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Assessment of growing seasons characteristics in the Dry zone of Sri Lanka based on stochastic simulation of rainfall and soil water status

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by

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Abstract of a thesis submitted in partial fulfilment of the
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ASSESSMENT OF GROWING SEASONS CHARACTERISTICS IN THE DRY
ZONE OF SRI LANKA BASED ON STOCHASTIC SIMULATION OF
RAINFALL AND SOIL WATER STATUS

by B.V.R. Punyawardena

Rainfall and crop water demand are two major agro-climatic variables that determine the crop production in the Dry zone of Sri Lanka. The lack of long series of historical data of these variables often hinders the proper understanding of the agricultural potential of the region. The large random variability displayed by such variables means that they are best simulated by appropriate stochastic models and can be used to replace the existing short series of data. The main objectives of this thesis are to characterise the major growing seasons of the Dry zone, Yala and Maha, using extended temporal variability of rainfall and crop water demand through the stochastic simulation and to predict the characteristics of upcoming seasons using the simulated and historical data.

The rainfall process was modelled using three Markovian models: the first-order discrete time Markov model, the second-order discrete time Markov model and the continuous time Markov model. Out of them, the first-order discrete time Markov model is the preferred model on the basis of its statistical performance and the practical ease. The crop water use was estimated using a single-layer water balance model which accounts evapotranspiration as a stochastic element.

A weekly system model was developed that incorporated the first-order Markov rainfall model and the soil water balance model. It characterises the two major growing seasons of the Dry zone using five agro-climatic indices: mean rainfall, dependable rainfall (DRF), moisture availability index (MAI), ratio of actual to potential evapotranspiration (AET/PET) and crop water satisfaction index (CWSI).

The simulated mean onset of the Yala and Maha seasons were the standard weeks 13 and 40, respectively. The mean end of the Yala season was the standard week 20 whereas the mean end of the Maha season could occur any time after the standard week 5 and it varied depending on the index used. The simulation also revealed that though the Maha season is ceased by late January, the soil moisture remains well above the 50% of available soil moisture during the inter-season dry month, February. According to the simulation, at least one out of every ten years the Yala season could experience a complete crop failure and the possibility of occurrence of such a catastrophic event during the Maha season is negligible. The onset time of the seasonal rains as a predictor of the seasonal characteristics of Yala or Maha season was not clearly evident in this simulation study though such links have been apparent in other monsoonal areas of the tropic. Nevertheless, cursory examination of observed rainfall data and the appearance of El Niño conditions in the Pacific ocean points towards a possible trend of seasonal rainfall in the Dry zone.

A special case of spatial interpolation of rainfall data was examined assuming that the spatial continuity of two neighbouring locations are exponentially correlated. It was shown that the exponential spatial interpolation model is a good candidate to estimate the mean parameters of weekly rainfall in the Dry zone.

Key words: stochastic; discrete; continuous; Markov chains; simulation; rainfall; soil water balance; spatial interpolation; Yala; Maha; seasonal characteristics; Dry zone; Sri Lanka.

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Chapter 1

Introduction

1.1 Climate and agriculture in Sri Lanka

Sri Lanka is a tropical island of 65,610 square kilometres, situated at the southern tip of the Indian sub-continent separated by the narrow Palk strait, about 35 km of distance, on its north-west. The climate of Sri Lanka is determined by the tropical location as well as by the monsoonal regime and thus, appears to be greatly varied spatially and temporally. Furthermore, the movement of the Inter Tropical Convergence Zone (ITCZ)[1] during the year has a major effect on the climate. The climatic effects of the topographical features of Sri Lanka also can not be neglected; the central highlands, a rough mountain terrain rising upto 2524 m above sea-level, also contribute to the spatial variation of climate in the island. The mean annual rainfall varies from 970 mm in the south-eastern coast and the north-western coast, to over 3500 mm in the south-western quadrant (Figure 1.1). The island is seasonally influenced by the southwest monsoon which occurs from May to September and northeast monsoon from late November to late January. The intermonsoonal convectional rains are effective during March to April and October to November which are caused by the movements of the Inter Tropical Convergence Zone (Suppiah, 1989). Because of the country's size and its location closer to the equator, the temperature at any given place remains high and relatively uniform throughout the year. Extreme fluctuations of temperature do not occur in any location in the country. The spatial variations of the temperature are related to the altitude and

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[1] The zone of general convergence, an area of low pressure, between northern and southern hemisphere trade winds.
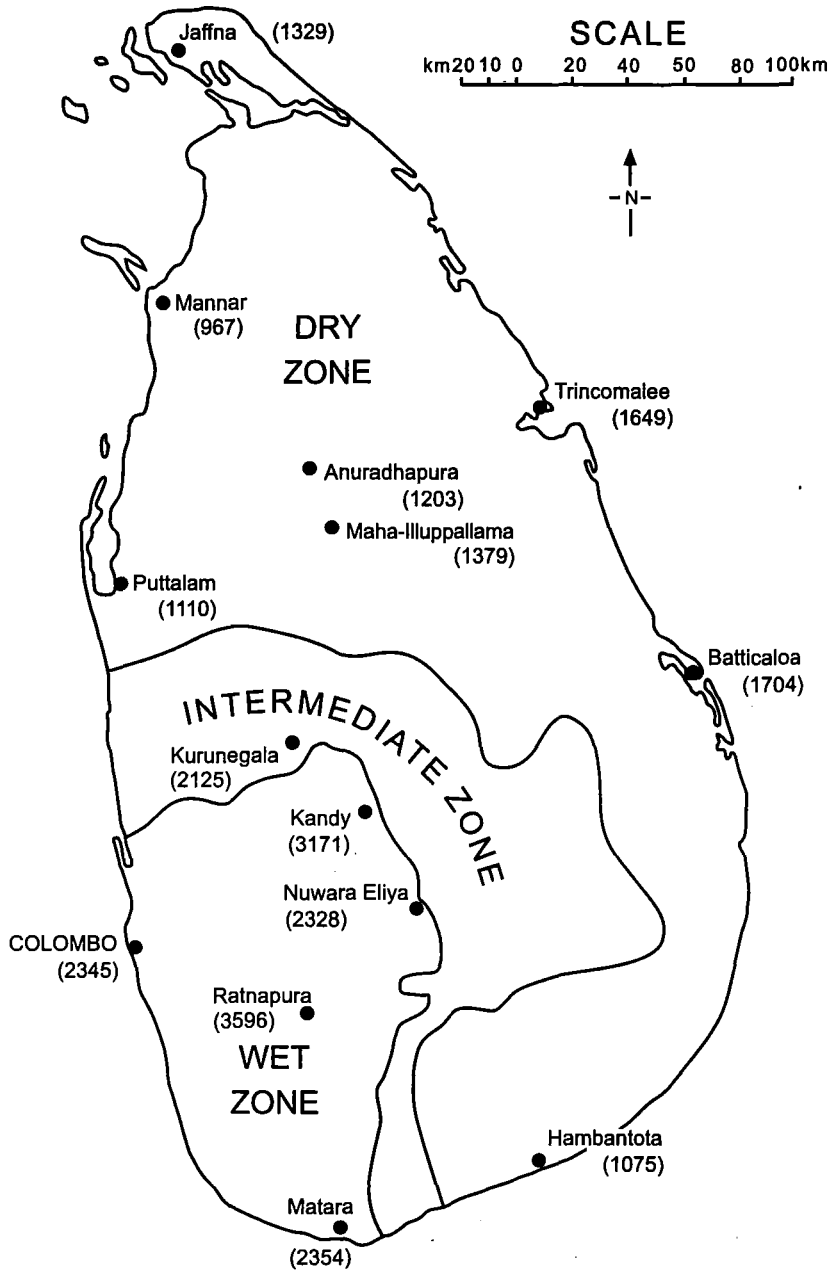
Figure 1.1 Agro-climatic zones of Sri Lanka with annual rainfall (mm) in some selected locations.

exposure. The variation is less than 5^0C between the weekly means of the summer months and the winter months. However, the daily maximum temperature can exceed 37^0C during March and April and also in late August. Given the prevailing uniform temperature conditions in the island, the rainfall is the most important climatic parameter which governs the agricultural production in Sri Lanka.

With respect to the rainfall, the island can be divided into three agro-climatic zones: Wet, Dry and Intermediate zones[2] (Figure 1.1). The Dry and the Intermediate zones account for 75 per cent of the surface area of the island. The Dry zone has 4.13 million hectares and Intermediate zone has 0.85 million hectares. These two zones consisting mainly of lowlands and are situated in the north, north-central and east. The Wet and the Intermediate zones mainly include land used for export oriented perennial crops such as tea, rubber and coconut and benefit from both the southwest and the northeast monsoons. Although there is a greater potential for cultivation of arable crops in the Dry zone because of fertile soils and high insolation, the lack of rainfall and relatively high evaporative demand constrain higher crop yields. Possibilities of finding adequate supplies of water for fully irrigated agriculture in this region are remote. The occurrence of adequate supplies of ground water and extractability of such reservoirs have not been fully investigated. The geology of the region is such that any ground water reserves may not exceed the domestic requirements (Somasiri, 1978). The estimated population in the Dry zone was 4.1 million in 1981, accounting for 28 per cent of the total population in the country and over 90 per cent are engaged in farming. Over 80 per cent of the farmers in the Dry zone districts are full time farmers for whom farming is the only means of livelihood. Traditionally, in the absence of irrigation facilities dryland farming[3] is the main land use type for subsistence.

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[2] The terms "Wet zone" and "Dry zone" are commonly used in Sri Lanka in order to express a wetter more humid part and a drier, more arid part of the island, respectively. Thus, they are not internationally-valid terms (Domorös, 1974).

[3] Dryland farming, also synonymous with rainfed agriculture, refers to a farming situation where, in the absence of irrigation, rainfall is inadequate to a greater or lesser extent to achieve the production potential set by other inputs such as solar radiation, soil properties and fertilisers.

Rainfall in the Dry zone is distinctly bi-modal (Figure 1.2), the larger peak occurring in November and the smaller one in late March or April. It is caused by regional (monsoonal) as well as local (convectional) meteorological phenomenon. Seventy percent of the total annual rainfall, approximately 1,200 mm, occurs during a limited rainy season known as Maha, major rainy season, from early October to late January. This is due to the convectional activity (October to November) and the northeast monsoonal circulation (late November to late January) of the atmosphere. Meanwhile, the Maha season rainfall is generally augmented by the frequent formation of cyclonic depressions in the Bay of Bengal especially from mid November to December. The period from mid March to mid May, known also as the Yala season, is a minor convective rainy season. The amount rainfall during this season hardly exceeds 400 mm, well below the requirement of any crop. Low rainfall during this period is due to the decreasing convectional activity towards north, north-east, east and south-east directions compared to the southwestern part of the country (Suppiah and Yoshino, 1983). There are two recognised dry seasons in between the two rainy seasons; from early February to early March and late May to late September. These dry seasons, which are quite common, are not helpful for the agricultural production throughout the year. Further, the extension of the dry season beyond late September or October due to the failure of convectional and monsoon rains causes severe consequences in the crop production (Somasiri, 1992).

1.2 Nature of the Dry zone agriculture

The Dry zone agriculture is centred around water tanks or reservoirs which provides sustenance for crops, livestock and humans. Dams have been built across the slopes of undulating landscape which is characteristic of the Dry zone. It is common to find more than one tank within a square kilometre. They range in capacity from 62 to 430 megalitres, the typical tank being around 185 megalitres (Mahendrarajah et al., 1996). Food and Agriculture Organization has estimated that there are 7,758 village tanks in the Dry zone and command area
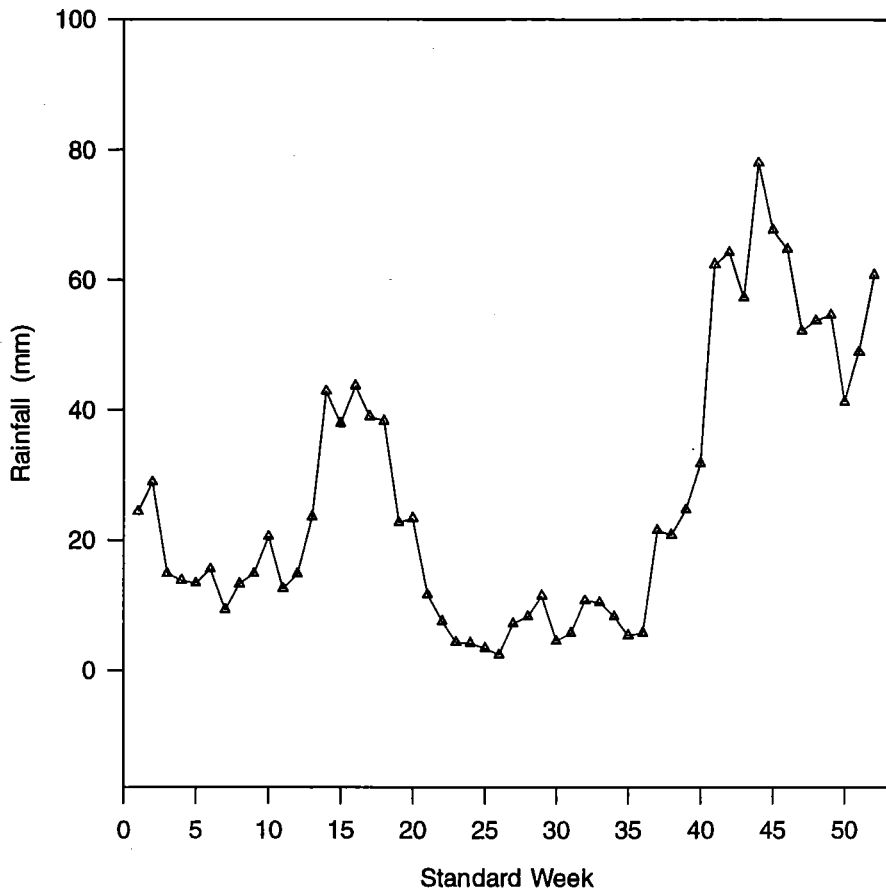
Figure 1.2 Mean weekly rainfall of the Dry zone, Maha-Illuppallama, Sri Lanka (1945-1995).

of a tank varies from 4 to 56 ha (Dayaratne, 1991). The lands under command of a tank are used for growing rice whereas adjoining highlands which have well drained soils are used for producing other commodities under rainfed conditions required by the community. The farming system of the Dry zone is a combination of irrigated rice cultivation during the Maha season supplemented by the dryland farming in highlands which produce cereals, pulses, spices, vegetables and other permanent crops. During the Yala season rainfed rice cultivation is not practiced in most parts of the Dry zone owing to inadequate water. As a result, land is used for cultivation of other field crops provided that drainage is satisfactory. In addition to the dryland farming, a large area of the Dry zone has now come under irrigated agriculture due to the rehabilitation or reconstruction of major tanks that were built during ancient times and the diversion of the longest river in Sri Lanka, the Mahaweli Ganga, into the Dry zone. Although these lands have been categorised as irrigated lands, cultivation of these lands is still an uncertain venture because the water levels of the tanks and the flow of the diverted river are dependent upon the amount of seasonal rainfall received. Thus, the determining factor of the Dry zone agriculture is the arrival and the spatial and temporal distribution of the seasonal rainfall.

As a result of extensive agronomic and agro-climatic research undertaken during the last three to four decades, the technological guidelines have been developed to establish a farming system in the Dry zone which is economically sound and environmentally and sociologically stable. For example, planting time and age of the crop cultivars are to be grown for each rainy season for different regions of the Dry zone have been formulated using monthly dependable rainfall, rainfall at 75% expectancy, and soil properties (Department of Agriculture, 1979). However, more often farmers are reluctant to use these recommendations as failures by implementing these recommendations are more common than successes. For example, frequent crop failures have been reported in the southern part of the Dry zone owing to mid season short dry spells despite high degree of reliability of seasons shown in the guidelines (Merrey and Somaratne, 1989).

There are several inappropriate aspects of assumptions and methods on which those recommendations have been based. For example, calculation of monthly dependable rainfall values have been based on the assumption that historical data are normally distributed. Use of normality assumption in climatological analyses is very common as it enables applications of certain statistical techniques such as analysis of variance, regression analysis, confidence interval determination and certain types of hypotheses. Indeed, it can not be so when there is a real chance of the whole period being dry (Stern et al., 1982). The preliminary work done with this study revealed that monthly rainfall totals over any part of the island are never normally distributed and either gamma or Weibull distributions, right skewed distributions, were the commonest in the most cases. It was revealed that 135 mm of monthly dependable rainfall for December at Maha-Illuppallama in the Dry zone with conventional analysis reduced to 105 mm when the Weibull distribution, the best fitted distribution for the data available, was considered. This type of overestimation of the system variables could easily lead to recommendation of unsuitable crops, probably a long-age crop, for the region which might end up with complete crop failures. Hence, the farmers who have a large number of years of farming experience in the Dry zone continue to use their centuries old agronomic practices which have been based on the experience of the past climate rather than analysis. This has become an important management problem in any attempt of introducing new technologies to increase the productivity of the Dry zone lands. Generally, the extent of area to be cultivated, date of commencement of water issues from the village tank for rice cultivation, and type of crops and cultivars to be grown in highlands are decided at the meetings attended by both the farmers and the planners in a particular agricultural region before the season. The technical officers from the relevant agencies such as the Department of Agriculture and the Department of Irrigation are the key people who guide this meeting. They always tend to adhere to the findings of the analysis of past rainfall data to come up with a suitable cropping calendar for the season in hand. Monthly rainfall analyses for many locations in the Dry zone are available (Department of Agriculture, 1993). Even though they have been centred on the spatial distribution of the rainfall,

the monthly time base is, however, too long to make any meaningful decisions for many agricultural operations (Huda, 1994). Monthly mean rainfall may meet the crop water requirement theoretically, but the distribution of rainfall within a particular month may not be favourable, allowing crops to be exposed to soil moisture stress (Hargreaves, 1975). For example, during some months total rainfall may be 100-150 mm which may have been received within two or three days, and the rest of the month will be extremely dry. Thus, farmers may have high probabilities of loss of the crop, leaving them in a desperate situation and making a significant impact on the economy of the country. Therefore, the use of shorter time intervals, such as a week, has been recommended for the tropical countries like Sri Lanka where the rainfall is showery and highly freakish in intensity, amount and distribution (Mavi, 1986 and Krishnan, 1980).

Crop production in the Dry zone is largely determined by the climatic and edaphic features. Development of an improved crop production technology to increase and stabilise the food production in these areas requires an understanding of temporal and spatial variation of the climate, especially the soil moisture adequacy. A rational and effective agro-climatic zoning system can be an effective tool in overcoming this situation. The present ecological zoning system, The Agro-Ecological Map of Sri Lanka (Department of Agriculture, 1979), has been drawn from considerations based mainly on monthly dependable rainfall, the rainfall at 75 per cent probability, altitude and major soil types. In this map, Sri Lanka has been divided into 24 agro-ecological regions (Figure 1.3). This map has been widely used by the planning authorities to select the crops for different regions, preparation of cropping calendars and even in land use planning for the whole country. Despite its usefulness as a base-line reference, the appropriateness of the map has been questioned owing to several inappropriate underlying assumptions. For example, predicting rainfall expectancy at 75 per cent probability level is based on the assumption that rainfall will behave in the same way as in the past. This assumption is unrealistic because atmospheric conditions could vary from time to time and any rhythm of this variability can be completely changed due to the changes of solar activity,
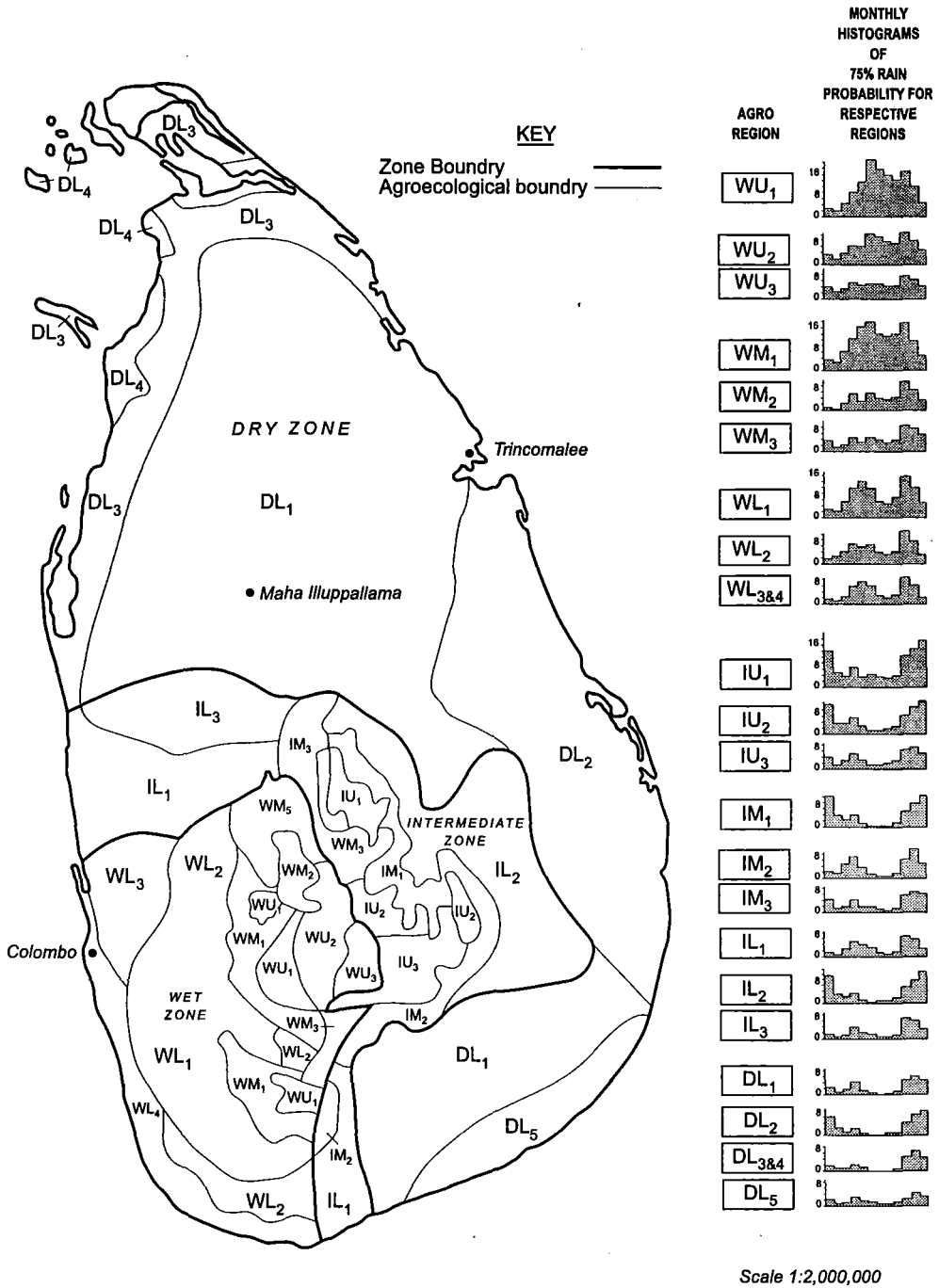
Figure 1.3   Agro-ecological regions of Sri Lanka.

appearance of abnormal sea surface temperatures and sudden volcanic eruptions. However, influence of such events on the probability calculations could be minimised if the data base, on which probabilities have been determined, has covered a long period of the history. Moreover, in addition to the inappropriate statistical aspects of the methodology on which map has been based, there are some agronomically important aspects that should have been considered in view of the suitability of the map for agricultural planning. From the plant growth point of view, though probability analysis will give some measure of expectancy of rainfall in an area depending on the variability represented in the historical data, the calculated probability values do not indicate the amount of water available for plant use. The same amount of rainfall can act differently depending upon atmospheric demand or drying potential of the air and soil conditions. Many crops have moisture sensitive periods during which a temporary shortage of water can markedly reduce the yields; severe water deficits immediately before flowering can lead to pollen sterility and decrease in grainset (Van Keulen and Wolf, 1986). Therefore, any method of agro-climatic zoning that takes into account the crop water demand as a cartographic expression would be much more realistic rather than quantification of rainfall variability alone.

Furthermore, boundaries of the current agro-ecological map has been based only on the rainfall values collected from 380 recording stations scattered throughout the island. Use of only 380 points to represent the whole island could be due to the fact that unavilability of reliable data and the large number of calculations involved in the study. But, in a country like Sri Lanka where the geography is so diverse such a networking intensity of rain gauging stations may be insufficient to account for the real spatial variability. Therefore, the introduction of more spatial variability by incorporating rainfall values from adjoining areas either by using available data or using appropriate spatial interpolation methods may produce more accurate boundaries of different agro-ecological regions of the island.

In addition to the proper understanding of the stochastic nature of the Dry zone rainfall and the crop water demand, the need for prior information about the seasonal rainfall is also important to reduce the risk and uncertainty associated with the farming in the Dry zone. With recent advances in understanding of factors affecting climatic variations, we have entered a new era where useful climatic prediction will be increasingly available. Use of such predictions along with the well understood stochastic structure of the seasonal rainfall in the Dry zone would increase the usefulness of the agro-climatic research on design and planning of ongoing and future operations related to the agriculture in the region.

1.3 Modelling the agro-climatology of the Dry zone

The Dry zone of Sri Lanka was not ecologically suitable for plantation crops such as coffee, tea, rubber and coconut which were introduced to the island in the early nineteenth century. Therefore, the Dry zone was not considered as a region with high potential for agriculture during the recent history. Thus, importance of monitoring the climate or weather change in the Dry zone was not properly undertaken. Much of the data records starts only from mid 20th century after the restoration of ancient tanks began resulting merely 30 to 40 years of length of records available. Even if records are available, sometimes they are incomplete and often have missing values. Moreover, weather records are only a sample of weather that existed and may not include the extremes (White, 1978). For example, rainfall being a random process, there may be indefinite number of realisations which we have not experienced and yet to be experienced. Thus, use of short series of historical data may not accurately account the real year to year variability of the weather and may not be a reasonable sample space to answer many questions (Stern and Coe, 1982). Especially, if the interest is in answering conditional questions such as:

- what is the probability of occurring a late arrival of monsoon rains in a given amount of years ?

- is "dry planting" (planting before the rains to use the subsequent rainfall for crop growth) a suitable agronomic practice compared to the planting after the onset ?

In this situation, long sequences of data by stochastic simulation of weather variables can be expected to provide better estimates of the frequency or return period of the infrequent notable events in the historic series simply by producing an increased number of such events in the longer sequences of simulated records (Shaw, 1994). Also, stochastic simulation provides an expanded spatial source of weather data by interpolating between the point-based parameters used to define the weather model (Semenov and Porter, 1995).

An assessment of different cropping patterns is important for the Dry zone to bring new lands under cultivation and to increase the productivity of lands that are already being cultivated. But, spatial and temporal variability of soil moisture complicates the short term evaluation of different cropping patterns. Water balance modelling techniques have been successfully used to provide information on this nature (Huda, 1994; Saxton et al., 1988 and Berndt and White, 1976). Modelling of soil water balance can be accomplished using the simulated weather data. A system model that consists of soil water balance models are of great importance in assessing the risk associated with cropping patterns as stochastically simulated weather data can provide a range of scenarios which may differ markedly from the details of the historical records, while retaining that record's statistical properties (Chapman, 1995).

1.4 Objectives

The overall goal of this study is to develop a methodology to characterise the growing seasons based on the stochastic simulation of some important weather variables and the crop water demand in the Dry zone of Sri Lanka. As the methodology would quantify the rainfall of the Dry zone in agronomically relevant terms, it may lead to the higher level of farmer acceptance and adaptability of technological guidelines proposed by the relevant authorities. In addition the

attention will be given to ascertain the predictability of the seasonal rainfall in the Dry zone. In order to realise this goal, the specific objectives of this study are as follows;

1. To develop a stochastic rainfall model with a convenient time base.
2. To develop a stochastic system model which can characterise the growing seasons of the Dry zone using water availability and demand from the crops.
3. To estimate of rainfall values by means of a spatial interpolation method.
4. To validate the models using available field data.
5. To examine the predictability of the rainy seasons.

1.5 Outline of the chapter contents

A review of modelling rainfall process is discussed in the Chapter 2. In order to find a suitable model which represents the weekly rainfall process in the Dry zone, both discrete and continuous Markov chain modelling of rainfall occurrence are considered. These two modelling approaches have been discussed in section 2.2. while section 2.3 mainly concentrates on the modelling of rainfall amounts. Section 2.4 discusses the development of the rainfall model presented here.

The implementation and the validation of developed rainfall models are presented in the Chapter 3 along with the procedure adapted to simulate the rainfall process from both discrete and continuous models. Chapter 4 reviews the most common soil-water balance models. Some of them are highly complex in nature restricting the application in broad scale climatological studies. Section 4.3 and 4.4 discuss the model structure presented here to achieve the objectives and its implementation.

The development of a rainfall data estimation model using a spatial interpolation technique is presented in the Chapter 5 along with a brief review on existing techniques. The relationships between the start of the season and the seasonal characteristics of both the Yala and Maha seasons are discussed in the Chapter 6 using large number of simulation runs produced from the selected stochastic rainfall model. The observed anomalies of seasonal rainfall of the Dry zone using global

meteorological phenomenon such as southern oscillation and its two extremes, El Niño and La Niña events are described in the sections 6.5 and 6.6.

Chapter 7 mainly concentrates on the characterising the two major growing seasons of the Dry zone, Yala and Maha, using five different agro-climatic indices. With a large number of simulations of the system model, some agronomically important information has been derived in the Chapter 8. A summary and the future directions of this study have also been included in this chapter.

Chapter 2

Stochastic rainfall models

2.1 Introduction

Simulation of growing seasons characteristics using a system model which combines rainfall and crop water demand can be used to asses the agricultural potential of an area. Since suitably long records of rainfall data are rarely available from large number of locations from the Dry zone, especially from remote areas, this approach requires in turn a capacity to simulate the rainfall. The large random variability displayed in rainfall process in the Dry zone means that it is best simulated by an appropriate stochastic model. Therefore, the following discussion will mainly be concentrated on the development of the stochastic rainfall models and subsequently a selection of the best from the developed models.

Use of deterministic models to describe the rainfall process is not satisfactory as the physical processes governing rainfall in a given geographical area are not properly understood. Some deterministic models have been formulated by fitting "best-fit" or heuristically relevant equations to available data. But, due to the implicit uncertainty, there will be noises about the modelled depiction. Such noises can not be treated as randomness within the system, but as a of result of unknown, often complex processes. Therefore, processes like rainfall which have random aspects or be governed by mechanisms too complicated to describe can best be represented by appropriate stochastic models. The statistical structure of the rainfall process can be considered as consisting of two sequences of random variables. The first sequence is concerned with the rainfall occurrence. The second sequence is concerned with the

rainfall amounts associated with each occureence. In stochastic rainfall models these two sequences are considered independently (Wilson et al., 1991).

A time step has to be decided to simulate the rainfall depths as a time series of discrete events. Daily time step is the most common time base in hydrological studies. But, when daily intervals are considered, its subsequent algorithms become cumbersome restricting the applicability in broad scales. Chang (1968) suggested that for the agricultural water balance computations, weekly intervals could give essentially the same results as daily intervals. A weekly time step has been considered adequate to capture the agricultural management practices used in the Dry zone and other parts of the country and it is the shortest time step available with accurate weather and soil moisture data. Considering these aspects plus the fact that plant water requirements over a period about seven to ten days can usually be met by water stored in the soil (Stern et al., 1982), weekly interval was chosen as the time increment for this study.

2.2 Rainfall occurrence

Although rainfall of months or longer time periods shows little or no persistence, the occurrence of shorter period rainfall at a given location can seldom be considered as an independent random event (Chin, 1977). There is a tendency for rainy periods and dry periods to cluster and to form respective sequences. When shorter time periods are concerned, complication arises from the presence of high number of zero values for the rainfall (Selvalingam and Miura, 1978). The structure of wet and dry periods can be modelled by using a Markov chain of discrete or continuous time or an alternating renewal process. An alternating renewal process consists of alternating dry and wet spells. The wet spells are independent and belong to a certain distribution. Similarly, the dry spells are independent and have another distribution. The alternating renewal process was used by Green (1964) and Cole and Sheriff (1972), who used exponential and empirical distributions for wet and dry spells, respectively. The Geometric distribution can also be used for this purpose (Williams,

1952 and Longley, 1953). However, estimates of the parameters of a Markov chain can be obtained more easily than for alternating renewal process (Buishand, 1978). Therefore, in this study, the modelling of rainfall occurrence will consider only the Markov process.

2.2.1 Discrete time Markov process

A stochastic process $X = \{X_i (t), t \in T\}$ is simply a collection of random variables $X_1, X_2, \ldots X_n$ which can be considered to describe the evolution of a system over discrete instants of time $t_1 < t_2, < \ldots < t_n \ldots$. It is assumed that there is a common probability space (Ω, A, P) in which the system operates, where Ω is the sample space, A is the σ-field and P is the probability measure (Kloeden and Platen, 1992). A realisation, a sample path or a trajectory of the stochastic process is the set of values X takes for each outcome $\omega \in \Omega$ over the time set T.

If we consider a stochastic process $X = \{X_n = i, n = 0, 1, 2, \ldots, n\}$ that takes a countable number of possible values for i in the set of non-negative integers $\{0, 1, 2, \ldots, n\}$, then a fixed probability p_{ij} can be defined to indicate the conditional probability of the process moving from state i to state j when the time changes from the present instance to a future instance. If p_{ij} only depends on the present state and is independent on the past states then the stochastic process is called a Markov chain, and since the transition occurs at discrete time intervals, we can further describe the process as a discrete time Markov chain. It should be noted that, as probabilities are non-negative and the process must make a transition into some state, the transition probability p_{ij} must satisfy the following conditions:

$$\sum_{j=0}^{\infty} p_{ij} = 1, \qquad i = 0, 1, \qquad\qquad [2.1]$$

$$p_{ij} \geq 0, i, j \geq 0$$

If p_{ij}^k is the probability that a process in state i will be in state j after k additional transitions, then the Kolmogorov equation can be used to compute p_{ij}^k using intermediatory transition probabilities (Ross, 1993).

$$p_{ij}^k = \sum p_{io}^l \, p_{oj}^m \qquad\qquad l, m \geq 0, \text{ all } i,j \qquad\qquad [2.2]$$

and

$$l + m = k \qquad\qquad\qquad [2.3]$$

Equation [2.2] states that if we denotes $P^{(k)}$ as the matrix of kth step transitional probabilities p_{ij}^k, then

$$P^{(k)} = P^{(l)} \, P^{(m)} \qquad\qquad\qquad [2.4]$$

Once the transitional probability matrices at specific time intervals are known, equation [2.4] can be used to compute the probability distribution of the states at any given instance (Ross, 1993). Based on the above equations, a variety of discrete time Markov chain models on rainfall occurrence has been developed for climatological and hydrological applications.

In rainfall modelling, a Markov chain has only two states; either wet or dry. Therefore, the event, the rainfall occurrence, is always in one of these states. At regular intervals such as hourly, daily or weekly a "transition" or change of state occurs. The probability of any time interval, say week, being in a wet or dry state is depend on the state of the previous week. The number of previous dependent weeks are then referred to as order of the Markov chain. For example, in a first-order Markov chain the state of the current week depends only on the state of the previous week whereas in a second order chain it depends on the states of two previous weeks.

2.2.2   Review of discrete time Markov chains in rainfall occurrence models

As described in the previous section, a Markov chain can be defined as a type of time ordered probabilistic process which goes from one state to another according to the probabilistic transition rules that are determined by the current state only. Discrete time Markov chains have been widely used with daily rainfall models in hydrological and climatological studies. The first stochastic model of the temporal precipitation with Markov chain (first-order two-state) was introduced by Gabriel and Neuman (1962) to model the rainfall of Tel Aviv, Israel. Feyerherm and Bark (1967) found

that, except for prolonged dry spells, the first-order Markov chain satisfactorily modelled the occurrence of wet and dry days at Garden City Kansas, USA. Richardson (1981) used a first-order Markov chain along with an exponential distribution for the rainfall amounts to describe the daily rainfall distribution in the USA. Brauhn et al. (1980) used a similar Markov chain to simulate the daily rainfall occurrence in Geneva and Fort Collins in the USA. A first-order Markov chain has also been used by Selavalingam and Miura (1978), Larsen and Pense (1982) and Woolhiser et al. (1993) to describe the occurrence of wet and dry day sequences in daily rainfall models. All of these studies revealed that the generated data using a Markov chain along with a suitable probability distribution preserve the seasonal and statistical characteristics of historical rainfall data. Being simple and requiring only two parameters are to be determined, the first-order two-state Markov chain is the most common one referred in the literature. Smith and Schriber (1973) have suggested that the first-order two-state Markov chains were superior to Bernoulli models which are based on sequential independence for describing wet and dry days. Models of second and higher orders have also been studied by Chin (1977), Singh et al. (1981) and Jones and Thronton (1993). When a second-order Markov chain is used, eight separate parameters have to be estimated. Jimoh and Webster (1996) found that the second-order models are not better than the first-order models under tropical environments in Nigeria. They also found that the performance of the first-order model in simulating the average monthly number of wet days was not affected by the threshold value used to define wet and dry days. However, Coe and Stern (1982) preferred choice of either the first or the second order if they fit reasonably well. Buishand (1978) commented that a second-order model was seldom justified within the context of practical applications.

Chin (1977) showed that the order of conditional dependence of daily rainfall occurrences depended on the season and the geographical location. He further concluded that at any station, the rainfall occurrences associated with cyclone passage would most likely to indicate a conditional dependence with Markov order higher than one while rainfall associated with convectional activity may account for the prevalence of first-order conditional dependence. Although several authors have

discussed the order of discrete Markov chains with daily rainfall models, the issue of choosing the proper order with weekly time interval has not been addressed. Also, being Dry zone's rainfall is a combination of several meteorological scenarios, the order of the Markov chain that describes the occurrence of weekly rainfall can not be assumed priori.

2.2.3 Continuous time Markov process

Numerous discrete time Markov rainfall models of rainfall occurrence are used in climatological and hydrological applications. This approach is in many ways an elegant one which achieves an appropriate balance between complexity and goodness of fit (Hutchinson, 1991). The chief inadequacies in discrete time Markov rainfall models appear to be in the modelling of rainfall extremes and not incorporating any dependance between amounts of precipitation falling on successive wet periods (Wight and Hanson, 1991 and Richardson, 1984). Moreover, rainfall occurrence is a continuous intermittent process over space and time, which is usually recorded as cumulative amounts of series of wet periods over fixed intervals and locations (Georgiou and Guttrop, 1986). But, in discrete time Markov chains the occurrence of rainfall is modelled at equal lengths of time intervals which is not realistic. The increased focussed on discrete event daily rainfall models has led to the recognition that rainfall in many areas does not represent the discrete time Markov models (Hutchinson, 1990 and Small and Morgan, 1986). Events may exhibit temporal dependence between amounts of rain falling on successive wet periods. Inter-event duration may no longer distributed in equal time intervals. One way to approach this problem is to hypothesise that transition occurs at intervals of variable duration and this approach leads to the continuous time Markov models.

In analogy with the definition of discrete time Markov chain described in section 2.2.1, the process $\{X(t), t \geq 0 \}$ is continuous time Markov chain having the properties that each time it enters state i;

(i) the amount of time it spends in that state before making a transition into a different state is exponentially distributed with intensity parameter λ_i, and

(ii) when the process leaves state i, it next enters state j with some probability p_{ij} that must satisfy the following conditions:

$$P_{ii} = 0 \qquad \textit{for all} \quad i$$

$$\sum_j p_{ij} = 1 \qquad \textit{for all} \quad i$$

If there exists an $N \times N$ intensity matrix where N is the number of states, with

$$a^{ij} = \begin{cases} \lim_{t \to 0} \dfrac{p^{i,j}(t)}{t} & : \ i \neq j \\[2ex] \lim_{t \to 0} \dfrac{p^{i,i}(t) - 1}{t} & : \ i = j \end{cases} \qquad [2.5]$$

which together with the initial probability vector $p(0)$, completely characterises the homogeneous continuous time Markov chain (Kloeden and Platen, 1992). If the diagonal components $a^{i,i}$ are finite for each $i = 1,\ldots,$ N, then the transition probabilities satisfy the Kolmogorov forward equation

$$\frac{\partial p^{i,j}(t)}{\partial t} - \sum_{k=1}^{N} p^{i,k}(t) a^{k,j} = 0 \qquad [2.6]$$

for all i = 1,......, N (Kloeden and Platen, 1992). The time between transition from a state to any other state, is then exponentially distributed with intensity parameter

$$\lambda_i = \sum_{j \neq i} a_i^{i,j} \qquad [2.7]$$

The exponential distribution is fundamental in modelling continuous Markov processes because of its memoryless property relating to the elapsed time, which is critical to the Markov property (Mesterton-Gibbons, 1989).

2.3 Rainfall amounts

Shorter period rainfall amounts usually resembles skewed distribution with smaller amount occurring more frequently than larger amounts. Several distributions and data transformations have been presented in the literature for modelling rainfall

amounts in a wet period. Log or cubic transformations were found to be useful in reducing skewness (Pickering, 1982). The exponential distribution has often been used in the rainfall simulation studies because of its simplicity (Todorovic and Woolihiser, 1975 and Richardson, 1981). Although the log-normal distribution has often been used in the stochastic stream flow modelling (see Loucks et al., 1981 for references), it has not been received much attention with regard to the rainfall modelling. However, Mielke and Johnson (1973) suggested that the log-normal distribution provides a good fit to the rainfall of short time intervals caused by the factors such as cumulus clouds and weather modification experiments. In contrast, the two-parameter gamma distribution has often been used in rainfall modelling studies especially with daily rainfall models (Jones et al., 1972; Brauhn et al., 1979; Coe and Stern, 1982; Larsen and Pense, 1982 and Jones and Thronton, 1993). It gives relatively high probability to small rainfall amounts whereas low probability for larger amounts. The general form of a gamma probability density function has a third parameter, λ, which establishes the lower bound for the random variable, X. For rainfall amounts in a wet period researchers assume that $\lambda = 0$ which indeed reasonable since amounts will approach zero but will never be equal to or less than zero. Gamma distribution has a disadvantage that the cumulative distribution function does not have a closed form and hence not integrable. But with the advancement of numerical methods and computers, this problem no longer inhibits any simulation studies with a gamma distribution. Skees and Shenton (1974) used the three-parameter gamma, the generalised gamma and the censored gamma along with many power transformations to model the rainfall amount in wet periods. None of the distributions were suitable in all cases, although the censored gamma distribution showed a promise.

Use of the Weibull distribution in meteorological and hydrological modelling is becoming popular. This distribution has been shown to provide a good fit to strongly skewed data (Wong, 1977). The advantage of the Weibull distribution over the gamma and the log-normal distributions is its closed form of cumulative distribution function (Wilks, 1989). That is, the probability density function is integrable. Wong (1977) concluded that the Weibull distribution provides a better fit than the

commonly used gamma distribution in many meteorological and hydrological applications.

