SYNTHETIC RAINFALL AND ITS USE IN HYDROLOGIC MODELING

By

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PREFACE

This study was stimulated by the need to overcome the problems associated with the prediction of watershed runoff in rural areas for which there is little or no climatic data available. The project was financed by the Oklahoma State University Agricultural Experiment Station under project R-1632, "Development of Hydrologic and Water Quality Models for Agriculture and Forestry".

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CHAPTER 1

INTRODUCTION

The term stochastic, in the hydrological context, refers to the random nature of a variate such as rainfall, stream flow, or wind velocity. Runoff modeling refers to the analytical simulation of runoff processes that take place in natural watersheds with a view to the prediction of runoff and the effect that changes in the watershed characteristics may have on the runoff on an annual, monthly, daily or storm basis.

The principal input for watershed models is rainfall data which is most costly and time consuming to collect. In remote or rural areas this data is often not available, is unreliable, or the records are of short duration. Furthermore, observed rainfall data, although essential, give the researcher the opportunity to study the hydrology of watersheds based upon only one realization of a rainfall sequence. The use of other rainfall sequences, having the same (or similar) properties as the observed sequence, could yield a range of useful runoff results that would be produced by equally likely rainfall series. Synthetic sequences of rainfall based upon the stochastic structure of the historic series are useful for this purpose.

Various methods have been used over the past two and a half decades to generate rainfall data stochastically. Two major techniques have emerged. One is to generate an annual rainfall sequence assuming a normal distribution about a long term mean. The annual rainfall amount is then disaggregated into monthly, biweekly or weekly values based upon annual fragment sets determined from observed records (Srikanthan and McMahon, 1980; Lane, 1982). The process is repeated for each year of the simulated annual time series. This process follows the principle of working from the whole to the part.

The second technique follows the principle of working from the part to the whole. Daily rainfall events are generated by way of a Monte Carlo process to determine the rainfall state and/or rainfall amount. Typically a Markov process is used to determine the dry or wet state of a day given the state of the previous day (Cole and Sherriff, 1972; Buishand, 1978; Nicks and Harp, 1980) and the 2x2 transitional probability matrix describing the probability of a wet or dry day occurring after the occurrence of a wet or dry day. The determination of the rainfall amount accumulated on a wet day is usually based upon the assumption that the daily rainfall amounts fit a predetermined distribution.

The choice of the generation technique would be governed in part by the purpose for which the rainfall data will be used. Such generated rainfall data may be used to supplement limited historical records or provide long term synthetic records which, together with a rainfall-runoff model, can be used:

a. to determine watershed yields for irrigation, urban or industrial use,

b. to generate stream flow records,

c. to determine the effect of land use or other hydrologic changes on watershed yield,

d. to design water storage structures for a particular assured water supply,

e. as a watershed management tool for erosion control,

f. to establish standards for agricultural practices to ensure hydrologic stability and agricultural productivity over the long term,

g. in the design of water resources systems which often require long term records of daily rainfall data.

Objectives

The objectives of this study were to

a. develop a stochastic daily rainfall model and

b. evaluate the use of simulated rainfall data and a runoff model to study watershed hydrologic responses.

Scope of the Study

The research covered two main aspects of hydrologic research - the generation of synthetic daily rainfall data and the use of this data to predict runoff from agricultural watersheds using an hydrologic model.

A stochastic model was developed to generate daily rainfall data assuming stationarity within each month. The similarity of the simulated and historic records were assessed with respect to the relative frequency of rainfall amounts, the number of consecutive wet and dry day runs, monthly accumulated rainfall and annual accumulated rainfall.

The hydrologic response of an agricultural watershed to the synthetic and historic rainfall data was examined by applying a rainfall-runoff model to a watershed (R-7) of 19.5 acres located at Chickasha, about 100 miles Southwest of Stillwater. This watershed, operated by the USDA-ARS Water Quality and Watershed Research Laboratory from 1966 to 1978, was used by Pathak (1983) to asses the performance of the CREAMS hydrologic model (Knisel, 1980) to predict runoff from a grassland watershed. The applicable soil profile data and watershed parameters established by Pathak (1983) were used with the CREAMS model on the Chickasha R-7 watershed on the strength of his findings. The predicted runoff produced by the model using the synthetic and observed rainfall input data respectively were compared in terms of the mean monthly runoff, mean annual runoff, accumulated annual runoff and frequency of monthly runoff amounts.

CHAPTER II

LITERATURE REVIEW

In accordance with the objectives of this study, literature in two distinct fields of hydrologic research were examined - rainfall simulation and runoff prediction. These two fields cannot, however, be divorced from each other and be studied independently. Rainfall data is the principle input of any runoff prediction model and the form in which it is available (or is synthesized) has a major bearing on the runoff model to which it can be applied. Previous work relating to the generation of daily rainfall and the prediction of daily runoff, aggregated to obtain weekly, biweekly, monthly and annual runoff values, was reviewed, adhering to the principle (adopted by Diskin et al. 1973) of working from the part to the whole.

Daily Rainfall Models

Most techniques for generating daily rainfall sequences use a separate process for the simulation of a rainfall occurrence (wet days or dry days) and another process to simulate the rainfall amount on a wet day (Buishand, 1978). The probability of the occurrence of a wet day appears to have been studied first by Newham (1916) in England. He concluded that wet (and dry) weather is persistent and that the probability of a wet day occurring is related to the number of preceding wet days. Although this was confirmed by Lawrence (1954) it was not supported by Longley (1953) in his studies in Canada. The latter showed that a wet day following a wet day (or a dry day following a dry day) is almost independent of the number of preceding wet (or dry) days. Gabriel and Neumann (1962) have been cited as being the first to use the Markov chain to describe the occurrence of daily rainfall events. Chin (1977) investigated the use of higher order Markov chains to model daily rainfall occurrence. He voiced doubt about the application of a 1st order Markov chain for this purpose due to the persistence of daily rainfall events. Evidence indicating the feasibility of using a 1st order Markov chain to describe a sequence of daily rainfall records has, however, been presented by other authors such as Gabriel and Neumann, 1962; Cole and Sherriff, 1972; Buishand, 1978; Nicks and Harp, 1980. The Markov chain used in hydrologic simulation is a special application of the more general Markov process.

The Markov Chain

Markov processes have been used by most researchers in developing stochastic rainfall models for more than twenty years (Buishand, 1978). A Markov process can be described as a process for generating a value (X_n) of a variable at the nth time interval while taking into account the value of the variable at each of the i preceding time intervals. A factor r(i) describes the relative influence of the value at the ith preceding time interval on the value of X_n. The maximum value of i describes the 'order' of the process.

The mathematical relationships defining the 1st order Markov process can be found in Haan (1977), Linsley et al. (1982) and others in the following form.

$$X_{n+1} = \mu_x + r_x(1)(X_n - \mu_x) + \varepsilon_{n+1}$$

where X_n = value of the process at time n

μ_x = mean value of X

$r_x(1)$ = first order serial correlation

ε_{n+1} = random component

If ε_{n+1} is selected from a distribution which is normally distributed with a mean equal to zero and variance equal to σ_x^2, then the above relationship can be written as

$$X_{n+1} = \mu_x + r_x(1)(X_n - \mu_x) + R_{n+1}\,\sigma_x\sqrt{1 - r_x^2(1)}$$

where σ_x^2 = variance of X

R_{n+1} = random component which is normally distributed with a mean equal to zero and variance equal to one.

A 1st order Markov chain is a special case of a Markov process in which the value of the variable (X_n) at time n depends only on its value (X_{n-1}) at time n-1 and is independent of the sequence of values X_{n-2}, X_{n-2}, ..., X_0 that the variable takes on before arriving at its value at time n (Haan, 1977). The variable (X_n) is further usually classified into an arbitrarily chosen number of classes (C) or ranges called 'states' of the variable. A CxC transitional probability matrix is required to describe the probability of occurrence of any state given an existing state. The probability (p_{ij}) of a transition from state i to j can be represented as

$$p_{ij} = \text{prob}(X_n = C_j | X_{n-1} = C_i) \qquad i, j > 0$$

The CxC transitional probability matrix $\underline{P}$ is written as follows:

$$\underline{P} = p_{ij} = \begin{vmatrix} p_{11} & p_{12} & \cdots & p_{1C} \\ p_{21} & p_{22} & & \vdots \\ \vdots & & & \vdots \\ p_{C1} & \cdots & \cdots & p_{CC} \end{vmatrix}$$

The Markov chain has become the tool most often used in modeling to generate rainfall events.

<u>Rainfall Occurrence</u>

Gabriel and Neumann (1962) found that a simple Markov chain probability model fitted the occurrence of daily rainfall in Tel Aviv. Caskey (1963) fitted a first order Markov chain model to the occurrence of wet and dry days at Denver, Colorado, for each of four seasons into which he divided the year. Weiss (1964) showed that a two state Markov chain probability model could fit sequences of wet and dry days in records of various lengths and for climatically different areas. Hopkins and Robillard (1964) also found that a two state Markov chain model gave acceptable approximations to the April-September frequency statistics for durations of dry spells recorded in 45 years of observations at three cities in Canada. The model was less satisfactory in predicting the total number of rainy days per month, tending to underestimate the frequency of months with few rainy days.

Feyerherm and Bark (1965) developed a procedure based upon a first order Markov chain to estimate the probability of occurrence of a given consecutive sequence of wet (and dry) days, beginning with any day of the year. In 1967 they reported the adequacy of a first order Markov chain for computing probabilities but found that it may not be satisfactory for long sequences. Research by Lowry and Gutherie (1968) showed that first order Markov chain models of daily rainfall occurrence are adequate for the prediction of the probability of wet or dry spells. They suggested that the threshold value indicating a wet day should be relatively small.

Selvalingam and Miura (1978) used a two state first order Markov chain model to generate daily rainfall events for each calendar month. They assumed that the system was stationary during each month. Snyder (1976) presented methods for estimating continuous, seasonally varying, transition probabilities using non-linear least squares methods. Richardson (1981), while also using a two state Markov chain to model the occurrence of rain, used a Fourier series to describe the seasonal nature of the transitional probabilities.

Rainfall Amount

In rainfall modeling, rainfall amounts can be determined only after the sequence of wet and dry spells have been generated (Cole and Sherriff, 1972; Selvalgingan and Miura, 1978). Besides multi-state Markov chain models the most common approach is to assume that daily rainfall amounts on successive days are independent and to fit some recognized probability distribution (Tordorovic and Woolhiser, 1974, 1975; Woolhiser et al 1973). Another approach is to assume that rainfall amounts are independent but that the distribution function depends upon whether the previous day was wet or dry (Katz, 1977). Buishand (1977) distinguished three different types of wet days, namely, solitary wet days, wet days bounded on one side by a wet day and by a dry day on the other side and a wet day bounded on both sides by a wet day.

While researchers have generally ignored any persistence in rainfaill amounts on successive wet day, no single distribution has been shown to be universally suitable for the simulation of rainfall amounts (Skees and Shenton, 1974). Jones, Colwick and Threadgill (1972) obtained rainfall amounts by Monte Carlo sampling from a two parameter Gamma distribution. The Gamma distribution parameters were based upon data for the year ignoring persistence in rainfall amounts on successive days.

Cole and Sherriff (1972) made three distinct analyses of rainfall amounts based upon three criteria. These were (a) a solitary wet day, (b) the first day of a wet spell, (c) the remaining days of a wet spell. Empirical distributions and transitional probabilities were then used to generate rainfall amounts.

Allen and Haan (1975) used a multi-state (7x7) Markov chain model and a uniform distribution within each of the wet states except for the last one. An exponential distribution was used in the last state to generate rainfall amounts. Twelve transition probability matrices were estimated, one for each calendar month. Due to sparseness of data in the last class for each month the values in this class were lumped together. Only one value of the exponential parameter was estimated to generate the rainfall amount in this class for all months. The simulated mean monthly rainfall amounts calculated from the generated daily rainfall data were in agreement with the historical mean monthly amounts. Simulated average annual rainfall was, however, always greater than the historical value (by approximately 2.5%) and there was a slight trend towards underestimating the largest rainfall. A large number of parameters (505) had to be estimated and the model appeared to require at least 40 years of historical data at the Kentucky location for satisfactory parameter estimation.

Selvalingan and Miura (1978) modified the multistate 1st order Markov chain model of Allen and Haan (1975). Separate parameters were estimated for the exponential distribution for each monthly season. These parameters were, however, determined by trial and error making the model unsuitable as a general model for the generation of daily rainfall amounts. The same authors also reported the performance of a model in which a three parameter Gamma distribution was fitted to the square root of the daily rainfall amounts for each month. The rainfall on wet days generated in this way did not preserve the correlation between rainfall amount and the duration of the rainfall event.

Carey and Haan (1978) also modified the Markovian Model of Allen and Haan so that it could be used when limited historical daily rainfall data were available. The daily rainfall amounts were divided into three states. State 1 = < 0.005 inches (assumed dry), state 2 = 0.005 - 0.145 inches, state 3 = > 0.145 inches. The last two states contained approximately the same number of observations. Transitional probabilities were used to describe the occurrence of any one of the states on a particular day in a season given the state on the preceeding day. A two parameter Gamma distribution was fitted to the rainfall amounts within each state for each month. To reduce the number of parameters that needed to be estimated they showed that a single distribution could be fitted to the rainfall from all three states. Thus a total of 60 parameters (5 per season - two for the Gamma distribution and three for the occurrence of a dry day (or wet day) following each wet state) were required for the model. This model proved to be superior to the Allen and Haan Model (1975) with respect to the rainfall amount simulated, the number of parameters to be estimated and historical record required for stable parameter estimates. The daily rainfall data generated by the modified model reduced the error in simulated annual rainfall from 2.5 percent to 0.5 percent and about 150 historical rainfall events per season were required for stable estimates of the distribution parameters.

Bridges and Haan (1972) showed that only as the number of observations approached 100 would the estimated values of the parameters of the Gamma distribution approximate the population values. They produced tables for the evaluation of the adequacy of a rainfall record that may be used to determine the parameters of a Gamma distribution. Matalas (1967) presented evidence on the limitations on the use of a Gamma distribution to generate synthetic rainfall when the skewness coefficient of the historic record used to estimate the distribution parameters is greater than $2\sqrt{2}$.

In his paper more recently, McMahon and Miller (1971) supported this inconsistency of the Gamma function to preserve all the lower moments of historical data. He showed that for a skewness coefficient between $\pm$ 2 the Gamma transformation of a normal variable successfully preserves the moments of the historical data. Beyond these limits, however, no moment preservation is assured. Todorovic and Woolhiser (1974) found the application of the exponential distribution very promising in describing daily rainfall amounts and suggested that further investigations were warranted. Woolhiser and Roldan (1982) compared the use of the exponential, Gamma and mixed-exponential distributions as potential models for the distribution of daily rainfall. Using the maximum likelihood method to estimate the parameters for each distribution they found that the mixed exponential distribution was the best on the basis of the Akaike information criterion (Akaike, 1974). Richardson (1982), however, found that all three of the above distributions were capable of reproducing the historical distribution of annual and monthly rainfall data.

Experience has shown that the lognormal distribution is particularly suited to modeling daily rainfall amounts (Haan, 1977; Nicks, 1984). Three techniques can be used to determine the distribution parameters of the lognormal distribution. One method is to transform the data (X_i) to some concomitant values (Y_i) using the transformation

$$Y_i = \ln(X_i) \ .$$

If the historic data (X_i) are lognormally distributed then by the Central Limit Theorem the Y_i's will be normally distributed with mean μ_Y and variance σ_Y^2. The parameters of μ_Y and σ_Y^2 can be estimated by $\bar{Y}$ and S_Y^2 using standard statistical procedures.

A second method, present by Chow (1954) provides for the calculation of $\bar{Y}$ and S_Y^2 without taking the logarithms of all the data using the relationships

$$\bar{Y} = 1/2 \ln(X^2/Cv^2 + 1)$$

$$S_Y^2 = \ln(Cv^2 + 1)$$

where Cv = coefficient of variation of the original data.

A third method presented by Brakensiek (1958) uses the least squares method for estimating the parameters of a lognormal distribution.

Snyder and Wallace (1974) show how the nonlinear least squares method of fitting a three parameter lognormal distribution could be executed but suggested that one could not distinguish whether a gamma or lognormal distribution was the best distribution to apply to hydrologic data. In a later paper, Snyder (1975, 1976) further showed how this method can be used to adapt the lognormal distribution to a seasonally continuous distribution by making two of its three parameters cyclic functions of annual time.

Hansen (1982) showed that the two parameter lognormal distribution could be used to generate synthetic annual rainfall series. Using a limited record of annual averages, he estimated the distribution parameters from the log-transformed observations of an annual rainfall series.

Srikanthan and McMahon (1978) used the two-parameter and three-parameter lognormal distributions to model hydrologic data in Australia. Determining the distribution parameters from the log-transformed data they found that the two-parameter distribution overestimated the skewness and did not preserve the lag-1 serial correlation. They nevertheless recommended that when the coefficient of skewness exceeded 1.0 the two-parameter lognormal distribution gave the best results. This recommendation was, however, reversed in a later paper (Srikanthan and McMahon, 1980) in which the value of the skewness coefficient was not mentioned.

Haan (1977) and Matalas (1967) both commented on the inability of the lognormal and power transformation to preserve the mean, variance, coefficient of skewness and lag-1 serial correlation. They both pointed out that the distribution characteristics could not be carried through from the original data to the transformed data with the non-linear transformations. In order to retain the original distribution characteristics in a synthetically generated series using a log-transformation, the technique proposed by Chow (1954), or a more sophisticated method of Matalas (1967) was recommended.

The choice of one of the forementioned models (or any other model) for the generation of synthetic rainfall data will be dictated by (a) the sequence (annual, monthly, daily, hourly, etc.) that is to be generated, (b) the historical record available from which the distribution parameters have to be estimated and (c) the purpose for which the synthetic series is to be used. In this study synthetic rainfall data was required to examine the effect of applying historical, or statistically similar synthetic, rainfall series to a watershed model for the prediction of runoff.

Watershed Models

Watershed or hydrologic models can be classified as either material or formal. A material model is a simpler physical representation of a more complex system and may be an iconic (look alike) system or an analog system. That is a system in which physical phenomena, difficult to measure, are substituted by measurable quantities such as voltage, current or deflection. Eagleson (1970) suggested that material models have limited application in watershed modeling and favored the use of formal or mathematical models.

The advances in computer technology has stimulated the development of mathematical watershed models. Renard et al (1982) lists 175 models currently available. Woolhiser and Brakensiek (1982) give a comprehensive description of six classes of hydrologic models. Haan (1977) notes that most quantitative hydrologic models can be identified as deterministic, parametric, stochastic or a combination of these. There is no distinct division among these three basic types of models. Such hydrologic models, used to predict runoff, are either event simulation models or continuous simulation models (Nicks, 1982). Rainfall data is the most important and sensitive input required by runoff models and may be required in daily, hourly or smaller time increments. Some of the major hydrologic models and their required rainfall inputs are given in Table I. The rainfall increments required by the models tabulated, range from breakpoint (short unequal time intervals bounded by slope breakpoints on the rainfall recorder chart trace) for the CREAMS (Knisel, 1980) and USDAHL (Holtan et al. 1975) models to daily (accumulated in 24 hours) rainfall for the majority of the other models.

Each individual component in a complex watershed system is described in an hydrologic model, in varying degrees of detail. These components may include surface storage, infiltration, evapotranspiration, geomorphology, surface runoff, snowmelt, ground water flow, water quality, sediment yield and nutrient transport. Model parameters may be lumped or distributed. The simpler models with lumped parameters require less input data than the more complex models with spatially distributed parameters. The parameters of the latter models may be more physically based but require more computer time for simulations. Such distributed parameter hydrologic models, although normally too

TABLE I

MAJOR HYDROLOGIC MODELS

MODEL	AUTHOR	DATE	INPUT
U.S. Soil Conservation Service	Mockus	1964	by storm daily
Stanford Mark IV	Crawford and Linsley	1966	15-min hourly daily
USDAHL	Holtan et al.	1975	break-point hourly daily
Kentucky	Haan	1972	daily
HEC-1	U.S.A.C.E	1973	incremental
SSARR	U.S.A.C.E	1974	10-24 hour
ARM	Donigian & Crawford	1976(a)	5min, 15min
NPS	Donigian & Crawford	1976(b)	5min, 15min
ANSWERS	Beasley	1977	1-24 hour
CREAMS	Knisel	1980	daily break point
SMAP	Lopes et al.	1982	daily
SWRRB	Williams and Nicks	1983	daily

time consuming for engineering applications, can be useful for research purposes (Linsley et al. 1982).

The rainfall data (input) available and the purpose for which the runoff (output) is required are usually the major factors that dictate which hydrologic model will be used. For field scale applications of the CREAMS, ARM or NPS models, for example, a single gage or point rainfall amount is considered adequate. For basin size watersheds, especially if the watersheds are large, several raingage stations around and within the basin should be considered. The Thiesen weighted mean of such rainfall amounts has been shown to be the best estimate of basin rainfall amount (Nicks, 1982) A single centrally located gage in a watershed will tend toward the Thiesen rainfall average from multipoints.

Rainfall Data Source

There are two major sources of rainfall data available.

1. Hydrological Data for Experimental Agricultural Watersheds in the United States (operated by the United States Federal and State agencies, universities and private organizations. USDA-ARS has operated networks for rainfall data collection for research purposes for more than 40 years at many locations in the United States of America (Burford et al. 1980).

2. United States National Weather Service Co-operative observers and first order weather stations.

Nicks (1982) noted that rainfall data are available in time increments and spatial distribution ranging from one minute, from several gages in a single watershed, to daily, from a single gage located outside the watershed of interest.

CHAPTER III

RAINFALL MODEL DEVELOPMENT AND EVALUATION

Daily rainfall data for Stillwater, Oklahoma were used in developing a stochastic daily rainfall model. The data was collected over 80 years from 1900 to 1979 under the auspices of the Oklahoma State University. Although originally collated on magnetic tape and archived at the National Climatic Center in Ashville, North Carolina, these data were made available through the Oklahoma State University Water Research Institute (Stadler et al. 1982). The data consisted of the daily accumulated rainfall amounts in one-hundredths of an inch. The smallest rainfall amount in the record was 0.01 inches. An analysis of the data showed that 5800 wet days occurred over the period 1900 to 1979 in Stillwater. The results of a statistical analysis of the 5800 observations are shown in Table II. All the data analyses and model development were done using the SAS language (SAS, 1982) on the Oklahoma State University IBM-3081D computer.

TABLE II

STATISTICAL ANALYSIS OF THE 5800 WET DAYS THAT OCCURRED OVER THE PERIOD 1900 TO 1979 IN STILLWATER, OKLAHOMA

MONTH	DAILY MEAN (1/100 inch)	STD[1]	VAR[2]	SKEWNESS	KURTOSIS	MONTHLY MEAN (inch)
1	24.06	34.28	1175.68	2.65	8.26	1.04
2	26.78	34.25	1173.68	2.85	11.48	1.27
3	38.16	43.85	1923.10	1.95	4.40	2.18
4	44.36	57.61	3319.25	2.70	11.44	3.34
5	50.47	70.07	4910.68	3.33	18.06	4.77
6	50.23	58.88	3467.36	2.28	8.18	3.94
7	49.97	70.36	4950.77	2.90	11.62	2.98
8	48.03	67.80	4597.65	3.28	18.50	2.96
9	59.45	79.89	6382.82	2.46	8.00	3.75
10	51.29	66.32	4399.06	2.97	15.21	2.83
11	44.29	58.59	3432.98	2.64	9.36	2.08
12	29.86	35.97	1293.91	1.90	4.03	1.28
	Annual Total					32.42

[1]STD = standard deviation, [2]VAR = variance

The rainfall model developed consisted of two distinct stages. The first stage generated the occurrence of a rainfall event. A 1st order, two state Markov chain was used in this stage following the recommendations of Gabriel and Neumann (1962), Gringorton (1966), Smith and Schreiber (1974), Haan (1977), Nicks et al. (1980) and Richardson (1981). The second stage of the model generated the amount of rainfall accumulated in a day given that a wet day occurred. This daily rainfall amount was generated using a log-normal distribution found to be applicable by Srikanthan and

McMahon (1978), and Nicks (1984). The Gamma distribution was not considered on the recommendation of Matalas (1967) and Srikanthan and McMahon (1978). Both authors suggested that the Gamma distribution should not be used to describe data if the coefficient of skewness of the data was not within the interval of $\pm$ 2. The skewness coefficients of the daily rainfall amounts for most months did not fall within this range (Table II).

