

**Changing Scenario of Kerala Agriculture -
*an overview***

By

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THESIS

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requirements for the degree of

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**Faculty of Agriculture
Kerala Agricultural University**

Department of Agricultural Statistics

**COLLEGE OF HORTICULTURE
VELLANIKKARA, THRISSUR - 680656**

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2009

DECLARATION

I hereby declare that this thesis entitled "Changing Scenario of Kerala agriculture - an overview" is a bonafide record of the research work done by me under the guidance and supervision of Smt. T.K. Ajitha, Assistant Professor, College of Horticulture, Vellanikkara. I further declare that the thesis has not previously formed the basis for the award of any degree, diploma, associateship, fellowship or other similar title of any other University or Society.

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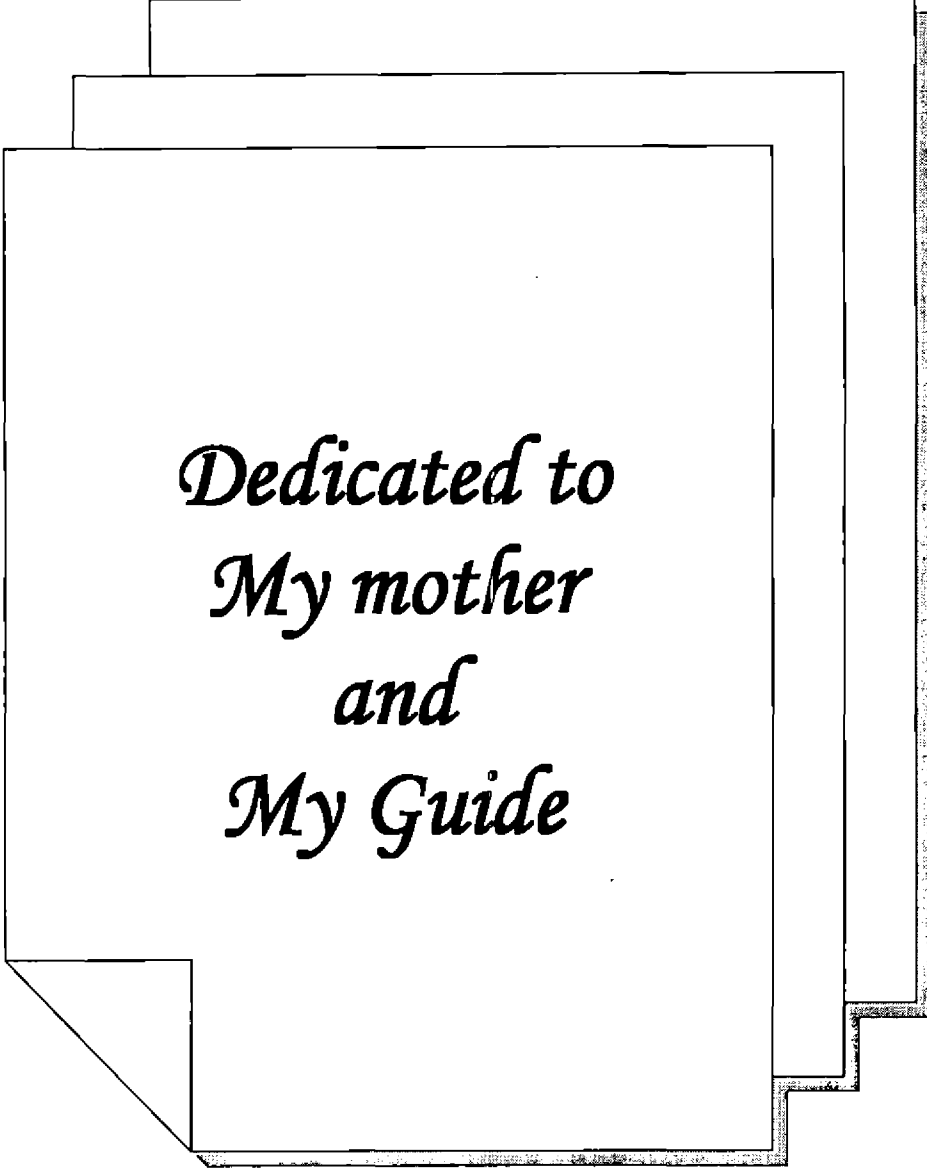
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Finally, a gentle plea of mine to the reader - be observant. It is a fascinating and interdisciplinary area of applied mathematics which may richly reward those who invest some time and effort to study it.

JUB. J. Unnikrishnan
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*Dedicated to
My mother
and
My Guide*

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LIST of ABBREVIATIONS

ACF	:	Autocorrelation Function
ADF	:	Augmented Dickey-Fuller
AIC	:	Akaike Information Criterion
ANFIS	:	Adaptive Neural Network-based Fuzzy Inference System
ANN	:	Artificial Neural Network
AR	:	Auto Regressive
ARIMA	:	Auto Regressive Integrated Moving Average
BP	:	Back Propagation
CNN	:	Computational Neural Network
DFT	:	Dickey Fuller Test
DMSNN	:	Direct Multi-Step Neural Network
FCED	:	Food and Consumer Economic Division
I	:	Integrated
IBGE	:	Instituto Brasileiro de Geografia e Estatística
MA	:	Moving Average
MAE	:	Mean Absolute Error
MAFE	:	Mean Absolute Forecasting Error
MAFPE	:	Maximum Absolute Forecasting Percentage Error
MAPE	:	Maximum Absolute Percentage Error
MaxAE	:	Maximum Absolute Error
MaxAFE	:	Maximum Absolute Forecasting Error
MSED	:	Mean Squared Error Difference
PACF	:	Partial Auto Correlation Function
PFI	:	Percentage Forecast Inaccuracy
R ²	:	R-Square
RBF	:	Radial Basis Function
RMNN	:	Recursive Multistep Neural Network
RMSE	:	Root Mean Square Error
RSSI	:	Required Supplemental Stewardship Information
SARIMA	:	Seasonal Auto Regressive Integrated Moving Average
SBC	:	Shwartz Bayes Criterion

Introduction

1. INTRODUCTION

Agriculture is the oldest occupation in the world and remains the largest one even today. In a developing country, agriculture provides the largest source not only of income but also of employment. Agriculture in Kerala is unique and totally different from that of other states in India by the prevalence of characteristic coconut based cropping pattern and predominance of cash crops. The bio-diversity of Kerala is amazing and the entrepreneurship of the Kerala farmer is comparable with any advanced agricultural countries in the world. Yet more and more people are turning away from agriculture as a primary occupation due to a variety of reasons like faulty agricultural policies, lack of remunerative prices, infrastructure facilities, lower productivity etc. Most of the income of Keralites is from agriculture. The peculiar agro climatic situations prevailing in the state of Kerala make it suitable to grow diversified crops. The average rainfall per year in Kerala is 290 cm. Kerala is blessed with many ever flowing rivers. Artificial dams and canals are also made for irrigating thousands of hectares of land. Kerala's agriculture has the distinction of having the highest gross income per net cropped area. On a national scale, 93% of black pepper, 92% of the rubber, 70 % of coconut, 60 % of tapioca and almost 100 % of lemon grass oil is produced from Kerala. It is also the single largest producer of a number of other crops like pineapple, cocoa, nutmeg and ginger, besides having tea and coffee in abundance.

Unlike the other regions in India, Kerala state is characterized by extreme diversity in its physical resources and agro-climatic endowments. In earlier periods, the choice of cropping pattern was guided by agronomic considerations and consumption needs of farmers but now the market forces decide it. Official reports show that agricultural income in Kerala showed a steady growth up to mid seventies, followed by a decline thereafter and an oscillating trend in the eighties. By the end of eighties, cash crops started generating higher income to the farm sector. The contribution of agriculture to the state's income has been on decline as the other sectors registered higher rates of growth. Even though the sector has recorded positive trend in growth performance in nineties, it has not been consistent. Food crops in general have suffered a set back in area and production despite a sizeable investment.

Marginalization of agricultural holdings due to extreme sub divisions and fragmentation and the decreasing trend in family participation in farm operations with resultant increase in production costs and dominance of perennial crops make Kerala agriculture more vulnerable. Agriculture development experience of the state since the late seventies has been characterized by sharp decline in the area under food crops mainly paddy and the substantial expansion

in the area under commercial agriculture dominated by plantation crops. Relatively higher profitability of cash crops and plantations, the higher labour intensive and seasonal nature of cultivation and the increasing wage rate, the exemption of plantation crops from land reform act, phenomenal increase in the export price of many of the plantation crops and the promotional activities by the government in the area of plantation and cash crops have definitely encouraged the cultivators in Kerala to opt for higher valued cash crops or plantations wherever possible and curtail the area under rice and other food grains to the minimum.

The declining growth rate of area under food crops in Kerala have well been documented by many scientists. In this context it is important to examine critically the past performance of agriculture and based on it, future prospects of growth can be estimated.

The agricultural scenario of Kerala indicates a heavy concentration of non-food crops. The major feature of the cropping pattern of agriculture in Kerala is the predominance of crops which are having high demand in the international market. Another notable feature of agricultural development in Kerala is the emergence of cash crops as a dominant sector over the last four decades. The dominance of plantation and spice crops which are export oriented, makes the prospects of Kerala farmers to be on the world market scenario.

Adverse ecological consequences have been aroused due to increasing conversion of low-lying paddy lands for non-agricultural purposes after filling the land. The filling of paddy lands and over exploitation of irrigation facilities too affected water conservation adversely and a growing tendency is also created to leave the paddy lands as fallow due to low income from cultivation. Since productivity of major commercial crops is low, the cost of production is higher in the state, which makes the product less competitive. Since most of the farms are owned and operated by persons whose primary occupation is non agriculture and they have a little interest in investing in lands or maximizing income from agriculture.

Keeping in view the importance of the agriculture, quantitative assessment of contribution of the various factors to growth, crop output etc. and fixing productivity at the state level will be helpful in reorienting the programmes and priorities of agricultural development so as to achieve higher growth.

In the present study, an earnest attempt is being made to evaluate the problem of decelerating trend of area, production and productivity through advanced statistical models. For this purpose the data on area, production, productivity, price etc. of the major crops of Kerala for the period from 1952 - 53 to 2006 - 07 have been analyzed to arrive at a genuine and valid conclusion. The study is shaped in such a way as to assimilate to the bygone and ongoing

transitional phase of the major crops taken for the study.

Several studies on Kerala Agriculture often concentrated on certain specific areas like the land utilization pattern and cropping pattern as the analysis of the specific trends related to area, production, productivity and price of one or two crops separately. Also the statistical techniques used were different. The present study has a special importance which lies in the fact that the prediction models for predicting the area, production, productivity and price of different crops in Kerala have not been addressed in a detailed and comprehensive manner taking so many crops as well as methodologies at a time in the earlier studies. Forecasts can be made in many different ways, the choice of the method depending on the purpose and importance of the forecasts as well as the costs of alternative methods. Hence a novel attempt is made in the present study to construct prediction models using ARIMA models as well as other standard techniques.

In time series analysis, an autoregressive integrated moving average (ARIMA) model is a generalisation of an autoregressive moving average (ARMA) model. These models are fitted to time series data either to better understand the data or to predict future points in the series. The model is generally referred to as an ARIMA(p,d,q) model where p, d and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. ARIMA models form an important part of the Box-Jenkins approach to time-series modelling.

The steady advancements achieved by Mathematicians, Statisticians and Economists in the area of forecasting especially using time series analysis increased the reliability on forecasts. One cannot spell out exactly where forecasts are more frequently needed as the forecasting techniques have become essential features in all the ministries, establishments, public and private sectors. As the food security corner of Kerala is concerned, such a forecasting will cradle the government to tide over grim situations with ease.

Keeping in view the importance of forecasting, the present study was carried out with the following objectives.

1. To study the trend and growth rates of area, production, productivity and price of major crops of Kerala.
2. To test the cointegrated movement of price and respective area of each crop.
3. To identify the best ARIMA model for prediction of area, production, productivity and price of major crops of Kerala.
4. To compare predictability of forecasting models developed by different techniques.

Review of Literature

2. REVIEW OF LITERATURE

A brief review of the available literature, on various topics related to the study is attempted and presented in this chapter under the following sub headings.

2.1 Trend and Growth rate

2.2 Co integration

2.3 ARIMA modeling

2.1. Trend and Growth rate

Lal, R.C. and Lavania, R.P. (1984) measured the growth rates of production of major crops of Agra district, and the contribution of the growth of area and productivity of the crops under study.

Castro, P., Nacamuli, S., De-Castro, P. (1986) discussed the geographical distribution of cereal production in Italy, noting the evolution in surface area, yield and production for each of the main products

Lakshmi, K.R and Pal, T.K. (1986) studied changes in trends and growth rates of area under cultivation, production and productivity of cassava in India and the contribution of such components as area and productivity and their interaction on the total production of the crop.

Lakshmi, K.R. and Pal, T.K. (1988) analysed the agricultural output growth in Kerala over the period 1952/53-1984/85. Compound growth rates of area, yield and production are presented for 10 crops, which together cover more than 80% of the total cropped area. Despite a decreasing trend in the yields of cashew and coffee, compound production growth rates were positive due to the increasing area under these crops. The declining yield of coconut resulted in a nonsignificant compound growth rate for output. The analysis by component elements for the period 1952-55 to 1982-85 showed that nearly 50% of the change in crop output was due to the change in the total area under the 10 crops, and 42% due to the change in yields.

Hashmi, S.N.I. and Singh, A.L. (1989) calculated compound growth rates of area, yield and production of rice in 13 districts of western Uttar Pradesh for the pre- and post-high yielding varieties periods. Six districts recorded relatively higher growth rates of production during the post-HYV period (1966/67-1985/86), mainly due to the increase in rice yield in these districts. One district recorded a higher growth rate in production due to the interaction of area and yields..

Tchuigoua, F.B. (1990) examined the Algerian and the Tanzanian models. Algeria, which inherited a poverty-ridden dualistic agriculture, was committed to industrialization and a reallocation of resources to satisfy the domestic market. Despite a policy of decolonizing agriculture, a high growth rate of agricultural production was not achieved, nor has production growth rate adjusted to population growth and rising income.

Salam, M.A., Babu, K.S and Balasubrahmanian, P.P. (1992) analysed the trends in area, production and productivity of cashew in Kerala for the past 27 years. The study revealed that the area under cashew in Kerala increased rapidly from 1975-76 to 1983-84 and declined thereafter. In the case of production it showed a steady increase from 1962 to 1975 and after it declined. Productivity showed high fluctuations during 1961 to 1988 and it contributed more to production during 1977 to 1988.

Gupta, B.S., Mathur, B.K. and Purohit, M.L. (1992) studied the effect of agro-climatic variations in the growth rates of area, production and productivity of pearl millet (*Pennisetum glaucum*) in the arid region of Rajasthan. The study was conducted during 1956/57-1966/67 (pre-Green Revolution) and 1967/68-1987/88 (post-Green Revolution). Compound growth rate of area during the post-Green Revolution period was less than that during the pre-Green Revolution period in all four micro-units. Growth rate during the Green Revolution period was found to be significant and positive in all the micro-units except in arid irrigated kharif and rabi cropping. Similarly, compound growth rate of production during pre-Green Revolution period was higher than that under the post-Green Revolution period. Compound growth rate of productivity was non-significant in the post-Green Revolution period and was less than that in pre-Green Revolution period in all the four micro-units

Gautam, D.S., Nahatker, S.B and Rajput, R.L. (1992) noted that the annual growth rate of production was positive for soyabeans but negative for sesame in Madhya Pradesh state as a whole as well as in Tawa Command area. Production costs and returns were obtained for the two crops.

Mahmud, Z., Akuba, R.H and Amrizal (1992) found that the high growth rate of production from government estates was mainly due to area expansion and high productivity. Lal, S.K., Srinivas, T and Srivastava, R. (1994) made an analysis of the growth rates of area, production and productivity of rice, wheat and maize in Bihar state, India over the period 1951/52-1987/88, which involved the pre- and post-Green Revolution period. The growth rate of production was significant for all crops due to the significant growth in productivity. The contribution of area to production was not significant for rice.

Jeromi, P.D. (1994) studied pepper (*Piper nigrum*) production in Kerala. Its specific objectives were to examine the growth and instabilities in area, production and productivity of pepper in comparison with its competing crops in the state; to estimate the contributions of area and productivity to pepper production; and to analyse the growth and instabilities in pepper exports. Results indicated that increased area under pepper had been the major contributor to growth of production since the 1960s and that growth in yield had been negative. Efforts should therefore be made to both increase and stabilize yields. The growth rates of area and production for rubber, coffee and cardamom revealed that pepper was facing acute competition from those crops. Pepper cultivation in the state was extensive rather than intensive. The amount exported had been increasing in recent years. However, it could be concluded that the growth of pepper in Kerala had not been encouraging in view of the high instabilities in production, stagnant yields and export uncertainties

Giriappa, S. (1995) analysed growth trends in area, production and yields of major plantation crops in India since the 1960s and examined the problems and prospects of cultivation of coffee, cocoa, rubber, black pepper (*Piper nigrum*) and cardamom in various regions of Karnataka and Kerala. Cultivation of intercrops had enabled growers to achieve better returns. The larger holdings had a better cost-benefit ratio. Rubber became a fast emerging plantation crop which has a promising future. Plantation crops became more export-oriented and competitive globally by means of technical progress, increased productivity and quality

Haque, M.E., Hossain, M.I. and Afroz, K. (1998) examined the growth rates for rice of acreage, production and yield both at Bangladesh national and regional levels and to compare them between the sub periods 1972/73 to 1979/80 (the first sub period) and 1980/81 to 1991/92 (the second sub period) using time series data. During the whole period the growth rate of area was positive and significant for both at national and regional levels. In the second subperiod the growth rate for area was lower than that in the first sub period in Chittagong.

Bezbaruah, M.P. (1998) examined trends in the production of rice in different seasons and across districts in Assam using area, production and yield data for the period 1974/75 to 1994/95. For the state as a whole, there had been a significant upward trend in production. But the rates of growth of both production and yield were modest in comparison to those achieved in West Bengal and Orissa and at the all India level. As for the seasonal composition of production there had been a shift towards summer and winter rice which were less prone to flood damage. This shift had been made possible by expansion of irrigation, particularly of lift irrigation in the private sector during the 1980s

Gangadharan, P. (2000) developed a decomposition formula for splitting production contribution of coconut in to area contribution and productivity contribution.

Sharma, J.K. et.al. (2000) made an attempt to fit non-linear regression options for estimating the parameters of all the selected models, i.e. logistic, Gompertz and monomolecular model, in knowing the past and future growth pattern of the rapeseed-mustard group of crops.

Singh, R.P., Pandey, R.K. and Kumar, A. (2003) carried out a study to examine the cropping pattern; growth rate, production and productivity; and variability in area, production and productivity of wheat, during the pre- and post-green revolution periods in the agro climatic sub zones IV, V and VI of Jharkhand, Bihar, India. The productivity per hectare increased during the green revolution period in all sub zones. Growth analysis showed that there was a positive trend in both periods, although the growth rate was more pronounced during the post-green revolution. A similar trend was observed in case of production. The rate of increase in area was more pronounced in sub zones IV and V in comparison to zone VI. However, no marked difference in the magnitude of variability in productivity during the pre- and post-green revolution period was observed.

Bordoloi, P.K. and Kakaty, S.C. (2003) estimated trends in tea production, exports and domestic consumption in India, Sri Lanka and Kenya during the period 1971-2000 using dummy variables and linear regression models

Chand, R. and Raju, S.S. (2008) divided the time series in to three parts (1) pre-green revolution period, (2) first phase of green revolution and (3) wider dissemination of technology period. The first phase was taken as 1951 to 1965, the second phase was taken from 1968 to 1988 and third phase covered the period 1989 to 2006 or 2007.

Sebastian, S., Thomas, K.J. and Thomas, E.K. (2009) evaluated the degree of response of the cashew producers to price and non-price factors affecting cashew nuts in the state. From the analysis it was revealed that the average relative price of cashew nut had a significant influence on area of cultivation and yield.

2.2. Cointegration

Weiss, D. (1992) derived cointegration models from time series analysis, to make it possible to present long term equilibrium relationships between economic variables even when the time series entered in the model did not satisfy stationarity characteristics. The method was illustrated by an empirical test of the "law of one price" using monthly and quarterly data on German import prices and world market prices for bananas, coffee, cocoa, tea and soya

chips for the period 1973-90..

Habibullah,MS., Baharumshah,A.Z.(1994) determined the existence of cointegration between black and white pepper markets in Malaysia. The theory held was that for a cointegrated pepper market, pepper farmers could use changes in the black pepper prices to forecast white pepper prices, and gain excess profit consistently by using the changes in black pepper prices as a trading rule.

Sinharo,S. and Nair,S.R.(1994) examined whether the movements in the international prices of Indian pepper had reflected the variations in prices in other exporting countries during the 1980s and whether the domestic price of pepper had moved synchronously with international price.

Zubaidi,A.,B and Shah,M.H (1994) applied cointegration tests of spatial price relationships to weekly black pepper and white pepper prices at six regional markets in Sarawak, Malaysia using data for the period 1986-91.

Thirtle,C et al. (1995) used cointegration to determine the structure of spill overs between the EU countries (and the USA) and to avoid spurious regressions.

Liang,C.L., Feuz,D.M. and Taylor, R. G. (1997) performed two sets of cointegration tests on regional dry bean prices. The results showed (1) prices for the same variety were cointegrated across geographically separated production areas, and (2) prices for different varieties grown in the same production area were not cointegrated.

Hompson,S. and Bohl,M.T.(1999) estimated the international wheat price transmission elasticity for Germany. A model of cointegration was examined over a period of policy regime changes. A threshold cointegration model was applied allowing the discernment of the existence of the long run equilibrium relationship among the statistic processors

Mainardi,S. (2001) applied the threshold and smooth transition cointegration models to quarterly wheat prices of 3 major world suppliers over the period 1973-99.

Naik,G and Jain,S.K.(2001) assessed the efficiency of major commodity futures markets in India, using the cointegration technique.

Ghoshray,A. (2002) examined price differentials in pairs for the international wheat market from July 1980-December 1998 using a cointegration model with asymmetric adjustment known as threshold autoregressive and momentum threshold autoregressive adjustment.

Naik,G, Jain,S.K.(2002) assessed the performance of Indian futures markets in terms of risk management and price discovery functions. The usefulness of futures markets in risk

management was evaluated by analysing the risk involved in the spot, futures, and basis of commodities, while their role in price discovery was evaluated by examining forward pricing ability through tests of cointegration between cash and futures prices and tests for efficiency and lack of bias.

Vickner, S.S. (2002) estimated that for every one unit increase in inventory turnover, market capitalization increased by \$479 million in the Food Away From Home (FAFH) industry over the analysis period using the cointegration model. The equity capital market placed a premium on the efficient management of inventories in the food system and rewarded those firms that developed, adopted and implemented supply chain management technologies.

Abdulai, A. (2006) employed a momentum-based threshold cointegration model that considered transaction costs to examine important maize markets in Ghana for different time periods.

Jun, W. and YaQing, L. (2007) examined the dynamic relationship between China's soyabean oil spot and future prices by using VAR model, cointegration test, error correction model, impulse response analysis and variance decomposition methods, etc.

2.3. ARIMA

Oliveira, R.A., Buongiorno, J. and Kmietek, A.M. (1977) fitted ARIMA models to weekly data by the Box-Jenkins time series modelling procedure and gave relatively accurate short run forecasts for lumber cash prices and lumber futures prices

Bessler, D.A. (1978) investigated empirical evidence on the structure of 1977 price expectations of farmers of seven California field crops. From the general class of auto-regressive integrated moving average models, it was found that 1933-1976 and 1947-1976 time series on past values of prices could be adequately represented by uncorrelated noise, and higher order moving average processes.

Carter, C. and Raussler, G.C. (1981) examined the efficiency of futures markets by investigating their forecasting ability in terms of both bias and variability measures. The "relative accuracy" condition for the soybean, soybean oil, and soybean meal futures markets was investigated via structurally based ARIMA models. The constructed models significantly outperformed the futures market for both long- and short-range forecasts.

Carter, C.A. (1981) applied powerful tests of efficiency to the commodity futures market. Expected market returns from this type of market were evaluated within a portfolio context. Two of the most interesting tests of efficiency included an analysis of residual returns

and the employment of ARIMA models to serve as a norm against which the ex-ante forecasting ability of the futures market was compared.

Gupta, S., and Mayer, T. (1981) performed a "semi-strong" form of test of market on five of the commodities in the United Nations Conference on Trade And Development (UNCTAD) Integrated Programme for Commodities list. The test consisted of comparing forecasts made by futures market and ARIMA models with the actual future spot prices. This approach was more rigorous than the "weak-form" tests and was an improvement over the studies which regressed the final spot price in period j on the future price $j-i$ period prior to maturity.

Lee, J.K. and Cheng, C.C. (1981) used Auto-Regressive Integrated Moving-Average model to analyse prices in Taiwan for the period 1962-1980 for the following species: *Chamaecyparis obtusa formosana*, *C. formosensis*, *Tsuga chinensis formosana*, *Cunninghamia lanceolata*, *Quercus* and *Shorea*.

Narayana, N.S.S. and Parikh, K.S. (1981) used ARIMA model and Box-Jenkins methodology in estimating these functions. The study considered nearly all crops grown in India. On the basis of sowing and harvesting periods in different states, an overall substitution pattern among crops was drawn up at the national level, by which they could be classified into ten groups, usually grown in different soils, seasons, or both. The essential data for estimating the acreage response consisted of area, production, yield, irrigation, prices and rainfall.

Standaert, J.E. (1981) determined that random walk models, as identified by ARIMA procedures, performed as well as or better than the econometric models in predicting basis. The results were altered for forecasts of price. Improvements in predictability were observed for models employing structural information on inventories relative to the statistically identified ARIMA models.

Dunn, D.L. (1983) generated farmland price forecasts equation models and two univariate ARIMA models established in the Box-Jenkins context. Comparisons of forecasts were made based on relevant criteria.

Rausser, G.C. and Carter, C. (1983) constructed a simple model to describe the price formulation process in the soyabean complex and estimated the implied ARIMA models of soyabean, soyabean oil, and soyabean meal prices. Employing the mean-square prediction error criterion, the forecasting accuracy of the multivariate and ARIMA models was compared with those of futures markets as well as the random walk representations and found that the multivariate and ARIMA models outperformed the futures markets for soyabeans and

soyabean meal.

Gordon, K., Lagrange, S and Riboud, C. (1984) made an approach to the quantification of national exposure to price shocks in agricultural commodities and shocks in the prices of specific goods in a nation's trade bundle. These measures involved the variances and covariances of price shocks and net import/export weights with ARIMA models fitted to the price series to characterize price uncertainty. This approach was implemented for the agricultural balance of trade in nine major international commodities for 17 countries, those countries representing industrialized, low income industrial based, low income primary export based and non-market economies.

Lin, T.L. and Liu, T.H. (1984) fitted autoregressive integrated moving average (ARIMA) models to population data obtained in 1975-82 in an experimental rice field of about 0.1 ha at Taichung, Taiwan, on *Nilaparvata lugens* (Stal), *Nephotettix cincticeps* (Uhl.), *Lycosa pseudoannulata* (Bosenberg & Strand) and *Oedothorax insecticeps* Bosenberg & Strand for forecasting. No insecticides were applied during the study.

Klugh, B. and Markham, J. (1985) developed Box-Jenkins time series models for the all-, fluid- and manufacturing-milk price series and it outperformed the preliminary milk price estimation procedure in five States and was competitive at the national level. The best performing time series model was developed from the long data series and contained differences at lags 1 and 12, moving average terms at lags 1 and 12, and an autoregressive term at lag 2.

Mesonada, S.J.C. (1985) made an attempt to find the relationship between food prices and agricultural prices from a stochastic dynamic point of view. Two ARIMA models were presented, indicated by consumer price indices for processed and unprocessed foods. The usefulness of the transfer function model was good for forecasting, particularly for early detection of trend changes

Herrmann, R. (1986) fitted the best ARIMA model and assumed to represent the autoregressive price expectation of non-speculative market participants. The forecasting accuracy of the selected ARIMA model had improved or even deteriorated under the influence of the buffer stock activities within the International Cocoa Agreement compared with the situation with no stabilization policy.

Tsui, P.S. and Guitjens, J.C. (1986) used autocorrelation functions (ACF) to evaluate the magnitude of temporal and spatial variations of electrical conductivity. Autoregressive integrated moving average (ARIMA) models for both temporal and spatial structures were established through the Box-Jenkins time-domain modelling process. The degree of uncer-

tainty of the forecasts were tested using after-the-fact forecast procedures.

Thomsen, M.(1987) made methods of yield estimation in the German Federal Republic, cereal production in Schleswig-Holstein, determination of the theoretical yield max., an illustration of long-term cereal yield development using a logistic function, and illustration, analysis and prediction of yield developments using ARIMA-models.

Bell, W. (1988) tried to provide some guidance on how time series methods can be applied in forecasting age-specific fertility. Forecasts were developed from univariate ARIMA(1,1,0) models for $\log(R_{it})$ fit separately for each age.

Olorunnipa, Z.I. (1988) found that the univariate ARIMA model gave lower PRMSE at short-term forecast horizons but was out-performed by the vector autoregression (VAR) models at longer forecast horizons. ARIMA models might be more reliable for tractor sales' forecasts required for short-term decisions such as inventory control, whereas, for longer-term forecasts required for planning production, the VAR models would be the appropriate choice.

Zapata, H.O. (1988) Econometric and time series forecasting models for monthly prices of slaughter steers (1100-1300 lb) were evaluated. Univariate autoregressive integrated moving average (ARIMA) models did well for short forecast horizons (1-3 months ahead). None of the econometric models performed well as evaluated by the Root Mean Square Error (RMSE) and Mean Square Error Difference (MSED). The turning point evaluation indicated that the ARIMAs and BVAR closely followed the movements of actual prices for the 1 month ahead forecast

Moore, D.L. (1989) compared single equation price expectation models of the form viz; simple, weighted, naive, autoregressive moving average (ARIMA) and futures price lagged 17 weeks (FPt-17) to determine accuracy of price prediction for different market positions relative to futures market delivery. Simple weighted and naive models exhibited 4 times less variability as measured by root mean square error (RMSE). FPt-17 exhibited low Durbin Watson values and outperformed ARIMA for RMSE evaluation of production. Theil's U statistic indicated that only ARIMA models accurately reflected time trend changes (turning points). Bootstrapping confirmed that the statistical accuracy of RMSE evaluation, with histograms of MSE frequency distributions was widest for ARIMA and narrowest for simple weighted and naive.

Endrighi, E.(1990) identified the main characteristics of the market for first quality Parmesan cheese (Parmigiano Reggiano) by analysing time series using new methodologies

such as Box-Jenkins. The use of ARIMA models proved extremely valid in this field, and allowed estimation of the time series model as well as of a short-term forecast which, in this case, showed a tendency for the margin to contract as a result of faster price increases at the wholesale than at the consumer level.

Chandran, K.P. and Pandey, N.K. (2007) analysed Potato wholesale prices of Delhi market using univariate seasonal ARIMA model. Seasonal indices showed that generally the price was low from December to May and it picked up from June, and reached the maximum in October. Based on the Schwartz Bayes Criterion (SBC) and Akaike Information Criterion (AIC), the estimated best model was $ARIMA(1,1,1)(1,0,0)_{12}$.

Ikeda, Y. (1990) vibrated intact fruits with random forces and derived a model to describe the dynamic behaviour of the fruit with respect to the forces. The autoregressive-moving average model (ARMA) was assumed, and the fruit parameters were estimated by the recursive least square method, derived from Kalman filter theory. Use of the ARMA parameters for quality evaluation by non-destructive testing was considered.

Rosa, F. (1990) dealt with methods of improving forecasts by combination. Econometric models, time series analysis using ARIMA models and subjective evaluation were the methods at present best known and used in combination. It also dealt with an application of the method to the dairy sector which combined forecasts from a simple econometric method and from an ARIMA model.

Sapsford, D., Varoufakis, Y. (1990) compared the effectiveness of the seasonal ARIMA and econometric approaches in the forecasting of monthly coffee prices. The ARIMA model's one month ahead forecasts, judged by the MSE criterion, outperformed those of the econometric model. The findings would therefore seem to provide some evidence to suggest that at least as far as coffee prices were concerned, the econometric approach to commodity price forecasting is to be preferred over short horizons while for horizons between one and two years ahead, the ARIMA approach appeared more satisfactory.

Shamsudin, M.N., Arshad, M.F. (1990) developed a short term forecasting model for natural rubber prices in Malaysia (Required Supplemental Stewardship Information (RSSI)) using a composite approach. A minimum variance criterion was used to combine the forecasts generated by the econometric and ARIMA models. Despite the fact that the econometric model outperformed the Box-Jenkins model, it was possible to use the minimum variance criterion and combine the two approaches to produce even more efficient forecasts.

Yu, Y.S. and Wang, G.T. (1990) proposed a rainfall-runoff model which combines an

ARMA (autoregressive, moving average) model and Philip's infiltration model. The model parameters were estimated by using a nonlinear minimization technique based on gradients.

Zapata,H.O. and Garcia,P (1990) evaluated forecasting performance of various multivariate as well as univariate ARIMA models in the presence of nonstationarity.

Rosa,F (1991) used ARIMA models to filter the price series

Usowicz,B. (1991) Presented a practical identification and validation of ARIMA type models for determining soil temperature. Results from the models correlated well with each other (+or- 1 degrees C)..

Vroomen,H. (1991) estimated ARIMA models to forecast wholesale prices for anhydrous ammonia, phosphoric acid, and potassium chloride. The wholesale price forecasts were incorporated into regression equations to generate retail price forecasts for anhydrous ammonia, concentrated super phosphate and potassium chloride.

Hudelson et. al. (1993) analyzed arcsine square root-transformed disease-incidence values for spatial patterns using auto-regressive integrated moving average (ARIMA) modeling.

Hudelson,B.D., et.al. (1993) analysed arcsine square root-transformed disease-incidence values for spatial patterns using auto-regressive integrated moving average (ARIMA) These patterns frequently occurred in commercial *P. vulgaris* fields..

Vroomen,H. and Douvelis,G. (1993) used autoregressive-integrated-moving-average (ARIMA) model to forecast the season-average soyabean price for the USA for the marketing years 1989/90 to 1991/92. These forecasts, made during each month of the marketing year, were compared with USDA forecasts. Results indicated that ARIMA models typically outperformed USDA forecasts, especially early in the marketing year, indicating that within-season USDA forecasts may be improved by incorporating information from ARIMA models..

Atan, I.B. and Metcalfe,A. V. (1994) made a 2-stage transformation so that rises were stretched, and recessions were squashed until the series was symmetric over time and then an autoregressive moving average (ARMA) model was fitted to the natural logarithms of this new series

Bender,M and Simonovic,S.P.(1994) compared long-range water-supply forecasting with statistical time-series tools, such as seasonal auto-regressive integrated moving-average modelling.

Briassoulis,-H (1994) used ARIMA (auto regressive-integrated-moving-average) time-

series modelling framework to assess the effectiveness of water-conservation measures in the Greater Athens area of Greece after May 1990, to cope with an impending water shortage. Carvalho, M.A and Silva, C.R.L. (1994) analysed monthly prices of rice and maize using ARIMA models and intervention analysis was used to estimate the effect of the plans to end inflation on the markets for these products. The results showed that maize prices were not significantly affected by the plans, in spite of the price freeze and the sudden change in rules. The rice market, on the other hand, was sensitive to the Cruzado, Verao and Collor plans. It was concluded that agricultural prices suffered more interference from the supply and demand fluctuations of their own markets than from shocks applied to the economy, but the impact of these shocks could not be ignored.

Carvalho, M.A.C., Silva, C.R.L. (1990) proposed a method which used ARIMA models to determine producer prices for Brazil as an alternative to the government intervention minimum prices policy (mean of 60 months).

Douvelis, G. (1994) used ARIMA model that could be used to forecast the US marketing year average price of sunflower seed, by month, for the upcoming year. The ARIMA forecasts came very close to the actual price early during the marketing season.

Jiao, Y. (1994) simulated annual variation in populations of the gelechiid *Pectinophora gossypiella* using the ARMA model and the periodic tendency model, for 1990. The sum of the remainder squares was 1.6901 for the ARMA model and 0.0428 for the periodic tendency model, more accurate than the logistic equation..

Margarido, M.A. et. al. (1994) evaluated the relationship between the wholesale and retail prices of tomatoes in Sao Paulo, Brazil, for the period 1970-92, and quantified through the calculation of the price elasticity. Time series related to wholesale and retail tomato prices were used and ARIMA models were applied. The results showed that tomato prices at wholesale level decisively affected price formation in the retail market.

Sridhar, V.N et. al. (1994) forecasted yield using a combination of the relationship between yield and spectral data (determined from a 2-year pooled regression), and time series analysis using ARIMA (autoregressive integrated moving average), in which 35 years of district wheat yields were used to develop ARIMA models to forecast 1991/92 yields. Wheat area was estimated for 7 districts in Madhya Pradesh in 1991/92 using digital data from LISS-I (Linear Imaging Self Scanner) on the Indian Remote Sensing Satellite (IRS-1B).

Vicente, J.R. (1994) used ARIMA, regression and structural models to analyse the effect on inflation behaviour of shocks in agricultural supply in Brazil during the 1970s and

1980s, when various types of indexation were in force. Nine years of the series were pre-selected to illustrate the hypothesis that inflation acceleration was brought about by expectations of crop failure. Results obtained by regression analysis for eight of the nine years indicated that the hypothesis should not be rejected. However, when the results were analysed in aggregated fashion, using structural and ARIMA models, the variables representing agricultural shocks also showed statistical significance.

Min, B.J. (1995) carried out a study to forecast the changes in the number of pigs and pig farms in the Korea Republic by total and herd size using ARIMA models. The ARIMA model for pig production was identified and estimated using quarterly data for 1985(1) to 1994 (4). The forecasting period was a 3-year horizon, from 1995 (1) to 1997 (4).

Norscia, S. (1995) analyzed the range of prices using ARIMA models applied to two different historical periods, 1970-79 and 1980-89. It demonstrates the existence of seasonal factors and indicates the importance of exports to northern Europe. It also shows the capacity of price to respond to changes in demand. Forecasts since November 1993 were confirmed through observation of actual market prices, suggesting that ARIMA models could be used to evaluate and plan pig supply.

Wang, J.H. and Leu, J.Y. (1995) developed a prediction model useful in predicting the mid-term price trend in Taiwan Stock Market. The system was based on a recurrent neural network trained by using features extracted from ARIMA analyses. By differencing the raw data and examining the ACF and PACF Plots the series was identified as a nonlinear version of the ARIMA(1,2,1).

Aiebrahiem, B.A. (1996) used ARIMA models to account for trend and seasonality, followed by analysis of the components of the regression error. Results indicated that the seasonally adjusted prices resulted from using the first method could be modelled as an ARIMA (0, 1, 0), while the residuals of the regression could be represented as an AR (1) process.

Denbaly, M. et. al. (1996) based on the first subset of the sample, a best-fitting, alternative ARIMA model for each series was computed. The second subset of the data was used to compute out-of-sample forecast errors for both the Food and Consumer Economic Division (FCED) model and the alternative ARIMA models. The bias and the reliability of both sets of forecasts for each price series were then compared. The results showed that forecasts computed using the alternative ARIMA model were more reliable than forecasts computed using the FCED model..

Hameed, T et. al. (1996) modelled the transmission losses series at the Imperial Irri-

gation District, California, USA, with autoregressive-integrated-moving average (ARIMA) process. The ARIMA models were plausible and appropriate models for such series.

Hameed, T., Marifio, M.A. and Cheema, M.N. (1996) observed the transmission losses series at the Imperial Irrigation District, California, USA and modeled as an autoregressive-integrated-moving average (ARIMA) process. The ARIMA models were found to be plausible and appropriate models for such series.

Martino, G. (1996) estimated ARIMA using monthly price series (1988-93) and the Granger-Wiener causality concept was used to analyse the markets' relationships and to verify the hypothesis of the existence of a central-peripheral market system for maize in Italy.

Martino, G. and Marchini, A. (1996) estimated ARIMA models to describe the heterogeneity of the declining importance of agriculture to GDP with respect to EU countries.

Santiago, M.M.D. et al. (1996) analysed the presence of outliers in the indices of prices received by farmers and prices paid by the agricultural sector in Sao Paulo State between 1966 and 1994 by Auto-regressive Integrated Moving Average Model

Fan, S. (1997) used an approach to measure growth in output, input and total factor productivity for Chinese agriculture. The conventional approach (constant price approach) overestimates both aggregate output and input, resulting in biased estimates of total factor productivity growth. Using these newly-estimated production and productivity growth indices, the impact of rural reforms had been reassessed.

Lindahl, J.B. and Plantinga, A.J. (1997) conducted a test for stationarity and fitted autoregressive integrated moving average (ARIMA) models to the data based on preliminary diagnostics. In-sample and out-of-sample price forecasts were then performed.

Lindahl, J.B. and Plantinga, A.J. (1997) done a test for stationarity and fitted (ARIMA) models to the data based on preliminary diagnostics.

Montanari, A, Rosso, R and Taqqu, M.S. (1997) evaluated fractionally differenced autoregressive integrated moving average (FARIMA) model. The lack of flexibility in representing the combined effect of short and long memory was the major limitation of stochastic models used to analyse hydrological time series. In contrast to using traditional ARIMA models, this approach allowed the modelling of short- and long-term persistence in a time series.

Stergiou, K.I., Christou, E.D., and Pettrakis, G. (1997) evaluated seven forecasting techniques on the basis of their efficiency to model and provide accurate operational forecasts of the monthly commercial landings of 16 species (or groups of species) in the Hellenic Marine waters. The results revealed that the univariate ARIMA, closely followed by the Multivariate

DREG time series model, outperformed the others .

Biondi,P., Monarca,D. and Panaro,A. (1998) presented univariate and multivariate ARIMA models for farm tractor demand in Italy, France and the United States. showed that the univariate (ARIMA) models had a lower statistical validity than multivariate ones only for France. The multivariate models presented a remarkable capacity for explanation even though in the case of Italy and France the tractor price index was not significant while the net farm income was not significant for the United States.

Chow,W.S., Shyu-JonChi and Wang-KuoChing (1998) employed the ARIMA and ARIMA transfer function model incorporated with the Box-Cox transformation function for the forecasting of occupancy rate in hotels.

Biondi,P., Monarca,D. and Panaro,A.(1998) presented Simple forecasting models for farm tractor demand in Italy, France and the USA. The models tested were both univariate (ARIMA) and multivariate.

Chow,W.S. (1998) employed the ARIMA and ARIMA transfer function model incorporated with the Box-Cox transformation function for the forecasting of occupancy rate in hotels.

Lech,P.M.(1998) described the application of the ARIMA procedure and discussed, with examples of its application to insect pest and fungal disease forecasting in Polish forests. urovic,N. et. al. (1998) calculated the dependence between rainfall and groundwater depth. The dependence of groundwater depths could be depicted by the ARMA model of the seventh order. Based upon the model, it was possible to create a diagram of groundwater table depth..

Cunha,M.S.da. and Margarido,M.A.(1999) analysed the impact of Brazil's stabilization programmes implemented after 1986 on the General Price Index (GPI). It used (ARIMA) Models, according to the Box-Jenkins approach and intervention analysis

Park, H.S. (1999) showed the forecasted values of ARIMA and U-GARCH did not follow the real data's pattern of TB3. Generally, the univariate forecast models like ARIMA reflected the trend of the last value's real data. In case of MAE and RMSE, the ARIMA model showed better values than U-GARCH and M-GARCH but the model indicated the largest value than others. In detail, the patterns of forecasting values in univariate model such as ARIMA and U-GARCH were similar to a straight line. But M-GARCH followed the pattern of real values and so multivariate models were better than univariate models.

San,N.N. and Deaton,B.J. (1999) utilized the autoregressive integrated moving av-

erage (ARIMA) process to forecast farmers' price expectations for the two primary enterprises: rubber and sheep. Results of the base model indicated that for a given level of resources, technology, and credit repayment policy, the optimal number of trees for a smallholder producer was 593.

Yin-Run Sheng (1999) conducted timber price forecasts with univariate (ARIMA) models employing the standard Box-Jenkins modelling strategy. Using quarterly price series from Timber Mart-South, results showed that most of the selected pine pulpwood and sawtimber markets in 6 southern US states could be evaluated using ARIMA models, and that short-term forecasts, especially those of one-lead forecasts, were fairly accurate.

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Lim, C and McAleer, M. (2000) used (ARIMA) models to explain the non-stationary seasonally unadjusted quarterly tourist arrivals from Hong Kong and Singapore to Australia in 1975-1996.

Saeed, N. et al., (2000) described an empirical study of modelling and forecasting time series data of Wheat Production in Pakistan. The Box Jenkins ARIMA methodology was used for forecasting. The diagnostic checking showed that ARIMA (2, 2, 1) was appropriate. The forecasts from 1998-99 to 2012-13 were calculated based on the selected model. Using ARIMA (2,2,1) the 15 years ahead forecasts and their 95% confidence interval were calculated.

Saeed, N. et al. (2000) described an empirical study of modeling and forecasting time series data of Wheat Production in Pakistan. The Box Jenkins ARIMA methodology had been used for forecasting. The diagnostic checking showed that ARIMA (2, 2, 1) was appropriate.

Santiago, M.M.D. (2000) modelled Autoregressive Integrated Moving Average Models (ARIMA) using the Box-Jenkins approach and including an error correction term .

Sen, L.K., Shitan, M. and Hussain, H. (2000) showed that Autoregressive Moving Average (ARMA) time series models fit the Malaysia's black pepper price series well and they have correctly predicted the future trend of the price series within the sample period of study.

Amongst a group of 25 fitted models, ARMA (1, 0) model was selected based on post-sample forecast criteria.

Krishnankutty, C.N. (2001) predicted future prices of teak in Kerala using the autoregressive integrated moving average (ARIMA) models.

Ahmad, S., Khan, I.H. and Parida, B.P. (2001) identified multiplicative ARIMA model having both non-seasonal and seasonal components as appropriate models. In the deseasonalized modelling approach, the lower order ARIMA models were found appropriate for the stochastic component. Water quality data collected from the river Ganges in India from 1981 to 1990 were used for forecasting using stochastic models. Initially the box and whisker plots and Kendall's tau test were used to identify the trends during the study period. For detecting the possible intervention in the data, the time series plots and cusum charts were used.

Mastny, V. (2001) demonstrated the possible usage of the Box-Jenkins methodology for the analysis of time series for agricultural commodities. A practical illustration of a price development forecast for a selected agricultural commodity. (Czech) was also made.

Shilu, T and Hu-WenBiao (2001) assessed the impact of climate variability on the Ross River virus (RRV) transmission and validated an epidemic-forecasting model in Cairns, Australia and developed autoregressive integrated moving average (ARIMA) models on the data collected between 1985 and 1994, and then validated the models using the data collected between 1995 and 1996.

Carpio, C.E.B.S (2002) used the Autoregressive Integrated Moving Average (ARIMA) model to estimate the expected price of a crop. From the Box-Jenkins approach to determine the order of an ARIMA process, it was concluded that both series, gross returns from cotton and competing crops in India, could be modeled using ARIMA (1,0,0) processes.

Kulendran, N. and Witt, S.F. (2002) provided a comprehensive comparison of the accuracy of modern forecasting methods. Seven forecasting models were examined, including the error correction model and various structural time-series and ARIMA models and found that testing for unit roots was likely to yield reasonably accurate results under certain conditions.

Lim, C. and McAleer, M. (2002) analyzed stationary and non-stationary international tourism time series data by formally testing for the presence of unit roots and seasonal unit roots prior to estimation, model selection and forecasting. Various Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) models were estimated over the period 1975(1)-89(4) for tourist arrivals to Australia from Hong Kong, Malaysia and Singapore.

Lim, C. and McAleer, M. (2002) estimated various Box-Jenkins (ARIMA) models over the period 1975(1)-89(4) for tourist arrivals to Australia from Hong Kong, Malaysia and Singapore.

Adhikari, M., Paudel, K.P. and Houston, J.E. (2003) developed a profit maximization model and an ARIMA model to assess and plan for future water demand needed in broiler production.

Alaba, W. (2003) used an iterative, powerful but rather complicated modelling procedure known as the Box-Jenkins methodology to model the Opeki River flow. ARIMA(2,1,2) was discovered to be the 'best' model that represents the observed records.

Calvo, P.I. et al. (2003) examined methodologies for consumer demand modelling and prediction in a real-time environment for an on-demand irrigation water distribution system. Approaches based on linear multiple regression, univariate time series models (exponential smoothing and ARIMA models), and computational neural networks (CNNs) were developed to predict the total daily volume demand.

Costa, M.C.N. et al. (2003) made a time-series study based on the Ministry of Health's Mortality Information System, Instituto Brasileiro de Geografia e Estatística (IBGE) Foundation and Fundação Nacional de Saúde (National Health Institute) database. Serial parameters were described using autoregressive integrated moving average (ARIMA) models, and the association between infant mortality rates and a number of determinants was evaluated using Spearman correlation coefficients.

Rajaraman, I. and Datta, A. (2003) said there was some broad similarity between the ARIMA processes for Punjab, Rajasthan and Andhra Pradesh, in terms of the autoregressive and moving average terms which best fitted the univariate process.

Rajaraman, I. and Datta, A. (2003) were motivated by the critical need for a short-term forecasting model for the agricultural sector at a sub-national level in India, since good and bad agricultural years, fitted univariate ARIMA models to past agricultural outcomes.

Me´ndez, M.C. et al. (2004) found that the Box-Jenkins models were a suitable method to study the long-term behaviour of hydrological variables such as monthly rainfall or runoff. The linear Box-Jenkins models did not obtain good results in those cases and found a prediction model that reproduced the behaviour of a physical system that would be very complex to treat from a deterministic physical point of view, because of the difficulties in identifying the physical process and the parameters involved.

Mohammadi, K. and Eslami, H.R. (2004) presented the study on minimizing the error

between the observed and calculated data on stream flow of Karun River (Iran) by autoregressive moving average (ARMA) method for a specific season of the year as well as the whole series. Goal programming was used to estimate the ARMA model parameters..

Duenas, C. et. al. (2005) used Studies of temporal series of data, spectral analyses of temporal series and ARIMA models. The performance of ARIMA models suggested that this kind of modelling could be suitable for ozone concentrations forecasting.

Ghafoor, A. and Hanif, S. (2005) designed a study to examine past trends in Pakistani (agricultural) trade both in the case of exports and imports. ARIMA model was used for forecasting imports and exports.

Hocking, T.D. and Lankin, D. (2005) examined the ratio of adults to elderly in the population of the U.S. and modeled as an ARIMA(1,1,0) process in order to formulate a forecast of the ratio for the next 30 years.

Kim, J.H. and Moosa, I.A. (2005) compared the use of direct and indirect forecasting of international tourist flows to Australia. Seasonal ARIMA models, regression-based models and Harvey's structural time series models were used to compare the accuracy of the two forecasting methods.

Koutroumanidis, T. (2005) used the univariate ARMA and ARIMA models to describe wine production in each country during the same period in order to forecast production for each country within the near future. Evaluation of the ARMA and ARIMA models proved their appropriateness, which was also confirmed by the comparisons of real production values with those obtained from the corresponding models

Yureklian, K., Kurunca, A. and Ozturk, F. (2005) presented a methodology on modeling of historical data for monthly flows from Kelkit Stream. For the modeling purpose, Box-Jenkins or ARIMA (Auto Regressive Integrated Moving Average) were used to simulate monthly data. Diagnostic checks were done for all the models selected from the autocorrelation function (ACF) and partial autocorrelation function (PACF). The models that had the minimum Schwarz Bayesian Criterion (SBC) among the selected models fulfilled all the diagnostic checks were assumed as the best model for monthly data. For five years, the predicted data using the best models was compared to the observed data. The basic statistical properties of the observed and predicted data were compared. The results showed that generated data preserved the basic statistical properties of the original series.

Ahmad, B. et. al. (2006) employed Log linear and ARIMA models to forecast export of mango.

Coshall, J. (2006) applied Time series models to outbound travel flows by air from the United Kingdom to 20 destinations. Objective assessments were made as to whether seasonal components in ARIMA processes should be modelled additively or multiplicatively. Selected ARIMA models outperformed Holt-Winters and Naive models in terms of goodness of fit and forecasting accuracy.

JoChau, V. and Turner, L. W. (2006) used the basic structural and seasonal autoregressive integrated moving average (ARIMA) models with an ex ante forecasting period from 2003 to 2004.

Mishra A.K. and Desai, V.R. (2006) compared linear stochastic models (ARIMA/SARIMA), Recursive Multistep Neural Network (RMSNN) and Direct Multi-Step Neural Network (DMSNN) for drought forecasting. Among the three ANN models (a feed forward Back Propagation (BP), a Radial Basis Function (RBF) and an Adaptive Neural Network-based Fuzzy Inference System (ANFIS)) employed for the investigation, the BP neural network was found to be superior to RBF and ANFIS type networks for the detection of pesticide occurrences in wells. The ARIMA/SARIMA models were developed for different SPI series using the correlation methods of Box and Jenkins based on AIC and SBC structure as selection criteria

Nochai, R. and Nochai, T. (2006) developed model for forecasting oil palm price of Thailand in three types and were found to be ARIMA(2,1,0) for the farm price model, ARIMA(1,0,1) for whole sale price, and ARIMA(3,0,0) for pure oil price.

Promptou, S. et al. (2006) developed autoregressive integrated moving average (ARIMA) models on the data collected between 1994-2005 and then validated the models using the data collected between January-August 2006.

Rajo, R.F.J. et al. (2006) developed predictive models of pollen concentrations using time series analysis. The prediction line proposed for Oviedo and Ponferrada was similar, while in Vigo and Leon, a more accurate ARIMA model was used.

Sahu, P.K. (2006) examined, using records from 1971 to 2001, the changes in yield, area under cultivation, and production efficiency, of the dry season crops: rice (*Oryza sativa*), wheat (*Triticum aestivum*), potato (*Solanum tuberosum*) and Indian mustard (*Brassica juncea*), which, in the future, might compete in time and space. Forecasting was made with respect to yield of each crop, area under cultivation, and production efficiency. Different Auto Regressive (AR) and Auto Regressive Integrated Moving Average (ARIMA) models explained the yield trends.

Sahu,P.K.(2006) examined records from 1971 to 2001, the changes in yield, area under cultivation, and production efficiency, of the dry season crops which, in the future, may compete in time and space. Forecasting was made with respect to yield of each crop, area under cultivation, and production efficiency. Different Auto Regressive (AR) and Auto Regressive Integrated Moving Average (ARIMA) models explained the yield trends.

Salayo,N.D.(2006) explained that ARIMA models showed instantaneous price relationships between monthly wholesale prices in Manila and the regional producing areas. The cross-correlations of the error terms of the ARIMA models showed that prices in Manila were related with prices in Lucena, Dagupan, Iloilo, and Zamboanga, not with prices in Cebu.

Antunes,J.L.F. et.al. (2007) sought to compare the age-specific mortality (65 years or older) before and after the onset of yearly vaccination, and to assess the impact of the intervention on health inequalities in relation to inner-city areas. Estimation of mortality attributable to influenza peaks used Serfling and ARIMA models.

Calvo,P.I. and Portela,M.M. (2007) used a hybrid methodology combining CNN and ARIMA models. The results showed that it was also possible to get daily flows forecasts at watersheds with insufficient flow data.

Czerwinski,I.A., Estrada,J.C.G. and Casal, J.A.H (2007) tested two univariate forecasting techniques ARIMA and Artificial Neural Network (ANN) to evaluate the short-term CPUE capacity forecast for *Pacific halibut, Hippoglossus stenolepis (Pleuronectidae)*. The best results from a seasonal ARIMA model indicated that one nonseasonal autoregressive term combined with a non-seasonal moving average term and a seasonal moving average term was suitable to explain a variance level of 32.6% in the validation phase, providing statistically acceptable but insufficiently satisfactory estimations. The results showed that the ARIMA models produced forecasts with explained variances close to 40% and percent standard error prediction around 41%.

Estrada, J.C.G. et. al (2007) analysed the performance of computational neural networks (CNNs) models to forecast 1-month ahead monthly anchovy catches in the north area of Chile considering only anchovy catches in previous months as inputs to the models. The results obtained in two different external validation phases showed that CNN having inputs of anchovy catches of the 6 previous months hybridised with ARIMA(2,0,0) provided very accurate estimates of the monthly anchovy catches. For this model, the explained variance in the external validation fluctuated between 84% and 87%, the standard error of prediction (SEP, %) was lower than 31% and mean absolute error (MAE) was around 18,000 tonnes.

Significant results were also obtained with recurrent neural networks and seasonal hybrid CNN+ARIMA models.

PeiChih, W. et. al. (2007) evaluated the impacts of weather variability on the occurrence of dengue fever in a major metropolitan city, Kaohsiung, in southern Taiwan using time-series analysis. Autoregressive integrated moving average (ARIMA) models showed that the incidence of dengue fever was negatively associated with monthly temperature deviation (beta =-0.126, p=0.044), and a reverse association was also found with relative humidity (beta =-0.025, p=0.048).

Rajarathinam, A, Dixit, S.K. (2007) used Auto Regressive Integrated Moving Average (ARIMA) methods to fit the trends for long term experiments on fertilizer nutrients and manures, the original data were of zig-zag in nature and there was a need to apply trend-fitting techniques to develop smooth trends to enable interpretation of the data in a better way. The treatment-wise yield data of the groundnut crop in cropping sequence groundnut-wheat-sorghum at Junagadh centres of the then Gujarat Agricultural University for 14 years were used. Among the different ARIMA models tried, the ARIMA (1, 1, 0) model was found to be best fitting trend equation.

Rajarathinam, A., Dixit, S.K. (2007) employed Auto Regressive Integrated Moving Average (ARIMA) methods to fit the trends. Among the different ARIMA models tried, the ARIMA (1, 1, 0) model was found to be best fitting trend equation.

Sabry, M. Latif, H.A.E. and Badra, N. (2007) investigated the application of two time series forecasting techniques, namely logistic regression and univariate auto regressive integrated moving average (ARIMA), to predict daily traffic volume for the Egyptian intercity roads. The forecasted traffic volumes for the two models were then compared with the actual traffic volumes. According to the analysis, the ARIMA model seemed to be the best forecasting method especially for the average monthly and average weekly and daily traffic volume.

Smeral, E. (2007) developed ARIMA models and 'absolute no change' forecast values computed in order to benchmark the forecast accuracy of the REGARIMA model.

Smeti, E.M. et. al. (2007) used the usage of a more sophisticated method based on time-series ARIMA models to overcome the problem of the autocorrelation.

Unakitan, G and Akdemir, B (2007) used an autoregressive integrated moving average (ARIMA) univariate model to predict the previous tractor demand in Turkey. The data used in the model were obtained for the period 1961-2003 from FAO statistics. The ARIMA model was determined as (2, 2, 2) in order to predict tractor demand by using logarithmic

transformation.

Yayar,R and Bal,H.S.G. (2007) found a method to predict corn oil price based on ARIMA methodology. These models based on time series analysis provided reliable and accurate forecasts. This approach was suitable for short term price forecasting, i.e. a weeks, a month, a quarter, a year.

Martínez,M.C.G. Caballero,P. and Zamudio,M.A.F (2008)determined trend and seasonality of original prices and the ARIMA models had been used to predict pepper prices in Almería. The ARIMA models were shown to be valid for short term forecasts of one season. Nevertheless, the results provided are of great interest in crops like the pepper grown in the greenhouse, where the response obtained in production and prices is evident with respect to the techniques and means employed.

Dobre,I. and Alexandru,A.A.(2008) modeled the evolution of unemployment rate using the Box- Jenkins methodology during the period 1998-2007 monthly data. The empirical study revealed that the most adequate model for the unemployment rate was ARIMA (2,1,2).

Hamdi,M.R., Bdour ,A.N. and Tarawneh,Z.S.(2008) described a seasonal time series Autoregressive and Moving Average (ARIMA) mathematical model. It was used for forecasting monthly reference crop evapotranspiration (ET_o) without using weather data based on past historical records (1973-2002) of measured pan evaporation at Central Jordan Valley: an arid to semi-arid region. The developed ARIMA (1, 0, 0) (0, 1, 1)₁₂ model provides reasonable and acceptable forecasts, comparing its performance with a computed reference evapotranspiration from measured pan evaporation parameter. The forecasting performance capability of three tentative ARIMA models was assessed using Root Mean Squared Forecasting Error, Mean Absolute Forecasting Percentage Error, and Maximum Absolute Forecasting Percentage Error. The developed model allowed local farmers and water resource managers to predict up to 60 months with a percentage error less than 11% of the mean absolute forecasting.

Holb,I.J.(2008) used auto-regressive integrated moving average (ARIMA) models and revealed that the temporal patterns of the number of airborne conidia was similar in all years in both integrated and organic orchards.

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Materials and Methods

3. MATERIALS AND METHODS

The present investigation was carried out in the Department of Agricultural Statistics, College of Horticulture, Vellanikkara during the period from 2006-09. This study on "Changing Scenario of Kerala Agriculture - an overview" aims to develop advanced statistical models to predict the area, production, productivity and price of major crops of Kerala and to have a comparison of the past scenario of Agriculture in Kerala with the present scenario and to predict for the future. A brief description of the methodology used for the study are discussed in detail in the following section under two different sub headings.

3.1. Sources of data

The changing scenario of major crops of Kerala viz; coconut, rubber, paddy, pepper, arecanut, tapioca, cashew, coffee and banana with respect to area, production, productivity and price were analysed and detailed below. The major status of the crops were judged on the basis of area of cultivation during 1999 to 2005 and those crops were selected for the study. Secondary data which were collected from the publications of Planning Board and various Economic Reviews were used for the study. Data from 1952-53 were used for fitting trends and study of growth rates for area, production and productivity. In the case of price, data from 1970-71 only were used for the above purpose. Trend study was carried out under three classifications, (i) at pre-green revolution period (upto 1965-66), (ii) at green revolution period (1966-67 to 1985-86) and (iii) at post green revolution period (after 1986-87). Annual growth rate was calculated for each crop. The cointegrated movement of area under each crop and their respective prices were studied using cointegration techniques. Forecasting models were developed for each crop using Auto Regressive Integrated Moving Average (ARIMA) models.

3.2. Statistical tools used for the analysis.

3.2.1 Trend

There are no proven automatic techniques for identification of trend components in the time series. However as long as the trend is monotonous that part of data analysis is typically not very difficult. If the time series data contain considerable error then the first step in trend identification is smoothing. The most common method is moving average smoothing which replaces each element of the series by either simple or weighted average of n surrounding elements where n denote the width of the smoothing used. Usually forecasts are based on the

assumption that the parameters do not change over time. But in practice they may change. In such cases there are several ways to update the parameters. One such important method is exponential smoothing which gives more weight to more recent observations. Here $X_{t+1} = \alpha X_t + \alpha(1-\alpha)^j X_{t-j}$, $0 < \alpha < 1$ and hence the name exponential smoothing.

3.2.2 Growth Rate

Annual growth rates of area, production, productivity and price of different crops are calculated using the formula

$$\frac{P_c - P_p}{P_p} \times 100$$

where P_c = Current year's data and P_p = Previous year's data

3.2.3 Modified P-Gan's Method for growth rate study

According to P-Gan's formula pertaining to production of any crop,

Production contribution = Area contribution + Productivity contribution.

This method is used to understand whether the variation is mainly due to area or productivity. Here the attempt is made to know the extent of variability in productivity and area of the crops over the past 50 years. The growth rate were split in to components, namely area contribution and productivity contribution so that one can understand whether the increase was due to area or productivity. A modification for this formula can be derived as below

Production (Y) = Area (A) X Productivity (P). If Δ denote the increment operator, then $Y + \Delta Y = (A + \Delta A)(P + \Delta P) = AP + A.\Delta P + P.\Delta A + \Delta A.\Delta P$.

Since $Y = AP$, cancelling from both sides, it should be

$$Y = A.\Delta P + P.\Delta A + \Delta A.\Delta P$$

Dividing by $Y (= AP)$ through out we get,

$$(\Delta Y)/Y = (\Delta P)/P + (\Delta A)/A + (\Delta A.\Delta P)/AP$$

Since the last term is negligibly small, the formula becomes $(\Delta Y)/Y = (\Delta P)/P + (\Delta A)/A$.

Multiplying both sides by 100, it gives the Modified P-Gan's result :

Growth rate of Y = Growth rate of A + Growth rate of P.

By this method an attempt is made to study the extent of variability in area and productivity of major crops of Kerala over the past half century. The growth rate of production as compared to the preceding years were split in to area component, productivity component and interaction component. As the interaction component is very small when comparing with the other two, it is neglected from the study. Growth rates for area, productivity and production

were worked out for each year and using the formula derived above production growth rate is split in to two components. Here the productivity component will be a cumulative factor as it depends on weather, irrigation, fertilizer application technological development, etc.

3.2.4 Cointegration

Cointegration was developed by the Nobel laureate Granger (1986). The Engle - Granger two-step approach is a residual based cointegration procedure which uses the ordinary least squares in the estimation process. In general, economic, financial and accounting variables are non-stationary. However, there may be a long-run relationship between variables which is stationary. Hence, we need another measure of the degree of association between variables that takes into account the possibility of a series not being jointly stationary in the short run, but which has a long-run equilibrium implying cointegration. The simple idea behind cointegration is that sometimes lack of stationarity of a multi-dimensional process is caused by common stochastic trends which can be eliminated by taking suitable linear combinations of the process thereby making the linear combination stationary. It describes the long-run relationship between variables and results from those variables having a common stochastic trend over time.

Engle-Granger's Test for cointegration between two variables

Granger and Weiss (1983) and Engle and Granger (1987) have shown that even though a given set of series may be non stationary, there may exist various linear combinations of the individual series that are stationary. The desire to estimate models that combine both short run and long run properties and that at the same time maintain stationarity in all the variables, has prompted a reconsideration of the problem of regression using variables measured in their levels. Engle and Granger (1987) give the formal definition of cointegration of two variables. According to that definition, cointegration between two variables occurs when two series are each integrated of order b ($I(b)$), but some linear combination of the two series results in a third series which is integrated of order a ($I(a)$), $a < b$. In this case, the two series following $I(b)$ are said to be cointegrated. For practical purposes $b = 1$ and $a = 0$, thus the cointegrated series will be $I(1)$ and the linear combination of the two series will be $I(0)$. Thus, if an equilibrium relationship exists, it will be possible to find some linear combination of the two variables, i.e. $aY + bX = Z$ such that Z is stationary, if there exists a and b such that $aY + bX$ is $I(0)$, then the linear combination will be stationary. Stationarity of the series can be tested by Augmented Dickey-Fuller Tests before cointegration.

Augmented Dickey Fuller Test for Stationarity

A non-stationary variable has a definite positive or negative trend and so mean, variance, and covariance are changing over time, so that standard t tests in regression are no longer valid. Dickey Fuller Test (DF) assumes the model $Y_t = \rho Y_{t-1} + e_t$, where e_t is assumed to define a sequence of independently and identically distributed (i.i.d.) random variables with expected value zero and variance σ^2 . The process in equation is stationary when ρ is less than one in absolute value; i.e., $-1 < \rho < 1$. The AR(1) process has a unit root if and only if ρ is one. In such a situation, the AR(1) process is nonstationary. But if the errors are dependent, it will be a violation of DF test. So to assure that the time series is non-stationary, Augmented Dickey-Fuller unit root test is used for the determination of the order of differencing and stationarity of the independent variable.

3.2.5 Auto Regressive Integrated Moving Average (ARIMA) models

Auto Regressive Integrated Moving Average models are specially suited for short term forecasting as most ARIMA models place great emphasis on recent past. In an Auto Regressive (AR) process each value is a linear combination of the preceding values. Integration component (I) of an ARIMA model is identified through the order of differencing to make the series stationary and the order of Moving Average (MA) process specifies how many previous disturbance are averaged to generate the new value. These models were developed by Box and Jenkins in 1970. The real power and attractiveness of this method is that it can handle complex patterns using a relatively well specified set of rules. The Box-Jenkins methodology of forecasting is different from most methods because it does not assume any particular pattern in the historical data of the series to be forecasted. It uses an iterative approach to identify a possible model from a general class of models. The chosen model is then checked against the historical data to see whether it accurately describes the series. The model fits well if the residuals are generally small, randomly distributed, and contain no useful information. If the specified model is not satisfactory, the process is repeated using a new model designed to improve on the original one. This iterative procedure continues until a satisfactory model is found.

A stochastic model can be used in two ways (i) to understand the stochastic system and (ii) for predicting the future values. In order to have any chance of success it is necessary to assume some a priori structure of the time series. A basic type of structure is stationary structure. A time series is stationary on the space R^{h+1} if the distribution of the vector of observations

$(X_t, X_{t+1}, X_{t+2}, \dots, X_{t+h})$ is independent of t , $h \in \mathbb{N}$. Many timeseries in real life are not stationary. A non-stationary sequence has to be transformed to a stationary sequence before attempting to apply a model for the same. The two important deviations from stationarity are Trend and Seasonality. For the annual data which are using for this study, there will not be a seasonality component. So the only non-stationary component will be the trend.

Box and Jenkins method is applied only to stationary time series data. A time series is said to be strictly stationary if all the moments of its probability distributions are invariant over time. However in time series literature a stochastic process $\{X_t\}$ is said to be stationary if both $E\{X_t\}$ and $E\{X_t X_{t+k}\}$ exist and are finite and do not depend on t . Stationarity of a time series can be tested by either plotting the data, or assessing from the autocorrelation functions or using some specified unit root tests. Most non stationary time series are transformed in to stationary time series by suitable transformations. The transformation method depends on whether the time series are difference stationary (DSP) or trend stationary (TSP). If the time series is found TSP then regress it on time and hence the residuals from this regression will be stationary. For this the regression $y_t = \alpha + \beta t + e_t$ is fitted and the residuals $e_t = y_t - \alpha - \beta t$ is studied, which is called the detrended time series. Even if the trend is nonlinear it can be removed as in the case of linear. Otherwise the simplest transformation is differencing. The consequence of DSP and TSP type errors are very serious depending on how one can handle the serial correlation of the resulting error terms. If a time series is DSP but treats as TSP it is called under differencing and if a timeseries is TSP but considering as DSP, it is called over differencing. Differencing beyond second order is very rare because if a series exhibits such extreme trend, it is nonstationary due to nonconstant variance. In such a situation we need to go for logarithmic or square root transformations to the series before estimating the model which will stabilize the variance. Variance of a time series is the most important statistic, since it is used to judge the performance of the stochastic controller. The three most popular ways to calculate variance are (i) Method of residue, (ii) Recursive method and (iii) State-Space model method. Among these, the method of residue is the most elegant method which is widely used.

According to Box and Jenkins (1970), an ARIMA (p,d,q) process can be identified by the equation $\Phi(B)\Delta^d X_t = \Theta(B)Z_t$, where B denote the back shift operator, $BX_t = X_{t-1}$, Δ denote the difference operator, d denote the order of differencing to make the sequence $\{X_t\}$ stationary and Z_t is the white noise process which is a mean zero iid sequence with finite variance. In general a time series X_t is an ARIMA (p,d,q) process if there exists polynomials

Φ and Θ of degrees p and q respectively and a white noise series Z_t such that the timeseries $\Delta^d X_t$ is stationary and $\Phi(B)\Delta^d X_t = \Theta(B)Z_t$ almost surely on the underlying probability space. When $d=0$, $X_t = \frac{\Theta(B)}{\Phi(B)}Z_t$, is a stationary ARMA(p,q) process. The sequence is stationary if all the zeroes of the polynomial $\Phi(z)$ lie outside the unit circle $|z| < 1$. When it has one or more values equal to one but no value inside the unit circle, it is nonstationary but integrated. In this case the time series is an ARIMA process. In general when function $\frac{\Theta(B)}{\Phi(B)}$ is well defined and analytic in the region $\{z \in \mathbb{C} \mid \Phi(z) \neq 0\}$. If Φ has no roots on the circle $\{z \mid |z|=1\}$, since it has p different roots there is an annulus $\{z/r < |z| < R\}$ with $r < 1 < R$ on which it has no root. On this annulus $\frac{\Theta(z)}{\Phi(z)}$ is analytic and it has a Laurent's series expansion $\Gamma(z) = \sum_{j=1}^{\infty} \gamma_j B^j$. This series is uniformly and absolutely convergent on every compact subset of the annulus and the coefficients are uniquely determined by the value of X_t on the annulus. Hence the random X_t and Z_t are defined on a probability space (Ω, \mathcal{U}, P) and satisfying $\Phi(B)\Delta^d X_t(\omega) = \Theta(B)Z_t(\omega)$ for almost every $\omega \in \Omega$. The polynomials are always written in the forms

$$\Phi(z) = 1 - \phi_1 z - \phi_2 z^2 - \dots - \phi_p z^p$$

and

$$\Theta(z) = 1 - \theta_1 z - \theta_2 z^2 - \dots - \theta_q z^q$$

Then the equation $\Phi(B)\Delta^d X_t = \Theta(B)Z_t$ takes the form

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots + \phi_p X_{t-p} + Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \dots + \theta_q Z_{t-q}$$

From the theory of complex analysis, the variance is the coefficient in the Laurent's series. The coefficient is given by $\gamma_n = \frac{1}{2\pi i} \oint_C \frac{\Gamma(z)}{z^{n+1}} dz$ where C is a simple closed Jordan curve.

$$\text{From above } \gamma_1 = \gamma_{-1} = \sigma_a^2 \frac{1}{2\pi i} \oint_C \frac{\theta(z)\theta(z^{-1})}{\phi(z)\phi(z^{-1})z} dz = \sigma_a^2 \times \text{Residue}_{z=0} \frac{\theta(z)\theta(z^{-1})}{\phi(z)\phi(z^{-1})}$$

The calculation of residue at a multiple pole is a little bit more complicated since we have to take the derivative first. As the multiplicity increase this complication will increase. This applies to the autocovariance at higher lags.

In the equation $\Phi(B)\Delta^d X_t = \Theta(B)Z_t$, $\Phi(B)$ is a polynomial of degree p and hence $\Phi(B)\Delta^d X_t$ is a polynomial of degree $p+d$ so that the ARIMA (p,d,q) model can also be written as an ARMA($p+d,q$) model with the understanding that some of the zeroes of $\Phi(B)$ are on the unit circle.

For a stationary time series the autocovariance and auto correlation at a lag $k \in \mathbb{Z}$ are defined by $\gamma_x(k) = \text{cov}(X_{t+k}, X_t)$ and $\rho_x(k) = \rho(X_{t+k}, X_t) = \gamma_x(k) / \gamma_x(0)$, where $\gamma_x(0) = \text{Var}(X_t)$ and $\rho_x(0) = 1$. The partial auto correlation at a lag k is defined as the correlation between $X_k - \Pi_{k-1}(X_k)$ and $X_0 - \Pi_{k-1}(X_0)$, where Π_k is the projection of the vector $y \in \mathbb{R}^k$ on

the subspace spanned by (X_1, X_2, \dots, X_k) in R^k which is a linear combination $y = \sum b_j x_j$ such that $\|y - \hat{y}\|$ is minimal. This is the correlation due to intermediate values X_1, X_2, \dots, X_{k-1} removed.

Causality and invertibility are important for predictions for ARIMA process. Invertibility is similar to stationarity. If the polynomial $\Theta(z)$ has no zero with z values inside the unit circle, the time series is invertible. The invertibility of the series is sure through model identification.

ARIMA model building

Wold decomposition theorem (Vaart, A. W. 2004) is the basis for time series analyses, in particular for ARIMA models. Let H be a Hilbert space, $L(H)$ be the bounded operators on H , and $V \in L(H)$ be an isometry. Then Wold decomposition states that every isometry V takes the form $V = (\bigoplus_{\alpha \in A} S) \oplus U$ for some index set A , where S is the unilateral shift on a Hilbert space H_α and U is a unitary operator (possibly vacuous). The family $\{H_\alpha\}$ consists of isomorphic Hilbert spaces. With a univariate covariance stationary process X_t with vanishing memory and the expectation $E(X_t) = \mu$ and the wold decomposition can be written as $X_t = \mu + \alpha(B)U_t$, where B denote the back shift operator given by $B^k(X_t) = X_{t-k}$ and $\alpha(B) = 1 + B + B^2 + \dots$. The function $\alpha(B)$ can be approximated arbitrarily close by ratio of two lag polynomials, $\theta_q(B)$ and $\phi_p(B)$ with orders q and p respectively in which at least $\phi_p(B)$ is invertible with inverse $\phi_p^{-1}(B)$. In particular for arbitrary $\varepsilon > 0$, there exists lag polynomials $\theta_q(B)$ and $\phi_p(B)$ such that $E[\{(\alpha(B) - \phi_p^{-1}(B)\theta_q(B))U_t\}^2] < \varepsilon$. This gives rise to the well known ARMA models for which it is assumed that $\alpha(B)$ is exactly of the form $\alpha(B) = \phi_p^{-1}(B)\theta_q(B)U_t$.

(i) Identification

The foremost step in time series modelling is to check for stationarity. Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) and Auto Correlogram are the chief tools for this purpose. ACF is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal which has been buried under noise. A cursory look at the graph of the data and structure of autocorrelation and partial auto correlation coefficients will give clues about stationarity. The time series is stationary if the autocorrelation function dies out fairly quickly. There are other ways of checking stationarity (i) fit a first order autoregressive model for the raw data and test whether the coefficient ϕ_1 is less than 1 or (ii) by specific tests like Dickey Fuller tests.

The next step is to find initial values for the orders of parameters p and q . They can be obtained from the significant autocorrelation and partial autocorrelation coefficients. When

autocorrelations drops off exponentially to zero it is an autoregressive model whose order is determined by the number of partial autocorrelations which are significantly different from zero. On the other hand, if partial autocorrelations drop off exponentially to zero it is a moving average model whose order is determined by the number of autocorrelations which are significantly different from zero. When both autocorrelation and partial autocorrelation move exponentially to zero it is an ARMA model. The final models are achieved after going through the stages repeatedly.

(ii) Estimation

At the identification stage one or more models are tentatively chosen that seem to provide statistically adequate representations of the available data. The precise estimates of the parameters of the model are obtained by the method of ordinary least squares as advocated by Box and Jenkins. Iterative procedure for finding the estimate can be done through SPSS. Finally, quality of the coefficients has to meet two requirements. They must be statistically significant, and the correlation between the coefficients must be less than 0.9. The estimated ARIMA model has to have a significant t-statistic for each coefficient of the estimated model.

(iii) Diagnostic Checking

After the model has been identified and the parameters have been estimated, the diagnostic checks should be applied to the model to see if the model is adequate. Four major criteria can be used to check each model for inadequacies so that any necessary revisions needed may be made. First, we need to check the independence of the random shock. An adequate model has statistically independent random shocks. This condition is necessary because if the random shocks are correlated, then there is an autocorrelation pattern in the data that has not been captured in the model, and one should search for another model that satisfies the independence assumption of the residual. The way to test for independence in the residual shock is to test the estimate of the residual of the model (a) at the estimation stage and then to look at the residual ACF to be sure that it has insignificant autocorrelation coefficients. This important evidence demonstrates that it is not possible to improve upon the model. Different models can be obtained for various combinations of AR and MA individually and collectively. The best model is obtained with the following diagnostics.