The models that have been used for describing the distribution of rainfall amounts contain different number of parameters and have various degree of complexity. Simple models require fewer parameters but are limited in their ability to describe the distribution of rainfall accurately. The more complex models can give a better description of rainfall distribution, but the complex models require the estimation of several parameters. Also, the choice of probability distributions can evidently have a larger impact on the output of the models and, potentially, on the quality of the decisions made with the simulation results (Law and Kelton, 1991).

2.4 Model development

2.4.1 Data collection

The data collected by the Dry Zone Agricultural Research Institute, Department of Agriculture, Maha-Illuppallama (8^0 07' N, 80^0 28'E) were used for the model development. This meteorological recording station represents the entire Dry zone in terms of general climate, cropping pattern and irrigation network. Fifty one consecutive years (1945-1995) of records of cumulative rainfall amounts of each standard week[1] of the year were available for the model development. An effective development of stochastic rainfall models requires data sets which are long enough to include some extreme events. Wight and Hanson (1991) suggested that for stochastic rainfall models, the historical records should be 20 years or more. Therefore, a target of 30 complete years of data was set for the parameter estimation leaving 21 years of data for the validation of the models. The allocation of each year either for parameter estimation or validation was performed using a random number table to ensure an unbiased estimation of parameters.

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[1] Refer Appendix 2 for the definition and the classification of standard weeks

2.4.2 Development of discrete time Markov rainfall models

As discussed in the preceding sections, there have been considerable number of investigations on stochastic simulation of rainfall at different time intervals. But these existing models are not suitable for direct use in agro-climatological studies in Sri Lanka, especially with the weekly time interval as most of the models being used are based on either daily or monthly rainfall events which either too short or long for agricultural applications. However, those information was the basis for the development of rainfall models discussed in the following sections.

The determination of whether any particular week is wet or dry necessitates to define a threshold value of rainfall that differentiate a week being wet or dry. A value of 7 mm or more rainfall per week was chosen as the threshold value because the Potential Evapotranspiration (PET) of at least 3 mm/day would make a weekly total of 21 mm and 33% of PET (7 mm) is considered to be the minimum requirement for the crop growth (Hargreaves, 1975). Any rainfall less than 7 mm/week would not make a substantial contribution to the crop growth; therefore, 7 mm of total rainfall during a week was decided to be the threshold value.

If weekly rainfall is modelled by a first-order two-state Markov chain, rain falling on any week depends only on the state (wet or dry) of the previous week. The changes of state from the current state to next state can be modelled by a 2×2 transition matrix. The transition matrix is also called probability matrix, Markov matrix or stochastic matrix. The elements of the transition matrix are called transition probabilities, conditional probabilities or transition percentages. The elements to be estimated are therefore the conditional probabilities:

$p_m(W_i | W_{i-1}) =$ conditional probability of a wet week on week i given

a wet week on week (i-1) in a certain period m

$p_m(D_i | W_{i-1}) =$ conditional probability of a dry week on week i given

a wet week on week (i-1) in a certain period m

$p_m(W_i | D_{i-1}) =$ conditional probability of a wet week on week i given

a dry week on week (i-1) in a certain period m

$$p_m(D_i \mid D_{i-1}) = \text{conditional probability of a dry week on week i given}$$
$$\text{a dry week on week (i-1) in a certain period m}$$

Thus, for each week four elements in the transition matrix were determined in the first-order Markov chains using 30 years of data (Table 2.1 and Table 2.2). For the second-order chain eight elements of the transitional probability matrix were determined (Table 2.3 and Table 2.4). These were transitional probabilities of a wet week following two wet weeks, $p_m(W_i \mid W_{i-1} W_{i-2})$; a wet week following a wet week and a dry week, respectively, $p_m(W_i \mid W_{i-1} D_{i-2})$; a wet week following a dry week and a wet week, respectively, $p_m(W_i \mid D_{i-1} W_{i-2})$; a wet week following two dry weeks, $p_m(W_i \mid D_{i-1} D_{i-2})$; a dry week following two wet weeks, $p_m(D_i \mid W_{i-1} W_{i-2})$; a dry week following a wet week and a dry week, respectively, $p_m(D_i \mid W_{i-1} D_{i-2})$; a dry week following a dry week and a wet week, respectively, $p_m(D_i \mid D_{i-1} W_{i-2})$; and, a dry week following two dry weeks, $p_m(D_i \mid D_{i-1} D_{i-2})$. As a result of seasonal variations in rainfall, the elements of the transitional matrices vary throughout the year. The usual method of handling this variation is fitting a Fourier series (Richardson, 1981 and Woolhiser et al., 1993) and other periodic functions such as polynomials (Coe and Stern, 1982) at the expense of some accuracy. But, in this study, the transition probability matrices for the first-order and the second-order models for each week were estimated using the respective weekly data as it would reflect the variation more realistically than approximating by a continuous function.

It is customary to assume that the amount of rainfall in a given time period follows a particular probability distribution and that it is the same for each time interval. But, under Dry zone conditions, the rainfall governing mechanisms are changing throughout the year consisting monsoons, convectional activity and cyclones and depressions. Thus, certain months are relatively wet while some other months could be extremely wet. There are some months such as February during which none of the rainfall governing mechanisms are effective over the Dry zone. Therefore, different periods of the year could be well represented by different probability distributions rather than employing a single pre-determined distribution for the whole year.

Table 2.1 **Transitional probabilities of the two major rainy seasons for the first-order discrete time Markov chain.**

Standard Week No.	$p_m(W_i \mid W_{i-1})$	$p_m(D_i \mid W_{i-1})$	$p_m(W_i \mid D_{i-1})$	$p_m(D_i \mid D_{i-1})$
Yala season				
12	0.3636	0.6364	0.3158	0.6842
13	0.7000	0.3000	0.5000	0.5000
14	0.9412	0.0588	0.4615	0.5385
15	0.9091	0.0909	0.5000	0.5000
16	0.6667	0.3333	0.5000	0.5000
17	0.8421	0.1579	0.4545	0.5455
18	0.6667	0.3333	0.2222	0.7778
19	0.7500	0.2500	0.3571	0.6429
20	0.5882	0.4118	0.3077	0.6923
21	0.2143	0.7857	0.2500	0.7500
Maha season				
40	0.7222	0.2778	0.5000	0.5000
41	0.7368	0.2632	0.8182	0.1818
42	0.9130	0.0870	0.5714	0.4286
43	0.9200	0.0800	0.6000	0.4000
44	0.9615	0.0385	1.0000	0.0000
45	0.9310	0.0690	0.0000	1.0000
46	0.7778	0.2222	0.6667	0.3333
47	0.9130	0.0870	0.8571	0.1429
48	0.7778	0.2222	1.0000	0.0000
49	0.7083	0.2917	1.0000	0.0000
50	0.6522	0.3478	0.7143	0.2857
51	0.7500	0.2500	0.8000	0.2000
52	0.9130	0.0870	0.7143	0.2857
1	0.4615	0.5385	0.5000	0.5000
2	0.5714	0.4286	0.4375	0.5625
3	0.3333	0.6667	0.3333	0.6667
4	0.4000	0.6000	0.3500	0.6500
5	0.4545	0.5455	0.3158	0.6842

Table 2.2   Transitional probabilities of the two major dry periods for the first-order discrete time Markov chain.

Standard Week No.	$p_m(W_i \mid W_{i-1})$	$p_m(D_i \mid W_{i-1})$	$p_m(W_i \mid D_{i-1})$	$p_m(D_i \mid D_{i-1})$
First dry period				
6	0.3636	0.6364	0.2105	0.7895
7	0.1250	0.8750	0.0909	0.9091
8	0.6667	0.3333	0.3333	0.6667
9	0.4545	0.5455	0.2105	0.7895
10	0.4444	0.5556	0.6190	0.3810
11	0.4118	0.5882	0.3077	0.6923
Second dry period				
22	0.2857	0.7143	0.1818	0.8182
23	0.0000	1.0000	0.1304	0.8696
24	0.0000	1.0000	0.0741	0.9259
25	0.5000	0.5000	0.1071	0.8929
26	0.0000	1.0000	0.1154	0.8846
27	0.3333	0.6667	0.3704	0.6296
28	0.2727	0.7273	0.2632	0.7368
29	0.1250	0.8750	0.2727	0.7273
30	0.2857	0.7143	0.0870	0.9130
31	0.0000	1.0000	0.1538	0.8462
32	0.7500	0.2500	0.1923	0.8077
33	0.2500	0.7500	0.1364	0.8636
34	0.2000	0.8000	0.2400	0.7600
35	0.2857	0.7143	0.2174	0.7826
36	0.7143	0.2857	0.0435	0.9565
37	1.0000	0.0000	0.2083	0.7917
38	0.4545	0.5455	0.3684	0.6316
39	0.6667	0.3333	0.5556	0.4444

Table 2.3 Transitional probabilities of the two major rainy seasons for the second-order discrete time Markov chain.

Standard Week	$p_m(W_i \mid W_{i-1} W_{i-2})$	$p_m(W_i \mid W_{i-1} D_{i-2})$	$p_m(W_i \mid D_{i-1} W_{i-2})$	$p_m(W_i \mid D_{i-1} D_{i-2})$	$p_m(D_i \mid W_{i-1} W_{i-2})$	$p_m(D_i \mid W_{i-1} D_{i-2})$	$p_m(D_i \mid D_{i-1} W_{i-2})$	$p_m(D_i \mid D_{i-1} D_{i-2})$
Yala season								
12	0.4286	0.3000	0.2500	0.3333	0.5714	0.7000	0.7500	0.6667
13	0.7500	0.2857	0.6667	0.6154	0.2500	0.7143	0.3333	0.3846
14	0.8571	0.6667	1.0000	0.4000	0.1429	0.3333	0.0000	0.6000
15	1.0000	0.0000	0.6667	0.5714	0.0000	1.0000	0.3333	0.4286
16	0.6500	0.5000	0.7500	0.5000	0.3500	0.5000	0.2500	0.5000
17	0.8125	0.3750	1.0000	0.6667	0.1875	0.6250	0.0000	0.3333
18	0.6250	0.0000	0.8000	0.3333	0.3750	1.0000	0.2000	0.6667
19	0.7857	0.0000	0.5000	0.7143	0.2143	1.0000	0.5000	0.2857
20	0.5833	0.5000	0.6000	0.2222	0.4167	0.5000	0.4000	0.7778
21	0.2000	0.0000	0.2500	0.4444	0.8000	1.0000	0.7500	0.5556
Maha season								
40	0.7500	0.0000	0.7000	0.7500	0.2500	1.0000	0.3000	0.2500
41	0.6154	0.8000	1.0000	0.8333	0.3846	0.2000	0.0000	0.1667
42	0.8571	0.6000	1.0000	0.5000	0.1429	0.4000	0.0000	0.5000
43	0.9048	0.0000	1.0000	0.6667	0.0952	1.0000	0.0000	0.3333
44	0.9565	1.0000	1.0000	1.0000	0.0435	0.0000	0.0000	0.0000
45	0.9600	0.0000	0.7500	0.0000	0.0400	1.0000	0.2500	0.0000
46	0.7778	1.0000	0.0000	0.0000	0.2222	0.0000	0.0000	1.0000
47	0.9048	0.8333	1.0000	1.0000	0.0952	0.1667	0.0000	0.0000
48	0.8095	1.0000	0.6667	1.0000	0.1905	0.0000	0.3333	0.0000
49	0.6667	1.0000	1.0000	0.0000	0.3333	0.0000	0.0000	0.0000
50	0.7059	0.7143	0.5000	0.0000	0.2941	0.2857	0.5000	0.0000
51	0.8000	0.7500	0.6000	1.0000	0.2000	0.2500	0.4000	0.0000
52	0.8667	0.8000	1.0000	0.5000	0.1333	0.2000	0.0000	0.5000
1	0.4762	0.5000	0.4000	0.5000	0.5238	0.5000	0.6000	0.5000
2	0.5833	0.4286	0.5000	0.5000	0.4167	0.5714	0.5000	0.5000
3	0.2500	0.3333	0.4286	0.3333	0.7500	0.6667	0.5714	0.6667
4	0.4000	0.4000	0.4000	0.3000	0.6000	0.6000	0.6000	0.7000
5	0.2500	0.6667	0.5714	0.1538	0.7500	0.3333	0.4286	0.8462

Table 2.4 Transitional probabilities of the two major dry periods for the second-order discrete time Markov chain.

Standard Week	$p_m(W_i \mid W_{i-1} W_{i-2})$	$p_m(W_i \mid W_{i-1} D_{i-2})$	$p_m(W_i \mid D_{i-1} W_{i-2})$	$p_m(W_i \mid D_{i-1} D_{i-2})$	$p_m(D_i \mid W_{i-1} W_{i-2})$	$p_m(D_i \mid W_{i-1} D_{i-2})$	$p_m(D_i \mid D_{i-1} W_{i-2})$	$p_m(D_i \mid D_{i-1} D_{i-2})$
First dry period								
6	0.4000	0.3333	0.3333	0.1538	0.6000	0.6667	0.6667	0.8462
7	0.2500	0.0000	0.0000	0.1333	0.7500	1.0000	1.0000	0.8667
8	0.0000	0.1429	1.0000	0.4000	1.0000	0.8571	0.0000	0.6000
9	0.0000	1.0000	0.5556	0.1667	1.0000	0.0000	0.4444	0.8333
10	0.2000	0.8333	0.7500	0.5233	0.8000	0.1667	0.2500	0.4667
11	0.5000	0.4000	0.3846	0.2500	0.5000	0.6000	0.6154	0.7500
Second dry period								
21	0.2000	0.0000	0.2500	0.4444	0.8000	1.0000	0.7500	0.5556
22	0.3333	0.0000	0.2500	0.3636	0.6667	1.0000	0.7500	0.6364
23	0.0000	0.2000	0.0000	0.1111	1.0000	0.8000	1.0000	0.8889
24	0.0000	0.0000	0.0000	0.1000	0.0000	1.0000	1.0000	0.9000
25	0.0000	0.3333	0.5000	0.0800	0.0000	0.6667	0.5000	0.9200
26	0.0000	0.0000	0.0000	0.1200	1.0000	1.0000	1.0000	0.8800
27	0.0000	0.7500	0.3333	0.3043	0.0000	0.2500	0.6667	0.6957
28	0.0000	0.0000	0.3000	0.2941	1.0000	1.0000	0.7000	0.7059
29	0.0000	0.3750	0.2000	0.2143	1.0000	0.6250	0.8000	0.7857
30	0.0000	0.0000	0.3333	0.1250	1.0000	1.0000	0.6667	0.8750
31	0.0000	0.2000	0.0000	0.1429	1.0000	0.8000	1.0000	0.8571
32	0.0000	0.2500	0.7500	0.1818	0.0000	0.7500	0.2500	0.8182
33	0.3333	0.0000	0.2000	0.1429	0.6667	1.0000	0.8000	0.8571
34	0.0000	0.3333	0.3333	0.2105	1.0000	0.6667	0.6667	0.7895
35	0.0000	0.0000	0.3333	0.2632	1.0000	1.0000	0.6667	0.7368
36	1.0000	0.0000	0.6000	0.0556	0.0000	1.0000	0.4000	0.9444
37	1.0000	0.0000	1.0000	0.2273	0.0000	1.0000	0.0000	0.7727
38	0.3333	0.0000	0.6000	0.3684	0.6667	0.0000	0.4000	0.6316
39	0.4000	0.5000	0.8571	0.5833	0.6000	0.5000	0.1429	0.4167

Hence, in this study, four right skewed probability distributions namely, gamma, Weibull, log-normal and exponential distributions were used to represent variation of rainfall amounts on wet weeks. Their probability density functions are given in the Table 2.5.

2.4.2.1 Parameter estimation of probability distributions

Weekly rainfall data of 30 years, the same data used for transitional probability matrix estimation in Markov chain, were used to the find appropriate distribution for each week. Each distribution was assigned a relative evaluation score from 0 to 100 (best) based on the heuristic ranking algorithm of UNIFIT II, a statistical software to determine the appropriate probability distribution for observed data (Law and Vincent, 1993). The higher the score of a distribution, the better it is relative to the other fitted distributions. Out of four probability distributions considered, the one with the highest score was selected to represent the weekly amount of rainfall for that particular week. Since no heuristic algorithm is perfect, the selected model was tested by Chi-square test and Anderson-Darling goodness of fit test to see whether the observed data could have been simulated from the specified probability distribution. A further evaluation of the selected model was done by making Distribution Function Differences Plot (DFDP), which is a graph of the differences between a sample distribution function computed from the data and the distribution function of the fitted model. If the fitted distribution were a perfect fit, the graph should be a horizontal line at height zero. Thus, the greater the vertical deviations from this line, the worse is the quality of the fitted distribution. If the model with the highest score does not satisfy the above tests criteria, the model with next highest score was considered and evaluated with the same tests mentioned above. Once a suitable candidate for the probability distribution was selected, its parameters were determined for each week. There are many ways such as maximum likelihood estimation, method of moments and least-squares estimation to estimate the parameters of a suitable probability distribution. But, in this study Maximum Likelihood Estimation (MLE) technique was chosen to estimate the parameters of the selected distribution as it has several desirable properties often not enjoyed by the

Table 2.5 Probability distributions and their density functions.

Distribution	Probability density function	
exponential	$f(x) = \begin{cases} 1 - e^{-x/\beta} \\ 0 \end{cases}$	$\text{if } x \geq 0$ otherwise
log-normal	$f(x) = \begin{cases} \dfrac{1}{x\sqrt{2\pi\sigma^2}} \exp \dfrac{-(\ln x - \mu)^2}{2\sigma^2} \\ 0 \end{cases}$	$\text{if } x > 0$ otherwise
gamma	$f(x) = \begin{cases} \dfrac{\beta^{-\alpha} x^{\alpha-1} e^{-x/\beta}}{\Gamma(\alpha)} \\ 0 \end{cases}$	$\text{if } x > 0$ otherwise
Weibull	$f(x) = \begin{cases} \dfrac{\alpha\beta^{-\alpha} x^{\alpha-1} e^{-(x/\beta)^{\alpha}}}{\Gamma(\alpha)} \\ 0 \end{cases}$	$\text{if } x > 0$ otherwise

α = shape parameter β = scale parameter μ = mean σ = standard deviation
Γ = gamma function

other alternative methods (Law and Kelton, 1991). For example, MLE has some stronger theoretical properties than the ordinary least squares method (Gujarati, 1995). Larsen and Pense (1982) have shown that method of moments estimators of the shape parameter of the gamma distribution are less precise than the MLE. Table 2.6 and 2.7 show the best fitted probability distribution and its distribution parameters based on the maximum likelihood estimation method for each week in the year.

2.4.3 Development of continuous time Markov rainfall model

The methodology developed here simulates the rainfall occurrences and rainfall amounts in continuous time. The continuous time Markov models attempt to describe the rainfall events independently of the time interval used for rainfall measurements. The conditional probabilities of $\{p_m (W_i \mid W_{i-1}) - 1\}$ and $\{p_m (W_i \mid D_{i-1})\}$ were fitted into an annual function of time and then each function was partitioned into three parts namely, January to mid April, mid-April to mid-July and then mid-July to the end of the year representing a simple curve for each part. The each part was then fitted to a polynomial equation using SigmaPlot non linear curve fitting routine (Kuo and Fox, 1992). This routine uses Marquardt-Levenberg algorithm to determine the parameters that minimise the sum of squares of differences between the dependent variable values in the fitted model and the observed values. The general form of the polynomial equation was decided priori to satisfy the conditions set by equation [2.6] in the section 2.2.3.

From January to mid April, the following two polynomial equations were found to be the best fitted equations for respective conditional probabilities with time (t) in months;

$$f(p_1) = -0.0234t^4 + 0.09628t^3 + 0.1445t^2 - 0.7456t \qquad [2.11]$$

where

$$f(p_1) = p_m (W_i \mid W_{i-1}) -1 \qquad [2.12]$$

$$\frac{f(p_1)}{t} = -0.0234t^3 + 0.09628t^2 + 0.1445t - 0.7456$$

Table 2.6   Best fitted probability distribution and its Maximum Likelihood Estimates (MLE) during the two major rainy seasons.

Standard Week No.	Distribution	Scale (β)	Shape (α)
Yala season			
12	Weibull	19.36	0.9321
13	exponential	33.17	-
14	Weibull	50.63	1.0400
15	Weibull	40.25	1.3900
16	gamma	47.61	0.9526
17	gamma	45.15	0.7620
18	gamma	71.98	0.6932
19	exponential	42.60	-
20	gamma	30.41	0.8503
21	exponential	8.23	-
Maha season			
40	Weibull	36.97	0.7478
41	gamma	100.73	0.7259
42	exponential	66.33	-
43	exponential	57.37	-
44	Weibull	85.90	1.5500
45	gamma	51.02	1.3800
46	gamma	86.86	0.7793
47	Weibull	42.53	1.3700
48	gamma	45.07	1.1789
49	Weibull	37.02	0.7466
50	gamma	56.70	0.8618
51	Weibull	44.22	1.0500
52	exponential	58.82	-
1	gamma	76.69	0.4296
2	gamma	72.56	0.5685
3	gamma	37.96	0.6505
4	Weibull	22.15	1.4116
5	Weibull	16.04	0.7806

Table 2.7 Best fitted probability distribution and its Maximum Likelihood Estimates (MLE) during the two major dry periods.

Standard Week No.	Distribution	Scale (β)	Shape (α)
First dry period			
6	Weibull	6.76	1.5615
7	exponential	9.86	-
8	Weibull	13.13	0.7971
9	Weibull	21.28	0.6679
10	Weibull	6.74	0.7836
11	Weibull	19.36	0.9321
Second dry period			
22	Weibull	9.22	0.7873
23	Weibull	5.86	0.8611
24	exponential	6.53	-
25	exponential	4.19	-
26	exponential	0.78	-
27	gamma	7.27	0.6706
28	Weibull	3.41	0.5621
29	log-normal	12.67	8.9700
30	exponential	3.26	-
31	Weibull	2.19	0.6189
32	gamma	33.15	0.2646
33	exponential	7.10	-
34	log-normal	1.46	1.9000
35	log-normal	1.72	1.3600
36	Weibull	3.65	0.7030
37	Weibull	18.42	0.4974
38	gamma	31.26	0.4368
39	Weibull	6.80	0.8278

As $t \rightarrow o$

$$\frac{f(p_1)}{t} = -0.7456 \qquad\qquad [2.13]$$

$$\text{If} \qquad f(p_2) = p_m(\ W_i \mid D_{i-1}), \qquad\qquad [2.14]$$

$$f(p_2) = 0.04919t^5 - 0.5377t^4 + 2.1465t^3 - 3.69t^2 + 2.4151t \qquad\qquad [2.15]$$

$$\frac{f(p_2)}{t} = 0.04919t^4 - 0.5377t^3 + 2.1465t^2 - 3.69t + 2.4151$$

As $t \rightarrow o$

$$\frac{f(p_2)}{t} = 2.4151 \qquad\qquad [2.16]$$

Assuming a homogeneous Markov chain, then the intensity matrix (equation [2.5]), A, is

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} -0.7456 & 0.7456 \\ 2.4151 & -2.4151 \end{bmatrix}$$

Thus, time between transition from any state to a next state is exponentially distributed with intensity parameters λ_w and λ_D (equation [2.7]) where,

λ_w = time between next state and current state provided current state is

wet

λ_D = time between next state and current state provided current state is

dry

and together with the initial conditional probability[2] vector (0.50,0.39), the transition probabilities satisfy the Kolmogorov forward equation [2.6].

$$\frac{\partial p^{i,j}(t)}{\partial t} - \sum_{k=1}^{N} p^{i,k}(t) a^{k,j} = 0$$

$$\frac{\partial p^{11}}{\partial t} = P^{11} a^{11} + P^{12} a^{21} \qquad\qquad [2.17]$$

$$\frac{\partial p^{11}}{\partial t} = P^{11}(-0.7456) + P^{12}(2.4151)$$

---

[2] The conditional probability of the states when time equals zero. This was determined from the annual functions of W/W and W/D at time equals zero for each part of the year.

$$\frac{\partial p^{11}}{\partial t} = P^{11}(-0.7456) + 2.4151(1 - P^{11})$$

By solving the differential equation with the initial value of 0.50

$$P = 0.764103 - 0.264103 e^{-3.1607t} \tag{2.18}$$

That is

$$P_m(W_i|W_{i-1}) = 0.764103 - 0.264103 e^{-3.1607t} \tag{2.19}$$

Similarly, with the initial value of 0.39,

$$P_m(W_i|D_{i-1}) = 0.764103 - 0.374103 e^{-3.1607t} \tag{2.20}$$

The same procedure was adapted to calculate other two parts of the annual function and their final equations are:

mid-April to mid-July;

$$P_m(W_i|W_{i-1}) = 0.747899 - 727.4814 e^{-2.38t} \tag{2.21}$$

$$P_m(W_i|D_{i-1}) = 0.747899 - 1185.6741 e^{-2.38t} \tag{2.22}$$

mid-July to the end of the year

$$P_m(W_i|W_{i-1}) = 0.888523 - 0.6977568 \times 10^{17} e^{-5.7815t} \tag{2.23}$$

$$P_m(W_i|D_{i-1}) = 0.888601 - 0.9317955 \times 10^{17} e^{-5.781t} \tag{2.24}$$

The detailed calculations of equations [2.21] through [2.24] are given in the Appendix 1. In this model, a single distribution (gamma) was used to generate the rainfall amounts as there is no historical data to determine the best fitted distributions when the rainfall occurrence is taking place at unknown intervals. It was so chosen by considering its well known wide application in meteorology and hydrology (Geng et al., 1986). The maximum likelihood estimates of scale and shape parameters of the gamma distribution were represented by polynomial curves for the three different parts of the year (January to mid April, mid-April to mid-July and mid-July to the end of the year) in order to obtain smoothly varying weekly mean parameters throughout the year.

2.4.4 Summary

This chapter presents the use of discrete and continuous time Markov chains, and probability distributions to model the weekly rainfall process in the Dry zone of Sri Lanka based on the historical data. Two states were used in the Markov chains: wet and dry. A wet week was defined to occur whenever a 7 mm or larger amount of rainfall is recorded. The dry weeks are weeks which are not wet. Rainfall occurrence was modelled using first-order and second order-discrete time Markov chains, and continuous time Markov chain. In discrete time Markov chain models, the amount of rainfall in a wet week was represented by the most suitable right skewed probability distribution out of gamma, Weibull, log-normal and exponential distributions whereas in the continuous time Markov chain model only the gamma distribution was used.

Chapter 3

Implementation and validation of stochastic rainfall models

3.1 Introduction

Any model of a complex natural phenomenon such as rainfall can only be an approximation of the reality. How closely a stochastic weather simulation model needs to represent the real system depends on the type of applications. Clearly, there has to be a balance between complexity and the foreseen uses (Larsen and Pense, 1982). Otherwise, the effort may be largely wasted within the context of the desired application. In view of this, the developed models are required to validate with the data from the real system in measures of central tendency, dispersion and distribution. In other words, a testing has to be done to see whether the model behaves with satisfactory accuracy consistent with the study objectives, within its domain of applicability. Therefore, a rather extensive model validation was done to assess these claims.

The term reproduced is used when the comparisons between generated and historical values are statistically the same. One way of evaluating the reproducibility is to test whether the two distributions of generated and historic data are the same, homogeneous. There are many tests of homogeneity available. For distributions that are normal or approximately normal, the Analysis of Variance (ANOVA) is equivalent to testing for the homogeneity of the means and the F distribution can be

used to test for homogeneity of the variance of pairs of the two populations (Hoover and Perry, 1990). The most cited distribution free tests in simulation studies are the Kolmogorov-Smirnov two-sample test and the Chi-Square test. Each of these tests have their own merits and in particular situations, one test may be more powerful than the other. A major limitation of the Kolmogorov-Smirnov test (K-S test) is that it can only be used on continuous distributions (Hoover and Perry, 1990). However, this test has been used by many researchers in weather simulation studies (Semenov and Porter, 1995; Larsen and Pense, 1982; and Brauhn et al., 1980).

Another method of comparison is to compare the statistical properties for both the average and extreme rainfall situations. The two-tailed t-test has been used in many occasions to compare the average weather situations in simulation studies (Larsen and Pense, 1982 and Nicks and Harp, 1980). Therefore, in this study weekly mean rainfall, weekly maximum rainfall and total annual rainfall of simulated sequences were tested against the observed sequence using two-tailed t-test. The mean rainfall occurrence, number of weeks with rainfall of 7 mm or more, and other extreme attributes such as number of events greater or less than a pre-determined amount of rainfall were tested using Chi-square test for contingency (Gangelosi et al., 1979).

3.2 Simulation procedure

Generally, long generated sequence of rainfall gives a more accurate interpretation of the simulation results. However, considering the fact that only 21 years of data was available for the validation, a same number of years of weekly rainfall data were generated by both discrete time Makov models and the continuous time Markov model described in the Chapter 2. The low annual autocorrelation[1] in the historic data suggests that years are virtually independent events. Thus, the method of dealing with annual dependence by the use of multiple runs was considered unnecessary (Fishman, 1973).

---

[1] first order autocorrelation for 51 years historical data was -0.20

Generation of synthetic sequences of weekly rainfall data using discrete time Markov chain models is straightforward. Once the transitional probability of rain occurring on a given week was determined using equation [2.4], the probability of rainfall occurrence for the current week was calculated given the initial conditional probability vector for the two states. A random number generated from a uniform probability distribution (*U (0,1)*) was then used to determine the occurrence of rain during the current week. If the random number exceeds the probability of rainfall, weekly rainfall was zero, literally less than 7 mm of rainfall, otherwise the amount of rainfall was determined by a random variate generated from the selected probability distribution of the current week. Generation process of rainfall occurrence and the amount of rain if rain occurred were similar for the both first and second-order discrete Markov chains.

In continuous time Markov model, rainfall occurrences is taking place at unequal distances. Once the probability of rain occurring given the previous wet state (equations [2.19], [2.21] and [2.23]) and given the previous dry state (equations [2.20], [2.22] and [2.24]) are known, then the unconditional probability of occurrence of rainfall is determined using initial conditional probability vector of the two states. This unconditional probability of state being wet is then compared with a random number generated from a uniform probability distribution to simulate the amount of rainfall. If the random number exceeds the probability of rainfall, amount of rainfall is zero and then make a transition to next state, otherwise a amount of rainfall is generated using a gamma distribution and then make the transition to the next state. The transition to the next state from any current state is exponentially distributed along with the conditions set by equation [2.6]. The weekly amount of rainfall from this model was determined by taking the cumulative amount of rainfall that occurred as a result of number of rainfall events within the week. The flow charts of the generation programs for the discrete time Markov models and the continuous time Markov model are given in Figures 3.1 and 3.2, respectively.

$i = i + 1$

$i = 1$

initial probability vector

$j = j + 1$

$j = 1$

rainfall occurrence
equation 2.4

generate a random
number, R_n

P_1

$R_n \langle P_1$

$R_n \rangle P_1$

generate RF for the
current week

RF = 0

stop

$j = 21$

stop

$i = 52$
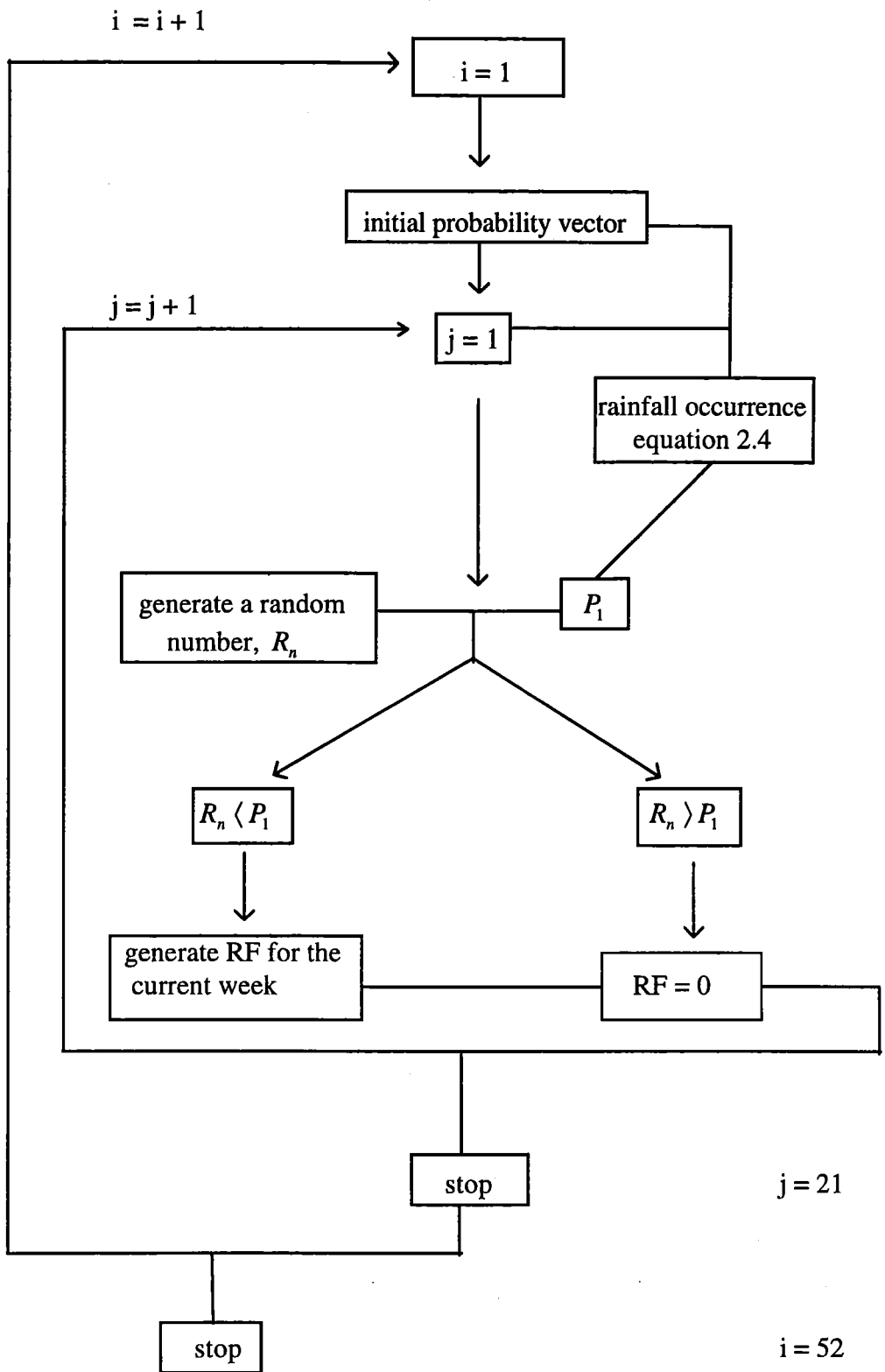
(RF = rainfall amount, P_1 = unconditional probability of rainfall occurrence)

Figure 3.1   Simplified flow chart for the discrete time Markov chains

i = i + 1 time = 0

i = 1

initial probability vector

probability of rainfall occurrence
equation 2.6

generate a random
number, R_n

P_1

$R_n \langle P_1$ $R_n \rangle P_1$

$RF=gamma(\alpha, \beta)$ RF = 0

eqn. 2.7 | transition to next state | eqn. 2.7

until time = 52

stop   i = 21
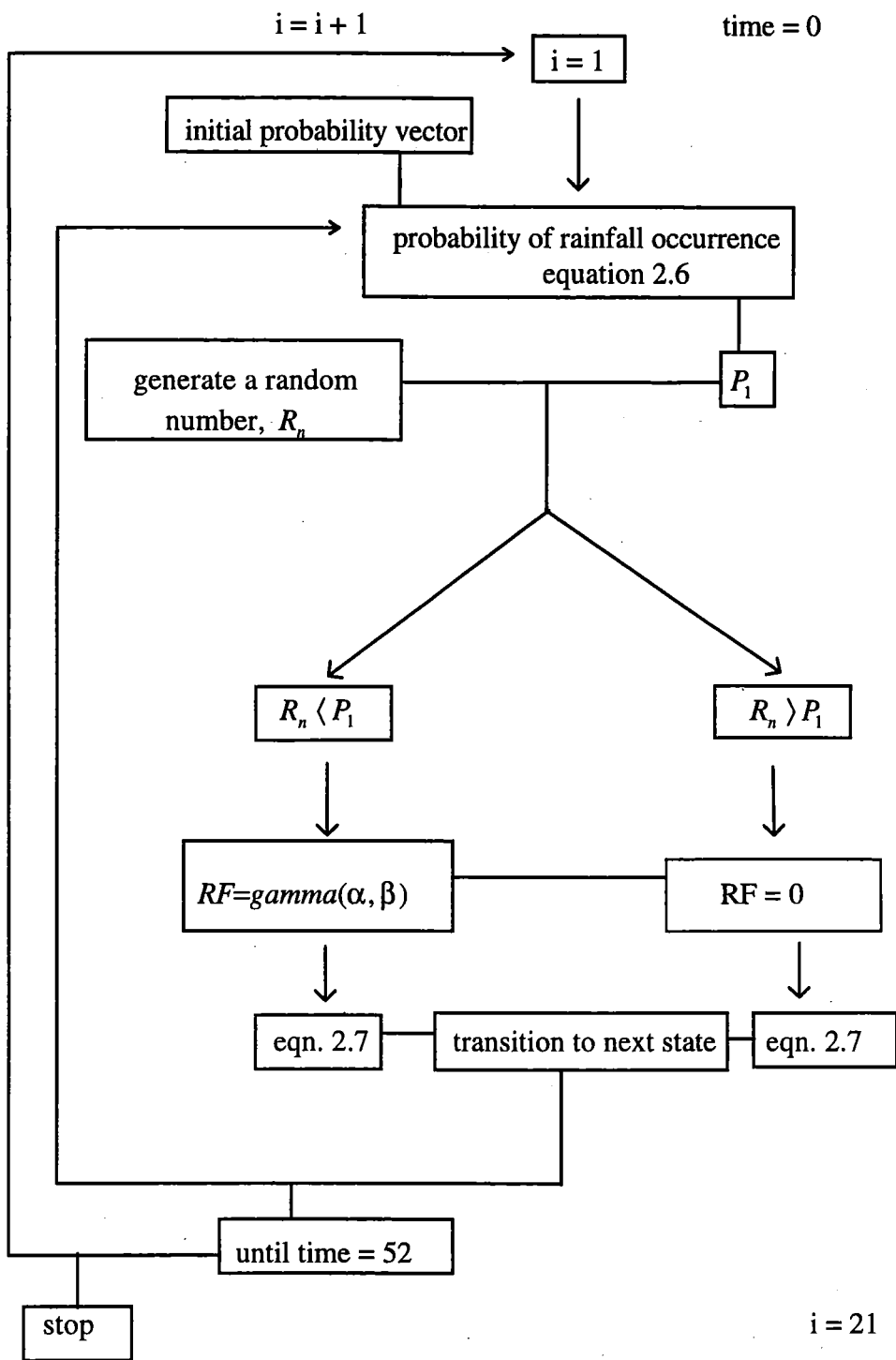
(RF = rainfall amount, P_1 = unconditional probability of rainfall occurrence)

Figure 3.2   Simplified flow chart for the continuous time Markov chain

3.3 Comparison between the first and the second-order discrete time Markov models

The 21 years observed rainfall time series of Maha-Illuppallama was compared to a time series of 21 years of weekly rainfall simulated by the first and second-order Markov chains. The ability of the stochastic model to preserve the observed year-to-year variability of historical rainfall events was the major evaluation criterion. Each rainfall time series was sorted by the standard week of the year and then assigned to four different periods of the year namely, Yala (minor rainy season), Maha (major rainy season), first dry period and second dry period.

3.3.1 Cumulative distribution functions

The hypothesis that the both observed and simulated data have come from the same distribution was tested using Kolmogorov-Smirnov two-sample test (K-S test). The test statistic, D, is the maximum value of the absolute difference between the Cumulative Distribution Functions (CDFs) of observed values and the corresponding simulated values from the first or the second-order model (Table 3.1 and Table 3.2). The critical value at the 5% probability level is 0.420. The K-S test shows that except in a few instances, both models represent the CDF of the observed values equally well. However, during the wet seasons performance of the first-order Markov model is better than the second-order model (Table 3.1). During both Yala and Maha seasons, CDFs of the second-order model have been significantly different at five different weeks whereas the standard week 4 was the only different one in the first-order model. Nevertheless, The performance of the both models were similar during the major dry seasons. Each model resulted one week on which CDF was different from the observed CDF. However, magnitude of the difference was less with the first-order model (Table 3.2).

Table 3.1 Kolmogorov-Smirnov test statistics between weekly simulated and observed rainfall during the two major rainy seasons with two discrete time Markov models, Maha-Illuppallama, Sri Lanka.

Standard Week No.	First-order	Second-order
Yala season		
12	0.286	0.476[*]
13	0.190	0.333
14	0.190	0.143
15	0.333	0.238
16	0.286	0.381
17	0.190	0.238
18	0.238	0.143
19	0.286	0.333
20	0.286	0.333
21	0.190	0.190
Maha season		
40	0.333	0.333
41	0.143	0.333
42	0.190	0.238
43	0.190	0.190
44	0.238	0.190
45	0.190	0.190
46	0.238	0.190
47	0.333	0.429[*]
48	0.190	0.143
49	0.333	0.190
50	0.381	0.286
51	0.286	0.286
52	0.333	0.143
1	0.238	0.190
2	0.190	0.429[*]
3	0.143	0.190
4	0.524[*]	0.524[*]
5	0.095	0.429[*]

[*] The weekly distribution function is significantly different from the corresponding distribution function of the observed values at the 5% probability level.

Table 3.2 Kolmogorov-Smirnov test statistics between weekly simulated and observed rainfall during the two major dry periods with two discrete time Markov models, Maha-Illuppallama, Sri Lanka.

Standard Week No.	First-order	Second-order
First dry period		
6	0.333	0.143
7	0.381	0.667*
8	0.238	0.238
9	0.238	0.190
10	0.429*	0.190
11	0.095	0.286
Second dry period		
22	0.280	0.286
23	0.143	0.095
24	0.190	0.190
25	0.143	0.095
26	0.048	0.000
27	0.095	0.238
28	0.238	0.143
29	0.143	0.190
30	0.095	0.143
31	0.143	0.143
32	0.048	0.238
33	0.238	0.286
34	0.095	0.095
35	0.143	0.143
36	0.190	0.048
37	0.286	0.286
38	0.095	0.190
39	0.095	0.286

* The weekly distribution function is significantly different from the corresponding distribution function of the observed values at the 5% probability level.

3.3.2 Rainfall amounts

The mean weekly rainfall of both the first and the second-order models and the observed time series are shown in Figure 3.3. Results demonstrate a reasonable agreement between the observed values and the simulated values of each model. However, during the period of November through the end of December, the northeast monsoon season, the both models have underestimated weekly rainfall amount. The Table 3.3 and 3.4 show the results of the two-tailed t-test that were used to compare the observed and simulated sets of means of weekly rainfall amount. It shows that the apparent discrepancy during the northeast monsoon season between the simulated and the observed rainfall amount is not reflected in the analysis except during the standard weeks 47 and 51 with the second-order model (Table 3.3). Discrepancies during the rainy seasons were never significant with the first-order model. The performance of the second-order model during the two major dry periods was not encouraging (Table 3.4). Out of total of 24 weeks during these two dry periods, nine weeks were significantly different from the observed sequence. However, there was only two such weeks, standard weeks 26 and 34, with the first-order model during the corresponding period. Despite the significant differences, the overall ability of the second-order model to simulate the weekly rainfall amount appeared adequate (Figure 3.3).

