THE UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

STOCHASTIC GENERATION OF HYDROLOGIC MODEL INPUTS

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

degree of

DOCTOR OF PHILOSOPHY

BY

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Chickasha, Oklahoma

1975

STOCHASTIC GENERATION OF HYDROLOGIC MODEL INPUTS

APPROVED BY

DISSERTATION COMMITTEE

ACKNOWLEDGMENTS

I wish to acknowledge the staff of the Southern Great Plains Research Watershed, U. S. Department of Agriculture, Agricultural Research Service located at Chickasha, Oklahoma for their dedication and efforts in collecting and processing the data used in this dissertation. I wish to particularly thank Drs. Donn G. DeCoursey and Maurice H. Frere, the past and present Directors of the Research Watershed, for their encouragement, counsel, and support. Without their help and cooperation the completion of this dissertation would not have been possible.

Thanks is also extended to all the members of my advisory committee, particularly Professor Jimmie F. Harp for their understanding of the interdisciplinary nature of this work.

Also, the work of Mrs. Betty Golden in typing the text is greatly appreciated.

Finally, I want to thank my wife, Janet, who assisted me through the preparation of the text and for her continuous encouragement and support under trying circumstances.

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STOCHASTIC GENERATION OF HYDROLOGIC MODEL INPUTS

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In this study stochastic generation models were developed to synthesize the daily rainfall and meteorological data that can be used as input to existing hydrologic models for simulation of runoff from watersheds. Synthetic rainfall records were generated at 168 locations of an existing rain gage network covering a 1,500-square-mile area of central Oklahoma. Mean daily temperature and solar radiation data were synthesized for this same area.

Spatial patterns of rainfall for input to hydrologic models were constructed by stochastically generating the occurrence or nonoccurrence of rainfall on each day, the location of the central or maximum amount within the area, the maximum amount, and the pattern rainfall over the 1,500-square-mile area corresponding to the central amount. Tests were made to determine the representativeness and consistency of generated data including means, extremes, and frequency of occurrence in both time and spatial distribution.

Models were also developed to stochastically generate the maximum and minimum daily temperature, mean daily temperature, and solar radiation for the area. These synthetic data were also tested against observed daily records and the representativeness of the synthetic data determined.

A Markov chain model for generating wet day-dry day sequence for the network area was highly satisfactory as was the method of generating mean rainfall for the area. Tests made on the data generated by the rainfall model show that 71 percent of the synthetic records at 168 stations would be accepted as being from the same population of observed data.

STOCHASTIC GENERATION OF HYDROLOGIC MODEL INPUTS

PART I - THEORY

CHAPTER 1

INTRODUCTION

This dissertation is addressed to the problem of generating synthetic hydrologic and meteorologic data of the type which could be used to simulate the long-term water cycle of an area. For more than a decade, mathematical models have been available which will describe quantitatively the hydrologic behavior of watersheds using observed data. However, even though the physical data required for these models such as rainfall, evaporation, and runoff are collected at thousands of stations throughout the United States and abroad, records of these data are often incomplete and of short duration. Thus, planners, designers, and hydrologists who must use the models as tools to evaluate, design, or plan water resource usage are forced to estimate missing data or extend existing records to project the hydrologic response of watersheds which may be modified by man's use in the future.

Another method available to planners to investigate the influence of man's activities on the environment is the generation of synthetic data for use in simulation studies of hydrologic designs. This method has in recent years come to be known in the literature as synthetic or operational hydrology.

Two general types of models come under the heading of operational hydrology. The first type consists mainly of a number of different models that stochastically generate sequences of synthetic streamflow data by using several parameters that are usually estimated from long sequences of observed monthly streamflow. Thomas and Fiering in 1962 (64)* and Fiering in 1967 (17) developed such models which do not reproduce records of streamflow, but do produce similiar streamflow records that are statistically indistinguishable from historical data. Models of this type are more prescriptive to hydrological design problems such as determining economical reservoir capacity for dependable water supplies, hydroelectric generation, flood control, and water quality management and less descriptive of phenomenicological processes of the hydrologic cycle. Because this type of model is less descriptive and more dependent on long-term historical records, it has been excluded from study in this dissertation.

The second type of operational hydrologic model is more descriptive of the causal process involved in runoff production and subsequent streamflow and considers as inputs; rainfall, evaporation, temperature, and measurable watershed characteristics. Several models of this type have been developed. The one most widely used and modified is the Stanford watershed model developed in 1966 by Crawford and Linsley (12). This model has been modified in 1970 by Ross (53) and Liou (38) and

*Numbers in parentheses refer to References.

evaluated on small agricultural watersheds in Virginia in 1972 by Shanholtz, et al. (54). Similar descriptive models have also been developed by the Tennessee Valley Authority (62), Holton, et al. (32), Haan (27), Dawdy, et al. (13), and Fogel, et al. (19). All these models require a common hydrologic input of rainfall amount or intensity estimates for the watershed area. Also required is some estimate of evaporation either measured or calculated from evaporation models and observed meteorological data. These models of the second type cited above have been developed for various regions of the United States and for various purposes. All have a common objective, that is, to simulate the runoff from watersheds using rainfall, meteorological data and watershed characteristics. Such simulation of runoff on ungaged areas from historical records is important for design and management purposes. However, it is becoming increasingly more apparent due to emphasis placed on environmental quality, that models such as these early attempts will be used as tools to simulate environmental systems well into the future. Changes due to man's activity and proposed uses of resources can be incorporated into these models. Submodels can be attached to the basic models to simulate related processes such as chemical and sediment transport within the streamflows. Similarly, the entire model could be incorporated in broader system models of which streamflow and hydrologic processes are only an integral part.

However, for these models to be used effectively as planning and design tools, there is a need to synthesize the inputs required such as rainfall and climatic data. Long-term rainfall and climatic data are available in many parts of the country which can be used to develop generation techniques. Experimental watershed studies of short term record length are available that can also be used which give detailed information important to development and testing of synthetic data generation techniques.

The objective of this dissertation is the development and testing of stochastic generation techniques which would supply representative hydrologic and meteorologic data to existing hydrologic models so that simulation of long-term watershed flows synthesized using these models are representative of climatic variation inherent in the historical records of an area. More specific objectives are: the development and testing of techniques to stochastically generate the minimum required rainfall inputs, and the development of techniques to generate meteorological data to calculate evaporation required by these simulation models.

CHAPTER 2

HYDROLOGIC MODEL INPUTS

In chapter 1 several operational hydrologic models that are in use today were cited. The models, their authors, and variable input requirements are given in table 1. Inputs to these models vary in the type of variable input and in the time scale of the data required. No two model requirements are exactly alike, however several have common variables that could be subsets of variables required for other models, such as air temperature as input to an evapotranspiration model.

The variables common to each model are rainfall, which may be entered in many forms ranging in time, scale, and length from daily, or 24-hour periods, to intervals as short as 5 minutes. Next common among the variables required is potential evaporation listed in four of the models, air temperature in three models, solar radiation in two models, and albedo and wind speed in one of the models.

Reasons for the varied input requirement of the models listed in table 1 are not readily apparent. Difference in inputs can be explained partly by the original purpose of the model, the location or region for which it was developed and the data that is available for input. More complete explanations can be made by reviewing the development of each of these models.

TABLE 1

RAINFALL, TEMPERATURE, EVAPORATION AND METEOROLOGICAL INPUTS REQUIREMENT FOR HYDROLOGIC MODELS

Model	Author	Date	Inputs		Evaporation	Other
			Rainfall	Temperature		
SCS	Mockus	1964 R-1969	Storm Amount Daily			
Stanford Mark IV	Crawford Linsley	1966	15-min, hourly Daily	Daily Max.-Min. (Optional)	Daily pan	Radiation
USDAHL	Holton, et al.	1970 R-1974	Breakpoint Hourly 24 Hour	Air weekly mean	Pan-weekly mean	
Arizona	Fogel, et al.	1974	Daily			
Kentucky	Haan	1972	Daily		Daily Potential	
USGS	Dawdy, et al.	1972	5-60 min. Daily			
SSARR	U.S. Army Corps of Engineers	1972 R-1974	.10-24 hour	Air-Daily Dew point daily	Pan-Daily	Solar radiation Albedo Windspeed
TVA	Tennessee Valley Authority	1972	Daily		Monthly	

SCS Model

Because the Soil Conservation Service (SCS) has the responsibility of the design of structures preventing floodwater erosion and sediment damage on a large percentage of the public and private lands, particularly agricultural lands, they have developed and adopted, over the years, methods and techniques that their field personnel can use in solving and designing watershed-protection and flood-prevention projects. These procedures were compiled in 1964 and revised in 1969 by Mockus (39). This collection of procedures has been programmed for electronic computer computations. Although not generally considered as a hydrologic model when first used, its stated purpose has all the qualifications of an operational hydrologic model. Hydrologic evaluation of flood-prevention and watershed-protection projects are a major concern for the SCS and as they state

> The evaluation is a detailed investigation of present (no project) and future (with project) conditions of a watershed to determine whether given objectives will be met, and is the basis on which recommendations for or against the project are founded.

As listed in table 1, the SCS model uses storm rainfall or daily amount as the input.

The SCS method of estimating direct runoff from storm rainfall is

$$Q = \frac{(P - 0.2S)^2}{P + 0.8S} \tag{2-1}$$

where Q is storm runoff (inches); P, storm rainfall (inches); and S, the potential maximum retention (inches) which is related to runoff by a family of curves related to antecedent conditions.

In the SCS model the value assigned to S is based on antecedent moisture condition which, in turn, is determined by the total rainfall occurring in a 5-day period before the runoff begins. Three levels of antecedent moisture are used in two seasons, dormant and growing seasons. S may be calculated by

$$S = \frac{1,000}{CN} - 10 \qquad (2\text{-}2)$$

where CN is the curve member of the family of curves developed from rainfall-runoff data collected at experimental and gaged watersheds throughout the United States. Curve numbers for the range of antecedent condition are given in tabular form.

The SCS model which uses storm rainfall as its primary hydrologic input with extensive use of soils, channel characteristics, and other watershed data from field surveys, possibly has been used more than any other model for the evaluation and design of watershed protection and flood prevention projects. Since 1952, approximately 5,300 structures on 714 watersheds have been evaluated by this model.

Stanford Mark IV

The Stanford Mark IV watershed simulation model was developed in 1966 by Crawford and Linsley (12) at a time when interest in digital simulation studies were increasing because of the computer revolution. The goals of this model according to the authors is

> a practical hydrologic model that is a skeleton of the hypothetical "absolute knowledge" model is the goal of digital simulation.

Some criteria they listed were:

> (1) The model should represent the hydrologic regimes of a wide variety of storms and rivers with a high order of accuracy.

(2) It should be easily applied to different watersheds with existing hydrologic data.

(3) The model should be physically relevant so that estimates of other useful data in addition to streamflow, such as overland flow or actual evapotranspiration,can be obtained.

A relative complex calculation is involved to calculate runoff from rainfall in the Stanford model. The simulation of infiltration and overland flow requires continuous estimates of detention storage and overland flow-outflow rates. The relationship given for overland flow discharge is

$$q = \frac{64,200\ S^{1/2}}{nL} \left[\frac{D}{L}\right]^{5/3} \left[1.0 + 0.6 \left[\frac{D}{De}\right]^{3}\right]^{5/3} \qquad (2\text{-}3)$$

where q is overland flow discharge (ft/sec/ft); S and L are the slope (ft/ft) and length of land surface (ft), respectively; n is Manning's coefficient; D_e, surface detention depth (ft) at equilibrium; and D, the current detention storage depth (ft).

Water which infiltrated into the land surface from rainfall is routed in two soil storage zones, an upper and lower zone. Evapotranspiration occurs from interception storage and from the upper zone at the potential rate which is estimated by daily lake evaporation or potential evapotranspiration data. Water which is routed to the lower zone is combined with overland flow in a time delayed sequence based on the time-area relationship developed in 1945 by Clark (9).

Output from the model consists of monthly summaries of soil moisture conditions, interflow discharge, actual evapotranspiration, complete hydrographs for all storms, and mean daily flows for each flow point. Other optional outputs are daily snowpack water equivalent, storm period summaries, statistical comparisons of simulated and observed streamflow and other summaries.

When first developed, the Stanford model was difficult for some users to apply because of the computer storage requirements and the computer language in which it was written. However, large computer installations at most universities and research centers have become more widely available throughout the United States; therefore the model came into common use. Modification and language conversion of the model have been made in 1972 by Shanholtz, et al. (54), and the optimization routines modified by Liou in 1970 (38) and Ross in 1970 (53). The model now is in use throughout the United States with many modified versions available.

USDA Hydrograph Laboratory Model

The USDAHL model was developed by Holton and Lopez in 1970 (31) to study hydrologic processes on small watersheds. The purpose of the model as stated by the authors is

> ...we are trying to reduce the entire system of watershed hydrology to a predictable pattern of physical probabilities that will account for dispersion of water and its subsequent concentration in channel systems. ...our model is currently a series of empiricicisms selected to provide a mathematical continuum from ridgetop to watershed outlet in terms of input information readily available to the analyst.

The USDAHL model requires detailed inputs consisting of a continuous record of rainfall weighted to represent the watershed and potential evapotranspiration based on weekly mean pan evaporation data. A revised version of the model by Holton, et al. in 1974 (32) adds weekly mean air temperature to the input requirements.

In addition to these continuous input data, input parameters for the watershed zones, soils, flow routing, cascading of overland flow, crops, and tillage procedures are also required. Because the model is based on infiltration and storage capacities, infiltration and storage capacity of the watershed soils are required. The infiltration model used is

$$f = a\ S_a^{1.4} + f_c \tag{2-4}$$

where f is infiltration capacity (inches/hour); a, the index of surface connected porosity (inches/hour); S_a, available storage in "A" horizons in agricultural soils (inches); and f_c, the constant infiltration after prolonged wetting (inches/hour).

Runoff in the channel is essentially determined by routing of rainfall in excess of infiltration by

$$P_e - Q_o = \Delta D \tag{2-5}$$

and

$$q_o = a\ D^n \tag{2-6}$$

where P_e is volume of rainfall excess per unit time; Q_o, the volume of outflow per unit time; q_o, the overland flow (inches/hour); D the average of flow in inches; Δ, the time in hours; and a and n, coefficients.

Channel and subsurface flows by simultaneous solution of continuity and storage function are routed to the watershed outlet. Storage functions are derived from analysis of hydrograph recession analysis. The equation for the recession curve is given as

$$q_t = q_o\ e^{-t/m} \tag{2-7}$$

where q_o is the initial rate of flow at time zero; q_t, the flow rate one time increment later; m, a constant for each straight line segment of the recession curve on semilog paper; e, the natural logarithmic base; and t, the time increment in hours.

The USDAHL model has been evaluated on watershed flow in Coshocton, Ohio; Tayler Creek, Florida; and other small watersheds in the United States. The model in its revised form uses continuous rainfall amounts ranging in time scale definition from 1 minute to a limiting 24-hour amount, mean weekly pan evaporation and air temperature data with supporting watershed parametric data, outputs of accumulated rainfall, surface and subsurface runoff, rates of outflow in inches/hour, and streamflow in cubic feet/second can be calculated.

Arizona Model

The Arizona model was developed in 1974 by Fogel, et al. (19) to model the effects of land use modification in the desert southwestern United States. The authors of this model disdained the use of Stanford and other models because their use would be restricted to gaged watersheds. Instead they developed a method of forecasting long-term hydrologic effects based on a probabilistic rainfall model and a method for converting runoff-producing rainfall to the desired variables. Once flow was determined, the model was extended to develop sediment yield, runoff volumes, and probabilistic peak flow rates.

The method used for estimating runoff volumes is the same as that used by SCS (equation 2-1). The translation function of rainfall into storm runoff is given by

$$F_V(v) = 1 - \exp^{-U/2}\left[\underline{\bar{V}} + 2A + (V^2 + 4SV)^{1/2}\right] \qquad (2\text{-}8)$$

where A is the initial abstraction of rainfall; U, a rainfall parameter readily obtained from daily rainfall data; and $F_V(v)$, the probability of a runoff event occurring.

Peak runoff volumes are determined by a method developed and used by the SCS, Mockus (39), given by

$$Q_p = \frac{484\ A_w\ Q}{0.5D + 0.6T_c} \tag{2-9}$$

where Q_p is peak rate of flow in cfs; A_w, the watershed area in square miles; D, the duration of excess rainfall in hours; T_c, the time of concentration in hours; and Q_p the storm volume of runoff in cfs.

Using the long-term daily rainfall records at Tucson, Arizona and experimental watershed data in the vicinity, probability estimates (equation 2-8) were derived to facilitate the use of the model.

This type of model is an example presented to show the trend of some users to simplify the estimation and number of parameters required, as well as the input data requirements. The model, as now developed, uses daily rainfall as the only data input. As the author notes, such data are available with long-term records at many locations through the country. Users of a model should be concerned with the trade off between model simplicity and accuracy of model results.

Kentucky Model

In 1972 C. T. Haan (27) developed a model to simulate runoff and water yield from watersheds in Kentucky. The objective and criteria of the model as given by the author was:

> The objective ... was to develop a mathematical model capable of simulating monthly streamflow. Some of the criteria for the model were that it should be simple in concept, be applicable over a wide range of conditions and require a minimum of input data.

The method of determining runoff is related to infiltration theory. When precipitation, P, is greater than the maximum infiltration rate, f_{max}, the infiltration, f, is equal to f_{max}. Accordingly, f is set equal to P when P equals f, and equal to zero when moisture-holding capacity of the soil is less than a maximum value of 1 inch. The method of determining runoff is then given as

$$V_s = (P - f)\ t \qquad P > f \tag{2-10}$$

and

$$V_s = 0 \qquad P \leq f \tag{2-11}$$

where V_s is the volume of surface runoff in inches and t is the time increment involved.

An estimate of evapotranspiration is also required by the model for the maintenance of soil moisture levels. Potential evapotranspiration computed by a method called the Thornthwaite method in 1948 (65) is used. Evapotranspiration is set equal to the potential rate when water is available and reduced by a ratio of moisture capacity and available water when it is not. Water that does not appear as streamflow or evapotranspiration is assigned to deep seepage and later a portion of it may reappear as return flow.

Four parameters of this model must be estimated and the best set of the four are optimized by minimizing the sum of squares of deviation between simulated and observed flow.

This model has been used to simulate flows and calculate water yields on several watersheds in Kentucky, Virginia, Tennessee, North and South Carolina. The model is a simple type requiring potential evapotranspiration and daily rainfall as inputs.

USGS Model

A simulation model of watershed hydrology has been developed in 1972 by the U. S. Geological Survey, Dawdy, et al. (13). This model as noted by the authors is similar to other models in some respects and they have listed as its criteria:

1. Require only input data that are generally available.
2. Be simple enough for user to operate and to understand.
3. Provide the output desired at an acceptable level of accuracy for the application for which it is used.

The structure of the model includes antecedent moisture conditions, an infiltration component and a routing component. Inputs required are daily rainfall, daily pan evaporation, and initial conditions. Outputs are amount of base-moisture storage, infiltration moisture storage, rainfall excess, and storm discharge. Four parameters are required to simulate runoff from rainfall. These are coefficients for converting pan evaporation to potential evapotranspiration, one for determining relative amounts of infiltration and surface runoff, one for determining the maximum effective amount of base moisture storage, and also a coefficient for controlling drainage rate from infiltrated moisture storage.

Runoff from precipitation excess, Q_r, is given as

$$Q_r = S_r^2/2f_r \qquad S_r < f_r \tag{2-12}$$

and

$$Q_r = S_r - f_r/2 \qquad S_r > f_r \tag{2-13}$$

where S_r is a supply rate of rainfall in inches/hour, and f_r, the maximum infiltration capacity in inches.

The model is currently still under development. It has been evaluated on watersheds in Southern California, South Carolina, and Rolla, Missouri. The authors found the accuracy of flood peaks simulated with a single rain gage at a limit of about 25 percent.

SSARR Model

The U. S. Army Engineer Division, North Pacific, in 1972 (66) has developed a "Streamflow Synthesis and Reservoir Regulation" (SSARR) model based upon a need for a model that is conceptual yet not so detailed as to prevent its use on a daily basis. The model is not complete, having the capability for expansion as the state of the art improves.

This model requires inputs of several hydrologic elements which are used in simulation of streamflow. These elements are; basin weighted precipitation, soil moisture as an index of runoff effectiveness, evapotranspiration loss determined from potential evapotranspiration, runoff excess, surface storage, subsurface storage, ground water storage, and flow separation relationships to compute portions of water excess which enters each storage zone.

Basic inputs to the model are; watershed Theissen weight precipitation for periods ranging from 0.1 to 24 hours, or the total precipitation distributed by a distribution percentage; weighted daily pan evaporation or month versus average daily potential evapotranspiration (inches/day); daily temperature; wind speed; solar radiation; and albedo data for determination of runoff from snowmelt.

This model is uniquely different from other models in one respect, that is, it has a provision for calculation of backwater and routing of outflow through lakes and reservoirs. Several types of flow regulation can be specified such as freeflow, outflow, or other storage change conditions in the reservoirs or lakes.

The model uses an antecedent moisture index for surface runoff determination given as

$$Q = ROP \times P_W \tag{2-14}$$

where Q is the generated runoff in inches, and ROP the runoff percent from a soil moisture. Generated runoff, Q, is later separated into surface and subsurface flow and routed to streamflow.

This model was developed for use in simulating small-to-large watershed flows. It has been used primarily in the simulation of flows on the Columbia River basin. However, it has been used to model numerous river systems in the United States and abroad by various Agencies, Organizations, and Universities.

TVA Model

The Tennessee Valley authority has developed in 1972 a mathematical continuous daily-streamflow model (62). The authors of this model recognized the complexity of hydrologic modeling and attempted to develop a simple model. As stated in the report of the model

> one significant drawback that most of the present watershed models have in common is that they rival the real hydrologic system in complexity. For the deterministic models in particular, the number of parameters to be estimated is large and data management so involved that adjusting the model to data is a time-consuming and expensive procedure.

The basic input to the TVA model is rainfall and monthly evapotranspiration estimates. The runoff is calculated from excess rainfall by

$$Q = (P_f^{\,2} + RI^2)^{1/2} - RI \qquad (2\text{-}15)$$

where Q is the daily surface runoff volume in inches; P_f, the daily rainfall minus interception; and RI, a retention index computed from soil moisture, ground water storage, and seasonal rainfall constants.

Surface runoff volumes and ground water contribution to flow are routed to determine total runoff. Evapotranspiration estimates are used to update soil moisture levels. The model also uses streamflow as input and has an optimizing routine to determine the best estimate of parameters. It has been calibrated to flows on Upper Bear Creek in the Tennessee River basin.

Minimum Input Requirements

Because of the development and accepted usage of large computers at universities and government and private research centers, there has been an avalanche of hydrologic model development in recent years. Therefore, the operational models listed in this chapter do not include all the models which have been developed. However, the ones listed do give a broad cross-section of the type of models which have been developed and list the ones that are in more common use today.

From the brief description of the models the author has attempted to put in perspective the flexibility of the model inputs and draw from the various models the minimum input requirements. These minimum requirements are rainfall daily amounts at one or more stations which is combined to a single value by weighting, and daily pan evaporation or an estimate of daily potential evapotranspiration which can be computed from evapotranspiration models.

To stochastically generate synthetic inputs to these models, a minimum requirement would be a generator that would supply continuous records of daily rainfall at one or more locations or for a watershed area, and generate daily pan evaporation estimates, or the necessary data to calculate potential evapotranspiration estimates by various models requiring meteorological data such as daily solar radiation, temperature, humidity, and wind. Ideally, the requirement would be the generation of a complete climate data set representative of each watershed to be simulated.

However, some of the data listed in table 1 are not always readily available. For instance pan evaporation data are collected at many stations throughout the country, but few of these records are continuous throughout the year in northern climes. Missing data would need to be estimated in order to develop a continuous record that would be necessary in the development of stochastic generation models.

Humidity records are rarely available except at first order weather stations. Usually these stations are distributed so that only one or two of them are located within a state. Thus, humidity data from these stations might not be representative of the watershed area especially in Oklahoma where the moisture regime from rainfall and the meteorological source, the Gulf of Mexico, decrease rapidly toward the western part of the state. The nearest station to a watershed in the western part of the state could be approximately 100 miles from the nearest first order station and the humidity of the area could be quite different.

Wind data are available where evaporation data are measured. However, when evaporation is not measured due to periods of freezing weather, wind data is sometimes not recorded, thus the records are not continuous.

Two variables, air temperature and solar radiation are generally available. Air temperature is measured and published at numerous stations throughout each state. Solar radiation although measured only at first order stations does not usually vary significantly with distance and can be easily estimated from sunshine and sky cover conditions. Therefore these two variables together with an appropriate evapotranspiration model would be the most logical selection for minimum data requirements.

CHAPTER 3

STOCHASTIC GENERATION TECHNIQUES IN HYDROLOGY

Stochastic generation is a term used which refers to the generation of synthetic data. In hydrology stochastic generation has been used to develop input data for deterministic physically descriptive models of a hydrologic process or to generate outputs directly of the process itself.

Many schemes for synthetic generation of data have been developed. One of the first attempts reported in the literature was by Sudler (61) who in 1927 generated synthetic annual stream flow data by writing a series of 50 observed annual flows on a deck of cards. After thoroughly shuffling the deck he drew a sequence of 50 annual flows. With successive shuffling and drawing, he constructed a series of synthetic annual flow records which could be used in design of reservoir storage. The method of Sudler's is an example of a prescriptive model where relatively little information is known about the physical process of the system producing annual flows. However, the outputs from the generator were close to observed records and fitted the need for a long-term synthetic record for design purposes.

Stochastic generation for simulation models input can be classified into two groups as in chapter 1, prescriptive and descriptive models.

Some of the same techniques used for one type of model can also be used as a generation technique for processes in another. Therefore, a review of synthetic data generation used in the broad field of stochastic hydrology is obligatory.

In hydrology text books of a decade ago one would find few references to stochastic hydrology. In one text recently published by Linsley, et al. in 1975 (37), a chapter was devoted to the discussion of this subject and explains its meaning in today's world.

> In statistics the word stochastic is synonymous with random, but in hydrology it has been used in a special way to refer to a time series which is partially random. Stochastic hydrology fills the gap between deterministic models...and probabilistic hydrology. ...in deterministic hydrology, the time variability is assumed to be totally explained by other variables as processed through an appropriate mode. In probabilistic hydrology we are not concerned with time sequence but only with the probability, or chance, that an event will be equalled or exceeded. In stochastic hydrology, the time sequence is all-important.

Stochastic Generation of Runoff

One method of generating a time series according to the explanation given previously by Linsley (37) and one which is most commonly used in stochastic generation of runoff is

$$X_i = \bar{X} + \rho_x (X_{i-1} - \bar{X}) + t_i \sigma_x \sqrt{1-\rho_x^2} \qquad (3\text{-}1)$$

where t_i is a random variate for period i with a zero mean and unit variance; σ_x, the standard deviation of X, ρ_x, the lag 1 serial correlation coefficient, and $\bar{X}$, the mean of the population of X.

This basic model for generation of synthetic sequences is the Markovian generation process of lag 1 and has been used by Thomas and

Fiering (64) in 1962, Fiering (17), and Matalas (41) in 1967 as a method of generating synthetic events representing a stationary process. It has a Markov structure because any event is dependent on the preceding event. The process is random because of the random component which is retained by Monte Carlo sampling of the probability distribution t, and stationary if the mean and standard deviation do not vary with time.

A more general development of the Markovian process is given by DeCoursey (16) in 1971 where a time series of events, X, can be represented by

$$X = f(t) + \varepsilon_t. \tag{3-2}$$

In this equation, f(t) is a deterministic function with a random component, ε. Both vary over a time period, t = 1, 2, 3 ··· n. If a trend is present in the series, that is, if the mean and standard deviation vary with time, then the series can be represented by polynomials or a Fourier series. If, however, there is no trend in the series, then the process is stationary and can be represented by linear autoregressive relation with lag 1 differences between indices of the elements as

$$X_i = \beta_0 + \beta_1 X_{i-1} + \beta_2 X_{i-2} + \cdots + \beta_m X_{i-m} + \varepsilon_t \tag{3-3}$$

where β_i are autoregressive coefficients and ε_i, the independent random component given in (3-2).

By taking the conditional expectation of equation (3-3)

$$E\ (X_i|X_{i-1}) = \mu_x + \rho_x\ (1)\ (X_{i-1} - \mu_x) \tag{3-4}$$

and

$$\text{Var}\ (X_i|X_{i-1}) = \sigma_x{}^2\ [1 - \rho_x(1)^2] \qquad (3\text{-}5)$$

the following can be developed

$$X_i = \mu_x + \rho_x\ (1)\ \ (X_{i-1} - \mu_x) + \omega_i\ \sigma_x\ \sqrt{1-\rho_x^2(1)} \qquad (3\text{-}6)$$

where μ_x is the population mean; σ_x, the standard deviation; ρ_x, the lag 1 correlation coefficient; and ω_t, a normal random deviate.

