MAIZE YIELD PREDICTION USING SEASONAL WEATHER FORECASTS AND A CROP GROWTH SIMULATION MODEL

By

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ABSTRACT

Maize production in marginal tropical regions is at great risk from rainfall variability. Farmers would benefit from the ability to forecast production likelihood. In this study we sought to develop a simple maize production decision support tool for Masvingo by using seasonal weather forecasts and a crop production model to forecast maize yields prior to the season. Downscaled ENSO-based statistical seasonal forecasts from RAINMAN were tested against those downscaled from a Global Circulation Model (GCM) using Climate Predictability Tool (CPT). RAINMAN was found to perform better at forecasting total seasonal rainfall than CPT. RAINMAN predictions were 69 % correct in all rainfall categories for the 1991/92 - 2006/07 seasons as opposed to 44 % for CPT ($p< 0.05$). RAINMAN had a higher hit rate than CPT and was not biased to any rainfall category while CPT was biased towards the normal and dry/below normal rainfall categories. Monthly rainfall predictions by RAINMAN were validated. The tool explained 65 % to 81 % ($p<0.05$) of the rainfall variability of the agricultural season (October to April), except for December and March where it explained 37 % and 48 % of the variability, respectively. We generated monthly weather series for the five phases of the Southern Oscillation Index (SOI). These formed the climatic scenarios used to run the crop production model (**AquaCrop**).

Simulated agrometeorological scenarios included three planting dates, optimal and poor fertility levels, and three maize cultivars. Simulated maize yields ranged from 1.2 t/ha to 5.9 t/ha. Average yields were low for poor fertility levels. 100-day (early maturing) maize cultivars produced better yields under poor fertility levels. 140-day (late maturing) maize cultivars attained highest yields (5.9 t/ha) for good rain conditions (neutral, rising, and positive SOI and (20 %) probability of rainfall occurrence) and minimum yields (1.2 t/ha) under poor fertility. 100-day and 140-day maize cultivars produced higher yields when planted late (7 December). 125-day cultivars produced better yields when planted early (29 October) or on the medium planting date (16 November). The variance in yields under the given agrometeorological scenarios point towards the importance of considering maize cultivar and planting date selection. It was clear that maize production at Masvingo should preferably be done under good fertility.

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ACRONYMS

AREX:	Agricultural Technical and Extension Services
B:	Biomass
CC:	Canopy Cover
CPT:	Climate Predictability Tool
CSI:	Critical Success Index
Dr:	Root zone depletion
DSSAT:	Decision Support System for Agrotechnology Transfer
ETo:	Reference Evapotranspiration
ENSO:	El Nino Southern Oscillation
FAO:	Food and Agriculture Organisation
FAOSTAT:	Food and Agriculture Organisation Statistics
GDD:	Growing Degree Day
GCM:	Global Circulation Model
HI:	Harvest Index
ITCZ:	InterTropical Convergence Zone
JA:	July- August
JFM:	January- February- March
Kcb:	Crop transpiration coefficient
Ke :	Crop evaporation
Kr :	Reduction coefficient
Ks :	Stress coefficient
KW:	Kruskal- Wallis
KS:	Kolmogorov-Smirnov
LAI:	Leaf Area Index
LEPS:	Linear Error in Probability Space
MAE:	Mean Absolute Error
MAGM:	Master of Science in Agricultural Meteorology
MAPE:	Mean Absolute Percentage Error
MSE:	Mean Square Error

NMSs:	National Meteorological Services
OND:	October- November- December
RCM:	Regional Circulation Model
RMSE:	Root Mean Square Error
SOI:	Southern Oscillation Index
SS:	Skill Score
SSTs:	Sea Surface Temperatures
Tbase:	Base temperature
Tavg:	Average temperature
Tr:	Crop Transpiration
Tupper:	Upper temperature limit
V.C:	Coefficient of Variation
WP:	Water Productivity
Wr:	Water stored in root zone
Y:	Yield
ZMSD:	Zimbabwe Meteorological Services Department

CHAPTER 1: INTRODUCTION

1.0 Introduction

In water limited environments, rainfall variability is the single most important factor in agricultural production and hence risks (Hansen, 2002). Management strategies developed to buffer against the uncertainties of rainfall are a common feature in dryland agricultural regions. Farmers need information that is relevant at the field scale, and that is expressed in terms of impacts and management implications within the systems they operate (Hansen, 2002). In practice however, such specific and detailed information is rarely available to the farmer. Instead, operational seasonal forecasts are often given for a large area. The content provided by these forecasts is not particularly useful in agricultural production terms.

Recent advances in the application of climate prediction to agriculture suggest potential for improved risk management strategies, enabling producers to better tailor management decisions to the season (Hansen, 2002). Farmers can use site specific seasonal forecasts to mitigate unwanted impacts or take advantage of favourable conditions. By providing advance information with a sufficient lead time to adjust critical agricultural decisions, seasonal forecasts have significant potential to contribute to the efficiency of agricultural management and to food and livelihood security (Appipattanavis et al., 2010). Integrating crop simulation models with seasonal climate forecast tools is a perceived opportunity to add value to seasonal climate forecasts for agriculture (Hansen, 2004).

The need for site and system specific information has been addressed in a number of research studies using crop models (Hansen, 2004). Often yield likelihoods are based on historical weather conditioned upon seasonal weather forecasts (Hammer et al., 2001). Hammer et al., (1996) used a wheat simulation model to determine the value of seasonal forecasting to crop management in northeast Australia using phases of the Southern Oscillation Index (SOI). Using the Decision Support System for Agrotechnology Transfer (DSSAT) crop simulation models, Jones et al., (2000) estimated the economic returns to decisions based on predictions of phases of the El Nino Southern Oscillation (ENSO) and terciles of growing season rainfall in southeast USA. They showed that the optimal mix of rainfed crops differed among ENSO phases, and that the modification of maize management based on rainfall terciles returned higher profits than the optimization based on only the phases of ENSO. Related studies have been carried out all over the world with relative success (Shin, 2009; Frassie et al., 2006; Baigorria et al., 2008).

Phillips et al., (1998) studied El Niño Southern Oscillation (ENSO) related maize yield variability in Zimbabwe, showing a significant relationship between ENSO and Zimbabwean maize yields. However, despite perennial food shortages, few studies have attempted to apply the best possible forecast methods and tailor forecast products to the expressed needs of farmers in the marginal areas of Zimbabwe.

1.1 Background

Zimbabwe lies between latitude 15º and 23º S and longitude 25º and 33º E, and covers 390,757 square kilometers. Agricultural land holds 85 % of the land resources in the country. 64 % of the total land area in Zimbabwe lies within agro-ecological regions IV (37 %) and V (27 %) which are marginal for rainfed crop production (Matarira et al., 2004). It is therefore apparent that studies carried out to improve decision making in marginal farming areas is critical for Zimbabwe.

1.1.1 Climate and rainfall

Zimbabwe lies entirely in the tropics (Hussein, 1987). The rainy season (mid October to late March) varies considerably over the country. Low rainfall is found in those areas where considerable rainfall variability is also found. High frequencies of drought coupled with considerable rainfall variability are usually associated with the most fragile ecosystems in the south of the country (Regions IV and V) (Ngara and Rukobo, 1999). Year to year rainfall variability in Zimbabwe has been associated with the El Nino Southern Oscillation (ENSO) (Matarira and Jury, 1992), hence the possibility of forecasts.

1.1.2 Soils and geology

Another factor important to crop production in Zimbabwe is soils. The soils in Zimbabwe are classified under eight subgroups based on soil depth, texture, chemistry and structure. Soils are closely related to the underlying parent rocks, such that soils from igneous and metamorphosised igneous rocks occupy 65 % and sedimentary origins occupy 25 % of the country's land area (Nyamapfene, 1991). Grant (1970) observed that many crops on the sandy soils in communal lands reveal multiple nutrient deficiencies of Nitrogen (N), Phosphorous (P), Sulphur (S), Magnesium (Mg) and Potassium (K).

1.2 Objectives of the study

The overall objective is to apply available seasonal weather forecasting and crop production simulation tools so as to improve agricultural decision making. The specific objectives are:

- To test the utility of downscaled ENSO-based statistical seasonal forecasts from RAINMAN against those downscaled from a GCM using CPT (Climate Predictability Tool).
- To run simulations using a crop growth simulation model and downscaled weather forecasts for a variety of scenarios.
- To develop and provide guidelines for a decision support tool for maize production at Masvingo.

1.3 Study area

The location under study is Masvingo. Masvingo is found in south-east Zimbabwe. It is located in agro-ecological region IV, where rainfall is inherently variable and unreliable. Masvingo has an altitude of 1100 m above sea level. Mean annual rainfall in agro-ecological region IV ranges between 400 and 650 mm, with Masvingo averaging 641 mm annually. Mean monthly maximum temperatures range from 25-29 ºC. Masvingo has a predominantly semi-arid climate

(Chenje et al., 1998). Soils in Masvingo are predominantly of a moderately deep coarse sandy loam (Phillips et al., 1998). Although the area is semi arid and marginal for maize production, a large proportion of the population still grows maize for food.

1.4 Study justification

Probabilistic crop yield forecasts are directly relevant to farmers' livelihood decisions and, at a different scale, to early warning. Masvingo is found in a marginal drought prone region in which a large proportion of the population grows maize despite its drought intolerance (Chenje et al., 1998). Investigating the relationship between various climatic scenarios in Masvingo and maize yields will be helpful to farmers. Farmers will be better prepared to take full advantage of potentially good rainfall seasons and to manage prospective poor rainfall seasons. Policy makers will be in a better position to ease any food security risk experienced by the region.

1.5 Scope of the Research

The study seeks to derive a decision support tool for the farming of maize at Masvingo. Considering that rainfall variability is the single most important factor in rainfed maize production (Hansen, 2002), a downscaled seasonal climate forecasting tool (RAINMAN) (Clewett, 1995) will be tested for Masvingo. The tool will be tested against predictions downscaled from a Global Circulation Model (GCM) by Climate Predictability Tool (CPT) (Ndiaye and Mason, 2006). RAINMAN will be integrated with a crop production simulation model (**AquaCrop**) (Stetudo et al., 2009) to produce maize yield predictions for various climatic and agrometerorological conditions. A decision support tool for maize production for Masvingo will be developed based on the results.

Within the framework of the research, some assumptions are made. The assumptions made are: **AquaCrop** has been tested and validated for locations similar to Masvingo, therefore **AquaCrop** can be applied to the study area without reservation (Heng et al., 2009; Hsiao et al., 2009); temperature and reference evapotranspiration (ETo) do not vary much seasonally, therefore, historical averages can be used for crop simulations. Climatological data is homogeneous and accurate.

1.6 Benefits of the study

The project has the potential to provide a quick and efficient concentration of information at a central point to enable quick decision making. The development of an easy to use decision support tool will help farmers decide on the best practices to partake during a particular season e.g. planting dates, maize cultivars to plant, and appropriate field management practices. Early maize yields forecasts enable planning for storage and sale of produce as well as for supplements in case of a poor yield forecasts. Aid organizations can plan for relief operations.

1.7 Thesis structure

The thesis comprises 5 chapters. **Chapter 1** gives an introduction of the study, its justification, objectives, and the general character of the research. **Chapter 2** reviews the available literature on the study. A critical review of previous research work on related topics is performed. An in-depth description of variables key to the study is found in this chapter. **Chapter 3** lays out the materials and methodology used to carry out the study. The results obtained and the discussions of the results are incorporated in **Chapter 4. Chapter 5** gives the recommendations and conclusion.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

If a reliable seasonal climate forecast is available at the beginning of a cropping season, the upcoming season's crop yield amount can be estimated reasonably well by using a dynamic crop production model. This will help farmers and/or crop decision-makers to prepare for the crop growing season (Jones et al., 2000; Hansen, 2002). A crop production model needs a season-long weather dataset to simulate a crop yield amount. A skillful seasonal forecast is necessary (Shin et al., 2006; Baigorria et al., 2007). The seasonal climate forecast should capture the high-frequency modes of weather/climate variability properly to use it in a crop model for a reliable yield projection. Since Zimbabwe has a strong teleconnection to the El Nino Southern Oscillation (ENSO) (Phillips et al., 1998; Cane et al., 1994), it is practical to develop a climate-based decision support system that uses the ENSO-based historical weather data to implement a probabilistic yield risk forecast for maize. The yield forecast should be based on location, planting date, soil type, maize variety, fertility and ENSO-based climate scenarios.

This chapter will review literature on ENSO-based yield forecasting. RAINMAN, an ENSO-based probabilistic weather forecasting tool will be discussed along with CPT; a downscaled dynamic weather forecasting tool also used by the Zimbabwe Meteorological Services Department (ZMSD). The crop modeling process will be described along with one major crop production model favoured by researchers and one proposed for this study. The chapter will however begin by reviewing the relationship between maize and the physical environment modeled by the crop production models.

<u>PART 1: MAIZE AND THE ENVIRONMENT</u>

Maize productivity is mainly governed by water availability, climate, soil characteristics and agronomic practices.

2.1 Maize phenology and development

For maize, the duration of growth stages and length of total crop season are climate dependent, and hence area specific. They also depend on the crop variety and planting date which determines the temperature regime of the cropping period. Since development is highly dependent on temperature, and since maize is grown from low lands to over 3500 m altitude in the tropics, it is impossible to generalize about the development patterns and time to maturity (Norman et al., 1984). However, Raes (1996) distinguished four main growth stages for annual crops which include: (1) initial stage- period from germination through establishment, showing a slight increase in vegetative cover, covering about 10 % of the soil; (2) crop development stage- period from end of initial stage to full ground cover, characterized by rapid increase in vegetative cover; (3) mid-season stage- full cover to start of maturity, senescence commences and ground cover is almost constant throughout this period; and (4) late-season stage- which is the time from maturity to harvest.

2.2 Maize/climate relations

2.2.1 Rainfall

Maize is an efficient user of water in terms of dry matter production such that among cereals, it is potentially the highest yielding (Norman et al., 1984). Frequency and depth of rain has a pronounced effect on grain yields. Initially, the moisture requirement is low and builds up to a maximum at the flowering stages. Thereafter, the moisture requirement decreases progressively to maturity (Sithole, 2003). Water requirements of a long season variety (150-day) ranges from 600 to 1000 mm of well distributed rainfall for the growing period. A medium maturity grain crop (110-140 day) requires from 500 to 800mm depending on climate (Sithole, 2003).

Water deficits at different stages of growth have different effects on maize yields. Soil moisture during flowering and early grain formation seems particularly critical at determining yield (Salter and Goode, 1967). East African work suggests that there are three main periods when water is most essential- germination, fertilization, and grain filling (Semb and Garberg, 1969). They state that after germination, maize can survive with very little water for some time. Stress-induced delays in silking lead to loss of synchrony in development of silks and tassels with particularly adverse effects. Ochse et al., (1961) suggest that in very general terms, optimum rainfall conditions for maize are a little rain at the start of the growth period, soaking rains every 4 to 5 days from the end of the first month up to about 3 weeks after flowering and a gradual tapering off of rain until harvest. The other limitation to yield is sensitivity to water stress. Where water stress cannot be avoided, maize is replaced by sorghum or pearl millet (Norman et al., 1984).

2.2.2 Crop response to water stress.

Plant water stress can have major impacts on plant growth and development. When it comes to crops, plant water stress can be the cause of lower yields and possible crop failure. Early recognition of water stress symptoms can be critical to maintaining the growth of a crop. The most common symptom of plant water stress is wilting. Drying to a condition of wilt will reduce growth. Low water availability can also cause physical limitations to a crop. During moisture stress, stomata close to conserve water. This also closes the pathway for the exchange of water, carbon dioxide, and oxygen resulting in decreases in photosynthesis (Bauder, 2003).

The processes of photosynthesis, respiration, and translocation are affected by water stress, partly through concentrations of active molecules in the fluids within the plant. Water stressed crops may redistribute assimilates towards the root system at the expense of vegetative growth and economic yield development, so as to increase the rate of root growth into deeper layers of the soil profile thereby increasing the amount of stored moisture the plant has access to (Bauder, 2003). Raes et al., (2009) assert that crop responses to possible water stress, which can occur at any time during the crop cycle, occur through three major feedbacks: (1) reduction of the canopy expansion rate (typically during initial growth), (2) acceleration of senescence (typically during completed and late growth), and (3) closure of stomata (typically during completed growth). They go on to suggest that water stress of particular relevance may also affect the water productivity parameter and the harvest index of a crop.

2.2.3 Temperature

Maize shoots elongate linearly with time, with a temperature optimum of about 30 ˚C and showing negligible elongation at 9 ˚C or above 40 ˚C (Norman et al., 1984). Photosynthetic rates peak at 30-40 ˚C; they are negligible at 44-50 ˚C. Rates of leaf emergence and lamina expansion also peak at about 30 ˚C (Norman et al., 1984). Duncan (1975) postulated that it would be expected that the greatest maize growth be in environments conducive to leaf temperatures of 30-33 ˚C during the day but with cool nights. Within the tropics, one would therefore expect higher dry matter yields in the wet and dry and the cool tropics than in the wet tropics, which has less diurnal variation and might be expected to produce less total growth.

Flowering in tropical maize is accelerated by short days. Critical day lengths are 14.5-15 hours whereas maize of a temperate origin is less sensitive to day length. Time to flowering is accelerated by rising temperature. Actual grain filling period for tropical maize is typically 20-30 days (Norman et al., 1984). The numbers of grains that fill depend on temperature, both directly through fertilization and photosynthate production, and indirectly through auxiliary tillering at low temperature. In the tropics, numbers of grains set per cob vary by only 10 % according to temperature, but tillering may change the number of grains per plant by 50 % (Norman et al., 1984). Maize is very sensitive to frost.

2.3 Maize/soil relations

While maize is adapted to a wide variety of soils in the tropics, ranging from sands to heavy clays, most maize is grown on well-structured soil of intermediate texture (Sandy loams to clay loams), which provide adequate soil water, aeration and penetrability (Norman et al., 1984). Although in deep soils the roots can reach a depth of 2 m, the highly branched system is located in upper 0.8 to 1 m and about 80 % of the soil water uptake occurs in this zone. In addition to soil water and nutrient status, the maize root development is strongly influenced by textural and structural stratification (Sithole, 2003).

Poor soil structure restricts root development and depresses yields of maize. High bulk density affects the growth of maize. Soil erosion has also been known for the deterioration of infiltration rate and soil structure. Maize yields on eroded slopes decline with slope angle and quantity of soil eroded. Where excessive erosion has occurred, maize yield reduction cannot be corrected by fertilizer application (Duncan, 1975).

PART 2: SEASONAL FORECAST TOOLS AND CROP YIELDS

2.4 Seasonal forecasting

For the sake of producing seasonal rainfall forecasts, the Zimbabwe Meteorological Services Department (ZMSD) divides the country into three homogeneous regions. These regions are determined through use of a statistical technique known as principal components regression (PCR). The regions differ slightly in aerial extent for the three-month averaged periods of October to December (OND) and January to March (JFM). Forecasts are made for three probable categories of below-normal (dry conditions), near-normal (around the average), and above-normal (wet conditions) for each region. A probability is assigned to each category, indicating the chance of the particular category to occur in each region during the target season. This is shown in Fig. 2.1 for the 2005/6 season.

An example is Region 3 (in which Masvingo lies) of the OND map in Figure 2.1 (a). There is a 35 % chance that the average rainfall for Region 3 will be above normal, 40 % chance that it will be in the normal range and a 25 % chance that it will be below normal. Any seasonal rainfall forecasts for this region are therefore also forecasts for the district. It is also possible to forecast rainfall at stations within the district when better resolution is required. Among other tools, the ZMSD also uses Climate Predictability Tool (CPT) to make station specific seasonal weather forecasts.

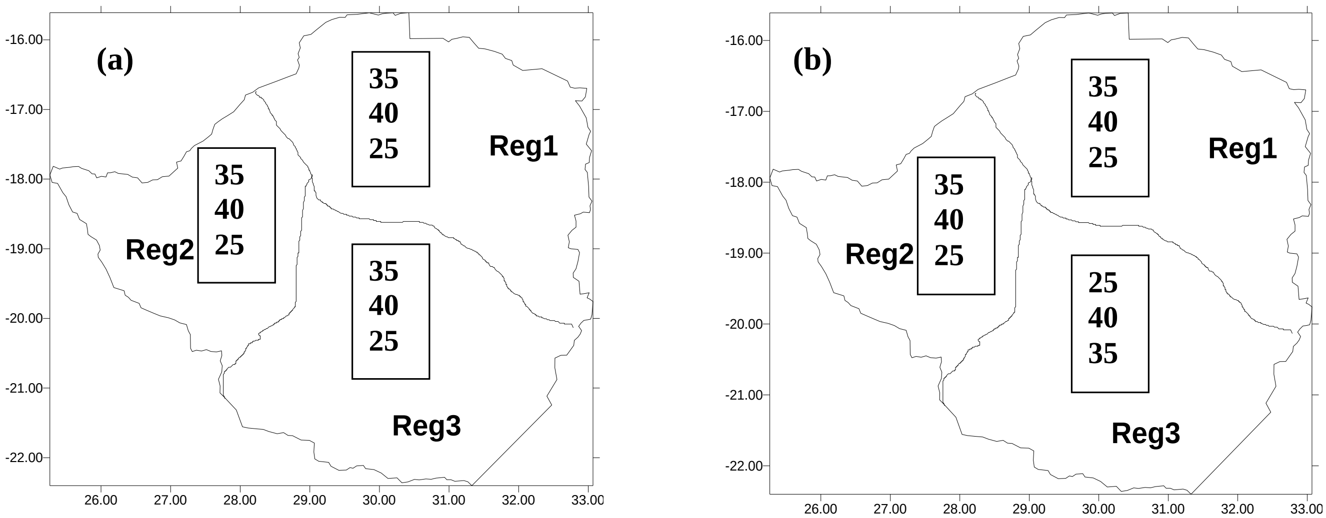


Figure 2.1: Forecast for the (a) first half (OND 2005), and (b) second half (JFM 2006) of the 2005/06 rainfall season

2.4.1 Climate Predictability Tool (CPT)

CPT is a software package developed by the International Research Institute for Climate and Society (IRI) designed for making seasonal climate forecasts. CPT was developed primarily to enable forecasters at National Meteorological Services (NMSs) in Africa to produce updated forecasts for their country (Ndiaye and Mason, 2006).

There are two main approaches used to generate seasonal forecasts: using large scale models of the global atmosphere, known as general circulation models (GCMs), or using a statistical approach to relate seasonal climate to changes in seas surface temperatures (SSTs), such as those associated with El Nino. Predictions by the GCMs are large scale and are often not relevant for specific locations. CPT adjusts the GCM predictions so that they are applicable locally. This process is called downscaling and involves a statistical correction to GCM predictions.

All analysis methods require two datasets: an “X variables” or “X Predictors” dataset which consists of ocean-atmosphere parameters being used to predict future weather e.g. Sea Surface Temperatures (SSTs); and a “Y variables” or “Y Predictands” dataset which consists of the weather parameter being predicted by the model e.g. rainfall. CPT takes into account local variations in altitude, and teleconnections between the major climate indicators (Ndiaye and Mason, 2006).

2.4.1.1 Advantages of CPT

- CPT forecasts can be made in a matter of hours; this eliminates the length and cost of forecasting workshops.
- CPT makes rigorous tests for estimating skill levels. And adjusts the forecast accordingly. The quality of the forecast is improved and artificial skill is avoided.
- Forecasts are produced in a variety of formats, and detailed information is provided so that the forecast can be communicated to the end users in easy to understand terms (Ndiaye and Mason, 2006)

2.4.2 RAINMAN

RAINMAN is a seasonal climate forecasting system developed by The Queensland Department of Primary Industries in Australia. It performs probabilistic prediction of rainfall at a seasonal lead time based on discrete categories or ‘‘phases’’ (i.e., positive, rapidly rising, negative, rapidly falling and neutral; falling, rising, and neutral) of the Southern Oscillation Index (SOI) and/or SSTs. The set of past years falling within a given category serve as equally probable analogs for predicting a distribution of rainfall outcomes conditioned on the observed SOI phase and/or SSTs. RAINMAN was developed in a series of workshops with strong support from Indonesia, Zimbabwe and India (George et al., 2003). The tool has monthly rainfall data from over 12,000 stations from Australia and locations throughout the world. Some 60 % of these locations have more than 50 years of good data and 10 per cent have more than 100 years of good data (Clewett, 1995). RAINMAN aims to develop knowledge and skills for managing climate variability in agriculture by analysing effects of ENSO on rainfall to derive probability-based seasonal climate forecasts.

RAINMAN analyses follow accepted scientific conventions by applying several statistical tests to seasonal forecasts so that: (a) users have some guidance regarding the statistical reliability of the forecast information, and (b) duty of care is discharged in providing forecast information to users. The statistical tests used in RAINMAN are:(1) the Kruskal-Wallis (KW) test as used by Stone and Auliciems (1992), the Kolmogorov-Smirnov (KS) test as described by Conover (1971) for comparing two probability distributions, and (3) the LEPS (Linear Error in Probability Space) skill score test as proposed by Ward and Folland (1990). The KW test is given precedence over the KS test. Results of analyses carried out by Clewett et al., (1992) show that the Forecast Phase System of RAINMAN has considerable skill for the period October to March (OND & JFM), using a one month lead time

2.4.2.1 Advantages of RAINMAN

- Meeting the needs of people by producing a package that is comprehensive, easy to use, locally relevant, and addressing the problems that people face in managing climatic risk by:

(a) Targeting the required location, season and lead-time.

(b) Providing clear information about risk and whether forecast skill is present or not

- Seasonal climate forecasts are perceived to be very useful in agricultural management and thus RAINMAN is seen as useful because it empowers people with the necessary knowledge and skills to apply seasonal forecasting technology to their management decisions.
- The compact disc technology used enables fast, reliable and comprehensive delivery of information, the computer programming software is at the forefront of technology, the combination of data, analytical capacity, tutorials and reference information give the product balance, and the package mix can grow to take on new information (e.g. streamflow and runoff) and new climate forecasting methods as the science improves (Clewett, 1995).

2.4.3 Forecasting and model selection

In the Forecasting procedure, an option is given to specify a number of data points to hold out for validation and a number of forecasts to generate into the future. The data which are not held out are used to estimate the parameters of the model, the model is then tested on data which has been held (validation period), and forecasts are then generated using combined data from the estimation and validation periods (Legates and McCabe, 1999).

