FORECASTING MODELS FOR THE YIELD OF COCONUT

BY

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THESIS

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DECLARATION

I hereby declare that this thesis entitled "FORECASTING MODELS FOR THE YIELD OF COCONUT" 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 to me of any degree, diploma, associateship, fellowship, or other similar title, of any other University or Society.

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Mannuthy,
16-9-1985.

CERTIFICATE

Certified that this thesis entitled "FORECASTING MODELS FOR THE YIELD OF COCONUT" is a record of research work done independently by Sri. Myint Swe under my guidance and supervision and that it has not previously formed the basis for the award of any degree, fellowship, or associateship to him.

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CONTENTS

INTRODUCTION

CHAPTER I

INTRODUCTION

1.1. General Introduction

Over the past decades, scientific research into crop-weather models has received considerable attention by the scientists working in a variety of disciplines such as agrometeorology, plant physiology, agronomy, plant breeding, ecology, agricultural economics and agricultural statistics among others. Numerous research projects and publications on specific aspects of weather and climatic factors in relation to crop yields and yield components have been brought about. The realization of effects of meteorological factors on crop production, and hence their impact on world food supply, has also led to renewed interest in a continuous world-wide watch of crop prospects and forecasts.

The various mathematical/statistical models and techniques on crop-weather relationship have been developed and utilized. Many scientists all over the world have been actively involved in various research projects on the development of crop-weather models. However, the practical exploitation of this knowledge and information on crop-weather relationship for the assessment of crop yields from weather data has not yet satisfactorily advanced and progressed to the extent that might be expected.

One reason for this slow development in assessing the crop yield based on crop-weather relationships has been apparent lack of interest by policy-making and production-planning bodies for real-time crop assessment. This may have been due to crop production policies which existed in 1950's and 1960's in the major food exporting countries and to the large surpluses at that time in these countries as well as on the world market. Under these conditions of food glut, there seemed to be no need for monitoring the effect of weather and climatic factors on crop yields from meteorological data on a real-time basis, since survey reports on crops and stocks provided adequate and plausible information. However, agricultural meteorologists and statisticians continued to develop such crop-weather models and demonstrated the feasibility and potentiality of providing weather based real-time estimates of regional crop production.

Annual fluctuations in crop production are accepted feature of regional or world food supply, but usually these fluctuations tend to offset one another on a regional or global scale. But because of the adverse weather conditions occurring in 1972 simultaneously over the major producing areas of the world, it was then realized that a repetition of this adverse weather pattern over successive years would have disastrous effects on both developing and developed countries.

In addition to the effect of these annual weather fluctuations, there was also evidence that, during the past one or two decades, the seasonal weather patterns did not show the disastrous variability or extremes that can be expected from long term climatic records for the region of Indian sub-continent. Eventhough the "good" weather trend resulted in a series of years with high crop yields in India, it cannot be expected that the crop yields of next several years will stay at these high levels. In this regards, the crop-weather models can be utilized as useful and important research tools for the interpretation of climatic fluctuations in terms of their impact on crop production over large areas of the nation.

The new food situation of India, with its dependence on weather variability, has led to renewed interest (i) in the need to give more serious consideration to an analysis of weather and climatic condition of India as a natural resource and (ii) in the need for monitoring and interpreting current and immediate weather data in terms of expected crop conditions and crop yields.

Other countries, such as USA, USSR, Canada, Israel, Brazil, Iran, Turkey, Australia, FRG, GDR, Italy, Japan and Argintina among others are already using such crop-weather models and weather based estimates for various agricultural crops on an experimental or operational basis.

International organizations such as World Meteorological Organization (WMO) and Food and Agriculture Organization (FAO) have also substantially increased their effort to provide real-time information on weather and climate fluctuations and their impact on regional and global surpluses and shortfalls in food production. The need for more research into crop-weather models, development of operational crop yield assessment models and their importance in national agricultural plannings have been more and more widely recognized in many countries of the world.

1.2. Present investigation and its objectives

In this advent of world-wide recognition of 'importance' and 'renewed interest' in the effects of meteorological factors on crop yields and development of crop-weather models for the assessment of crop yields, as discussed in section 1.1, the present investigation on the development of statistical crop-weather models for the pre-harvest forecast of agricultural crops, with special reference to coconut crop which is one of the most important agricultural crops of India, is carried out with the following views and objectives:

1. to develop a suitable and reliable statistical methodology for the pre-harvest forecast of coconut crop yields by evolving different empirical-statistical crop-weather models using the original and generated weather variables as predictor variables.

2. to perform a comparative study of relative efficiency, adequacy and performance of each of these crop forecasting models evolved and to select the "best", most promising and plausible crop forecasting models for the purpose of future use in predicting the coconut crop yield reliably in advance of harvest.
3. to investigate the effect and influence of changes in weather variables on the yield of coconut crop based on the crop forecasting models selected as the "best" fitted models.
4. to render suggestions and guidelines for further development of statistical crop-weather models, criteria for their selection and relevant statistical analysis.

1.3. Development and classification of crop-weather models

In the physical sciences, the term "model" is used "to provide an explanation for certain phenomena and to postulate underlying processes which give a rise to the observations under inspection" (Yarranton, 1971). The use of high degree polynomials to represent biological situations should properly be defined as a mathematical representation rather than a model (Mead, 1971). However, this distinction between a 'mathematical representation' as a description of biological observations and 'a model' with its normally associated properties in the physical sciences has not yet been made in ecology and agrometeorology. Because of the common use of the term "model", it is essential to identify the various models on the basis of the approaches used in crop-weather models.

Regardless of the approach, "a crop-weather model" may be defined as "a simplified representation of the complex relationship between weather and climatic factors on the one hand and crop performance such as growth, yield or yield components, on the other hand by using established mathematical/statistical theory and techniques" (Baier, 1978).

Crop-weather models can be of the steady state type or dynamic type. The latter usually include some sort of function of time with a procedure which summarizes, weighs and integrates the results from the steady state condition model over periods of seconds, minutes, hours or days. Other crop-weather models use crop development phases as time basis.

McQuigg (1976) described two basic approaches to modelling the impact of weather variability on crop yields:

i) the physiological or causal approach which is based on detailed knowledge of the biological and physical processes and the immediate atmospheric and soil environment of the plant; and

ii) the statistical or correlative approach which is based on the application of some sort of statistical, techniques, mostly regression analysis, to a sample of crop yield data from an area and a sample of weather or climatic data from the same area.

In the present investigation, the second approach has been followed in developing the crop-weather models for the purpose of forecast of coconut crop yields.

Newman (1974) distinguished basically between two approaches:

i) modelling based on mathematically formulated relationships with empirical constants when necessary; and

ii) modelling usually involving some type of statistical regression techniques for fitting statistically the "best" possible empirical relationship between climatological variables and crop-production statistics.

The former approach is called deterministic approach and the latter stochastic approach. Therefore, according to Newman's definition of crop-weather models, the models developed in the present investigation can be termed as "stochastic crop-weather models". The deterministic models using meteorological data taken over short periods are more applicable to a specific crop production system. Stochastic models are more adaptable to relating 'climatological data' to 'agricultural production' in a particular geographical region.

Baier (1978) classified crop-weather models into three categories: (i) crop growth simulation models, defined as a simplified mathematical representation of the complex physical, chemical and physiological mechanism underlying the plant growth response; (ii) crop weather analysis models, providing a running account of the accumulated (daily) crop responses to selected agrometeorological variables as a function of time or crop development; and (iii) empirical-statistical models, in which one or several variables representing weather or climate, soil characteristics or a time trend are statistically related mostly to a seasonal yield or other crop statistics. In the crop growth simulation models, it is considered that the impact of meteorological variables such as temperature, rainfall, radiation, wind velocity, relative humidity, etc. on specific processes, such as photosynthesis, transpiration or respiration, can be adequately simulated by means of a set of mathematical equations which are based on experiments or available knowledge of particular process.

In crop-weather analysis models, the variables such as soil moisture or evapotranspiration and other derived or observed data on a day-by-day basis are used and these variables are related, together with other information, to morphological development, vegetative growth or crop yields. The standard climatic data are used as primary input; some processes or crop response function, such as soil moisture distribution or fertilizer response, are pre-programmed but conventional statistical techniques (e.g. multiple linear regression analysis techniques) are usually used to evaluate the weighting coefficients in the final equations. Crop-weather models such as those proposed by Baier (1973) and Haun (1974) belong to this category.

In empirical-statistical crop-weather models, a sample of yield data from an area (e.g. experimental station or field, crop district or region) and a sample of weather data from the same area or from another area, which is nearest to the area under study and having the weather conditions which are identical to or almost the same as that of the area under study, are used to produce estimates of regression coefficients by some sort of linear or non-linear multiple regression techniques. The validity and potential application of these empirical-statistical crop-weather models depends on the representativeness of the input weather data, the relation of weather variables and the design of the model. The approach does not easily lead to an explanation of cause-and-effect relationship. But it is a feasible and potential procedure which makes use of available yield and climatic data for weather based evaluations of historical, current and to some extent expected crop yield statistics. Typical examples here are almost all the papers reviewed in the Chapter II of "Review of Literature" where almost all the papers employed multiple linear or curvilinear regression analysis techniques in one way or the other.

Therefore, according to Baier's classification of crop-weather models, the crop-weather models developed in this investigation come under the category of empirical-statistical crop-weather models.

REVIEW OF LITERATURE

CHAPTER II

REVIEW OF LITERATURE

2.1. Introduction

Recently there has been an increased effort to develop and utilize statistical crop-weather models. Among other things, this effort has been stimulated by the desires: (1) to forecast crop yields from current weather forecasts and crop-weather models, and (2) to assess the impact on food production of a hypothetical climatic change whether inadvertent or intentional, as by weather modification. The statistical crop-weather models predict crop yields from climatic variables using empirical relation derived from substantial records of crop yields and weather variables.

The "rediscovered" importance of the effect of weather and climate on crop yields and "renewed" interest in the development of crop-weather models have brought about numerous research projects and publications dealing with crop-weather relationships and forecasting of crop yields therefrom, at different scales. Various statistical and mathematical techniques for analysing these crop-weather relationships have been evolved and the terminology, such as 'crop-weather models' and 'yield forecasting models', have emerged as popular expressions in this type of research work.

The scientists involved in crop-weather modelling and yield forecast modelling are not only agrometeorologists but also plant physiologists, agronomists, plant breeders, ecologists, agricultural statisticians, agricultural economists, and many other experts. Because of their different academic backgrounds, they use different approaches and interpretations in their research and applications.

2.2. Crop forecasting models and their classification

Crop yields depend to some extent upon a number of factors such as quantity of seeds, use of fertilizers, irrigation, area under high yielding varieties, called agricultural inputs, weather variables and biometrical characters. Therefore, crop forecasting models can be divided into four broad categories as follows:

1. Forecasting models using 'weather variables' as predictor variables.
2. Forecasting models using the 'biometrical characters' as predictor variables.
3. Forecasting models using 'agricultural inputs' as predictor variables.
4. Forecasting models using 'combinations of weather variables, biometrical characters and agricultural inputs' as predictor variables.

In this literature review, only research papers concerning with empirical-statistical crop-weather models and yield forecasting models using 'weather variables' as predictor variables are reviewed in detail.

Since almost all the research papers consulted and reviewed here used multiple linear and curvilinear regression techniques in one way or the other, the papers reviewed in this chapter are in their cronological order, but not in crop-wise or variable-wise.

In order to comprehend and appreciate the trend and direction in crop forecasting in India today, a brief history of crop forecasting in India is presented before elaborate review of literature on crop forecasting models, followed by a short review of literature on weather forecasting with special reference to rainfall, because rainfall plays, both qualitatively and quantitatively, the most important role in influencing the crop growth, hence the yield components and yield response of the crop.

2.3. A brief history of crop forecasting in India

The systematic application of statistical methods to prediction of natural phenomena was begun in India in 1909 by Sir Gilbert Walker, the Director-General of Observatories. His investigations on the forecasting of seasonal rainfall in India from a knowledge of prior weather conditions over those parts of the world which affect subsequent weather in India have become classical.

According to Ramdas and Kalarkar (1938), Jacob (1916) was the first scientist in India to apply the statistical methods to the study of crop-weather relationship with particular reference to wheat crop of Punjab. Jacob correlated the areas of matured crop over the years 1887 to 1906 in 30 villages chosen from each of 5 tahsils of Sialkot district with rainfall of the preceding six months, in the case of autumn and spring harvested crops respectively. Rainfall in September was found to be slightly beneficial to the autumn crop and considerably so to the spring crop. The year-to-year variation of rainfall was examined by fitting both Pearsonian frequency curves and periodic curves. The effect of varying distribution of rainfall, treating the more important crops separately was also studied.

The value of systematic work on the subject of crop-weather relationship was stressed by the 'Royal Commission on Agriculture' in India. Effect was given to the recommendations of the Commission in 1932 when a section of Agricultural Meteorology was started at the Meteorological Office, Poona under the auspices of the 'Imperial Council of Agricultural Research'.

In 1945, the Indian Council of Agricultural Research (ICAR) launched an All-India Co-ordinated Crop Weather Scheme (AICWS). Under this scheme, specialised meteorological observatories were set up for the systematic recording of crop-weather observations on paddy, wheat and jowar as a net work of selected experimental farms throughout the country. These observations were later extended to sugarcane and cotton as well. The objective of the scheme was to formulate, in quantitative terms, the effect of different growth factors on the growth and yield of crops under observation.

Reviewing the status of AICWS, Sarker (1977) reported:

"Some tentative crop-weather relationship have been established with respect to the crops at different crop weathor stations by applying statistical methods. Response of a few crops in yield to distribution of rainfall during the life cycle of the crop has also been obtained. Similar studies in relation to other meteorological parameters like maximum temperature, sunshine and humidity are in progress".

2.4. Literature review on empirical-statistical crop-weather models

After launching the section on Agricultural Meteorology, rainfall and its impact on the yield of coconut crop was first investigated by Patel and Anandan (1936). The data utilized for the study were collected at the Agricultural Research Station, Kasaragod on the West Coast of India. The number of rainy days, the total rainfall for the different seasons and years were also collected. The yield data utilized in various correlation was collected from 105 regular bearing palms. The trees were of the ordinary tall type and they were about twentyfive years old in 1919. Patel and Anandan obtained the correlation coefficients between the yield of coconut and different combination of rainfall.

It was reported that the maximum correlation of yield of coconut and different combination of rainfall was 0.8104. The combination of rainfall for the maximum correlation was the total rainfall in January, February and March of the previous year of harvest and the second year previous to the harvest. It was also reported that January to April rains for two years previous to the harvest had maximum correlation with the yield of coconut. The multiple regression equations of the yield on the three predictor variables X_1, X_2 and X_3 was worked out, where X_1 was the total rainfalls in January, February, March and April during the year of harvest, X_2 was total rainfall in the same months during the year previous to harvest and X_3 stood for the total rainfalls in the months during the second year previous to harvest. From the multiple regression equation, multiple correlation coefficient of 0.798 was also obtained. It was also found that multiple correlation coefficient was very close to the co-efficient of correlation for the total rainfall in three years during January to April. The total as well as the partial correlations were not significant, thereby indicating that the rainfall of one year was not related to the rainfall of another year for the observations made, and found that the correlation, wherever significant, were not spurious.

Patel and Anandan (1936) drew the conclusion that the crop yield in any year was influenced by January to April rainfalls for two years previous to the harvest, together with the rainfalls in January to April of the harvest year.

Balasubramanian (1956) conducted the investigation of influence of rainfall - monthly as well as seasonal on the bearing capacity of coconuts. The yield data were obtained from Pilicode for 26 years and from Kasaragod for 29 years. The monthly rainfall data were compiled from the station records for the years for which the yield data were available. Balasubramanian reported that (i) the rains received in January influenced apparently the performance of coconut plantations, (ii) next to January rains, the February rains appeared to be important at Kasaragod, whereas the rains of March and April assumed similar important influence at Pilicode and (iii) rains in September were essential for coconuts at Kasaragod. But at Pilicode rains in the months of October and November appeared to be very necessary.

The climatic requirements and qualitative effects of weather on the performance of the coconut crop was reviewed by Marar and Pandalai (1957). It was found that the seasonal differences did not affect the different characters of the palm and that the yield of a particular year was influenced by January to April rainfalls for two years prior to harvest together with the rains during similar period of harvest year. It was also found that the rains received in the months of May, June, July, August and December had no marked influence on coconut plantations in both the stations and that the influence of September rainfalls was felt in the crop yield obtained in the next two years at Kasaragod but the effects are of different nature. At Pilicode they had no significance on crop yield at all.

The joint effects of rainfall and maximum daily temperature on the yields of corn crop were investigated by Stacy et al. (1957). In their work, the maximum daily temperature and rainfall averaged by 5-day period for 18 periods during each growing season of a 38-year span were related to the corn yields using a set of second degree orthogonal polynomials as regression integrals. Results indicated that high temperature near the end of growing season were beneficial to crop yields if the rainfall was adequate. When no rain occurred high temperature causes great damage to the crop yields in the first of June.

Mallik (1958a) examined nine year's data for the crops of wheat, jowar and cotton at the Dharwar Research Station and found that in two years when the wheat yield were very low due to rust attack, the number of hours of sunshine days during November was abnormally low. On the other hand, in jowar, on the basis of comparison of rainfall during growing season in two years of very good harvest with wheat in two years of very poor harvest, Mallik argued that jowar crop at Dharwar is rather susceptible to excessive rainfalls during the growing period. Using similar approach it was further suggested the spell of cloudy and rainy weather extending over 3 consecutive weeks during growing season of cotton appeared to create conditions favourable to pests like shoot borer and red cotton bug.

In his another paper, Mallik (1958b) attempted a more elaborate analysis of ten years' data relating to jowar from five stations. It was postulated, partly for lack of any other basis, that the optimum amount and distribution of rainfall during the growing period of kharif jowar was approximated by the amount of rainfall and its distribution in each of 12 weeks prior to ear emergence. Mallik then estimated the correlation coefficient between (i) height and yield, (ii) the percentage of deviation of actual weekly rainfall during the growing period in each year from the rainfall in corresponding weeks of the optimum year (i.e. the year of maximum in sample) and percentage deviation from the maximum height, and (iii) deviation in rainfall for the year of optimum yield and deviation from the optimum yield using a similar procedure as in (ii).

In a subsequent paper, Mallik et al. (1960) attempted a rather more elaborate analysis of data for the cotton crop from some 12 stations. Here again, the stations were pooled into two groups on the basis of rainfall in the reproductive period to get a sufficient number of observations for studying correlation coefficients between (i) different growth features and yield and (ii) meteorological factors and some growth features.

This kind of analysis which tried to scan the strength and pattern of relations between a variety of meteorological variables which were expected on a priori grounds to affect the crop yield was valuable especially when there was no well-formulated hypotheses on the precise nature of crop-weather relationship. The problem posed by pooling of observations could be overcome once sufficient number of observations were available for a particular variety.

Pillai and Satyabalan (1960) studied the seasonal variation in yield, nut characters and copra contents in a few exotic cultivars of coconuts growing at the Central Coconut Research Station, Kasaragod. It was reported that the variation in yield was very high during different seasons. In the majority of the cultivars, the highest yield was observed in summer and lowest during north east monsoon period. In the case of west coast tall variety, it was during summer that large nut and maximum copra content were obtained. The relationship between the volume of husked nut and weight of copra was found only in some cultivars.

It was concluded that the seasonal variations observed might be a peculiarity of the exotic coconut cultivars.

Gangopadhyaya and Sarker (1964) applied the techniques of curvilinear correlation study in investigating the effect of weather variables on the growth of sugar cane. It has been found that at Poona, of all weather variables, the maximum and minimum temperatures influenced elongation most and that their optimum values were equal to 87.5^{o}F and less than or equal to 68^{o}F respectively. Rainfall had slight effect as the crop was irrigated. They reported that curvilinear study could be satisfactorily used to bring out a series of crop weather relationship which were not observable on the surface and to provide a basis of estimating the probable effect of new combinations of independent factors upon the dependent one.

Lakshmanachar (1965) fitted orthogonal polynomial curves of the fourth degree to the distribution of rainfall at Kasaragod during 1926-1950 for each year. It was found that (i) average weekly rainfall had a tendency to increase as the linear component was positive, (ii) 75 per cent of rainfall from the middle of May to the middle of September, (iii) the remaining quantity was distributed over other 8 months and (iv) there was every certainty of the occurrence of rainfall during the weeks 23rd to 30th while during the first 14 weeks, probability was very low.

Sarker (1965) suggested the use of method of successive graphic approximations to examine the influence of prevailing weather on yield of sugarcane crop at Poona. It was found that the weather during the tilling phase accounts for 50 per cent of the variations in the yield.

Sen et al. (1966) investigated the influence of weather variables on the yields of tea crop in the Assam Valley in India. Mean values of rainfall, relative humidity, sunshine hours, diurnal temperature were tried as predictor variables. A separate analysis was undertaken for each of the early, main and late crops (April–June, July–September and October–December). In their study, time variable was added as predictor for changes in growth rate of tea plant as it aged.

After some initial trials, Sen et al. (1966) used the logarithm of rainfall in place of rainfall itself, an increase in precipitation proving to be more beneficial when rainfall was low than when it was high. It was found that for the early crop, the significant predictors were mean temperature and logarithm of rainfall, each with a lag of 3 months; the yield was greater than warm and wet weather (upto about 18 cm of rainfall) than after cool and dry condition.

Ramamurti and Banerjee (1966) carried out a curvilinear regression analysis of weather variables with the yields of wheat crop at the region of Dharwar, India using successive approximation technique developed by Ezekiel and Fox (1959). Various weather factors were tried in their study. They reported that an optimum of about 16°C maximum temperature and 22°C to 23°C mean temperature with 60 to 65 hours of bright sunshine per week and 50 to 60 per cent humidity appeared to be the most favourable condition for wheat in Dharwar.

Aboywardena (1968) endeavoured to develop the relationship between rainfall and coconut crop using multiple regression technique. It was found that the influence of a particular spell of rainfall on the yield of most fruit crops was dependent on the moisture sensitivity of the stage of development of the crop during the spell of rainfall. It was confirmed from the study that the period May to August with a longer day length was more moisture sensitive. The sub-periods of January to April and September to December were not only less moisture sensitive but also differed widely in their moisture sensitivities in spite of the fact that their day-length were identical.

Thompson (1969) employed multiple curvilinear regression analysis in order to investigate the influence of weather variables on corn yields in U.S.A. In his study, the influence of weather was separated from the influence of technology on the yield of corn by the use of time trends for technology and multiple curvilinear regression for weather variables in five corn belt states of U.S.A. The weather variables employed were total rainfall from September through June, June temperature, July rainfall, July temperature and August temperature.

Thompson (1970) conducted another investigation of influence of weather and technology in the production of soybean in the Central United States. In his study Thompson used multiple curvilinear regression analysis. Time trend was introduced to measure the influence of technology as in his previous study (Thompson, 1969). It was concluded that (i) the highest yield has been associated with warmer than normal temperature in July and August and (ii) the highest yield has been associated with normal precipitation from September through June and with above normal rainfall in July and August.

Suryanarayana et al. (1971) studied the relationship between the groundnut yield and rainfall pattern at Hebal and Bangalore for the period from 1957 to 1966. The various aspects of rainfall, both quantitative as well as qualitative, were taken into account to explain variation in the yield. The qualitative aspects of rainfall were studied through the parameters namely co-efficient of variation of rainfall, percentage number of rainy days and severity of dry spell. Simple correlations of these parameters with the crop yield revealed importance of qualitative aspects rainfall also.

It was found that the multiple correlation of these qualitative parameters with yield revealed that yield variation to the extent of 50 per cent was attributable to the variation in these four factors. It was concluded that the yield of groundnut depended not only to a smaller degree on the amount of rainfall but also to a higher degree on the pattern and distribution of rainfall and the stage at which the dry spell occurred and that any attempt to relate rainfall with the yield of crops in general and groundnut in particular should take into consideration along with the quantity of rainfall, qualitative aspects and stage of crop growth to obtain a comprehensive picture of the several intrinsic factors.

Das, Mehra and Madhani (1971) evolved prediction equations for forecasting the yield of autumn paddy rice in Mysore State using weather variables with the help of multiple linear regression analysis. In coastal Mysore restricted rainy days during July to 15 September and frequency of occasions of drought and floods in August and September were principal weather factors having significant effect on yield. In the Interior Mysore South, June and September rainfall had significant effect on yield. By testing the formulae for the yields for 1965 to 1968, it was found that they agreed well with the reported yields. All the correlation coefficients obtained were also significant at 0.1 per cent level.

Carr (1972) reviewed research and observations on the weather variables affecting the growth and yield of tea plant and attempted to define quantitatively the climatic conditions needed to maintain growth rates at a high level despite differences in the type of tea grown and cultural techniques practised in the different tea areas. It was found that long sunshine hours were probably essential for maximum yield if the nutrient status of the tea (with particular reference to nitrogen) was adequate, and so long as other factors such as excessive air and leaf temperatures and low air humidity did not in turn become limiting.

Sreenivasan (1972) carried out comparative analysis of relative performance of the two statistical Methods brings out the slow continuous change in the response of crop yield to the weather pattern experienced by the cultivated soil and crop and (ii) regression function in which the weather pattern was subjected to continuous screening to obtain a few well defined weather periods of significance to the soil and crop. It was also found that in the case of wheat crop at Jalgaon and Niphad regions, the regression function had better multiple correlation co-efficient than the regression integral. Sreenivasan concluded that it might be due to the differential response of some of adjacent hypotheses of crop and changing soil characteristic to the weather variables.

Sreenivasan and Banerjee (1973) analysed systematically crop and weather observations twice-a-day on rabi. Jewar at Raichur Agrometeorological Observatory during 1948-67 using multiple curvilinear regression techniques and concluded that the pattern and magnitude of responses of the crop to the weather factors, viz., mean maximum temperature, total rainfall, number of rainy days and mean minimum temperature differed among themselves, temperature showing greater influence than rainfall. It was also found that the two varieties of wheat M 35-1 and PJ-4R showed a range of weather factors. The study also confirmed advantage of applying curvilinear multiple correlations as to the behaviour of the crop-weather relations as postulated by Gangopadhyaya and Sarker (1965).