(a) Coefficient of determination (R^2)

The accuracy of the models was measured by R^2 , which is an in-sample indicator that measures the percentage of the output variance that is explained by importing the inputs into

the model. It is the proportion of variability in a data set that is accounted for by the statistical model. It provides a measure of how well future outcomes are likely to be predicted by the model. The most general definition of the coefficient of determination is $R^2 = 1 - (\text{Error Sum of Squares} / \text{Total Sum of Squares})$.

(b) Akaike Information Criteria (AIC) / Bayesian Information Criteria (BIC)

AIC is given by the relation $AIC = (-2 \log L + 2m)$ where $m = p + q$ and L is the likelihood function. $-2 \log L$ is approximately equal to $\{n(1 + \log 2\pi) + n \log \sigma^2\}$ where σ^2 is the model Mean Square Error. AIC can be written as $\{n(1 + \log 2\pi) + n \log \sigma^2 + 2m\}$. As the first term is a constant it is usually omitted while comparing the models. BIC is also similar to AIC as $BIC = \{n(1 + \log 2\pi) + n \log \sigma^2 + m \ln(n)\}$. So It can be written as $AIC = BIC - m(\ln(n) - 2)$. As an alternative to AIC, Schwarz Bayesian Criterion (SBC) = $\{\log \sigma^2 + (m \log n) / n\}$ is also used.

(c) Portmanteau tests - Box Pierce or Ljung-Box Q-tests

Statistical significance of ρ_k can be judged by its standard error, where k denotes the lag length. A rule of thumb to compute the ACF is up to one third to one - quarter of the length of the time series. Best practice is to start with sufficiently large lags and then reduce by AIC or SIC. Bartlett has shown that if a time series is purely random (i.e, if it exhibits whitenoise) $\rho_k \sim N(0, 1/\sqrt{n})$. The 95% confidence interval for ρ_k is $\rho_k \pm 1.96/\sqrt{n}$. Rather than studying the ρ_k values one at a time an alternate approach is to consider a whole set of ρ_k values and develop a test to see whether the set is significantly different from a zero set. Tests of this sort is known as portmanteau tests. A common portmanteau test is the Box - Pierce Q, where $Q = n \sum \rho_i^2$, n being the number of observations in the series and k the maximum lag. This test was designed by Box and Pierce in 1970 for testing the residuals from a forecast model. This Q is compared with $\chi^2_{(k)}$. An alternative test is the Ljung-Box $Q^* = n(n+2) \sum_{i=1}^k \rho_i^2$, where the summation extends from 1 to k . If the data are white noise Ljung-Box Q^* has exactly same distribution as Box-Pierce Q.

(d) The Percentage Forecast Inaccuracy (PFI)

The measure of the Percentage Forecast Inaccuracy (PFI) gives the percentage of the deviation of the forecasted value from the actual value for each year. PFI had been used to measure the inaccuracy of ex-post forecast. The PFI can be expressed in mathematical terms as $PFI = (\text{Forecast} - \text{Actual}) / \text{Actual}$.

(e) Root Mean Square Error (RMSE)

The RMSE is given by the relation
$$RMSE = \sqrt{\frac{\sum_1^n |X_t - \hat{X}_t|^2}{n}}$$

(e) Mean Absolute Error (MAE)

The MAE is given by the relation
$$MAE = \frac{1}{n} \sum_1^n |X_t - \hat{X}_t|$$

(f) Mean Absolute Percentage Error (MAPE)

The MAPE is given by the relation
$$MAPE = \frac{1}{n} \sum_1^n \frac{|X_t - \hat{X}_t|}{X_t} \times 100 \%$$

The smaller the values of MAE, RMSE and MAPE, better the model is considered to be.