3.3.3 Rainfall occurrence

In analogy with the definition of threshold rainfall level that differentiated wet and dry states of Markov models, the number of weekly rainfall occurrences, weeks with rainfall of greater than or equal to 7 mm, from both models were determined with 21 simulation runs. These statistics were tested against the observed sequence using the Chi-square test. Both models simulated weekly rainfall occurrence that were in general closer to the historical values (Figure 3.4). However, with the Chi-square test, the first-order model failed at six weeks (standard weeks 3, 4, 6, 17, 29, and 40) whereas the second-order model failed only during standard weeks 4, 6 and 40 (Table 3.5 and 3.6). In most cases, failure was due to the magnitude of the values rather
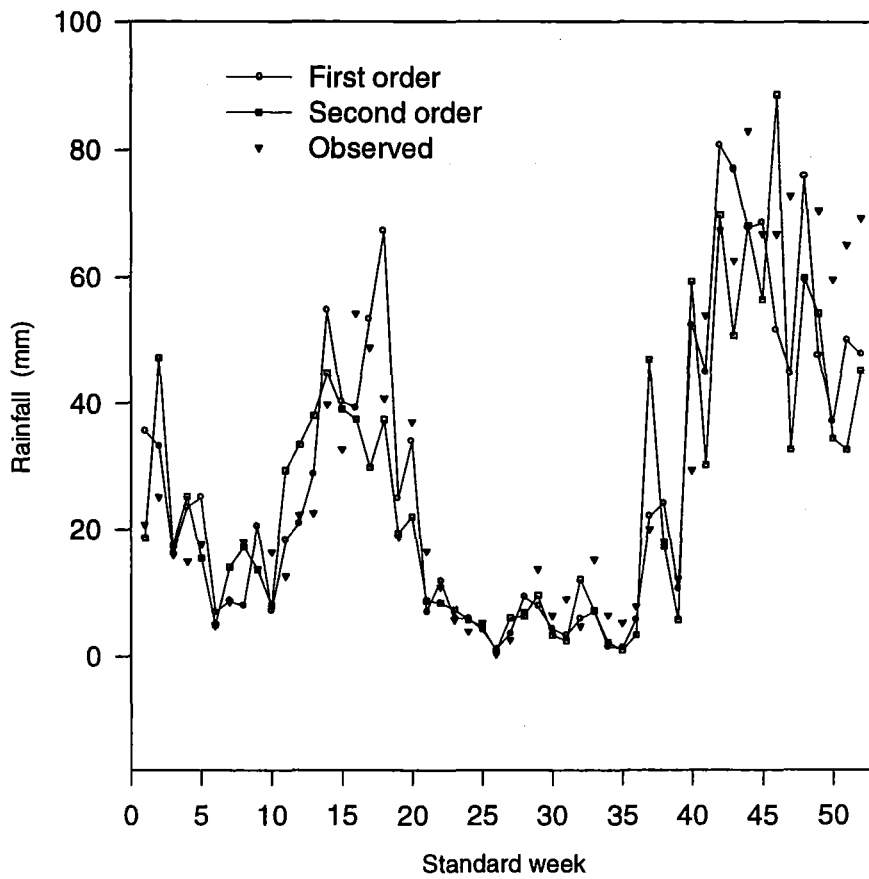
Figure 3.3   Simulated weekly rainfall from discerete time Markov models. Observed values are represented in small dark triangles.

Table 3.3 **Simulated and observed average weekly rainfall amount of the two major rainy seasons with discrete time Markov models, Maha-Illuppallama, Sri Lanka.**

Standard Week No.	First-order rainfall (mm)	Second-order rainfall (mm)	Observed rainfall (mm)
Yala season			
12	20.8	33.4	22.2
13	28.8	38.0	22.5
14	54.7	44.7	39.8
15	40.3	39.0	32.6
16	39.2	37.4	54.2
17	53.2	29.7	48.8
18	67.2	37.4	40.8
19	24.9	19.3	18.7
20	33.9	21.9	37.0
21	7.0	8.7	16.5
Maha season			
40	52.4	59.2	29.4
41	44.9	30.1	53.8
42	80.6	69.7	67.2
43	76.8	50.6	62.5
44	67.7	67.9	82.8
45	68.4	56.3	66.7
46	51.6	88.5	66.6
47	44.7	32.6*	72.6
48	75.7	59.7	59.4
49	47.5	54.1	70.3
50	37.0	34.3	59.4
51	49.9	32.6*	65.0
52	47.6	45.1	69.2
1	35.6	18.6	20.6
2	33.1	47.2	25.1
3	16.2	17.4	16.0
4	23.5	25.2*	14.9
5	25.0	15.4	17.6

* The means are significantly different from the observed mean at the 5% probability level

Table 3.4 Simulated and observed average weekly rainfall amount of the two major dry periods with discrete time Markov models, Maha-Illuppallama, Sri Lanka.

Standard Week No.	First-order rainfall (mm)	Second-order rainfall (mm)	Observed rainfall (mm)
First dry period			
6	7.0	5.0	4.9
7	8.7	14.0	8.6
8	7.9	17.2	18.0
9	20.5	13.6	13.8
10	7.1	8.0^*	16.4
11	18.2	29.3	12.6
Second dry period			
22	11.8	8.3	10.8
23	6.0	7.2	5.8
24	6.0	5.7	3.9
25	4.1	4.7	5.2
26	1.0^*	0.8^*	0.3
27	3.6	6.0^*	2.6
28	9.4	6.4	7.0
29	7.8	9.6	13.7
30	4.4	3.4	6.5
31	3.2	2.4^*	9.0
32	6.0	12.0	4.7
33	6.9	7.2^*	15.3
34	1.5^*	2.2^*	6.5
35	1.2	0.9^*	5.2
36	5.8	3.3^*	7.8
37	22.0	46.9	20.0
38	24.1	17.2	18.0
39	10.5	5.7^*	12.1

* The means are significantly different from the observed mean at the 5% probability level
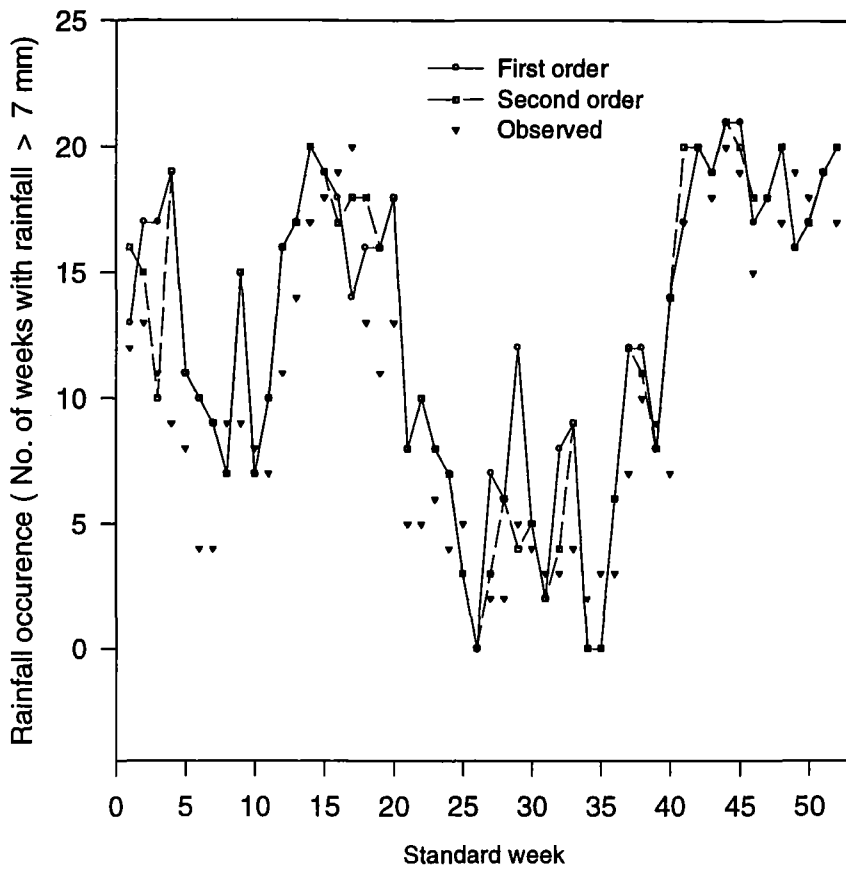
Figure 3.4   Simulated weekly rainfall occurence from discrete
time Markov model. Observed values are
represented in small dark triangles.

Table 3.5 **Simulated and observed rainfall occurrence during the two major rainy seasons with discrete time Markov models, Maha-Illuppallama, Sri Lanka.**

Standard Week No.	First-order rainfall occurrence	Second-order rainfall occurrence	Observed rainfall occurrence
Yala season			
12	16	16	11
13	17	17	14
14	20	20	17
15	19	19	18
16	18	17	19
17	14*	18	20
18	16	18	13
19	16	16	11
20	18	18	13
21	8	8	5
Maha season			
40	14*	14*	7
41	17	20	17
42	20	20	20
43	19	19	18
44	21	21	20
45	21	20	19
46	17	18	15
47	18	18	18
48	20	20	17
49	16	16	19
50	17	17	18
51	19	19	19
52	20	20	17
1	13	16	12
2	17	15	13
3	17*	10	11
4	19*	19*	9
5	11	11	8

* The means of simulated and observed values are significantly different at the 5% probability level.

Table 3.6 Simulated and observed rainfall occurrence during the two major dry periods with discrete time Markov models, Maha-Illuppallama, Sri Lanka.

Standard Week No.	First-order rainfall occurrence	Second-order rainfall occurrence	Observed rainfall occurrence
First dry period			
6	10*	10*	4
7	9	9	4
8	7	7	9
9	15	15	9
10	7	7	8
11	10	10	7
Second dry period			
22	10	10	5
23	8	8	6
24	7	7	4
25	3	3	5
26	0	0	0
27	7	3	2
28	6	6	2
29	12*	4	5
30	5	5	4
31	2	2	3
32	8	4	3
33	9	9	4
34	0	0	2
35	0	0	3
36	6	6	3
37	12	12	7
38	12	11	10
39	8	8	9

* The means of simulated and observed values are significantly different at the 5% probability level.

than due to excessive variability. Out of six weeks that have failed to simulate the rainfall occurrence on par with the historical sequence, three weeks, standard weeks 4, 6 and 40, are common for both models. These three weeks represent either very early stages or the tail end of the rainy seasons. The rest of the weeks, standard weeks 17 and 29, which failed in the first-order model come within the characteristics inter-season dry period of the Dry zone. None of the above mentioned weeks other than the standard week 4 failed in the analysis of mean rainfall amount with the both models. Thus, results presented give no clear evidence as to the basis for selection of an appropriate order of a Markov chain for the different seasons or periods of the year.

3.3.4 Extreme rainfall events

The most important property of stochastic rainfall models is their ability to simulate the extreme values. A failure to do so is a major shortcoming of the developed models (Wight and Hanson, 1991 and Richardson, 1984). Therefore, additional comparisons were made with the mean annual rainfall, mean annual weekly maxima, number of weeks which receive more than 150 mm of rainfall, storm situations and number of weeks which receive less than 10 mm of rainfall, dry conditions (Table 3.7). Except the criterion of number of weeks which receive less than 10 mm of rainfall, all the other attributes were not significantly different from the observed values with the both models. The both models have simulated less number of weeks which receive less than 10 mm of rainfall compared to the observed sequence. This concludes that both models are capable of reproducing the annual and storm sequences but, ability of simulating the drought situations are yet to be improved.

The results of the foregoing discussion suggest that first-order model performs better than the second-order model in simulating the weekly rainfall amount in the Dry zone of Sri Lanka. The situation becomes opposite in terms of the weekly rainfall occurrence where the second-order model is more representative than that of the first order model. However The capability of simulating annual and extreme events of

Table 3.7 Simulated and observed annual rainfall and other extreme attributes, Maha-Illuppallama, Sri Lanka.

Attribute	Simulated		Observed
	1st order	2nd order	
Mean annual rainfall (mm)	1504	1424	1481
Mean annual weekly maxima (mm)	210	207	201
No. of weeks $\geq$ 150 (mm)	36	33	33
No. of weeks < 10 (mm)	513*	507*	587

* Means are significantly different from the observed values at the 5% probability level.

rainfall are almost similar in the both models. However, in general, there is no discernible difference in the performance of the first and second-order models.

3.4 Performance of the continuous time Markov model

The test statistics of the Kolmogorov-Smirnov goodness of fit between the CDFs of the observed and the simulated values of weekly rainfall are shown in the Table 3.8 and 3.9 for the wet and dry seasons respectively. The performance of the continuous time Markov chain during the Dry periods of the year was poor. Most of CDFs between the observed and the simulated rainfall were significantly different at the 5% probability level (Table 3.9). The performance during the Yala season was also not encouraging (Table 3.8). However, during the Maha season the CDFs of the simulated rainfall were reasonably matched with the observed CDFs (Table 3.8).

The Figure 3.5 shows the 95% confidence band width of the simulated rainfall data of the continuous time Markov model along with the corresponding observed values. In general, the simulated weekly means are in a reasonable agreement with the observed means. But, 50% of the means lie outside the confidence interval band indicating a significant departure from the reality. During the Maha season, the model has underestimated the weekly rainfall whereas during the Yala season weekly means are within the band limits. The underestimation of the model during the period from May to September, the characteristics inter-season dry period of the Dry zone, was also significant. These results contradict the discussion in terms of the weekly CDFs of rainfall where the model's performance during the Maha season was reasonably acceptable.

The Figure 3.6 shows the number of weeks which receive rainfall of 7 mm or more, rainfall occurrence, with the 21 simulation runs of the continuous model. The simulated values are always greater than that of the observed values. However, some differences during the Yala season, standard weeks 13 through 17, and during the Maha season, standard weeks 42, 43, 44, 45, 47, 49, 50, 51 and 52, were not significantly different at the 5% probability level with the Chi-square test. All these

Table 3.8 Kolmogorov-Smirnov test statistics between weekly observed and simulated rainfall during the two major rainy seasons with the continuous time Markov model, Maha-Illuppallama, Sri Lanka.

Standard Week No.	K-S test statistics
Yala season	
12	0.476[*]
13	0.286
14	0.429[*]
15	0.286
16	0.238
17	0.381
18	0.381
19	0.571[*]
20	0.381
21	0.667[*]
Maha season	
40	0.667[*]
41	0.333
42	0.190
43	0.286
44	0.238
45	0.190
46	0.286
47	0.286
48	0.333
49	0.286
50	0.333
51	0.286
52	0.286
1	0.429[*]
2	0.381
3	0.330
4	0.524[*]
5	0.524[*]

* The weekly distribution function is significantly different from the corresponding distribution function of the observed values at the 5% probability level.

Table 3.9 **Kolmogorov-Smirnov test statistics between weekly observed and simulated rainfall during the two major dry periods with the continuous time Markov model, Maha-Illuppallama, Sri Lanka.**

Standard Week No.	K-S test statistics
First dry period	
6	0.762^*
7	0.619^*
8	0.429^*
9	0.476^*
10	0.571^*
11	0.619^*
Second dry period	
22	0.714^*
23	0.714^*
24	0.667^*
25	0.571^*
26	0.857^*
27	0.857^*
28	0.857^*
29	0.762^*
30	0.667^*
31	0.143
32	0.524^*
33	0.524^*
34	0.667^*
35	0.524^*
36	0.619^*
37	0.619^*
38	0.429^*
39	0.333

* The weekly distribution function is significantly different from the corresponding distribution function of the observed values at the 5% probability level.
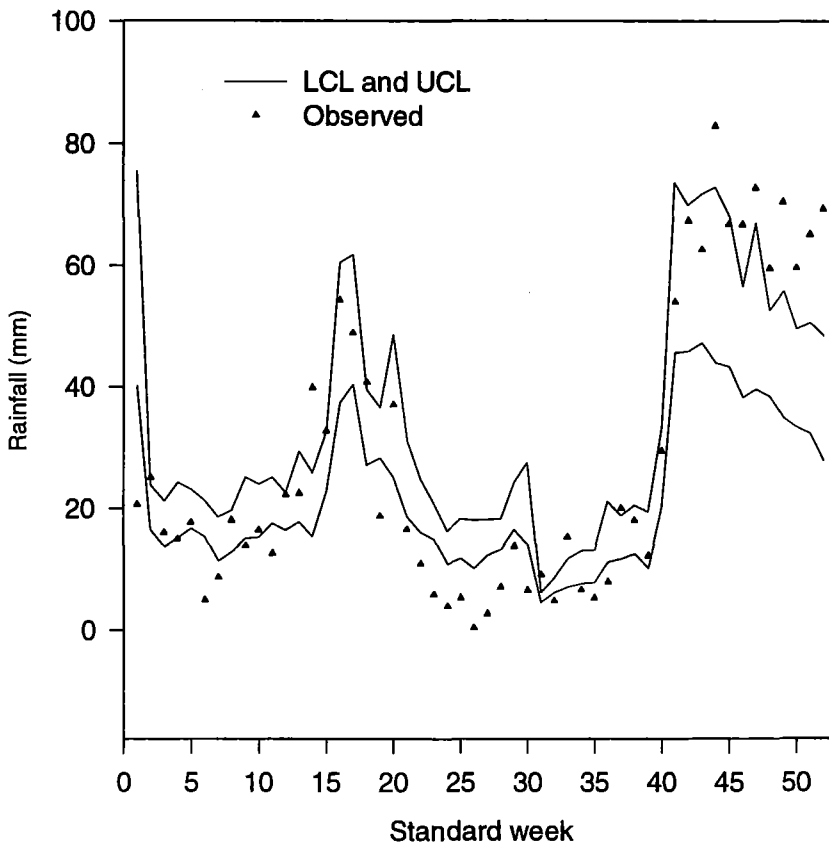
Figure 3.5   The 95% confidence interval band of simulated weekly rainfall with the continuous time Markov model.   Observed values are represented in small dark triangles.
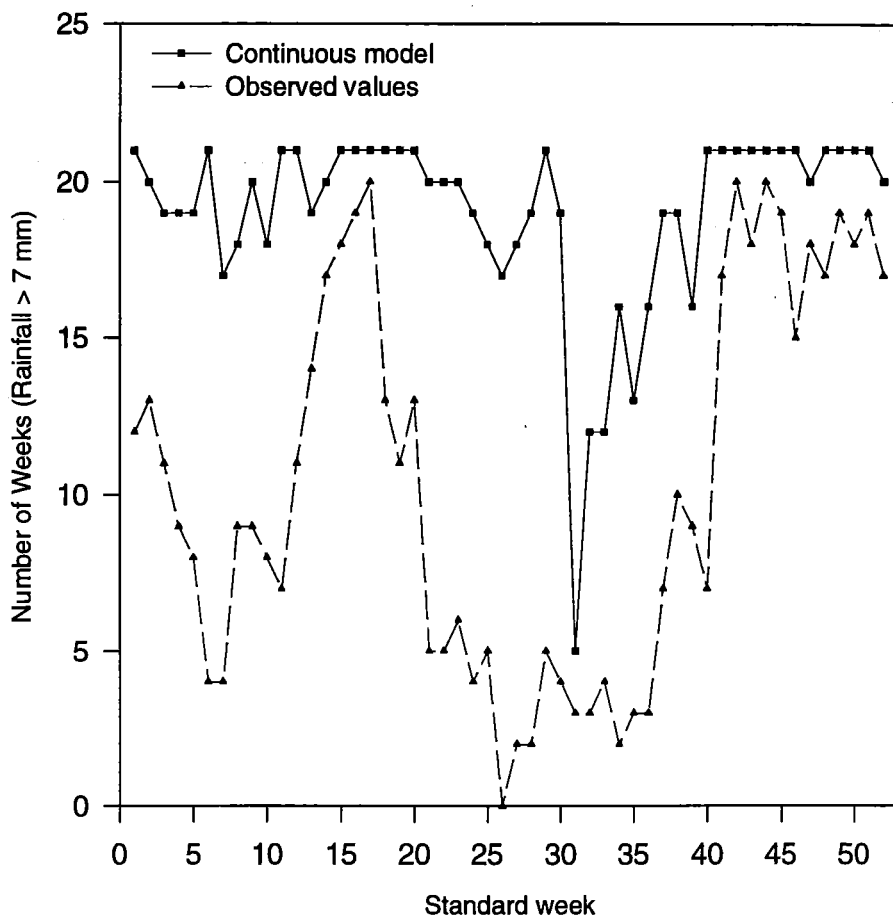
Figure 3.6   Observed and simulated rainfall occurence with the continuous time Markov model.

weeks which were not significantly different from the observed sequence represent peak rainfall periods of the respective seasons. This indicates the capability of the continuous model in simulating the weekly rainfall occurrence of the Dry zone during rainy seasons. However, the ability of the model to simulate the weekly rainfall occurrence during the dry periods was very poor (Figure 3.6). In general, the performance of the continuous model was not convincing. The representativeness of the model was not consistent with the different criteria tested. However, the indication of possible applications in modelling wet seasons rainfall process show a promise. The chief limitation of the model in its current form could be the time interval. The continuous Markov models attempt to describe the rainfall process independently from the time interval used for rainfall observations and in a way the model relates more or less to directly the real rainfall occurrence structure. Therefore, the estimated parameters based on the weekly measurements may not be sensitive enough to represent the actual rainfall process which is highly dynamic in nature. It is anticipated that the most of the shortcomings of the model could be minimised with a more shorter observation time scale and will be the subject of further study.

3.5 Summary

The validation analysis in the previous sections of this chapter has revealed that the both the discrete and the continuous Markov models can model the weekly rainfall process in the Dry zone of Sri Lanka with a reasonable agreement to the historical data. Although, only the first-order discrete Markov model gives good results statistically, errors encountered with the second-order Markov model are small and hence, in terms of functionality either of the discrete model could be used. The overall performance of the continuous Markov model was poor although it shows a promise in modelling rainfall process. The first-order discrete model is the preferred model since the number of parameters to be estimated is less and the resulting output gives slightly smaller errors over the historical sequence.

Chapter 4

Modelling soil water balance of the Dry zone

4.1 Introduction

Water use in crops takes place in the process of transpiration, by which the water absorbed by the roots is transformed into water vapour exhaled by the stomata of the leaves. This process is necessary not only for the transportation of nutrients and photosynthetic products to all parts of the plant, but also for the cooling of the leaves when these are exposed to the sun for long periods. Kramer (1963) pointed out that water is:

1. the major constituent of physiologically active plant tissues;

2. a reagent in photosynthesis and in hydrolytic processes such as starch degradation;

3. the solvent in which sugar, salts and other solutes move from cell to cell and organ to organ; and,

4. an essential element for the maintenance of plant turgidity, necessary for cell enlargement and growth.

Thus, it is obvious that lack of water or moisture stress reduces the growth and development of the plants. The close relationship between dry matter production increase in plants and the quantity of water transpired by those plants has been well documented (Lawes, 1850, Briggs and Shantz, 1913 and many others). Tanner and Sinclair (1983) and Monteith (1986) discussed the physical and physiological principles that underlie this phenomenon. Almost all the moisture consumed by the

plants comes from the soil. The soil is supplied with water through rain, snow or hail out of which rain is the most important source in the tropics. The entire amount of water supplied to the soil by rain is not available for plant growth because it can be lost in several ways. Only a portion of water taken up by plants is useful for producing plant dry matter. This component is called transpiration. As the amount of water transpired by the plants and the dry matter production are closely related (Campbell and Diaz, 1988), the fraction of the rainfall which is available for transpiration must be determined to explore the agricultural potential in a given region. The rapid progress in the study of evapotranspiration has lead to the development of the water balance technique as a method of estimating plant water requirement or the soil moisture adequacy for crop growth (Chang, 1968).

A soil water balance model is a method of calculating crop water use (Mavi, 1986). The way in which we define the water balance and its intended use depends greatly on the space and time scales of interest. The most precise definition is needed for the smallest scales, where the local water balance has several important agricultural applications (Henderson-Sellers and Robinson, 1986). The equation for soil water balance is generally written as in the form given below using moisture mass conservation equation (Rosenberg et al., 1983):

$$RF - RO - D - ET + \Delta W = 0 \qquad [4.1]$$

where,

RF = Rainfall

RO = Run off

D = Deep drainage

ET = Evapotranspiration

ΔW = Change in soil water storage

The equation [4.1] can be used on any scale, ranging from continental land masses and hydrological catchments down to individual plants. On the basis of equation [4.1], numerous models of water transfer between soils and crops have been formulated (See reviews by Jury, 1979). To run these models spatially for agro-climatological purposes, it is necessary to estimate the spatial distribution of their input data, state parameters and boundary conditions (Wagenet et al., 1991). As the

kind and number of input values depend on the degree of model complexity, the experimental investment will differ for each model. The lower the possibility of measuring the input parameters, more simpler the model. Generally, model simplification increases with the extent of the application area (Leenhardt et al., 1995).

4.2 Review of soil water balance models

Two types of soil water models are recognised based on the details with which soil water redistribution in the soil profile is described; models based on physics and soil water budget models. The models based on physics describe the soil-water-plant relations in terms of fluxes, using Darcy's law for soils and electrical analogy for evapotranspiration (Brisson et al., 1992). This approach requires a detailed knowledge of soil physical and hydro-dynamic properties and they are not readily available for operational use on agro-climatological purposes.

Models of the soil water budget types range in complexity from simple book keeping methods such as that of Thornwaite and Mather (1955) to complex computer models such as that described by Norman and Cambell (1983). Complex models rely on limited number of assumptions and extensive experimental information for their parameters which restrict their applicability directly at the field level. Carneiro da Silva (1984) compared a model based on physics and a water budget model with field measurements of water under sugar cane and corn grown in Brazil. He reported that the model based on physics was a better predictor at high water contents whereas the water budget model performed better at low water contents.

4.3 Selection of a model to be used at broad scale studies

In reality, simplified approaches are preferred in spatial applications for practical reasons (Leenhardt et al., 1995). A simple soil water balance using long term values of monthly rainfall and potential evapotranspiration could give some indication of availability soil water and of surplus water (Thornwaite, 1948). However, extreme

simplicity of the model, equally available soil water at all soil water potential, renders the questionable results for agro-climatic classification studies. To improve this type of simple water balance models, Baier and Robertson (1965) developed a versatile soil water budget which involved several soil layers, a knowledge on rooting depth and behaviour of the specific crop in question, information on water release characteristics of each soil layer and other relevant climatic data. Considering the large uncertainty in even the best measurement of soil water and other relevant parameters over a large area (Robertson, 1973), it appears that estimation by detailed soil water models involving many parameters of unknown certainty may be over extending the model's complexity and ability to provide a reasonable estimate of the soil water status (Robertson, 1988). This is why simple conceptual models of soil water balance such as single layer models have been preferred in many studies (Robertson, 1988 and Rao, 1987). On the other hand, in the areas of where only the rudimentary meteorological data are available, simple models using minimal inputs are required (ICRISAT, 1978). Since it is a relatively easy task to estimate the soil water status of a particular region, without the need for, or with a minimum of, field measurements, from rainfall and other climatological data, the calculation of such balances seems to be the most useful and easiest way to characterise the climate of a region for its agricultural potential.

4.3.1 Single-layer soil water balance model

Single-layer water balance models have been widely used for many years in irrigation and hydrologic investigation and in general descriptive climatology (Porteous et al., 1994; Rao, 1987; NZMetS, 1986 and Fitzpatric and Nix, 1969). These models are straightforward to derive and apply, and explain the variation of soil moisture availability for crop use adequately (Porteous et al., 1994). There are two commonly used single-layer water balance models. The simplest one, "Veihmeyer and Hendrickson" model (Veihmeyer and Hendrickson, 1955 and Coulter, 1973) assumes a constant evapotranspiration from field capacity (FC) to permanent wilting point (PWP) and fell sharply thereafter. This concept assumes that plant functions remain

unaffected by decrease in soil water, and evaporation is at its potential rate until the PWP is reached at which plant activity curtailed abruptly.

The second one, "Two-phase" models assume a first phase of constant evapotranspiration rate upto a critical point somewhere between FC and PWP, and a second phase of linearly declining evapotranspiration rate from that point to zero at the wilting point (Porteous et al., 1994; Scotter et al., 1979 and Denmead and Shaw, 1962). These two concepts are depicted in the Figure 4.1. Still others, propose a compromise between these two extremes. They propose that the actual evapotranspiration (AET) proceeds at the potential rate for some time, and then decreases rapidly in exponential manner (Pierce, 1958). However, there are considerable discrepancies in research findings as to where the actual evapotranspiration begins to drop (Chang, 1968). As the model developed here intended to be applied in broad scale agro-climatological surveys, it necessitates a certain level of simplification and therefore linear version of the "Two-phase" model was chosen for the development of the soil water balance sub-model of the system model.

4.4 A soil water balance sub-model for the Dry zone

In order to asses the possible crop water usage in the Dry zone by means of a soil water balance model, the physical characteristics of the predominant soil type and climatic conditions must be determined. In this study, attention is mainly focussed on the most important and prevalent great soil group of the Dry zone, the Reddish Brown Earths (RBE) which covers approximately 2.5 million ha (Amarasiri, 1987). According to the USDA soil taxonomy classification, RBE soils are in the Alfisol order and fall into the Great Group Rhodustalfs. These soils are formed from residuum or colluvium from mixed intermediate and basic metamorphic crystalline rocks of the Vijayan series and Khondalite series. These soils are well, moderately well and imperfectly drained and occur in undulating landscapes (De Alwis and Panabokke, 1972). The texture becomes heavier with depth, varying from sandy clay loam at the surface to clay loam or sandy clay with gravel in sub-soil.
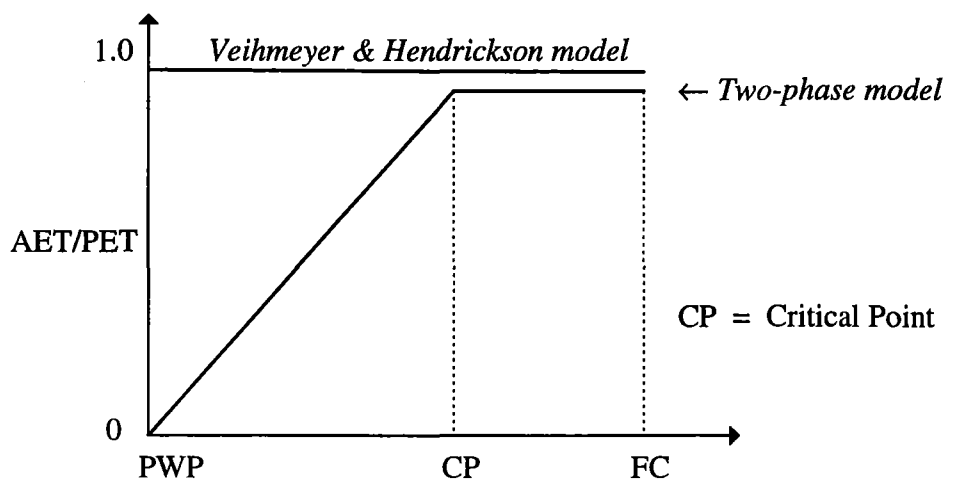
Figure 4.1 Relationship between AET/PET ratio and soil moisture status with two conceptual models.

The gravelly B horizon is typical for RBE soils and is underlain by the partly weathered parent material or saprolite, usually of coarse sandy texture (Joshua, 1985). Much of the elementary soil physical information of RBE soils needed for water balance calculations are available as modal values based on the frequency distribution of measurements made with soil surveys for many development projects over the years (Joshua 1985).

4.4.1 Components of the soil water balance model

4.4.1.1 Available soil moisture

The physical limits of available soil moisture are defined by the concepts of the field capacity (FC) and the permanent wilting point (PWP). Field capacity is a soil characteristics and has been defined as the water content of soil when free drainage of an initially saturated profile under gravity has decreased to a negligible rate (Chang, 1968). Wilting point is a plant characteristic occurring when leaves lose their turgor and depends on the plant and the factors influencing water loss (transpiration) and water intake from the soil (Jackson, 1989). Most plants have an osmotic potential of 15 to 20 bar and therefore a value of 15 bar matric suction is commonly taken as the water potential at which soil moisture becomes severely limiting (Kramer, 1983). It is generally considered that the water held between FC and PWP is the available water for crop use, and for a given root zone it can be expressed as:

$$ASM = \frac{(FC - PWP) \times \rho \times D}{100}$$ [4.2]

where,

ASM = Available soil moisture in the root zone as an
       equivalent depth of water, cm/cm

FC   = Percentage gravimetric water content at the FC

PWP = Percentage gravimetric water content at the PWP

ρ = Relative density of the soil

D   = Depth of the root zone, cm

Field drainage studies on RBE soils have shown that the moisture content at 0.1 bar matric suction corresponds to the FC (Joshua, 1985). Modal values of soil moisture retention at 0.1 bar and 15 bar tensions for different horizons have been calculated based on the frequency distribution of routine measurements on undisturbed core samples of RBE soils (Joshua, 1985) and these are shown in Table 4.1.

The determination of available soil moisture (ASM) component in a water balance model has to be in accordance with the dynamic nature of growth of plant roots (Cassel and Nielsen, 1986). Different models deal differently with the root extraction or sink term. The objective of the sink term is to distribute the atmospheric demand for water over the root zone, and to estimate the water uptake from each layer taking into account its water status. Incorporation these aspects, within a model based upon limited and generalised data with intended applications at a broader scale, may lead to unnecessary model complications. Therefore, in this study, a constant root zone depth was assumed for the whole growth period. In RBE soils average rooting depth is around 60 cm attributing to the high mechanical impedance of underlying horizons, (Joshua, 1985). Thus, 60 cm depth was considered as the hypothetical single-layer for the proposed water balance model. Since the RBE soils consist of different soil horizons with variable water holding capacities, a weighted average of ASM for 60 cm depth was calculated as suggested by Gardner (1986). When 60 cm rooting depth is considered, the RBE soils contain 185 mm and 115 mm of water at field capacity and permanent wilting point respectively, leaving 70 mm of water as the total available soil moisture.

4.4.1.2 Evapotranspiration

Evapotranspiration is the combined loss of water from a given area by evaporation from the soil surface and by transpiration from plants. Evapotranspiration is governed by the same factors which govern the open water evaporation, namely supply of energy to provide the latent heat of vaporisation and the ability to transport vapour away from the evaporative surface. In addition, a third factor enters to the picture;

Table 4.1 Modal values of field capacity (FC) and permanent wilting point (PWP) of RBE soils in the Dry zone of Sri Lanka (Joshua, 1985).

Horizon	FC % (v/v)	PWP % (v/v)
Surface (0-15 cm)	26.0	16.0
Sub-surface (15-35 cm)	30.5	18.5
Gravely (35-60 cm)	34.0	21.5

the supply of moisture at the evaporative surface (Chow et al., 1988). As the soil dries out, the rate of evapotranspiration drops below the level it would have maintained in a well watered soil. Therefore, it is advisable to consider the case when the water supply is unlimited because the rate of evapotranspiration from a partially wet surface is greatly affected by the nature of the ground (Chang, 1968). This leads to the concept of Potential Evapotranspiration (PET). The PET is meant to define the upper limit of the evaporation rate from a given soil-vegetation unit under a given set of meteorological conditions. Multiplicity of definitions in the literature draws a rather confusing picture, and therefore, sometimes the usefulness of the PET concept has been questioned. Part of the problem in defining PET unambiguously may be because several earlier workers considered it to be solely a property of the atmosphere (Sharma, 1985). In fact, it depends on soil, vegetative as well as climatic factors, but it is difficult to define these influences exactly. Despite variety of definitions, the one proposed by Penman (1956) has been widely accepted. He defines the PET as "the amount of water transpired in unit time by a short green crop, actively growing, completely shading the ground, of uniform height and never short of water". For a given crop and its stage of development, the PET is given by (Rao, 1987);

$$PET = K_c \ ET_o \qquad\qquad [4.3]$$

where,

K_c = Crop factor which depends on the stage of
crop growth

ET_o = Reference evapotranspiration

4.4.1.2.1 Reference evapotranspiration

Reference evapotranspiration (ET_o) has recently come into widespread use (Burman et al., 1983). Two definitions of ET_o are commonly used. Doorenbos and Pruit (1984) used the definition as "the maximum rate of evapotranspiration from an extended surface of 8-15 cm height green grass cover, completely shading the ground under unlimited supply of water." The second definition is based upon alfalfa (*Medicago sativa*) and was proposed by Jensen et al. (1971). In their definition ET_o

represents "the upper limit or maximum evapotranspiration that occurs under given climatic conditions with a field having a well watered agricultural crop with an aerodynamically rough surface, such as alfalfa, with 30 to 50 centimetres of top growth." The present study will be based on the definition of Doorenbos and Pruit (1984). They have reviewed four methods of estimating ET_o ; Blaney and Criddle method, the radiation method, the modified Penman method and the evaporation pan method. They concluded that the choice of the method is determined by the availability of climatic data and the accuracy required. Out of four methods, the pan evaporation method was chosen for this study in view of data availability and its relative accuracy (Shih et al., 1983 and Pruit, 1960). The reference evapotranspiration (ET_o) is given by (Doorenbos and Pruitt, 1984);

$$ET_o = K_{pan} \; E_{pan} \qquad\qquad [4.4]$$

where,

K_{pan} = Pan coefficient

E_{pan} = Evaporation from a Class A pan

Pan coefficient, K_{pan}, is a empirically derived coefficient which take into account climate and pan environment such as relative humidity, wind speed and pan location. Given the average climatic condition of the Dry zone, a value of 0.8 was chosen as the pan coefficient (Doorenbos and Pruitt, 1984). This is in agreement with the generalised value proposed by Jätzold (1977) for semi arid climates.

4.4.1.2.2 Crop coefficient (K_c) values

The K_c values relates the evapotranspiration of a disease free crop grown in large fields under optimum soil water and fertility conditions and achieving full production potential to that of a green grass surface growing under the same environment (Doorenbos and Pruitt, 1984). The value of K_c is dependent on crop characteristics and varies with time based on variations in leaf area index (LAI) as shown in Figure 4.2. The initial value of K_c for well watered soil with little ground cover, is approximately 0.35. As the ground cover develops, K_c increases to a maximum value, which can be greater than 1 for crops with large vegetative cover such as corn
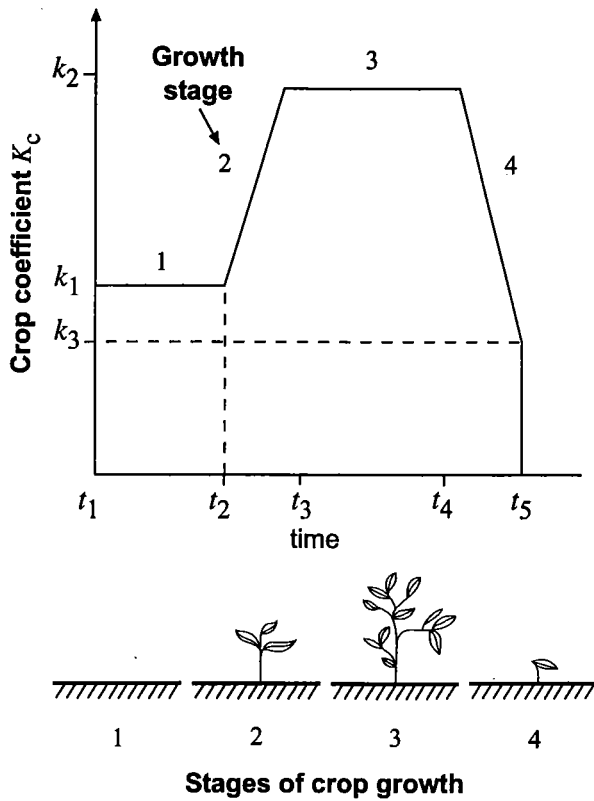
Stage	Crop condition
1	Initial stage - less than 10% ground cover.
2	Development stage - from initial stage to attainment of effective full ground cover (70 - 80%).
3	Mid-season stage - from full ground cover to maturation.
4	Late season stage - full maturity and harvest.

Figure 4.2 The relationship between the crop coefficient and the stage of crop growth (Chow et al., 1988).

(Chow et al., 1988). As the crop matures or ripens, its moisture requirements diminish because LAI decreases and grains and pod form.

4.4.1.2.3 Crop coefficient values for the water balance sub-model

The water balance for different crops may differ each other because the evaporating surface, the total area of stomata of the leaves, can be different from one crop to another. But, in the Dry zone, most of the Maha (major rainy season) or Yala (minor rainy season) upland crops bear approximately similar crop coefficient values, in other words, similar water requirements. For example, maize a commonly grown cereal crop in the Maha season bears an average crop coefficient value of 0.75 to 0.9 for the entire growing period while an average value of 0.75 to 0.8 is reported for the groundnut which is a common legume crop during the Yala season. Thus, selection of a modal crop which represents the entire cropping pattern in the Dry zone may be easier in this exercise rather than considering the whole set of crops that are being grown in the region. The general trend of cropping pattern of rainfed farming in the region is to sow for cereals with high water consumption during the Maha season and low water demanding legumes during the Yala season. But considering the fact that wide popularity of cowpea (*Vigna unguiculata*)[1], a legume crop, among the rainfed farmers in both cropping seasons, it was selected as the modal crop. According to several authors (Nieuwolt, 1975; Pruitt et al., 1972 and Denmead and Shaw, 1959), the crop factor (K_c) depends on the stage of development of the crop, development of the leaves and density of the crop cover. Therefore, K_c values for different growth phases of the cowpea crop were determined using values given by Smith (1991) and it is presented in the Table 4.2. The period in between two rainy seasons during which land becomes fallow was considered as covered with natural grasses. Water balance during this period was calculated assuming an average value of crop coefficient for dry season grasses owing to the lack of better information on K_c values (Nieuwolt, 1975).

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[1] An important characteristics of cowpea over other grain legumes under drought environment is its ability to delay the crop development so that flowering and reproductive growth can resume when the soil moisture is replenished (Sinclair et al., 1987).

