series, the tentatively identified models are as(p, d, q)(P, D, Q) follows:- $(2,1,3)(2,1,1)_{12}$; $(2,1,4)(1,1,1)_{12}$; $(2,1,3)(1,1,1)_{12}$; $(2,1,4)(2,1,1)_{12}$ and $(2,1,3)(1,0,1)_{12}$.

4.1.1.2.2 Estimation of parameters

After identifying the models tentatively, the next step is to obtain the estimate by method of least square estimation of parameters such that error sums of square is to be minimum *i.e.,* $s(\phi,\theta)=\sum_{t=1}^{n} e_t^2(\phi,\theta)$. The parameters of the tentatively identified models were estimated by an iterative process and then residuals of each of model are to be obtained.

4.1.1.2.3 Diagnostic checking

The AIC, Box-Ljung's Q-statistic for residuals obtained from all the tentatively identified model is tabled in Table-4.2. Plots and values of ACF, its Q-value and PACF of residual series are shown in Fig-4(b), Fig-5(b) and Appendix-III. The model (2, 1, 3) $(1, 1, 1)_{12}$ was found to be best model since it had the lowest value of AIC and Q-statistic. Model with its parameters, MAPE, Theil's-U value is listed in Table 4.9. The model is:

$Y_t = 0.679 + 0.382Y_{t-1} - 0.614Y_{t-2} - 0.027Y_{t-12} + 0.227e_{t-1} - 0.617e_{t-2} + 0.529e_{t-3} + 0.886e_{t-12}$

Table 4.2: Tentatively identified models for groundnut prices : Challakere market

Model	AIC	Q-VALUE
(2,1,3)(2,1,1)	2451.7601	21.45
(2,1,4)(1,1,1)	2451.8734	19.92
(2,1,3)(1,1,1)	2449.9563	13.78
(2,1,4)(2,1,1)	2453.6651	26.59
(2,1,4)(1,0,1)	2577.2069	38.14*

* Significant at 5% level

Table 4.9: Estimates of Parameters of ARIMA models fit to the series of Challakere market

Series	Constant	Autoregressive terms			Moving Average terms				Theil's-U	MAPE
		Non-seasonal		Seasonal	Non-seasonal			Seasonal		
		Y_{t-1}	Y_{t-2}	Y_{t-12}	e_{t-1}	e_{t-2}	e_{t-3}	e_{t-12}		
Groundnut Arrivals	-10.207^{NS} (19.355)	0.712** (0.069)	-0.331** (0.069)	0.238* (0.081)	0.993** (0.069)	-	-	-0.827** (0.095)	0.283	19.662
Groundnut Prices	0.679 ^{NS} (0.504)	0.382* (0.135)	-0.614** (0.126)	-0.027* (0.013)	0.227* (0.108)	-0.617** (0.081)	0.529** (0.072)	0.886** (0.083)	0.198	11.2
Sunflower Arrivals	246.81* (91.8)	0.295* (0.147)	-	0.37* (0.175)	-0.203* ((0.097)	-	-	0.805** (0.157)	0.103	8.261
Sunflower Prices	0.912* (0.43)	0.586** (0.086)	0.295** (0.076)	0.068* (0.102)	0.988** ((0.116)	-	-	0.995* (0.399)	0.083	7.026

Note: Values in parenthesis indicate standard errors

* Significant at 5% level, ** Significant at 1% level, NS: non-significant

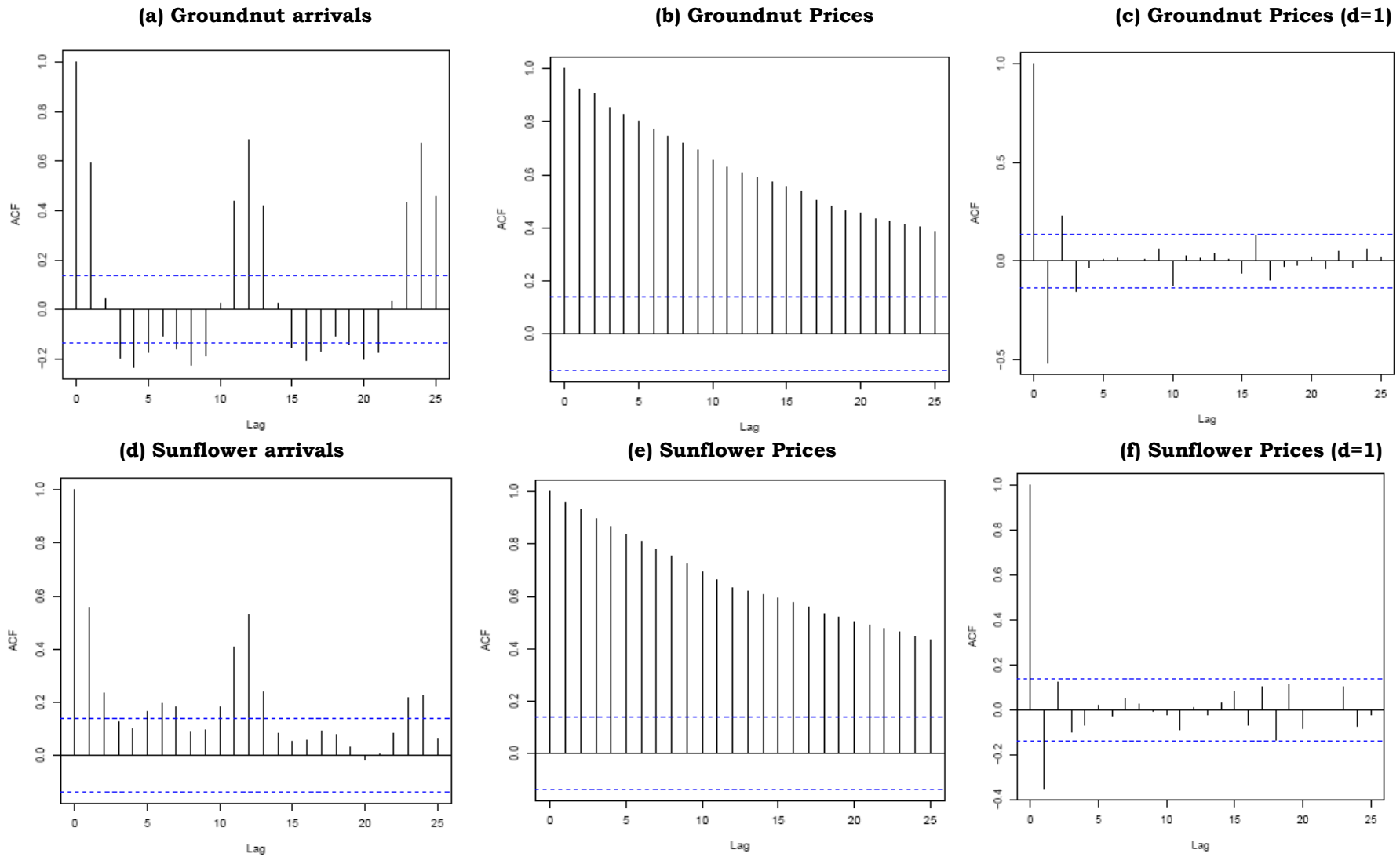


Figure-1 : Autocorrelation Function(ACF) Plots for series of Challakere Market

4.1.1.2.4 Forecasting

The forecasts were done up to December 2009. The forecast value of prices of groundnut at Challakere market is shown in the Table 4.15 and Fig- 7

4.1.1.3 Sunflower Arrivals:

4.1.1.3.1 Identification

The plot and value of Auto Correlation Function (ACF) and PACF presented in Fig-1(d), Fig-3(c) and Appendix-I suspects for seasonality effect, so D=1. Each individual coefficient of ACF and PACF are tested for their significance using Box-Ljung's Q-statistic. Based on ACF and PACF, the tentatively identified models are as(p, d, q)(P, D, Q) follows:- $(1,1,3)(1,2,2)_{12}$; $(1,1,2)(1,2,1)_{12}$; $(1,1,3)(1,2,1)_{12}$; $(1,1,1)(1,1,1)_{12}$; $(1,1,1)(1,0,1)_{12}$ and $(1,0,1)(1,1,1)_{12}$.

4.1.1.3.2 Estimation of parameters

After identifying the models tentatively, the next step is to obtain the estimate by the method of least square estimation of the parameters such that error sums of square is to be minimum *i.e.,* $s(\phi,\theta)=\sum_{t=1}^{n} e_t^2(\phi,\theta)$.

An iterative process estimated the parameters of tentatively identified models and then residuals of each model are obtained.

4.1.1.3.3 Diagnostic checking

AIC and Q values for all the tentatively identified models are obtained and listed in Table-4.3. Among them model$(1,0,1)(1,1,1)_{12}$ has least AIC and Q-value thus, it is identified to be the best. Plot and values of ACF, its Q-value and PACF for residuals are listed in Fig-4(c), Fig-5(c) and Appendix-II. Models and parameters, MAPE, Theils-U value are listed in Table 4.9. The model is:

$Y_t = 246.81 + 0.295\ Y_{t-1} + 0.370\ Y_{t-12} - 0.203 e_{t-1} + 0.805\ e_{t-12}$.

4.1.1.3.4 Forecasting

The forecasted monthly sunflower arrivals, up to December 2009, at Challakere market is listed in Table-4.16 and Fig -8.

Table 4.3: Tentatively identified models for Sunflower arrivals: Challakere market

Model	AIC	Q-Value
(1,1,3)(1,2,2)	3381.079	31.87
(1,1,2)(1,2,1)	3293.746	18.95
(1,1,3)(1,2,1)	3340.868	26.53
(1,1,1)(1,1,1)	3287.690	17.96
(1,1,1)(1,0,1)	3289.129	17.48
(1,0,1) (1,1,1)	3242.975	16.23

4.1.1.4 Sunflower Prices:

4.1.1.4.1 Identification

The plot and values of Auto Correlation Function (ACF) for the series listed in Fig- 1(e), and Appendix-I indicates non-stationarity so, differenced series (d=1) is considered for further analysis. The plots and values of ACF, its Q value and PACF for new series are presented in Fig-1(f), Fig-2(f) and Appendix-I. Based on ACF and PACF of new series, the tentatively identified models are as(p, d, q)(P, D, Q) follows: $(2,1,1)(1,1,1)_{12}$; $(3,1,2)(1,1,1)_{12}$; $(2,1,2)(1,1,1)_{12}$; $(2,1,2)(1,1,2)_{12}$; $(2,1,1)(2,1,1)_{12}$ and $(2,1,2)(2,1,1)_{12}$.

4.1.1.4.2 Estimation

After identifying the models tentatively, the next step is to obtain the estimates by the method of least square estimation of the parameters such that error sums of square is to be minimum. *i.e.,* s $(\phi, \theta) = \sum_{t=1}^{n} e_t^2(\phi, \theta)$.

The parameters of the tentatively identified models were estimated by a iterative process and then residuals of each model are to be obtained.

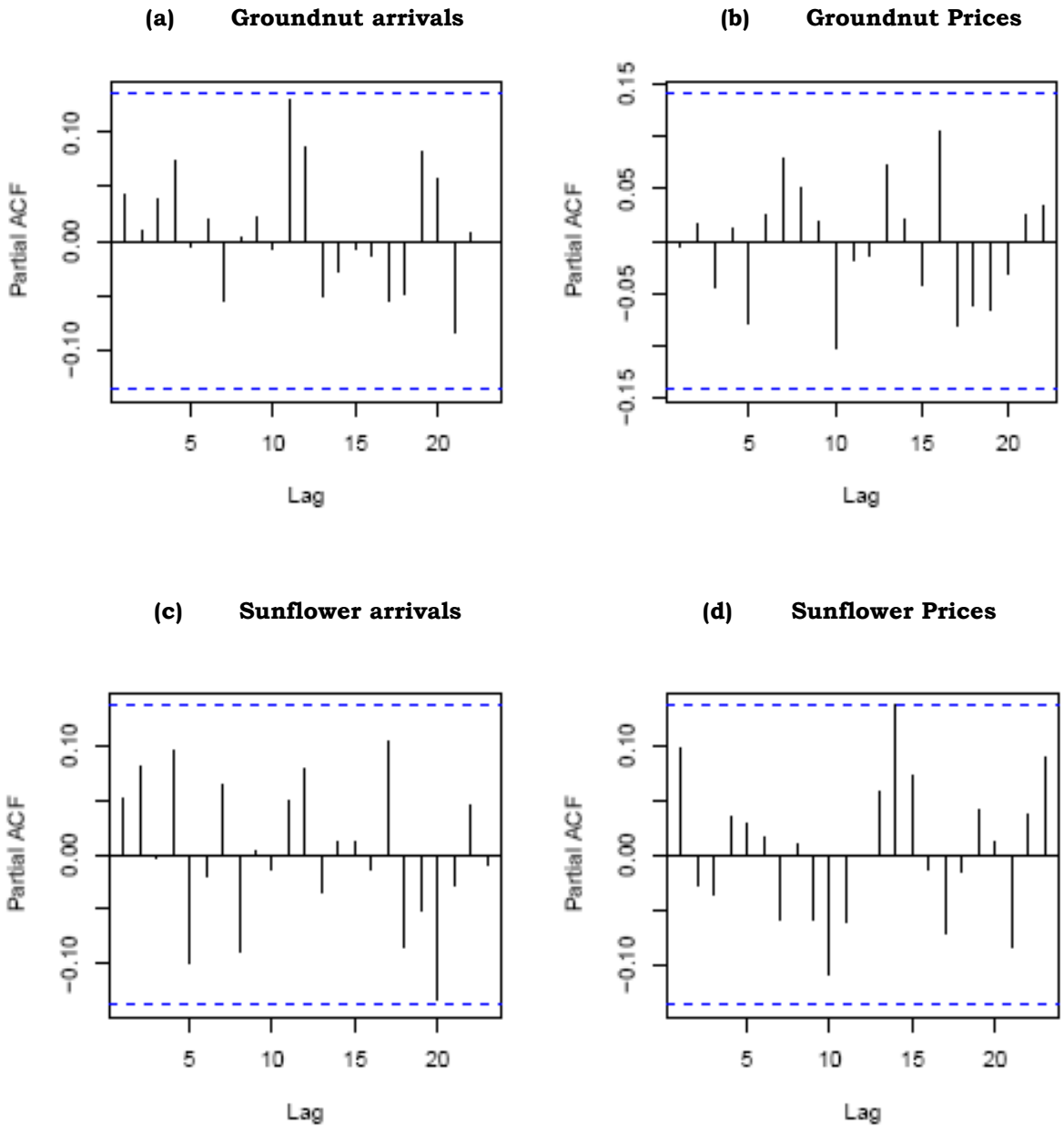


Figure-4: Partial Autocorrelation Function (PACF) plots of residuals obtained from ARIMA models of all series

