COINTEGRATED MOVEMENT OF FOOD GRAINS PRODUCTION AND AGRICULTURAL INPUTS: A TIME SERIES ASSESSMENT

By

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(2019-19-008)

DEPARTMENT OF AGRICULTURAL STATISTICS

COLLEGE OF AGRICULTURE

VELLANIKKARA, THRISSUR- 680656

KERALA, INDIA

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THESIS

Submitted in partial fulfillment of the requirement for the degree of

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DEPARTMENT OF AGRICULTURAL STATISTICS

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KERALA, INDIA

2021

DECLARATION

I hereby declare that the thesis entitled "**Cointegrated Movement of Food grains Production and Agricultural inputs: A Time series Assessment**" is a bonafide record of research work done by me during the course of research and the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or other similar title, of any other University or Society.

Place: Vellanikkara

Date: 09.11.2021

Sisira P

(2019-19-008)

CERTIFICATE

Certified that the thesis entitled **"Cointegrated Movement of Food grains Production and Agricultural inputs: A Time series Assessment"** is a record of work done independently by **Ms. Sisira P** under my guidance and supervision and that it has not previously formed the basis for the award of any degree, diploma, fellowship or associateship to her.

Place: Vellanikkara
Date: 09.11.2021

Dr. Ajitha T K
(Chairman, Advisory Committee)
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CERTIFICATE

We, the undersigned members of the advisory committee of **Ms. Sisira P (2019-19-008)**, a candidate for the degree of **Master of Science in Agricultural Statistics**, with major field in **Agricultural Statistics**, agree that the thesis entitled **"Cointegrated Movement of Food grains Production and Agricultural inputs: A Time series Assessment"** may be submitted by **Ms. Sisira P**, in partial fulfilment of the requirement for the degree.

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Dedicated to My Beloved Father and Mother

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CONTENTS

LIST OF TABLES

LIST OF TABLES (Contd.)

LIST OF TABLES (Contd.)

LIST OF TABLES (Contd.)

LIST OF TABLES (Contd.)

LIST OF TABLES (Contd.)

LIST OF TABLES (Contd.)

LIST OF FIGURES

LIST OF FIGURES(Contd.)

LIST OF FIGURES (Contd.)

LIST OF FIGURES(Contd.)

LIST OF FIGURES(Contd.)

Abbreviations

ACF	Auto Correlation Function
AP	Andhra Pradesh
AR	Auto Regressive
ARMA	Auto Regressive Moving Average
ARIMA	Auto Regressive Integrated Moving Average
BIC	Bayesian Information Criteria
CAGR	Compound Annual Growth Rate
DW	Durbin Watson
IQR	Inter Quartile Range
KL	Kerala
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MaxAE	Maximum Absolute Error
MaxAPE	Maximum Absolute Percentage Error
MSE	Mean Square Error
MT	Metric Tonnes
PACF	Partial Autocorrelation Function
$\mathbf{R^2}$	R-Square
RMSE	Root Mean Square Error
SD	Standard Deviation
SE	Standard Error
SES	Simple Exponential Smoothing
SPSS	Statistical Package for the Social Sciences
TE	Triennium Ending
TN	Tamil Nadu
VAR	Vector Auto Regression

Introduction

CHAPTER 1

INTRODUCTION

Agriculture is India's most important economic sector since it ensures food and livelihood security. One of the oldest occupations in world is agriculture and still it is the largest one even today. The modernization of agriculture has supported the use of a wide range of agrochemicals in agricultural fields, including fertilizers, pesticides, micro nutrients and plant growth regulators. Inputs such as total cropped area, fertilizer consumption, pesticide consumption and food grains production as well as its contribution are essential for enhanced growth of agricultural production.

Ahmad *et al*. (2015) has pointed out that cereal grains have been considered as the principal component of human diet for thousands of years and have played a major role in shaping human civilization. Around the world, rice, wheat, and maize and to a lesser extent, sorghum and millets are important staples critical to daily survival of billions of people. More than 50 percent of world inhabitant’s daily caloric intake is derived directly from cereal grain consumption. Most of the grains used for human food are milled to remove the bran (pericarp) and embryo, primarily to meet sensory expectations of consumers.

Today, cereal grains are the single most important source of calories to a majority of the world population. Developing countries depend more on cereal grains for their nutritional needs than the developed world. Close to 60 percent of calories in developing countries are derived directly from cereals, with values exceeding 80 percent in the poorest countries. By comparison, approximately 30 percent of calories in the developed world are derived directly from cereals.

Kumar and Indira (2017) have reported that India has faced shortages of food during the time of independence and was a dependent on other countries and had to import food grains from there. However, with concentrated efforts, the country could attain self-sufficiency and agricultural production has significantly increased.

Sharma (2014) in his study, revealed that according to ministry of agriculture data, total food grains production rose from about 102 million tons in the triennium ending (TE) 1973–1974 to about 253 million tons in TE2012–2013, a 148 percent increase (GoI 2013). Meanwhile, the total area under food grains, which accounted for nearly three-fourths of the total cropped area in early 1970's, declined to 63.6 percent in TE2011–2012 and total area under food grains declined from 125 million hectares (ha) in the 1970s to 122 million ha in the 2000s. This dramatic increase in food grains production was the result of a 133 percent increase in crop yields between TE1973–1974 and TE2011–2012. During the past two decades, India has lost 2 to 3 million ha of net sown area to non agriculture purposes.

Using food grains as a proxy for food, availability of food grain is given by domestic production net of feed, seed and wastage plus net imports plus draw-down of stocks (Swaminathan and Bhavani, 2013). Demand is described as a consumer's need or desire and willingness to pay a price for a specific good or service. Demand and supply prospects of food commodities are important indicators to the country's food security concerns. Therefore, analysing and forecasting demand and supply of agricultural commodities are a challenging task.

Regarding fertilizers and its consumption, fertilizer together with seed and irrigation, has been highlighted as one of the three most critical variables for increasing agricultural production and sustaining food self-sufficiency in India. For agricultural production, fertilizer is an important component. And it is one of the key instruments to maintain the tempo of agricultural production as studies have indicated that it has contributed about 50 per cent of increased food grain production in the world.

Sharma and Thaker (2011) stated that fertilizer consumption in India has been increasing over the years and today India is one of the largest producers and consumer of fertilizers in the world. By 2009- '10, total fertilizer consumption in the country was 26.49 million nutrient tonnes. Importance of fertilizes in yield improvement, which is essential for achieving increased agricultural production, further increases because there is little scope for bringing more area under cultivation as well as majority of Indian soils are deficient in many macro and micro nutrients.

The key to enhanced and maintained crop production is the administration of essential plant nutrients, notably macro and micro nutrients, in the precise quantity and proportion, using the proper method and timing. Because the intensity of fertiliser use varies from state to state and area to area, it is critical to understand fertiliser use pattern in the country over time, as well as the impact of factors influencing fertiliser consumption at the national and state levels.

Sharma (2014) has opined that fertilizer use has been and will continue to be a major factor in increasing agricultural production and very few countries, even advanced ones, has relied entirely on the free market system for fertilizer pricing.

There has been a shift in consumption pattern of fertilizer over the years. In the beginning of eighties, the fertilizer consumption was nearly one third but now it stands at around 50 per cent. This change in the consumption pattern is mainly due to shift in cropping pattern from food to cash crops during the past two decades caused by spread of irrigation facilities.

Yadav and Dutta (2019) stated that pesticides are an integral part of modern agriculture. The use of pesticides in agriculture is obvious for the prevention of crop-damaging pests, fungus, unwanted plants (weeds) and a number of crop-eating animals like rodents etc.

The adverse effects of agriculture on environment are direct and indirect in nature (Karunakaran, 2016). The overuse of chemical fertilisers and pesticides are coming under direct effects. Meanwhile comparing with other states in India, consumption of chemical fertilisers in Kerala was high. Nearly 20,000 people in developing countries die each year because of pesticide consumption through their food (Bhardwaj and Sharma, 2013).

Agricultural land area or total cropped area is typically, land devoted to agriculture, the systematic and controlled use of other forms of life particularly the rearing of livestock and production of crops to produce food for humans. Agricultural land area under cultivation of food grains production is an important key element to increase the food production.

The total land area of the world is 13.2 billion hectares. Currently, 12 percent (1.6 billion ha) is used for agricultural crop cultivation, 28 percent (3.7 billion ha) is covered by forest, and 35 percent (4.6 billion ha) is made up of grasslands and woodland ecosystems. Over the last 50 years, the world's agricultural land has increased by 12% (Kanianska, 2016). Many researchers have already revealed that growth rate of area under food crops in Kerala was declining. Kerala's agricultural landscape shows a high concentration of non-food crops.

The crops which are having high demand in the international market are selected by the farmers and it is the major feature of the cropping pattern of agriculture in Kerala. Another remarkable aspect of Kerala’s agricultural development is the emergence of cash crops as 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 (Unnikrishnan, 2009).

Indian agriculture has seen a huge increase in crop yield and productivity. The disparity between supply and demand has an impact on prices and profitability, which has a negative impact on the poor people and farming community, and requires policy interventions to address the problem in the future.

Sharma (2014) pointed out in his study that the rise in the share of N and the decline in the share of P and K fertilizers during the 1990s was mainly because of slow growth in the consumption of P and K fertilizers compared with N fertilizers due to the decontrol of P and K fertilizers and the relatively high increase in their prices via N fertilizers, which remained almost stable during the decade, but still prices of these fertilizers were higher than nitrogenous fertilizers.

The production capacity of food grains of Kerala being comparatively low, it depends mainly on Andhra Pradesh and Tamil Nadu for the import of food grains. There exists a significant amount of disparity in total food grain production and different agricultural inputs like cropped area, fertiliser consumption and pesticide consumption in different states of India viz; Kerala, Andhra Pradesh and Tamil Nadu. The co integrated movement of food grain production with different agricultural inputs also attracts our attention and time series models can be well employed to study phenomenon like this. With this background, an attempt was made:

- To study the trend and co integrated movement of food grains production and agricultural inputs for India and selected states viz; Kerala, Andhra Pradesh and Tamil Nadu
- To develop suitable time series models for total cropped area, fertiliser consumption, pesticide consumption and food grains production with respect to India as well as for selected states
- To capture the statistical divergence between selected states
- To estimate the imbalance in the use of fertilizers in different districts of Kerala

Scope of the study

This is a pioneering study to assess the cointegrated movement of food grains production and agricultural inputs for India as well as selected states of India based on secondary data. It also tries to identify the input factors which discriminates Kerala from other chosen states of India. Normally farmers do not follow the actual recommendation dose of fertilizers. The farmers' concept regarding the ratio of fertilizers significantly deviates from the recommended dose. Hence an attempt to estimate the imbalance in the use of fertilizers in different districts of Kerala also has been made.

Review of Literature

CHAPTER 2

REVIEW OF LITERATURE

A critical review of literature to give evidence and support to the study conducted and conclusions made have been incorporated. It assisted in determining the methodologies employed in previous studies on the same or related themes. The review of literature is presented in different parts below in accordance with the objectives.

2.1 Demand for food grains and performance of agricultural inputs

2.2 Trend Analysis

2.3 Compound Annual Growth Rate

2.4 Time series modeling for forecasting

2.5 Imbalance in nutrients

2.6 Cointegrated movement of variables

2.1 Demand for food grains and performance of agricultural inputs

Hazell (1982) made a systematic investigation into the elements of change in the variability of food grains production in India. Decomposition analysis was used to deal with the decomposition of the components of change in the mean and variance of total cereal production.

The pesticide consumption and output pattern in agriculture in India, and state wise were reported by Agnihotri (2000). And they mentioned that the decline in pesticide consumption was mostly due to the ban or restriction on the use of organochlorine pesticides with high application rates, such as HCH (BHC), DDT, aldrin, and others, as well as the implementation of an Integrated Pest Management programme.

Sharma *et al*. (2006) in their study attempted to quantify the changes in instability in the production of food grains between two time periods and to identify the sources of increase or decrease in the instability through decomposition analysis.

Hasan *et al*. (2008) measured the change and instability in area, production and yield of two major cereal crops namely wheat and maize in Bangladesh using different statistical techniques such as correlation and regression techniques.

Kumar *et al*. (2009) estimated future demand for food grains to provide credible estimates of future demand. The added-up estimates obtained at the disaggregated level, in terms of income, lifestyle, and area have been used to arrive at national level estimates.

Sharma and Thaker (2011) gave an idea about the fertilizer consumption trends and then identified the main aspects of fertilizer demand and established the fertilizer demand scenarios for India.

Devi *et al*. (2017) described the trend and growth rate of pesticide consumption across the states in India and pointed out the need for a detailed look on the pesticide-use pattern, distribution systems and regulatory mechanism at a micro level.

Priscilla *et al*. (2017) conducted an investigation and revealed that, the yield effect was greater than the area effect for food grains, which could be attributable to increased usage of high yielding vegetable and fruit kinds. The area effect contributed more than the yield effect and interaction effects, implying that steps should be taken to boost their productivity.

Shiksha and Mittal (2017) examined the factors that influenced the production of different types of food grains in India and identified the factors which affected the production of food grains and emphasized the impact of production variables (inputs) on the expansion of India's food grain production. The OLS regression model was used in that analysis.

Subash *et al*. (2017) opined about the brief issues in the context of Indian pesticide industry, trend in consumption of pesticides in India and regulations and procedures for testing pesticides in India. They came to a conclusion that, to regulate and encourage the use of cost-effective and environmentally safe pesticides, uniformity in testing procedures, deregistration of out-of-date hazardous pesticides, safe application properties, and farmer awareness, strengthening the pesticide industry and safe application of pesticides were required.

Mary and Paul (2018) made a modest attempt to analyse changes in fertiliser consumption growth rate, cultivated area, irrigated area, and climatic conditions. And the study's findings show that the area under cultivation, production, and yield of rice in India has gradually increased over the study period, with the growth in productivity of major crops being the primary reason for this outstanding performance in agriculture production.

Shabbir and Yaqoob (2019) made an investigation for a comparative analysis about whether the productivity or area of the crop, in the countries especially India and Pakistan and also examined which country had exploited natural and technological inputs most. Tools such as ARDL (autoregressive distributed lag regression model) and TFPC (total factor productivity) were used for the analysis.

Yadav and Dutta (2019) conducted a research survey to assess the consumption pattern of pesticides, farmer's knowledge about the handling and application of pesticides and their practices on pesticide usage. They had undertaken a field survey with 500 farmers and concentrated on group discussion, field observation, interviews and questionnaires. The results showed that organophosphates were the most frequently used pesticide followed by neonicotinoid and pyrethroid. And also observed that scientific knowledge about the handling and spraying of pesticides by farmers were very poor.

2.2 Trend Analysis

Kannan and Sundaram (2011) had made an attempt to study and discussed the trends and patterns in the growth of the crop sector both national and state levels. It has also estimated crop output growth model to analyse its determinants at the all-India level.

Sharma and Thaker (2011) gave an idea about the fertilizer consumption trends and then identified the main aspects of fertilizer demand and established the fertilizer demand scenarios for India.

Sharma (2012) reported from a study of trends in location, demand and productivity of food grains that the linear, quadratic and exponential functions were excellent to evaluate the area, productivity and production of food grains. Linear functions were used to match the trend. The compound growth rate, coefficient of variation, and instability index were also determined.

Abid *et al*. (2014) conducted a study with a view to analyse growth and trend in area, production and yield of major crops of Pakistan using compound growth rate as well as trend analysis and semi-log model.

Ahmad *et al*. (2015) compared the significant growth rates and trends for variables such as area, production and productivity of cereals in India and Nigeria, as well as investigated the significant growth rates and trends for those variables in India and Nigeria.

Desai *et al*. (2017) did an investigation to analyse consumption pattern and production of chemical fertilizers and to study various factors influencing the consumption pattern, determinants of fertilizer use among states and districts in the country. Results from the investigation showed that regarding production and consumption of fertilisers in India and across the states over the years (1980-2013) there was a substantial growth. Production showed an increasing trend and consumption showed a positive and significant growth during kharif and rabi.

Devi *et al*. (2017) described the trend and growth rate of pesticide consumption across the states in India and pointed out the need for a detailed look on the pesticide-use pattern, distribution systems and regulatory mechanism at a micro level.

Devi *et al*. (2017) examined the trend and growth in area, production and yield of pulses and to estimate the interaction between the area and yield through decomposition analysis for increasing production of pulses.

Ganesan and Dhanalakshmi (2017) investigated the process of crop diversification from low-value food grains to high-value non-food grain crops, as well as the trend in India's food grain production. The use of statistical instruments such as percentage and growth rate had been used.

Handral *et al.* (2017) had undertaken a study to analyse the trends in area, production and productivity of rice, wheat and maize. The compound annual growth rate (CAGR) and coefficient of variation were used to see the growth pattern and instability in the production and productivity of those cereals over time.

Kumar *et al*. (2017) verified the growth trends in area, production, and productivity of major cereal crops in Sikkim, India using of Sen's slope method. Correlation and correlation-based measures were used to determine the goodness-of-fit of linear, exponential, and logarithmic models for observing trend in production, productivity and area. And also measured the issues and suggestions regarding the production of food grains of rice.

Subash *et al*. (2017) opined about the brief issues in the context of Indian pesticide industry, trend in consumption of pesticides in India and regulations and procedures for testing pesticides in India. They came to a conclusion that, to regulate and encourage the use of cost-effective and environmentally safe pesticides, uniformity in testing procedures, deregistration of out-of-date hazardous pesticides, safe application properties, and farmer awareness, strengthening the pesticide industry and safe application of pesticides were required.

Gautam and Sisodia (2018) made an attempt to evaluate the growth and trend in area, production, and productivity of wheat as well as the relationship between them using trend and growth rate.

Usma (2018) made an attempt to assess fertiliser use patterns and production trends in India and to recommend fertiliser usage that would be sustainable based on the needs of various crops, agroclimatic zones, soil and environment.

Halawar (2019) conducted a study to examine the trend and correlation coefficient were used for analysing the differences in the food grains production and to estimate its future production.

In order to emphasize the importance of rice production in India, Nain et al. (2019) made an investigation on the efficiency of rice production by estimating linear and exponential functions using quantitative analysis. Decomposition analysis was used to investigate the relationship between area and yield, as well as their interaction in order to boost rice production in both the state and the country.

Praveen (2020) attempted to use time series data to examine national and state-level fertiliser use patterns, the impact of key policies on consumption of fertilisers using interrupted time series analysis and bibliometric analysis to identify the research emphasis on fertilisers in India and future challenges.

2.3 Compound Annual Growth Rate

Devi *et al*. (1991) emphasized the need for a detailed examination of the various aspects of fertilizer usage in the state on a micro level. Statistical tools like trend and annual compound growth rate were used to estimate the growth in fertilizer use and the difference in total nutrient consumption in different districts in the state were derived.

Sinha and Thakur (1993) examined the growth performance of major food crops in Bihar. During the study era, significant increase in the area under cultivation, demand, and productivity of wheat, followed by rice and maize were discovered. The yield for all three crops was found to be more stable in the post-green revolution era than in the pre-green revolution period, according to the variability study. Furthermore, the Chow test confirmed that the latest production technology had a major effect on the production of Wheat and Maize during the Green Revolution. In the case of rice, technological advancement had been observed over time, though it had no major effect on rice production during that period.

Kannan and Sundaram (2011) had made an attempt to study and discussed the trends and patterns in the growth of the crop sector both national and state levels. It has also estimated crop output growth model to analyse its determinants at the all-India level.

Abid *et al*. (2014) conducted a study with a view to analyse growth and trend in area, production and yield of major crops of Pakistan using compound growth rate as well as trend analysis and semi-log model.

Ahmad *et al*. (2015) compared the significant growth rates and trends for variables such as area, production and productivity of cereals in India and Nigeria, as well as investigated the significant growth rates and trends for those variables in India and Nigeria.

According to Eswaran and Revathi (2017), an effort was made to investigate economic aspects such as maize production, consumption, and India's export direction. The study made use of tools like trend analysis and CAGR.

Desai *et al*. (2017) did an investigation to analyse consumption pattern and production of chemical fertilizers and to study various factors influencing the consumption pattern, determinants of fertilizer use among states and districts in the country. Results from the investigation showed that regarding production and consumption of fertilisers in India and across the states over the years (1980-2013) there was a substantial growth. Production showed an increasing trend and consumption showed a positive and significant growth during kharif and rabi.

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Kumar and Indira (2017) made an analysis to study the trend in the consumption of chemical fertilizers and food grain production in India and to identify the relation between them. Tools such as co-integration technique and CAGR were used for the purpose.

Gautam and Sisodia (2018) made an attempt to evaluate the growth and trend in area, production, and productivity of wheat as well as the relationship between them using trend and growth rate.

Murindahabi *et al*. (2018) measured the crop grain growth in terms of area, production and productivity and determined the growth rate, variability and contribution of various agricultural components to overall production growth of various grains crops. The study also discovered that all grain crops experienced instability in terms of area, production and productivity, with wheat, maize and rice showing the most instability. It demonstrated that the area was the primary contributor to changes in grain crop production during the reform period.

Nisha *et al*. (2019) in their study made an attempt to examine the growth and instability of wheat crop with respect to area, production and productivity in Haryana and India. Linear and exponential functions were used to examine the growth rates. In order to determine the variability and instability among three aspects, coefficient of determination and Cuddy-Della Valle Index were computed.

Sekhara and Devarajulu (2019) conducted a study on trend in area, production and productivity of paddy and analyzed the growth rates such as linear growth rates, compound growth rates etc. Growth rates of area, production and productivity of paddy during the period were 0.39,1.33 and 0.94 respectively.

Sivagnanam and Murugan (2019) attempted to investigate the growth and pattern of fertiliser use as well as the state of soil health in Tamil Nadu and also the functional relationship between them. The results showed that due to utilization of land for industrial and other development purposes which would lead to fluctuation in status of soil and soil status may vary from one district to another resulting in imbalance in the use of nutrients in Tamil Nadu.

Kumari *et al*. (2020) analyzed the trends in area, production and productivity of major food grain crops. Compound annual growth rate (CAGR) was computed and trend in area, production and productivity of major food grain crops were also examined. The relative contribution of area and yield to the total output change of the major food grain crops was studied.

Singh (2020) focused on how Indian agriculture performed after the green revolution and during the economic reform era. The compound annual growth rate of major food and non-food crops was calculated using a semi-log model. The land use pattern changes and cropping pattern change were investigated using descriptive statistics. The fertilizer usage ratio was measured to see whether chemical fertilizers were being used wisely.

2.4 Time series modeling and forecasting

Mishra (2014) used ARIMA modelling to investigate consumption data of potassic fertilisers during the period 1961 to 2002 and also observed the production and consumption of Nitrogen and Phosphorus in India for the same period. Result showed that the ARIMA (1, 1, 1) model was the most effective for estimating Nitrogen production data. From the forecast values obtained by the constructed model the anticipated production would increase to some level in the future. Regarding potassic fertiliser based on current trends, it appeared that the use of potassium fertiliser was declining.

The ARIMA and GARCH models were used to examine the production scenario, growth, trend and projection of pulses in major growing states of India. Factors such as rainfall and fertiliser had been used for the study by Vishwajith (2014). From the forecasted value, it was apparent that Madhya Pradesh would play a significant role in increasing India's pulse production. They came to the conclusion that pulse output in India had increased during the previous three decades or more. For modelling pulse production in India, both ARIMA and GARCH models could be employed; including parameters like fertiliser and rainfall which improved the model's accuracy.

Stability in terms of area and production of food grains in different states of India has been studied by Mishra *et al.* (2015). The study developed a model and forecasted the production of total food grains with or without using the factors of production. The best models were selected based on minimum value of RMSE, MAE, MSE, and MAPE and maximum value of coefficient of determination (R^2).

Soumik and Banjul (2018) estimated demand and supply for food products such as rice, wheat, coarse cereals, and pulses, as well as total food grains and population projections. Using appropriate statistical techniques and packages, a comparison of supply and demand projections were made.

2.5 Imbalance in nutrients

The exact nature of imbalance in fertilizer use against norm of balance use of N, P and K has been estimated by Chand and Pandey (2008) for different states in India. The required or normative quantity of fertiliser use for a state was estimated based on area under various crops and the recommended dose of NPK for the respective crops as per the package of practices published by SAUs and ICAR institutes.

A study was done by Ardeshna and Shiynai (2012) to investigate the growth of fertilizer consumption and to analyse the disparity in growth of fertilizer consumption throughout the districts of Gujarat. Compound growth rate was used for the purpose of the study and the results showed that disparity in consumption of fertilisers existed among the districts in Gujarat. The consumption of N, P and K in Gujarat significantly increased at the rate of 8.43, 8.02 and 7.28 percent per annum respectively during 1960-2008.

Sharma (2014) reported in his study which was conducted to understand fertilizer use behaviour and efficiency over time and space, the changing structure of fertilizer markets, the policy environment, and the role of various factors influencing fertilizer consumption. They arrived at the conclusion that by combining high yielding variety seeds and irrigation on limited arable land, they could improve food security while simultaneously safeguarding the environment. It was also recommended to use fertiliser consumption policies to educate farmers on the importance of balanced fertiliser application, fertiliser subsidies, and so forth. If the pattern of fertiliser consumption could be maintained, changes in agricultural production would be reflected as well.

Chand and Pavithra (2015) estimated the optimal ratio of N for the prevalent cropping pattern in India and also studied about the trends, composition of fertilizer uses and imbalances of fertilizers.

Karunakaran (2016) tried a comparison between the overuse and recommended dose of chemical fertilizers in Kerala, the northern most Kasaragod district. Six crops such as rubber, cashew nut, arecanut, coconut, paddy and banana were selected for comparison and identified the elements those would be the reasons for the overuse of fertilizers. Lack of availability, high price of organic manures, difficulty in handling of application area were some of the reasons for the over usage of fertilisers. The study also estimated the quantity of nutrients favorable for the better growth of selected crops.

Motesharezadeh *et al*. (2016) attempted to examine the pattern of fertilizer application in Iran, Malaysia, and Australia and discovered that fertilizer application should be based on soil testing results and expert recommendations and found that erratic and imbalanced nutrient application should be avoided. Not only did this provide a suitable field for experts to work in, but it could also contribute to environmental conservation and pollution reduction by reducing fertilizer use.

Mishra *et al*. (2017) carried out a study to check whether fertilizer consumption imbalance existed or not with the help of trend and pattern of fertilizer consumption across states in India. With respect to K, growth rate was highest followed by P and N. In case of N, P, K as well as total fertilisers the imbalance was highest in eastern states followed by the western, northern and southern states. For nitrogen, coefficient of variation was least followed by P and K. This reflected that there was a greater stability in fertiliser use of N and P across states than K. To manage the imbalance in fertiliser, use training of farmers were required in proper crop and farming practices and also monitoring by the officials.

Sivagnanam and Murugan (2019) attempted to investigate the growth and pattern of fertiliser use as well as the state of soil health in Tamil Nadu and also the functional relationship between them. The results showed that due to utilization of land for industrial and other development purposes which would lead to fluctuation in status of soil and soil status may vary from one district to another resulting in imbalance in the use of nutrients in Tamil Nadu.

2.6 Cointegrated movement of variables

Abu (2015) investigated the relationship between sorghum yield, rainfall and producer price in Nigeria, using the Johansen co integration test and the vector error correction model (VECM) to test for the long-run relationship between the variables and the stability of the long-run equilibrium. The stationarity of the variables was tested using the Augmented Dickey-Fuller (ADF) test.

De and Mallik (2017) examined the impact of climate change on agricultural productivity in India’s North Eastern region using cointegration analysis and vector error correction model (VECM).

Kumar and Indira (2017) made an analysis to study the trend in the consumption of chemical fertilizers and food grain production in India and to identify the relation between them. Tools such as co-integration technique and CAGR were used for the purpose.

Shiksha and Mittal (2017) examined the factors that influenced the production of different types of food grains in India and identified the factors which affected the production of food grains and emphasized the impact of production variables (inputs) on the expansion of India's food grain production. The OLS regression model was used in that analysis.

Chandio *et al*. (2018) examined the association between fertilizer consumption and production of rice in Pakistan. For checking the stationarity of the data, Augmented Dickey Fuller (ADF) and Phillips Perron (PP) unit root tests were used and to detect the long-term relationship among the series, Johansen co-integration test was used. Autoregressive Distributed Lag (ARDL) model was employed to evaluate the impact of fertilizer consumption on the production of rice.

Neog (2018) made an attempt to assess the impact of chemical fertilizers on soil acidification. Soil pH was a significant indicator of soil health. The coefficient of correlation and simple linear regression method were employed to assess the meaningful relationship between average fertilizer consumption and acidity of soil.

Using cointegration analysis and vector error correction model (VECM), Ahmed and Jie (2019) investigated the short-run effect of livestock export on Somalia's economic development.

Materials and Methods

CHAPTER 3

MATERIALS AND METHODS

The study on "Co integrated movement of food grains production and agricultural inputs: A time series assessment" has focused to investigate the trend and co integrated movement of food grains production and agricultural inputs such as total cropped area, fertilizer consumption and pesticide consumption. More advanced models were developed to predict and compare relationship between each variable with respect to India as well as for the states Kerala, Andhra Pradesh and Tamil Nadu. An attempt to identify the factors which discriminates Kerala from Andhra Pradesh and Tamil Nadu based on the variables under study was also made. A brief description of materials and statistical methods employed to analyse the data pertaining to the objectives under study are discussed.

3.1 Sources of data

The study was based on secondary data obtained from various sources such as Ministry of Agriculture & Farmers Welfare, Government of India, Reserve Bank of India, WWW.indiaagristat.com, WWW.indiastat.com , Economic survey, etc. The data pertaining to India for the variables namely total cropped area, fertiliser consumption, pesticide consumption and food grains production were for a period of 70 years from 1950-'51 to 2019-'20. The data on food grains production for the selected states viz; Kerala, Andhra Pradesh and Tamil Nadu were taken for the same period. Whereas for the other variables, data was taken according to the availability for different states. In the case of total cropped area, the data for the period from 1980-'81 to 2019-'20 were taken for all the states. For fertiliser consumption, the data from 1980'81 to 2019-'20 for Kerala and the data for the period from 1970-'71 to 2019-'20 was taken for Andhra Pradesh and Tamil Nadu. In the case of pesticide consumption, the data for the period from 1970-'71 to 2019-'20 were taken for Andhra Pradesh and Tamil Nadu and for the period from 1990-'91 to 2019-'20 for Kerala.

3.2 Statistical tools used for analysis

3.2.1 Trend

Trend analysis refers to techniques for extracting an underlying pattern of behavior in a time series. To analyze the trend pertaining to India and states namely, Kerala, Andhra Pradesh and Tamil Nadu for the variables such as total cropped area, fertilizer consumption, pesticide consumption and food grains production, functional forms like linear, quadratic and cubic were selected.

1. Linear function $Y = a + bt$
2. Quadratic function $Y = a + bt + ct^2$
3. Cubic function $Y = a + bt + ct^2 + dt^3$

Where,

Y = Total cropped area, fertilizer consumption, pesticide consumption and food grain production

t = Time variable

The functional form having the highest Coefficient of Determination (R^2) is selected for fitting the trend.

3.2.2 Compound Annual Growth Rate

Compound Annual Growth Rate (CAGR) was computed for India as well as the states with respect to variables, total cropped area, consumption of fertilizer and pesticide and food grains production using yearly time-series data for the study period. The study period was divided into two, period from 1950 - '51 to 1984 - '85 (period I) and 1985 - '86 to 2019 - '20 (period II) for India to make comparisons across the period for each variable and drawing conclusions. Coming to state wise growth rate analysis, the data were divided into two sub periods according to the available data.

The growth rates of total cropped area, fertilizer consumption, pesticide consumption, and food grains production of India and states such as Kerala, Andhra Pradesh and Tamil Nadu were computed by using the formula,

$$\mathbf{CAGR = [V\ Final/V\ Begin]^{1/t} - 1}$$

Where,

V Final: Final value

V Begin: Beginning value

t: number of years

3.2.3 Time series models for forecasting

A collection of quantities that are assembled over even intervals of time and are arranged in chronological order is called a time series data. The assumptions of conventional statistical methods may be violated by the characteristics of time series data. Therefore, analyzing time series data requires a unique set of tools and methods collectively known as time series analysis.

Time series analysis can be used for non-stationary data also that are constantly fluctuating over time or are affected by time.

In time series analysis, model validation assists in determining the best model for fitting time series data. That is, the type of data relevant to resolving the question must be defined in time series analysis and forecasting models. Analysts decide which type of analysis and procedures are ideal for the data they wish to examine after they've chosen the relevant data.

To ensure consistency and reliability, time series analysis generally requires a huge number of data points.

The yearly data on total cropped area, fertilizer consumption, pesticide consumption, and food grains production of India and states such as Kerala, Andhra Pradesh and Tamil Nadu were taken for the analysis.

The data for the period from 1950 - 2020 were taken for forecasting the total cropped area, fertilizer consumption, pesticide consumption and food grains production in India. An attempt was made to develop time series models for Kerala using the data from 1980 - 2020 for variables such as total cropped area and fertiliser consumption, data obtained from 1990 - 2020 for pesticide consumption and 1950 - 2020 years data collected for food grains production. And with respect to Andhra Pradesh and Tamil Nadu, information from 1980 to 2020 for total cropped area and pesticide consumption and 1970-2020 for fertiliser consumption and 1950-2020 for food grains production respectively

3.2.3.1 Auto Regressive Integrated Moving Average (ARIMA) models

ARIMA is an acronym for "autoregressive integrated moving average". It's a model used in statistics and econometrics to measure events that happen over a period of time. It is an extension of ARMA model which applies differencing into the model. The model is used to understand past data and to predict future values in a series. It is used when a metric is recorded in regular intervals, from fractions of a second to daily, weekly or monthly periods. ARIMA is a type of model known as Box-Jenkins model.

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.

Steps involving in ARIMA model building

1. Make the time series stationary by differencing or logging or both if it was non stationary
2. Identify ARIMA model using ACF and PACF
3. Estimate ARIMA model parameters
4. Diagnose ARIMA residual series
5. Choose most suitable ARIMA model

An ARIMA model has three component terms:

AR (p) : the number of lag observations or autoregressive terms in the model

I (d) : the number of differencing required to make the series stationary

MA (q): the size of the moving average window

AR (p) model is given by

$$X_t = \mu + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t$$

MA (q) model is given by

$$X_t = \mu - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

A stationary ARMA (p, q) process is defined by the equation

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

$$\text{i.e.,}\quad \left(\mathbf{1} - \sum_{\mathbf{i=1}}^{\mathbf{p}} \boldsymbol{\varphi}_{\mathbf{i}} \mathbf{B}^{\mathbf{i}}\right) X_t = \left(\mathbf{1} - \sum_{\mathbf{j=1}}^{\mathbf{q}} \boldsymbol{\theta}_{\mathbf{j}} \mathbf{B}^{\mathbf{j}}\right) \boldsymbol{\varepsilon}_{\mathbf{t}}$$

$X_t, X_{t-1} \ldots X_{t-p}$ are the values of the time series at times t, t-1, t-2…t-p ;

B is the backshift operator such that $B^i X_t = X_{t-i}$ and $B^j \varepsilon_t = \varepsilon_{t-j}$.

ε_t, ε_{t-1}, ε_{t-2}, ……, ε_{t-p}'s are random errors at times t, t-1, t-2…, t-q; independently and normally distributed with zero mean and constant variance σ^2 .

When the time series is non-stationary the ARIMA (p, d, q) model is obtained as

$$\left(\mathbf{1} - \sum_{\mathbf{i=1}}^{\mathbf{p}} \boldsymbol{\varphi}_{\mathbf{i}} \mathbf{B}^{\mathbf{i}}\right)(\mathbf{1} - \mathbf{B})^{\mathbf{d}} \mathbf{X}_{\mathbf{t}} = \left(\mathbf{1} - \sum_{\mathbf{j=1}}^{\mathbf{q}} \boldsymbol{\theta}_{\mathbf{j}} \mathbf{B}^{\mathbf{j}}\right) \boldsymbol{\varepsilon}_{\mathbf{t}}$$

where,

ϕ_i, i=1, 2…p are Auto Regressive (AR) parameters

θ_j, j= 1, 2…q are Moving Average (MA) parameters

$(1-B)^d X_t$ is the non-seasonal difference of order d on X_t

An ARIMA model is depicted as ARIMA (p, d, q) with values for the order or number of times the function occurs in running the model.

The ARIMA model uses differenced data to make the data stationary, which means there's a consistency of the data over time. This function removes the effect of trends or seasonality. Seasonality occurs when data exhibits predictable, repeating patterns. It is critical to control for seasonality because it could impact the accuracy of the results.

Annual time series data on total cropped area, fertilizer consumption, pesticide consumption and food grains production for India and states Kerala, Andhra Pradesh and Tamil Nadu, were obtained from official websites. Time series data for the years 1950-'51 to 2019-'20 was used to forecast the total cropped area, fertiliser consumption, pesticide consumption and food grains production in India. Out of 70 years data, 65 years of data were taken for modelbuilding. The model was validated using the 5 years out of sample data. After validation if the model was found adequate to fit the data, prediction was done for next five years using the same model to forecast the total cropped area, fertilizer consumption, pesticide consumption and food grains production for Kerala, Tamil Nadu and Andhra Pradesh for the next 5 years. That is from 2020-'21 to 2025-'26. ARIMA, holts, and simple exponential smoothing model were identified from the analysis and those models were fitted by using the statistical software package, SPSS 22.

3.2.3.2 Simple Exponential Smoothing Model (SES)

The simplest and natural method among the exponential smoothing methods is named as the simple exponential smoothing model (SES). When there is no peculiar trend or when the data do not show any seasonality, in such case the most apt method is SES.

In this approach the forecasted future values are said to be equal to the last observed value of the sequence.

$$\mathbf{\hat{Y}_{T+h|T} = Y_T}$$

Where h = 1,2, … Hence, this method implies that, the most recent observed values were given more importance and all preceding observations showed no information for future. This can be revealed by weighted averages, where the whole weight is given to the last observation.

All future forecasts are equal to a simple average of the observed data when using the average approach.

$$\hat{\mathbf{Y}}_{\mathbf{T+h|T}} = \frac{\mathbf{1}}{\mathbf{T}} \sum_{\mathbf{t=1}}^{\mathbf{T}} \mathbf{Y_t}$$

For h=1,2, … Hence from the equation it is clear that while making forecasts, the average method gives equal importance to all data points and gives them equal weight.

We frequently seek a compromise between these two extremes. It may be sensible to attach larger weights to more recent observations than to observations from the distant past. This is exactly the concept behind simple exponential smoothing.

Weighted averages are used to make forecasts, with the weights falling exponentially as the number of observations rises in the past - the smallest weights are associated with the oldest observations:

$$\hat{\mathbf{y}}_{\mathbf{T+1|T}} = \boldsymbol{\alpha}\mathbf{y_T} + \boldsymbol{\alpha}(\mathbf{1}-\boldsymbol{\alpha})\mathbf{y}_{\mathbf{T-1}} + \boldsymbol{\alpha}(\mathbf{1}-\boldsymbol{\alpha})^{\mathbf{2}}\mathbf{y}_{\mathbf{T-2}} + \ldots..$$

Where $0 \leq \alpha \leq 1$ is the smoothing parameter. The one-step-ahead forecast for time T+1 is a weighted average of all of the observations in the series $y_1,\ldots,y_T$. The rate at which the weights decrease is controlled by the smoothing coefficient α.

3.2.3.3 Holt's exponential smoothing Model

The Holt-Winters method is an exponential smoothing technique for forecasting time series data with both trend and seasonal variation. And the model was introduced by Holt in the year 1957. It is designed to predict outcomes, provided that the data points include seasonality

It is an expansion of Simple Exponential Smoothing Model with two smoothing parameters: level adjustment and other for trend in the data. It is also called the Double Exponential Smoothing Model.

