MAIZE YIELD WEATHER MODELING AIMED AT FORECASTING AT KATUMANI.

BY

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Declaration

This thesis is my original work and has not been presented for a degree in any other University.

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ABSTRACT

The effects of weather on maize (Zea mays L.) yield in Katumani for the period 1974-1992 were studied by using three methods namely correlation analysis, Caprio (1966) and Principal Component Analysis (PCA) method. The crop and meteorological data were obtained from the Kenya Meteorological Department headquarters in Dagoretti Corner, Nairobi.

Results obtained from correlation analysis indicated that interphase rainfall and evaporation were the most important meteorological parameters affecting the maize growth and the subsequent yield. These two interphase meteorological parameters plus the linear trend in the yield data series were used to develop a Yield Weather Technology model. This model accounted for 83.0 % of the yield variation and was capable of predicting the maize yield two months in advance.

In the second approach crop weather dependence was analyzed using Caprio's (1966) method which employed the χ^2 statistic and was thereafter quantified by regression on Principal Components (PCs). The yield data was generally classified into three categories namely: good, normal and poor yield years and the climatic conditions in the good and poor years compared to those of the normal years. The degree of disproportionate was tested by using the χ^2-statistic.

Good yield years were characterized by abundance of days with high rainfall during planting, emergence to

ninth leaf appearance and grain filling interphases. The same interphase periods were characterized by deficit of days with high evaporation and maximum temperature. Poor yield years on the other hand were characterized by a deficit of days with high rainfall, excess of days with high evaporation and excess of days with high maximum temperature during the floral-initiation stage when the plants demand for water was high.

The climatic variables obtained from the Zones of Significant Assosiation (ZSA) were subjected to PCA. By applying the Kaiser's (1961) criterion of eigenvalue of one or more four principal components were found to be significant and explained 78.3% and 77.4% of the variance in 15 and 11 raw variables during the long and short rains season respectively. These components were loaded heavily on rainfall and maximum temperature during the beginning of the crop growing season and during vegetative growth. When the principal component were subjected to Stepwise Multiple Regression Analysis (SMRA) the ones with heavy loadings on rainfall and maximum temperature were selected first and the ones with heavy loadings on minimum temperature were omitted. The order of selection of components into the regression model depended on the magnitude of the correlation coefficient between the yield and the PCs. The resulting regression model for the short and long rains season explained 76.6% and 72.9% of the yield variance respectively.

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CHAPTER I

1 INTRODUCTION

Kenya's economy has for many years been very much dependent on agriculture with over 80 per cent of the population living in the rural areas and deriving their livelihood from agricultural activities. Agricultural production in Kenya largely depends on agricultural land classified as having high to medium rainfall. This constitutes 20 per cent of the total agricultural land. Although there is large scale farming, agricultural production depends to a large extent on small scale farming.

However, climate is the main determinant of what crops the farmer can grow. Weather influences the annual or seasonal yield and hence how much food there is to eat (Wang'ati, 1982). It is a well known fact that yield from any crop depends on the extent to which optimum conditions of soil moisture supply, radiant energy, photoperiod and temperatures are satisfied during different stages of crop growth. The effects of weather on crop yields may be direct or indirect. Indirect effects on crop production occur when weather situations:

(i) lead to outbreak of pests and diseases of crops,
(ii) interfere with timely agricultural operations and
(iii) bring about deterioration in the quality of seed in store.

Directly, weather affects the structural characteristics of a crop, for example, leaf area index, number of heads per plant, number of kernels per head etc.

Hence, meteorological considerations becomes part of the realm of agriculture in its own right.

In many tropical regions rainfall is the most important climatic determinant in rainfed agriculture, especially in the semi-arid areas which are characterized by low precipitation with a marked seasonal variability. Effects of weather anomalies such as prolonged drought and periodic excessive rainfall are influenced by the soil characteristics and vegetation cover. Incomplete vegetation cover subjects the soil to more runoff hence reduced infiltration, while high evaporation rates result in soil moisture deficit.

Crop development for the semi-arid areas has centered on the genetic manipulation to produce drought tolerant or drought-escaping varieties (Acland, 1971). A good example is the Katumani composite B (KCB) developed at Katumani National Dryland Research Center (NDRC) and found to be a suitable maize variety for the semi-arid regions of Eastern Kenya. Nadar (1984) found that this cultivar requires 120 days from sowing to physiological maturity at Katumani. Nevertheless, there are seasons when the crop yield either falls below the potential or the crop fails completely. The main causes of yield reduction and/or failure being probably due to variability in rainfall, solar radiation, potential evapotranspiration and temperature regimes.

Numerous attempts to quantify crop weather relationships have been made (Baier, 1973, de Wit, 1982, Fischer, 1984 among others). However, these efforts have only met with partial success for a variety of reasons.

The major problems in crop-weather analysis is the gradual change of the effect of weather variables on crop development during the growing season. This gradual change is complex and therefore difficult to quantify.

For the purpose of statistical analysis and meaningful interpretation of results from the crop-weather analysis model, reliable and continuous data covering many years are essential. The need for reliability is obvious. A continuous long run of data on the other hand is necessary in order to incorporate the many variables that affect yields and for getting representativeness where there are cyclic changes. When data for a short run are used the analysis may just show the random effects of explaining variables as the systematic effects may be low (Lukando, 1980).

The yield fluctuations commonly experienced are often a consequence of weather fluctuations. It is therefore unlikely that crop yield variations can be linked exclusively to one climatic parameter although one or two such parameters may have a dominant influence (Wang'ati, 1982). Studies in this field have found that a realistic crop-weather analysis model must account for the daily interaction of at least temperature, soil moisture and an energy term on the yield components. Considerations should also be given to the non-meteorological factors such as farm input and land management practices. Both are included under the term 'agrotechnical' factors. These non-meteorological factors account for significant changes in trend of yield/time series (Benci and Runge, 1976; Thompson, 1976; Swanson and

Nyankori; 1979). Some of the agrotechnical factors which cause yield time series to be non-stationary are fertilizer applications, herbicides and pesticides use, timeliness of farming operations and total acreage in production. It is therefore important to discern agrotechnical trends from those due to weather in cases where they are significant.

The high multi-collinearity among non-meteorological factors and lack of data necessitates the trend in the yield time series to be accounted for by the surrogate time variables. These surrogate time variables are treated as independent predictors along with meteorological variables. The coefficients of all variables are estimated by least squares regression. For these models, the linear combination of surrogate variables multiplied by their estimated coefficients results in a piecewise continuous linear trend.

However serious draw-backs in designing crop-weather model range from the apparent failure of the technology and weather to behave independently, data aggregation to multi-collinearity among candidate predictors (Jones, 1982; Katz, 1977). The effects of spatial aggregation can be overcome either by avoiding it altogether or by selecting zones of investigation such that the degree of variability exhibited by the data is minimal. The temporal aggregation can be overcome by disaggregating the variables. In case of multi-collinearity, Thompson (1976) suggested the use of the squared deviations from mean rather than the actual weather variables or to use ridge regression (Katz,1979) which gives biased estimators where intercorrelations is not very high. In case of the two alternatives failing the highly intercorrelated variables ought to be discarded.

The difficulties encountered in attempting to quantify crop-weather relationship should be apparent from the foregoing discussions. The main objectives of this study were therefore to;

(i) investigate how the climatic variables at different growth stages affect maize growth and the subsequent yield.

(ii) use the results of (i) above to formulate Maize Yield-Weather prediction model.

(iii) test sensitivity of the regression coefficient of Maize Yield-Weather Model in (ii) above.

To achieve these objectives Multiple Regression Analysis which is an ideal technique for studying cause and effect relationships (Jones,1982) was adopted using two different approaches. In the first approach the interphase climatic and derived climatic variables namely; maximum, minimum, mean and range of daily air temperature; solar radiation; rainfall; evaporation and crop rainy days were correlated with maize yields during the interphase periods. The most influential interphase climatic variables at different phytophases were selected and regressed on maize yield in an attempt to formulate a maize-weather model based on Chen and Fonseca (1980) principles. In the second approach, the above climatic variables were analyzed by a method initially suggested by Caprio (1966) and adopted by Pochop et al. (1975) and Jones (1982). The important growth periods were selected from the Zones of Significant Associations (ZSA). Principal Component Analysis (PCA) was then performed on the climatological data consisting the selected variables. The Principal Components (PCs) were then regressed on the historic maize yield resulting in predictive multiple regression models.

CHAPTER II

2.0 LITERATURE REVIEW

2.1 INFLUENCE OF CLIMATIC FACTORS ON MAIZE GROWTH AND FINAL YIELD

2.1.1 RAINFALL AND EVAPORATION

Crop production from rainfed agriculture is very much dependent on the intensity, spatial and temporal distribution of rainfall. In the dry regions, rains are notoriously variable between years, seasons and even within a season. Water is the main limiting factor for agricultural productivity, and terrestrial plants occasionally suffer from water stress in these areas.

Crop water demands during the growing season vary, rising to a peak in the period between maximum elongation of the stem to the flowering and then tapering off to maturing (Glover, 1948; Salter and Goode, 1967). The plant is therefore variably sensitive to either moisture stress or excess, both of which ultimately depress the yield to an extent depending on the magnitude and duration of their effect and on the stage of growth and development.

The damage arising from water stress at various stages and its impact on yield has also been extensively studied (Goldson, 1963; Dowker, 1963; Allan, 1972; Copper and Law, 1976 among others). Water stress during tasseling, silking and pollination has been found to cause particularly large yield reductions of maize but at other stages of growth, stress is not that harmful (Robbins and Domingo, 1953; Moss and Downey, 1971). A more elaborate analysis of water stress at various stages is reported in the works of Stewart (1972), Misra (1973) and Stewart *et al.* (1975).

Rainfall is only one aspect of crop water status, another being evapotranspiration, and in studies of crop water relations it is necessary to consider both concurrently. Evaporation integrates a number of weather factors the principal one being solar radiation. Other include temperature, humidity and wind. Plants in their utilization of water (i.e evapotranspiration or ET), respond to the same weather factors as open water in evaporation pans (E_p). In fact a high correlation exists between ET by a given crop adequately watered and evaporation from open water surfaces. Moreover, it has been established by researchers that evaporation data from pans can be used to predict potential evapotranspiration rates (ET_m) provided ET_m/E_p ratios at different growth periods are known (Jensen *et al.* 1961; Doorenbos and Pruitt, 1977).

Yield can be correlated statistically with water stress defined from the water balance. Bruyn *et al.* (1978) demonstrated that the estimation of the number of stress days occurring during given periods offers an excellent technique for identifying drought sensitive periods during the growing season especially under marginal water conditions. They found that the flowering period is ultra-sensitive to water stress and suggested that the planting should be done such that flowering does not occur near or during water deficit periods.

2.2.2 AIR TEMPERATURE AND SOLAR RADIATION

Temperatures in the hot arid and semi-arid climates have been recorded to be the highest in the world (Critchfield, 1966). The generally clear skies facilitate maximum radiation in daytime and rapid loss of heat at night, causing wide diurnal ranges of temperatures. The harmful effects of excessive temperatures in the semi-arid areas are usually aggravated by lack of soil moisture.

Plant biological processes that are affected by environmental temperatures include photosynthesis, respiration, translocation, cell growth and plant development. The most important effect of temperature is that high temperatures, particularly at night, shorten the ripening period thus greatly reducing the yield (Wilson et al., 1973). Temperature has been identified as one important environmental factor for maize growth and development. Given amounts of heat units must be accumulated by plants at successive phenological stages. The idea of accumulated heat units finds its basis from this consideration. The concepts have been extended to include growth degree days and accumulated growth degree days for estimating the maturation time of a given crop and the zonation areas for maize crop (Treidl, 1976). Many crop development and ripening forecasting modelers have also given a lot of emphasis on the role of temperature in this respect (Major et al., 1975; Williams and Joseph, 1970; Blackburn et al., 1982 among others).

Light is one of the essential environmental parameters for plants growth and development. The role of light within maize is not limited to photosynthesis.

Light is also necessary for photohormonal reactions, e.g phytochrome, and energy for evaporative and heating processes within the micro-climate of the canopies.

As a C_4 plants maize leaves are not light saturated even at high radiation intensity. Most studies have shown that the number of ears per plant increases with increasing solar radiation (Searbsook and Doss; 1973). The removal of tassel that casts a shadow on the corn plant may increase grain yield by 4 to 12 per cent depending upon the population density (Duncan et al., 1967). Lee, (1978) has shown that the effect of solar radiation on corn yield is not uniform throughout its life cycle. Solar radiation during the third month of the plant's growth corresponding to the grain filling period, is far more important than during any other period.

2.2 WEATHER-YIELD RELATIONSHIPS

Since the beginning of agriculture, farmers have always been interested in assessing the size of their future harvest in relation to what they have sown. On a wider scale, it has also influenced Governments wishing to make conservative food balance estimates for their countries (FAO, 1986).

To achieve the above objective there have been numerous attempts to quantify the crop-weather relationships for forecasting purposes. Baier (1979) classified growth simulation models into three categories;

(i) Mechanistic type crop-growth simulations models,

(ii) Crop-weather analysis models,

(iii) Empirical-statistical models.

The selection of the appropriate approach depends upon the available data, purpose of investigation, and time scale as well as the size and nature of the area concerned.

In crop-growth simulation models, complex physical, chemical, and physiological processes based on both laboratory and field experiments are mathematically presented. Rates of photosynthesis and transpiration are calculated to estimate biomass production. Studies by Stewart (1970), Splinter (1974), and Runge and Benci (1975) provide good examples. Because of their mechanistic integration of the process of plant growth and development, this class of models, tends to have a wide application and good predictive capacity. However, due to their large size and complexity they have restricted their appeal to workers without computing skills. In addition the multiplicity of factors considered makes validation difficult (Fischer, 1984).

Crop-weather analysis models are defined as the product of two or more factors, each representing the functional relationship between a particular plant response (e.g yield) and the variations in selected variables at different development phases. The overall effects are expressed by the numerical values of the factors that modify each other but are not additive as in the case of a multivariate linear regression. Conventional statistical techniques are often used to evaluate the weighting coefficients in the yield equations. Typical examples include studies by Denmead and Shaw (1960), and Dale and Shaw (1965) and the NOAA report (1979). Chang, (1981) observed that most of these studies considered only soil moisture. Thermal and radiative parameters were ignored presumably because they did not vary much during respective growing seasons.

Empirical-statistical models use a sample of yield data from the same area to produce estimates of coefficients by regression technique. The validity and potential application of such models depend on the representativeness of the input data, the selection of variables and the design of model. The weighting coefficients in the equation are by necessity obtained in an empirical manner, using standard statistical procedures, such as multivariate regression analysis. Thompson's (1969) investigation of the yield fluctuations in the corn Belt in the U.S.A. as a function of temperature, rainfall and technological change is a well-documented example. Studies by Das (1974); Huda et al., (1975, 1976), Taylor and Bailey (1979); Chen and Fonseca (1980) and Wigley and Quipu (1983) are examples of empirical-statistical models.

Over the years, so much has been done to relate maize yield to weather as evident from the voluminous literature available. Much of the work looked at the influence of weather variables acting jointly or independently on the yield of maize grown at single or various stations using different techniques.

Smith (1914) used simple linear regression to relate average maize yield for Ohio state using June and August rainfall in 10-day periods for Sixty years (1854-1913). He noted that rainfall from flowering to ripeness was most important and that rainfall for 10 days following the date of flowering had an almost dominating effect upon the yield of corn.

Fisher (1924) developed a special technique for analyzing the effects of rainfall at any time of growing season on annual wheat yields. This technique has been successfully applied in studies where lack of rainfall is a dominant factor limiting crop yields (Gangopadyapa and Sarker, 1975; Lomas, 1972; Lomas and Shashoua, 1973).

Hendricks and Scholl (1943) and Stacy et al., (1957) modified the Fisher's (1924) model and looked at the joint effect of temperature and rainfall on maize yields. Those results showed higher than normal temperatures towards the end of season to be beneficial to the crop by increasing yield if rainfall was adequate. A detrimental effect was noted in the absence of adequate rainfall. Huda et al., (1975, 1976) adopted Hendrick's and Scholl (1943) approach in an attempt to quantify the relationship between rice and maize yield and climatic variability respectively. They found the maize yield to be affected differently by each variable during the different stages of growth of the crop. Above-average weekly rainfall totals had a favorable effect on maize yield during emergence but a markedly reduced effect during silking and from tasseling to maturity.

Nix and Fitzpatrick (1969) proposed a quadratic equation for the relationship between wheat yield and a crop-water stress index. The Index is defined as the ratio between estimated available water in the root zone at the start of the defined 'critical' period and the mean potential evapotranspiration during the critical period. The index value indicates (in weeks) the period that available soil water supply would last under the potential evaporation conditions prevailing during the critical-development period. The simple index gave highly significant correlations with grain yields, accounting for 60-83 per cent of the yield variations within individual wheat (and grain sorghum) varieties at one location. Mean potential evapotranspiration for the two week period following ear emergence was found to give best results.

Lomas and Shashoua (1973) analyzed the effect of rainfall distribution on wheat in an arid region during a three year sampling period by using orthogonal polynomial of the fifth degree. They concluded that in low rainfall areas where wheat is grown on freely draining soils, fairly good results can be obtained by correlating annual wheat yield with annual rainfall and this relationship was linear. Lomas and Shashoua (1974) also determined the combined effect of rainfall and hot, dry spell on wheat yields and on grain weight in the Northern Negev. Linear regression on total annual rainfall accounted for 60 percent of the variability of wheat yield, the number of hot, dry spells for about 50 per cent, and the two variables altogether for 64 per cent. Lomas (1972) analyzed rainfall/wheat yield relationships by means of simple and multiple regressions, principal components and Fisher's orthogonal polynomial method. All gave good results and Fisher's technique was then employed to estimate the effect on final yield of a unit change in rainfall.

Das (1974) developed a regression equation for forecasting maize yield in Zambia using daily rainfall, daily maximum and minimum temperature, daily available period of sunshine, number of crop rainy days and a technological term as predictors. He observed that for better maize yield a rainfall of 58 mm during land preparation and sowing was essential. An excess might reduce yield by washing away seeds and thereby reduce the plant population. He also found that some rain was essential during the growth period and yield increases with number of crop rainy days at the rate of 95.44 % Kg/ha. A higher daily average range of temperature during maturation period was conducive to grain formation and for each $5/9^{O}$ C rise in temperature, yield increased by 106.8 Kg/ha.

Baier and Williams (1974) found that moisture explains a major yield part of crop district cereal yield variability particularly in the drier parts of the Canadian prairies. This led to the development of equations which were used during June in 1973 and 1974 to make periodic estimates of probable wheat, oats and barley yields. By the end of June, such estimates were realistic enough to be quite useful for the purpose of grain marketing agencies.

In recent years, Principal Components Analysis (PCA) has been used on numerous occasions in the analysis and modeling of crop yield data. Pochop et al., (1975) used the method of PCA to study the influence of precipitation augmentation on wheat production in the semi-arid regions of the Great Plains. They observed that the benefits of added rainfall to increased winter wheat production were greatest during the middle portion of the growing season and negative, late in the season.

Dennett et al. (1980) used the PCA to identify regions in Europe where temporal yields of tobacco, wheat and sugar beet are coherent with climate variations. Having done so however, they then analyzed crop-climate links separately in these coherent regions using traditional multiple regression techniques. They observed that tobacco yields were positively correlated with summer rainfall anomalies in northern and southern Europe. Wheat yields were generally negatively correlated with rainfall anomalies and positively with winter and spring temperatures anomalies.

Jones (1982) studied the crop-weather dependence using short-period weather variables derived from Caprio (1966) method and then subjected them to the method of PCA Three PCs extracted from the seven raw variables accounted for 72 % of the total variance. The first component loaded heavily on the temperature variables for early-March and April-May. Late summer rainfall (July, August) was strongly represented in second component whilst third component loaded substantially on April-May precipitation and June-July mean temperature. He further observed that variables which were seasonal might have applications in a marketing framework if the marketing process responds more effectively to events occurring earlier in the season.

In Kenya, a few efforts have been made to quantify crop-weather relationships. Glover, (1948) related maize yield from large scale farms in western Kenya, to seasonal rainfall from April to August. He obtained a curvilinear relationship with 750 mm as the optimum rainfall.

Simango (1976) related maize yields to rainfall during three growth periods of the plant in an attempt to explain the difference in maize yield between Embu, Kitale and Katumani on basis of radiation regimes. He found that the difference in maize yield could not be attributed to inadequate radiation being received in these areas. This is because most of these areas had comparable net potential photosynthesis values throughout the year.

Lukando (1980) related maize yield data to rainfall and air temperature (maximum, minimum and range) variables in 3, 5, 7 and 10 day periods. He noted that the combinations of rainfall and temperature range in 3-day periods in a second degree equation explained the variability in yield best. He further showed that 1 mm of rainfall above three day average was beneficial from 10 days prior to sowing to about tasseling/flowering time, then a negative effect to maturity. A one degree temperature range above 3-day average had a similar trend. Rainfall of 1 mm or temperature range of 1°C below average had opposing effect of the same magnitude. He concluded that the major limitation to yield is either poor distribution of rainfall or inadequate rainfall in the presence of high temperature in Katumani.

Stewart and Wang'ati (1978) used 'effective rainfall' estimates for predicting crop yield and relating water production functions to crop yields. They established the essential linearity of relation between yields and actual evapotranspiration (ET_a) during a growing season. They further showed that the ratio of relative decline in yield to relative ET deficits (difference between potential evapotranspiration when the water is adequate, and (ET_a) termed the 'yield reduction ratio' (YRR) is a genetic characteristic, thus is constant for any given crop-variety.

Keating et al. (1989) applied CERES maize growth simulation model to examine the effect of plant population on the long term returns and risks of maize production at two contrasting sites in Eastern Kenya (Makindu and Katumani). They found that in the presence of non-limiting soil fertility, high populations were predicted to increase long term average yields with only small increase in the risks of crop failure when nitrogen was strongly limiting. High populations were predicted to reduce the long term yield averages and markedly increase the risks of crop failure.

Corbett (1990) developed an agro-climate simulation model which offers both conceptual and literal structure to evaluate environmental parameters and crop production in the semi-arid regions of Kitui district. The model shows management as holding the key to coping successfully with the rather adverse climatic conditions experienced. The simulation of recommended or 'optimal' practices demonstrated that the potential for maize is good if proper care is taken in cultivar and plant density selection and when coupled with water harvesting techniques. Further, the model showed that shorter season maize varieties yielded a substantial harvest in good rainfall years whereas timely planting was imperative during the short rains.