Table 4.2 **Crop coefficient (K_c) values for Cowpea (*Vigna unguiculata*) (Smith, 1991).**

Growth stage	Age of the crop	Crop coefficient (K_c)
Initial development	4 weeks	0.567
Vegetative phase	4 weeks	1.103
Reproductive phase	4 weeks	0.967
Maturity	4 weeks or more	0.740

4.4.1.2.4 Actual evapotranspiration

Actual evapotranspiration (AET) is usually considered to be occurring at a potential (maximum) rate (PET) when all the water needs of crops are being met. As the soil dries, it becomes more difficult for plants to extract the water from the soil. Hence, actual evapotranspiration will, at some stage, fall below the potential rate. Considerable controversy exists as to the effect of the soil moisture tension on the depletion rate (Chang, 1968). It has shown that the actual evapotranspiration can typically be considered to occur at the potential rate until some critical soil moisture deficit has been reached. This often occurs when about 50-80% of the available soil moisture has been used up (Porteous et al., 1994). The method of determining actual evapotranspiration in this study is a single-layer two-phase model which is already been discussed in the section 4.3.1. Based on the assumption listed below and the previous attempts made by Porteous et al. (1994), Rao (1987), Doorenbos and Kassam (1979), and Denmead and Shaw (1962), the expression for actual evapotranspiration (AET) in this study was considered as follows:

$$AET = PET \qquad , \qquad ASM \geq CP \qquad [4.5]$$

$$AET = PET\left[\frac{ASM - PWP}{CP - PWP}\right] \quad , \qquad PWP \leq ASM \leq CP \qquad [4.6]$$

where,

AET = Actual Evapotranspiration, mm

PET = Potential Evapotranspiration, mm

ASM = Available soil moisture over the rooting depth (mm/root depth) at time t

CP = Available soil moisture over the rooting depth (mm/root depth) at the critical point

PWP = Available soil moisture over the rooting depth (mm/root depth) at the PWP

The graphical representation and proof of equation [4.6] is given in Appendix 3.

The following assumptions were made during the development of the model (equation [4.6]):

1. the rainfall is absorbed to the soil through the surface and leaf interception of rainfall is negligible;

2. the total depth of effective rainfall from discrete storm events occurring in the week was assumed as input to the root zone of 60 cm at the beginning of the week;

3. the infiltrated water is redistributed uniformly over the root zone, and the water remaining in excess of the corresponding soil storage capacity is negligible;

4. roots distribution within the depth is uniform and roots take water preferentially from the whole depth considered; and,

5. the contribution to soil moisture storage from capillary rise is negligible.

Experiments conducted on RBE soils with many crops under different soil moisture regimes have shown that soil moisture depletion upto 75% of total available soil moisture do not cause any depression in the yield due to the moisture stress (Joshua, 1985). Thus, readily available soil moisture is more likely to be 75% of total available soil moisture and it was considered as the critical point (CP) at which evapotranspiration begins to drop from its potential rate. Evidence in support of such a conclusion can also be found from moisture retention curves of RBE soils where more than 75% of total available soil moisture is released below 1 bar tension (Joshua, 1985).

4.4.1.3 Effective rainfall

The use of direct rainfall values in water balance studies is often misleading because when it exceeds the maximum infiltration rates of the top soil, a proportion of the rainfall is lost by surface runoff and is not available to replenish the soil moisture reservoir. For RBE soils, the proportion of rain that will be lost as surface runoff is considerable when the rain is in excess of 25 mm/hr particularly if the profile is moist (Panabokke and Walgama, 1974). Thus, there could be an appreciable amount of

surface run off when very high rainfall intensities are experienced especially during the convectional rainy months.

The term effective rainfall is defined by different workers to overcome the runoff problem in relation to the anticipated role of rain water in their field of interest. Any factor which affects infiltration, runoff or through-drainage affects the portion of total rainfall that is effective. Higher intensities of rainfall normally increase runoff and drainage thus reduce the fraction of rainfall that is effective. In water budget models, effective rainfall is the amount of rain infiltrated into the soil since these models either estimate deep percolation based on soil properties or assume negligible. In this case effective rainfall equals rainfall minus runoff; runoff water could be used at another location as an input into the soil water balance. Most of the rainfall is effective during periods when rainfall intensity, frequency and amounts are low (Dastane, 1974). Flat and level land retains water on the soil surface and increases rainfall effectiveness relative to sloping land where rapid runoff occurs. In tropics, 100% acceptance of the rainfall is possible when land is terraced and bunded (Rao, 1987).

Percentage acceptance of total fortnightly rainfall for the RBE soils in the Dry zone of Sri Lanka is presented Figure 4.3. These estimates have been obtained by matching infiltration rates at the prevailing soil moisture with the rainfall intensities, using data from five-year period for the RBE soils in the Dry zone of Sri Lanka (Joshua, 1985). The percentage acceptance of rainfall is low for the period from October to late January (major rainy season) and is 100% for the dry period (May to September) because the rainfall is low.

4.5 Meteorological inputs of the water balance sub-model

4.5.1 Rainfall

Rainfall data for the soil water balance model are supplied by the first-order discrete time Markov model discussed in the Chapter 2. This model was found to be the
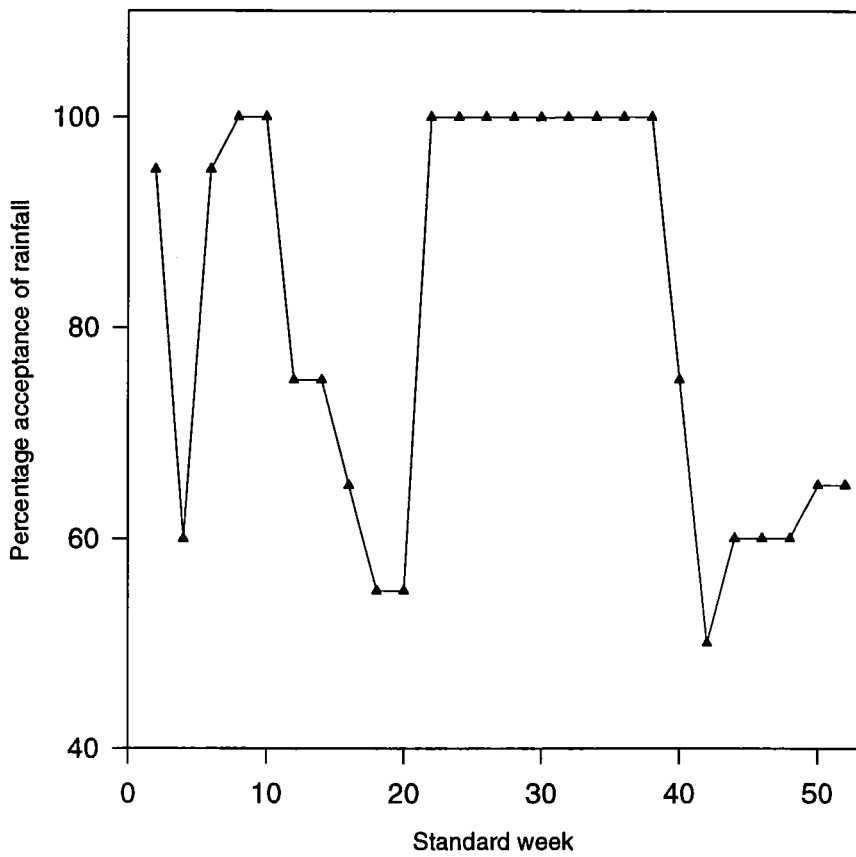
Figure 4.3   The percentage acceptance of total fortnightly rainfall for the Dry zone of Sri Lanka (Joshua, 1985).

most practical one in modelling the Dry zone's weekly rainfall climatology among the three models considered in this study. Rainfall data coming from the rainfall sub-model was converted to an effective rainfall value to account the runoff loss using weekly percentage acceptances given by Joshua (1985) before being used in the soil water model. The model has been designed in such a way that user can decide the number of years of rainfall data to be used as the input for the soil water balance model.

4.5.2 Pan evaporation

The drying power of the atmosphere or the evaporation component of the water balance sub-model was accounted using another model. For this purpose, a stochastic evaporation sub-model was developed using historical weekly pan evaporation data from 1976 to 1995 recorded at the same location where the other meteorological data of the study were obtained. Generally, meteorological parameters tend to be correlated. For example evaporation in an area is determined to a larger extent by energy available from the sun for latent heat used in the process and it is a function of cloudiness (Nieuwolt, 1975). As the cloudiness is related to the rainfall process (Brauhn et al., 1980), it was hypothesised that weekly evaporation from open water pan is correlated with amount of rainfall (Jones et al., 1972). Table 4.3 shows the coefficient of determination (r^2) values for the standard weeks of the second intermonsoon season (convectional) and northeast monsoon season. No significant correlation was evident between amount of rainfall and the open pan evaporation during those two seasons except standard weeks 37, 40 and 46. Even with these three weeks, r^2 value was less than 50% exhibiting the weakness of the relationship. A similar trend was found for the rest of the year and therefore these two variables were considered as independent in this study.

Historical weekly pan evaporation values were evaluated for their best fitted probability distribution out of gamma, Weibull, log-normal and normal distributions using the same methodology adapted in section 2.5.2.5. The use of normal

Table 4.3 Coefficient of determination (r^2) between weekly amount of rainfall and pan evaporation, Maha-Illuppallama, Sri Lanka (1976-1995).

Standard week	Coefficient of determination (r^2)	P - value[2]
Intermonsoon season		
36	0.02	0.55
37	0.44	0.01
38	0.23	0.05
39	0.00	0.97
40	0.32	0.01
41	0.09	0.20
42	0.09	0.21
43	0.12	0.16
44	0.00	0.79
Monsoon season		
45	0.23	0.05
46	0.29	0.04
47	0.02	0.56
48	0.14	0.13
49	0.12	0.15
50	0.17	0.08
51	0.19	0.06
52	0.09	0.21

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[2] P- value provides a measure of the extent to which data support or do not support the Null hypothesis. More specifically, if the P-value is *large,* we should not reject the Null hypothesis. If the P-value is *small*, we should reject the Null hypothesis.

distribution for simulation of pan evaporation introduces the possibility of generating negative values. An additional restriction to the model was introduced by setting the pan evaporation (E) equal to zero if a negative value is generated (Jones et al., 1972); therefore, E is equal or greater than zero for all weeks.

With each run of the model, a random variate will be produced from the best fitted probability distribution for the pan evaporation. This value then will be converted to reference evapotranspiration value using equation [4.4] and then to potential evapotranspiration using equation [4.3]. This sub-model has been embedded in the soil water balance model in such a way that it produces a weekly potential evapotranspiration value for each generated effective rainfall value from the rainfall model.

4.6 Field data collection and the validation of the soil water balance sub-model

Validation of the soil water balance sub-model was performed using the volumetric soil moisture content measurements (v/v%) made during the period of 1992/1993. These volumetric soil moisture content measurements were obtained from a Troxler model Neutron probe in a well drained RBE soils grown for cowpea (variety MI-35) under rainfed conditions. The experimental site (Maradankadawala) was located at 17 km areal distant from Maha-Illuppallama where the other meteorological data of this study were obtained. Four plots of 10 × 8 m were established in the uppermost portion of the catena of a micro catchment. The slope of the area was around 3 to 4 percent. The first crop was planted on November 5, 1992 (standard week No. 45) with the arrival of northeast monsoon rains. Five measurements of soil water content were made at fortnightly during the life cycle of the crop before the crop was being damaged completely by the wild elephants. The second crop was planted on March 25, 1993 (standard week No. 13) with the arrival of first convectional rains. Fifteen measurements were made starting from March 4, 1993 (standard week No. 9), upto September 9, 1993 (standard week No. 37) fortnightly though crop was harvested on August 7, 1993 (standard week No. 32).

Neutron probe readings were taken at 15 cm intervals from 15 cm to the maximum depth of 60 cm of three aluminium access tubes installed in each plot about 2 m apart. Moisture content of the surface horizon (0-15 cm) was measured gravimetrically as the use of Neutron probe near the surface soil is limited by the functional requirements of the instrument. Soil water content in millimetres was determined from summation of the volumetric measurements.

4.6.1 Comparison of simulated and observed soil moisture contents

Soil moisture regimes of the first 60 cm horizon of Reddish Brown Earths soils, cropped with cowpea, in the Dry zone of Sri Lanka were compared with the simulated values of soil moisture. Comparison was made possible only with five measurements during the Maha season while there were continuous measurements for the following Yala season. These measurements were available fortnightly through the long dry spell of the Dry zone (mid may to mid September) until the onset of next convectional rains in mid September.

Figure 4.4 shows the 95% confidence interval band width of the simulated soil moisture contents along with the observed data. The band width is wider in the rainy seasons than the dry period attributed to the high variability of rainfall during rainy seasons. Thus, for agriculturists, this might well be thought of as a perversity of the nature, in that the critical decisions such as sowing, fertilising and harvesting have to be taken when the variability is highest. However, the confidence interval band width is less than 18 mm for any week of the year; therefore, the maximum difference between any simulated value and the mean of the simulated value is less than 9 mm with a 95% probability. In general, observed values are always higher than that of the simulated values. This trend was more prominent during the major rainy periods. Nevertheless, difference between the simulated and the observed values does not exceed 15 mm for any week of the year. During the dry period where the effect of canopy cover is minimum, the simulated values are very closer to the observed values. In rainfed conditions, crops seldom attain full canopy conditions (leaf area index > 3). But the crop coefficients used in the model to estimate the crop water usage assume
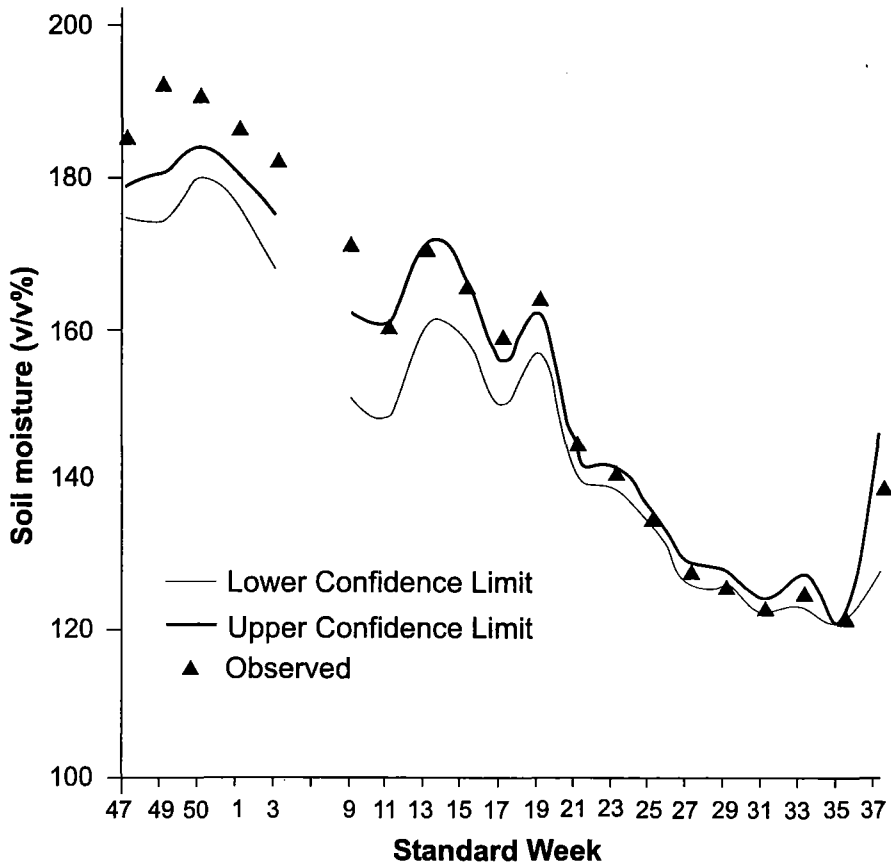
Figure 4.4 Field validation of soil moisture contents results of simulation.

full canopy conditions. Thus, if adjustments are not made accordingly, the estimated crop water consumption is higher than that of the actual values because reduced leaf cover reduces the water requirement of the crops (Stewart, 1988). This in turn increases the discrepancy between the simulated and the observed values of soil water. The poor crop establishments under rainfed conditions is inevitable because of some factors that adversely affect the germination and seedling emergence (Unger et al., 1988).

RBE soils are strange in water balance modelling mainly due to the presence of a gravel layer. Gravel retains a thin film of clay that absorb moisture and retain dampness which will give a higher estimate of Neutron probe readings (Lal, 1979). As the single layer water balance models are not meant to account for such complicated aspects, the predicted values may always differ from the observed values. Although the Neutron probes are the one of the best way to measure the volumetric soil water content in-situ, it should be cautioned that Neutron probe meter readings from moderately wet to wet status of the soil can be very confusing (Stewart, 1988). Thus, noted deviation of the observed values from the simulated values especially during the major rainy season could be attributed to the insensitivity of the instruments. The discrepancy between the simulated and observed values also could be due to the question of validity of assumptions made on development of the single layer water balance model. The most concern would be on the contribution of soil water from the capillary rise when the root zone moisture is diminishing. Although the model assumes that there is no capillary rise from the lower layers of the soil profile, due to the presence of large number of micro pores[3] in RBE soils, there would be a substantial amount of capillary rise especially during the rainy period when the soil water table is comparatively high.

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[3] Clay content is nearly 25-30% in both surface and sub-surface horizons and increases to about 40% in the gravel layer (Joshua, 1985).

4.7 Summary

The main objective of this Chapter was to test the validity of a single-layer water balance model for weekly time scale in the Dry zone of Sri Lanka. This study confirms that the model can provide estimates of soil moisture and crop water requirement or the consumptive use in the 60 cm profile that agree reasonably with field measurements with exception of a few instances. The disagreement of soil water contents appears basically only when the soil moisture approaches its potential storage as a result heavy of downpours during the Maha season. Thus, it may not hamper the use of the model in future efforts as the maximum storage phase of soil water is not so crucial to the crop growth compared to the soil moisture deficit.

The model has successfully differentiated fallow and cropped periods of the year by accounting the differences in evaporative demand during two periods. Provided that the available water capacities and crop factors such as crop coefficients and rooting depth are known, calculation of temporal variation of soil moisture in a 60 cm horizon of RBE soils from this model can be used with confidence for various agricultural applications such as irrigation planning, growing season characterisation, as well as for demarcating homogeneous zones of available soil water for crop production. However, the major limitation of the model for specific applications is, it has been developed with one crop, so that a thorough validation with other crops is required.

Chapter 5

Point estimation of rainfall in the Dry zone

5.1 Introduction

The complex, interacting atmospheric processes which give rise to rainfall make it a variable phenomenon across the landscape. Hence, recorded rainfall from a rain gauge usually represents only an extremely small area of the catchment. This necessitates of having a highly dense network of gauges to record the real spatial variability in a region. In the Dry zone, one of the problems which often arises is missing or ungauged rainfall data. But, a proper understanding of the spatial variability of rainfall in the Dry zone is a must to apprehend the agricultural potential of the region. However, the current network of gauges in the Dry zone is not adequate enough to account the real spatial variability of the region. Thus, there is a need for a methodology to interpolate the data with minimum number of neighbouring locations having reliable data.

Spatial interpolations of data available at other sites are being used in the field of hydrology and climatology to generate the data for ungauged locations. In most cases, simple methods of point estimation are applied (Abtew et al., 1993). The availability of high powered computing facilities has encouraged the development of advanced methods of interpolation. As a result, a number of spatial interpolation techniques are available today with varying degree of complexity such as local mean, Thiesen polygon, inverse distance, inverse square distance, isohytal and krigging

(Abtew et al., 1993 and, Singh and Chowdhury, 1986). Some of them are very simple with limited applicability while others involve complex mathematical frameworks and needs large number of data points to obtain a reasonable level of accuracy. This chapter is intended to examine the validity and applicability of a spatial correlation model in estimating weekly rainfall in the Dry zone of Sri Lanka.

5.2 Modelling the spatial correlation structure

Spatial continuity exists in the most earth science data sets and two data sets close to each other are expected to have closer values than those that are far apart (Isaaks and Srivastava, 1989). A function can be developed to describe the continuity of the relationship between the value of one variable at a point and the value of the same variable at another point, a given distance away (Abtew et al., 1993). Correlation, covariance and variogram functions have been used to express the spatial continuity of a random variable. Similar assumptions have been made about rainfall phenomena over an area, and estimation methods used in earth science have been applied to rainfall data to estimate the values of ungauged sites.

The spatial correlation models for rainfall have been presented in inverse power and exponential forms (Yevjevich and Karplus, 1973):

$$\gamma_{ab} = (1+\alpha d)^{-c} \qquad\qquad [5.1]$$

$$\gamma_{ab} = e^{-\alpha d} \qquad\qquad [5.2]$$

where,

γ_{ab} = spatial correlation coefficient between two stations (A and B)

α = a coefficient

c = a power coefficient

d = distance between the pair of stations

The spatial correlation coefficient γ_{ab} between two locations can be determined using contemporaneous observation pairs from the two locations. Using the calculated γ_{ab}

and the distance between the two locations, the coefficient (α) of equation [5.2] can be found.

$$\gamma_{ab} = e^{-\alpha d}$$

$$\ln \gamma_{ab} = -\alpha d$$

$$\alpha = -\frac{\ln \gamma_{ab}}{d} \qquad [5.3]$$

The spatial correlation coefficient values between the two sample stations and the third station (γ_{ac} and γ_{bc}) where the point estimation is to be done can be calculated from equation [5.2]. Let the unbiased[1] linear estimator for the normalised rainfall at the third station (C) be:

$$R_c^* = w_a R_a^* + w_b R_b^* \qquad [5.4]$$

where

R_c^* = estimated normalised rainfall at station C

R_a^* = observed normalised rainfall at station A

R_b^* = observed normalised rainfall at station B

w_a = weight assigned to the station A

w_b = weight assigned to the station B

The least squares regression for equation [5.4] can be written in matrix notation:

$$
\begin{array}{ccc}
\tilde{C} & w & = \quad \gamma
\end{array}
$$

$$
\begin{bmatrix} 1 & \gamma_{ab} & 1 \\ \gamma_{ab} & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix}
\begin{bmatrix} w_a \\ w_b \\ \mu \end{bmatrix}
=
\begin{bmatrix} \gamma_{ac} \\ \gamma_{bc} \\ 1 \end{bmatrix} \qquad [5.5]
$$

The matrix $\tilde{C}$ consists of the covariance value of rainfall between the two sample locations. The vector γ consists of the covariance values of rainfall between two sample locations and the location where we need the estimation. The vector w consists of the weight given to the each location and the Lagrange parameter μ (Isaaks and Srivastava, 1989). To solve for the weights, multiply equation [5.5] on both sides by $\tilde{C}^{-1}$.

---

[1] weights add upto one

$$\tilde{C} \ w \quad = \gamma$$

$$\tilde{C}^{-1} \ \tilde{C} \ w \quad = \tilde{C}^{-1} \ \gamma$$

$$I \ w \quad = \tilde{C}^{-1} \ \gamma$$

$$w \quad = \tilde{C}^{-1} \ \gamma \qquad\qquad [5.6]$$

The estimated mean and the standard deviation of the station C can be calculated using following linear estimation:

$$\hat{R}_c = AC \left[\frac{\overline{R}_a - \overline{R}_b}{AB} \right] \qquad\qquad [5.7]$$

$$\hat{\sigma}_c = AC \left[\frac{\sigma_a - \sigma_b}{AB} \right] \qquad\qquad [5.8]$$

where

$\hat{R}_c$ = estimated mean rainfall at station C

$\overline{R}_a$ = observed mean rainfall at station A

$\overline{R}_b$ = observed mean rainfall at station B

$\hat{\sigma}_c$ = estimated standard deviation of rainfall at station C

σ_a = observed standard deviation of rainfall at station A

σ_b = observed standard deviation of rainfall at station B

AB = distance between stations A and B, km

AC = distance between stations A and C, km

Having determined all those parameters, equation [5.4] can be used to estimate the rainfall in an ungauged location given the corresponding rainfall data from two neighbouring stations.

5.3 Prerequisites of spatial interpolation models

Rain storms vary greatly in space and time. The annual amount of rainfall that a particular location may receive depend mainly on controlling factors of geography such as latitude, distance from the coast, elevation, slope, shape of the terrain, orientation of the ground and exposure (Linacre, 1992). Thus, it is obvious that rainfall in a large area could be different from one location to another, with no

correlation among them, owing to the complexity of the geographical features of the area. This requires spatial interpolation of rainfall to be applied only when the geography of the area under consideration is homogeneous. That is, the area has no marked diversity in topography, so that range in altitude is small and hence variation in rainfall amounts is minimal. A further important prerequisite of spatial correlation models of rainfall is isotropy. This implies that there should be no directional influence for the covariance of rainfall between the two stations. There are some instances where anisotropy could be present. For example, when either of the two stations is more closer to the sea while the other is more towards the interior of the region, the rainfall at the coastal location tends be higher than that of the interior location due to the effect of the sea causing specific increased or decreased rainfall in one direction.

5.4 A spatial correlation model for the Dry zone of Sri Lanka

In this study, two distinctive regions of the Dry zone were considered, the north-central part and the southern part of the Dry zone (Figure 5.1). Both regions exhibit fairly similar physiography of gently-undulating to rolling, with 3 to 4 per cent slopes. However, some geographical features are not alike. The north-central part of the Dry zone, abbreviated NCDZ, where the other stochastic models of this study were focussed is a inland region. The southern part of the Dry zone, abbreviated SDZ, resembles an area that is more closer to the ocean. Therefore, the amount of water vapour in the atmosphere, what is available to become cloud with the chance of subsequently becoming rain, may not be comparable in the two regions. Thus, correlation structure of the rainfall process may be different at the two regions. This necessitates the evaluation of the spatial correlation model for the two regions separately to meet the assumptions made on the isotropicity and homogeneity. The selected rainfall recording stations from the NCDZ region are located at Maha-Illuppallama (MI), Pelwehera (PWR) and Maradankadawala (MDK). Out of these three stations MDK which lies in between other two stations was considered as the location where rainfall values to be estimated. The areal distance from MDK to MI and MDK to PWR is 17 km and 25 km respectively while areal distance between MI

SCALE

km 20 10 0   20   40   50   80 100km

-N-

DRY
ZONE

MI   -   Maha-Illuppallama
MDK -   Maradankadawala
PWR -   Pelwehera
ANK -   Angunakolapellessa
AMB -   Ambalantota
WWL -   Weerawila
COL -   Colombo

MI   MDK

• PWR

INTERMEDIATE ZONE

COL

WET
ZONE

WWL

ANK

AMB
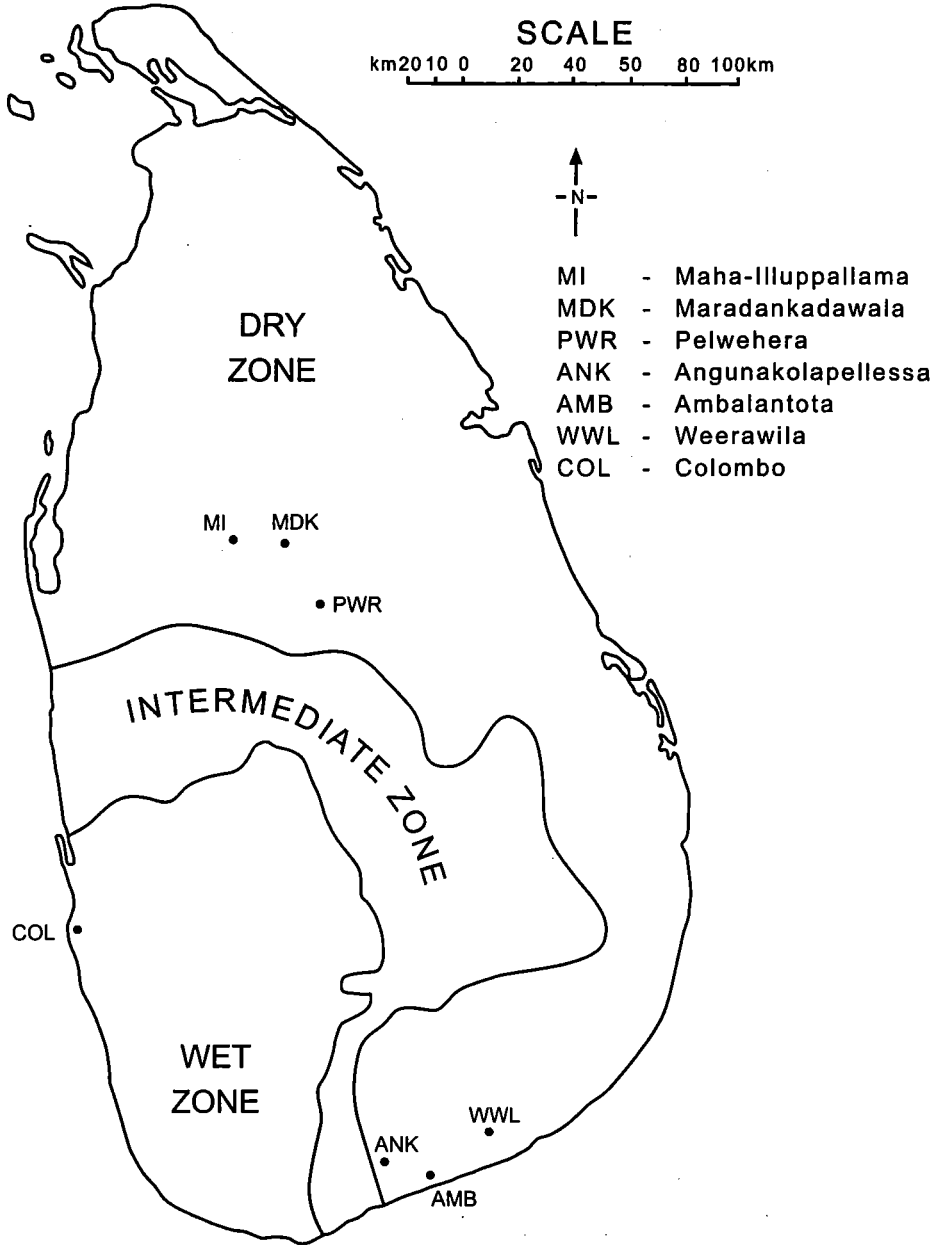
**Figure 5.1   Location of the reference rainfall stations in the Dry
zone of Sri Lanka.**

and PWR is 38 km. From the SDZ region which represents a coastal area, Angunakolapellessa (ANK), Ambalantota (AMB) and Wirawila (WWL) locations were selected for the study. In this region, Ambalantota (AMB) which lies in between other two stations was considered as the location where the rainfall values to be estimated. The areal distance from AMB to ANK and AMB to WWL is 15 km and 27 km respectively while the areal distance between ANK and WWL is 38 km. In the selection of the rainfall recording stations, care was given to select the locations with reliable data with maximum number of record lengths to be on par with the guidelines stipulated by the Hydrology and Water Resources Program, Department of Civil Engineering, Colorado State University (Tabios and Salas, 1985). The said guidelines prescribe the data records with more than 30 years to be used. But most of the time, the available length of the records from the selected locations were twenty years. Although there are some other locations in the Dry zone which have minimum of 30 years of records, a large number of missing data and unreliability of the measurements forced not to select them for the study.

5.5 Model validation

The validity and applicability of the foregoing interpolation model was examined by comparing the model output with the observed data from the two locations. In addition, a further comparison of the model output was made with the other two interpolation techniques, local mean and inverse distance method. Use of local mean or the arithmetic mean in spatial interpolation is the most simplistic approach. It assumes that equal weight from all nearby sample locations, using the sample mean as the estimate. Inverse distance method is a technique which gives more weight to the closet samples and less to those that are fathest away instead giving naively equal weight to all samples. Thus, weight for each sample is inversely proportional to its distance from the point being estimated:

$$\hat{R} = \frac{\sum_{i=1}^{n} \frac{1}{d_i} v_i}{\sum_{i=1}^{n} \frac{1}{d_i}} \qquad [5.9]$$

where

$\hat{R}$ = estimate of rainfall for ungauged location

v_i = observed value at the ith location

d = distance from each location to the point being estimated

5.5.1 Comparison of estimated and observed rainfall at the two regions

Figure 5.2 and 5.3 show the mean estimated and observed rainfall in each week for Maradankadawala (MDK) and Ambalantota (AMB) respectively. Typically, we want a set of estimates that comes as close as possible to the true values. Thus, we would prefer the results shown in Figure 5.2 and 5.3. There was no significant difference between the observed values and the estimated values at both locations. The standard deviations of the observed sequences of rainfall were comparable with the estimated sequences of rainfall from the exponential model (Table 5.1 and 5.2). However, the variability of the estimated values from the exponential model was less than that of the observed variability in general. This trend was more apparent at Ambalantota in the SDZ region. Reduced variability of estimated values is often referred to as "smoothing" and is a consequence of combining two or more sample values to form an estimate (Isaaks and Srivastava, 1989). As more sample values are incorporated in a weighted linear combination, the resulting estimates generally become less variable. Overall, the results show that means of the both stations are well preserved. However, the discrepancy between the observed and the estimated values at MDK is less than the same at AMB. The correlation of rainfall between any two locations is highest for places, which are close to each other, in flat country away from the coast (Linacre, 1992). The areal distance between the two sample locations at both regions are almost equal. The topography of the two regions also comparable each other. Thus, closeness to the coast could be the main determining factor for the small discrepancy between observed and estimated values at AMB in the SDZ region.
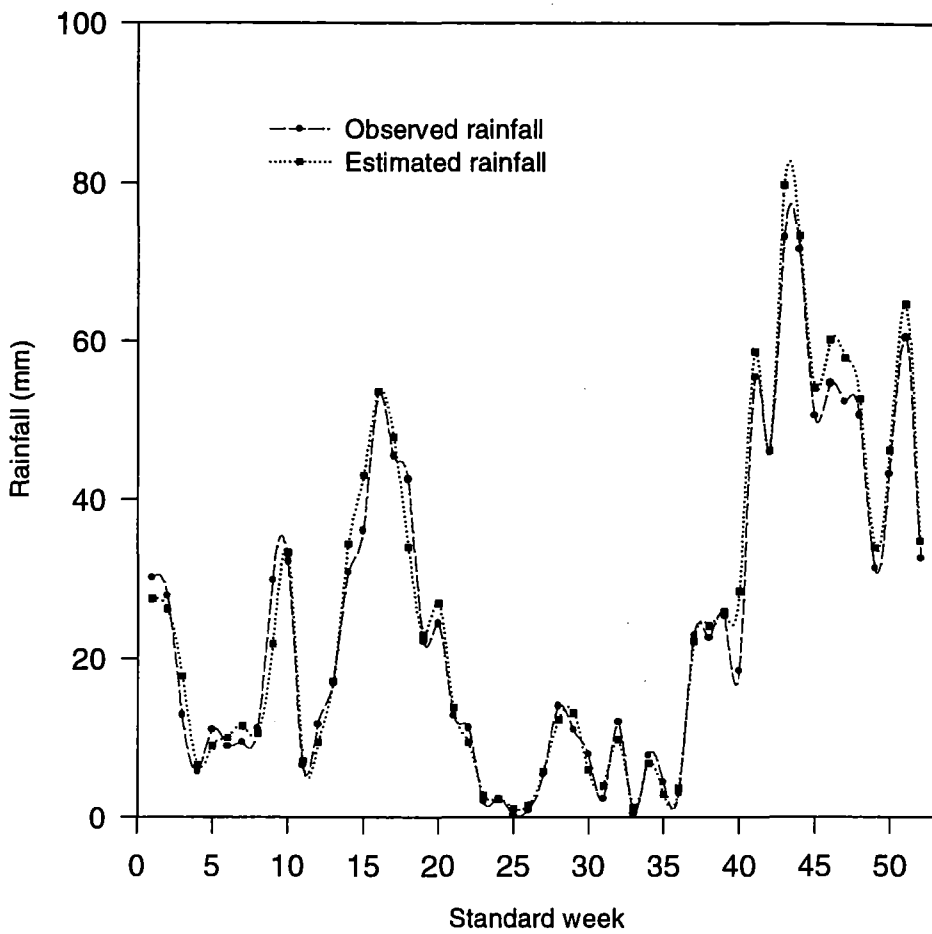
Figure 5.2   Observed and estimated rainfall at Maradankadawala in the Dry zone of Sri Lanka.
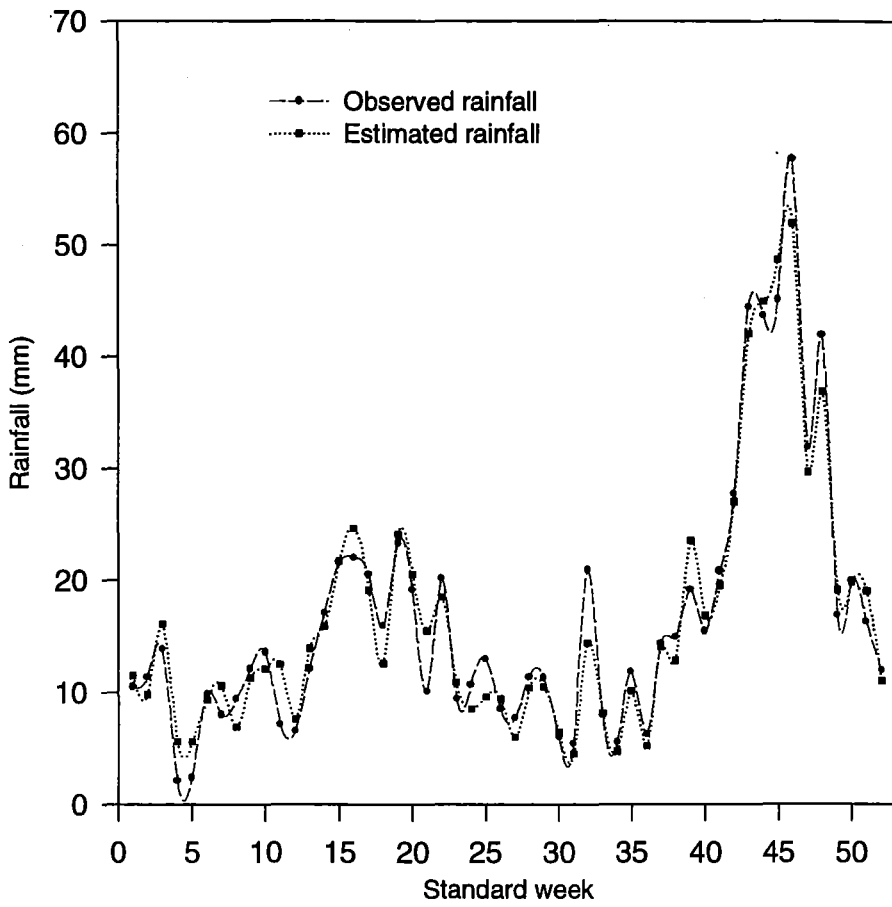
Figure 5.3 Observed and estimated rainfall at Ambalantota in the Dry zone of Sri Lanka.

Table 5.1 **Standard deviations of the observed and the estimated rainfall from the exponential model during major rainy seasons at Maradankadawala (MDK) and Ambalantota (AMB) in the Dry zone of Sri Lanka.**

Standard week No.	Maradankadawala		Ambalantota	
	Observed	Estimated	Observed	Estimated
Yala season				
12	16.0	14.5	14.6	12.6
13	31.6	17.2	19.8	14.9
14	31.3	33.8	14.6	21.0
15	30.8	37.1	26.9	24.7
16	57.8	54.8	22.0	29.5
17	43.8	50.1	14.8	19.9
18	48.4	43.6	18.3	14.7
19	25.7	18.7	23.2	25.8
20	29.7	33.0	27.1	21.0
21	27.0	29.7	20.2	28.7
Maha season				
40	42.8	51.6	17.1	16.2
41	49.6	57.6	18.5	16.3
42	49.4	44.4	26.5	26.2
43	58.7	62.2	50.3	26.2
44	62.8	51.4	39.1	28.9
45	39.9	38.0	40.9	26.0
46	60.8	59.5	62.6	49.0
47	52.2	56.6	29.0	24.4
48	50.9	47.3	37.1	26.0
49	27.0	31.3	18.5	17.6
50	34.0	30.6	30.2	24.6
51	60.5	63.3	14.4	19.6
52	33.4	30.9	16.6	10.9
1	52.3	47.9	26.3	20.1
2	51.6	45.8	19.5	15.1
3	21.3	33.5	30.6	35.2
4	10.5	11.6	4.3	8.1
5	21.6	14.7	4.6	7.4

Table 5.2 Standard deviations of the observed and the estimated rainfall from the exponential model during major dry periods at Maradankadawala (MDK) and Ambalantota (AMB) in the Dry zone of Sri Lanka.

Standard week No.	Maradankadawala		Ambalantota	
	Observed	Estimated	Observed	Estimated
First dry period				
6	21.5	27.0	20.7	19.8
7	27.4	31.5	19.1	33.1
8	15.5	14.3	16.2	13.1
9	41.6	45.0	21.2	14.0
10	40.6	55.3	29.1	19.5
11	13.4	10.1	13.3	17.0
Second dry period				
22	30.9	14.6	26.9	24.6
23	4.2	5.5	12.6	11.1
24	6.4	5.1	16.2	11.6
25	0.9	2.5	27.8	13.7
26	1.8	4.2	10.6	9.0
27	10.9	11.7	12.6	7.1
28	28.6	29.0	15.2	10.0
29	25.5	23.5	18.2	17.0
30	21.6	10.1	10.5	8.1
31	4.6	11.3	11.9	7.8
32	28.2	18.8	26.4	16.2
33	1.4	2.3	16.1	9.5
34	15.4	13.6	11.9	5.4
35	9.5	4.2	26.6	11.1
36	5.7	7.9	8.5	6.3
37	38.2	38.7	19.5	17.9
38	35.3	23.5	21.2	16.0
39	33.7	44.3	22.2	17.5

5.5.2 Comparison between different interpolation methods

The results of the other two interpolation methods described in the Section 5.4 were compared with the outcome of exponential correlation model. As the first criteria for comparing the different methods, the means in each week were computed. Figure 5.4 and 5.5 show the means of weekly interpolated rainfall values from the three methods for MDK and AMB locations respectively. It may be seen that practically all of the interpolation techniques reproduce the means well. None of these means were significantly different from each other and also from the observed mean values. The estimated mean values from all three models at MDK are almost identical (Figure 5.4). At AMB, though it is not significant, a small discrepancy between estimated values from the three models is noticeable during the two dry periods and during the first rainy season, Yala (Figure 5.5).

Another way of checking the appropriateness of the model is to calculate the correlation coefficient between the observed and the estimated values. It is a good index for summarising how close the points on a scatter plot come to falling on a straight line, and therefore can make use to compare different estimation models. A value 0.70 was considered as the threshold level of the correlation coefficient. Chatfield and Collins (1992) suggested the same value of the correlation coefficient to be considered as a reasonably "large" correlation.