4.1.1.4.3 Diagnostic checking

The values of Box-Ljung's 'Q' statistics and Akike Information Coefficient (AIC) for tentatively identified models are listed in Table-4.4. The model (2, 1, 1) $(1, 1, 1)_{12}$ was found to be the best model since it had the lowest value of AIC and Q-statistics. The plots and values of ACF, its Q-value and PACF of residual series from best model are shown in Fig-4(d), Fig-5(d) and Appendix-II. Model with its parameters, MAPE, Theil's-U value are listed in Table 4.9. The model is:

$$Y_t = 0.912 + 0.586Y_{t-1} + 0.295Y_{t-2} + 0.068Y_{t-12} + 0.988e_{t-1} + 0.995e_{t-12}$$

Table 4.4: Tentatively identified models for sunflower prices: Challakere market

Model	AIC	Q-Value
(2,1,1)(1,1,1)	2393.125	16.22
(3,1,2)(1,1,1)	2454.373	31.86
(2,1,2)(1,1,1)	2395.849	18.54
(2,1,2)(1,1,2)	2436.944	26.94
(2,1,2)(2,1,1)	2396.329	18.23
(2,1,1)(2,1,1)	2421.430	28.27

4.1.1.4.4 Forecasting

The forecast of monthly sunflower prices at Challakere market for year-2009 is listed in Table-4.17 and Fig-9.

4.1.2 SIRA MARKET

4.1.2.1 Groundnut Arrivals:

4.1.2.1.1 Identification

The tentative models are identified based on the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF). The plots and values of ACF, its Q-value and PACF for the series are presented in Fig-2(a), Fig-3(e) and Appendix-III. Based on ACF and PACF, the

tentatively identified models are as(p, d, q)(P, D, Q) follows:- $(1,1,2)(1,1,2)_{12}$; $(2,1,1)(2,1,1)_{12}$; $(2,0,1)(2,1,1)_{12}$; $(1,1,2)(2,0,1)_{12}$; $(2,1,2)(1,0,1)_{12}$ and $(2,1,2)(2,0,1)_{12}$.

4.1.2.1.2 Estimation of parameters

After identifying the models tentatively, the next step is to obtain the estimate by the method of least square estimation of the parameters such that error sums of square is to be minimum. *i.e.,* s $(\phi,\theta)=\sum_{t=1}^{n} e_t^2(\phi,\theta)$.

The parameters of tentatively identified models were estimated by an iterative process and then residuals of are obtained fro each model.

4.1.2.1.3 Diagnostic checking

The tentatively identified models with its AIC and Q values are listed in Table-4.5. Model $(2,1,2)(2,0,1)_{12,}$ is said to be adequate because of its lowest AIC and Non-significant, least Q-value. The plots of ACF, its Q-value and PACF of residuals are shown in Fig-4(e), Fig-5(e) and Appendix-IV. Model with its parameters, MAPE, Theil's-U values are listed in Table 4.10. The model is

$$Y_t = 108.295 - 0.820Y_{t-1} - 0.053\ Y_{t-2} - 0.528Y_{t-12} - 0.49Y_{t-13} - 0.958e_{t-1} - 0.492e_{t-2} + 0.426e_{t-12}$$

Table 4.5: Tentatively identified models for groundnut arrivals: Sira market

Model	AIC	Q-Value
(1,1,2)(1,1,2)	2343.125	38.94*
(2,1,1)(2,1,1)	2241.047	31.08
(2,0,1)(2,1,1)	2238.364	29.73
(1,1,2)(2,0,1)	2135.979	23.51
(2,1,2)(1,0,1)	2269.924	28.96
(2,1,2)(2,0,1)	2077.651	21.48

* Significance at 5% level

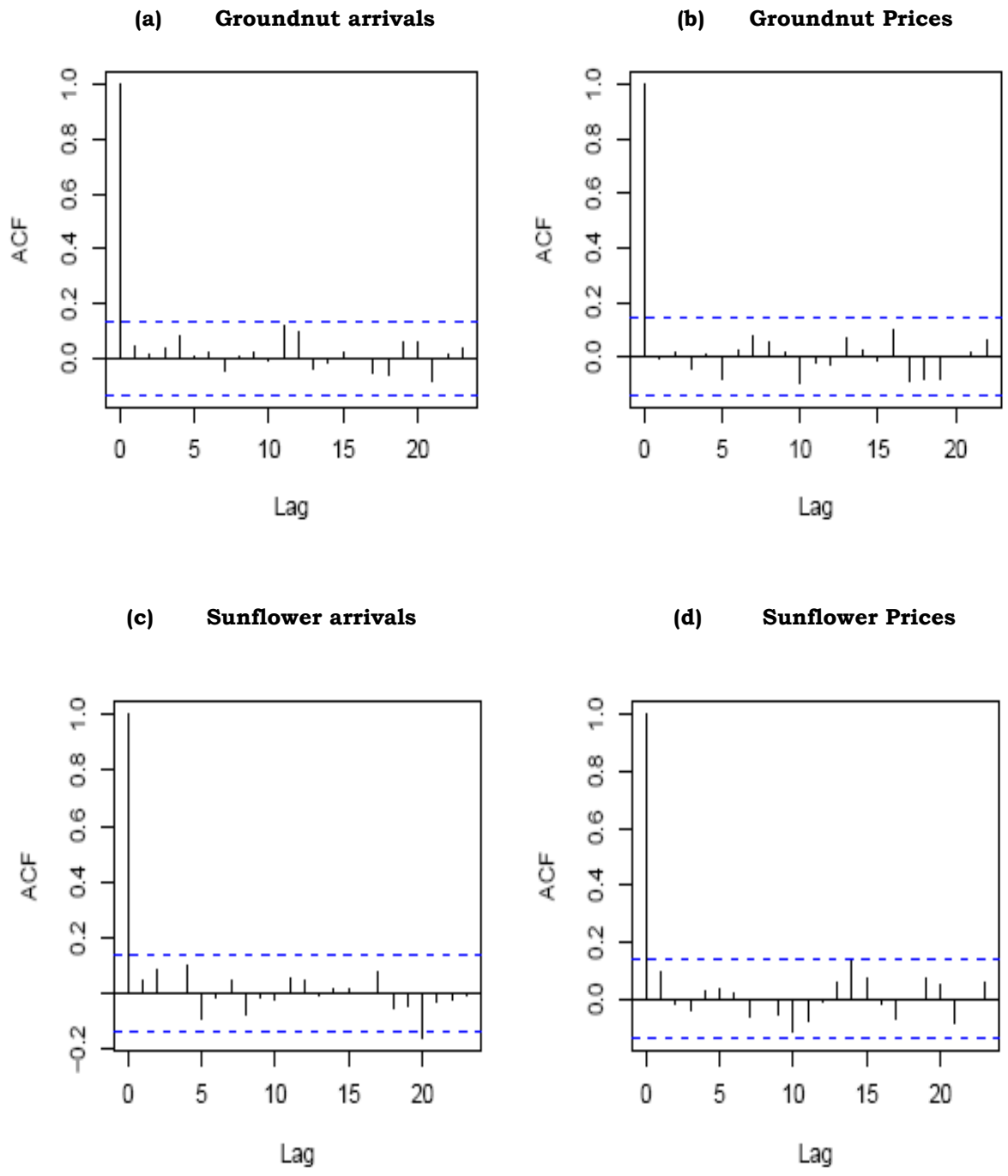


Figure-3: Autocorrelation Function (ACF) plots of residuals obtained from ARIMA models of all series

4.1.2.1.4 Forecasting

The forecasts of groundnut arrivals to Sira market was done up to December 2009. The values are listed in Table4.18 and Fig -10.

4.1.2.2 Groundnut Prices:

4.1.2.2.1 Identification

The plot and values of Auto Correlation Function (ACF) listed in Fig-2(b), and Appendix-III, clearly indicate nonstationarity. So the series is differenced with d=1, the plots and values of ACF and PACF of differenced series are presented in Fig-2(c), Fig-3(f) and Appendix-III. Further, the presence of peak at first values clearly indicate suitability of the choice of seasonal difference D=1, to accomplish stationary series. Based on ACF and PACF of differenced series, the tentatively identified models are as(p, d, q)(P, D, Q) follows:- $(3,1,2)(1,1,1)_{12}$; $(4,1,2)(1,1,1)_{12}$; $(4,1,3)(1,1,1)_{12}$; $(4,1,3)(1,1,2)_{12}$; $(4,1,2)(1,1,2)_{12}$ and $(4,1,2)(2,1,2)_{12}$.

4.1.2.2.2 Estimation of parameters

After identifying the models tentatively, next step is to obtain the estimate by the method of least square estimation of the parameters such that error sums of square is minimum. *i.e.,* s $_{(\phi,\theta)} = \sum_{t=1}^{n} e_t^2(\phi,\theta)$.The parameters of the tentatively identified models were estimated by a iterative process and then residuals of each model are to be obtained.

4.1.2.2.3 Diagnostic checking

The AIC, Box-Ljung's Q-statistic for residuals obtained from all the tentatively identified models are listed in Table-4.6. The plots and values of ACF, its Q value and PACF of residual series are shown in Fig-4(f), Fig-5(f) and Appendix-IV. The model (4,1,2) $(1,1,1)_{12}$ was found to be the best model because it had the lowest value of AIC and Q-statistics. Model with its parameters, MAPE, Theil's-U value is listed in Table 4.10. The model is:

$$Y_t = 2.366 + 0.159Y_{t-1} + 0.664Y_{t-2} - 0.239Y_{t-3} - 0.460Y_{t-4} + 0.237Y_{t-12} + 0.476e_{t-1} - 0.562e_{t-2} + 0.981e_{t-12}$$

Table 4.10 : Estimates of Parameters of ARIMA models fit to the series of Sira market

Series	Constant	Autoregressive terms						Moving Average terms				Theil's-U	MA
		Non-seasonal				Seasonal		Non-seasonal		Seasonal			
		Y_{t-1}	Y_{t-2}	Y_{t-3}	Y_{t-4}	Y_{t-12}	Y_{t-13}	e_{t-1}	e_{t-2}	e_{t-12}	e_{t-13}		
Groundnut Arrivals	108.295^{NS} (220.653)	0.820** (0.237)	-0.053^{NS} (0.226)	-	-	-0.528** (0.145)	-0.49** (0.110)	-0.958** (0.182)	-0.492* (0.185)	0.426* (0.176)	-	0.357	25.8
Groundnut Prices	2.366^{NS} (2.804)	0.159^{NS} (0.156)	0.664** (0.120)	-0.239^{NS} (0.187)	-0.46** (0.103)	0.237* (0.154)	-	0.476** (0.157)	-0.562** (0.134)	0.981* (0.388)	-	0.074	6.2
Sunflower Arrivals	27.612* (14.048)	0.277* (0.099)	-0.016* (0.097)	-	-	0.883** (0.152)	-	0.991** (0.067)	-	0.483* (0.187)	0.179* (0.065)	0.271	21.9
Sunflower Prices	2.550* (1.024)	0.595** (0.139)	-	-	-	0.857** (0.094)	-	-0.061* (0.027)	-	0.961* (0.345)	-	0.156	19.2

* Significant at 5% level, ** Significant at 1% level, NS: Non-significant

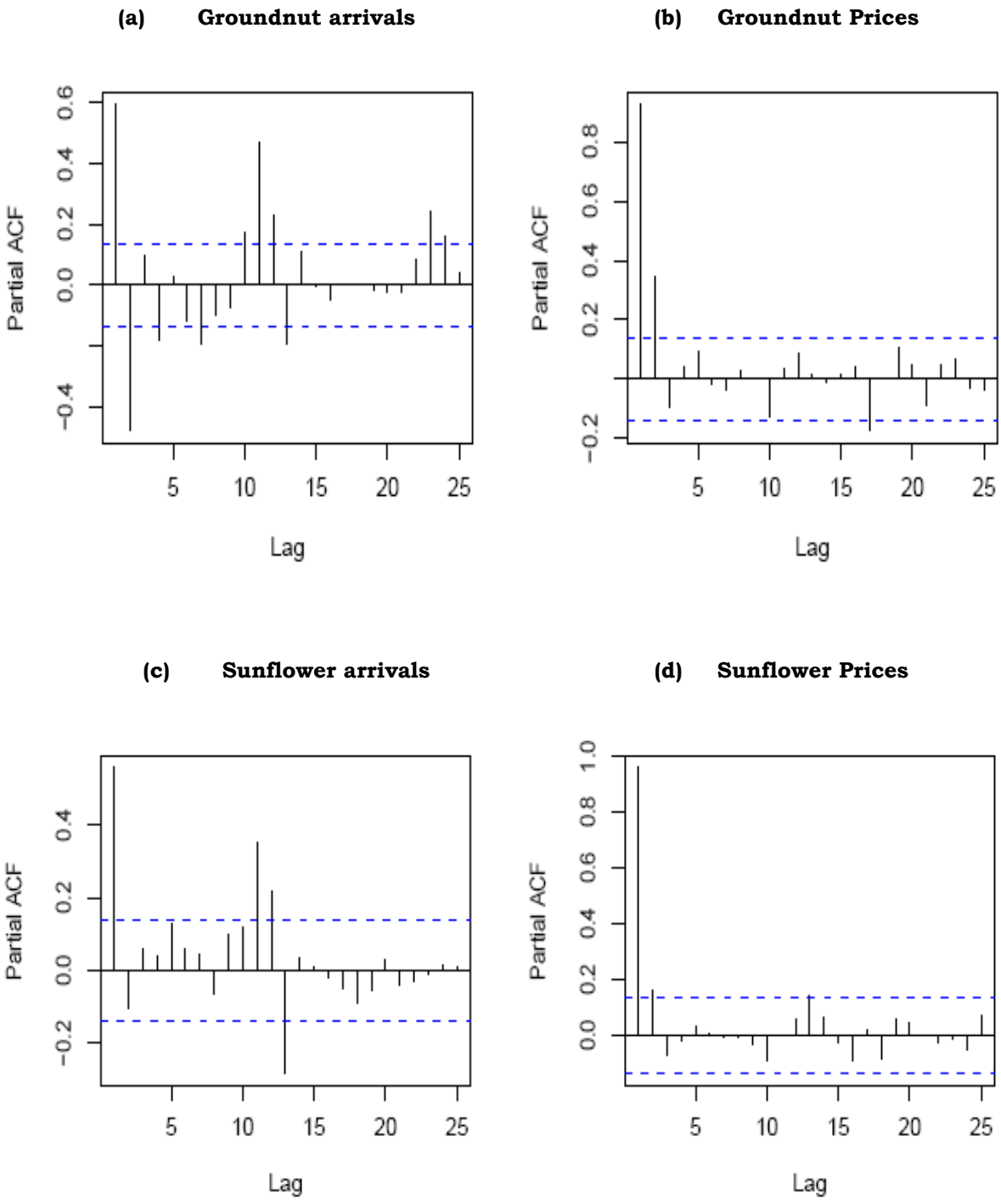


Figure-2: Partial Autocorrelation Function (PACF) plots of all series

4.1.2.2.4 Forecasting

The forecasts of groundnut prices was done up to December 2009, the same is listed in Table4.19 and Fig-11.