From the foregoing review it is apparent that rainfall, temperature, solar radiation and evapotranspiration have major influence on maize growth, development and final yield. These meteorological parameters are critical at different phenological stages. In developing crop-weather analysis models its therefore desirable to use short period weather variables in order to capture the sensitive periods during the crop growth and also avoid the problem of temporal data aggregation. Finally, calendar time is not synonymous with phenological time and failure to recognize this will lead to derivation of crop-weather relationships which are measures of crop performance by chance.

In the next chapter, we will present the various methods which were used in this study to investigate crop-weather relationships in Katumani area.

CHAPTER III

3.0 MATERIALS AND METHODS

3.1 DATA USED

The data used in this study runs for 17 years starting from 1974 to 1991 with a total of 34 crop seasons comprising the short rains and long rains season. The two crop seasons have been treated independently.

The meteorological data were obtained from the Kenya Meteorological Department headquarters in Dagoretti corner, Nairobi. The department runs a network of Agrometeorological stations country-wide. In these stations concurrent observations of weather variables and crops are made. The crop data are observed in two ways. One, the phenological phases or development stages and two, the state and yield observations.

3.1.1 CROP DATA

3.1.1.1 PHENOLOGICAL PHASES

Determination of phenological phases involve the sampling of 40 representative plants from emergence to full ripeness. Then observation of respective stages of development or phenological phases at every Monday, Wednesday and Friday are made. The information is entered in form Agro.1 (See the appendix).

Six phenological stages of maize crop were noted namely; emergence of the the plant above the soil surface, appearance of the ninth leaf, appearance of the tassel, flowering of the tassel, wax ripeness and lastly full ripeness.

3.1.1.2 STATE AND YIELD OBSERVATIONS

These observations were made while considering all plants in a field for the phenological observations. The information was entered in form Agro.4 (See the appendix). The observations included;

(i) A general assessment of the state of the crop every ten days

(ii) Determination of the plant density at the beginning and at the end of the season

(iii) Assessing weed infestation every ten days

(iv) Recording any damage due to adverse meteorological phenomena, pests and diseases and the period when such damage occurred in the course of the season.

(v) Recording the final yield at harvesting.

3.1.2 METEOROLOGICAL OBSERVATIONS

The surface climatic variables were observed from an Agrometeorological station built within the farm premises at Katumani and the surrounding maintained as per World Meteorological Organization (WMO) recommendations. The surface climatic variables observed include rainfall, maximum and minimum daily air temperatures, soil and grass minimum temperature, sunshine hours, cloud cover, solar radiation, pan evaporation, wind speed, wind run and relative humidity.

3.1.3 SOIL MOISTURE OBSERVATIONS

The soil moisture was normally observed on the, 7^{th}, 17^{th} and 27^{th} of each month, roughly at 10 days interval. The soil was augured and dried in an oven and the soil moisture content determined. The homogeneity of soil moisture dictated the number of replications to be used. The soil moisture data was taken in the same plots used for the phenological, state and yield observations.

The details of procedure for making the agrometeorological observations are as described by Todorov (1977).

3.2 STATION SELECTION

Currently, Kenya Meteorological Department (KMD) runs thirteen Agrometeorological stations spread all over the country. Most of these stations were installed in the 1970's and a few in early 1980's. Yield data in many of these stations are discontinuos and inadequate for the statistical analysis anticipated. However, Katumani Agrometeorological station established in 1973 contained a continuous record of meteorological and crop data series. This station was then chosen for this study.

3.3 SITE DESCRIPTION

Katumani National Dry land Research Center (NDRC) is located 10 Km South of the Machakos town, in the Eastern province of Kenya. It lies at $01^{\circ}35'S$ and $37^{\circ}14'E$ and at an elevation of 1575 m above mean sea level.

The soil in this area is well drained, dark reddish-brown sandy clay. It is hard when dry, friable when moist, and sticky plastic when wet. It is classified as oxic paleustalf (chromic luvisol). It has a relatively low water storage capacity and medium depth. Average depth is 120 cm with a total water storage capacity of 100 mm (Nadar, 1984).

TABLE 1: Monthly means of temperature (°C), daily solar radiation ($MJM^{-2}d^{-1}$), rainfall (mm) and evaporation (mm). Temperature record is from 1956-1980; daily solar radiation, 1974-1980; rainfall, 1958-80 and monthly evaporation, 1965-1980.

MONTH	TEMPERATURE(°C)		RADIATION ($MJM^{-2}d^{-1}$)	RAINFALL (mm)	EVAPORATION (mm)
	MAX	MIN			
JAN	25.8	13.8	22.2	50	170
FEB	27.1	14.3	22.9	45	183
MARCH	26.4	15.3	22.2	89	200
APRIL	25.1	15.7	19.1	147	162
MAY	24.2	14.3	17.5	65	121
JUNE	23.0	12.0	15.3	11	102
JULY	22.1	11.6	13.5	7	99
AUG	22.6	11.6	14.1	5	115
SEP	25.1	12.2	19.5	9	160
OCT	26.3	13.8	21.4	35	199
NOV	24.1	15.1	19.1	164	149
DEC	24.2	14.3	20.9	84	147

(After Wafula, 1989)

The station receives monsoonal rainfall with strongly bimodal distribution that produces two distinct growing seasons each year, referred to as long and short rains (Jaetzold and Smith, 1983; Alusa, 1978a; Stewart and Hash, 1982 and Keating et al., 1989). These rainfall seasons are influenced by the north and south movement across the equator of the Intertropical Convergence Zone (ITCZ) (Alusa, 1978b, Agumba, 1985). Solar radiation and temperature are generally favorable to crop production throughout the year. The monthly mean air temperatures ranges from 17° to 24°C while the daily solar radiation totals are typical of the sub-humid tropics with mean monthly values ranging between 14 and 23 $MJM^{-2}d^{-1}$ (Keating et al., 1989). Table 1 shows the mean monthly rainfall, solar radiation, air temperature and class A pan evaporation at Katumani. In this tropical region, rainfall variability dominates an otherwise relatively constant environment in terms of day length, temperature and evaporative demand (Wafula, 1989).

3.4 SCRUTINY OF TREND IN BOTH MAIZE YIELD AND METEOROLOGICAL DATA

For any statistical predictions, a good knowledge of the nature of fluctuations in the yield-time series is required. The major components in the yield-time series include trend and random variations. The trend can be analyzed by either graphical approach or statistical approach. In the former the graph is visualized from a graphical representation of yield time-series. In the latter the series is subjected to some statistical tests to examine the statistical significance of the observed trends. The Mann-Kendall rank test was used to test the statistical significance of the linear trend (see appendix). Similarly, the trend in weather data was determined and their significance tested by using the Von-Neumann ratio (see appendix).

Reasons were obtained for low yields in 1975, zero yields in 1976 and 1984 during the long rains seasons. During the 1975 long rains season, dry weather conditions were experienced during grain filling stage and some of the maize cobs were harvested when still green and given to the farm workers while the remainder were left to dry and harvested later (Agro.1, 1975). In 1976 long rains season drought struck when the maize were tasseling and the maize crops were harvested prematurely and fed to domestic animals (Agro.1, 1976). The rainfall distribution during this season was more favorable compared to some where yields were reported. This implies that if the maize crop was left to mature, then a definite amount of yield would have been realized different from the zero Kg/ha reported. The 1984 drought was so severe that no sowing took place (Agro.1, 1984).

3.5.0 METHOD OF ANALYSIS

In relating yield to meteorological data, for example rainfall (RF), temperature (T), solar radiation (SRAD) and evaporation (EVAP) over a number of phenological stages during the crop growing season, the expected yield E(y) is a function of RF_1, RF_2, ... ,RF_M ; T_1, T_2......, T_M ;$SRAD_1$, $SRAD_2$ .....$SRAD_M$ and $EVAP_1$, $EVAP_2$ ...... $EVAP_M$.

The subscript $_{1,2}$ ..., m refers to the number of phenological stages.

If the function is estimated, knowledge of the predictors will enable us to predict the expected yield. However, restrictions have to be made in choosing the function and the number of predictor variables. This is because yield for a short duration can be perfectly fitted using different types of functions especially when the meteorological factors are many. In such a situation, one possibility is a linear function of rainfall only. Different functions will give totally different predictions. For purposes of simplicity and understanding of the prediction method, a simple regression function and a small number of predictors is best.

With this in mind, the author set out to investigate the crop weather relationship using a model suggested by Chen and Fonseca (1980). They developed this model for predicting maize yields in Sao Paulo state in Brazil well in advance of the harvest in order to assist market strategy planning in agribusiness sector. Climatic and crop data which were readily available in Katumani for a reasonable length of time was used to calibrate the model. Simple relationships between yield and weather variables used accounted for most of the yield variations. This exercise formed the first part of this study. The model development, validation and testing based on Chen and Fonseca (1980) principles is outlined in the following sections.

3.5.1 ANALYSIS BY FIRST APPROACH: AN INQUIRY INTO MAIZE-YIELD WEATHER DEPENDENCE USING CHEN AND FONSECA (1980) METHOD

3.5.1.1 YIELD MODEL DEVELOPMENT

Rainfall, air and soil temperature, solar radiation, evapotranspiration, soil moisture and nutrient applications are important factors influencing crop growth and yield. The variables used in this study were daily Maximum Air Temperature (MAXT), daily MINimum air Temperatures (MINT), daily RainFall (RF), Solar RADiation (SRAD) and pan EVAPoration (EVAP) rates. It was apparent that other variables might be useful for defining crop-weather relationship, for instance, Baier and Robertson (1968) showed that the soil moisture measurement is a superior yield estimator when compared to the direct use of climatological data for estimating wheat yields. However, the availability of soil moisture, soil temperature, nutrient applications and evapotranspiration data was not adequate throughout the crop growing season rendering these data unsatisfactory for statistical analysis. A few climatic variables such as the number of Crop Rainy Days (CRD), daily MEAN air Temperature (MEAN) and Range of Air Temperature (RAT) were generated from the basic climatic variables.

The above climatic and derived climatic variables were grouped into nine inter-phases (see Table 2) namely; Planting to Emergence (PEM), Emergence to Appearance of

Ninth leaf (EAN), appearance of the Ninth leaf to Appearance of the Tassel (NAT), appearance of the Tassel to Flowering of Tassel (TFT), Flowering of the the tassel to Wax Ripeness (FWR), Wax ripeness to Full Ripeness (WFR) with an additional 10-days Prior To Sowing (PTS), 10 days Prior to Sowing to FLowering of the tassel (PSFL) and 10 days Prior to Sowing to Wax Ripeness (PSWR).

TABLE 2: INTERPHASE PERIODS IN DAYS FOR MAIZE (KCB) GROWN NEAR KATUMANI AGROMETEOROLOGICAL STATION.

INTERPHASE / SEASON	PEM	EAN	NAT	TFT	FWR	WFR	TOTAL NUMBER OF DAYS IN SEASON
SHORT RAINS	8	20	24	14	25	19	110
LONG RAINS	12	25	25	11	22	17	112

The above abbreviations will be henceforth used in the rest of the study. In selecting the best yield predictors simple correlation analysis between the historic maize yield and interphase climatic variables was carried out. The correlation coefficients (r) was computed by using the following equation,

$$r = \frac{\sum_{i=1}^{N} xy}{N \sigma_x \sigma_y} \qquad \ldots\ldots\ldots\ldots [1]$$

where,

r is the correlation coefficient

x is the departure from the mean interphase meteorological variable

y is the departure from the mean maize yield

N is the sample size

σ_x is the standard deviation of the interphase meteorological variable

σ_y is the standard deviation of the maize yield.

The resultant correlation coefficient were then tested for their statistical significance using the t-test statistic. The equation used for t-test with $(n-2)$ degrees of freedom was

$$t_{n-2} = \frac{r\sqrt{N-2}}{\sqrt{1-r^2}} \quad \ldots\ldots\ldots\ldots\ldots\ldots [2]$$

where,

n is the number of data points

t is the computed t-statistic and N and r are as defined above.

The correlation coefficient between any two data sets was significantly different from zero at any desired level of significance when the computed t in equation (2) was more than the tabulated value in the Student's $t_{(n-2)}$ statistical tables. The secular trend in the historic maize yield data (Das, 1974) was investigated and its significance tested (as explained in section 3.4). In order to correlate the linear trend with historic maize yields, a series of numbers from 1 was coded to each year for analysis (i.e 1974-1, 1975-2,........., and 1988-15) (Thompson, 1976). All the statistically significant interphase climatic variables and linear technology trend were then employed as candidate predictors during the regression analysis.

3.5.1.2 YIELD-WEATHER-TECHNOLOGY (YWT) MODEL

A time series of crop yield may be divided into three components, namely, the mean yield, the trend in the yield with time and the residual variations (Dennet, 1980). Investigation carried out in section (3.4) revealed that the time series for the short rains season comprised of the three components above. Chen and Fonseca (1980) viewed such a time series as a function of weather and technology trend and expressed it as;

$$E(y) = a + \sum b_i X_i + cTT + \epsilon \text{ ....[3]}$$

where,

y is maize yield (Kg/ha)

TT is technology trend

a is regression constant

c and b_i are partial regression coefficients and

ϵ is the random error

The best Yield-Weather-Technology model was developed by regressing the historic maize yields with departures from the 15 years averages of interphase meteorological data and linear technology trend (from 1974 to 1988) as independent variables. The Stepwise Multiple Regression Analysis (SMRA) program of the BMDP statistical package (Dixon et al., 1983) was run to select the independent variables. In this procedure the variables are selected in order of their maximum improvement in the coefficient of multiple determination (R^2). R^2 indicates how reasonable or how good an equation is in estimating or reproducing the yield value. For each independent variable, the F-statistic which reflects the variable contribution to the model, is calculated. If the F-statistic is insignificant the procedure is terminated. The regression coefficients are then tested for their statistical significance using the t-statistic defined as

$$t_{cal} = \frac{b_i}{\text{standard error } (b_i)} \quad \text{...............[5]}$$

where,

t_{cal} is the calculated t-statistic

b_i is the regression coefficient

Among the various multiple regression yield models generated the one with least number of predictors and explained a reasonable amount of yield variability was selected for this study. Analysis of variance (ANOVA) techniques can be used to determine the proportion of variance of maize yield accounted for by the selected climatic variables based on the linear model. Details of the analysis of variance can be obtained from Haan (1977) or any standard statistics references.

3.5.1.2.1. YIELD MODEL TESTING

3.5.1.2.2. STABILITY OF REGRESSION COEFFICIENTS

Chen and Fonseca (1980) emphasized the need to test the stability of the regression coefficient in the selected YWT model. This was accomplished by running the regression equations of the YWT model for periods of one year increments i.e 1974-1986, 1974-1987, ..., and 1974-1991. The resulting partial regression equations were then compared to observe their variations through time.

3.5.1.2.3. MODEL VALIDATION

Validation is the comparison of the predictions of the selected YWT model with independent maize yield data set of the same variety and site. This was accomplished by multiplying the stable regression coefficients of the selected YWT model with interphase climatic variables and the extrapolated technology variable of the independent year(s) following each corresponding data period used for calibrating the YWT model. The relative differences between the model predicted maize yields and the reported amount of harvested maize were calculated.

One difficulty associated with the use of regression techniques involving more than one variable is the imposed necessity to adjust for high correlations among variables . Certain variables may contribute substantially to the predictand of the regression equation could be excluded as in stepwise approach, or else they could lead to compromising the statistical significance of a multiple regression model (Bernett and Hasselmann, 1979). To overcome problems inherent to regression techniques, the second method of analysis includes Principal Component Analysis (PCA). PCA is used to avoid the liabilities of multicollinearity.

3.5.2.0 ANALYSIS BY SECOND METHOD: CROP-CLIMATE MODELING USING TEMPORAL PATTERNS OF YIELD AND SHORT PERIOD CLIMATIC VARIABLES

3.5.2.1. CROP-WEATHER ANALYSIS BY USING CAPRIO (1966) METHOD

By way of initial inquiry into crop-climate dependence the crop and weather data were subjected to analysis suggested by Caprio (1966) and adopted by Pochop et al. (1975) and Jones (1982) which employs the χ^2 statistic.

The yield series was broadly described as being good, poor and normal yield years. This was achieved by using the long term mean yield and the standard deviation. For any yield variable $Y_i > \bar{Y} + \sigma_i$, the year was grouped good, $Y_i = \bar{Y} \mp \sigma_i$ normal and $Y_i < \bar{Y} - \sigma_i$ poor yield years, where Y_i is the yield for a given season, $\bar{Y}$ is the long term mean yield, and σ_i the standard deviation from the long term mean yield. Diagrammatically, this is described as follows:

good yield years

——————————————— $\bar{Y} + \sigma_i$

normal yield

——————————————— $\bar{Y}$

years

——————————————— $\bar{Y} - \sigma_i$

poor yield years

This resulted into three good yield years, three poor yield years and 9 normal yield years during the short rains season. The same was done for the long rains season resulting into three good , three poor and 7 normal yield years respectively.

The growing season of the maize crop was also divided into 21 day periods with an overlap of 14 days. This arbitrary length of period was used to provide an adequate number of daily measurement to test statistical significance. This might also be justified by the fact that phenological events can usually be expected to vary by at least 10 days from the normal over a long series of years. The climatic variables occurring in the 21 day periods were grouped into convenient intervals as shown in Table 3.

The purpose of the test is to compare the climatic conditions of good and poor harvest years with conditions experienced during the normal years. A 21 day period was selected and a count made of the number of daily occurrences of each temperature, rainfall, solar radiation and evaporation interval for each category of good, poor and normal yield years. The significance of any disproportionality shown by the count was assessed by computing the χ^2 statistic.

TABLE 3. METEOROLOGICAL INTERVALS FOR THE 3 GROUPED YIELD YEARS.

RAINFALL (MM)	MAXIMUM TEMP. (°C)	MINIMUM TEMP. (°C)	EVAPORATION (MM)	SOLAR RADIATION ($MJM^{-2}D^{-1}$)
> 50.0	≥ 30.0	≥ 15.0	≥ 10.0	≥ 29.00
35.1-50.0	28.0-29.9	14.0-14.9	9.0-9.9	27.00-28.99
25.1-35.0	27.0-27.9	13.0-13.9	8.0-8.9	24.00-26.99
20.1-25.0	26.0-26.9	12.0-12.9	7.0-7.9	21.00-23.99
16.1-20.0	25.0-25.9	11.0-11.9	6.0-6.9	18.00-20.99
14.1-16.0	24.0-24.9	10.0-10.9	5.0-5.9	15.00-17.99
12.1-14.0	23.0-23.9	9.0-9.9	4.0-4.9	12.00-14.99
10.1-12.0	22.0-22.9	8.0-8.9	3.0-3.9	9.00-11.99
8.1-10.0	20.0-21.9	7.0-7.9	2.0-2.9	6.00-8.99
6.1-8.0	18.0-19.9	≤ 6.9	≤ 1.9	≤ 5.99
4.1-6.0	≤ 17.9			
2.1-4.0				
0.1-2.0				
NR ; NO RAINFALL				

An analysis of 8^{th} - 28^{th} October daily maximum temperature is used to illustrate the statistical procedure. The first step is to divide the number of daily maximum temperature occurrences into the specified groups for each set of years as shown in Table 4. Significance of disproportionate number of occurrence of high maximum temperature during poor years is made by the χ^2 test first for the highest group having a temperature ≥ 30.°C, next in the two highest group combined etc, until all the occurrences are included. To determine the significance of association for high maximum temperatures ≥ 27.°C having n = 17 for three good years and n = 100 for the 9 normal years the total number of days (117) in the 12 years is determined. Then the theoretical 1:3 ratio of occurrences comes to 29.25 during the three good yield years and 87.75 during the 9 normal yield years. The χ^2 statistic is computed as:

TABLE 4: NUMBER OF OCCURRENCES OF DAILY MAXIMUM TEMPERATURES MEASUREMENT FROM 8 TH TO 28TH OCTOBER DURING THE 3 GOOD YIELD AND 9 NORMAL YIELD YEARS.

TEMPERATURE INTERVAL (°C)	NUMBER OF OCCURRENCES 3 GOOD YIELD YEARS	NUMBER OF OCCURENCES 9 NORMAL YIELD YEARS
> 30.0	0	2
28.0-29.9	4	51
27.0-27.9	13	47
26.0-26.9	11	39
25.0-25.9	8	27
24.0-24.9	9	11
23.0-23.9	6	5
22.0-22.9	8	5
20.0-21.9	4	2
18.0-19.9	0	0
≤ 17.9	0	0
TOTAL	63	189

$$\chi^2 = \frac{(OB - TH)^2}{TH} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [6]$$

where;

OB is the observed number of high maximum temperature

TH is theoretical number of high maximum temperature occurrences

$$\text{i.e} \qquad \chi_{(1)}^2 = \frac{(17 - 29.25)^2}{29.25} + \frac{(100 - 87.75)^2}{87.75} = -6.8$$

The $\chi_{(1)}^2$ value obtained was significant at least at 5 % level of significance. This implied that good yield years were associated with deficit days with maximum temperature during 8^{th} - 28^{th} October.

By combining maximum temperature intervals, significance testing was also effected for accumulative occurrences of temperatures as shown in the Table 5. The index of association for high maximum temperature in good years is the highest value of the $\chi_{(1)}^2$. An imposed negative value of $\chi_{(1)}^2$ implies a deficit of maximum temperature days and vice versa for an imposed positive value. The index of association, determined just for high maximum temperature during good years can be written as;

$$I.A.gH.MAXT. = - 7 \geq 27.0^{\circ}C$$

where;

I.A. is index of association,

g is good yield years relative to normal years,

H.MAXT. is high maximum temperature,

"-" indicates that the observed number of occurrence is less than the theoretical number of occurrences during good years (deficit).

7 is the $\chi_{(1)}^2$ value and

$\geq$ 27.0°C is high maximum temperature association limits

TABLE 5: ACCUMULATED OCCURRENCES FROM HIGH TO LOW GROUPS OF MAXIMUM TEMPERATURES AND $\chi_{(1)}^2$ TESTS FOR GOOD YIELD YEARS ASSOCIATION OF HIGH MAXIMUM TEMPERATURE FOR THE PERIOD 8TH TO 28TH OCTOBER.

TEMPERATURE INTERVAL(°C)	HIGH TO LOW OCCURRENCES 3 GOOD YEARS	HIGH TO LOW OCCURRENCES 9 NORMAL YEARS	$\chi_{(1)}^2$
> 30.0	0	2	0
28.0-29.9	4	53	-11
27.0-27.9	17	100	-7
26.0-26.9	28	139	-6
25.0-25.9	36	166	-3
24.0-24.9	45	177	-1
23.0-23.9	51	182	0
22.0-22.9	59	187	0
20.0-21.9	63	189	0
18.0-19.9	63	189	0
≤ 17.9	63	189	0

Negative sign indicates less than expected

The 'index of association' for low maximum temperature for the same 21 day period is computed in a similar manner except that the accumulated number of occurrences is from low to high as shown in Table 6. The index of association for low maximum temperature during good years can be written as:

I.A.gL.MAXT. = + 6 $\leq$ 26.9°C

where;

I.A. is index of association,

g is good years relative to normal years,

L.MAXT is low maximum temperature,

"+" indicates that the observed number of occurrences is more than the theoretical number of occurrences (excess),

6 is $\chi_{(1)}^2$ value and

$\leq 26.9^{\circ}C$ is low maximum temperature association limits.