Holt's exponential smoothing has level and trend parameters and can be described by the following equations:

Level: $L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$

Trend: $T_t = \gamma (L_t - L_{t-1}) + (1-\gamma) T_{t-1}$

Forecast: $F_{t+1} = L_t + k\, T_t$

Where,

L_t: Level estimate of the time series at time t

T_t: Trend estimate of the time series at time t

α: smoothing coefficient of the level equation ranges from 0 to 1

γ: smoothing coefficient of the trend equation ranges from 0 to 1

3.2.4 Boxplot analysis

The "box plot" (also known as a schematic plot or box-and-whiskers plot) is a basic graphical tool for quickly summarizing and interpreting tabular data. The box plot is one of the statistical approaches known as exploratory data analysis that would be used to visually identify patterns in a data set that might otherwise remain undiscovered.

A boxplot is a standardized way of displaying the distribution of data based on five measures of the data viz; minimum value, the first quartile (Q1), median, the third quartile (Q3), and maximum value of the data.

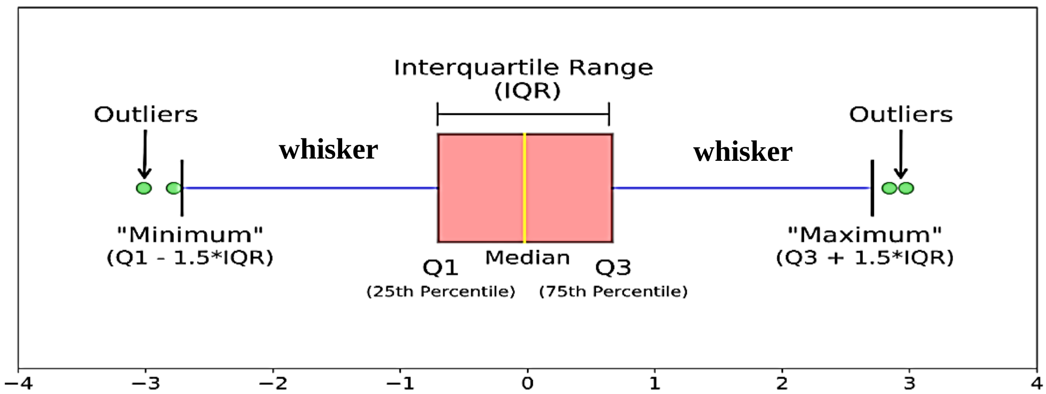

Fig.3.2.4: Box Plot

The boxplot in Fig.3.2.4 has been plotted along the first quartile and third quartile. Whiskers pass though both quartiles and define maximum and minimum value. It also informs about the outliers and its values. The vertical line in the box indicates its median.

The box plot is used to determine if data is normally distributed, how much variability is there, and whether it is positively or negatively skewed. Although boxplots seem unsophisticated when compared to a histogram or density plot, they have the advantage of taking up less space, which is beneficial for comparing distributions across multiple groups or datasets.

Median (Q2/50th Percentile): The middle value of the dataset

First quartile (Q1/25th Percentile): The middle number between the smallest number (not the "minimum") and the median of the dataset

Third quartile (Q3/75th Percentile): The middle value between the median and the highest value (not the "maximum") of the dataset

Inter Quartile Range (IQR): 25th to the 75th percentile

Whiskers (shown in blue)

Outliers (shown as green circles)

Maximum: Q3 + 1.5*IQR

Minimum: Q1 -1.5*IQR

3.2.5 Imbalance in fertiliser usage:

The imbalance in the composition of fertiliser use is adverse only if one or more nutrients are used in excess of the prescribed norm. In situations where all the nutrients are used below their normative levels, the imbalance in N, P, K do not matter or cause any adverse effect on productivity of the soil.

N, P and K consumption in whole Kerala were taken for the period from 1995-2020 and for district wise analysis in Kerala, data for the period from 1993-2009 were used and imbalance in fertiliser use was computed.

To estimate exact nature of imbalance in fertiliser use the equation is given by

$$\mathbf{I} = \sqrt{[(\mathbf{N_a} - \mathbf{N_n})^2 + (\mathbf{P_a} - \mathbf{P_n})^2 + (\mathbf{K_a} - \mathbf{K_n})^2]/3}$$

This was estimated by using an indicator of imbalance adopted in earlier studies (Rajiv 2007). Where I is the difference in proportion of actual use of N, P, and K from the norm, and the subscripts a' and n' indicate actual and norm, respectively. The magnitude of the imbalance is measured by the value of I away from zero. I is 0 when N, P, and K are used in the suggested ratio. As a result, I can be anywhere between 0 and 0.49, or 0% and 49%, reflecting perfect balance and extreme imbalance.

3.2.6 Mahalanobis D^2

Mahalanobis distance is a descriptive statistic that provides a relative measure of a data point's distance (residual) from a common point (Arathi, 2014), or the distance between different dimensional spaces. The concept was introduced by P. C. Mahalanobis in 1936.

If a stepwise method is used to estimate the discriminant function, the mahalanobis D^2 can be used which is based on Generalized Squared Euclidean Distance that adjusts for unequal variances. This method is preferred when the number of variables increases because it does not result in any dimensionality. This procedure performs a step wise discriminant analysis similar to a step wise regression analysis. In this procedure our aim is to maximize Mahalanobis D^2 between groups. A measure of the difference between the groups is given by the Mahalanobis distance.

To compute Mahalanobis D^2, the yearly data for a period from 1990-2020 on total cropped area, fertilizer consumption, pesticide consumption and food grains production for each state viz; Kerala, Andhra Pradesh and Tamil Nadu were used. According to the magnitude of the values possessed by a particular state they were given weights as 3,2,1. A three yearly weighted average was computed for each of the variables with respect to each state. Thus, 30 years data for each state with respect to each variable was reduced to 10 indices. This was done to avoid any autocorrelation that may exist for each variable pertaining to the time series data. Now using these 10 indices for each variable, Mahalanobis distance was computed by using the formula, Mathematically,

$$\mathbf{D^2} = (\overline{\mathbf{X}} - \overline{\mathbf{Y}})^{\mathbf{T}}\mathbf{S^{-1}}(\overline{\mathbf{X}} - \overline{\mathbf{Y}})$$

$$\mathbf{S} = [(\mathbf{n_1} - \mathbf{1})\mathbf{S_1} + (\mathbf{n_2} - \mathbf{1})\mathbf{S_2}]/\mathbf{N}$$

Where,

$\overline{X}, \overline{Y}$ = Sample means

S = covariance matrix

$(X\text{-}Y)^T$ = transpose of the matrix

$N = n_1 + n_2 - 2$

3.2.7. Discriminant analysis

It is a statistical technique used to classify observations into non-overlapping groups, based on scores on one or more quantitative predictor variables. It helps to determine which of the independent variables associate the most for the differences in the average score profiles of the group. Statistical software SPSS 22 was used for the analysis.

In this case dependent variable is categorical in nature, dividing the set of observations into mutually exclusive and collectively exhaustive groups.

The purpose of discriminant analysis is to use information from independent variables to obtain the most precise separation or discrimination feasible between or among groups.

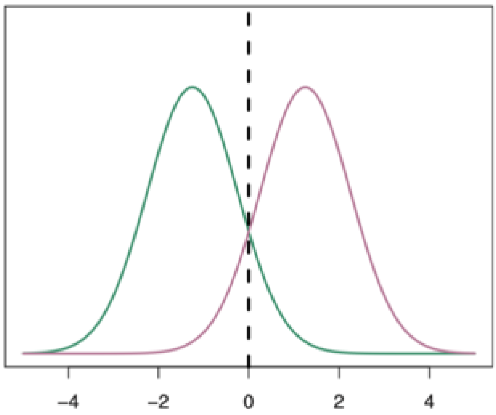

Fig.3.2.7: Discriminant analysis

From the Fig.3.2.7 the two groups were overlapping with each other. If the overlapping is less the discriminant function has succeeded in best discriminating the groups.

Based on 4 variables for each state using the 10 indices computed in section 3.2.6 discriminant analysis was performed.

The discriminant analysis involves the linear combinations of k variables in the following form called the discriminant function and can be employed to discriminate two population.

$$\mathbf{D = W_0 + W_1X_1 + W_2X_2 + W_3X_3 + \ldots\ldots\ldots + W_kX_k}$$

Where,

D = Discriminant score

W’s = Discriminant coefficient or weight

X’s = predictor or independent variable

If we have k number of groups then k-1 represents the maximum number of discriminant functions that can be extracted from the analysis.

Moreover, the discriminant functions are uncorrelated;

- The coefficients or weights (W) are estimated so that the groups differ as much as possible on the values of the discriminant function.
- Discriminant analysis - creates an equation which will minimize the possibility of misclassifying cases into their respective groups or categories.

3.2.8 Vector Auto Regression

Vector **A**uto **R**egression (VAR) is a Multivariate forecasting algorithm as it is used in scenarios where forecasting with two or more time-series influences each other is considered. The term 'Autoregressive' stands because each time-series variable is modelled as a function of its own past values and lags are used as predictor (Dissanayak 2020).

In studies where several variables are involved with mutual dependence, the change in one variable can be forecasted based on the lagged values of all the variables involved including the dependent variable. Such feedback relationships are allowed for in the Vector Auto Regressive (VAR) frame work. Here all variables are treated symmetrically and they are all modelled as if they all influence each other. Formally all variables can be treated as 'endogenous.'

A VAR model is a generalisation of the univariate auto regressive model for forecasting a vector of time series. It comprises one equation per variable in the system. The right-hand side of each equation includes a constant and original or lags of all the variables in the system. For example, if we consider a two variable VAR with one lag,

The two-dimension VAR (1) can be written as,

$$y_{1,t} = C_1 + \emptyset_{11} y_{1,t-1} + \emptyset_{12,1} y_{2,t-1} + \varepsilon_{1,t}$$

$$y_{2,t} = C_2 + \emptyset_{21} y_{1,t-1} + \emptyset_{22,1} y_{2,t-1} + \varepsilon_{2,t}$$

Where $\varepsilon_{1,t}$ *and* $\varepsilon_{2,t}$ are white noise that may be correlated. The coefficient $\emptyset_{ii,l}$ captures the influence of the l^{th} lag of variable y_l on itself, while the coefficient $\emptyset_{ij,l}$ l^{th} lag of variable y_j on y_i.

Usually, when two or more series are non-stationary and cannot be cointegrated, VAR model can be employed by making the series stationary. The model is estimated by using the principle of least squares.

The data pertaining to total cropped area, fertilizer consumption, pesticide consumption and food grains production in India from 1950-2020 were made use of to construct a VAR model in India. An attempt was made to develop VAR model for the selected states using the data from 1980-2020.

Results and Discussion

CHAPTER 4

RESULTS AND DISCUSSION

Agriculture is a vital factor to the Indian economy as 65% of the Indian population depends on farming and related areas (Soumik, 2018). For better development in farming sector, the commitment of sources of information like total cropped area, fertilizer consumption, pesticide consumption and food grains production are profoundly huge.

In the current study, an attempt is made to inspect the pattern and movements of production of food grains along with agricultural inputs and to distinguish the link between them in India as well as in three selected states of India viz; Kerala, Andhra Pradesh and Tamil Nadu. The factors which discriminate the states with respect to these variables also have been identified.

With the objectives of the study in view, the results obtained are explained and discussed in this section.

4.1 Trend analysis

The secondary data on total cropped area, fertilizer consumption, pesticide consumption, and food grains production for respective periods were subjected to trend analysis for India (1950-2020) as well as for the states (1980-2020) viz; Kerala, Andhra Pradesh and Tamil Nadu.

4.1.1 Trend analysis - India

Table 4.1.1: Descriptive statistics for the time series data of total cropped area, fertilizer consumption, pesticide consumption and food grains production in India from 1950 to 2020

Variables	Min.	Max.	Range	Mean	Std. Deviation	Stationarity check (P value)	Stationarity status
Total cropped area (000'ha)	131893	200951	69058	174523.35	18442.55	0.13	NS*
Fertilizer consumption (000'tonnes)	66	28122.2	28056.2	10520.7	9624.66	0.995	NS*
Pesticide consumption (Metric Tonne)	2350	75890	73540	39003.8	22484.67	0.79	NS*
Food grains production(000'tonnes)	50825	296649.2	245824.2	152906	68908.89	0.992	NS*

*NS-Non-Stationary

Table 4.1.1 revealed that maximum food grains production in India was 296649.20 thousand tonnes in the year 2019-2020. It indicated an increasing trend in the case of food grains production. Even though the production was high, at the same time corresponding year area obtained was not at all high while comparing with whole data of total cropped area with respect to the food grains production. Fortunately, during the year of high production of food grains, the fertilizer consumption and pesticide consumption were not high, indicating high production with less consumption of fertilizers and pesticides. In the year 2010-'11 highest consumption of fertilizers were obtained and it was 28122.20 thousand tonnes. At the same time food grains production was 244491.8 thousand tonnes and pesticide consumption was 55540 metric tonnes. But the area was 197683 thousand hectare and the value has been almost high when compared with maximum value.

In the case of pesticide consumption, it was 61702 MT during the year 2019-'20. From Table 4.1.1 it could be noticed that the maximum consumption of pesticide was 75890 MT, in the year 1988-'89 and the corresponding food grains production was 140916 thousand tonnes. Comparatively low production and low area were noticed when the consumption of pesticide was high. Food grains production was found to be 140916 thousand tonnes and area was 182277 thousand hectares.

There are various statistical tests that can be performed to describe the time series data. Time series modelling requires the data to be in a certain way and these requirements vary from model to model. For fitting time series models, most commonly, the stationarity of the data is checked and it is taken as an assumption for model building. The data need to be checked for its underlying attributes and there exists a variety of tests to explore these attributes. The most basic approach for understanding stationarity is to plot the data and check if there is any hint at the presence of underlying trends and seasonality. This visual practice rarely helps and often it is difficult for human eye to detect it. In such cases Augmented Dickey Fuller test which performs a classic null hypothesis test and returns a p- value can be used. If p-value is greater than 0.05, the null hypothesis of existence of unit root is accepted and determine the data to be non stationary. From Table 4.1.1 it can be noted that the p-value for stationarity check with respect to all variables pertaining to India were greater than 0.05 and thus all the time series were non stationary. Even though there is no meaning in giving the mean and S.D of a non stationary time series it is depicted just to give an idea about the particular portion of the data under study.

4.1.1.1 Total cropped area

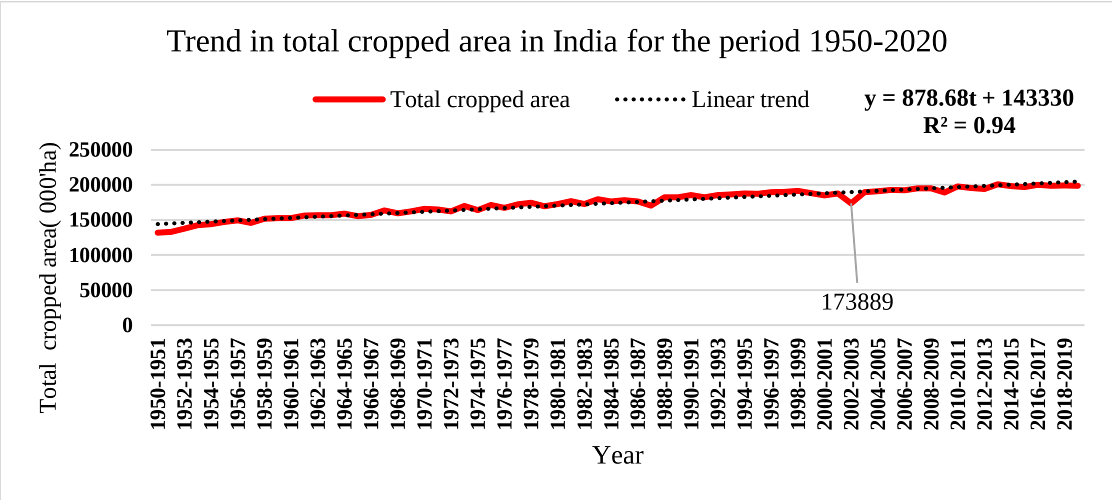

Fig:4.1.1.1 Trend in total cropped area for the period 1950-2020

From Fig.4.1.1.1 it is quite visible that there has been almost a linear trend in the growth of total cropped area since 1950-2020 with little fluctuation during some of the years. But in the year 2002-'03 a sudden decline was observed, in contrast to the preceding years and it showed somewhat lesser area cultivated.

4.1.1.2. Fertilizer consumption

Fig:4.1.1.2 gives information about the consumption of fertilizer in India over 70 years period from 1950-2020. Consumption of fertilizer during 1950-'51 was 70 thousand tonnes, then the consumption was decreased to 66 thousand tonnes during 1951-'53 year and after that it frequently increased and minute fluctuations was there during 1958-'59 and 1960-'61. Even though, from 1950-'64, the graph showed straight line trend, it showed an increasing trend and small undulations were there in the trend line. While considering the overall consumption of fertilizer, highest consumption was in the year 2010-'11 and it was 28122.2 thousand tonnes and lowest consumption was in the year 1950-'52 and it was 66 thousand tonnes.

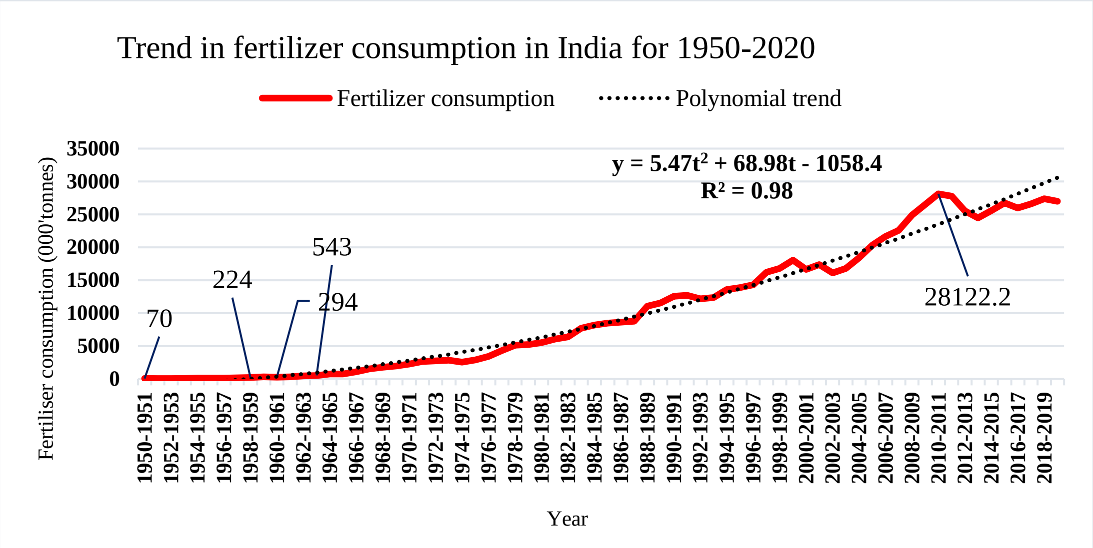

Fig:4.1.1.2 Trend in fertilizer consumption for the period 1950-2020

Fluctuations were observed in consumption rate and after 2011, highest consumption was in the year 2018-'19 (27375.2 thousand tonnes). In the next year that is 2019-'20 it was decreased to 26984.3 thousand tonnes showing an overall decreasing trend of fertilizer consumption. The reason may be that the people were becoming aware of the ill effects of higher consumption of chemical fertilizers and they were attracted towards bio fertilizers.

4.1.1.3 Pesticide consumption

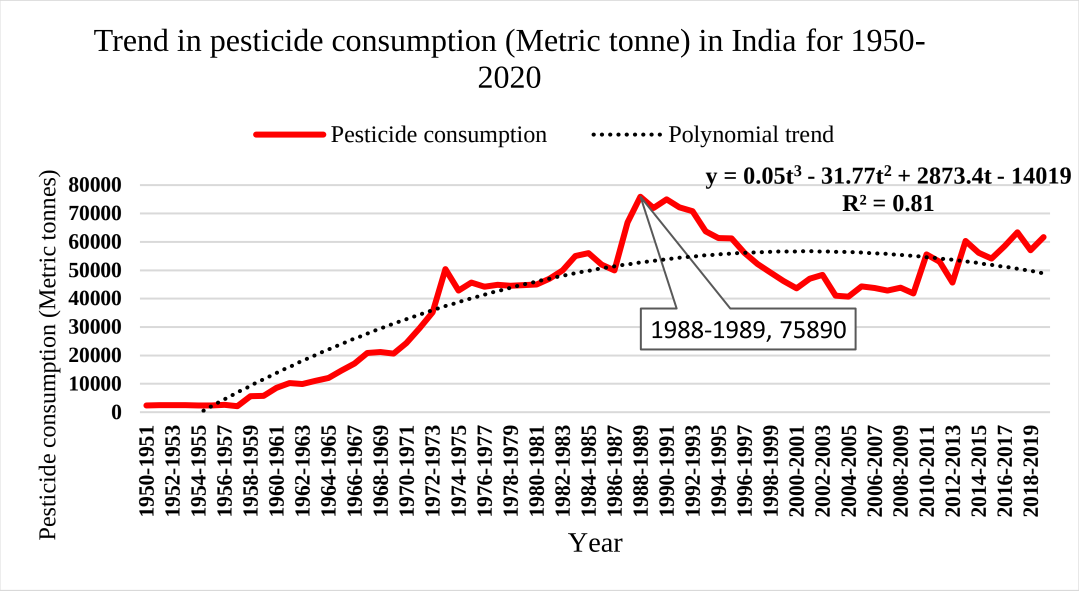

Fig:4.1.1.3 Trend in pesticide consumption for the period 1950-2020

The Fig:4.1.1.3 shows the consumption of pesticide in India in metric tonnes (MT). During the period of years from 1950-’57, it showed linear trend and the consumption was found to be below 3000 MT in those years. From 1959-’60 onwards, more fluctuations were found at certain years and overall, an increased trend was observed in the graph. Highest consumption of pesticide (75890 MT) was observed in the year 1988-1989. During 1989-’93 period, above 70000 MT and below 80000 MT consumption were observed.

From 1995-’96 up to 2000-’01, downward trend was identified. After 2000-’01 to 2019-’20 rate of consumption was noticed within the range of 40000 MT to 65000 MT and it was not more than previous few years of consumption rate.

4.1.1.4. Food grains production

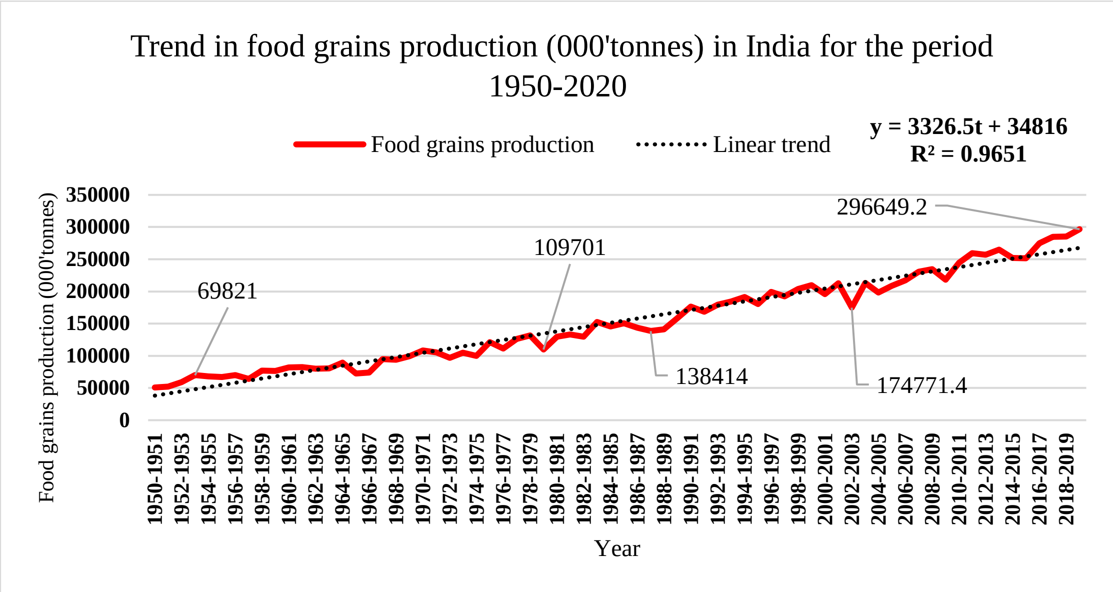

Fig:4.1.1.4 Trend in food grains production for the period 1950-2020

From the Fig:4.1.1.4 it can be observed that overall production of food grains showed a linear trend.

From 1950 to 1954 the graph depicted an increasing trend and after that trend was declined in the next two years, that was 1955 and 1956. During the year 1957 the production was again increased and then decreased in such a way that the growth in the production of food grains had been fluctuating than that of fertilizer consumption (Fig:4.1.1.2).

Highest production was found in the year 2019-’20 and the production was 296649.2 thousand tonnes. And the production of food grains in the year 2002-‘03 (174771.4 thousand tonnes) was diminishing at a higher rate.

4.1.2 Trend analysis - Kerala

Table 4.1.2: Descriptive statistics for the time series data of total cropped area, fertilizer consumption, pesticide consumption, and food grains production in Kerala during 1980-2020.

Variables	Min.	Max.	Range	Mean	Std. Deviation	Stationarity Check (P-value)	Stationarity status
Total cropped area(000'ha)	2446	3066	620	2784.88	188.48	0.31	NS*
Fertilizer consumption(000'tonnes)	94.76	322.17	227.41	197.62	52.98	0.11	NS*
Pesticide consumption (MT)	273	1793	1520	886	357.54	0.03	NS*
Food grains production(000'tonnes)	228.40	1427.00	1198.6	946.27	306.62	0.68	NS*

*NS- Non-Stationary

Table 4.1.2 showed that the maximum fertilizer consumption was 322.170 thousand tonnes in the year 2013-'14 and the corresponding food grains production obtained during the same year was very low, 512.4 thousand tonnes. Regarding pesticide consumption, the maximum was found to be 1793 MT in the year 2014-'15. Here also the production of food grains was found to be comparatively low (560 thousand tonnes). Thus, in Kerala the production of food grains was low. Diminishing production of food grains might be because of the fact that Kerala's cropping pattern was focused more on selectively chosen crops such as cash crops. The dominance of plantation and spice crops which were export oriented made the prospects of Kerala farmers to be on the world market. With respect to total cropped area also, during 1996-'97 it was found to be maximum and coming to food grains production in the same year it was not high.

4.1.2.1 Total cropped area

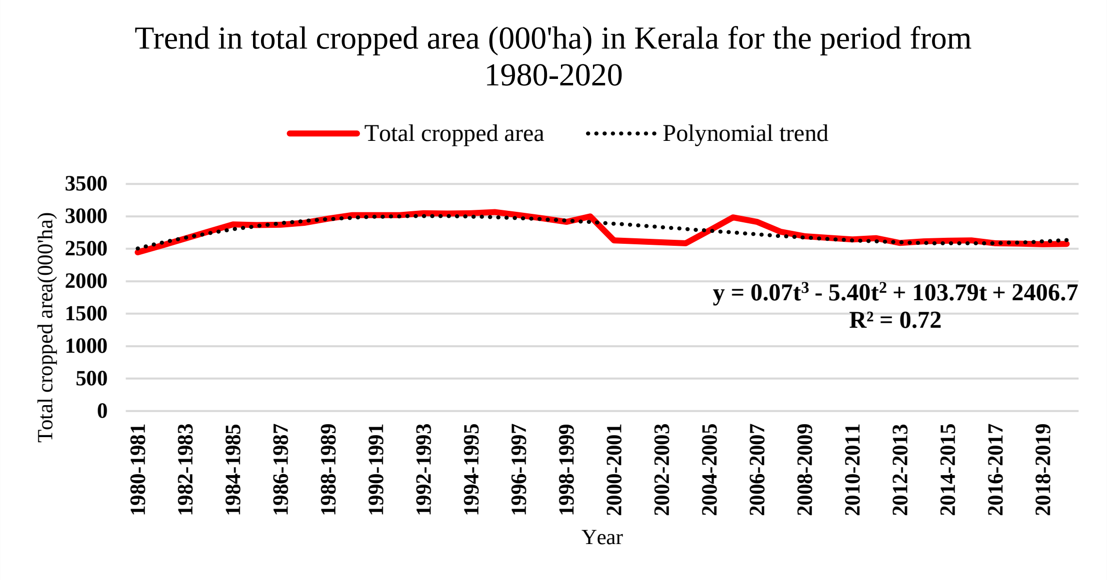

Fig:4.1.2.1 Trend in total cropped area for the period 1980-2020

With respect to total cropped area even though small fluctuation were there, the trend was increasing up to the year 1999-2000. After that a small decline was found and then again it has increased. From 2007-'08, almost steady growth in area was found along with narrow fluctuations. Comparing 1980-'81 with 2019-2020 the total cropped area has been increased.

When total cropped area along with production of food grains were considered, it showed a negative association. While the area increased, the production decreased.

4.1.2.2 Fertilizer consumption

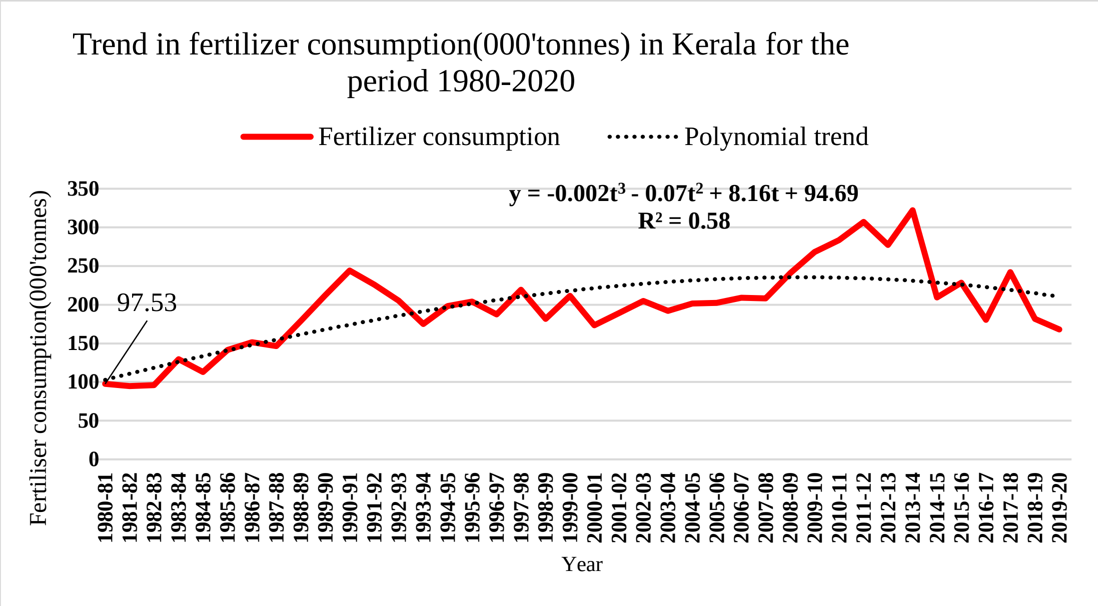

Fig.4.1.2.2: Trend in fertilizer consumption(000'tonnes) in Kerala for the period 1980-2020

Due to the limited availability of the data, the trend regarding fertilizer consumption for the period 1980 to 2020 only was examined. During this period highest consumption was observed in the year 2013-’14 and it was 322.17 thousand tonnes. In the overall consumption during the period mainly three peaks were found. Comparing to consumption of fertilizer in the year 1980-’81, it almost doubled during the year 2019-2020. Between 1980 to 2020, lot of fluctuations and steady growth was also there. From Fig:4.1.2.2, an increasing trend in the overall fertilizer consumption could not be visualized.

During 1980-’81 the production of food grains was 1298 thousand tonnes and consumption of fertilizer was 97.53 thousand tonnes. After 40 years, that is in the year 2019-2020 the production was found to be 617.1 thousand tonnes and fertiliser consumption was 167.955 thousand tonnes. Observing the food grains production along with fertilizer consumption, the production comparatively reduced and the fertiliser consumption increased.

4.1.2.3 Pesticide consumption

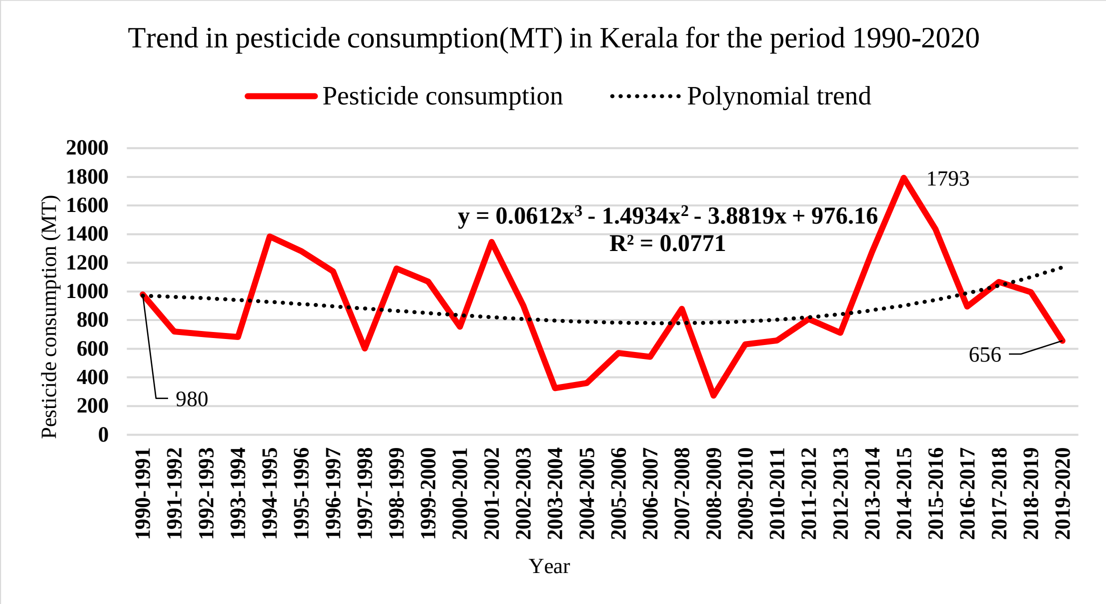

Fig:4.1.2.3 Trend in pesticide consumption in Kerala for the period 1990-2020

Regarding the pesticide consumption in Kerala during the period 1990-2020, the consumption was 980 MT during the starting year and it was 656 MT during the ending year. Observing these two values, it gave a positive approach because the usage of pesticide was reduced.

Between these periods, so many high peak fluctuations were found. It might be because of the fact that the farmers might have applied high level of pesticides to increase the production. From the Fig:4.1.2.3 highest peak was found in the year 2014-'15 and it was 1793 MT. The corresponding food grains production was only 560 thousand tonnes. It reflected that even though the consumption of pesticides was increased the production was not increased.

4.1.2.4. Food grain production

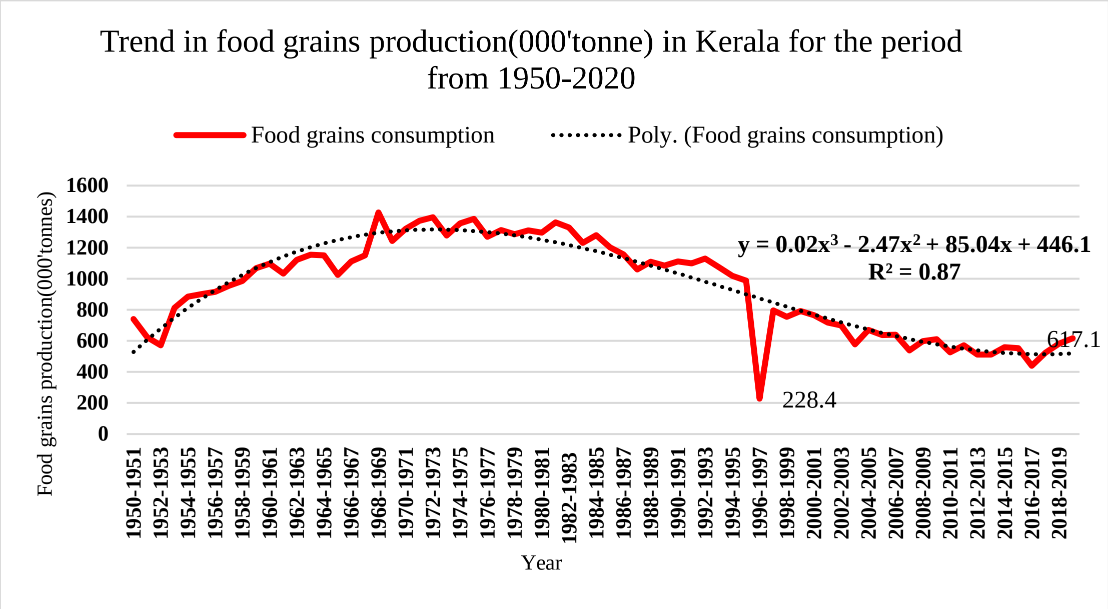

Fig:4.1.2.4 Trend in food grains production in Kerala for the period 1950-2020

While seeing the overall food grains production during the period 1950 to 1966 from the Fig: 4.1.2.4, an increasing trend was observed, even though small fluctuations were also there. But, in the year 1966-1997 a huge decline was found and the corresponding production was 228.4 thousand tonnes in that year. After 1996-1997 up to 2019-2020 the production increased while comparing with production in the year 1996-1997. If comparing the production with previous years that is before 1996-97, the production was very low.

Over all, the adjusted R^2 values for variables under study in Kerala were 0.72, 0.58, 0.08 and 0.87 for total cropped area, fertilizer consumption, pesticide consumption and food grains production respectively for the trend line estimated. This implied that time trend lines could account for 72 percent, 58 percent ,8 percent and 87 percent of the variations noticed in total cropped area, fertilizer consumption, pesticide consumption and food grains production respectively. The pesticide consumption seemed to be highly erratic with no particular trend.

4.1.3. Trend analysis - Andhra Pradesh

Table 4.1.3: Descriptive statistics for the time series data of total cropped area, fertilizer consumption, pesticide consumption, and food grains production in Andhra Pradesh during 1980-2020.

Variables	Min.	Max.	Range	Mean	Std. Deviation	Stationarity check (P - value)	Stationarity status
Total cropped area (000'ha)	6030	15800	9770	12066.7	2516.11	0.81	NS*
Fertilizer consumption (000'tonnes)	263.70	3496.80	3233.1	1532.76	887.99	0.54	NS*
Pesticide consumption (MT)	1015	14061.36	13046.36	7189.79	4189.97	0.65	NS*
Food grains production (000'tonnes)	4165	20421	16256	10653.6	4110.28	0.37	NS*

*NS- Non - Stationary

The maximum value of fertilizer consumption from Fig:4.1.3 obtained was 3496.80 thousand tonnes (2010-11) and in this year the production showed very high value (20315 thousand tonnes). It means in Andhra Pradesh; food grains production was highly influenced by fertilizer consumption. The consumption of pesticides was maximum during 1981-'82 and it was 14061.36 MT. While analysing the pesticide consumption with production of food grains, it showed average production with high pesticide consumption. Total cropped area was maximum during the year 1980-'81 and in that year comparatively low production was obtained. But during next year's even though the area was decreasing the production was increasing. It was a positive sign regarding food grains production.