SPSS Syntax used for the ARIMA modelling

```
TSMODEL
/MODELSUMMARY PRINT=[MODELFIT RESIDACF RESIDPACF]
/MODELSTATISTICS DISPLAY=YES MODELFIT=[ SRSQUARE RSQUARE
RMSE MAPE MAE MAXAPE MAXAE NORMBIC]
/MODELDETAILS PRINT=[ PARAMETERS RESIDACF RESIDPACF]
/SERIESPLOT OBSERVED FORECAST FIT FORECASTCI FITCI
/OUTPUTFILTER DISPLAY=ALLMODELS
/AUXILIARY CILEVEL=95 MAXACFLAGS=24
/MISSING USERMISSING=EXCLUDE
/MODEL DEPENDENT=VAR00001
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/EXPERTMODELER TYPE=[ARIMA]
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Results and Discussion

4. RESULTS AND DISCUSSION

Agriculture is the back bone of Kerala's economy since it contributes to the economic and social welfare of the state through its influence on the gross domestic production and employment. The race between increasing population and food supply is a real grim. It is most apt at this juncture to forecast area, production, productivity and price of major crops of the state. This would enable the policy makers to predict ahead of time the future requirements for grain storage, import and export of these crops there by enabling them to take appropriate safe guards. The forecasts would thus help save much of the precious resources of our state. Keeping in view the importance of agriculture, quantitative assessment of contribution of various factors to growth and crop productivity at the state level will be helpful in reorienting the programmes and fixing priorities of agricultural development so as to achieve higher growth.

Fig. 4.1(a) Comparison of wage of men in paddy field and construction field

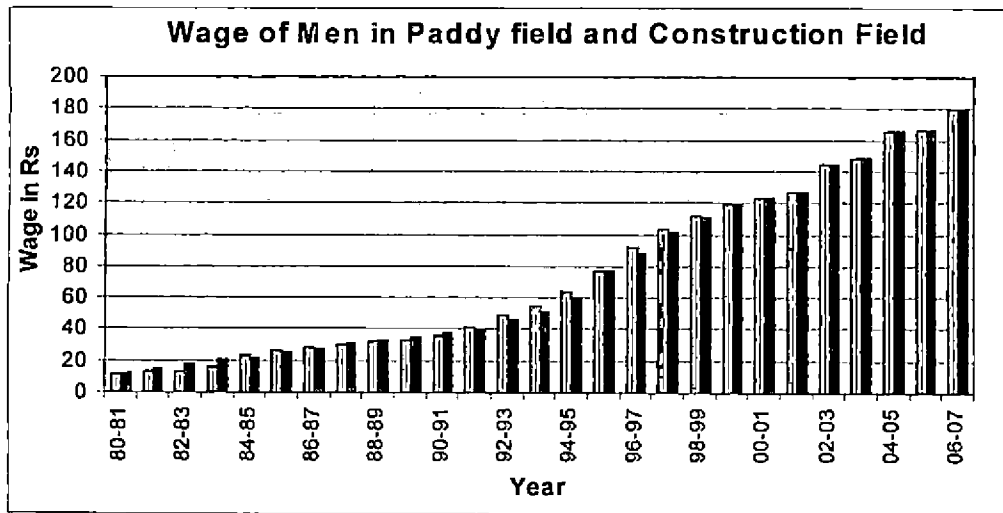
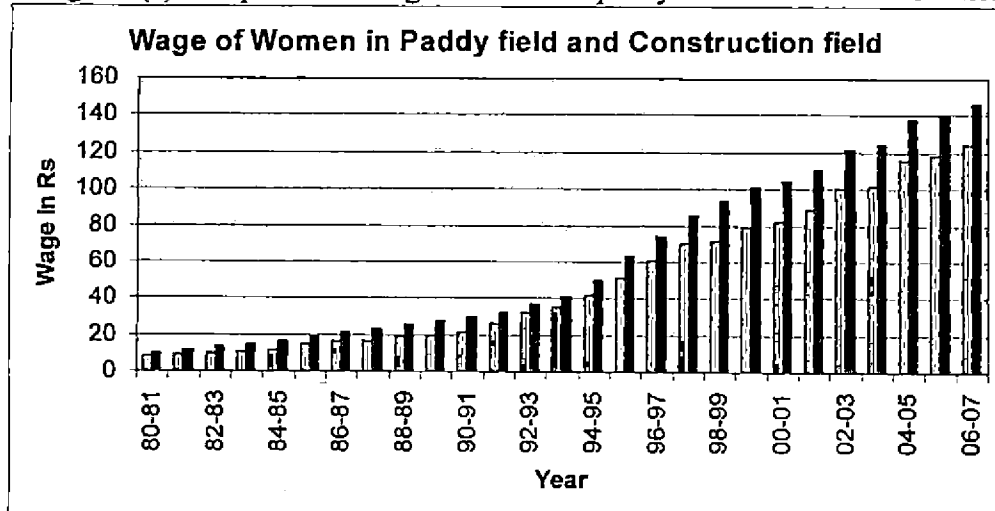


Fig. 4.1 (b) Comparison of wage of women in paddy field and construction field



Forecasts can be made in many different ways, the choice of the method depending on the purpose and importance of the forecasts as well as the costs of alternative methods. In the present study an earnest attempt is being made to evaluate the problem of decelerating trend of area, production and productivity through advanced statistical models. For this purpose the data on area, production, productivity, price etc. of the major crops of Kerala for the period from 1952-53 to 2006-07 have been collected from the Directorate of Economics and Statistics, Thiruvananthapuram to arrive at a genuine and valid conclusion about the changing scenario of Kerala agriculture.

With the objectives of the study in view, the results and discussions are arranged under the following five major sections viz;

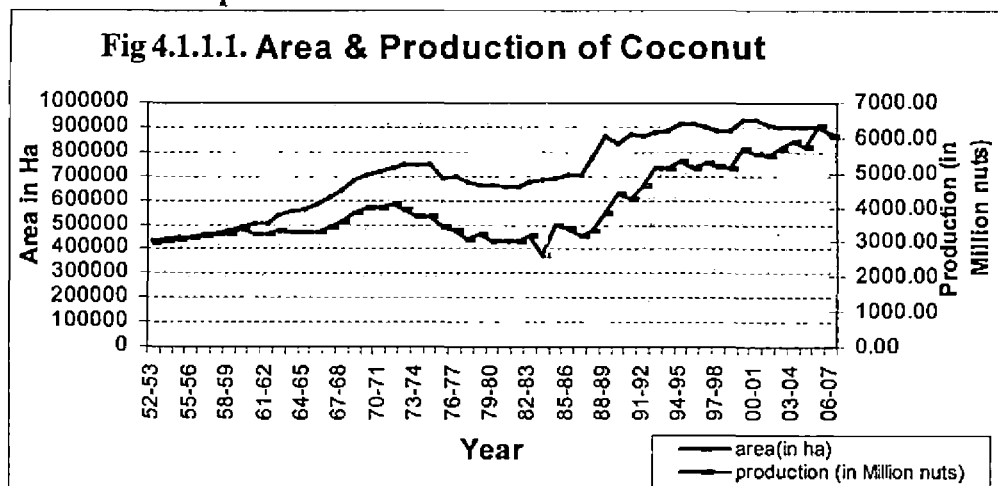
- 4.1 Trend analysis
- 4.2 Growth rate analysis
- 4.3 Modified P - Gan's method
- 4.4 Co - integration technique
- 4.5 ARIMA modeling

4.1 Trend analysis

The secondary data on area, production, productivity and price of major crops of Kerala viz; coconut, rubber, paddy, pepper, cashew, arecanut, coffee, tapioca and banana for the period from 1952-53 to 2006 - '07 were used for studying the trend of major agricultural crops of Kerala. In the case of paddy data from 1960-61 and in the case of banana data from 1978 onwards only were available for the study

4.1.1. Coconut

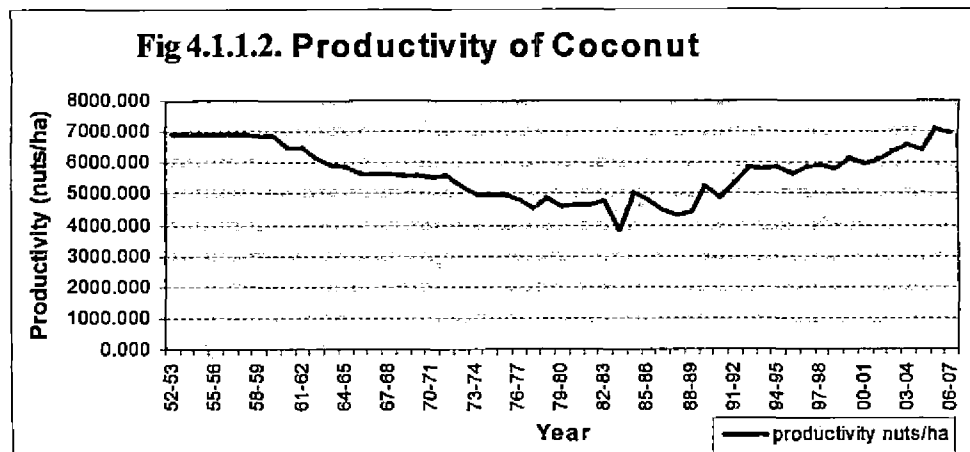
4.1.1.1 Area and production



Area of coconut was 430400 ha in 1952-53. It showed an increasing trend upto to 1976-77 and then decreased. The area was maximum during 2000-01 and touched 925783ha. During 2006-07 it was 870939 ha. Thus it is showing a decreasing trend.

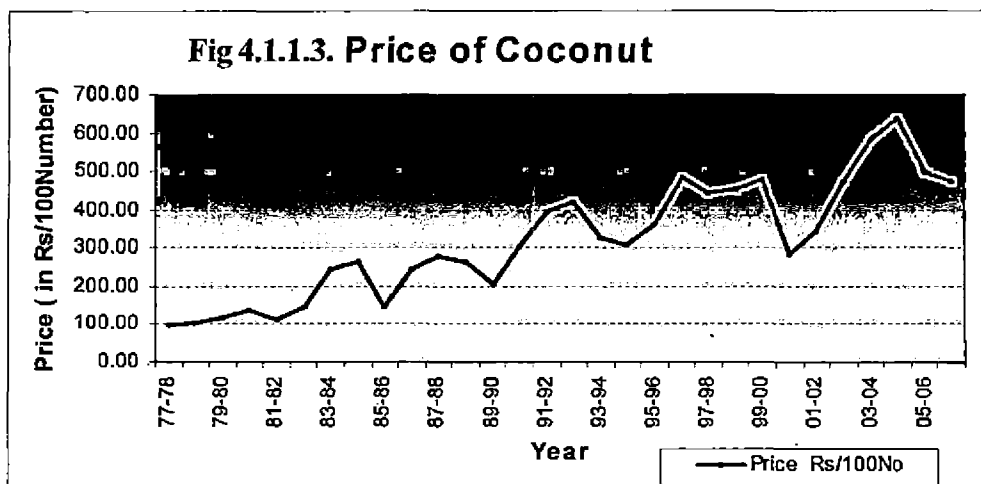
The overall production of coconut during 1952-53 was 2978 million nuts. The minimum production was 2602 million nuts during 2005-06. Maximum production was 6326 Million nuts which was during 2005-06. But next year it had declined to 6054 million nuts.

4.1.1.2 Productivity



Data on productivity showed a decreasing trend upto 1984 and showed a minimum during 1983-84 of about 3813.678 nuts/ha. During 2005-06 it showed the maximum of 7045.854 nuts/ha. During 2006-07 it was about 6951.118 nuts/ha showing a decreasing trend which was almost the same as that of 1952-53 of about 6919.145 nuts/ha.

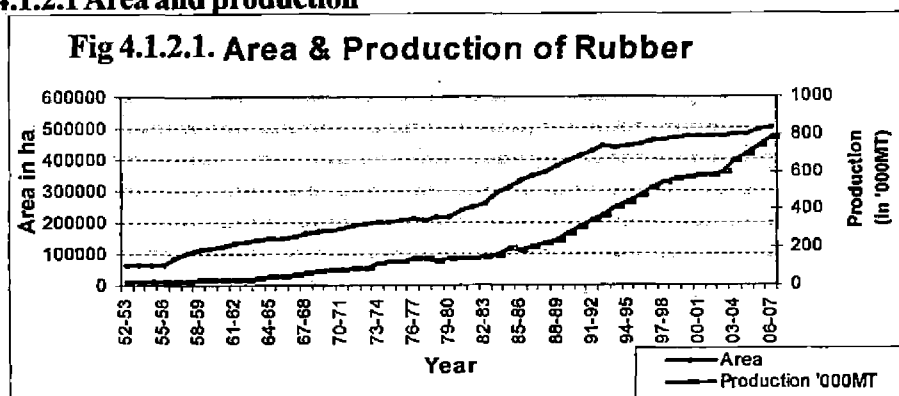
4.1.1.3 Price



Price of coconut during 1956-57 was Rs.15.36 for 100 nuts. The maximum price was about Rs. 635/ 100 nuts during 2004-05. During 2006-07 it was Rs.473.36/ 100 nuts showing a decreasing trend.

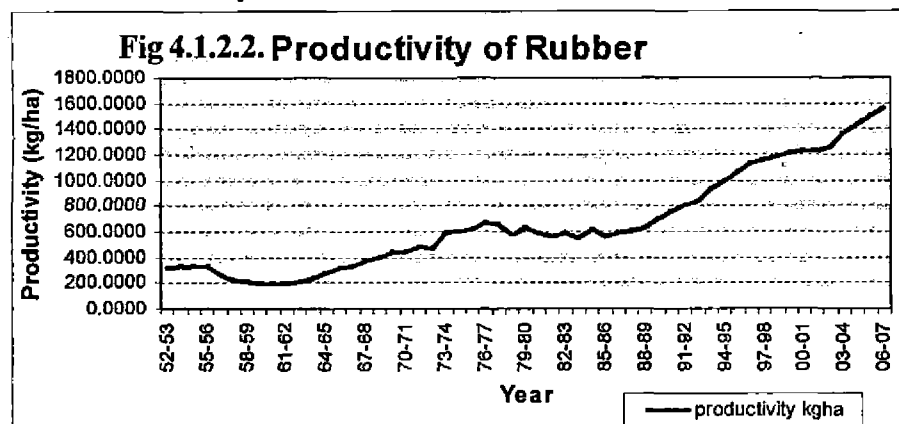
4.1.2. Rubber

4.1.2.1 Area and production



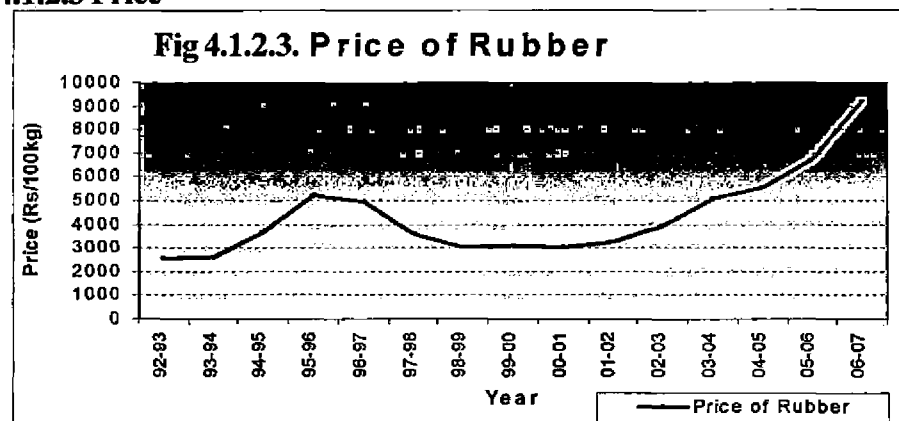
Area of rubber was 62580 ha in 1952-53. It was showing an increasing trend both for area and production. The area hit the maximum during 2006-07 of 502240ha. Production of rubber during 1952-53 was 19260 MT. Maximum production was 780405 MT. during 2006-07 showing an upward trend.

4.1.2.2 Productivity



Data on productivity showed the minimum during 1960-61 of about 187.515 kg/ha. During 2006-07 it showed the maximum of 1553.8488 kg/ha. Though it was 307.7663 kg/ha in 1952-53, it was moving with some fluctuations after 1985-86 showing an increasing trend.

4.1.2.3 Price



The price of rubber during 1992-93 was Rs. 2550/100kg.. The maximum price was during 2006-07 of about Rs. 9204/ 100kg. and showing a steady increasing trend.

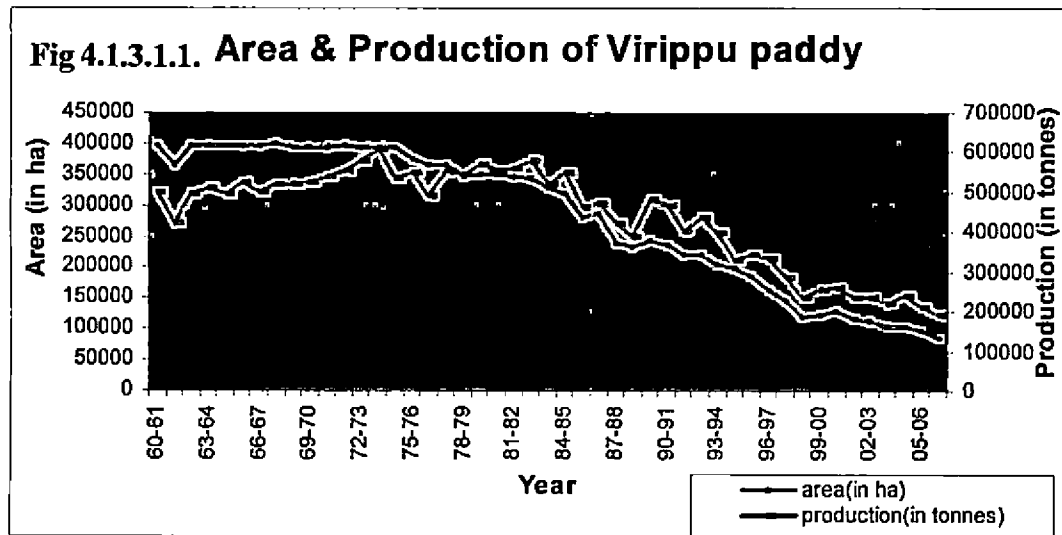
4.1.3. Paddy

4.1.3.1 Area and production

Though rice is an important food crop, its area was continuously decreasing from 1960. In 1960-61, the total area of cultivation was 781913 ha , in 2006-2007 it was 263529ha. The area hit the maximum during 1974-75 of 881466 ha. Production of paddy was 1067560t in 1960-61 . The production touched its zenith in 72-73 of about 1376326t. The minimum production was 570045t during 2003-04. During 2006-07 it was 641576t showing an increasing trend.

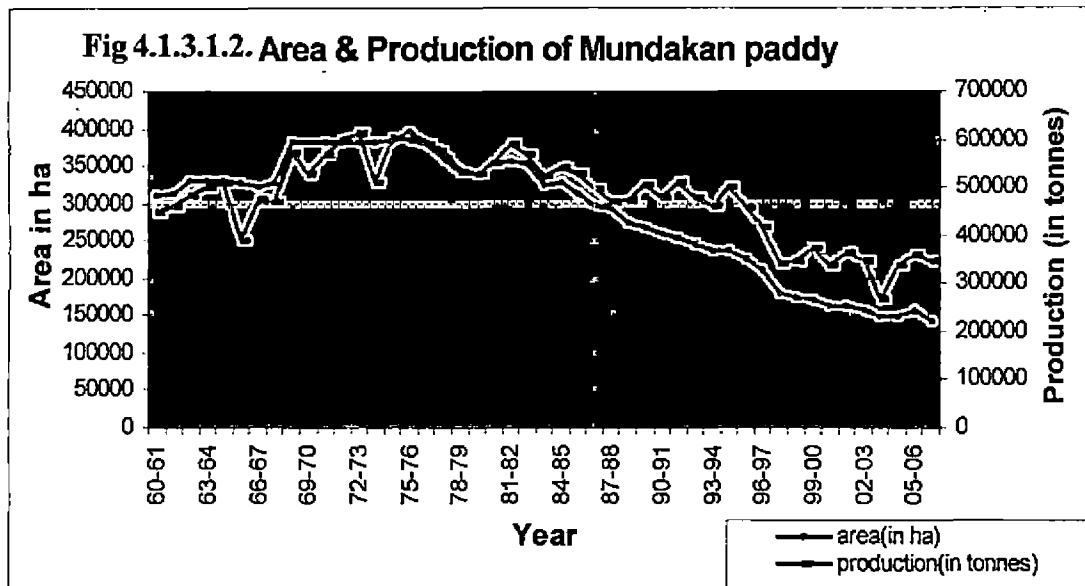
4.1.3.1.1 Virippu

Area of virippu paddy was 396132 ha during 1960-61. It was showing a continuously decreasing trend for both area and production. The area hit the maximum during 1967-68 at 398993 ha. During 2006-07 it showed a decreasing value of 89859 ha. Production of virippu paddy was 500348t. during 1960-61. Maximum production was 605595t. during 1973-74. During 2006-07 it showed the minimum 191241t. with negative trend.



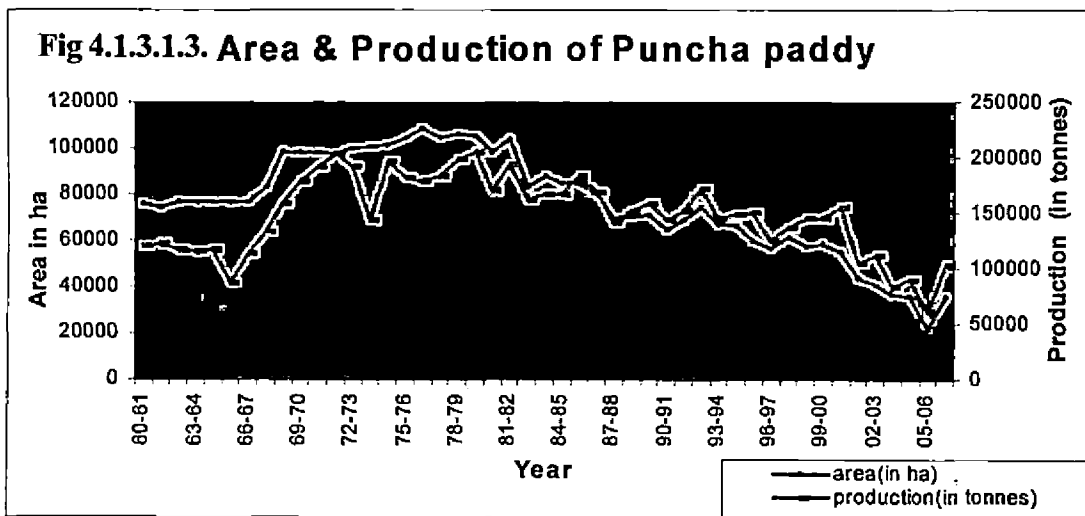
4.1.3.1.2 Mundakan

Area of Mundakan paddy was 310028 ha during 1960-61. It is now showing a decreasing trend for both area and production. The area hit the maximum during 1975-76 of 396392 ha. During 2006-07 it showed the minimum at 143724 ha. Production of mundakan paddy during 1960-61 was 447712t. Maximum production was 609234t. in 1972-73. During 2003-04 it showed the minimum of 266674t and in 2006-07 it reached 346763t with negative trend.



4.1.3.1.3 Puncha

Area of virippu paddy was 75753 ha during 1960-61. It was showing a continuously decreasing trend from 1976-77 in the case of area. The area hit the maximum during 1976-77 at 108874 ha. During 2005-06 it showed the minimum of 21857 ha and then showed an increasing trend of 35946 ha during 2006-07. Production of puncha paddy during 1960-61 was 11950t. Maximum production was 20553lt. during 1979-80. 2005-06 showed the minimum of 59733t. with an increase of 103572t in the following year.



4.1.3.2 Productivity

Data on productivity showed an increasing trend with a little fluctuation. It showed about 1365.318 kg/ha in 1960-61. During 1965-66 the productivity was very poor ie about 1244.885kg/ha. The year 2006-07 showed the maximum productivity of 2434.556 kg/ha.

4.1.3.2.1 Virippu

Data on productivity of virippu paddy showed an increasing trend with a minimum of 1147.14kg/ha in 1961-62. It showed its maximum in the year 2004-05 of about 2295.46kg/ha. But 2260.51 kg/ha was recorded in 2006-07 showing a small increasing trend just after 2005-06 which resulted in a productivity of 2162.92 kg/ha.

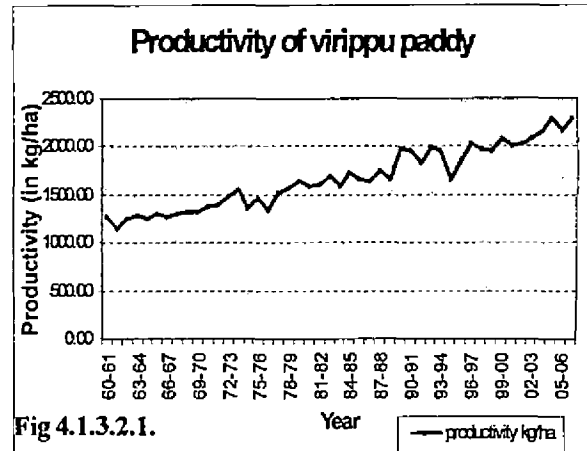


Fig 4.1.3.2.1.

4.1.3.2.2 Mundakan

In the case of Mundakan paddy it showed an increasing trend for productivity with a minimum of about 1188.99 kg/ha during 1965-66. In the year 1960-61, the productivity was about 1444.10 kg/ha. The year 2006-07 showed the maximum of 2412.70 kg/ha.

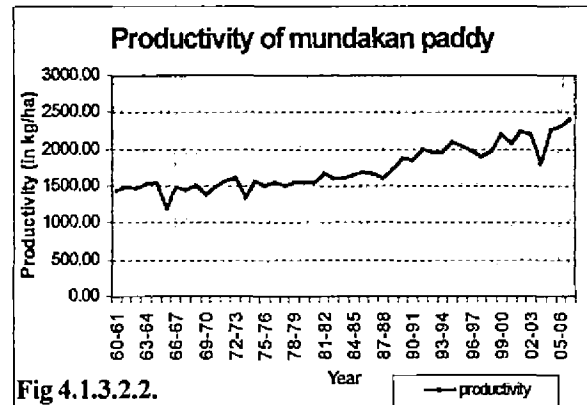


Fig 4.1.3.2.2.

4.1.3.2.3 Puncha

For productivity, Puncha paddy showed an increasing trend with a bit of fluctuations year after year. The minimum was during 1965-66 of about 1139.49 kg/ha. During 1960-61 it was 1577.50 kg/ha. The maximum productivity of puncha paddy was during 2006-07 of about 2889.49kg/ha.

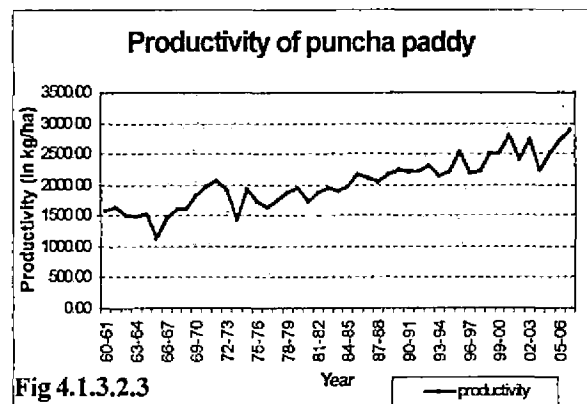


Fig 4.1.3.2.3

4.1.3.3. Price of paddy

Price of paddy during 1960-61 was Rs. 41.20/100kg. The maximum price of paddy was during 2003-04 i.e., Rs. 694.34/100kg. But it decreased to Rs. 610.78/100kg during 2005-06 and afterwards showing an increasing trend in 2006-07 of about Rs. 681.72/100kg in 2006-07.

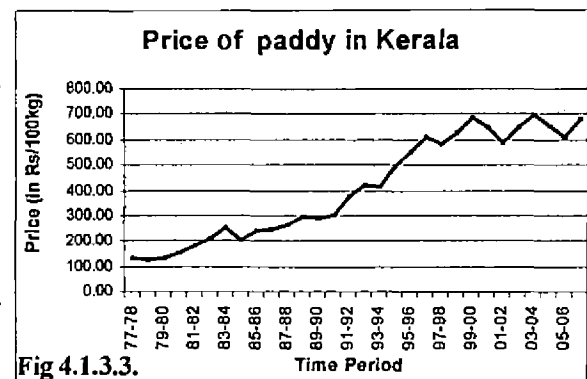
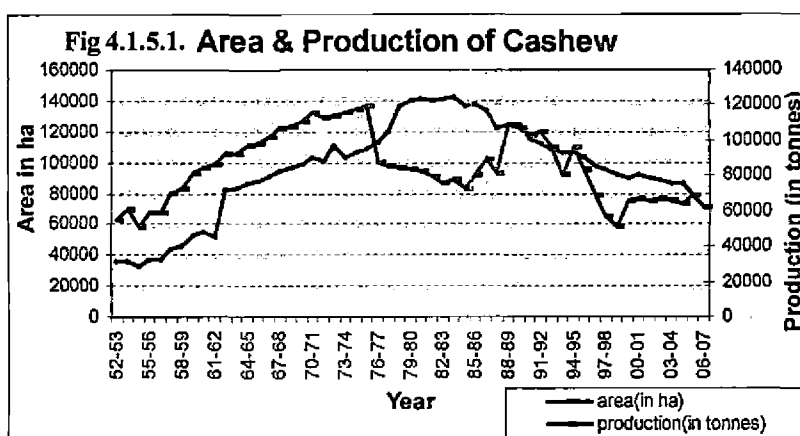


Fig 4.1.3.3.

4.1.5. Cashew

4.1.5.1. Area and production

Area of cashew was 35410ha in 1952-53. But it was showing an increasing trend up to 1983-84, production was also showing an increasing trend up to 1975-76. During 2006-07, the cashew cultivating area was 70461ha. The minimum area was during 1954-55 showing 32940ha only. Production was also showing a decreasing trend from 1988-89. It touched the maximum in 1975-76 at 119890t and the minimum was during 1954-55 of 51320t. The same was almost repeated in 1998-99 with 51336t. The production was 54750t in 1952-53 and in 2006-07, it was 61680t.

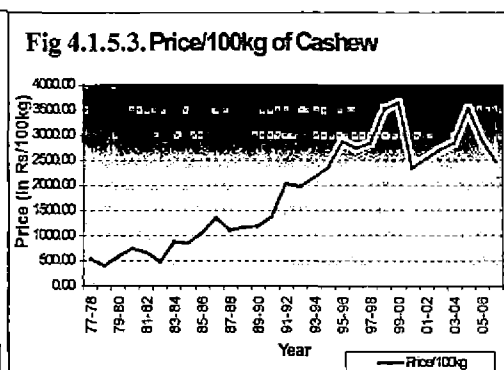
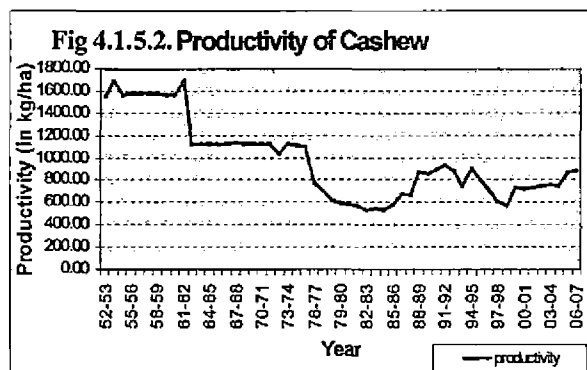


4.1.5.2. Productivity

Productivity of cashew was 1682.95kg/ha in 1960-61 showing the maximum and then it decreased to 448.79 in 1986-87 and then showed an increment to 875.38 in 2006-07. During 1952-53 it was 1546.17kg/ha.

4.1.5.3. Price

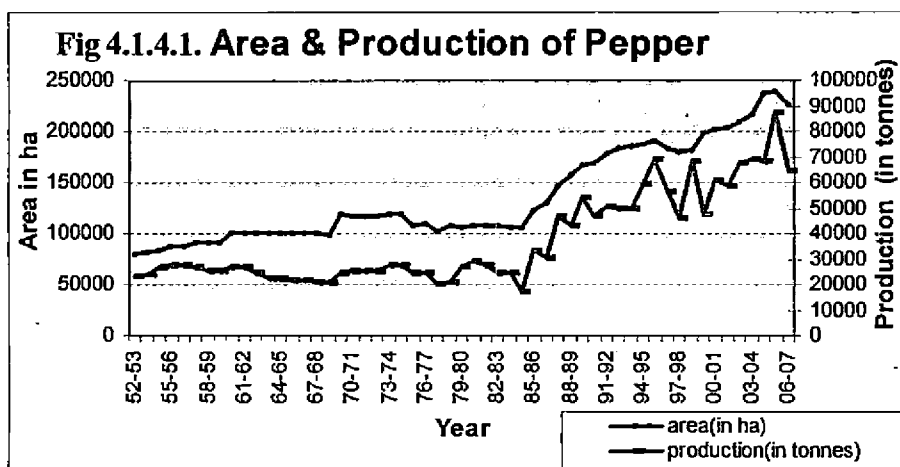
Price of cashew was showing an increasing trend and reached its maximum in 1999-00 at Rs.3638.50/100kg and it suddenly decreased to Rs2336.70 in 2000-01 then reached 3533 in 04-05. The minimum price was during 1958-59 of about Rs. 48.30/100kg and during 2006-07 it was Rs. 2463.90/100kg.



4.1.4. Pepper

4.1.4.1 Area and production

Area under pepper was only 78800 ha in 1952-53 with production of 22630T. The area and production of pepper showed an increasing trend and it showed a considerable increment from 1984-85 to 2005 06. The area hit the maximum at 237998 ha in the year 2005-06. Production of pepper was minimum during 1984-85 of about 17350T. The maximum production of pepper was 87605T during 2005-06.

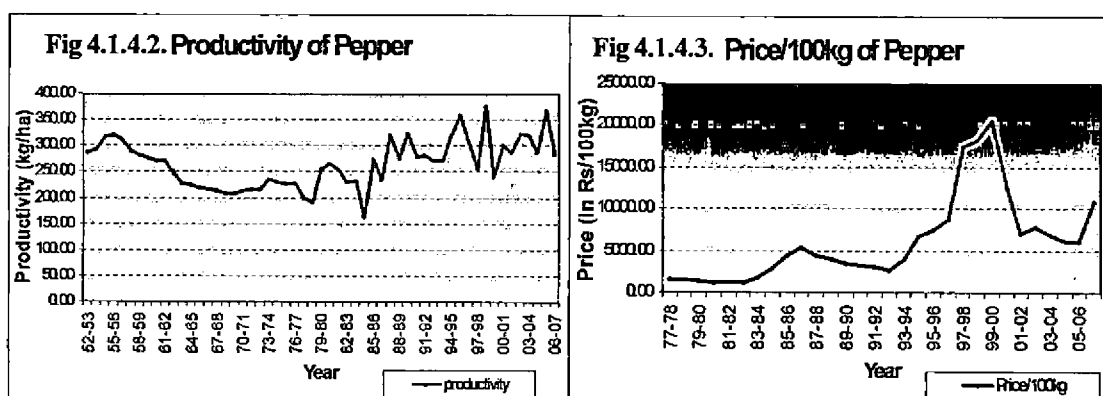


4.1.4.2. Productivity

There was high fluctuations in productivity of pepper during the sampling period. The minimum was during 1984-85 and maximum was in 1998-99 with 163.93 and 375.64 kg/ha respectively. It was 287.18kg/ha in 1952-53 and was 284.24kg/ha in 2006-07.

4.1.4.3. Price

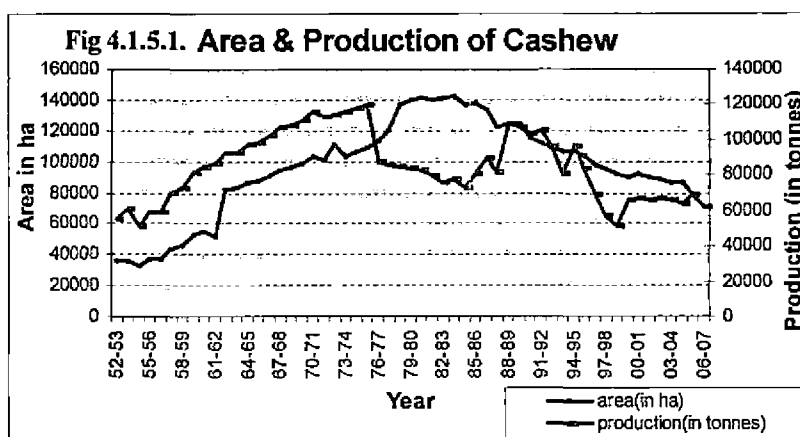
Price showed an increasing trend upto 1999-2000 and reached its maximum in 1999-2000 at Rs. 20506.16/100kg. After that it steadily decreased up to 2005-06 and during 2006-07 it was Rs. 10730.62/100kg. The minimum price was during 1956-57 (Rs. 189.68/100kg.)



4.1.5. Cashew

4.1.5.1. Area and production

Area of cashew was 35410ha in 1952-53. But it was showing an increasing trend up to 1983-84, production was also showing an increasing trend up to 1975-76. During 2006-07, the cashew cultivating area was 70461ha. The minimum area was during 1954-55 showing 32940ha only. Production was also showing a decreasing trend from 1988-89. It touched the maximum in 1975-76 at 119890t and the minimum was during 1954-55 of 51320t. The same was almost repeated in 1998-99 with 51336t. The production was 54750t in 1952-53 and in 2006-07, it was 61680t.

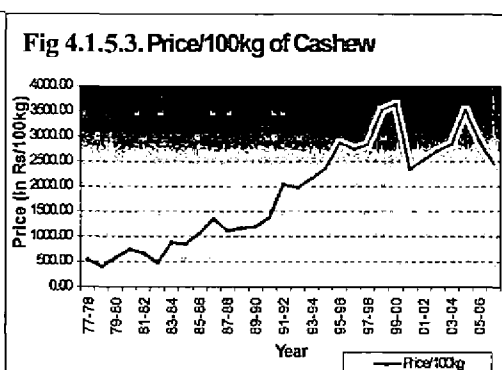
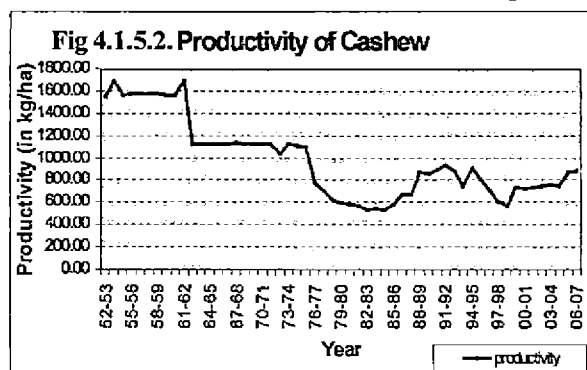


4.1.5.2. Productivity

Productivity of cashew was 1682.95kg/ha in 1960-61 showing the maximum and then it decreased to 448.79 in 1986-87 and then showed an increment to 875.38 in 2006-07. During 1952-53 it was 1546.17kg/ha.

4.1.5.3. Price

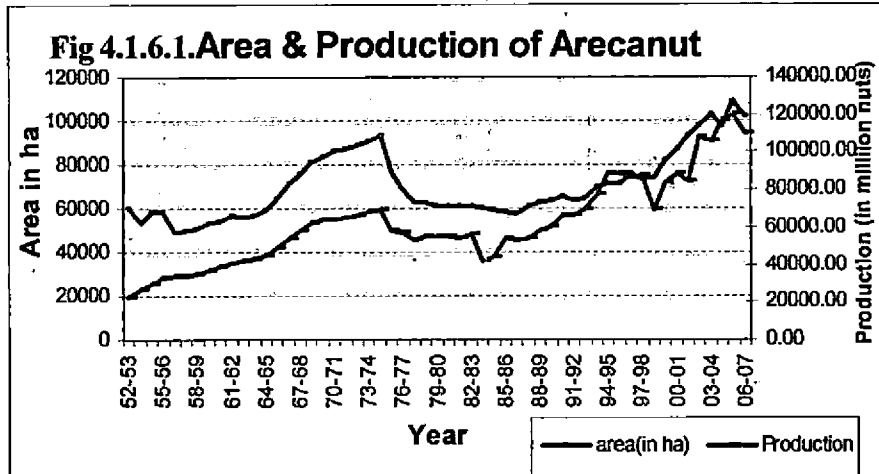
Price of cashew was showing an increasing trend and reached its maximum in 1999-00 at Rs.3638.50/100kg and it suddenly decreased to Rs2336.70 in 2000-01 then reached 3533 in 04-05. The minimum price was during 1958-59 of about Rs. 48.30/100kg and during 2006-07 it was Rs. 2463.90/100kg.



4.1.6. Arecanut

4.1.6.1. Area and production

Area and production of arecanut showed an increasing trend upto 1974-75 and then decreased up to 1983-84 and then showed increasing trend. The minimum area was during 1956-57 of about 49130ha and the maximum was during 2005-06 of 108590ha. During 1952-53 it was 60000ha and in 2006-07 it was 102078ha.

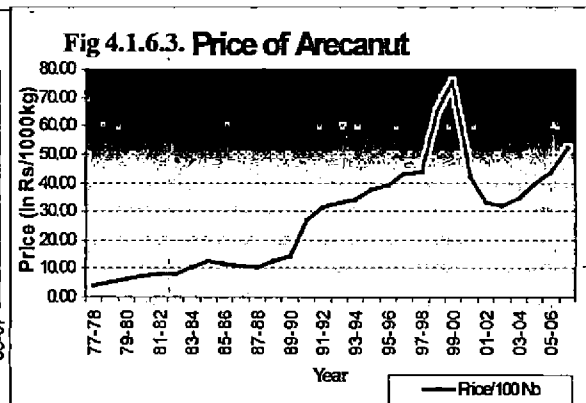
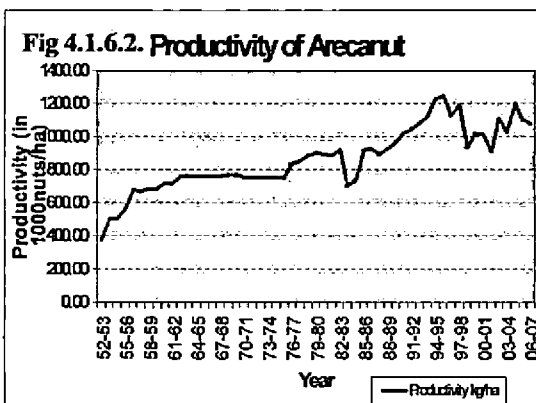


4.1.6.2. Productivity

The productivity was steadily increasing Up to 1995-96, thereafter it was fluctuating. The productivity was very poor during 1952-53 of about 373.43kg/ha and in 2006-07 it was 1077.29kg/ha. The maximum productivity was during 2006-07 of 1077.29kg/ha.

4.1.6.3. Price

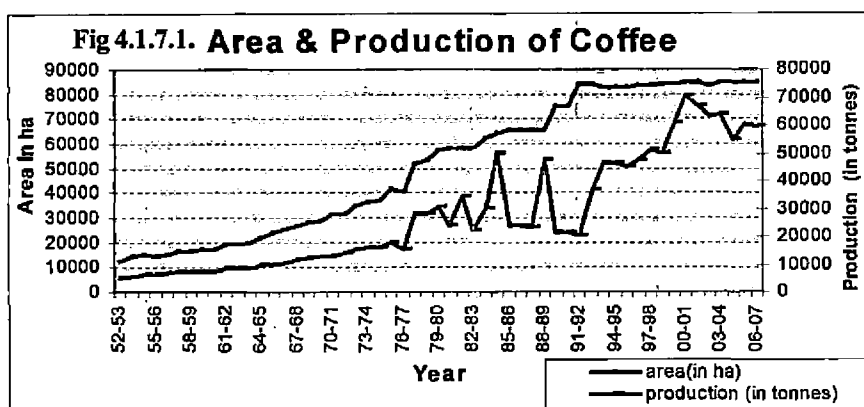
In the case of price it showed an increasing trend and reached a maximum of Rs. 75.25 per 100 number during 1999-2000 after that it showed a steady decrease of Rs 41.93/100No in 2000-01 and Rs.32.95/100No in 2001-02 and 2002-03 After that it increased to Rs 52.07/100No during 2006-07.



4.1.7. Coffee

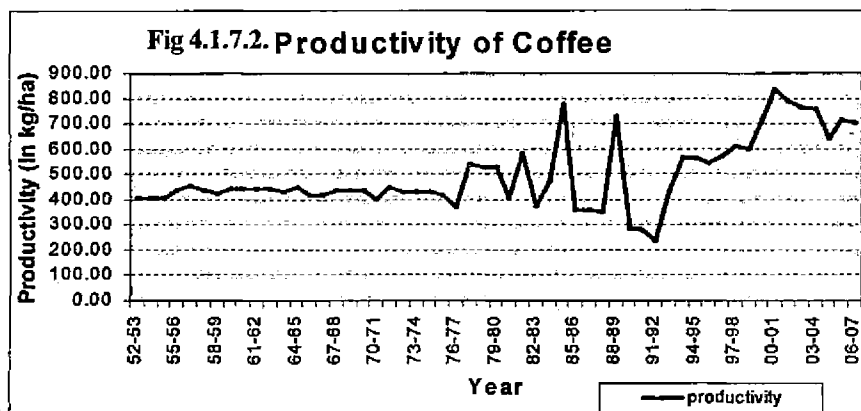
4.1.7.1. Area and production

Eventhough area of coffee showed an increasing trend, its production recently showed a negative trend. Area of coffee hits its maximum during 2001-02 at 84795ha. The lowest area of cultivation in the sampling period was during 1952-53 of about 12610ha. During 2006-07 it was 84571ha with very small decrease. Production hits its maximum during 2000-01 of 70550t and the lowest was recorded in 1952-53 at 51110t. The production during 2006-07 was 59475t which showed a steady growth as compared to that of 2005-06.



4.1.7.2. Productivity

Productivity of coffee showed an increasing trend. During 1991-92 it showed the minimum of 238.53kg/ha. The maximum productivity was in 2000-01 which showed 832.60kg/ha. During 1952-53 it was only 405.23kg/ha while in 2006-07 it showed 703.26kg/ha.

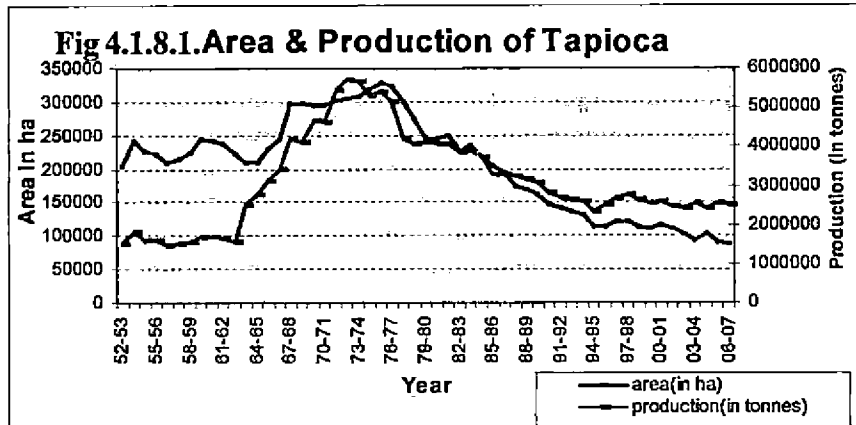


4.1.8. Tapioca

4.1.8.1. Area and production

Area of Tapioca reached its maximum in 1975-76 of 326865ha and production reached its maximum in 1972-73 of 5692360t. After that both showed a steady decrease. During 2006-07 area was 87128ha which showed the lowest in the sample period and Production was 2518999t. The minimum production was during 1956-57 of 1448820t. During 1952-53

area was 204720ha and the production was 1514360t showing the influence of productivity growth in production.

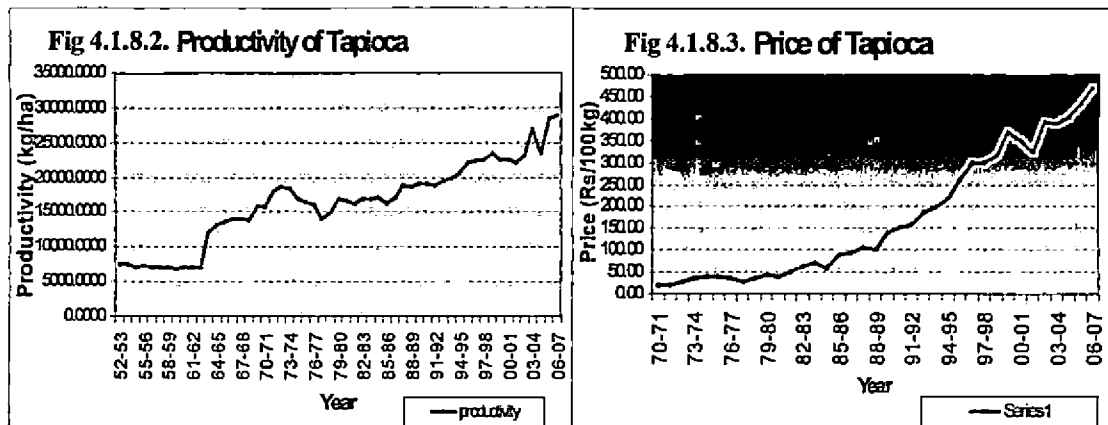


4.1.8.2. Productivity

Productivity and price of Tapioca showed an increasing trend. During 1952-53 productivity was only 7397.2 kg/ha and in 2006-07 it showed the maximum of 28911.5kg/ha and the minimum was 6840.1kg/ha. during 1959-60 .

4.1.8.3. Price

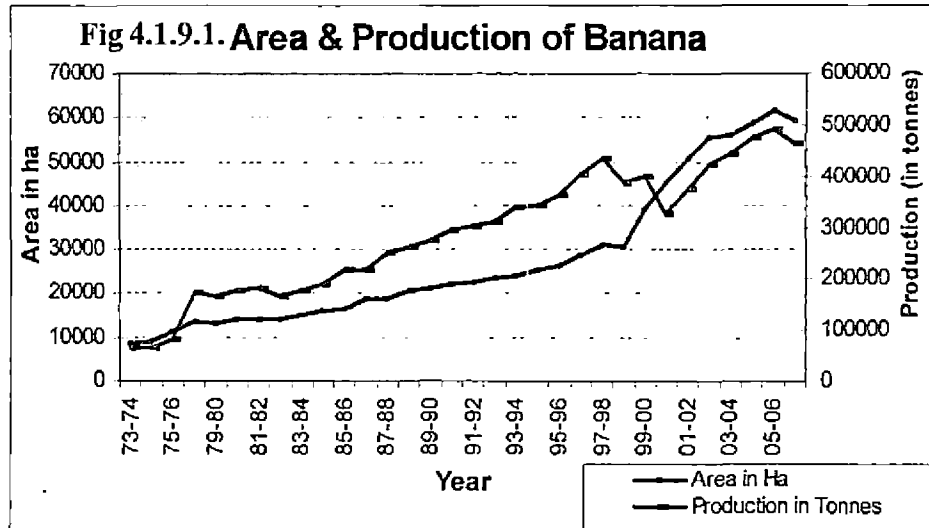
Productivity and price of Tapioca showed an increasing trend from the beginning of the sample period. The minimum was Rs. 20.59/100kg during 1970-71 and it reached Rs. 469.54/100kg in 2006-07.



4.1.9. Banana

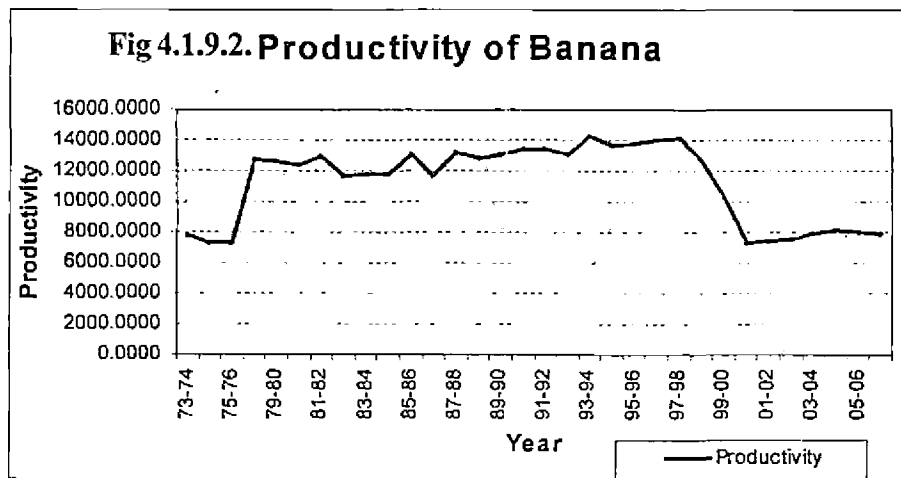
4.1.9.1. Area and production

Area and production of banana showed an increasing trend by reaching the maximum of 61400 ha area and production of 491823t. in 2005-06. During 2006-07 area was reduced to 59143ha and production came down to 463766t. The lowest value for both area and production were recorded in 1973-74 with 8378ha and 65560t respectively.



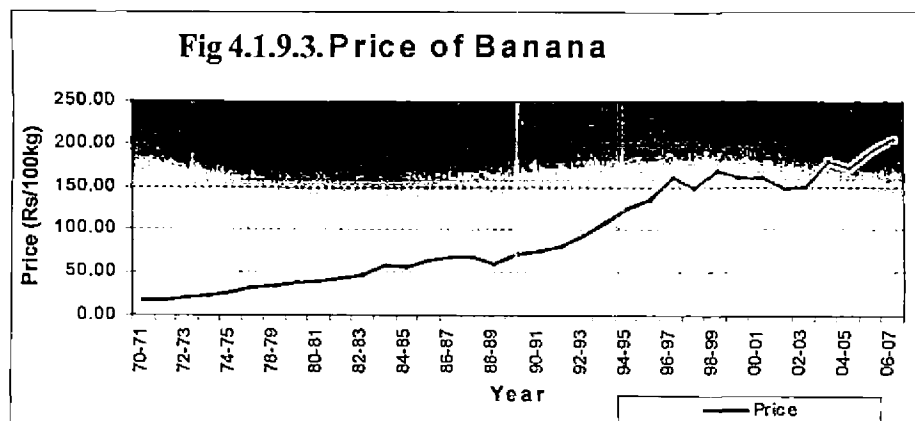
4.1.9.2. Productivity

Productivity was very low in 2000-01 with 7278.3kg/ha. The maximum was during 1993-94 showing 14255.5kg/ha. During 2006-07 it was 7841.4352kg/ha.



4.1.9.3. Price

Price of banana was Rs. 16.69/100No. during 1970-71 while in 2006-07 it showed the overall maximum of Rs. 205.17/100 number.



4.2. Growth rate

The declining growth rate of area under food crops in Kerala has well been documented. According to Pillai (1982) the seventies was the period of decelerated growth in agricultural output in Kerala mainly due to the sharp decline in area under crops especially food crops. Sawal (1981) observed Kerala to be the only state to register a deceleration in the growth of food grain production brought about mainly by fall in acreage. George and Mukherjee (1984) Kannan and Pushpangadan (1988) and Krishnan et.al. (1991) also reported negative growth rates in area under food crops. According to Lakshmi and Pal (1988) one of the major changes that has been taking place in Kerala was the gradual shifting of the area from food crops like rice to plantation crops like rubber and coffee and cash crops coconut and cashew. Persistently deteriorating food crop scenario and perpetually poor yielding commercial crops along with the wide gap between the productivity potential and the productivity realized were the main factor of challenge, which was reported by Bustine , C.L. and Palanisamy (1994). The rapid shift in cropping pattern away from food crops has been reported by Joseph (1996).

Mani and Jose (1997) reported that significant shifts in cropping pattern had taken place in the northern districts of the state and area diverted for non economic activities had risen. A shift in cropping pattern in favour of cash and plantation crops at the expense of probably the less remunerative crops had seen in the analysis by Jayalexman and Velayudhan (2002). Mani (2004) noted a significant reduction in area under rice and increased area under coconut and rubber and claimed that Kerala farmers was shifting the area under rice to coconut and rubber . Thomas (2004) observed from the analysis of changes in cropping pattern of the state that since its formation in 1956 it clearly showed that there had been a persistent shift in favour of garden crops and plantation crops at the expense of food crops. Cropping pattern of Kerala irrigated by marked conditions and most important structural changes in the relative decline in proportion of food grains was noted by Mohandas (2005)

There are many factors, which affect the growth of crop output and productivity. The sources of output growth like area effect, yield effect and cropping pattern effect have relevance in deciding the programmes of agricultural development and priorities of investment in it (Ranade, 1988). The growth rates as such offer no explanation for desperate performance of agriculture. Thus it becomes important to find why these growth rates differ from one another so that the bottle necks could be removed to achieve the speedy development of agricultural sector (Sikka and Vaidya, 1985).

4.2.2. Growth rate of paddy during different periods

Dividing the period from 1960-61 to 2006-2007 into three subdivisions, as Pre-Green revolution Period (up to 1966-67), Green revolution period (1966-67 to 1986-87) and post - Green revolution Period (1986-87 to 2006-07) it was observed that the average growth rate of paddy cultivating area was 2.98% increase during 1966-67 to 1986-87 while in post - Green revolution Period , the area declined at the rate of 47.83%. In the case of production, the period 1966-67 to 1986-87 showed an increment of 18.43% but during 1986-87 to 2006-2007 it declined at the rate of 32.42%. But the productivity growth rate showed increasing trend as it moved from 17.31 to 30.49%.

By studying the season wise paddy cultivation in Kerala, in the case of area, production and productivity the table below give a comparison between them during 1960-61, 1986-87 and 2006-2007.

Table 4.2.2.1. Statistics of virippu paddy

Virippu	Area (ha)	Production (t)	Productivity (kg/ha)
1960-61	396132	500348	1263.084
1986-87	286569	468409	1634.542
2006-07	83859	191241	2280.507

Table 4.2.2.2. Statistics of mundakan paddy

Mundakan	Area (ha)	Production (t)	Productivity (kg/ha)
1960-61	310028	447712	1444.102
1986-87	297068	496623	1671.749
2006-07	143724	346763	2412.701

Table 4.2.2.3. Statistics of puncha paddy

Puncha	Area (ha)	Production (t)	Productivity (kg/ha)
1960-61	75753	119500	1577.495
1986-87	80166	168754	2105.057
2006-07	35946	103572	2881.322

The above tables show the fast decrease of the area and production due to the highly decreasing growth rate of paddy cultivation eventhough there is increment in productivity.

Fig. 4.2.1. Five yearly growth rate for area of crops

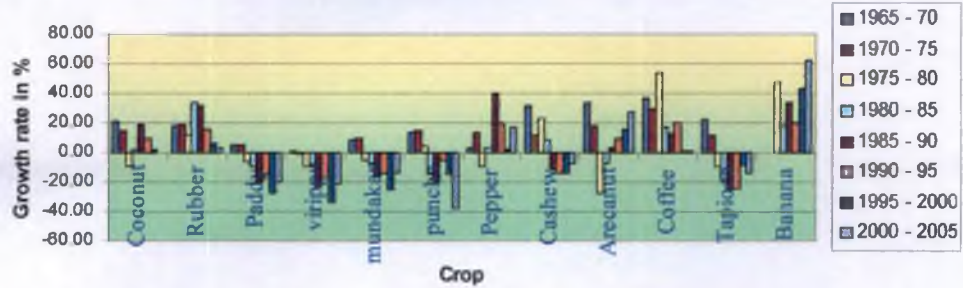


Fig. 4.2.2. Five yearly growth rate for production of crops

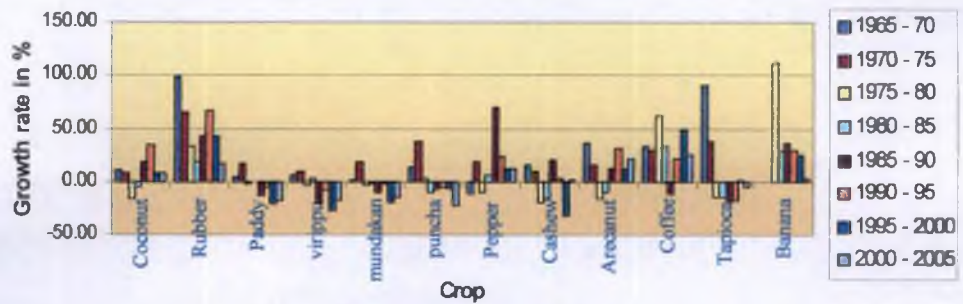


Fig. 4.2.3. Five yearly growth rate for productivity of crops

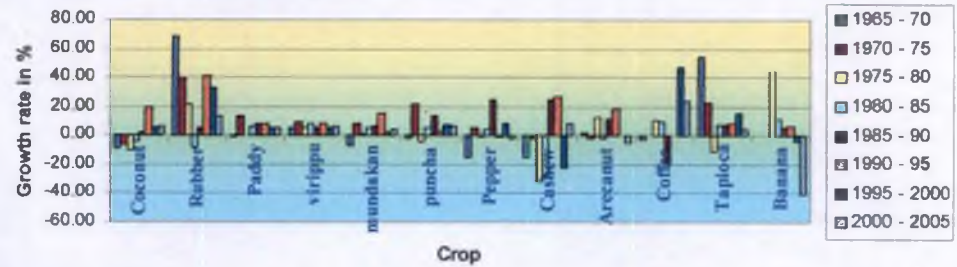


Fig. 4.2.2. Average Price Before and After 1994



4.3. Modified P-Gan's Method

P-Gan's formula was to understand whether the fluctuation in crop production was due to area or productivity .By this formula,

$$\text{Production contribution} = \text{Area contribution} + \text{Productivity contribution}$$

Modification to P-Gan's formula is given by

$$\text{Growth rate of Y} \approx \text{Growth rate of A} + \text{Growth rate of P}$$

Table 4.3.1. Results of the modified P - Gan's method for the last 5 decades

Crop	% of increase in production due to increase in			% of decrease in production due to decrease in		
	Area alone	Productivity alone	Area and Productivity	Area alone	Productivity alone	Area and Productivity
Coconut	32.35	17.65	50.00	15.00	55.00	30.00
Rubber	18.37	2.04	79.59	0.00	60.00	40.00
Paddy	0.00	44.44	55.56	42.86	14.29	42.86
Virippu	8.70	39.13	52.17	27.27	9.09	63.64
Mundakan	8.70	39.13	52.17	17.39	13.04	69.57
Puncha	3.70	51.85	44.44	11.11	38.89	50.00
Pepper	20.00	16.00	64.00	0.00	65.52	34.48
Arecanut	25.64	28.21	46.15	40.00	46.67	13.33
Tapioca	20.00	40.00	40.00	46.67	16.67	36.67
Coffee	36.84	5.26	57.89	0.00	56.25	43.75
Cashew	43.33	23.33	33.33	25.00	25.00	50.00
Banana	34.62	3.85	61.54	0.00	50.00	50.00

From the above table it could be assessed that the increase in production of a crop was due to the increase in area or increase in productivity of the crop. In the case of all the crops except paddy and tapioca, the increase in area was the main contributor towards the increased production.

For all the crops except paddy, Tapioca and Arecanut the decrease in production was due to the declined productivity in most of the years under study.

4.4. Cointegration Technique

The long run relationship between area and Price of various crops of Kerala using the annual data over a period from 1970-71 to 2006-07 was analysed using cointegration technique. For a non-stationary series mean, variance, and covariance would change over time, and the standard t tests in regression would no longer be valid (Karbus and Jumah, 1995). Holden and Perman (Rao, 1994) derived a relationship between stationarity and the existence of a unit root. Dickey and Fuller (1979 and 1981) demonstrated that if under the null hypothesis that a series has a unit root (i.e., if the series is nonstationary), then the t statistics for parameter estimates in a regression is not distributed as a Student t any more.

In the simplest form, a time series is said to be having a unit root if it is well characterized by an AR(1) model with white noise. But the time series have a complicated dynamic structure than is computed by a simple AR(1) model. So the errors may not be independently and identically distributed and hence most form of Dickey Fuller unit root test are of low power in the sense that they tend to accept the null hypothesis of having a unit root more frequently than is warranted (Damodar and Gujarati, 2005). More over if ρ is not exactly equal to one but close to it, the result will be there exist a unit root.

Dickey Fuller Test assumes the model $Y_t = \rho Y_{t-1} + e_t$, where e_t is assumed to define a sequence of independently and identically distributed (IID) random variables with expected value zero and variance σ^2 . The process in equation is stationary when ρ is less than one in absolute value; i.e., $-1 < \rho < 1$. The AR(1) process has a unit root if and only if ρ is one, then the AR(1) process is nonstationary (Rao, 1994). But if the error are dependent it will be a violation of DF test. Here a new method for unit root testing is given which assume the errors are dependent in the case of fitting an AR(1) model.

Most economic series exhibit variation that increases in both the mean and the dispersion in proportion to the absolute level of the series. Much as the application of the difference operator frequently removes a time-dependent mean, but has little effect on stabilizing the variance of empirical time series. Cryer (1986) argues that, if the standard deviation of a series is proportional to its level, then the data expressed in terms of logarithms will exhibit approximately constant variance. Given that most empirical time series are integrated of order one, that is, require first differencing to remove time dependence in the mean, a useful result emerges when the difference and the logarithmic transformations are combined. This transformation also leads to the loss of long-run properties and the inability to obtain a long-run solution.

In the present study, ACF of all the series showed a non-stationary pattern as the ACF remained significant over half a dozen or more lags rather than quickly declining to zero. To assure the time series was non-stationary, augmented Dickey-Fuller unit root test was additionally used for testing stationarity of the variable using the computer software gretl 1.8. Results of the ADF test were supporting the results of ACF and the ADF result of the probability of accepting the null hypothesis of having a unit root are given in table 4.1. According to this test it was seen that the entire variables were found to be non-stationary as all the probabilities were above 0.05. So the differenced series was used for forecasting purposes as it was seen that the DSP series was stationary.

Table 4.4.1 Probability of presence of unit root in the data to assess non-stationarity

Variables	Coconut	Rubber	Arecanut	Tapioca	Coffee	Cashew
Area	0.7487	0.9850	0.6315	0.5258	0.9850	0.3375
Production	0.9924	1.0000	0.4486	0.0985	1.0000	0.5483
Productivity	0.1951	0.9983	0.0904	0.7821	0.9983	0.4680
Price	1.0000	1.0000	1.0000	1.0000	-	0.9930

Variables	Pepper	Paddy	Virippu	Mundaka	Puncha	Banana
Area	0.9908	0.9999	0.8683	0.8419	0.8082	0.9892
Production	0.9955	0.9550	0.9618	0.9998	0.5158	0.5278
Productivity	0.3287	0.9997	0.1934	1.0000	0.9552	0.4349
Price	1.0000	0.7514	-	-	-	0.9999

To determine the existence of a long-run relationship between area and price, a co-integration test was applied. In the present study the Engle and Granger (1987) two step procedure for modeling the relationship between co-integrated variables has been employed. The co-integration between the two series viz; area and price, were tested by conducting the ADF test on residuals obtained from running the OLS regression, called the co-integrating regression. Co-integration theory suggests that if two non-stationary time-series are co-integrated, residuals of the linear combination of these two non-stationary series are stationary. Therefore, co-integrated series indicate stable long-run relationship between them. Evidence of co-integration between non-stationary price series and area under cultivation indicated that there was a stable long-run relationship between them.

Granger (1981, 1991), Granger and Weiss (1983), and Engle and Granger (1987) have shown that, even though a given set of series may be non-stationary, there may exist

various linear combinations of the individual series that are stationary. The desire to estimate models that combine both short-run and long-run properties and that at the same time maintain stationarity in all of the variables, has prompted a reconsideration of the problem of regression using variables measured in their levels. Cointegration is a statistical framework to test for long-run or steady-state equilibrium relationships among several non-stationary series.

Engle and Granger (1987) gives the formal definition of cointegration of two variables as two time series x_{1t} and x_{2t} are said to be cointegrated of order d, b , where $d \geq b \geq 0$ written as $x_{1t}, x_{2t} \sim CI(d, b)$, if

1. both series are integrated of order d ,
2. there exists a linear combination of these variables, say $\alpha_1 x_{1t} + \alpha_2 x_{2t}$,

which is integrated of order $(d-b)$. The vector $[\alpha_1, \alpha_2]$ is called a cointegrating vector. If there is a long-run relationship between two (or more) nonstationary variables (all integrated of the same order), the idea is that deviations from this long-run path are stationary if the variables are to be cointegrated. The results of the cointegration study are presented below.

Table 4.4.2. Cointegration results for Coconut

Regressor	coefficient	std. error	t-ratio	p-value
const	665277	18692.6	35.59	0 ***
Price	486.603	58.6542	8.296	0 ***

Mean	797647.4	S.D.	100596.1
Sum squared	1.23×10^{11}	S.E. of regression	59235.20
R-squared	0.662897	Adjusted R-squared	0.653265
Log-likelihood	-458.0757	Akaike criterion	920.1514
Schwarz criterion	923.3733	Hannan-Quinn	921.2873
rho	0.735637	Durbin-Watson	0.525439

Augmented Dickey-Fuller test for the estimate of error

1st-order autocorrelation coeff. for error	:	0.151
lagged differences: F(16, 3)	:	3.145 [0.1878]
estimated value of $(a - 1)$:	-1.93684
test statistic: tau_c(2)	:	-4.08804
asymptotic p-value	:	0.005312

ADF test on the residuals were done to see if they had a unit root. Here the Null Hypothesis was rejected indicating that the residuals were stationary and the variables could be cointegrated at lag 16. The cointegration model could be defined by the relation

$$A_t = 665277 + 486.603R_{t-16} \dots\dots\dots(4.4.1)$$

where A_t denotes the area and R_t the price of coconut at the t th year. Since adjusted R^2 is 65, 65% of the variations was due to the variation in price only and can be explained through the above model.

Table 4.4.3. Cointegration results for Rubber

Regressor	coefficient	std. error	t-ratio	p-value
const	437980	10115.8	43.3	1.93e-015 ***
Price	6.87167	2.15723	3.185	0.0072 ***

Mean dependent var	467863.3	S.D. dependent var	18846.33
Sum squared resid	2.79e+09	S.E. of regression	14656.98
R-squared	0.438369	Adjusted R-squared	0.395167
Log-likelihood	-164.1009	Akaike criterion	332.2018
Schwarz criterion	333.6179	Hannan-Quinn	332.1867
rho	0.841560	Durbin-Watson	0.270571

Augmented Dickey-Fuller test for error

1st-order autocorrelation coeff. for e :	0.158
lagged differences: F(3, 7) :	2.889 [0.1120]
estimated value of (a - 1) :	-0.505137
test statistic: tau_c(2) :	-3.26298
asymptotic p-value :	0.06005

ADF test on the residuals were done to see if they had a unit root. Here the residuals were stationary and the variables were cointegrated at lag 3. The cointegration model could be defined by the relation

$$A_t = 437980 + 6.87167R_{t-3} \dots\dots\dots(4.4.2)$$

where A_t denotes the area and R_t the price of rubber at the t th year. Since adjusted R^2 was 0.39, 39% of the variation in are was due to the variation in price only and could be explained through the above model.

Table 4.4.4. Cointegration results for Paddy

Regressor	coefficient	std. error	t-ratio	p-value
const	960811	19916.1	48.24	1.31e-033 ***
Price	-995.403	47.8363	-20.81	2.72e-021 ***

Mean	601221.4	S.D. dependent var	217135.1
Sum squared	1.27e+11	S.E. of regression	60222.75
R-squared	0.925213	Adjusted R-squared	0.923076
Log-likelihood	-458.6875	Akaike criterion	921.3750
Schwarz criterion	924.5968	Hannan-Quinn	922.5108
rho	0.731437	Durbin-Watson	0.538284

Augmented Dickey-Fuller test for error including 4 lags of (1-L)error

1st-order autocorrelation coeff. for e	:	0.049
lagged differences: F(4, 27)	:	1.595 [0.2042]
estimated value of (a - 1)	:	-0.515178
test statistic: tau_c(2)	:	-3.58969
asymptotic p-value	:	0.02527

ADF test on the residuals were done to see if they had a unit root. Here the residuals were stationary and the variables could be cointegrated at lag 4. The cointegration model could be defined by the relation

$$A_t = 960811 - 995.403R_{t-4} \dots\dots\dots (4.3.3)$$

Where A_t denotes the area and R_t the price of Paddy at the t th year. Since adjusted R^2 was 92, 92% of the decrease in area was due to the variation in price only and could be explained through the above model.

Table 4.4.4.1. Cointegration results for Virippu paddy

Regressor	coefficient	std. error	t-ratio	p-value
const	428337	10044.3	42.64	9.16e-032 ***
Price	-489.97	24.1253	-20.31	5.97e-021 ***

Mean dependent var	251334.8	S.D. dependent var	107079.7
Sum squared resid	3.23e+10	S.E. of regression	30372.17
R-squared	0.921783	Adjusted R-squared	0.919548
Log-likelihood	-433.3601	Akaike criterion	870.7202
Schwarz criterion	873.9421	Hannan-Quinn	871.8561
rho	0.715900	Durbin-Watson	0.566127

Augmented Dickey-Fuller test for error including 4 lags of (1-L)error

model : $(1-L)y = b_0 + (a-1)*y(-1) + \dots + e$
 1st-order autocorrelation coeff. for e : 0.082
 lagged differences: F(4, 27) : 1.363 [0.2729]
 estimated value of (a - 1) : -0.532587
 test statistic: tau_c(2) : -3.59835
 asymptotic p-value : 0.02465

ADF test on the residuals were done to see if they had a unit root. Here the residuals were stationary and the variables could be cointegrated at lag 4. The cointegration model could be defined by the relation

$$A_t = 428337 - 489.97R_{t-4} \dots \dots \dots (4.4.3.1)$$

where A_t denotes the area and R_t the price of Paddy at the t^{th} year. Since adjusted R^2 was 92, 92% of the decrease in area was due to the variation in price only and could be explained through the above model.

Table 4.4.4.2. Cointegration results for Mundakan paddy

Regressor	coefficient	std. error	t-ratio	p-value
const	419392	7815.39	53.66	3.31e-035 ***
Price	-399.625	18.7717	-21.29	1.30e-021 ***
Mean dependent var		275027.7	S.D. dependent var	87027.82
Sum squared resid		1.95e+10	S.E. of regression	23632.39
R-squared		0.928309	Adjusted R-squared	0.926261
Log-likelihood		-424.0765	Akaike criterion	852.1530
Schwarz criterion		855.3748	Hannan-Quinn	853.2889
rho		0.709045	Durbin-Watson	0.582040

Augmented Dickey-Fuller test for error including 4 lags of (1-L)error

1st-order autocorrelation coeff. for e : -0.015
 lagged differences : F(4, 27) L : 1.393 [0.2628]
 estimated value of (a - 1) : -0.56935
 test statistic: tau_c(2) : -3.54777
 asymptotic p-value : 0.02843

ADF test on the residuals were done to see if they had a unit root. Here the residuals were stationary and the variables could be cointegrated at lag 4. The cointegration model could be defined by the relation

$$A_t = 419392 - 399.625R_{t-4} \dots\dots\dots (4.4.3.2)$$

where A_t denotes the area and R_t the price of Paddy at the t th year. Since adjusted R^2 was 93, 93% of the decrease in area was due to the variation in price only and could be explained through the above model.

Table 4.4.4.3. Cointegration results for Puncha paddy

Regressor	coefficient	std. error	t-ratio	p-value
const	113082	3281.12	34.46	1.33e-028 ***
Price	-105.808	7.88091	-13.43	2.28e-015 ***

Mean dependent var	74858.89	S.D. dependent var	24260.80
Sum squared resid	3.45e+09	S.E. of regression	9921.552
R-squared	0.837402	Adjusted R-squared	0.832757
Log-likelihood	-391.9639	Akaike criterion	787.9277
Schwarz criterion	791.1496	Hannan-Quinn	789.0636
rho	0.625296	Durbin-Watson	0.742539

Augmented Dickey-Fuller test for error including 8 lags of (1-L)error

1st-order autocorrelation coeff. for e	:	-0.132
lagged differences: F(8, 19)	:	2.024 [0.0989]
estimated value of (a - 1)	:	-1.17635
test statistic: tau_c(2)	:	-3.56727
asymptotic p-value	:	0.02692

ADF test on the residuals were done to see if they had a unit root. Here the residuals were stationary and the variables could be cointegrated at lag 8. The cointegration model could be defined by the relation

$$A_t = 113082 - 105.808R_{t-8} \dots\dots\dots (4.4.3.3)$$

where A_t denotes the area and R_t the price of Paddy at the t th year. Since adjusted R^2 was 83, 83% of the decrease in area was due to the variation in price only and could be explained through the above model.

Table 4.4.5. Cointegration results for Pepper

Regressor	coefficient	std. error	t-ratio	p-value
const	126820	8163.07	15.54	2.82e-017 ***
Pricef	5.58346	1.14333	4.883	2.28e-05 ***

Mean dependent var	155231.2	S.D. dependent var	44532.58
Sum squared resid	4.25e+10	S.E. of regression	34830.62
R-squared	0.405253	Adjusted R-squared	0.388260
Log-likelihood	-438.4280	Akaike criterion	880.8560
Schwarz criterion	884.0779	Hannan-Quinn	881.9919
rho	0.892140	Durbin-Watson	0.240524

Augmented Dickey-Fuller test for error including 17 lags of (1-L)error

1st-order autocorrelation coeff. for e	:	-0.177
lagged differences: F(17, 1)	:	16.405 [0.1921]
estimated value of (a - 1)	:	-2.04393
test statistic: tau_c(2)	:	-4.98668
asymptotic p-value	:	0.0001

ADF test on the residuals were done to see if they had a unit root. Here the residuals were stationary and the variables are cointegrated at lag 17. The cointegration model could be defined by the relation

$$A_t = 126820 + 5.58346R_{t,17} \dots \dots \dots (4.3.4)$$

where A_t denotes the area and R_t the price of Pepper at the t th year. Since adjusted R^2 was 39, 39% of the decrease in area was due to the variation in price only and could be explained through the above model.

Table 4.4.6. Cointegration results for Cashew

Regressor	coefficient	std. error	t-ratio	p-value
const	96361.3	7687.9	12.53	4.27e-014 ***
Priceg	-11.3154	6.14372	-1.842	0.0745 *
time	5316.22	1057.1	5.029	1.69e-05 ***
timesq	-141.524	23.5634	-6.006	9.48e-07 ***

Mean dependent var	112552.8	S.D. dependent var	24411.66
Sum squared resid	6.98e+09	S.E. of regression	14547.38
R-squared	0.674473	Adjusted R-squared	0.644880
Log-likelihood	-405.0353	Akaike criterion	818.0706
Schwarz criterion	824.5143	Hannan-Quinn	820.3423
rho	0.188988	Durbin-Watson	1.620850

Augmented Dickey-Fuller test for error including one lag of (1-L)error

1st-order autocorrelation coeff. for e : -0.007
 estimated value of (a - 1) : -0.734835
 test statistic: tau_ctt(2) : -3.33125
 asymptotic p-value : 0.2884

ADF test on the residuals were done to see if they had a unit root. Here the residuals were stationary and the variables could be cointegrated at lag 1. The cointegration model could be defined by the relation

$$A_t = 96361.3 - 11.3154R_{t-1} + 5316.22t - 141.524t^2 \dots\dots\dots(4.4.5)$$

where A_t denotes the area and R_t the price of Cashew at the t^{th} year. Since adjusted R^2 was 64, 64% of the decrease in area was due to the variation in price only and could be explained through the above model.

Table 4.4.7. Cointegration results for Arecanut

Regressor	coefficient	std. error	t-ratio	p-value
const	96208.6	2558.7	37.6	1.13e-028 ***
Price	-49.6213	84.3648	-0.5882	0.5604
time	-4264.83	322.679	-13.22	9.84e-015 ***
timesq	128.495	7.90996	16.24	2.64e-017 ***

Mean dependent var 75073.68 S.D. dependent var 15191.87
 Sum squared resid 7.82e+08 S.E. of regression 4868.049
 R-squared 0.905876 Adjusted R-squared 0.897320
 Log-likelihood -364.5307 Akaike criterion 737.0615
 Schwarz criterion 743.5051 Hannan-Quinn 739.3332
 rho 0.520112 Durbin-Watson 0.917474

Augmented Dickey-Fuller test for error including 2 lags of (1-L)error

1st-order autocorrelation coeff. for e : -0.120
 lagged differences: F(2, 31) : 4.468 [0.0197]
 estimated value of (a - 1) : -0.792448
 test statistic: tau_ctt(2) : -4.16699
 asymptotic p-value : 0.04826

ADF test on the residuals were done to see if they had a unit root. Here the residuals

were stationary and the variables could be cointegrated at lag 2. The cointegration model could be defined by the relation

$$A_t = 96208.6 - 49.6213R_{t-2} - 4264.83t + 128.495t^2 \dots\dots\dots (4.4.6)$$

where A_t denotes the area and R_t the price of Arecanut at the t th year. Since adjusted R2 is 90, 90% of the decrease in area was due to the variation in price only and could be explained through the above model.

Table 4.4.8. Cointegration results for Tapioca

Regressor	coefficient	std. error	t-ratio	p-value
const	274413	9884.07	27.76	1.99e-025 ***
Price	-496.426	44.4359	-11.17	4.32e-013 ***
Mean dependent var	189575.2	S.D. dependent var	81081.55	
Sum squared resid	5.18e+10	S.E. of regression	38483.47	
R-squared	0.780987	Adjusted R-squared	0.774729	
Log-likelihood	-442.1181	Akaike criterion	888.2362	
Schwarz criterion	891.4580	Hannan-Quinn	889.3720	
rho	0.937792	Durbin-Watson	0.143229	

Augmented Dickey-Fuller test for error

1st-order autocorrelation coeff. for e	:	-0.570
lagged differences: F(16, 3)	:	1.438 [0.4318]
estimated value of (a - 1)	:	-1.53789
test statistic: tau_c(2)	:	-3.32645
asymptotic p-value	:	0.05125

ADF test on the residuals were done to see if they had a unit root. Here the residuals were stationary and the variables could be cointegrated at lag 16. The cointegration model could be defined by the relation

$$A_t = 274413 - 496.426R_{t-16} \dots\dots\dots (4.4.7)$$

where A_t denotes the area and R_t the price of Arecanut at the t th year. Since adjusted R2 was 77, 77% of the decrease in area was due to the variation in price only and could be explained through the above model.

Table 4.4.9. Cointegration result for Banana

Regressor	coefficient	std. error	t-ratio	p-value
Price	42.2133	1.65954	25.44	2.48e-022 ***

Mean dependent var	27647.16	S.D. dependent var	16445.39
Sum squared resid	1.50e+09	S.E. of regression	6959.898
R-squared	0.954279	Adjusted R-squared	0.954279
Log-likelihood	-328.0315	Akaike criterion	658.0630
Schwarz criterion	659.5287	Hannan-Quinn	658.5488

Augmented Dickey-Fuller test for error

1st-order autocorrelation coeff. for e	:	-0.015
lagged differences: F(3, 21)	:	3.324 [0.0394]
estimated value of (a - 1)	:	-0.435545
test statistic: tau_nc(2)	:	-3.18936
asymptotic p-value	:	0.01594

ADF test on the residuals were done to see if they had a unit root. Here the residuals were stationary and the variables could be cointegrated at lag 3. The cointegration model could be defined by the relation

$$A_t = 42.2133R_{t-3} \dots \dots \dots (4.4.8)$$

where A_t denotes the area and R_t the price of arecanut at the t th year. 95% of the decrease in area was due to the variation in price and could be explained through the above model.

Table 4.4.10. Regression models developed through cointegration for different crops

Crop	Regression of Area on Price	R ² (%)
Paddy	$A_t = 960811-995.403R_{t-4}$	92.5
Virippu	$A_t = 428337-489.97R_{t-4}$	92.2
Mundakan	$A_t = 419392-399.625 R_{t-4}$	92.8
Puncha	$A_t = 113082-105.808 R_{t-8}$	83.7
Tapioca	$A_t = 274413-496.426 R_{t-16}$	78.1
Banana	$A_t = 42.2133 R_{t-3}$	95.4
Coconut	$A_t = 665277+486.603 R_{t-16}$	66.2
Arecanut	$A_t = 96208.6-49.6213 R_{t-2}-4264.83t+128.495t^2$	90.6
Cashew	$A_t = 96361.3-11.3154 R_{t-1}+5316.22t-141.524t^2$	67.4
Rubber	$A_t = 437980+6.87167 R_{t-3}$	43.8
Pepper	$A_t = 126820+5.58346 R_{t-17}$	40.5

4.5. Building ARIMA Model for predicting area, production, productivity and price of major crops of Kerala

Yearly data for the period from 1952-53 to 2002-03 pertaining to area, production, productivity and price of the crops viz; coconut, rubber, paddy, pepper, arecanut, tapioca, coffee, cashew and banana in Kerala were analyzed. Identification of the model was done as per the ACF and PACF generated by the software MINITAB 15 and the estimation of the parameters in the model was done using SPSS 16.0. Results of the ADF test were in consonance with the results of ACF. The probability of accepting the null hypothesis of having a unit root worked out using ADF test are given in table 4.1. According to this test, the time series data of the various crops under consideration were found to be non-stationary. So the first order differenced series was used for forecasting purposes as it was stationary for all the data except price of rubber and area under total paddy where second order differencing were needed to attain stationarity. Appropriate Box-Jenkins autoregressive integrated moving average model (ARIMA) was fitted. Validity of the models was tested using standard statistical techniques. The ARIMA models developed were used to forecast the area, production, productivity and price for the post sample period (2003-04 to 2006-07) as well as for five leading years (2007-08 to 2011-12) in future. This would enable the policy makers to predict ahead of time the future requirements for grain storage, import and export of these crops there by enabling them to take appropriate safeguards.