During the two rainy seasons, Yala and Maha, all the three models were performed in a similar manner at MDK where the exponential model resulted 10 weeks with a correlation coefficient value less than the threshold value. The inverse distance and local mean models also had 11 and 10 weeks respectively which were poorly correlated with the observed values (Table 5.3). The estimated values at AMB with each model during the rainy seasons were not well correlated with the observed data. There were 19 weeks with low correlations between the simulated and observed values with each model at this location (Table 5.3).
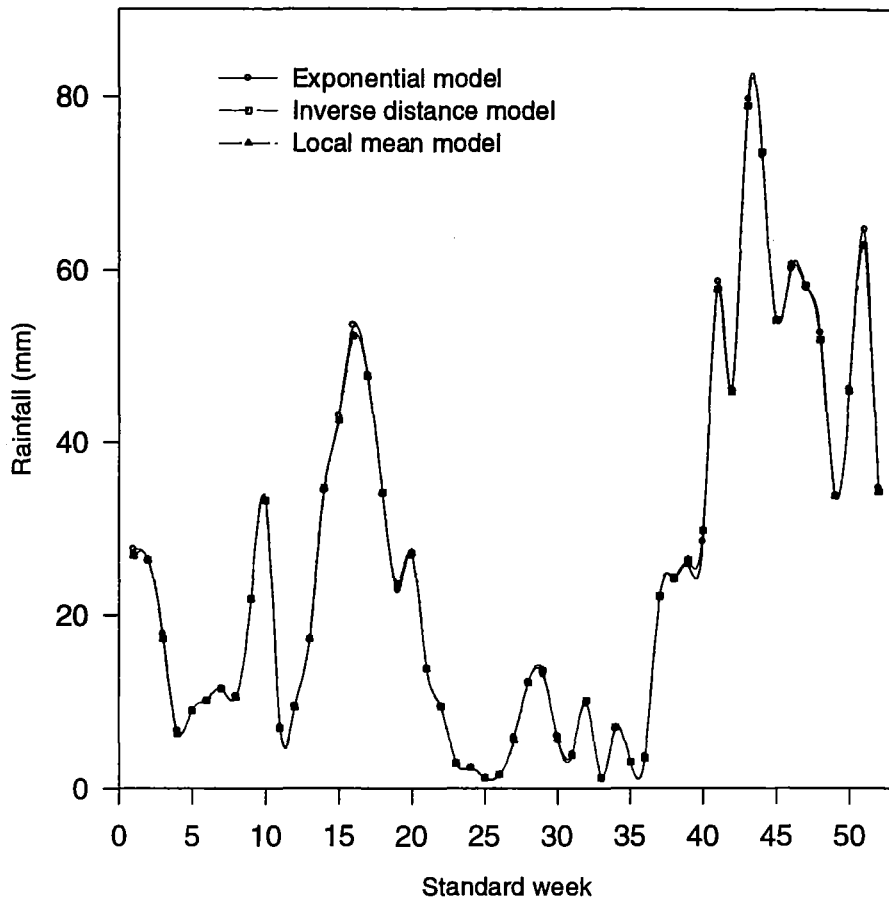
Figure 5.4 **Estimated weekly rainfall from three models at Maradankadawala in the Dry zone of Sri Lanka.**
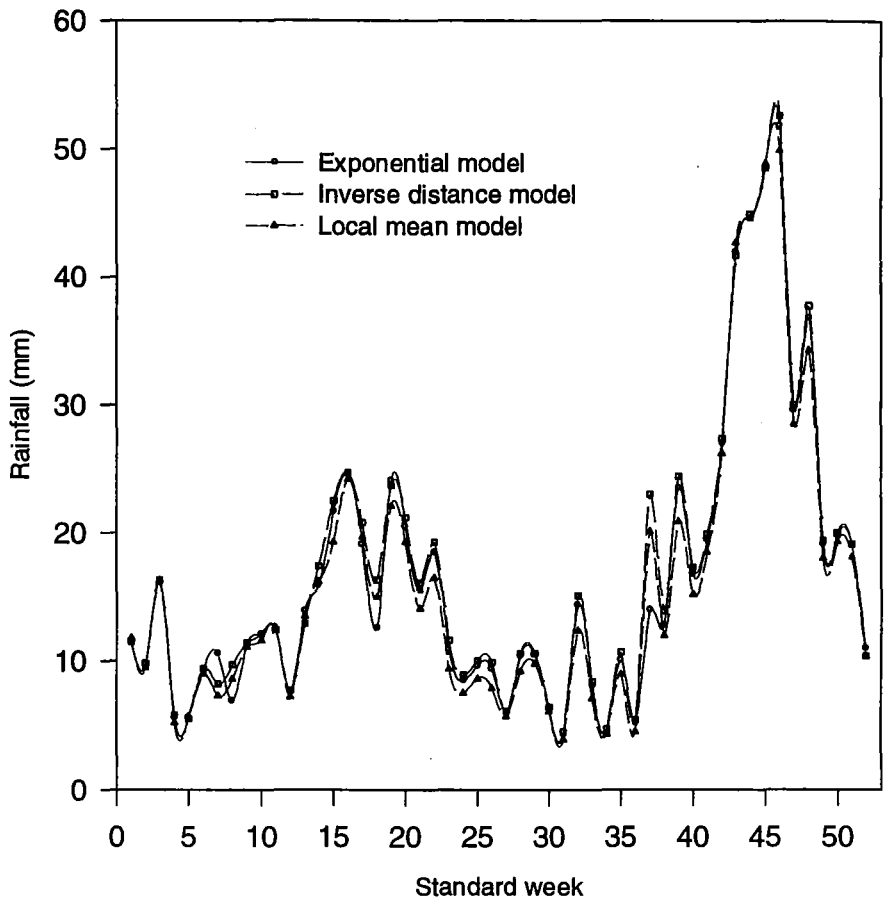
**Figure 5.5 Estimated weekly rainfall from three
models at Ambalantota in the Dry
zone of Sri Lanka.**

Table 5.3 Correlation coefficients between observed and estimated values from the three models during the major rainy seasons at Maradankadawala (MDK) and Ambalantota (AMB) in the Dry zone of Sri Lanka.

Standard Week No.	Exponential model		Inverse distance model		Local mean model	
	MDK	AMB	MDK	AMB	MDK	AMB
Yala season						
12	0.37	0.58	0.36	0.58	0.35	0.58
13	0.74	0.42	0.74	0.21	0.73	0.09
14	0.66	0.55	0.67	0.56	0.70	0.54
15	0.64	0.11	0.65	0.10	0.65	0.12
16	0.60	0.41	0.68	0.41	0.70	0.42
17	0.81	0.31	0.80	0.36	0.77	0.33
18	0.89	0.87	0.89	0.88	0.86	0.86
19	0.63	0.11	0.63	0.12	0.63	0.06
20	0.93	0.17	0.94	0.17	0.94	0.17
21	0.91	0.58	0.91	0.60	0.94	0.58
Maha season						
40	0.96	0.86	0.95	0.86	0.95	0.86
41	0.87	0.64	0.93	0.68	0.93	0.60
42	0.68	0.67	0.66	0.68	0.66	0.66
43	0.70	0.53	0.71	0.56	0.71	0.60
44	0.70	0.68	0.68	0.66	0.68	0.69
45	0.62	0.28	0.59	0.28	0.56	0.27
46	0.83	0.95	0.83	0.95	0.83	0.93
47	0.93	0.66	0.93	0.66	0.95	0.69
48	0.79	0.51	0.76	0.50	0.76	0.51
49	0.68	0.75	0.57	0.74	0.57	0.71
50	0.65	0.88	0.72	0.87	0.72	0.86
51	0.90	0.91	0.89	0.90	0.89	0.92
52	0.28	0.73	0.27	0.74	0.27	0.72
1	0.93	0.81	0.95	0.79	0.95	0.76
2	0.94	0.65	0.94	0.66	0.94	0.65
3	0.94	0.87	0.93	0.87	0.93	0.88
4	0.76	0.56	0.63	0.45	0.63	0.53
5	0.72	0.49	0.84	0.52	0.84	0.39

During the two dry periods, performance all the three models were similar at both locations. At MDK, there were 10 weeks on which correlation coefficient value was less than the threshold level with the exponential model. The inverse distance and local mean models resulted 10 and 8 weeks respectively with low correlations with the observed values. At AMB, a similar pattern was observed where the exponential model resulted eight weeks with the correlation coefficient value less than 0.70. There were six and five weeks with such low correlations with the inverse distance and local mean models respectively (Table 5.4).

In general, individual estimations during the dry periods are reasonably accurate whereas during the rainy seasons their deviations from the observed values are substantial. This trend is common for all the three models tested. This assertion, however, does not undermine the usefulness of the models as they are well capable of estimating the mean rainfall situations in the Dry zone.

The above analyses show that the performance of all the three models are similar at both locations in the Dry zone. Thus, if one is interested only in mean weekly rainfall, as is often the case in climatological applications, then there is no particular advantage in computing complex exponential correlations; rather a simple local mean or inverse distance method will suffice.

5.6 Summary

In this chapter, an exponential spatial correlation model was developed to estimate the weekly rainfall amount in ungauged locations of the Dry zone. Results were validated against the historical observations. The estimated values from the exponential model were compared with the estimated values from other two methods, local mean and inverse distance methods.

The exponential correlation model is a promising candidate for estimating the mean weekly rainfall parameters in the Dry zone. Its performance was equally comparable at both tested geographical regions of the Dry zone with the criteria used herein.

Table 5.4 Correlation coefficients between observed and estimated values from the three models during the major dry periods at Maradankadawala (MDK) and Ambalantota (AMB) in the Dry zone of Sri Lanka.

Standard Week No.	Exponential model		Inverse distance model		Local mean model	
	MDK	AMB	MDK	AMB	MDK	AMB
First dry period						
6	0.92	0.86	0.91	0.84	0.92	0.86
7	0.59	0.96	0.53	0.95	0.60	0.96
8	0.88	0.81	0.88	0.73	0.86	0.80
9	0.82	0.38	0.82	0.38	0.82	0.38
10	0.80	0.77	0.80	0.80	0.80	0.76
11	0.63	0.75	0.67	0.74	0.70	0.71
Second dry period						
22	0.56	0.81	0.66	0.84	0.75	0.84
23	0.93	0.76	0.94	0.79	0.94	0.78
24	0.89	0.84	0.90	0.85	0.86	0.82
25	0.81	0.96	0.81	0.98	0.82	0.97
26	0.58	0.87	0.58	0.81	0.58	0.82
27	0.73	0.10	0.76	0.09	0.74	0.03
28	0.73	0.88	0.74	0.92	0.75	0.91
29	0.80	0.88	0.73	0.88	0.79	0.87
30	0.63	0.63	0.49	0.63	0.44	0.63
31	0.68	0.43	0.42	0.48	0.37	0.47
32	0.84	0.64	0.91	0.75	0.88	0.72
33	0.20	0.70	0.24	0.75	0.19	0.72
34	0.63	0.41	0.64	0.42	0.60	0.29
35	0.14	0.93	0.23	0.93	0.21	0.94
36	0.75	0.79	0.79	0.75	0.79	0.77
37	0.71	0.55	0.72	0.56	0.67	0.55
38	0.38	0.88	0.41	0.88	0.45	0.88
39	0.85	0.68	0.85	0.78	0.85	0.74

The less sophisticated local mean and inverse distance methods rate quite well along with the exponential model. Thus, there is no particular basis to claim that the exponential model is significantly better than the other two methods tested, although in a given situation it might be preferable to other methods.

Chapter 6

Potential of the rainy seasons

6.1 Introduction

Many agronomic experiments conducted in the Dry zone for decades have taken only a little account of the variation in climatic potential in the region. This has led to a slow progress in exploiting the agricultural potential of the Dry zone. Even under highly erratic rainfall regimes, years with more favourable rainfall distribution could occur and it is necessary to strive for product-maximising strategies in such years. Hence, early identification of the "potential" of a season is very important in designing appropriate strategies for increased food production in the Dry zone. Recent studies of rainfall from 18 countries in Asia, Africa and North America suggest that prediction of the rainy season potential could be possible using correlation between onset and seasonal characteristics such as total seasonal rainfall and the time of the withdrawal of rains (Stewart, 1988). Nevertheless, the association between start of the rains and seasonal characteristics has not been specifically studied for the Dry zone's environment mainly because of the restricted availability of long series of historical data and high computational requirements of this type of studies. Both these problems may no longer exist with the availability of the stochastic rainfall model developed in this study. If any association between start of the season and seasonal characteristics is to be found, it could be used to predict the behaviour of upcoming seasons in advance. Such information has profound practical implications. For example, it enables to minimise the effects of drought by making the most efficient use of the scarce

rainfall in a poor (dry) season, but maximise the production in good seasons by exploiting the rainfall.

6.2 Time of onset, ending of rains and length of the rainy season

The three key parameters which characterise the rainfall season for crop production have been identified as time of the onset and the ending of rains, and the length of the rainy season for each year (Sivakumar, 1990). Various definitions of the onset of the rains exist in the literature depending upon the time scale of the data used and the geographical location of the study (Sivakumar, 1988; Stern et al., 1982; Benoit, 1977; Virmani, 1975 and Raman, 1974). To decide a criterion for the onset of the season which is favourable for commencement of cultivation operations, two basic requirements have to be satisfied (Mavi, 1986). First, that a sustained rain spell, which more or less represents the transition from dry season to wet season should be identified. Secondly, in the spell so chosen, the rain that falls should percolate into the soil upto a reasonable depth and also build a moisture profile therein after loss through evaporation. Keeping in view of the above requirements in association with the physical properties such as water holding capacity, expected evaporative conditions in the atmosphere and normal depth of seed placement of the major soil group of the Dry zone, RBE soils, the following criterion was chosen to define the onset of the seasons in terms of rainfall; a spell of at least 20 mm of rain per week in three consecutive weeks after pre-specified weeks for the minor rainy season (Yala) and the major rainy season (Maha). If three weeks criteria was not satisfied the condition was relaxed upto two consecutive weeks with rainfall equal or greater than 20 mm. This relaxation was particularly important for the Yala season where the continuity of the rains is always uncertain. In the literature, criterion for the onset does not consider continuity upto two or three weeks. For example Raman (1974) defined the growing season in Maharasta, India as the first appearance of a week with cumulative rainfall of 25 mm without considering the post-conditions. But under Dry zone's conditions where the rainfall is patchy and

intermittent in nature, an evaluation of the continuity upto two to three weeks is necessary to avoid false start of the seasons. Similarly, the first occurrence of long dry spell, three consecutive weeks after a pre-specified week with less than 20 mm of rainfall, was used as the criterion for the end of a season. Length of the season was taken as the number of weeks between the end of the season and the onset of the season. Using these criteria, onset and withdrawal of the rainy season and the amount of the rainfall within each season were determined from the model with 1000 simulation runs. Such a large number of simulation runs were made to ensure the inclusion of all possible extreme values of the rainfall process.

6.3 Relationship between the onset of rains and the length of the seasons

6.3.1 Yala season

The average time of onset of rains for the minor rainy season (Yala) with 1000 simulation runs was in late March, standard week 13, while end of the season was in late April (between standard weeks 18 and 19). The average length of the season was around 5 weeks. (Table 6.1). The coefficient of variation of the start and end of the seasons are 0.30 and 0.27 respectively. Thus, the variability of the start and end of the Yala season are almost similar. With the data of 1000 simulation runs, a significant positive correlation was evident (equation [6.1]) between the onset and the withdrawal of the Yala season rains ($r^2 = 0.64$).

$$E = 4.70 + 1.05 \ S \hspace{3cm} [6.1]$$

where,

E = standard week number of the end of the season

S = standard week number of the start of the season

This relationship confirms the underlying trend that would account average of five weeks period for the end of the season from the start of the season. The correlation between the start of the season and the length of the season was very poor ($r^2 = 0.003$; Figure 6.1). This indicates that irrespective of the start of the

Table 6.1 Descriptive statistics of the Yala season rainfall in the Dry zone, Maha-Illuppallama, Sri Lanka after 1000 simulation runs.

	Mean	SD	CV	Minimum	Maximum
Onset (week No.)	13.0	3.8	0.30	0.0	22.0
End (week. No.)	18.2	5.1	0.27	0.0	25.0
Length of the season (weeks)	5.3	3.1	0.58	0.0	19.0
Amount of rainfall (mm)	265.3	165.4	0.62	0.0	1022.9

SD = standard deviation   CV = coefficient of variation
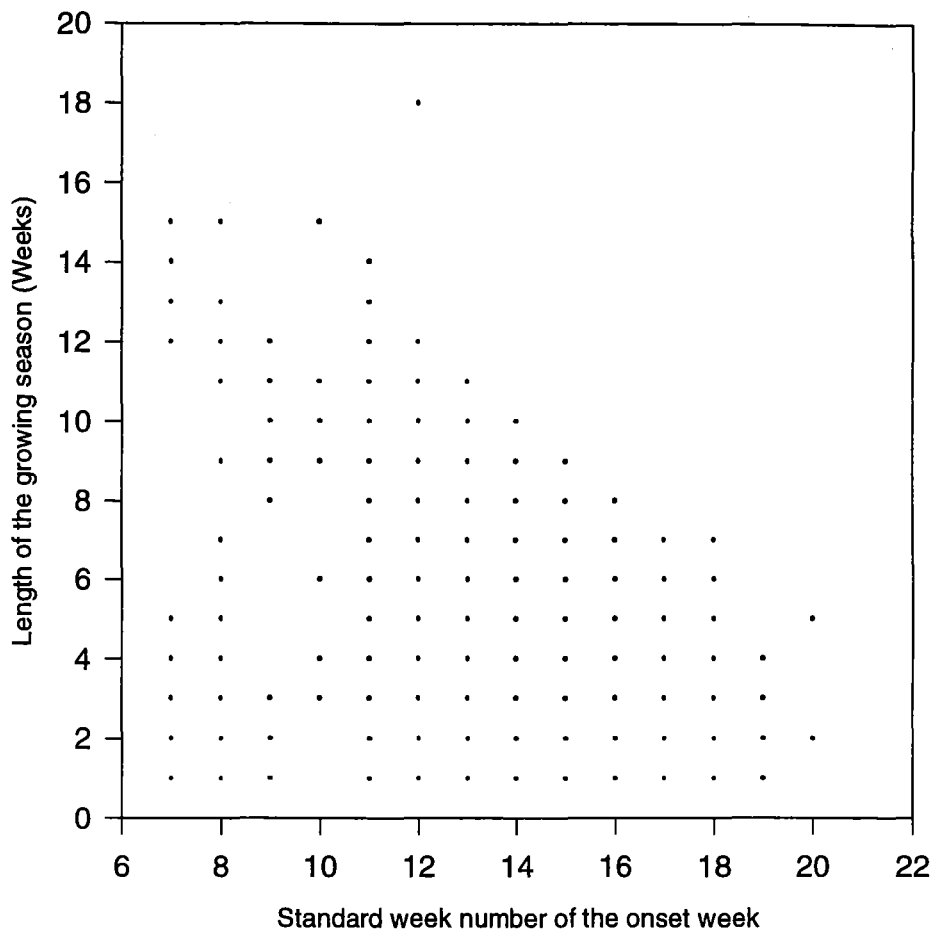
Figure 6.1   Length of the season as related to the onset of rains during the Yala season.

season, the Yala rains pause around five to six weeks from the onset. The relationship between the seasonal rainfall during the Yala season and the onset of the rains was also very weak (r^2 = 0.02; Figure 6.2), implying that the onset time can not be used for predicting the seasonal rainfall. The probabilities of different weeks to be the onset week was calculated using simulated data (Table 6.2). It shows that even the average start of the Yala season, the standard week 13, has only 18% probability to be the onset week. The following week also has a similar chance to be the onset week. There is also 4% probability of not having a Yala season at all and 20% probability to season become extremely late, after the standard week 16 (Table 6.2). There is a cumulative probability of 18% to season become effective as early as in standard weeks 11 and 12. The above analysis suggests that agricultural planning in the Dry zone during the Yala season can not be formulated from the alternatives based on the agro-meteorological relationship between the onset time of the Yala rains and the post-onset seasonal characteristics.

6.3.2 Maha season

The computed average onset of rains in the Maha season was around mid October, the standard week number 42, and these rains remain effective until late January of the following year, the standard weeks 4 and 5 (Table 6.3). The coefficient of variation of the onset of the Maha rains (CV = 0.06) was relatively lower than that of the onset the Yala rains (CV = 0.30). The relationship was opposite for the end of rains where the withdrawal of the Maha rains (CV = 0.53) was more variable than the Yala rains (CV = 0.27). The highest probability of the occurrence of onset was on the standard week 40 while the cumulative probability of the weeks 40 and 41 accounted 44 per cent (Table 6.4). Thus, unlike the Yala season, it is certain that Maha season should start within the first couple of weeks of October. This can be further confirmed by comparing the coefficient of variation values of the onset during two seasons. The coefficient of variation of the Yala onset is 0.30 whereas the corresponding figure for the Maha season is only 0.06 (Tables 6.1 and 6.3). Average length of the season was around 14 weeks exhibiting a fairly longer
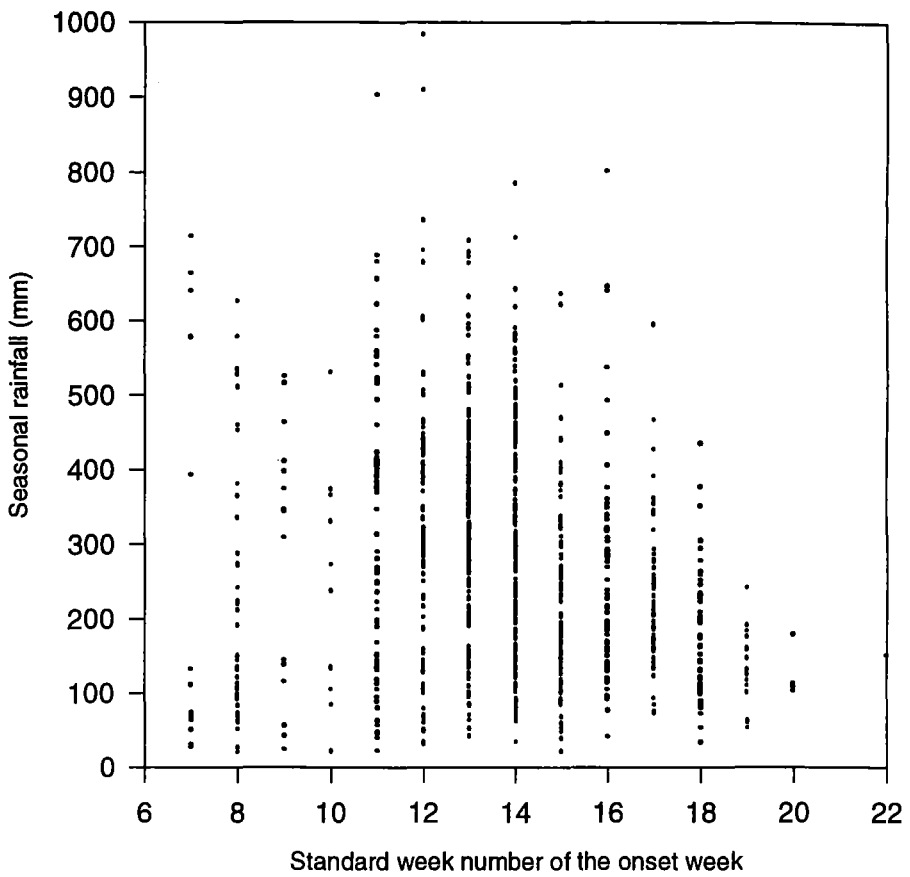
**Figure 6.2   Seasonal rainfall as related to the onset
of rains during the Yala season.**

Table 6.2 Probability of a week being the onset of the Yala season in the Dry zone, Maha-Illuppallama, Sri Lanka.

Onset week	Probability
Absence of a season	0.042
On or before the week number 8	0.071
Week number 9	0.016
Week number 10	0.010
Week number 11	0.084
Week number 12	0.098
Week number 13	0.180
Week number 14	0.192
Week number 15	0.093
Week number 16	0.066
On or after the week number 17	0.148

Table 6.3 **Descriptive statistics of the Maha season rainfall in the Dry zone, Maha-Illuppallama, Sri Lanka after 1000 simulation runs.**

	Mean	SD	CV	Minimum	Maximum
Onset (week No.)	42.0	2.9	0.06	3.0	50.0
End (week. No.)	4.2	2.2	0.53	1.0	20
Length of the season (weeks)	14.2	3.5	0.25	1.0	43.0
Amount of rainfall (mm)	800.0	278.8	0.35	24.4	1937.4

SD = standard deviation   CV = coefficient of variation

Table 6.4 Probability of a week being the onset of the Maha season in the Dry zone, Maha-Illuppallama, Sri Lanka.

Onset week	Probability
Absence of a season	0.000
On or before the week number 38	0.031
Week number 39	0.031
Week number 40	0.234
Week number 41	0.204
Week number 42	0.146
Week number 43	0.123
Week number 44	0.118
Week number 45	0.024
On or after the week number 47	0.089

season compared to the Yala season. The amount of Maha seasonal rainfall was less variable than the rainfall in the Yala season. These comparative statistics between the Yala and Maha seasons confirm the general rule of Kalma et al. (1991); rainfall variability is the highest, and its reliability least, where the total rainfall is the lowest.

Unlike in the Yala season, any significant correlation between onset of the rains and its withdrawal was not evident in the Maha season ($r^2 = 0.001$). However, the suggested regression equation consists a constant, the intercept, of 5.1 which was highly significant ($P < 0.000$). This again confirms that the end of the season should occur after the standard week 5, last week of January, and it is common for any year irrespective of the onset time of the Maha rains. The relationship between the onset and the length of the Maha season was interesting (equation 6.2) and it was significant ($r^2 = 0.40$; $P < 0.000$).

$$L = 46.7 - 0.776 \, S \qquad\qquad [6.2]$$

where,

L = length of the season in weeks

S = starting standard week

The above relationship suggests that later the onset the shorter the season's length because the end of the season is almost constant in any year. But, the correlation of determination (r^2) of this relationship was only 0.40 which implies that the strength of the relationship is 0.63. Chatfield and Collins (1992) reported that any relationship having a correlation coefficient value greater than 0.70 is only worthwhile to consider for any predictive purposes because it can explain at least 50% of the total variation. Hence, as the correlation is weak, the onset time of the Maha rains can not be used for predicting the duration of the Maha season without wide margins of error.

The Figure 6.3 shows the relationship between the onset of the Maha season and the total rainfall during the season. There was no evidence to suggest that onset of season has an impact on the amount of rainfall received during the Maha season. The correlation coefficient between the two parameters was only 0.44 which is not
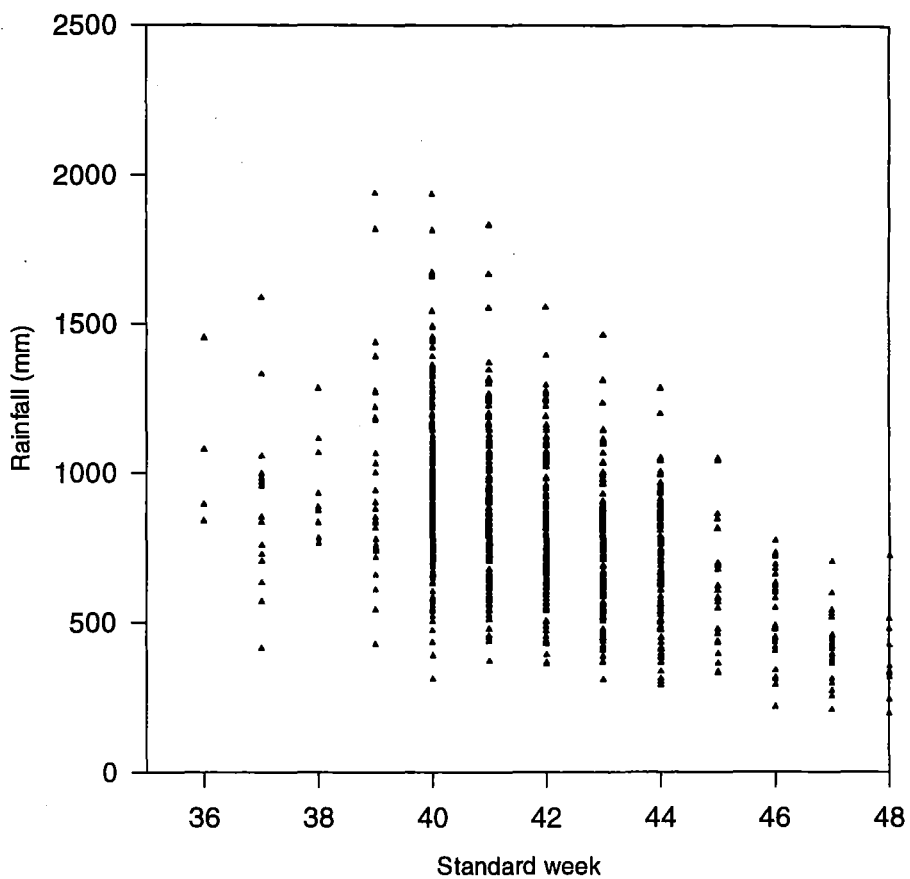
**Figure 6.3 Seasonal rainfall as related to the onset
of the rains during the Maha season.**

strong enough to draw any meaningful conclusions. This implies that even a late season could produce as same rainfall as early seasons. A similar conclusion was made by Stewart (1988) for the Dry zone of Sri Lanka. But he did not put forward a meaningful explanation for this unusual behaviour of the Dry zone's rainfall compared to the other tropical countries in the world. Thus, one can hypothesise that:

- late seasons always bring heavy down pours causing seasonal average to
  push towards the long term seasonal average;

- early seasons may have fluctuations in rainfall which causes seasonal
  average to fluctuate around the long term seasonal average; and,

- late seasons bring moderate amount of rainfall consistently through out
  the season making the average closer to the long term seasonal average.

To test whether any of the above scenarios is causing the fairly equal rainfall amounts in every year irrespective of the start of the Maha season, the model was run for 1000 times while tracking the occurrences of different arbitrary very high and very low values of rainfall with every run of the model. The correlations were determined between the onset of rains and the occurrences of such very high and low rainfall events. These correlations are given in the Table 6.5 and none of them were significant at the 5% probability level indicating that occurrence of very low values or very high values may not be the cause to end up with a fairly equal amount of rains in every year irrespective of the onset time of the Maha season.

Figure 6.4 depicts the changes of the average seasonal weekly rainfall for the seasons with different weeks of onset for the Maha season. If the season is early, either week 37 or 38, the associated average seasonal weekly rainfall seems to be lower than that of average seasonal weekly rainfall when the onset is on its most probable periods (standard weeks 40 and 41). The variation between average values when the onset is after the standard week 39 is not highly distinct. This suggests that early start of the rains may bring some extreme rainfall events, possibly some low rainfall weeks during the season, that causes the average weekly seasonal rainfall to approach a lower value and then ending up with a same long term seasonal average. But, it should be cautioned that this explanation is neither

Table 6.5 Correlation coefficients of onset of the rains and the occurrence of extreme rainfall events in the Maha rainy season of the Dry zone, Maha-Illuppallama, Sri Lanka.

Extreme value (mm)	Correlation coefficient (r)
High - 40 >	-0.29
- 50 >	-0.26
- 80 >	-0.20
Low - 5 <	-0.16
- 10 <	-0.19
- 15 <	-0.23
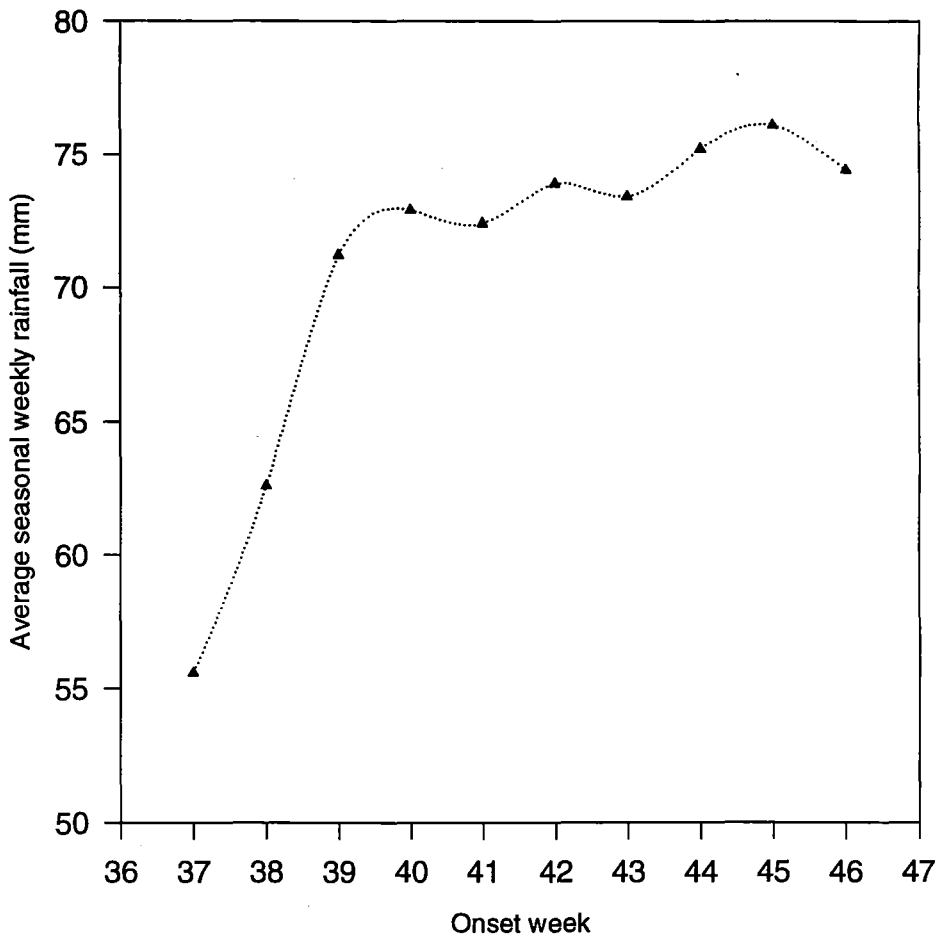
Figure 6.4   Average seasonal weekly rainfall with different onset weeks during the Maha season in the Dry zone.

complete nor definitive, but is simply intended to describe the extraordinary behaviour of rainfall in the Dry zone.

6.4 Influence of the global meteorological phenomenon on the seasonal rainfall in the Dry zone

The need for prior information about the seasonal rainfall is remained important since a sustainable development of the Dry zone requires a risk management strategy, adjusting agricultural practices with anticipated seasonal characteristics. Despite the use of long time series of data by means of a stochastic simulation model, the possibility of foreseeing the upcoming seasons in the Dry zone using the onset time of the seasonal rains was not clearly evident in this study. Therefore, the most obvious next alternative is to look for possible deterministic predictability of the seasonal characteristics of the Dry zone.

Climate prediction for agriculture began in the Indian sub-continent in early 1990s by developing rainfall prediction equations using selected variables. Subsequently, with the addition of more data, it was found that these relationships are less promising than originally thought (Das, 1986). In recent years, there has been increasing recognition that some components of the atmospheric and oceanic circulations vary only slowly and have teleconnections with rainfall and other climatic parameters. The best known of these are the southern oscillation and the El Niño episodes.

The Southern Oscillation phenomenon is the see-saw pressure pattern between the Indian-western Pacific (Indonesian low) and central-east Pacific oceans (south Pacific sub-tropical high). On average, pressure is low, relative to the zonal mean, over the Indian-western Pacific oceans and tends to be high over the central east Pacific ocean (Behrend, 1987). A simple index, the Southern Oscillation Index (SOI), is often used to study these pressure variations. This index is the difference between normalized monthly mean atmospheric pressures at Darwin (12^0S, 131^0E), normally low, and Tahiti (18^0S, 150^0W), normally high. Extreme

anomalies in this pattern involve dislocations of the rainfall distribution in the tropics, bringing drought to some regions and torrential rains to others (Nicholls, 1991).

El Niño events occur during periods when sea surface temperatures (SSTs) are warmer and the trade winds are weaker than the normal in the central and eastern Pacific, and SSTs are cooler than normal in the eastern Indian ocean and western Pacific oceans (Philander, 1990). The opposite extreme, when the east Pacific is cool and pressure there are higher than the normal, is called anti-ENSO events or La Niña episodes. The two phenomena, the southern oscillation and the El Niño, are often referred to jointly as the ENSO phenomenon. The SOI is negative during the ENSO events and positive during the anti-ENSO events.

The relationship between El Niño events and/or SOI and rainfall in Sri Lanka has been subjected to a limited number of studies during the recent past (Suppiah, 1997; Philander, 1990; Suppiah, 1989 and Ramusson and Carpenter, 1983). Most of these studies have concentrated only the meteorological aspects such as upper level wind velocities and movement of the Inter Tropical Convergence Zone (ITCZ), or have focussed the rainfall considering Sri Lanka as a single geographic unit. The influence of the SOI and El Niño events on the agriculturally important aspects of the rainfall in the Dry zone has not been adequately addressed. Therefore, the main purpose this part of the study was to ascertain the possibility of foreseeing the Yala and Maha rains, the onset and the seasonal rainfall, with respect to their teleconnections with the SOI, the El Niño and the La Niña events of the global circulation.

The rainfall data at Maha-Illuppallama, the same data used for other part of this thesis, were used to represent the Dry zone. The status of each year, either El Niño or La Niña, during the period from 1945 to 1995 was identified using published information and was verified against the SOI data taken from the Bureau of Meteorology, Australia (1997). A year has been considered from March of the

current year to February of the subsequent year. This period includes the peak months of the El Niño and La Niña events during October to December.

Although some of the relationships between the SOI and climatic fluctuations are not linear, it has been reported that the linearity assumption seems to work well for many areas in the world (Ropelewski and Halpert, 1989). Assuming such a linear relationship, the association between the SOI and the normalized monthly rainfall of both Yala and Maha seasons were determined by simultaneous correlation and lag-correlation analysis. The long term mean and the standard deviation used for normalization of the monthly rainfall was calculated only using rainfall in neutral years, excluding the years with extreme phases of the SOI.

6.4.1 Relationship between the Yala season rainfall and the SOI

Table 6.6 shows the correlations and lag-correlations between the rainfall of each month in the Yala season and the SOI. The strongest correlation observed was a positive correlation of 0.24 between the rainfall in March with the SOI of December. The correlations of April rainfall with the SOI of December were also showed an almost similar strength. All the other correlations were very weak. Above correlations reveal that only the SOI of December carries a reasonable "memory" of the monthly rainfall of the following Yala season. But, the observed correlations between monthly rainfall of the Yala season and SOI of December were small in magnitude. Therefore, they are of little use in predicting the Yala season rainfall. This is in agreement with the observation made by Suppiah (1989). He reported that the relationship between the first-intermonsoon rains, Yala rains, and the SOI was not clear when Sri Lanka is considered as a single unit.

Table 6.6 Correlation coefficients between monthly normalized rainfall of the Yala season and the SOI, Maha-Illuppallama, Sri Lanka.

	March rainfall	April rainfall	May rainfall
SOI			
October	0.06		
November	0.09	0.10	
December	0.24	0.22	0.12
January	0.05	0.04	0.09
February	0.16	0.16	0.17
March	-0.07	0.01	0.02
April		0.04	0.05
May			-0.08

6.4.2 Relationship between the Yala season rainfall and the El Niño and La Niña episodes

Even in areas where the correlation between the SOI and the rainfall is quite small, if the SOI is substantially different from the average, extreme phases of the SOI, the rainfall also can be expected to depart from the average. Under these circumstances, use of extreme phases of the SOI, El Niño and La Niña events, as a predictor and frequency of rainfall in three climatologically-equiprobable categories namely, below normal, normal, and above normal, as predictands can provide easily understandable and potentially useful results (Nicholls, 1991).

On the basis of El Niño and La Niña years given in Table 6.7, monthly normalized rainfall anomalies of the Yala season in the Dry zone were determined for El Niño and La Niña events and are shown in Figure 6.5. The effect of El Niño episodes on the monthly rainfall of the current Yala season was not clear and may appear as random having both positive and negative anomalies. This trend was evident in each month of the Yala season (March, April and May). The weak association between the Yala season rainfall and the El Niño events was further evident when the mean rainfall of the entire Yala season in neutral years was compared with the corresponding means of the El Niño Years. The average mean of the Yala season rainfall in neutral years was 289 mm whereas in El Niño years it was 302 mm. The difference between these two means was not significant at the 5% probability level. The lack of any link between the occurrence of El Niño events and the seasonal rainfall of the Yala season in the Dry zone could be attributed to the fact that El Niño events are at their early stages of the development in the east and central Pacific oceans when the Yala season is effective in Sri Lanka. The magnitude of the increased sea surface temperature over the Pacific ocean with a newly developed El Niño event is rather small. Such a small increase of sea surface temperature would not be strong enough to influence global weather patterns.

Nevertheless, the influence of occurrence of El Niño episodes on the following year reveals a coherent pattern. The anomalies of a Yala season which has been

Table 6.7 El Niño and La Niña years used in the comparisons.

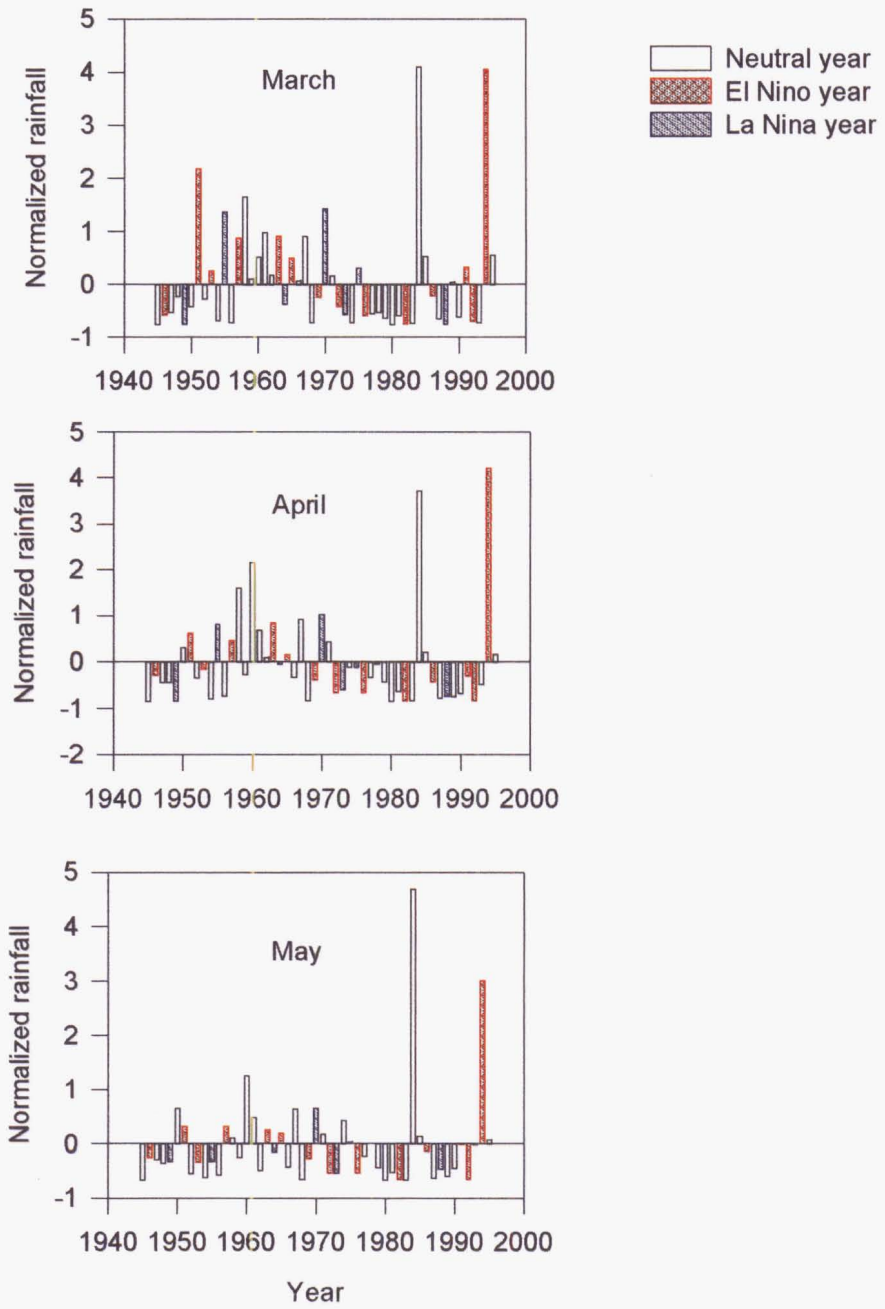| El Niño years	La Niña years
1946 1951 1953 1957 1963	1949 1955 1964 1970
1965 1969 1972 1976 1982	1973 1975 1988
1986 1991 1992 1994	

Figure 6.5 Normalized monthly rainfall anomalies during
the Yala season of the Dry zone in El Nino
and La Nina years (1945 - 1995).

preceded by an El Niño event in the previous year have often been negative. The 14 El Niño events during the study period caused below normal monthly rainfall in 11 years in March, 12 years in both April and May at Maha-Illuppallama (Table 6.8). Thus, it is highly likely that decaying stages of El Niño events cause abnormal dry spells during the Yala season of the Dry zone. This indicate a clear forecasting possibility of five to six months in advance so that, farmers and policy makers can be geared themselves for any short term impact of the drought. But, when the whole Yala season is considered there was no difference between the neutral Yala seasons and the Yala seasons preceded by an El Niño event. The mean rainfall in the Yala season preceded by an El Niño event in the previous year was 307 mm and it was not significantly different from 289 mm of mean rainfall of the Yala seasons in neutral years.