4.1.3.1 Total cropped area

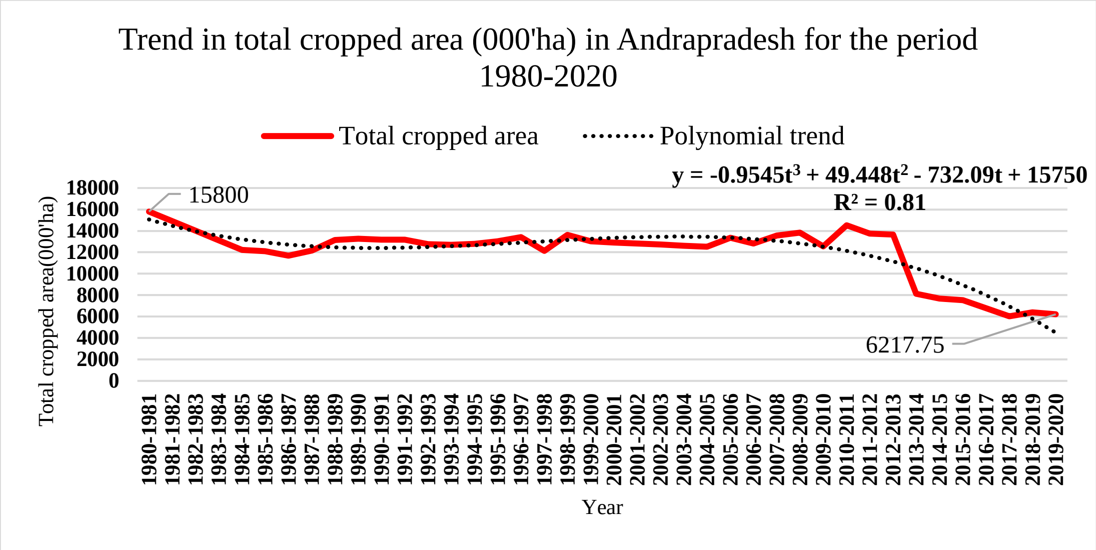

Fig: 4.1.3.1 Trend in total cropped area (000'ha) in Andhra Pradesh for the period 1980-2020

Regarding total cropped area in Andhra Pradesh, from Fig:4.1.3.1 it could be noticed that the area was declining.

4.1.3.2. Fertilizer consumption

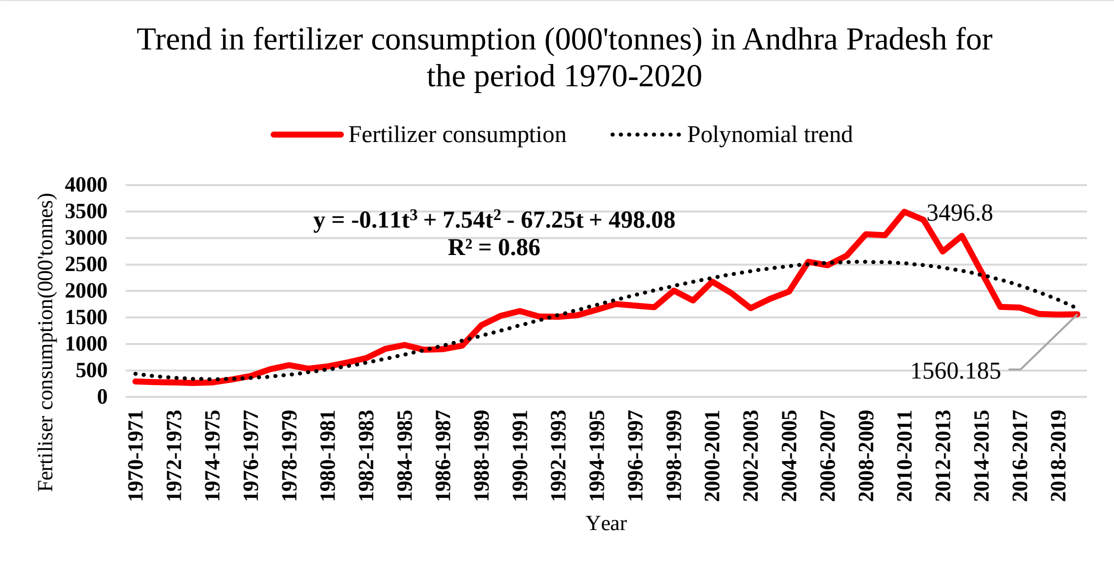

Fig:4.1.3.2 Trend in fertilizer consumption in Andhra Pradesh for the period 1970-2020

Fig:4.1.3.2 shows that the highest fertilizer consumption for Andhra Pradesh was in the year 2010-'11 and it was 3496.8 thousand tonnes. Up to this year the consumption of fertilizer in every year was increasing and decreasing, though the whole growth showed an increasing trend.

Movement of food grains production along with its fertilizer consumption in general showed more food grains production corresponding to an increased consumption of fertilisers.

4.1.3.3 Pesticide consumption

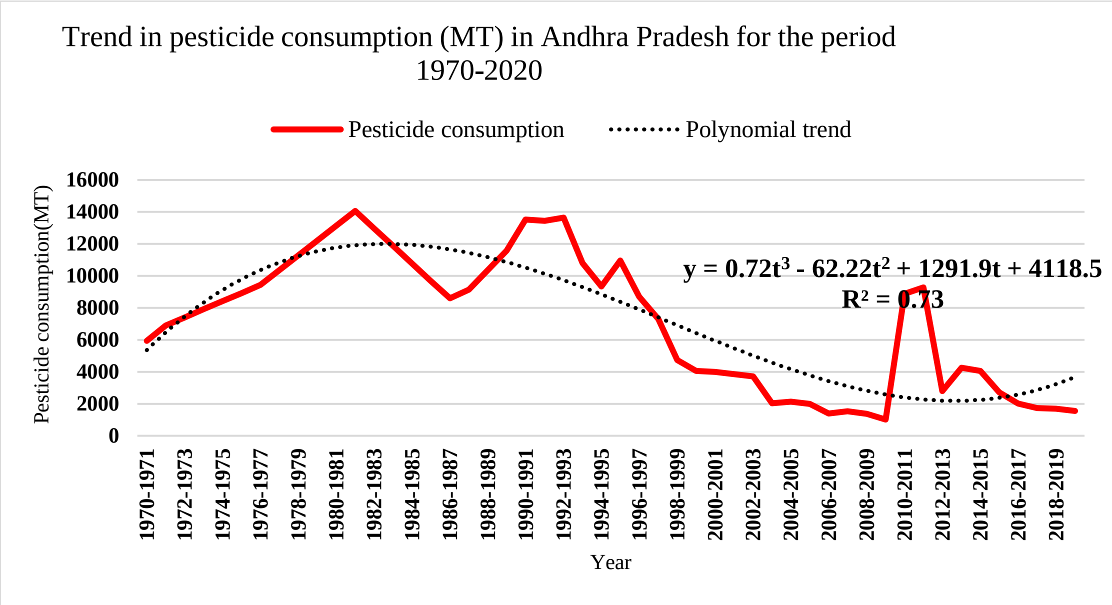

Fig: 4.1.3.3 Trend in pesticide consumption in Andhra Pradesh for the period 1970-2020

In the case of pesticide consumption in Andhra Pradesh, its application moved in the downward direction, although few high-level fluctuations could be seen in Fig:4.1.3.3.

4.1.3.4. Food grains production

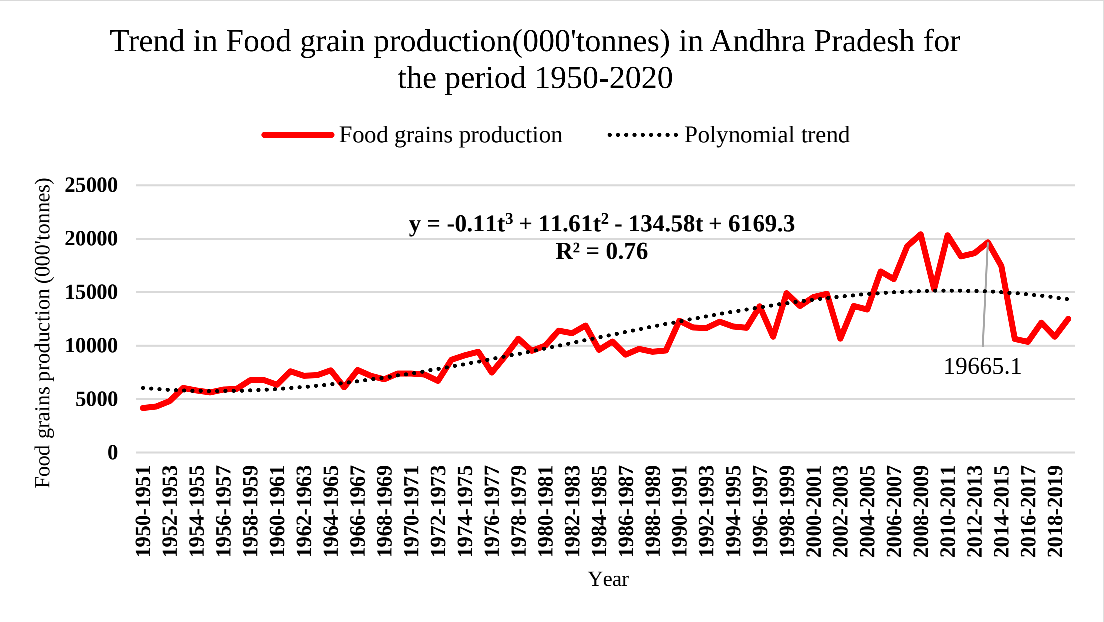

Fig:4.1.3.4 Trend in food grains production in Andhra Pradesh for the period 1950-2020

Fig: 4.1.3.4 explained that lot of fluctuations were there in food grains production, but growth was increasing up to 2011-'12. After that a sudden decline and then increased very slowly. Observing the growth throughout for the period 1950-2020, the production was increasing.

To conclude it can be stated that out of the 4 variables considered for the period 1980-2020, food grains production and consumption of fertilizers led an upward growth trend whereas cropped area and pesticide consumption had declining trend.

4.1.4. Trend Analysis - Tamil Nadu

Table 4.1.4: Descriptive statistics for the time series data of total cropped area, fertilizer consumption, pesticide consumption, and food grains production in Tamil Nadu

Variables	Min.	Max.	Range	Mean	Std. Deviation	Stationarity check (P - value)	Stationarity status
Total cropped area (000'ha)	5129	8519	3390	6424.94	737.345	0.03	NS*
Fertilizer consumption (000'tonnes)	105.50	1564.02	1458.52	715.72	386.17	0.22	NS*
Pesticide consumption (MT)	1434	10360.04	8926.04	4371.86	2982.379	0.58	NS*
Food grains production(000'tonnes)	1588	11478.5	9890.5	6664.58	2032.71	0.002	S*

*NS- Non-Stationary *S- Stationary

Table 4.1.4 depicts that the maximum fertilizer consumption was obtained as 1564.02 thousand tonnes during the year 2015-'16 and in the same year the food grains production was also high (11478.5 thousand tonnes). While examining the pesticide consumption with food grains production, it was found that high consumption of pesticide resulted only in medium range food grains production. In the case of total cropped area, highest area was found during the year 1980-'81(8519 thousand tonnes), meanwhile the corresponding production was low (5487 thousand tonnes).

4.1.4.1 Total cropped area

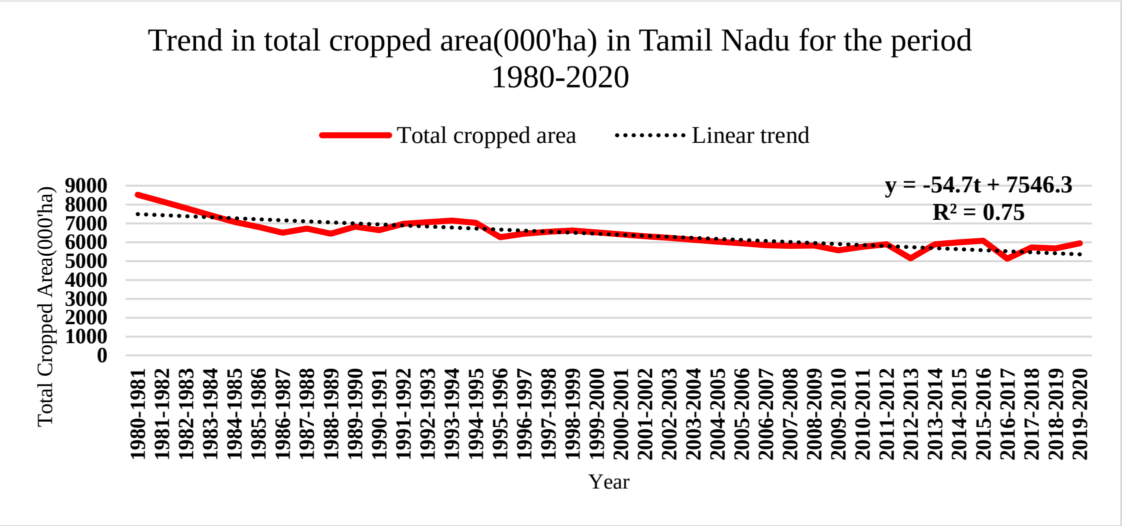

Fig:4.1.4.1 Trend in total cropped area in Tamil Nadu for the period 1980-2020

The progress of total cropped area in Tamil Nadu was declining as seen from Fig:4.1.4.1 and it was less in the year 2019-2020 when compared to the year 1980-'81. Relating the cropped area to other agricultural inputs, the production was increased according to the increase in the consumption of fertilizer but the area and pesticide consumption was reduced.

4.1.4.2 Fertilizer consumption

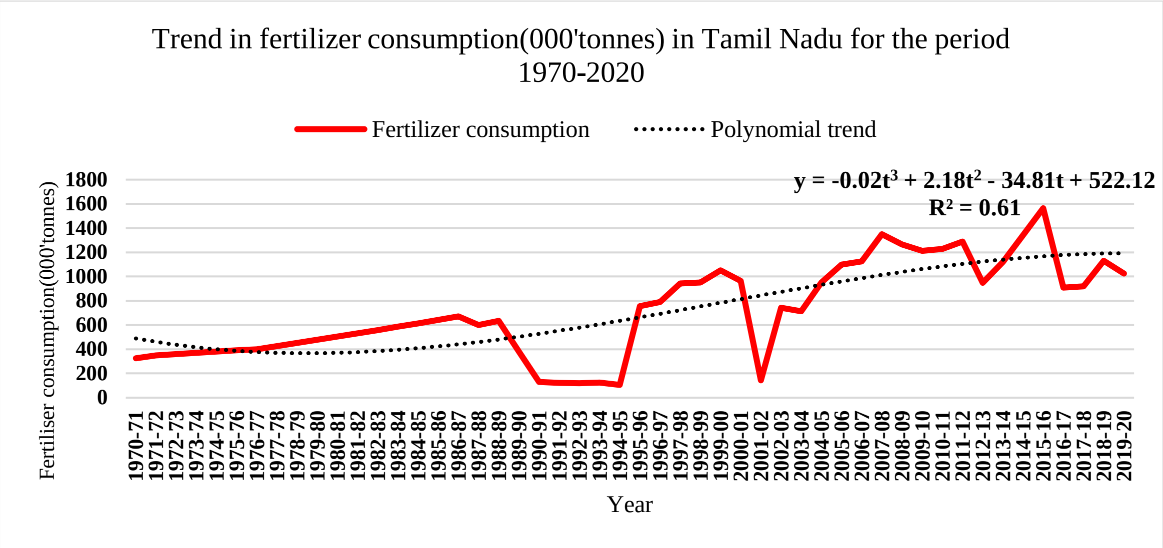

Fig:4.1.4.2 Trend in fertilizer consumption in Tamil Nadu for the period 1970-2020

Regarding the agricultural input, fertilizer consumption, its consumption was directly proportional to production of food grains except for some years.

4.1.4.3 Pesticide consumption

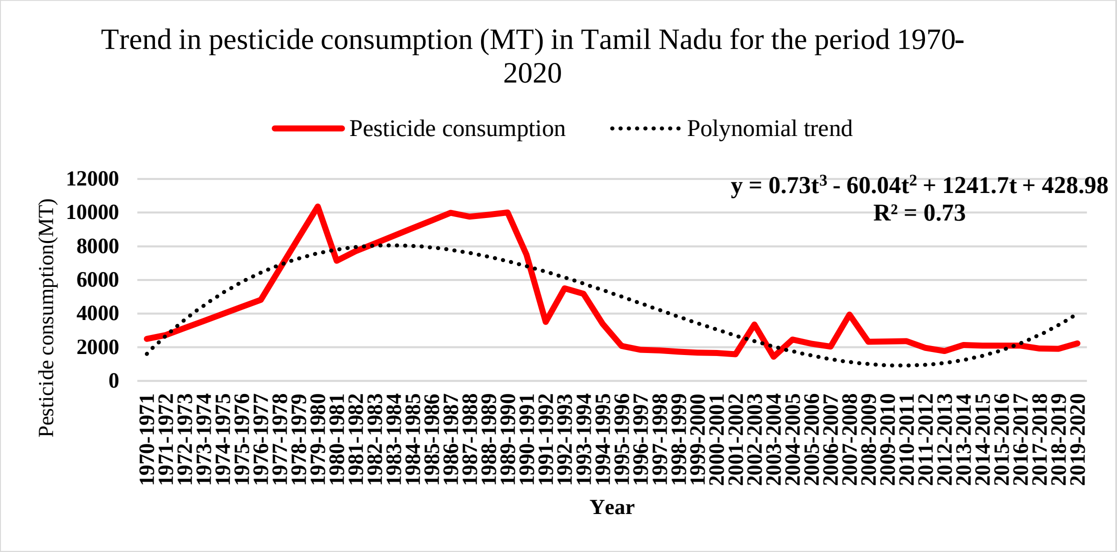

Fig 4.1.4.3 Trend in pesticide consumption in Tamil Nadu for the period 1970-2020

Highest two peaks in pesticide consumption were in the year 1979-1980 (10360.04 MT) and 1989-’90(10000 MT) and during those periods of 10 years a high level of pesticide consumption was there when compared with overall consumption in the entire period. After that there was a decline in the level of consumption and the curve became somewhat straight with few fluctuations.

4.1.4.4 Food grain production

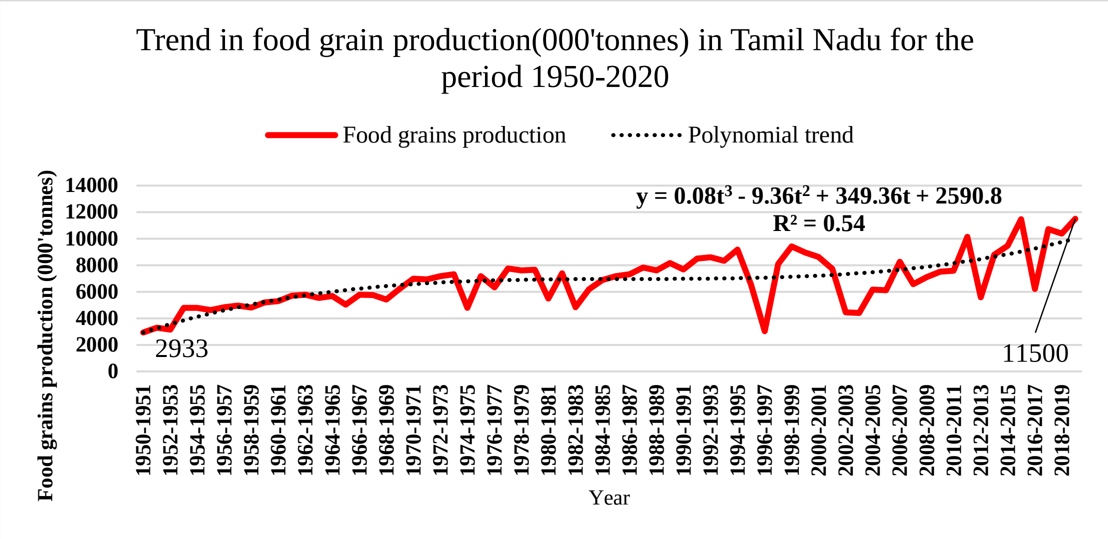

Fig: 4.1.4.4 Trend in food grains production in Tamil Nadu for the period 1950-2020

When food grains production in Tamil Nadu was considered, in very recent years the production was increasing. Highest production was found in the year 2019-2020 (11500 thousand tonnes) and the lowest was observed in the year 1950-1951 (2933 thousand tonnes) respectively.

Summarising the overall results of India, Kerala, Andhra Pradesh and Tamil Nadu for the variables under study it was found that the food grains production showed an increased growth in India.Total cropped area in India were decreasing by observing overall data of cultivated area, even though little fluctuations were found. Regarding fertilizer consumption variations were observed in rate of consumption and showed an overall decreasing trend. The reason might be that the people were becoming aware of the ill effects of higher consumption of chemical fertilizers and they were attracted towards bio fertilizers. During 1970’s to 1990’s the consumption rate in pesticide was comparatively high. After that there was a decline in the level of consumption. This decline might be due to the introduction of Integrated Pest management, ban of some pesticides etc.

When total cropped area along with production of food grains were considered in Kerala, it showed a negative association. While the area was increased, the production was decreased. Coming to food grains production along with fertilizer consumption, the production was comparatively reduced and the fertiliser consumption was increased. The reason might be because of the fact that farmers focused more on cash crops which were having high demand in international market. The dominance of plantation and spice crops, which were export oriented, made the prospects of Kerala farmers to be on the world market. Regarding pesticide consumption in Kerala, so many high peak fluctuations were found. It might be because of the fact that the farmers might have applied high level of pesticides to increase the production. From the Fig.4.1.2.3 highest peak was found in the year 2014 -'15 and it was 1793 MT. And the corresponding food grains production was only 560 thousand tonnes. Hence it can be concluded that when the consumption of pesticides was increased the production need not be increased.

In the case of Andhra Pradesh, when overall total cropped area along with food grains production was considered, the area was decreasing but the production was increasing, probably due to the consumption of a huge quantity of fertilizers. The total cropped area was almost constant for several years but it has declined during the recent years. Fertiliser consumption showed an increasing trend but it has started declining recently. Pesticide consumption showed somewhat fluctuating but declining trend. The food grain production showed exactly a similar trend like fertilizer consumption showing a significant positive association between them

In the case of Tamil Nadu, the food grains production was increasing, at the same time consumption of fertilizer and food grains were directly proportional except for some years. However, the pesticide consumption and total cropped area showed declining trend. In this state also the food grain production was highly influenced by fertilizer consumption. The overall trend in consumption of pesticides has also been declined.

4.2 Growth rate

For studying the growth rates of total cropped area, fertilizer consumption, pesticide consumption, and food grains production the whole study period was divided into two equal parts comprising of 35 years each. The period 1950-’51 to 1984-’85 was categorized as period I and 1985-’86 to 2019-’20 as period II respectively.

Compound Annual Growth Rate of total cropped area, fertilizer consumption, pesticide consumption and food grain production in India and for the states viz; Kerala, Andhra Pradesh and Tamil Nadu have been computed and the results are presented in Table 4.2.1, Table 4.2.2, Table 4.2.3 and are discussed for each period separately.

4.2.1 Growth rate - India

Table:4.2.1 Compound Annual Growth Rates of total cropped area, fertilizer consumption, pesticide consumption and food grains production in India for the period 1950-2020

Period	**Total Cropped Area**	**Fertilizer Consumption**	**Pesticide Consumption**	**Food Grains Production**
	CAGR	CAGR	CAGR	CAGR
I	0.008	0.145	0.095	0.030
II	0.003	0.034	0.005	0.020
Overall	0.006	0.089	0.048	0.026

4.2.1.1 Total cropped area

It can be seen from Table 4.2.1 that the total cropped area increased at the rate of about 0.006 during the whole period of study. During 1st period the growth rate was 0.008 followed by 0.003 growth rate in the second period.

4.2.1.2. Fertilizer consumption

India ranks third in the world in fertilizer consumption but the average use is very low. Kumar and Indira (2017) revealed that the growth rate of fertilizer consumption in India has reduced after the year 2000. While it has grown at an annual growth rate of 5.83 percent between 1986-‘87 and 1999-2000, it has grown at an annual growth rate of 2.79 percent between 2000-’01 and 2013-’14. While coming to results from Table 4.2.1 it explained that consumption of fertilizer has increased at the rate of about 0.089 during the whole period of study. Consequently, the compound growth rate was higher (0.145) during first period as compared to that of about 0.034 during the second period.

4.2.1.3. Pesticide consumption

Pesticides are an integral part of modern agriculture. In India, pesticides are registered for agriculture, public health and for use in households. The use of pesticides in agriculture is obvious for the prevention of crop-damaging pests, fungus, unwanted plants (weeds) and a number of crop-eating animals like rodents etc. as examined by Yadav and Dutta, 2019.

Regarding pesticide consumption, first decade had witnessed comparatively maximum growth rate of 0.095 as against 0.005 during the second decade of study which was significantly a lower rate of growth.

4.2.1.4 Food grains production

Kumar and Indira (2017) reported that food grains production has registered a marginal reduction in growth rate from 2.95 percent to 2.34 percent during the period 1986-’87 to 1999-’00 and 2000-’01 to 2013-’14. But the growth rate of food grains production was always lower than the growth rate of fertilizer consumption. It can be observed from Table 4.2.1 that the production of food grains in the country had an annual growth rate of about 0.026 during 1950-2020. First period had witnessed maximum growth rate of 0.030 as against 0.020 during the second period.

4.2.2 Growth rate - Kerala

Table 4.2.2 Compound Annual Growth Rates in Kerala for total cropped area and fertilizer consumption, pesticide consumption and for food grains production

Period	Total cropped area	Fertilizer consumption	Pesticide consumption	Food grains production
	CAGR (1980-2020)	CAGR (1980-2020)	CAGR (1990-2020)	CAGR (1950-2020)
I	0.01	0.04	-0.06	0.02
II	-0.001	-0.002	0.009	-0.02
Overall	0.001	0.01	-0.01	-0.002

With respect to total cropped area in Kerala, Table 4.2.2 showed an overall growth rate of 0.001. Coming to consumption of fertilizer, the overall growth rate was 0.01. In case of pesticide consumption and food grains production it showed a diminishing growth rate, and obtained value for growth rate as -0.01 and -0.002 respectively.

4.2.3 Growth rate - Andhra Pradesh

Table4.2.3 Compound Growth rates in Andhra Pradesh for total cropped area, fertiliser consumption, pesticide consumption and for food grains production

Period	Total cropped area	Fertilizer consumption	Pesticide consumption	Food grains production
	CAGR (1980-2020)	CAGR (1970-2020)	CAGR (1970-2020)	CAGR (1950-2020)
I	-0.01	0.07	0.02	0.02
II	-0.04	-0.005	-0.08	0.005
Overall	-0.02	0.03	-0.03	0.02

In the case of Andhra Pradesh, the compound annual growth rate (Table 4.2.3) for total cropped area was -0.02 showing a decline and the overall growth rate of consumption of fertiliser came to be 0.03 and for pesticide consumption the declining rate was -0.03. But there was not much pretty consistency regarding production of food grains and compound growth rate came to be 0.02.

4.2.4 Growth rate - Tamil Nadu

Table 4.2.4 Compound Annual Growth rates in Tamil Nadu for total cropped area, fertiliser consumption, pesticide consumption and for food grains production

Period	Total cropped area	Fertilizer consumption	Pesticide consumption	Food grains production
	CAGR (1980-2020)	CAGR (1970-2020)	CAGR (1970-2020)	CAGR (1950-2020)
I	-0.009	-0.04	0.01	0.02
II	-0.01	0.01	0.003	0.01
Overall	0.004	0.02	-0.002	0.02

Regarding growth rate in Tamil Nadu from Table 4.2.4, the overall growth rate of total cropped area reached 0.004, the compound growth rate of fertilizer consumption was 0.02, that of pesticide consumption was -0.002 - a huge decline. As like that of Andhra Pradesh, in case of Tamil Nadu also there was not much pretty consistency in overall production and overall compound annual growth rate which came to be 0.02.

4.3 Time series model building

Construction of time series models for predicting total cropped area, fertilizer consumption, pesticide consumption and food grains production in India and states such as Kerala, Andhra Pradesh and Tamil Nadu have been attempted.

To analyse the time series model for total cropped area, fertilizer consumption, pesticide consumption and food grains production in India, annual time series data for 65 years pertaining to the period from 1950-’51 to 2019-2020 was used as training period. Identification and estimation of the parameters were done using SPSS 22 software. Adjusted R^2, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Maximum Absolute Error (MaxAE), and Maximum Absolute Percentage Error (MaxAPE) were used to identify the best model. These models were used to predict the future values.

4.3.1 Time series modelling – India

The main aim of time series modelling is to carefully collect and rigorously study the past observations of a time series to develop an appropriate model which describes the inherent structure of the series. This model is then used to generate future values for the series, i.e., to make forecasts. Time series forecasting thus can be termed as the act of predicting the future by understanding the past (Raicharoen et al. 2003). Time series models have been tried in the study using the data pertaining to total cropped area, fertiliser consumption, pesticide consumption and food grain production for the period from 1950 - 2020 for India and for available periods for the respective states Kerala, Andhra Pradesh and Tamil Nadu.

In the case of India, the time series data for the period from 1950 - 2014 were taken and time series models were fitted. The resulted model was validated using out of sample data for the period from 2015 - 2020. As the models seemed to be outstanding, the predictions were made for the period from 2020 - 2025. The results are depicted in different tables and figures.

4.3.1.1 Total cropped area - India

Using 65 years data of total cropped area (Table 4.3.1.1.1) in India, forecasted values for next five years have been computed and compared with actual values for total cropped area for validation. Best model formulated was Holts' model and results area depicted in tables and figures.

Table 4.3.1.1.1(a): Comparison of actual and forecasted values of total cropped area (000'ha) in India

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	197054	200203	198628.5	199415.75	199022.125
Forecast	199905.81	200816.98	201728.15	202639.32	203550.50
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	201161.12	202039.81	202918.50	203797.20	204675.89

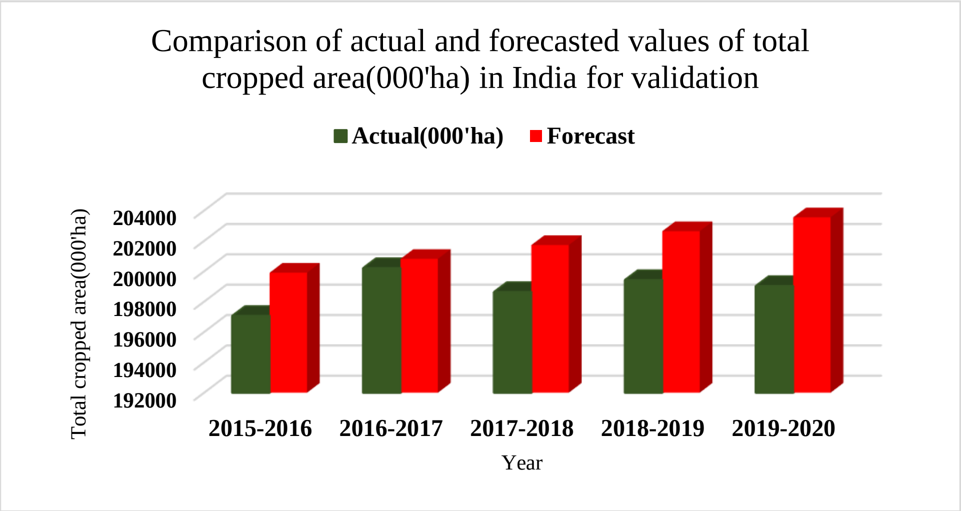

Fig:4.3.1.1.1: Comparison of the original and forecasted values of total cropped area(000'ha) in India for validation

From the above Table 4.3.1.1.1(a) and Fig.4.3.1.1.1 it can be seen that there was a close agreement between actual and forecasted values of total cropped area in India. It is indicating that the identified model was best one to predict the future values.

Table.4.3.1.1.1(b): Statistics for the best diagnosed Holts' model for total cropped area in India

R-squared	0.96
RMSE	3747.43
MAPE	1.66
MaxAPE	9.29
MAE	2843.12
MaxAE	16154.66
Normalized BIC	16.58

From Table 4.3.1.1.1(b), the adjusted R^2 was 0.96, for these proposed models which was significantly high with very low MAPE (1.66), Minimum Normalized Bayesian Information Criteria (16.58).

Table: 4.3.1.1.1(c): Estimates of the parameters for Holts model for total cropped area in India

	Estimate	SE	t	Sig.
Alpha (Level)	0.397	0.092	4.289	0
Gamma (Trend)	1.60E-06	0.014	0	1

The final model could be written in the form,

Level: $L_t = 0.397Y_t + (1-0.397)\ (L_{t-1} + T_{t-1})$

$= 0.397Y_t + 0.603\ (L_{t-1} + T_{t-1})$

Trend: $T_t = \gamma\ (L_t - L_{t-1}) + (1-\gamma)\ T_{t-1}$

$= 1.60E\text{-}06(L_t - L_{t-1}) + (1\text{- }1.60E\text{-}06)\ T_{t-1}$

$= 1.60E\text{-}06\ (L_t - L_{t-1}) + 0.98\ T_{t-1}$

Forecast: $F_{t+1} = L_t + k\ T_t$

$= 00.397Y_t + 0.603\ (L_{t-1} + T_{t-1}) + 1.60E\text{-}06\ (L_t - L_{t-1}) + 0.98\ T_{t-1}$.............4.3.1.1.1(c)

Where k = 1, 2, 3, 4, 5. (Forecasting for the period from 2021-2025)

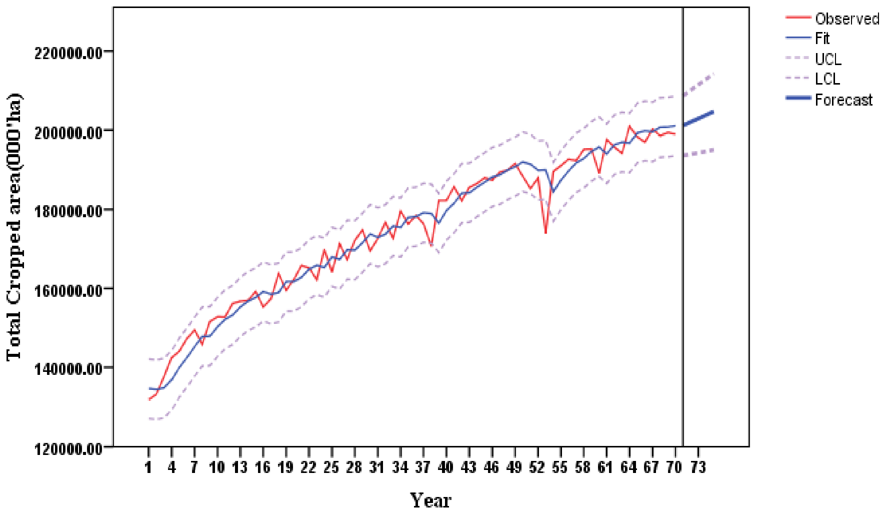

Fig:4.3.1.1.2(a) Actual and forecasted values for total cropped area in India by Holts' model

From the Fig:4.3.1.1.2(a), it can be seen that the actual and forecasted values move almost closely together.

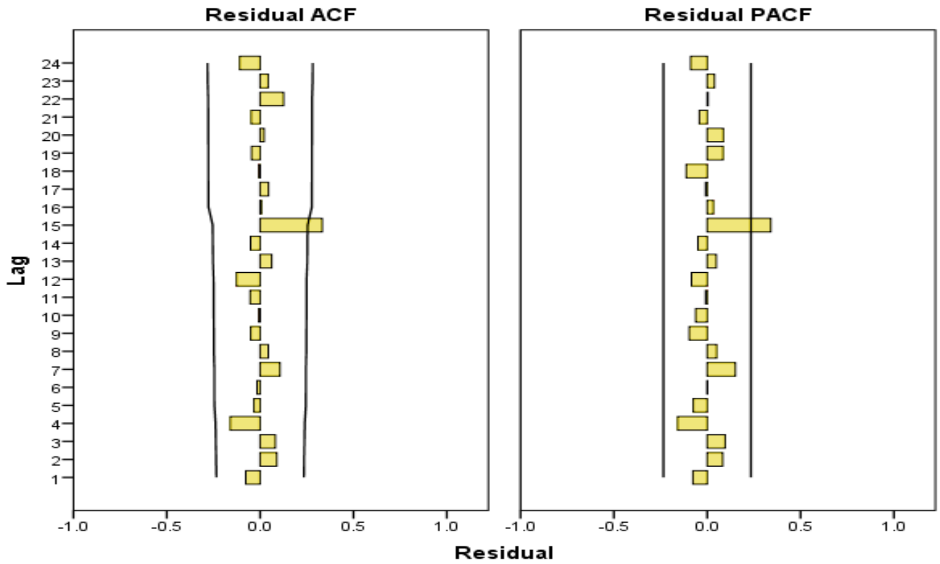

Fig:4.3.1.1.2(b) ACF and PACF through Holts' model for the total cropped area in India

Coming to residuals from the Fig:4.3.1.1.2(b) it can be seen that except for lag-15 the residual ACF and PACF were within the control limits.

4.3.1.2. Fertilizer consumption

For fertilizer consumption in India, the best model fitted was Holts' model and the adjusted R^2 was 99.2% which was significantly high. The results are depicted in Table 4.3.1.2(a).

Table:4.3.1.2.1(a) Comparison of actual and forecasted values of fertilizer consumption (000'tonnes) in India

Year	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020
Actual	26752.6	25949.2	26593.4	27375.2	26984.3
Forecast	26022.42	26463.56	26904.71	27345.86	27787.00
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	27432.71	27881.10	28329.49	28777.88	29226.27

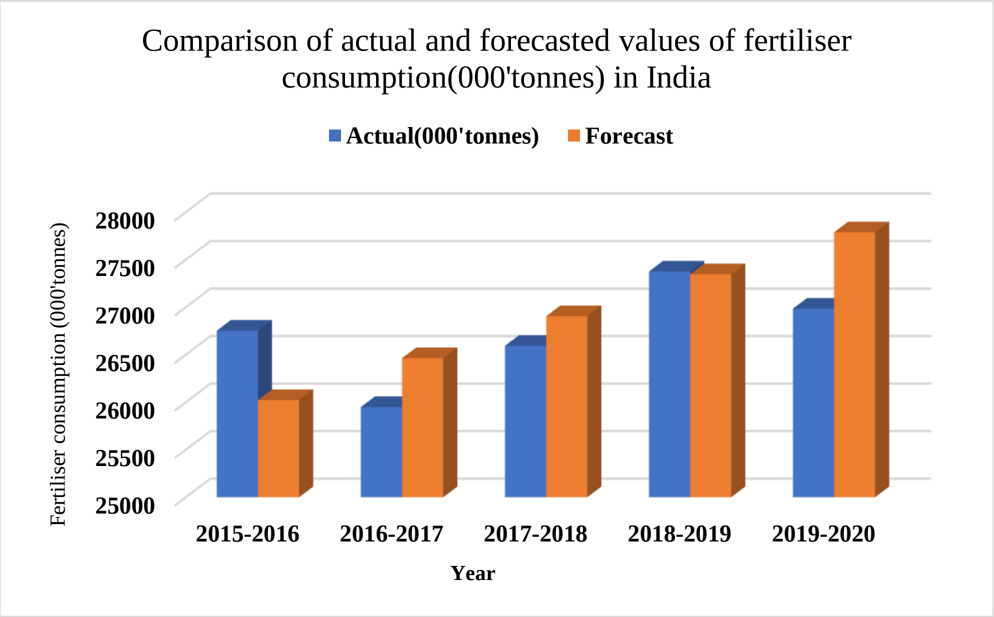

Fig:4.3.1.2.1: Comparison of the original and forecasted values of fertilizer consumption(000'tonnes) in India

From the above Table 4.3.1.2.1(a) and Fig:4.3.1.2.1, it revealed that identified model was best one due to the actual and forecasted values were move in a close agreement with respect to fertiliser consumption.