The $\chi_{(1)}^2$ value obtained was significant at least at 5% level of significance. This implied that good yield years were associated with an excess of days with low maximum temperature during the period 8^{th}- 28^{th} October.

TABLE 6: ACCUMULATED OCCURRENCES FROM LOW TO HIGH GROUPS OF MAXIMUM TEMPERATURES AND $\chi_{(1)}^2$ TESTS FOR GOOD YIELD YEARS ASSOCIATION OF LOW MAXIMUM TEMPERATURE FOR THE PERIOD 8^{TH} - 28^{TH} OCTOBER

TEMPERATURE INTERVAL (°C)	LOW TO HIGH OCCURRENCES 3 GOOD YEARS	LOW TO HIGH OCCURRENCES 9 NORMAL YEARS	$\chi_{(1)}^2$
> 30.0	63	189	0
28.0-29.9	63	187	0
27.0-27.9	59	136	+3
26.0-26.9	46	89	+6
25.0-25.9	35	50	+12
24.0-24.9	27	23	+25
23.0-23.9	18	12	+20
22.0-22.9	12	7	+15
20.0-21.9	4	2	+6
18.0-19.9	0	0	0
≤ 17.9	0	0	0

Positive sign indicates more than expected

By combining meteorological intervals, from low to high frequencies and vice versa significance testing was also effected for accumulative occurrences of temperatures, solar radiation, rainfall and evaporation. The above procedure was repeated for each 21 day period. The following abbreviations; MINT, RF, SRAD, EVAP and p were used to represent minimum temperature, rainfall, solar radiation, evaporation and poor yield years respectively during the analysis.

Values of $\chi_{(1)}^2$ obtained in the above analysis are displayed in figures 2 to 11. The 21 day time interval associated with each statistic is represented by the central date in the respective period. Where the $\chi_{(1)}^2$ is significant at 5 %, the relevant meteorological interval is identified and is thereafter referred to as Zone of Significant Association.

The role of χ^2 can only be of inference and extreme values of the statistic should not ascribe significance to a meteorological factor in any quantified sense (Jones, 1982). Quantification of the climatic influence on crop performance necessitates the use of estimating equation. Factor scores derived from subjecting the raw meteorological parameters to PCA are subjected to Stepwise Multiple Regression Analysis (SMRA) in an attempt to quantify the inference made by employing the χ^2 test.

3.5.2.2. CROP-WEATHER ANALYSIS BY USING THE METHOD OF PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal Component Analysis (PCA) is a variant form of Factor Analysis (FA). The method of PCA permits a set of observed variables to be expressed as a linear combination of a smaller set of orthogonal components. The method of PCA can employ either a covariance, correlation or cross-product input matrix. Each of these inputs into the PCA has its own advantages and disadvantages. The correlation matrix was used because the original variates measured in different units and their absolute variance bear no relation to each other.

A major difference between PCA and FA is that, while components are derived by PCA to explain as much variance of the total data set as possible, factors derived by FA explain only the variance shared by the variables considered (i.e a subset of the total variance). In the PCA model each observable variable is assumed to be a product of the interactions of the various Principal Component (PCs). Based on their mathematical relationships with observed variables, the PCs can often be identified as the underlying influences on the data (e.g meteorological regimes).

PCA has the ability to reduce statistical interdependence between a group of variables and this has given it considerable respectability in meteorological research (e.g Bernett and Hasselman, 1979 and Wilgley and Quipu, 1983). The method requires no particular assumptions about the underlying structures of the variables, each component simply seeks a linear combination of variables that accounts for as much as possible of the variance displayed by that data. Thus, the first PC provides the single best summary of linearity exhibited by the data. The second PC gives the best linear summary of the residual variance. Each succeeding PC accounts for as much as possible of the remaining variance not accounted for by the previous PCs

The first step in common PCA is the transformation of the observed data into dimensionless standardized observations;

$$Z_{ik} = \frac{(X_{ik} - \bar{X}_i)}{\sigma_i} \quad \ldots\ldots\ldots\ldots[7]$$

where;

$i = 1, 2, \ldots\ldots, n$ is total number of variables in the analysis,

$k = 1, 2, \ldots\ldots, m$ is the number of observation,

Z_{ik} (often termed the Z-score) is the standardized value of the i^{th} variable for observation k,

X_{ik} is the value of that variable observation,

$\bar{X}_i$ is the mean value for the i^{th} variable over all observations, and

σ_i is the standard deviation about the mean variable i.

If this standardization were not conducted there would be a tendency to deemphasize those variables with smaller absolute magnitudes during the subsequent PCA.

Hence standardization of the data prior to the PCA tends to equalize the opportunity of both large and small magnitude variables to influence the analysis.

The classic Factor Analysis (FA) model in terms of n empirical orthogonal functions may be expressed as;

$$Z_{ik} = \sum_{j}^{n} A_{ij} P_{jk} + U_i \beta_i \quad \ldots\ldots\ldots\ldots [8]$$

where;

Z_{ik} is the k^{th} value of the i^{th} standardized variable

P_{jk} is the k^{th} value of the j^{th} principal component

A_{ij} is standard multi-regression coefficients of variable i on factor j (factor loading)

U_i is standardized regression c o efficient of variable i on unique factor j

β_i is unique factor for variable i

For many meteorological variables, the unique component of the variable $\beta_i U_i$ is difficult to estimate and necessitates a principal component approach in factoring. Under PCA, the uniqueness is ignored. That is, the correlation or covariance matrix used in factoring the correlation of a variable with itself, r_{ii} is given by

$$r_{ii} = 1 \quad \text{for all} \quad i \ldots\ldots\ldots\ldots [9]$$

and therefore , equation [8] becomes

$$Z_{ik} = \sum_{j}^{n} A_{ij} P_{jk} \quad \text{.................[10]}$$

This simplified model of PCA in equation (10) was then employed to explore the relationship between a given variable and the regressor variables now expressed in terms of smaller number of orthogonal components. For a more detailed account of the method the reader is referred to Harman (1976), Child (1970) and Dutta (1975) among many other advanced statistics textbooks dealing with data analysis and simplifications. In the following sections we shall only highlight the relevant features of PCA as applied in this study.

3.5.2.2.1 NUMBER OF EIGENVECTOR TO BE RETAINED FOR ROTATION AND SUBSEQUENT ANALYSIS.

The primary objective of applying PCA to the previously described independent data sets is to derive a limited number of components for each data set which explain most of the variance in the original variables. However, a major problem is to determine the number of significant components (eigenvector) to be retained for the final rotated solutions and the subsequent regression analysis.

Numerous statistical techniques have been proposed to guide the 'proper' number of unrotated components for rotation procedure. This include the Kaiser's (1961) criterion; Scree test (Child, 1978); Lev method (Craddock, 1973) and a sampling errors in the eigenvalues (North et al., 1982). However, it is often the case that these criteria give conflicting guidance for a data set (e.g Hakistan et al., 1982). As a result, the number of components retained for analysis is often decided judgementally, taking into account both a statistical criterion and component interpretability (Thurtson et al., 1985). Kaiser's (1961) criterion was used to determine the number of eigenvectors to be subjected to rotation. This condition was relaxed during the regression analysis to allow the analytical technique reveal the underlying structure to the investigator rather than imposing upon the analytical technique what the underlying structure is (e.g Mungai, 1984).

3.5.2.2.2. ROTATION OF COMPONENTS

In order for the PCA reduction in dimensionality to be useful, the new variables (PCs) must have simple substantive interpretations. However, it is found empirically that several different underlying sources of variation may be incorporated into the unrotated PCs. Thus, the components resulting from unrotated PCA frequently do not have straight forward or unique interpretations (Harris, 1975). For this reason, PCA often includes the subsequent rotation of a limited number of the PCs, resulting in components which have been found to be more representative of individual sources of variation (e.g

Walsh and Richman, 1981). This in turn results in more interpretable and useful PCs.

Many methods are available for the rotations of PCs. These may be classified into either;

(i) orthogonal rotations, where the components remain uncorrelated with one another, or

(ii) oblique rotations, where the PCs are allowed to be intercorrelated.

Each rotation class has its own advantages and disadvantages in addressing multivariate problems. The scores of orthogonally rotated PCs may be employed in subsequent multivariate regression or correlation analysis without concern that multi-collinearities might confound the results, since they are by definition, uncorrelated. Based upon these considerations, orthogonal Varimax rotated PCA has been employed in the analysis of meteorological data sets.

The orthogonal Varimax employed in this study is based on maximizing the variance of the squared loadings in each row by the factor matrix (Nie <u>et</u> <u>al</u>., 1975). The computational formula for varimax rotation is ;

$$V = n \sum_{i=1}^{m} \sum_{i=1}^{n} \left(\frac{a_{ij}}{h_i} \right)^4 - \sum_{i=1}^{m} \left(\sum_{i=1}^{n} \frac{a_{ij}^2}{h_i^2} \right) \longrightarrow \max \quad ...[11]$$

where;

V is the variance

n is the number of variables

m is the number of common factors

a_{ij} is the loading of variable i on factor j

h_i is the communality of variable i given by

$$h_i^2 = \sum_{k=1}^{m} a_{ij}^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots[12]$$

$(i = 1, 2, \ldots\ldots, m)$

with a_{ij}, m and n defined as above.

The orthogonal varimax rotation has been the most widely used in meteorological research (Ogallo, 1980; 1985; 1987; Mungai, 1984, Oludhe, 1987, Barrings, 1987 and Basalirwa, 1991 and in crop-weather analysis (Jones, 1982).

3.5.2.2.3 REGRESSION ON PRINCIPAL COMPONENTS

To explore the dependence of maize yield on the principal components, the PCA analysis was done only on the independent variable, and then multiple regression analysis was employed using maize yield as the dependent variable and the principal components as the independent variables. To accomplish this, the individual P_{jk} values were computed by solving for the P_{jk} matrix which was done by inverting A_{ij}, the result is

$$P_{jk} = \sum_{i=1}^{n} \left[\frac{A_{ij}}{\lambda_j} \right] Z_{ik} \quad \ldots\ldots\ldots\ldots\ldots[13]$$

where λ_j is the eigenvalue associated with P_j. The dependence of yield on the Principal Component scores is determined by employing a Stepwise Multiple Regression Analysis (SMRA) of the BMDP statistical program (Dixon et al., 1983). The working principles of the SMRA is explained in section (3.5.1.2). An assumption made in this work is that there is a linear combination between yield and the principal components. In this case the form of the regression equation is

$$E(y) = a + \sum_{j=1}^{n} b_j P_j \qquad \text{.......................[14]}$$

where y is the value of the dependent variable,

a is the intercept and b_j is the regression coefficient for P_j.

CHAPTER IV

4.0 RESULTS AND DISCUSSIONS

4.1.0 SHORT RAINS

4.1.1 YIELD MODEL DEVELOPMENT

The correlation coefficient of maize yields and interphase meteorological parameters and technology trend during the short rains for the period 1974-1988 are shown in Table 8. The interphase crop rainy days show significant correlation with yield during the 10 days prior to sowing (r=0.654) and emergence to appearance of the ninth leaf (r=0.744). They however, show relatively high correlations during the planting to emergence (r=0.431) and ninth leaf appearance to tasseling (r=0.417) compared to those obtained with other phenological stages. The summation of the interphase crop rainy days from 10 days prior to sowing (PTS) to flowering gives the second highest correlation coefficient of all the interphase meteorological parameters (r=0.865). The behavior of interphase crop rainy days tally closely to that of interphase total rainfall and can be concluded that the interphase rainfall day accounts for much of the yield variations.

Interphase total evaporation was significantly correlated in three out of the nine interphase periods under consideration. When the summation of total evaporation from 10 days PTS to flowering was considered it explained a high amount of the yield variation than the discrete interphases (r= -0.699). This implied that the effect of evaporation on crop growth and final yield was additive. In comparison to other interphase weather parameters, evaporation shows comparatively high

TABLE 8: CORRELATION COEFFICIENTS OF MAIZE YIELDS WITH INTERPHASE METEOROLOGICAL VARIABLES AND TECHNOLOGY TREND IN KATUMANI DURING THE SHORT RAINS SEASON

VARIABLES	SYMBOLS	10 DAYS PRIOR TO SOWING	PLANTING TO EMERGENCE	EMERGENCE TO 9TH LEAF APPEARANCE	9TH LEAF APPEARANCE TO TASSELING	TASSELING TO FLOWERING	FLOWERING TO WAX RIPENESS	WAX RIPENESS TO FULL RIPENESS	10 DAYS PRIOR TO SOWING TO FLOWERING	10 DAYS PRIOR TO SOWING TO WAX RIPENESS
CROP RAINY DAYS (days)	CRP	+0.654*	+0.431	+0.744**	+0.417	+0.178	−0.032	−0.046	+0.865**	+0.794**
RAINFALL (mm)	RF	+0.592*	+0.385	+0.753**	+0.421	+0.095	−0.038	+0.018	+0.874**	+0.705**
TEMPERATURE MAXIMUM (deg.C)	MAXT.	−0.287	−0.575*	−0.349	−0.095	−0.211	−0.221	−0.099	−0.111	−0.341
TEMPERATURE MINIMUM (deg.C)	MINT	+0.260	+0.013	−0.137	−0.131	−0.087	−0.175	−0.122	+0.173	−0.131
TEMPERATURE MEAN (deg.C)	MEANT	−0.107	−0.107	−0.316	−0.160	−0.218	−0.370	−0.177	+0.150	+0.321
TEMPERATURE RANGE (deg.C)	RAT	−0.232	−0.232	−0.075	−0.068	−0.103	−0.139	+0.232	+0.341	0.231
EVAPORATION (mm	EVAP	−0.321	−0.473	−0.584**	−0.599	−0.419	−0.464	−0.583*	−0.899**	−0.702**
SOLAR RAD. ($MJM^{-2}d^{-1}$)	SRAD	−0.307	−0.041	−0.017	+0.187	+0.374	+0.298	+0.361	+0.214	+0.301

* SIGNIFICANCE AT P = 0.05
** SIGNIFICANCE AT P = 0.01
*LINEAR TECHNOLOGY TREND (TT) r = 529**

correlation coefficients in most of the interphase e.g tasseling to flowering (r=-0.419), flowering to wax ripeness (r=-0.464) and the wax ripeness to full ripeness (r=-0.583). All the correlation coefficients between the interphase pan evaporation and yield showed negative relationships. This may be explained by problems of water stress induced by high evaporation rates. This is also in agreement with Linvill et al., (1978) and Chen and Fonseca (1980) work.

The correlation coefficient between total interphase rainfall and yield, contrary to the findings of Lukando (1980), indicate the existence of a significant dependence between ten days prior to sowing and yield (r=0.592). The dependence is lower during planting to emergence (r=0.385) and rises during emergence to ninth leaf appearance (r=0.753) which corresponds to the start of floral primordial (Copper and Law, 1976). The magnitudes of correlation coefficients decrease onwards for the rest of the interphases. The summation of total interphase rainfall from the ten days prior to sowing to flowering of the tassel gives the highest correlation coefficient (r=0.874) of all the interphase climatic variables. All the significant correlation coefficients between interphase rainfall with yield gave a positive relationship, implying an increase in rainfall above the mean during these interphases will result in higher yields.

Other interphase meteorological parameters showing significant correlations are mean temperature (r=-0.574) and the maximum temperature (r=-0.575) which occur during the planting to emergence interphase. During this period the ground is bare and high temperatures as experienced in this area will result in increased evaporation from the soil, stressing the germinating plants. In this study solar radiation, minimum temperature and range of temperature had no significant correlations. This should not be construed to mean that these interphase climatic variables are not important in determining the maize growth, and the grain yield, rather their influence might have been obscured by other climatic factors.

Sixteen interphase meteorological variables showing significant correlation coefficients qualified to be candidate predictors. The high degree of multi-collinearity among candidate predictors which normally leads to unstable regression coefficients necessitated the selection of a few candidate predictors which would still explain a reasonable variations in the yield. The selected predictors are; total interphase rainfall from 10 days prior to sowing to flowering of tassel (RF_{prf}), crop rainy days from ten days prior to sowing to flowering of the tassel (CRP_{prf}), total interphase evaporation from ten days prior to sowing to flowering of the tassel ($EVAP_{prf}$), mean temperature from planting to emergence ($MEANT_{pe}$), maximum temperature during the planting to emergence ($MAXT_{pe}$) and linear technology trend (TT).

4.1.2: YIELD-WEATHER-TECHNOLOGY (YWT) MODELING

Thompson (1976) recommended the use of departures of climatic variables from their normals rather than the original data in Yield-Weather modeling. The departures of interphase meteorological variables were generated from the fifteen years (1974-1988) normals and used as predictors.

The Stepwise Multiple Regression Analysis (SMRA) program of the BMDP statistical package (Dixon et al., 1983) was then used to generate Yield-Weather-Technology (YWT) models. A total of four models were generated. The first model consisted of RF_{prf} as a predictor and explained 78.3 per cent of the yield variations. This predictor had the highest partial correlations with maize yield and as such was selected first. Table 9 shows the detailed information of the four yield weather models. Model 2 picked RF_{prf} and TT as predictors and accounted for 80.7 per cent of the yield variations. $EVAP_{prf}$, RF_{prf} and TT were incorporated in model 3 which accounted for 83.0 per cent of the yield variation.

TABLE 9: CONSTANTS AND COEFFICIENTS OF MAIZE YIELD MODELS FOR THE SHORT RAINS SEASON

VARIABLE	NORMAL	MODEL NUMBER 1	2	3	4
CONSTANT		1477.79	1217.76	1394.24	1420.91
RF_{prf} (DFN)	267.4	7.90	7.24	6.48	0.84
TT			32.51	10.44	5.70
$EVAP_{prf}$ (DFN)	410.7			-4.17	-5.61
CRP_{prf} (DFN)	16				85.44
Std error of estimation		413.7	406.5	397.76	378.88
Coefficient of determination		0.78	0.81	0.83	0.86

Model 4 comprised of RF_{prf}, TT, $EVAP_{prf}$ and CRP_{prf} as predictors and explained 86.0 per cent of the yield variations. However, CRP_{prf} was highly correlated with

RF_{prf} and may lead to variability in the regression coefficient. In view of this the CRP_{prf} was removed from model 4 with the remaining predictors explaining a reasonable amount of yield variations (83 per cent). The Durbin-Watson test and residual plot showed that the error terms were uncorrelated (D = 1.97) and no model inadequacy was indicated (see appendix). Thus, the Yield-Weather-Technology (YWT) model was chosen and expressed as;

$$E(v) = a + b_1(\text{DFN of } RF_{prf}) + b_2(\text{DFN of } EVAP_{prf}) + cTT$$

............[15]

where;

v is the maize yield in Kg/ha,

a is regressional coefficient

b_1, b_2 and c are partial regression coefficients,

DFN is the departure from the 1974-1988 average interphase meteorological variables,

TT is the linear technology trend,

$_{prf}$ is the 10 days prior to sowing to flowering of the tassel

RF_{prf} is summation of total interphase rainfall from a 10 days prior to sowing to flowering of the tassel

$EVAP_{prf}$ is summation of total interphase evaporation from 10 day prior to sowing to flowering of the tassel.

The selected YWT model is

$$E(v) = 1394.24 + 6.48(\text{DFN of } RF_{prf}) - 4.17(\text{DFN of } EVAP_{prf}) + 10.44TT \text{ ....[16]}.$$

TABLE 10: ANALYSIS OF VARIANCE OF THE SELECTED YWT MODEL.

VARIABLE NAMES	REGRESSION COEFFICIENT	STD ERROR OF ESTIMATE.	100 R^2 %	F-STATISTIC
RF_{prf}	6.48			
$EVAP_{prf}$	-4.48	397.759	83.03	17.94**
TT	10.44			
Constant (a)	1394.94			

**Significant at 1 % level
*ignificant at 5 % level

Table 10 shows the proportion of maize yield variance accounted for by the selected climatic variables based on the linear model.

4.1.3 MODEL TESTING

4.1.3.1 STABILITY OF REGRESSION COEFFICIENTS

Regression coefficient and R^2 values of the Yield-Weather-Technology model for five different data periods are shown in Table 11. The addition of 1987, which was a poor crop year modified the regression coefficient of the 1974 -1986 equation.

TABLE 11: REGRESSION COEFFICIENTS AND R^2 VALUES OF SELECTED YWT MODEL BASED ON DIFFERENT DATA PERIODS

DATA PERIOD	COEFFICIENT				R^2
	a	b_1	b_2	c	
1974-1986	1422.11	7.24	-4.03	7.58	0.85
1974-1987	1328.90	6.93	-3.62	12.85	0.84
1974-1988	1394.24	6.48	-4.17	10.44	0.83
1974-1989	1396.51	6.52	-3.91	9.42	0.84
1974-1990	1391.83	6.52	-3.88	10.44	0.85

The poor yields which were 16 per cent lower than the 14 normal years were caused by a dry spell during the month of December which correspond with the second growth stage when drought stress has very harmful effects (Nadar, 1984). The regression coefficient for the variable RF_{prf} changed from 7.24 to 6.39, variable $EVAP_{prf}$ changed from -4.03 to -3.62 and from 7.58 to 12.85 for variable TT. The good crop yield of 1988 further modified the regression coefficient of the 1974 -1987 equation. The yield and RF_{prf} were higher than the 14 years normal by 60% and 56% respectively with variable $EVAP_{prf}$ showing 12% lower than normal. The high yield may be explained by timely onset and evenly distributed rainfall simultaneously with low evaporation through out the crop growing season. This abnormal data substantially changed the regression coefficient of the 1974-1987 equation. Any additional years beyond 1988 did not substantially change the regression coefficient of the YWT model. To calibrate the YWT model for this study, it can be concluded that 15 years data from 1974-1988 should be adequate.

4.1.3.2: MODEL VALIDATION

Validation is the comparison of the predictions of a verified model with experimental observations made on the same variety and at the same site. In this study, the stable YWT model based on data period (1974-1988, 1974-1989 and 1974-1990) were tested for their yield prediction accuracies using meteorological data of the year(s) following each data period. Comparisons of the YWT model predictions with the reported harvested yields are shown in

Table 12. The relative differences of the six estimates ranged from 2.3% to 7.2%.