The influence of La Niña years on the monthly rainfall of the current Yala season was not clear having both below and above normal rainfall in every month (Figure 6.5). The average Yala season rainfall of the La Niña years was 320 mm and this was not significantly different from 289 mm, the mean of neutral years. But, there was a distinct link between La Niña years and the monthly rainfall of the next Yala season. Out of seven La Niña events occurred during the study period, six events caused below normal monthly rainfall during the Yala season of the following year (Table 6.8). However, since the number of La Niña events during the study period were small, seven events compared to 14 El Niño events, insufficient data were available to obtain an unbiased estimate. Therefore, strong conclusions cannot be drawn until further data become available.

Table 6.9 shows the relative time of the onset of the Yala season during El Niño and La Niña years. During the period of 1945 to 1995, no dependency was found between the time of onset of the Yala season and the appearance of El Niño episodes in the Pacific ocean. Out of 14 El Niño years, 10 years caused the onset of the Yala season to occurred in its most probable time (standard weeks 12 through 14). Three El Niño years resulted late onsets, after the standard week 15. There was an El Niño year in 1963 which resulted an early onset of the Yala

Table 6.8 Number of years with below normal monthly rainfall in El Niño and La Niña years during the Yala season at Maha-Illuppallama, Sri Lanka.

	El Niño years[*]		La Niña years[**]	
	Current Yala	Next Yala	Current Yala	Next Yala
March	7	11	4	6
April	9	12	5	6
May	9	12	5	6

* No. of El Niño years = 14   ** No. of La Niña years = 7

Table 6.9 Change of onset time of the Yala season of the Dry zone during El Niño and La Niña years.

	Early onset	Late onset	Normal onset
El Niño years	1963	1951, 1972, 1993	1946, 1953, 1957, 1965, 1969, 1976, 1982, 1986, 1991, 1994
La Niña years	1964	-	1949, 1955, 1970, 1973, 1975, 1988

season, before the standard week 11. The recent intense El Niño events occurred in 1982, 1986 and 1994 caused normal onsets of the Yala season indicating that influence of the developments of El Niño conditions in the Pacific ocean is least on the start of the Yala season. There was no evidence of link between El Niño conditions and the onset of the Yala season in the following year. Out of 14 El Niño events, seven events caused normal onsets in the Yala season of the following year. There were three Yala seasons with early onsets and four Yala seasons with late onsets. Any change of the time of onset of the Yala rains with the La Niña events was also not evident. Out of seven La Niña years occurred in the study period, a normal start of the Yala season has been reported in six years. There was an early start in the season in 1964 La Niña event. The most recent strong La Niña event that occurred in 1988 also resulted a usual onset of the Yala rains. The influence of the La Niña episodes on the onset of the Yala season in the next year was also not evident.

In conclusion, the influence of the El Niño and La Niña episodes on the rainfall of current Yala season is varied having both negative and positive anomalies. Their influence on the start of the Yala season was also not detectable. Irrespective of the El Niño, the La Niña or neutral years, the start of the season is more likely to occur in its most probable time. The influence of the decaying stages of El Niño episodes on the Yala season of the following year is substantial which shows a below normal seasonal rainfall more often, but not exclusively.

6.4.3 Relationship between the Maha season rainfall and the SOI

The correlation coefficients between the SOI and the normalized monthly rainfall of the Maha season is given in the Table 6.10. Among the four months in the period concerned, October and November months are under the influence of the second intermonsoonal convectional rains, the wettest months in Sri Lanka. December and January experience the northeast monsoon rains. The Table 6.10 reveals that neither the intermonsoonal convectional rains nor the northeast monsoon rains are well correlated with the SOI of previous months, upto -7 lags.

Table 6.10 Correlation coefficients between monthly normalized rainfall of the Maha season and the SOI, Maha-Illuppallama, Sri Lanka.

SOI	Rainfall			
	October	November	December	January
March	0.14			
April	0.05	0.05		
May	-0.17	-0.12	-0.07	
June	-0.05	-0.07	-0.16	0.09
July	0.08	0.06	-0.01	0.07
August	0.12	0.14	0.09	0.03
September	0.04	0.07	0.08	0.02
October	0.01	0.02	-0.06	0.16
November		0.16	0.11	0.18
December			0.11	0.28
January				0.09
February				

The strongest observed correlation for October rainfall was -0.17 with the SOI of May. The highest correlations for November rainfall was reported with its concurrent SOI values indicating a limited possibility of foreseeing the rainfall. The observed highest correlation for December was -0.16 with the SOI of June. The rainfall of January and the SOI of December was linked with a correlation of 0.28, the highest reported correlation in the Maha season. Thus, though the rainfall in October, December and January months of the Maha season showed a teleconnection with the SOI values of previous months, the strength of those associations was rather low. Therefore, use of the SOI in predicting the Maha season rainfall in any month is not possible in the absence of strong correlations and reasonable time lags. These results contradict the findings of Suppiah (1989). He reported that a negative correlation of -0.50 for the entire intermonsoonal convectional rainy periods in the Dry zone, October to November, with the average SOI of August through October. The possible cause for this discrepancy could be attributed to the fact that the use of mean rainfall of the entire island for normalisation process in his study. Although the second intermonsoonal rains are the wettest months for the entire island, a considerable spatial variation exists across the island owing to the minor changes in atmospheric circulation at meso-scales (20-200 km). Such changes can occur due to the local variability of soil moisture, vegetation and albedo across the land. However, his findings were in agreement with the observations between the northeast monsoon rainfall of the Dry zone and the SOI where the association was found weak (Table 6.10).

6.4.4 Relationship between the Maha season rainfall and the El Niño and La Niña episodes

Figures 6.6 and 6.7 depict the anomalies of monthly rainfall of intermonsoonal convectional and northeast monsoonal rains respectively within the Maha season during El Niño and La Niña years. The association between El Niño events and the intermonsoonal convectional rains of October was not strong. Out of total 14 of El Niño years, there were seven years with above normal rainfall during October resulting similar number of below normal rainfall. However, in November there
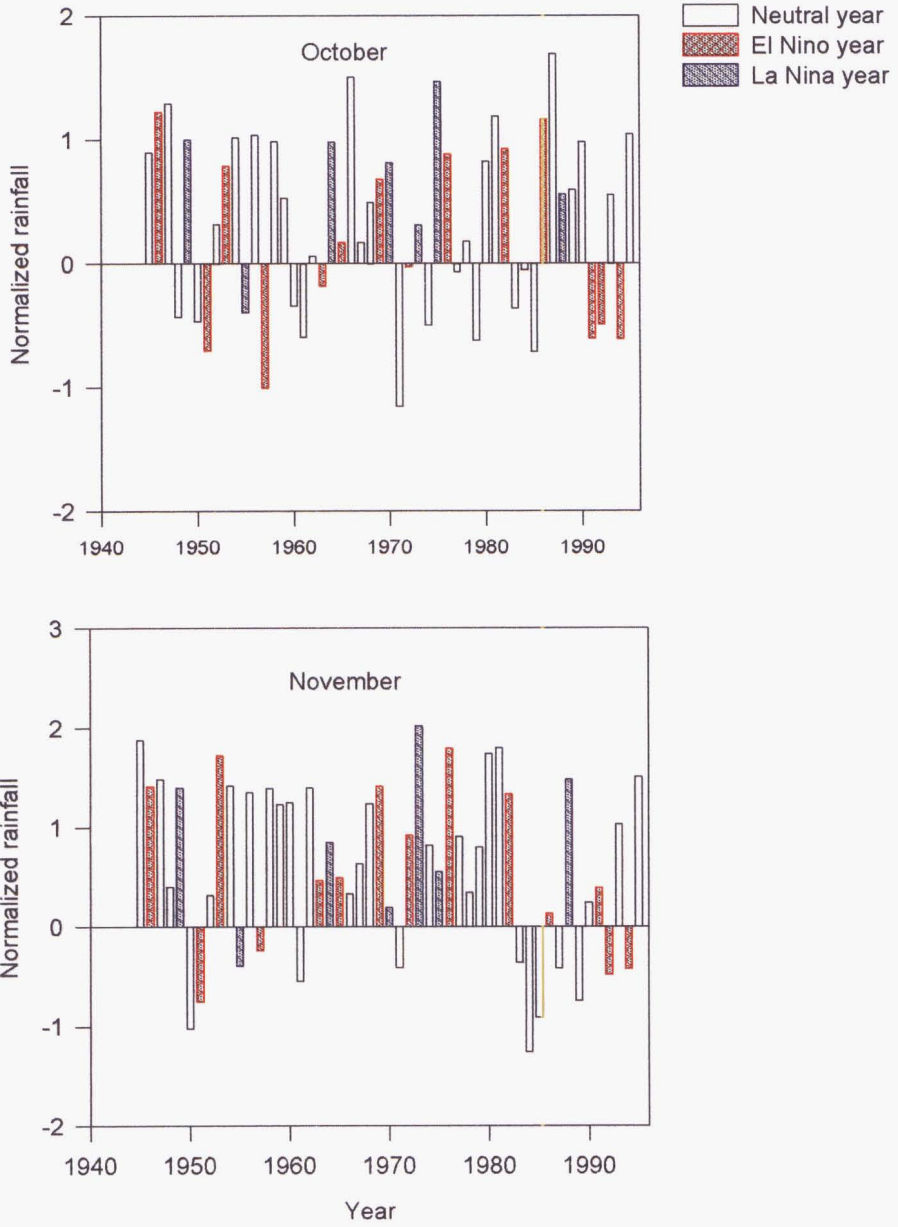
132

**Figure 6.6   Normalized monthly rainfall anomalies during
the intermonsoonal convectional rains of the Maha
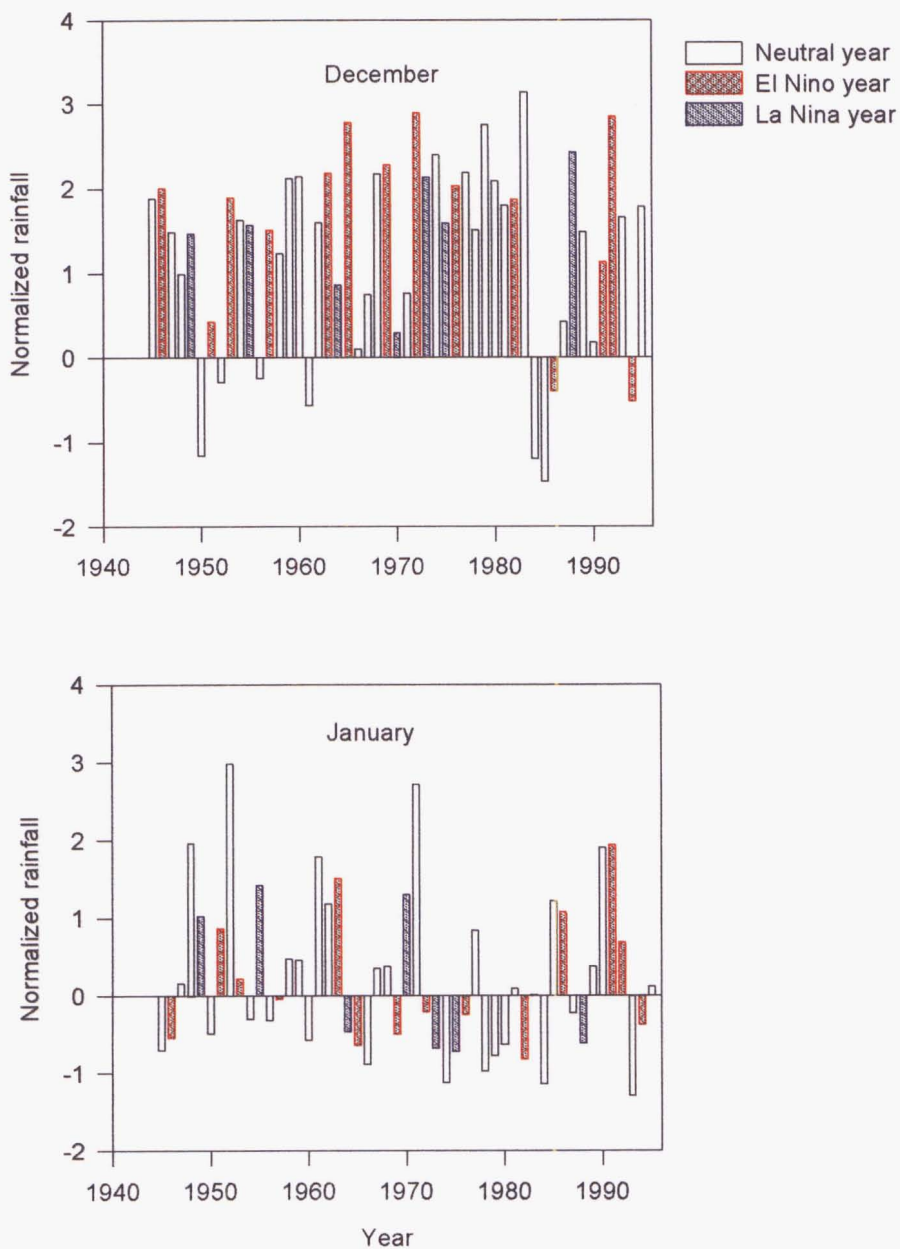season in El Nino and La Nina years (1945 - 1995).**

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**Figure 6.7 Normalized monthly rainfall anomalies during the
northeast monsoon rains of the Maha season
in El Nino and La Nina years (1945 - 1995).**

was 10 years with above normal rainfall. This trend was true for the first month of the northeast monsoon rains, December, where 12 years of above normal rainfall were reported during the El Niño years (Figure 6.6). In January there was only six years with above normal rainfall with El Niño years. Thus, it is clear that the influence of El Niño events is higher in November and December where the El Niño events are in their peak. Nevertheless, despite 160 mm of difference, the mean rainfall of the whole Maha season was not significantly different between neutral and El Niño years. This could be attributed to the fairly high standard deviation associated with the Maha season rainfall in El Niño years. The standard deviation of the Maha season rainfall with El Niño years was 416 mm with a mean of 966 mm whereas in neutral years it was 216 mm with a mean of 806 mm.

In the case of La Niña events, October, November and December months were associated with above normal rainfall (Figures 6.6 and 6.7). October and November months were linked to five and six years of above normal rainfall respectively out of seven La Niña years during the study periods. The rainfall in December was always above the normal during La Niña years. However, the association was weak in January where only three years was above the normal rainfall while four years with below normal rainfall. It is worthwhile to note that the most recent intense La Niña event occurred in 1988 have resulted an above normal rainfall during October, November and December months where as the rainfall in January was below the normal. The trend was similar even for the immediate previous La Niña event occurred in 1975. However, as mentioned in the section 6.5.3, the remarks with La Niña years are inconclusive since the number of La Niña episodes available for comparison are small.

The temporal pattern of the onset of the Maha season with respect to the El Niño and La Niña years on is given in the Table 6.11. As in the case of the Yala season, any link between the El Niño events and the onset of the Maha rains was not evident during the period of 1945 to 1995. Out of 14 El Niño years, 10 years caused the onset of the Maha season to occurred in its most probable time, standard weeks 39 through 41. Two El Niño years resulted late onsets, after the standard week 42 and similar number of years resulted early onsets of the Maha season. The recent three

Table 6.11   Change of onset time of the Maha season of the Dry zone during El Niño and La Niña years.

	Early onset	Late onset	Normal onset
El Niño years	1951, 1994	1957, 1991	1946, 1953, 1963, 1965, 1969, 1972, 1976, 1982, 1986, 1992
La Niña years	1955, 1970, 1973	1949	1964, 1975, 1988

El Niño events occurred in 1991, 1992 and 1994 caused the onset be occurred at three different times indicating that the influence of the El Niño episodes is least on the start of the Maha season (Table 6.11). Departures of the onset time from its most probable time did not show a clear association to the appearance La Niña events. Out of seven La Niña years occurred in the study period, a normal start of the Maha season has been reported in three years while there was similar number of years with early onset of the season. There was a late start in the season in 1949 La Niña event. It is likely that neither El Niño events nor the La Niña events show a clear link to the start of the Maha season.

In conclusion, the association of monthly rainfall of the Maha season with the SOI was not enduring though some trends were apparent. These trends are not all exactly the same, and the statistical significance of any relationship tends to be low. The Maha season rainfall was positively linked to the El Niño and La Niña events especially during the last two months of the year, November and December. Nevertheless, the influence of these two events on the start of the rains of the Maha season was not clear.

6.5 Summary

In this chapter, the relationship between onset of the both Yala and Maha seasons and their seasonal characteristics were examined using 1000 years of simulated data. In general, onset time of the rains as a predictor for amount of rainfall or the duration of the season in both Yala or Maha seasons was not clearly evident in this simulation study despite its well known practical importance. At the absence of any predicability of the both seasons in relation to their respective time of onsets, the observed data were compared with the SOI data and its two extreme phases, El Niño and La Niña events. The El Niño events seem to be foreseeing the Maha season rainfall and the Yala season of the following year. Although some trends were evident with the La Niña episodes, they should remain inconclusive as the number of La Niña events occurred during the study period were small. The observed trends in this study could use to develop precautionary awareness among the farmers and other relevant authorities.

Chapter 7

Growing seasons characteristics with different agro-climatic indices

7.1 Introduction

In the Chapter 6, the determination of onset and end of the growing seasons in the Dry zone was solely defined on the basis of weekly amount of rainfall. It is recognised that the amount of rainfall cannot by itself provide a good index of the productivity of the season, because the potential evapotranspiration or water loss, and the soil's water holding capacity dictate the fraction of rainfall which is available for crop growth. The mean amount of rainfall can provide a general understanding of the season for generalised applications. But, more often the problems of persistency and the adequacy of rainfall to meet the crop needs are not adequately accounted. Therefore, it is important to characterise growing seasons of the Dry zone considering crop water demand and probability concepts to relate climatic data more closely to agricultural problems such as crop growth, land use planning and zonation of homo-climates.

7.2 Characterisation of growing seasons

To characterise the growing seasons of the Dry zone, a system model was developed with respect to the major soil group of the region, RBE soils, by integrating the rainfall (Chapter 3) and soil water balance (Chapter 4) sub-models. The system model was designed in such a way that the growing seasons could be defined using

five different ago-climatic indices; two conventional approaches, mean rainfall method and probability method, moisture availability index method, MAI, (Hargreaves, 1975), ratio of actual to potential evapotranspiration, AET/PET, (Chang, 1968) and soil moisture satisfaction index method, SMRI, after desired number of simulation runs.

7.2.1 Mean rainfall method

The unsuitability of mean rainfall as a measure of crop production potential of a region has already been mentioned in a preceding section. However, much of the early studies on rainfall climatology of the Dry zone have been based on the mean amount of rainfall. This could be attributed to the fact that large number of data arrays that must be manipulated with the use of advanced techniques yet with the primitive computing power that was available in those days. Although the recent climatological studies hardly use simple average of rainfall as a measure of agricultural potential of an area, in this study, it was taken to consideration as a reference to the previous studies. Considering the fact that Dry zone has an average PET of 3 mm/day, 20 mm of weekly rainfall was considered as the cut-off value in determination of seasonal characteristics in the Dry zone assuming that the evapotransipiration is maintained at the potential rate to avoid any soil moisture stress for the crops.

7.2.2 Probability method

The uncertainty of water availability caused by the large variability of rainfall in the Dry zone could be quantified upto some extent by determining the likelihood of receiving a given amount rainfall with any specified degree of reliability. The level of the reliability, in other words the probability, required is a function of the rainfall regime as well as the nature of the crop water requirements. In Sri Lanka, 75 per cent probability is considered sufficient for most agricultural purposes and is used as the basis for agricultural planning and management decisions. The rainfall at 75 per cent probability level is also referred as the dependable rainfall (Hargreaves, 1975)

and, it is the rainfall that may be expected to occur three out of four years. A dependable rainfall value of 10 mm or more per week has been considered as the threshold value in many studies to decide the growing season characteristics (Weerasinghe, 1989 and Department of Agriculture, 1979) and therefore, the same value was used to define the boundaries of growing seasons in this model.

7.2.3 Moisture availability index (MAI) method

Rainfall, solar radiation, temperature and humidity are the most important climatic elements which affect the crop growth. Under the prevailing Dry zone climatic conditions, temperature, solar radiation and humidity do not play any significant role in agricultural production except in some extreme cases. The most dominant stress which affect the crop growth in the Dry zone is intensity and duration of the soil moisture stress.

Hargreaves (1975) proposed a classification of climate on the basis of degree of moisture adequacy or deficit for agricultural production. He defined the moisture availability index (MAI) as the ratio between amount of rainfall at 75 per cent probability level and potential evapotranspiration. According to Hargreaves, the MAI value of 0.33 could be considered as the lower cut-off point for rainfed crops. Sarker et al., (1978) used the weekly MAI to estimate the agricultural potential in Rajastan, Maharashtra and Gujarat of India. They also used the same value of the index as the threshold value to define the boundaries of the growing seasons. Mavi (1986) reported that major limitation of this method, especially with short time intervals, is need for long series of historical data to account the real year to year variability. But with the availability of the stochastic rainfall sub-model, this problem no longer exists. In this model, the limits of the growing seasons were identified when the MAI value is greater than or equal to 0.33.

7.2.4 Ratio of actual to potential evapotranspiration (AET/PET)

Irrespective of the fact that only an insignificant part of the water that passes into a crop is utilised for photosynthesis, moisture stress seriously retards the rate of photosynthesis in crops. When the actual evapotranspiration falls short of the potential, the actual yield will also be less than the maximum because photosynthesis become limited when water stress occurs due to closing of stomata and reduction in other activities in the plant (Hanks and Ramussen, 1982). The choice of the threshold soil water content at which crops suffer drought stress sufficiently to appreciably and irreversibly reduce the growth cannot be easily defined. It depends on both of the soil physical properties of the soils and the ability of the crop to extract the water (Jamieson, 1985). In fact crops appear to suffer, to some extent, any reduction in soil water below maximum water holding capacity, but may survive increasing stresses right down to the permanent wilting point. Relationship between evapotranspiration and yield in the field may or may not be linear. This is partly because the fraction of evaporation that does not contribute to the plant growth varies throughout the crop life cycle (Chang, 1968). However, for practical purposes, a linear relationship between yield and actual evapotranspiration (AET) is often used to predict the yield. These relations have been widely used for managing water deficient areas as a guide to planting (Hanks and Ramussen, 1982). Chang (1968) reported the significance of ratio of actual evapotranspiration (AET) to potential evapotranspiration (PET) as an index of cropping potential in an area. He reported that the AET/PET ratio between 0.75 to 1.00 represents conditions of relatively adequate soil water for crop growth and yields are at or near maximum assuming no restrictions due to other deficiencies. When this ratio drops from 0.75 to 0.40 the expected yield vary widely between 10 to 75 per cent depending on the stage of the crop at which the stress occurs. Values less than 0.40 could be expected to be associated with low yields or some times complete crop failures under rainfed farming. In this model, an index value greater than or equal to 0.75 was considered as the threshold value to define the limits of the growing seasons.

7.2.5 Crop water Satisfaction Index (CWSI)

All the above agro-climatic indices have been defined to measure and compare the agricultural potential of a season in quantitative terms. When critically examined, it is clear that these indices do not account some of the important characteristics of the rainfall of the Dry zone. The mean rainfall approach does not account the likelihood of rainfall. Although, the probability approaches including moisture availability index could overcome such problems, much of the details about extremes of rainfall are lost in the calculation process. The extreme rainfall values play a major role in determining the limits of the distribution of the crop plants (Mavi, 1986) and such rainfall events are common in the Dry zone during the convectional and cyclonic rainfall regimes. The indices based on soil moisture status give more practical agro-climatic indices. However, the lack of basic data on soil physical characteristics such as permanent wilting point and field capacity, and changing canopy characteristics as the season progresses, may hinder their use in large scale delineating studies.

While there seems to be an inverse relationship between the total amount of seasonal rainfall and its variability[1], the weekly 95% confidence interval band of the observed weekly amount of rainfall suggests that such a generalisation is less obvious with weekly intervals (Figure 7.1). The both Yala and Maha season have shown a wider band width compared to the inter-seasonal dry period, May to September, indicating a more variability associated with rainfall during the wet seasons. As an alternative measure of this variability, the mean rainfall can compare with the dependable rainfall. When a week consists several high rainfall values in its time series, wet extreme, the magnitude of the difference between the mean rainfall and the dependable rainfall becomes large. If those high values were replaced by small values, dry extreme, the difference become small. In either case the changing parameter is the mean and the dependable rainfall is less sensitive to the occurrence of extreme values. Taking this phenomenon into consideration, an index was defined using mean rainfall, dependable rainfall and the potential evapotranspiration.

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[1] seasonal coefficient of variations are 0.60 and 0.48 for the Yala and Maha seasons respectively with 51 years of observed data.
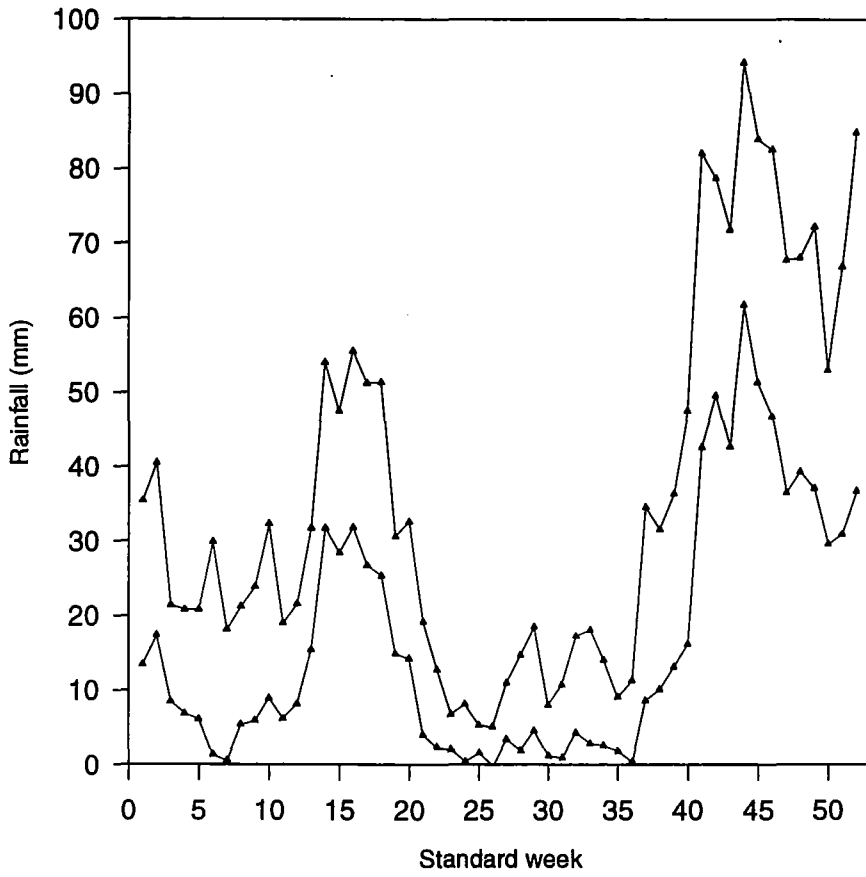
Figure 7.1 The 95% confidence interval band width for observed weekly rainfall at Maha-Illuppallama in the Dry zone of Sri Lanka.

$$CWSI = \frac{RF - DRF}{PET}$$ [7.1]

where,

CWSI = crop water satisfaction index

RF = weekly mean rainfall in mm

DRF = weekly dependable rainfall in mm

PET = weekly potential evapotranspiration in mm

This index is capable of capturing the extreme rainfall events and the probable water supply in a definite proportion of years such as three out of four years through the inclusion of the dependable rainfall into the index calculation. Apart from that, the index also accounts the potential water demand of the crops through the PET. The rainy seasons which are conductive for crop production carries a reasonable variability of the rainfall amounts. This intermediate state of the index could be termed as "Hydro-neutral" where the soil moisture is neither limiting nor deficit for the crop growth. When the variability of weekly rainfall is high as a result of occurrence of several stormy rainfall events, the index approaches large values. This situation of the index could be termed as "Hyper-hydral" where the excess soil moisture may hamper the crop growth. The less variability of rainfall amount and the high evaporative demand which is the case in dry periods result small index values. This situation could be termed as the "Hypo-hydral" where the crops are under soil moisture stress. The classification of the index is as follows:

0 - 0.75 Hypo-hydral (too little moisture)

0.75 - 2.50 Hydro-neutral (ideal moisture for most of the crops)

above 2.50 Hyper-hydral (excess moisture)

Before being used in the model, the CWSI was tested with an another location of the Dry zone, Angunakolapellessa, where both relevant meteorological data and published information on the onset of the growing seasons are available. The analysis showed that the boundary values set in CWSI are capable of identifying the onset of the two growing seasons that occurs during the standard weeks 17 and 42 in Yala and Maha seasons respectively (Joshua, 1985). However, the reported excess soil moisture conditions that occur during the five weeks period between standard week

43 and 48 at Angunakolapellessa was not properly signalled by the CWSI although values were in the upper range of the hydro-neutral conditions.

7.3 Description of the system model

The schematic diagram of the system model has shown in the Figure 7.2. It is essentially a simple water balance model that run on a weekly basis. User supplied values of location specific transitional probabilities, distribution parameters of rainfall and pan evaporation and soil properties were used as input to the system model. After the number of simulation runs specified by the user, the model calculates the number of climatic indices discussed in the previous section, soil moisture storage of the root zone and the probability of each week of the year being dry. To avoid any false starts of the growing season and to make sure its subsequent continuity, each index was evaluated for three consecutive weeks. If the three week criteria was not fulfilled the pre-conditions were relaxed upto two consecutive weeks. The end of the growing season was set as the immediately following week where the continuity ceases. As the ripening stage of crop growth does not require much moisture, it is reasonable to set the end of the season as one week after the threshold value is reached. This will facilitate more room for long age crops or varieties in the cropping program. All these climatic indices were then used to define the onset, withdrawal and length of the growing seasons within a year.

7.4 Implementation

The system model was coded in SIMSCRIPT II.5, a general programming language containing the capabilities for building discrete event, continuous or combined simulation models. It is English like that makes simulation programs easy to read and almost self-documenting. The source code is given in the Appendix 4. The accompanying diskette contains the executable program of the system model that runs on a Windows 3.1 operating system with a C compiler. The data files containing the transition probabilities and distribution parameters of each week of the year are also supplied.
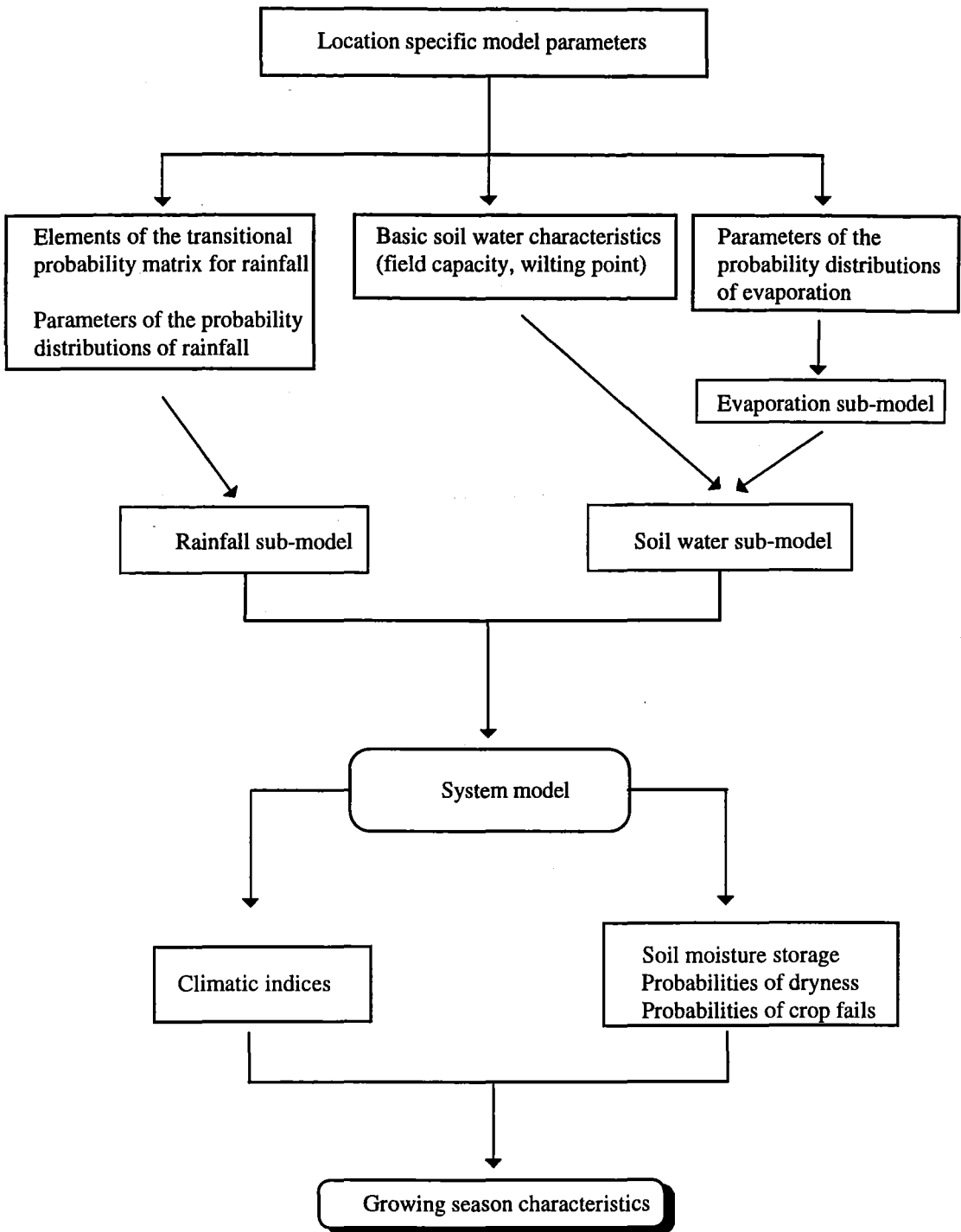
Figure 7.2 Simplified flow chart showing the inter-relationships of the system model.

As this simulation study aims to develop a model to characterise the growing seasons of the Dry zone using all possible notable yet infrequent rainfall events, 1000 simulations runs were made to ensure the inclusion of maximum number of extreme events. The outcome of the model was compared with the previous published information on the Dry zone's seasonal characteristics that have used real time data of both rainfall and soil moisture.

7.5 Characteristics of the two major growing seasons with different climatic indices

7.5.1 Mean rainfall method

Figure 7.3 shows the weekly mean rainfall after 1000 simulation runs along with the reference line at 20 mm of rainfall which serves as the threshold value that defines the growing seasons. The results suggest that the most probable onset of the Yala season is on the standard week 11 while the end of the season is on the standard week 21 resulting a 11 weeks longer growing season. The simulation results the onset of the Maha season as on the standard week 40 which continues to receive 20 mm or more rainfall upto the last week of January of the following year, the standard week 5, resulting a 18 weeks longer season. Simulation also shows that the first half of the Maha season, between the second week of October and the second week of November, would receive ample amount of rain, above 60 mm (Figure 7.3).

7.5.2 Probability method

The onset of the Yala season with respect to the dependable rainfall method where the threshold value is 10 mm or more per week at 75 per cent probability, was in the standard week 14, the first week of April. The predicted end of the season falls on the standard week 20, the second week of May resulting a seven weeks longer season. However, three weeks after the onset, reliability of the rain diminishes with a subsequent increase at latter part of the season, early May (Figure 7.4). Thus, with
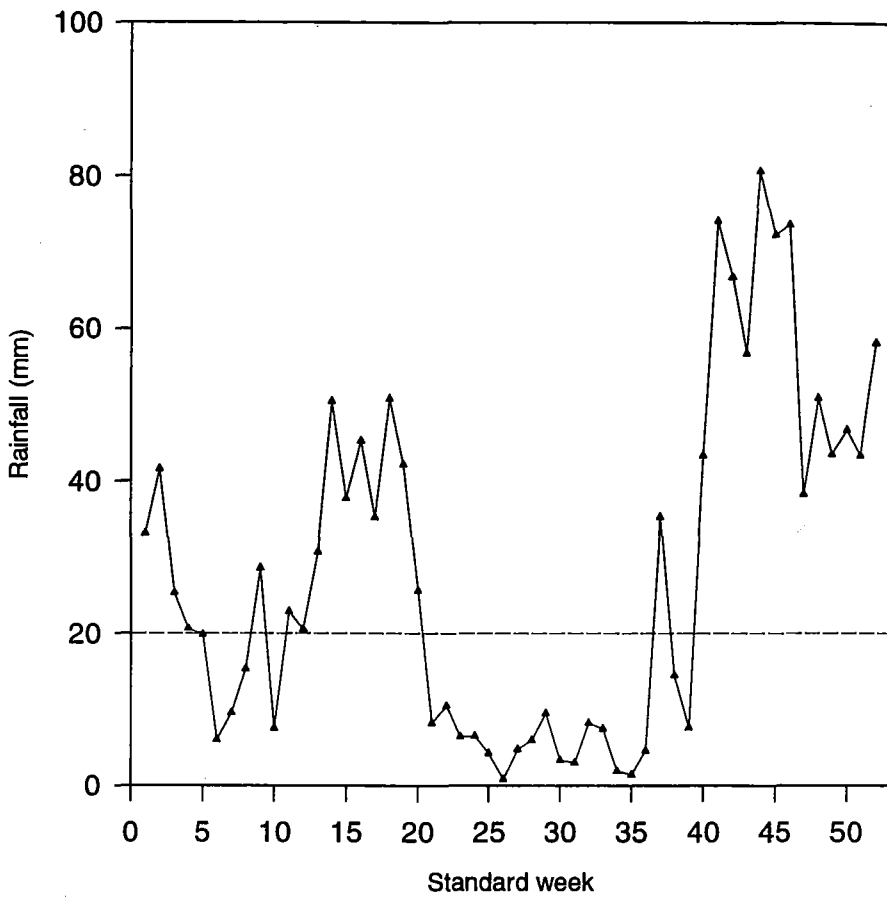
**Figure 7.3   Mean weekly rainfall after 1000 simulation runs.
The broken line represents the threshold rainfall value.**

Figure 7.4 Weekly rainfall at 75 % probabilty level after 1000 simulation runs. The broken line represents the threshold value.

respect to the dependable rainfall, a proper Yala season can not be identified. The boundaries of the Maha season were identified as standard weeks 41 and 1 as onset and end of the season respectively (Figure 7.4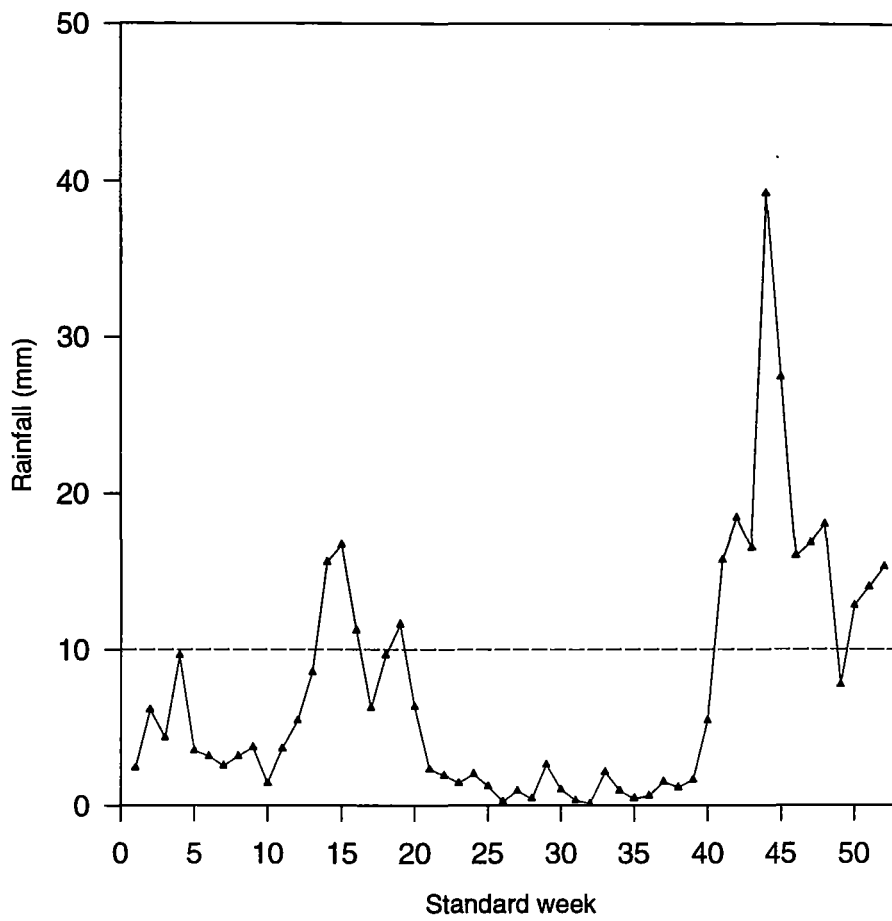). However, the length of the season is only 13 weeks, a remarkable drop compared to the mean rainfall method. During the Yala season, the dependable rainfall of each week never exceeds the total potential evapotranspiration of the week. Therefore, it can be concluded that the probability of low moisture stress expectancy during the Yala season is quite low. However, during the Maha season, especially during the first phase of the season, convectional rains, the dependable rainfall was well above the potential evapotranspiration. This was evident even with the mean rainfall method which showed an ample amount of rainfall during the first phase of the season.