If the mean, μ_x, standard deviation, σ_x, and random component, ω_t, are substituted with $\overline{X}$ as the mean, and ρ_x as the lag 1 serial correlation coefficient in the historical series, then equation (3-1) results which can be used to generate a stationary stochastic representation of the historical series.

Matalas (41) found that for streamflow, the random component in equation (3-1) would be weakly stationary and that the random normal variate should be modified. He suggested that the random component ε_i be replaced by ξ_i which is defined as

$$\xi_i = \frac{2}{\gamma\xi}\left[1 + \frac{\gamma\xi}{6}\,\varepsilon - \gamma_\xi{}^2\right] - \frac{2}{\gamma\xi} \qquad (3\text{-}7)$$

where the skewness of ξ is denoted by γ_ξ and is related to the estimate of the skewness of X in the historical series. This modification of the random component was given by Fiering and Jackson (18). When ξ_{i-1} is used as the random component, the lag 1 Markov process becomes a third order stationary process according to Papoulis (46).

The problem of generating nonstationary processes can be dealt with by appropriate modification of the parameters used and assumption made about the underlying distribution of the historic series itself. The method previously given can also be used to develop season elements of a time series such as monthly flows.

Equation (3-1) can be modified to become

$$X_{i,j} = \overline{X}_x + \rho_j \; (X_{i-1,j} - \overline{X}_{x,j}) + t_i \, \sigma_{x,j} \sqrt{1-\rho_j{}^2} \qquad (3\text{-}8)$$

where j seasonal parameters can be developed throughout the index i.

The lag 1 process can be expanded to a multiple-lag Markov process. Fiering in 1967 (17) illustrated the problem of multiple-lag in a discussion of storage-yield function of reservoirs and gave an equation to generate data as

$$X_i = B_0 + B_1 \, X_{i-1} + \cdots \, B_m \, X_{i-m} \, \sigma_x \, t_i \sqrt{1-R^2} \qquad (3\text{-}9)$$

where R is the multiple correlation coefficient, B_i is the least squares partial regression coefficient of lag i, X_i is the variable value at time period i, and t is the random normal sampling deviate.

More details on the derivation and use of the equation developed in this section can be found in Yevdjevich (75) in 1964, Beard (4) in 1965, Benson and Matalas (5) in 1967, Young and Pisano (76) in 1961, Payne, et al. (45) in 1969, and Gupta and Fordham (26) in 1974.

Stochastic Generation of Rainfall

Many types of schemes have been developed to stochastically generate rainfall events in both amount and sequence of occurrence. The models and methods used are more varied than those usedin runoff because of the rainfall process, which is not continuous. The dry periods in rainfall records are more pronounced than the no flow periods in streamflow records and require special event generation procedures.

One method which has been used to generate the occurrence or nonoccurrence of rainfall was given in 1962 by Gabriel and Neumann (24). They studied the rainfall records at Tel Aviv examining in particular the distribution of wet and dry spells and developed a model for daily rainfall occurrence. An assumption was made that the probability of rainfall on any day depends on the previous day condition, either wet or dry; that is, whether it did or did not rain on the previous day. The two conditional probabilities, referred to as a Markov chain, given the event on the previous day are:

$$P_a = P_{ww} \text{ (wet} \mid \text{previous day wet)} \tag{3-10}$$

and

$$P_b = P_{wd} \text{ (wet} \mid \text{previous day dry)} \tag{3-11}$$

where P_a is the probability of a wet day following a wet day, and P_b is the probability of a wet day following a dry day.

Other investigations have extended the application of the Markov chain to rainfall records in other parts of the world. Caskey (8) in 1963 applied these probabilities to Colorado rainfall and developed probability of rainfall occurrence as a function of length of period. Pattison (48) in 1964 used multistate Markov chains of higher order to distribute total volume of rainfall or storm periods. Wiser (72,73) in 1964 and 1966 applied this method based on an urn model to develop the frequency of precipitation occurrence in North Carolina. DeCoursey (15) used the

Markov chain model to generate wet and dry day sequences of rainfall in Texas. Khanal and Hamrick (35) proposed a first-order Markov chain model to synthesize daily rainfall values at Bithlo, Florida. Smith and Schrieber (55) fitted a Markov chain model with assumed homogeneity to long-term rainfall data at Douglas, Fairbank, and Tombstone, Arizona. In 1970 Hershfield (29,30) applied the method to dry day frequency in Georgia and wet and dry seasons in Michigan.

The Markov Chain model or modifications of it appear to be an adequate method of generating the sequence of occurrence of daily rainfall. Successive wet days have been found to be independent of each other. The same is true for dry-period days as well. Fogel, et al. (20) proposed another method of generating sequence rainfall events based on the total number of events per rainy season in the southwestern United States. Their model assumed independence in the occurrence of thunderstorm rainfall in time and space and was based on the probability mass function

$$f_n(j) = \frac{e^{-m}\, m^j}{j!} \qquad (3\text{-}12)$$

where m is the total number of events, n is the number of events per season, and $f_n(j)$ is the probability of occurrence of the j^{th} event.

Osborn, et al. in 1974 (43) in a study of thunderstorm rainfall in Arizona used a Bernoulli model in the absence of persistence in daily rainfall. Tordorovic and Woolhiser in 1974 (67) proposed a Markov chain exponential model which was fitted to daily rainfall data at Austin, Texas. This model was a variation of the model given by Gabriel and Neumann in 1962 (24) for periods of 1 to 30 days.

The Markov model has not been limited to the generation of rainfall events. Jackson (33) proposed to use the model to generate low flow periods in synthetic streamflow records. He developed a Markovian mixture model with two states, dry flows and normal flows. Such a model would generate more nearly representative drought period flows which are the critical periods in reservoirs designed for water supply and hydroelectric power generation. Previous studies by Askew, et al. (3) had indicated that the Thomas-Fiering type models (64) did not produce drought periods as long or as severe as those found in observed records.

Stochastic Generation of Hourly or Short-Time Interval Rainfall

Several methods have been reported for synthesizing rainfall for hourly or short periods of time. Pattison (48,49) developed two models for simulating sequences of hourly rainfall data. The first model was a first-order Markov chain using periods of rainfall where the current hour was assumed to be independent of all other previous hours. The second method distributed daily rainfall amount over time, giving an hourly rainfall sequence.

Grace and Eagleson (25) developed a short time increment rainfall simulation model for summertime storms in Vermont and Nova Scotia. Statistical distributions were fitted to the length of storm and periods between storms then a sequence of storm amounts generated. An empirical urn model was used to generate the increments to match the length and depth of the storm sampled from their distribution, respectively. A Weibull probability distribution was used for the length of time between storms.

In 1964 and 1974 Wiser (72,74) developed models to generate the length of runs in daily and hourly precipitation. Wiser used an urn model in the first work to simulate the length of runs and sampled probability distribution of hourly depths to simulate amount. In the second study, daily rainfall amounts were simulated by using an autoregressive scheme with a storminess parameter having a cyclic behavior similar to that caused by movement of air masses. Wiser found the hourly generator to be inadequate, however the autoregressive scheme proved to be satisfactory when used to simulate daily rainfall for several stations in North Carolina.

Franz in 1970 (21) using a multivariate approach, generated hourly data at a network of three stations in California. Storms and interstorm periods were defined as hours with rainfall >.01 inch and hours with no rainfall, respectively. Two models were developed, one each for both storm and interstorm periods. With lag covariance matrix for transformed rainfall, and a corresponding matrix of lag 1 covariance between stations, a Markovian process with lag 1 dependence was developed to generate rainfall simultaneously at all three stations. Franz, in another work (22), discussed some of the problems encountered with the multivariate methods used in the model. Storm lengths were not as expected and some characteristics were not reproduced well leading him to conclude:

> The current state of statistical theory requires that considerable ingenuity be used to develop a workable rainfall generation model. The characteristics of rainfall are often very difficult to mimic with the statistical tools currently available. Empirical adjustments and modification of parameters must often be used to obtain an acceptable level of performance. Considerable judgment and trial and error testing will be required for some application of these models.

This particular model was later used by Ott (44) to generate hourly rainfall input for the Stanford watershed digital simulation model. While errors occurred in the generation of rainfall characteristics, these did not appear to change the characteristics of the synthetic streamflows.

Sorman and Wallace (57) reported the development of a rainfall generation model that digitally simulated thunderstorm rainfall in the Coastal Plains area of Georgia. Probability density function parameters were developed from observed records collected on an experimental watershed rain gage network. These included 16 distributions describing wind velocity and direction, cell duration, major axis, minor axis, rainfall distribution along axes, and other parameters relating cell development. They concluded that the model would be adequate and was considered to be successful when compared with the observed rainfall characteristics of the experimental network.

Generation of Storm Patterns

Several investigators have reported on the location and development of storm patterns with stochastic models of rainfall. Amorocho and Brandstetter (2) analyzed precipitation patterns over a California watershed and developed a method of spatial representation of total storm pattern and short-term rainfall patterns by trend surface fitting. They indicated the significant features of storms appeared be preserved by this method and that the method would be useful in network analysis and design. They related the development of storm patterns to orographic precipitation development over the watershed. No consideration was given to cell development.

Osborn and Lane (43) considered cell development randomly located on or near the catchment. Once a cell is developed and its location determined, following cells are clustered about it. Any cell has an equal chance of occurring at any point on a predetermined grid. The center depth and corresponding pattern were then generated by the following circular cell relationship

$$D = 0.9\, D_o\, [1 - K \ln (\sqrt{\pi}\, r)] \tag{3-13}$$

for $r \geq 1/\sqrt{\pi}$ miles

and

$$D = D_o \left[1 - \sqrt{\pi}\, \frac{r}{10} \right] \tag{3-14}$$

for $r \leq 1/\sqrt{\pi}$ miles

where r is the distance from storm center, D_o is the cell depth and $K = 1/\ln(\sqrt{\pi}R)$; R is the cell radius.

Randomness is incorporated into the depth-area model by generating a uniform random variate, U, so that individual cell depths are given by

$$D_o = \overline{D}_o \ln (1 - U) \tag{3-15}$$

where $\overline{D}_o$ is the mean cell center depth from observed data. The authors reported good agreement with the 10 years of observed data, but found evidence of persistence in the data. Further sophistication of this model was indicated.

Sorman and Wallace (57) also used cell development in their stochastic rainfall generation model. They observed the occurrence of cellular structure in summertime air-mass thunderstorms in Georgia. They developed distribution with the aid of observed data on the cell size, shape, and movement within wind patterns. The location of the initial cell was randomly selected. Pattern distribution was accomplished by the relationship

$$I_t\ (X,Y) = (I_o)_t\ \exp - [b_2X^2 + b_1Y^2] \qquad (3\text{-}16)$$

where X,Y are rain gage coordinates with respect to a cell center, I_t is maximum precipitation intensity at time t, I_o is a function of cell duration, and b_1 and b_2 are the distribution coefficients along the minor and major axes of the cell.

A "magic carpet" model to simulate area rainfall was proposed by Cole and Sherriff (10) in England which combines the stochastic incident of storm centers with systematic movement of these centers across a watershed. The pattern resulting from such a scheme is a pattern of daily rainfall amounts at several rain gage locations on the watershed. The model as described by the authors would generate rainfall patterns as if a "magic carpet" moved across a catchment area and deposited rainfall amounts using stochastic processes found in nature and estimated by observed daily rainfall patterns.

Stochastic Generation of Evaporation, Temperature, and Solar Radiation

Many of the hydrologic models cited in chapter 2 required inputs of evaporation, temperature, and solar radiation. Very little information is available in the literature outlining methods of generating these data. In descriptions of the hydrologic models themselves, the authors have generally stated the need for potential evaporation, pan evaporation, or estimated evapotranspiration values on a daily, weekly, or monthly basis without devoting much attention as to how these values should be obtained or what consequences may be suffered due to poor estimates. However, for generation of complete inputs for hydrologic simulation models, these variables in some form must be included as a minimum stochastically generated input.

Linsley (37) noted that the variability of potential evapotranspiration is less than that of precipitation, therefore the importance to the error in simulation has little effect on the results. However, Parmele (47) found that a 20 percent bias in potential evapotranspiration had an appreciable accumulated effect in hydrograph peak and recession characteristics computed with the Stanford model using watersheds in Pennsylvania and North Carolina. Randomly distributed error in potential evapotranspiration was not measurable on these watersheds or with the model used. However, possible limitations in the hydrologic models used, such as parameter estimation, may make them insensitive to evaporation inputs and there still exists uncertainties on its specific effects.

A method of stochastically generating synthetic evaporation data was reported by DeCoursey and Seely (14). Their method consisted of generating monthly evaporation data directly from a relationship between current months and the previous month's evaporation total much the same way as streamflow was generated in the first section of this chapter. Monthly evaporation was generated by

$$E_i = \overline{E}_i + a\,(E_{i-1} - \overline{E}_{i-1}) + b\,(P_i - \overline{P}_i) + t_i\, S_{E_i}\,(1 - r^2)^{1/2} \qquad (3\text{-}17)$$

where E_i and E_{i-1} are the present and previous monthly evaporation, respectively; $\overline{P}_i$, $\overline{E}_i$, and $\overline{E}_{i-1}$ are the average monthly evaporation and precipitation, S_{E_i} is the standard deviation of E_i, r is the multiple correlation coefficient, and t_i is a skewed, standardized, random, normal and independently distributed variate.

Evaporation and evapotranspiration can be simulated by various models. They could also be stochastically generated by techniques listed in this chapter. This would require determination of multiple dependence of the necessary variables such as temperature, solar radiation, wind speed, rainfall, percent sunshine, etc. No examples of such a generation process was found in the hydrologic literature researched by the author.

Random Number Generators

One of the most important components of any stochastic generation model is the method used to select the random variate. Several methods are available but few were listed in the works cited in this chapter. Studies have been made to test the randomness of random number generating schemes. One such investigation by Speed and Broadwater (59) lists a series of programs developed from computer testing of random number generators. These tests included frequency tests, run tests, gap tests, lagged product tests, and a matrix test. MacLaren and Marsaglia (40) and Van Gelder (71) also tested random number generators and found congruential or multiplicative generators to perform the best.

A direct method of generating by the congruence method given by Abramowitz and Stegon (1) is

$$X_{n+1} = a\, X_n + b \pmod{T} \qquad (3\text{-}18)$$

where X_n and X_{n+1} are consecutive variates, T is determined by the capacity and base of the computer used, and a and b are chosen so that the sequence of numbers possess the desired statistical properties of random numbers.

Random normal numbers can be generated directly by

$$V_1 = (-2 \ln X_1)^{1/2} \cos 2\pi X_2 \qquad (3\text{-}19)$$

where V_1 is an independent random normal variate with zero mean and unit variance, X_1 and X_2 are a pair of random numbers. Congruential generators of this type have been tested and do not repeat sequences in a period of over one billion numbers.

Summary

The methods and applications of stochastic generation of hydrologic data presented in this chapter ranged from synthetic streamflow generation to the generation of synthetic evaporation data. A few of the techniques checked such as the Thomas-Fiering method of streamflow generation and the Markov chain model for rainfall sequence generation appear to have wide application and are generally accepted for use in hydrology at this state of the art. However, it could be concluded that the hydrologist is never really completely satisfied with the results obtained with these methods and proposed refinements that may be applicable only to specific areas and climates. Some of these refinements have led to other areas of investigation and to the continuous quest of removing more uncertainties from the inexact science of hydrology. Perhaps hydrology is an art as well as a science.

PART II - APPLICATION

CHAPTER 4

DESCRIPTION OF STUDY AREA AND AVAILABLE DATA

The area chosen for study in this dissertation is a 1,130-square-mile section of the Washita River basin including the tributary watersheds located between Anadarko and Alex, Oklahoma on the mainstem of the river. Within this reach of the river basin, the Southern Great Plains Watershed Research Center, Agricultural Research Service (ARS), United States Department of Agriculture, maintains and operates an experimental watershed. This research watershed was established in 1961 with the following overall objective as stated in its charter (58):

> Objectives of the research are to: (1) determine the effects of regulated flows resulting from combined land treatment and structural measures in tributary watersheds upon floodflows, annual and seasonal water yields, ground water levels, and stream channel stability of the main channel of the river; (2) determine the amount, character, and movement of pollutants such as sediment, salt, and plant nutrients in the river system and develop possible procedures for water quality improvement; (3) analyze and interpret available data to determine what might have been the effect along the mainstem with alternative treatment programs in the tributary watersheds; (4) develop concepts and procedures for use in other river basins; and (5) develop conservation practices for better overall watershed performance.

In order to achieve these objectives, the study area was densely instrumented with rain gages, stream gages, ground water wells, sediment measuring stations and soil moisture measuring profiles. The location of the study area and part of these instrumentations are shown in figure 1.

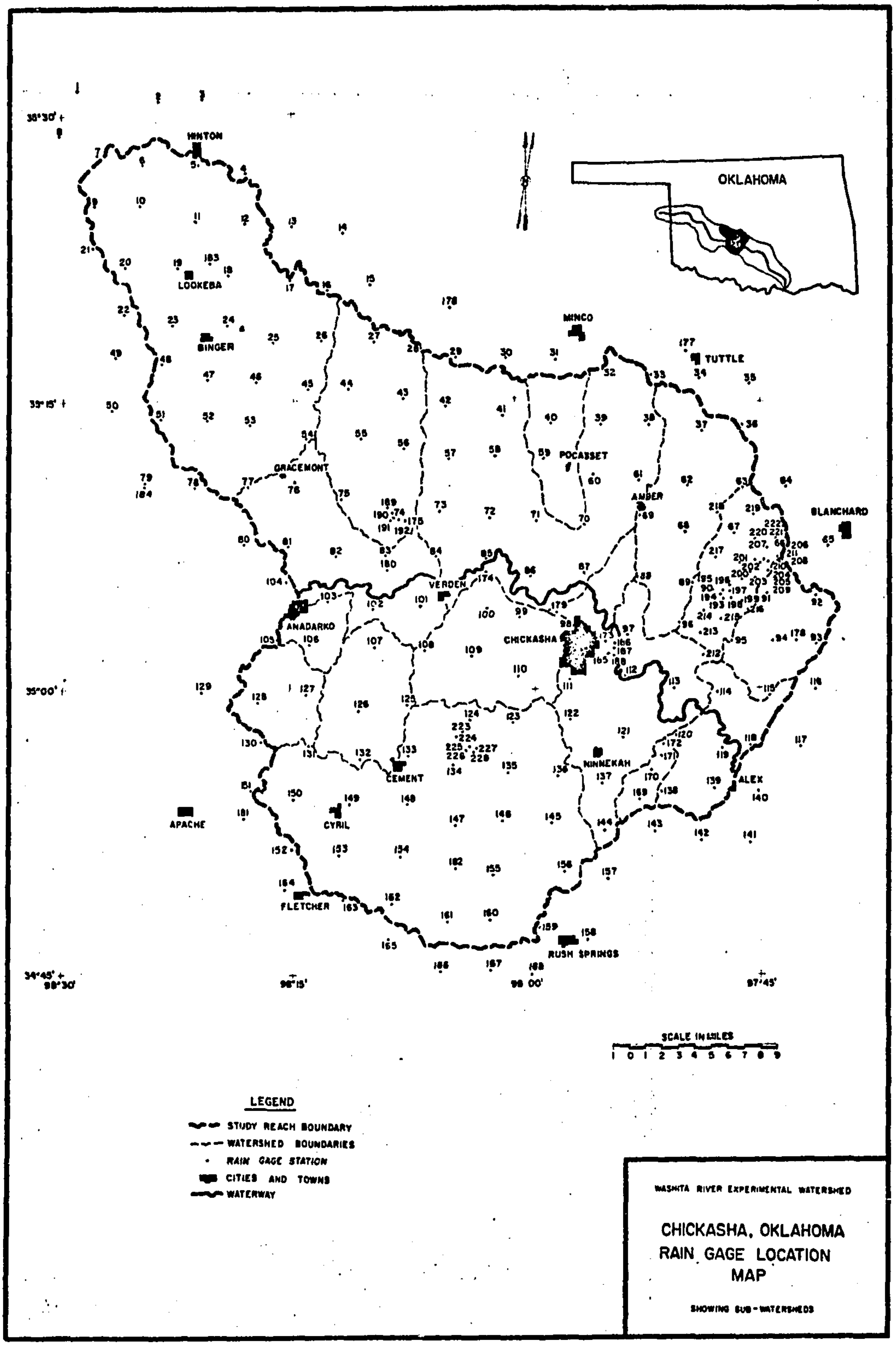

Figure 1 ARS rain gage network and research study area-Southern Great Plains Research Watershed

Rain gages of the network shown in figure 1 are all weighing recording gages with either 24- or 12-hour charts. Gages numbered 1 to 168 have been in continuous operation. Several gages (169-230) were added to the network as smaller experimental watersheds within the area were installed. In addition to the rain gage network, some river stations, tributary, and unit source watersheds were instrumented to measure streamflow. Outlines of these areas are shown as dashed lines in figure 1. There are 50 streamflow measuring stations ranging in size from 1.48 acres to 4,783 square miles, including 4 stations on the Washita River, 12 stations on tributary watersheds, 8 stations on a subdivided watershed, and 22 stations on small unit source watersheds. Sediment concentrations are collected at 40 of the streamflow measuring stations. Evaporation from buried Young screened pans is measured at 3 stations. Class "A" pan data is measured at one station with air temperature, humidity and total wind miles recorded at each of the pan evaporation sites.

Land use data have been monitored yearly with complete inventories made at 5-year intervals. Water quality data on total dissolved solids in the streamflow waters have been collected periodically since 1966.

The data base developed by the personnel of the Center from this experimental watershed is ideally suited for testing and development of existing and proposed hydrologic models. The data collected is also well suited for the purposes of this study; i.e., to develop stochastic rainfall and meteorological models to synthetically generate input data to hydrologic models. There is no place in the free world where there exists such a complete set of hydrologic data on the scale and density as that maintained on this experimental watershed.

Topography of the Network Area

The rain gage network lies between latitudes 34° 45' to 35° 45' and longitudes 97° 30' to 98° 30'. The topography of the area is characterized by rolling plains cut by deeply eroded valleys. Maximum relief is approximately 450 feet occurring in the northwest quadrant of the network between gages 13 and 104. The predominant topographic features of this area are the Washita River and associated flood plains which comprise 10 percent of the area.

Precipitation Climatology

The network area is in a region of moist to dry subhumid climate. Normal annual precipitation according to the U. S. Weather Bureau data (68) varies from 33 inches on the east to 28 inches on the west edge of the network. The 30-year normal annual precipitation pattern for the network area is shown in figure 2. Normal annual rainfall for Chickasha near the center of the area is 31.60 inches. Annual precipitation totals at points in the watershed have been as large as 51.47 inches and as small as 16.0 inches. About 98 percent of the yearly precipitation occurs as rainfall with the remaining 2 percent occurring as sleet or snow. Snow falls on the average of 5 days during the period November through March and is not a factor contributing to flooding. Flooding can occur at any time during the year, but is most frequent during late spring and early fall and is associated with thunderstorm rainfall.

During 13 years of network operation some interesting observations of precipitation characteristics which are pertinent to this study have been made. The average annual precipitation determined from network

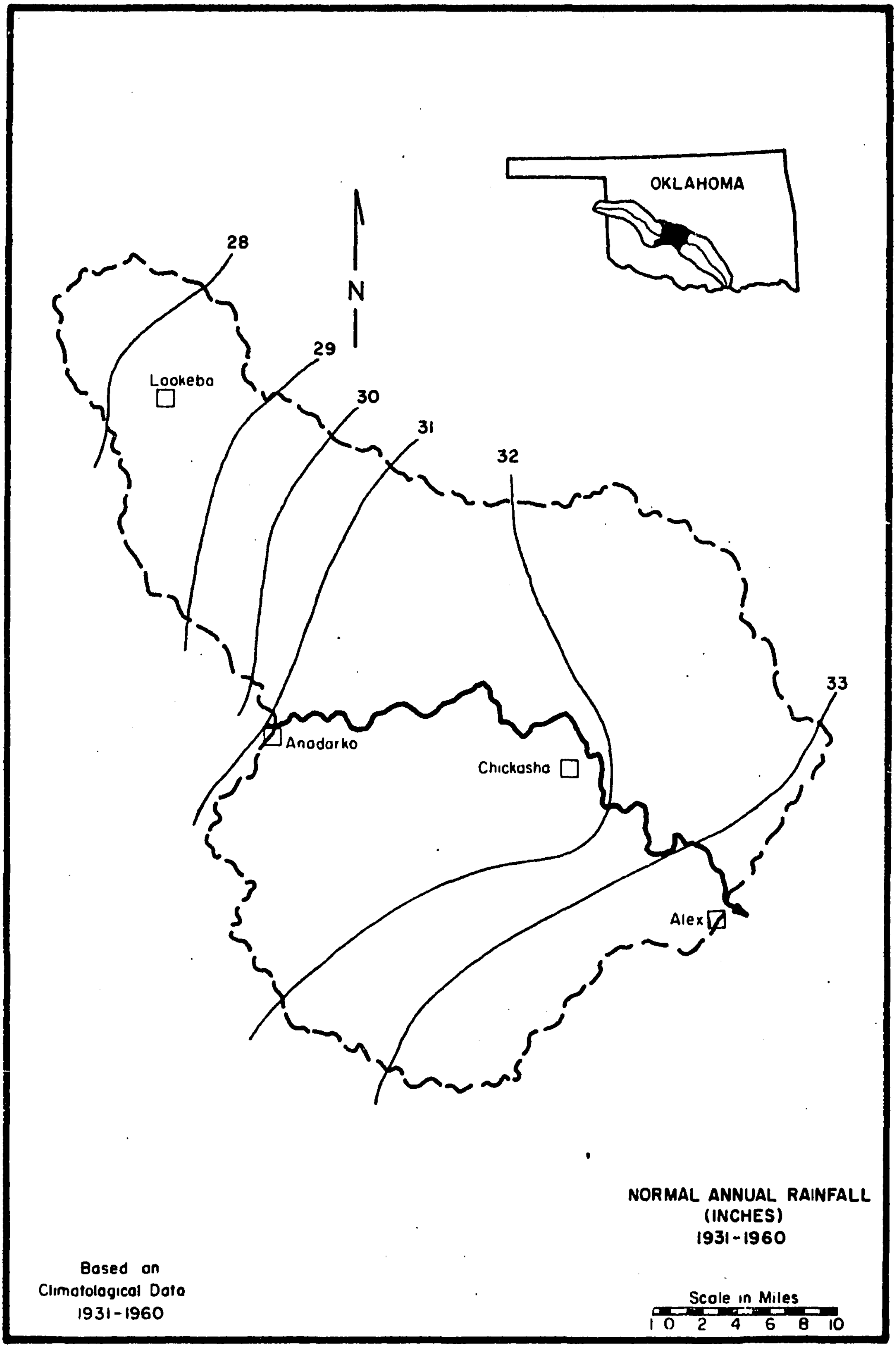

Figure 2 Normal annual rainfall distribution for ARS network area (1931-1960).

measurements from 1962 to 1974 was 27.81 inches. The areal distribution of average annual precipitation for the network is shown in figure 3. During this 156-month period, 49 months have had above normal rainfall. Only 2 years, 1968 and 1974 have been above normal. A tabular listing of the monthly and annual rainfall is given in table 2. Most of the period of record has been dry compared to the 30-year normal rainfall for this area.

Despite the below-normal annual precipitation during the period of record, several storms have produced large point amounts. Some of the larger storms are listed in table 3. The average return period indicated for these storms are based on the data given in U. S. Weather Bureau Technical Paper 40 (28). Return periods exceeding 100 years have been experienced at 13 percent of the stations. However, for 79 percent of the network stations, the maximum recorded storm rainfall has been less than the 10-year storm, for 5 percent, more than 50 but less than 100 years.

A cellular structure appears to be a characteristic of the frontal-type thunderstorm that occurs in the climatic region. One of the storms listed in table 3, September 20, 1965, has been analyzed to show the cellular structure found in such storms. This storm, the largest precipitation event recorded yet by the network, occurred in the northwest section of the study area, producing a maximum point rainfall of 8.77 inches in 5 hours. The pattern of total rainfall from this storm, figure 4, shows a uniform increase from the 2-inch isohyetal near Gracemont to an 8-inch value near Hinton. However, this storm was composed of several small intense cells traversing the watershed at speeds up to 30 miles per hour. Isohyetal plottings of 10-minute interval

Table 2.--ARS raingage network average rainfall 1962-1974.