Table 4.3.1.2.1(b): Statistics for the best diagnosed Holts' model for fertilizer consumption in India

R-squared	0.99
RMSE	806.35
MAPE	58.27
MaxAPE	691.45
MAE	574.67
MaxAE	2706.62
Normalized BIC	13.50

From the Table 4.3.1.2.1 (b) with respect to fertiliser consumption in India, the minimum Normalized Bayesian Information Criteria obtained was 13.50, and very high adjusted R^2 0.99, it shows that the identified model was best one.

Table 4.3.1.2.1(c): Estimates of the parameters for Holts model for fertiliser consumption in India

	Estimate	**SE**	**t**	**Sig.**
Alpha (Level)	1	0.122	8.182	0
Gamma (Trend)	0.001	0.01	0.105	0.917

The final model could be written in the form,

Level: $L_t = Y_t$

Trend: $T_t = 0.001\ (L_t - L_{t-1}) + (1-0.001)\ T_{t-1}$

$= 0.001(L_t - L_{t-1}) + 0.99T_{t-1}$

Forecast: $F_{t+1} = L_t + k\ T_t$

$= Y_t + k\ [0.001(L_t - L_{t-1}) + 0.99T_{t-1}]$ ……………4.3.1.2.1(c)

Where k = 1, 2, 3, 4, 5. (Forecasting for the period from 2021-2025)

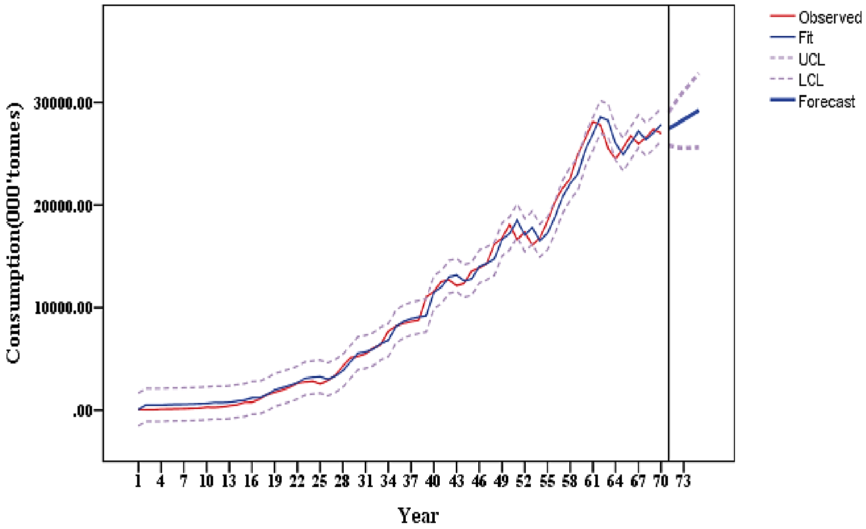

Fig:4.3.1.2.2 (a) Actual and forested values for fertilizer consumption in India by Holts' model

From Fig:4.3.1.2.2 (a) it could be in seen that the actual and forecasted values of fertilizer consumption in India were in close agreement. And the forecasted line showed the increasing trend.

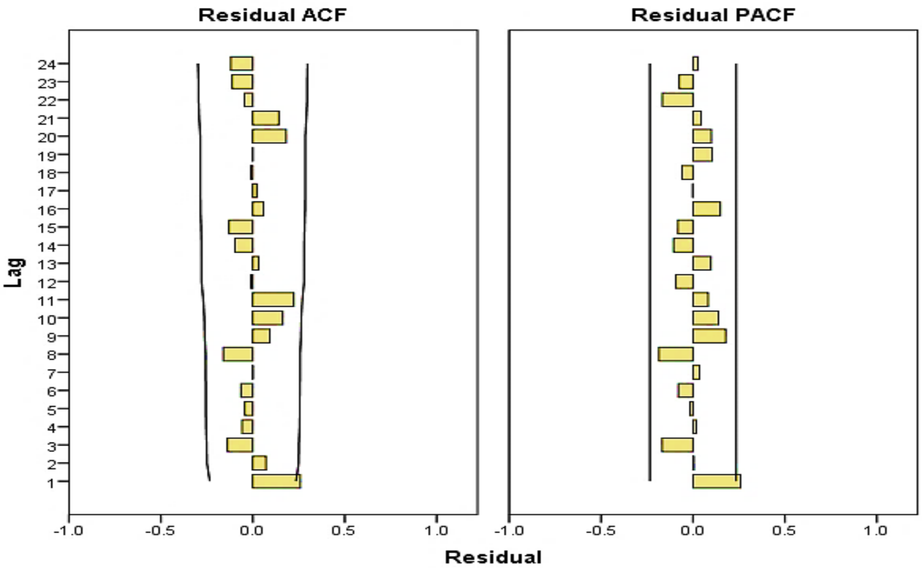

Fig: 4.3.1.2.2 (b) ACF and PACF through Holts' model for the fertilizer consumption in India

From Fig:4.3.1.2.2(b) it can be seen that all the residuals in the ACF and PACF plots were within the confidence limits, except for lag 1. Thus, almost all the information in the series could be captured by the model.

4.3.1.3. Pesticide consumption

From the results obtained from the analysis which was done for the pesticide consumption in India it was found that the best model suitable for fitting the series of consumption of pesticide was simple trend with an adjusted R^2 value of 0.95. Since the fitted model was simple trend, the forecasted values were same for next five out of sample years showing a stagnant movement of the pesticide consumption. The results are depicted below.

Table 4.3.1.3.1(a): Comparison of actual and forecasted values of pesticide consumption (Metric Tonnes) in India

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Original	54121	58546	63406	57022	61702
Forecast	56190.68	56190.68	56190.68	56190.68	56190.68
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	61509.78	61509.78	61509.78	61509.78	61509.78

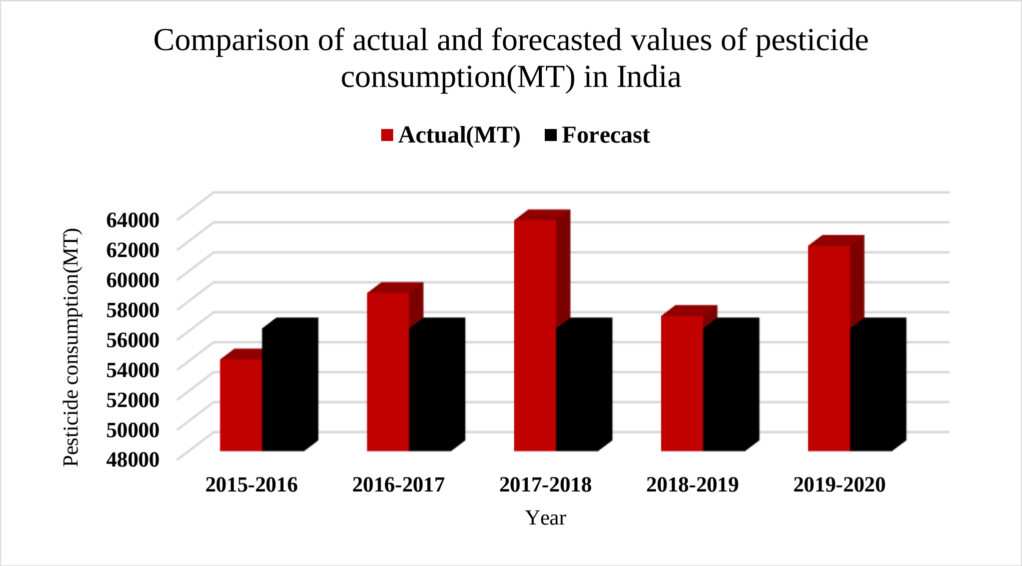

Fig: 4.3.1.3.1 Comparison of the original and forecasted values of pesticide consumption (MT) in India

Table: 4.3.1.3.1(b) Statistics for the best diagnosed simple exponential smoothing for pesticide consumption India

R-squared	0.95
RMSE	5009.72
MAPE	9.91
MaxAPE	52.08
MAE	3387.41
MaxAE	16805.36
Normalized BIC	17.10

Table 4.3.1.3.1(b) showed that the adjusted R^2 was 0.95, minimum Normalized Bayesian Information Criteria was 17.10 and low MAPE (9.91). Based on these criteria it was revealed that the identified model was best to forecast.

Table 4.3.1.3.1(c): Estimates of the parameters for simple exponential smoothing model for pesticide consumption in India

	Estimate	SE	t	Sig.
Alpha (Level)	0.9	0.121	7.913	0.00

The final model could be written in the form,

(Level of the series at time 't') $L_t = \alpha\, Y_t + (1-\alpha)\, L_{t-1}$

$$= 0.9\, Y_t + (1-0.9)\, L_{t-1}$$

$$= 0.9\, Y_t + 0.1\, L_{t-1}$$

Forecast for k step ahead $F_t(k) = L_t$ ………………………...4.3.1.3.1(c)

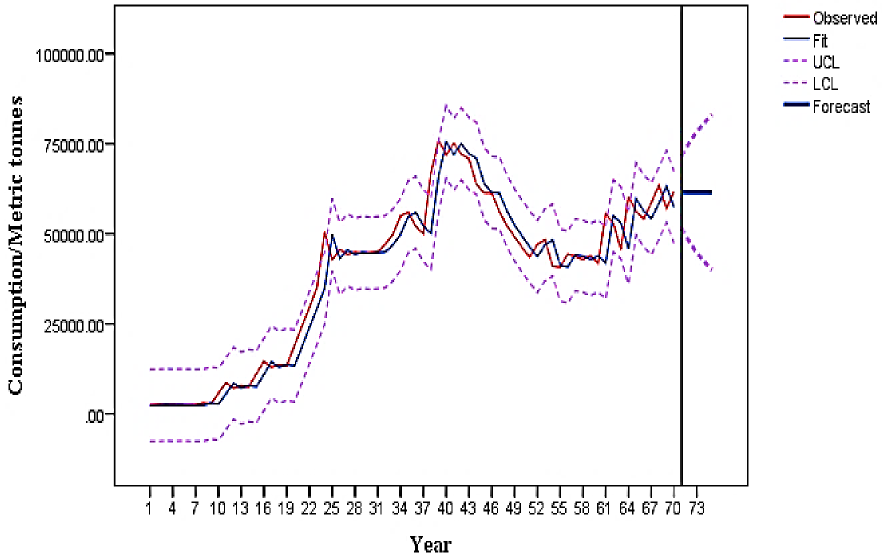

Fig:4.3.1.3.2(a) Actual and forested values for pesticide consumption of India by simple trend model

From the Fig:4.3.1.3.2(a), it can be inferred that the two series, actual and forecasted values of pesticide consumption move together very closely depicting the efficiency of the model developed.

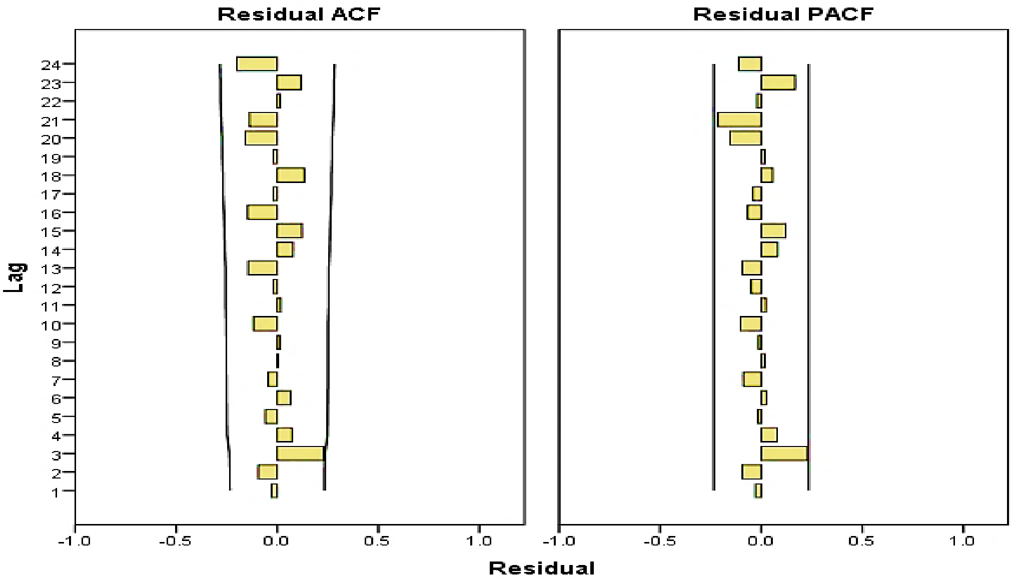

Fig: 4.3.1.3.2 (b) ACF and PACF through simple exponential smoothing model for the pesticide consumption in India

From the Fig:4.3.1.3.2(b), it can be seen that all the residuals in the ACF and PACF plots were within the confidence limits and so the residuals were almost white noise.

4.3.1.4. Food grains production

In the case of food grains production, from the Table 4.3.1.4.1(a) and Fig:4.3.1.4.1 it could be visualised that actual and forecasted values were closely associated

Table:4.3.1.4.1(a) Comparison of the original and forecasted values of food grain production(000'tonnes) in India

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	251566	275111.9	284828.4	285209.3	296649.2
Forecast	260886.94	264075.33	267263.71	270452.10	273640.49
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	292977.87	296304.36	299630.85	302957.34	306283.84

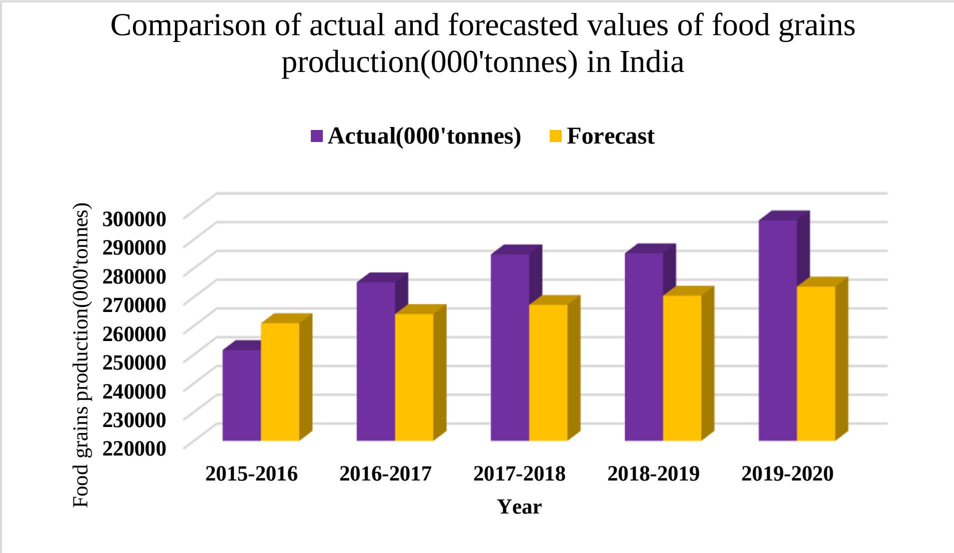

Fig:4.3.1.4.1 Comparison of the original and forecasted values of the food grains production(000'tonnes) in India

Table:4.3.1.4.1(b): Statistics for the best diagnosed Holts' model for food grains production

R-squared	0.98
RMSE	10624.2
MAPE	5.97
MaxAPE	27.19
MAE	8321.40
MaxAE	38136.61
Normalized BIC	18.66

The expert modeller in SPSS 22 identified holts' model as the best to predict the future values of food grains production. The model was validated using 5 years data from 2015-2020 years (Table: 4.3.1.4.1 (a)). As the validation results were satisfactory an attempt was made to predict the food grains production for future. The various statistics obtained for the best diagnosed Holts' model is depicted in Table: 4.3.1.4.1(b). The model has good prediction power with a high value of R^2 = 98% and MAPE = 5.97.

Table 4.3.1.4.1(c): Estimates of the parameters for Holts model for food grains production in India

	Estimate	**SE**	**t**	**Sig.**
Alpha (Level)	0.4	0.104	3.848	0
Gamma (Trend)	1.04E-06	0.064	1.61E-05	1

The final model could be written in the form,

Level: $L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$

$L_t = 0.4Y_t + 0.6(L_{t-1} + T_{t-1})$

Trend: $T_t = \gamma (L_t - L_{t-1}) + (1-\gamma) T_{t-1}$

$T_t = 1.04E\text{-}06(L_t - L_{t-1}) + 0.99T_{t-1}$

Forecast: $F_{t+1} = L_t + k\, T_t$

$= 0.4Y_t + 0.6(L_{t-1} + T_{t-1}) + 1.04E\text{-}06(L_t - L_{t-1}) + 0.99T_{t-1}$ ……………4.3.1.4.1(c)

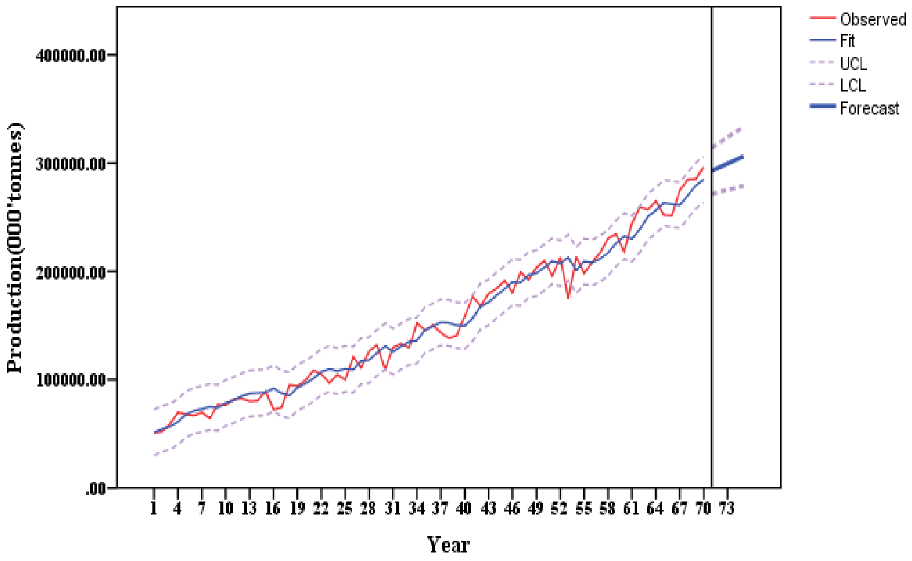

Fig: 4.3.1.4.2 (a) Actual and forested values for food grains production of India by Holts' model

From Fig:4.3.1.4.2 (a) it is evident that the actual and forecasted values of food grains production in India move together almost closely.

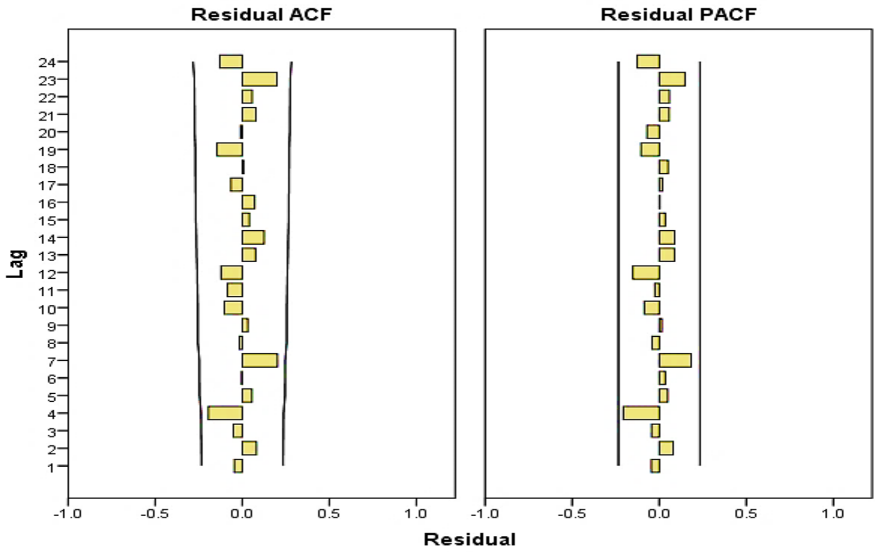

Fig: 4.3.1.4.2 (b) ACF and PACF through Holts' model for the food grains production in India

It is evident from Fig:4.3.1.4.2(b) that, all the residuals in the ACF and PACF plots were within the confidence limits and thus the residuals could be considered as white noise.

The time series models developed for total cropped area, fertilizer consumption, pesticide consumption and food grains production were really promising with high degree of predictability with respect to India. So, an attempt was made to apply the time series models on different states viz; Kerala, Andhra Pradesh and Tamil Nadu.

4.3.2 Time series modelling - Kerala

4.3.2.1. Total cropped area

For modelling total cropped area in Kerala, the data for the period from 1980-2014 were taken to train the model and validation of the model was done using the data for the period from 2015 – 2020. From the Table:4.3.2.1.1(a) and Fig: 4.3.2.1.1 it could be visualised that actual and forecasted values were almost closely associated. The expert modeller in SPSS 22 identified simple exponential smoothing model as the best to predict the future values of total cropped area. As already did in India here also the model was validated using 5 years data from 2015-2020 years (Table: 4.3.2.1.1 (a)). As the validation results were satisfactory an attempt was made to predict the total cropped area for future in Kerala. The various statistics obtained for the best diagnosed simple exponential smoothing model is depicted in Table: 4.3.2.1.1(b). The model has good prediction power with a high value of R^2 = 76% and MAPE = 2.00.

Table:4.3.2.1.1(a) Comparison of actual and forecasted values of total cropped area in Kerala

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	2628	2584	2579.69	2571.1	2575.395
Forecast	2625	2625	2625	2625	2625
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	2575.39	2575.39	2575.39	2575.39	2575.39

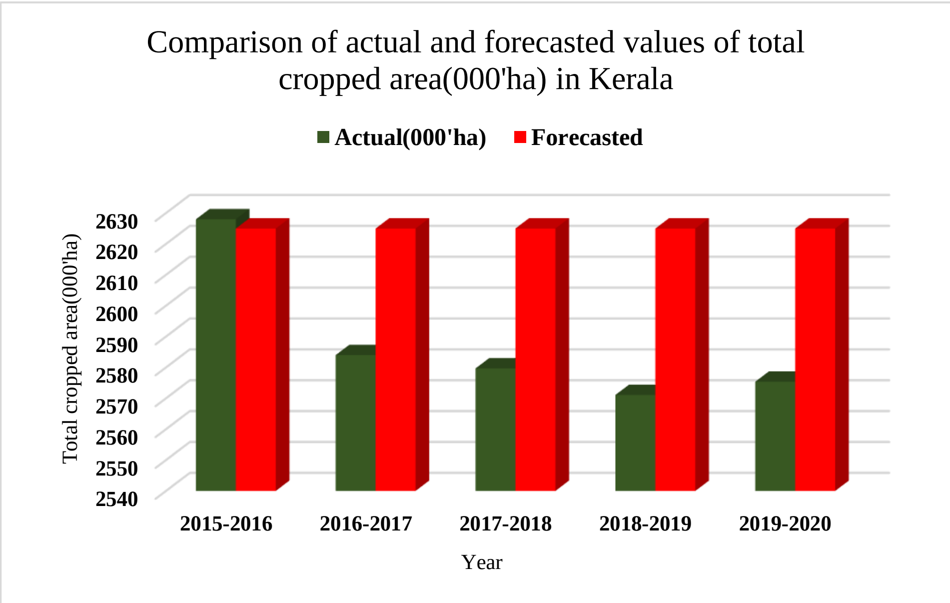

Fig:4.3.2.1.1 Comparison of actual and forecasted values of total cropped area(000'ha) in Kerala

Table: 4.3.2.1.1 (b) Statistics for the best diagnosed simple exponential smoothing model for total cropped area in Kerala

R-squared	0.76
RMSE	92.42
MAPE	2.003
MaxAPE	14.19
MAE	55.53
MaxAE	372.99
Normalized BIC	9.14

Table 4.3.2.1.1(c): Estimates of the parameters for simple exponential smoothing model for total cropped area in Kerala

	Estimate	**SE**	**t**	**Sig.**
Alpha (Level)	1	0.157	6.351	0

The model can be written in the form

(Level of the series at time 't') $L_t = \alpha\, Y_t + (1-\alpha)\, L_{t-1}$

$= Y_t + (1-1)\, L_{t-1}$

$= Y_t$

Forecast for k step ahead $F_t(k) = L_t$……………………4.3.2.1.1(c)

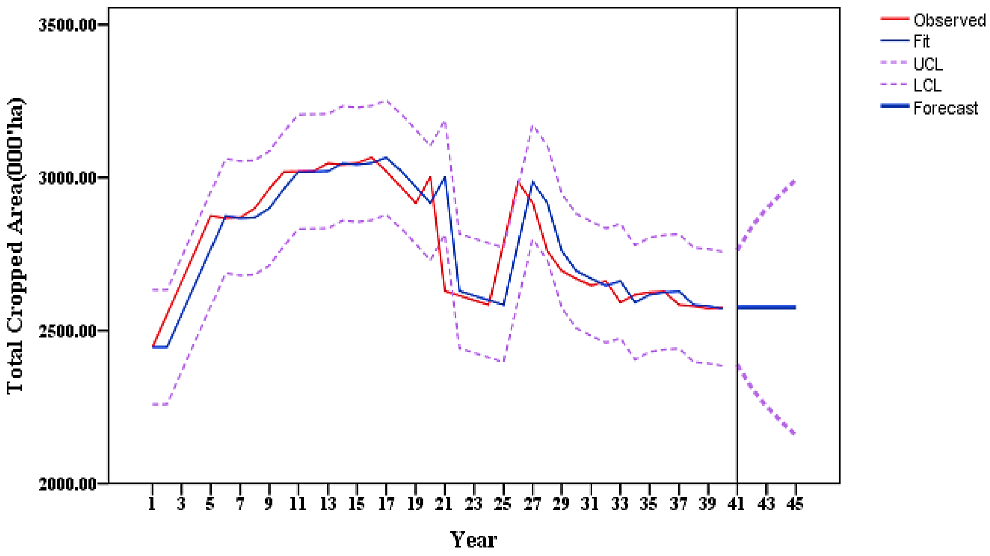

Fig:4.3.2.1.2 (a) Actual and forested values for total cropped area in Kerala by simple exponential smoothing model

The actual and predicted values of total cropped area in Kerala move together very closely as shown in Fig:4.3.2.1.2(a).

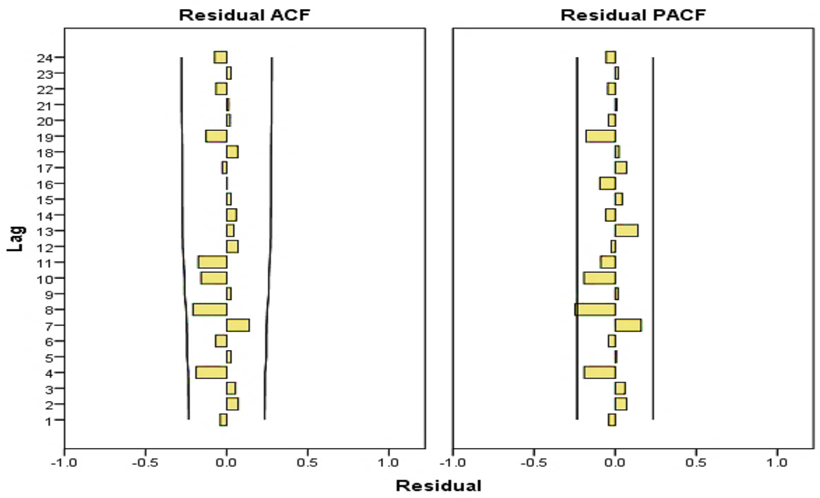

Fig.4.3.2.1.2 (b): ACF and PACF through simple exponential smoothing model for the total cropped area in Kerala

From Fig:4.3.2.1.2(b), it can be seen that all the residuals in the ACF and PACF plots were within the confidence limits and the residuals were almost white noise.

4.3.2.2. Fertilizer Consumption

With respect to fertiliser consumption in Kerala, the model building was attempted taking the data from 1980-2014 as the training period and 2015- 2020 as the validation period. The results are depicted as follows.

Table:4.3.2.2.1(a) Comparison of actual and forecasted values of fertilizer consumption in Kerala

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	228.63	180.42	241.98	181.80	167.96
Forecast	268.50	236.40	251.96	241.91	244.95
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	175.10	173.67	175.58	176.17	177.29

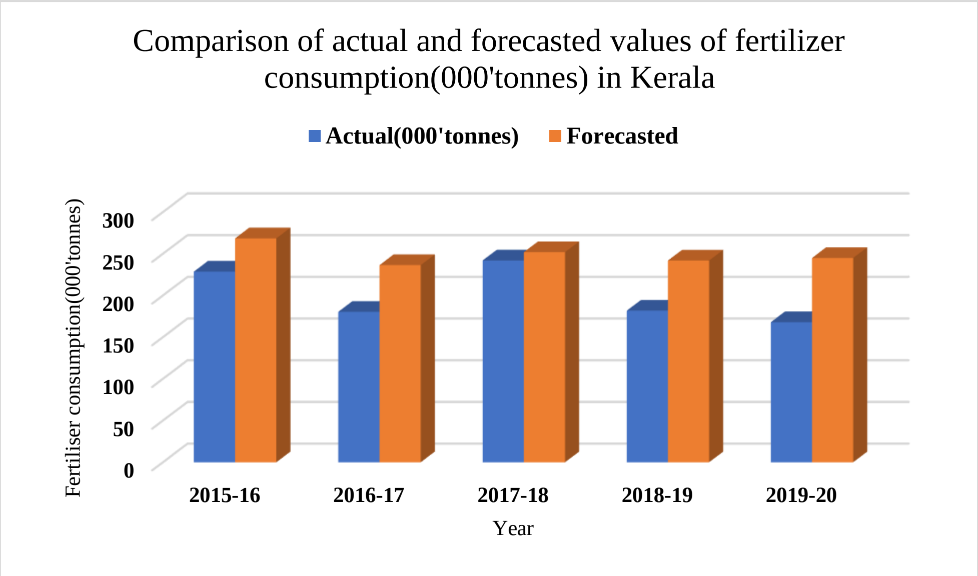

Fig:4.3.2.2.1 Comparison of actual and forecasted values of fertilizer consumption (000'tonnes) in Kerala

It was observed that there was close association between actual and forecasted values of fertiliser consumption in Kerala. That is the identified model, ARIMA (1,1,0) proved to be a good model to predict the future values of fertiliser consumption.

Table 4.3.2.2.1(b): Statistics for the best diagnosed ARIMA (1,1,0) model for fertilizer consumption of Kerala

R-squared	0.66
RMSE	29.97
MAPE	11.53
MaxAPE	46.51
MAE	23.17
MaxAE	97.55
Normalized BIC	6.89

With respect to fertiliser consumption, adjusted R^2 obtained was 0.66 and MAPE was 11.53 with minimum Normalized Bayesian Information Criteria 6.89 as can be seen from the Table: 4.3.2.2.1(b).

Table 4.3.2.2.1(c): Estimates of the parameters for ARIMA (1,1,0) model for fertilizer consumption in Kerala

		Estimate	**SE**	**t**	**Sig.**
AR	**Lag 1**	-0.39	0.15	-2.63	0.012
Difference		1			

The final model could be written in the form

$$(1+0.39B)\ (1-B)\ Y_t = \varepsilon_t \ldots\ldots\ldots\ldots\ldots \ 4.3.2.2.1(c)$$

Where Y_t denotes the fertilizer consumption in Kerala in the year 't'.

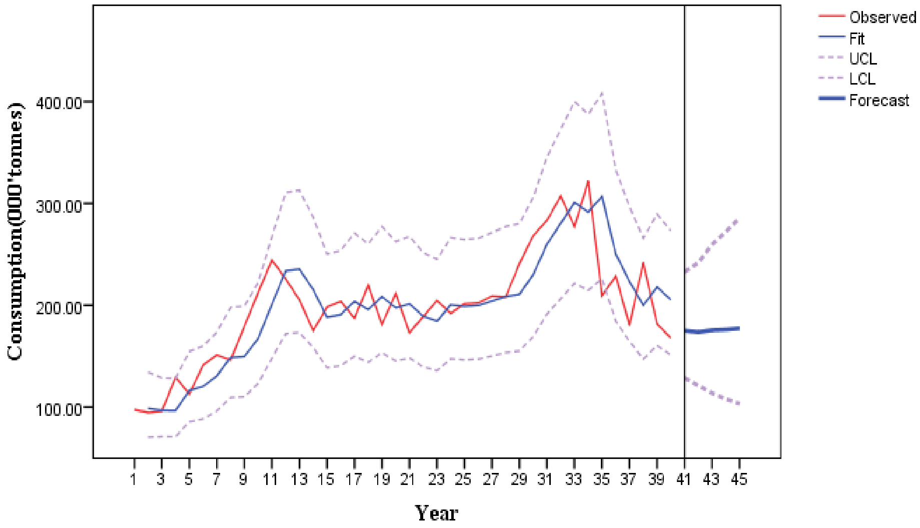

Fig:4.3.2.2.2(a) Actual and forecasted values for fertilizer consumption of Kerala by ARIMA (1,1,0) model

Fig:4.3.2.2.2(a) depicts that, actual and predicted values of fertilizer consumption were moving closely.

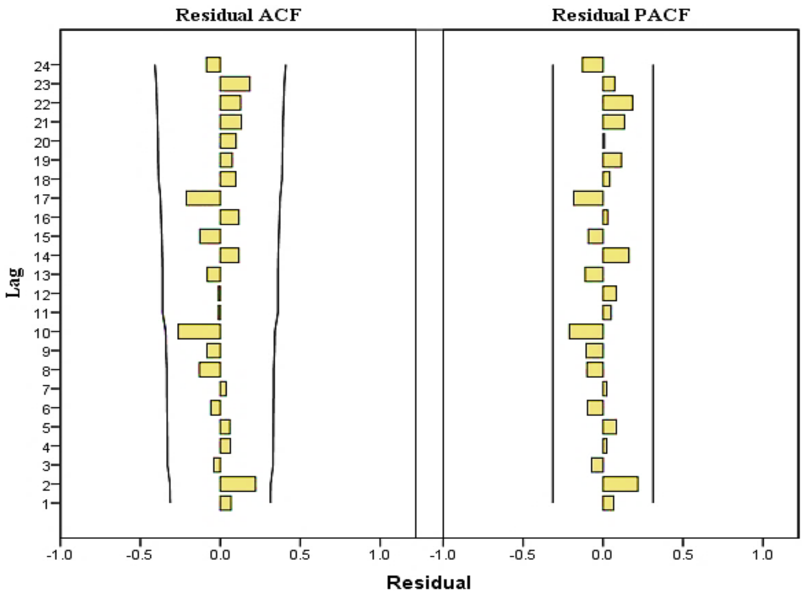

Fig: 4.3.2.2.2 (b) ACF and PACF plots for the fertilizer consumption in Kerala

From Fig:4.3.2.2.2(b), it can be seen that all the residuals in the ACF and PACF plots were within the confidence limits and so the residuals were almost white noise.

4.3.2.3 Pesticide consumption

In the case of pesticide consumption in Kerala time series model building was tried taking the data for the period from 1990-2014 as the training period and 2015-2020 as the validation period. The results are depicted below. Table:4.3.2.3.1(a) shows that actual and forecasted values were closely associated and that can be visualised from the bar diagram (Fig:4.3.2.3.1).

Table 4.3.2.3.1(a): Comparison of actual and forecasted values of pesticide consumption (Metric Tonnes) in Kerala

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	1434	895	1067	995	656
Forecast	1342.35	1136.55	1043.84	1003.34	986.97
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	782.7	838.73	863.51	874.47	879.31

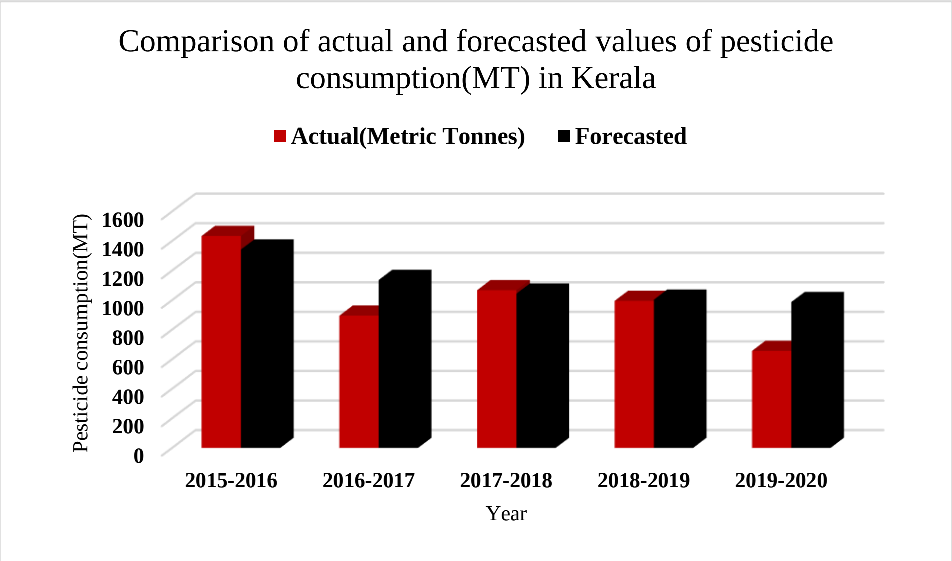

Fig:4.3.2.3.1: Comparison of actual and forecasted values of pesticide consumption (Metric Tonnes) in Kerala

Table 4.3.2.3.1(b): Statistics for the best diagnosed ARIMA (1,0,0) model for pesticide consumption in Kerala

R-squared	0.205
RMSE	324.51
MAPE	36.27
MaxAPE	222.99
MAE	246.67
MaxAE	736.12
Normalized BIC	11.79

As the validation results were satisfactory an attempt was made to predict the pesticide consumption for future in Kerala. The various statistics obtained for the best diagnosed ARIMA (1,0,0) model is depicted in Table: 4.3.2.3.2(b).

Table 4.3.2.3.1(c): Estimates of the parameters for ARIMA (1,0,0) model for pesticide consumption in Kerala

		Estimate	**SE**	**t**	**Sig.**
Constant		883.15	103.56	8.53	0
AR	**Lag 1**	0.44	0.17	2.60	0.02

The final model could be written in the form

$$(1-0.44B)\ Y_t = 883.15 + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots 4.3.2.3.1(c)$$

Where Y_t denotes the pesticide consumption in Kerala for the year 't'.

