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STOCHASTIC MODELS APPLIED TO OPERATION OF RESERVOIRS IN THE UPPER COLORADO RIVER BASIN IN TEXAS

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FOREWORD

A severe water shortage, both for domestic and industrial purposes, developed in the upper Colorado River basin in Texas in the spring of 1971. In particular, the Concho River basin, a tributary, experienced extremely low flows during the period 1962-71. These low flows created real difficulties for the city of San Angelo during the spring and early summer of 1971. The purpose of this study was to investigate the feasibility of using "extended range" forecasts of precipitation and temperature in a stochastic hydrometeorological model to optimize the operation of a connected system of multi-purpose reservoirs. The three-reservoir system located immediately above San Angelo, Texas, was investigated in this study.

A detailed discussion of the stochastic model utilized in determination of the optimal policy for operation of this link-system of reservoirs is presented in Texas Water Resources Institute Technical Report No. 41. The model was developed in connection with this project.

ABSTRACT

A hydrometeorological model is presented that utilizes 30-day meteorological forecasts of temperature and precipitation issued every 15 days by the National Weather service to provide an estimate of the future hydrometeorological conditions of a river basin. The model is entitled "Monthly Operational Hydrometeorological Simulator (MOHS)." Use of the 30-day meteorological forecast categories of light, moderate, or heavy precipitation and below normal, near normal, or above normal temperature provide physical constraints upon quantitative values which were synthesized by a Monte-Carlo simulation technique. Estimates of monthly precipitation for meteorological stations semi-randomly located within the river basin are simulated from the square-root-normal distribution, while monthly mean data of ambient-air temperature are simulated using the Gaussian distribution. This initial simulation assumed a "perfect" forecast.

Contingency tables of forecast versus observed weather for the 24 forecast periods per year were obtained. It was demonstrated that, in general, the forecast periods of temperature provided information that verified better than chance. The precipitation periods did not verify as well. The contingency tables also provided conditional probabilities for each forecast category and period. These then were used to calculate an "expected value" forecast of temperature and precipitation for each station by assuming an "imperfect" forecast. Both simulation methods used an objective analysis scheme that fitted the station data to a rectangular grid-coordinate system. The analyses reproduced the rainfall and temperature patterns well and facilitated computations of surface runoff, reservoir evaporation, and consumptive-use by crops.

Three reservoirs located in the Concho River basin in west Texas were modeled and tested in this study. The reservoir system was described by a system of linear equations to provide some measure of the operational efficiency of the system. The purpose of MOHS is to provide information about hydrometeorological uncertainties which affect the decision-making process involved in water resources management.

The results indicate that the model provides valuable information when "expected value" forecasts are used. The validity of these results rests upon obtaining a more reliable rainfall-runoff relationship that will provide accurate estimates of streamflow. Monthly precipitation values are not representative of the intensity and duration of rainfall events which greatly influence the quantity of surface runoff. It is suggested that simulation of individual storm events be included in MOHS to improve the estimates of streamflow.

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LIST OF SYMBOLS

a, a^*	empirical coefficient
$a_{i\ j}$	activity coefficient of linear programming matrix
A	physical state
API, $(API)_t$	antecedent precipitation index
b_m	linear constraint limit
B	physical state
B_1, B_j	regression coefficients
c_n	cost or benefit coefficient of objective function
c_t^k	capacity of reservoir k at time t
Cf	crop factor
Ck	coefficient of kurtosis
Cs	coefficient of skewness
$\bar{d}$	average distance between data points
d_t^k	demand on reservoir k at time t
D	monthly duration of sunlight in percent
DF	degrees of freedom
$\|e\|$	mean deviation
exp, e	base of natural logarithms

LIST OF SYMBOLS (CONTINUED)

e_t^k	percentage of reservoir storage remaining after evaporation
E_o, ET	potential evaporation or evapotranspiration
Ep	pan evaporation
E_e^i	expected value for class i
E_o^i	observed value for class i
ER_k^I	error for k^{th} data point on I^{th} iteration
F	temperature dependent variable
G	empirical coefficient
H	monthly percentage of daylight hours
i, j	subscripts to denote two-dimensional variable
I	iteration or scan of data points
IR	irrigation requirement
j	subscript of one-dimensional variable
J	empirical coefficient
k	API recession factor
K_1, K_j	empirical consumptive-use coefficient
L_j	number of acres of crop j
m	number of reservoirs in system

LIST OF SYMBOLS (CONTINUED)

mm	number of rows in contingency tables
M	number of station observations or data points
MOHS	Monthly Operational Hydrometeorological Simulator
MOSS	Monthly Streamflow Simulation
Mx	median
n	sample size; number of cases
nn	number of columns in contingency tables
N_x, N_1, N_2, N_3, N	30-yr normal for specified stations
O_k	k^{th} station observation or data point
P	probability of an event
Pc	probability of being exceeded by chance
P_x, P_1, P_2, P_3	data points for specified stations
$P_{i,j}$	conditional probabilities
PE	potential evapotranspiration
Q_x, Q_1, Q_j	streamflow values
r	distance from a grid point to the k^{th} data point
R	precipitation; rainfall
R^*	annual mean precipitation

LIST OF SYMBOLS (CONTINUED)

s_{t-1}	reservoir storage or inventory at time $t-1$
s'_{t-1}	reservoir storage at time $t-1$ adjusted for evaporation losses
s^{k}_{t}	reservoir storage at time t for reservoir k
$\underline{s}^{k}_{t}$	minimum reservoir storage at time t for reservoir k
SE	standard error of skewness
SR	scan radius
St	skewness test
Sx	standard deviation
t	time; number of days; time period
$\overline{T}$	monthly mean temperature
T^{*}_{i}	climatological normal temperature for month i
$TC^{I}_{i,j}$	total correction for grid point (i,j) for I^{th} iteration
U, U_j	monthly crop consumptive-use
v^{k}_{t}	upper storage space required for reservoir k at time t
$w_{i,j}$	weighting factor for grid point (i,j) for k^{th} observation
x_t	reservoir release for time t

LIST OF SYMBOLS (CONTINUED)

x_t^k	scheduled downstream release for reservoir k at time t
$\bar{x}_t^k$	maximum downstream release for reservoir k at time t
$\underline{x}_t^k$	minimum downstream release for reservoir k at time t
X_i, x_i, x_j	values of variate
X_{MAX}	maximum value of variables
$\bar{X}$	mean
Y_k^I	estimate of observation for k^{th} station for I^{th} iteration
$\underline{Y}_{i,j}^I$	estimate of grid point (i,j) for I^{th} iteration
Z_t, Z_{t+1}	physical system represented by some state in time
Z^*	mathematical objective function
α_i, α_1^k, α_2^k	probability of an event for reservoir k
β_t	decision parameter
γ_t	inflow to a reservoir at time t
γ_t^k	inflow to the k^{th} reservoir at time t
$\Gamma^{\frac{1}{2}}$	square-root of a random component
ΔS	surface runoff or streamflow
χ^2	Chi-square value or test

1. INTRODUCTION

a. Statement of the problem

The synthesis of the hydrologic cycle to obtain optimal use of water resources is extremely difficult due to the complex interrelationships between meteorological and hydrological variables. Past research has concentrated on the statistical analysis of surface runoff records used as stochastic input into models which simulate streamflow records for periods of days, months, and years. Streamflow is a variable and erratic parameter. A forecast of runoff will include a certain amount of error or imply some uncertainty as to the accuracy of the forecast.

Surface runoff is the result of precipitation and antecedent hydrologic conditions in a river basin. Accurate forecasts of precipitation and temperature, from which evaporation, evapotranspiration, soil-moisture conditions, and surface runoff can be determined, could give better results than using statistical properties of the streamflow records. Any error, of course, in the meteorological forecasts will produce error in the resulting streamflow amounts. Also, the following may introduce additional errors which could be cumulative: precipitation amounts will vary in time and space; basin conditions will vary with geology, surface cover, crops, irrigation, and soil conditions; and adequate precipitation and runoff relationships may not have been determined.

The hypothesis underlying the research presented in this paper is that "extended-range" or 30-day meteorological forecasts of precipitation and temperature can provide better estimates for adequate management of a water resource system than methods using monthly streamflow statistics of climatology. The validity of this hypothesis will depend upon:

1. the accuracy of the 30-day meteorological forecasts in predicting precipitation and temperature conditions;
2. the adequacy of the empirical relationship between rainfall and surface runoff;
3. the exactness of the relationship between temperature and evaporation, evapotranspiration, and consumptive use; and
4. the effectiveness of the mathematical model to incorporate forecast values of streamflow, evaporation, consumptive use, and other demands into operational decisions for a reservoir system.

Several operational policies were programmed and tested to determine which gave the optimal result or the "most satisfying" policy. Stochastic meteorological forecasts were considered to improve the application of simulation methods for periods of 15 days to one month. Instead of generating completely random sequences of precipitation and temperature values by Monte Carlo techniques, the range of the variables was constrained by the 30-day meteorological forecasts. At present, the 30-day forecasts or "outlooks" are the only forecasts made for extended periods of time. For long-term information on the variability of the weather, climatology must be used. When current techniques of numerical weather prediction are improved, they may provide the means for simulating hydrometeorological data for time periods of several months or years.

b. Related studies

The field of water resources research has prompted the collaboration of hydrologists, meteorologists, and systems engineers to develop realistic models which adequately synthesize the hydrologic cycle. The hydrologists have provided models to simulate streamflow or runoff; the meteorologists have provided numerical forecast models to predict rainfall, temperature, and other atmospheric parameters; and the systems engineers have developed computer algorithms and programming techniques which optimize the operations of individual reservoirs or multiple-reservoir systems. Water resources management requires a complete analysis of the physical variables involved in any proposed model to minimize the mathematical errors. Many of the parameters must be described through statistics rather than through deterministic relationships. This necessitates the use of stochastic models.

Amorocho and Hart (1964) provide an overview and critique of present methods of synthetic hydrology. Parametric and stochastic hydrology are concerned with determination of input and output factors for the prediction of future conditions or the evaluation of past decisions. Parametric hydrology deals with correlation, linear, and non-linear analysis. Stochastic methods use the Markov-Chain and/or Monte-Carlo simulation and offer promise as a tool for operational planning and management. However, such methods are vulnerable to error due to their dependence upon the statistical properties of the data considered. Synthetic hydrology combines into one complex of factors, ideas or elements from the entire field of hydrology. Synthetic hydrometeorology must consider the field of meteorology, as well as hydrology.

Fiering and Jackson (1971) present a summary of the current methods used in hydrologic modeling and the management of water resources. Their monograph contains a description of the statistical techniques of operational hydrology, an evaluation of frequency distributions applied to stochastic hydrology, and examples of Markov and multi-lag hydrologic models. However, these models consider only the analyses of hydrologic data for the simulation of streamflow and the synthesis of water resource systems. Previous to this monograph, Fiering (1967) introduced the basic theory for synthesis and simulation, as well as formulating techniques and objective functions for applying the fundamentals of decision theory to the problems involved in this new field of interdisciplinary engineering.

Recently, the Texas Water Development Board (1970a, 1970b, 1971a) developed specialized computer programs for the planning, development, and management of the water resources of Texas. A systems approach is used on this complex problem that incorporates mathematical programming algorithms, economic evaluation, and simulation techniques. The programs were designed to find a minimum-cost solution for the water distributed in a constrained system. The water resource system operates on monthly time increments for the simulation of physical variables. This eliminates the necessity for routing of flood waves or hydrographs which must be considered for time periods of hours or days. To generate hydrologic input into the system, a program entitled "Monthly Streamflow Simulation (MOSS)," was used (see Hydrologic Engineering Center, 1971). The program was designed to analyze interrelated monthly streamflow records and, using a regression equation, generate hypothetical streamflows that maintain their statistical characteristics for some specified length of time. Much of this work has been accomplished under the guidance of Beard (1965, 1967), who has done extensive work on hydrologic simulation schemes using historic streamflow records as input.

Maass *et al*. (1962) provide a detailed summary of the techniques used in the design and formulation of an operating policy for operation of water resource systems by simulation analysis. Stated in simple terms, an operating policy is a set of rules for releasing and retaining water from surface-water reservoirs. The three major decisions that constitute the policy are the apportionment of water: (1) between reservoirs, (2) for various purposes or demands, and (3) among time periods. Whatever factors constitute the policy, they must be consistent with feasible management. The length of the time interval and the degree of knowledge of future hydrological or meteorological conditions are the crucial factors in attaining a consistent operational policy. Benson and Matalas (1967) deviated from the conventional method of simulating streamflow which utilizes statistics determined from historic records by use of a generalized multiple-regression equation between the hydrologic characteristics of the river basin.

Wolman (1963) summarized the status of water resources management and planning and provided a stimulating overview of the hydrologic disposition of precipitation. He included a discussion of arid and semi-arid basin characteristics emphasizing the need for more accurate meteorological forecasts, both short-term and long-range.

Sewell (1968) discussed the social and economic effects of atmospheric management and the role of simulation techniques applied to various physical systems. He emphasized the need for work to be done on the application of synthetic precipitation sequences to the simulation of water resource systems. A summary of several watershed models, such as the Fiering multi-lag and Stanford (Crawford-Linsley) systems is presented along with suggested additions and changes that are needed. One suggestion is the inclusion of precipitation simulation in current models. He also describes a river-system model to handle weather data that would require (1) historic precipitation and climatological data, (2) a synthetic precipitation generator, (3) a precipitation-runoff model, (4) a streamflow-forecast model, (5) an operational policy scheme, and (6) a sub-model concerned with economic evaluation. Further elaboration is made upon each section of the proposed model, presenting the current status, deficiencies, and needs of each section.

The Committee on Hydrometeorology of the American Society of Civil Engineers (1967) analyzed hydrometeorological systems requirements with emphasis on day-to-day operations. The requirements suggested for a satisfactory system must include river and reservoir conditions, meteorological elements affecting runoff and water use, and basin physical conditions that regulate the amount of surface runoff. They state that, "Longer-range weather forecasts are highly desirable, and the hydrologist should be prepared with hydrologic procedures which will utilize extended-range weather forecasts, for the time in which these technical advances are made in meteorology."

The two prior presentations omit any mention of stochastic meteorological forecasts which could be relevant to the problem of forecasting or simulating streamflows. Since most streamflow is a result of precipitation or rainfall that occurs, short range (3- to 5-day) forecasts or extended (30-days or longer) forecasts may provide valuable input for hydrologic models. Namias (1951) presented a summary of statistical methods used in extended forecasting. Some of these are the pressure-trend method, the multiple-correlation procedure, the method of singularities, the concept of symmetry points, and the classification of "weather types." His research showed that mean maps of atmospheric parameters coincide to a large extent with the average temperature and precipitation anomalies. This in turn can be used to predict general characteristics or broad trends in the weather.

Namias (1953, 1968) also presented summaries of an experiment conducted by the United States Weather Bureau* designed to provide weather forecasts for monthly time periods. The 30-day precipitation and temperature forecasts are projected from frequency distributions and patterns of normal tropospheric circulation. The forecasts utilize methods of synoptic, dynamic, kinematical, physical, and statistical meteorology. The forecast procedure involves preparation of a monthly mean prognostic chart for the 700-mb level from which temperature, precipitation, and sea-level pressure patterns can be estimated. Values are obtained using regression equations between atmospheric variables. Although the forecast procedure is weighted toward synoptic and statistical analysis, the forecasts do provide an improved knowledge of future weather. Forecast verification (Namias, 1964 and U.S. Weather Bureau, 1961) has shown they are more useful than climatological probabilities.

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* Renamed in 1971, National Weather Service of the National Oceanic and Atmospheric Administration.

O'Connor (1963) discussed the large-scale atmospheric motions and planetary waves in relation to extended forecasts of precipitation and temperature. He notes that these forecasts are best suited for large geographical regions and that decisions utilizing any forecast should be tempered by probabilities expressing their accuracy for that geographical region.

Krick (1959) considers accurate streamflow forecasts as the foundation of water resources management because streamflow variability affects decisions concerning flood control, hydroelectric power supply, irrigation of crops, and municipal water supply. He outlines procedures which can be used to forecast values of precipitation and temperature for a water year and explains how the forecasts are converted to representative values of surface runoff. The procedure synthesizes forecasts of "weather types," i.e., sequential pressure patterns representing stable flow in the atmosphere, from historical patterns. From these forecasts, streamflow is synthesized by matching historical records. Results showed that the computed inflows were within 20 percent of the observed values. This research was conducted in the Columbia River basin where weather patterns are well-defined and orographic rainfall is predominant. Other methods need to be developed for arid and semiarid regions of the United States where convective precipitation during the summer months produces highly variable streamflow.

c. Objectives

The objectives of this study were to investigate the use of hydrometeorological forecasts in providing critical information for operational decision-making in water resources management; to provide a hydrometeorological model that can be used in the current monthly operation of existing reservoirs; to determine if optimal operation of an existing reservoir system (the Concho River basin in west Texas) can be realized through hydrometeorological forecasting for a period of historical observations and forecasts; and to determine if this model will provide a means of obtaining optimal use of water resources.

To obtain these objectives, the solution approach was organized:

1. to establish a complete biweekly and monthly stochastic data base for meteorological and hydrological variables in the Concho River basin in west Texas;
2. to determine the following statistical parameters for streamflow, evaporation, precipitation, mean ambient air temperature, and antecedent precipitation index (API) for either a minimum 15-year period of record, or for the maximum record length available:

   a. mean or normal,
   b. median,
   c. standard deviation,
   d. mean deviation,
   e. coefficient of kurtosis, and
   f. coefficient of skewness;

3. to fit hydrometeorological data which can be used to generate synthetic sequences of data to the following frequency distributions:
   a. normal,
   b. square-root-normal,
   c. cube-root-normal, and
   d. log-normal;

4. to test Markov transitional probabilities or "Markov-Chains" for biweekly and monthly sequences of hydrometeorological data when temperatures are <u>above</u> <u>normal</u>, <u>normal</u>, or <u>below</u> <u>normal</u>, and when precipitation is <u>heavy</u>, <u>moderate</u>, or <u>light</u>;

5. to verify the forecast accuracy of the 30-day meteorological forecasts of the National Weather Service (NWS) for the Concho River basin in west Texas;

6. to use the 30-day temperature and precipitation forecasts published by the Extended Forecast Division, National Weather Service, as input for a "Monthly Operational Hydrometeorological Simulator (MOHS)," and to establish and verify empirical

relationships between precipitation and runoff, and temperature and evaporation;

7. to use an objective analysis program to analyze randomly distributed data synthesized from the hydrometeorological forecasts in a rectangular coordinate system;
8. to use linear and stochastic-linear programming techniques to incorporate operations research, decision analysis, and hydrometeorological risk criteria into the operating policy for a reservoir system; and
9. to compare the historical operation of the reservoirs in the Concho River basin with the operating policy established by the model to determine if 30-day meteorological forecasts provide a better operation of the reservoir system. This was done by comparing results using:
    a. the 30-day forecasts as "perfect" predictors,
    b. the 30-day forecasts adjusted by their accuracy or probabilities of being correct to obtain an "expected value" forecast, and
    c. the historical streamflow records from which decisions were based on statistical information.

2. THE PHYSICAL SYSTEM

a. Geography and climatology

Any study of a physical system or phenomenon usually begins with the scientific observation of the pertinent parameters which provide a sufficient description of the system. Man has long realized the need for an adequate water supply and has measured its availability and loss. Rainfall and streamflow measurements provide knowledge of the availability of water, while measurements of evaporation and soil retention provide an estimation of water unavailable for the needs of man. The geographical location and climatology of any river basin or system also will affect the design of any model that describes that system.

The basin chosen for analysis and synthesis is the Concho River basin in west Texas. Figure 1 shows the location of the basin within the state of Texas. The basin is a subset of a larger river system, the upper Colorado River shown in Fig. 2. A schematic of the existing and proposed reservoirs and their relationships to each other within the upper Colorado River basin is presented in Fig. 3. A description of these reservoirs is given in Table 1. The portion of the Concho River basin considered in this study is located west of the city of San Angelo, between 31 and 32 deg North latitude, and between 100 and 102 deg West longitude. The maximum

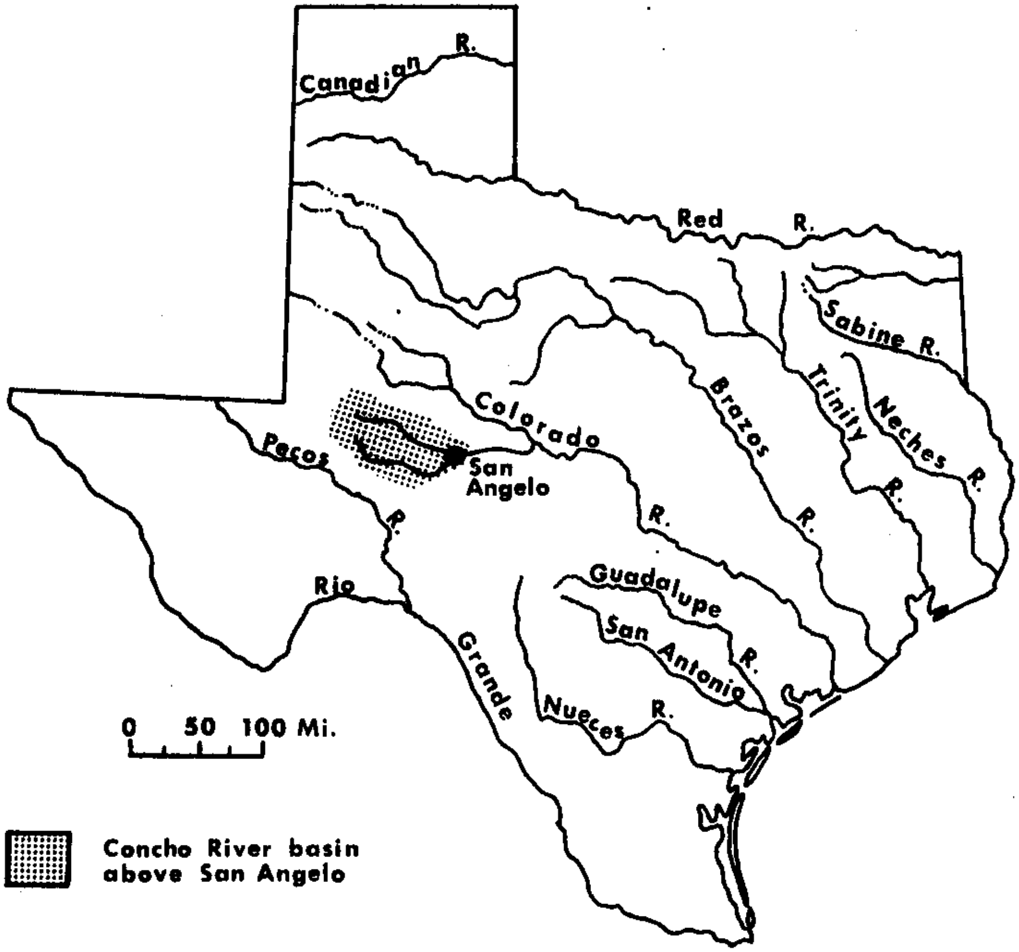


Fig. 1. Location of the Concho River basin in west Texas.

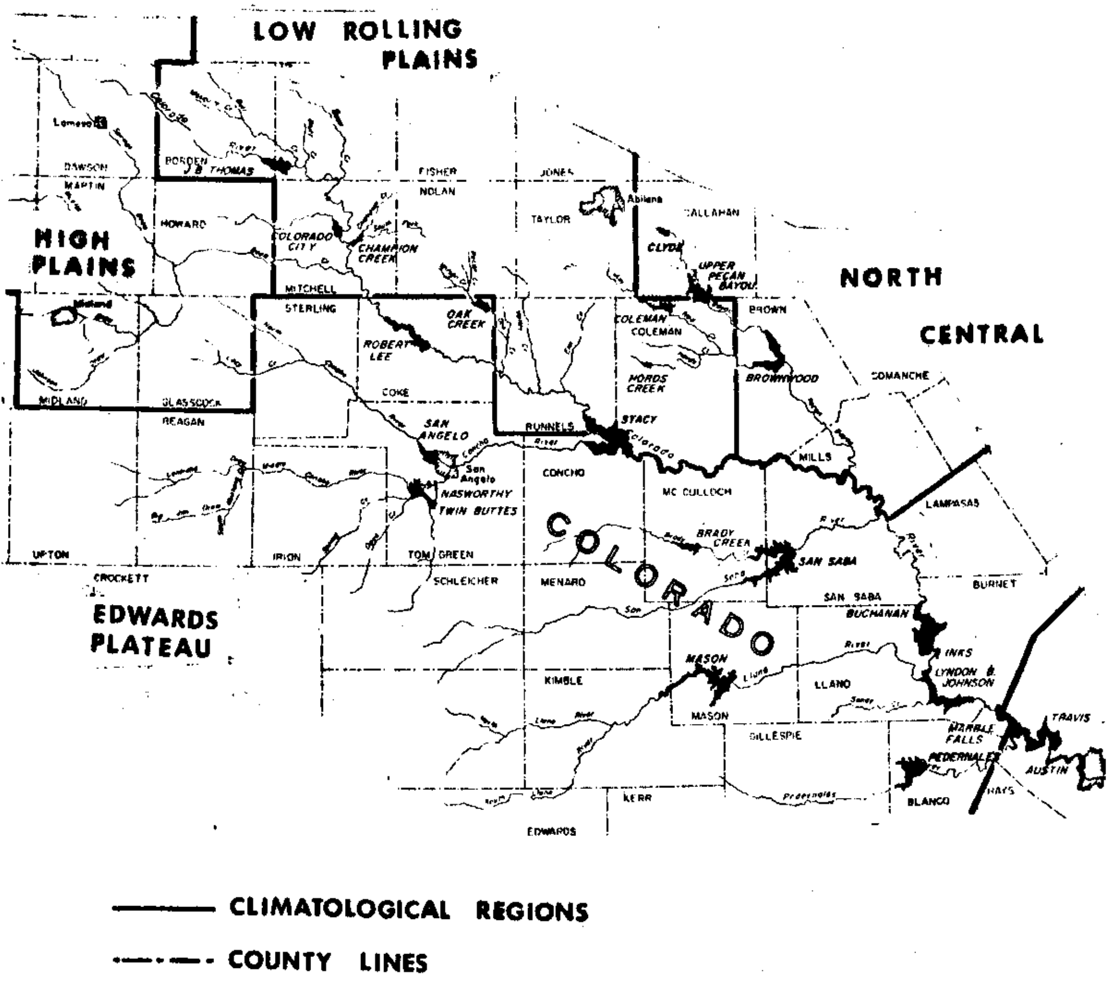
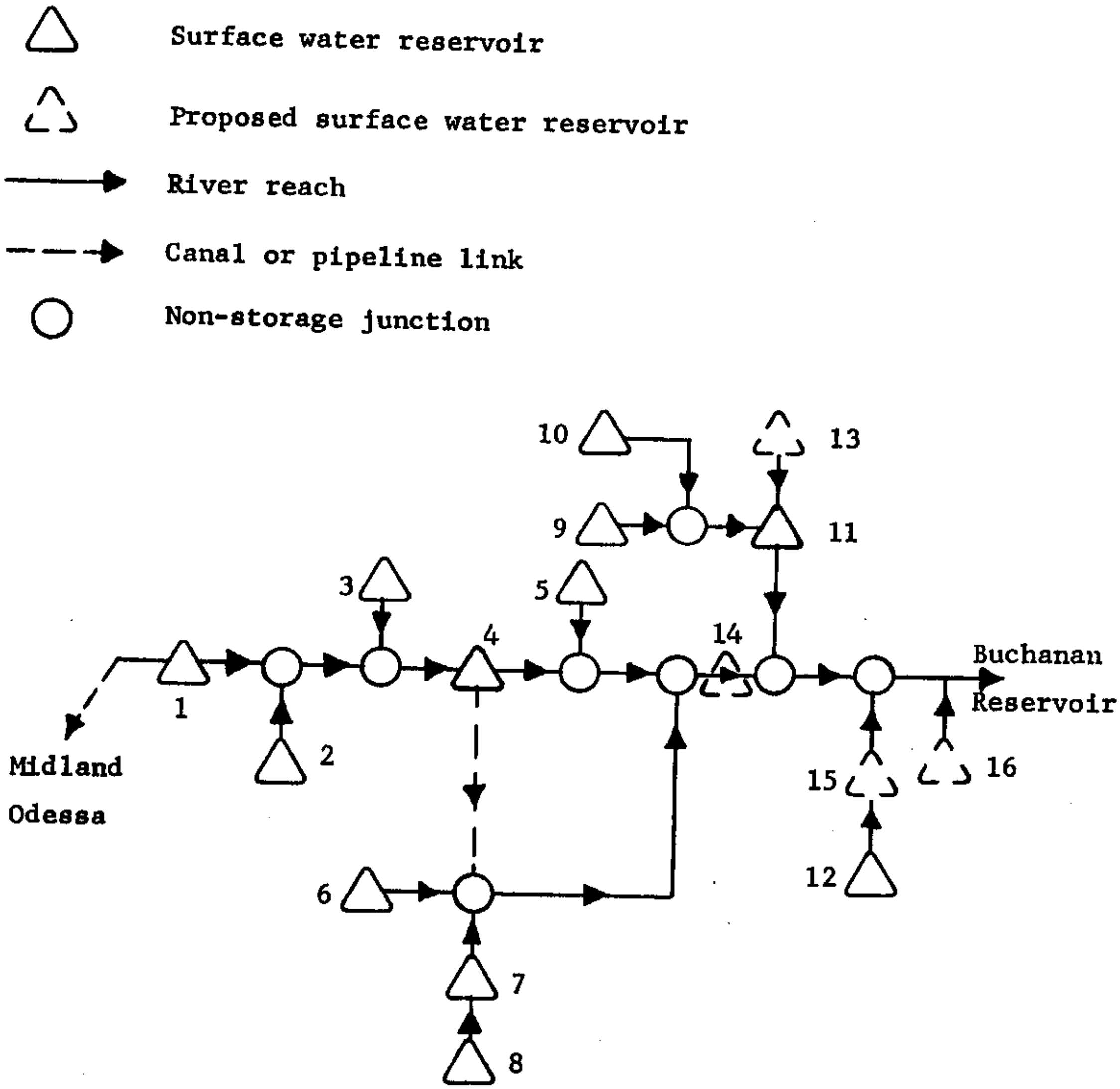


Fig. 2. The upper Colorado River basin in west Texas.