Year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Annual
1962	.38	.81	.83	2.39	2.68	7.82*	1.96	1.26	5.20*	2.53	1.33	1.25	28.44
1963	.23	.37	1.74	2.70	1.60	3.43	2.71*	1.08	2.19	.54	2.66*	.66	19.91
1964	.94	2.12*	1.20	1.27	5.97*	1.19	.84	3.97*	4.33*	.80	5.45*	.69	28.77
1965	1.05	.78	1.13	2.51	3.92	3.57	.82	5.16*	4.53*	1.49	.04	1.40	26.40
1966	.50	1.55*	1.04	3.72*	.87	2.06	1.34	5.93*	3.47*	.41	.49	.31	21.69
1967	.30	.10	2.13*	5.55*	3.24	2.44	2.22	1.14	5.24*	2.69	.29	1.07	26.41
1968	2.47*	1.26	1.38	2.56	5.57*	2.55	3.65*	2.01	3.80*	2.15	4.62	1.10	33.12*
1969	.50	2.06*	2.20*	2.24	5.63*	3.29	1.37	2.89*	4.50*	1.59	.18	1.01	27.46
1970	.11	.48	2.65*	3.25*	3.56*	2.19	1.45	1.25	5.25*	1.94	.66	.31	23.10
1971	.82	1.64	.07	.63	4.43	4.12	2.40	4.05*	4.92*	4.23*	.69	2.73*	30.73
1972	.12	.44	.48	3.72	3.20	1.10	1.22	1.75	.91	7.57*	2.18*	.73	23.42
1973	3.30*	.53	6.06*	2.78	4.37	4.77	4.58*	1.14	7.49	3.01	2.04*	.32	40.49*
1974	.12	1.92*	2.53*	3.47	4.17	1.80	1.23	4.98*	3.49	4.44*	1.97*	1.41	31.53
Ave	.83	1.08	1.80	2.83	3.79	3.10	1.98	2.82	4.26	2.57	1.74	1.00	27.81
Normal	1.35	1.47	1.90	3.07	5.36	4.16	2.42	2.57	3.13	3.03	1.63	1.51	31.60

* Above Normal Rainfall

1/ Normal rainfall based on Chickasha Weather Bureau record (1931-1960)

Table 3.--Summary of maximum storm rainfall
ARS Network 1962-1974

Date	Amount Inches	Duration Hours	Average return Period/Years
06/01/62	5.40	12	15
09/03/62	6.14	6	75
09/20/62	5.82	10	25
06/23/63	5.76	8	30
09/16/63	5.87	16	15
05/09/64	4.08	3	20
05/10/64	5.16	12	10
06/21/65	6.00	4	>100
09/20/65	8.77	5	>100
06/08/66	3.72	2	20
08/11/66	3.62	4	5
04/12/67	4.34	6	10
08/17/67	3.47	4	5
06/15/68	4.70	2	80
05/31/68	4.62	8	15
05/04/69	6.43	7	85
09/21/69	4.11	9	10
05/29/70	4.25	3	30
09/22/70	8.76	15	>100
10/02/71	4.51	11	10
10/30/72	4.88	17	10
07/09/72	3.11	4	5
07/22/73	5.22	4	60
09/03/73	3.89	2	30
08/09/74	5.80	3	>100

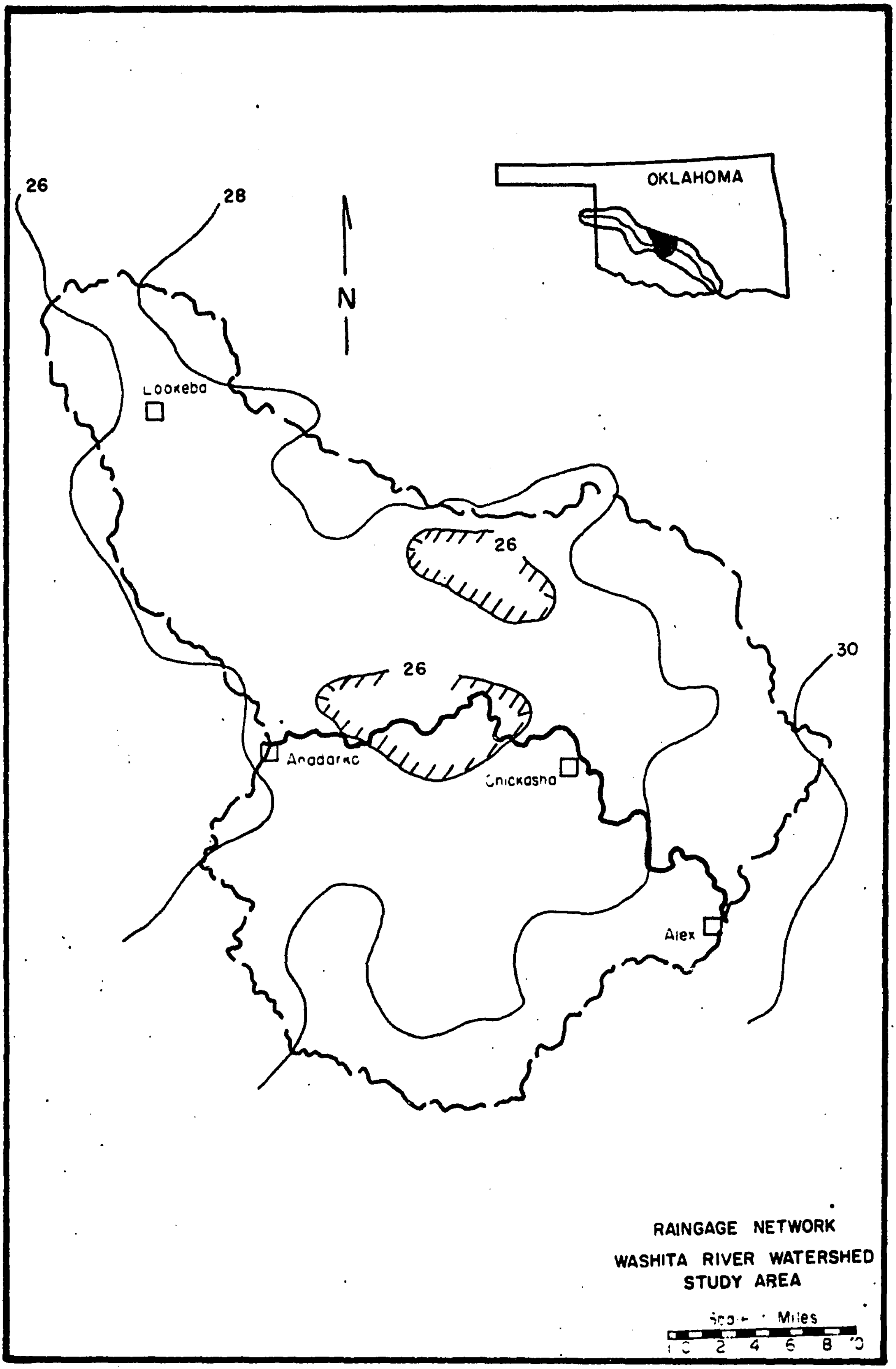

Figure 3 Average annual rainfall from ARS network stations (1962-1974).

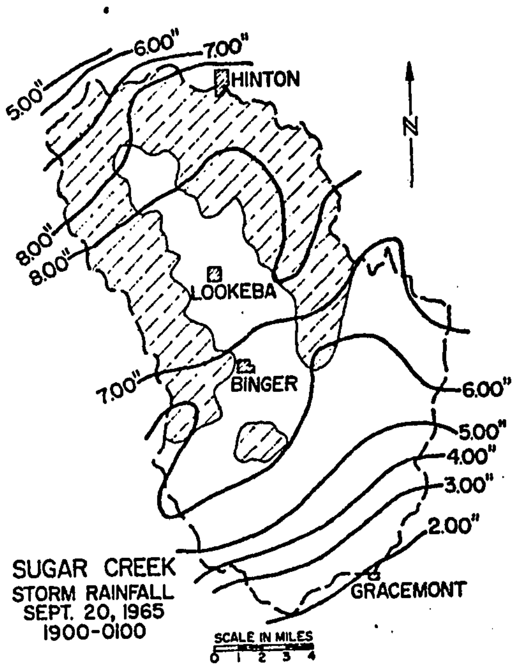

Figure 4 Sugar Creek storm rainfall pattern
September 20, 1965 - ARS network

rainfall amounts at network stations in this area depicts the relative size and shape of these cells as shown in figure 5.

The cellular structure shown in figure 5 is not unlike those for which stochastic models were developed in the Arizona and Georgia studies cited in chapter 3. However, the movement and intensity of the cells were probably much greater. Modeling of such cellular movement and intensity would be most difficult and models would require a large number of parameters.

The data from the rain gage network is recorded on charts. After these charts are collected from the field each week they are processed in the office by annotating the dates, times and amounts of rainfall. Daily amounts for the 24-hour period from midnight to midnight are tabulated and punched on cards for computer processing. Card values are then loaded to magnetic disks and tape files for storage and retrieval for further processing and analysis.

In addition to the daily totals, break point intensity data (time and gage height at slope changes on the chart trace) are taken from the charts by an automatic analog-to-digital converter chart reading system. The cards from this process are also converted to magnetic tape files consisting of storm intensities at all stations. Only the major storms which produces direct runoff have been processed for break point data, therefore the records of intensity data are not continuous. Small storms, generally less than .25 inch total, have not been processed for intensity.

Daily rainfall has been processed for the entire period of record through December 1974. These data were made available for use in

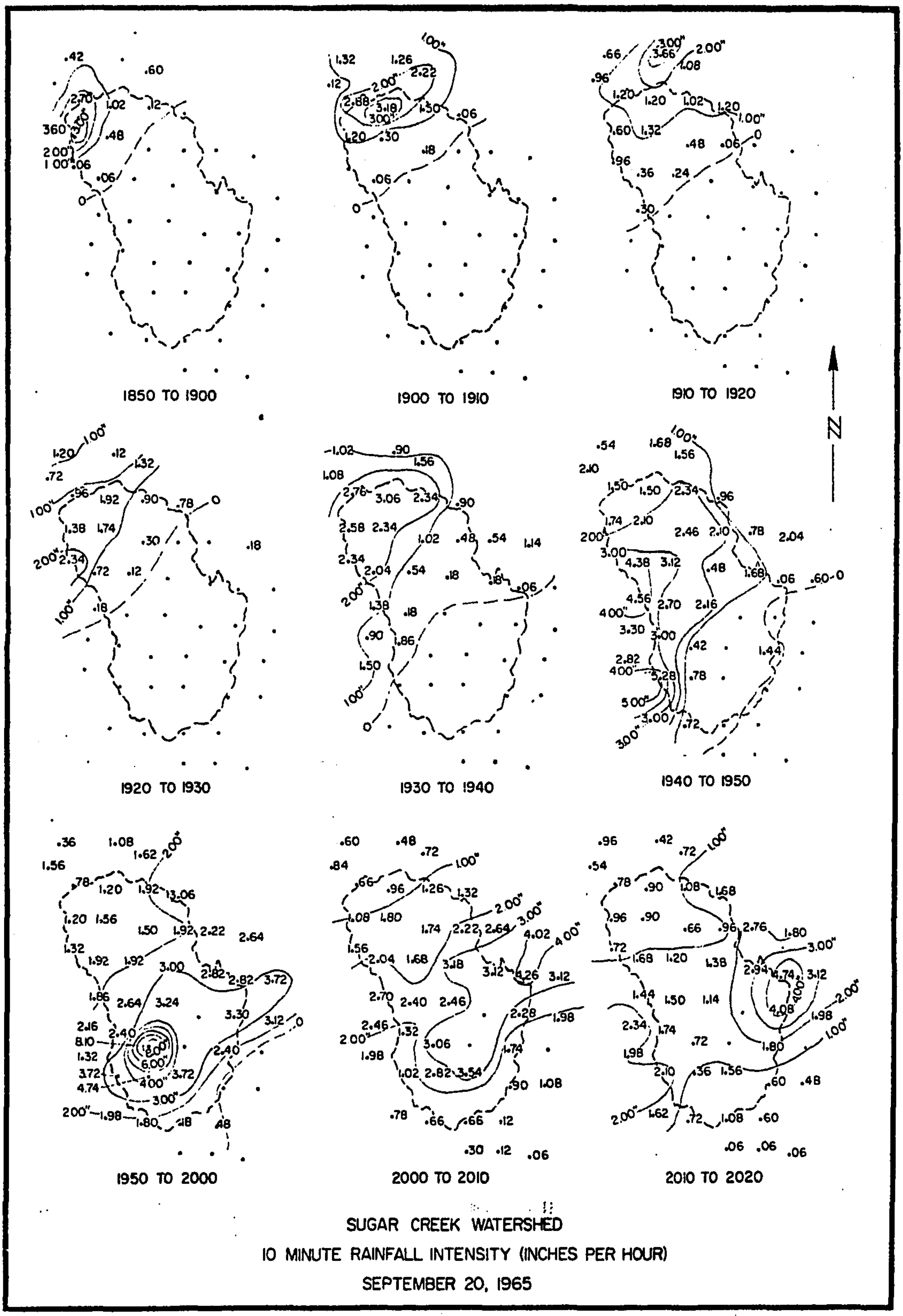

Figure 5 Rainfall intensities for 10-minute time intervals, September 20, 1965 storm

this study. Records from the basic network, gages 1 to 168, are stored on magnetic disk files in an array for each daily rain event.

Evaporation, Air Temperature, Wind and Solar Radiation Data

Evaporation data are collected at 20 climatic stations in Oklahoma (64). The data are taken usually by cooperative observers at research stations, reservoirs, and first order weather stations. Most of this data consists of daily measurement from National Weather Service Class "A" pans. Only at 1 station out of the 20 are records of evaporation continuously reported throughout the year. Most stations are discontinued during the winter months, December through March, to prevent damage to the pan due to freezing. Therefore, if the model user wishes to use pan evaporation data in the hydrologic models which require this input, they must make estimates from other sources.

Evaporation data has been collected on a regular basis at the Southern Great Plains Watershed Research Center since 1963. The data are measured at sunken Young screened pans at three sites which are located at rain gage stations numbered 90 and 124 shown in figure 1, and at the South Central Oklahoma Cotton Research Station near gage 173. The Cotton Research Station (CRS) record is the longest of the three stations and is located within a National Weather Service climatic station enclosure adjacent to a Class "A" pan.

The Young pan data recorded at the CRS is continuous and could be used to fill missing gaps in the class "A" pan record. Ratios published in U. S. Geological Survey Professional Paper 269 (70) can be used to convert Young's pan to class "A" pan. Ratios also have been published at sites in Texas (63). The ratio from these studies as well as those ratios computed from available months at CRS are given in table 4. There are no ratios listed at CRS for January, February, November, and December because no Class "A" pan data were available for these months.

In addition to evaporation, wind and air temperature data are also measured at the three climatic stations on a daily basis. Air temperature is a long-term record of more than 30 years in length. The normal mean temperature data from the Chickasha station based on the 1931-1960 period are shown in figure 6.

Because of missing evaporation data such as that noted in table 4, some model developers have used alternate methods of obtaining potential evapotranspiration estimates. Some of the methods require a quite detailed array of variables including solar radiation and relative humidity. Humidity is measured at the CRS station with a hygrothermograph strip chart recorder. Solar radiation data on a daily basis can be obtained from a first order weather station at Oklahoma City approximately 20 miles away. Such data does not vary appreciably in this short a distance and should be considered adequate for the purposes of this study.

TABLE 4

CONVERSION RATIOS FOR CONVERTING YOUNG EVAPORATION PAN DATA TO CLASS "A" PAN DATA FOR LAKE HEFNER OKLAHOMA, TEXAS, AND COTTON RESEARCH STATION, CHICKASHA, OKLAHOMA

Month	Lake Hefner	Texas	CRS
January	1.03	1.06	*
February	1.46	1.56	*
March	1.18	1.25	*
April	1.30	1.26	1.72
May	1.47	1.52	1.60
June	1.46	1.52	1.60
July	1.46	1.47	1.56
August	1.47	1.49	1.71
September	1.40	1.39	1.66
October	1.31	1.33	1.32
November	.99	1.03	*
December	.95	.96	*

* Class "A" pan data missing for these months.

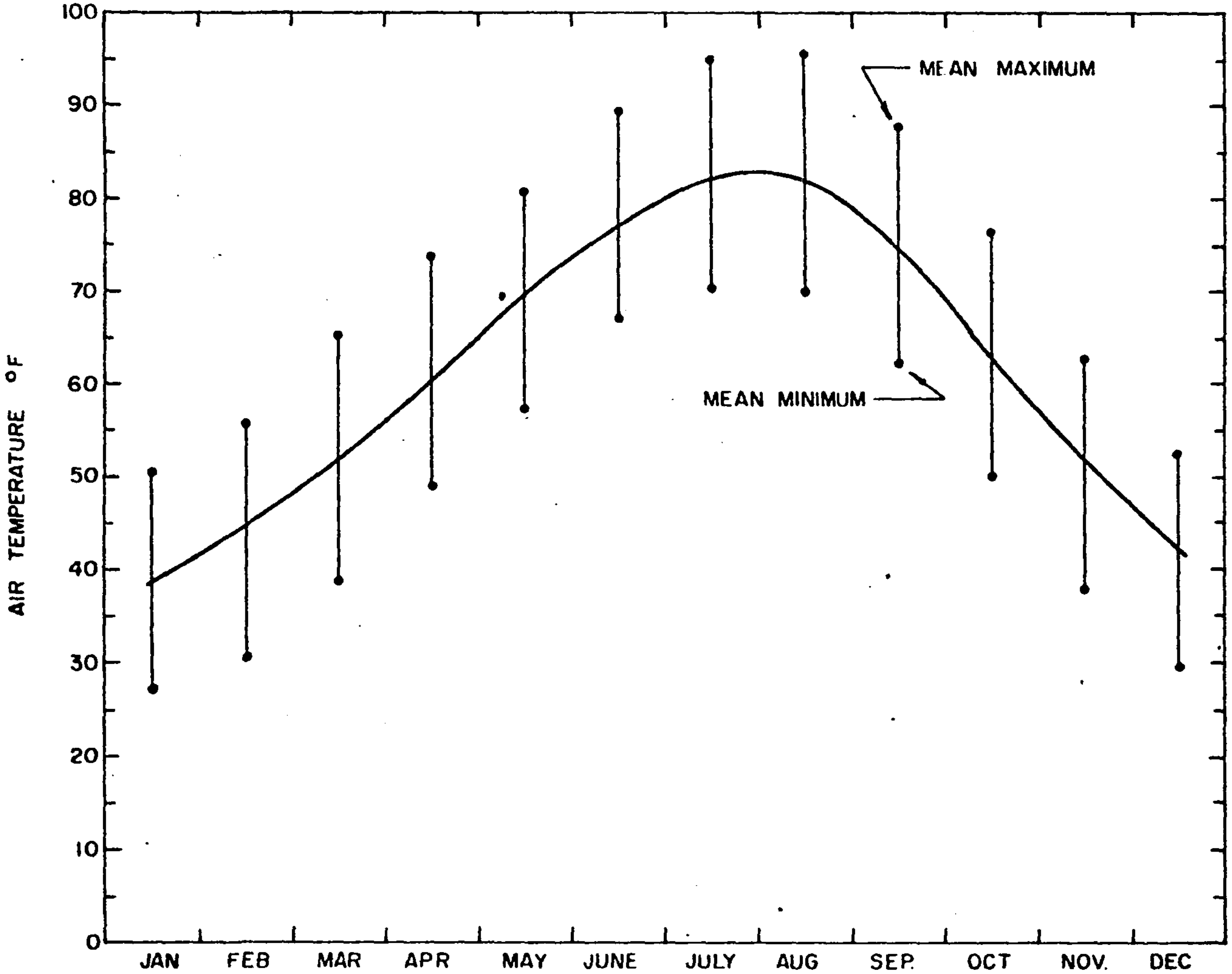

Figure 6 Normal mean maximum, minimum and daily mean air temperature at Chickasha, Oklahoma (1931-1960).

CHAPTER 5

STOCHASTIC RAINFALL MODEL

The methods chosen to develop a stochastic rainfall model are based partly on the methods described in chapter 3 and partly on the author's observations of the rainfall characteristics of the area. The proposed model should also be capable of meeting the objectives set forth in chapter 1 which states that the objective of the rainfall model is to stochastically generate the minimum required synthetic rainfall inputs for hydrologic models. From the review of models currently in use, the minimum for all models is daily rainfall amounts at one or more stations, or a single input which can be generated independently or is calculated from generated multiple point values.

The first step in the proposed model is the generation of wet and dry day sequences. This can be accomplished quite well with the Markov chain model. The next step is to size the rainfall pattern for the day to be generated; i.e., select from probability distribution developed from the observed rainfall records what would be the most probable maximum rainfall for an area, then generate the location of this maximum within the area. Based on this maximum value, the mean rainfall and an associated pattern distribution are then generated. A flow chart of the model general component of the overall generating scheme is given in figure 7. The following sections discuss in more detail the individual components and the reasoning behind their selection.

Generation of Wet and Dry Day Sequences

The method selected for generating the number and distribution of rainfall events in the model was a two-state Markov chain. In chapter 3, nine different studies have been made which successfully use this method to generate sequence of rain events in California (48), Isreal (24), Colorado (8), North Carolina (72,74), Texas (15), Florida (35), Arizona (55), Georgia (29), and Michigan (30). The use of this method appears to be well justified considering its accepted use in various parts of this country and the world.

This method involves the calculation of two conditional probabilities: α, the probability of a wet day following a dry day, and β, the probability of a dry day following a wet day. The two-state Markov chain for the combination of conditional probabilities is:

$$\begin{array}{llcc} & & \multicolumn{2}{c}{\text{Future State}} \\ & & \text{Dry} & \text{Wet} \\ \text{Present State} & \text{Dry} & 1-\alpha & \alpha \\ & \text{Wet} & \beta & 1-\beta \end{array} \tag{5-1}$$

To generate sequences of events throughout a year using this method, it is required to provide some type of transition from one season to another. Examination of the mean monthly number of wet day occurrences shown in figure 8 indicated that dividing the year into monthly periods and calculating conditional probability for each period

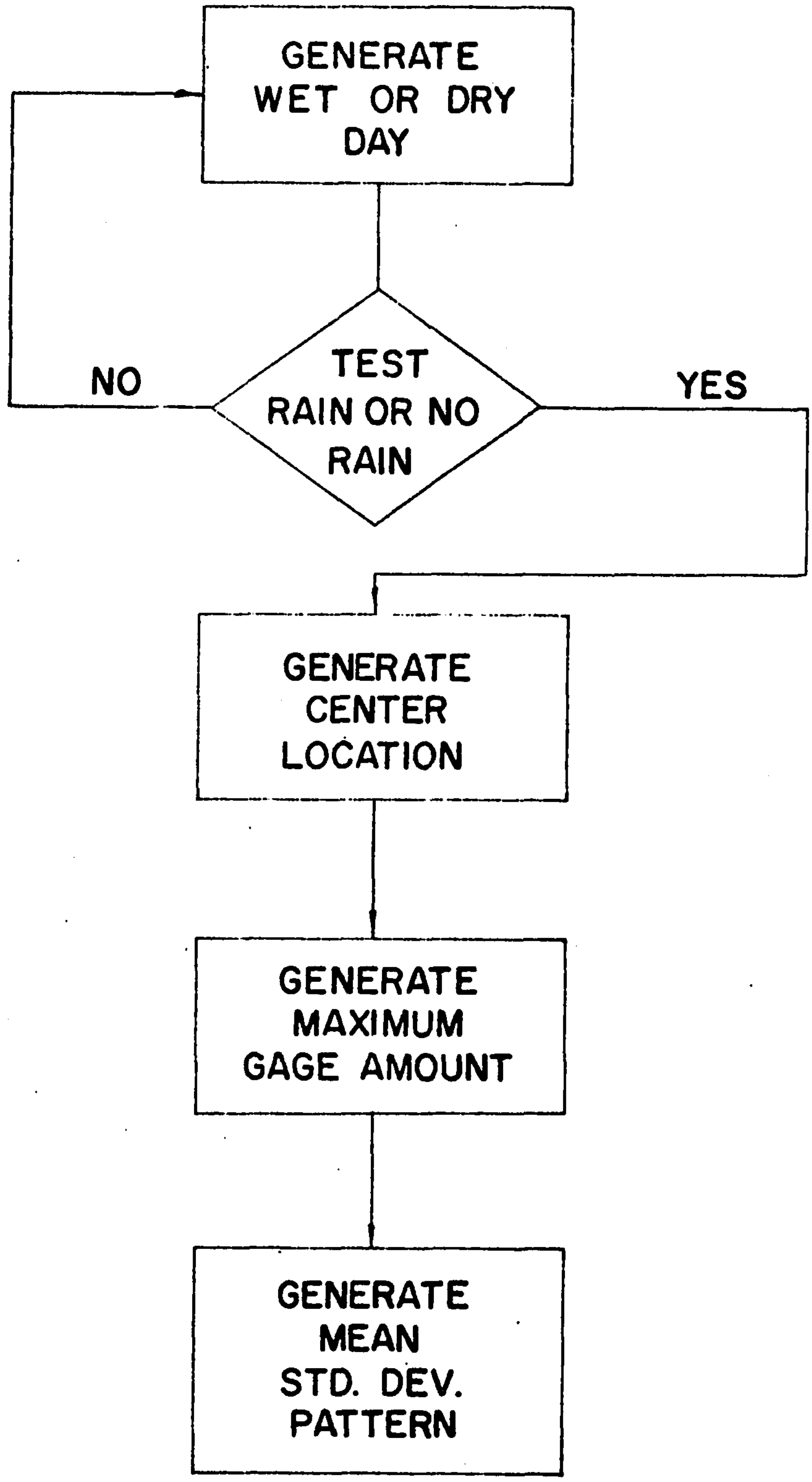

Figure 7 Flow chart of the rainfall generation model

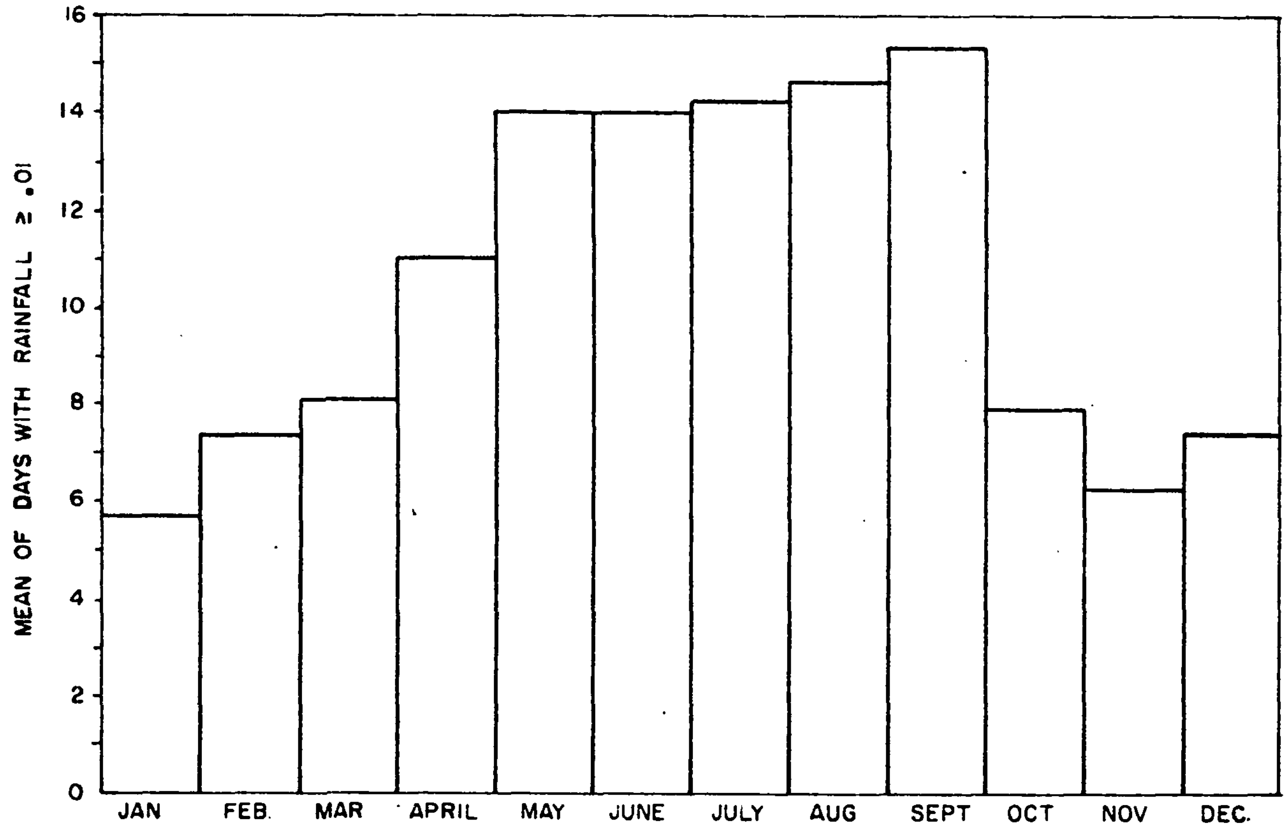

Figure 8 Mean number of rain day occurrences for each month

would provide the necessary transition. The criterion for a wet day is the occurrence of $\geq$ .01 inch of rainfall at one or more stations of the network.