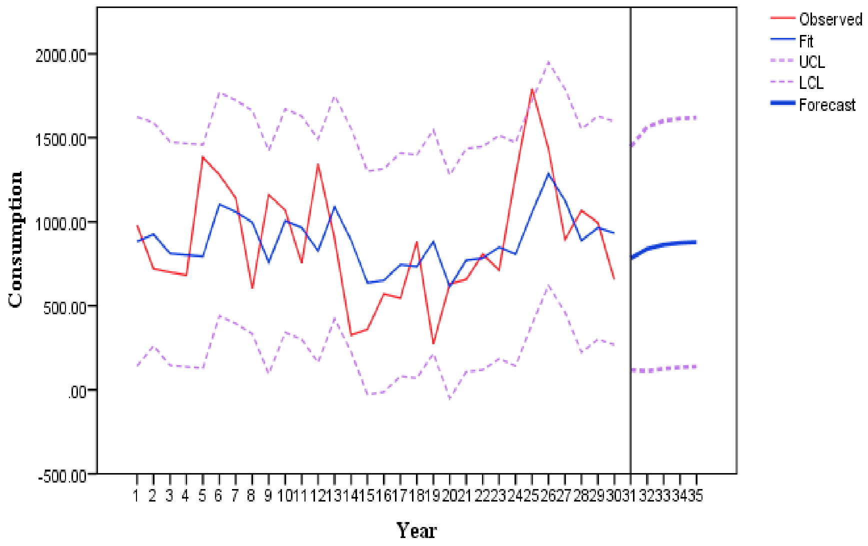

Fig.4.3.2.3.2(a): Actual and forested values for pesticide consumption in Kerala by ARIMA (1,0,0) model

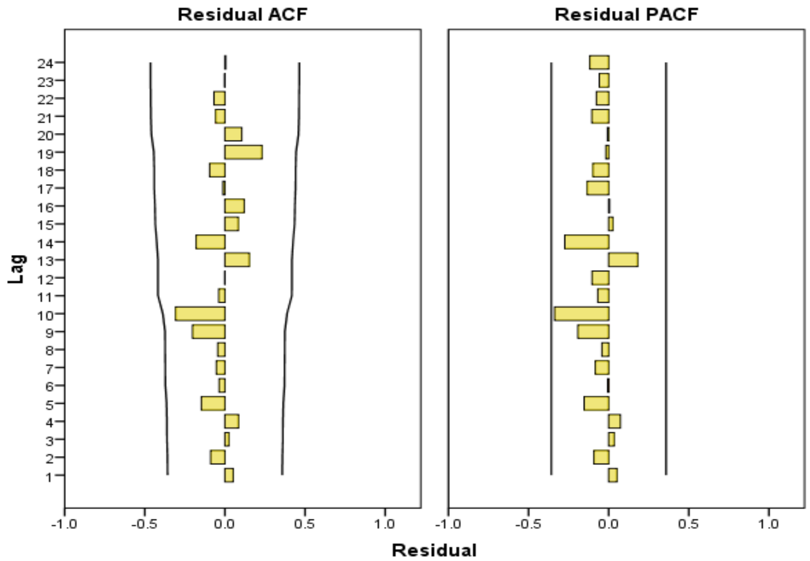

Fig.4.3.2.3.2 (b): ACF and PACF plots through ARIMA (1,0,0) for the pesticide consumption of Kerala

The residual ACF and PACF plots were within the confidence limits as shown in Fig:4.3.2.3.2 (b) and hence the residuals were almost white noise.

4.3.3.4. Food grains production

For model building the training period was taken as 1950-2014 and validation period as 2015 – 2020. From the Table:4.3.3.4.1(a) It can be seen that with respect to food grains production the actual and forecasted values were almost closely associated and that can be visualized from the Fig:4.3.3.4.1.

Table.4.3.3.4.1(a): Comparison of actual and forecasted values of food grains production (000’tonnes) in Kerala

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	553.8	439	523.8	581.2	617.1
Forecast	562.51	568.61	574.71	580.8	586.9
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	560.31	562.48	564.65	566.82	568.99

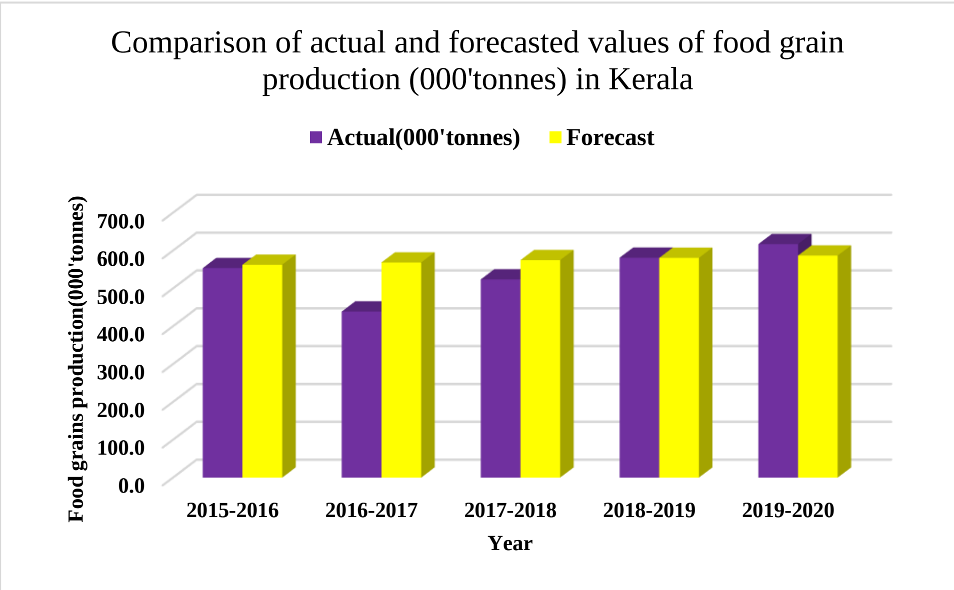

Fig.4.3.3.4.1: Comparison of actual and forecasted values of food grain production (000'tonnes) in Kerala

The various statistics obtained for the best diagnosed Holts’ model is depicted in Table: 4.3.3.4.1(b). The model has good prediction power with a high value of R^2 = 85% and MAPE = 12.41.

Table 4.3.3.4.1(b): Statistics for the best diagnosed Holts' model for food grains production in Kerala

R-squared	0.85
RMSE	121.08
MAPE	12.41
MaxAPE	301.52
MAE	79.28
MaxAE	688.67
Normalized BIC	9.71

Table 4.3.2.4.1(c): Estimates of the parameters of Holts' model for food grains production in Kerala

	Estimate	**SE**	**t**	**Sig.**
Alpha (Level)	0.059	0.053	1.107	0.272
Gamma (Trend)	1	0.966	1.035	0.305

The model could be written in the form

Level: $L_t = 0.059Y_t + (1-0.059)\ (L_{t-1} + T_{t-1})$

Trend: $T_t = (L_t - L_{t-1})$

Forecast: $F_{t+1} = L_t + k\ T_t$

$$= 0.059Y_t + (1-0.059)\ (L_{t-1} + T_{t-1}) + 1\ (L_t - L_{t-1})$$

$$= 0.059Y_t + 0.94(L_{t-1} + T_{t-1}) + 1\ (L_t - L_{t-1}) \quad \ldots\ldots\ldots\ldots 4.3.2.4.1(c)$$

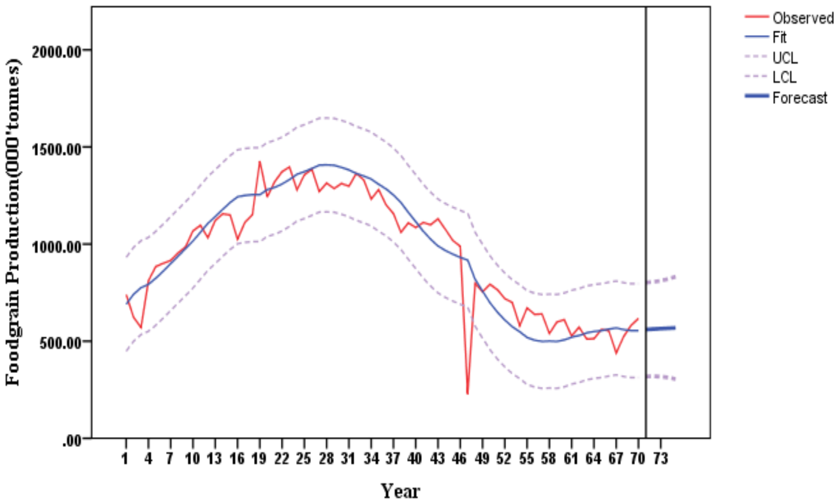

Fig.4.3.3.4.2(a): Actual and forested values for food grains production in Kerala by Holts' model

From the Fig.4.3.3.4.2(a), it can be concluded that the two series of actual and predicted values of food grains production of Kerala were not moving very closely.

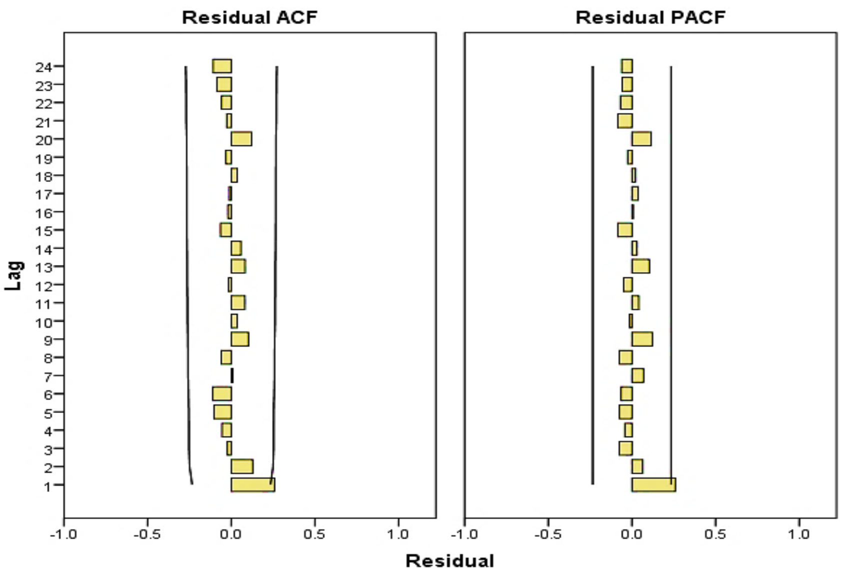

Fig. 4.3.3.4.2(b): ACF and PACF through Holts' model for food grains production in Kerala

From the Fig.4.3.3.4.2(b) of the residuals of ACF and PACF plots of food grains production in Kerala, lag - 1 was significant and lie outside the confidence interval meaning that all the higher-order autocorrelations were effectively explained by the lag-1 autocorrelation.

4.3.3 Time series modeling - Andhra Pradesh

4.3.3.1. Total cropped Area

Coming to time series modeling in Andhra Pradesh, for total cropped area, the model was trained by taking the data for 1980-2014 and validated for 2015-2020. ARIMA (0,1,0) model was the best to predict the future values of total cropped area. The model was validated using 5 years data from 2015-2020 years (Table.4.3.3.1.1(a)). Here the validation results were satisfactory due to close association between actual and forecasted values and an attempt was made to predict the total cropped area for future in Andra Pradesh. Results are depicted in Table.4.3.3.1.1(a) and Fig.4.3.3.1.1.

Table 4.3.3.1.1(a): Comparison of actual and forecasted values of total cropped area in Andhra Pradesh

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	7532	6781	6030	6405.5	6217.75
Forecast	7451.47	7212.94	6974.41	6735.88	6497.35
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	5972.05	5726.35	5480.65	5234.96	4989.26

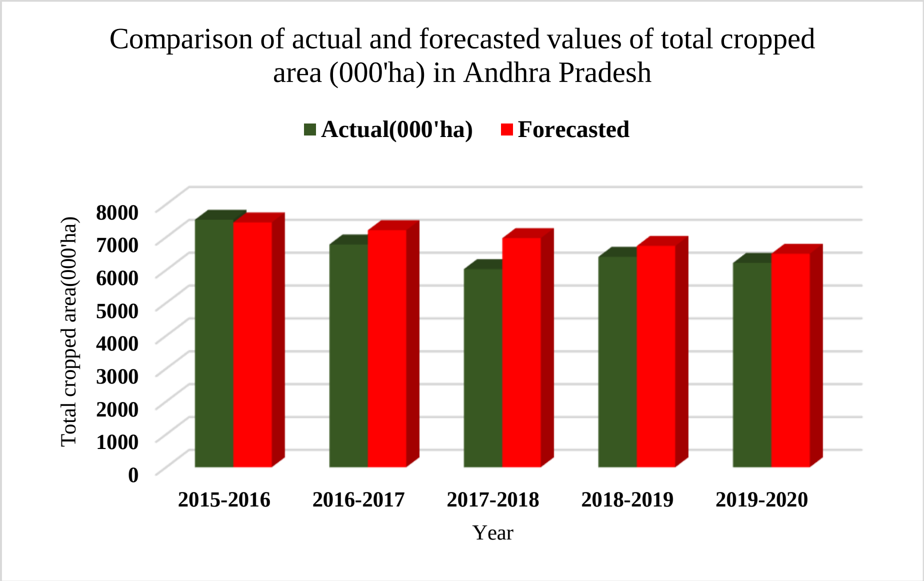

Fig.4.3.3.1.1: Comparison of actual and forecasted values of total cropped area (000'ha) in Andhra Pradesh

The various statistics obtained for the best diagnosed ARIMA (0,1,0) model is depicted in Table: 4.3.3.1.1(b). The model had good prediction power with a value of R^2 = 80% and MAPE = 5.93.

Table 4.3.3.1.1(b): Statistics for the best diagnosed ARIMA (0,1,0) model for total cropped area in Andhra Pradesh

R-squared	0.80
RMSE	1107.41
MAPE	5.93
MaxAPE	64.92
MAE	649.27
MaxAE	5276.30
Normalized BIC	14.11

Table 4.3.3.1.1(c): Estimates of the parameters for ARIMA (0,1,0) model for total cropped area in Andhra Pradesh

	Estimate	SE	t	Sig.
Constant	-245.70	177.33	-1.39	0.17
Difference	1			

The final model could be written as

$$Y_t = Y_{t-1} - 245.70 \ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.3.3.1.1(c)$$

Where Y_t denotes the total cropped area in Andhra Pradesh in the year 't'.

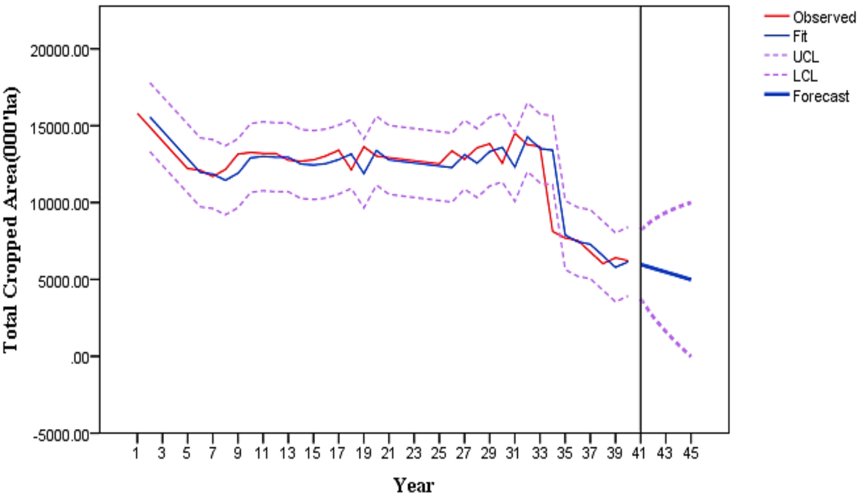

Fig:4.3.3.1.2 (a): Actual and forested values for total cropped area in Andhra Pradesh by ARIMA (0,1,0) model

The actual and predicted values of total cropped area in Andhra Pradesh were moving closely together as seen from the Fig.4.3.3.1.2(a). It depicted the efficiency of the model developed.

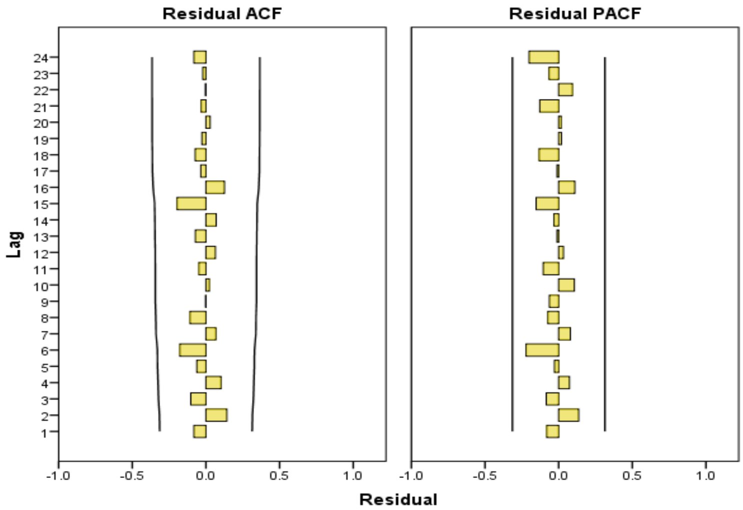

Fig:4.3.3.1.2 (b): ACF and PACF through ARIMA (0,1,0) model for the total cropped area in Andhra Pradesh

From the Fig.4.3.3.1.2 (b) it can be noticed that all the residuals of ACF and PACF plots were within the confidence limits and so the residuals were almost white noise.

4.3.3.2.1 Fertilizer Consumption

In this case the training period was 1970-2014 and validation period was 2015-12020 which was taken for model building. Close association of actual and forecasted values of fertiliser consumption in Andhra Pradesh are depicted in Table 4.3.3.2.1(a) and Fig.4.3.3.2.1.

Table 4.3.3.2.1(a): Comparison of actual and forecasted values of fertilizer consumption in Andhra Pradesh

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	1698.15	1686.96	1564.02	1556.35	1560.185
Forecast	2434.70	2434.70	2434.70	2434.70	2434.70
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	1560.18	1560.18	1560.18	1560.18	1560.18

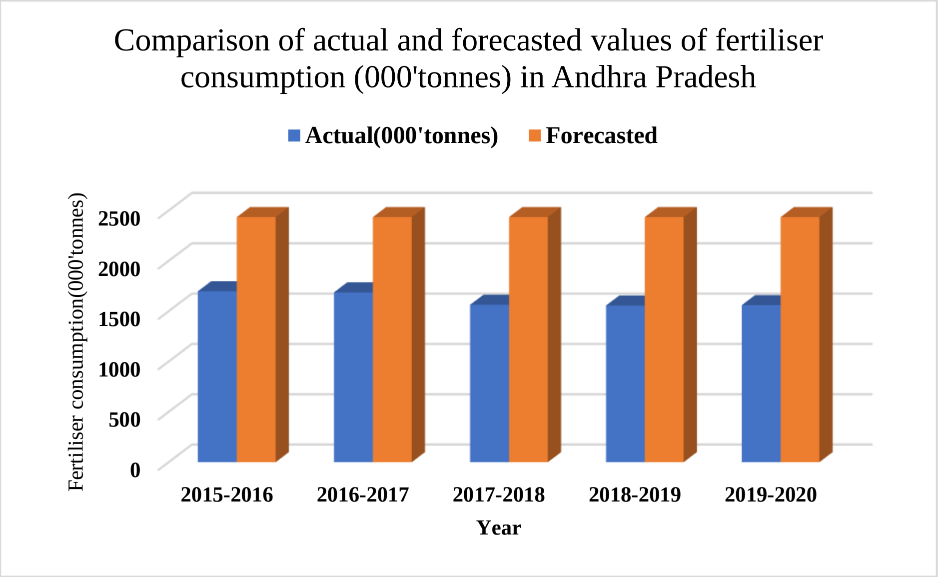

Fig.4.3.3.2.1: Comparison of actual and forecasted values of fertilizer consumption (000'tonnes) in Andhra Pradesh

The simple exponential smoothing model was identified as the best to predict the future values of total cropped area and the various statistics obtained for the best diagnosed simple exponential smoothing model is depicted in Table.4.3.3.2.1(b). The model had good prediction power with high value of R^2 = 93% and MAPE = 11.51.

Table.4.3.3.2.1(b): Statistics for the best diagnosed simple exponential smoothing model for fertilizer consumption in Andhra Pradesh

R-squared	0.93
RMSE	241.30
MAPE	11.51
MaxAPE	40.60
MAE	160.38
MaxAE	640.16
Normalized BIC	24.95

Table.4.3.3.2.1(c): Estimates of the parameters for simple exponential smoothing model for fertilizer consumption in Andhra Pradesh

	Estimate	**SE**	**t**	**Sig.**
Alpha (Level)	1	0.143	7	0

The final model could be written as

(Level of the series at time 't') $L_t = \alpha\ Y_t + (1\text{-}\alpha)\ L_{t-1}$

$= Y_t + (1\text{-}1)\ L_{t-1}$

$= Y_t$

Forecast for k step ahead $F_t(k) = L_t$ …………………………4.3.3.2.1(c)

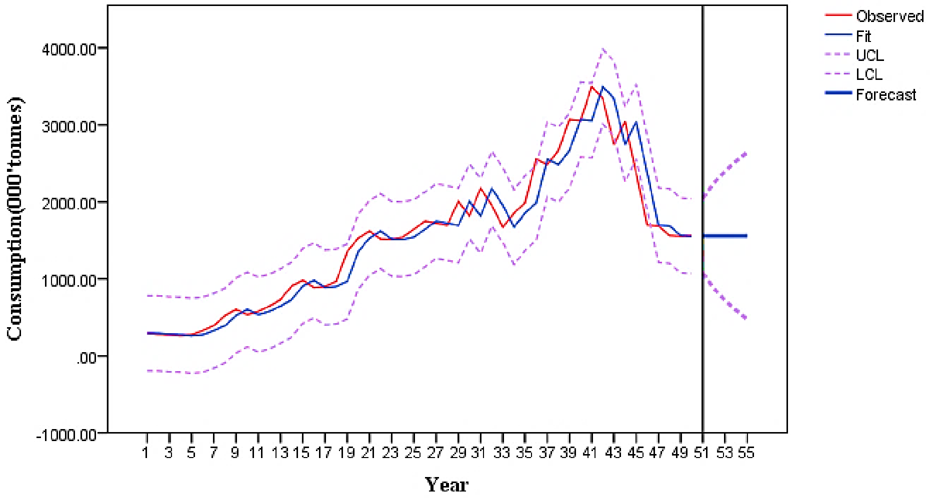

Fig.4.3.3.2.2(a): Actual and forecasted values for fertilizer consumption in Andhra Pradesh by simple exponential smoothing model

From Fig.4.3.3.2.2(a), it can be concluded that the two series of actual and predicted values of fertilizer consumption of Andhra Pradesh move together very closely depicting the efficiency of the simple exponential smoothing model developed.

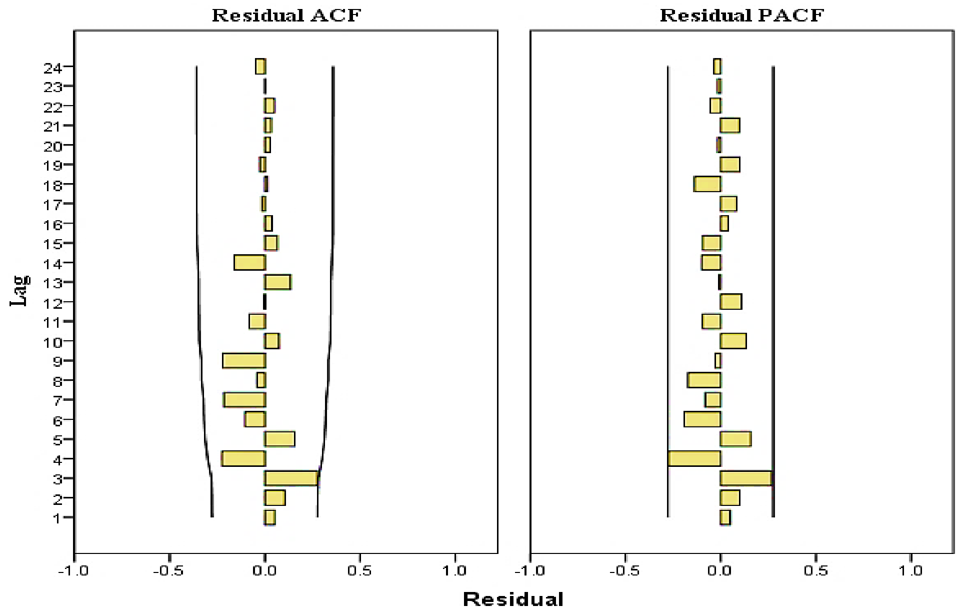

Fig.4.3.3.2.2(b): ACF and PACF through simple exponential smoothing model for the fertilizer consumption in Andhra Pradesh

And with respect to residuals, from Fig.4.3.3.2.2(b) all the residuals were within the limits.

4.3.3.3. Pesticide Consumption

With respect to pesticide consumption the training period for model building was 1970-2014 and validation period was 2015-2020. The results obtained regarding to comparison of actual and forecasted values of pesticide consumption in Andhra Pradesh are depicted in Table 4.3.3.3.1 and Fig.4.3.3.3.1.

Table 4.3.3.3.1(a): Comparison of actual and forecasted values of pesticide consumption in Andhra Pradesh

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	2712	2015	1738	1689	1558.63
Forecast	4050	4050	4050	4050	4050
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	1559.01	1559.01	1559.01	1559.01	1559.01

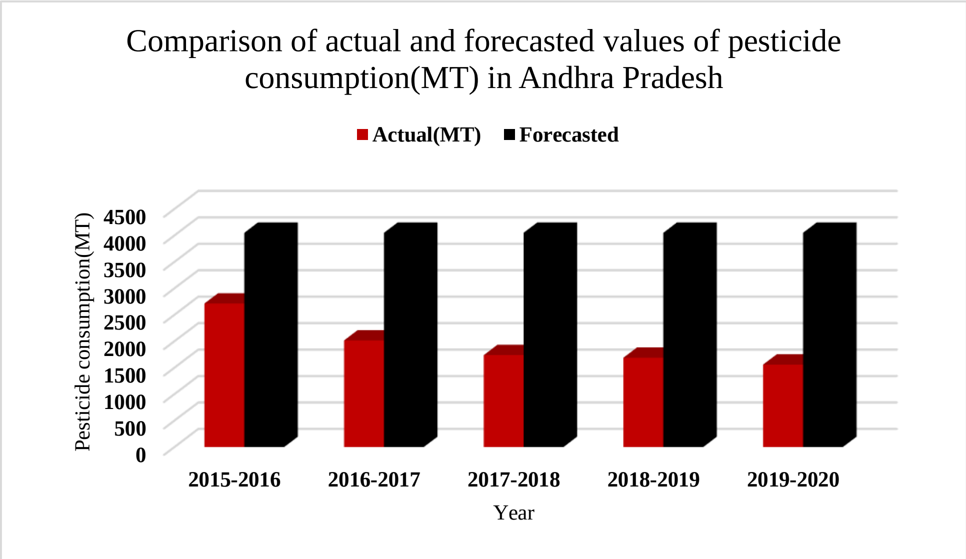

Fig.4.3.3.3.1: Comparison of actual and forecasted values of pesticide consumption (MT) in Andhra Pradesh

The best model obtained for predicting the future values of pesticide consumption was simple exponential smoothing model and the various statistics obtained for the model is depicted in Table. 4.3.3.3.1(b). The model has good prediction power with a value of R^2 = 82% and MAPE = 20.63.

Table 4.3.3.3.1(b): Statistics for the best diagnosed simple exponential smoothing model for pesticide consumption in Andhra Pradesh

R-squared	0.82
RMSE	1797.62
MAPE	20.60
MaxAPE	231.39
MAE	1081.55
MaxAE	7853.98
Normalized BIC	15.07

Table 4.3.3.3.1(c): Estimates of the parameters for simple exponential smoothing model for pesticide consumption in Andhra Pradesh

	Estimate	SE	t	Sig.
Alpha (Level)	1	0.142	7.02	0

The final model could be written in the form

Level of the series at time 't') $L_t = \alpha\, Y_t + (1\text{-}\alpha)\, L_{t-1}$

$$= Y_t + (1\text{-}1)\, L_{t-1}$$

$$= Y_t$$

Forecast for k step ahead $F_t(k) = L_t$ …………………...4.3.3.3.1(c)

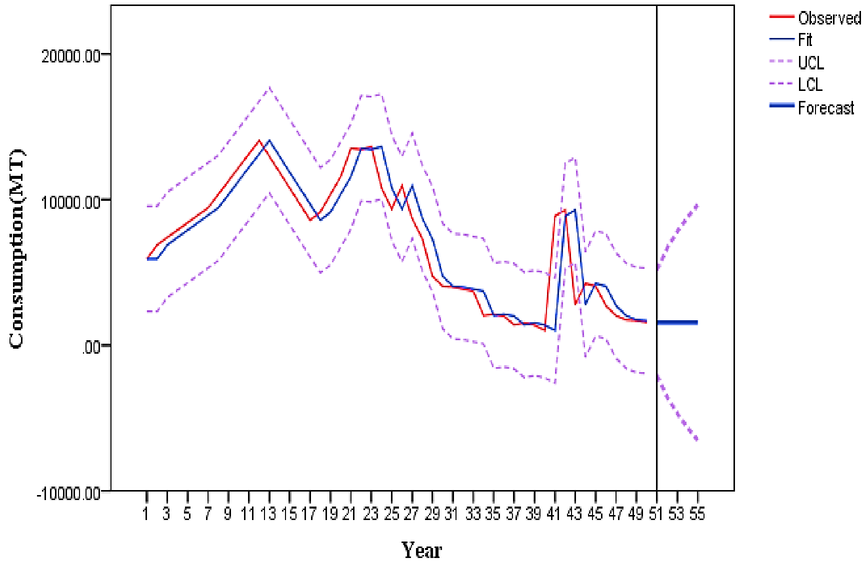

Fig.4.3.3.3.1(a): Actual and forecasted values for pesticide consumption in Andhra Pradesh by simple exponential smoothing model

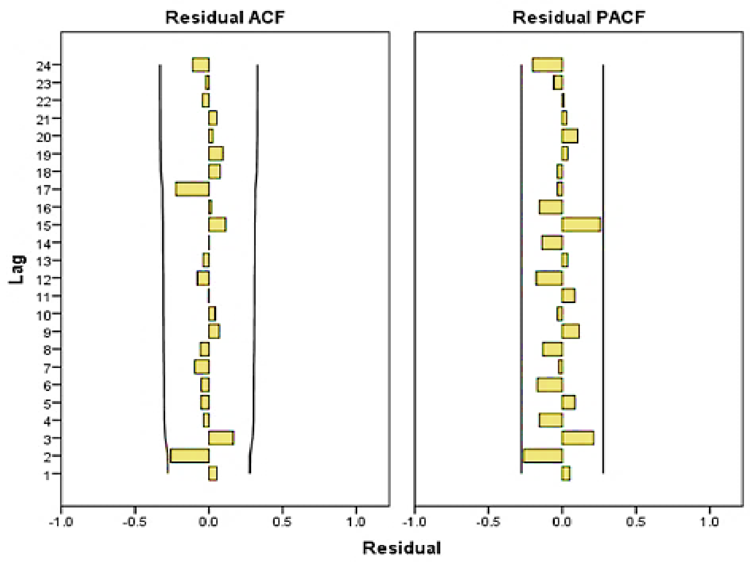

Fig. 4.3.3.2.2(b): ACF and PACF through simple exponential smoothing model for the pesticide consumption in Andhra Pradesh

From the Fig.4.3.3.2.2(b), it can be seen that all the residuals in the ACF and PACF plots were within the confidence limits and so the residuals were almost white noise.

4.3.3.4. Food grains production

In this case the model building was done taking the data from 1950-2014 as the training period and validation period as 2015-2020. The association of actual and forecasted values of food grains production in Andhra Pradesh is depicted in Table.4.3.3.4.1(a) and Fig.4.3.3.4.1. Simple exponential smoothing model was identified as the best model to predict the values of food grains production

Table 4.3.3.4.1(a) Comparison of actual and forecasted values of food grains production (000’tonnes) in Andhra Pradesh

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	10633.7	10365.4	12159.8	10838.8	12504.7
Forecast	18287.95	18287.95	18287.95	18287.95	18287.95
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	12044.29	12044.29	12044.29	12044.29	12044.29

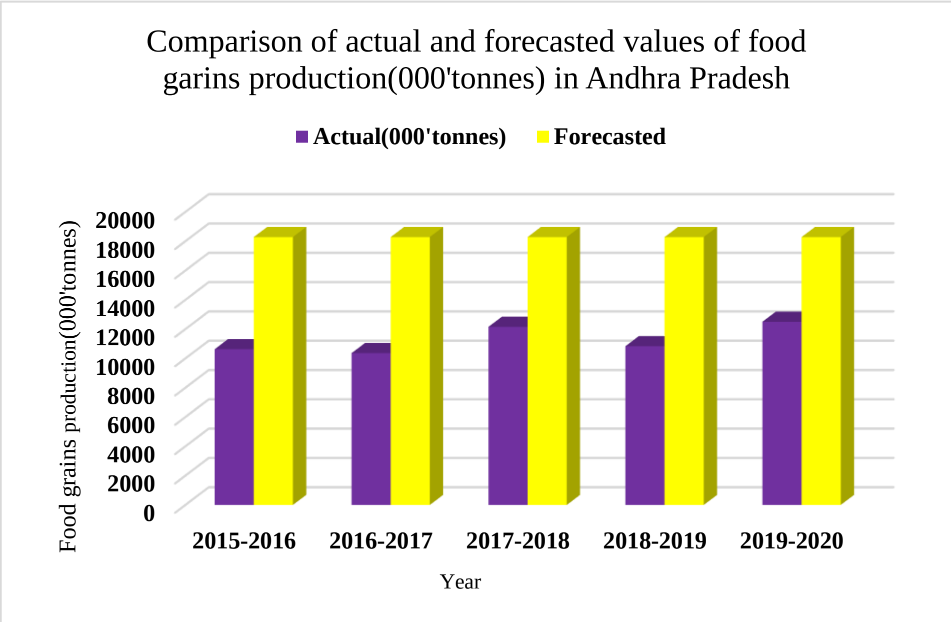

Fig.4.3.3.4.1: Comparison of actual and forecasted values of food grains production (000'tonnes) in Andhra Pradesh

Various statistics obtained for the model is depicted in Table 4.3.3.4.1(b). The model has good prediction power with R^2 = 82% and MAPE = 10.24.

Table 4.3.3.4.1(b): Statistics for the best diagnosed simple exponential smoothing model for food grains production in Andhra Pradesh

R-squared	0.82
RMSE	1747.11
MAPE	10.24
MaxAPE	70.28
MAE	1133.74
MaxAE	7472.89
Normalized BIC	14.99

Table 4.3.3.4.1(c): Estimates of parameters for simple exponential smoothing model for food grains production in Andhra Pradesh

	Estimate	**SE**	**t**	**Sig.**
Alpha (Level)	0.643	0.112	5.722	0

The final model is given by,

(Level of the series at time ‘t’) $L_t = \alpha\, Y_t + (1\text{-}\alpha)\, L_{t-1}$

$= Y_t + (1\text{-}1)\, L_{t-1}$

$= Y_t$

Forecast for k step ahead $F_t(k) = L_t$ …………………………..4.3.3.4.1(c)

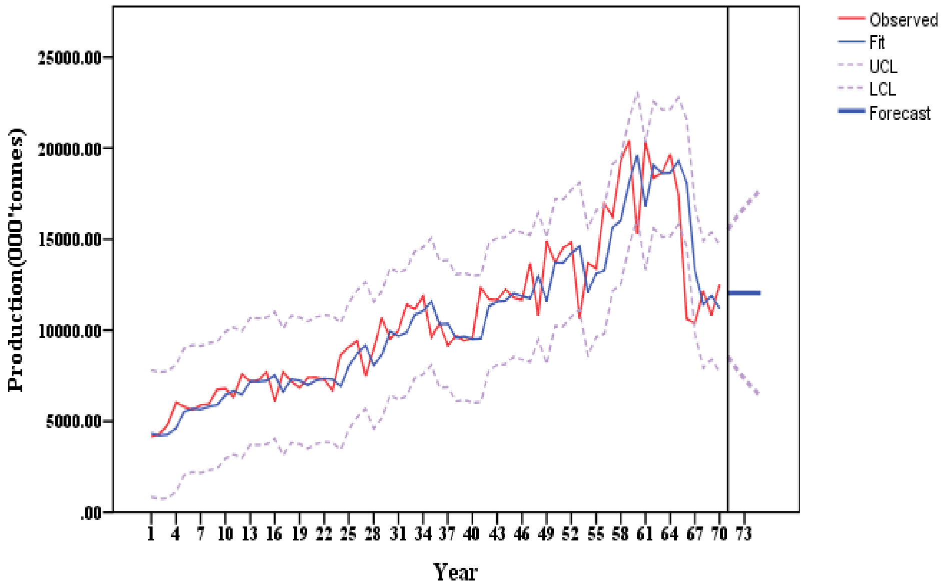

Fig. 4.3.3.4.2(a): Actual and forecasted values for food grains production of Andhra Pradesh by simple exponential smoothing model

Here the actual and forecasted values were closely moving together depicting the efficiency of the model developed.

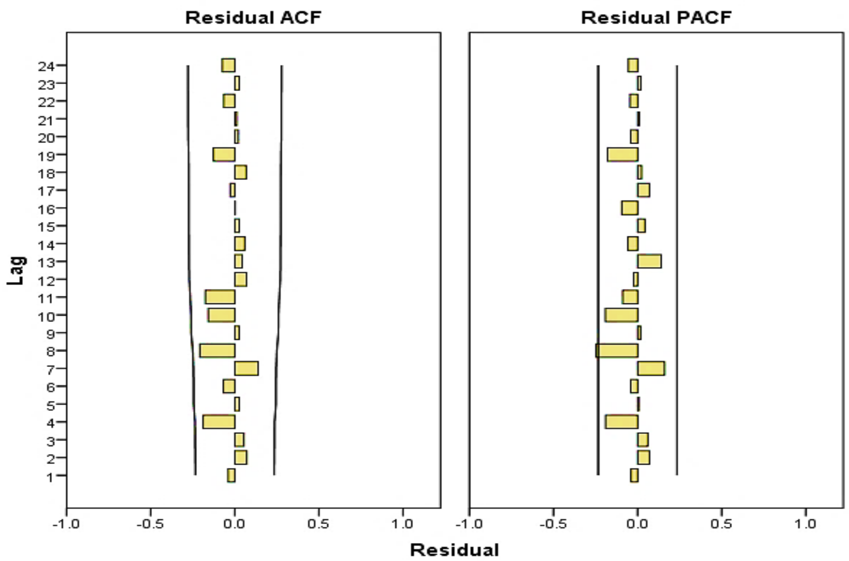

Fig. 4.3.3.4.2 (b): ACF and PACF through simple exponential smoothing model for the food grains production in Andhra Pradesh

From the Fig.4.3.3.4.2(b), it can be seen that almost all the spikes in the residual plots are within the confidence limit. Hence the residuals were almost white noise.

4.3.4 Time series modeling – Tamil Nadu

4.3.4.1. Total cropped Area

Coming to modelling in Tamil Nadu, the models were tried taking the data for the period 1980- 2014 as the training period and 2015-2020 as the validation period. Expert modeller in SPSS 22 identified ARIMA (0,1,0) model as the best to predict the future values of total cropped area. From the Table:4.3.4.1.1(a) and Fig: 4.3.4.1.1 it could be visualised that actual and forecasted values were closely connected. The model was validated using 5 years data from 2015-2020 years (Table: 4.3.4.1.1 (a)). As the validation results were satisfactory an attempt was made to predict the total cropped area for future in Tamil Nadu.

