STRUCTURAL EQUATION MODELLING IN PADDY

By

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(2019 - 19 - 002)

DEPARTMENT OF AGRICULTURAL STATISTICS
COLLEGE OF AGRICULTURE
VELLANIKKARA, THRISSUR – 680656
KERALA, INDIA
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THESIS

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DECLARATION

I hereby declare that this thesis entitled **"Structural equation modelling in paddy"** is a bonafide record of research work done by me during the course of research and that the thesis has not previously formed the basis for the award of any degree, diploma, fellowship or other similar title, of any other University or Society.

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Certified that this thesis entitled **"Structural equation modelling in paddy"** is a record of research work done independently by **Ms. Pooja B. N. (2019-19-002)** under my guidance and supervision and that it has not previously formed the basis for the award of any degree, diploma, associateship or fellowship to her.

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We, the undersigned members of the advisory committee of **Ms. Pooja B. N. (2019-19-002)** a candidate for the degree of **Masters of Science in Agriculture**, with major field in **Agricultural Statistics**, agree that the thesis **"Structural equation modelling in paddy"** may be submitted by **Ms. Pooja B. N. (2019-19-002),** in partial fulfillment of the requirement for the degree.

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DEDICATED TO MY PARENTS,
BROTHER &
MY GUIDE

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LIST OF ABBREVIATION AND SYMBOLS USED

ACF	:	Auto correlation Function
ADF	:	Augmented Dickey-Fuller
AGFI	:	Adjusted Goodness of Fit Index
AIC	:	Akaike Information Criterion
AMOS	:	Analysis of Moment Structures
ANOVA	:	Analysis of Variance
AR	:	Auto Regressive
ARMA	:	Auto Regressive Moving Average
ARIMA	:	Auto Regressive Integrated Moving Average
BIC	:	Bayesian Information Criterion
CFA	:	Confirmatory Factor Analysis
CFI	:	Comparative Fit Index
CV	:	Coefficient of Variation
DW	:	Durbin Watson
GOF	:	Goodness of Fit
IQR	:	Inter Quartile Range
MA	:	Moving Average
MAD	:	Mean Absolute Deviation
MAPE	:	Mean Absolute Percentage Error
MLR	:	Multiple Linear Regression

MM	:	Method of Moments
MSD	:	Mean Squared Deviation
NFI	:	Normed Fit Index
PACF	:	Partial Autocorrelation Function
R^2	:	R square
RMSE	:	Root Mean Squared Error
RMSEA	:	Root Mean Squared Error of Approximation
S.D	:	Standard Deviation
SEM	:	Structural Equation Model
SLR	:	Simple Linear Regression
SPSS	:	Statistical Package for the Social Sciences
TLI	:	Tucker Lewis Index

INTRODUCTION

Chapter 1

INTRODUCTION

Agriculture is the world's oldest occupation and it continues to be the most popular today. It is the most important source of both income and employment in a developing country. Kerala's agriculture is distinct from that of other Indian states due to the prevalence of several crops and the predominance of cash crops. However, agriculture in Kerala has witnessed substantial structural changes in the form of drop in its proportion of Gross State Domestic Product (GSDP) from 26.9 per cent in 1990 -'91 to 9.1 per cent in 2011-'12, with a projected loss of 6.6 percent in 2020 -'21 owing to pandemic (Maneesh and Deepa, 2016). Kerala is now facing a significant food security problem due to its low food production base. In 1960- '61, Kerala had 7.53 lakh ha under paddy, 8.7 lakh ha in 1970-'71 and merely 1.97 lakh ha in 2012-'13. During the last 30 years, Kerala has lost 6.25 lakh ha of paddy land, leaving only 2.05 lakh ha. The Ockhi storm of 2017 and the accompanying dry spell also had negative impact on paddy cultivation.

Kerala requires 40 lakh tonnes of rice each year, but only 8 lakh tonnes are produced (Anonymous, 2017). Rice is now supplied to the state by Tamil Nadu, Andhra Pradesh, Bihar, and Madhya Pradesh. Coconut is Kerala's most widely grown crop with 7.7 lakh ha under cultivation with 5.5 lakh ha rubber in second place. Rubber cultivation has expanded to one lakh ha in the last 20 years according to official publications. (Directorate of Economics and Statistics).

Over 95 per cent of the state's total food grain production is rice. To increase paddy production, the government has started several initiatives like the Intensive Agriculture District Programme (IADP) of 1960-'61; the Intensive Agriculture Development Programme (IADP) of 1971-'72; the Operational Research Project in Integrated Rice Pest Control (ORPIRC) of 1975-'95; the Group Farming Programme of 1989-'90; the Integrated Rice Development Programme (IRDP) of 1994-'95; Introduction of the Scheme on Promotion of Paddy cultivation in Fallow lands in 2004-'05 etc. Local governments have established special programmes in 2008-'09 as well as the Kerala Paddy Wet Land Conservation Act, 2008-‘09. Despite these efforts, the paddy farming sector in the state has underperformed.

The severe drop in paddy yield has impacted food security and resulted in rural unemployment, environmental and ecological challenges. Any change in the agricultural sector would inevitably affect the lives of a large number of people, the environment and society as a whole. Filling of low-lying paddy areas and increased conversion to non- agricultural uses have had detrimental ecological consequences. Filling paddy fields and over using irrigation infrastructure has a negative influence on water conservation and there is a growing trend of leaving paddy fields, fallow due to low crop yields. Since most farms are owned and operated by persons whose primary occupation is not agriculture, they have little motivation in investing in land or increasing agricultural income. In this prevailing situation the present study to investigate the net income of real paddy farmers in Kerala is highly relevant.

Keeping in view of the importance of agriculture, a quantitative assessment of the various aspects which contribute to crop growth, production, and productivity at the state level would aid in reorienting agriculture development programmes and goals to achieve higher growth.

The current study was undertaken to evaluate the issues of Kerala's decelerating trend in area, production and productivity of paddy across three seasons with the following specific objectives:

- To study the season wise trend as well as breaks in trends of area, production and productivity of paddy in Kerala
- To estimate the compound growth rates in each of the different phases corresponding to the trend breaks
- To develop appropriate time series forecast models with respect to each variable
- To study the relative contribution of change in area, yield, price per ha and their interaction effect on the growth of output of paddy using a regression approach
- To identify the important factors in paddy production ultimately leading to the net income of farmers through structural equation modelling

The statistics on area, production, productivity, price and other aspects of paddy crop in Kerala from 1960- ‘61 to 2019-’20 have been analysed in order to get a real and valid conclusion on the trend. The study is designed to fit within the past and present transitional phases of the paddy crop used in the research.

Several studies on Kerala agriculture have focused on specific areas such as land use patterns, cropping patterns as well as the research on specific trends in area, production, productivity and price of crops. But the statistical approaches and tools used were traditional. The significance of this work comes in the fact that it has employed advanced timeseries models for predicting the area, production and productivity of paddy crop in three different seasons in Kerala. A novel attempt is made to discover the breaks in trend by applying trend break analysis which will aid in planning and decision-making processes as well as for predicting events which is very critical, as forecasting can help in making rational decisions (Armstrong, 2001). Quantitative forecasting approaches extrapolate past and current behaviour into the future using historical data and a forecasting model. Temporal dynamics of a long-term sequence of data can be characterised using some extremely valuable time series models and can be used for prediction purpose. The current study has attempted to build ARIMA, (Auto Regressive Integrated Moving Average) Exponential smoothing, Holt’s and Brown’s models *etc*. for prediction.

Structural equation modelling (SEM) is an extension of the general linear model (GLM) and can be a more powerful alternative to multiple regression, path analysis, factor analysis, time-series analysis and analysis of covariance (Garson, 2010). An SEM model is essentially a composite hypothesis made up of a series of cause-and-effect relationships between variables using statistical dependencies (Shipley, 2000). SEM can account for additional complexities including nonlinearity, correlated independents, measurement error, correlated error terms and multiple latent variables. Latent variables are unobserved variables or factors that are measured by their respective indicators. Unlike the ordinary multiple linear regression, we can simultaneously consider several independent and dependent variables to fit a model. The dependent variables in one stage may become independent variable in the next stage making SEM an extra ordinary tool to accommodate a number of variables in the whole network of analysis. Most of the literature available on SEM is related to the area of social sciences. A pioneer work in paddy using SEM has been initiated.

An attempt is made to perform an empirical analysis to identify the factors perceived by 150 registered paddy farmers randomly selected from Ollukkara block of Thrissur district in Kerala. The views of farmers on complex cause and effect relationships are often difficult to extract. So, a path analysis framework has been adopted to determine the main factors contributing to paddy yield and ultimately leading to their net income from paddy cultivation. A cause and effect model using several variables was drawn initially and structural equation model was then used to extract meaningful models through an iterative approach to assess the inter relationship among the variables in the model.

Presentation of the thesis

The thesis entitled “Structural Equation modelling in paddy” is organized and presented in five chapters. Chapter I presents a brief introduction and objectives of the study. Chapter II “Review of literature” provides the current position where the related areas of research has reached so that new steps can be taken for introducing innovative statistical tools as well as new approaches of research to materialise the outlined objectives. Chapter III is devoted to the methodology of research in which details of secondary time series data collected, selection of study area, sampling procedure, sample size and list of variables under the empirical study on paddy farmers along with detailed description of the statistical tools used are given. The results and discussion have been explained in Chapter IV. Finally, Chapter V gives the summary of results with respect to each objective of the study. The references and abstract are given at the end.

REVIEW OF LITERATURE

Chapter 2

Review of Literature

A comprehensive analysis of previous literature is helpful in developing concepts, methodologies, and analysis tools for any research. The reports of Structural Equation Modelling are given in literature. Reviews related to the concepts are given below.

2.1 Trend

2.2 Trend break analysis

2.3 Compound growth rate

2.4 Time series forecast models

2.5 Regression approach

2.6 Structural Equation Modelling

2.1 Trend

Ananya, B. (2013) found that though there had been a notable shift in the state's economy from primary to secondary and tertiary sectors in recent years, Assam continued to support more than 75 per cent of the state's population directly or indirectly, providing employment to more than 53 per cent of the total work force (Economic survey, Assam, 2011-12). Assam's primary crop was rice. As a result, rice cultivation's growth and development were critical in Assam. There was an increase in area, production, and productivity from 1950-‘51 to 2010-‘11, with total rice production ranging from 1.41 million tonnes to 5.086 million tonnes and an average rice crop yield ranging from 855 kg/ha to 1983 kg/ha.

Karunakaran (2014) found a downward trend in area, production, and productivity of rice in Kerala from 1960-‘61 to 2009-‘10 due to crop diversification, with non-food crops covering the majority of the land. Food security, particularly rice, was a major concern in Kerala. According to the findings of the study, Kerala experienced a rice deficit of 40.12 per cent in 1960-‘61. In 2009-‘10 fiscal year, it gradually increased by 83.45 per cent. As a result, it could be predicted that rice demand would increase in Kerala in the next years, posing a danger to the state's food security. In Kerala, the rice output should be increased.

Athira and Kumar (2016) found that from 1980 onwards, the area under rice cultivation had decreased dramatically. Paddy fields in Kerala had been converted to other uses. Some of the variables that were responsible for the decreasing trend in rice production and area in the study, included technological, economic, social or ecological, and political issues.

Maneesh and Sankaranarayanan (2016) investigated the long-term viability of rice production in Kerala and Tamil Nadu in his study. Kerala had a recurrent food shortage and relied heavily on Tamil Nadu for both grains and vegetables. Food security for all, defined as the availability of a sufficient quantity of food to meet people's nutritional needs, had become a priority in government programmes. As a result, food security concerns included not just difficulties about the availability and stability of food sources, but also those concerning food accessibility. The study discovered that due to diminishing area, production and productivity of rice, Kerala had begun to rely on the neighbouring state of Tamil Nadu, where rice production was increasing. In order to meet future food demand, Kerala's implementation of sustainable agriculture policies has necessitated a greater focus on food grain production.

Maheshand and Deepa (2016) announced that the downward trend in paddy area, production, and productivity was a source of concern and should be highlighted as a threat to India's food security. The area under paddy climbed from 228938 hectares in 2007-‘08 to 234265 hectares in 2008-‘09, but dropped by 2, 02,109 hectares in 2014-‘15. Total area under food grains had decreased by 40 per cent since 2001-‘02, necessitating increased cultivation and supply, as well as judicious use of inputs, linking MGNREGS with farming activity, providing low-interest loans with insurance coverage to farmers, and promoting mechanisation and management techniques, as appropriate.

According to a study of Sekhara and Devarajulu (2019), the area under paddy crop and its production patterns in different crop periods had been discussed and found that paddy output in India had grown abnormally in terms of quantity in the last 65 years 1950-‘51 compared to previous and post-independence periods, making India not only self- sufficient in paddy production but also a major exporter of paddy. However, paddy output had fluctuated throughout the last two decades, particularly during this study period 1991-‘92 to 2015-‘16 in both the global and Indian contexts. In 2014-‘15, global paddy production was 479 million tonnes, but by the end of 2015-‘16, it had dropped to 473 million tonnes, indicating a 1.2 per cent decrease in total paddy production. The area under paddy cultivation declined to 43.39 MHs by the end of the reporting year 2015- ‘16, from a low of 41.78 MHs in 1992-‘93 to a high of 45.91 MHs in 2007-‘08. As a result, the study proposed that India should take the required actions to increase paddy yield and production. Merging the MGNREGS scheme with the agriculture sector, as well as effective monitoring of the supply of seeds and fertilisers, in addition to the required irrigation and other modern paddy cultivation inputs, would increase paddy productivity and area

2.2 Trend Break Analysis

Bai and Perron (1998) addressed the problem of estimating break dates first, and an efficient approach for obtaining global minimizers of the sum of squared residuals. For any number of breaks, this algorithm was based on the notion of dynamic programming and required at most least-squares operations of order O (T2). Both pure and partial structural change models could be used with their technique. Second, the challenge of constructing confidence intervals for break dates based on alternative hypotheses about the data structure and segment defects was tried. In the third step, looked at how to test for structural changes in data and errors under extremely generic conditions. The issue of estimating the number of breaks was addressed in the fourth section. Finally, some empirical applications were shown to demonstrate the processes' utility. A GAUSS programme was used to implement all of the approaches presented.

Ghosh and Madusudan (2002) investigated random walks and structural breaks in Indian agriculture and it was found that productivity growth, rather than area growth, had been the primary source of agricultural output growth. Wheat crop output climbed by 2.08 per cent and rice crop output increased by 1.64 per cent, respectively resulted from 2.38 per cent and 1.80 per cent in the first phase (1966-‘67 to 1970-‘71) and 2.38 per cent and 1.80 per cent in the second phase (1971-‘72 to 1974-‘75).

Paul *et al*. (2014) reported India as one of the Asian countries that was most vulnerable to climate change. In India, the surface temperature had been steadily rising over the last century. The behaviour of mean monthly temperature over four agro-climatic zones in India from 1901 to 2001 were studied and tried to discover structural changes in the temperature series. Between 1970 and 1980, a structural break in the series was noted at both the national and regional levels. The chow test was used to conduct the analysis. Since 1972, there had been a considerable increase in temperature during July in the arid zone according to a review of data before and after the structural break.

Biswas (2020) Used the Bai-Perron multiple structural break analysis and attempted to comprehend West Bengal's economic growth. The Bengal economy had two output growth phases between 1960 and 2014. The first break happened in 1983, and it was affected by a break in the agriculture sector, which was triggered by a change in the political regime and policy prescriptions. The second break occurred in 1993, following a break in the service sector and a shift in policy paradigm within the same political dispensation. This research looked into the characteristics of distinct growth periods in terms of sectoral composition. The West Bengal economy had transitioned from a low to a medium to balanced growth period, followed by a high growth phase. Agrarian stagnation, industrial slowdown and political instability characterised the low-growth phase. The medium-growth phase, on the other hand saw unparalleled agrarian development and political stability. During the second half of the high-growth phase, the tertiary sector grew rapidly, while political instability raised.

Lekshmi and Venkataraman (2020) observed that Kerala's paddy land was rapidly disappearing. The Kerala Conservation of Paddy Land and Wetland Act, 2008 significantly changed the decadal decreasing tendency. According to this research, the Bai-Perron test demonstrated a structural break in area, production and productivity between 2007-‘08 and 2009-‘10, which could be attributed to the conservation act. The compound annual growth rates for both area and production were discovered to be negative. Growth in area slowed both before and after the interruption, but the rate of loss was lower after the break (-2.52 per cent vs. -4.40 per cent). An exponential growth model was used to forecast the future. The expected area and production showed a declining tendency until 2030. According to projected calculations, the area loss in another 12 years would be around 36,444 ha. and Production would also be lowered to 3,70,795 tonnes.

2.3 Compound Growth Rate

Oommen (1962) made a study on soil productivity in 1950-‘51 to 1960-‘61 with respect to significant crops with the exception of rubber in Kerala. The growth rate was determined by a simple linear regression. Although the productivity of cereals and pulses had typically been increasing, there had been no steady increase in productivity, particularly with many other crops, especially cash crops.

George and Mukherjee (1986) evaluated the rice growing patterns of Kerala region for time periods such as 1960-‘61 to 1974-‘75 as period I and 1975-‘76 to 1983-‘84 as period II. These changes were examined throughout the seasons of winter and summer. They covered all the important districts, farming rice. Regression technique was used to estimate the area and production. Compound growth rate was also computed. To determine the contribution of area and the yield on production changes during the period, an additive decomposition model had been utilised.

Kannan and Pushpangadhan (1988) found two distinct stages of agricultural growth between 1962-‘63 and 1985-‘86. There was an overall increase in the rate of growth of area, production and yield for all crops during the 1960s and early 1970s (1962-‘63 to 1974-‘75), but the period (1975-‘76 to 1985-‘86) saw a near-stagnation in the rate of growth of aggregate area, output and land productivity.

Kumar and Rosegrant (1994) tried to measure the overall increase of rice production factor in various regions of India and examined the productivity sources. The study used the growth accounting index number technique. Time series data from multiple regions had been pooled, and dummy variables for regions had been incorporated, which retained the seven eastern regions as the reference area. The analysis showed that the growth in crop acreage and output was strongly linked to its relative profitability.

Job and Nandamohan (2004) tried to investigate changes in the growth pattern of rice in Kerala through time and across seasons. Data on area, production, and productivity were compiled from secondary time series sources. The methodology was based on the computation of compound growth rate, growth decomposition, and stability metrics. The exponential growth model was used to estimate compound growth rates of area, production, and productivity of rice in the three crop seasons for the state. Rice production was estimated using a multiplicative model based on area and yield effects. The study's findings revealed a substantial negative trend in rice acreage and production, as well as a considerable positive trend in productivity.

Using time series data from the Haryana Statistical Abstract for 1966-‘67 to 1996-‘97 Chethana and Singh (2005), computed compound growth rates and quinquennial changes in cotton acreage, production, and productivity in Haryana. Results showed that between 1966 and 1997, the acreage, production, and productivity of American cotton increased at yearly rates of 6.62 and 1.02 per cent, respectively. During the same time period, both the acreage and production of desi cotton grew at a rate of 1.14 and 0.50 per cent, respectively. During the study period, the total area, production, and productivity of cotton (both desi and American) all increased at a positive rate of 4.06 and 0.70 per cent each year, respectively.

Prajneshu and Chandran (2005) opined that growth rates were commonly used in agriculture because they had significant policy consequences. The standard parametric strategy for growth rate analysis was to assume multiplicative error in the underlying nonlinear geometric model, then fit the linearized model using the method of least squares. The flaws in the technique had been identified and suggested that nonlinear estimation approaches could be used to fit the model, and only then growth rates should be computed. The use of growth models such as monomolecular, logistic and Gompertz to compute the compound growth rate had been studied. Furthermore, the entire food grain output of the country from 1980 to 2001 was evaluated, and its growth rate was calculated.

In the dry zone of Rajasthan, researchers Gajja *et al.* (2008) investigated the growth and instability in area, production, and productivity of wheat, as well as acreage response to wheat crop. The research was limited to nine arid-zone regions with more than 10,000 acres of wheat-growing land in the previous decade. The data was collected from 1966-‘67 to 2006-‘07, and it was analysed using the exponential function, the instability index, and the Nerlovian adjustment model. The findings revealed that in Rajasthan's dry zone, area and production had increased, with considerable volatility.

Dhakre and Sharma (2010) found that the maximum decrease in maize crop area was (-) 16.02 per cent in 1999-2000, and the maximum increase in maize crop area was 30.23 per cent in 2000-‘01, whereas the maximum increase in maize crop production and productivity in Nagaland was 103.05 per cent in 1988-‘89 and 101.26 per cent in 1988-‘89, respectively. The most unstable aspect of maize farming was its area, production, and productivity. The growth rates were statistically significant at 1per cent level.

Chaudhari *et al.* (2016) examined the compound growth rates of area, production and productivity of summer bajra in Gujarat's Banaskatha district. Six villages and 20 market functionaries in two market areas, Dessa and Tharadin Banaskantha district of Gujarat were randomly selected to collect the data from 126 farmers. Compound growth rates by exponential function were fitted. The results indicated that there was an increasing compound growth rate of production of 11.11 per cent per annum and productivity of 3.93 per cent per annum, In case of Gujarat the production of bajra increased by 13.5 per cent per annum mainly due to introduction of Narmada canal for past 4 years.

Mech (2017) used a log-linear function to calculate the annual compound growth rates of area, production and productivity, as well as three types of models, namely linear, log-linear, and a log-linear model with auto correlation corrections, to explain the growth trend, instability, and factors influencing rice production in Assam from 1972-‘73 to 2014-‘15. Among numerous factors influencing rice production from 1972 to 2014, the estimated result of a log-linear model with auto correlation corrections showed that the area under rice cultivation in hectares had significant positive impact on rice production in Assam and temperature was found to have negative influence.

Jain (2018) opined that in India, agricultural growth that was stable had been a source of concern. To explore the subject of rice production volatility in India, the study examined 41 years of data on area, production, and productivity under paddy from 1970-‘71 to 2011-‘12. The analysis demonstrated that while the compound annual growth rate of area, production, and yield of rice was positive at the national level, it had been gradually dropping over time. In the last decade (2000-‘01 to 2011-‘12), there had been an increase in rice area, output, and yield instability across India. Low per centage of irrigated area to total cultivated area, drop in seed and manure use, and other agricultural inputs could all be contributing to the increase in instability. In the post-reform period 1990-91 to 2016-17, wholesale paddy price volatility increased across states, whereas farm harvest paddy price volatility decreased.

Sunitha and Rajashekar (2018) investigated rice growth rates in 10 Telangana districts using time series data from 1986-‘87 to 2015-‘16. The data was separated into two periods of fifteen years each for the study, resulting in a total of thirty years of data. Compound growth rate (CGR) and linear growth rate (LGR) were used to study the growth pattern (LGR). CGR was calculated using the exponential model $Y_t = \beta_0\ \beta_t\ e_t$ and LGR was calculated using the linear model $Y_t = \beta_0 + \beta_1 + e_t$. Production growth rates were higher than area and productivity growth rates in the state as a whole. In comparison to all other eras of area and productivity, production grew at the fastest pace during Period-II. However, growth rates for production and productivity were positive and significant at a probability level of 5 per cent and 1per cent in both eras, while growth rates for area were positive and non-significant in both periods.

Meena and Prabakaran (2019) examined the technological performance of a few crops. Paddy crop from Cereals had been chosen specifically for the investigation. Five agroclimatic zones and one district within each zone were purposefully chosen for the study and used secondary data from 1990 to 2010. The result revealed that the area under paddy had a negative growth rate and a significant level of volatility. Paddy production had a steady rate of increase but was highly volatile. Paddy yields were increasing at a steady rate, with little volatility. Cauvery Delta Zone – Thanjavur district, Western Zone – Erode district, and North Eastern Zone – Villupuram district were regarded safe zones for paddy cultivation, according to the agroclimatic zone classification.

Rasoul *et al.* (2020) studied the growth performance of Egypt's most major cereal crops (wheat, rice, and maize) as well as the sources of their output increased from 1975 to 2017. Using component analysis, the research could implement appropriate policies that would increase the production of those crops. In addition to the complete period 1975-2017, the study was separated into three periods based on the results of the Chow Breakpoint test as 1975-1986, 1987-2000, and 2001-2017. The findings revealed that during the study period, changes in yield mattered more than changes in area for wheat, rice, and maize production. As a result, the study emphasised the importance of vertical expansion above horizontal expansion. This reflected the impact of scientific research and development (R&D) on the growth of Egypt's cereal crops.

2.4 Timeseries forecast model

Iqbal *et al.* (2005) made a study on wheat which was the single most important crop playing a vital role in Pakistan's economy. On the basis of historical trends, it was critical to determine scientifically the crop's precise future output potentials. As a result, the study was conducted in order to forecast wheat production and area in Pakistan until 2022. Wheat production would be 29774.8 million tonnes in 2021-'22, according to the

ARIMA model. Higher area and production potential were based on proper input availability, farmer education and training, soil protection and reclamation, and most importantly, supporting government policies addressing wheat agriculture in the country. The ARIMA (1,1,1) and ARIMA (2,1,2) models were estimated for the wheat area and production data using the MINITAB computer package.

Raghavendra (2009) discovered ARIMA (2, 2, 1) to be the best model for rice yield in his investigation for rice yield projections supplemented with lower control limits (LCL) and upper control limits (UCL). The veracity of the forecasted values were confirmed using the data for the lead periods. Researchers can use the algorithm to forecast rice yields in Andhra Pradesh. It should, however, be updated from time to time to reflect current information. The study didn’t demonstrate a larger increasing tendency in rice yield based on the forecasted analysis. In this situation, the various courses of action need to be implemented to boost rice output by taking appropriate positive steps.

Raghavender (2010) employed timeseries methods to evaluate annual rice production data of Andhra Pradesh from 1955-‘56 to 2007-‘08. For the data, autocorrelation and partial autocorrelation functions were constructed. An appropriate Box-Jenkins autoregressive integrated moving average model was fitted. Standard statistical approaches were used to test the model's validity. Rice output was forecasted for three leading years using the forecasting power of an autoregressive integrated moving average model. ARIMA (2,2,0) was discovered to be the developed model for rice production and the veracity of the forecasted values were verified using the data available for the lead periods. Researchers can use the algorithm to forecast rice production in Andhra Pradesh.

Awal and Siddique (2011) forecasted Aus, Aman, and Boro rice output in Bangladesh by estimating growth patterns and examining the best ARIMA model. The time series data for Aus and Aman appeared to be 1st order homogeneous stationary, but Boro appeared to be 2nd order stationary. ARIMA (4,1,4), ARIMA (2,1,1), and ARIMA (2,2,3) were shown to be the best models for Aus, Aman, and Boro rice production, respectively. Short-term projections were more efficient for ARIMA models than deterministic models. Rice production uncertainty might have been reduced if production was accurately projected and precautions were taken to avoid losses. Policymakers, academicians and producers would benefit from the findings of the study in order to more precisely anticipate future national rice output in the short term.

Sivapathasundaram and Bogahawatte (2012) studied the trends of paddy production in Sri Lanka, as well as created a time series model to detect the long-term trend and forecast future changes in paddy output. The data set was fitted using Autoregressive Integrated Moving Average (ARIMA. Secondary data from Sri Lanka's Department of Census and Statistics for the period 1952 to 2010was used in the time series forecasting analysis. Since ARIMA (2, 1, 0) had the lowest AIC and BIC values, it was the best model chosen. For paddy production, the Mean Absolute Per centage Error (MAPE) was 10.5. Paddy production forecasts for 2011 to 2013 were 4.07, 4.12, and 4.22 million Mt, respectively, with production in 2011 and 2012 being lower than in 2010. However, in the second half of 2013, production was higher. Researchers can use this model to forecast paddy production in Sri Lanka using this approach. However, it should be updated on a regular basis to include new information.

Biswas and Bhattacharya (2013) opined that crop yield forecasting and crop area estimation were critical procedures in supporting policy decisions on land use allocation, food security, and environmental concerns. A complete picture of West Bengal's current rice production situation had been explained. The ARIMA (p, d, q) model, developed by Box and Jenkins and involving autoregression, moving average, and integration terms were used. The ARIMA (2,1,3) model was shown to be the best fit for the series of gross cultivated area, whereas the ARIMA (2,1,1) model was found to be the best fit for the series of production. For future projections of rice acreage and output in the state, the model had a high level of accuracy.

Ramakrishna and Boiroju (2013) used Box-Jenkins approach and feed forward neural networks to anticipate rice yield per hectare (kg) in Andhra Pradesh. Mean absolute error, mean absolute per centage error, and root mean squared error were used to assess the models' forecasting abilities. In comparison to the Box-Jenkins model, the neural networks model performed well. ARIMA (0,1,1) model was found to give a good fit for the data. According to ARIMA forecasts for the years 2011 to 2015, there was a need to use high yielding rice varieties and a better package of techniques in Andhra Pradesh to increase rice productivity.

Rahman *et al.* (2013) found the best-fitting ARIMA model that could be used to forecast boro rice production in Bangladesh from 2008 to 2012. Local, modern, and total boro time series were found to be 1st order homogeneous stationary in the study. The ARIMA (0,1,0), ARIMA (0,1,3), and ARIMA (0,1,2) models were determined to be the best for local, modern, and complete boro rice production, respectively. Short-term projections were more efficient for ARIMA models. The production uncertainty of boro rice could be reduced if output could be accurately forecasted and necessary losses would be avoided. ARIMA algorithms were used by both the government and producers to anticipate future production more correctly in the short term.

Tripati *et al.* (2014) developed ARIMA model to anticipate area, production and productivity of rice in Odisha. When it was important to anticipate production and acreage before the crop harvest, the ARIMA model deemed to be the best model. Since the non-normally disturbed nature of the time series data was confirmed by the skewness and kurtosis, the non-parametric Mann-Kendall test was chosen as the best method for detecting trend. Based on the results of the forecasting and validation, it could be stated that the ARIMA model could be successfully employed for rice forecast research.

Kumari *et al.* (2014) developed various Autoregressive Integrated Moving Average (ARIMA) models using time series data for sixty-two years to anticipate rice yield. The performance of those models was evaluated using a variety of selection measure criteria. The model with the lowest value of those criteria being designated as the best forecasting model. Based on the findings, it was discovered that, among the eleven ARIMA models tested, ARIMA (1, 1, 1) was the best suited model for accurately predicting rice yield.

Kumari *et al.* (2014) made a study to construct several exponential smoothing models for predicting rice crop yield. The predicted values of the developed models were evaluated using a variety of selection metrics and the model with the lowest value of all of the measures being designated as the best explained model. Based on the findings, the Holt's two-parameters linear model was found to be the best-fitting model for accurately predicting rice productivity among all forecasting models.

The projections of maize production in Telangana state were done by Raghavendar and Guguloth (2015) using the Box-Jenkins approach. Maize projections could be employed in the newly created Telangana state's agriculture and poultry sector planning. According to projections, the state's maize production would reach 3.74 million tonnes by 2020-‘21. If the current trend continues, the districts of Karimnagar and Nizamabad would form a maize belt in the state. The ARIMA (1, 1, 0) model was identified using the Box-Jenkins approach.

Using time series data from 1972 to 2015, Rahman and Hasan (2017) developed several Autoregressive Integrated Moving Average (ARIMA) models to simulate carbon dioxide emissions. The performance of those models was evaluated using several selection measure criteria. Model with the lowest value of those criteria was designated as the best forecasting model. Based on the findings ARIMA (0, 2, 1) was found as the best fitted model for estimating carbon dioxide emissions in Bangladesh. The anticipated value of carbon dioxide emission in Bangladesh, as calculated by ARIMA (0, 2, 1), for the years 2016, 2017, and 2018 were 83.94657 Metric Tons, 89.90464 Metric Tons, and 96.28557 Metric Tons, respectively.

The presence of a pattern in the paddy production statistics was discovered by Saranyadevi and Mohideen (2017). The typical techniques of smoothing of data, such as basic exponential, Brown exponential, and Damped exponential smoothening models were employed to forecast paddy in Tamil Nadu. Holt's winter smoothening was promoted to be a superior model based on model selection criteria, and ARIMA (0,1,1) was shown to be a better model to forecast paddy output among the various exponential smoothening approaches.

Hemavathi and Prabakaran (2018) used time series models to forecast rice production and productivity in Thanjavur district of Tamil Nadu. The data for the period from1990-‘91 to 2014-‘15 were used to fit the Box Jenkin ARIMA model. The selection of models were based on the AIC and SBC. ARIMA (0,1,2) had the lowest

AIC and SBC values for area, production, and productivity under rice. According to the forecast, the area, production, and productivity would be around 158.15 hectares, 637.05 thousand tonnes, and 3.79 thousand kg per ha by 2020.

Miah (2019) developed a time series model and forecasted rice production in Bangladesh. This was accomplished by identifying preliminary Autoregressive Integrated Moving Average (ARIMA) models for rice production in Bangladesh that fitted and forecasted well. Aus, Aman, and Boro rice were the three main types of rice grown in Bangladesh throughout the year. To estimate rice production in Bangladesh, Autoregressive Integrated Moving Average (ARIMA) model with varied lag orders were used. To choose the optimal ARIMA(p, d, q) model, the least values of AIC, BIC, RMSE, and MAPE criteria were used. The results suggested that ARIMA (2, 1, 5) and ARIMA (1, 1, 1) were the best models for Aus, Aman, and Boro productions, respectively, compared to other preliminary ARIMA(p, d, q) models. Prediction of rice output for the next seven years were made and the original and forecasted series were compared which showed that the fitted model was statistically well behaved to anticipate rice production in Bangladesh. The investigation revealed that the ARIMA model provided more accurate forecasts only for short periods.

Paidipati and Banik (2019) compared the analysis of ARIMA and LSTM-NN models and forecasted rice cultivation in India, using secondary data from 1950-‘ 51 to 2017-‘18 of rice cultivation. The well-fitting model for area under cultivation was ARIMA (0,1,1) and the model for production and productivity was ARIMA (0,1,1) and ARIMA (2,2,1) respectively. The ACF and PACF plots in each of those models indicated a large spike. However LSTM-NN models outperformed ARIMA models. The LSTM-NN model was more flexible and accurate than ARIMA models for predicting agricultural parameter behaviour.

2.5 Regression Approach

Karunakaran (2015) established that many variables influenced the increase in agricultural crop output and productivity. The sources of output increase, such as the area impact, yield effect, and cropping pattern effect were important in determining agricultural development programmes and investment objectives. The rise in agricultural crop yield was split into two parts: actual and monetary. Area effect, yield effect, cropping pattern effect, and interaction effect were all part of the actual component. The pure price effect, price yield effect, price cropping pattern effect and total interaction effect were the monetary factors. The general conclusions reached from the analysis of the decomposition of output growth into real and monetary components of Kerala agriculture over the last five decades were that the price factor was the most important factor in determining the relative contribution of different elements to the growth of crop output, and the overall growth in Kerala agriculture was monetary growth rather than real growth.

Shiu and Chuang (2019) pointed out that rice yield estimation using satellite data was commonly done with global regression models. But since spatial variation was not taken into account, estimation mistakes might occur. As a result, 26 to 63 ground survey sample fields, accounting for around 0.05 per cent of the total farmed area were gathered and amassed, as training samples for regression models. Global models such as ordinary least squares (OLS), support vector regression (SVR), and the local model geographically weighted regression (GWR) were used to build the yield estimation models to demonstrate whether spatial autocorrelation or spatial heterogeneity existed and dominated the estimation. To determine the optimal variable combination, feature selection based on the Pearson c coefficient was used. According to a case study conducted in central Taiwan, the error rate ranged from 0.06 per cent to 13.22 per cent. The GWR model's yield estimate performance was more relatively stable than the OLS and nonlinear SVR models due to feature selection. The GWR model considered the spatial autocorrelation and spatial heterogeneity of the relationships between the yield and the independent variables, whereas the OLS and nonlinear SVR models did not. As a result, the GWR model's rice yield estimation was more stable than the other two models in the study.

2.6 Structural Equation Modelling

Ibrahim *et al.* (1984) randomly recruited a total of 225 paddy farmers in the Muda irrigation area of Kedah for a study, with the goal of evaluating food access among rural households. According to the study, Paddy farmers were more likely to buy food from grocery shops, markets, and night markets or farmers' markets than from supermarkets and mini-markets. The findings of the study revealed that all three areas have access to food and have a favourable association with food security among paddy farmers in the Muda irrigation basin, according to Structural Equation Modelling. Grocery stores contributed the most to the value of food security, accounting for 0.38 of the total. The congruity index model had a value of $\chi 2$= 34.89 CMIN / DF = 0.918, whereas the Goodness of Fit Index (GFI), Incremental Fit Indexes (IFI), Tuckers-Lewis Index (TLI), and Comparative Fit Index (CFI) all surpassed 0.90, and the RMSEA was less than 0.08. The model's index showed that it had a good correspondence and could be trusted.