Conditional probabilities, α and β, were calculated for each month of the year. These values are listed in table 5. Sequences of wet and dry days can be determined by alternately generating uniform random numbers between 0 and 1 and testing against the seasonal value of α and β. For example, if a random number, .53, was selected and the previous January day had been dry, then .53 would be tested against the value, $1-\alpha$ (.56). Because the probability of being wet is .56 and the shown probability is .53, a wet state would have been chosen for the day. Correspondingly, if the previous state had been wet and the probability generated was greater than .096, a dry state would have been chosen for the day.

Spatial Distribution of Pattern Centers

The spatial distribution of the rainfall pattern centers or maximum amounts is assumed to be random. If this assumption is correct, then stations of a network such as the ARS network studied here should have an equal chance of recording the maximum amount over a long period of time. In chapter 3 at least two of the generation schemes, one in Arizona (43) and the other in England (10) implied the same assumption on the distribution of the spatial occurrence of storms. It seems reasonable to assume without prior knowledge that no point within an area the size of this network is more favored for rain occurrence than another point a few miles away. Furthermore, with sampling of many storm systems by a network, a uniform random distribution of the

Table 5. Seasonal α and β conditional probabilities

Month	β2/	α1/
January	0.560	0.096
February	.446	.190
March	.440	.206
April	.536	.260
May	.686	.230
June	.623	.350
July	.699	.237
August	.636	.313
September	.671	.354
October	.479	.184
November	.473	.135
December	.448	.175

1/ Probability of a wet day following a dry day

2/ Probability of a dry day following a wet day maximum daily amount should result.

However, in order to verify this assumption, daily rainfall records from the network were analyzed with respect to the location of the maximum recorded amount for each rain day. Figure 9 shows the distribution of maximum daily rainfall occurrence at each station during the historical record. The number of occurrences range from 36 at the extreme northwest gage to zero near the center of the network. In general, the larger number of maximums occurred on or near the boundaries. The large values at these stations are attributed to storms which were centered off the netwo[illegible] yet close enough so that their patterns extended to just a [illegible] gages near the boundary. Storms of this type give a boundary effect to the distribution of maximum occurrences, thus making the edges appear to have more chance of receiving the pattern maximum, when actually the maximum of some of the storms was located out of the range of the network sampling area. In most cases in the interior of the network, the maximums were considered to be uniformly distributed.

The high number of pattern maximum occurrences near the edge of the network presents a problem in generating the location of the pattern maximum. One method of solving the problem would be to make the area for which the pattern could be located much larger than the actual network and try to generate patterns uniformly over it. However, the boundary of this area would still have the nonuniform effect.

Another method, and the one chosen for this study, was to modify the uniform random number-generating scheme for gage locations. This method consists of generating a uniform random number between 0 and 1. This number is multiplied by the number of stations in the

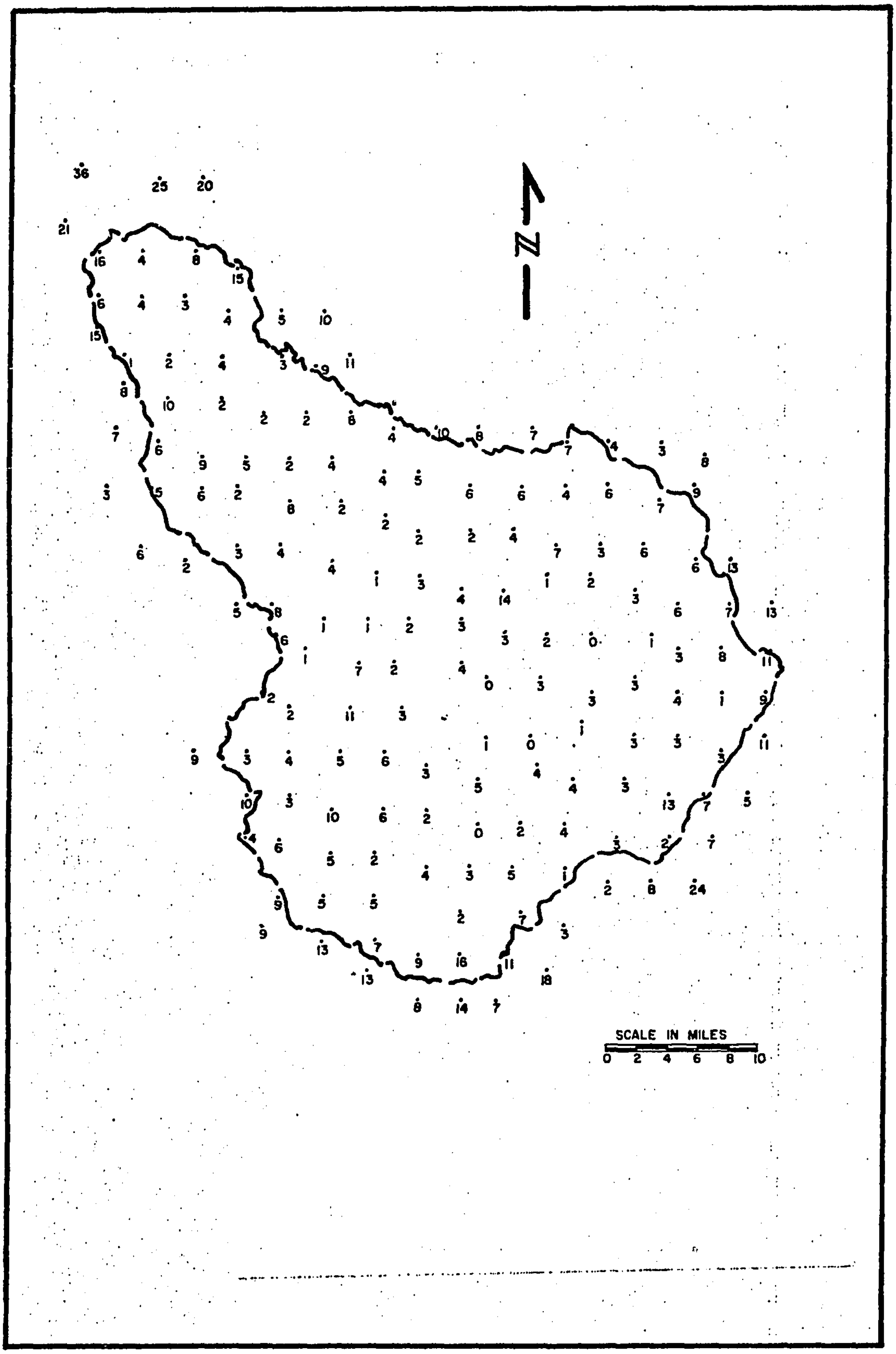

Figure 9 Number of maximum daily rainfall occurrences at each station of the 168-gage ARS network, 1962-1974.

network and rounded to the nearest nonzero integer. The resulting number is the station number selected for the pattern center. To compensate for the larger number of occurrences at the boundary of the network, this procedure was modified by adding a pseudo number of gages at the location having the larger number of occurrences. A ratio of the observed value to the expected value at stations with large occurrences was used to determine the additional station number that should be added. The expected value at a station for the historical record is 6. Using this adjustment, an array of 220 station numbers was found.

Generation of a gage location for the storm center consisted of generating a random number between 0 and 1, multiplying it by the 220 and rounding to an integer value. This is the array element which contains the station number for the pattern maximum.

Maximum Daily Rainfall

Daily rainfall amounts have been fitted to many types of frequency distributions. Brakensiek (6) fitted a log normal distribution to daily rainfall while Stidd (60) used a cube root normalizing procedure. Kotz and Neumann (36) have found the gamma distribution to adequately fit daily rainfall amounts. More recently, Snyder and Wallace (56) have proposed a three-parameter, log-normal distribution which may have application to daily rainfall frequency determination. The best fit for maximum daily rainfall on the network was a skewed normal distribution of the form attributed to Fiering (18) given as

$$x = \frac{6}{g}\left[\left[\frac{g}{2}\left|\frac{X-\mu}{\sigma}\right| + 1\right]^{\frac{1}{3}} - 1\right] + \frac{g}{6} \qquad (5\text{-}2)$$

where x is the skewed normal variate; X, the raw variate; and μ, σ, and g, the mean standard deviation and skew coefficient of the raw variate.

Maximum daily rainfall amounts for each event were determined for each month of the year. From these data the mean, standard deviation, and skew were calculated for each monthly set of maximums. Using equation (5-2) and the mean, standard deviation and skew, skewed normal frequency distribution curves were calculated. Two of these curves are shown in figures 10 and 11.

To generate a daily maximum amount, a random normal number is drawn and the raw variate, X, is calculated using equation (5-2).

Rainfall Pattern

Many studies of area-depth or isohyetal-depth relationships for storm rainfall have been made. Courtʹ (11) summarized most of the studies made in the United States and Europe and suggested a possible model for depth of rainfall at a given distance from the storm center as:

$$P_{x,y} = P_{max} \exp\left(-a^2X^2 - b^2Y^2\right) \qquad (5\text{-}3)$$

In this equation a and b are constants for scale and ellipticity; P_{max}, the storm center rainfall; and $P_{x,y}$, the rainfall at the coordinates X and Y miles from the center. A similar model, which is given below, is

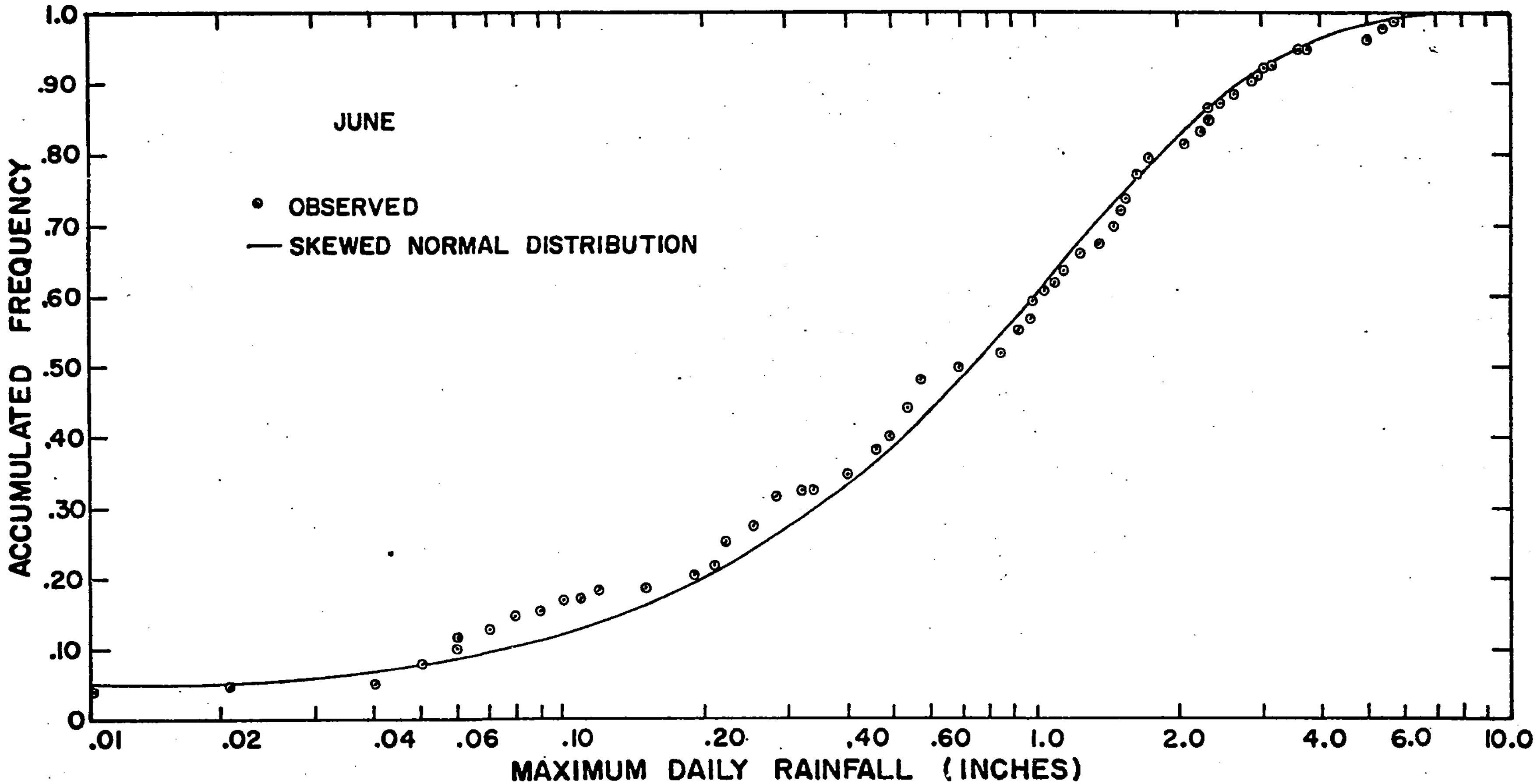

Figure 10 Distribution of maximum daily point rainfall for the month of June

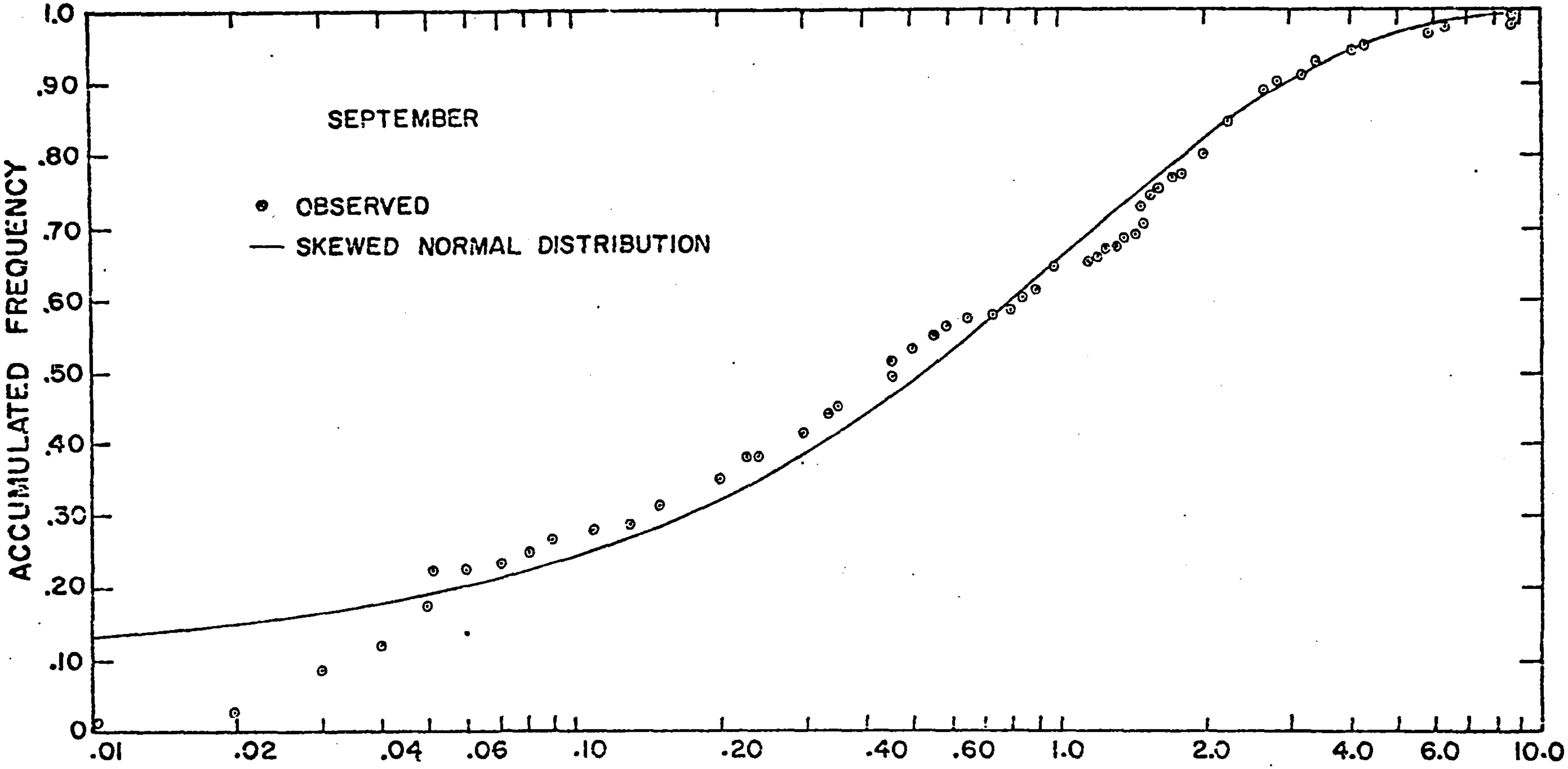

Figure 11 Distribution of maximum daily rainfall for the month of September

used for the deterministic portions of a pattern generator.

Rainfall depths at stations of the network were generated using the deterministic and probabilistic model

$$P_j = P_{max}\, r_j + \sigma\, z \sqrt{1-r_j^{\,2}} \qquad (5\text{-}4)$$

where P_j is rainfall amount at station j; P_{max}, the maximum rainfall; σ, the standard deviation of the storm rainfall; r_j, the reduction factor for station j; and z, a standard normal deviate.

The reduction factor, r_j, was estimated from observed data by calculating the interstation correlation between P_{max} and P_j. Correlation coefficients for patterns near the center of the network were calculated and composited. These correlations were fitted by nonlinear least squares to

$$r_j = \exp - (aX^2 + bY^2) \qquad (5\text{-}5)$$

where a and b are regression constants, and X and Y are coordinate distances in miles from the center station to station j. Values of a and b from the nonlinear least squares fit were 0.1386 and 0.0693 respectively, with a multiple correlation of 0.82.

Before generating patterns of daily rainfall using equation (5-4), the mean and standard deviation of the pattern are required. For generation of these two parameters, the mean and variance of each daily event from 168 gages were calculated for each month of the historical record. Linear regressions on the logarithms of the mean versus maximum amount, and standard deviation versus mean and maximum amount were fitted to these data. Figures 12 and 13 show plots of the mean versus the

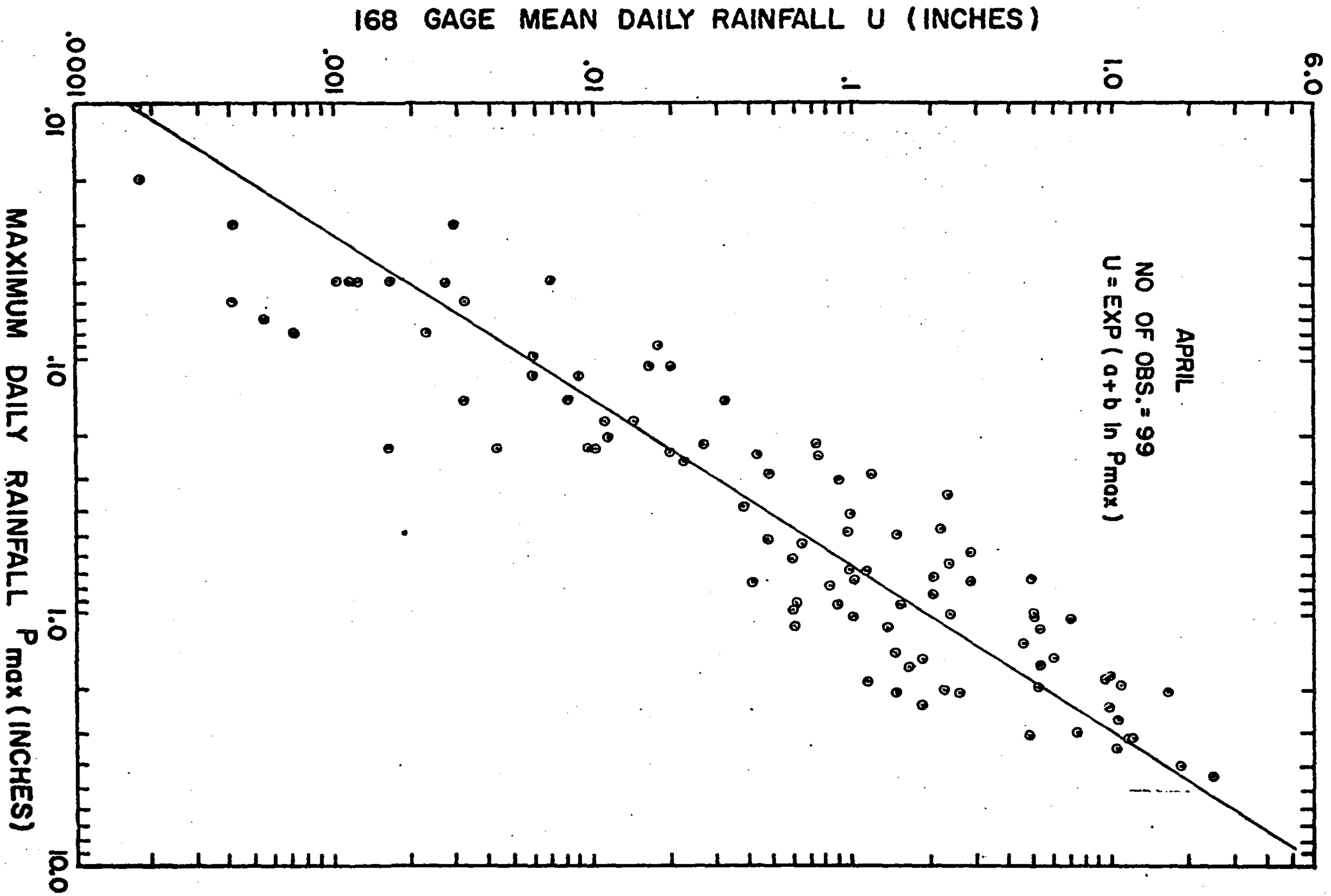

Figure 12 Relationship between mean daily network rainfall and maximum daily point rainfall for the month of April

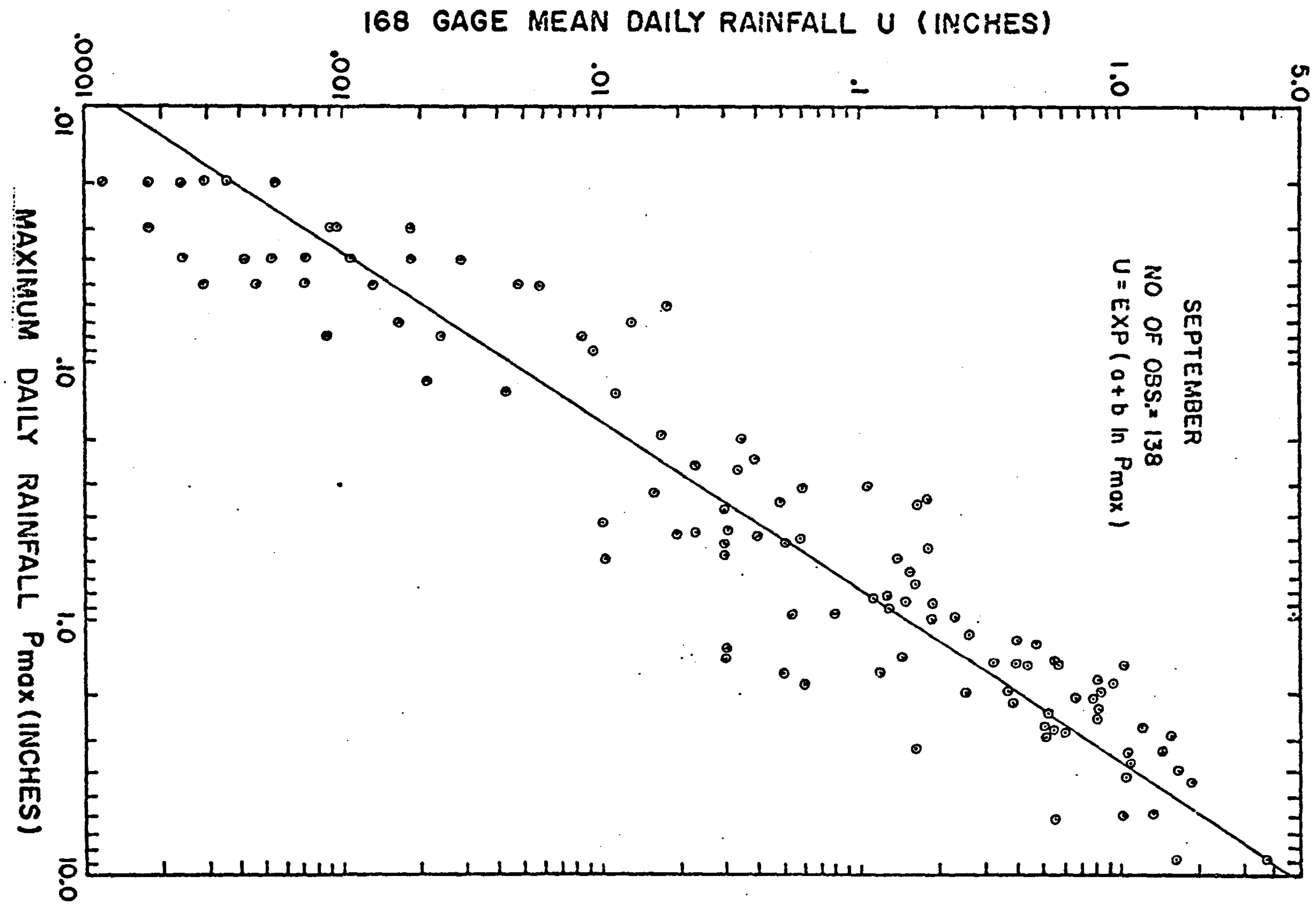

Figure 13 Relationship between mean daily network rainfall and maximum daily point rainfall for the month of September

maximum amounts for two months, April and September. Stochastic models were developed from these regressions by adding the deviation about the mean line as shown in the plots. The models developed for the mean and standard deviation of patterns were

$$\mu = \exp\ (a + b \ln P_{max} + \sigma_{\mu}\ z \sqrt{1 - r^2}) \tag{5-6}$$

$$\sigma = \exp\ (c + d \ln P_{max} + f \ln \mu + \sigma_{\sigma}\ z \sqrt{1 - r^2}) \tag{5-7}$$

where a, b, c, d, and f are regression constants; z, a random normal deviate; σ_{μ} and σ_{σ}, the standard deviations of the log values of μ and σ; and r, the multiple correlation coefficient. Regression statistics for these two models for months are listed in tables 6 and 7.

The procedure for generating patterns of daily rainfall, given a pattern center location and amount, was first to generate a mean and standard deviation for the pattern using equations (5-6) and (5-7). Next, using the X-Y coordinates of each gage, with respect to the center gage, the correlation coefficient, r_j, for each station was calculated from equation (5-5). Starting at the center gage and moving outward to the next nearest gage from the center, rainfall amounts were calculated using equation (5-4). Rainfall amounts were calculated at each gage in this manner until the mean of the pattern equaled the generated pattern mean from equation (5-6).

Table 6. Regression constants for estimating μ, the mean of the rainfall pattern, in equation (5-6)

Month	a	b	r	Standard deviation
January	-1.171	1.481	.903	2.317
February	-0.515	1.698	.950	2.463
March	-1.049	1.528	.915	2.269
April	-1.716	1.524	.925	2.359
May	-1.886	1.581	.927	2.693
June	-2.206	1.524	.923	2.511
July	-2.495	1.595	.938	2.598
August	-2.426	1.584	.926	2.571
September	-1.945	1.561	.950	2.878
October	-1.547	1.554	.914	2.604
November	-0.729	1.745	.949	2.814
December	-0.507	1.693	.899	2.093

Table 7. Regression constants for estimating σ, standard deviation of the rainfall pattern, in equation (5-7)

Month	c	d	f	r	Standard deviation
January	-1.464	.883	.136	.989	1.554
February	-1.596	.708	.194	.980	1.465
March	-1.558	.767	.170	.981	1.429
April	-1.400	.801	.181	.989	1.569
May	-1.257	.721	.250	.994	1.792
June	-1.185	.699	.272	.993	1.725
July	-1.099	.684	.293	.997	1.785
August	-1.195	.727	.264	.996	1.748
September	-1.280	.719	.249	.996	1.962
October	-1.388	.709	.231	.989	1.672
November	-1.562	.672	.225	.987	1.663
December	-1.553	.782	.167	.976	1.222

CHAPTER 6

METEOROLOGICAL DATA MODELS

The requirements for meteorological data inputs to hydrologic models listed in chapter 2, table 1, are mean daily air temperature, daily pan evaporation or potential evapotranspiration and daily solar radiation. One model required wind speed and albedo, but these data were optional requirements used in a modified snowmelt routine. Considering the first four variables as the minimum inputs required, stochastic models to generate synthetic representation of them were developed.

Very little information was found in the literature which dealt with stochastic generation of meteorological data for hydrologic model input. One reference (15) cited in chapter 3 did present a method of obtaining daily pan evaporation from generated monthly values. Therefore, the writer relied upon the statistical theory and techniques presented in chapter 3 and the characteristics of the available data to develop models for generating air temperature, solar radiation and calculated potential evapotranspiration from these values.