In his another paper, Sreenivasan (1974) employed regression integral techniques of Fisher (1924) to evaluate the influence of rainfall on the wheat grown at Jalgaon and Niphad (Maharashtra State) for a period of 22 years. It was found that the pattern of response was similar at these two stations and the two varieties in each station but the magnitude of responses of wheat crop grown in the heavy black soils of Niphad. These studies supported the current views of physiologists and agronomists.

Coomans (1975) drew the conclusions, based on results from four countries, that the available water, temperature and sunshine have an influence on seasonal fluctuations in coconut yields. Their action intervened at various moments in the development of the inflorescence and the fruit. It was found that water deficit played the main role in the fluctuations in the yield of coconuts.

Devanathan (1975) advocated the use of the product of rainfall per month (R) and average daily hours of sunshine per month (S) as predictor variable in relating yield of tea crop to weather variables. It was found that the best fitted regression equation of yield on (RS) for the previous month was linear giving the correlation co-efficient of 0.972. Therefore, it was concluded that the empirical weather parameter (RS) could provide a good quantitative estimate of interaction of main climatic factors, which promoted plant growth, at least for yields of tea crop under constant treatment.

Murata (1975) reviewed statistical and simulation studies as to the effect of climatic factors on rice yield in Japan and carried out correlation studies at various locations in the past half century. It was concluded that the most important and limiting climatic factors for rice yield was solar radiation or sunshine hours, while it was mean air-temperature during the same period in northern regions of Japan. Several regression models were postulated to express the structural relationship which were supported by various physiological knowledge and experimental data so far collected.

Bridge (1976) related Kharkov winter wheat yields at four locations, spanning over 12° latitude on the Great Plains to climatic parameters. For each locations, a step-wise multiple regression techniques was used to relate winter yields to climatic parameters generated by a constant rust zone (CRZ) water budget and expanding root zone (ERZ) water budget. It was found that (i) compared to those for CRZ model, the multiple regression using ERZ model parameters explained an average of 12 per cent more of the total variation in winter wheat yield and (ii) the regression employing only potential evapotranspiration and precipitation variables explained an average of 63 per cent less of the variation in winter wheat yield compared to the regression formed with ERZ model parameters.

Dyer and Gillooly (1977) employed a step-wise linear regression technique to describe hay yield with nitrogen application, last years' yield, mean warm season and cold season temperature. The study set out to show that the useful structural equations could be obtained for a crop in Iceland, a marginal region of earth's surface. It was found that the current year's hay yield had a significant structural relationship with mean cold season temperatures, application of nitrogen and mean warm season temperature in that order. It was also found that when the previous year's yield was added as a predictor, nitrogen application and mean warm season temperature make no significant contribution to the relationship.

Bedekar et al. (1977) carried out forecasting the yield of wheat in India from weather parameters. Regression equations were developed to forecast rabi wheat yield for the meteorological sub-divisions: Madhya Maharashtra, Rajasthan (east), Gujarat region and Himachal Pradesh. First, the mean crop yield for a particular sub-division was linearly correlated with different weather elements for different overlapping spells ranging from 7 to 60 days. Those spells which gave high correlation and called 'sensitive periods' were selected. Different combinations of the sensitive periods for different weather variables were selected and subjected to multiple correlation analysis, with yield as dependent variables. After numerous permutations and combinations, the combination of meteorological parameters were selected which gave high and significant multiple correlation and thereby explained a very large percentage of total variation of crop yield.

Rao et al. (1978) attempted to develop the prediction equation for the forecasting of the rice yield for the regions of Marathwada, Rayalaseema, Gujarat and Himachal Pradesh. The method of analysis was the same as the method used by Bedekar et al. (1977). They all used 6 variables including the variable of technological trend because recent advances in the field of agricultural technology like increased use of chemical fertilisers (N,P,K), better irrigation and drainage facilities, control of pests and diseases, better seeds, improved agricultural practices, etc., have resulted in sharp rise in crop yield. This increase for all these factors is called the technological trend. On plotting yield versus years, technological trend was noticed in the yield figures of Marathwada from 1975-76, for Rayalaseema from 1960-61, for Himachal Pradesh from 1951-52, and for Gujarat from 1952-53.

Katz (1979) performed a sensitivity analysis of statistical crop weather models. The models in his study were of the type which predicted yields from climatic variables using empirical relationships derived from historical yields and weather. Ridge regression techniques were used to perform the sensitivity analysis. The results indicated that the estimates of regression coefficients could be quite variable due to multicollinearity of the predictor weather variables. Katz reported that the sensitivity results had significant implications concerning (i) the appropriate statistical methodology for developing yield models (ii) the limitations inherent in using these models in order to assess the impact of climatic variability or change on food production.

Other attempts for forecasting of the crops using log-normal diffusion process were made by Saraswathy and Thomas (1975, 1976).

In their first paper, Saraswathy and Thomas used log-normal diffusion process in order to forecast some important crops of Kerala State. The forecasted crops were rice, tapioca, coconut, arecanut, pepper, tea, coffee, rubber and cashewnut. Tintner and Patel (1965) applied log-normal diffusion model to the data on national income of India, using the government expenditure as the exogenous variable. Tintner and Patel (1969) also utilized the same model to explain the trend in per hectare yield of crops, viz. rice, wheat and sugarcane in India, taking the proportion of irrigated area under the crop as exogenous variable.

In their second paper, Saraswathy and Thomas (1976) adopted the same method to explain the trends in production of the crops cited above, taking the area under the crop as the exogenous variable. The base year was taken as the year 1952-53. It was found that coefficient of determination reported by Saraswathy and Thomas were very high and forecast values were very satisfactory. They reported that the stochastic model used, namely, the log-normal diffusion model offered a reasonably close fit to the data and hence these models could forecast the pre-harvest production of crops for the periods which were not very far removed from the year 1973-74, the data upto which have been used in the construction of the models to forecast the production of crops.

Runge (1968) studied the effects of rainfall and maximum temperature interactions on the yield of corn crop during the growing season. It was found that rainfall and temperatures during the growing season were correlated with corn yield under constant management for the 54 years period 1903-1956. It was found that maximum daily temperatures and rainfalls had a large effect on corn yield from 25 days before to 15 days after anthesis. That corresponded to the average calendar interval of June 30 through August 8 at Urbana, U.S.A. Maximum effect of temperature and rainfall on corn yield occurred approximately one week before anthesis and remained at a high level one week before anthesis and remained at a high level one week before to either side of maximum. The models developed in this investigation indicated that high temperatures between 32.2 and 37.8°C could be beneficial to corn yield if moisture available to corn plant is adequate. Fisher's polynomial techniques, modified by Hardricks and Scholl (1943), were used to study interaction of rainfall and temperatures on the corn yield. In his study, Runge used fourth degree multiple regression equation having nine generated variables. Runge and Odell (1938) investigated the relation between precipitation, temperature and the yield of corn using the same fourth degree multiple regression equations. In their prediction models, the following assumptions were introduced.

i) A unit of maximum temperature or a unit of rainfall has the same effect on crop yield for the average temperature or total rainfall above and below average, but in opposite directions.

ii) The total effect on yield is directly proportional to the number of units of maximum temperature or units of total rainfall above and below average.

iii) The effect on crop yield in each period is independent of the effect in any other time period.

Bhargava et al. (1978) investigated influence of moist days and humid days on the yield of jowar crop in Jalgaon district pertaining to 1950-1971. It was reported that the yield has linear relationship with the number of moist days and number of humid days. It was found that the span of humid period extended between the 3rd week of June to 2nd week of September while that of the moist period extended between 2nd week of June to the end of September.

Rao (1980) studied the effects of rainfall and maximum temperature on yields of tossa jute crop. In his study, the maximum daily temperature and rainfall averaged for 20 weekly periods during growing season of 1960-1977 were related to fibre yields of tossa jute. As in the investigation conducted by Stacy et al. (1937), second degree polynomials were used as regression integrals. It was found that these weather variables explained 87% of the total variation in fibre yields. The maximum effect of temperature and rainfall on the yields of jute was observed at about 75 days after germination. It was also reported that temperature higher than 36°C gave positive yield response at all levels of rainfalls and that rainfall between 45 and 100 days of crop age was beneficial to crop yields.

Agrawal et al. (1980) made an attempt to develop a forecasting model of rice yield using weather variables in Raipur district of Madhya Pradesh. The weather parameters used in the forecasting models were weekly weather variables, viz., maximum temperature, relative humidity, total rainfall and number of rainy days. Two models were found suitable to forecast the rice yield. In the first model, weighted averages of weekly weather variables and their interactions using powers of week numbers as weights were used. The respective correlation coefficients with yield in place of week number were taken in the second model. The stepwise regression technique was used to select significant generated variables. Further analysis were carried out using significant generated variables. To study the consistency of the forecasting models, simulated forecasts of subsequent years, not included for obtaining regression equation, were worked out.

Mustafi and Chaudhuri (1981) developed a stochastic process model for the monthly tea crop production as function of stochastic variables like past value of monthly tea crop production and also of both past and current values of weather parameters of rainfall and Penman's evaporation records. The study involved generation of regression polynomials of optimal complexity through the use of a heuristic method called multilayer group method of data handling (GMDH). It was found that the method of GMDH provided a prediction of tea crop production a month ahead of the crop's picking. It was reported that optimum level of precipitation needed for a possible desired level of tea crop production could be determined with the help of GMDH method.

In their another paper, Agrawal and Jain (1982) proposed a composite model for forecasting of the yield of rice crop in Raipur district using the weather parameters of maximum temperature, relative humidity, total rainfall, number of rainy days, fertilizer consumption, percentage area under HYV and irrigation and fertilizer:rice price ratio. Two weighted weather indices were constructed to reduce the number of weather variables for inclusion in the composite model. Forecast models based on weather indices and agricultural inputs along with time trend were worked out. It was also found that the additional contribution of agricultural inputs over the trend as a variable in the forecasting model was negligible, suggesting that inclusion of trend as a predictor variable in the forecasting model took care of agricultural inputs and change in technology. Agrawal and Jain reported that weather variables along with trend could explain more than 70 per cent of the total variation in yield at about 2 months and a half before harvest, suggesting that the rice yield could be forecast from weather variables alone. The adjusted coefficient of determination was used to remove upward bias when based on small number of observations.

Jones (1982) reviewed some of the methodology employed for investigating aggregate crop-weather relationship, together with the problems encountered in the process. It was supported by an attempt to estimate such a relationship from a short data series for the control Norfolk region of UK. Chi-square tests were used to determine the seasonal significance of weather variables which then subjected to analysis of principal components. Employing the components as explanatory variables in multiple regression, the utility of the approach for exploring the economics of the agro-climatic factors were assessed.

Ong (1982a) introduced exploratory identification analysis (EIA) as a systematic and objective method of determining the relationship between oil palm bunch yields and changes in rainfalls and dry spells. Monthly oil palm bunch yields were related with monthly rainfall and dry spell as far back as 42 months before harvest (i.e. LAG 42) through a series of simple correlations and then re-evaluated through a series of partial correlations. It was found that oil palm yields were associated with rainfall at LAG 5-7, 16-18, 22-23, 28-30 and dry spell at LAG 5-6, 9-12, 16-18, 22-24 and 29-30.

Ong (1982b) continued exploratory identification analysis (EIA) in determining the relationships between oil palm monthly bunch yield to temperature and sunshine of various months (or LAG) before harvest. It was found that oil palm bunch yields had relationship with diurnal temperature range at LAG 7-9, 13-16, 19-23 respectively.

Rao (1984) made an attempt to study the relationship between the annual coconut crop yields (West Coast Tall) and annual rainfall trends using 20 years moving averages for the region of Pilicode, Northern Kerala. The onset of effective monsoon was determined on the basis of Raman (1978) criteria which stipulate that the first day's rain in a period of 7 days should be at least 5 mm with total rain of 35 mm with 4 rainy days in that period. The 20 years moving averages of annual rainfall and coconut yields were used to analyse the relationship between them. It was found that both high rainfall during the months of June, July and August, as well as the absence of post and pre-monsoon showers adversely affect the subsequent years' coconut yields in the Pilicode region.

2.5. A brief literature review on weather forecasting models with special reference to rainfall

In order to study the crop-weather relationship we must acknowledge the high role played by the rainfall and its quantitative and qualitative aspects. Many studies of distribution and forecast of rainfall have been made in the recent past. Among them were Gabriel and Neumann (1957), 1962), Medhi (1976), Thomas (1977), Nguyen and Rousselle (1981), Nguyen (1982), Krishnan and Suryanarayana (1982) and Manohar and Siddappa (1984).

Gabriel and Neumann (1957, 1962) employed a Markov-chain model for daily rainfall occurrence at Tel-Aviv, Israel. They described the occurrences and non-occurrences of rainfall of Tel-Aviv by a two-state Markov-chain. A dry date was denoted by state 0 and a wet date by state 1.

Medhi (1976) utilized the same two state Markov-chain model as in Gabriel and Neumann (1957, 1962) in his study of occurrence and non-occurrence of rainfall in Gauhati, India. The statistical hypothesis testing on the order of chain, zero or one, was also carried out using the statistical inference techniques for Markov-chains developed by Anderson and Goodman (1957).

Thomas (1977) predicted the monthly and annual amount of precipitation and also number of rainy days at Pattambi Rice Research Station. The point estimate, viz. arithmetic mean of monthly and annual precipitation have been worked out. It was found that the mean annual precipitation at Pattambi was 2606.3 mm and the standard deviation of amount of precipitation was 336.05 mm. The mean number of rainy days per year is 118.24 days and the standard deviation was 13.52 days.

Nguyen and Rousselle (1981) presented a stochastic characterization of temporal storm pattern and proposed a model to determine probability distributions of rainfall accumulated at the end of each time unit within a total storm duration. It was found that probability of any given number of consecutive rainy hours was determined by first and second-order Markov chains. Statistical tests were performed to test the fit of the Markov model to the sequence of wet hours.

Nguyen (1982) reported that there was agreement between the observations and the proposed model, and concluded that the methodology in their study was more flexible and more general than those that have been used in previous investigations. By using the stochastic model developed by Nguyen and Rousselle, a storm profile could be characterized in terms of the time of occurrence of a storm which was defined as an interrupted sequence of consecutive hourly rainfalls, the total storm depth, and the probability estimates of accumulated rainfalls at the end of each time unit within the total storm duration.

Krishnan and Suryanarayana (1982) analysed theoretical distribution of rainfall accumulated during 2 weeks, 4 weeks, 6 weeks, etc. upto 30 weeks from the commencement weeks of growing season for each individual year at Bangalore region, during the period of 1907 to 1977. It was found that accumulated rainfall was not normal for second and fourth weeks, so also, non-normality was found for 10 week and 14 to 28 weeks respectively.

Manohar and Siddappa (1984) also carried out a study of weather spells and weather cycles at Raichur district using first order Markov chain model. The daily rainfall data for 59 years from 1917 to 1975 for the monsoon months (June to October) at Raichur were used to fit the first order Markov chain model. It was reported that the first order Markov chain model seemed to fit better for the wet spells than dry spells as judged by the chi-square tests.

The reliability analysis of rainfalls during crop growing season in Bangalore and Kolar districts in Karnataka was conducted by Rao and Rao (1968). Application of conditional rainfall probability estimates to agriculture and planning was reviewed by Singh and Pavate (1968).

Basu (1971) conducted fitting of a Markov chain model for daily rainfall data at Calcutta. The study of occurrence of rainfall in Raipur district was made by Bhargava et al. (1973) using first order Markov chain model. Mathematical distribution of rainfall in arid and semi-arid zones of Rajasthan State were developed and analysed by Krishna and Kushwaha (1972).

Weather condition at Tamil Nadu Agricultural University, Coimbatore was analysed by Kulandaivelu et al. (1979). Analysis of rainfall pattern and cropping system in Kinathakadavu Block, Coimbatore district was carried out by Kulandaivelu et al. (1979).

Prediction of North East Monsoon rainfall at Coimbatore was done by Raj (1979) and seasonal rainfall in Pondicherry was analysed by Raju et al. (1983). Bahagavamdoss and Ramalingam (1983) investigated monthly and annual rainfall pattern at Pondicherry.

The nature of the frequency distribution of Indian rainfall (Monsoon and annual) was investigated by Rao et al. (1974). Victor and Sastry (1979) analysed the probability of dry spell using the first order Markov chain models and thereby dry spell probabilities were applied to the study of crop development stages effectively.

2.6. Coverage of review of literature and conclusion

The above literature review is obviously far from complete in its coverage of the work done in India and other foreign scientific bodies on statistical crop-weather models. But in so far as the papers covered and reviewed here form a fairly representative cross-section of the work done in this area of crop-weather models, we could, at some risk, attempt to summarise the state of knowledge they reflect.

The forecasting models based on macro data, being highly empirical in their approach, are of doubtful value for understanding crop-weather relationships, but seems to be quite good for statistical predictions of yield, given the values of weather parameters. Therefore, it would be useful to examine the forecasting power or predictive power of these empirical-statistical crop-weather models in the case of other crops and regions for which they have been developed and attempted.

MATERIALS AND METHODS

CHAPTER III

MATERIALS AND METHODS

3.1. Materials

In order to develop a statistical crop-weather model for the purpose of forecasting the yields of a crop, it is inevitably needed to collect a sample of yield data from an area under study as well as a sample of weather data from the same area or from a station which is nearest to the area and having identical climatic conditions, if the original weather data is not available with the area under study. This fact is no exception to the present investigation since crop-weather models developed in this investigation come into the category of empirical-statistical crop-weather models in which one or several weather variables are statistically related to crop yields as response or predicted variable.

The present study of empirical-statistical crop-weather models for the yields of coconut crop was carried out for the region of Pilicode, Hosdurg Taluk in Kasaragod district, which is situated at 13°N and 75°E latitude and longitude respectively at an elevation of 91.40-121.86 metres above mean sea level (MSL). Pilicode region is about 58 km north of Cannanore Town on the eastern side of the West Coast Road, NH 17.

The maximum temperature of this region ranges from 26.90°C to 33.92°C with a mean of 31.03°C and the minimum temperature ranges from 18.42°C to 27.41°C with a mean of 22.50°C. During the south west monsoon period of June to September an average precipitation of 250 cm is received at Pilicode. The north east monsoon usually started in October and continues upto January. During this period, 43 cm of rain on an average is received in Pilicode. The soil in Pilicode region is a laterite soil, i.e., a fairly heavy loam containing laterite sand or gravel.

3.1.1. Collection of data on yields of coconut

The required coconut yield data utilized in the present study were collected from the coconut Research Station (Nileshwar I), Regional Agricultural Research Station, Pilicode, under Kerala Agricultural University. The 91 palms (from palm No.86 to 176) were selected from Block I of 1.19 hectare in area, one of 24 blocks maintained by the Research Station. The data on monthly coconut yields of the trees for 13 years from 1968 to 1980 were collected from the monthly yield register books maintained at the Station. The trees were of ordinary West Coast Tall (WCT) type and reserved for the purpose of control in experimentations conducted by the Stations. They had not been given any special treatment or irrigation in the course of time under study. Some trees (palm numbers) which were dead and cut were deliberately excluded from the study. Based on monthly coconut yield data collected from the Station, average yield of nuts per bearing tree per half calendar year, taking first half-year as from January to June and second half-year as from July to December, were computed excluding those trees which were not bearing female flowers and giving any nut for the year as a whole, being treated as abnormal trees for that year. Thus, for the span of 13 years from 1968 to 1980, 26 values of average yield of coconuts per bearing trees per half year were obtained. The average yield of nuts per bearing tree per half year was used as response (predicted) variable in our statistical crop-weather models for the yields of coconut.

The annual rainfall of Pilicode region are abundant. However, the crop yields are low due to its uneven distribution of rainfall and high intensity during monsoon. The region also experiences soil moisture deficit from October to May due to lack of rain, which inhibits the growth of coconut crop and production

3.1.2. Collection of data on weather variables and formation of seasons

Following Marar and Pandalai (1957), the meteorological variables utilized in our statistical crop-weather models for the yields of coconut crop were the total rainfall, hours of bright sunshine, wind velocity, relative humidity per cent and maximum temperature. Since the required data on all these five weather variables for the span of 13 years from 1968 to 1980 were not available with the Pilicode Coconut Research Station, we had resorted to the Central Plantation Crop Research Institute (CPCRI) at Kasaragod for collection of required weather data on five weather parameters stated above. From the station records at CPCRI, the weather data on weekly total rainfall in millimetre, weekly mean of daily sunshine hours, weekly mean of daily wind velocity in km/hr, weekly mean of relative humidity in percentage at forenoon and afternoon and weekly mean of daily maximum temperature in centigrade at forenoon were collected. The reason for collecting the required weather data from CPCRI is as follows:

In the light of study of rainfall data at the two stations (Pilicode and Kasaragod) based on 26 years weather data (from 1929-1954), conducted by Balasubramanian (1956), it was found that the pattern of rainfall were similar in these two stations. In the first five months of the year, forming the Dry Weather and Hot Weather periods the total rain received at two stations were 8.8% of the annual rainfall for Pilicode and 8.7% of the annual rainfall at Kasaragod. During the remaining seven months, constituting the south west and north east monsoon period, the rain received were 91.2% and 91.3% of the annual rainfall for Pilicode and Kasaragod respectively. It was also found that the amount of rainfall received at the two Stations for the year as a whole was almost the same. In both places, south west monsoon was importent than north east monsoon.

Since the weather pattern of the two stations are almost the same it is concluded that the data on five weather variables aforementioned can be undoubtedly and fruitfully employed in developing the empirical-statistical crop-weather models for the yields of coconut in the region of Pilicode.

Based on the weekly weather data collected from CPCRI, the monthly data for these five weather variables were formed using the 'standard weeks for a year', set by Indian Meteorological Department. Then, following Marar and Pandalai (1957), the weather data for different months of the year were reduced to the following 3-month and 6-months seasons having more uniformity in environmental effect on the crop for the purpose of their application as 'periods' in our crop forecasting models developed in this investigation.

1. 3-month season formation

   i) December, January and February
   ii) March, April and May
   iii) June, July and August
   iv) September, October and November

2. 6-month season formation

   i) December, January, February, March, April and May
   ii) June, July, August, September, October and November.

Monthly data for total rainfall, monthly means of daily bright sunshine hours, wind velocity, mean relative humidity for forenoon and afternoon, and maximum temperature were converted into seasonal (3-month and 6-month)weather data on total rainfall in cm, seasonal mean of daily bright sunshine hours, seasonal mean of daily wind velocity, seasonal mean of daily mean relative humidity percentage and seasonal mean of daily maximum temperature respectively. Thus, the above seasonal (3-month and 6-month) weather data on these five weather variables were employed as original predictor weather variables in our crop-weather models for the yields of coconut crop.

Since the data on relative humidity were expressed in percentages, they were transformed into arc-sine root proportions so that the distribution of transformed relative humidity percents would follow normal distribution with a stabilized and constant variance in our forecasting models for the yields of coconut crop.

3.2. Methods

The weather variables affect the crop differently during its different stages of development. Therefore, the effect of weather variables at different growth stages of the crop may help in understanding the response in terms of final yields and also provide a forecast of crop yield in advance of harvest.

The extent of influence of weather variables on crop yields depends not only on the magnitude of weather variables themselves but also on the distribution pattern of these weather variables over the crop season which, as such, calls for the necessity of dividing the whole crop season into fine intervals. This will increase the number of predictor variables in the model and in turn a large number of constants have to be estimated from the data collected. This will require a long series of data for precise estimation of these constants, which may not be available in practice. Further, since environmental factors, including weather variables, are inter-related to each other, the serious problem of multicollinearity may also creep in.

3.2.1. The problem of large number of predictor variables in crop-weather models

The problem of large number of predictor variables, discussed in the above section, can be tackled by the following ways:

i) Increasing the sample size.

ii) Decreasing the number of variables

i) Increasing the sample size

The sample size is generally increased artificially through the application of cross sectional method. In this method several set of weather variables are taken in the geographically homogeneous region and these are matched with the yields of the region. The increase in degrees of freedom due to this method becomes fictitious as several sets of weather data are matched with the same yield. Further there is strong correlation between weather variables measured at the neighbouring locations which contradicts the assumption of statistically independent variables in crop-weather models. Besides that, the statistical value of information contained in such a sample does not increase proportionally to the increase in number of observation in the sample. The estimated constants in the models based on this method would have inflated sampling errors. Therefore, this is not an efficient way of tackling the problem of large number of variables in the models.

ii) Decreasing the number of predictor variables

The other alternative approach to the problem of large number of variables is to decrease the number of the variables in the forecasting model by taking weather variables during some intervals only when these variables show the significant correlation with yields. But in this method information over complete crop season is not utilized in the model which as such does not represent the distribution of the weather variables over the crop season. Fisher (1924) tackled this problem by fitting distribution constants. It was assumed that the effect of change in weather variables in successive periods would not be an abrupt or erratic change but an orderly one which follows some mathematical law.

3.2.2. Formulation of forecasting models with one weather variable

Let (O,M) be the crop season of a crop, over which the effect of a weather variable X is required to be investigated to build a statistical crop-weather model for the purpose of forecasting the yields of the crop. The crop season period (O,M) is divided into n equal parts, then the multiple regression equation of yield response Y upon the different magnitude of weather variable X at w^{th} period (or) interval, denoted by X_w (w=1, 2, ... n) is given by

$$Y = A_o + \sum_{w=1}^{n} A_w X_w + e \qquad (3.2.1)$$

where A_o is constant, A_w is the linear effect of one unit change in weather variable X on the crop yield at w^{th} period or interval within the crop season (O,M) and A_w (w=1,2, ...n) are constants to be estimated by the method of ordinary least square (OLS) based on Gauss-Markov Theorem, and X_w's are the values of weather variable X at w^{th} period.

In the limiting case, when the length of period in crop-season (O,M) is made infinitesimally very small (i.e., number of periods, n, is infinitely large) forecasting equation (3.2.1) becomes

$$Y = A_o + \int_0^M A(t)\, X(t)\, dt + e \qquad (3.2.2)$$

where X(t)dt is the amount or value of weather variable X in the infinitesimally small interval of time dt and A(t) is a continuous function of time t and represents the average effect or benefit to the crop corresponding to an additional unit of weather variable X(t)dt at any point of time t during the crop season (O,M) under study. This function (A(t) is called regression function and its graph is called Fisher's Response Curve.