Ghane *et al. (*2011) made a study with a goal to see how social impact and innovation characteristics affected paddy farmers' adoption of integrated pest management (IPM) strategies in three Iranian districts. Using proportionate stratified sampling, a total of 190 paddy farmers were chosen. A series of questionnaires was used to collect data, which was administered by personal interview. A team of specialists confirmed the questionnaire's validity. Cronbach's alpha was used to determine the questionnaire's reliability. The data fitted well the hypothesised model, according to the results of structural equation modelling. There was a direct and beneficial link between social influence and compatibility and trialability and adoption of IPM practices.

Sefriadi and Malekmohammadi (2013) carried out a path analysis for cocoa production in West Sumatra, Indonesia. Structural Equation Model (SEM) was developed based on the views of the cocoa farmers regarding the constraints they faced during the cocoa production that affected their income. By using linear causal model through path analysis, the correlation between the variables was interpreted. Based on Root mean squares error (RMSEA), Comparative Fit Index (CFI) and Tucker Lewis Index (TLI) the goodness of fit model was identified and observed CFI to be 0.94

(>0.9), TLI to be (>0.9) and RMSEA to be 0.070(<0.08), based on those values the model was absolutely fit.

Shadfar and Malekmohammadi (2013) established a model for constructing state intervention policies in the improvement of rice production in Iran. The Structural Equation Model (SEM) and Confirmatory Factor Analysis (CFA) were used to investigate those policies. SEM was used to create a theoretical model, which was then tested for validity and reliability using CFA. The suggested model was initially assessed for GOF (Goodness of Fit) indices, after which it was examined for validity and reliability. The GOF statistic was SRMS (Standardized Root Mean Square Residual), with a value of 0.064(0.08) and RMSEA (Root Mean Squared Error of Approximation) of 0.087, indicating that the model was well-fit.

Yasar *et al.* (2015) looked at the elements that influenced paddy farming sustainability in IADA KETARA: economy (EKN), environment (EKL), society (SOS), institutions (INS), and technology based on five constructs. From the Northern Terengganu Integrated Agricultural Development Area's Water Consumer Group, 350 farmers were selected for the study as the respondents (IADA KETARA). Cronbach's alpha >0.7, construct reliability (CR) >0.6, and average variance extracted (AVE) >0.5 were examples of desirable characteristics. From the absolute fit [$\chi 2$ (397.501 >0.05), RMSEA (0.077=0.08)], the model also demonstrated an excellent fit. The findings of the SEM analysis revealed that different indicators could be used to gauge all five components. With the exception of INS, the inter-construct interaction revealed that the other four constructs were important indicators for promoting paddy farming sustainability in the IADA KETARA area. Despite the fact that INS was not statistically significant, the relevance of government backing and marketing help deemed critical, especially in order to generate synergy in farmers' reactions when considering the low education level of knowledge of farmers.

Langerodi and Dinpanah (2017) were of the opinion that rural regions were important because of their proximity to nature and the influence they had on nature. As a result, environmental preservation would be impossible to achieve without the participation and contribution of the people who lived in those areas. The goal of the study was to develop a structural equation model of rice farmers' environmental protection participation. The statistical population of the study (N=24502) consisted of rice farmers from the Iranian country of Sari, of whom 290 were chosen as statistical samples using the Cochran formula. The required information was gathered using a questionnaire whose validity had already been examined by experts. For the entire questionnaire, the Cronbach's Alpha coefficient was 0.937. The participants' average age and work experience were 48.53 and 23.82 years, respectively. The social characteristics and information resources accounted for 27.1 per cent of the variation in rice farmers' environmental protection engagement.

Renitha and Aninditha (2017) summarised local knowledge of farmers' perceptions of climate change and examined farmers' intent to adapt to climate change using the theory of planned behaviour. Simple random sampling was utilised, with the population being the farmers in the research location. According to the findings, 57.5 per cent of respondents believed that the intensity of the rainy season and the temperature were changing considerably, and 40 per cent believed that the temperature was rising. Deforestation or logging, according to 65 per cent of respondents, was the primary cause of climate change. However, 17.5 per cent of respondents believed that factories were to blame for climate change. Climate change had resulted in an increase in pests and diseases targeting paddy crops, as well as a considerable decrease in land production. Subjective norm and perceived behaviour control influenced the intention of farmers to adjust to climate change positively in structural equation modelling.

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Anika and Kato (2019) created a structural equation model to assess the complex relationship between several factors that influenced rice production in the Sumani Watershed, as well as to identify the key factors and constraints that influenced paddy production in the current state as a foundation for future investment. The real-world condition in Sumani Watershed could be explained by a structural equation model. The irrigation system, which included both technical and semi-technical irrigation, has had a significant impact on rice improvement in the Sumani watershed. Pest problems and farmer poverty were the two main restrictions to rice production in the Sumani watershed since the increasing yield in the Sumani watershed was still low, investments in all factors that affected rice production were needed. However, the improved irrigation system was found to be a crucial component in enhancing rice production by increasing cropping index and yield.

Kim and sung (2019) used multi-group structural equation modelling to compare the causality of meteorological factors influencing Italian ryegrass (IRG) yield in upland and paddy areas. Second, the cause-and-effect connection between autumn and spring precipitation and temperatures in upland fields was 0.53 and 0.93, respectively ($p < 0.05$), and 0.11 and 0.96 in paddy fields. Only the autumn associations differed ($p < 0.05$) between upland and paddy fields, indicating that fall in temperature in upland fields were more susceptible to precipitation than in paddy fields. Through this study, they observed several discrepancies in the causation of climatic elements that affected the output from highlands to paddy fields. The indirect effect of precipitation on temperature output was obvious in both fields, while the direct influence of precipitation was only noticeable in the upper field. Italian ryegrass should therefore be farmed further south in the paddy fields, with a longer ideal temperature, given that the rice-rotations are shorter than in the upland fields in terms of rice growth time.

MATERIALS AND METHODS

Chapter 3

MATERIALS AND METHODS

A study on "Structural Equation modelling in Paddy" was carried out in the Department of Agricultural Statistics, College of Agriculture, during period 2019-2021 Vellanikkara. It was also aimed to develop advanced statistical models to predict the area, production and productivity of paddy in Kerala for different seasons using time series modelling. An attempt was also made to identify the important factors leading to the net income of paddy farmers. A brief description of the materials and methods used are discussed.

The study was conducted in two phases. In the first phase, secondary data was collected on area, production and productivity of paddy in Kerala with respect to the seasons viz; Autumn, Winter and Summer for the period 1960-'61-2019-'20 from official websites (DES) Directorate of Economics and Statistics. Trend analysis, Trend break analysis, Compound annual growth rate analysis and Time series modelling were done using this data.

To predict the change in production of paddy, a regression approach was adopted making use of the data on cultivated area, yield as well as price of paddy. Since the data in this respect were available only for the periods from 1996-2019 from official website GOK(Government of Kerala 1978) the prediction equations were made using this data only.

In phase II an empirical analysis was done to perform Structural Equation Modelling by collecting primary data from 150 paddy farmers randomly selected from Ollukkara block of Thrissur district who were engaged in raising 'Mundakan' paddy crop. The data was collected through a pre-structured questionnaire. First a pilot study was conducted and using the refined questionnaire, information on demographic details of the farmers, paddy cultivation practices, details of paddy yield and their net income were collected.

The information such as farmers' name, gender, age, educational qualification, occupation, family size, land size (leased or not), experience in paddy farming, organisational membership, extension contact, number of trainings attended, source of training, details of seed procured, bio-fertilizers used, chemical fertilizer used, irrigation details, weeding practices, pesticides used, plant protection measures used, quantity of paddy produced, price per kg of paddy, Expenditure incurred under different heads namely seed, labour cost, manure, pesticides and plant protection measures, transportation charges, pumping and sprayer charges, miscellaneous expenditure, loan availed and its source, constraints faced by the farmers in paddy cultivation such as financial, production and labour management, marketing, insects, pests and animal attacks, lack of knowledge on paddy farming *etc*. were noted.

Outline of the study:

- Computation of trend and compound annual growth rate of area, production and productivity of paddy for three seasons viz; Autumn, Winter and Summer in Kerala
- Trend break analysis
- Construction of suitable time series forecast models for area, production and productivity of paddy in Kerala
- Estimation of the relative contribution of different elements and their interaction effects on change in paddy production using regression approach.
- A path analysis through structural equation modelling to identify the significant factors leading to the net income of paddy farmers

Statistical tools used for the analysis.

3.1 Trend

There are no automated strategies for detecting trend components in time series that have been demonstrated. However, as long as the trend is consistent, this aspect of data analysis is usually not too challenging. Smoothing is the initial stage in trend discovery if the time series data contains a lot of inaccuracy. Moving average smoothing is the most prevalent method, which replaces each element of the series with a simple or weighted average of 'n' surrounding elements, where 'n' denotes the smoothing width. Forecasts are frequently done on the assumption that the parameters remain constant over time. However, they may vary in practise. There are numerous options for updating the parameters in such instances. Exponential smoothing is a useful technique for giving more weight to recent observations.

3.2 Structural Break Analysis:

The chow test, as stated by Gujarathi *et al.* (2018) and Greene (2019), can be used to determine structural change. This entails determining the most likely breakpoints and exposing the periods to F statistics derived using their unrestricted residual sum of squares (RSS UR) and restricted residual sum of squares (RSS SR) values (RSS). The Chow test assumes uniform variance of the disturbance term in all regressions and relies on the researchers' subjective judgement to determine break points. As a result, Bai and Perron (1998) methodology was employed to solve these drawbacks.

Consider the following multiple linear regression model with m breaks (n+1, rules) and h as the shortest segment length:

$$b_t = a_t{}' \alpha + c_t{}' \gamma_j + \varepsilon_t$$

For $j = 1, \dots \dots, n + 1.$ $\quad t = K_{j-1} + 1, \dots \dots \dots, K_j$

Where,

b_t = dependent variable at time t

$a_t(p \times 1)$ *and* $c_t(q \times 1)$ = Vectors of covariates

α *and* γ_j $(j = 1, \dots \dots, n + 1)$ = coefficients' corresponding vectors

ε_t = Disturbance at time t.

The break points, or indices $K_1, \dots, K_n$ are explicitly considered as unknowns, but ($K_0 = 0$ and $K_{n+1} = K$) are assumed. When K observations on b_t, a_t, c_t are available the goal is to estimate the unknown regression coefficients as well as the break points. Since the parameter vector α is not subject to shifts and is estimated using the complete sample, this is a partial structural change model. When p = 0, a pure structural change model is obtained, with all coefficients subject to change, ε_t variance need not be constant. As a result, breakdowns in variance are allowed as long as they occur at the same time as breaks in the regression parameters.

The multiple linear regression may be expressed in matrix form as,

$$b = a\ \alpha + \bar{c}\gamma + F$$

Where,

$$b = (b_1, \dots, b_K)'$$

$$a = (a_1, \dots, a_K)'\ F = (f_1, \dots, f_r)'$$

$$\gamma = (\gamma_1', \gamma_2', \dots, \gamma_{n+1}')'$$

$\bar{c}$ = The matrix which diagonally partitions

$c\ at\ (K_1, \dots, K_M),\ i.e.\ \bar{c} = diag(K_1, \dots, K_{n+1})$ with $c_i = (cr_{i-1} + 1, \dots cr_i)'$.

A "0" superscript denotes the true value of a parameter. The symbols $\gamma^o = (\gamma_1^o, \gamma_2^o, \dots, \gamma_{n+1}^o)'$ and $K_1^o, \dots, K_n^o$ are used to represent the true values of the parameter γ and the true break points respectively. The $\bar{c^o}$ matrix is the one that divides c at $K_1^o, \dots, K_n^o$. diagonally. As a result, the data collection procedure is expected to be

$$b = a\alpha^o, + \bar{c^o}\gamma^o + F$$

As a result, the least-squares principle is used to estimate the data. The corresponding least-squares estimates of α and γ_j for each m-partition $K_1, \dots, K_n$ are produced by minimizing the sum of squared residuals.

$$(b - a\alpha - c\bar{\gamma})'(b - a\alpha - \bar{c}\gamma) = \sum_{i=1}^{n+1}\sum_{t=T_{i-1}+1}^{K_i}[b_t - a_t'\alpha - c_t'\gamma_i]^2$$

Let $\hat{\alpha}(\{K_j\})$ and $\hat{\gamma}(\{K_j\})$ stand for estimates based on the supplied m-partition abbreviated $\{T_j\}$. When these are substituted in the objective function and the sum of squares residuals are denoted as $S_K(K_1, \dots, K_n)$, the estimated break points $(\widehat{K}_1, \dots, \widehat{K}_n)$ are such that points $(\widehat{K}_1, \dots, \widehat{K}_n) = \text{argmin}_{K_1, \dots K_n}\ S_K(K_1, \dots, S_n)$, where minimization is taken entire partitions $(K_1, \dots, K_n)$ such that $K_i - K_{i-1} \geq q^2$. As a result, the break-point estimators are global objective function minimizers. The estimates for the regression parameters are those related with the m-partition $\{\widehat{K}_j\}$. i.e. $\hat{\alpha} = \hat{\alpha}(\{\widehat{K}_j\})$, $\hat{\gamma} = \hat{\gamma}(\{\widehat{K}_j\})$. Since the break points are discrete parameters with a finite number of possible values, a grid search can be used to estimate them. When m>2, this method quickly becomes computationally inefficient. Minimizers of the sum of squared residuals can be created to efficiently estimate the ideal break points for the series starting from one to the maximum allowed by K and h instead of a dynamic programming technique that permits computation of estimates of the break points as global.

Breakpoints on log-transformed data of area, production, and productivity of paddy crop were calculated using the “Strucchange” package in R Studio. A sample size of 60 observations on paddy acreage, production, and productivity of three seasons during the period from 1960-‘61 to 2019-‘20 was employed in this study. The program was set to get the most potential breakpoints among the various combinations of breakpoints because h was not set. A two-step validity test on the residual sum of squares (RSS) and the Bayesian Information Criterion were used to determine the best breakpoints (BIC). As a first step, the RSS with the lowest value was considered optimum. The optimal breakpoint was chosen if the optimal breakpoints determined in step one coincided with the lowest BIC. As a result, validity was determined by the lowest BIC. The preliminary part of section 4 discusses the results of the breaks.

3.3 Compound Annual Growth Rates

To better understand the historical trend and performance of acreage, production, and productivity of paddy crop of different seasons in Kerala, Compound Annual Growth Rates (CAGRs) were calculated. The exponential growth function of the following form was used for estimation:

$$z_t = ab^t e^u$$

Where,

z_t = growth rate computed for the dependent variable

a = intercept term

b= The regression coefficient is equal to (1+S), with s denoting the compound growth rate.

t = time (years) taking values 1, 2, … , n

u = Disturbance term for the year ‘t’

By using students t-test the significance of b was tested

CAGR values were calculated using Microsoft Excel's LOGEST function. Instead of calculating the CAGR based simply on the beginning and ending values, this function uses the OLS approach to take into account, all of the values in the series to offer the CAGR the best fit of the historical trend. As a consequence, the LOGEST method was shown to be superior since it uses transitional values to generate the final output. The LOGEST method was employed throughout the investigation to maintain uniformity.

3.4 Cuddy-Della valley Instability index

The Cuddy-Della Valley Instability Index (CDVI) was utilized to determine the fluctuations or instabilities in paddy acreage, production and productivity in Kerala. The first step is to estimate the parameter of a log-linear trend line for the variable z_t that will be used to calculate instability. The Instability Index (IIN) is defined as follows, if the estimated parameter is statistically significant:

Instability index, $IIN = (\frac{\sigma}{\mu} \times 100) \times (1 - \bar{R}^2)^{0.5}$

Where,

$\bar{R}^2$ = Adjusted coefficient of determination

μ = Overall mean

σ = Standard deviation

The CV is the instability index if the estimated parameter in the regression equation is not significant. Low instability is defined as a value between 0 and 15 per cent, medium instability is defined as 15 per cent to 30 per cent, and high instability is defined as a value greater than 30 per cent.

3.5 ARIMA and Exponential smoothing model

The yearly data in three seasons viz; Autumn, Winter and Summer on area, production and productivity of paddy in Kerala was obtained from the official website of "Department of Economics and Statistics (DES)", Kerala. Univariate time series data for the years 1960-'61 to 2019-'20 were analyzed to forecast the area, production and productivity of paddy in Kerala.

Appropriate models were fitted to the entire data set to forecast paddy area, production, and productivity in Kerala. The analysis was done using the statistical software package SPSS 22 to fit ARIMA (Auto Regressive Integrated Moving Average), Simple exponential smoothing, and Holt's exponential smoothing model, as well as Brown's exponential smoothing model.

First the time series data from 1960-‘61 to 2009-‘10 was taken and time series models was built. The model was validated using the actual data for the period from 2010-‘11 to 2019-‘20. After validation of the model forecasts were made for next five years from 2020-‘21 to 2024-‘25 using the confirmed model.

Forecasting is primarily used in business, industry, government, and many other institutions to make policies and plan for the future. Forecasting can be done in a variety of ways, the method used is determined by the aim and relevance of the prediction, as well as the cost of the procedures involved. The Box and Jenkins Auto Regressive Integrated Moving Average (ARIMA) model is a popular time series forecasting approach. The univariate time series data in the context Box and Jenkins ARIMA model is a data where the observations are collected at a particular sequence of time interval and predictions are generated based on the prior values. The dependence of the subsequent observations is an important feature of this data. The values in the observed data series, z_t, are considered as a realization of a stochastic process, $\{z_t\}$. A stochastic model can be applied in two ways

1) To comprehend the stochastic system
2) To forecast future values, which is a collection of random variables $\{z_t, t \epsilon T\}$, where $T = \{0, \pm1, \pm2, \dots\}$.

Throughout 1960-‘61, Box and Jenkins conducted substantial research on ARIMA models, and their names became synonymous with the ARIMA approach for time series forecasting. To forecast future values, a stochastic model for time series data is utilized. The stochastic process is either stationary or non-stationary and the majority of the time series are non-stationary.

3.5.1 The major steps:

1) **Identification**

Checking for stationarity is the first step in time series modelling. The main instruments for this are the Auto Correlation Function (ACF), Partial Auto Correlation Function (PACF) and Correlogram. ACF is a mathematical method for detecting patterns that repeat themselves, such as the presence of a periodic signal buried behind noise. A quick examination of the graph of the data and the structure of autocorrelation and partial autocorrelation coefficients will reveal stationarity. If the autocorrelation function goes out rapidly, the time series is stationary. There are several approaches for ensuring stationarity. A first order autoregressive model can be fitted the raw data and see if the coefficients were smaller than 1, or use Dickey Fuller tests.

Finding initial values for the orders of parameters p and q is the next stage. The significant autocorrelation and partial autocorrelation coefficients can be used to calculate them. It is an autoregressive model whose order is determined by the number of partial autocorrelations that are significantly different from zero when autocorrelations drop off exponentially to zero.

On the other hand, a moving average model whose order is determined by the number of autocorrelations that are significantly different from zero, in which partial autocorrelations fall off exponentially to zero. An ARMA model is one in which both autocorrelation and partial autocorrelation exponentially decay to zero. After passing through the processes several times, the final models are created.

ii) Estimation

At the identification stage, one or more models that appear to provide statistically appropriate representations of the relevant data are tentatively chosen. The method of ordinary least squares, as proposed by Box and Jenkins, is used to obtain precise estimations of the model's parameters. SPSS can be used to perform an iterative approach for determining the estimate. Finally, the coefficients must be statistically significant. i.e. the computed ARIMA model must have a significant t-statistic for each of its' coefficients.

iii) Diagnostic Checking

The diagnostic checks should be applied to the model after it has been recognized and the parameters have been approximated to see if it is adequate. Each model may be checked for inadequacies using four major criteria, which can then be utilized to make any necessary adjustments. We must first verify the random shock's independence. Random shocks in an appropriate model are statistically independent. If the random shocks are correlated, there is an autocorrelation pattern in the data that has not been represented by the model, and another model that satisfies the residual's independence assumption should be checked.

To ensure that the residual shock is independent, evaluate the model's residual estimate (a) during the estimation stage, and then examine the residual ACF to ensure that it has insignificant autocorrelation coefficients. This crucial evidence reveals that the model cannot be improved upon. For various combinations of AR and MA, both individually and together, different models can be generated. With the diagnostics that follow, the best model is obtained.

(a) Coefficient of determination (R^2)

R^2, an indicator that reflects the percentage of the output variance explained by importing the inputs into the model, was used to assess the models' accuracy. The statistical model accounts for a certain percentage of the variability in a data collection. It is a method that indicates how well the model can predict future outcomes. R^2 = 1-(Error sum of Squares/Total Sum of Squares) is the most general definition of the coefficient of determination.

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

The AIC=(-2logL+2m), where m=p+q and L is the likelihood function. -2logL is approximately equivalent to $\{n(1 + \log 2\pi) + n \log \sigma^2\}$. The model mean square error is σ^2 is this case. The AIC can be expressed as $\{n(1 + \log 2\pi) + n \log \sigma^2 + 2m\}$. Because the first term is a constant, it is frequently ignored when comparing the models. BIC=$\{n(1 + \log 2\pi) + n \log \sigma^2 + m \ln(n)\}$is a BIC variant that is similar to AIC. As a result, AIC = BIC-m(ln(n)-2). Schwarz Bayesian Criterion (SBC) = $\{n \log \sigma^2 + (m\ logn)/n\}$ is also used as an alternative to AIC.

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

The standard error of ρ_k can be used to determine its statistical significance, where k is the lag length. The ACF can be computed using a rule of thumb of one-third to one- quarter of the length of the time series. Starting with suitably long lags and then reducing by AIC or SIC is the best technique. If a time series is fully random (i.e., shows whitenoise) $\rho k \sim N(0,1/\sqrt{n})$, For ρ_k , the 95 per cent confidence interval is $\rho_k \pm 1.96/\sqrt{n}$. Rather than investigating the ρ_k values one at a time, evaluate the entire set of ρ_k values and construct a test to assess if the set is significantly different from a Zero set. This type of test is known as a portmanteau test. The Box-Pierce Q is a popular portmanteau test, with Q = n$\sum \rho_i^2$, n being the number of observations in the series and K being the maximum lag. Box and Pierce created this test in 1970 to examine the residuals from a forecast model. This Q will be compared against $\chi^2_{(K)}$. The Ljung-Box $Q^* = n(n + 2) \sum(n - 1)^{-1} \rho_i^2$ an alternate test in which the summation ranges from 1 to k. If the information is white noise the Ljung-Box Q^* distribution is identical to the Box-Pierce Q distribution.

(d) The percentage forecast Inaccuracy (PFI)

The Percentage Forecast Inaccuracy (PFI) is the proportion of the years' forecasted value that differs from the actual value. PFI was used to determine the degree of ex-post inaccuracy.

(e) Root Mean Square Error (RMSE)

The RMSE = $\sqrt{\frac{\sum_1^n |Z_t - \hat{Z}_t|^2}{n}}$

(f) Mean Absolute Error (MAE)

The MAE = $\frac{1}{n}\sum_1^n \left|Z_t - \hat{Z}_t\right|$

(g) Mean Absolute Percentage Error (MAPE)

The MAPE = $\frac{1}{n}\sum_1^n \left|Z_t - \hat{Z}_t\right|$

If the values of MAE, RMSE, MAPE are smaller then, it is considered as the best model.

Autocorrelation functions

The correlation between the observation z_t at time t and the observation, z_{t-p}, which lags at p periods from the current observation z_t, is measured by autocorrelation. The correlation between the two observations (z_t, z_{t-p}) is calculated as follows:

$$r_p = \frac{\sum_{t=1}^{n-p}(Z_t - \bar{Z})(Z_{t-p} - \bar{Z})}{\sum_{t=1}^{n}(Z_t - \bar{Z})^2}$$

The value of r_p range from -1 to 1. The maximum number of relevant r_p was also discovered to be N/4, where N is the number of periods for which information on z_t is accessible.

Partial autocorrelation

The statistical method of partial autocorrelation is utilized in forecasting. When the y-effects at other time delays 1, 2, 3, ..., p-1 are removed from a time series data, it is a measure of the degree of association between the two values z_t and z_{t-p}.

Tripati *et al.* (2014) declared that the Autocorrelation function (ACF) and partial autocorrelation function (PACF) are derived for various models with varying orders of autoregressive and moving average components, i.e. p and q respectively. As a result, for a given set of TS data, a correlogram is created by plotting the sample ACFs against the lags and comparing them to the theoretical ACF/PACFs in order to discover the best fit and choose one or more ARIMA models. Table 3.1 summarizes the general characteristics of theoretical ACFs' and PACFs' (here, the term "spike" refers to the line in the plot at various lags with a length equal to the magnitude of autocorrelations).

Table 3.1: Description of various time series models

Model	ACFs'	PACFs'
AR (p)	With an exponential pattern, spikes decay to zero.	Spikes cut-off to lag p
MA (q)	Spikes cut-off after lag q	Spikes decay to zero with exponential pattern
ARMA (p, q)	Spikes decay to zero with exponential pattern	Spikes decay to zero with exponential pattern

3.5.2 Description of ARIMA models

Autoregressive (AR) Model

A stochastic model known as an auto regressive model is commonly employed in the depiction of practical series. The current value z_t is determined by the finite and linear addition of the process's prior values with ε_t. If the time series values are evenly spaced at time intervals t, t-1, t-2, … by z_t, z_{t-1}, z_{t-2}, …, then z_t can be expressed as follows:

$$Z_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + \varepsilon_t$$

The autoregressive operator of order p is expressed by

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$$

The autoregressive model can be expressed as $B(Z_t)=Z_{t-1}$, where B is the backshift operator.

$$\varphi(B)z_t = \varepsilon_t$$

Moving Average (MA) Model

A moving average model is an MA(q) model with a wide range of applications, where y_t is the weighted moving average of the error of the lag values. The regression equation looks like this

$$z_t = \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\, \varepsilon_{t-q}$$

The moving average operator of order q is represented by

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

The moving average model can be expressed as $B(z_t) = z_{t-1}$, where B is the backshift operator, $z_t = \theta(B)\varepsilon_t$.

3.5.3 Autoregressive Moving Average (ARMA) Model

It is important to integrate the autoregressive and moving average models, which leads to the ARMA model, in order to forecast future values with high accuracy using actual time series data.

$$z_t = \varphi_1\, z_{t-1} + \varphi_2\, z_{t-2} + \cdots + \varphi_p\, z_{t-p} + \varepsilon_t - \theta_1\, \varepsilon_{t-1} - \theta_2\, \varepsilon_{t-2} \ldots - \theta q\, \varepsilon_t - q$$

Or

$$\varphi(B)\, z_t = \theta(B)\, \varepsilon_t$$

An ARMA model is a combination of autoregressive and moving average models, symbolized by the letters ARMA (p, q). Only stationary time series data are forecasted using it.

3.5.4 Autoregressive Integrated Moving Average (ARIMA) Model

An ARIMA model is a leading model than ARMA model that incorporates differencing. The ARIMA model is superior than ARMA model, which is commonly used to fit non-stationary time series data. Random walk is a basic example of a non-stationary process being reduced to a stationary one following differencing. An Integrated ARMA model, indicated by y_t, is used to describe a process.

ARIMA (p, d, q), if $\nabla^d\, z_t = (1 - B)^d\, \varepsilon_t$, is ARMA (p, q). The model is expressed as

$$\varphi(B)\,(1 - B)^d\, z_t = \theta(B)\varepsilon_t$$

Where, $\varepsilon_t \sim WN(0, \sigma^2)$, WN indicating White Noise. The integration parameter d is an integer that is not negative. When d = 0, ARIMA (p, d, q) = ARMA (p, q).

ARIMA is a three-step technique that involves selecting a model, estimating model parameters, and diagnosing the fitted model. The ARIMA is tentatively chosen in the first stage. In the second step, the parameters of the chosen model are evaluated, and the model's accuracy is tested in the third step *i.e.* the diagnostic check. When the model is proven to be insufficient, all three processes are repeated until the most satisfactory model for the time series data is identified. The many components of this approach have been discussed by Box *et al.* (2011). Standard software tool SPSS 22 was used to analyze and fit the ARIMA model.

3.5.5 Exponential smoothing methods

It is an effective forecasting method that can be used to replace the most commonly used Box-Jenkins ARIMA model. The technology of exponential smoothing is used to estimate univariate time series data. The forecasts in this technique are based on weighted averages of previous values. The weights in the exponential smoothing approach decrease exponentially as the values get older, as the name implies. This signifies that recent values are given more weight than previous values. The primary idea underlying this technique is that in a time series, recent values are highly significant in time series. As values get older, their relevance diminishes exponentially. Exponential smoothing methods are classified into the following categories.

1. One-parameter method: Smoothing using a single axis (also called Simple exponential smoothing)
2. A two-parameter technique is used: Double exponential smoothing
   a. Brown's linear method (single parameter)
   b. With two parameters, Holt's linear method
3. A three-parameter technique is used: Winter's smoothing model is based on exponential growth.
   a. Winter's multiplication method
   b. Winter's additive method

3.5.6 Simple exponential smoothing

Since it is the most basic of the exponential smoothing methods, it is referred to as Simple Exponential Smoothing (SES). This method is suitable for predicting data with no discernible trend and data that do not exhibit seasonal behavior. All expected future values are stated to be equal to the series of last observation in this approach.

$$Z_{Y+h/_T} = Z_T$$

for h=1, 2, ….

In this technique, it is considered that recent values, rather than previous observations, supply the majority of the information. This is explained by the weighted average, which gives more weight to the most recent observations. The future forecasted values by using the average method are a simple average of the observed data.

$$Z_{Y+h/_T} = \sum_{t=1}^{T} Z_t$$

h=1, 2, ….

According to the following equation, all observations are given equal value, resulting in equal weights during predicting between the extreme values of the observed data, we expect something more. It is more significant to give current data, larger weights than those that are far behind. This is the idea behind the simple exponential method. Forecasts are derived using weighted averages, in which the weights decrease exponentially as the number of observations increases, and the older observations have smaller weights.

$$Z_{Y+h/_T} = \alpha z_T + \alpha (1-\alpha) z_{T-1} + \alpha (1-\alpha)^2 z_{T-2} + \cdots$$

α is a smoothing coefficient that can range from 0 to 1. It controls how quickly the weights are reduced. The weighted average of all the observations in the series z_1, …, z_t is validated by the above equation for the one-step forward forecast for the period T+1.

3.5.7 Holt's exponential smoothing model

The simple exponential smoothing technique is extended by Holt's winter exponential smoothing model. Holt's two parameter model (or) Holt's double exponential model is the name given to this model because it considers two parameters. This approach was created by Holt (1957) to forecast time series data with a trend. The forecasting equation in this method is based on the time series trend and level.

Level equation $L_t = \alpha\ zt + (1-\alpha)[L_{t-1} + T_{t-1}]$

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

Forecast equation $F_{t+1} = L_t + K\ T_t$

Where L_t denotes the time series' level estimate at time t, T_t signifies the time series' trend estimate at time t, and α is the level equation's smoothing coefficient, which varies from 0 to 1. γ is the smoothing coefficient of trend equation, ranging from 0 to 1.

3.5.8 Brown's exponential Smoothing

The Brown's exponential smoothing model is suitable to model the time series with trend but without seasonality. Non-adaptive Brown's linear exponential smoothing are provided

For non- adaptive Brown's exponential smoothing, let S_t and T_t be the simply smoothed value and doubly smoothed value for the $(t+1)^{th}$ time period respectively. Let a_t and b_t be the intercept and the slope

- $S_t = \alpha\ X_t + (1-\alpha)\ S_{t-1}$
- $T_t = \alpha\ S_t + (1-\alpha)\ T_{t-1}$
- $a_t = 2S_t - T_t$
- $b_t = \frac{\alpha}{1-\alpha} \times (S_t - T_t)$
- $F_{t+1} = a_t + b_t$

3.6 Regression Approach:

To measure the relative contribution of different elements to the growth of output of paddy during different periods from 1960-‘61 to 2019-‘20 in Kerala, the model used by Karunakaran (2014) is applied in this study. Observing the value of output in period zero (v_0) and in period t (v_t), the difference between the two is decomposed into four component elements, like, change in area (X), change in price effect (Y), change in productivity (Z), interaction between price and area (X,Y), The regression equation is as follows.

- $\Delta_t (V_t - V_{t-1}) = \Delta_t (X_t - X_{t-1}) \sum iYi\ Zi + \Delta_t (Y_t - Y_{t-1}) \sum iXi\ Zi + \Delta_t (Z_t - Z_{t-1}) \sum\ iXi\ Yi + (X_t - X_{t-1}) (Y_t - Y_{t-1}) \sum Zi$

$(X_t - X_0)$ = Difference in area under paddy crop of current year and previous year.

$(Y_t - Y_0)$ = Difference in paddy price of current year and previous year

$(Z_t - Z_{t-1})$ = Difference in paddy productivity of the previous period by lagged 1.

$(X_t - X_t)\ (Y_t - Y_t)$ = Interaction effect of area change and price change of paddy

The regression coefficients were tested for their significance using t test.

3.7 Durbin Watson test

This test is derived by James Durbin and Geoffrey Watson. Durbin-Watson (DW) test which measures the autocorrelation between the residuals in the time series data. The hypothesis of DW test is

H_0 = No first order autocorrelation

H_1 = First order autocorrelation

Test statistic:

$$DW = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}$$

The standard rule is that, if the value of test statistic lies between 1.5 to 2.5 then the autocorrelation is considered to be normal

3.8 Structural Equation Modelling

Sample and study region:

The goal of this study was to use the structural equation model (SEM) to conduct a path analysis and build a model based on the essential aspects of paddy cultivation practices productivity *etc*. that influence paddy farmers' net income in Kerala.

Methodology

SEM is a structural model that describes how dependent and independent factors interact. The variable can be discrete (or continuous) in this case. SEM is a multidimensional approach that enables the researcher to calculate modification indices, which aid in the development of the best-fit model for the data.

SEM has a subset called path analysis. Path analysis is a statistical method for analyzing the strength of direct and indirect links between variables. It is a type of multiple regression that's been taken to the next level. SEM is a type of sophisticated regression analysis in which researchers examine more than two causal hypotheses. It investigates the statistical relationship between the independent and dependent variables.

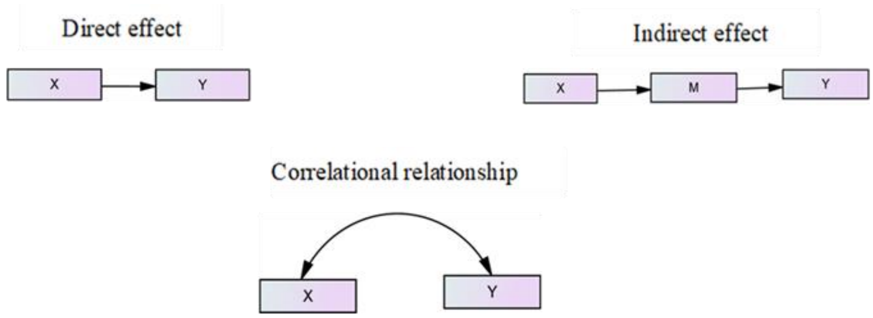

Figure 3.1 SEM model components

Different steps in conducting SEM

1. Collecting research articles and reviews to aid in the development of a model
2. Establishing a model
3. Go to model identification
4. Determine the measurements for all of the model's variables
5. Data collection

6. Putting together the path model
7. Choosing a model of best fit

Goodness of fit indices - GFI, AGFI, NFI, CFI, TLI should be > 0.9 (Hair *et al*. 2010)

Badness of fit indices - RMSEA ≤ 0.08 (Hair *et al*. 2010)

Model comparison - AIC, BIC and CFI

The “Amos” software suite is used to create the SEM model. SEM is a diagrammatic model made up of a number of observable and latent variables. The observed variables are represented in this path diagram by rectangles or squares. The variables that aren't observed are represented by circles or ellipses. A single headed arrow depicts the direct effect of one variable on the other variable. The curve with two headed arrows connects the covariance between the two independent variables.