Table 4.6 : Tentatively identified models for groundnut prices:

Sira market

Variable	AIC	Q-Value
(3,1,2)(1,1,1)	1404.543	13.576
(4,1,2)(1,1,1)	1398.353	12.322
(4,1,3)(1,1,1)	1401.95	14.689
(4,1,3)(1,1,2)	1403.611	14.458
(4,1,2)(1,1,2)	1399.984	12.781
(4,1,2)(2,1,2)	1401.687	15.940

4.1.2.3 Sunflower Arrival:

4.1.2.3.1 Identification

The plot and value of Auto Correlation Function (ACF), its Q-value and PACF presented in Fig-2(d), Fig-3(g) and Appendix-III clearly indicates seasonality effect, so D=1. P, p, q, Q are identified to be 1 or 2 each. Thus, based on ACF and PACF, the tentatively identified models are as(p, d, q)(P, D, Q) follows:- $(2,0,2)(2,1,3)_{12}$; $(2,1,2)(2,1,3)_{12}$; $(2,1,3)(2,1,3)_{12}$; $(3,1,3)(2,1,3)_{12}$; $(2,1,2)(2,1,2)_{12}$ and $(2,1,3)(2,1,2)_{12}$.

4.1.2.3.2 Estimation of parameters

After identifying the models tentatively, the next step is to obtain the estimate by using method of least square estimation of the parameters such that error sums of square is to be minimum. *i.e.,* $s(\phi,\theta)=\sum_{t=1}^{n} e_t^2(\phi,\theta)$. The parameters of the tentatively identified models were estimated by an iterative process and then residuals of each model are to be obtained.

4.1.2.3.3 Diagnostic checking

AIC and Q-values for all the tentatively identified models are obtained and listed in Table-4.7. Among studied models, $(2,1,2)(2,1,2)_{12}$ has least AIC and Q-value thus, it is identified to be the best. Plot and values of ACF, its Q-value and PACF for residuals are listed in Fig-4(g), Fig-5(g) and Appendix-IV. Models and parameters, MAPE, Theil's-U value are listed in Table 4.10. The final model structure is

$Y_t = 27.612 + 0.277Y_{t-1} - 0.016Y_{t-2} + 0.883Y_{t-12} + 0.991e_{t-1} + 0.483e_{t-12} + 0.179e_{t-13}$

Table 4.7 : Tentatively identified models for sunflower arrivals :

Sira market

VARIABLE	AIC	Q-Value
(2,0,2) (2,1,3)	1972.073	21.417
(2,1,2) (2,1,3)	1961.252	19.659
(2,1,3) (2,1,3)	1962.563	20.048
(3,1,3) (2,1,2)	1994.476	22.486
(2,1,2) (2,1,2)	1960.698	18.231
(2,1,3) (2,1,2)	1961.943	19.114

4.1.2.3.4 Forecasting

The forecasts of monthly sunflower arrivals, up to December 2009 are listed in Table-4.20 and Fig -12.

4.1.2.4 Sunflower Prices :

4.1.2.4.1 Identification

The plot and values of Auto Correlation Function (ACF), its Q-value for the series listed in Fig-2(e) and Appendix-III indicates non-stationarity so, differenced series (d=1) is considered for further analysis. The plots and values of ACF, its Q-value and PACF for new series are presented in Fig-1(f), Fig-2(f) and Appendix-III. Based on ACF and PACF of new series, the tentatively identified models are as (p, d, q)(P, D, Q)

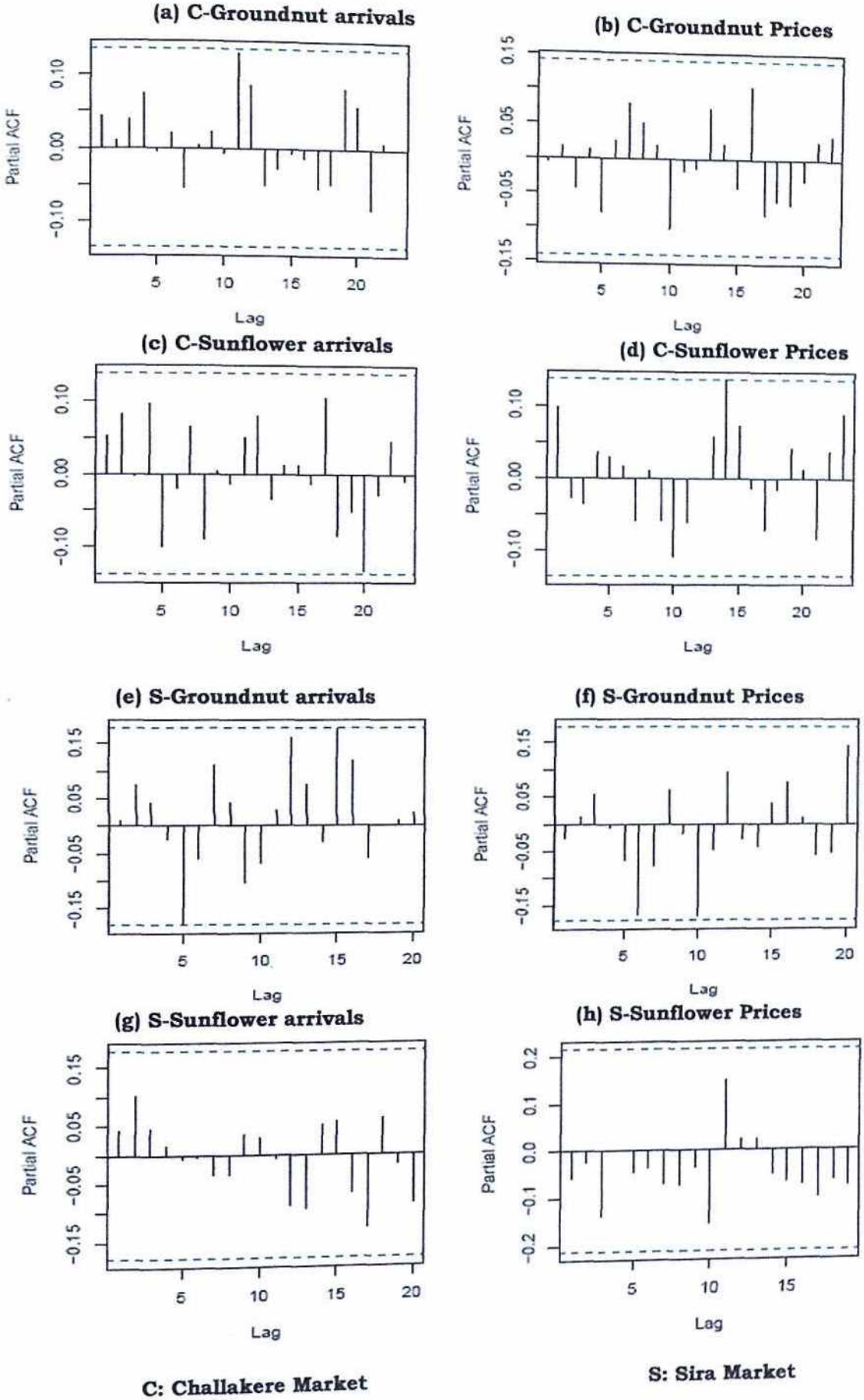


Figure-5: Partial Autocorrelation Function (PACF) plots of residuals obtained from ARIMA models of all series and from both markets

follows:- $(2,1,2)(2,1,2)_{12}$; $(2,1,1)(2,1,2)_{12}$; $(3,1,1)(1,1,2)_{12}$; $(2,1,1)(1,1,2)_{12}$; $(1,1,2)(1,1,2)_{12}$ and $(1,1,1)(1,1,1)_{12}$.

4.1.2.4.2 Estimation of parameters

After identifying the models tentatively, the next step is to obtain the estimate by using method of least square estimation of the parameters such that error sums of square is to be minimum *i.e.,* $S_{(\phi,\theta)} = \sum_{t=1}^{n} e_t^2(\phi,\theta)$. Parameters of the tentatively identified models were estimated by an iterative process and then residuals are obtained for each of the model.

4.1.2.4.3 Diagnostic checking

The values of Box-Ljung's Q-value and Akike Information Coefficient (AIC) for tentatively identified models are listed in Table-4.8. The model (1, 1, 1) $(1, 1, 1)_{12}$ was found to be the best model since it had the lowest value of AIC and Q- value. The plots and values of ACF, its Q-value and PACF of residual series from best model are shown in Fig-4(h), Fig-5(h) and Appendix-IV. Model with its parameters, MAPE, Theil's-U value are listed in Table 4.10. The structure of the model is

$Y_t = 2.55 + 0.595\ Y_{t-1} - 0.061\ Y_{t-12} + 0.857\ e_{t-1} + 0.961\ e_{t-12}$

Table 4.8 : Tentatively identified models for sunflower prices :

Sira market

Variable	AIC	Q-Value
(2,1,2) (2,1,2)	1431.299	20.531
(2,1,1) (2,1,2)	1433.111	19.984
(3,1,1) (1,1,2)	1432.657	21.287
(2,1,1) (1,1,2)	1430.128	18.335
(1,1,2) (1,1,2)	1429.014	16.795
(1,1,1) (1,1,1)	1427.116	15.236

4.1.2.4.4 Forecasting the Prices

The forecasts of sunflower prices at sira market was done up to December 2009 and the same is listed in Table-4.21 and Fig -13.

4.2 VOLATILITY MODELS

4.2.1 CHALLAKERE MARKET

4.2.1.1 Groundnut Arrivals :

ARMA (2, 1) was fit and the residuals (u_t) were used to check for ARCH effects. Chi-square value in Table-4.11 rejects the hypothesis: "No ARCH effect". So an ARCH (1) and GARCH (1,1) model was fit. Among them ARCH (1) had high R^2 and low AIC. The parameters estimated are listed in Table-4.12. The result of t-test for significance of ARCH coefficients make ARCH (1) model to be acceptable. Model fit says each month's variance of arrivals has its dependence with previous month's arrivals variance as,

$$\sigma^2_t = 1.0079 + 0.1953\ \hat{u}^2_{t-1}$$

$$Y_t = -573.5 + 0.2119Y_{t-1}$$

As required, estimated ARCH coefficients obey stationarity rule, i.e., their sum is less than unity. Table-4.13 show that residuals obtained from ARCH (1) model, under LM test gave no-ARCH effect. Forecasted groundnut arrivals at challakere market are listed in Table-4.14 and Fig-6.

Table 4.11: Test for ARCH effects

Residuals from Best fit autoregressive models	LM (TR^2)	
	CHALLAKERE	SIRA
Groundnut Arrivals	4.58*	4.12*
Groundnut Prices	6.72**	5.64*
Sunflower Arrivals	2.44	3.93*
Sunflower Prices	5.39*	5.77*

Lag length: 1, X^2 (0.05, 1 df) = 3.841, X^2 (0.01, 1 df) = 6.634

4.2.1.2 Groundnut Prices :

ARIMA (1,1,1) was fit and the residuals (u_t) were used in checking for ARCH effects. Chi-square value in Table-4.11 rejects the hypothesis: "No ARCH effect". So an ARCH (1), ARCH (2) and GARCH (1,1) models were fit. Among these, ARCH (1) had high R^2 and low AIC. The parameters estimated and the result of t-test for significance of ARCH coefficient is listed in Table-4.12. Thus, ARCH (1) model is fit and model says each month's variance of prices has its dependence with previous month's prices variance as,

$$\sigma^2_t = 0.2077 + 0.2517\ \hat{u}^2_{t-1}$$

$$Y_t = 1361 + 0.7417\ Y_{t-1}$$

It is clear that, as required, estimated ARCH coefficients obey the stationarity rule, i.e., their sum is less than unity. Table-4.13 show that residuals obtained from ARCH (1) model, under LM test gave no-ARCH effect. The forecasted groundnut prices at challakere market are listed in Table-4.15 and Fig-7.

4.2.1.3 Sunflower Arrivals :

ARMA (1, 1) was fit and the residuals (u_t) were used to check for ARCH effects. Chi-square value in Table-4.11 does not reject the hypothesis: "No ARCH effect". Thus, ARCH-GARCH model cannot be fit.