Following this two stage procedure, the model generates observations only for wet days.

Model for Rainfall Occurrence

A 1st order, two state, Markov chain was used to describe the occurrence of wet days and dry days. The notation $P(W|W)$ was used to describe the probability of a wet day occurring given that the previous day was wet and $P(W|D)$ was used to describe the probability that a wet day occurred given that the previous day was dry.

Using the above probabilities, the probability of a dry day occurring given the previous day was wet, $P(D|W)$, and the probability of a dry day occurring given that the previous day was dry, $P(D|D)$, was determined from

$$P(D|W) = 1 - P(W|W)$$

$$P(D|D) = 1 - P(W|D)$$

Thus calculating the probabilities $P(W|W)$ and $P(W|D)$ fully defined the 2x2 transitional probability matrix required to implement the Markov chain model. The matrix can be written as

	e_i	
e_{i-1}	D	W
D	$P(D\|D)$	$P(W\|D)$
W	$P(D\|W)$	$P(W\|W)$

where e_i is the occurrence of event e on day i. The transitional probability matrix shown in Table III was determined from the eighty years of daily rainfall data for Stillwater, Oklahoma. In calculating these transitional probabilities it was noted that the number of transition counts $N(W|D)$ from a dry to wet state was equal to the number transition counts $N(D|W)$ from a wet to dry state. It was therefore only necessary to count the number of transitions from a dry to wet state $N(W|D)$ and from a wet to wet state $N(W|W)$.

Since

$$N(W|D) = N(D|W)$$

The count

$$N(D|D) = T - 2N(W|D) + N(W|W)$$

where T = total number of days in 80 years.

TABLE III

OVERALL TRANSITIONAL PROBABILITY MATRIX, FROM 80 YEARS OF DAILY RAINFALL DATA FOR STILLWATER, OKLAHOMA

	D	W
D	.846	.154
W	.623	.377

Since the transitions to a wet or dry state from a given state are mutually exclusive, the sum of the transitional probabilities to the two states from a given state is equal to one. That is since

$$P(D|D) + P(W|D) = 1$$

Then,

$$P(D|D) = N(D|D)/(N(D|D) + N(W|D))$$

and

$$P(W|D) = N(W|D)/(N(D|D) + N(W|D))$$

Also, since

$$P(D|W) + P(W|W) = 1$$

Then,

$$P(D|W) = N(D|W)/(N(D|W) + N(W|W))$$

and

$$P(W|W) = N(W|W)/(N(D|W) + N(W|W))$$

Applying the above procedures to the monthly data for Stillwater, aggregated over the 80 years of record, twelve monthly transitional probability matrices were calculated. These matrices are shown in Table IV.

The above estimation procedure is a maximum likelihood procedure and can be expressed in the following terms (Allen and Haan, 1975).

$$P_{ij}^{(k)} = f_{ij}^{(k)} / \sum_{j=0}^{i} f_{ij}^{(k)} \qquad (i,j = 0,1 \text{ and } k = 1,...12)$$

where $P_{ij}^{(k)}$ is the probability, for season k of the transition from state i to state j,

$f_{ij}^{(k)}$ is the transition count from state i to state j,

i,j=0 represents a dry day,

i,j=1 represents wet day and

k = 1,2,...12 denotes month of the year.

TABLE IV

MONTHLY TRANSITIONAL PROBABILITY MATRICES CALCULATED FROM 80 YEARS OF DAILY RAINFALL FOR STILLWATER, OKLAHOMA

	D	W	D	W	D	W
	JANUARY		FEBRUARY		MARCH	
D	.895	.105	.870	.130	.852	.148
W	.651	.349	.646	.354	.656	.344
	APRIL		MAY		JUNE	
D	.799	.201	.746	.254	.792	.208
W	.600	.400	.579	.421	.589	.411
	JULY		AUGUST		SEPTEMBER	
D	.845	.155	.838	.162	.840	.160
W	.652	.348	.653	.347	.600	.400
	OCTOBER		NOVEMBER		DECEMBER	
D	.826	.134	.884	.116	.890	.110
W	.621	.379	.622	.378	.683	.317

A first order, two state Markov chain model to generate rainfall occurrence was built around the transitional probabilities $P(W|W)$, $P(W|D)$ and a uniform random number generator. The flowchart for the model is shown in Figure 1. The SAS (SAS, 1982) program is included in the program listed in Appendix A.

Model for Rainfall Amount

The amount of rainfall accumulated on a wet day was assumed to be independent of the amount accumulated on the previous day. This assumption was verified by examing the relative frequency of the occurrence of rainfall amounts on all the wet days (total data), on wet days following dry days (dry data) and on wet days following wet days (wet data). Daily rainfall amounts were catagorized into 0.1 inch classes for the analyses which were performed on the monthly aggregated data for the 80 year record. The relationship of the relative frequency versus daily rainfall amount was plotted, for each month, for the total data, the dry data and the wet data. The graphical comparison of these curves for the month of December, illustrated in Figure 2, show that there is no marked difference among the rainfall amounts on the three types of wet days. Similar plots for the other months in the year can be seen in Appendix B. In these plots there is no evidence to reject the assumption of independence stated above.

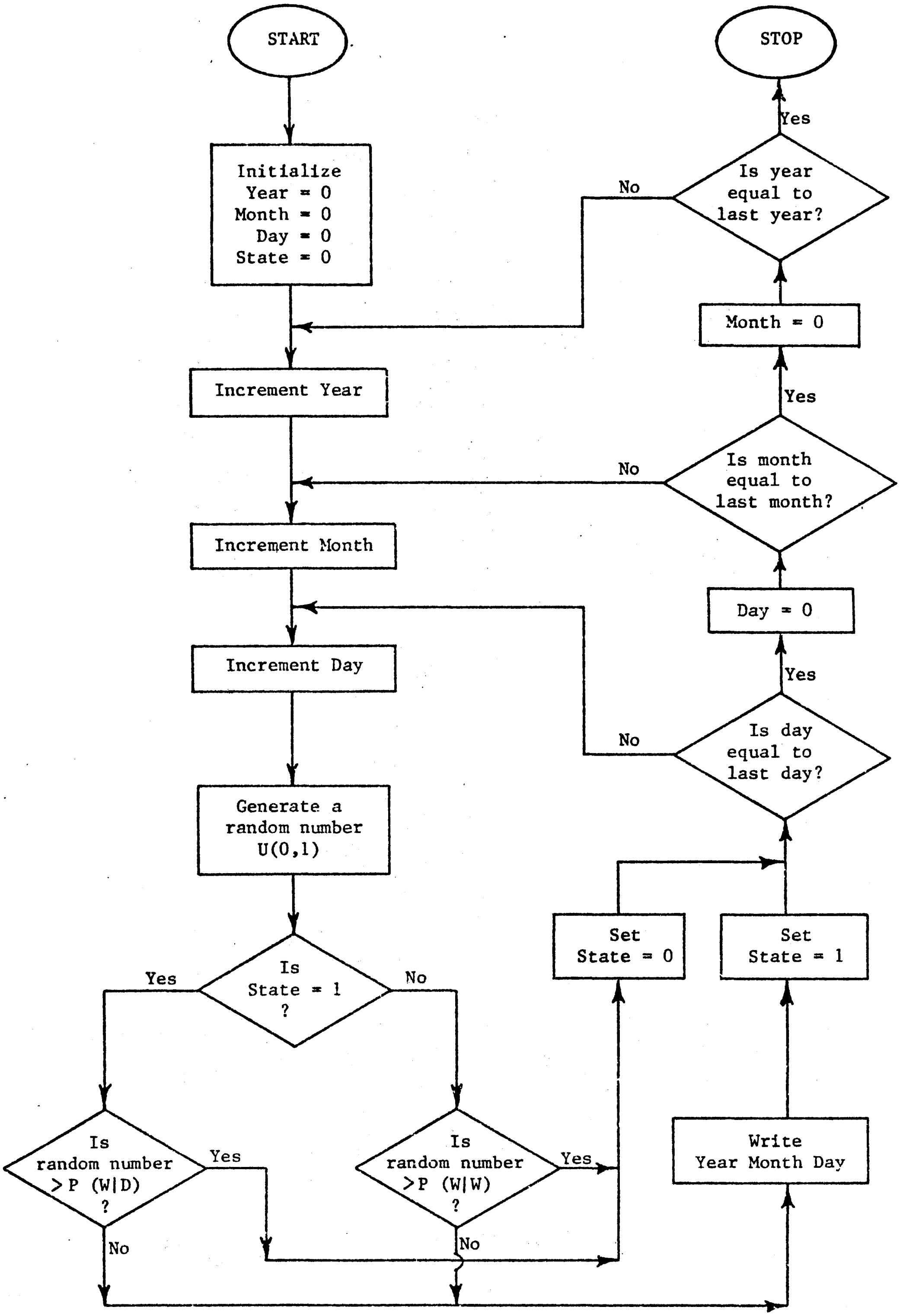

Figure 1. Flow Chart for a 1st Order, Two State Markov Chain Model for Rainfall Occurrence.

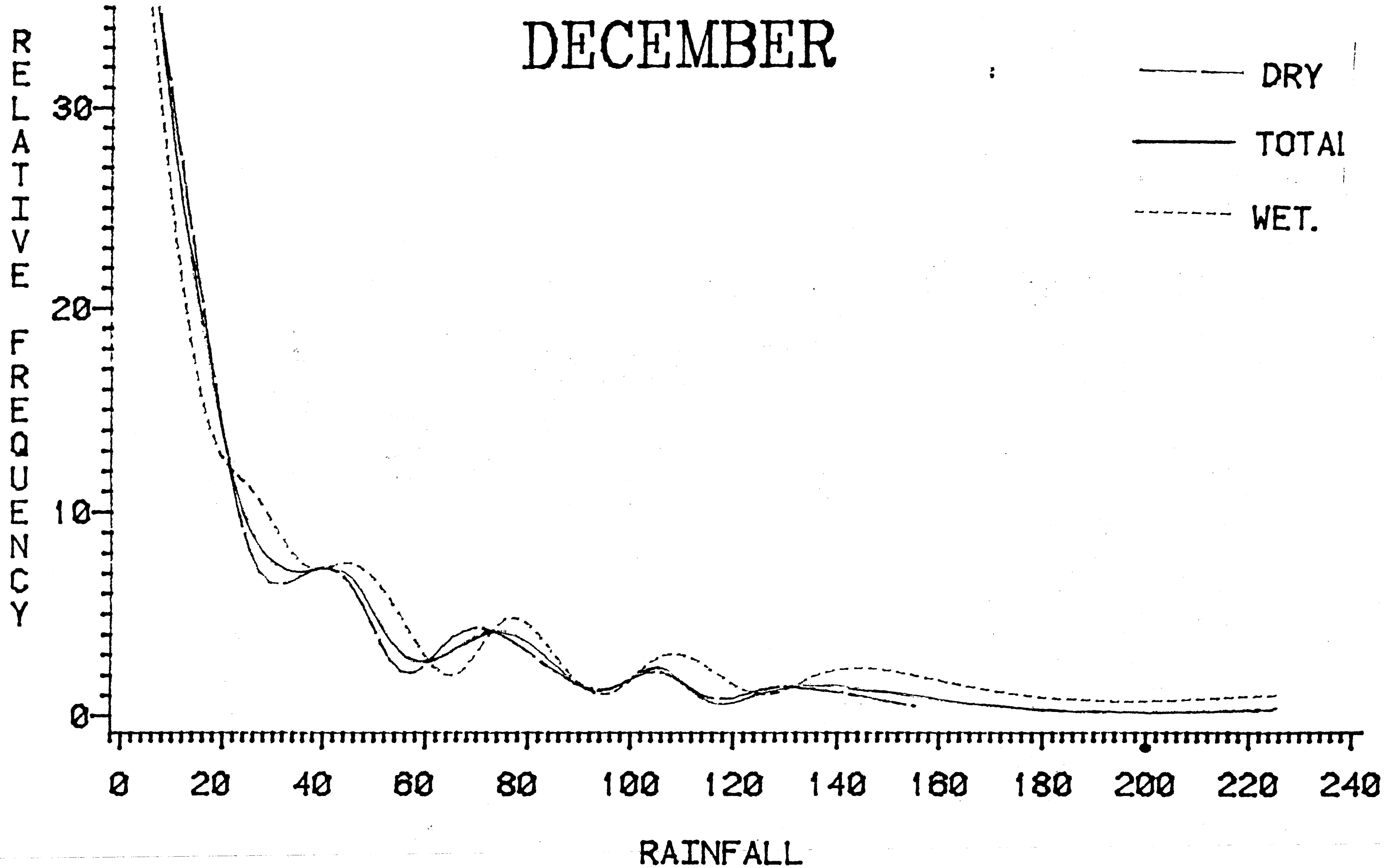

Figure 2. Relative Frequency Curves of Daily Rainfall Amounts for Wet Days (Total), Wet Days Following Dry Days (Dry) and Wet Days Following Wet Days (Wet) for the Month of December.

With the above substantiating evidence, a single distribution could be fitted to the daily rainfall amounts with confidence. The single parameter exponential and two parameter lognormal distribution were selected for examination. The parameters for these two distributions were determined by the method of moments. Haan (1977) and De Coursey et al. (1982) showed that the method of moments and the generally prefered maximum likelihood procedure yield the same parameter estimates for the exponential distribution. It is shown in Appendix C, that for the lognormal distribution, however, the maximum likelihood procedure yields parameter estimates which are quite different to the moment method developed by Chow (1954). The use of this moment method for parameter estimates is recommended by De Coursey (1982), Selvalingam and Miura (1978) and McMahon (1971) as it leads to the better preservation of the lower order moments of the historical data in subsequently simulated data. The degree of bias in the estimate of the variance of the lognormal distribution resulting from the maximum likelihood procedure approaches zero as the sample size from which it is estimated is increased. Increasing the sample size when using the maximum likelihood procedure nevertheless, does not improve the preservation of the historical moments in the simulated data as Chow's (1954) method does.

The means and variances for the daily rainfall amounts from the historical record were determined, on a monthly basis, (see Table II) using SAS (SAS, 1982). The total rainfall record was used in the calculation of these moment estimates in an attempt to obtain the closest approximation of the true population values.

Exponential Model

The exponential distribution was selected for possible use because of its simplicity and ease of application. The single parameter exponential distribution has a density function given by

$$p_x(X) = \lambda e^{-\lambda X} \qquad X > 0, \lambda > 0$$

where $\hat{\lambda} = 1/\bar{X}$ and can be estimated by the reciprocal of the sample mean. A value for $\hat{\lambda}$ was calculated for each month from the eighty year historical daily rainfall record. The daily rainfall amounts on wet days (X_i) were simulated using the SAS (SAS, 1982) procedure to generate a random exponential deviate using the appropriate values for λ. The generating function is

$$X_i = -\ln(R)/\lambda_i$$

where X_i = rainfall amount generated for the ith month,

R = a random number uniformly distributed between zero and one, and

λ_i = the reciprical of the mean daily rainfall for the ith month.

A separate seed was used to initiate the random number streams for the exponential model and the Markov chain to ensure that the random nature of each stream was retained.

Lognormal Model

The two parameter lognormal distribution was selected as an alternative to the exponential distribution to examine whether the greater flexibility it offers was meaningful. The lognormal density function is given by

$$P_x(X) = (2\pi X^2 \sigma_y^2)^{-1/2} \exp(-(Y - \mu_u)^2/2\sigma_y^2)$$

where $Y = \ln(X)$

μ_y = mean of the logarithms of the data

σ_y^2 = variance of the logarithms of the data.

Using the lognormal distribution, daily rainfall amounts on wet days (X_i) were generated using the SAS (SAS, 1982) procedure to generate a random lognormal deviate. The generating function is

$$X_i = \exp(M_i + S_i(R))$$

where X_i = rainfall amount generated for the ith month,

R = a random number, normally distributed with mean equal to zero and variance equal to one,

S_i = a standard deviation for the ith month calculated in one of two ways described below, and

M_i = a mean for the ith month calculated in one of two ways described below.

As with the exponential model, separate seeds were used to initiate the random number streams for the lognormal model and the Markov chain. Two methods can be used to determine the lognormal distribution parameters.

The first method of parameter estimation for a lognormal distribution involves the transformation of each observation of the historical data (X) using the relationship

$$Y = \ln(X).$$

The mean and variance of the transformed data are determined and used as estimates for the parameters M and S in the generating function.

The second method of lognormal parameter estimation utilizes the mean and standard deviation of the historical data shown in Table II. The logarithms of the data are not required and estimates of the parameters used in the generating function are determined using the parameter transformation relationships

$$M = 1/2 \ln(\bar{X}^2/(C_v^2 + 1))$$

$$S^2 = \ln(C_v^2 + 1)$$

where $C_V = S_x/\bar{X}$ (coefficient of variations of the original data)

S_x = standard deviations of the original data

$\bar{X}$ = mean of the original data.

The parameters calculated using the two methods above are shown in Table V. The table shows that values of the means determined from the log-transformed data (1st method) are smaller and the variances larger than the values of the same parameters determined using the parameter transformation relationships (2nd method). Forty years of daily rainfall were simulated using the distribution parameters calculated using the first method (log-transformed data). Five such simulations were performed. The mean annual rainfall calculated for each simulation, shown in Table VI, was consistently larger than the historical mean annual rainfall of 32.42 inches (Table II). The mean of the five mean annual rainfall amounts, 40.05 inches, was approximately twenty four percent greater than the historical value.

Similar simulations were performed using the parameters calculated using the second method (parameter transformation). The mean annual rainfall amounts of the five simulations (Table VI) were well distributed about the historical mean annual rainfall of 32.42 inches. The mean of the five mean annual rainfall amounts was within one percent of the historical value. The parameter transformation relationships thus yielded the best lognormal distribution parameter estimates with respect to the preservation of the means.

TABLE V

LOGNORMAL DISTRIBUTION PARAMETERS DETERMINED FROM LOG-TRANSFORMED DATA AND BY USING THE PARAMETER TRANSFORMATION RELATIONSHIPS

	M		S^2	
Month	Log-Transformed Data	Parameter Transformation	Log-Transformed Data	Parameter Transformation
1	2.35	2.63	1.78	1.35
2	2.55	2.80	1.77	1.22
3	2.93	3.22	1.78	1.14
4	2.96	3.30	2.03	1.26
5	3.07	3.38	2.04	1.33
6	3.17	3.48	1.93	1.59
7	3.01	3.37	2.15	1.34
8	3.00	3.32	2.09	1.35
9	3.18	3.45	2.23	1.29
10	3.11	3.29	2.11	1.26
11	2.98	3.28	1.96	1.28
12	2.61	2.95	1.94	1.19

TABLE VI

MEAN ANNUAL RAINFALL AMOUNTS FROM FORTY YEARS OF DATA SIMULATED USING THE LOGNORMAL DISTRIBUTION PARAMETERS CALCULATED BY THE TRANSFORMED DATA AND PARAMETER TRANSFORMATION METHODS

	MEAN ANNUAL RAINFALL (INCH)	
SIMULATION RUN	LOG-TRANSFORMED DATA	PARAMETER TRANSFORMATION
1	40.29	30.88
2	39.56	33.98
3	38.74	32.13
4	39.75	32.97
5	41.80	33.29
MEAN	40.05	32.65

Historical mean annual rainfall = 32.42 inches

Comparison of Models

The expected relative frequencies for each month of the year, for the exponential and lognormal distribution, based upon the parameter estimates in Table II were calculated using the approximation

$$f_{xi} = \Delta X_i \quad p_x(X_i)$$

where f_{xi} = expected relative frequency for the ith class interval,

ΔX_i = the midpoint of the ith class interval.

X_i = range of the ith class interval (0.09 for the first class interval and 0.10 for all sub sequent class intervals).

$p_x(X_i)$ = the probability density function evaluated at the midpoint of the ith class interval.

The frequencies of daily rainfall amounts for each month of the year for the historical data over the eighty year record were also calculated using 0.10 inch class intervals (Appendix D). The Kolmogorof-Smirnof test and the Chi-square test (two sample tests) were performed on the historical frequencies and the exponential and lognormal distribution relative frequencies respectively, to determine whether the relative frequencies and the historical data could be from the same population.

The monthly Kolmogorof-Smirnof test statistics shown in Table VII for both the exponential and lognormal distributions were all less than the tabulated values of Seigel (1954). This shows that there is no evidence to indicate that the historical data cannot be described equally well by both the distributions. The Chi-square test statistics shown in Table VIII, however, indicated that the exponential distribution did not describe the historical data for three and ten months at the 0.10 and 0.01 levels respectively. The Chi-square tests for the lognormal distribution were not significant for any month at the 0.005 level. This indicates that we have to reject the hypothesis that the historical data can be described by the exponential distribution for all months. There is no evidence to make the same conclusion for the lognormal distribution.

The plots of the relative frequencies of the historical data, the exponential probability density function and the lognormal probability density function for the month of December are shown in Figure 3. This graphical comparison supports the above conclusion as the two parameter, lognormal distribution fits the historical data better than the one parameter exponential distribution. The same conclusion can be drawn from similar plots for the other months of the year shown in Appendix E. The lognormal distribution was therefore the distribution chosen for inclusion in the daily rainfall simulation model.

TABLE VII

KOLMOGOROF-SMIRNOF TEST OF EXPONENTIAL AND LOG-NORMAL DISTRIBUTIONS WITH THE HISTORICAL DAILY RAINFALL AMOUNTS

MONTH	LOGNORMAL	EXPONENTIAL
1	4.75847	13.0493
2	6.91527	7.6481
3	7.79362	8.1554
4	4.84700	11.4224
5	4.36175	11.6524
6	6.68631	6.4628
7	4.41388	13.6132
8	4.69974	12.4578
9	5.26779	13.8454
10	5.10661	10.8213
11	5.00746	10.8160
12	5.65610	8.8881

Critical value at 0.01 level = 22

TABLE VIII

CHI-SQUARE TEST OF EXPONENTIAL AND LOGNORMAL DISTRIBUTIONS WITH THE HISTORICAL DAILY RAINFALL AMOUNTS

MONTH	LOGNORMAL	EXPONENTIAL
1	7.9934	73.4008*
2	7.6083	68.2607*
3	9.9285	13.7595*
4	9.1776	17.5343**
5	8.5141	20.7507*
6	9.3257	9.7913
7	11.8849	34.2788*
8	7.7609	23.6096*
9	12.4910	26.6565*
10	9.7854	15.2602**
11	7.0361	18.1246**
12	12.7495	21.6251*

*Chi-square value at 0.10 level = 39.1

**Chi-square value at 0.01 level = 14.3

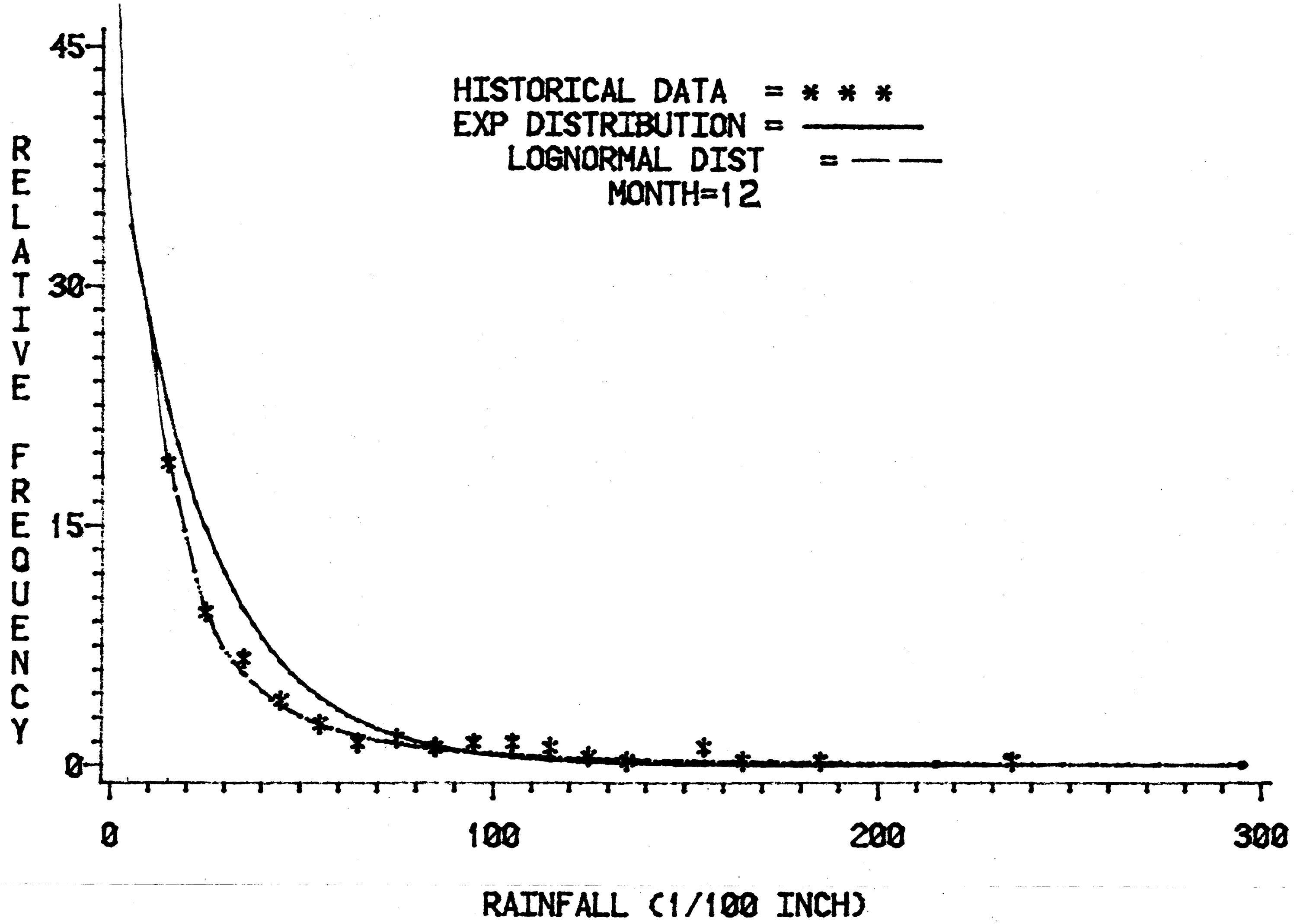

Figure 3. Relative Frequency Curves of Daily Rainfall Amounts for the Historical Data and the Exponential and Lognormal Probability Density Functions for December.