• Fig. 3. Schematic of water resource system in the upper Colorado River basin in west Texas. (Numbers refer to reservoirs listed in Table 1 and shown in Fig. 2.)

Table 1. Existing and proposed reservoirs in the upper Colorado River basin in west Texas.

RESERVOIR	STREAM	DRAINAGE AREA*	CONSERVATION STORAGE**
Existing			
1. Lake J.B. Thomas	Colorado	3,524	172.0
2. Lake Colorado City	Morgan Creek	322	21.6
3. Champion Creek	Champion Creek	203	36.8
4. E.V. Spence (Robert Lee)	Colorado	15,740	454.8
5. Oak Creek	Oak Creek	244	34.5
6. San Angelo	North Concho	1,488	107.0
7. Lake Nasworthy	South Concho	3,833	12.4
8. Twin Buttes	Middle Concho	3,724	171.9
9. Hords Creek	Hords Creek	48	8.5
10. Coleman	Jim Ned	299	36.9
11. Brownwood	Pecan Bayou	1,535	133.7
12. Brady Creek	Brady Creek	513	28.6
Proposed			
13. Upper Pecan Bayou	Pecan Bayou		93.5
14. Stacy	Colorado		650.0
15. San Saba	San Saba		195.6
16. Mason	Llano		319.9

* This is total drainage area in sq mi including areas that are non-contributing to surface runoff.

** Storage capacity in thousands of acre-ft.

dimensions of the basin are about 80 mi in width by about 110 mi in length. The drainage area is approximately 5,380 sq mi, of which about 4,100 sq mi contribute to surface runoff.

The climate of the region can be classified as sub-humid to semi-arid with an average annual temperature of 67F. The variation of precipitation from year-to-year is very great, with a range from 5 in. to 40 in. per year. The average annual precipitation is nearly 20 in. at the eastern edge of the basin and decreases to about 15 in. at the western edge. Any drastic variation in precipitation amounts from month-to-month and year-to-year can produce "critical periods" in the operation of the reservoir system. These "critical periods" must be planned for so that the supply of water in the reservoir system is not depleted by inconsistent operational policies.

Portig (1962) presents a map and graphs, Fig. 4, which describe the climatological rainfall regimes in Texas. For zone C, the graph indicates two wet periods in the spring and fall with a drier period during the summer months. In June and July when the need for water is high, the amount of water received is only 8 percent of the annual total or approximately 0.20 in. Another important consideration is that the evapotranspiration and evaporation exceed the rainfall during the summer months. This results in a lack of soil moisture which inhibits the amount of surface runoff through increased infiltration of precipitation. Since the graphs

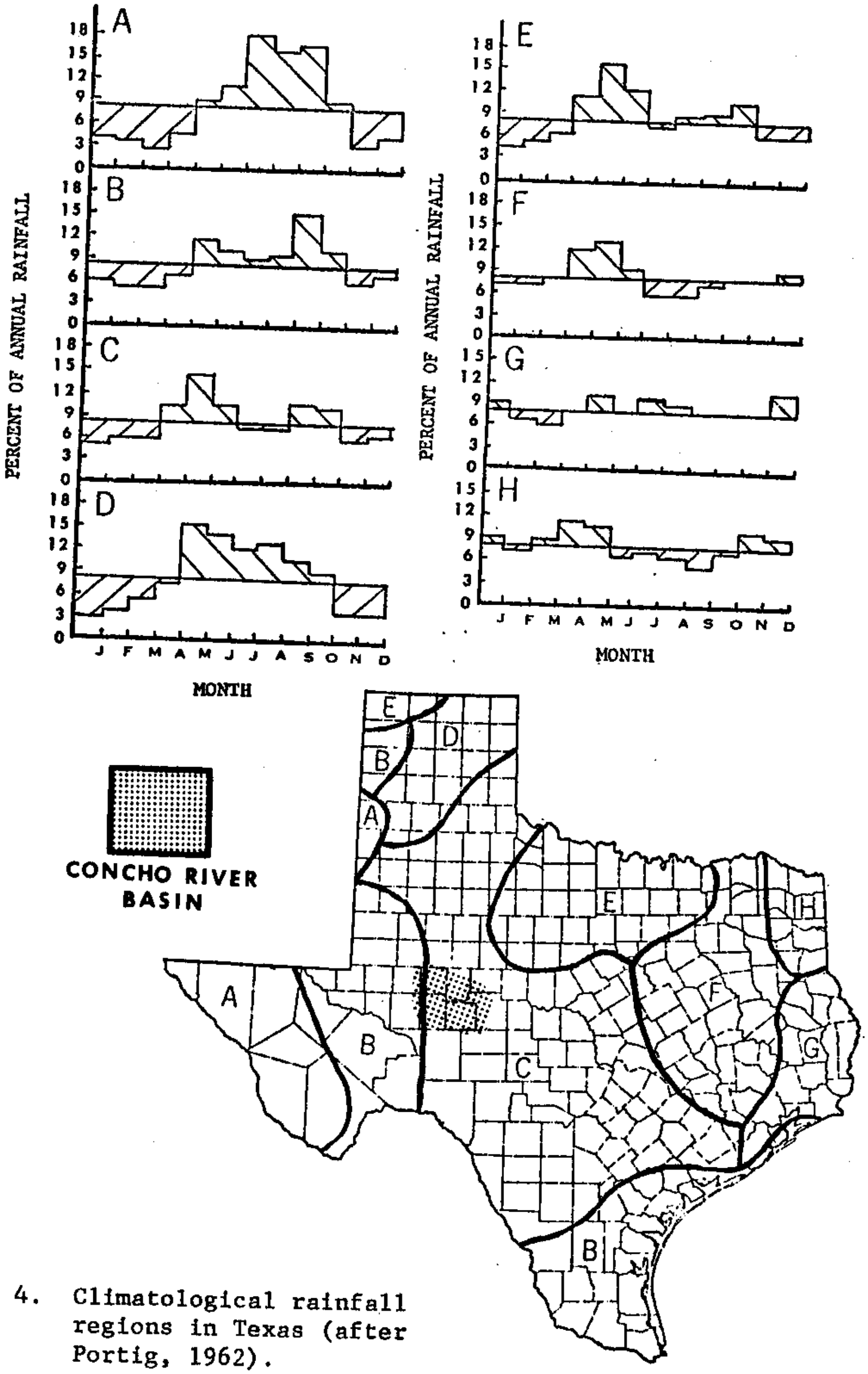


Fig. 4. Climatological rainfall regions in Texas (after Portig, 1962).

in Fig. 4 represent average conditions, the variability of the weather will cause considerable variability in the hydrologic conditions of any river basin. Long periods of persistent weather may create conditions unfavorable to surface runoff, e.g., hot and dry weather causes dry soil conditions due to the absence of rainfall and considerable evaporation of soil moisture.

Sauer (1970) provides information on the geology of the Concho River basin and the surrounding regions. In Fig. 2 are shown the climatological regions assigned by the NWS and the counties in relation to the Colorado River basin. The Concho River basin includes the counties of Upton, Glasscock, Reagan, Sterling, Irion, Crockett, Coke, Tom Green, and Schleicher which lie within three climatological regions. Along the North Concho River, the uppermost portion of the basin (about 10 percent) is located in two divisions - the High Plains and the Low Rolling Plains. These regions are characterized by deep soils and fairly level topography. The remaining 90 percent of the basin is in the region of the Edwards Plateau, which is characterized by rolling to rough terrain. On steep slopes the soil is non-existent and there are exposed rocks composed mainly of highly fractured limestone. In the plains areas the soils are 12 in. or more thick. This combination of soil cover and geology cause high infiltration of minor rainfall amounts which inhibits surface runoff. About one-third of the region is covered by heavy brush, composed mainly of juniper (called "cedar" locally) and mesquite. There are numerous stock ponds and small reservoirs that cover not more than 8 percent of the basin.

b. The reservoir system

A surface water resource system is defined as the physical configuration of streams, rivers, reservoirs, and river basins that considers surface water inputs to those facilities to provide water to meet the demands of water services and water-related products. The physical capacities of reservoirs and the structure of the system are designed to meet the demands of conservation water storage, power supply, flood control, and/or the irrigation of crops.

The Concho River basin contains three reservoirs which are shown in detail by Fig. 5. They are the Twin Buttes Reservoir, Lake Nasworthy, and the San Angelo Reservoir. Lake Nasworthy is located below Twin Buttes. Its water level is generally controlled by releases from the larger reservoir, since it has very little drainage area contributing to direct runoff. Inflow to the Twin Buttes Reservoir is supplied by streamflow in the South Concho River, the Middle Concho River, Dove Creek, and Spring Creek. Inflow to the San Angelo Reservoir is supplied by streamflow in the North Concho River. Table 2 provides information on the physical configuration of the three reservoirs. In addition, Lake Nasworthy has a minimum

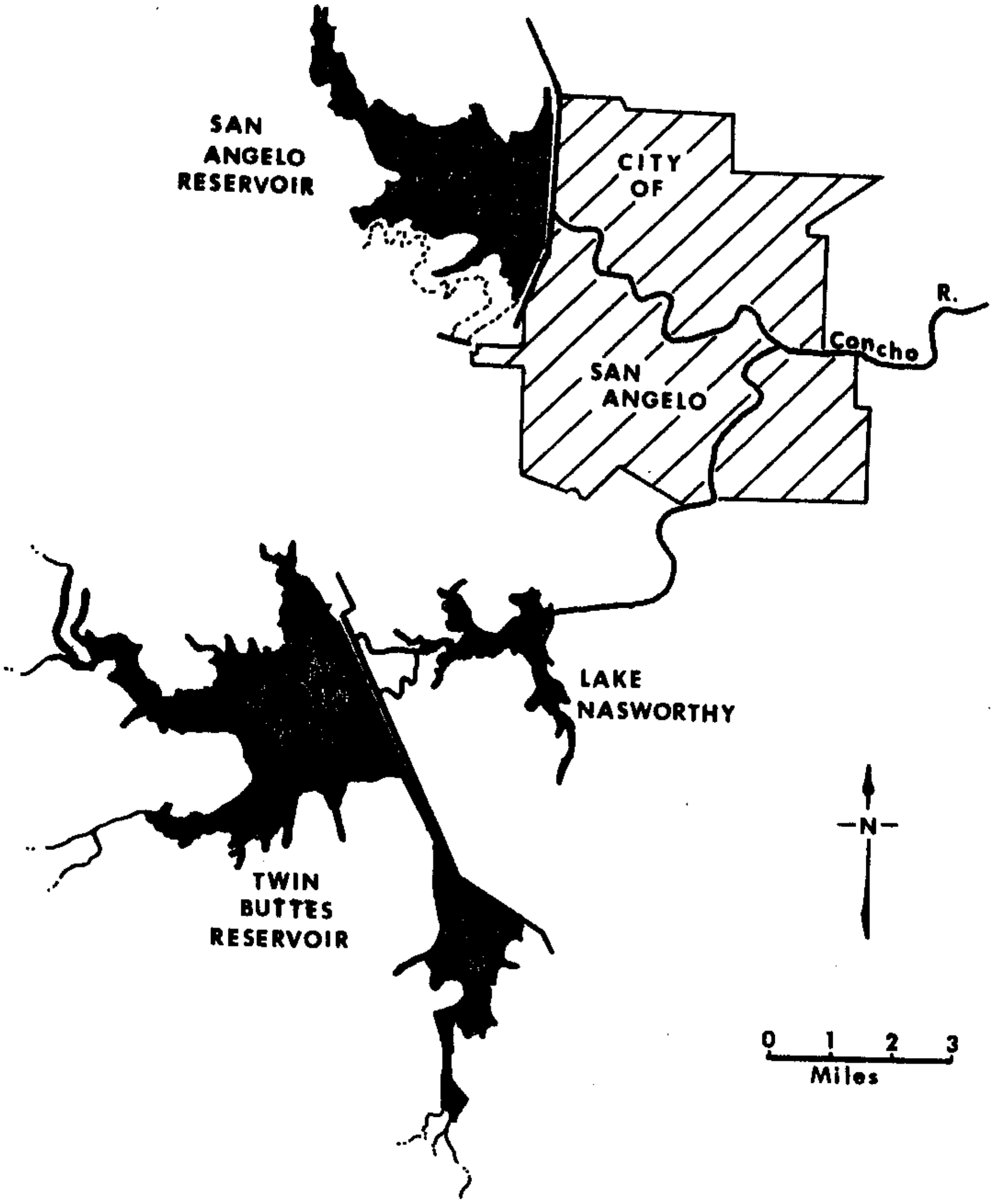


Fig. 5. A detailed map of the reservoirs in the Concho River basin in relation to the city of San Angelo.

operation level of 7,000 acre-ft for a cooling plant that cannot operate when this level is violated.

Table 2. Drainage area and incremental capacities of each reservoir.

Reservoir	Drainage Area *	Flood** Control	Conservation Storage **	Dead ** Storage	Total** Storage
San Angelo	1511	277.2(12.7)	119.2(5.4)	0.0	396.4(12.7)
Twin Buttes	2550	454.4(23.5)	186.2(9.1)	8.3	640.6(23.5)
L.Nasworthy	100	0.0	12.4(1.6)	0.0	12.4(1.6)

* area in sq mi contributing to surface runoff.

** capacities in thousands of acre-ft and in parentheses is surface area in thousands of acres.

The reservoir system is defined by the configuration of the reservoirs and by the purposes to which water or water storage are allocated. The multi-reservoir system in the Concho River basin has a parallel and series configuration. Twin Buttes and Lake Nasworthy represent reservoirs that are linked in series and, when San Angelo reservoir is considered, the three reservoir system has a parallel operation. The flood control storage for each reservoir is that portion of reservoir storage designed to control the Project Design Flood for that particular drainage basin. The conservation storage is the total amount of water that will be required to sustain a particular reservoir over periods of drought for recreation, municipal, power, and agricultural purposes. Dead storage is the water that cannot be emptied from the reservoir. Figure 6 is a schematic of a typical water storage allocation to a reservoir.

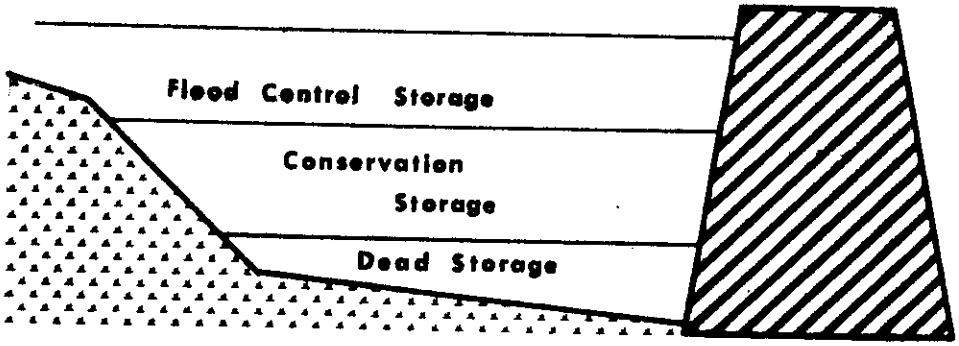


Fig. 6. A schematic of reservoir storage allocation.

Figure 7 (Texas Water Development Board, 1971b) contains the storage-capacity and surface-area curves for various water-surface elevations for the Twin Buttes and San Angelo reservoirs. Similar curves for Lake Nasworthy are not available; however, estimates were obtained from values given in the description of the reservoir design. The surface area of each reservoir is needed to estimate the amount of evaporation. The water contained in these reservoirs is allocated mainly to recreation, irrigation, municipal, and industrial purposes. The main municipal and industrial diversions are by the city of San Angelo located downstream of the three reservoirs. The average monthly diversion of water by the city of San Angelo is 900 acre-ft (2.9×10^8 gal). On the South Concho River, water is diverted for the irrigation of crops by the South Concho Irrigation Canal before the water reaches the Twin Buttes Reservoir. The average monthly diversion of water by

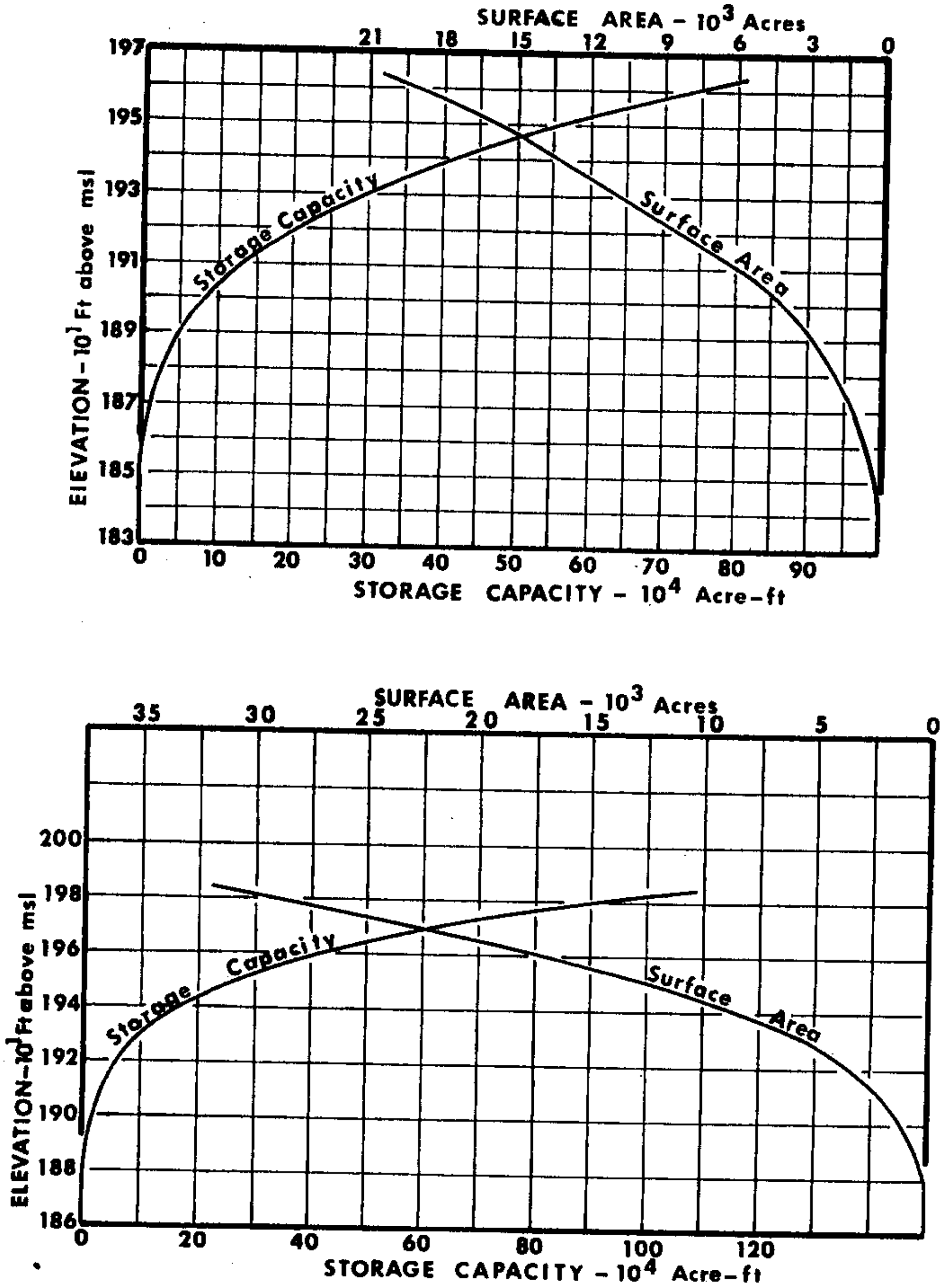


Fig. 7. Elevation, storage capacity, and surface area curves for the San Angelo (above) and Twin Buttes (below) Reservoirs.

the canal is 200 acre-ft. Also, Spring Creek and Dove Creek have many small diversions above the recording gage for the purpose of irrigating crops. The streamflow in Dove Creek also is regulated partly by two small channel dams located upstream of the streamflow gage.

c. Hydrometeorological data

In order to formulate an adequate mathematical model for the operation of a reservoir system that will include meteorological and hydrological information, historical data must be studied. Sources of the data used to construct the hydrometeorological model are the U. S. Geological Survey (U.S.G.S.), the Texas Water Development Board (T.W.D.B.), and the National Oceanic and Atmospheric Administration (N.O.A.A.). Meteorological data used in this study, including the station number, assigned code name, and period of record used, are listed in Table 3. The hydrological data used are listed in Table 4. The data chosen for analysis were:

1. precipitation in inches,
2. adjusted pan evaporation (gross or lake evaporation) in inches,
3. streamflow in acre-ft,
4. mean ambient air temperature in degrees Fahrenheit,
5. antecedent precipitation index (API) in inches,
6. reservoir water storage in acre-ft, and
7. water demand in gallons or acre-ft.

A detailed map of the Concho River basin is given in Fig. 8, which shows the location of stations situated within the confines of the basin. Additional stations listed in Table 3, but not shown, were

Table 3. Stations providing precipitation and antecedent precipitation index (API), mean ambient air temperature, and evaporation data.

Station Number	Station Name	Code	Biweekly** Mid-monthly	No. Yrs.	Monthly	No. Yrs.
PRECIPITATION AND API						
0493	Ballinger	BAL	1921-70	50	1901-70	70
0528	Barnhart	BRN	1949-65*	17	1941-65*	25
0776	Big Lake	BGL	1949-70	22	1941-70	30
1511	Case Ranch	CSR	1949-70	22	1941-70	30
1735	Christoval	CHR	1949-65*	17	1941-65*	25
1974	Cope Ranch	CPR	1949-70	22	1941-70	30
2066	Cox Ranch	CXR	1949-65*	17	1941-65*	25
2741	Eden 1	EDN	1939-70	32	1931-70	40
2812/2317	Eldorado 11NW	ELD	1949-70	22	1941-70	40
3253	Forsan	FSN	1949-70	22	1949-70	22
3401	Funk Ranch	FKR	1949-70	22	1941-70	30
3445	Garden City 1E	GDC	1921-70	50	1916-70	55
5822	Menard	MEN	1921-70	50	1916-70	55
5825/5832	Menard 13WNW	MN3	1949-65*	17	1941-65*	25
5859	Mertzon	MER	1941-70	30	1941-70	30
6747	Paint Rock	PRK	1931-70	40	1921-70	50
7669	Robert Lee	RLE	1949-70	22	1941-70	30
7942/7943	San Angelo	SAG	1921-70	50	1911-70	60
8630	Sterling City	STC	1931-70	40	1926-70	45
8920	Tennyson	TEN	1949-65*	17	1941-65*	25
9304	Vancourt	VAN	1949-65*	17	1941-65*	25
9499	Water Valley	WTV	1949-70	22	1941-70	30
MEAN AMBIENT AIR TEMPERATURE						
0493	Ballinger	BAL	1921-70	50	1921-70	50
0786	Big Spring	BGS	1944-70	27	1944-70	27
2741	Eden 1	EDN	1939-70	32	1939-70	32
6734	Ozona	OZA	1948-70	23	1948-70	23
7943	San Angelo	SAG	1931-70	40	1931-70	40
EVAPORATION						
7940	San Angelo Dam	SAD	1954-70	17	1954-70	17

* station discontinued

** API monthly values obtained from these periods of record

Table 4. Stations providing streamflow data.

Station Number	Station Name	Code	Period of Record	No. Years
8-1275	S. Concho R. at Christoval	SCC	1931-70	40
8-1280	S. Concho Irrigation Canal	SCI	1940-70	31
8-1284/85	Middle Concho R. above Tankersly	MCT	1931-70	40
8-1293	Spring Creek near Tankersly	SPT	1931-70	40
8-1305	Dove Creek at Knickerbocker	DCK	1961-70	10
8-1335	N. Concho R. near Sterling City	NCS	1941-70	30
8-1340	N. Concho R. near Carlsbad	NCC	1926-70	45
8-1350	N. Concho R. at San Angelo	NSA	1948-70	23
8-1360	Concho R. near San Angelo	CSA	1921-70	50

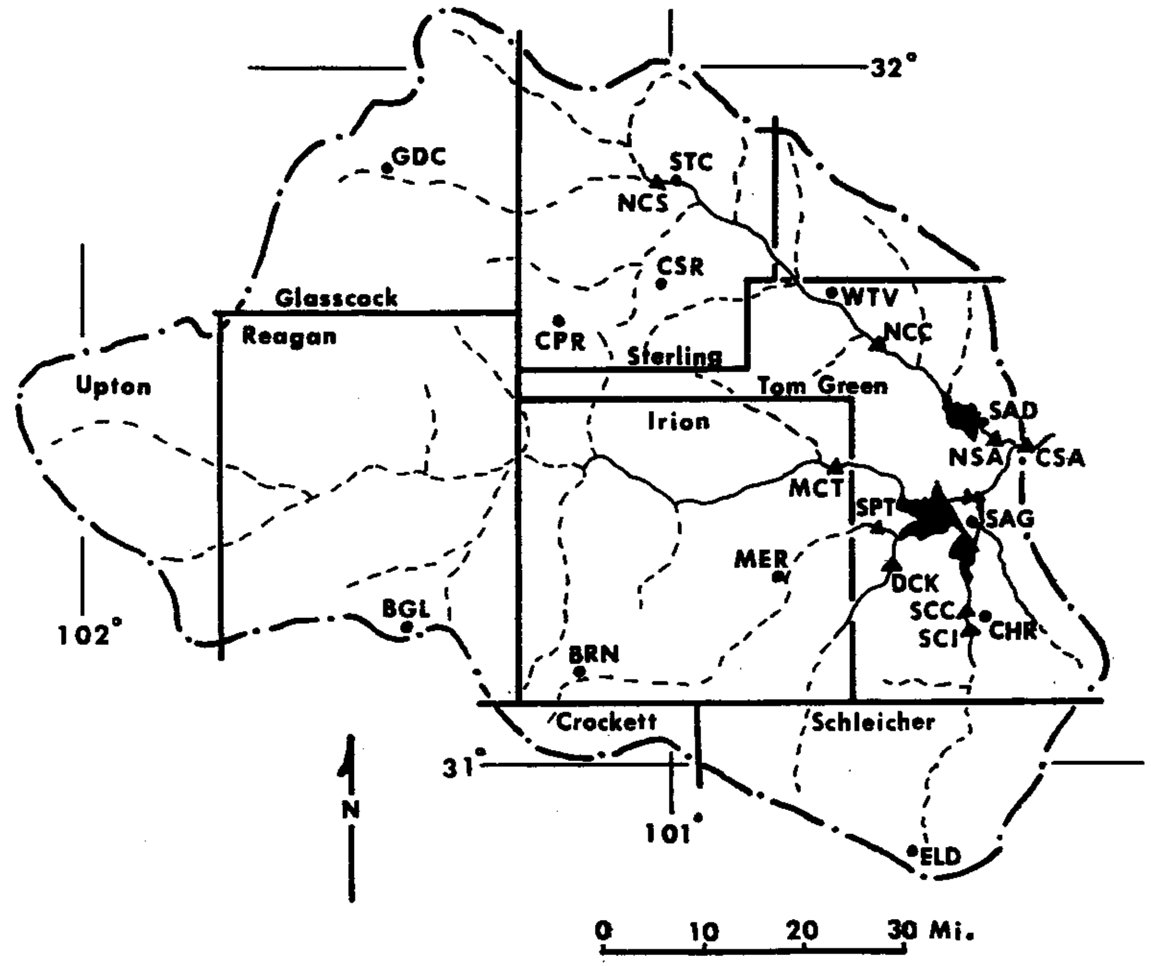


Fig. 8. A detailed map of the Concho River basin.

needed for an objective analysis procedure. This procedure is described in Section 3f1.

Daily data were extracted from the station records and summed or averaged into biweekly, "mid-monthly" (periods 1a through 12a), and monthly values. The periods used can be found in Table 5 with a period number to facilitate later discussion of simulated sequences of hydrometeorological data. These time periods were used because they conform to the forecast periods of the 30-day meteorological forecasts which begin on the 1st and 16th day of each month. Several inconsistencies, which are apparent in Tables 3 and 4, require explanation at this time. In the list of precipitation and API stations, there are three with dual station numbers. These stations are within 5 mi of each other or were involved in minor changes in the station location. Their records were combined or used to supplement existing records in order to provide a more complete and longer period of record. Also, the length of record for monthly data beginning on the 1st and 16th day of the month are not the same. This occurred because daily records were not available for the entire period of monthly data. Monthly data are readily available and widely published. Complete daily records for some meteorological stations are available from published climatological records only since 1949.

For the streamflow records, the Middle Concho above Tankersly has two numbers listed because the records for two locations were combined to give

Table 5. Time periods used in data analysis.