The results of this study were obtained by using structural equation modelling to analyse the interdependence of elements such as demographic information and paddy farming data provided by chosen paddy farmers in Kerala.

Model fit summary of SEM

It is crucial to make sure whether the SEM model adequately fits the data well. The goodness of fit test is used to determine the model's correctness. The statistical methods that test the model's Goodness of Fit include the root mean squared error of approximation (RMSEA), comparative fit index (CFI), and Tucker Lewis index (TLI). When the degrees of freedom and sample size are changed, the value of RMSEA changes. The RMSEA value decreases as the number of degrees of freedom increases with a larger sample size. When the RMSEA is zero, the model is the best fit, and when it is less than or equal to 0.08, it is considered an excellent fit. CFI and TLI values are two more goodness of fit indices that compare the base model's fitness to the hypothesised model. CFI should be > 0.90, which is in the middle of the range of 0 to1.

Model specification

In SEM there are two kinds of variables. One is the observed or manifest variable that can be measured and the other is latent or unobserved variable. The SEM model is represented diagrammatically where the variables which are observed are included in the squares or rectangles and the latent variables are included in the circles or ellipses. Since SEM contains the dependent and independent variables, the relationship among them is interpreted by regression equations as,

$$y_i = \alpha_i + BX + \varepsilon_i$$

Where, y_i signifies the dependent variable, i symbolises the i^{th} intercept in a regression equation, X defines the vector of independent variables, B denotes the vector of regression coefficients corresponding to variables in X, and ε_i denotes random error associated with the i^{th} dependent variable.

Calculating Path Coefficients

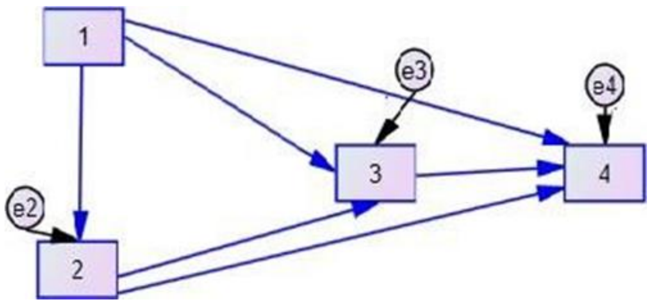

Figure 3.2 Outline for evaluating the path coefficients

In path analysis, we work with path coefficients to show the direct effect of one variable on another. There is a standard way of expressing the variable. i.e. in terms of Y scores. Let us consider a path diagram as follows:

Then

$$Y_1 = \varepsilon_1$$

$$Y_2 = P_{21}Y_1 + \varepsilon_2$$

$$Y_3 = P_{31}Y_1 + P_{32}Y_2 + \varepsilon_3$$

$$Y_4 = P_{41}Y_1 + P_{42}Y_2 + P_{43}Y_3 + \varepsilon_4$$

From the model it can be seen that the variable Y_1 is not explained by any other variable except the external cause, which is unobserved, in the model. The second variable y_2 which is directly affected by the first variable $y_1$and some external causes (or) error ε_2. The above equations are in accordance with the path diagram. In each equation the variable y is associated only with the effect not by the indirect effect. Thus, in a path diagram, the effect of the independent variable on the dependent variable is connected by a single headed arrow, and this effect is assessed in terms of path coefficient. The path coefficient is equal to the correlation coefficients when the dependent variable is related with a single independent variable.

Table 3.2 Description of variables in the SEM model of Paddy production

Variable	Description	Measures
Age	Age	Numbers
Edn	Education	Illiterate Primary school High school Intermediate/+2 Graduate Post gradate
Lnsize	Land size (acres)	<= 1 01-03 03-05 05-07 07-09
Excont	No. of Extension contact	<=3 >3
Trng	No. of Trainings	<=3 >3
Kgprc	Price per Kg of paddy	Numbers
Biofert	Usage of Bio fertilizer	Yes No
Loan	Loan	Yes No
Expdfrmng	Experience in paddy farming	No. of years
Wdng	Weeding	Yes No
Usepesti	Pesticide price	Yes No
Pdcularea	Paddy cultivated area (acres)	<=1 01-03 03-05 05-07 07-09
Manur	Expenditure on Manure	In Rupees
Miscexp	Miscellaneous Expenditure	In Rupees
Tract	Tractor charge	In Rupees
Lbrwg	Labour wage	In Rupees
Ldngchrg	Loading charge	In Rupees
Pestiprc	Pesticide price	In Rupees
Leaseprc	Lease rate	In Rupees
Pdyinc	Paddy income	In Rupees
Netinc	Net income	In Rupees

Kendall's coefficient of concordance

Kendall's coefficient of concordance 'W' is a measure of the relation among several ranking of 'n' objects or individuals where there are 'K' sets of rankings the allocation among them is determined by 'W'. It express the degree of association among the 'K' variables. To ascertain the overall agreement among 'K' sets of rankings this can be used.

To compute 'w' the sum of ranks R_j in each column of a KxN table are found. Then the sum R_j is divided by N to obtain the mean value of R_j. Each of the R_j may then be expressed as the deviation from the mean value. Larger these deviations, greater the degree of association among the 'K' sets of ranks. Finally, the sum of squares 'S' of these deviations is found and 'W' is computed as,

$$W = \frac{12S}{K^2(N^3 - \mathrm{N})}$$

Where,

S = Sum of the squares of observed deviations from the mean R_j $S = \Sigma(R_j - \Sigma \frac{\mathrm{Rj}}{N})^2$

K = number of sets rankings or no respondents

N = number of entities or objects ranked

The significance of 'W' is tested using the $\chi 2$ test, when 'N' is larger then 7

$$W = \frac{12S}{\mathrm{KN(N+1)}} \sim \chi 2(\mathrm{N-1})\ \mathrm{d + d.f}$$

Therefore, $K\ (N-1)\ W \sim \chi 2$ (N-1) d.f

If the computed value of $\chi 2$ is greater than tabular value with d.f (N-1), the null hypothesis that the 'K' rankings are unrelated may be rejected at the required level of significance.

RESULTS AND DISCUSSION

Chapter 4

RESULTS AND DISCUSSION

A study entitled "Structural Equation Modelling in Paddy" was carried out and the results and a detailed discussion with respect to each objective of the study are presented in this chapter under different sub headings.

4.1 Trend Analysis

Trend analysis of area, production, and productivity of paddy in Kerala over the course of three seasons: Autumn, Winter and Summer

Table 4.1: Descriptive statistics for the time series data of Autumn paddy cultivation in Kerala (1960-'61 to 2019-'20)

Variables	Min.	Max.	Mean	Std. Deviation	Variance	Skewness	Kurtosis	CV(%)
Area (hectares)	51922	398993	234584	133502.39	1.78E+10	-0.051	-1.685	56.9
Production (tonnes)	101943	605595	377420	15,90,80,421	2.53E+10	-0.261	-1.567	42.14
Productivity (kg per ha)	1147	2954	1845.96	459.99	211590.6	0.473	-0.752	24.91

In the year 1967-'68, Kerala's maximum Autumn paddy acreage was 398993 hectares. Due to increase in area, production also increased in the year 1973-'74, the maximum production was 605595 tonnes. The area and production had been growing at a negative rate since 2012-'13 and 2018-'19 respectively. Due to the adoption of non-food crops such as rubber etc. both acreage and production were decreased in the next years. However from 2015-'16 onwards, productivity had gradually increased. It showed that productivity has been rising in recent years. The highest productivity in Kerala was 2954 kg per ha.

The variance for the area, production, and productivity indicated that the data was highly dispersed. The coefficient of variation (a measure of consistency) was 56.9 per cent for area, 42.14 per cent for production, and 24.91 per cent for productivity. The skewness and kurtosis values revealed that the time series data on area, production and productivity of paddy was non-normal in character. The area under paddy and production had negative skewness, suggesting that a larger number of values were concentrated on the right side of the density curve, with a few smaller values pulling the mean towards the left, making it smaller than the median and mode. However, the productivity showed a positive skewness, with a long right tail caused by a concentration of more values on the left side of the probability density curve and a few high values tugging the mean to the right making the mean greater than the mode and median.

Table 4.2: Descriptive statistics for the time series data of Winter paddy cultivation in Kerala (1960-‘61 to 2019-‘20)

Variables	Min.	Max.	Mean	Std. Deviation	Variance	Skewness	Kurtosis	CV (%)
Area (hectares)	72253	396392	245272.5	108944.3	1.19E+10	-233	-1.475	44.4
Production (tonnes)	141397	609234	426254.03	126510.9	1.60E+10	-428	-1.048	29.67
Productivity (Kg per ha)	1189	3160	1924.64	474.087	224758.7	0.822	-0.162	24.63

The maximum acreage in the winter paddy was 396392 hectares in Kerala in 1975-‘76. In 1972-‘73, the additional acreage resulted in greater production, with a peak of 609234 tonnes. Since 2016-‘17, both area and production had decreased. As a result of changes in the usage of non-food crops such as rubber *etc*. both the area and production were deteriorated in the next years. However, from 2018-‘19 onwards, productivity had gradually increased. It illustrated that productivity had risen in recent years. Maximum productivity of winter paddy was 3160 kg per ha.

The variance for area, production and productivity indicated that the data was highly scattered. The coefficients of variation for area, production and productivity respectively were 44.44 per cent, 29.67 per cent and 24.63 per cent. As demonstrated by the values of skewness and kurtosis, the winter paddy acreage, production and productivity were not normal during the reported period. In the area under paddy and production, negative skewness were observed indicating that the right side of the density curve was concentrated with more number of values, while smaller values pulling the mean to the left making it lower than median and mode. On the other hand, the productivity was positive, with a long right tail created by concentration of more values on the left side of the probability density curve and a few high values pulling the mean to the right which made the mean significantly higher than the mode and median.

Table 4.3: Descriptive statistics for the time series data of Summer paddy cultivation in Kerala (1960-‘61 to 2019-‘20)

Variables	Min.	Max.	Mean	Std. Deviation	Variance	Skewness	Kurtosis	CV (%)
Area (hectares)	21857	108874	70186.8	22705.4	5.2E+08	0.079	-1.063	32.34
Production (tonnes)	59733	205531	148053	32897.9	1.1E+09	-0.264	-0.201	22.22
Productivity (Kg per ha)	1139	4028	2244.54	583.56	340543	0.651	0.293	25.99

The maximum summer paddy acreage was 10,8874 hectares in Kerala, which was in 1976-‘77. The increase in area also resulted in increased production in 1979-‘80 with a maximum output of 205531 tonnes. Since 2005-‘06, area and production showed a negative growth. In the following years, both the area and production had deteriorated as a result of adoption of non-food crops such as rubber, *etc*. But productivity had increased gradually from 2018-‘19 onwards. It demonstrates that in recent years productivity has increased. Kerala produced 4028 kg per ha as the maximum productivity during the study period.

The variance for area, production, and productivity suggested that the data was highly dispersed. The coefficient of variation for area, production, and productivity was 32.34 per cent, 22.22 per cent and 25.99 per cent respectively. The reported time series data of Summer paddy acreage, production and productivity was non-normal in character as evidenced by the skewness and kurtosis values.

Negative skewness was seen in the production, indicating that a greater number of values were concentrated on the right side of the density curve with a few smaller values tugging the mean to the left, making it smaller than the median and mode. The productivity and acreage, on the other hand, had a positive skewness, with a long right tail created by a concentration of more values on the left side of the probability density curve and a few high values pulling the mean to the right, causing the mean to be significantly higher than the mode and median.

4.1.1 Trend in area under Autumn paddy in Kerala

The trend was computed using the area under Autumn paddy in Kerala for the period from 1960-‘61 to 2019-‘20. From Fig. 4.1 it could be observed that the trend was declining. The linear regression model exhibited significant coefficients of the time variable (β_1) and the area of paddy in subsequent years showed a decreasing trend with R^2 equal to 0.94. The largest area was found in 1967-‘67.

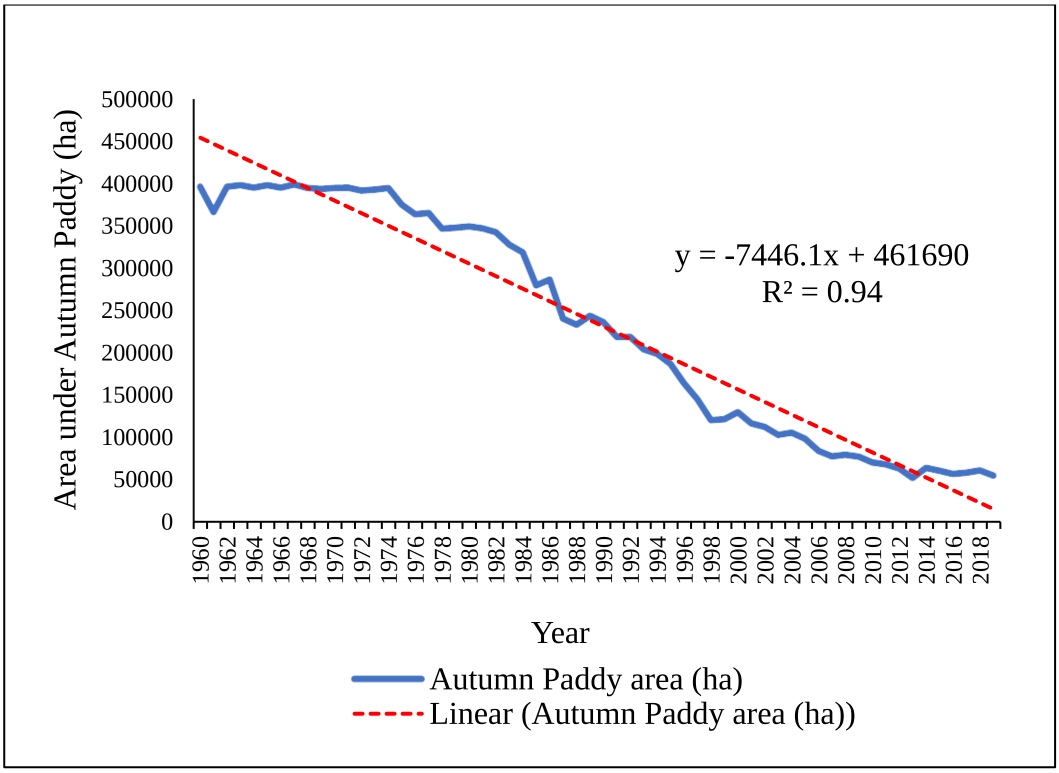

Fig 4.1: Area under Autumn paddy in Kerala during 1960-‘61 to 2019-‘20

4.1.2 Trend in Autumn paddy production in Kerala

Table 4.4: Linear regression model with estimated parameters for area under Autumn paddy in Kerala (1960-‘61 to 2019-‘20)

Equation	Model summary					Estimated parameters	
	R square	F	df1	df2	P-value	Constant	β_1
Linear	0.94	1074.97	1	58	<0.001	461690	-7446.1

The trend line of Autumn paddy production in Kerala for the years 1960-‘61-2019-‘20 revealed more or less a stochastic behaviour with a declining tendency. In Fig 4.2 it can be observed that there was a lot of fluctuations in production. The production was 500348 tonnes at the start of 1960-‘61, 420461 tonnes in 1962-‘63 and 142946 tonnes at the end of 2018-‘19. The linear regression model revealed that the coefficient of the time variable (β_1) was significant, with a R^2 value of 0.82. As a result, the linear regression model was significant and the graph revealed a downward trend in the time series data on paddy output in Kerala.

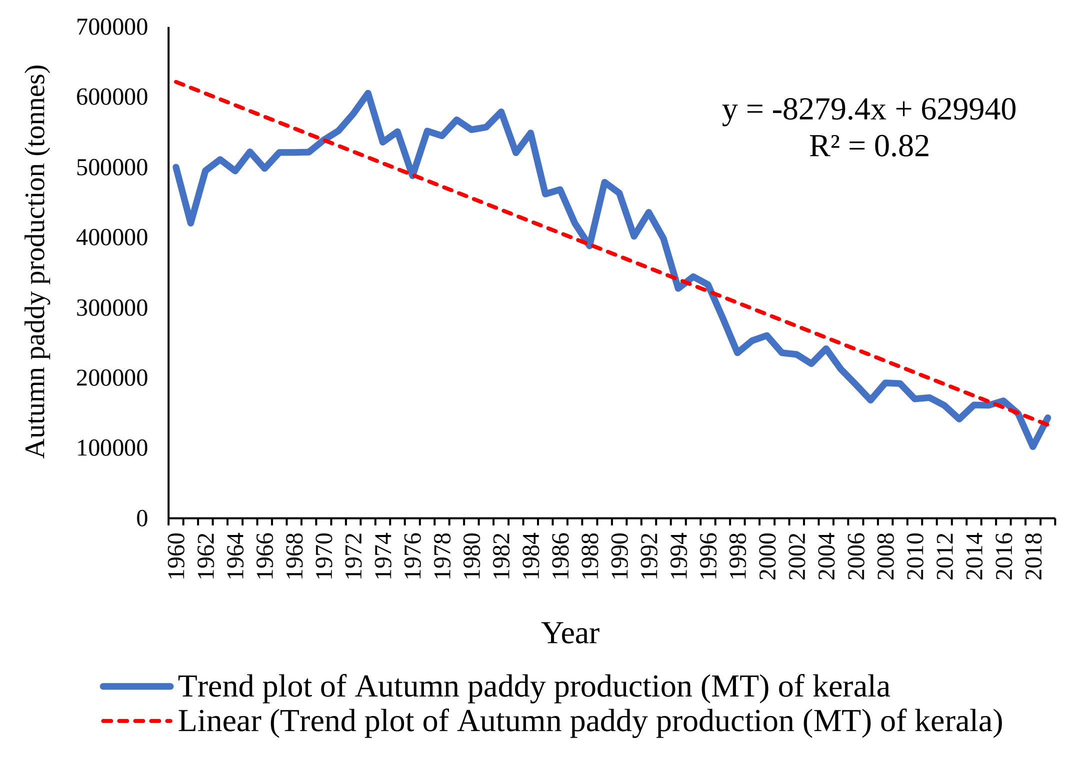

Fig 4.2: Autumn paddy production of Kerala during 1960-'61 to 2019-'20

Table 4.5: Linear Regression model with estimated parameters for Autumn paddy production in Kerala (1960-'61 to 2019-'20)

Equation	Model summary					Estimated parameters	
	R square	F	df1	df2	P-value	Constant	β_1
Linear	0.82	275.62	1	58	<0.001	629940	-8279.4

4.1.3 Trend in Autumn paddy productivity in Kerala

In the year 1962-'63 of the study period, productivity was only 1147 kg per ha, which was extremely low. After increasing to 2029 kg per ha in 1997-'98 and 2954 kg per ha in 2016-'17, productivity has declined to 2613 kg per ha by the end of 2018-'19. The huge drop in productivity during 2018-'19 might be due to the adverse effect of climate. The linear regression model revealed that the coefficient of the time variable (β_1) was significant, with an R^2 equal to 0.87.

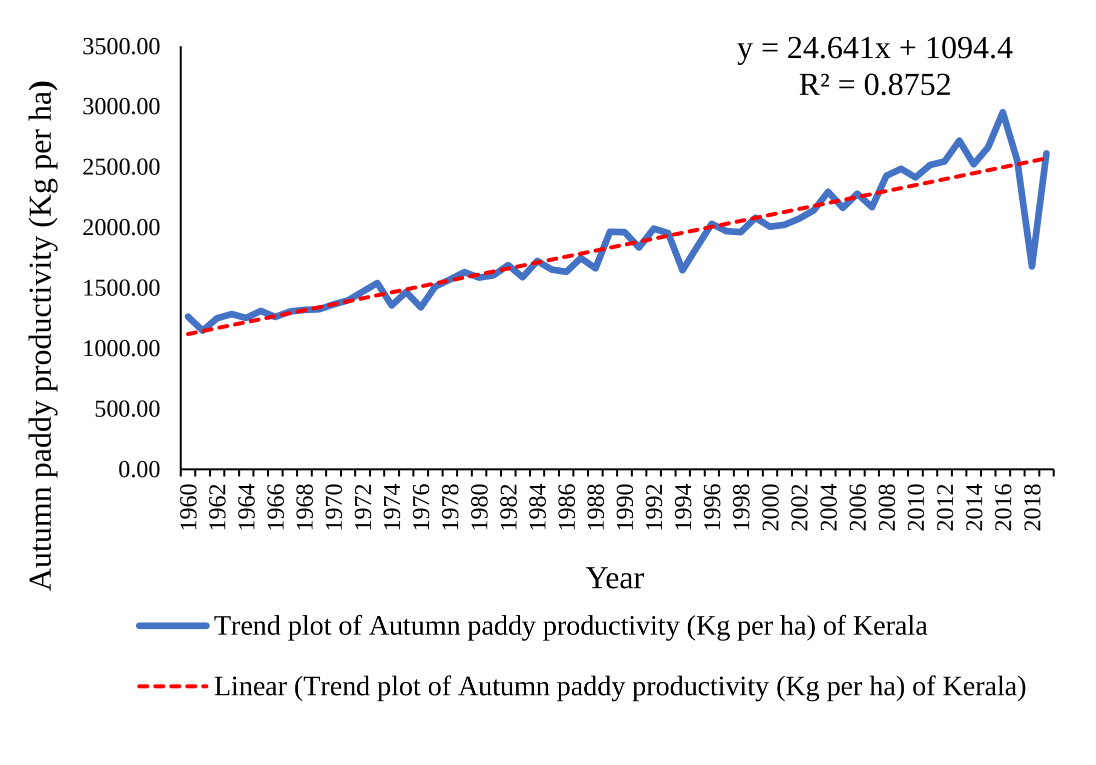

Fig 4.3: Autumn paddy productivity of Kerala during 1960-‘61 to 2019-‘20

Table 4.6: Linear Regression model with estimated parameters for Autumn paddy productivity in Kerala (1960-‘61 to 2019-‘20)

Equation	Model summary					Estimated parameters	
	R square	F	df 1	df2	P-value	Constant	β_1
Linear	0.87	406.7	1	58	<0.001	1094.4	24.64

4.1.4. Trend in Winter paddy area in Kerala

The trend was determined using the area under winter paddy in Kerala from 1960-‘61 to 2019-‘20. The resulted graph as in Fig 4.4 was slanting downward. The results of the linear regression model fitted taking time as the independent variable showed that the time variable had significant coefficient (β_1) and the area under winter paddy in subsequent years exhibited a decreasing trend with R^2 equal to 0.86, with the highest area covered in 1975.

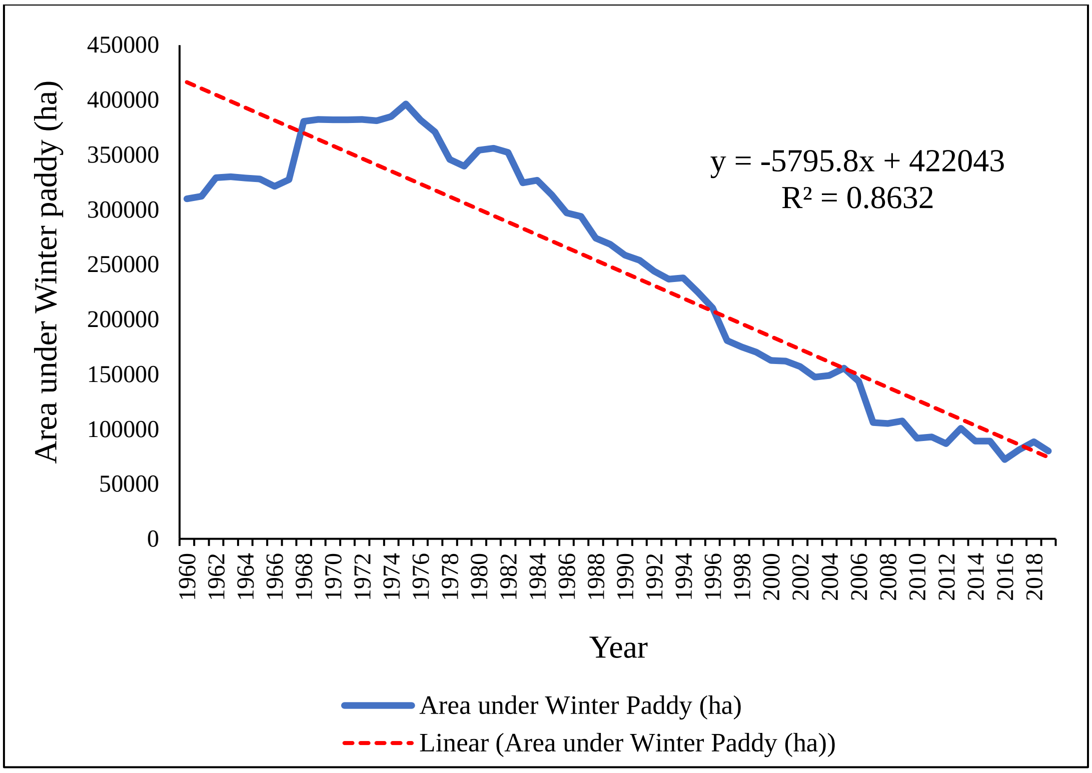

Fig 4.4: Area under Winter paddy in Kerala during 1960-'61 to 2019-'20

Table 4.7: Linear regression model with estimated parameters for area under Winter paddy in Kerala (1960-'61 to 2019-'20)

Equation	Model summary					Estimated parameters	
	R square	F	df1	df2	P-value	Constant	β_1
Linear	0.86	365.984	1	58	<0.001	422043	-5795.8

4.1.5 Trend in Winter paddy production in Kerala

For the years 1960-'61 to 2019-'20 Fig 4.5 shows that winter paddy production in Kerala exhibited a stochastic declining trend. There was a lot of fluctuations occurred in the data. By the start of 1960-'61, production was 447712 tones, 481886 tonnes in 1962-'63, and 141397 tonnes at the end of 2018. The coefficient of the time variable (β_1) was significant in the linear regression model, with an R^2 value of 0.68. As a result, the linear regression model was significant and the graph demonstrated a declining trend in Kerala paddy production on time series data.

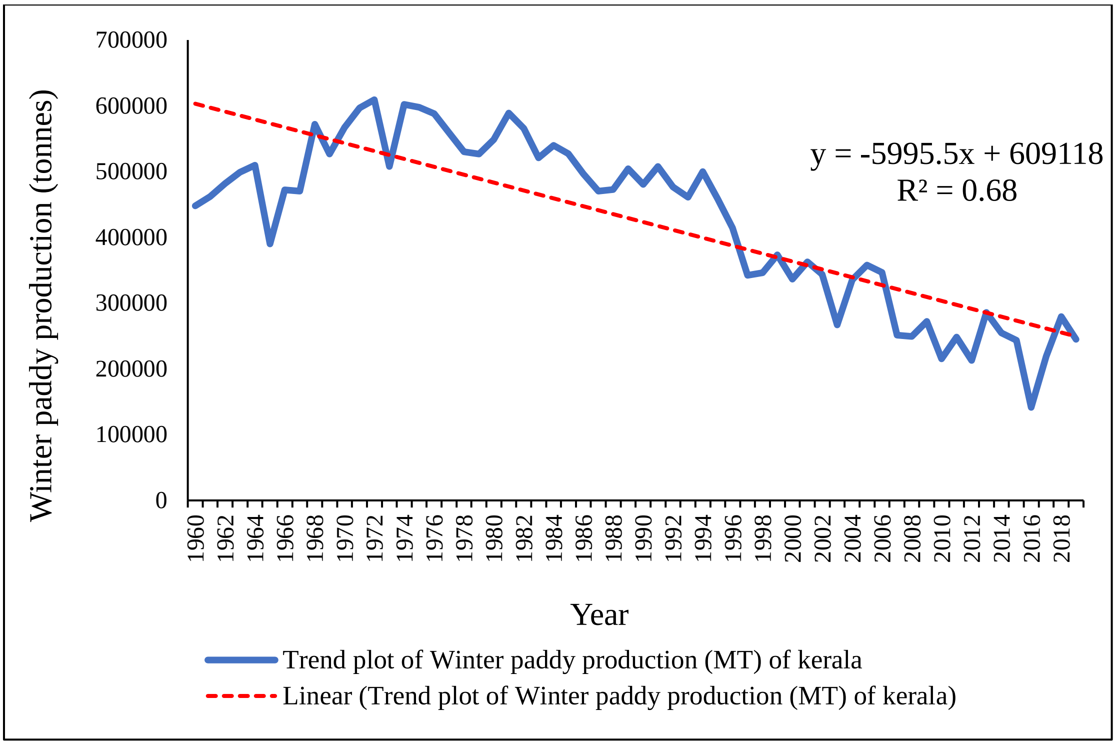

Fig 4.5: Winter paddy production of Kerala during 1960-‘61 to 2019-‘20

Table 4.8: Linear regression model with estimated parameters for Winter paddy production in Kerala (1960-‘61-2019-‘20)

Equation	Model summary					Estimated parameters	
	R square	F	df1	df2	P-value	Constant	β_1
Linear	0.68	126.136	1	58	<0.001	609118	-5995.5

4.1.6. Trend in Winter paddy productivity in Kerala

The productivity in the year 1961-‘62 was only 1463 kg per ha, which was remarkably low. In 1965-‘66, the lowest productivity occurred and it was 1188 kg per ha. From Fig 4.6 an increasing trend could be visualised and the maximum productivity was in the year 2018-‘19 which was equal to 3160 kg per ha. The coefficient of the time variable (β_1) was significant in the linear regression model to explain the trend in winter paddy productivity with an R^2 of 0.83.

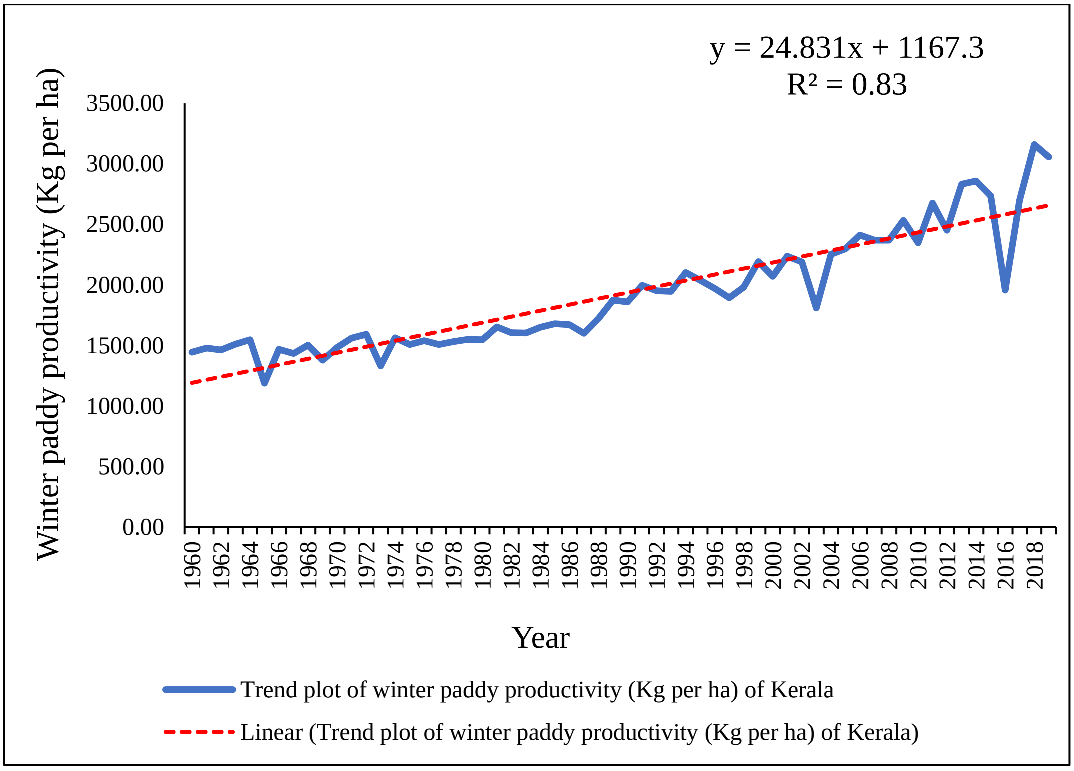

Fig. 4.6: Winter paddy productivity of Kerala during 1960-‘61 to 2019-‘20

Table 4.9: Linear regression model with estimated parameters for Winter paddy productivity in Kerala (1960-‘61 to 2019-‘20)

Equation	Model summary					Estimated parameters	
	R square	F	df1	df2	P-value	Constant	β_1
Linear	0.83	297.233	1	58	<0.001	1167.3	24.831

4.1.7. Trend in Summer paddy area in Kerala

From 1960-‘61 to 2019-‘20, the trend was determined using the area under Summer paddy in Kerala. The resulted trend in Fig 4.7 had a declining tendency. Linear trend fitted had significant coefficient for the time variable (β_1) and the summer paddy area in succeeding years showed a decreasing trend with R^2 equal to 0.63 with maximum area covered in the year 1976-‘77.

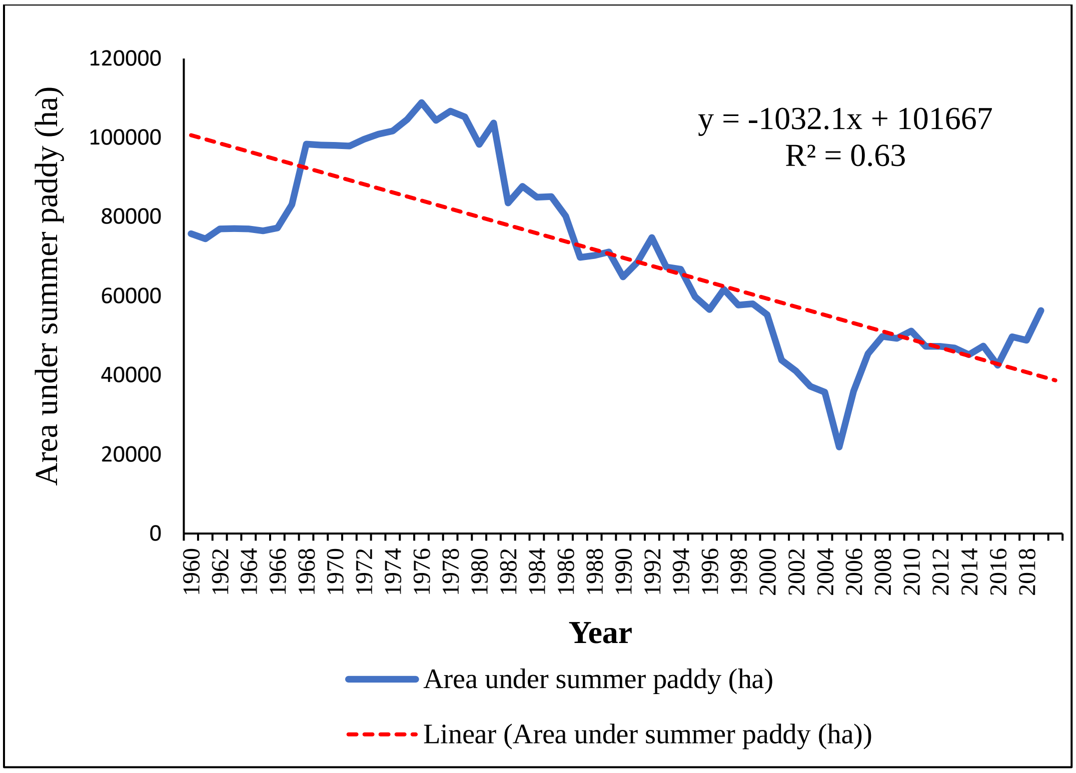

Fig. 4.7: Area under Summer paddy in Kerala during 1960-‘61 to 2019-‘20

Table 4.10: Linear regression model with estimated parameters for area under Summer paddy in Kerala (1960-‘61 to 2019-‘20)

Equation	Model summary					Estimated parameters	
	R square	F	df1	df2	P-value	Constant	β_1
Linear	0.63	98.86	1	58	<0.001	101667	-1032.1

4.1.8. Trend in Summer paddy production in Kerala

The production in the year, 1960-‘61 was only 119500 tonnes, which was comparatively low. Production fell to 59733 tonnes at the end of 2005-‘06 after rising to 198558 tonnes in 1979-‘78. Therefore there existed a lot of fluctuation in the data. The coefficient of the time variable (β_1) was not at all significant to fit any model due to lot of variations in the data which has resulted in a low value of R^2 0.64.