Description of Model Developed

The daily rainfall model developed incorporates two sub-models: (a) rainfall event model, to generate the occurrence of a rainfall event (wet day) and (b) a rainfall amount model to generate the amount of rainfall that would accumulate on a wet day. The rainfall event model consists of a first order, two state, Markov chain in which a one and zero denote an event (wet day) and nonevent (dry day) respectively. The model requires twelve 2x2 transitional probability matrices, each of the form

		event on day i	
		1	0
event on day i-1	1	P(1|1)	P(0|1)
	0	P(1|0)	P(0|0)

These matrices describe the occurrence of a wet day or dry day occurring given the state of the previous day for each month of the year. The twelve transitional matrices are calculated from the historical data assuming that the transitional probabilities are stationary within each month. The transitional probabilities P(1|0) and P(1|1) for the twelve months of the year are entered into the model together with the record length (years) to be simulated. An initial dry state is assumed. For each day of the synthetic record, a random number, uniformly distributed between zero and one, is generated and compared with P(1|0) or P(1|1) depending upon the state of the previous day. If the random number is larger than the appropriate transitional probability a dry day results, otherwise a wet day is generated and the second sub-model is invoked.

The rainfall amount model is based upon two assumptions: (a) there is no persistence in daily rainfall and (b) the daily rainfall amounts are lognormally distributed. The two distribution parameters (M and S^2) are calculated from the mean and the variance of the historical data using the following moment relationships developed by Chow (1954).

$$M = 1/2 \ln(\bar{X}^2/C_v^2 + 1)$$

$$S^2 = \ln(C_v^2 + 1)$$

where $C_v = S/\bar{X}$ coefficient of variation of the original data

S = standard deviation of the original data and

$\bar{X}$ = mean of the original data.

The values of M and S^2 are calculated in the model from the predetermined values of the monthly means and monthly variances of the historical data as appropriate. The statistics of the historical data are calculated using standard procedures and the model must be modified with respect to these values for each location to which it is applied. The rainfall amount (X) on a simulated wet day is generated using the parameters M and S^2 for the appropriate month, and a normally distributed random number (R) with mean equal to zero and variance equal to one using the relationship.

X = exp(M + S(R))

The output from the model consists of the date and rainfall amount for each wet day in the synthetically generated record. A flowchart of the daily rainfall simulation model is presented in Figure 4. A listing of the SAS (SAS, 1982) computer program of the model can be found in Appendix A. This program was used to generate the synthetic rainfall data used in this study.

Simulation of Daily Rainfall Data

A synthetic daily rainfall record of any length can be generated using the daily rainfall model developed in this study. Some historical data are required to determine the model parameters (transitional probabilities and the distribution parameters). The length of historic record available would influence how accurately the model parameters can be determined. The assumptions that rainfall occurrence is weakly persistent and that daily rainfall amounts on consecutive days are independent must be verified before the model is applied to any location other than Stillwater, Oklahoma.

The following steps describe the application of the daily rainfall simulation model for data generation.

1. Determine the 2x2 transitional probability matrices for each month of the year from the historical daily rainfall record.

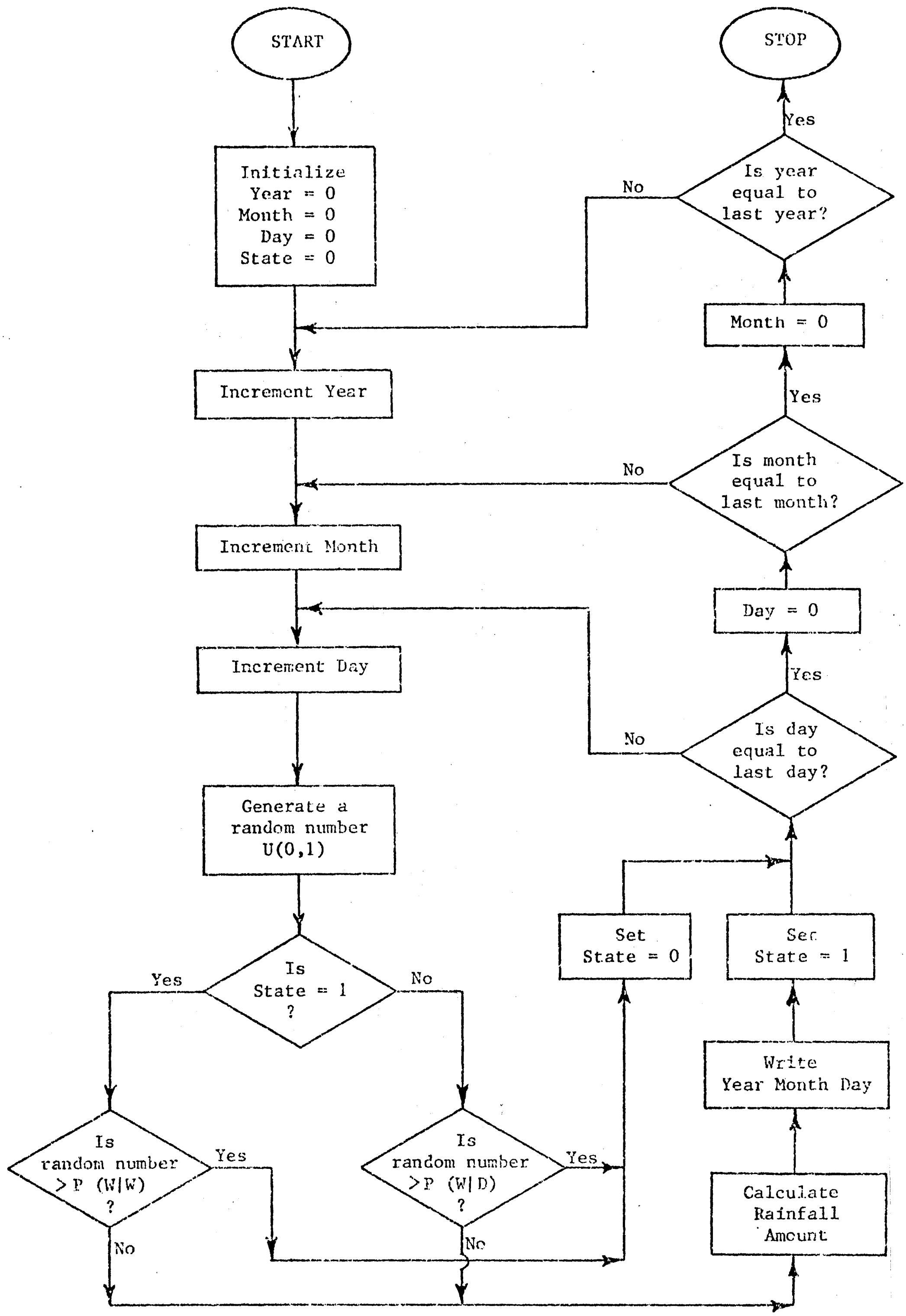

Figure 4. Flow Chart for the Daily Rainfall Simulation Model.

2. Enter the transitional probabilities P(1 0) and P(1 1) for each month in the model (24 values).

3. Determine the mean and variance of the daily rainfall amounts for each month for the wet days in the historical record.

4. Enter the values of the monthly means and variances of the historical record in the model (24 values).

5. Enter two random number generation seeds for the generation of the uniform and normal random number sequences (2 values).

6. Enter a year, greater than 1900, to indicate the imaginary period, starting at year 1900, for which rainfall data is to be simulated (1 value).

The above steps were executed and the daily rainfall model was used to generate the synthetic rainfall data for this study.

Evaluation of the Daily Rainfall Model

The rainfall data generated by the daily rainfall model were analyzed and compared with the historical data in terms of (a) consecutive wet and dry days, (b) distribution of daily rainfall amounts, (c) mean monthly rainfall, (d) mean annual rainfall and (e) accumulated annual rainfall.

The curves in Figure 5 indicate that the historical consecutive wet day and dry day runs were well reproduced in the synthetic data.

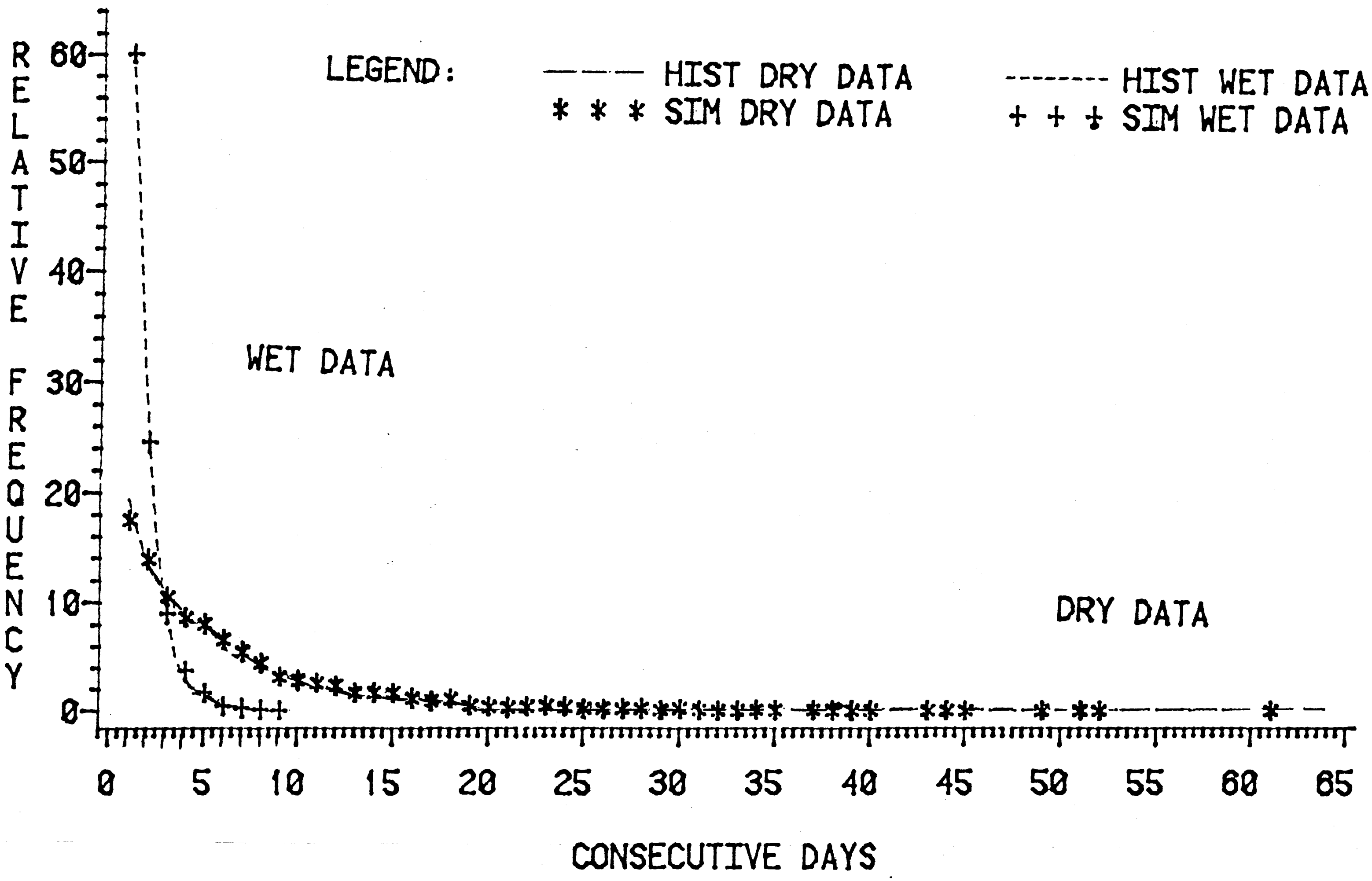

Figure 5. Consecutive Wet and Dry Day Runs for 40 Years of Simulated and Historical Rainfall Data.

The results of the statistical analyses of four, forty year synthetic daily rainfall records are shown in Table IX. These results compare favorably with the historical data. The mean monthly and mean annual rainfall amounts from the simulated records are normally distributed about the values of the historical data shown in Table II. The total number of wet days generated in each of the four simulated records compared favorably with the historical number of wet days in forty years. A double mass plot of accumulated annual rainfall for synthetic and historical records for 80 years is shown in Figure 6. The points plotted almost coincice with the equal value line and the slope of a fitted regression line is very close to one. The regression equation fitted was

$$Q_h = 56 + .996\ Q_s$$

where Q_h = accumulated annual historical rainfall

Q_s = accumulated annual synthetic rainfall.

These results indicate that a forty year synthetic rainfall record generated with the daily rainfall model developed would be an acceptable realization of a possible record. With this evidence it was assumed that it is not necessary to route a number of synthetic rainfall records through an hydrologic model, in this study, to asses the use of synthetic rainfall and a runoff model to predict watershed runoff.

TABLE IX

STATISTICAL ANALYSES OF RAINFALL ON WET DAYS GENERATED IN THE FOUR, FORTY-YEAR SYNTHETIC RAINFALL RECORDS

MONTH	MONTHLY MEAN (INCH)	DAILY MEAN (1/100 INCH)	STD OF DAILY MEAN
1	1.24	28.71	35.89
2	1.16	25.97	28.38
3	1.87	34.86	34.35
4	3.69	48.78	66.04
5	4.15	48.02	51.81
6	4.09	51.66	60.28
7	2.91	49.12	61.24
8	2.62	42.62	57.96
9	4.06	63.33	86.45
10	3.04	49.35	51.18
11	2.18	42.05	44.14
12	1.35	28.93	33.49
ANNUAL TOTAL	32.42		

MONTHLY	MONTHLY MEAN (INCH)	DAILY MEAN (1/100 INCH)	STD OF DAILY MEAN
1	.81	20.15	10.49
2	1.27	26.13	30.85
3	2.01	38.17	43.84
4	1.89	41.62	46.74
5	4.36	46.95	66.50
6	3.73	47.53	54.09
7	1.89	48.24	58.09
8	3.29	49.97	70.08
9	3.68	58.30	80.67
10	3.25	57.61	69.92
11	2.70	56.01	118.91
12	1.18	27.41	25.14
ANNUAL TOTAL	32.11		

TABLE IX CONTINUED

MONTH	MONTHLY MEAN (INCH)	DAILY MEAN (1/100 INCH)	STD OF DAILY MEAN
1	1.08	25.38	29.39
2	1.30	26.01	27.21
3	1.92	35.75	41.73
4	3.07	40.86	43.71
5	4.96	54.28	78.54
6	3.98	52.56	58.38
7	2.97	56.93	93.30
8	2.59	46.84	74.34
9	3.90	62.26	85.49
10	2.77	47.97	51.88
11	2.47	43.73	51.94
12	1.04	29.31	34.87
ANNUAL TOTAL	32.09		

MONTH	MONTHLY MEAN (INCH)	DAILY MEAN (1/100 INCH)	STD OF DAILY MEAN
1	.96	25.27	35.10
2	1.36	27.79	39.10
3	2.51	39.45	44.10
4	2.75	38.83	50.16
5	4.15	46.71	52.66
6	3.73	50.02	52.65
7	3.22	52.82	135.91
8	2.65	45.53	51.96
9	3.16	53.40	60.64
10	3.07	50.27	58.96
11	2.36	46.88	52.70
12	1.44	33.55	48.81
ANNUAL TOTAL	31.42		

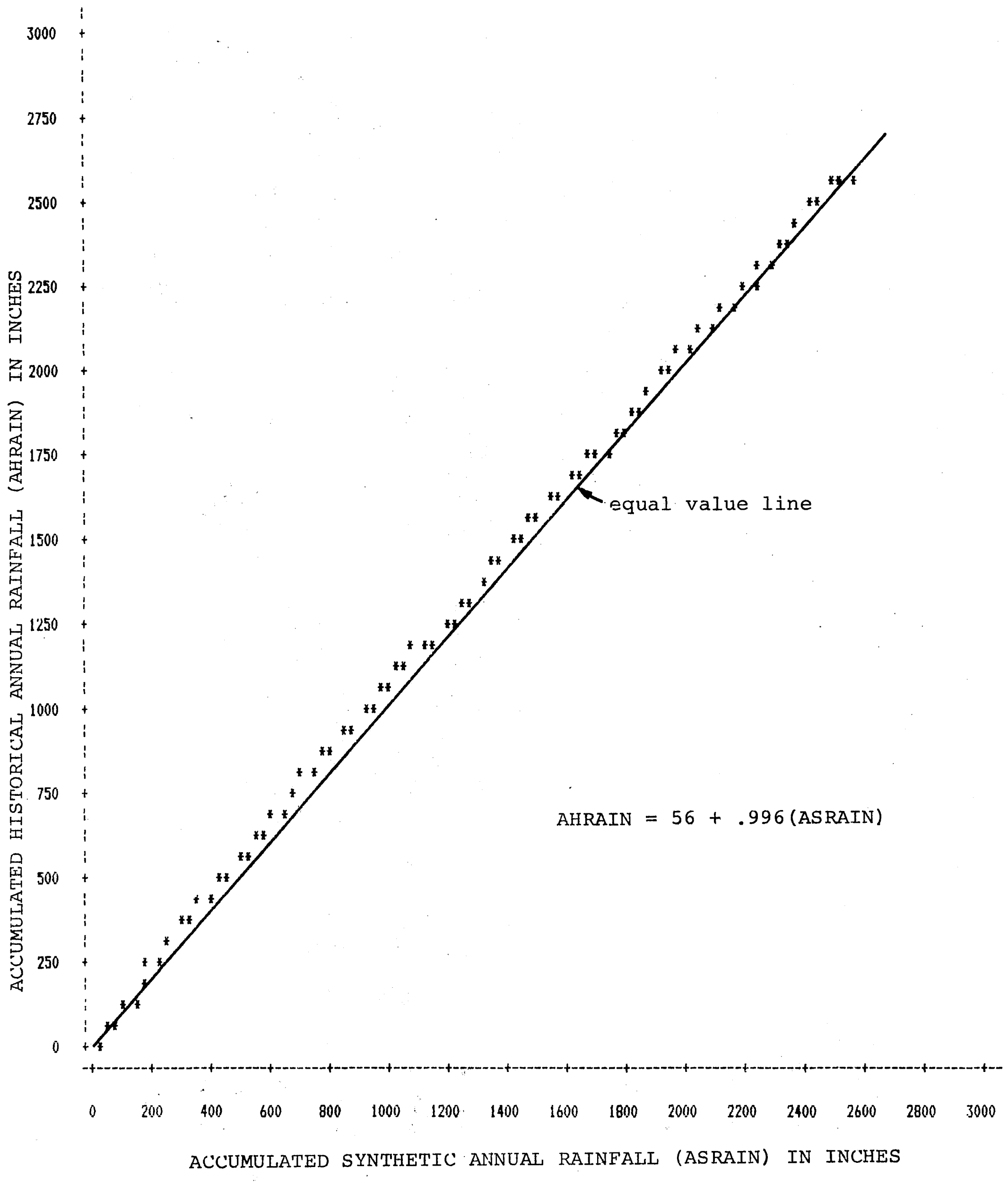

Figure 6. Double Mass Plot of Accumulated Annual Rainfall for Synthetic (ASRAIN) and Historic (AHRAIN) Rainfall for 80 Years.

CHAPTER IV

APPLICATION OF SYNTHETIC AND HISTORICAL DATA TO AN HYDROLOGIC MODEL

The model developed and described in the previous chapter was used to generate forty years of rainfall data. This synthetic rainfall data and the observed rainfall data for Stillwater, Oklahoma, were used independently as input data in an hydrologic model chosen from a list of seventy-five currently available models (Renard et al. 1982) to predict watershed response in terms of runoff.

The USDAHL Model (Holtan and Lopez, 1971) and the CREAMS Model (Knizel, 1980) were subjected to extensive evaluation in the Department of Agricultural Engineering, at Oklahoma State University by Bengston (1980), Crow et al. (1977, 1980), Pathak (1983), Pathak et al. (1984). This previous research and experience served as a basis in deciding which model and watershed would be appropriate for this study.

Choice of Hydrologic Model and Watershed

The CREAMS hydrologic model was chosen to examine watershed response to synthetic rainfall data. This model was developed specifically for research purposes (Knisel, 1980). It was designed for field size watersheds which have single land use, a single management practice, relatively homogeneous soils and uniform rainfall. There are four components in the model, namely, the hydrologic, erosion, nutrient and pesticide components. Only the first, hydrologic component, of the model was used. Of the two model input options available (daily rainfall and break-point rainfall), option one for daily rainfall input was used. This option utilizes the SCS curve number model to estimate runoff.

Pathak (1983) applied the CREAMS Model to four watersheds in central Oklahoma. Of these four watersheds, the model performed most successfully for the 19.5 acre R-7 grassland watershed near Chickasha, Oklahoma. The model performance was assessed in terms of the predicted versus observed monthly and annual runoff resulting from observed daily rainfall. The CREAMS Model and the R-7 Chickasha watershed were chosen for use in this study.