Now, let $P_1(t)$, $P_2(t)$, ... $P_n(t)$ be a set of polynomials functions of time t, which are orthonormal to each other within the crop season (O,M). It means that

$$\int_0^M P_k(t)P_j(t)dt = \begin{cases} 1 & \text{for } k=j \\ 0 & \text{for } k \neq j \end{cases}$$

where k and m are any two positive integers.

Assuming further that the values of weather variable at w^{th} period can be expressed in terms of orthonormal function of time t as follows:

$$X(t) = \sum_{k=0}^{m} b_k\, P_k(t) \qquad (3.2.4)$$

where b_k's are constants, called meteorological distribution constants (MDC) in Fisher's terminology. If the effect of change in weather variable in successive periods could not be an abrupt or erratic change but an orderly one which followed some mathematical law and it was assumed that the weather effect A(t) could be expressed in term of a polynomial function of time t, we have

$$A(t) = \sum_{k=0}^{m} a_k \, P_k(t) \qquad (3.2.5)$$

where a's are also constants.

Substituting the equations (3.2.4) and (3.2.5) in equation (3.2.2) and using the property of orthonormal transformations in equation (3.2.3), we have

$$Y = A_0 + \int_0^M \left[\sum_{k=0}^{m} a_k P_k(t)\right]\left[\sum_{k=0}^{m} b_k P_k(t)\right] dt + e$$

$$Y = A_0 + \sum_{k=0}^{m} a_k b_k \int_0^M P_k^2(t)dt + \sum_{k \neq j}^{m} b_k a_j \int_0^M P_k(t)P_j(t)dt + e$$

$$Y = A_0 + \quad_{k=0}^{m} a_k b_k + e \qquad (3.2.6)$$

The statistical crop-weather model given by the above equation (3.2.6) was developed by Fisher (1924) for examining the influence of rainfall on the wheat crop at Rothamstead, England. This model takes into account not only total rainfall during a certain period but also the manner in which rainfall was distributed over the crop season

(0,M) under consideration. Fisher suggested to use m = 5 for most of the practical situations. In fitting statistical crop-weather model of equation (3.2.6) for m=5, the number of regression coefficients to be estimated by OLS will remain seven only, no matter how finely crop-season (0,M) is sub-divided.

In the above crop-weather model (3.2.6), the two assumptions of expressibility of X(t), the magnitude of weather variable, and A(t), its effect on the crop yield in terms of polynomial functions $P_k(t)$ of time t were introduced by Fisher.

Eventhough the two assumptions may be satisfied in case of annual crops like rice, wheat, sugarcane, groundnuts, etc. whose crop-seasons are relatively short, the first assumption of expressibility of weather variable X(t) in term of polynomial function would not be satisfied for the perennial crop like coconut because (i) the magnitude of weather variables as far back as one or two years more from the year of harvest has influence the crop yield and (ii) the span of two years back contains the critical period from the endogenous point of view as it covers the setting of female flowers and the young stages of all bunches of coconut maturing in a given harvest year (Abeywardena, 1968).

In case of coconut, the critical period during which its weather variables significantly influence on the crop yield is fairly long, covering one or two years more;

extreme changes in weather variables do occur and these changes do influence on the yields of coconut crop. Therefore, the first assumption of expressibility of X(t) in terms of polynomial functions discussed above would not be satisfied for the coconut crop.

We, therefore, would not follow Fisher's method of decreasing the number of predictor variables in our forecasting models for the yields of coconut. Instead, we would follow the method suggested by Hendricks and Scholl (1943) in which the crop-season (O,M) is divided into a finite number of intervals or periods and it is assumed that only effect of weather variable on the crop-yield at w^{th} period can be expressed in terms of polynomial functions of some variables such as interval or period number w.

3.2.3. Formulation of forecasting model with two weather variables

Hendricks and Scholl (1943) modified Fisher's techniques of decreasing number of predictor variables in the crop-weather model. In their method, the crop-season (O,M) was equally divided into n periods or intervals and it was assumed that a polynomial of degree k in the variable of period or interval number w would be sufficiently flexible to express the linear effect A_w in the linear regression equation (3.2.1) as follows:

$$A_w = \sum_{k=0}^{m} a_k w^k \qquad (3.2.7)$$

where a_k's are also constants

Substituting equation (3.2.7) in equation (3.2.1) the crop-weather model becomes

$$Y = A_0 + \sum_{k=0}^{m} a_k \left[\sum_{w=1}^{n} w^k X_w \right] + e \qquad (3.2.8)$$

Letting

$$Z_k = \sum_{w=1}^{n} w^k X_w$$

We get another type of forecasting equation:

$$Y = A_0 + \sum_{k=0}^{m} a_k Z_k + e \qquad (3.2.9)$$

For m=2 in equation (3.2.9) the number of predictor variables Z_k reduces to 4, irrespective of the number of periods, n, within the crop-season (0,M).

The crop weather model (3.2.8) can be extended straightforward for two weather variables, say rainfall (X_1) and maximum temperature (X_2), to study their joint or interaction effects.

Modifying crop-weather model given by equation (3.2.1) for two weather variables X_1 and X_2, taking into consideration their interaction effects, we obtain the basic linear model as follows:

$$Y = A_0 + \sum_{w=1}^{n} A_w X_{1w} + \sum_{w=1}^{n} B_w X_{2w} + \sum_{w=1}^{n} C_w X_{1w} X_{2w} + e \quad (9.2.10)$$

where X_{1w} and X_{2w} are the magnitude of weather variables X_1 and X_2 at w^{th} period or interval within the crop season (0,M).

As in crop-weather model (3.2.8), assuming that the effects A_w, B_w and C_w can be expressed in polynomial of w as follows:

$$A_w = \sum_{k=0}^{m} a_k w^k$$

$$B_w = \sum_{k=0}^{m} b_k w^k$$

$$C_w = \sum_{k=0}^{m} c_k w^k$$

and putting them in equation (3.2.10) to get

$$Y = A_0 + \sum_{k=0}^{m} a_k \left[\sum_{w=1}^{n} w^k X_{1w} \right] + \sum_{k=0}^{m} b_k \left[\sum_{w=1}^{n} w^k X_{2w} \right]$$

$$+ \sum_{k=0}^{m} c_k \left[\sum_{w=1}^{n} w^k X_{1w} X_{2w} \right] + e \quad (3.2.11)$$

Herdricks and Scholl (1943), Runge and Odell (1959), Stacy (1957) and Rao (1980) employed the above crop-weather model (3.2.11), taking m=2 as quadractic polynomial in period number w in their studies of effects of rainfall, maximum temperature and their interaction on the crop yields.

3.2.4. Formulation of forecasting models with many weather variables

For the purpose of developing crop-weather models in order to forecast the yields of coconut crop using many weather variables, the basic forecasting model (3.2.10) was modified and the complete second-order response surface type crop-weather model was developed using p weather variables with a view to achieve a wider scope and description of the system of generated predictor variables which are influencing the yields of coconut crop at various periods within the crop-season (0,M).

The original statistical linear model adopted for our crop forecasting models is as follows:

$$Y = A_0 = \sum_{i=1}^{p} \sum_{w=1}^{n} A_{iw} X_{iw} + \sum_{i=1}^{p} \sum_{w=1}^{n} B_{iw} X_{iw}^2 + \sum_{i<j}^{p} \sum_{w=1}^{n} G_{(ij)w} X_{iw} X_{jw} + h_0 T + e \qquad (3.2.12)$$

where A_{iw} = linear effect of i^{th} weather variable X_{iw} at w^{th} period on the coconut crop yield. B_{iw} = quadratic effect of i^{th} weather variable X_{iw} at w^{th} period on the coconut crop yield. $G_{(ij)w}$ = effect of two factor interaction of i^{th} and j^{th} weather variables X_{iw} and X_{jw} at w^{th}

period within the crop-season (0,M). T = half year number or observation number of coconut harvest, included to correct for the long term upward and downward trend, if any, in the yields of coconut, and e is random error or disturbance.

Assuming that it would be sufficiently flexible to express the effects A_{iw}, B_{iw} and $G_{(ij)w}$ in terms of the polynomials of degree m in the variables of functions $H_1(w)$, $H_2(w)$ and $H_3(w)$ of period number w, we have the following relations.

$$A_{iw} = \sum_{k=0}^{m} a_{ik} \, H_1^k(w) \qquad (3.2.13)$$

$$B_{iw} = \sum_{k=0}^{m} b_{ik} \, H_2^k(w) \qquad (3.2.14)$$

$$G_{(ij)w} = \sum_{k=0}^{m} g_{(ij)k} \, H_3^k(w) \qquad (3.2.15)$$

where a_{ik}, b_{ik} and $g_{(ij)k}$ are constants in the polynomials of $H_1(w)$ and $H_2(w)$ and $H_3(w)$ respectively. Substituting equations (3.2.13), (3.2.14) and (3.2.15) in equation (3.2.12) to obtain

$$Y = A_0 + \sum_{i=1}^{p} \sum_{k=0}^{m} a_{ik} \sum_{w=1}^{n} H_1^k(w) X_{iw} + \sum_{i=1}^{p} \sum_{k=0}^{m} b_{ik} \sum_{w=1}^{n} H_2^k(w) X_{iw}^2$$

$$+ \sum_{i<j}^{p} \sum_{k=0}^{m} g_{(ij)k} \sum_{w=1}^{n} H_3^k(w) \, X_{iw} X_{jw} + h_0 T + e \qquad (3.2.16)$$

Letting $$Z_{ik} = \sum_{w=1}^{n} H_1^k(w)\ X_{iw},$$

$$Z'_{ik} = \sum_{w=1}^{n} H_2^k(w)\ X_{iw}^2 ,$$

and $$Q_{(ij)k} = \sum_{w=1}^{n} H_3^k(w) X_{iw} X_{jw} \qquad (i\ j)$$

Equation (3.2.16) becomes as follows:

$$Y = A_0 + \sum_{i=1}^{p} \sum_{k=0}^{m} a_{ik}\ Z_{ik} + \sum_{i=1}^{p} \sum_{k=0}^{m} b_{ik}\ Z'_{ik} + \sum_{i<j}^{p} \sum_{k=0}^{m} g_{(ij)k}\ Q_{(ij)k} + h_0 T + e \qquad (3.2.17)$$

Within the class of complete second-order response-surface type statistical crop-weather models, the above crop-weather model (3.2.17) is the most general form of crop-weather model from which many forecasting models for the yields of coconut crop can be derived and brought out for different values of the parameters p, m, n and for different forms of the generated predictor variables depending upon the various functional forms of $H_1(w)$, $H_2(w)$ and $H_3(w)$ respectively.

The forecasting model (3.2.17) for the yields of coconut crop with the first-order generated variable Z_{ik} and the second-order generated variable Z'_{ik} and $Q_{(ij)k}$ is more general than all the empirical-statistical crop-weather models recently developed and employed in forecasting the crop yields, in the context of second-order response surface type crop-weather model.

1) If we take $H_1^k(w) = H_2^k(w) = H_3^k(w) = w^k$, $m=2$ and $b_{ik} = 0$ for all i and k, our forecasting model (3.2.17) reduces to the crop-weather models used by Hendricks and Scholl (1943), Stacy et al. (1947) and Rao (1980).

2) If we take $H_1^k(w) = H_2^k(w) = H_3^k(w) = w^k$, $m=4$ and $b_{ik} = 0$ for all i and k, our forecasting model (3.2.17) reduces to the forecasting models employed by Runge and Odel (1957), Runge (1968).

3) If we take in our model (3.2.17) as

   i) $H_y^k(w) = w^k \Big/ \sum_{w=1}^{n} w^k$ for $y = 1,2,3.$

   ii) $b_{ik} = 0$ for all i and k,

   then forecasting model (3.2.17) reduces to the forecasting Model I of Agrawal et al. (1980).

4) If we take in our model (3.2.17) as

   i) $H_1^k(w) = r_{iw}^k(1) \Big/ \sum_{w=1}^{n} r_{iw}^k(1)$

   ii) $b_{ik} = 0$ for i and k

   iii) $H_3^k(w) = r_{(ij)w}^k(3) \Big/ \sum_{w=1}^{n} r_{(ij)w}^k(3)$

where $r_{iw}(1)$ is correlation coefficient of Y with X_{iw},

$r_{(ij)w}(3)$ is correlation coefficient of Y with the product of X_{iw} and X_{jw} at w^{th} period, then our forecasting model (3.2.17) reduces to the forecasting Model II of Agrawal et al. (1980) and Jain et al. (1980). Therefore, our forecasting model (3.2.17) is more general than those models recently considered and it can be consequently expected that our forecasting model (3.2.17) would render a wider scope and structure of the system of generated predictor variables which are influencing the yields of coconut crop than these models do.

3.3. Forecasting models for the yields of coconut crop in the present investigation

The general form of the forecasting models employed in the present investigation is given by the equation (3.2.17) from which different forecasting models are derived for different values of parameters and predictor variables contained in the model.

3.3.1. Model I

In this class of Model I, we take the generated predictor variables in the general forecasting model (3.2.17) as follows:

$$Z_{ik} = \sum_{w=1}^{n} H_1^k(w)\ X_{iw}$$

$$Z'_{ik} = \sum_{w=1}^{n} H_2^k(w)\ X_{iw}^2$$

$$Q_{(ij)k} = \sum_{w=1}^{n} H_3^k(w) X_{iw} X_{jw} \text{ for } i<j$$

Model I(1)

In this model I(1), we take the generated predictor variables in the general forecasting model (3.2.17) as follows:

$$Z_{ik} = \sum_{w=1}^{n} w^k X_{iw}$$

$$Z'_{ik} = \sum_{w=1}^{n} w^k X_{iw}^2$$

$$Q_{(ij)k} = \sum_{w=1}^{n} w^k X_{iw} X_{jw} \text{ for } i<j$$

Model I(2)

In this Model I(2), we take the generated predictor variables in the general forecasting model (3.2.17) as follows:

$$Z_{ik} = \sum_{w=1}^{n} w^k X_{iw} \Big/ \sum_{w=1}^{n} w^k$$

$$Z'_{ik} = \sum_{w=1}^{n} w^k X_{iw}^2 \Big/ \sum_{w=1}^{n} w^k$$

$$Q_{(ij)k} = \sum_{w=1}^{n} w^k X_{iw} X_{jw} \Big/ \sum_{w=1}^{n} w^k$$

Model I(3)

In this model I(3), we take the generated predictor variables in our general forecasting model (3.2.17) as follows:

$$Z_{ik} = \sum_{w=1}^{n} r_{iw}^{k}(1)X_{iw} \Big/ \sum_{w=1}^{n} r_{iw}^{k}(1)$$

$$Z_{ik}' = \sum_{w=1}^{n} r_{iw}^{k}(2)\ X_{iw}^{2} \Big/ \sum_{w=1}^{n} r_{iw}^{k}(2)$$

$$Q_{(ij)k} = \sum_{w=1}^{n} r_{(ij)w}^{k}(3)\ X_{iw}X_{jw} \Big/ \sum_{w=1}^{n} r_{(ij)w}^{k}(3)$$

where $r_{iw}(1)$, $r_{iw}(2)$ and $r_{(ij)w}(3)$ are the correlation coefficients of coconut crop yield Y with (i) X_{iw}, (ii) X_{iw}^{2} and (iii) $X_{iw}X_{jw}$ ($i<j$) respectively.

3.3.2. Forecasting model II

In this class of Model II, we take the generated predictor variables in the general forecasting model (3.2.17) as follows:

$$Z_{ik} = \sum_{w=1}^{n} H_{1}^{k}(w)X_{iw}$$

$$Z_{ik}' = \sum_{w=1}^{n} H_{2}^{k}(w)\ X_{iw}^{1/2}$$

$$Q_{(ij)k} = \sum_{w=1}^{n} H_{3}^{k}(w)\ X_{iw}^{1/2}\ X_{jw}^{1/2} \text{ for } i<j$$

Model II(1)

In this Model II(1), we take the generated predictor variables in the general forecasting model (3.2.17) as follows:

$$Z_{ik} = \sum_{w=1}^{n} w^k X_{iw}$$

$$Z'_{ik} = \sum_{w=1}^{n} w^k X_{iw}^{1/2}$$

$$Q_{(ij)k} = \sum_{w=1}^{n} w^k X_{iw}^{1/2} X_{jw}^{1/2} \qquad (i<j)$$

Model II(2)

In this model II(2), we take the generated predictor variables in the general forecasting models (3.2.17) as follows:

$$Z_{ik} = \sum_{w=1}^{n} w^k X_{iw} \Big/ \sum_{w=1}^{n} w^k$$

$$Z'_{ik} = \sum_{w=1}^{n} w^k X_{iw}^{1/2} \Big/ \sum_{w=1}^{n} w^k$$

$$Q_{(ij)k} = \sum_{w=1}^{n} w^k X_{iw}^{1/2} X_{jw}^{1/2} \Big/ \sum_{w=1}^{n} w^k$$

Model II(3)

In this model II(3), we take the generated predictor variables in the general forecasting model (3.2.17) as follows:

$$z_{ik} = \sum_{w=1}^{n} r_{iw}^{k}(1)\ X_{iw} \Big/ \sum_{w=1}^{n} r_{iw}^{k}(1)$$

$$z'_{ik} = \sum_{w=1}^{n} r_{iw}^{k}(4)\ X_{iw}^{1/2} \Big/ \sum_{w=1}^{n} r_{iw}^{k}(4)$$

$$Q_{(ij)k} = \sum_{w=1}^{n} r_{(ij)w}^{k}(5)\ X_{iw}^{1/2}\ X_{jw}^{1/2} \Big/ \sum_{w=1}^{n} r_{(ij)w}^{k}(5)$$

where $r_{iw}(1)$, $r_{iw}(4)$ and $r_{(ij)w}(5)$ are the correlation coefficients of yield response Y with (i) X_{iw}, (ii) $X_{iw}^{1/2}$, (iii) $X_{iw}^{1/2}\ X_{jw}^{1/2}$ respectively.

3.4. Selection of duration of effective crop season for the crop forecasting models

Here the effective crop season is defined as length of time interval in which the values of weather variables in that interval are considered to have actual and significant influence on the crop yield.

Firstly, for each of six different crop forecasting models proposed above, the effective crop season is taken to be as far back as three years (36 months) from the first month just before a particular 6-month harvest (i.e. total coconut production for 6 months periods). The effective crop season of 3 years back is taken and considered as an extension and further exploration of research findings of Patel and Anandan (1936) on the influence of rainfall on the coconut crop yields.

Then, in order to suit our forecasting models, this effective crop season of 3 years is equally divided into 12 periods, each having an interval of 3 months so as to be in conformity with the formation of climatic seasons following Marer and Pandalai (1957), as discussed in section 3.1.2. Therefore, for this effective crop season of 3 years with 12 equally divided periods, we can develop six different crop forecasting models denoted by I(1), I(2), I(3), II(1), II(2) and II(3) respectively as in section 3.3.1 and 3.3.2.

Further, all the six different crop forecasting models are developed under the given effective crop season of 3 years which is equally divided into six periods each having an interval of 6 months (6-month season). Therefore, for this effective crop season of 3 years with six equally divided periods, we can develop six different crop forecasting models denoted by I(1), I(2), I(3), II(1), II(2) and II(3) respectively as in section 3.3.1 and 3.3.2. Formation of 3-month and 6-month seasons (periods) are carried out as discussed in section 3.1.2.

Therefore, totally 12 crop forecasting models are fitted in the present investigation using five weather variables, viz., total rainfall (X_1), duration of bright sunshine hours (X_2), wind velocity (X_3), transformed relative humidity (X_4) and maximum diurnal temperature (X_5) respectively.

Under the effective crop season of 3 years equally divided into twelve 3-month periods, the values of the parameters in the crop forecasting models fitted are $p=5$, $m=2$ and $n=12$ respectively, implying that $i = 1,2,3,4,5$; $k = 0,1,2$; and $w = 1,2,3,4,5,6,7,8,9,10,11$ and 12 respectively.

Similarly, under the effective crop season of 3 years equally divided into six 6-month periods, the values of the parameters in the crop forecasting models fitted are $p=5$, $m=2$ and $n=6$ respectively, implying that $i = 1,2,3,4,5$; $k = 0,1,2$; and $w = 1,2,3,4,5,6$ respectively.

From here onwards, these forecasting models will be designated and referred as Model I(1) (3Y,3M), Model II(3) (3Y,6M) and so on. Here, Model I(1) (3Y,3M) stands for the forecasting Model I(1) which is developed and fitted under the effective crop season of 3 years with 3-month period (season), and Model II(3) (3Y,6M) stands for the forecasting Model II(3) which is developed under the effective crop season of 3 years with 6-month period (season) and so on.

3.5. Generation of predictor variables for the forecasting models

Firstly we generate first and second-order predictor variables denoted by Z_{ik}, Z_{ik}^2 and $Q_{(ij)k}$ for i j where i $j = 1,2,3,4,5$ and $k = 0,1,2$. Therefore, 15 different predictor variables are generated for Z_{ik}, 15 different predictor variables are generated for the variable Z'_{ik} and 30 different second-order predictor variables are generated for the variable $Q_{(ij)k}$ for i j. Then time variable T is also included as a predictor variable for the purpose of checking downward or upward trend in coconut production. Therefore, totally 61 predictor variables are considered for each forecasting models proposed above.

Then 61 correlation coefficients of yield response Y, average nuts per bearing tree per half year, with each of 61 predictor variables are worked out and twenty predictor variables having the highest correlation coefficient with yield response Y are selected as 'preliminary selected predictor variables'. Then, the most plausible candidate variables to be included in the final crop forecasting models are selected from these 20 preliminary predictor variables through the application of step-wise regression technique using forward selection procedure as explained by Draper and Smith (1981), for each crop forecasting models proposed above.

3.6. Step-wise regression techniques using forward selection procedure

In order to select the significant and plausible generated weather predictor variables from the preliminary variables Z_{ik}, Z'_{ik} and $Q_{(ij)k}$ of twelve crop forecasting models, step-wise regression technique with forward selection procedure is employed for all the models. Further analysis is carried out using these predictor variables selected through step-wise regression procedure.

A brief note and salient features of step-wise regression technique using the forward selection procedure is presented in the context of crop forecasting models proposed above.

As a first step we select a predictor variable which is most highly correlated with yield response Y from all the generated variables denoted by Z_{ik}, Z'_{ik} and $Q_{(ij)k}$ for i j and let this variable be Z_{10}. Then, the first-order linear regression equation $Y=f(Z_{10})$ is worked out and the significance of regression coefficient of the variable Z_{10} is checked. If it is not, we quit and adopt the model $Y=\bar{y}$ as the best model, where $\bar{y}$ is the average of observed yield response Y. If the regression coefficient of the variable Z_{10} is significantly different from zero, the variable Z_{10} is retained in the regression equation, coefficient of multiple determination R^2 and adjusted R^2, denoted by R_a^2, are noted along with improvement in R^2, and then a search for a second candidate predictor variable to enter the regression is made as a second step.

At the second step, the partial regression coefficients of all the predictor variables not included in the first regression equation (i.e. except the variable Z_{10}) with yield response Y are examined; that is Y and other predictor variables Z_{ik} ($i\neq1$, $k\neq0$), Z'_{ik} and $Q_{(ij)k}$ are adjusted for their straight line relationships with Z_{10}; and correlation with these adjusted variables are computed for $i\neq1$ and $k\neq0$ in case of Z_{ik}. Theoretically, this is equivalent to finding correlations between (1) residuals from the regression equation $Y=f(Z_{10})$ and (2) residuals from each of the regression (i) $Z_{ik}\neq f_{ik}(Z_{10})$ for $i\neq1$ and $k\neq0$, (ii) $Z'_{ik} = f'_{ik}(Z_{10})$ and (iii) $Q_{(ij)k} = f_{(ij)k}(Z_{10})$ (which we do not actually performed). The predictor variable having the highest partial correlation with yield response Y is now selected at the second step (suppose that this variable is Z'_{12} and a second regression equation $Y = f(Z_{10}, Z'_{12})$ is fitted. The overall regression is checked for the significance of regression coefficients again, then corresponding R^2 and R_a^2 are noted, along with improvement in R^2 in the second step. If the regression coefficient of the predictor variable which enters the equation at the second step is significant, a search for the third candidate predictor variable is made in the same fashion. The procedure is terminated when the last predictor variable entering the regression equation has insignificant regression coefficient or all the predictor variables are included in the regression equation.

The significance of the regression coefficient of the latest predictor variable to be introduced into the equation is judged by the standard t-statistic computed from the latest regression equation. If the regression equation contains all the predictor variables, the step at which the corresponding regression equation produces the highest adjusted R^2 is taken as optimum step and the regression equation at this step is taken as the 'best' crop forecasting model for the given set of generated predictor weather variables (Draper and Smith, 1981; Banerjee and Price, 1977). The 'step-wise regression technique' using the 'forward selection procedure' is usually referred to as "step-up regression technique". Therefore, in the present investigation, we shall use this terminology 'step-up regression technique' from here onwards.

3.7. Statistical analysis for the crop forecasting models developed through step-up regression technique

Let the final functional form of a crop forecasting model fitted through step-up regression procedure be as follows:

$$Y = A_0 + \sum_i \sum_k a_{ik} Z_{ik} + \sum_i \sum_k b_{ik} Z'_{ik} + \sum_i \sum_j \sum_k g_{(ij)k} Q_{(ij)k} + h_0 T + e \qquad (3.7.1)$$

Here the upper and lower limits of the indices i, j and k are deliberately omitted because the finally selected forecasting model through step-up regression procedure is not the same as the full term general crop forecasting models I and II formulated in section 3.3.1. and 3.3.2.

Assume that there are s observations on Y and r parameters in the fitted forecasting model (3.7.1), including constant intercept term A_0. Since this forecasting model is linear in the parameters A_0, a_{ik}, b_{ik} and $g_{(ij)k}$, the routine analysis of variance and statistical inference based on normality assumption can be carried out.