In general, the data in the estimation period are used to help select the model and to estimate its parameters. Forecasts made in this period are not completely "honest" because data on both sides of each observation are used to help determine the forecast. The one-step-ahead forecasts made in this period are usually called fitted values (They are said to be "fitted" because software estimates the parameters of the model so as to "fit" them as well as possible in a mean-squared-error sense.) The corresponding forecast errors are called residuals. The residual statistics (Mean Square Error (MSE),Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) etc) may understate the magnitudes of the errors that will be made when the model is used to predict the future, because it is possible that the data have been overfitted i.e., the model may have inadvertently fitted some of the "noise" in the estimation period (Legates and McCabe, 1999).

The data in the validation period are held out during parameter estimation. One-step-ahead forecasts made in this period are often called backtests. Ideally, these are "honest" forecasts and their error statistics are representative of errors that will be made in forecasting the future. However, if one tests a great number of models and chooses the model whose errors are smallest in the validation period, they may end up overfitting the data within the validation period as well as in the estimation period. If the model has good predictive ability and if the data have not been badly overfitted, the error measures in the validation period should be similar to those in the estimation period (Legates and McCabe, 1999).

2.5 Linking forecasts tools and crop models

Predictions of rainfall fluctuations throughout the season offer farmers the opportunity to improve agricultural risk management. By providing information about growing season characteristics in advance of the season, agricultural decision making is improved. However, climatic forecasts are more useful to farmers when they are translated into probabilistic forecasts of production and outcomes of management alternatives. A mismatch between the spatial and temporal scale of dynamic climate models and crop simulation models must be addressed if crop models are to contribute to the task. Hansen and Indeje (2004) proposed methods for linking crop models with seasonal climate forecasts. The methods include classification and selection of historic analogs, stochastic disaggregation, direct statistical prediction, probability-weighted historic analogs and use of corrected daily climate model output.

Daily weather inputs for the crop model can come directly from the daily output of a dynamic atmospheric general circulation model or high-resolution regional climate model (RCM) nested within GCM output fields. An alternative to using daily climate model output is to use lower-frequency (e.g. monthly or seasonal) predictions. A disaggregating process to produce realizations of daily weather as input to the crop model can be applied to the monthly or seasonal predictions. What has been the "standard approach" for some time is to categorize the observed predictor variables (e.g. ENSO phases), and use the predictor category to select sets of analog years from the observed station time series as input to the crop model. The potential information pathways in Figure 2.2 suggest several potential approaches for linking dynamic crop simulation models with climate predictors via dynamic climate models (Hansen and Indeje, 2004).

2.5.1 Historical analogues approach

The most common approach to using seasonal forecasts with agricultural models has been to divide the range of variability of climatic predictors into a small set of categories or "phases" based on some objective criterion, then select the set of past years falling within a given category as equally-probable analogs (pathway in Figure 2.2). Historic analogs are easily interpreted at any spatial and temporal scale for which data are available, and provide weather series at individual stations for driving crop simulation models (Hansen and Indege, 2004).

Distributions of climatic realizations or simulated production for the set of analog years associated with a given category provide an intuitive probabilistic interpretation. To date, most efforts to predict crop response at a seasonal time scale, and most quantitative studies of agricultural decisions tailored to seasonal climate forecasts have used the historic analogues approach. The historic analogues are conditioned with categorical indices based on sea surface temperatures or the Southern Oscillation Index (SOI), both associated with ENSO (Hansen and Indege, 2004). RAINMAN uses this approach.

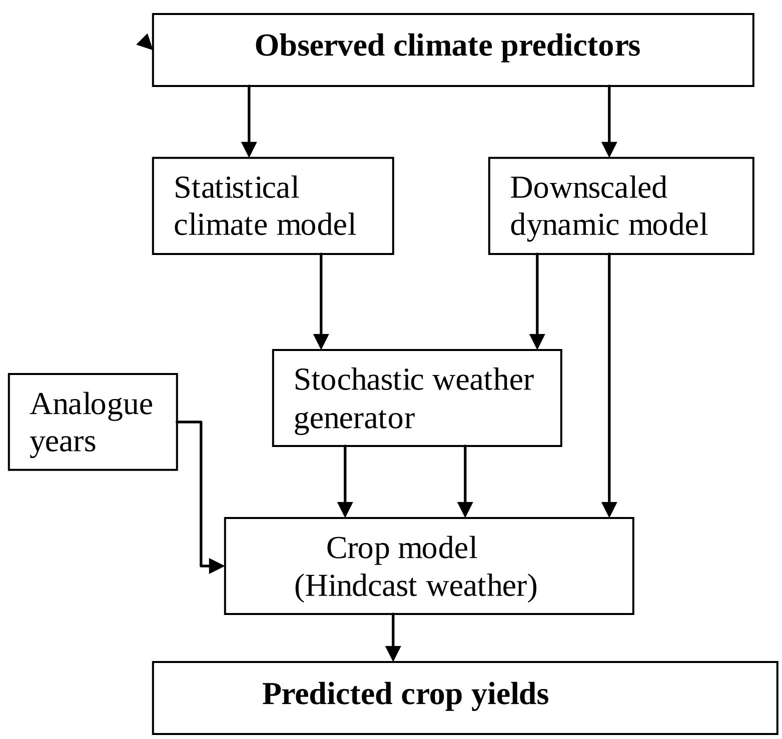


Figure 2.2 Potential pathways to localized simulation-based predicted crop yields from large scale observed climate predictors (adapted from Hansen and Indeje, 2004).

2.5.2 El Nino Southern Oscillation (ENSO).

ENSO is associated with rainfall variability in Southern Africa and Zimbabwe (Phillips et al., 1998). The El Nino phenomenon which occurs every 3 to 8 years involves changes in the circulation system of the atmosphere (Ngara and Rukobo, 1999). In broad terms, the pressure near Australia increases while sea surface temperatures (SSTs) decrease. The combined effect of these changes is the tendency for trade winds to ease in strength; cutting off a major source of moisture to the tropical monsoons. This tends to reduce rainfall over Southern Africa. The reduction of rainfall is usually not uniform and varies with seasons (Ngara and Rukobo, 1999). The reversal of the Tahiti (18º S, 150º W) and Darwin (12º S, 131º E) pressure gradient as part of the Southern Oscillation is associated with the intensification of El Nino events, hence the term ENSO episode. The pressure swings between these two places is known as the Southern Oscillation Index (SOI). The SOI monitors the difference in surface pressure across the Pacific Ocean and as such is useful for keeping track of El Nino episodes (Ngara and Rukobo, 1999).

2.5.3 The Southern Oscillation Index (SOI).

The strength of the Southern Oscillation is measured by the difference in air pressure between Darwin and Tahiti. The SOI usually ranges from - 30 to + 30. Extreme phases of the Southern Oscillation usually last for about nine months once they have become established. Dry spells often break when the SOI rises rapidly from extremely low values even if it does not become positive, for example, when it changes from - 15 to 0 (Clewett et al., 1992). When the Southern Oscillation Index is strongly positive or rising, the trade winds blow strongly across the warm Pacific picking up plenty of moisture; above- average rainfall is likely to be experienced in certain locations around the world. When the SOI is strongly negative or falling, trade winds are weak, and rainfall in the Indonesian and Australian region and parts of southern Africa can be below average. A neutral SOI is likely to result in normal rainfall in these locations (Clewett et al., 1992). The trends or phases up or down of the SOI are used as indicators of future weather.

While the Southern Oscillation modifies the climate pattern, the weather continues its natural variability under the other influences. These are sometimes so dominant that the Southern

Oscillation cannot be a totally reliable indicator of future weather. Not every drought is caused by an El Nino, nor do all La Ninas (non-El Nino phases) cause floods; however, the chances, or probabilities, of their influence can be estimated. The SOI can be used to improve the estimates of probability of rainfall in certain locations and during certain months but it cannot give an absolute forecast (Clewett, 1995).

2.5.4 ENSO and crop yields simulations.

The ability to forecast some aspects of ENSO signals for time scales of months to over one year are currently being used to extrapolate the potential occurrences of ENSO related weather/climate events for specific seasons and regions of the world which have strong ENSO signals. Such information now forms crucial components of early warning systems, including the planning, management and operations of agricultural activities in some parts of the tropical regions. For some of these agricultural applications, models have been developed which transfer projected ENSO signals directly into agricultural stress indices (Ogallo et al., 2000). A strong relationship is known to exist between the El Nino Southern Oscillation and annual precipitation in southern Africa (Phillips et al., 1998). Sea surface temperatures and pressures in the Atlantic and the Indian Ocean have also been found to correlate to varying degrees with precipitation patterns in Africa (Phillips et al., 1998).

Indication of the potential impacts of ENSO on agriculture in Zimbabwe was shown in the study by Cane et al., (1994) in which it was found that SSTs in some regions of the Pacific are good indicators of national level Zimbabwean maize yields. Years which had a strongly positive SST anomaly (El Nino years) were associated with lower than average precipitation and maize yields. Years with negative SST anomaly (La Nina years) were associated with higher than average precipitation and maize yields. However, it was found that the correlation between SSTs and maize yields were slightly higher than SSTs and annual precipitation, indicating that the influence of ENSO on climate and crop yields may be more complex than simple annual precipitation averages reveals (Cane et al., 1994). RAINMAN analyses more than just annual precipitation by relating ENSO with monthly rainfall if required.

Phillips et al., (1998) carried out further studies to identify the aspects of climate, particularly rainfall, in Zimbabwe that are associated with the ENSO signal, and to test the usefulness of predictions for maize crop management at various sites. They concluded that ENSO is a strong determinant of inter-annual climate variability at the investigated sites (including Masvingo) in all the agroecological zones of Zimbabwe. Forecasts based simply on ENSO categories were found to be unlikely to provide the highest quality information for maize management decision-making. However, with improvements in both climate forecasts and crop simulation models, there was potential for identifying management strategies that reduce agricultural risk associated with climate in Zimbabwe and other ENSO-affected regions (Phillips et al., 1998).

PART 3: MODELING

2.6 The modeling process

Models are meant to help solve problems, both practical and academic. The stages by which they can do this are:

Stage 1: Problem formulation: What is the question? Questions must be specific, in the form of a hypothesis to be tested or the prediction of some alternative actions or scenarios of the future.

Stage 2: model choice: the essential controlling factors are identified. A range of existing models which have been applied to similar problems and can be used or modified. As a last resort, a new model can be built.

Stage 3: model calibration: Parameters to be used for the chosen model must be found from literature, or, if necessary from subsidiary experiments.

Stage 4: model validation: ideally, the model is run to predict something where the answer is known- perhaps from previous data or a simplified example.

Stage 5: model application: The model is used to test the initial hypothesis or give an answer to the question posed. Whether the model is adequate depends on the decisions which depend on the outcome and the nature of the initial question (Hillel, 1977).

2.6.1 Types of models

Depending on the scientific discipline, there are different types of models, ranging from very simple models that are based on one equation to extremely advanced models, which include thousands of equations.

Hillel, (1977) identified two broad types of models as **mechanistic** and **empirical.** The **mechanistic** models are based on the known processes that make up the system which is being modeled, using the laws of physics, biochemistry etc. **Empirical** models on the other hand do not rely on insight into the cause and effect in the system being modeled; rather they seek to find a statistical relationship between a measurable quantity e.g. maize yield and related predictor variables e.g. Climatological parameters. **Empirical** models are limited because they often have no generality and no guarantee that relationships which have worked in the past will continue to work in the future. **Mechanistic** models are more elegant and elaborate, but may not always be possible to quantify; it is also very hard to be sure that all relevant mechanisms have been included.

2.7 Crop modeling

One of the main goals of crop production simulation models is to estimate agricultural production as a function of weather and soil conditions as well as crop management. Dynamic crop production model systems, as decision supporting tools, have extensively been utilized by agricultural scientists to evaluate possible agricultural consequences from interannual climate variability and/or climate change (e.g Paz et al., 1998; Semenov et al., 1996). DSSAT is one such model which is commonly used by scientists for these purposes.

2.7.1 DSSAT CERES-Maize

The Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM) is a commonly used decision support tool. It provides a shell that allows the user to organize and manipulate data, run crop models, and analyze the output. It can simulate 27 different crops and, since they all share common input and output data formats, the same climate and soil datasets can be used to simulate all crops. The DSSAT models have been employed at a variety of scales (from field to regional/national) in an assortment of research applications such as simulating the impact of climate change on agriculture (Attri and Rathore, 2003; Carbone et al., 2003), quantifying the impact of climate variability on agricultural production (Andresen et al., 2001; Xie et al., 2001), and forecasting yield prior to or during the growing season (Bannayan et al., 2003; Chipanshi et al., 1997).

DSSAT models are dynamic simulation models that rely on an understanding of the basic physiological processes. They have undergone rigorous evaluation in a wide range of different climate and soil conditions and for many different crop hybrids. The CERES-Maize model is found within DSSAT, it is one of the oldest, most advanced, and most widely used crop simulation models. CERES-Maize simulates maize growth, water, and soil nitrogen dynamics at the field scale. It simulates the development of roots and shoots, growth and senescence of leaves and stems, biomass accumulation and partitioning between roots and shoots, leaf area index, root, stem, leaf, and grain growth. Six phenological stages are simulated and the length of each stage is controlled by plant genetics, weather, and other environmental factors. Air temperatures (or more specifically growing degree-days) are the primary control of plant development. Genetic coefficients are used to set the genotype-specific aspects of maize development (Quiring, 2004).

Potential dry matter production is calculated as a function of radiation, leaf area index (LAI) and reduction factors for temperature and moisture stress. Final grain yield is calculated as the product of plant population, kernels per plant, and weight per kernel. CERES-Maize accounts for the effects of weather, soil type, genotype, nitrogen, and management options on crop growth and yield and it utilizes a daily time step to calculate crop growth and to simulate the water and nitrogen balances (Quiring, 2004).

2.7.2 AquaCrop

In this study, the use of a recently developed crop growth simulation model named **AquaCrop (**Raes et al., 2009) is proposed. It integrates the effects of crop phenotype, soil profiles, weather data, and management options into a crop production model. The crop model uses maximum and minimum air temperatures (Tx and Tn), rainfall, and reference evapotranspiration (ETo) from season-long weather records. It computes plant growth and development processes on a daily basis in a specific location, from planting date to maturity date. As a result, the impact of weather, soils, and management decisions on a crop yield can be well estimated (Shin et al., 2006). Daily seasonal climate data are preferred as inputs for the **AquaCrop** crop model. However, it can generate daily weather from an input of 10 day or monthly weather data.

AquaCrop is a dynamic water-driven production simulation model that requires a relatively low number of parameters and input data to simulate the yield response to water of most of the major field and vegetable crops cultivated worldwide. Its parameters are explicit and mostly intuitive and the model maintains sufficient balance between accuracy, simplicity and robustness (Steduto et al., 2009). The model has a structure that overarches the soil-plant-atmosphere continuum (Figure 2.3). It includes the soil, with its water balance; the plant, with its development, growth and yield processes; and the atmosphere, with its thermal regime, rainfall, evaporative demand and carbon dioxide concentration (CO_2). Additionally, some management aspects are explicitly considered (e.g., irrigation, fertilization, etc.) as they will affect the soil water balance, crop development and therefore final yield (Raes et al., 2009).

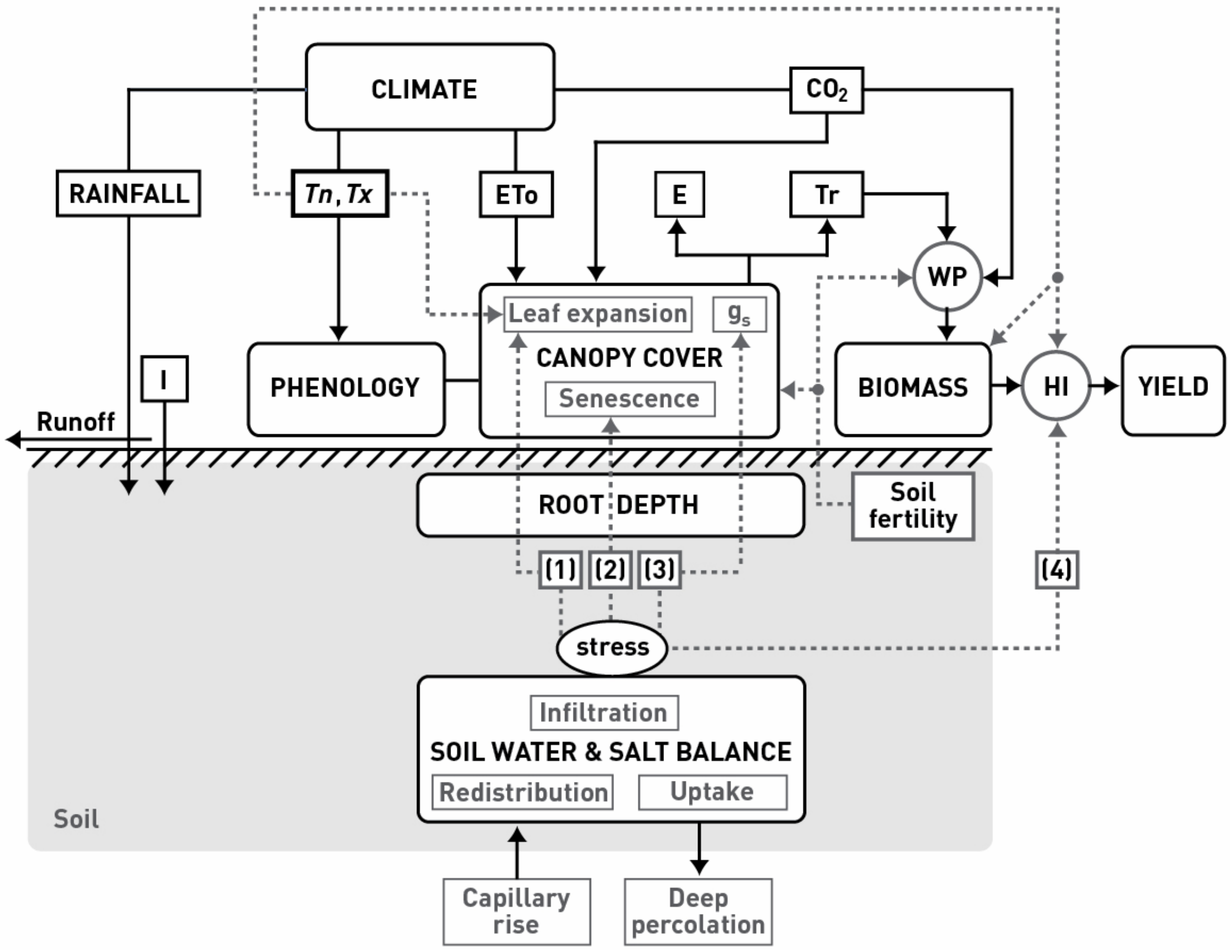


Figure 2.3 Flowchart of Aquacrop indicating the main components of the soil-plant-atmosphere continuum (Raes et al., 2009)

2.7.2.1 The soil

The soil component of **AquaCrop** is configured as a dispersed system of a variable depth allowing up to five horizons of different texture composition along the profile. As default, the model includes all the classical textural classes but the user can input own specific values. For each texture class, the model associates a few hydraulic characteristics which can be estimated from soil texture through pedotransfer functions. The hydraulic characteristics include the hydraulic conductivity at saturation, and the volumetric water content at saturation, field capacity and wilting point (Steduto et al., 2009).

For the soil profile explored by the root system, the model performs a water balance that includes the processes of runoff (through the curve number), infiltration, redistribution or internal drainage, deep percolation, capillary rise, uptake, evaporation and transpiration. A daily step soil water balance keeps track of the incoming and outgoing water fluxes at the boundaries of the root zone and of the stored soil water retained in the root zone.

When calculating the soil water balance, the amount of water stored in the root zone can be expressed as an equivalent depth (Wr) or as depletion (Dr). Expressing the water content in a particular soil volume as an equivalent depth (Wr) is useful when computing the soil water balance of the root zone. It makes the adding and subtracting of gains and losses of water straightforward since the various parameters of the soil water balance such as rain and evapotranspiration are usually expressed in terms of water depth. The stored soil water in the root zone expressed as a depth is given by:

$$\mathrm{Wr} = 1000\mathrm{q}\ Z \qquad \text{(Eq. 2.1)}$$

where Wr is soil water content of the root zone expressed as a depth [mm]; 1000q is average soil water content for the root zone expressed as equivalent depth per unit soil depth [mm(water)/m(soil depth)]; q is average volumetric water content in the root zone [m3/m3]; Z is the effective rooting depth [m] (Raes et al., 2009).

2.7.2.2 The plant

In **AquaCrop**, the crop system has five major components and associated dynamic responses: phenology, aerial canopy, rooting depth, biomass production and harvestable yield. The crop grows and develops over its cycle by expanding its canopy and deepening its rooting system while at the same time the main developmental stages are established. The canopy represents the source for actual transpiration that gets translated in a proportional amount of biomass produced through the water productivity parameter, (WP), i.e.

$$B = WP \cdot \Sigma Tr. \qquad \text{(Eq. 2.2a)}$$

Where Tr is the crop transpiration (in mm). The harvestable portion (Y) of such biomass (B) is then determined via the harvest index (HI), i.e.

$$Y = B \cdot HI \qquad \text{(Eq. 2.2b)}$$

The basis for using equation. 2.2a as the core of the model growth engine for **AquaCrop** lies on the conservative behaviour of WP (Steduto and Albrizio, 2005; Steduto et al., 2007). The WP parameter of **AquaCrop** is normalized for reference evapotranspiration (ETo) and the carbon dioxide (CO_2) concentration of the bulk atmosphere, it may vary moderately in response to the fertility regime, and remains constant under water deficits except when severe water stress is reached. The normalization of WP for climate makes the model applicable to diverse locations and seasons, including future climate scenarios. Once the biomass (B) is obtained (Eq. 2.2a), the crop yield is derived by multiplying B and the harvest index, HI (Eq. 2.2b). Starting from flowering, HI can be adjusted for water deficits depending on the timing and extent of the water stress during the crop cycle (Raes et al., 2009).

Even though **AquaCrop** uses a HI parameter, it does not calculate the partitioning of biomass into various organs (e.g., leaves, roots, etc.), i.e. biomass production is decoupled from canopy expansion and root deepening. This choice avoids dealing with the complexity and uncertainties associated with the partitioning processes, which remain among the least understood and most difficult to model (Raes et al., 2009).

2.7.2.2i Growing degree days

Depending on the data availability, preference of the user and/or simulation modes, crop growth and development is described dynamically either in calendar days or in thermal time. **AquaCrop** uses Growing Degree Days (GDD) (Eq. 2.3) to compute thermal time. Different crop developmental stages are completed once a given number of calendar days or GDD are reached.

$$\text{GDD} = Tavg - Tbase \quad \text{(Eq. 2.3)}$$

The base temperature (*Tbase*) is the temperature below which crop development does not progress. In **AquaCrop** an upper threshold temperature (Tupper) is considered as well. The upper temperature threshold specifies the temperature above which crop development no longer increases with an increase in air temperature. The average air temperature (*Tavg*) is given by:

$$Tavg = \frac{(Tx + Tn)}{2} \quad \text{(Eq. 2.4)}$$

where *Tx* is the daily maximum air temperature and *Tn* is the daily minimum air temperature (Raes et al., 2009)

The genetic variation among species and cultivars may be implemented in the model through the variation in timing and duration of the various developmental stages, as well as through the rate of canopy expansion, rate of root deepening, the water productivity parameter and other response factors to environmental conditions.

2.7.2.2ii Canopy cover

The canopy is a crucial feature of **AquaCrop** through its expansion, ageing, conductance and senescence, as it determines the amount of water transpired, which in turn determines the amount of biomass produced. The canopy expansion is expressed through the fraction of green canopy ground-cover (CC). Having canopy development expressed through CC and not via leaf area index (LAI) is one of the distinctive features of **AquaCrop**. It introduces a significant simplification in the simulation, reducing the overall aboveground canopy expansion to a growth function and allowing the user to enter actual values of CC even estimated by eye. Moreover, CC may be easily obtained also from remote sensing (Stetudo et al., 2007). Canopy development is simulated by two equations:

- (exponential growth) is valid when CC ≤ CCx/2

$$CC = CCo\, e^{t\, CGC} \qquad \text{(Eq. 2.5a)}$$

- (exponential decay) is valid when CC > CCx/2

$$CC = CC_X - 0.25 \frac{(CCx)^2}{CCo} e^{-tCGC} \qquad \text{(Eq. 2.5b)}$$

where CC is canopy cover at time t [fraction ground cover]; CCo - initial canopy size at t= 0 [fraction ground cover]; CCx - maximum canopy cover [fraction ground cover]; CGC - canopy growth coefficient [increase of fraction ground cover per day or growing degree day]; t - time [day or growing degree day] (Stetudo et al., 2007).

2.7.2.2iii Root development

The root system in **AquaCrop** is simulated through its effective rooting depth. The effective rooting depth (Z) is defined as the soil depth where most of the root water uptake is taking place, even though some crops may have a few roots beyond that depth. The root deepening rate is a function of crop type and time. In **AquaCrop,** the development of the rooting depth is simulated by considering the n^{th} root of time. Once half of the time required for crop emergence (or plant recovery in case of transplanting) is gone (*to*/2), the rooting depth starts to increase from the sowing depth (Zo) till the maximum effective rooting depth Zx is reached:

$$Z = Z_o + (Z_X - Z_o) \sqrt[n]{\frac{\left(t - \frac{t_o}{2}\right)}{\left(t_x - \frac{t_o}{2}\right)}} \qquad \text{(Eq. 2.6)}$$

where Z is the effective rooting depth at time t [m]; Zo is sowing depth [m]; Zx is maximum effective rooting depth [m]; to time to reach crop emergence [days or growing degree days]; tx is time after planting when Zx is reached [days or growing degree days]; t is the time after planting [days or growing degree days]; n is shape factor (Raes et al., 2009).

2.7.2.3 The atmosphere

The atmospheric environment of the crop is described in **AquaCrop** and deals with key input meteorological variables. Five weather input variables are required to run **AquaCrop**: daily maximum and minimum air temperatures (T), daily rainfall, daily evaporative demand of the atmosphere expressed as reference evapotranspiration (ETo) and the mean annual carbon dioxide concentration in the bulk atmosphere. While the first four are derived from typical agro-meteorological stations, the CO^2 concentration uses the Mauna Loa Observatory records in Hawaii (Raes et al., 2009).

Temperature (minimum and maximum), rainfall and ETo may be provided at different time scales, specifically daily, 10-day, and monthly records. However, at run time **AquaCrop** processes the 10-day and monthly records into daily values. This flexibility for different time scales of weather input variables is required to use **AquaCrop** in areas of limited weather records and for simplicity.