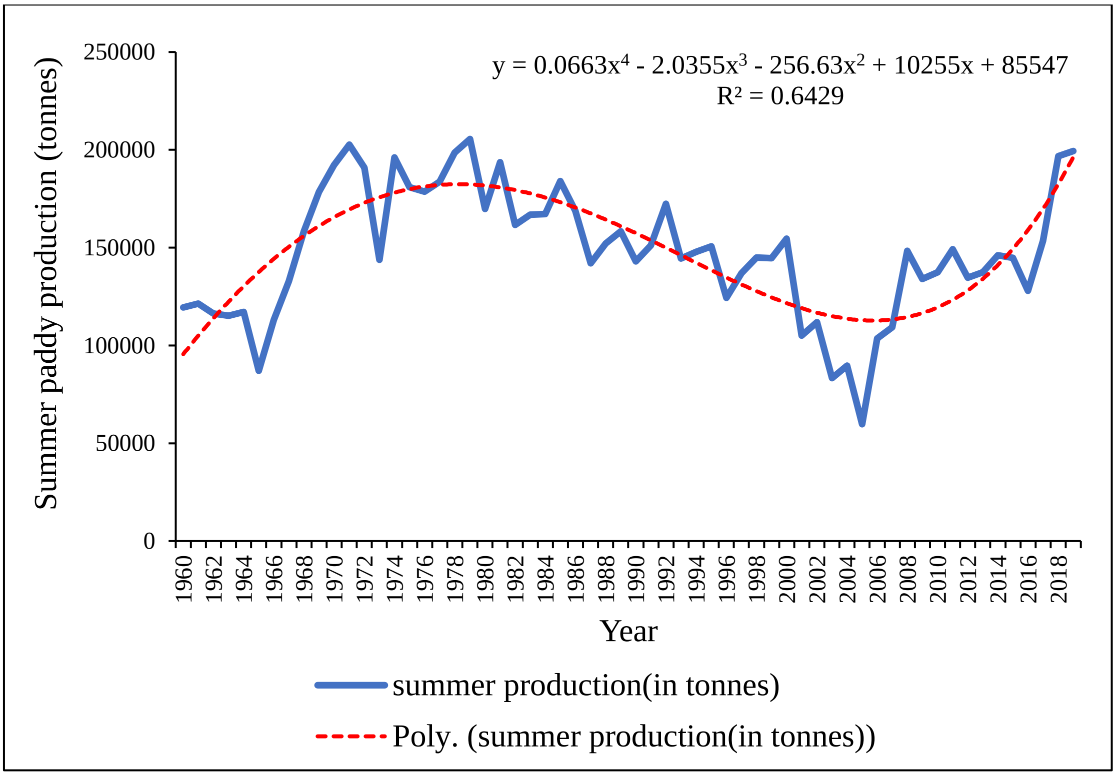

Fig. 4.8: Summer paddy production of Kerala during 1960-'61 to 2019-'20

4.1.9. Trend in Summer paddy productivity in Kerala

The productivity in the year, 1960-'61 was only 1512 Kg per ha, which was very low. In 1965-'66, the minimal productivity occurred and it was 1139 Kg per ha and the maximum productivity was in the year 2018-'19 which was equal to 3088 Kg per ha. Fig 4.9 showed a rising trend. The coefficient of the time variable (β_1) was significant in the linear regression model fitted to detect trend with an R^2 0.86.

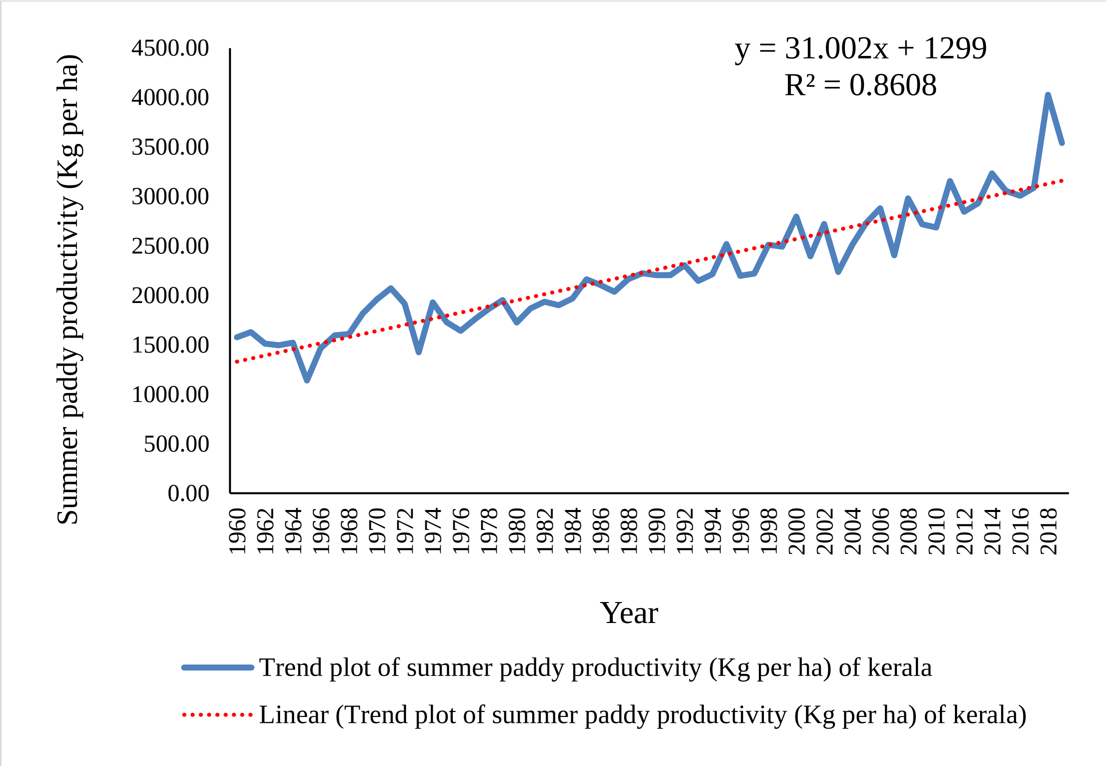

Fig. 4.9: Summer paddy productivity of Kerala during 1960-‘61 to 2019-‘20

Table 4.11: Linear regression model with estimated parameters for Summer paddy productivity in Kerala (1960-‘61 to 2019-‘20)

Equation	Model summary					Estimated parameters	
	R square	F	df1	df2	P-value	Constant	β_1
Linear	0.86	358.68	1	58	<0.001	1299	31.002

4.2 Structural Break Analysis

In statistics a structural break is an unexpected change over time in the parameters of regression models, which can lead to huge forecasting errors and before going to do forecast analysis, we need to perform trend break analysis. Structural break tests helps us to determine when and whether there is a significant change in data, breaks identified from paddy production in Kerala helped in determining the phases of growth of area, production and productivity which plays a major role in agriculture production. Therefore there is a need to understand the volatility and breaks in the time series data.

During the period 1960-‘61 to 2019-‘20, breaks were identified in season-by-season collected paddy cultivation statistics in Kerala to study the performance of paddy farming in the state and to identify different growth phases. As a result, it was necessary to comprehend the breakpoints. The methodology utilised to identify the breakpoints was due to Bai and Perron (1998), which involved utilising the “Strucchange package” in R Studio software to obtain the m breakpoints.

The package was programmed to find the best breakpoints. This was similarly true in terms of the differences in factors that contributed to the series' volatility and changes in mean over time. The best breakpoints were chosen using a two-step validity test involving the Residual Sum of Squares (RSS) and Bayesian Information Criteria (BIC). In the first step, the RSS value with the lowest value was deemed ideal. If the optimal breakpoints discovered in step one matched with the lowest BIC, the lowest BIC was considered the optimal breakpoint, and the lowest BIC had precedence on validity. The best breakpoints were those with the smallest BIC.

Lekshmai and Venkataramana (2020) demonstrated how the cropping pattern in Kerala changed when the wet land act was implemented. A number of studies have also confirmed that Kerala's growth dynamisms were suitable for the development of cash crops (Karunakaran, N., 2014 and Unnikrishnan, S., 2009).

A discussion on the area, production and productivity of paddy in Kerala in three seasons, and trend break analysis is followed.

4.2.1. Area under Autumn paddy

In the trend of area under Autumn paddy in Kerala, there were four breakpoints. The optimal five-segment partition was realized by the lowest BIC of -61.53 and RSS of 0.63. The first gap occurred between 1960-‘61 and 1976-‘77, when the yearly growth rate fell to -0.24 per cent. Because of the Intensive Agricultural District Program (IADP) of 1960-‘61 and the Intensive Paddy Development of 1971-‘72, the area under paddy was generally static for the better portion of this phase. However, the area under paddy began to decline in 1975-‘76, which could be described to the year's poor rainfall, which was reduced by more than half from 3528 mm to 1781.5 mm. The decrease in gross irrigated area from 395077 ha in 1966-‘67 to 363822 ha in 1976-‘77 has harmed paddy production in Kerala.

From 1977-‘78 to 1985-‘86, Kerala's paddy acreage went through a second phase. The annual growth rate has dropped to -2.72 per cent. After reaching a high point in the 1970s, the price of paddy began to fall in 1982-‘83. The cost of inputs increased dramatically. All of these factors affected the profitability of paddy farming, perhaps forcing farmers to quit the crop, resulting in a break in area and a further decrease in paddy area from 365111 ha in 1977-‘78 to 279699 ha in 1985-‘86.

The third phase, from 1986 -‘87 to 1995-‘96, was when the group farming program was implemented in 1980-‘90 and paddy area decreased by 3.84 per cent per year. In 1995-‘96, the area under paddy began to shrink dramatically. As a result of this drop, rice prices had increased. In 1995 -‘96, the average wage for paddy field labourers grew to 64.17. From 1986-‘87 to 1995 - ‘96, the area under paddy reduced from 286569 ha to 198725 ha.

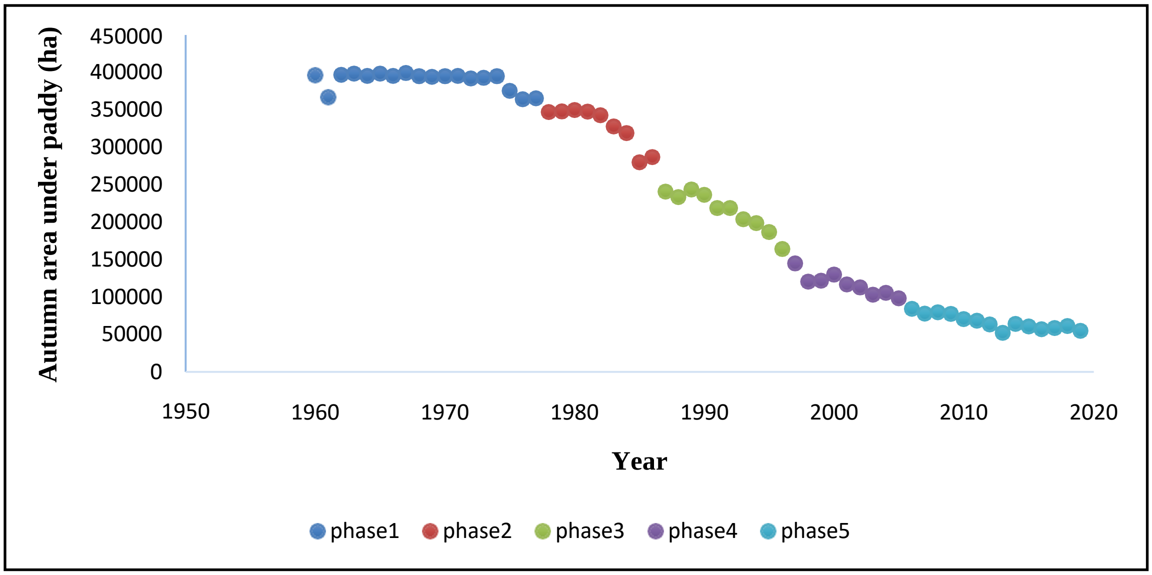

Fig 4.10: Area (ha) under Autumn paddy in Kerala during 1960-‘61 to 2019-‘20

The area under paddy was reduced in the fourth phase 1996-‘97 to 2004-‘05 and the annual growth rate has dropped to -3.95 per cent. There was a minor rise in area in 2004-‘05 owing to the implementation of a scheme to promote paddy cultivation on fallow land. This split could be due to the rapid increase from 2002-‘03 to 2003-‘04.

The area under paddy in this phase has declined throughout the last decade 2005-‘06 to 2019-‘20. However, compared to the previous break, the yearly growth rate improved, owing to the enactment of the Kerala Conservation of Paddy Land and Wetland Act in 2008. This act has a good influence on paddy producers because the area under paddy has risen. This fast increase could be the cause of the break.

4.2.2. Autumn paddy production

The 3 breakpoints with optimal 4 segment partition in Kerala’s autumn paddy production was validated by the lowest BIC of -61.32 and RSS value of 0.68. The initial phase of the time series paddy production lasted from 1960-‘61 to 1985-‘86, with an annual growth rate of 0.29. The Intensive Paddy Development Program which was implemented in 1975-‘76 resulted in a small increase in production. The split could be due to a substantial increase in production.

The second break period in Kerala lasted from 1986-‘87 to 1996-‘97, with the third break occurring from 1997-‘98 to 2004-‘05. Annual growth rates were -2.45 and -3.10 per cent per annum, respectively. The average wage of paddy labourers grew, which might have contributed to the break between 1986-‘87 to 1996-‘97. Paddy production declined to 220132 hectares from 2002-‘03 to 2004-‘05. However there was a modest gain of 241824 hectares in 2004-‘05 because a scheme to promote paddy cultivation in fallow land was launched in 2004-‘05 to boost paddy production in the state. This might be a good reason to occur a break.

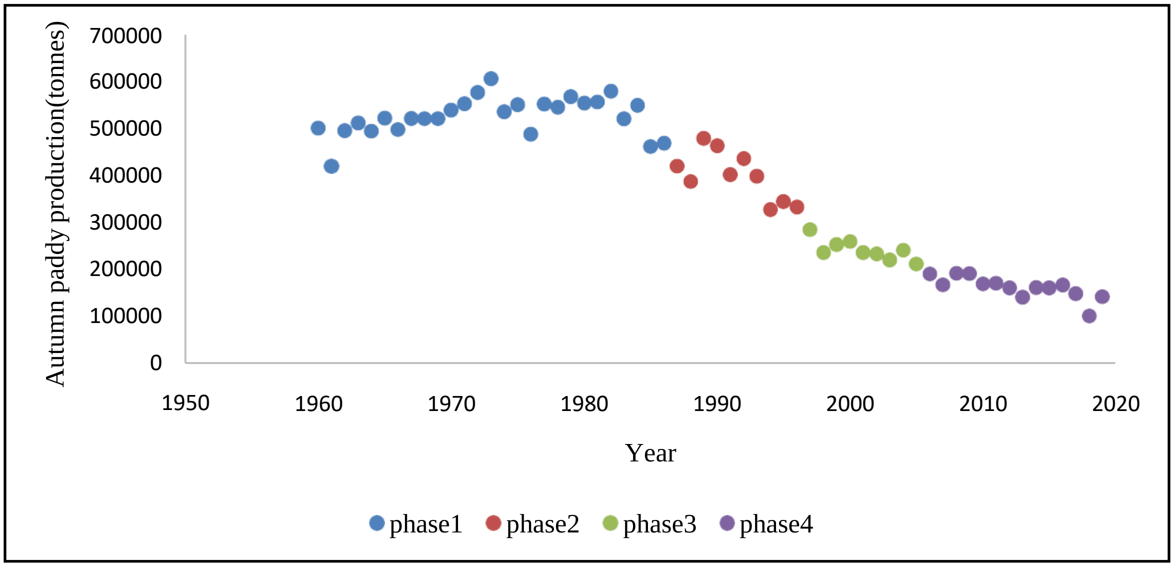

Fig 4.11: Autumn paddy production (tonnes) of Kerala during 1960-‘61 to 2019-‘20

Paddy production fell across the last phase of this phase 2006-‘07 to 2019-‘20. However, due to the enactment of the Kerala Conservation of Paddy Land and Wetland Act in 2008, the yearly growth rate increased compared to the previous break of -2.854. This act has a good influence on paddy producers because the area under paddy has risen. This fast increase could be the cause of the break.

4.2.3. Autumn paddy productivity

Kerala’s autumn paddy showed three breakpoints. In the years 1960-‘61 to 1977-‘76, the optimal four-segment partition was validated by the lowest BIC -97.33 and

RSS value of 0.30. The yearly rate of growth has grown to 1.13. This pause is primarily due to the high yielding varieties programme (HYVP), sometimes known as the Green Revolution, which began in 1965-‘66. Productivity increased dramatically from 7.14 tonnes ha in 1960-‘61 to 7.20 tonnes ha in 1975-‘76.

The following break occurred in the years 1975-‘76 to 1987-‘88 and the third break occurred in the years 1987-‘88 to 2002-‘03 with annual growth rates of 0.83 and 0.73 per cent per annum, respectively. Productivity was significantly reduced due to pest and disease attacks. Rice farming was also unprofitable, if not uneconomical, due to a lack of quality rice on the open market. Productivity in 1987-‘88 was 1663.17 tonnes per hectare, but in 1994-‘95 it fell to 1647.38 tonnes per hectare. This could be the source of the problem.

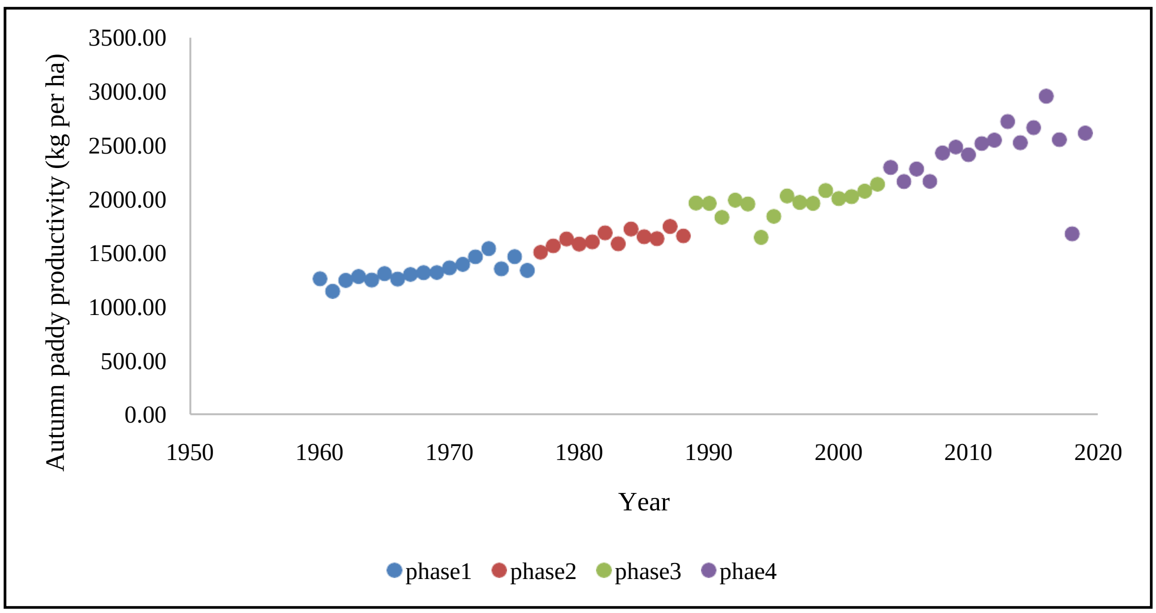

Fig 4.12: Autumn paddy productivity (kg per ha) in Kerala during 1960-61 to 2019-‘20

Paddy productivity has fallen in this phase since 2002-‘03 to 2019-‘20. However, due to investment in the National Food Security Program (NFSM) in 2007, the annual growth rate climbed to 0.55 which might have led to greater productivity, and that act had a beneficial influence on paddy farmers. However, in 2003-‘04, productivity was

2295.46 kg per ha, and as could be seen in the graph, productivity dropped sharply in 2017-‘18 to 1679.00 kg per ha. The main reason for that was because of the paddy farmers were switching to other non-agricultural food crops.

4.2.4. Winter paddy area

In Kerala, there were five breakpoints in the trend of area under winter paddy. The best six-segment partition was determined by a lowest BIC of -88.40 and RSS of 0.35. The frequency of breaks was largest in the winter season. The first interruption occurred between the years 1960-‘61 and 1967-‘68, when the annual growth rate jumped to 1.52 per cent per year, owing mostly to the government's implementation of the Land Reform Act in 1967.

The second break 1967-‘68 to 1976-‘77 and the third break 1976-‘77 to 1986-‘87 were followed by the fourth break 1986-‘87 to 1995-‘96. And the annual growth rate was -0.069, -2.008, and -3.010 respectively. The area under winter paddy had decreased from 327509 ha in 1967-‘68 to 210309 ha in 1995-‘96. The main reason for the decline was that paddy farmers have changed their lands into rubber plantations as working in paddy fields was much harder and labour wages had also increased and there would be more pest attacks, in spite of all these there was a significant increase in 2009-‘10 due to the introduction of paddy wet land and conservation act.

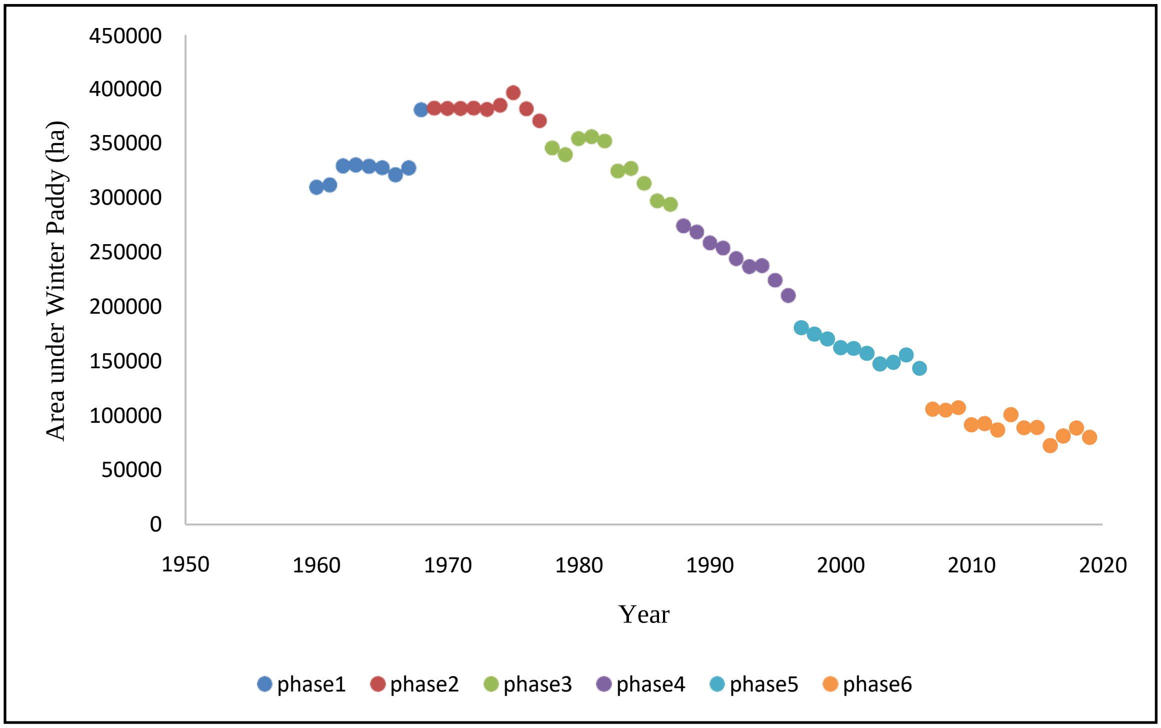

Fig 4.13: Area (ha) under winter paddy in Kerala during 1960-61 to 2019-‘20

The yearly growth rates were -2.31 and -2.40 respectively for the last two breaks 1995-‘96 to 2005-‘06 and 2005-‘06 to 2019-‘20. This was primarily due to a flood occurred in August 2018, which resulted in significant losses in the paddy area.

4.2.5. Winter paddy production

Kerala's winter paddy crop production trend had four breakpoints. The best five-segment partition, was determined by the lowest BIC of -61.07 and RSS of 0.35. The frequency of breaks was largest in the Winter season. The first break came from the previous year 1960-‘61 to 1967-‘68. The annual growth rate had been boosted to 1.24 per cent. The government enacted the Land Reform Act in 1967, which became subordinate legislation under the Essential Commodities Act in 1995.

Second break point 1967-‘68 to 1984-‘85, third break 1984-‘85 to 1995-‘96 and fourth break 1995-‘96 to 2005-‘06 occurred with annual growth rates of -0.21, -0.38 and -0.93, respectively. The rate of production was steadily reduced. Because the average farmer salary grew to 64.17 in 1995-‘96 from 52.73 in 1994-‘95, the rising cost of labour might have alienated paddy farmers from continuing to produce paddy, and as a result, irrigation facilities were not being used as farmers left their land fallow. As a result, there was a break. The scheme to promote paddy planting in fallow lands was started in 2004-‘05, which resulted in a minor increase in production in 2005-‘06. This could be the reason for the break during this year.

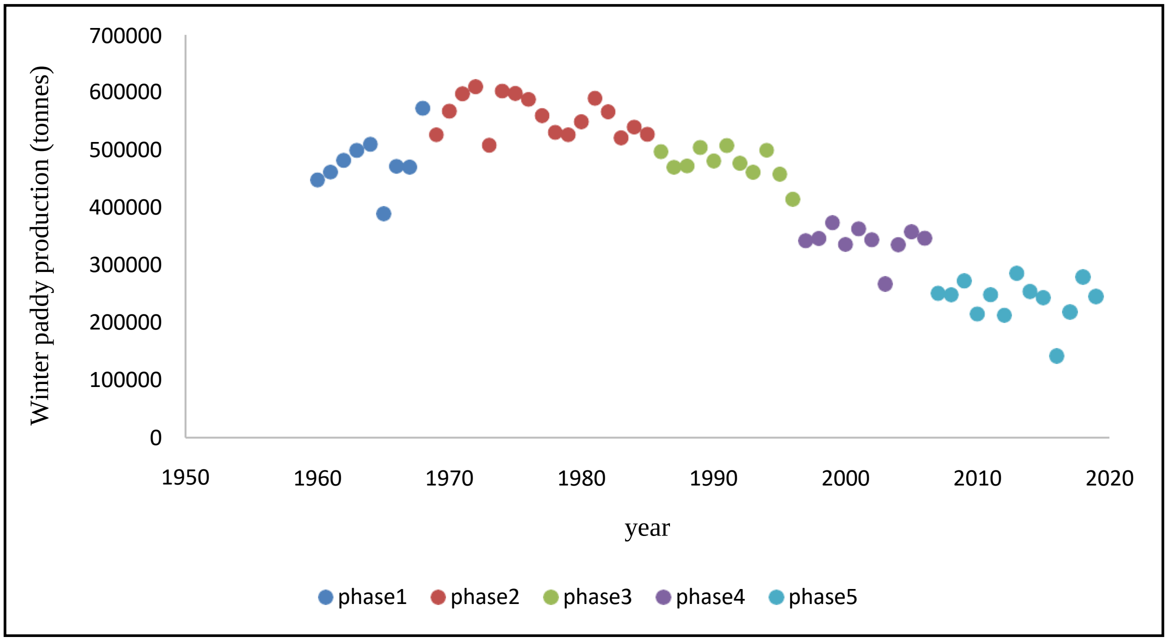

Fig 4.14: Winter paddy production (tonnes) in Kerala during 1960-‘61 to 2019-‘20

In the most recent era (2005-‘06 to 2019-‘20), the annual growth rate fell to -0.85, the year 2016-‘17 saw a sharp drop in productivity, owing primarily to pest attacks.

4.2.6. Winter paddy productivity

There were three breakpoints in Kerala’s trend in winter paddy productivity. The optimal four-segment division contained the breaks, as evidenced by the lowest BIC -100.65 and RSS 0.33. The first break occurred between the years 1960-‘61 and 1967-‘68, when the yearly growth rate increased to 0.36. This increase was mostly attributable to the introduction of the High Yielding Variety (HYV) in Green revolution, which might be the cause of higher productivity and the break**.**

The annual growth increased to 0.76 and 0.75 during the second 1967-‘68 to 1984-‘85 and third 1984-‘85 to 1995-‘96 breaks. When the group farming program was started in 1989-‘90, production also increased. When the Essential Commodity Act was passed in 1995, productivity increased again.

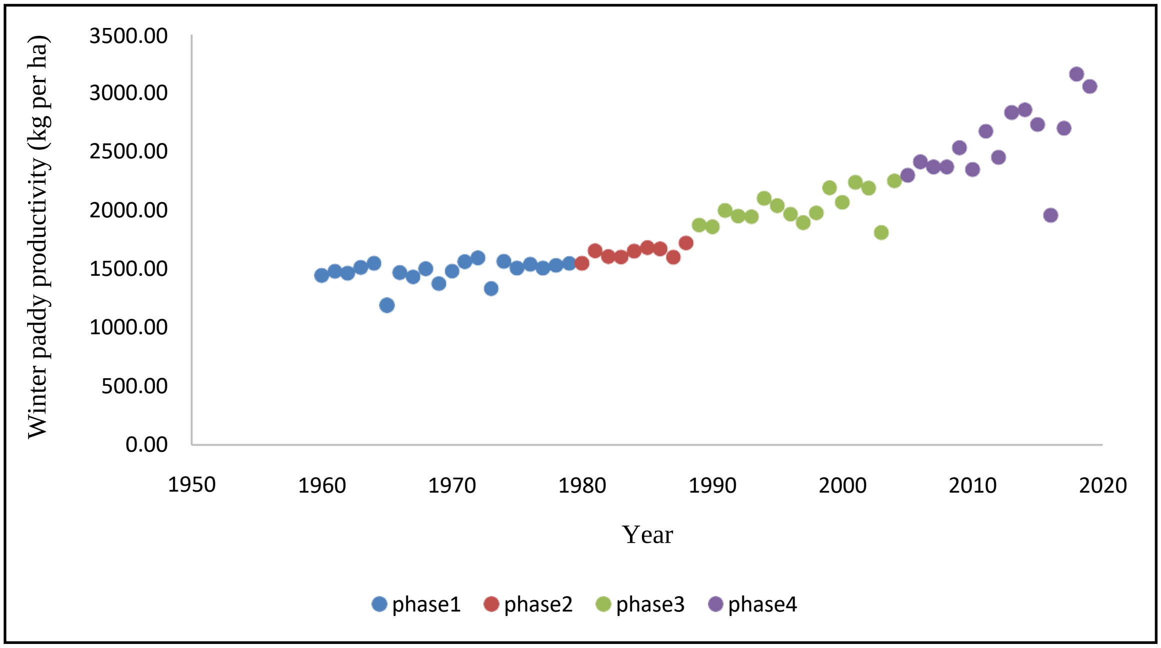

Fig 4.15: Winter paddy productivity (kg per ha) in Kerala during 1960-‘61 to 2019-‘20

The yearly growth rate has improved by 1.50 after the last gap 2005-‘06 to 2019-‘20, owing primarily to the Mahatma Gandhi National Rural Employment Guarantee (MGNREGA) Act on 2006. Harvesting was mechanized in practically every section of the state, therefore there would be a minor increase. The year 2016-‘17 saw a sharp drop in productivity, owing to pest and disease attacks.

4.2.7. Summer paddy area

In Kerala, there were four breakpoints in the trend of area under Summer paddy. The best five-segment partition was determined by the lowest BIC of -41.308 and RSS of 0.819. The number of breaks was more in the Summer. The first break came from theyear 1960-‘61 to 1967-‘68. The yearly rate of growth grew by 2.31 per cent. Summer paddy area grew mostly owing to the introduction of High Yielding Variety (HYV), which might be the explanation for the rise in paddy fields during that year. Also, the government began to provide loans to paddy farmers, which might account for the increase. And that might have resulted in a break.

Annual growth rates fell by -1.10 and -1.95 during the second and third breaks, respectively, from 1967-‘68 to 1985-‘86 and 1985-‘86 to 2000-‘01. Pest and disease attacks were primarily to blame. Due to the rise in rubber prices, some paddy farmers have turned their acreage to rubber plantations.

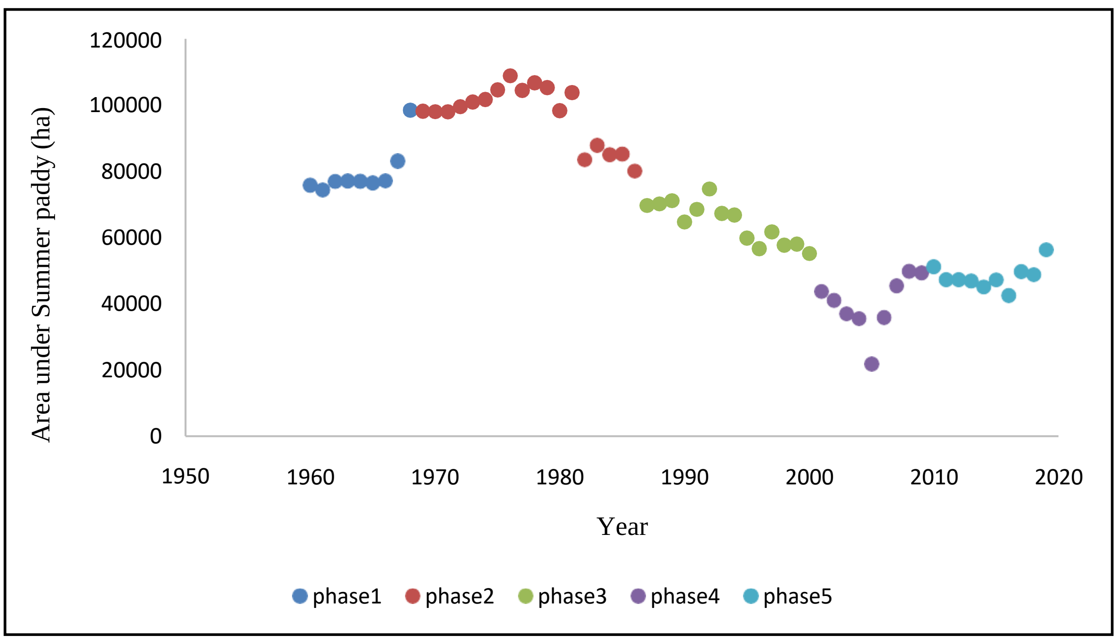

Fig 4.16: Area (ha) under Summer paddy in Kerala during 1960-‘61 to 2019-‘20

The fourth break from 2000-‘01 to 2008-‘09 was the most recent 2008-‘09 to 2019-‘20. In comparison to the previous break, the yearly growth rate was boosted to

2.45 and 0.66, respectively. That was primarily owing to the government's high focus for rice culture resuscitation, with the 11th five-year plan 2007-‘12 aiming to bring at least 40000 extra hectares under rice. The price increase had sparked a lot of excitement and optimism among farmers. (Kerala calling December 2015).

4.2.8. Summer paddy production

In Kerala, there were four breakpoints in the trend of area under summer paddy production. The best 5-segment partition was determined by the lowest BIC of -23.83 and RSS of 1.19. The number of breaks was greater in the summer. The first break came from the year 1960-‘61 to 1967-‘68. And the yearly growth rate increased to 1.77 per cent in 1967-‘68 owing primarily to the government's implementation of the Land Reform Act. In 1965-‘66 there was a significant drop in production due to pest and disease attacks, resulting in a significant loss. In 1966-‘67 production had increased once more owing primarily to (HYV) in 1966.

Second and third breaks occurred during 1967-‘68 to 1985-‘86 and 1985-‘86 to 2000-01 and fourth break was 2000-‘01 to 2008-‘09. And the annual growth rates were -0.45 and -0.41, 4.27 per cent respectively per year. Low rainfall in 1991 and 2002 might have been a factor in the occurrence of a hiatus. However, due to the paddy wet land act in 2008, there was a significant increase in 2008-‘09. This had a good effect on paddy growers, which could be the cause of another break.