Table 4.3.4.1.1(a): Comparison of actual and forecasted values of total cropped area in Tamil Nadu

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	6074	5129	5730	5672	5942
Forecast	5920.76	5846.53	5772.29	5698.06	5623.82
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	6006.38	6077.28	6154.7	6238.65	6329.12

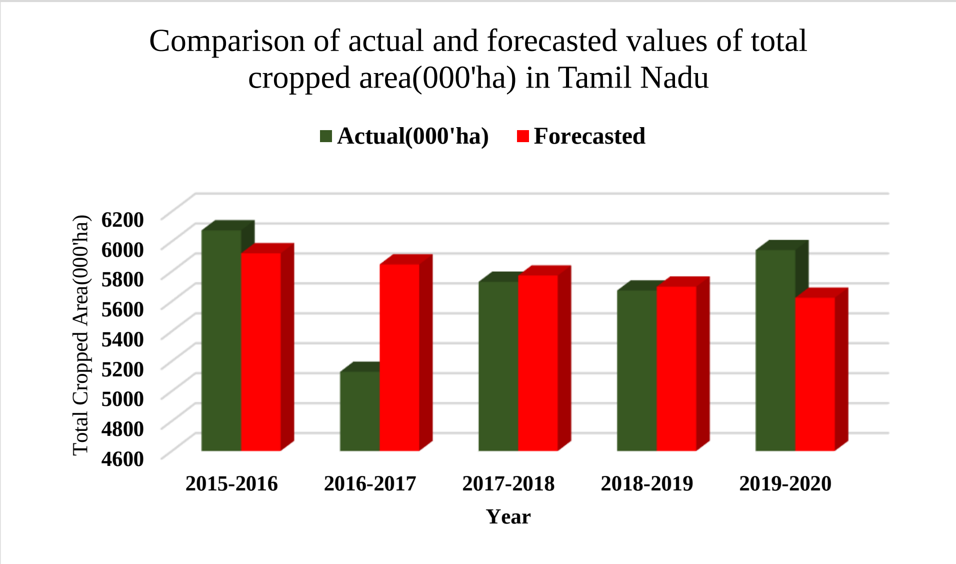

Fig.4.3.4.1.1: Comparison of actual and forecasted values of total cropped area (000'ha) in Tamil Nadu

The various statistics obtained for the best diagnosed ARIMA (0,1,0) model is depicted in Table 4.3.4.1.1(b). The model had good prediction power with a value of R^2 = 78%, MAPE = 3.65 and normalized BIC = 11.79.

Table 4.3.4.1.1(b): Statistics for the best diagnosed ARIMA (0,1,0) model for total cropped area in Tamil Nadu

R-squared	0.76
RMSE	330.91
MAPE	3.65
MaxAPE	19.17
MAE	222.52
MaxAE	983.28
Normalized BIC	11.79

Table 4.3.4.1.1(c): Estimates of parameters for ARIMA (0,1,0) model for total cropped area in Tamil Nadu

		Estimate	SE	t	Sig.
Constant		-203.06			
Difference			112.176	-1.81	0.078
Numerator	**Lag0**	1			

The final model could be written in the form,

$$Y_t = Y_{t-1} - 203.06 \text{ ……………………………...4.3.4.1.1(c)}$$

Where Y_t denotes the total cropped area in Tamil Nadu in thousand hectares for the year 't'.

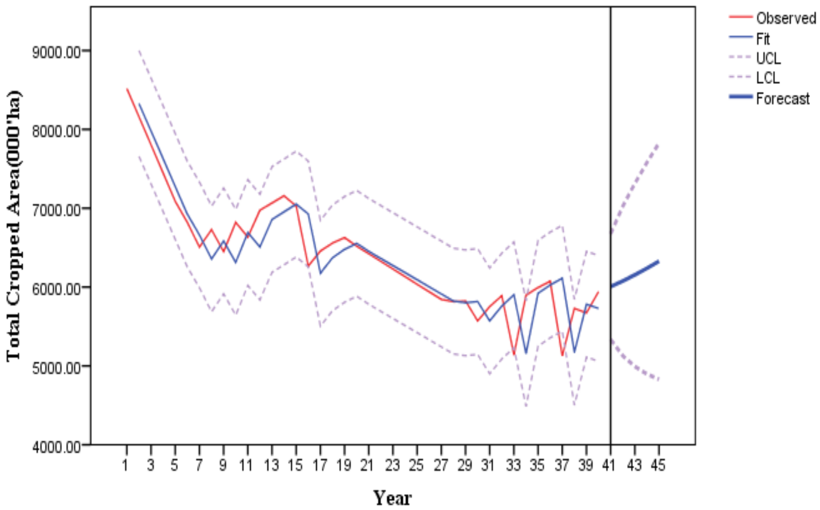

Fig.4.3.4.1.2 (a): Actual and forecasted values for total cropped area in Tamil Nadu by ARIMA (0,1,0) model

From the Fig.4.3.4.1.2(a) regarding total cropped area in Tamil Nadu, the actual and observed values move together very closely.

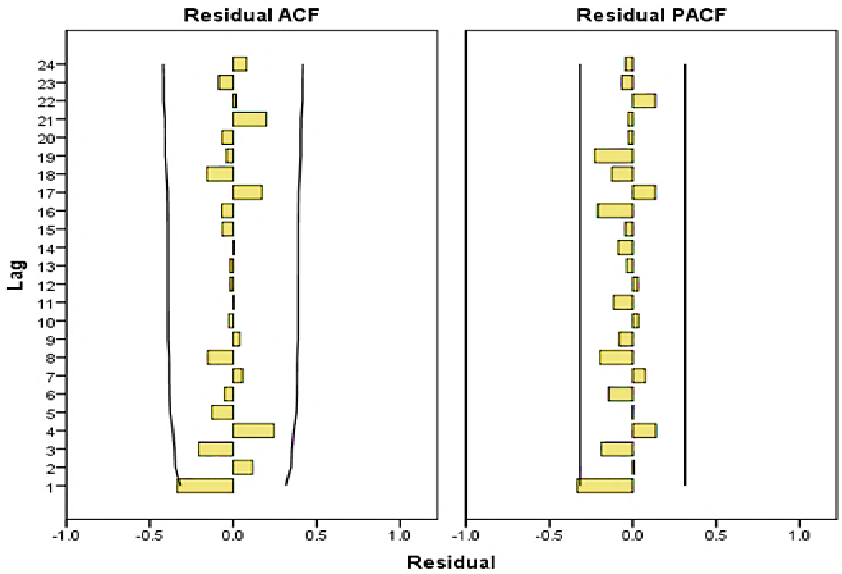

Fig. 4.3.4.1.2(b): ACF and PACF through ARIMA (0,1,0) model for the total cropped area in Tamil Nadu

PACF as well as ACF for lag-1 is significant when the bar lies outside the confidence interval as evident from Fig.4.3.4.1.2(b) showing that all the higher-order autocorrelations are effectively explained by the lag-1 autocorrelation.

4.3.4.2. Fertilizer consumption

With respect to fertiliser consumption in Tamil Nadu, the training period was 1970-2014 and validation for the model fitted was done using the data from 2015-2020.

Table 4.3.4.2.1(a): Comparison of actual and forecasted values of fertilizer consumption(000'tonnes) in Tamil Nadu

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	1564.02	908.45	919.95	1129.30	1024.62
Forecast	1355.34	1288.76	1213.82	1384.49	1312.56
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	830.87	712.18	1029.83	970.48	963.82

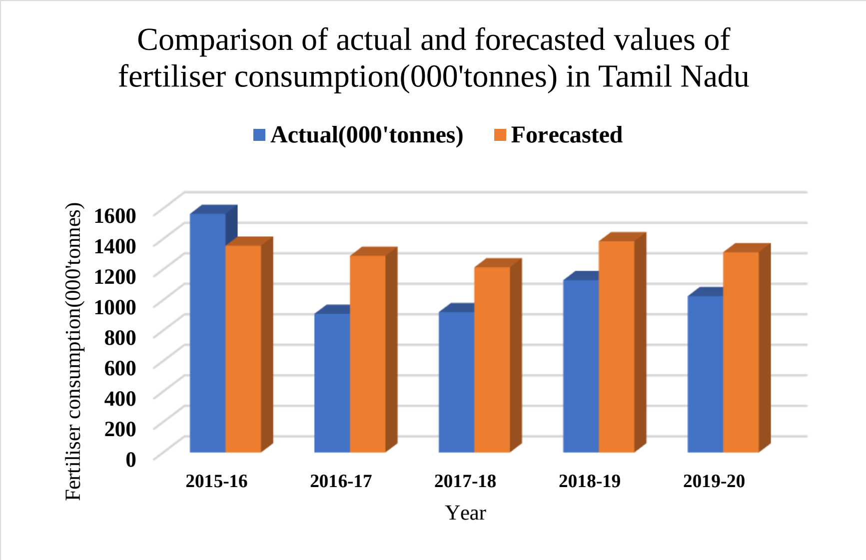

Fig.4.3.4.2.1: Comparison of actual and forecasted values of fertilizer consumption (000'tonnes) in Tamil Nadu

The various statistics obtained for the best diagnosed ARIMA (0,1,6) model is depicted in Table.4.3.4.2.1(b). The model had good prediction power with a value of R^2 = 74%, MAPE = 25.19 and normalized BIC = 24.47 respectively.

Table 4.3.4.2.1(b): Statistics for the best diagnosed ARIMA (0,1,6) model for fertilizer consumption in Tamil Nadu

R-squared	0.74
RMSE	198.14
MAPE	25.19
MaxAPE	366.31
MAE	123.44
MaxAE	568.65
Normalized BIC	24.47

Table 4.3.4.2.1(c): Estimates of the parameters for ARIMA (0,1,6) model for fertilizer consumption in Tamil Nadu

		Estimate	SE	t	Sig.
Difference		1			
MA	**Lag 6**	0.559	0.169	3.303	0.002

The final model could be written in the form

$$(1\text{-}B)Y_t = (1\text{-}\Theta_1 B^1 - \Theta_2 B^2 - \Theta_3 B^3 - \Theta_4 B^4 - \Theta_5 B^5 - \Theta_6 B^6) \text{ ……………...4.3.4.2.1(c)}$$

Where Y_t is the fertilizer consumption in Tamil Nadu in thousand tonnes for the year 't'

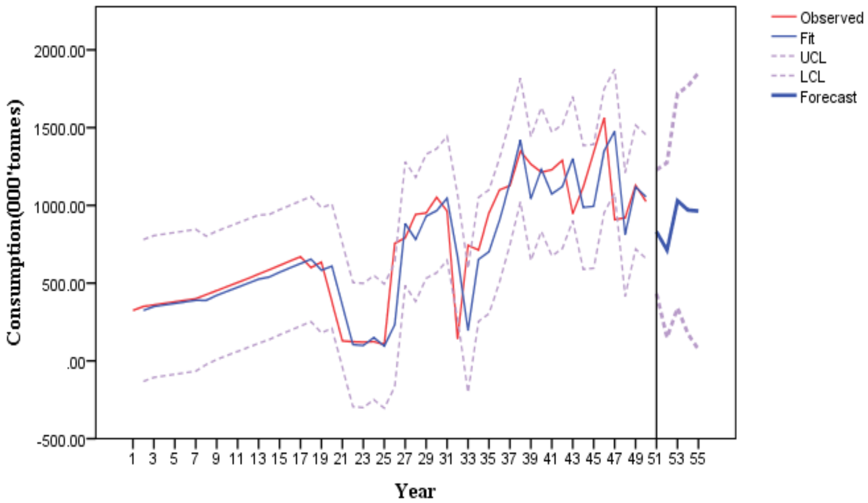

Fig. 4.3.4.2.2 (a): Actual and forested values for fertilizer consumption in Tamil Nadu by ARIMA (0,1,6) model

Regarding fertilizer consumption in Tamil Nadu from the Fig.4.3.4.2.2 (a), it can be seen that all the values with respect to actual versus forecasted were moving together moderately well.

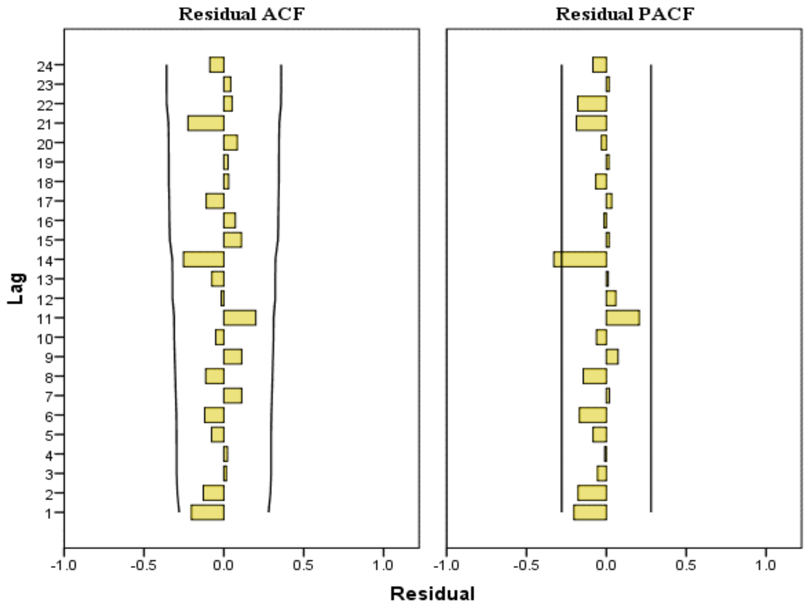

Fig.4.3.4.2.2 (b) ACF and PACF for the fertilizer consumption of Tamil Nadu

From Fig. 4.3.4.2.2 (b), it is evident that all spikes in the residual plot except for lag - 14 was within the confidence limit.

4.3.4.3. Pesticide Consumption

With respect to pesticide consumption in Tamil Nadu, the training period was taken as the period from 1970-2014 and validation of the model was done for the period 2015-2020. There was close agreement between actual and predicted values as given in Table 4.3.4.3.1(a) and these results are visually depicted in Fig:4.3.4.3.1.

Table 4.3.4.3.1(a): Comparison of actual and forecasted values of pesticide consumption in Tamil Nadu

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	2096	2092	1929	1901	2225
Forecast	2097.44	2097.44	2097.44	2097.44	2097.44
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	2206.61	2206.61	2206.61	2206.61	2206.61

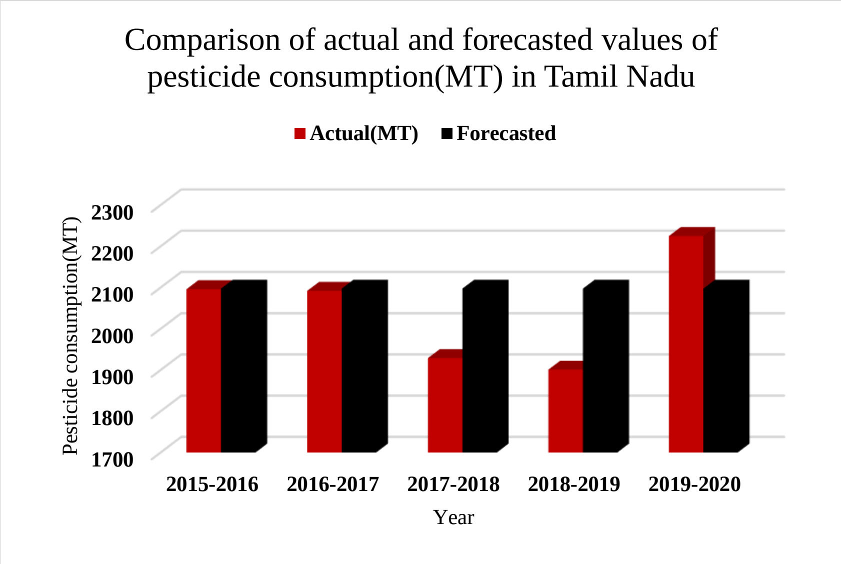

Fig.4.3.4.3.1: Comparison of actual and forecasted values of pesticide consumption (MT) in Tamil Nadu

The various statistics obtained for simple exponential smoothing model is depicted in Table 4.3.4.3.1(b). The model had

good prediction power with a value of R^2 = 84% and MAPE = 19.73.

Table 4.3.4.3.1(b): Statistics for the best diagnosed simple exponential smoothing model for pesticide consumption in Tamil Nadu

R-squared	0.84
RMSE	1185.29
MAPE	19.73
MaxAPE	126.30
MAE	738.76
MaxAE	4142.42
Normalized BIC	14.23

Table 4.3.4.3.1(c): Estimates of the parameters of simple exponential smoothing model for pesticide consumption in Tamil Nadu

	Estimate	SE	t	Sig.
Alpha (Level)	0.943	0.143	6.61	0

The final model could be written in the form,

$$\text{(Level of the series at time 't')}\ L_t = \alpha\ Y_t + (1-\alpha)\ L_{t-1}$$

$$= Y_t + (1-1)\ L_{t-1}$$

$$= Y_t$$

Forecast for k step ahead $F_t(k) = L_t$ ………………………………....4.3.4.3.1(c)

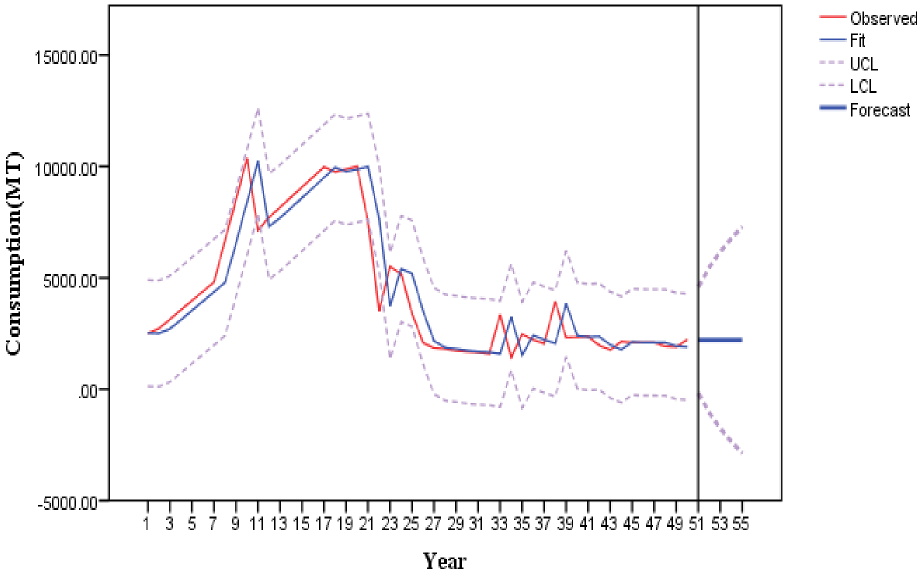

Fig.4.3.4.3.2(a): Actual and forecasted values for pesticide consumption in Tamil Nadu by simple exponential smoothing model.

From the Fig:4.3.4.3.2(a) could be observed that the actual and forecasted values of pesticide consumption in Tamil Nadu were moving almost closely together. It indicates that, the model developed was efficient.

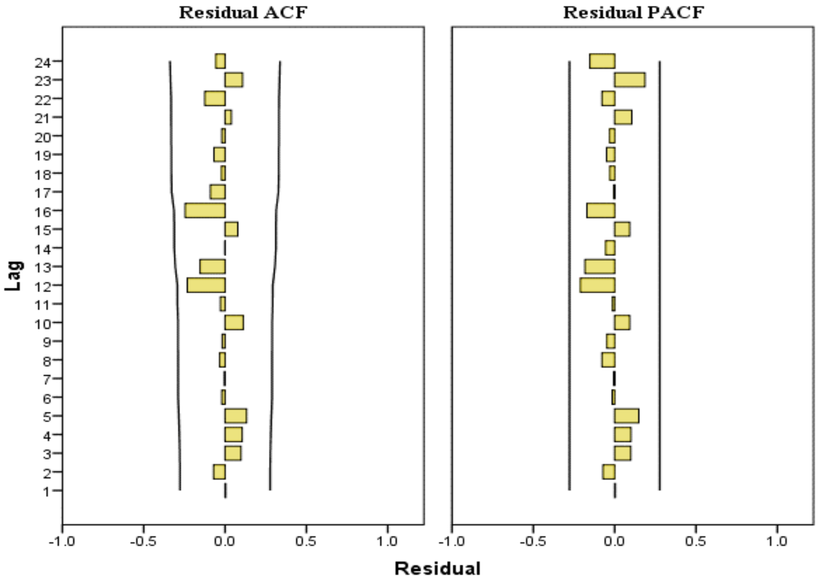

Fig.4.3.4.3.2(b): ACF and PACF through simple exponential smoothing model for the pesticide consumption in Tamil Nadu

From the Fig.4.3.4.3.2 (b), it can be seen that all the residuals in the ACF and PACF plots were within the confidence limits and so the residuals were almost white noise.

4.3.4.4. Food grains production

Coming to food grains production in Tamil Nadu, the training period for model building was taken as 1950-2014 and validation period as 2015-2020.The association between actual and forecasted values in this case are depicted in Table.4.3.4.4.1(a).

Table 4.3.4.4.1(a): Comparison of actual and forecasted values of food grains production (000'tonnes) in Tamil Nadu

Year	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
Actual	11478	6219	10714	10390	11500
Forecast	8249.65	8249.65	8249.65	8249.65	8249.65
Year	**2020-2021**	**2021-2022**	**2022-2023**	**2023-2024**	**2024-2025**
Forecast	10132.87	10132.87	10132.87	10132.87	10132.87

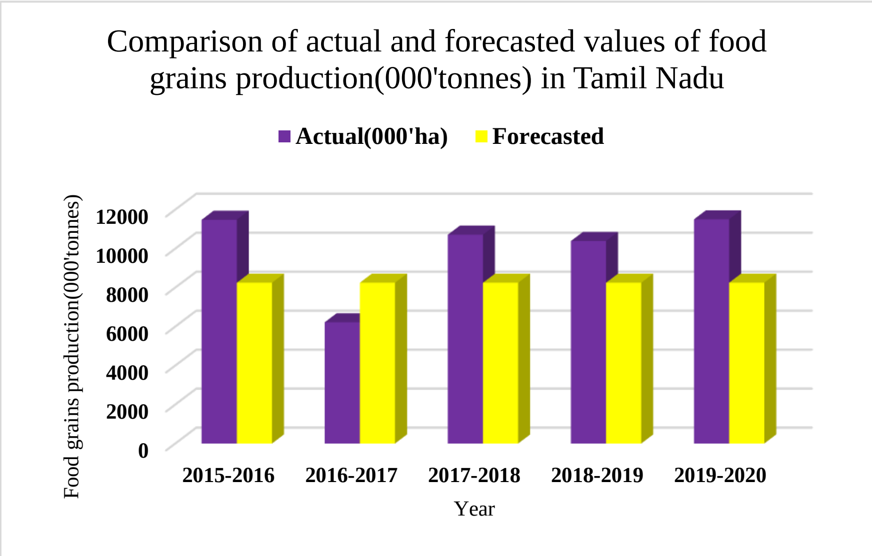

Fig.4.3.4.4.1: Comparison of actual and forecasted values of food grains production (000'tonnes) in Tamil Nadu

The best model was found to be simple exponential smoothing model. The various statistics obtained for best diagnosed model for food grains production in Tamil Nadu is shown in Table 4.3.4.4.1(b).

Table 4.3.4.4.1(b): Statistics for the best diagnosed simple exponential smoothing model for food grains production in Tamil Nadu

R-squared	0.431
RMSE	1457.68
MAPE	17.48
MaxAPE	160.34
MAE	1075.68
MaxAE	4855.002
Normalized BIC	14.63

Table 4.3.4.4.1(c): Estimates of the parameters for simple exponential smoothing model

	Estimate	SE	t	Sig.
Alpha (Level)	0.32	0.09	3.49	0.001

The final model could be written in the form

Level of the series at time 't') $L_t = \alpha Y_t + (1-\alpha) L_{t-1}$

$= 0.32Y_t + (1-0.32) L_{t-1}$

$= 0.32Y_t + 0.68 L_{t-1}$

Forecast for k step ahead $F_t(k) = L_t$……….……………………….4.3.4.4.1(c)

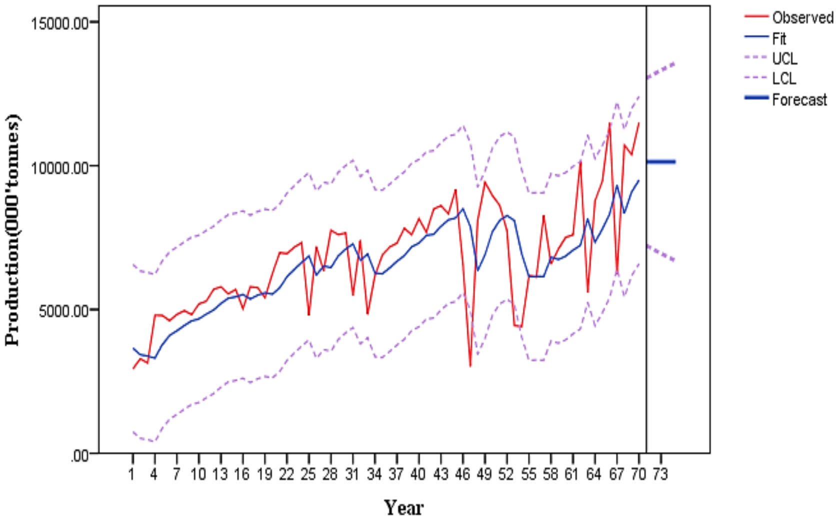

Fig.4.3.4.4.2(a): Actual and forested values for food grains production in Tamil Nadu by simple exponential smoothing model

From Fig.4.3.4.3.2(a) it can be seen that the actual and forecasted values of food grains production in Tamil Nadu showed high degree of variation since the adjusted R^2 was only 0.43.

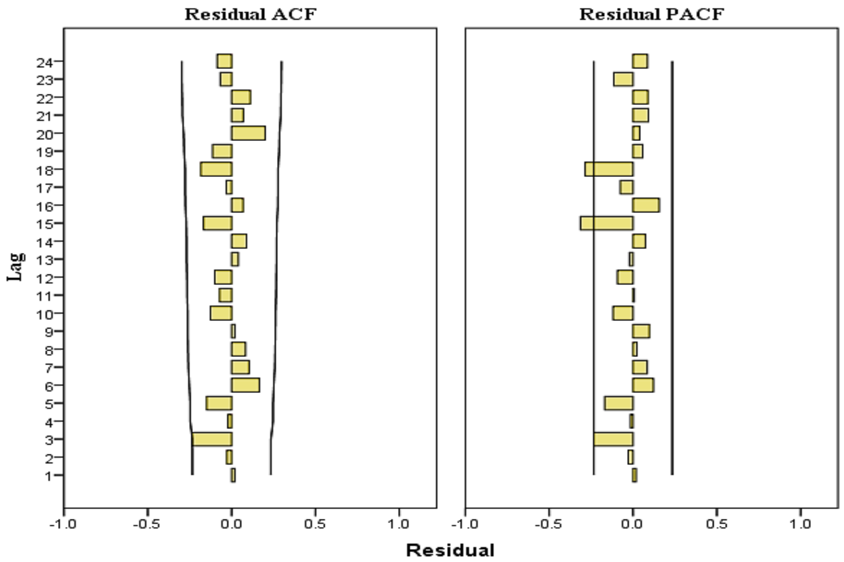

Fig. 4.3.4.4.2 (b): ACF and PACF through simple exponential smoothing model for the food grains production in Tamil Nadu.

From Fig. 4.3.4.4.2 (b) lag-15 and lag-17 were lying outside the limits.

4.4 Box-plot analysis:

A box-plot is a representation that shows how the values in the data are distributed. Although box-plots seem unsophisticated when compared to a histogram or density plot, they have the advantage of taking up less space, which is beneficial for comparing distributions across multiple groups or datasets.

With the use of a box-plot, one can acquire more information than the measures of central tendency for some distributions or datasets.

4.4.1 Boxplots for Total Cropped Area

Coming to the boxplots for the total cropped area in Andhra Pradesh, Tamil Nadu and Kerala, the structure of boxes and whiskers define the skewness of the total cropped area. Andhra Pradesh showed negative skewness and rest of the other two states showed positive skewness. Extreme outlier was spotted at lower whiskers of the box plot for Andhra Pradesh and upper whiskers of the box plot for Tamil Nadu.

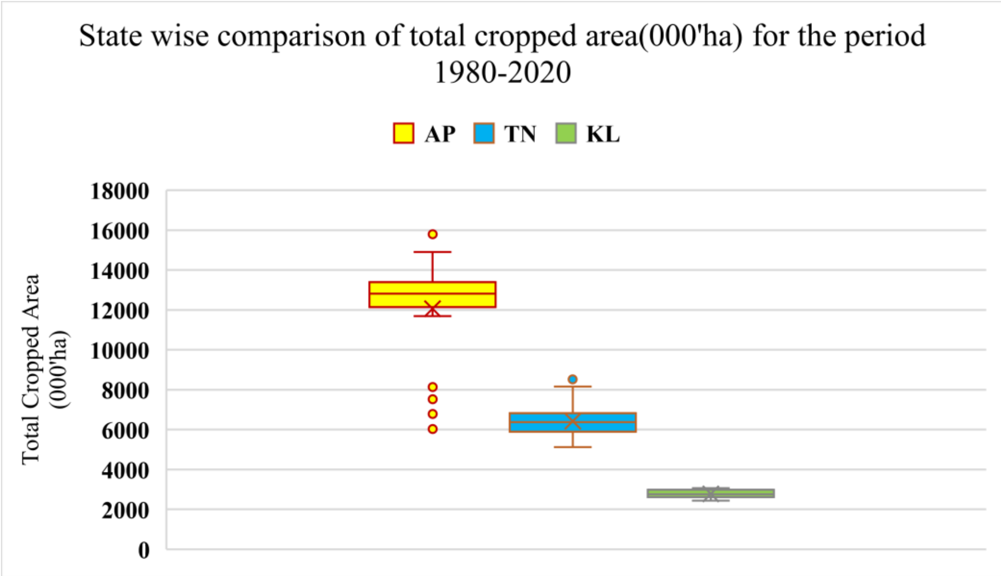

Fig: 4.4.1 State wise comparison of total cropped area for the period 1980-2020

From the Fig:4.4.1 it was clear that in the three states total cropped area were not symmetrically distributed as the median was not in the middle of the box.

Table:4.4.1 Descriptive statistics of total cropped area in three states

Constants	**AP**	**TN**	**KL**
Min.	6030	5129	2446
Q1	12150	5895.25	2616.25
Median	12816.05	6374.14	2764
Q3	13374.06	6819.75	2973.25
Max.	15800	8519	3066
Mean	12066.75	6424.93	2784.88
Range	9770	3390	620
IQR	1224.06	924.5	357

Descriptive statistics for total cropped area in three states from Table 4.4.1 showed that highest median was in Andhra Pradesh and lowest value of median was in Kerala. Since, highest width of the box was for Andhra Pradesh it indicated that maximum dispersion of the data was for Andhra Pradesh. So, it can be concluded that the highest total cropped area and variability in area existed for Andhra Pradesh

4.4.2 Box-plots for Fertilizer Consumption

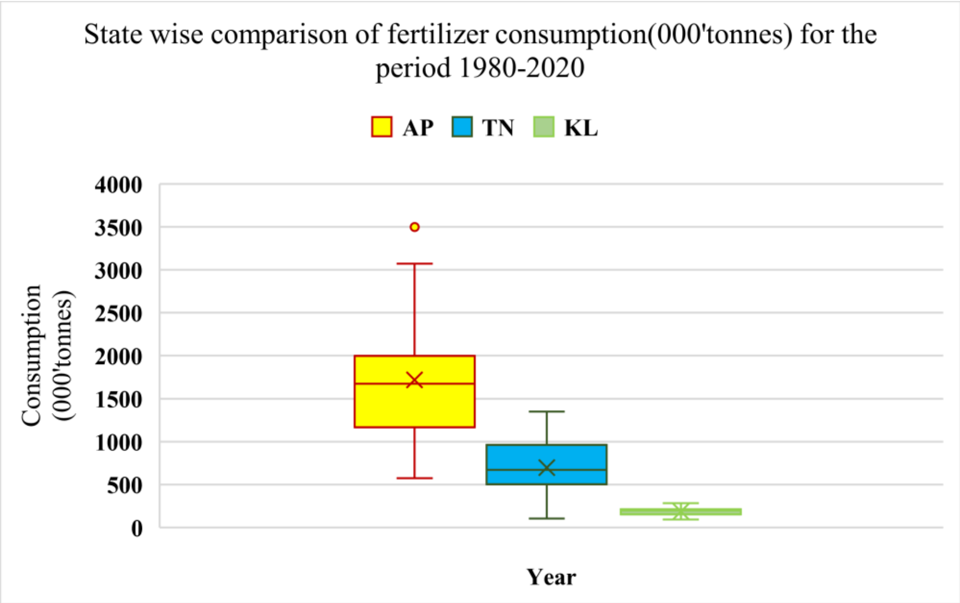

Fig: 4.4.2 State wise comparison of fertilizer consumption(000'tonnes) for the period 1980-2020

Regarding fertilizer consumption, the distribution was not symmetric for the three states as seen from Fig:4.4.2. The median was not in the middle of the boxplot instead it was closer to the bottom of the box or closer to the top of the box.

The mean in the box-plot for Andhra Pradesh was above the median and whisker was shorter on the lower end of the box. Thus, the distribution of food grains production of Andhra Pradesh was found to be positively skewed. But in the case of Tamil Nadu and Kerala the mean was lower than the median, it revealed that for these two states the data were negatively skewed.

In the case of Andhra Pradesh an outlier was found in upper whisker showing that the data was having high dispersion.

Table: 4.4.2 Descriptive statistics of fertilizer consumption in 3 states

Constants	AP	TN	KL
Min.	575.4	105.5	94.76
Q1	1518.02	579	174.69
Median	1690.48	849.72	202.03
Q3	2224.05	1104.02	221.09
Max.	3496.8	1564.02	322.17
Mean	1821.70	796.36	197.62
Range	2921.4	1458.52	227.40
IQR	706.02	525.02	46.39

From Table 4.4.2, highest median was observed in Andhra Pradesh followed by Tamil Nadu and Kerala. Since, highest width of the box was for Andhra Pradesh it indicated that maximum dispersion of the data with regard to fertiliser consumption was for Andhra Pradesh. So, it can be concluded that the highest consumption of fertiliser existed for Andhra Pradesh

4.4.3 Box-plots for Pesticide Consumption

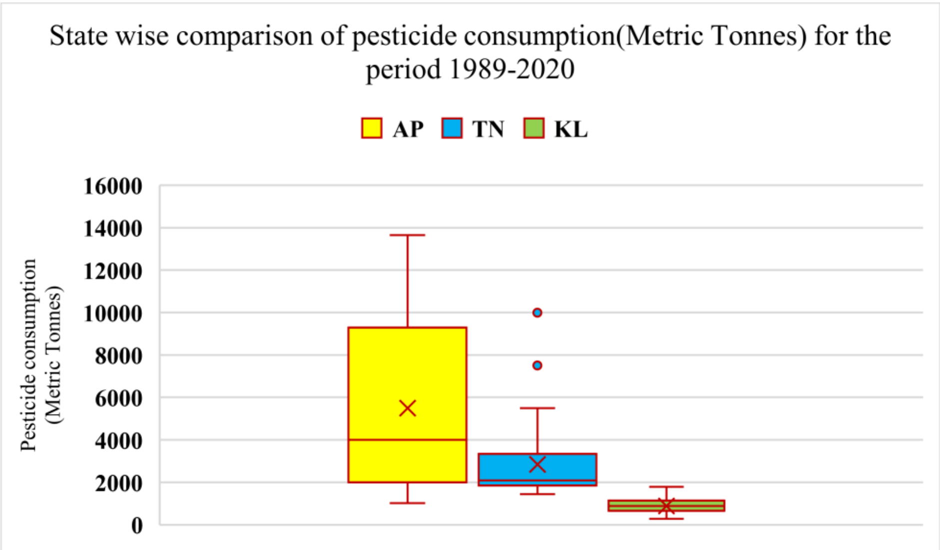

Fig:4.4.3 State wise comparison of pesticide consumption for the period 1989-2020

In this case, all the three states showed positive skewness, since the mean was greater than its median. And Tamil Nadu showed two outliers. And median was not in the middle of the box, it indicated that the distribution was not symmetric for the three states.

Table: 4.4.3 Descriptive statistics of pesticide consumption in 3 states

Constants	AP	TN	KL
Min.	1015	1434	273
Q1	2006	1876	656.69
Median	4000	2096	880
Q3	9079	2906	1105
Max.	13650	10000	1793
Mean	5487.79	2843.32	889.30
Range	12635	8566	1520
IQR	7073	1030	448.30

With respect to consumption of pesticides, highest median was observed in Andhra Pradesh and lowest value of median was observed in Kerala as it is depicted in Table 4.4.3. Since, highest width of the box was for Andhra Pradesh it indicated that maximum spread of the data in pesticide consumption was for Andhra Pradesh.

4.4.4 Box-plots for Food grains Production

Deviation from standard box-plots was studied to compare the food grains production. Fig:4.4.4 constitutes the boxplots of food grains production of Andhra Pradesh, Kerala and Tamil Nadu for the period 1950-2020. The structure of boxes and whiskers defined the skewness of the production of food grains.

From the box-plot (Fig:4.4.1) it can be found that distribution of the data for production of food grains was not symmetric. Here upper quartile was not equal to lower quartile, meaning that the data was not normally distributed. Regarding food grains production there was no outliers for these three states and the median was different for different states. So, it can be concluded that the average food grains production with respect to the three states were different.

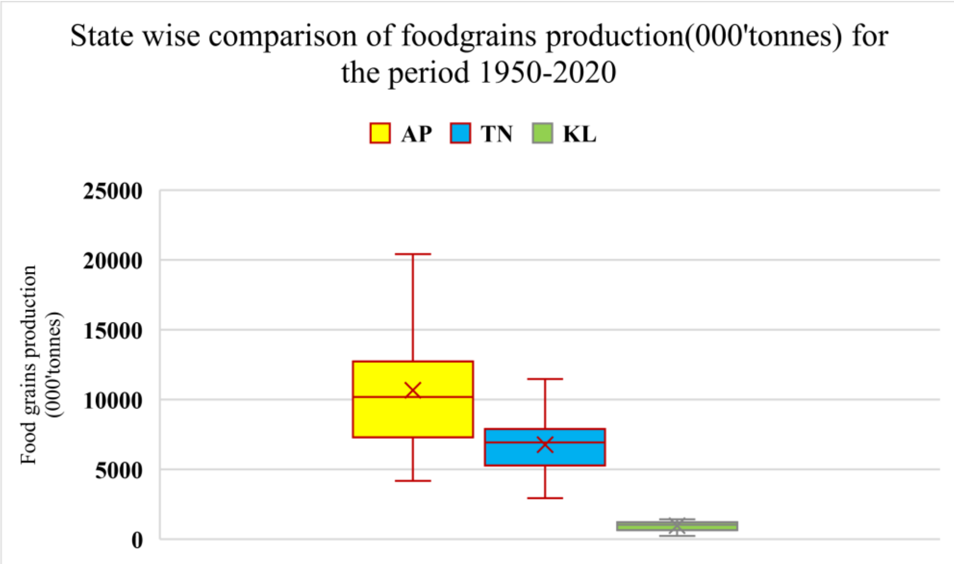

Fig:4.4.4 State wise comparison of food grains production(000’tonnes) for the period 1950-2020

Table: 4.4.4 Descriptive statistics of food grains production in 3 states

Constants	AP	TN	KL
Min.	4165	2933	228.4
Q1	7317.5	5324.25	638.85
Median	10178.7	6919	1021.55
Q3	12461.03	7803.5	1190.75
Max.	20421	11478.5	1427
Mean	10653.64	6755.83	946.268
Range	16256	8545.5	1198.6
IQR	5143.525	2479.25	551.9

From Table 4.4.4, highest median was observed in Andhra Pradesh and lowest value of median was observed in Kerala. Since, highest width of the box was for Andhra Pradesh it indicated that maximum spread of the data was for Andhra Pradesh. So, it can be concluded that the highest production and variability in production existed for Andhra Pradesh.

4.5 Mahalanobis D^2

An idea about the progress of total cropped area, consumption of fertilizers and pesticides and food grains production could be visualized through box plots. It was observed that with respect to Kerala the figures corresponding to total cropped area, fertilizer consumption, pesticide consumption and food grains production were lower than that of Andhra Pradesh and Tamil Nadu. It is well known that Kerala imports food grains, particularly cereals and vegetables, from Andhra Pradesh and Tamil Nadu.

Mahalanobis D^2 is an efficient tool which can be applied to estimate the distance between these three states with respect to the variables under study.

The data for the period from 1990-2020 pertaining to total cropped area, fertiliser consumption, pesticide consumption and food grains production were taken to compute the Mahalanobis D^2. To overcome the autocorrelation that might exist in the data, the original data was transformed to weighted indices.