The R-7 watershed topographical shape approximated a regular fan shape (Figure 7) with a slope ranging from 2.0 to 2.5 percent. The vegetation cover is blue stem grass and threeawn grass in areal proportions of 69 percent and 31 percent respectively. The soils are described in the soil survey of Grady County (USDA-SCS, 1978) as 38 percent Kingfisher silt loam, 39 percent Renfrow silt loam and 23 percent Kingfisher-Lucien complex. The watershed topographical

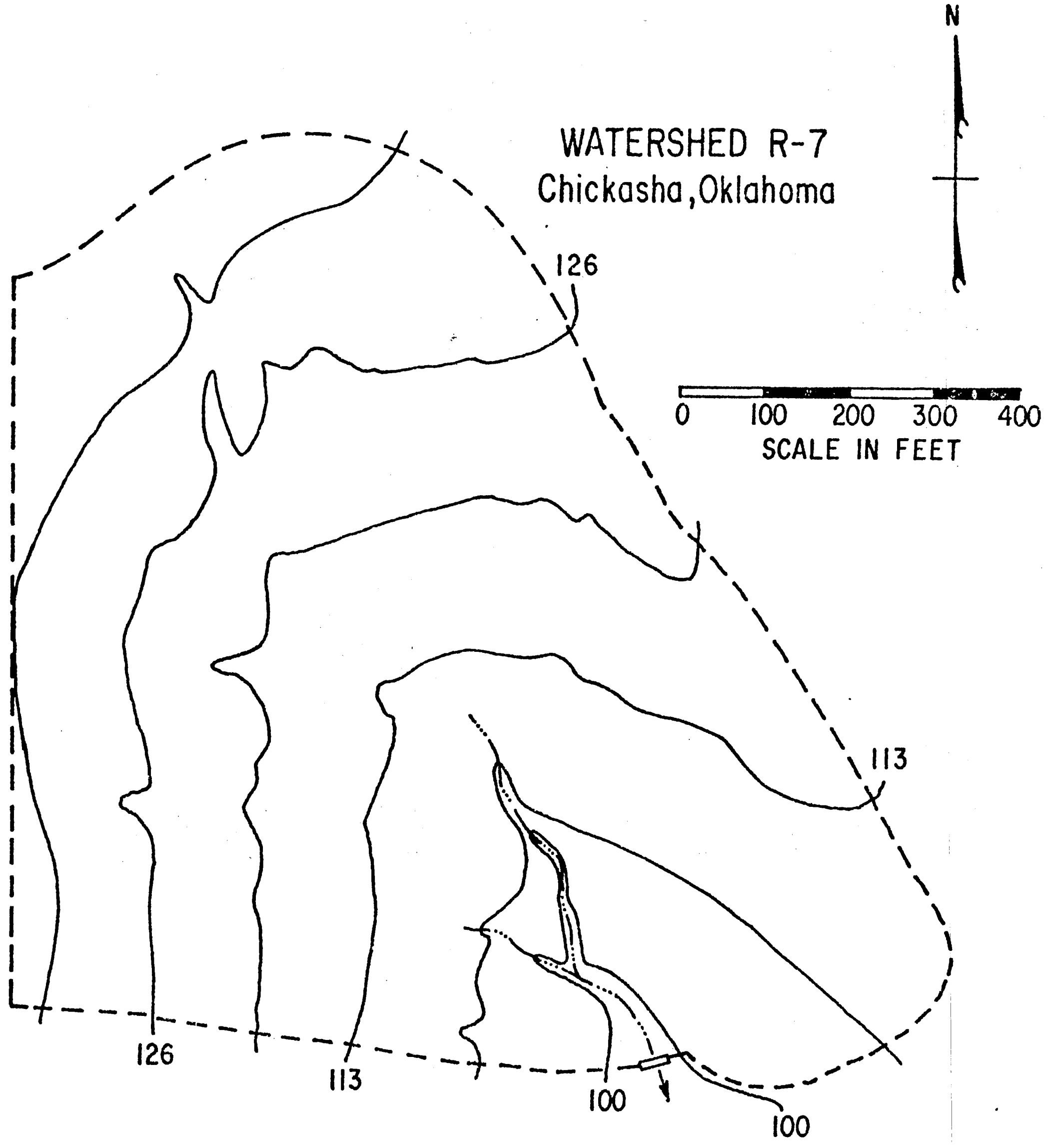

Figure 7. Topographic Map for Chickasha R-7 Watershed.

characteristics, soil profile ad plant cover condition parameters determined by Pathak (1983) were used.

Model Inputs

The CREAMS model reads input from two files, namely, the precipitation file and the input parameter file. These files must be prepared in the format specified in the CREAMS manual (Knisel et al. 1980).

The precipitation file contains the daily rainfall data for each year (365 values per year, 10 values per line, 37 lines per year) in the period for which runoff is to be determined. A maximum of twenty years data can be included in the file.

The input parameter file contains the title information, option parameters, watershed parameters, climatological data, plant cover data and a line with three instruction codes for each year of simulation. The optimum watershed parameters, established by Pathak (1983), for the R-7 watershed at Chickasha were used. These parameters are shown in Table X. Table XI shows the plant cover data included in the input parameter file. The grass cover on the watershed was rated a "good cover" by Pathak (1983) thus one-half of the recommended leaf area index values for a pasture in excellent condition given in the CREAMS manual (Knisel, 1980) were used. The recommended winter cover factor of 0.5 was used.

Table X

CREAMS MODEL INPUT PARAMETERS FOR R-7 WATERSHED
AT CHICKASHA, OKLAHOMA
(FROM PATHAK, 1983)

Field area (acres)	19.5
Effective saturated hyd. conductivity (in/hour)	0.04
Fractions of pore space filled at field capacity	0.87
Initial fraction of available water storage filled	0.50
Soil evaporation parameter	4.5
Soil porosity (in/in)	0.48
Immobile soil water content (in/in)	0.22
Depth of surface soil layer (in)	2
Depth of maximum root growth layer (in)	36
Effective capillary tension (in)	16.4
Mannings n for overland flow	0.03
Effective hydraulic slope (ft/ft)	0.038
Effective hydraulic slope length (ft)	290

TABLE XI

LEAF AREA INDEX FOR NATIVE GRASS
(FROM PATHAK, 1983)

Julian Day	Leaf Area Index
001	0.00
091	0.00
114	0.92
137	1.50
160	1.50
188	1.50
206	1.50
220	1.50
252	1.35
275	1.07
298	0.98
321	0.25
366	0.00

The mean monthly solar radiation data (Table XII) were taken from the CREAMS manual (Knisel, 1980). The mean monthly temperature data (Table XIII) were compiled from the temperature data used by Pathak (1983).

The above input data were used in the CREAMS model to predict runoff from the Chickasha R-7 watershed using synthetic and historical rainfall respectively.

Predicted Runoff Using Synthetic and Historical Rainfall Data

The CREAMS hydrologic model predicts runoff on a daily, monthly and annual basis from daily rainfall data. The annual and monthly runoff amounts predicted for the Chickasha R-7 watershed from the historical and synthetic rainfall records respectively were used to evaluate the effect of using synthetic rainfall. A frequency analysis (Table XIV) of the annual runoff for an eighty year period was performed using half inch class intervals. This analysis showed that more small runoff events were predicted from the synthetic rainfall and more large runoff events were predicted from the historical rainfall. The frequency analysis on the monthly runoff data (Appendix F) indicate that the increased number of small runoff events from the synthetic rainfall occurred during the months of March, June, August, September, and October. The increased number of large runoff events from the historical rainfall occurred during the months of May, July, October, and November.

TABLE XII

MEAN MONTHLY SOLAR RADIATION FOR OKLAHOMA CITY, OKLAHOMA (FROM, KNISEL, 1980)

Month	Mean Radiation (Langleys)
January	251
February	319
March	409
April	494
May	536
June	615
July	610
August	593
September	487
October	377
November	291
December	240

TABLE XIII

MEAN MONTHLY TEMPERATURE USED FOR THE R-7 WATERSHED, AT CHICKASHA, OKLAHOMA

Month	Mean Temperature (°F)
January	40.7
February	39.9
March	44.6
April	53.6
May	64.5
June	74.4
July	80.5
August	81.3
September	26.6
October	67.6
November	56.8
December	66.9

TABLE XIV

RELATIVE FREQUENCY TABLE OF ANNUAL RUNOFF

	Frequency		Percent	
Runoff (0.5 inches intervals)	Synthetic Data	Historical Data	Synthetic Data	Historical Data
.24	10	6	12.50	7.50
.75	13	8	16.25	10.00
1.25	8	7	10.00	8.75
1.75	8	7	10.00	8.75
2.25	10	13	12.50	16.25
2.75	6	7	7.50	8.75
3.25	1	8	1.25	10.00
3.75	4	2	5.00	2.5
4.25	4	3	5.00	3.75
4.75	5	2	6.25	2.5
5.25	3	4	3.75	5.00
5.75	3	2	3.75	2.50
6.25	1	0	1.25	0.00
6.75	0	2	0.00	2.50
7.25	1	1	1.25	1.25
7.75	2	0	2.5	0.00
8.25	0	1	0.00	1.25
8.75	0	0	0.00	0.00
9.25	0	3	0.00	3.75
9.75	0	0	0.00	0.00
10.00	1	4	1.25	5.00

The means and the standard deviations of the monthly runoff amounts are shown in Table XV. These results indicate that the means and standard deviation of the monthly runoff were fairly well preserved. Notable differences were found for the months of September, October, and November.

A summary of the input and output data for the CREAMS model is presented in Appendix G. In the table, the ratio of the accumulated annual runoff determined from the historical and synthetic rainfall varies from 1.24 to 3.69. This shows that the runoff predicted from the synthetic rainfall record is consistently less than the runoff from the historical rainfall record. The difference is 73.25 inches, or 25.6 percent, less than the runoff from historical rainfall over the eighty year record used. Figure 8 shows the scatter of the double mass plot of the accumulated annual runoff from the synthetic and historical rainfall tabulated in Appendix G. The regression equation fitted to the points was found to be

$$R_H = 20 + 1.25\ R_s$$

where R_H = accumulated annual historical runoff

R_s = accumulated annual simulated runoff

The deviation from the equal value line is significant especially when related to the corresponding plot of the input rainfall data in Figure 6. This result is evidence that the hydrologic model is very sensitive to the rainfall input

TABLE XV

MONTHLY RUNOFF (INCHES) PREDICTED FROM SYNTHETIC AND HISTORICAL RAINFALL

Month	Mean		STD	
	Synthetic Data	Historical Data	Synthetic Data	Historical Data
January	0.08	0.05	0.40	0.15
February	0.06	0.06	0.24	0.24
March	0.17	0.23	0.43	0.50
April	0.38	0.49	0.86	0.94
May	0.54	0.59	0.96	1.25
June	0.17	0.26	0.50	0.56
July	0.23	0.26	0.89	0.98
August	0.15	0.22	0.42	0.48
September	0.46	0.58	1.67	1.22
October	0.17	0.47	0.45	1.32
November	0.19	0.29	0.43	0.74
December	0.06	0.08	0.23	0.25

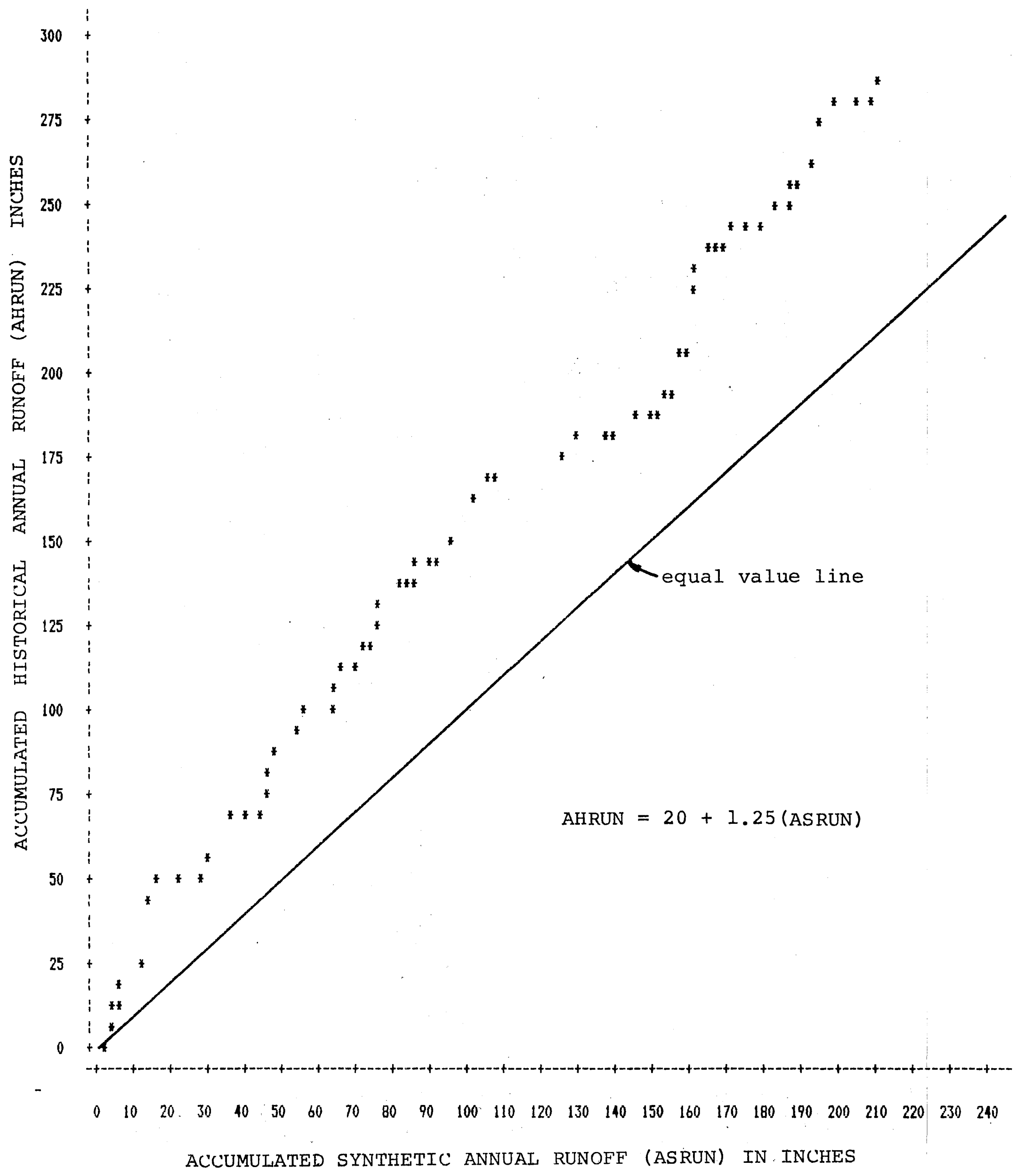

Figure 8. Double Mass Plot of Accumulated Annual Runoff Determined from the Synthetic (ASRUN) and Historic (AHRUN) Rainfall for 80 Years.

data. It further suggests that great caution should be exercised in the use of synthetic rainfall to predict watershed runoff using an hydrologic model. While statistically similar rainfall records can be generated or found from two different locations, the differences in the daily rainfall amounts and the wet day sequences may be significant. These differences can lead to marked differences in predicted runoff when the rainfall is applied to the CREAMS hydrologic model. The under prediction of approximately 25% resulting from the application of synthetic rainfall to CREAMS is, however, within the acceptable limits for runoff prediction (Beasley et al. 1980).

CHAPTER V

SUMMARY AND CONCLUSIONS

Summary

A study was conducted to examine the use of synthetic rainfall in operational hydrology. The objectives of the study were to (a) develop a stochastic daily rainfall model and (b) to evaluate the use of synthetic rainfall data and a runoff model to study watershed hydrologic responses.

The rainfall model developed consisted of a first order, two state Markov chain to generate wet days, and the lognormal distribution to generate a rainfall amount for each wet day. The probabilities describing the four transitions (wet|wet, wet|dry, dry|wet, dry|dry) in the Markov chain were determined for each calendar month using eighty years of observed daily rainfall. The two parameters for the lognormal distribution were also determined for each month using the moment method of Chow (1954) and the observed daily rainfall data. A computer program using the SAS language was developed to generate synthetic daily rainfall. The synthetic rainfall data compared favorably with the historical data in terms of the consecutive wet and dry day runs, frequency of daily rainfall amount, mean monthly and annual rainfall and accumulated annual rainfall over eighty years.

The synthetic and historical daily rainfall were used independently as input data for the CREAMS hydrologic model. The same watershed parameters, climatological data, soil data, and plant cover data were used in each simulation. The runoff predicted by the CREAMS model using the synthetic and historic rainfall data respectively, were compared in terms of the mean monthly runoff, mean annual runoff and accumulated annual runoff.

The runoff data from the synthetic and historical rainfall data did not compare as favorably as did the two types of rainfall input data itself. Although the means and standard deviations of the monthly runoff data appeared to be well reproduced, the annual runoff from the synthetic rainfall was consistently less than the annual runoff from the historical rainfall for each year in the eighty year record.

Conclusions

A satisfactory daily rainfall simulation model was developed. The analysis of the rainfall data generated by the model indicated that the inclusion of the Markov chain and the lognormal distribution was valid for the Stillwater area. The use of stationary transitional probabilities for each calendar month is not a major limitation of the model. The model could probably be applied to other areas after making appropriate changes to the monthly transitional probabilities and the lognormal distribution parameters. It is important that Chow's (1954) method be used to determine the lognormal distribution parameters. Although representative synthetic rainfall data can be generated, discretion must be used in the application of such data.

The CREAMS rainfall-runoff model is sensitive to rainfall input data. Even with the marked similarities in the synthetic and historical rainfall data, the runoff predicted by CREAMS, using these two rainfall sequences as input, are somewhat different. The runoff from synthetic rainfall data was substantially less than the runoff from the historical data. From this it could be concluded that the slight differences between the hydrologic model input rainfall data were magnified in the output runoff data. There is insufficient evidence from this study, however, to place great confidence in this conclusion. Further work is needed to determine which components among those of evapotranspiration, antecedent soil moisture and curve number are most sensitive to rainfall and establish possible reasons for the runoff discrepancies.

The sensitivity of the hydrologic model to rainfall data emphasises the point that it is essential to use accurate, representative rainfall data when calibrating a rainfall-runoff model. The stochastic generation of synthetic rainfall data is a useful tool that may be used to extend limited rainfall records. Such extended rainfall records, used in conjunction with a precalibrated hydrological model could provide valuable information regarding the long-term water resource potential of a watershed.

Recommendations For Future Research

From the foregoing discussion and conclusions with respect to this study, the following areas for possible future research are identified:

a. Determine whether the rainfall model may be significantly improved through the use of continuously varying transitional probabilities and distribution parameters.

b. Determine the minimum length of rainfall record in arid and humid areas required for stable estimates of the rainfall model parameters.

c. Determine the effect on runoff, predicted by a rainfall-runoff model, when alternate rainfall data, collected from individual gages spatially distributed over the watershed, are used.

d. Determine the cause of the runoff discrepancies in the study reported by monitoring the values of the curve number, the soil moisture and evapotranspiration in the CREAMS model as the synthetic and historical rainfall input data are applied.

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APPENDIX A

SAS COMPUTER PROGRAM LISTING OF THE DAILY RAINFALL SIMULATION MODEL

```
//U14520A JOB (14520,442-76-6277),CLASS=A,TIME=(0,40),
// MSGCLASS=X,NOTIFY=*
/*PASSWORD BREE
/*ROUTE PRINT RMT4
// EXEC SAS
//FREQ DD UNIT=3380,DSN=U14520A.RUNS.FREQ1.DATA,DISP=OLD
//RUN DD UNIT=3380,DSN=U14520A.SAS.RUNS.DATA40,DISP=OLD
//STAT DD UNIT=STORAGE,DSN=U14520A.SAS.STAT.TABLE,DISP=OLD
//SYSIN DD *

*********************************************************************;
*          RAINFALL SIMULATION MODEL                                *;
*                     BY                                            *;
*                J.E.PETER GREEN                                    *;
*                                                                   *;
*  MARKOV CHAIN - LOGNORMAL PROBABILITY DISTRIBUTION   FUNCTION     *;
*                  PROCESS                                          *;
*                                                                   *;
*********************************************************************;

           SIMDRY(KEEP=YEAR JDAY MONTH PRECIP);
     SEED=41011;
     MAX=365;
     DO YEAR=1900 TO 1939;
     IF (YEAR/4-INT(YEAR/4))=0 THEN D=1;
     ELSE D=0;
     LASTDAY=MAX+D;
     DO JDAY=1 TO LASTDAY;
     IF YEAR=1900 AND JDAY=1 THEN EVENT=0;

*********************************************************************;
*       INITIALISE THE MONTHLY TRANSITIONAL PROBABLITIES            *;
*                    P(W/W)  AND  P(W/D)                            *;
*                FOR THE MARKOV CHAIN PROCESS                       *;
*********************************************************************;

     IF JDAY GE 1 AND JDAY LE 31 THEN
    DO; DTW=.105; WTW=.349; LN_MEAN=2.3586; MONTH=1;VAR=1.77929; END;
ELSE IF JDAY GE 32 AND JDAY LE (59+D) THEN
    DO; DTW=.130; WTW=.354; LN_MEAN=2.5455; MONTH=2;VAR=1.77360;; END;
ELSE IF JDAY GE (60+D) AND JDAY LE (90+D) THEN
    DO; DTW=.146; WTW=.353; LN_MEAN=2.9256; MONTH=3;VAR=1.78117; END;
ELSE IF JDAY GE (91+D) AND JDAY LE (120+D) THEN
    DO; DTW=.199; WTW=.407; LN_MEAN=2.9627; MONTH=4;VAR=2.03071; END;
ELSE IF JDAY GE (121+D) AND JDAY LE (151+D) THEN
    DO; DTW=.249; WTW=.427; LN_MEAN=3.0728; MONTH=5;VAR=2.04375; END;
ELSE IF JDAY GE (152+D) AND JDAY LE (181+D) THEN
    DO; DTW=.208; WTW=.411; LN_MEAN=3.1706; MONTH=6;VAR=1.93085; END;
ELSE IF JDAY GE (182+D) AND JDAY LE (212+D) THEN
    DO; DTW=.152; WTW=.361; LN_MEAN=3.0173; MONTH=7;VAR=2.14966; END;
ELSE IF JDAY GE (213+D) AND JDAY LE (243 +D) THEN
    DO; DTW=.162; WTW=.347; LN_MEAN=2.9976; MONTH=8;VAR=2.09077; END;
ELSE IF JDAY GE (244+D) AND JDAY LE (273+D) THEN
    DO; DTW=.157; WTW=.412; LN_MEAN=3.1821; MONTH=9;VAR=2.23437; END;
```

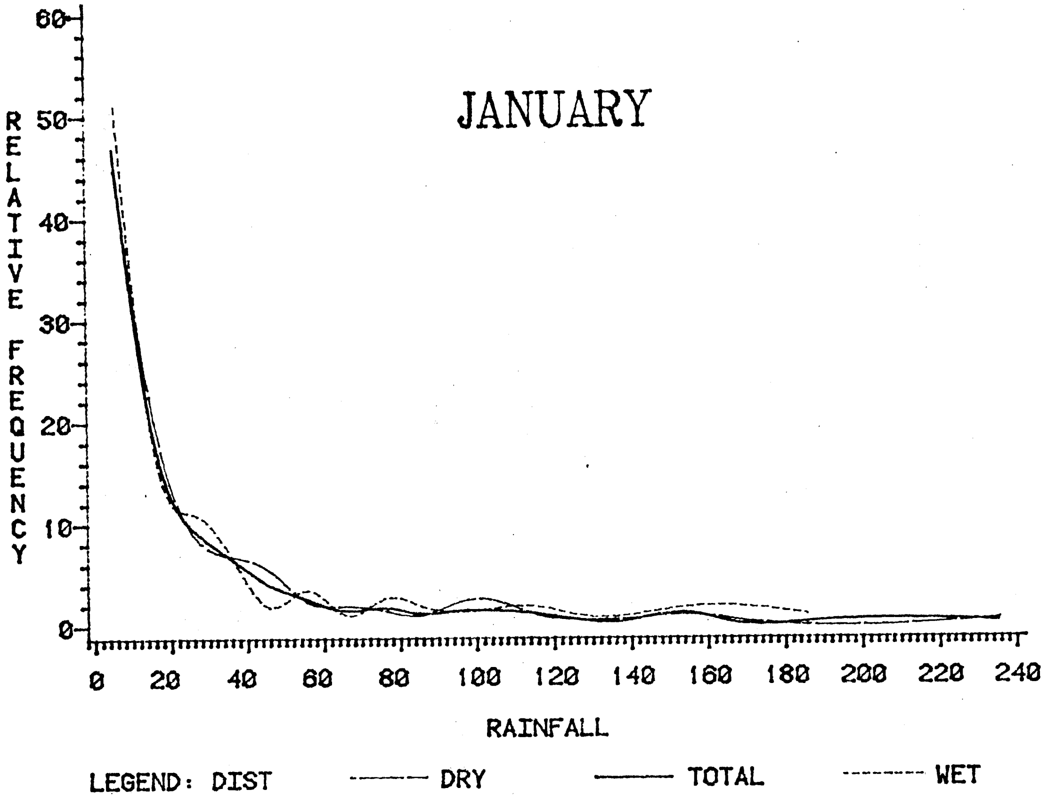
```
ELSE IF JDAY GE (274+D) AND JDAY LE (304+D) THEN
    DO; DTW=.132; WTW=.390; LN_MEAN=3.1081; MONTH=10;VAR=2.11499; END;
ELSE IF JDAY GE (305+D) AND JDAY LE (334+D) THEN
    DO; DTW=.113; WTW=.394; LN_MEAN=2.9793; MONTH=11;VAR=1.96010; END;
ELSE IF JDAY GE (335+D) AND JDAY LE (MAX+D) THEN
    DO; DTW=.110; WTW=.320; LN_MEAN=2.6060; MONTH=12;VAR=1.94277; END;

    LAMBDA=1/LN_MEAN;
*******************************************************************;
*        SIMULATION OF DAILY RAINFALL AMOUNTS                     *;
*                      USING                                      *;
*        LOGNORMAL PROBABLITY DENSITY FUNCTION                    *;
*******************************************************************;

     IF EVENT=1 THEN
     DO; IF RANUNI(SEED) LT WTW THEN
         DO; EVENT=1;
             RAIN1: PRECIP=EXP(LN_MEAN+SQRT(VAR)*RANNOR(SEED));
                  IF PRECIP LT 1 THEN PRECIP = 1;
             ELSE IF PRECIP GT 750 THEN GO TO RAIN1;
         END;
         ELSE DO; EVENT=0;OUTPUT SIMDRY; END;
     END;
ELSE IF EVENT=0 THEN
     DO; IF RANUNI(SEED) LT DTW THEN
         DO; EVENT=1;
             RAIN2: PRECIP=EXP(LN_MEAN+SQRT(VAR)*RANNOR(SEED));
                  IF PRECIP LT 1 THEN PRECIP = 1;
             ELSE IF PRECIP GT 750 THEN GO TO RAIN2;
         END;
         ELSE DO; EVENT=0; OUTPUT SIMDRY; END;
     END;

     RETAIN EVENT;
     END;
     END;

*******************************************************************;
*                     DETERMINATION                               *;
*                          OF                                     *;
*              CONSECUTIVE WET AND DRY DAY RUNS                   *;
*******************************************************************;

DATA RUN.LN1DRY40(KEEP=DRUN) RUN.LN1WET40(KEEP=WRUN);

     IF (YEAR/4-INT(YEAR/4))=0 THEN
     DO;D=1;MAX=366;PREMAX=365;END;
ELSE IF (YEAR/4-INT(YEAR/4))=.25 THEN
     DO;D=0;MAX=365;PREMAX=366;END;
ELSE DO;D=0;MAX=365;PREMAX=365;END;

     IF _N_ EQ 1 AND JDAY EQ 1 THEN
     DO;WN=1;
     END;
```