7.5.3 Moisture availably index (MAI)

The boundaries of the growing seasons were determined when the MAI equals or exceeds the value of 0.33. The onset of the Yala season was in the standard week 13, the last week of March. After the standard week 20, the second week of May, the MAI value started to decline indicating the end of the season thus leaving eight weeks for the season length (Figure 7.5). The model suggests that the Maha season start would be on the standard week 41. The MAI value was well above the threshold value until the last week of January in the following year, standard week 5. Thus, there are 17 weeks for the total growing season. During the period from standard weeks 43 to 52, the MAI was over 1.00 most of the time. This indicates that soil is wet and there is hardly any risk to crop cultivation due to the soil water stress. However, excess water may pose problems with some cultivation practices such as weeding and application of agro-chemicals and even outright crop failures due to the poor aeration of the root zone. Such a catastrophic situation could appear in standard weeks 44 and 45 where the convectional rains are in their peak and also in late December due to the formation of cyclonic depressions in the Bay of Bengal (Figure 7.5). Unlike in the Maha season, the Yala season MAI values are always between 0.3 and 0.6 which implies marginal soil water storage. Also, the standard week 17 showed a decrease in MAI value below the threshold value (Figure 7.5).
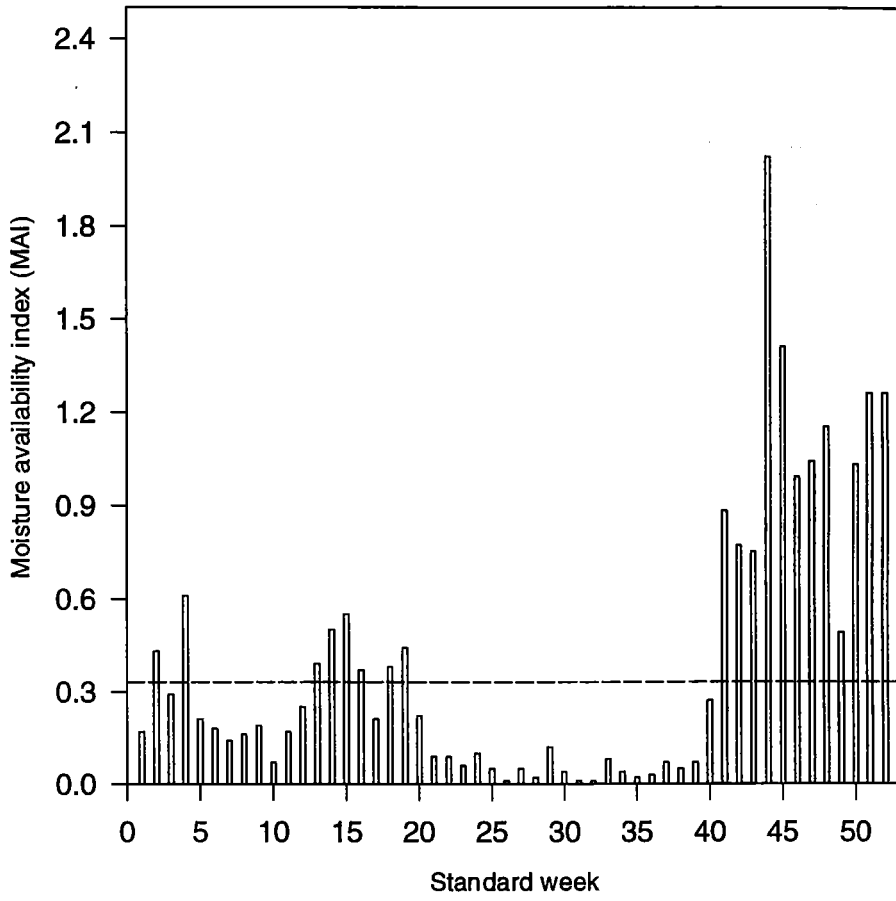
Figure 7.5 Weekly moisture availability index after 1000 simulation runs. The broken line represents the threshold value.

Therefore, cultivation of drought sensitive crops during this season could be impossible unless supplementary irrigation is provided.

7.5.4 Ratio of actual to potential evapotranspiration (AET/PET)

The ratio of actual to potential evapotranspiration, better known as AET/PET ratio, between 0.75 to 1.00 can be regarded as a condition of adequate soil moisture for the crop growth (Chang, 1968). At this level of the ratio, yield is at or near maximum for a given environment assuming no limitation due to other deficiencies. According to the AET/PET ratio, the model suggests that the onset of the Yala season occurs on the standard week 13 while the end of the season is on the standard week 20. The length of the season is eight weeks. During the Yala season, the value never reaches 1.00 which is the maximum (Figure 7.6). This indicates that the crop never receives its full water requirement during the Yala season.

The Maha season starts on the standard week 41, the first week of October and the ratio continues to be around 1.00 as the season progresses. The soil moisture becomes limiting for the crop growth from the standard week 5 onwards resulting a 17 weeks longer season (Figure 7.6). It is interesting to note that two weeks after the onset of the Maha season, the ratio reaches its maximum phase and remains at the same level until the first week of January. Thus, during this period crop growth is hardly affected by the soil moisture stress.

7.5.5 Crop water satisfaction index (CWSI)

The newly defined crop water satisfaction index in the model shows that the start of the Yala season is on the standard week 13, the last week of March. The critical value of 0.75 or above, the hydro-neutral condition, was observed upto the standard week 20 resulting a eight weeks longer season. However, two weeks after the onset, the standard week 15, the value of the ratio dropped well below the critical value which showed a hypo-hydral condition according to the definition (Figure 7.7). Thus, crops are likely to have a moisture deficit on this week. Such a early stage drought,
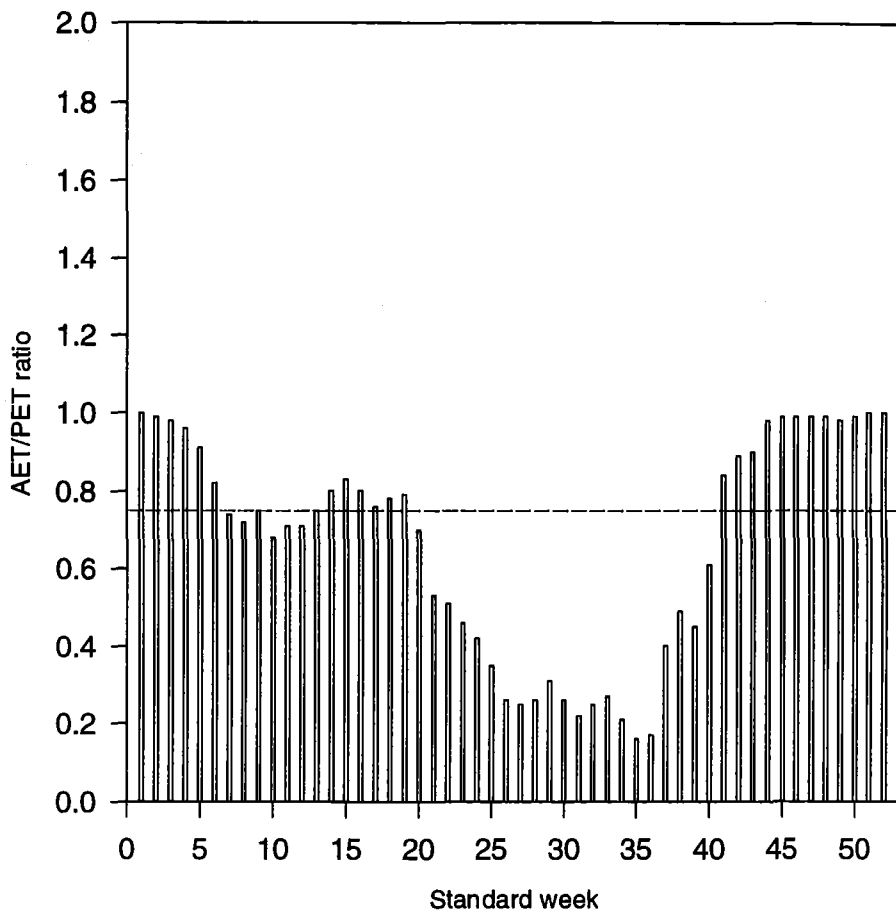
**Figure 7.6 Weekly AET/PET ratio after 1000 simulation runs.
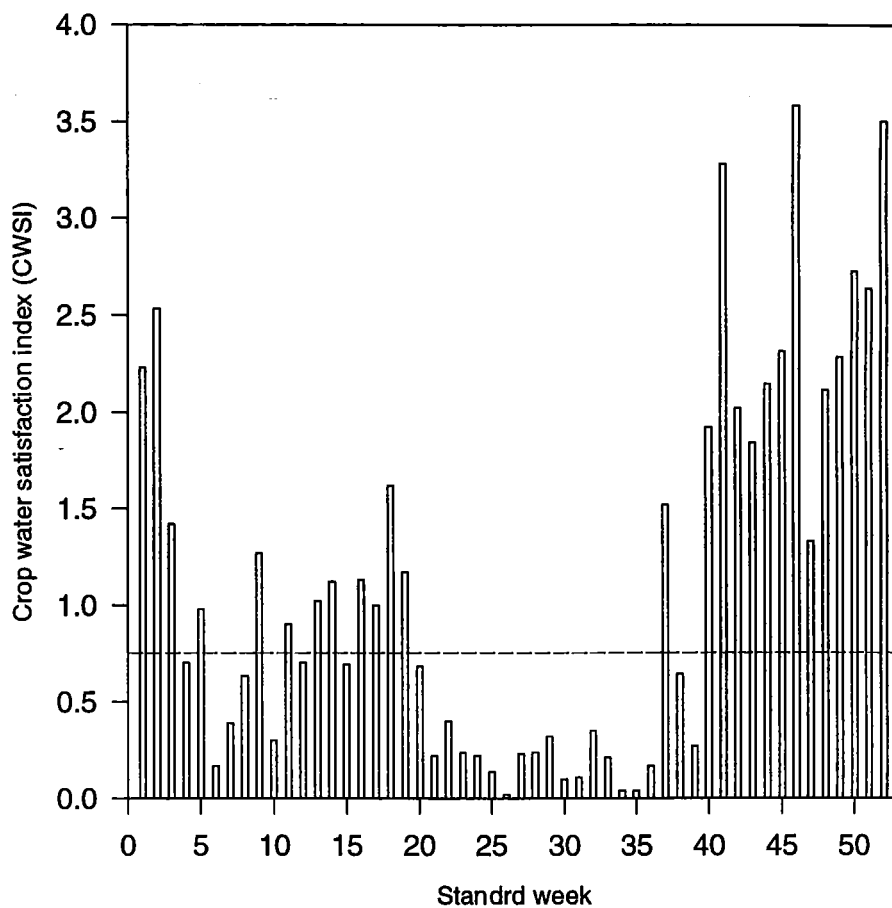The broken line represents the threshold value.**

Figure 7.7 **Weekly crop water satisfaction index after 1000 simulation runs. The broken line represents the threshold value.**

shortly after the establishment may cause high seedling mortality, and hence reduced plant population.

The model simulates that the start of the Maha season is on the standard week 40 while the end of the season is on the standard week 6 which signals the end of the hydro-neutral state of the index. The resulting length of the Maha season is 19 weeks which is well suited for crops taking 120-140 days to mature. The value of the CWSI on the standard week 4 was just below the hydro-neutral condition. However, by this time of the season, the crops have reached the harvesting time. Therefore, such a short dry spell does not hamper the crop performance. Nevertheless, the hyper-hydral conditions that may prevail in standard weeks of 41, 46 and the last three weeks of December may curtail the crop growth due to the excess soil moisture (Figure 7.7). During the whole Maha season CWSI is well within the hydro-neutral state. Therefore, the more flexibility there is in farming systems such as wider choice of crops and cultivars, and higher likelihood achieving economic returns from the inputs.

7.6 Comparison of indices

The growing seasons characteristics are varied with the index used. For example, some indices apparently suggest existence of moisture stress within the season either in the form of deficit or excess while others have shown no such stress periods. As one of the major objective of the system model was to identify a generally acceptable agro-climatic index for quantifying agricultural potential of the growing seasons, there is evidently a need to determine a more practically suitable index. The Table 7.1 summarise the characteristics of both Yala and Maha seasons with different indices. The time of onset of the Yala season has been simulated as the last week of March, standard week 13, with three indices out of five indices used in the model. The mean rainfall method has predicted an early onset of the Yala season. There was an one week delay of the onset when the weekly dependable rainfall amount was used as the index for defining the seasonal characteristics (Table 7.1). The prediction of standard week number 13 as the most probable onset week of the Yala season is comparable with the previous studies that have been based on extensive field verifications

Table 7.1 Comparison of growing seasons characteristics of the Dry zone with different agro-climatic indices.

Criteria	Yala			Maha		
	Start	End	Length	Start	End	Length
Rainfall	11	21	11	40	5	18
DRF*	14	20	7	41	1	13
MAI	13	20	8	41	5	18
AET/PET	13	20	8	41	7	19
CWSI	13	20	8	40	6	19

*DRF = Dependable rainfall

(Kannangara, 1989 and Somasiri, 1978). The second week of May, standard week 20, has been found to be the end of the Yala season with four indices. Again, mean rainfall method has predicted a late end of the season causing season become longer (Table 7.1). The reported end of the Yala season in previous field studies is also the standard week number 20 (Kannangara, 1989 and Somasiri, 1978). Thus, other than the mean rainfall method, all other indices are well capable of identifying the effective end of Yala season.

In the Maha season, the predicted onset of the season is on the standard week 41, the second week of October, when the dependable rainfall method, MAI and AET/PET ratio are the determining indices. The predicted onset was one week earlier, standard week 40, when the mean rainfall method and the newly defined CWSI were used. The previous studies have shown that the standard week 40, the first week of October, is a reliable choice of sowing time for the region (Panabokke and Walgama,1974). This has been further confirmed with the follow up studies (Kannangara, 1989). Withdrawal of the Maha season was variable with different indices. The dependable rainfall method has predicted that the end of the season is on the first week of January as a result of high uncertainty of rainfall at the tail end of the season. All other indices have suggested that the end of the growing season is either in late January or early February. The AET/PET ratio which takes into account the soil moisture status has lengthen the season upto the standard week 7, the second week of February. In general, the cease of the Maha season does not make substantial influence to the crop production if it occurs after late January. The general cropping practice during the Maha season in the Dry zone is sowing for crops that take 120-130 days to mature. If the sowing has done with the early showers of the Maha rains, by late January crops should be completed its active growth phases. The only remaining phase would be perhaps the late maturity or ripening phase which does not need much moisture other than a life saving amount. Such a small amount of rainfall could be expected during January in every year. Therefore, to define the end of the Maha season, all the indices could be used other than the dependable rainfall method.

Mean rainfall and the dependable rainfall are the simplest indices that have been used widely in the past to characterise the moisture regime of a region. These two indices can be a useful local indication of production potential. However, the foregoing discussion suggests that both the mean rainfall method and the dependable rainfall method do not yield meaningful seasonal characteristics in both seasons in the Dry zone. Out of other three indices which predicted both onset and end of the seasons on par with the previous published information, both MAI and CWSI indices reserved special consideration. The AET/PET ratio depends exclusively on the basic soil and plant characteristics such as field capacity, permanent wilting point, crop coefficients, stage of the crop growth and rooting depth. In view of the variability of soils and crops over a region particularly where there are marked diversity of crops grown on soil catenal sequence, it may not be worth using AET/PET ratio as an index in broad scale climatological studies though may be of academic interest. But, MAI and CWSI indices use only the meteorological data and do not depend much on the soil physical data of the location yet accounts the plant water demand through the PET component. Parry (1991) reported that a prospective agro-climatic index should not demand large amounts of detailed data, and can therefore be employed for assessment of agricultural potential of a large area based on the mean climatic data across a network of climatological stations. In addition, these two indices are capable of tracking the excess soil moisture conditions which could be a crucial problem during the Maha season in the Dry zone. Therefore, their usefulness as indices to represent the agricultural potential of the Dry zone was highly evident in this simulation study. However, it should be worthwhile to note that compared to the AET/PET ratio, these two indices do not reflect the true nature of the moisture deficit for the purpose of crop production but they do give information regarding the degree of aridity which is an important criterion for crop and land use planning.

7.7 Summary

This chapter presents a stochastic model to characterise the two major growing seasons of the Dry zone using five different agro-climatic indices namely, mean rainfall, dependable rainfall, MEI, AET/PET and CWSI. The major inputs to the

model were rainfall, open pan evaporation and, the soil and plant characteristics such as field capacity, permanent wilting point, rooting depth and crop coefficients. Upon input of the model parameters, 1000 runs were made. This had the advantage of allowing a wider range of conditions to be examined than would be possible using only observed data.

The output of the model was compared with the published information of growing seasonal characteristics of the Dry zone. Comparable results were obtained between the observed and the simulated characteristics of the both Yala and Maha seasons mainly with three indices, AET/PET, MAI and CWSI. The simulated seasonal characteristics of the both Yala and Maha seasons with respect to the mean rainfall and the dependable rainfall were not acceptable.

Chapter 8

The use of the model, overall summary and future directions

8.1 Introduction

The results presented in the previous chapters confirm that the system model developed in this study is characterised by its analogical approach to crop water demand in the Dry zone and by the use of readily available inputs to derive the simple yet informative agro-climatic indices while accounting the stochasticity of the meteorological variables. Apart from that, the model is also capable of deriving some more useful basic information such as temporal variation of soil moisture, probabilities of dry spells and crop failures. These information are quite useful in agricultural planning and decision making in the Dry zone of Sri Lanka. This chapter discusses such complimentary information that can be derived from the system model and possible use of such information in assessing the agricultural potential and some specific management options.

Also in this chapter, the work of the thesis is summarised in relation to the objectives given in the Chapter 1. The important scenarios against which the models developed here should further tested have also been suggested in this chapter.

8.2 Use of the models

8.2.1 Delineation of agro-ecological zones in the Dry zone

An agro-ecological zone is defined as a major area of land that is broadly homogeneous in its rainfall regime and is made up of a grouping of soils that reflect broad similarities in the profile development. The probabilistic estimates of assured rainfall amounts have been used to identify the homogeneous rainfall regimes in the Dry zone that would reflect the water availability for crop growth. However, in practical situations, it would be more realistic to demarcate the homogeneous regions in relation to the potential water demand and the water availability of the soils in the region. Virmani et al. (1982) have concluded that the classification using rainfall and PET as inputs have a definite advantage because these are the two parameters of primary importance in the evaluation of climatic water adequacy. The two indices shown to be promising in the model, MAI and CWSI, do consist both rainfall and the PET as parameters. Thus, when compared with the monthly rainfall at 75% probability level, the methodology which used for assessing the water availability for crop growth in the current agro-ecological map of Sri Lanka, the model appears to be a promising alternative to employ in evaluating the water aspects of crop growing for future agro-ecological delineation studies. This could be done by grouping sub-zones within the Dry zone either by making use of the simple climatic indices in the model or by grouping areas together which have similar seasonal characteristics as predicted by the model.

8.2.2 Dry spells

In the Dry zone where the soil moisture availability is the most important determinant of crop productivity, it is essential to match the planting and crop phenology with the dry spells. Therefore, information on dry spells is a useful guide to select the crops and/or varieties for the seasons. Figure 8.1 depicts the probability of a week being dry with 1000 simulation runs. These probabilities have been calculated after re-
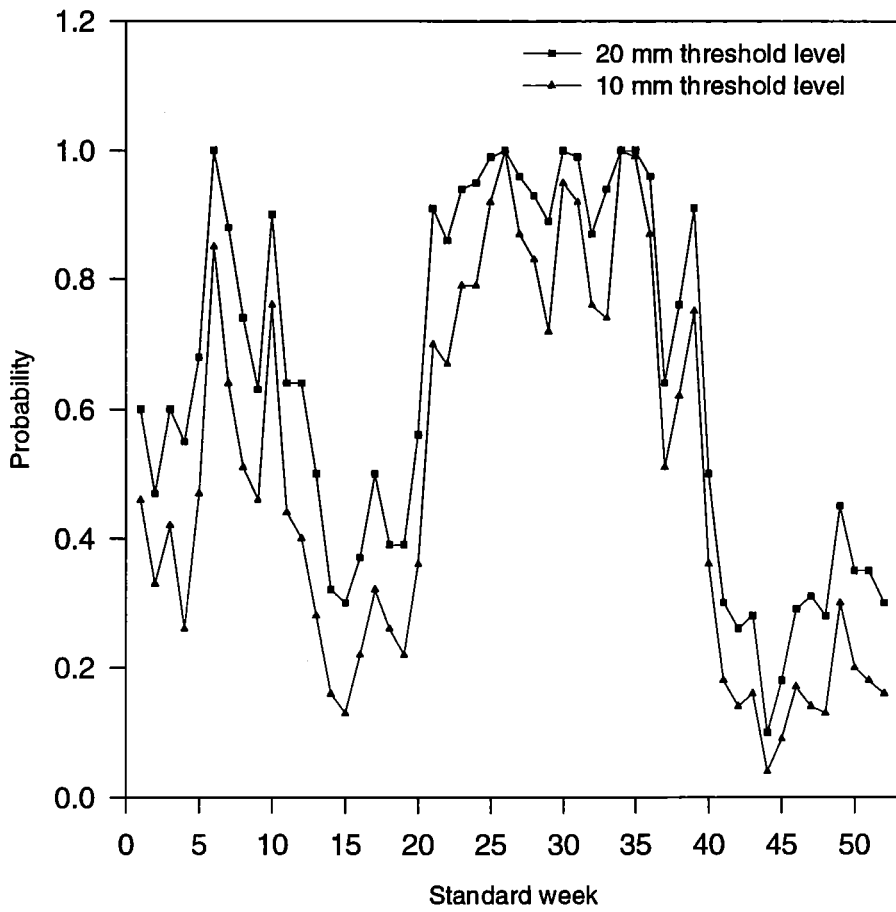
Figure 8.1 **Probability of a week being dry after 1000 simulation runs.**

defining "dry' state with threshold levels of 10 and 20 mm, compared with the original threshold of 7 mm used in the model development. Note that the model does not have to re-designed to obtain these results. The rational of choosing 20 mm has been discussed in the Chapter 7 and 10 mm was chosen to represent more drought conditions. At the prevailing average potential evaporative demand of 21 mm per week especially when the canopy is fully developed, 10 mm of rainfall per week would not suffice to maintain the metabolic activities of any crop in the Dry zone.

It is important to asses the true nature of probabilities of dry spells at the tail end of the growing season when the crops are generally in the reproductive phase. Therefore, immediate attention was given to the month January where the Maha season crop are in their grain filling or early maturity phase. Figure 8.1 reveals that the each week of January carries 40-60% probability of being dry with the threshold level of 20 mm or less rainfall. When the extreme situation is considered, rainfall of 10 mm or less, still the probability ranges from 30-45 per cent. This concludes that there is a likelihood of one out of every two years in January to be a moderately dry month while one out of every three years a more worsen situation. A crop that fails in January not only makes the whole investment in Maha season un-productive but often discourages and holds back a farmer from proceeding with his Yala season cultivation which comes after another two months time. This could make a devastating effect on the domestic economy and therefore an adequate attention should be given in agronomic research and policy planning to minimise the effect of possible drought conditions in January.

Again in the standard week 49, there is a 45% of probability of being moderately dry and a 30% of probability of aggravated dry conditions (Figure 8.1). This is a more crucial situation as the following week does carry a 35% probability, a reasonably high level of being dry. The possibility of both weeks becomes dry, first-order conditional probability, is 16 per cent. Thus, in long run, it is likely that one to two out of every 10 years, the Maha season may experience a 14 days dry spell starting from the first week of December. Such a long dry spell is strong enough to affect the

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crop growth. Therefore, selection of the crops/cultivars for the Maha season could be an important management decision and hence, care should be given not to coincide these two weeks with panicle initiation or flowering stages of crops. These two phenological phases of crops are very sensitive to the drought stress.

Being a weak rainy season in the Dry zone, the whole Yala season resembles a high probability of being dry with a range of 30 to 50 per cent with 1000 simulation runs (Figure 8.1). This implies that the Yala season cultivation is a risky venture in view of the high uncertainty of the water availability unless supplementary irrigation is provided through a major irrigation project. However, rational use of available physical resources such as conservation of residual moisture from the preceding Maha season (Section 8.2.3) and the use of ground water could minimise the possible crop failures during the Yala season while maximising the use of direct rainfall with reduced pressure on the irrigation water resources.

The probabilities of dry spells after the standard week 21, mid-May, to the standard week 39, last week of September, are almost 90 per cent except in a few weeks (Figure 8.1). It is usual to have this dry season in the Dry zone as none of the rainfall governing mechanisms in Sri Lanka are effective over the Dry zone during this period. Therefore, it would be almost impossible to establish or maintain any shallow rooted annual crops during this period.

8.2.3 Temporal variation of available soil moisture

The figure 8.2 shows the variation of weekly available soil moisture content in the top 60 cm of the RBE soils in the Dry zone of Sri Lanka with 1000 simulation runs. The horizontal line which goes through 150 mm point represents the 50% of available soil moisture in RBE soils. Although the Maha season is ceased by late January, standard week 5, the soil moisture remains well above the 50% of the available soil moisture during the dry month, February, before the next Yala season starts. According to the simulation, this situation prevails at least nine out of every ten years. This signals a
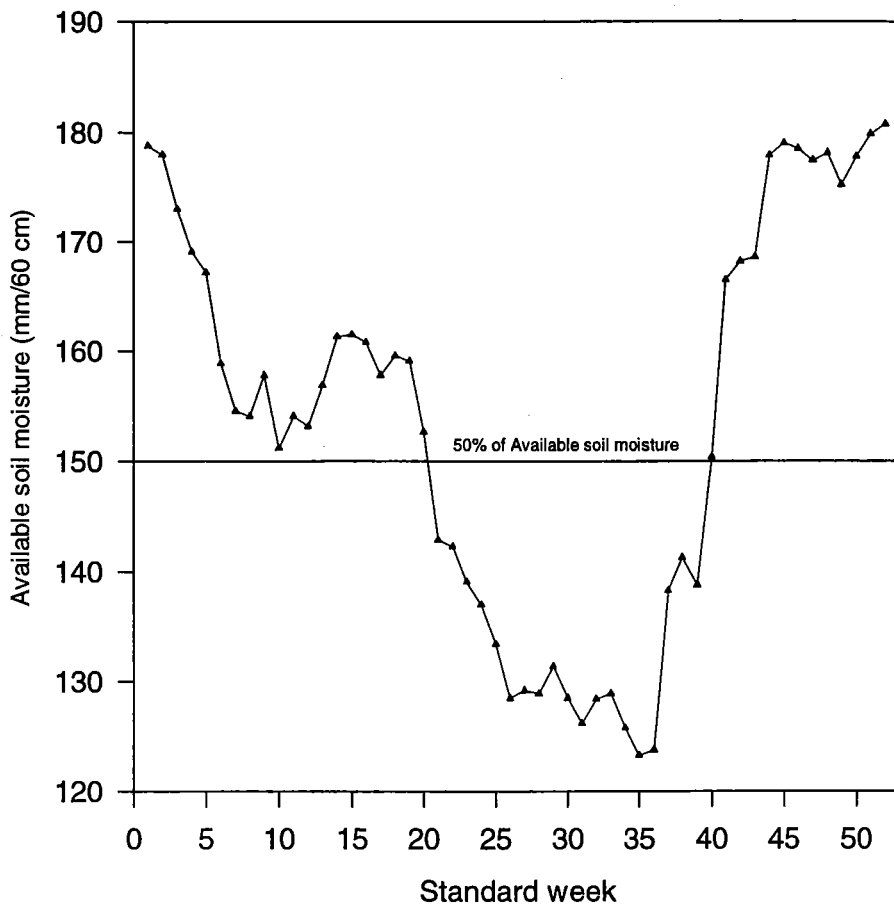
**Figure 8.2   Variation of availble soil moisture in the
root zone of RBE soils in the Dry zone
of Sri Lanka with 1000 simulation runs.**

possibility of an alternative strategy to increase the cropping intensity, a second crop, possibly a short age variety, that may be established after the harvesting of the Maha season crop with supplementary irrigation. An another option is to conserve these moisture to be used for the upcoming Yala season. This may include harvest the crop as soon as practical after physiological maturity, uprooting remaining plant materials and spread them out on the soil as a mulch. Such a conservation of residual soil moisture could be used by subsequent crops in the Yala season or may be sufficient to permit early and more timely tillage and seed bed preparation in the next Yala season.

Only a portion of available soil moisture is readily available to the crop and, in RBE soils it is considered as 75% of the total available soil moisture (Chapter 4). The Figure 8.2 also reveals that during the whole Yala season, available soil moisture level is below the critical point of 75% of total available soil moisture, 167 mm/60 cm. When the available soil moisture is below the critical point, it can affect the crop yields substantially depending on the magnitude of the stress and development stage of the crop. Simulation reveals that every week of the Yala season, except the standard week 14, bears more than 70% of probability being available soil moisture less than 167 mm/60 cm (Table 8.1). Therefore, any crop in this season should have the capability of withstanding high soil moisture tensions in any time of the life cycle. During the Maha season the probability of week being below the critical soil moisture level is quite low except during early weeks of the season and the tail end of the season (Table 8.1). The possibility of having mid-season drought during the Maha season is highly unlikely. However, from the third week of January, there is more than 30% chance of soil moisture become below the critical point, 167 mm/60 cm. The same was evident, but for whole January, when the dry spell was defined in terms of less than 20 mm of rainfall per week (Section 8.2.2). Nevertheless, from the stand point of available soil moisture, the possibility of crops being subjected to a moisture stress at the first two weeks of January is rather low, less than 20 per cent. But, since the probabilities are still reasonably high from the third week of January onwards, the discussion in the section 8.2.2 regarding the dry spells in month January is still worthwhile to be considered. Hence, a delayed cultivation with the anticipation of rains towards the end of the Maha season should not be done.

Table 8.1 **Probability of available soil moisture being less than 167 mm/60 cm for each week of the two growing seasons with 1000 simulation runs.**

Yala		Maha	
Week	Probability	Week	Probability
12	0.89	40	0.78
13	0.78	41	0.51
14	0.67	42	0.52
15	0.71	43	0.52
16	0.70	44	0.17
17	0.77	45	0.13
18	0.72	46	0.11
19	0.76	47	0.11
20	0.90	48	0.12
21	0.99	49	0.23
		50	0.14
		51	0.03
		52	0.02
		1	0.03
		2	0.13
		3	0.29
		4	0.41
		5	0.59
		6	0.98

8.2.4 Crop failures

The possibility of complete crop failures in both seasons of the Dry zone was investigated using simulated soil moisture results with the following assumptions. First, planting or sowing may take place with the simulated onset time. Second, a dry week, available soil moisture below 50 per cent, immediately after the sowing or planting may dry out the top soil and produce a failure to germinate or seedlings to wither. After the second week, when the plants are well established, their roots have capacity to absorb moisture from deeper layers and therefore can survive upto further two weeks under dry conditions. Any soil moisture depletion below the 50% available soil moisture level which lasts more than two consecutive weeks causes a complete crop failure. The model was run for 10 times with different random number streams, each simulates 1000 years. The objective was to account as much as possible the randomness of the rainfall. The Table 8.2 shows the probability of complete crop failures in the both growing seasons of the Dry zone with 10 different runs. Results indicate that crop failure probabilities are converging to the values of 0.10 and 0.02 for the Yala and Maha seasons respectively. Thus, at least one out of every ten years there would be a complete crop failure during the Yala season. However, occurrence of complete crop failures during the Maha season would be only one year out of fifty years.

8.3 Overall summary

In this thesis, a system model was developed which is capable of simulating the growing seasonal characteristics of the Dry zone of Sri Lanka. It consists of two major sub-models; rainfall model and soil water balance model.

The suitable rainfall sub-model was chosen out of three Markovian models studied; the first-order discrete time Markov model, the second-order discrete time Markov model and the continuous time Markov model. Out of them, the first-order discrete time Markov model was integrated into the system model as it was a reasonable representation of the weekly rainfall process in the Dry zone on the basis of statistical

Table 8.2 Probabilities of a complete crop failure during the two major growing seasons in the Dry zone of Sri Lanka.

	Probabilities of crop failures in the season	
Run	Yala	Maha
1	0.11	0.03
2	0.10	0.01
3	0.10	0.02
4	0.10	0.02
5	0.10	0.02
6	0.09	0.03
7	0.07	0.02
8	0.11	0.01
9	0.11	0.02
10	0.09	0.02

performances and practical ease. The soil water balance sub-model was a single-layer water balance model which treated the entire root zone as a reservoir for soil water. Simulated values from these both sub-models were in reasonable agreement with the observed data collected from a representative location of the Dry zone.

The system model used five agro-climatic indices to define the two major growing seasons in the Dry zone out of which four indices are already in use in the literature. A new index, crop water satisfaction index (CWSI) was defined using mean rainfall, dependable rainfall and potential evapotranspiration. Considering the stochasticity of weather variables especially the rainfall, the system model was run for 1000 times to provide a better estimate of the frequency of extreme events. The predicted growing season characteristics were compared with the published information on growing seasons characteristics of the Dry zone. It revealed that the model can predict the growing season characteristics of both Yala and Maha seasons of the Dry zone with a reasonable agreement with the real time data. The newly defined crop water satisfaction index (CWSI) in this study rate quite well with the other mostly recognised agro-climatic indices such as AET/PET ratio and moisture mvailability index (MAI) in defining the growing seasons in the Dry zone. Furthermore, the study bared some useful seasonal characteristics such as probabilities of dry spells, temporal variation of available soil moisture and crop failures with the extended temporal variation through the simulation.

The system model is capable of determining the correlation between onset of the season and seasonal characteristics on request. The onset time of the seasonal rains as a predictor for amount of rainfall or duration of the both Yala or Maha seasons was not clearly evident in this simulation study though such links have been apparent in other monsoonal areas of the tropic. The deterministic predictability of the rainfall in the Dry zone was also examined using the Southern Oscillation Index (SOI) and its two extreme phases, El Niño and La Niña episodes. The observed data signalled the influence of the El Niño events on the both Yala and Maha seasons indicating a possibility of forecasting the upcoming growing seasons. The link between La Niña events and the seasonal rainfall of the Dry zone was inconclusive at the absence of

enough data. The importance of the SOI as a predictor of the seasonal rainfall of the Dry zone was not evident.

An additional model was also developed to estimate the missing or ungauged data of weekly rainfall in the Dry zone assuming spatial continuity of rainfall between two neighbouring locations are exponentially correlated. This model could provide missing or unavailable data in a rainfall time series when they are needed for parameter estimation of the stochastic rainfall models or for any other relevant uses. Although the individual estimated values of weekly rainfall from the developed model were not well represented the observed weekly rainfall values, its performance of estimating mean weekly parameters was excellent.

8.4 Future directions

8.4.1 Rainfall models

The ability of stochastic model to reproduce or preserve the statistical properties of historical data is the main evaluation criterion for stochastic models. The validation has shown that both first-order and second-order discrete time Markov rainfall models are capable of producing time series of weekly rainfall of arbitrary length for future studies. We have concentrated only the Dry zone of Sri Lanka. An important extension of this study would be to test for neighbouring regions especially the Wet zone. One aspect being to determine whether the simple order chain is appropriate at other regions of the Sri Lanka.

Although the continuous time Markov model does not seem to be promising for the intended purpose, it does show a potential in modelling weekly rainfall during the wet periods of the year. Therefore, it may be worthwhile to do a rigorous and comprehensive study to investigate its potential especially with a more shorter time base because parameters of the continuous model then would relate more or less directly to the time frame of physical mechanisms that govern the rainfall.

8.4.2 Soil water balance model

Many alternate water balance models are available and use in today and several have been mentioned in the Section 4.2. The model presented here is a simple one that treat the entire root zone as a reservoir for soil water, and includes various assumption about the water movement in the soil and availability to crops. The complex models that consider instantaneous root growth and portioning evapotranspiration into its components, evaporation and transpiration, are substantially better than the model presented here. Time and data availability have not permitted comparisons of the model with more complex models, but such comparisons need to be made.

The water balance model presented here assumes that the entire Dry zone is completely occupied by the RBE soils. However, there is a wide range of soil groups in well drained soils in the Dry zone such as Non-Calcic Brown soils (Haplustalf) and Red-Yellow Latosols (Haplustox). These two major soil groups do not contain the characteristics gravel layer of the RBE soils. In addition, their textural classes also differ from the RBE soils. Both these deviations from the RBE soils can have a significant effect on the water movement within the soil and the extraction by the crops. Therefore, more comprehensive field studies are required to generalise the applicability of the soil water balance sub-model for the entire Dry zone.

8.4.3 Spatial interpolation model

The spatial interpolation model developed in this thesis allows an expanded spatial source of rainfall data for parameter estimation in stochastic models or any other climatological applications. Although, it appears to be no real advantage in exponential correlation model developed here over the simpler models such as local mean and inverse distance method under the Dry zone's environment, its use in complex topographical situations like the Wet zone environment could be more appropriate over the simple models. Therefore, an extensive validation of the exponential correlation model should be undertaken with the Wet zone rainfall data.

In particular, validations are required at transitional areas between Dry and Wet zones where the rainfall data are meagre so that the model can provide the extended spatial data for delineation of the smooth boundaries of transitional zones.

8.4.4 System model

The ultimate intended application of the system model was simulation of growing season characteristics in the Dry zone. At present, the model accomplish this task using only the rainfall and crop water demand. The other two climatic factors that may influence the crop growth in the Dry zone of Sri Lanka are high temperature regimes during flowering and grain filling, and the incidence of diseases as a result of high humidity. Thus, to be most useful, the model will need to have the temperature and saturation deficit as input variables. Unfortunately, the increase of number of weather variables in the model would result in unreasonably large parameter set. One possible method is to use the Fourier series or other periodic functions such as polynomials to represent the variability of parameters of these two variables through the year. As the temporal changes of temperature and saturation deficit in the Dry zone are fairly uniform in the absence of abrupt changes, such a generalisation would not diminish the performance of the model.

The system model does not contain any component of the productivity. The next major step in the model development is to include a simplified representation of crop physiology, a deterministic approach, to predict the crop yields. Such a combination of stochastic and deterministic models should help to understand how different amounts of rainfall or irrigation can impact on the crop production in the Dry zone.

8.4.5 Programming language

The entire model has been written in SIMSCRIPT II.5. As the SIMSCRIPT is a highly specific language, a common object oriented programming language may be more appropriate to enable the wider usage of the model. However, this may lead to re-coding some of the routines as common programming languages may not carry

some specialised algorithms available in the SIMSCRIPT that have been used in the system model developed in this study.

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Appendix 1

The conditional probabilities in continuous Markov chain

mid-April to mid-July;

$$f(p_1) = -0.06748t^4 - 0.09551t^3 + 0.405t^2 - 0.60t \qquad [1]$$

where

$$f(p_1) = p_m (W_i | W_{i-1}) - 1 \qquad [2]$$

$$\frac{f(p_1)}{t} = -0.06748t^3 + 0.09551t^2 + 0.405t - 0.60$$

As $t \to o$

$$\frac{f(p_1)}{t} = -0.60 \qquad [3]$$

If $f(p_2) = p_m (W_i | D_{i-1})$, $\qquad [4]$

$$f(p_2) = 0.022691t^5 - 0.04646t^4 + 0.356t^3 - 1.245t^2 + 1.78t \qquad [5]$$

$$\frac{f(p_2)}{t} = 0.022691t^4 - 0.04646t^3 + 0.356t^2 - 1.245t + 1.78$$

As $t \to o$

$$\frac{f(p_2)}{t} = 1.78 \qquad [6]$$

The intensity matrix A;

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} -0.6 & 1.78 \\ 1.78 & -0.6 \end{bmatrix}$$

Together with the initial probability vector (0.90,0.50), the transition probabilities satisfy the Kolmogorov forward equation;

$$\frac{\partial p^{i,j}(t)}{\partial t} - \sum_{k=1}^{N} p^{i,k}(t) a^{k,j} = 0$$

$$\frac{\partial p^{11}}{\partial t} = P^{11}a^{11} + P^{12}a^{21} \qquad [7]$$

$$\frac{\partial p^{11}}{\partial t} = P^{11}(-0.60) + P^{12}(1.78)$$

$$\frac{\partial p^{11}}{\partial t} = P^{11}(-0.60) + 1.78(1 - P^{11})$$

By solving the differential equation with the initial value of 0.90

$$P = 0.747899 - 727.4814e^{-2.38t} \qquad [8]$$

That is

$$P_m(W_i|W_{i-1}) = 0.747899 - 727.4814e^{-2.38t} \qquad [9]$$

Similarly, with the initial value of 0.50,

$$P_m(W_i|D_{i-1}) = 0.747899 - 1185.6741e^{-2.38t} \qquad [10]$$

mid-July to the end of the year

$$f(p_1) = -0.0007035t^4 + 0.0901t^3 + 0.04426t^2 - 0.644985t \qquad [11]$$

where

$$f(p_1) = p_m(W_i|W_{i-1}) - 1 \qquad [12]$$

$$\frac{f(p_1)}{t} = -0.0007035t^3 + 0.0901t^2 + 0.04426t - 0.644985$$

As $t \to o$

$$\frac{f(p_1)}{t} = -0.644985 \qquad [13]$$

If $f(p_2) = p_m(W_i|D_{i-1})$, $\qquad [14]$

$$f(p_2) = 0.0006806t^5 - 0.02619t^4 + 0.3707t^3 - 2.276t^2 + 5.137t \qquad [15]$$

$$\frac{f(p_2)}{t} = 0.0006806t^4 - 0.02619t^3 + 0.3707^2 - 2.276t + 5.137$$

As $t \to o$

$$\frac{f(p_2)}{t} = 5.137 \qquad [16]$$

The intensity matrix A;

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} -0.644985 & 5.137 \\ 5.137 & -0.644985 \end{bmatrix}$$

Together with the initial probability vector (0.30,0.10), the transition probabilities satisfy the Kolmogorov forward equation;

$$\frac{\partial p^{i,j}(t)}{\partial t} - \sum_{k=1}^{N} p^{i,k}(t) a^{k,j} = 0$$

$$\frac{\partial p^{11}}{\partial t} = P^{11} a^{11} + P^{12} a^{21} \qquad \qquad [17]$$

$$\frac{\partial p^{11}}{\partial t} = P^{11}(-0.644985 + P^{12}(5.137)$$

$$\frac{\partial p^{11}}{\partial t} = P^{11}(-0.644985) + 5.137(1 - P^{11})$$

By solving the differential equation with the initial value of 0.30

$$P = 0.8885237 - 0.6977568 \times 10^{17} \, e^{-5.7815t} \qquad \qquad [18]$$

That is

$$P_m(W_i|W_{i-1}) = 0.8885237 - 0.6977568 \times 10^{17} \, e^{-5.7815t} \qquad \qquad [19]$$

Similarly, with the initial value of 0.10,

$$P_m(W_i|D_{i-1}) = 0.888601 - 0.9317955 \times 10^{17} \, e^{-5.781t} \qquad \qquad [20]$$

Appendix 2

The standard weeks

Week No.		Dates	Week No.		Dates
1	January	1 - 7	27	July	2 - 8
2		8 - 14	28		9 - 15
3		15 - 21	29		16 - 22
4		22 - 28	30		23 - 29
5		29 - 4	31		30 - 5
6	February	5 - 11	32	August	6 - 12
7		12 - 18	33		13 - 19
8		19 - 25	34		20 - 26
9		26 - 4*	35		27 - 2
10	March	5 - 11	36	September	3 - 9
11		12 - 18	37		10 - 16
12		19 - 25	38		17 - 23
13		26 - 1	39		24 - 30
14	April	2 - 8	40	October	1 - 7
15		9 - 15	41		8 - 14
16		16 - 22	42		15 - 21
17		23 - 29	43		22 - 28
18		30 - 6	44		29 - 4
19	May	7 - 13	45	November	5 - 11
20		14 - 20	46		12 - 18
21		21 - 27	47		19 - 25
22		28 - 3	48		26 - 2
23	June	4 - 10	49	December	3 - 9
24		11 - 17	50		10 - 16
25		18 - 24	51		17 - 23
26		25 - 1	52		24 - 31$^{\Psi}$

* In a leap year the week No. 9 will be 26th February to March 4th March.