In each year the states were ranked according to the quantity of each variable under study. Then three years weighted mean were computed. Thus, the three yearly weighted indices will form 10 observations for each state. Mahalanobis D^2 was then performed to obtain the distance between the states.

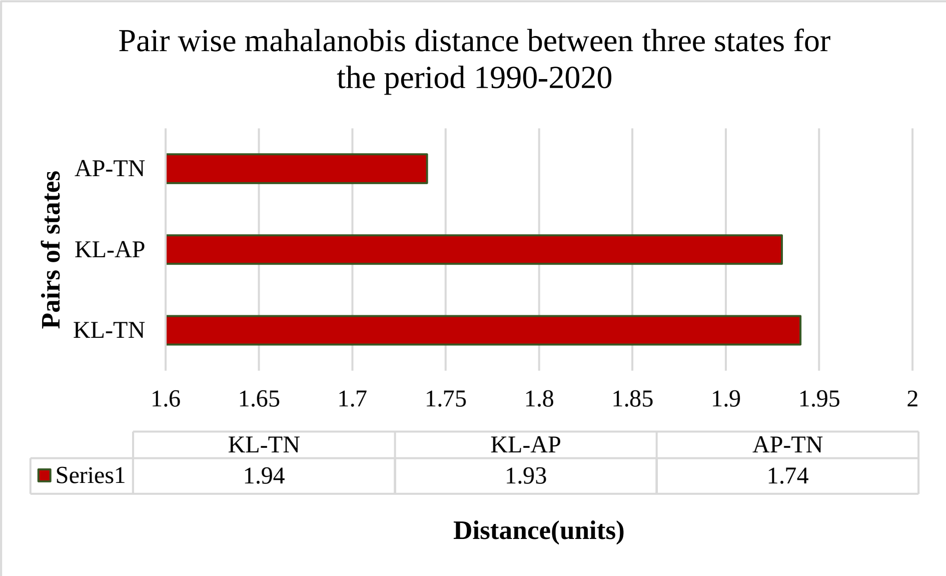

Fig:4.5 Pair wise Mahalanobis distance for the period 1990-2020

Fig:4.5 depicts that distance between Kerala - Tamil Nadu obtained was more when compared with Kerala and Andhra Pradesh. The distance between Andhra Pradesh and Tamil Nadu was comparatively low when compared with Kerala v/s Andhra Pradesh and Kerala v/s Tamil Nadu. So, an attempt was made to identify the root cause for this huge distance between Kerala and other states. Discriminant analysis paves a way to pinpoint the causal factor which contribute to this discrepancy between the states.

4.6 Discriminant function analysis

Discriminant function analysis is a statistical technique used for classifying observations (Klecka, 1980). In research this technique may be used to identify variables that best discriminate two or more groups with respect to a criterion under study. In the present study the interest is to distinguish three states viz; Kerala, Andhra Pradesh and Tamil Nadu with respect to the variables under study such as total cropped area, fertiliser consumption, pesticide consumption and food grains production. It was also intended to identify which independent variable is more powerful in discriminating a state from the other. The maximum number of discriminant functions that can be defined is one less than the number of groups. The functions first seek to distinguish the first group from the others, then the second group from the rest, and so on. These are identified by the eigen values on the output. The eigen values also show what percent of variance is accounted for with each function. In addition, Wilks's lambda tests the significance of each function.

In the present research two states were taken at a time to perform discriminant analysis. Therefore, one discriminant function has been extracted by SPSS 22. The function gives the projection of the data that best discriminates between the states

Eigen Values

The eigen values describe how best discriminating ability the function possess. The percentage of variances is the discriminating ability of the two groups.

4.6.1 Discriminant Analysis for Kerala and Andhra Pradesh

Kerala and Andhra Pradesh were taken at a time to perform discriminant analysis. Total number of observations were 20. Discriminant analysis was done to identify the most significant variable that discriminates the two states under study with respect to the variables viz; total cropped area, fertilizer consumption, pesticide consumption and food grains production.

Table 4.6.1.1 Mean and S.D of variables included in discriminant analysis - KL and AP

Grouping	Mean	Std. Deviation
1.00 Total cropped area	2782.47	184.502
Fertilizer consumption	217820.67	36997.01
Pesticide Consumption	886.62	267.88
Food grains production	695.13	209.70
2.00 Total cropped area	11676.09	2636.27
Fertilizer consumption	2112712.17	608759.74
Pesticide Consumption	5375.29	3902.88
Food grain Production	14386.04	2863.701

Table 4.6.1.1 showed that, in terms of fertilizer consumption for group 1 (Kerala) its mean was 217820.67 and for group 2 (Andhra Pradesh) it was 2112712.17.

Table:4.6.1.2 Table of Eigen value - KL and AP

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	47.44	100	100	0.99

From the Table: 4.6.1.2, eigen value gives the proportion of variance explained. A larger eigen value explains a strong function. The canonical correlation is a correlation between the discriminant scores and the levels of the dependent variables. The higher the correlation value, better the function that discriminates the values. One is considered as perfect. The correlation of 0.99 is comparatively very high.

Table:4.6.1.3 Table of Wilks' Lambda - KL and AP

Test of Function	Wilks' Lambda	Chi-square	df	Sig.
1	.02	62.08	4	.000

From Table:4.6.1.3 the wilks lambda showed that the function was statistically significant, so it helped to distinguish between groups or there was a statistically significant discriminating power in the variables included in the model. It is good to have a low value of wilks' lambda. In the present case the value is 0.021. The chi-square was 62.085 with 4 degrees of freedom, which was based on the groups present in the categorical variables. A wilks lambda of 1.00 is realised when the observed group means are equal, while a small wilks lambda is obtained when the within-group variability is small when compared to the total variability. From the above results it can be concluded that the between group means differ significantly.

Checking for relative importance of each independent variable (KL Vs AP)

The standardized canonical discriminant function coefficient is used to calculate the discriminant score. In discriminant analysis, it is possible to identify which independent variable has more impact in discriminating one group from the other by comparing the standardised coefficients. Higher standardised discriminant coefficients reveal higher discriminating power. Standardised Canonical discriminant function coefficients is given in Table 4.6.1.4.

Table 4.6.1.4: Standardized Canonical Discriminant Function Coefficients

Variables	Function
Total cropped area	-.130
Fertilizer Consumption	-3.789
Pesticides Consumption	.420
Food grains Production	4.398

The standardized weights show the relative importance of each variable compared to each other which is given in Table 4.6.1.4. The relative importance of each component variables is interpreted using the absolute values of the discriminant function coefficients. The variable, "food grains production," had the most prominent effect for predicting membership into the group, followed by "fertiliser consumption". pesticide consumption and total cropped area.

Table:4.6.1.5 Classification Statistics - KL and AP

Variables			**Predicted Group Membership**		
			KL	**AP**	**Total**
Original	**Count**	**KL**	10	0	10
		AP	0	10	10
	%	**KL**	100	.0	100.0
		AP	.0	100.0	100.0

100% of original grouped cases correctly classified

Table: 4.6.1.5 showed that the power of the discriminant function used in the study was very high and all the members of the groups were correctly classified. The original classification and the predicted classification fall with 100% of accuracy.

4.6.2 Discriminant Analysis for Kerala and Tamil Nadu

Here Kerala and Tamil Nadu were taken at a time to perform discriminant analysis. Total number of cases were 20.

Table 4.6.2.1 Mean and S.D of variables included in discriminant analysis - KL and TN

Grouping	Mean	Std. Deviation
1.00 Total cropped area	2782.47	184.502
Fertilizer consumption	217820.67	36997.005
Pesticide consumption	886.62	267.88
Food grain production	695.13	209.701
3.00 Total cropped area	6155.03	478.96
Fertilizer consumption	893322.78	369739.04
Pesticide consumption	2605.16	1154.65
Food grains production	7867.01	1482.485

Here group 1 represented Kerala and group 3 represented Tamil Nadu. From Table:4.6.2.1 it could be followed that 4 variables included in the study regarding KL and TN were highly varying with respect to group mean.

Table: 4.6.2.2 Table of Eigen value - KL and TN

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	218.618	100.0	100.0	0.998

Normally, the eigen value gives the proportion of variance explained. A larger Eigen value explains a strong function. For Kerala and Tamil Nadu from the Table:4.6.2.2 eigen value was 218.618. The canonical correlation is a correlation between the discriminant scores and the levels of these dependent variables. The higher the correlation value, better the function that discriminates the values. The correlation of 0.998 was comparatively very high.

Table:4.6.2.3 Table of Wilks' Lambda - KL and TN

Test of Function	Wilks' Lambda	Chi-square	df	Sig.
1	.005	86.24	4	.000

A wilks' lambda of 1.00 is realised when the observed group means are equal, while a small wilks' lambda is obtained when the within-group variability is small compared to the total variability. From the Table:4.6.2.3 the significance of wilks' lambda showed that the function was statistically significant, so it helped to distinguish between groups or there was a statistically significant discriminating power in the variables included in the model. It is good to have a low value of wilks' lambda. In the present case the value was 0.005. The Chi-square was 86.24 with 4 degrees of freedom, which was based on the groups present in the categorical variables. From the above results it can be concluded that there was a difference in group means between Kerala and Andhra Pradesh.

Checking for relative importance of each independent variable (KL vs TN)

With respect to Kerala and Tamil Nadu standardised canonical discriminant function coefficients is given below.

Table:4.6.2.4 Standardized Canonical Discriminant Function Coefficients

Variables	Function
Total cropped area	1.916
Fertilizer Consumption	2.379
Pesticides Consumption	0.858
Food grains Production	.346

The standardized weights show the relative importance of each variable compared to each other which is given in Table 4.6.2.4. The relative importance of each component variables is interpreted using the absolute values of the discriminant function coefficients. The variable, “fertilizer consumption,” had the greatest effect for predicting membership into the group, followed by “total cropped area”.

From the Table:4.6.2.4 it can be concluded that fertiliser consumption was the best factor that discriminates Kerala and Tamil Nadu, followed by total cropped area, pesticide consumption and food grains production.

Table:4.6.2.4 Classification Statistics - KL and TN

Variables			**Predicted Group Membership**		
			KL	**TN**	**Total**
Original	**Count**	**KL**	10	0	10
		TN	0	10	10
	%	**KL**	100.0	0	100.0
		TN	0	100.0	100.0

100% of original grouped cases correctly classified

Table 4.6.2.4 shows that the power of the discriminant function used in the study was very high and all the cases of the groups were correctly classified. The original classification and the predicted classification fall with 100% of accuracy.

Comparing with Kerala and Andhra Pradesh food grains production had less discriminating power in this case.

4.6.3 Discriminant Analysis for Andhra Pradesh and Tamil Nadu

Table 4.6.3.1 Mean and S.D of variables included in Discriminant analysis - AP and TN

Grouping	**Mean**	**Std. Deviation**
2.00 Total cropped area	11676.095	2636.27
Fertilizer consumption	2112712.17	608759.74
Pesticide Consumption	5375.29	3902.88
Food grain Production	14386.04	2863.70
3.00 Total cropped area	6155.03	478.96
Fertilizer consumption	893322.78	369739.04
Pesticide Consumption	2605.16	1154.65
Food grain Production	7867.01	1482.48

Discriminant analysis was also done to discriminate Andhra Pradesh and Tamil Nadu with respect to the four variables under study.

Table:4.6.3.2: Table of Eigen value - AP and TN

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	3.896	100.0	100.0	.892

From the Table:4.6.3.2 the Eigen value was 3.896. The eigen value gives the proportion of variance explained. A larger eigen value explains a strong function. The canonical correlation is a correlation between the discriminant scores and the levels of the dependent variables. The higher the correlation value, better the function that discriminates the values. One is considered as perfect. In this case the correlation was 0.892 and it was comparatively very high.

Table:4.6.3.3 Table of wilks' lambda - AP and TN

Test of Function	Wilks' Lambda	Chi-square	df	Sig.
1	0.20	25.41	4	.000

The significance of wilks' lambda showed that the function was statistically significant, so it helped to distinguish between groups or there was a statistically significant discriminating power in the variables included in the model. It is good to have a low value of Wilks' Lambda. In the present case the value is 0.20. The chi-square is 25.41 with 4 degrees of freedom, which is based on the groups present in the categorical variables. A wilks Lambda of 1.00 is realised when the observed group means are equal, while a small wilks' lambda is obtained when the within-group variability is small compared to the total variability. The above results from the Table:4.6.3.3 showed that the between group means were significantly different. But compared to above two group comparison such as Kerala - Andhra Pradesh and Kerala - Tamil Nadu, here the discrimination was comparatively less due to the fact that wilks lambda was higher in the case of AP-TN.

Checking for relative importance of each independent variable (AP vs TN)

The standardized weights show the relative importance of each variable compared to each other regarding AP and TN, which is given in Table 4.6.3.4.

Table:4.6.3.4 Standardized Canonical Discriminant Function Coefficients

Variables	Function
Total cropped area	0.441
Fertilizer Consumption	0.315
Pesticides Consumption	0.324
Food grains production	0.484

The relative importance of each component variables is interpreted using the absolute values of the discriminant function coefficients. The variable, “food grains production,” had the greatest effect for predicting membership into the group, followed by “total cropped area, pesticide consumption and fertiliser consumption.

Table:4.6.3.5 Classification Statistics - AP and TN

Variables			**Predicted Group Membership**		
			AP	**TN**	**Total**
Original	**Count**	**AP**	9	1	9
		TN	0	10	10
	%	**AP**	90.0	10.0	100.0
		TN	.0	100.0	100.0

95.05% of original grouped cases correctly classified

Table shows that the power of the discriminant function used in the study was very high and almost all the cases of the groups were correctly classified. The original classification and the predicted classification fall with 95.05% of accuracy.

4.7 Imbalance in the use of N, P, and K for Kerala

Fertiliser has to play an important role in future growth of agriculture. It seems that practically the future prosperity in farm output has to come from the increase in productivity. This would require improved technology and increased application of yield enhancing plant nutrients. A large number of studies have shown that most of the increase in food grain output during the first two decades of green revolution were attributable to chemical fertilisers (Desai and Vaidyanathan 1995). Therefore, growth in fertiliser consumption in the country is of paramount importance to raise agricultural production and to meet future requirements of the country.

Even though there exists some standard recommendation for fertilizer consumption, the farmers didn’t follow such recommendation suggested by higher officials from agriculture department. Some kinds of imbalances were reflected in fertilizer consumption and it has resulted in variation in food grains production also. Recommended ratio of N, P and K are 4:2:1. That is 57.14, 28.57 and 14.28 out of 100 respectively.

From Table 4.7.1 the imbalance in the use of nutrients such as nitrogen, phosphorous and potassium in Kerala for the period 1995-2020 can be noticed.

Table 4.7.1 Consumption of N, P and K in Kerala for the period 1995-2020

Year	N(kg/ha)	P(kg/ha)	K(kg/ha)	Total(kg/ha)
1995-1996	28.62	14.15	24.11	66.88
1996-1997	28.33	13.59	19.6	61.52
1997-1998	29.29	15.23	29.4	73.92
1998-1999	29.5	14.58	18.14	62.22
1999-2000	29.85	15.08	27.54	72.47
2000-2001	28.43	12.66	20.82	61.91
2001-2002	25.54	12.44	21.21	59.19
2002-2003	29.18	13.53	26.19	68.9
2003-2004	28.92	13.2	22.93	65.05
2004-2005	29.87	14.14	24.2	68.21
2005-2006	28	15	25	68
2006-2007	31	16	43	90
2007-2008	32	15	25	72
2008-2009	38	19	32	89
2009-2010	39	20	32	91
2010-2011	40	24	33	97
2011-2012	44	22	32	98
2012-2013	47	23	37	107
2013-2014	53	27	45	125
2014-2015	41	16	24	81
2015-2016	42	16	29	87
2016-2017	30	16	22	68
2017-2018	49	16	27	92
2018-2019	28	15	26	69
2019-2020	28	14	21	63

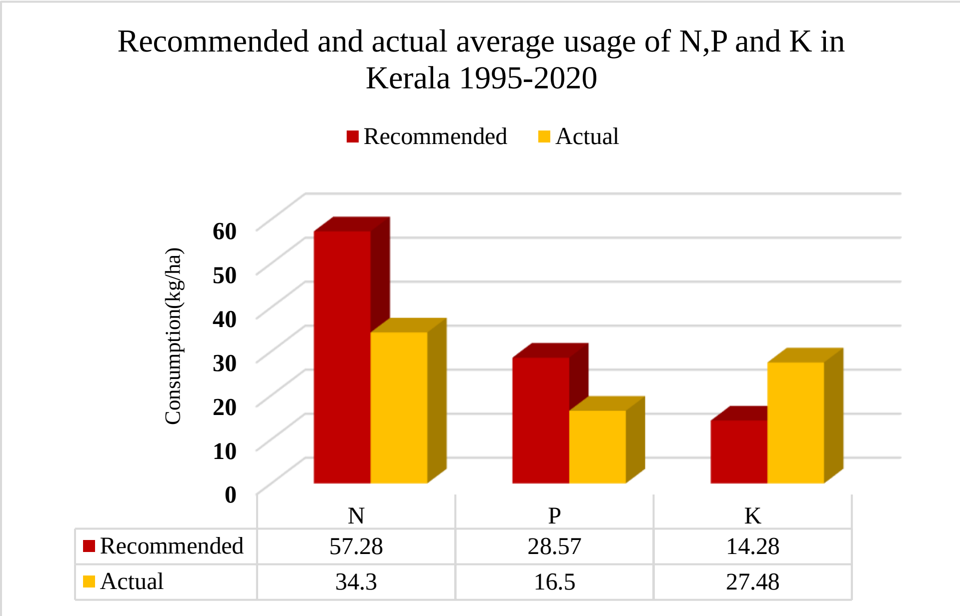

Fig:4.7.1 Recommended and actual average usage of N, P and K in Kerala during 1995-2020

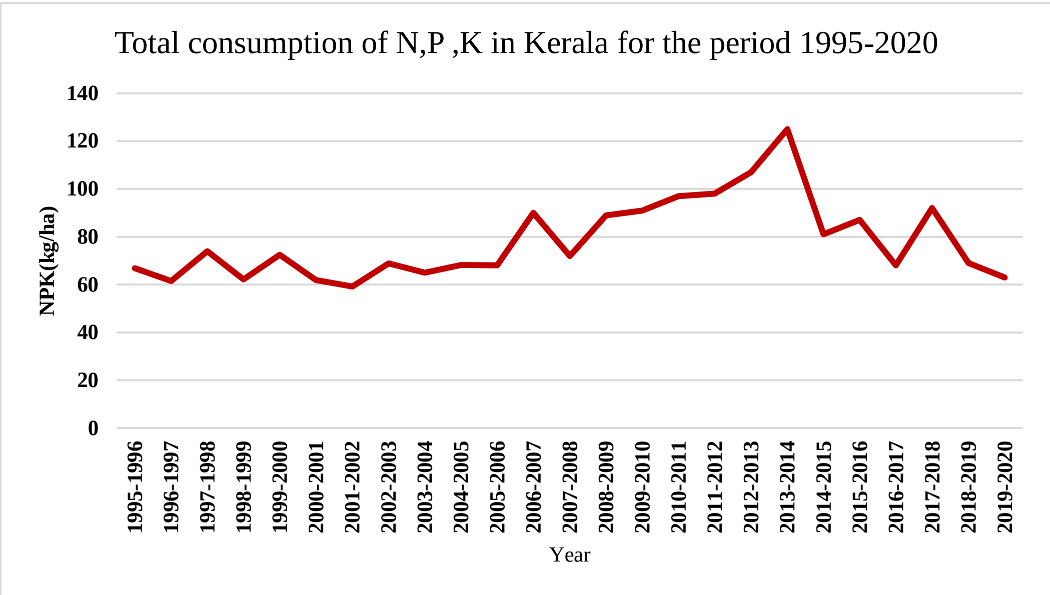

Fig:4.7.2 Total consumption N, P, K in Kerala for the period 1995-2020

Due to limitations of data, the process of computing fertilizer use imbalance has been re-formulated. The data on consumption of fertilizer is available at an aggregate level, but the district wise information on the recommended levels of fertilizer use is available only for few periods 1993-2008.

So, the analysis covered was done for the period 1995 to 2020 for Kerala and 1993 to 2008 for districts in Kerala. The analysis was performed by examining the imbalance in fertilizer use, first at the state level and then at district level, by observing the trend in use of N, P and K during respective years of study.

From Table 4.7.1 it can be observed that during 1995- ‘96 the total consumption of NPK was 66.8 kg/ha and consumption of N alone was 28.62 kg/ha and consumption of P and K were 14.15 and 24.11 kg/ha respectively in Kerala. The consumption of N, P, K and total NPK are depicted in Table 4.7.1 based on 25 years for the periods from 1995-1996 to 2019-2020. The least consumption of total NPK was during the year 2001-’02 (59.19 kg/ha) and it was highest in 2013-’14 (125 kg/ha). The average annual consumption of N was 34.30 kg/ha, consumption of P was 16.50 kg/ha and 27.48 kg/ha was the consumption of K for the study period in Kerala. Average annual consumption of NPK was 79.28 kg/ha.

From Fig:4.7.1 the recommended and actual average usage of N, P, K can be visualised and it can be seen that the average use of N, P and K are significantly lower than that of the recommended quantity.

The Fig:4.7.2 gives an idea about the growth level of consumption of plant nutrients in Kerala for the period 1995-2020. From the Fig:4.7.3 it was clearly seen that so many fluctuations were there regarding the total consumption of NPK in Kerala.

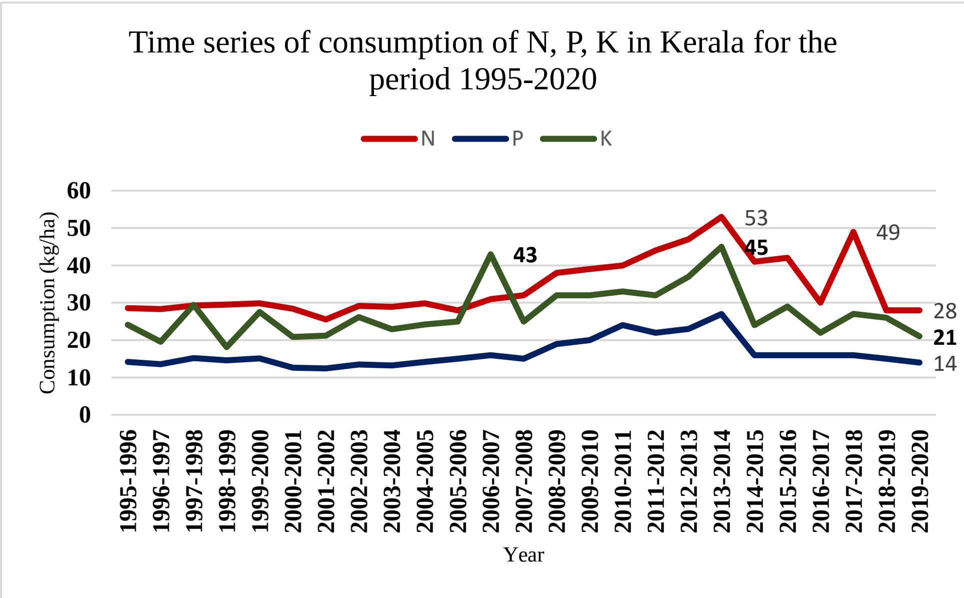

Fig: 4.7.3 The annual consumption of NPK in Kerala

During the year 2013- '14 the total consumption of NPK was 125 kg/ha and the consumption of each nutrient was 53 kg/ha (N), 27 kg/ha (P) and 45 kg/ha (K) respectively. The consumption of nitrogen and phosphorous with its recommended dose was to be normal but potassium was 45kg/ha. A cursory look at Fig: 4.7.3 showed that absolute gap between use of different nutrients existed. However, this is a misleading indicator of unbalanced use of fertiliser. The imbalance is better captured by relative growth and ratios which are presented in Table 4.7.2 and Table 4.7.3 and in Fig:4.7.2

Table 4.7.2: Five yearly growth rate in the consumption of N, P and K (%)

Period	**N**	**P**	**K**	**NPK**
1995-2000	0.85	1.28	2.70	1.62
2000-2005	0.99	2.24	3.05	1.96
2005-2010	6.85	5.92	5.06	6.00
2010-2015	0.50	-7.79	-6.17	-3.78
2015-2020	-7.79	-2.64	-6.25	-6.25
1995-2020	**-0.09**	**-0.04**	**-0.55**	**-0.24**

Table 4.7.3 Share of N, P and K in total consumption of N+P+K

Period	Share of NPK in total (%)			Ratios of N, P and K		
	N	P	K	N	P	K
1995-2000	43.20	21.55	35.25	1.22	0.61	1.00
2000-2005	43.91	20.41	35.68	1.23	0.57	1.00
2005-2010	40.98	20.73	38.29	1.07	0.54	1.00
2010-2015	44.29	22.05	33.66	1.31	0.66	1.00
2015-2020	46.7	20.32	32.98	1.42	0.62	1.00

Growth rate in fertilizer use in different periods corresponding to these dips and for entire period of 25 years beginning from 1995 to 2020 are provided in Table 4.7.2.

Table 4.7.3 shows the share of N, P, K in total N+P+K percentage as well as the corresponding ratio of N, P, K. As it was already mentioned the standard ratio of N, P, K is 4:2:1. The smallest figure being the value corresponding to K the share values of N, P, K given in Table 4.7.3 was divided by the values of K in each period separately. The discrepancy in the fertiliser consumption against the standard ratio could be visualised from Table 4.7.3. According to the standard values, the dose of P should be two times as that of K, but in Kerala none of the periods met the standard ratio. Similarly in the case of N also it should be 4 times as that of K. Here also in any of the periods mentioned the usage of N have not come up to the standard level. The usage range of N came to be 1.07 to 1.42 showing an increasing trend. Thus, imbalance in the average usage level of N, P, K has been widened from the results.

Table 4.7.4 Average of actual and normative use of N, P and K in Kerala for the period 1995-2020

Average of actual and normative use of N, P and K in Kerala for the period 1995-2020								
Year	**Actual use**				**Normative values***			
	N	**P**	**K**	**Total**	**N**	**P**	**K**	**Total**
1995-2000	29.12	14.53	23.76	67.40	75.67	54.67	116.33	246.67
2000-2005	28.39	13.19	23.07	64.65	75.67	54.67	116.33	246.67
2005-2010	33.6	17	31.4	82	75.67	54.67	116.33	246.67
2010-2015	45	22.4	34.2	101.6	75.67	54.67	116.33	246.67
2015-2020	35.4	15.4	25	75.8	75.67	54.67	116.33	246.67

* Denotes the average normative values for Kerala reported by Chand, R and Pavithra, S (2015)

Table 4.7.4 shows the average use of N, P, K in Kerala for the period from 1995-2020. The normative values of N, P, K in Kerala were taken from the reports of Chand, R and Pavithra, S (2015).

Here the normative values don't coincide with actual values of N, P and K and this reflected the presence of imbalance in the consumption of NPK.

Table 4.7.5: Deficit of average NPK (%) in Kerala for the 5-yearly period from 1995-2020

Deficit of average NPK (%) in Kerala for the 5-yearly period from 1995-2020				
Year	**N**	**P**	**K**	**NPK(Total)**
1995-2000	-61.52	-73.43	-79.58	-72.68
2000-2005	-62.48	-75.87	-80.17	-73.79
2005-2010	-55.60	-68.90	-73.01	-66.76
2010-2015	-40.53	-59.03	-70.60	-58.81
2015-2020	-53.23	-71.83	-78.51	-69.27

Table 4.7.5 gives an idea about the deficiency of average consumption of N, P, K in Kerala for the 5-yearly period from 1995-2020. The figures depicted shows the deficiency in the consumption of all nutrients namely Nitrogen, phosphorous and potassium.

This prompted to estimate the exact nature of imbalance in fertiliser use against norm of balance use of N, P and K which is recommended to be in the ratio of 4:2:1. This was estimated by using an indicator of imbalance adopted in earlier studies (Rajiv 2007) as given by,

$$\mathbf{I} = \sqrt{}[(\mathbf{N_a} - \mathbf{N_n})^2 + (\mathbf{P_a} - \mathbf{P_a})^2 + (\mathbf{K_a} - \mathbf{K_n})^2]/3$$

In the imbalance equation, '**I**' indicates the deviation in the proportion of actual use of N, P and K from the norm. Actual value of nutrients is marked by the letter a, and norm value is marked by the letter n. I is 0 when N, P, and K are used in the recommended ratio. The magnitude of the imbalance is measured by the value of I away from zero. The range of imbalance (I) would lie between 0 and 0.49, or 0% and 49%, symbolizing perfect balance and otherwise extreme imbalance, etc. The imbalance index for Kerala is shown in Table 4.7.6

Table 4.7.6 Imbalance index (I) for the period 1995-2020 for Kerala

Year	Imbalance index
1995-1996	0.16
1996-1997	0.13
1997-1998	0.18
1998-1999	0.11
1999-2000	0.17
2000-2001	0.14
2001-2002	0.15
2002-2003	0.17
2003-2004	0.15
2004-2005	0.15
2005-2006	0.16
2006-2007	0.24

Year	Imbalance index
2007-2008	0.15
2008-2009	0.16
2009-2010	0.15
2010-2011	0.15
2011-2012	0.13
2012-2013	0.15
2013-2014	0.16
2014-2015	0.11
2015-2016	0.13
2016-2017	0.13
2017-2018	0.11
2018-2019	0.17
2019-2020	0.14

From the Table 4.7.6 it was clear that imbalance index was highest (0.24) during the year 2006-07 and lowest value (0.11) which was observed during the year 1998-’99, 2014-’15 and 2017-’18. None of the years showed perfect balance or extreme imbalance in Kerala

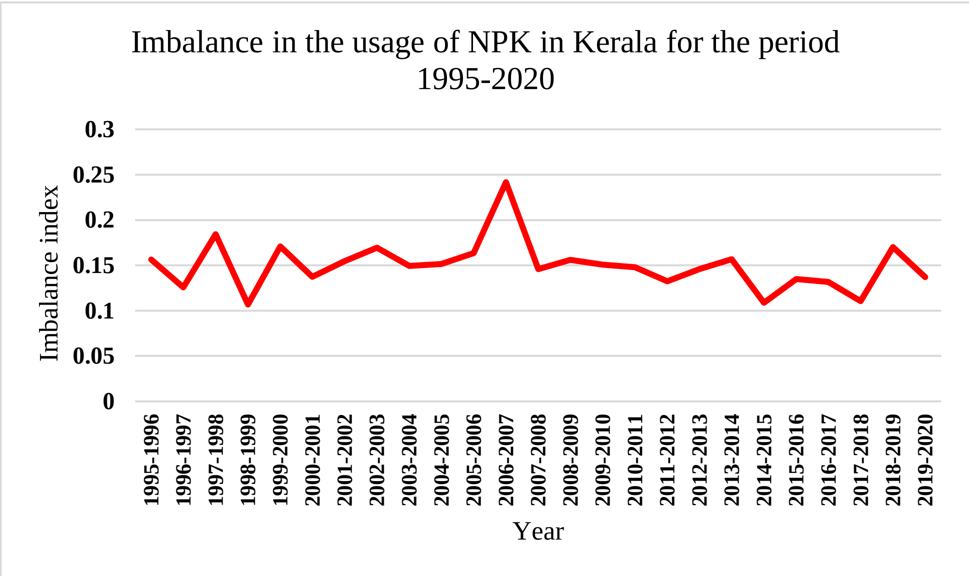

Fig:4.7.4 NPK imbalance in Kerala during the period 1995-2020

Fig:4.7.4 shows so many fluctuations in imbalance identified in Kerala. It may be due to the fact that farmers might not be following the recommended ratio given by the higher officials from the agricultural department. The soil conditions, variability in the crops cultivated etc. may also influence the consumption of N, P, K.

Table 4.7.7: Imbalance in fertiliser use in various districts of Kerala during 1993-2009

Year	**TVM**	**ALP**	**ERN**	**MLP**	**KNR**	**KLM**	**KTM**	**TCR**	**CLT**	**KSD**	**PAT**	**IDU**	**PLD**	**WND**
1993-94	0.1	0.2	0.2	0.1	0.2	0.1	0.2	0.2	0.3	0.2	0.1	0.2	0.1	0.2
1994-95	0.1	0.1	0.2	0.1	0.2	0.1	0.2	0.2	0.2	0.1	0.1	0.2	0.1	0.2
1995-96	0.1	0.1	0.2	0.1	0.1	0.1	0.2	0.1	0.2	0.2	0.1	0.2	0.1	0.2
1996-97	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.2	0.2	0.1	0.1	0.2	0.1	0.2
1997-98	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.2
1998-99	0.1	0.1	0.2	0.1	0.2	0.1	0.2	0.2	0.2	0.1	0.1	0.2	0.1	0.2
1999-00	0.1	0.1	0.2	0.1	0.2	0.1	0.2	0.2	0.2	0.1	0.2	0.2	0.1	0.2
2000-01	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.1	0.2
2001-02	0.1	0.2	0.1	0.2	0.2	0.1	0.1	0.1	0.2	0.1	0.2	0.3	0.1	0.2
2002-03	0.1	0.1	0.3	0.2	0.2	0.2	0.1	0.2	0.2	0.1	0.2	0.2	0.1	0.2
2003-04	0.1	0.1	0.2	0.2	0.2	0.2	0.1	0.1	0.3	0.1	0.2	0.2	0.1	0.2
2004-05	0.1	0.1	0.2	0.2	0.2	0.2	0.1	0.1	0.2	0.1	0.2	0.2	0.1	0.2
2006-07	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.1	0.2
2007-08	0.1	0.1	0.1	0.2	0.1	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.3
2008-09	0.1	0.1	0.1	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.3
0verall	**0.114**	**0.1**	**0.18**	**0.15**	**0.17**	**0.16**	**0.16**	**0.15**	**0.205**	**0.15**	**0.16**	**0.202**	**0.099**	**0.212**

From Table 4.7.7 it could be observed that the district Wayanad was having the highest imbalance index (0.212) followed by Kozhikode (0.205) and Idukki (0.202). The district Palakkad was having the least value of imbalance index which was equal to 0.099.

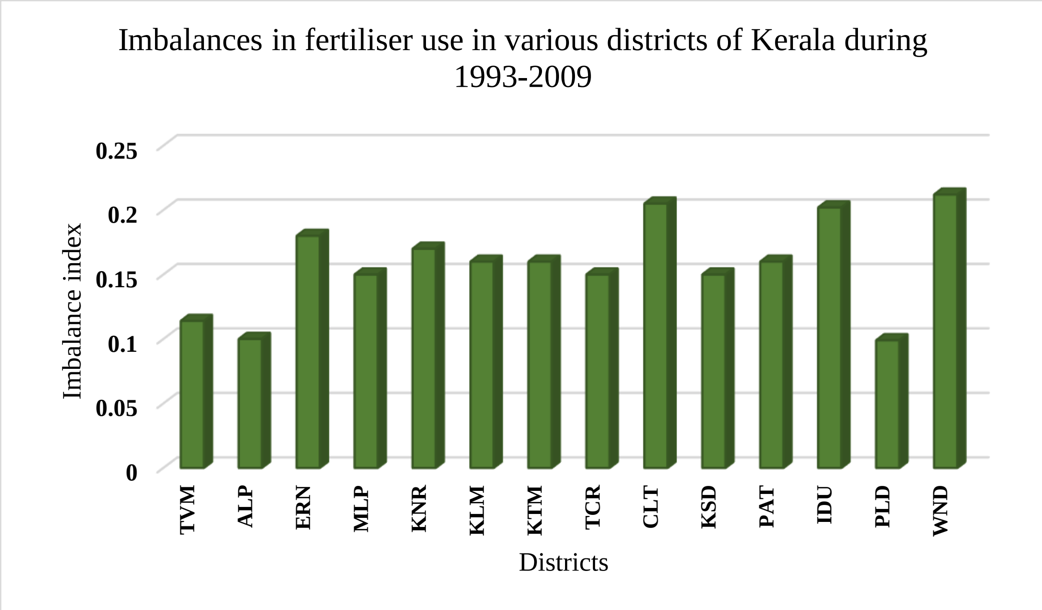

Fig:4.7.5 Imbalance in fertiliser use in various districts of Kerala during 1993-2009

Observing the district wise imbalance index, Idukki, Wayanad and Calicut were found to have the highest imbalance index value, whereas Palakkad showed the low imbalance index as depicted in Fig:4.7.5. There was no perfect balance or extreme imbalance in any district of Kerala.

The common and strongly held view is that balanced fertilisers are three major plant nutrients, namely nitrogen, phosphorous and potassium to be used in the ratio of 4:2:1 and any deviation in fertiliser use from this norm would constrain growth in productivity (Chand and Pavithra 2015). Therefore, it is very important from an output - growth point of view to ascertain whether fertiliser is used judiciously and optimally.

To reduce the imbalance of fertiliser, use in Kerala, the use of N, P and K have to be raised to the standard or recommended level in order to achieve sufficient or targeted crop output.

4.8 Vector Auto Regression

Vector Auto Regression (VAR) is a multivariate forecasting algorithm that is used when two or more time series influence each other. In the VAR model, each variable is modeled as a linear combination of past values of itself and original and past values of other variables in the system. That is, one can predict the series with past values of itself along with other series in the system. To fit the vector auto regression model Statistical Software Gretl 2016c has been utilised. As a first step, the VAR lag selection was made using the lag selection tool and for all the variables under study, the selected lag was 1 with respected to India as well as all other states.

4.8.1 Vector Auto Regression - India

For demonstrating the VAR model for India, the data from 1950 to 2020 pertaining to four variables viz; total cropped area, fertilizer consumption, pesticide consumption and food grains production were taken for the analysis.

4.8.5 VAR models using lagged values of dependent and independent variables

If VAR models can be developed using lagged dependent and lagged independent variables, the same can be used to predict one variable well in advance say one year before the next year food grain production etc. Using the previous year's data on food grain production, total cropped area, fertiliser consumption and pesticide consumption. Similarly, each of the variables can be predicted using the lagged value of itself and lagged values of other independent variables.

4.8.5.1 VAR models for India using lagged variables

4.8.5.1.1 Total cropped area -India

Table 4.8.5.1.1(a) Estimated coefficients in VAR model for total cropped area in India

	Coefficient	**Std. Error**	**t-ratio**	**p-value**	
Constant	49522.6	18457.7	2.68	0.009	***
Total cropped area: $V2_{-1}$	0.71	0.13	5.35	1.24e-06	***
Fertilizer consumption: $V3_{-1}$	0.78	0.30	2.65	0.01	**
Pesticide consumption: $V4_{-1}$	0.13	0.05	2.50	0.02	**
Food grains production: $V1_{-1}$	−0.08	0.05	−1.45	0.15	NS

Table 4.8.5.1.1(b) Estimated goodness of fit measures of VAR model for total cropped area in India

Mean dependent variable	175141.2	**S.D. dependent variable**	17833.02
Sum squared residual	1.05e+09	**S.E. of regression**	4042.74
R-squared	0.95	**Adjusted R-squared**	0.95
F (4, 64)	4.441.72	**P-value(F)**	7.87e-46
rho	-0.40	**Durbin-Watson**	2.75

From Table 4.8.5.1.1(a) it is evident that, the lagged variables such as total cropped area, fertiliser consumption and pesticide consumption of previous years were significant while regressing total cropped area on other lagged variables. The resulted vector auto regression equation for India with adjusted R^2 value equal to 0.95 was

$V2 = 49522.6 + 0.71\ V2_{-1}^{***} – 0.78\ V3_{-1}^{**} + 0.13\ V4_{-1}^{**} - 0.08\ V1_{-1}$ ….4.8.5.1.1(a)

Where V2 = total cropped area for the next year, $V2_{-1}$ is the total cropped area during the current year, $V3_{-1}$ is the fertiliser consumption during current year, $V4_{-1}$ is the pesticide consumption during current year, $V1_{-1}$ is the food grains production during current year.