Several models have been developed that can be used to calculate potential daily evapotranspiration and evaporation from climatic data. Perhaps the best known of these is the Penman model developed by H. L.

Penman in England (51). This model can be used to compute daily potential evaporation if the necessary data are available such as the net solar radiation,maximum and minimum temperature, wind movement, and vapor pressure. Ritchie (52) developed a model which can be used to calculate evaporation from a crop surface. This model may also be modified to calculate evaporation from watersheds that are typical of those within the study area. It also uses approximately the same required data as the Penman equation except procedures have been developed to estimate net radiation from total radiation.

There have been simpler and less detailed models proposed for estimating potential evaporation. Thornthwaite (65) developed a model that uses mean air temperature to estimate monthly potential evaporation. However, this model may not be detailed enough for hydrologic modeling purposes. Pelton, et al. (50) found this model not to be reliable for short-period estimates of potential evapotranspiration.

Jensen amd Haise (34) have proposed a model that requires daily mean air temperature and solar radiation as variables necessary to calculating evapotranspiration. This model has several advantages that make its use desirable in hydrologic modeling applications. First, it is a simple model requiring just two variables and two parameters. The data required, solar radiation and air temperature, are easily obtained from published data. In addition to these features, the use of solar radiation in the model provides an energy budget approach to estimating the potential evapotranspiration. The model is given as

$$E_p = (0.014\ T - 0.37)\ R_s \qquad (6\text{-}1)$$

where E_p represents potential evapotranspiration (in/day); T is the mean air temperature (°F); and R_s represents total solar radiation (in/day).

This model has been used in many parts of the United States. It has been especially useful in scheduling irrigation in arid regions. It could also be used to calculate evapotranspiration estimates using synthetic temperature and solar radiation data.

The method proposed to generate the required meteorological data for input to the hydrologic models listed in table 1 consist of generating synthetic daily air temperature and solar radiation. Air temperature data would meet the requirement for those models which require it such as the USDAHL, Stanford, and SSARR models. The combination of air temperature, and solar radiation used with the Jensen-Haise potential evapotranspiration model would meet the requirements of the hydrologic models that require daily or monthly evaporation input.

Air Temperature Model

The model proposed for stochastically generating daily air temperature data is similar to the Thomas-Fiering model for streamflow listed in chapter 3 (equation 3-1). The model for temperature is

$$T_i = \overline{T} + r_T \ (T_{i-1} - \overline{T}) + t \ \sigma_T \sqrt{1-r_T{}^2} \qquad (6\text{-}2)$$

where T_i is the current day temperature (°F); T_{i-1} is the previous days temperature (°F); r_T is the lag 1 correlation coefficient; σ_T, the standard deviation of daily temperature; and t, a standardized, random, normal, and independently distributed variate.

Both mean daily temperature and maximum and minimum temperatures could be generated with this equation. However, in order to generate synthetic air temperature data representative of the rain sequence it was necessary to relate the rain day to that which would be expected on rainy days. Correspondingly, dry day temperatures should be related to that which would be expected on dry days.

To achieve this relation, four equations were developed which correspond to the four possible rain day conditions which could exist. These are a dry day following a dry day, a wet day following a dry day, a dry day following a wet day, and a wet day following a wet day. To provide transition between seasons, a further division was made to develop models for each month of the year. Finally it was considered desirable to generate both maximum and minimum daily temperature, thus another subscript was added to the model. Equation 6-2 was modified to

$$T_i\ (K,M,N) = \overline{T}\ (K,M,N) + [T_{i-1}\ (K,M,N) - \overline{T}\ (K,M,N)]$$
$$r_T\ (K,M,N) + t\ \sigma_T\ (K,M,N)\ \sqrt{1 - r_T^2\ (K,M,N)} \qquad (6\text{-}3)$$

In which K = 1, 2 ···, 4, the four rain conditions; M = 1, 2, ···, 12, the number of months; and N = 1, 2, representing maximum and minimum temperatures respectively.

Generation of synthetic daily temperatures with equation (6-3) consists of generating a standardized, random, normal variate and then testing it against the two-state conditional probability listed in chapter 5, table 5, in order to select one of four rain day conditions. Using the condition code selected from this test, the appropriate monthly mean and standard deviation for maximum and minimum temperature are selected. Next, another standardized, random normal variate is generated and the daily temperature calculated using equation (6-3). A flow chart of the temperature generating scheme is given in figure 14.

Mean and standard deviation for maximum and minimum temperature were calculated from the available data collected at CRS. These values are listed in table 8.

Solar Radiation Model

The model selected to generate daily total solar radiation is similar to the one developed for daily temperature. The general model is

$$S_i = \overline{S} + r_s\ (S_{i-1} - \overline{S}) + t\ \sigma_s \sqrt{1-r_s^{\ 2}} \qquad (6\text{-}4)$$

where S_i is the total radiation on day i (langleys); S_{i-1} is the total radiation on the previous day (langleys); $\overline{S}$ is the mean daily solar radiation (langleys); r_s is the lag 1 correlation coefficient; σ_s is the standard deviation of daily radiation; and t is a standardized, normal, random variate.

Equation (6-4) was modified in much the same way as the temperature model to provide monthly transition in generation, and to relate the solar radiation values to rain conditions. The modified model is given as

$$\begin{aligned} S_i\ (K,M) = \overline{S}\ (K,M) + r_s\ (K,M)\ [S_{i-1}\ (K,M) - \overline{S}\ (K,M)] \\ + t\ \sigma_s\ (K,M) \sqrt{1 - r_s\ (K,M)^2} \end{aligned} \qquad (6\text{-}5)$$

where K = 1, ···, 4 and M = 1, 2, ···, 12.

In order to generate a total radiation value for a day, the previous and present day rain conditions are tested and the state code selected. Next, with the appropriate monthly mean, standard deviation,

Table 8. Monthly air temperature mean μ, standard deviation σ, and lag 1 correlation coefficient r, for the four rain state conditions.

Month	State 1 Dry-Dry						State 2 Dry-Wet						State 3 Wet-Dry						State 4 Wet-Wet					
	Maximum			Minimum			Maximum			Minimum			Maximum			Minimum			Maximum			Minimum		
	μ	σ	r	μ	σ	r	μ	σ	r	μ	σ	r	μ	σ	r	μ	σ	r	μ	σ	r	μ	σ	r
1	49.0	13.3	.666	24.5	9.9	.698	46.8	14.2	.749	30.5	11.9	.537	40.8	15.7	.586	23.2	12.6	.910	48.3	14.6	.431	35.3	12.1	.648
2	55.2	11.0	.399	28.0	8.0	.413	50.5	11.4	.350	31.8	8.3	.217	48.6	10.2	.560	27.8	9.0	.838	45.1	10.8	.518	32.0	9.7	.522
3	63.6	13.1	.583	36.6	10.3	.604	61.2	14.1	.792	42.4	10.2	.675	60.2	11.9	.452	36.8	8.8	.743	58.2	12.5	.779	41.9	9.4	.753
4	75.7	9.8	.478	47.7	10.7	.599	72.7	11.0	.537	54.3	8.0	.582	73.6	9.5	.489	49.2	9.5	.801	69.6	8.5	.555	52.1	6.7	.413
5	83.5	7.5	.610	57.3	8.0	.720	79.4	8.5	.605	58.7	6.9	.596	78.3	7.5	.406	54.3	8.3	.743	74.9	8.4	.297	58.2	5.2	.531
6	91.2	5.1	.735	67.4	5.8	.757	88.4	6.5	.352	67.1	4.2	.175	88.0	6.3	.765	66.0	5.7	.709	82.6	7.6	.394	65.0	4.2	.703
7	95.3	5.3	.765	71.3	5.4	.769	92.3	6.7	.503	71.7	3.6	.584	92.3	6.7	.633	70.2	4.7	.800	89.9	6.7	.521	70.6	3.9	.476
8	93.7	5.4	.784	68.9	5.7	.785	91.3	6.4	.636	69.0	3.6	.535	90.1	4.3	.575	67.5	4.9	.648	85.8	6.5	.299	68.2	3.8	.581
9	85.3	7.5	.787	62.2	7.6	.839	82.5	9.7	.536	63.8	7.6	.614	82.8	8.6	.761	61.1	9.2	.877	78.1	9.6	.521	62.5	6.7	.544
10	77.0	8.8	.704	49.7	9.4	.757	72.1	11.0	.660	52.8	7.8	.300	68.6	10.8	.438	48.2	8.4	.854	61.3	9.0	.443	47.4	6.7	.647
11	63.6	11.4	.640	38.0	10.1	.696	59.5	12.2	.867	42.9	8.9	.481	57.2	10.3	.566	36.3	8.0	.847	52.0	8.2	.565	40.1	7.3	.594
12	52.6	11.6	.619	28.7	8.1	.572	51.2	14.3	.815	34.0	10.8	.589	47.1	12.6	.593	28.1	9.5	.528	44.7	13.1	.737	31.7	8.5	.659

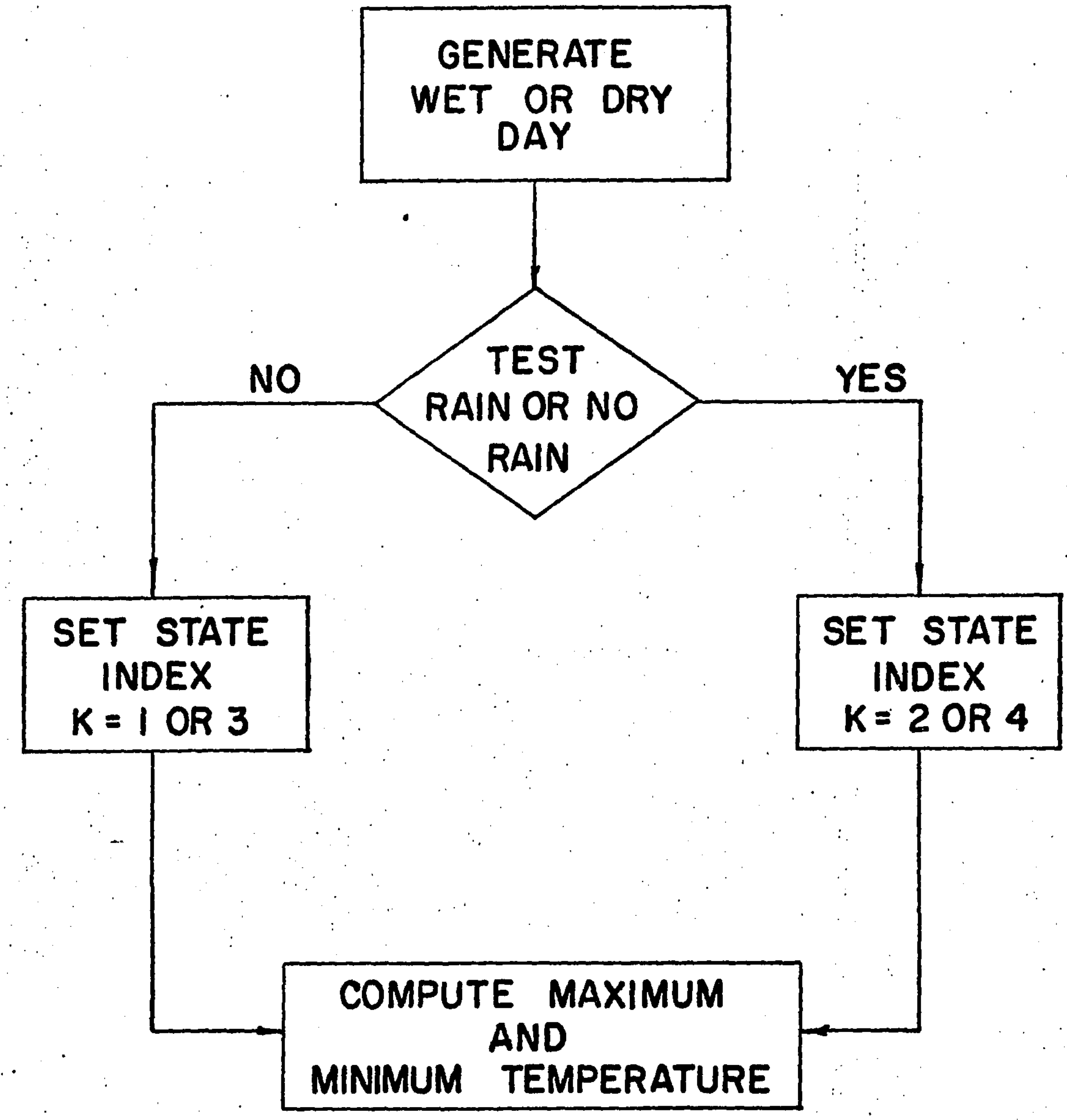

Figure 14 Flow chart of air temperature generating model

and a generated standardized, normal, random variate, the solar radiation is calculated using equation (6-5). A flow chart showing the general generating scheme for the solar radiation model is illustrated in figure 15. The monthly mean, standard deviation and correlation coefficient are listed in table 9.

Table 9 Monthly solar radiation means μ, standard deviation σ, and lag 1 correlation coefficient r, for the four rain state conditions.

Month	State 1 Dry-Dry			State 2 Dry-Wet			State 3 Wet-Dry			State 4 Wet-Wet		
	μ	σ	r	μ	σ	r	μ	σ	r	μ	σ	r
January	250.1	85.2	.415	194.2	99.6	-.017	90.0	61.0	-.022	68.4	43.0	.128
February	324.6	100.2	.218	308.3	120.0	.043	164.5	130.7	.300	144.0	116.0	.171
March	421.1	127.6	.225	337.5	172.0	.140	273.7	162.4	.368	169.7	123.5	.197
April	520.8	129.9	.270	459.9	155.1	.152	339.8	179.7	.122	246.8	148.6	.163
May	597.0	103.9	.402	511.9	161.8	.265	383.0	106.4	.080	377.0	169.7	.174
June	616.4	89.8	.391	573.5	103.3	.270	444.6	153.0	-.045	415.8	137.6	.054
July	594.7	98.6	.333	571.5	106.6	.414	452.5	122.6	.224	415.9	131.1	.013
August	561.5	88.3	.321	530.7	84.0	.301	436.5	132.1	.178	411.2	152.8	.242
September	460.3	103.2	.588	431.7	95.9	.164	323.9	137.8	.250	266.4	146.4	.332
October	368.4	104.2	.314	343.2	106.1	.087	183.8	125.1	.185	209.7	116.7	.168
November	265.3	84.5	.346	257.0	87.7	-.123	131.2	113.8	.407	118.4	123.7	.121
December	222.8	82.7	.256	184.3	83.7	.172	102.1	78.7	.206	84.3	72.1	.039

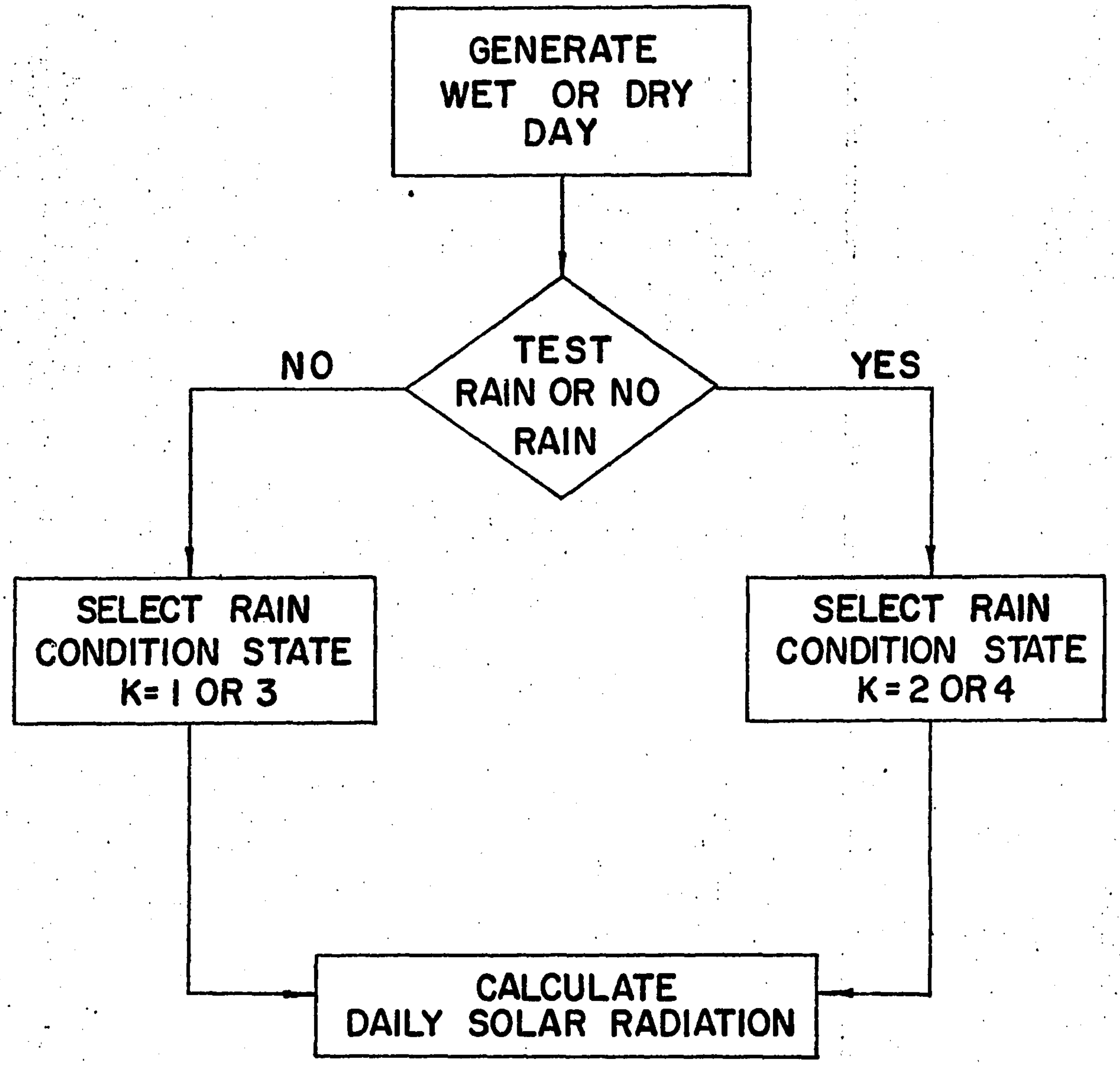

FIGURE 15 Flow chart of solar radiation generating model

CHAPTER 7

DISCUSSION OF RESULTS

The models for daily rainfall and meteorological data were programmed for digital computer processing and synthetic data generating runs were made. Using these generated data, tests were made for the adequacy of each model to mimic the actual data.

Tests of Results

A summary of results of the rainfall data generated in 10 runs of the model is given in table 10. The maximum daily rainfall for each year, the number of days of rainfall, and the mean annual rainfall for 168 gages are shown in this table. The maximum daily rainfall generated, 10.05 inches, occurred in the month of September. The maximum number of wet days generated in a year was 158 and the minimum was 88 days. The maximum mean annual rainfall was 36.86 inches and the minimum was 14.76 inches.

Two types of tests were applied to the synthetic records (42). A two-sided t test was used for testing differences between means of the observed and synthetic records. A nonparametric test (Kolmogorov-Smirnov) was used to test differences in distributions.

The generation procedures for the occurrence of wet and dry days were tested for the number of dry days in the synthetic record

TABLE 10

MAXIMUM DAILY RAINFALL, NUMBER OF WET DAYS AND MEAN ANNUAL RAINFALL FOR EACH SYNTHETIC RUN

	Year								
Run 1	1	2	3	4	5	6	7	8	9
Maximum P	4.31	4.86	5.16	8.36	4.92	4.91	4.31	4.60	4.76
No. of days	137	141	134	128	127	126	110	136	113
Mean annual P	22.94	34.52	36.86	31.47	23.13	30.23	25.79	24.78	26.12
Run 2									
Maximum P	4.54	8.32	7.56	5.67	7.89	7.94	4.28	5.37	6.30
No. of days	119	135	124	127	140	109	88	134	120
Mean annual P	27.91	23.41	25.30	27.04	29.67	30.69	22.94	21.39	21.57
Run 3									
Maximum P	7.52	6.29	4.48	8.14	4.66	6.47	8.06	4.87	4.41
No. of days	106	112	120	121	130	117	106	123	132
Mean annual P	15.12	24.05	29.51	27.38	24.77	24.28	28.42	26.10	20.23
Run 4									
Maximum P	4.91	3.77	6.72	4.22	7.46	4.15	5.36	5.77	4.85
No. of days	126	107	115	107	133	138	116	127	112
Mean annual P	31.78	17.63	22.15	19.81	27.16	27.42	24.87	29.26	15.71
Run 5									
Maximum P	3.94	5.41	4.68	7.33	7.68	6.41	7.71	4.64	5.96
No. of days	126	112	118	138	143	135	117	119	126
Mean annual P	17.27	22.83	16.96	30.30	30.77	34.10	24.33	18.43	22.57
Run 6									
Maximum P	3.95	5.38	6.33	4.69	6.41	5.37	6.86	5.80	6.46
No. of days	124	107	132	138	124	158	126	153	129
Mean annual P	29.85	20.65	30.27	28.74	28.75	27.20	27.86	30.61	18.90
Run 7									
Maximum P	4.69	7.50	4.81	4.63	7.34	5.76	4.37	6.73	4.70
No. of days	134	139	125	114	110	139	115	103	127
Mean annual P	23.91	33.94	19.79	14.76	21.73	28.96	22.57	23.27	21.71
Run 8									
Maximum P	5.00	5.10	5.13	8.11	10.05	5.39	8.67	8.20	3.33
No. of days	107	137	120	119	109	121	126	135	137
Mean annual P	18.78	21.13	29.80	27.78	21.63	24.36	31.57	27.76	30.53
Run 9									
Maximum P	5.35	3.17	7.89	4.48	7.75	5.09	6.81	5.97	6.09
No. of days	142	114	130	119	140	115	138	129	136
Mean annual P	26.61	24.59	25.65	21.52	32.32	20.57	25.41	30.20	26.43
Run 10									
Maximum P	4.22	7.15	3.17	6.55	6.77	5.38	4.93	4.84	6.45
No. of days	96	117	125	130	133	128	126	133	131
Mean annual P	20.29	23.79	21.26	26.82	28.57	24.64	24.02	35.66	25.08

and the distribution of the length of dry day periods. The results of these tests are given in table 11 for the distribution of the length of dry periods for two of the runs, and in table 12 for the total number of dry days in all runs combined. Neither test shows a significant difference at the .05 level of significance between the synthetic and observed data sets. The serial correlation coefficients for rainfall amounts on wet days following wet days during each month were calculated. Tests made on these data at the .05 level indicated that rainfall amounts were independent.

Kolmogorov-Smirnov two-sample tests were made on the distribution of maximum amount for each month. An example of this test for the month of June is shown in table 13. Results of tests for all months showed no significant difference between the generated and observed distributions.

In order to test the system as a whole, two tests were made on the synthetic data. The first was a two-sided t test on the accumulated monthly and annual means for the entire network, and the second was a test on the monthly and annual records at each individual gage in the network. The test statistics for the network means are given in table 14.

Mean monthly rainfall for the 10 synthetic runs was not significantly different from the means of the historical record except in two months, April and August. The difference between the means of the generated and observed data for these months was only slightly larger than the critical difference at the .05 level. Despite these two test failures, the annual mean was not significantly different from the observed annual mean, indicating that the overall generation of the mean rainfall for the network area was acceptable.

Table 11.--Cumulative distributions of length of dry periods for observed and synthetic records

Length of Dry Period	Observed Record	Synthetic Record	Maximum Difference %	Synthetic Record	Maximum Difference %
1	.589	.593		.594	
2	.686	.708	2.2	.688	
3	.764	.775		.757	
4	.805	.816		.825	2.0
5	.845	.847		.854	
6	.875	.880		.883	
7	.902	.905		.906	
8	.923	.927		.949	
9	.941	.942		.934	
10	.952	.957		.943	
11	.962	.968		.955	
12	.973	.974		.961	
13	.978	.978		.964	
14	.981	.985		.973	
15	.986	.987		.977	
16	.989	.990		.980	
17	.992	.990		.984	
18	.993	.991		.984	
19	.995	.993		.987	
$\geq$ 20	1.000	1.000		1.000	
Total number of events	1,135	1,152		1,096	
Maximum length (days)	31	28		41	
		$*D_{.05} = 5.7$		$D_{.05} = 5.8$	

$*D_{.05} = 1.36/\sqrt{n_1 n_2/n_1+n_2}$

Table 12.--Number of dry days in the observed and 10 synthetic records

Observed	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10	Mean	Difference	Standard Deviation of mean
2152	2135	2191	2220	2207	2153	2096	2181	2177	2144	2168	2167.2	15.2	11.6

Table13.--Kolmogorov-Smirnov two-sample test on the distribution of maximum amounts during the month of June

Rainfall Amount	Hist. Cum.Dist.	Sample 1 Cum.Dist.	Max. Diff. %	Sample 2 Cum.Dist.	Max. Diff. %
.01	.008	.007		.008	
.02	.048	.080		.118	
.03	.056	.088		.125	
.04	.063	.10		.140	
.05	.095	.11		.156	
.06	.127	.125		.164	
.08	.143	.147		.187	
.10	.175	.161		.203	
.15	.190	.191		.296	
.20	.222	.242		.343	12.1
.25	.286	.272		.382	
.30	.319	.285		.416	
.35	.341	.301		.446	
.40	.349	.331		.461	
.45	.364	.346		.468	
.50	.397	.387		.500	
.60	.490	.492		.547	
.70	.513	.520		.570	
.80	.541	.572		.609	
.90	.556	.618		.646	
1.00	.587	.676		.664	
1.2	.658	.753	9.5	.734	
1.4	.686	.756		.774	
1.6	.763	.822		.802	
1.8	.804	.860		.836	
2.0	.821	.904		.868	
2.5	.882	.928		.900	
3.0	.924	.958		.915	
3.5	.949	.973		.960	
4.2	.964	.974		1.000	
4.5	.968	.986			
5.0	.979	.988			
5.5	.986	.990			
6.0	1.000	.991			
7.0		.992			
8.3		1.000			
Number of Observations	126	136		128	
		$D_{.05}$ = 16.8		$D_{.05}$ = 17.08	

Table 14.--Monthly and annual means for 10 runs of 9-year synthetic records

	Run	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Annual
	1	0.78	1.04	1.93	2.99	3.99	2.38	1.79	3.01	4.63	2.03	2.28	1.61	28.41
	2	0.42	0.81	1.23	2.77	3.71	2.28	1.71	2.61	6.51	1.16	1.10	1.25	25.56
	3	1.46	0.64	1.52	1.87	2.54	3.51	1.26	2.50	5.45	1.46	1.31	0.91	24.43
	4	0.52	0.94	1.63	1.69	1.80	4.19	1.59	3.02	4.47	2.09	1.21	0.83	26.98
	5	0.21	0.91	1.53	2.52	2.90	3.17	2.21	2.24	5.06	1.37	1.32	0.74	24.18
	6	0.68	0.49	2.65	3.18	2.85	4.11	1.72	2.12	3.35	2.46	2.31	1.06	26.98
	7	1.20	1.03	1.57	2.52	2.83	3.78	1.19	2.00	3.95	1.63	1.13	0.57	23.40
	8	0.92	0.81	1.51	2.67	3.56	2.93	1.17	1.67	6.10	2.29	1.68	0.62	25.93
	9	0.70	0.93	1.27	2.78	3.67	3.87	1.98	2.87	3.47	1.44	2.05	0.91	25.94
	10	1.11	1.36	2.02	2.40	4.28	3.50	1.89	2.12	3.42	1.61	1.19	0.67	25.57
Mean		0.80	0.90	1.69	2.54	3.21	3.37	1.65	2.42	4.64	1.75	1.56	0.92	25.74
Observed mean		0.75	1.07	1.62	2.91	3.74	3.29	1.90	2.78	4.41	1.63	1.77	0.91	26.78
Difference		0.05	0.17	0.07	0.37	0.53	0.08	0.25	0.36	0.24	0.12	0.21	0.01	1.04
Critical difference		0.27	0.19	0.30	0.33	0.53	0.49	0.25	0.33	0.80	0.31	0.35	0.22	1.07
Standard deviation		0.38	0.24	0.42	0.46	0.75	0.68	0.35	0.46	1.13	0.43	0.48	0.32	1.49
Standard deviation of mean		0.12	0.07	0.13	0.15*	0.24	0.22	0.11	0.15*	0.36	0.14	0.15	0.10	0.47

*Significant at $t_{.05} = 2.262$, d.f. = 9

The two-sided t test described previously was applied to the individual gages of the network. It is not possible to show all of the tests; however, a summary of the tests by month of the number of gages as well as annual mean rainfall is shown in table 15. A significance level of 0.05 was used in all tests. Approximately 71 percent of the gage individual records were accepted as being representative of the observed record on an annual basis. Percentages of gages accepted on a monthly basis ranged from a low of 56 percent in December to a high of 97 percent in March.