ETo is the evapotranspiration rate from a grass reference surface, not short of water and is an index for the evaporating power of the atmosphere. **AquaCrop** does not include the routines for calculating ETo, but a separate software program (ETo calculator) based on the procedures described in the FAO *Irrigation and Drainage Paper* 56 (Allen et al., 1998) where not all the required input variables for calculating ETo are available is provided to the user for such purpose (Raes et al., 2009).

2.7.2.3i Evapotranspiration

The dual crop coefficient approach (Allen et al., 1998) is used to determine evapotranspiration. Crop transpiration (Tr) and soil evaporation (E) are calculated by multiplying ETo with their specific coefficients (Eq. 2.7a). The effects of characteristics that distinguish the crop transpiration and soil evaporation from grass are integrated into the crop transpiration coefficient (Kcb) and the soil water evaporation coefficient (Ke). Soil evaporation, crop transpiration and

ETo are expressed in mm/day. When the root zone is well watered and the soil surface wet, crop transpiration as well as soil evaporation are at their maximum rate and ET is given by:

$$ETc = Kcb + Ke\ ETo \qquad \text{(Eq. 2.7a)}$$

The value of both coefficients depends on canopy cover. The crop transpiration coefficient is proportional to the fractional canopy cover (Kcb ~ CC) and the soil water evaporation coefficient is proportional to the fraction of the soil surface not shaded by the canopy (Ke ~ (1-CC)) (Raes et al., 2009).

The rate of soil evaporation and crop transpiration drops below their maximum rates, when insufficient water is available in the soil to respond to the evaporative demand of the atmosphere. This is simulated by multiplying the crop transpiration coefficient with the water stress coefficient for stomatal closure (Kssto) and the soil water evaporation coefficient with a reduction coefficient (Kr) (Raes et al., 2009):

$$ET = Ks\ Kcb + Kr\ Ke\ ETo \qquad \text{(Eq. 2.7b)}$$

2.7.2.3ii Processing of 10-day and monthly climatic data

The input data may consist of daily, 10-day or monthly temperature (max and min), ETo and rainfall data. At run time, the 10-day and monthly data are processed to derive daily minimum and maximum air temperatures, ETo and rain data. By weighing the evapotranspiration rates and air temperatures in the previous, actual and next 10-day period or month, daily ETo rates, and the daily maximum and minimum air temperatures are obtained in **AquaCrop**. The calculation procedure is based on the interpolation procedure presented by Gommes (1983).

The same holds for the rainfall data but since it is highly unlikely that rainfall is homogenously distributed over all the days of the 10-day period or month, some further processing is carried out to determine the amount of rainfall that is stored in the top soil as effective rainfall, lost by surface runoff and by deep percolation. Effective rainfall is that part of rainfall that is stored in the root zone and not lost by surface runoff or deep percolation. After the subtraction of the amount of rainfall lost by surface runoff, the effective rainfall is estimated by one or another procedure determined by the user (Stetudo et al., 2007).

The following procedures can be selected to determine the effective rainfall when 10-day or monthly rainfall data is used:

- 100 percent effective
- USDA-SCS procedure (SCS, 1993; Naesens, 2002).
- Expresses as a percentage of rainfall.

2.7.2.4 Major advantages of AquaCrop

AquaCrop combines the benefits of more empirical modelling methods (low input data requirements, validity over large areas) with the benefits of a process-based approach (the potential to capture variability due to different sub seasonal weather patterns and hence increased validity under future climates). It also includes several key biophysical processes that are important in determining crop response to climate variability, particularly in future climate. (Raes et al., 2009).

CHAPTER 3: METHODOLOGY

3.0 Introduction

The Zimbabwe Meteorological Services Department (ZMSD) is responsible for weather services in Zimbabwe. The department offers forecasts for farmers to plan for maize production and other farming activities. However, the forecasts are non-specific with regard to decision making in maize production. The first part of the study entailed comparing the proposed probabilistic weather forecasting tool (RAINMAN) with Climate predictability tool (CPT), one of the forecast tools used by the ZMSD. The comparison will be done in order to assess RAINMAN´s suitability for integration into the decision support tool intended for maize production at Masvingo. The second part of the project entailed the generation of weather series to be used for running the crop model. The third part involved crop simulations and the development of the decision criteria for maize production at Masvingo.

PART 1: COMPARISON OF RAINMAN AND CPT

3.1 Climatic data: Rainfall

The data used in the analyses consisted of monthly precipitation for Masvingo station (long- 30º52’ E; Lat- 20º04’ S; Alt- 1100 m). The data was provided by the ZMSD. To compare the two forecast tools, seasonal rainfall analyses were done on rainfall for one season (October to March) over a validation period of 16 seasons (1991/92-2006/07) and an estimation period of 41 seasons (1950/51-1990/91) using RAINMAN and CPT. Observed rainfall data for RAINMAN was preexistent in the software tool and was assumed to be accurate since the tool was created with the input of the ZMSD. However, the data available in RAINMAN International version 4.1 was for 1899/90–1989/90. This data was appended and updated to 2006/07 using monthly rainfall data obtained from the MAGM data base courtesy of the ZMSD. CPT input data was also obtained from the same data base. The monthly rainfall data used in CPT was for 1950/51-2006/07.

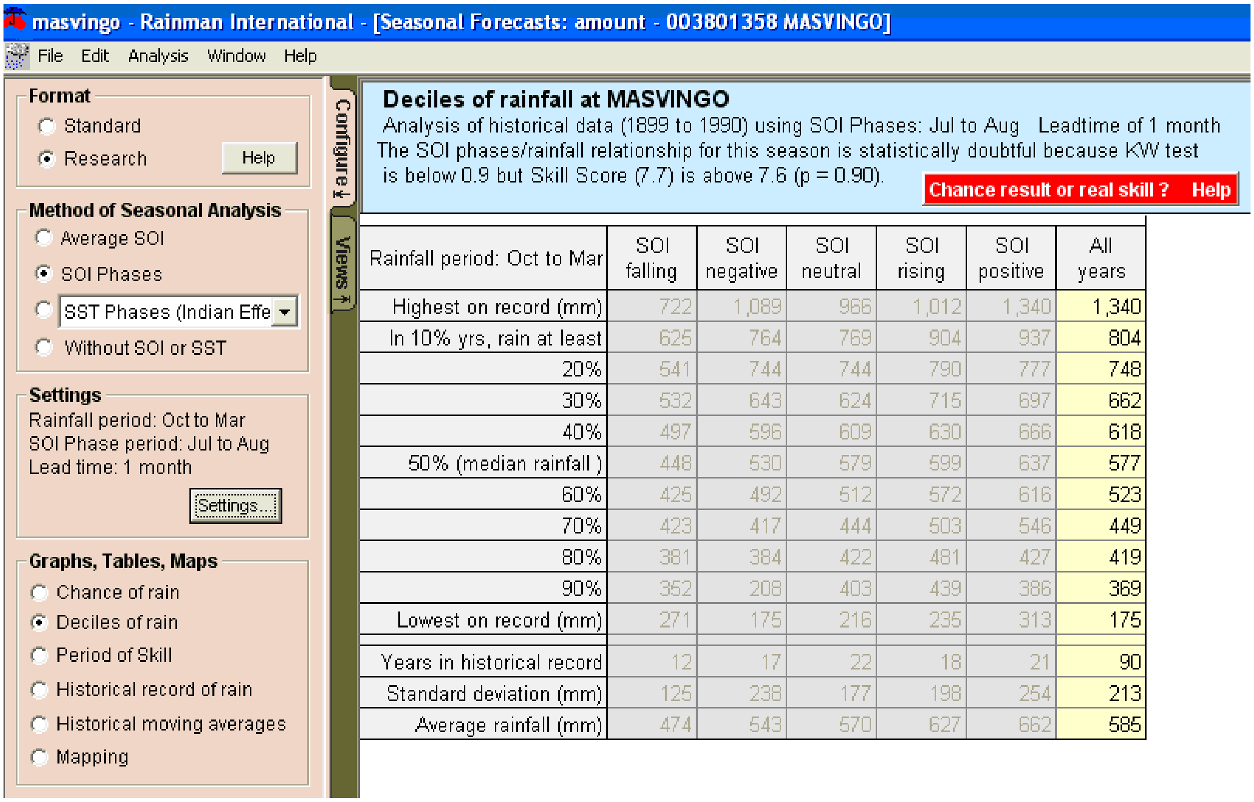
3.2 RAINMAN simulations

Probabilities of rainfall for Masvingo station were computed using RAINMAN version 4.1 through the SOI forecast phase system. Results of seasonal analyses for Masvingo for the season October-March were represented by deciles of rainfall tables (Figure 3.1; Appendix A). The SOI forecast phase system has five phases namely; negative, falling, neutral, rising and positive. The seasonal analysis in RAINMAN to obtain predicted amounts of rainfall was performed in the research format.

3.2.1 Settings

Results of analyses carried out by Clewett et al., (1992) show that the SOI forecast phase system of RAINMAN has considerable skill for the period October- March (ONDJFM), using one month lead time. The duration of the rainfall season was therefore set at October- March and the SOI phase months were set at July – August (JA) giving a one month lead time as shown in Figure 3.1.

The SOI for the forecast months (JA) prior to the season under investigation were set in the "which phase? Calculator". The SOI values were found within RAINMAN under the SOI/SST manual update in the Masvingo file. With the above settings, RAINMAN seasonal analysis was carried out for the SOI phase system for the seasons 1950/51- 1990/91 and 1991/92- 2006/2007 (Appendix A: Table A-1; Table A- 2).



Rainfall period: Oct to Mar	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	722	1,089	966	1,012	1,340	1,340
In 10% yrs, rain at least	625	764	769	904	937	804
20%	541	744	744	790	777	748
30%	532	643	624	715	697	662
40%	497	596	609	630	666	618
50% (median rainfall)	448	530	579	599	637	577
60%	425	492	512	572	616	523
70%	423	417	444	503	546	449
80%	381	384	422	481	427	419
90%	352	208	403	439	386	369
Lowest on record (mm)	271	175	216	235	313	175
Years in historical record	12	17	22	18	21	90
Standard deviation (mm)	125	238	177	198	254	213
Average rainfall (mm)	474	543	570	627	662	585

Figure 3.1 RAINMAN simulation window showing settings and predicted seasonal total rainfall for Masvingo for the season October to March with a 1 month lead time for the SOI phase period of July-August.

3.2.2 Skill analysis

The major statistical tests used in RAINMAN are the Kruskal-Wallis (KW), and the LEPS (Linear Error in Probability Space) skill score test and the probability score (p). The statistical relationship of the ENSO indicators with rainfall is classified in Table 3.1. Forecasts with statistical relationships considered significant were applied with no reservations. Doubtful statistical relationships were applied with a degree of caution. Statistical relationships that were insignificant were discarded or applied with extreme caution on the basis that skill score values below 7.6 are not sufficiently skilful. Forecast skill reduces from 7.6 and forecasts with skill scores below 0.0 have no skill.

Table 3.1 Measures of the strength of statistical relationship between ENSO indicators and rainfall amounts

	KW test result	LEPS Skill Score
Significant	0.9 or above	7.6 or above
Doubtful	below 0.9	7.6 or above
Doubtful	0.9 or above	below 7.6
Not significant	below 0.9	below 7.6

3.2.3 Seasonal analysis

Depending on the SOI phases (falling, negative, neutral, rising positive), rainfall amounts in the deciles of rainfall at Masvingo were selected under the 20 % (above normal/wet), 50 % (normal) or 80 % (below normal/dry) categories of probability of rainfall occurrence based on the realisations summarized in Table 3.2

Table 3.2 Selection criteria for seasonal analysis results based on SOI phase system. – indicates a negative value; + indicates a positive value; +(0-10) indicates positive but between 0 and 10;

SOI PHASE													
FALLING		NEGATIVE		NEUTRAL				RISING		POSITIVE			
July	Aug	July	Aug	July	Aug	July	Aug	July	Aug	July	Aug	July	Aug
-	-	-	-	-	-	+	+	-	+	+(0 – 10)		+ (> 10)	
80 % (dry)		80 % (dry)		50 % (normal)		20% (wet)		20 % (wet)		50 % (normal)		20 % (wet)	

3.3 CPT simulations

Seasonal total rainfall for Masvingo station was also carried out by means of the statistical software package, Climate Predictability Tool (CPT) version 9.10. CPT provides a Windows package for seasonal climate forecasting given updated data (Ndiaye and Mason, 2006).

3.3.1 Settings

CPT simulations were performed under the settings shown in the input window in Figure 3.2. The principle component method of analysis was selected as advised by Ndiaye and Mason (2006). The X domain limits were selected as: Northernmost latitude: 30; Southern most latitude: - 40; Westernmost latitude: - 70; Easternmost latitude: 290. Rainfall amounts at Masvingo station from 1900/01 to 2006/07 were used as input response (Y) variables. The Y domain variables were selected as: Northernmost latitude: - 19; Southern most latitude: - 21; Westernmost latitude: 29; Easternmost latitude: 32. CPT simulations were run based on the above settings and the results obtained were summarised in Appendix A: Table A-5; Table A-6; Table A-7; Table A-8.

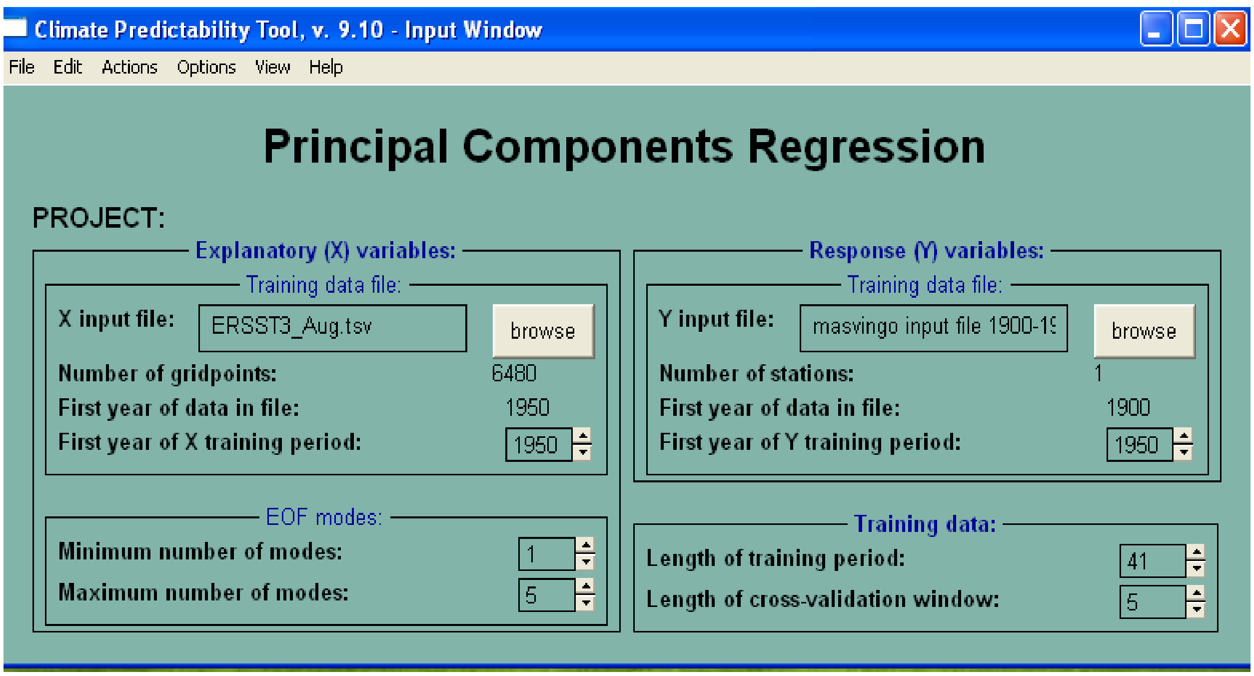


Figure 3.2 CPT input window where simulation settings are applied and training data characteristics

<u>PART 2: GENERATION OF RAINFALL DATA SERIES</u>

The second part of the study entailed the generation of rainfall weather series for Masvingo. The generated weather series represent weather scenarios for the five phases of the Southern

Oscillation Index in three categories of rainfall i.e. wet (20 %); dry (80 %) and normal (50 %) categories. The weather series were used to run the crop production simulations for a variety of agrometerorological scenarios (three planting dates, three maize cultivars and two fertility levels).

3.4 Monthly rainfall predictions

Predictions of monthly rainfall for the growing season (October to March) were performed using RAINMAN. April was included in case of late planting. Historical rainfall from 1899/00 to 1989/90 was available within the RAINMAN database. The records were appended with rainfall amounts obtained from the ZMSD up to the 2006/07 season. RAINMAN divided the years from 1899/90 to 2006/07 into the five phases of the SOI, negative, falling, neutral, rising and positive. The period from 1899/90 to 2006/07 was used for making rainfall predictions.

3.4.1 Settings

The rainfall predictions were carried out in the research format of RAINMAN. The rainfall period was set to the month being predicted e.g. January-January for the month of January. The SOI phase period was set for July-August (JA), giving lead times from one month for October predictions to seven months for April. The resultant predictions were found in the deciles of rainfall tables (Appendix B) under the wet (20 %), normal (50 %) and dry (80 %) categories of the five SOI phases.

3.4.2 Skill analysis

Skill analysis was based on Table 3.1. However, since the lead times ranged from 1 month to 7 months the level of skill was expected to decline. Therefore, for monthly rainfall predictions, a KW score under 0.9 and an LEPS score below 7.6 were considered acceptable as long as LEPS was above 0 and the probability value was greater than 0.5.

3.4.3 Seasonal analysis

In order to assess the accuracy of RAINMAN probabilistic monthly predictions, they were validated against the observed rainfall for each month for a validation period from 1991/92 to 2006/07. The predicted rainfall amount was selected based on whichever of the three categories of rainfall (20 %, 50 %, and 80 %) was found to bear a resemblance to the observed monthly rainfall category.

PART 3: CROP SIMULATIONS

3.5 The modeled environment

Simulations of maize yields were carried out using **AquaCrop** v 3.0 (Raes et al., 2009). **AquaCrop** was chosen for its combined simplicity and robustness. The model allows for the use of monthly weather data despite quantifying plant physiological response on a daily time-step. **AquaCrop** has been tested for a variety of locations, some similar to Masvingo. Required model inputs include the climate (minimum and maximum temperature, precipitation and reference evapotranspiration (ETo), crop characteristics, planting date, field management (fertility), and soil properties as shown in Figure 3.2.

3.5.1 Soil characteristics

The soil texture characteristics at Masvingo were considered to be a moderately deep coarse loam (Phillips et al., 1998). The field capacity and wilting point for textural classes of Zimbabwe are found at -10 kPa and -1500 kPa suction pressure respectively (Hussein, 1983). Important soil parameters for rainfed agriculture at Masvingo are given in Table 3.3.

Figure 3.2 Aquacrop main menu showing the modeled environment and the basic input parameters.

Table 3.3 Physical characteristics of soil sandy clay loam texture group at Masvingo (Adapted from Sithole, 2003. pp 36)

Property	Sandy clay loam
Bulk density (g cm^{-3})	1.48
Soil water content at saturation (θ_{SAT}) (% Vol)	43.2
Soil water content at field capacity θ_{FC} (10) (% Vol)	28.8
Soil water content at wilting point θ_{WP}(1500) (% Vol)	16.1
Total available water TAW mm/m	127

3.5.2 Climate data

Mean monthly maximum and minimum air temperature data were obtained from the ZMSD. Precipitation data was obtained from predictions made by RAINMAN. ETo values were generated using ETo calculator.

3.5.3 Crop characteristics

Conservative characteristics applicable to all maize cultivars were considered as summarized in Table 3.4(a). All the other crop characteristics not defined are as presented by **AquaCrop** (default).

Table 3.4 (a) Conservative crop characteristics applicable to all the three maize cultivars considered.

Description	Value	Units
Biomass water productivity (WP)	29	g m^2
Reference harvest index (HI)	36	%
Plant density	37 037	Plants/ha
Maximum canopy cover	75	%
Maximum rooting depth	1.2	m

The length of season for Masvingo is sometimes as short as 95 days (dry years) and as long as 145 days (wet years) (Sithole, 2003). The variations are large enough to command careful selection of crop cultivars. The characteristics of crop cultivars for maize used in the simulations are summarized in Table 3.4(b), Table 3.4(c) and Table 3.4(d). The length of growth stages of maize were based on calendar days and not growing degree days (GDDs) since the temperature variation within the season over the years was assumed to be negligible. The calendar days for each growth stage were developed as a proportion of the days to maturity of the maize cultivar.

Table 3.4(b) Growth stages for 100-day maize cultivar

Growth stage	Length (days)
Days from sowing to emergence	5
To flowering	50
To maximum rooting depth	71
To start of canopy senescence	86
To maturity	100
Length of flowering stage	9

Table 3.4(c) Growth stages for 125-day maize cultivar

Growth stage	Length (days)
Days from sowing to emergence	5
To flowering	63
To maximum rooting depth	88
To start of canopy senescence	108
To maturity	125
Length of flowering stage	11

Table 3.4(d) Growth stages for 140-day maize cultivar

Growth stage	Length (days)
Days from sowing to emergence	6
To flowering	70
To maximum rooting depth	108
To start of canopy senescence	120
To maturity	140
Length of flowering stage	13

3.5.4 Planting dates

The planting dates used for the study were based on the optimal planting dates generated by Sithole (2003) as shown in Table 3.5. In this study, the method applied is the Depth criterion which was developed by quantifying methods used by farmers to determine planting dates. The method is quantified by taking a cumulative rainfall depth required to bring the top 0.25 m of the soil profile to field capacity within 4 days before planting.

Table 3.5 Optimal early, mean and late onset of planting dates for Masvingo based on criteria used in Zimbabwe (Adapted from Sithole (2003), pp 52.)

Method	Onset dates		
	Early	Mean	Late
MET (Meteorological office, Zimbabwe)	24- Oct	10-Nov	30- Nov
AREX (Agriculture, research & extension)	20- Oct	6- Nov	26- Nov
FAO (Food & agric organization)	18- Oct	5- Nov	23- Nov
DEPTH	29- Oct	16 Nov	7- Dec

3.5.5 Fertiliser management

Two levels of fertilizer application were used: an ´optimal´ level and a lower level more representative of resource poor farming communities.

3.6 Data analysis

3.6.1 Use of Contingency Tables and Associated Scores

A summary of the predicted and observed climate events was represented in the form of contingency tables. Contingency tables are used to record and analyze the relationship between two or more categorical variables which in this study are represented by observed and predicted rainfall in three categories of dry/below normal (< 500 mm), normal (500-650 mm) and wet/above normal (> 650 mm). These tables provided the basis from which a number of useful scores were obtained.

Table 3.3 Framework contingency table for calculating associated scores

		Predicted			
		Below normal(B)	Normal (N)	Above normal(A)	TOTAL
Observed	Below normal (B)	A_{11}	A_{12}	A_{13}	J
	Normal (N)	A_{21}	A_{22}	A_{23}	K
	Above normal (A)	A_{31}	A_{32}	A_{33}	L
	TOTAL	M	N	O	T

Percent correct gives the percentage of total predictions made which were correct and is given by:

Percent correct= $(A_{11} + A_{22} + A_{33}) / T * 100$ (Eq. 3.1a)

The **hit rate** is the number of correct predictions divided by the number observed in each category. It is a measure of the ability to correctly forecast a certain category and is given by:

Hit Rate = A_{11}/j, A_{22}/k, A_{33}/l for the three different categories (Eq. 3.1b)

Bias is the number of predictions divided by the number observed for each category. It measures the ability to forecast events at the same frequency as found in the sample without regard to forecast accuracy.

Bias = M/J, N/K, O/L for the three categories, (Eq. 3.1c)

Where Bias = 1 implies no Bias.
Bias >1 implies over-forecasting the event
Bias <1 implies under-forecasting the events

The **Critical Success Index (CSI)** shows the percentage of correctness of a prediction in each category and is given by

$$CSI= A_{11}/ ((M+J)-A_{11}),\ A_{22}/ ((N+K)- A_{22}),\ A_{33}/((O+L)- A_{33}) \qquad \text{(Eq. 3.1d)}$$

3.6.2 Significance tests

Contingency tables for the observed and predicted rainfall were investigated for any significant association by performing χ^2 significance tests at a 5 % level of significance. The tests were important in assessing the relevance of contingency tables results on the accuracy of CPT and RAINMAN in predicting seasonal total rainfall. The null hypothesis *Ho,* used was: *there is no association between observed and predicted seasonal total rainfall.*

Ho was accepted when χ^2_{calc} was less than χ^2, otherwise it was rejected for alternative hypothesis H_1 which stated: *there is a significant association between observed and predicted seasonal total rainfall.*

The comparison between observed frequencies (O_i) and predicted frequencies (E_i), for $_i$= 1,2…,*n* i.e. for *n* pairs of values, or classes is made by considering the statistic

$$\chi^2_{calc} = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \qquad \text{(Eq. 3.2a)}$$

Regression equations of observed and predicted rainfall were investigated for significant correlation by performing a significance t- test at a 5 % significance level. The null hypothesis *Ho* used was: *there is no significant difference between observed and predicted rainfall.* This was tested against an alternative hypothesis H_i stating *there is a significant difference between observed and predicted rainfall*. A two-tailed test was performed for which the null hypothesis was accepted for the following conditions:

$$-t_\alpha = 0.025 < t < +t_\alpha = {}_{0.025} \qquad \text{(Eq. 3.2b)}$$

The t-distribution degrees of freedom were given by *df(v)*= *n*-1 where *n* was the number of seasons under investigation. The t- statistic value corresponding to correlation coefficient was based on the equation within excel 2007 for t- distribution.

3.6.3 Error statistics

We employed standard descriptive measures of goodness-of-fit to evaluate the accuracy of seasonal rainfall predictions made by the seasonal forecast models.

The **Mean Square Error (MSE)** is one of the most commonly used measures of accuracy. Forecasters usually choose the models which minimize MSE.

$$MSE= \frac{1}{n}\sum_{i=1}^{n}(y_o - y_i)^2 \qquad \text{(Eq. 3.3a)}$$

Where: n is the total number of observations

y_o is the observed amount

y_i is the predicted amount

Mean Absolute Percentage Error (MAPE) combines the individual percentage errors without offsetting the negative and the positive values. This measure is similar to the Mean Absolute Error (MAE).

$$MAPE= \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_o - y_i}{y_o}\right| \times 100 \qquad \text{(Eq. 3.3b)}$$

However, MAPE treats each error equally without taking account of the sign. It is useful in comparing different forecasting models. MAPE assumes that the cost of errors is more closely related to the percentage error than to the unit error.