The models fitted proved to be the best as the residuals were scattered randomly about the horizontal level through zero. The best model was selected by using the measures of R^2 , Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Maximum Absolute Error (MaxAE) and Maximum Absolute Percentage Error (MaxPE). These models were used to forecast the future values of the transformed time series. The forecasting capability for the post sample period of the ARIMA models was assessed using Root Mean Squared Forecasting Error (RMSFE), Mean Absolute Forecasting Percentage Error (MAFPE) and Maximum Absolute Forecasting Percentage Error (MXAFPE).

The RMSFE is the error accumulated in the forecasted observations and MAFPE is the absolute error in the desired prediction length, which consider a measure of how much a dependent series vary from its model-predicted level. MXAFE is the largest forecasted error which is considered a measure useful in imagining a worse case scenario for the forecasts. Assuming that the estimated model is a true representative of the forecasting period, the post sample RMSFE should be consistent with the residual standard error of the estimated model.

As a result the comparison of forecast performance based on the MAFE, MAFPE, RMSFE and MXAFE are made.

The principal objective of developing an ARIMA model for a variable is to generate post sample period forecasts for that variable. Its strength lies in the fact that the method is suitable for any time series with any pattern of change and it does not require the forecaster to choose a priori the value of any parameter. Its limitations include its requirement of a long time series and short term prediction.

From the developed ARIMA models to forecast area, production, productivity and price of major crops of Kerala it could be observed that the most frequently used model was the Random Walk Model (ARIMA(0,1,0)) followed by the Random Walk Model with Drift (ARIMA(1,1,0)) and then by the Simple Exponential Smoothing Model (ARIMA(0,1,1)). The other types of models which were rarely used were ARIMA(1,1,1), ARIMA(0,1,2), ARIMA(0,1,4), ARIMA(0,2,0) and ARIMA(0,2,1). In all these cases the order of differencing needed to make the data stationary was not more than two. Also these models are parsimonious in the sense that it uses less number of parameters without losing the quality of the model and just depends on the most recent observation for forecasting.

Excellent reviews are documented in the field of ARIMA modelling for the forecast of area, production and price of different crops. Similar results have been established by several authors in developing ARIMA models with respect to the fact that the model parameters have not gone beyond three. Thus making the model building a much easier task even for the non-statisticians. Saeed N. et.al.(2000) found that the best model for forecasting of wheat production in Pakistan was ARIMA(2, 2, 1). Forecasting sugarcane production in India was done using ARIMA(2, 1, 0) model by Mandal, B.N.(2004). Carpio, C.E.B.S.(2002) explained the production response of cotton in India, Pakistan, and Australia using ARIMA(1,0,0) model. Price of oil palm was predicted efficiently using ARIMA(2,1,0) model (Rangsan et.al (2006)). ARIMA model for forecasting wholesale price of oil palm was ARIMA(1,0,1) and pure oil price of oil palm was ARIMA(3,0,0). Sen, L.K. (2000) found that time series modelling and forecasting of Black Pepper price could be done using ARIMA(1,0,0).

Analytical studies in the field of agricultural crops especially pertaining to Kerala are not available and hence a detailed study in this respect is essential to have an insight to the present scenario as well as future changes in the development of agriculture in Kerala. So the ARIMA modelling technique has been applied on the major crops of Kerala. The outstanding results in this aspect are summarised below.

4.5.1. Coconut

4.5.1.1. Area

Figure 4.5.1.1(a)
ACF for the area of coconut

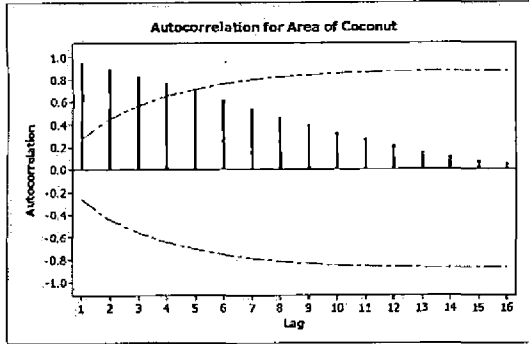
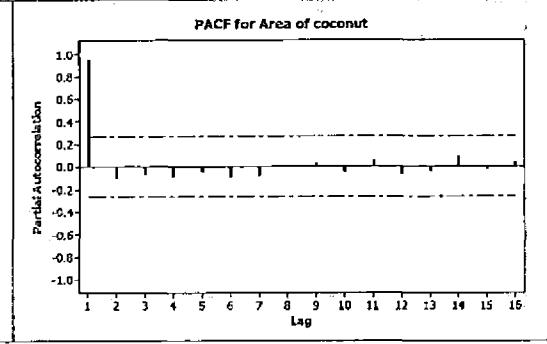


Figure 4.5.1.1(b)
PACF for the area of coconut



The data for 50 years have been used for the analysis. Hence the lag length for calculating ACF and PACF was taken as 16, i.e. 1/3rd of the total number of years. The ACFs were exponentially decaying. The PACF had a significant spike only at lag 1, meaning that all the higher-order autocorrelations were effectively explained by the lag 1 autocorrelation. Hence it assumes an AR(1) model. From Table 4.5.1.1 (a) also it is evident that all the Q statistics are statistically significant and hence the series is non stationary.

Table 4.5.1.1(a) ACF and PACF for area of coconut with Q Stat and Significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9409	0.9409	-0.2801	0.2801	46.9739	0.0000
2	0.8761	-0.0803	-0.2801	0.2801	88.5459	0.0000
3	0.8025	-0.1090	-0.2801	0.2801	124.1710	0.0000
4	0.7231	-0.0861	-0.2801	0.2801	153.7265	0.0000
5	0.6488	0.0071	-0.2801	0.2801	178.0454	0.0000
6	0.5687	-0.0933	-0.2801	0.2801	197.1571	0.0000
7	0.4825	-0.1074	-0.2801	0.2801	211.2355	0.0000
8	0.3982	-0.0362	-0.2801	0.2801	221.0530	0.0000
9	0.3175	-0.0155	-0.2801	0.2801	227.4464	0.0000
10	0.2432	-0.0083	-0.2801	0.2801	231.2913	0.0000
11	0.1827	0.0522	-0.2801	0.2801	233.5160	0.0000
12	0.1258	-0.0292	-0.2801	0.2801	234.5995	0.0000
13	0.0687	-0.0723	-0.2801	0.2801	234.9307	0.0000
14	0.0300	0.1029	-0.2801	0.2801	234.9959	0.0000
15	-0.0108	-0.0734	-0.2801	0.2801	235.0047	0.0000
16	-0.0291	0.1302	-0.2801	0.2801	235.0695	0.0000
17	-0.0273	0.1167	-0.2801	0.2801	235.1283	0.0000
18	-0.0219	-0.0037	-0.2801	0.2801	235.1672	0.0000
19	-0.0134	-0.0338	-0.2801	0.2801	235.1822	0.0000
20	-0.0042	-0.0132	-0.2801	0.2801	235.1838	0.0000

The software SPSS 16.0 ranked ARIMA(0,1,0) as the best model with minimum Normalised Bayesian Information Criteria (BIC). The nonstationarity of the series was made stationary by taking the first order difference (d=1). The brief outputs are given in Table 4.5.1.1(b) and Table 4.5.1.1(c).

Table 4.5.1.1(b) Statistics calculated for the best diagnosed model for area of coconut

R-squared	0.976	Normalized BIC	20.22
RMSE	23687.974	Ljung-Box Q	36.05
MAPE	2.197	DF	18
MAE	16125.794	Sig.	0.007
MaxAPE	9.432	Transformation	Nil
MaxAE	81729.040	Difference	1

Table 4.5.1.1(c) : Estimates of the Parameters for ARIMA(0,1,0) model for area of coconut

	Estimate	SE	t	Sig.
Constant	9375.96	3349.986	2.799	0.007

The most suitable model was ARIMA (0,1,0) for predicting area of coconut in Kerala as it was apparently parsimonious with MAPE = 2.197% indicating that the forecasting inaccuracy was very low. This is evident from the fig. 4.5.1.1(c) in which the actual and forecasted line graphs move with out much variability with a significantly high value of $R^2 = 98\%$ and statistically significant regression estimates. From the fig. 4.5.1.1(d) it is evident that the distribution of forecast errors follow $N(0, \sigma_e^2)$. i.e., the residuals are white noise which assures independence of errors and is an essential requirement for any statistical testing procedure. The model is given by, $A_t = A_{t-1} + 9375.96$,(4.5.1.1)

Where A_t denotes the area of coconut in the year 't'.

Table 4.5.1.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
16440.7100	1.8622	20036.5975	36269.9600

Table 4.5.1.1(d) shows that the maximum absolute percentage error was reduced to a great extent for the forecasts of the post sample period as well as for the future years. The trend in the long-term forecasts might be due to the fact that the model included one nonseasonal difference and a constant term. This model is basically a random walk model. All of these measures, as well as the graph of the relationship between the estimated and actual area, indicated that the model has a fairly good explanatory power. The area under coconut predicted for the future 5 years shows an increasing trend with decreasing growth rate. The growth rates for the years from 2007-08 to 2011-12 are 1.07, 1.05, 1.04, 1.03 respectively.

Figure 4.5.1.1.(c) Actual and estimated values for area of coconut using ARIMA(0,1,0)

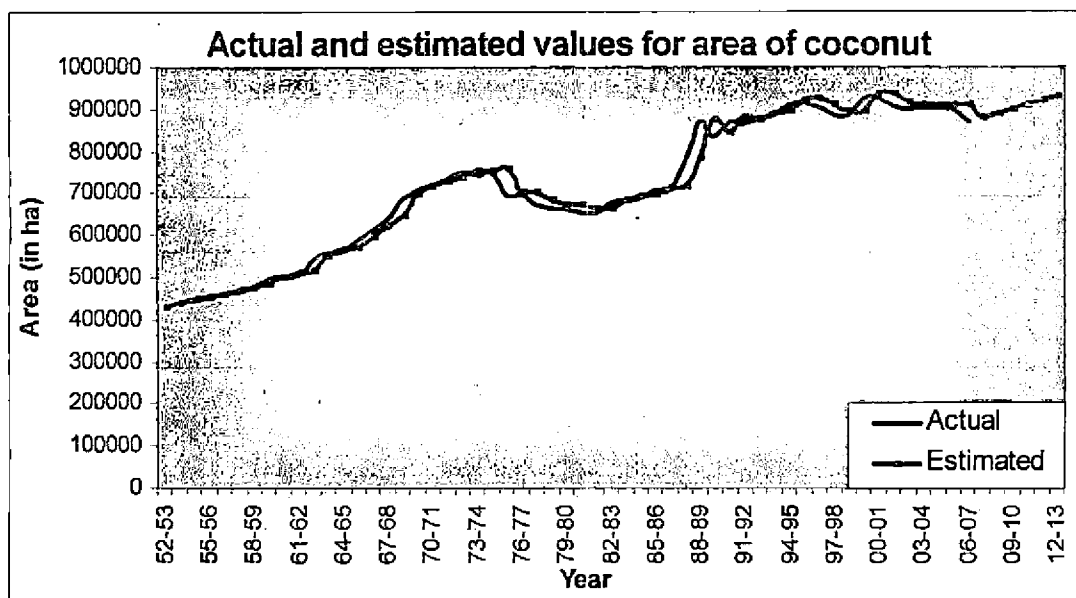


Figure 4.5.1.1.(d) Deviation from forecasts for area of coconut using ARIMA(0,1,0)

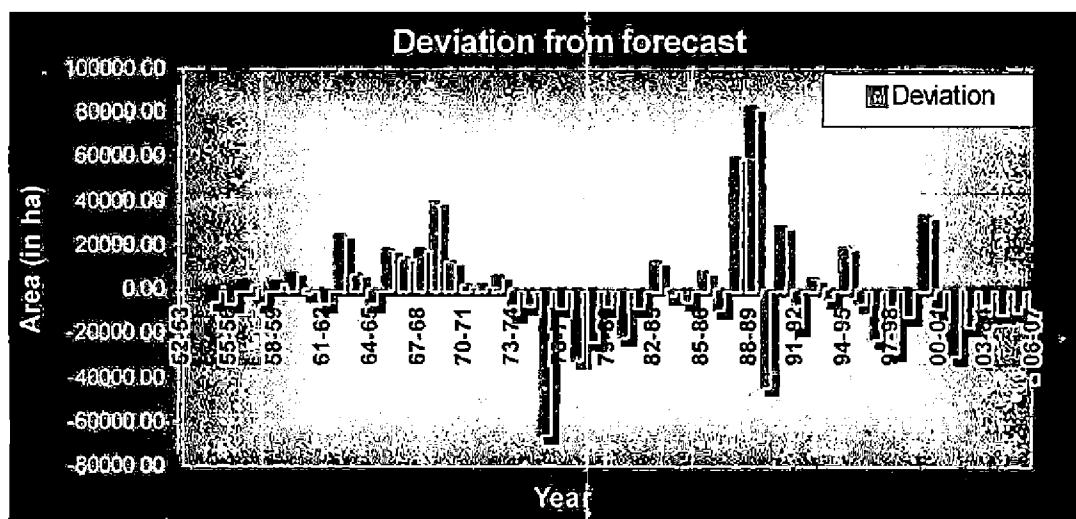


Table 4.5.1.1(e) : Comparison of ARIMA(0,1,0) model for the post sample period

Year	Actual	Forecast	Percentage Error
03-04	898498.000	908573.960	-1.12
04-05	897767.000	907873.960	-1.13
05-06	897833.000	907142.960	-1.04
06-07	870939.000	907208.960	-4.16

Table 4.5.1.1(f) : Estimated values for area of coconut from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
880314.960	889690.920	899066.880	908442.840	917818.80

4.5.1.2. Production

Figure 4.5.1.2 (a)
ACF for the production of coconut

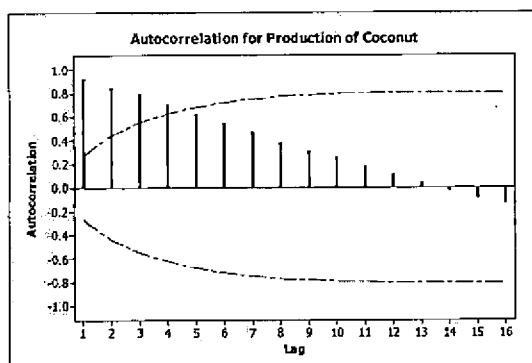
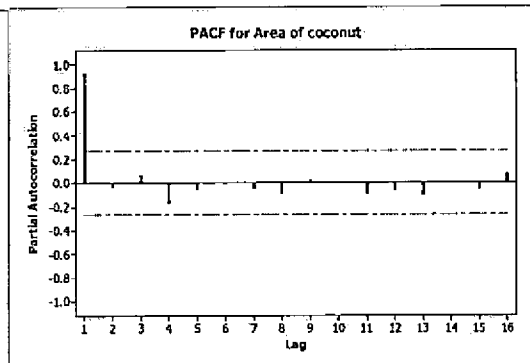


Figure 4.5.1.2 (b)
PACF for the production of coconut



As in the case of area, the autocorrelations were exponentially decaying. The PACF showed that autocorrelations at lag 2 and above were merely due to the propagation of the autocorrelation at lag 1. From Table 4.5.1.2 (a) also it is evident that all the Q statistics were statistically significant and hence the series was non stationary.

Table 4.5.1.2 (a) ACF and PACF for production of coconut with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9069	0.9069	-0.2801	0.2801	42.8218	0.0000
2	0.8352	0.0714	-0.2801	0.2801	79.9101	0.0000
3	0.7534	-0.0837	-0.2801	0.2801	110.7422	0.0000
4	0.6440	-0.2141	-0.2801	0.2801	133.7751	0.0000
5	0.5482	-0.0230	-0.2801	0.2801	150.8436	0.0000
6	0.4464	-0.0681	-0.2801	0.2801	162.4268	0.0000
7	0.3501	-0.0245	-0.2801	0.2801	169.7215	0.0000
8	0.2528	-0.0849	-0.2801	0.2801	173.6160	0.0000
9	0.1375	-0.1847	-0.2801	0.2801	174.7964	0.0000
10	0.0522	0.0467	-0.2801	0.2801	174.9711	0.0000
11	-0.0486	-0.1252	-0.2801	0.2801	175.1267	0.0000
12	-0.1237	0.0568	-0.2801	0.2801	176.1607	0.0000
13	-0.1736	0.0532	-0.2801	0.2801	178.2527	0.0000
14	-0.2233	-0.0179	-0.2801	0.2801	181.8130	0.0000
15	-0.2420	0.0592	-0.2801	0.2801	186.1169	0.0000
16	-0.2402	0.0913	-0.2801	0.2801	190.4868	0.0000
17	-0.2079	0.1848	-0.2801	0.2801	193.8621	0.0000
18	-0.1797	-0.0647	-0.2801	0.2801	196.4657	0.0000
19	-0.1610	-0.0978	-0.2801	0.2801	198.6253	0.0000
20	-0.0915	0.2025	-0.2801	0.2801	199.3468	0.0000

The best ranked model for predicting the production of coconut was ARIMA(0,1,0). The brief outputs are given in tables 4.5.1.2(b) and Table 4.5.1.2(c).

Table 4.5.1.2(b): Statistics calculated for the best diagnosed model for Production of coconut

R-squared	0.924	Normalized BIC	11.07
RMSE	243.338	Ljung-Box Q	23.86
MAPE	4.520	DF	18
MAE	170.519	Sig.	0.160
MaxAPE	24.467	Transformation	Nil
MaxAE	796.380	Difference	1

Table 4.5.1.2.(c) : Estimates of the Parameters for ARIMA(0,1,0) model for area of coconut

	Estimate	SE	t	Sig.
Constant	54.62	34.41	1.59	0.119

The final model could be written in the form

$$Y_t = Y_{t-1} + 54.62, \dots\dots\dots(4.5.1.2)$$

where Y_t denotes the production of coconut in million nuts for the year 't'.

This model is used to forecast the future values of the time series. The forecasting performance capability for the post sample period of the ARIMA models was assessed using MAFE, RMSFE, MAFPE and MXAFPE.

Table 4.5.1.2.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
296.7500	4.8671	338.0535	544.3800

From the value of MAFPE (4.87%) it is evident that the predictions can be done with very low forecasting error using equation (4.5.1.2). The production of coconut predicted for 2007-08 to 2011-12 shows an increasing trend with more or less constant growth rate. The growth rates for the years from 2007-08 to 2011-12 are 0.89, 0.89, 0.88, 0.87 respectively.

The advance estimates of crop production are needed much before the actual harvest of the crops for making various decisions such as pricing, distribution, export and import etc. However, the final estimates of crop production which are based on area through complete enumeration and yield rate through crop cutting experiments are made available much after the harvest of the crop. Therefore, there is great need for developing suitable and reliable models. Since coconut is a crop which can tolerate abnormality in weather its production will not be affected more due to this and the prediction gives better estimates.

Figure 4.5.1.2 (c) Actual and estimated values for production of coconut using ARIMA(0,1,0)

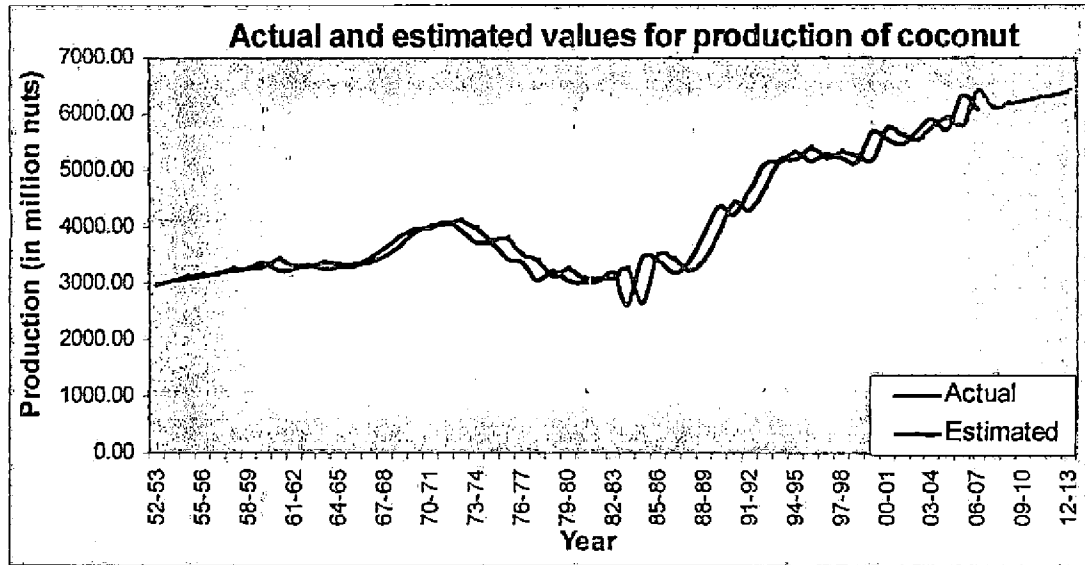


Figure 4.5.1.2.(d) Deviation from forecasts for production of cococnut

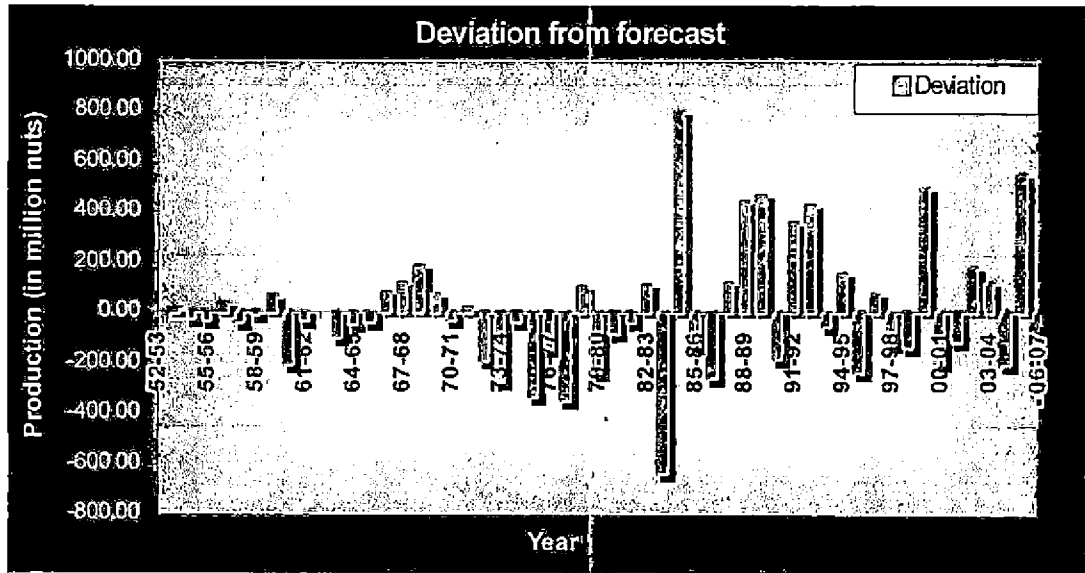


Table 4.5.1.2(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	5876.000	5763.620	1.91
04-05	5727.000	5930.620	-3.56
05-06	6326.000	5781.620	8.61
06-07	6054.000	6380.620	-5.40

Table 4.5.1.2 (f): Estimated production in million nuts of coconut from 2008-09 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
6108.620	6163.240	6217.860	6272.480	6327.100

4.5.1.3. Productivity

Figure 4.5.1.3 (a)
ACF for the productivity of coconut

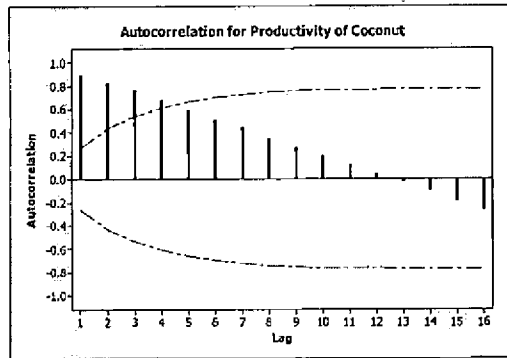
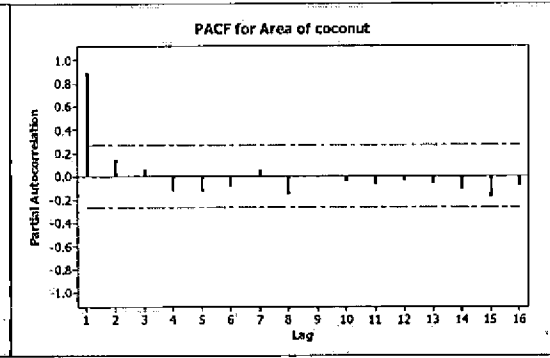


Figure 4.5.1.3 (b)
PACF for the productivity of coconut



In the case of productivity also the ACF and PACF plots show similar structure as in the case of area and production.

Table 4.5.1.3 (a) ACF and PACF for productivity of coconut with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8914	0.8914	-0.2801	0.2801	42.1610	0.0000
2	0.8387	0.2149	-0.2801	0.2801	80.2641	0.0000
3	0.7793	0.0039	-0.2801	0.2801	113.8575	0.0000
4	0.6983	-0.1418	-0.2801	0.2801	141.4221	0.0000
5	0.6104	-0.1403	-0.2801	0.2801	162.9463	0.0000
6	0.5071	-0.1704	-0.2801	0.2801	178.1413	0.0000
7	0.4368	0.0685	-0.2801	0.2801	189.6768	0.0000
8	0.3386	-0.1015	-0.2801	0.2801	196.7756	0.0000
9	0.2444	-0.0778	-0.2801	0.2801	200.5647	0.0000
10	0.1665	-0.0093	-0.2801	0.2801	202.3675	0.0000
11	0.0736	-0.1064	-0.2801	0.2801	202.7283	0.0000
12	-0.0028	-0.0306	-0.2801	0.2801	202.7288	0.0000
13	-0.0585	0.0897	-0.2801	0.2801	202.9695	0.0000
14	-0.1241	-0.0707	-0.2801	0.2801	204.0814	0.0000
15	-0.1779	-0.0370	-0.2801	0.2801	206.4331	0.0000
16	-0.2391	-0.1055	-0.2801	0.2801	210.8046	0.0000
17	-0.2754	-0.0123	-0.2801	0.2801	216.7824	0.0000
18	-0.3227	-0.0720	-0.2801	0.2801	225.2454	0.0000
19	-0.3868	-0.1634	-0.2801	0.2801	237.7949	0.0000
20	-0.4022	0.0667	-0.2801	0.2801	251.8172	0.0000

The best model for predicting the productivity of coconut was ARIMA(1,1,0) with minimum Normalised Bayesian Information Criteria (BIC) and other statistics such as RMSE, MAE, MAPE, R². Since there was no role for variance in the nonstationarity no further transformation was needed except the first order differencing. The brief outputs are given in Table 4.5.1.3(b) and Table 4.5.1.3(c).

Table 4.5.1.3 (b): Statistics calculated for the best diagnosed model for productivity of coconut

R-squared	0.861	Normalized BIC	11.48
RMSE	298.537	Ljung-Box Q	16.26
MAPE	3.783	DF	17
MAE	194.582	Sig.	0.505
MaxAPE	23.021	Transformation	Nil
MaxAE	907.544	Difference	1

Table 4.5.1.3 (c): Regression results for ARIMA(1,1,0) for predicting productivity of coconut

	Estimate	SE	t	Sig.
AR (1)	-0.33	0.14	-2.45	0.018

The best model could be written in the form

$$P_t = 0.668P_{t-1} + 0.332P_{t-2}, \dots \dots \dots (4.5.1.3)$$

Where P_t denotes the productivity of coconut in the year 't'.

Table 4.5.1.3.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
281.8885	4.1227	348.5600	613.3597

From the forecasted figures of productivity of coconut, it can be seen that there was not much growth for productivity in the future years of prediction as the growth rates were -0.15, 0.05, -0.02, 0.01 respectively.

From the analysis of area, production and productivity of coconut in Kerala, it can be understood that there is some force regulating the production of coconut by making the productivity fluctuate around a constant value. The regulating forces that cannot be included in the univariate ARIMA model forecasting may be technological developments, weather changes and such other forces. Here by studying the past behaviour of the data as an ARIMA model just tells what will happen if it is going like that in the past.

Figure 4.5.1.3 (c) Actual and estimated values for productivity of coconut using ARIMA(1,1,0)

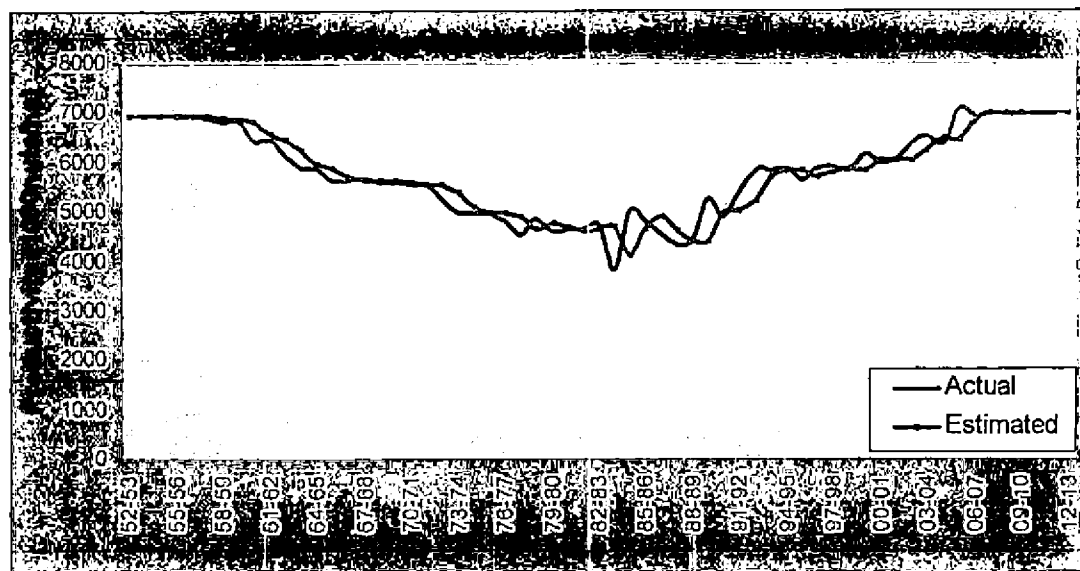


Figure 4.5.1.3 (d) Deviation from forecasts for the productivity of coconut

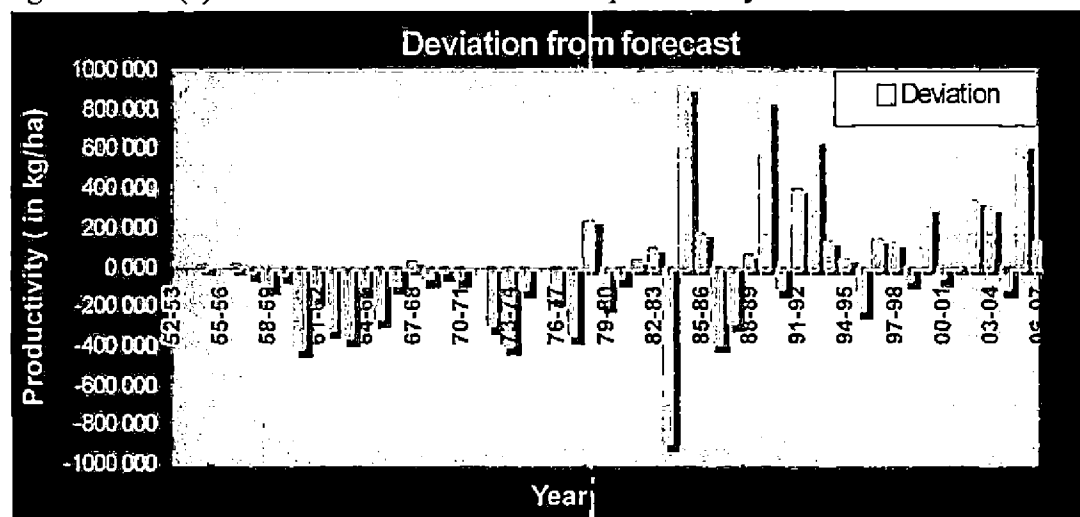


Table 4.5.1.3(e) : Comparison of the ARIMA(1,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	6539.803	6249.508	4.44
04-05	6379.161	6476.453	-1.53
05-06	7045.854	6432.494	8.71
06-07	6951.118	6824.512	1.82

Table 4.5.1.3 (f) : Estimated Values for productivity of coconut from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
6982.57	6972.128	6975.595	6974.444	6974.826

4.5.1.4. Price

Figure 4.5.1.4(a)
ACF for the price of coconut

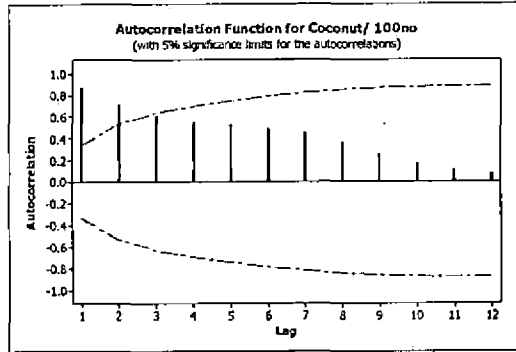
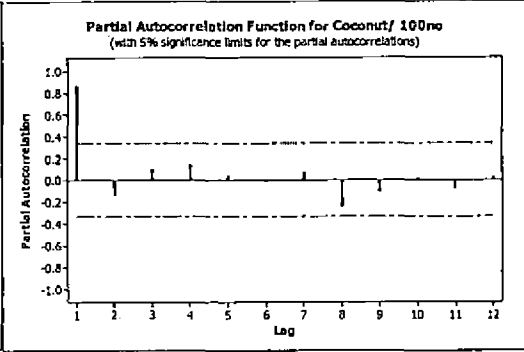


Figure 4.5.1.4(b)
PACF for the price of coconut



The ACF of Price of coconut was also exponentially decaying. The PACF showed that autocorrelations at lag 2 and above were merely due to the propagation of the autocorrelation at lag 1. From Table 4.5.1.4 (a) also it was evident that all the Q statistics were statistically significant and hence the series was non stationary.

Table 4.5.1.4(a) ACF and PACF for price of coconut with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8153	0.8153	-0.3536	0.3536	22.6659	0.00
2	0.6871	0.0667	-0.3536	0.3536	39.3176	0.00
3	0.6893	0.3360	-0.3536	0.3536	56.6788	0.00
4	0.6306	-0.0762	-0.3536	0.3536	71.7468	0.00
5	0.5462	-0.0099	-0.3536	0.3536	83.4837	0.00
6	0.4568	-0.1636	-0.3536	0.3536	92.0216	0.00
7	0.3415	-0.1869	-0.3536	0.3536	96.9932	0.00
8	0.2529	-0.0828	-0.3536	0.3536	99.8377	0.00
9	0.1680	-0.1106	-0.3536	0.3536	101.1501	0.00
10	0.0936	0.0247	-0.3536	0.3536	101.5767	0.00
11	0.0029	-0.1012	-0.3536	0.3536	101.5771	0.00
12	-0.0758	0.0110	-0.3536	0.3536	101.8867	0.00
13	-0.1391	-0.0566	-0.3536	0.3536	102.9865	0.00
14	-0.1701	0.0842	-0.3536	0.3536	104.7284	0.00
15	-0.2189	-0.0692	-0.3536	0.3536	107.7912	0.00
16	-0.2869	-0.0797	-0.3536	0.3536	113.4054	0.00
17	-0.3447	-0.1273	-0.3536	0.3536	122.0900	0.00
18	-0.3325	0.0922	-0.3536	0.3536	130.7918	0.00
19	-0.3865	-0.2407	-0.3536	0.3536	143.5245	0.00
20	-0.4341	0.0114	-0.3536	0.3536	161.0500	0.00

The best ranked model was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in Table 4.5.1.4(b) and Table 4.5.1.4(c). Stationarity was not attained by the first differencing of the series. The heterogeneity of variance might be the reason for the nonstationary behaviour of the data. So a logarithmic transformation was taken before differencing to attain stationarity.

Table 4.5.1.4(b) Statistics for the best diagnosed model for price of coconut

R-squared	0.815	Normalized BIC	8.77
RMSE	72.293	Ljung-Box Q	21.84
MAPE	20.487	DF	17
MAE	48.836	Sig.	0.191
MaxAPE	83.896	Transformation	Natural Log
MaxAE	235.906	Difference	1

Table 4.5.1.4 (c) : Regression results for ARIMA(0,1,2) for predicting price of coconut

Parameters	Estimate	SE	t	Sig.
Constant	0.065	0.027	2.453	0.020
MA(2)	0.390	0.164	2.374	0.024

The final model could be written in the form

$$R_t = R_{t-1} e^{(0.065 - 0.39 \varepsilon_{t-2})}, \dots\dots\dots(4.5.1.4)$$

where R_t denotes the price of 100 coconuts and ε_t , the error in forecast at the t^{th} year.

This model is used to forecast the future values of the transformed time series.

Table 4.5.1.4 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
75.6767	14.4127	87.7935	135.7545

The R^2 was fairly good indicating that the model could explain about 81.5% of the variation in the data. The MAPE was 20.49%. But for the post sample period the MAPE came down to 14.13% ensuring the forecasting power of the model.

From the forecasted figures of price of coconut, it could be seen that the growth rate for the period 2007-08 to 2008-09 were fairly satisfactory as the same were 10.81, 6.72,6.72,6.72 respectively.

It may be concluded that the returns from coconut was static, if inflationary tendencies were not taken into account.

Figure 4.5.1.4 (c) Actual and estimated values for price of coconut by ARIMA(0,1,2) model

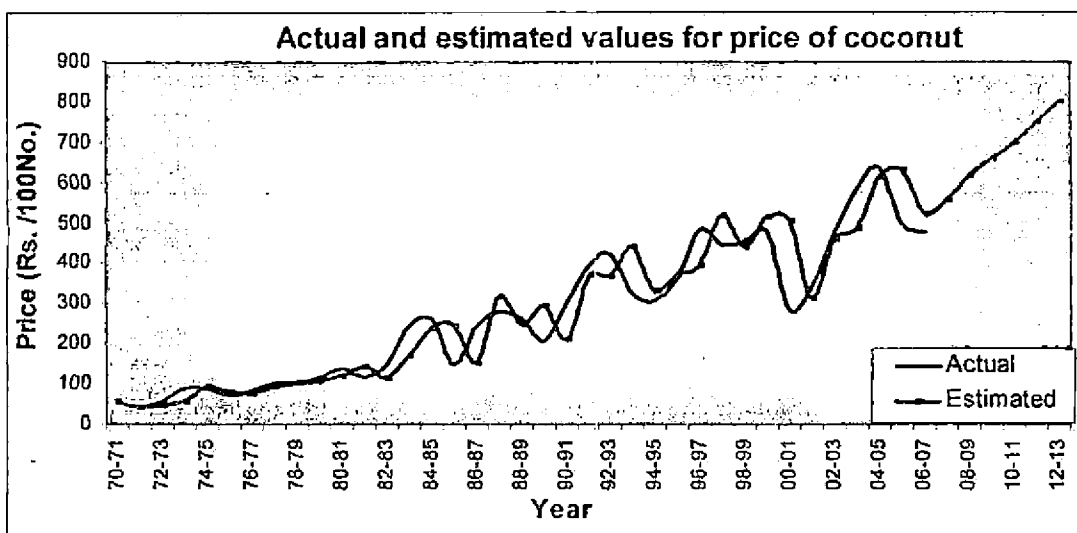


Figure 4.5.1.4 (d) Deviation from forecasts for the price per 100 coconuts

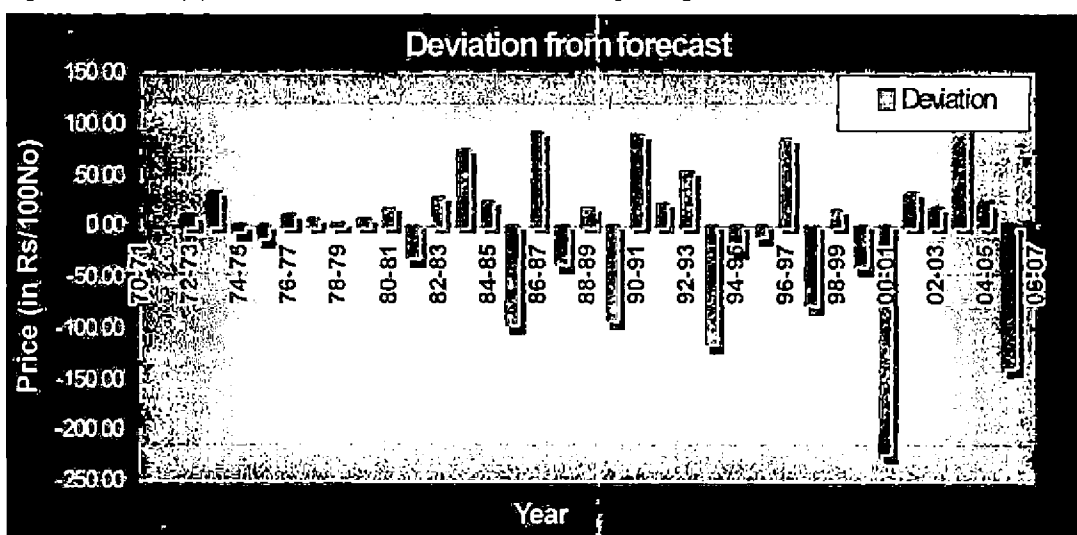


Table 4.5.1.4 (e) : Comparison of the ARIMA(0,1,2) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	584.25	485.91	16.833
04-05	635.00	614.41	3.242
05-06	494.89	630.64	-27.431
06-07	473.36	521.38	-10.145

Table 4.5.1.4 (f) : Estimated values for price per 100 coconuts from 2008-09 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
555.24	615.28	656.60	700.70	747.76

4.5.2. Rubber
4.5.2.1.Area

Figure 4.5.2.1(a)
 ACF for the area of rubber

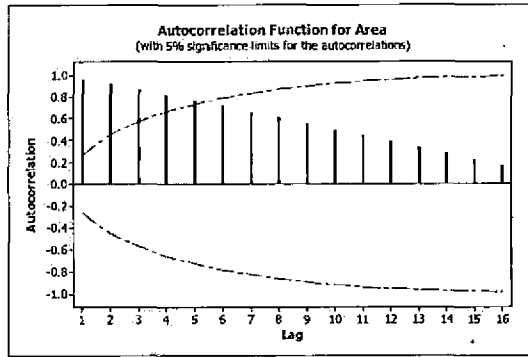
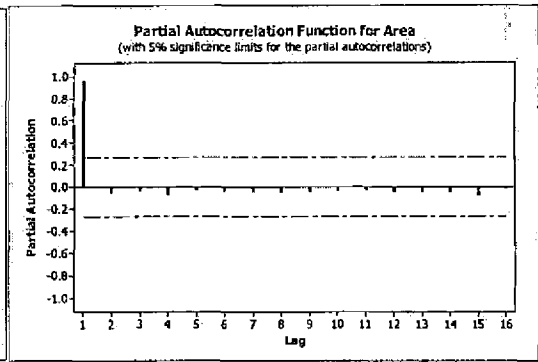


Figure 4.5.2.1(b)
 PACF for the area of rubber



The ACF declined very slowly and PACF had only one significant spike which was at lag 1. Hence the series were non-stationary with initial guess of an AR(1) model. From Table 4.5.2.1 (a) also it was evident that the series was non stationary as all the Q statistics were statistically significant.

Table 4.5.2.1(a) ACF and PACF for area of rubber with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9525	0.9525	-0.2801	0.2801	47.2390	0.00
2	0.9008	-0.0711	-0.2801	0.2801	90.3797	0.00
3	0.8446	-0.0723	-0.2801	0.2801	129.1359	0.00
4	0.7842	-0.0733	-0.2801	0.2801	163.2885	0.00
5	0.7242	-0.0247	-0.2801	0.2801	193.0729	0.00
6	0.6645	-0.0279	-0.2801	0.2801	218.7323	0.00
7	0.6055	-0.0269	-0.2801	0.2801	240.5477	0.00
8	0.5461	-0.0431	-0.2801	0.2801	258.7266	0.00
9	0.4861	-0.0464	-0.2801	0.2801	273.4879	0.00
10	0.4264	-0.0364	-0.2801	0.2801	285.1368	0.00
11	0.3636	-0.0747	-0.2801	0.2801	293.8320	0.00
12	0.3032	-0.0173	-0.2801	0.2801	300.0426	0.00
13	0.2442	-0.0314	-0.2801	0.2801	304.1818	0.00
14	0.1869	-0.0286	-0.2801	0.2801	306.6753	0.00
15	0.1316	-0.0305	-0.2801	0.2801	307.9489	0.00
16	0.0809	-0.0025	-0.2801	0.2801	308.4447	0.00
17	0.0317	-0.0374	-0.2801	0.2801	308.5230	0.00
18	-0.0142	-0.0160	-0.2801	0.2801	308.5393	0.00
19	-0.0565	-0.0134	-0.2801	0.2801	308.8048	0.00
20	-0.0950	-0.0117	-0.2801	0.2801	309.5825	0.00

The best ranked model was ARIMA(1,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.2.1(b) and 4.5.2.1(c).

Table 4.5.2.1(b) Statistics calculated for the best diagnosed model for area of rubber

R-squared	0.998	Normalized BIC	17.82
RMSE	6855.361	Ljung-Box Q	24.61
MAPE	2.502	DF	17
MAE	4845.874	Sig.	0.104
MaxAPE	15.745	Transformation	Nil
MaxAE	24994.613	Difference	1

Table 4.5.2.1(c) : Estimates of the parameters for ARIMA(1,1,0) model for area of rubber

	Estimate	SE	t	Sig.
Constant	8061.311	1657.455	4.864	0.000
AR(1)	0.424	0.132	3.223	0.002

The final model with $R^2 = 99.8\%$ could be written in the form

$$A_t = 1.424A_{t-1} - 0.424A_{t-2} + 8061.311, \dots\dots\dots(4.5.2.1)$$

Where A_t denotes the area of rubber in the year 't'.

This model was used to forecast the future values of the transformed time series. The forecasting performance for the post sample period was assessed using (RMSFE), (MAFPE) and (MXAFPE).

Table 4.5.2.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
6009.2795	1.2311	6052.9671	6918.8310

From the value of MAPE (2.5%) it was evident that the predictions could be done with very low forecasting error using equation (4.5.2.1). It was made much better by reducing the forecasting error to 1.2% for the post sample period. The maximum absolute error was 24994.61 during the sample period and it is much reduced to 6918.83 for the prediction of post sample period. The area of rubber predicted for 2007-08 to 2011-12 showed an increasing trend with more or less constant growth rate. The growth rates for the period from 2007-08 to 2011-12 were 2.51, 2.57, 2.55, 2.51 percent respectively. It could be inferred that there was a tendency to increase the area under rubber according to the previous year's price.

Figure 4.5.2.1.(c) Actual and estimated values for area of rubber using ARIMA(1,1,0)

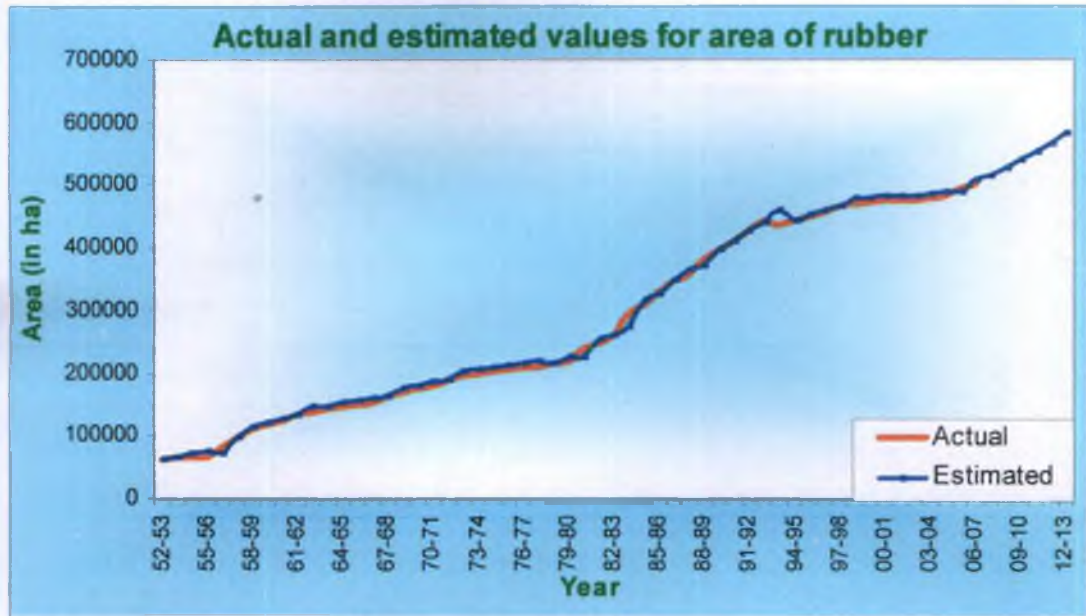


Figure 4.5.2.1.(d) Deviation from forecasts for area of rubber

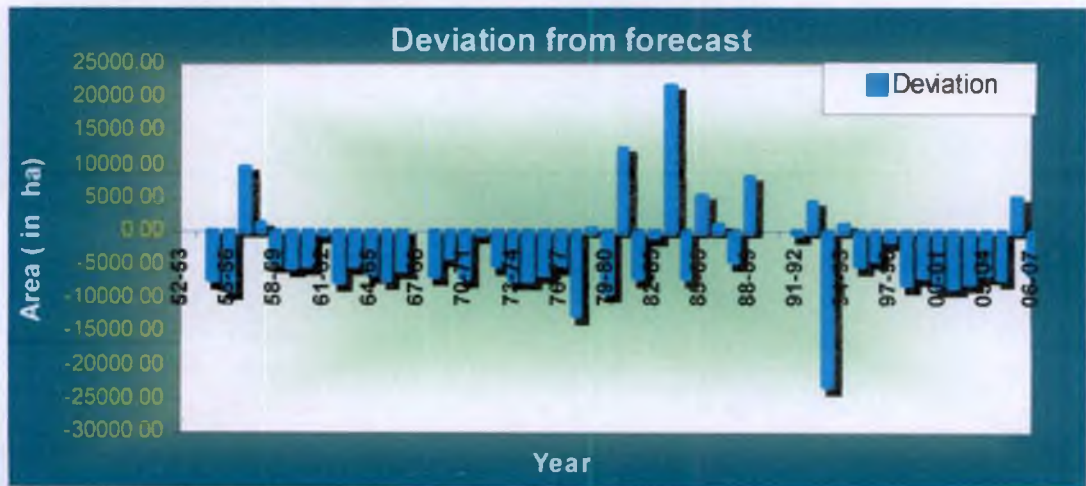


Table 4.5.2.1(e) : Comparison of the ARIMA(1,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	478402.000	484535.703	-0.013
04-05	480543.000	487461.831	-0.014
05-06	494400.000	489512.095	0.010
06-07	502240.000	508336.679	-0.012

Table 4.5.2.1(f) : Estimated values for area of rubber from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
513625.471	526514.222	540040.363	553836.758	567747.74

4.5.2.2. Production

Figure 4.5.2.2 (a)
ACF for the production of rubber

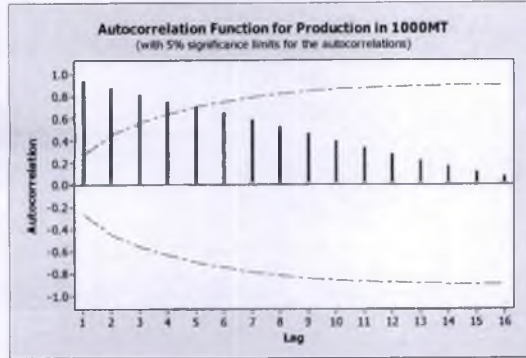
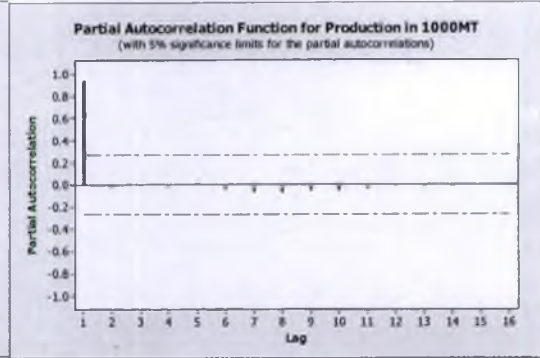


Figure 4.5.2.2 (b)
PACF for the production of rubber



As area of rubber, its production also showed the same pattern for ACF. ACF had a significant spike only at lag 1. Hence the series was identified as an AR(1) model. From Table 4.5.2.2 (a) all the Q statistics were statistically significant and the series could be judged as a non stationary so that differencing was necessitated to attain stationarity of the series.

Table 4.5.2.2 (a) ACF and PACF for production of rubber with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9415	0.9415	-0.2801	0.2801	46.1501	0.00
2	0.8797	-0.0597	-0.2801	0.2801	87.2929	0.00
3	0.8111	-0.0917	-0.2801	0.2801	123.0294	0.00
4	0.7375	-0.0796	-0.2801	0.2801	153.2311	0.00
5	0.6610	-0.0631	-0.2801	0.2801	178.0479	0.00
6	0.5829	-0.0559	-0.2801	0.2801	197.7968	0.00
7	0.5064	-0.0311	-0.2801	0.2801	213.0576	0.00
8	0.4338	-0.0135	-0.2801	0.2801	224.5290	0.00
9	0.3645	-0.0222	-0.2801	0.2801	232.8298	0.00
10	0.2997	-0.0150	-0.2801	0.2801	238.5851	0.00
11	0.2413	0.0012	-0.2801	0.2801	242.4154	0.00
12	0.1865	-0.0249	-0.2801	0.2801	244.7658	0.00
13	0.1384	0.0021	-0.2801	0.2801	246.0963	0.00
14	0.0961	-0.0027	-0.2801	0.2801	246.7562	0.00
15	0.0608	0.0094	-0.2801	0.2801	247.0277	0.00
16	0.0295	-0.0134	-0.2801	0.2801	247.0938	0.00
17	0.0006	-0.0276	-0.2801	0.2801	247.0938	0.00
18	-0.0250	-0.0145	-0.2801	0.2801	247.1441	0.00
19	-0.0531	-0.0634	-0.2801	0.2801	247.3786	0.00
20	-0.0755	0.0114	-0.2801	0.2801	247.8701	0.00

The best model ranked first was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in table 4.5.2.2(b) and 4.5.2.2(c).

Table 4.5.2.2(b): Statistics calculated for the best diagnosed model for Production of Rubber

R-squared	0.995	Normalized BIC	5.18
RMSE	12.798	Ljung-Box Q	46.21
MAPE	5.024	DF	18
MAE	8.270	Sig.	0.000
MaxAPE	17.978	Transformation	Natural Log
MaxAE	41.944	Difference	1

Table 4.5.2.2(c): Estimates of the Parameters of ARIMA(0,1,0) for production of Rubber

	Estimate	SE	t	Sig.
Constant	0.069	0.009	7.656	0.000

The final model could be written in the form

$$Y_t = Y_{t-1} e^{0.069}, \dots\dots\dots(4.5.2.2)$$

Where Y_t denotes the production of Rubber in the year 't'.

This model was used to forecast the future values of the transformed time series. The forecasting performance capability for the post sample period of the ARIMA models was assessed using MAFE, RMSFE, MAFPE and MXAFPE.

Table 4.5.2.2(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
10.3508	1.4829	11.9862	17.7194

The value of MAFPE = 1.48% indicated that the predictions could be done with very low forecasting error using equation (4.5.2.2). The production of rubber predicted for 2007-08 to 2011-12 showed an increasing trend with constant growth rate of 7.14

With the advent of high yielding clones and improved production technologies, the productivity and thereby the total production of natural rubber in the state which accounts for 96% of the total production in India had recorded a linear trend for the past five decades. However, it is paradoxical to note that the positive upward trend is being badly affected by the acute shortage of skilled labour for tapping. Malaysia, which was a leading rubber producing country in the world has already shifted from rubber plantation to industry sector because of the aforesaid reason. The ever increasing demand for natural rubber in our day today life and increasing price for rubber will definitely help to sustain rubber plantation in the country.

Figure 4.5.2.2 (c) Actual and estimated values for production of rubber using ARIMA(0,1,0)

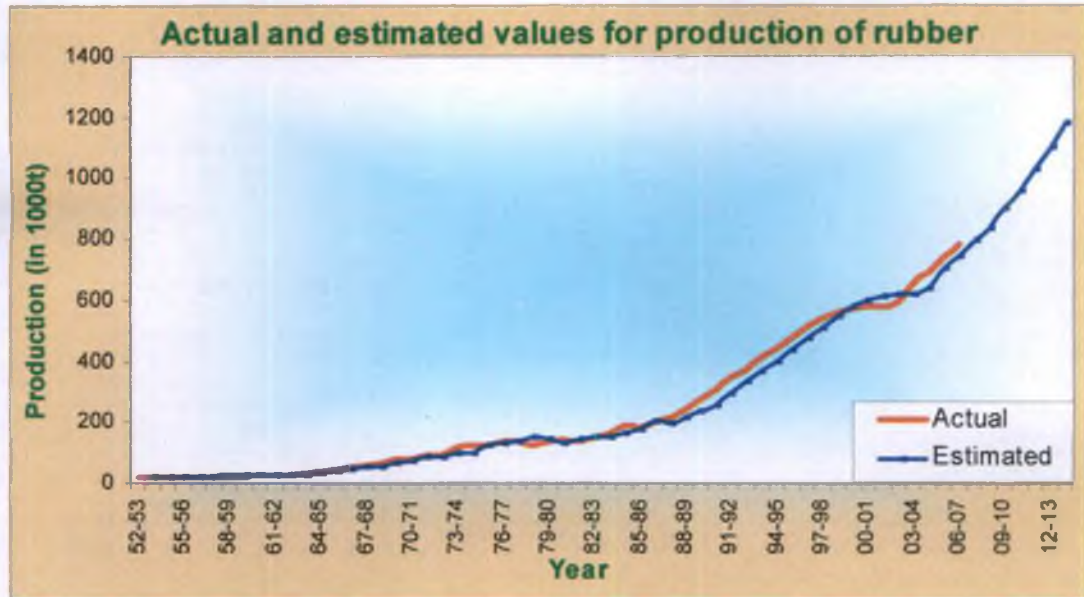


Figure 4.5.2.2.(d) Deviation from forecasts for production of rubber

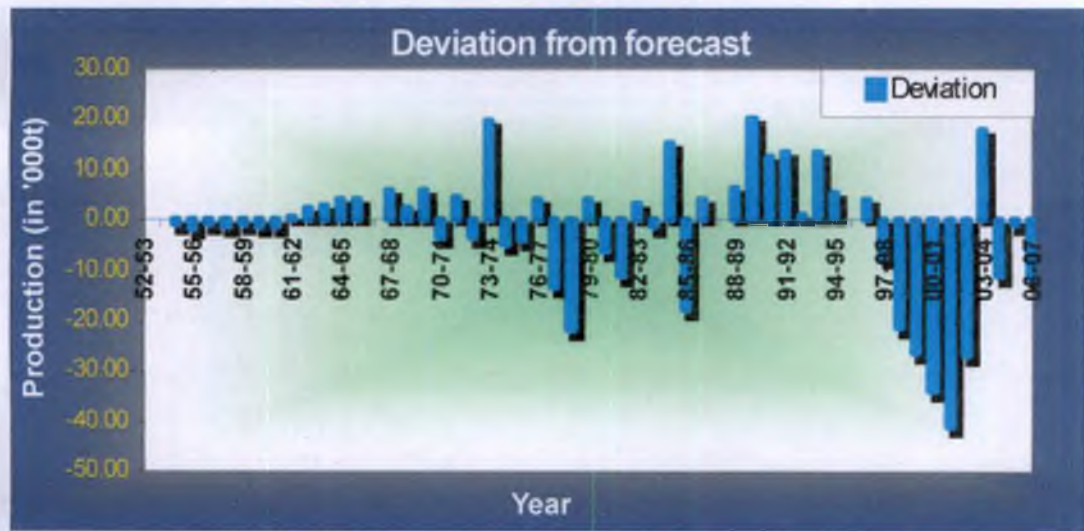


Table 4.5.2.2(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	655.135	637.416	2.70
04-05	690.768	701.935	-1.62
05-06	739.225	740.114	-0.12
06-07	780.405	792.032	-1.49

Table 4.5.2.2 (f): Estimated production of rubber from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
836.154	895.886	959.885	1028.455	1101.92

4.5.2.3. Productivity

Figure 4.5.2.3 (a)
ACF for the productivity of rubber

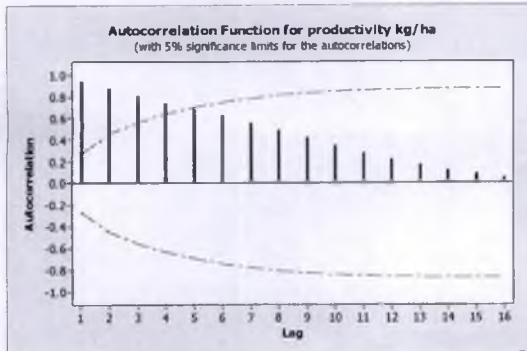
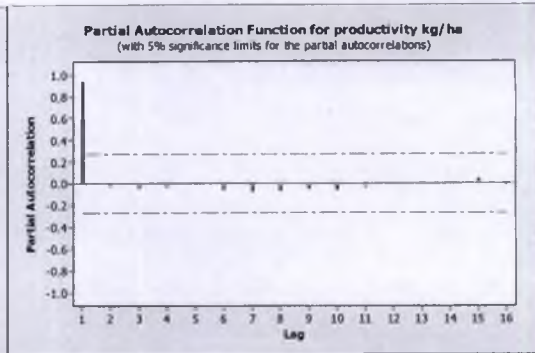


Figure 4.5.2.3 (b)
PACF for the productivity of rubber



Here also the ACF and PACF showed the same pattern as in the case of area and production. Hence the model was identified as an AR(1) model with a nonstationary behaviour. From Table 4.5.2.3 (a) it was evident that all the Q statistics were statistically significant and hence the series was non stationary.

Table 4.5.2.3 (a) ACF and PACF for productivity of rubber with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9410	0.9410	-0.2801	0.2801	46.0999	0.00
2	0.8803	-0.0453	-0.2801	0.2801	87.3011	0.00
3	0.8104	-0.1123	-0.2801	0.2801	122.9797	0.00
4	0.7332	-0.1016	-0.2801	0.2801	152.8355	0.00
5	0.6498	-0.0947	-0.2801	0.2801	176.8144	0.00
6	0.5620	-0.0813	-0.2801	0.2801	195.1720	0.00
7	0.4743	-0.0471	-0.2801	0.2801	208.5580	0.00
8	0.3918	-0.0036	-0.2801	0.2801	217.9127	0.00
9	0.3148	-0.0028	-0.2801	0.2801	224.1028	0.00
10	0.2444	-0.0006	-0.2801	0.2801	227.9312	0.00
11	0.1890	0.0693	-0.2801	0.2801	230.2809	0.00
12	0.1370	-0.0323	-0.2801	0.2801	231.5494	0.00
13	0.0965	0.0259	-0.2801	0.2801	232.1957	0.00
14	0.0659	0.0242	-0.2801	0.2801	232.5062	0.00
15	0.0446	0.0196	-0.2801	0.2801	232.6525	0.00
16	0.0293	-0.0042	-0.2801	0.2801	232.7175	0.00
17	0.0191	-0.0047	-0.2801	0.2801	232.7461	0.00
18	0.0141	0.0063	-0.2801	0.2801	232.7621	0.00
19	0.0012	-0.1070	-0.2801	0.2801	232.7622	0.00
20	-0.0037	0.0401	-0.2801	0.2801	232.7634	0.00

The best ranked model for prediction of productivity of rubber was ARIMA(1,1,1) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.2.3(b) and 4.5.2.3(c)

Table 4.5.2.3 (b): Statistics calculated for the best diagnosed model for productivity of rubber

R-squared	0.987	Normalized BIC	7.41
RMSE	37.499	Ljung-Box Q	15.13
MAPE	5.743	DF	16
MAE	28.440	Sig.	0.515
MaxAPE	25.412	Transformation	Nil
MaxAE	109.975	Difference	1

Table 4.5.2.3 (c): Regression results for ARIMA(1,1,1) model for productivity of rubber

	Estimate	SE	t	Sig.
AR(1)	0.895	0.111	8.083	0.000
MA(1)	0.64	0.194	3.291	0.002

The final model could written in the form

$$P_t = 1.895P_{t-1} - 0.895P_{t-2} - 0.64\epsilon_{t-1}, \dots\dots\dots(4.5.2.3)$$

where P_t denotes productivity and ϵ_t the error in prediction for rubber in the t^{th} year.

Table 4.5.2.3.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
41.0088	2.9122	55.3777	104.8576

The low value of MAFPE (2.91%) justified that the predictions could be done with very low forecasting error using equation (4.5.2.3). The productivity of rubber predicted for 2007-08 to 2011-12 showed an increasing trend with decreasing growth rate. The growth rates for the years from 2007-08 to 2011-12 were 2.35, 2.06, 1.81, 1.59 respectively.

The productivity of rubber in Kerala is the highest in the world. The larger share of small holders among rubber growers has helped the state to achieve tremendous productivity increase in rubber in the past fifty years. Development and research programmes have to be strengthened to increase the productivity further as the forecasted figures show a decreasing trend for the future years. The need for insuring the plantations in the backdrop of unexpected weather conditions has to be considered.

Figure 4.5.2.3 (c) Actual and estimated values for productivity of rubber using ARIMA(1,1,1)

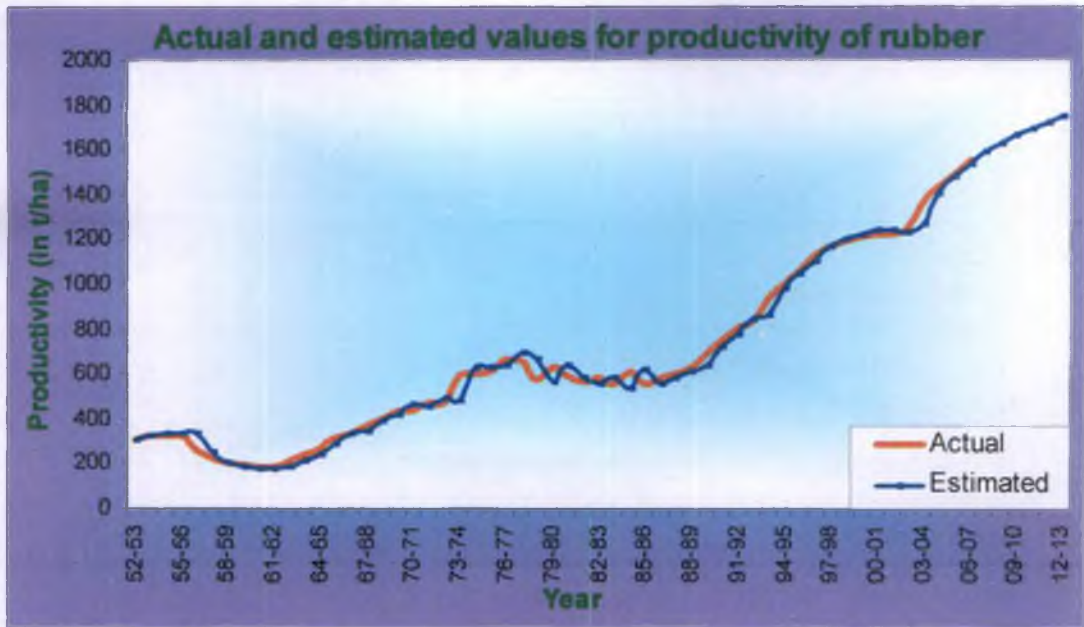


Figure 4.5.2.3 (d) Deviation from forecasts for the productivity of rubber

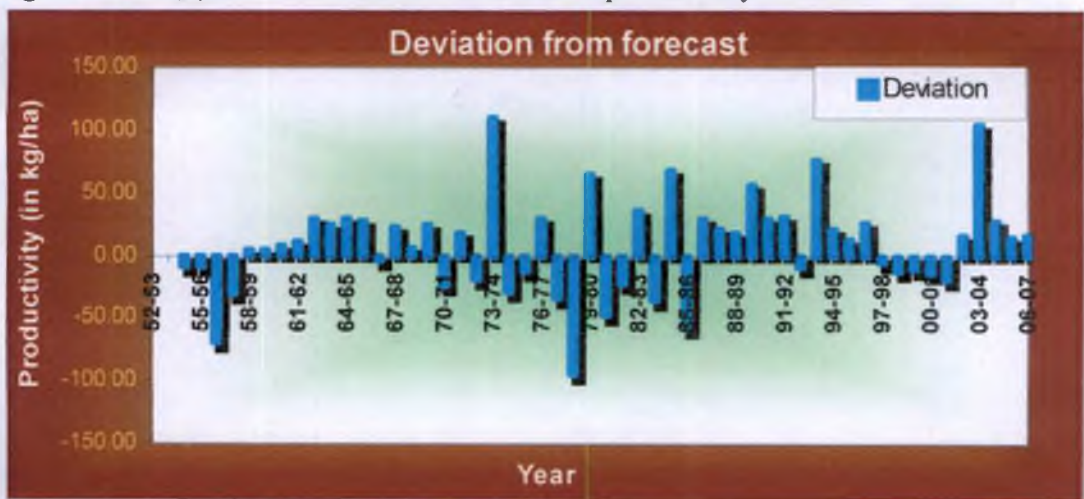


Table 4.5.2.3(e) : Comparison of the ARIMA(1,1,1) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	1369.424	1264.566	7.66
04-05	1437.474	1409.465	1.95
05-06	1495.196	1480.453	0.99
06-07	1553.849	1537.422	1.06

Table 4.5.2.3 (f) : Estimated values for productivity of rubber from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
1595.830	1633.403	1667.031	1697.128	1724.06

4.5.2.4. Price

Figure 4.5.2.4(a)
ACF for the price of rubber

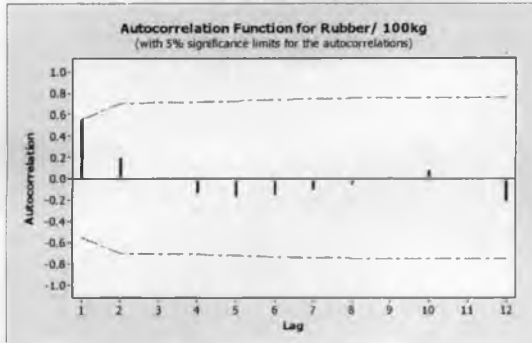
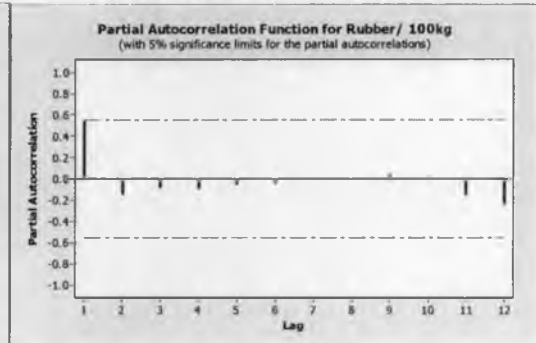


Figure 4.5.2.4(b)
PACF for the price of rubber



Data from 1992-93 was used for the analysis of price . Since price of rubber had significant Q values at all lags as given in table 4.5.2.4 (a) it was nonstationary and needed to be differenced.

Table 4.5.2.4(a) ACF and PACF for price of rubber with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.5089	0.5089	-0.6030	0.6030	3.2043	0.07
2	-0.2678	-0.7108	-0.6030	0.6030	4.2187	0.12
3	-0.5903	0.0124	-0.6030	0.6030	9.9681	0.02
4	-0.4064	-0.2368	-0.6030	0.6030	13.2376	0.01
5	-0.1064	-0.2748	-0.6030	0.6030	13.5177	0.02
6	0.1211	-0.0100	-0.6030	0.6030	14.0015	0.03
7	0.1998	-0.2043	-0.6030	0.6030	15.9769	0.03
8	0.1053	-0.2199	-0.6030	0.6030	17.0748	0.03

ARIMA(0,2,0) were identified as the best with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.2.4(b) and 4.5.2.4(c)

Table 4.5.2.4(b) Statistics for the best diagnosed model for price of rubber

R-squared	0.754	Normalized BIC	13.78
RMSE	892.091	Ljung-Box Q	-
MAPE	15.307	DF	0
MAE	678.604	Sig.	-
MaxAPE	42.037	Transformation	Nil
MaxAE	2060.231	Difference	2

Table 4.5.2.4 (c) : Regression results for ARIMA(0,2,0) model for predicting price of rubber

	Estimate	SE	t	Sig.
Constant	191.231	247.421	0.773	0.455

The final model could be written in the form

$$R_t = 2R_{t-1} - R_{t-2} + 191.231, \dots \dots \dots (4.5.2.4)$$

Where R_t denote the price of rubber at the t^{th} year.

Table 4.5.2.4 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
653.3845	9.4351	748.1392	1184.7690

The price of rubber predicted for 2007-08 to 2011-12 showed an increasing trend with decreasing growth rate. The growth rates for the years from 2007-08 to 2011-12 were 24.26, 20.82, 18.30, 16.38 percent respectively

Figure 4.5.2.4 (c) Actual and estimated values for price of rubber by ARIMA(0,2,0) Model



Figure 4.5.2.4 (d) Deviation from forecasts for the price of rubber

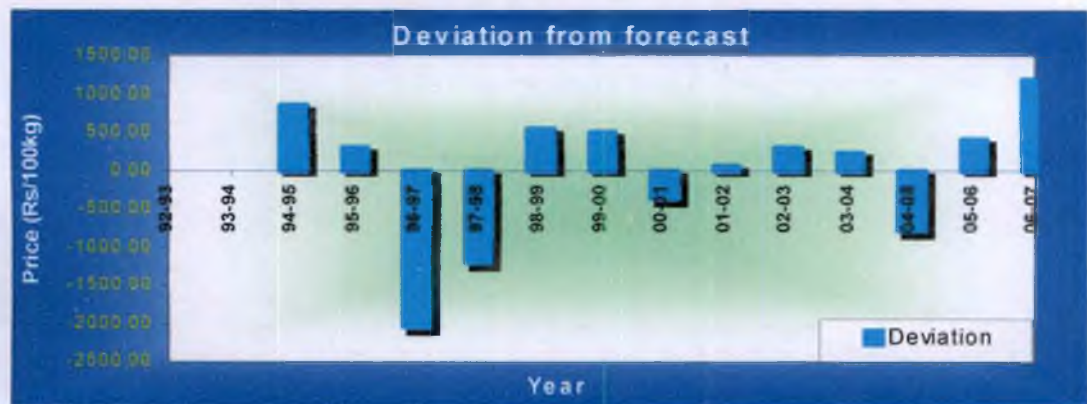


Table 4.5.2.4 (e) : Comparison of the ARIMA(0,2,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	5040.000	4801.231	4.74
04-05	5570.000	6352.231	-14.04
05-06	6699.000	6291.231	6.09
06-07	9204.000	8019.231	12.87

Table 4.5.2.4 (f) : Estimated values for price per quintal of rubber from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
11900.231	14787.693	17866.386	21136.310	24597.47

4.5.3. Paddy

4.5.3.1.Area

Figure 4.5.3.1(a)
ACF for the area of paddy

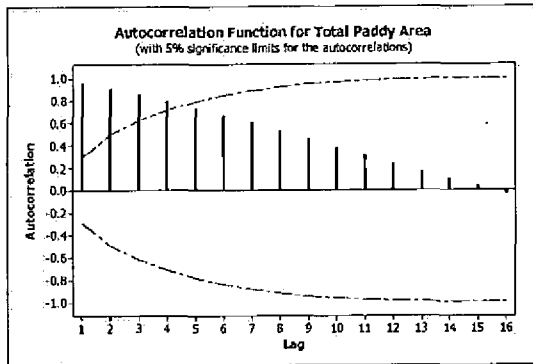
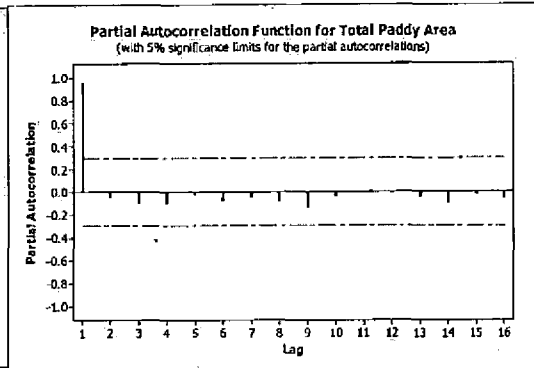


Figure 4.5.3.1(b)
PACF for the area of paddy



The ACF decayed exponentially and the PACF was significant only at lag 1 which indicated an AR(1) model. But as there were alrge number of significant ACFs, it showed the nonstationarity of the model. Significance of Q-statistics from Table 4.5.3.1 (a) also showed the nonstationary behaviour of the data.

Table 4.5.3.1(a) ACF and PACF for area of Paddy with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9403	0.9403	-0.3050	0.3050	38.9656	0.00
2	0.8777	-0.0553	-0.3050	0.3050	73.7873	0.00
3	0.8109	-0.0687	-0.3050	0.3050	104.2969	0.00
4	0.7376	-0.0926	-0.3050	0.3050	130.2214	0.00
5	0.6600	-0.0772	-0.3050	0.3050	151.5523	0.00
6	0.5828	-0.0390	-0.3050	0.3050	168.6597	0.00
7	0.5094	-0.0105	-0.3050	0.3050	182.1156	0.00
8	0.4414	0.0015	-0.3050	0.3050	192.5266	0.00
9	0.3719	-0.0637	-0.3050	0.3050	200.1459	0.00
10	0.2980	-0.0955	-0.3050	0.3050	205.1959	0.00
11	0.2268	-0.0389	-0.3050	0.3050	208.2188	0.00
12	0.1515	-0.0946	-0.3050	0.3050	209.6149	0.00
13	0.0757	-0.0645	-0.3050	0.3050	209.9759	0.00
14	0.0018	-0.0476	-0.3050	0.3050	209.9761	0.00
15	-0.0762	-0.1083	-0.3050	0.3050	210.3700	0.00
16	-0.1486	-0.0345	-0.3050	0.3050	211.9270	0.00
17	-0.2045	0.0631	-0.3050	0.3050	214.9991	0.00
18	-0.2559	-0.0328	-0.3050	0.3050	220.0205	0.00
19	-0.2931	0.0472	-0.3050	0.3050	226.9033	0.00
20	-0.3278	-0.0615	-0.3050	0.3050	235.9227	0.00

The best ranked model for the prediction of area of cultivation was identified as ARIMA(0,2,1) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.3.1(b) and 4.5.3.1(c). When the area under paddy were analysed separately for three seasons the best ranked model for each of them was ARIMA(0,1,0). Table 4.5.3.1(b) Statistics calculated for the best diagnosed model for area of paddy.

R-squared	0.984	Normalized BIC	20.24
RMSE	23778.448	Ljung-Box Q	13.91
MAPE	2.783	DF	17
MAE	17568.987	Sig.	0.673
MaxAPE	9.724	Transformation	Nil
MaxAE	78054.000	Difference	1

Table 4.5.3.1.(c) : Estimates of the parameters for ARIMA(0,2,1) model for area of paddy

	Estimate	SE	t	Sig.
MA(1)	0.813	0.100	8.120	0.000

The final model with $R^2=98\%$ and $MAPE = 2.78\%$ could be written in the form

$$A_t = 2A_{t-1} - A_{t-2} + 0.813\epsilon_t, \dots\dots\dots (4.5.3.1)$$

Where A_t denote the area of paddy cultivation and ϵ_t denote the error in prediction for t^{th} year

ARIMA(0,2,1) is the linear exponential smoothing model which use two nonseasonal differences in conjunction with MA terms. A second difference of a discrete function is analogous to a second derivative of a continuous function: it measures the "acceleration" or "curvature" in the function at a given point in time. The forecast errors used in the model also were significant with a very low standard error = 0.1 showing the importance of including the MA term in the model to increase the predictability to a great extent.

Table 4.5.3.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
7810.315	2.731	11586.363	22547.047

From Table 4.5.3.1(d) it could be observed that the forecast error percentage can be much reduced using the ARIMA(0,2,1) model for the prediction of area under paddy. The negative growth rates for the years 2007-08 to 2011-12 are given by -5.96, -6.34, -6.77 and -7.26 respectively.

For all the three seasons a gradual decrease in the area under cultivation over the years was evident from fig (4.5.3.1.(e)). The cumulative effect in decrease in area is also much evident from the figure.

Figure 4.5.3.1.(c) Actual and estimated values for area of paddy by ARIMA (0,2,1) model

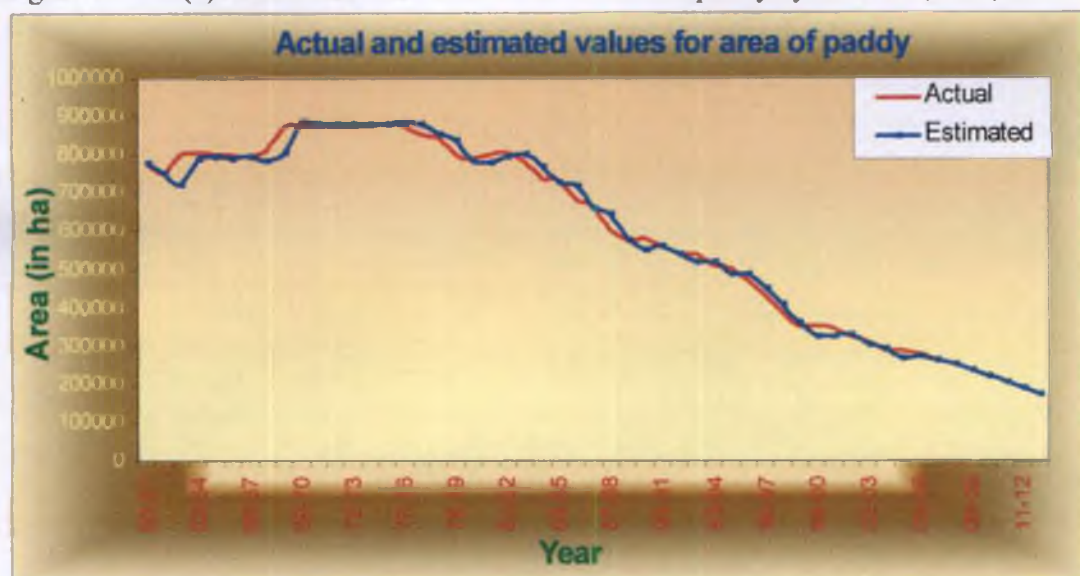


Figure 4.5.3.1.(d) Deviation from forecasts for area of paddy

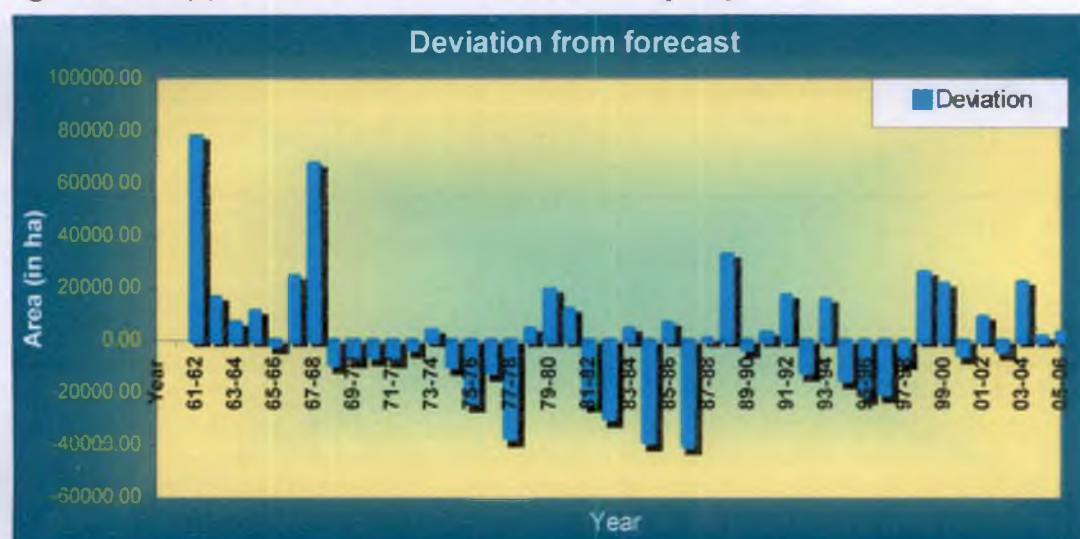


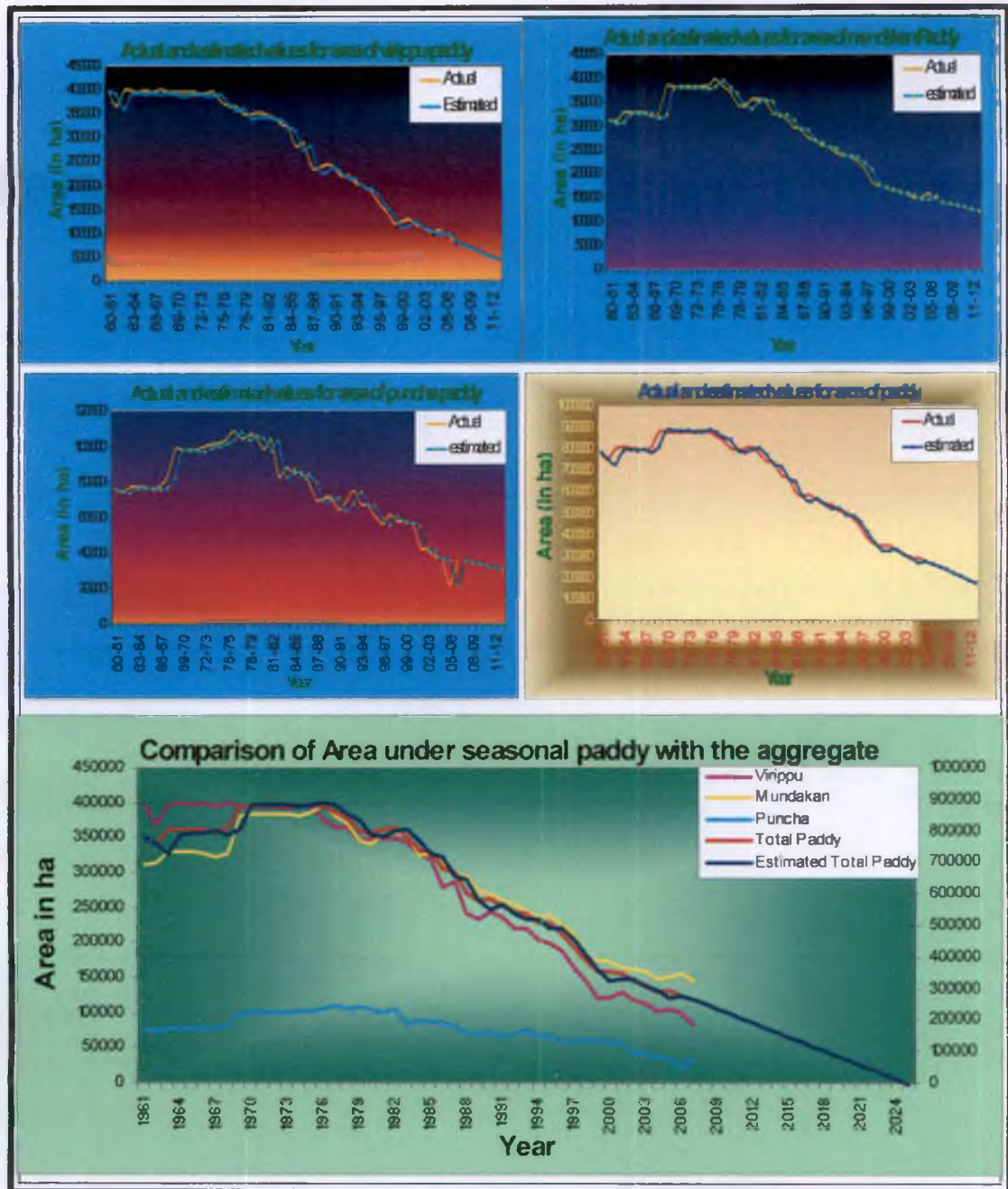
Table 4.5.3.1(e) : Comparison of the ARIMA(0,2,1) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	287340	291359.62	-1.40
04-05	289974	267426.95	7.78
05-06	275742	274277.25	0.53
06-07	263529	260319.16	1.22

Table 4.5.3.1 (f): Estimated area of paddy from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
248706.40	233883.80	219061.20	204238.60	189416.00

Fig. 4.5.3.1(e) Comparison of area under seasonal paddy with the area under total paddy



The area under paddy, the main food crop of Kerala, has come down significantly over the years, which has led to the State depending more and more on outside supplies to meet its domestic requirement. According to the report of the Department of Economics and Statistics, in 2005-06, the total area under paddy stood at 2.76 lakh hectares as against around 7.53 lakh hectares in 1961-62. This means that the State witnessed a decrease of 63% in area under paddy over a period of 44 years. The forecast tells there should not be any paddy cultivation by 2025. So there should be some action for posting permanent labourers in each panchayath to meet the unavailability of labourers and to make interest in paddy cultivation.

Paddy fields in Kerala are typical wetland ecosystems. They provide numerous important ecological and economic functions that benefit people. It is argued that economic return from paddy cultivation is not attractive to induce conservation. Land owners, most of them not full-time farmers basically argue for profit maximisation through the freedom of individual choice to shift away from paddy and it seems that they have accepted conversion inevitable to ensure adequate return. Conversion of paddy involves irreversible transformation of the ecosystem. Despite the fact that the soil and climate provide ideal conditions for plant growth, landowners resort to massive conversion of paddy fields. Kerala ranks top in literacy and environmental awareness, but there was more than 65% fall in the wetland area under paddy in the last 35 years. Unabated massive conversion still continues and that may result in a total abandonment of rice cultivation in the near future.

The State's deficit in rice, which is the staple food, has increased steadily from 50 to 55 percent during early fifties to mid-seventies and hence forth to more than 80 per cent of its requirement at present. In fact, Kerala has ceased to be a food grain producing state of any significance. This tendency is likely to have its impact on the food security of the absolutely poor if the public distribution system happens to fail.(Gopikuttan and Parameswarakurup,2004).

4.5.3.2. Production

In general the total production of rice has also come down in tandem. It stood at 6.42 lakh tonnes in 2006-07 compared to 13.39 lakh tonnes in 1981-82. Thus, over a period of 25 years, the rice production has fallen by more than 50 per cent. Several factors have been cited for the steady decline of paddy cultivation in Kerala, starting with high wages that resulted from an increase in the bargaining capacity of workers through the formation of strong labour unions and rule by different Governments that implemented the most successful land reforms in the country. During 1981-'82, the average wage of a woman labourer for working in the paddy field was Rs. 8.81 whereas the wage was Rs.123.96 during 2006-07. The wage for women in construction works was still higher than that for paddy field works which attracted them towards the more income generating areas of works and they might not want their children to take the paddy field works to earn their livelihood. Also the former tenants quickly converted their new assets into improving education for their children that helped them abandon farming and take up white-collar jobs. Many built houses on their plots or took to growing cash crops.

Figure 4.5.3.2 (a)
ACF for the production of paddy

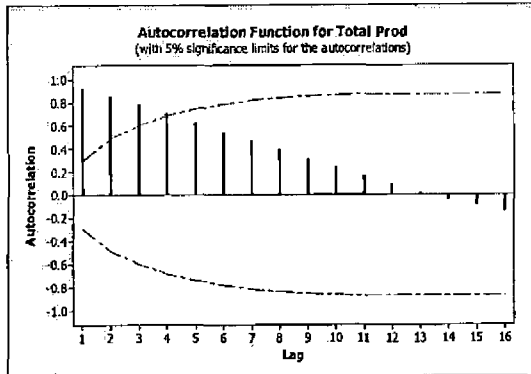
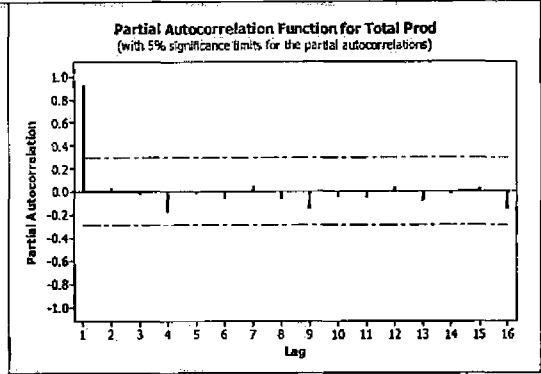


Figure 4.5.3.2 (b)
PACF for production of paddy



The ACF decayed exponentially and the PACF was significant only at lag 1 which indicated an AR(1) model. But as there were large number of significant ACFs, it showed the nonstationarity of the model. Significance of Q-statistics from Table 4.5.3.2 (a) also showed the nonstationary behaviour of the data.

Table 4.5.3.2 (a) ACF and PACF for production of Paddy with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8888	0.8888	-0.3050	0.3050	35.6054	0.00
2	0.7898	-0.0007	-0.3050	0.3050	64.4247	0.00
3	0.7057	0.0182	-0.3050	0.3050	88.0214	0.00
4	0.6186	-0.0566	-0.3050	0.3050	106.6314	0.00
5	0.4975	-0.2131	-0.3050	0.3050	118.9919	0.00
6	0.3828	-0.0683	-0.3050	0.3050	126.5134	0.00
7	0.3062	0.0888	-0.3050	0.3050	131.4641	0.00
8	0.2451	0.0424	-0.3050	0.3050	134.7304	0.00
9	0.1816	-0.0137	-0.3050	0.3050	136.5764	0.00
10	0.1293	-0.0011	-0.3050	0.3050	137.5418	0.00
11	0.0770	-0.1010	-0.3050	0.3050	137.8956	0.00
12	0.0080	-0.1664	-0.3050	0.3050	137.8995	0.00
13	-0.0573	-0.0476	-0.3050	0.3050	138.1089	0.00
14	-0.1058	0.0240	-0.3050	0.3050	138.8474	0.00
15	-0.1932	-0.2280	-0.3050	0.3050	141.4035	0.00
16	-0.2863	-0.1080	-0.3050	0.3050	147.2301	0.00
17	-0.3246	0.1563	-0.3050	0.3050	155.0185	0.00
18	-0.3473	-0.0098	-0.3050	0.3050	164.3052	0.00
19	-0.3658	0.0274	-0.3050	0.3050	175.0540	0.00
20	-0.3818	-0.0052	-0.3050	0.3050	187.2958	0.00

The best ranked model for the prediction of production of paddy was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in table 4.5.3.2(b) and 4.5.3.2(c).

Table 4.5.3.2(b): Statistics calculated for the best diagnosed model for production of paddy

R-squared	0.888	Normalized BIC	22.28
RMSE	65905.655	Ljung-Box Q	14.04
MAPE	4.952	DF	18
MAE	54012.497	Sig.	0.726
MaxAPE	12.782	Transformation	Nil
MaxAE	137689.690	Difference	1

Table 4.5.3.2.(c): Estimates of the parameters of ARIMA(0,1,0) for production of paddy

	Estimate	SE	t	Sig.
Constant	-9016.690	10169.463	-0.887	0.380