In general, the locations of gages for which tests indicated the synthetic record was different from the observed record were clustered in the northwest corner of the network. Figure 16 shows the distribution of these gages for the test on mean annual rainfall. Gages where monthly records were different were located in the same general area.

Discussion

On the basis of tests made on the generating system, it appears that some phases performed satisfactorily while others will require further refinement. The Markov chain method of generating the wet day-dry day sequences for a large area was highly satisfactory and comparable to results on point rainfall obtained by other investigators. Also, the method for generating maximum daily amounts gave satisfactory results. However, needed improvement in the method of generating patterns of rainfall is indicated by the poor results obtained in the northwest section of the network.

Generation of mean and standard deviation of daily rainfall patterns using equations (5-6) and (5-7) appears to be a satisfactory

Table 15.--Number of synthetic records accepted

Month	Gages Accepted	Percent
January	119	71
February	111	66
March	163	97
April	125	74
May	118	70
June	125	74
July	154	92
August	122	72
September	119	71
October	159	95
November	119	71
December	94	56
Annual	120	71

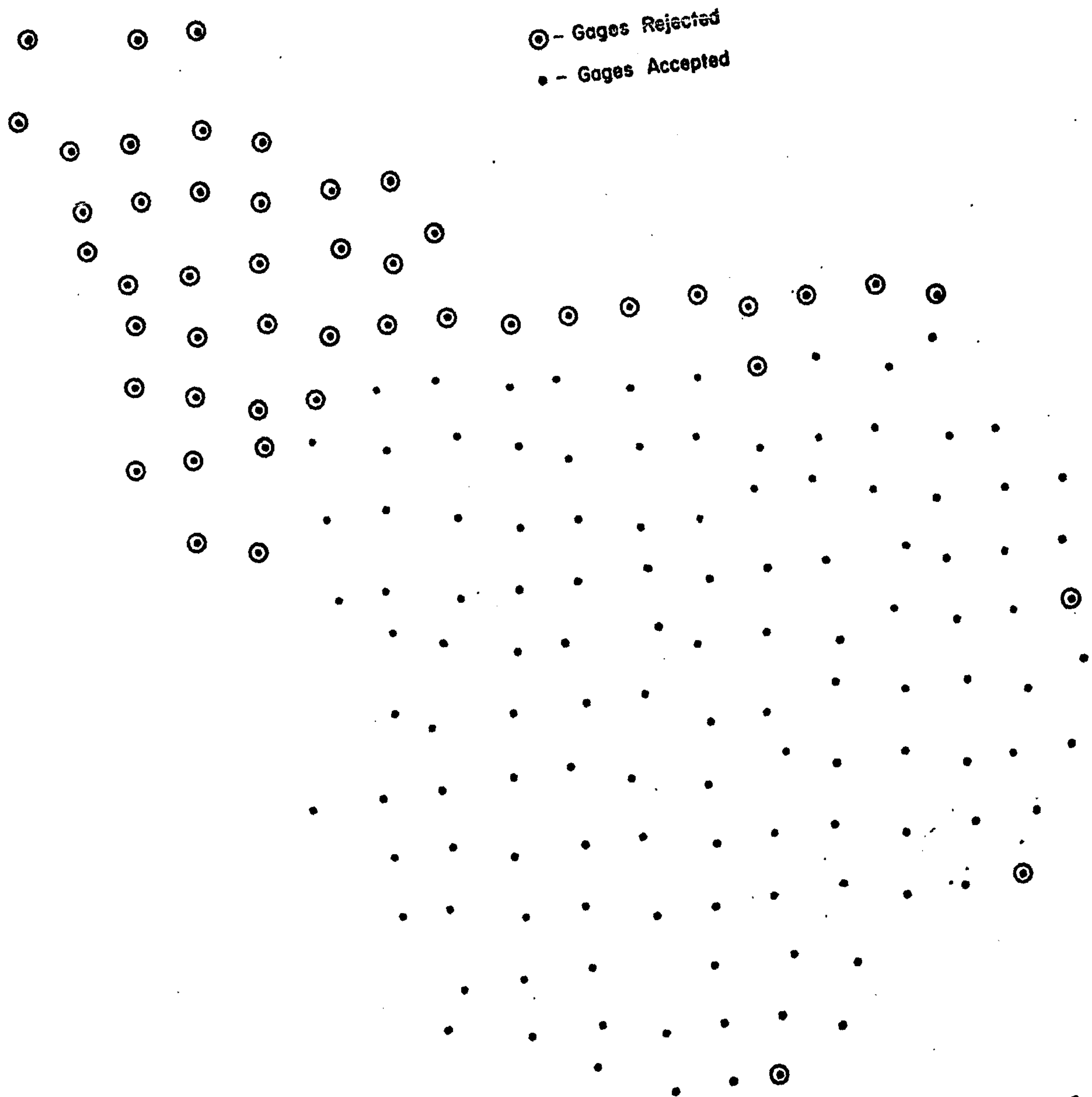

Figure 16--Distribution of accepted and rejected gages for annual rainfall records

method of controlling the volume of rainfall that should be distributed to network gages. Results in table 9 indicate that the synthetic monthly and annual rainfall for the network was not significantly different from the mean of the historical record. However, the distribution of rainfall at individual gages, especially those in the northwest part of the network was not satisfactory. This can be attributed to the distribution model given by equations (5-4) and (5-5). The interstation correlation patterns calculated from equation (5-5) were essentially fixed in size and orientation. It may be necessary to treat the reduction factor, r_j, as a random variable because of the low amount of explained variance indicated by the multiple correlation obtained in fitting equation (5-5) to the observed data. Also, it is possible that these correlation patterns should vary with the magnitude of the maximum storm amount, the orientation of storm pattern, and the season of the year.

For example, a storm pattern for a day in October is shown in figure 17. The maximum rainfall was 2.08 and the mean rainfall for the network, generated by equation (5-6) was 0.40 inch with a standard deviation (from equation 7) of 0.615. The calculated mean and standard deviation of the rainfall pattern, using the individual gage data generated by equation (5-4), was 0.40 and 0.613 inch, respectively. The standard deviation, mean, interstation correlation pattern, and orientation all act to limit the size and distribution of the pattern rainfall. If a storm with these same characteristics were centered in the northwest section of the network, a much different pattern would have been developed. The generation method used would have produced a pattern elongated to the southeast.

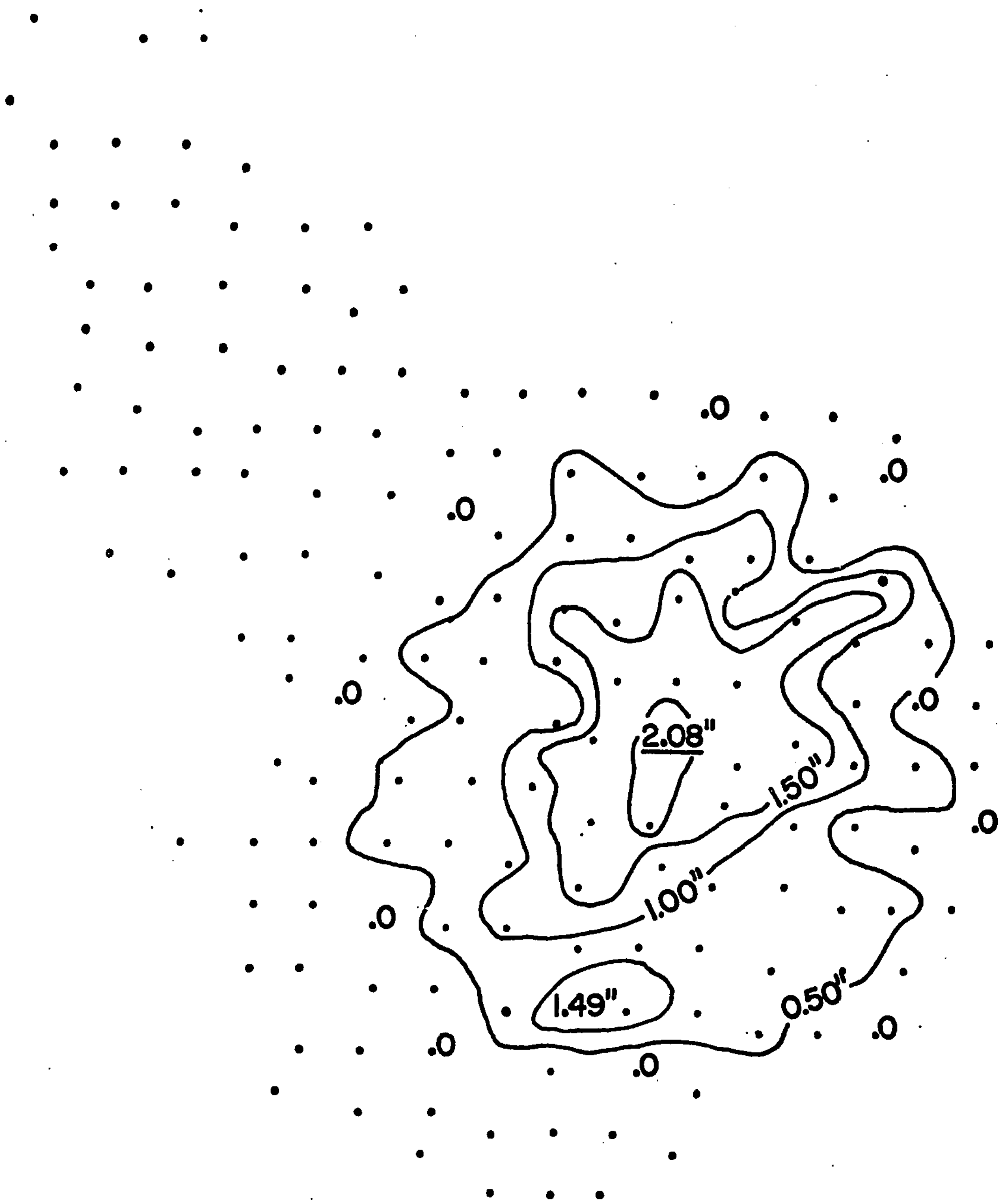

Figure 17--Isohyetal map of daily rainfall pattern in October

The generation of meteorological data was made much the same way as with the rainfall data model. The models presented in chapter 6 equations 6-3 for maximum and minimum air temperature and 6-5 for daily total solar radiation were programed for a digital computer so that synthetic data runs could be made. The necessary statistical parameters, tables 8 and 9 chapter 6, mean, standard deviation and lag 1 correlation coefficients were calculated using data from the CRS station near Chickasha. These data consisted of 11 years of air temperature from CRS, solar radiation data from the Oklahoma City Airport first order weather station, and daily rainfall data at CRS. Also it was necessary to calculate the wet-dry day conditional probabilities α and β from the rainfall data at CRS because this rainfall data would correspond to the record length for the solar radiation and temperature data.

The conditional rainfall probabilities α and β were somewhat different than those calculated from the network because the period of record of available data were not the same. However, these data shown in table 16 compare well with those from the network that were given in table 5 chapter 5.

Ten synthetic data generating runs of 11 year lengths were made with the program. Output consisted of a summary of mean monthly maximum and minimum temperature and solar radiation values for each run. The program also performed a t test on significant differences between the observed means. The results of these tests are listed in tables 17, 18, and 19.

Tests on the air temperature data showed means of all months but one not to be significantly different at the 99% confidence level, than those

Table 16. Conditional probabilities α and β computed from CRS data.

Month	β[1/]	α[2/]
January	0.519	0.093
February	.588	.165
March	.639	.171
April	.542	.222
May	.455	.216
June	.524	.244
July	.531	.214
August	.481	.292
September	.521	.294
October	.532	.118
November	.559	.122
December	.667	.125

2/ Probability of a wet day following a dry day

1/ Probability of a dry day following a wet day

Table 17. Monthly mean maximum air temperature for 10 runs of 11-year synthetic records (deg. F).

	Run	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
	1	51.95	53.19	64.04	75.39	81.02	88.54	93.31	91.70	84.97	74.59	61.27	51.47
	2	50.73	53.83	65.02	73.37	81.45	89.93	94.12	90.64	83.43	75.48	62.00	51.50
	3	48.51	54.14	64.50	73.35	81.51	87.97	92.19	92.46	82.17	74.17	63.01	52.50
	4	50.21	53.87	63.10	74.51	81.25	89.50	93.71	90.58	83.07	74.68	62.74	52.24
	5	52.19	52.37	61.06	74.08	79.96	88.66	92.87	90.47	84.46	75.05	63.28	52.40
	6	50.17	52.45	62.68	74.44	80.61	89.59	93.28	90.48	85.15	71.51	62.72	52.58
	7	50.09	54.46	61.77	74.30	82.05	89.62	92.94	90.09	82.30	76.39	62.24	54.71
	8	50.34	54.71	63.68	76.25	81.38	88.99	92.79	92.17	82.94	74.07	61.71	52.29
	9	50.91	53.86	62.80	75.38	81.12	88.53	94.92	89.71	82.19	73.20	59.53	52.88
	10	51.30	51.45	63.87	74.57	80.64	89.39	92.18	90.38	83.64	73.35	62.52	50.83
Mean		50.64	53.43	63.25	74.56	81.10	89.07	93.18	90.87	83.43	74.25	62.10	52.34
Observed mean		48.10	52.90	62.37	74.05	80.57	88.93	93.66	91.04	83.07	74.39	61.62	51.45
Difference		2.54*	0.53	0.88	0.51	0.53	0.14	-0.48	-0.17	0.36	-0.14	0.48	0.89
Critical difference		1.23	1.22	1.43	1.07	0.69	0.74	0.87	1.08	1.31	1.59	1.27	1.22
Standard deviation		1.05	1.05	1.23	0.92	0.59	0.63	0.75	0.92	1.12	0.43	1.09	1.04
Standard deviation of mean		0.33	0.33	0.39	0.29	0.19	0.20	0.24	0.29	0.35	1.36	0.35	0.33

*Significant at $t_{.01} = 3.690$, d.f. = 9

Table 18. Monthly mean minimum air temperature for 10 runs of 11-year synthetic records (deg. F).

	Run	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
	1	24.07	27.69	37.88	48.67	57.80	66.94	70.00	68.87	58.88	48.44	36.35	27.68
	2	24.23	28.71	34.72	48.41	57.86	68.12	70.85	68.10	62.16	51.22	39.23	28.18
	3	21.96	28.90	37.66	46.37	57.63	66.97	70.54	69.39	58.86	49.03	36.49	29.21
	4	22.98	27.59	35.82	48.12	57.41	66.34	70.29	68.77	60.75	49.92	35.69	27.84
	5	22.90	27.35	35.51	47.43	57.30	67.66	70.70	68.30	60.27	47.85	37.35	29.25
	6	23.31	27.61	35.63	49.53	57.25	66.67	70.90	69.10	62.35	47.20	36.30	27.34
	7	22.30	28.63	36.73	48.43	55.59	66.76	69.42	67.96	60.71	50.10	37.73	28.79
	8	22.24	30.41	35.27	48.76	56.58	66.36	70.12	68.43	61.04	48.43	36.72	28.02
	9	24.42	27.42	35.12	47.29	56.68	66.86	70.70	69.74	61.85	49.32	37.16	28.15
	10	24.03	26.84	37.49	47.96	58.36	66.73	71.50	68.30	60.38	49.10	37.30	28.33
Mean		23.24	28.11	36.18	48.10	57.26	66.94	70.50	68.70	60.72	49.06	37.03	28.28
Observed mean		25.73	28.80	37.36	49.04	57.21	66.76	71.07	68.55	62.08	49.68	38.13	28.85
Difference		-2.49*	-0.69	-1.18	-.94	0.05	0.18	-0.57	0.15	-1.36	-0.62	-1.10	-.57
Critical difference		1.06	1.22	1.35	1.04	0.91	0.66	0.68	0.69	1.42	1.36	1.15	0.74
Standard deviation		.91	1.05	1.16	0.89	0.78	0.57	0.58	0.59	1.22	1.17	0.98	0.63
Standard deviation of mean		.29	.33	0.37	0.28	0.25	0.18	0.18	0.19	0.38	0.37	0.31	0.20

*Significant at $t_{.01}$ = 3.690, d.f. =9

Table 19. Monthly solar radiation for 10 runs of 11-year synthetic records (langleys).

Run	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
1	212.84	233.30	339.31	413.32	538.12	531.56	525.05	501.60	385.58	331.00	221.03	180.61
2	199.49	262.44	356.62	415.44	535.04	533.70	528.33	493.06	405.95	329.90	212.43	193.05
3	202.54	268.91	300.07	429.54	520.82	542.27	526.35	507.08	366.61	346.44	214.64	181.42
4	225.99	270.75	321.61	432.62	528.32	531.40	544.67	502.44	384.36	329.25	231.56	172.91
5	207.97	251.18	340.78	441.21	510.12	542.40	537.76	497.46	378.24	314.30	227.47	177.00
6	211.20	263.14	342.17	439.22	524.63	549.89	548.54	493.34	373.87	290.44	233.57	180.93
7	207.81	266.62	324.36	432.42	534.86	555.03	534.77	499.13	372.65	327.24	228.96	196.01
8	222.78	272.09	326.81	439.30	529.57	549.89	545.02	510.21	378.64	335.79	216.73	193.00
9	214.97	278.80	322.43	407.12	524.18	543.38	541.19	504.93	359.29	314.13	181.33	181.10
10	219.41	263.48	351.19	429.04	487.34	553.94	542.10	493.79	381.65	318.73	230.52	192.14
Mean	212.50	263.07	332.53	427.92	523.30	543.35	537.38	500.30	378.68	323.72	219.82	184.82
Observed mean	219.50	275.61	351.83	439.04	511.10	553.50	544.30	501.30	392.50	332.00	237.20	197.40
Difference	-7.00	-12.54	19.30	11.12	12.20	-10.15	-6.92	1.00	-13.82	-8.28	-17.38	-12.58*
Critical difference	9.95	14.87	19.49	13.93	17.55	10.41	9.86	7.00	14.62	17.86	18.07	9.33
Standard deviation	8.53	12.75	16.70	11.94	15.04	8.92	8.45	6.01	12.53	15.31	15.48	7.99
Standard deviation of of mean	2.70	4.03	5.28	3.77	4.76	2.82	2.67	1.90	3.96	4.84	4.90	2.53

*Significant at $t_{.01} = 3.690$, d.f. =9 of the 11 years of observed data. The month of January was significantly different from the observed data both for maximum and minimum temperature. The January maximum temperature was 2.54 degrees higher than the observed January mean maximum as shown in table 17. The minimum generated temperature for the same month was 2.49 degrees below the observed mean, table 18, indicating that perhaps the difference in the two monthly mean values may be compensating.

Minimum and maximum temperatures for each of the runs were averaged to obtain a mean monthly air temperature and tests made against the observed mean monthly obtained in the same manner. The results of this test shown in table 20 indicate no monthly mean generated temperatures were different from the observed values. A graphical representation of the monthly maximum, minimum, and mean temperatures generated from the models are shown in figure 20. This figure can also be compared with figure 6.

Solar radiation values generated by the program were also tested in the same way as the temperature data. The results of the test shown in table 19 indicate that only one monthly mean radiation value was different from the observed data. The difference between observed and generated mean monthly solar radiation for December was only slightly larger than the critical value calculated with the standard error of the mean and a t value of 3.69 at the 99% confidence level.

The stochastic generation models for generating daily air temperature and solar radiation data as proposed in chapter 6 and tested according to the previous discussion are considered to be

Table 20. Monthly mean air temperature for 10 runs of 11-year synthetic records (deg. F).

	Run	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
	1	38.01	40.44	50.96	62.03	69.41	77.74	81.96	80.28	71.92	61.52	48.81	39.58
	2	37.48	41.27	49.87	60.89	69.66	79.02	82.48	79.37	72.80	63.35	50.62	39.84
	3	35.24	41.52	51.08	59.86	69.57	77.47	81.36	80.92	70.52	61.60	49.75	41.20
	4	36.60	40.73	49.46	61.32	69.33	77.92	82.00	79.68	71.91	62.15	49.22	40.04
	5	37.54	39.86	48.28	60.76	68.63	78.16	81.78	79.38	72.36	61.45	50.32	40.82
	6	36.74	40.03	49.16	61.99	68.93	78.13	82.09	79.79	73.75	59.36	49.51	39.36
	7	36.20	41.54	49.25	61.36	68.92	78.19	81.18	79.02	71.50	63.24	49.99	41.75
	8	36.29	42.56	49.48	62.50	68.98	77.68	81.46	80.32	71.99	61.25	49.22	40.16
	9	37.66	40.64	48.96	61.34	68.90	77.70	82.81	79.72	72.02	61.26	48.34	40.52
	10	37.66	39.14	50.68	61.26	69.50	78.06	81.84	79.34	72.01	61.22	49.91	39.58
Mean		36.94	40.77	49.72	61.33	69.17	78.01	81.90	79.78	72.80	61.64	49.57	40.28
Observed mean		36.92	40.85	49.86	61.82	68.89	77.84	82.36	79.80	72.70	62.04	50.03	40.41
Difference		0.02	0.08	0.14	0.49	0.26	0.17	0.46	0.02	0.10	0.40	0.46	0.13
Critical difference		0.52	1.11	1.10	1.00	0.51	0.52	0.92	0.62	1.18	1.32	0.92	0.88
Standard deviation		1.36	2.97	3.03	2.72	1.40	1.39	2.45	1.72	3.18	3.61	2.54	2.36
Standard deviation of mean		0.14	0.30	0.30	0.27	0.14	0.14	0.25	0.17	0.32	0.36	0.25	0.24

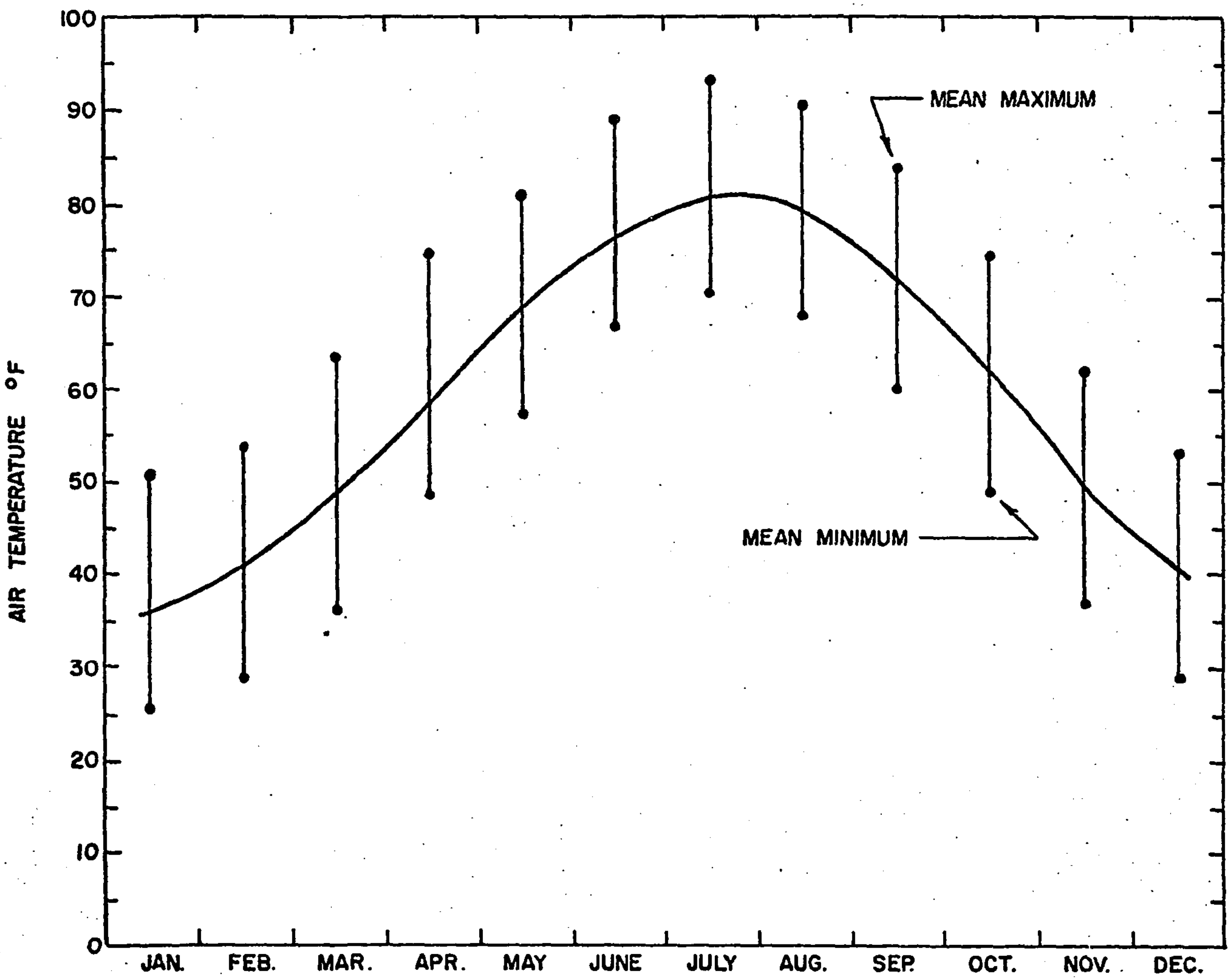

Figure 18. Mean maximum, minimum and daily mean air temperature from generated data.

adequate to generate snythetic data for periods of 11-years in length. These models should not however be used to generate longer records as presently developed. To generate longer records or records representative of a long period, say 30 years, would require the development of the model's statistical parameters from records at least as long as 30 years.

In addition to the test made on solar radiation and temperature data, the generated data was used to calculate evapotranspiration using the Jensen-Haise model equation 6-1. The monthly mean evapotranspiration for each month and t test statistics with values calculated from observed data are shown in table 21. No monthly means calculated from synthetic data were significantly different from the observed values, further indicating that the meteorological data models preformed satisfactorily.

As a matter of interest, additional comparisons were made with the generated data. Extreme values, i.e., the maximum and minimum generated temperature data and the maximum solar radiation data were obtained from the 111-years of the 10 runs. These values with the associated observed values from the 11-year records are compared in table 22. While the generated values are larger for maximums and smaller for minimums than those in the observed record they may be representative of those expected from a 111-year historical trace.

The programs developed for the rainfall data generation model are listed in appendix A. Programs developed for meteorological data generation are presented in appendix B.

Table 21.--Monthly mean calculated evapotranspiration by the Jensen-Haise model using synthetically generated air temperature and solar radiation data (inches).

	Run	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
	1	0.73	0.94	2.44	4.14	6.75	7.69	8.42	7.85	4.94	3.45	1.42	0.69
	2	0.68	1.05	2.44	4.01	6.74	7.91	8.61	7.58	5.31	3.57	1.53	0.78
	3	0.59	1.12	2.19	4.05	6.57	7.79	8.42	8.04	4.60	3.59	1.45	0.80
	4	0.72	1.07	2.17	4.26	6.63	7.70	8.81	7.76	4.95	3.51	1.50	0.74
	5	0.70	0.94	2.22	4.27	6.30	7.91	8.65	7.66	4.92	3.27	1.58	0.75
	6	0.66	1.01	2.25	4.41	6.49	8.02	8.86	7.65	4.97	2.87	1.55	0.76
	7	0.62	1.08	2.22	4.28	6.62	8.09	8.51	7.62	4.73	3.57	1.56	0.91
	8	0.67	1.18	2.20	4.48	6.59	7.93	8.71	7.99	4.89	3.42	1.43	0.80
	9	0.69	1.12	2.12	3.98	6.51	7.85	8.82	7.83	4.65	3.26	1.19	0.75
	10	0.74	0.92	2.52	4.21	6.11	8.06	8.75	7.60	4.91	3.29	1.55	0.78
Mean		0.68	1.04	2.28	4.21	6.53	7.89	8.65	7.76	4.89	3.38	1.48	0.78
Obs. mean		0.62	1.11	2.59	4.50	6.34	8.05	8.86	7.82	5.21	3.51	1.57	0.81
Difference		0.08	-.07	-.31	-.29	0.19	-.16	-.21	-.06	-.32	-.13	-.09	-.03
Critical diff.		0.28	0.39	1.25	1.22	0.98	0.76	0.95	0.95	1.38	-.90	0.53	0.24
Stand. dev.		0.24	0.33	1.07	1.05	0.84	0.65	0.82	0.53	1.18	0.77	0.45	0.21
Stand. dev. of mean		0.07	0.11	0.34	0.33	0.27	0.21	0.26	0.17	0.37	0.24	0.14	0.07

Table 22. Comparison of generated daily extreme values from 10 runs of 11-year synthetic records with observed extreme values for each month.

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
						Synthetic						
Max. temp.*	99	95	102	103	110	108	109	110	107	101	101	98
Min. temp.	-8	-1	-9	21	31	50	56	55	37	23	0	2
Max solar rad.	490	661	670	723	971	980	921	975	874	722	562	502
						Observed						
Max. temp.	81	83	94	100	103	107	107	106	101	97	87	82
Min. temp.	-3	-1	-2	20	32	43	60	57	58	25	10	2
Max. solar rad.	422	492	607	723	903	780	738	711	627	756	492	485

*Units for temperature are Deg. F. and solar radiation are langleys/day.