Period No.	Time Period	No. Days
1	1 January - 31 January	31
2	1 February - 29 February	29
3	1 March - 31 March	31
4	1 April - 30 April	30
5	1 May - 31 May	31
6	1 June - 30 June	30
7	1 July - 31 July	31
8	1 August - 31 August	31
9	1 September - 30 September	30
10	1 October - 31 October	31
11	1 November - 30 November	30
12	1 December - 31 December	31
1a	16 January - 15 February	31
2a	16 February - 15 March	29
3a	16 March - 15 April	31
4a	16 April - 15 May	30
5a	16 May - 15 June	31
6a	16 June - 15 July	30
7a	16 July - 15 August	31
8a	16 August - 15 September	31
9a	16 September - 15 October	30
10a	16 October - 15 November	31
11a	16 November - 15 December	30
12a	16 December - 15 January	31
1b	1 January - 15 January	15
2b	16 January - 31 January	16
3b	1 February - 15 February	15
4b	16 February - 29 February	14
5b	1 March - 15 March	15
6b	16 March - 31 March	16
7b	1 April - 15 April	15
8b	16 April - 30 April	15
9b	1 May - 15 May	15
10b	16 May - 31 May	16
11b	1 June - 15 June	15
12b	16 June - 30 June	15
13b	1 July - 15 July	15
14b	16 July - 31 July	16
15b	1 August - 15 August	15
16b	16 August - 31 August	16
17b	1 September - 15 September	15
18b	16 September - 30 September	15
19b	1 October - 15 October	15
20b	16 October - 31 October	16
21b	1 November - 15 November	15
22b	16 November - 30 November	15
23b	1 December - 15 December	15
24b	16 December - 31 December	16

a longer period of record. The streamflow gage for this station was moved only a short distance on the same stream and was assumed to be representative of the runoff for that stream. Also, all pan evaporation data were converted to reservoir evaporation (also called gross or lake evaporation) by applying mean monthly pan coefficients (see p.30, Texas Water Development Board, 1967).

The antecedent precipitation index (API) was generated from daily precipitation values for each station by an equation given by Linsley et al. (1958), viz.,

$$(API)_t = (API)_o k^t \quad . \tag{1}$$

$(API)_t$ represents the API at day t, $(API)_o$ is the initial index, k is a recession factor that is a function of physiographic characteristics of the river basin, and t is the number of days without rain between $(API)_o$ and the API of day t. From Eq. 1 it is apparent that the index for any particular day is equal to that of the previous day multiplied by k. If rain occurs, the rainfall amount is added to the current API and the new value is used to determine successive values of the API. It is apparent that the API for a basin is a measure of previous rainfall and is related to evapotranspiration, soil percolation, and infiltration, as well as to the amount of water required for the irrigation of crops. In the generation of API values, a recession factor (k) of 0.85 was used. The values of API were determined for the 15th day and last day of of each month. The average API for each biweekly, mid-monthly, and monthly period was calculated so the API could be analyzed statistically.

d. Stochastic data base

In water resources management and planning a recurring problem is the lack of sufficient hydrological and meteorological data. The length or period of data is usually 30 yr or less with frequent periods of missing data. In this study, incomplete records of daily precipitation, evaporation, temperature, and streamflow hindered the calculation of biweekly, mid-monthly, and monthly statistical values. This problem prompted Wade *et al*. (1971) to test MOSS (see Hydrologic Engineering Center, 1971) as a means of estimating missing data in historical records and to provide a complete stochastic data base for Texas. The program uses a multivariate regression technique similar to one devised by Beard *et al*. (1970). The equation used was

$$Q_x = B_1Q_1 + B_2Q_2 + \ldots\ldots + B_jQ_j + \ldots. + \Gamma^{\frac{1}{2}} , \tag{2}$$

where Q_x represents a missing streamflow value, Q_j are known streamflows for j nearby streams, B_j are the regression coefficients for the j streams, and $\Gamma^{\frac{1}{2}}$ is the square-root of a random component. Considerable effort is required to obtain accurate regression coefficients when data points are missing and a tremendous number of calculations are required to maintain mathematical integrity.

Paulhus and Kohler (1952) have proposed a greatly simplified means, called the "Normal-Ratio Method," for the "fill-in" of meteorological data. It involves a simplification of Eq. 2 written as

$$P_x = \frac{1}{3} \sum_{k=1}^{3} B_k P_k \tag{3}$$

In Eq. 3, B_k is approximated by N_x/N_k, where N_x is the 30-yr normal for station x and N_k is the 30-yr normal for station k, k varying from 1 to 3. The method requires only the use of three nearby stations which should be spaced as equally around station x as possible (i.e., located in 120-deg sectors around station x). N_x, N_1, N_2, and N_3 can be either the 30-yr normal annual precipitation or normal monthly precipitation. These values provide a weighting factor for the respective index stations. If the normals are within 10 percent of one another, the ratio of N_x/N_k is approximately equal to 1.0, and Eq. 3 simply becomes a three-station average. It was found that increasing the number of stations beyond three does not improve significantly the estimated value. This method reduces the computation time for estimating missing data and reduces the need for complicated mathematical techniques for obtaining the regression coefficients.

e. Errors in the data

Any technique used to "fill-in" or estimate missing data points is subject of errors which may be large and cumulative. McDonald (1957) stated that the errors in the estimation of missing precipitation data may be 25 percent or more and that errors of this magnitude must be expected. He remarks, however, that when errors of this magnitude are compared to the coefficient of variability of the data, these errors are small and the use of a "fill-in" method is better than ignoring the missing values.

The following errors may or may not exist within the station records of precipitation, temperature, and evaporation:

1. small errors in observation which frequently accumulate into larger errors;
2. instrument error which can be cumulative and is perhaps the largest encountered; and
3. error which can be introduced into station records through a change of instrument type, observers, or of exposure or location of the instrument.

For streamflow records, the following errors may or may not exist:

1. errors induced by assuming a constant volume in the channel section, i.e., ignoring scouring of channel during heavy flows;
2. error introduced because of a change in instrument location or type; and
3. observational errors caused by misreading the river stage or conversion to discharge using the stage-discharge curves.

Keypunch or typographical errors may exist in the records of both hydrological and meteorological data.

Kohler (1949) presented the method of "double-mass" analysis to check the consistency of station records. A specific variable is plotted against the average of the same variable for stations surrounding the one being checked. If there is a break or change in the slope of the double-mass curve, which is usually a straight line, this indicates that the records are inconsistent because of instrument changes, observer changes, station location changes, or some other cause. Records then can be adjusted from the curve. This method involves a large amount of time and numerous mathematical calculations. For this study this precision was considered unnecessary since the region of study was essentially homogeneous in a climatological sense. It was assumed that the data were representative of the regional meteorology and climatology and that they enjoyed the level of accuracy required by the techniques employed.

3. ANALYTICAL PROCEDURES

a. General

In order to formulate a mathematical model that requires both meteorological and hydrological information, historical data must be studied. The analysis of large amounts of hydrometeorological data and the modeling of the reservoir system were facilitated by the use of the IBM 360/65 computer at Texas A&M University. Daily data were extracted from the published records and magnetic tapes of these data and punched into computer cards. Programs were written to convert daily values of precipitation, evaporation, API, mean ambient air temperature, and streamflow into biweekly, "mid-monthly," and monthly values. Statistical analyses were accomplished and the data were fitted to frequency distributions using various tests for normality. The 30-day meteorological forecasts then were used to synthesize empirical values of temperature and precipitation from the frequency distribution which best represented the historical data. A mathematical programming algorithm was used to fit the data for selected stations, which are semi-randomly distributed in space, to a cartesian coordinate system with a rectangular grid. The objective analysis scheme provided basin maps of the forecast parameters and the historical data patterns needed to evaluate the forecast procedure. The grid system of uniformly spaced values facilitated computations of streamflow, evaporation, and consumptive use.

Decisions concerning the monthly reservoir operation were determined using a linear programming algorithm.

b. Statistical parameters

The sample size of the data varied from 17 to 70 yr and was analyzed for biweekly, mid-monthly, and monthly periods. The following statistical measures (Brooks and Carruthers, 1953; Chow, 1964) were calculated for the normal, the square-root-normal, the cube-root-normal, and the log-normal frequency distributions.

1. The mean is defined by

$$\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i \quad , \tag{4}$$

where X_i is the values of the variate and n is the sample size.

2. The median, Mx, is defined as the middle value where half of the observations lie above and half below this value.

3. The mean deviation is represented by

$$|e| = \frac{1}{n} \sum_{i=1}^{n} |X_i - \bar{X}| \quad . \tag{5}$$

4. The standard deviation, defined as the square-root of the second moment or variance, is expressed by

$$Sx = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})^2} \quad . \tag{6}$$

5. The coefficient of skewness, Cs, is defined by

$$Cs = \frac{1}{nSx^3} \sum_{i=1}^{n} (X_i - \overline{X})^3 \quad . \qquad (7)$$

6. The coefficient of kurtosis, Ck, is given by

$$Ck = \frac{1}{nSx^4} \sum_{i=1}^{n} (X_i - \overline{X})^4 \quad . \qquad (8)$$

7. The standard error of skewness is defined by

$$SE = \sqrt{(6n)(n-1)/(n-2)(n+1)(n+3)} \quad . \qquad (9)$$

c. Significance tests for normality

To determine the "goodness of fit" of biweekly, mid-monthly, and monthly values of precipitation, API, evaporation, and mean ambient air temperature, three tests for significance of normality were programmed. The goodness of fit was tested for the normal, square-root-normal, cube-root-normal, and log-normal frequency distributions. Values for a 5-percent level of confidence were used for all significance tests. If the data fit those values, it was assumed that there is a 95-percent chance that the data are acceptable and a 5-percent chance that the data are unacceptable. Therefore, a conclusive determination of normality cannot be assumed even when the data pass the statistical tests. This type of data evaluation can lead to two types of error. A Type I error is to find the data statistically unacceptable when they are valid, and a Type II error is to find the data acceptable when they are not. The statistical tests used (Brooks and Carruthers, 1953) were as follows.

1. The Cornu criterion for an infinite sample, defined as

$$\frac{|e|}{Sx} = \sqrt{2/\pi} = 0.80 \quad . \tag{10}$$

Table 6 gives the values of the Cornu criterion for the various sample sizes. The values are dependent upon the sample size and the acceptable limits decrease as the sample size increases.

2. The skewness test is expressed by

$$St = \frac{Cs}{SE} \quad , \tag{11}$$

where St is the same as "Student's" t values found in Table 6. When St exceeds those values, the distribution is considered excessively skewed and is assumed not to be normal. The values of t are related to the number of degrees of freedom involved in the calculation of SE. Values in Table 6 are for n-1 degrees of freedom. For large sample sizes the limiting t value is 1.96.

Table 6. "Goodness of fit" values for the 95-percent level of confidence (see Brooks and Carruthers, 1953).

Sample size n	Cornu criterion	Skewness values (two tail "Student's" t values)	Chauvenet criterion
10	0.710 to 0.911	± 2.26	1.96
15-17	0.720 to 0.891	± 2.13	2.13
20	0.728 to 0.879	± 2.09	2.24
22-27	0.734 to 0.870	± 2.07	2.33
30-32	0.739 to 0.864	± 2.04	2.39
40	0.746 to 0.855	± 2.02	2.50
45	0.749 to 0.851	± 2.02	2.54
50	0.751 to 0.849	± 2.02	2.58
60	0.751 to 0.849	± 2.01	2.64
70	0.759 to 0.839	± 2.01	2.69

3. The Chauvenet criterion is a test on the maximum value of a sample to determine if it is an "outlier" or extreme value. The criterion is determined by

$$\frac{| X_{MAX} - \overline{X} |}{Sx} . \qquad (12)$$

Brooks and Carruthers (1953) state that "given n observations with a standard deviation of Sx, we can assess the value $\frac{X_{MAX}}{Sx}$ such that, with a normal distribution, X_{MAX} will be exceeded less frequently than once in 2n observations, i.e., the probability that it will occur once in n times is less than 0.5." Values for the Chauvenet criterion also are given in Table 6.

The kurtosis test which uses the coefficient of kurtosis divided by the standard error of kurtosis was not used because it is not independent of the Cornu test. Also, the Chi-square (χ^2) test was not used to test the data for normality because of the small sample sizes and because the Cornu and skewness tests are the more rigorous tests for normality. A frequency distribution which combines all of the monthly, mid-monthly, or biweekly observations into a single distribution was not considered. The simulation model was designed to operate only for the periods listed in Table 5.

d. Markov transitional probabilities

Taha (1971), Benjamin and Cornell (1970), and Hillier and Lieberman (1967) present discussions on stochastic processes and Markov chains. A Markov process is a stochastic process where the conditional probability of any future physical state, given the condition of the immediate past state, is independent of that past state and depends only upon the present state of the system. Such a process is said to be memoryless and has the Markovian property. The conditional probabilities are called one-step transitional probabilities, and are represented by

$$P\ (Z_{t+1} = A | Z_t = B) \tag{13}$$

for t going from 0 to infinity and Z having the physical state A at time $t+1$ and the physical state B at time t. Equation 13 implies that the probabilities are stationary, i.e., that they do not change with time. From the preceeding definitions it is possible to define a finite-state Markov chain which is a stochastic process with

1. a finite number of physical states,
2. the Markovian property,
3. stationary conditional probabilities, and
4. a set of initial probabilities, $P_{i,j}$, for each state where

$$P_{i,j} \geq 0 \text{ for all } i \text{ and } j, \text{ and } \Sigma_j\, P_{i,j} = 1.0$$

for a given i.

Extension of the number of steps between events or physical states is called an m-step transitional Markov chain. In this study, the probabilities for a one-step Markov chain were determined using contingency tables of the observed weather at time t and time t+1. Further probabilities were obtained for a two-step Markov chain to determine if persistence of weather conditions is significant. The physical states used to determine the probabilities were below normal (B), near normal (N), and above normal (A) for temperature data, and light (L), moderate (M), and heavy (H) for precipitation data. Such probabilities can be valuable in assessing information being used to make operational decisions and can be applied as weighting factors in making quantitative estimates.

e. Contingency tables

Brooks and Carruthers (1953) and Benjamin and Cornell (1970) present examples of contingency tables. An example of the type of table used in this study is shown in Fig. 9. The purpose of the contingency table is to test for independence between two sets of events or data sets. Contingency tables were used to test for independence between the 30-day meteorological forecasts and the observed weather as verified and published by the NWS, and between monthly weather observed at time t and observed over the following month at time t+1.

In Fig. 9, the numerical values given in the upper edge and left edge of the tables are the theoretical conditional probabilities associated with each forecast category and observed category.

REGION____________________ MONTH____________________

TEMPERATURE

			OBSERVED	
		M Below/Below	N Normal	Above/M Above
		.375	.250	.375
FORECAST	M Below Below	.375		
		0.14 2.25	0.095 1.50	0.14 2.25
	N Normal	.250		
		0.095 1.50	0.06 1.00	0.095 1.50
	Above M Above	.375		
		0.14 2.25	0.095 1.50	0.14 2.25

PRECIPITATION

			OBSERVED	
		Light	Moderate	Heavy
		.333	.333	.333
FORECAST	Light	.333		
		0.11 1.78	0.11 1.78	0.11 1.78
	Moderate	.333		
		0.11 1.78	0.11 1.78	0.11 1.78
	Heavy	.333		
		0.11 1.78	0.11 1.78	0.11 1.78

Fig. 9. Conditional probabilities and expected values (E_e^1) for the contingency tables.

The probabilities correspond to those given in the NWS 30-day forecasts. At the center of each of the nine squares within a table, the theoretical joint probabilities are presented. These are obtained by multiplying the two conditional probabilities for each square and represent the individual probabilities for all possible events. At the lower right-hand corner of each square is a number which represents the expected number of occurrence of an event, given the total number of events being tested. If 16 sets of forecasts and observations are considered, the numbers given in the tables are obtained by multiplying the joint probabilities by the number of data sets.

To test whether or not the data are independent at the 5-percent level of confidence, the Chi-square test was used (see Brooks and Carruthers, 1953). The test is based upon a comparison between the observed number of events falling into the various classes and the expected number for each class. The Chi-square test is defined by

$$\chi^2 = \sum_{i=1}^{n} \left[\frac{(E_o^i - E_e^i)^2}{E_e^i} \right] , \qquad (14)$$

where n is equal to 9 for a 3 by 3 contingency table, E_o^i is the number of observations in each of the 9 classes, and E_e^i is the expected number for each class. The expected number for each class is obtained by multiplying the joint probabilities by the total number of observations. It should be cautioned, however, that the value of X^2 becomes larger for the case where the value of E_e^i is rounded off rather than carried to several decimal places. The test should be considered as a guide to significance and not an exact measure. The number of degrees of freedom for the test can be determined by

$$DF = (mm-1)(nn-1) \quad , \tag{15}$$

where mm is the number of rows and nn is the number of columns of the contingency table. For a 3 by 3 table, DF is equal to 4. Table 7 gives the X^2 values for DF=4, where the values have the probabilities, Pc, of being exceeded by chance. For example, a Pc equal to 0.05 means that the X^2 value of 9.49 will be exceeded by a random sample only 5 percent of the time, or if the determined value of X^2 exceeds 9.49, the observed distribution is significantly different from the hypothetical distribution at the 5-percent level.

Table 7. Chi-square values for 4 degrees of freedom.

X^2	5.99	7.78	9.49	11.67	13.28
Pc	0.20	0.10	0.05	0.02	0.01

f. • The grid system and objective analysis

The advent of electronic computers capable of storing and processing large quantities of data, and the development of mathematical programming algorithms which provide answers to decision situations make it desirable to use such procedures in water resources research. Solomon _et_ _al_. (1968) describe an application of a square grid system to analyze precipitation, temperature, and surface-runoff data over a large geographical area. The grid system also was used to store physical, hydrological, economic, and geographical characteristics of the region under study. Estimation of the areal distribution of the variables, which were assumed to be representative of each square within the system, was accomplished using regression equations. Maine and Gauntlett (1968) made modifications to an operational numerical analysis scheme designed by Cressman (1959) and applied the procedure to analyze climatic normal and monthly total rainfall patterns. They obtained favorable results in analyzing rainfall, a parameter that is discontinuous in time and space.

Since weather stations are located semi-randomly in space, the use of a rectangular or square grid coordinate system requires a mathematical procedure to fit the data to each grid point within the system. The grid system allows for ease in computation of mathematical equations because the data points are distributed uniformly. Cressman (1959) introduced a numerical scheme for the objective analysis of weather maps involving parameters which are continuous in time and space. The random data are fitted to the grid points by a first-guess field. The method then analyzes the data by applying corrections to the first-guess and subsequent-guess fields. An advantage of the Cressman technique is that it requires very few computations because the procedure decreases the scan radius after each iteration. This, however, can lead to an amplification of observation errors.

To help alleviate the problem of error amplification, Barnes (1964) introduced a technique in which the scan radius is fixed for all iterations. The first-guess field of all values equal to zero also are used. The convergent weighted-averaging interpolation technique developed by Barnes (1964) scans the station observations with a preselected scan radius, SR, for each grid point. The SR is the radial distance from a grid point expressed in grid units. When a station observation is within the SR, it will influence the analysis value at the grid point; the closer a data point is to a grid point, the greater is its influence on that point.

The analysis procedure starts by calculating the error which is the difference between the observation and the first-guess value at the station. For the specified iteration (an integer), I, the error for the k^{th} data point, is defined by

$$ER_k^I = O_k - Y_k^I \quad , \tag{16}$$

where Y_k^I is the current estimate of the observation obtained by using the current values of the four surrounding grid points $(Y_{i,j}^I)$ and bi-linear interpolation, and O_k is the k^{th} data point for a group of M station observations. This error then is used with a weighting factor that varies with the distance between the grid point (i,j) and the data point and with the SR. The weighting factor, $W_{i,j}$, for grid point (i,j), is given by

$$W^k_{i,j} = \exp\left[-4r^2/(SR)^2\right] \quad , \qquad (17)$$

where r is the distance from the grid point to the k^{th} data point, and exp is the base of the natural logarithms. Only the grid points that are within a distance equal to the SR are influenced by the k^{th} data point. $W^k_{i,j}$ approaches zero as the distance between the grid point and the data point increases and becomes unity when they coincide.

When a particular grid point (i,j) is influenced by several data points on the I^{th} iteration, the total correction is determined from

$$TC^I_{i,j} = \frac{\sum\limits_{k=1}^{K} (ER^I_k)\ (W^k_{i,j})}{\sum\limits_{k=1}^{K} (W^k_{i,j})} \quad , \qquad (18)$$

where K is the number of observations influencing the grid point, $ER^I_{i,j}$ is given by Eq. 16, and $W^k_{i,j}$ is defined by Eq. 17. An estimation of the observation for the $I+1$ iteration is obtained using

$$\underline{Y}^{I+1}_{i,j} = \underline{Y}^{\,I}_{i,j} + TC^{\,I}_{i,j} \quad , \qquad (19)$$

where $\underline{Y}_{i,j}^{I+1}$ is a new estimate at the grid point, $\underline{Y}_{i,j}^{I}$ is the prior estimate used on the I^{th} iteration, and $TC_{i,j}^{I}$ is given by Eq. 18 . The above procedure is continued until the difference between the analysis and the observations becomes small. Barnes (1964) has demonstrated mathematically the convergence of this method of objective analysis.

Figure 10 shows the rectangular grid system and the locations of the meteorological stations used in this study relative to the river system in the Concho River basin. The three-letter abbreviations correspond to the stations listed in Table 3. Barnes (1964) suggests that the optimum SR occurs when the relationship $SR \simeq 1.6\bar{d}$ is satisfied. Based on the average spacing between data points, $\bar{d}$, of approximately 25 mi, a value of $SR \simeq 2$ grid units was obtained. The grid interval was 22 mi and each grid area represents 484 sq mi. Four iterations through the data were performed to fit the semi-random station data to the grid points. The resulting analyses appeared to be representative of the various data patterns.

g. <u>Simulation and linear programming</u>

Hall and Dracup (1970) and Hufschmidt and Fiering (1966) define simulation as a process which reproduces or duplicates the essence of a system or activity without actually attaining reality or without completely defining all the characteristics of the

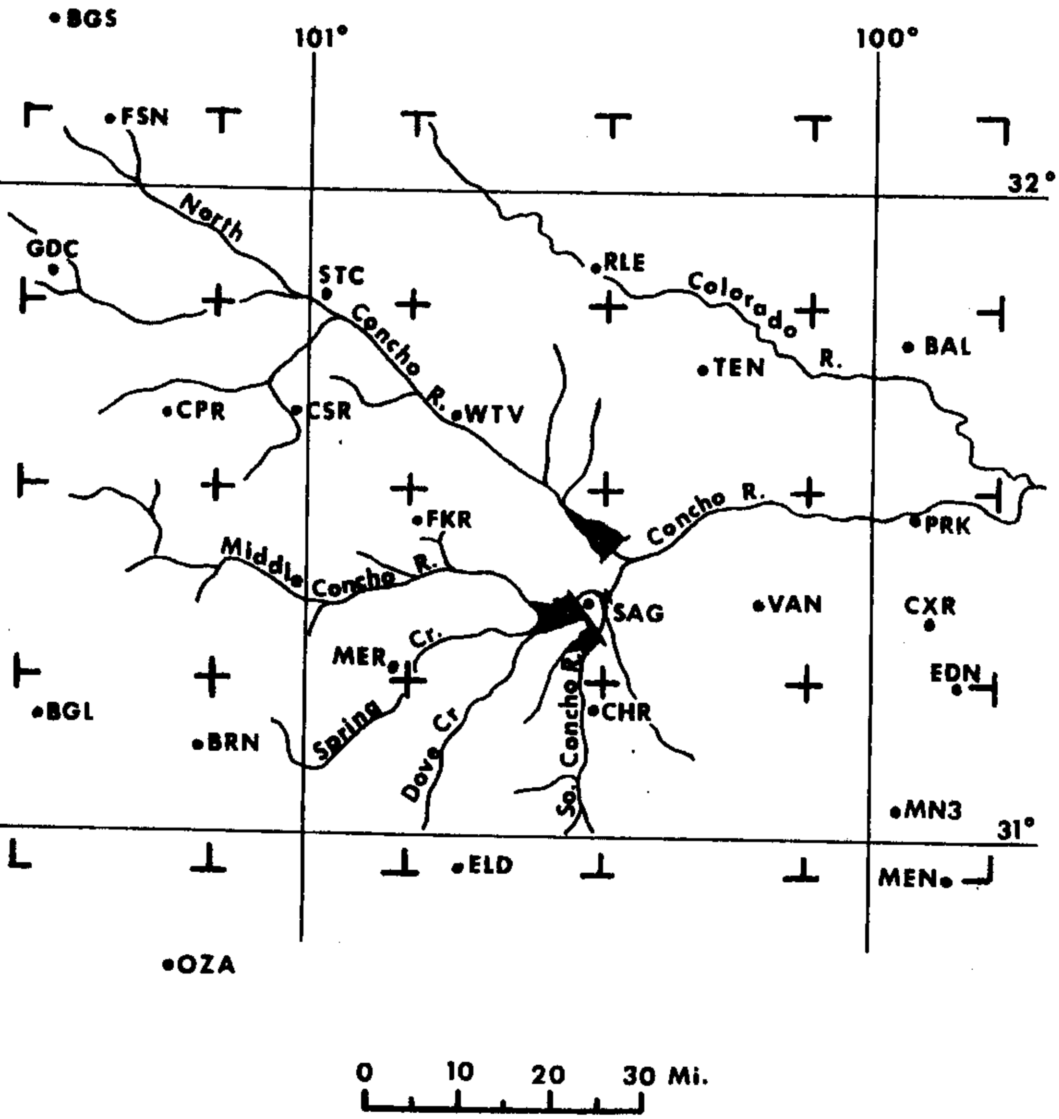


Fig. 10. The rectangular grid system for the Concho River basin.

system. It is a method found to be very effective in handling large and complex problems for which analytical solutions are difficult to obtain. In situations where physical phenomena are not reproducible by scientific experiments, simulation has found wide application. Digital simulation, or simulation by digital computer, involves the determination of physical relationships that can be defined numerically. The major components of any simulation model and some examples (in parentheses) are:

1. state variables which describe the condition of any physical activity contained within the system and impose constraints upon the generated events (limits of precipitation and temperature values, basin configuration, and reservoir characteristics);
2. exogenous variables which describe the behavior or conditions outside the physical system (economic or legal constraints, and meteorological forecasts);
3. functional relations which describe relationships between the internal components of the physical system (rainfall-runoff, temperature-evaporation, and temperature-consumptive use equations). These mathematical or logical relations determine changes that occur within the system as a result of exogenous variables operating over some specified time span; and
4. status variables which describe some activity state at the beginning of the time period (inputs) and at the end of the time period (outputs).

Naylor _et_ _al_. (1966) state that simulation techniques have precipitated from Monte Carlo analysis which "involves the solution of a non-probabilistic mathematical problem by simulating a stochastic process that has moments or probability distributions satisfying the mathematical relations of the non-probabilistic problem" also they presented techniques on how to formulate a simulation problem, how to collect and analyze data, means of constructing the mathematical model, and ways of generating sequences of pseudo-random numbers. In this study, a program called "RANDU" was used to generate the pseudo-random numbers by using residues of numbers of modulo 2^n.

Some of the problems associated with simulation procedures are:

1. They do not yield an immediate answer that optimizes the physical system;
2. they are inherently imprecise where the accuracy depends upon the statistical validity of the historical data;
3. they are a slow and costly means of studying a problem or physical system; and
4. they provide no insight into cause-and-effect relationships.

Delininger (1969) presents a discussion of generalized linear programming for hydrologic analysis, while Chow and Meredith (1969) review programming techniques for water resources systems analysis. Taha (1971) states that the linear programming problem "calls for optimizing (maximizing or minimizing) a linear function of variables, called the 'objective function,' subject to a set of linear equalities and/or inequalities, called 'constraints or restrictions.'" Hillier and Lieberman (1967) view the problem as a means of deciding how to allocate some limited resources among competing activities so that it is done in an optimal manner. The adjective "linear" specifies that the equations describing the system must be linear in time and space. The general form of a linear programming problem is to find $x_1, x_2, \ldots . x_n$, which optimizes, or, in this case, maximizes the objective function

$$\text{MAX} \sum_{j=1}^{n} c_j x_j \quad \text{or} \quad \text{MAX} \quad Z^* = c_1x_1 + c_2x_2 + \ldots + c_nx_n \quad , \tag{20}$$

subject to the restrictions or constraints

$$\begin{array}{l} a_{11}x_1 + a_{12}x_2 + \ldots\ldots\ldots\ldots + a_{1n}x_n \leq b_1 \\ a_{21}x_1 + a_{22}x_2 + \ldots\ldots\ldots\ldots + a_{2n}x_n \leq b_2 \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ a_{m1}x_1 + a_{m2}x_2 + \ldots\ldots\ldots\ldots + a_{mn}x_n \leq b_m \\ x_i \geq 0.0 \quad \text{for all} \quad i. \end{array} \tag{21}$$

There are n competing activities and m scarce resources in which the mathematical objective function, Z^*, provides an overall measure of effectiveness for the allocation of the resources within the physical system. c_j reflects the change in the overall effectiveness for each unit change of the allocation of a scarce resource to activity x_j, and a_{ij} represents the quantity of resource i that is used by each unit of activity j. The nonnegativity restraints, $x_i \geq 0.0$, eliminate the use of negative quantities. The variables that are being determined by using this type of mathematical programming technique are labeled "decision variables."

Stochastic linear programming (see Taha, 1971) considers some or all of the parameters of a physical system as random variables rather than deterministic values. Charnes and Cooper (1959) introduced a technique called "chanced-constrained programming." The basic idea is to convert the probabilistic problem into an equivalent deterministic model which can be solved by mathematical programming algorithms. The objective function is the same as Eq. 20, while the constraints are of the form

$$P \left\{ \sum_{j=1}^{n} a_{ij} x_j \leq b_i \right\} \geq 1 - \alpha_i \ , \quad i=1,2,3, \ldots . \ m \ . \tag{22}$$

where each constraint is realized with a minimum probability of $1 - \alpha_i$, for $0.0 \leq \alpha_i \leq 1.0$.

In general, the values of a_{ij}, b_i, and c_j can be considered as random variables which are distributed according to known distributions. For most cases when c_j is a random variable, it simply can be replaced by its expected or mean value. The analysis for the a_{ij} and b_j parameters being random variables has been restricted to normal distributions and recently to chi-squared (χ^2) distributions. However, in the instance when only the values of b_j are random variables, the form of the distribution is immaterial.

4. STOCHASTIC HYDROMETEOROLOGICAL MODEL

a. Stochastic meteorological forecasts

The Extended Forecast Division of the National Weather Service prepares prognostic 30-day maps of precipitation and temperature. Figure 11 is an example of the maps published twice a month, near the beginning and middle of each month, for 30-day periods that start on the first and 15th. The maps presented cover the period from February 1 to February 28, 1961. Figure 12 is a map of Texas with a numbered and gridded region created by lines of latitude and longitude. Regions 8 and 9 correspond to the location of the Concho River basin and were used to determine the forecast categories of precipitation and temperature.