The **Root mean square error (RMSE)** is measured in the same units as the data, rather than in squared units, and is representative of the size of a "typical" error. It is a valid indicator of relative model quality only if it can be trusted.

$$\text{RMSE}= \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_o - y_i\right)^2} \qquad \text{(Eq. 3.3c)}$$

Coefficient of Variation (VC) is similar to the statistical inference coefficient of variation. It relates RMSE to the average of the actual data. The smaller the value the better the performance of the model.

$$\text{VC}= \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_o - y_i\right)^2}}{\frac{1}{n}\sum_{i=1}^{n} y_o} \qquad \text{(Eq. 3.3d)}$$

The **Mean Absolute Error** (**MAE**) gives an equal weight to the individual error of each period, while not offsetting the positive and negative values of the individual error. MAE is less sensitive than RMSE to errors in large predicted departures from the mean, and is therefore considered a more robust measure of accuracy.

$$\text{MAE}= \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_o\right| \qquad \text{(Eq. 3.3e)}$$

There is no absolute criterion for a "good" value of the error statistics mentioned in section 3.6.3: it depends on the units in which the variable is measured and on the degree of forecasting accuracy, as measured in those units, which is sought in a particular application (Legates and MacCabe, 1999).

3.6.4 Regression analysis

Regression is the amount of change in one variable that is associated with unit change in the other. Regression analysis is a statistical approach that is used to investigate the relationship between two or more variables (Boyce, 2005). The closeness of the relationship is measured by the coefficient of determination R^2. The strength of R^2 ranges from 0 to 1, with 1 representing a perfect positive relationship. The analysis was done using EXCEL. Observed rainfall was plotted against predicted rainfall.

CHAPTER 4: RESULTS AND DISCUSSION

4.0 Introduction

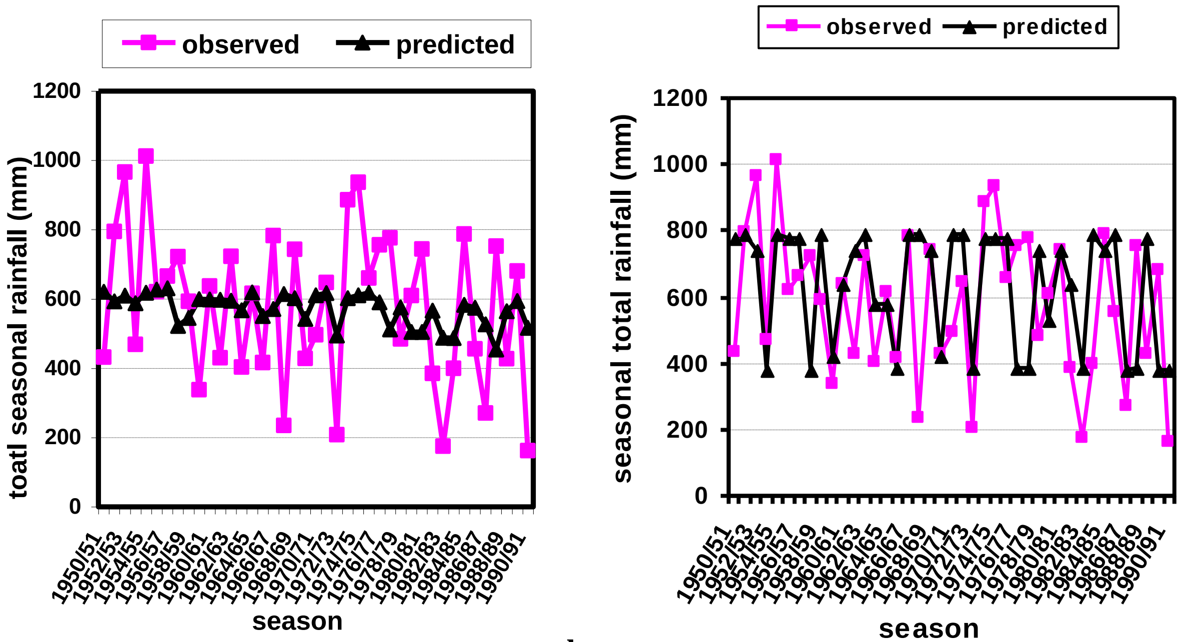
This section presents and discusses the results of the study. Initially, the proposed seasonal weather forecast tool (RAINMAN) is tested and compared for utility against CPT with the aim of determining the tool's appropriateness for use in an integrated yield forecasting tool with **AquaCrop.** Simulations are run with seasonal forecasts and a variety of agricultural scenarios. Ultimately, a decision support tool for maize production in Masvingo is developed.

PART 1: UTILITY OF RAINMAN

4.1 Comparison of RAINMAN and CPT

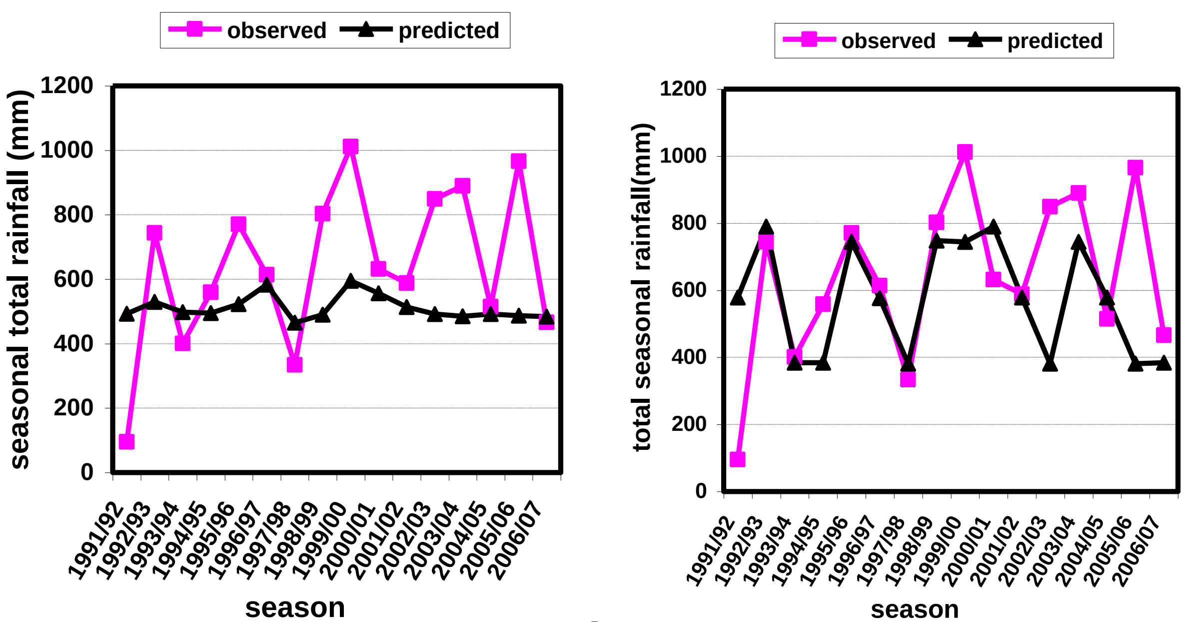
The seasonal total rainfall predictions from CPT and RAINMAN and the observed rainfall amounts for the validation period and the estimation period are summarized in Appendix A.

The trend analyses of the predicted seasonal total rainfall amounts by CPT and observed seasonal total rainfall amounts shows that CPT has a poor predictive ability compared to RAINMAN. Figure 4.1(a) shows that CPT makes most of its predictions in the normal (500-650 mm) and below normal range of rainfall amounts. Figure 4.1 (b) shows that the predictions made by RAINMAN in the estimation period (1950/51-1990/91) have a trend which is similar to that of the observed rainfall amounts. On the other hand, Figure 4.2 (a) shows the rainfall amounts predicted by CPT to be very different from the observed values, the model makes most predictions within the normal range of rainfall.



a b

Figure 4.1 Comparison of the trends of total observed and predicted seasonal rainfall for a 1950/51-1990/91 estimation period. (a) CPT, (b) RAINMAN.



a b

Figure 4.2 Comparison of the trends of total predicted and observed seasonal rainfall for a 1991/92-2006/07 validation period. (a) CPT, (b) RAINMAN.

It was noted over the validation period (Figure 4.2) that the predicted rainfall from RAINMAN varied as the observed rainfall. However, the tool was considerably off the mark in the 1999/00, 2002/03 and 2005/06 seasons. Although RAINMAN predicted above normal rainfall for the 1999/00 season, the observed rainfall was much higher than the predicted. Zimbabwe experienced cyclone Eline late in the season and it is noted as the reason for the difference. The month of February received 412 mm. highly anomalous rainfall totals falling in March 2003 (412 mm) and December 2005 (457 mm) led to poor predictions by RAINMAN in the 2002/03 and 2005/06 seasons since there were rarely any analogous years to be compared.

The predicted and observed seasonal rainfall totals were plotted against each other in order to view the relationship between the two as shown in Figure 4.3. An R^2 value of 0.13 was found between the rainfall amounts predicted by RAINMAN (Figure 4.3 (b)) and the observed, indicating a weak positive correlation. An R^2 value of 0.11 was found between the rainfall amounts predicted by CPT and the observed seasonal total rainfall amounts (Figure 4.3 (a)), indicating a poor positive correlation. However, despite the poor linear relationships, the patterns presented in Figures 4.3 (b) and 4.3 (d) show that RAINMAN makes predictions in all categories of rainfall while CPT (Figures 4.3 (a) and (c)) predominantly makes predictions of rainfall in the normal to below normal categories only.

The similar coefficients of determination and patterns for RAINMAN within the estimation period (0.13) and the validation period (0.13) show that the data used to train the model is ‘honest” and therefore there is no chance of overfitting of the model data. The estimation period (0.10) and validation period (0.11) coefficients of determination and similar patterns for CPT also point towards a minimal chance of overfitting. Based on the patterns shown in Figures 4.3 (a), (b), (c), and (d), RAINMAN has a better predictive ability than CPT.

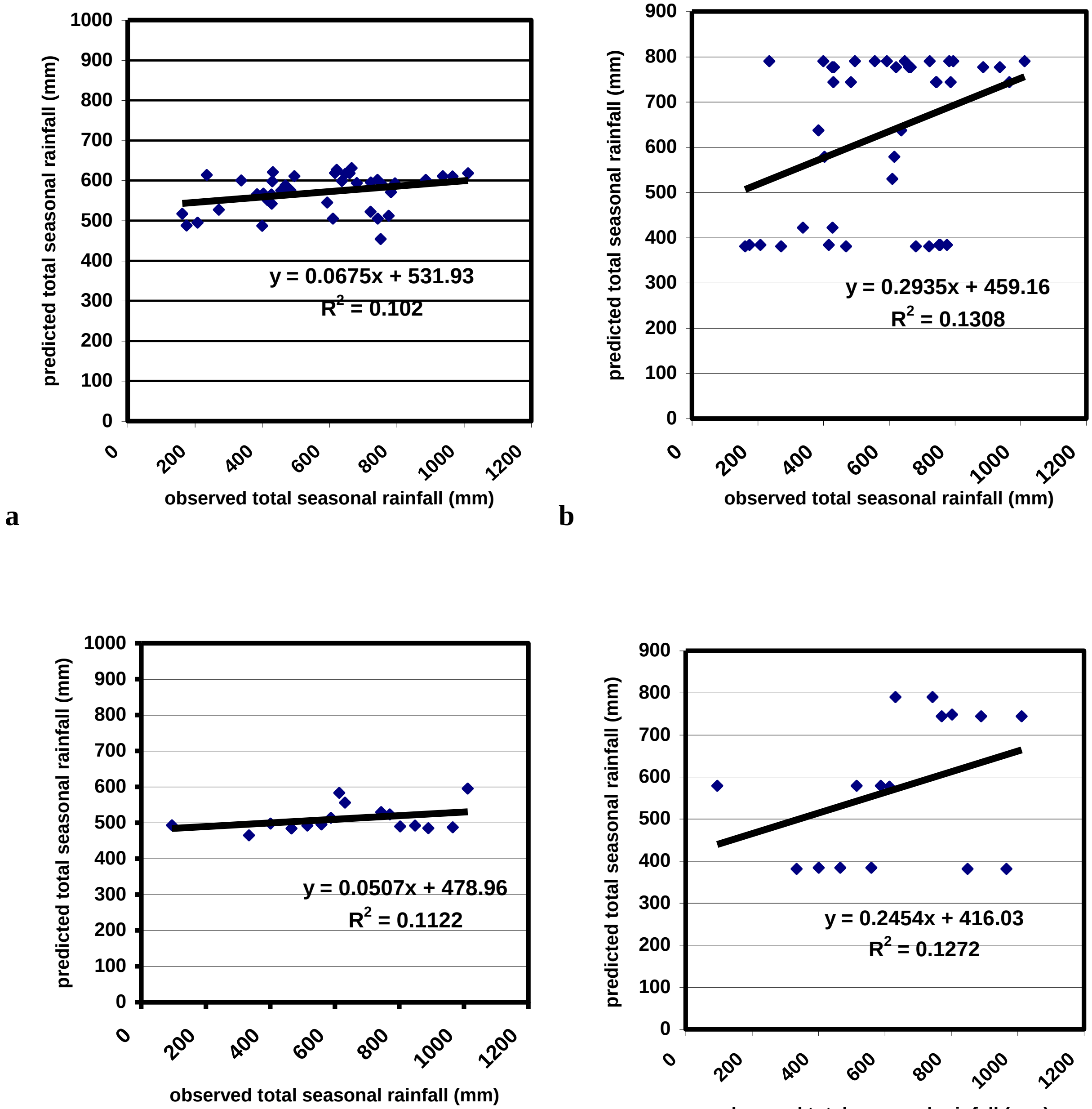


Figure 4.3 predicted total seasonal rainfall plotted against observed total seasonal rainfall for the estimation period (1950/51- 1990/91); (a) CPT, (b) RAINMAN and the validation period (1991/92- 2006/07); (c) CPT, (d) RAINMAN.

Table 4.1(a) Contingency table for observed and predicted (RAINMAN) rainfall in estimation period (1950/51-1990/91), showing percentage of correct predictions, the hit rate per rainfall category, BIAS and the Critical Success Index (CSI) for each category.

		Predicted			
		Below normal	Normal	Above normal	TOTAL
	Below normal	8	2	7	17
Observed	Normal	0	3	4	7
	Above normal	5	1	11	17
	TOTAL	13	6	22	41

Percent correct = 54 %

	Below normal	Normal	Above normal
Hit rate:	47 %	43 %	65 %
BIAS:	0.77	0.87	1.29
CSI:	36 %	30 %	39 %

.

Table 4.1(b) Contingency table for observed and predicted (CPT) rainfall in estimation period (1950/51-1990/91), showing percentage of correct predictions, the hit rate per rainfall category, BIAS and the Critical Success Index (CSI) for each category.

		Predicted			
		Below normal	Normal	Above normal	TOTAL
Observed	Below normal	3	15	0	18
	Normal	0	6	0	6
	Above normal	1	16	0	17
	TOTAL	4	37	0	41

Percent correct = 22%

	Below normal	Normal	Above normal
Hit rate =	17 %	100 %	0 %
BIAS =	0.22	6.16	0
CSI:	16 %	16 %	0 %

Within the estimation period, the predictive ability of RAINMAN is much better than that of CPT. Tables 4.1 (a) and 4.1 (b) show that RAINMAN makes at least twice as many accurate predictions in each category than CPT over the same period. RAINMAN has a 54 % correct forecast hit rate to CPT's 22 %. RAINMAN shows only a slight bias in all the rainfall categories while CPT has a considerable bias in all the categories. Furthermore, RAINMAN has a superior Critical Success Index (CSI) in all forecast categories

Table 4.2(a) Contingency table for observed and predicted (RAINMAN) rainfall in validation period (1990/91-2006/07), showing percentage of correct predictions, the hit rate per rainfall category, BIAS and the Critical Success Index (CSI) for each category.

		Predicted			
		Below normal	Normal	Above normal	TOTAL
	Below normal	3	1	0	4
Observed	Normal	1	3	1	5
	Above normal	2	0	5	7
	TOTAL	6	4	6	16

Percent correct = 69 %

	Below normal	Normal	Above normal
Hit rate:	75 %	60 %	71 %
BIAS:	1.5	0.8	0.86
CSI:	43 %	50 %	63 %

The predictive ability of RAINMAN in the validation period as shown in Table 4.2 (a) is better than that of CPT (Table 4.2 (b)). RAINMAN has 69 % correct predictions while CPT makes 44 % correct predictions. RAINMAN and CPT have similar hit rates in the below normal category of 75 % and 80 % respectively. Their bias and Critical Success Index (CSI) in the below normal category are also similar. RAINMAN shows better predictive ability in the normal and above normal categories. CPT has a 75 % hit rate to RAINMAN's 60 %. However, CPT is greatly biased towards the normal category with a bias of 1.75 to RAINMAN's 0.8. RAINMAN has a stronger critical CSI of 50 % to CPT's 38 %. While RAINMAN has a good predictive ability in the above normal category (Hit rate – 71 %; Bias- 0.86; CSI- 63 %), CPT makes no predictions in the above normal category.

Table 4.2(b) Contingency table for observed and predicted (CPT) rainfall in validation period (1990/91-2006/07), showing percentage of correct predictions, the hit rate per rainfall category, BIAS and the Critical Success Index (CSI) for each category.

		Predicted			
		Below normal	Normal	Above normal	TOTAL
	Below normal	4	1	0	5
Observed	Normal	1	3	0	4
	Above normal	4	3	0	7
	TOTAL	9	7	0	16.

Percent correct = 44 %

	Below normal	Normal	Above normal
Hit rate:	80 %	75 %	0 %
BIAS:	1.8	1.75	0 %
CSI:	40 %	38 %	0 %

Table 4.2(c) Values of χ^2- statistics for the contingency tables

	N	χ^2_{calc}
RAINMAN(1991/92- 2006/07)	16	25.3
RAINMAN (1950/51-1990/91)	41	9.63
CPT (1991/92-2006/07)	16	1.8
CPT(1951/52- 1990/91)	41	2.3

χ^2 significance tests carried out for the contingency tables (Table 4.2 (c)) revealed a significant association between observed rainfall and predicted (RAINMAN) rainfall for the validation and estimation periods ($\chi^2_{calc} \geq \chi^2_{5\%\ 9.49}$). The significance test also showed no association between observed rainfall and predicted (CPT) rainfall amounts for the validation and estimation periods

($\chi^2_{\text{calc}} \leq \chi^2_{5\%\ 9.49}$). Based on the contingency tables results in the validation and estimation periods, RAINMAN is a better probabilistic seasonal total rainfall predictor than CPT. RAINMAN makes good predictions in all the categories of rainfall while CPT makes most predictions within the normal category of rainfall.

Table 4.3(a) Summary of the error statistics of the observed and predicted rainfall for the validation period (1990/91-2006/07).

	RAINMAN	CPT
MSE	60 304	68 888
RMSE	246	262
MAE	167	209
MAPE	49.7	50.6
Variation coefficient (VC)	38.4	41

The error statistics as summarized in Table 4.3 (a) reaffirm the stronger predictive abilities of RAINMAN to CPT. In all cases in the validation period, RAINMAN shows a slight superiority over CPT by having lesser error values for all the statistics. However, in the estimation period (Table 4.4 (b)), CPT tends to minimize the forecast errors more than RAINMAN. The MAPE for CPT and RAINMAN is identical. CPT has better statistics for MSE, RMSE, MAE and VC. CPT minimizes its errors over the larger data in the estimation period because it mostly makes its forecasts in the normal rainfall category. CPT therefore evens out all the anomalies over the longer test period from 1950/51 to 1990/91, hence the smaller errors.

Table 4.3(b) Summary of the error statistics of the observed and predicted rainfall for the estimation period (1950/51-1990/91).

	RAINMAN	CPT
MSE	52 382	42 868
RMSE	228	207
MAE	184	178
MAPE	42	42
Variation coefficient (VC)	39	36

4.2 Conclusion

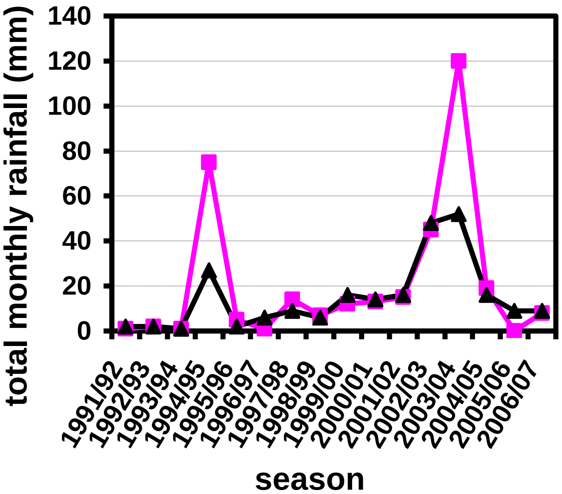
RAINMAN has a better ability in predicting total seasonal rainfall in all categories of rainfall (wet/above normal (20 %), normal (50 %), and dry/below normal (80 %)) for the validation and estimation periods. RAINMAN makes better predictions per rainfall category than CPT. RAINMAN's ability to make good predictions in all the three categories of rainfall makes it an appropriate tool for this study since Masvingo is found in agro-ecological region IV of Zimbabwe, which experiences high rainfall variability and considerable below normal rainfall activity.

Furthermore, RAINMAN has the ability to make rainfall predictions for each of the months within the full agricultural season. This ability is useful in the maize yield simulation phase, since the crop production simulation model proposed for this study makes use of daily, dekadal or monthly rainfall totals for simulation. Based on the results presented, RAINMAN was found to be a suitable forecasting tool for integration into the decision support tool for maize production in Masvingo.

PART 2: GENERATION OF RAINFALL TIME SERIES

4.3 RAINMAN monthly rainfall predictions

Figure 4.4 and Table 4.4 show that RAINMAN has a significantly useful ability in predicting the variance of rainfall per month during the validation period 1991/92-2006/07. RAINMAN explained more that two-thirds of the variance of monthly rainfall in October, November, January, February and April as shown by the coefficients of determination which range from 0.67-0.81(Appendix B). The relationship was marginally significant for the months of December (0.37) and March (0.48). A highly anomalous rainfall amount of 413 mm received in March 2003 resulted in only 48 % of rainfall variance being explained. This was a result of cyclone Japheth which the tool is not positioned to predict.


total monthly rainfall (mm)
0
20
40
60
80
100
120
140
1991/92
1992/93
1993/94
1994/95
1995/96
1996/97
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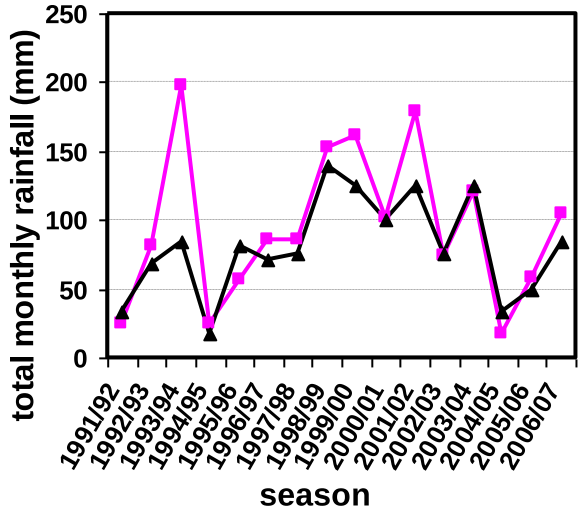
2005/06
2006/07
season

a


total monthly rainfall (mm)
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100
150
200
250
1991/92
1992/93
1993/94
1994/95
1995/96
1996/97
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2002/03
2003/04
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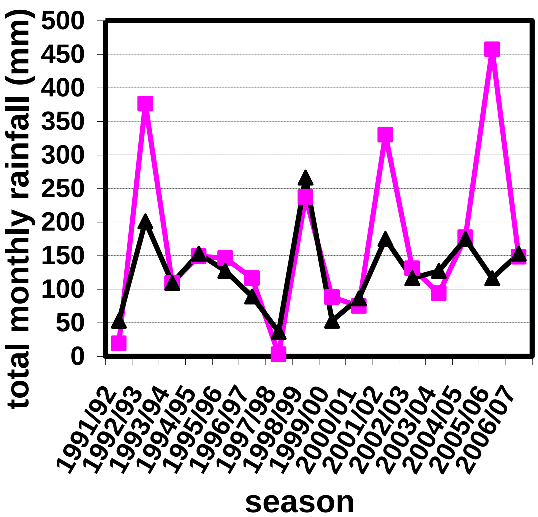
2005/06
2006/07
season

b


total monthly rainfall (mm)
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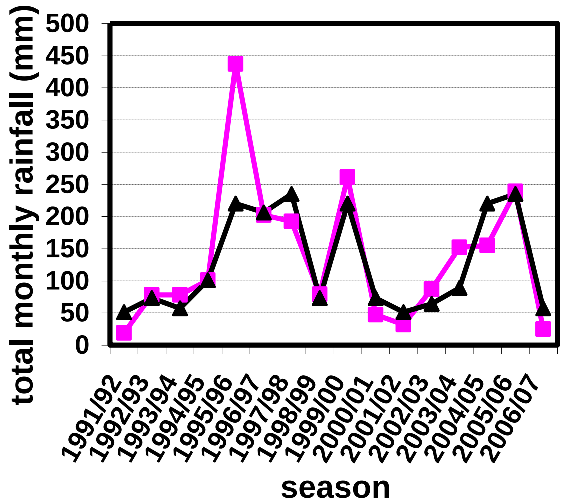
2005/06
2006/07
season

c


total monthly rainfall (mm)
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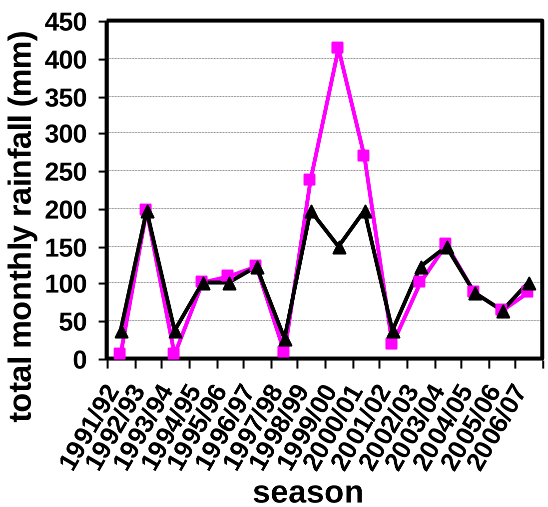
2005/06
2006/07
season

d


total monthly rainfall (mm)
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2002/03
2003/04
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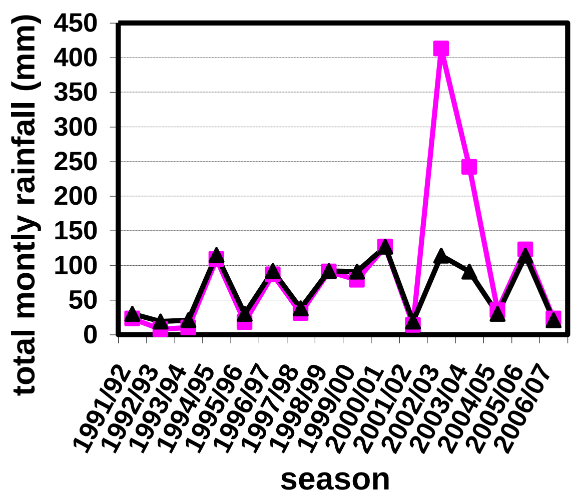
2005/06
2006/07
season

e


total montly rainfall (mm)
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1991/92
1992/93
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1998/99
1999/00
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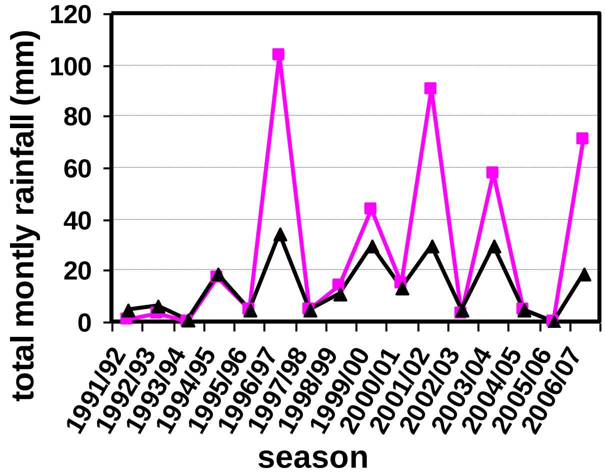
2001/02
2002/03
2003/04
2004/05
2005/06
2006/07
season

f



g

Figure 4.4 Comparison of the observed (squares) and predicted (triangles) monthly rainfall for the months of October to April for the period 1991/92 – 2006/07; (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

Table 4.4 Showing R^2, t-statistics (Appendix C), the error statistics MSE, RMSE, MAE, and the percentage variance of the MAE from the mean rainfall in (brackets).