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

A rainfall model for generating spatial and temporal patterns of rainfall on a 1,500-square-mile area was developed. The system which is considered to be a first approximation to a rainfall generation model, could be used to generate synthetic input data for a hydrologic model. Tests made on the data generated by the system show that 71 percent of the synthetic records at 168 stations would be accepted as being from the same population of observed data. A Markov chain model for generating wet day-dry day sequence for the network area was highly satisfactory as was the method of generating mean rainfall for the area. Further refinement of the method of generating the rainfall pattern is needed.

Meteorological data generating models were developed that will stochastically generate daily maximum and minimum temperature and total solar radiation. The data generated from these models were tested against historical records and found to be adequate, representing the observed data in 11 out of 12 months of the year. Mean daily temperature calculated from the maximum and minimum synthetic temperature data were also found not significantly different from mean daily air temperature calculated from the observed data. A further test of the data showed mean monthly evapotranspiration calculated using the synthetic daily temperature and solar radiation to be statistically the same as mean monthly evapotranspiration calculated from historical data.

Both the rainfall and meteorological data generating systems as described in this study should not be considered as replacements for observations, but should be considered as supplements to existing records to provide not an extension of existing records but a method of providing the variations that exists in the historical observations. That is to say, if an evaluation was required for a watershed or basin using a given existing hydrologic model, and only a short period of historical data were available, then one might use synthetic records such as these to provide sequences of hydrologic events that are different from the observed data. Wet and dry periods, extreme values as well as means would be present in the synthetic data yet in a different order of occurrence. Even long records might be generated from short historical records such as used in this study, if the user is careful to construct the records by generating synthetic data for intervals not to exceed the historical record length.

Recommendations

Recommendations for further study as a result of this investigation are:

1. Further testing of the generated data from the models is recommended by first selecting a hydrologic model and then using the generated data as input. Testing of the hydrologic model output against output using observed data would be the ultimate test of the generating

system. The models developed in this study were intended to be used to generate hydrologic model input, however, the outputs were only tested against observed rainfall and meteorological data to determine their representativeness.

2. More refinement is needed in the rainfall pattern generating model. Depth-Area relationships other than the average one used in this study should be investigated.

3. More testing of the meteorological data models should be made. Such testing should include investigation of all the data including dry days as well as wet days to insure that the temperature and solar radiation data are compatible with observed conditions on such days.

4. The rainfall and meteorological data generation models developed in this study should be tested in other climatic areas. Locations in both wetter and dryer climates should be selected and model parameters developed from observed data, then synthetic data generated and tested by the methods outlined previously.

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APPENDIX A

RAINFALL MODEL PROGRAMS

```
C     ****************************************************************
C     *1130 PROGRAM TO CALCULATE THE WET- DRY STATE CONDITIONAL      *
C     *PROBABLITIES.  PROGRAM USES DISK FILE CRSCL AND SUBROUTINES   *
C     *JULIN AND DAYC.                                               *
C     ****************************************************************
      DEFINE FILE 1(4384,11,U,MR)
      DIMENSION X(366),NR(230),SS1(12),SSI(12),SI(12),SXST(12),NWC(12),
     1NDC(12),NTC(12),NRC(12),S1(12),NGN(60),LABEL(20)
      DO 141 I=1,12
      SS1(I)=0.0
      SSI(I)=0.0
      SXST(I)=0.0
      SI(I)=0.0
      S1(I)=0.0
      NWC(I)=0
      NDC(I)=0
      NTC(I)=0
  141 NRC(I)=0
      READ(2,60)(LABEL(I),I=1,20)
   60 FORMAT(20A1)
      READ(2,26)NGW
      READ(2,26)(NGN(I),I=1,NGW)
      AW=NGW
      NL=0
      NCON=1
      ST = 0.0
      READ(2,26)MR,ML,NYS,MOF,NDF,NYF,MOL,NDL,NYL
   26 FORMAT(20I4)
    1 DO 98 I = 1,366
   98 X(I) = 0.0
    2 READ(1'MR)NT,MO,NY,(NR(I),I=1,8)
      CALL JULIN(MO,ND,NY,NT)
      AM=0.0
      DO 27 I=1,NGW
      NI=NGN(I)
      XCT=NR(NI)
   27 AM=AM+(XCT*0.01)
      AM=AM/AW
      IF(NY-NYS)2,6,5
    6 CALL DAYC (MO,ND,NY,NCON,NL)
      X(NCON) = AM
      GO TO 2
    5 IF (NL)8,9,8
    8 JC = 366
      GO TO 7
    9 JC = 365
    7 DO 100 I = 1, JC
      CALL JULIN (MD,NDO,NY,I)
```

```
      NTC(MD)=NTC(MD)+1
      IF (ST) 10, 10, 11
   10 IF(X(I))12,12,99
   12 NDC(MD)=NDC(MD)+1
      GO TO 99
   11 IF(X(I))130,130,13
   13 NWC(MD)=NWC(MD)+1
  130 NRC(MD)=NRC(MD)+1
      S1(MD)=S1(MD)+ST
      SS1(MD)=SS1(MD)+(ST*ST)
      SI(MD)=SI(MD)+X(I)
      SSI(MD)=SSI(MD)+(X(I)*X(I))
      SXST(MD)=SXST(MD)+(X(I)*ST)
   99 ST=X(I)
  100 CONTINUE
      IF(MR-ML)4,200,200
    4 NYS=NY
      MR=MR-1
      GO TO 1
  200 DO 201 I=1,12
      WC=NWC(I)
      RC=NRC(I)
      DC=NDC(I)
      TC=NTC(I)
      PWW=WC/RC
      PWD = 1.0 - PWW
      PDW=(RC-WC)/(TC-RC)
      PDD=1.0-PDW
      SQ1=SS1(I)-((S1(I)*S1(I))/RC)
      SQI=SSI(I)-((SI(I)*SI(I))/RC)
      SQI1=SXST(I)-((SI(I)*S1(I))/RC)
      R = SQI1/SQRT(SQ1*SQI)
      WRITE(3,140)
  140 FORMAT(1H1)
      WRITE(3,30)I,MOF,NDF,NYF,MOL,NDL,NYL
   30 FORMAT(46X,'  TWO STATE PROBABILITIES ',//71X,' FOR MONTH ',I3,//
     1 46X,'PERIOD OF RECORD',6I3)
      WRITE(3,40)(LABEL(K),K=1,20),NGW
   40 FORMAT(45X,20A1,' WATERSHED',/45X,'NUMBER OF GAGES =',I4)
      WRITE (3,20) NTC(I),NWC(I),NDC(I)
   20 FORMAT(1H ,'TOTAL NUMBER OF DAYS =',I6,1X,'WET DAYS =',I6,1X,'DRY
     1 DAYS =',I6)
      WRITE (3,21)
   21 FORMAT (1H0,14X,'STATE PROBABILITY')
      WRITE (3,22)
   22 FORMAT (1H0,15X,'WET',6X,'DRY')
      WRITE(3,23) PWW,PWD
   23 FORMAT (1H0,10X,'WET',F8.5,F9.5)
```

```
      WRITE (3,24) PDW, PDD
   24 FORMAT (1HO,10X,'DRY',F8.5,F9.5)
  201 WRITE (3,25) R,NRC(I)
   25 FORMAT (1HO,'WET - WET DAY CORRELATION',F9.5,'  NUMBER OF CASES',
     1I5)
      CALL EXIT
      END
```

```
      SUBROUTINE DAYC (MO,NDA,NYR,NCON,NL)
      GO TO ( 1,2,3,4,5,6,7,8,9,10,11,12 ),MO
    1 NCON = 0
      GO TO 20
    2 NCON = 31
      GO TO 20
    3 NCON = 59
      GO TO 20
    4 NCON = 90
      GO TO 20
    5 NCON = 120
      GO TO 20
    6 NCON = 151
      GO TO 20
    7 NCON = 181
      GO TO 20
    8 NCON = 212
      GO TO 20
    9 NCON = 243
      GO TO 20
   10 NCON = 273
      GO TO 20
   11 NCON = 304
      GO TO 20
   12 NCON = 334
   20 NL = NYR/4
      IF (NYR - (NL*4)) 13, 14, 13
   14 NL = 1
      GO TO 15
   13 NL = 0
   15 IF (NL) 16, 17, 16
   16 IF (MO-2) 17, 17, 18
   18 NCON = NCON + NDA + 1
      GO TO 21
   17 NCON = NCON + NDA
   21 RETURN
      END
```

```
C     *****************************************************************
C     *                    MAINLINE PROGRAM GENP                       *
C     *1130 PROGRAM TO SYNTHETICALLY GENERATE PATERNS OF DAILY RAINFALL *
C     *SUBROUTINES USED ARE GENR,JULIN,RANDN,GENPX,PATG,GENS,MAP2, AND *
C     *GENO.            INPUT INCLUDE CODES FOR NUMBER OF SYNTHETIC    *
C     *RUNS RANDOM NUMBER GENERATOR INDEX VALUES,WET- DRY DAY CONDITION *
C     *-AL PROBABILITIES,MEAN AND STANDARD DEVIATION PARAMETERS,RAIN   *
C     *GAGE LOCATION VALUES AND MAXIMUM RAINFALL FREQUENCY PARAMETERS  *
C     *FOR EACH MONTH.  OUTPUT IS MAP OF DAILY RAINFALL PATTERN,MEAN AND*
C     *STANDARD DEVIATION OF THE PATTERN                               *
C     *****************************************************************
      DEFINE FILE1(338,320,U,MG)
      DEFINE FILE2(338,320,U,MK)
      DEFINE FILE3(168,320,U,MZ)
      DEFINE FILE 4(1,320,U,MRG)
      DEFINE FILE 5(26,320,U,MN)
      DIMENSION C(3,12),PR(4,12),PMAX(12),      K1(4),K2(4),NC(15)
      DIMENSION K3(4),K4(4),PG(168),XSUM(168),TSUM(168)
      DIMENSION CM(9,12),RD(168),NR(228)
      DIMENSION K5(4)
      READ(2,190)NRUN,MPRN
  190 FORMAT(2I3)
      READ(2,12)(K5(I),I=1,4)
   12 FORMAT(4I4)
      CALL GENR      (K1,K2,K3,K4,C,PR,NY,JL,L,MR,TSUM,XSUM,        PMAX
     1,PG,AL,NC,CM)
   99 FORMAT(1H1)
      DO 999 NUMR=1,NRUN
      DO 129 I=1,168
  129 RD(I)=0.0
      MN=1
      DO 149 I=1,13
      WRITE(5'MN)(RD(J),J=1,160)
      WRITE(5'MN)(RD(J),J=161,168)
  149 CONTINUE
      DO 16 M=1,JL
      IF(NY-((NY/4)*NY))13,14,13
   13 JN=365
      GO TO 15
   14 JN=366
   15 DO 18 N=1,12
      NC(N)=0
   18 PMAX(N)=0.0
      DO 180 N=1,168
  180 XSUM(N)=0.0
      DO 1 II=1,JN
      NL=II
      CALL JULIN(MD,ND,NY,NL)
```

```
      MO=MD
      CALL RANDN(K1,XN)
      GO TO (2,3),L
    2 IF(XN-PR(1,MO))4,5,5
    3 IF(XN-PR(3,MO))4,5,5
    4 CALL GENPX(C,K2,NC,P,PT,MO)
      IF(P-PMAX(MO))77,77,6
    6 PMAX(MO)=P
C     LOCATION GENERATOR
   77 CALL RANDN(K3,XG)
      MRG=1
      READ(4'MRG)(NR(I),I=1,220)
      LG=1.0+(219.0*XG+0.5)
      IG=NR(LG)
      MR=(IG*2)-1
      MG=MR
      READ(1'MG)(PG(I),I=1,160)
      READ(1'MG)(PG(I),I=161,168)
      MZ=IG
      READ(3'MZ)(NR(I),I=1,168)
      CALL PATG(IG,K4,PT,PG,XSUM,CM, PM,SDG,MO,SM,SIG,RD,NR,K5)
      MN=(MO*2)-1
      READ(5'MN)(RD(I),I=1,160)
      READ(5'MN)(RD(I),I=161,168)
      DO 707 I=1,168
  707 RD(I)=RD(I)+PG(I)
      MN=MN-2
      WRITE(5'MN)(RD(I),I=1,160)
      WRITE(5'MN)(RD(I),I=161,168)
      CALL DATSW(1,IVAR)
      GO TO (75,7),IVAR
   75 WRITE(3,60)MO,ND,NY,IG,PT
   60 FORMAT(1H1,45X,'STORM',3I3,'  CENTERED AT GAGE NO.',I4,'  MAX=',F6
     1.2)
      WRITE(3,79)SM,SIG,PM,SDG
   79 FORMAT(1H ,35X,'MEAN =',F7.5,' STD. DEV. =',F7.5,' CAL. MEAN =',
     1F7.5,' STD. DEV. =',F7.5)
      CALL MAP2(PG)
    7 L=1
      GO TO 1
    5 P=0.0
      L=2
    1 CONTINUE
      CALL GENS(PMAX,NC,XSUM,NY,TSUM,AL)
      CALL MAP2(XSUM)
      AVP=0.0
      DO 105 I=1,168
  105 AVP=AVP+XSUM(I)
```

```
      AVP=AVP/168.0
   16 CONTINUE
      DO 363 I=1,168
  363 TSUM(I)=TSUM(I)+XSUM(I)/AL
      WRITE(3,99)
      CALL MAP2(TSUM)
      AVP=0.0
      DO 106 I=1,168
  106 AVP=AVP+TSUM(I)
      AVP=AVP/168.0
      WRITE(3,99)
      MN=1
      DO 691 J=1,13
      READ(5'MN)(RD(I),I=1,160)
      READ(5'MN)(RD(I),I=161,168)
      DO 740 LMO=1,168
  740 RD(LMO)=RD(LMO)/9.0
      WRITE(3,690)(J,I,RD(I),I=1,168)
      WRITE(2,711)NUMR,J
  691 WRITE(2,710)(RD(I),I=1,168)
  711 FORMAT(2I4)
  710 FORMAT(12F6.3)
  690 FORMAT(8(1X,2I4,F6.3))
  999 CONTINUE
      WRITE(3,99)
      CALL GENO(K1,K2,K3,K4)
      WRITE(3,199)(K5(I),I=1,4),L
  199 FORMAT(1H ,'GENERATOR 5=',4I4,'  STATE=',I4)
      CALL EXIT
      END
```

```
      SUBROUTINE JULIN (MO,NDAY,NYER,JDAY)
      DIMENSION II(12)
      KDAY = JDAY
      II(1) = 31
      II(2) = 28
      II(3) = 31
      II(4) = 30
      II(5) = 31
      II(6) = 30
      II(7) = 31
      II(8) = 31
      II(9) = 30
      II(10) = 31
      II(11) = 30
      II(12) = 31
      NYT = NYER/ 4
      NYT = NYT*4
      IF ( NYT - NYER ) 20,10,20
   10 II(2) = 29
   20 DO 30 J = 1,12
      JDAY = JDAY -II(J)
      IF (JDAY) 40,40,30
   30 CONTINUE
   35 JDAY = KDAY
      RETURN
   40 NDAY = JDAY +II(J)
      MO = J
      GO TO 35
      END
```

```
      SUBROUTINE RANDN(K,SUM)
      DIMENSION K(4)
      K(4)=3*K(4)+K(2)
      K(3)=3*K(3)+K(1)
      K(2)=3*K(2)
      K(1)=3*K(1)
      I=K(1)/1000
      K(1)=K(1)-I*1000
      K(2)=K(2)+I
      I=K(2)/100
      K(2)=K(2)-100*I
      K(3)=K(3)+I
      I=K(3)/1000
      K(3)=K(3)-I*1000
      K(4)=K(4)+I
      I=K(4)/100
      K(4)=K(4)-100*I
      SUM   =(((FLOAT(K(1))* .001+FLOAT(K(2)))*.01+FLOAT(K(3)))*.001+FLO
     1AT(K(4)))*.01
      RETURN
      END
```

```
      SUBROUTINE GENR(K1,K2,K3,K4,C,PR,NY,JL,L,MR,TSUM,XSUM,          PMAX
     1,PG,AL,NC,CM)
      DIMENSION C(3,12),PR(4,12),PMAX(12),          K1(4),K2(4),NC(15)
      DIMENSION K3(4),K4(4),PG(168),XSUM(168),TSUM(168)
      DIMENSION  CM(9,12)
      DO 340 I=1,168
  340 TSUM(I)=0.0
      READ(2,20)(K1(I),I=1,4),(K2(N),N=1,4),(K3(N),N=1,4),(K4(N),N=1,4),
     1NY,JL,L,MR
   20 FORMAT(20I4)
      AL=JL
      DO 260 I=1,12
  260 READ(2,26) C(1,I),C(2,I),C(3,I)
   26 FORMAT(5F10.5)
      DO 270 I=1,12
  270 READ(2,27) PR(1,I),PR(2,I),PR(3,I),PR(4,I)
   27 FORMAT(4F10.5)
   28 FORMAT(5F10.5)
      READ(2,27)(CM(1,I),CM(2,I),CM(3,I),CM(4,I),I=1,12)
      READ(2,28)(CM(5,I),CM(6,I),CM(7,I),CM(8,I),CM(9,I),I=1,12)
      WRITE(3,99)
      WRITE(3,35)(K1(I),I=1,4),(K2(I),I=1,4),(K3(I),I=1,4),(K4(I),I=1,4)
     1,NY,JL,L,MR
   35 FORMAT(1H ,'RANDOM NUMBER GENERATOR 1 =',4I4,/1X,'RANDOM NUMBER GE
     1NERATOR 2 =',4I4,/1X,'RANDOM NUMBER GENERATOR 3 =',4I4,/1X,'RANDOM
     2 NUMBER GENERATOR 4 =',4I4,/1X,'YEAR =',I3,/1X,'NUMBER OF YEARS TO
     3 BE RUN =',I3,/1X,'WET-DRY STATE =',I3,/1X,'MR =',I3)
      WRITE(3,40)((C(I,MO),I=1,3),MO=1,12)
   40 FORMAT(46X,'FREQUENCY CONSTANTS',/50X,'M',11X,'S',11X,'K',/(45X,3F
     110.5))
      WRITE(3,41)((PR(I,MO),I=1,4),MO=1,12)
   41 FORMAT(45X,'STATE PROBABILITIES ',/(26X,4F10.5))
   99 FORMAT(1H1)
      RETURN
      END
```

```
      SUBROUTINE GENPX(C,K2,NC,P,PT,MO)
      DIMENSION C(3,12),K2(4),NC(15)
      CALL RANDN(K2,XL)
      V1=XL
      CALL RANDN(K2,XL)
      V2=XL
      XLV=SQRT(-2.0*ALOG(V1))*COS(2.0*3.14159*V2)
      XLV=((XLV-(C(3,MO)/6.0))*C(3,MO)/6.0)+1.0
      XLV=((XLV**3.0)-1.0)*(2.0/C(3,MO))
      P=(XLV*C(2,MO))+C(1,MO)
      IF(P-0.01)23,23,24
   23 P=0.01
   24 PT=P
      NC(MO)=NC(MO)+1
      RETURN
      END
```

```
      SUBROUTINE PATG(IG,K4,PT,PG,XSUM,CM, PM,SDG,MO,SM,SIG,RD,NR,K5)
      DIMENSION PG(168),XSUM(168),CM(9,12),RD(168)
      DIMENSION NR(228),K4(4)
      DIMENSION K5(4)
   20 CALL RANDN(K4,XR)
      V1=XR
      CALL RANDN(K4,XR)
      V2=XR
      XLM=SQRT(-2.0*ALOG(V1))*COS(2.0*3.14159*V2)
      CALL RANDN(K4,XR)
      V1=XR
      CALL RANDN(K4,XR)
      V2=XR
      XLS=SQRT(-2.0*ALOG(V1))*COS(2.0*3.14159*V2)
      SIG=EXP(CM(5,MO)+(CM(6,MO)*ALOG(PT))+(CM(7,MO)*ALOG(PT))+(CM(9,MO)
     1*XLS*SQRT(1.0-(CM(8,MO)**2.0))))
      SM=EXP(CM(1,MO)+(CM(2,MO)*ALOG(PT))+(CM(4,MO)*XLM*SQRT(1.0-(CM(3,M
     1O)**2.0))))
      IF(SM-PT)21,20,20
   21 PL=PT
      PS=0.0
      A=0.0
      PG(IG)=PT
      PLZ=(PT-SM)/SIG
  498 DO 49 J=2,168
      I=NR(J)
  490 CALL RANDN(K5,XR)
      V1=XR
      CALL RANDN(K5,XR)
      V2=XR
      XLR=SQRT(-2.0*ALOG(V1))*COS(2.0*3.14159*V2)
      XLY=SQRT(-2.0*ALOG(V1))*SIN(2.0*3.14159*V2)
      ZR=SQRT(1.0-(PG(I)**2.0))
      XLY=(XLR*PG(I))+(ZR*XLY)
      PZ=(PLZ*PG(I))+(XLY*ZR)
      PZ=(PZ*SIG)+SM
      IF(PZ-PT)491,491,490
  491 IF(PZ)490,490,489
  489 PG(I)=PZ
      PS=PS+PZ
      A=A+1.0
      PL=PS/A
      PM=PS/168.0
      PLZ=(PL-SM)/SIG
      IF(PG(I))46,492,492
   46 PG(I)=0.0
  492 XSUM(I)=XSUM(I)+PG(I)
      IF(PM-SM)49,493,493
```

```
493 JK=J
    GO TO 496
 49 CONTINUE
    GO TO 500
496 DO 494 I=JK,168
    M=NR(I)
494 PG(M)=0.0
500 IF((PM+0.05)-SM)498,501,501
501 PSS=0.0
    DO 4 I=1,168
  4 PSS=PSS+(PG(I)*PG(I))
    SDG=(PSS-((PS*PS)/(168.0)))/(167.0)
    SDG=SQRT(SDG)
    RETURN
    END
```

```
      SUBROUTINE GENS(PMAX,NC,XSUM,NY,TSUM,AL)
      DIMENSION PMAX(168),NC(15),XSUM(168),TSUM(168)
   99 FORMAT(1H1)
      PMAXY=0.0
      DO 9 I=1,12
      IF(PMAX(I)-PMAXY)9,9,8
    8 PMAXY=PMAX(I)
    9 CONTINUE
      WRITE(3,99)
      WRITE(3,10)NY,(PMAX(I),I=1,12),PMAXY
   10 FORMAT(1H0,26X,'MAXIMUM DAILY RAINFALL AMOUNT GENERATED FOR EACH M
     1ONTH DURING YEAR',I3,//1X,'   JAN   FEB   MAR   APR   MAY   JUN
     2JUL   AUG   SEP   OCT   NOV   DEC   YEAR',/1X,13F6.2)
      NSUM=0
      DO 30 I=1,12
   30 NSUM=NSUM+NC(I)
      NC(13)=NSUM
      WRITE(3,31)(NC(I),I=1,13)
   31 FORMAT(1X,13I6)
      WRITE(3,99)
      XMAXA=0.0
      DO 36 I=1,168
      IF(XSUM(I)-XMAXA)36,36,37
   37 NGA=I
      XMAXA=XSUM(I)
   36 CONTINUE
      XMIN=XMAXA
      DO 360 I=1,168
      IF(XSUM(I)-XMIN)361,360,360
  361 XMIN=XSUM(I)
      NGM=I
  360 CONTINUE
      AVE=0.0
      DO 362 I=1,168
  362 AVE=AVE+XSUM(I)/168.0
      WRITE(3,38)NY,XMAXA,NGA,XMIN,NGM,AVE
   38 FORMAT( 1X,'ANNUAL RAINFALL TOTALS FOR YEAR',I3,'  MAX.'F6.2,' AT
     1GAGE',I4,'  MIN.',F6.2,'  AT GAGE',I4,/45X,'AVE.='F6.2)
      NY=NY+1
      RETURN
      END
```

```
      SUBROUTINE GENO(K1,K2,K3,K4)
      DIMENSION K1(4),K2(4),K3(4),K4(4)
      WRITE(3,50)(K1(I),I=1,4)
      WRITE(3,51)(K2(I),I=1,4)
      WRITE(3,53)(K3(I),I=1,4)
      WRITE(3,54)(K4(I),I=1,4)
      WRITE(3,52)
   51 FORMAT(1H ,'GENERATOR 2=',4I4)
   50 FORMAT(1H ,'GENERATOR 1=',4I4)
   53 FORMAT(1H ,'GENERATOR 3=',4I4)
   54 FORMAT(1H ,'GENERATOR 4=',4I4)
   52 FORMAT(1H ,'END OF RUN')
      RETURN
      END
```

```
      SUBROUTINE MAP2 (X)
C     ******************************************************************
C     *THIS SUBROUTINE WILL MAP 168 VALUES OF DATA IN THE RAIN GAGE     *
C     *NETWORK SPACING. VALUES SHOULD BE IN THE FORM XX.XX.             *
C     *HEADINGS AND OTHER PERTINENT DATA SHOULD BE SPECIFIED AND WRITTEN*
C     * BY THE MAIN.                                                    *
C     ******************************************************************
      DIMENSION X(185)
   99 FORMAT(1H )
    1 FORMAT (1H+,11X,F5.2)
    2 FORMAT(1H ,20X,2F5.2)
    3 FORMAT(1H 9X,F5.2)
    6 FORMAT(1H ,13X,2F5.2,F6.2)
    7 FORMAT(1H ,29X,F5.2)
    9 FORMAT(1H ,13X,3F5.2)
   10 FORMAT(1H ,28X,F5.2,F6.2,F5.2)
   11 FORMAT(1H ,13X,F5.2)
   13 FORMAT (1H ,16X,2F5.2,F6.2,F7.2,F8.2)
   14 FORMAT (1H ,38X,F5.2)
   15 FORMAT (1H ,16X,F5.2)
   16 FORMAT (1H ,21X,F5.2,F6.2)
   17 FORMAT (1H ,32X,3F5.2)
   18 FORMAT (1H ,15X,F5.2,27X,3F5.2,F6.2)
   19 FORMAT (1H ,20X,F5.2,42X,2F5.2,F6.2)
   20 FORMAT (1H ,25X,4F5.2,38X,F5.2)
   21 FORMAT (1H ,46X,F5.2,F4.2)
   22 FORMAT (1H ,14X,2F5.2,F6.2,F4.2,21X,2F6.2,2F5.2,F10.2)
   23 FORMAT (1H ,35X,F5.2,F6.2,32X,F5.2)
   24 FORMAT (1H ,46X,F5.2)
   25 FORMAT (1H ,50X,F5.2,F6.2,F5.2)
   26 FORMAT (1H ,18X,F5.2,6X,2F5.2,27X,3F5.2)
   27 FORMAT (1H ,23X,F5.2,12X,F5.2,37X,F5.2,F4.2)
   28 FORMAT (1H ,45X,2F5.2,10X,2F5.2)
   29 FORMAT (1H ,55X,2F5.2,10X,F5.2)
   30 FORMAT (1H ,29X,F5.2,F4.2,42X,F5.2,F6.2,F5.2)
   31 FORMAT (1H ,39X,3F5.2,F6.2)
   32 FORMAT (1H ,33X,F5.2,22X,F5.2,F5.2,F5.2,F7.2)
   33 FORMAT (1H ,37X,F5.2,38X,3F5.2)
   34 FORMAT (1H ,43X,F5.2,F4.2,F8.2)
   35 FORMAT (1H ,58X,F5.2,F6.2,6X,F5.2)
   36 FORMAT (1H ,32X,F5.2,33X,F5.2,5X,3F5.2)
   37 FORMAT (1H ,35X,F5.2,F7.2,F6.2,F5.2)
   38 FORMAT (1H ,69X,F5.2)
   39 FORMAT (1H ,58X,2F5.2,7X,2F5.2,5X,F5.2)
   40 FORMAT (1H ,24X,F5.2,F6.2,F5.2,F6.2,F5.2,34X,F5.2)
   41 FORMAT (1H ,51X,F5.2,8X,F5.2)
   42 FORMAT (1H ,57X,F5.2,6X,F5.2,F6.2)
   43 FORMAT (1H ,30X,2F5.2,39X,F5.2,F4.2,F5.2)
```

```
44 FORMAT (1H ,40X,F5.2,F6.2,F5.2)
45 FORMAT (1H ,57X,3F5.2)
46 FORMAT (1H ,30X,F5.2,F4.2,34X,F5.2,F6.2,F5.2)
47 FORMAT (1H ,40X,2F5.2)
48 FORMAT (1H ,51X,3F5.2,F6.2)
49 FORMAT (1H ,72X,3F5.2)
50 FORMAT (1H ,34X,2F5.2,F6.2)
51 FORMAT (1H ,55X,F5.2,F7.2)
52 FORMAT (1H ,32X,F5.2,30X,F5.2)
53 FORMAT (1H ,39X,F5.2,F6.2)
54 FORMAT (1H ,50X,3F5.2)
55 FORMAT (1H ,44X,F5.2,16X,F5.2)
56 FORMAT (1H ,50X,2F5.2,F4.2)
   WRITE (3,1)X(1)
   WRITE(3,2)X(2),X(3)
   WRITE (3,99)
   WRITE(3, 99)
   WRITE (3,3)X(8)
   WRITE (3, 99)
   WRITE (3,6) X(7),X(6),X(5)
   WRITE (3,7) X(4)
   WRITE (3, 99)
   WRITE(3,9)(X(I),I=9,11)
   WRITE (3,10)(X(I),I=12,14)
   WRITE (3,11)X(21)
   WRITE (3,99)
   WRITE (3,13) X(20),X(19),X(18),X(17),X(15)
   WRITE (3,14)X(16)
   WRITE (3,15)X(22)
   WRITE (3,16)X(23),X(24)
   WRITE (3,17)(X(I),I=25,27)
   WRITE (3,18)X(49),(X(I),I=28,31)
   WRITE (3,19)X(48),X(32),X(33),X(34)
   WRITE (3,20)X(47),X(46),X(45),X(44),X(35)
   WRITE (3,21)X(43),X(42)
   WRITE (3,22)X(50),X(51),X(52),X(53),X(41),X(40),X(39),X(38),X(36)
   WRITE (3,23)X(54),X(55),X(37)
   WRITE (3,24)X(56)
   WRITE (3,25)(X(I),I=57,59)
   WRITE (3,26)X(79),X(77),X(76),X(60),X(61),X(62)
   WRITE (3,27)X(78),X(75),X(63),X(64)
   WRITE (3,28)X(74),X(73),X(70),X(69)
   WRITE (3,29)X(72),X(71),X(68)
   WRITE (3,30)X(80),X(81),X(67),X(66),X(65)
   WRITE (3,31)X(82),X(83),X(84),X(85)
   WRITE (3,32)X(104),(X(I),I=86,89)
   WRITE (3,33)X(103),X(90),X(91),X(92)
   WRITE (3,34)X(102),X(101),X(100)
```

```
WRITE (3,35)X(99),X(98),X(96)
WRITE (3,36)X(105),X(97),X(95),X(94),X(93)
WRITE (3,37)(X(I),I=106,109)
WRITE (3,38)X(112)
WRITE (3,39)X(110),X(111),X(113),X(114),X(116)
WRITE (3,40)X(129),X(128),X(127),X(126),X(125),X(115)
WRITE (3,41)X(124),X(122)
WRITE (3,42)X(123),X(121),X(120)
WRITE (3,43)X(130),X(131),X(119),X(118),X(117)
WRITE (3,44)X(132),X(133),X(134)
WRITE (3,45)(X(I),I=135,137)
WRITE (3,46)X(151),X(150),X(138),X(139),X(140)
WRITE (3,47)X(149),X(148)
WRITE (3,48)X(147),X(146),X(145),X(144)
WRITE (3,49)X(143),X(142),X(141)
WRITE (3,50)(X(I),I=152,154)
WRITE (3,51)X(155),X(156)
WRITE (3,52)X(164),X(157)
WRITE (3,53)X(163),X(162)
WRITE (3,54)X(161),X(160),X(159)
WRITE (3,55)X(165),X(158)
WRITE(3,99)
WRITE (3,56)(X(I),I=166,168)
RETURN
END
```