TABLE 12: COMPARISONS OF ESTIMATED MAIZE YIELD BY YWT MODEL AND REPORTED HARVESTED YIELDS.

TEST YEAR	HARVESTED YIELD	YWT MODEL ESTIMATE USING THE DATA PERIOD OF: 1974-1988	1974-1989	1974-1990
1989	2376	2505 (5.4%)		
1990	2445	2487 (3.4%)	2554 (4.4%)	
1991	2356	2413 (7.2%)	2383 (5.9%)	2307 (2.3%)

The smallest differences for the test years 1989, 1990 and 1991, lies on the leading diagonal of the Table 12. This suggests that the best current yield prediction can be achieved by applying all the available historic data to the preceding prediction year in computing the regression coefficients.

4.1.4 EFFECT OF 10 mm OF RAINFALL AND EVAPORATION ON YIELD DURING TEN DAYS PRIOR TO SOWING TO FLOWERING INTERPHASE.

From the selected YWT model,

$$E(y) = 1394.24 + 6.48\ (\text{DFN of } RF_{prf}) - 4.17\ (\text{DFN of } EVAP_{prf}) + 10.44TT \text{ -------}[16]$$

We can now investigate the effect of 10 mm increase in rainfall from 10 days prior to sowing to flowering of the tassel. Assuming the other parameters remain constant, yield E(y) in equation (16) is given by

$$E(y) = K + 6.48\ (\text{DFN of } RF_{prf}) \text{ ....}[17]$$

Therefore 10 mm increase in interphase total rainfall above the normal will result in an increase of 64.8 Kg/Ha of maize yield. A 10 mm decrease below the normal in total interphase rainfall will result in a decrease of 64.8 Kg/Ha of maize yield. Lukando (1980) found that from flowering of tassel to wax ripeness through grain filling period, rainfall above average had a harmful effect whereas below average was beneficial. This is in support of the results from correlation analysis where the summation of rainfall from 10 days prior to sowing up to flowering showed higher correlation coefficient ($r = 0.874$) than from 10 days prior to sowing up to wax ripeness ($r = 0.705$).

Similarly, the effect of $EVAP_{prf}$ can be investigated by holding all the parameters in equation (16) constant except the variable $EVAP_{prf}$ such that;

$$E(y) = K - 4.17 \ (DFN \text{ of } EVAP_{prf}) \text{ ....[18]}$$

where all the variables retain their earlier meaning. From the above equation a 10 mm increase in total evaporation from the 10 days prior to sowing to flowering of the tassel above the normal will result in a decrease of 41.7 Kg/ha of maize yields. A decrease of 10 mm of $EVAP_{prf}$ would increase the yields by a similar amount.

Technology improvements during the study period were significant and explained over 28% of the yield variation. The technological advancement had constant effects on yield at the rate of 10.44 Kg/ha per year.

4.1.5: SEASONAL YIELD VARIATION AND PREDICTION

The seasonal interphase total rainfall from the 10 days prior to sowing to flowering of the tassel showed a coefficient of variation of 359.2% when the deviations from the normal were considered. The seasonal interphase total rainfall ranged from 140.1 mm in 1981 season to 458.9 mm in 1982 season. The seasonal interphase total evaporation showed large seasonal interphase variations which had a coefficient of variation of 2355.3% when the deviations from the normal were considered. It also ranged from 340.4 mm in 1985 season to 496.9mm in 1976 season. In a similar fashion the yield varied considerably, ranging from 405 kg/ha in 1976 to 3119 kg/ha in 1982 season. Although low yields were generally observed in seasons with low rainfall, it did not follow that in the seasons with high rainfall the yields were proportionally high. For instance, the 1978 season had 297.4 mm of rainfall with maize yield of 1284 Kg/ha whereas 1979 had 289.8 mm of rainfall which yielded 2250 kg/ha of maize.

The mismatch between the yield and the total rainfall received in a season can be partly explained by studying the temporal rainfall distribution in each season. The distribution was such that there was no match between the moisture supply and crop demand. This was particularly true in the poor seasons when most of the rain was concentrated in small periods of the growing season thereby subjecting the crop to severe stress in the rest of the season. Depending on when stress occurs, the plants either failed to produce any ears or produced ears with few scattered and shriveled grains.

TABLE 13: OBSERVED AND PREDICTED YIELDS USING THE YWT IN KATUMANI.

SEASON	OBSERVED YIELDS (Kg/ha)	PREDICTED YIELD (Kg/ha)	RESIDUAL YIELD %
1974	815	900	-10.43
1975	750	780	- 4.00
1976	405	400	1.23
1977	2250	1860	17.33
1978	1284	1600	- 24.61
1979	541	900	- 66.36
1980	1210	1100	9.09
1981	661	460	30.41
1982	3119	3020	3.17
1983	1036	1100	-6.18
1984	2539	2510	1.14
1985	1306	1300	0.46
1986	2570	2380	7.39
1987	1406	1240	11.81
1988	2278	2410	- 5.79
1989	2376	2505	- 5.43
1990	2445	2554	- 4.46
1991	2356	2307	2.08

Despite the limitation in seasonal interphase total rainfall in representing the poor rainfall distribution it was successfully used in conjunction with seasonal interphase total evaporation and linear trend as predictors in developing a YWT model. The model not only accurately represent yield fluctuations during the data period from 1974 -1988, but also the successive independent test years 1989, 1990 and 1991. The negative sign on the residual yield indicates that model predicted higher than the observed.

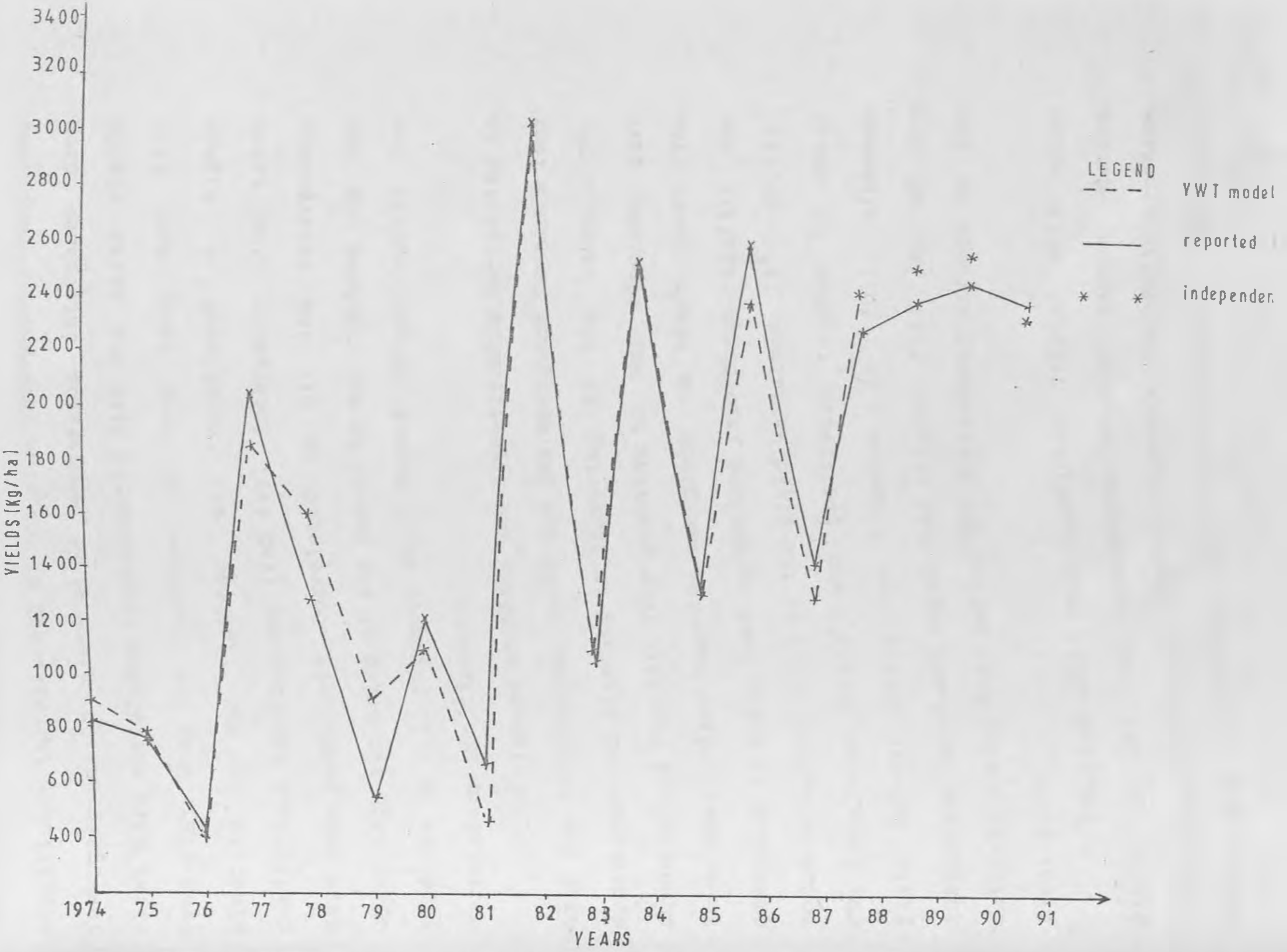


Fig1: Comparison between harvested maize yield and the YWT model based on the data period 1974-88

4.2.0: LONG RAINS SEASON

4.2.1: YIELD MODEL DEVELOPMENT

The correlation coefficient in Table 14 shows that interphase rainfall and crop rainy days are statistically significant in three out of the nine interphases considered. The emergence to ninth leaf appearance interphase crop rainy days correlated significantly with the maize yields (r=0.676). When the summation of crop rainy days from planting to wax ripeness was considered a higher coefficient was obtained (r=0.697). Interphase crop rainy days were positively correlated in all the interphases apart from flowering of the tassel to wax ripeness and wax ripeness to full ripeness which showed insignificantly low correlation coefficients.

Interphase rainfall was significantly correlated in only two interphases. These are the emergence to ninth leaf appearance and planting to flowering of the tassel. The summation of rainfall from planting to wax ripeness gave lower coefficient than the emergence to ninth leaf. The emergence to ninth leaf appearance interphase rainfall was found to explain most of the yield variation (R^2 =32.1%). The interphase rainfall was positively related to maize yield except during wax ripeness to full ripeness interphase which was negatively related. This implied that rainfall during this period had detrimental effects on the final yield.

Sunshine hours were negatively related with maize yields in all the interphases studied except during tasseling to flowering and wax ripeness to full ripeness interphases which were positively related. Interphase

TABLE 4: CORRELATION COEFFICIENTS OF MAIZE YIELDS WITH INTERPHACE METEOROLOGICAL VARIABLES

AND TECHNOLOGY TREND IN KATUMANI DURING THE SHORT RAINS SEASON

VARIABLES	SYMBOLS	10 DAYS PRIOR TO SOWING	PLANTING TO EMERGENCE	EMERGENCE TO 9TH LEAF APPEARANCE	9TH LEAF APPEARANCE TO TASSELING	TASSELING TO FLOWERING	FLOWERING TO WAX RIPENESS	WAX RIPENESS TO FULL RIPENESS	10 DAYS PRIOR TO SOWING TO FLOWERING	10 DAYS PRIOR TO SOWING TO WAX RIPENESS
CROP RAINY DAYS (days)	CRP	0.156	0.331	0.676**	0.343	0.078	0.061	-0.210	0.672**	0.697**
RAINFALL (mm)	RF	0.107	0.242	0.567*	0.312	0.146	0.142	-0.154	0.524*	0.498
TEMPERATURE MAXIMUM (deg.C)	MAXT.	0.149	-0.178	-0.168	-0.087	0.115	-0.330	0.042	-0.151	0.213
TEMPERATURE MINIMUM (deg.C)	MINT	-0.195	0.090	-0.049	0.016	-0.032	0.308	-0.041	0.010	-0.051
TEMPERATURE MEAN (deg. C)	MEANT	0.005	-0.173	-0.232	-0.023	0.030	0.039	-0.020	0.021	-0.124
TEMPERATURE RANGE (deg.C)	RAT	0.196	-0.175	-0.141	-0.099	-0.131	-0.614*	0.048	0.243	0.346
EVAPORATION (mm)	EVAP	0.164	-0.167	-0.293	-0.151	0.049	-0.368	0.226	0.084	-0.397
SUNSHINE HOURS	SSH	-0.033	-0.310	-0.565*	-0.210	0.510	-0.053	0.228	0.423	0.487
SOLAR RAD. (MJM^{-2})	SRAD	0.116	-0.099	-0.003	0.253	0.302	-0.153	0.154	0.008	0.214

* SIGNIFICANCE AT P = 0.05
** SIGNIFICANCE AT P = 0.01

sunshine hours during emergence to ninth leaf appearance was the only interphase significantly related with maize yields. The emergence to the ninth leaf interphase meteorological parameters correlated significantly with maize yield than any other interphase. This confirm the importance of this interphase in explaining the maize yield variations. The interphase range of temperature was negatively related in most of the interphases with only the flowering to wax ripeness showing significant correlation coefficients. Interphases of maximum, mean and minimum air temperature, evaporation and solar radiation were insignificantly related with maize yields. Only seven interphase climatic variables were significant for the entire study period and were considered as potential predictors. However, due to the high degree of multicollinearity only three interphase variables were selected namely; sunshine hours during the emergence to ninth leaf appearance interphase, range of maximum temperature during the flowering to wax ripeness interphase and crop rainy days from planting to flowering of the tassel.

From the discussions above the selected interphase variables explained dismally low variation in the yield variations. It was also found in section (3.4) that the time-yield series was stationary and oscillated about a given mean yield (1421.33 kg/ha) and standard deviation (844.42). The data points available were for only 12 seasons having been cut short by missing/unreliable data. With this constraints it was found that the Chen and Fonseca (1980) model could not appropriately be used to investigate yield-weather relationship for the long rainy season. Yield-weather relationship during the long rains season have successufully been accounted for by regression on principal components in the successive sections.

4.3.0 : ZONES OF SIGNIFICANT ASSOCIATIONS (Z.S.A) DERIVED BY EMPLOYING THE CHI-SQUARE STATISTIC.

This section discusses the results obtained by using a method suggested by Caprio (1966) and employing the χ^2 statistic. A number of weather parameters were found to have confounding effect on the growth and the subsequent yield. For instance, during periods of excess rainfall days associated with good yields, the same period was charaterized by deficit evaporation and deficit maximum temperature days. In such a situation it is unreasonable to have lengthy independent discussions of factors which might have confounding effects. In this study it was decided to use the most commonly and easily available meteorological parameters (i.e. air temperature and rainfall) to discuss the yield-weather relationships and then use evaporation and solar radiation indices of associations in supporting the deductions made.

4.3.1: SHORT RAINS SEASON

4.3.1.1: RAINFALL AND GOOD YIELD YEARS

The analysis of rainfall shows three zones of significant association (Z.S.A) for the high rainfall (fig. 2). The most extended ZSA occurs from October spanning to early November and is indicated as: I.A.gH.RF.+ 18 $\geq$ 0.1 mm (10/11-11/8). The number in the parenthesis refers to the beginning and end of the ZSA. This period falls within the onset of short rains (Stewart <u>et al</u>., 1982) which is also the planting period. This period is also characterized by a deficit of high evaporation days indicated as: I.A.gH.EVAP.-12 $\geq$6.0mm (10/25-11/8) (fig 5). This association may be related to germination and survival of the young seedlings through the favorable weather regimes. The second ZSA showing excess high rainfall during good yield years is as follows: I.A. gH.RF. +18≥4.1 mm (11/4-12/5). This falls within the emergence to ninth leaf interphase which is sensitive to water stress. A one week long ZSA during February indicated as: I.A. gH.RF. +8≥4.1 mm (2/8-2/15) shows the importance of rainfall during the grain filling period. The last Z.S. for deficit low rainfall is indicated as: I.A.gL.RF.- 5=0 (10/17-11/3). This ZSA falls within a more significant ZSA (I.A. gH.RF. +18≥0.1 mm) and confirms the importance of high rainfall during the above specified period.

4.3.1.2 RAINFALL AND POOR YIELD YEARS

The analysis of rainfall shows that there is a greater association of fluctuating maize yields with variations in high rainfall days, than with variations in low rainfall days. This implies that high rainfall represents better the yield variation compared to the low rainfall (fig. 2).

Only one ZSA for high rainfall associated with poor yield years exists and is indicated as: I.A. pH.RF. -11≥2.1 mm (11/21-12/7) exists.This period is also characterized by excess of days of high evaporation indicated as I.A. pH.EVAP. +10≥ 6.0 mm (fig.5). The I.A. of rainfall for poor yield years may prove useful for indicating periods when soil moisture deficit or drought can adversely affect crop yields. The I.A. coming late in November suggests that this is the most hazardous time for moisture stress effects on the maize crop in Katumani. Nadar (1984) found that this period falls within the floral-initiation stage when the plants demand for water is high. As such drought stress during this period may have detrimental effects to crop development and final yield.

4.3.1.3 MAXIMUM TEMPERATURE AND POOR YIELD YEARS

The analysis of maximum temperature during the entire season shows only one ZSA for the high maximum temperature indicated as I.A.pH.MAXT.+16≥24.0°C (11/22-12/10) (fig.4). This ZSA falls within a time period corresponding to deficit high rainfall (I.A.pH.RF.-11≥2.1mm) and excess high evaporation (I.A.pH.EVAP.+10≥6.0mm).This period also corresponds with the start of floral-initiation stage of the maize crop. High temperatures and large evaporative demand aggravated by deficit rainfall may cause temporary wilting hence impairing the crop photosynthetic activities.

Three ZSA for low maximum temperatures are shown in fig.4 and are specified as: I.A. pL MAXT - 15, ≤ 22.9°C(11/15-1/3), I.A.pL.MAXT-15≤25.9°C (12/26-1/7) and I.A.pL.MAXT +19≤26.9°C (2/28-3/14). The 1st ZSA occurs simultaneously with a more significant I.A. for high maximum temperature (I.A.pH.MAXT +16≥24.0°C) and helps to confirm the detrimental effects of high maximum temperature on the maize yield in the absence of rainfall. Second ZSA occurs from late December to early January when the crop is on its second growth stage (Nadar, 1984). The association may be related, either directly through weather influences or indirectly through the intermediary of biological

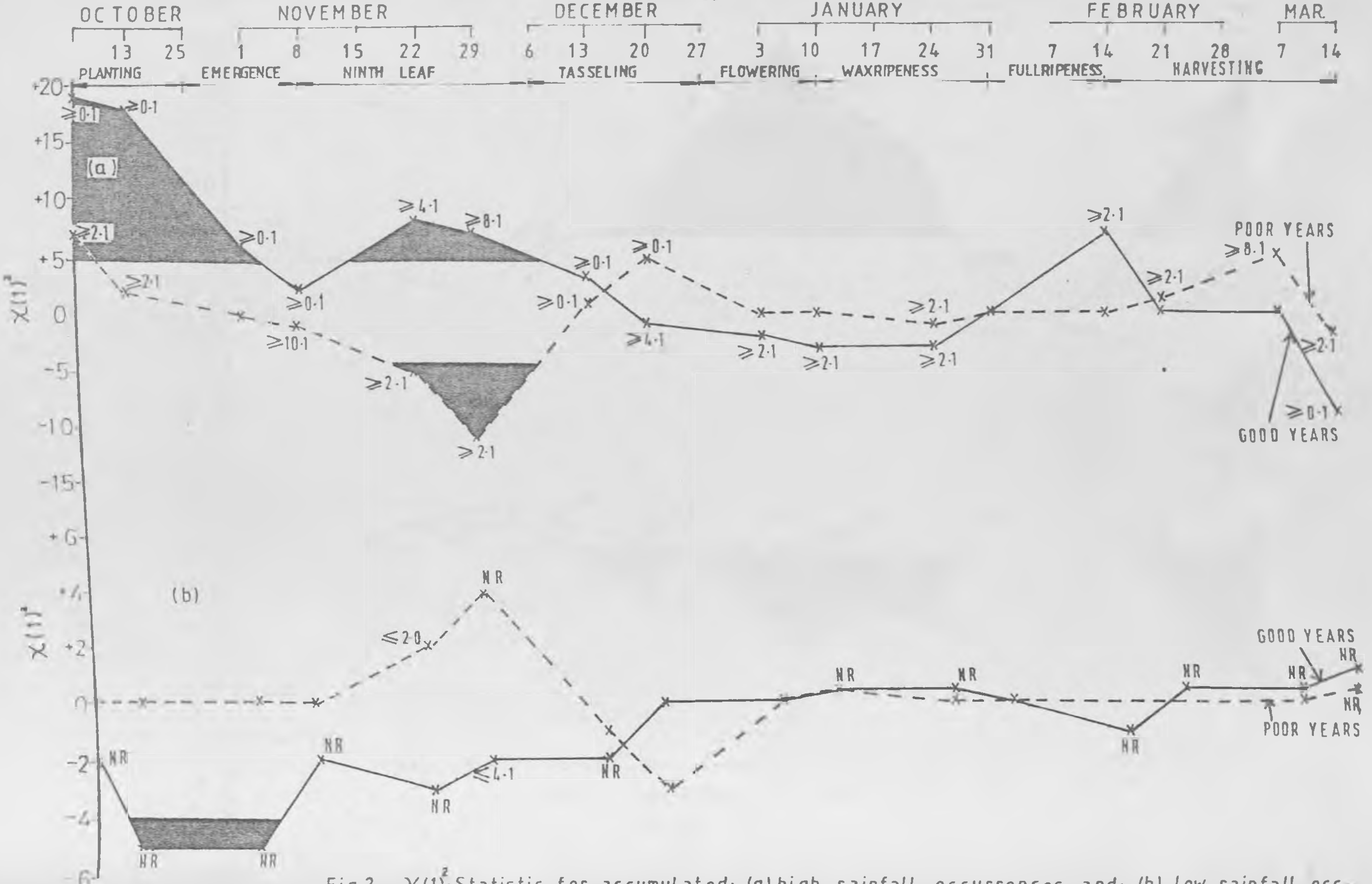


Fig 2 $\chi(1)^2$: Statistic for accumulated; (a) high rainfall occurrences and; (b) low rainfall occurrences for good and poor harvest years relative to normal years.