The final model could be written in the form

$$Y_t = Y_{t-1} - 9016.69, \dots \dots \dots (4.5.3.2)$$

Where Y_t denotes the production of Paddy in the year 't'.

This model had an R^2 of 88.8% indicating the explanatory power of the variation in the model with a MAPE of 4.95%. In the case of post sample period, the error increased due to large fluctuation in the production of mundakan and puncha.

Table 4.5.3.2.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
66145.250	10.709	78297.496	109797.310

The forecasted growth rate of production of paddy showed a decreasing trend from '07-'08 to '11-'12 and are -1.43, -1.45, -1.47 and -1.49 respectively. Since the growth rates are more or less constant, it can be improved by suitable precautions and remedies for harvest. Timely availability of labourers and affordable wage are also to be assured to increase the paddy production with accurate long range weather prediction to do the operations in time. Kerala government has already initiated developmental programmes like Paddy Mission and enacted rules to cultivate paddy lands which are kept barren. All these efforts, no doubt, will help to improve area under paddy in the state. However, more concerted efforts and interventions from the part of the state/central governments like scientific and systematic marketing system so as to ensure remunerative floor price to the farmers, subsidies, crop insurance, healthy interference by political parties etc. are warranted to curtail the decreasing trend in paddy cultivation in the state and to attract more and more people to the sector.

Figure 4.5.3.2 (c) Actual and estimated values for production of paddy using ARIMA(0,1,0)

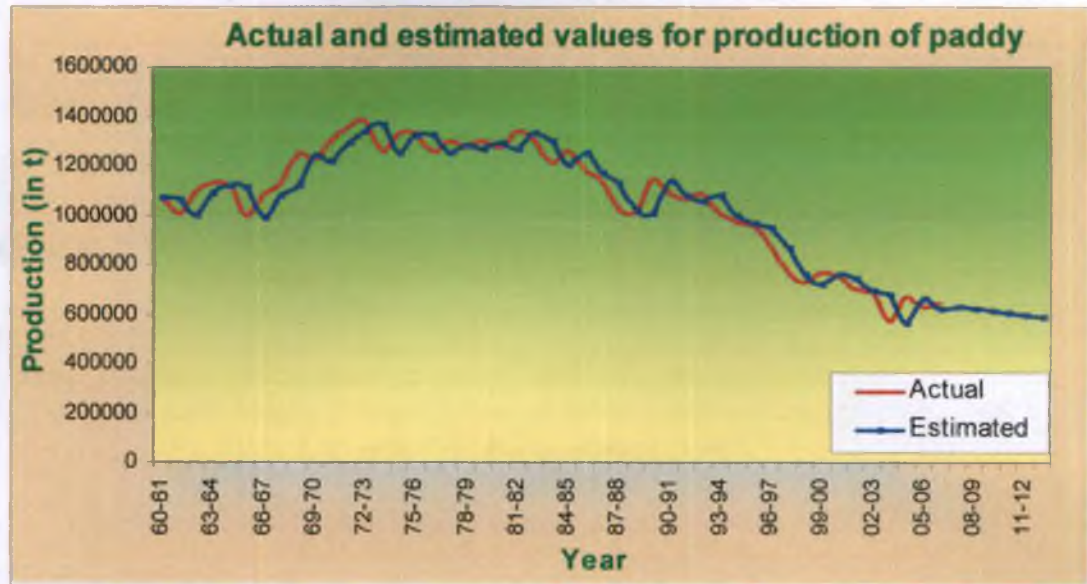


Figure 4.5.3.2.(d) Deviation from forecasts for production of paddy

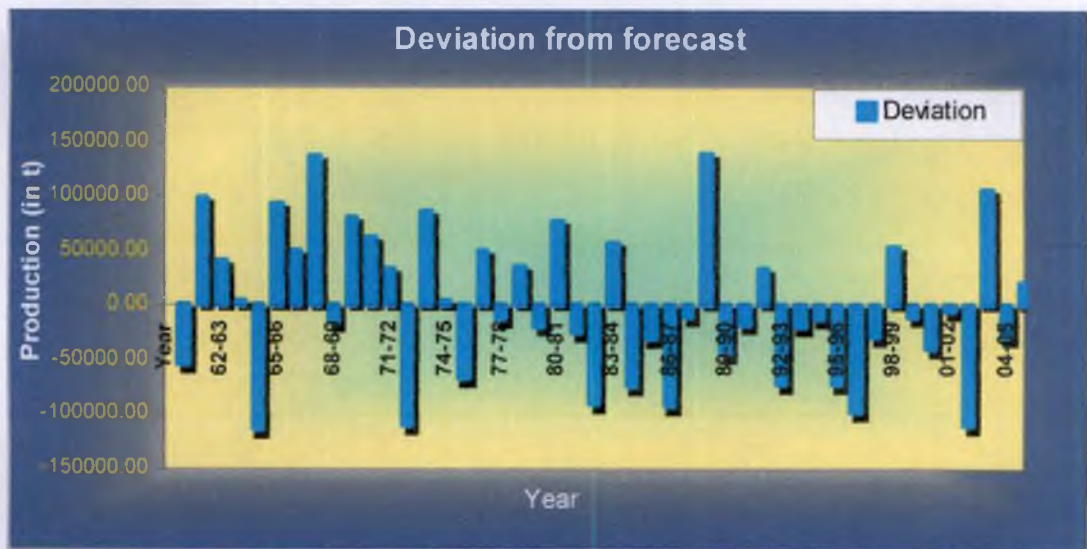


Table 4.5.3.2(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	570045	679842.31	-19.26
04-05	667105	561028.31	15.90
05-06	629987	658088.31	-4.46
06-07	641576	620970.31	3.21

Table 4.5.3.2 (f): Estimated production of paddy from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
632559.31	623542.62	614525.93	605509.24	596492.55

4.5.3.3. Productivity

Figure 4.5.3.3 (a)
ACF for the productivity of paddy

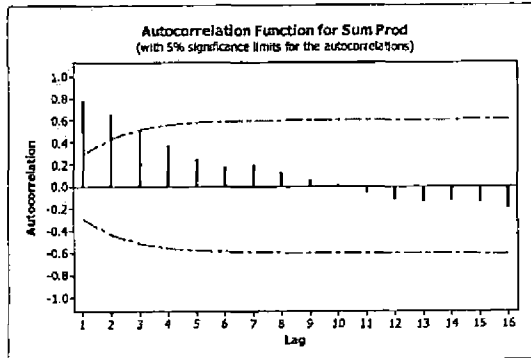
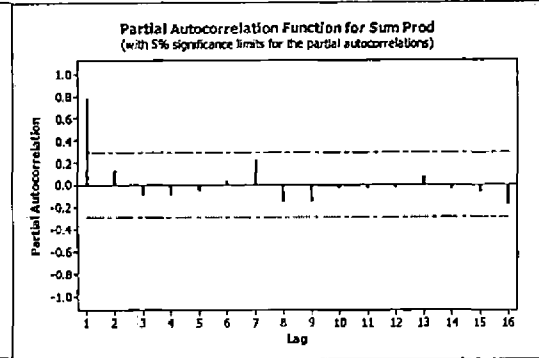


Figure 4.5.3.3 (b)
PACF for the productivity of paddy



The ACF decayed exponentially and the PACF was significant only at lag1 which indicated an AR(1) model. But as there were alrge number of significant ACFs, it showed the nonstationarity of the model. Significance of Q-statistics from Table 4.5.3.2 (a) also showed the nonstationary behaviour of the data.

Table 4.5.3.3 (a) ACF and PACF for productivity of Paddy with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9102	0.9102	-0.3050	0.3050	36.5146	0.00
2	0.8316	0.0181	-0.3050	0.3050	67.7743	0.00
3	0.7692	0.0558	-0.3050	0.3050	95.2270	0.00
4	0.6917	-0.1132	-0.3050	0.3050	118.0253	0.00
5	0.6229	0.0049	-0.3050	0.3050	137.0258	0.00
6	0.5628	0.0003	-0.3050	0.3050	152.9830	0.00
7	0.5090	0.0172	-0.3050	0.3050	166.4162	0.00
8	0.4443	-0.0954	-0.3050	0.3050	176.9629	0.00
9	0.3892	0.0094	-0.3050	0.3050	185.3071	0.00
10	0.3313	-0.0653	-0.3050	0.3050	191.5490	0.00
11	0.2581	-0.1124	-0.3050	0.3050	195.4650	0.00
12	0.1891	-0.0537	-0.3050	0.3050	197.6384	0.00
13	0.1263	-0.0262	-0.3050	0.3050	198.6428	0.00
14	0.0489	-0.1317	-0.3050	0.3050	198.7988	0.00
15	0.0033	0.1202	-0.3050	0.3050	198.7996	0.00
16	-0.0438	-0.0767	-0.3050	0.3050	198.9351	0.00
17	-0.0797	0.0643	-0.3050	0.3050	199.4019	0.00
18	-0.1191	-0.0946	-0.3050	0.3050	200.4894	0.00
19	-0.1662	-0.0717	-0.3050	0.3050	202.7033	0.00
20	-0.1886	0.0757	-0.3050	0.3050	205.6894	0.00

ARIMA(0,1,0) is identified as the best model with minimum Normalised Bayesian Information Criteria (BIC) for predicting the productivity of Paddy. The brief outputs is given in table 4.5.3.3(b) and 4.5.3.3(c).

Table 4.5.3.3 (b): Statistics calculated for the best diagnosed model for productivity of paddy

R-squared	0.941	Normalized BIC	8.51
RMSE	67.386	Ljung-Box Q	34.28
MAPE	3.084	DF	18
MAE	50.610	Sig.	0.012
MaxAPE	14.082	Transformation	Nil
MaxAE	182.727	Difference	1

Table 4.5.3.3 (c): Regression results for ARIMA(0,1,0) model for predicting productivity of Paddy

	Estimate	SE	t	Sig.
Constant	20.311	10.398	1.953	0.058

The final model could be written in the form

$$P_t = P_{t-1} + 20.311, \dots\dots\dots(4.5.3.3)$$

Where P_t denotes the productivity of paddy in the year 't'.

This model was used to forecast the future values of the time series with an R^2 of 94% and MAPE = 3.08% indicating the power of the model.

Table 4.5.3.3 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
179.239	8.158	206.688	296.388

The proverb 'Rice is Life' itself reflects the importance of rice as a primary food source to Keralites. Food preference is unique to the State, which is a part of tradition and culture. The future of rice production in Kerala lies in improving the productivity with reasonable cost of production through promotion of high yielding varieties, scientific management of cultivation thereby making rice production a remunerative enterprise for farmers. Government have to identify areas where paddy cultivation can be carried out profitably and to proclaim these areas for exclusive paddy production areas and to encourage the farmers by giving necessary helps so that paddy production can be increased to a very good extent. Programmes aim to reduce cost of cultivation, increase production; productivity and marketing facilities for making paddy cultivation profitable have to be chalked out sincerely by all concerned. Reclamation of paddy field should be totally banned and the ban order has to be stringently executed.

Figure 4.5.3.3 (c) Actual and estimated values for productivity of paddy using ARIMA(0,1,0)

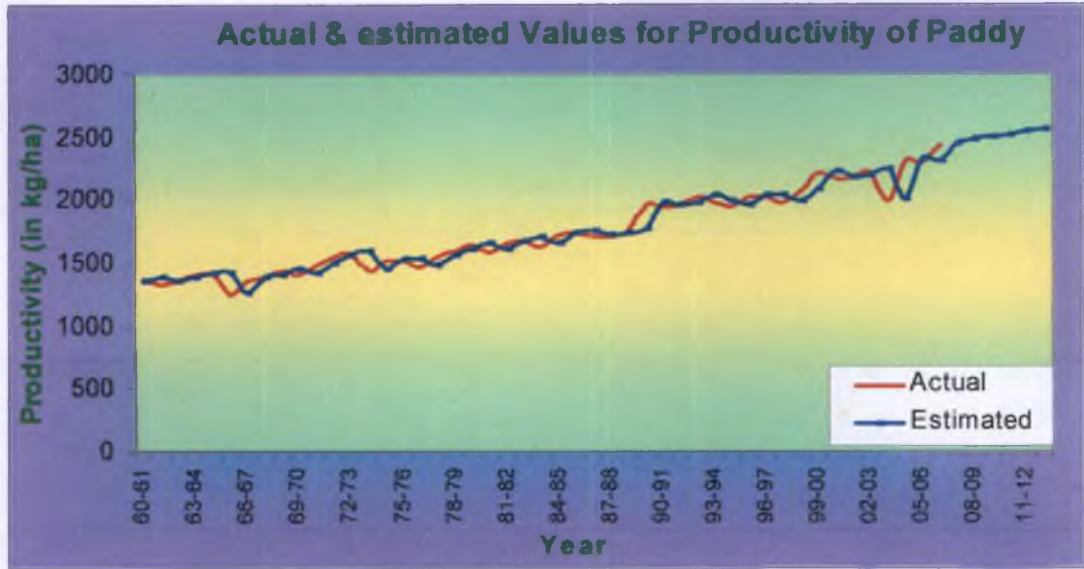


Figure 4.5.3.3 (d) Deviation from forecasts for the productivity of paddy

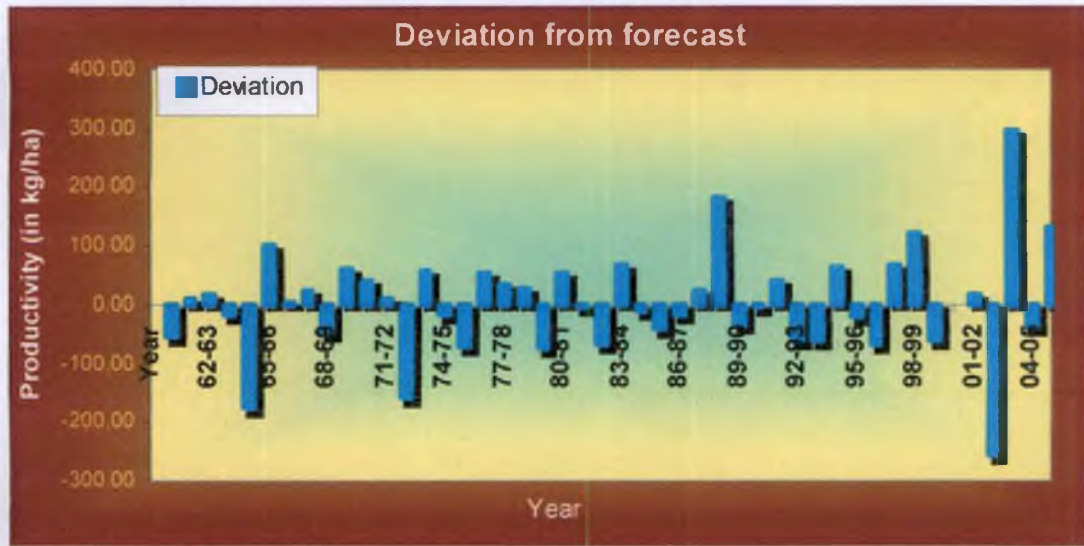


Table 4.5.3.3(e) : Comparison of the ARIMA(1,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	1984	2238.71	-12.85
04-05	2301	2004.18	12.88
05-06	2285	2320.88	-1.58
06-07	2435	2305.01	5.32

Table 4.5.3.3 (f) : Estimated Values for productivity of paddy from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
2454.87	2475.18	2495.49	2515.80	2536.11

4.5.3.4. Price

Figure 4.5.3.4(a)
ACF for the price of paddy

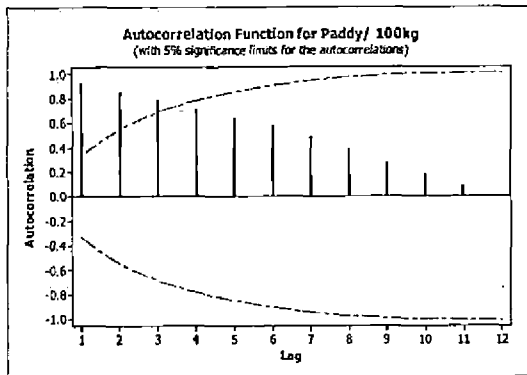
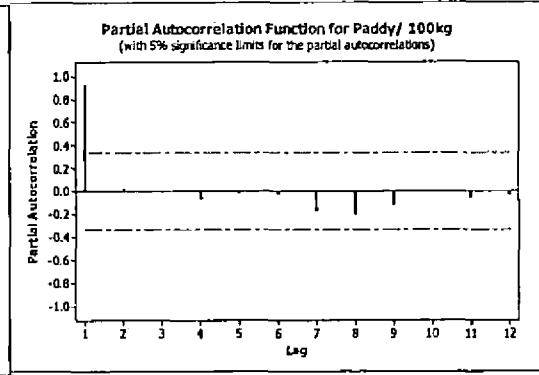


Figure 4.5.3.4(b)
PACF for the price of paddy



The ACF decayed exponentially and the PACF was significant only at lag 1 which indicated an AR(1) model. But as there were alrge number of significant ACFs, it showed the nonstationarity of the model. Significance of Q-statistics from Table 4.5.3.4 (a) also showed the nonstationary behaviour of the data.

Table 4.5.3.4(a) ACF and PACF for price of paddy with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9053	0.9053	-0.3536	0.3536	27.9457	0.00
2	0.8194	-0.0004	-0.3536	0.3536	51.6329	0.00
3	0.7230	-0.1041	-0.3536	0.3536	70.7287	0.00
4	0.6207	-0.0937	-0.3536	0.3536	85.3241	0.00
5	0.5342	0.0257	-0.3536	0.3536	96.5514	0.00
6	0.4447	-0.0619	-0.3536	0.3536	104.6439	0.00
7	0.3345	-0.1893	-0.3536	0.3536	109.4121	0.00
8	0.2308	-0.0611	-0.3536	0.3536	111.7813	0.00
9	0.1260	-0.0661	-0.3536	0.3536	112.5200	0.00
10	0.0465	0.0586	-0.3536	0.3536	112.6253	0.00
11	-0.0282	-0.0583	-0.3536	0.3536	112.6658	0.00
12	-0.0946	-0.0402	-0.3536	0.3536	113.1474	0.00
13	-0.1332	0.0942	-0.3536	0.3536	114.1557	0.00
14	-0.1884	-0.1314	-0.3536	0.3536	116.2912	0.00
15	-0.2383	-0.0764	-0.3536	0.3536	119.9229	0.00
16	-0.2739	-0.0171	-0.3536	0.3536	125.0404	0.00
17	-0.3067	-0.0187	-0.3536	0.3536	131.9116	0.00
18	-0.3409	-0.1176	-0.3536	0.3536	141.0582	0.00
19	-0.3578	-0.0062	-0.3536	0.3536	151.9701	0.00
20	-0.3874	-0.0965	-0.3536	0.3536	165.9282	0.00

ARIMA(0,1,0) was identified as the best ranked model for predicting the price of paddy with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in table 4.5.3.4(b) and 4.5.3.4(c).

Table 4.5.3.4(b) Statistics for the best diagnosed model for price of paddy.

R-squared	0.949	Normalized BIC	7.79
RMSE	46.687	Ljung-Box Q	15.72
MAPE	11.400	DF	18
MAE	34.746	Sig.	0.612
MaxAPE	50.089	Transformation	Natural Log
MaxAE	107.994	Difference	1

Table 4.5.3.4 (c) : Regression results for ARIMA(0,1,0) model for predicting price of Paddy

	Estimate	SE	t	Sig.
Constant	0.058	0.026	2.231	0.032

The final model could be written in the form

$$R_t = R_{t-1} e^{(0.058)}, \dots \dots \dots (4.5.3.4)$$

Where R_t denotes the price of paddy in the t^{th} year.

The model could explain 94.9% of the variation in the data with MAPE = 11.4%. For the forecasts of post sample period, the MAPE has reduced to 8.07% indicating the power of the model in predicting the price of paddy for future years. Even though the RMSE and MAE are increased, the maximum error in prediction was low in the post sample period.

Table 4.5.3.4 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
51.742	8.068	60.641	84.703

According to the above model, the price of paddy will be Rs 965 during 2012-13. According to the economic review it is stated that the domestic price of paddy moved to a higher trajectory during 2007 and 2008 in the state from Rs.682 during 2006-07 and the average retail price of rice (Matta) has reached up to Rs. 13.50/Kg in December 2005. The higher domestic price of paddy is expected to act as an incentive for the paddy farmers of the state. The crucial question is the relative profitability of paddy in the state .

Figure 4.5.3.4 (c) Actual and estimated values for price of Paddy by ARIMA(0,1,0) model



Figure 4.5.3.4 (d) Deviation from forecasts for the price of Paddy

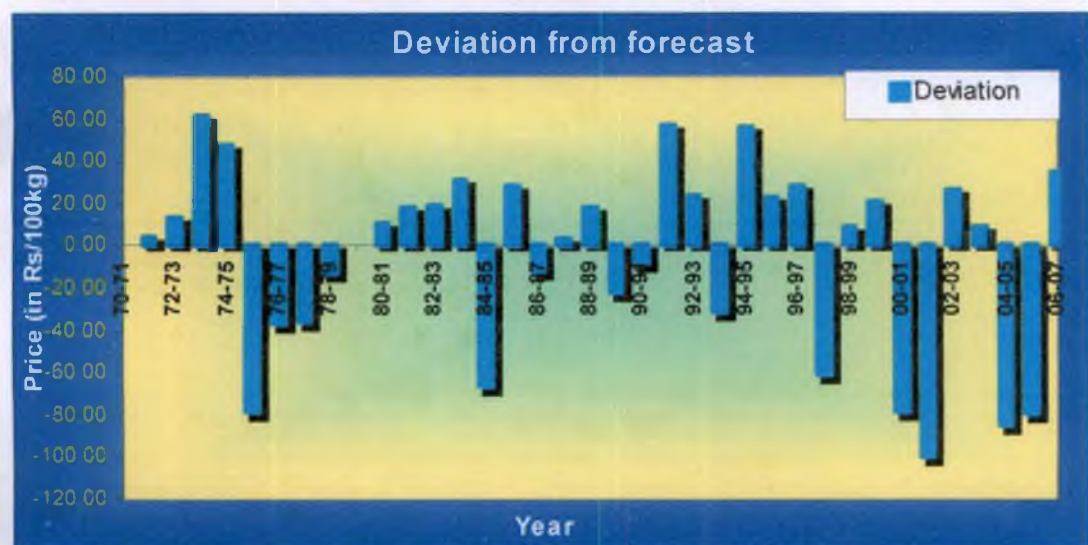


Table 4.5.3.4 (e) : Comparison of the ARIMA(0,1,2) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	694.34	685.74	1.24
04-05	651.10	735.80	-13.01
05-06	610.78	689.98	-12.97
06-07	681.72	647.25	5.06

Table 4.5.3.4 (f) : Estimated Values for price per Quintal of Paddy from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
722.43	765.57	811.28	859.73	911.07

4.5.3.1. Virippu Paddy

4.5.3.1.1.Area

Figure 4.5.3.1.1(a)
ACF for the series of area of virippu

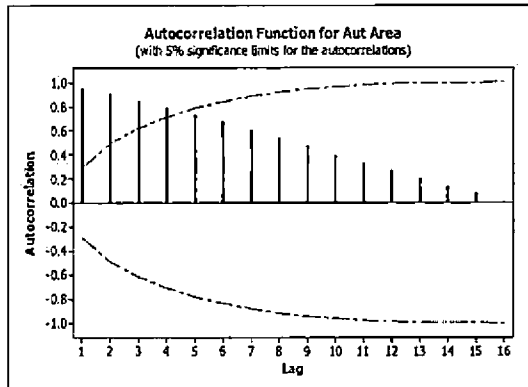
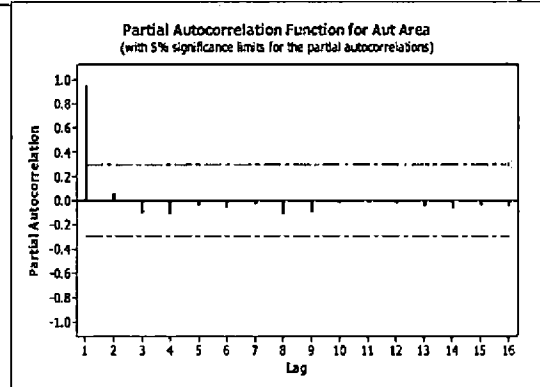


Figure 4.5.3.1.1(b)
PACF for the series of area of virippu



The ACF was declining exponentially and PACF has only one significant spike which was at lag 1 indicating an AR(1) model. But as there were more than half a dozen significant ACFs, the series was nonstationary and needed to be differenced. Table 4.5.3.1 also showed nonstationarity as the Q statistics are significant for large number of lags.

Table 4.5.3.1.1(a) ACF and PACF for area of virippu Paddy with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9368	0.9368	-0.3050	0.3050	38.6825	0.00
2	0.8804	0.0228	-0.3050	0.3050	73.7240	0.00
3	0.8164	-0.0896	-0.3050	0.3050	104.6479	0.00
4	0.7414	-0.1324	-0.3050	0.3050	130.8363	0.00
5	0.6625	-0.0829	-0.3050	0.3050	152.3287	0.00
6	0.5892	0.0055	-0.3050	0.3050	169.8175	0.00
7	0.5202	0.0078	-0.3050	0.3050	183.8498	0.00
8	0.4559	0.0011	-0.3050	0.3050	194.9556	0.00
9	0.3935	-0.0367	-0.3050	0.3050	203.4844	0.00
10	0.3272	-0.0923	-0.3050	0.3050	209.5728	0.00
11	0.2613	-0.0632	-0.3050	0.3050	213.5841	0.00
12	0.1892	-0.1030	-0.3050	0.3050	215.7597	0.00
13	0.1207	-0.0240	-0.3050	0.3050	216.6771	0.00
14	0.0534	-0.0322	-0.3050	0.3050	216.8632	0.00
15	-0.0222	-0.1265	-0.3050	0.3050	216.8965	0.00
16	-0.0933	-0.0548	-0.3050	0.3050	217.5101	0.00
17	-0.1424	0.1123	-0.3050	0.3050	218.9992	0.00
18	-0.1975	-0.0821	-0.3050	0.3050	221.9884	0.00
19	-0.2331	0.0775	-0.3050	0.3050	226.3434	0.00
20	-0.2671	-0.0581	-0.3050	0.3050	232.3339	0.00

The best ranked model was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in Tables 4.5.3.1.1(b) and (c)

Table 4.5.3.1.1(b) Statistics calculated for the best diagnosed model for Area of Virippu

R-squared	0.982	Normalized BIC	19.11
RMSE	13500.280	Ljung-Box Q	7.25
MAPE	4.065	DF	18
MAE	10098.546	Sig.	0.988
MaxAPE	16.374	Transformation	Nil
MaxAE	39369.381	Difference	1

Table 4.5.3.1.1(c) : Estimates of the Parameters for ARIMA(0,1,0) model for Area of Virippu

	Estimate	SE	t	Sig.
Constant	-6754.619	2083.138	-3.243	0.002

The final model could be written in the form

$$A_t = A_{t-1} - 6754.62, \dots \dots \dots (4.5.3.1.1)$$

Where A_t denotes the area of Virippu Paddy cultivation in the year 't'.

The R-squared was fairly good indicating that the model could explain about 98.2% of the variation in the data with MAPE 4.07% and a considerable reduction in RMSE for the post sample period which ensured the forecasting power of the model

Table 4.5.3.1.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
5056.940	5.288	6207.349	9333.620

From the forecasted figures of area of virippu paddy cultivation, it can be seen that there is significant growth rate from the year 2007-08 to 2008-09 but then the price shows a steady decrease with large deceleration in the future years of prediction and the growth rates are -8.76, -9.60, -10.62 and -11.88 respectively. It should be noted that even though there is an increasing trend with increasing growth rate for the price of paddy, the area is declining very fast. This is due to the shortage of labourers to the paddy field due to increasing wage rate in the construction field and laziness and time shortage of farmers to look at the paddy cultivation with timely deeds for it. Changing culture is also affecting this agriculture well. If the movement is in the same way virippu paddy cultivation will be ended in 2019-20.

Figure 4.5.3.1.1.(c) Actual and estimated values for area of virippu using ARIMA(0,1,0)

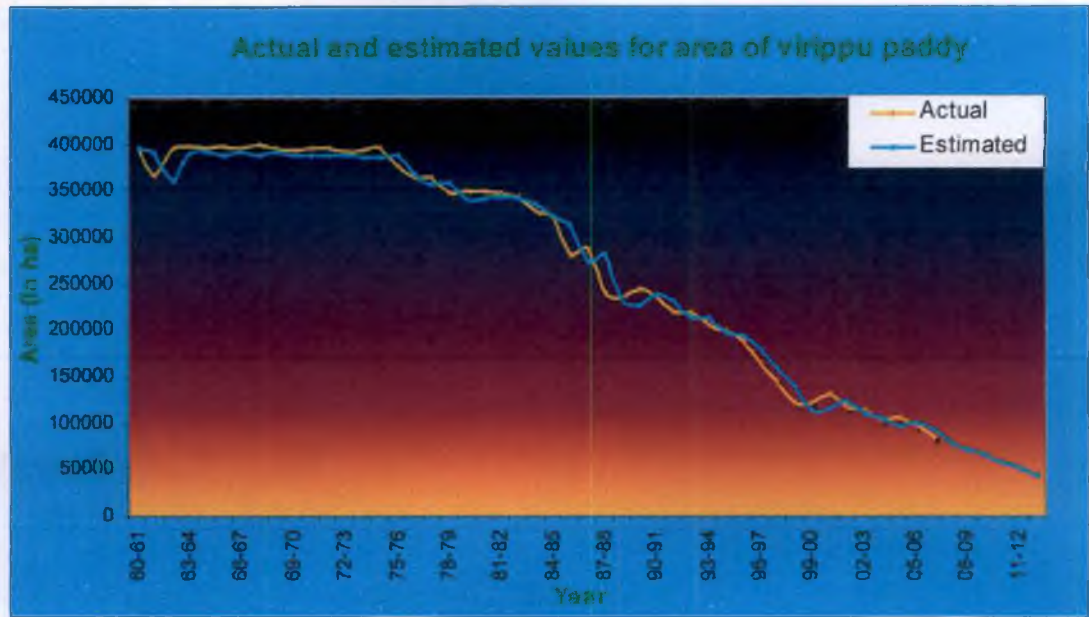


Figure 4.5.3.1.1.(d) Deviation from forecasts for area of virippu paddy

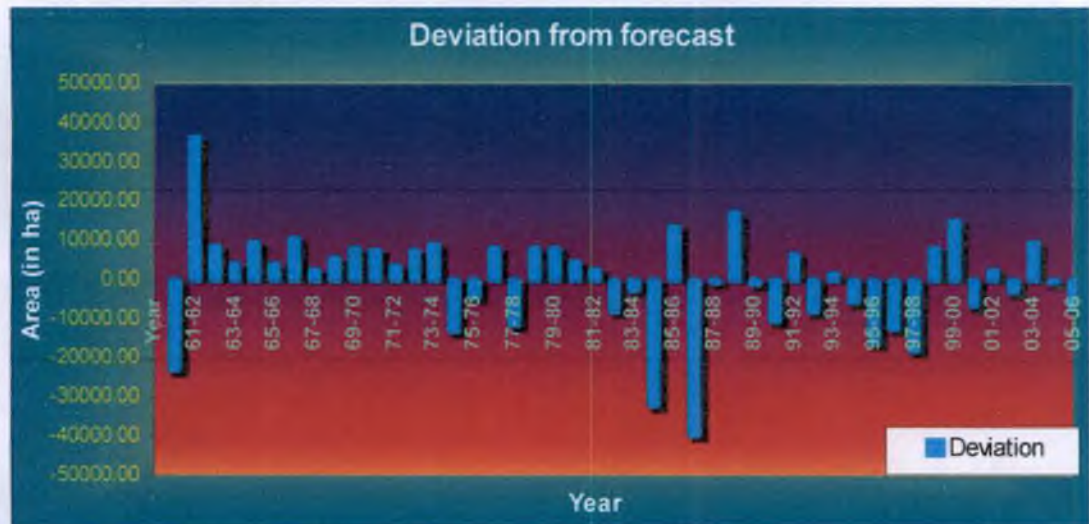


Table 4.5.3.1.1.(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	102770	105683.38	-2.83
04-05	105349	96015.38	8.86
05-06	98256	98594.38	-0.34
06-07	83859	91501.38	-9.11

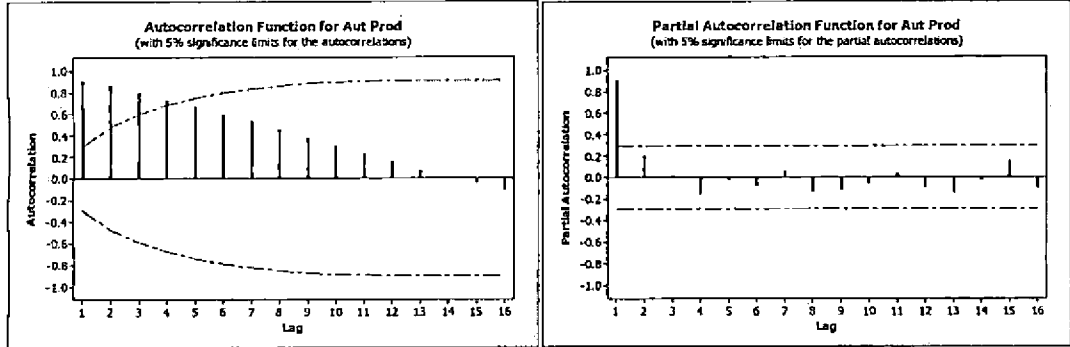
Table 4.5.3.1.1.(f) : Estimated Values for area of Virippu Paddy from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
77104.38	70349.76	63595.14	56840.52	50085.90

4.5.3.1.2. Production

Figure 4.5.3.1.2 (a)
ACF for the production of virippu paddy

Figure 4.5.3.1.2 (b)
PACF for the production of virippu paddy



The autocorrelations were significant for a large number of lags, but the PACF showed that autocorrelations at lags 3 and above were merely due to the propagation of the autocorrelation at lag 1 and 2. Hence we assumed an AR(2) model. Also from the ACF and Qstatistics given in Table 4.5.3.1.2 it was evident that the data was nonstationary.

Table 4.5.3.1.2 (a) ACF and PACF for production of virippu with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8726	0.8726	-0.3050	0.3050	33.5574	0.00
2	0.7996	0.1602	-0.3050	0.3050	62.4598	0.00
3	0.7241	-0.0068	-0.3050	0.3050	86.7885	0.00
4	0.6229	-0.1494	-0.3050	0.3050	105.2737	0.00
5	0.5267	-0.0842	-0.3050	0.3050	118.8590	0.00
6	0.4422	-0.0144	-0.3050	0.3050	128.7104	0.00
7	0.3885	0.1088	-0.3050	0.3050	136.5369	0.00
8	0.3135	-0.0738	-0.3050	0.3050	141.7879	0.00
9	0.2367	-0.1052	-0.3050	0.3050	144.8758	0.00
10	0.1857	0.0077	-0.3050	0.3050	146.8361	0.00
11	0.1381	0.0249	-0.3050	0.3050	147.9576	0.00
12	0.0533	-0.1762	-0.3050	0.3050	148.1300	0.00
13	0.0021	0.0044	-0.3050	0.3050	148.1302	0.00
14	-0.0506	-0.0442	-0.3050	0.3050	148.2974	0.00
15	-0.1308	-0.1501	-0.3050	0.3050	149.4575	0.00
16	-0.2082	-0.1126	-0.3050	0.3050	152.5140	0.00
17	-0.2400	0.1101	-0.3050	0.3050	156.7468	0.00
18	-0.2953	-0.1071	-0.3050	0.3050	163.4306	0.00
19	-0.2993	0.1792	-0.3050	0.3050	170.6076	0.00
20	-0.3285	-0.1304	-0.3050	0.3050	179.6687	0.00

ARIMA(1,1,0) was the best model with minimum Normalised Bayesian Information Criteria (BIC) and the brief outputs are given in Table 4.5.3.1.2 (b) and 4.5.3.1.2.(c).

Table 4.5.3.1.2(b): Statistics calculated for the best diagnosed model for production of virippu

R-squared	0.867	Normalized BIC	21.27
RMSE	39739.238	Ljung-Box Q	6.66
MAPE	7.362	DF	17
MAE	30763.810	Sig.	0.988
MaxAPE	27.722	Transformation	Nil
MaxAE	83565.655	Difference	1

Table 4.5.3.1.2.(c): Estimates of the parameters of ARIMA(1,1,0) model for production of virippu

	Estimate	SE	t	Sig.
AR(1)	-0.336	0.147	-2.292	0.027

The final model could be written in the form

$$Y_t = 0.664Y_{t-1} + 0.336Y_{t-2}, \dots\dots\dots(4.5.3.1.2)$$

Where Y_t denotes the production of virippu paddy in the year 't'.

This model is used to forecast the future values of the transformed time series. Assuming that the estimated model is a true representative of the forecasting period, the post sample RMSFE should be consistent with the residual standard error of the estimated model. As a result the comparison of forecast performance based on the RMSFE, MAFPE and MAXAFPE are made. From the reduction in the value of RMSE it is evident that the predictions can be done with very low forecasting error using equation (4.5.3.1.2) The maximum absolute error was 83565.66 during the sample period and it is halved (31125).

Table 4.5.3.1.2.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
21100.432	10.033	22065.970	31125.144

The production of virippur predicted for 2007-08 to 2011-12 showed a decreasing trend with fluctuating growth rate. The fluctuations for the years from 2007-08 to 2011-12 are -1.21, 0.41, -0.14, 0.05 percent respectively. Even though the area is continuously decreasing the production is fluctuating which implies the high growth rate in productivity and unpredictable weather conditions.

Figure 4.5.3.1.2 (c) Actual and estimated values for production of virippu using ARIMA(1,1,0)

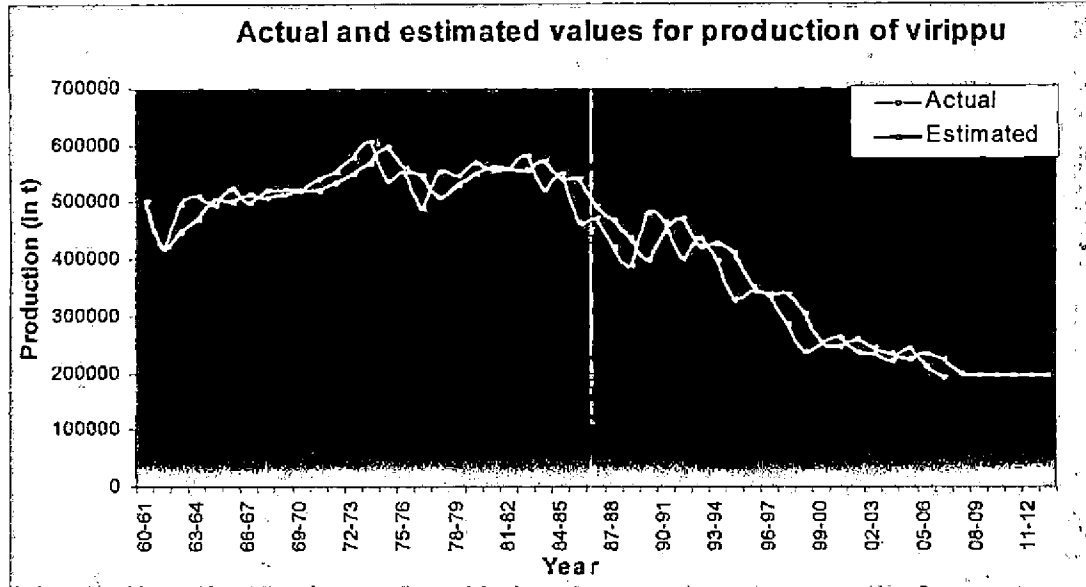


Figure 4.5.3.1.2.(d) Deviation from forecasts for production of virippu cultivation

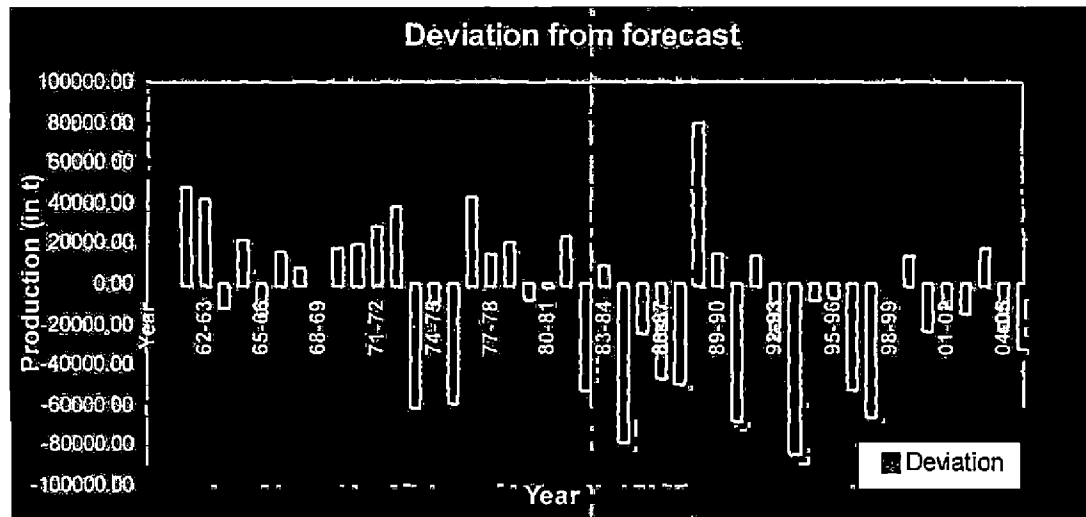


Table 4.5.3.1.2(e) : Comparison of the ARIMA(1,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	220132	234097.66	-6.34
04-05	241824	224528.56	7.15
05-06	212520	234535.49	-10.36
06-07	191241	222366.14	-16.28

Table 4.5.3.1.2 (f): Estimated production of virippu cultivation from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
198390.74	195988.43	196795.61	196524.40	196615.52

4.5.3.1.3. Productivity

Figure 4.5.3.1.3 (a)
ACF for the productivity of virippu

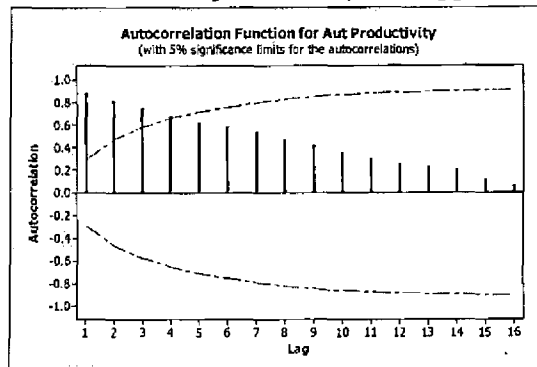
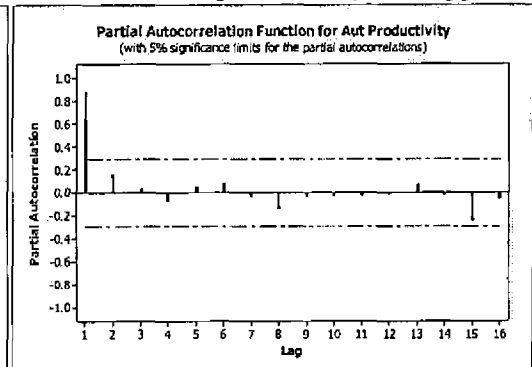


Figure 4.5.3.1.3 (b)
PACF for the productivity of virippu



From the ACF and PACF it was evident that the data was nonstationary and should be differenced. Significance of Q statistics in Table 4.5.3.1.3(a) also confirmed the nonstationarity of the series of productivity of virippu paddy.

Table 4.5.3.1.3 (a) ACF and PACF for productivity of virippu with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8690	0.8690	-0.3050	0.3050	33.2818	0.00
2	0.7904	0.1439	-0.3050	0.3050	61.5201	0.00
3	0.7509	0.1578	-0.3050	0.3050	87.6775	0.00
4	0.6572	-0.1814	-0.3050	0.3050	108.2575	0.00
5	0.6007	0.0614	-0.3050	0.3050	125.9286	0.00
6	0.5676	0.0561	-0.3050	0.3050	142.1561	0.00
7	0.4975	-0.0818	-0.3050	0.3050	154.9894	0.00
8	0.4390	-0.0442	-0.3050	0.3050	165.2830	0.00
9	0.4180	0.0906	-0.3050	0.3050	174.9113	0.00
10	0.3449	-0.1467	-0.3050	0.3050	181.6751	0.00
11	0.2633	-0.1312	-0.3050	0.3050	185.7484	0.00
12	0.2087	-0.0558	-0.3050	0.3050	188.3974	0.00
13	0.1249	-0.0918	-0.3050	0.3050	189.3801	0.00
14	0.0671	0.0316	-0.3050	0.3050	189.6742	0.00
15	0.0126	-0.1003	-0.3050	0.3050	189.6850	0.00
16	-0.0456	-0.0021	-0.3050	0.3050	189.8317	0.00
17	-0.0782	0.0493	-0.3050	0.3050	190.2806	0.00
18	-0.1161	-0.0576	-0.3050	0.3050	191.3139	0.00
19	-0.1623	-0.0505	-0.3050	0.3050	193.4240	0.00
20	-0.1847	0.0456	-0.3050	0.3050	196.2885	0.00

Figure 4.5.3.1.3 (c) Actual and Estimated values for productivity of virippu by ARIMA(0,1,0)

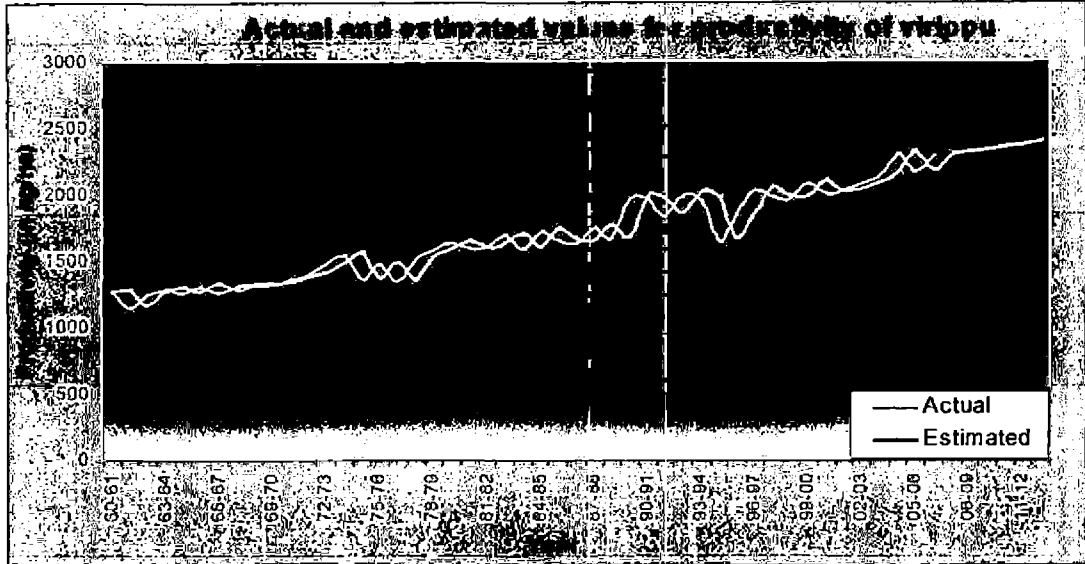


Figure 4.5.3.1.3 (d) Deviation from forecasts for the productivity of virippu

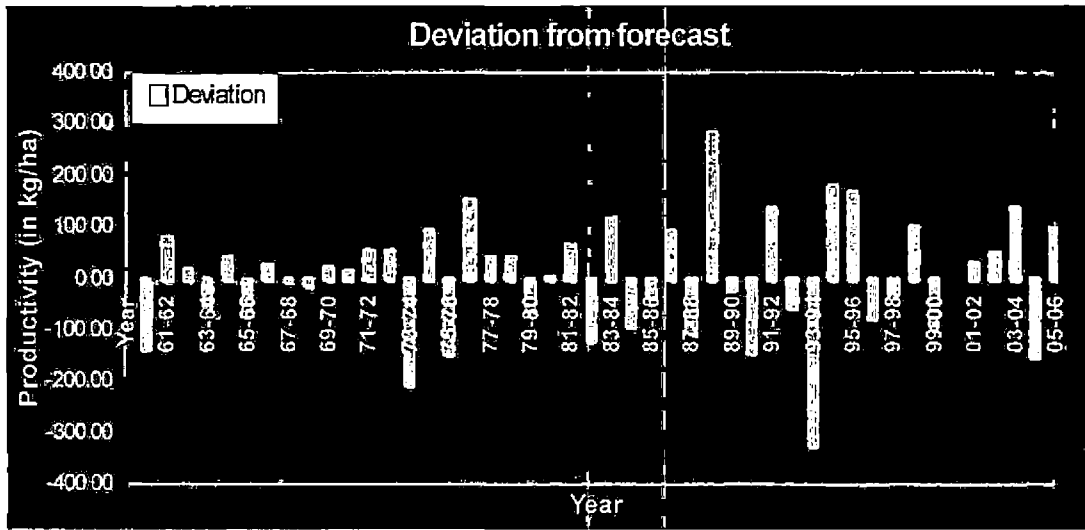


Table 4.5.3.1.3(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	2142	2093.50	2.26
04-05	2295	2161.30	5.84
05-06	2163	2314.77	-7.02
06-07	2281	2182.23	4.31

Table 4.5.3.1.3 (f) : Estimated Values for productivity of Virippu from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
2299.82	2319.13	2338.44	2357.75	2377.07

4.5.3.2. Mundakan paddy

4.5.3.2.1. Area

Figure 4.5.3.2.1(a)
ACF for the area of mundakan

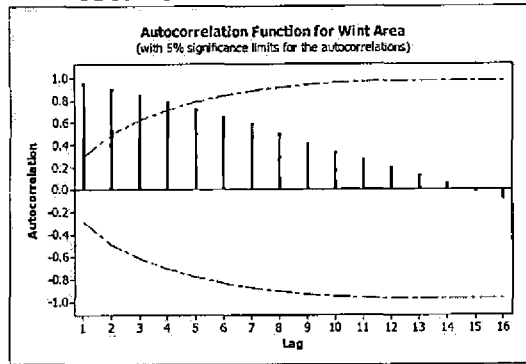
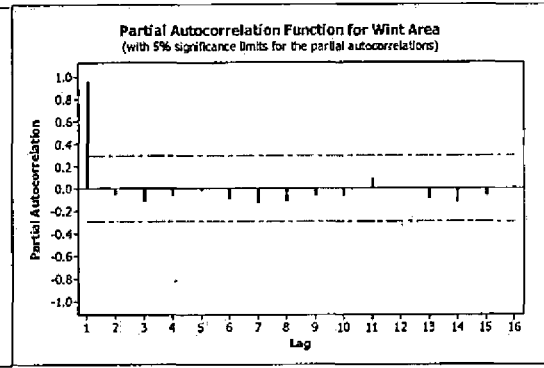


Figure 4.5.3.2.1(b)
PACF for the area of mundakan



From the figure it was seen that the ACF were declining exponentially and only one significant spike for PACF which was at lag1. Since there were large number of significant ACF it was evident that the series had a unit root. Also from Table 4.5.3.2.1(a) the Q-statistics were highly significant emphasising the nonstationarity of the series.

Table 4.5.3.2.1(a) ACF and PACF for area of mundakan with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9356	0.9356	-0.3050	0.3050	38.5810	0.00
2	0.8638	-0.0924	-0.3050	0.3050	72.3133	0.00
3	0.7862	-0.0828	-0.3050	0.3050	100.9901	0.00
4	0.7100	-0.0273	-0.3050	0.3050	125.0087	0.00
5	0.6325	-0.0544	-0.3050	0.3050	144.6010	0.00
6	0.5480	-0.1049	-0.3050	0.3050	159.7305	0.00
7	0.4727	0.0264	-0.3050	0.3050	171.3145	0.00
8	0.3936	-0.0848	-0.3050	0.3050	179.5906	0.00
9	0.3206	-0.0109	-0.3050	0.3050	185.2544	0.00
10	0.2430	-0.0932	-0.3050	0.3050	188.6130	0.00
11	0.1691	-0.0298	-0.3050	0.3050	190.2941	0.00
12	0.0992	-0.0376	-0.3050	0.3050	190.8920	0.00
13	0.0212	-0.1297	-0.3050	0.3050	190.9203	0.00
14	-0.0552	-0.0667	-0.3050	0.3050	191.1191	0.00
15	-0.1324	-0.0726	-0.3050	0.3050	192.3085	0.00
16	-0.1914	0.0536	-0.3050	0.3050	194.8931	0.00
17	-0.2461	-0.0469	-0.3050	0.3050	199.3411	0.00
18	-0.2877	0.0279	-0.3050	0.3050	205.6872	0.00
19	-0.3187	0.0067	-0.3050	0.3050	213.8281	0.00
20	-0.3557	-0.1254	-0.3050	0.3050	224.4489	0.00

The best ranked model for area of Mundakan Paddy was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief output was given in Table 4.5.3.2.1(b) and 4.5.3.2.1(c).

Table 4.5.3.2.1(b) Statistics calculated for best diagnosed model for Area of Mundakan.

R-squared	0.967	Normalized BIC	19.09
RMSE	13390.054	Ljung-Box Q	26.58
MAPE	2.911	DF	18
MAE	8668.408	Sig.	0.087
MaxAPE	14.911	Transformation	Nil
MaxAE	56754.429	Difference	1

Table 4.5.3.2.1.(c) : Estimates of the Parameters for ARIMA(0,1,0) for Area of Mundakan

	Estimate	SE	t	Sig.
Constant	-3643.429	2066.13	-1.763	0.085

The final model could be written in the form

$$A_t = A_{t-1} - 3643.43, \dots \dots \dots (4.5.3.2.1)$$

Where A_t denotes the area of Mundakan in the year 't'.

The R^2 was fairly good indicating that the model could explain about 96.7% of the variation in the data with MAPE 2.9%. For the post sample period the MAPE became 4.98% and it was an indication of lower error for the forecasting model with much reduced RMSE = 7717.72 and MXAFE = 10379.

Table 4.5.3.2.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
7442.500	4.983	7717.724	10379.430

From the model developed for Mundakan Paddy it can be observed that the area under cultivation is steadily decreasing with an increasing rate as given by -2.60, -2.67, -2.74 and -2.82 for the years 2007-08 to 2011-12 respectively. Among the three seasonal paddy crops viz; virippu, mundakan, puncha, the Mundakan paddy is having the highest area (143724 ha) under cultivation and production (346763 t). Next comes the virippu paddy (Area = 83859ha and Production = 191241 t) and then the puncha paddy (Area = 35946ha and Production = 103572 t) with respect to the data for the period 2006-07.

Figure 4.5.3.2.1.(c) Actual and estimated values for area of mundakan by ARIMA(0,1,0)

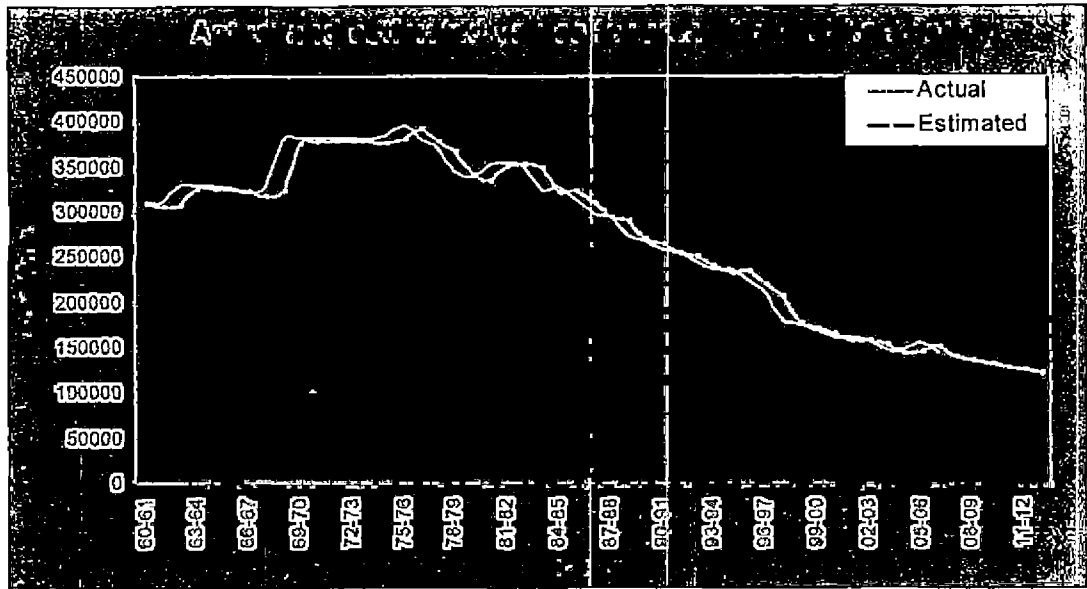


Figure 4.5.3.2.1.(d) Deviation from forecasts for area of mundakan Paddy

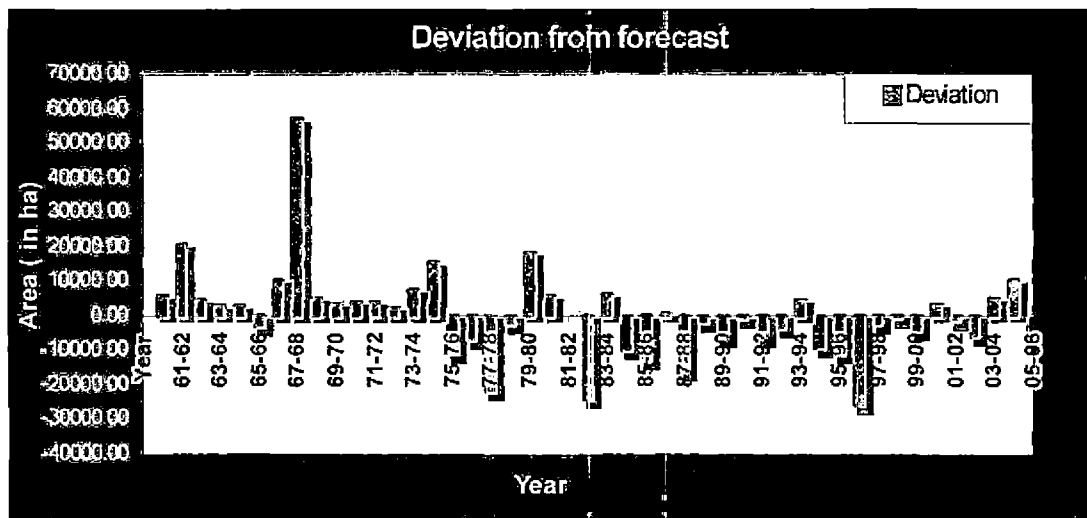


Table 4.5.3.2.1(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	147384	153360.57	-4.06
04-05	148893	143740.57	3.46
05-06	155629	145249.57	6.67
06-07	143724	151985.57	-5.75

Table 4.5.3.2.1(f) : Estimated values for area of mundakan from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
140080.57	136437.14	132793.71	129150.28	125506.85

4.5.3.2.2. Production

Figure 4.5.3.2.2 (a)
ACF for the production of mundakan

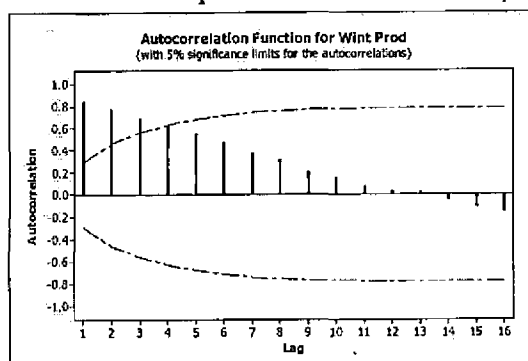
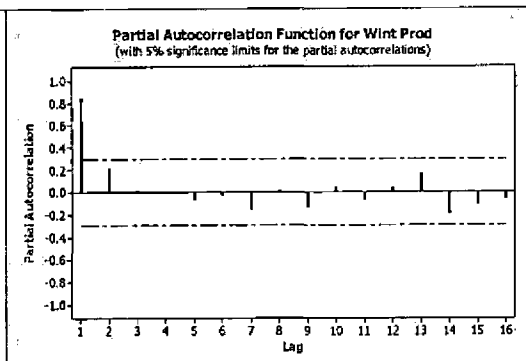


Figure 4.5.3.2.2 (b)
PACF for the production of mundakan



The autocorrelations were significant for a large number of lags but the PACF showed that autocorrelations at lags 3 and above were merely due to the propagation of the autocorrelation at lags 1 and 2. The significant ACFs for large number of lags and significant Q-statistics given in Table 4.5.3.2.2(a) indicated the nonstationarity behaviour of the sequence.

Table 4.5.3.2.2(a) ACF and PACF for production of Mundakan with Q Stat and Significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.7841	0.7841	-0.3050	0.3050	27.7138	0.00
2	0.6888	0.1919	-0.3050	0.3050	49.6307	0.00
3	0.5554	-0.0849	-0.3050	0.3050	64.2479	0.00
4	0.5198	0.1526	-0.3050	0.3050	77.3889	0.00
5	0.3938	-0.1648	-0.3050	0.3050	85.1348	0.00
6	0.2665	-0.1854	-0.3050	0.3050	88.7799	0.00
7	0.1824	0.0520	-0.3050	0.3050	90.5357	0.00
8	0.1504	0.0698	-0.3050	0.3050	91.7656	0.00
9	0.1069	-0.0220	-0.3050	0.3050	92.4059	0.00
10	0.0817	0.0703	-0.3050	0.3050	92.7917	0.00
11	0.0097	-0.1312	-0.3050	0.3050	92.7973	0.00
12	-0.0040	-0.0156	-0.3050	0.3050	92.7983	0.00
13	-0.0233	0.0296	-0.3050	0.3050	92.8329	0.00
14	-0.0890	-0.2111	-0.3050	0.3050	93.3552	0.00
15	-0.1870	-0.1622	-0.3050	0.3050	95.7493	0.00
16	-0.2695	-0.0666	-0.3050	0.3050	100.9101	0.00
17	-0.2626	0.0942	-0.3050	0.3050	106.0081	0.00
18	-0.2616	0.0697	-0.3050	0.3050	111.2775	0.00
19	-0.2743	0.0091	-0.3050	0.3050	117.3236	0.00
20	-0.2977	-0.0635	-0.3050	0.3050	124.7685	0.00

The best ranked model for production of Mundakan paddy was ARIMA(1,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in Tables 4.5.3.2.2(b) and 4.5.3.2.2(c).

Table 4.5.3.2.2(b): Statistics calculated for best diagnosed model for production of mundakan

R-squared	0.697	Normalized BIC	21.40
RMSE	42381.244	Ljung-Box Q	16.09
MAPE	6.966	DF	17
MAE	33001.180	Sig.	0.518
MaxAPE	29.863	Transformation	Nil
MaxAE	116420.759	Difference	1

Table 4.5.3.2.2(c): Estimates of the Parameters of ARIMA(1,1,0) for production of mundakan

	Estimate	SE	t	Sig.
AR(1)	-0.313	0.148	-2.113	0.041

The final model could be written in the form

$$Y_t = 0.687Y_{t-1} + 0.313Y_{t-2}, \dots \dots \dots (4.5.3.2.2)$$

Where Y_t denotes the production of mundakan paddy in the year 't'.

The R^2 is significant and can explain about 69.7% of the variation in the data with MAPE 6.97%. The prediction models already discussed earlier yielded a high value of R^2 together with a very low value of MAFPE. But it could be visualised that when the value of R^2 decreases the corresponding increase in the value of MAFPE can be expected there by increasing the forecast error. In the case of Mundakan Paddy the MAFPE has increased to 14.46% with corresponding increase in the computed value of other measures of error statistics.

Table 4.5.3.2.2(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
43877.516	14.462	52014.434	83015.546

In the case of Mundakan paddy production also a more or less constant growth rate was observed for the years 2007-08 to 2011-12 and the growth rates were -0.31, 0.10, -0.03 and 0.01 percent respectively.

Figure 4.5.3.2.2 (c) Actual and estimated values for production of mundakan by ARIMA(1,1,0)

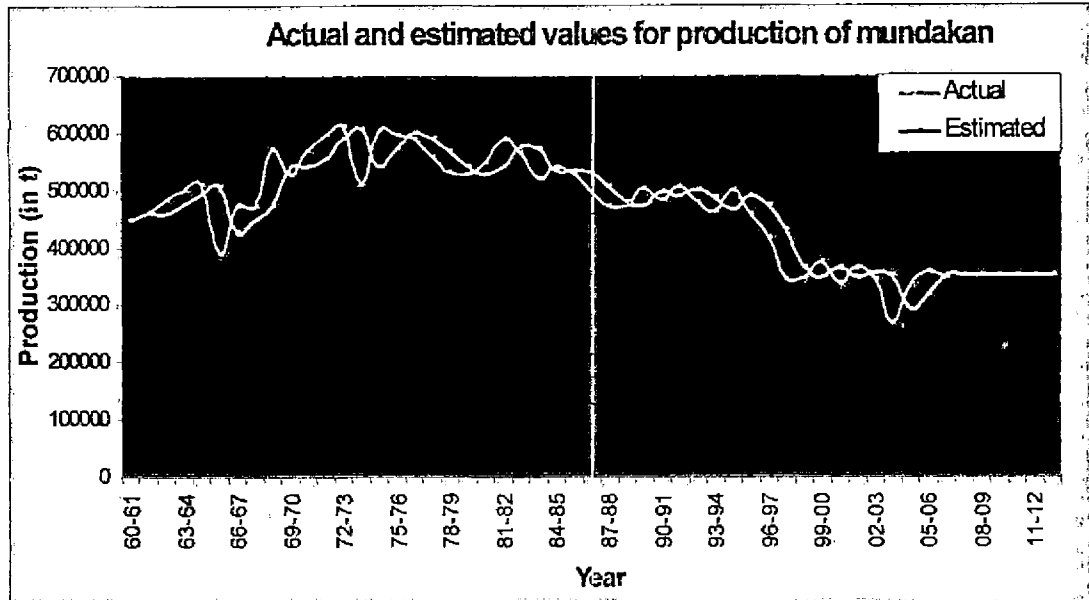


Figure 4.5.3.2.2.(d) Deviation from forecasts for production from mundakan cultivation

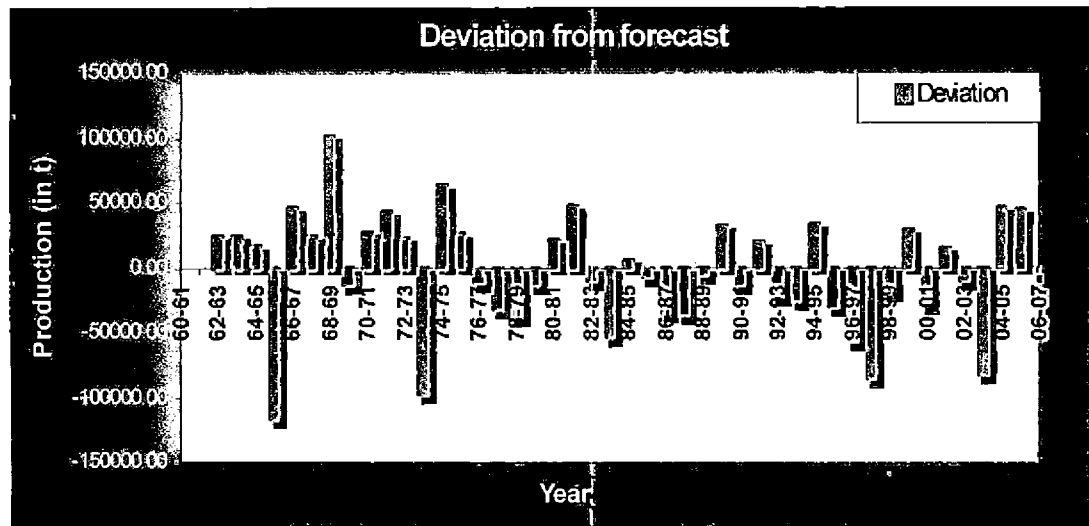


Table 4.5.3.2.2(e) : Comparison of the ARIMA(1,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	266674	349689.55	-31.13
04-05	335529	290811.93	13.33
05-06	357734	313977.39	12.23
06-07	346763	350783.84	-1.16

Table 4.5.3.2.2 (f): Estimated production of mundakan from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
350196.92	349122.11	349458.52	349353.22	349386.18

4.5.3.2.3. Productivity

Figure 4.5.3.2.3 (a)
ACF for the productivity of mundakan

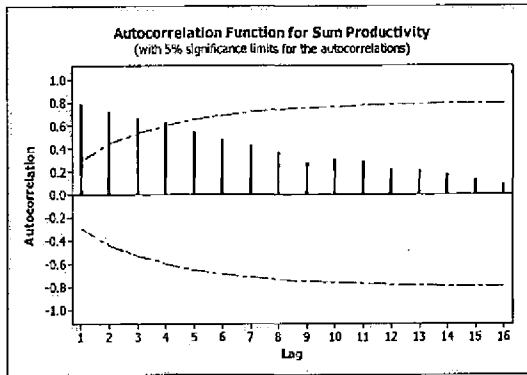
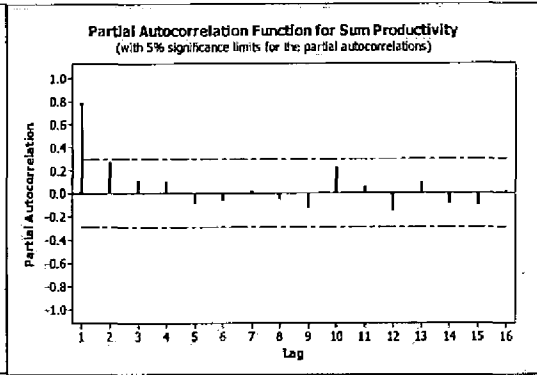


Figure 4.5.3.2.3 (b)
PACF for the productivity of mundakan



In the case of productivity of mundakan paddy, both the ACF and PACF showed a declining trend indicating an ARMA model. Since there were a large number of significant ACFs in the figure the series needed to be differenced to attain stationarity. The significant Q-statistics from Table 4.5.3.2.3(a) also revealed the nonstationarity of the data.

Table 4.5.3.2.3(a) ACF and PACF for productivity of Mundakan with QStat and Significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8394	0.8394	-0.3050	0.3050	31.0560	0.00
2	0.7687	0.2171	-0.3050	0.3050	57.7710	0.00
3	0.7114	0.0851	-0.3050	0.3050	81.2513	0.00
4	0.6537	0.0141	-0.3050	0.3050	101.6106	0.00
5	0.6010	0.0032	-0.3050	0.3050	119.2988	0.00
6	0.5305	-0.0791	-0.3050	0.3050	133.4727	0.00
7	0.4856	0.0208	-0.3050	0.3050	145.7013	0.00
8	0.4423	0.0066	-0.3050	0.3050	156.1538	0.00
9	0.3398	-0.2201	-0.3050	0.3050	162.5153	0.00
10	0.2956	0.0384	-0.3050	0.3050	167.4844	0.00
11	0.2060	-0.1561	-0.3050	0.3050	169.9780	0.00
12	0.1236	-0.1072	-0.3050	0.3050	170.9067	0.00
13	0.0814	0.0601	-0.3050	0.3050	171.3238	0.00
14	-0.0038	-0.1335	-0.3050	0.3050	171.3247	0.00
15	-0.0465	0.0122	-0.3050	0.3050	171.4714	0.00
16	-0.0889	0.0255	-0.3050	0.3050	172.0286	0.00
17	-0.0990	0.1250	-0.3050	0.3050	172.7489	0.00
18	-0.1374	-0.1017	-0.3050	0.3050	174.1952	0.00
19	-0.1799	0.0082	-0.3050	0.3050	176.7900	0.00
20	-0.2008	-0.0141	-0.3050	0.3050	180.1737	0.00

The best ranked model for predicting the productivity was ARIMA(0,1,1) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in Table 4.5.3.2.3(b) and (c).

Table 4.5.3.2.3 (b): Statistics for the best diagnosed model for Productivity of Mundakan

R-squared	0.854	Normalized BIC	9.40
RMSE	100.470	Ljung-Box Q	12.07
MAPE	4.093	DF	17
MAE	66.340	Sig.	0.796
MaxAPE	30.260	Transformation	Nil
MaxAE	359.790	Difference	1

Table 4.5.3.2.3 (c): Regression results for ARIMA(0,1,1) for predicting productivity of Mundakan

	Estimate	SE	t	Sig.
Constant	17.858	5.872	3.041	0.004
MA(1)	0.638	0.128	4.997	0.000

The final model with an R² of 85% and MAPE = 4.09% could be written in the form

$$P_t = P_{t-1} - 0.638\epsilon_{t-1} + 17.858, \dots\dots\dots(4.5.3.2.3)$$

where P_t denotes the productivity for the year t and ε_t denote the error in prediction.

The model given by equation (4.5.3.2.3) was also called the simple exponential smoothing model (SES) as the one-period-ahead forecasts from this model were qualitatively similar to those of the SES model, except that the trajectory of the long-term forecasts was typically a sloping line (whose slope is equal to mean) rather than a horizontal line. The predicted value P_t is the weighted average of its own past values plus an innovation. By implementing the SES model as an ARIMA model, we can gain some flexibility. First of all, the estimated MA(1) coefficient is allowed to be negative. This corresponds to a smoothing factor larger than 1 in an SES model. Second, we have the option of including a constant term in the ARIMA model if we wish, in order to estimate an average non-zero trend.

Table 4.5.3.2.3 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
223.703	10.812	243.251	386.527

The forecasts for future could be materialised with a MAFPE = 10.81 which is more than that for the sample period forecast. The increase in MAFPE may be due to inclusion of the forecast errors as regressors which will exponentially increase for the prediction year after year

Figure 4.5.3.2.3 (c) Actual and estimated values for productivity of mundakan by ARIMA(0,1,1)

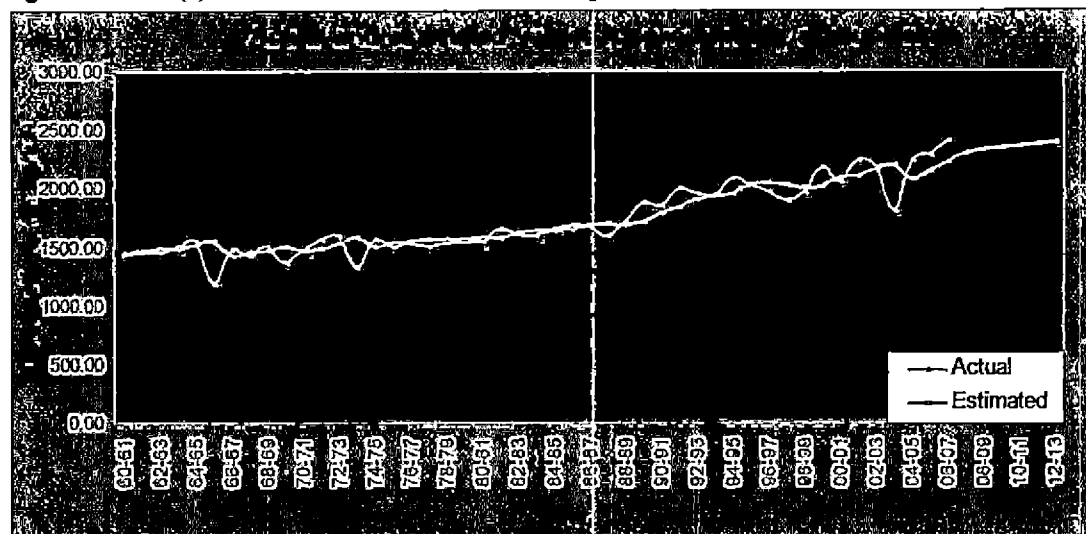


Figure 4.5.3.2.3 (d) Deviation from forecasts for the productivity of mundakan

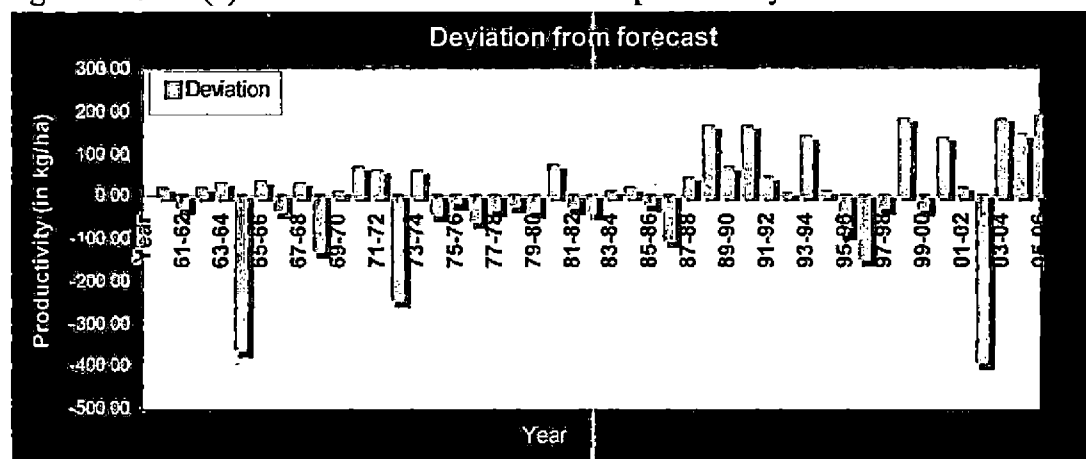


Table 4.5.3.2.3(e) : Comparison of the ARIMA(0,1,1) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	1809	2195.91	-21.36
04-05	2253	2073.84	7.97
05-06	2299	2156.73	6.17
06-07	2413	2225.96	7.74

Table 4.5.3.2.3 (f) : Estimated values for productivity of mundakan from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
2311.42	2329.28	2347.13	2364.99	2382.85

The estimated values of productivity of mundakan paddy show an increasing trend with more or less constant growth rate which are given by 0.77,0.77,0.76 and 0.76 respectively for the period 2007-08 to 2011-12.

4.5.3.3. Puncha Paddy

4.5.3.3.1. Area

Figure 4.5.3.3.1(a)
ACF for the area of puncha

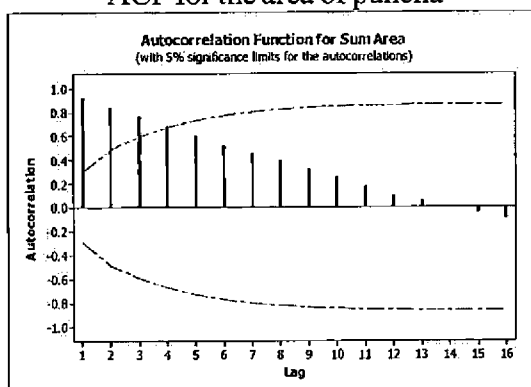
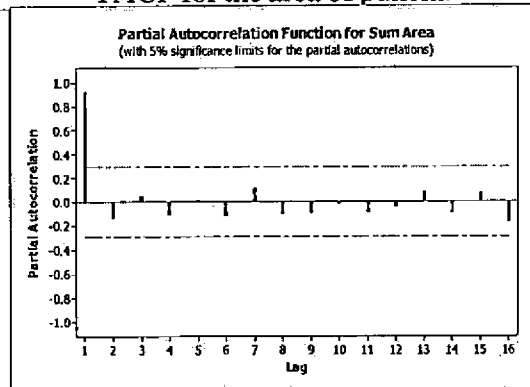


Figure 4.5.3.3.1(b)
PACF for the area of puncha



From the figure, the ACFs were declining exponentially and the PACF had only one significant spike indicating an AR model. The significant ACFs for larger number of lags and the highly significant Q-statistics from Table 4.5.3.3.1(a) indicated the nonstationarity behaviour of the data.

Table 4.5.3.3.1(a) ACF and PACF for area of puncha paddy with Q Stat and Significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8939	0.8939	-0.3050	0.3050	36.0146	0.00
2	0.8033	0.0211	-0.3050	0.3050	65.8248	0.00
3	0.7321	0.0516	-0.3050	0.3050	91.2227	0.00
4	0.6560	-0.0529	-0.3050	0.3050	112.1527	0.00
5	0.5887	0.0042	-0.3050	0.3050	129.4633	0.00
6	0.5057	-0.1186	-0.3050	0.3050	142.5892	0.00
7	0.4024	-0.1590	-0.3050	0.3050	151.1369	0.00
8	0.3060	-0.0681	-0.3050	0.3050	156.2253	0.00
9	0.2078	-0.0973	-0.3050	0.3050	158.6435	0.00
10	0.1204	-0.0295	-0.3050	0.3050	159.4805	0.00
11	0.0660	0.0957	-0.3050	0.3050	159.7399	0.00
12	-0.0202	-0.1725	-0.3050	0.3050	159.7651	0.00
13	-0.0991	-0.0281	-0.3050	0.3050	160.3907	0.00
14	-0.1775	-0.1060	-0.3050	0.3050	162.4697	0.00
15	-0.2498	-0.0463	-0.3050	0.3050	166.7402	0.00
16	-0.3131	-0.0899	-0.3050	0.3050	173.7099	0.00
17	-0.3604	-0.0078	-0.3050	0.3050	183.3112	0.00
18	-0.3894	0.0484	-0.3050	0.3050	194.9892	0.00
19	-0.4144	-0.0285	-0.3050	0.3050	208.7885	0.00
20	-0.4352	-0.0080	-0.3050	0.3050	224.6997	0.00

The best ranked model for the area of cultivation of puncha paddy was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.3.3.1(b) and 4.5.3.3.1(c).

Table 4.5.3.3.1(b) Statistics calculated for the best diagnosed model for area of puncha

R-squared	0.903	Normalized BIC	17.40
RMSE	5726.939	Ljung-Box Q	20.47
MAPE	5.334	DF	18
MAE	4006.803	Sig.	0.307
MaxAPE	24.133	Transformation	Nil
MaxAE	19326.429	Difference	1

Table 4.5.3.3.1(c) : Estimates of the Parameters for ARIMA(0,1,0) model for area of puncha

	Estimate	SE	t	Sig.
Constant	-825.571	883.686	-0.934	0.356

The final model could be written in the form

$$A_t = A_{t-1} - 825.571, \dots \dots \dots (4.5.3.3.1)$$

Where A_t denotes the area of puncha paddy in the year 't'.

This model has a high R^2 and it could explain about 90.3% of the variation in the data and so this model was used to forecast the future values of the transformed time series with a MAPE of 5.33% indicating a good fit.

Table 4.5.3.3.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
7914.965	27.801	10031.651	14914.571

From the forecasted figures of area of cultivation of Puncha Paddy, it can be seen that there is significant decrease with an increasing rate from the year 2007-08 to 2008-09 and is given by -2.35, -2.41, -2.47 and -2.53 respectively. Among the three seasonal paddy cultivations, the area under puncha cultivation is the least when compared to the other two. It is showing a slight increase in area from 2008-09 onwards. From the trend of virippu and mundakan paddy a steep decline could be observed for the area under cultivation whereas for puncha the decline in area is comparatively small. During this season the cultivation can be well maintained by providing sufficient irrigation facilities and essential cultural practices.

Figure 4.5.3.3.1.(c) Actual and estimated values for area of pancha by ARIMA(0,1,0)

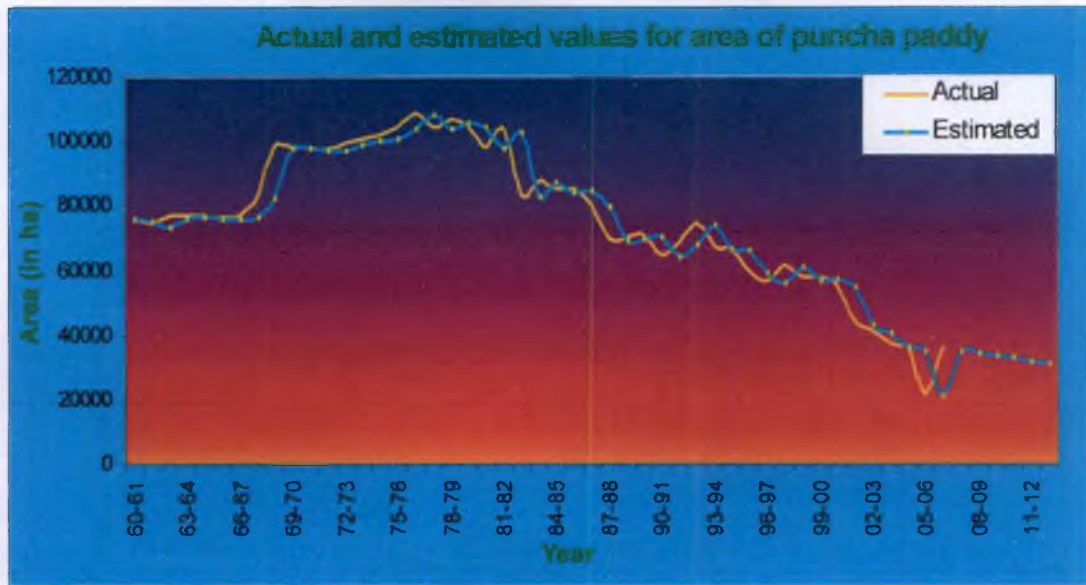


Figure 4.5.3.3.1.(d) Deviation from forecasts for area of pancha paddy

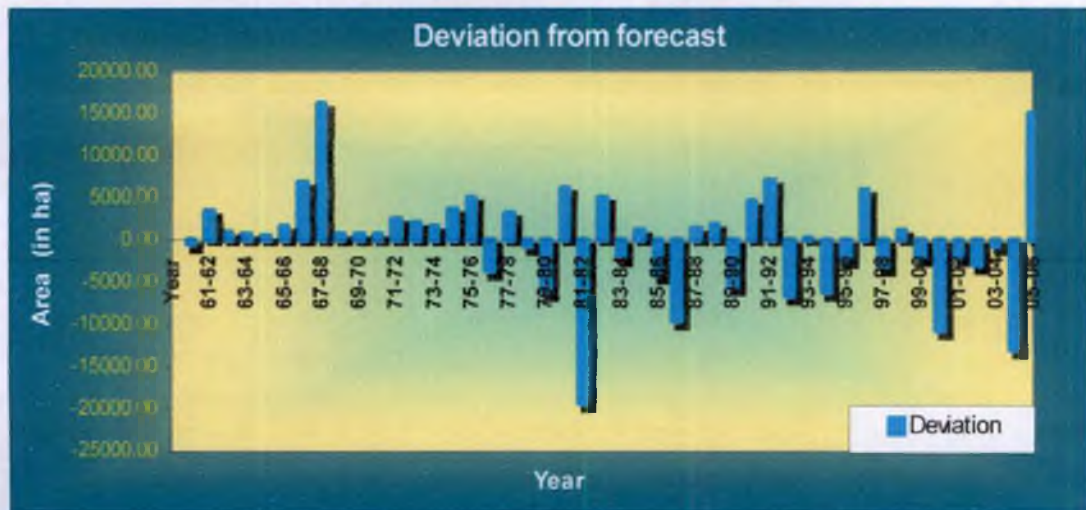


Table 4.5.3.3.1.(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	37186	40253.43	-8.25
04-05	35732	36360.43	-1.76
05-06	21857	34906.43	-59.70
06-07	35946	21031.43	41.49

Table 4.5.3.3.1.(f) : Estimated values for area of pancha paddy from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
35120.43	34294.86	33469.29	32643.72	31818.15

4.5.3.3.2. Production

Figure 4.5.3.3.2 (a)
ACF for the production of puncha

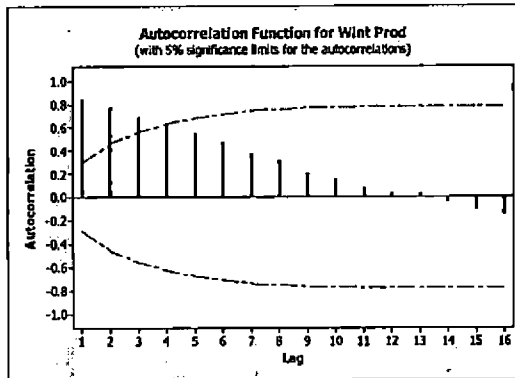
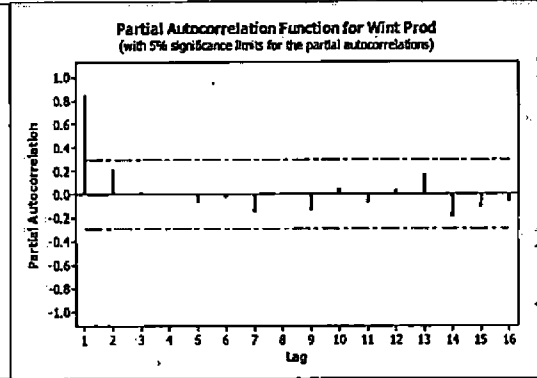


Figure 4.5.3.3.2 (b)
PACF for the production of puncha



From the figure, the ACFs were declining exponentially and the PACF had only one significant spike indicating an AR(1) model. The significant ACFs for larger number of lags and the highly significant Q-statistics from Table 4.5.3.3.2(a) indicated the nonstationarity behaviour of the data.

Table 4.5.3.3.2 (a) ACF and PACF for production of puncha with Q Stat and Significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.7137	0.7137	-0.3050	0.3050	22.9604	0.00
2	0.5691	0.1216	-0.3050	0.3050	37.9223	0.00
3	0.4819	0.0792	-0.3050	0.3050	48.9251	0.00
4	0.3460	-0.1020	-0.3050	0.3050	54.7456	0.00
5	0.2522	-0.0221	-0.3050	0.3050	57.9218	0.00
6	0.1448	-0.0931	-0.3050	0.3050	58.9986	0.00
7	0.1141	0.0761	-0.3050	0.3050	59.6862	0.00
8	0.0160	-0.1373	-0.3050	0.3050	59.7001	0.00
9	-0.0878	-0.1120	-0.3050	0.3050	60.1321	0.00
10	-0.1247	-0.0208	-0.3050	0.3050	61.0296	0.00
11	-0.1362	0.0483	-0.3050	0.3050	62.1360	0.00
12	-0.2254	-0.1772	-0.3050	0.3050	65.2664	0.00
13	-0.2307	0.0407	-0.3050	0.3050	68.6568	0.00
14	-0.2265	-0.0375	-0.3050	0.3050	72.0427	0.00
15	-0.2606	-0.0671	-0.3050	0.3050	76.6919	0.00
16	-0.3471	-0.2266	-0.3050	0.3050	85.2570	0.00
17	-0.3203	0.0926	-0.3050	0.3050	92.8420	0.00
18	-0.3160	-0.1148	-0.3050	0.3050	100.5303	0.00
19	-0.3098	0.0452	-0.3050	0.3050	108.2402	0.00
20	-0.2654	-0.0281	-0.3050	0.3050	114.1556	0.00

ARIMA(0,1,0) model was identified as the best with minimum Normalised Bayesian Information Criteria (BIC) for predicting the production from puncha cultivation. The brief outputs are given in Table 4.5.3.3.2(b) and 4.5.3.3.2(c).

Table 4.5.3.3.2(b): Statistics calculated for the best diagnosed model for Production of Puncha

R-squared	0.491	Normalized BIC	20.01
RMSE	21171.001	Ljung-Box Q	18.23
MAPE	11.028	DF	18
MAE	16171.129	Sig.	0.441
MaxAPE	47.026	Transformation	Nil
MaxAE	52663.143	Difference	1

Table 4.5.3.3.2.(c): Estimates of the Parameters of ARIMA(0,1,0) for production of Puncha

	Estimate	SE	t	Sig.
Constant	-182.143	3266.756	-0.056	0.956

The final model with $R^2= 49.1\%$ could be written in the form

$$Y_t = Y_{t-1} - 182.143, \dots\dots\dots(4.5.3.3.2)$$

Where Y_t denotes the production of Puncha Paddy in the year 't'.

Table 4.5.3.3.2.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
27245.500	33.517	30336.133	44021.143

The forecasted figures of production shows a steady decreasing trend with constant deceleration of -0.18 from 2007-08 to 2011-12. Unexpected out break of rainfall and other weather calamities greatly affect the production and harvest of puncha paddy. The farmers and the official machinery are usually racing against time to catch up with the puncha season which usually fall behind schedule by nearly a month. Incessant rains force farmers to defer their plans. The harvest of the puncha crop if every thing have gone by schedule would begin by early March. During this season there is a severe scarcity of labourers as they may be attracted towards the construction works which will give more earnings to them and also once if they are involved in such works they may not be able to come back to work in the paddy field. Production can be improved by bringing the puncha schedule back on track.

Figure 4.5.3.3.2 (c) Actual and estimated values for production of puncha by ARIMA(0,1,0)

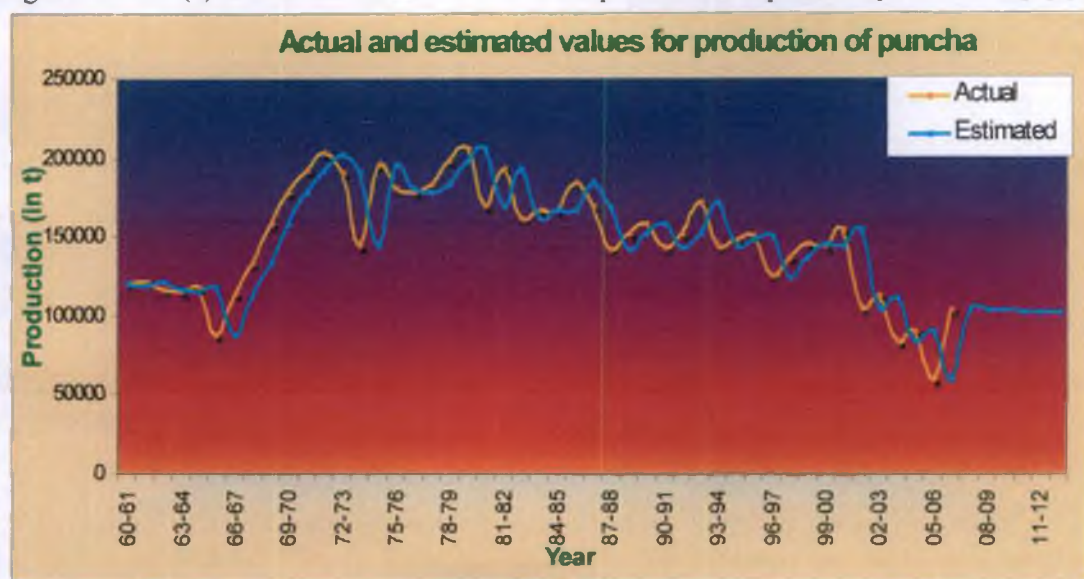


Figure 4.5.3.3.2.(d) Deviation from forecasts for production of puncha cultivation

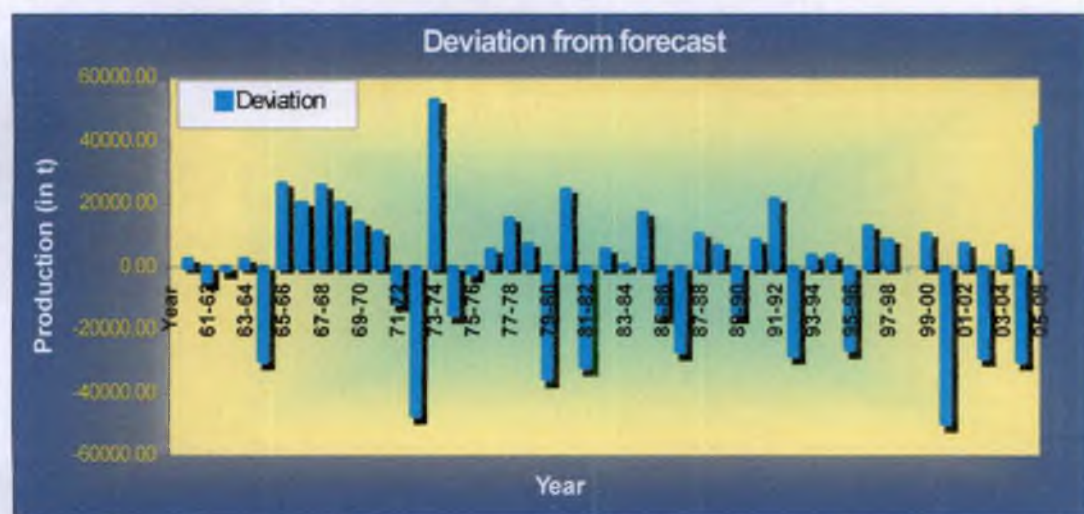


Table 4.5.3.3.2(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	83239	111667.86	-34.15
04-05	89752	83056.86	7.46
05-06	59733	89569.86	-49.95
06-07	103572	59550.86	42.50

Table 4.5.3.3.2 (f): Estimated production of puncha from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
103389.86	103207.71	103025.57	102843.43	102661.29

4.5.3.3.3. Productivity

Figure 4.5.3.3.3 (a)
ACF for the productivity of puncha paddy

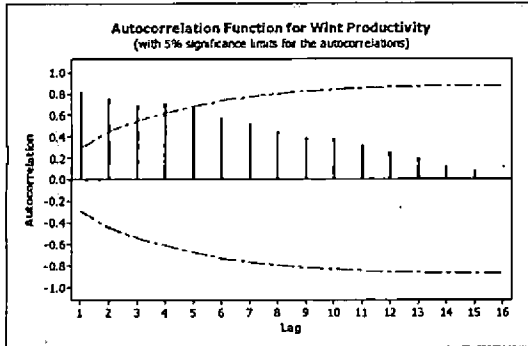
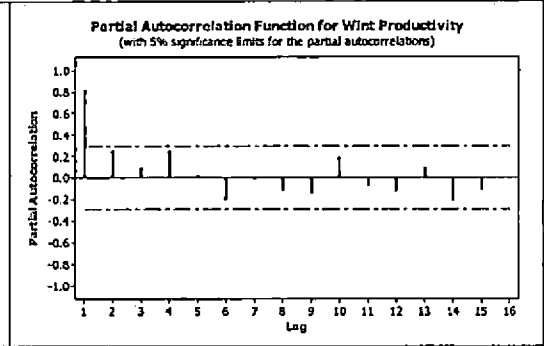


Figure 4.5.3.3.3 (b)
PACF for the productivity of puncha paddy



From the above figures it could be seen that the ACF decayed very slowly and PACF had one significant spike at lag 1 which indicated a nonstationary AR(1) model. The significance of Q-Statistics from Table 4.5.3.3.3(a) also showed the nonstationarity behaviour.

Table 4.5.3.3.3 (a) ACF and PACF for productivity of puncha with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.7764	0.7764	-0.3050	0.3050	26.5716	0.00
2	0.7291	0.3178	-0.3050	0.3050	50.6002	0.00
3	0.6419	0.0251	-0.3050	0.3050	69.7172	0.00
4	0.5406	-0.1004	-0.3050	0.3050	83.6415	0.00
5	0.4573	-0.0559	-0.3050	0.3050	93.8822	0.00
6	0.3606	-0.0754	-0.3050	0.3050	100.4337	0.00
7	0.3791	0.2423	-0.3050	0.3050	107.8845	0.00
8	0.3218	0.0126	-0.3050	0.3050	113.4166	0.00
9	0.2401	-0.2006	-0.3050	0.3050	116.5938	0.00
10	0.2643	0.1244	-0.3050	0.3050	120.5677	0.00
11	0.2256	0.0291	-0.3050	0.3050	123.5596	0.00
12	0.1773	-0.1054	-0.3050	0.3050	125.4714	0.00
13	0.1632	0.0670	-0.3050	0.3050	127.1493	0.00
14	0.1027	-0.1407	-0.3050	0.3050	127.8380	0.00
15	0.0668	-0.1092	-0.3050	0.3050	128.1403	0.00
16	0.0208	0.1095	-0.3050	0.3050	128.1708	0.00
17	-0.0304	-0.0962	-0.3050	0.3050	128.2385	0.00
18	-0.0871	-0.1981	-0.3050	0.3050	128.8201	0.00
19	-0.1415	0.0483	-0.3050	0.3050	130.4255	0.00
20	-0.1564	0.0128	-0.3050	0.3050	132.4802	0.00

The best ranked model for prediction of Productivity of puncha paddy was identified as ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.3.3.3(b) and 4.5.3.3.3(c).

Table 4.5.3.3.3 (b): Statistics calculated for the best diagnosed model for productivity of puncha

R-squared	0.678	Normalized BIC	10.76
RMSE	207.732	Ljung-Box Q	25.95
MAPE	8.278	DF	18
MAE	154.632	Sig.	0.101
MaxAPE	36.486	Transformation	Nil
MaxAE	519.539	Difference	1

Table 4.5.3.3.3 (c): Regression results for ARIMA(0,1,0) for predicting productivity of puncha

	Estimate	SE	t	Sig.
Constant	27.269	32.054	0.851	0.4

The final model can be written in the form

$$P_t = P_{t-1} + 27.269, \dots \dots \dots (4.5.3.3.3)$$

Where P_t denotes the productivity of puncha paddy in the year 't'.

This model has a MAPE of 8.28% which is fairly good for forecasting in this situation. Also this model has an $R^2 = 67.8\%$ indicating that 67.8% of the variation in the data can be explained through this model.

Table 4.5.3.3.3 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
268.172	10.988	306.007	511.621

The growth rate of productivity of Puncha paddy is in a decreasing trend from 2007-08 to 2011-12 and is given by 0.94, 0.93, 0.92 and 0.91 respectively.

To maintain the productivity of puncha crop the damage caused by unexpected rain and other natural calamities should be minimised. In areas where the seeds were already sown, rains will submerge the fields leading to decay of seeds. Adequate fertilizers and irrigation facilities have to be provided. Temporary paddy shelters should be constructed to help the farmers well in advance of harvest and thus ensure that the harvest process is not disrupted.

Figure 4.5.3.3 (c) Actual and estimated values for productivity of puncha by ARIMA(0,1,0)

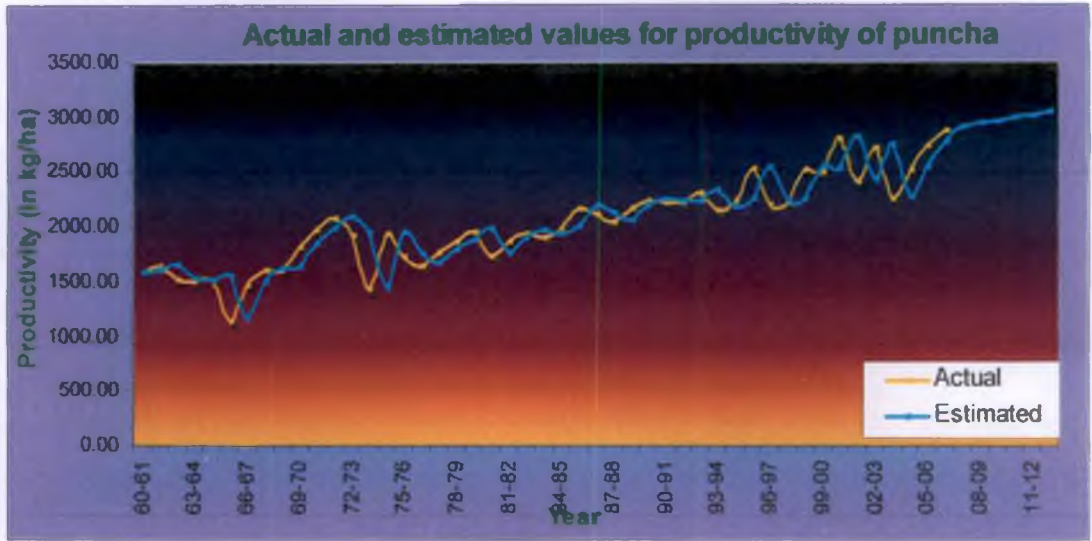


Figure 4.5.3.3 (d) Deviation from forecasts for the productivity of puncha paddy

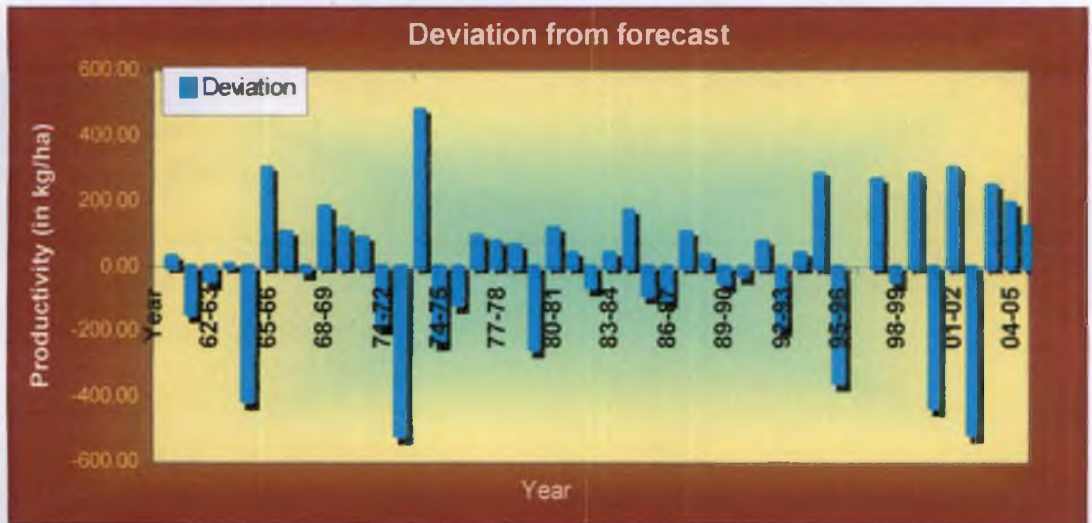


Table 4.5.3.3.3(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	2238	2750.07	-22.86
04-05	2512	2265.72	9.80
05-06	2733	2539.08	7.09
06-07	2881	2760.17	4.20

Table 4.5.3.3.3 (f) : Estimated Values for productivity of puncha from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
2908.59	2935.86	2963.13	2990.40	3017.67

4.5.4. Pepper

4.5.4.1. Area

Figure 4.5.4.1(a)
ACF for the series of area of pepper

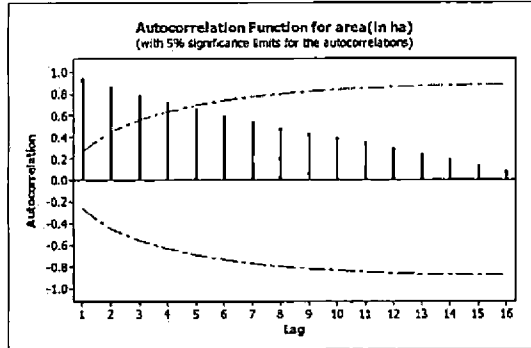
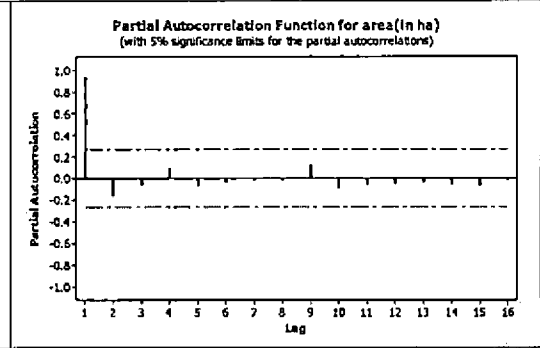


Figure 4.5.4.1(b)
PACF for the series of area of pepper



From the above figure, the ACF showed an exponential decay while PACF had one significant spike at lag 1 indicating an AR(1) model. But as there were large number of significant ACFs the series was nonstationary and should be transformed to a stationary one. The significance of Q-statistics also from Table 4.5.4.1(a) showed the nonstationary behaviour of the data.