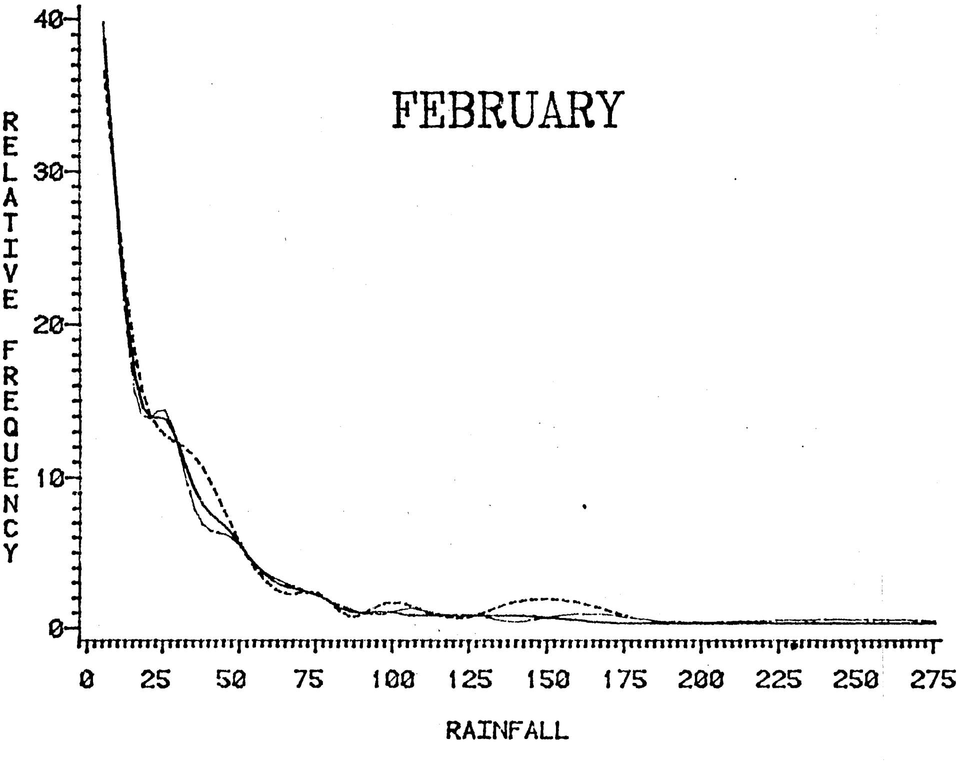
```
ELSE IF _N_ EQ 1 AND JDAY NE 1 THEN
     DO;WN=1;
      DRUN=JDAY-1;        OUTPUT RUN.LN1DRY40;
        DI=JDAY;
     END;

ELSE IF JDAY EQ DI+1 THEN
     DO;WN=WN+1;
        DI=JDAY;
     END;
ELSE IF JDAY GT DI+1 THEN
     DO;WRUN=WN;              OUTPUT RUN.LN1WET40;
        DRUN=JDAY-(DI+1);   OUTPUT RUN.LN1DRY40;
          DI=JDAY;
          WN=1;
     END;

ELSE IF JDAY LT DI AND DI LT PREMAX THEN
     DO;WRUN=WN;              OUTPUT RUN.LN1WET40;
        DRUN=PREMAX-DI+JDAY-1; OUTPUT RUN.LN1DRY40;
          DI=JDAY;
          WN=1;
     END;
ELSE IF JDAY EQ 1 AND DI EQ PREMAX THEN
     DO;WN=WN+1;
        DI=JDAY;
     END;
ELSE IF JDAY LT DI AND DI EQ PREMAX THEN
     DO;WRUN=WN;              OUTPUT RUN.LN1WET40;
        DRUN=JDAY-1;        OUTPUT RUN.LN1DRY40;
          DI=JDAY;
          WN=1;
     END;

ELSE DO;PUT 'CHECK DATA AT 'YEAR  JDAY ;
        DI=JDAY;
     END;

RETAIN WN;
RETAIN DI;

**********************************************************************;
*                  FREQUENCY ANALYSIS                                *;
*                          OF                                        *;
*            CONSECUTIVE WET AND DRY DAY RUNS                        *;
**********************************************************************;

PROC FREQ DATA=RUN.LN1WET40;
   TABLE WRUN/OUT=FREQ.LN1WET40;
TITLE FREQUENCY TABLE FOR CONSECUTIVE WET DAYS;
TITLE2 40 YEARS - SIMULATED DATA - RUN 1B;

PROC FREQ DATA=RUN.LN1DRY40;
   TABLE DRUN/OUT=FREQ.LN1DRY40;
```

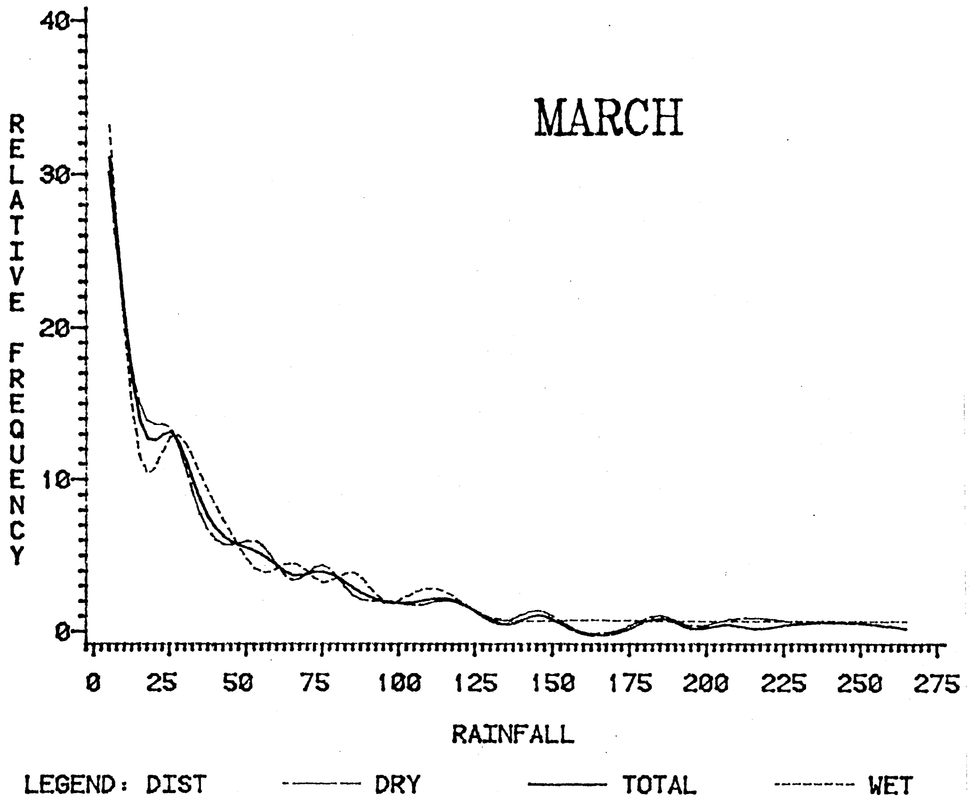
```
TITLE FREQUENCY TABLE FOR CONSECUTIVE DRY DAYS;
TITLE2 40 YEARS - SIMULATED DATA - RUN 1B;
*********************************************************************
*                    FREQUENCY ANALTSIS                             *
*                            OF                                     *
*               SIMULATED DAILY RAINFALL AMOUNTS                    *
*                   (LOGNORMAL DISTRIBUTION)                        *
*********************************************************************;
DATA ONE ;
 PPT=INT(PRECIP/10)*10+5;
PROC SORT DATA=ONE ;BY MONTH;
PROC FREQ DATA=ONE; BY MONTH;
  TABLES PPT/OUT=FREQ.LN1MD40;
  TITLE FREQUENCY TABLE FOR 40 YEARS OF SIMULATED DATA - RUN 1B;
  TITLE2 MARKOV CHAIN - LOGNORMAL DISTRIBUTION;
*********************************************************************;
*               CALCULATE THE STATISTICAL PARAMETERS                *
*                            FOR THE                                *
*                SIMULATED DAILY RAINFALL AMOUNTS                   *
*                   (LOGNORMAL DISTRIBUTION)                        *
*********************************************************************;
   BY MONTH ; VAR PRECIP;
   OUTPUT OUT=STAT1
   SUM=SUM MEAN=D_MEAN STD=STD VAR=VAR;
 DATA STAT.LN1DAT40;
    SET STAT1;
      IF MONTH = 1 THEN TOTAL = 0;
       YEARS=40;
       M_MEAN=SUM/40;
       TOTAL=TOTAL+M_MEAN;
       DROP SUM;
       OUTPUT;
RETAIN TOTAL;
PROC PRINT DATA=STAT.LN1DAT40;
  VAR M_MEAN D_MEAN STD VAR TOTAL;
TITLE STATISTICS FOR RAIN EVENTS FOR ;
TITLE2 40 YEARS OF SIMULATED DATA;
TITLE3 LOGNORMAL DISTRIBUTION - RUN 1B;
READY
```

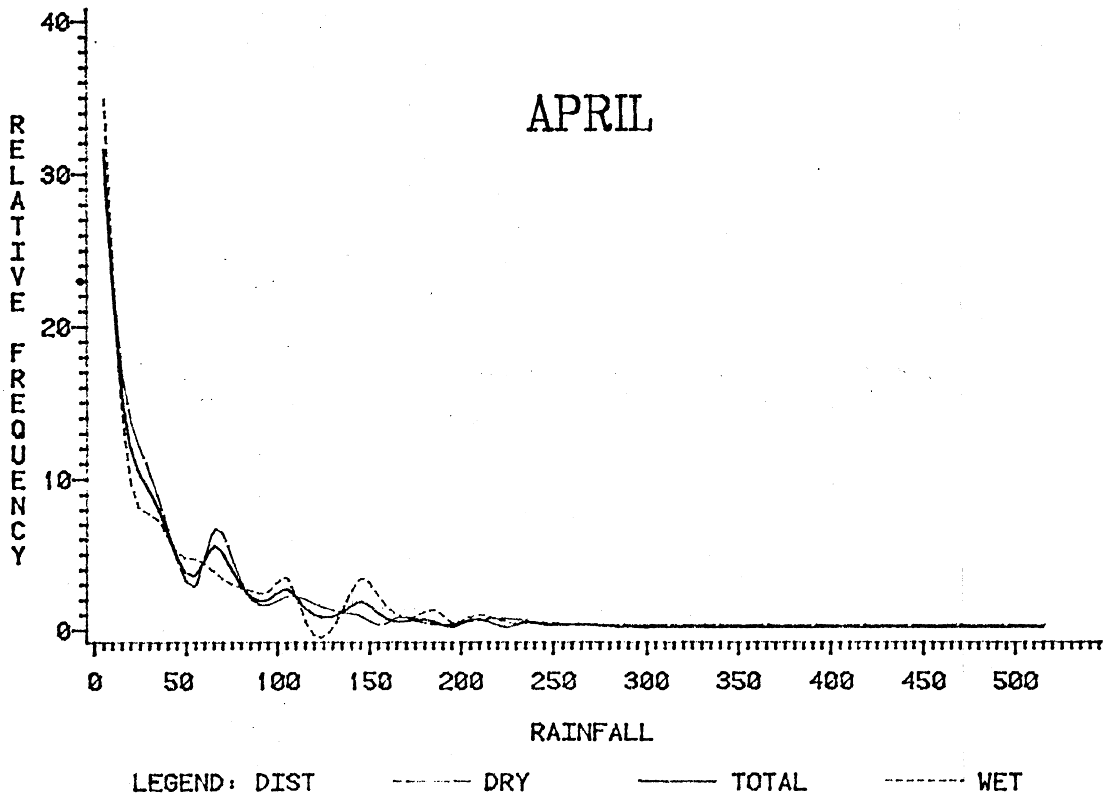
APPENDIX B

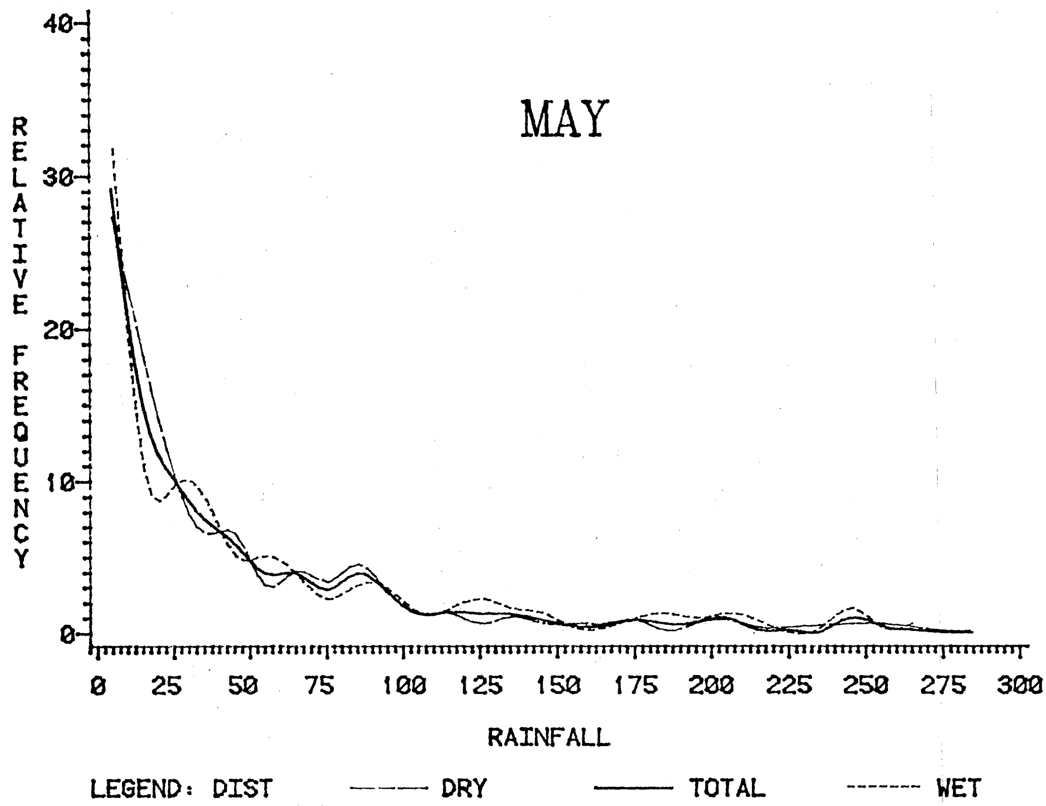
RELATIVE FREQUENCY CURVES OF DAILY RAINFALL AMOUNTS FOR WET DAYS (TOTAL), WET DAYS FOLLOWING DRY DAYS (DRY) AND WET DAYS FOLLOWING WET DAYS (WET) FOR EACH MONTH

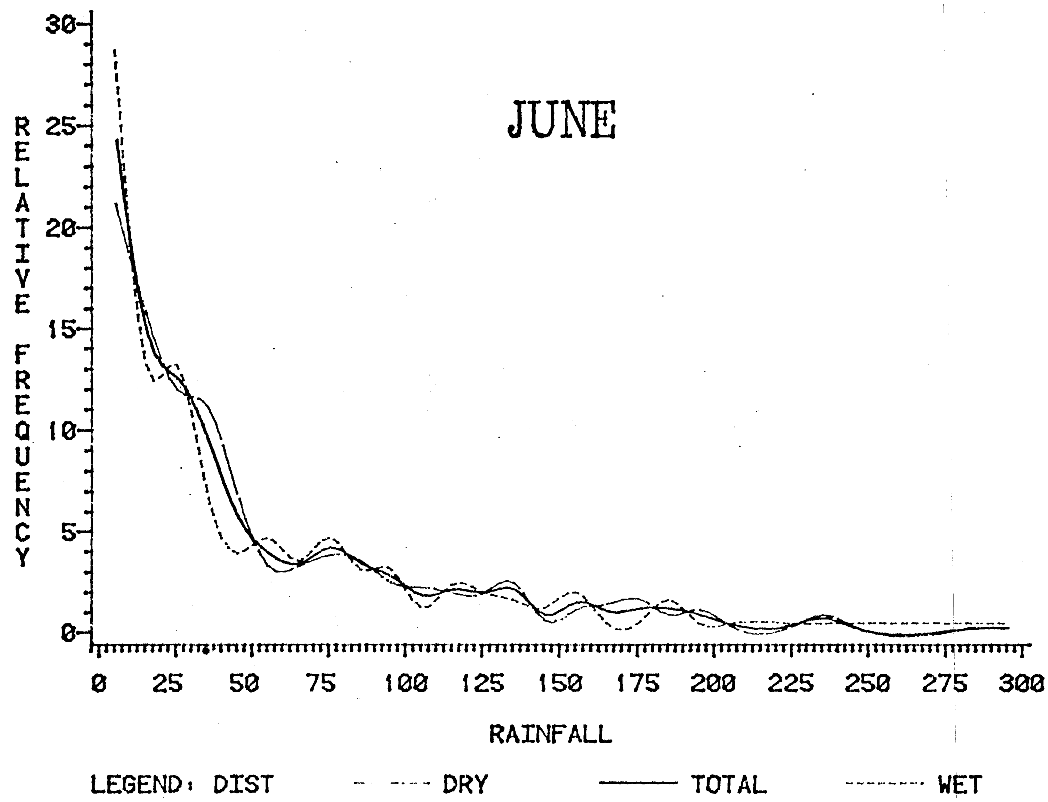

JANUARY
RELATIVE FREQUENCY
0
10
20
30
40
50
60
0 20 40 60 80 100 120 140 160 180 200 220 240
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET

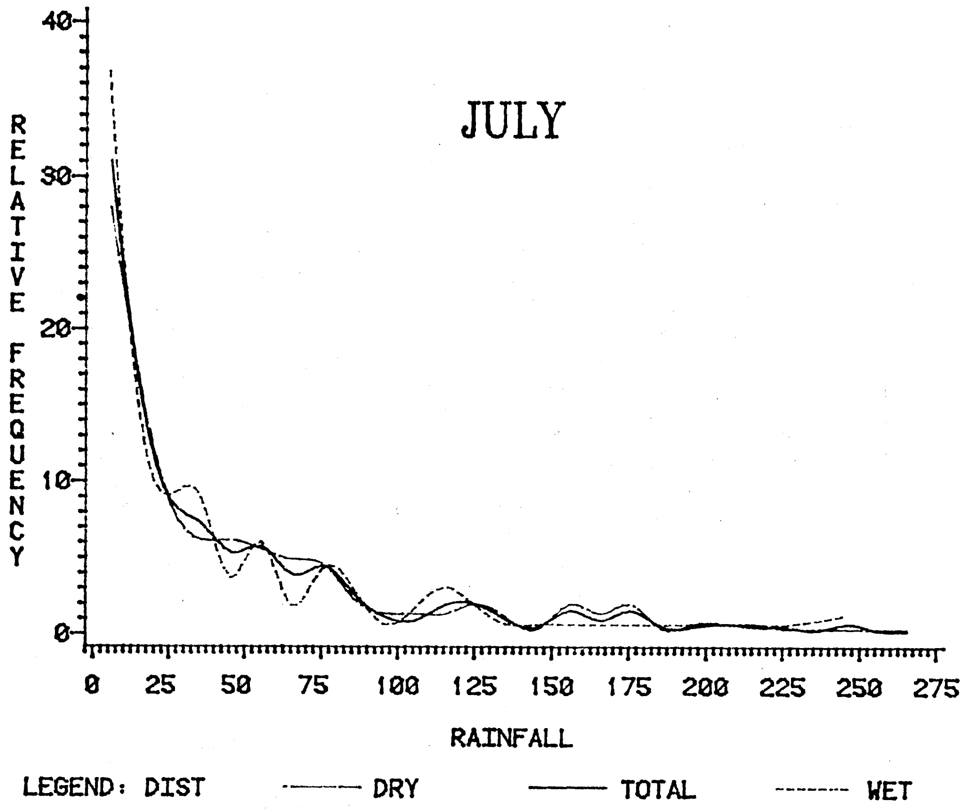

FEBRUARY
RELATIVE FREQUENCY
0
10
20
30
40
0 25 50 75 100 125 150 175 200 225 250 275
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET

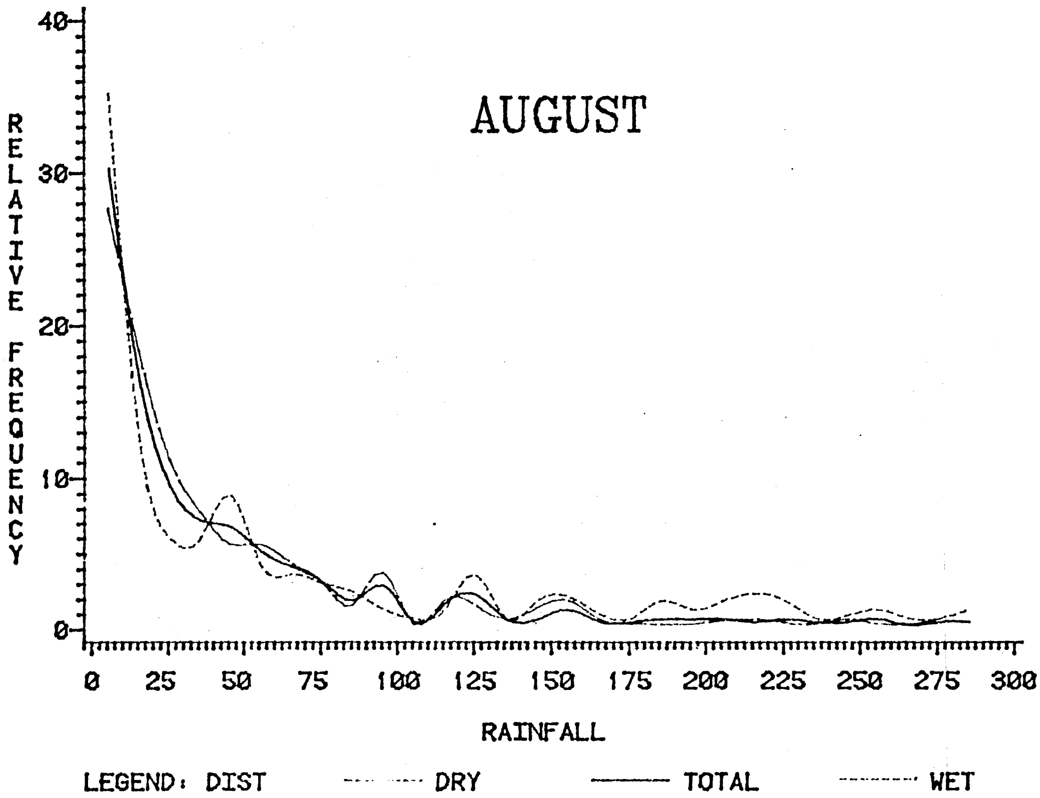

MARCH
RELATIVE FREQUENCY
40
30
20
10
0
0 25 50 75 100 125 150 175 200 225 250 275
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET