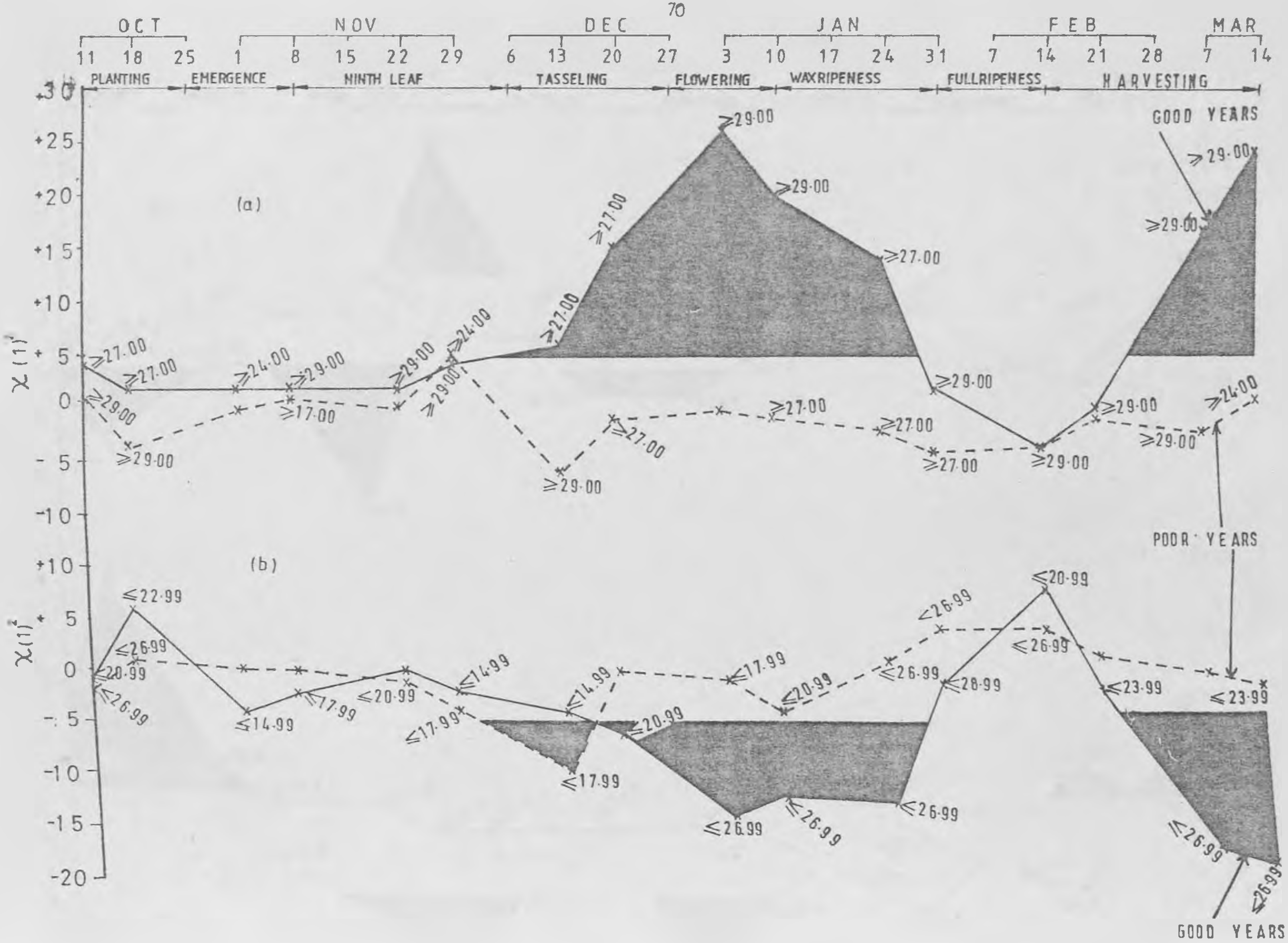


Fig3 $\chi(1)^2$: Statistic for accumulated; (a) high solar radiation and ;(b) low solar radiation occurrences for good and poor yield years relative to n-ormal years.

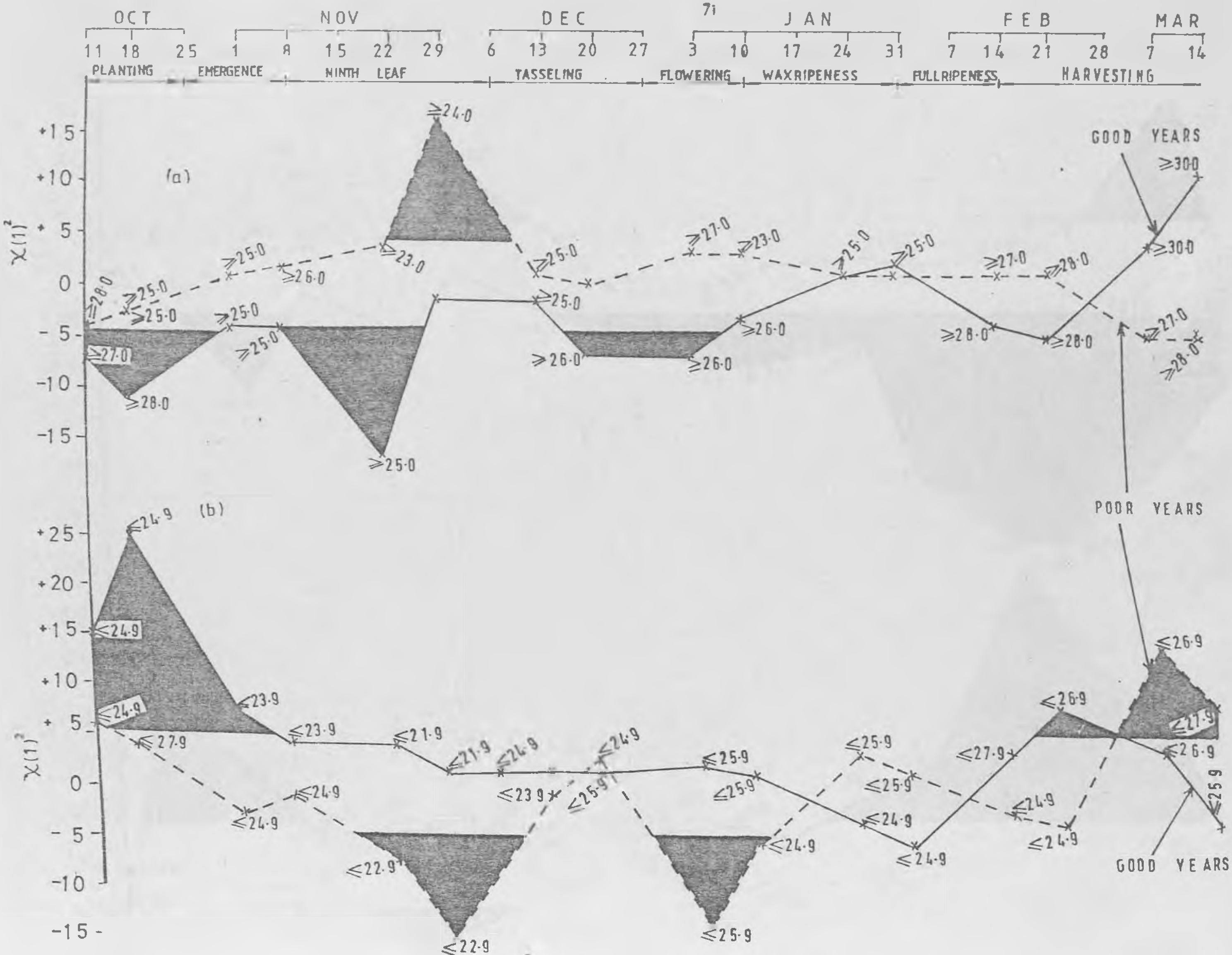


Fig 4 $\chi(1)^2$. Statistic for accumulated; (a) high maximum temperature occurrences and; (b) low maximum temperature occurrences for good and poor harvest years relative to normal years.

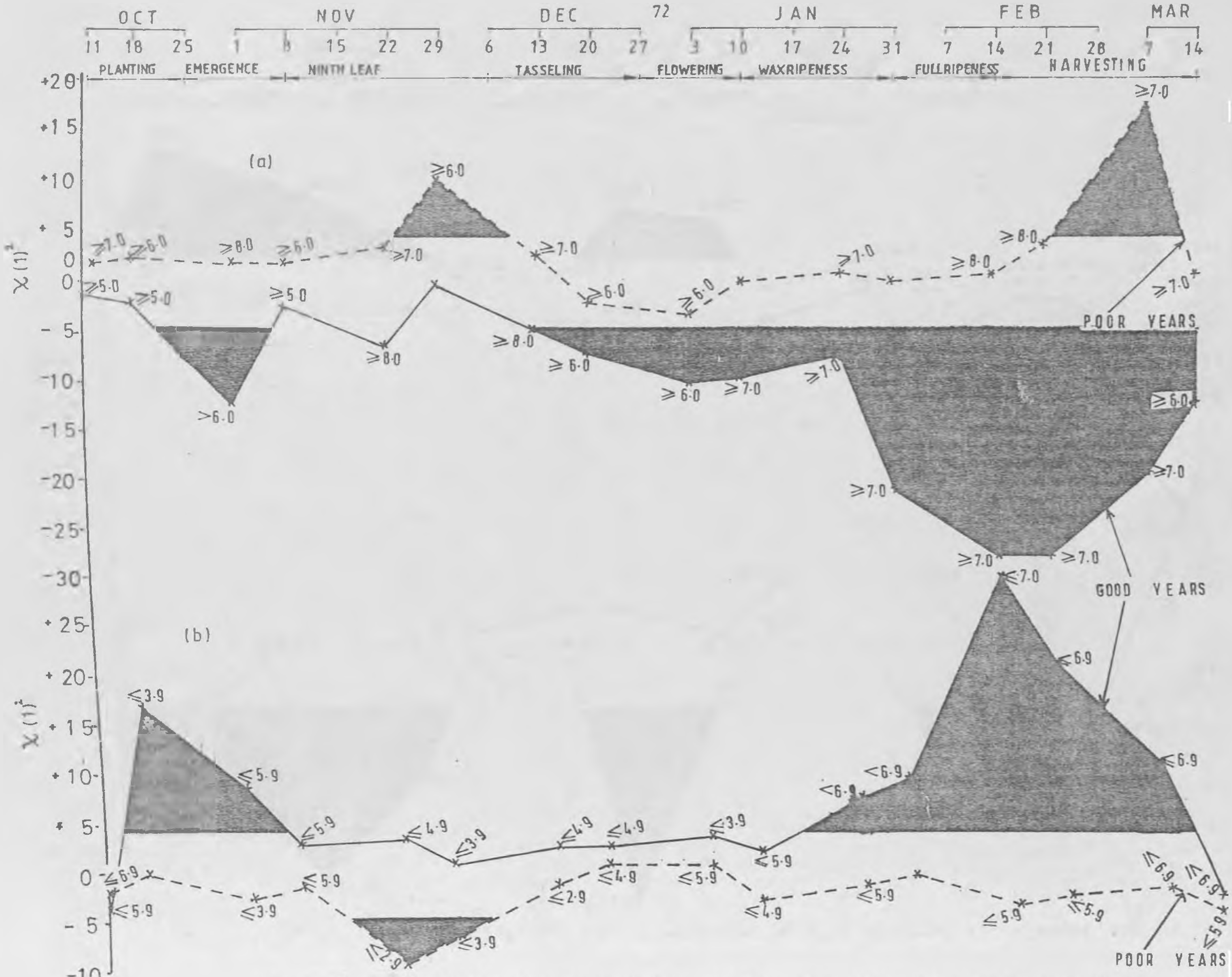


Fig 5 $\chi(1)^2$: Statistic for accumulated; (a) high evaporation occurrences and; (b) low evaporation occurrences for good and poor harvest years, relative to normal years

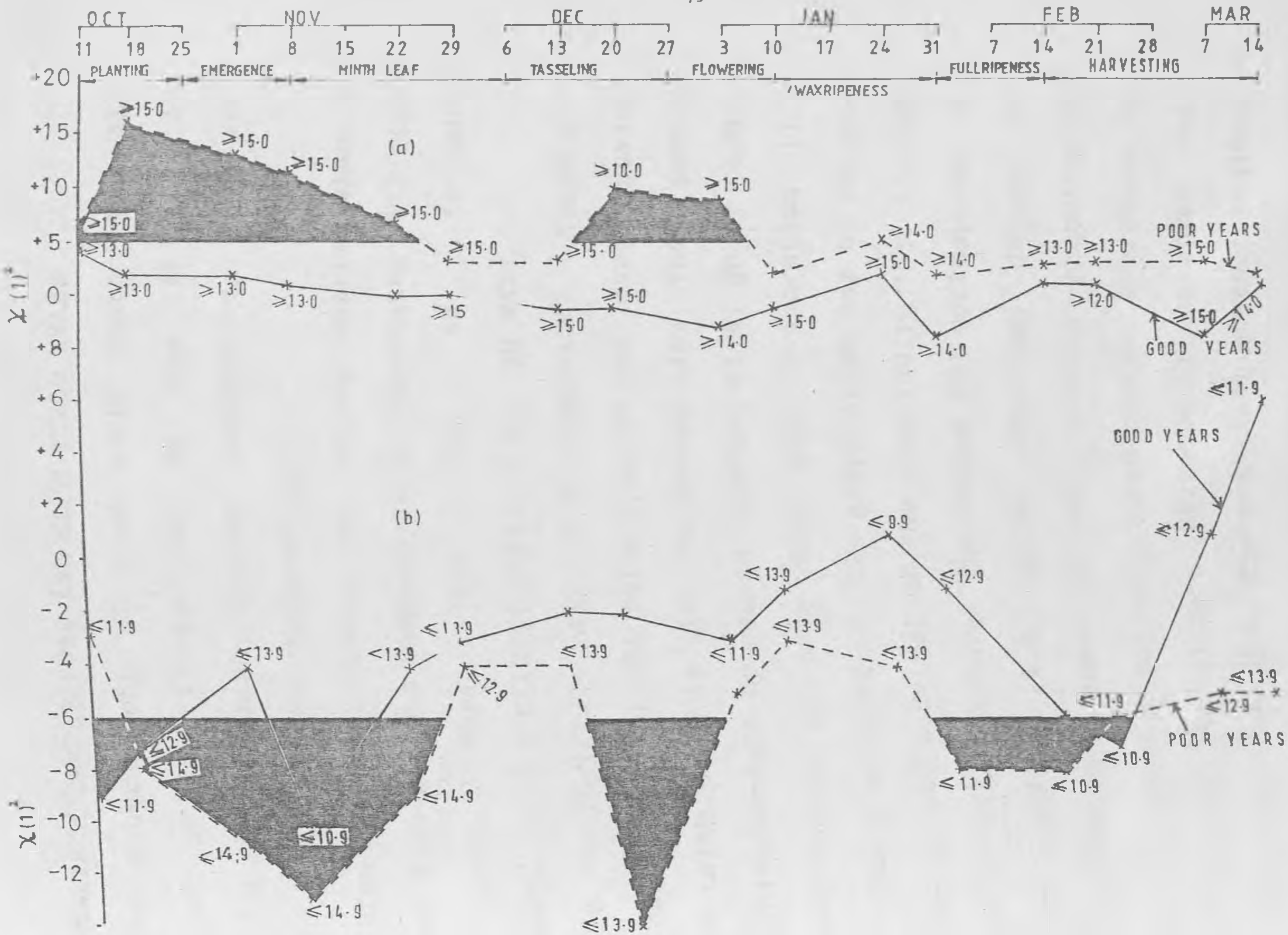


Fig 6 $\chi(1)^2$: Statistic for accumulated; (a) high minimum occurrences and; (b) low minimum temperature occurrences for good and poor harvest years relative to normal years.

functions. The third ZSA occurs during early-March when the crop is in its ripening stages and ample temperatures are required. However, the excess days of high maximum temperature in this ZSA appears less likely to have a direct influence on the maize yield.

4.3.1.4 MAXIMUM TEMPERATURE AND GOOD YIELD YEARS

The fluctuations of good yield years are well represented by the fluctuation in the indices of association for the high maximum temperature, than the variation in low maximum temperatures.

Three ZSA occur during the entire season when a deficit of high maximum temperature is associated with good yield years. These ZSA are as follows: I.A.gH.MAXT.-11≥28.0°C(10/11-11/1), I.A. gH.MAXT. -17≥25.0°C (11/8-11/27) and I.A. gH.MAXT -12≥26.0°C (12/18-1/8). The first ZSA falls within the onset period for short rains which is also the sowing time. This period is also characterized by excess rainfall (I.A. gH.RF +19 ≥ 0.1 mm) and deficit of days with high evaporation (I.A gH.EVAP.-12≥6.0 mm) (fig.4). The association may be related to germinating and survival of the crop indirectly through the conserved soil moisture. The second ZSA corresponds to excess high rainfall (I.A. gH.RF. +8≥4.1mm) during the emergence of the crop above the soil surface phenological phase. The association may be related to the emergence of the crop, through the indirect influence of conserved soil moisture which is favored by the prevalent weather regimes. The third ZSA occurs during the appearance of ninth leaf and tasseling interphase. This ZSA is also characterized by deficit high evaporation (I.A. gH.EVAP -10 ≥6.0mm). The above interphase is sensitive to water stress which normally has harmful effects on the crop growth. A fourth ZSA occurs on March when maize crop is ripening and is indicated as: I.A. gH.MAXT.+10 ≥10.0°C (3/7-3/4) and also corresponds to excess of high solar radiation (I.A.gL.SRAD. +24≥29.00MJM^{-2}) (Fig 3). The association may be related to favourable conditions which discourage rotting of grains in Cobs.

Only two ZSA for low minimum temperature exists for the entire season. These ZSA are as follows: I.A. gL.MAXT. +25 ≤24.9°C (10/11-11/8) and I.A. gH.MAXT. +7≤26.9°C (2/16-3/3). The first ZSA corresponds with the occurrence of high maximum temperature (I.A.gH.MAXT. -11≥28.0°C) helps to confirm the importance of low temperatures during this period. The second ZSA occurs from mid February to early March when the crop is ripening.

4.3.1.5 MINIMUM TEMPERATURES AND POOR YIELD YEARS

An extended ZSA for excess high minimum temperature covering the months of October and November is shown in (fig.6) and specified as: I.A.pH.MINT.+16≥15.0°C (10/11-11/27) and followed by I.A.pH.MINT.+15≥10.0°C (12/48-1/8). When minimum temperature is considered as a variable affecting the yield it is worth noting their joint influence with maximum temperature on the Net Assimilation Rate (NAR) i.e the dry matter produced by photosynthesis less what is broken down by respiration. Other factors not limiting high temperatures increase both the rates of photosynthesis and respiration (Duncan and Hasketh, 1968). Whereas photosynthesis is a daytime process respiration is both a day and night process. Consequently, for a large NAR, there should be reasonably high temperatures during the daylight hours to accelerate photosynthesis and reasonably low temperatures at night to lower respiration. Peters et al.,(1971) found a reduction in growth of the order 40% in corn yield when the temperature range was reduced by high night temperatures. Turning to our ZSA the maximum temperature received at the same time is ≥24.0°C giving a small band of temperature range and the poor yield realised may be due to this factor.

Three ZSA for deficit low temperature are indicated as: I.A.pL.MINT.-13≤14.9°C (10/6-11/26), I.A.pL.MINT.-12≤ 13.9°C (12/4-1/2) and I.A. pL.MINT -6≤11.9°C (1/27-2/21). The first two ZSA occur at the same time with a more significant zone of high minimum temperature. It is naturally expected that excess of high minimum temperature will correspond to deficit of low minimum temperature and hence the above results are not surprising. The third ZSA occurs late in the growth season when the crop has attained its physiological maturity and is less likely to have a direct influence on the final yield.

4.3.1.6 MINIMUM TEMPERATURES AND GOOD YIELD YEARS

The minimum temperature shows no significant associations with yield in good yield years during the entire season. Nevertheless, three ZSA for low minimum temperature are as follows: I.A.gL.MINT.$-7 \leq 11.9^{\circ}$C (10/11-10/24), I.A.gL.MINT.$-10 \leq 10.9^{\circ}$C (11/2-11/7) and I.A.gL.MINT.$-6 \leq 11.9^{\circ}$C (1/27-2/21). Bearers (1964) grew rye plants under three temperature regimes and found that plants growing continuously at 12.0°C had a higher carbohydrate and nitrogen content than plants grown in warm regimes. He concluded that the relatively high carbohydrates were caused by decreased respiration at lower temperatures. The minimum temperatures observed in the three zones of significance are above the minimum required for maize growth and ideal for low respiration. Other factors not limiting this minimum temperature can then be assumed to be associated with good yields.

4.3.2 0: LONG RAINS SEASON

4.3.2 1.: GOOD YIELD YEARS AND RAINFALL

Analysis of rainfall shows only one ZSA throughout the entire period for high rainfall and is indicated as: I.A.gH.RF.$+13 \geq 6.1$mm (3/18-4/9) (fig. 7). The ZSA falls within the onset bracket for the long rain season which is also the planting period. This ZSA occurs together with deficit maximum temperature days indicated as: I.A.gH.MAXT. $-15 \geq 28.0^{\circ}$C (3/12-4/1), deficit solar radiation days: I.A.gH.SRAD.$-6 \geq 27.00$ $MJM^{-2}d^{-1}$(4/1-4/12) and deficit of evaporation: I.A.gH.EVAP.$-9 \geq 6.0$mm (3/28-4/19). The association is related to germination and survival of plants directly through the soil moisture received from rainfall and indirectly by favorable weather conditions prevalent during this period.