Table 4.5.4.1(a) ACF and PACF for area of Pepper with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9305	0.9305	-0.2801	0.2801	45.9417	0.00
2	0.8590	-0.0506	-0.2801	0.2801	85.9135	0.00
3	0.7820	-0.0796	-0.2801	0.2801	119.7455	0.00
4	0.7066	-0.0307	-0.2801	0.2801	147.9645	0.00
5	0.6416	0.0356	-0.2801	0.2801	171.7465	0.00
6	0.5787	-0.0261	-0.2801	0.2801	191.5384	0.00
7	0.5118	-0.0775	-0.2801	0.2801	207.3797	0.00
8	0.4322	-0.1402	-0.2801	0.2801	218.9443	0.00
9	0.3632	0.0367	-0.2801	0.2801	227.3088	0.00
10	0.2927	-0.0529	-0.2801	0.2801	232.8783	0.00
11	0.2233	-0.0597	-0.2801	0.2801	236.2026	0.00
12	0.1585	-0.0359	-0.2801	0.2801	237.9212	0.00
13	0.1013	0.0129	-0.2801	0.2801	238.6424	0.00
14	0.0424	-0.0628	-0.2801	0.2801	238.7725	0.00
15	-0.0096	-0.0070	-0.2801	0.2801	238.7794	0.00
16	-0.0514	0.0153	-0.2801	0.2801	238.9811	0.00
17	-0.0793	0.0707	-0.2801	0.2801	239.4761	0.00
18	-0.0886	0.0923	-0.2801	0.2801	240.1141	0.00
19	-0.0851	0.0589	-0.2801	0.2801	240.7215	0.00
20	-0.0860	-0.0616	-0.2801	0.2801	241.3627	0.00

The best model identified for the prediction of area of cultivation of pepper was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.4.1(b) and 4.5.4.1(c).

Table 4.5.4.1(b) Statistics calculated for the best diagnosed model for area of rubber

R-squared	0.978	Normalized BIC	17.44
RMSE	5894.616	Ljung-Box Q	13.46
MAPE	3.317	DF	18
MAE	4171.830	Sig.	0.763
MaxAPE	14.081	Transformation	Nil
MaxAE	16621.860	Difference	1

Table 4.5.4.1(c) : Estimates of the parameters for ARIMA(0,1,0) model for area of rubber

Estimate	SE	t	Sig.
2596.14	833.625	3.114	0.003

The final model could be written in the form

$$A_t = A_{t-1} + 2596.14, \dots \dots \dots (4.5.4.1)$$

Where A_t denotes the area of pepper in the year 't'.

The model had an $R^2 = 97.8\%$ with a very low MAPE = 3.32% .

Table 4.5.4.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
10159.2500	4.4063	12144.9800	18632.8600

Price of pepper greatly influence the farmers in deciding whether the crop is to be continued in the coming years or not. The decrease in the price resulted in a corresponding decrease in the area of cultivation. The growth rate of area under pepper shows a decelerating trend from 2007-08 to 2011-12 by 1.14, 1.12, 1.11 and 1.10 respectively. The pepper area in the state as well as in the country have increased during the last pentinnium. However, the rate of increase has shown a decreasing trend. Pepper is cultivated as a monocrop only in a few districts of Kerala i.e, Idukki, Wayanad, Kannore and Kozhikkode. In all other areas pepper is grown in the homestead as an intercrop mainly in coconut garden. The scope for area expansion in pepper in the state is very much limited. When the price of pepper goes up, a nominal increase in area may occur. However, subsequent decrease in price may not result in corresponding decrease in area. This has resulted in continued increase in area. Spices Board have initiated programmes for introduction of pepper in the non-traditional areas like north east region, Orissa, Maharashtra etc.

Figure 4.5.4.1.(c) Actual and estimated values for area of pepper by ARIMA (0,1,0) model

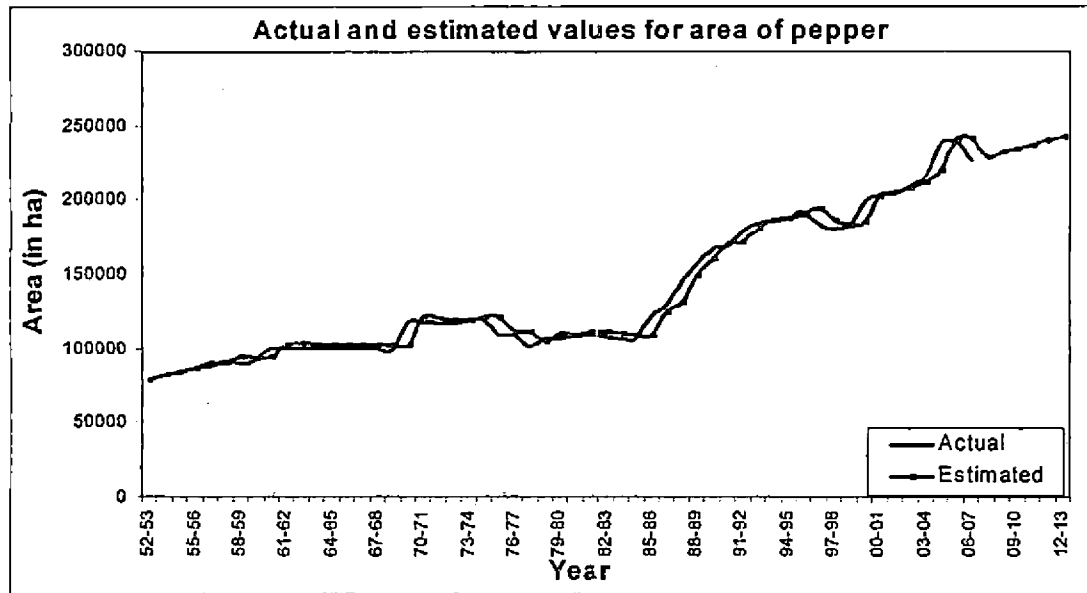


Figure 4.5.4.1.(d) Deviation from forecasts for area of pepper

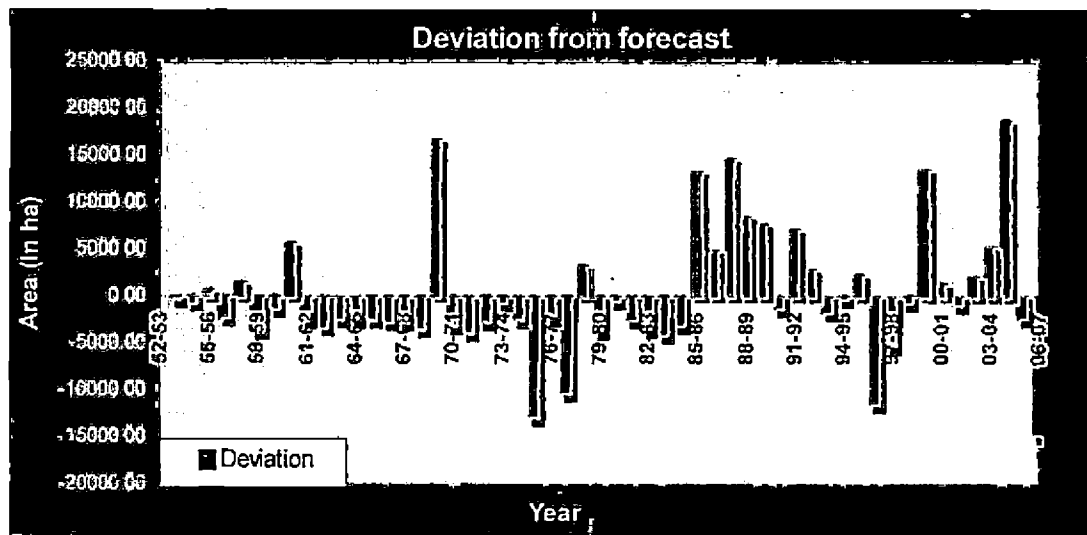


Table 4.5.4.1(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	216440.000	211203.140	2.42
04-05	237669.000	219036.140	7.84
05-06	237998.000	240265.140	-0.95
06-07	226094.000	240594.140	-6.41

Table 4.5.4.1(f) : Estimated values for area of pepper from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
228690.140	231286.280	233882.420	236478.560	239074.70

4.5.4.2. Production

Figure 4.5.4.2 (a)
ACF for the production of pepper

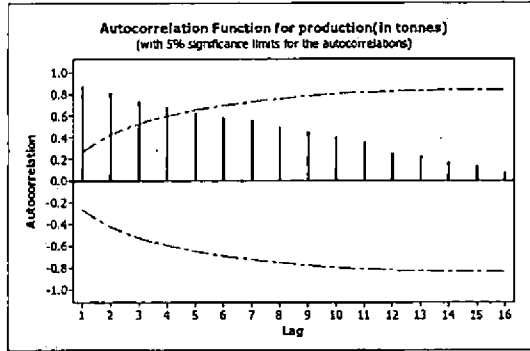
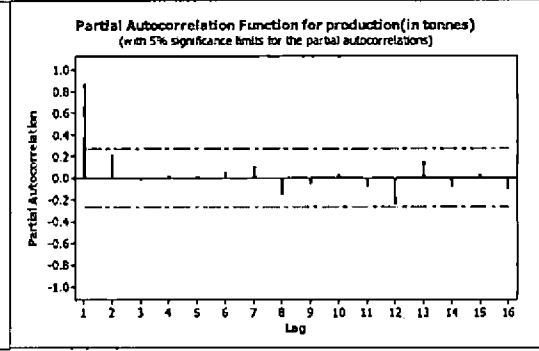


Figure 4.5.4.2 (b)
PACF for the production of pepper



Form the figure it is clear that the ACFs are exponentially decaying and PACF had 2 significant spikes at lags 1 and 2. Since the ACFs are significant for large number of lags the series is nonstationary and should be transformed to a stationary one. The significance of Q-statistics from table 4.5.4.1(a) also showed the nonstationary behaviour of the data.

Table 4.5.4.2 (a) ACF and PACF for production of pepper with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8302	0.8302	-0.2801	0.2801	35.8801	0.00
2	0.8076	0.3810	-0.2801	0.2801	70.5575	0.00
3	0.7139	-0.0652	-0.2801	0.2801	98.2487	0.00
4	0.6995	0.1295	-0.2801	0.2801	125.4191	0.00
5	0.5952	-0.1677	-0.2801	0.2801	145.5392	0.00
6	0.5936	0.1272	-0.2801	0.2801	166.0162	0.00
7	0.5327	0.0174	-0.2801	0.2801	182.9011	0.00
8	0.4176	-0.4051	-0.2801	0.2801	193.5285	0.00
9	0.3399	-0.0252	-0.2801	0.2801	200.7459	0.00
10	0.2508	-0.1123	-0.2801	0.2801	204.7774	0.00
11	0.2061	0.0678	-0.2801	0.2801	207.5718	0.00
12	0.1246	0.0220	-0.2801	0.2801	208.6210	0.00
13	0.1156	-0.0037	-0.2801	0.2801	209.5488	0.00
14	0.0127	-0.1275	-0.2801	0.2801	209.5604	0.00
15	-0.0081	0.1027	-0.2801	0.2801	209.5652	0.00
16	-0.0975	-0.0840	-0.2801	0.2801	210.2844	0.00
17	-0.1297	-0.0947	-0.2801	0.2801	211.5975	0.00
18	-0.1678	0.1223	-0.2801	0.2801	213.8678	0.00
19	-0.1509	0.0528	-0.2801	0.2801	215.7659	0.00
20	-0.1678	0.0547	-0.2801	0.2801	218.1933	0.00

ARIMA(1,1,0) was identified as the best model with minimum Normalised Bayesian Information Criteria (BIC) for the prediction of production of pepper in Kerala. The brief outputs are given in Table 4.5.4.2 (b) and 4.5.4.2(c).

Table 4.5.4.2(b): Statistics calculated for the best diagnosed model for production of pepper

R-squared	0.833	Normalized BIC	17.52
RMSE	6124.216	Ljung-Box Q	18.94
MAPE	11.226	DF	17
MAE	4117.968	Sig.	0.332
MaxAPE	41.423	Transformation	Nil
MaxAE	16935.068	Difference	1

Table 4.5.4.2.(c): Estimates of the Parameters of ARIMA(1,1,0) for production of pepper

	Estimate	SE	t	Sig.
AR(1)	-0.527	0.123	-4.273	0.000

The final model with $R^2=83.3\%$ and $MAPE=11.23\%$ could be written in the form

$$Y_t = 0.47Y_{t-1} + 0.527Y_{t-2}, \dots\dots\dots (4.5.4.2)$$

Where Y_t denotes the production of Pepper in the year 't'.

Table 4.5.4.2.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
9695.3083	12.9497	11970.9439	18898.8690

From the above statistics it could be observed that the MAPE is relatively high and results in production forecast errors more frequently. The actual trend of production is fluctuating below and above the forecasted trend (fig. 4.5.4.2(c)).

Unlike the other crops, the growth rate for production of pepper from 2007-08 to 2011-12 shows high fluctuations with values -8.47,4.87,-2.45 and 1.32 respectively. There is a decline in pepper farming with farmers, who are losing interest on the crop. According to figures made available by the Kerala State Farmers' Debt Relief Commission, the pepper growers have lost heavily in the last five years and are in debts. The estimates of cost of production and realization for a hectare for the last few years reveal that farmers have lost 80-87% of their investment. Disease and drought have wrecked the farmers with production and productivity dropping to alarming levels. Almost two thirds of the vines are unproductive and farmers are not inclined to re-planting due to volatility in prices. Black pepper is a perennial export spice, the production of which is highly influenced by the vagaries of climate. The

devastating malady-foot rot is the major biotic factor which limits the production of pepper in the state. Another important factor is the non-adoption of scientific cultivation practices which in turn is influenced by the prevailing market price of the produce. Being an export oriented crop, the domestic price of pepper is also governed by the international prices. Once the price shoots up, the farmers do adopt good agricultural practices which results in increased production in the ensuing year. The high fluctuation in the growth rate of pepper production observed in this study could be attributed to the aforesaid reasons.

Figure 4.5.4.2 (c) Actual and estimated values for production of pepper using ARIMA(1,1,0)

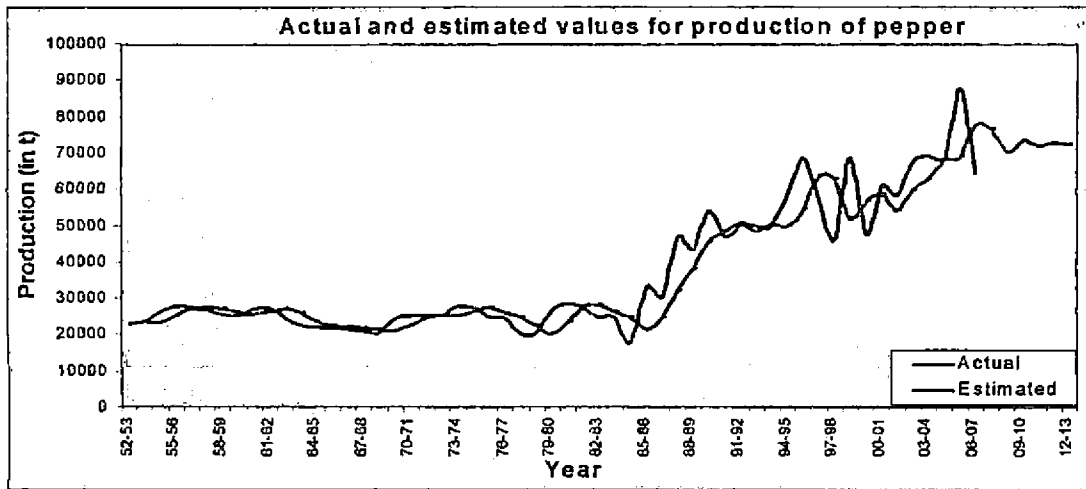


Figure 4.5.4.2.(d) Deviation from forecasts for production of pepper

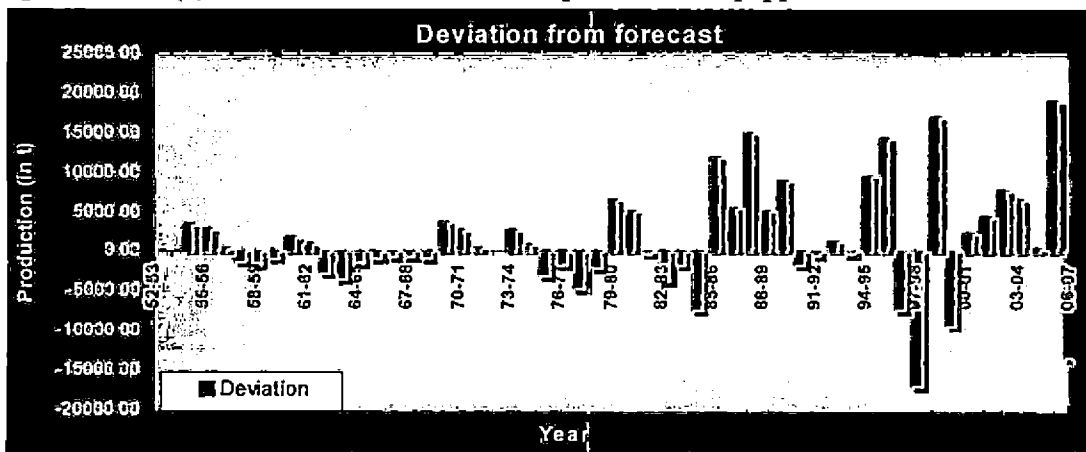


Table 4.5.4.2(e) : Comparison of the ARIMA(1,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	69015.000	62552.814	9.36
04-05	68362.000	68141.761	0.32
05-06	87605.000	68706.131	21.57
06-07	64264.000	77463.939	-20.54

Table 4.5.4.2 (f): Estimated production of pepper from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
76564.707	70082.234	73498.497	71698.127	72646.92

4.5.4.3. Productivity

Figure 4.5.4.3 (a)
ACF for the productivity of pepper

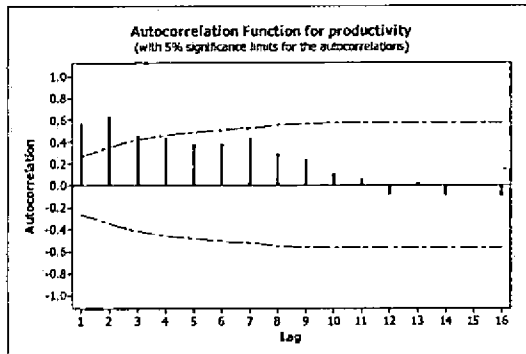
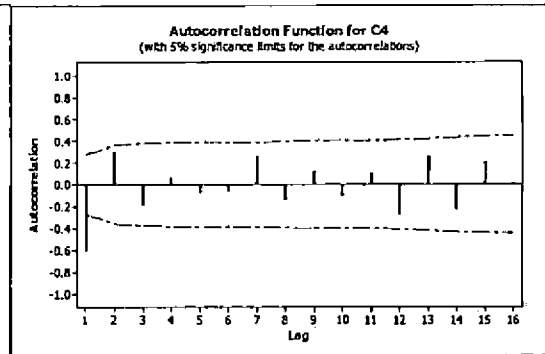


Figure 4.5.4.3 (b)
PACF for the productivity of pepper



From the above figure the ACF showed an exponential decay while PACF had one significant spike at lag 1 and 2 indicating an AR(2) model. But as there were large number of significant ACFs the series was nonstationary and should be transformed to a stationary one. The significance of Q-statistics also from Table 4.5.4.3(a) showed the nonstationary behaviour of the data.

Table 4.5.4.3 (a) ACF and PACF for productivity of Pepper with Q Stat and Significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	-0.7855	-0.7855	-0.2857	0.2857	31.5039	0.00
2	0.4641	-0.3990	-0.2857	0.2857	42.7427	0.00
3	-0.2810	-0.2619	-0.2857	0.2857	46.9532	0.00
4	0.1958	-0.0977	-0.2857	0.2857	49.0438	0.00
5	-0.1986	-0.2371	-0.2857	0.2857	51.2453	0.00
6	0.1558	-0.3215	-0.2857	0.2857	52.6326	0.00
7	-0.0421	-0.0970	-0.2857	0.2857	52.7365	0.00
8	-0.0599	-0.1840	-0.2857	0.2857	52.9520	0.00
9	0.1573	0.0457	-0.2857	0.2857	54.4754	0.00
10	-0.1964	0.0095	-0.2857	0.2857	56.9123	0.00
11	0.2144	0.1979	-0.2857	0.2857	59.8952	0.00
12	-0.2984	-0.1236	-0.2857	0.2857	65.8294	0.00
13	0.3584	0.0024	-0.2857	0.2857	74.6365	0.00
14	-0.3602	-0.0507	-0.2857	0.2857	83.7964	0.00
15	0.2902	-0.1667	-0.2857	0.2857	89.9215	0.00
16	-0.1395	0.0491	-0.2857	0.2857	91.3808	0.00
17	0.0342	-0.0279	-0.2857	0.2857	91.4713	0.00
18	-0.0476	-0.1957	-0.2857	0.2857	91.6529	0.00
19	0.1011	-0.0671	-0.2857	0.2857	92.4983	0.00
20	-0.0973	0.0337	-0.2857	0.2857	93.3102	0.00

The best ranked model for prediction of productivity of pepper was identified as ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.4.3(b) and 4.5.4.3(c).

Table 4.5.4.3 (b): Statistics calculated for the best diagnosed model for productivity of pepper

R-squared	0.447	Normalized BIC	7.13
RMSE	33.908	Ljung-Box Q	25.09
MAPE	9.373	DF	17
MAE	24.617	Sig.	0.093
MaxAPE	39.984	Transformation	Nil
MaxAE	88.583	Difference	1

Table 4.5.4.3 (c): Regression results for ARIMA(1,1,0) for predicting productivity of pepper

	Estimate	SE	t	Sig.
AR(1)	-0.59	0.12	-5.102	0.000

The final model with an $R^2 = 44.7\%$ and $MAPE = 9.4\%$ could be written in the form

$$P_t = 0.41P_{t-1} + 0.59P_{t-2}, \dots \dots \dots (4.5.4.3)$$

Where P_t denotes the productivity of pepper in the year 't'.

The low value of R^2 indicate that only 45% of the variation in productivity can be predicted through the model. However the prediction was made with relatively low value of MAPE.

Table 4.5.4.3.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
37.5066	11.7458	40.6980	62.0309

The productivity of pepper also showed the same performance as that of production in the trend analysis . The growth rate for productivity from 2007-08 to 2011-12 are -8.75, 5.66, -3.16 and 1.92 respectively. The highly fluctuating figures of growth affect the predictibility of the model used. Forecasting of productivity of pepper should be made incorporating other regressors and making use of suitable regression models which can capture the highly fluctuating growth patterns in the productivity figures.

Black pepper cultivation in Kerala was initiated from time immemorial and the crop is popularly known as King of spices. However, we couldn't achieve improvement with respect to productivity for the last 50 years. while in many other countries like Vietnam, Indonesia, Brazil etc. wherein the cultivation of pepper has started in the recent past, the productivity realized is above 2kg/standard but with a productivity of 300g/vine. Even though many reasons are attributed to low productivity of pepper in the state, disease drought and non-adoption of scientific management practices due to highly oscillating price are the most crucial

than a dozen of high yielding improved varieties which are capable of giving an annual average yield of more than 2.5kg/standard have been released in Kerala Agricultural University. Central government have already launched pepper development programmes in the state initially in idukki district for improving productivity and production of black pepper in the country.

Figure 4.5.4.3 (c) Actual and estimated values for productivity of pepper using ARIMA(1,1,0)

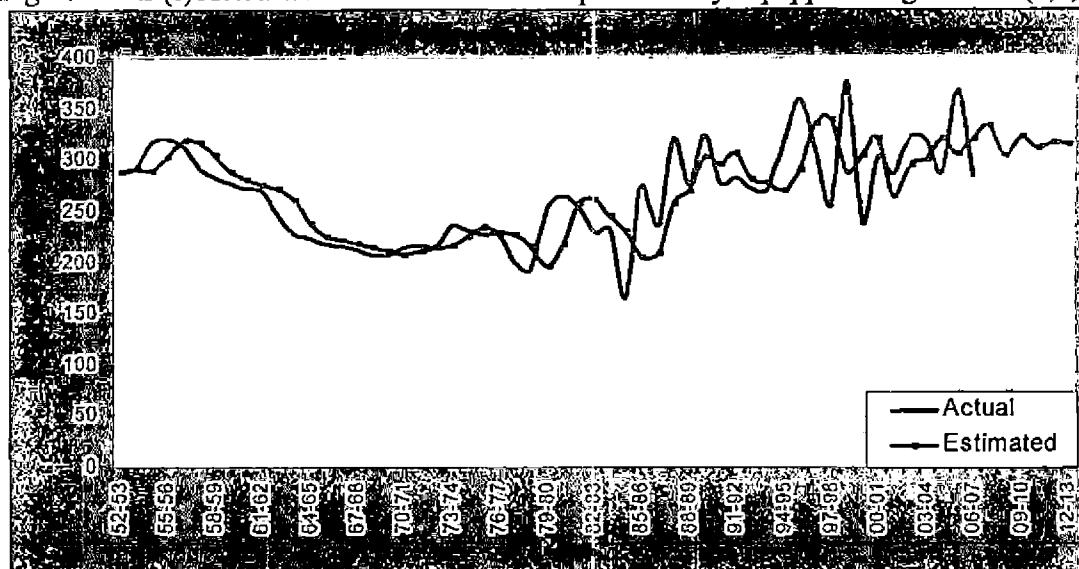


Figure 4.5.4.3.(d) Deviation from forecasts for productivity of pepper

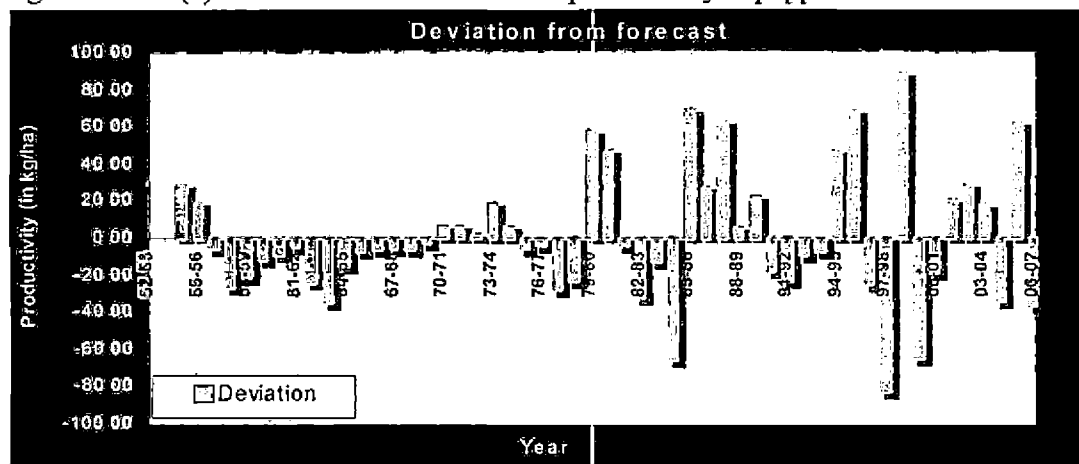


Table 4.5.4.3(e) : Comparison of the ARIMA(1,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	318.864	300.862	5.65
04-05	287.635	321.242	-11.68
05-06	368.091	306.060	16.85
06-07	284.236	320.622	-12.80

Table 4.5.4.3 (f) : Estimated values for productivity of pepper from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
333.711	304.520	321.743	311.582	317.58

4.5.4.4. Price

Figure 4.5.4.4(a)
ACF for the price of pepper

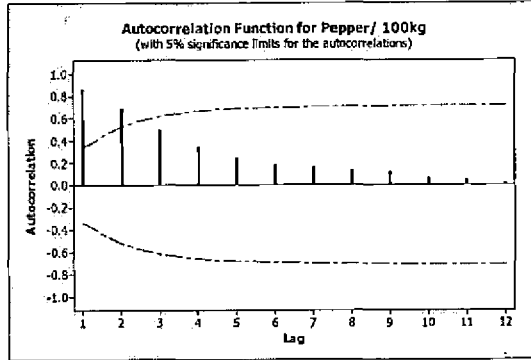
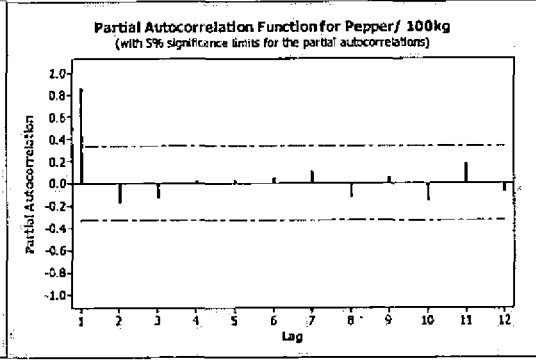


Figure 4.5.4.4(b)
PACF for the price of pepper



From the above figure, the ACF showed an exponential decay while PACF had one significant spike at lag1 indicating an AR(2) model. As there were large number of significant ACFs the series was nonstationary and should be transformed to a stationary one. The significance of Q-statistics also from Table 4.5.4.4(a) showed the nonstationary behaviour of the data.

Table 4.5.4.4(a) ACF and PACF for price of pepper with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8738	0.8738	-0.3536	0.3536	25.2735	0.00
2	0.6919	-0.3026	-0.3536	0.3536	41.6864	0.00
3	0.4842	-0.1808	-0.3536	0.3536	50.0231	0.00
4	0.3027	0.0146	-0.3536	0.3536	53.4059	0.00
5	0.1851	0.1242	-0.3536	0.3536	54.7209	0.00
6	0.0772	-0.1845	-0.3536	0.3536	54.9594	0.00
7	0.0318	0.1582	-0.3536	0.3536	55.0016	0.00
8	0.0258	0.0713	-0.3536	0.3536	55.0306	0.00
9	0.0250	-0.1017	-0.3536	0.3536	55.0591	0.00
10	0.0257	-0.0499	-0.3536	0.3536	55.0907	0.00
11	0.0286	0.1288	-0.3536	0.3536	55.1319	0.00
12	0.0127	-0.1426	-0.3536	0.3536	55.1405	0.00
13	-0.0229	-0.1160	-0.3536	0.3536	55.1702	0.00
14	-0.0789	-0.0029	-0.3536	0.3536	55.5441	0.00
15	-0.1348	0.0081	-0.3536	0.3536	56.7063	0.00
16	-0.1710	-0.0673	-0.3536	0.3536	58.7109	0.00
17	-0.1959	-0.0111	-0.3536	0.3536	61.5461	0.00
18	-0.2089	-0.0152	-0.3536	0.3536	65.0387	0.00
19	-0.2169	-0.0826	-0.3536	0.3536	69.1427	0.00
20	-0.2232	-0.0656	-0.3536	0.3536	73.9243	0.00

The best ranked model for prediction of price was identified as ARIMA(1,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.4.4(b) and 4.5.4.4(c).

Table 4.5.4.4(b) Statistics calculated for the best diagnosed model for price of Pepper

R-squared	0.715	Normalized BIC	15.93
RMSE	2735.098	Ljung-Box Q	21.27
MAPE	20.167	DF	17
MAE	1425.660	Sig.	0.215
MaxAPE	80.414	Transformation	Natural Log
MaxAE	10026.036	Difference	1

Table 4.5.4.4 (c) : Regression results for ARIMA(1,1,0) model for predicting price of pepper

	Estimate	SE	t	Sig.
AR(1)	0.447	0.164	2.726	0.010

The final model with $R^2 = 71.5\%$ could be written in the form

$$R_t = e^{(1.447 \ln(R_{t-1}) - 0.447 \ln(R_{t-2}))}, \dots \dots \dots (4.5.4.4)$$

Where R_t denotes the price of pepper for the t^{th} year.

From the table 4.5.4.4(b) it could be observed that the model was fitted by transforming the actual data using logarithmic transformation and this shows that the data on price of pepper is highly fluctuating.

Table 4.5.4.4 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
1672.3368	18.4876	2477.9508	4773.9494

The growth rate of price of pepper for the period from 2007-08 to 2011-12 shows an increasing trend with decreasing growth rate and the values are 12.39, 5.36, 2.36 and 1.05 respectively. The prices of pepper are highly volatile like other spices. The world production and demand plays the major role in pepper prices. The stockists and speculators also play a major role in its prices. The availability of pepper futures have given the exporters an opportunity to hedge their risks. The return on investment has affected the pepper farmers and they are not keen to investing in the crop even as an inter-crop. The price of pepper is highly influenced by the changing international pepper scenario. Only 8.10% of our interval production of pepper is being exported and the rest is utilised for the domestic consumption. This demands the need for expansion of our export basket so as to exploit the ever increasing demand of Indian pepper which is much superior with its intrinsic qualities. In the context of globalisation,

liberalization and open market pepper from other countries especially from Srilanka is being imported to India and re-exported under Indian label after minimal value addition. This will affect our credibility and reputation of Indian pepper in the international market. Unlike area and production which have shown an increasing trend with decreased growth rate, trend analysis with respect to price has recorded a highly fluctuating trend. In November 1999, pepper price was as high as Rs. 300/kg. which was nose dived to Rs. 60/kg. in 2002 and to the present price of Rs. 117/kg. Pepper price is influenced by the production in pepper producing countries, diseases, international market, policies of the governments etc. Unless and until a scientific and systematic marketing strategy is formulated, price fluctuation will continue. Figure 4.5.4.4 (c) Actual and estimated values for price of pepper by ARIMA(1,1,0) model

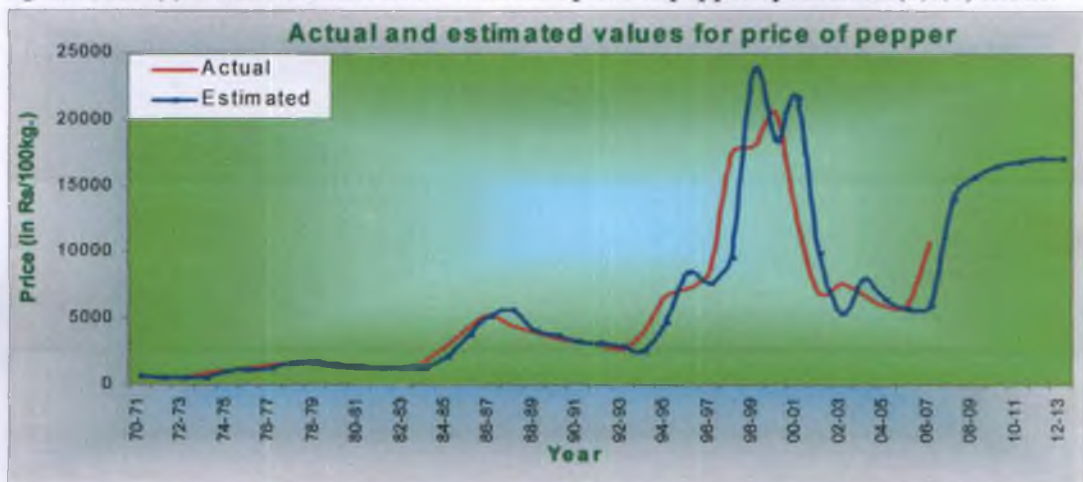


Figure 4.5.4.4 (d) Deviation from forecasts for the price of pepper

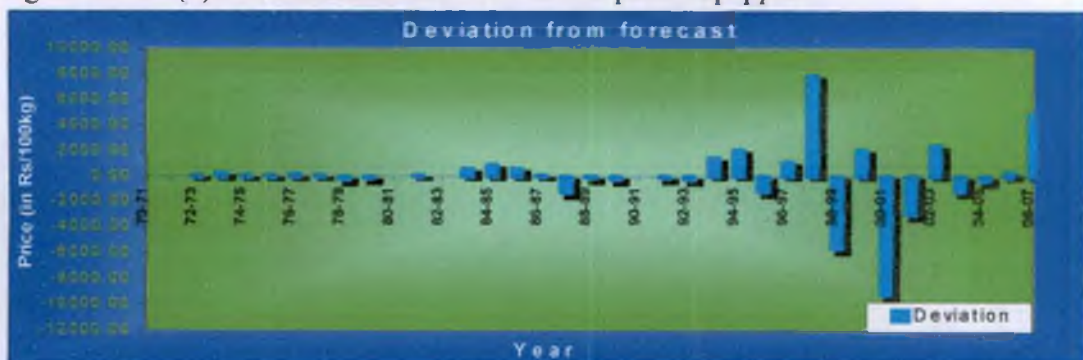


Table 4.5.4.4 (e) : Comparison of the ARIMA(1,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	6806.000	8042.389	-18.17
04-05	6032.000	6446.282	-6.87
05-06	5979.840	5715.113	4.43
06-07	10730.620	5956.671	44.49

Table 4.5.4.4 (f) : Estimated values for price per quintal of pepper from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
13935.863	15662.909	16502.607	16892.369	17069.56

4.5.5. Arecanut

4.5.5.1. Area

Figure 4.5.5.1(a)
ACF for the area of arecanut

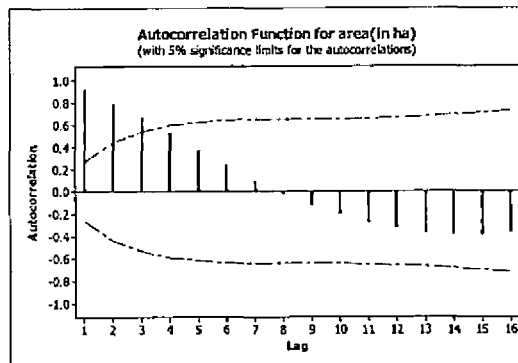
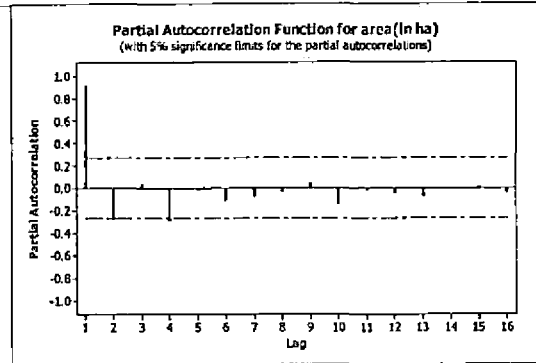


Figure 4.5.5.1(b)
PACF for the area of arecanut



Since the ACF was decaying and PACF had 2 significant lags it was a clear indication of an AR(2) model. Large number of significant ACFs and the significant Q-values from Table 4.5.5.1(a) showed the nonstationarity of the data.

Table 4.5.5.1(a) ACF and PACF for area of arecanut with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8840	0.8840	-0.2801	0.2801	40.6871	0.00
2	0.7346	-0.2147	-0.2801	0.2801	69.3792	0.00
3	0.5888	-0.0491	-0.2801	0.2801	88.2124	0.00
4	0.4414	-0.1068	-0.2801	0.2801	99.0339	0.00
5	0.3100	-0.0214	-0.2801	0.2801	104.4926	0.00
6	0.1743	-0.1434	-0.2801	0.2801	106.2573	0.00
7	0.0141	-0.2248	-0.2801	0.2801	106.2690	0.00
8	-0.1267	-0.0338	-0.2801	0.2801	107.2468	0.00
9	-0.2606	-0.1544	-0.2801	0.2801	111.4898	0.00
10	-0.3691	-0.0459	-0.2801	0.2801	120.2193	0.00
11	-0.4331	0.0066	-0.2801	0.2801	132.5540	0.00
12	-0.4742	-0.0536	-0.2801	0.2801	147.7428	0.00
13	-0.5000	-0.0644	-0.2801	0.2801	165.0954	0.00
14	-0.5062	-0.0602	-0.2801	0.2801	183.3898	0.00
15	-0.4958	-0.0332	-0.2801	0.2801	201.4560	0.00
16	-0.4644	-0.0472	-0.2801	0.2801	217.7861	0.00
17	-0.4023	0.0185	-0.2801	0.2801	230.4225	0.00
18	-0.3214	0.0087	-0.2801	0.2801	238.7500	0.00
19	-0.2197	0.0575	-0.2801	0.2801	242.7698	0.00
20	-0.1293	-0.0775	-0.2801	0.2801	244.2107	0.00

The best ranked model for predicting area of arecanut was ARIMA(1,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.5.1(b) and 4.5.5.1(c).

Table 4.5.5.1(b) Statistics calculated for the best diagnosed model for area of arecanut

R-squared	0.898	Normalized BIC	16.72
RMSE	4116.435	Ljung-Box Q	9.18
MAPE	4.141	DF	17
MAE	2730.259	Sig.	0.935
MaxAPE	22.600	Transformation	Nil
MaxAE	17315.824	Difference	1

Table 4.5.5.1(c) : Estimates of the Parameters for ARIMA(1,1,0) model for area of arecanut

	Estimate	SE	t	Sig.
AR(1)	0.381	0.133	2.862	0.006

The final model with an R² of 89.8% with MAPE = 4.14% could be written in the form

$$A_t = 1.38A_{t-1} - 0.38A_{t-2}, \dots\dots\dots(4.5.5.1)$$

Where A_t denotes the area of arecanut in the year 't'.

Table 4.5.5.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
8461.496	8.174	9213.568	12902.616

From the forecasted figures of area of cultivation of arecanut, it could be observed that there is decrease in growth rate of area with lose pace in the future years of prediction for 2007-08 to 2011-12 and it is given by -0.95, -0.37, -0.14 and -0.05 respectively.

High price increase especially during seventies have encouraged more people to take up arecanut cultivation which resulted in high growth rate in area during that period. However subsequent steep fall in prices, shortage of skilled labourers and ever mounting cultivation costs have pushed arecanut growers, who enjoyed a respectable status here in the olden days, into a deep debt trap. While prices of manure and pesticides registered a steady rise over the years, successive governments have failed to provide adequate subsidy. Climbing charges have increased exorbitantly and skilled climbers are becoming extinct. There was an acute shortage of skilled labourers as new generation shy away from taking up the traditional job.

Figure 4.5.5.1.(c) Actual and estimated values for area of arecanut by ARIMA (1,1,0) model

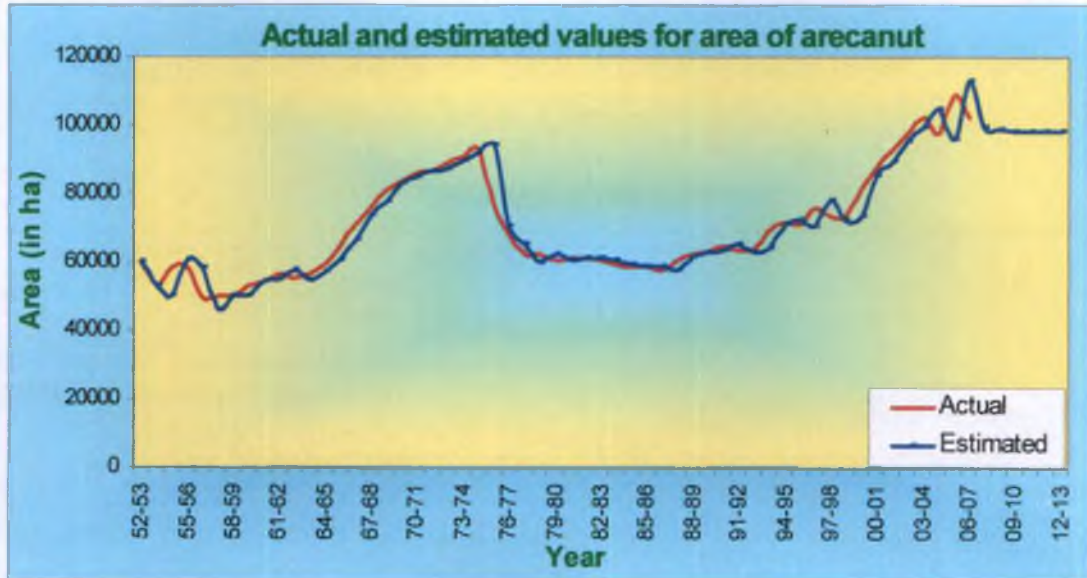


Figure 4.5.5.1.(d) Deviation from forecasts for area of arecanut

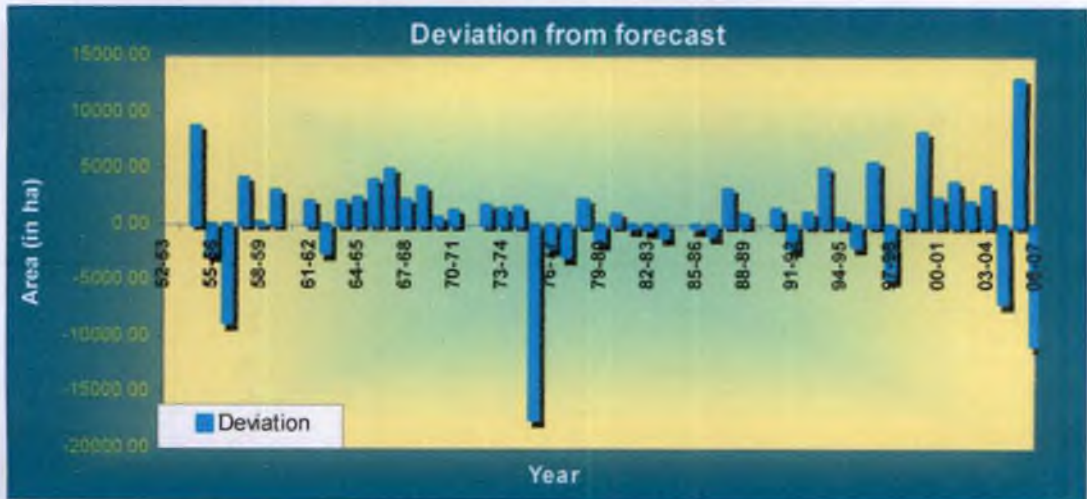


Table 4.5.5.1(e) : Comparison of the ARIMA(1,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	102504.000	99120.252	3.30
04-05	97568.000	104416.239	-7.02
05-06	108590.000	95687.384	11.88
06-07	102078.000	112789.382	-10.49

Table 4.5.5.1(f) : Estimated values for area of arecanut from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
99596.928	98651.640	98291.485	98154.266	98101.99

5.4.2. Production

Figure 4.5.5.2 (a)
ACF for the production of arecanut

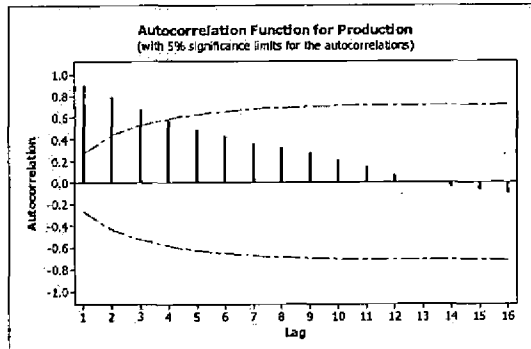
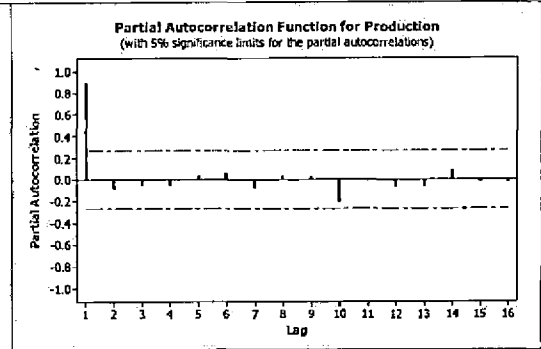


Figure 4.5.5.2 (b)
PACF for the production of arecanut



The ACF was decaying exponentially and PACF had one significant spike at lag 1 which indicate an AR(1) model. Since there was a large number of significant ACFs in the figure it was a clear indication of nonstationarity of the data. From table 4.5.5.2(a) the significance of Q-values also indicated the nonstationarity behaviour very well.

Table 4.5.5.2 (a) ACF and PACF for production of arecanut with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8360	0.8360	-0.2801	0.2801	37.0801	0.00
2	0.7512	0.1738	-0.2801	0.2801	67.6444	0.00
3	0.6595	-0.0159	-0.2801	0.2801	91.7034	0.00
4	0.5581	-0.0848	-0.2801	0.2801	109.3069	0.00
5	0.5267	0.1619	-0.2801	0.2801	125.3358	0.00
6	0.4332	-0.1450	-0.2801	0.2801	136.4248	0.00
7	0.3333	-0.1526	-0.2801	0.2801	143.1412	0.00
8	0.2309	-0.1158	-0.2801	0.2801	146.4416	0.00
9	0.1137	-0.1022	-0.2801	0.2801	147.2610	0.00
10	0.0166	-0.1068	-0.2801	0.2801	147.2789	0.00
11	-0.0418	0.0538	-0.2801	0.2801	147.3952	0.00
12	-0.0841	0.0637	-0.2801	0.2801	147.8796	0.00
13	-0.1341	-0.0470	-0.2801	0.2801	149.1437	0.00
14	-0.1518	0.0771	-0.2801	0.2801	150.8078	0.00
15	-0.1616	0.0990	-0.2801	0.2801	152.7482	0.00
16	-0.1652	0.0097	-0.2801	0.2801	154.8352	0.00
17	-0.1409	0.0320	-0.2801	0.2801	156.3989	0.00
18	-0.1207	0.0333	-0.2801	0.2801	157.5823	0.00
19	-0.0693	0.0817	-0.2801	0.2801	157.9851	0.00
20	0.0080	0.1209	-0.2801	0.2801	157.9907	0.00

ARIMA(0,1,0) was identified as the best model with minimum Normalised Bayesian Information Criteria (BIC) for the prediction of production of arecanut. The brief outputs are given in Tables 4.5.5.2(b) and 4.5.5.2(c).

Table 4.5.5.2(b): Statistics calculated for the best diagnosed model for Production of arecanut

R-squared	0.886	Normalized BIC	17.51
RMSE	6101.532	Ljung-Box Q	17.65
MAPE	5.664	DF	18
MAE	3478.239	Sig.	0.479
MaxAPE	36.616	Transformation	Nil
MaxAE	20900.778	Difference	1

Table 4.5.5.2(c): Estimates of the Parameters of ARIMA(0,1,0) model for production of arecanut

	Estimate	SE	t	Sig.
Constant	1697.22	862.887	1.967	0.055

The final model with an R² of 88.6% and MAPE = 5.66% could be written in the form

$$Y_t = Y_{t-1} + 1697.222, \dots \dots \dots (4.5.5.2)$$

Where Y_t denote the production of arecanut in the year 't'.

For the post sample period the MAPE is further reduced to 4.5.57% indicating the high forecasting power of the model.

Table 4.5.5.2(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
6237.250	5.568	7418.962	11038.222

From the forecasted figures of production of arecanut it is clear that the production shows an increasing trend with decreasing growth rate for 2007-08 to 2011-12 and is given by 1.52,1.50,1.48 and 1.45 percent respectively.

Unlike coconut, arecanut palms have to be irrigated regularly and are more prone to natural calamities. Due to the increased rate of cost of production, the farmer will not be able to make any repayments of the loans availed and he will be totally immersed in the mounting liability of high rate of interest and the principal which will ultimately swallow his farm itself. With the release of improved varieties, the areca production in the country has gone up considerably and the country has reached self sufficiency in production during nineties. This has prompted the central government to ban import of areca and its products to India and to withdraw the promotional activities in arecanut sector and as such the government of India is not encouraging expansion of area under arecanut in the country. However the increased area is continuing with very little annual addition.

Figure 4.5.5.2(c) Actual and estimated values for production of arecanut using ARIMA(0,1,0)

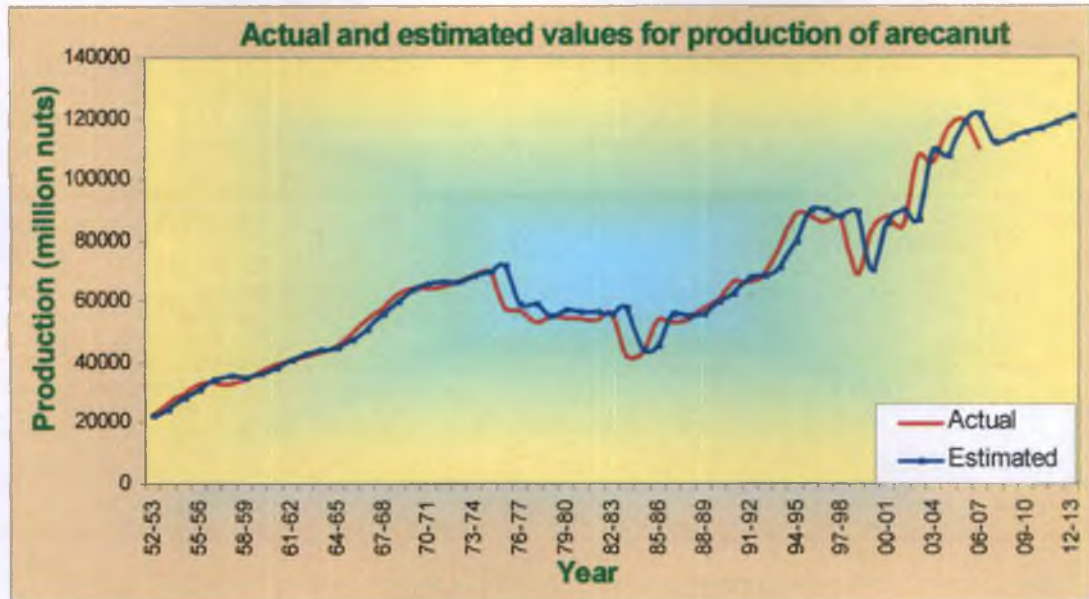


Figure 4.5.5.2.(d) Deviation from forecasts for production of arecanut

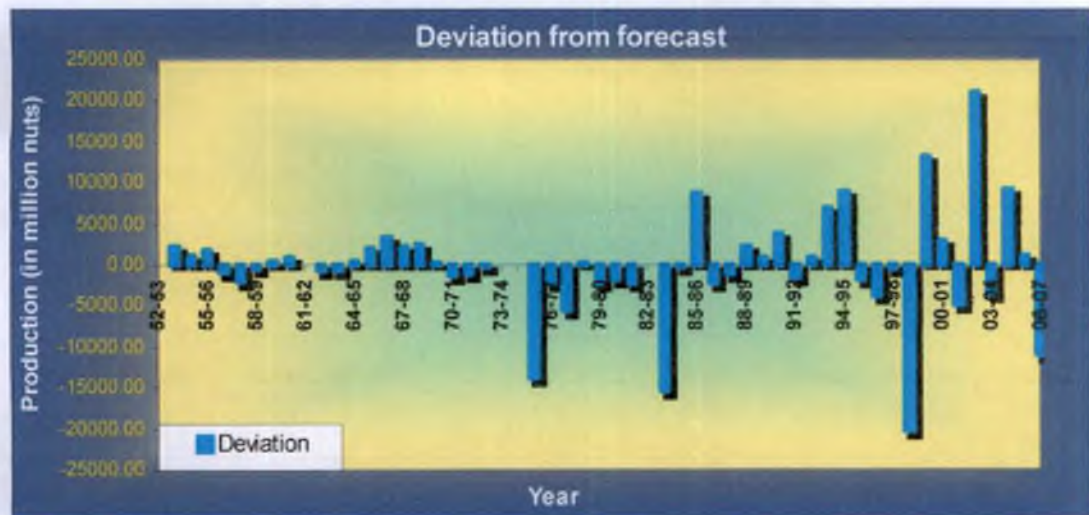


Table 4.5.5.2(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	105490.000	108976.222	-3.30
04-05	116389.000	107187.222	7.91
05-06	119309.000	118086.222	1.02
06-07	109968.000	121006.222	-10.04

Table 4.5.5.2 (f): Estimated production in million nuts of arecanut from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
111665.222	113362.444	115059.666	116756.888	118454.11

4.5.5.3. Productivity

Figure 4.5.5.3 (a)
ACF for the productivity of arecanut

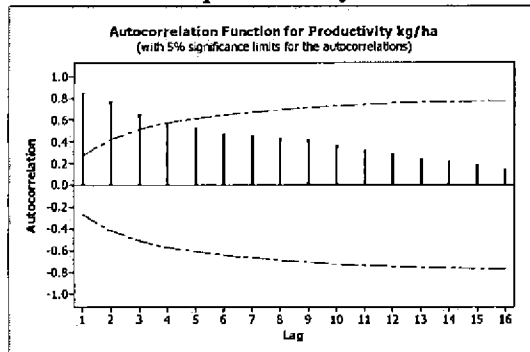
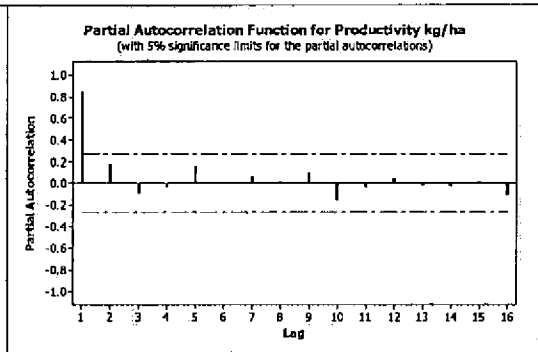


Figure 4.5.5.3 (b)
PACF for the productivity of arecanut



From the above figures, the ACFs decayed exponentially and PACF had only one significant spike. So the initial approximation of this model could be identified as AR(1). Since there were significant ACFs for large number of lags it was nonstationary and should be differenced before estimation. significance of Q-values in Table 4.5.5.3(a) also ensured the nonstationary behaviour of the data.

Table 4.5.5.3 (a) ACF and PACF for productivity of arecanut with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8332	0.8332	-0.2801	0.2801	36.8403	0.00
2	0.7597	0.2138	-0.2801	0.2801	68.0995	0.00
3	0.6740	-0.0064	-0.2801	0.2801	93.2261	0.00
4	0.5658	-0.1264	-0.2801	0.2801	111.3231	0.00
5	0.5386	0.1714	-0.2801	0.2801	128.0812	0.00
6	0.4543	-0.0959	-0.2801	0.2801	140.2745	0.00
7	0.3977	-0.0196	-0.2801	0.2801	149.8382	0.00
8	0.3391	-0.0455	-0.2801	0.2801	156.9562	0.00
9	0.2859	0.0365	-0.2801	0.2801	162.1400	0.00
10	0.2242	-0.1076	-0.2801	0.2801	165.4080	0.00
11	0.1846	0.0404	-0.2801	0.2801	167.6806	0.00
12	0.1686	0.0721	-0.2801	0.2801	169.6253	0.00
13	0.1459	0.0198	-0.2801	0.2801	171.1207	0.00
14	0.1389	-0.0083	-0.2801	0.2801	172.5146	0.00
15	0.1302	0.0395	-0.2801	0.2801	173.7746	0.00
16	0.0972	-0.0810	-0.2801	0.2801	174.4967	0.00
17	0.0791	-0.0240	-0.2801	0.2801	174.9892	0.00
18	0.0358	-0.0888	-0.2801	0.2801	175.0931	0.00
19	-0.0048	-0.0418	-0.2801	0.2801	175.0951	0.00
20	-0.0134	0.0361	-0.2801	0.2801	175.1105	0.00

The best ranked model was ARIMA(0,1,0) for predicting the productivity of arecanut with minimum Normalised Bayesian Information Criteria (BIC). The brief output is given in Tables 4.5.5.3(b) and 4.5.5.3(c).

Table 4.5.5.3 (b): Statistics calculated for best diagnosed model for productivity of arecanut

R-squared	0.816	Normalized BIC	8.71
RMSE	74.713	Ljung-Box Q	19.46
MAPE	5.422	DF	18
MAE	45.413	Sig.	0.364
MaxAPE	31.994	Transformation	Nil
MaxAE	271.207	Difference	1

Table 4.5.5.3 (c): Regression results for ARIMA(0,1,0) for predicting productivity of arecanut

	Estimate	SE	t	Sig.
Constant	14.54	10.566	1.376	0.175

The final model could be written in the form

$$P_t = P_{t-1} + 14.537, \dots \dots \dots (4.5.5.3)$$

Where P_t denotes the productivity of arecanut in the year 't'.

This model has an R-square of 81% which is fairly good with MAPE = 5.4%. But in the case of post sample period the statistics calculated was a bit more than the maximum error. This may be due to the fall in price during 2000 and the lack of interest in this crop in the later years. Even though the area of cultivation has an increasing trend production fluctuated after it. and due to this abnormality errors in prediction increased.

Table 4.5.5.3.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
94.947	8.522	103.392	149.234

The forecasted figures show an increasing trend with a slight decrease in growth rate. The predicted growth rates for the years from 2007-08 to 2011-12 are given by 1.33, 1.31, 1.30 and 1.28 respectively. The fluctuations of production reflects its effect on productivity also. The increased labour cost and maintenance of the crop by providing sufficient irrigation facilities make the crop of arecanut distress stricken . Even though the production of arecanut in kerala contributes nearly 25% to the nation, the productivity is far below than that of the national level. The productivity of arecanut in the state is much less than the realizable yield. The major factor that influenced areca productivity is the highly fluctuating price.

Figure 4.5.5.3 (c) Actual and Estimated values for productivity of arecanut by ARIMA(0,1,0)

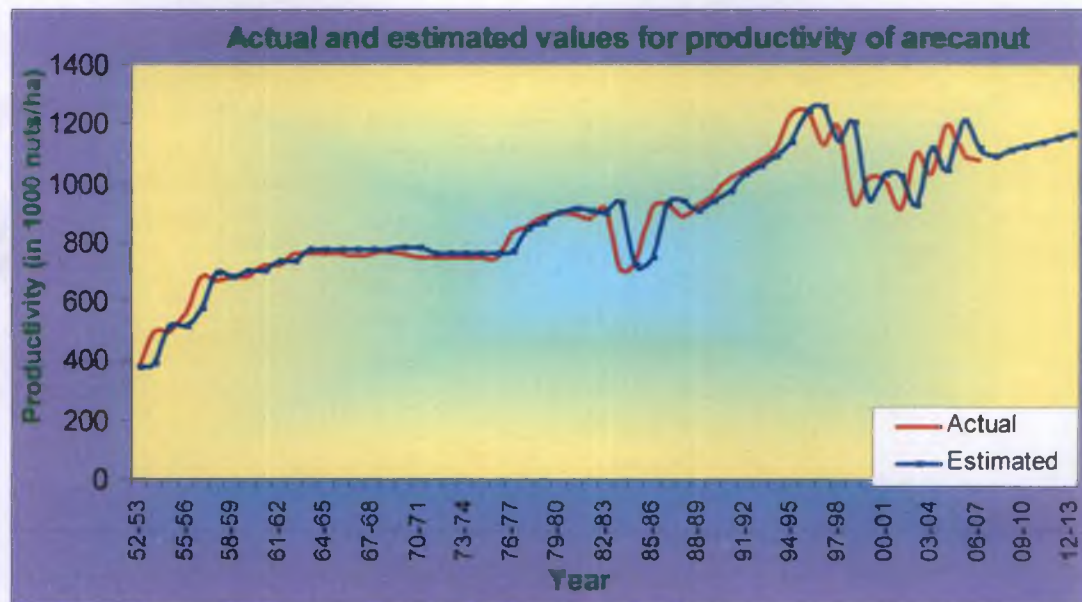


Figure 4.5.5.3 (d) Deviation from forecasts for the productivity of arecanut

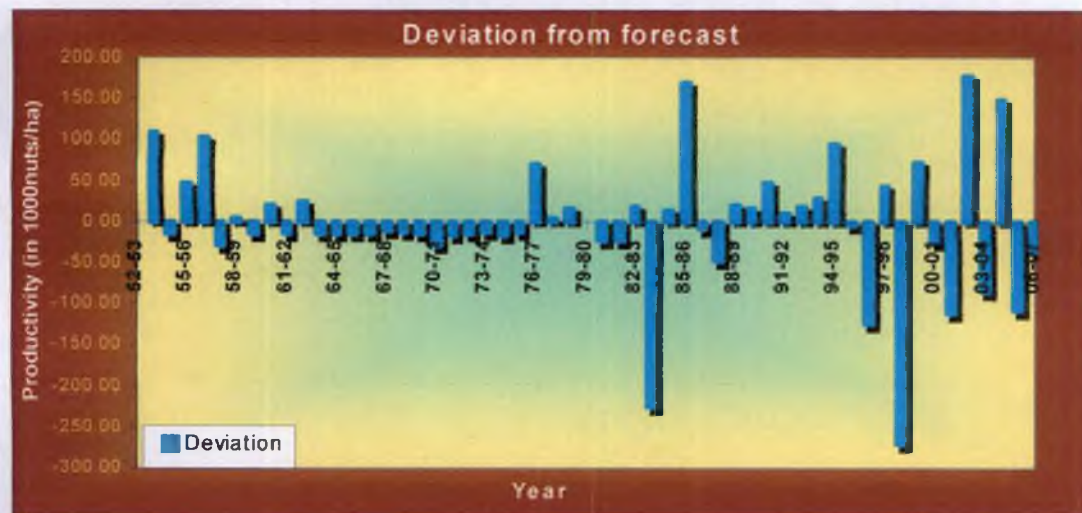


Table 4.5.5.3(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	1029.131	1115.004	-8.34
04-05	1192.901	1043.668	12.51
05-06	1098.711	1207.438	-9.90
06-07	1077.294	1113.248	-3.34

Table 4.5.5.3 (f) : Estimated values for productivity of arecanut from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
1091.831	1106.368	1120.905	1135.442	1149.98

4.5.5.4. Price

Figure 4.5.5.4(a)
ACF for the price of arecanut

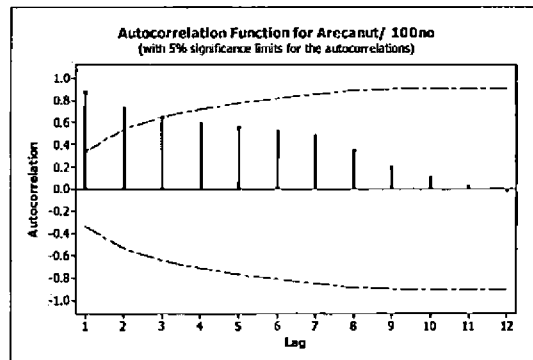
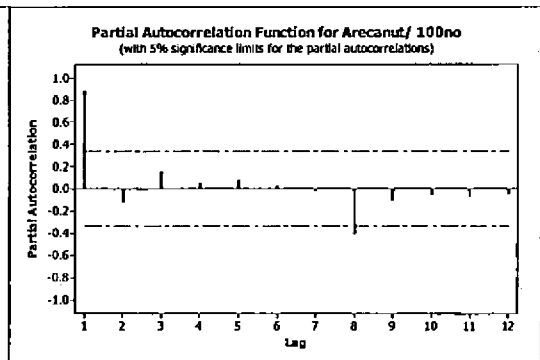


Figure 4.5.5.4(b)
PACF for the price of arecanut



From the above figures the ACFs decayed exponentially and PACF had only one significant spike. So the initial approximation of this model could be identified as AR(1). Since there were significant ACFs for large number of lags it was nonstationary and should be differenced before estimation. Table 4.5.5.3(a) also ensured the nonstationary behaviour of the data.

Table 4.5.5.4(a) ACF and PACF for price of arecanut with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8948	0.8948	-0.3536	0.3536	27.3024	0.00
2	0.7592	-0.2080	-0.3536	0.3536	47.6348	0.00
3	0.6680	0.1757	-0.3536	0.3536	63.9390	0.00
4	0.5542	-0.2567	-0.3536	0.3536	75.5741	0.00
5	0.4500	0.1065	-0.3536	0.3536	83.5434	0.00
6	0.3667	-0.0902	-0.3536	0.3536	89.0458	0.00
7	0.2851	0.0112	-0.3536	0.3536	92.5093	0.00
8	0.1992	-0.1187	-0.3536	0.3536	94.2745	0.00
9	0.0932	-0.1664	-0.3536	0.3536	94.6782	0.00
10	-0.0074	-0.0221	-0.3536	0.3536	94.6809	0.00
11	-0.0745	0.0291	-0.3536	0.3536	94.9652	0.00
12	-0.1280	-0.0088	-0.3536	0.3536	95.8469	0.00
13	-0.1671	0.0214	-0.3536	0.3536	97.4336	0.00
14	-0.1888	-0.0293	-0.3536	0.3536	99.5781	0.00
15	-0.2174	-0.0782	-0.3536	0.3536	102.6013	0.00
16	-0.2568	-0.0799	-0.3536	0.3536	107.0989	0.00
17	-0.2939	-0.0507	-0.3536	0.3536	113.4111	0.00
18	-0.3225	-0.0296	-0.3536	0.3536	121.5979	0.00
19	-0.3502	-0.1008	-0.3536	0.3536	132.0517	0.00
20	-0.3588	0.0481	-0.3536	0.3536	144.0259	0.00

The best ranked model for the prediction of price of arecanut ARIMA(1,1,0) was identified as the best with minimum Normalised Bayesian Information Criteria (BIC). The brief output is given in tables 4.5.5.4(b) and 4.5.5.4(c)

Table 4.5.5.4(b) Statistics for the best diagnosed model for price of arecanut.

R-squared	0.817	Normalized BIC	4.33
RMSE	8.296	Ljung-Box Q	21.70
MAPE	14.060	DF	18
MAE	3.537	Sig.	0.246
MaxAPE	97.376	Transformation	Natural Log
MaxAE	40.830	Difference	1

Table 4.5.5.4 (c) : Regression results for ARIMA(0,1,0) model for predicting price of arecanut

	Estimate	SE	t	Sig.
Constant	0.075	0.034	2.237	0.032

The final model could be written in the form

$$R_t = R_{t-1} e^{(0.075)}, \dots \dots \dots (4.5.5.4)$$

Where R_t denotes the price of arecanut at the t^{th} year.

The model given by equation (4.5.5.4) is having an R-square of 0.82 with MAPE 14.06% and low RMSE. For the post sample period MAPE has significantly reduced to 4.5%, the low value of RMSFE (2.86) indicates the forecasting ability of the model for future years. The MAE and MXAE also reduced considerably in the post sample period.

Table 4.5.5.4 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
2.101	4.495	2.864	5.034

The price of arecanut for future years show an exponential increasing trend with constant growth rate 7.79% for all the years from 2007-08 to 2011-12. From Rs 75.25 per 100no. during the year 1999-2000, the price of arecanut has collapsed to Rs 32.81 in 2001-02, suffering from shrinking consumption in the state. From the predicted figures it can be observed that the price is enhanced to the amount Rs. 76 itself during 2011-12 and still showing an increasing trend. By adopting marketing techniques as in the state of Karnataka giving new proposals to mouth freshners and beverages and allied products the price of arecanut in Kerala can be enhanced. Arecanut is used mainly as a masticatory and the industrial uses of the crop are not fully tapped. The chewing habit of newer generation is practically nil. The medicinal properties of areca as a germicide, edible properties of kernel for extraction of butter, industrial properties as an ingredient for black ink preparation and utilisation of biproducts like sheath, husk etc. are yet to be tapped to the fullest extent. Unless and until the above mentioned uses are promoted the price of areca can't be stable and remunerative.

Figure 4.5.5.4 (c) Actual and estimated values for price of arecanut by ARIMA(0,1,0) Model

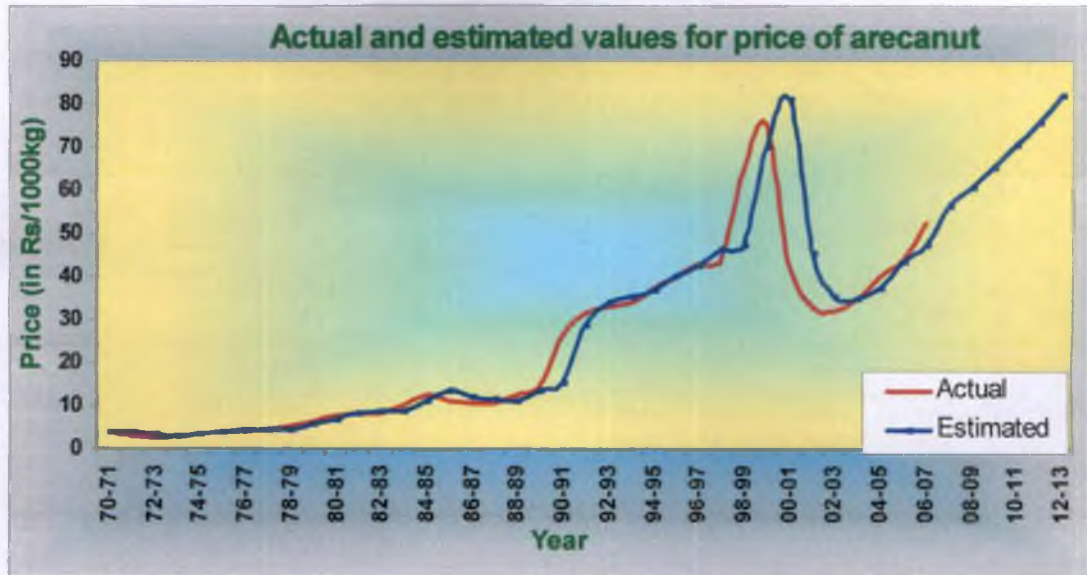


Figure 4.5.5.4 (d) Deviation from forecasts for the price of arecanut

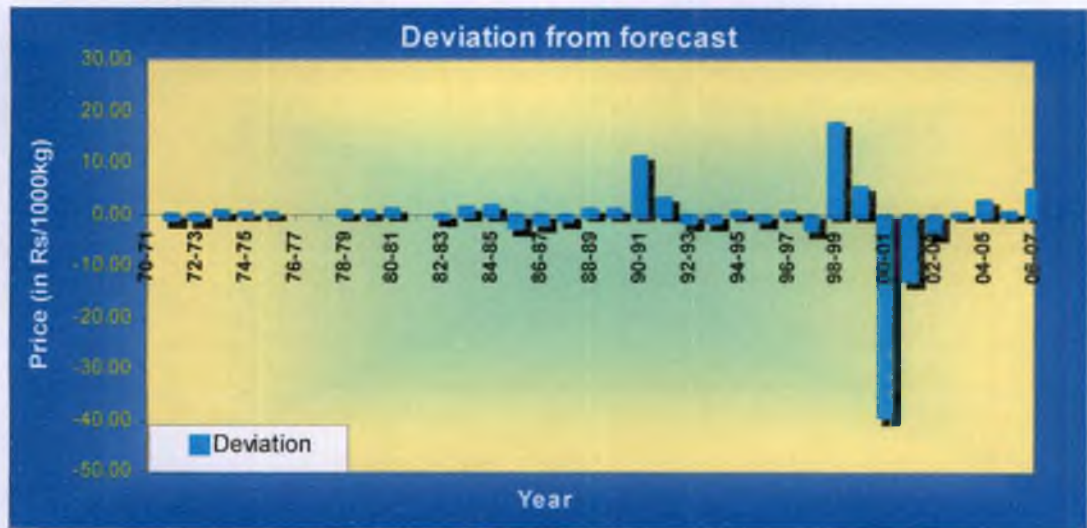


Table 4.5.5.4 (e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	34.640	34.546	0.27
04-05	40.000	37.338	6.66
05-06	43.730	43.115	1.41
06-07	52.170	47.136	9.65

Table 4.5.5.4 (f) : Estimated values for price of arecanut from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
56.233	60.613	65.334	70.422	75.91

4.5.6. Tapioca

4.5.6.1. Area

Figure 4.5.6.1(a)
ACF for the area of tapioca

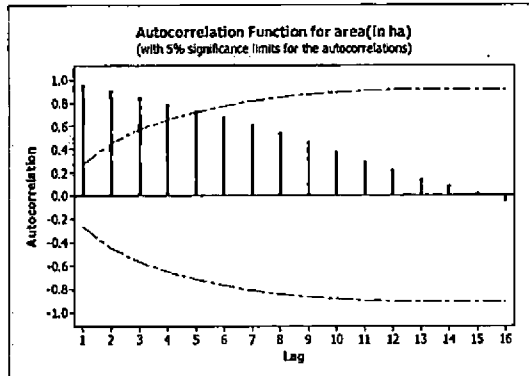
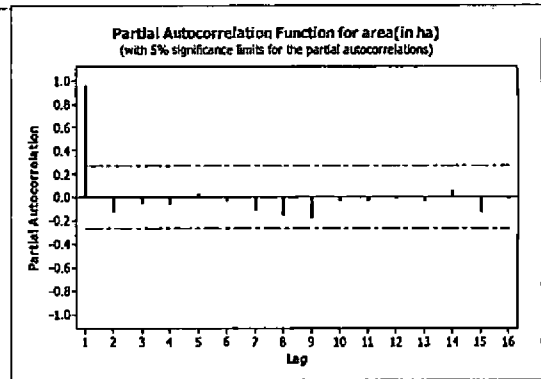


Figure 4.5.6.1(b)
PACF for the area of tapioca



From the above figures the decaying of ACFs and only one significant spike for the PACF gives the clear indication of an AR(1) model. The large number of significant ACFs and significance of Qs from Table 4.5.6.1(a) indicate nonstationary behaviour of the data.

Table 4.5.6.1(a) ACF and PACF for area of tapioca with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9490	0.9490	-0.2801	0.2801	46.8856	0.00
2	0.8890	-0.1163	-0.2801	0.2801	88.9070	0.00
3	0.8199	-0.1170	-0.2801	0.2801	125.4285	0.00
4	0.7518	-0.0143	-0.2801	0.2801	156.8164	0.00
5	0.6847	-0.0238	-0.2801	0.2801	183.4427	0.00
6	0.6198	-0.0213	-0.2801	0.2801	205.7718	0.00
7	0.5448	-0.1508	-0.2801	0.2801	223.4309	0.00
8	0.4560	-0.1815	-0.2801	0.2801	236.1067	0.00
9	0.3511	-0.2049	-0.2801	0.2801	243.8072	0.00
10	0.2493	-0.0181	-0.2801	0.2801	247.7906	0.00
11	0.1520	-0.0291	-0.2801	0.2801	249.3103	0.00
12	0.0695	0.0459	-0.2801	0.2801	249.6361	0.00
13	-0.0051	-0.0162	-0.2801	0.2801	249.6379	0.00
14	-0.0685	0.0373	-0.2801	0.2801	249.9731	0.00
15	-0.1368	-0.0929	-0.2801	0.2801	251.3495	0.00
16	-0.2029	-0.0253	-0.2801	0.2801	254.4671	0.00
17	-0.2664	-0.0333	-0.2801	0.2801	260.0112	0.00
18	-0.3228	-0.0499	-0.2801	0.2801	268.4104	0.00
19	-0.3669	-0.0040	-0.2801	0.2801	279.6223	0.00
20	-0.3942	0.0249	-0.2801	0.2801	293.0146	0.00

ARIMA(0,1,0) was the best ranked model for predicting the future values of area of tapioca cultivation in Kerala with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in table 4.5.6.1(b) and 4.5.6.1(c).

Table 4.5.6.1(b): Statistics calculated for the best diagnosed model for Area of tapioca

R-squared	0.952	Normalized BIC	19.29
RMSE	14828.109	Ljung-Box Q Statis	30.65
MAPE	4.808	DF	18
MAE	10306.394	Sig.	0.032
MaxAPE	18.482	Transformation	Nil
MaxAE	55009.820	Difference	1

Table 4.5.6.1 (c) : Estimates of the parameters for ARIMA(0,1,0) model for Area of tapioca.

	Estimate	SE	t	Sig.
Constant	-2010.820	2097.011	-0.959	0.342

The final model could be written as

$$A_t = A_{t-1} - 2010.82, \dots \dots \dots (4.5.6.1)$$

Where A_t denotes the area of tapioca in the year 't'.

The low value of MAPE (4.8%) with highly significant R^2 (95%) ensures the forecasting power of the model for future. Also the RMSE has come down to 9360 for the post sample period indicating the goodness of fit for the model for future. The maximum error occurred during the sample period also reduced to 1/5th with reduction of mean absolute error during post sample period. So this model was used to forecast the future area of tapioca in Kerala.

Table 4.5.6.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
8302.840	8.656	9360.990	12101.820

The area of tapioca predicted for 2007-08 to 2011-12 showed a decreasing trend with increasing growth rate. The growth rates for the years from 2007-08 to 2011-12 are -2.36, -2.42, -2.48 and -2.54 percent respectively.

The area under tapioca has declined drastically from 326865 ha in 1975-76 to 88528 ha in 2006-07. And the forecasted figures states that it still continue to decline and reach 77000 ha during 2011-12. The increasing labour charges and availability of other vegetables at our disposal highly influence the cultivation of the crop.

Figure 4.5.6..1.(c) Actual and estimated values for area of tapioca using ARIMA (0,1,0)

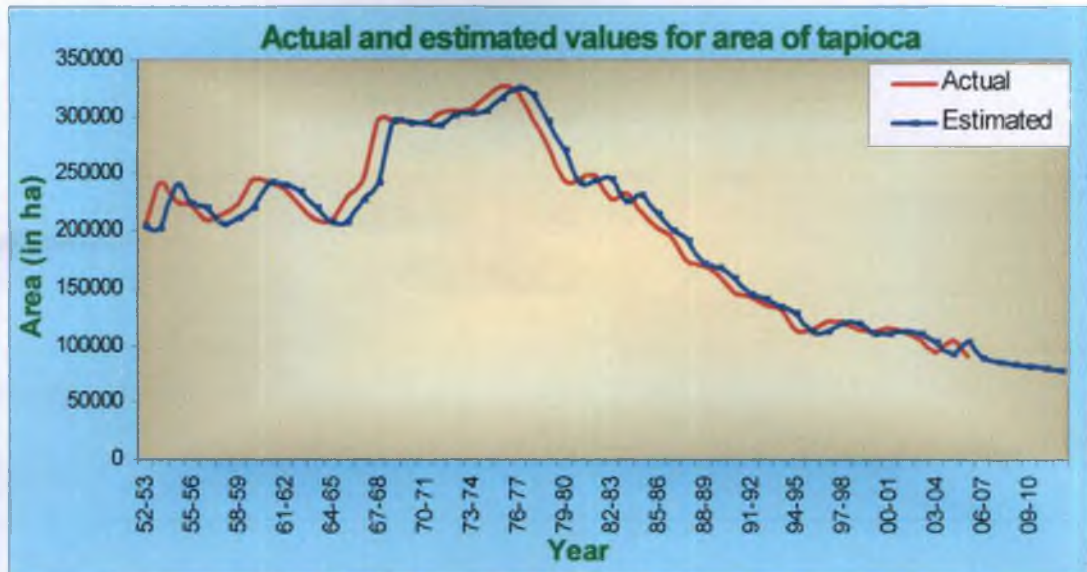


Figure 4.5.6..1.(d) Deviation from forecasts for area of tapioca

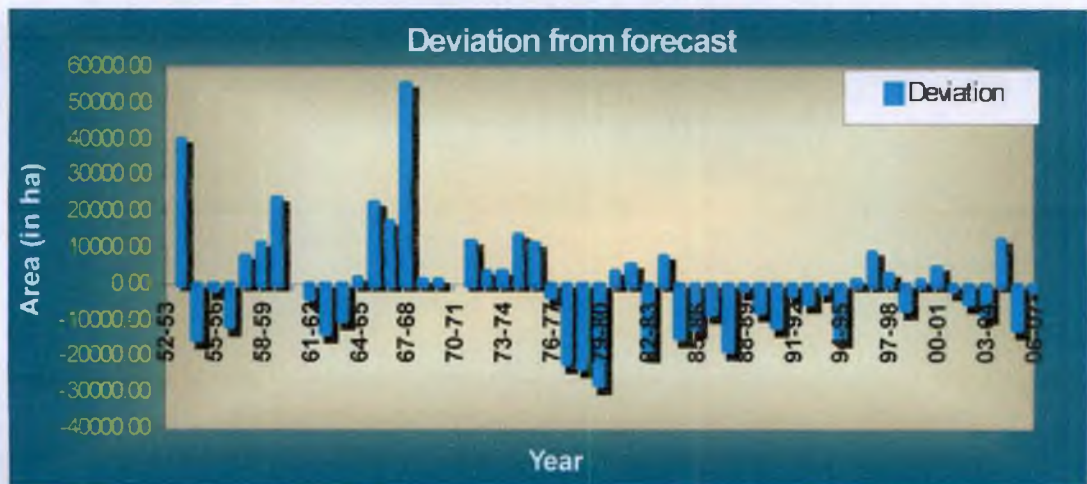


Table 4.5.6..1(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	94297.000	102168.180	-8.35
04-05	104388.000	92286.180	11.59
05-06	90539.000	102377.180	-13.08
06-07	87128.000	88528.180	-1.61

Table 4.5.6..1(f) : Estimated values for area of tapioca from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
85117.180	83106.360	81095.540	79084.720	77073.90

4.5.6.2. Production

Figure 4.5.6.2 (a)
ACF for the production of tapioca

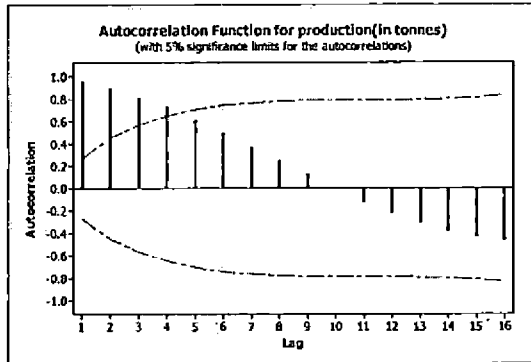
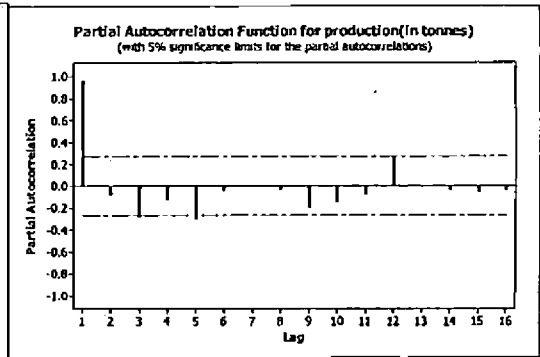


Figure 4.5.6.2 (b)
PACF for the production of tapioca



The autocorrelations were significant for a large number of lags with exponentially decayed values and the PACF also had some significant spikes decaying in the next lag which indicated an ARMA model. Since the Q-values from Table 4.5.6.2(a) were significant this indicated the nonstationarity of the data also.

Table 4.5.6.2 (a) ACF and PACF for production of tapioca with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9467	0.9467	-0.2801	0.2801	46.6651	0.00
2	0.8879	-0.0814	-0.2801	0.2801	88.5820	0.00
3	0.8058	-0.2540	-0.2801	0.2801	123.8582	0.00
4	0.7131	-0.1393	-0.2801	0.2801	152.0959	0.00
5	0.5934	-0.2902	-0.2801	0.2801	172.0919	0.00
6	0.4754	-0.0320	-0.2801	0.2801	185.2276	0.00
7	0.3529	-0.0416	-0.2801	0.2801	192.6362	0.00
8	0.2320	-0.0517	-0.2801	0.2801	195.9174	0.00
9	0.0966	-0.2213	-0.2801	0.2801	196.5002	0.00
10	-0.0351	-0.1404	-0.2801	0.2801	196.5790	0.00
11	-0.1614	-0.0626	-0.2801	0.2801	198.2923	0.00
12	-0.2539	0.2558	-0.2801	0.2801	202.6472	0.00
13	-0.3407	0.0236	-0.2801	0.2801	210.7061	0.00
14	-0.4084	-0.0401	-0.2801	0.2801	222.6172	0.00
15	-0.4602	-0.0577	-0.2801	0.2801	238.1804	0.00
16	-0.4865	-0.0092	-0.2801	0.2801	256.1060	0.00
17	-0.5167	-0.1568	-0.2801	0.2801	276.9532	0.00
18	-0.5320	-0.0339	-0.2801	0.2801	299.7655	0.00
19	-0.5362	-0.0199	-0.2801	0.2801	323.7137	0.00
20	-0.5095	0.1238	-0.2801	0.2801	346.0837	0.00

The best ranked model for prediction of production of tapioca was identified as ARIMA(0,1,4) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in table 4.5.6.2(b) and 4.5.6.2(c).

Table 4.5.6.2(b): Statistics calculated for best diagnosed model for production of tapioca

R-squared	0.942	Normalized BIC	25.25
RMSE	293035.644	Ljung-Box Q Statis	16.23
MAPE	6.513	DF	17
MAE	204185.570	Sig.	0.508
MaxAPE	37.582	Transformation	Nil
MaxAE	948550.134	Difference	1

Table 4.5.6.2.(c): Estimates of the parameters of ARIMA(0,1,4) for production of tapioca

	Estimate	SE	t	Sig.
MA(4)	-0.295	0.140	-2.112	0.040

The final model could be written in the form

$$Y_t = Y_{t-1} - 0.295\epsilon_{t-4}, \dots\dots\dots(4.5.6.2)$$

Where Y_t denote the production and ϵ the error in prediction for tapioca in the year 't'.

The moving average term in the model given in 4.5.6.2 was significant and was having an R^2 of 94% with very low MAPE = 6.5% which has still came down to 3.5% in the post sample period. All the statistics calculated for the post sample period are less than that in the sample period ensuring the power of the model for future predictions.

Table 4.5.6.2.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
88991.239	3.530	90017.436	108188.333

The production of tapioca predicted for 2007-08 to 2011-12 showed a fluctuating trend and growth rate. The growth rates for the years from 2007-08 to 2011-12 are 0.86, -1.11, 0.95, 0.00 percent respectively. During the recent years it can be seen that the production of tapioca has a steady march due to the increased productivity. Though Kerala ranks first in cultivation and production in the country, Tamilnadu stands first in respect of processing of tapioca into starch and sago and hence this crop has now acquired a status of one of the important commercial crops.

Figure 4.5.6.2 (c) Actual and Estimated values for production of tapioca using ARIMA(0,1,4)

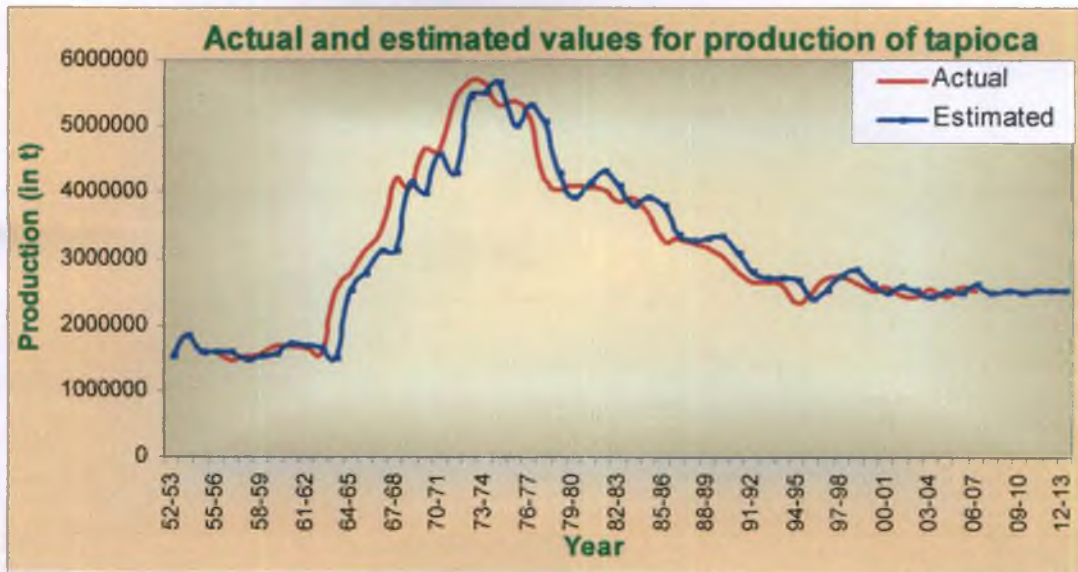


Figure 4.5.6.2.(d) Deviation from forecasts for production of tapioca

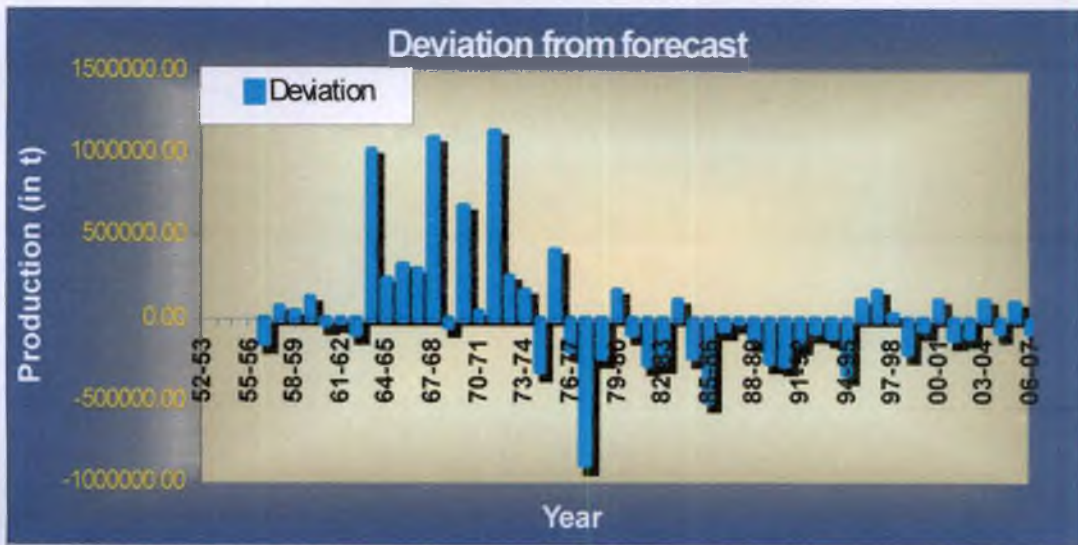


Table 4.5.6.2(e) : Comparison of the ARIMA(0,1,4) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	2540790.000	2432601.667	4.26
04-05	2436771.000	2509696.767	-2.99
05-06	2568284.000	2473673.127	3.68
06-07	2518999.000	2599238.983	-3.19

Table 4.5.6.2 (f): Estimated production of tapioca from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
2487083.442	2508596.543	2480686.335	2504357.130	2504357.13

4.5.6.3. Productivity

Figure 4.5.6.3 (a)
ACF for the productivity of tapioca

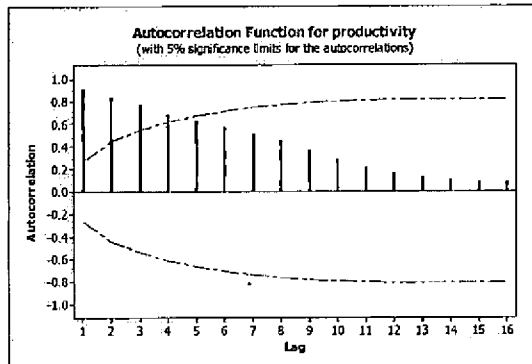
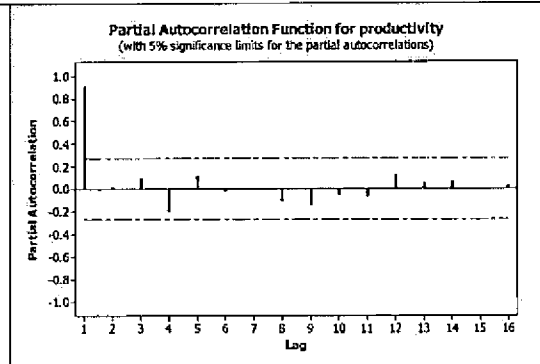


Figure 4.5.6.3 (b)
PACF for the productivity of tapioca



The exponentially decaying ACFs and one significant spike for PACF as in the case of area of tapioca indicated an AR(1) model with nonstationarity behaviour. The significance of Q-values in the Table 4.5.6.3(a) also indicated the nonstationarity of the series.

Table 4.5.6.3 (a) ACF and PACF for productivity of tapioca with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9328	0.9328	-0.2801	0.2801	46.1689	0.00
2	0.8654	-0.0363	-0.2801	0.2801	86.7349	0.00
3	0.7904	-0.0947	-0.2801	0.2801	121.2941	0.00
4	0.7117	-0.0707	-0.2801	0.2801	149.9240	0.00
5	0.6291	-0.0741	-0.2801	0.2801	172.7886	0.00
6	0.5563	0.0287	-0.2801	0.2801	191.0725	0.00
7	0.4784	-0.0821	-0.2801	0.2801	204.9101	0.00
8	0.3978	-0.0809	-0.2801	0.2801	214.7061	0.00
9	0.3115	-0.1029	-0.2801	0.2801	220.8613	0.00
10	0.2262	-0.0597	-0.2801	0.2801	224.1867	0.00
11	0.1449	-0.0239	-0.2801	0.2801	225.5860	0.00
12	0.1034	0.2498	-0.2801	0.2801	226.3179	0.00
13	0.0715	0.0406	-0.2801	0.2801	226.6773	0.00
14	0.0459	-0.0250	-0.2801	0.2801	226.8297	0.00
15	0.0314	0.0271	-0.2801	0.2801	226.9030	0.00