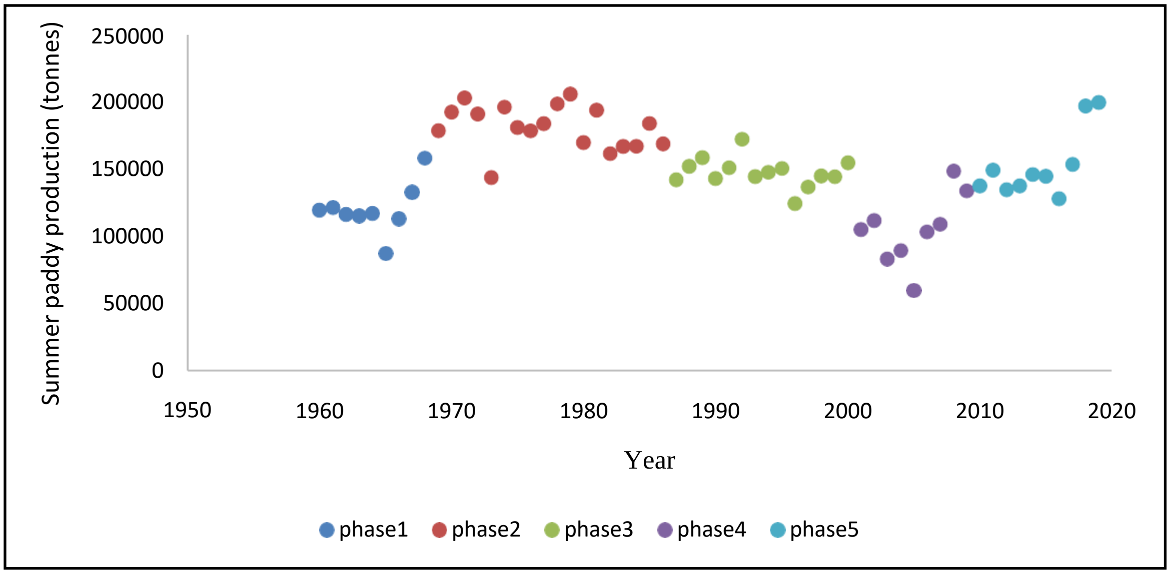

Fig 4.17: Summer paddy production (tonnes) in Kerala during 1960-‘61 to 2019-‘20

The final break was during 2008-‘09 to 2019-‘20. And the annual growth rate had climbed to 3.52 per cent every year, but it has declined after the last break. However, the 11th five-year plan has had a significant influence on paddy farmers, resulting in higher productivity. The government began providing loans to paddy growers. compared to all, this season showed an increasing production trend.

4.2.9. Summer paddy productivity

Kerala's summer paddy productivity trend had four breakpoints. The best 5-segment partition was determined by the lowest BIC of -86.37 and RSS of 0.42. Thefirst gap occurred between the years 1960-‘61 and 1967-‘68 and the annual growth rate fell to -0.52 per cent per year due to a dip in rice prices. This could be the cause of the break**.**

The second break was from 1967-‘68 to 1983-‘84, the third break was from 1983-‘84 to 1996-‘97, and the fourth break was from 1996-‘97 to 1997-‘98. And the fifth break was from 1996-‘97 to 2009-‘10. Annual growth rates increased by 0.22, 0.69, and 0.78 per cent, respectively, owing to the state's plans to launch a massive people effort combining technology, funding and legal support to assist paddy farmers, as well as new government programs to create a permanent path for protecting rice fields and making rice culture economic and profitable. This might have caused the break.

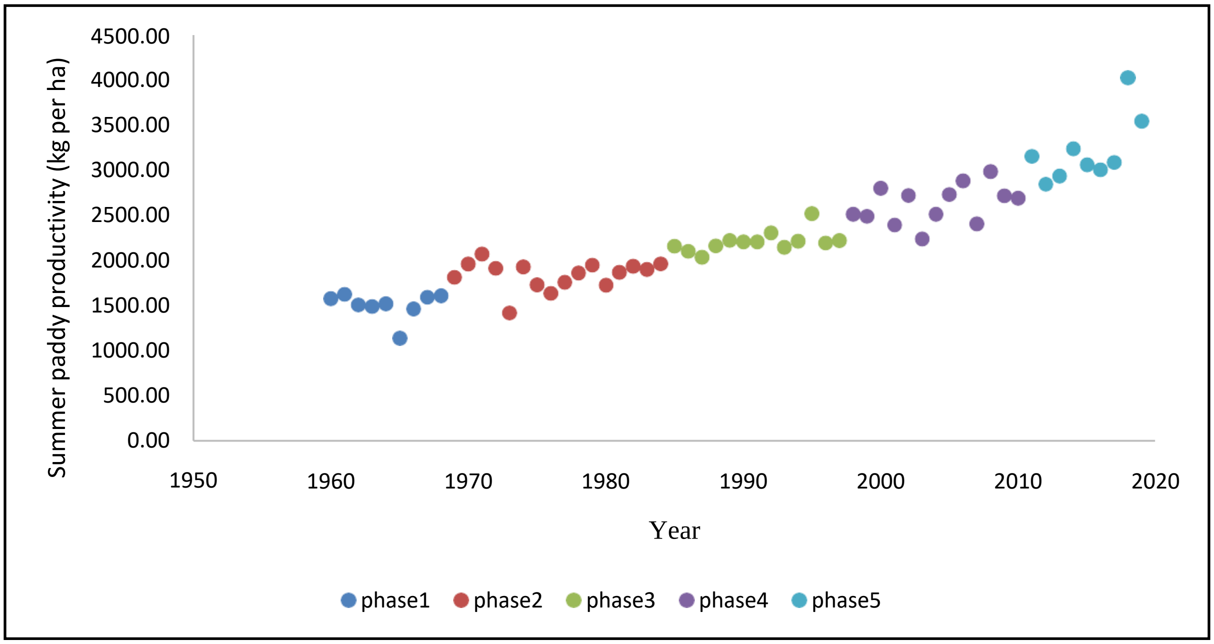

Fig 4.18: Summer paddy productivity (kg per ha) in Kerala during 1960-‘61 to 2019-‘20

The yearly growth rate grew by 2.58 per cent per annum from the previous break in the season 2009-‘10 to 2019-‘20. The main reason for the interruption was that the number of soil samples being tested was increasing. 1.5 lakh soil samples were gathered, a soil health map was created for each unit, and a manuring program was advised. This world-record-breaking feat has aided in the reduction of fertilizer costs and the implementation of optimal plant nutrient use. Paddy productivity increased as a result of this.

4.3 Compound Growth Rate Analysis

Growth and instability in area, production and productivity of three seasons in Kerala

For several periods of expansion in the economy, the annual growth rates of area, production, and productivity as well as the instability of paddy crop in three seasons were analyzed using trend break analysis. To better understand the growth and instability of crops in Kerala over the course of the study, an analysis was carried out for the full period of study. The Cuddy-Della Valle Index (CDVI) was used to assess the stability of rice crop area, production, and productivity, while Compound Annual Growth Rate(CAGR) were used to examine annual growth in paddy crop area, production, and productivity in the state.

4.3.1. Autumn season

4.3.1.1. Growth and instability in area under Autumn paddy

By using trend break analysis the entire data was divided into 5 phases viz,

Period I - 1960-‘61 to 1976-‘77

Period II -1977-‘78 to 1985-‘86

Period III -1986-‘87 to 1995-‘96

Period IV -1996-‘97 to 2004-‘05

Period V - 2005 -‘06 to 2019-‘20.

Table 4.12: Growth and instability in area under Autumn paddy in Kerala for the period from 1960-’61 to 2019-‘20

	No. of breaks	Compound Annual Growth Rate (%)	Cuddy Della Valley Index (CDVI) (%)
Autumn area	1	-0.257	2.91
	2	-2.72	4.16
	3	-3.843	4.24
	4	-3.95	5.75
	5	-3.106	7.3

The first phase 1960- ‘61 to 1976-‘77 which coincided with the Green Revolution had a negative growth rate as shown in Table 4.12. Nevertheless, when compared to all other phases, the first was better, and it also had the lowest CDVI value, implying that it would be more stable. The growth rate was slightly lower in the second phase 1977-‘78 to 1985-’86 and the CDVI value was likewise less consistent than in the first phase, owing to the conversion of paddy lands to plantation crops. Phase three 1986-’87 to 1995 -‘96 and phase four 1996-‘97 to 2004-‘05 faced a decrease in growth rate, as well as an increase in the instability as depicted by CDVI values. The decrease in paddy prices might be the main reason for that. These factors made paddy farming less profitable.

The final stage was 2005-‘06 to 2019-‘20. In comparison to the last break, the growth rate increased marginally. The CDVI value became unstable due to the introduction of conservation of paddy land and wet land act in 2008.

4.3.1.2. Growth and instability of Autumn paddy production

By using trend break analysis the entire data was divided into 4 phases,

Period I - 1960- ‘61 to 1985-‘86

Period II -1986-‘87 to 1996-‘97

Period III - 1996-‘97 to 2004-‘05

Period IV - 2005-‘06 to 2019- ‘20

Table 4.13: Growth and instability of Autumn paddy production in Kerala for the period from 1960-’61 to 2019-‘20

	No. of breaks	Compound Annual Growth Rate (%)	Cuddy Della Valley Index (CDVI) (%)
Autumn production	1	0.29	7.41
	2	-3.1	9.97
	3	-2.45	6.24
	4	-2.85	9.76

From Table 4.13. it could be noticed that Autumn paddy production trend showed four breakpoints, with the exception of period I, all remaining phases showed a negative growth rate and only period I showed a positive growth rate, owing to the government's intensive paddy development program during 1975-‘76 in the first phase. Period III had a comparatively more stable value since it had the lowest CDVI value, while period II had the highest CDVI value, resulted in an extremely unstable phase.

4.3.1.3. Growth and instability of Autumn paddy productivity

By using trend break analysis the entire data was divided into 4 phases,

Period I - 1960-‘61 to 1975-‘76

Period II - 1976-‘77 to 1987-‘88

Period III - 1988-‘89 to 2002-‘03

Period IV - 2003-‘04 to 2019- ‘20

Table 4.14: Growth and Instability of Autumn paddy productivity in Kerala for the period from 1960-’61 to 2019-‘20

	No. of breaks	Compound Annual Growth Rate (%)	Cuddy Della Valley Index (%)
Autumn productivity	1	1.137	4.5
	2	0.838	2.9
	3	0.738	5.2
	4	0.557	11.78

It could be observed from Table 4.14 that autumn paddy productivity trend showed 4 breakpoints, among that, period I showed the highest growth rate followed by period II, and the least growth rate was in period IV, the least growth rate might be mainly due to pest and disease attack, and highest CDVI value was in period III, it was more unstable and the lowest CDVI value was in period II with high stability.

4.3.2. Winter season

4.3.2.1. Growth and instability in area under Winter paddy

By using trend break analysis the entire data was divided into 6 phases,

Period I - 1960-‘61 to 1967-‘68

Period II -1968-‘69 to 1976-‘77

Period III - 1977-‘78 to 1986-‘87

Period IV - 1987-‘88 to 1995-‘96

Period V -1996-‘97 to 2005-‘06

Period VI - 2006-‘07 to 2019-‘20

The area under winter paddy had six breakpoints, the highest CDVI was in period I, with the exception that all other periods showed a negative growth rate. Since, paddy lands had been converted to various non-agriculture food crops, the area under cultivation of winter paddy had declined in recent years. Period IV showed the lowest growth rate, and period I had the highest CDVI value, which indicated that the area under winter paddy was extremely instable, whereas period IV showed the lowest CDVI value, which indicated more stability but the growth rate was negative.

Table 4.15: Growth and instability of area under Winter paddy in Kerala for the period from 1960-'61 to 2019-'20

	No. of breaks	Compound Annual Growth Rate (%)	Cuddy Della Valley Index (CDVI) (%)
Winter Area	1	1.52	4.81
	2	-0.069	1.8
	3	-2.008	3.77
	4	-3.01	1.48
	5	-2.313	2.76
	6	-2.408	7

4.3.2.2. Growth and instability of Winter paddy production

By using trend break analysis the entire data was divided into 5 phases,

Period I - 1960-'61 to 1967-'68

Period II-1968-'69 to 1984-'85

Period III - 1985-'86 to 1995-'96

Period IV - 1996-'97 to 2005-'06

Period V - 2006-'07 to 2019-'20

Table 4.16: Growth and instability of Winter paddy production in Kerala for the period from 1960-'61 to 2019-'20

	No. of breaks	Compound Annual Growth Rate (%)	Cuddy Della Valley Index (CDVI) (%)
Winter production	1	1.24	10.22
	2	-0.383	5.7
	3	-0.932	5.04
	4	-0.565	8.5
	5	-0.854	16.05

Winter paddy production trend had 5 breakpoints as shown in Table 4.16 with period I showing a positive growth rate and the subsequent periods showing negative growth rates. Production had also fallen over time, since paddy farmers were not profiting from their crop due to low prices. Period I had the highest growth rate and period V had the lowest growth rate. Period III had the lowest CDVI value of all the periods, indicating that it was the most stable period. Period V had the greatest CDVI value, indicating that it was the most unstable of all the periods.

4.3.2.3. Growth and instability of Winter paddy productivity

By using trend break analysis the entire data was divided into 5 phases,

Period I - 1960-'61 to 1967-'68

Period II-1968-'69 to 1984-'85

Period III - 1985-'86 to 1995-'96

Period IV - 1996-'97 to 2005-'06

Period V -2006-'07 to 2019-'20

Table 4.17: Growth and instability in Winter paddy productivity in Kerala for theperiod from 1960-'61 to 2019-'20

	No. of breaks	Compound Annual Growth Rate (%)	Cuddy Della Valley Index (CDVI) (%)
Winter productivity	1	0.364	6
	2	0.763	2.6
	3	0.758	5.99
	4	1.5	10.35

Winter paddy productivity had 4 break points, as seen in Table 4.17 period IV had the highest growth rate of all, followed by period III, owing to the act 'Mahatma Gandhi National Rural Employment Guarantee' (MGNREGA) raising the paddy price, which could be the reason for the increase. Period I had the slowest growth rate, indicating that productivity grew over the previous eras. Period II had the lowest CDVI, which indicated good stability, whereas period IV had the greatest CDVI, which indicated low stability. Period I came after that.

4.3.3 Summer season

4.3.3.1. Growth and instability in area under Summer paddy

Period I - 1960-'61 to 1967-'68

Period II - 1968-'69 to 1985-'86

Period III- 1986-'87 to 2000-'01

Period IV - 2001-'02 to 2008-'09

Period V - 2009-'10 to 2019-'20

Table 4.18: Growth and instability of area under Summer paddy in Kerala for the period from 1960-'61 to 2019-'20

	No. of breaks	Compound Annual Growth Rate (%)	Cuddy Della Valley Index (CDVI) (%)
Summer area	1	2.31	6.99
	2	-1.10	7.4
	3	-1.95	5.4
	4	2.44	21.6
	5	0.66	7.77

The Summer area had 5 break points, as shown in Table 4.18 periods I, IV, and V had positive growth rates, whereas periods II and III had negative growth rates. Period IV had the largest growth rate, which could possibly be attributable to the implementation of the Wet Land Paddy Act during that time period. Period III, on the other hand, had the lowest growth rate due to a drop in paddy cultivation area. And in comparison to all other periods, period IV had the greatest CDVI value indicating that it was the most unstable, while period III had the lowest CDVI value indicating that it was the most stable.

4.3.3.2. Growth and instability of Summer paddy production

Period I - 1960-'61 to 1967-'68

Period II - 1968-'69 to 1985-'86

Period III -1986-'87 to 2000-'01

Period IV- 2000-'01 to 2008-'09

Period V - 2009-'10 to 2019-'20

Table 4.19: Growth and instability of Summer paddy production in Kerala for the period from 1960-'61 to 2019-'20

	No. of breaks	Compound Annual Growth Rate (%)	Cuddy Della Valley Index (CDVI) (%)
Summer production	1	1.77	15.44
	2	-0.45	8.83
	3	-0.41	7.49
	4	4.27	23.13
	5	3.52	12.43

Summer paddy production is depicted in Table 4.19 having 5 breakpoints, all of which, with the exception of periods I and III, indicated a positive growth rate. Period IV had the highest growth rate, followed by period V, owing to the implementation of the 11th five-year plan, which could explain the abrupt increase in output and the lowest CDVI value recorded in period III showing maximum stability when compared to all other periods and the highest CDVI value recorded in period IV resulted in extreme instability when compared to all other periods and period I turned out highly unstable.

4.3.3.3. Growth and instability of Summer paddy productivity

By using trend break analysis the entire data was divided into 5 phases,

Period I - 1960-'61 to 1967-'68

Period II - 1968-'69 to 1983-'84

Period III - 1984-'85 to 1996-'97

Period IV-1997-'98 to 2009-'10

Period V - 2010-'11 to 2019-'20

Table 4.20: Growth and instability of Summer paddy productivity in Kerala for the period from 1960-'61 to 2019-'20

	No. of breaks	Compound Annual Growth Rate (%)	Cuddy Della Valley Index (%)
Summer productivity	1	-0.522	10.44
	2	0.22	8.7
	3	0.697	4.5
	4	0.786	8.15
	5	2.586	9.31

Summer paddy productivity had five break points, as explained in Table 4.20. Except for period I, every year had a positive growth rate. Period V had the highest growth rate, followed by period IV owing to the government's new programs to create a permanent path for conserving rice fields and making rice cultivation more economic and profitable. And it was the slowest growth rate since period I. Period I had the greatest CDVI value, which indicated that it was highly unstable, followed by period V, and period III had the lowest CDVI value, which indicated that it was stable in comparison to all other periods, followed by period IV.

4.4 Time Series Modelling

Time series forecasting uses information regarding historical values and associated patterns to predict future activity. The Box-Jenkins model, for instance, is a technique designed to forecast data ranges based on inputs from a specified time series. It forecasts data using autoregressive, differencing, and moving average component terms. These three components are denoted as p, d, q respectively.

4.4.1. Forecasting of Area under Autumn paddy in Kerala

The data for the years from 1960-‘61 to 2009-‘10 was taken as a training period with respect to area under Autumn paddy in Kerala for fitting forecast models. From among several models tried the Browns’ exponential smoothing model was found to be the best model to forecast the area under autumn paddy in Kerala. After validation of the model, forecasts for the next five years were made using Browns exponential smoothing model. The results are outlined in Table 4.22, which showed high value of R^2 alongwith other values of RMSE, MAPE, MAE and BIC.

Table 4.21: Parameters of the Browns’ exponential smoothing model for area under Autumn paddy in Kerala during training period

Alpha (Level)	**Estimate**	**SE**	**t**	**P-value**
	0.412	0.05	7.09	<0.001

Accuracy measures of Browns’ exponential smoothing model are given in Table 4.22. The model showed a high R^2 value of 98.9 per cent and a low MAPE of 4.39.

Table 4.22: Accuracy measures of Browns’ exponential smoothing model during training period

Fit statistic	**Brown model**
R^2	0.98
RMSE	12616.25
MAPE	4.39
MAE	8925.54
BIC	18.96

From Fig. 4.19 it is evident that the actual and forecasted values of area under Autumn paddy were in close agreement.

Table 4.23: Actual and forecasted values of area under Autumn paddy in Kerala

Year	Actual	Forecast	UCL	LCL
2010-'11	70498	70269.1	95622.4	44915.79
2011-'12	68135	65557.28	98395.02	32719.54
2012-'13	63232	60845.46	102216.2	19474.74
2013-'14	51922	56133.64	106920.8	5346.48
2014-'15	63981	51421.83	112402.2	-9558.51
2015-'16	60418	46710.01	118586.4	-25166.4
2016-'17	56601	41998.19	125419.3	-41422.9
2017-'18	58278	37286.37	132858.7	-58285.9
2018-'19	60718	32574.56	140870.8	-75721.6
2019-'20	54693.89	27862.74	149427.4	-93701.9

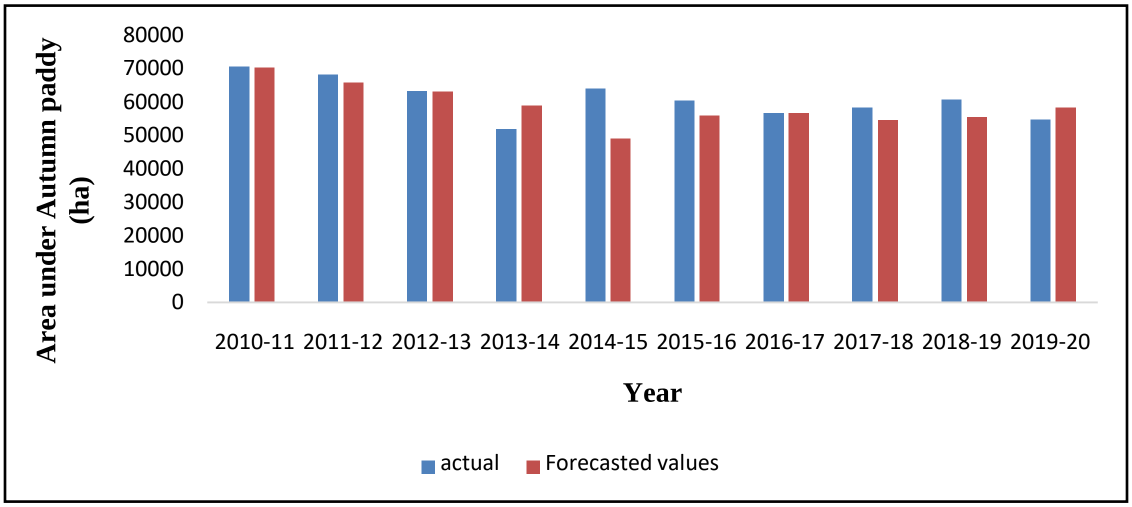

Fig 4.19: Validation of predicted area under Autumn paddy in Kerala using Brown's exponential smoothing model for 2010-'11 to 2019-'20

The parameters of the Browns' exponential smoothing model for area under paddy are summarized in Table 4.24. The coefficients of the model were α = 0.412 which was significant at 1 per cent level. Thus, the Brown's exponential smoothing model could be used to forecast the area under Autumn paddy in Kerala for the next 5 years from 2020- '21 to 2024-'25

Table 4.24: Parameters of the final Browns' exponential smoothing model for area under Autumn paddy in Kerala

Alpha (Level)	**Estimate**	**SE**	**t**	**P-value**
	0.41	0.53	7.84	<0.001

In general, the Brown's exponential smoothing model can be represented as

- $S_t = \text{a } X_t + (1-\text{a})S_{t-1}$
- $T_t = \text{a } S_t + (1-\text{a})T_{t-1}$
- $a_t = 2S_t - T_t$
- $b_t = \frac{1-\propto}{\propto} \text{ x}(S_t - T_t)$
- $F_{t+1} = a_t + b_t$

Therefore in the particular case of autumn paddy data in Kerala, Brown's exponential smoothing model,

$S_t = 0.41X_t + 0.59S_{t-1}$

$T_t = 0.16X_t + 0.24S_t + 0.59T_{t-1}$

$a_t = 0.82X_t - 0.41S_{t-1} + 1.77T_{t-1}$

$b_t = 0.28X_t + 0.40S_{t-1} - 0.28S_t + 0.40T_{t-1}$

$F_t = 0.82X_t - 0.41S_t + 1.77T_{t-1} + 0.28X_t + 0.40S_{t-1} - 0.28S_t + 0.40T_{t-1}$

Accuracy measures of Browns' exponential smoothing model are given in Table4.25. The model shows a high R^2 value of 99.3 per cent and a low MAPE of 4.83.

Table 4.25: Accuracy measures of final Brown's exponential smoothing model

Fit statistic	Browns' model
R^2	0.99
RMSE	11757.34
MAPE	4.83
MAE	8140.003
BIC	18.81

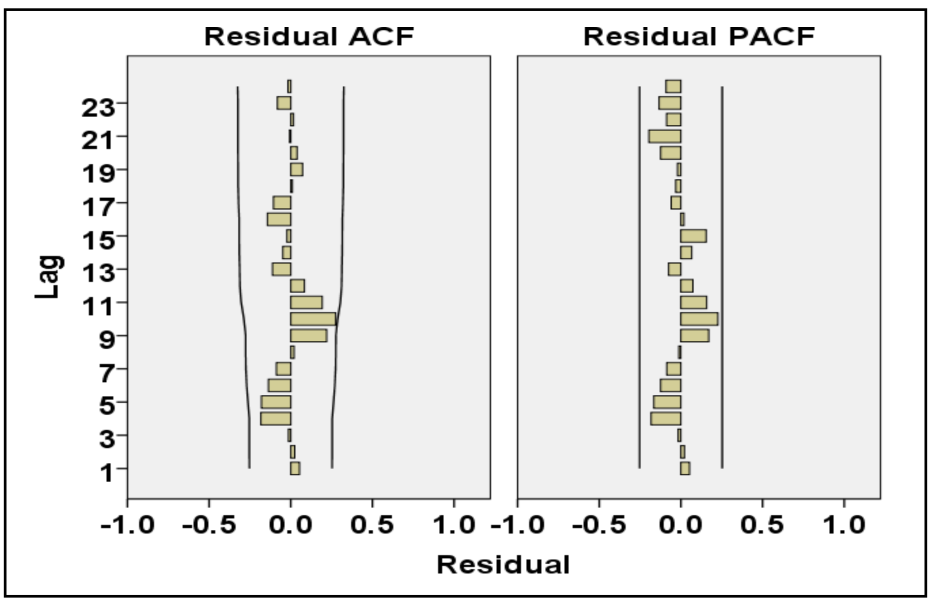

Fig 4.20: Residual ACF and PACF plots of Brown's exponential smoothing model for Autumn paddy area

From the Fig 4.20, it could be observed that ACF and PACF values lie within the confidence limits or the residuals were almost close to white noise.

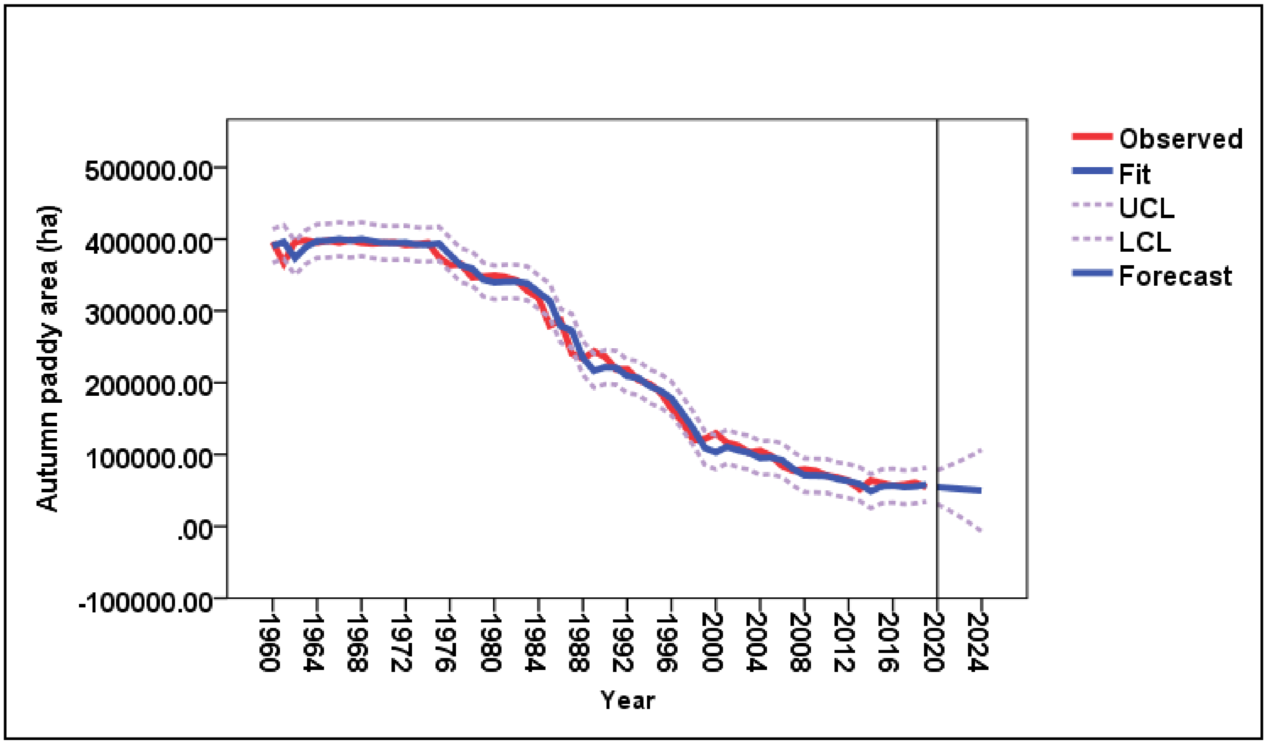

Fig 4.21: Actual and predicted area under Autumn paddy in Kerala during 1960-'61 to 2024-'25

Area under Autumn paddy in Kerala were forecasted for a period from year 2020-'21 to 2024-'25 based on the fitted model. Results are given in table 4.26.

Table 4.26: Forecasted area under Autumn paddy in Kerala for the period 2019-'20-2024-'25

Year	2020-'21	2021-'22	2022-'23	2023-'24	2024-'25
Forecasted area (ha)	54724.89	53507.39	52289.89	51072.39	49854.89

Table 4.26 depicts the forecasted Autumn paddy area in Kerala for the years from 2020-2025. The graph in Fig 4.21 showed a decreasing trend for the area under Autumn paddy for the period from 2020-2025 by an amount of 54724.89 to 49854.89.

4.4.2. Forecasting of Autumn Paddy production

The data for the years from 1960-‘61 to 2009-‘10 was taken as a training period with respect to Autumn paddy production in Kerala for fitting forecast models. From among several models tried, the Browns’ exponential smoothing model was found to be the best model to forecast the Autumn paddy production in Kerala. After validation of the model, forecasts for five years were made using Browns exponential smoothing model. The results are outlined in Table 4.28, which showed high value of R^2 along with other values of RMSE, MAPE, MAE and BIC.

The parameters of the exponential smoothing coefficients of the Browns model for Autumn paddy production are summarized in Table 4.27. The coefficient of the model was α = 0.291 which was significant at 1 per cent level. Thus, the Brown’s exponential smoothing model could be used to forecast the Autumn paddy production in Kerala

Table 4.27: Parameters of Brown’s exponential smoothing model for Autumn paddy production in Kerala during training period

Alpha (Level)	Estimate	SE	t	P-value
	0.29	0.05	5.70	<0.001

Accuracy measures of Browns’ exponential smoothing model are given in the Table 4.28. The model showed a high R^2 value of 92.6 Per cent and a low MAPE of 7.27.

Table 4.28: Accuracy measures of Brown's exponential smoothing model for Autumn paddy production during training period

Fit statistic	Brown's model
R^2	0.92
RMSE	36593.82
MAPE	7.27
MAE	27637.28
BIC	21.09

Table 4.29: Actual and forecasted values of Autumn paddy production in Kerala

Year	Actual	forecast	UCL	LCL
2010-'11	170262	171914.4	245452.4	98376.34
2011-'12	171662	163782.6	248851.1	78714
2012-'13	161083	155650.8	253813.3	57488.18
2013-'14	141234	147519	260137.1	34900.83
2014-'15	161477	139387.1	267663.5	11110.8
2015-'16	160894	131255.3	276269.6	-13758.9
2016-'17	167181	123123.5	285859.8	-39612.8
2017-'18	148913	114991.7	296358.8	-66375.4
2019-'20	142946	98728.1	319852.4	-122396

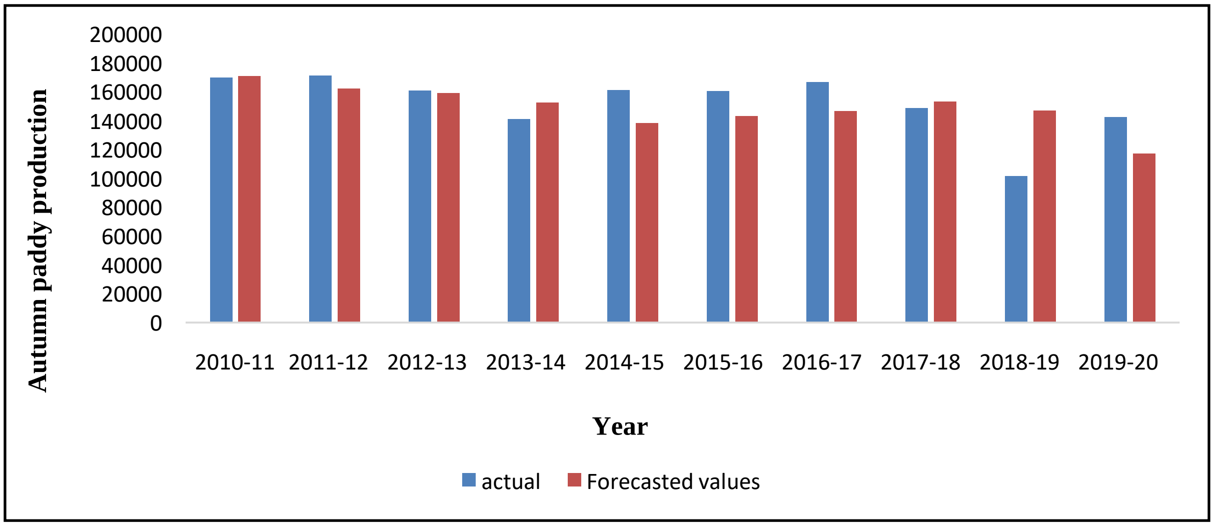

Fig 4.22: Validation of predicted Autumn paddy production in Kerala using Brown's exponential smoothing model for 2010-'11 to 2019-'20

The parameters of the exponential smoothing coefficients of the Browns' model for Autumn paddy production are summarized in Table 4.30. The coefficient of the model was α = 0.287 which was significant at 1per cent level. Thus, the Brown's exponential smoothing model could be used to forecast the autumn paddy production in Kerala for thenext 5 years from 2020-'21 to 2024-'25.

Table 4.30: Parameters of the final Browns' exponential smoothing model for Autumn paddy production in Kerala

Alpha (Level)	Estimate	SE	t	P-value
	0.287	0.04	6.30	<0.001

Brown's exponential smoothing model, $S_t = 0.28X_t + 0.72S_{t-1}$

$T_t = 0.078X_t + 0.02S_t + 0.72T_{t-1}$

$a_t = 0.482X_t + 1.64S_{t-1} + 0.72T_{t-1}$

$b_t = 0.077X_t + 0.27S_{t-1} - 0.007S_t + 0.27T_{t-1}$

$F_t = 0.559X_t + 1.91S_{t-1} + 0.007S_t + 0.99T_{t-1}$

Accuracy measures of Browns' exponential smoothing model are given in Table 4.31. The model showed a high R^2 value of 95.3 per cent and a low MAPE of 8.026.

Table 4.31: Accuracy measures of final Browns' exponential smoothing model for Autumn paddy production

Fit statistic	Brown model
R^2	0.95
RMSE	34399.446
MAPE	8.026
MAE	25693.166
BIC	20.960

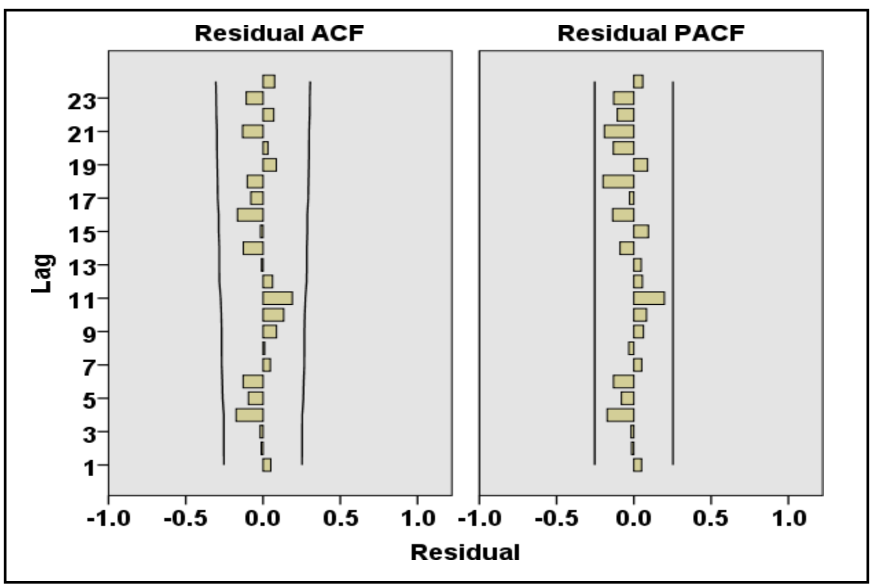

Fig 4.23: Residual ACF and PACF plots of Brown's exponential smoothing model for Autumn paddy production

From the Fig 4.23 it could be observed that ACF and PACF values lie within the confidence limits or the residuals were almost close to white noise.