Rewriting equation (3.6.1) in conventional matrix and vector notation we get the linear model

$$\underline{Y} = \underset{\sim}{X}\,\underline{B} + \underline{e} \qquad (3.7.2)$$

where $\underline{Y}$ is (sx1) vector of observations on the yield response Y, $\underset{\sim}{X}$ is (sxr) matrix of observations on r predictor variables Z_{ik}, Z'_{ik} and $Q_{(ij)k}$ and dummy variable $Z_0=1$ for constant A_0, $\underline{B}$ is (rx1) vector of parameters to be estimated in the model (3.7.1) and $\underline{e}$ is (sx1) vector of random disturbances or errors with the following assumptions:

i) the random errors are independently and identically (normally) distributed with mean zero and constant variance σ^2, that is $E(\underline{e})=\underline{0}$, $V(\underline{e}) = E(\underline{e}\underline{e}') = \sigma^2 \underset{\sim}{I}_s$, where $\underline{0}$ and $\underset{\sim}{I}_s$ are null vector of dimension (sx1) and identity matrix of (sxs) respectively.

ii) the Z_{ik}, Z'_{ik} and $Q_{(ij)k}$ are non-stochastic and hence independent of random error e's, that is $E(X'\underline{e}) = \underline{0}$ and

iii) the Z_{ik}, Z'_{ik} and $Q_{(ij)k}$ are linearly independent. Hence, rank $(\underset{\sim}{X}'\underset{\sim}{X})$ = rank $(\underset{\sim}{X})$ = r and $(\underset{\sim}{X}'\underset{\sim}{X})^{-1}$ exists.

Under these assumptions, the best linear unbiased estimator (BLUE) $\hat{\underline{B}}$ of $\underline{B}$ is given $\hat{\underline{B}} = (\underset{\sim}{X}'\underset{\sim}{X})^{-1}\,\underset{\sim}{X}'\underline{Y}$ and its dispersion matrix $V(\hat{\underline{B}})$ is given by $V(\hat{\underline{B}}) = \sigma^2\,(\underset{\sim}{X}'\underset{\sim}{X})^{-1}$ and unbiased estimate of σ^2 is given by $\hat{\sigma}^2 = (\underline{Y}'\underline{Y}-\hat{\underline{B}}'\underset{\sim}{X}'\underline{Y})/(s-r)$ respectively.

The classical ANOVA (Analysis of variance) table for the linear model 3.7.2 is as follows:

ANOVA Table

SV	df	SS	MS	F-ratio
Regression/A_0	(r-1)	$SSR=\hat{\underline{B}}'\underset{\sim}{X}'\underset{\sim}{X}\hat{\underline{B}}-\underline{Y}'\underset{\sim}{J}Y/s$	$MSR=\frac{SSR}{(r-1)}$	$F=\frac{MSR}{MSE}$ (r-1,s-r)
Error (Residual)	(s-r)	$SSE=\underline{Y}'\underline{Y}-\hat{\underline{B}}'\underset{\sim}{X}'\underset{\sim}{X}\hat{\underline{B}}$	$MSE=\frac{SSE}{(s-r)}$	
Total	(s-1)	$SST=\underline{Y}'\underline{Y}-\underline{Y}'\underset{\sim}{J}\underline{Y}/s$		

In the above ANOVA Table, $\underset{\sim}{J}$ is (sxs) matrix with elements all equal to unity.

3.8. Criteria functions for the comparison of efficiencies and performance of the forecasting models developed through step-up regression procedures

A number of criteria measures have been proposed for selecting and deciding on the most efficient and plausible crop forecasting models. These criteria are stated in terms of the behaviour of certain functions as a function of the predictor variables included in the different crop forecasting models selected through step-up regression procedure. Many of these criterion functions are simple functions of the residual mean squares (RMS) for each crop forecasting models which is assumed to have r parameters including constant A_0 and number of observations on crop yield response Y to be s.

An exhaustive list of these criteria functions is found in Hocking (1976). In the present investigation the following criteria functions are employed.

1) Residual mean squares(RMS)

RMS is a measure that is used to judge the adequacy of a fitted regression equation. With a r-parameter regression equation, the RMS is defined as follows:

$$RMS = MSE = SSE/(s-r)$$

Theil (1961) and Schmidt (1971) advocated the use of minimum RMS for predictive purposes. Among the several regression equations, the one with the smallest value of RMS is usually preferred and selected, if the objective of the regression analysis is extrapolation and prediction (Banerjee and Price, 1977).

2) Squared multiple correlation coefficients(R^2)

R^2 is an index of goodness of fit of the model, most widely used. It can be viewed as a measure of the strength or adequacy of fit, which is usually used as summary measure to judge the fit of the linear model to a given body of data. It is defined as follows:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$$

However, Crocker (1972) suggested that the statistical significance of R^2 may not give a true picture of the adequacy of the model fitted to a given body of data. The recommendation of Crocker is that, in some cases, it may be more appropriate and reasonable to consider the per cent reduction in standard deviation of the response variable, achieved by the model. Another limitation of R^2, noted by Barrett (1974), is that for fixed residual sum of squares, R^2 increases with the steepness of the regression surfaces.

3) <u>Adjusted squared multiple correlation coefficient</u> (R_a^2)

As an alternative to R^2, some users recommend the adjusted squared multiple correlation coefficient, denoted by R_a^2, and suggest using the value of r for which R_a^2 is maximum. This procedure is exactly equivalent to looking for the minimum RMS, as an adjustment to remove upward bias when based on small number of observations. Here, R_a^2 is defined as follows:

$$R_a^2 = 1-(1-R^2)\cdot\frac{(s-1)}{(s-r)}$$

This criterion function (R_a^2) was first formulated and proposed by Ezekiel and Fox (1959).

4) <u>Total prediction variance</u> (J_r)

J_r is also a criterion function which is simply related to RMS. J_r arises by computing the total prediction variance over the current data for a given subset of predictor variables and then estimating variance by RMS. J_r is defined as follows:

$$J_r = \frac{(s+r)}{(s-r)}\cdot(SSE) = (s+r)(RMS)$$

Mallow (1967), Rothman (1968) and Hocking (1972) discussed and recommended the use of this criterion of total prediction. Variance (J_r) when the objective of regression equation is to predict the future response. But theoretically the criterion function J_r has the drawback of ignorance of bias in prediction.

5) Prediction mean square error (MSEP)

Tukey (1967) and Sclove (1971) advocated the use criterion of MSEP if the objective of regression analysis is prediction of a future response and estimation of the mean response for a given input. MSEP expressed in term of RMS is defined as follows:

$$MSEP = \frac{(s^2-1)}{s} \cdot \frac{RMS}{(s-r-1)}$$

According to Hocking (1976), if the assumption of multivariate normality of the yield response Y and the predictor variables Z_{ik}, Z'_{ik} and $Q_{(ij)k}$ are acceptable, then the above development suggests looking at sub-sets with values of MSEP close to minimum MSEP if the objective of regression analysis is to use the resulting equation for prediction purposes.

6) Average estimated variance (AEV)

Another criterion function, called the average estimated variance (AEV), has been suggested by Helms (1974). In one vary special case, AEV was defined as follows:

$$AEV = r(RMS)/s$$

This criterion involves averaging the prediction variance over the whole regression region of interest, rather than for just the data points given, and using a weight function which attaches more weight to the more "important" points in the region (Seber, 1977).

7) Amemiya prediction criterion (APC)

Amemiya (1980) developed a criterion measure (function) based on prediction mean square error (MSEP) in order to include a consideration of the losses associated with choosing an incorrect model. Amemiya prediction criterion (APC) function is defined in terms of R^2 and SST as follows:

$$APC = \frac{(s+r)}{(s-r)} (1-R^2) . \frac{SST}{s}$$

where SST is total sum of squares shown in ANOVA Table.

According to Judge et al. (1980), APC criterion function has a higher penalty for adding predictor variables than the adjusted R^2 (R_a^2) criterion is. It means that APC is more sensitive to adding variables to forecasting models than R_a^2 is. Therefore, APC is also a reasonable and satisfactory criterion function to be employed in selecting the 'best' fitted crop forecasting models.

8) Akaike information criterion (AIC)

An information measure (criterion) seeks to incorporate in selecting the predictor variables the divergent considerations of accuracy of estimation and the 'best' approximation to reality. Thus, information criterion involves a statistic that incorporates a measure of the precision of the estimate and a measure of the rule of parsimony in the parametrigation of a statistical crop forecasting model (Judge et al., 1980).

Akaike (1978), using a Bayesian frame work, proposed a modified form of his original AIC (Akaike, 1973). The AIC function in terms of R^2 and SST is defined as follows:

$$AIC = (s-r)\cdot \ln\left[\frac{(1-R^2)}{(s-r)}\cdot(SST)\right] + r\cdot \ln\left[\frac{R^2}{r}(SST)\right]$$

Akaike (1978) noted that this criterion was more parsimonious in selecting the predictor variables than his original AIC function, which was really the same as APC function when the variance was estimated by RMS of the fitted crop forecasting model.

From the above discussions on various criteria functions to be employed in selecting the "best" crop forecasting models, it is clear that the choice of criterion depends very much on how the chosen model will be used. Because further research is obviously needed on the properties of the various criteria measures, it is recommended that several of the measures should always be calculated when comparing the different crop forecasting models (Seber, 1977).

3.9. Mathematical analysis for the crop forecasting models developed through step-up regression technique

Let the functional form of a crop forecasting model constructed through step-up regression using forward selection procedure be as in equation (3.7.1). Here the values of Z_{ik}, Z'_{ik} and $Q_{(ij)k}$ are changing from a forecasting model to another. The functional form of the predictor variables are given in section 3.3.1 and 3.3.2 respectively, for each forecasting models proposed above.

From the point of view of mathematical analysis, we can carry out analysis of the influence of each weather variables at each period or season on the coconut crop yield as follows:

The effect on the coconut crop yields of a change of one unit in i^{th} weather variable X_{iw} at w^{th} period or season, holding other weather variables constant at w^{th} period, can be studied by partially differentiating the resulted regression equation with respect to X_{iw} for i=1,2,3 ....., p and w=1,2,3, ... n.

The partial derivative of yield response Y with respect to X_{iw} is given as follows:

For general forecasting model I (square model)

$$\frac{\partial Y}{\partial X_{iw}} = \sum_k a_{ik} H_1^k(w) + 2 \sum_k H_2^k(w) X_{iw} + \sum_j \sum_k g_{(ij)k} H_3^k(w) X_{jw} \quad (3.9.1)$$

here $i \neq j$

For general forecasting model II (square root model)

$$\frac{\partial Y}{\partial X_{iw}} = \sum_k a_{ik} H_1^k(w) + (1/2). \sum_k b_{ik} H_2^k(w) \Big/ X_{iw}^{1/2}$$

$$+ \frac{1}{2} \sum_j \sum_k g_{(ij)k} H_3^k(w).(X_{jw}/X_{iw})^{1/2}, (i \neq j) \quad (3.9.2)$$

Here also the functional form of the functions $H_1^k(w)$, $H_2^k(w)$ and $H_3^k(w)$ are changing from a forecasting model to another as defined in sections 3.3.1 and 3.3.2.

RESULTS

CHAPTER IV

RESULTS

4.1. Introduction

The present investigation was carried out with the following views and objectives:

1) To develop a suitable and reliable statistical methodology for the pre-harvest forecast of coconut crop yields by evolving different empirical-statistical crop-weather models using the original and generated weather variables as predictor variables.

2) To perform a comparative study of relative efficiency, adequacy and performance of each of these crop forecasting models evolved and to select the 'best', most promising and plausible crop forecasting models for the purpose of future use in predicting the coconut crop yields reliably in advance of harvest.

3) To investigate the effect and influence of changes in weather variables on the yield of coconut crop, based on the crop forecasting models selected as the 'best' fitted models.

4) To render suggestions and guidelines for further development of statistical crop-weather models, criteria for their selection, and relevant statistical analysis.

In order to get a clearer picture of crop-weather relationship in the region of Pilicode and performance of crop forecasting models developed for that region, a brief and relevant information on the weather variables involved in the forecasting models were presented in section 4.2.

The important results from the step-up regression analysis on each of the twelve different crop forecasting models prpposed in chapter II under the effective crop season of 3 years (i.e. as far back as 36 months from the first month just before a particular half-year harvest) with 3-month and 6-month seasonal pool of original weather variables were presented in section 4.3 onwards.

4.2. A brief statistical analysis of weather condition with special reference to five weather variables included in this study

The period-or season-wise average of total rainfall (in cm) for the span of 15 years from 1965-1980 under the formation of 3-month and 6-month period or season was shown in Table 1, along with standard deviation and coefficient of variation in percentage. From table 1, it was noted that averages of total rainfall on 3-month and 6-month period basis were 83.0058 cm and 171.3316 cm respectively.

It was observed that the averages of daily bright sunshine hours, wind velocity in km/hr, transformed relative humidity in percentage and maximum temperature in centigrade were the same but for the rounding error for the two different pools of weather

Table 1. Weather variables involved in crop forecasting models and their brief analysis for the region of Pilicode (1965-1980)

i) 3-month period (season) for the years (1965-1980)

Weather variables	Mean	Standard deviation	Coefficient of variation
1. Total rainfall	88.0058	109.8703	124.4447
2. Sunshine hours	7.3087	2.1810	29.8411
3. Wind velocity	2.1237	0.9223	43.4289
4. Relative humidity*	62.2885	5.1348	8.2436
5. Maximum temperature	30.9065	1.4581	4.7178

ii) 6-month period (season) for the years (1965-1980)

Weather variables	Mean	Standard deviation	Coefficient of variation
1. Total rainfall	171.3516	149.0235	86.9694
2. Sunshine hours	7.3723	1.7796	24.1386
3. Wind velocity	2.1790	0.8996	41.2849
4. Relative humidity*	62.1771	4.4131	7.0976
5. Maximum temperature	31.0057	1.3053	4.2098

* = Transformed into arc-sine root proportion

variables of 3-month and 6-month period respectively. It was further noted that the standard deviation and coefficient of variation were also almost the same for two different pools.

4.3. Statistical analysis for the forecasting Model I(1)(3Y,3M) (effective crop season of 3 years with 3-month period)

This forecasting Model I(1)(3Y,3M) came under the category of general forecasting Model I developed in section 3.3.1 as a complete second-order response surface type crop forecasting model (square model).

The 20 preliminary selected variables having maximum absolute correlation coefficients with the yield response 'Y' for fitting this Model I(1)(3Y,3M) were Z_{30}, Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z_{52}, Z'_{30}, Z'_{50}, Z'_{31}, Z'_{51}, Z'_{32}, Z'_{52}, $Q_{(12)0}$, $Q_{(23)0}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(34)0}$, $Q_{(34)1}$, $Q_{(34)2}$ and $Q_{(35)1}$ respectively.

The eleven predictor variables to be included in the final crop forecasting model, selected through step-up regression procedure, were Z_{30}, Z_{32}, Z'_{50}, Z'_{31}, $Q_{(12)0}$, $Q_{(23)0}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(34)0}$, $Q_{(34)2}$ and $Q_{(35)1}$ respectively. The estimated regression coefficients for these corresponding predictor variables, along with their standard deviation and computed t-statistics, were presented in Table 2. From table 2, it was seen that all the regression co-efficients of selected predictor variables, except that of the variable Z'_{50}, were significant even at 1% level of

Table 2. Step-up regression analysis for the crop forecasting Model I(1) (3Y,3M) (effective crop season of 8 years with 3-month period)

Variables selected	Regression Coefficient	Estimate	Standard error	Computed t-value
Z_{30}	a_{30}	261.5590	25.2000	10.3793**
Z_{32}	a_{32}	-2.4406	0.2374	-10.2805**
Z'_{50}	b_{50}	-0.0023	0.0037	- 0.6216^{NS}
Z'_{31}	b_{31}	0.1319	0.0359	3.6741**
$Q_{(12)0}$	$g_{(12)0}$	0.0011	0.0002	5.5000**
$Q_{(23)0}$	$g_{(23)0}$	-5.2728	0.5148	-10.2424**
$Q_{(23)1}$	$g_{(23)1}$	-1.1269	0.1255	-8.9793**
$Q_{(23)2}$	$g_{(23)2}$	0.1543	0.0161	9.5839**
$Q_{(34)0}$	$g_{(34)0}$	-3.2513	0.3113	-10.4427**
$Q_{(34)2}$	$g_{(34)2}$	0.0297	0.0029	10.2414**
$Q_{(35)1}$	$g_{(35)1}$	-0.0034	0.0008	-4.2500**

s = 26 R^2 = 0.9482 R_a^2 = 0.9075 A_0 = 116.7730

t(0.025,14) = 2.145 at 5% t(0.005,14) = 2.797 at 1%

* = Significant at 5%

** = Significant at 1%

NS = Non-significant

significance. It was also noted, on the basis of R^2 and adjusted R^2 (denoted by R_a^2) that the adequacy of fitted crop forecasting model was highly satisfactory, since R_a^2 = 0.9075 and R^2 = 0.9482. This showed that 94.82% of the total variance from the mean in the yield response Y was accounted for or explained by the predictor variables in the fitted forecasting Model I(1)(3Y,3M). It was also found that R^2 was highly significant even at 1% level of significance.

Since R^2 and R_a^2 were satisfactorily high and statistically significant, it could be concluded that the strength or adequacy of fit of a linear regression model to the given set of data on the eleven predictor variables selected through step-up regression procedure was also highly satisfactory and consequently it might also be expected that residual mean square (RMS) of the selected forecasting model would also be satisfactorily small so that the resulted crop forecasting model could be used to serve the future purpose of prediction and forecast of coconut crop yield in advance of harvest.

The final functional form of crop forecasting Model I(1)(3Y,3M) developed through step-up regression procedure was given as follows:

$$Y = 116.7730 + 261.5590\ Z_{30} - 2.4406\ Z_{32} - 0.0023\ Z'_{50}$$
$$+ 0.1319\ Z'_{31} + 0.0011\ Q_{(12)0} - 5.2728\ Q_{(23)0}$$
$$- 1.1269\ Q_{(23)1} + 0.1543\ Q_{(23)2} - 8.2513\ Q_{(34)0}$$
$$+ 0.0297\ Q_{(34)2} - 0.0034\ Q_{(35)1}$$

The functional forms of the predictor variables included in the above crop forecasting Model I(1) (3Y,3M) were given in section 3.3.1.under the head of the general crop forecasting Model I, hence not reproduced here again.

4.4. Statistical analysis for the forecasting Model I(2)(3Y,3M) (effective crop season of 3 years with 3-month period)

This forecasting Model I(2) (3Y,3M) belonged to the same family of general forecasting Model I in section 3.3.1 of Chapter III.

The 20 preliminary selected variables having maximum absolute correlation coefficients with the yield response Y for fitting the model were Z_{30}, Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z_{52}, Z'_{31}, Z'_{51}, Z'_{32}, Z'_{52}, $Q_{(12)0}$, $Q_{(13)2}$, $Q_{(23)0}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(25)0}$, $Q_{(34)0}$, $Q_{(34)1}$, $Q_{(34)2}$ and $Q_{(35)1}$ respectively.

The thirteen predictor variables to be included in the final crop forecasting model, selected through step-up regression technique, were Z_{30}, Z_{52}, Z'_{31}, Z'_{51}, Z'_{32}, $Q_{(12)0}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(25)0}$, $Q_{(34)0}$, $Q_{(34)1}$, $Q_{(34)2}$ and $Q_{(35)1}$ respectively. The estimated regression coefficients for these corresponding predictor variables, along with their standard deviations and computed t-statistics were presented

Table 3. Step-up regression analysis for the crop forecasting Model I(2) (3Y,3M) (effective crop season of 3 years with 3-month period)

Variables selected	Regression Coefficients	Estimate	Standard error	Computed t-value
Z_{30}	a_{30}	-562.5090	229.3700	-2.4524*
Z_{52}	a_{52}	90.1274	21.5500	4.1822**
Z'_{31}	b_{31}	98.0748	21.6630	4.5273**
Z'_{51}	b_{51}	-2.6224	0.5652	-4.6398**
Z'_{32}	b_{32}	-63.3173	16.7600	-3.7779**
$Q_{(12)0}$	$g_{(12)0}$	0.0939	0.0407	2.3071*
$Q_{(23)1}$	$g_{(23)1}$	10.3116	14.4240	0.7149^{NS}
$Q_{(23)2}$	$g_{(23)2}$	-12.5098	10.5550	-1.1852^{NS}
$Q_{(25)0}$	$g_{(25)0}$	1.6880	0.6397	2.6387*
$Q_{(34)0}$	$g_{(34)0}$	9.0241	3.3847	2.6661*
$Q_{(34)1}$	$g_{(34)1}$	-12.5740	3.3075	-3.8017**
$Q_{(34)2}$	$g_{(34)2}$	5.6116	1.5149	3.7043**
$Q_{(35)1}$	$g_{(35)1}$	9.4322	3.4984	2.6961*

s = 26 R^2 = 0.8320 R_a^2 = 0.6500 A_0 = -520.2540

t(0.025,12) = 2.179 at 5% t(0.005,12) = 3.055 at 1%

* = Significant at 5%
** = Significant at 1%
NS = Non-significant

in Table 3. From the Table 3, it was seen that all the regression coefficients of selected predictor variables, except that of the variables $Q_{(23)1}$ and $Q_{(23)2}$, were satisfactorily significant at 5% level. The squared multiple correlation coefficient (R^2) was also highly significant at 5% level and even at 1% level of significance. Since R^2 value for this model was 0.8320, 83.20% of the total variance from the mean in the yield response Y was explained by the thirteen predictor variables in the fitted forecasting Model I(2) (3Y,3M).

The final functional form of crop forecasting Model I(2) (3Y,3M) developed through step-up regression technique was given as follows:

$$Y = -320.2540 - 562.5090\ Z_{30} + 90.1274\ Z_{52} + 98.0748\ Z'_{31}$$
$$- 2.6224\ Z'_{51} - 63.3173\ Z'_{32} + 0.0939\ Q_{(12)0} + 10.3116\ Q_{(23)1}$$
$$- 12.5098\ Q_{(23)2} + 1.6880\ Q_{(25)0} + 9.0241\ Q_{(34)0}$$
$$- 12.5740\ Q_{(34)1} + 5.6116\ Q_{(34)2} + 9.4322\ Q_{(35)1}$$

The functional form of the predictor variables included in the above crop forecasting Model I(2) (3Y,3M) were defined in terms of original weather variables and their corresponding weights in section 3.3.1, hence not reproduced here again.

4.5. Statistical analysis for the forecasting Model I(3)(3Y,3M) (effective crop season of 3 years with 3-month period)

This crop forecasting model also belonged to the family of general forecasting Model I developed in section 3.3.1 as a complete second-order response surface type crop forecasting model (square model).

The 20 preliminary selected variables having maximum absolute correlation coefficients with yield response Y for fitting this model were Z_{50}, Z_{31}, Z_{51}, Z_{22}, Z_{32}, Z_{52}, Z'_{50}, Z'_{31}, Z'_{51}, Z'_{12}, Z'_{32}, Z'_{52}, $Q_{(12)0}$, $Q_{(12)2}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(25)2}$, $Q_{(34)1}$, $Q_{(34)2}$ and T respectively.

The ten predictor variables to be included in the final crop forecasting model, selected through step-up regression technique, were Z_{50}, Z_{22}, Z_{32}, Z'_{50}, Z'_{12}, Z'_{52}, $Q_{(12)0}$, $Q_{(12)2}$, $Q_{(23)2}$ and T respectively. The estimated regression coefficients for these corresponding predictor variables, along with their standard deviations and computed t-statistics were presented in Table 4. From Table 4 it was seen that all the regression coefficients were statistically significant at 5% level and even at 1% level of significance.

It was also noted from Table 4 that the R^2 and R_a^2 were satisfactorily high and statistically significant. Therefore it could be concluded that the adequacy of fit of a linear regression model to the given set of data on these ten predictor variables was also highly satisfactory and consequently the crop forecasting Model I(3)(3V,3M) should be used for future purpose of predicting the coconut crop yield in advance of harvest.

Table 4. Step-up regression analysis for the crop forecasting Model I(3) (3Y,3M) (effective crop season of 3 years with 3-month period)

Variables selected	Regression Coefficient	Regression Estimate	Standard error	Computed t-value
Z_{50}	a_{50}	65.8204	13.3980	4.9127**
Z_{22}	a_{22}	-29.7842	4.7072	-6.3274**
Z_{52}	a_{52}	609.0960	62.8640	9.6891**
Z'_{50}	b_{50}	-2.2427	0.2985	-7.5132**
Z'_{12}	b_{12}	-0.0008	0.0002	-4.0000**
Z'_{52}	b_{52}	-9.5624	0.9701	-9.8571**
$Q_{(12)0}$	$g_{(12)0}$	-0.0322	0.0086	-3.7442**
$Q_{(12)2}$	$g_{(12)2}$	-0.0403	0.0114	-3.5351**
$Q_{(23)2}$	$g_{(23)2}$	-0.2084	0.0176	-11.8409**
T	h_0	-1.4025	0.2407	-5.8267**

s = 26 R^2 = 0.9408 R_a^2 = 0.9013 A_0 = -9239.4700

t(0.025,15) = 2.131 at 5% t(0.005,15) = 2.947 at 1%

* = Significant at 5%

** = Significant at 1%

NS = Non-significant

The final functional form of crop forecasting Model I(3) (3Y,3M) developed through step-up regression techniques was given as follows:

$$Y = -9239.4700 + 65.8204\, Z_{50} - 29.7842\, Z_{22} + 609.0960\, Z_{52} - 2.2427\, Z'_{50} - 0.0008\, Z'_{12} - 9.5624\, Z'_{20} - 0.0322\, Q_{(12)0} - 0.0403\, Q_{(12)2} - 0.2084\, Q_{(23)2} - 1.4025\, T$$

The functional forms of the predictor variables included in the above forecasting Model I(3) (3Y,3M) were defined in section 3.3.1, hence not reproduced here again.

4.6. Statistical analysis for the forecasting Model II(1)(3Y,3M) (effective crop season of 3 years with 3-month period)

This forecasting Model II(1) (3Y,3M) came under the category of general crop forecasting Model II (square root model).

The 20 preliminary selected variables having maximum absolute correlation coefficients with the yield response Y for fitting this model II(1) (3Y,3M) were Z_{30}, Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z'_{30}, Z'_{50}, Z'_{31}, Z'_{51}, Z'_{12}, Z'_{52}, $Q_{(13)1}$, $Q_{(13)2}$, $Q_{(15)1}$, $Q_{(23)0}$, $Q_{(25)0}$, $Q_{(34)0}$, $Q_{(34)1}$, $Q_{(35)0}$ and T respectively.