4.2.1.4 Sunflower prices:

ARIMA (1,1,1) was fit and the residuals (u_t) was used to check for ARCH effects. Chi-square value in Table-4.11 rejects the hypothesis: "No ARCH effect". So an ARCH (1) and GARCH (1,1) model was fit. ARCH(1) model had significant coefficients with low AIC and high R^2. The parameters estimated for ARCH (1) are listed in Table-4.41. Model fit indicate that each month's variance of arrivals has its dependence with previous month's arrivals variance as,

$$\sigma^2_t = 0.1375 + 0.0732\ \hat{u}^2_{t-1}$$

$$Y_t = 580.2076 - 0.6494\ Y_{t-1}$$

It is clear that, as required, estimated ARCH coefficients obey the stationarity rule, i.e., their sum is less than unity. Table-4.13 show that residuals obtained from ARCH (1) model, under LM test gave no-ARCH effect. The forecasted sunflower prices at challakere market are listed in Table-4.17 and Fig-9.

Table 4.12 : Estimates of ARCH Model

Series	Variance Equation		Actual series		R^2	AIC
	Constant	$\hat{u}^2_{t-1}$	Constant	Y_{t-1}		
C: Groundnut Arrivals	1.0079** (0.1053)	0.1953* (0.0871)	-573.5** (76.8000)	0.2119* (0.0865)	0.5150	622.7
C: Groundnut Prices	0.2077** (0.0145)	0.2517* (0.1417)	1361** (52.6798)	0.7417** (0.1413)	0.8914	2614.03
C: Sunflower Prices	0.1375** (0.0107)	0.0732** (0.0151)	580.2076^{NS} (1240)	-0.6494** (0.0925)	0.9535	2515.19
S: Groundnut Arrivals	0.5884** (0.0763)	0.3773* (0.168)	2493** (955.06)	-0.5485* (0.2766)	0.5170	2416.11
S: Groundnut Prices	0.2208** (0.0439)	0.3552* (0.1497)	1650** (67.2358)	0.8157** (0.1546)	0.8722	1547.13
S: Sunflower Prices	0.2909** (0.0731)	0.3312** (0.1254)	1079^{NS} (710.1872)	0.9209** (0.1889)	0.8956	1586.46

Note: * Significant at 5% level ** Significant at 1% level

NS: non-significant

C: Challakere market and S: Sira market

Values in parenthesis are standard errors

AIC: Akaike Information Criteria.

Table 4.13: Test for ARCH effects in residuals

Residuals from Best fit Models	LM (TR^2)	
	CHALLAKERE MARKET	SIRA MARKET
Groundnut Arrivals	1.63	2.41
Groundnut Prices	0.59	0.94
Sunflower Prices	0.38	1.66

Note: Lag length: 1, X^2 (0.05, 1 df) = 3.841

4.2.2 Sira Market

4.2.2.1 Groundnut Arrivals:

ARMA (1, 1) was fit and the residuals (u_t) was used to check for ARCH effects. Chi-square value in Table-4.11 rejects the hypothesis: "No ARCH effect". So an ARCH (1) and GARCH (1,1) model was fit. ARCH (1) model had significant coefficients with low AIC and high R^2. The parameters estimated are listed in Table-4.12. Model fit says each month's variance of arrivals has its dependence with previous month's arrivals variance as,

$$\sigma^2_t = 0.5884 + 0.3773\ \hat{u}^2_{t-1}$$

$$Y_t = 2493 - 0.5485\ Y_{t-1}$$

It is clear that, as required, estimated ARCH coefficients obey the stationarity rule, i.e., their sum is less than unity. Table-4.13 show that residuals obtained from ARCH (1) model, under LM test gave no-ARCH effect. The forecasted groundnut arrivals at sira market are listed in Table-4.18 and Fig-10.

4.2.2.2 Groundnut Prices :

ARIMA (1,1,1) was fit and the residuals (u_t) was used to check for ARCH effects. Chi-square value in Table-4.11 rejects the hypothesis: "No ARCH effect". So an ARCH (1) and GARCH (1, 1) model was fit. Among

these, ARCH (1) had high R^2 and low AIC. The parameters estimated and the result of t-test for significance of ARCH coefficient is listed in Table-4.12. Thus, ARCH (1) model is fit and model says each month's variance of prices has its dependence with previous month's prices variance as,

$$\sigma^2_t = 0.2208 + 0.3552\ \hat{u}^2_{t-1}$$

$$Y_t = 1650 + 0.8157\ Y_{t-1}$$

As required, estimated ARCH coefficients obey stationarity rule, i.e., their sum is less than unity. Table-4.13 show that residuals obtained from ARCH(1), under LM test gave no-ARCH effect. Forecasted groundnut prices at sira market are listed in Table-4.19 and Fig-11.

4.2.2.3 Sunflower Arrivals :

ARMA (1, 2) was fit and the residuals (u_t)were used to check for ARCH effects. Chi-square value in Table-4.11 does not reject the hypothesis: "No ARCH effect". Thus, ARCH-GARCH model cannot be fit.

4.2.2.4 Sunflower Prices :

ARIMA (1,1,1) was fit and the residuals (u_t) was used to check for ARCH effects. Chi-square value in Table-4.11 rejects the hypothesis: "No ARCH effect". So an ARCH (1) and GARCH (1,1) model was fit. ARCH (1) model had significant coefficients with low AIC and high R^2. The parameters estimated for ARCH (1) are listed in Table-4.12. Model fit indicate that each month's variance of arrivals has its dependence with previous month's arrivals variance as,

$$\sigma^2_t = 0.2909 + 0.3312\ \hat{u}^2_{t-1}$$

$$Y_t = 1079 + 0.9209\ Y_{t-1}$$

It is clear from the findings, as required, estimated ARCH coefficients obey the stationarity rule, i.e., their sum is less than unity. Table-4.13 show that residuals obtained from ARCH (1) model, under LM test gave no-ARCH effect. The forecasted sunflower prices at sira market are listed in Table-4.21 and Fig-13.

Table 4.14 : Forecasted Groundnut Arrivals (Qtl) at Challakere Market using ARIMA and ARCH MODELS.

Month	ARIMA	ARCH
Jan-2009	15,423	15,721
Feb-2009	2,135	1,850
Mar-2009	2,826	3,750
Apr-2009	6,785	6,760
May-2009	3,112	2,630
Jun-2009	2,765	2,660
Jul-2009	3,658	4,125
Aug-2009	3,470	3,251
Sep-2009	1,105	967
Oct-2009	6,632	7,985
Nov-2009	807	605
Dec-2009	18,216	21,143

Table 4.15: Forecasted Groundnut Prices (Rs\Qtl) at Challakere Market using ARIMA and ARCH MODELS.

Month	ARIMA	ARCH
Jan-2009	2,317	2,630
Feb-2009	2,510	2,362
Mar-2009	2,524	2,250
Apr-2009	2,242	2,475
May-2009	2,315	2,495
Jun-2009	2,551	2,775
Jul-2009	2,614	2,465
Aug-2009	2,614	2,619
Sep-2009	2,490	2,489
Oct-2009	2,655	2,461
Nov-2009	2,473	2,634
Dec-2009	2,355	2,590

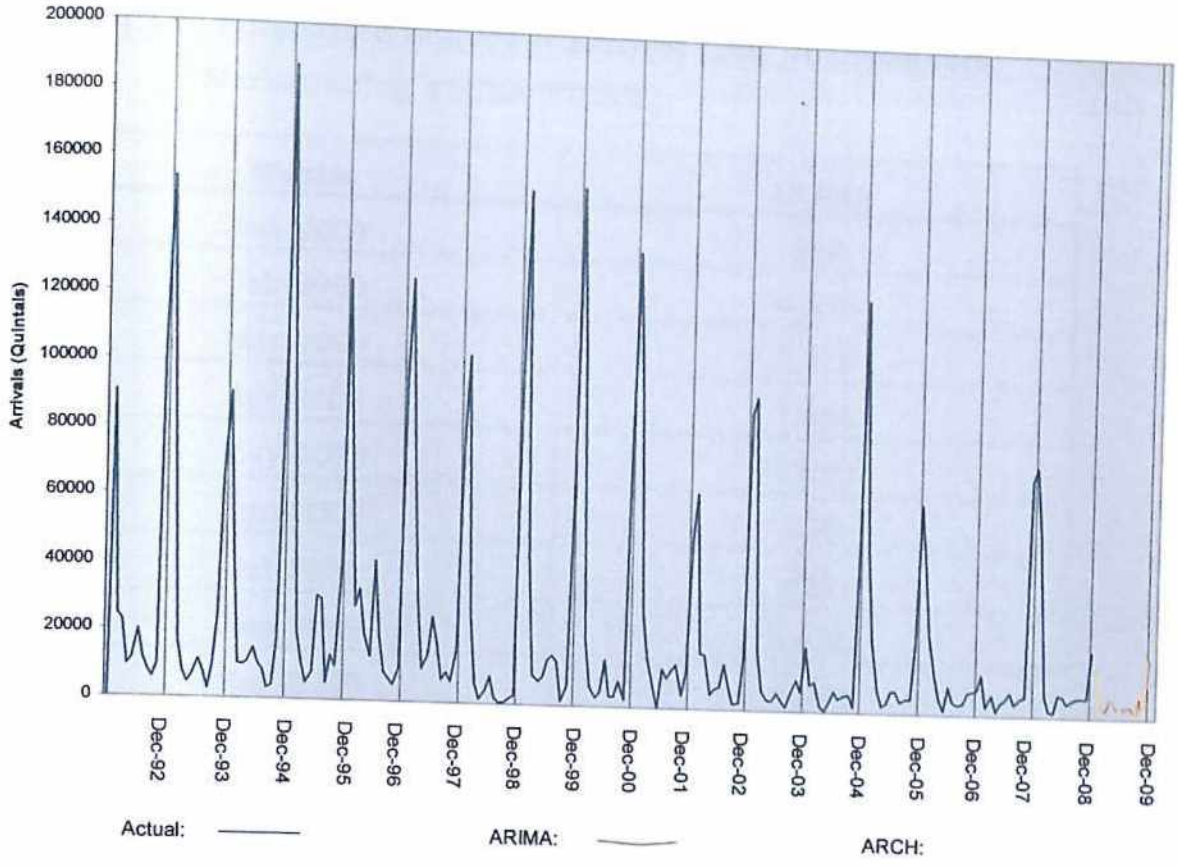


Figure-6: Plot of Actual Groundnut Arrivals and Forecasts of ARIMA and ARCH model at Challakere Market

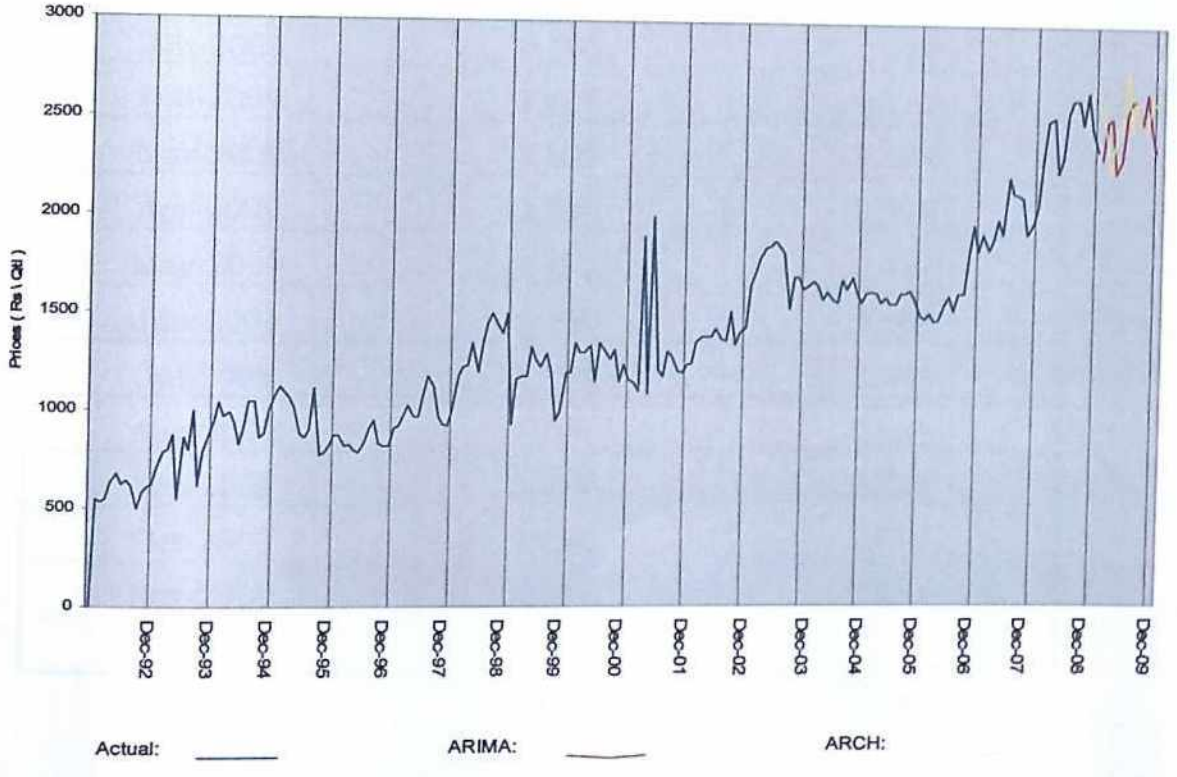


Figure -7: Plot of Actual Groundnut Prices and Forecasts of ARIMA and ARCH model at Challakere Market

Table 4.16 : Forecasted Sunflower Arrivals (Qtl) at Challakere Market using ARIMA MODEL.

Month	ARIMA
Jan-2009	300
Feb-2009	4,590
Mar-2009	3,370
Apr-2009	1,460
May-2009	1,620
Jun-2009	550
Jul-2009	487
Aug-2009	6,430
Sep-2009	2,050
Oct-2009	2,190
Nov-2009	1,245
Dec-2009	450

Table 4.17 : Forecasted Sunflower prices (Rs\Qtl) at Challakere Market using ARIMA and ARCH MODELS.