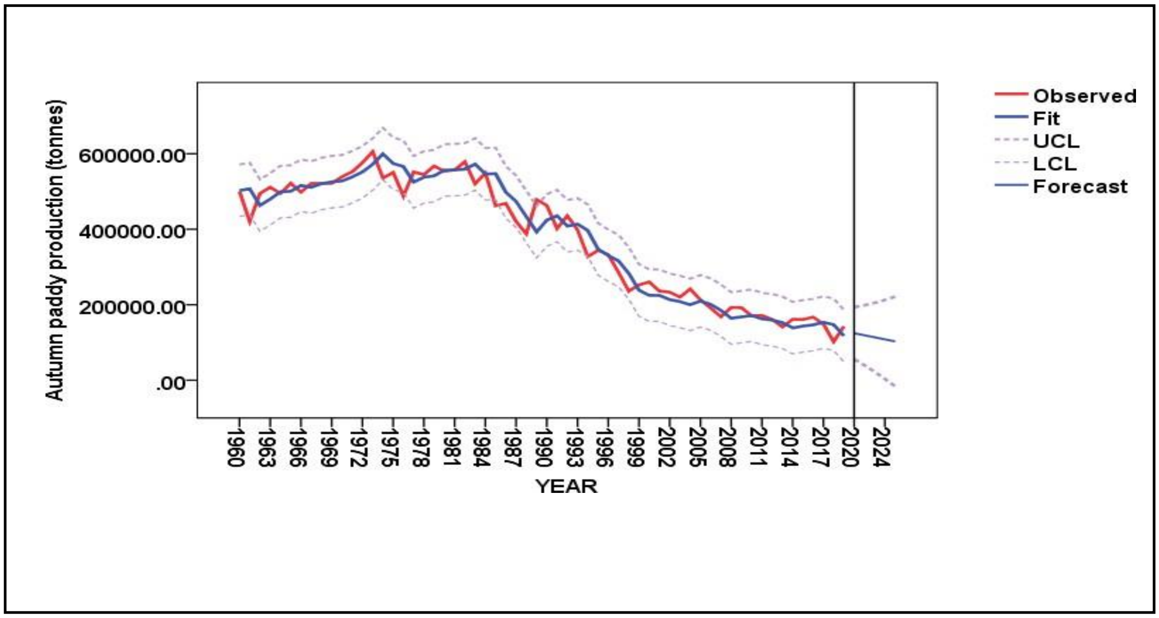

Fig 4.24: Actual and predicted Autumn paddy production in Kerala during 1960-’61 to 2024-‘25

Autumn paddy production in Kerala were forecasted for a period from year 2020 -‘21 to 2024 -‘25 based on the fitted model. Forecasts for autumn paddy production in Kerala for the years from 2020-‘21 to 2024-‘25 are given in the Table 4.32. The graph in the Fig 4.24 showed a decreasing trend for the production of autumn paddy in Kerala for the period from 2020-‘21 to 2024-’25 by an amount of 124579.03 to 102799.13 tonnes.

Table 4.32: Forecasted Autumn paddy production in Kerala for the period from 2020-‘21-2024-‘25

Year	2020-‘21	2021-‘22	2022-‘23	2023-‘24	2024-‘25
Forecasted area (ha)	124579.03	119134.05	113689.08	108244	102799.13

4.4.3. Forecasting of Autumn paddy productivity

The data for the years from 1960-‘61 to 2009-‘10 was taken as a training period with respect to Autumn paddy productivity in Kerala for fitting forecast models. From among several models tried, the Holts’ exponential smoothing model was found to be the best model to forecast the Autumn paddy productivity in Kerala. After validation of the model, forecasts for five years were made using Holts’ exponential smoothing model. The results are outlined in Table 4.34, which showed a high value of R^2 along with other values of RMSE, MAPE, MAE and BIC.

The parameters of the Holts’ exponential smoothing model for paddyproductivity in Kerala are summarized in Table 4.33. The coefficients of the model were α = 0.093and γ = 0.0012 where α and γ both were significant at 1 per cent level. Thus, the Holt’s exponential smoothing model could be used to forecast the autumn paddy productivity in Kerala

Table 4.33: Parameters of Holt’s exponential smoothing model for Autumn paddy productivity in Kerala during the training period

	Estimate	SE	t	P-value
Alpha (Level)	0.093	0.101	0.923	0.361
Gamma (trend)	0.0012	0.014	3.930e-6	1.000

Holt’s exponential smoothening model

(Level of the series time ‘t’, coefficient α= 0.093)

(Trend of the series time ‘t’, coefficient γ= 0.0012)

Forecast for k step ahead

Level equation: $L_t = 0.093Z_t + 0.907L_{t-1} + 0.907T_{t-1}$

Trend equation: $T_t = 0.0019Z_t - 0.0019L_{t-1} + 0.99T_{t-1}$

Forecast equation: $F_t = L_t + KT_t$

Where, K=1, 2, 3, 4, 5 (forecasted from the period from 2020-21 to 2024-'25)

Accuracy measures of Holts' exponential smoothing model are given in Table 4.34. The model showed a high R^2 value of 93.2 per cent and a low MAPE of 3.981.

Table 4.34: Accuracy measures of Holt's exponential smoothing model during the training period

Fit statistic	Holts' Exp. Smoothing model
R^2	0.93
RMSE	92.630
MAPE	3.981
MAE	68.270
BIC	9.214

Table 4.35: Actual and forecasted values of Autumn paddy productivity in Kerala

Year	Actual	forecast	UCL	LCL
2010-'11	2415.00	2329.5	2515.75	2143.26
2011-'12	2519.00	2352.85	2539.91	2165.8
2012-'13	2547.00	2376.2	2564.06	2188.34
2013-'14	2720.00	2399.55	2588.21	2210.89
2014-'15	2524.00	2422.9	2612.35	2233.44
2015-'16	2663.00	2446.25	2636.5	2256
2016-'17	2954.00	2469.59	2660.63	2278.55
2017-'18	2555.00	2492.94	2684.77	2301.12
2018-'19	1679.00	2516.29	2708.9	2323.68
2019-'20	2613.50	2539.64	2733.03	2346.25

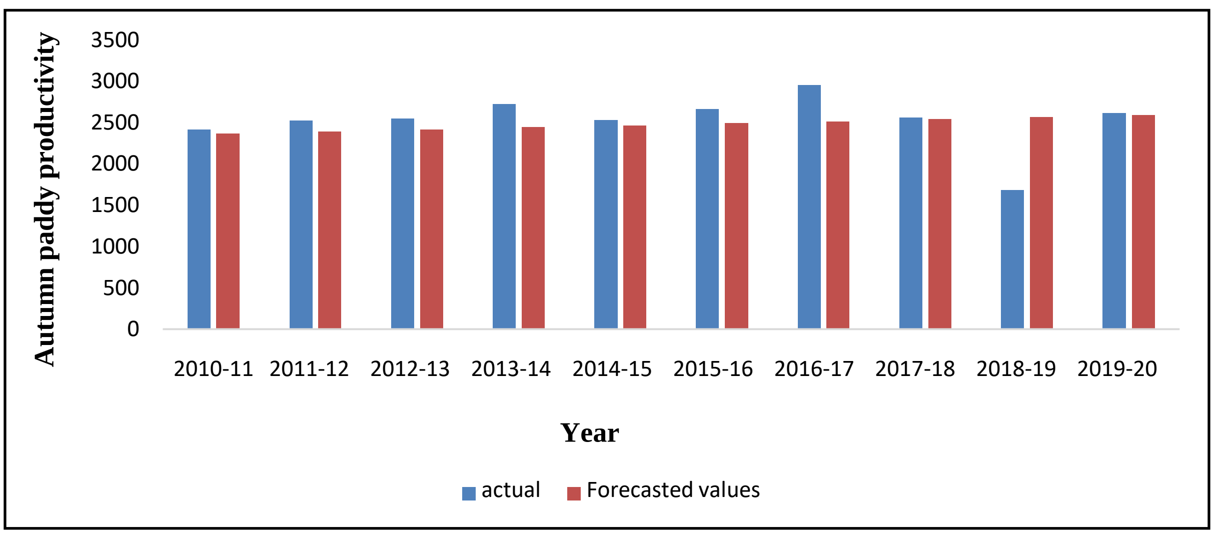

Fig 4.25: Validation of predicted Autumn paddy productivity in Kerala usingHolt's exponential smoothing model for 2010-'11 to 2019-'20

The parameters of the Holts' exponential smoothing model for paddy productivity are summarized in Table 4.36. The coefficients of the model were α = 0.001and γ = 4.772e-5, where α and γ both are significant at 1per cent level Thus, the Holt's exponential smoothing model could be used to forecast the autumn paddy productivity in Kerala for the next 5 years from 2020-'21 to 2024-'25.

Table 4.36: Parameters of the final Holt's exponential smoothing model for Autumn paddy productivity in Kerala

	Estimate	**SE**	**t**	**P-value**
Alpha (Level)	0.001	0.015	0.067	0.947
Gamma (trend)	4.772e-5	2.061	2.315e-5	1.000

Accuracy measures of Holts' exponential smoothing model are given in Table 4.37. The model shows a high R^2 value of 96.87 per cent and a low MAPE of 5.225.

Table 4.37: Accuracy measures of final Holt's exponential smoothing model for Autumn paddy productivity

Fit statistic	**Holts' Exp. smoothing**
R^2	0.96
RMSE	164.651
MAPE	5.225
MAE	96.873
BIC	10.344

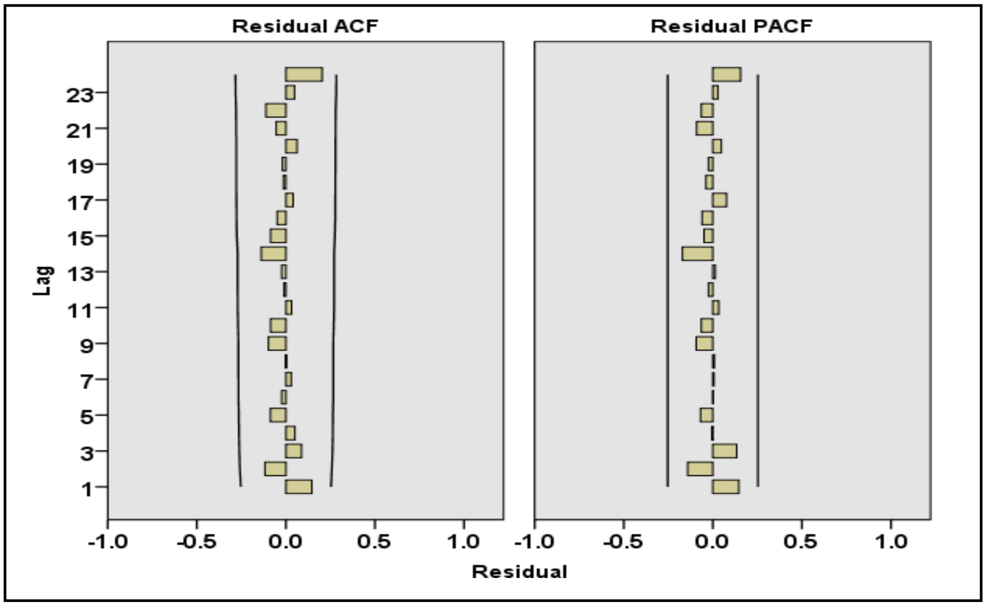

Fig 4.26: Residual ACF and PACF plots of Holt's exponential smoothing model for Autumn paddy productivity

From the Fig 4.26 it could be observed that ACF and PACF values lie within the confidence limits or the residuals were almost close to white noise.

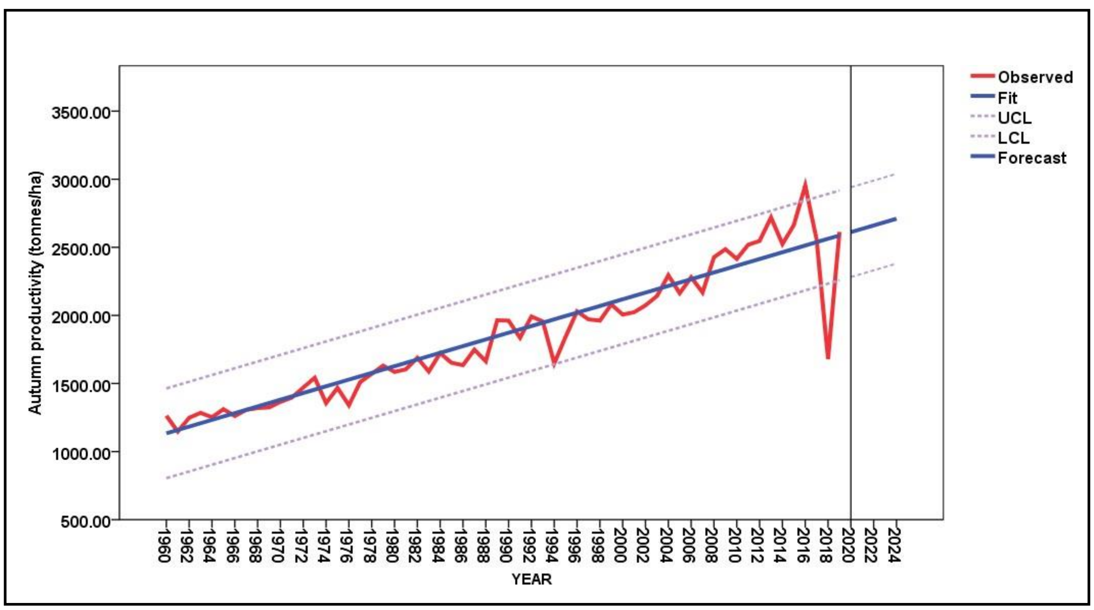

Fig 4.27: Actual and predicted Autumn paddy productivity in Kerala during 1960-'61 to 2024-'25

Autumn paddy productivity in Kerala were forecasted for a period from 2020-‘21-2024-‘25 based on the fitted model. Forecasts for autumn paddy productivity in Kerala for the years from 2020-‘21 to 2024-‘25 are given in Table 4.38. The graph in Fig.4.27 showed an increasing trend for the production of autumn paddy productivity for the period from 2020-‘21 to 2024-‘25 by an amount of 2611.69 to 2710.25 tonnes.

Table 4.38: Forecasted Autumn paddy productivity in Kerala for the period from 2020-‘21- 2024-‘25

Year	2020-‘21	2021-‘22	2022-‘23	2023-‘24	2024-‘25
Forecasted area (ha)	2611.69	2636.33	2660.97	2685.61	2710.25

4.4.4. Forecast of Winter paddy area in Kerala

The data for the years from 1960-‘61 to 2009-‘10 was taken as a training period with respect to area under winter paddy in Kerala for fitting forecast models. From among several models tried, the ARIMA (0,1,0) model was found to be the best model to forecast the area under winter paddy in Kerala. After validation of the model, forecasts for five years were made using ARIMA (0,1,0) model. The results are outlined in Table 4.40, which showed a high value of R^2 along with other values of RMSE, MAPE, MAE and BIC. The parameters of the exponential smoothing coefficients of the ARIMA (0,1,0) model for area under winter paddy are summarized in Table 4.40. ARIMA (0,1,0) model could be effectively used to forecast the area under winter paddy in Kerala.

Table 4.39: Parameters of the ARIMA (0,1,0) model for area under Winter paddy in Kerala during the training period

Variable	Parameters	Estimate	SE	t	P-value
Area under winter paddy	Constant	-4133.53	1932.737	-2.139	0.031
	Difference	1			

Accuracy measures of ARIMA (0,1,0) model are given in Table 4.40. The model showed a high R^2 value of 97.8 Per cent and a low MAPE of 3.713.

Table 4.40: Accuracy measures of ARIMA (0,1,0) model during training period for Winter paddy area

Fit statistic	ARIMA (0,1,0)
R^2	0.97
RMSE	13529.157
MAPE	3.713
MAE	8917.439
BIC	19.105

Table 4.41: Actual and forecasted values of area under Winter paddy in Kerala

Year	Actual	forecast	UCL	LCL
2010-'11	91556	103351.5	130553.7	76149.28
2011-'12	92735	99217.94	137687.7	60748.23
2012-'13	86751	95084.41	142200	47968.83
2013-'14	100824	90950.88	145355.3	36546.49
2014-'15	88990	86817.35	147643.3	25991.4
2015-'16	89118	82683.82	149315.3	16052.32
2016-'17	72253	78550.29	150520.5	6580.05
2017-'18	81115	74416.76	151356.2	-2522.66
2018-'19	88450	70283.22	151889.8	-11323.4
2019-'20	80048.72	66149.69	152170.6	-19871.2

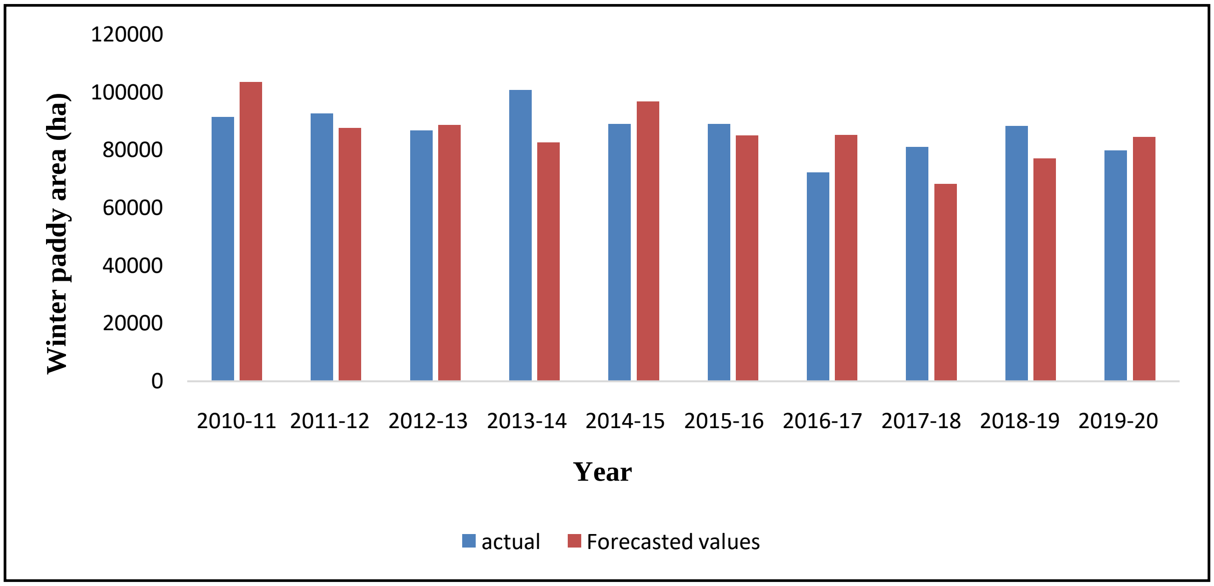

Fig 4.28: Validation of predicted area under Winter paddy in Kerala using ARIMA (0,1,0) model for 2010-'11 to 2019-'20

The parameters of the ARIMA (0,1,0) model for area under paddy are summarized in Table 4.42. Thus, the ARIMA (0,1,0) model could be used to forecast the area under winter paddy in Kerala for the next 5 years from 2020-'21 - 2024-'25.

Table 4.42: Parameters of the final ARIMA (0,1,0) model for area under Winter paddy in Kerala

Variable		Estimate	SE	t	P-value
Area under winter paddy	Constant	3897.95	1695.9	-2.298	0.025
	Difference	1			

$(1-\beta)\ Y_t = 3897.95 + e_t$

Accuracy measures of ARIMA (0,1,0) model are given in the Table 4.43. The model showed a high R^2 value of 98.6 per cent and a low MAPE of 4.857.

Table 4.43: Accuracy measures of final ARIMA (0,1,0) model for area under Winter paddy

Fit statistic	ARIMA (0,1,0)
R^2	0.98
RMSE	13027.150
MAPE	4.857
MAE	8937.445
BIC	19.019

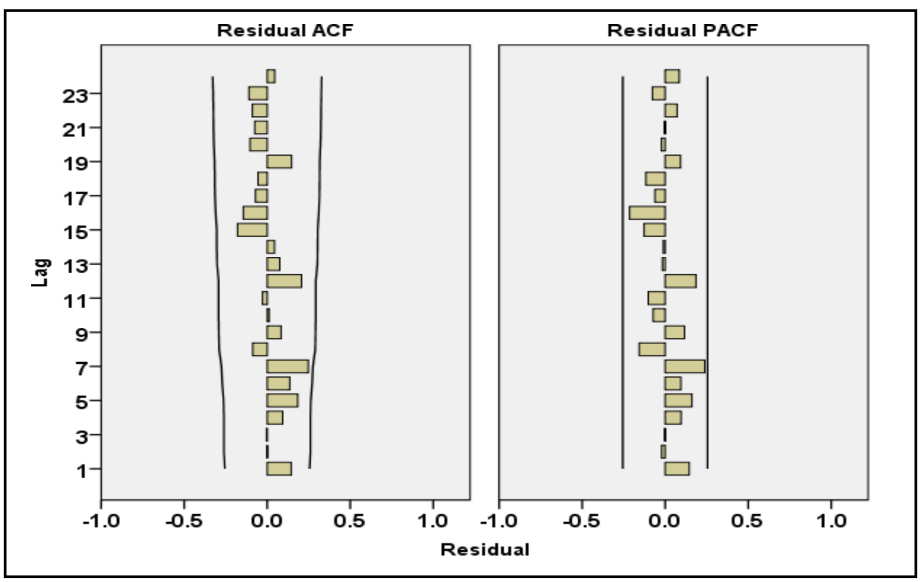

Fig 4.29: Residual ACF and PACF plots of ARIMA (0,1,0) model for Winter paddy area

From Fig 4.29 it could be observed that ACF and PACF values lie within the confidence limits or the residuals were almost close to white noise.

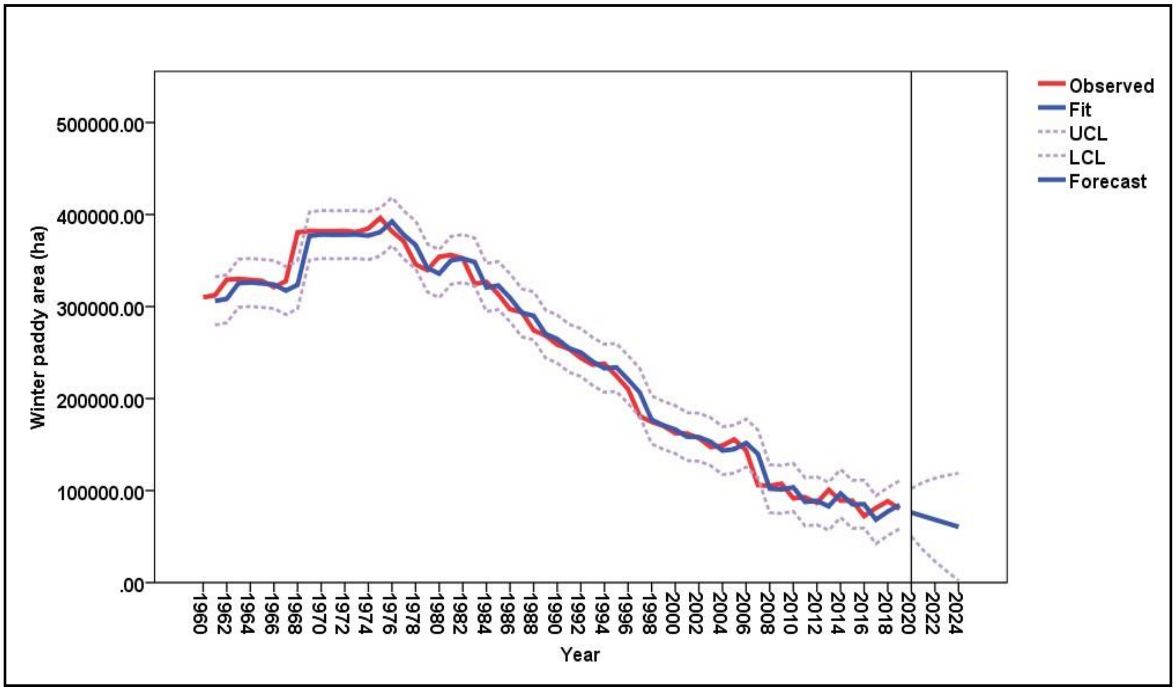

Fig 4.30: Actual and predicted area under Winter paddy in Kerala period during 1960-'61 to 2024-'25

Area under winter paddy in Kerala were forecasted for a period from year 2020-'21 to 2024-'25 based on the fitted model. Forecasted area under winter paddy in Kerala for the years from 2020-'21 to 2024-'25 are given in Table 4.45. The graph in Fig. 4.30 showed a decreasing trend for the area under paddy for the period from 2020-'21-2024-'25 by an amount of 76150.77 to 60558.95.

Table 4.44: Forecasted area under Winter paddy in Kerala for the period from 2020-'21- 2024-'25

Year	2020-'21	2021-'22	2022-'23	2023-'24	2024-'25
Forecasted area (ha)	76150.77	72252.81	68354.86	64456.90	60558.95

4.4.5. Forecasting of Winter paddy production

The data for the years from 1960-'61 to 2009-'10 was taken as a training period with respect to winter paddy production in Kerala for fitting forecast models. From among several models tried, the Simple exponential smoothing model was found to be the best model to forecast the winter paddy production in Kerala. After validation of the model, forecasts for five years were made using Simple exponential smoothing model. The results are outlined in Table 4.46, which showed a high value of R^2 along with other values of RMSE, MAPE, MAE and BIC.

The parameters of the exponential smoothing coefficients of the simple model for winter paddy production are summarized in Table 4.45. The coefficients of the model were $\alpha = 0.637$ which was significant at 1 per cent level. Thus, the simple exponential smoothing model could be used to forecast the winter paddy production in Kerala

Table 4.45: Parameters of Simple smoothing exponential model for Winter paddy production in Kerala using training period

	Estimate	SE	t	P-value
Alpha (Level)	0.637	0.133	4.803	< 0.001

Accuracy measures of simple exponential smoothing model are given in Table 4.46. The model showed a high R^2 value of 80.9 per cent and a low MAPE of 8.030.

Table 4.46: Accuracy measures of Simple exponential smoothing model for Winter paddy production in Kerala during training period

Fit statistic	Simple model
R^2	0.80
RMSE	43595.751
MAPE	8.030
MAE	33592.214
BIC	21.444

Table 4.47: Actual and forecasted values of Winter paddy production in Kerala

Year	Actual	forecast	UCL	LCL
2010-'11	215011	268671.9	356280.9	181063
2011-'12	248114	268671.9	372536.6	164807.2
2012-'13	212607	268671.9	386572	150771.9
2013-'14	285614	268671.9	399105.8	138238.1
2014-'15	254450	268671.9	410536.4	126807.5
2015-'16	243675	268671.9	421112.4	116231.5
2016-'17	141397	268671.9	431000.7	106343.2
2017-'18	218934	268671.9	440320.4	97023.49
2018-'19	279529	268671.9	449159.4	88184.43
2019-'20	244793.8	268671.9	457585.4	79758.49

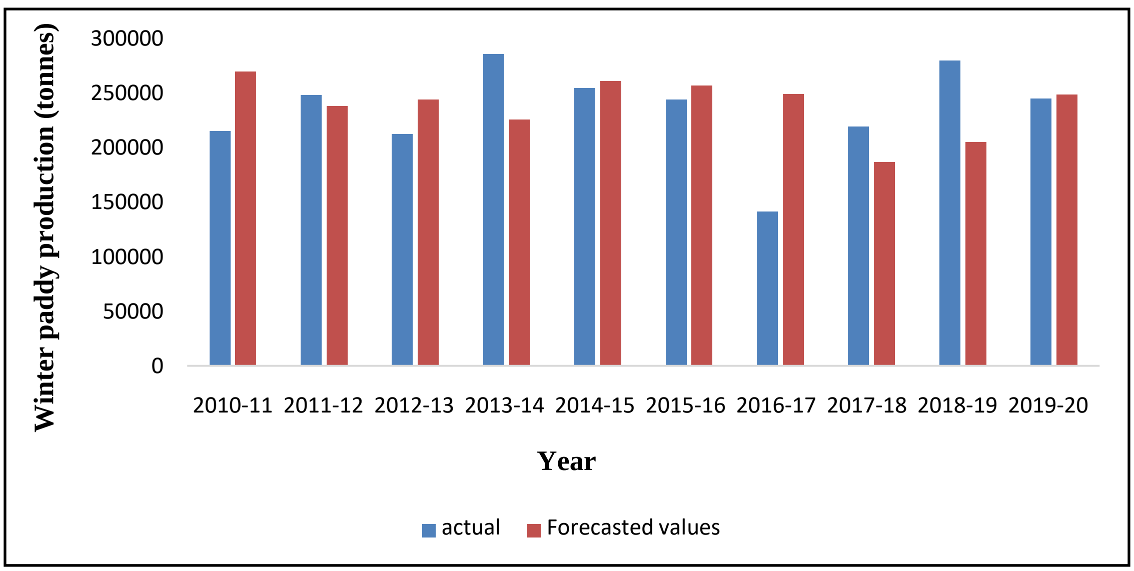

Fig 4.31: Validation of predicted Winter paddy production in Kerala using Simple exponential smoothing model for 2010-‘11 to 2019-2020

The parameters of the exponential smoothing coefficients of the Simple model for winter paddy production are summarized in Table 4.48. The coefficients of the model were α = 0.583 which was significant at 1 per cent level. Thus, the Simple exponential smoothing model could be used to forecast the winter paddy production in Kerala for the next 5 years from 2020-‘21 to 2024-‘25.

Table 4.48: Parameters of the final Simple exponential smoothing model for Winter paddy production in Kerala

	Estimate	SE	t	P-value
Alpha (Level)	0.583	0.118	4.93	<0.001

Simple exponential smoothening model

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

$$L_t = 0.58Z_t + 0.42L_{t-1}$$

Forecast for k step ahead, $F_t(k) = L_t$

Accuracy measures of Simple exponential smoothing model are given in Table 4.49. The model showed a high R^2 value of 87.3 per cent and a low MAPE of 9.890.

Table 4.49: Accuracy measures of Simple exponential smoothing model for Winter paddy production

Fit statistic	Simple model
R^2	0.873
RMSE	45006.886
MAPE	9.890
MAE	34484.321
BIC	21.497

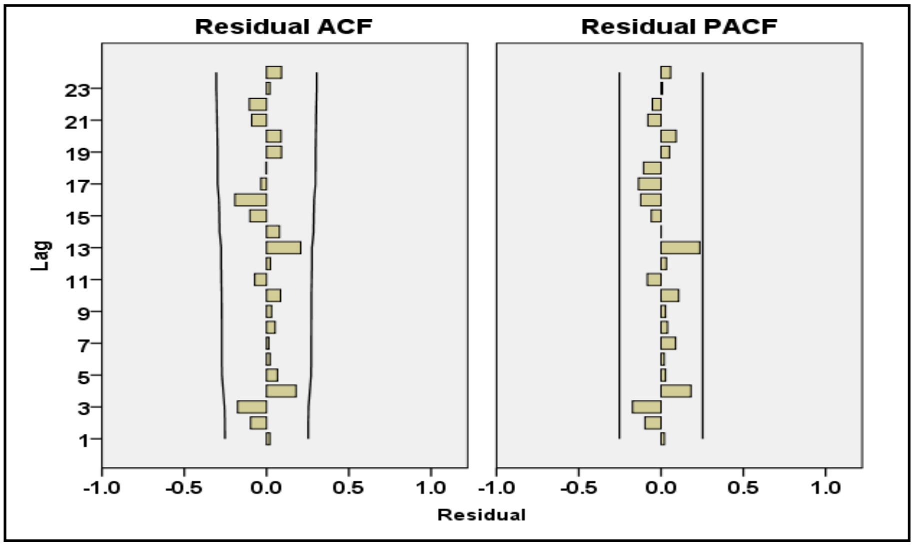

Fig 4.32: Residual ACF and PACF plots of Simple exponential smoothing model for Winter paddy production

From Fig 4.32, it could be observed that ACF and PACF values lie within the confidence limits or the residuals were almost close to white noise.

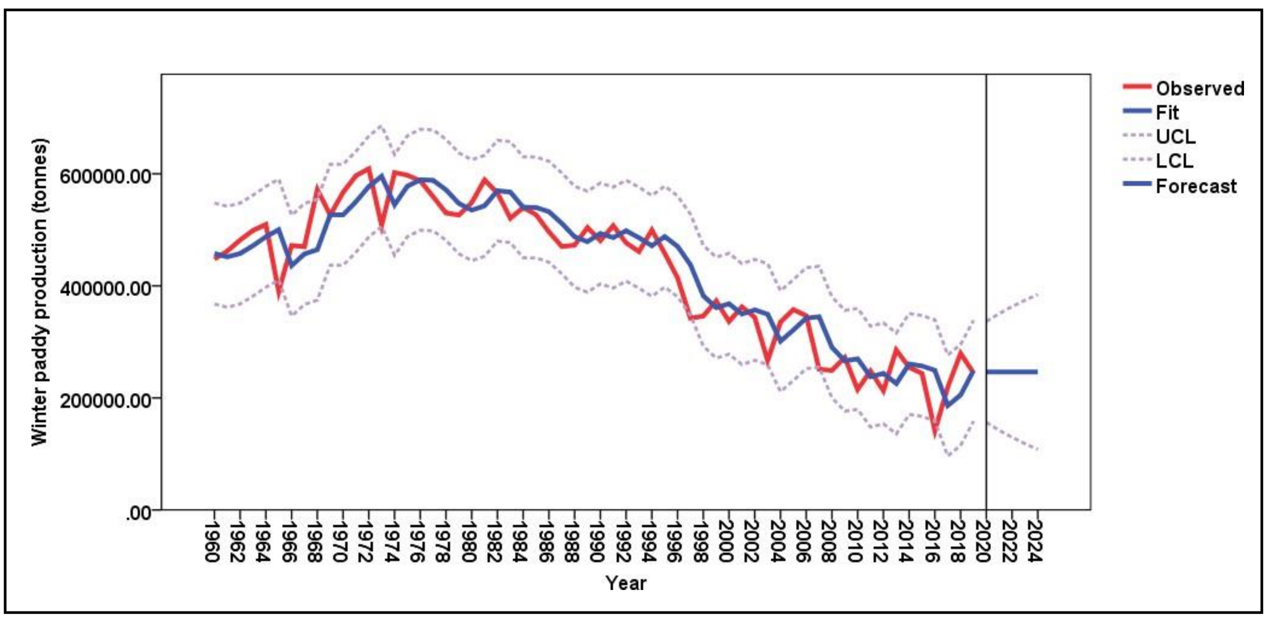

Fig 4.33: Actual and predicted Winter paddy production in Kerala during 1960-'61 to 2024-'25

Winter paddy production in Kerala was forecasted for a period from year 2020-‘21-2024-‘25 based on the fitted model. Forecasts for winter paddy production in Kerala for the years from 2020-‘21 to 2024-‘25 are given in Table 4.51. The graph in Fig.4.33 showed a decreasing trend for the production of winter paddy for the period from 1960-‘61 to 2024-‘25

Table 4.50: Forecasted Winter paddy production in Kerala for the period from 2020-‘21 to 2024-‘25

Year	2020-‘21	2021-‘22	2022-‘23	2023-‘24	2024-‘25
Forecasted area (ha)	246371.68	246371.68	246371.68	246371.68	246371.68

4.4.6. Forecasting of Winter paddy productivity

The data for the years from 1960-‘61 to 2009-‘10 was taken as a training period with respect to winter paddy productivity in Kerala for fitting forecast models. From among several models tried the Browns’ exponential smoothing model was found to be the best model to forecast the winter paddy productivity in Kerala. After validation of the model, forecasts for five years were made using Browns’ exponential smoothing model. The results are outlined in Table 4.59 which showed a high value of R^2 along with other values of RMSE, MAPE, MAE and BIC. The parameters of the Browns’ exponential smoothing model for winter paddy productivity are summarized in Table 4.51 the coefficients of the model were $\alpha = 0.172$ which significant at 1 per cent level. Thus, the Browns’ exponential smoothing model could be used to forecast the winter paddy productivity in Kerala

Table 4.51: Parameters of Browns' exponential model of Winter paddy productivity during training period

	Estimate	SE	t	P-value
Alpha (Level)	0.172	0.40	4.317	<0.001

Accuracy measures of Browns' exponential smoothing model are given inTable 4.52 the model showed a high R^2 value of 87.5 per cent and a low MAPE of 4.670.