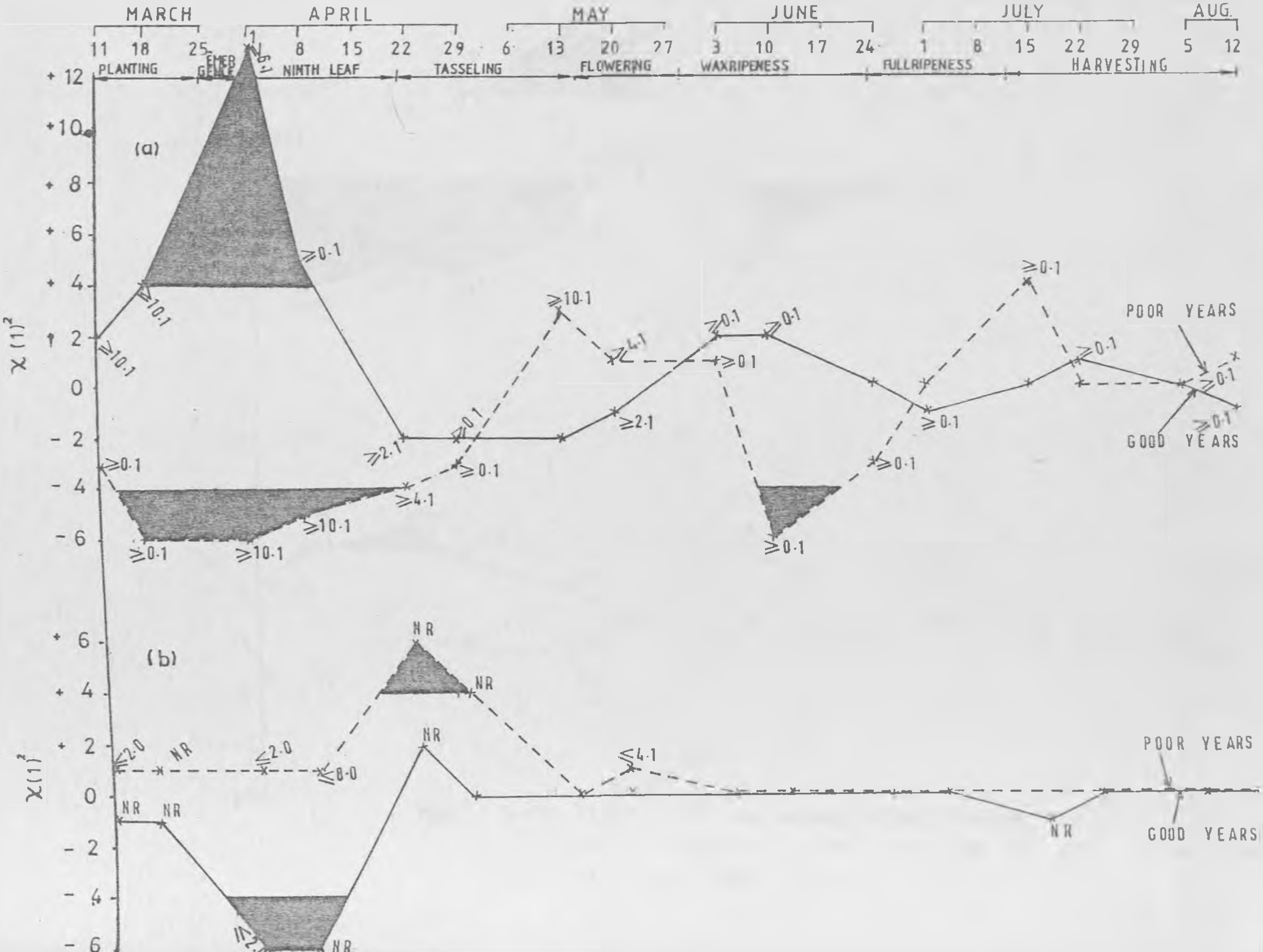


Fig 7 $\chi(1)^2$: Statistic for accumulated; (a) high rainfall occurrences and, (b) low rainfall occurrences for good and poor harvest years relative

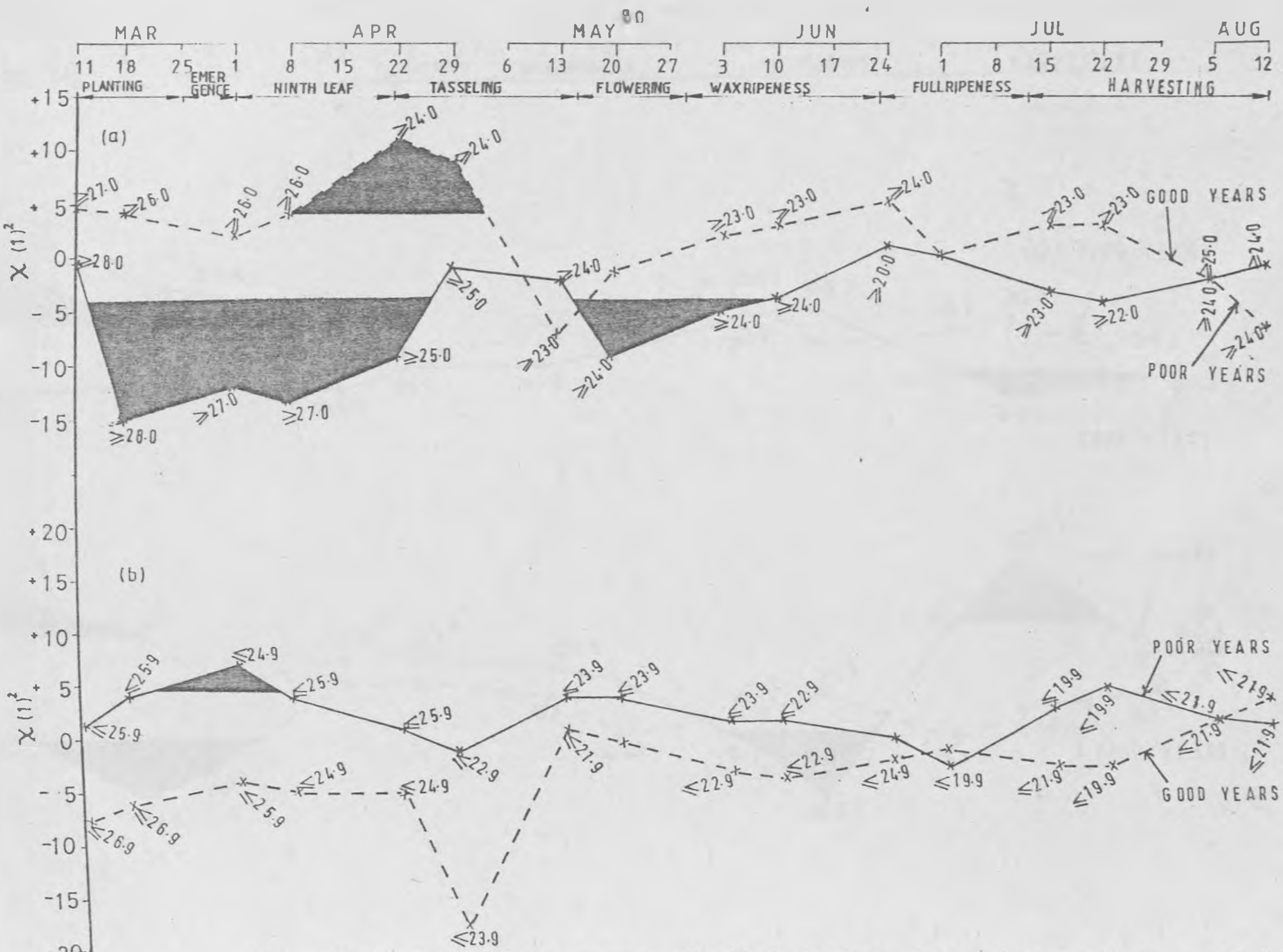


Fig 8 $\chi(1)^2$: Statistic for accumulated; (a) high maximum temperature occurrences and; (b) low maximum temperature occurrences for good and poor years relative to normal years.

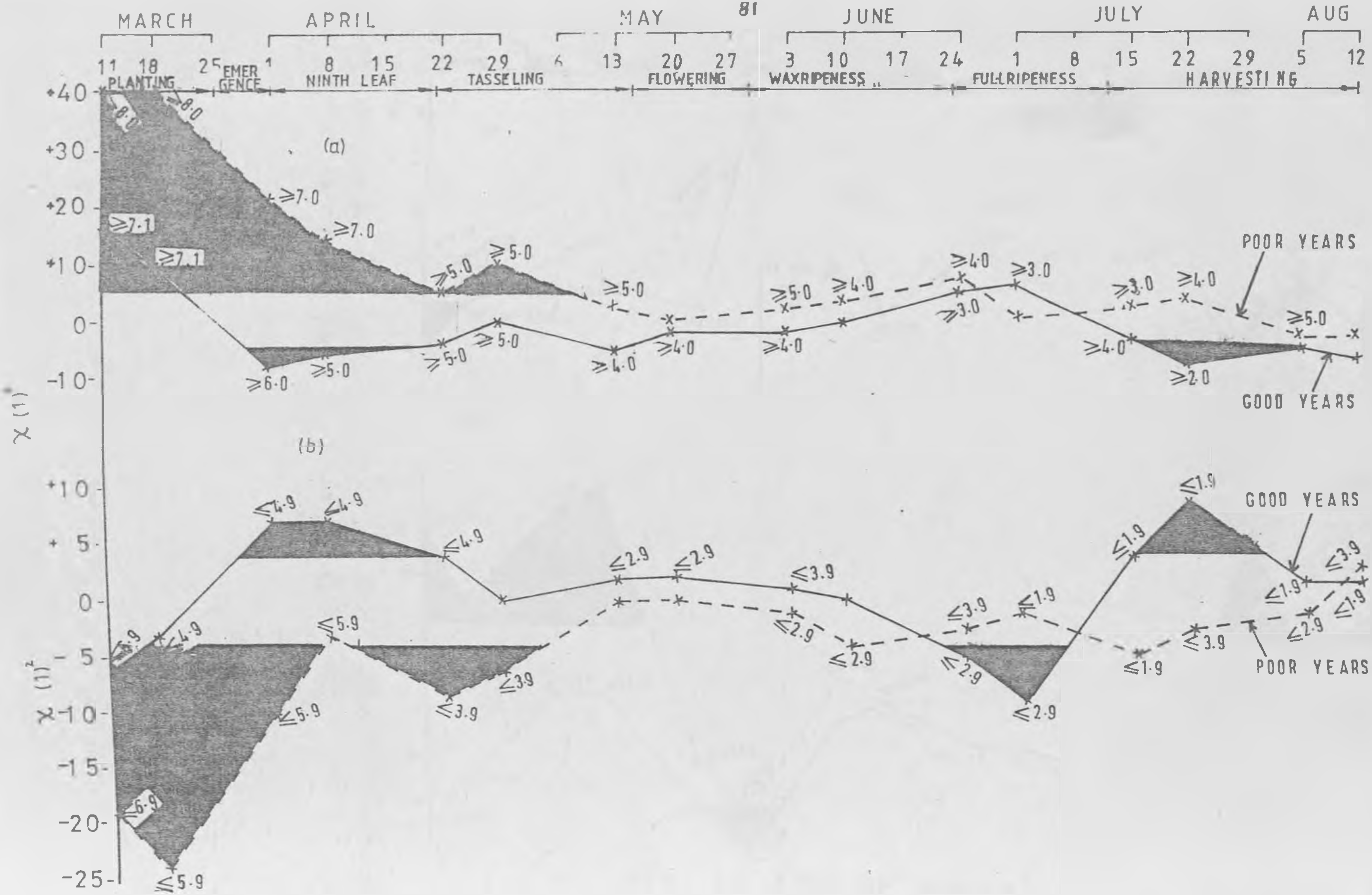


Fig 9 $\chi(1)^2$: Statistic for accumulated; (a) high evaporation occurrences and; (b) low evaporation occurrences for good and poor harvest years relative to normal yield years.

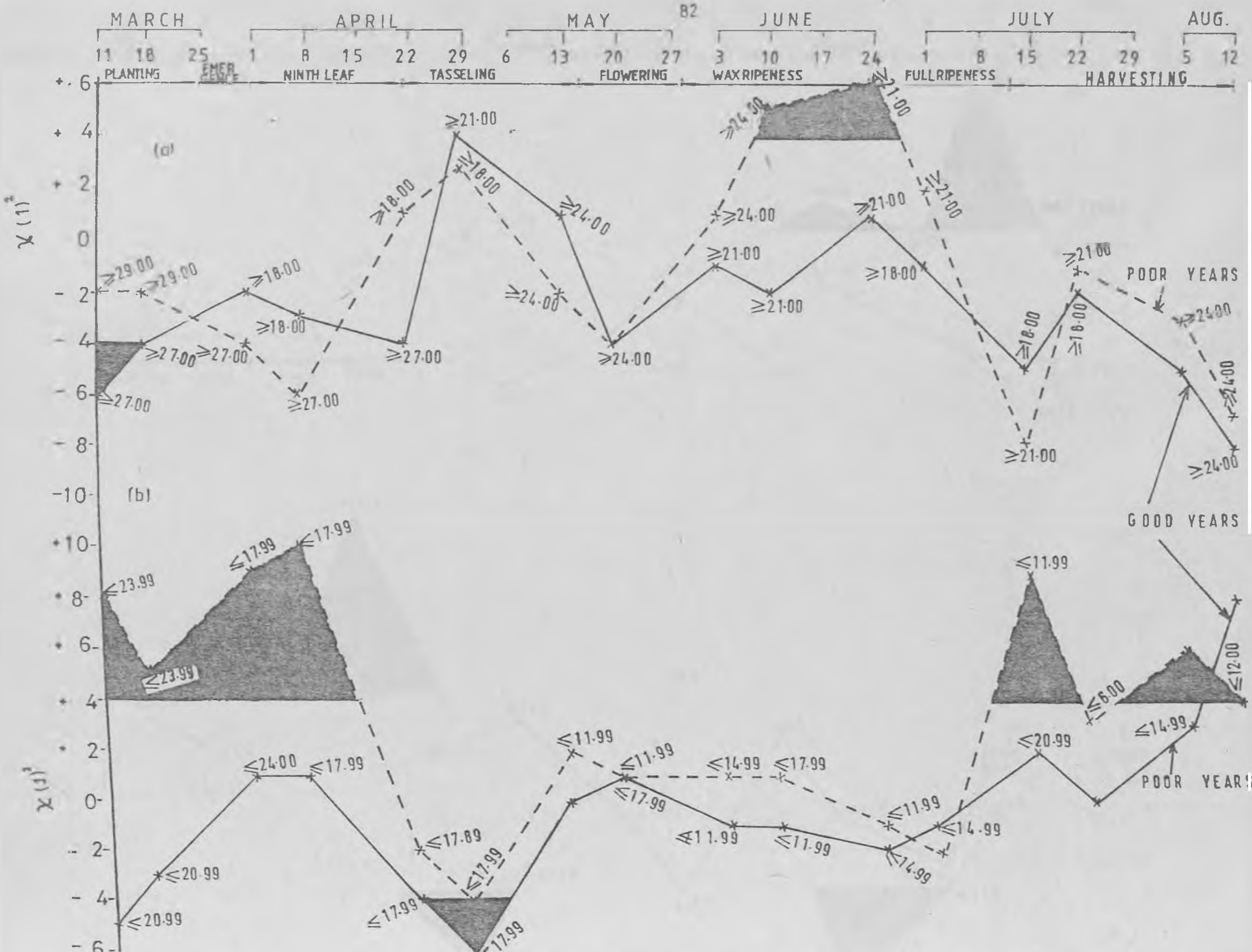


Fig 10 $\chi(1)^2$: Statistic for accumulated; (a) high solar radiation occurence and; (b) low solar radiation occurrences for good and poor harvest years relative to normal years.

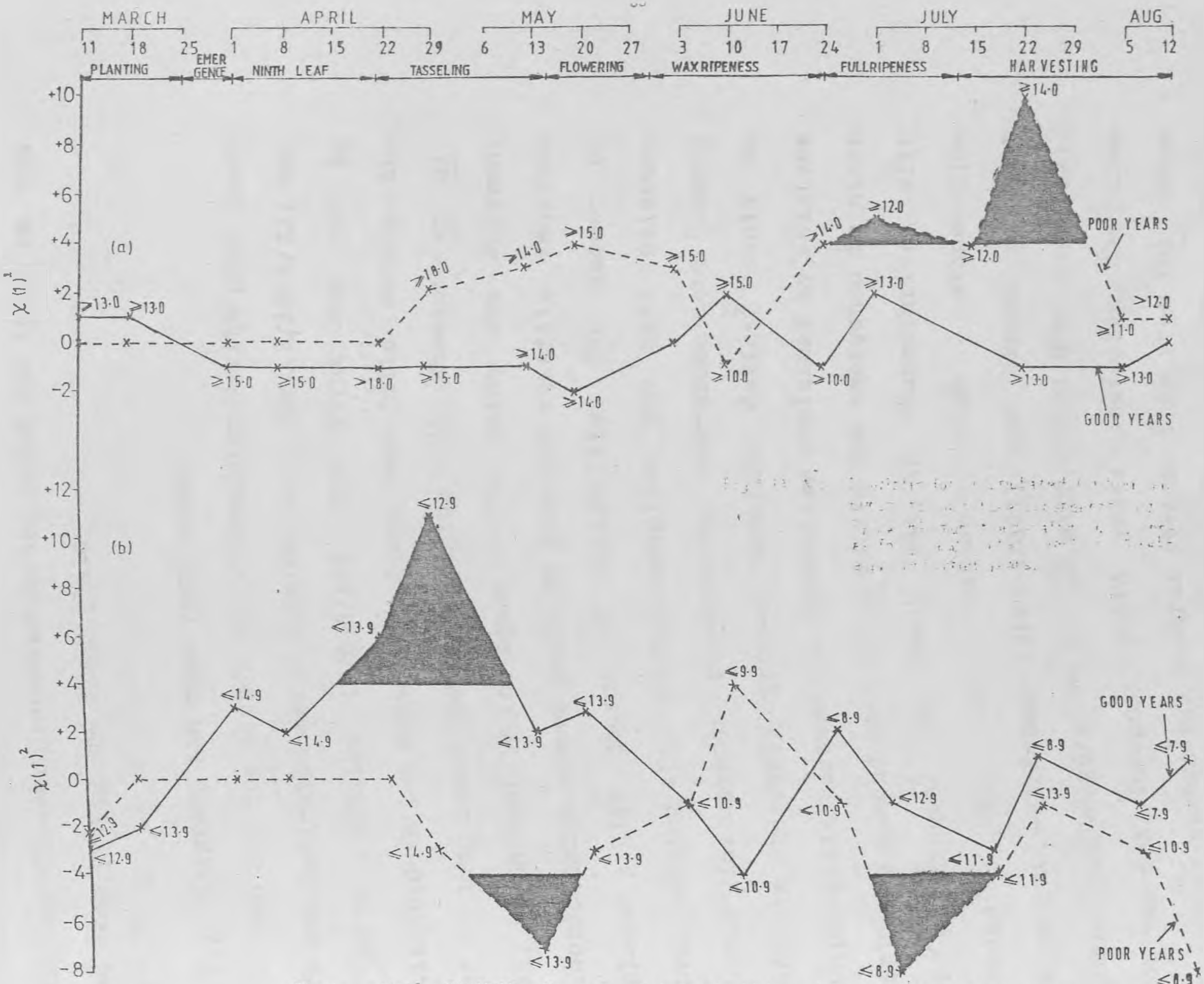


Fig 11 $\chi(1)^2$ Statistic for accumulated; (a) high minimum temperature occurrences and; (b) low minimum temperature occurrences for good and poor harvest years relative to normal years.

Only one ZSA indicated as: I.A.gL.RF.-6≤2.0mm (3/26-4/12) exists for low rainfall. This ZSA occurs within a more significant period indicated as: I.A.gH.RF.+13≥6.1mm (3/18-4/9) and emphasizes the beneficial effects of sufficient rainfall received during March and April to the maize crop growth and final yield.

4.3.2.2 RAINFALL AND POOR YIELD YEARS

Two ZSA for high rainfall associated with poor yield years are indicated as: I.A.pH.RF.-6≥10.1mm (3/13-4/22) and I.A. gH.RF. 6≥0.1mm (6/8-6/19). The first ZSA can be partitioned in two zones. The first zone falls within the onset of long rains and the planting time. Stewart *et al.* (1982) found that if the onset of the rains was delayed, the anticipated season would be poor and rainfall received displayed a high degree of variability. The amount of rainfall during this period supplies the soil moisture required for proper germination, emergence and early growth. In the early growth, moisture deficit could be reducing yield through the mechanisms explained by Slatyer (1967). The second part falls within the emergence to ninth leaf appearance. The whole ZSA is characterized with extended ZSA of excess high evaporation (I.A.pH.EVAP.+40≥8.0mm (3/11-4/22)) and excess of high maximum temperature (I.A. pH.MAXT.+11≥24.0°C (4/8-5/2). Since the I.A. for poor yield years indicates the time when water stress has harmful effects then from the above analysis the months of April and March are critical to maize growth in Katumani. The second ZSA falls in early

June and is characterized by excess of solar radiation days indicated as :I.ApH.SRAD.+6≥24.0 $MJM^{-2}d^{-1}$(6/10-6/27). The ZSA falls within the flowering to wax ripeness interphase and the I.A. shows that soil moisture deficits have harmful effects. These results are in agreement with the findings of Glover (1948), Denmead and Shaw (1961) and Salter and Goode (1967) that about tasseling/flowering time the soil moisture demand is high. The results are also in agreement with Lukando (1980) findings that during grain filling period, higher amounts of soil moisture are conducive to high yield.

Only one ZSA for low rainfall in the entire season existed and is expressed as: I.A. pL.RF. +6=0 mm(4/16-4/29) and shown in fig 7. The association is related to the ninth leaf appearance as affected by excess of dry days.

4.3.2.3 MAXIMUM TEMPERATURE AND POOR YIELD YEARS

The high maximum temperature graph shows only one ZSA indicated as: I.A.pH.MAXT. +11≥24.0°C (4/8-5/2) (fig 8) occurring during the vegetative stage. Deficit of high rainfall (I.A.pH.RF.-6≥0.1mm) and excess of high evaporation (I.A.pH.EVAP.+10≥6.0mm) characterize this period. The association seem to be due to limitations in photosynthesis when soil moisture is limiting, a common phenomenon in the area (Lukando, 1980). This argument is in support of the observation that during the vegetative growth stage high temperature has an unfavorable effect in the absence of adequate moisture (Smith, 1914; Stacy *et al.*, 1957 and Nadar, 1984).

The analysis of low maximum temperature shows deficit of maximum temperature for poor yield years spanning from 11th March to 9th of May with different indices and limits of associations. However, three highly associated indices and limits of association are specified as: I.A.pL.MAXT.-5≤26.9°C (3/11-4/1), I.A.pL.MAXT.≤24.9°C (4/2-4/22) and I.A.pL.MAXT.-17≤23.9°C (4/23-5/8). The first ZSA occurs within the onset bracket of the long rains season. This period is also characterized by deficit of low evaporation (I.A.pL.EVAP.-24≤5.9mm (3/11-4/7) and dry days. The second and third ZSA occur within the same period with the excess of high maximum temperature and seem to support the idea of the detrimental effects of high temperature in the absence of adequate soil moisture.

4.3.2.4: MAXIMUM TEMPERATURE AND GOOD YIELD YEARS

The high maximum temperature graph shows two ZSA over the entire period of study with both indicating deficiency during good yield years. The first ZSA extends from 12th of March to 27th of April comprising of two peaks. The specifications are as :I.A.gH.MAXT.-15≥28.0°C (3/12-4/1) and I.A.gH.MAXT.-14≥27.0°C (4/2-4/27) as shown in fig 8. The extended ZSA falls within the onset of long rains season when planting and germination takes place. This period is also characterized by deficit of high evaporation (I.A.gH.EVAP.-9≥6.0mm) (fig 9) and excess of high rainfall (I.A.gH.RF.+13≥6.1mm). Since the maximum temperature is below the maximum cardinal for maize (Duncan and Hasketh, 1968) and the soil moisture is not limiting then the photosynthetic activity is expected to be unlimited and hence good yields.