Namias (1953, 1964) presented the basic variables used in the preparation of these "extended-range" charts. They are:

1. monthly mean zonal wind profiles;
2. temperature patterns at the surface of the Earth, sea-surface temperatures, snow cover, and sea ice;
3. 30-day mean 700-mb heights, 1000-to-700-mb thickness maps, and short- and long-range numerical weather forecasts; and
4. climatology.

The basic means of forecasting for the 30-day period is through time average maps of the atmospheric circulation. Attention is given to slowly developing large-scale weather patterns as input to the

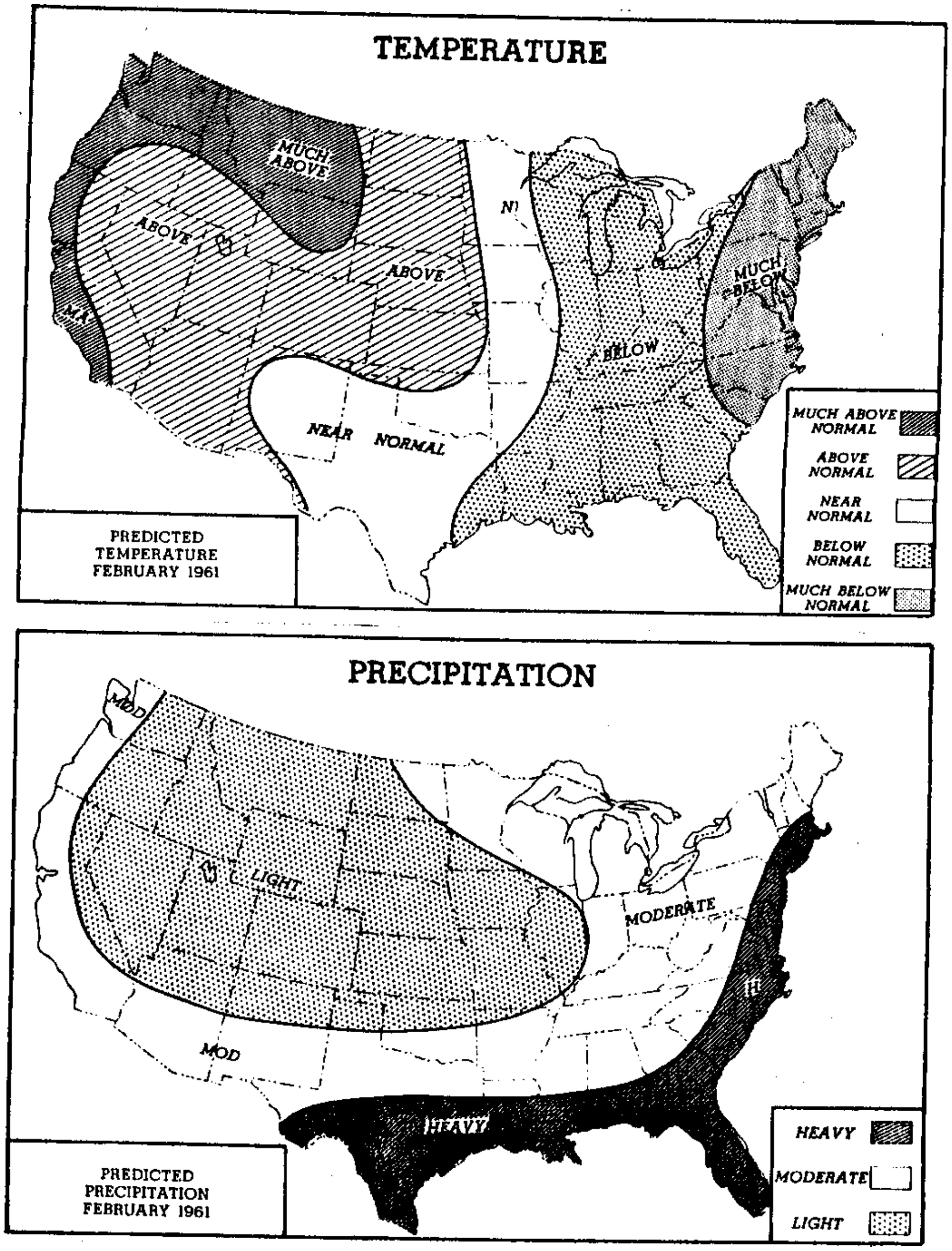


Fig. 11. Thirty-day meteorological forecasts published by the Extended Forecast Division of the National Weather Service.

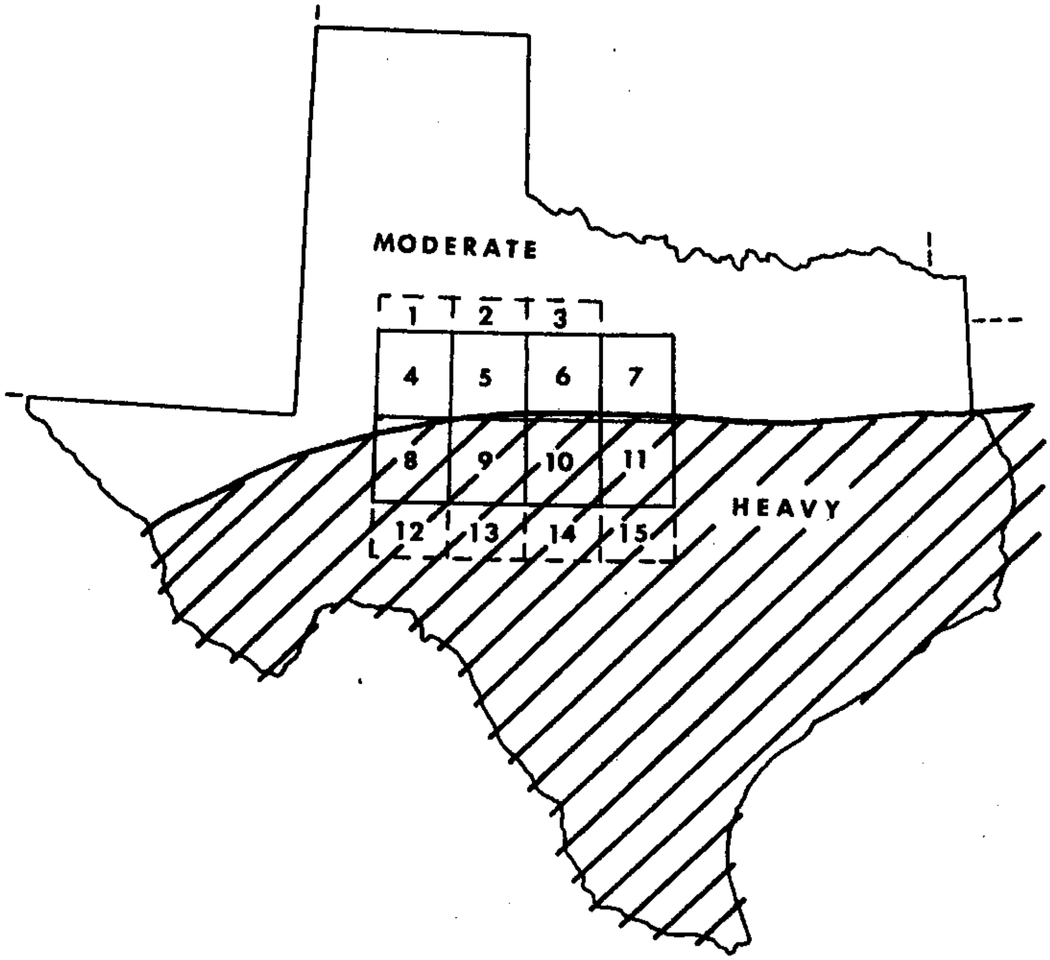


Fig. 12. A detailed map of a 30-day precipitation forecast for Texas (shown in Fig. 11).

forecasts, with emphasis upon

1. long-term development of circulation systems and trends;
2. evaluation of seasonal changes estimated by tendency fields; and
3. expected changes in circulation due to upper-air and surface-atmosphere interactions.

Precipitation forecasts are given by three categories: light, moderate, and heavy. The precipitation amounts which determine these categories are obtained from climatological records where limiting values allow an equal number of observations to occur within each category. If the normal probability distribution is considered, each category has a probability of occurrence of 0.33.

Monthly mean temperature forecasts are given by five categories and probabilities listed below:

much below normal	0.125
below normal	0.250
near normal	0.250
above normal	0.250
much above normal	0.125

For this study, a minor change was made to the categories and probabilities for the temperature categories; however, the probability distributions for precipitation were not changed. This was done to facilitate computations within the model, evaluation of the first-order Markov transitional probabilities, and verification of the accuracy of the model. The change involved combining the two highest and the two lowest categories and adjusting the probabilities so that there would be an equal number of observations within each category. The result was the following three categories, each having a probability of occurrence of 0.33: below normal, near normal, and above normal. This arrangement allows for some inconsistency between the original forecast categories and the new limits placed upon each category. The empirical differences between categories are of the order of 0.1F to 0.01F. This error is not significant enough to affect the overall model operation.

The 30-day forecasts of temperature and precipitation are verified by quantitative values determined from the analysis of climatological data for the stations located within that region. For example, if some station has temperatures that are normally distributed in the month of August with a $\overline{X}$ of 83.5F and a Sx of 2.0F, the bounds for each category would be:

$$79.5F \le \text{below normal} < 82.7F$$
$$82.7F \le \text{near normal} \le 84.3F$$
$$84.3F < \text{above normal} \le 87.5F$$

By applying values from ordinate-area tables for the Gaussian distribution, equal areas under the curve representing the normal-distribution are obtained for each category. For example, the limits for the category of near normal temperatures are obtained by adding and subtracting 0.43 times Sx. The upper and lower limits of the above normal and below normal categories were obtained by adding and subtracting 2.0 times Sx, respectively.

b. Monthly operational hydrometeorological simulator (MOHS)

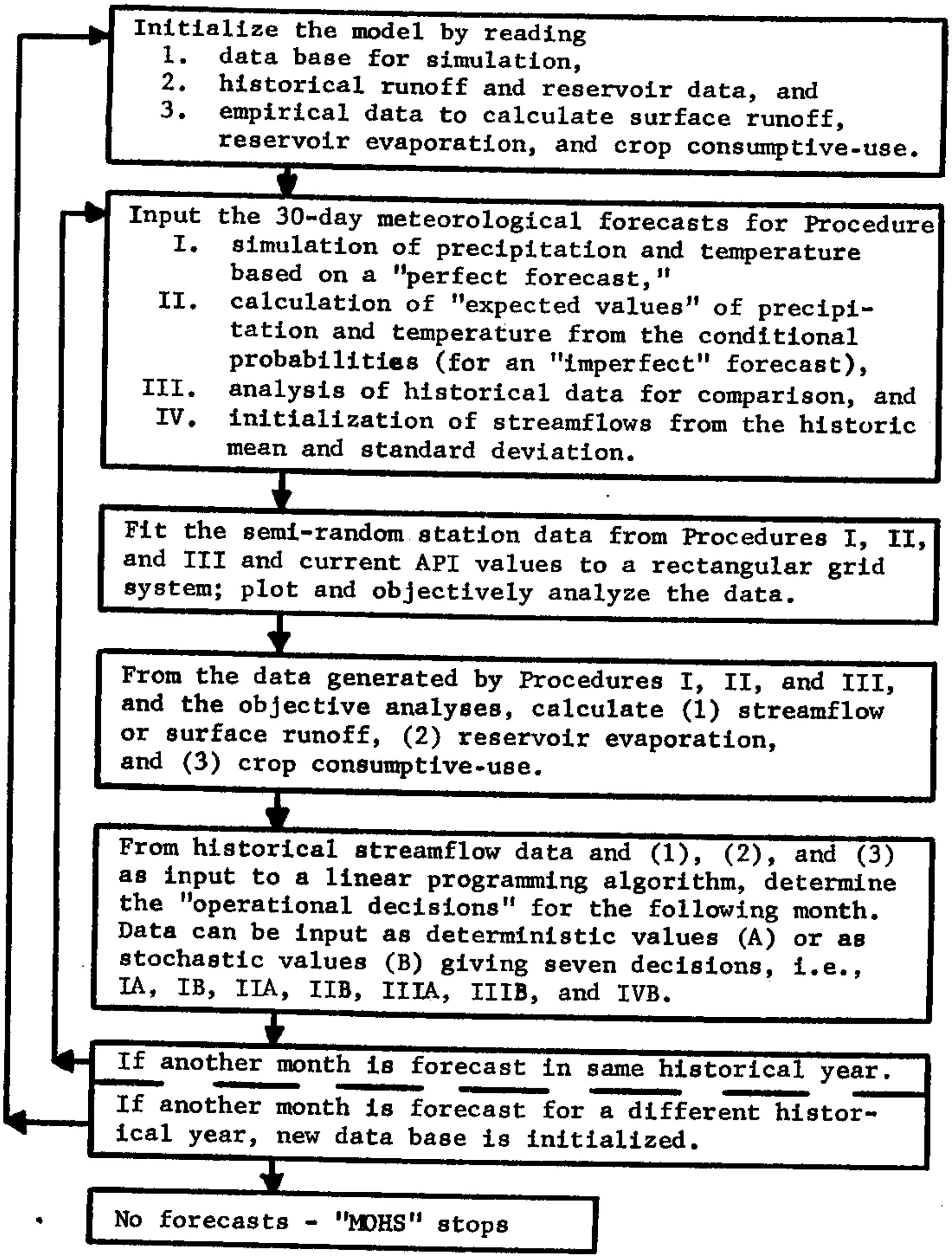
A stochastic model is one which has at least one of the operational characteristics are described and defined by a probability function. When the model considers interactions that are a function of time, it is called a dynamic stochastic model. If time is not explicitly considered in the model, the configuration is labeled static. MOHS is considered a static stochastic model because the variation of parameters within the time period of a month is not considered. Hufschmidt and Fiering (1966) introduced their "monthly operational hydrology generator" to provide synthetic sequences of streamflow based upon a) normally, b) log-normally, c) gamma, or d) historically distributed data. Historical measures of central tendency, variability, correlation, and lag-correlation were maintained by using multivariable regression equations to simulate the surface runoff. Chorfas (1965) presented information on the prediction of surface runoff based upon runoff classes and a Markov transitional probability matrix which was used to simulate sequences of runoff in time.

An important portion of the simulation scheme of MOHS was to use temperature and precipitation data which conformed to one of the frequency distributions presented in 3b as a stochastic data base. The most appropriate distribution was used to simulate quantitative values of precipitation and temperature based upon the 30-day forecast category. In Fig. 13, Procedure I involves the generation of a pseudo-random number between 0.0 and 1.0. This number then is multiplied by a value equal to the mean plus two standard deviations. From the result it is possible to decide if the adjusted value conforms to the 30-day forecast category limits, as determined by the appropriate frequency distribution. This procedure considers the 30-day meteorological forecasts as a "perfect forecast." From precipitation amounts streamflow is calculated, and from temperature values evaporation and consumptive-use are determined.

The following is a breakdown of the forecast categories relative to the quantitative values:

Mean temperature: $\bar{X}-2Sx \leq$ Below Normal $< \bar{X}-0.43Sx$
$\bar{X}-0.43Sx \leq$ Near Normal $\leq \bar{X}+0.43Sx$
$\bar{X}+0.43Sx <$ Above Normal $\leq \bar{X}+2Sx$
Precipitation: $0.0 \leq$ Light $< \bar{X}-0.43Sx$
$\bar{X}-0.43Sx \leq$ Moderate $\leq \bar{X}+0.43Sx$
$\bar{X}+0.43Sx <$ Heavy $\leq \bar{X}+2Sx$

$\bar{X}$ refers to the mean of the frequency distribution and Sx refers to the standard deviation of the distribution. This breakdown of the data provides equal probabilities of occurrence for



Initialize the model by reading
1. data base for simulation,
2. historical runoff and reservoir data, and
3. empirical data to calculate surface runoff, reservoir evaporation, and crop consumptive-use.

Input the 30-day meteorological forecasts for Procedure
- I. simulation of precipitation and temperature based on a "perfect forecast,"
- II. calculation of "expected values" of precipitation and temperature from the conditional probabilities (for an "imperfect" forecast),
- III. analysis of historical data for comparison, and
- IV. initialization of streamflows from the historic mean and standard deviation.

Fit the semi-random station data from Procedures I, II, and III and current API values to a rectangular grid system; plot and objectively analyze the data.

From the data generated by Procedures I, II, and III, and the objective analyses, calculate (1) streamflow or surface runoff, (2) reservoir evaporation, and (3) crop consumptive-use.

From historical streamflow data and (1), (2), and (3) as input to a linear programming algorithm, determine the "operational decisions" for the following month. Data can be input as deterministic values (A) or as stochastic values (B) giving seven decisions, i.e., IA, IB, IIA, IIB, IIIA, IIIB, and IVB.

If another month is forecast in same historical year.

If another month is forecast for a different historical year, new data base is initialized.

No forecasts - "MOHS" stops

Fig. 13. Flow diagram of "MOHS."

each of the categories when a Gaussian distribution is assumed. After a value has been simulated that conforms to the forecast category, it must be transformed to a precipitation or temperature value representative of actual values. This was done by squaring the value if the square-root-normal distribution was appropriate, cubing the value if the cube-root-normal distribution was appropriate, and so on. If the normal distribution was appropriate, the value could be used directly. The lower limit of the category of light precipitation is zero because there cannot be negative rainfall. It was necessary also to bound the mean temperatures in the low and high regions because, if this were not done, unrealistic or extreme temperatures would be simulated. The limits on mean temperature data account for 95 percent of all possible values. The limits on precipitation account for slightly more than 95 percent of all data values because of the zero lower limit. Also, in the semi-arid Concho River basin, precipitation distributions are highly skewed toward low rainfall amounts due to many periods of zero rainfall.

In Fig. 13, Procedure II assumes the forecasts are "imperfect" and the forecast values of temperature and precipitation for each station are modified by conditional probabilities. These probabilities were obtained by verifying historical 30-day forecasts through the use of contingency tables (see Section 3e and Appendix A). This portion of MOHS determines an "expected value" of temperature and precipitation from which streamflow, evaporation, and crop consumptive-use were calculated. To obtain an "expected value," a mean value for each category (light, moderate, etc.) was established from the frequency distribution; the values were transformed when necessary; each transformed value was multiplied by the conditional probability; and then the products were added together to obtain a quantitative value. For example, given a forecast of near normal temperatures for the month of August, the following demonstrates how an "expected value" of temperature is determined:

forecast/observed	A conditional probability	B category mean	product of A times B
normal/below normal	0.20	80.9	16.18
normal/normal	0.60	83.5	50.10
normal/above normal	0.20	86.1	17.22
expected temperature			83.50

The same process was followed to determine quantitative values of precipitation for each imperfect forecast.

Procedure III allows MOHS to be operated over some historical time period where actual precipitation, evaporation, streamflow, temperature, and reservoir data are available for comparison with the simulated and "expected values." Historical data also can be used to evaluate the accuracy of the empirical relationships used to determine surface runoff, evaporation, and crop consumptive-use. Under actual operation of the reservoir system, this portion of the model can be deleted.

c. Precipitation-runoff relationship

Chow (1964) summarizes the two major groups of hydrologic factors which influence the surface runoff for any river basin. They are:

Climatic	Physiographic
precipitation	geometric factors of basin
interception	physical factors of basin
evaporation	physical capacity of river channel
transportation	storage capacity of river channel

Allison (1967) reiterates the importance of regional climatological differences and the effects of differences in basin characteristics for obtaining a general empirical method for surface runoff calculations. He also considers the availability of relevant data as a problem which limits the application of any technique. For this study, several techniques were tested to determine which one provided the best approximation to historical flows. Appendix B contains a summary of the empirical methods tested for the prediction of surface runoff in the Concho River basin. Included are empirical relationships by the U.S. Soil Conservation Service (1971), Kohler and Richards (1962), Beard (1962), Chow (1964), and Linsley *et al*. (1958). All of the methods included in Appendix B were found to be inadequate for the purposes of this study.

An equation presented by Sellers (1965) provided guidance for the precipitation runoff equation used. He presented a simplified equation of the form,

$$\Delta S = a R^2 \quad , \left(R \leq \frac{1}{a}\right), \tag{23}$$

where ΔS is surface runoff, a is an empirically determined coefficient, and R is the annual precipitation in inches. Eq. 21 implies that, if a is constant, an increase in runoff of 44 percent would result from a 20 percent increase in precipitation. Since runoff also is dependent upon soil-moisture conditions, a cannot be considered a constant. a will be large when the soil moisture content is high and small when the soil is dry. It was therefore necessary to develop a relationship which adjusts the coefficient a for soil-moisture. Sellers (1965) also summarized the work of previous experimenters to develop an "all-inclusive" equation from precipitation and runoff data. He presents one which is similar to Eq. 23, viz.,

$$\Delta S = R \exp\left(-E_o/R\right). \tag{24}$$

From Eqs. 23 and 24 it can be seen that a can be approximated by

$$a = \frac{1}{R} \exp\left(-E_o/R\right), \tag{25}$$

where R is rainfall and E_o is potential evaporation or potential evapotranspiration. Eq. 25 allows a to vary depending on precipitation and evaporation conditions. Sellers (1965) also presented a plot of the annual runoff ratio $\frac{\Delta S}{R^*}$ versus R* (mean annual precipitation in inches) for watersheds in the United States (see Fig. 27, p.87 of Sellers, 1965). In the range of annual precipitation for semi-arid regions, the value of the coefficient a is approximately 0.005 $\mathrm{in.}^{-1}$. If Eq. 24 is used on a monthly basis, it must reflect the soil-moisture conditions. Therefore, in this study, modifications were made to Eqs. 24 and 25 that maintained the validity of the coefficient a while providing a variable coefficient which adjusts runoff for soil-moisture conditions. The equation used was

$$a^* = \frac{1}{R} \exp\left[- (E_o + R - API)/R \right] , \qquad (26)$$

where E_o is approximated by monthly adjusted pan evaporation, R is rainfall, and API is the antecedent precipitation index.

The factor needed to maintain the validity of the coefficient a was determined empirically to be

$$\exp \left[- (R - API)/R\right] . \qquad (27)$$

Eq. 27 allows for an increase in a^* when API is a large value, i.e., when there is a high soil-moisture content. This increases the surface runoff due to lower infiltration of precipitation by the less permeable soil. When both the API and E_o are small, a^* approaches the value 1/e and provides a value for a which is approximately the same as that established by Sellers (1965). The validity of this approximation also satisfies the obvious condition that when no rainfall occurs (R=0), there is no surface runoff. Likewise, when R becomes infinitely large, rainfall approaches surface runoff. Figure 14 is a graphical representation of Eqs. 23, 24, and 26 with consideration of the soil moisture factor (API) excluded. For varying values of potential evapotranspiration, E_o, a family of curves can be obtained. It can be seen that as E_o becomes larger, the amount of surface runoff decreases. If the effect of API is considered for E_o equal to unity, when the API is greater than zero but less than R the runoff curve will lie between curves A and C. Under conditions when the API is equal to R, the surface runoff will be approximated by curve A. When API is greater than R, the surface runoff curve will lie to the left of curve A.

The rectangular grid system and objective analysis scheme presented in Section 3f are integral parts of the model for calculation of surface runoff. By using the values of precipitation at each of the grid points and averaging over the geographical area contributing to the streamflow of the rivers in the basin, one can approximate the monthly inflow (acre-ft) to each reservoir. These forecast inflows are extremely important in the determination of the reservoir operation for the succeeding month. Deterministic inflows which were used as decision variables were calculated in this manner.

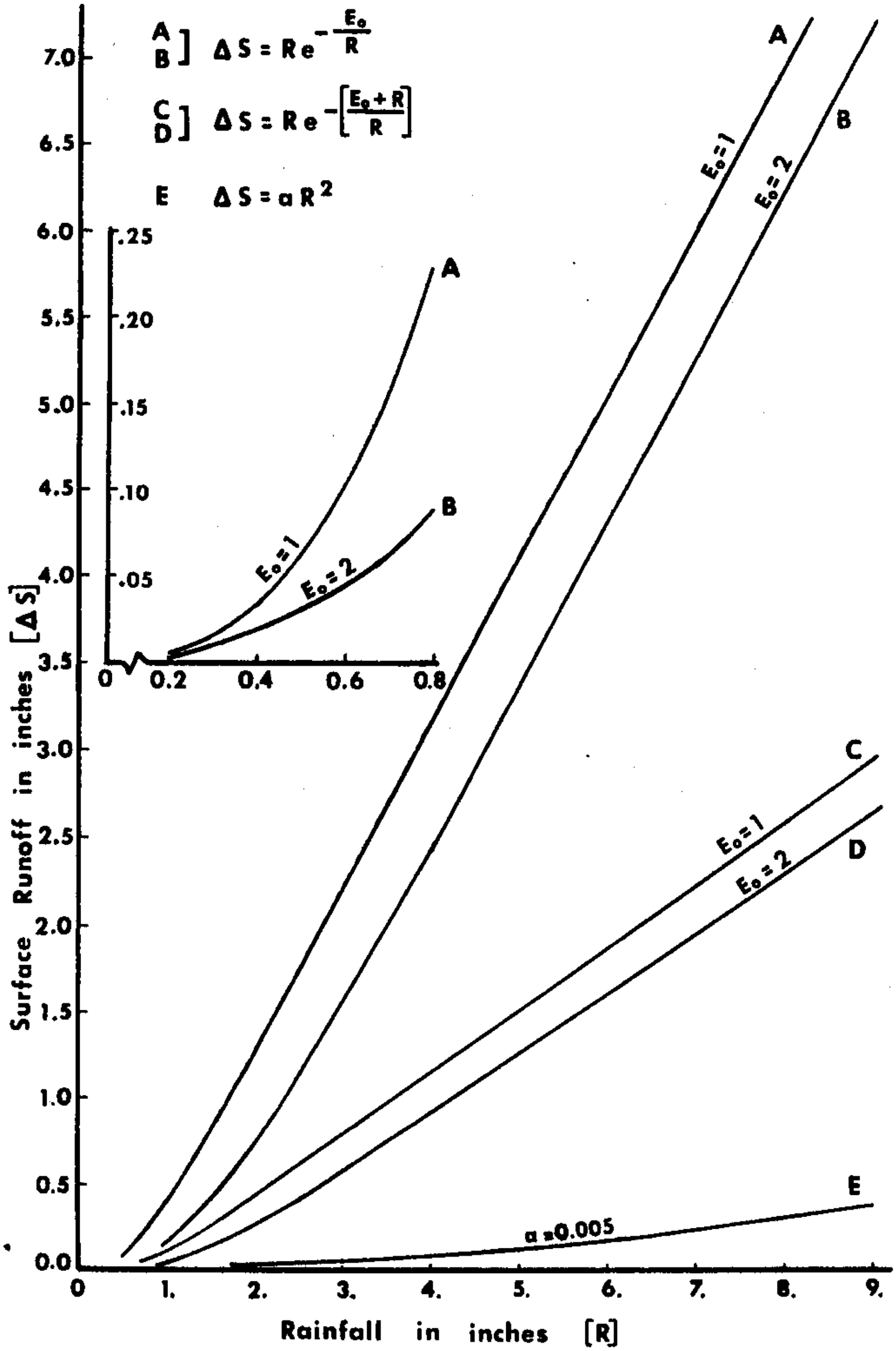


Fig. 14. A graphical representation of the rainfall-runoff equations.

d. Evaporation and crop consumptive-use

The MOHS uses the simulated values of mean monthly temperature to provide a quantitative estimate of reservoir evaporation and crop consumptive-use. Since temperature values were simulated, one of the simplest relationships that can be used to calculate evaporation is that developed by Thornthwaite and Hare (1965). The relationship is also discussed by Sellers (1965), Van Hylckama (1959), Hamon (1961), and Eagleson (1970). The relationship is developed for the concept of potential evapotranspiration (PE), which is defined as the quantity of water lost from plants through transpiration or evaporated from the ground if there were a continuous supply of water. If one considers the water surface of a reservoir with its unlimited supply of water, Thornthwaite's equation can be used to estimate reservoir or lake evaporation from temperature values. The PE in cm/month is determined by

$$PE = 1.6\ D \left[\frac{10\ \bar{T}}{J}\right]^{G} \quad , \qquad (28)$$

where PE is the potential evapotranspiration, $\bar{T}$ is the mean temperature for a month in degrees Celsius, and D is the duration of sunlight in percent for a given month. J and G are empirical relationships defined by

$$J = \sum_{i=1}^{12} \left[\frac{T_i^*}{5}\right]^{1.514} \quad , \qquad (29)$$

$$G = 6.75 \times 10^{-7} J^3 - 7.71 \times 10^{-5} J^2 + 1.792 \times 10^{-2} J + 0.49239 \quad . \tag{30}$$

T_i^* is the climatological normal temperature for month i in degrees Celsius and the summation is over the 12 months of the year. The PE value can be converted easily to inches per month or to feet per month using appropriate conversion factors. A table for values of D for given latitudes can be found in Van Hylckama (1959).

PE was used as an estimate of reservoir evaporation or water lost to the atmosphere for a given month. Historical mean monthly temperatures were substituted into the Thornthwaite equations and PE calculated. The calculated values were compared to the adjusted evaporation data for the evaporation pan located at the San Angelo reservoir. It was found that Eq. 28 underestimated actual pan evaporation for the Concho River basin and, therefore, PE values had to be adjusted upward to conform more nearly to historical evaporation data.

Criddle (1953) presents a method for determining crop consumptive-use and irrigation requirements. He defines consumptive-use as "the sum of the volumes of water used by the vegetative growth of a given area in transpiration and building of plant tissue and that evaporated from the adjacent soil or intercepted precipitation on the area in any specified time divided by the given area." Consumptive-use usually is expressed as the depth of water required in inches or feet or as acre-ft per acre.