Table 4.52: Accuracy measures of Browns' exponential smoothing model for Winter paddy productivity during training period

Fit statistic	Brown model
R^2	0.87
RMSE	116.579
MAPE	4.670
MAE	81.305
BIC	9.595

Table 4.53: Actual and forecasted values of Winter paddy productivity in Kerala

Year	Actual	forecast	UCL	LCL
2010-'11	2348	2474.82	2709.1	2240.55
2011-'12	2676	2509.43	2757.13	2261.73
2012-'13	2451	2544.04	2806.68	2281.39
2013-'14	2833	2578.64	2857.68	2299.6
2014-'15	2859	2613.25	2910.05	2316.44
2015-'16	2734	2647.85	2963.71	2332
2016-'17	1957	2682.46	3018.59	2346.34
2017-'18	2699	2717.07	3074.6	2359.54
2018-'19	3160	2751.67	3131.68	2371.66
2019-'20	3058	2786.28	3189.78	2382.78

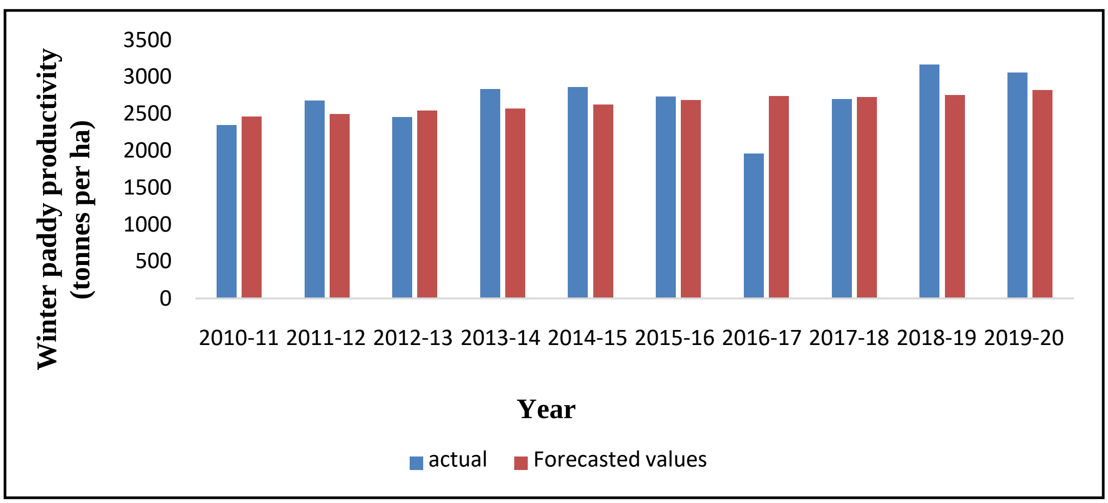

Fig 4.34: Validation of predicted Winter paddy productivity in Kerala usingBrown's exponential smoothing model for 2010-'11 to 2019-'20

The parameters of the Brown's exponential smoothing model for winter paddy productivity are summarized in Table 4.54. The coefficient of the model was $\alpha = 0.182$, which was significant at 1 per cent level. Thus, the Brown's exponential smoothing model could be used to forecast the winter paddy productivity in Kerala for the next 5 years from 2020-'21 to 2024-'25.

Table 4.54: Parameters of the final Brown's exponential smoothing model for Winter paddy productivity in Kerala

	Estimate	SE	t	P-value
Alpha (Level)	0.182	0.45	4.31	<0.001

Brown's exponential model, $S_t = 0.18X_t + 0.82S_{t-1}$

$T_t = 0.032X_t + 0.14S_t + 0.82T_{t-1}$

$a_t = 0.32X_t + 0.3S_{t-1} + 0.82T_{t-1}$

$b_t = 0.032X_t + 0.180S_{t-1} - 0.030S_t + 0.18T_{t-1}$

$F_t = 0.352X_t + 0.48S_{t-1} - 0.03S_t + T_{t-1}$

Accuracy measures of Browns' exponential smoothing model are given in Table 4.55. The model showed a high R^2 value of 87.2 per cent and a low MAPE of 5.654.

Table 4.55 Accuracy measures of final Browns' exponential smoothing model for Winter paddy productivity

Fit statistic	Brown model
R^2	0.87
RMSE	171.389
MAPE	5.654
MAE	109.820
BIC	10.424

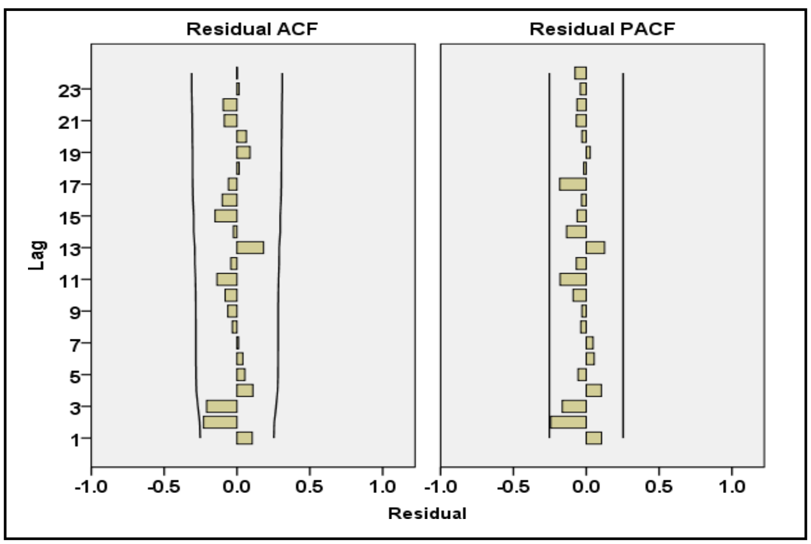

Fig 4.35: Residual ACF and PACF plots of Brown's exponential smoothing model for Winter paddy productivity

From Fig 4.35 it could be observed that ACF and PACF values lie within the confidence limits or the residuals were almost close to white noise.

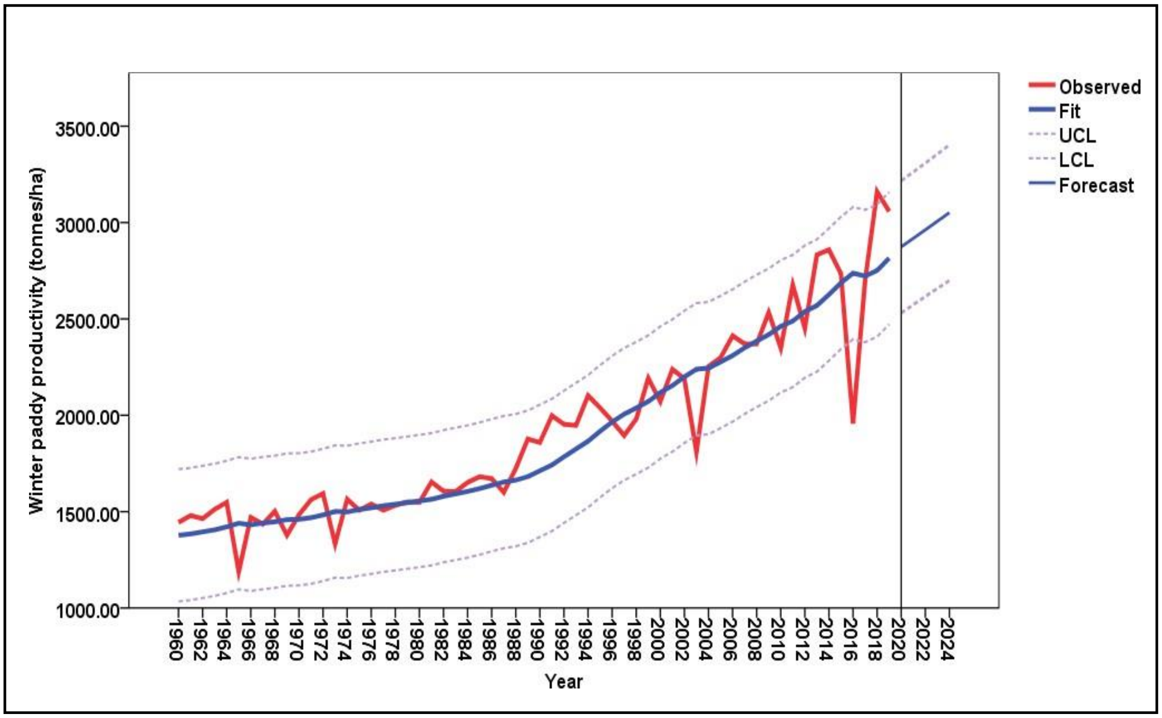

Fig 4.36: Actual and predicted Winter paddy productivity in Kerala during 1960-’61 to 2024-‘25

Winter paddy productivity in Kerala were forecasted for a period from the year 2020-‘21-2024-‘25 based on the fitted model. Results are given in Table 4.56.

Table 4.56: Forecasted Winter paddy productivity in Kerala for the period from 2020-‘21-2024-‘25

Year	**2020-‘21**	**2021-‘22**	**2022-‘23**	**2023 -‘24**	**2024‘25**
Forecasted area (ha)	2873.85	2918.16	2962.47	3006.79	3051.10

Fig 4.35 showed that the observed series of winter paddy productivity moved close to the forecasted values. Forecasts for winter paddy productivity in Kerala for the years from 2020-‘21-2024-‘25 are given in Table 4.56. The graph in Fig 4.36, showed increasing trend for the productivity of winter paddy for the period from 2020-‘21 to 2024-‘25 by an amount of 2873.85 to 3051.10 tonnes.

4.4.7. Forecast of Summer paddy Area

The data for the years from 1960-‘61 to 2009-‘10 was taken as a training period with respect to area under summer paddy in Kerala for fitting forecast models. From among several models tried, the Simple exponential smoothing model was found to be the best model to forecast the area under summer paddy in Kerala. After validation of the model, forecasts for five years were made using Simple exponential smoothing model. The results are outlined in Table 4.62, which showed a high value of R^2 along with other values of RMSE, MAPE, MAE and BIC.

The parameters of the exponential smoothing coefficients of the Simple exponential smoothing model for area under summer paddy are summarized in Table 4.57. The coefficient of the model was $\alpha = 0.957$which was significant at 1 per cent level. Thus, the Simple exponential smoothing model could be used to forecast the area under summer paddy in Kerala for the next 5 years from 2020-‘21 to 2024-‘25.

Table 4.57: Parameters of the Simple exponential smoothing model for area under Summer paddy in Kerala during training period

	Estimate	SE	t	P- value
Alpha (Level)	0.957	0.143	6.707	<0.001

Accuracy measures of Simple exponential smoothing model are given in Table 4.58. The model showed a high R^2 value of 92.3 per cent and a low MAPE of 7.408.

Table 4.58: Accuracy measures of Simple exponential smoothing model during training period for area under Summer paddy

Fit statistic	Simple model
R^2	0.92
RMSE	6204.983
MAPE	7.408
MAE	4205.033
BIC	17.544

Table 4.59: Actual and forecasted values of area under Summer paddy in Kerala

Year	Actual	forecast	UCL	LCL
2010-'11	51133	49290.99	61760.37	36821.61
2011-'12	47290	49290.99	66549.63	32032.36
2012-'13	47294	49290.99	70272.79	28309.2
2013-'14	46865	49290.99	73428.33	25153.66
2014-'15	45188	49290.99	76216.56	22365.43
2015-'16	47334	49290.99	78741.99	19840
2016-'17	42544	49290.99	81067.34	17514.65
2017-'18	49693	49290.99	83233.76	15348.23
2018-'19	48858	49290.99	85269.96	13312.02
2019-'20	56308	49290.99	87196.95	11385.04

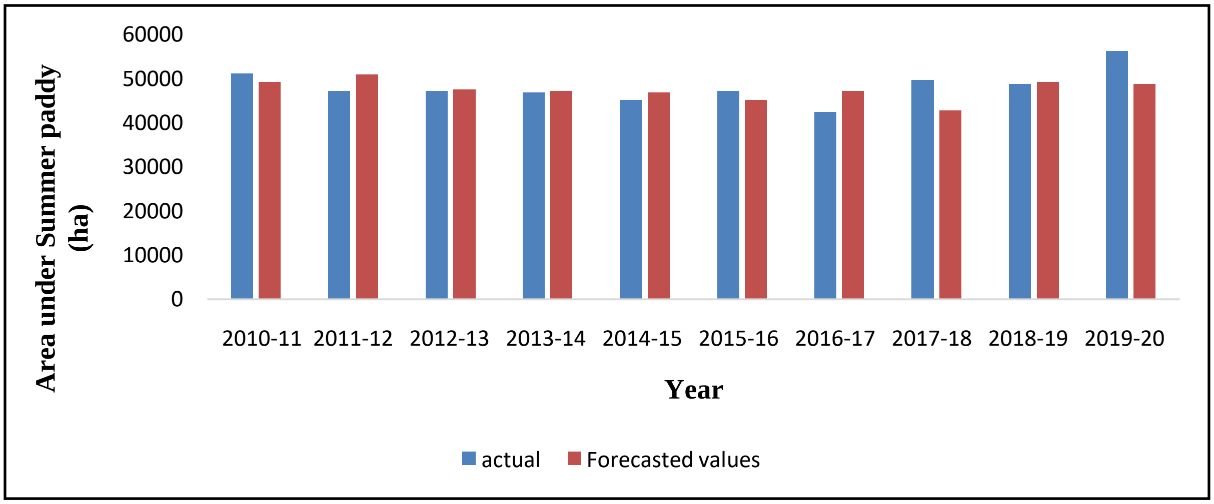

Fig 4.37: Validation of predicted area under Summer paddy in Kerala using Simple exponential smoothing model for 2010-2011 to 2019-'20

The parameters of the simple exponential smoothing model for area under Summer paddy are summarized in Table 4.60. The coefficient of the model was α = 0.936 which was significant at 1 per cent level. Thus, the simple exponential smoothing model could be used to forecast the area under Summer Paddy in Kerala for the next 5 years from 2020-'21 to 2024-'25.

Table 4.60: Parameters of the final Simple exponential smoothing model for area under Summer paddy in Kerala

	Estimate	**SE**	**t**	**P-value**
Alpha (Level)	0.936	0.132	7.108	<0.001

Simple exponential smoothening model

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

$$L_t = 0.94Z_t + 0.06L_{t-1}$$

Forecast for k step ahead, $F_t(k) = L_t$

Table 4.61: Accuracy measures of final Simple exponential smoothing model for area under Summer paddy

Fit statistic	Simple model
R^2	0.933
RMSE	5874.633
MAPE	7.187
MAE	3999.053
BIC	17.425

Accuracy measures of Simple exponential smoothing model are given in Table 4.61. The model showed a high R^2 value of 93.3 per cent and a low MAPE of 7.19.

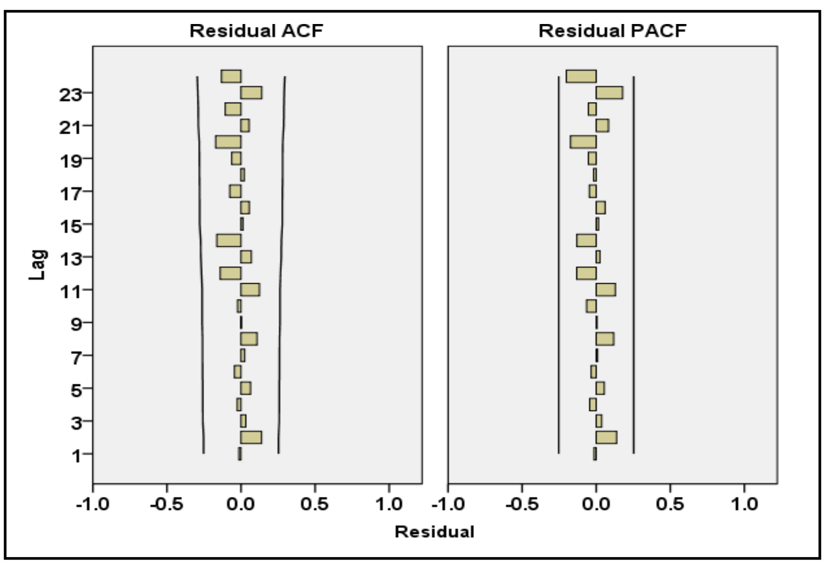

Fig 4.38: Residual ACF and PACF plots of Simple exponential smoothing model for area under Summer paddy

From the Fig 4.38, it could be observed that ACF and PACF values lie within the confidence limits or the residuals were almost close to white noise.

Area under summer paddy in Kerala were forecasted for a period from the year 2020-‘21-2024-‘25 based on the fitted model. Results are given in Table 4.62.

Table 4.62: Forecasted area under Summer paddy in Kerala for the period from 2020-‘21-2024-‘25

Year	2020-‘21	2021-‘22	2022-‘23	2023-‘24	2024-‘25
Forecasted area (ha)	55833.46	55833.46	55833.46	55833.46	55833.46

Fig 4.39 depicted that the observed series of area under summer paddy moved close to the forecasted values. Forecasts for area under summer paddy in Kerala for the years from 2020-‘21 to 2024 -‘25 are given in Table 4.62. The graph in Fig 4.39 showed more or less the same area under summer paddy for the period from 2020-‘21 to 2024-‘25

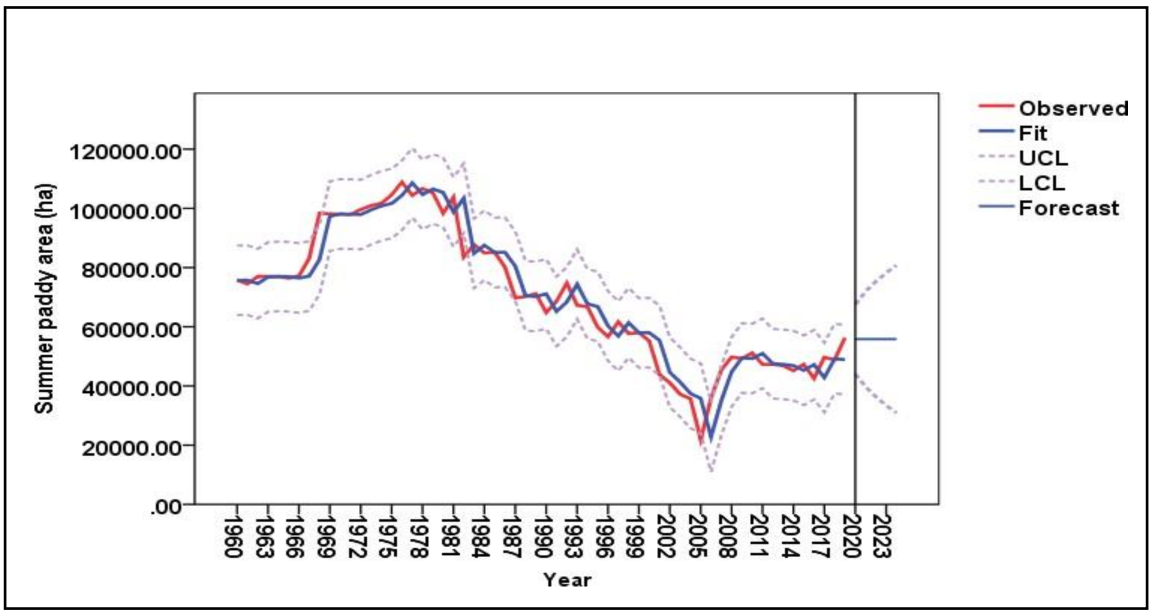

Fig 4.39: Actual and predicted area under Summer paddy in Kerala during 1960- ’61 to 2024-‘25

4.4.8. Forecasting of Summer paddy production

The data for the years from 1960-‘61 to 2009-‘10 was taken as a training period with respect to summer paddy production in Kerala for fitting forecast models. From among several models tried, the Simple exponential smoothing model was found to be the best model to forecast the summer paddy production in Kerala. After validation of the model, forecasts for five years were made using Simple exponential smoothing model. The results are outlined in Table 4.68, which showed a high value of R^2 along with other values of RMSE, MAPE, MAE and BIC.

The parameters of the Simple exponential smoothing model for summer paddy production are summarized in Table 4.63. The coefficient of the model was $\alpha = 0.725$ which was significant at 1 per cent level. Thus, the Simple exponential smoothing model could be effectively used to forecast the summer paddy production in Kerala

Table 4.63: Parameters of Simple exponential smoothing model for Summer paddy production in Kerala during training period

	Estimate	SE	t	P-value
Alpha (Level)	0.725	0.138	5.265	<0.001

Accuracy measures of Simple exponential smoothing model are given in Table 4.64. The model showed a high R^2 value of 62.3 per cent and a low MAPE of 12.034.

Table 4.64: Accuracy measures of Simple exponential smoothing model for Summer paddy production during training period

Fit statistic	Simple model
R^2	0.62
RMSE	21108.880
MAPE	12.034
MAE	15885.255
BIC	19.993

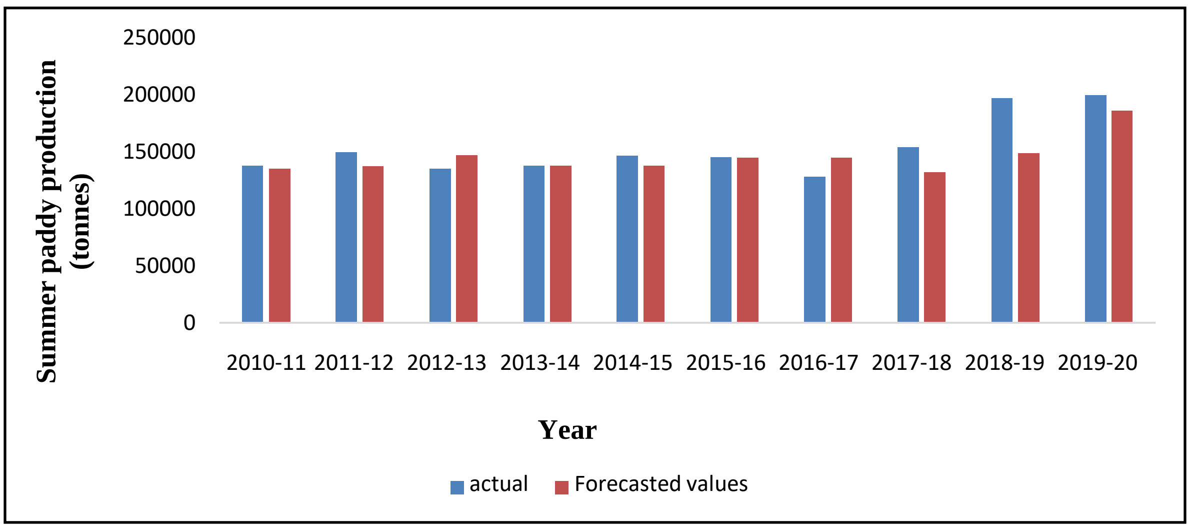

Fig 4.40: Validation of predicted Summer paddy production in Kerala using Simple exponential smoothing model for 2010-‘11 to 2019-’20

Table 4.65: Actual and forecasted values of Summer paddy production in Kerala

Year	Actual	forecast	UCL	LCL
2010-‘11	137465	134679.9	177099.7	92259.97
2011-‘12	149217	134679.9	187081.9	82277.78
2012-‘13	134609	134679.9	195445.9	73913.85
2013-’4	137477	134679.9	202790.3	66569.37
2014-‘15	146165	134679.9	209416.5	59943.2
2015-‘16	144706	134679.9	215501.2	53858.46
2016-‘17	127905	134679.9	221158.9	48200.79
2017-‘18	153463	134679.9	226468.5	42891.2
2018-‘19	196784	134679.9	231487.3	37872.38
2019-‘20	199338	134679.9	236258.5	33101.22

The parameters of the Simple exponential smoothing model for summer paddy production are summarized in Table 4.66. The coefficient of the model was α = 0.767.

Which was significant at 1 per cent level Thus, the Simple exponential smoothing model could be used to forecast the summer paddy production in Kerala for the next 5 years from 2020-‘21 to 2024-‘25.

Table 4.66: Parameters of the final Simple exponential smoothing model for Summer paddy production in Kerala

	Estimate	SE	t	P-value
Alpha (Level)	0.767	0.128	5.979	<0.001

Simple exponential smoothening model

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

$$L_t = 0.77Z_t + 0.23L_{t-1}$$

Forecast for k step ahead, $F_t(k) = L_t$

Accuracy measures of Simple exponential smoothing model are given in Table 4.67. The model showed a high R^2 value of 60.0 per cent and a low MAPE of 11.416.

Table 4.67: Accuracy measures of final Simple exponential smoothing model for Summer paddy production

Fit statistic	Simple model
R^2	0.60
RMSE	20801.398
MAPE	11.416
MAE	15524.345
BIC	19.954

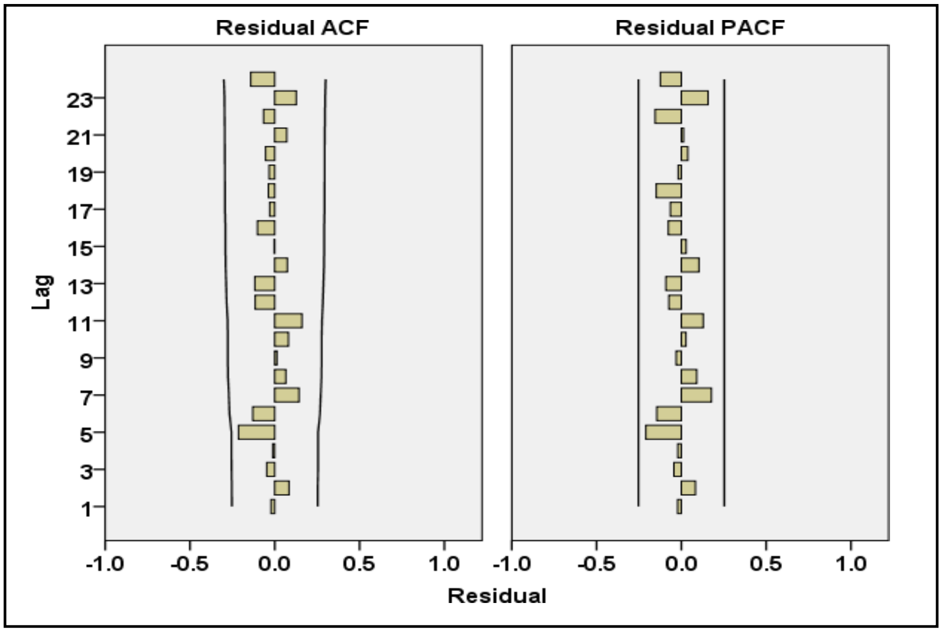

Fig 4.41: Residual ACF and PACF plots of Simple exponential smoothing model for Summer paddy production

From the Fig 4.41 it could be observed that ACF and PACF values lie within the confidence limits or the residuals were almost close to white noise.

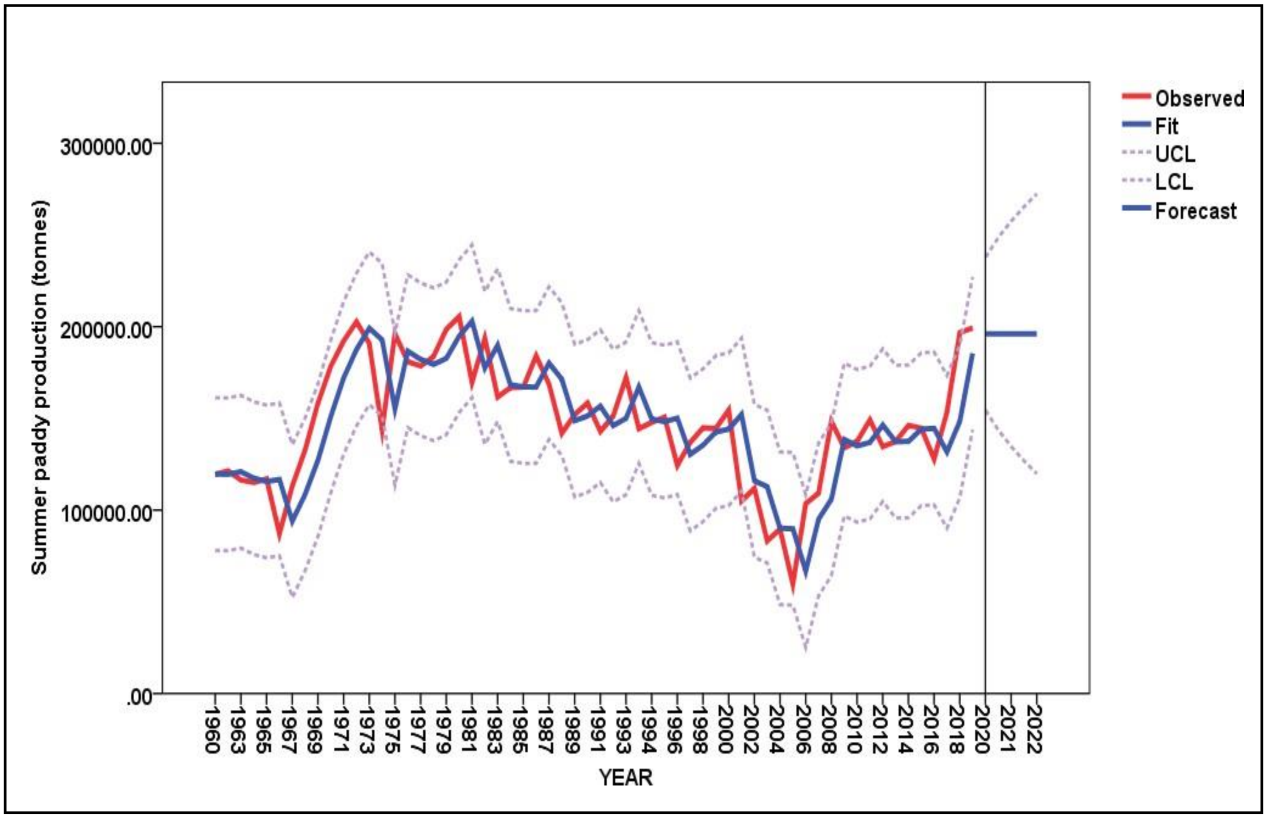

Fig 4.42: Actual and predicted Summer paddy production in Kerala during 1960-'61 to 2024-'25

Summer paddy production in Kerala was forecasted for a period from year 2020-'21-2024-'25 based on the fitted model. Results are given in the Table 4.68.

Table 4.68: Forecasted Summer paddy production in Kerala for the period from 2020-'21-2024-'25

Year	2020-'21	2021-'22	2022-'23	2023-'24	2024-'25
Forecasted area (ha)	196123.78	196123.78	196123.78	196123.78	196123.78

Fig 4.42 showed that the observed series of summer paddy production move close to the forecasted values. Forecasts for summer paddy production in Kerala for the years from 2020-'21- 2024-'25 are given in Table 4.68.

4.4.9. Forecast of summer paddy productivity in Kerala

The data for the years from 1960-‘61 to 2009-‘10 was taken as a training period with respect to summer paddy productivity in Kerala for fitting forecast models. From among several models tried, the Holts’ exponential smoothing model was found to be the best model to forecast the summer paddy productivity in Kerala. After validation of the model, forecasts for five years were made using Holts’ exponential smoothing model. The results are outlined in Table 4.73, which showed a high value of R^2 along with other values of RMSE, MAPE, MAE and BIC.

The parameters of the Holt’s exponential smoothing model for summer paddy productivity are summarized in Table 4.69. The coefficients of the model were α = 0.001and γ = 1.000, where α and γ both were significant at 1 per cent level. Thus, the Holts’ exponential smoothing model could be used to forecast the summer paddy productivity in Kerala**.**

Table 4.69: Parameters of Holts’ exponential smoothing model of Summer paddy productivity in Kerala during training period

	Estimate	SE	t	P-value
Alpha (Level)	0.001	0.58	0.009	0.99
Gamma (trend)	1.000	121.750	0.008	0.99

Accuracy measures of Holts’ exponential smoothing model are given in Table 4.70. The model showed a high R^2 value of 83.5 per cent and a low MAPE of 6.749.

Table 4.70: Accuracy measures of Holt's exponential smoothing model for Summer paddy productivity during training period

Fit statistic	Holt model
R^2	0.833
RMSE	173.656
MAPE	6.749
MAE	133.077
BIC	10.471

Table 4.71: Actual and forecasted values of Summer paddy productivity in Kerala

Year	Actual	forecast	UCL	LCL
2010-'11	2688.00	2719.54	3068.7	2370.38
2011-'12	3155.00	2746.08	3095.24	2396.92
2012-'13	2846.00	2772.62	3121.78	2423.46
2013-'14	2933.00	2799.17	3148.33	2450.01
2014-'15	3235.00	2825.71	3174.87	2476.55
2015-'16	3057.00	2852.25	3201.41	2503.09
2016-'17	3006.00	2878.79	3227.96	2529.63
2017-'18	3088.00	2905.34	3254.5	2556.17
2018-'19	4028.00	2931.88	3281.05	2582.7
2019-'20	3540.00	2958.42	3307.6	2609.24

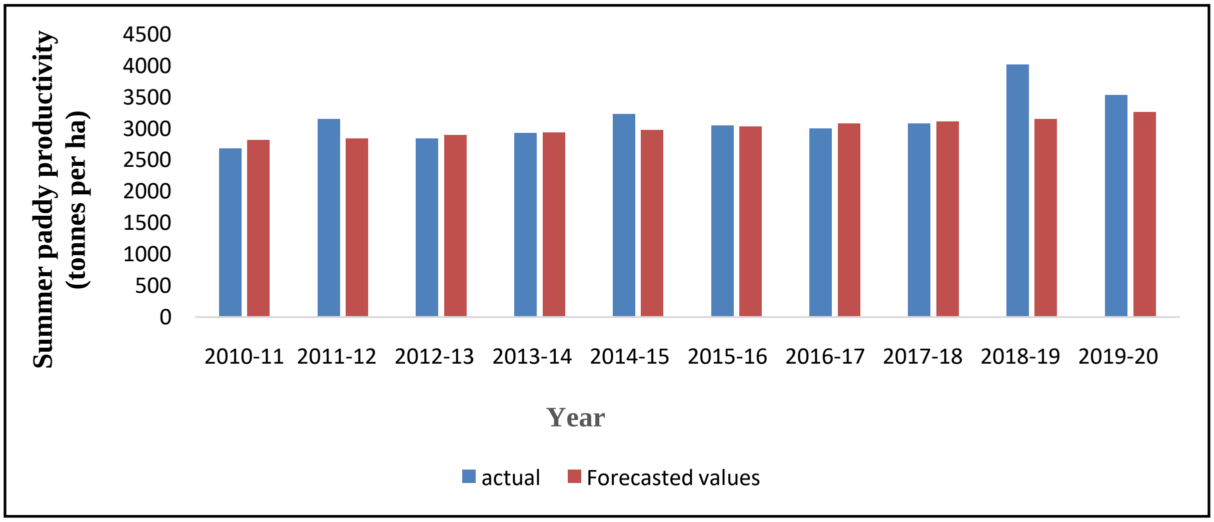

Fig 4.43: Validation of predicted Summer paddy productivity in Kerala using Holt's model for 2010-'11 to 2019-'20

The parameters of the final Holts' exponential smoothing model for Summer paddy productivity are summarized in Table 4.72. The coefficients of the model were α = 0.061 and γ = 0.309, where α and γ both were significant at 1 per cent level Thus, the Holts' exponential smoothing model could be used to forecast the summer paddy productivity in Kerala for the next 5 years from 2020-'21 to 2024-'25.