Month	ARIMA	ARCH
Jan-2009	2,100	2,178
Feb-2009	1,939	1,931
Mar-2009	1,800	1,948
Apr-2009	2,339	2,204
May-2009	2,550	2,457
Jun-2009	2,450	2,509
Jul-2009	2,714	2,644
Aug-2009	2,794	2,688
Sep-2009	2,819	2,729
Oct-2009	2,614	2,770
Nov-2009	2,574	2,653
Dec-2009	2,419	2,566

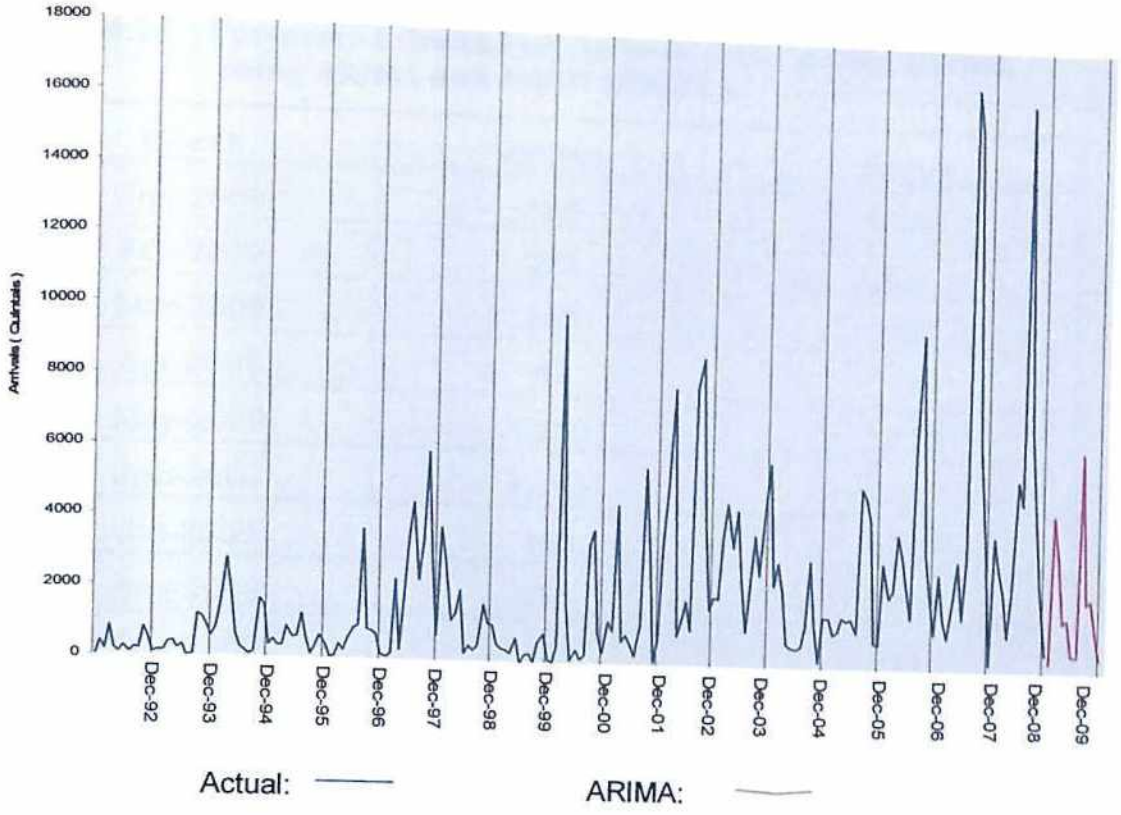


Figure-8: Plot of Actual Sunflower Arrivals and Forecasts of ARIMA model at Challakere Market

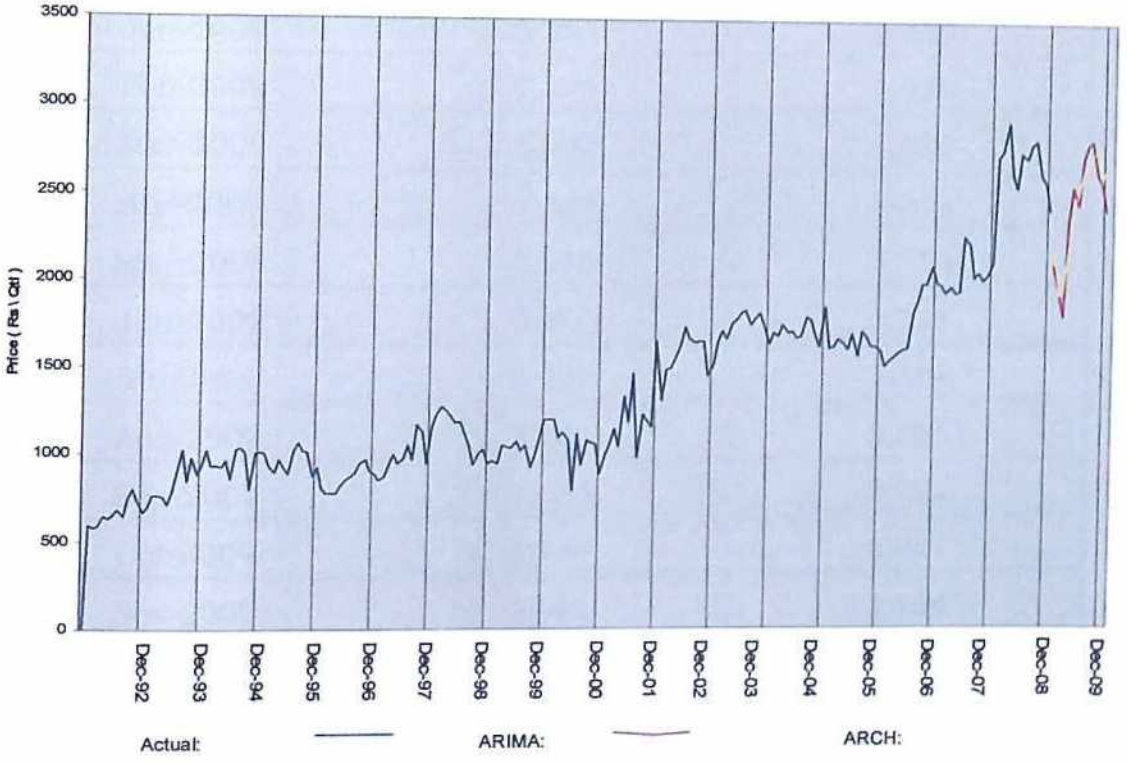


Figure -9 : Plot of Actual Sunflower Prices and Forecasts of ARIMA and ARCH model at Challakere Market

Table 4.18 : Forecasted Groundnut Arrivals (Qtl) at Sira Market using ARIMA and ARCH MODELS

Month	ARIMA	ARCH
Jan-2009	560	644
Feb-2009	223	201
Mar-2009	120	80
Apr-2009	83	49
May-2009	1,226	1,350
Jun-2009	1,265	1,317
Jul-2009	141	176
Aug-2009	275	193
Sep-2009	125	110
Oct-2009	2,140	2,675
Nov-2009	14,990	15,120
Dec-2009	9,912	10,375

Table 4.19 : Forecasted Groundnut Prices (Rs\Qtl) at Sira Market using ARIMA and ARCH MODELS.

Month	ARIMA	ARCH
Jan-2009	2,223	2,207
Feb-2009	1,825	1,939
Mar-2009	1,907	1,850
Apr-2009	2,300	2,434
May-2009	2,486	2,550
Jun-2009	2,476	2,521
Jul-2009	2,322	2,304
Aug-2009	2,533	2,105
Sep-2009	2,475	2,222
Oct-2009	2,126	2,227
Nov-2009	2,046	2,168
Dec-2009	2,124	2,270

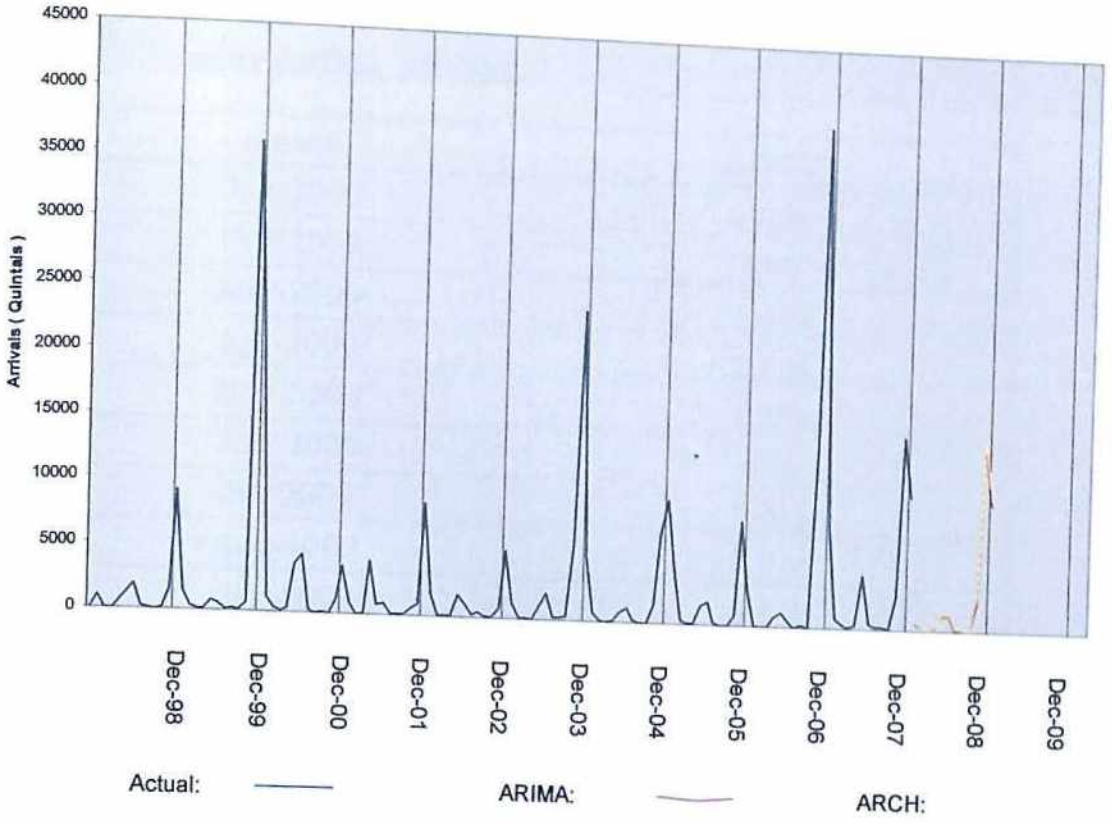


Figure -10 : Plot of Actual Groundnut Arrivals and Forecasts of ARIMA and ARCH model at Sira Market

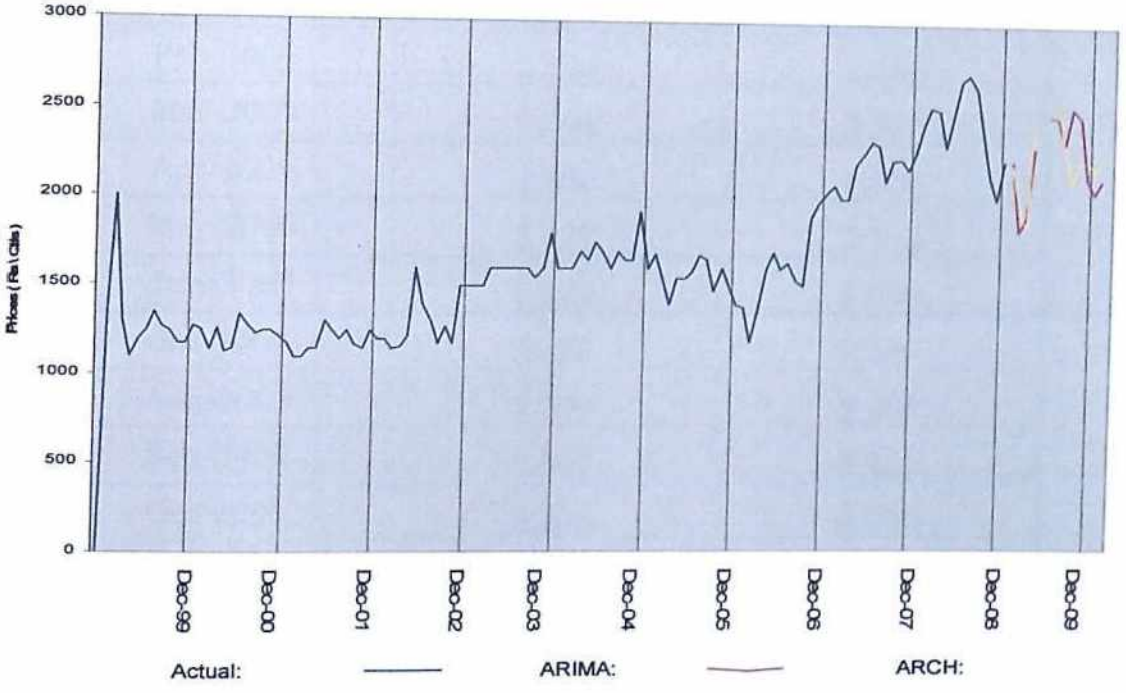


Figure -11 : Plot of Actual Groundnut Prices and Forecasts of ARIMA and ARCH model at Sira Market

Table 4.20 : Forecasted Sunflower Arrivals (Qtl) at Sira Market using ARIMA MODEL.

Month	ARIMA
Jan-2009	150
Feb-2009	980
Mar-2009	1,607
Apr-2009	2,438
May-2009	2,181
Jun-2009	544
Jul-2009	1,115
Aug-2009	2,474
Sep-2009	9,787
Oct-2009	6,430
Nov-2009	1,957
Dec-2009	438

Table 4.21 : Forecasted Sunflower prices (Rs\Qtl) at Sira Market using ARIMA and ARCH MODELS.