The fourteen predictor variables to be included in the final crop forecasting model, selected through step-up regression technique, were Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z'_{30}, Z'_{50}, Z'_{31}, Z'_{51}, Z'_{12}, Z'_{52}, $Q_{(13)1}$, $Q_{(15)1}$, $Q_{(34)1}$ and $Q_{(35)0}$ respectively. The estimated regression coefficients for these corresponding predictor variables, along with their standard deviations and computed t-statistics, were presented in Table 5. From the Table 5, it was seen that all the regression coefficients of predictor variables, except the coefficients of the two variables Z'_{31} and Z'_{12}, were statistically significant at 5% level. It was also noted that R^2 values (0.9151) was also satisfactorily high and significant at 5% and 1% level of significance. On the basis of R^2, adequacy and fit of the forecasting model was highly satisfactory, but for the purpose of future use of this forecasting model in predicting the coconut crop yield in advance of harvest, we should examine other criteria measures corresponding to this model. Elaborate analysis of these measures were presented in Chapter V.

The final functional form of crop forecasting Model II(1) (3Y,3M) developed through step-up regression technique was given as follows:

$$Y = 1095.6000 + 234.7730\, Z_{50} - 588.1940\, Z_{31} - 260.9230\, Z_{51} + 216.4380\, Z_{32} + 22.5327\, Z'_{30} - 3.9563\, Z'_{50} - 12.4222\, Z'_{31} + 4.6030\, Z'_{51} - 0.0004\, Z'_{12} - 0.8356\, Z'_{52} - 0.0652\, Q_{(13)1} - 0.0005\, Q_{(15)1} + 5.4714\, Q_{(34)1} - 0.7599\, Q_{(35)0}$$

The functional form of the predictor variables included in the crop forecasting Model II(1) (3Y,3M) were defined in section 3.3.2 under the head of the general crop forecasting Model II, hence not reproduced here again.

Table 5. Step-up regression analysis for the crop forecasting Model II(1) (3Y,3M) (effective crop season of 3 years with 3-month period)

Variables selected	Regression Coefficient	Regression Estimate	Standard error	Computed t-value
Z_{50}	a_{50}	234.7730	73.0620	3.2133**
Z_{31}	a_{31}	-588.1940	140.1200	-4.1978**
Z_{51}	a_{51}	-260.9230	106.7400	-2.4495*
Z_{32}	a_{32}	216.4380	61.3370	3.5275**
Z'_{30}	b_{30}	22.5327	10.1540	2.2191*
Z'_{50}	b_{50}	-3.9563	1.1381	-3.4762**
Z'_{31}	b_{31}	-12.4222	9.8320	-1.2634^{NS}
Z'_{51}	b_{51}	4.6030	1.7371	2.6498*
Z'_{12}	b_{12}	-0.0004	0.0003	-1.3333^{NS}
Z'_{52}	b_{52}	-0.8356	0.1697	-4.9239**
$Q_{(13)1}$	$g_{(13)1}$	-0.0652	0.0293	-2.2253*
$Q_{(15)1}$	$g_{(15)1}$	-0.0005	0.0002	-2.5000*
$Q_{(34)1}$	$g_{(34)1}$	5.4714	1.8525	2.9535*
$Q_{(35)0}$	$g_{(35)0}$	-0.7599	0.2867	-2.6505*

s = 26 R^2 = 0.9151 R_a^2 = 0.8070 A_0 = 1095.6000

t(0.025,11) = 2.201 at 5% t(0.005,11) = 3.106 at 1%

* = Significant at 5%

** = Significant at 1%

NS = Non-significant

4.7. Statistical analysis for the forecasting Model II(2) (3Y,3M) (effective crop season of 3 years with 3-month period)

This crop forecasting Model II(2) (3Y,3M) also belonged to the family of general forecasting Model II defined in section 3.3.2 (square root model).

The 20 preliminary selected predictor variables having maximum absolute correlation coefficients with the yield response Y for fitting this forecasting Model II(2) (3Y,3M) were Z_{30}, Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z_{52}, Z'_{30}, Z'_{50}, Z'_{31}, Z'_{51}, $Q_{(12)0}$, $Q_{(13)1}$, $Q_{(13)2}$, $Q_{(23)0}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(25)0}$, $Q_{(34)0}$, $Q_{(35)1}$ and T respectively.

The six predictor variables to be included in the final forecasting model, selected through step-up regression technique, were Z_{31}, Z'_{30}, Z'_{50}, $Q_{(23)0}$, $Q_{(25)0}$ and $Q_{(34)0}$ respectively. The estimated regression coefficients for these corresponding predictor variables, along with their standard deviations and computed t-statistics, were presented in Table 6. From Table 6, it was seen that all the regression coefficients of selected predictor variables were statistically significant at 5% and even at 1% level of significance.

It was also noted from Table 6 that the values of R^2 and R_a^2 were 0.9161 and 0.8896 respectively and they were satisfactorily high and statistically significant at 5% and 1% levels. Therefore, it could be concluded that the adequacy of fit of a linear regression model to the given set of data

Table 6. Step-up regression analysis for the crop forecasting Model II(2) (3Y,3M) (effective crop season of 3 years with 3-month period)

Variables selected	Regression Coefficient	Regression Estimate	Standard error	Computed t-value
Z_{31}	a_{31}	37.5524	4.1717	9.0017**
Z'_{30}	b_{30}	-2.1867	0.5341	-4.0944**
Z'_{50}	b_{50}	-659.1850	47.8920	-13.7640**
$Q_{(23)0}$	$g_{(23)0}$	-177.4570	15.1610	-11.7048**
$Q_{(25)0}$	$g_{(25)0}$	69.2921	6.8501	10.1155**
$Q_{(34)0}$	$g_{(34)0}$	44.7271	3.7604	11.8942**

s = 26 $R^2 = 0.9161$ $R_a^2 = 0.8896$ $A_0 = 2757.4610$

t(0.025,19) = 2.093 at 5% t(0.005,19) = 2.861 at 1%

** = Significant at 1%

on those six variable was also highly satisfactory and consequently the crop forecasting Model II(2) (3Y,3M) should be used for future purpose of predicting the coconut crop yield in advance of harvest.

The final functional form of crop forecasting Model II(2) (3Y,3M) developed through step-up regression technique was given as follows:

$$Y = 2757.4610 + 37.5524\, Z_{31} - 2.1867\, Z'_{30} - 689.1850\, Z'_{50} - 177.4570\, Q_{(23)0} + 69.2921\, Q_{(25)0} + 44.7271\, Q_{(34)0}$$

The functional form of the predictor variables included in the above crop forecasting Model II(2) (3Y,3M) were defined in terms of original weather variables in section 3.3.2 under the head of general crop forecasting Model II, hence not reproduced here again.

4.8. Statistical analysis for the forecasting Model II(3)(3Y,3M) (effective crop season of 3 years with 3-month period)

This forecasting Model II(3) (3Y,3M) came under the category of general forecasting Model II (square root model).

The 20 preliminary selected variables having maximum absolute correlation coefficients with the yield response Y for fitting this model II(3) (3Y,3M) were Z_{30}, Z_{31}, Z_{32}, Z_{52}, Z'_{50}, Z'_{31}, Z'_{22}, Z'_{32}, Z'_{52}, $Q_{(12)2}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(25)0}$, $Q_{(25)2}$, $Q_{(34)2}$, $Q_{(35)1}$, $Q_{(35)2}$, $Q_{(45)1}$, $Q_{(45)2}$ and T respectively.

The nine predictor variables to be included in the final crop forecasting model, selected through step-up regression procedure, were Z_{50}, Z_{52}, Z'_{50}, Z'_{22}, Z'_{52}, $Q_{(12)2}$, $Q_{(23)2}$, $Q_{(35)2}$ and $Q_{(45)1}$ respectively. The estimated regression coefficients for these corresponding predictor variables, along with their standard deviations and computed t-statistics, were presented in Table 7. From Table 7, it was seen that all the regression coefficients of selected predictor variables, except that of the variable $Q_{(23)2}$, were statistically significant at 5% level. The R^2 and R_a^2 were found to be 0.8249 and 0.7264 and the R^2 value was also significant at 5% level and even at 1% level. But, on the basis of R_a^2, this crop forecasting model was not satisfactorily reliable and adequate for future use in predicting coconut crop yield in advance of harvest.

The final functional form of crop forecasting Model II(3) (3Y,3M) fitted through step-up regression technique was given as follows:

$$Y = 7820.3800 + 61.7530\, Z_{50} + 498.8170\, Z_{52} - 1.7982\, Z'_{50} - 1.6836\, Z'_{22} - 7.9738\, Z'_{52} - 0.0322\, Q_{(12)2} + 0.6499\, Q_{(23)2} - 0.4228\, Q_{(35)2} + 0.0050\, Q_{(45)1}$$

The functional forms of the predictor variables included in the above crop forecasting Model II(3) (3Y,3M) were defined in terms of original weather variables in section 3.3.2, hence not reproduced here again.

Table 7. Step-up regression analysis for the crop forecasting Model II(3)(3Y,3M) (effective crop season of 3 years with 3-month period)

Variables selected	Regression Coefficient	Regression Estimate	Standard error	Computed t-value
Z_{50}	a_{50}	61.7530	22.1480	2.7882*
Z_{52}	a_{52}	498.8170	94.3390	5.2875**
Z'_{50}	b_{50}	-1.7982	0.4290	-4.1916**
Z'_{22}	b_{22}	-1.6836	0.5147	-3.2710**
Z'_{52}	b_{52}	-7.9738	1.4883	-5.3577**
$Q_{(12)2}$	$g_{(12)2}$	-0.0322	0.0148	-2.1757*
$Q_{(23)2}$	$g_{(23)2}$	0.6499	0.6073	1.0701[NS]
$Q_{(35)2}$	$g_{(35)2}$	-0.4228	0.1849	-2.2866*
$Q_{(45)1}$	$g_{(45)1}$	0.0050	0.0021	2.3809*

$s = 26$ $R^2 = 0.8249$ $R_a^2 = 0.7264$ $A_0 = -7820.3800$

$t(0.025,16) = 2.120$ at 5% $t(0.005,16) = 2.921$ at 1%

* = Significant at 5%

** = Significant at 1%

NS = Non-significant

4.9. Statistical analysis for the forecasting Model I(1) (3Y,6M) (effective crop season of 3 years with 6-month period)

This forecasting model came under the category of general forecasting model I developed in section 3.3.1 as complete second-order response surface type crop forecasting model (square model).

The 20 preliminary selected variables having maximum absolute correlation coefficients with yield response Y for fitting this Model I(1) (3Y,6M) were Z_{30}, Z_{50}, Z_{31}, Z_{51}, Z_{52}, Z'_{30}, Z'_{50}, Z'_{31}, Z'_{51}, Z'_{32}, Z'_{52}, $Q_{(12)0}$, $Q_{(23)0}$, $Q_{(23)1}$, $Q_{(25)0}$, $Q_{(34)1}$, $Q_{(34)2}$, $Q_{(35)1}$, $Q_{(45)0}$, and T respectively.

The eight predictor variables to be included in the final crop forecasting model, selected through step-up regression technique, were Z_{50}, Z_{52}, Z'_{50}, Z'_{51}, Z'_{52}, $Q_{(12)0}$, $Q_{(23)1}$ and $Q_{(35)1}$ respectively. The least square estimates of regression coefficients for these corresponding predictor variables, along with their standard deviations and computed t-statistics, were presented in Table 8. From the Table 8, it was seen that all the regression coefficients were statistically significant at 5% level of significance. The R^2 and R_a^2 were found to be 0.8394 and 0.7264 respectively and the R^2 value was also significant at 5% and 1% levels respectively. But, on the basis of R_a^2, this forecasting model was not satisfactorily adequate and reliable for future use in predicting coconut crop yield in advance of harvest.

Table 8. Step-up regression analysis for the crop forecasting Model I(1) (3Y,6M) (effective crop season of 3 years with 6-month period)

Variables selected	Regression Coefficient	Regression Estimate	Standard error	Computed t-value
Z_{50}	a_{50}	44.7209	19.8260	2.2557*
Z_{52}	a_{52}	253.6790	61.5410	4.1221**
Z'_{50}	b_{50}	-0.9249	0.3393	-2.7259*
Z'_{51}	b_{51}	0.0832	0.0372	2.2365*
Z'_{52}	b_{52}	-4.4421	0.9460	-4.6957**
$Q_{(12)0}$	$g_{(12)0}$	-0.0329	0.0112	-2.9375**
$Q_{(23)1}$	$g_{(23)1}$	-0.5914	0.1669	-3.5434**
$Q_{(35)1}$	$g_{(35)1}$	0.0305	0.0118	2.5847*

$s = 26$ $R^2 = 0.8349$ $R_a^2 = 0.7638$ $A_0 = -4115.1200$

$t(0.025,17) = 2.110$ at 5% $t(0.005,17) = 2.898$ at 1%

* = Significant at 5%

** = Significant at 1%

The final functional form of crop forecasting Model I(1) (3Y,6M) fitted through step-up regression technique was given as follows:

$$
\begin{aligned}
Y = & - 4115.1200 + 44.7209\ Z_{50} + 253.6790\ Z_{52} \\
& - 0.9249\ Z_{50} + 0.0832\ Z'_{51} - 4.4421\ Z'_{52} \\
& - 0.0329\ Q_{(12)0} - 0.5914\ Q_{(23)1} + 0.0305\ Q_{(35)1}
\end{aligned}
$$

The functional forms of the predictor variables included in the above crop forecasting Model I(1) (3Y,6M) were defined in terms of original weather variables and their corresponding weights in section 3.3.1, hence not reproduced here again.

4.10. Statistical analysis for the crop forecasting Model I(2) (3Y,6M) (effective crop season of 3 years with 6-month period)

This forecasting Model I(2) (3Y,6M) also belonged to the family of general forecasting Model I developed in section 3.3.1 as a complete second-order response surface type crop forecasting model (square model).

The 20 preliminary selected variables having maximum absolute correlation coefficients with the yield response Y for fitting this model I(2) (3Y,6M) were Z_{30}, Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z_{52}, Z'_{30}, Z'_{50}, Z'_{31}, Z'_{51}, Z'_{32}, Z'_{52}, $Q_{(12)0}$, $Q_{(23)0}$, $Q_{(23)1}$, $Q_{(25)0}$, $Q_{(34)1}$, $Q_{(34)2}$, $Q_{(45)0}$ and T respectively.

The eight predictor variables to be included in the final crop forecasting model, selected through step-up regression technique, were Z_{50}, Z_{52}, Z'_{50}, Z'_{51}, Z'_{52}, $Q_{(12)0}$, $Q_{(23)1}$ and $Q_{(45)0}$ respectively. The estimates of regression coefficients for these corresponding predictor variables, along with their standard deviations and computed t-statistics, were presented in Table 9. From Table 9, it was seen that all the regression coefficient of the selected predictor variables, except that of the variable Z'_{51}, were statistically significant at 5% level of significance. The R^2 and R_a^2 were found to be 0.8346 and 0.7568 respectively and the R^2 value was also significant at 5% and 1% levels of significance respectively. But, on the basis of R_a^2, this forecasting model was not satisfactorily adequate and reliable for future use in predicting coconut crop yield in advance of harvest.

The final functional form of crop forecasting Model I(2) (3Y,6M) fitted through step-up regression technique was given as follows:

$$Y = -4169.9200 + 44.6960\ Z_{50} + 257.281\ Z_{52} - 0.9259\ Z'_{50} + 0.0837\ Z'_{51} - 4.5022\ Z'_{52} - 0.0327\ Q_{(12)0} - 0.4658\ Q_{(23)1} + 0.00012\ Q_{(45)0}$$

The functional forms of the predictor variables included in the above crop forecasting Model I(2) (3Y,6M) were defined in terms of original weather variables and their corresponding weights in section 3.3.1, hence not reproduced here again.

Table 9. Step-up regression analysis for the crop forecasting Model I(2) (3Y,6M) (effective crop season of 3 years with 6-month period)

Variables selected	Regression		Standard error	Computed t-value
	Coefficient	Estimate		
Z_{50}	a_{50}	44.6960	20.1280	2.2206*
Z_{52}	a_{52}	257.2810	62.3160	4.1287**
Z'_{50}	b_{50}	-0.9259	0.3444	-2.6884*
Z'_{51}	b_{51}	0.0857	0.0485	1.7670^NS
Z'_{52}	b_{52}	-4.5022	0.9586	-4.6966**
$Q_{(12)0}$	$g_{(12)0}$	-0.0327	0.0115	-2.8435*
$Q_{(23)1}$	$g_{(23)1}$	-0.4658	0.1706	-2.7304*
$Q_{(45)0}$	$g_{(45)0}$	0.00012	0.000049	2.4489*

s = 26 $R^2 = 0.8346$ $R_a^2 = 0.7568$ $A_0 = -4169.9200$

t(0.025,17) = 2.110 at 5% t(0.005,17) = 2.898 at 1%

* = Significant at 5%

** = Significant at 1%

NS = Non-significant

4.11. Statistical analysis for the crop forecasting Model I(3Y,6M) (effective crop season of 3 years with 6-month period)

This forecasting Model I(3)(3Y,6M) came under the category of general forecasting Model I developed in section 3.3.1 as a complete second-order response surface type crop forecasting model (square model).

The 20 preliminary selected predictor variables having maximum absolute correlation coefficients with the yield response Y for fitting this Model I(3) (3Y,6M) were Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z_{52}, Z'_{50}, Z'_{31}, Z'_{12}, Z'_{32}, Z'_{52}, $Q_{(12)2}$, $Q_{(14)2}$, $Q_{(15)2}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(25)2}$, $Q_{(35)1}$, $Q_{(35)2}$, $Q_{(45)0}$, $Q_{(45)2}$ respectively.

The eighteen predictor variables to be included in the final crop forecasting model, selected through step-up regression techniques, were Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z'_{50}, Z'_{31}, Z'_{12}, Z'_{32}, Z'_{52}, $Q_{(12)2}$, $Q_{(14)2}$, $Q_{(15)2}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(35)1}$, $Q_{(35)2}$, $Q_{(45)0}$ and $Q_{(45)2}$ respectively. The least square estimates of the regression coefficients for these corresponding predictor variables, along with their standard deviations and computed t-statistics, were presented in Table 10. From Table 10, it was seen that all the regression coefficients of the selected predictor variables, except that of three predictor variables, viz. Z'_{50}, Z'_{12}, $Q_{(12)2}$, $Q_{(35)1}$ and $Q_{(45)2}$, were statistically significant at 5% level of significance. The R^2 and R_a^2 were found to be 0.9149 and

Table 10. Step-up regression analysis for the crop forecasting Model I(3)(3Y,6M) (effective crop season of 3 years with 6-month period)

Variables selected	Regression Coefficient	Regression Estimate	Standard error	Computed t-value
Z_{50}	a_{50}	85.2925	30.6790	2.7802*
Z_{31}	a_{31}	85.9060	14.5870	5.8892**
Z_{51}	a_{51}	10.3168	3.5942	2.8704*
Z_{32}	a_{32}	27.2409	10.9980	2.4769*
Z'_{50}	b_{50}	-1.3085	0.5784	-2.2623^{NS}
Z'_{31}	b_{31}	-69.2092	27.0940	-2.5544*
Z'_{12}	b_{12}	0.0006	0.0004	1.5000^{NS}
Z'_{32}	b_{32}	47.6328	20.0930	2.3706*
Z'_{52}	b_{52}	-0.6713	0.2149	-3.1238*
$Q_{(12)2}$	$g_{(12)2}$	-0.0915	0.0395	-2.3165^{NS}
$Q_{(14)2}$	$g_{(14)2}$	-0.0579	0.0167	-3.4671*
$Q_{(15)2}$	$g_{(15)2}$	0.1287	0.0389	3.3085*
$Q_{(23)1}$	$g_{(23)1}$	17.3665	6.8176	2.5473*
$Q_{(23)2}$	$g_{(23)2}$	-15.8868	6.4815	-2.4511*
$Q_{(35)1}$	$g_{(35)1}$	6.9058	6.2651	1.1023^{NS}
$Q_{(35)2}$	$g_{(35)2}$	-7.4725	3.0614	-2.4409*
$Q_{(45)0}$	$g_{(45)0}$	-2.2112	0.0328	-6.4390**
$Q_{(45)2}$	$g_{(45)2}$	0.1792	0.1319	1.3586^{NS}

$s = 26$ $R^2 = 0.9149$ $R_a^2 = 0.6961$ $A_0 = -1022.3600$

$t(0.025, 7) = 2.365$ at 5% $t(0.005, 7) = 3.499$ at 1%

* = Significant at 5%

** = Significant at 1%

NS = Non-significant

0.6961 respectively and R^2 value was also significant at 5% level and 1% level of significance, but not highly significant. But, on the basis of R_a^2, this forecasting model was not satisfactorily adequate and reliable for future use in predicting the coconut crop yield in advance of harvest. Therefore, the performance of this forecasting model should be judged from the other criterion measures.

The final functional forms of crop forecasting Model I(3) (3Y,6M) fitted through step-regression technique was given as follows:

$$
\begin{aligned}
Y = & -1022.3600 + 85.2925\, Z_{50} + 85.9060\, Z_{31} + 10.3168\, Z_{51} \\
& + 27.2409\, Z_{32} - 1.3085\, Z'_{50} - 69.2092\, Z'_{31} \\
& + 0.0006\, Z'_{12} + 47.6328\, Z'_{32} - 0.6713\, Z'_{52} - 0.0915\, Q_{(12)2} \\
& - 0.0579\, Q_{(14)2} + 0.1287\, Q_{(15)2} + 17.3665\, Q_{(23)1} \\
& - 15.8868\, Q_{(23)2} + 6.9058\, Q_{(35)1} - 7.4725\, Q_{(35)2} \\
& - 0.2112\, Q_{(45)0} + 0.1792\, Q_{(45)2}
\end{aligned}
$$

The functional forms of the predictor variables included in the above crop forecasting Model I(3) (3Y,6M) were defined in terms of original weather variables and their corresponding weights in section 3.3.1, hence not reproduced here again.

4.12. Statistical analysis for the forecasting Model II(1) (3Y,6M) (effective crop season of 3 years with 6-month period)

This forecasting Model II(1) (3Y,6M) came under the category of general forecasting Model II developed in section 3.3.2 (square root model).

The 20 preliminary selected variables having maximum absolute correlation coefficients with the yield response Y for fitting the Model II(1) (3Y,6M) were Z_{30}, Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z_{52}, Z'_{30}, Z'_{50}, Z'_{31}, Z'_{51}, Z'_{52}, $Q_{(13)2}$, $Q_{(23)0}$, $Q_{(23)1}$, $Q_{(25)0}$, $Q_{(34)1}$, $Q_{(34)2}$, $Q_{(35)2}$, $Q_{(45)2}$ and T respectively.

The seven predictor variables to be included in the final crop forecasting model, selected through step-up regression technique, were Z_{52}, Z'_{30}, Z'_{50}, Z'_{51}, Z'_{52}, $Q_{(23)0}$ and $Q_{(35)2}$ respectively. The least square estimates of the regression coefficients for these predictor variables, along with their standard deviations and computed t-statistics, were presented in Table 11. From Table 11, it was found that all the regression coefficients were highly significant at 5% and 1% levels of significance respectively. The R^2 and R_a^2 were found to be 0.9893 and 0.9831; and R^2 values was very highly significant even at 1% level of significance. Therefore, on the basis of R^2 and R_a^2, the adequacy of fit of the crop forecasting Model II(1) (3Y,6M) is very highly satisfactory and consequently this crop forecasting model should be selected as the "best" crop forecasting model to be used in predicting the coconut crop yield in advance of harvest.

The final functional form of the crop forecasting Model II(1) (3Y,6M) developed through step-up regression procedure was given as follows:

Table 11. Step-up regression analysis for crop forecasting Model II(1) (3Y,6M) (effective crop season of 3 years with 6-month period

Variables selected	Regression Coefficient	Regression Estimate	Standard error	Computed t-value
Z_{32}	a_{52}	645.0530	24.1540	26.7058**
Z'_{30}	b_{30}	16.0323	0.7377	21.7328**
Z'_{50}	b_{50}	-1.2749	0.0585	-21.7932**
Z'_{51}	b_{51}	-0.1046	0.0151	-6.9272**
Z'_{52}	b_{52}	-10.1382	0.3609	-28.0914**
$Q_{(23)0}$	$g_{(23)0}$	-12.8148	0.5715	-22.4231**
$Q_{(35)2}$	$g_{(35)2}$	0.0015	0.0004	3.7500**

s = 26 R^2 = 0.9893 R_a^2 = 0.9851 A_0 = -8765.4000

t(0.025,18) = 2.101 at 5% t(0.005,18) = 2.878 at 1%

** = Significant at 1%

$$Y = - 8765.4000 + 645.0530\, Z_{52} + 16.0323\, Z'_{30} - 1.2749\, Z'_{50} - 0.1046\, Z'_{51} - 10.1382\, Z'_{52} - 12.8140\, Q_{(23)0} + 0.0015\, Q_{(35)2}$$

The functional forms of the predictor variables included in the above crop forecasting Model II(1) (3Y,6M) were defined in terms of original weather variables and their corresponding heights, hence not reproduced here again.

4.13. Statistical analysis for the forecasting Model II(2) (3Y,6M) (effective crop season of 3 years with 6-month period)

This forecasting model II(2) (3Y,6M) belonged to the family of general forecasting Model II developed in section 3.3.2 as square root model.

The 20 preliminary selected predictor variables having maximum absolute correlation coefficients with the yield response Y for fitting this model were Z_{30}, Z_{31}, Z_{51}, Z_{32}, Z_{52}, Z'_{50}, Z'_{51}, Z'_{52}, $Q_{(13)0}$, $Q_{(13)1}$, $Q_{(14)0}$, $Q_{(15)0}$, $Q_{(23)0}$, $Q_{(24)0}$, $Q_{(25)0}$, $Q_{(25)1}$, $Q_{(34)0}$, $Q_{(35)0}$, $Q_{(45)0}$ and T respectively.