In the Criddle method, monthly consumptive-use (U) is determined by

$$U = KF \quad , \tag{31}$$

where K is an empirical consumptive-use coefficient for a particular crop or vegetative type and F is defined as

$$F = \frac{H\ \overline{T}}{100} \quad . \tag{32}$$

H is the monthly percentage of daylight hours and $\overline{T}$ is the mean monthly temperature in degrees Fahrenheit. For a region in which there are multiple crops and each crop j planted on L_j acres requires an amount of water equal to U_j, the total irrigation requirement can be determined by

$$U = \sum^{m} L_j\ U_j = \sum^{m} L_j\ K_j\ F \quad , \tag{33}$$

where the summation is over m types of crops. Table 8 gives some values of K for the various crops grown in the Concho River basin in west Texas.

Table 8. Criddle consumptive-use coefficients.

Vegetation	Growing season	K
cotton	7 months	0.62
pasture, grass, hay	frost-free	0.75
small grains	3 months	0.75
grain sorgum	5 months	0.70
alfalfa	frost-free	0.85

In MOHS, since most of the crops do not require water during the winter months, no consumptive-use or irrigation demand was computed for the period from November through February. The number of acres and the types of crops under surface water irrigation in the Concho River basin were obtained from Texas Water Development Board (1971c).

Hargreaves (1968) developed a method to obtain consumptive-use from pan evaporation data. His method involves the determination of the irrigation requirement (IR) from the difference between evapotranspiration (ET) and total precipitation (R). Difficulty arises in this method when R exceeds ET. Since the model is based upon a time increment of one month, large short-duration rainfall amounts, such as during a thunderstorm, may provide an R somewhat greater than ET. This results in an unrealistic negative value for IR. Also, irrigation demand probably will exist even when there is sufficient rainfall because of the unequal distribution of rainfall in time. A careful consideration of the various techniques described indicated that the method described by Criddle (1953) would be most appropriate for use in MOHS to determine water demand for crop irrigation.

e. Reservoir operating policy

Operating rules and policy for single or multi-reservoir systems have been postulated and tested to provide some measure with which to obtain "optimal" risk of water resources. Schweig and Cole (1968) studied a system of linked reservoirs which met a common demand. To determine how best to operate the system, the objective function was set up to minimize costs but could have been established to maximize benefits. Complete assessment of any reservoir system is complicated by 1) the randomness of monthly inflows; 2) digressive goals of determination of operational effectiveness (viz., to maximize profit or water yield); and 3) the nonlinearity of the complete system.

ReVelle *et al*. (1969) and Revelle and Kirby (1970) present what is termed the "linear decision rule (LDR)" which allows the solution of reservoir management problems by using linear programming techniques. The authors state that "the linear decision rule specifies the release during any period of reservoir operation as the difference between the storage at the beginning of the period and a decision parameter for the period." In equation form, the LDR is

$$x_t = s_{t-1} - \beta_t \quad , \tag{34}$$

where x_t is the release during a specified period of reservoir operation, s_{t-1} is the storage at the end of the time period prior to the one specified, and β_t is a decision parameter chosen to optimize some criterion function. Two methods can be applied in treating the input (streamflow or surface runoff) to the model. The first is to treat the magnitudes of the inflow into the reservoir as random variables, i.e., as a stochastic system. The second method is to treat the system deterministically where each input is specified in advance by synthesis or simulation of inflows based upon the statistical properties of historic streamflow data. ReVelle and Kirby (1970) extended the linear decision rule to consider evaporation losses. Eq. 34 then becomes

$$x_t = s'_{t-1} - \beta_t \quad , \tag{35}$$

where x_t is the release commitment for time period t, s'_{t-1} is the projected storage based on the actual storage at the beginning of the period with an estimated evaporation loss considered for the time period, and β_t is the decision parameter. To measure the effectiveness of the LDR, several alternative measures can be applied. They are:

1. maximizing the expected values of storages or releases;
2. minimizing the expected value of total losses;
3. maximizing the storage or commitment attainable with stated reliability; or
4. minimizing the risk of failure, where this is considered as a probability that insufficient commitments are made or insufficient storages maintained.

They further refine the treatment of the chance constraints of the system where releases, storages, and inflows are considered random variables.

Eisel (1970) considers the work by ReVelle et al. (1969) as a formidable contribution to the field of water resources. However, he deemed the operational value of the LDR limited because it is independent of the current monthly inflow, x_t. The implication that all linear policies are "near optimal" or "optimal" for any prescribed form of economic loss functions is examined by Eisel. He concludes that this implication may or may not be correct and that linear rules, opposed to more complicated ones such as quadratic or cubic, may not provide good or better reservoir operation data. Loucks (1970) praises the presentation of the application of chance constraints and their deterministic equivalents by ReVelle et al. (1969) for its clarity and timeliness. He also presents another form of the LDR which would consider current inflow and be expressed by

$$x_t = \Upsilon_t + s_{t-1} - \beta_t \quad , \tag{36}$$

where Υ_t is the inflow for time period t. Loucks (1970) also stresses the need for expanding the chance constrained model to a multi-reservoir system with multiple operations or decisions.

Curry et al. (1972) presented a stochastic model for a single multi-purpose and linked multi-purpose reservoir system.

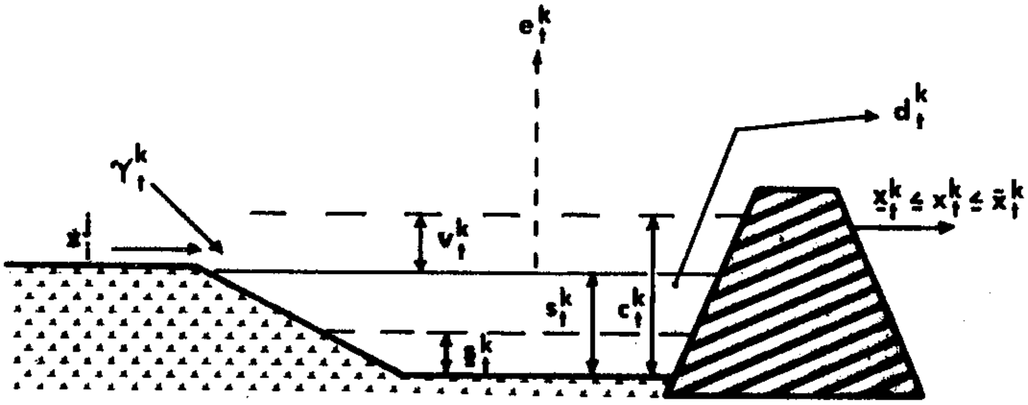
This research is concerned with modeling the linked three-reservoir system located in the Concho River basin in west Texas, where the linkage between the reservoirs is normal channel flow from reservoir releases. The model constructed by Curry et al. (1972) also is capable of considering linkages which are pipelines or pumping canals between the reservoirs and is completely general in that any specified connecting system can be modeled. For any time period, each reservoir can receive a) random unregulated inflow, b) pumped inflow from other reservoirs, and c) regulated inflow from reservoir releases. Since the reservoirs in the Concho basin are not interconnected by pipelines, the system was not modeled for this interaction, although this could be accomplished to test a variety of possible system designs. The reservoir storage is depleted by a) scheduled releases, b) deterministic demands, and c) evaporation and seepage losses.

Parts a and **b** of Fig. 15 contain the operational configuration for the k^{th} reservoir and a schematic diagram of the three reservoir system in the Concho River basin. The following notation is given to provide explanation of the model design and system operation:

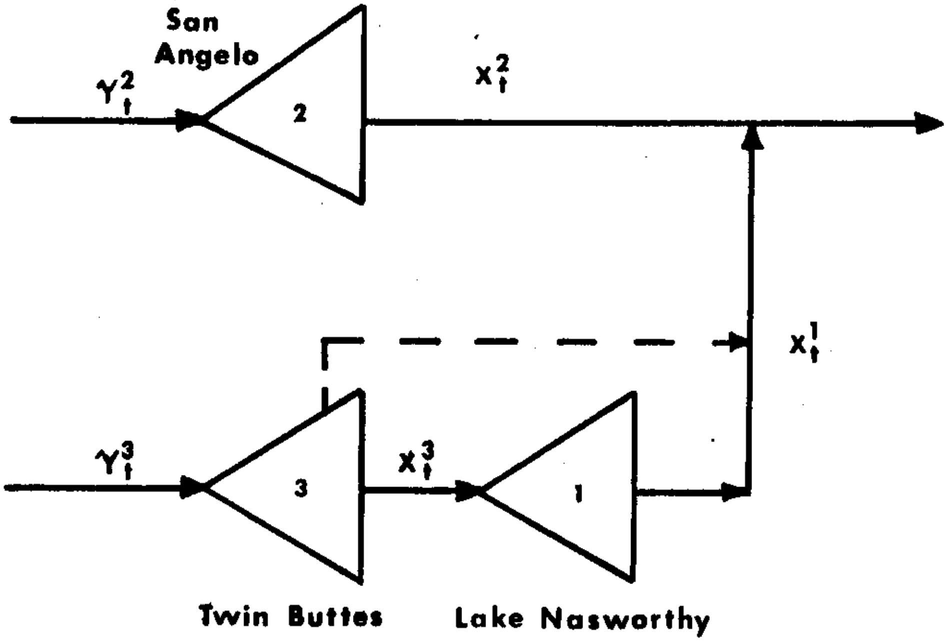
m - the number of reservoirs (m=3 for the Concho basin);

γ_t^k - random unregulated inflow into reservoir k in time period t;

c_t^k - capacity of reservoir k in period t;



a. Operational configuration for the kth reservoir.



b. Reservoir system schematic.

Fig. 15. The operational configuration for the kth reservoir and a reservoir system schematic for the Concho River basin.

v_t^k - upper storage space required for reservoir k in time period t;

s_t^k - ending reservoir inventory level for period t;

$\underline{s}_t^k$ - minimum specified inventory level;

e_t^k - fraction of inventory remaining after evaporation and seepage losses;

x_t^k - scheduled downstream release from reservoir;

$\bar{x}_t^k$ - maximum downstream release;

$\underline{x}_t^k$ - minimum downstream release; and

d_t^k - deterministic demand directly extracted from the reservoir (e.g., by a pipe line).

The parameters which remain fixed in time for each reservoir were $\underline{x}_t^k$, c_t^k , $\underline{s}_t^k$, and $\bar{x}_t^k$. $\bar{x}_t^k$ was established to be 60,000 acre-ft per month for each river channel, $\underline{s}_t^k$ is given in Table 2 as the dead storage of each reservoir, $\underline{x}_t^k$ was taken to be zero, and c_t^k is the total storage of each reservoir. For all three reservoirs d_t^k was equal to zero because all demands or water requirements are supplied by downstream releases and not directly taken from the reservoirs.

The other parameters were determined as follows:

1. γ_t^k is calculated from rainfall and API data by use of Eq. 23 and 26 in which the basin rainfall values are simulated from the 30-day forecasts or an "expected"

value using conditional probabilities. γ_t^k also can be obtained from the historic mean and standard deviations of streamflow. Inflow is deterministic when described by a single value and stochastic when an upper and lower bound are used;

2. e_t^k is calculated from simulated or expected values of temperature from Eq. 28. It is then converted to a fraction of reservoir contents that will remain after evaporation losses occur, e.g., for an evaporation loss ratio of 0.05, e_t^k will equal 0.95. The amount of seepage was not calculated directly but is implied in the magnitude of e_t^k ; and
3. x_t^k was determined by computing crop consumptive-use from Eq. 31 and assuming that the reservoirs would satisfy only 25 percent of the water requirements for irrigation and to that was added the city water requirements obtained from historical records.

The physical configuration of the existing reservoir system is shown in Fig. 15b. The dashed line represents the capability of Twin Buttes reservoir to supply downstream demands by releasing water through Lake Nasworthy. Physically, it is the same as replacing water released from Lake Nasworthy.

The continuity equation for the k^{th} reservoir in time period t is

$$s_t^k = e_t^k \, s_{t-1}^k + \gamma_t^k - d_t^k - x_t^k \quad , \tag{37}$$

where explanation of the variables was given previously. The chance-constraints $\left(\alpha_1^k \text{ and } \alpha_2^k\right)$ for the probability of not exceeding the maximum capacity and for the storage to exceed the minimum pool level are, respectively,

$$P\left\{s_t^k \leq c_t^k - v_t^k\right\} \geq \alpha_1^k \qquad (k = 1 \ldots\ldots m;\ t = 1\ldots\ldots T) \quad , \tag{38}$$

and

$$P\left\{s_t^k \geq \underline{s}_t^k\right\} \geq \alpha_2^k \qquad (k = 1 \ldots\ldots m;\ t = 1 \ldots\ldots T) \ . \tag{39}$$

Also, the downstream releases must satisfy the minimum and maximum reservoir release constraints, where

$$\underline{x}_t^k \leq x_t^k \leq \overline{x}_t^k \qquad (\text{for all } k,t) \ . \tag{40}$$

These chance-constraints are converted then to their equivalent linear deterministic constraints by convolution (Curry <u>et al</u>., 1972). The structure of the problem will then be in the form of Eqs. 20 and 21, where the decision variables must satisfy the equivalent deterministic constraints and the upper and lower limits on releases.

The final consideration of the three-reservoir model was to determine some means of pricing the water in the system or determining a water-utility value. James (1968) stated that operation of any reservoir depends upon rules prescribing the quantity of water which should be held within the reservoir from month-to-month. When these rules are derived from economic considerations, the operating policy will maximize the benefits for the existing facility. Maunder (1970) discusses the reliability and value of long-range forecasts stating that "the inability to forecast the 'extreme' categories (those occurring about 20 percent of the time) on most occasions is the most serious deficiency to be remedied." He also presents the means to determine the economic and/or social value of weather prediction.

In this study consideration of the percentage of evaporation (water loss from each reservoir) predicted with some degree of accuracy from the temperature forecasts, and the minimum downstream releases required to meet consumptive-use and city water demand, a benefit-loss factor (BLF) was established for each reservoir. Based upon these variables, releases were made from the reservoir having the smallest BLF. It was assumed that the benefits accrued from satisfying the demands for water were the same for each reservoir. Therefore, the decision to release water from a reservoir was based upon the evaporation losses. In this case, the reservoir that will have the greatest evaporation losses will benefit most from releasing water. The BLF for each reservoir was represented by the negative of the percentage of water remaining in each reservoir for the time period, since the linear programming solution maximizes the objective function. The result is that water is released from the least negative BLF or from the reservoir having the largest percentage of evaporation loss.

5. DISCUSSION OF RESULTS

a. Statistical analyses

To provide information about the future meteorological and hydrometeorological conditions of the Concho River basin a stochastic data base was established for each hydrological and climatological data station. From the data base, quantitative values of temperature and precipitation can be simulated. In order to simulate data which conformed to the 30-day meteorological forecast categories, historical data were analyzed statistically and tested for goodness of fit to the normal, square-root-normal, cube-root-normal, and log-normal frequency distributions. Based upon statistical properties of the frequency distribution which provided the best fit, forecast data values were simulated for the meteorological stations listed in Table 3 and shown in Figs. 8 and 10. The MOHS also can be modified to simulate monthly values of API and reservoir evaporation by using as input, the 30-day temperature and precipitation forecasts.

Table 9 provides a summary of the fit of the data to the various frequency distributions that were tested. The results show that the adjusted pan evaporation data (reservoir evaporation) conformed best to either the cube-root-normal or the log-normal distribution although the other frequency distributions fit the data quite adequately. For the temperature data similar results

Table 9. Percent of data conforming to the frequency distributions.

	MONTHLY				MID-MONTHLY				BIWEEKLY			
STA.	NORM	SQ-RT	CB-RT	LOG	NORM	SQ-RT	CB-RT	LOG	NORM	SQ-RT	CB-RT	LOG
Evaporation												
SGD	100	100	100	100	100	100	100	100	79	88	92	92
Mean ambient air temperature												
BAL	84	84	92	92	100	92	92	84	84	92	92	92
BGS	92	92	92	92	100	92	92	92	96	96	92	92
EDN	84	84	84	84	92	92	92	92	92	92	92	88
OZA	92	92	92	92	100	100	100	100	96	96	96	100
SAG	84	84	84	84	100	100	92	92	96	96	96	96
Precipitation												
BAL	0	75	67	0	0	84	67	8	4	38	46	12
BRN	58	84	100	50	75	84	92	67	29	100	92	66
BGL	25	100	84	42	50	92	84	16	25	75	84	54
CSR	25	84	75	25	58	84	84	50	38	92	71	50
CHR	42	100	100	67	58	100	92	33	33	92	92	71
CPR	25	84	92	33	58	92	100	25	33	84	66	38
CXR	58	92	84	50	50	92	84	58	33	88	88	88
EDN	42	92	84	0	16	92	92	8	4	92	88	62
ELD	16	84	84	33	67	92	84	42	4	88	75	50
FSN	58	92	84	42	50	100	84	25	38	66	71	50
FKR	25	92	84	42	50	100	84	58	25	96	92	62
GDC	0	58	58	8	8	75	75	16	0	29	25	8
MEN	0	75	84	0	0	84	84	0	25	58	75	21
MN3	42	84	75	8	92	92	75	50	12	88	75	54
MER	16	100	100	58	8	84	92	33	8	84	96	54
PRK	8	92	84	0	25	100	75	8	0	58	75	33
RLE	50	84	67	25	50	92	67	58	33	75	58	46
SAG	8	84	75	0	8	75	92	25	0	33	71	42
STC	0	84	75	0	16	75	84	8	4	54	62	17
TEN	42	92	92	42	58	92	84	42	42	88	84	46
VAN	50	100	67	33	42	100	92	50	38	84	71	58
WTV	25	84	75	33	84	100	92	58	38	84	66	33
Antecedent Precipitation Index												
BAL	0	67	84	58	0	75	100	25	0	54	88	80
BRN	67	75	84	75	58	92	92	92	50	88	96	96
BGL	50	75	100	92	25	84	84	84	4	92	100	84
CSR	50	92	92	92	16	92	84	67	29	88	92	88
CHR	67	84	92	92	42	48	75	84	33	84	88	84
CPR	50	92	100	75	8	92	84	75	17	96	92	80
CXR	50	75	84	75	50	75	75	75	50	84	88	88
EDN	33	84	75	67	0	75	100	58	4	84	100	92
ELD	50	92	92	75	25	84	84	58	12	88	92	84
FSN	50	92	92	84	42	92	84	58	42	88	96	96
FKR	42	100	100	92	42	92	100	58	21	92	100	96
GDC	8	75	75	25	8	67	84	33	4	46	80	42
MEN	0	75	75	50	0	50	67	50	4	46	84	80

Table 9. Continued.

	MONTHLY				MID-MONTHLY				BIWEEKLY			
STA.	NORM	SQ-RT	CB-RT	LOG	NORM	SQ-RT	CB-RT	LOG	NORM	SQ-RT	CB-RT	LOG
MN3	75	84	84	75	67	92	92	67	46	92	84	92
MER	25	75	92	75	0	84	92	84	0	54	96	88
PRK	25	84	67	50	0	75	95	58	8	71	88	71
RLE	50	100	100	84	58	92	84	58	29	92	96	80
SAG	0	58	84	50	0	67	84	50	0	50	80	71
STC	33	84	84	33	8	84	100	25	4	66	92	75
TEN	67	75	75	67	58	75	75	75	38	92	92	84
VAN	42	92	75	84	50	92	92	75	33	80	92	92
WTV	58	92	92	75	50	100	92	58	33	92	92	80

are obtained in that all frequency distributions seem to represent the temperature values equally well. MOHS was programmed to simulate temperature data which were normally distributed. The best fit for precipitation data was to the square-root-normal frequency distribution. For the monthly data, 87 percent satisfied the tests for normalcy, while 90 percent of the mid-monthly data and 75 percent of the biweekly data conformed. The API data fit the cube-root-normal distribution best. The percentages for the monthly, mid-monthly and biweekly data were 86, 87, and 91 percent, respectively. General agreement between these results and those of O'Connor (1970), O'Connor and Clark (1971), and Albrecht (1971) has been found.

After the frequency distribution most representative of the data has been determined, the statistical properties described in Section 3b are used in the simulation procedure. Tables 10 and 11 are examples of the statistical analyses of the data. The heading describes the station, the data considered, and the frequency distribution most representative. Under the column entitled "FIT," an "X" indicates that the data conform to that distribution while the blank space in the column means the data did not pass the statistical tests for normalcy for that time period. The other six columns are labeled with the symbols for the various statistical properties described in Section 3b. It

Table 10. Statistical and Markov first-order transitional probability analyses for Mertzon.

	STATION- MERTZON DATA- PRECIPITATION DISTRIBUTION- SQUARE-ROOT							DATA- API DISTRIBUTION- CUBE-ROOT						
PERIOD	FIT	$\bar{X}$	Sx	|e|	Cs	Ck	Mx	FIT	$\bar{X}$	Sx	|e|	Cs	Ck	Mx
1	X	.75	.57	.48	.28	1.8	.65	X	.52	.29	.24	-.34	2.0	.55
2	X	.81	.46	.39	.25	1.9	.83	X	.58	.22	.19	.31	1.9	.57
3	X	.79	.52	.41	.67	2.8	.81	X	.57	.21	.15	.61	2.5	.53
4	X	1.19	.52	.44	-.09	1.7	1.37	X	.67	.23	.19	.04	1.7	.67
5	X	1.41	.58	.46	.52	3.1	1.44	X	.81	.23	.18	.74	3.1	.78
6	X	1.27	.62	.51	.16	2.3	1.29	X	.77	.23	.19	.14	2.4	.76
7	X	1.02	.60	.47	.46	2.9	1.03	X	.68	.24	.20	.67	2.9	.67
8	X	1.19	.66	.54	.67	2.9	1.03	X	.67	.24	.19	.47	2.5	.66
9	X	1.50	.58	.47	-.14	2.1	1.53	X	.82	.24	.20	-.18	2.3	.86
10	X	1.15	.59	.48	.32	2.5	1.03	X	.76	.25	.19	.36	2.9	.74
11	X	.82	.55	.45	-.04	1.9	.88		.57	.21	.16	-.57	3.1	.59
12	X	.78	.50	.42	.18	1.8	.82	X	.53	.24	.20	-.45	2.4	.52
1a	X	.83	.40	.33	.15	2.0	.85	X	.55	.21	.18	.06	1.9	.57
2a	X	.81	.50	.40	.43	2.4	.78	X	.58	.24	.20	.14	1.9	.61
3a	X	.95	.50	.38	.76	3.0	.87	X	.59	.20	.15	.33	2.8	.58
4a	X	1.31	.62	.49	.63	2.9	1.30		.76	.26	.18	.54	2.8	.76
5a	X	1.36	.61	.50	.23	2.5	1.39	X	.80	.22	.17	.79	3.9	.83
6a	X	1.20	.69	.54	.73	2.6	1.14	X	.74	.26	.20	.47	2.5	.72
7a	X	.91	.60	.50	.38	2.1	.85	X	.62	.22	.18	.11	1.8	.63
8a	X	1.38	.69	.55	.38	3.2	1.40	X	.77	.26	.21	.37	2.7	.77
9a	X	1.38	.75	.59	.15	2.7	1.46	X	.83	.27	.22	-.07	2.2	.86
10a		.90	.46	.40	-.05	1.7	1.03	X	.63	.21	.17	.16	1.9	.66
11a		.81	.53	.46	.11	1.7	.80	X	.55	.25	.21	-.41	2.5	.61
12a	X	.79	.49	.39	.37	2.7	.76	X	.57	.17	.14	-.06	1.9	.60
1b	X	.48	.49	.41	.71	2.4	.33	X	.50	.31	.27	.00	1.8	.43
2b	X	.52	.42	.36	.38	1.6	.39	X	.50	.29	.24	-.23	1.9	.53
3b	X	.52	.35	.30	.34	2.1	.48	X	.53	.23	.18	.30	3.3	.53
4b	X	.53	.47	.39	.59	2.1	.47	X	.57	.30	.25	.12	2.2	.58
5b		.46	.44	.33	1.46	4.9	.33		.53	.25	.18	.06	3.2	.54
6b	X	.55	.46	.37	.83	3.9	.62	X	.55	.26	.21	.46	2.4	.59
7b	X	.58	.56	.47	.52	1.8	.46	X	.56	.25	.19	.16	2.6	.52
8b	X	.90	.56	.43	.44	2.4	.93	X	.71	.28	.24	.03	1.9	.76
9b	X	.82	.58	.49	.26	2.3	.94	X	.76	.29	.22	.70	2.8	.76
10b	X	1.06	.55	.45	.16	2.1	1.02	X	.82	.24	.18	.50	2.9	.81
11b	X	.80	.54	.44	.44	2.2	.71	X	.76	.26	.20	.78	3.6	.77
12b	X	.75	.74	.61	.72	2.4	.60	X	.71	.31	.24	.28	3.0	.74
13b		.68	.61	.49	1.01	4.1	.55	X	.69	.29	.23	.76	3.3	.68
14b		.55	.51	.38	1.05	4.0	.53	X	.62	.27	.21	.65	2.6	.59
15b	X	.61	.53	.41	.85	3.0	.52	X	.55	.25	.20	.57	2.5	.54
16b	X	.87	.66	.51	.86	3.9	.84	X	.72	.29	.23	.57	2.8	.68
17b	X	.95	.55	.45	-.20	1.8	.97	X	.78	.29	.24	-.13	2.1	.81
18b	X	.98	.67	.57	.11	2.0	1.03	X	.81	.27	.22	.04	2.2	.84
19b	X	.81	.64	.52	.56	2.3	.72	X	.80	.34	.26	.37	2.7	.81
20b	X	.61	.47	.39	.44	2.3	.66	X	.65	.25	.20	-.10	2.8	.62
21b	X	.48	.46	.39	.60	1.9	.41	X	.56	.24	.21	-.10	2.3	.60
22b		.45	.49	.44	.49	1.6	.33	X	.51	.29	.24	-.34	1.9	.53
23b	X	.56	.42	.34	.50	2.4	.51	X	.54	.27	.22	-.09	2.1	.54
24b	X	.46	.43	.35	.55	2.0	.45	X	.50	.23	.19	-.09	2.1	.52

	MARKOV FIRST-ORDER TRANSITIONAL PROBABILITIES DATA- PRECIPITATION									DATA- API								
PERIOD	B-B	B-N	B-A	N-B	N-N	N-A	A-B	A-N	A-A	B-B	B-N	B-A	N-B	N-N	N-A	A-B	A-N	A-A
1	.20	.06	.13	.10	.10	.06	.10	.06	.17	.20	.10	.06	.10	.10	.06	.10	.10	.17
2	.11	.24	.07	.20	.00	.03	.14	.06	.17	.17	.20	.03	.17	.10	.03	.00	.14	.17
3	.17	.07	.20	.17	.06	.06	.07	.03	.17	.17	.04	.14	.21	.14	.10	.03	.07	.14
4	.11	.05	.24	.11	.06	.00	.10	.20	.14	.14	.10	.17	.10	.14	.00	.13	.06	.17
5	.17	.06	.07	.17	.06	.10	.10	.11	.17	.21	.07	.10	.07	.21	.03	.07	.10	.17
6	.17	.14	.14	.07	.10	.07	.10	.10	.14	.17	.03	.14	.17	.10	.10	.10	.07	.14
7	.11	.07	.17	.10	.14	.10	.10	.14	.11	.11	.17	.17	.10	.03	.07	.17	.14	.07
8	.14	.14	.03	.20	.07	.07	.00	.14	.24	.24	.07	.07	.14	.14	.06	.00	.07	.24
9	.17	.14	.03	.14	.03	.17	.13	.07	.14	.24	.10	.03	.03	.10	.14	.03	.20	.14
10	.11	.14	.20	.03	.14	.07	.17	.06	.11	.14	.13	.03	.00	.30	.10	.10	.07	.14
11	.17	.03	.11	.14	.10	.10	.10	.10	.17	.17	.07	.00	.13	.18	.20	.03	.03	.21
12	.20	.10	.06	.10	.03	.10	.06	.14	.17	.17	.10	.03	.03	.14	.10	.14	.06	.21
1a	.13	.16	.06	.13	.06	.06	.06	.13	.17	.17	.13	.06	.10	.06	.06	.13	.06	.20
2a	.14	.14	.06	.10	.14	.24	.14	.10	.07	.17	.20	.03	.10	.10	.06	.10	.06	.17
3a	.10	.17	.10	.17	.14	.07	.10	.07	.10	.17	.10	.10	.17	.14	.06	.00	.20	.07
4a	.14	.07	.17	.21	.14	.03	.07	.10	.10	.10	.14	.10	.21	.21	.03	.00	.17	.04
5a	.21	.06	.14	.10	.17	.03	.10	.07	.14	.17	.07	.07	.21	.21	.10	.03	.07	.11
6a	.10	.17	.14	.17	.08	.10	.17	.06	.07	.17	.10	.14	.10	.14	.10	.00	.17	.14
7a	.17	.10	.17	.14	.10	.03	.07	.06	.17	.17	.10	.07	.07	.14	.14	.17	.03	.14
8a	.21	.07	.10	.03	.17	.06	.10	.06	.21	.24	.10	.06	.06	.14	.07	.00	.14	.21
9a	.17	.00	.17	.14	.07	.10	.14	.06	.17	.21	.07	.03	.10	.14	.14	.10	.07	.17
10a	.21	.03	.21	.10	.00	.03	.14	.14	.17	.17	.03	.20	.10	.07	.10	.07	.14	.14
11a	.27	.10	.07	.10	.00	.06	.07	.17	.17	.21	.10	.04	.10	.03	.10	.06	.14	.21
12a	.11	.14	.18	.07	.14	.07	.14	.07	.10	.11	.10	.17	.21	.03	.00	.07	.12	.22
1b	.23	.13	.06	.13	.10	.00	.06	.03	.23	.30	.06	.03	.06	.10	.03	.00	.13	.27
2b	.21	.10	.14	.07	.03	.17	.17	.03	.10	.24	.10	.03	.10	.14	.06	.03	.10	.21
3b	.31	.03	.10	.06	.03	.07	.07	.17	.17	.24	.10	.03	.14	.07	.14	.03	.10	.17
4b	.18	.14	.14	.00	.13	.10	.20	.07	.07	.24	.14	.03	.07	.17	.03	.03	.10	.21
5b	.14	.14	.10	.13	.10	.10	.07	.06	.17	.21	.10	.03	.17	.17	.06	.03	.03	.21
6b	.07	.10	.17	.20	.04	.07	.20	.06	.10	.17	.07	.17	.17	.07	.06	.06	.14	.10
7b	.14	.17	.17	.07	.06	.06	.10	.20	.04	.21	.06	.14	.17	.06	.03	.03	.07	.24
8b	.10	.14	.07	.20	.03	.20	.10	.04	.14	.24	.10	.07	.03	.17	.00	.17	.06	.18
9b	.20	.10	.10	.04	.06	.10	.17	.06	.17	.24	.17	.03	.03	.21	.10	.03	.06	.14
10b	.17	.14	.10	.17	.00	.07	.10	.10	.17	.24	.07	.00	.13	.21	.10	.03	.10	.14
11b	.14	.17	.14	.07	.06	.10	.20	.03	.10	.24	.03	.13	.10	.14	.14	.03	.17	.03
12b	.07	.24	.10	.20	.00	.07	.14	.10	.10	.18	.14	.07	.20	.07	.07	.06	.03	.20
13b	.24	.07	.10	.04	.17	.14	.14	.10	.03	.24	.14	.06	.10	.06	.06	.06	.14	.14
14b	.21	.14	.07	.14	.03	.17	.07	.14	.06	.24	.07	.10	.14	.06	.14	.00	.17	.10
15b	.24	.10	.06	.07	.10	.14	.10	.10	.10	.24	.03	.10	.10	.10	.10	.03	.14	.17
16b	.21	.14	.06	.06	.14	.10	.07	.03	.20	.13	.14	.07	.17	.07	.03	.03	.10	.27
17b	.14	.07	.14	.14	.14	.03	.14	.03	.21	.17	.10	.06	.14	.06	.10	.03	.14	.21
18b	.17	.14	.11	.11	.03	.10	.14	.10	.14	.21	.10	.03	.14	.10	.07	.03	.14	.21
19b	.10	.17	.14	.14	.10	.03	.17	.00	.17	.14	.10	.14	.21	.06	.06	.06	.17	.14
20b	.14	.14	.14	.17	.00	.10	.14	.10	.10	.27	.03	.03	.14	.06	.14	.03	.03	.27
21b	.27	.04	.14	.07	.03	.14	.14	.10	.10	.21	.06	.17	.03	.06	.03	.10	.10	.24
22b	.24	.17	.07	.06	.03	.07	.07	.14	.17	.24	.10	.00	.06	.06	.10	.03	.17	.24
23b	.21	.10	.06	.14	.10	.10	.10	.07	.14	.24	.07	.03	.10	.17	.07	.00	.07	.29
24b	.28	.14	.03	.07	.03	.14	.10	.07	.14	.25	.03	.03	.10	.14	.07	.06	.03	.29

Table 11. Statistical and Markov first-order transitional probability analyses of temperature and evaporation data.