16	0.0108	-0.1026	-0.2801	0.2801	226.9120	0.00
17	-0.0144	-0.0493	-0.2801	0.2801	226.9283	0.00
18	-0.0217	0.1052	-0.2801	0.2801	226.9667	0.00
19	-0.0348	-0.0932	-0.2801	0.2801	227.0680	0.00
20	-0.0340	0.0447	-0.2801	0.2801	227.1684	0.00

ARIMA(0,1,0) was identified as the best model for predicting the productivity of tapioca with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in table 4.5.6.3(b) and 4.5.6.3(c).

Table 4.5.6.3 (b): Statistics calculated for the best diagnosed model for Productivity of tapioca

R-squared	0.958	Normalized BIC	14.01
RMSE	1060.987	Ljung-Box Q Statis	25.95
MAPE	4.910	DF	18
MAE	698.323	Sig.	0.101
MaxAPE	39.588	Transformation	Nil
MaxAE	4760.055	Difference	1

Table 4.5.6.3 (c): Regression results for ARIMA(0,1,0) model for predicting productivity of tapioca

	Estimate	SE	t	Sig.
Constant	315.338	150.046	2.102	0.041

The final model with an $R^2 = 96\%$ and $MAPE = 4.9\%$ can be written in the form

$$P_t = P_{t-1} + 315.338, \dots \dots \dots (4.5.6.3)$$

Where P_t denotes the productivity of tapioca in the year 't'.

The increment in area and reduction in production contributed a fall in productivity during 2004-05. Due to this, the statistics measured during post sample period were a bit more than that in the sample period. But for the year 2006-07 in the post sample period the error considerably decreased indicating a good fit further.

Table 4.5.6.3.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
3079.738	11.757	3520.022	4707.865

The productivity of tapioca predicted for 2007-08 to 2011-12 showed an increasing trend with more or less constant growth rate. The growth rates for the years from 2007-08 to 2011-12 are 1.08, 1.07, 1.06 and 1.05 percent respectively.

tapioca is a major food crop of the Kerala and is cultivated mainly in less fertile regions. It is a good source of highly digestible starch which can be totally substituted for corn and broken rice in animal diets without any adverse effects on performance and has lower cost so that it can be used in pigs, beef and dairy cattle, broilers and fishes diets both at on-farm and commercial feed production. The returns from tapioca is more when compared to the cost of cultivation and management practices. Hence the area of cultivation should be increased to enhance the production.

Figure 4.5.6.3 (c) Actual and estimated values for productivity of tapioca using ARIMA(0,1,0)

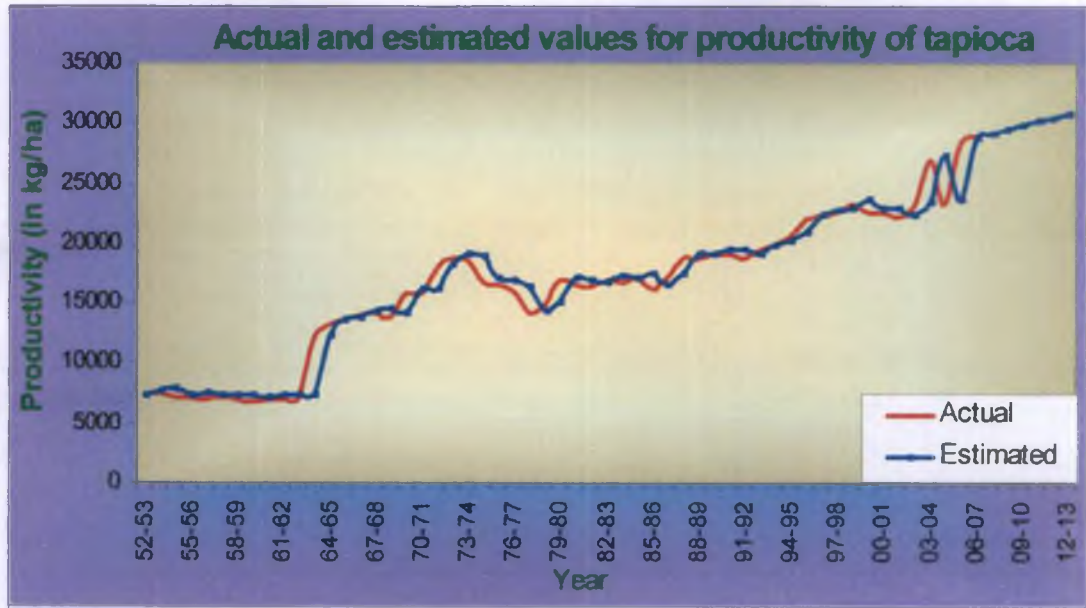


Figure 4.5.6.3 (d) Deviation from forecasts for the productivity of tapioca

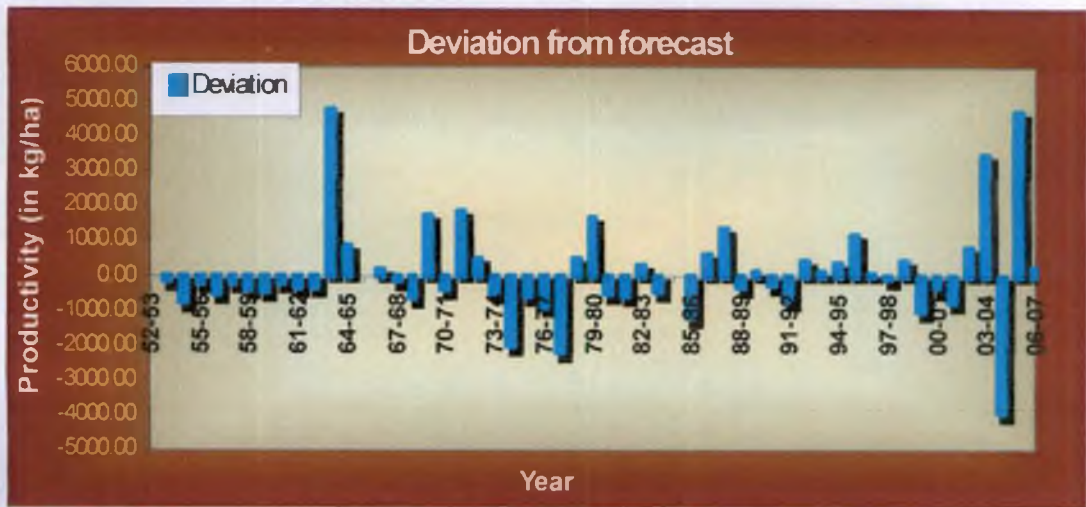


Table 4.5.6.3(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	26944.548	23479.479	12.86
04-05	23343.402	27259.886	-16.78
05-06	28366.604	23658.740	16.60
06-07	28911.475	28681.942	0.79

Table 4.5.6.3 (f) : Estimated values for productivity of tapioca from 2008-09 to 2011-12

2007-08	29226.813	2008-09	29542.151	2009-10	29857.489	2010-11	30172.827	2011-12	30488.17
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4.5.6.4. Price

Figure 4.5.6.4(a)
ACF for the price of tapioca

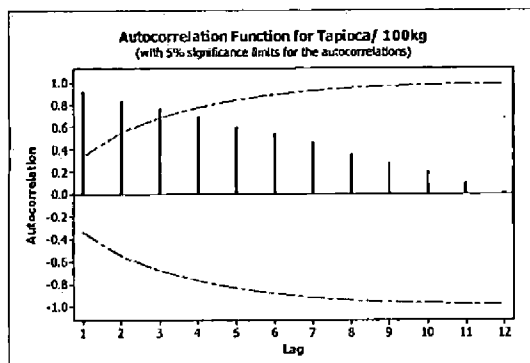
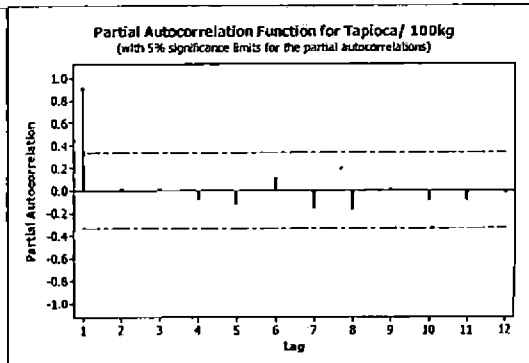


Figure 4.5.6.4(b)
PACF for the price of tapioca



As in the case of area, price of tapioca also showed a similar pattern. Hence the forecasting model identified was an AR(1) model. The significant spikes at large number of lags and the significant Q-values form Table 4.5.64 (a) showed the nonstationary behaviour of the data.

Table 4.5.6.4(a) ACF and PACF for price of tapioca with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8949	0.8949	-0.3536	0.3536	27.3119	0.00
2	0.8247	0.1192	-0.3536	0.3536	51.3015	0.00
3	0.7393	-0.0889	-0.3536	0.3536	71.2696	0.00
4	0.6241	-0.2209	-0.3536	0.3536	86.0280	0.00
5	0.5242	-0.0405	-0.3536	0.3536	96.8391	0.00
6	0.4321	0.0144	-0.3536	0.3536	104.4806	0.00
7	0.3243	-0.1120	-0.3536	0.3536	108.9642	0.00
8	0.2229	-0.0942	-0.3536	0.3536	111.1745	0.00
9	0.1433	0.0333	-0.3536	0.3536	112.1290	0.00
10	0.0683	0.0183	-0.3536	0.3536	112.3562	0.00
11	-0.0113	-0.1056	-0.3536	0.3536	112.3628	0.00
12	-0.0737	-0.0482	-0.3536	0.3536	112.6556	0.00
13	-0.1307	-0.0125	-0.3536	0.3536	113.6261	0.00
14	-0.1957	-0.0884	-0.3536	0.3536	115.9308	0.00
15	-0.2349	0.0034	-0.3536	0.3536	119.4582	0.00
16	-0.2743	-0.0444	-0.3536	0.3536	124.5895	0.00
17	-0.3085	-0.0216	-0.3536	0.3536	131.5449	0.00
18	-0.3494	-0.1338	-0.3536	0.3536	141.1543	0.00
19	-0.3602	0.0570	-0.3536	0.3536	152.2133	0.00
20	-0.3744	-0.0094	-0.3536	0.3536	165.2515	0.00

The best ranked model for prediction of price of tapioca was identified as ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.6.4(b) and 4.5.6.4(c).

Table 4.5.6.4(b) Statistics for the best diagnosed model for price of tapioca by ARIMA(0,1,0)

R-squared	0.976	Normalized BIC	6.33
RMSE	22.534	Ljung-Box Q	21.02
MAPE	11.229	DF	18
MAE	15.596	Sig.	0.278
MaxAPE	53.924	Transformation	Natural Log
MaxAE	65.523	Difference	1

Table 4.5.6.4 (c) : Regression results for ARIMA(0,1,0) model for predicting price of tapioca

	Estimate	SE	t	Sig.
Constant	0.089	0.025	3.551	0.001

The final model can be written in the form

$$R_t = R_{t-1} e^{(0.089)}, \dots\dots\dots(4.5.6.4)$$

Where R_t denotes the price of tapioca at the t^{th} year.

The constant in the model is highly significant and the R^2 indicates 97.6% of the variation in the data can be explained through this model. Also there was high reduction in MAPE (4.4%) for the post sample period. The reduction in RMSE (22.12) and maximum error also gives the clear indication of the high forecasting power of the model.

Table 4.5.6.4 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
17.834	4.436	22.121	37.401

The price of tapioca predicted for 2007-08 to 2011-12 showed an increasing trend with a constant growth rate of 9.31%.

Emphasis should be put on the reduction of raw material costs, and policy that advocates the production of bio-fuel. The stabilized growth rate of price of tapioca is to be maintained and new products should be created by higher technologies and innovation. Moreover, with no colour, no odor and no taste, tapioca is suitable for food industry and other industries such as paper, textile, and adhesives, pharmaceutical, cosmetic and packaging.

Figure 4.5.6.4 (c) Actual and estimated values for price of tapioca by ARIMA(0,1,0) Model

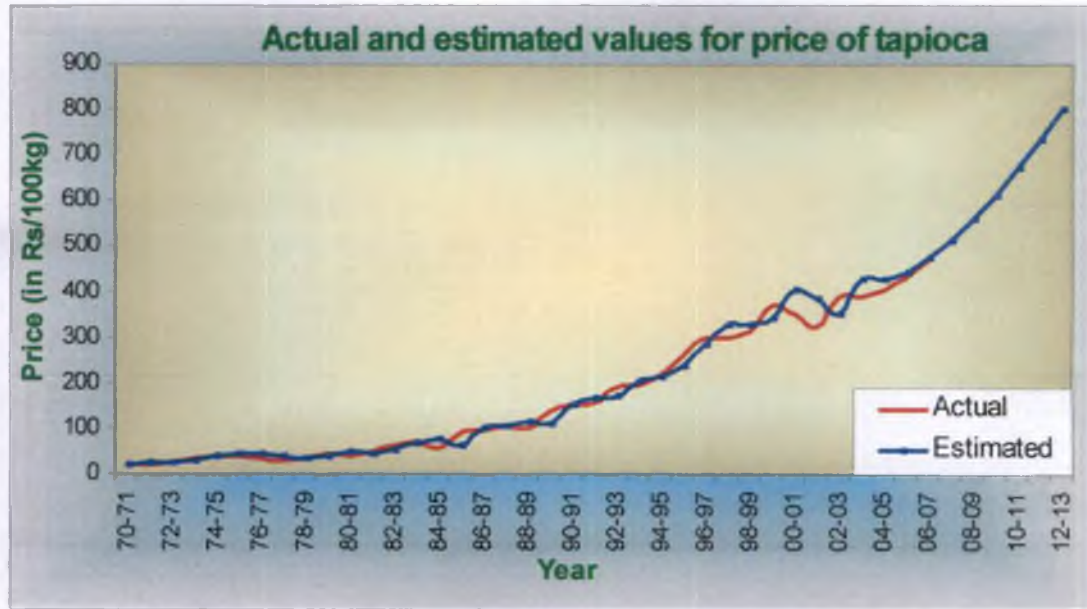


Figure 4.5.6.4 (d) Deviation from forecasts for the price of tapioca

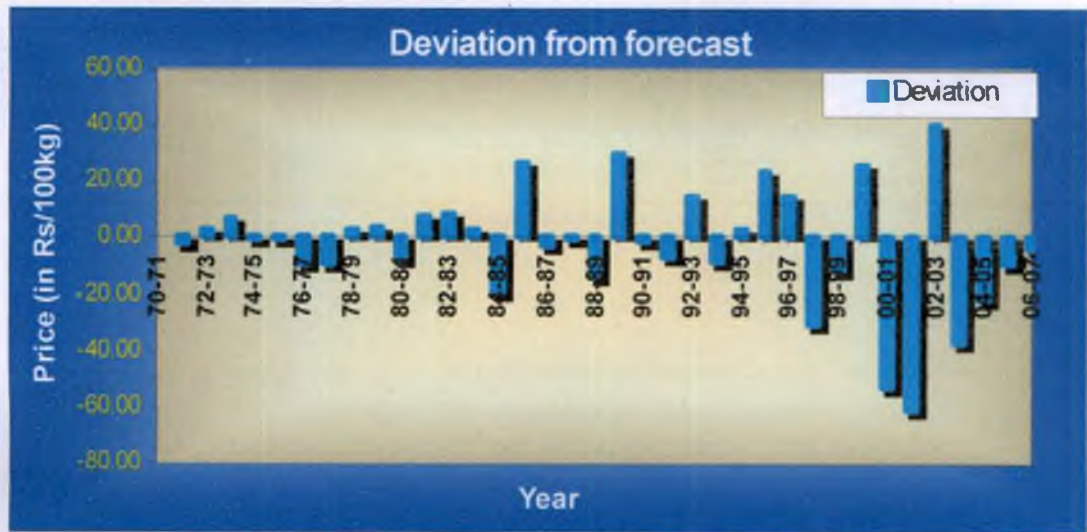


Table 4.5.6.4 (e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	389.360	426.761	-9.61
04-05	404.000	425.602	-5.35
05-06	432.630	441.605	-2.07
06-07	469.540	472.899	-0.72

Table 4.5.6.4 (f) : Estimated values for price of tapioca from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
513.245	561.018	613.238	670.319	732.71

4.5.7. Coffee

4.5.7.1.Area

Figure 4.5.7.1(a)
ACF for the area of coffee

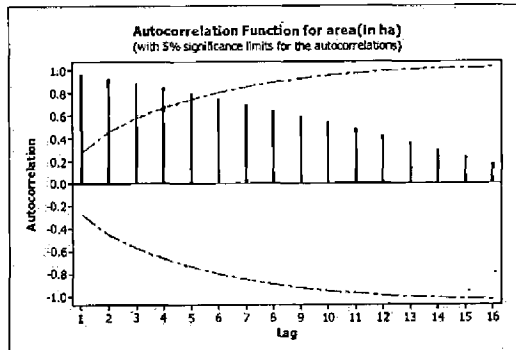
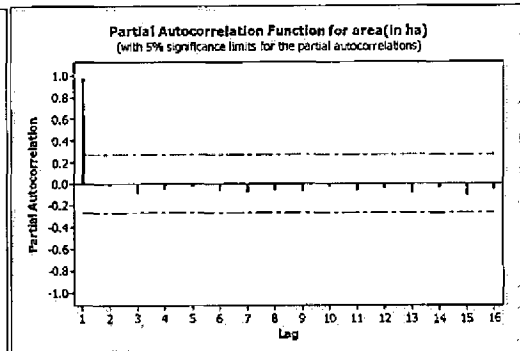


Figure 4.5.7.1(b)
PACF for the area of coffee



The ACF showed nonstationary behaviour of the series with exponential decay . The significance of Q-values from Table 4.5.7.1(a) also showed the nonstationarity of the data.

Table 4.5.7.1(a) ACF and PACF for area of coffee with Q Stat. and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9584	0.9584	-0.2801	0.2801	47.8254	0.00
2	0.9154	-0.0395	-0.2801	0.2801	92.3797	0.00
3	0.8671	-0.0865	-0.2801	0.2801	133.2281	0.00
4	0.8174	-0.0417	-0.2801	0.2801	170.3343	0.00
5	0.7666	-0.0370	-0.2801	0.2801	203.7111	0.00
6	0.7150	-0.0355	-0.2801	0.2801	233.4254	0.00
7	0.6594	-0.0799	-0.2801	0.2801	259.2928	0.00
8	0.6014	-0.0600	-0.2801	0.2801	281.3375	0.00
9	0.5399	-0.0747	-0.2801	0.2801	299.5484	0.00
10	0.4783	-0.0367	-0.2801	0.2801	314.2095	0.00
11	0.4129	-0.0862	-0.2801	0.2801	325.4195	0.00
12	0.3462	-0.0609	-0.2801	0.2801	333.5164	0.00
13	0.2847	0.0213	-0.2801	0.2801	339.1434	0.00
14	0.2238	-0.0371	-0.2801	0.2801	342.7185	0.00
15	0.1683	0.0176	-0.2801	0.2801	344.8007	0.00
16	0.1134	-0.0406	-0.2801	0.2801	345.7752	0.00
17	0.0573	-0.0675	-0.2801	0.2801	346.0316	0.00
18	0.0006	-0.0582	-0.2801	0.2801	346.0316	0.00
19	-0.0526	-0.0136	-0.2801	0.2801	346.2625	0.00
20	-0.1064	-0.0651	-0.2801	0.2801	347.2387	0.00

The best ranked linear model for prediction of area of coffee was ARIMA(0,1,1) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 5.2.1 (b) and 5.2.1(c).

Table 5.2.1(b) Statistics calculated for the best diagnosed model for area of coffee

R-squared	0.940	Normalized BIC	17.78
RMSE	6715.095	Ljung-Box Q Stat	6.80
MAPE	4.999	DF	17
MAE	3480.528	Sig.	0.986
MaxAPE	101348.794	Transformation	Nil
MaxAE	35472.078	Difference	1

Table 4.5.7.1.(c) : Estimates of the parameters for ARIMA(0,1,1) model for area of rubber

	Estimate	SE	t	Sig.
Constant	1474.052	442.718	3.33	0.002
MA(1)	0.546	0.124	4.407	0.000

The final model could be written in the form

$$A_t = A_{t-1} - 0.546\epsilon_{t-1} + 1474.052, \dots\dots\dots(4.5.7.1)$$

Where A_t denotes the area of Cashew and ϵ denote the error in prediction for the year 't'. The high value of R-square with small MAPE of 4.99% which reduced to 3.37% for the post sample period forecast indicate the high forecasting power of the model.

Table 4.5.7.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
2855.075	3.374	2870.536	3192.743

The area of coffee predicted for 2007-08 to 2011-12 showed an increasing trend with decreasing growth rate. The growth rates for the years from 2007-08 to 2011-12 are given by 1.68, 1.65, 1.62 and 1.60 percent respectively.

Coffee cultivation in Kerala is yet to pick up on a large scale. It can have a definite edge because the Robusta variety grown here has a rich market in the global trade. As far as Kerala is concerned coffee has limited regional adaptability. Idulikki and Wayanad, the two hill districts are the regions suited for coffee cultivation. With the introduction of newer varieties coffee cultivation has spread to lower areas mainly as intercrop in coconut garden. With the introduction of speciality coffee which has great demand in the international market, coffee cultivation has attained momentum after a phase of set back.

Figure 4.5.7.1.(c) Actual and estimated values for area of coffee using ARIMA(0,1,1)

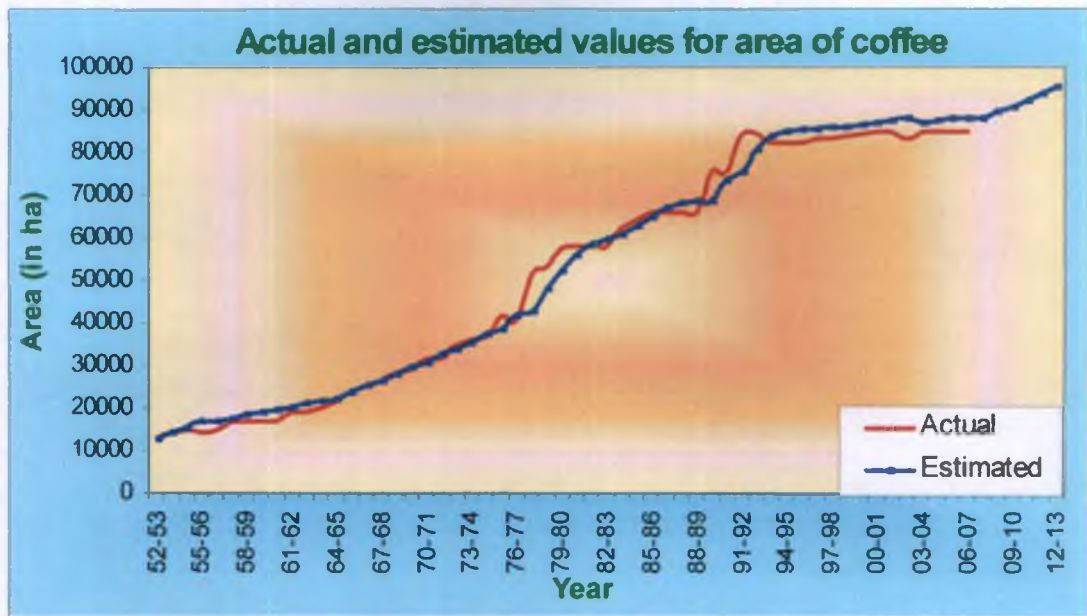


Figure 4.5.7.1.(d) Deviation from forecasts for area of coffee

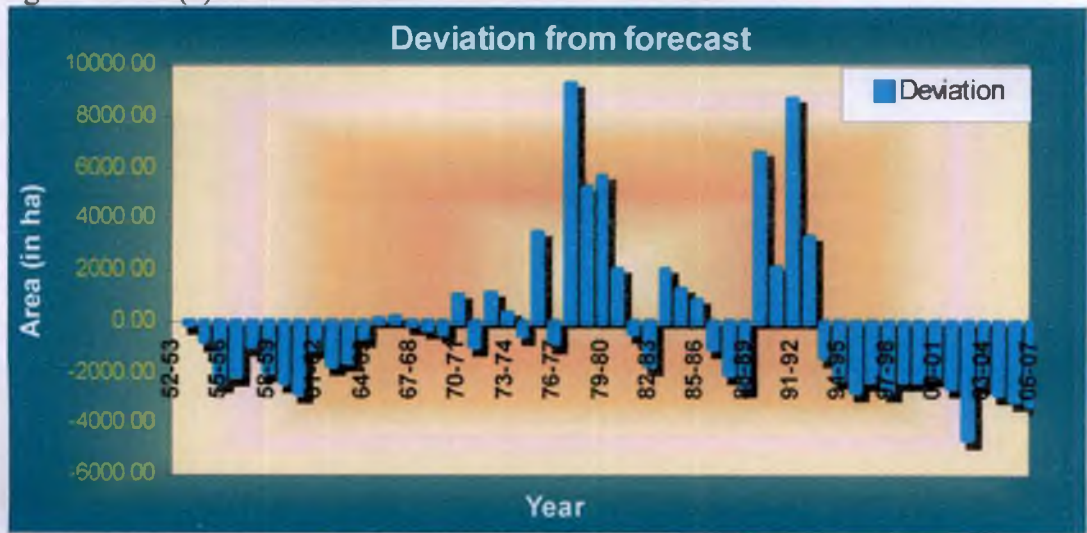


Table 4.5.7.1(e) : Comparison of the ARIMA(0,1,1) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	84684.000	87076.897	-2.83
04-05	84644.000	87464.574	-3.33
05-06	84644.000	87658.085	-3.56
06-07	84571.000	87763.743	-3.78

Table 4.5.7.1(f) : Estimated values for area of coffee from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
87788.289	89262.341	90736.393	92210.445	93684.50

4.5.7.2. Production

Figure 4.5.7.2 (a)
ACF for the production of coffee

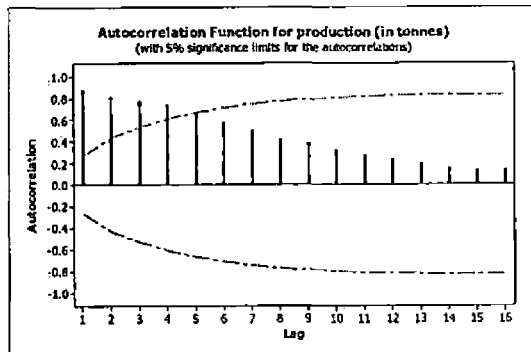
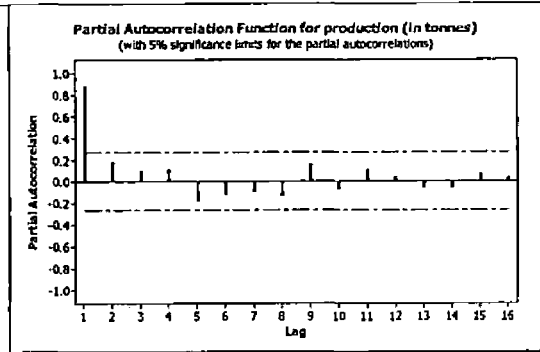


Figure 4.5.7.2 (b)
PACF for the production of coffee



The autocorrelations were significant for a large number of lags but the PACF showed that autocorrelations at lags 2 and above are merely due to the propagation of the autocorrelation at lag 1.

Table 4.5.7.2 (a) ACF and PACF for production of coffee with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8401	0.8401	-0.2801	0.2801	36.7416	0.00
2	0.7390	0.1130	-0.2801	0.2801	65.7765	0.00
3	0.6437	-0.0063	-0.2801	0.2801	88.2885	0.00
4	0.6139	0.1793	-0.2801	0.2801	109.2158	0.00
5	0.5407	-0.0966	-0.2801	0.2801	125.8198	0.00
6	0.4680	-0.0601	-0.2801	0.2801	138.5497	0.00
7	0.4177	0.0633	-0.2801	0.2801	148.9326	0.00
8	0.3423	-0.1423	-0.2801	0.2801	156.0755	0.00
9	0.3021	0.0586	-0.2801	0.2801	161.7759	0.00
10	0.2240	-0.1102	-0.2801	0.2801	164.9921	0.00
11	0.1996	0.0621	-0.2801	0.2801	167.6126	0.00
12	0.1964	0.1499	-0.2801	0.2801	170.2191	0.00
13	0.1978	-0.0091	-0.2801	0.2801	172.9359	0.00
14	0.1868	0.0352	-0.2801	0.2801	175.4286	0.00
15	0.1425	-0.0990	-0.2801	0.2801	176.9220	0.00
16	0.1459	0.0593	-0.2801	0.2801	178.5334	0.00
17	0.1185	-0.0551	-0.2801	0.2801	179.6293	0.00
18	0.0931	-0.1051	-0.2801	0.2801	180.3281	0.00
19	0.0169	-0.1423	-0.2801	0.2801	180.3518	0.00
20	-0.0171	-0.0110	-0.2801	0.2801	180.3771	0.00

The best ranked model was ARIMA(0,1,0) for predicting the production of Coffee with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in table 4.5.7.2(b) and 4.5.7.2(c)

Table 4.5.7.2(b): Statistics calculated for the best diagnosed model for production of coffee

R-squared	0.854	Normalized BIC	17.89
RMSE	7076.212	Ljung-Box Q Stat	18.20
MAPE	15.645	DF	17
MAE	4413.303	Sig.	0.377
MaxAPE	77.176	Transformation	Natural Log
MaxAE	17954.099	Difference	1

Table 4.5.7.2(c): Estimates of the parameters of ARIMA(0,1,1) model for production of coffee

	Estimate	SE	t	Sig.
Constant	0.051	0.010	5.065	0.000
MA(1)	0.698	0.106	6.608	0.000

The final model with an $R^2 = 85.4\%$ and $MAPE = 15.65\%$ could be written in the form

$$Y_t = Y_{t-1} e^{(0.051 - 0.698 \epsilon_{t-1})}, \dots\dots\dots(4.5.7.2)$$

Where Y_t denotes the production and ϵ the error in prediction for coffee in the year 't'. Since the production from coffee depends on other variables such as weather parameters and disease incidents some more error in prediction was occurred. However the maximum error occurred during post sample period was less in comparison with that of the sample period.

Table 4.5.7.2.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
11279.773	19.436	11989.992	17915.380

The production of coffee predicted for 2007-08 to 2011-12 showed an increasing trend with constant growth rate. The growth rates for the years from 2007-08 to 2011-12 are 5.23 percent.

Kerala is the second-largest coffee-growing state in India after Karnataka, accounting for around 15-20 per cent of the total output. The basic infrastructure of post harvest processes is largely lacking in the state with not even an auction centre in the state. Coffee cultivation is an organised sector wherein the research and development activities are undertaken by Coffee Board.. Marketing is also regulated by the Board. However, pest and disease incidence, vagaries of climate etc. influence the production and productivity of coffee.

Figure 4.5.7.2 (c) Actual and estimated values for production of coffee using ARIMA(0,1,1)

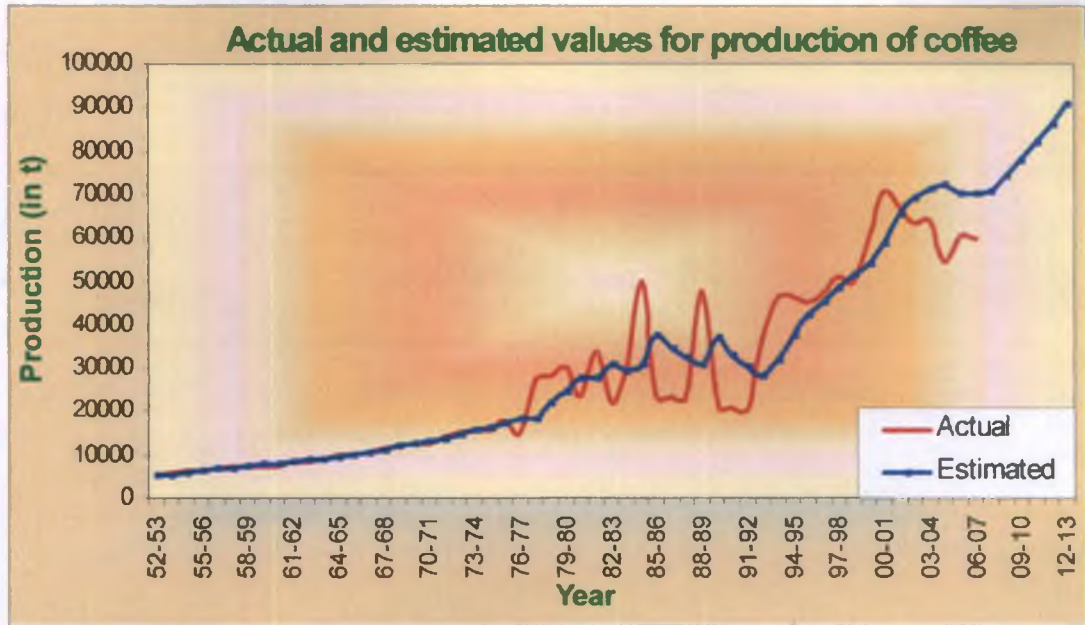


Figure 4.5.7.2.(d) Deviation from forecasts for production of coffee

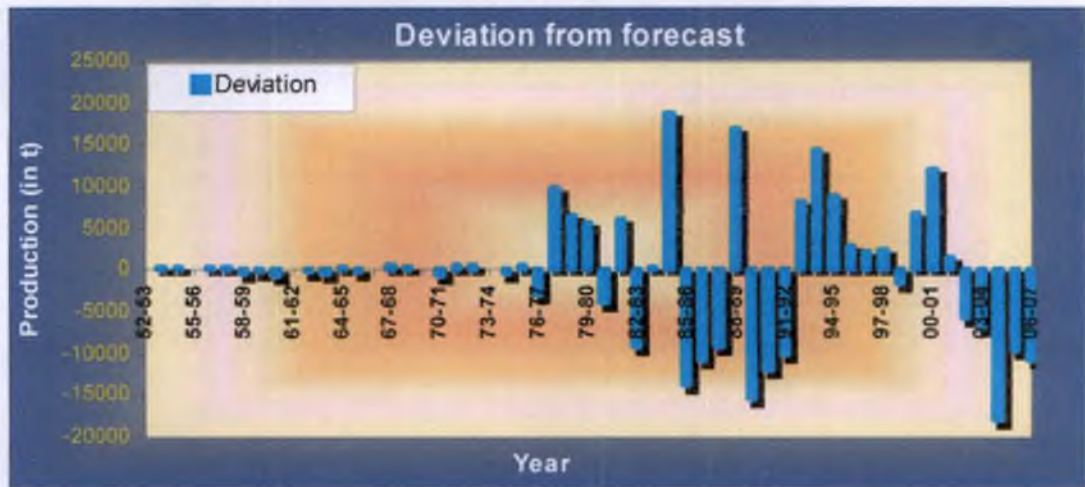


Table 4.5.7.2(e) : Comparison of the ARIMA(0,1,1) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	63850.000	70799.738	-10.88
04-05	54300.000	72215.380	-32.99
05-06	60175.000	69723.969	-15.87
06-07	59475.000	70180.004	-18.00

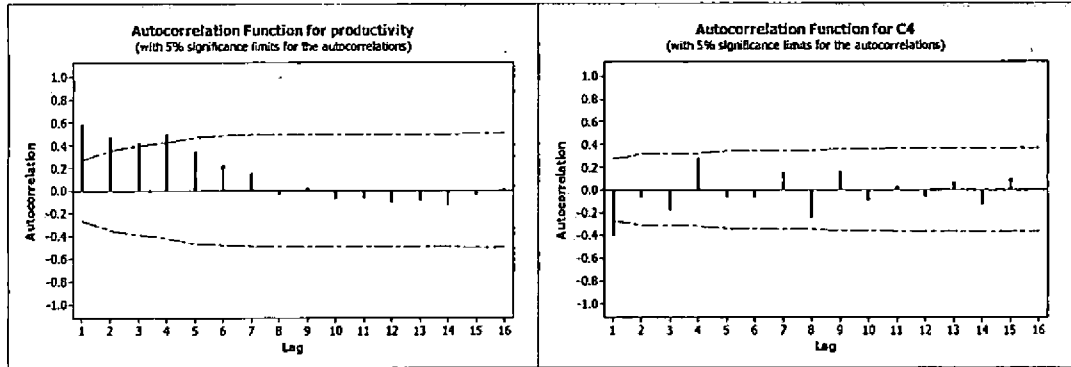
Table 4.5.7.2 (f): Estimated production of coffee from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
70251.397	73927.154	77795.236	81865.708	86149.16

4.5.7.3. Productivity

Figure 4.5.7.3 (a)
ACF for the productivity of coffee

Figure 4.5.7.3 (b)
PACF for the productivity of coffee



From the figure, the ACF was declining and has an indication of unit root. From table 4.5.7.3(a) also as the Q-statistics were highly significant the series showed a nonstationarity behaviour of the data.

Table 4.5.7..3 (a) ACF and PACF for productivity of coffee with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	-0.6196	-0.6196	-0.2857	0.2857	19.2190	0.00
2	0.1626	-0.3592	-0.2857	0.2857	20.5716	0.00
3	-0.2145	-0.5592	-0.2857	0.2857	22.9788	0.00
4	0.2979	-0.3722	-0.2857	0.2857	27.7326	0.00
5	-0.1178	-0.2075	-0.2857	0.2857	28.4933	0.00
6	-0.0929	-0.4314	-0.2857	0.2857	28.9781	0.00
7	0.2308	0.0606	-0.2857	0.2857	32.0443	0.00
8	-0.2905	-0.1169	-0.2857	0.2857	37.0290	0.00
9	0.2336	-0.0479	-0.2857	0.2857	40.3373	0.00
10	-0.1381	0.1377	-0.2857	0.2857	41.5252	0.00
11	0.0833	-0.1299	-0.2857	0.2857	41.9688	0.00
12	-0.0667	-0.0504	-0.2857	0.2857	42.2613	0.00
13	0.0885	0.1206	-0.2857	0.2857	42.7919	0.00
14	-0.1119	-0.2088	-0.2857	0.2857	43.6652	0.00
15	0.0372	-0.0749	-0.2857	0.2857	43.7646	0.00
16	0.0486	-0.1895	-0.2857	0.2857	43.9398	0.00
17	-0.0049	-0.2392	-0.2857	0.2857	43.9416	0.00
18	-0.0621	-0.0642	-0.2857	0.2857	44.2478	0.00
19	0.0522	-0.0732	-0.2857	0.2857	44.4716	0.00
20	-0.0184	-0.0008	-0.2857	0.2857	44.5006	0.00

The best ranked model for the prediction of productivity of coffee was ARIMA(0,1,1) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.7.3(b) and 4.5.7.3(c).

Table 4.5.7.3 (b): Statistics calculated for the best diagnosed model for Productivity of Coffee

R-squared	0.298	Normalized BIC	9.49
RMSE	110.358	Ljung-Box Q Stat	13.61
MAPE	15.785	DF	17
MAE	72.498	Sig.	0.694
MaxAPE	86.767	Transformation	Nil
MaxAE	315.437	Difference	1

Table 4.5.7.3 (c): Regression results for ARIMA(0,1,1) model for productivity of Coffee

	Estimate	SE	t	Sig.
MA(1)	0.614	0.118	5.187	0.000

The final model could be written in the form

$$P_t = P_{t-1} + 0.614\epsilon_{t-1}, \dots\dots\dots(4.5.7.3)$$

Where P_t denotes the productivity and ϵ_t the error in prediction for coffee in the year 't'.

From the model 4.5.7.3 it was clear that the moving average term was highly significant. Even though the R^2 was very small the post sample period measures of error gave a clear indication that the model was very much suitable for future forecasts. MAPE = 14.5.79% has come down to a very small value of 4.75% for the post sample period.

Table 4.5.7.3 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
30.904	4.750	54.491	108.600

The productivity of coffee predicted for 2007-08 to 2011-12 showed a constant value. The abnormality in weather and pests and diseases cause great damage in the crop. The deadly pest berry borer poses threat to the crop and it has caused high fluctuations in the coffee production from 1980-81 onwards. Kerala growers do not have a regular organised channel for primary marketing of coffee and are dependent exclusively on private dealers operating at different levels. The peasants and other workers living in the coffee growing area are facing total ruin due to the steep fall in price for coffee.

Introduction of new improved varieties like Canvery has helped to improve the productivity of the crop. But it requires intensive management practices which the small scale farmers do fail to give and as a result the productivity go below the normal level.

Figure 4.5.7.3 (c) Actual and estimated values for productivity of coffee using ARIMA(0,1,1)

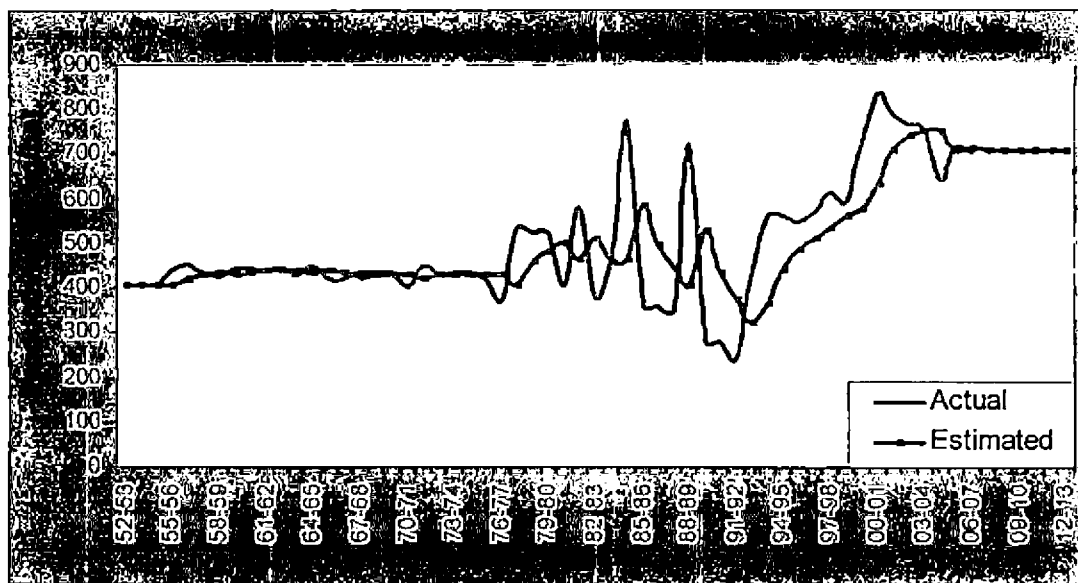


Figure 4.5.7.3 (d) Deviation from forecasts for the productivity of coffee

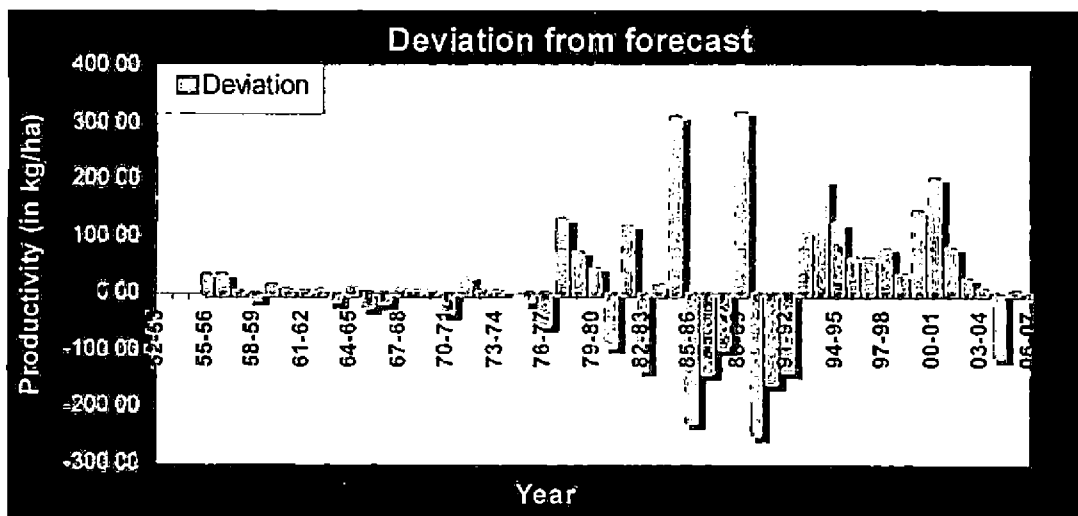


Table 4.5.7.3(e) : Comparison of the ARIMA(0,1,1) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	753.980	747.678	0.008
04-05	641.510	750.111	-0.169
05-06	710.919	708.191	0.004
06-07	703.255	709.244	-0.009

Table 4.5.7.3 (f) : Estimated Values for productivity of Coffee from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
706.932	706.932	706.932	706.932	706.93

4.5.8. cashew

4.5.8.1.Area

Figure 4.5.8.1(a)
ACF for the area of cashew

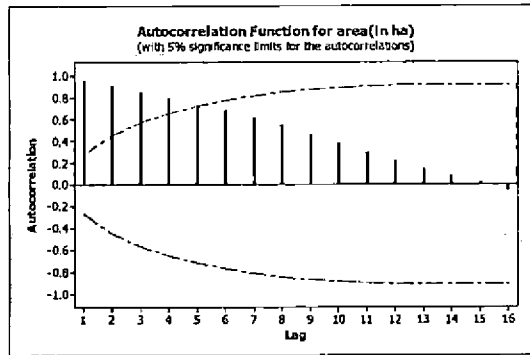
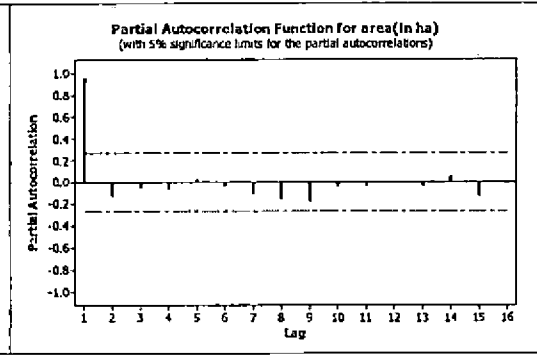


Figure 4.5.8.1(b)
PACF for the area of cashew



The figures above show the exponential decay of ACF and one significant spike of PACF leading to an AR(1) model. The large number of significant ACFs and highly significant values of Q-statistics from Table 4.5.8.1(a) showed the nonstationarity of the sequence.

Table 4.5.8.1(a) ACF and PACF for area of cashew with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9490	0.9490	-0.2801	0.2801	46.8856	0.00
2	0.8890	-0.1163	-0.2801	0.2801	88.9070	0.00
3	0.8199	-0.1170	-0.2801	0.2801	125.4285	0.00
4	0.7518	-0.0143	-0.2801	0.2801	156.8164	0.00
5	0.6847	-0.0238	-0.2801	0.2801	183.4427	0.00
6	0.6198	-0.0213	-0.2801	0.2801	205.7718	0.00
7	0.5448	-0.1508	-0.2801	0.2801	223.4309	0.00
8	0.4560	-0.1815	-0.2801	0.2801	236.1067	0.00
9	0.3511	-0.2049	-0.2801	0.2801	243.8072	0.00
10	0.2493	-0.0181	-0.2801	0.2801	247.7906	0.00
11	0.1520	-0.0291	-0.2801	0.2801	249.3103	0.00
12	0.0695	0.0459	-0.2801	0.2801	249.6361	0.00
13	-0.0051	-0.0162	-0.2801	0.2801	249.6379	0.00
14	-0.0685	0.0373	-0.2801	0.2801	249.9731	0.00
15	-0.1368	-0.0929	-0.2801	0.2801	251.3495	0.00
16	-0.2029	-0.0253	-0.2801	0.2801	254.4671	0.00
17	-0.2664	-0.0333	-0.2801	0.2801	260.0112	0.00
18	-0.3228	-0.0499	-0.2801	0.2801	268.4104	0.00
19	-0.3669	-0.0040	-0.2801	0.2801	279.6223	0.00
20	-0.3942	0.0249	-0.2801	0.2801	293.0146	0.00

The best ranked model for prediction of area of cashew cultivation was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 5.2.1(b) and 5.2.1(c)

Table 4.5.8.1(b): Statistics calculated for the best diagnosed model for area of cashew

R-squared	0.957	Normalized BIC	17.614
RMSE	6423.879	Statistics	17.946
MAPE	4.64	DF	18
MAE	4094.31	Sig.	0.459
MaxAPE	36.63	Transformation	Nil
MaxAE	30084.24	Difference	1

Table 4.5.8.1(c) : Estimates of the Parameters for ARIMA(0,1,0) model for Area of cashew

	Estimate	SE	t	Sig.
Const	1062.76	908.474	1.17	0.248

The final model could be written in the form

$$A_t = A_{t-1} + 1062.76, \dots\dots\dots(4.5.8.1)$$

Where A_t denotes the area of cashew in the t^{th} year.

The R-square value of the model given by equation (4.5.8.1) was significant and could explain about 95.7% of the variation in the stationary data which was obtained through differencing of the logarithmic transformed values of the time series. Eventhough the MAPE was slightly increased for the post sample period when comparing with that of the sample period, its value is still small and the reduction in the values of other statistics showed the forecasting power of the model for future. The area of cashew predicted for 2007-08 to 2011-12 showed an increasing trend with constant growth rate. The growth rate from 2007-08 to 2011-12 is a constant and is equal to 1.82 %.

Table 4.5.8.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
6521.512794	7.313243273	5584.51	8886.76

Even though Kerala was in the first position it has now come down to sixth with respect to area under cashew. Shift to more lucrative cash crops mainly rubber has brought down the area under cashew cultivation in Kerala. Unlike rubber, cashew is not treated as a plantation crop. If it were given plantation status, there would be farmers reverting or switching over to cashew. Because of the pressure on land, wasteland could be used for cashew planting.

Figure 4.5.8.1.(c) Actual and estimated values for area of cashew using ARIMA(0,1,0)

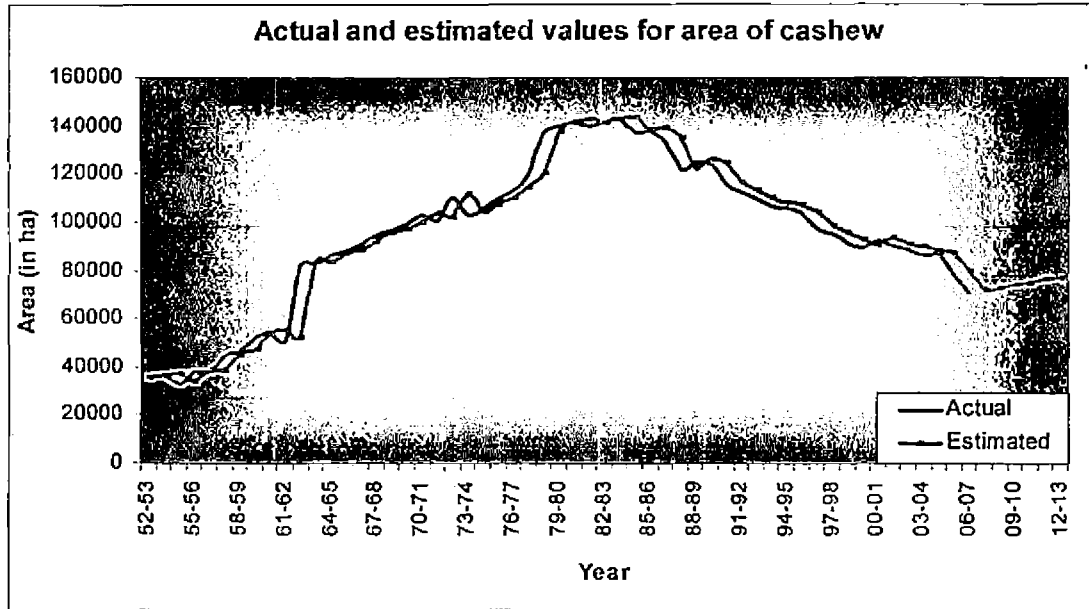


Figure 4.5.8.1.(d) Deviation from forecasts for area of cashew

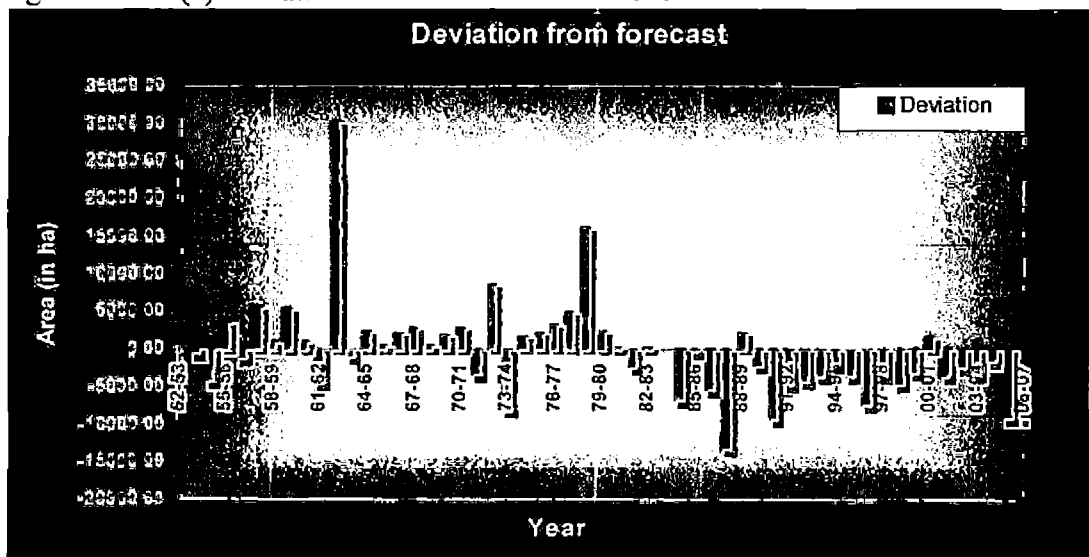


Table 4.5.8.1(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	86376.000	89610.760	-3.74
04-05	86105.000	87438.760	-1.55
05-06	78285.000	87167.760	-11.35
06-07	70461.000	79347.760	-12.61

Table 4.5.8.1(f) : Estimated values for area of cashew from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
71523.760	72586.520	73649.280	74712.040	75774.80

4.5.8.2. Production

Figure 4.5.8.2 (a)
ACF for the production of cashew

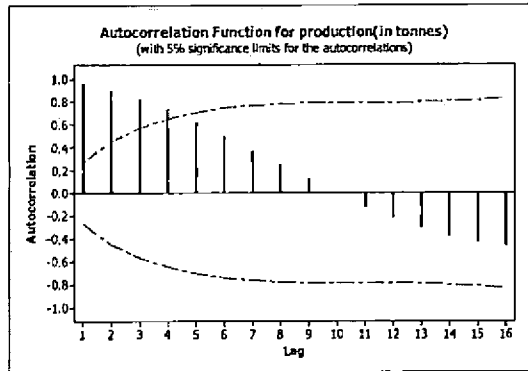
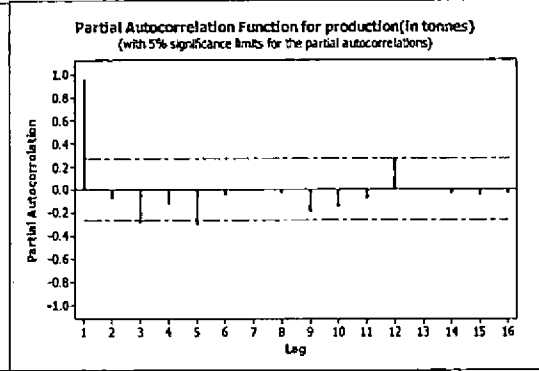


Figure 4.5.8.2 (b)
PACF for the production of cashew



From the figures above, the decaying ACFs and the significant spike at lag 1 for the PACF gave a clear identification of an AR(1) model. Since the ACF decayed for large number of lags and the significance in Q-values for large number of lags from table 4.5.8.2(a) indicated the nonstationary behaviour of the data.

Table 4.5.8.2 (a) ACF and PACF for production of cashew with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9467	0.9467	-0.2801	0.2801	46.6651	0.00
2	0.8879	-0.0814	-0.2801	0.2801	88.5820	0.00
3	0.8058	-0.2540	-0.2801	0.2801	123.8582	0.00
4	0.7131	-0.1393	-0.2801	0.2801	152.0959	0.00
5	0.5934	-0.2902	-0.2801	0.2801	172.0919	0.00
6	0.4754	-0.0320	-0.2801	0.2801	185.2276	0.00
7	0.3529	-0.0416	-0.2801	0.2801	192.6362	0.00
8	0.2320	-0.0517	-0.2801	0.2801	195.9174	0.00
9	0.0966	-0.2213	-0.2801	0.2801	196.5002	0.00
10	-0.0351	-0.1404	-0.2801	0.2801	196.5790	0.00
11	-0.1614	-0.0626	-0.2801	0.2801	198.2923	0.00
12	-0.2539	0.2558	-0.2801	0.2801	202.6472	0.00
13	-0.3407	0.0236	-0.2801	0.2801	210.7061	0.00
14	-0.4084	-0.0401	-0.2801	0.2801	222.6172	0.00
15	-0.4602	-0.0577	-0.2801	0.2801	238.1804	0.00
16	-0.4865	-0.0092	-0.2801	0.2801	256.1060	0.00
17	-0.5167	-0.1568	-0.2801	0.2801	276.9532	0.00
18	-0.5320	-0.0339	-0.2801	0.2801	299.7655	0.00
19	-0.5362	-0.0199	-0.2801	0.2801	323.7137	0.00
20	-0.5095	0.1238	-0.2801	0.2801	346.0837	0.00

The best ranked model for prediction of production for cashew was identified as ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in table 4.5.8.2(b) and 4.5.8.2(c).

Table 4.5.8.2(b): Statistics calculated for the best diagnosed model for production of cashew

R-squared	0.778	Normalized BIC	18.27
RMSE	8906.969	Ljung-Box Q	20.02
MAPE	7.408	DF	18
MAE	5917.851	Sig.	0.332
MaxAPE	37.654	Transformation	Nil
MaxAE	32856.740	Difference	1

Table 4.5.8.2.(c): Estimates of the parameters of ARIMA(0,1,0) for production of cashew

	Estimate	SE	t	Sig.
Constant	226.74	1259.636	0.18	0.858

The final model could be written in the form:

$$Y_t = Y_{t-1} + 226.74, \dots\dots\dots(4.5.8.2)$$

Where Y_t denotes the production of cashew in the year 't'.

The model given by the equation (4.5.8.2) with an R^2 of 78% was used for forecasting purpose of the time series. Since the constant in the model was not significant, the model is not statistically different from a model with out constant. The low value of MAE, MAPE, RMSE and MaxPE indicate the high forecasting capacity of the model for future years.

Table 4.5.8..2.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
3495.620	5.454	4193.278	6808.740

The production of cashew predicted for 2007-08 to 2011-12 showed an increasing trend with more or less constant growth rate. The growth rates for the years from 2007-08 to 2011-12 are 0.37, 0.36, 0.36, 0.36 percent respectively.

Today, India as a whole is facing tough competition from other cashew producing countries. The situation demands that the country should reduce its dependence on imported raw nuts. At the same time to be competitive, the productivity is to be increased to the level of other producing countries and that demands support from the government and other agencies.

Figure 4.5.8.2 (c) Actual and estimated values for production of cashew using ARIMA(0,1,0)

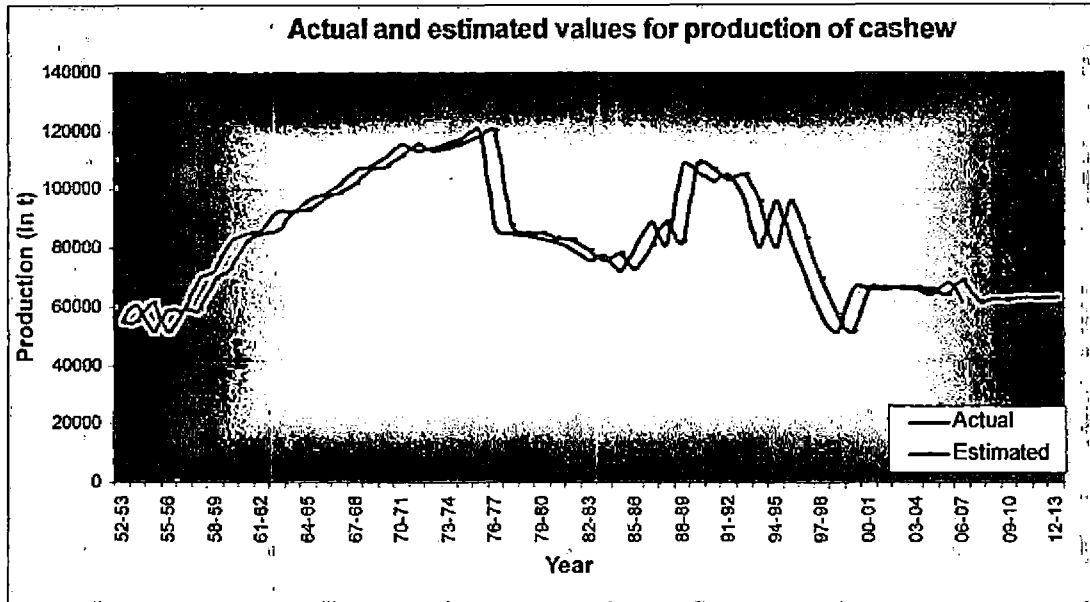


Figure 4.5.8.2.(d) Deviation from forecasts for production of cashew

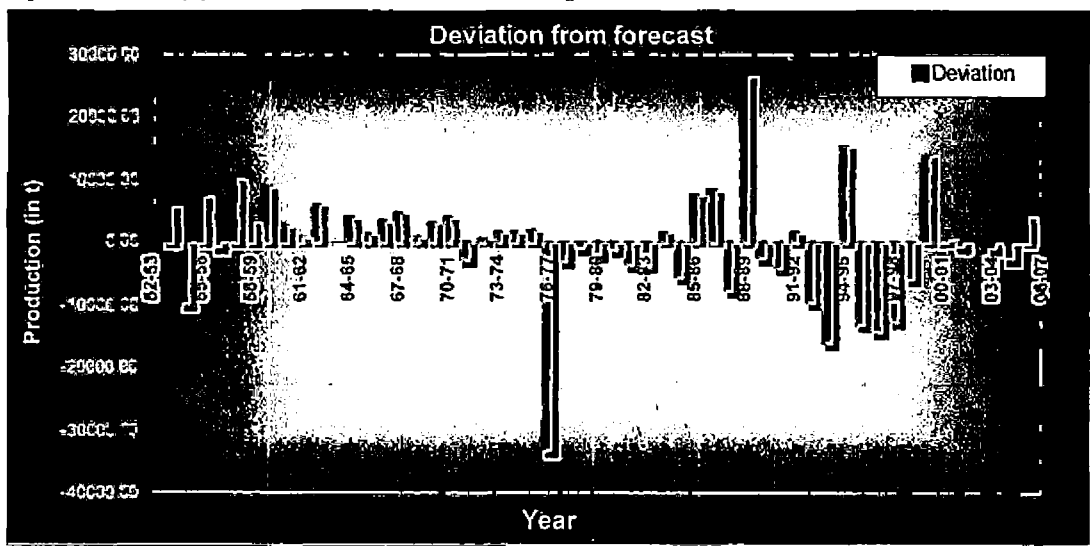


Table 4.5.8.2(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	65655.000	66313.740	-1.00
04-05	63701.000	65881.740	-3.42
05-06	68262.000	63927.740	6.35
06-07	61680.000	68488.740	-11.04

Table 4.5.8.2 (f): Estimated production of cashew from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
61906.740	62133.480	62360.220	62586.960	62813.70

4.5.8.3. Productivity

Figure 4.5.8.3 (a)
ACF for the productivity of cashew

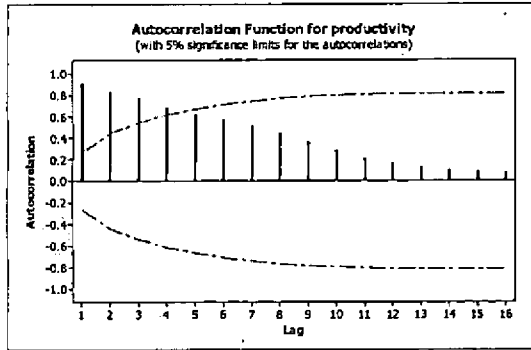
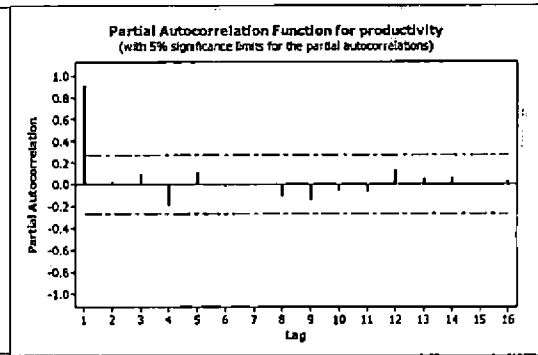


Figure 4.5.8.3 (b)
PACF for the productivity of cashew



As in the case of area and production, productivity also showed the decaying of ACF and Significant spike at lag 1 for the PACF leading to an AR(1) model. The presence of unit root was assumed as the ACF has large number of significant spikes and significant Q-values as given in Table 4.5.8.3(a)

Table 4.5.8.3(a) ACF and PACF for productivity of cashew with QStat. and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9328	0.9328	-0.2801	0.2801	46.1689	0.00
2	0.8654	-0.0363	-0.2801	0.2801	86.7349	0.00
3	0.7904	-0.0947	-0.2801	0.2801	121.2941	0.00
4	0.7117	-0.0707	-0.2801	0.2801	149.9240	0.00
5	0.6291	-0.0741	-0.2801	0.2801	172.7886	0.00
6	0.5563	0.0287	-0.2801	0.2801	191.0725	0.00
7	0.4784	-0.0821	-0.2801	0.2801	204.9101	0.00
8	0.3978	-0.0809	-0.2801	0.2801	214.7061	0.00
9	0.3115	-0.1029	-0.2801	0.2801	220.8613	0.00
10	0.2262	-0.0597	-0.2801	0.2801	224.1867	0.00
11	0.1449	-0.0239	-0.2801	0.2801	225.5860	0.00
12	0.1034	0.2498	-0.2801	0.2801	226.3179	0.00
13	0.0715	0.0406	-0.2801	0.2801	226.6773	0.00
14	0.0459	-0.0250	-0.2801	0.2801	226.8297	0.00
15	0.0314	0.0271	-0.2801	0.2801	226.9030	0.00
16	0.0108	-0.1026	-0.2801	0.2801	226.9120	0.00
17	-0.0144	-0.0493	-0.2801	0.2801	226.9283	0.00
18	-0.0217	0.1052	-0.2801	0.2801	226.9667	0.00
19	-0.0348	-0.0932	-0.2801	0.2801	227.0680	0.00
20	-0.0340	0.0447	-0.2801	0.2801	227.1684	0.00

The best model for predicting the productivity of cashew was identified as ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in table 4.5.8.3(b) and 4.5.8.3(c).

Table 4.5.8.3 (b): Statistics calculated for the best diagnosed model for Productivity of cashew

R-squared	0.887	Normalized BIC	9.66
RMSE	120.306	Ljung-Box Q	13.61
MAPE	8.047	DF	18
MAE	69.321	Sig.	0.754
MaxAPE	48.745	Transformation	Nil
MaxAE	546.273	Difference	1

Table 4.5.8.3(c): Regression results for ARIMA(0,1,0) model for predicting productivity of cashew

	Estimate	SE	t	Sig.
Constant	-15.997	17.014	-0.94	0.352

The final model could be written in the form

$$P_t = P_{t-1} - 15.997, \dots \dots \dots (4.5.8.3)$$

Where P_t denotes the productivity of cashew in the year 't'.

The value of R^2 indicates that the model can explain about 88.7% of the variation in the data and for the post sample period forecasts calculated for the model was less than that calculated for the sample period ensuring the forecasting power of the model for future years.

Table 4.5.8.3. (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
50.408	5.926	76.210	148.159

The productivity predicted for 2007-08 to 2011-12 showed a decreasing trend with high deceleration. The growth rates for the years from 2007-08 to 2011-12 are given by -1.86, -1.90, -1.93 and -1.97 percent respectively.

The industry fears that cashew is not getting adequate priority in the hands of the State Governments. According to the industry, since cashew is an export-oriented agricultural crop, it should be fully taken care of by a Central Government organisation. A major reason for the unpredictability of cashew cultivation is the fact that nearly 70 % of the cashew trees in the state are aged, local varieties, which start yielding late in the season. Efforts to motivate the farmers to take up cashew cultivation are at a low key in Kerala. Cashew was considered as a waste land crop. But now with the advent of high yielding varieties, the concept has changed. However this is not fully reflected in th management of the crop which has kept the productivity almost constant irrespective of increase in area.

Figure 4.5.8.3 (c) Actual and estimated values for productivity of cashew by ARIMA(0,1,0)

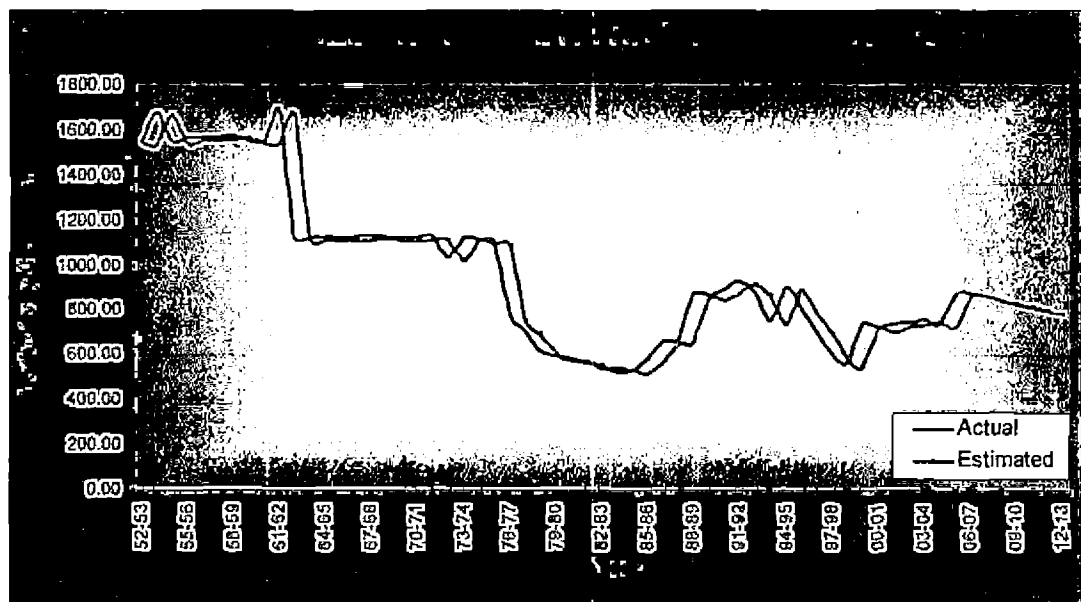


Figure 4.5.8.3 (d) Deviation from forecasts for the productivity of cashew

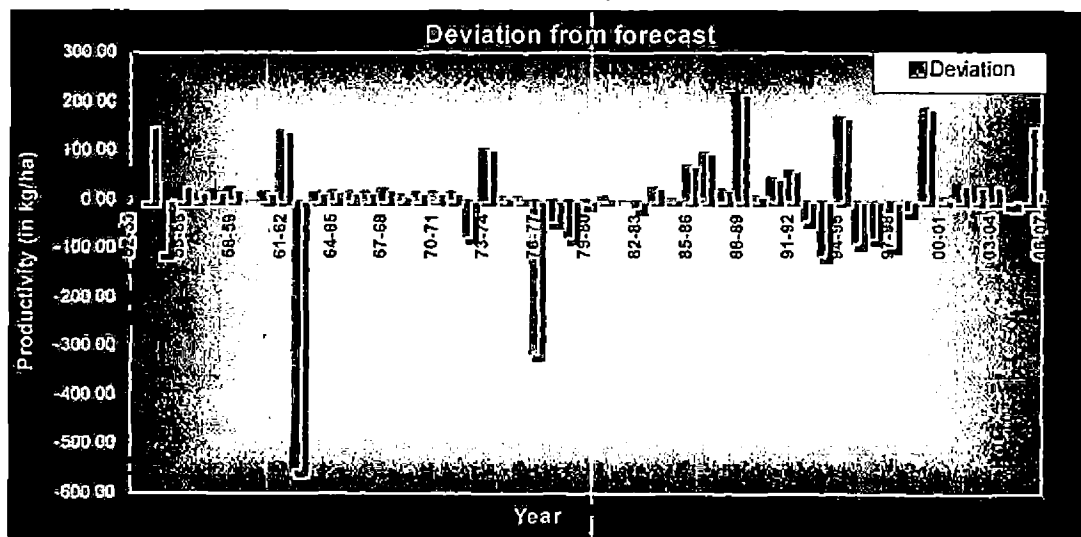


Table 4.5.8.3(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	760.107	730.344	3.92
04-05	739.806	744.110	-0.58
05-06	871.968	723.809	16.99
06-07	875.378	855.971	2.22

Table 4.5.8.3 (f) : Estimated values for productivity of cashew from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11
859.381	843.384	827.387	811.390

4.5.8.4. Price

Figure 4.5.8.4(a)
ACF for the price of cashew

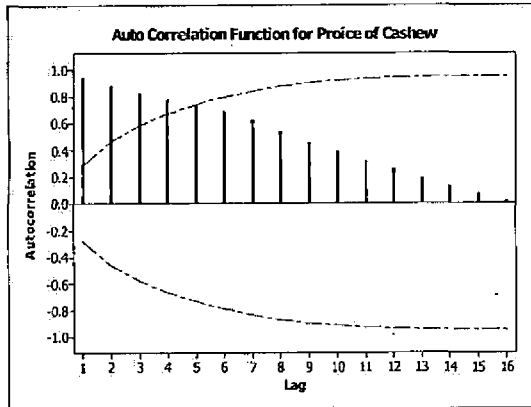
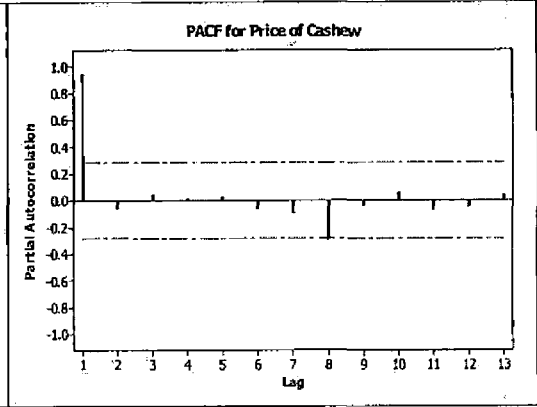


Figure 4.5.8.4(b)
PACF for the price of cashew



Price series also showed the decaying of ACF and Significant spike at lag1 for the PACF. Hence an AR(1) model was assumed with the presence of a unit root as the ACF had large number of significant spikes and significant Q-values as given in Table 4.5.8.4(a)

Table 4.5.8.4(a) ACF and PACF for price of cashew with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8949	0.8949	-0.3536	0.3536	27.3119	0.00
2	0.8247	0.1192	-0.3536	0.3536	51.3015	0.00
3	0.7393	-0.0889	-0.3536	0.3536	71.2696	0.00
4	0.6241	-0.2209	-0.3536	0.3536	86.0280	0.00
5	0.5242	-0.0405	-0.3536	0.3536	96.8391	0.00
6	0.4321	0.0144	-0.3536	0.3536	104.4806	0.00
7	0.3243	-0.1120	-0.3536	0.3536	108.9642	0.00
8	0.2229	-0.0942	-0.3536	0.3536	111.1745	0.00
9	0.1433	0.0333	-0.3536	0.3536	112.1290	0.00
10	0.0683	0.0183	-0.3536	0.3536	112.3562	0.00
11	-0.0113	-0.1056	-0.3536	0.3536	112.3628	0.00
12	-0.0737	-0.0482	-0.3536	0.3536	112.6556	0.00
13	-0.1307	-0.0125	-0.3536	0.3536	113.6261	0.00
14	-0.1957	-0.0884	-0.3536	0.3536	115.9308	0.00
15	-0.2349	0.0034	-0.3536	0.3536	119.4582	0.00
16	-0.2743	-0.0444	-0.3536	0.3536	124.5895	0.00
17	-0.3085	-0.0216	-0.3536	0.3536	131.5449	0.00
18	-0.3494	-0.1338	-0.3536	0.3536	141.1543	0.00
19	-0.3602	0.0570	-0.3536	0.3536	152.2133	0.00
20	-0.3744	-0.0094	-0.3536	0.3536	165.2515	0.00

The best ranked model for prediction of price of cashew was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in tables 4.5.8.4(b) and 4.5.8.4(c).

Table 4.5.8.4 (b): Statistics calculated for the best diagnosed model for Price of cashew

R-squared	0.844	Normalized BIC	12.27
RMSE	437.922	Ljung-Box Q	20.73
MAPE	20.566	DF	18
MAE	277.097	Sig.	0.293
MaxAPE	74.651	Transformation	Natural Log
MaxAE	1744.373	Difference	1

Table 4.5.8.4 (c) : Regression results for ARIMA(0,1,0) model for predicting price of cashew

	Estimate	SE	t	Sig.
Constant	0.082	0.043	1.893	0.067

The final model could be written in the form

$$R_t = R_{t-1} e^{(0.082)}, \dots\dots\dots(4.5.8.4)$$

Where R_t denotes the price of cashew at the t^{th} year.

This model given by equation (4.5.8.4) has an R-square of 84% and was used to forecast the future values of the time series. The reduction in MAPE also showed the reduction in error for the post sample period.

Table 4.5.8.4 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
547.890	19.257	625.115	935.375

The price of cashew predicted for 2007-08 to 2011-12 showed an increasing trend with constant growth rate. The growth rates for the years from 2007-08 to 2011-12 are 8.55 percent. From the trend of price of cashew it could be observed that when it reached a peak there was a steep fall in price with a period of four years. Good price for rubber in the market is luring a large number of farmers to rubber cultivation. Most of the farmers cut down cashew trees to plant rubber. Troubled by the fluctuation in the price of raw cashew nut in domestic market and encouraged by the attractive price of rubber, cashew farmers in Kerala seem to take over rubber cultivation. The investment in raising a cashew plantation is comparatively much less while the return is remunerative. The cashew corporation should enter the market to prevent owners of private cashew processing units from controlling the procurement price.

Figure 4.5.8.4 (c) Actual and estimated values for production of cashew by ARIMA(0,1,0)

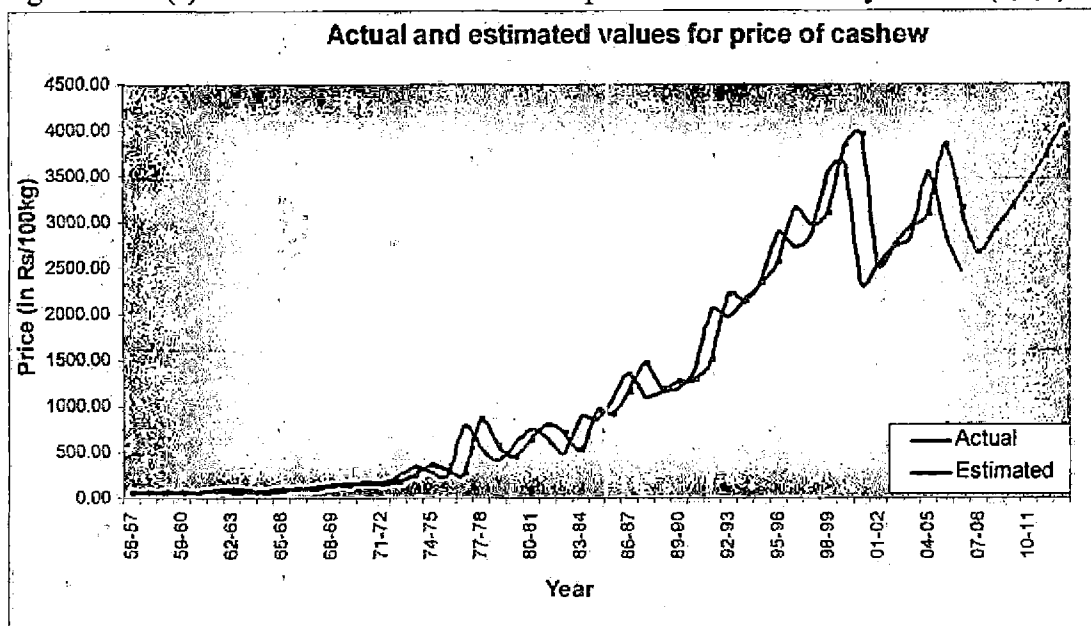


Figure 4.5.8.4 (d) Deviation from forecasts for the price of cashew

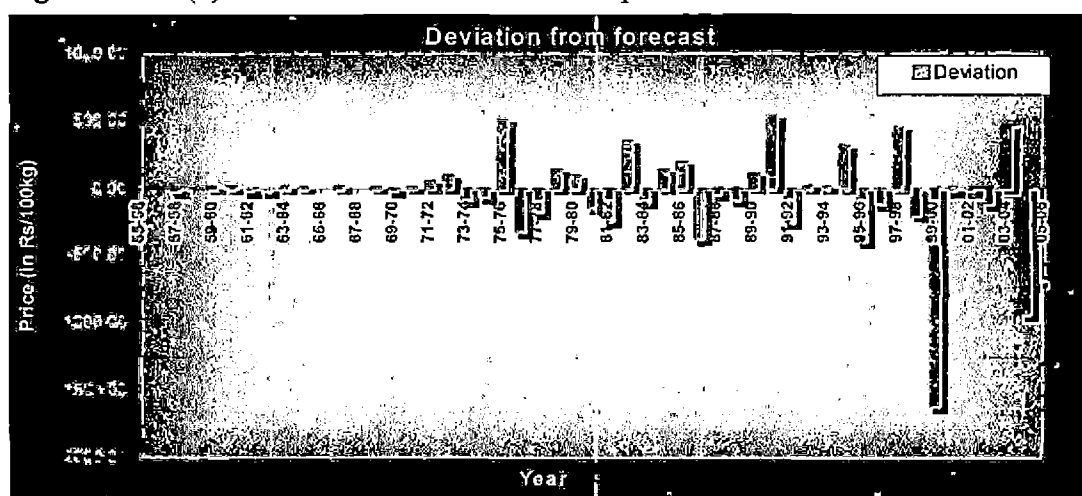


Table 4.5.8.4 (e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	2835.420	2952.907	-4.14
04-05	3533.000	3077.723	12.89
05-06	2899.540	3834.915	-32.26
06-07	2463.900	3147.323	-27.74

Table 4.5.8.4 (f) : Estimated values for price of cashew from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
2674.455	2903.002	3151.081	3420.359	3712.65

4.5.9. Banana

4.5.9.1. Area

Figure 4.5.9.1(a)
ACF for the area of banana

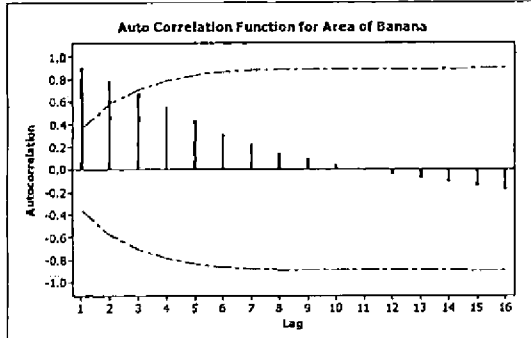
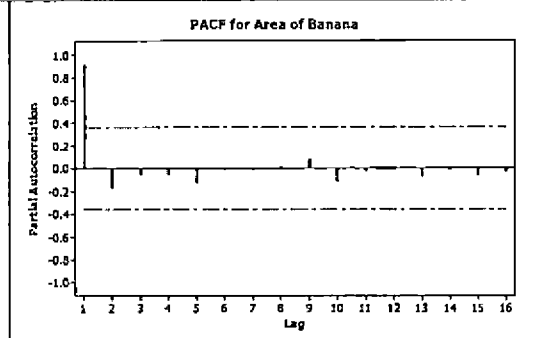


Figure 4.5.9.1(b)
PACF for the area of banana



The ACFs are decaying exponentially and PACF had only one significant lag. So the autocorrelations at lags 2 and above were merely due to the propagation of that at lag 1. Hence the model can be identified as an AR(1) model. The significant Q-values from table 4.5.9.2.(a) and the large number of significant lags of ACF ensured nonstationarity of the series.

Table 4.5.9.1(a) ACF and PACF for area of banana with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8117	0.8117	-0.3780	0.3780	19.8396	0.00
2	0.6325	-0.0769	-0.3780	0.3780	32.3710	0.00
3	0.4807	-0.0289	-0.3780	0.3780	39.9085	0.00
4	0.3655	0.0075	-0.3780	0.3780	44.4555	0.00
5	0.3074	0.0875	-0.3780	0.3780	47.8180	0.00
6	0.2358	-0.0803	-0.3780	0.3780	49.8916	0.00
7	0.1695	-0.0251	-0.3780	0.3780	51.0167	0.00
8	0.1163	-0.0019	-0.3780	0.3780	51.5742	0.00
9	0.0672	-0.0239	-0.3780	0.3780	51.7707	0.00
10	0.0241	-0.0385	-0.3780	0.3780	51.7975	0.00
11	-0.0244	-0.0542	-0.3780	0.3780	51.8267	0.00
12	-0.0653	-0.0220	-0.3780	0.3780	52.0496	0.00
13	-0.1086	-0.0601	-0.3780	0.3780	52.7089	0.00
14	-0.1469	-0.0426	-0.3780	0.3780	54.0080	0.00
15	-0.1875	-0.0681	-0.3780	0.3780	56.3031	0.00
16	-0.2180	-0.0282	-0.3780	0.3780	59.6873	0.00
17	-0.2535	-0.0817	-0.3780	0.3780	64.7178	0.00
18	-0.2719	-0.0160	-0.3780	0.3780	71.1495	0.00
19	-0.2908	-0.0650	-0.3780	0.3780	79.4258	0.00
20	-0.3035	-0.0382	-0.3780	0.3780	89.7291	0.00

The best ranked model for the prediction of area of banana was identified as ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in Table 5.2.1(b) and 5.2.1(c).

Table 5.2.1(b) Statistics calculated for the best diagnosed model for area of banana

R-squared	0.982	Normalized BIC	15.48
RMSE	2178.678	Ljung-Box Q	10.95
MAPE	5.082	DF	18
MAE	1448.722	Sig.	0.897
MaxAPE	16.561	Transformation	Natural log
MaxAE	6466.553	Difference	1

Table 4.5.9.1.(c) : Estimates of the parameters for ARIMA(0,1,0) model for area of banana

	Estimate	SE	t	Sig.
Constant	0.063	0.012	5.169	0.000

The final model could be written in the form

$$A_t = A_{t-1} e^{0.063}, \dots\dots\dots(4.5.9.1)$$

Where A_t denotes the area of banana in the year 't'.

This model was used to forecast the future values of area under banana which could explain about 98.2% of variation in the data. For the post sample period forecasts, the MAPE came down to 4.97% from that of the sample period which was 5.08% indicating the high forecasting power of the model.

Table 5.2.1 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
2900.206	4.968	3627.178	6249.648

The area of banana predicted for 2007-08 to 2011-12 showed an increasing trend with more or less constant growth rate. The growth rates for the years from 2007-08 to 2011-12 are 6.50 percent.

The shift from rice farming to other agricultural occupations served as a significant factor in the spread of banana cultivation in paddy lands. Since banana cultivation requires heavy irrigation, the initial plantations are seen naturally beside the river. The return per rupee of investment was less than unity for rice and it was substantially more than unity for banana. Nonavailability of labour and higher profit from banana were the major factors leading to shift in area from rice to banana.

Figure 4.5.9.1.(c) Actual and estimated values for area of banana using ARIMA (0,1,0)

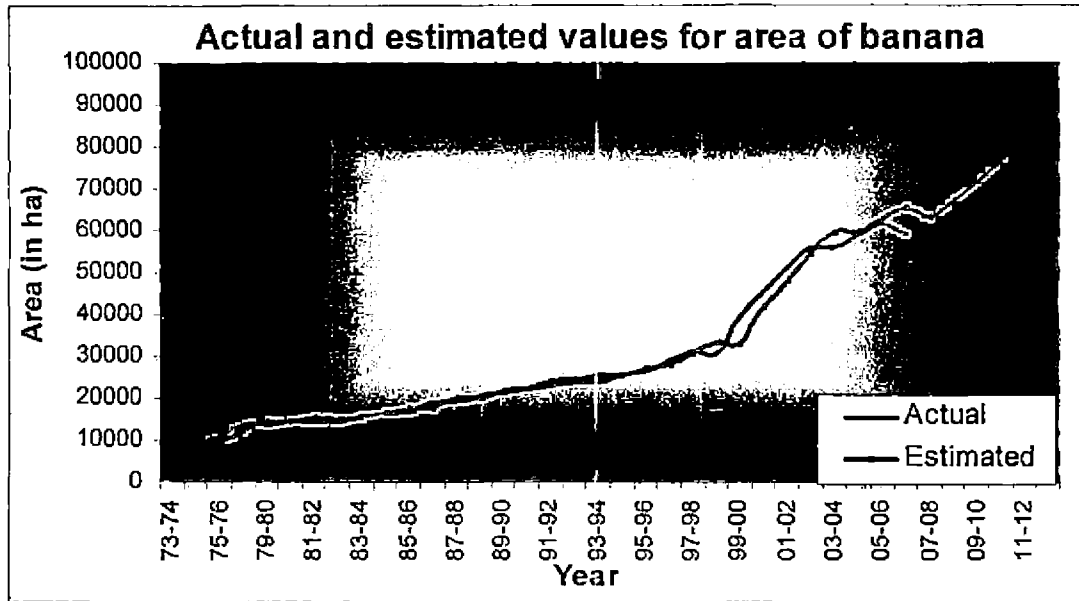


Figure 4.5.9.1.(d) Deviation from forecasts for area of banana

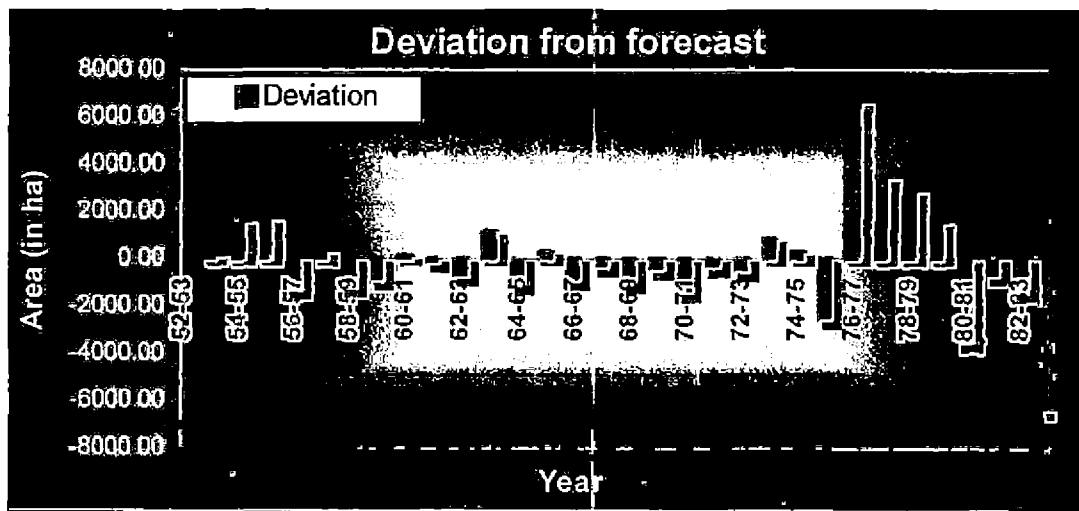


Table 4.5.9.1(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	55906.000	59287.914	-6.05
04-05	58866.000	59541.390	-1.15
05-06	61400.000	62693.870	-2.11
06-07	59143.000	65392.648	-10.57

Table 4.5.9.1(f) : Estimated Values for area of banana from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
62988.882	67084.850	71447.166	76093.149	81041.25

4.5.9.2. Production

Figure 4.5.9.2 (a)
ACF for the production of banana

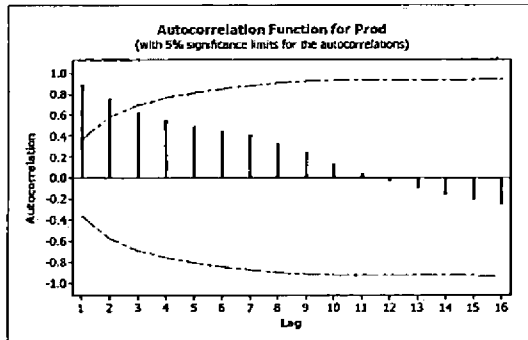
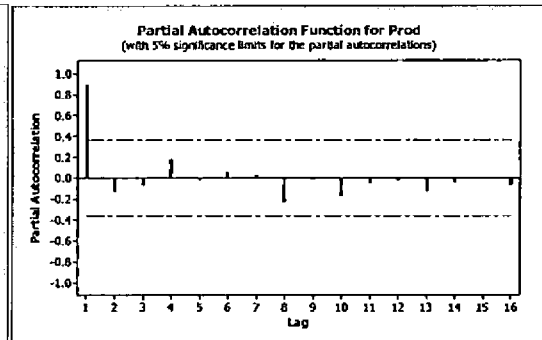


Figure 4.5.9.2 (b)
PACF for the production of banana



The autocorrelations were significant for a large number of lags indicating the nonstationarity behaviour of the data and ACFs were decaying exponentially with the PACF showed only one significant lag which showed that the autocorrelations at lags 2 and above were merely due to the propagation of the autocorrelation at lag 1. Hence the model could be identified as an AR(1) model. The significant Q-values from table 4.5.9.2.(a) ensured nonstationarity of the series.

Table 4.5.9.2 (a) ACF and PACF for production of banana with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.8572	0.8572	-0.3780	0.3780	22.1261	0.00
2	0.7360	0.0050	-0.3780	0.3780	39.0933	0.00
3	0.6368	0.0180	-0.3780	0.3780	52.3227	0.00
4	0.5599	0.0342	-0.3780	0.3780	62.9951	0.00
5	0.4899	-0.0072	-0.3780	0.3780	71.5383	0.00
6	0.3916	-0.1387	-0.3780	0.3780	77.2561	0.00
7	0.2918	-0.0763	-0.3780	0.3780	80.5904	0.00
8	0.1909	-0.0901	-0.3780	0.3780	82.0925	0.00
9	0.0984	-0.0682	-0.3780	0.3780	82.5139	0.00
10	-0.0042	-0.1318	-0.3780	0.3780	82.5148	0.00
11	-0.0834	-0.0077	-0.3780	0.3780	82.8554	0.00
12	-0.1617	-0.0775	-0.3780	0.3780	84.2204	0.00
13	-0.2316	-0.0534	-0.3780	0.3780	87.2194	0.00
14	-0.2827	-0.0100	-0.3780	0.3780	92.0319	0.00
15	-0.3258	-0.0258	-0.3780	0.3780	98.9566	0.00
16	-0.3565	-0.0285	-0.3780	0.3780	108.0036	0.00
17	-0.3759	-0.0095	-0.3780	0.3780	119.0668	0.00
18	-0.3975	-0.0671	-0.3780	0.3780	132.8131	0.00
19	-0.4047	-0.0157	-0.3780	0.3780	148.8439	0.00
20	-0.4156	-0.0871	-0.3780	0.3780	168.1629	0.00

The best ranked model for the forecasting of production of banana was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in Table 4.5.9.2 (b) and 4.5.9.2(c)

Table 4.5.9.2(b): Statistics calculated for the best diagnosed model for production of banana

R-squared	0.940	Normalized BIC	20.66
RMSE	29015.734	Ljung-Box Q	13.47
MAPE	7.211	DF	18
MAE	18889.140	Sig.	0.763
MaxAPE	45.118	Transformation	Nil
MaxAE	83035.355	Difference	1

Table 4.5.9.2(c): Estimates of the parameters of ARIMA(0,1,0) model for production of banana

	Estimate	SE	t	Sig.
Constant	12845.355	5211.380	2.465	0.020

The final model could be written in the form

$$Y_t = Y_{t-1} + 12845.36, \dots\dots\dots (4.5.9.2)$$

Where Y_t denotes the production of banana in the year 't'.

This model had an R^2 of 94% so that it could explain 94% variation in the data and for the post sample period the MAPE was reduced to 3.88% which is a clear indication of the forecasting power of the model for future years. All the measures for post sample period were less than that of the sample period indicating high forecasting performance of the model.

Table 4.5.9.2.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
18095.070	3.884	23214.052	40902.360

The production of banana predicted for 2007-08 to 2011-12 showed an increasing trend with decreasing growth rate. The growth rates for the years from 2007-08 to 2011-12 are 2.70, 2.62, 2.56 and 2.49 percent respectively.

At present, the major part of the area under commercial banana cultivation is spread in paddy fields on the river side. Banana cultivation has been recognized as one of the best remunerative crop suited for Kerala due to its attractive marketing facility. Programmes should be implemented focussing the increase in the production, productivity and regulate cultivation to ensure best market price for the growers.

Figure 4.5.9.2(c) Actual and estimated values for production of banana using ARIMA(0,1,0)

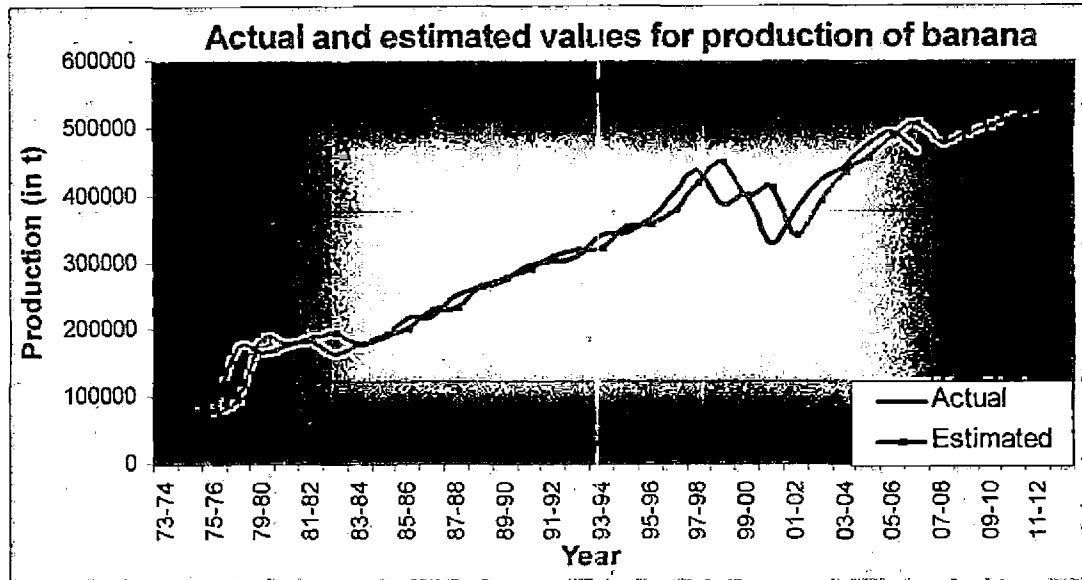


Figure 4.5.9.2.(d) Deviation from forecasts for production of banana

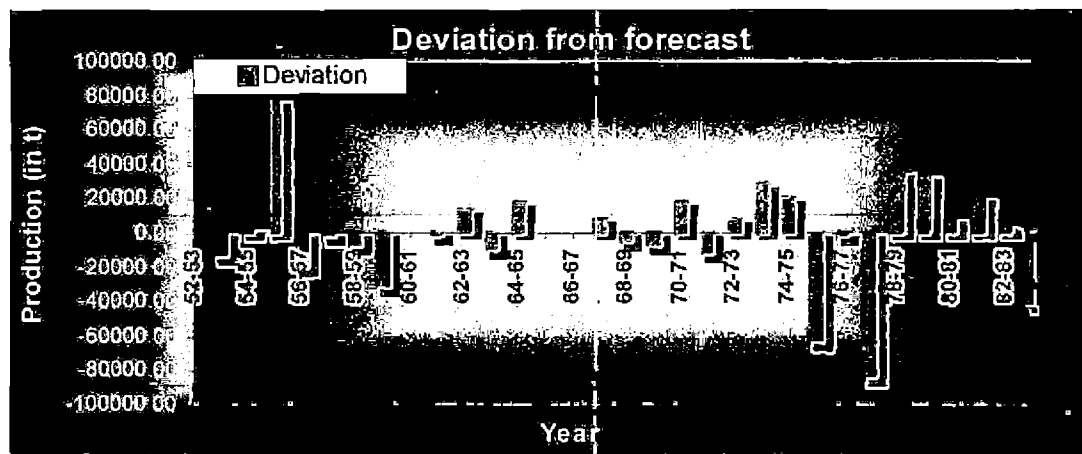


Table 4.5.9.2(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	442220.000	434654.360	1.71
04-05	475371.000	455065.360	4.27
05-06	491823.000	488216.360	0.73
06-07	463766.000	504668.360	-8.82

Table 4.5.9.2 (f): Estimated production of banana from 2007-08 to 2011-12.

2007-08	2008-09	2009-10	2010-11	2011-12
476611.360	489456.720	502302.080	515147.440	527992.80

4.5.9.3. Productivity

Figure 4.5.9.3 (a)
ACF for the productivity of banana

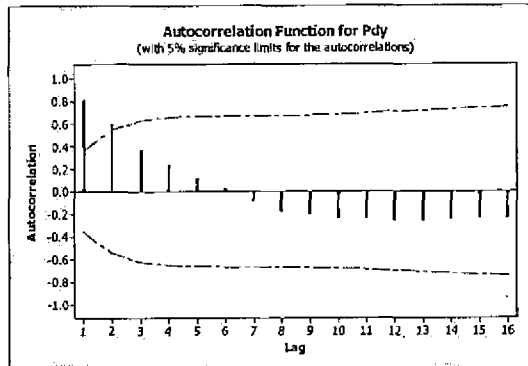
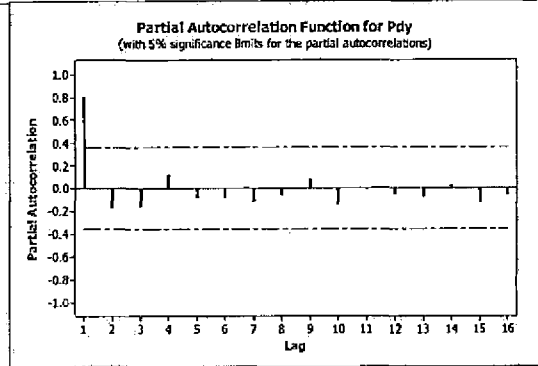


Figure 4.5.9.3 (b)
PACF for the productivity of banana



The ACFs were decaying exponentially and PACF showed only one significant lag which says that the autocorrelations at lags 2 and above were merely due to the propagation of the autocorrelation at lag 1. Hence the model could be identified as an AR(1) model. The significant Q-values from table 4.5.9.3.(a) also ensured nonstationarity of the series.

Table 4.5.9.3 (a) ACF and PACF for productivity of banana with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.7185	0.7185	-0.3780	0.3780	15.5472	0.00
2	0.4006	-0.2390	-0.3780	0.3780	20.5746	0.00
3	0.0657	-0.2614	-0.3780	0.3780	20.7155	0.00
4	-0.0597	0.1793	-0.3780	0.3780	20.8370	0.00
5	-0.0973	-0.0226	-0.3780	0.3780	21.1738	0.00
6	-0.0727	-0.0600	-0.3780	0.3780	21.3709	0.00
7	-0.0657	-0.0246	-0.3780	0.3780	21.5399	0.00
8	-0.0978	-0.0975	-0.3780	0.3780	21.9344	0.00
9	-0.1068	0.0366	-0.3780	0.3780	22.4302	0.00
10	-0.1328	-0.0854	-0.3780	0.3780	23.2429	0.00
11	-0.1466	-0.0863	-0.3780	0.3780	24.2944	0.00
12	-0.1660	-0.0359	-0.3780	0.3780	25.7327	0.00
13	-0.1688	-0.0553	-0.3780	0.3780	27.3271	0.00
14	-0.1653	-0.0556	-0.3780	0.3780	28.9732	0.00
15	-0.1534	-0.0564	-0.3780	0.3780	30.5097	0.00
16	-0.1415	-0.0655	-0.3780	0.3780	31.9349	0.00
17	-0.1553	-0.1099	-0.3780	0.3780	33.8243	0.00
18	-0.1611	-0.0574	-0.3780	0.3780	36.0817	0.00
19	-0.1958	-0.1533	-0.3780	0.3780	39.8349	0.00
20	-0.2426	-0.1938	-0.3780	0.3780	46.4175	0.00