Ψ The last week will have 8 days.

Appendix 3

Relationship between soil moisture availability and relative evapotranspiration (AET/PET)
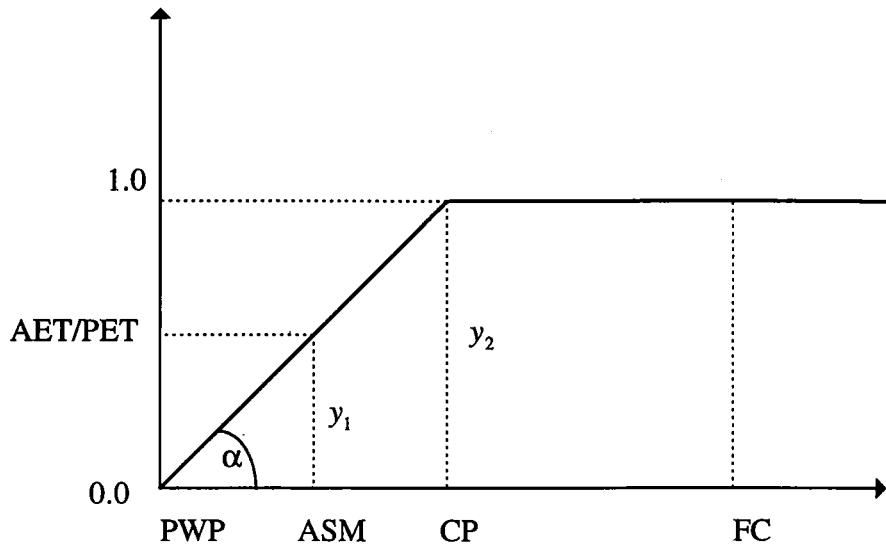
Let ASM = Available soil moisture at a given point

    CP = Available soil moisture at the critical point

  PWP = Soil moisture content at the permanent wilting point

   FC = Field capacity

  AET = Actual evapotranspiration

  PET = Potential evapotranspiration

$$\frac{y_1}{ASM - PWP} = \frac{y_2}{CP - PWP}$$

$$y_2 = 1$$

$$\frac{AET}{PET}(CP - PWP) = ASM - PWP$$

$$\therefore \quad AET = PET\left[\frac{ASM - PWP}{CP - PWP}\right]$$

Appendix 4

SIMSCRIPT II.5 source code of the sytem model

preamble

define EFFRF, RAINFALL, " rainfall values
  SCALE, SCALE1, SHAPE, SHAPE1, " used for prob. distribution parameters

  P1, P2, PB1, PB2, ALPHA,
  1_ALPHA, BETA, 1_BETA, " used in transition probabilities

MEAN.EFFRF, MEAN.EVAPOR, MEAN.AET, MEAN.PET, MEAN.RF,
MEAN.ASM " mean values after completing the simulation

PET, AET, REFEVAP, ASM, SIMASM, MAI, RAINVALUE,
  " values required to calculate the required criteria

 CRITLEVEL, INPUT.CRITLVL and INDEX as real variables
   " critical levels of the selected criteria
define ASM.LEVEL as a real variable " ASM probability value
define ASM.COUNT, YALA.CROP.FAIL.COUNT and MAHA.CROP.FAIL.COUNT as integer
   variables
define ASM.ARRAY as a 2-dimensional real array " weekly ASM data
define CROP.FAIL as a text variable " crop failure statistics wanted or not

define CODE1," code for the prob. distributions with rainfall
  CODE, " code for prob. distribution with evaporation

SIM.NO, I, NUM.RUN, NO.SIM, "simulation counters

WEEK.OR.AVERAGE, MAHA.OR.YALA, RF.OR.AETPET,
    " selection criteria methods

COUNT, COUNT2, K, J and WEEK.NO as integer variables" loop counters

define ASM.STATISTICS and ONSET.CORR as integer variables
    " at the user inteface decide whether these
    " two statistics are to be determined

define DRYWEEK.CALC,CROP.FAIL.PROB
  and PARTICULAR.WEEKRF as integer variables
   " whether dryweek probs are wanted

define DRYTHRESHOLD as a integer variable " specify the threshold value to
    " consider week as a dry one
define DRYWEEK.COUNT.ARRAY as a 2-dimensional integer array
 " counts of initial, W/W , D/W , W/D , D/D conditional counts

define REQ.WEEK as an integer variable " user entered value of week to be examined

```
define WEEKLY.DATA.REQUIRED as a text variable
       " whether a particular weeks RF data is wanted

define CRIT,CRITERIA as text variables

define WEEKLY.RF.ARRAY as a 2-dimensional real array
           " stores weekly RF data for each run

define INDEX1.ARRAY as a 2-dimensional real array
           " stores mean data for the selected criteria

define RAINPROB as a 1-dimensional real array
           " used to calculate 75% rainfall prob value

define MAHA.CHAR, YALA.CHAR  as 2-dimensional real arrays
       " arrays to store season start,finish, length and RF values

define WEEKLY.DATA.ARRAY as a 2-dimensional real array
           " stores the weekly selceted criteria data for each run

define RAINVALUE.ARRAY as a 1-dimensional real array
           " stores 75% rainfall values

define RFVALUE.ARRAY as a 1-dimensional real array
           " stores RF values for a week if user needs
end
```

main

```
ASM.LEVEL=0

Call SELECTCRITERIA "criteria to determine the
               " seasonal characteristics using average of simulations

 reserve INDEX1.ARRAY as 7 by 52     " array to store average characteristics
 reserve WEEKLY.RF.ARRAY as NUM.RUN by 52
           " storing RF or AET/PET of each simulation run
 reserve RAINPROB as NUM.RUN         " store the RF, but this is purely to
                                     " calculate the 75% probability
 reserve WEEKLY.DATA.ARRAY as NUM.RUN by 52
 reserve RAINVALUE.ARRAY as 52  " storing 75% weekly rainfall values
 reserve RFVALUE.ARRAY as NUM.RUN  " rf value array
 reserve ASM.ARRAY as NUM.RUN by 52  " stores weekly ASM data
 reserve DRYWEEK.COUNT.ARRAY as 5 by 52  " stores initial and conditional dryweek counts


P1=0.8667 " initial probabilities
P2=0.1333 "  ditto

PWP = 114.6 " Available water at PWP
CP  = 167.3  " availble water at critical point, 75% of total ASM
FC  = 184.9  " Available water at FC
ASM = FC " availble water at the begining of the year

open unit 9 for output, File name is "Output.dat"
use unit 9 for output
```

```
open unit 2 for input, file name is "Evapdist.txt"

open unit 3 for input, file name is "Midist.dat"

open unit 8 for input, file name is "Mitrmat7.dat"

for WEEK.NO = 1 to 52
 do
   use unit 2 for input
   read CODE,SCALE, SHAPE   "reading evaporation distribution parameters

   use unit 3 for input
   read CODE1,SCALE1, SHAPE1  " reading rainfall distribution parameters

   use unit 8 for input
   read ALPHA, 1_ALPHA,BETA,1_BETA " reading elements of transition matrix

   PB1 = (P1*ALPHA + P2*BETA)   " calculating unconditional probabilty of week being wet
   PB2 = (P1*1_ALPHA + P2*1_BETA) "        week being dry

   P1=PB1
   P2=PB2

   MEAN.EFFRF = 0
   MEAN.AET   = 0
   MEAN.PET   = 0
   MEAN.ASM   = 0
   ASM.COUNT  = 0

   for SIM.NO = 1 to NUM.RUN
    do
      Call MarkovRF given P1 yielding EFFRF and RAINFALL
      Call Evaporation yielding EVAPOR

      compute MEAN.RF as the mean of RAINFALL
      compute MEAN.EFFRF as the mean of EFFRF
      compute MEAN.EVAPOR as the mean of EVAPOR

      WEEKLY.RF.ARRAY(SIM.NO,WEEK.NO)=RAINFALL  " storing weekly rainfall
      RAINPROB(SIM.NO)=RAINFALL  "storing rainfall to calculate 75% value

      Call CROPFACTOR yielding CROPFACT " crop coefficients across the season

      PANFACT = 0.8    " Pan factor Kp
      REFEVAP = EVAPOR * PANFACT " calculating Ref.Et, Et0
      PET = CROPFACT * REFEVAP   " calculating PET

      SIMASM= -((ASM+EFFRF+((PET*PWP)/(CP-PWP)))/(-1-(PET/(CP-PWP))))
                   " calc. ASM for each run,MAPLE

      if SIMASM < PWP   "setting lower boundary condition
        SIMASM = PWP
       always

      if SIMASM > FC  " setting upper boundary condition
        SIMASM = FC
       always
```

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```
if SIMASM < CP  " calculating AET when soil is under tension (soil moisture stress)
  AET = PET*((SIMASM-PWP)/(CP-PWP))
 else
  AET = PET  " AET is at its potential rate when there is no soil moisture stress
 always

if ASM.LEVEL<>0
  if SIMASM<ASM.LEVEL      " calculating prob < ASM critical level
    ASM.COUNT=ASM.COUNT+1
  always
 always

ASM.ARRAY(SIM.NO,WEEK.NO)=SIMASM  " storing weekly ASM in array

compute MEAN.AET as the mean of AET
compute MEAN.PET as the mean of PET
compute MEAN.ASM as the mean of SIMASM

select case CRITERIA " storing data to enable season determination
  case "Mean Rainfall Method"

  case "75% Probability Method"
   WEEKLY.DATA.ARRAY(SIM.NO,WEEK.NO)=RAINFALL
  case "MAI Method","CWSI Method"
   WEEKLY.DATA.ARRAY(SIM.NO,WEEK.NO)=PET
  case "AET/PET Method"
   WEEKLY.DATA.ARRAY(SIM.NO,WEEK.NO)=AET/PET
 endselect

if WEEK.NO=REQ.WEEK and PARTICULAR.WEEKRF <> 0
    " if rainfall data required for a particular week number
  RFVALUE.ARRAY(SIM.NO)=RAINFALL
 always

loop  " Sim.No loop

ASM = MEAN.ASM

Call SORTRAIN  " getting 75% RF value

RAINVALUE.ARRAY(WEEK.NO)=RAINVALUE

INDEX1.ARRAY(1,WEEK.NO)=MEAN.AET  " writing mean AET into the array
INDEX1.ARRAY(2,WEEK.NO)=MEAN.PET  " writing mean PET into the array
INDEX1.ARRAY(3,WEEK.NO)=MEAN.ASM  " writing mean ASM into the array
INDEX1.ARRAY(5,WEEK.NO)=MEAN.RF
INDEX1.ARRAY(6,WEEK.NO)=RAINVALUE
INDEX1.ARRAY(7,WEEK.NO)=ASM.COUNT/NUM.RUN

select case CRITERIA  " is to get the desired criteria for season definition
  case "Mean Rainfall Method"
   INDEX1.ARRAY(4,WEEK.NO)=MEAN.RF
  case "75% Probability Method"
   INDEX1.ARRAY(4,WEEK.NO)=RAINVALUE
  case "MAI Method"
   INDEX1.ARRAY(4,WEEK.NO)=RAINVALUE/MEAN.PET
  case "AET/PET Method"
   INDEX1.ARRAY(4,WEEK.NO)=MEAN.AET/MEAN.PET
```

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```
    case "CWSI Method"
       INDEX1.ARRAY(4,WEEK.NO)=(MEAN.RF-RAINVALUE)/MEAN.PET
    endselect


loop  " Week.No loop

close unit 2
close unit 3


for K = 1 to NUM.RUN
  do
    for J = 1 to 52
      do
        select case CRITERIA " storing the determined index value using specified index
          case "Mean Rainfall Method","AET/PET Method"

          case "75% Probability Method"
            WEEKLY.DATA.ARRAY(K,J)=WEEKLY.DATA.ARRAY(K,J)-RAINVALUE.ARRAY(J)
          case "MAI Method"

WEEKLY.DATA.ARRAY(K,J)=WEEKLY.RF.ARRAY(K,J)/WEEKLY.DATA.ARRAY(K,J)
          case "CWSI Method"
            WEEKLY.DATA.ARRAY(K,J)=(WEEKLY.RF.ARRAY(K,J)-
RAINVALUE.ARRAY(J))/WEEKLY.DATA.ARRAY(K,J)
        endselect
      loop
    loop

print 6 lines with NUM.RUN and CRITERIA as follows

Characteristics of Agro-climate at Maha-Illuppallama with **** Simulation runs

  Week No   Mean RF   75% RF   Mean AET   MEAN PET   Mean ASM   ASM PROB
  ************************
   =======  =========  ======  ========  ========  ========  ========
==============================

for COUNT= 1 to 52  " printing average of each criteria for each week
  do
  print 1 line with COUNT, INDEX1.ARRAY(5,COUNT),
INDEX1.ARRAY(6,COUNT),INDEX1.ARRAY(1,COUNT),INDEX1.ARRAY(2,COUNT),
      INDEX1.ARRAY(3,COUNT), INDEX1.ARRAY(7,COUNT) and
INDEX1.ARRAY(4,COUNT) thus
    ***     ***.*   ***.*   ***.**   ***.**   ***.*   **.**   ***.**
  loop

WEEK.OR.AVERAGE=1  " a condition for case statement
            " use the average conditions to characterise the seasons


I=35  " printing seasonal characteristics, maha should start afeter week 35
Call FINDSTART yielding MAHA
I=MAHA+1
Call FINDEND yielding MAHAEND
I=MAHAEND+1
Call FINDSTART yielding YALA
if YALA>14 " setting 2 weeks criteria to start the yala season
```

" if 3 weeks criteria fails
WEEK.OR.AVERAGE=2
I=MAHAEND+1
Call FINDSTART yielding YALA
always
I=YALA+1
Call FINDEND yielding YALAEND

Call SEASONCHARAC given YALA,YALAEND,MAHA,MAHAEND

Call ONSETCORRELATION

Call CROPFAILURE

close unit 8

close unit 9

" printing rf values of the specified week to a file

Call WEEKLYDATA

" printing initial and conditional probabilities to a file

Call DRYWEEK

Call OUTPUT_FILES

end

Routine CROPFACTOR yielding CF

```
select case WEEK.NO  " crop factor determination
      case 10,11,12,13,38,39,40,41    CF=0.7
      case 14,15,16,17,42,43,44,45    CF=1.103
      case 18,19,20,21,46,47,48,49    CF=0.967
      case 22,23,50,51,52,1,2,3,4,5   CF=0.74
      case 6,7,8,9,24,25,26,27,28,
         29,30,31,32,33,34,35,36,37 CF = uniform.f(.54,0.85,6)
endselect

return
end
```

Routine CROPFAILURE
" determining the probability of crop failure when ASM is < the 50% ASM soon after
" the onset or 3 consecutive weeks < 50% ASM for the yala and maha seasons

define YALA.START.WEEK and MAHA.START.WEEK as integer variables
define CRIT.ASM.LEVEL as a real variable
define FAILED.CROP as a text variable
" boolean variable to ensure that the crop only fails once in a season

```
open unit 7 for output, file name is "CROPFAIL.DAT"
use unit 7 for output

if CROP.FAIL.PROB = 0  "if specified by user
  print 3 lines as follows

  This option was not selected

 else
  if CRITERIA="75% Probability Method" or CRITERIA="MAI Method"
    print 3 lines with CRITERIA thus

  The crop failure probabilities can not be determined using
    the **********************
  else

YALA.CROP.FAIL.COUNT=0
MAHA.CROP.FAIL.COUNT=0
CRIT.ASM.LEVEL=150  " 50% ASM

for SIM.NO = 1 to NUM.RUN    " crop failure during yala season
do
  FAILED.CROP="NO"  " initialising varaible
  YALA.START.WEEK = YALA.CHAR(1,SIM.NO)
    " getting yala start week from the array written in season charac

  if YALA.START.WEEK=0    " when no yala season is encountered
   YALA.CROP.FAIL.COUNT=YALA.CROP.FAIL.COUNT+1
   FAILED.CROP="yes"
   always

if ASM.ARRAY(SIM.NO,YALA.START.WEEK+1)<CRIT.ASM.LEVEL and
FAILED.CROP<>"yes"
     " checking the ASM level in the first week of the growing season
    YALA.CROP.FAIL.COUNT=YALA.CROP.FAIL.COUNT+1
    FAILED.CROP="yes"  " crop can only fail once in a season
    always

  until FAILED.CROP="yes" or (YALA.CHAR(2,SIM.NO)-YALA.START.WEEK)<2
   do    " looking at 3 consecutive weeks
    if ASM.ARRAY(SIM.NO,YALA.START.WEEK)<CRIT.ASM.LEVEL and
ASM.ARRAY(SIM.NO,YALA.START.WEEK+1)<CRIT.ASM.LEVEL
      and ASM.ARRAY(SIM.NO,YALA.START.WEEK+2)<CRIT.ASM.LEVEL
      YALA.CROP.FAIL.COUNT=YALA.CROP.FAIL.COUNT+1
      FAILED.CROP="yes"
      always

    YALA.START.WEEK=YALA.START.WEEK+1
   loop

loop


for SIM.NO = 1 to NUM.RUN   " crop failure during maha season
  do                " comments same as above
  FAILED.CROP="NO"
  MAHA.START.WEEK = MAHA.CHAR(1,SIM.NO)
```

```
    if MAHA.START.WEEK=0 or MAHA.START.WEEK<35    " or start week early in the year
      MAHA.CROP.FAIL.COUNT=MAHA.CROP.FAIL.COUNT+1
      FAILED.CROP="yes"
    always

    if ASM.ARRAY(SIM.NO,MAHA.START.WEEK+1)<CRIT.ASM.LEVEL and
FAILED.CROP<>"yes"
      MAHA.CROP.FAIL.COUNT=MAHA.CROP.FAIL.COUNT+1
      FAILED.CROP="yes"  " crop can only fail once in a season
    always

until FAILED.CROP="yes" or (MAHA.CHAR(2,SIM.NO)-MAHA.START.WEEK)<2 or
MAHA.START.WEEK>50
    do
      if ASM.ARRAY(SIM.NO,MAHA.START.WEEK)<CRIT.ASM.LEVEL and
ASM.ARRAY(SIM.NO,MAHA.START.WEEK+1)<CRIT.ASM.LEVEL
        and ASM.ARRAY(SIM.NO,MAHA.START.WEEK+2)<CRIT.ASM.LEVEL
        MAHA.CROP.FAIL.COUNT=MAHA.CROP.FAIL.COUNT+1
        FAILED.CROP="yes"
      always

      MAHA.START.WEEK=MAHA.START.WEEK+1
    loop

loop

" printing results

Print 4 line with YALA.CROP.FAIL.COUNT/NUM.RUN and
MAHA.CROP.FAIL.COUNT/NUM.RUN thus

The probability of crop failure in the yala season is *.**
The probability of crop failure in the maha season is *.**

    always
  always

close unit 7

return

end
```

Routine DRYWEEK
```
    " finding probability of each week being dry, as well as conditional probabilities
    " and printing results to a file

define H,I and PREVWEEK as integer variables

for WEEK.NO = 1 to 52
  do
    for H=1 to NUM.RUN
      do
        if WEEK.NO=1    " looking at week-1 for week 1
          PREVWEEK=52
          else
          PREVWEEK=WEEK.NO-1
```

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always

    if WEEKLY.RF.ARRAY(H,WEEK.NO) < DRYTHRESHOLD " initial prob.

DRYWEEK.COUNT.ARRAY(1,WEEK.NO)=DRYWEEK.COUNT.ARRAY(1,WEEK.NO)+1
   always

    if WEEKLY.RF.ARRAY(H,WEEK.NO) > DRYTHRESHOLD and
WEEKLY.RF.ARRAY(H,PREVWEEK) > DRYTHRESHOLD
      " P(W/W)

DRYWEEK.COUNT.ARRAY(2,WEEK.NO)=DRYWEEK.COUNT.ARRAY(2,WEEK.NO)+1
   else
    if WEEKLY.RF.ARRAY(H,WEEK.NO) < DRYTHRESHOLD and
WEEKLY.RF.ARRAY(H,PREVWEEK) > DRYTHRESHOLD
      " P(D/W)

DRYWEEK.COUNT.ARRAY(3,WEEK.NO)=DRYWEEK.COUNT.ARRAY(3,WEEK.NO)+1
    else
    if WEEKLY.RF.ARRAY(H,WEEK.NO) > DRYTHRESHOLD and
WEEKLY.RF.ARRAY(H,PREVWEEK) < DRYTHRESHOLD
      " P(W/D)

DRYWEEK.COUNT.ARRAY(4,WEEK.NO)=DRYWEEK.COUNT.ARRAY(4,WEEK.NO)+1
    else
    if WEEKLY.RF.ARRAY(H,WEEK.NO) < DRYTHRESHOLD and
WEEKLY.RF.ARRAY(H,PREVWEEK) < DRYTHRESHOLD
      " P(D/D)

DRYWEEK.COUNT.ARRAY(5,WEEK.NO)=DRYWEEK.COUNT.ARRAY(5,WEEK.NO)+1
    always
    always
    always
    always

  loop
 loop

open unit 11 for output, file name is "condprob.dat"
use unit 11 for output

if DRYWEEK.CALC = 0
  Print 3 lines as follows

  This option was not selected.

 else

print 6 lines with NUM.RUN thus

Probabilities after ***** simulation runs

WEEK P(Dry) P(Wet/Wet) P(Dry/Wet) P(Wet/Dry) P(Dry/Dry)
==== ====== ========== ========== ========== ==========

for I= 1 to 52
 do

```
     print 1 line with I, DRYWEEK.COUNT.ARRAY(1,I)/NUM.RUN,
DRYWEEK.COUNT.ARRAY(2,I)/NUM.RUN,
     DRYWEEK.COUNT.ARRAY(3,I)/NUM.RUN, DRYWEEK.COUNT.ARRAY(4,I)/NUM.RUN
and
     DRYWEEK.COUNT.ARRAY(5,I)/NUM.RUN thus
**    *.**    *.**    *.**    *.**    *.**
loop

 always

close unit 11

return

end
```

Routine EVAPORATION yielding EVAP

```
if CODE=1
 EVAP=Gamma.f(SCALE*SHAPE,SHAPE,8)
 else
  if CODE=2
   EVAP=Weibull.f(SHAPE,SCALE,3)
   else
    if CODE=3
     EVAP=Log.normal.f(SHAPE,SCALE,4)
     else
      EVAP=Normal.f(SHAPE,SCALE,9)
    always
   always
 always

return

end
```

Routine FINDEND yielding SEASEND
```
 " finding the seasons end
define INDICATOR,M as an integer variable

INDICATOR=0 " only a boolean variable

" M is used to check whether it has been gone through whole 52 weeks
" so that the number weeks (either 2 or 3) can be changed

M=I

until INDICATOR=1 " loop to detect the season end
 do
  if I=51 " resetting to week 1
   I=1
   always

   select case WEEK.OR.AVERAGE " whether to characterise by weekly data or
              " bymean weekly data after the total number of
              " simulations (average) specified
```

```
case 1 " using average (3 week) conditions

  if INDEX1.ARRAY(4,I)<CRITLEVEL and INDEX1.ARRAY(4,I+1)<CRITLEVEL
      and INDEX1.ARRAY(4,I+2)<CRITLEVEL
    SEASEND=I

    INDICATOR=1
    always

case 2 " using average (2 week) conditions

  if INDEX1.ARRAY(4,I)<CRITLEVEL and INDEX1.ARRAY(4,I+1)<CRITLEVEL
    SEASEND=I

    INDICATOR=1
    always


case 3  " finding season end using weekly data (3 week criteria)
  select case CRITERIA
    case "Mean Rainfall Method"  " rainfall
    if WEEKLY.RF.ARRAY(NO.SIM,I)<CRITLEVEL and
WEEKLY.RF.ARRAY(NO.SIM,I+1)<CRITLEVEL
        and WEEKLY.RF.ARRAY(NO.SIM,I+2)<CRITLEVEL
      SEASEND=I
      INDICATOR=1
      always
      if I=M-1  " changes to 2 week criteria
        WEEK.OR.AVERAGE=4
        I=M
        always

    case "MAI Method","AET/PET Method","CWSI Method"
                                      " MAI,AETPET,SMRI
    if WEEKLY.DATA.ARRAY(NO.SIM,I)<CRITLEVEL and
WEEKLY.DATA.ARRAY(NO.SIM,I+1)<CRITLEVEL
        and WEEKLY.DATA.ARRAY(NO.SIM,I+2)<CRITLEVEL
      SEASEND=I
      INDICATOR=1
      always
      if I=M-1  " changes to 2 week criteria
        WEEK.OR.AVERAGE=4
        I=M
        always
      endselect

case 4  " finding season end using weekly data (2 week criteria)
  select case CRITERIA
    case "Mean Rainfall Method"  " rainfall
    if WEEKLY.RF.ARRAY(NO.SIM,I)<CRITLEVEL and
WEEKLY.RF.ARRAY(NO.SIM,I+1)<CRITLEVEL
      SEASEND=I
      INDICATOR=1
      always
      if I=M-1
        SEASEND=0
        always
```

```
          case "MAI Method","AET/PET Method","CWSI Method" " MAI,AETPET,SMRI
            if WEEKLY.DATA.ARRAY(NO.SIM,I)<CRITLEVEL and
WEEKLY.DATA.ARRAY(NO.SIM,I+1)<CRITLEVEL
              SEASEND=I
              INDICATOR=1
              always
            if I=M-1
              SEASEND=0
              always
            endselect

        endselect

        I=I+1 " increasing the counter to next week

      loop  " until

  return

  end



```

Routine FINDSTART yielding SEASONSTART
" finding seasons start

define INDICATOR,M as an integer variable

INDICATOR=0 "boolean indicator

" comments are identical to routine FINDEND
M=I

```
until INDICATOR=1
  do
    if I=51
    I=1
    always

    select case WEEK.OR.AVERAGE
      case 1 "determining the season start using the average of the simulated years
        if INDEX1.ARRAY(4,I)>=CRITLEVEL and INDEX1.ARRAY(4,I+1)>=CRITLEVEL
          and INDEX1.ARRAY(4,I+2)>=CRITLEVEL
        SEASONSTART=I
        INDICATOR=1
        always

      case 2 "determining the season start using the 2 week average of the simulated years
        if INDEX1.ARRAY(4,I)>=CRITLEVEL and INDEX1.ARRAY(4,I+1)>=CRITLEVEL
        SEASONSTART=I
        INDICATOR=1
        always


      case 3 " finding season end using weekly data (3 week criteria)
        select case CRITERIA
          case "Mean Rainfall Method" " rainfall
```

```
        if WEEKLY.RF.ARRAY(NO.SIM,I)>=CRITLEVEL and
WEEKLY.RF.ARRAY(NO.SIM,I+1)>=CRITLEVEL
           and WEEKLY.RF.ARRAY(NO.SIM,I+2)>=CRITLEVEL
           SEASONSTART=I
           INDICATOR=1
           always
           if I=M-1
            WEEK.OR.AVERAGE=4
           always

        case "MAI Method","AET/PET Method","CWSI Method" " MAI,AETPET,SMRI
           if WEEKLY.DATA.ARRAY(NO.SIM,I)>=CRITLEVEL and
WEEKLY.DATA.ARRAY(NO.SIM,I+1)>=CRITLEVEL
             and WEEKLY.DATA.ARRAY(NO.SIM,I+2)>=CRITLEVEL
           SEASONSTART=I
           INDICATOR=1
           always
           if I=M-1
            WEEK.OR.AVERAGE=4
           always
         endselect

    case 4  " finding season end using weekly data (2 week criteria)
      select case CRITERIA
       case "Mean Rainfall Method"  " rainfall
          if WEEKLY.RF.ARRAY(NO.SIM,I)>=CRITLEVEL and
WEEKLY.RF.ARRAY(NO.SIM,I+1)>=CRITLEVEL*0.75
             SEASONSTART=I
             INDICATOR=1
             always
             if I=M-1
             SEASONSTART=0
             always

       case "MAI Method","AET/PET Method","CWSI Method"  " MAI,AETPET,SMRI
          if WEEKLY.DATA.ARRAY(NO.SIM,I)>=CRITLEVEL and
WEEKLY.DATA.ARRAY(NO.SIM,I+1)>=CRITLEVEL*0.75
             SEASONSTART=I
             INDICATOR=1
             always
             if I=M-1
             SEASONSTART=0
             always
          endselect


    endselect

    I=I+1

    loop

return
end
```

Routine MARKOVRF given PROB1 yielding EFRAIN and RAIN

```
let X=1 " random number

until X < PROB1
  do
   let X = random.f(6)
  loop

if CODE1=1
  RAIN=Gamma.f(SCALE1*SHAPE1,SHAPE1,2)
  else
   if CODE1=2
    RAIN= weibull.f(SHAPE1,SCALE1,4)
    else
     if CODE1=3
      RAIN= Log.normal.f(SHAPE1,SCALE1,3)
      else
      RAIN=exponential.f(SCALE1,2)
      always
     always
    always


select case WEEK.NO "correcting for effective rainfall

  case 1,2
   let EFRAIN=0.95*RAIN
  case 3,4
   let EFRAIN=0.60*RAIN
  case 5,6,7,8,9,10,11
   let EFRAIN=0.95*RAIN
  case 12,13,14,15
   let EFRAIN=0.75*RAIN
  case 16,17
   let EFRAIN=0.65*RAIN
  case 18,19,20,21
   let EFRAIN=0.55*RAIN
  case 22,23,24,25,26,27,28,29,30,31,32,33,34,
     35,36,37,38,39
   let EFRAIN=RAIN
  case 40,41
   let EFRAIN=0.75*RAIN
  case 42,43
   let EFRAIN=0.5*RAIN
  case 44,45,46,47,48,49
   let EFRAIN=0.60*RAIN
  case 50,51,52
   let EFRAIN=0.65*RAIN
endselect "end of case statements

return

end
```

Routine ONSETCORRELATION " determining season's characteristics for
" each simulated year

reserve MAHA.CHAR as 4 by SIM.NO " stores the maha characteristics
reserve YALA.CHAR as 4 by SIM.NO " store the yala charateristics

open unit 4 for output, file name is "ONSET.DAT"
use unit 4 for output

if ONSET.CORR = 0
  print 3 lines as follows

    This option was not selected.

  else
   if CRITERIA="75% Probability Method" or CRITERIA="MAI Method"
    print 3 lines with CRITERIA thus

   The season characteristics can not be determined using
    the ************************
   else

for NO.SIM=1 to NUM.RUN " loop to read each simulated year
  do

" following will produce rainfall of each simulation run
"   for L=1 to 52
"   do
"   print 1 line with NO.SIM,L,WEEKLY.DATA.ARRAY(NO.SIM,L) thus
" **   ***   *** *
"   loop

   Call SEASONDETERMINATION yielding MSTART,MFIN,YSTART and YFIN

   MAHA.OR.YALA=1 " tells to which array results should be written (1=maha , 2=yala)
   Call SEASONRAINFALL given MSTART,MFIN
   MAHA.OR.YALA=2
   Call SEASONRAINFALL given YSTART,YFIN

 loop " loop for No. Sim

print 7 line with CRIT as follows " printing rainfall output weekly

Relationship between the Onset and Season Characteristics using the
****

M Start M Fin Length RF   Y Start Y Fin Length RF
------- ----- ------ ----   ------- ----- ------ ----

for A=1 to SIM.NO
  do
   print 1 line with MAHA.CHAR(1,A),MAHA.CHAR(2,A),MAHA.CHAR(3,A),
    MAHA.CHAR(4,A),YALA.CHAR(1,A),YALA.CHAR(2,A),YALA.CHAR(3,A) and
YALA.CHAR(4,A) thus
***   ***   ***   **** *   ***   ***   ***   **** *

 loop " for A

```
    always
    always

close unit 4

return
end
```

Routine OUTPUT_FILES
```
" shows a dialogue box with the name of different
" output files

define FORM.PTR as a pointer variable
define FIELD.ID as a text variable

show FORM.PTR with "output.frm"

FIELD.ID = ACCEPT.F(FORM.PTR,0)

if FIELD.ID = "EXIT"
  stop
  always
return
end
```

Routine SEASONCHARAC given YALA1,YALAEND1,MAHA1,MAHAEND1
```
YALALENGTH=YALAEND1-YALA1 + 1  " finding the seasons length
 if MAHAEND1<35 " when end is in the next year
   MAHALENGTH=52-MAHA1+MAHAEND1 + 1
   else
   MAHALENGTH=MAHAEND1-MAHA1 + 1" end is within the same year
 always

print 20 lines with CRITERIA,YALA1,YALAEND1,MAHA1,MAHAEND1,YALALENGTH and
MAHALENGTH as follows
```

Season Characteristics determined using **

  By Week No. *** soil moisture is sufficient
      for sowing of short age yala crop

  BY Week No. *** Yala season ceases

  By Week No. *** soil moisture is sufficient
      for sowing of Maha crop

  BY Week No. *** Maha season ceases

Length of the yala season is only **** weeks

Length of the maha season is **** weeks

```
Return
end
```

Routine SEASONDETERMINATION yielding
MAHASTART,MAHAFIN,YALASTART and YALAFIN

" this determines the start and finish of both yala and maha seasons

```
WEEK.OR.AVERAGE=3  " condition for the case statement
              " to determine the seasons start and end
              " using either average or each week conditions


I=35  " look start from this week

Call FINDSTART yielding MAHASTART

if MAHASTART<35 " if no start is found by week 52
         " then use a 2 week criteria
  WEEK.OR.AVERAGE=4
  I=35
  Call FINDSTART yielding MAHASTART
  always


I=1 "  find season end

WEEK.OR.AVERAGE=3  " resetting to 3 week criteria

if MAHASTART=0 " if a maha season with zero is found,
  MAHAFIN=0    " so the maha finish also zero
  else
  Call FINDEND yielding MAHAFIN
  always


I=MAHAFIN+1  " yala start should be after week 5

Call FINDSTART yielding YALASTART

I=YALASTART+1
if YALASTART=0  " if a yala season with zero is found,
  YALAFIN=0     " yala finish also zero
  else
  Call FINDEND yielding YALAFIN
  always

if MAHAFIN>10  " if maha finish is >10 then use 2 week criteria to find end
  I=1
  WEEK.OR.AVERAGE=4
  Call FINDEND yielding MAHAFIN
  always

if YALASTART=MAHASTART " if yala and maha starts are equal find another
          " yala start using 2 week criteria

  I=MAHAFIN+1
   WEEK.OR.AVERAGE=4
  Call FINDSTART yielding YALASTART

  I=YALASTART+1
  Call FINDEND yielding YALAFIN
  always
```

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" checking if there is no yala season

    if YALASTART=MAHASTART or MAHAFIN=YALAFIN or YALASTART>MAHASTART or
YALASTART>25
      YALASTART=0
      YALAFIN=0
      always

return

end

Routine SEASONRAINFALL given STARTWEEK,FINISHWEEK
" determining the season length and its rainfall
" for each simulated run to be used in CORRELATION routine

define COUNTER and SEASONLENGTH as integer variables
define TOTRAIN as a real variable

TOTRAIN=0

if FINISHWEEK<STARTWEEK " if the season end in next year
  SEASONLENGTH=52-STARTWEEK+FINISHWEEK

  " following 2 FOR loops will determine the RF
  for COUNTER= STARTWEEK to 52
    do
      TOTRAIN=WEEKLY.RF.ARRAY(NO.SIM,COUNTER)+TOTRAIN
    loop

  for COUNTER= 1 to FINISHWEEK-1 "
    do
      TOTRAIN=WEEKLY.RF.ARRAY(NO.SIM,COUNTER)+TOTRAIN
    loop

else " if end is within the same year

  SEASONLENGTH=FINISHWEEK-STARTWEEK
  for COUNTER= STARTWEEK to FINISHWEEK-1
    do
    TOTRAIN=TOTRAIN+WEEKLY.RF.ARRAY(NO.SIM,COUNTER)
    loop
  always

"print 1 line with NO.SIM,STARTWEEK,FINISHWEEK,SEASONLENGTH and TOTRAIN thus
" ***   ***   ***   ***   ***.*

select case MAHA.OR.YALA " writing the results to array
  case 1 " for maha
    MAHA.CHAR(1,NO.SIM)=STARTWEEK
    MAHA.CHAR(2,NO.SIM)=FINISHWEEK
    MAHA.CHAR(3,NO.SIM)=SEASONLENGTH
    MAHA.CHAR(4,NO.SIM)=TOTRAIN
  case 2 " for yala
    YALA.CHAR(1,NO.SIM)=STARTWEEK

```
      YALA.CHAR(2,NO.SIM)=FINISHWEEK
      YALA.CHAR(3,NO.SIM)=SEASONLENGTH
      YALA.CHAR(4,NO.SIM)=TOTRAIN
    endselect

  return
  end
```

Routine SELECTCRITERIA

" Using Dialog Box to get simulation requirements

define FORM.PTR and CRITLEVEL.PTR as pointer variables

define FIELD.ID as a text variable

" initialising default values

```
NUM.RUN=100
ASM.LEVEL=170
DRYTHRESHOLD=7
REQ.WEEK=0
```

SHOW FORM.PTR with "input.frm"

" setting current parameter values on form

```
DDVAL.A(DFIELD.F("NUM.OF.RUNS", FORM.PTR)) = NUM.RUN
DDVAL.A(DFIELD.F("ASM.PROBABILITY", FORM.PTR)) = 0
DDVAL.A(DFIELD.F("ONSET.CORRELATION", FORM.PTR)) = 0
DDVAL.A(DFIELD.F("CRITASM.LEVEL", FORM.PTR)) = ASM.LEVEL
DDVAL.A(DFIELD.F("CROP.FAILURE", FORM.PTR)) = 0
DDVAL.A(DFIELD.F("DRY.WEEK", FORM.PTR)) = 0
DDVAL.A(DFIELD.F("DRY.LEVEL", FORM.PTR)) = DRYTHRESHOLD
DDVAL.A(DFIELD.F("PARTICULAR.WEEK", FORM.PTR)) = 0
DDVAL.A(DFIELD.F("WEEKRF.REQ", FORM.PTR)) = REQ.WEEK
```

let FIELD.ID= ACCEPT.F(FORM.PTR,0)

```
if FIELD.ID= "EXIT"
  stop
  always
```

" setting the new parameter values

```
NUM.RUN = DDVAL.A(DFIELD.F("NUM.OF.RUNS", FORM.PTR))
CRITERIA = DTVAL.A(DFIELD.F("SEASON.METHOD", FORM.PTR))
```

```
select case CRITERIA
  case "Mean Rainfall Method"
    CRITLEVEL=20
  case "75% Probability Method"
    CRITLEVEL=10
  case "MAI Method"
    CRITLEVEL=0.33
  case "AET/PET Method"
    CRITLEVEL=0.33
```

```
    case "CWSI Method"
       CRITLEVEL=0.75
   endselect


" getting dialogue box for the critical values

SHOW CRITLEVEL.PTR with "critlevel.frm"
DDVAL.A(DFIELD.F("CRIT.LEVEL", CRITLEVEL.PTR)) = CRITLEVEL " getting
                              " default value
let FIELD.ID= ACCEPT.F(CRITLEVEL.PTR,0)
CRITLEVEL = DDVAL.A(DFIELD.F("CRIT.LEVEL", CRITLEVEL.PTR))


" getting onset correlation field

ONSET.CORR = DDVAL.A(DFIELD.F("ONSET.CORRELATION", FORM.PTR))
CROP.FAIL.PROB = DDVAL.A(DFIELD.F("CROP.FAILURE", FORM.PTR))


" getting ASM field

ASM.STATISTICS = DDVAL.A(DFIELD.F("ASM.PROBABILITY", FORM.PTR))
  if ASM.STATISTICS <> 0
    ASM.LEVEL=DDVAL.A(DFIELD.F("CRITASM.LEVEL",FORM.PTR))
    always


" getting onset weekly prob. calculation field

DRYWEEK.CALC = DDVAL.A(DFIELD.F("DRY.WEEK", FORM.PTR))
  if DRYWEEK.CALC <> 0
    DRYTHRESHOLD= DDVAL.A(DFIELD.F("DRY.LEVEL",FORM.PTR))
    always


" getting weekly Rf calculation field

PARTICULAR.WEEKRF = DDVAL.A(DFIELD.F("PARTICULAR.WEEK", FORM.PTR))
  if PARTICULAR.WEEKRF <> 0
    REQ.WEEK = DDVAL.A(DFIELD.F("WEEKRF.REQ", FORM.PTR))
    always


return
end
```

Routine SORTRAIN

```
            " This will sort the simulated RF data in an ascending
            " order and calculate the 75% probability value of
            " weekly RF
define DONE as a text variable
define CURRENT as a real variable
define NEXTPOS,REMAINDER,DIVISOR and UNSORTED as integer variables

for UNSORTED= 2 to NUM.RUN " using insertion sort of pascal language
  do               " sort the data into an ascending order
   DONE="false"
   CURRENT=RAINPROB(UNSORTED)
   NEXTPOS=UNSORTED

   while (NEXTPOS>1) and (DONE="false")
     do
```

```
    if RAINPROB(NEXTPOS-1)>CURRENT
     RAINPROB(NEXTPOS)=RAINPROB(NEXTPOS-1)
     NEXTPOS=NEXTPOS-1
    else
     DONE="true"
    always
   loop "while

  RAINPROB(NEXTPOS)=CURRENT
 loop " for

DIVISOR=div.f(NUM.RUN+2,4)
REMAINDER=mod.f(NUM.RUN+2,4)

IF (REMAINDER=0)  " getting RF value for corresponding position
 RAINVALUE=RAINPROB(DIVISOR)
else
 RAINVALUE=(RAINPROB(DIVISOR)+RAINPROB(DIVISOR+1))/2
always

return
end
```

Routine WEEKLYDATA

```
open unit 10 for output, file name is "WeekRf.dat"
use unit 10 for output

if PARTICULAR.WEEKRF = 0
  Print 3 lines as follows

   You did not specify a week

 always

if PARTICULAR.WEEKRF <> 0

Print 3 lines with REQ.WEEK thus

The weekly simulated rainfall data for week **

for I= 1 to NUM.RUN
 do
  print 1 line with RFVALUE.ARRAY(I) thus
***.**
 loop

 always

close unit 10

return
end
```