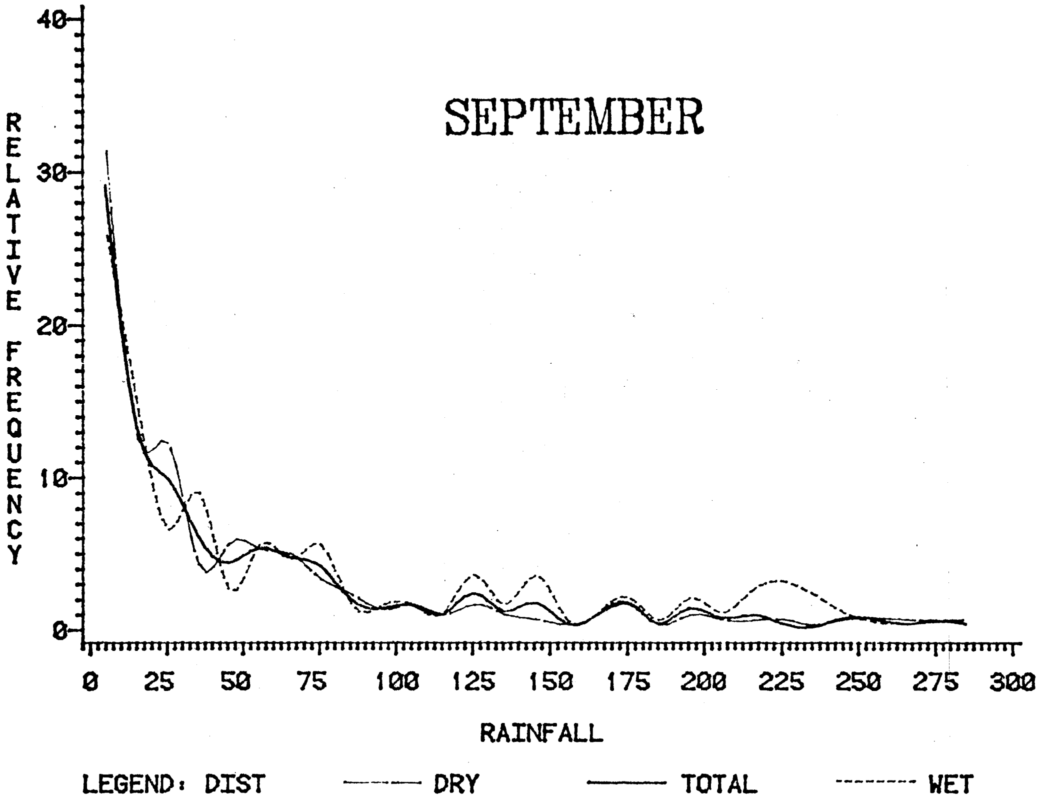

APRIL
RELATIVE FREQUENCY
40
30
20
10
0
0 50 100 150 200 250 300 350 400 450 500
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET

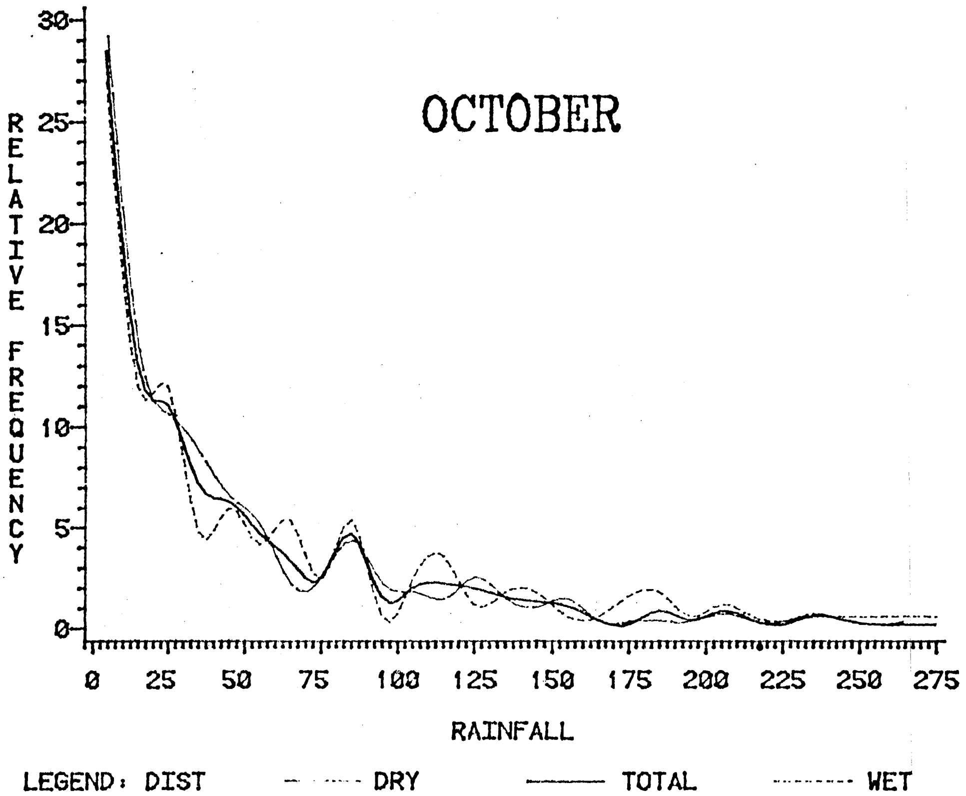

MAY
RELATIVE FREQUENCY
0
10
20
30
40
0 25 50 75 100 125 150 175 200 225 250 275 300
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET

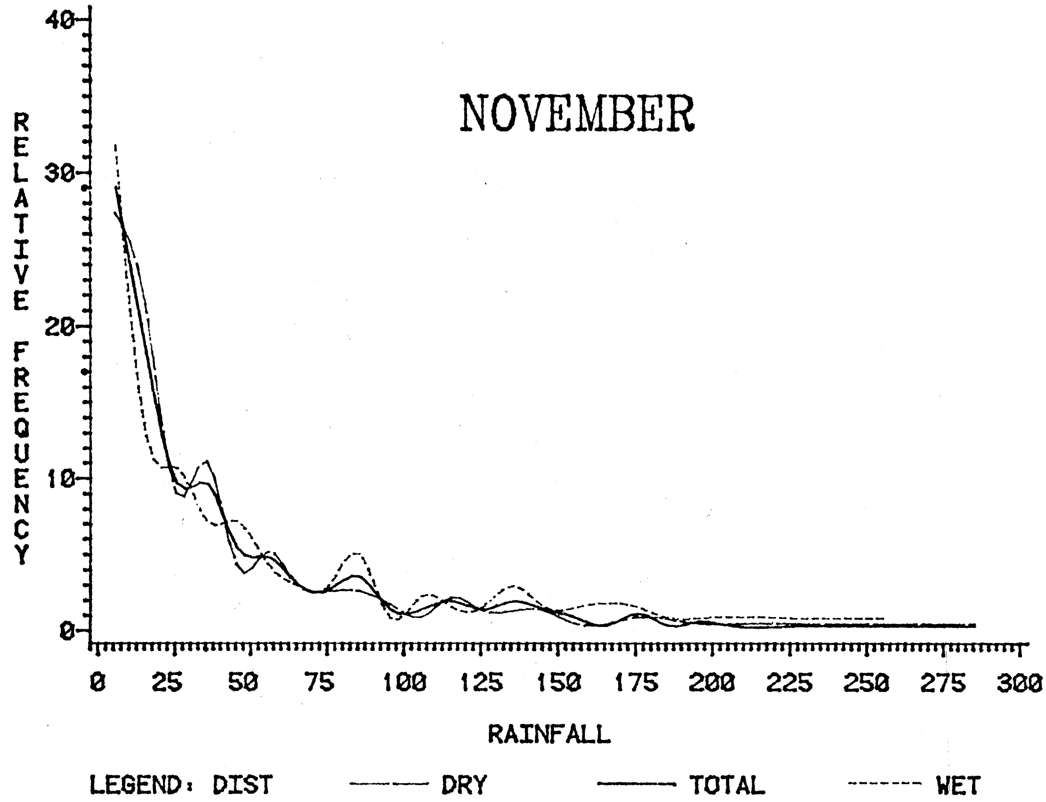

JUNE
RELATIVE FREQUENCY
0
5
10
15
20
25
30
0 25 50 75 100 125 150 175 200 225 250 275 300
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET

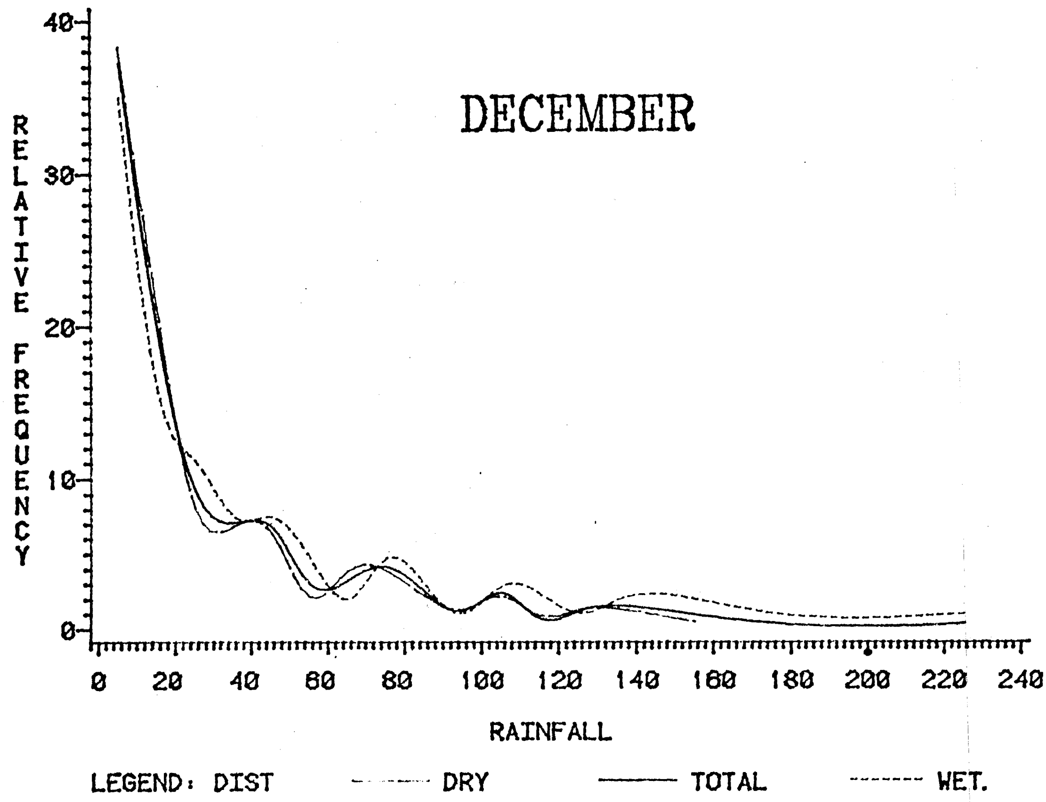

JULY
RELATIVE FREQUENCY
40
30
20
10
0
0 25 50 75 100 125 150 175 200 225 250 275
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET


AUGUST
RELATIVE FREQUENCY
40
30
20
10
0
0 25 50 75 100 125 150 175 200 225 250 275 300
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET


SEPTEMBER
RELATIVE FREQUENCY
40
30
20
10
0
0
25
50
75
100
125
150
175
200
225
250
275
300
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET


OCTOBER
RELATIVE FREQUENCY
30
25
20
15
10
5
0
0
25
50
75
100
125
150
175
200
225
250
275
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET


NOVEMBER
RELATIVE FREQUENCY
0
10
20
30
40
0 25 50 75 100 125 150 175 200 225 250 275 300
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET


DECEMBER
RELATIVE FREQUENCY
0
10
20
30
40
0 20 40 60 80 100 120 140 160 180 200 220 240
RAINFALL
LEGEND: DIST
DRY
TOTAL
WET.

APPENDIX C

PARAMETER ESTIMATION FOR THE LOGNORMAL DISTRIBUTION

I. Method of Moments (Haan, 1977) Yields

$$\theta_1 = \bar{Y} = \sum_{i=1}^{n} (Y_i/n)$$

$$\theta_2^2 = Sy^2 = \sum_{i=1}^{n} (Y_i - \bar{Y})^2/(n-1)$$

II. Chow's (1954) Method Yields

$$\theta_1 = 1/2 \ln(\bar{x}^2/(C_v^2 + 1))$$

$$\theta_2^2 = \ln(C_v^2 + 1)$$

where $C_v = S_x/\bar{x}$ (coefficient of variation of the original data)

S_x = standard deviation of the original data and

$\bar{x}$ = mean of the original data.

III. Method of Maximum Likelihood

The lognormal probability density function is

$$p_x(x) = (2\pi\theta_2^2)^{-1/2}\ x^{-1} \exp(-(\ln x - \theta_1)^2/2\theta_2{}^2)$$

and the maximum likelihood function is

$$L(\theta_1, \theta_2^2) = (2\pi\theta_2^2)^{-n/2} \prod_{i=1}^{n} x_i^{-1} \exp(-\sum_{i=1}^{n} (\ln x_i - \theta_1)^2/2\theta_2^2)$$

Taking the natural logarithms yields

$$\ln L(\theta_1, \theta_2^2) = -n/2 \ln(2\pi) - n/2 \ln(\theta_2^2) - $$

$$-\sum_{i=1}^{n} \ln x_i - \sum_{i=1}^{n} (\ln x_i - \theta_1)^2/2\theta_2^2$$

Maximizing with respect to θ_1 yields

$$0 = d(\ln L(\theta_1, \theta_2^2)/d\theta_1$$

$$= \sum_{i=1}^{n} (\ln x_i - \theta_1)$$

$$= \sum_{i=1}^{n} \ln x_i - n\theta_1$$

Thus $\theta_1 = \sum_{i=1}^{n} (\ln x_i)/n$

How if $Y_i = \ln x_i$

Then $\bar{Y} = \sum_{i=1}^{n} (\ln x_i)/n$

and $\theta_1 = \bar{Y}$

Maximizing with respect to θ_2^2 yields

$$0 = d(\ln L(\theta_1, \theta_2^2)/d\theta_2^2$$

$$= n/2\ \theta_2^2 + \sum_{i=1}^{n} (\ln x_i - \theta_1)^2/2\theta_2^4$$

$$= -(n - \sum_{i=1}^{n} (\ln x_i - \theta_1)^2/\theta_2^2)/2\theta_2^2$$

Thus $\theta_2^2 = \sum_{i=1}^{n} (\ln x_i - \theta_1)^2/n$

Since $Y_i = \ln x_i$

$\theta_1 = \bar{Y}$

and $S_y^2 = \sum_{i=1}^{n} (Y_i - \bar{Y})^2/(n-1)$

$$\text{Then } \theta_2^2 = \sum_{i=1}^{n} (Y_i - \overline{Y})^2 (n-1)/(n-1)n$$

$$= S_y^2(n-1)/n$$

APPENDIX D

CUMULATIVE FREQUENCY TABLES OF HISTORICAL AND SYNTHETIC DAILY RAINFALL AMOUNTS

COLUMN HEADINGS

P	MID POINT OF RAINFALL CLASS
CUM _ PER	CUMULATIVE PERCENT OF HISTORICAL DATA
CUM _ LN	CUMULATIVE PERCENT OF SYNTHETIC DATA

MONTH=1

OBS	P	CUM_PER	CUM_LN
1	5	46.802	45.9796
2	15	65.698	65.2456
3	25	75.291	74.9625
4	35	81.977	80.6763
5	45	86.047	84.3633
6	55	88.663	86.8965
7	65	90.116	88.7183
8	75	91.860	90.0748
9	85	93.023	91.1130
10	95	94.477	91.9257
11	105	95.930	92.5737
12	115	97.093	93.0987
13	125	97.674	93.5297
14	135	97.965	93.8877
15	145	97.965	94.1883
16	155	99.128	94.4428
17	165	99.419	94.6601
18	175	99.419	94.8471
19	185	99.709	95.0089
20	195	99.709	95.1499
21	205	99.709	95.2734
22	215	99.709	95.3821
23	225	99.709	95.4782
24	235	100.000	95.5635
25	245	100.000	95.6396
26	255	100.000	95.7077
27	265	100.000	95.7688
28	275	100.000	95.8239
29	285	100.000	95.8736
30	295	100.000	95.9187
31	305	100.000	95.9597

MONTH=2

OBS	P	CUM_PER	CUM_LN
32	5	38.624	42.1194
33	15	55.026	61.9417
34	25	68.783	72.4862
35	35	77.778	78.9064
36	45	84.392	83.1578
37	55	88.360	86.1396
38	65	91.005	88.3209
39	75	93.122	89.9690
40	85	94.180	91.2466
41	95	95.238	92.2579
42	105	96.032	93.0726
43	115	96.825	93.7387
44	125	97.619	94.2902
45	135	98.413	94.7519
46	145	98.413	95.1422
47	155	98.942	95.4750
48	165	98.942	95.7610
49	175	99.206	96.0084
50	185	99.471	96.2238
51	195	99.471	96.4125
52	205	99.471	96.5785
53	215	99.735	96.7253
54	225	99.735	96.8558
55	235	99.735	96.9721
56	245	99.735	97.0763
57	255	99.735	97.1698
58	265	99.735	97.2542
59	275	100.000	97.3304
60	285	100.000	97.3996
61	295	100.000	97.4624
62	305	100.000	97.5197

MONTH=3

OBS	P	CUM_PER	CUM_LN
63	5	31.140	33.0848
64	15	44.956	52.7498
65	25	58.114	64.4215
66	35	66.667	72.0624
67	45	72.588	77.4046
68	55	77.632	81.3180
69	65	81.360	84.2865
70	75	85.307	86.6003
71	85	88.158	88.4435
72	95	90.132	89.9384
73	105	92.105	91.1693
74	115	94.298	92.1958
75	125	95.614	93.0614
76	135	96.053	93.7983
77	145	97.149	94.4312
78	155	97.368	94.9788
79	165	97.368	95.4558
80	175	97.588	95.8739
81	185	98.465	96.2424
82	195	98.684	96.5688
83	205	99.123	96.8593
84	215	99.342	97.1189
85	225	99.781	97.3518
86	235	99.781	97.5616
87	245	99.781	97.7511
88	255	99.781	97.9229
89	265	100.000	98.0790
90	275	100.000	98.2214
91	285	100.000	98.3514
92	295	100.000	98.4706
93	305	100.000	98.5800

MONTH=4

OBS	P	CUM_PER	CUM_LN
94	5	31.5615	32.1031
95	15	46.8439	50.4712
96	25	56.9767	61.4898
97	35	64.7841	68.8257
98	45	69.4352	74.0461
99	55	73.0897	77.9367
100	65	78.5714	80.9370
101	75	82.3920	83.3124
102	85	84.5515	85.2331
103	95	86.5449	86.8129
104	105	89.2027	88.1312
105	115	90.5316	89.2448
106	125	91.3621	90.1953
107	135	92.5249	91.0142
108	145	94.3522	91.7253
109	155	95.3488	92.3473
110	165	95.8472	92.8948
111	175	96.5116	93.3795
112	185	97.0100	93.8109
113	195	97.1761	94.1966
114	205	97.8405	94.5430
115	215	97.8405	94.8554
116	225	98.0066	95.1380
117	235	98.5050	95.3946
118	245	98.8372	95.6284
119	255	99.1694	95.8420
120	265	99.1694	96.0376
121	275	99.1694	96.2173
122	285	99.3355	96.3827
123	295	99.3355	96.5353
124	305	99.3355	96.6764

MONTH=5

OBS	P	CUM_PER	CUM_LN
125	5	29.2328	29.7467
126	15	44.3122	47.7549
127	25	54.4974	58.8591
128	35	62.0370	66.3907
129	45	67.9894	71.8265
130	55	71.9577	75.9243
131	65	75.9259	79.1147
132	75	78.8360	81.6617
133	85	82.8042	83.7362
134	95	85.5820	85.4537
135	105	86.9048	86.8954
136	115	88.3598	88.1199
137	125	89.6825	89.1702
138	135	91.0053	90.0793
139	145	91.9312	90.8721
140	155	92.4603	91.5684
141	165	92.9894	92.1836
142	175	93.9153	92.7302
143	185	94.5767	93.2183
144	195	95.3704	93.6561
145	205	96.4286	94.0505
146	215	96.6931	94.4072
147	225	96.9577	94.7309
148	235	97.0899	95.0256
149	245	98.1481	95.2947
150	255	98.6772	95.5411
151	265	98.9418	95.7675
152	275	99.0741	95.9758
153	285	99.2063	96.1680
154	295	99.2063	96.3457
155	305	99.2063	96.5104

MONTH=6

OBS	P	CUM_PER	CUM_LN
156	5	24.2424	27.4931
157	15	38.9155	45.6018
158	25	51.3557	57.0789
159	35	60.7656	64.9733
160	45	66.3477	70.7186
161	55	70.1754	75.0731
162	65	73.5247	78.4756
163	75	77.6715	81.1985
164	85	81.0207	83.4199
165	95	83.7321	85.2612
166	105	85.4864	86.8078
167	115	87.5598	88.1218
168	125	89.4737	89.2491
169	135	91.5470	90.2248
170	145	92.3445	91.0755
171	155	93.7799	91.8223
172	165	94.7368	92.4820
173	175	95.8533	93.0678
174	185	96.9697	93.5906
175	195	97.7671	94.0593
176	205	98.0861	94.4812
177	215	98.0861	94.8625
178	225	98.4051	95.2083
179	235	99.0431	95.5228
180	245	99.2026	95.8099
181	255	99.2026	96.0726
182	265	99.2026	96.3136
183	275	99.2026	96.5353
184	285	99.3620	96.7396
185	295	99.5215	96.9285
186	305	99.5215	97.1033

1SAS

MONTH=7

OBS	P	CUM_PER	CUM_LN
187	5	31.0273	30.8877
188	15	46.5409	48.6286
189	25	55.1363	59.4101
190	35	62.2642	66.6780
191	45	67.5052	71.9088
192	55	73.1656	75.8475
193	65	76.9392	78.9134
194	75	81.3417	81.3618
195	85	83.8574	83.3575
196	95	84.9057	85.0113
197	105	85.7442	86.4011
198	115	87.6310	87.5828
199	125	89.5178	88.5979
200	135	90.3564	89.4775
201	145	90.7757	90.2458
202	155	92.2432	90.9214
203	165	93.0818	91.5192
204	175	94.5493	92.0511
205	185	94.9686	92.5268
206	195	95.3878	92.9540
207	205	96.0168	93.3394
208	215	96.4361	93.6885
209	225	96.8553	94.0056
210	235	97.0650	94.2948
211	245	97.6939	94.5592
212	255	97.9036	94.8016
213	265	98.1132	95.0246
214	275	98.1132	95.2301
215	285	98.1132	95.4199
216	295	98.1132	95.5957
217	305	98.9518	95.7588

MONTH=8

OBS	P	CUM_PER	CUM_LN
218	5	30.2231	31.3262
219	15	46.4503	49.3548
220	25	55.7809	60.2624
221	35	62.8803	67.5801
222	45	69.5740	72.8227
223	55	74.6450	76.7536
224	65	78.7018	79.8015
225	75	81.7444	82.2267
226	85	83.5700	84.1966
227	95	86.4097	85.8239
228	105	86.8154	87.1873
229	115	88.4381	88.3432
230	125	90.6694	89.3334
231	135	91.2779	90.1894
232	145	91.8864	90.9350
233	155	93.1034	91.5892
234	165	93.5091	92.1668
235	175	93.9148	92.6795
236	185	94.5233	93.1370
237	195	95.1318	93.5472
238	205	95.7404	93.9165
239	215	96.1460	94.2502
240	225	96.7546	94.5530
241	235	97.1602	94.8285
242	245	97.5659	95.0800
243	255	98.1744	95.3102
244	265	98.3773	95.5216
245	275	98.7830	95.7161
246	285	99.1886	95.8955
247	295	99.1886	96.0613
248	305	99.3915	96.2150