Month	ARIMA	ARCH
Jan-2009	2,150	2,040
Feb-2009	2,274	2,146
Mar-2009	2,191	2,015
Apr-2009	2,400	2,233
May-2009	2,187	2,152
Jun-2009	2,022	2,008
Jul-2009	2,486	2,150
Aug-2009	2,500	2,200
Sep-2009	2,307	2,200
Oct-2009	2,298	2,091
Nov-2009	2,196	2,411
Dec-2009	2,284	2,187

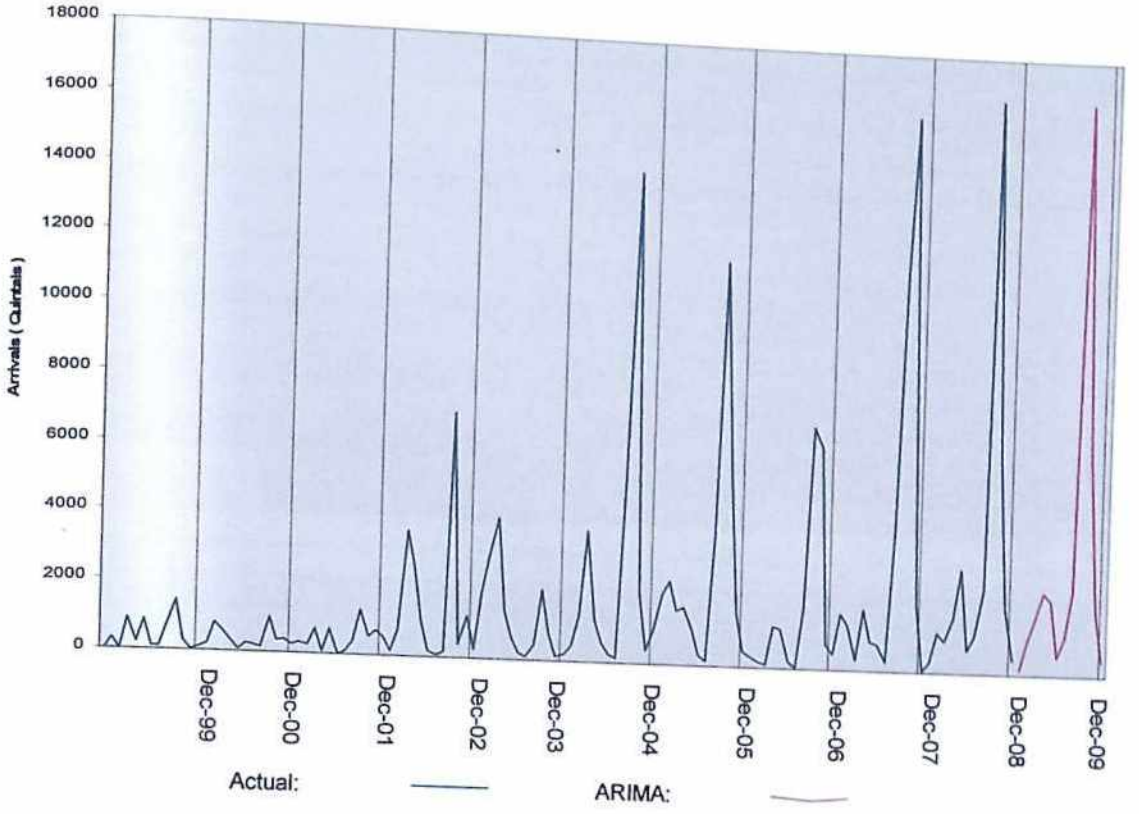


Figure -12 : Plot of Actual Sunflower Arrivals and Forecasts of ARIMA model at Sira Market

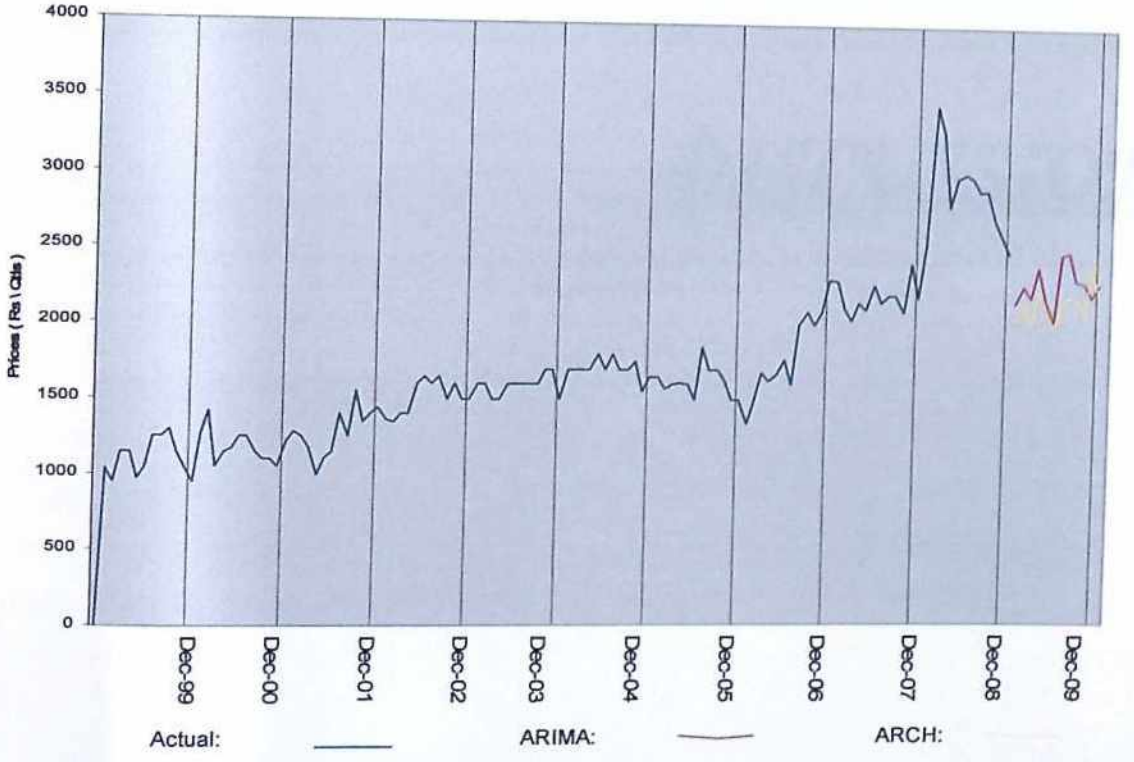


Figure -13 : Plot of Actual Sunflower Prices and Forecasts of ARIMA and ARCH model at Sira Market

DISCUSSION

V. DISCUSSION

Having forecasting as main theme, in this chapter, brief discussions of the findings of the results are presented under different headings such as:

5.1 Autoregressive models

5.1.1 Identification of Models

5.1.2 Estimation

5.1.3 Diagnostic Checks

5.1.4 Forecasting

5.2 Volatility Analysis

5.2.1 Test for ARCH/ GARCH effects

5.2.2 Model Estimation

5.2.3 Forecasting

5.1 AUTOREGRESSIVE MODEL :

The Box-Jenkins approach is used in fitting autoregressive models, which is based on three types of filters: the autoregressive, the integration and the moving average filters in finding the structure, identifying the form and constructing the model for the series. The Box-Jenkins model provides a verified approach for identifying which filters are most appropriate for the series being analyzed, for diagnosing the accuracy and reliability of the models that have been estimated and finally, used for forecasting.

Since ARIMA models are used only to stationary series, there was a need to change the non-stationary series into stationary series by applying the appropriate order of differencing to the series. Further, the autocorrelation and partial autocorrelation plots of the differenced series were plotted and computed for the data series.

In all the cases, except for Groundnut arrivals at Sira, the autocorrelation function (ACF) were turned out to be significant at 95 per cent probability level at fixed interval between lag k and lag k-12 (i.e. at lag 12) indicating the presence of seasonality component of the 12 months. Therefore, the seasonal ARIMA model was found to be the most appropriate among the classes of the model on account of the presence of a marked seasonality component in both series of both Challakere and Sira markets under study.

Four stages of Box-Jenkins models were discussed with respect to arrivals and prices of both Groundnut and sunflower. Mastny (2001) has also employed the same in forecasting of prices of selected agricultural commodities. The discussion is presented in the same order.

5.1.1 Identification of the model

Identification is concerned with deciding the appropriate values of p, q, d, P, Q, and D. The autocorrelation function (ACF) helps to choose appropriate values of order of moving average terms (MA) and partial-autocorrelation function (PACF) for those autoregressive terms (AR). The number of non-zero-coefficient in ACF determines order of MA terms and a number of non-zero-coefficient in PACF determines order of AR terms.

The seasonality nature of the series is determined by significance of coefficients at the lag 12 of the autocorrelation coefficients functions, which is consistently noticed in both groundnut and sunflower in both Challakere and Sira markets. The following models have been identified as the best model through iteration process.

BEST MODELS

5.1.1.1 Challakere Market

1. Groundnut-arrivals : $(2, 1, 1)\ (1, 1, 1)_{12}$
2. Groundnut-prices : $(2, 1, 3)\ (1, 1, 1)_{12}$
3. Sunflower-arrivals : $(1, 0, 1)\ (1, 1, 1)_{12}$
4. Sunflower-prices : $(2, 1, 1)\ (1, 1, 1)_{12}$

5.1.1.2 Sira Market

1. Groundnut-arrivals : $(2, 1, 2)\ (2, 0, 1)_{12}$

2. Groundnut-prices : $(4, 1, 2)\ (1, 1, 1)_{12}$

3. Sunflower-arrivals : $(2, 1, 2)\ (2, 1, 2)_{12}$

4. Sunflower-prices : $(1, 1, 1)\ (1, 1, 1)_{12}$

5.1.2 Estimation

Having tentatively identified the model, the parameters, which minimize the sums of squares of errors, are estimated through iterative process.

The coefficients of estimated models were subjected to statistical t-test for its significance. Some of the coefficient were found not significant, however, such models were chosen depending upon their over all efficiency and reliability, based on MAPE and Theil's-U coefficient. It could be observed that in all series, both seasonal MA and AR process were present. Thus, it could be inferred that all series under study are linearly related to both the previous year's error terms and previous year's values of arrivals and prices. The estimated equations of the selected models for the series are presented below,

5.1.2.1 Challakere Market : ARIMA equations

1. Groundnut-Arrivals

$$Y_t = -10.207 + 0.712Y_{t-1} - 0.331Y_{t-2} + 0.238Y_{t-12} + 0.993e_{t-1} - 0.827e_{t-12}$$

2. Groundnut- Prices

$$Y_t = 0.6797 + 0.3822Y_{t-1} - 0.614Y_{t-2} - 0.027Y_{t-12} + 0.227e_{t-1} - 0.617e_{t-2} + 0.5295e_{t-3} + 0.8857e_{t-12}$$

3. Sunflower-Arrivals

$$Y_t = 246.813 + 0.295\ Y_{t-1} + 0.370\ Y_{t-12} - 0.203e_{t-1} + 0.805\ e_{t-12}$$

4. Sunflower-Prices

$$Y_t = 0.912 + 0.586Y_{t-1} + 0.295Y_{t-2} + 0.068Y_{t-12} + 0.988e_{t-1} + 0.995e_{t-12}$$

5.1.2.2 SIRA MARKET : ARIMA equations

1. Groundnut-Arrivals

$$Y_t = 108.295 - 1.020Y_{t-1} - 0.053\ Y_{t-2} - 0.528Y_{t-12} - 0.49Y_{t-13} - 1.458e_{t-1} - 0.492e_{t-2} + 0.426e_{t-12}$$

2. Groundnut- Prices

$$Y_t = 2.366 + 0.159Y_{t-1} - 0.664Y_{t-2} - 0.239Y_{t-3} - 0.460Y_{t-4} + 0.237Y_{t-12} + 0.476e_{t-1} - 0.562e_{t-2} + 0.981e_{t-12}$$

3. Sunflower-Arrivals

$$Y_t = 27.612 + 0.277Y_{t-1} - 0.16Y_{t-2} + 0.883Y_{t-12} + 0.991e_{t-1} + 0.483e_{t-12} - 0.075e_{t-13}$$

4. Sunflower-Prices

$$Y_t = 2.55 + 0.595Y_{t-1} - 0.061Y_{t-12} + 0.857e_{t-1} + 0.961e_{t-12}$$

5.1.3 Diagnostic Checks

Model verification is concerned with checking the residuals obtained from estimated models i.e., to see if they contain or follows any systematic pattern, which can still be removed to improve the chosen ARIMA models. Box-Ljung 'Q' statistic for the Autocorrelation function (ACF) of residuals for each model and its AIC are listed in Tables.

The residuals of the estimated models were found to be random (white-noise) in all the cases as none of coefficients were significantly different from zero which is also supported by the non-significance of Box-Ljung 'Q' statistic and minimum AIC values of prices and arrivals of all the crops. Alebrahiem, (1996), Ansari and Ahmed (2001) and Mastny (2001) arrived at similar conclusion with the present study regarding validation of ARIMA modeling in their study.

5.1.4 Forecasting

The principal objective of developing ARIMA model for a variable is to generate post sample period forecasts for the same variable. Forecasting was done for a period of 12 months. The forecast obtained by the Box-Jenkins models are provided in Tables 4.14 to 4.21.

The predictive performances of the models were tested by test statistics like Mean Absolute Percentage Error (MAPE), and Theil's U-coefficient, the same were recommended by Makridakis and Hibbon (1979). Particularly, the score turned by Theil's U-coefficient is 1-U for consistency where 'U' lies between 0 to 1 with 1 meaning inconsistence of the actual and forecasted values of the series.

MAPE and Theil's-U coefficients are listed in Table 4.9 and 4.10. As all the computed models had low MAPE and value of Theil's-U was nearer to zero, we can say that forecasts were consistent and had narrow variations from actual recorded data.