The five predictor variables to be included in the final crop forecasting model, selected through step-up regression technique, were Z_{52}, Z'_{50}, Z'_{52}, $Q_{(14)0}$ and $Q_{(45)0}$ respectively. The least square estimates of the regression coefficients for the corresponding predictor variables, along with their standard deviations and computed t-statistics, were presented in Table 12. From Table 12, it was seen that

Table 12. Step-up regression analysis for the crop forecasting Model II(2) (3Y,6M) (effective crop season of 3 years with 6-month period)

Variables selected	Regression Coefficient	Regression Estimate	Standard error	Computed t-value
Z_{52}	a_{52}	303.0740	71.8260	4.2196*
Z'_{30}	b_{30}	-0.4233	0.0774	-5.4689**
Z'_{52}	b_{52}	-4.9425	1.1638	-4.2469*
$Q_{(14)0}$	$g_{(14)0}$	-0.0039	0.0014	-2.7857*
$Q_{(45)0}$	$g_{(45)0}$	0.000106	0.000036	2.9444**

$s = 26$ $R^2 = 0.6883$ $R_a^2 = 0.6104$ $A_0 = -4177.6900$

$t(0.025, 20) = 2.086$ at 5% $t(0.005, 20) = 2.845$ at 1%

* = Significant at 5%

** = Significant at 1%

all the regression coefficients of the selected predictor variables were statistically significant at 5% level. The R^2 and R_a^2 values were found to be 0.6383 and 0.6104; R^2 value was significant at 5% and 1% levels of significance respectively. But, on the basis of R^2 and R_a^2, adequacy of fit of this forecasting Model II(2) (3Y,6M) was not satisfactorily and therefore, this model should not be selected as the 'best' model to be used in predicting the coconut crop yield in advance of harvest.

The final functional form of crop forecasting Model II(2) (3Y,6M) fitted through step-up regression technique was given as follows:

$$Y = -4177.6900 + 303.0740\, Z_{52} - 0.4233\, Z'_{50} - 4.9425\, Z'_{52} - 0.0039\, Q_{(14)0} + 0.0001\, Q_{(45)0}$$

The functional form of the predictor variables included in the above crop forecasting Model II(2) (3Y,6M) were defined in terms of the original weather variables and their corresponding weights in section 3.3.2, hence not reproduced here again.

4.14. Statistical analysis for the crop forecasting Model II(3) (3Y,6M) (effective crop season of 3 years with 6-month period)

This crop forecasting Model II(3) (3Y,6M) came under the general forecasting Model II developed in section 3.3.2 as the square root forecasting model.

The 30 preliminary selected variables having maximum absolute correlation coefficients with the yield response Y for fitting this Model II(3) (3Y,6M) were Z_{50}, Z_{31}, Z_{51}, Z_{32}, Z_{52}, Z'_{50}, Z'_{31}, Z'_{51}, Z'_{32}, Z'_{52}, $Q_{(14)1}$, $Q_{(23)1}$, $Q_{(23)2}$, $Q_{(25)2}$, $Q_{(34)2}$, $Q_{(35)1}$, $Q_{(35)2}$, $Q_{(45)0}$, $Q_{(45)2}$ and T respectively.

The seven predictor variables to be included in the final crop forecasting model, selected through step-up regression technique, were Z_{50}, Z_{52}, Z'_{50}, Z'_{51}, Z'_{52}, $Q_{(23)1}$ and $Q_{(35)1}$ respectively. The least square estimates of the regression coefficients for these corresponding predictor variables, along with their standard deviations and computed t-statistics, were presented in Table 13. From Table 13, it was seen that all the regression coefficients were statistically significant at 5% level of significance. The R^2 and R_a^2 values were found to be 0.7594 and 0.6658 respectively, the R^2 value was significant even at 1% level of significance. But, on the basis of R^2 and R_a^2, adequacy and fit of this Model II(3) (3Y,6M) was not satisfactory and reliable and therefore, this model should not be selected as the "best" model to be used in predicting the coconut crop yield in advance of harvest.

The final functional form of the crop forecasting Model II(3) (3Y,6M) developed through step-up regression technique was given as follows:

$$Y = 3765.6200 + 48.4005\, Z_{50} + 227.3270\, Z_{52} - 0.9281\, Z'_{50} + 0.1205\, Z'_{51} - 4.1267\, Z'_{52} - 0.4955\, Q_{(23)1} + 0.0413\, Q_{(35)1}$$

Table 13. Step-up regression analysis for the crop forecasting Model II(3) (3Y,6M) (effective crop season of 3 years with 6-month period)

Variables selected	Regression Coefficient	Regression Estimate	Standard error	Computed t-value
Z_{50}	a_{50}	48.4005	20.3350	2.3802*
Z_{52}	a_{52}	227.3270	72.6120	3.1307**
Z'_{50}	b_{50}	-0.9281	0.4037	-2.2989*
Z'_{51}	b_{51}	0.1205	0.0541	2.2274*
Z'_{52}	b_{52}	-4.1267	1.1214	-3.6799**
$Q_{(23)1}$	$g_{(23)1}$	-0.4955	0.1946	-2.5462*
$Q_{(35)1}$	$g_{(35)1}$	0.0413	0.0133	3.1053**

$s = 26$ $R^2 = 0.7594$ $R_a^2 = 0.6658$ $A_0 = 3765.6200$

$t(0.025,18) = 2.101$ for 5% $t(0.005,18) = 2.878$ for 1%

* = Significant at 5%

** = Significant at 1%

The functional forms of the predictor variables included in the above crop forecasting Model II(3) (3Y,6M) were defined in terms of the original weather variables and their corresponding weights in section 3.3.2, hence not reproduced here again.

4.15. Comparative study of efficiency, adequacy and performance of crop forecasting models on the basis of criteria functions

From the above twelve crop forecasting models, fitted through step-up regression technique, the "best", the most efficient, adequate and promising crop forecasting models which would serve our purpose of predicting the coconut crop yield in advance of harvest were selected on the basis of criteria functions discussed in Chapter III. The criteria measures employed in the selection, were mean square error (MSE) or residual mean square (RMS), squared multiple correlation coefficient (R^2), adjusted R^2 (R_a^2), total prediction variance (J_r), prediction mean square error (MSEP), average estimated variance (AEV), Amemiya prediction criterion (APC), and Akaike information criterion (AIC) defined in section 3.8 of Chapter III.

The combined ANOVA tables for all the crop forecasting models to be selected on the basis of mean square errors (MSE) and computed (observed) F-values were presented in Table 14. Additionally, the tabular F-values at 5% and 1% levels of

Table 14. Combined ANOVA Tables for all the crop forecasting models fitted through step-up regression procedure

Model	Total		Regression			Residual(error)			Computed F-value	Tabular F-value	
	df	SST	df	SSR	MSR	df	SSE	MSE		at 5%	at 1%
I(1)(3Y,3M)	25	1219.1676	11	1156.0147	105.0923	14	63.1529	4.5109	23.2973	2.56	3.86
I(2)(3Y,3M)	25	1219.1676	13	1014.3474	78.0267	12	204.8202	17.0683	4.5714	2.64	4.05
I(3)(3Y,3M)	25	1219.1676	10	1146.9929	114.6993	15	72.1747	4.8116	23.8378	2.55	3.80
II(1)(3Y,3M)	25	1219.1676	14	1115.6603	79.6900	11	103.5073	9.4098	8.4689	2.70	4.21
II(2)(3Y,3M)	25	1219.1676	6	1116.8794	186.1466	19	102.2882	5.3836	34.5767	2.63	3.94
II(3)(3Y,3M)	25	1219.1676	9	1005.6914	111.7435	16	213.4763	13.3423	8.3752	2.54	3.78
I(1) (3Y,6M)	25	1219.1676	8	1023.3699	129.9212	17	195.7977	11.5175	11.1066	2.55	3.79
I(2) (3Y,6M)	25	1219.1676	8	1017.5173	127.1897	17	201.6503	11.8618	10.7226	2.55	3.79
I(3) (3Y,6M)	25	1219.1676	18	1115.4164	61.9676	7	103.7512	14.8216	4.1809	3.47	6.21
II(1)(3Y,6M)	25	1219.1676	7	1206.1225	172.3032	18	13.0451	0.7247	237.7490	2.58	3.85
II(2)(3Y,6M)	25	1219.1676	5	839.1531	167.8306	20	380.0145	19.0008	8.8329	2.71	4.10
II(3)(3Y,6M)	25	1219.1676	7	925.8359	132.2623	18	293.3317	16.2962	8.1161	2.58	3.85

significance were also provided in Table 14 for handy reference in the test of overall significance of crop forecasting models and the significance of R^2 respectively.

From Table 14, it was seen that the crop forecasting models having the smallest values of MSE and the largest values of computed (observed) F-values were the Model I(1) (3Y,3M), Model I(3) (3Y,3M), Model II(2) (3Y,3M) and Model II(1) (3Y,6M) respectively. Finally, these four forecasting models were selected as the 'best' ones on the basis of other criteria functions also. The elaborate discussions on the selection of forecasting models were presented in Chapter V.

The other criteria measures computed for all the crop forecasting models fitted through step-up regression technique were presented in Table 15. Computed F-values were also included in the Table 15 for the purpose of convenience of the reader in selecting the 'best' and most 'efficient' crop forecasting models on the basis of all the criterion functions and measures from the same table and for the convenience of comparing and judging simultaneously the degree of all the criteria measures on the same line for a particular crop forecasting model. The elaborate discussions on the selection of the 'best' forecasting models on the basis of these criteria measures were given in Chapter V.

Table 15. Computed criteria measures for all the crop forecasting models fitted through step-up regression procedure

Model	RMS	F	R2	R_a^2	J_r	MSEP	AEV	APC	AIC
I(1)(3Y,3M)	4.5109	23.2973	0.9482	0.9075	171.4154	9.0084	2.0819	6.5929	75.9049
I(2)(3Y,3M)	17.0683	4.5714	0.8320	0.6500	682.7314	40.2835	9.1906	26.2590	94.0079
I(3)(3Y,3M)	4.8116	23.8378	0.9408	0.9013	178.0298	8.9226	2.0357	6.8474	74.6825
II(1)(3Y,3M)	9.4098	8.4689	0.9151	0.8070	395.8010	24.4293	5.4287	14.8385	89.2965
II(2)(3Y,3M)	5.3836	34.5767	0.9161	0.8896	177.6580	7.7648	1.4494	6.8330	67.4905
II(3)(3Y,3M)	13.3423	8.3752	0.8249	0.7264	480.3214	23.0924	5.1317	18.4739	87.5635
I(1)(3Y,6M)	11.5175	11.1066	0.8394	0.7638	403.1118	18.6882	3.9868	15.5044	84.1484
I(2)(3Y,6M)	11.8618	10.7226	0.8346	0.7568	415.1628	19.2469	4.1060	18.9678	84.3969
I(3)(3Y,6M)	14.8216	4.1809	0.9149	0.6961	666.9708	64.1318	10.8312	25.6528	96.2509
II(1)(3Y,6M)	0.7247	237.7490	0.9893	0.9851	24.6376	1.1067	0.2229	0.9477	34.3298
II(2)(3Y,6M)	19.0008	8.8329	0.6883	0.6104	608.0022	25.9666	4.3848	23.3855	88.5334
II(3)(3Y,6M)	16.2962	8.1161	0.7594	0.6658	554.0704	24.8867	5.0142	21.3104	88.2468

4.16. Study of influence of changes in weather variables on coconut yield for selected forecasting models

As discussed in section 3.9 of Chapter III, the effect on the coconut crop yield of a change of one unit in i^{th} weather variable of w^{th} period, denoted by X_{iw}, with any assumed level of other weather variables X_{jw} ($i \neq j$) could be studied by the partial derivative of yield response Y in the corresponding crop forecasting model with respect to X_{iw} for i = 1,2,3,4,5 and w = 1,2,3, ..., 12 respectively.

4.16.1. Effect of changes in weather variables on the coconut crop yield for forecasting Model I(1) (3Y,3M)

At first theoretical (algebraic) functional form of crop forecasting Model I(1) (3Y,3M) selected through step up regression was worked out. The partial derivative of yield response Y with respect to X_{iw} for i = 1,2,3,4,5 were obtained as follows:

1) $$\frac{\partial Y}{\partial X_{1w}} = g_{(12)0}\, X_{2w}$$

2) $$\frac{\partial Y}{\partial X_{2w}} = g_{(12)0}X_{1w} + \left[g_{(23)0} + wg_{(23)1} + w^2 g_{(23)2}\right] X_{3w}$$

3) $$\frac{\partial Y}{\partial X_{3w}} = a_{30} + a_{32}w^2 + 2wb_{31}\, X_{3w} + \left[g_{(23)0} + wg_{(23)1} + w^2 g_{(23)2}\right] X_{2w} + \left[g_{(34)0} + w^2 g_{(34)2}\right] X_{4w}$$

4) $\frac{dY}{dX_{4w}} = \left[g_{(34)0} + w^2\, g_{(34)2}\right] X_{3w}$

5) $\frac{dY}{dX_{5w}} = 2b_{50}\, X_{5w} + w\, g_{(35)1}\, X_{3w}$

The period-wise effects of change of one unit in weather variables on the coconut crop yield under the forecasting Model I(1) (3Y,3M), at the assumed level of average of all five weather variables for all the twelve 3-month periods (seasons) were depicted in Table 16. Elaborate discussion was presented in Chapter V.

4.16.2. Effect of changes in weather variables on the coconut crop for the crop forecasting Model I(3) (3Y,3M)

As in section 4.16.1, the algebraic functional form of the forecasting Model I(3) (3Y,3M) fitted through step-up regression technique was worked out. The partial derivatives of yield response Y with respect to the original weather variables involved in the forecasting model were obtained as follows:

1) $\frac{dY}{dX_{1w}} = \frac{2b_{12}}{R_1^{(2)}} \cdot r_{1w}^2(2) X_{1w} + \left[\frac{g_{(12)0}}{T_{12}(0)} + \frac{g_{(12)2}}{T_{12}(2)}\, r^2_{(12)2}(3)\right] X_{2w}$

2) $\frac{dY}{dX_{2w}} = \frac{a_{22}}{D_2^{(2)}} \cdot r_{2w}^2(1) + \left[\frac{g_{(12)0}}{T_{12}(0)} + \frac{g_{(12)2}}{T_{12}(2)} \cdot r^2_{(12)2}(3)\right] X_{1w}$

$+ \frac{g_{(23)2}}{T_{23}(2)} \cdot r^2_{(23)w}(3)\; X_{3w}$

Table 16. Period-wise effect of change (increase) of one unit in a weather variable on the coconut crop yields under the forecasting Model I(1)(3Y,3M) at the average level of weather variables

w	$\partial Y/\partial X_{1w}$	$\partial Y/\partial X_{2w}$	$\partial Y/\partial X_{3w}$	$\partial Y/\partial X_{4w}$	$\partial Y/\partial X_{5w}$
1	0.0079	-13.1673	13.3650	-6.8417	-0.1499
2	0.0079	-14.5773	7.3044	-6.6523	-0.1571
3	0.0079	-15.3319	2.3208	-6.3368	-0.1643
4	0.0079	-15.4309	-1.5856	-5.8949	-0.1714
5	0.0079	-14.8745	-4.4148	-5.3269	-0.1786
6	0.0079	-13.6625	-6.1669	-4.6326	-0.1857
7	0.0079	-11.7950	-6.8419	-3.8121	-0.1929
8	0.0079	-9.2720	-6.4398	-2.8654	-0.2000
9	0.0079	-6.0936	-4.9606	-1.7923	-0.2072
10	0.0079	-2.2596	-2.4042	-0.5932	-0.2144
11	0.0079	2.2299	1.2293	0.7323	-0.2215
12	0.0079	7.3749	5.9399	2.1839	-0.2287

4) $$\frac{\partial Y}{\partial X_{5w}} = \frac{a_{50}}{D_5(0)} + \frac{a_{52}}{D_5(2)} \cdot r^2_{5w}(1) + \left[2X_{5w}\right] \cdot \left[\frac{b_{50}}{R_5(0)} + \frac{b_{52}}{R_5(2)} r^2_{5w}(2)\right]$$

$$\text{where } D_i(k) = \sum_{w=1}^{n} r^k_{iw}(1); \quad R_i(k) = \sum_{w=1}^{n} r^k_{iw}(2);$$

$$T_{ij}(k) = \sum_{w=1}^{n} r^k_{(ij)w}(3)$$

The periodwise effects of change (increase) of one unit in each of the weather variables X_{1w}, X_{2w}, X_{3w}, X_{5w} on the coconut crop yields at the assumed levels of averages of weather variables for all the twelve 3-month periods (seasons) were shown in Table 17. Elaborate interpretations and discussions were presented in Chapter V.

4.16.3. Effect of changes in weather variables on the coconut crop yields for the crop forecasting Model II(2)(3Y,3M)

As in section 4.16.1, the partial derivatives of the yield response Y with respect to the original weather variables involved in the fitted forecasting model were obtained as follows:

1) $$\frac{\partial Y}{\partial X_{2w}} = \frac{1}{2M_0 X^{1/2}_{2w}} \left[g_{(23)0}\, X^{1/2}_{3w} + g_{(25)0}\, X^{1/2}_{5w} \right]$$

2) $$\frac{\partial Y}{\partial X_{3w}} = \frac{w}{M_1} a_{31} + \frac{1}{2M_0 X^{1/2}_{3w}} \left[b_{30} + g_{(23)0}\, X^{1/2}_{2w} + g_{(34)0}\, X^{1/2}_{4w} \right]$$

3) $$\frac{\partial Y}{\partial X_{4w}} = \frac{1}{2M_0}\, g_{(34)0} \left[X_{3w} / X_{4w} \right]^{1/2}$$

Table 17. Period-wise effect of change (increase) of one unit in a weather variable on the coconut crop yields under the forecasting Model I(3)(3Y,3M) at the average level of other weather variables

W	$\partial Y/\partial X_{1W}$	$\partial Y/\partial X_{2W}$	$\partial Y/\partial X_{3W}$	$\partial Y/\partial X_{5W}$
1	-0.0566	-3.3513	-1.0822	-5.4414
2	-0.0275	-2.0344	-0.8858	-6.0207
3	-0.0528	-2.9745	-0.0613	-3.1493
4	-0.0905	-7.0131	-0.0221	-0.9591
5	-0.1173	-3.0024	-1.1877	-5.7491
6	-0.0226	-1.4343	-2.6723	-6.0547
7	-0.0381	-4.8946	-0.0098	-3.4549
8	-0.0235	-1.1122	-0.0613	-5.0275
9	-0.0715	-3.2652	-1.5337	-2.7394
10	-0.0716	-5.5339	-2.6723	-5.4414
11	-0.0706	-2.9293	-0.0613	-4.8323
12	-0.0261	-1.5658	-0.0025	-5.6960

$$4)\ \frac{\partial Y}{\partial X_{5w}} = b_{50} + g_{(23)0}\, X_{2w}^{1/2} \Big/ 2M_0\, X_{5w}^{1/2}$$

where $M_0 = n$, $M_1 = n(n+1)/2$ respectively.

The periodwise effects of change (increase) of one unit in each of the weather variables X_{2w}, X_{3w}, X_{4w} and X_{5w} on the coconut crop yields (average nuts per bearing tree per half year) at the assumed level of averages of other weather variables as shown in Table 1 were presented in Table 18. Elaborate interpretations and discussions were made in Chapter V.

4.16.4. Effect of changes in weather variables on the coconut crop yields for the crop forecasting Model II(1)(3Y,6M)

As in section 4.16.1, the partial derivatives of the yield response Y with respect to the original weather variables involved in the fitted forecasting model were obtained as follows:

$$1)\ \frac{\partial Y}{\partial X_{2w}} = g_{(23)0}\left[X_{3w} \big/ X_{2w}\right]^{1/2}$$

$$2)\ \frac{\partial Y}{\partial X_{3w}} = \frac{1}{2X_{3w}^{1/2}}\left[b_{30} + g_{(23)0}\, X_{2w}^{1/2} + w^2\, g_{(35)2}\, X_{5w}^{1/2}\right]$$

$$3)\ \frac{\partial Y}{\partial X_{5w}} = a_{52}w^2 + \left[b_{50} + b_{51} + b_{52}\, w^2\ \frac{1}{2X_{5w}^{1/2}}\right] + w^2\, g_{(35)2}\, (X_{3w}/X_{5w})^{1/2}$$

The period-wise effects of change (increase) of one unit in each of the weather variables, viz., X_{2w}, X_{3w} and X_{5w} on the coconut crop yield at the assumed levels of averages of all weather variables as shown in Table 1 were pre-

Table 18. Period-wise effect of change (increase) of one unit in weather variables on the coconut crop yield under forecasting Model II(2)(3Y,3M) at the average level of the weather variables

w	$\partial Y/\partial X_{2w}$	$\partial Y/\partial X_{3w}$	$\partial Y/\partial X_{4w}$	$\partial Y/\partial X_{5w}$
1	1.9514	-3.2050	0.3441	-3.5365
2	1.9514	-2.7236	0.3441	-3.5365
3	1.9514	-2.2422	0.3441	-3.5365
4	1.9514	-1.7607	0.3441	-3.5365
5	1.9514	-1.2793	0.3441	-3.5365
6	1.9514	-0.7978	0.3441	-3.5365
7	1.9514	-0.3164	0.3441	-3.5365
8	1.9514	-0.1650	0.3441	-3.5365
9	1.9514	0.6465	0.3441	-3.5365
10	1.9514	1.1279	0.3441	-3.5365
11	1.9514	1.6094	0.3441	-3.5365
12	1.9514	2.0908	0.3441	-3.5365

presented in Table 19. Elaborate interpretations and discussions were made in Chapter V.

The relevant complete data pertaining to the yield response Y (average yields of nuts per bearing tree per half year) and selected predictor variables for each of forecasting models were presented in Appendix Tables.

Table 19. Period-wise effect of change (increase of one unit in weather variables on the coconut crop yield under forecasting Model II(1)(3Y,6M) at the average level of the weather variables

w	$\partial Y/\partial X_{2w}$	$\partial Y/\partial X_{3w}$	$\partial Y/\partial X_{5w}$
1	-6.9078	-8.1069	0.0648
2	-6.9078	-8.0920	0.2592
3	-6.9078	-8.0672	0.5833
4	-6.9078	-8.0324	1.0369
5	-6.9078	-7.9877	1.6202
6	-6.9078	-7.9329	2.3330
7	-6.9078	-7.8683	3.1755
8	-6.9078	-7.7939	4.1476
9	-6.9078	-7.7092	5.2494
10	-6.9078	-7.6147	6.4807
11	-6.9078	-7.5103	7.8417
12	-6.9078	-7.3959	9.3322

DISCUSSION

CHAPTER V

DISCUSSION

5.1. Introduction

In the present investigation attempts were made to:

1) to develop a suitable and reliable statistical methodology for the pre-harvest forecast of coconut crop yields by evolving different empirical-statistical crop-weather models using the original and generated weather variables as predictor variables.

2) to perform a comparative study of relative efficiency, adequacy and performance of each of these crop forecasting models evolved and to select the 'best', most promising and plausible crop forecasting models for the purpose of future use in predicting the coconut crop yields reliably in advance of harvest.

3) to investigate the effect and influence of changes in weather variables on the yield of coconut crop, based on the crop forecasting models selected as the 'best' fitted models.

4) to render suggestions and guidelines for further development of statistical crop-weather models, criteria for their selection, and relevant statistical analysis.

5.2. Crop forecasting models fitted through step-up regression technique using forward selection procedure

The twelve crop forecasting models were developed under the effective crop season of 3 years with 3-month period and 6-month period respectively. The two general forecasting models were of the square model and square root model. Under the square model, the complete second-order response surface type crop forecasting model was developed. Further, under each general forecasting model, three different crop forecasting models were developed giving the different weights to the weather effects on the crop yields. Therefore, the six basic crop forecasting models could be developed under the two general forecasting models, denoted by Model I and Model II in section 3.3.1 and 3.3.2 of Chapter III. Again, the above six forecasting models were developed under the effective crop season of 3 years with 3-month and 6-month period. Therefore, the twelve crop forecasting models were discussed one after another. However, it should be mentioned here that there were very few investigations in coconut crop, which attempted to develop crop forecasting models using several weather variables as in the present study. The forecasting models for the yields of coconut, developed so far, have taken into consideration linear effect of only one or two weather variables at a time or simultaneously, excluding the interaction effect of these weather variables on the crop. In this investigation, we have taken into consideration the linear, quadratic and interaction effects of five weather variables on the crop yields at each and every period (season). Therefore, unfortunately, we could not perform a reasonable comparative study between the present crop forecasting models and the other ones. Instead, we could carry out only comparative study within our fitted crop forecasting models

1. Forecasting Model I(1)(3Y,3M) (effective crop season of 3 years with 3-month period)

Under this model the linear functional relationship of yield response Y (average yield of nuts per bearing per half year) with the generated weather predictor variables selected through step-up regression techniques was presented in section 4.3 of Chapter IV.

This model I(1)(3Y,3M) produced R^2 value of 0.9482 and R_a^2 value of 0.9075. Therefore, 94.82% of the total variance from the mean in the yield response Y was explained by the predictor variables in the model. Here, the R^2 values was also highly significant therefore, the regression equation (crop forecasting model) on the predictor variables was also highly significant on 5% and 1% levels.

The R^2 and R_a^2 values per predictor variable were 0.0862 and 0.0825 respectively. On the basis of R^2 and R_a^2, this forecasting model was very satisfactory in the adequacy and goodness of fit of the model to the given set of data on the selected predictor variables. Therefore, this model should be considered one of the 'best' crop forecasting models.

2. Forecasting Model I(2)(3Y,3M) (effective crop season of 3 years with 3-month period)

Under the model, the linear functional relationship of yield response Y with the generated predictor variables fitted through step-up regression techniques was presented in section 4.4 of Chapter IV.

This forecasting model produced R^2 value of 0.8320 and R_a^2 value of 0.6500 respectively. Therefore, the model could explain only 83.20% of the total variance from the mean in the response variable Y. Here, R^2 value was significant at 1% level of significance, but not highly. On the basis of R^2 and R_a^2, the model was not satisfactory in the adequacy of fit of the model to the given set of data. Since many predictor variables were employed in the model, its R_a^2 value decreased sharply to the level of 0.6500. Therefore, the R^2 and R_a^2 per predictor variable were 0.064 and 0.050 respectively.

Comparing forecasting Model I(1) (3Y,3M) and Model I(2) (3Y,3M), the former was much more efficient and adequate in the fit of linear relationship with the crop yield Y. Elaborate comparison of these forecasting models were made in section 5.3.