	STATION- SAN ANGELO DATA- MEAN AIR TEMPERATURE DISTRIBUTION- NORMAL							STATION- SAN ANGELO DAM DATA- EVAPORATION DISTRIBUTION- CUBE-ROOT								MARKOV FIRST-ORDER TRANSITIONAL PROBABILITIES DATA- MEAN AIR TEMPERATURE									DATA- EVAPORATION								
PERIOD	FIT	$\bar{X}$	Sx	|e|	Cs	Ck	Mx	FIT	$\bar{X}$	Sx	|e|	Cs	Ck	Mx	PERIOD	B-B	B-N	B-A	N-B	N-N	N-A	A-B	A-N	A-A	B-B	B-N	B-A	N-B	N-N	N-A	A-B	A-N	A-A
1	X	45.8	3.9	3.1	.08	2.3	46.1	X	1.44	.12	.10	-.50	2.1	1.49	1	.13	.15	.08	.10	.15	.08	.13	.05	.15	.18	.12	.00	.00	.05	.18	.16	.05	.24
2	X	49.9	3.8	3.0	.62	3.8	50.0	X	1.46	.15	.12	.28	2.2	1.46	2	.20	.00	.15	.05	.08	.23	.10	.15	.05	.19	.06	.12	.05	.05	.13	.13	.12	.19
3	X	56.7	4.3	3.5	-.26	1.9	57.4	X	1.69	.21	.18	-.52	1.7	1.77	3	.11	.18	.08	.13	.05	.06	.10	.20	.13	.25	.06	.06	.00	.18	.06	.00	.24	.19
4	X	66.2	3.2	2.4	.26	2.5	66.0	X	1.87	.14	.11	-.58	2.8	1.91	4	.13	.15	.05	.15	.13	.15	.08	.08	.10	.19	.06	.00	.12	.06	.30	.05	.07	.19
5	X	73.4	2.3	1.8	-.10	2.4	73.7	X	1.98	.15	.13	-.15	1.6	2.04	5	.15	.15	.05	.10	.15	.10	.05	.13	.13	.25	.06	.05	.06	.06	.07	.12	.12	.21
6		81.0	2.4	1.7	-.36	4.3	81.1	X	2.14	.12	.10	.14	1.6	2.17	6	.20	.08	.03	.13	.10	.20	.05	.10	.17	.19	.06	.13	.00	.12	.12	.00	.15	.19
7	X	83.8	2.1	1.8	-.29	2.3	84.4	X	2.28	.15	.12	-.80	2.5	2.36	7	.23	.10	.05	.10	.05	.13	.08	.05	.23	.19	.00	.01	.18	.13	.06	.18	.01	.31
8	X	83.5	2.0	1.7	.42	2.5	83.5	X	2.30	.09	.08	.41	1.6	2.30	8	.13	.13	.15	.13	.03	.05	.08	.10	.23	.13	.35	.05	.13	.00	.00	.07	.12	.19
9	X	76.3	2.7	2.2	-.20	2.6	77.1	X	2.08	.12	.10	-.15	2.0	2.11	9	.23	.08	.03	.10	.05	.10	.10	.05	.28	.18	.08	.06	.13	.18	.18	.12	.00	.13
10		67.0	3.1	2.8	.08	1.6	66.3	X	1.88	.13	.10	-.11	2.5	1.90	10	.16	.15	.13	.05	.08	.05	.15	.05	.21	.19	.18	.06	.19	.06	.01	.06	.00	.25
11	X	54.6	3.0	2.4	-.02	2.2	54.5	X	1.69	.12	.10	-.19	1.6	1.73	11	.08	.18	.10	.10	.05	.13	.15	.13	.11	.25	.12	.06	.01	.12	.12	.06	.05	.25
12	X	48.1	2.9	2.4	-.14	2.7	48.3	X	1.55	.14	.11	-.39	1.8	1.58	12	.13	.13	.08	.10	.08	.18	.13	.10	.05	.13	.06	.13	.06	.06	.19	.13	.06	.19
1a	X	47.9	4.7	3.7	-.11	2.6	47.9	X	1.44	.13	.11	-.44	1.8	1.51	1a	.10	.13	.10	.15	.10	.10	.10	.07	.15	.24	.05	.12	.00	.00	.12	.15	.12	.15
2a	X	52.1	3.6	2.9	-.61	3.4	53.2	X	1.55	.18	.15	-.20	1.9	1.61	2a	.18	.13	.05	.08	.08	.15	.12	.15	.08	.25	.18	.00	.00	.17	.00	.01	.06	.33
3a	X	61.5	3.6	2.8	.39	2.5	61.3	X	1.80	.16	.12	-.84	2.5	1.86	3a	.18	.13	.08	.12	.12	.10	.10	.08	.10	.25	.01	.00	.12	.19	.12	.00	.12	.26
4a	X	70.0	3.1	2.4	.46	2.9	69.8	X	1.93	.14	.11	-.37	1.8	1.93	4a	.18	.10	.13	.13	.13	.07	.03	.10	.15	.25	.00	.12	.13	.13	.06	.05	.13	.19
5a	X	77.5	2.4	1.9	.09	2.5	77.4	X	2.06	.15	.13	-.06	1.3	2.11	5a	.13	.15	.03	.05	.18	.10	.10	.07	.18	.13	.12	.18	.13	.00	.13	.00	.24	.13
6a	X	82.8	2.6	2.0	-.17	2.5	83.1	X	2.22	.14	.10	-.78	2.7	2.28	6a	.10	.15	.00	.13	.05	.25	.05	.07	.18	.18	.00	.07	.13	.00	.24	.12	.07	.24
7a	X	84.6	2.0	1.7	-.44	2.3	85.2	X	2.30	.13	.10	-.57	2.5	2.36	7a	.10	.15	.05	.13	.07	.08	.07	.10	.25	.19	.12	.12	.00	.06	.01	.18	.06	.31
8a	X	80.3	2.5	2.1	-.40	1.9	81.1	X	2.23	.08	.07	.14	1.9	2.23	8a	.13	.10	.07	.15	.05	.13	.13	.10	.16	.13	.18	.06	.12	.06	.06	.07	.24	.14
9a	X	72.1	3.1	2.6	.22	2.2	71.6	X	1.96	.15	.11	-.38	2.5	1.93	9a	.23	.10	.07	.07	.07	.10	.03	.18	.15	.06	.13	.12	.24	.12	.12	.06	.07	.13
10a	X	60.5	2.8	2.2	-.06	2.8	60.6	X	1.79	.12	.10	.15	2.4	1.83	10a	.16	.05	.13	.10	.20	.05	.15	.07	.10	.12	.13	.13	.25	.00	.06	.05	.05	.24
11a	X	50.5	3.4	2.7	.32	2.7	50.1	X	1.61	.16	.13	-.42	2.3	1.68	11a	.23	.10	.07	.07	.13	.13	.03	.13	.13	.18	.18	.06	.13	.00	.06	.06	.18	.19
12a	X	46.4	2.9	2.3	-.15	2.4	46.5	X	1.48	.09	.07	.08	1.7	1.49	12a	.08	.16	.10	.13	.08	.13	.13	.11	.11	.07	.07	.25	.20	.00	.13	.13	.14	.07
1b	X	45.5	4.7	3.9	-.38	2.1	47.4	X	1.13	.11	.10	-.19	1.5	1.20	1b	.07	.18	.10	.07	.00	.10	.15	.15	.15	.18	.18	.00	.00	.05	.12	.05	.29	.12
2b	X	46.2	6.4	4.9	-.33	2.6	46.7		1.14	.11	.08	.17	2.7	1.16	2b	.10	.15	.05	.13	.18	.05	.07	.07	.20	.13	.13	.00	.18	.00	.36	.06	.14	.08
3b	X	49.6	5.4	4.1	.44	3.0	48.8	X	1.14	.15	.12	-.34	2.7	1.17	3b	.10	.13	.07	.15	.13	.13	.05	.18	.08	.18	.13	.05	.13	.12	.02	.06	.15	.18
4b	X	50.1	4.8	3.8	.16	2.6	50.2	X	1.18	.13	.09	.52	2.8	1.18	4b	.13	.05	.13	.15	.10	.10	.07	.07	.13	.13	.06	.18	.24	.00	.18	.00	.13	.13
5b	X	54.2	5.3	4.4	-.18	2.2	54.9	X	1.27	.21	.18	-.33	1.3	1.44	5b	.20	.10	.05	.07	.05	.10	.02	.15	.25	.24	.12	.01	.07	.00	.13	.00	.06	.42
6b	X	59.3	4.2	3.9	-.18	2.2	59.6	X	1.40	.15	.12	-.58	2.0	1.47	6b	.13	.05	.13	.18	.10	.02	.10	.13	.13	.19	.13	.00	.00	.12	.06	.00	.30	.26
7b	X	63.8	4.3	3.5	.42	2.4	64.0		1.45	.12	.08	-.74	2.9	1.47	7b	.15	.15	.10	.07	.15	.05	.13	.05	.16	.19	.00	.00	.12	.18	.24	.00	.14	.19
8b	X	68.6	3.6	2.8	.35	3.1	68.2	X	1.51	.12	.10	-.31	2.3	1.56	8b	.18	.10	.07	.15	.13	.07	.07	.05	.18	.31	.00	.00	.06	.07	.19	.05	.06	.31
9b	X	71.4	3.7	3.1	-.04	1.9	71.9	X	1.55	.11	.10	-.01	1.5	1.60	9b	.18	.10	.13	.05	.13	.10	.15	.05	.13	.25	.12	.05	.06	.00	.07	.06	.18	.25
10b	X	75.4	2.8	2.2	-.17	2.9	75.9	X	1.58	.15	.12	-.07	1.5	1.81	10b	.18	.13	.07	.10	.07	.10	.07	.05	.23	.31	.06	.00	.06	.12	.12	.06	.13	.19
11b	X	79.6	2.9	2.4	-.24	2.3	80.0	X	1.67	.12	.10	.04	2.1	1.70	11b	.07	.18	.10	.10	.13	.02	.10	.07	.23	.25	.12	.05	.05	.13	.13	.13	.00	.19
12b	X	82.3	3.0	2.3	-.34	3.4	82.6	X	1.72	.12	.10	-.28	2.3	1.75	12b	.23	.02	.02	.02	.20	.15	.10	.05	.21	.19	.18	.06	.00	.13	.13	.06	.12	.19
13b	X	83.2	2.8	2.3	-.09	1.9	83.6	X	1.80	.11	.09	-.78	2.4	1.83	13b	.13	.18	.05	.07	.13	.07	.02	.20	.16	.19	.07	.00	.12	.06	.24	.06	.13	.19
14b		84.3	2.4	1.7	-.74	3.6	84.8	X	1.81	.14	.12	-.69	2.5	1.86	14b	.18	.05	.00	.10	.15	.25	.05	.13	.10	.19	.18	.00	.06	.00	.19	.12	.13	.19
15b	X	84.8	2.5	2.1	-.08	2.3	85.0	X	1.84	.09	.07	.10	2.0	1.83	15b	.15	.15	.02	.02	.15	.16	.10	.13	.13	.25	.13	.00	.13	.00	.13	.06	.06	.25
16b	X	82.1	2.4	1.9	.07	2.6	82.2	X	1.81	.07	.06	.48	1.7	1.80	16b	.20	.05	.02	.15	.10	.18	.02	.05	.23	.31	.18	.00	.01	.05	.13	.06	.18	.13
17b	X	78.5	3.3	2.7	-.29	2.4	78.4	X	1.72	.07	.06	.13	2.0	1.73	17b	.18	.15	.05	.07	.05	.07	.07	.20	.16	.20	.19	.00	.12	.18	.13	.06	.01	.18
18b	X	74.2	3.3	2.5	.35	2.9	73.8	X	1.58	.15	.12	-.25	1.8	1.63	18b	.18	.13	.02	.15	.10	.15	.07	.03	.15	.19	.13	.05	.00	.19	.19	.12	.00	.19
19b	X	70.0	3.9	3.3	.34	2.2	69.1	X	1.52	.12	.10	-.13	1.8	1.51	19b	.20	.16	.02	.15	.00	.10	.02	.18	.15	.07	.24	.00	.12	.13	.07	.06	.12	.25
20b	X	64.0	3.4	2.7	.34	2.5	64.0	X	1.45	.13	.10	-.27	2.8	1.48	20b	.18	.10	.10	.05	.18	.13	.10	.07	.10	.18	.01	.05	.18	.06	.24	.12	.06	.13
21b	X	57.0	3.9	3.1	.24	2.5	57.0	X	1.38	.12	.10	-.14	1.6	1.41	21b	.13	.07	.13	.18	.08	.10	.10	.10	.13	.19	.18	.12	.07	.00	.07	.18	.00	.24
22b	X	52.2	4.4	3.6	.31	2.3	51.4	X	1.30	.14	.12	-.12	1.8	1.33	22b	.15	.15	.10	.15	.05	.05	.05	.18	.13	.19	.13	.13	.12	.00	.06	.07	.12	.25
23b	X	48.8	3.9	3.2	.33	2.1	48.8	X	1.25	.16	.13	-.54	2.1	1.29	23b	.13	.05	.18	.18	.13	.07	.07	.07	.13	.25	.00	.13	.06	.12	.06	.06	.13	.25
24b	X	47.3	3.8	3.2	-.17	2.0	47.3	X	1.20	.12	.10	-.21	1.7	1.23	24b	.23	.00	.16	.00	.13	.13	.13	.03	.21	.20	.06	.13	.13	.07	.06	.06	.07	.27

is interesting to note that the mean ($\bar{X}$) of the precipitation data for MER (Mertzon) follows the climatic trend, Fig. 4, described by Portig (1962). The early summer and early fall maximums of rainfall are shown clearly by the precipitation as well as the API data. The trend of monthly mean temperatures demonstrates the influence of the annual solar cycle upon this meteorological variable. The evaporation data also follow the same annual cycle thus demonstrating the strong influence of temperature on evaporation.

The streamflow data for the North Concho River at Carlsbad (NCC), the Middle Concho River (MCT), Spring Creek (SPT), and the South Concho River (SCC) conform best to the log-normal frequency distribution. These rivers are the main contributors of water to the three reservoirs located in the Concho River basin. The data for the North Concho River at San Angelo (NSA) are a measure of the releases from San Angelo reservoir, while data for the Concho River at San Angelo (CSA) (located below the city of San Angelo) provide information about the releases from the entire reservoir system and the water demand of the city of San Angelo. The South Concho Irrigation Canal near Christoval provides an estimate of the amount of water required for irrigation of crops by surface water supplies. The statistical properties of the untransformed historical streamflow data were needed to provide upper and lower limits for the decision variables of the linear programming algorithm. Reservoir operation using expected high flows (streamflow mean plus one-half standard deviation) and low flows (zero inflow) as decision variables was tested for comparison with the use of 30-day hydrometeorological forecasts.

Table 12 presents the statistical analyses for the monthly and mid-monthly streamflows for seven of the hydrologic data stations. Periods correspond to those listed in Table 5. Again, as with the precipitation data, the mean streamflow values have two maximums, one in early summer (periods 4a and 5) and the other in early fall (periods 9 and 9a). These periods also provide some of the periods of most variable streamflow, as demonstrated by the large standard deviations. The winter season generally is a period of low streamflow. The periods 4a, 5, 9, and 9a represent the time of year when frontal systems are most effective in producing rainfall and subsequent surface runoff. The summer season generally is characterized by the absence of frontal systems and the presence of mesoscale shower and thunderstorm activity. This usually occurs when the ambient air temperatures are very warm and the reservoir evaporation is very large. Even though the mean summer streamflows are low, runoff is highly variable due to frequent heavy rainshowers. This is apparent from the large

Table 12. Monthly and mid-monthly streamflow statistics in acre-ft.

PERIOD		1	1a	2	2a	3	3a	4	4a	5	5a	6	6a	7	7a	8	8a	9	9a	10	10a	11	11a	12	12a
STATION	DATA																								
#8-1275	$\bar{X}$	883	930	690	858	992	990	1633	2334	2036	1418	1415	1482	2306	2028	854	1340	1920	2404	1950	1082	816	820	934	940
	Sx	668	803	802	662	692	668	4436	7380	4674	2412	2212	2390	7800	8018	916	2022	3740	4594	4008	1372	668	632	870	880
SCC	|e|	542	584	556	502	572	574	1456	2656	2104	1168	1332	1464	2582	2650	614	1266	2092	2662	2076	868	532	536	514	568
	Mx	838	910	816	774	870	634	866	858	946	932	732	730	616	536	560	584	640	762	694	600	626	716	762	750
#8-1280	$\bar{X}$	425	416	366	360	392	402	400	396	420	426	416	426	454	452	438	438	438	452	504	490	434	426	472	470
	Sx	218	194	172	186	220	236	236	248	272	266	258	288	324	332	326	292	272	264	362	340	210	222	346	346
SCI	|e|	166	150	134	132	166	184	190	200	214	216	212	230	270	280	276	242	214	208	244	232	166	172	232	200
	Mx	428	416	376	358	392	376	356	362	416	188	410	392	378	360	270	342	424	424	242	450	386	404	410	410
#8-1284	$\bar{X}$	190	344	346	304	332	794	3116	4990	5504	5132	2760	1868	1690	806	1214	1794	4042	5300	2754	692	262	314	316	177
	Sx	470	928	910	818	894	3330	8528	11294	10520	11462	7300	4660	4424	1924	2556	3006	10708	13320	7630	2244	664	872	660	365
MCT	|e|	290	502	480	446	514	1228	4622	6686	6378	6706	3480	2552	2390	1183	1674	2196	5638	7570	4240	1025	390	486	596	238
	Mx	0	0	0	0	0	0	114	642	1000	568	312	86	68	0	0	418	56	18	2	0	0	0	0	1
#8-1293	$\bar{X}$	1078	1068	764	802	834	696	2046	4066	3714	2344	1828	1768	1800	1030	734	1510	2614	2696	1620	982	712	732	834	884
	Sx	1554	1544	796	1252	1578	1412	5040	11732	10744	5240	3216	3748	4022	3126	1922	3278	6468	6602	3742	1664	1110	1022	1098	956
SPT	|e|	956	974	678	742	876	782	2552	5794	5006	2670	2201	2486	2608	1530	1026	2100	3522	3614	1973	1170	824	770	844	794
	Mx	806	686	446	508	306	200	432	582	800	582	330	88	84	64	62	92	196	184	174	160	132	332	456	736
#8-1340	$\bar{X}$	224	350	388	290	766	994	2314	4942	5418	4102	2152	2144	2754	1266	890	1246	2024	2786	1616	556	258	259	252	220
	Sx	158	708	772	376	2836	3008	4344	5630	9644	6654	3952	6992	7386	3710	2708	2600	6358	8630	5024	810	605	322	330	220
NCC	|e|	137	329	380	258	984	1296	3000	6144	6490	4862	2600	3088	4036	1802	1178	1538	2336	4392	2302	576	266	240	236	170
	Mx	180	232	202	198	218	236	360	984	1360	1072	218	154	62	156	156	234	284	118	192	68	88	146	196	208
#8-1350	$\bar{X}$	252	172	228	278	264	394	2130	2482	1562	1404	966	1428	1270	866	876	698	958	2790	2790	2710	360	308	276	233
	Sx	310	168	294	308	232	440	6394	7476	3464	2958	1112	3370	2672	942	870	604	1902	1738	11090	11412	764	756	596	314
NSA	|e|	176	136	190	214	174	338	2882	3328	1636	1320	750	1410	1328	762	648	503	910	696	4418	4550	366	342	280	194
	Mx	124	124	156	184	210	206	282	600	782	692	726	828	742	734	896	728	774	801	458	276	130	146	134	170
#8-1360	$\bar{X}$	2558	2726	2328	2090	2990	3640	8682	14192	13604	10898	6926	5456	5912	3502	2588	4762	6500	7846	7062	4094	2344	2504	2796	2600
	Sx	2733	2932	2428	2086	5194	6204	15880	27170	24210	17504	10540	10696	11938	8568	4044	7392	14546	16000	13160	3752	3078	3082	3362	2754
	|e|	2046	2256	1982	1704	2872	3676	9848	17530	15682	12666	7692	7316	8110	4674	2976	5284	7716	9298	8156	4275	2266	2430	2606	2029
	Mx	2272	2192	1562	1578	1534	1440	2606	3510	3046	3246	1034	1094	854	788	644	1076	1114	768	1710	1724	1110	1174	1710	2226

standard deviations of streamflow during periods 6 through 8. A comparison between the mean and median of the data indicates that the median may be more representative of the normal streamflow conditions, since the streamflows are generally low. The supply of water in semi-arid regions is highly variable and a knowledge of future supplies would be extremely important to the operational policy of reservoir systems.

b. Conditional probabilities

The importance of the simulation portion of MOHS depends upon the accuracy of the 30-day meteorological forecasts, as well as the accuracy of the rainfall-runoff relationship. For this region of Texas, forecasts were extracted from the published maps (see Fig. 11), from which a forecast category was determined (see Fig. 12). Appendix A contains a series of contingency tables which present the results of verifying the 30-day forecasts for the period 1955 through 1970. Verification of the forecasts is provided in the publication of the Extended Forecast Section entitled, "Average Monthly Weather Resume and Outlook." A study of the results in Appendix A shows that the temperature forecasts verify well, while the precipitation forecasts are not as accurate. However, if the results are compared to the probability of chance occurrence (0.33), some forecasts verify exceedingly well. The X^2 values for each contingency table can be compared with the values given in Table 7 to determine the level of significance for the forecasts. Very accurate temperature forecasting is reflected by the following forecast dates: 1 January, 15 February, 1 March, 1 April, 1 May, 15 May, 15 July, 1 August, 15 September, 1 November, 15 November, and 15 December. The annual forecast verification of precipitation and temperature categories shows that they verify better than chance. Namias (1964) also studied the accuracy and reliability of the 30-day outlooks. He concludes that: "The outlooks are designed primarily for users with a consistent month-to-month need for weather information. Since a poor verification can be expected from time to time, too much weight should not be given to any one forecast. In the long run, however, benefit should be obtained by judicious use of the outlooks, since on the average they have demonstrated positive skill beyond chance."

Also contained in Appendix A are the conditional probabilities for each forecast category. These can be used to determine an expected value forecast, as described in Section 4b. For a given forecast category and time period, for example, a 1 January forecast of below normal temperatures and moderate precipitation, the conditional probabilities discussed below can be obtained. For the forecast period the conditional probabilities are of the form

$$\text{Probability} \left\{ \text{Forecast Category} \mid \text{observed category} \right\} .$$

For temperature they are

$$P\left\{\text{below normal} \mid \text{below normal}\right\} = 0.50,$$
$$P\left\{\text{below normal} \mid \text{near normal}\right\} = 0.50,$$
$$P\left\{\text{below normal} \mid \text{above normal}\right\} = 0.00.$$

For the precipitation forecast the conditional probabilities are

$$P\left\{\text{moderate} \mid \text{light}\right\} = 0.25,$$
$$P\left\{\text{moderate} \mid \text{moderate}\right\} = 0.50,$$
$$P\left\{\text{moderate} \mid \text{heavy}\right\} = 0.25.$$

Each category that might be forecast for any given month will have a set of conditional probabilities with the exception of above normal temperatures on 15 January and 1 November. Here, the category was never forecast so there is no measure of its accuracy.

An example of contingency tables of transitional probabilities is shown in Table 13. For the temperature categories, the transitional probabilities show that the probability of persistent weather phenomena is greater than the probability of change. During the summer months of July and August, it is more probable that the temperatures will persist as either below normal or above normal, while for precipitation it appears more probable to have light amounts of rainfall from one period to the next. The Chi-square values demonstrate varying levels of significance when checked against the values presented in Table 7. These results are in general agreement with those of Namias (1952) in which he found

Table 13. Examples of contingency tables of Markov first-order transitional probabilities for observed weather for the Concho River basin.

REGION CONCHO MONTH 1 Jul - 31 Aug

OBSERVED [T]	OBSERVED [T+1] Below	Normal	Above
Below	5 0.31	2 0.13	0 0.00
Normal	1 0.06	1 0.06	1 0.06
Above	1 0.06	1 0.06	4 0.25

$\chi^2 = 8.27$

OBSERVED [T]	OBSERVED [T+1] Light	Moderate	Heavy
Light	4 0.25	2 0.13	2 0.13
Moderate	2 0.13	0 0.00	3 0.19
Heavy	1 0.06	1 0.06	1 0.06

$\chi^2 = 6.50$

REGION CONCHO MONTH 1 Oct - 30 Nov

OBSERVED [T]	OBSERVED [T+1] Below	Normal	Above
Below	3 0.19	3 0.19	3 0.19
Normal	0 0.00	1 0.06	2 0.13
Above	2 0.13	0 0.00	2 0.13

$\chi^2 = 5.23$

OBSERVED [T]	OBSERVED [T+1] Light	Moderate	Heavy
Light	0 0.00	1 0.06	4 0.25
Moderate	2 0.13	4 0.25	1 0.06
Heavy	0 0.00	2 0.13	2 0.13

$\chi^2 = 9.87$

the greatest persistence of weather phenomena between April to May and from October to November. He also found that temperature appears to be more persistent in winter. Verification of 700-mb pattern persistence in relation to temperature and precipitation patterns also was tested to provide a preliminary groundwork for establishing forecast procedures for the 30-day forecasts. Dickson (1967) provided further supporting evidence of month-to-month persistence of mean temperatures, but found that this persistence is independent of long-term temperature trends and that persistence is a local phenomenon dependent upon the thermal state of the surface of Earth. Tables 10 and 11 also provide information on the transitional probabilities for individual stations. Again persistence of weather phenomena is apparent when the temperature and evaporation data are studied. The precipitation and API data show less persistence from summer through early fall, thereby demonstrating the high variability of these parameters.

The next consideration was to test whether or not there was persistence in weather phenomena over a period of three months. To establish if this occurred, Markov second-order transitional probabilities were determined for the period 1955 through 1970; these are presented in Table 14. It can be seen that there is general agreement of persistent weather between temperature and precipitation categories (the higher probabilities have been

Table 14. Markov second-order transitional probabilities for the Concho River basin (* high probabilities).