A third ZSA occurs during the middle of May to early-June when the crop is in its tasseling/flowering phenological stages and is indicated as: I.A.gH.MAXT.-9≥24.0°C (5/15-6/10). During this period, high temperatures in the absence of adequate soil moisture have been found to have very unfavourable effects (Smith, 1914; Hendrick's and Scholl, 1943 and Runge, 1968) by dehydrating the photosynthetic apparatus, reducing the rate of initiation and dehydrating and impairing the germination or growth of the pollen tubes from the stigma to the ovules (Robbins and Domingo, 1953) as quoted by Lukando (1980). Since in this case good yields are associated with deficient occurence of high maximum temperature, it appears that the maximum temperature received during this period is adequate for the plants needs.

Only one ZSA for low maximum temperature indicated as: I.A. gL.MAXT. +7≤24.9°C (3/18-4/8) exists. This ZSA occurs within a more significant zone of high maximum temperature and its effects are less likely to have a direct bearing on maize yields (Caprio, 1966).

4.3.2.5 : MINIMUM TEMPERATURES AND POOR YIELD YEARS

An extended ZSA for high minimum temperature occurs from 24th June to 31st July with two peaks is as shown in fig. 11. These ZSA are indicated as: I.A.pL.MINT.+ 5≥12.0°C(6/24-7/15) and I.A.pH.MINT.+10≥14.0°C(7/16-7/31). The period is also characterized by excess of low maximum temperature values (24.0°C), hence reducing the temperature range. The excess high minimum temperatures increases the respiration at night and hence decreasing the NAR.

Two ZSA for low minimum temperatures are as follows: I.A.pL.MINT.-7≤13.9°C (4/29-5/20) and I.A.pL.MINT.-8≤8.9°C (6/27-7/15). The first ZSA occurs at the same time as deficit of low maximum temperatures days: I.A.pL.MAXT.-17 ≤23.9°C (4/22-5/8). This period occurs during the vegetative period. The second ZSA occurs at the same time with a less significant zone of high minimum temperature.

4.3.2.6: MINIMUM TEMPERATURE AND GOOD YIELD YEARS

Yield and high minimum temperature shows no significant association in good yield years. However, the low minimum temperature has one ZSA characterized by excess of minimum temperature and indicated as: I.A.gL.Mn.T. -11≤12.9°C (4/15-5/9). This zone falls within the vegetative stage and the association may be related to direct influence of low night temperatures which reduce the respiration at night.

A subjective presentation of the above account is given in tables 15 and 16, the significant periods being related to the approximate state of the crop. During the long and short rains seasons, good yield years were characterized by abundance of days with rainfall and relative lack of hot days and days with high evaporation from the 10 days prior to sowing through the grain filling stage. From wax ripeness to full ripeness heavy rains are seen to have had a harmful effect as they may delay harvesting and cause loss due to rotting by fungus and/or germination of mature grains while in the cob. Poor yield years on the other hand are characterized by abundance of hot days, days with high evaporation and a relative lack of rainfall days during the same period.

TABLE 15: PERIODS OF SIGNIFICANT CLIMATE VARIABLES FOR MAIZE CROP DURING THE LONG RAINS SEASON.

PERIOD	CROP STATUS	CLIMATE OF GOOD YIELD YEARS	CLIMATE OF POOR YIELD YEARS
March	land prepar-tion and sowing	moderate solar radiation, deficit hot days,high evap. excess rainfall	deficit warm days, excess high evaporation deficit rainfall
April	Emergence and ninth leaf appearance	cool nights,deficit hot days, low evaporation excess rainfall,deficit solar radiation	deficit solar radiation,warm days, high evap. deficit heavy rainfall
May	tasseling and flowering	cool nights, deficit warm days	deficit cool nights,warm days and moderate evap.
June	wax ripeness	deficit lot evaporation	deficit light rainfall, moderate solar radiation
July - August	full ripeness and harvesting	low solar radiation deficit; low evaporation followed by excess low evap.and deficit solar radiation	deficit cold nights followed by warm nights, deficit low solar radiation

TABLE 16: PERIODS OF SIGNIFICANT CLIMATIC VARIABLES FOR MAIZE CROP DURING THE SHORT RAINS SEASON.

PERIOD	CROP STATUS	CLIMATE OF GOOD YIELD YEARS	CLIMATE OF POOR YIELD YEARS
October	Land prepa- ation and sowing	deficit hot days and cool nights, excess rainfall and low evaporation	excess warm nights
November	emergence and ninth leaf appearance	deficit warm days cool nights, excess rainfall, deficit evaporation	excess warm days, deficit rainfall and low evaporation
December	tasseling and flowering	deficit hot days and moderate evap., exc- ess solar radiation	deficit warm da- ys, cool nights and solar rad.
January	wax ripeness	excess high solar radiation and moder- ate evaporation	deficit warm days
February - March	full ripeness and harvesting	warm days followed by hot days. deficit cold nights and moderate evaporation	warm days deficit cold nights and high evaporation

4.4.0: REGRESSION ON PRINCIPAL COMPONENTS

This section attempts to quantify the crop-weather relationship obtained by using the Caprio (1966) method and employing the χ^2-statistic. From the Zones of Significant Association (ZSA) eighteen and seventeen short term climatic variables covering the entire crop growth season during the long and short rains season respectively were isolated. These variables were found to have significant influence during the crop growth and the subsequent yield. Since the main objective was to design a regression model capable of predicting the final maize yield two months in advance, this necessitated the reduction of the time period under consideration. Consequently the climatic variables were reduced to fifteen and eleven during the long and short rains respectively. These climatological data formed the input correlation matrix of the Principal Component Analysis (PCA).

The method of selecting variables that fall within a given ZSA helped in solving the problem of temporal data aggregation as evident from the low coefficient of skewness. In this light the selected short term climatic variables for each season were subjected to the method of PCA without any transformations.

4.4.1: LONG RAINS SEASON

Table 17 shows the proportion of variance accounted for by the first ten components, while fig.18 shows the plot of the eigenvalues against component number.

TABLE 17: AMOUNT OF VARIANCE EXPLAINED BY THE 10 FACTORS DURING LONG RAINS SEASON

COMPONENT NUMBER	VARIANCE EXPLAINED BY UNROTATED EIGENVALUE	% VARIANCE EXTRACTED	CUMULATIVE PROPORTION OF TOTAL VARIANCE
1	5.84	38.9	38.9
2	2.68	17.9	56.8
3	1.75	11.7	68.5
4	1.46	9.8	78.3
5	0.83	5.5	83.8
6	0.72	4.8	88.6
7	0.58	3.9	92.5
8	0.33	2.3	94.8
9	0.30	1.9	96.7
10	0.25	1.7	96.4

According to Kaiser's (1961) criterion four components were significant and they explained 78.3% of the variance in the 15 raw variables with the first two components explaining 56.8% of the variance in the original data set. The initial factor matrix had several components loading on a given variable making it ambiguous in an interpretive sense. The factor structure was simplified by rotating the initial factor structure matrix by using the varimax rotation method. Table 18 shows the variance explained by the four components before rotation and after rotation respectively.

TABLE 18: COMPARISON OF VARIANCE EXPLAINED BY UNROTATED AND ROTATED COMPONENTS DURING THE LONG RAINS SEASON.

COMPONENT NUMBER	UNROTATED EIGENVALUE		ROTATED EIGENVALUE	
	% VARIANCE EXPLAINED	% VARIANCE EXTRACTED	% VARIANCE EXPLAINED	% VARIANCE EXTRACTED
1	5.84	38.9	4.65	31.0
2	2.68	17.9	2.72	18.1
3	1.75	11.7	2.66	17.7
4	1.46	9.8	1.71	11.4

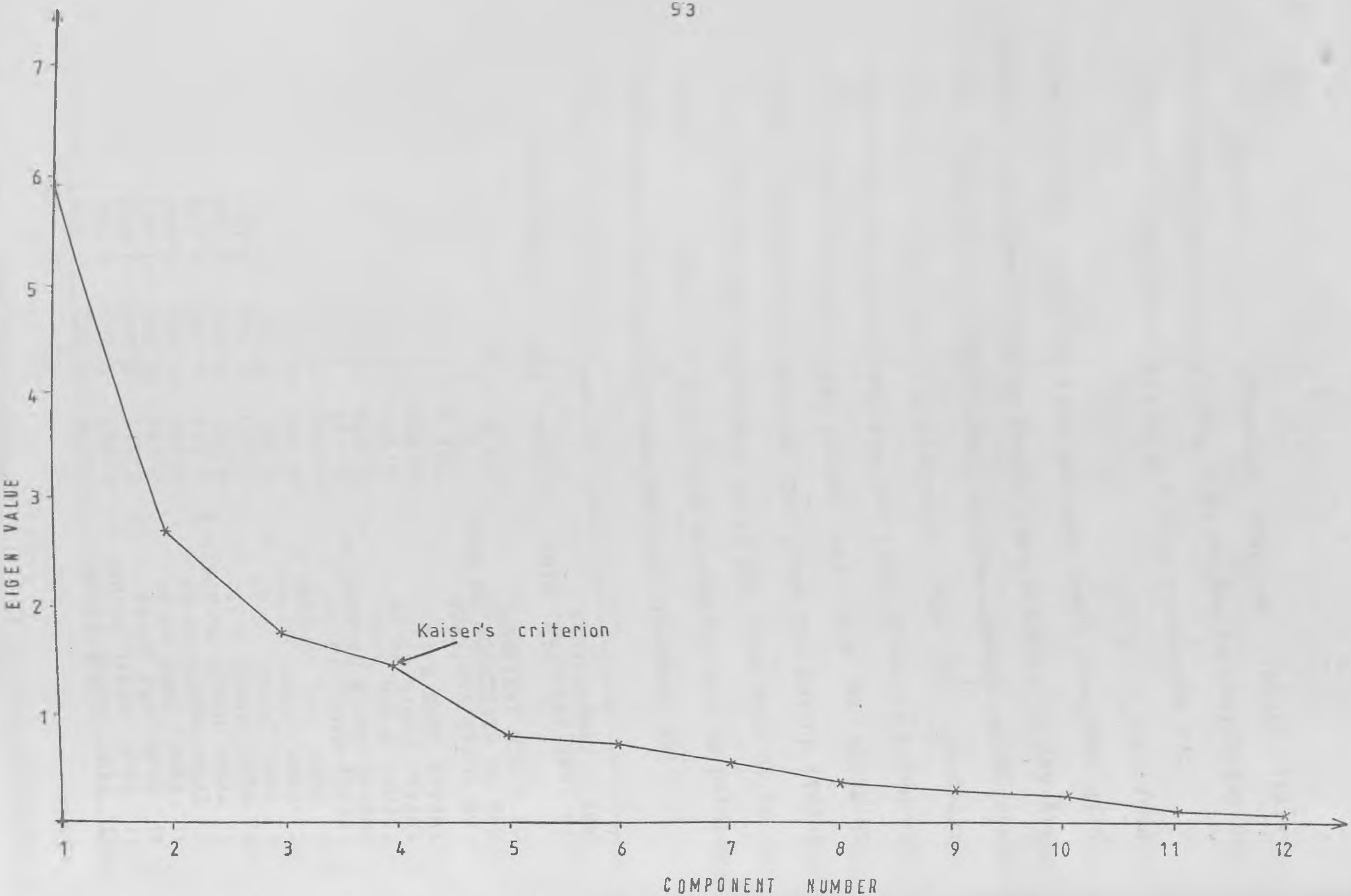


Fig12 : Graph of eigen values against component number

TABLE 19: COMPONENT LOADINGS ON COMPONENTS C_1, C_2, C_3 AND C_4 AFTER ROTATION DURING THE LONG RAINS SEASON

VARIABLE NAME	COMPONENT LOADINGS C_1	C_2	C_3	C_4
MINI. TEMP. APRIL 15-26	-0.005	0.101	0.859	0.064
MINI. TEMP. APRIL 27-MAY 9	-0.007	-0.105	0.930	-0.188
MINI. TEMP. MAY 10-18	0.110	-0.659	0.602	0.138
MINI. TEMP. JUNE 24-30	-0.150	0.130	0.441	0.747
MAX. TEMP. MARCH 13-25	0.650	-0.491	0.151	0.199
MAX. TEMP. MARCH 26-APRIL 1	0.814	-0.394	-0.104	-0.171
MAX. TEMP. APRIL 2-15	0.767	-0.422	0.246	0.036
MAX. TEMP. APRIL 16-22	0.517	-0.384	0.011	0.547
MAX. TEMP. APRIL 23-MAY 9	0.836	-0.239	0.005	-0.305
MAX. TEMP. MAY 15-JUNE 3	-0.799	-0.108	-0.013	0.093
RAINFALL MARCH 13-25	-0.606	-0.072	-0.474	-0.286
RAINFALL MARCH 26-APRIL 8	-0.489	0.799	0.074	-0.087
RAINFALL APRIL 9-22	-0.855	-0.104	0.130	-0.070
RAINFALL APRIL 23-29	0.035	0.022	-0.347	0.691
RAINFALL JUNE 9-18	-0.064	0.902	0.191	0.218
% OF TOTAL VARIANCE	31.0	18.1	17.7	11.4
ORDER OF SELECTION IN SMRA	1	2	3	N/S
% OF YIELD VARIANCE	17.5	15.3	9.7	-

N/S -not selected; MINI - minimum; MAX - maximum and TEMP - temperature

The component loadings associated with components employed in the regression model [19] is shown in table 19. It is seen that the first component loads heavily on rainfall during mid-April and maximum temperature during late-March to May. The second PC loads heavily on late-March to early-April and mid-June rainfall. The period correspond to the germination and grain filling phenological stages. Minimum temperature from mid-April to early May is strongly represented in third component, whilst fourth component loads substantially on late June minimum temperature.

The dependency of yield on the principal component was determined by employing a Stepwise Multiple Regression Analysis (SMRA). In this procedure the variables were selected in the order of the maximum improvement in coefficient of determination (R^2). For each of the independent variable, the F-statistic which reflected the variable contribution to the model, was calculated. If the F-statistic was insignificant the procedure was terminated.

Table 19 shows the order of selection of the rotated component in equation [19] in Table 20. The three selected components accounted for 68.5% of the variance displayed by the 15 raw variables and also accounted for 42.5% of the yield variation. The first component was selected first and accounted for 17.5% of the yield variance. This component loaded heavily on rainfall during late-March when planting and germination of the maize crop takes place and maximum temperature during May-June when the crop is in the second vegetative stage (Nadar,1984). Second component accounted for 15.3% of the yield variance and loaded heavily on rainfall during April to mid-June. The fourth component which loads substantially on minimum temperature during June did not account for any significant amount of yield variance.

The dependence of yield on the unrotated components utilized components from a wide cross-section. The first component was selected first and explained 33.0% of the yield variance followed by component 9^{th} and 8^{th} which accounted for 28.3% and 11.5% of the yield variance respectively. To simplify the interpretation of the above results Table 22 shows the three selected components in their rotated form. The three unrotated components accounted for 43.1% of the variance displayed by the 15 raw variables and 72.9% of yield variance.

TABLE 20: WEATHER YIELD RESPONSE: REGRESSION ESTIMATES WITH ROTATED COMPONENT FOR KATUMANI MAIZE DURING THE LONG RAINS SEASON.

$$E(Y) = a + b_1F_1 + b_2F_2 + b_3F_3 \ldots\ldots\ldots\ldots\ldots [19]$$

VARIABLE NAME	REGRESSION COEFFICIENT	STD ERROR OF ESTIMATE	100 R^2	F-STATISTIC
F_1	-381.045			
F_2	369.268	789.4	42.51	2.46
F_3	-364.628			

Constant (a) 1271.830
STD- standard

The first component loaded heavily on rainfall from early to mid-April and maximum temperature during late-April to early-May. Rainfall during late April to early-May loaded substantially on the 8th component, whilst minimum temperature during mid-May loaded heavily on the 9th component. From the above analysis, it can be concluded that the weather conditions prevalent during the months of April and early May are most critical for maize growth in Katumani during the long rains season.

Regression model [20] showing the dependence of yield on unrotated components is shown in Table 23. Comparing the predictive abilities of equation [19] and [20], it is clear that the unrotated components were superior in accounting for the yield variance.Table 21 and 24 compares the predictive abilities of the rotated and unrotated principal component respectively.

TABLE 21: OBSERVED AND PREDICTED YIELDS USING ROTATED PRINCIPAL COMPONENTS

SEASON	OBSERVED YIELDS (KG/HA)	PREDICTED YIELDS (KG/HA)	RESIDUAL (%)
1974	2805	2449	12.7
1975	96	256	-166.7
1976	0	329	-
1977	955	1287	-34.8
1978	1139	1534	-34.8
1979	840	1319	-57.0
1980	630	922	-46.3
1981	2945	2668	9.4
1982	668	937	-40.3
1983	792	569	28.2
1984	0	293	-
1986	1426	1030	27.8
1987	1353	978	27.7
1988	2513	2083	17.1
1989	981	1290	-31.5

The negative sign on the residual yield indicates that the model predicted higher than the observed.

TABLE 22 LOADINGS OF COMPONENT C_1, C_2 AND C_3 AFTER ROTATION DURING THE LONG RAINS SEASON.

VARIABLES NAME	COMPONENT LOADINGS C_1	C_2	C_3
MIN. TEMP. APRIL 15-26	0.040	-0.036	0.061
MIN. TEMP. APRIL - MAY 9	-0.018	-0.219	0.247
MIN. TEMP. MAY 10-18	0.054	0.001	0.796
MIN. TEMP. JUNE 24-30	0.074	0.103	0.048
MAX. TEMP. MARCH 13-25	-0.469	-0.061	0.240
MAX. TEMP.MARCH 26-APRIL 1	-0.593	-0.0248	-0.000
MAX. TEMP. APRIL 2-15	-0.468	-0.023	0.197
MAX. TEMP. APRIL 16-22	-0.188	0.116	0.102
MAX. TEMP. APRIL 23-MAY 9	-0.725	-0.151	0.160
MAX. TEMP. MAY 15-JUNE 3	-0.348	0.019	0.045
RAINFALL MARCH 13-25	0.252	-0.035	-0.156
RAINFALL MARCH 26-APRIL 8	0.227	-0.140	-0.175
RAINFALL APRIL 9-22	0.941	-0.115	0.113
RAINFALL APRIL 23-29	-0.029	0.9981	-0.002
RAINFALL JUNE 9-18	0.079	0.109	-0.135
% OF TOTAL VARIANCE	38.9	2.2	2.0
ORDER OF SELECTION IN SMRA	1	2	3
% OF YIELD VARIATION	33.0	28.3	11.5

MINI- minimum; MAX - maximum and TEMP - temperature

TABLE 23: WEATHER-YIELD RESPONSE: REGRESSION ESTIMATES WITH UNROTATED COMPONENTS FOR KATUMANI MAIZE DURING THE LONG RAINS SEASON.

$$E(Y) = a + b_1C_1 + b_2C_2 + b_3C_3 \quad \text{............[20]}$$

VARIABLE NAMES	REGRESSION COEFFICIENT	STD ERROR OF ESTIMATE.	100 R^2	F-STATISTIC
C_1	542.705			
C_2	320.760	554.772	72.9	9.85
C_3	-502.356			

Constant (a) 1143.356
STD- standard

TABLE 24 OBSERVED AND PREDICTED YIELDS USING UNROTATED PRINCIPAL COMPONENTS

SEASON	OBSERVED YIELDS (KG/HA)	PREDICTED YIELDS (KG/HA)	RESIDUAL YIELDS (%)
1974	2805	2589	7.7
1975	96	156	-62.5
1976	0	274	-
1977	955	1285	-34.6
1978	1139	1510	-32.6
1979	840	1242	-47.8
1980	630	822	-30.5
1981	2945	2784	5.5
1982	668	884	-32.2
1983	792	897	-13.3
1984	0	395	-
1985	990	1208	-22.0
1986	1426	1186	16.0
1987	1353	984	27.3
1988	2513	2141	14.8
1989	981	1121	-14.3

The negative sign on the residual yield indicates that the model predicted higher than the observed.

The magnitude of the eigenvalue extracted from data set is also not linearly related to the yield. Therefore in choosing the number of eigenvalues to be retained for rotation and the subsequent regressions the objectivity of the analysis is somewhat questionable in that the investigator might impose upon the analytical technique what the underlying structure is, rather than allowing the model to reveal the structure to the investigator.

4.4.2: SHORT RAINS SEASON

An upward trend existed in the yield data. It was removed by fitting a linear equation to the data and calculating the deviations from the straight line. Thus, the yield data actually used in the analysis were deviations from the trend.

Table 25 shows the variance accounted for by the first 10 components while fig.13 shows the plot of eigenvalues against component number. Using Kaiser's (1961) criterion, only four factors were significant and explained 77.4% of the variance in the 11 raw variables. The initial factor structure was simplified by use of varimax rotation method. The variance explained by both rotated and unrotated components are shown in Table 25.

Some of the components loadings used in the regression model (17) are shown in Table 26. The first component loads heavily on minimum temperature during November to December. On the other hand the second component loads substantially on maximum temperature during-mid December to January. Also the third component loads heavily on maximum temperature and rainfall during

October to early-November, whilst the fourth component loads substantially on rainfall and maximum temperature during mid-November to early-December.

TABLE 25: AMOUNT OF VARIANCE ACCOUNTED FOR BY THE FIRST TEN FACTORS DURING THE SHORT RAINS SEASON

COMPONENT NUMBER	UNROTATED EIGENVALUE		% CUMULATIVE PROPORTION OF TOTAL VARIANCE EXPLAINED
	VARIANCE EXPAINED	% VARIANCE EXTRACTED	
1	3.00	27.3	27.3
2	2.60	23.7	51.0
3	1.72	15.6	66.6
4	1.18	10.8	77.4
5	0.84	7.6	85.0
6	0.73	6.6	91.6
7	0.32	2.9	94.5
8	0.26	2.4	96.9
9	0.17	3.9	98.4
10	0.12	2.6	99.5

TABLE 26. COMPARISON OF VARIANCE EXPLAINED BY THE UNROTATED AND ROTATED EIGENVALUES DURING THE SHORT RAINS.