In this case fertiliser consumption and pesticide consumption during past year were having significant influence on total cropped area and the corresponding regression coefficients were significant at 5% level of significance.

4.8.5.1.2 Fertiliser consumption - India

Table 4.8.5.1.2(a) Estimated coefficients in VAR model for fertiliser consumption in India

	Coefficient	Std. Error	t-ratio	p-value	
Constant	-5858.66	3169.92	-1.85	0.07	*
Fertilizer consumption: $V3_{-1}$	1.03	0.05	19.27	2.44e-03	***
Food grains production: $V1_{-1}$	-0.02	0.01	-1.43	0.16	NS
Pesticide consumption: $V4_{-1}$	-0.002	0.009	-0.25	0.80	NS
Total cropped area: $V2_{-1}$	0.05	0.02	1.96	0.05	*

Table 4.8.5.1.2(b) Estimated goodness of fit measures of VAR model for fertiliser consumption in India

Mean dependent variable	10672.18	**S.D. dependent variable**	9610.78
Sum squared residual	39563513	**S.E. of regression**	786.24
R-squared	0.99	**Adjusted R-squared**	0.99
F (4, 64)	2524.101	**P-value(F)**	1.24e-69
rho	0.14	**Durbin-Watson**	2.75

While regressing fertiliser consumption on other lagged variables, Table 4.8.5.1.2(a) showed that, the variables such as total cropped area and fertiliser consumption of previous year were significant. The resulted vector auto regression equation for India with adjusted R^2 value equal to 0.99 was

$V3 = -5858.66 + 1.03\ V3_{-1}^{***} – 0.02\ V1_{-1} - 0.002\ V4_{-1} + 0.05\ V2_{-1}^{*}$….4.8.5.1.2(a)

Where V3 = fertiliser consumption for the next year, $V3_{-1}$ is the fertiliser consumption during the current year, $V1_{-1}$ is the food grains production during current year, $V4_{-1}$ is the pesticide consumption during current year, $V2_{-1}$ is the total cropped area during current year.

Here total cropped area during previous year was having significant influence on fertiliser consumption and the corresponding regression coefficients were significant at 1% level of significance.

4.8.5.1.3 Pesticide consumption - India

Table 4.8.5.1.3(a) Estimated coefficients in VAR model for pesticide consumption in India

	Coefficient	Std. Error	t-ratio	p-value	
Constant	-8680.95	17246.1	-0.50	0.62	
Pesticide consumption: $V4_{-1}$	0.94	0.06	16.89	2.83e-0.25	***
Food grains production: $V1_{-1}$	-0.06	0.08	-0.70	0.48	NS
Total cropped area: $V2_{-1}$	0.10	0.13	0.72	0.47	NS
Fertilizer consumption: $V3_{-1}$	0.25	0.42	0.60	0.55	NS

Table 4.8.5.1.3(b) Estimated goodness of fit measures of VAR model for pesticide consumption in India

Mean dependent variable	40015.45	**S.D. dependent variable**	21627.22
Sum squared residual	1.57E+09	**S.E. of regression**	4952.99
R-squared	0.95	**Adjusted R-squared**	0.95
F (4, 64)	786.54	**P-value(F)**	1.20E-53
rho	-0.09	**Durbin-Watson**	2.15

In the case of regressing pesticide consumption on all lagged variables from Table 4.8.5.1.3(a) it can be observed that pesticide consumption during past year was a significant variable and rest of them were non - significant.

The resulted vector auto regression equation for India with adjusted R^2 equal to 0.95 and D.W = 2.15 was

$$V4 = -8680.95 + 0.94\, V4_{-1}^{***} - 0.06\, V1_{-1} + 0.10\, V2_{-1} + 0.25\, V3_{-1} \quad \ldots\ldots 4.8.5.1.3(a)$$

Where V4 = pesticide consumption for the next year, $V4_{-1}$ is the pesticide consumption during the current year, $V1_{-1}$ is the food grains production during current year, $V2_{-1}$ is the total cropped area during current year, $V3_{-1}$ is the fertiliser consumption during current year.

Here it is revealed that none of the variable during past year was having any significant influence on pesticide consumption.

4.8.5.1.4 Food grains Production – India

Table 4.8.5.1.4(a) Estimated coefficients in VAR model for food grains production in India

	Coefficient	Std. Error	t-ratio	p-value	
Constant	47983.8	43247.6	1.11	0.27	
Food grains production: $V1_{-1}$	0.43	0.15	2.94	0.005	***
Total cropped area: $V2_{-1}$	-0.05	0.33	-0.15	0.88	NS
Fertilizer consumption: $V3_{-1}$	3.67	0.73	5.03	4.26E-06	***
Pesticide consumption: $V4_{-1}$	0.3	0.12	2.56	0.01	**

Table 4.8.5.1.4(b) Estimated goodness of fit measures of VAR model for food grains consumption in India

Mean Dependent variable	154384.9	**S.D. dependent variable**	68284.72
Sum squared residual	7.56E+09	**S.E. of regression**	10871.23
R-squared	0.98	**Adjusted R-squared**	0.97
F (4, 64)	809.7	**P-value(F)**	5.06E-54
rho	-0.32	**Durbin-Watson**	2.56

From the Table 4.8.5.1.4(a), lagged variables such as food grains production, fertiliser consumption and pesticide consumption were found to be significant.

The resulted vector auto regression equation for India with adjusted R^2 value equal to 0.97 was

$V1=47983.8 + 0.43\ V1_{-1}^{***} - 0.05\ V2_{-1} + 3.67\ V3_{-1}^{***} + 0.30\ V4_{-1}^{**}$….4.8.5.1.4(a)

Where V1 = food grains production for the next year, $V1_{-1}$ is the food grains production during the current year, $V2_{-1}$ is the total cropped area during current year, $V3_{-1}$ is the fertiliser consumption during current year, $V4_{-1}$ is the pesticide consumption during current year.

In this case fertiliser consumption and pesticide consumption during past year were having significant influence on food grains production and the corresponding regression coefficients were significant at 1% and 5% level of significance respectively.

4.8.5.2 VAR models for Kerala using lagged variables

4.8.5.2.1 Vector Auto Regression model for total cropped area – Kerala

Table 4.8.5.2.1(a) Estimated coefficients of VAR model for total cropped area in Kerala

	Coefficient	Std. Error	t-ratio	p-value	
Constant	524.16	195.86	2.68	0.01	**
Total cropped Area: $V1_{-1}$	0.80	0.08	10.34	3.47e-012	***
Fertilizer Consumption: $V2_{-1}$	-0.24	0.21	-1.14	0.26	NS
Food grains production: $V3_{-1}$	0.09	0.05	1.98	0.06	*

Table 4.8.5.2.1(b) Estimated goodness of fit measures of VAR model for total cropped area in Kerala

Mean dependent variable	2793.57	**S.D. dependent variable**	182.65
Sum squared residual	249532.6	**S.E. of regression**	84.44
R-squared	0.80	**Adjusted R-squared**	0.79
F (4, 64)	81.32	**P-value(F)**	7.59e-16
rho	0.10	**Durbin-Watson**	1.80

For Kerala, lagged variables with respect to total cropped area and food grains production were found to be significant.

The resulted vector auto regression equation for Kerala with adj. $R^2 = 0.79$ and DW = 1.80 was

$$V1 = 524.16 + 0.80\, V1_{-1}^{***} - 0.24\, V2_{-1} + 0.09\, V3_{-1}^{*} \qquad \text{…………4.8.5.2.1(a)}$$

Where V1 = total cropped area for the next year, V_{1-1} is the total cropped area during the current year, $V2_{-1}$ is the fertiliser consumption during current year, $V3_{-1}$ is the food grains production during current year.

4.8.5.2.2 Fertiliser consumption – Kerala

Table 4.8.5.2.2(a) Estimated coefficients in VAR model for fertiliser consumption in Kerala

	Coefficient	**Std. Error**	**t-ratio**	**p-value**	
Constant	48.78	64.19	0.76	0.45	NS
Fertilizer consumption: $V2_{-1}$	0.59	0.16	3.59	0.001	***
Total cropped area: $V1_{-1}$	0.03	0.03	0.98	0.34	NS
Food grains production: $V3_{-1}$	-0.05	0.02	-2.60	0.01	**

Table 4.8.5.2.2(b) Estimated Goodness of fit measures of VAR model for fertiliser consumption in Kerala

Mean dependent variable	200.18	**S.D. dependent variable**	51.10
Sum squared residual	32154.39	**S.E. of regression**	30.31
R-squared	0.68	**Adjusted R-squared**	0.65
F (4, 64)	39.84	**P-value(F)**	2.21e-11
rho	-0.16	**Durbin-Watson**	2.27

From Table 4.8.5.2.2(a) it is evident that, food grains production and fertiliser consumption during previous year were significant and rest of the other variables such as total cropped area during previous year was non-significant while regressing fertiliser consumption on other lagged variables.

The resulted vector auto regression equation for Kerala with adjusted R^2 equal to 0.65 was

$$V2 = 48.78 + 0.59\, V2_{-1}^{***} + 0.03\, V1_{-1} - 0.05\, V3_{-1}^{**} \quad \ldots\ldots\ldots\ldots\ldots 4.8.5.2.2(a)$$

Where V2 = fertiliser consumption for the next year, $V2_{-1}$ is the fertiliser consumption during the current year, $V1_{-1}$ is the total cropped area during the current year, $V3_{-1}$ is the food grains production during the current year.

In this case food grains production and fertiliser consumption during current year were having significant influence on fertiliser consumption during next year and the corresponding regression coefficients were significant.

4.8.5.2.3 Food grains production – Kerala

Table 4.8.5.2.3(a) Estimated coefficients of VAR model for food grains production in Kerala

	Coefficient	Std. Error	t-ratio	p-value	
Constant	382.29	490.85	0.79	0.44	NS
Food grains production: $V3_{-1}$	0.68	0.18	3.68	0.0008	***
Fertilizer consumption: $V2_{-1}$	0.04	0.22	0.17	0.86	NS
Total cropped area: $V1_{-1}$	-1.20	0.78	-1.55	0.13	NS

Table 4.8.5.2.3(b) Estimated goodness of fit measures of VAR model for food grains production in Kerala

Mean dependent variable	812.15	**S.D. dependent variable**	294.87
Sum squared residual	831039.9	**S.E. of regression**	154.09
R-squared	0.75	**Adjusted R-squared**	0.73
F (4, 64)	103.58	**P-value(F)**	1.80e-17
rho	-0.27	**Durbin-Watson**	2.51

From Table 4.8.5.2.3(a) it is evident that, lagged values of food grains production were found to be significant while regressing food grains production on other lagged variables. The resulted regression equation with adjusted R^2 equal to 0.73 and DW = 2.51 respectively was,

$$V3 = 382.29 + 0.68\, V3_{-1}^{***} + 0.04\, V2_{-1} - 1.20\, V1_{-1} \quad \ldots\ldots\ldots\ldots\ldots 4.8.5.2.3(a)$$

Where V3 = food grains production for the next year, $V3_{-1}$ is the food grains production during the current year, $V2_{-1}$ is the fertiliser consumption during current year, $V1_{-1}$ is the total cropped area during current year.

4.8.5.3 VAR models for Andhra Pradesh using lagged variables

Vector Auto Regression for total cropped area – Andra Pradesh

Table 4.8.5.3.1(a) Estimated coefficients of VAR model for total cropped area in Andhra Pradesh

	Coefficient	Std. Error	t-ratio	p-value	
Constant	1987.72	1316.58	1.51	0.14	NS
Total cropped Area: $V1_{-1}$	1.01	0.08	12.80	1.49e-014	***
Fertilizer Consumption: $V2_{-1}$	1.11	0.43	2.59	0.01	**
Food grains production: $V3_{-1}$	-0.32	0.12	-2.58	0.01	**
Pesticide consumption: $V4_{-1}$	−0.01	0.04	−0.36	0.72	NS

Table 4.8.5.3.1(b) Estimated goodness of fit measures of VAR model for total cropped area in Andhra Pradesh

Mean dependent variable	11971.02	**S.D. dependent variable**	2474.11
Sum squared residual	37031094	**S.E. of regression**	1043.62
R-squared	0.84	**Adjusted R-squared**	0.82
F (4, 64)	79.36	**P-value(F)**	9.32e-17
rho	-0.08	**Durbin-Watson**	2.16

With respect to Andhra Pradesh from Table 4.8.5.3.1(a) it showed that lagged variables such as total cropped area, fertiliser consumption and food grains production were significant.

The resulted vector auto regression equation for Andhra Pradesh (adj. $R^2 = 0.82$ and DW = 2.16) was,

$$V1 = 1987.72 + 1.01\ V1_{-1} + 1.11\ V2_{-1} - 0.32\ V3_{-1} - 0.01\ V4_{-1} \quad \ldots\ldots 4.8.5.3.1(a)$$

Where V1 = total cropped area for the next year, $V1_{-1}$ is the total cropped area during the current year, $V2_{-1}$ is the fertiliser consumption during current year, $V3_{-1}$ is the food grains production during current year, $V4_{-1}$ is the pesticide consumption during the current year.

4.8.5.3.2 Fertiliser consumption – Andhra Pradesh

Table 4.8.5.3.2(a) Estimated coefficients of VAR model for fertiliser consumption in Andhra Pradesh

	Coefficient	Std. Error	t-ratio	p-value	
Constant	119.95	175.24	0.68	0.50	NS
Fertilizer Consumption: $V2_{-1}$	0.98	0.11	9.01	1.58e-01	***
Total cropped Area: $V1_{-1}$	0.08	0.02	5.14	1.11e-05	***
Food grains production: $V3_{-1}$	-0.06	0.02	-2.58	0.01	**
Pesticide consumption: $V4_{-1}$	-0.04	0.01	−3.95	0.0004	***

Table 4.8.5.3.2(b) Estimated goodness of fit measures of VAR model for fertiliser consumption in Andhra Pradesh

Mean dependent variable	1853.66	**S.D. dependent variable**	729.04
Sum squared residual	1386533	**S.E. of regression**	201.94
R-squared	0.93	**Adjusted R-squared**	0.92
F (4, 64)	112.88	**P-value(F)**	3.94e-18
rho	-0.06	**Durbin-Watson**	2.10

From Table 4.8.5.3.2(a) it is evident that, all the lagged variables such as total cropped area, fertiliser consumption, pesticide consumption and food grains production during previous year were significant while regressing fertiliser consumption on other lagged variables.

The resulted vector auto regression equation for Andhra Pradesh with adjusted R^2 value equal to 0.92 was

$V2=119.95 + 0.98\ V2_{-1}{***} + 0.08\ V1_{-1}{***} - 0.06\ V3_{-1}{**} - 0.04\ V4_{-1}{***}$…4.8.5.3.2(a)

Where V2 = fertiliser consumption for the next year, $V2_{-1}$ is the fertiliser consumption during the current year, $V1_{-1}$ is the total cropped area during current year, $V3_{-1}$ is the food grains production during current year, $V4_{-1}$ is the pesticide consumption during the current year.

In this case total cropped area and pesticide consumption during past year were having significant influence on fertiliser consumption and the corresponding regression coefficients were significant at 1% level of significance. And lagged value of food grains production was significant at 5%.

4.8.5.3.3 Food grains production – Andhra Pradesh

Table 4.8.5.3.3(a) Estimated coefficients of VAR model for food grains production in Andhra Pradesh

	Coefficient	Std. Error	t-ratio	p-value	
Constant	3853.46	1695.94	2.27	0.03	**
Food grains production: $V3_{-1}$	-0.09	0.22	-0.40	0.69	**
Pesticide consumption: $V4_{-1}$	-0.20	0.08	-2.33	0.03	**
Total cropped Area: $V1_{-1}$	0.49	0.16	3.04	0.004	***
Fertilizer Consumption: $V2_{-1}$	3.33	0.84	3.96	0.0004	***

Table 4.8.5.3.3(b) Estimated goodness of fit measures of VAR model for food grains production in Andhra Pradesh

Mean dependent variable	13411.76	**S.D. dependent variable**	3327.80
Sum squared residual	1.04e+08	**S.E. of regression**	1751.64
R-squared	0.75	**Adjusted R-squared**	0.72
F (4, 64)	30.72	**P-value(F)**	7.35e-11
rho	-0.11	**Durbin-Watson**	2.17

Table 4.8.5.3.3(a) revealed that, lagged variables such as food grains production, pesticide consumption, total cropped area and fertiliser consumption during previous year were significant while regressing food grains production on other lagged variables.

The resulted vector auto regression equation for Andhra Pradesh with adjusted R^2 value equal to 0.72 was,

$V3 = 3853.46 - 0.09\ V3_{-1}^{**} - 0.20\ V4_{-1}^{**} + 0.49\ V1_{-1}^{**} + 3.33\ V2_{-1}$……4.8.5.3.3(a)

Where V3 = food grains production for the next year, $V3_{-1}$ is the food grains production during the current year, $V4_{-1}$ is the pesticide consumption during the current year, $V1_{-1}$ is the total cropped area during current year, $V2_{-1}$ is the fertiliser consumption during the current year.

In this case pesticide consumption, total cropped area and fertiliser consumption during previous year were having significant influence on food grains production and the corresponding regression coefficients were significant.

4.8.5.4 VAR models for Tamil Nadu using lagged variables

4.8.5.4 Total cropped area - Tamil Nadu

Table 4.8.5.4.1(a) Estimated coefficients of VAR model for total cropped area in Tamil Nadu

	Coefficient	Std. Error	t-ratio	p-value	
Constant	2949.94	650.55	4.54	6.84e-05	***
Total cropped Area: $V1_{-1}$	0.63	0.08	7.93	3.10e-09	***
Fertilizer Consumption: $V2_{-1}$	-0.34	0.18	-1.89	0.07	*
Food grains production: $V3_{-1}$	-0.05	0.03	-1.88	0.07	*
Pesticide consumption: $V4_{-1}$	0.01	0.02	0.80	0.43	NS

Table 4.8.5.4.1(b) Estimated goodness of fit measures of VAR model total cropped area in Tamil Nadu

Mean dependent variable	6371.24	**S.D. dependent variable**	663.04
Sum squared residual	2419298	**S.E. of regression**	266.75
R-squared	0.86	**Adjusted R-squared**	0.84
F (4, 64)	59.43	**P-value(F)**	7.17e-15
rho	-0.11	**Durbin-Watson**	2.14

In the case of Tamil Nadu from Table 4.8.5.3.1(a) it is evident that, variables such as total cropped area, fertiliser consumption and food grains production during previous year were significant while regressing food grains production on other lagged variables.

The resulted vector auto regression equation for India with adj. $R^2 = 0.84$ and DW = 2.14 was,

$$V1 = 2949.94 + 0.63\ V1_{-1} - 0.34\ V2_{-1} - 0.05\ V3_{-1} + 0.01\ V4_{-1} \quad \text{.........4.8.5.4.1(a)}$$

Where V1 = total cropped area for the next year, $V1_{-1}$ is the total cropped area during the current year, $V2_{-1}$ is the fertiliser consumption during the current year, $V3_{-1}$ is the food grains production during the current year, $V4_{-1}$ is the pesticide consumption during the current year.

In this case fertiliser consumption and food grains production were having significant influence on total cropped area and the corresponding regression coefficients were significant.

4.8.5.4.2 Fertiliser consumption - Tamil Nadu

Table 4.8.5.4.2(a) Estimated coefficients of VAR model for fertiliser consumption in Tamil Nadu

	Coefficient	Std. Error	t-ratio	p-value	
Constant	995.31	423.51	2.35	0.02	**
Fertilizer Consumption: $V2_{-1}$	0.63	0.14	4.41	9.97e-05	***
Total cropped Area: $V1_{-1}$	-0.05	0.05	-1.06	0.30	NS
Food grains production: $V3_{-1}$	-0.03	0.02	-1.53	0.13	NS
Pesticide consumption: $V4_{-1}$	−0.03	0.01	−1.93	0.06	*

Table 4.8.5.4.2(b) Estimated goodness of fit measures of VAR model for fertiliser consumption in Tamil Nadu

Mean dependent variable	803.87	**S.D. dependent variable**	393.98
Sum squared residual	1811376	**S.E. of regression**	230.82
R-squared	0.69	**Adjusted R-squared**	0.66
F (4, 64)	35.28	**P-value(F)**	1.16e-11
rho	-0.11	**Durbin-Watson**	2.23

Table 4.8.5.4.2(a) showed that, lagged variables such as fertiliser consumption and pesticide consumption during past year were significant while regressing fertiliser consumption on other lagged variables.

The resulted vector auto regression equation for Tamil Nadu with adjusted R^2 value equal to 0.66 was,

$$V2 = 1987.72 + 1.01\ V1_{-1} + 1.11\ V2_{-1}{}^{***} - 0.32\ V3_{-1} - 0.01\ V4_{-1}{}^{*} \ldots\ldots\ldots 4.8.5.4.2(a)$$

Where V2 = fertiliser consumption for the next year, $V1_{-1}$ is the total cropped area during the current year, $V3_{-1}$ is the food grains production during the current year, $V4_{-1}$ is the pesticide consumption during the current year.

In this case lagged values of pesticide consumption and fertiliser consumption during past year were significant regressors.

4.8.5.4.3 Food grains production - Tamil Nadu

Table 4.8.5.4.3(a) Estimated coefficients of VAR model for food grains production in Tamil Nadu

	Coefficient	Std. Error	t-ratio	p-value	
Constant	616.34	8122.66	0.08	0.94	NS
Food grains production: $V3_{-1}$	0.15	0.21	0.72	0.48	NS
Pesticide consumption: $V4_{-1}$	0.26	0.20	1.34	0.19	NS
Total cropped Area: $V1_{-1}$	0.35	0.89	0.40	0.69	NS
Fertilizer Consumption: $V2_{-1}$	-0.66	1.19	-0.55	0.59	NS

Table 4.8.5.4.3(b) Estimated Goodness of fit measures VAR model for food grains production in Tamil Nadu

Mean dependent variable	7707.36	**S.D. dependent variable**	1883.75
Sum squared residual	1.02e+08	**S.E. of regression**	1761.12
R-squared	0.24	**Adjusted R-squared**	0.12
F (4, 64)	1.87	**P-value (F)**	0.13
rho	0.01	**Durbin-Watson**	1.93

Table 4.8.5.4.3(a) showed none of the variables to be significant while regressing food grains production on other lagged variables.

The resulted vector auto regression equation for Tamil Nadu was

$$V3 = 616.34 + 0.15\ V3_{-1} + 0.26\ V4_{-1} + 0.35\ V1_{-1} - 0.66\ V2_{-1} \ldots\ldots\ldots\ldots\ldots 4.8.5.4.3(a)$$

Where V3 = food grains production for the next year, $V3_{-1}$ is the food grains production during the current year, $V4_{-1}$ is the pesticide consumption during the current year, $V1_{-1}$ is the total cropped area during current year, and $V2_{-1}$ is the fertiliser consumption during current year.

In Tamil Nadu variables during past years were having no significant influence on food grains production.

Summary and Conclusion

CHAPTER 5

SUMMARY AND CONCLUSIONS

Agriculture is India's most important economic sector since it ensures food and livelihood security. One of the oldest occupations in world is agriculture and still is the largest one even today. The modernization of agriculture has supported the use of a wide range of agrochemicals in agricultural fields, including fertilizers, pesticides, micro nutrients and plant growth regulators.

The study intends to scrutinize the co integrated movement of food grains production and agricultural inputs through a time series assessment in India and for the selected states viz., Kerala, Andhra Pradesh and Tamil Nadu using secondary information collected from various sources. Total cropped area, fertiliser consumption, pesticide consumption and food grains production were selected as the variables for the study. For the entire study, yearly time series data for the period from 1950-2020 were collected for India. For Kerala the data for the period 1980-2020 for total cropped area and fertilizer consumption, pesticide consumption for the period from 1990-2020 and food grains production for the period 1950-2020 were used. With respect to Andhra Pradesh and Tamil Nadu data for the period 1980-2020 for total cropped area, 1970-2020 for fertiliser consumption and pesticide consumption, and for the period 1950-2020 for food grains production were used.

The study envisioned estimation of the general trend in food grains production and agricultural inputs such as total cropped area, fertilizer consumption and pesticide consumption and prediction for those variables using advanced statistical techniques. The predictability of the various forecasting models was examined as well. The study's key findings are summarized below.

Trend analysis with respect to India depicted an overall growth movement in an upward direction for the variables under study with almost linear trend. When coming to trend analysis of Kerala, Andhra Pradesh and Tamil Nadu total cropped area, fertilizer consumption and pesticide consumption showed a declining trend. In the case of food grains production, a slow increase was noted in very recent years for all the three states.

Considering the total production of food grains in India, Uttar Pradesh was contributing more followed by Madhya Pradesh, Punjab, Rajasthan etc. Similarly for total cropped area, fertiliser consumption and pesticide consumption also the three states selected for the study were ranking below the other states. This might be the reason for the linear upward trend of all variables with respect to India and at the same time a down trend for the states KL, AP and TN.

Puducherry, Telangana and Punjab were top in fertilizer consumption, notwithstanding their small size and population compared to other states and Union Territories. Puducherry tops the chart in consumption of major fertilizers from 2015-'16 to 2019-'20 followed by Telangana and Punjab. Total pesticide consumption was highest in Maharashtra, followed by Uttar Pradesh, Punjab and Haryana. Since Kerala mainly depends on Andhra Pradesh and Tamil Nadu for cereals and vegetables, the states Kerala, Andhra Pradesh and Tamil Nadu were selected for a comparative study.

To observe the growth rate of variables under study for India and states viz; Kerala, Andra Pradesh and Tamil Nadu, compound annual growth rate was computed. Overall growth rate in the variables under study was positive in India. For total cropped area it was +0.006, for fertiliser consumption it was + 0.089, for pesticide consumption it was +0.048 and for food grain production it was +0.026. However, in Kerala, the total cropped area (+0.001) and fertiliser consumption (+0.01) showed positive CAGR whereas negative growth rate for pesticide consumption (-0.01) and for food grain production (-0.002). In Andhra Pradesh the CAGR was -0.02 showing a negative growth rate in the case of total cropped area and for fertiliser consumption it was 0.03 for pesticide consumption it was -0.03 and for food grain production it was 0.02. In the case of Tamil Nadu, for total cropped area and fertiliser consumption CAGR was 0.004 and 0.02 respectively whereas for pesticide consumption it was -0.002 and for food grain production it was 0.02. It could be noticed from the results that pesticide consumption got a negative CAGR in the states, Kerala, AP and TN. So, it can be inferred that farmers might be aware of the ill effects of increased use of pesticides which would result in severe health issues and environmental hazards. The negative growth rate of food grain production in Kerala needs serious attention and it is also worth to identify the factors which discriminates Kerala from AP and TN

To identify the best fit model and to forecast the future values of the variables under study time series model building was used. To forecast total cropped area, fertiliser consumption and food grains production in India, Holts' model was identified as the best with adjusted R^2 values as 0.96, 0.99 and 0.98 respectively. Simple exponential smoothing model was obtained as the best model for pesticide consumption in India with 0.95 adjusted R^2. For Kerala, simple exponential smoothing, ARIMA (1,0,0) and Holts' model were obtained for total cropped area (adj. $R^2 = 0.76$), fertiliser consumption (adj. $R^2 = 0.66$) and food grains production (adj. $R^2 = 0.85$) respectively. For Andhra Pradesh, ARIMA (0,1,0) model was obtained for total cropped area with adj. $R^2 = 0.80$, simple exponential smoothing model for fertiliser consumption with adj. $R^2 = 0.93$, pesticide consumption with adj. $R^2 = 0.82$ and for food grains production with adj. $R^2 = 0.82$. When coming to Tamil Nadu ARIMA (0,1,0) was the best for total cropped area with adj. $R^2 = 0.76$, ARIMA (0,1,6) for fertiliser consumption with adj. $R^2 = 0.74$, simple exponential smoothing model for pesticide consumption with adj. $R^2 = 0.84$ and simple exponential smoothing model for food grains production with adj. $R^2 = 0.43$.

A box plot is a standardised way of displaying the distribution of data based on the measures of data like minimum value, first quartile (Q_1), median, third quartile and maximum value. Basically, it is a graphical tool for quickly summarizing and interpreting tabular data and used to visually identify patterns in a data that might otherwise be undiscovered. The results of box plot analysis revealed that, among the three states (Kerala, Tamil Nadu and Andhra Pradesh), Andhra Pradesh showed highest dispersion in the data followed by Tamil Nadu and Kerala with respect to food grain production, total cropped area, fertilizer and pesticide consumption respectively. It was also observed that in Kerala, the average figures corresponding to total cropped area, fertilizer consumption and food grain production were lower than that of Andhra

Pradesh and Tamil Nadu. It is well known that Kerala imports food grain, particularly cereals and vegetables from Andhra Pradesh and Tamil Nadu.

Mahalanobis D^2 was used to estimate the distance between the three states, with respect to variables under study. The distance between Kerala - Tamil Nadu (1.94) was more compared with Kerala - Andhra Pradesh (1.93). The distance between Andhra Pradesh and Tamil Nadu (1.74) was the lowest.

Discriminant analysis paves a way to pinpoint the casual factors which contribute to the discrepancy between the states and it identifies the root cause for this huge distance obtained from Mahalanobis D^2 between Kerala and other states. From the results obtained from discriminant analysis, it could be observed that with respect to Kerala and Andhra Pradesh, the most powerful discriminating factor was food grains production followed by fertilizer consumption. While, for Kerala and Tamil Nadu most powerful discriminating factor was fertilizer consumption followed by total cropped area.

From these findings, it can be concluded that the climatic conditions, soil conditions, as well as the consumption pattern of fertilisers might be highly favourable for the production of food grains in Andhra Pradesh than Kerala. With respect to Kerala Vs Tamil Nadu, fertiliser consumption was the most important discriminating factor. Consumption was more in Tamil Nadu. The area of cultivation was also comparatively higher than that of Kerala. Hence, total cropped area was the second most important discriminating factor. In Tamil Nadu the fertiliser consumption was very high, leading to high food grains production.

Except small farmers, the marginal and big farmers depend farming mainly to earn money. Hence, to enhance the production they apply more fertilisers and pesticides focussing on high production from small area.

The growth in fertiliser consumption in the country is of paramount importance to raise agricultural production and to meet future requirements of the country. Even though there exists some standard recommendation for fertilizer consumption, the farmers do not follow such recommendations suggested by officials from agriculture department. Some kinds of imbalances were reflected in fertilizer consumption and it has resulted in variation in food grains production also. Recommended ratio of N, P and K are 4:2:1. That is 57.14, 28.57 and 14.28 out of 100 respectively. The analysis of fertiliser use imbalance was done for the period 1995 to 2020 for Kerala and 1993 to 2008 for different districts of Kerala. The analysis was performed by examining the imbalance in fertilizer use at the state level and then at district level, by observing the trend in use of N, P and K during respective years of study.

For all Kerala the recommended and actual average usage of N, P, K was compared and it could be observed that the average use of N, P and K were significantly lower than that of the recommended quantity. Growth in consumption of plant nutrients in Kerala for the period 1995-2020 clearly showed that so many fluctuations were there regarding the total consumption of N, P and K. This is an indicator of unbalanced use of fertiliser.

To estimate the exact nature of imbalance in fertiliser use against norm of balance use of N, P and K, Kerala showed the highest imbalance index (0.24) during the year 2006-'07 and lowest value (0.11) observed during the year 1998-'99, 2014-'15 and 2017-'18. None of the years showed perfect balance or extreme imbalance in Kerala. For district wise study it could be observed that the districts Wayanad was having the highest imbalance index (0.212) followed by Kozhikode (0.205) and Idukki (0.202). The Palakkad district was having the least value of imbalance index which was equal to 0.099.

To reduce the imbalance of fertiliser use in Kerala, the use of N, P and K should be raised to the standard level. Also, the norm for N, P and K should be estimated with respect to specific regions considering the crops raised in that region as well as total cropped area under each crop etc.

To assess the cointegrated movement of the variables like food grains production and various agricultural inputs like total cropped area, fertiliser consumption and pesticide consumption, Vector Auto Regression model was used. In VAR each variable is modelled as a linear combination of past values of itself and past values of other variables in the system.

For demonstrating the VAR model for India, the data from 1950 to 2020 and for Kerala, Andhra Pradesh, Tamil Nadu, the data from 1980-2020 pertaining to four variables were taken. In the case of India, it is evident that, while regressing total cropped area on other lagged variables (fertiliser consumption, pesticide consumption and food grains production) including total cropped area, the variables such as fertiliser consumption, pesticide consumption and total cropped area were found to be significant with adjusted $R^2 = 0.95$. When fertiliser consumption was regressed on all other lagged variables, total cropped area and fertiliser consumption was found to be significant with adjusted R^2 equal to 0.99. While regressing pesticide consumption on all lagged variables it resulted in adjusted. $R^2 = 0.95$. In the case of food grains production all the three variables except total cropped area was found to be significant with adj. $R^2 = 0.97$.

Coming to VAR model for state wise analysis each variable like total cropped area, fertiliser consumption and pesticide consumption was regressed on its own lagged values as well as lagged values of the other three variables. it was found that total cropped area for the next year could be modelled using lagged values of itself and lagged variables of fertiliser consumption, pesticide consumption and food grains production which had resulted in an adjusted $R^2 = 0.80$ for Kerala ,0.84 for AP and 0.86 for TN. To predict fertiliser consumption during the next year VAR model resulted in an adjusted R^2 of 0.68, 0.93 and 0.69 for Kerala, AP and TN. VAR modelling resulted in an adjusted R^2 of 0.75, 0.75 and 0.24 to predict food grains production for Kerala, AP and TN.

The study revealed that the variables under study were highly associated each other and the co integrated movement of food grains production and agricultural inputs could be well quantified through Vector Auto Regression Approach. For state wise analysis also the VAR modelling had resulted in significantly high value of R^2 in almost all cases.

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CHAPTER 6

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Abstract

COINTEGRATED MOVEMENT OF FOOD GRAINS PRODUCTION AND AGRICULTURAL INPUTS: A TIME SERIES ASSESSMENT

By

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ABSTRACT OF THE THESIS

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CHAPTER 7

ABSTRACT

Introduction of the green revolution, modernization of agriculture, encouragement to research and extension in agriculture are some of the factors that contributed to the growth in agriculture. Increasing crop production and productivity are not just about the new technologies or crop management. Environmental sustainability is also of vital importance. The complexity of these issues now faced make improving crop production and productivity a more challenging task. Water, fertilisers, crop protection-inputs and professional advice all need to be managed in the most efficient manner.

Fertiliser use has seen a tremendous increase in India and in other parts of the world with the spread of green revolution. Fertiliser was identified as one of the three most important factors, along with seed and irrigation for raising agricultural production and sustaining food self-sufficiency in India. In Kerala, farmers mostly depend on agriculture as a means to earn more money and concentrate more on cash crops other than crops those belong to staple food grains category which is one of the most important factors for human existence.

The study intends to scrutinize the movement of food grains production and agricultural inputs through a time series assessment in India and three selected states viz., Kerala, Andhra Pradesh and Tamil Nadu using secondary information collected from various official sources.

To identify the trend in production of food grains and agricultural inputs in India for the period 1950-2020 and the states (1980-2020), the linear, quadratic and cubic functional forms were selected with high values of adjusted R^2. Trend analysis for India depicted an overall growth in an upward direction for the variables under study realizing almost linear trend. Whereas the trend analysis for Kerala, AP and TN with respect to total cropped area, fertilizer consumption and pesticide consumption showed a declining trend. In the case of food grain production, a slow increase was noted in very recent years for all the three states.

CAGR was computed to observe the growth rate of the variables and for India, overall growth rate in the variables under study was positive. For total cropped area it was +0.006, +0.089 for fertiliser consumption and +0.048 for pesticide consumption and +0.026 for food grains production. However, in Kerala, the total cropped area (+0.001) and fertiliser consumption (+0.01) showed positive CAGR whereas negative growth rate for pesticide

consumption (-0.01) and for food grains production (-0.002). In Andhra Pradesh, CAGR was -0.02 showing a negative growth rate in the case of total cropped area and 0.03 for fertiliser consumption, -0.03 for pesticide consumption and 0.02 for food grain production. In the case of Tamil Nadu, for total cropped area and fertiliser consumption CAGR was 0.004 and 0.02 respectively. Whereas for pesticide consumption it was -0.002 and for food grain production it was 0.02. Overall pesticide use had a negative CAGR in the states of Kerala, AP and TN. Also, the negative growth rate of food grain production in Kerala needs serious attention and it is also worth to identify the factors which discriminates Kerala from AP and TN.

Time series model building was used to determine the best fit model and forecast future values of the variables under consideration. In India, Holts' model was identified as the best to forecast total cropped area, fertiliser consumption and food grains production with adjusted R^2 values as 0.96, 0.99 and 0.98 respectively. Regarding pesticide consumption Simple exponential smoothing model was the best with adjusted R^2 = 0.95. For Kerala, Simple exponential smoothing model, ARIMA (1,0,0) and Holts' model were obtained for total cropped area (adj. R^2=0.76), fertiliser consumption (adj. R^2=0.66) and food grains production (adj. R^2=0.85) respectively. For Andhra Pradesh, ARIMA (0,1,0) model was identified for total cropped area with adj. R^2= 0.80, Simple exponential smoothing model for fertiliser consumption with adj. R^2=0.93, for pesticide consumption with adj. R^2=0.82 and for food grains production with adj. R^2=0.82. When coming to Tamil Nadu, ARIMA (0,1,0) was the best for modeling total cropped area with adj. R^2=0.76, ARIMA (0,1,6) for fertiliser consumption with adj. R^2=0.74, Simple exponential smoothing model for pesticide consumption with adj R^2= 0.84 as well as for food grains production with adj. R^2=0.43.

It is well known that Kerala imports food grains mainly cereals and vegetables from Andhra Pradesh and Tamil Nadu. To examine the pattern and dispersion of variables viz; total cropped area, fertiliser consumption, pesticide consumption and food grains production in Kerala, AP and TN, Box plot analysis was done and found that AP had highest dispersion and Kerala showed lowest dispersion with respect to variables under study. Since variability was found among the states, Mahalanobis D^2 was used to estimate the pairwise distance between the states with respect to variables under study. The distance between Kerala - TN (1.94) was more when compared with Kerala - AP (1.93) and the distance between AP - TN (1.74) was the lowest.

Discriminant analysis paves a way to pinpoint the casual factors which contribute to the discrepancy between the states and it identifies the root cause for the distance obtained by Mahalanobis D^2 among states. Food grain production followed by fertiliser consumption was found to be the discriminating factors in Kerala - AP analysis. The distinguishing factors in Kerala - TN analysis was fertiliser consumption followed by total cropped area.

Consumption pattern of fertiliser nutrients such as N, P and K in Kerala was entirely different from the recommended dose. On all Kerala basis, the average use of N, P and K were significantly lower than that of the recommended quantity depicting imbalanced use of fertilisers during the period 1995 - 2020 and for the period 1993 - 2009 for all districts in Kerala. Kerala showed highest imbalance index of 0.24 during the study period. None of the years showed perfect balance or extreme imbalance in Kerala. For district wise study it could be observed that the district Wayanad was having the highest imbalance index (0.212) followed by Kozhikode (0.205) and Idukki (0.202). The Palakkad district was having the least value of imbalance index which was equal to 0.099.

To assess the co integrated movement of food grains production and agricultural inputs in India and the states under study, Vector Auto Regression was used by modeling each variable as a linear combination of past values of itself and past values of other variables in the system. The VAR models resulted in an adjusted R^2 ranging from 0.95 - 0.99 for India with respect to different variables and for all the states also with significantly high values of adjusted R^2 showing the potential of the VAR approach to quantify the co integrated movement of the variables under study.