MONTH=9

OBS	P	CUM_PER	CUM_LN
249	5	29.1089	27.6212
250	15	42.3762	44.5412
251	25	52.2772	55.2136
252	35	58.4158	62.6049
253	45	62.7723	68.0401
254	55	68.1188	72.2067
255	65	72.8713	75.5007
256	75	77.0297	78.1675
257	85	79.0099	80.3678
258	95	80.3960	82.2117
259	105	81.9802	83.7770
260	115	82.9703	85.1206
261	125	85.3465	86.2848
262	135	86.5347	87.3021
263	145	88.3168	88.1974
264	155	88.7129	88.9904
265	165	89.7030	89.6970
266	175	91.4851	90.3298
267	185	91.8812	90.8991
268	195	93.2673	91.4137
269	205	94.0594	91.8805
270	215	95.0495	92.3055
271	225	95.4455	92.6938
272	235	95.6436	93.0495
273	245	96.4356	93.3765
274	255	96.4356	93.6777
275	265	96.8317	93.9559
276	275	97.4257	94.2135
277	285	97.8218	94.4525
278	295	97.8218	94.6747
279	305	98.2178	94.8817

MONTH=10

OBS	P	CUM_PER	CUM_LN
280	5	28.5068	29.0357
281	15	41.6290	46.6447
282	25	52.7149	57.5857
283	35	59.9548	65.0614
284	45	66.2896	70.4931
285	55	71.0407	74.6129
286	65	74.4344	77.8365
287	75	76.9231	80.4268
288	85	81.6742	82.5451
289	95	83.2579	84.3067
290	105	85.2941	85.7917
291	115	87.5566	87.0578
292	125	89.5928	88.1481
293	135	91.1765	89.0950
294	145	92.5339	89.9237
295	155	93.6652	90.6538
296	165	94.1176	91.3009
297	175	94.3439	91.8775
298	185	95.2489	92.3939
299	195	95.7014	92.8585
300	205	96.6063	93.2781
301	215	97.0588	93.6585
302	225	97.2851	94.0045
303	235	97.9638	94.3204
304	245	98.4163	94.6095
305	255	98.6425	94.8749
306	265	98.8688	95.1191
307	275	99.0950	95.3444
308	285	99.0950	95.5527
309	295	99.0950	95.7457
310	305	99.0950	95.9250

MONTH=11

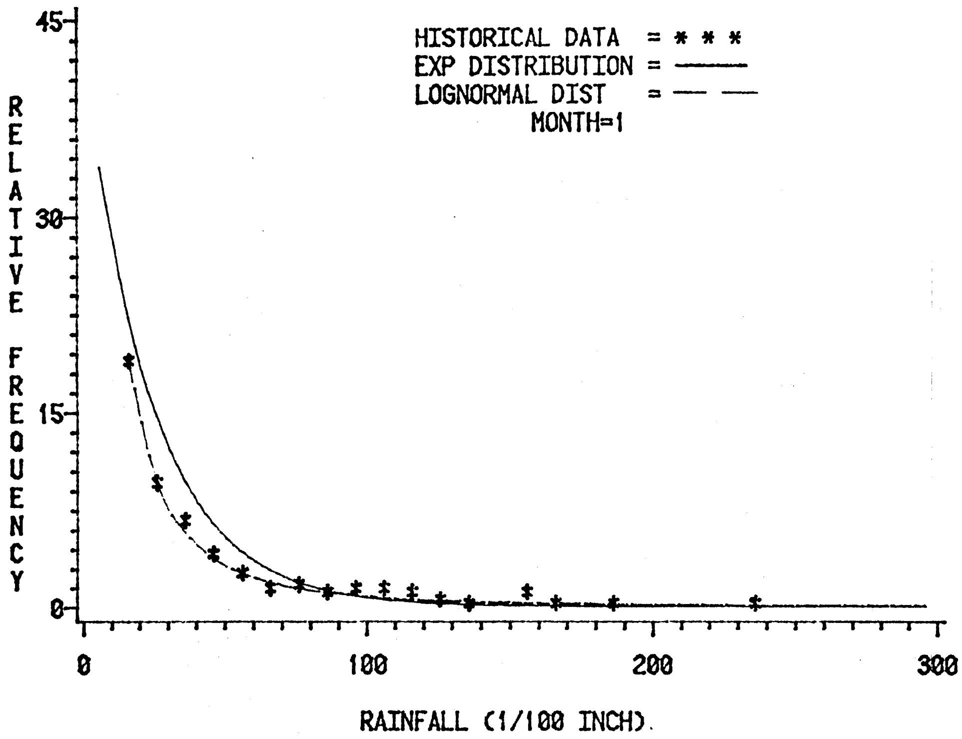
OBS	P	CUM_PER	CUM_LN
311	5	28.9894	31.7805
312	15	47.0745	50.4240
313	25	56.6489	61.6564
314	35	66.2234	69.1370
315	45	71.5426	74.4547
316	55	76.3298	78.4113
317	65	79.2553	81.4566
318	75	81.9149	83.8627
319	85	85.3723	85.8041
320	95	86.7021	87.3977
321	105	88.0319	88.7247
322	115	89.8936	89.8434
323	125	91.2234	90.7964
324	135	93.0851	91.6158
325	145	94.4149	92.3261
326	155	95.2128	92.9461
327	165	95.4787	93.4909
328	175	96.5426	93.9724
329	185	96.8085	94.4002
330	195	97.3404	94.7820
331	205	97.6064	95.1244
332	215	97.6064	95.4326
333	225	97.8723	95.7110
334	235	98.1383	95.9634
335	245	98.1383	96.1931
336	255	98.4043	96.4025
337	265	98.6702	96.5941
338	275	98.9362	96.7698
339	285	99.2021	96.9313
340	295	99.2021	97.0802
341	305	99.4681	97.2176

MONTH=12

OBS	P	CUM_PER	CUM_LN
342	5	37.209	39.8986
343	15	56.686	58.9289
344	25	65.698	69.3228
345	35	72.674	75.8077
346	45	79.360	80.1968
347	55	82.267	83.3363
348	65	85.465	85.6743
349	75	89.535	87.4701
350	85	91.860	88.8835
351	95	93.023	90.0183
352	105	95.349	90.9445
353	115	95.930	91.7113
354	125	97.093	92.3537
355	135	98.547	92.8976
356	145	98.547	93.3622
357	155	99.419	93.7625
358	165	99.419	94.1098
359	175	99.709	94.4131
360	185	99.709	94.6795
361	195	99.709	94.9149
362	205	99.709	95.1237
363	215	99.709	95.3099
364	225	100.000	95.4766
365	235	100.000	95.6264
366	245	100.000	95.7615
367	255	100.000	95.8837
368	265	100.000	95.9947
369	275	100.000	96.0957
370	285	100.000	96.1878
371	295	100.000	96.2721
372	305	100.000	96.3495

APPENDIX E

PLOTS OF THE MONTHLY RELATIVE FREQUENCIES OF THE HISTORICAL DATA, THE EXPONENTIAL PROBABILITY DENSITY FUNCTION AND THE LOGNORMAL PROBABILITY DENSITY FUNCTION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0
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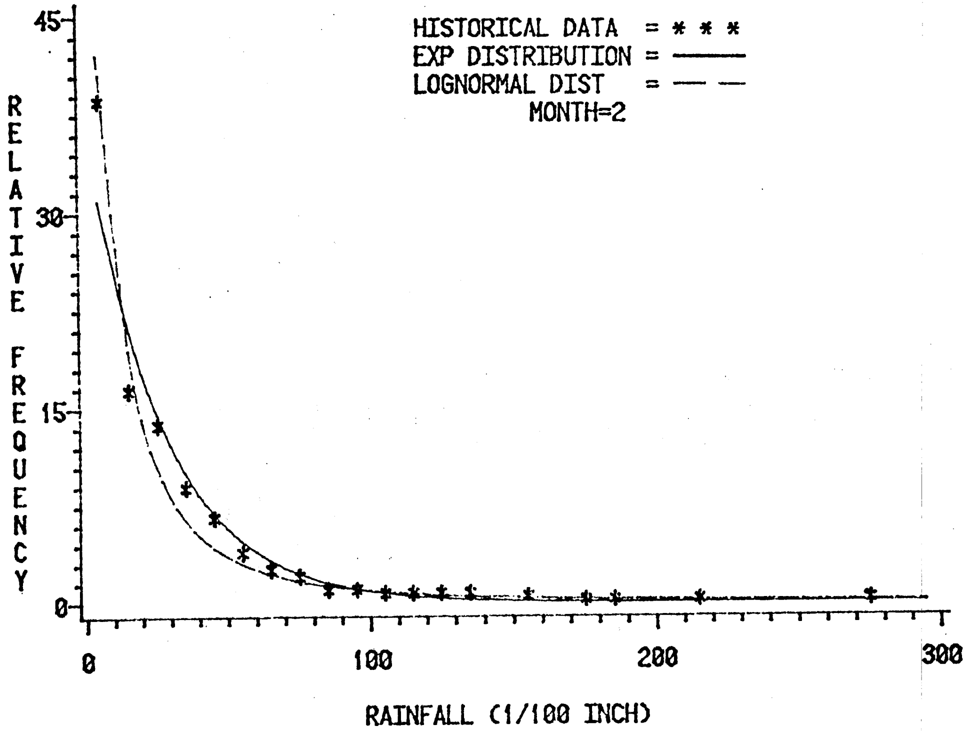
200
300
RAINFALL (1/100 INCH)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EXP DISTRIBUTION =
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RELATIVE FREQUENCY
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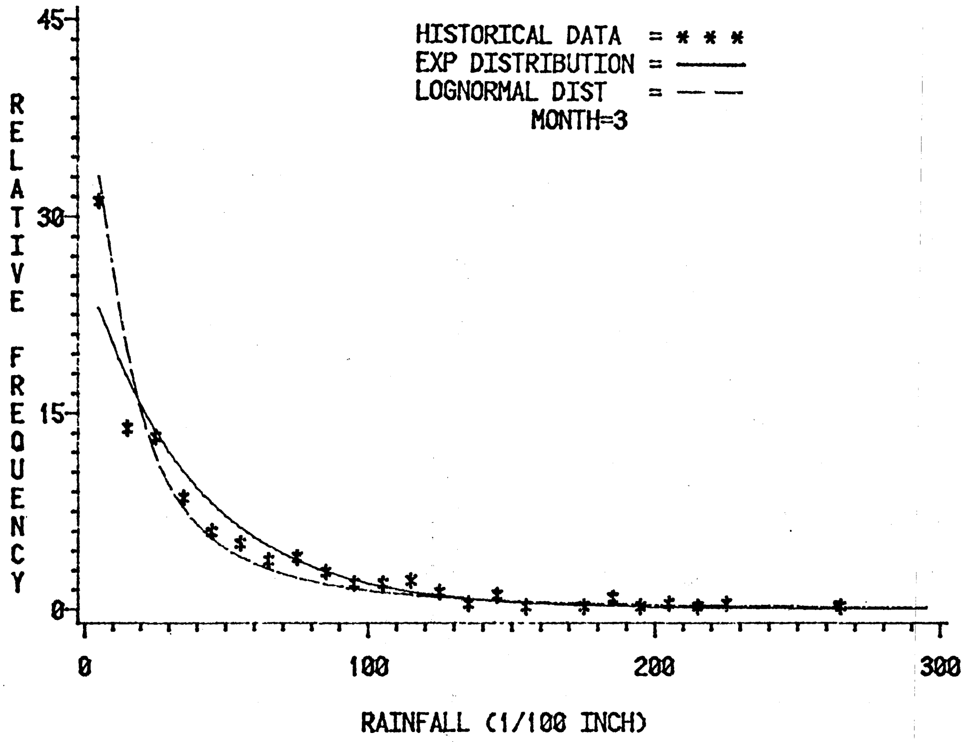
RAINFALL (1/100 INCH)


HISTORICAL DATA = * * *
EXP DISTRIBUTION =
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MONTH=3
RELATIVE FREQUENCY
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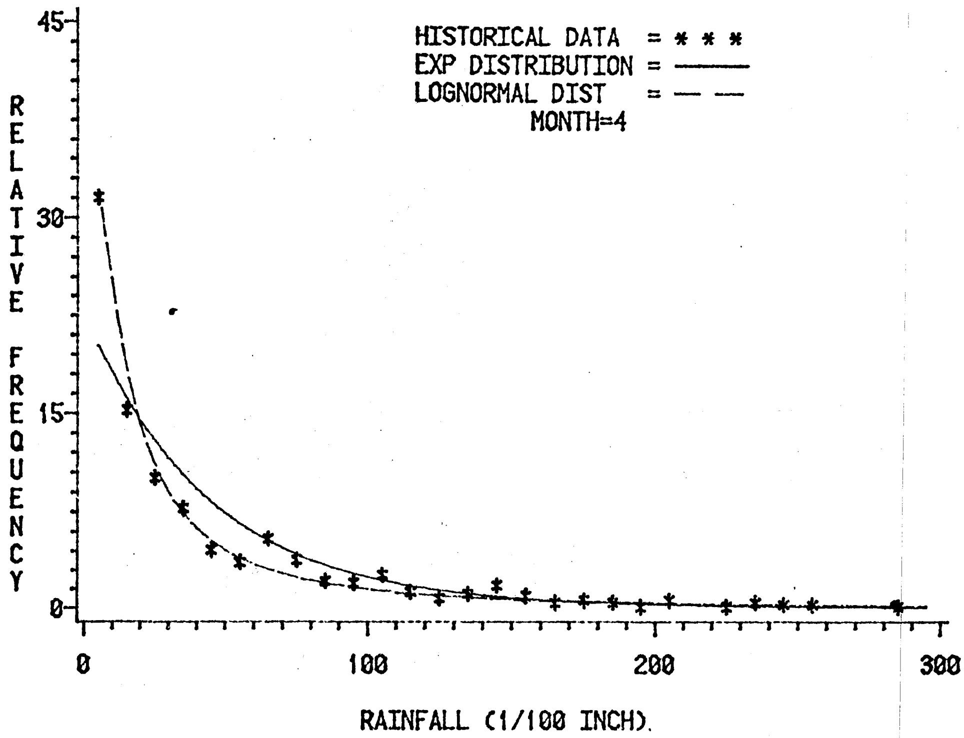
300
RAINFALL (1/100 INCH)


HISTORICAL DATA = * * *
EXP DISTRIBUTION =
LOGNORMAL DIST =
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RELATIVE FREQUENCY
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30
15
0
0
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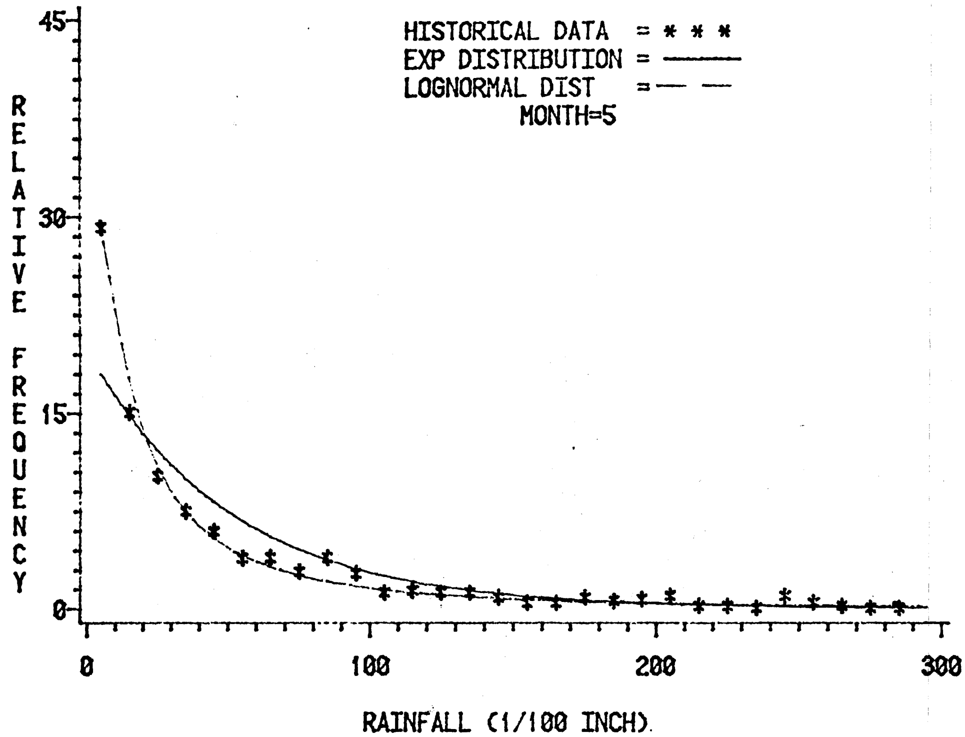
200
300
RAINFALL (1/100 INCH)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LOGNORMAL DIST = — —
MONTH=5
RELATIVE FREQUENCY
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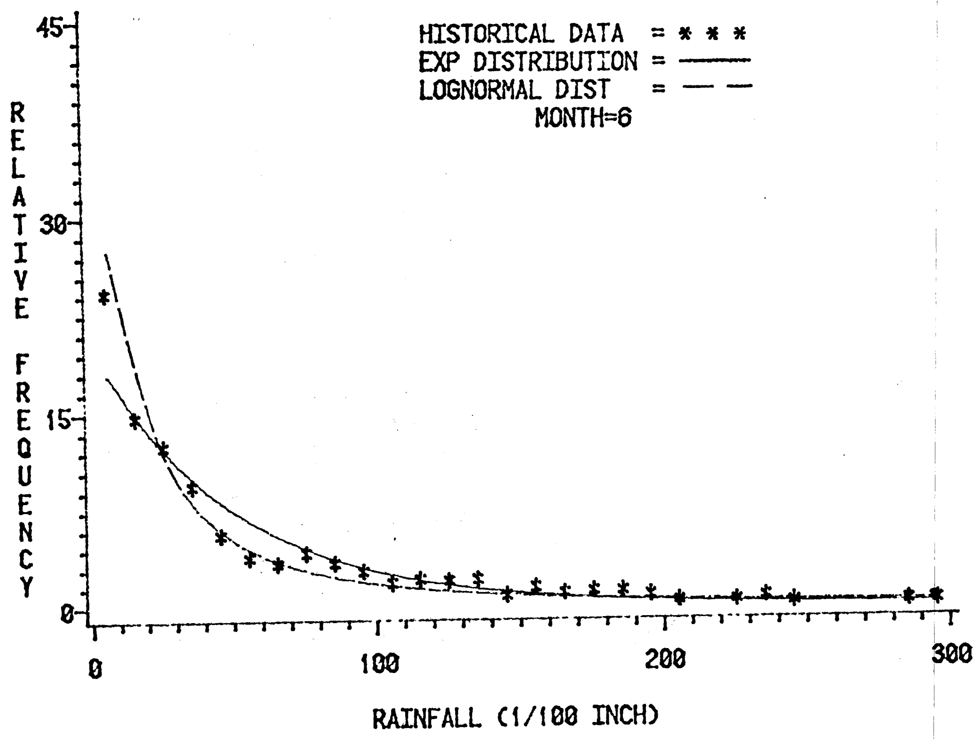
30
15
0
0
100
200
300
RAINFALL (1/100 INCH)


HISTORICAL DATA = * * *
EXP DISTRIBUTION = ———
LOGNORMAL DIST = — —
MONTH=6
RELATIVE FREQUENCY
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0
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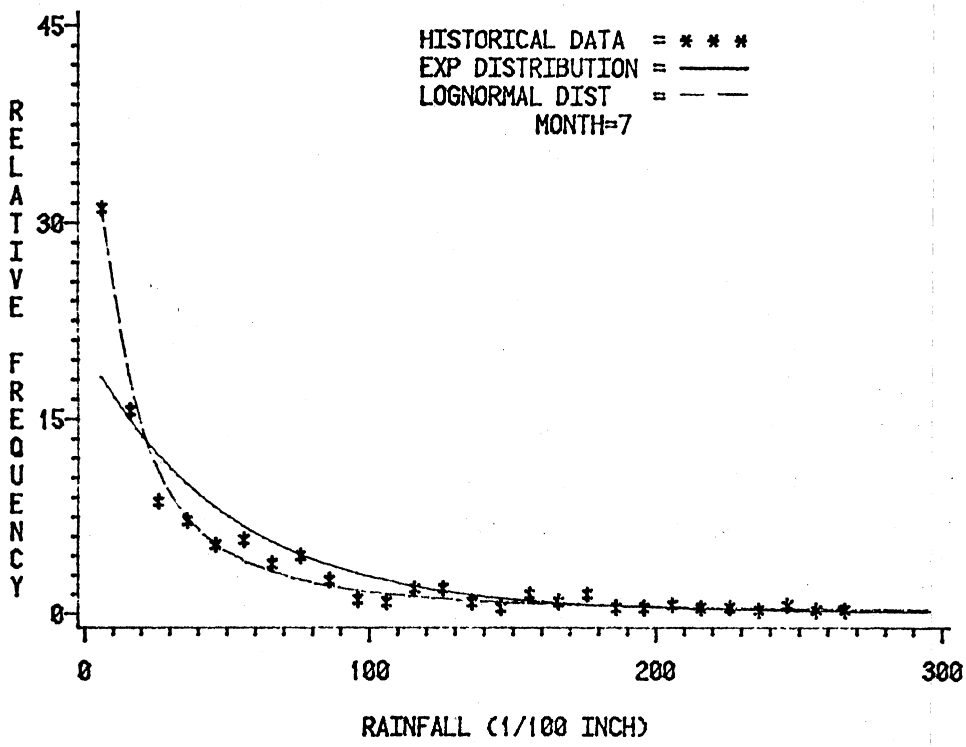
200
300
RAINFALL (1/100 INCH)



HISTORICAL DATA = * * *
EXP DISTRIBUTION =
LOGNORMAL DIST =
MONTH=7
RELATIVE FREQUENCY
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0
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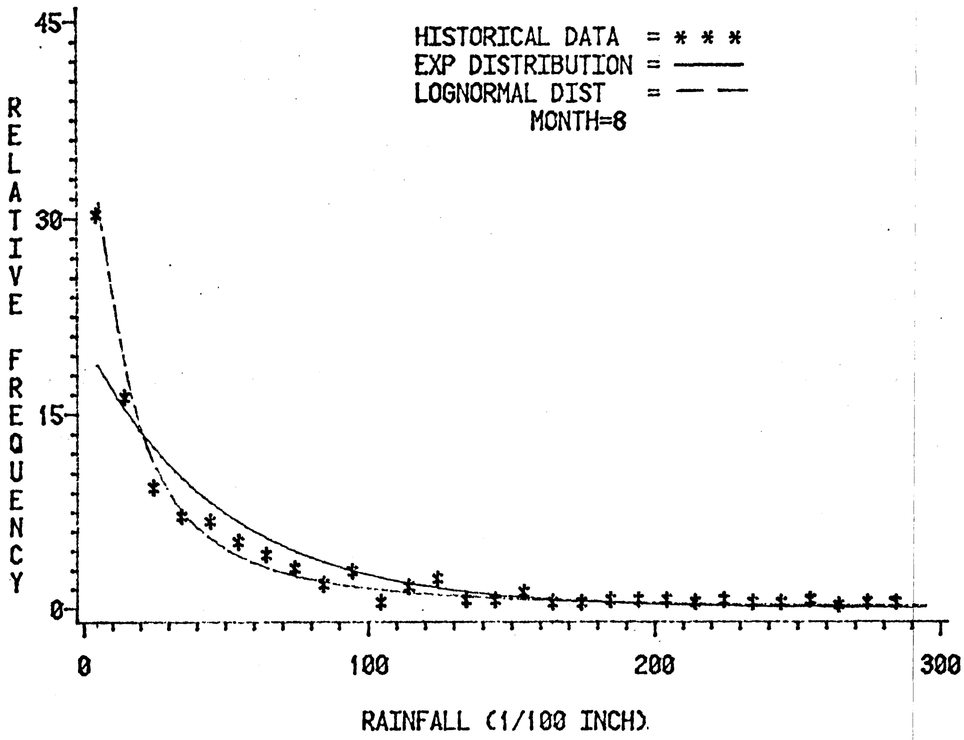
300
RAINFALL (1/100 INCH)