Month	Mean Rainfall (mm)	R^2	t	MSE (mm)	RMSE (mm)	MAE (mm)
October	25	0.76	1.24	444	21	9.6(36)
November	80	0.70	1.86	1180	34	21(26)
December	145	0.37	2.18	11113	105	57(39)
January	144	0.68	0.62	3935	63	38(26)
February	119	0.67	0.86	4941	70	32(27)
March	82	0.48	1.17	7064	84	34(42)
April	22	0.81	2.18	764	28	15(68)

t-distribution significance tests carried out for the correlation coefficients on the relationship between observed and predicted rainfall accepted *Ho* ($t < t_{\alpha = 0.025\ (2.49)}$) for all months thereby showing that a significant relationship exists between RAINMAN predictions and observed rainfall for all months.

Despite RAINMAN explaining only 37 % variance of monthly rainfall variance in December, the MAE of the December predictions was 39 % of average rainfall which shows that December predictions are much better than R^2 reflects. RAINMAN had difficulty predicting highly anomalous rainfall amounts experienced in December of 1992/93 (376 mm), 2001/02 (330 mm) and 2005/06 (457 mm). April rainfall predictions showed a very significant relationship to the observed rainfall (R^2 = 0.87). However, a MAE of 68 % of mean rainfall shows that April predictions are not as accurate as the relationship may imply. Figure 4.4 (g) showing the trend analysis for April rainfall confirms that RAINMAN underestimates rainfall in April. In general, RAINMAN shows a significant predictive ability in making monthly predictions of rainfall for the period of October to March for Masvingo. April predictions were however cautiously included in the seasonal predictions.

Figure 4.5 and Appendix B; Tables B- 22 to 26 show the predictions of rainfall made by RAINMAN using the SOI phase system for the months October to March for the three categories of rainfall (dry/below normal (80 %), normal (50 %), wet/above normal (20 %)). The month of April has been included to account for seasons which overlap the month of March. The rainfall series shown in figure 4.5 and Appendix B-22 to 26 are the weather scenarios used as rainfall input in crop yield simulations.

The rainfall amounts generated by RAINMAN (Figure 4.5; Appendix D: D- 22 to D- 26) show the expected trend of lower total monthly rainfall amounts for a falling and negative SOI index and higher rainfall amounts for the rising and positive SOI index for the growing season relative to the neutral phase. As expected, rainfall peaks for the season were found between December and February for all SOI phases and probabilities of occurrences.

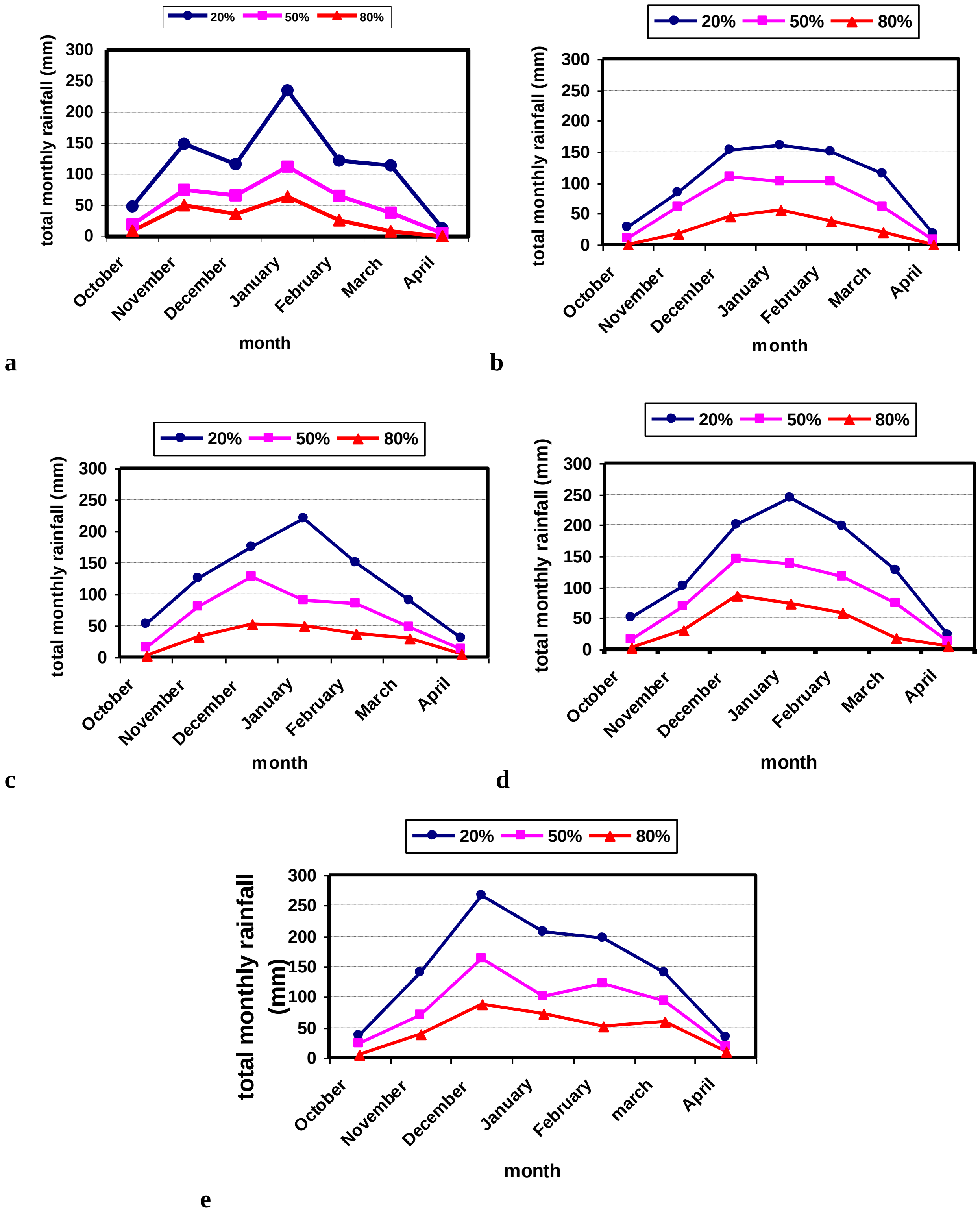


Figure 4.5 Monthly rainfalls generated using RAINMAN by SOI phase and probability of occurrence for the growing season at Masvingo. (a) SOI falling, (b) SOI negative (c) SOI neutral (d) SOI rising (e) SOI positive.

Table 4.5 Mean monthly maximum and minimum temperatures and ETo for the growing season at Masvingo.

	Oct	Nov	Dec	Jan	Feb	March	April
Mean monthly maximum temperature (˚ C)	29	29.3	28.5	28.6	27.7	27.6	26.1
Mean monthly minimum temperature (˚C)	14.5	16.2	16.9	17.3	16.9	15.7	12.5
ETo (mm/day)	5.5	5.7	5.5	5.4	5.0	4.7	4.0

The mean monthly maximum and minimum temperatures were calculated using data obtained from the ZMSD for a period of at least 30 years. ETo values were obtained using the FAO ETo calculator using the minimum and maximum temperatures in Table 4.5 for a semi arid location and moderate wind speed.

PART 3: CROP SIMULATION AND DECISION CRITERIA

In order to achieve a clear picture of the dynamics between maize growth and agrometerorological factors at Masvingo, maize production simulations were carried out bearing probabilistic rainfall predictions by RAINMAN based on the SOI phase, fertility levels, and optimal planting dates. Grain yields were obtained for these scenarios for 3 maize cultivars as shown in Tables 4.6 (a) - (c). Simulated maize yields ranged from 1.2 t/ha to 5.9 t/ha. Sowing date was found to have no particular impact on the maize yields for all the SOI phases under poor fertility. However, planting date was found to be significant for the maize cultivars under optimal fertility especially for the 140-day cultivar given normal rainfall conditions (50 %) for a falling, negative and neutral SOI phase. Under these conditions, yields varied by as much as 1.9 t/ha. For the 100-day and 125-day maize cultivars, planting date was significant given a neutral SOI, and normal rainfall (50 %). Yields varied by as much as 1.3 t/ha.

Table 4.6(a) Simulated maize yields by SOI phase for a 100-day maize cultivars, sowing dates for Masvingo for poor and near optimal fertility and wet/above normal (20 %), normal (50 %) and dry/below normal (80 %) rainfall conditions for each phase.

		Fertility level		Mean yields (tons/ha)		
				early (29 Oct)	mid(16 Nov)	late (7 Dec)
SOI PHASE	FALLING	poor	20%	2.3	2.3	2.3
			50%	2.2	2.2	1.9
			80%	2.1	2.1	2.1
		near optimal	20%	4.3	4.3	4.3
			50%	3.7	3.9	4
			80%	3.3	3.3	3.4
	NEGATIVE	poor	20%	2.2	2.2	2.3
			50%	2.1	2.1	2.3
			80%	2.1	2.1	2.2
		near optimal	20%	4.1	4.3	4.4
			50%	3.9	4.1	4.2
			80%	3.2	3.2	3.4
	NEUTRAL	poor	20%	2.3	2.3	2.4
			50%	2.2	2.3	2.3
			80%	2.1	2.1	2.2
		near optimal	20%	4.3	4.4	4.4
			50%	4.1	4.2	3.6
			80%	3.2	3.3	3.5
	POSITIVE	poor	20%	2.3	2.4	2.3
			50%	2.2	2.3	2.4
			80%	2.1	2.2	2.2
		near optimal	20%	4.3	4.4	4.3
			50%	4.1	4.3	4.4
			80%	3.5	3.5	3.6
	RISING	poor	20%	2.2	2.3	2.2
			50%	2.2	2.3	2.2
			80%	2.1	2.2	2.2
		near optimal	20%	4.2	4.4	4.4
			50%	4.1	4.3	4.4
			80%	3.4	3.5	3.6

Table 4.6(b) Simulated maize yields by SOI phase for a 125-day maize cultivars and sowing dates for Masvingo for poor and near optimal fertility and wet/above normal (20 %), average (50 %) and dry/below normal (80 %) rainfall for each phase.

				Mean yields (tons/ha		
		Fertility level		early (29 Oct)	mid(16 Nov)	late (7Dec)
		poor	20%	2	2	2
			50%	1.8	1.8	1.9
	FALLING		80%	1.7	1.8	1.9
		near optimal	20%	5.3	5.1	5.2
			50%	3.1	3.5	3.2
			80%	1.9	2	2
		poor	20%	2.2	2.3	2.3
			50%	1.8	1.9	1.9
	NEGATIVE		80%	1.7	1.7	1.8
		near optimal	20%	5	5.1	5.2
			50%	4.6	4.9	4.9
			80%	1.9	2	2.1
		poor	20%	1.9	2	2
			50%	1.9	1.9	1.9
SOI PHASE	NEUTRAL		80%	1.7	1.8	1.8
		near optimal	20%	5.1	5.2	5.3
			50%	4.9	4.3	3.6
			80%	1.9	2	2.1
		poor	20%	2	2	2
			50%	1.9	2	2
	POSITIVE		80%	1.7	1.8	1.9
		near optimal	20%	5.1	5.3	5.2
			50%	5	5.2	5.3
			80%	2	1.9	2
		poor	20%	1.9	2	2
			50%	1.8	1.9	1.9
	RISING		80%	1.7	1.8	1.9
		near optimal	20%	5.1	5.2	5.3
			50%	5	5.1	5.2
			80%	2	1.9	2

Table 4.6(c) Simulated maize yields by SOI phase for a 140-day maize cultivar and sowing dates for Masvingo for poor and near optimal fertility and wet/above normal (20 %), average (50 %) and dry/below normal (80 %) rainfall for each phase.

				Mean yields (tons/ha)		
		Fertility level		early (29 Oct)	mid(16 Nov)	late (7 Dec)
		poor	20%	1.9	2	2
			50%	1.8	1.8	1.9
	FALLING		80%	1.7	1.8	1.8
		near optimal	20%	5.7	5.7	5.7
			50%	2.3	2.7	2
			80%	1.5	1.6	1.6
		poor	20%	1.8	2	2
			50%	1.7	1.8	1.9
	NEGATIVE		80%	1.5	1.6	1.7
		near optimal	20%	5.4	5.6	5.8
			50%	3.5	4.5	4
			80%	1.7	1.6	1.6
		poor	20%	1.9	2	2
			50%	1.8	1.9	1.9
SOI PHASE	NEUTRAL		80%	1.5	1.7	1.7
		near optimal	20%	5.6	5.8	5.8
			50%	4.2	3.1	2.3
			80%	1.5	1.6	1.6
		poor	20%	1.9	2.1	2.1
			50%	1.8	2	2
	POSITIVE		80%	1.6	1.8	1.8
		near optimal	20%	5.7	5.9	5.8
			50%	5.4	5.8	5.8
			80%	1.3	1.2	1.3
		poor	20%	1.8	2	2
			50%	1.8	2	2
	RISING		80%	1.6	1.7	1.8
		near optimal	20%	5.5	5.7	5.8
			50%	5.4	5.7	5.8
			80%	1.4	1.3	1.2

4.4 SOI impacts by maize cultivar

The 100-day maize cultivar experienced highest grain yields during the neutral, positive and rising phases of the SOI. Maximum yields of 4.4 t/ha and minimum yields averaging 2.1 t/ha were obtained (Table 4.6 (a); Figure 4.5). 125-day maize cultivars experienced maximum yields of 5.3 t/ha. Minimum yields of 1.7 t/ha were experienced for all SOI phases for predicted dry (80 %) rainfall conditions. 140-day maize cultivars produced the highest grain yields of 5.9 t/ha for a positive SOI phase and predicted wet/above normal (20 %) rainfall conditions (Figure 4.9). Figures 4.5 to 4.9 show that under near optimal fertility, grain yields fluctuate with the maize cultivar for all SOI phases for predicted dry conditions (80 %). The longer the maize cultivar takes to mature, the lower the grain yields attained.

4.5 SOI impacts by fertility level

Figures 4.5 to 4.9 show that maize yields were depressed under poor fertility and higher for near optimal fertility for all maize cultivars given expected good rains as shown for a rising, positive and neutral SOI phase and rainfall predictions of 20 % (wet) and 50 % (normal). Maximum predicted yields of 5.9 t/ha were obtained for optimal fertility, a positive SOI and predicted wet (20 %) rainfall conditions for the 140-day maize cultivar (Table 4.6c). The 140-day maize cultivar yielded the maximum yields for near optimal fertility levels whilst the 100-day cultivar did better under poor fertility levels for all rainfall probabilities, yielding no less than 2 t/ha (Table 4.6a; Figure 4.5a-4.9a).

Poor grain yields were obtained by all maize cultivars for all the five SOI phases given poor fertility. The least amount of grain was found to occur under dry (80 %) rainfall predictions. However, minimum yields of as little as 1.2 t/ha were obtained for the 140-day maize cultivar for dry rainfall (80 %) conditions for a rising and positive SOI phase and near optimal fertility levels (Figure 4.8 (b) and 4.9 (b)). This shows that fertility levels add no value to 140-day maize when low rainfall is expected. On the contrary, increased fertility tends to boost yields for 100-day maize cultivars even under predicted dry rainfall conditions (80 %) for all SOI phases. Grains yields as much as 3.6 t/ha were obtained for near optimal fertility levels and rising and positive SOI phases (Table 4.6 (a)). Grain yields for 125-day maize under predicted dry (80%) rainfall conditions and near optimal fertility averaged 1.9 t/ha.

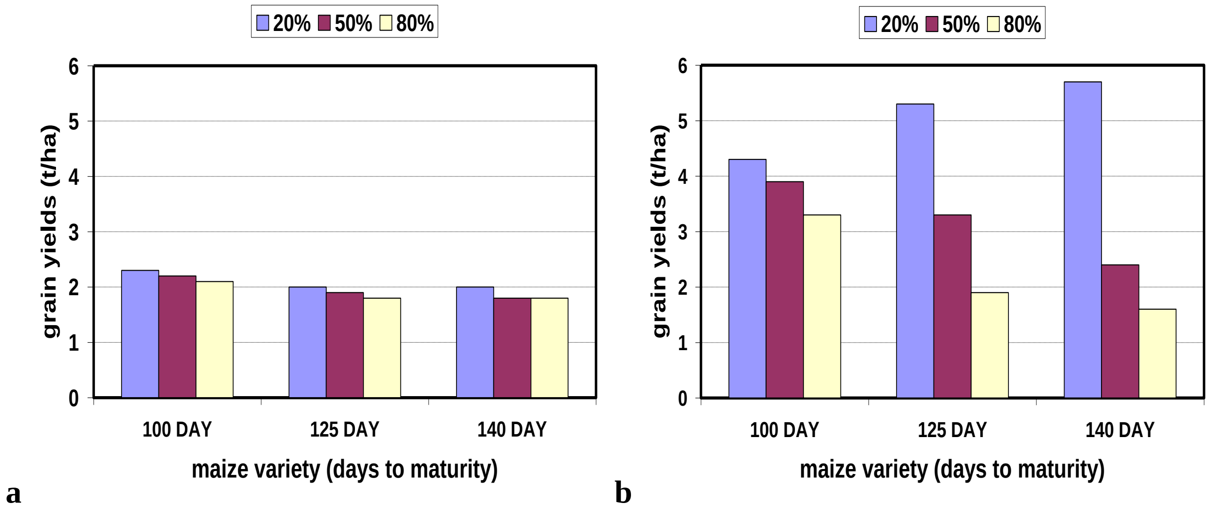


Figure 4.5 Simulated average grain yields for different maize cultivars for a falling SOI index for wet/above normal (20 %), normal (50 %) and dry/below normal (80 %) rainfall conditions given (a) poor fertility and (b) near optimal fertility.

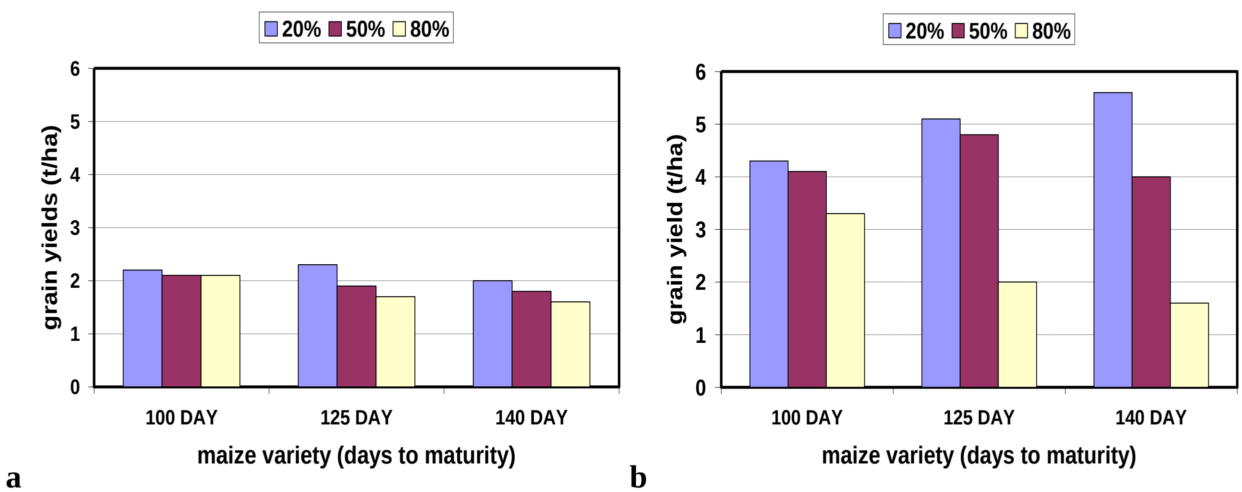


Figure 4.6 Simulated average grain yields for different maize cultivars for a negative SOI index for wet/above normal (20 %), normal (50 %) and dry/below normal (80 %) rainfall conditions given (a) poor fertility and (b) near optimal fertility.

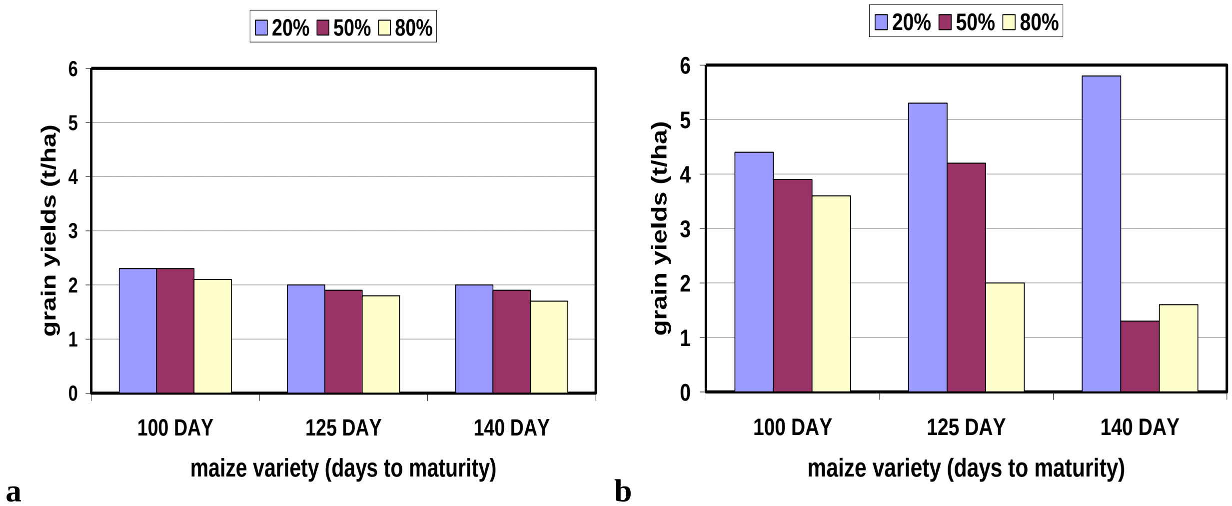


Figure 4.7 Simulated average grain yields for different maize cultivars for a neutral SOI index for wet/above normal (20 %), normal (50 %) and dry/below normal (80 %) rainfall conditions given (a) poor fertility and (b) near optimal fertility.