5.2 VOLATILITY ANALYSIS

Prices and arrivals of groundnut and sunflower from both Sira and Challakere market were analyzed for its volatility. The data in which the expected value of the error terms is not equal, and in which the variance of the error terms are reasonably expected to be larger for some points or ranges of the data than for others, is said to be heteroscedastic or volatile. These time series with varying variance are modeled by autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models.

5.2.1 Test for ARCH or GARCH effects

Based on the autocorrelation function (ACF) and partial-autocorrelation function (PACF), the orders of p, d and q were obtained. ARMA or ARIMA models with respective orders were fit to each series. Residuals were obtained for all the series. These residuals were

subjected to Lagrange-Multiplier test, supported by Engel (1982), to identify the ARCH or GARCH effect.

5.2.1.1 Challakere Market

1. Groundnut-arrivals : had ARCH effect
2. Groundnut-prices : had ARCH effect
3. Sunflower-arrivals : had no ARCH effect
4. Sunflower-prices : had ARCH effect

5.2.1.2 Sira Market

1. Groundnut-arrivals : had ARCH effect
2. Groundnut-prices : had ARCH effect
3. Sunflower-arrivals : had no ARCH effect
4. Sunflower-prices : had ARCH effect

5.2.2 Model Estimation

ARCH with different orders and GARCH (1, 1) models were fit to series with ARCH or GARCH effect. Based on R^2 value and AIC, it was found that every series had ARCH (1) as best model. Diongue (2006) and Satheesh (1988) used the same to arrive at best models.

Generalized least square estimation procedure was used in estimating the parameters of variance equation. As the parameters estimated has the value of a_0 and a_1 are positive, conditions for variance to be positive is satisfied. As, the sum of coefficients are within range 0 to 1 and $3a_1^2<1$, it is ascertained that residuals from ARCH (1) are stationary as supported by Nikolaos (2001).

5.2.2.1 Challakere Market : ARCH equations

1. Groundnut-arrivals

Variance Equation : $\sigma^2_t = 1.0079 + 0.1953\ \hat{u}^2_{t-1}$

Arrivals Equation : $Y_t = -0.5735 + 0.2119Y_{t-1}$

2. Groundnut- prices

Variance Equation : $\sigma^2_t = 0.2077 + 0.2517\ \hat{u}^2_{t-1}$

Arrivals Equation : $Y_t = 1361 - 0.7417\ Y_{t-1}$

3. Sunflower-prices

Variance Equation : $\sigma^2_t = 0.1375 + 0.0732\ \hat{u}^2_{t-1}$

Arrivals Equation : $Y_t = 580.2076 - 0.6494\ Y_{t-1}$

5.2.2.2 SIRA MARKET: ARCH equations

1. Groundnut-arrivals

Variance Equation : $\sigma^2_t = 0.5884 + 0.3773\ \hat{u}^2_{t-1}$

Arrivals Equation : $Y_t = 2493 - 0.5485\ Y_{t-1}$

2. Groundnut- prices

Variance Equation : $\sigma^2_t = 0.2208 + 0.3552\ \hat{u}^2_{t-1}$

Arrivals Equation : $Y_t = 1650 - 0.8157\ Y_{t-1}$

3. Sunflower-prices

Variance Equation : $\sigma^2_t = 0.2909 + 0.3312\ \hat{u}^2_{t-1}$

Arrivals Equation : $Y_t = 1079 - 0.9209\ Y_{t-1}$

5.2.3 Forecasting

ARCH (1) model was used in forecasting the variance. Later these variances were used in getting the actual arrivals and prices. As recommended by Engel (2001), residuals were obtained and were tested for ARCH or GARCH effect.

5.2.3.1 Challakere Market

1. Groundnut-arrivals : had no ARCH effect

2. Groundnut-prices : had no ARCH effect

3. Sunflower-prices : had no ARCH effect

5.2.3.2 Sira Market

1. Groundnut-arrivals : had no ARCH effect

2. Groundnut-prices : had no ARCH effect

3. Sunflower-prices : had no ARCH effect

Engle (1982) used the same measure to arrive at best model in estimating the mean and variance of inflation in U.K.

SUMMARY

V. SUMMARY

India was self sufficient in vegetable oils in the 1950s; however, by the 1960s the domestic demand-supply equilibrium almost vanished. The turning point arrived in the year 1988, when the country faced shortfall of 2 million tonnes of oil, necessitating imports worth $1bn. Alarmed at this situation, government made a concerted effort to make oilseeds more attractive to growers, through a combination of specialized extension campaign including the high-profile Technology Mission. In this regard, among the nine major oilseed crops, Groundnut and sunflower was the two predominant and most preferred oilseed crops. In Karnataka, Groundnut and sunflower occupy the major share with respect to both area and production. Now, the problem faced by farmer is in getting remunerative prices for the produce. Hence, present study is undertaken to attempt the suitable and appropriate model all variations witnessed in the prices and arrivals at Sira and Challakere, Agriculture Produce Market Committee (APMC) and to forecast the same.

Database of the study:

Ten years monthly prices and arrivals of groundnut and sunflower at sira market and sixteen years monthly prices and arrivals of groundnut and sunflower at Challakere market were considered for the present research study. The data for the above period was collected from the respective APMC.

Specific objectives of the study :

I. Forecasting arrivals and prices of groundnut and sunflower by Autoregressive models and

II. To analyze the volatility in the arrivals and prices of groundnut and sunflower

Autoregressive Models

Box-Jenkins procedure was used to fit autoregressive model and to forecast the mean prices and arrival for next 12 months. Since, there was seasonality in the data seasonal ARIMA model was used. As prices of both groundnut and sunflower, of both Sira and Challakere markets were non-stationary, differenced series were used.

Autocorrelation function (ACF) and Partial Autocorrelation function (PACF) were used in identifying the tentative models. Parameters of tentatively identified models were estimated by iterative process. Measures like MAPE, Theil's-U coefficient, R^2 value and AIC were used in getting the adequate models. As diagnostic check, The ACF and PACF of residuals, obtained from estimated models were examined for its randomness and its significance was tested using Box-Jenkins Q-value. Thus, the best fit models are established below

Challakere Market

Groundnut-arrivals : $(2, 1, 1)\ (1, 1, 1)_{12}$

Groundnut-prices : $(2, 1, 3)\ (1, 1, 1)_{12}$

Sunflower-arrivals : $(1, 0, 1)\ (1, 1, 1)_{12}$

Sunflower-prices : $(2, 1, 1)\ (1, 1, 1)_{12}$

Sira Market

Groundnut-arrivals : $(2, 1, 2)\ (2, 0, 1)_{12}$

Groundnut-prices : $(4, 1, 2)\ (1, 1, 1)_{12}$

Sunflower-arrivals : $(2, 1, 2)\ (2, 1, 2)_{12}$

Sunflower-prices : $(1, 1, 1)\ (1, 1, 1)_{12}$

All the series of Challakere market says that their arrivals and prices depend on previous one year's values and on two months back

values (except for sunflower arrivals- it depends on one month back values). In Sira market the prices had its dependence on previous year's value and arrivals have its dependence on two years back values.

Volatility Analysis :

Volatility in prices and arrivals of groundnut and sunflower crops from challakere and sira markets is modeled using ARCH model. These models forecast the variance of prices and the variance of arrivals. Later, these variances are used in obtaining the actual prices and arrivals. Lagrange-Multiplier (LM) test declared the presence of ARCH effect in all series except for Sunflower arrivals in both challakere and sira markets.

High value of R^2 and low value of AIC has shown that ARCH (1) model was adequate in modeling all the series. Residuals obtained from these models are tested for ARCH effects using LM-test. The Result shows that there was no residual ARCH effect. Thus, ARCH (1) model is used in forecasting the prices and arrivals of groundnut and sunflower in both challakere and sira markets, for a duration of 12 months.

FUTURE LINE OF WORK

- Here seasonality is considered to be 12 and as the crop is having two harvests in a year, seasonality can be considered for two seasons and ARIMA model can be fit.
- ARCH or GARCH models are having its existence and used in studying Inflation or Exchange rate, Savings ratio, Stock prices etc… The results of the present study emphasize and forethought in using the above models in modeling other Agricultural commodities of similar phenomenon.
- In general, weekly or daily data is used in fitting ARCH or GARCH models. Here monthly data was used and they even could be used in fitting ARCH models.

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APPENDICES

APPENDIX-I: ACF and PACF values for series of Challakere market.

Groundnut Arrivals

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	0.033	.072	0.208	1	.648	.033	.072
2	-0.117	.072	2.874	2	.238	-.118	.072
3	0.081	.071	4.170	3	.244	.091	.072
4	0.006	.071	4.178	4	.382	-.015	.072
5	-0.046	.071	4.606	5	.466	-.026	.072
6	0.034	.071	4.838	6	.565	.030	.072
7	0.016	.071	4.887	7	.674	.005	.072
8	-0.020	.070	4.970	8	.761	-.008	.072
9	0.005	.070	4.976	9	.836	.003	.072
10	-0.077	.070	6.185	10	.799	-.086	.072
11	-0.075	.070	7.343	11	.771	-.064	.072
12	0.055	.070	7.965	12	.788	.043	.072
13	-0.136	.069	11.802	13	.544	-.151	.072
14	-0.039	.069	12.117	14	.597	-.001	.072
15	0.024	.069	12.240	15	.661	-.023	.072
16	0.016	.069	12.297	16	.723	.033	.072

Groundnut Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	.924	.070	176.836	1	.000	.924	.070
2	.905	.069	347.139	2	.000	.347	.070
3	.855	.069	499.944	3	.000	-.092	.070
4	.827	.069	643.817	4	.000	.040	.070
5	.801	.069	779.466	5	.000	.091	.070
6	.773	.069	906.339	6	.000	-.016	.070
7	.744	.068	1024.503	7	.000	-.037	.070
8	.719	.068	1135.456	8	.000	.027	.070
9	.693	.068	1238.933	9	.000	.002	.070
10	.654	.068	1331.704	10	.000	-.126	.070
11	.630	.068	1418.222	11	.000	.033	.070
12	.608	.068	1499.021	12	.000	.083	.070
13	.590	.067	1575.648	13	.000	.016	.070
14	.572	.067	1647.919	14	.000	-.009	.070
15	.553	.067	1715.928	15	.000	.016	.070
16	.539	.067	1780.762	16	.000	.039	.070

Differenced (D=1) Series of Groundnut Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-0.516	.070	54.759	1	.000	-.516	.070
2	0.228	.069	65.475	2	.000	-.052	.070
3	-0.154	.069	70.433	3	.000	-.079	.070
4	-0.031	.069	70.639	4	.000	-.185	.070
5	0.008	.069	70.652	5	.000	-.116	.070
6	0.017	.069	70.713	6	.000	-.022	.070
7	0.004	.069	70.716	7	.000	-.018	.070
8	0.007	.068	70.726	8	.000	-.025	.070
9	0.060	.068	71.496	9	.000	.079	.070
10	-0.122	.068	74.706	10	.000	-.070	.070
11	0.025	.068	74.839	11	.000	-.112	.070
12	0.012	.068	74.871	12	.000	.003	.070
13	0.035	.068	75.142	13	.000	.067	.070
14	0.011	.067	75.171	14	.000	.030	.070
15	-0.063	.067	76.054	15	.000	-.082	.070
16	0.133	.067	79.969	16	.000	.128	.070

Sunflower Arrivals

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	.556	.070	64.076	1	.000	.556	.070
2	.236	.069	75.672	2	.000	-.106	.070
3	.125	.069	78.949	3	.000	.057	.070
4	.102	.069	81.152	4	.000	.038	.070
5	.164	.069	86.847	5	.000	.130	.070
6	.197	.069	95.043	6	.000	.061	.070
7	.182	.068	102.122	7	.000	.043	.070
8	.089	.068	103.815	8	.000	-.064	.070
9	.095	.068	105.751	9	.000	.097	.070
10	.180	.068	112.800	10	.000	.120	.070
11	.408	.068	148.980	11	.000	.350	.070
12	.528	.068	209.942	12	.000	.218	.070
13	.237	.067	222.336	13	.000	-.282	.070
14	.084	.067	223.895	14	.000	.033	.070
15	.051	.067	224.475	15	.000	.008	.070
16	.057	.067	225.191	16	.000	-.022	.070

Sunflower Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.003	.072	0.002	1	.967	-.003	.072
2	-.003	.071	0.003	2	.999	-.003	.072
3	.018	.071	0.069	3	.995	.018	.072
4	-.001	.071	0.069	4	.999	-.001	.072
5	-.031	.071	0.263	5	.998	-.031	.072
6	.028	.071	0.424	6	.999	.028	.072
7	.119	.070	3.292	7	.857	.120	.072
8	-.037	.070	3.569	8	.894	-.035	.072
9	.005	.070	3.575	9	.937	.004	.072
10	-.009	.070	3.593	10	.964	-.014	.072
11	.096	.070	5.506	11	.904	.102	.072
12	-.017	.070	5.567	12	.936	-.011	.072
13	-.114	.069	8.271	13	.826	-.126	.072
14	-.007	.069	8.282	14	.874	-.024	.072
15	.031	.069	8.484	15	.903	.045	.072
16	.006	.069	8.491	16	.933	.017	.072

Differenced (D=1) Series of Sunflower Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.349	.070	25.160	1	.000	-.349	.070
2	.121	.069	28.180	2	.000	-.002	.070
3	-.100	.069	30.261	3	.000	-.066	.070
4	-.066	.069	31.178	4	.000	-.139	.070
5	.022	.069	31.277	5	.000	-.046	.070
6	-.028	.069	31.447	6	.000	-.037	.070
7	.049	.069	31.963	7	.000	.012	.070
8	.025	.068	32.097	8	.000	.043	.070
9	-.005	.068	32.102	9	.000	.013	.070
10	-.023	.068	32.217	10	.000	-.025	.070
11	-.090	.068	33.969	11	.000	-.108	.070
12	.008	.068	33.984	12	.001	-.058	.070
13	-.021	.068	34.079	13	.001	-.040	.070
14	.032	.067	34.297	14	.002	-.013	.070
15	.083	.067	35.826	15	.002	.078	.070
16	-.070	.067	36.914	16	.002	-.031	.070