Temperature Categories	Probability	Precipitation Categories	Probability
BBB	0.495*	LLL	0.350*
BBN	0.125	LLM	0.190*
BBA	0.090	LLH	0.095
BNB	0.010	LML	0.020
BAB	0.020	LHL	0.000
BNN	0.045	LMM	0.110*
BAA	0.090	LHH	0.080
BAN	0.020	LHM	0.060
BNA	0.090	LMH	0.095
NNN	0.000	MMM	0.380*
NNB	0.270*	MML	0.018
NNA	0.030	MMH	0.040
NBN	0.000	MLM	0.090
NAN	0.000	MHM	0.010
NBB	0.400*	MLL	0.120*
NAA	0.220*	MHH	0.150*
NAB	0.080	MHL	0.000
NBA	0.000	MLH	0.030
AAA	0.350*	HHH	0.430*
AAB	0.200*	HHL	0.070
AAN	0.060	HHM	0.170*
ANN	0.040	HMM	0.170*
ABB	0.200*	HLL	0.060
ANB	0.060	HML	0.060
ABN	0.020	HLM	0.020
ABA	0.070	HLH	0.000
ANA	0.000	HMH	0.020

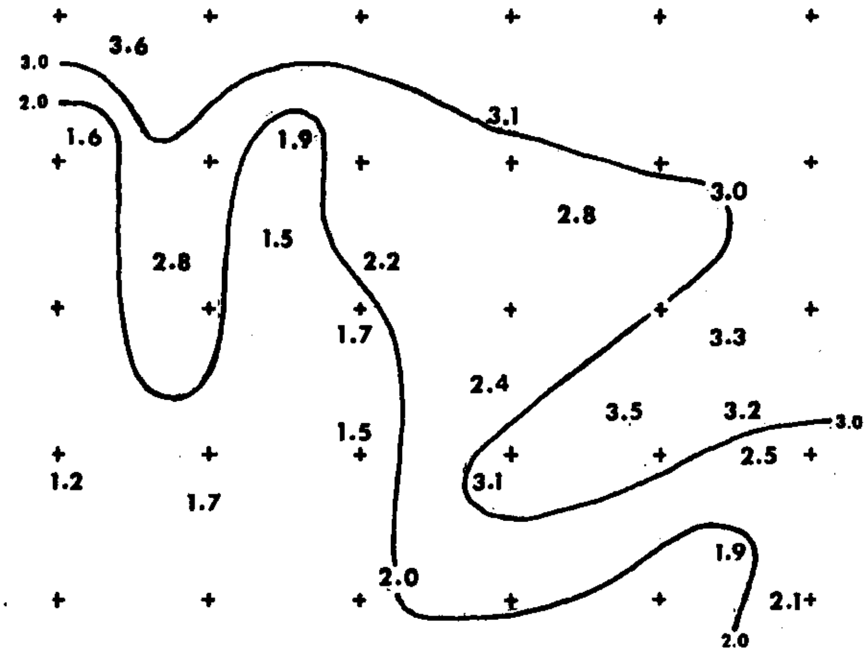
marked with an asterisk in Table 14). The results also show that the persistence of categories of weather such as BBB, AAA, LLL, MMM, and HHH appear to predominate in this semi-arid region of Texas. Also, abrupt changes in weather ending persistent periods or abrupt changes in weather followed by persistent weather conditions are reflected by the probabilities of categories BBN, NNB, NBB, AAB, ABB, LLM, MML, MLL, MHH, HHM, and HMM. When trends or changes in weather can be forecast with some degree of accuracy and reliability, important information can be gained which will affect reservoir operational decisions.

c. Meteorological simulation and accuracy of empirical relationships

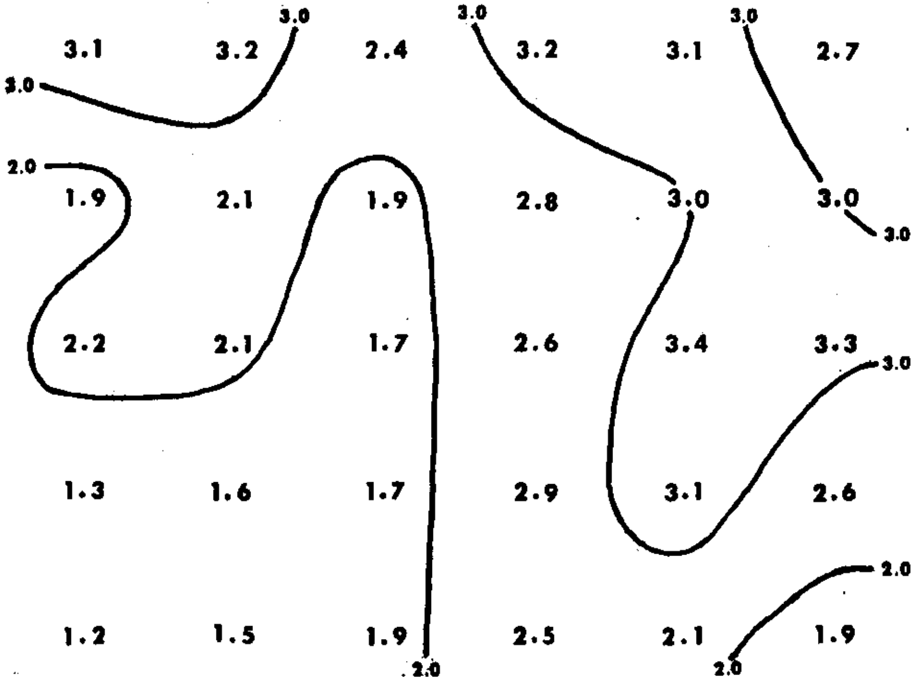
The use of Monte Carlo or simulation techniques to establish fields of meteorological data offers a means of predicting temperature and precipitation data rather than placing great reliability upon strictly climatological values. The validity and use of the 30-day meteorological forecasts to simulate data depend upon:

1. the accuracy of the forecasts;
2. the spatial distribution of simulated data; and
3. the accuracy of the empirical equations relating precipitation and temperature to other decision parameters.

Figures 16 and 17 present the results of simulating data from the 30-day meteorological forecasts. The grid points on the maps correspond to those in Fig. 10.

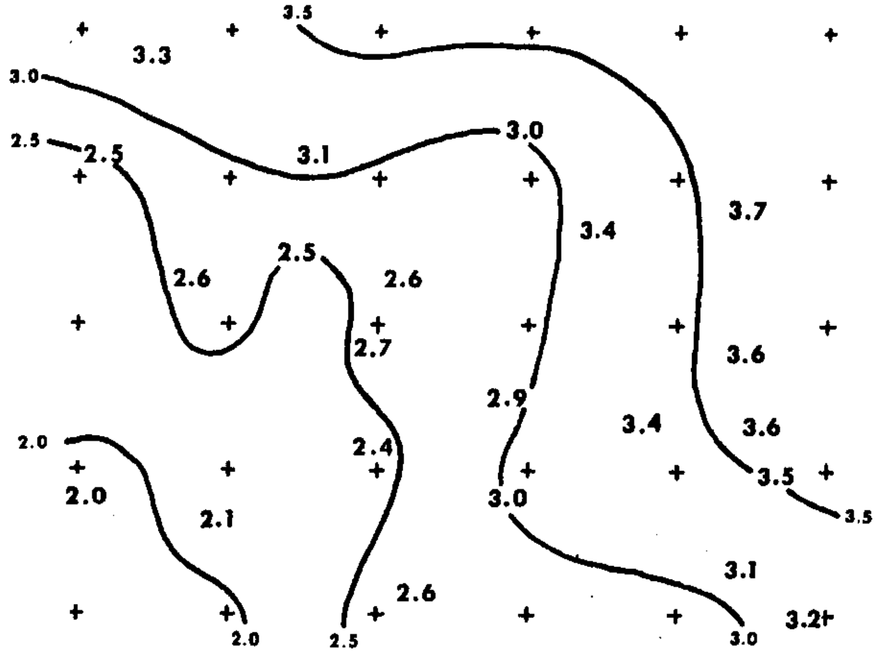


a. Plot of simulated station data.

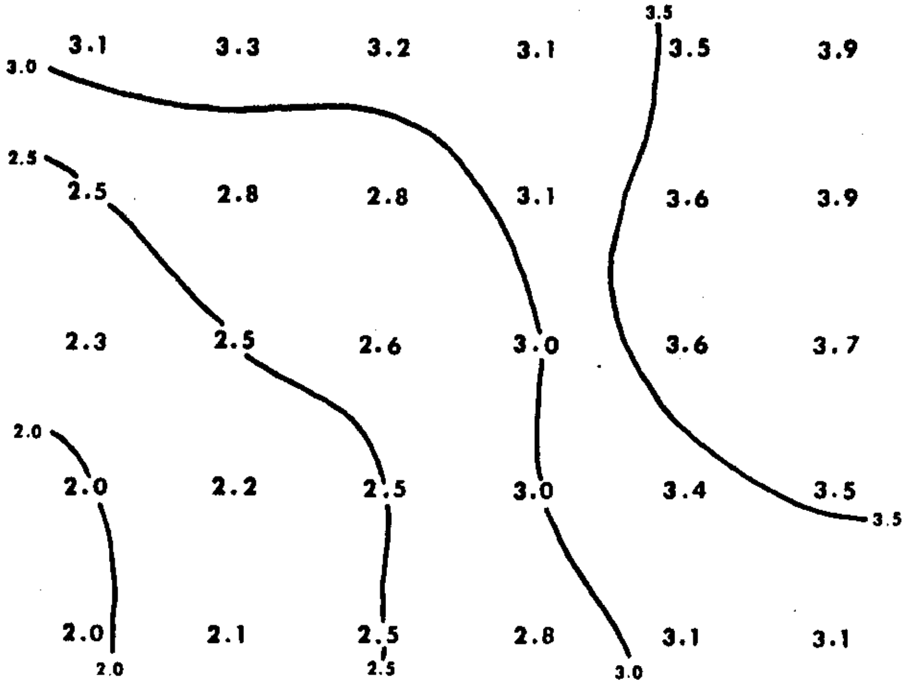


b. Objective analysis of simulated data.

Fig. 16. Maps of moderate precipitation data (1 May 1968).

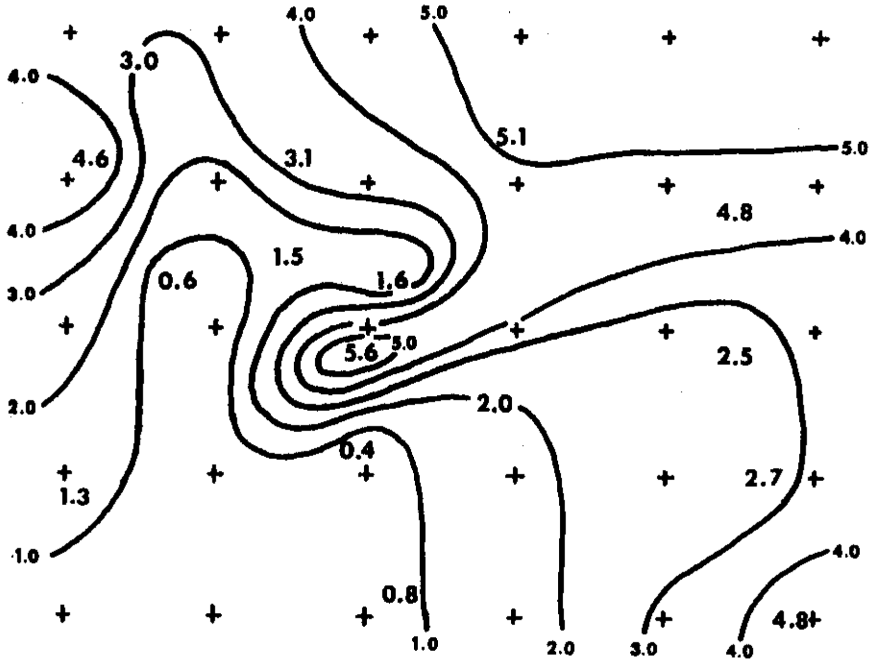


c. Plot of "expected value" station data.

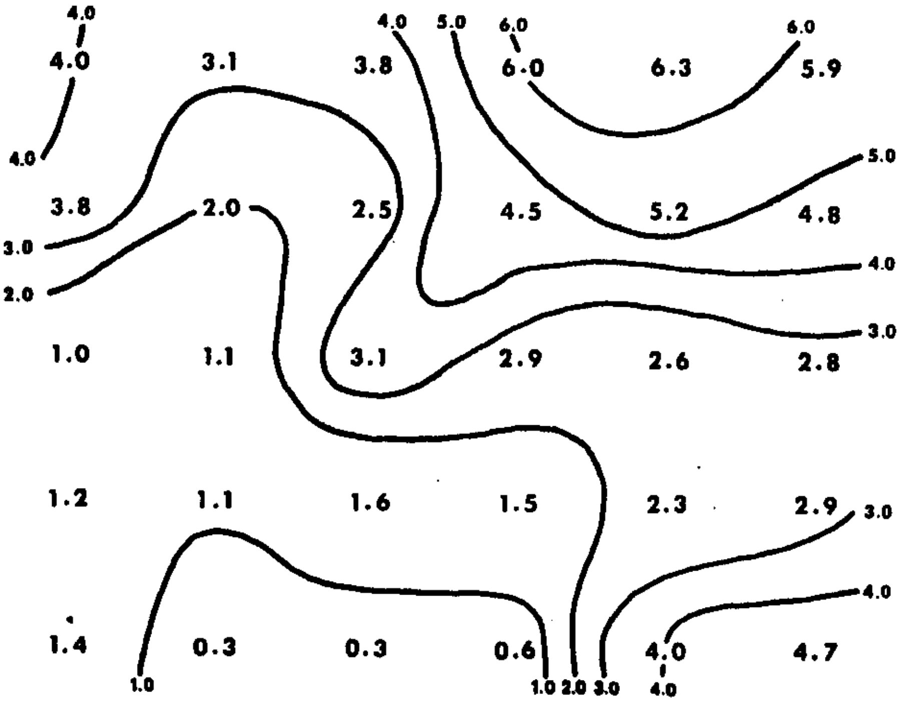


d. Objective analysis of "expected value" data.

Fig. 16. Continued.

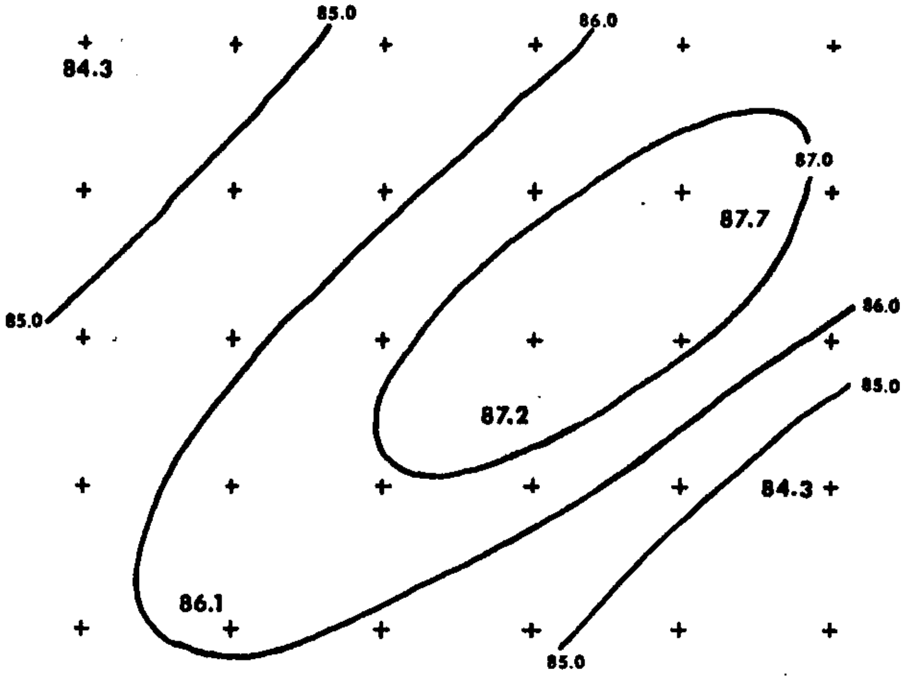


e. Plot of historical station data.

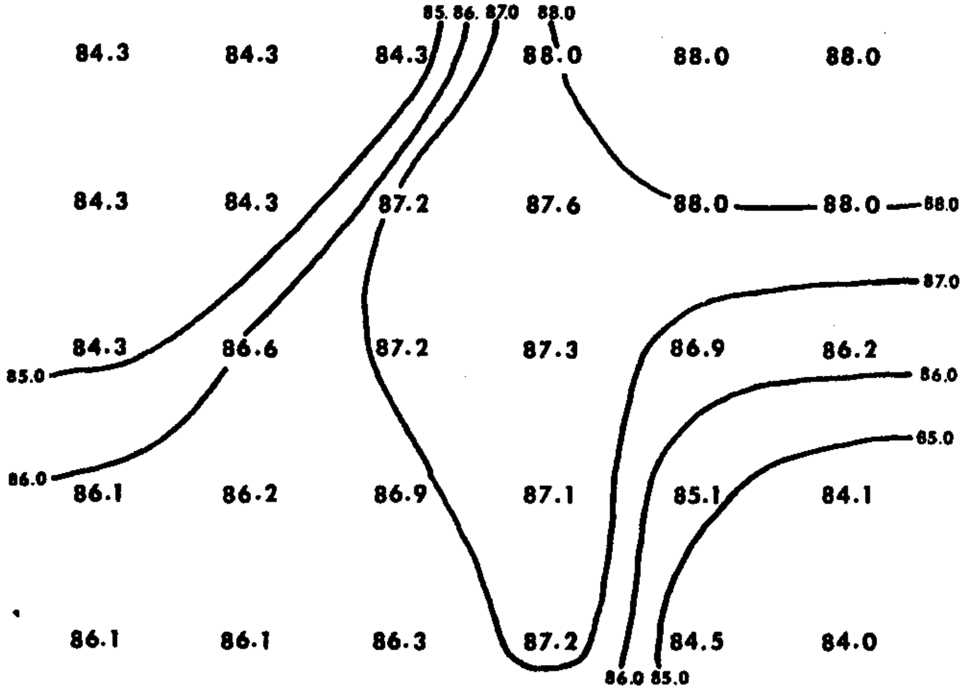


f. Objective analysis of historical data.

Fig. 16. Continued.

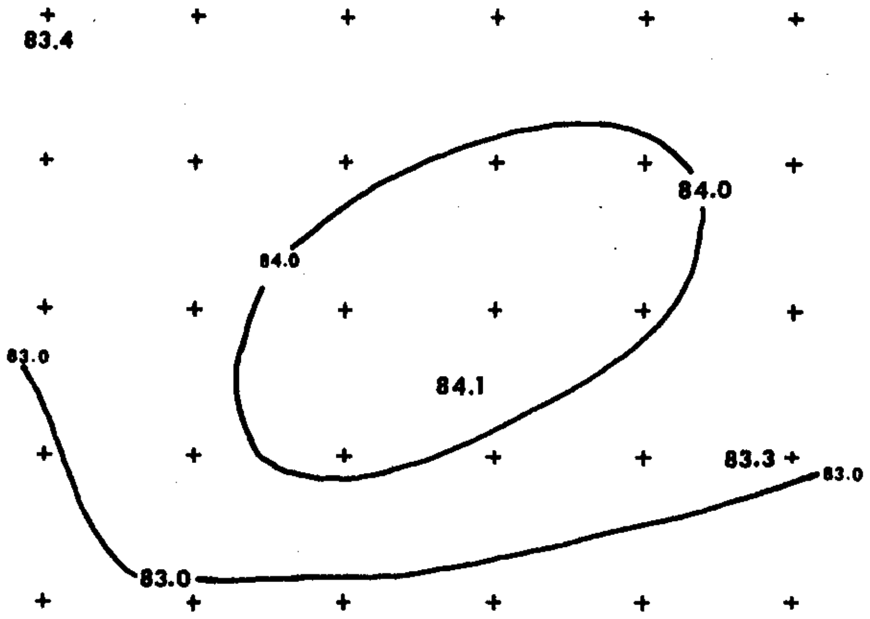


a. Plot of simulated station data.

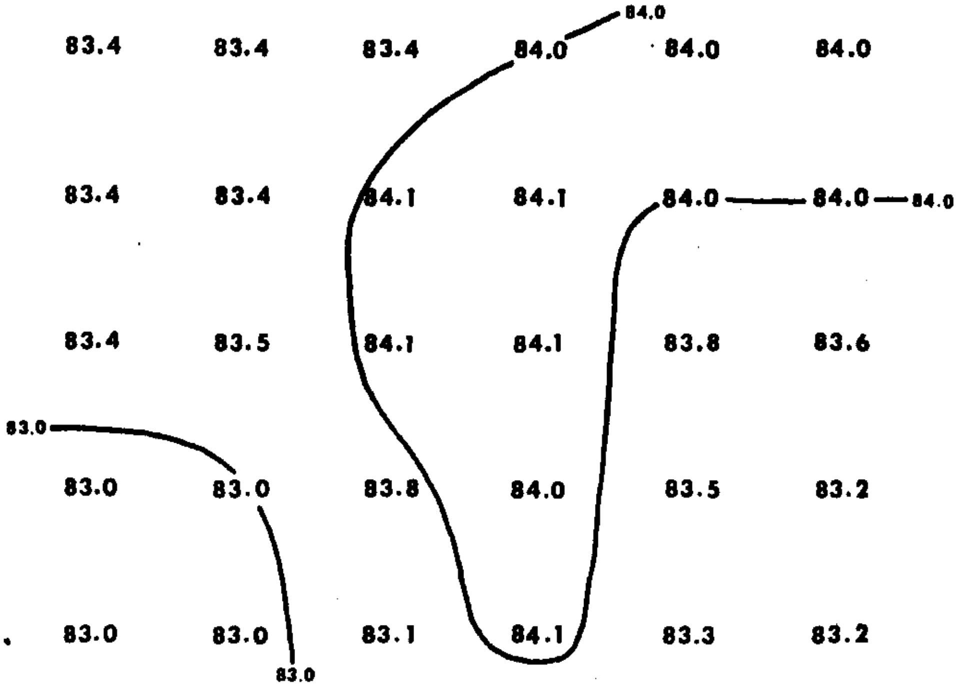


b. Objective analysis of simulated data.

Fig. 17. Maps of above normal temperature data (1 July 1965).

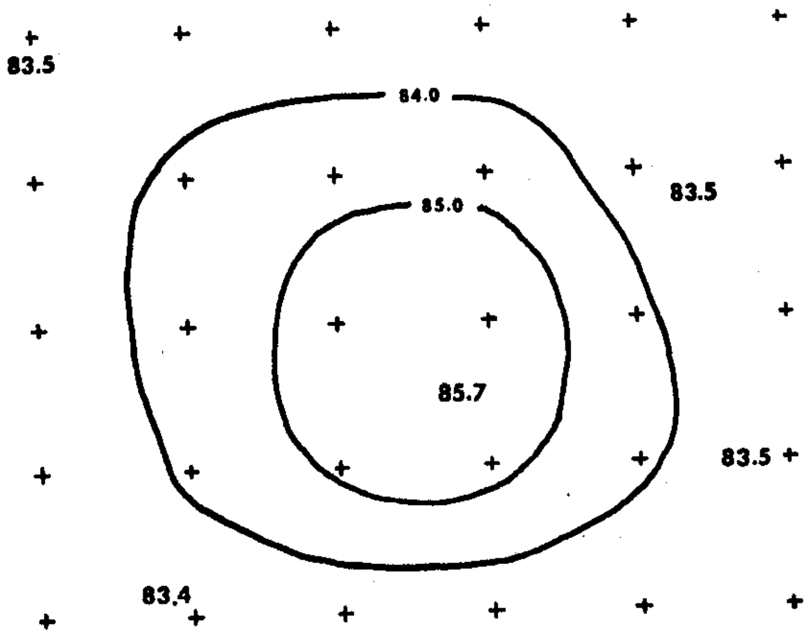


c. Plot of "expected value" station data.

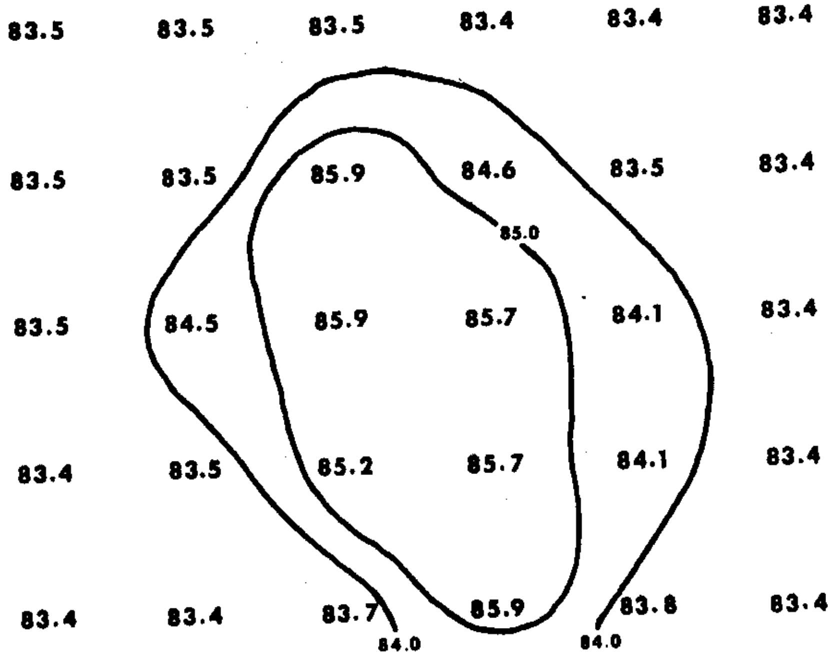


d. Objective analysis of "expected value" data.

Fig. 17. Continued.



e. Plot of historical station data.



f. Objective analysis of historical data.

Fig. 17. Continued.

The maps show that the use of the 30-day meteorological forecasts to simulate data can, in some cases, provide useful knowledge needed for the decision-making process. Parts a, c, and e of Figs. 16 and 17 show the data plotted at the approximate location of each station. The objective analyses of the data shown in parts b, d, and f of Figs. 16 and 17 were obtained by fitting the semi-randomly located data to the system of grid coordinates. The technique developed by Barnes (1964) and presented in Section 3b of this study was used.

Figure 16 presents simulated, expected value, and historical precipitation data for the forecast period of 1 May through 31 May 1968. The forecast was for moderate precipitation and the period verified within this category with the exception of the 5.6-in. value for FKR shown in Fig. 16e. The maps demonstrate that the simulated and expected value patterns of precipitation data are similar to the historical conditions. Although identical results were not expected, the spatial distribution of rainfall demonstrates an increase in the amounts from left to right or from west to east, geographically, in Fig. 16. The use of the objective analysis scheme results in precipitation patterns much like those obtained from analyzing the semi-randomly located data points. The most obvious error that arises when the data are analyzed objectively is the smoothing of extreme values. In

Fig. 16e, the very large rainfall value of 5.6 in. is smoothed considerably, thereby resulting in a value of only 3.1 in. in Fig. 16f. Also in Fig. 16f, large values are generated in the upper right-hand corner of the map. This is due to the absence of information at the edges of these maps. It should be expected that the values at the periphery of the rectangular grid area will be the least accurate. One means of alleviating this problem would be to expand the grid system and include additional meteorological stations. Other techniques such as collapsing the grid and decreasing the scan radius (SR) also might improve the results.

The patterns presented in Fig. 17 are similar but lack the detail obtained by the analyses of precipitation data. The main cause of these results is the paucity of meteorological stations having temperature data. The temperature forecast category was for above normal temperatures and verified within that category. Figure 17 shows there is a temperature maximum located in the central region of the grid system (San Angelo). This maximum appears in all of the maps where the largest values were obtained from the simulated data values. The isolines of temperature were constructed independently of each other, thus possibly explaining the wide diversity of patterns. Again, improvement of the analyses would be obtained by expanding the area encompassed by the grid system to include more stations measuring ambient air temperature. Another alternative would have been to generate stochastic data bases for the other stations used in the study. This, however, may be conducive to the amplification of errors for the simulated data.

Perhaps the most critical components of the design and operation of MOHS are the empirical relationships used to convert the meteorological data to hydrological and hydrometeorological variables needed in the decision portion of the model. Figure 18 shows the results of using Eq. 28 to provide an estimate of the amount of reservoir evaporation. Historical values of adjusted pan evaporation data were compared to evaporation data calculated from mean monthly air temperature. Results show that the relationship underestimates evaporation during the winter months and overestimates evaporation during the summer months. Also shown in Fig. 18 are evaporation amounts determined from simulated and expected temperature values for the summer months. The entire plot of data in Fig. 18 indicates that the forecasts can be of significant value in providing estimates of the evaporation that will occur from each reservoir. To determine the water-loss from each reservoir, a linear relationship between evaporation estimates and surface area of each reservoir was assumed so that multiplying the two values would give a quantitative estimate of the total volume of reservoir evaporation.

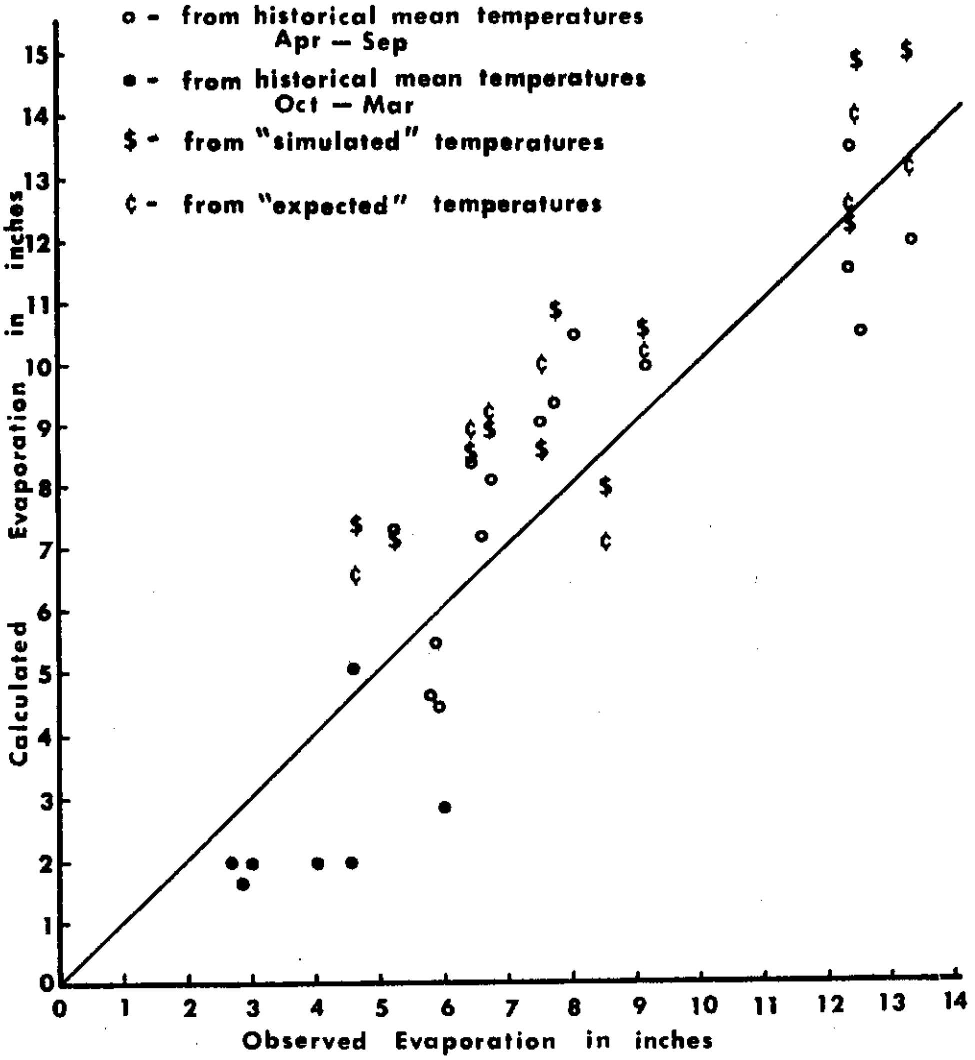


Fig. 18. Accuracy of the temperature-evaporation relationship.