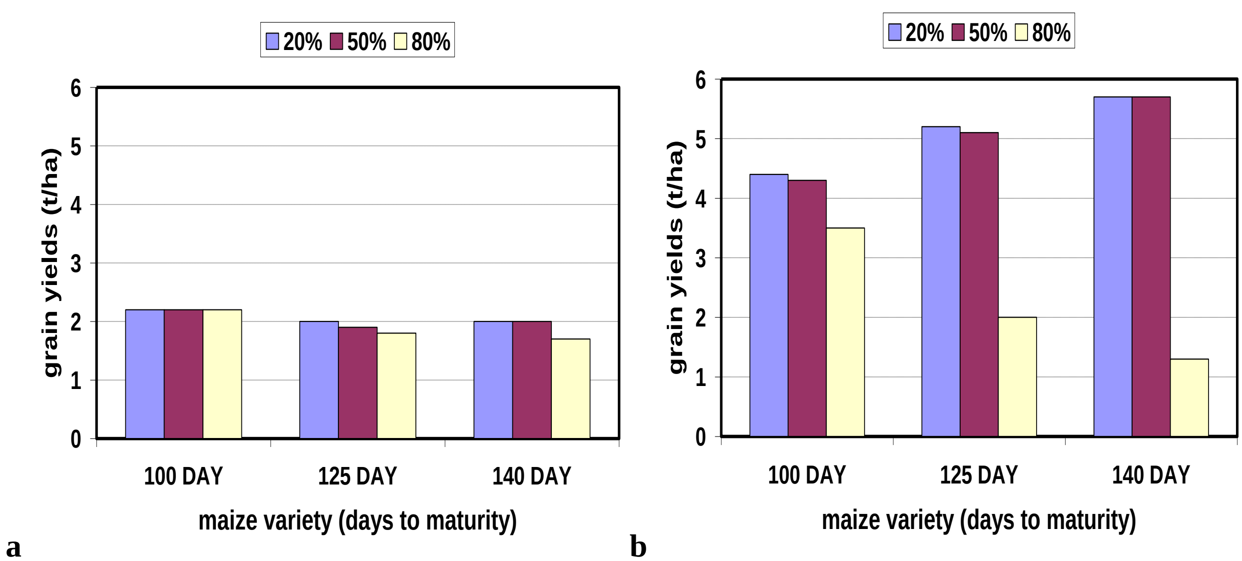


Figure 4.8 Simulated average grain yields for different maize cultivars for a rising SOI index for wet/above normal (20 %), normal (50 %) and dry/below normal (80 %) rainfall conditions given (a) poor fertility and (b) near optimal fertility

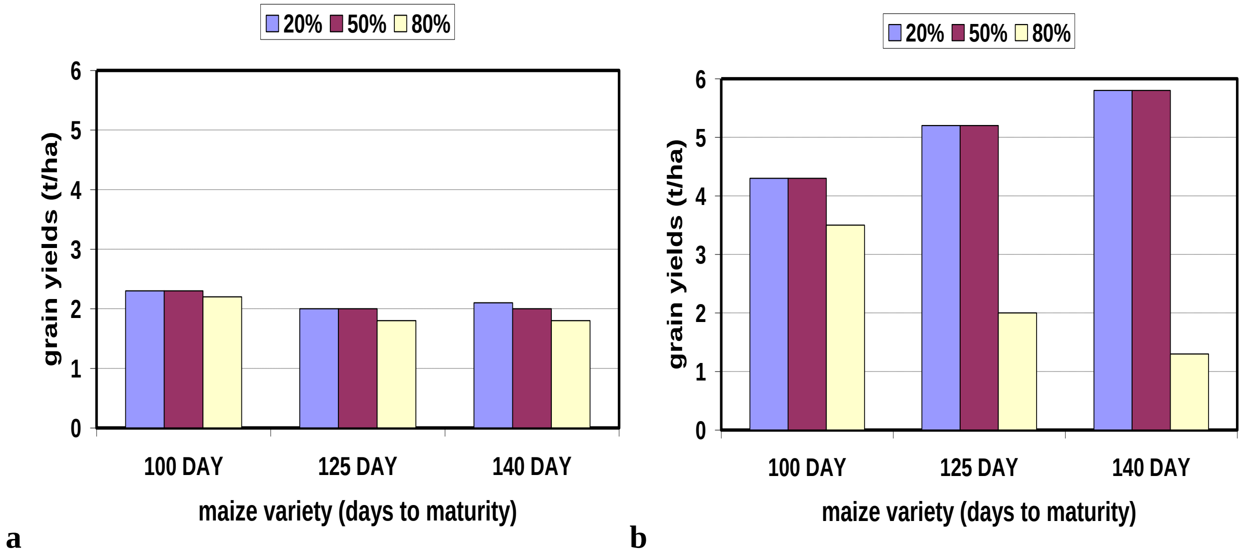


Figure 4.9 Simulated average grain yields for different maize cultivars for a positive SOI index for wet/above normal (20 %), normal (50 %) and dry/below normal (80 %) rainfall probabilities given (a) poor fertility and (b) near optimal fertility

Given 50 % probability of rainfall occurrence under optimal fertility for a falling SOI phase, the 100- day maize cultivar is most likely to produce the highest yields. The 125-day maize cultivar produces higher yields for a negative and neutral SOI phase. For the 140-day maize cultivars, higher yields are expected for a rising and positive SOI phase for the 50 % probability of occurrence.

4.6 Decision support criteria

4.6.1 Falling SOI

Given a falling SOI phase, farmers are better placed planting 100-day maize cultivars late (7 December) (Figure 4.10 (a)). However, given wet conditions (20 %) for a falling SOI phase, 140-day maize cultivars produce higher maize yields. given dry rainfall conditions (80 %), maize yields can be as low as 1.3 t/ha under optimal fertility if 140-day maize is planted. For the 20 % and 80 % probabilities, any of the three planting dates achieves the given yields.

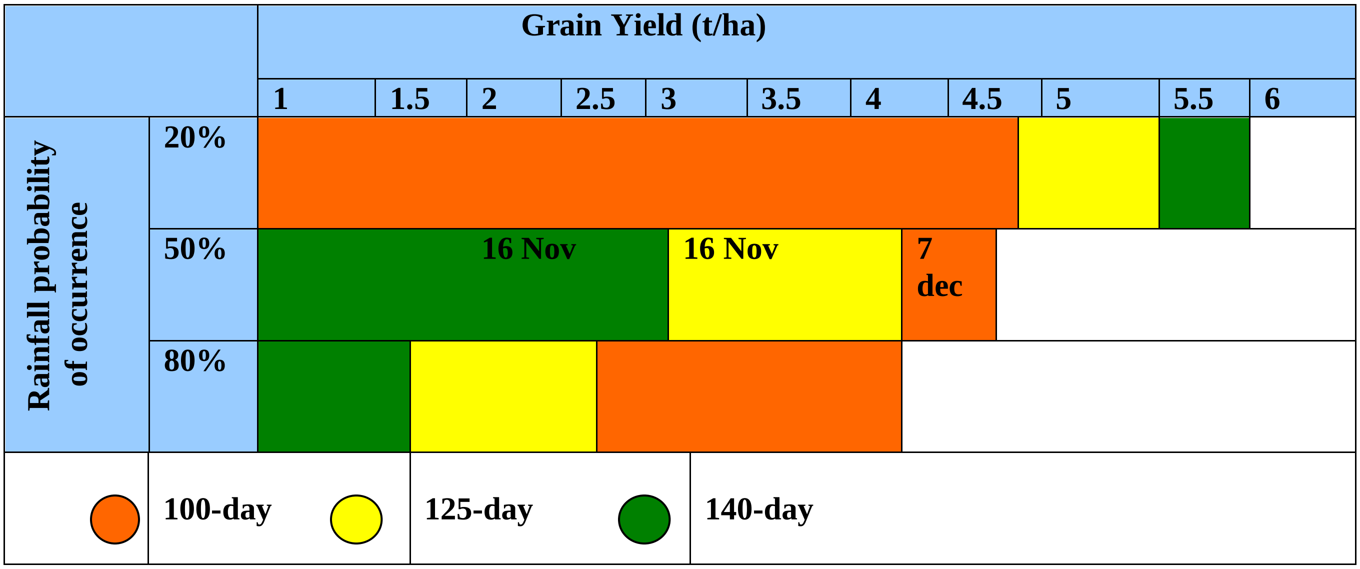


Figure 4.10 (a) guidelines for maize production at Masvingo, showing expected grain yields based on a falling SOI phase (wet (20 %), normal (50 %) and dry (80 %) rainfall conditions), optimal fertility, maize cultivar and planting date.

4.6.2 Negative SOI

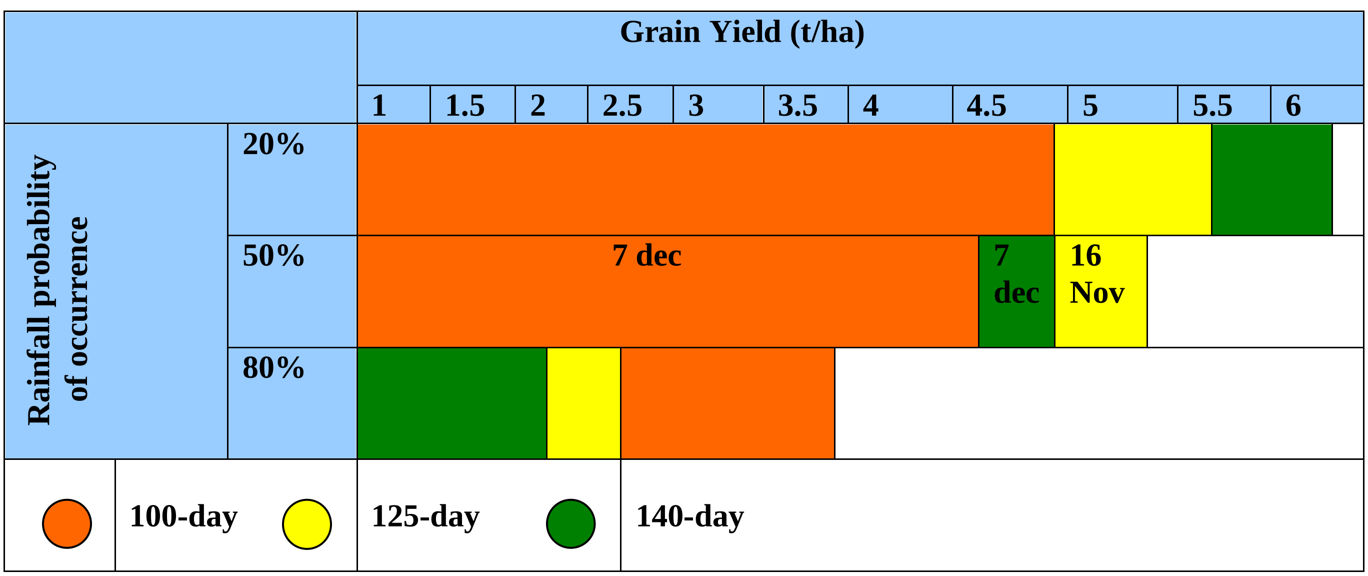


Figure 4.10 (b) guidelines for maize production at Masvingo, showing expected grain yields based on a negative SOI phase (wet (20 %), normal (50 %) and dry (80 %) rainfall conditions), optimal fertility, maize cultivar and planting date.

Figure 4.10 (b) shows that given a negative SOI phase, farmers are likely to obtain better yields by planting 125-day maize on 16 November. Given wet rainfall conditions (20 %) for a negative SOI, 140-day maize produces higher yields. 100-day maize performs better for dry rainfall conditions (80 %) for the negative SOI phase. For the 20 % and 80 % rainfall probabilities, any of the three planting dates achieves the given yields.

4.6.3 Nuetral SOI

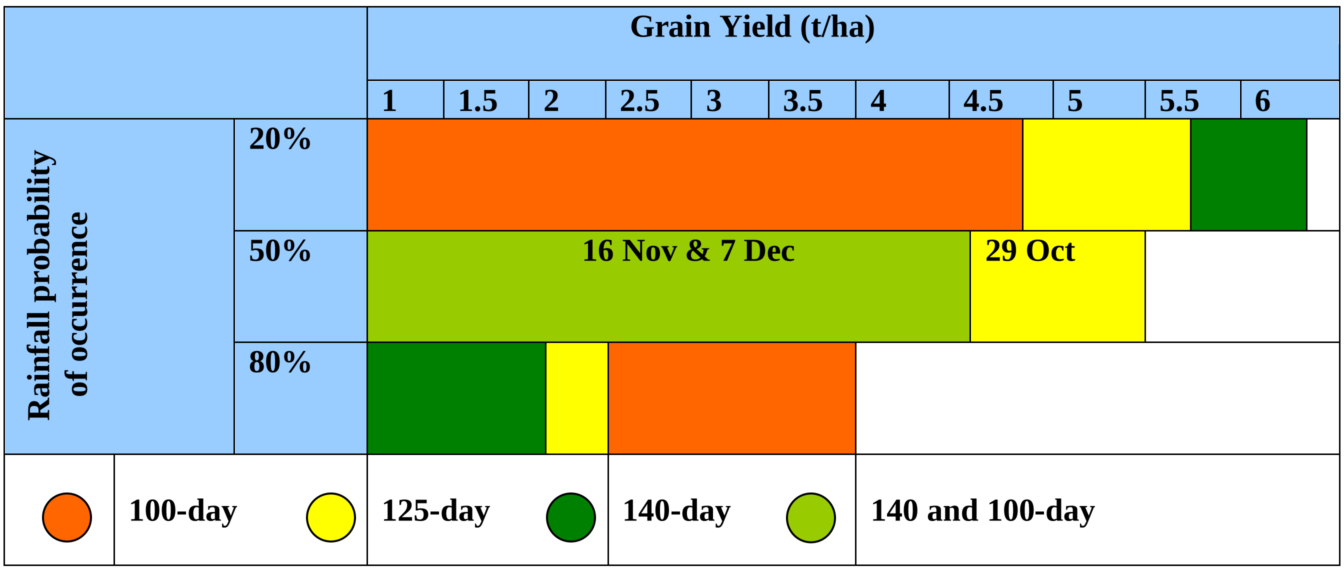


Figure 4.10 (c) guidelines for maize production at Masvingo, showing expected grain yields based on a neutral SOI phase (wet (20 %), normal (50 %) and dry (80 %) rainfall conditions), optimal fertility, maize cultivar and planting date.

If the SOI is neutral (Figure 4.10 (c)), 125-day maize cultivars produce higher yields (5 t/ha) if planted early (29 October). Given wet (20 %) conditions for the neutral phase, 140-day maize performs best. For the dry (80 %) conditions under a neutral phase, 100-day maize cultivars perform best. Yields can be as low as 1.5 t/ha if 140-day maize is planted under dry (80 %) conditions. For the 20 % and 80 % rainfall probabilities, any of the three planting dates achieves the given yields.

4.6.4 Rising SOI

If the SOI is rising, better yields of up to 5.8 t/ha are obtained if the 140-day maize is planted late (7 December). Given dry (80 %) rainfall conditions, the 100-day maize cultivar produces better yields. Minimum yields of 1.3 t/ha are obtained for the 140-day variety under dry (80 %) conditions. Given the 20 % and 80 % rainfall probabilities, any of the three planting dates achieves the given yields (Figure 4.10 (d)).

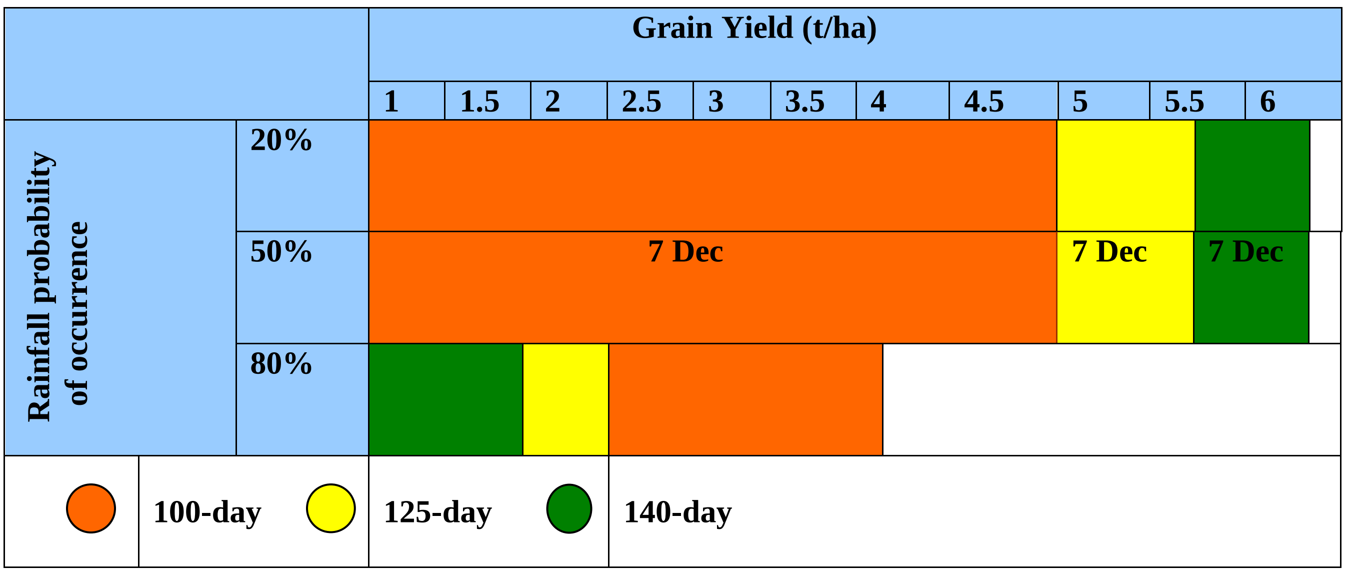


Figure 4.10 (d) guidelines for maize production at Masvingo, showing expected grain yields based on a rising SOI phase (wet (20 %), normal (50 %) and dry (80 %) rainfall conditions), optimal fertility, maize cultivar and planting date.

4.6.5 Positive SOI

Given a rising SOI (Figure 4.10 (e)), farmers are advised to plant the 140-day maize cultivar late (7 December) in order to attain yields of as much as 5.9 t/ha. As with all the other SOI phases, 100-day maize cultivars perform better for dry (80 %) conditions. Given the 20 % and 80 % rainfall probabilities, any of the three planting dates achieves the given yields.

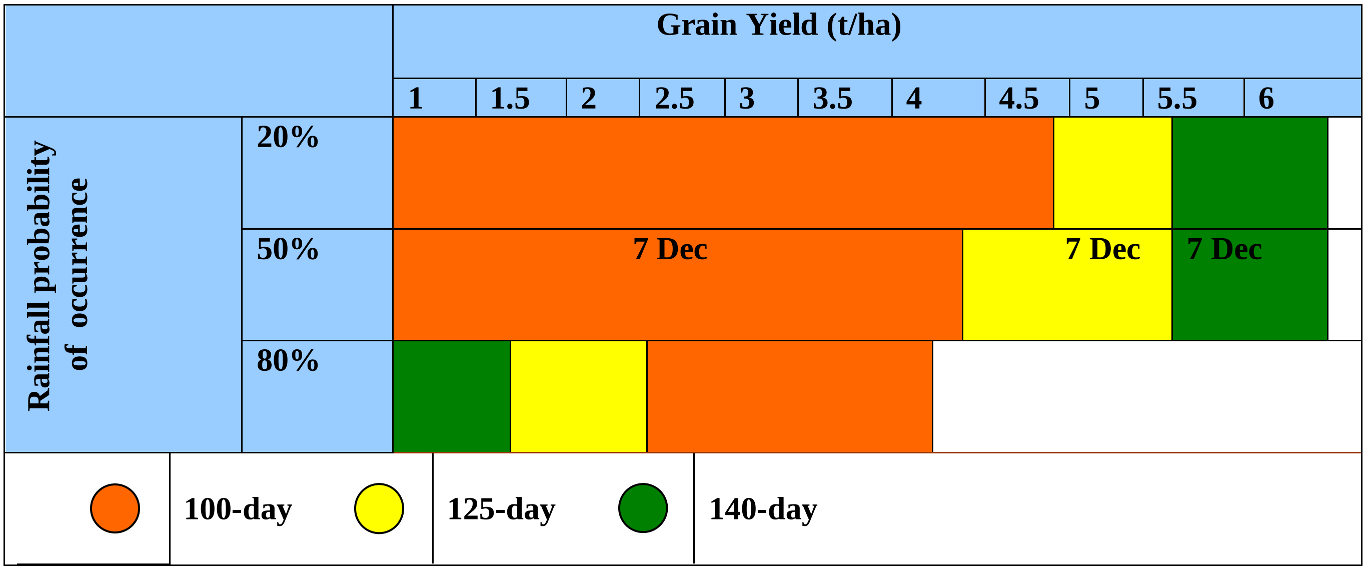


Figure 4.10 (e) guidelines for maize production at Masvingo, showing expected grain yields based on a positive SOI phase (wet (20 %), normal (50 %) and dry (80 %) rainfall conditions), optimal fertility, maize cultivar and planting date.

Figure 4.11 shows the decision criterion for maize production at Masvingo. The decision support tool was developed based on the normal (50 %) rainfall conditions for all the SOI phases. The 50 % probability of occurrence represents rainfall which can be received once in every two years. Only optimal fertility levels were considered since yields are mostly depressed for poor fertility levels despite rainfall probability, maize cultivar or planting date. The decision criterion shows the optimal grain yields which can be obtained for each maize cultivar and optimal planting date.

The Decision Support tool shows that for a rising and positive SOI phase, yields can be as high as 5.8 t/ha if the 140-day maize cultivar is planted late (7 December). In effect, all the maize cultivars attain their highest possible yields if planted late for a rising and positive SOI phase. 100-day maize cultivars yield as much 4.2 t/ha. 125-day maize yields up to 5.2 t/ha for a rising SOI and 5.3 t/ha for a positive SOI. For a neutral SOI phase, the best possible yields of as much as 5 t/ha are obtained when a 125-day maize cultivar is planted early (29 October). If the 140-day and 100-day cultivars are planted on median (16 November) and late planting dates respectively, the best yields attainable for the neutral SOI are 4 t/ha. The 125-day maize cultivar also attains highest yields for a negative SOI phase if planted on the median planting date (16 November).

The 100-day maize cultivar is best planted late (7 December) for all the SOI phases if maximum yields are to be obtained. The 100-day cultivar is the most productive given a falling SOI phase.

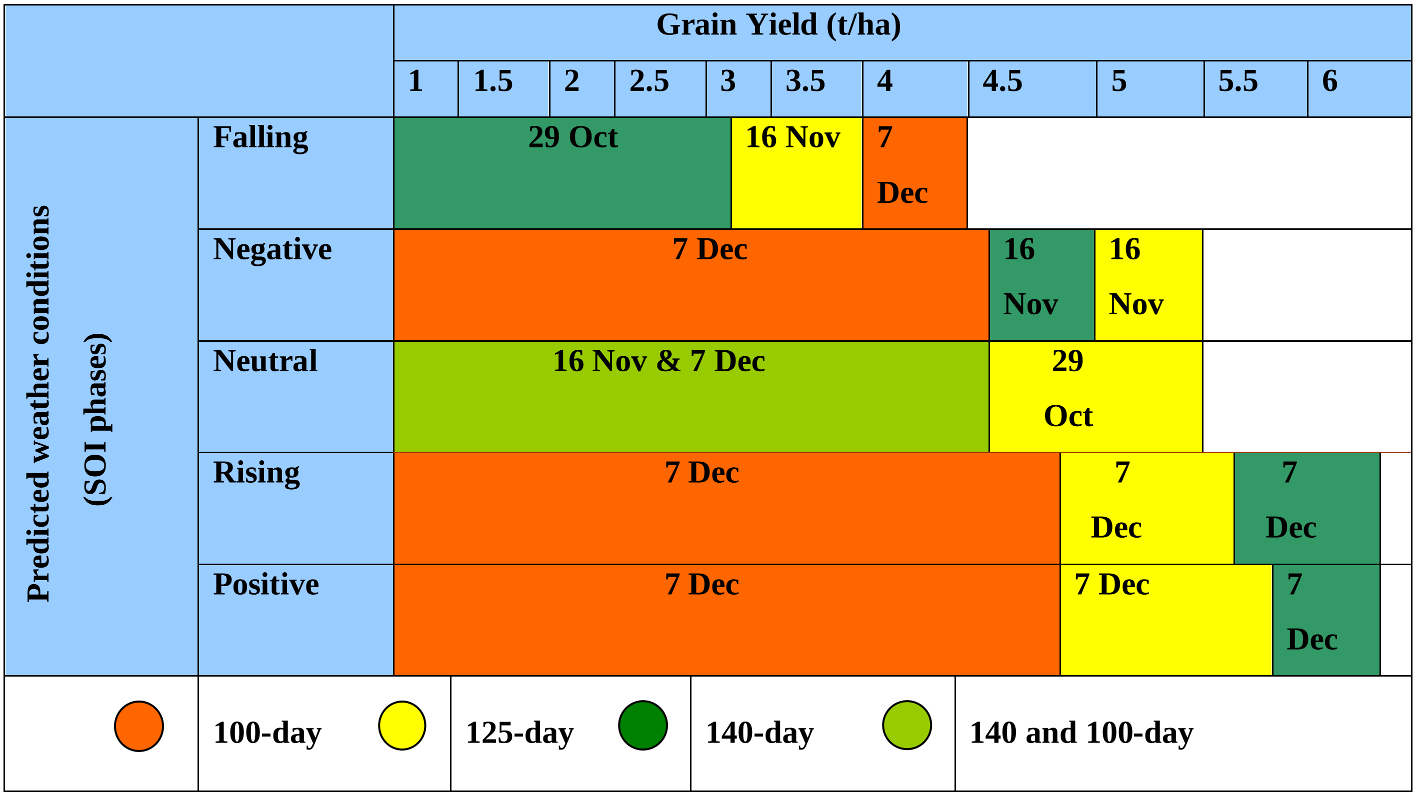


Figure 4.11 decision criterion for maize production at Masvingo, showing expected grain yields based on SOI phases (normal (50 %) probability of occurrence), optimal fertility, maize cultivar and planting date.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

The main aim of the study was to apply available seasonal weather forecast and crop production simulation tools so as to improve decision making in maize production. A simple to use decision support tool for maize production at Masvingo was to be developed using an ENSO-based seasonal weather forecasting tool (RAINMAN) and a crop production simulation model (**AquaCrop**). In this section, we conclude on the tests carried out for the utility of RAINMAN, and the generation of weather series to be used for crop production simulation. Conclusions are also made about simulated maize yields. Recommendations for maize production at Masvingo and further research are highlighted.

5.1 Comparison of RAINMAN and CPT

RAINMAN was found to have a better predictive ability than CPT over a season-long period from October to March. CPT made most of its predictions within the average/normal rainfall category while RAINMAN tended to make predictions within all rainfall categories. Contingency tables clearly showed that RAINMAN makes more correct predictions in total and per rainfall category than CPT (Tables 4.1 (a) and (b); Table 4.2 (a) and (b)). The error statistics for the validation period (1991/92-2006/07) showed RAINMAN to minimize errors more, thereby confirming its better predictive ability (Table 4.3 (a)). However, the longer estimation period (1951/52- 1990/91) showed CPT to minimize errors better than RAINMAN (Table 4.3(b)). This was seen to be misleading since CPT minimized errors by simply making “safe” predictions within the average/normal rainfall category. Conclusions were therefore made based on validation period results. RAINMAN’s ability to forecast on a monthly scale made it even more useful for the purposes of this study. RAINMAN was found to be suitable for making seasonal analyses and forecasts for the decision support tool at Masvingo.

5.2 Rainfall series generation

RAINMAN was found to be practical in monthly rainfall analysis and the generation of rainfall time series for use with the crop model. The tool was used to make forecasts which were out of its optimal forecast zone of no more than a two- month lead time. However, despite weaker statistical significance (LEPS< 7.6; SS< 0.9), the tool still managed to make good monthly rainfall predictions within the validation period (1991/92 – 2006/07). RAINMAN managed to account for more than 65 % of the rainfall variation within that period for the months of October, November, January, February, and April (R^2 ranging from 0.67 to 0.81). For the months of December and March, R^2 values were 0.48 and 0.37 respectively.

The SOI conditioned rainfall series (Figure 4.5; Appendix D: Table D- 29 to D- 33) produced by RAINMAN was aligned to expectations of rainfall during certain phases of the SOI. Rainfall amounts were generally lesser for the falling and negative SOI and higher for the rising and positive SOI relative to the neutral SOI phase.

5.3 Crop simulations and decision criterion

AquaCrop was able to simulate maize yields with only monthly climatic data for the various agrometeorological scenarios. Although the simulated yields were not validated, they resembled average maize yields for Zimbabwe of 4-8 t/ha (Seedco, 2005) under good management and 0.4–2.3 t/ha (FAOSTAT, 2007) under communal fertility levels.