FACTOR NUMBER	UNROTATED EIGENVALUE		ROTATED EIGENVALUE	
	VARIANCE EXPLAINED	% VARIANCE EXTRACTED	VARIANCE EXPLAINED	% VARIANCE EXTRACTED
1	3.00	27.3	2.63	23.9
2	2.60	23.7	2.08	18.9
3	1.72	15.6	2.06	18.7
4	1.18	10.8	1.74	15.8

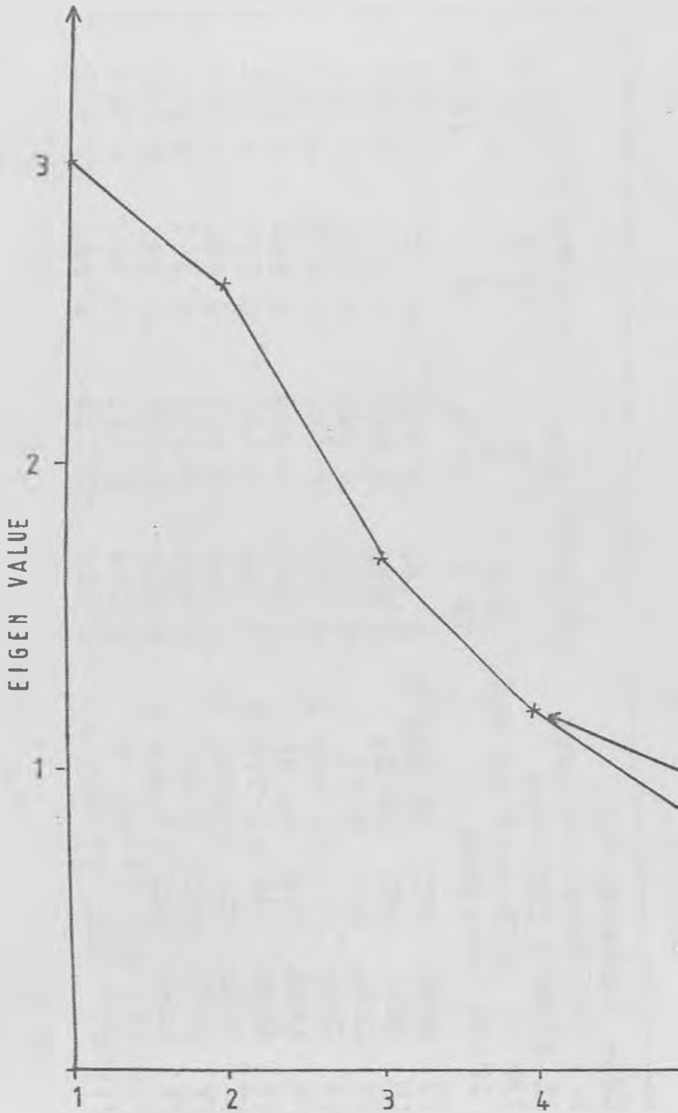
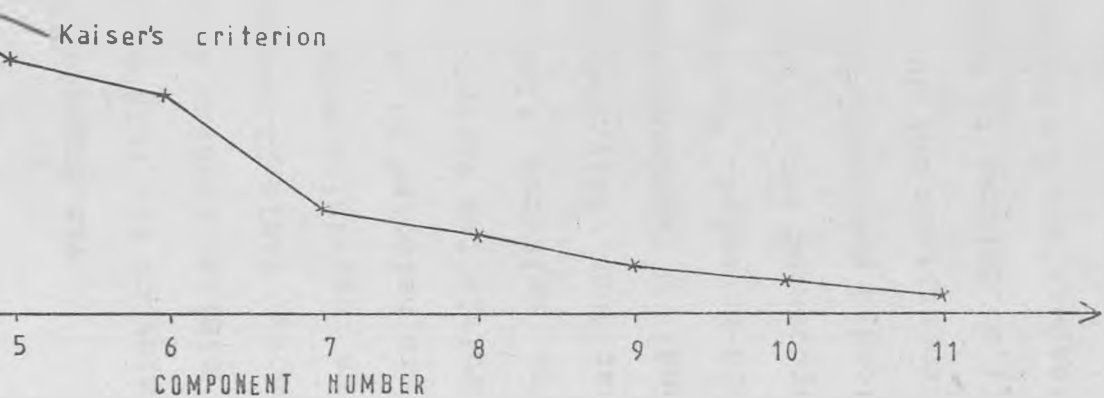


Fig13



Graph of eigen values against component number

TABLE 27: COMPONENT LOADINGS ON COMPONENTS C_1, C_2, C_3 AND C_4 AFTER ROTATION DURING THE SHORT RAINS.

VARIABLE NAME	COMPONENT LOADINGS C_1	C_2	C_3	C_4
RAINFALL OCT. 11-NOV.3	-0.116	-0.170	-0.899	-0.085
RAINFALL NOV.14-DEC.6	0.229	0.097	-0.293	-0.804
MAX. TEMP. OCT.11-NOV.1	0.016	0.007	0.961	0.139
MAX. TEMP. NOV. 8-26	0.498	0.141	0.351	0.333
MAX. TEMP. NOV.27-DEC.10	0.068	0.161	-0.005	0.921
MAX. TEMP. DEC.17-JAN.8	-0.225	0.826	0.266	0.124
MAX. TEMP. JAN. 24-31	0.067	0.905	0.061	0.122
MIN. TEMP. OCT.11-NOV.1	0.797	-0.020	-0.138	-0.241
MIN. TEMP. NOV. 2-22	0.939	0.048	0.064	-0.051
MIN. TEMP. DEC. 14-27	0.833	0.061	0.135	0.058
MIN. TEMP. DEC. 28-JAN.8	0.257	0.697	-0.058	-0.111
% TOTAL VARIANCE	23.9	18.9	18.7	15.8
ORDER OF SELECTION IN SMRA	N/S	3	2	1
% OF YIEELD VARIANCE	-	1.3	17.6	33.5

N/S - not selected; MAX - maximum; MINI - minimum and TEMP- temperature

The dependence of maize yield during the short rains on the rotated and unrotated PCs was investigated in a similar fashion as for the long rains season discussed above. Table 27 shows the order of entry of components in the regression model [21] given in Table 28. The components were selected in a reverse order of their ability to explain the variance in the 11 raw variables. Component 4 was selected first and explained 33.5% of the yield variance. This component had heavy loadings on rainfall and maximum temperature during mid-December to mid-November. The third component was second in line and accounted for 17.6% of the yield variance. This component loaded substantially once again on rainfall and maximum temperature but during early stages of the crop growth (i.e. October to early-November). The effect of maximum temperature during mid December and January was significant as displayed by the heavy loadings in the second component and its subsequent inclusion in the the regression model [21]. The influence of minimum temperature during November to December was insignificant. This led to the omission of the first component in regression equation [21].

TABLE 28: WEATHER YIELD RESPONSE: REGRESSION ESTIMATES WITH ROTATED COMPONENTS FOR KATUMANI MAIZE DURING THE SHORT RAINS SEASON.

$$E(y) = a + b_2F_2 + b_3F_3 + b_4F_4 \quad \ldots\ldots\ldots\ldots (21)$$

VARIABLE NAMES	REGRESSION COEFFICIENT	STD ERROR OF ESTIMATE.	$100R^2$	F-STATISTIC
F_2	-133.007			
F_3	289.520	519.441	54.76	4.85
F_4	-400.212			
Constant (a) 0.493				

The dependence of yield on unrotated components have been represented by regression equation [22] shown in Table 31,while the order of selection in stepwise regression is shown in Table 30. The second component was selected first and accounted for 21.6% of the yield variance. This component loaded heavily on maximum temperature from mid-December and January. It was also observed that the first component was second in line and explained 28.1% of the yield variance. This component loaded heavily on rainfall and maximum temperature from mid-October to early-November. The inclusion of rainfall in the first component assisted in explaining a higher amount of the yield variance than the second component, attesting the importance of rainfall in determining the yield variance.

TABLE 29: OBSERVED AND PREDICTED YIELDS USING ROTATED PRINCIPAL COMPONENTS

SEASON	OBSERVED YIELDS (KG/HA)	PREDICTED YIELDS (KG/HA)	RESIDUAL YIELDS (%)
1974	815	982	-20.49
1975	750	812	-8.27
1976	405	520	-28.40
1977	2250	1871	16.84
1978	1284	1600	-24.61
1979	541	817	-51.02
1980	1210	1120	7.44
1981	661	464	29.80
1982	3119	3224	-3.37
1983	1036	1121	-8.20
1984	2539	2400	5.47
1985	1306	1200	8.12
1986	2570	2410	6.23
1987	1406	1250	11.10
1988	2278	2410	-5.79
1989	2376	2600	-9.43

The negative sign on the residual yield indicates that the model predicted higher than the observed.

TABLE 30: COMPONENTS LOADING ON COMPONENTS C_1, C_2, C_7 AND C_{10} AFTER ROTATION DURING THE SHORT RAINS.

VARIABLES NAME	COMPONENT LOADINGS C_1	C_2	C_7	C_{10}
RAINFALL OCT.11-NOV3	0.945	-0.182	-0.012	-0.310
RAINFALL NOV.14-DEC.6	0.217	-0.000	0.069	-0.010
MAX.TEMP.OCT.11-NOV.1	-0.889	0.050	-0.063	-0.007
MAX.TEMP. NOV.8-26	-0.206	0.045	0.128	-0.003
MAX.TEMP.NOV.27-DEC.10	-0.309	0.173	-0.055	0.004
MAX.TEMP.DEC.17-JAN.8	-0.227	0.868	0.128	0.370
MAX.TEMP.JAN.24-31	-0.053	0.953	0.213	-0.255
MIN.TEMP.OCT.11-NOV.1	0.062	-0.001	-0.060	-0.015
MIN.TEMP.NOV.2-22	-0.059	-0.045	0.192	0.022
MIN.TEMP.DEC.14-27	-0.134	-0.007	0.131	-0.028
MIN.TEMP.DEC.28-JAN.8	0.034	0.271	0.937	0.006
% TOTAL VARIANCE	17.7	15.9	9.3	2.7
ORDER OF SELECTION IN SMRA	2	1	4	3
% OF YIELD VARIANCE	28.1	21.6	9.5	17.1

MAX - maximum; MIN - minimum and TEMP - temperature

TABLE 31: WEATHER-YIELD RESPONSE: REGRESSION ESTIMATES WITH UNROTATED COMPONENTS FOR KATUMANI MAIZE DURING THE SHORT RAINS

$$E(y) = a + b_1C_1 + b_2C_2 + b_7C_7 + b_{10}C_{10} \quad \ldots\ldots\ldots\ldots [22]$$

VARIABLE NAME	REGRESSION COEFFICIENT	STD ERROR OF ESTIMATE	$100R^2$	F-STATISIC
C_1	448.409			
C_2	468.347	391.266	76.56	8.94
C_7	215.306			
C_{10}	-289.484			

Constant (a) -76.361

TABLE 32 OBSERVED AND PREDICTED YIELDS USING THE UNROTATED PRINCIPAL COMPONENTS

SEASON	OBSERVED YIELDS (KG/HA)	PREDICTED YIELDS (KG/HA)	RESIDUAL YIELDS (%)
1974	815	915	-12.27
1975	750	790	-5.33
1976	405	500	-23.46
1977	2250	1921	14.62
1978	1284	1514	-17.91
1979	541	713	-31.79
1980	1210	1123	7.19
1981	661	521	21.18
1982	3119	3021	3.14
1983	1036	1098	-5.98
1984	2539	2419	4.73
1985	1036	1098	-5.98
1986	2570	2473	3.37
1987	1406	1312	6.69
1988	2278	2390	-4.71
1989	2376	2518	-5.98

The negative sign on the residual yield indicates that the model predicted higher than the observed.

The 10^{th} and 7^{th} component were selected in that order with each explaining 17.1% and 9.5% of the yield variance respectively. The 10^{th} component loaded substantially on rainfall from mid-October to early-November and maximum temperature from December to early-January, with minimum temperature loading heavily on the 7^{th} component during the same period. Tables 29 and 32 shows the predictive abilities of the linear model using the rotated and unrotated principal components respectively. From the above analysis, component loading A_{ij}, such that $\pm$ $0.3 \leq A_{ij} \leq 1$, had a moderate to strong dependence with variable i on component j which consequently determined the yield variance.

CHAPTER V

5.0: SUMMARY OF WORK DONE AND CONCLUSION

The crop-weather relationship in Katumani have been investigated successfully by correlation analysis and subsequent regression analysis in the first approach. Maize yields in Katumani are usually limited by lack of soil moisture resulting from low rainfall and high Potential Evapotranspiration (ETm). Because of this, an increase in soil moisture due to increased rainfall or decreased ETm is almost always reflected in a yield increase, the amount of which depends on the amount of change in rainfall or ETm. This was indicated by high positive correlations of yield with rainfall during the 10 days prior to sowing and emergence above the soil surface to appearance of the ninth leaf interphase and high negative correlations with pan evaporation during the emergence above the soil surface to tasseling interphase. Much of the yield variation could be explained by only a few weather variables, so that it was relatively easy to estimate the maize yields from weather data and input improvements.

A Yield-Weather-Technology (YWT) model was then developed by using interphase meteorological parameters and linear technology trend. The data from 1974-1988 were used to develop the YWT model whilst data for 1989, 1990 and 1991 were used to validate the model. The YWT model simulates the fluctuation of yield for the entire period and utilizes rainfall and pan evaporation from 10 days prior to sowing to flowering interphase plus linear trend as predictors. The YWT model using only two meteorological variables accounted for 83.0% of the yield variation.

This model could be used to predict the final maize yield two months in advance of the harvesting time which corresponds to the flowering of the tassel. This would give the farmers and agribusiness sector enough time to plan for food reserves and marketing strategies well in advance of the actual harvest. Caution should be taken in applying the model if there is leveling of the technology. In such a case, other time trend variables should be added to the YWT model.

In the second approach crop weather dependence was analyzed by Caprio (1966) method which employed the χ^2 statistic and was thereafter quantified by regression on principal components. The yield data was generally classified into three categories namely: good, normal and poor yield years and the climatic conditions in the good and poor years compared to those of the normal years. The degree of disproportionality was tested by using the χ^2-statistic.

Good yield years were characterized by abundance of days with high rainfall during planting, emergence to ninth leaf appearance and grain filling interphases. The same interphase periods were characterized by deficit of days with high evaporation and maximum temperature. Poor yield years on the other hand were characterized by a deficit of days with high rainfall during the floral-initiation stage when the plants demand for water is high. As such drought stress during this period had detrimental effects on crop development and the subsequent yield. This interphase was also characterized by excess days with high evaporation and maximum temperature.

The climatic variables obtained from the Zones of Significant Association (ZSA) were subjected to PCA. Four principal components were found to be significant by applying the Kaiser's (1961) criterion of eigenvalue of one or more. The four principal component explained 78.3% and 77.4% of the variance in the 15 and 11 raw variables during the long and short rains season respectively. These components loaded heavily on rainfall and maximum temperature during the beginning of the crop growing season and the vegetative growth. When the principal components were subjected to stepwise multiple regression analysis the ones with heavy loadings on rainfall and maximum temperature were selected first and the ones with heavy loadings on minimum temperature were left out. This attested the importance of rainfall and maximum temperature during the crop growth especially in the semi-arid areas where the harmful effect of deficit soil moisture on crop growth is aggravated by the presence of high temperatures.

The rotated and unrotated components gave different coefficients of determination when subjected to stepwise multiple regression analysis with maize yield as the dependent variable. The unrotated principal component explained more of the yield variance than the rotated ones. The order of selection of components into the regression model did not depend on the ability of the component to explain more of the raw variables variance. Rather the correlation coefficient between the yield and the PCs was a major determinant. Occasionally PCs with eigenvalues less than one were found to account for a higher amount of yield variance as compared to PCs with eigenvalues greater than one. The resulting regression model for the short and long rains season explained about 76.6% and 72.9% of the yield variance respectively.

The present work suffers from several limitations that are inherent in many regression based analysis of crop weather relationships. Specifically, the assumption of linearity in the crop weather relationships and the implicit assumption of the independence of the temperature and rainfall effects are not strictly valid (Katz, 1977). For example, maize yields are adversely affected by both positive and negative extremes of rainfall. While parabolic predictors have occasionally been used in regression models (e.g McQuigg, 1975),the use of linear terms was dictated by the need to limit artificial component of the explained variance (Mostek and Walsh, 1981).

5.1 RECOMMENDATIONS FOR FUTURE WORK

The results from the Chen and Fonseca (1980) model are quite promising and encouraging for two main reasons. First, the model simulated the past maize yields and gives good predictions; and second, the model can be used to assess the effect of interphase rainfall and evaporation on yield as the season progressed. However, the study is handicapped in that Chen and Fonseca (1980) model is linear contrary to most biological functions and the span of data used was short and as such no definite conclusions can be made at the present.

It is therefore suggested that work on the subject be continued and based on similar lines after more data are accumulated. Such work should start by developing the model with only climatic variables significant at 5 % level. Later on, improvements may be done. The improvements may start by introducing non-linear terms in the present model. Later the model should be enlarged to include interactions terms.

The results in the second approach are quite encouraging and promising for two main reasons. Firstly, by using Caprio (1966) method the problem of temporal data aggregation is overcomed ; and secondly, the method of PCA gives components that are orthogonal to one another thus overcoming the problem of multicollinearites among variables. However, studies of this kind are few and hence the need for more work to be done on similar lines in order to obtain results for comparison purposes.

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APPENDIX: STATISTICAL TESTS

1. MANN-KENDALL RANK STATISTIC

The Mann-Kendall rank test uses a non-parametric measure of correlation based on the ranks. Details of this test have been discussed by Kendall (1961), Mitchell et al (1966) and applied by Ogallo (1980) among others. This test has been suggested as the most powerful test when the most likely alternative to randomness is linear or non-linear trend (Ogallo, 1980). The test is applied by considering the relative values of all terms in the time series x_i is replaced by their respective ranks l_i such that each is assigned a number ranging from 1 to N that reflects the magnitude of other terms.

The statistic 'τ', is then computed using the formula shown below

$$\tau = 4 \frac{\sum_{i=1}^{N-1} n_i - 1}{N(N-1)}$$

where n_i is the number of values larger than the i^{th} value in the series subsequent to its position in the time series of N variables.

The statistic approaches closely to a normal distribution,

$$N\left\{0, \frac{4N+10}{9N(N\ 1)}\right\} \text{ for N larger than 10.}$$

The value of τ can be used to asses the significance of trend by comparing with the statistic τ_g defined by

$$\tau_g = \pm Z \frac{4N+10}{9N(N-1)}$$

2. DURBIN-WATSON STATISTIC

Consider the regression model given by

$$Y_i = \alpha + \beta_1 f_{i1} + \beta_2 f_{i2} + \varepsilon_i , \quad i = 1,2, \ldots\ldots ,n$$

Let us assume that the error terms ε_i are independently distributed $N(0,\sigma)$. The error term are tested for normality by the graphical approach. In this approach the cumulative residuals are plotted on a normal probability paper. If a straight line results, the residuals are normal.

Errors may be associated in time, so that those adjacent in time have the correlation ρ. Further if the special model holds, in which errors two units apart have correlation ρ^2. Those three units apart ρ^3....., those k units apart ρ^k, it is possible to test for independence. A test appropriate to testing for independence disturbances in a regression equation has been worked by Durbin and Watson (1950)

Durbin-Watson test, is based on thee statistic

$$d = \frac{\sum_{t=2}^{n} \left(U_t - U_{t-1} \right)^2}{\sum_{t=1}^{n} U_t^2}$$

where

$U_t = Y_t - \hat{Y}_{t-1}$, $t = 1, 2 \ldots\ldots ,n$ ar e the residuals in time order. Further details on this approach are given in many standard textbooks on econometric models and methods.

3. VON NEUMANN RATIO

The existence of any trend in weather parameters used in the regression model have been investigated by computing the Von Neuman ratio (Hart, 1942). Thus the statistic is the ratio of the mean square successive difference to the variance. It is usually symbolized by δ^2/s^2, and for a series of T observations x_1, x_2, ...,x_T it is thus defined as

$$\frac{\delta^2}{s^2} = \frac{\sum_{2}^{T} \left(X_t - X_{t-1}\right) / (T-1)}{\sum_{1}^{T} \left(X_t - \bar{X}\right)^2 / T}$$

where T is the total number of observations.

TABLE A: RESULTS OF MANN-KENDALL RANK TEST, DURBIN-WATSON TESTS, AND VON-NEUMANN RATIO FOR THE HISTORICMAIZE YIELDS AND CLIMATIC VARIABLES.

(a)	Short rains season	
1.	Number of years of data used	15
2.	Mann-Kendall rank test	
	Statistic τ	-0.514
	Statistic τ_g at 5% level of significance	±0.37
3.	Durbin-Watson test	
	Statistic d	1.97
	Significance at 5% level	1.23
4.	Von Neumann ratio variables	
	RF_{prf}	2.24
	$EVAP_{prf}$	1.11
	Significance at 5% level	1.36
(b)	Long rains season	
1.	Number of years of data used	13
2.	Mann-Kendall test	
	Statistic τ	-0.179
	Statistic τ_g at 5% level of significance	±0.411

AGRO. 4

KENYA METEOROLOGICAL DEPARTMENT

TEN DAYS AGROMETEOROLOGICAL REPORT FOR THE STATE & YIELD OF THE CROPS

COUNTRY KENYA DISTRICT MACHAKOS STATION KATUMANI DATE OF OBSERVATION 20/11/1986 NAME OF OBSERVER MET. STAFF.

Kind of Observation / Agr. Crops	Phenological Phase at the Date of Observation	General Assessment of the State in Marks	Density of The Sowing Area		Height of the Plants in CM	Damage From Adv. Met. Phenomena				Damage From Pests & Diseases				Extent of Spreading of the Weeds in Marks	Yield of the Crops	
			Number of Plants per Hectare or per 1 M^2	Number of Stems per 1 M^2		Name of The Met. Phenomena	Date & Duration	Kind of the Damage	Extent of the Damage in %	Name of The Pests or Diseases	Date of the Damage	Kind of the Damage	Extent of the Damage in %		Dates of Harvesting	Yield
KATUMANI MAIZE	Flowering	4	—	—	—	—	—	—	—	NIL	—	—	—	5	—	—

AGRO. 1

KENYA METEOROLOGICAL DEPARTMENT

MONTHLY PHENOLOGICAL REPORT FOR ANNUAL CROPS

COUNTRY......KENYA...... DISTRICT......MACHAKOS...... STATION......KATUMANI......

FIELD......1...... CROP......MAIZE...... VARIETY......KATUMANI...... DATE OF SOWING..............

YEAR......1996...... MONTH......NOVEMBER...... NAME OF OBSERVER......[illegible]......

Date of the Observation	Phenological Phase	Number of Plants with the Features of the given Phase — REPLICATIONS 1	2	3	4	Total	Number of Plants with the Features of the given Phase in % from the 40 Plants
7/11/1986	Tasseling						25%
14/11/86	Tasseling						35%
28/11/86	Flowering						10%

FIELD WORK CARRIED OUT ON THE SAME FIELD: 1)......[illegible]......

2)..

3)..

4)..