3. Forecasting Model I(3)(3Y,3M) (effective crop season of 3 years with 3-month period)

Under this model the linear functional relationship of yield response Y with the generated predictor variables selected through step-up regression technique was presented in section 4.5 of Chapter IV.

This forecasting model produced R^2 value of 0.9408 and R_a^2 value of 0.9013 respectively. Therefore the forecasting model could explain 94.08% of the total variation from the mean in the response variable Y. The R^2 value was also highly significant. On the basis of R^2 and R_a^2, the forecasting model was highly satisfactory in the adequacy and goodness of fit of the model to the given set of data on the selected predictor variables. But this model employed only ten predictor variable. The R^2 and R_a^2 values per predictor variable were 0.0941 and 0.0901 respectively in this model. On the basis of R^2, this model could be considered as one of the 'best' models.

4. Forecasting Model II(1)(3Y,3M) (effective crop season of 3 years with 3-month period)

Under this model, the linear functional relationship of yield response Y with the generated predictor variables selected through step-up regression techniques was presented in section 4.6 of Chapter IV.

This forecasting model produced R^2 value of 0.9151 and

R_a^2 value of 0.8070 respectively. Therefore, the model could explain 91.51% of the total variance from the mean in the response variable Y. R^2 value was significant even at 1% level of significance. The R^2 and R_a^2 per predictor variable in this forecasting model were 0.0654 and 0.0576 respectively. This model had used many predictor variables; hence the MSR (regression mean square) decreased and consequently the computed F-value also went down sharply to 8.4689 which was not commensurate to its high R^2 value of 0.9151. Therefore, eventhough the R^2 is satisfactorily high, on the basis of adequacy and efficiency, this model would not serve our purpose of predicting the coconut crop yield in advance of the harvest.

5. Forecasting Model II(2) (3Y,3M) (effective crop season of 3 years with 3-month period)

Under this model, the linear functional relationship of yield response Y with generated predictor variables selected through step-up regression technique was presented in section 4.7 of Chapter IV.

This model produced R^2 value of 0.9161 and R_a^2 value of 0.8896 respectively. Therefore, 91.61% of the total variance from the mean in the response variable Y was explained by the predictor variables included in the forecasting model. Here, R^2 value was also highly significant. Therefore, the crop forecasting model on the selected six predictor variables was highly efficient.

All the regression coefficients of the selected predictor variables were highly significant even at 1% level of significant. The R^2 and R_a^2 per predictor variable were found to be 0.1527 and 0.1483 respectively. Therefore this forecasting model should be maintained for the future use in predicting the coconut crop yield in advance of harvest.

6. Forecasting Model II(3) (3Y,3M) (effective crop season of 3 years with 3-month period)

Under this model, the linear functional relationship of yield response Y with the predictor variables selected through step-up regression technique was presented in section 4.8 of Chapter IV.

This model produced R^2 value of 0.8249 and R_a^2 value of 0.7264 respectively. Therefore, the variables in the model explained only 82.49% of the total variance from the mean in the yield response Y. Here, R^2 was also significant both at 5% and 1% levels. All the regression coefficients of the selected variables, except that of variable $Q_{(23)2}$, was significant at 5% level. The R^2 and R_a^2 values per predictor variable were 0.0917 and 0.0807 respectively. On the basis of R^2 values, this model explained less variation in comparison to the previous models, hence not be considered for further use in predicting coconut yields in advance of harvest.

7. <u>Forecasting Model I(1) (3Y,6M) (effective crop season of 3 years with 6-month period)</u>

Under this model, the linear functional relationship of yield response Y with the selected predictor variables was presented in section 4.9 of Chapter IV.

This model produced R^2 value of 0.8394 and R_a^2 value of 0.7638 respectively. Therefore, the predictor variables in the model explained only 83.94% of the total variance from the mean in the response variable Y. Here, R^2 was also significant at 5% and 1% levels. All the regression coefficients of the predictor variables, were significant at 5% level of significance. The R^2 and R_a^2 values per predictor variable were 0.1049 and 0.0955 respectively. Therefore, on the basis of R^2 and R_a^2, this model was not satisfactorily adequate in the fit of linear relationship with the selected predictor variables; hence not to be considered and maintained for future use in predicting the coconut yields in advance of harvest.

8. <u>Forecasting Model I(2) (3Y,6M) (effective crop season of 3 years with 6-month period)</u>

Under this model, the linear functional relationship of yield response Y with the selected predictor variables was presented in section 4.10 of Chapter IV.

This model produced R^2 value of 0.8346 and R_a^2 value of 0.7568 respectively. Therefore, the predictor variables in the model explained only 83.46% of the total variance from the mean in the response variable Y. Here, R^2 was significant at 5% level of significance. All the regression coefficients, except that of the variable Z'_{51}, were significant at 5% level. The R^2 and R_a^2 per predictor variable were 0.1042 and 0.0946 respectively. Therefore, on the basis of R^2 and R_a^2, this model was not satisfactorily adequate in the fit of linear relationship with the selected predictor variables; hence not to be considered and maintained for future use in predicting the coconut yields in advance of harvest.

9. <u>Forecasting Model I(3) (3Y,6M) (effective crop season of 3 years with 6-month period)</u>

Under this model, the linear functional relationship of yield response Y with the selected predictor variables was presented in section 4.11 of Chapter IV.

This model produced R^2 value of 0.9149 and R_a^2 value of 0.6911 respectively. Therefore, the predictor variables in the model explained 91.49% of the total variance from the mean in the response variable Y. Here, it was found that R^2 was significant at 5% level and but not significant at 1% level eventhough the model had high R^2 value of 0.9149. All the regression coefficients of the predictor variables, except that of the variables, viz. Z'_{50}, Z'_{12}, $Q_{(12)2}$, $Q_{(35)1}$ and $Q_{(45)2}$, were significant at 5% level. The R^2 and R_a^2 values per predictor variable were 0.0508 and 0.0387 respectively.

Therefore, on the basis of R^2 and R_a^2, this model was not satisfactorily adequate in the fit of linear relationship with the selected predictor variables, hence not to be considered and maintained for future use in predicting the coconut yields in advance of harvest.

10. Forecasting Model II(1) (3Y,6M) (effective crop season of 3 years with 6-month period)

Under this model, the linear functional relationship of yield response Y with the selected predictor variables was presented in section 4.12 of Chapter IV.

This model produced R^2 value of 0.9893 and R_a^2 value of 0.9831 respectively. Therefore, the predictor variables in the model explained 98.93% of the total variation from the mean in the response variable Y. The R^2 and R_a^2 values per predictor variable were also as very satisfactorily high as 0.1407 and 0.1318 respectively. Here it was found that R^2 values was satisfactorily very high and statistically highly significant even at 1% level of significance. All the regression coefficients were also highly significant even at 1% level. Therefore, this model should be maintained and used in future prediction of coconut crop yield in the experimental fields and research stations.

11. Forecasting Model II(2) (3Y,6M) (effective crop season of 3 years with 6-month period)

Under this model, the linear functional relationship of yield response Y with the selected predictor variables was presented in section 4.13 of Chapter IV.

This model produced R^2 value of 0.6883 and R_a^2 value of 0.6104 respectively. Therefore, the predictor variables in the model explained only 68.83% of the total variance from the mean in the response variable Y. Here, it was found that R^2 was significant at 5% and 1% levels and all the regression coefficients were also significant at 5% level. The R^2 and R_a^2 values per predictor variable were 0.1221 and 0.1085 respectively.

However, on the basis of R^2 and R_a^2, this model was not satisfactorily adequate in the fit of linear relationship with the selected predictor variables, hence not to be considered and maintained for future use in predicting the coconut yields in advance of harvest.

12. Forecasting Model II(3) (3Y.6M) (effective crop season of 3 years with 6-month period)

Under this model, the linear functional relationship of yield response Y with the selected predictor variables was presented in section 4.14 of Chapter IV.

This model produced R^2 value of 0.7594 and R_a^2 value of 0.6688. Therefore, 75.94% of total variance from the mean in the response variable Y was explained by the predictor variables in the model. R^2 value was significant at 5% and 1% levels respectively and all the regression coefficients were also significant at 5% level. The R^2 and R_a^2 values per predictor variable were 0.1085 and 0.0951 respectively.

However, on the basis of R^2 and R_a^2, this model was not satisfactorily adequate in the fit of linear relationship with the selected predictor variables, hence not to be considered and maintained for future use in predicting the coconut yields in advance of harvest.

In the above discussion, we have introduced a new criterion, viz., "R^2 and R_a^2 values per predictor variable" to be used in selecting the fitted forecasting models. If the R^2 and R_a^2 values of the two forecasting models, which measured the strength of adequacy and goodness of fit of the models to their corresponding data sets, were the same, we should select the forecasting model with higher values of R^2 and R_a^2 per predictor variable. It amounted to the fact that we should select the forecasting model having the smaller number of predictor variables because such selection would save and economize time, cost and manpower required to collect the required weather data and to compute the generated predictor variables to substantial extent.

Therefore, the four crop forecasting models, viz., Model I(1) (3Y,3M), Model I(3) (3Y,3M), Model II(2) (3Y,3M) and Model II(1) (3Y,6M), should be considered to be the 'best' models on the basis of (i) computed R^2 and R_a^2 and (ii) computed R^2 and R_a^2 per predictor variable selected in fitted forecasting models.

5.3. Comparative study of fitted crop forecasting models and selection of the "best" models

Comparative investigation of efficiency, adequacy and performance of the crop forecasting models fitted through step-up regression procedure and their final selection for the "best" fitted and most efficient forecasting models to be used in future prediction of coconut crop yield was carried out in the following sections based on comparison of their analysis of variance (ANOVA) and other criteria measures computed from the criteria functions defined and discussed in section 3.8 of Chapter III.

5.3.1. Comparison and selection of fitted crop forecasting models on the basis of ANOVA and its related measures

ANOVA Table for all the crop forecasting models fitted through step-up regression procedure was presented in Table 14.

i) Selection on the basis of mean square error (MSE)

From the mean square error (MSE) column of the Table 14 for each of forecasting models, it would be seen that the forecasting models having the smallest values of MSE were Model I(1) (3Y,3M), Model I(3) (3Y,3M), Model II(2) (3Y,3M) and Model II(1) (3Y,6M) respectively.

The MSE in the ANOVA Table 14 was the same as residual mean squares (RMS) discussed in Chapter III as a criterion function to be used in selecting the "best" fitted regression equations. RMS is a measure for judging adequacy of fit of a forecasting model. Therefore, on the basis of the MSE or RMS criterion, the above four crop forecasting models would be selected as the 'best' and most promising crop forecasting models for the purpose of future use in predicting the coconut crop yields especially in the region of Pilicode. Consequently, the linear functional form of these forecasting models with their respective predictor variables would be considered to be satisfactorily adequate to describe and explain on the response variable, coconut crop yield.

ii) Selection on the basis of computed F-value

In order to select the 'best' crop forecasting models on the basis of criterion of computed (observed) F-values, some practical guidelines in selection of regression equations, as explained in Appendix 2C (How significant should my regression be?) of Draper and Smith (1981) was reproduced here for handy reference.

"For a useful as distinct from a significant regression, the observed F-value for regression should exceed the usual percentage point by a multiple .... In summary, it is clear that an observed F-value must be at least four or five times the usual percentage point for the minimum level of proper representation".

From Table 14, it could be seen that all the crop forecasting models were statistically significant at 5% level of significance on the basis of overall F-value. It was also clear from the Table 14 that the forecasting models having the highest values of computed (observed) F-value were Model I(1) (3Y,3M), Model I(3) (3Y,3M), Model II(2) (3Y,3M) and Model II(1) (3Y,6M) with their computed F-values 23.2973, 23.8378, 34.5767 and 237.7490 respectively. Further the ratio of these computed F-values to their corresponding tabular F-values were found to be 6.04, 6.27, 8.78 and 61.75 respectively at 1% level of significance and 9.10, 9.35, 13.15 and 92.15 respectively at 5% level of significance.

Therefore, on the basis of '<u>usefulness</u>' rather than '<u>statistical significance</u>' of crop forecasting models, as expounded by Draper and Smith (1981) in the above paragraph, these four forecasting models should be selected as the most useful (best) crop forecasting models for future purpose of predicting the coconut crop yields based on weather variables in advance of harvest.

It was interesting to note that the crop forecasting models selected as the 'best' fitted models on the basis of two criteria of mean square error (MSE) or residual mean square (RMS) and computed (observed) F-values were exactly the same.

5.3.2. Comparison and selection of fitted crop forecasting models on the basis of other criteria functions

Eight different criteria functions were also made use of in comparing the twelve forecasting models to select the 'best' models suited to the situation, over and above the comparison on the basis of ANOVA.

Table 15 showed the criteria measures computed for each of crop forecasting models fitted through step-up regression procedure. The computed criteria measures shown in Table 15 were residual mean squares (RMS), squared multiple correlation coefficient (R^2), adjusted squared multiple correlation coefficient (R_a^2), total prediction variance (J_r), prediction mean square error (MSEP), average estimated variance (AEV), Amemiya prediction criterion (APC) and Akaike information criterion (AIC).

i) Selection on the basis of RMS

On the basis of RMS criterion, the crop forecasting models having the smallest values of RMS were the same as the models selected as the 'best' fitted models based on MSE criterion in section 5.3.1 because RMS and MSE were equal in value, but only different in terminology. Therefore, it was not discussed here again.

ii) Selection on the basis of R^2

On the basis of criterion of squared multiple correlation coefficient (R^2), the crop forecasting models in

Table 15, whose R^2 values were satisfactorily high and greater than 90% were the forecasting Model I(1) (3Y,3M), Model I(3) (3Y,3M), Model II(1) (3Y,3M), Model II(2)(3Y,3M), Model I(3) (3Y,6M) and Model II(1) (3Y,6M) with their corresponding R^2 values of 0.9482, 0.9408, 0.9151, 0.9161, 0.9149 and 0.9893 respectively.

Therefore, on the basis of R^2 criterion, the above six crop forecasting models should be selected as the 'best' models in the sense that they possessed the 'highest'strength' or 'adequacy' of fit to the given body of data. From Table 15, it was also found that all the R^2 values were statistically significant at 5% level and also at 1% level of significance, with the exception of only one model, viz. Model I(3)(3Y,6M) eventhough it had R^2 value of 0.9149.

iii) <u>Selection on the basis of R_a^2</u>

Since the statistical significance of R^2 would not give a true picture of adequacy of the crop forecasting models, we should continue the search for the 'best' and most promising models on the basis of other criteria measures which were compatible with our objective of prediction of crop yield and appropriate to our system of different models with different set of data as predictor variables.

On the basis of R_a^2 criterion, it was seen from Table 15 that the most promising crop forecasting models which were having the highest values of R_a^2 were the same as the four models selected in section 5.3.1 as the 'best' ones on the basis of RMS criterion and computed F-value criterion.

In the criterion of R_a^2, an adjustment has been made for the corresponding degrees of freedom of the two quantities SSE and SST (corrected), the idea being that the R_a^2 measure can be used to compare regression equations fitted not only to a specific set of data but also two or more entirely different set of data (Draper and Smith, 1981). Therefore, selection of the 'best' crop forecasting models fitted to the different sets of data on the different predictor variables included in the different form of crop forecasting models on the basis of R_a^2 would be more appropriate and compatible with our conditions of different models and data.

iv) <u>Selection on the basis of J_r</u>

On the basis of total prediction variance, the crop forecasting models in Table 15 having the smallest values of total prediction variance (J_r) were the Model I(1)(3Y,3M), Model I(3) (3Y,3M), Model II(2) (3Y,3M) and Model II(1)(3Y,6M) respectively. These forecasting models were the same as the four models selected on the basis of RMS criterion and R_a^2 criterion. Therefore, selection on the basis of the total prediction variance (J_r) confirmed the previous results with respect to the selection of forecasting models.

v) Selection on the basis of MSEP

On the basis of prediction mean square error (MSEP), the 'best' crop forecasting models selected from the Table 15 were found to be the models having the smallest values of MSEP, viz. Model I(1) (3Y,3M), Model I(3)(3Y,3M), Model II(2) (3Y,3M) and Model II(1) (3Y,6M) respectively, which were the same as the above four models selected on the RMS, R_a^2 and J_r criterion. Since one of the primary objectives of developing crop forecasting models in the present investigation was the prediction of coconut crop yield in advance of harvest, selection for the 'best' crop forecasting on the basis of MSEP criterion would be more meaningful, appropriate, reliable and compatible with our objectives of this study.

vi) Selection on the basis of AEV

On the basis of average estimated variance, the crop forecasting models in Table 15 having the smallest values of AEV were the Model I(1) (3Y,3M) Model I(3) (3Y,3M), Model II(2) (3Y,3M) and Model II(1) (3Y,6M) respectively. These models were the same as the four models selected on the criteria of RMS, R_a^2, J_r and MSEP respectively. Therefore, the average estimated variance (AEV) confirmed the previous results.

vii) Selection on the basis of APC

On the basis of Amemiya prediction criterion (APC), the forecasting models having the smallest values of average prediction variance were the same as the models selected on the basis of above criteria functions. Therefore, selection on the basis of APC also confirmed the previous results with respect to the selection of the forecasting models.

viii) Selection on the basis of AIC

On the basis of Akaike information criterion (AIC), it was also seen that the forecasting models having the smallest values in the AIC column of Table 15 were the same forecasting models selected on the basis of other criteria functions. Therefore, the selection on the basis of AIC also confirmed the previous results with respect to the selection of forecasting models.

Here, it was found that the above four crop forecasting models always overlapped in any selection based on any criterion measure discussed above. Therefore, it was finally decided that these four crop forecasting models were the 'best' and most 'promising, plausible and efficient' forecasting models which highly satisfied our objective of prediction of coconut crop yields in advance of harvest. It was also highly recommended to maintain and utilize these crop forecasting models for the purpose of future use in predicting the coconut crop yields in advance of harvest, especially for the region of Pilicode and to try these forecasting models in other different places in order to investigate predictive power and validity of the models.

5.4. Effect of weather changes on the coconut crop yield under the 'best' crop forecasting models selected

Here the effect of change in a particular weather variable on the coconut crop yield was studied in term of the rate of change in the coconut crop yield for a change of one unit in the weather variable when other variables were kept constant at their average levels. Therefore, mathematically, the effect of change in weather variable on the crop yield is a partial derivative of yield response Y with respect to the weather variable under study. The partial derivatives of Y with respect to the weather variables included in the 'best' four models were shown in sections 4.15.1-4.15.4.

5.4.1. Effect of changes in weather variables on the coconut crop yield under the Model I(1) (3Y,3M)

From the five partial derivatives computed in section 4.15.1 of Chapter IV it was noted that effect of X_{1w} was constant which showed that the effect of change of one centimetre in total rainfall on the coconut crop yield was uniform over all the 12, 3-month periods covering effective crop season of 3 years (36 months). The effect of X_{5w} was a linear function of w, while all the other partial derivatives were parabolic function of w at assumed level of other weather variables.

From Table 16, it was noted that the effect of change (increase) of one cm in the total rainfall on the coconut yield was constant for all the periods w. For other three variables viz., sunshine hours, wind velocity and transformed relative humidity, the effect of one unit change (increase) in these weather variables on the coconut yield response was negative upto 10th period or season. From 11th period onwards the effect of these weather variables showed positive response. But, when this was taken conversely, effect of unit changes (decrease) in these weather variables showed positive response on the coconut crop yield.

For example, an increase of one hour in bright sunshine hour (X_2) above its average at 11th period or season, assuming other weather variables to be constant at their average levels as shown in Table 1, increased the yield response Y of average nuts per bearing tree per half year by 2.2299 3 nuts and similarly 7.37 8 nuts for 12th period. However, it would be practically impossible to control and keep other variables at their average level simultaneously for each and every period.

5.4.2. Effect of changes in weather variables on the coconut crop yield under the Model I(3) (3Y,3M)

From the partial derivatives computed in section 4.15.2, it was noted that the effect of change in weather variable at each period were always changing because the correlation coefficients of Y with the weather variable were also changing from one period (season) to another. Due to difference in formation of weight functions given to the weather variables under this model, the partial derivatives were also independent of period number w.

From Table 17, it was found that the effect of change (increase) of one unit in all the weather variables under this model had negative response on the coconut crop yield for all the periods (seasons). It showed that the decrease of one unit in the weather variables had increased the coconut crop yields by the amount of nuts shown respectively in Table 17.

5.4.3. Effect of changes in weather variables on the crop yield under the Model II(2) (3Y,3M)

From the partial derivatives computed in section 4.15.3 of Chapter IV, it was seen that all the partial derivatives, except that of Y with respect to X_{3w} (wind velocity), were constant for all periods. From Table 18, it was found that the variables X_{2w} (sunshine hour) and X_{4w} (relative humidity) has positive response on the crop yield Y while the variable X_{5w} (maximum temperature) had negative effect on the crop yield. Upto the 7th period, the effect of X_{3w} (wind velocity) has negative effect on the crop yield Y and from the 8th period onwards, it was found that it had increased the crop yield, by one nut at 10th period, by 2 nuts at 11th period and 2 nuts at 12th period, respectively.

5.4.4. Effect of changes in weather variables on the coconut crop yield under the Model II(1) (3Y,6M)

From the partial derivatives computed in section 4.13.4 of Chapter IV, it was seen that partial derivatives of Y with respect to X_{2w} (sunshine hours) was constant for all the periods and hence the effect of this weather variable was also uniform over all the periods. However, the partial derivatives of Y with respect to X_{3w} (wind velocity) and X_{5w} (maximum temperature) were parabolic functions of w. Therefore, the effects on the crop yield were always changing for all the periods (seasons).

From the Table 19, it was interesting to note that the effect of X_{3w} had negative response on the yield while effect of X_{5w} had positive response on the coconut crop yield for all the periods (seasons) considered within effective crop season of 3 years with 6-month period or seasons.

5.5. Comparative study of the 'best' and most 'efficient' four forecasting models selected on the basis of various criteria measures

Among the 'best' four forecasting models selected based on different criteria functions, the Model II(2)(3Y,3M) and Model II(1)(3Y,6M) were the 'best' and the most 'convenient' (handy, suitable and easy to use) model on the basis of R^2 and R_a^2 per predictor variable involved in the models, because only 6 and 7 variables were employed in these two models. The R^2 and R_a^2 per predictor variable were 0.1527 and 0.1483 for Model II(2) (3Y,3M) and 0.1413 and 0.1407 for Model II(1) (3Y,6M) respectively. The corresponding values for the rest two models were 0.0862 and 0.0825 for Model I(1) (3Y,3M) and 0.0941 and 0.0901 for Model I(3) (3Y,3M) respectively.

Therefore, by using the two models, viz. Model II(2) (3Y,3M) and Model II(1) (3Y,6M), we have to make collection of the weather data and computation for only 6 and 7 variables while the other 'best' two models contained 11 and 13 predictor variables. Consequently, we can substantially save and economize time, manpower, energy and cost, by the adoption of the 'best',most efficient and 'convenient' crop forecasting models like Model II(2) (3Y,3M) and Model II(1) (3Y,6M).

5.6. Further suggestions and guidelines for the development of statistical crop-weather models, relevant statistical analysis and criteria for selection of the models.

The suggestions and guidelines for further development of empirical-statistical crop-weather models with special reference to perennial crops, relevant statistical analysis and criteria for selection of the models were proposed in the following sections.

5.6.1. Further development of crop-weather models

In this investigation, the effective crop season of 3 years (i.e. as far back as 36 months from the first month just before a half-year harvest) has been equally divided into 12 and 6 periods (seasons) respectively. In the future investigations, the periods (seasons) should be formed in conformity with the different stages of development or growth of crop because the weather parameters affect the crop yields and yield components differently during the different stages of development or growth of crop. In this regard, we should consult and collaborate with plant physiologists and agronomists.

In this investigation, a quadratic polynomial of degree 2 was taken for all the periods to approximate the linear, quadratic and interaction effect of weather variables on the crop yields. In order to get a better and precise estimate of weather effects on the crop, the degree of polynomial should be increased from m=2 to m=5 in line with the suggestion of Fisher (1924).

From the point of view of 'econometrics', the crop forecasting models developed in this investigation were actually the 'multivariable finite distributed lag models' using the 'Almon polynomial lag' (Almon, 1965) in all the periods (seasons) within effective crop season of three years.

There are some problems with the Almon lag specification. First, it is difficult to capture any long tailed effect of weather variables spread over the whole effective crop season by mean of a single second degree polynomial as in our crop forecasting models. This problem can be solved using a piecewise polynomial or by some other methods using the 'Almon method' in conjunction with other models. In this regard, it is highly recommended and suggested that the '<u>infinite distributed lag models</u>' in the future development of crop-forecasting models should be used because the infinite distributed lag approach is more appropriate to our crop-forecasting models for the perennials like coconut crop.

Since it is very difficult to know the exact length of effective crop season of perennial crops, the following infinite distributed lag models were highly recommended to be tried and used in the crop forecasting models for other perennial crops:

i) Geometric lag
ii) Pascal lag
iii) Jorgenson's rational lag
iv) Gamma distributed lag
v) Geometric polynomial lag
vi) Exponential lag, and
vii) Revised Gamma lag.

A thorough treatment and illustration of these infinite lags were given in Johnston (1972) and Maddala (1977).

After developing the appropriate theoretical crop forecasting models through the above 'infinite distributed lag methods', selection of the candidate variables and fitting of the model should be carried out through the following statistical analysis techniques.

5.6.2. Statistical analysis technique

In developing and fitting the crop forecasting models, we may come across a situation in which it becomes difficult to disentangle the separate effect of the predictor variables on the crop yield (response variable) because of strong inter-relationship among the predictor variables. It is referred to as multicollinearity problem. The question is how strong these inter-relationships have to be to cause a 'problem'. Thus, with the multicollinearity, the problem is one, not of existence or non-existence, but of how serious or problematical it is. Usually, the multicollinearity problem creeps into the ill-conditioned data, like data on weather variables included in the forecasting models, because most of the weather variables were usually more or less inter-related to each other. Therefore, in future statistical analysis for the crop-forecasting models developed through infinite distributed lag methods discussed above, the following statistical analysis techniques were highly recommended to be used in order to detect and eliminate the multicollinearity problem which weakens the efficiency, performance and precision forecasting models:

i) Ridge regression

ii) Principal component regression

iii) Step-wise regression using forward and downward selection procedures

iv) Latent root regression

v) Stage-wise regression

vi) Robust regression

vii) Weather index regression

The regression procedures from (i) to (vi) were thoroughly treated in texts by Banerjee and Price (1977), Draper and Smith (1981), Hocking (1976) and Vinod and Ullah (1981).