APPENDIX B

METEOROLOGICAL DATA MODEL PROGRAMS

```
C     ******************************************************************
C     *PROGRAM TO CALCULATE CORRELATION OF MAXIMUM-MINIMUM TEMPERATURES *
C     *SOLAR RADIATION FOR EACH MONTH USING A TWO STATE MARKOV CHAIN TO *
C     *SELECT ONE OF FOUR CONDITIONS  DRY-DRY DRY-WET WET-DRY AND WET-  *
C     *WET.                                                             *
C     *INPUT FROM 1130 DISK FILE CRSCL                                  *
C     *THIS FILE CONTAINS IN ONE WORD INTEGERS                          *
C     *   NT - DAY OF THE YEAR                                          *
C     *   MO - MONTH                                                    *
C     *   NY - YEAR                                                     *
C     *   NMAX - MAXIMUM DAILY TEMPERATURE                              *
C     *   MHX - MAXIMUM DAILY HUMDITY                                   *
C     *   MHX - MAXIMUM DAILY HUMIDITY                                  *
C     *   MHM - - MINMUM DAILY HUMIDITY                                 *
C     *   NSO - DAILY TOTAL SOLAR RADIATION                             *
C     *   NWN - WIND MILES/DAY                                          *
C     *   NEV - YOUNG SCREENED PAN WEEKLY EVAPORATION                   *
C     *   NC - CODE FOR RAIN  1 = RAIN  0 = NO RAIN DURING DAY          *
C     *OUTPUT PRINTOUT AND PUNCH CARDS OF MEAN STANDARD DEVIATION AND   *
C     *CORRELATION COEFFICIENT FOR EACH STATE AND EACH MONTH.           *
C     *MEAN MONTHLY EVAPOTRANSPIRATION ESTIMATES BY THE JENSEN-HAISE    *
C     *MODEL ARE ALSO CALCULATED.                                       *
C     ******************************************************************
      DEFINE FILE 1(4384,11,U,MR)
      DIMENSION XTMX(12),XTMN(12),SOR(12),NDC(12)
      DIMENSION  SX(4,2,12),SY(4,2,12),SSX(4,2,12),SSY(4,2,12),
     1SXY(4,2,12),X(2),Y(2),NA(4,2,12)
      DIMENSION  SIGX(4,2,12),SIGY(4,2,12),SIGXY(4,2,12),R(4,2,12)
      DIMENSION SLX(4,12),SLY(4,12),SSLX(4,12),SSLY(4,12),RL(4,12),SGLXY
     1(4,12),SGLX(4,12),SGLY(4,12),SL(2),NL(4,12)
      DIMENSION PEN(13)
      PEN(13)=0.0
      DO 100 M=1,12
      NDC(M)=0
      PEN(M)=0.0
      DO 100 K=1,4
      SLX(K,M)=0.0
      SLY(K,M)=0.0
      SSLX(K,M)=0.0
      SSLY(K,M)=0.0
      SGLXY(K,M)=0.0
      NL(K,M)=0
      DO 100 I=1,2
      SX(K,I,M)=0.0
      SY(K,I,M)=0.0
      SSX(K,I,M)=0.0
      SSY(K,I,M)=0.0
      SXY(K,I,M)=0.0
```

```
100 NA(K,I,M)=0
    MR=1
    READ(1'MR)NT,MO,NY,NMAX,NMIN,MHX,MHM,NSO,NWN,NEV,NC
    NP=NC
    NDC(MO)=NDC(MO)+1
    XTMX(MO)=XTMX(MO)+NMAX
    XTMN(MO)=XTMN(MO)+NMIN
    SOR(MO)=SOR(MO)+NSO
    DO 200 M=2,4017
    READ(1'MR)NT,MO,NY,NTMAX,NTMIN,MHX,MHM,NSOR,NWN,NEV,NC
    T=NTMIN+NTMAX
    T=T/2.0
    RS=NSOR
    RS=RS*0.00066728
    PEND=(0.014*T-0.37)*RS
    PEN(MO)=PEN(MO)+PEND
    PEN(13)=PEN(13)+PEND
    IF(NP+NC-1)5,4,8
  3 K=3
    GO TO 7
  4 IF(NP-NC)6,8,3
  5 K=1
    GO TO 7
  6 K=2
    GO TO 7
  8 K=4
  7 NP=NC
    X(1)=NTMAX
    Y(1)=NMAX
    X(2)=NTMIN
    Y(2)=NMIN
    SL(1)=NSO
    SL(2)=NSOR
    NDC(MO)=NDC(MO)+1
    XTMX(MO)=XTMX(MO)+NTMAX
    XTMN(MO)=XTMN(MO)+NTMIN
    SOR(MO)=SOR(MO)+NSOR
    NL(K,MO)=NL(K,MO)+1
    NMAX=NTMAX
    NMIN=NTMIN
    NSO=NSOR
    SLX(K,MO)=SLX(K,MO)+SL(1)
    SLY(K,MO)=SLY(K,MO)+SL(2)
    SSLX(K,MO)=SSLX(K,MO)+SL(1)*SL(1)
    SSLY(K,MO)=SSLY(K,MO)+SL(2)*SL(2)
    SGLXY(K,MO)=SGLXY(K,MO)+SL(1)*SL(2)
    DO 200 I=1,2
    SX(K,I,MO)=SX(K,I,MO)+X(I)
```

```
      SY(K,I,MO)=SY(K,I,MO)+Y(I)
      SXY(K,I,MO)=SXY(K,I,MO)+X(I)*Y(I)
      SSX(K,I,MO)=SSX(K,I,MO)+X(I)*X(I)
      SSY(K,I,MO)=SSY(K,I,MO)+Y(I)*Y(I)
  200 NA(K,I,MO)=NA(K,I,MO)+1
      DO 300 M=1,12
      DO 300 K=1,4
      ANS=NL(K,M)
      SGLX(K,M)=SSLX(K,M)-(SLX(K,M)*SLX(K,M)/ANS)
      SGLY(K,M)=SSLY(K,M)-(SLY(K,M)*SLY(K,M)/ANS)
      SGLXY(K,M)=SGLXY(K,M)-(SLY(K,M)*SLX(K,M)/ANS)
      DO 300 I=1,2
      AN=NA(K,I,M)
      SIGX(K,I,M)=SSX(K,I,M)-(SX(K,I,M)*SX(K,I,M)/AN)
      SIGY(K,I,M)=SSY(K,I,M)-(SY(K,I,M)*SY(K,I,M)/AN)
  300 SIGXY(K,I,M)=SXY(K,I,M)-(SY(K,I,M)*SX(K,I,M)/AN)
      DO 400 M=1,12
      DO 400 K=1,4
      ANS=NL(K,M)
      RL(K,M)=SGLXY(K,M)/SQRT(SGLX(K,M)*SGLY(K,M))
      SGLX(K,M)=SQRT(SGLX(K,M)/(ANS-1.0))
      SGLY(K,M)=SQRT(SGLY(K,M)/(ANS-1.0))
      SLX(K,M)=SLX(K,M)/ANS
      SLY(K,M)=SLY(K,M)/ANS
      SGLXY(K,M)=SQRT(SGLXY(K,M)/(ANS-1.0))
      DO 400 I=1,2
      AN=NA(K,I,M)
      R(K,I,M)=SIGXY(K,I,M)/SQRT(SIGX(K,I,M)*SIGY(K,I,M))
      SIGX(K,I,M)=SQRT(SIGX(K,I,M)/(AN-1.0))
      SIGY(K,I,M)=SQRT(SIGY(K,I,M)/(AN-1.0))
      SX(K,I,M)=SX(K,I,M)/AN
      SY(K,I,M)=SY(K,I,M)/AN
  400 SIGXY(K,I,M)=SQRT(SIGXY(K,I,M)/(AN-1.0))
      DO 80 I=1,12
      AM=NDC(I)
      XTMX(I)=XTMX(I)/AM
      XTMN(I)=XTMN(I)/AM
      PEN(I)=PEN(I)/11.0
   80 SOR(I)=SOR(I)/AM
      PEN(13)=PEN(13)/11.0
      WRITE(3,75)(PEN(I),I=1,13)
   75 FORMAT(1X,13F6.2)
      WRITE(3,71)(XTMX(I),I=1,12)
      WRITE(3,71)(XTMN(I),I=1,12)
      WRITE(2,70)(XTMX(I),I=1,12)
      WRITE(2,70)(XTMN(I),I=1,12)
      WRITE(3,72)(SOR(I),I=1,12)
      WRITE(2,73)(SOR(I),I=1,12)
```

```
70 FORMAT(12F6.2)
71 FORMAT(1X,12F6.2)
72 FORMAT(1X,12F6.1)
73 FORMAT(12F6.1)
   DO 60 K=1,4
   DO 60 M=1,12
   WRITE(2,51)M,K,SLX(K,M),SLY(K,M),SGLX(K,M),SGLY(K,M),SGLXY(K,M),
  1RL(K,M)
60 WRITE(3,51)M,K,SLX(K,M),SLY(K,M),SGLX(K,M),SGLY(K,M),SGLXY(K,M),
  1RL(K,M)
   DO 40 M=1,12
   DO 40 K=1,4
   WRITE(2,50)(M,K,I,SX(K,I,M),SY(K,I,M),SIGX(K,I,M),SIGY(K,I,M),
  1SIGXY(K,I,M),R(K,I,M),I=1,2)
40 WRITE(3,50)(M,K,I,SX(K,I,M),SY(K,I,M),SIGX(K,I,M),SIGY(K,I,M),
  1SIGXY(K,I,M),R(K,I,M),I=1,2)
50 FORMAT(2X,3I5,6F10.5)
51 FORMAT(2X,I5,5X,I5,6F10.5)
   CALL EXIT
   END
```

```
C     ********************************************************************
C     *                                                                  *
C     *THIS PROGRAM IS WRITTEN FOR 360/65 SYSTEM                         *
C     *TO STOCHASTIC GENERATE MAX. AND MIN. AIR TEMP. AND TEST AGAINST   *
C     *OBSERVED DATA                                                     *
C     *SUBROUTINES USED  ITEST, JULIN, RANDN                             *
C     *INPUT DATA =                                                      *
C     *FIRST CARD IN I4 FORMAT, FIRST VALUE IS NO. OF RUNS=NRUN, SECOND  *
C     *IS NO. OF YEARS GENERATED FOR EACH RUN, THIRD IS WET-DRY STATE,   *
C     *FOURTH IS THE BEGINNING YEAR OF THE RUN, NEXT IS THE GENERATOR    *
C     *VALUES                                                            *
C     *SECOND CARD HAS A BEGINNING MAX.-MIN. AIR TEMP. AND SOLAR RAD.    *
C     *VALUES AND CONSTANT FOR THE MEAN T VALUE AT THE 95  CONF, LIMIT.  *
C     *NEXT 2 CARDS HAS THE OBSERVED MAX. AND MIN. TEMP. FOR 12 MONTHS   *
C     *NEXT CARD CONTAINS THE MEAN MONTHLY SOLAR RADIATION VALUES        *
C     *NEXT CARD CONTAINS THE MEAN MONTHLY JENSEN-HAISE EVAPO-           *
C     *TRANSPIRATION VALUES                                              *
C     *NEXT SET OF CARDS HAS THE PROBABILITY VALUES FOR THE 4 WET-DRY    *
C     *STATES                                                            *
C     *NEXT SET OF CARDS, FIRST VALUE IS MONTH, SECOND IS WET-DRY STATE,*
C     *THIRD DESIGNATES 1 FOR MAX. AND 2 FOR MIN. TEMP. VALUES WHICH ARE*
C     *THE FOUTH VALUES ON THESE CARDS, SIXTH AND EIGHTH VALUES ARE THE *
C     *CORRESPONDING STANDARD DEVIATION VALUES                           *
C     *THE NEXT VALUES ARE THE MEAN,STANDARD DEVIATION AND LAG-1 CORR    *
C     *COEF. FOR THE FOUR SOLAR RADIATION STATES FOR EACH MONTH.         *
C     *OUTPUT CONSISTS OF MONTHLY MEAN VALUE SUMMARIES FOR MAX AND MIN. *
C     *TEMPERATURE AND SOLAR RADIATION FROM THE GENERATED DATA.          *
C     *PROGRAM MAY BE MODIFIED TO OUTPUT DAILY VALUES IF DESIRED.        *
C     *T - TESTS FOR SIGNIFICANCE OF GENERATED DATA ARE LISTED IN TABLE *
C     *FORM.                                                             *
C     *                                                                  *
C     ********************************************************************
      DIMENSION PR(4,12),SX(4,2,12),SY(4,2,12),R(4,2,12),K1(4),K2(4),K3(
     14),NC(12),SIGX(4,2,12),SIGY(4,2,12),TMA(12,31),TMM(12,31),SMA(12)
     2,SMM(12),SIGXY(4,2,12)
      DIMENSION OBMX(12),OBMN(12),GENMX(10,12),GENMN(10,12)
      DIMENSION SUMX(12),SUMN(12),SSX(12),SSN(12),SDM(12)
      DIMENSION SLX(4,12),SLY(4,12),SGLX(4,12),SGLY(4,12),SGLXY(4,12),
     1RL(4,12),OBSL(12),GENSO(10,12),SML(12),SMLD(12,31),SUMS(12),
     2SSS(12),K4(4)
      DIMENSION GENEJ(10,12),GENTA(10,12),SSE(12),SST(12),OBJH(12),OBTA
     1(12),EJH(12,31),SUME(12),SUMT(12),SME(12),SMT(12),SMTA(12,31)
      READ(2,190)NRUN,JL,L,NY,(K1(I),I=1,4),(K2(I),I=1,4),(K3(I),I=1,4),
     1(K4(I),I=1,4)
      READ(2,44)TMXL,TMML,SOLP,T95
   44 FORMAT(4F10.5)
      READ(2,45)(OBMX(I),I=1,12)
      READ(2,45)(OBMN(I),I=1,12)
```

```
 45 FORMAT(12F6.2)
    READ(2,43)(OBSL(I),I=1,12)
 43 FORMAT(12F6.1)
190 FORMAT(20I4)
    READ(2,45) (OBJH(I),I=1,12)
    DO 30 I=1,12
 30 OBTA(I)=(OBMX(I) + OBMN(I))/2.0
    DO 270 I=1,12
270 READ(2,27)PR(1,I),PR(2,I),PR(3,I),PR(4,I)
 27 FORMAT(4F10.5)
    DO 51 MB=1,96
 51 READ(2,50)M,K,I,SX(K,I,M),SY(K,I,M),SIGX(K,I,M),SIGY(K,I,M),
   1SIGXY(K,I,M),R(K,I,M)
 50 FORMAT(2X,3I5,6F10.5)
    DO 56 MB=1,48
 56 READ(2,55)M,K,SLX(K,M),SLY(K,M),SGLX(K,M),SGLY(K,M),SGLXY(K,M),
   1RL(K,M)
 55 FORMAT(2X,I5,5X,I5,6F10.5)
    DO 60 N=1,NRUN
    DO 60 M=1,12
    GENSO(N,M)=0.0
    GENMX(N,M)=0.0
    GENEJ(N,M)=0.0
    GENTA(N,M)=0.0
 60 GENMN(N,M)=0.0
    KS=4
    DO 999 KA=1,NRUN
    DO 16 MA=1,JL
    NY=NY+1
    IF(NY-((NY/4)*4))13,14,13
 13 JN=365
    GO TO 15
 14 JN=366
 15 DO 18 N=1,12
    SMA(N)=0.0
    SME(N)=0.0
    SMT(N)=0.0
    SMM(N)=0.0
    SML(N)=0.0
    DO 18 M=1,31
    EJH(N,M)=0.0
    SMTA(N,M)=0.0
    TMA(N,M)=0.0
    TMM(N,M)=0.0
    SMLD(N,M)=0.0
 18 NC(N)=0
    CALL RANDN(K2,XL)
    V1=XL
```

```
      CALL RANDN(K3,XR)
      V3=XR
      DO 1 II=1,JN
      NL=II
      CALL JULIN(MD,ND,NY,NL)
      MO=MD
      CALL RANDN(K1,XN)
      GO TO (2,3),L
    2 IF(XN-PR(4,MO))4,4,5
    3 IF(XN-PR(1,MO))64,64,65
    4 K=1
      L=1
      GO TO 200
    5 K=2
      L=2
      GO TO 200
   64 K=3
      L=1
      GO TO 200
   65 K=4
      L=2
  200 TMXL=(TMXL-SY(K,1,MO))/SIGY(K,1,MO)
      TMML=(TMML-SY(K,2,MO))/SIGY(K,2,MO)
  201 CALL RANDN(K2,XL)
      V2=XL
      XLV=SQRT(-2.0*ALOG(V1))*COS(2.0*3.14159*V2)
      TMAX=(R(K,1,MO)*TMXL)+(XLV*SQRT(1.0-(R(K,1,MO)*R(K,1,MO))))
      V1=V2
      CALL RANDN(K3,XR)
      V4=XR
      XLY=SQRT(-2.0*ALOG(V3))*COS(2.0*3.14159*V4)
      TMIN=(R(K,2,MO)*TMML)+(XLY*SQRT(1.0-(R(K,2,MO)*R(K,2,MO))))
      V3=V4
      TEMXL=(TMAX*SIGX(K,1,MO))+SX(K,1,MO)
      TEMML=(TMIN*SIGX(K,2,MO))+SX(K,2,MO)
      IF(TEMML-TEMXL)202,202,201
  202 TMA(MO,ND)=TEMXL
      TMM(MO,ND)=TEMML
      CALL RANDN(K4,XL)
      V1=XL
      CALL RANDN(K4,XR)
      V2=XR
      XLS=SQRT(-2.0*ALOG(V1))*COS(2.0*3.14159*V2)
      SOLF=(SOLP-SLY(K,MO))/SGLY(K,MO)
      SOLF=(RL(K,MO)*SOLF)+(XLS*SQRT(1.0-(RL(K,MO)*RL(K,MO))))
      SOLF=(SOLF*SGLX(K,MO))+SLX(K,MO)
      SMLD(MO,ND)=SOLF
      SMTA(MO,ND)=(TEMXL + TEMML)/2.0
```

```
      RSIN=SMLD(MO,ND)*0.0006678
      EJH(MO,ND)=(0.014 * SMTA(MO,ND) - 0.37)*RSIN
      SMT(MO)=SMT(MO) + SMTA(MO,ND)
      SME(MO)=SME(MO) + EJH(MO,ND)
      SOLP=SOLF
      TMXL=TEMXL
      TMML=TEMML
      SMA(MO)=SMA(MO)+TMXL
      SMM(MO)=SMM(MO)+TMML
      SML(MO)=SML(MO)+SOLF
      KS=K
    1 CONTINUE
      DO 400 I=1,12
      GO TO(401,403,401,402,401,402,401,401,402,401,402,401),I
  401 AN=31.0
      GO TO 405
  402 AN=30.0
      GO TO 405
  403 AN=28.0
      IF(JN-365)405,405,404
  404 AN=29.0
  405 SMA(I)=SMA(I)/AN
      SMM(I)=SMM(I)/AN
      SML(I)=SML(I)/AN
      GENTA(KA,I)=GENTA(KA,I) + SMT(I)
      GENEJ(KA,I)=GENEJ(KA,I) + SME(I)
      GENSO(KA,I)=GENSO(KA,I)+SML(I)
      GENMX(KA,I)=GENMX(KA,I)+SMA(I)
  400 GENMN(KA,I)=GENMN(KA,I)+SMM(I)
      WRITE(3,506)NY
  506 FORMAT(1X,' GENERATED MAXIMUM-MINIMUM TEMPERATURE FOR YEAR',I3)
      WRITE(3,502)(SMA(I),SMM(I),I=1,12)
  502 FORMAT(1X,24F4.0)
      WRITE(3,510)(SML(I),I=1,12)
  510 FORMAT(1X,'GENERATED SOLAR RADIATION',/1X,12F10.2)
   16 CONTINUE
      AN=JL
      DO 601 J=1,12
      GENSO(KA,J)=GENSO(KA,J)/AN
      GENMX(KA,J)=GENMX(KA,J)/AN
      GENTA(KA,J)=GENTA(KA,J)/AN
      GENEJ(KA,J)=GENEJ(KA,J)/AN
  601 GENMN(KA,J)=GENMN(KA,J)/AN
      J=1
      WRITE(3,800)J,(K1(I),I=1,4)
      J=2
      WRITE(3,800)J,(K2(I),I=1,4)
      J=3
```

```
      WRITE(3,800)J,(K3(I),I=1,4)
      J=4
      WRITE(3,800)J,(K4(I),I=1,4)
  800 FORMAT(1X,'GENERATER',I2,'=',4I4)
      WRITE(3,801)L
  801 FORMAT(1X,'WET-DRY STATE = ',I2)
  999 CONTINUE
      WRITE(3,98)
   98 FORMAT(1H1)
      DO 605 J=1,12
      SUMS(J)=0.0
      SUMX(J)=0.0
      SUMN(J)=0.0
      SUME(J)=0.0
      SUMT(J)=0.0
      SSX(J)=0.0
      SSN(J)=0.0
      SSS(J)=0.0
      SST(J)=0.0
      SSE(J)=0.0
  605 SDM(J)=0.0
      DO 606J=1,12
      DO 606 I=1,NRUN
      SUMS(J)=SUMS(J)+GENSO(I,J)
      SUMX(J)=SUMX(J)+GENMX(I,J)
      SUME(J)=SUME(J) + GENEJ(I,J)
      SUMN(J)=SUMN(J)+GENMN(I,J)
      SUMT(J)=SUMT(J) + GENTA(I,J)
      DIFF=GENSO(I,J) - OBSL(J)
      SSS(J)=SSS(J) + (DIFF*DIFF)
      DIFF=GENMX(I,J) - OBMX(J)
      SSX(J)=SSX(J) + (DIFF*DIFF)
      DIFF=GENMN(I,J) - OBMN(J)
      SSN(J)=SSN(J) + (DIFF*DIFF)
      DIFF=GENEJ(I,J) - OBJH(J)
      SSE(J)=SSE(J)+(DIFF*DIFF)
      DIFF=GENTA(I,J) - OBTA(J)
  606 SST(J)=SST(J) + (DIFF*DIFF)
      AN=NRUN
      DO 607 J=1,12
      SSS(J)=SQRT(SSS(J))
      SSX(J)=SQRT(SSX(J))
      SSN(J)=SQRT(SSN(J))
      SSE(J)=SQRT(SSE(J))
      SST(J)=SQRT(SSE(J))
      SUMS(J)=SUMS(J)/AN
      SUMN(J)=SUMN(J)/AN
      SUME(J)=SUME(J)/AN
```

```
      SUMT(J)=SUMT(J)/AN
  607 SUMX(J)=SUMX(J)/AN
      WRITE(3,560)
  560 FORMAT(1X,'T TEST ON MAXIMUM MONTHLY VALUES')
      CALL TTEST(NRUN,GENMX,SUMX,SSX,SDM,T95,OBMX)
      WRITE(3,98)
      WRITE(3,561)
  561 FORMAT(1X,'T TEST ON MINIMUM MONTHLY VALUES')
      CALL TTEST(NRUN,GENMN,SUMN,SSN,SDM,T95,OBMN)
      WRITE(3,98)
      WRITE(3,562)
  562 FORMAT(1X,'T TEST ON SOLAR RADIATION VALUES')
      CALL TTEST(NRUN,GENSO,SUMS,SSS,SDM,T95,OBSL)
      WRITE(3,98)
      WRITE(3,563)
  563 FORMAT(1X,'T TEST ON MEAN TEMPERATURE')
      CALL TTEST(NRUN,GENTA,SUMT,SST,SDM,T95,OBTA)
      WRITE(3,98)
      WRITE(3,564)
  564 FORMAT(1X,'T TEST ON JENSEN EVAPOTRANSPIRATION')
      CALL TTEST(NRUN,GENEJ,SUME,SSE,SDM,T95,OBJH)
      CALL EXIT
      END
```

```
      SUBROUTINE TTEST(NRUN,GENMX,SUMX,SSX,SDM,T95,OBMX)
      DIMENSION GENMX(10,12),SUMX(12),SSX(12),SDM(12),OBMX(12)
      AN=NRUN
      DO 608 I=1,NRUN
  608 WRITE(3,609)I,(GENMX(I,J),J=1,12)
  609 FORMAT(1X,I4,12F7.2)
      WRITE(3,621)(SUMX(I),I=1,12)
      WRITE(3,612)
  612 FORMAT(1X)
      WRITE(3,631)(SSX(J),J=1,12)
      DO 613 J=1,12
  613 SDM(J)=SSX(J)/SQRT(AN)
      WRITE(3,641)(SDM(J),J=1,12)
      DO 614 J=1,12
  614 SDM(J)=SDM(J)*T95
      WRITE(3,651)(SDM(J),J=1,12)
      DO 615 J=1,12
  615 SUMX(J)=SUMX(J)-OBMX(J)
      WRITE(3,661)(SUMX(J),J=1,12)
      WRITE(3,671)(OBMX(J),J=1,12)
      DO 616 J=1,12
      IF(SDM(J)-ABS(SUMX(J)))617,618,618
  617 SDM(J)=1.0
      GO TO 616
  618 SDM(J)=0.0
  616 CONTINUE
      WRITE(3,619)(SDM(J),J=1,12)
  619 FORMAT(5X,12F7.0)
  621 FORMAT(1X,'MEAN',12F7.2)
  631 FORMAT(1X,'ST.D',12F7.2)
  641 FORMAT(1X,'SD.M',12F7.2)
  651 FORMAT(1X,'CR.U',12F7.2)
  661 FORMAT(1X,'DIFF',12F7.2)
  671 FORMAT(1X,'OB.R',12F7.2)
      WRITE(3,672)
  672 FORMAT(1X,'1 - SIGNIFICANT.  0 - NONSIGNIFICANT')
      RETURN
      END
```