Table 4.72: Parameters of the final Holt's exponential smoothing model for Summer paddy productivity in Kerala

	Estimate	SE	t	P-value
Alpha (Level)	0.061	0.033	1.873	0.06
Gamma (trend)	0.309	0.173	1.788	0.07

Holt's exponential smoothening model

(Level of the series time 't', coefficient α= 0.061)

(Trend of the series time ‘t’, coefficient γ= 0.309)

Forecast for k step ahead

Level equation: $L_t = 0.061Z_t + 0.93L_{t-1} + 0.93T_{t-1}$

Trend equation: $T_t = 0.018Z_t - 0.02L_{t-1} + 0.97T_{t-1}$

Forecast equation: $F_t = L_t + KT_t$

Where, K=1, 2, 3, 4, 5 (forecasted from the period from 2020-‘21 to 2024-‘25)

Accuracy measures of final Holts’ exponential smoothing model are given in Table 4.73. The model showed a high R^2 value of 87.0 per cent and a low MAPE of 7.032.

Table 4.73: Accuracy measures of final Holt’s exponential smoothing model for Summer paddy productivity

Fit statistic	**Holt model**
R^2	0.87
RMSE	212.430
MAPE	7.032
MAE	152.105
BIC	10.854

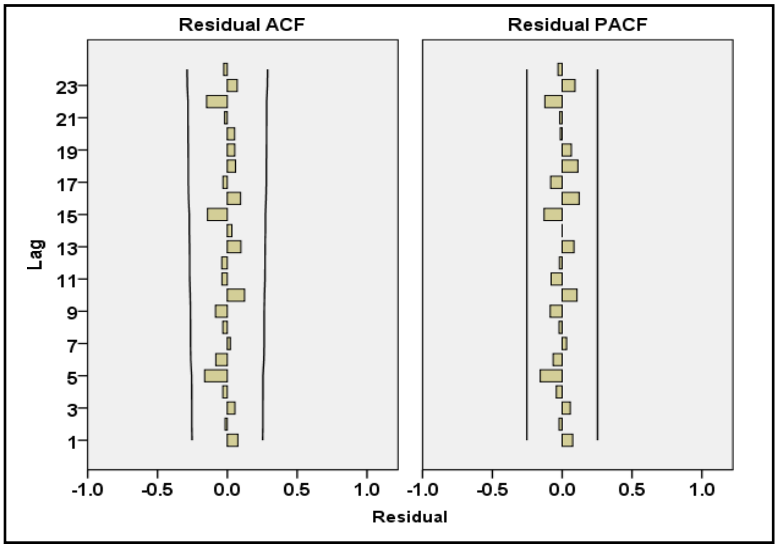

Fig 4.44: Residual ACF and PACF plots of Holt's exponential smoothing model for Summer paddy productivity

From the Fig 4.44 It could be observed that ACF and PACF values lie within the confidence limits or the residuals were almost close to white noise.

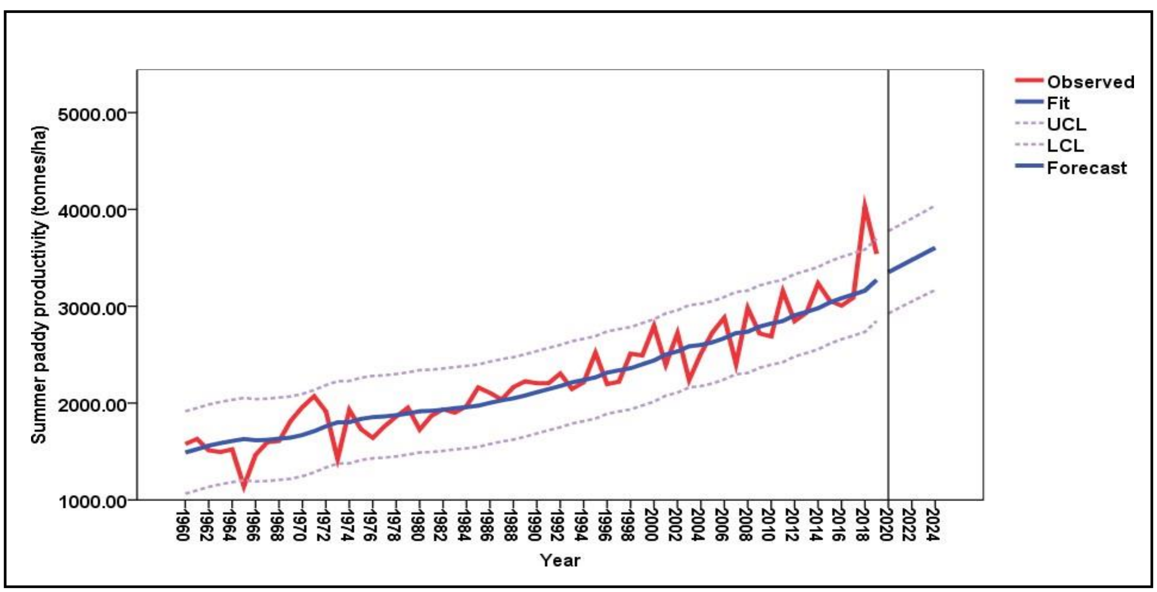

Fig 4.45: Actual and predicted Summer paddy productivity in Kerala during 1960-'61 to 2024-'25

Summer paddy productivity in Kerala was forecasted for a period from year 2020-‘21-2024-‘25 based on the fitted model. Results are given Table 4.74.

Table 4.74: Forecasted Summer paddy productivity in Kerala for the period from 2020-‘21-2024-‘25

Year	2020-‘21	2021-‘22	2022-‘23	2023-‘24	2024-‘25
Forecasted area (ha)	3351.74	3414.90	3478.07	3541.24	3604.41

Fig4.45 depicted that the observed series of summer paddy productivity moved close to the forecasted values. Forecasts for summer paddy productivity in Kerala for the years from 2020-‘21- 2024-‘25 are given in Table 4.74. The graph in Fig 4.45 showed an increasing trend for the productivity of summer paddy for the period from 2020-‘21 to 2024-‘25 as 3351.74 to 3604.41.

4.5 Regression approach

The secondary data collected from the year 1996-‘97 to 2018-‘19 on area, production, productivity and price of paddy from the official website (DES), Kerala was made use of for this study. To fit the regression model change in paddy production was taken as the dependent variable and change in area, change in productivity, change in price, and interaction effect of price and area were taken as independent variables.

Table 4.75: Accuracy measures of Regression analysis

Mode	R	R Square	Adjusted R^2	Std. Error of the Estimate	Durbin-Watson
1	0.88	0.788	0.739	32453.67	1.584

Table 4.75 shows that an Adjusted R^2 of 0.739 could be achieved by the regression model. Durbin Watson (DW) statistic is a test for autocorrelation in the residuals from a

statistical regression analysis. The Durbin-Watson statistic will always have a value between 0 and 4. Practically a value lying between1.5 to 2.5 is considered to be normal.

Table 4.76: Estimated parameters in the regression equation

	Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta		
Constant	27289.68	11717.71		2.329	0.03
Price	-4.902	77.007	-0.008	-0.064	0.95
Area	3.449	0.768	0.752	4.493	0.001
Interaction effect of price& area	0.004	0.009	0.068	0.451	0.65
Productivity	-34.394	15.179	-0.267	-2.266	0.03

4.6. Structural Equation Modelling:

An empirical analysis was conducted on a sample of 150 farmers to discover the elements considered by farmers to influence their paddy yield which would ultimately lead to their net income. The survey was conducted among registered farmers in Ollukkara block of Thrissur district. A structured questionnaire was used to collect primary data on demographic details of farmers, paddy cultivation and management practices, constraints faced by farmers etc. The data collected was analyzed, and identified the factors that maximized paddy production and improved farmers' revenue. Barrett (2007) defined SEM as a modelling technique that fit models to data, making model testing a crucial prerequisite for determining the fit of a model to original data.

Table 4.77: Demographic characteristics of the respondents

Variables		Frequency	Percentage
Age	<50	56	37.33
	50-70	83	55.33
	>70	11	7.33
Education	Illiterate	3	2
	Primary School	35	23.33
	High School	71	47.33
	Intermediate/+2	20	13.33
	Graduate	15	10
	Post graduate	6	4
	<=2	19	12
Family Size	>2	131	87
Land size (acres)	<= 1	63	42
	01-03	73	48.66
	03-05	11	7.33
	05-07	1	0.66
	07-09	2	1.33
Trainings received	<=3	146	97
	>3	4	4
Extension contact	<=3	132	87.98
	>3	18	12
Usage of weedicide	No	64	42.66
	Yes	86	57.33
Usage of pesticide	No	52	34.66
	Yes	98	65.32
Paddy cultivated area (ha)	<=1	93	62
	01-03	46	30.66
	03-05	3	2
	05-07	6	4
	07-09	2	1.33

As a first step, a base model was constructed through SEM using the variables like farmers' age, educational qualification, occupation, family size, land size, experience in paddy farming, organizational membership, extension contact, number of trainings attended, source of training, biofertilizers used, chemical fertilizers used, irrigation details, weeding practices, pesticides used, plant protection measures used, quantity of paddy produced, price per kg of paddy, expenditure incurred under different heads namely seed, labour cost, manure, pesticides and plant protection measures, transportation charges, pumping and sprayer charges, miscellaneous expenditure, loan availed and its source.

After fitting the SEM model using all the variables under consideration its validity was tested using the goodness of fit measures. Based on the goodness of fit, the base model was tested for how better it fitted the data. As the values of CFI, TLI and RMSEA was not satisfied by the base model, it was necessary to improve the goodness of fit and the model needed to be modified by removing insignificant variables and redefining the paths in the model. The other tests do improve the model was based on the modification indices test which enabled to add or remove the paths in the base model to improve the fit.

4.6.1. Modification of the fitted model using modification indices

Modification indices test can be used to modify models first fitted which would provide a satisfactory fit and can be used for further analysis and interpretation. The modification indices (also called as a range multiplier score test) is an estimate of the amount by which the chi-square would be reduced according to many modification we apply, it enables us to add or remove the paths to improve the model fit. The error terms which showed the high modification indices values in the model were joined by two headed arrows (covariances) and repeated the same process until modification indiceswere on par and all the error terms were cleared with modification indices values.

Covariances between the independent variables or between the errors of dependent variables determine the non-causal connections between the respective variables. Standardized residual covariances are much like modification indices. Modification indices identify the discrepancies between the proposed and estimated models. Hence, we use modification indices for the covariances.

The modified SEM model was fitted using the exogeneous variables namely Age, Extension contact, education, no. of trainings attended, land size, price per kg of paddy and endogenous variables like experience in paddy farming, loan, paddy cultivated area, method of weeding, usage of pesticide, usage of biofertilizers, leased price, price for pesticide, tractor charges, wage for labourers, loading charges, Miscellaneous expenditure, expenditure for chemical fertilizer, paddy yield, quantity of straw produced, income from paddy and net income. The generated final SEM model is given in Fig: 4.46. The figure depicts the opinion of paddy farmers regarding the cultivation and management practices, constraints they are facing and other important factors that are influencing the income of paddy famers. It can be seen that all the variables are represented by rectangles since they are observed variables. But the errors are unobserved or latent variables and are drawn in circles. The model shows the different pathways where the independent variables lead to dependent variables. Paddy yield is an important variable where most of the variables act as independent variables to it. Farmer's net income is the ultimate factor where the pathways get end up. The whole model speaks about the pathways that run from the cultivation and management practices during paddy production, constraints faced during the production and ends up with the economic condition of paddy farmers.

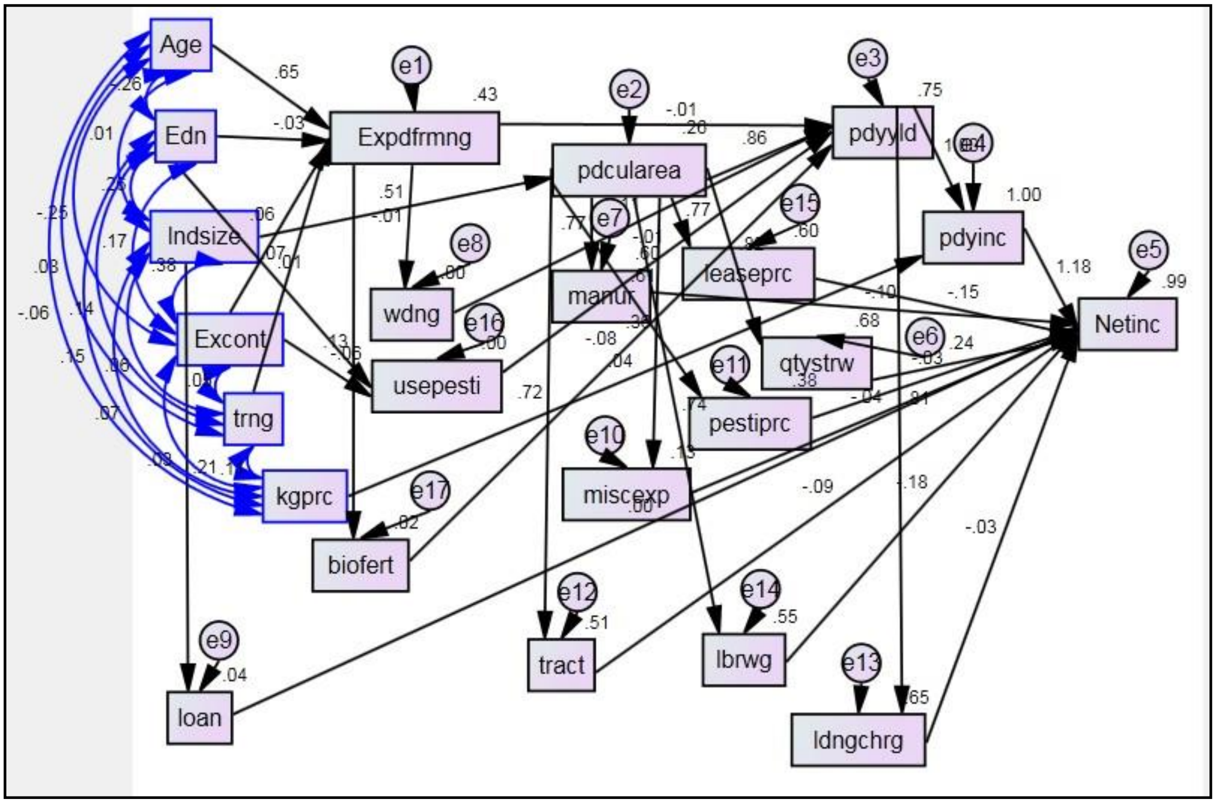

Fig 4.46: Final SEM model for net income from paddy

Expdfrmng	- Experience in paddy farming
Edn	- Education
Tract	- Tractor charges
Miscexp	- Miscellaneous expenditure
Pdcularea	- Paddy cultivated area
Pdyinc	- Paddy income
Usepesti	- Use of pesticide
Qtystrw	- Quantity of straw
Wdng	- Type of weeding
ldngchrg	- Loading charge
Lbrwg	- Labour wage
Excont	- Extension contact

biofert - Bio – fertilizer

Kgprc - Price per kg

Leaseprc - Lease price

Netinc -Net income

pestiprc - Pesticide price

pdyyld - Paddy yield

qtystrw - Quantity of straw

In Fig.4.46, the numbers near the arrows are standardized coefficients between the variables; the R^2 value for the dependent variable is shown above its rectangle in the diagram. The final SEM model resulted in an R^2 value of 0.75 for paddy yield and 0.99 for net income from paddy. Hence 99 per cent of the variation in net income of paddy farmers could be explained using final SEM model through a network of variables.

Table 4.78: Model fit summary of Final SEM model on paddy production

Parameters	**Value**	**Suggested value**
Chi – square value	332.608	-
DF	168	-
CFI	0.95	>0.90
TLI	0.93	>0.90
RMSEA	0.08	≤0.08

From Table 4.78, it can be seen that the value of CFI, TLI and RMSEA were 0.95, 0.93 and 0.08 respectively. It indicated that the model had very good fit. The value of CFI and TLI satisfied the suggested value which was >0.90 and RMSEA<= 0.08. The goodness of fit of the final SEM model was examined to see how well it suited the data. Since CFI, TLI, and RMSEA values were up-to the standard, the null hypothesis was accepted that the fitted model had a good fit. A brief discussion has been made to illustrate the application of structural equation modelling to study the causal relationship of the critical factors of paddy production that influenced income of farmers of Ollukkara block of Thrissur district in Kerala. The SEM model was developed to study the interdependence of factors related to demographic details, paddy cultivation and management practices and production data and to evaluate how these variables influenced the income of paddy farmers using SEM. Several structural equations (19) could be generated to predict each of the endogenous variable involved in the study.

Model coefficients and their significance

The estimation result should be reported in the form of standardised coefficients for the purpose of comparing the predictive power of the predictor variables. Unstandardized regression coefficients, according to Kline (2010), cannot be used to compare the effect of predictor variables in the model since they reflect the scales of their respective predictors with distinct raw score metrics. The causal model's standardised route coefficients for paddy production are shown in Table 4.79.

Table 4.79: Maximum likelihood estimation of the final model

Endogenous variable	Exogenous variable	Standardized path coefficient	p-value
Expdfrmng	Age	0.657	***
	Excont	0.068	0.263
	Edu	-0.028	0.661
	trng	0.056	0.353
Loan	lndsize	0.204	0.008
Pdyyld	Expdfrmng	-0.030	0.128
	Pdcularea	0.862	***
	Wdng	0.000	0.996
	Usepesti	-0.034	0.066
	biofert	-0.053	0.005
Pdcularea	lndsize	0.519	***
Wdng	Expdfrmng	-0.030	0.710
Usepesti	Excont	-0.095	0.244
	Edn	0.045	0.575
Leaseprc	pdcularea	0.767	***
Pestiprc	pdcularea	0.606	***
Miscexp	pdcularea	0.375	***
Tract	pdcularea	0.721	***
Lbrwg	Pdcularea	0.744	***
Ldngchrg	pdyyld	1.00	***
Pdyinc	Kgprc	0.035	***
	pdyyld	0.998	***
Netinc	Leaseprc	-0.146	***
	Qtystrw	0.240	***
	Pdyinc	1.182	***
	Manur	-0.100	***
	Pestiprc	-0.025	0.008
	Miscexp	-0.044	***
	Tract	-0.093	***
	Lbrwg	-0.178	***
	Ldngchrg	-0.033	0.079
	loan	-0.001	0.89
Qtystrw	pdcularea	0.818	***
Manur	pdcularea	0.892	***
biofert	Expdfrmng	0.117	0.140

The linear equations developed through SEM are as follows

Experience paddy farming = $\alpha_1 + \beta_1\ Age - \beta_{12}\ edn + \ \beta_{13} Excont + \beta_{14} trng + \varepsilon_1$

Paddy cultivated area = $\alpha_2 + \beta_2 landsize + \varepsilon_2$

Paddy yield $= a_3 - \beta_{31}\ Expdfrmg + \beta_{32}\ Pdcularea + \beta_{33}\ Wdng - \beta_{34}\ Usepesti - \beta_{35}\ Biofert + \varepsilon_3$

Paddy income $= a_4 + \beta_{41}\ Pdyyld + \beta_{42}\ Kgprc + \varepsilon_4$

Quantity straw $= a_6 + \beta_6\ Pdcularea + \varepsilon_6$

Manure $= \alpha_7 + \beta_7\ Pdcularea + \varepsilon_7$

Weeding $= a_8 - \beta_8\ Expdfrmng + \varepsilon_8$

Loan $= \alpha_9 + \beta_9\ landsize + \varepsilon_9$

Miscellaneous $Expenditure = \alpha_{10} + \beta_{10}\ Pdcularea + \varepsilon_{10}$

Pesticide price = $\alpha_{11} + \beta_{11}\ Pdcularea + \varepsilon_{11}$

Tractor $Charge = a_{12} + \beta_{12}\ Pdcularea + \varepsilon_{12}$

Loading charge $= \alpha_{13} + \beta_{13}\ Pdyyld + \varepsilon_{13}$

Labour wage $= \alpha_{14} + \beta_{14}\ Pdcularea + \varepsilon_{14}$

Lease price $= a_{15} + \beta_{15}\ Pdcularea + \varepsilon_{15}$

Usage of pesticide $= \alpha_{16} + \beta_{161}\ Edn - \beta_{162}\ Excont + \varepsilon_{16}$

Bio fertilizer $= a_{17} + \beta_{17}\ Expdfrmg + \varepsilon_{17}$

Net income$= a_5 + \beta_{51}\ Pdyinc - \beta_{52} Leaseprc + \beta_{53}\ qtystrw - \beta_{54}\ pestiprc - \beta_{55}\ Misexp - \beta_{56}\ loan - \beta_{57}\ tract - \beta_{58}\ lbrwg - \beta_{59}\ ldngchrg - \beta_{510} mannur + \varepsilon_5$

The path coefficients from the determinant variables to net paddy income were correlated with Kg price ($\beta_1 = 0.035$) and paddy yield ($\beta_{51} = 0.99$) both were significant at 0.05 level. Among the variables, paddy cultivated area, paddy yield and price per kg of paddy played an important role in the net paddy income.

Paddy yield was directly correlated with paddy cultivated area ($\beta_{32} = 0.86$), use pesticides ($\beta_{34} = -0.034$), biofertilizers($\beta_{35} = -0.053$), paddy cultivated area played a major role to increase the paddy yield. In general the paddy yield was increased according to the usage of chemical fertilizers and above average farmers didn't prefer to use bio fertilizers.

Net income was directly correlated with lease price ($\beta_{52} = -0.014$) , quantity straw($\beta_{53} = 0.024$), paddy income($\beta_{51} = 1.18$), manure ($\beta_{510} = -0.010$), pesticide price($\beta_{54} = -0.025$) , miscellaneous expenditure ($\beta_{55} = -0.044$), tractor charge (β_{57} =0.09), labour wage ($\beta_{58} = -0.0178$), loading charge ($\beta_{59} = -0.03$), loan ($\beta_{56} = -0.01$). Among this quantity of straw and paddy income were positively correlated, except pesticide price, loan and loading charge all other variables were significant at 0.05 level.

Experience on paddy farming was directly correlated with age ($\beta_1 = 0.657$), extension contact (β_{13}=0.068), education (β_{12}=-0.028) and training (β_{14}= 0.056). Among this except education all other variables were positively correlated, age played an important role and it was significant at 0.05 level. When age increased, naturally experience on paddy farming also increased.

Usage of pesticide was directly correlated with two variables namely extension contact and education and among that education was positively correlated.

In short, the Structural Equation Model (SEM) is an important statistical framework that can be used to represent complex relationships between observed and unobserved (latent) variables in a diagrammatic pathway which can be effectively used to study the factors affecting paddy yield and thus farmer's net income. It is a powerful regression analysis that solves systems of several linear equations at the same time. Each predictor variable is assumed to be measured without error, the error or residual variable is the only latent variable permitted in the model, and multi-collinearity among the predictors may occur. Amos can fit models that are not restricted by these constraints. Thus, SEM has become more popular in recent times to study the interdependence of variables involved in different crop production programs also.

Constraints faced by paddy farmers in Ollukkara Block of Thrissur District

In general the farmers are satisfied with the net income returns from paddy farming. Now these days they are in a competition to lease lands and cultivate paddy as much as possible and to enhance their income. Due to conservation of wet land act in Kerala, people are now becoming more farming oriented but there are some constraints they are facing in spite of their high enthusiasm and active participation in paddy farming.

To quantify the constraints as perceived by the farmers, they were directed to rank the constraints according to their severity by giving rank 5 to the most severe and rank 1 to the least severe. The ranks given by the whole 150 farmers for five major constraints under different heads were subjected to compute Kendall's coefficient of concordance and resulted in W = 0.423, which was significant at 1 per cent level. Therefore, it was concludedthat farmers had strong agreement among themselves to rank the constraints in paddy farming in the order of severity as "financial, labour management, pest, disease and animal attack, Marketing, lack of knowledge in paddy farming". The farmers identified financial constraints as the most severe one. Actually, they faced financial constraints like difficulty in securing working capital and to meet the expenditure on various cultivation operations. In general, the paddy farmers faced problems of non-availability of labourers and high labour cost. Attack from pigs, peacocks and other birds in their field were the next constraint. Marketing constraint came next. Poor farmers faced the problem of keeping the harvested paddy safe in adverse climatic conditions until supply- co collect their produce. If the quality of produce is not up to the standard mark, the selling price would reduce. Almost all the farmers were of the opinion that they didn't face any problem of lack of knowledge about paddy farming. This showed the awareness created by the extension personnel and the adequate number of trainings received.

In spite of all the constraints in farming, the farmers are now ready to engage in paddy farming as it is becoming more and more profitable. Government has taken every step to promote paddy cultivation by giving seeds free of charge, providing subsidy to the farmers with respect to different cultivation operations and also by taking utmost care to implement conservation of paddy land and wet land act. Since most of the cultivation operations are now mechanized the whole cultivation operations can be managed by the farmers themselves and can save a large amount of money in that respect. Quantity of straw is an additional income from paddy farming and the selling price of straw is increasing in a good rate which would ultimately lead to a farmers' net income.

SUMMARY

Chapter 5

SUMMARY

Rice cultivation in Kerala dates back to 3000 BC and it is one of the prominent food of most of the Keralites. But since 1980, paddy cultivation has been in steady decline from 8,500,000 ha in 1980-‘81 to 1,980,000 ha in 2016-‘17. Area under cultivation was decreasing day by day mainly due to adoption of non-agricultural food crops like rubber etc. Net income of paddy farmers in Kerala showed a declining trend over the years. Structural Equation Modelling can be fruitfully used to identify the factors influencing the net income of paddy farmers.

To know the causal relationship between dependent and independent variables and also to know the interdependency between variables we use one of the statistical techniques called Structural Equation Modelling (SEM). The views of farmers can be taken into account and identify the factors which influence the production of paddy which would ultimately lead to their net income. In this context a study on “Structural Equation Modelling in Paddy” was carried out to investigate how different independent variables and intermediate dependent variables were interrelated each other and finally leads to net income through the whole network of several variables.

The study also dealt with the shift in area, production and productivity of paddy using the data collected from the official website of Directorate of Economics and Statistics (DES), Kerala, for the period from 1960-‘61 to 2019-‘20 for different seasons like Autumn, Winter and Summer. The study envisaged assessment of the general trend in area, production and productivity of paddy crop. It was found that Autumn and Winter area and production had a declining trend which could be quantified using a linear trend equation with a significantly high value of R^2 = 0.94, R^2=0.86 for Autumn and Winter area under paddy and R^2 = 0.82, R^2 = 0.68 for Autumn and Winter paddy production Summer area as well as production showed an increasing linear trend with R^2 = 0.64 and 0.65 respectively. The reason behind this increasing trend in summer season might be because of the water logging, flood or drought in other seasons, the farmers were ready to use leased lands and cultivate paddy in summer season. Introduction of conservation of paddy and wet land act in year 2007 had also influenced the increased cultivation of paddy. In the case of productivity it was increased in all seasons and the linear trend equations for autumn, winter and summer showed R^2 equal to 0.87, 0.83 and 0.86 respectively.

In trend break analysis, structural breaks tests helped to determine when and whether there was a significant change in the data. Breaks were identified in paddy production data in Kerala which depicted the phases of growth, and found that among all the seasons, area under winter paddy found maximum number of breaks and production and productivity data in winter and autumn identified minimum number of breaks indicating that maximum variability existed in the data of area under winter paddy. Compound Annual Growth Rate Analysis (CAGR) and Cuddy-Della Valley Index (CDVI) were found to identify the growth rate as well as instability index. Results showed that area under autumn paddy was adversely affected which resulted in negative growth rate in all the phases. And highest instability observed in summer paddy production.

To forecast area, production and productivity of paddy in three different seasons namely Autumn, Winter and Summer in Kerala, the time series data collected for 60 years from 1960-‘61 to 2019-‘20 were subjected to time series modelling. Browns’ exponential smoothing model was identified as the best model with significantly high value of $R^2 = 0.99$ for area under paddy in Autumn, ARIMA (0,1,0) with $R^2 = 0.98$ in Winter and Simple exponential smoothing model with $R^2 = 0.93$ in Summer. Coming to paddy production in Autumn, Brown’s exponential smoothing model resulted in an $R^2 = 0.95$ and simple exponential smoothing model seemed to be the best for Winter and Summer season with $R^2 = 0.87$ and 0.60 respectively. Holt’s exponential smoothing model was found as the best with $R^2 = 0.87$ to predict paddy productivity in Autumn and Summer and Brown’s exponential smoothing model with $R^2 = 0.87$ for winter paddy productivity.

Regression analysis was done to predict the change in production of paddy in Kerala (adjusted $R^2 = 0.78$) using the data collected from the year 1996-‘97 to 2018-‘19 of area, production, productivity and price of paddy. Change in area, change in productivity, change in price, and interaction between change in price and change in area were the significant variables to predict the change in paddy production. Results demonstrated that for one unit decrease in change in price, there would be a -4.9 unit change in production and for one unit increase of change in area, there would be an increase of 3.4 unit in production, one unit increase in change of interaction effect of area and price there would be a 0.004 increase in production.

An empirical analysis to identify the factors perceived by farmers to influence their paddy production and ultimately leading to their net income was done taking a sample of 150 farmers from Ollukkara block of Thrissur district. Out of 150, 37.33 per cent respondents belonged to an age group of below 50 years and 55 per cent were in between 50-70 years and 7 per cent were above 70 years. While considering the educational qualification, only 2 per cent illiterates were there, 23 per cent had primary school level education, 47 per cent acquired high school level, 20 per cent had intermediate level, 10 per cent had graduate level and 4 per cent had post graduate level education. Among the respondents, 12 per cent had family size less than or equal to 2 and 87 per cent had family size greater than 2. For 42 per cent of the respondents, land size was less than or equal to one acre, for 58 per cent it was in between 1 to 9 acres. Trainings received were less than or equal to three for 97 per cent of farmers and 4 per cent of farmers received more than three trainings. Extension personnel made a minimum of three visits in 87.98 per cent of farmers' fields and greater than three visits in 12 per cent cases. Usage of pesticides was common among 65.32 per cent of farmers and 34.66 per cent avoided that. Paddy cultivated area were less than or equal to one acre for 62 per cent cases, in between 3 to 4 acres for 32.66 per cent cases, and in between 5 to 7acres for 4 per cent and greater than 7 acres for1.33 per cent respondents.

Among the demographic characters as well as details of cultivation practices of the farmers, endogenous variables for constructing Structural equation model were net income, experience in paddy farming, loan, paddy yield, paddy cultivated area, paddy income, weeding, pesticide price, miscellaneous expenditure, tractor charge, quantity of straw, biofertilizers used, extension contact, labour wage, loading charge, lease price and expenditure on manure. and exogenous variables were age, education, training, land size, extension contact, price per kg of paddy. Structural equation modelling was done using those exogenous and endogenous variables to develop paddy yield prediction models as well as model for net income from paddy. Since a large number of exogenous and endogenous variables were to be simultaneously considered which had both direct and indirect effects on paddy yield and net income of farmers, a large number of simultaneous regression equations were to be analysed and the path analysis through SEM resulted as an efficient tool to manage such situation.

From Structural equation modelling, 19 structural equations could be developed for various types of predictions and the SEM developed was tested for its efficiency using the goodness of fit indices like CFI and TLI both were > 0.9 satisfying the criterion for the best model and the badness of fit index RMSEA should be ≤ 0.08 which was also satisfied in the present case resulting in a powerful model with R^2=0.99.

To quantify the constraints faced by the paddy farmers in Ollukkara block of Thrissur district, they were directed to rank the constraints according to their severity by giving rank 5 to the most severe and rank 1 to the least severe one The ranks given by the whole 150 farmers were subjected to compute Kendall’s coefficient of concordance and resulted in W=0.423, which was significant at 1 per cent level. Therefore, it was concluded that farmers had strong agreement among themselves to rank the constraints in the order of severity as “financial, labour management, pest, disease and animal attack, marketing, lack of knowledge in paddy farming”. The farmers identified financial constraints as the most severe one. Actually, they faced financial constraints like difficulty in securing working capital and to meet the expenditure on various cultivation operations. In general, the paddy farmers faced problems of non-availability of labourers and high labour cost. Attack from pigs, peacocks and other birds in their field were the next constraint. Marketing constraint came next. Poor farmers faced the problem of keeping the harvested paddy safe in adverse climatic conditions until supply- co collect their produce. If the quality of produce is not up to the standard mark, the selling price would reduce. Almost all the farmers were of the opinion that they didn’t face any problem of lack of knowledge about paddy farming.

In spite of all the constraints in farming, the farmers are now in a competition to lease lands and cultivate paddy as it is becoming more and more profitable now. Government has taken every step to promote paddy cultivation by giving seeds free of charge, providing subsidy to the farmers with respect to different cultivation operations and also by taking utmost care to implement conservation of paddy land and wet land act.

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STRUCTURAL EQUATION MODELLING IN PADDY

By

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ABSTRACT OF THE THESIS

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Abstract

Agriculture is the largest sector of economic activity in Kerala and has a crucial role to play in economic development by providing food and raw materials, employment to a very large proportion of the population, capital for its own development and surpluses for economic development. In this context a study on the analysis of the trends regarding the data for a period from 1960-‘61 to 2019-‘20 on area under cultivation, production and productivity of paddy in Kerala has great importance. An empirical study was also attempted to identify the vital factors leading to the enhancement of net income of paddy farmers using Structural equation modelling on the primary data collected from 150 registered paddy farmers of Ollukkara block of Thrissur district.

The trend analysis of area, production and productivity of paddy in Kerala for the period from 1960-‘61 to 2019-‘20 pertaining to autumn, winter and summer seasons revealed that area under paddy and production had a declining trend in autumn and winter seasons whereas an increasing trend in the case of summer paddy. Paddy productivity has an increasing trend in all the seasons.

Employing Bai and Perron (1998) methodology, breaks in the time series of area, production and productivity of paddy in Kerala for different seasons were identified and were used to explore volatilities of paddy production in different phases. Compound Annual Growth Rate (CAGR) and instability indices were computed with respect to each break points of the trend and used to explain the growth pattern of the variables over the study period owing to the fact that paddy is one of the most essential food crops in Kerala. In the recent past, area under cultivation of paddy had been declining due to several factors including the adoption of non-agricultural food crops like rubber and coconut which would provide better returns to farmers. CAGR on area, production and productivity showed a declining trend upto 2008-‘09. Area under autumn paddy was the most affected variable resulted in negative growth rates in all phases. In contrast, the growth rate was positive for productivity in almost all phases of different seasons. However, in the subsequent year to the enactment of the Kerala paddy conservation and wetland act, the area and production of paddy for all the three seasons gradually started increasing depicting a positive impact of the act on paddy cultivation in the state. The growth instability was maximum for summer paddy production.

Time series modelling and forecasting analysis identified Browns' exponential smoothing model as the best with significantly high value R^2 = 0.99 for area under paddy in autumn, ARIMA (0,1,0) with R^2 = 0.98 in winter and Simple exponential smoothing model resulted in an R^2 = 0.93 in summer. Coming to paddy production in autumn, Browns' exponential smoothing model resulted in an R^2 = 0.95 and Simple exponential smoothing model seemed to be the best for winter and summer season with R^2 = 0.87 and R^2 = 0.60 respectively. Holts' exponential smoothing model was found as the best with R^2 = 0.87 to predict paddy productivity in autumn and summer and Browns' exponential smoothing model with R^2 = 0.87 for winter paddy productivity.

The secondary data collected from the year 1996-'97 to 2018-'19 on area, production, productivity and price of paddy from the official website (DES), Kerala were made use of to forecast the yearly change in paddy production by fitting a regression of change in production on yearly change in cultivated area, yearly change in productivity, yearly change in price, and the interaction of yearly change in price and area. The regression equation resulted in an adjusted R^2 of 0.73 and yearly change in area and productivity were the significant regressors.

An empirical analysis was conducted using a sample of 150 registered paddy farmers from Ollukkara block of Thrissur district to determine the factors considered by farmers to influence their paddy production and, ultimately leading to their net income. Several linear regression equations could be constructed simultaneously from a path analysis using structural equation modelling, leading to prediction equations for paddy production and net income. The final model iterated, resulted in goodness of fit measures viz; comparative fit index = 0.90 and Tucker Lewis index = 0.90 and RMSEA = 0.08 emphasising the potential of SEM in plant science studies as powerful as in social science. Finally the constraints faced by the farmers in paddy farming were ranked according to their severity and coefficient of concordance was computed as w= 0.423 which was significant at 1 per cent level showing strong agreement among the farmers to rank the constraints as "financial, labour management, pest, disease and animal attack, marketing and lack of knowledge in paddy farming". However in spite of all these constraints farmers are now attracted towards paddy farming because of the enriched net returns from it.