5.6.3. Criteria functions for the selection of the 'best' crop forecasting models

After fitting the crop forecasting models through the variable selection techniques discussed above, all the criteria functions given in Chapter III are highly recommended to be used in selecting the best, most promising and plausible crop forecasting models. The other two criteria functions, compatible with our predictive purposes are given as follows:

i) Prediction sum of squares (PRESS)

ii) Mallows' C_r statistic

The computational procedures for these criteria functions were thoroughly discussed by Hocking (1976), Seber (1977) and Draper and Smith (1981).

SUMMARY

SUMMARY

The yield data of 91 coconut palms (ordinary West Coast Tall type), maintained at Coconut Research Station (Nileshwar I), Regional Agricultural Research Station, Pilicode, under the Kerala Agricultural University, and the meteorological data for the region of Pilicode, collected from the Central Plantation Crops Research Institute (CPCRI), Kasaragod District, Kerala were utilized in the present study with the following objectives:

1) to develop a suitable and reliable statistical methodology for the pre-harvest forecast of coconut crop yields by evolving different empirical-statistical crop-weather models using the original and generated weather variables as predictor variables,

2) to perform a comparative study of relative efficiency, adequacy and performance of each of these crop-forecasting models evolved and to select the 'best', most promising and plausible crop forecasting models for the purpose of future use in predicting the coconut crop yields reliably in advance of harvest.

3) to investigate the effect and influence of changes in weather variables on the yield of coconut crop, based on the crop forecasting models selected as the 'best' fitted models.

4) to render suggestion and guidelines for further development of statistical crop-weather models, criteria for their selection, and relevant statistical analysis.

The coconut trees under study were reserved for the purpose of control in experimentations conducted by the Station. They had not been given any special treatment or irrigation during the course of study (1968-1980). Based on the monthly yield data, the average yield of nuts per bearing tree per half-year, taking first half-year as from January to June and second half-year as from July to December, were computed excluding those trees which were not bearing female flowers and not giving any nut for the year as a whole, being treated as the abnormal trees for that year.

The weekly data on the weather variables, viz. total rainfall in cm, bright sunshine hours, wind velocity in km/hr, relative humidity in percentage and maximum temperature in centigrade were converted into 3-month and 6-month seasonal weather data for the span of 16 years (1965-1980). Since the data on relative humidity were expressed in percentages, they were transformed into arc-sine root proportions.

At first the two general crop forecasting models were developed: one is complete second-order response surface type model (square model) and the other is square root model.

Time variable was also included to correct the long term upward and downward trend in the coconut crop yields.

In the crop forecasting models, average yield of nuts per bearing tree per half-year was taken as response (predicted) variable. While the generated first and second-order weather variables were taken as predictor variables. With the three different weights given to the effect of weather variables, six different crop forecasting models were developed for the two general forecasting models. Further these six models were considered under the effective crop season of 3 years (i.e. as far back as 36 months from the first month just before a half-year harvest) with 3-month and 6-month period (season) formation. Therefore, totally twelve crop forecasting models for the yields of coconut crop were developed and fitted. The second degree polynomial was used to approximate the linear, quadratic and interaction effects of weather variables. Therefore, 61 predictor variables, including the time variable, were obtained for each forecasting model and 61 simple correlation coefficients of yield response Y with each of predictor variables were worked out. The 20 preliminary variables having the maximum absolute correlation coefficients were selected.

Further, the final crop forecasting models for the yields of coconut crop were fitted through step-wise regression technique using the forward selection procedure (step-up regression technique) based on the data for those 20 preliminary selected variables. Comparative study of efficiency and performance of the fitted forecasting models were carried out and the 'best', most efficient and promising crop forecasting models were selected through the criteria functions, viz. residual mean square (RMS), computed F-value, squared multiple correlation coefficient (R^2), adjusted R^2(R_a^2), total prediction variance (J_r), prediction mean square error (MSEP), average estimated variance (AEV), Amemiya prediction criterion (APC) and Akaike information criterion (AIC) respectively.

The four crop forecasting models, selected from all the twelve fitted forecasting models and considered to be the 'best', most efficient and promising crop forecasting models on the basis of all the criteria functions stated above, were found to be as follows:

1) <u>Crop forecasting Model I(1) (3Y,3M)</u>

$$Y = 116.7730 + 261.5590\, Z_{30} - 2.4406\, Z_{32} - 0.0023\, Z'_{50} + 0.1319\, Z'_{31} + 0.0011\, Q_{(12)0} - 5.2728\, Q_{(23)0} - 1.1269\, Q_{(23)1} + 0.1543\, Q_{(23)2} - 3.2513\, Q_{(34)0} + 0.0297\, Q_{(34)2} - 0.0034\, Q_{(35)1}$$

with $RMS = 4.5109$, $F = 23.2973$, $R^2 = 0.9482$

$R_a^2 = 0.9075$, $J_r = 171.4154$, $MSEP = 9.0084$

$AEV = 2.0819$, $APC = 6.5929$, $AIC = 75.9049$

2) Crop forecasting Model I(3) (3Y.3M)

$$Y = -9239.4700 + 65.8204\ Z_{50} - 29.7842\ Z_{22} + 609.0960\ Z_{52} - 2.2427\ Z'_{50} - 0.0008\ Z'_{12} - 9.5624\ Z'_{20} - 0.0322\ Q_{(12)0} - 0.0403\ Q_{(12)2} - 0.2084\ Q_{(23)2} - 1.4025\ T$$

with RMS = 4.8116, F = 23.8378, R^2 = 0.9408
R_a^2 = 0.9013, J_r = 178.0298, MSEP = 8.9226
AEV = 2.0359, APC = 6.8474, AIC = 74.6825

3) Crop forecasting Model II(2) (3Y.3M)

$$Y = 2757.4610 + 37.5524\ Z_{31} - 2.1867\ Z'_{30} - 659.1850\ Z'_{50} - 177.4570\ Q_{(23)0} + 69.2921\ Q_{(25)0} + 44.7271\ Q_{(34)0}$$

with RMS = 5.3836, F = 34.5767, R^2 = 0.9161, R_a^2 = 0.8896
J_r = 177.6580, MSEP = 7.7648, AEV = 1.4494,
APC = 6.8330, AIC = 67.4905

4) Crop forecasting Model II(1) (3Y.6M)

$$Y = -8765.4000 + 645.0530\ Z_{52} + 16.0323\ Z'_{30} - 1.2749\ Z'_{50} - 0.1046\ Z'_{51} - 10.1382\ Z'_{52} - 12.8148\ Q_{(23)0} - 0.0015\ Q_{(35)2}$$

with RMS = 0.7247, F = 237.7490, R^2 = 0.9893
R_a^2 = 0.9851, J_r = 24.6376, MSEP = 1.1067
AEV = 0.2229, APC = 0.9477, AIC = 34.3298

The above four crop forecasting models could be used confidently and reliably in order to predict the coconut crop yield in advance of harvest, especially for the region of Pilicode.

Based on the 'best' four forecasting models, effect of weather changes on the coconut crop yields were investigated. Suggestions and guidelines for further development of crop-weather models, selection criteria functions and relevant statistical analysis were also presented.

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APPENDIX

APPENDIX III

Data on yield response Y (average nuts per bearing tree per half year) and ten generated predictor variables selected through step-up regression procedure under Model I(3)(3Y,3M)

Y	Z_{50}	Z_{22}	Z_{52}	Z'_{50}	Z'_{12}	Z'_{20}	$Q_{(12)0}$	$Q_{(12)2}$	$Q_{(23)2}$	T
33.69	31.35	7.16	30.70	985.04	14695.08	943.95	333.11	345.92	12.40	1
26.20	31.29	7.86	31.94	981.07	20777.29	1021.29	372.61	526.21	6.30	2
34.91	31.15	6.93	30.19	972.34	21109.68	912.45	448.69	419.47	13.91	3
29.02	31.18	7.81	31.99	974.38	32163.26	1025.12	448.75	627.86	9.15	4
22.25	31.16	7.35	30.39	973.27	18075.17	924.95	472.00	373.82	18.00	5
19.05	31.10	7.79	31.97	969.32	26753.72	1023.75	486.08	746.51	10.37	6
27.52	30.93	7.22	30.04	959.26	23029.97	903.85	518.17	445.59	19.63	7
25.14	30.84	7.76	31.85	953.31	29543.02	1016.61	547.59	691.75	10.01	8
31.52	30.77	6.79	29.79	949.25	19492.38	889.10	467.04	381.27	18.13	9
24.23	30.66	7.69	31.58	942.41	28756.68	998.58	462.80	622.41	9.09	10
39.86	30.73	7.04	29.70	946.60	19253.60	883.68	466.68	420.89	16.87	11
36.96	30.80	7.69	31.43	950.94	24987.65	988.86	448.79	644.17	8.55	12
28.26	30.82	7.33	29.95	952.06	15129.78	898.28	397.95	311.99	17.30	13
28.36	30.86	7.81	31.56	954.77	20001.50	997.84	388.32	614.95	7.43	14
38.05	30.86	7.18	30.09	954.66	14680.93	907.10	407.88	364.87	17.84	15
32.49	30.79	7.96	31.88	950.25	21028.35	1018.51	411.97	556.72	7.66	16
37.78	30.59	6.86	29.63	938.62	18566.30	879.69	396.20	277.40	23.14	17
28.33	30.39	7.62	31.28	925.99	28473.11	980.41	401.18	579.81	10.60	18
46.79	30.46	6.96	29.54	930.08	17069.98	873.74	418.77	332.33	30.09	19
45.26	30.51	7.68	31.14	932.84	27537.68	970.60	425.90	530.63	14.75	20
35.75	30.60	6.73	29.64	938.28	19840.79	879.74	404.69	353.94	31.42	21
35.48	30.68	7.64	31.34	943.52	25507.24	983.05	438.31	529.55	16.50	22
30.24	30.73	6.76	29.98	946.26	21684.13	899.95	418.45	344.29	29.76	23
30.48	30.92	7.46	31.78	958.35	30605.79	1012.05	400.34	520.37	16.12	24
24.22	30.95	6.40	30.00	960.22	20636.04	901.81	388.24	309.60	30.56	25
34.61	31.04	7.05	31.73	966.15	30322.76	1007.95	388.77	552.10	15.62	26

Note: The generated predictor variables were defined in section 3.3.1 of Chapter III.

APPENDIX V

Data on yield response Y (average nuts per bearing tree per half year) and six generated predictor variables selected through step-up regression procedure under Model II(2)(3Y,3M)

Y	Z_{31}	Z'_{30}	Z'_{50}	$Q_{(23)0}$	$Q_{(25)0}$	$Q_{(34)0}$
33.69	1.12	1.07	5.59	2.93	15.21	8.46
26.20	1.31	1.09	5.59	2.97	15.11	8.59
34.81	1.53	1.15	5.57	3.14	15.14	9.09
22.02	1.84	1.22	5.58	3.34	15.16	9.56
22.25	1.84	1.27	5.58	3.49	15.27	9.99
19.05	1.97	1.34	5.57	3.67	15.21	10.49
27.52	1.88	1.37	5.56	3.73	15.10	10.80
25.14	1.84	1.37	5.55	3.73	15.02	10.86
31.52	1.70	1.34	5.54	3.61	14.88	10.58
24.23	1.72	1.31	5.53	3.51	14.83	10.37
39.86	1.56	1.28	5.54	3.47	14.99	10.10
36.96	1.65	1.27	5.54	3.46	15.07	10.02
28.26	1.49	1.23	5.54	3.39	15.10	9.73
28.36	1.63	1.25	5.55	3.44	15.16	9.82
28.05	1.55	1.24	5.55	3.43	15.18	9.77
32.49	2.09	1.32	5.54	3.66	15.16	10.34
37.70	2.42	1.43	5.52	3.79	14.68	11.23
28.33	2.85	1.51	5.51	4.06	14.71	11.84
46.79	2.98	1.62	5.51	4.32	14.76	12.73
45.26	3.12	1.68	5.52	4.50	14.75	13.21
35.75	3.18	1.78	5.53	4.71	14.64	14.10
35.48	3.23	1.78	5.53	4.70	14.62	14.13
30.24	3.14	1.78	5.54	4.69	14.65	14.12
30.48	3.28	1.78	5.55	4.65	14.55	14.17
24.22	3.30	1.80	5.56	4.63	14.36	14.32
34.61	3.33	1.81	5.56	4.62	14.29	14.38

Note: The generated predictor variables were defined in section 3.3.2 of Chapter III.

APPENDIX VI

Data on yield response Y (average nuts per bearing tree per half year) and nine generated predictor variables selected through step-up regression procedure under Model II(3)(3Y,3M)

Y	Z_{50}	Z_{52}	Z'_{50}	Z'_{22}	Z'_{52}	$Q_{(12)2}$	$Q_{(23)2}$	$Q_{(35)2}$	$Q_{(45)1}$
33.69	31.35	30.70	5.59	2.61	5.53	16.76	3.46	6.37	41.27
26.20	31.29	31.94	5.59	2.79	5.65	19.41	2.46	5.74	47.53
34.81	31.15	30.19	5.57	2.57	5.49	17.67	3.61	6.69	41.11
26.02	31.18	31.99	5.58	2.79	5.65	19.56	2.86	6.48	46.91
22.25	31.16	30.39	5.58	2.66	5.51	16.68	4.06	7.46	40.13
19.05	31.10	31.97	5.57	2.78	5.65	19.96	3.11	7.22	46.66
27.52	30.93	30.04	5.56	2.64	5.48	16.88	4.34	8.11	40.99
25.14	30.84	31.85	5.55	2.78	5.64	20.88	3.18	7.28	46.62
31.52	30.77	29.79	5.54	2.54	5.45	15.95	4.26	7.85	40.99
24.23	30.66	31.58	5.53	2.77	5.61	20.50	2.98	6.84	46.22
39.86	30.73	29.70	5.54	2.59	5.44	16.72	4.08	7.53	40.92
36.96	30.80	31.43	5.54	2.77	5.60	21.56	2.89	6.69	46.25
28.26	30.82	29.95	5.54	2.66	5.47	14.65	4.12	7.37	41.02
28.36	30.86	31.56	5.55	2.78	5.61	19.68	2.70	6.39	46.40
38.05	30.86	30.09	5.55	2.63	5.48	15.75	4.16	7.54	40.71
32.49	30.79	31.88	5.54	2.82	5.64	18.17	2.75	6.48	46.67
37.78	30.59	29.63	5.44	2.55	5.40	13.23	4.66	8.28	36.54
28.33	30.39	31.28	5.51	2.74	5.59	18.82	3.06	7.60	46.51
46.79	30.46	29.44	5.51	2.54	5.23	14.03	5.27	9.66	40.01
45.26	30.51	31.14	5.52	2.72	5.58	18.93	3.67	8.88	45.37
35.75	30.60	29.64	5.53	2.52	5.44	15.54	5.54	10.20	40.33
35.48	30.68	31.34	5.53	2.74	5.59	18.52	3.97	9.54	45.83
30.24	30.73	29.98	5.54	2.52	5.47	14.47	5.45	10.14	41.22
30.48	30.92	31.78	5.55	2.71	5.63	18.40	3.94	9.61	46.05
24.22	30.95	30.00	5.56	2.43	5.47	14.78	5.46	10.38	41.14
34.61	31.04	31.73	5.56	2.64	5.63	20.55	3.90	9.74	46.09

Note: The generated predictor variables were defined in section 3.3.2 of Chapter III.

APPENDIX VII

Data on yield response Y (average nuts per bearing tree per half year) and eight generated predictor variables selected through step-up regression procedure under Model I(1)(3Y,6M)

Y	Z_{30}	Z_{52}	Z'_{50}	Z'_{51}	Z'_{52}	$Q_{(12)0}$	$Q_{(23)1}$	$Q_{(35)1}$
33.69	188.15	2825.75	5907.74	20409.57	87858.19	5621.07	174.35	740.23
26.20	187.78	2867.84	5883.71	20757.68	90482.00	5533.27	218.97	862.24
34.81	186.92	2806.58	5831.82	20180.77	86691.18	6494.11	237.44	985.02
22.02	187.11	2859.26	5844.10	20651.40	89976.16	6512.11	307.71	1199.10
22.25	187.00	2802.37	5837.54	20128.38	86444.01	6665.87	290.32	1192.24
19.05	186.64	2847.55	5814.26	20492.57	89235.20	7423.92	324.11	1287.40
27.52	185.63	2776.53	5754.13	19815.19	84885.63	7201.71	291.00	1220.87
25.14	195.08	2825.94	6413.72	20800.42	87971.58	7588.65	299.46	1226.11
31.52	184.66	2758.06	5694.11	19544.67	83732.30	6810.05	261.50	1100.67
24.23	184.02	2806.28	5653.04	19906.56	86673.05	6744.46	279.73	1117.28
39.86	184.40	2783.98	5675.81	19711.27	85259.50	6899.28	249.40	1013.92
36.96	184.82	2854.94	5703.00	20400.28	89701.76	6673.14	280.83	1089.85
28.26	184.94	2789.44	5710.03	19876.39	85678.84	5945.43	241.68	976.94
28.36	185.19	2835.10	5725.97	20306.51	88477.08	5819.34	280.08	1071.89
39.05	185.21	2771.61	5727.14	19745.55	84580.11	5802.25	250.98	1009.77
32.49	184.78	2798.44	5700.00	19911.58	86175.19	5875.05	358.70	1351.82
37.78	183.60	2734.22	5630.22	19250.62	82286.30	5970.04	352.56	1531.22
28.33	182.42	2777.38	5554.74	19532.39	84887.24	6031.95	464.87	1810.61
46.79	182.83	2752.28	5579.00	19302.31	83325.20	6160.57	454.09	1889.86
45.26	183.09	2823.51	5595.71	19963.67	87741.84	6066.99	507.39	2013.51
35.75	183.64	2788.70	5628.28	19728.43	85573.05	6027.46	472.94	2047.57
35.48	184.14	2832.14	5659.87	20182.86	88240.75	6470.01	509.66	2107.22
30.24	184.41	2768.04	5675.59	19656.36	84335.16	6431.60	452.01	2024.27
30.48	185.54	2839.21	5747.81	20326.06	88769.84	6210.20	503.82	2152.53
24.22	185.74	2799.01	5759.77	19974.65	86243.94	6082.87	460.41	2147.14
34.61	186.29	2871.37	5795.55	20669.91	90784.66	6096.53	496.64	2199.01

Note: The generated predictor variables were defined in section 3.3.1 of Chapter III

APPENDIX VIII

Data on yield response Y (average nuts per bearing tree per half year) and eight generated predictor variables selected through step-up regression procedure under Model I(2)(3Y,6M)

Y	Z_{50}	Z_{52}	Z'_{50}	Z'_{51}	Z'_{52}	$Q_{(12)0}$	$Q_{(23)1}$	$Q_{(45)0}$
33.69	31.35	31.05	984.62	971.88	965.47	936.84	8.30	1944.23
26.20	31.29	31.51	980.61	988.46	994.30	922.21	10.42	1935.91
34.81	31.15	30.84	971.97	960.98	952.65	1082.35	11.30	1922.54
22.02	31.18	31.42	974.01	983.39	988.74	1085.35	14.65	1916.44
22.25	31.16	30.79	972.92	958.49	949.93	1110.97	13.82	1911.65
19.05	31.10	31.29	969.04	975.83	980.60	1237.32	15.43	1910.29
27.52	30.93	30.51	959.02	943.58	932.80	1200.28	13.85	1911.15
25.14	32.51	31.05	1068.95	990.49	966.72	1264.77	14.26	2026.70
31.52	30.77	30.30	949.01	930.69	920.13	1135.00	12.45	1917.94
24.23	30.67	30.83	942.17	947.93	992.45	1124.07	13.32	1920.65
39.86	30.73	30.59	945.96	938.63	936.91	1149.88	11.87	1911.53
36.96	30.80	31.37	950.50	971.44	985.73	1112.19	13.37	1910.82
28.26	30.88	30.65	951.67	946.49	941.52	990.90	11.50	1910.83
28.36	30.86	31.15	954.32	966.97	972.27	969.89	13.33	1911.29
38.05	30.86	30.45	954.52	940.26	929.45	967.04	11.95	1909.31
32.49	30.79	30.75	950.00	948.17	946.93	979.17	17.08	1897.40
37.78	30.60	30.04	938.37	916.69	904.24	995.00	16.78	1892.59
28.33	30.40	30.52	925.79	930.11	932.82	1005.32	22.13	1880.62
46.79	30.47	30.24	929.83	919.15	915.66	1026.76	21.62	1883.18
45.26	30.51	31.02	932.61	950.65	964.19	1011.16	24.16	1890.16
35.75	30.60	30.64	938.04	939.44	940.36	1004.57	22.52	1904.82
35.48	30.69	31.12	943.31	961.08	969.67	1078.33	24.26	1919.29
30.24	30.75	30.41	945.93	936.01	926.75	1071.93	21.52	1930.19
30.48	30.92	31.20	957.96	967.90	975.49	1035.03	23.99	1944.72
24.22	30.95	30.75	959.96	951.17	947.73	1013.81	21.92	1950.88
34.61	31.04	31.55	965.92	984.28	997.63	1016.09	23.64	1955.08

Note: The generated predictor variables were defined in section 3.3.1 of Chapter III

APPENDIX XII

Data on yield response Y (average nuts per bearing tree per half year) and seven generated predictor variables selected through step-up regression procedure under Model II(3)(3Y,6M)

Y	Z_{50}	Z_{52}	Z'_{50}	Z'_{51}	Z'_{52}	$Q_{(23)1}$	$Q_{(35)1}$
33.69	31.35	30.47	5.59	5.41	5.51	3.56	6.42
26.20	31.29	32.16	5.59	5.76	5.67	2.35	5.74
34.81	31.15	30.21	5.58	5.38	5.49	3.76	6.78
22.02	31.18	32.21	5.58	5.78	5.67	2.76	6.50
22.25	31.16	30.21	5.58	5.38	5.49	4.16	7.51
19.05	31.10	32.12	5.57	5.77	5.66	2.95	7.08
27.52	30.93	29.92	5.56	5.34	5.46	4.45	8.08
25.14	30.84	32.03	5.55	5.76	5.66	3.04	7.21
31.52	30.77	29.75	5.54	5.32	5.45	4.41	7.97
24.23	30.67	31.75	5.53	5.74	5.63	2.84	6.86
39.86	30.73	29.53	5.54	5.33	5.43	4.23	7.57
36.96	30.80	31.63	5.54	5.74	5.62	2.78	6.63
28.26	30.82	29.82	5.55	5.35	5.46	4.22	7.47
20.36	30.86	31.89	5.55	5.76	5.64	2.61	6.31
38.05	30.86	29.97	5.55	5.35	5.47	4.35	7.64
32.49	30.79	32.02	5.54	5.75	5.65	2.58	6.47
37.78	30.60	29.56	5.53	5.30	5.43	4.93	8.65
20.33	30.40	31.48	5.51	5.71	5.61	2.91	7.56
46.79	30.47	29.44	5.51	5.32	5.42	5.48	9.63
45.26	30.51	31.26	5.52	5.70	5.59	3.41	8.69
35.75	30.60	29.55	5.53	5.34	5.43	5.73	10.24
35.48	30.69	31.56	5.53	5.72	5.61	3.82	9.58
30.24	30.73	29.94	5.54	5.37	5.47	5.67	10.22
30.48	30.92	31.92	5.55	5.76	5.64	3.81	9.62
24.22	30.95	29.86	5.56	5.35	5.46	5.64	10.38
34.61	31.04	31.98	5.57	5.78	5.65	3.77	9.75

Note: The generated predictor variables were defined in section 3.3.2 of Chapter III.

FORECASTING MODELS FOR THE YIELD OF COCONUT

BY

MYINT SWE

ABSTRACT OF A THESIS

submitted in partial fulfilment of
the requirements for the degree of

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ABSTRACT

An analysis of the yield data of 91 coconut palms, maintained at Coconut Research Station (Nileshwar I), Regional Agricultural Research Station, Pilicode, under Kerala Agricultural University and the weather data for the region of Pilicode, collected from Central Plantation Crops Research Institute (CPCRI), Kasaragod District, Kerala was carried out with the following views and objectives:

1) To develop a suitable and reliable statistical methodology for the pre-harvest forecast of coconut crop yields by evolving different empirical-statistical crop-weather models using the original and generated weather variables as predictor variables.

2) To perform a comparative study of relative efficiency, adequacy and performance of each of these crop-forecasting models evolved and to select the 'best', most promising and plausible crop forecasting models for the purpose of future use in predicting the coconut crop yields reliably in advance of harvest.

3) To investigate the effect and influence of changes in weather variables on the yield of coconut crop, based on the crop forecasting models selected as the 'best' fitted models.

4) To render suggestion and guidelines for further development of statistical crop-weather models, criteria for their selection, and relevant statistical analysis.

In this study, the twelve crop forecasting models for the yields of coconut were developed and fitted under the effective crop season of 3 years (i.e., as far back as 36 months from the first month just before a half-year harvest) with 3-month and 6-month period (season), using the generated weather predictor variables. The response variable was taken as average yield of nuts per bearing tree per half year, and the original weather variables were total rainfall, duration of bright sunshine hours, wind velocity, relative humidity and maximum temperature. Since the relative humidity is expressed in percentages, the data were transformed into arc-sine root proportion.

The final crop forecasting models were fitted through step-wise regression technique using the forward selection procedure (step-up regression). The comparative study of adequacy, predictive efficiency and performance of these fitted crop forecasting models were carried out. The 'best' and most promising crop forecasting models were finally selected on the basis of the various criteria functions, viz., residual mean square, squared multiple correlation coefficient, total prediction variance, adjusted squared multiple correlation coefficient, prediction mean square error, average estimated variance, Amemiya prediction criterion and Akaike information criterion.

The effect of weather changes on the coconut crop yields was studied based on the 'best' forecasting models selected. Important suggestions and guidelines for further development of empirical-statistical crop-weather models, their relevant statistical analysis and selection criteria were presented.