HISTORICAL DATA = * * *
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LOGNORMAL DIST =
MONTH=8
RELATIVE FREQUENCY
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0
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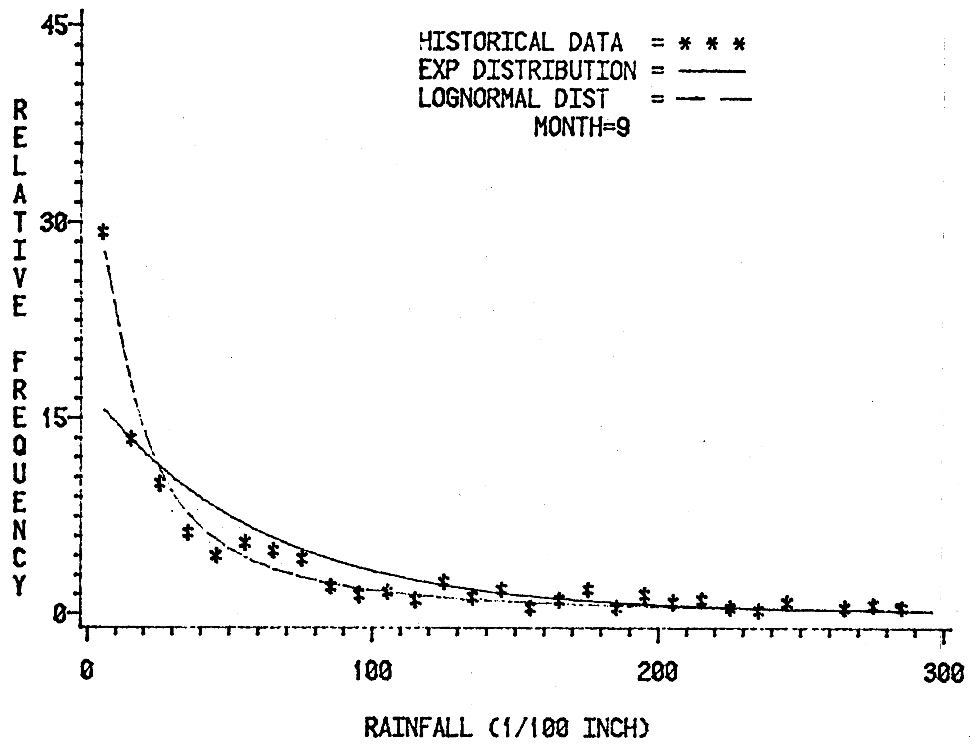
200
300
RAINFALL (1/100 INCH)


HISTORICAL DATA = * * *
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LOGNORMAL DIST =
MONTH=9
RELATIVE FREQUENCY
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0
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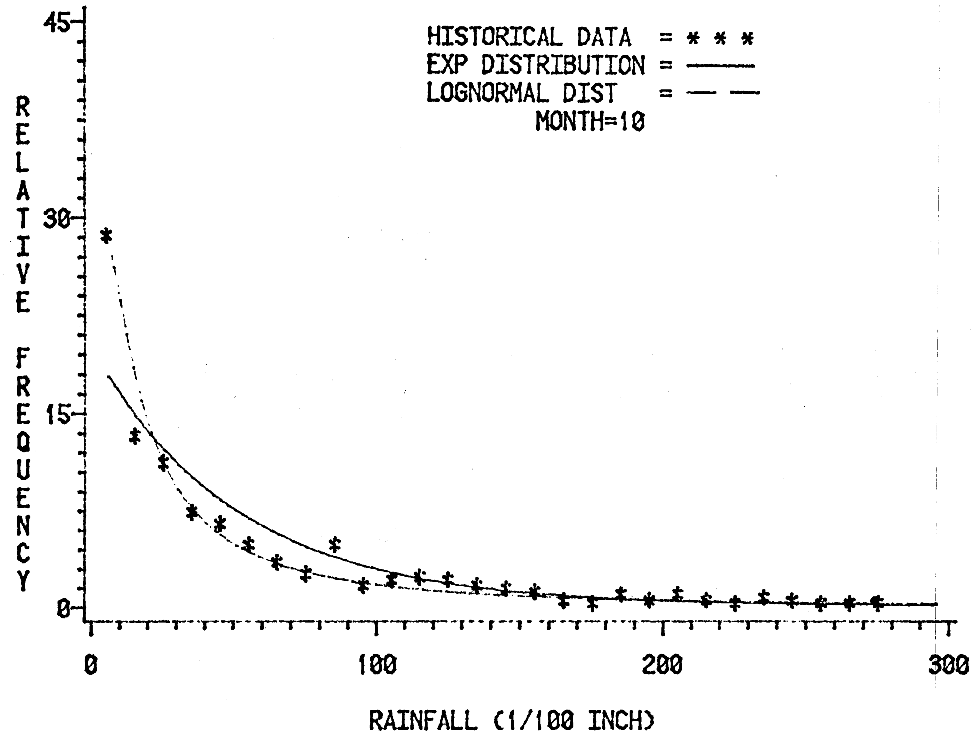
200
300
RAINFALL (1/100 INCH)


HISTORICAL DATA = * * *
EXP DISTRIBUTION =
LOGNORMAL DIST =
MONTH=10
RELATIVE FREQUENCY
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0
0
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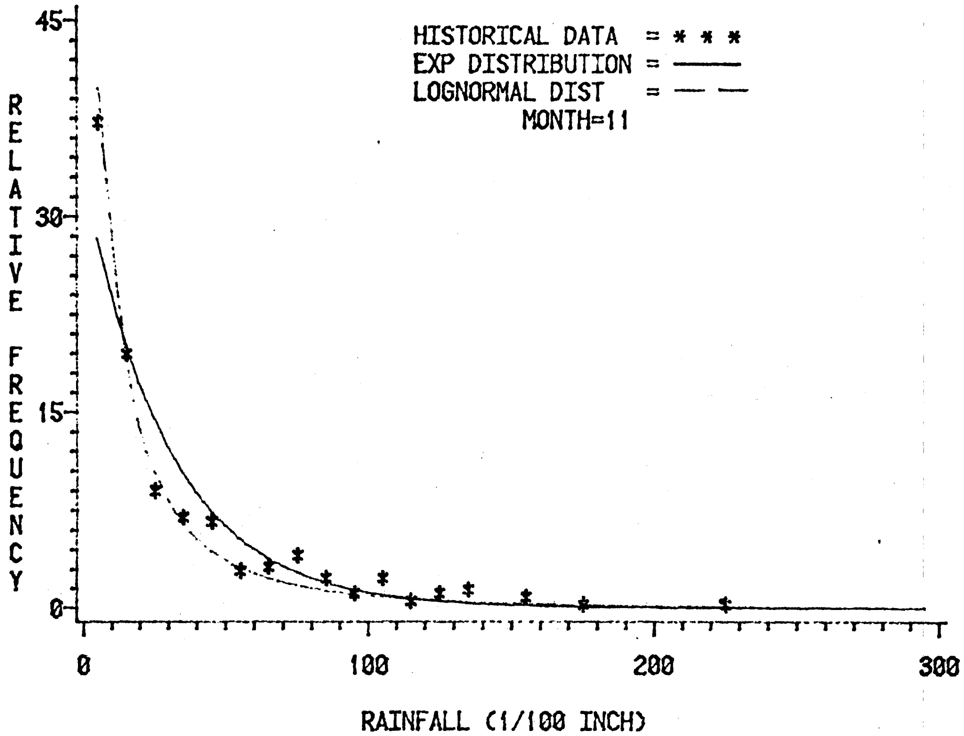
200
300
RAINFALL (1/100 INCH)


HISTORICAL DATA = * * *
EXP DISTRIBUTION =
LOGNORMAL DIST = — —
MONTH=11
RELATIVE FREQUENCY
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0
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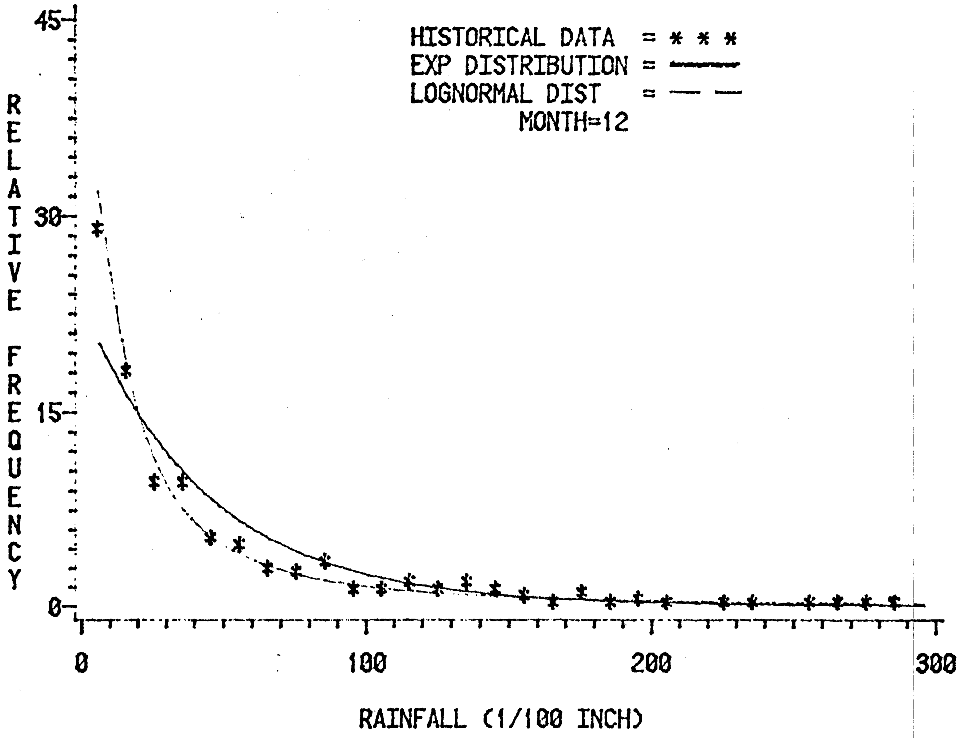
100
200
300
RAINFALL (1/100 INCH)


HISTORICAL DATA = * * *
EXP DISTRIBUTION =
LOGNORMAL DIST = — —
MONTH=12
RELATIVE FREQUENCY
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30
15
0
0
100
200
300
RAINFALL (1/100 INCH)

APPENDIX F

FREQUENCY ANALYSES OF MONTHLY RUNOFF DATA

FREQUENCY TABLES FOR MONTHLY RUNOFF
MONTH=JAN

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	77	77	96.250	96.250
75	3	80	3.750	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	77	77	96.250	96.250
125	2	79	2.500	98.750
325	1	80	1.250	100.000

MONTH=FEB

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	78	78	97.500	97.500
125	1	79	1.250	98.750
175	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	77	77	96.250	96.250
75	2	79	2.500	98.750
175	1	80	1.250	100.000

MONTH=MAR

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	69	69	86.250	86.250
75	5	74	6.250	92.500
125	2	76	2.500	95.000
175	3	79	3.750	98.750
325	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	73	73	91.250	91.250
75	2	75	2.500	93.750
125	3	78	3.750	97.500
225	2	80	2.500	100.000

FREQUENCY TABLES FOR MONTHLY RUNOFF
MONTH=APR

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	58	58	72.500	72.500
75	10	68	12.500	85.000
125	5	73	6.250	91.250
175	1	74	1.250	92.500
225	2	76	2.500	95.000
275	2	78	2.500	97.500
425	1	79	1.250	98.750
525	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	65	65	81.250	81.250
75	6	71	7.500	88.750
125	6	77	7.500	96.250
325	1	78	1.250	97.500
375	1	79	1.250	98.750
525	1	80	1.250	100.000

MONTH=MAY

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	63	63	78.750	78.750
75	3	66	3.750	82.500
125	6	72	7.500	90.000
225	3	75	3.750	93.750
275	1	76	1.250	95.000
425	1	77	1.250	96.250
525	1	78	1.250	97.500
575	1	79	1.250	98.750
625	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	54	54	67.500	67.500
75	12	66	15.000	82.500
125	5	71	6.250	88.750
175	3	74	3.750	92.500
225	2	76	2.500	95.000
275	2	78	2.500	97.500
475	2	80	2.500	100.000

FREQUENCY TABLES FOR MONTHLY RUNOFF

MONTH=JUN

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	65	65	81.250	81.250
75	7	72	8.750	90.000
125	4	76	5.000	95.000
175	2	78	2.500	97.500
225	1	79	1.250	98.750
325	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	75	75	93.750	93.750
75	1	76	1.250	95.000
125	2	78	2.500	97.500
225	1	79	1.250	98.750
325	1	80	1.250	100.000

MONTH=JUL

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	73	73	91.250	91.250
75	2	75	2.500	93.750
125	1	76	1.250	95.000
175	2	78	2.500	97.500
225	1	79	1.250	98.750
825	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	74	74	92.500	92.500
75	1	75	1.250	93.750
125	2	77	2.500	96.250
175	1	78	1.250	97.500
375	1	79	1.250	98.750
675	1	80	1.250	100.000

FREQUENCY TABLES FOR MONTHLY RUNOFF
MONTH=AUG

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	69	69	86.250	86.250
75	5	74	6.250	92.500
125	4	78	5.000	97.500
175	1	79	1.250	98.750
325	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	72	72	90.000	90.000
75	3	75	3.750	93.750
125	3	78	3.750	97.500
175	1	79	1.250	98.750
275	1	80	1.250	100.000

MONTH=SEP

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	60	60	75.000	75.000
75	5	65	6.250	81.250
125	3	68	3.750	85.000
175	4	72	5.000	90.000
225	4	76	5.000	95.000
325	1	77	1.250	96.250
425	1	78	1.250	97.500
525	1	79	1.250	98.750
675	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	66	66	82.500	82.500
75	4	70	5.000	87.500
125	5	75	6.250	93.750
175	1	76	1.250	95.000
225	1	77	1.250	96.250
275	1	78	1.250	97.500
375	1	79	1.250	98.750
1025	1	80	1.250	100.000

FREQUENCY TABLES FOR MONTHLY RUNOFF
MONTH=OCT

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	66	66	82.500	82.500
75	3	69	3.750	86.250
125	5	74	6.250	92.500
225	1	75	1.250	93.750
275	2	77	2.500	96.250
425	1	78	1.250	97.500
575	1	79	1.250	98.750
675	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	72	72	90.000	90.000
75	3	75	3.750	93.750
125	4	79	5.000	98.750
225	1	80	1.250	100.000

MONTH=NOV

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	69	69	86.250	86.250
75	4	73	5.000	91.250
125	2	75	2.500	93.750
175	3	78	3.750	97.500
325	1	79	1.250	98.750
475	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	67	67	83.750	83.750
75	8	75	10.000	93.750
125	2	77	2.500	96.250
175	2	79	2.500	98.750
225	1	80	1.250	100.000

MONTH=DEC

RUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	76	76	95.000	95.000
75	3	79	3.750	98.750
175	1	80	1.250	100.000

SRUN	FREQUENCY	CUM FREQ	PERCENT	CUM PERCENT
25	77	77	96.250	96.250
125	3	80	3.750	100.000

APPENDIX G

SYNTHETIC AND HISTROIC ANNUAL RAINFALL DATA AND RESULTING RUNOFF PREDICTED BY CREAMS

COLUMN HEADINGS

HRAIN	HISTORICAL RAINFALL
SRAIN	SYNTHETIC RAINFALL
HRUNOFF	HISTORICAL RUNOFF
SRUNOFF	SYNTHETIC RUNOFF
AHRAIN	ACCUMULATED HISTORICAL RAINFALL
ASRAIN	ACCUMULATED SYNTHETIC RAINFALL
AHRUNOFF	ACCUMULATED HISTORICAL RUNOFF
ASRUNOFF	ACCUMULATED SYNTHETIC RUNOFF
R _ RUNOFF	RATIO OF ACCUMULATED HISTORIC AND SYNTHETIC RUNOFF
R _ RAIN	RATIO OF ACCUMULATED HISTORIC AND SYNTHETIC RAINFALL

YEAR	HRAIN	SRAIN	HRUNOFF	SRUNOFF	AHRAIN	ASRAIN	AHRUNOFF	ASRUNOFF	R_RAIN	R_RUNOFF
0	29.79	29.80	2.355	1.753	29.79	29.80	2.355	1.753	0.99966	1.34341
1	19.98	22.89	0.644	0.354	49.77	52.69	2.999	2.107	0.94458	1.42335
2	40.29	30.58	5.164	1.631	90.06	83.27	8.163	3.738	1.08154	2.18379
3	31.98	23.71	2.834	0.234	122.04	106.98	10.997	3.972	1.14077	2.76863
4	31.35	35.61	3.373	1.479	153.39	142.59	14.370	5.451	1.07574	2.63621
5	38.59	24.64	2.474	0.063	191.98	167.23	16.844	5.514	1.14800	3.05477
6	41.47	19.90	4.019	0.137	233.45	187.13	20.863	5.651	1.24753	3.69191
7	35.69	33.33	3.281	5.874	269.14	220.46	24.144	11.525	1.22081	2.09492
8	60.26	36.80	19.175	2.736	329.40	257.26	43.319	14.261	1.28042	3.03759
9	31.73	31.73	3.245	0.472	361.13	288.99	46.564	14.733	1.24963	3.16052
10	19.06	24.13	0.960	0.549	380.19	313.12	47.524	15.282	1.21420	3.10980
11	34.43	38.07	2.014	7.349	414.62	351.19	49.538	22.631	1.18061	2.18894
12	27.60	40.08	2.973	4.534	442.22	391.27	52.511	27.165	1.13022	1.93304
13	36.91	28.88	4.781	2.502	479.13	420.15	57.292	29.667	1.14038	1.93117
14	16.79	28.57	0.455	1.298	495.92	448.72	57.747	30.965	1.10519	1.86491
15	48.02	43.94	10.203	4.713	543.94	492.66	67.950	35.678	1.10409	1.90454
16	28.01	30.54	2.241	3.873	571.95	523.20	70.191	39.551	1.09318	1.77470
17	24.66	33.40	1.217	3.724	596.61	556.60	71.408	43.275	1.07188	1.65010
18	39.86	28.47	4.014	1.897	636.47	585.07	75.422	45.172	1.08785	1.66966
19	33.16	22.74	1.865	0.385	669.63	607.81	77.287	45.557	1.10171	1.69649
20	47.34	33.21	5.827	0.837	716.97	641.02	83.114	46.394	1.11848	1.79148
21	33.87	31.86	4.568	1.598	750.84	672.88	87.682	47.992	1.11586	1.82701
22	34.80	37.65	4.298	5.980	785.64	710.53	91.980	53.972	1.10571	1.70422
23	42.33	32.13	9.057	1.867	827.97	742.66	101.037	55.839	1.11487	1.80943
24	23.98	26.98	0.781	0.457	851.95	769.64	101.818	56.296	1.10695	1.80862
25	22.44	42.02	0.688	7.954	874.39	811.66	102.506	64.250	1.07729	1.59542
26	32.09	26.46	3.041	0.740	906.48	838.12	105.547	64.990	1.08156	1.62405
27	38.10	36.70	5.303	0.682	944.58	874.82	110.850	65.672	1.07974	1.68793
28	32.52	43.25	2.743	5.297	977.10	918.07	113.593	70.969	1.06430	1.60060
29	37.14	25.40	5.963	0.548	1014.24	943.47	119.556	71.517	1.07501	1.67171
30	25.69	35.49	2.055	2.899	1039.93	978.96	121.611	74.416	1.06228	1.63421
31	27.31	25.18	2.393	0.745	1067.24	1004.14	124.004	75.161	1.06284	1.64984
32	34.94	20.86	3.735	0.397	1102.18	1025.00	127.739	75.558	1.07530	1.69061
33	32.39	27.44	3.244	1.009	1134.57	1052.44	130.983	76.567	1.07804	1.71070
34	30.67	31.33	2.655	0.282	1165.24	1083.77	133.638	76.849	1.07517	1.73897
35	33.59	38.37	2.702	4.262	1198.83	1122.14	136.340	81.111	1.06834	1.68091
36	18.29	31.91	0.518	2.152	1217.12	1154.05	136.858	83.263	1.05465	1.64368
37	25.59	37.15	1.274	2.603	1242.71	1191.20	138.132	85.866	1.04324	1.60869
38	35.29	22.30	2.627	1.031	1278.00	1213.50	140.759	86.897	1.05315	1.61984
39	26.95	31.88	1.739	2.200	1304.95	1245.38	142.498	89.097	1.04783	1.59936

YEAR	HRAIN	SRAIN	HRUNOFF	SRUNOFF	AHRAIN	ASRAIN	AHRUNOFF	ASRUNOFF	R_RAIN	R_RUNOFF
40	33.93	29.19	2.330	2.038	1338.88	1274.57	144.828	91.135	1.05046	1.58916
41	43.68	41.89	6.866	4.962	1382.56	1316.46	151.694	96.097	1.05021	1.57855
42	45.33	31.19	9.258	5.520	1427.89	1347.65	160.952	101.617	1.05954	1.58391
43	31.07	32.03	6.845	4.142	1458.96	1379.68	167.797	105.759	1.05746	1.58660
44	31.24	37.80	1.748	2.250	1490.20	1417.48	169.545	108.009	1.05130	1.56973
45	34.04	41.22	7.317	17.520	1524.24	1458.70	176.862	125.529	1.04493	1.40893
46	28.18	23.04	1.096	0.766	1552.42	1481.74	177.958	126.295	1.04770	1.40907
47	27.21	30.13	3.022	3.066	1579.63	1511.87	180.980	129.361	1.04482	1.39903
48	31.64	37.94	1.748	7.710	1611.27	1549.81	182.728	137.071	1.03966	1.33309
49	30.16	32.74	1.525	2.201	1641.43	1582.55	184.253	139.272	1.03721	1.32297
50	22.80	44.57	0.162	6.364	1664.23	1627.12	184.415	145.636	1.02281	1.26627
51	34.67	31.60	1.948	3.650	1698.90	1658.72	186.363	149.286	1.02422	1.24836
52	24.12	24.83	0.213	0.622	1723.02	1683.55	186.576	149.908	1.02344	1.24460
53	32.71	28.91	2.712	1.541	1755.73	1712.46	189.288	151.449	1.02527	1.24985
54	18.33	35.82	0.465	1.443	1774.06	1748.28	189.753	152.892	1.01475	1.24109
55	27.98	26.77	3.957	0.828	1802.04	1775.05	193.710	153.720	1.01521	1.26015
56	16.68	32.42	0.183	2.492	1818.72	1807.47	193.893	156.212	1.00622	1.24122
57	42.72	27.11	9.276	1.191	1861.44	1834.58	203.169	157.403	1.01464	1.29076
58	31.85	26.01	1.413	2.219	1893.29	1860.59	204.582	159.622	1.01758	1.28167
59	61.87	25.86	23.273	1.547	1955.16	1886.45	227.855	161.169	1.03642	1.41376
60	35.99	33.26	3.105	1.629	1991.15	1919.71	230.960	162.798	1.03721	1.41869
61	38.89	34.82	5.488	2.244	2030.04	1954.53	236.448	165.042	1.03863	1.43265
62	32.43	30.68	2.203	0.905	2062.47	1985.21	238.651	165.947	1.03892	1.43812
63	27.14	38.47	0.788	2.779	2089.61	2023.68	239.439	168.726	1.03258	1.41910
64	25.95	35.01	1.070	1.229	2115.56	2058.69	240.509	169.955	1.02762	1.41513
65	27.78	34.34	2.463	2.111	2143.34	2093.03	242.972	172.066	1.02404	1.41209
66	25.39	37.36	2.494	3.750	2168.73	2130.39	245.466	175.816	1.01800	1.39615
67	31.48	39.52	1.396	4.639	2200.21	2169.91	246.862	180.455	1.01396	1.36800
68	32.60	29.46	1.082	2.596	2232.81	2199.37	247.944	183.051	1.01520	1.35451
69	27.84	38.61	0.802	4.056	2260.65	2237.98	248.746	187.107	1.01013	1.32943
70	28.68	18.43	3.134	0.193	2289.33	2256.41	251.880	187.300	1.01459	1.34479
71	31.45	32.81	2.234	1.076	2320.78	2289.22	254.114	188.376	1.01379	1.34897
72	27.96	32.99	1.701	0.935	2348.74	2322.21	255.815	189.311	1.01142	1.35129
73	46.43	37.16	8.441	5.440	2395.17	2359.37	264.256	194.751	1.01517	1.35689
74	45.74	22.51	10.342	0.532	2440.91	2381.88	274.598	195.283	1.02478	1.40615
75	39.65	42.94	5.224	5.210	2480.56	2424.82	279.822	200.493	1.02299	1.39567
76	20.73	36.25	0.764	4.783	2501.29	2461.07	280.586	205.276	1.01634	1.36687
77	32.47	43.41	2.459	4.443	2533.76	2504.48	283.045	209.719	1.01169	1.34964
78	25.87	32.40	0.456	0.823	2559.63	2536.88	283.501	210.542	1.00897	1.34653
79	32.73	28.64	2.482	2.191	2592.36	2565.52	285.983	212.733	1.01046	1.34433

V

VITA

James Edward Peter Green

Candidate for the Degree of

Doctor of Philosophy

Thesis: SYNTHETIC RAINFALL AND ITS USE IN HYDROLOGIC MODELING

Major Field: Agricultural Engineering

Biographical:

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