The best ranked model for the prediction of productivity was ARIMA(0,1,0) with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in Table 4.5.9.3 (b) and 4.5.9.3(c).

Table 4.5.9.3 (b): Statistics calculated for the best diagnosed model for Productivity of banana

R-squared	0.706	Normalized BIC	14.56
RMSE	1374.291	Ljung-Box Q	3.19
MAPE	7.036	DF	18
MAE	774.019	Sig.	1.000
MaxAPE	42.561	Transformation	Nil
MaxAE	5399.356	Difference	1

Table 4.5.9.3(c): Regression results for ARIMA(0,1,0) model for predicting productivity of banana

	Estimate	SE	t	Sig.
Constant	1.123	246.830	0.005	0.996

The final model could be written in the form

$$P_t = P_{t-1} + 1.123, \dots\dots\dots(4.5.9.3)$$

Where P_t denotes the productivity of banana in the year 't'.

Even though equation 4.5.9.3 has an R-square of 71%, its MAPE has considerably reduced to 2.31% indicating the forecasting capability of the model with high reduction in RMSE also for the forecasts of post sample period. All the post sample period statistics are showing the high forecasting power of the above model.

Table 4.5.9.3.(d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
183.073	2.306	206.328	331.715

The productiity of banana predicted for 2007-08 to 2011-12 showed a steady trend with more or less constant growth rate. The growth rates for the years from 2007-08 to 2011-12 are 0.01 percent. Hence the increase in production can only be achieved through the increase in area unless new technological development is developed.

In order to sustain the production and growth potential, it is essential to produce value added products based on banana, so that farmers get an assured price for their produce all the time.

Figure 4.5.9.3 (c) Actual and estimated values for productivity of banana using ARIMA(0,1,0)

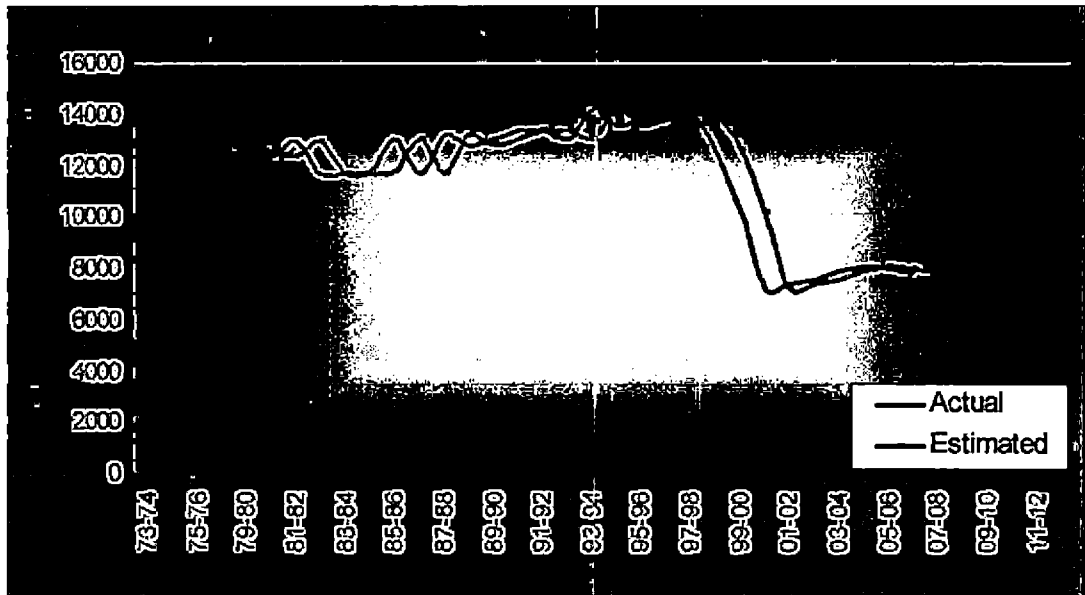


Figure 4.5.9.3 (d) Deviation from forecasts for the productivity of banana

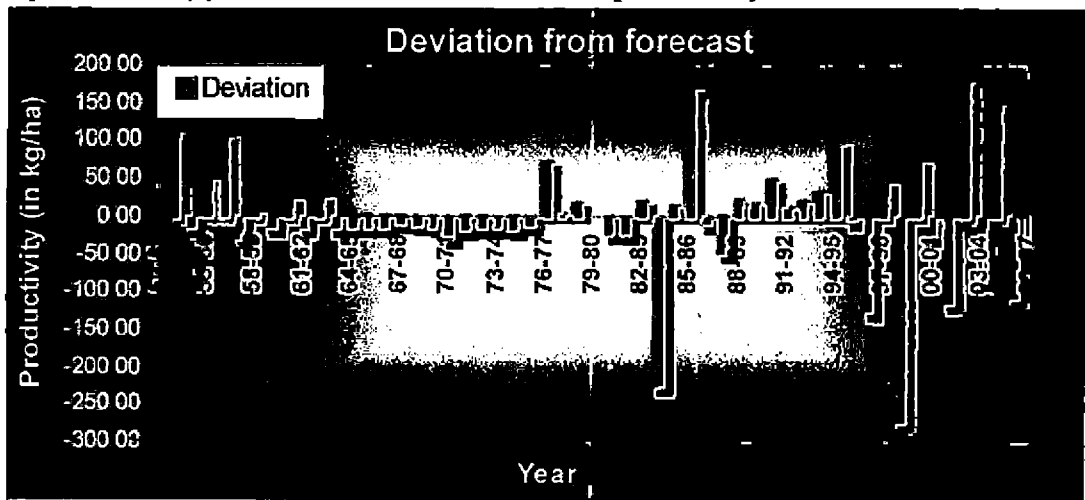


Table 4.5.9.3(e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year.	Actual	Forecast	Percentage Error
03-04	7910.063	7578.349	4.19
04-05	8075.477	7911.186	2.03
05-06	8010.147	8076.600	-0.83
06-07	7841.435	8011.270	-2.17

Table 4.5.9.3 (f) : Estimated values for productivity of banana from 2007-08 to 2011-12

2007-08	2008-09	2009-10	2010-11	2011-12
7842.558	7843.681	7844.804	7845.927	7847.05

4.5.9..4. Price

Figure 4.5.9.4(a)
ACF for the price of banana

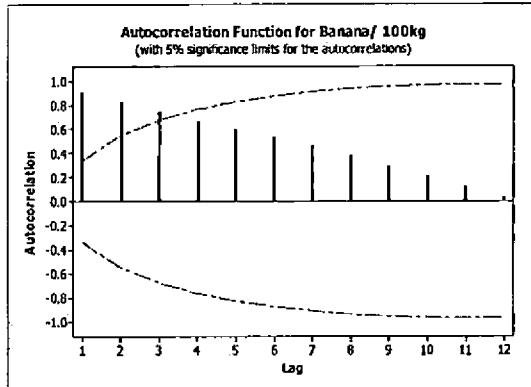
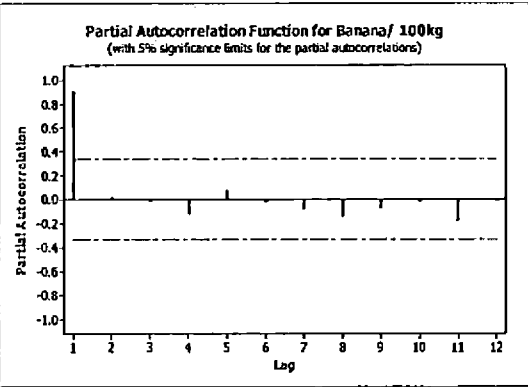


Figure 4.5.9.4(b)
PACF for the price of banana



The ACF showed a declining trend with only one significant spike for the PACF which is a clear indication of an AR(1) model. The large number of significant ACFs and the significant Q-values in Table 4.5.9.4 (a) showed the nonstationarity behaviour of the data.

Table 4.5.9.4(a) ACF and PACF for price of banana with Q Stat and significance

Time Lag	AC	PAC	Lower Bound	Upper Bound	Q-Stat	Prob
1	0.9262	0.9262	-0.3536	0.3536	28.4003	0.00
2	0.8534	-0.0315	-0.3536	0.3536	53.3731	0.00
3	0.7489	-0.2630	-0.3536	0.3536	73.3140	0.00
4	0.6425	-0.0814	-0.3536	0.3536	88.5562	0.00
5	0.5191	-0.1491	-0.3536	0.3536	98.9048	0.00
6	0.4184	0.0915	-0.3536	0.3536	105.9084	0.00
7	0.3016	-0.1495	-0.3536	0.3536	109.7053	0.00
8	0.2052	0.0066	-0.3536	0.3536	111.5421	0.00
9	0.1214	0.0599	-0.3536	0.3536	112.2157	0.00
10	0.0467	-0.0712	-0.3536	0.3536	112.3205	0.00
11	-0.0153	0.0215	-0.3536	0.3536	112.3322	0.00
12	-0.0684	-0.0712	-0.3536	0.3536	112.5817	0.00
13	-0.1094	0.0182	-0.3536	0.3536	113.2578	0.00
14	-0.1560	-0.1205	-0.3536	0.3536	114.7176	0.00
15	-0.1881	-0.0098	-0.3536	0.3536	116.9817	0.00
16	-0.2290	-0.0847	-0.3536	0.3536	120.5779	0.00
17	-0.2700	-0.1187	-0.3536	0.3536	125.9627	0.00
18	-0.3185	-0.0798	-0.3536	0.3536	134.0785	0.00
19	-0.3523	0.0069	-0.3536	0.3536	144.9086	0.00
20	-0.3866	-0.0016	-0.3536	0.3536	159.2567	0.00

ARIMA(0,1,0) was identified as the best model for the prediction of price of banana with minimum Normalised Bayesian Information Criteria (BIC). The brief outputs are given in Table 4.5.9.4(b) and 4.5.9.4(c).

Table 4.5.9.4(b) Statistics for the best diagnosed model for price of banana

R-squared	0.968	Normalized BIC	8.54
RMSE	68.073	Ljung-Box Q	19.63
MAPE	7.094	DF	18
MAE	46.216	Sig.	0.354
MaxAPE	22.632	Transformation	Natural Log
MaxAE	169.717	Difference	1

Table 4.5.9.4(c) : Regression results for ARIMA(0,1,0) model for predicting price of banana

	Estimate	SE	t	Sig.
Constant	0.072	0.015	4.916	0.000

The final model could be written in the form

$$R_t = R_{t-1} e^{(0.0722)}, \dots\dots\dots (4.5.9.4)$$

Where R_t denotes the price of banana in the t^{th} year.

This model equation (4.5.9.4) had an R^2 of 97% and can be used to forecast the future values of the price of banana. All the post sample period statistical measures of error series were small when compared to that of the sample period which indicate the high power of the model for future predictions.

Table 4.5.9.4 (d) : Post sample period statistics computed for verification of the model

MAFE	MAFPE	RMSFE	MXAFE
12.336	6.929	14.812	21.865

The price of banana predicted for 2007-08 to 2011-12 showed an exponentially increasing trend with more or less constant growth rate. The growth rates for the years from 2007-08 to 2011-12 are 7.47 percent .

Eventhough cultivation of banana is profitable, out of the total production, about 25% goes as waste due to spoilage and only 2% is processed into value added products, the remaining being used in the raw form. Hence major quantity is used as banana as such and that is the only commercial outlet for banana. This causes price imbalance and the price variation is so much, which disheartens the farmers very often. This situation may force the farmers to use another crop and the result would be as same as in the case of banana.

Figure 4.5.9.4 (c) Actual and estimated values for price of banana by ARIMA(0,1,0) model

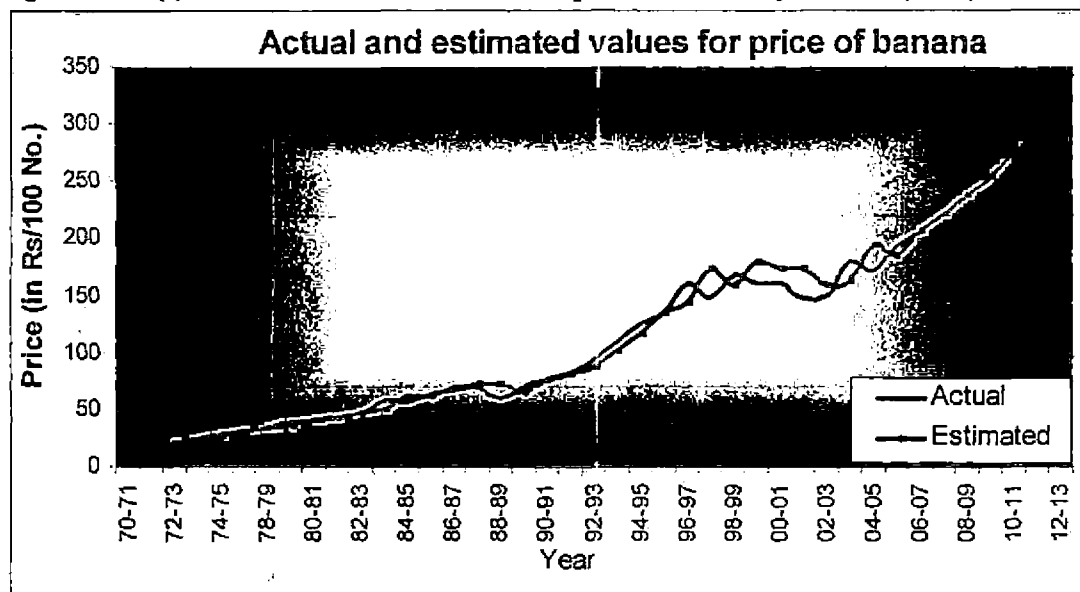


Figure 4.5.9.4 (d) Deviation from forecasts for the price of banana

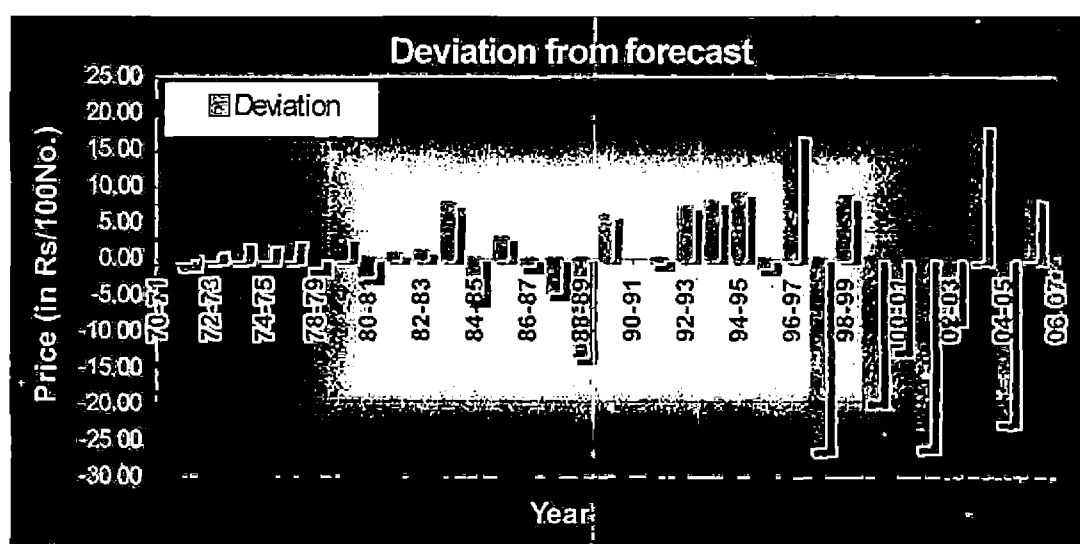


Table 4.5.9.4 (e) : Comparison of the ARIMA(0,1,0) model for 2003-04 to 2006-07

Year	Actual	Forecast	Percentage Error
03-04	179.538	161.309	10.15
04-05	171.077	192.942	-12.78
05-06	191.971	183.849	4.23
06-07	205.174	206.302	-0.55

Table 4.5.9.4 (f) : Estimated values for price of banana from 2007-08 to 2011-12.

2007-08	220.491	2008-09	236.952	2009-10	254.642	2010-11	273.652	2011-12	294.08
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Table 4.5.10. ARIMA models developed for different crops

Crops	Area	Production	Productivity	Price
Coconut	0,1,0	0,1,0	1,1,0	LN 0,1,2
Rubber	1,1,0	LN 0,1,0	1,1,1	0,2,0
Paddy	0,2,1	0,1,0	0,1,0	LN 0,1,0
Virippu	0,1,0	1,1,0	0,1,0	LN 0,1,0
Mundakan	0,1,0	1,1,0	0,1,1	LN 0,1,0
Puncha	0,1,0	0,1,0	0,1,0	LN 0,1,0
Pepper	0,1,0	1,1,0	1,1,0	LN 1,1,0
Cashew	0,1,0	0,1,0	0,1,0	LN 0,1,0
Areca nut	1,1,0	0,1,0	0,1,0	LN 0,1,0
Coffee	0,1,1	LN 0,1,1	0,1,1	-
Tapioca	0,1,0	0,1,4	0,1,0	LN 0,1,0
Banana	LN 0,1,0	0,1,0	0,1,0	LN 0,1,0

Comparison of Regression models developed through cointegration and ARIMA

Comparison of predictability of forecasting models developed by different techniques viz; cointegration technique and ARIMA were compared.

Table : 4.5.11. Comparison of Regression models developed by cointegration and ARIMA

Crop	R ² (%) using cointegration	R ² (%) using ARIMA
Paddy	92.5	98.4
Virippu	92.2	98.2
Mundakan	92.8	96.7
Puncha	83.7	90.3
Tapioca	78.1	95.2
Banana	95.4	98.2
Coconut	66.2	97.6
Areca nut	90.6	89.8
Cashew	67.4	94.5
Rubber	43.8	99.8
Pepper	40.5	97.8

ARIMA models were superior to other models developed achieving a maximum value of R² = 99.8% for the prediction of area of rubber with a very low value of MAFPE = 1.23%. Excellent parsimonious forecasting equations could be generated using the ARIMA technique for all the crops studied.

An overview of changing scenario of Kerala agriculture

Fig. 4.5.10(a) Average area of cultivation during different periods

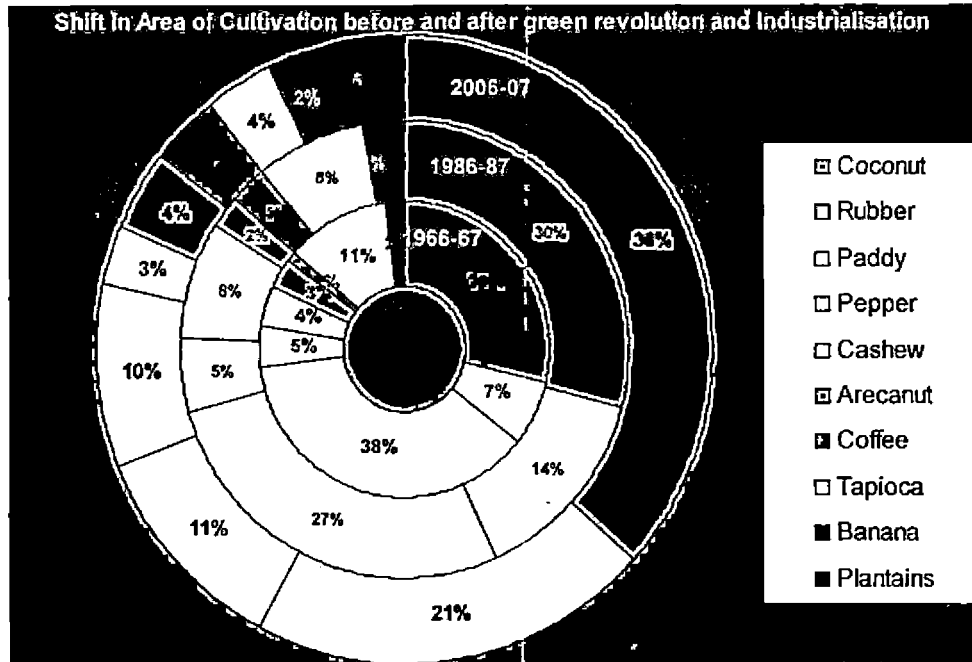
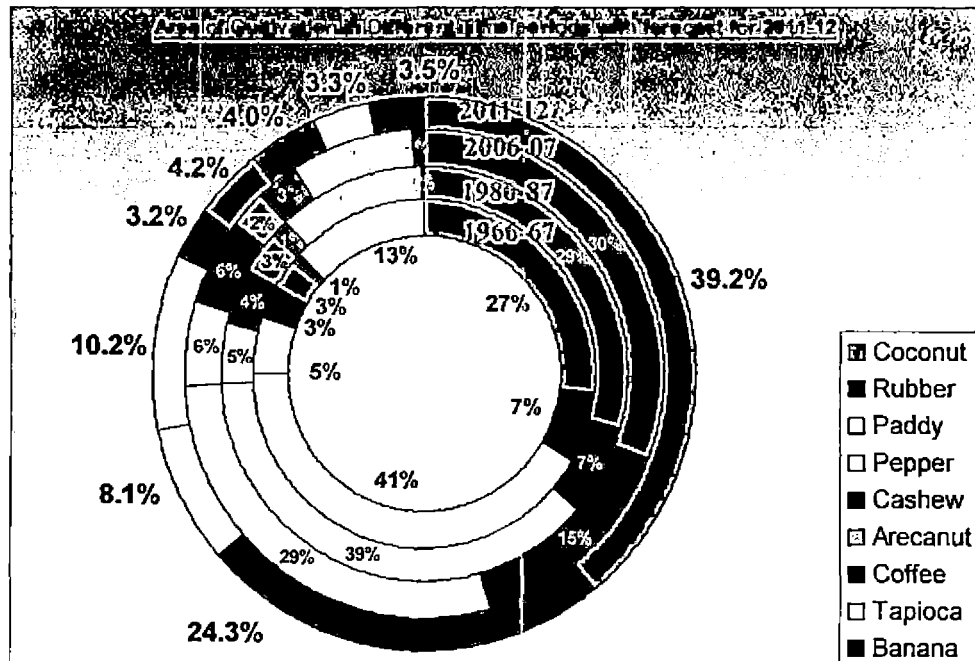


Fig. 4.5.10(b) Area of cultivation in an interval of 20 years with forecast to 2011-12



From the forecasted figures of area under cultivation using ARIMA models, the forecasted figures for rubber recorded the maximum growth (from 7% in 1960 to 24.3% in 2011-12) followed by coconut (from 27% to 39.2%). There was a drastic decline in growth in the case of area under paddy (from 41% in 1960 to 8.1% in 2011-12). Similar declining trend was observed for tapioca also (from 13% to 3.3%). Pepper was a gainer in the case of area under cultivation (5% in 1960 to 10.2% in 2011-12).

Summary

5. SUMMARY

The present study on “Changing scenario of Kerala agriculture – an overview” was carried out in the Department of Agricultural Statistics, College of Horticulture, Vellanikkara during 2006-‘09.

The study dealt with the analysis of shift in area under cultivation, production, productivity and prices of major crops of Kerala using the secondary data for the period from 1952-53 to 2006-07 collected from the Directorate of Economics and Statistics, Thiruvananthapuram. The study envisaged assessment of the general trend in area, production, productivity and prices of the crops and prediction of these values for the future using advanced statistical techniques. The predictability of different forecasting models were also compared. The salient findings of the study are summarized below:

From the results on area, production, productivity and price of different crops, it could be observed that the area and production of the food crops paddy and tapioca had a decreasing trend while that for banana showed an increasing trend. Among the cash crops, coconut, arecanut and pepper were gainers in area and production while cashew showed a decreasing trend for area and production. In the case of plantation crops, there was a tremendous increase in the area and production of rubber. Similar moderate positive growth trend was observed in the case of coffee also. The productivity of all the crops except for cashew had an increasing trend. The prices of almost all the crops showed an increasing trend. The prices of coconut were highly fluctuating during the study period. For pepper and arecanut, the price trends showed similar peaks in 1999-2000.

Modified P-Gan’s method was used to study the individual contribution of area and productivity towards the total production of a crop. In the case of all the crops except paddy and tapioca, the increase in area was the main contributor towards the increased production.

The results of cointegration technique revealed that the series of price of all the crops and their respective area under cultivation could be cointegrated and the regression equations of area on price were fitted to predict the future area under cultivation for different crops. The resulted models showed moderately high values of R^2 . The maximum value of R^2 (95.4%) achieved by this method was in the case of the prediction of area under banana by using its price at a lag of three years. This method of prediction was a failure in the case of the crops like rubber and pepper. Hence alternate methods of forecasts were tried to increase the efficiency of forecasting.

ARIMA models are the most general class of models for forecasting a stationary time series. There was a tremendous increase in the value of R^2 for the prediction equations. The models fitted proved to be the best as the residuals scattered randomly about the horizontal level through zero. Also the models were parsimonious. The best model was selected by SPSS 16.0 by using the measures of R^2 , RMSE (Root Mean Square Error), MAE (Mean absolute Error), MAPE (Maximum Absolute Percentage Error) etc.

From the ARIMA models developed to forecast area, production, productivity and price of major crops of Kerala, it could be observed that the most frequently used model was the Random Walk Model (ARIMA(0,1,0)) followed by Random Walk Model with Drift (ARIMA(1,1,0)) and Simple Exponential Smoothing Model (ARIMA(0,1,1)). All these models were parsimonious and gave more weightage to the recent observations for fitting the regression models. The maximum value of R^2 achieved through this method was for the prediction of area and production of rubber and attained a value of 99.8% and 99.5% respectively.

From the results of the study on relative growth rate of area and production of crops and also from the different forecasting models the following points could be arrived at.

Growth rates of area and production of the cash crop coconut showed a rise during the initial period followed by a decline during 1975-80 and thereafter it recovered gradually and there was a tendency to repeat the same trend of deceleration in the following years.

The plantation crop rubber was a gainer in the area and production due to the conversion of the area from food crops to rubber. This is due to the relative non-profitability of the food crops. Rubber attained the highest positive growth rate among all the crops studied.

The major food crop rice showed declining growth rates in area and production. The decline in area was due to the large scale conversion of area from rice to another crop and also for other non agricultural purposes.

Pepper recorded positive growth rates in area and production during 1985-90, whereas the highest decline of area under tapioca and relatively higher decline for the rice had happened during the period from 1981-82 to 1991-92. Thus shift in cropping pattern has occurred from food crops to non- food crops, which is confirmed by the analysis.

Cashew recorded positive growth rates in area and production only in the initial stages of the study along with rubber and coffee. In all other periods, negative growth rates were recorded in the case of cashew

Even though arecanut lost area and production during initial stages, it recovered during the final stages of the study period with high positive growth rate.

In the case of coffee, area and production showed positive growth rate during the study period due to the combined growth of area and productivity. Among the plantation crops, the only gainer of area was coffee before 1980.

Tapioca, which is a substitute of rice, also followed the same pattern of decline in growth rates both in area and production. Since the tendency of conversion of area under food crops to cash crops was visible from 1975 onwards, the same reason could be attributed here also.

In the case of banana, though growth rates of area and production were positive, growth rate of production was in a decreasing manner.

Most of the studies about cropping pattern of Kerala showed the tendency of coconut in the gain of area from rice. Large portions of the paddy fields were converted during 1981-82 to 1991-92 since the coconut cultivation was profitable at that time. The rational decision of the farmers to convert the paddy fields into coconut gardens had experienced during the eighties.

From the forecasted figures of area under cultivation using ARIMA models, the forecasted figures for rubber recorded the maximum growth (from 7% in 1960 to 24.3% in 2011-12) followed by coconut (from 27% to 39.2%). There was a drastic decline in growth in the case of area under paddy (from 41% in 1960 to 8.1% in 2011-12). Similar declining trend was observed for tapioca also (from 13% to 3.3%). Pepper was a gainer in the case of area under cultivation (5% in 1960 to 10.2% in 2011-12).

References

REFERENCES

- Abdulai, A. 2006. Spatial integration and price transmission in agricultural commodity markets in sub-Saharan Africa. *Agricultural Commodity Markets and Trade: New Approaches to Analyzing Market Structure and Instability* (Ed. Sarris, A. and Hallam, D.). Edward Elgar Publishing Ltd., U.K. pp.163-186.
- Adhikari, M., Paudel, K.P. and Houston, J.E. 2003. Water resources planning for broiler production: econometric and time series analysis. *J. Environ. Syst.* 30(4): 289-301.
- Ahmad, B., Mustafa, K. and Mehdi, M. 2006. Forecasting mango export from Pakistan: an econometric analysis of time series data. *Science-International-Lahore.* 18(3): 253-256.
- Ahmad, S., Khan, I.H. and Parida, B.P. 2001. Performance of stochastic approaches for forecasting river water quality. *Wat. Res. Oxford.* 35(18): 4261-4266
- Alaba, W. 2003. Modelling Opeki river flow for sustainable rural development [online], 29th WEDC International Conference, pp 173-174. <http://wedc.lboro.ac.uk/conferences/pdfs/29/Alaba.pdf> [28-10-08].
- AlEbrahiem, B.A., Timeseries analysis of retail prices of eggs in Saudi Arabia. *Bulletin of Faculty of Agriculture, University of Cairo.* 1996; 47(4): 523-540.
- Antunes, J.L.F. et al. 2007. Effectiveness of influenza vaccination and its impact on health inequalities. *Inter. J. Epidemiology.* 36(6): 1319-1326.
- Atan, I.B. and Metcalfe, A.V., Estimation of seasonal flood risk using a two-stage transformation. *Water-Resources-Research.* 1994; 30(7): 2197-2206.
- Bell, W. 1988. Applying time series models in forecasting Age-specific fertility rates [online], statistical research division report series srd research report number: census/srd/kr-88/19 Available : <http://www.census.gov/srd/papers/pdf/rr88-19.pdf>. [22-09-08].
- Bender, M. and Simonovic, S.P. 1994. Time-series modelling for long-range stream-flow forecasting, *J. Wat. Resour. planning. Mgmt.* 120(6): 857-870.
- Bessler, D.A. 1978. Foresight and inductive reasoning: analysis of expectations on economic variables with California field crop farmers, *Dissertation-Abstracts International, A.* 38: 12, p.74-59; *Diss., Univ. of Calif.,* 209pp.
- Bezbaruah, M.P. 1998. Regional and seasonal variations in the trends of rice production in Assam from 1974-75 to 1994-95. *Indian J. Reg. Sci.* 30(2): 70-83.
- Biondi, P., Monarca, D. and Panaro, A. 1998. Simple forecasting models for farm tractor demand in Italy, France and the United States. *J. agric. Engng Res.* 71(1): 25-35.

- Bordoloi, P.K. and Kakaty, S.C. Variations in production, export and domestic consumption of tea: an econometric study, *Econ. Affairs Calcutta*. 2003; 48(2): 115-120.
- Box, G.E.P. and Jenkins, G.M. (1970), *Time Series Analysis: Forecasting and Control*, San Francisco: Holden-Day.
- Briassoulis, H. 1994. Effectiveness of water-conservation measures in Greater Athens area, *J. Wat. Resour. planning. Mgmt.*. 120(6): 764-777.
- Bustine, C.L. and Palaniswamy. 1994. An analysis of growth trends in principal crops in Kerala, *Agric. Situ. in India* 48(12).
- Calvo, P.I. and Portela, M.M. 2007. Application of neural approaches to one-step daily flow forecasting in Portuguese watersheds. *J. Hydrology*, 332(1/2): 1-15.
- Calvo, P.I., Roldan, J., Luque, L.R. and Estrada, G.J.C. 2003. Demand forecasting for irrigation water distribution systems. *J. Irrig. and Drain. Engng.* 129(6): 422-431.
- Carpio, C.E.B.S. 1981. Production Response Of Cotton In India, Pakistan, And Australia [online], Msc Thesis In Agricultural And Applied Economics, Texas Tech University Available: <http://etd.lib.ttu.edu/theses/available/etd-07312008-31295018555515/unrestricted/31295018555515.pdf> [27-02-09].
- Carter, C. Rausser, G.C. 1981. Commodity futures market efficiency in the soybean complex. *Giannini Foundation of Agricultural Economics, Univ. of Calif.* 139(2), 30pp.
- Carter, C.A. 1981. Grain and oilseeds futures markets: portfolio and efficiency analyses. *Diss. Abstr. Int.* 42(1), p.301. *Diss., Calif. Univ.*
- Carvalho, M.A.C. and Silva, C.R.L. 1990. A method for determining intervention prices. *Agricultura em Sao Paulo*. 37(3): 183-198.
- Carvalho, M.A. and Silva, C.R.L. 1994. Adjustment policies and agricultural prices: a case study. *Agricultura em Sao Paulo*. 41(2): 17-28.
- Castro, P.de., Nacamuli, S. and De-Castro, P. 1986. The production of principal cereals in Italy: evolution and trends. *Options-Mediterraneennes*. pp.193-206.
- Chand, R. and Raju, S.S. 2008. Instability in Indian Agriculture during Different Phases of Technology and Policy [online], *National Centre for Agr. Econ. and Pol. Res. (Indian Council Agr. Res.)*, http://www.ncap.res.in/upload_files/other/oth_12.pdf [29 July 08].
- Chandran, K.P. and Pandey, N.K. 2007. Potato Price Forecasting Using Seasonal Arima Approach [online], *Potato J.* 34(1-2): 137-138, Available: <http://www.nobelonline.net/UserFiles/File/3Fozturk.pdf> [17-02-09].
- Chow, W.S., JonChi, S. and KuoChing, W. 1998. Developing a forecast system for hotel

- occupancy rate using integrated ARIMA models. *Journal of International Hospitality, Leisure and Tourism Management*. 1(3): 55-80
- Chow, W.S., Jon Chi, S. and Kuo Ching, W. 1998. Developing a forecast system for hotel occupancy rate using integrated ARIMA models. *J. Int. Hospitality Leisure and Tourism Mgmt*. 1(3): 55-80
- Coshall, J. 2006. Time series analyses of U.K. outbound travel by air. *J. Travel. Res.* 44(3): 335-347
- Costa, M.C.N., Mota, E.L.A., Paim, J.S. Silva, L.M.V., Teixeira, M.G, and Mendes, C.M.C., 2006. Infant mortality in Brazil during recent periods of economic crisis. *Revista de Saude Publica*. 37(6): 699-706
- Cunha, M.S. da and Margarido, M.A. 1999. Evaluating the impact of post 1986 stabilization programmes on the General Price Index: an application of the Box & Jenkins methodology. *Agricultura em Sao Paulo*. 46(2): 1-18
- Czerwinski, I.A., Estrada, J.C.G. and Casal, J.A.H. 2007. Short term forecasting of halibut CPUE: Linear and non-linear univariate approaches, *Fisheries Research* 86:120-12
- Denbaly, M., Hallahan, C., Joutz, F., Reed, A and Trost, R. 1996. Forecasting seven components of the food CPI: an initial assessment. *Tech. Bull. U.S. Dep. of Agric Washington, D.C., USA* 1851.
- Dickey, D. A., and W. A. Fuller .1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root" *Econometrica*, 49: 1057-1072.
- Dobre, I. and Alexandru, A.A. 2008. Modelling Unemployment Rate Using Box-Jenkins Procedure [online], *Quantitative Methods Inquires. J. Appl. Quantitative Methods*, 3(2) Available: http://jaqm.ro/issues/volume-3,issue-2/pdfs/dobre_alexandru.pdf [22-09-08].
- Doganis, P. et.al. 2006. Time series sales forecasting for short shelf-life food products based on artificial neural networks and evolutionary computing *Journal of Food Engineering* 75: 196-204 Available: www.elsevier.com/locate/jfooden [06-03-09].
- Douvelis, G. 1994. Forecasting sun flower seed prices in the United States: the case of an ARIMA model. *Oil-Crops, Situ. and Outl. (OCS-40)*: 13-15.
- Duenas, C. et.al. 2005. Stochastic model to forecast ground-level ozone concentration at urban and rural areas. *Chemosphere* - .61(10): 1379-1389.
- Dunn, D.L. 1983. An econometric analysis of US farmland prices, 1941 to 1980, *Diss. Abstr. Int., A*. 44(6), p.1866. *Diss. Univ. of New Hampshire*. 139pp.
- Endrighi, E. 1990. The dynamics of price in marketing first quality Parmesan cheese

- (decomposition and Box-Jenkins approach). *Rivista di Economia Agraria*. 45(2): 261-293.
- Estrada, J.C.G. et. al. 2007. Monthly catch forecasting of anchovy *Engraulis ringens* in the north area of Chile: Non-linear univariate approach, *Fisheries Research* 86 : 188–200.
- Fan, S. 1997. Production and productivity growth in Chinese agriculture: new measurement and evidence, *Food Policy*, Elsevier Sci. Ltd. Great Britain, 22(3) , pp. 213-228,
- Gangadharan, P. 2000. Growth component analysis of coconut by P-Gan's method – a relative study of Kerala and India, *Recent Adv. in Plantn. Crops Res.* pp462-465
- Gautam, D.S., Nahatker, S.B. and Rajput, R.L. 1992. Economic analysis of major kharif oilseed crops in Narmada valley: soyabean and sesame. *Bhartiya Krishi Anusandhan Patrika*. 7(4): 285-290.
- Ghafoor, A. and Hanif, S. 2005. Analysis of the trade pattern of Pakistan: past trends and future prospects. *J. Agric. and Social Sciences*. 2005, 1(4): 346-349
- Ghoshray, A. 2002. Agricultural economics society prize essay: asymmetric price adjustment and the world wheat market. *J. Agr. Econ*. 53(2): 299-317
- Giriappa, S. 1995. *Plantn. econ. in India*, M.D. Publications. 151p.
- Gopikuttan, G. and K.N.P. Kurup .2004. Paddy land conversion in Kerala: An inquiry into ecological and economic aspects in a midland watershed region. Kerala Research Programme on Local Level Development, Centre for Development Studies, Thiruvananthapuram. Available: <http://krpcds.org/report/parameswarakurup.pdf>
- Gordon, K., Lagrange, S. and Riboud, C. 1984. Measuring country exposure to commodity price uncertainty. *Eur. Rev. of Agric. Econ.*, 11: 3, 285-301.
- Gujarati, D.N. 2005. *Basic Econometrics*, 4th Edition, Mc.Grawhill, 1013p.
- Gupta, B.S., Mathur, B.K. and Purohit, M.L. 1992. Trend, growth and technological development of pearl millet (*Pennisetum glaucum*) crop in different agro-climatic zones of western Rajasthan. *Indian J. Agr. Sci.* 62(4): 273-275.
- Gupta, S., Mayer, T., A test of the efficiency of futures markets in commodities. *Weltwirtschaftliches-Archiv*. 1981, 117: 4, 661-671.
- Habibullah, M.S., Baharumshah, A.Z. 1994. Can pepper farmers predict white pepper prices using changes in black pepper prices? An empirical study. *Borneo-Rev.* 5(2): 157-178
- Hamdi, M.R., Bdour, A.N. and Tarawneh, Z.S. 2008. Developing Reference Crop Evapotranspiration Time Series Simulation Model Using Class a Pan: A Case Study for

- the Jordan Valley /Jordan Jordan[online] *J. Earth and Environ. Sci.* 1(1) 1, pp. 33 - 44. Available : <http://jjees.hu.edu.jo/files/Vol1/N1/004.pdf> [27-02-09]
- Hameed, T., Marino, M.A. and Cheema, M.N. 1996. Time series modeling of channel transmission losses. *Agric. Wat. Mgmt.* 29(3): 283-298
- Haque, M.E., Hossain, M.I., Afroz, K. 1998. Acreage, production and yield growth of rice during last two decades in Bangladesh. *Bangladesh J. Training and Development.* 11(1/2): 47-56.
- Hashmi, S.N.I. and Singh, A.L. 1989. Trend of rice production in western Uttar Pradesh. *Agr. Situation in India*, 44(8): 649-652.
- Herrmann, R. 1986. Better price forecasts with international buffer stocks? A Box-Jenkins approach for the 1980 International Cocoa Agreement. *Stud. in Econ. Anal.* 10: 1, 34-59;
- Hocking, T.D. and Lankin, D. 2005. Fitting an ARIMA model to U.S. Population Data [online] Available : <http://www.ocf.berkeley.edu/~tdhock/science/USPopRatio.pdf>. [06-03-09]
- Holb, I.J. 2008. Monitoring conidial density of *Monilinia fructigena* in the air in relation to brown rot development in integrated and organic apple orchards. *Eur. J. Plant Pathol.* 2008; 120(4): 397-408.
- Holden, D. and Perman, R. (1994): Unit Roots and Cointegration for the Economist, in Rao, B.B. (1994) pp.47-112.
- Hudelson, B.D., Clayton, M.K., Smith, K.P. and Upper, C.D. 1993. Modeling of superimposed spatial patterns of bacterial brown spot of snap bean., *Phytopathology* 83(4): 430-438
- Ikeda, Y. 1990. Quality evaluation of agricultural products by their dynamic properties. Description of dynamic properties by an autoregressive-moving average model and its application to quality evaluation. *J. Jpn. Soc. Agric. Mach.* 52(2): 43-49
- Jeromi, P.D. 1994. Growth of pepper economy of Kerala, *Agr. Situ. India.* 48(11): 805-812.
- Jiao, Y et.al. 1994. A study of time series models for *Pectinophora gossypiella*. *J. Huazhong Agric. Univ.* 13(3): 246-249.
- JoChau, V. and Turner, L.W., Regional data forecasting accuracy: the case of Thailand. *Journal-of-Travel-Research.* 2006; 45(2): 186-193.
- Jun, W. and YaQing, L. 2007. Research on the dynamic relationship between China's soybean oil futures and spot price: empirical analysis based on daily data. *J. China Agric. Univ.* 12(6): 6-13.

- Karbus, S. and Jumah, A. 1995. Cointegration and commodity arbitrage, *Agribusiness* 11(3): 235 - 243.
- Kim, J.H. and Moosa, I.A. 2005. Forecasting international tourist flows to Australia: a comparison between the direct and indirect methods. *Tourism-Management*. 2005; 26(1): 69-78 PB: Oxford, Pergamon Press, UK.
- Kim, J.H. 1999. Forecasting monthly tourist departures from Australia. *Tourism Econ.* 5(3): 277-291.
- Klugh, B. and Markham, J. 1985. A Comparison Of Box-Jenkins Time Series Forecasts To Preliminary Milkprice Estimates. Statistical Reporting Service, U.S. Dep. of Agric. Wash. U.S.
- Koutroumanidis, T 2005. A fuzzy classification system and time series modeling of wine production data in EU. *Bulletin-de-l'-OIV*. 2005; 78(887/888): 58-77
- Krishnan, M. Vasisht, A.K. and Sharma, B.M. 1991. Growth and Instability in Kerala Agriculture, *Agric.Situ.India*. 46(1).
- Krishnankutty, C.N. 2001. Forecasting of teak prices in Kerala State, India, using autoregressive integrated moving average models. *Indian J. Forestry*. 24(2): 119-122 PB: Dehra Dun, India: M/S Bishen Singh Mahendra Pal Singh.
- Kulendran, N and Witt, S.F. 2002. Forecasting the demand for international business tourism. *J. Travel Res.* 41(3): 265-271.
- Lakshmi, K.R. and Pal, T.K. 1986. Trend of area, production and productivity of cassava in India, *Agr. Situ. India*. 41: 8, 609-614.
- Lakshmi, K.R. and Pal, T.K. 1988. Growth of crop output in Kerala, *Agr. Situ. India*. 43: 9, 767-771.
- Lal, R.C. Lavania, R.P. 1984. A study of growth rates of major crops of Agra district (U.P.). *J. Agr. and Scient. Res.* 26: 1-2, 29-36:6.
- Lal, S.K., Srinivas, T. and Srivastava, R. 1994. Growth and resource productivity in Bihar agriculture, *Bihar J. Agr. Marketing*. 2(2): 107-111 .
- Lech, P.M. 1998. ARIMA model in forecasting pest outbreaks and fungal epiphytosis, Methodology of forest insect and disease survey in Central Europe Proceedings, First Workshop of the IUFRO WP 70310, Ustron Jaszowiec, Poland, 2124 April, 2328.
- Lee, J.K. and Cheng, C.C 1981. Application of time series analysis and forecasting model on the study of timber prices in Taiwan. *Tech. Bull. Experimental Forest, National Taiwan University*, 47 pp.

- drology 296 38–58 Available: www.elsevier.com/locate/jhydrol. [04-08-08]
- Mesonada, S.J.C. 1985. The consumer price index (IPC) for food and agricultural prices: a dynamic model. *Agricultura-y-Sociedad*. 1985, No. 34, 9-59.
- Miller, S.E. 1982. Predicting time series turning points with ARIMA models. *Dep. of Agric. Econ. and Rural Sociology, Clemson Univ.*, 1206(82), 17pp.
- Min, B.J. 1995. Forecasting for the changes in number of hogs and hog farms. *Korean J. Anim. Sci.* 37(5): 558-566.
- Mishra, A.K. and Desai, V.R. 2006. Drought forecasting using feed-forward recursive neural network Available : www.elsevier.com/locate/ecolmodel ecological modelling 198 : 127–138.
- Mohammadi, K. and Eslami, H.R. 2004. Parameter estimation of seasonal and nonseasonal ARMA model for Karun River streamflow forecasting using goal programming. *J. Agric. Sci., Islamic Azad University. Tehran, Iran* 9(4).
- Mohandas, M. 2005. Agricultural development in Kerala, Kerala Economy-Trajectories Challenges and Implications (Ed. Rajasenan, D. and Gerald, G).
- Montanari, A., Rosso, R. and Taqqu, M.S., Fractionally differenced ARIMA models applied to hydrologic time series: identification, estimation, and simulation. *Water Resources Research*. 1997; 33(5): 1035-1044.
- Moore, D.L. 1989. Price and basis relationships and the use of futures prices to forecast cash prices for live slaughter and feeder cattle markets in and out of position. *Diss. Abstr. Int.* 50(4): p.1024
- Naik, G. and Jain, S.K. 2001. Efficiency and unbiasedness of Indian commodity futures markets. *Indian J. Agr. Econ.* 56(2): 185-197
- Naik, G. and Jain, S.K. 2002. Indian agricultural commodity futures markets: a performance survey. *Econ. and Polit. Weekly*. 37(30): 3161-3173
- Narayana, N.S.S. and Parikh, K.S. 1981., Estimation of farm supply response and acreage allocation: a case study of Indian agriculture, Research Report, International Institute for Applied Systems Analysis. 81-1, 35pp
- Nochai, R. and Nochai, T. 2006. ARIMA Model for Forecasting Oil Palm Price. 2nd IMT GT Regional Conference on Mathematics, Statistics and Applications, [online] Univ. Sains Malaysia, 13-15, June, 2006. Available : [http://math.usm.my/research/ OnlineProc/ST03.pdf](http://math.usm.my/research/OnlineProc/ST03.pdf) [25-08-2008].

- Norscia, S. 1995. A model for forecasting prices of pigs for fattening. *Rivista di Suinicoltura*. 36(6): 51-58.
- Oliveira, R.A., Buongiorno, J. and Kmietek, A.M. 1977. Time series forecasting models of lumber cash, futures, and basis prices. *Forest Sci.*, 23: 2, 268-280.
- Olorunnipa, Z.I. 1988. Alternative forecasting models for farm wheel tractor horsepower purchases. *Diss. Abstr. Int.*, 49:(3), p.565.
- Park, H.S. 1999. Forecasting three-month treasury bills Using ARIMA and GARCH models, [online] <http://www.sdi.re.kr/hspark/wp199911.pdf> [2-09-2008]
- Pei Chih, W. et.al. 2007. Weather as an effective predictor for occurrence of dengue fever in Taiwan. *Acta Tropica*. 103(1): 50-57.
- Promprou, S., Jaroensutasinee, M. and Jaroensutasinee, K. 2006. Forecasting dengue haemorrhagic fever cases in Southern Thailand using ARIMA models. *Dengue Bull.* 30: 99-106.
- Pushpangadan. 1988. Agricultural stagnations in Kerala : an econometric study of tapioca, C.D.S., Trivandrum.
- Rajaraman, I. and Datta, A. 2003. May 3. Univariate Forecasting of State-Level Agricultural Production, *Econ. and Polit.*
- Rajaraman, I. and Datta, A. Univariate forecasting of state-level agricultural production. *Econ. Polit. Weekly*. 2003; 38(18): 1800-1803 PB: Mumbai, India: Sameeksha Trust.
- Rajarathinam, A. and Dixit, S.K. 2007. Fitting of groundnut yield trends in long-term fertilizer experiment a time series model approach. *Crop Research Hisar*. 34(1/3): 92-96.
- Rajo, R.F.J., et.al. 2006. Prediction of airborne *Alnus* pollen concentration by using ARIMA models. *Annals of Agric. and Environ. Med.* 13(1): 25-32.
- Ranade. 1988. Impact of cropping pattern in agricultural production, *Indian J. Agric. Econ.* 35(2).
- Rausser, G.C. and Carter C. 1983. Futures market efficiency in the soybean complex, *Rev. of Econ. and Stat.*, 65: 3, 469-478..
- Rosa, F. 1990. Single and combined forecasts: an example from the dairy sector. *Rivista di Economia Agraria*. 45(1): 27-53.
- Rosa, F. 1991. Lead-lag structures for testing the efficiency of the Italian poultry market. *Rivista di Economia Agraria*. 46(4): 601-631.
- RunSheng, Y. 1999. Forecasting short-term timber prices with univariate ARIMA models. *S. J. Appl. For.* 23(1): 53-58.

- Sabry, M. Latif, H.A.E. and Badra, N. 2007. Comparison Between Regression and Arima Models in Forecasting Traffic Volume [online], Australian Journal of Basic and Applied Sciences, 1(2): 126-136, Available: <http://www.insinet.net/ajbas/126-136.pdf>.
- Saeed, N. et al., Forecasting of Wheat Production in Pakistan using Arima Models Int. J. Agri. Biol., 2(4): 352-353. Available (online) http://www.fspublishers.org/ijab/past-issues/IJABVOL_2_NO_4/25.pdf.
- Sahu, P.K. 2006. Forecasting yield behavior of potato, mustard, rice, and wheat under irrigation. J. Veg. Sci. 12(1): 81-99.
- Salam, M.A., Babu, K.S and Balasubrahmanian, P.P. 1992. trends in cashew production in Kerala - an analysis, The Cashew. 6(3): 3-7.
- Salayo, N.D. 2006. Price relationships in Philippine milkfish markets: univariate and causality analysis. Aquaculture-Economics-and-Management. 10(1): 59-80 PB: Philadelphia, USA: Taylor & Francis.
- San, N.N. and Deaton, B.J. 1999. Feasibility of Integrating Sheep and Crops with Smallholder Rubber Production Systems in Indonesia. (Online) J. Agribusiness 17, 2 (Fall, 1999): 105_122 <http://www.agecon.uga.edu/~jab/Library/F99-03.pdf> [06-03-09].
- Santiago, M.M.D. Camargo, L.B. and Margarido, M.M.A. 1996. The detection and analysis of outliers in the time series of agricultural price indexes in Sao Paulo State. Agricultura em Sao Paulo. 43(2): 89-115.
- Santiago, M.M.D. 2000. An econometric analysis of Brazil's agricultural debt: the case of rural savings. Agricultura em Sao Paulo. 47(2): 21-40.
- Sapsford, D. and Varoufakis, Y. 1990. Forecasting coffee prices: ARIMA versus econometric approaches. Rivista Internazionale di Scienze Economiche e-Commerciali. 37(6): 551-563.
- Sebastian, S., Thomas, K.J. and Thomas, E.K. 2009. Supply response of cashew nuts in Kerala, The Icfai Univ. J. Agric. Econ. 6(4): 79-86.
- Sen, L.K., Shitan, M. and Hussain, H. 2000. Time Series Modelling and Forecasting of Sarawak Black Pepper Price, Malaysia, November 2000.
- Shamsudin, M.N., Arshad, M.F. 1990. Composite models for short term forecasting for natural rubber prices. Pertanika 13(2): 283-288.

- Sharma, J.K., Bharati, R.C., Mandal, S.S. and Pandey, A. 2000. Selection of statistical model to study the growth pattern of the area and production of rapeseed and mustard (*Brassica* spp.). *J. App. Biol.* 10(2): 202-206.
- Shilu, T and WenBiao, H. 2001. Climate variation and incidence of Ross River virus in Cairns, Australia: a time-series analysis. *Environ. Health Perspectives.* 109(12): 1271-1273.
- Singh, R.P., Pandey, R.K. and Kumar, A. 2003. Analysis of growth performance of wheat crop in Jharkhand, *J. res. Birsa Agr. Univ.* 15(2): 217-223.
- Sikka, B.K. and Vaidya, C.S. 1985. Growth rates and cropping pattern changes in agriculture in Himachal Pradesh, *Agric. Situ. India*, 45(11).
- Sinharo, S. and Nair, S.R. 1994. International trade and pepper price variations: a cointegration approach, *Indian J. Agr. Econ.* 49(3): 417-425.
- Sloboda, B.W. 2003. Assessing the effects of terrorism on tourism by use of time series methods. *Tourism Econ.* 9(2): 179-190 PB: London, UK: IP Publishing Limited.
- Smeral, E. 2007. World tourism forecasting - keep it quick, simple and dirty. *Tourism-Economics.* 13(2): 309-317.
- Smeti, E.M., Koronakis, D.E. and Golfopoulos, S.K. 2007. Control charts for the toxicity of finished water modeling the structure of toxicity. *Water Research Oxford.* 41(12): 2679-2689.
- Sridhar, V.N., Dadhwal, V.K., Chaudhari, K.N., Sharma, R., Bairagi, G.D. and Sharma, A.K. 1994. Wheat production forecasting for a predominantly unirrigated region in Madhya Pradesh (India). *Int. J. Remote Sensing.* 15(6): 1307-1316.
- Standaert, J.E. 1981. A comparison of alternative forecasting methods: econometric versus ARIMA. *Diss. Abstr. Int.*, 42(5), p.2229; *Diss., Wash. State Univ.*, 202pp.
- Stergiou, K.I., Christou, E.D., and Pettrakis, G. 1997. Modelling and forecasting monthly fisheries catches: comparison of regression, univariate and multivariate time series methods, *Fisheries Research* 29: 55-95.
- Subbarao, A.V. and Nageswararao, C.R. 1986. An analysis of growth rates in area, production and yield per hectare of burley tobacco. *Agr. Situ. India* 40: 10, 497-900.
- Tchuigoua, F.B. 1990. Agricultural development without de-linking: lessons to be drawn. *African agriculture-the critical choices.* pp.192-216.
- Thirtle, C., Ball, V.E., Bureau, J.C. and Townsend, R. 1995. Accounting for productivity differences in European agriculture: cointegration, multilateral TFPs and R&D spillovers. *Agricultural competitiveness: market forces and policy choice Proceedings of the twenty*

- second International Conference of Agricultural-Economists, Harare, 22-29 August, 1994. 1995; 652-669.
- Thompson,S. and Bohl,M.T.1999. International wheat price transmission and CAP reform. *Agrarokonomische Diskussions beitrage Universitat Giessen.*(53): 11 pp.
- Thomsen, M. 1987. Investigation of the historic and future development of cereal yields in Schleswig-Holstein.. *Wissenschaftsverlag Vauk* 209 pp. 12 pp.
- Tsui,P.S. and Guitjens J.C .1986. Predicting EC for drainage water management. *J. Irrig. and Drain. Engng.* 112: 3, 274-281.
- Unakitan,G. and Akdemir,B. 2007. Tractor demand projection in Turkey, *Biosystems Engineering*, 97: 19–25.
- urovic, N, Gajic, B and Stricevic, R.1998. Influence of rainfall on the groundwater table in irrigation-drainage areas. *Rev.Res.work, Faculty of Agriculture,Belgrade.*43(2):55-62.
- Usowicz,B., Paszczyk,J. and Walczak,R.1991. Description and analysis of the soil temperature dynamics with ARIMA models part II. Analysis., *Zeszyty Problemowe Postepow Nauk Rolniczych.* 396: 173-180.
- Vandervaart, A. W. 2004. Timeseries Analysis, Lecture Note, Vrije Universiteit Amsterdam , 212p.Available : <http://www.scribd.com/doc/2559474/Time-Series-Notes>.
- Vicente, J.R.1994. Agricultural shock, indexation and inflationary acceleration: test of a post-Keynesian model. *Agricultura-em-Sao-Paulo.* 41(3): 39-60.
- Vickner,S.S. 2002. Equity market valuation of supply chain management technology adoption, Paradoxes in food chains and networks Proceedings of the Fifth International Conference on Chain and Network Management in Agribusiness and the Food Industry, Noordwijk, 6-8 June 2002. 352-357.
- Vroomen, H.1991. Forecasting retail fertilizer prices. A combined time series regression analysis approach. *Tech. Bull. U.S. Dep. of Agric.* 1789p.
- Vroomen,H; Douvelis,G .1993. A short-run forecasting model for soybean prices. *Oil-Crops, Situ. and Outlook.* (OCS-37): 15-19.
- Wang,J.H. and Leu, J.Y. 1995. Stock Market Trend Prediction Using ARIMA based Neural Networks [online] Available : http://softcomp.ee.ntou.edu.tw/publications/conference/arima_nn.pdf. [06-03.09].
- Weiss,D. 1992. International price relationships in the light of cointegration models: an introduction to the method from the example of the 'law of one price' for agricultural raw materials. *Agrarokonomische Diskussionsbeitrage Universitat Giessen.*(16): 39p.

- Yayar,R. and Bal,H.S.G.2007. Forecasting of corn oil price in Turkey. *J. App. Sci. Res.*
- Yu,YS. and Wang,G.T.1990. An ARMA model for rainfall-runoff with applications. *Tropical hydrology and Caribbean water resources: Proceedings of the International International Symposium on Tropical Hydrology and fourth Caribbean Islands Water Resources Congress, San Juan, Puerto Rico.* pp. 81-89.
- Yurekcia,K., Kurunca,A. and Ozturkb,,F. 2005. Application of linear stochastic models to monthly flow data of Kelkit Stream *Ecological Modelling* 183 : 67–75.
- Zapata,H.O. and Garcia,P. 1990. Price forecasting with time-series methods and nonstationary data: an application to monthly U.S. cattle prices. *W.J. Agric. Econ.* 15(1): 123-132.
- Zapata,H.O.1988. Bayesian and non Bayesian techniques for forecasting monthly cattle prices. *Diss. Abstr. Int.* 49(1), p.124.
- Zubaidi,A.,B. and Shah,M.H.1994. Price efficiency in pepper markets in Malaysia: a cointegration analysis, *Indian J. Agr. Econ.* 49(2): 205-216.

**Changing Scenario of Kerala Agriculture -
*an overview***

By

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ABSTRACT OF THE THESIS

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ABSTRACT

The present investigations on “Changing scenario of Kerala agriculture – an overview” was carried out in the Department of Agricultural Statistics, College of Horticulture, Vellanikkara during 2006 – ’09. The secondary data on area, production, productivity and price of major crops of Kerala viz; coconut, rubber, paddy (season wise), pepper, cashew, arecanut, coffee, tapioca and banana collected from the Directorate of Economics and Statistics for the period from 1952-53 to 2006-07 were used for the analysis. The main objectives of the study included assessment of trend and growth rates of area, production, productivity and price, testing of the cointegrated movement of price and respective area of each crop, identification of the best ARIMA (Auto Regressive Integrated Moving Average) model for prediction of area, production, productivity and price and comparison of predictability of forecasting models developed by different techniques.

Modified P-Gan’s method helped to understand whether the growth rate in crop production was mainly due to area or productivity. The series of prices and areas of respective crops could be co-integrated and the regression models evolved through this technique resulted in moderately high values of predictability.

ARIMA models were superior to other models developed achieving a maximum value of $R^2 = 99.8\%$ for the prediction of area of rubber with a very low value of MAFPE = 1.23%. Excellent parsimonious forecasting equations could be generated using the ARIMA technique for all the crops studied.

The general findings of the study showed that there was a shift in area from food crops to non-food crops. The production of major food crops, rice and tapioca reached at negative growth rates due to the declining trend of their areas. But production rate of banana has increased due to increase in both area and yield. Among cash crops, both area and productivity growths influenced the production rates. The major cash crops coconut, arecanut and pepper showed positive growth rates. Compared to food crops, cash crops in general showed better growth trends in production. Negative growth rate in the production of cashewnut was due to the decline in area. Among plantation crops, rubber and coffee attained a high production growth rate due to the combined growth of area and productivity. The highest production growth rate and area growth rate were recorded by rubber among all the crops studied.