Appendix-II: ACF and PACF values for residuals from ARIMA models fit for series of Challakere market

Groundnut Arrivals

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	0.037	.072	0.260	1	.610	.037	.072
2	-0.105	.072	2.412	2	.299	-.107	.072
3	0.090	.071	3.994	3	.262	.099	.072
4	0.034	.071	4.228	4	.376	.015	.072
5	-0.048	.071	4.691	5	.455	-.031	.072
6	0.023	.071	4.796	6	.570	.024	.072
7	0.015	.071	4.842	7	.679	.000	.072
8	-0.047	.070	5.277	8	.728	-.036	.072
9	0.012	.070	5.308	9	.807	.016	.072
10	-0.054	.070	5.900	10	.824	-.070	.072
11	-0.086	.070	7.416	11	.764	-.070	.072
12	-0.014	.070	7.457	12	.826	-.020	.072
13	-0.170	.069	13.425	13	.416	-.185	.072
14	-0.038	.069	13.730	14	.470	-.007	.072
15	0.022	.069	13.834	15	.538	-.013	.072
16	-0.002	.069	13.835	16	.611	.016	.072

Groundnut Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.005	.072	0.005	1	.944	-.005	.072
2	.017	.072	0.060	2	.970	.017	.072
3	-.045	.071	0.460	3	.928	-.045	.072
4	.012	.071	0.490	4	.975	.012	.072
5	-.080	.071	1.770	5	.880	-.079	.072
6	.027	.071	1.917	6	.927	.024	.072
7	.075	.071	3.044	7	.881	.079	.072
8	.057	.070	3.692	8	.884	.050	.072
9	.016	.070	3.745	9	.927	.019	.072
10	-.098	.070	5.700	10	.840	-.102	.072
11	-.023	.070	5.810	11	.886	-.019	.072
12	-.029	.070	5.980	12	.917	-.014	.072
13	.072	.069	7.051	13	.899	.071	.072
14	.022	.069	7.156	14	.929	.021	.072
15	-.012	.069	7.186	15	.952	-.042	.072
16	.103	.069	9.406	16	.896	.106	.072

Sunflower Arrivals

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.003	.072	0.002	1	.967	-.003	.072
2	-.003	.071	0.003	2	.999	-.003	.072
3	.018	.071	0.069	3	.995	.018	.072
4	-.001	.071	0.069	4	.999	-.001	.072
5	-.031	.071	0.263	5	.998	-.031	.072
6	.028	.071	0.424	6	.999	.028	.072
7	.119	.070	3.292	7	.857	.120	.072
8	-.037	.070	3.569	8	.894	-.035	.072
9	.005	.070	3.575	9	.937	.004	.072
10	-.009	.070	3.593	10	.964	-.014	.072
11	.096	.070	5.506	11	.904	.102	.072
12	-.017	.070	5.567	12	.936	-.011	.072
13	-.114	.069	8.271	13	.826	-.126	.072
14	-.007	.069	8.282	14	.874	-.024	.072
15	.031	.069	8.484	15	.903	.045	.072
16	.006	.069	8.491	16	.933	.017	.072

Sunflower Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.005	.072	0.004	1	.948	-.005	.072
2	.001	.072	0.005	2	.998	.001	.072
3	-.097	.071	1.860	3	.602	-.097	.072
4	-.063	.071	2.647	4	.619	-.065	.072
5	.015	.071	2.689	5	.748	.014	.072
6	-.005	.071	2.694	6	.846	-.014	.072
7	.066	.071	3.558	7	.829	.054	.072
8	.078	.070	4.774	8	.781	.079	.072
9	.006	.070	4.781	9	.853	.008	.072
10	-.054	.070	5.380	10	.864	-.045	.072
11	-.091	.070	7.092	11	.792	-.072	.072
12	-.072	.070	8.162	12	.772	-.068	.072
13	.026	.069	8.297	13	.824	.014	.072
14	.043	.069	8.678	14	.851	.022	.072
15	.083	.069	10.116	15	.812	.058	.072
16	.010	.069	10.136	16	.859	.005	.072

APPENDIX-III: ACF and PACF values for series of Sira market.

Groundnut Arrivals

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	.395	.090	19.200	1	.000	.395	.091
2	-.075	.090	19.903	2	.000	-.274	.091
3	-.136	.089	22.218	3	.000	.013	.091
4	-.134	.089	24.474	4	.000	-.117	.091
5	-.070	.089	25.093	5	.000	.009	.091
6	.021	.088	25.147	6	.000	.015	.091
7	-.051	.088	25.484	7	.001	-.123	.091
8	-.133	.087	27.806	8	.001	-.081	.091
9	-.146	.087	30.618	9	.000	-.100	.091
10	-.097	.087	31.861	10	.000	-.046	.091
11	.113	.086	33.567	11	.000	.150	.091
12	.276	.086	43.928	12	.000	.134	.091
13	.140	.085	46.620	13	.000	-.045	.091
14	-.046	.085	46.917	14	.000	-.041	.091
15	-.109	.085	48.578	15	.000	-.039	.091
16	-.083	.084	49.536	16	.000	-.005	.091

Groundnut Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	.922	.090	104.622	1	.000	.922	.091
2	.884	.090	201.519	2	.000	.223	.091
3	.852	.089	292.262	3	.000	.090	.091
4	.816	.089	376.375	4	.000	.002	.091
5	.796	.089	457.093	5	.000	.093	.091
6	.768	.088	532.743	6	.000	-.017	.091
7	.714	.088	598.864	7	.000	-.191	.091
8	.667	.087	657.018	8	.000	-.090	.091
9	.630	.087	709.296	9	.000	.019	.091
10	.589	.087	755.476	10	.000	-.026	.091
11	.559	.086	797.406	11	.000	.022	.091
12	.524	.086	834.689	12	.000	.002	.091
13	.482	.085	866.424	13	.000	-.034	.091
14	.444	.085	893.677	14	.000	-.014	.091
15	.399	.085	915.920	15	.000	-.087	.091
16	.363	.084	934.437	16	.000	-.009	.091

Differenced (D=1) Series of Groundnut Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.184	.091	4.112	1	.043	-.184	.092
2	-.143	.090	6.637	2	.036	-.183	.092
3	-.055	.090	7.018	3	.071	-.129	.092
4	-.166	.089	10.458	4	.033	-.254	.092
5	.046	.089	10.720	5	.057	-.103	.092
6	.198	.089	15.733	6	.015	.110	.092
7	-.010	.088	15.747	7	.028	.027	.092
8	-.038	.088	15.935	8	.043	-.006	.092
9	-.034	.087	16.084	9	.065	-.001	.092
10	-.085	.087	17.032	10	.074	-.041	.092
11	.058	.087	17.486	11	.094	.020	.092
12	.094	.086	18.674	12	.097	.056	.092
13	-.032	.086	18.809	13	.129	-.007	.092
14	.050	.085	19.158	14	.159	.074	.092
15	-.075	.085	19.930	15	.175	-.014	.092
16	-.042	.085	20.181	16	.212	-.003	.092

Sunflower Arrivals

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	.423	.090	21.976	1	.000	.423	.091
2	-.027	.090	22.066	2	.000	-.250	.091
3	-.150	.089	24.871	3	.000	-.038	.091
4	-.032	.089	25.001	4	.000	.072	.091
5	.027	.089	25.092	5	.000	-.028	.091
6	.066	.088	25.659	6	.000	.062	.091
7	.014	.088	25.685	7	.001	-.039	.091
8	-.047	.087	25.972	8	.001	-.034	.091
9	-.112	.087	27.629	9	.001	-.078	.091
10	-.054	.087	28.016	10	.002	.027	.091
11	.341	.086	43.666	11	.000	.437	.091
12	.599	.086	92.345	12	.000	.361	.091
13	.312	.085	105.672	13	.000	-.045	.091
14	-.058	.085	106.132	14	.000	-.048	.091
15	-.142	.085	108.932	15	.000	.004	.091
16	-.082	.084	109.889	16	.000	-.073	.091

Sunflower Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	.935	.090	107.487	1	.000	.935	.091
2	.880	.090	203.507	2	.000	.048	.091
3	.850	.089	293.832	3	.000	.174	.091
4	.805	.089	375.535	4	.000	-.106	.091
5	.757	.089	448.549	5	.000	-.021	.091
6	.711	.088	513.448	6	.000	-.060	.091
7	.664	.088	570.559	7	.000	-.026	.091
8	.618	.087	620.405	8	.000	-.028	.091
9	.578	.087	664.431	9	.000	.030	.091
10	.529	.087	701.708	10	.000	-.089	.091
11	.474	.086	731.938	11	.000	-.073	.091
12	.442	.086	758.362	12	.000	.105	.091
13	.435	.085	784.294	13	.000	.221	.091
14	.421	.085	808.771	14	.000	.027	.091
15	.401	.085	831.184	15	.000	-.010	.091
16	.376	.084	851.057	16	.000	-.128	.091

Differenced (D=1) Series of Sunflower Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.156	.091	02.971	1	.085	-.156	.092
2	-.245	.090	10.338	2	.006	-.276	.092
3	.094	.090	11.439	3	.010	.003	.092
4	-.018	.089	11.480	4	.022	-.074	.092
5	-.023	.089	11.547	5	.042	-.015	.092
6	.031	.089	11.667	6	.070	.001	.092
7	-.004	.088	11.669	7	.112	-.001	.092
8	-.018	.088	11.710	8	.165	-.011	.092
9	-.070	.087	12.350	9	.194	-.087	.092
10	-.011	.087	12.365	10	.261	-.052	.092
11	-.023	.087	12.435	11	.332	-.084	.092
12	-.123	.086	14.483	12	.271	-.175	.092
13	.055	.086	14.890	13	.314	-.041	.092
14	.058	.085	15.344	14	.355	-.019	.092
15	.041	.085	15.579	15	.411	.075	.092
16	-.154	.085	18.879	16	.275	-.151	.092

Appendix-IV: ACF and PACF values for residuals from ARIMA models fit for series of Sira market

Groundnut Arrivals

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.082	.091	0.830	1	.362	-.082	.092
2	.004	.090	0.832	2	.660	-.003	.092
3	-.087	.090	1.778	3	.620	-.088	.092
4	-.024	.089	1.850	4	.763	-.039	.092
5	-.076	.089	2.573	5	.765	-.083	.092
6	.065	.089	3.108	6	.795	.044	.092
7	-.027	.088	3.202	7	.866	-.026	.092
8	-.055	.088	3.591	8	.892	-.075	.092
9	-.040	.087	3.796	9	.924	-.049	.092
10	-.084	.087	4.722	10	.909	-.103	.092
11	.053	.087	5.101	11	.926	.031	.092
12	-.012	.086	5.119	12	.954	-.028	.092
13	.052	.086	5.484	13	.963	.023	.092
14	-.001	.085	5.484	14	.978	.003	.092
15	-.036	.085	5.666	15	.985	-.052	.092
16	-.032	.085	5.811	16	.990	-.026	.092

Groundnut Prices

Lag	ACF	S.E(ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.069	.095	0.517	1	.472	-.069	.097
2	.003	.095	0.518	2	.772	-.002	.097
3	-.038	.094	0.684	3	.877	-.039	.097
4	.064	.094	1.143	4	.887	.059	.097
5	-.003	.094	1.144	5	.950	.005	.097
6	-.088	.093	2.037	6	.916	-.090	.097
7	.010	.093	2.048	7	.957	.003	.097
8	.006	.092	2.052	8	.979	.003	.097
9	.071	.092	2.657	9	.976	.067	.097
10	-.003	.091	2.658	10	.988	.018	.097
11	-.031	.091	2.774	11	.993	-.032	.097
12	.116	.090	4.439	12	.974	.111	.097
13	-.072	.090	5.077	13	.973	-.066	.097
14	-.005	.089	5.080	14	.985	-.016	.097
15	-.093	.089	6.187	15	.976	-.073	.097
16	.017	.088	6.225	16	.985	-.012	.097

Sunflower Arrivals

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.053	.091	0.342	1	.558	-.053	.092
2	-.015	.090	0.369	2	.832	-.017	.092
3	-.129	.090	2.438	3	.487	-.131	.092
4	.021	.089	2.494	4	.646	.007	.092
5	-.033	.089	2.627	5	.757	-.037	.092
6	-.008	.089	2.636	6	.853	-.029	.092
7	-.062	.088	3.123	7	.873	-.063	.092
8	-.049	.088	3.433	8	.904	-.068	.092
9	-.015	.087	3.464	9	.943	-.031	.092
10	-.117	.087	5.277	10	.872	-.145	.092
11	.176	.087	9.417	11	.583	.149	.092
12	.025	.086	9.499	12	.660	.025	.092
13	.050	.086	9.832	13	.708	.023	.092
14	-.091	.085	10.972	14	.688	-.052	.092
15	-.045	.085	11.255	15	.734	-.070	.092
16	-.062	.085	11.795	16	.758	-.067	.092

Sunflower Prices

Lag	ACF	S.E (ACF)	Box-Ljung Statistic			PACF	S.E (PACF)
			Value	df	Sig.(Value)		
1	-.053	.095	.304	1	.581	-.053	.097
2	.053	.095	.614	2	.736	.050	.097
3	-.013	.094	.633	3	.889	-.008	.097
4	-.012	.094	.648	4	.958	-.015	.097
5	-.037	.094	.802	5	.977	-.037	.097
6	.020	.093	.848	6	.991	.018	.097
7	-.058	.093	1.245	7	.990	-.053	.097
8	-.078	.092	1.966	8	.982	-.087	.097
9	-.068	.092	2.521	9	.980	-.073	.097
10	-.096	.091	3.640	10	.962	-.100	.097
11	-.044	.091	3.881	11	.973	-.054	.097
12	-.042	.090	4.098	12	.982	-.051	.097
13	.030	.090	4.209	13	.989	.018	.097
14	-.023	.089	4.273	14	.994	-.028	.097
15	.135	.089	6.588	15	.968	.116	.097
16	-.121	.088	8.472	16	.934	-.125	.097