It can be concluded from the results that crop yields vary significantly with SOI phase, fertility level and maize cultivar. Maize yields are overally depressed under poor fertility levels with maximum attainable yields of 2.4 t/ha for all agrometeorological scenarios. However, under near optimal fertility, yields are generally high for all maize cultivars. Early maturing maize cultivars (100-day) are most favourable under falling and negative SOI phases especially when planted late (7 December), yields can be as high as 4.3 t/ha. The 100-day maize cultivar is very productive for dry conditions (80 %) for all SOI phases. The 125-day maize cultivar is favourable for a neutral SOI phase. The late maturing (140- day) maize cultivar is the most productive cultivar for a rising and positive SOI phase and for all wet (20 %) rainfall conditions in each SOI phase. For use in planning and management, a decision criterion was developed for all SOI phases (50 %), near optimal fertility, planting date and maize variety for Masvingo (Figure 4.11).

5.4 Recommendations

The study showed that climate (SOI phase), maize cultivar, planting date and fertility affect maize yields considerably. It is therefore important for farmers to put all these agrometeorological factors into consideration as they plan for an upcoming agricultural season in order to optimize their yields. This study showed that RAINMAN can be used to make predictions of expected rainfall for the season based on the phase of the SOI during July and August. SOI phases can therefore be the bases of planned activities for maize production at Masvingo.

Farmers at Masvingo are advised to apply optimal amounts of fertilizer since it is clear that poor fertility levels depress yields despite rainfall levels. Farmers would miss out on potentially good yields during good quality rainfall seasons as expected during the neutral, rising and positive SOI phases. Farmers' choice of maize cultivar is vital. Considering that the length of the agricultural season at Masvingo varies from 95 –145 days (Sithole, 2003), farmers are advised to select maize cultivars which are within this range. The three maize cultivars used in this study can be used as a guide. Farmers can also select their planting dates based on the SOI phase. We suggest three planting dates which can be used as guides for early (29 October), mid (16 November), and late (7 December) planting.

5.5 Further research

Although **Aquacrop** was able to simulate reasonable crop yields using monthly seasonal forecast rainfall data and mean monthly temperature and ETo data, there is considerable room for improvement if daily or 10-day climate data can be obtained. The shorter rainfall periods will help to account for rainfall distributions which are known to affect maize growth e.g. dry spells. Later versions of RAINMAN can be used to generate the daily forecasts for rainfall and temperature. This study has exposed the potential of integrated modeling in maize production management. We therefore recommend similar studies to be expanded to the rest of Zimbabwe and to include other crops which are vital for food security in Zimbabwe.

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APPENDICES

APPENDIX A: COMPARISON OF RAINMAN AND CPT

Table A- 1: RAINMAN prediction table using the SOI Phase method (July-august) for the validation period (1991/92- 2006/07)

Deciles of rainfall at MASVINGO
Analysis of historical data (1899 to 2001) using SOI Phases: Jul to Aug Leadtime of 1 month
The SOI phases/rainfall relationship for this season is statistically significant because KW test is above 0.9, and Skill Score (8.9) is above 7.6 (p = 0.93).

Rainfall period: Oct to Mar	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	849	1,089	1,012	1,012	1,340	1,340
In 10% yrs, rain at least	687	760	779	901	927	840
20%	560	729	747	785	793	753
30%	534	619	684	729	719	667
40%	488	573	611	638	666	621
50% (median rainfall)	427	530	584	616	637	579
60%	424	480	553	585	616	529
70%	381	416	454	542	578	446
80%	347	391	420	488	429	416
90%	296	208	371	450	393	340
Lowest on record (mm)	162	175	95	235	313	95
Years in historical record	15	19	26	20	23	103
Standard deviation (mm)	175	227	211	189	244	220
Average rainfall (mm)	469	536	577	633	666	584

Table A- 2: RAINMAN prediction table using the SOI phases method (July –Aug) for the estimation period (1950/51)

Deciles of rainfall at MASVINGO

Analysis of historical data (1899 to 1990) using SOI Phases: Jul to AugLeadtime of 1 month

The SOI phases/rainfall relationship for this season is statistically doubtful because KW test is below 0.9 but Skill Score (7.7) is above 7.6 (p = 0.90).

Rainfall period: Oct to Mar	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	722	1,089	966	1,012	1,340	1,340
In 10% yrs, rain at least	625	764	769	904	937	804
20%	541	744	744	790	777	748
30%	532	643	624	715	697	662
40%	497	596	609	630	666	618
50% (median rainfall)	448	530	579	599	637	577
60%	425	492	512	572	616	523
70%	423	417	444	503	546	449
80%	381	384	422	481	427	419
90%	352	208	403	439	386	369
Lowest on record (mm)	271	175	216	235	313	175
Years in historical record	12	17	22	18	21	90
Standard deviation (mm)	125	238	177	198	254	213
Average rainfall (mm)	474	543	570	627	662	585

Table A- 3: SOI phases for July and August, and RAINMAN predictions per tercile of rainfall for the validation period. Highlighted are the selected rainfall values based on Table 3. 3.

YEAR	SOI PHASE										Terciles of Rainfall Occurrence (mm)			Actual R/fall Recorded(mm)
	falling		negative		neutral		rising		positive					
	July	Aug	July	Aug	July	Aug	July	Aug	July	Aug	20%	50%	80%	
1991/92					-1.7	-7.6					744	579	422	95
1992/93							-6.9	+1.4			790	599	481	744
1993/94			-10.8	-14.0							744	530	384	401
1994/95			-18.0	-17.2							744	530	384	559
1995/96					+4.2	+0.8					744	579	422	771
1996/97									+6.8	+4.6	748	577	419	614
1997/98	-9.5	-19.8									541	448	381	334
1998/99									+14.6	+9.8	748	577	419	803
1999/00					+4.8	+2.1					744	579	422	1012
2000/01							-3.7	+5.8			790	599	481	632
2001/02					-3.0	-8.9					744	579	422	588
2002/03	-7.4	-14.9									541	448	381	849
2003/04					2.8	-1.5					744	579	422	890
2004/05					-7.1	-7.6					744	579	422	515
2005/06	1.2	-7.3									541	448	381	966
2006/07			-9.7	-14.9							744	530	384	466

Table A- 4: SOI phases for July and August, and RAINMAN predictions per tercile of rainfall for the estimation period. Highlighted are the selected rainfall values based on Table 3. 3.

YEAR	SOI PHASE										Terciles of Rainfall Occurrence (mm)			Actual R/fall Recorded(mm)
	falling		negative		neutral		rising		positive					
	July	Aug	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	20%	50%	80%	
1950/51									21.1	12.3	777	637	427	432
1951/52							-8.2	-0.5			790	599	481	795
1952/53					3.5	-3.7					744	579	422	966
1953/54	-1.0	-17.2									541	448	381	469
1954/55							4.2	10.4			790	599	481	1012
1955/56									19.2	14.9	777	637	427	621
1956/57									12.6	11.0	777	637	427	666
1957/58	0.9	-9.5									541	448	381	722
1958/59							2.2	7.8			790	599	481	593
1959/60					-5.0	-5.0					744	579	422	338
1960/61									4.8	6.6	777	637	427	637
1961/62					2.2	0.1					744	579	422	430
1962/63							-0.4	4.6			790	599	481	723
1963/64					-1.0	-2.4					744	579	422	403
1964/65									6.8	14.3	777	637	427	616
1965/66			-22.6	-11.4							744	530	384	416
1966/67							-1.0	4.0			790	599	481	783
1967/68							1.6	5.9			790	599	481	235
1968/69					7.4	0.1					744	579	422	743
1969/70					-6.9	-4.4					744	579	422	428
1970/71							-5.6	4.0			790	599	481	496
1971/72							1.6	14.9			790	599	481	647
1972/73			-18.6	-8.9							744	530	384	208
1973/74									6.1	12.3	777	637	427	886
1974/75									12.0	6.6	777	637	427	937
1975/76									21.1	20.7	777	637	427	660
1976/77			-12.8	-12.1							744	530	384	756
1977/78			-14.7	-12.1							744	530	384	776
1978/79					6.1	1.4					744	579	422	484
1979/80			-8.2	-5.0							744	530	384	610

1980/81					-1.7	1.4					744	579	422	744
1981/82									9.4	5.9	777	637	427	385
1982/83			-19.3	-23.6							744	530	384	175
1983/84							-7.3	0.1			790	599	481	400
1984/85					2.2	2.7					744	579	422	787
1985/86							-2.3	8.5			790	599	481	556
1986/87	2.2	-7.6									541	448	381	271
1987/88			-18.6	-14.0							744	530	384	752
1988/89									11.3	14.9	777	637	427	427
1989/90	9.4	-6.3									541	448	381	681
1990/91	5.5	-5.0									541	448	381	162

Table A- 5: CPT predictions and probability of occurrence of rainfall for the validation period (1991/92- 2006/07).

Season	Prediction	Lower bound	Upper bound	Terciles of rainfall		
				Below normal	normal	Above Normal
1991/92	493	249	755	38	33	29
1992/93	530	272	763	36	34	30
1993/94	498	244	755	39	33	28
1994/95	495	254	755	39	33	29
1995/96	523	268	762	36	34	33
1996/97	583	319	776	33	34	33
1997/98	465	208	751	43	31	25
1998/99	490	244	755	39	33	25
1999/00	595	333	777	33	34	33
2000/01	556	296	760	37	34	30
2001/02	514	264	760	37	34	30
2002/03	492	247	755	38	33	28
2003/04	485	234	754	40	33	27
2004/05	492	247	755	38	33	28
2005/06	487	236	754	40	33	28
2006/07	484	231	754	40	33	27

Table A- 6: CPT predictions and probability of occurrence of rainfall for the estimation period (1950/51- 1990/91).

Season	Prediction	Lower bound	Upper bound	Terciles of rainfall		
				Below normal	normal	Above normal
1950/51	621	339	937	32	32	36
1951/52	593	201	780	58	27	15
1952/53	610	266	850	45	32	23

1953/54	588	225	818	54	29	17
1954/55	618	268	887	42	38	28
1955/56	627	416	958	28	31	41
1956/57	631	288	930	35	31	34
1957/58	522	216	798	56	28	16
1958/59	545	234	839	50	29	21
1959/60	600	252	841	48	31	21
1960/61	599	270	851	45	32	23
1961/62	598	274	856	42	33	25
1962/63	595	399	934	31	33	36
1963/64	567	275	857	42	33	26
1964/65	619	395	953	30	31	39
1965/66	551	126	739	66	23	11
1966/67	571	223	826	53	29	18
1967/68	614	240	851	48	29	23
1968/69	602	278	878	39	33	28
1969/70	542	278	877	39	33	28
1970/71	611	434	958	27	32	42
1971/72	617	439	962	26	32	43
1972/73	495	199	816	56	27	17
1973/74	602	572	1067	14	26	60
1974/75	611	439	961	25	32	43
1975/76	618	495	985	20	29	50
1976/77	590	224	814	55	29	17
1977/78	512	225	815	54	29	17
1978/79	576	280	877	38	33	29
1979/80	505	259	882	47	31	21
1980/81	505	273	855	43	32	25
1981/82	566	895	895	38	33	30
1982/83	488	743	743	65	23	11
1983/84	487	863	863	44	30	26
1984/85	583	943	943	31	32	37
1985/86	575	921	921	34	34	33
1986/87	527	831	831	50	31	19
1987/88	454	856	856	45	31	25
1988/89	565	1101	1101	11	24	65
1989/90	594	1033	1033	16	27	57
1990/91	517	288	900	36	33	30

Table A- 7: predicted and observed total seasonal rainfall (mm) in validation period.

Season	Predicted rainfall (mm)		Observed
	RAINMAN	CPT	
1991/92	579	493	95
1992/93	790	530	744
1993/94	384	498	401
1994/95	384	495	559
1995/96	744	523	771
1996/97	577	583	614
1997/98	381	465	334
1998/99	748	490	803
1999/00	744	595	1012
2000/01	790	556	632
2001/02	579	514	588
2002/03	381	492	849
2003/04	744	485	890
2004/05	579	492	515
2005/06	381	487	966
2006/07	384	484	466

Table A- 8: predicted and observed total seasonal rainfall (mm) in estimation period

Season	Predicted rainfall (mm)		Observed
	RAINMAN	CPT	
1950/51	777	621	432
1951/52	790	593	795
1952/53	744	610	966
1953/54	381	588	469
1954/55	790	618	1012

1955/56	777	627	621
1956/57	777	631	666
1957/58	381	522	722
1958/59	790	545	593
1959/60	422	600	338
1960/61	637	599	637
1961/62	744	598	430
1962/63	790	595	723
1963/64	579	567	403
1964/65	579	619	616
1965/66	384	551	416
1966/67	790	571	783
1967/68	790	614	235
1968/69	744	602	743
1969/70	422	542	428
1970/71	790	611	496
1971/72	790	617	647
1972/73	384	495	208
1973/74	777	602	886
1974/75	777	611	937
1975/76	777	618	660
1976/77	384	590	756
1977/78	384	512	776
1978/79	744	576	484
1979/80	530	505	610
1980/81	744	505	744
1981/82	637	566	385
1982/83	384	488	175
1983/84	790	487	400
1984/85	744	583	787
1985/86	790	575	556
1986/87	381	527	271
1987/88	384	454	752
1988/89	777	565	427
1989/90	381	594	681
1990/91	381	517	162

APPENDIX B: GENERATION OF RAINFALL DATA SERIES

Table B- 1: RAINMAN predictions using the SOI phases method (July –Aug) for the month of October.

Deciles of rainfall at MASVINGO
Analysis of historical data (1899 to 2007) using SOI Phases: Jul to AugLeadtime of 1 month
The SOI phases/rainfall relationship for this season is statistically not significant because KW test is below 0.9 and Skill Score (5.0) is below 7.6 (p = 0.69).

Rainfall period: Oct	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	56	75	120	86	58	120
In 10% yrs, rain at least	52	45	75	66	45	57
20%	48	27	52	50	37	45
30%	38	21	37	38	30	32
40%	32	16	25	19	27	23
50% (median rainfall)	19	9	16	14	23	16
60%	16	6	8	13	15	13
70%	14	3	4	7	11	6
80%	9	1	2	2	6	2
90%	4	0	0	0	1	0
Lowest on record (mm)	0	0	0	0	0	0
Years in historical record	13	19	32	21	23	108
Standard deviation (mm)	20	20	33	26	17	25
Average rainfall (mm)	26	17	29	25	22	24

Table B- 2: SOI phases for July (Jul) and August(Aug), and RAINMAN predictions per tercile of rainfall (mm) for the month of October over the validation period (1991/92- 2006/07). Highlighted are the selected rainfall amounts based on which probability closely resembles the actual rainfall.

	SOI PHASE													
year	falling		Negative		neutral		rising		positive		Terciles of rainfall			actual rainfall (mm)
	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	20 %	50 %	80 %	
1991/92					-7.7	-7.6					52	16	2	1
1992/93							-6.9	1.4			50	14	2	2
1993/94			-11	-14							27	9	1	1
1994/95			-18	-17							27	9	1	75
1995/96					4.2	0.8					52	16	2	5
1996/97									6.8	4.6	37	23	6	1
1997/98	-9.5	-19.8									48	19	9	14
1998/99									14.8	9.3	37	23	6	7
1999/00					4.8	2.1					52	16	2	12
2000/01							-3.7	5.3			50	14	2	13
2001/02					-3	-8.9					52	16	2	15
2002/03	-7.6	-14.5									48	19	9	45

2003/04					2.9	-1.8					52	16	2	120
2004/05					-7.1	-7.7					52	16	2	19
2005/06	1.2	-7.3									48	19	9	0
2006/07			-9.6	-15							27	9	1	8

Table B- 3: predicted and observed rainfall (mm) for the month of October over the validation period (1991/92- 2006/07).

Season	observed	predicted
1991/92	1	2
1992/93	2	2
1993/94	1	1
1994/95	75	27
1995/96	5	2
1996/97	1	6
1997/98	14	9
1998/99	7	6
1999/00	12	16
2000/01	13	14
2001/02	15	16
2002/03	45	48
2003/04	120	52
2004/05	19	16
2005/06	0	9

2006/07	8	9

Table B- 4: RAINMAN predictions using the SOI phases method (July –Aug) for the month of November.

Deciles of rainfall at MASVINGO
Analysis of historical data (1899 to 2007) using SOI Phases: Jul to AugLeadtime of 2 months
The SOI phases/rainfall relationship for this season is statistically not significant because KW test is below 0.9 and Skill Score (1.3) is below 7.6 (p = 0.53).

Rainfall period: Nov	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	178	197	179	154	228	228
In 10% yrs, rain at least	152	98	143	121	153	151
20%	149	85	125	101	139	121
30%	126	76	117	87	114	101
40%	91	66	100	77	87	82
50% (median rainfall)	75	61	81	69	71	73
60%	72	50	70	63	68	63
70%	60	28	60	42	49	47
80%	50	18	33	30	38	32
90%	36	13	19	25	30	18
Lowest on record (mm)	0	5	4	7	15	0
Years in historical record	13	19	32	21	23	108
Standard deviation (mm)	54	46	49	39	56	49
Average rainfall (mm)	90	60	85	69	87	78

Table B- 5: SOI phases for July and August, and RAINMAN predictions per tercile of rainfall (mm) for the month of November over the validation period (1991/92- 2006/07). Highlighted are the selected rainfall amounts based on which probability closely resembles the actual rainfall.

	SOI PHASE										terciles of rainfall			actual rainfall (mm)
year	falling		negative		neutral		rising		positive					
	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	20 %	50 %	80 %	
1991/92					-7.7	-7.6					125	81	33	25
1992/93							-6.9	1.4			101	69	30	82
1993/94			-10.8	-14							85	61	18	197
1994/95			-18	-17.2							85	61	18	24

1995/96					4.2	0.8					125	81	33	57
1996/97									6.8	4.6	139	71	38	86
1997/98	-9.5	-19.8									149	75	50	86
1998/99									14.8	9.3	139	71	38	153
1999/00					4.8	2.1					125	81	33	162
2000/01							-3.7	5.3			101	69	30	102
2001/02					-3	-8.9					125	81	33	179
2002/03	-7.6	-14.5									149	75	50	74
2003/04					2.9	-1.8					125	81	33	121
2004/05					-7.1	-7.7					125	81	33	18
2005/06	1.2	-7.3									149	75	50	58
2006/07			-9.6	-15							85	61	18	104

Table B- 6: predicted and observed rainfall (mm) for the month of November over the validation period (1991/92- 2006/07).

season	observed	predicted
1991/92	25	33
1992/93	82	69
1993/94	197	85
1994/95	24	18
1995/96	57	81
1996/97	86	71
1997/98	86	75
1998/99	153	139
1999/00	162	125
2000/01	102	101
2001/02	179	125
2002/03	74	75
2003/04	121	125
2004/05	18	33
2005/06	58	50
2006/07	104	85

Table B- 7: RAINMAN predictions using the SOI phases method (July –Aug) for the month of December.

Deciles of rainfall at MASVINGO
Analysis of historical data (1899 to 2007) using SOI Phases: Jul to AugLeadtime of 3 months
The SOI phases/rainfall relationship for this season is statistically significant because KW test is above 0.9, and Skill Score (9.1) is above 7.6 (p = 0.93).

Rainfall period: Dec	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	457	378	330	492	398	492
In 10% yrs, rain at least	128	226	251	376	291	292
20%	116	153	175	201	266	205
30%	115	147	162	180	226	166
40%	80	142	142	160	208	144
50% (median rainfall)	66	109	127	145	162	123
60%	58	76	114	121	122	106
70%	48	69	88	89	114	82
80%	36	47	53	86	89	65
90%	9	31	32	75	77	35
Lowest on record (mm)	0	27	19	13	34	0
Years in historical record	13	19	32	21	23	108
Standard deviation (mm)	116	97	81	123	96	102
Average rainfall (mm)	97	126	131	172	177	144

Table B- 8: SOI phases for July and August, and RAINMAN predictions per tercile of rainfall (mm) for the month of December over the validation period (1991/92- 2006/07). Highlighted are the selected rainfall amounts based on which probability closely resembles the actual rainfall

	SOI PHASE										Terciles of rainfall			actual rainfall (mm)
season	falling		negative		neutral		rising		positive					
	July	Aug	July	Aug	July	Aug	July	Aug	July	Aug	20%	50%	80%	
1991/92					-7.7	-7.6					175	127	53	19
1992/93							-6.9	1.4			201	145	86	376
1993/94			-10.8	-14							153	109	47	109
1994/95			-18	-17.2							153	109	47	149
1995/96					4.2	0.8					175	127	53	146
1996/97									6.8	4.6	266	162	89	116
1997/98	-9.5	-19.8									116	66	36	3
1998/99									14.8	9.3	266	162	89	237
1999/00					4.8	2.1					175	127	53	88
2000/01							-3.7	5.3			201	145	86	75
2001/02					-3	-8.9					175	127	53	330
2002/03	-7.6	-14.5									116	66	36	131
2003/04					2.9	-1.8					175	127	53	94
2004/05					-7.1	-7.7					175	127	53	177
2005/06	1.2	-7.3									116	66	36	457
2006/07			-9.6	-15							153	109	47	148

Table B- 9: predicted and observed rainfall (mm) for the month of December over the validation period (1991/92- 2006/07).

season	observed	predicted
1991/92	19	53
1992/93	376	201
1993/94	109	109
1994/95	149	153
1995/96	146	127
1996/97	116	89
1997/98	3	36
1998/99	237	266
1999/00	88	53
2000/01	75	86
2001/02	330	175
2002/03	131	116
2003/04	94	127
2004/05	177	175
2005/06	457	116
2006/07	148	153

Table B- 10: RAINMAN predictions using the SOI phases method (July –Aug) for the month of January.

Deciles of rainfall at MASVINGO
Analysis of historical data (1899 to 2007) using SOI Phases: Jul to AugLeadtime of 4 months
The SOI phases/rainfall relationship for this season is statistically not significant because KW test is below 0.9 and Skill Score (-1.3) is below 7.6 (p = 0.43).

Rainfall period: Jan	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	313	449	437	331	527	527
In 10% yrs, rain at least	291	210	259	314	309	306
20%	235	161	220	243	206	216
30%	214	151	191	199	165	186
40%	194	126	149	181	120	148
50% (median rainfall)	112	101	89	138	102	109
60%	85	91	79	109	91	87
70%	74	81	68	78	81	76
80%	64	57	51	73	73	60
90%	31	41	35	47	46	38
Lowest on record (mm)	6	2	7	12	8	2
Years in historical record	13	19	33	21	23	109
Standard deviation (mm)	104	99	107	98	121	105
Average rainfall (mm)	147	126	138	155	146	142

Table B- 11: SOI phases for July and August, and RAINMAN predictions per tercile of rainfall (mm) for the month of January over the validation period (1991/92- 2006/07). Highlighted are the selected rainfall amounts based on which probability closely resembles the actual rainfall

	SOI PHASE										terciles of rainfall			Actual rainfall (mm)
season	falling		negative		neutra		rising		positive					
	July	Aug	July	Aug	July	Aug	July	Aug	July	Aug	20%	50%	80%	
1991/92					-7.7	-7.6					220	89	51	19
1992/93							-6.9	1.4			243	138	73	78
1993/94			-10.8	-14							161	101	57	78
1994/95			-18	-17.2							161	101	57	101
1995/96					4.2	0.8					220	89	51	437
1996/97									6.8	4.6	206	102	73	202
1997/98	-9.5	-19.8									235	112	64	192
1998/99									14.8	9.3	206	102	73	79
1999/00					4.8	2.1					220	89	51	261
2000/01							-3.7	5.3			243	138	73	47
2001/02					-3	-8.9					220	89	51	32
2002/03	-7.6	-14.5									235	112	64	87
2003/04					2.9	-1.8					220	89	51	152

2004/05					-7.1	-7.7	220	89	51	155
2005/06	1.2	-7.3					235	112	64	239
2006/07			-9.6	-15			161	101	57	25

Table B- 12: predicted and observed rainfall (mm) for the month of January over the validation period (1991/92- 2006/07).

season	observed	predicted
1991/92	19	51
1992/93	78	73
1993/94	78	57
1994/95	101	101
1995/96	437	220
1996/97	202	206
1997/98	192	235
1998/99	79	73
1999/00	261	220
2000/01	47	73
2001/02	32	51
2002/03	87	64
2003/04	152	89
2004/05	155	220
2005/06	239	235
2006/07	25	57

Table B- 13: RAINMAN predictions using the SOI phases method (July –Aug) for the month of February.

Deciles of rainfall at MASVINGO
Analysis of historical data (1899 to 2007) using SOI Phases: Jul to AugLeadtime of 5 months
The SOI phases/rainfall relationship for this season is statistically not significant because KW test is below 0.9 and Skill Score (1.0) is below 7.6 (p = 0.60).

Rainfall period: Feb	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	186	401	412	321	275	412
In 10% yrs, rain at least	161	237	301	268	232	248
20%	122	151	149	198	197	171
30%	86	141	122	169	158	145
40%	70	129	106	137	144	121
50% (median rainfall)	65	101	89	118	122	99
60%	55	87	77	98	96	81
70%	44	54	68	91	81	66
80%	26	37	37	58	53	40
90%	12	26	19	50	15	19
Lowest on record (mm)	8	6	4	10	3	3
Years in historical record	13	19	33	21	23	109

Standard deviation (mm)	58	97	104	87	80	90
Average rainfall (mm)	75	118	119	139	123	118

Table B- 14: SOI phases for July and August, and RAINMAN predictions per tercile of rainfall (mm) for the month of February over the validation period (1991/92- 2006/07). Highlighted are the selected rainfall amounts based on which probability closely resembles the actual rainfall

	SOI PHASE										terciles of rainfall			actual rainfall (mm)
season	falling		negative		neutral		rising		positive					
	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	20 %	50 %	80 %	
1991/92					-7.7	-7.6					149	89	37	4
1992/93							-6.9	1.4			198	118	58	198
1993/94			-10.8	-14							151	101	37	6
1994/95			-18	17.2							151	101	37	101
1995/96					4.2	0.8					149	89	37	108
1996/97									6.8	4.6	197	122	53	122
1997/98	-9.5	-19.8									122	65	26	8
1998/99									14.8	9.3	197	122	53	236
1999/00					4.8	2.1					149	89	37	412
2000/01							-3.7	5.3			198	118	58	268
2001/02					-3	-8.9					149	89	37	18
2002/03	-7.6	-14.5									122	65	26	100
2003/04					2.9	-1.8					149	89	37	151
2004/05					-7.1	-7.7					149	89	37	89
2005/06	1.2	-7.3									122	65	26	65
2006/07			-9.6	-15							151	101	37	87

Table B- 15: predicted and observed rainfall (mm) for the month of February over the validation period (1991/92- 2006/07).

season	observed	predicted
1991/92	4	37
1992/93	198	198
1993/94	6	37
1994/95	101	101
1995/96	108	101
1996/97	122	122
1997/98	8	26
1998/99	236	197
1999/00	412	149
2000/01	268	198
2001/02	18	37
2002/03	100	122
2003/04	151	149
2004/05	89	89
2005/06	65	65
2006/07	87	101

Table B- 26: RAINMAN predictions using the SOI phases method (July –Aug) for the month of March.

Deciles of rainfall at MASVINGO
Analysis of historical data (1899 to 2007) using SOI Phases: Jul to AugLeadtime of 6 months
The SOI phases/rainfall relationship for this season is statistically not significant because KW test
is below 0.9 and Skill Score (1.0) is below 7.6 (p = 0.60).

Rainfall period: Mar	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	413	239	266	203	289	413
In 10% yrs, rain at least	143	151	180	150	191	179
20%	114	115	91	127	140	128
30%	76	108	75	100	126	103
40%	61	89	64	78	107	78
50% (median rainfall)	38	60	48	75	92	68
60%	26	36	47	31	84	48
70%	20	27	39	27	68	32
80%	8	21	30	19	60	23
90%	4	14	18	8	44	11
Lowest on record (mm)	4	3	1	3	1	1
Years in historical record	12	19	33	21	23	108
Standard deviation (mm)	115	68	69	60	71	74
Average rainfall (mm)	80	78	76	72	108	83

Table B- 17: SOI phases for July and August, and RAINMAN predictions per tercile of rainfall (mm) for the month of March over the validation period (1991/92- 2006/07). Highlighted are the selected rainfall amounts based on which probability closely resembles the actual rainfall

	SOI PHASE										terciles of rainfall			Actual rainfall (mm)
season	falling		negative		neutral		rising		positive					
	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	20 %	50 %	80 %	
1991/92					-7.7	-7.6					91	48	30	23
1992/93							-6.9	1.4			127	75	19	8
1993/94			-10.8	-14							115	60	21	10
1994/95			-18	-17.2							115	60	21	109
1995/96					4.2	0.8					91	48	30	18
1996/97									6.8	4.6	140	92	60	87
1997/98	-9.5	-19.8									114	38	8	31
1998/99									14.8	9.3	140	92	60	91
1999/00					4.8	2.1					91	48	30	79
2000/01							-3.7	5.3			127	75	19	127
2001/0					-3	-					91	48	19	14

2						8.9				
2002/03	-7.6	-14.5					114	38	8	413
2003/04					2.9	-1.8	91	48	30	242
2004/05					-7.1	-7.7	91	48	30	35
2005/06	1.2	-7.3					114	38	8	123
2006/07			-9.6	-15			115	60	21	23

Table B- 18: predicted and observed rainfall (mm) for the month of March over the validation period (1991/92- 2006/07).

season	observed	predicted
1991/92	23	30
1992/93	8	19
1993/94	10	21
1994/95	109	115
1995/96	18	30
1996/97	87	92
1997/98	31	38
1998/99	91	92
1999/00	79	91
2000/01	127	127

2001/02	14	19
2002/03	413	114
2003/04	242	91
2004/05	35	30
2005/06	123	114
2006/07	23	21

Table B- 19: RAINMAN predictions using the SOI phases method (July –Aug) for the month of April.

Deciles of rainfall at MASVINGO
Analysis of historical data (1899 to 2007) using SOI Phases: Jul to AugLeadtime of 7 months
The SOI phases/rainfall relationship for this season is statistically significant because KW test is above 0.9, and Skill Score (11.7) is above 7.6 (p = 0.96).

Rainfall period: Apr	SOI falling	SOI negative	SOI neutral	SOI rising	SOI positive	All years
Highest on record (mm)	56	73	93	127	104	127
In 10% yrs, rain at least	42	37	57	49	66	58
20%	13	19	30	22	34	29
30%	7	16	22	18	30	20
40%	5	9	17	15	24	15
50% (median rainfall)	5	7	13	13	19	13
60%	3	6	8	13	16	8
70%	2	1	6	10	13	6
80%	0	1	5	6	11	3
90%	0	0	3	0	4	1
Lowest on record (mm)	0	0	0	0	1	0
Years in historical record	13	19	32	21	23	108
Standard deviation (mm)	19	22	24	32	26	25
Average rainfall (mm)	12	15	22	24	28	21

Table B- 20: SOI phases for July and August, and RAINMAN predictions per tercile of rainfall (mm) for the month of April over the validation period (1991/92- 2006/07). Highlighted are the selected rainfall amounts based on which probability closely resembles the actual rainfall

	SOI PHASE										terciles of rainfall			actual rainfall (mm)
Season	falling		negative		neutral		rising		positive					
	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	Jul	Aug	20 %	50 %	80 %	
1991/92					-7.7	-7.6					30	13	5	1
1992/93							-6.9	1.4			22	13	6	3
1993/94			-10.8	-14							19	7	1	0
1994/95			-18	17.2							19	7	1	17

1995/96					4.2	0.8					30	13	5	5
1996/97									6.8	4.6	34	19	11	104
1997/98	9.5	19									13	5	0	5
1998/99									14.	9.3	34	19	11	14
1999/00					4.8	2.1					30	13	5	44
2000/01							-3.7	5.3			22	13	6	15
2001/02					-3	-8.9					30	13	5	90
2002/03	7.6	14									13	5	0	3
2003/04					2.9	-1.8					30	13	5	58
2004/05					7.1	-7.7					30	13	5	5
2005/06	1.2	-7.3									13	5	0	0
2006/07			-9.6	-15							19	7	1	71

Table B- 21: predicted and observed rainfall (mm) for the month of April over the validation period (1991/92- 2006/07).

season	observed	predicted
1991/92	1	5
1992/93	3	6
1993/94	0	1
1994/95	17	19
1995/96	5	5
1996/97	104	34
1997/98	5	5
1998/99	14	11
1999/00	44	30
2000/01	15	13
2001/02	90	30
2002/03	3	5
2003/04	58	30
2004/05	5	5
2005/06	0	0
2006/07	71	19

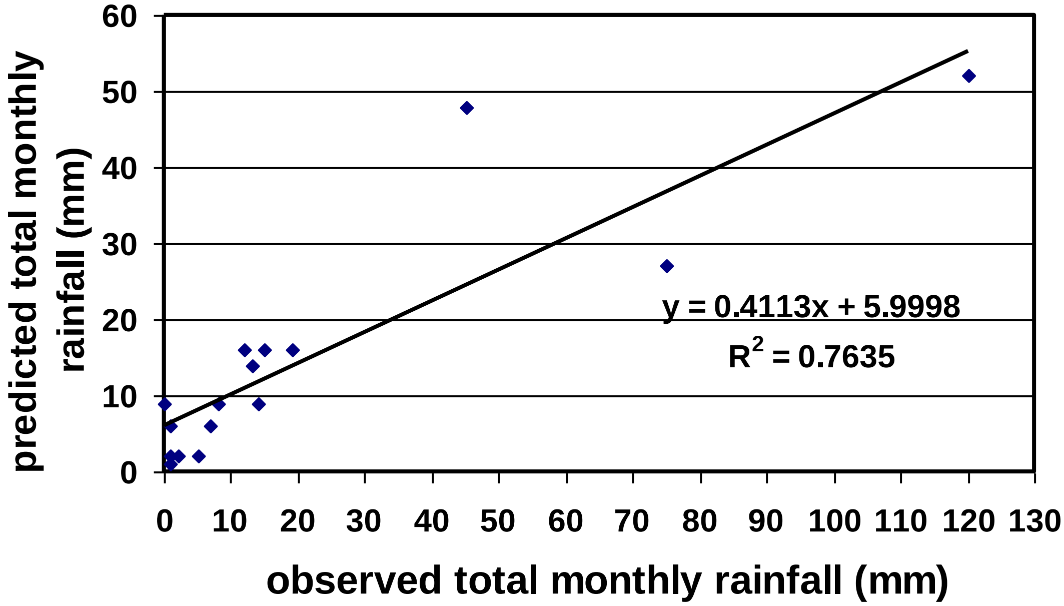

Figure B-1: Observed and predicted monthly rainfall for the month of October for the validation period (1991/92-2006/07

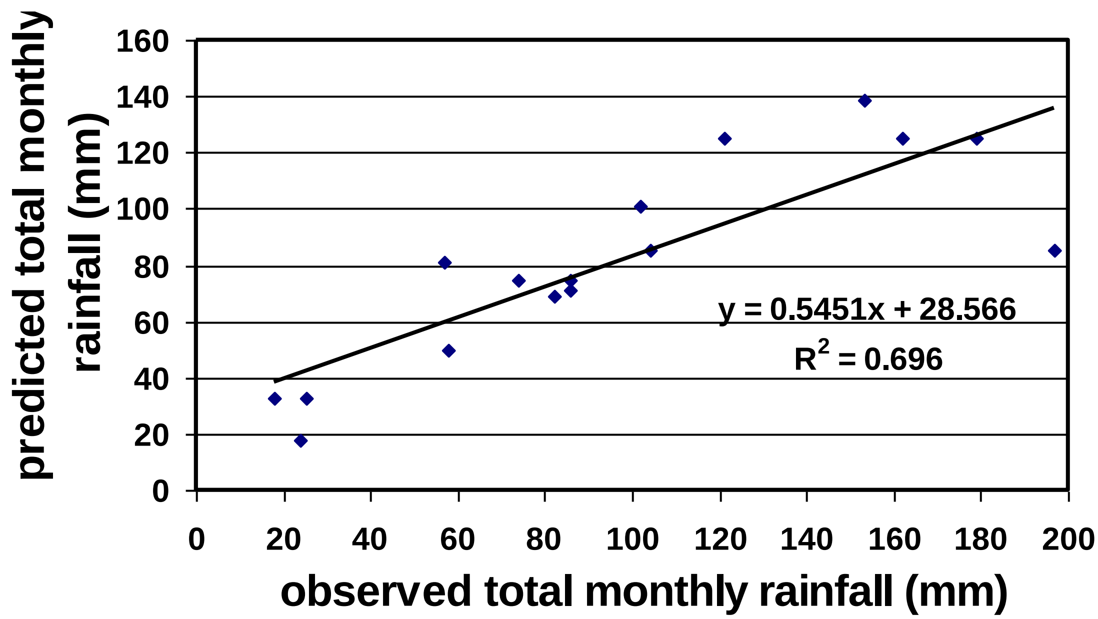

Figure B-2: Observed and predicted monthly rainfall for the month of November for the validation period (1991/92-2006/07.

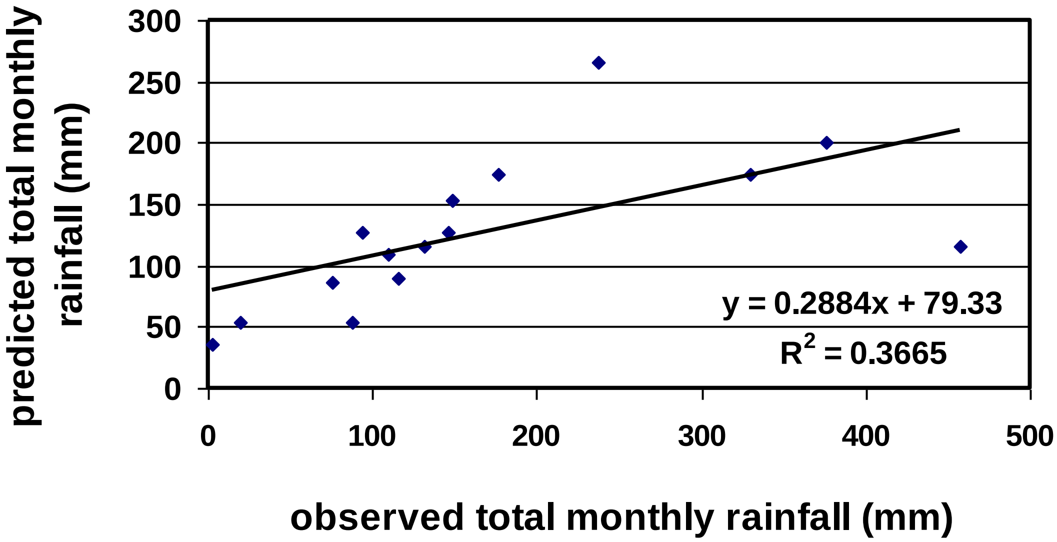

Figure B-3: Observed and predicted monthly rainfall for the month of December for the validation period (1991/92-2006/07.

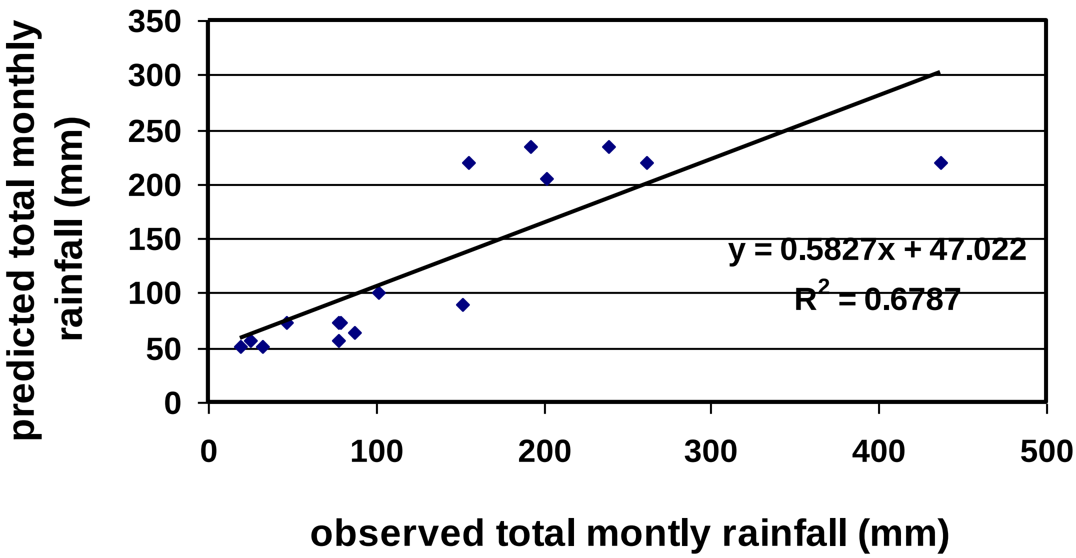

Figure B-4: Observed and predicted monthly rainfall for the month of January for the validation period (1991/92-2006/07.

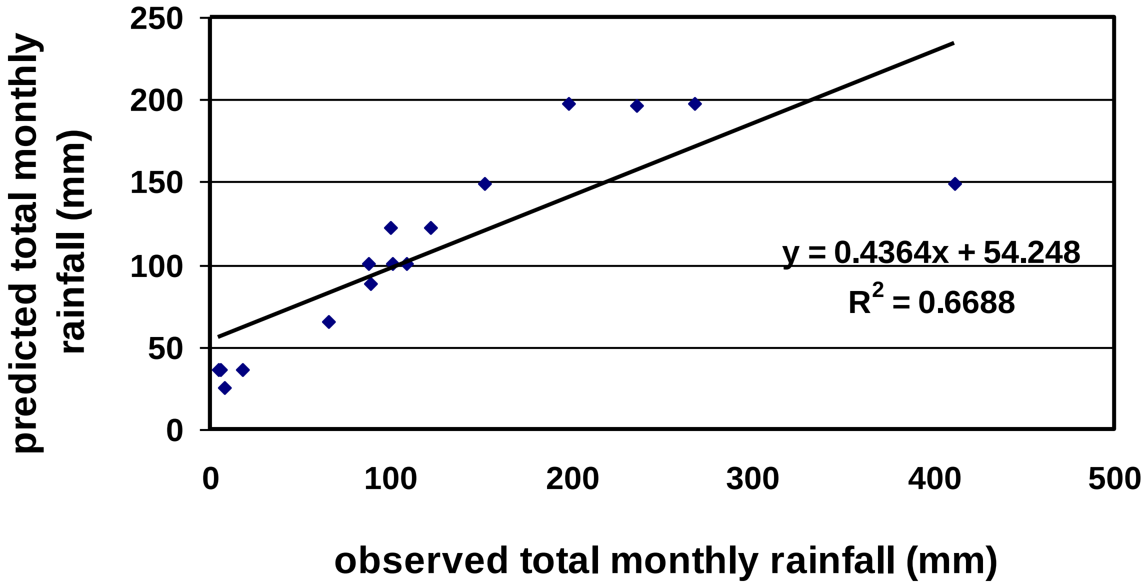

Figure B-5: Observed and predicted monthly rainfall for the month of February for the validation period (1991/92-2006/07.

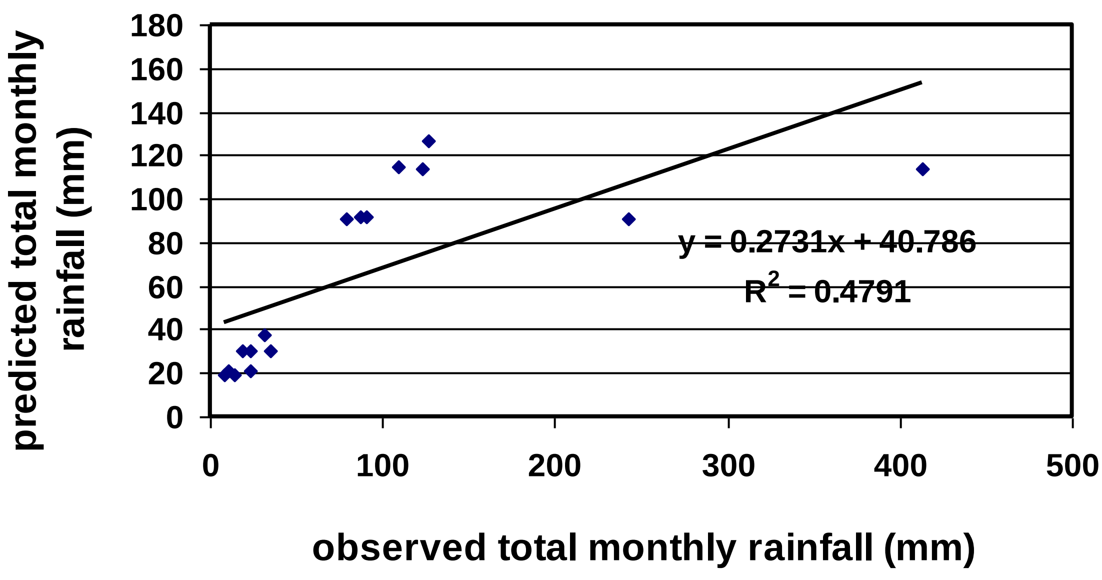

Figure B-6: Observed and predicted monthly rainfall for the month of March for the validation period (1991/92-2006/07.

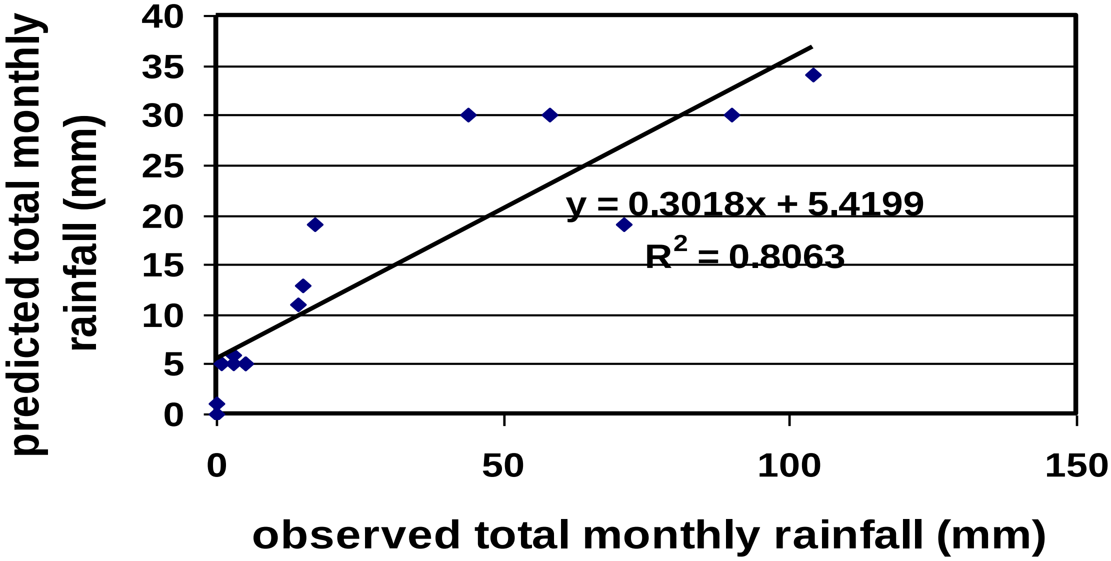

Figure B-7: Observed and predicted monthly rainfall for the month of April for the validation period (1991/92-2006/07.

Table B- 22: monthly predictions of rainfall (mm) for a falling SOI for each probability of rainfall occurrence

MONTH	SOI PHASE Falling		
	20%	50%	80%
October	48	19	9
November	149	75	50
December	116	66	36
January	235	112	64
February	122	65	26
March	114	38	8
April	13	5	0

Table B- 23: monthly predictions of rainfall (mm) for a negative SOI for each probability of rainfall occurrence

MONTH	SOI PHASE Negative		
	20%	50%	80%
October	27	9	1
November	85	61	18
December	153	109	47
January	161	101	57
February	151	101	37
March	115	60	21
April	19	7	1

Table B- 24: monthly predictions of rainfall (mm) for a neutral SOI for each probability of rainfall occurrence

MONTH	SOI PHASE Neutral		
	20%	50%	80%
October	52	16	2
November	125	81	33
December	175	127	53
January	220	89	51
February	149	86	37
March	91	48	30
April	30	13	5

Table B- 25: monthly predictions of rainfall (mm) for a rising SOI for each probability of rainfall occurrence

MONTH	SOI PHASE Rising		
	20%	50%	80%
October	50	14	2
November	101	69	30
December	201	145	86
January	243	138	73
February	198	118	58
March	127	75	19
April	22	13	6

Table B- 26: monthly predictions of rainfall (mm) for a positive SOI for each probability of rainfall occurrence

MONTH	SOI PHASE Positive		
	20%	50%	80%
October	37	23	6
November	139	71	38
December	266	162	89
January	206	102	73
February	197	122	53
March	140	92	60
April	34	19	11

APPENDIX C: SIGNIFICANCE TESTING

Number of variables 16

Critical values of t for two tailed test = ±2.49, i.e. Reject Ho if $|t| \geq 2.49$

Table C- 1: statistic (t stat) for the month of October for the validation period (1991/92-2006/07)

	Variable 1	Variable 2
Mean	21.125	14.6875
Variance	1076.65	238.4958
Observations	16	16
Pearson Correlation	0.873787	
Hypothesized Mean Difference	0	
Df	15	
t Stat	1.242359	
P(T<=t) one-tail	0.116588	
t Critical one-tail	2.13145	
P(T<=t) two-tail	0.233177	
t Critical two-tail	2.48988	

Ho was accepted. Hence there is no significant difference between observed and predicted rainfall.

Table C- 2: t statistic (t stat) for the month November for the validation period (1991/92-2006/07)

	Variable 1	Variable 2
Mean	95.5	80.625
Variance	3038	1297.05
Observations	16	16
Pearson Correlation	0.834268	
Hypothesized Mean Difference	0	
Df	15	
t Stat	1.860359	
P(T<=t) one-tail	0.041277	
t Critical one-tail	2.13145	
P(T<=t) two-tail	0.082555	
t Critical two-tail	2.48988	

Ho was accepted. Hence there is no significant difference between observed and predicted rainfall.

Table C- 3: t statistic (t stat) for the month December for the validation period (1991/92-2006/07

	Variable 1	Variable 2
Mean	27.1875	13.625
Variance	1215.629	137.3167
Observations	16	16
Pearson Correlation	0.897958	
Hypothesized Mean Difference	0	
Df	15	
t Stat	2.180147	
P(T<=t) one-tail	0.022794	
t Critical one-tail	2.13145	
P(T<=t) two-tail	0.045588	
t Critical two-tail	2.48988	

Ho was accepted. Hence there is no significant difference between observed and predicted rainfall.

Table C- 4: t statistic (t stat) for the month January for the validation period (1991/92-2006/07)

	Variable 1	Variable 2
Mean	136.5	126.5625
Variance	12219.33	6113.463
Observations	16	16
Pearson Correlation	0.823825	
Hypothesized Mean Difference	0	
Df	15	
t Stat	0.621392	
P(T<=t) one-tail	0.271835	
t Critical one-tail	2.13145	
P(T<=t) two-tail	0.54367	
t Critical two-tail	2.48988	

Ho was accepted. Hence there is no significant difference between observed and predicted rainfall.

Table C- 5: t statistic (t stat) for the month February for the validation period (1991/92-2006/07)

	Variable 1	Variable 2
Mean	123.3125	108.0625
Variance	12191.83	3471.929
Observations	16	16
Pearson Correlation	0.817795	
Hypothesized Mean Difference	0	
Df	15	
t Stat	0.860739	
P(T<=t) one-tail	0.201466	
t Critical one-tail	2.13145	
P(T<=t) two-tail	0.402931	
t Critical two-tail	2.48988	

Ho was accepted. Hence there is no significant difference between observed and predicted rainfall.

Table C- 6: t statistic (t stat) for the month March for the validation period (1991/92-2006/07)

	Variable 1	Variable 2
Mean	89.5625	65.25
Variance	11329.86	1764.2
Observations	16	16
Pearson Correlation	0.692205	
Hypothesized Mean Difference	0	
Df	15	
t Stat	1.17036	
P(T<=t) one-tail	0.130058	
t Critical one-tail	2.13145	
P(T<=t) two-tail	0.260115	
t Critical two-tail	2.48988	

Ho was accepted. Hence there is no significant difference between observed and predicted rainfall.

Table C- 7: t statistic (t stat) for the month April for the validation period (1991/92-2006/07)

	Variable 1	Variable 2
Mean	27.1875	13.625
Variance	1215.629	137.3167
Observations	16	16
Pearson Correlation	0.897958	
Hypothesized Mean Difference	0	
Df	15	
t Stat	2.180147	
P(T<=t) one-tail	0.022794	
t Critical one-tail	2.13145	
P(T<=t) two-tail	0.045588	
t Critical two-tail	2.48988	

Ho was accepted. Hence there is no significant difference between observed and predicted rainfall.