The rainfall-runoff relationship given by Eqs. 23 and 26 provided results that need further study and improvement. Of all the methods studied, including the four presented in Appendix B, this relationship gave values which deviated least from observed streamflows. Figure 19 presents a plot of streamflows calculated from historical precipitation values, simulated precipitation data, and expected values of rainfall. It is apparent that the majority of streamflows are overestimated using historical precipitation data, simulated values, and expected values. The establishment of an adequate rainfall-runoff predictor for the Concho River basin was not successfully accomplished in this study. Any relationship that considers total monthly rainfall without considering the duration and intensity of rainfall events possible can predict highly erroneous streamflow values. The wide dispersion of data points from the line of equality clearly reflects these errors and the need for establishing a better empirical relationship. However, Eqs. 23 and 26 predicted low and zero flows quite accurately. Information on low streamflows is important and cannot be discounted. In general, the inadequancy of the empirical relationship to supply accurate streamflow information inhibited the accuracy of the decision-making process of this model.

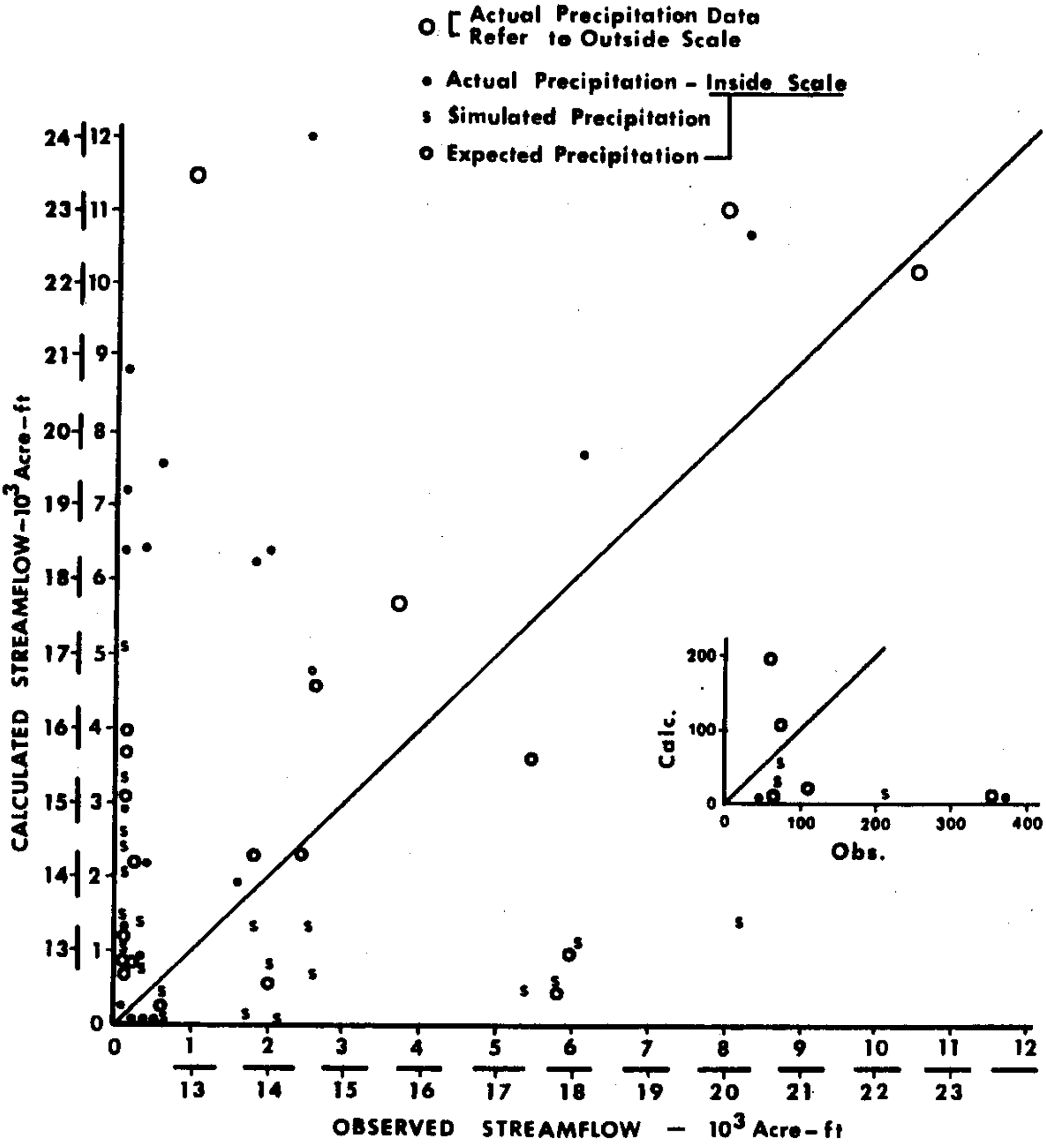


Fig. 19. Accuracy of the rainfall-surface runoff relationship.

The reservoir system in the Concho River basin was not completed until late in 1963. This restricted simulation of data considered to the period from 1964 through 1970. The meteorological drought that occurred in west Texas during this period of time has made analysis and study of the precipitation-runoff relationship difficult. Namias (1966) discussed the variability of the precipitation categories of light, moderate, and heavy in west Texas for the period 1962 through 1965 as they related to the atmospheric circulation. In general, the region was characterized by light precipitation. Sauer (1970) related the low streamflow conditions from 1962 to 1968 to meteorological and hydrological conditions. He concluded that the low surface runoff was due mainly to the absence of high-intensity long-duration rainstorms in the Concho River basin. The frequency of monthly precipitation amounts was significantly less than the long-term averages. He also mentions that physical changes in the basin or changes in agricultural practices had little or no influence on streamflow conditions. Sauer's (1970) conclusion agrees with a difficulty encountered in connection with the simulation scheme, i.e., the scheme inadequately provides information on the intensity and duration of rainfall events, within each monthly time period, which greatly affects the amounts of surface runoff.

d. Reservoir system operation

Examples of the MOHS scheme for operation of the reservoir system are presented for two time periods - 15 May 1965 through 15 June 1965, and 15 April 1968 through 15 June 1968. These were chosen because they represented periods when the water levels in the reservoirs changed and when the 30-day forecasts were valid for several monthly periods. Figures 20a and b present a comparison of the methods of forecasting reservoir evaporation along with an estimation of evaporation losses calculated by multiplying the surface area of each reservoir by the adjusted pan evaporation values from historical records. The reservoirs are labeled 1, 2, and 3, and refer to Lake Nasworthy, San Angelo, and Twin Buttes, respectively. The numbering system corresponds to that presented in Fig. 15. The results of this portion of the model demonstrate that fairly accurate estimates of reservoir evaporation can be obtained from Eq. 28 by using simulated or expected temperatures.

The results concerning operation of the reservoir system under stochastic inflows by parts IB, IIB, and IIIB of MOHS were identical to those obtained under deterministic inflows by parts IA, IIA, and IIIA. One possible explanation for this result lies in the design of the stochastic linear programming algorithm by

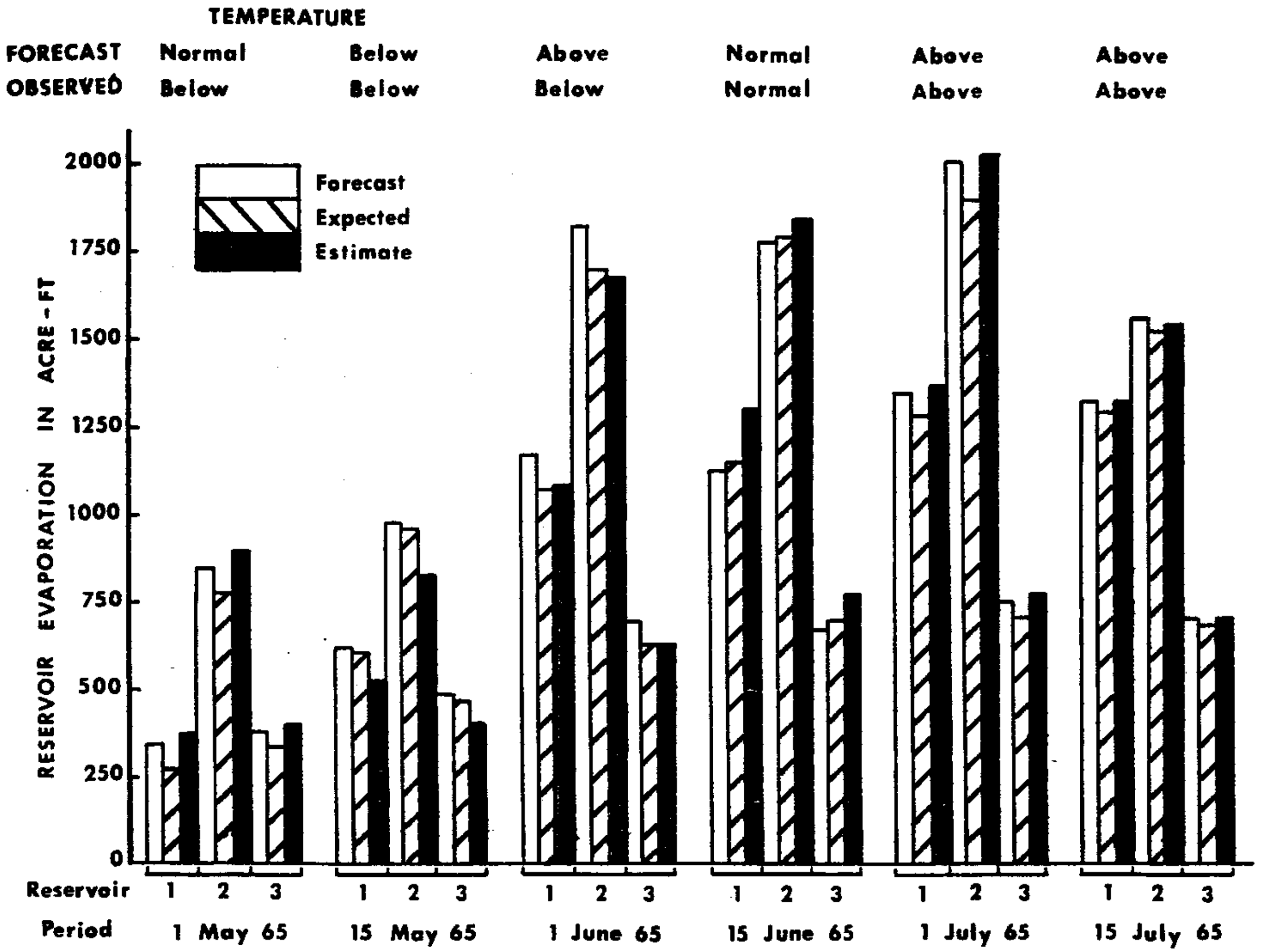


Fig. 20a. A comparison of the reservoir evaporation losses - 1965 forecasts.

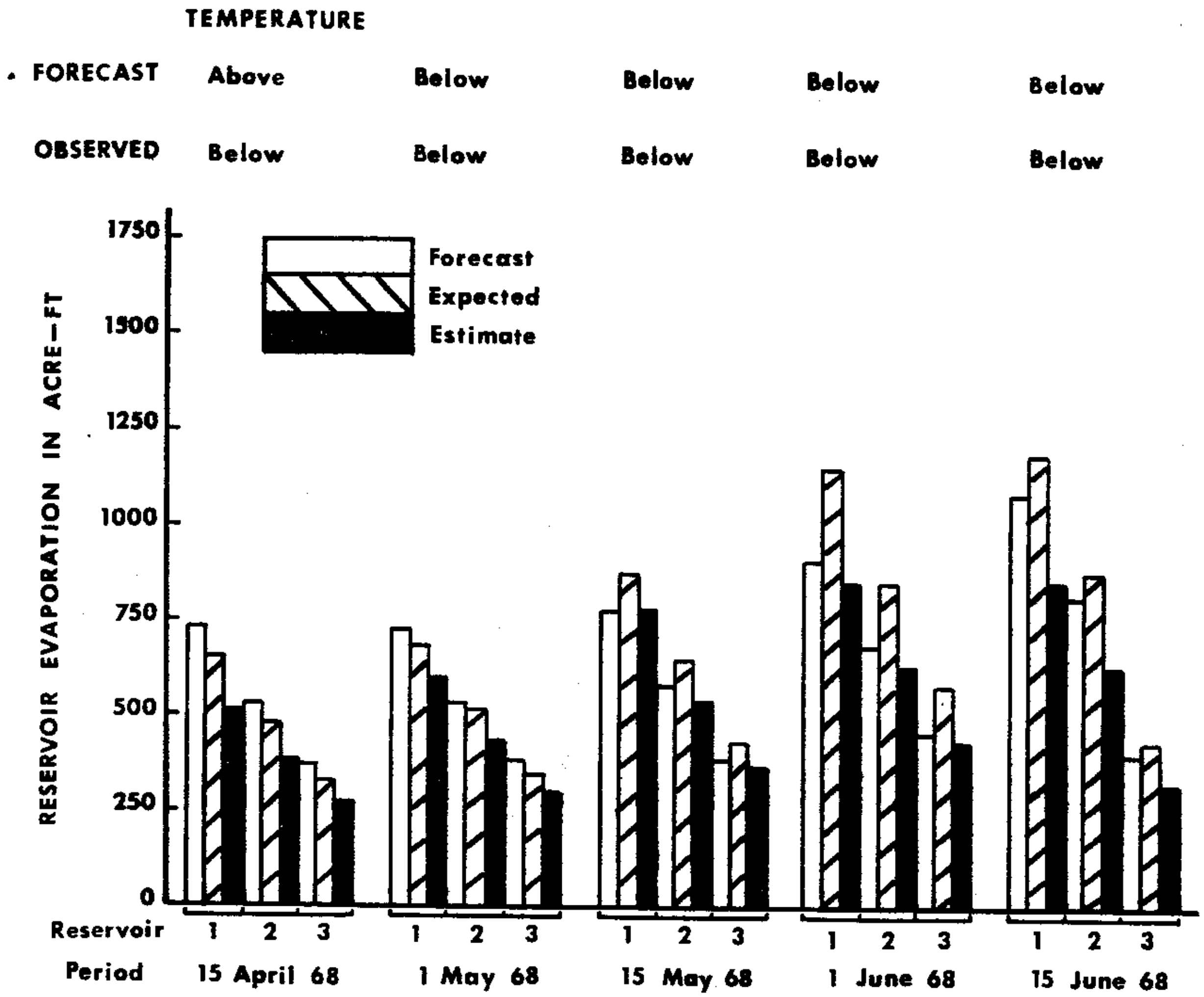


Fig. 20b. A comparison of the reservoir evaporation losses - 1968 forecasts.

Curry _et_ _al_. (1972) and in the configuration of the reservoir system chosen for the model. The problem that arises is that it is difficult for the system to meet demands within the constraints of the minimum and maximum stochastic inflows, i.e., those constraints on reservoir storages must not be violated. Since the storage in the various reservoirs was close during the periods studied to the minimum reservoir storage constraint, adequate operation was difficult to achieve. Also, the lower limit of the stochastic inflows was usually zero and the range between zero and the upper limit was usually quite large. Satisfaction of both the upper and lower values would force violation of the system constraints. Any water associated with the region violated was given a high cost. Since the entire reservoir system was not completed until 1964 and the period 1964 through 1968 experienced drought conditions, the reservoirs never contained an adequate supply of water. The maximum water content in Lake Nasworthy was 11,210 acre-ft in late 1967; San Angelo reservoir contained 37,910 acre-ft at the beginning of 1964; and Twin Buttes had 18,240 acre-ft in late 1964. These quantities represent only a small percentage of the water each is capable of holding and this did not allow for much variability of inflows in which to maintain operational capabilities of the reservoirs.

Tables 15 and 16 are the results of operating the reservoir system using MOHS and the BLF means of pricing the water within the system. The meteorological forecasts begin at the date given and cover the month or 30-day period following the date, i.e., the forecast for 15 May 1965 covers the period until 15 June 1965. The column labeled "MOHS" lists the method of obtaining the evaporation, consumptive-use, and streamflow data. The "FCST" represents data obtained by simulation from the 30-day forecasts; "EXP" represents data calculated from expected-values of temperature and precipitation; "STAT" represents data obtained from the statistical analysis of historical streamflow data to determine the mean and standard deviation; and "ACT" is the historical data used as a standard from which a comparison of the methods can be made. For each reservoir the reservoir evaporation expressed as percent of total reservoir content, the inflows in acre-ft for the forecast period, and reservoir storages in acre-ft of water for the end of the time period are listed for each method. The starting reservoir storages are presented for comparison purposes in parentheses below the actual ending storage. The releases in acre-ft of water are listed under the number which corresponds to the reservoirs indicated in Fig. 15 and listed in Tables 15 and 16. The last column on the right of each table is an estimate of the crop consumptive-use or irrigation requirements calculated using Eqs. 31, 32, and 33.

Table 15. Results of the multi-reservoir operation for periods in 1965.

FORECAST INFORMATION	MOHS	1 - L. Nasworthy			2 - San Angelo			3 - Twin Buttes			Releases			Est. C.U.
		%E	Infl.+	Stor.	%E	Infl.	Stor.	%E	Infl.	Stor.	1	2	3	
Date: 15 May 1965	FCST	9.0	1988	7000	3.8	2435	27862	4.2	6421	14990	0	0	1991	1038
Forecast: Moderate precip.	EXP	8.8	1991	7000	3.7	1170	26620	4.2	5039	13360	0	0	1991	1041
Below norm temp.	STAT	9.3	2003	7000	3.9	4100	29500	4.4	8894	17394	0	0	2003	1053
Observed: Moderate precip.	ACT	8.4	*	10000	3.2	5880	32580	3.5	8198	12420	*	380	*	*
Below norm temp.				(7000)			(26420)			(11680)				
Date: 1 June 1965	FCST	12.	0	8539	5.9	31	26977	5.3	101	12504	0	2152	0	1152
Forecast: Moderate precip.	EXP	11.	762	9392	5.5	1131	27472	4.9	360	12824	0	2122	0	1122
Above norm temp.	STAT	11.	0	8638	5.4	2152	29295	4.8	6002	18473	0	2152	0	1107
Observed: Moderate precip.	ACT	11.	*	10460	5.3	2214	30760	4.7	688	10380	*	496	*	*
Below norm temp.				(9710)			(30930)			(13090)				
Date: 15 June 1965	FCST	11.	793	9659	5.5	9391	38038	5.4	9168	20133	0	2148	0	1148
Forecast: Heavy precip.	EXP	11.	801	9656	5.5	0	29485	5.4	0	10945	0	1296	855	1151
Normal temp.	STAT	12.	863	9630	5.9	2150	31388	5.4	5118	15949	0	1410	752	1162
Observed: Light precip.	ACT	12.	*	10000	5.7	38	28820	5.6	432	8650	*	782	*	*
Normal temp.				(10000)			(32580)			(12420)				

+ inflow values were determined by linear programming algorithm.

* data are unavailable because historical records do not contain a measure of this value.

Table 16. Results of the multi-reservoir operation for periods in 1968.

FORECAST INFORMATION	MOHS	1 - L. Nasworthy			2 - San Angelo			3 - Twin Buttes			Releases			Est. C.U.
		%E	Infl.+	Stor.	%E	Infl.	Stor.	%E	Infl.	Stor.	1	2	3	
Date: 15 April 1968	FCST	7.3	0	7623	4.7	841	11680	3.9	3550	12590	1775	99	0	974
Fcst: Moderate precip.	EXP	6.4	0	7654	4.2	3649	14648	3.5	13353	22439	1835	0	0	935
Above norm temp.	STAT	5.7	0	7755	3.7	4900	15592	3.1	11400	20552	1805	0	0	905
Obs: Moderate precip.	ACT	5.7	*	10380	3.7	2580	14590	3.1	914	8660	*	144	*	*
Below norm temp.				(10140)			(11480)			(9410)				
Date: 1 May 1968	FCST	7.0	0	7863	4.8	2362	13067	4.2	7139	15395	1895	44	0	989
Fcst: Moderate precip.	EXP	6.5	0	7878	4.5	4884	15666	4.0	13437	21715	1926	0	0	976
Below norm temp.	STAT	7.9	0	7854	5.5	5418	15924	4.8	11249	19454	1804	169	0	1024
Obs: Moderate precip.	ACT		*	10270	4.0	2606	13800	4.0	514	8070	*	400	*	*
Below norm temp.				(10490)			(11290)			(8620)				
Date: 15 May 1968	FCST	7.5	0	8227	3.9	17801	31818	4.5	45500	53200	1376	0	585	1011
Fcst: Heavy precip.	EXP	8.4	0	8215	4.4	1406	15349	5.0	4985	12509	1291	0	699	1041
Below norm temp.	STAT	9.2	0	8204	4.8	4100	17918	5.5	8894	16362	1220	64	729	1064
Obs: Moderate precip.	ACT	7.4	*	10280	3.6	26	13370	4.0	400	7460	*	702	*	*
Below norm temp.				(10380)			(14590)			(8660)				
Date: 1 June 1968	FCST	8.8	0	7738	4.9	8414	21539	5.6	17600	24730	1623	0	430	1054
Fcst: Heavy precip.	EXP	11.	0	7719	6.1	6	12241	7.1	47	7445	1406	716	0	1122
Below norm temp.	STAT	10.	0	7728	5.6	2152	14606	6.4	6002	12557	1507	579	0	1087
Obs: Moderate precip.	ACT	8.1	*	10290	4.7	0	12920	5.7	334	7360	*	610	*	*
Below norm temp.				(10270)			(13800)			(8070)				
Date: 15 June 1968	FCST	10.	0	7638	6.1	0	12004	5.4	28	7084	1553	557	0	1110
Fcst: Moderate precip.	EXP	11.	0	7632	6.6	0	11817	5.9	0	7024	1466	676	0	1142
Below norm temp.	STAT	10.	0	7640	5.9	2150	14300	5.3	5118	12184	1574	528	0	1130
Obs: Moderate precip.	ACT	10.	*	10350	5.6	0	12680	5.1	386	6640	*	276	*	*
Below norm temp.				(10280)			(13370)			(7460)				

+ inflow values were determined by linear programming algorithm.

* data are unavailable because historical records do not contain a measure of this value.

First, a comparison of the three methods used will be made. For 15 May and 1 June 1965, the inflows to the reservoirs were almost equal to the historical mean flows. The use of statistical streamflow values proves to be adequate in operating the reservoirs. However, the statistical method is inadequate when the inflows are low, such as for the 15 June 1965 period and the 1968 periods. During these periods of low flow, it appears that using the method of expected value forecasts yields the best values. Again, some of the error in the system lies within the simulation portion of MOHS and the remainder lies in the precipitation-runoff relationship described by Eqs. 23 and 26. In some cases, such as the forecast inflows (FCST) for Twin Buttes for the periods beginning 15 May and 1 June 1968, the error was compounded and excessive streamflow estimates resulted. Even with the inadequate precipitation-runoff relationship, the method of using streamflow estimates based on expected values,which were calculated from the conditional probabilities of the forecasts of 30-day precipitation, provide adequate information for the management of the reservoir system.

Although consumptive use was considered in the model, the reservoir system did not supply surface water for irrigation during the period 1964 to 1970. These estimates have been supplied in Tables 15 and 16 to provide a means to determine the water demand by the City of San Angelo. An Asterisk (*) under this column indicates that there are no historical values for comparison. There also are several other places in Tables 15 and 16 where asterisks appear, again indicating the lack of historical records. This makes it difficult to analyze accurately the operation of the system. It appears that the starting and ending storage would provide information about releases and losses. These, however, do not always supply usable information, as can be seen in the 1965 results for Twin Buttes. Here, much of the inflow was probably lost to seepage because the reservoir had been completed recently.

The utility factor or BLF used to price the water in the system is another portion of the model which is suspect. The releases from each reservoir are determined by the percent of water lost by evaporation, (see Tables 15 and 16). Whether or not this policy is "optimal" over a long-term operation was not determined by this study. If the model were run without updating the reservoir storages from historical records, the validity of this policy possibly could be established. It seems plausible, however, that the greatest benefit would be obtained from the reservoir losing the greatest amount of water due to evaporation because 1) evaporation cannot be eliminated and 2) releasing water would change the reservoir surface area and decrease the evaporation rate. Perhaps the only means to establish an optimal operating policy is to price all the water in the system, such as water remaining in storage, water used for releases, and water lost to evaporation. In this case, long-term considerations must be considered and the linear programming model utilized would require modification.

In summary of the system and model as constructed, it appears that use of 30-day meteorological forecasts can provide information needed for decision-making in reservoir system management. The study and improvement of portions of the model could provide a valuable operational tool for water resources management.

6. CONCLUSIONS AND RECOMMENDATIONS

a. Conclusions

The following general conclusions were reached:

1) Monthly and mid-monthly precipitation conformed best to the square-root-normal frequency distribution; mean ambient air temperature conformed well to all distributions tested; reservoir evaporation conformed best to the cube-root-normal and log-normal distributions; and the API conformed best to the cube-root-normal distribution. These distributions can be used to synthesize hydrometeorological data using Monte Carlo simulation techniques.

2) Thirty-day meteorological forecasts provide a means of establishing physical limits on simulated data needed for decision-making and management of water resource systems. Contingency tables demonstrate that some forecast periods are more accurate than others and provide conditional probabilities which can be used to provide "expected values" of hydrometeorological variables.

3) Markov first- and second-order transitional probabilities for the forecast categories of light, moderate, and heavy demonstrate persistence of meteorological

patterns and conditions in the Concho River basin, which has a semi-arid climate.

4) The use of an objective analysis scheme in water resources studies can be extremely valuable, especially when dealing with variables such as temperature and precipitation. The application of this type of analysis to discontinuous parameters such as precipitation, facilitates the computation of surface runoff.

5) An adequate empirical relationship for predicting streamflow from rainfall has not been determined for this semi-arid region. The relationship tested, however, provides adequate information about conditions of low flow.

6) The use of 30-day meteorological forecasts appears to merit further research to determine its value to water resources management and research. The use of these forecasts in reservoir system management will depend upon their reliability and accuracy, as well as the accuracy of the empirical relationships used to convert meteorological variables to hydrometeorological and hydrological variables.

b. Recommendations for further research

On the basis of the results of this study the following recommendations for further research are made:

1) A more accurate measure of soil moisture possibly might improve estimates of surface runoff with use of Eqs. 23 and 26. Possible modifications to one of the methods presented in Appendix B.also might improve streamflow calculations.
2) An improvement in the forecasts of temperature and precipitation might be accomplished either by improving the techniques for constructing the 30-day outlooks or by improving the forecast based upon regional meteorological conditions. Perhaps the simulation procedure could be improved by considering spatial correlations between stations.
3) Since the intensity and duration of precipitation events greatly influences the amount of surface runoff, MOHS could be modified to simulate individual rainfall events within the monthly time period using the 30-day forecast categories.
4) By considering the past weather or trends in the weather, one might improve the forecast. Since the transitional probabilities represent persistent

or non-persistent trends, forecasting a "break" or change in the weather would provide valuable information for the decision-making process.

5) Further study of the pricing policy should be conducted to determine if it optimizes the system over the long-term operation. The linear programming scheme could be designed to optimize the total amount of water within the system with evaporation losses being priced.

6) Several configurations of the physical design of the reservoir system could be tested to determine if the current design is optimal. Such testing could include pumping and pumpback capabilities between each of the reservoirs which were not considered by this study.

REFERENCES

Albrecht, J.E., 1971: A statistical study of precipitation and streamflow in the Concho River basin of west Texas. M.S. Thesis, Dept. of Meteorol., Texas A&M University, 137 pp.

Allison, S.V., 1967: Review of small basin runoff prediction methods. J. Irrig. Drain. Div., A.S.C.E., 93(IR1), 1-6.

Amorocho, J. and W.E. Hart, 1964: A critique of current methods in hydrologic systems investigation. Trans. Am. Geophys. Union, 45(2), 307-321.

Barnes, S.L., 1964: A technique for maximizing details in numerical weather map analysis. J. Appl. Meteorol., 396-409.

Beard, L.R., 1962: Statistical Methods in Hydrology. Scaramento, Calif., U.S. Army Corps of Engineers, 120 pp.

______, 1965: Use of interrelated records to simulate streamflow. J. Hydraul. Div., A.S.C.E., 91(HY5), 13-22.

______, 1967: Hydrologic simulation in water yield analysis. J. Irrig. Drain. Div., A.S.C.E., 93(IR1), 33-42.

______, A.J. Fredrich, and E.F. Hawkins, 1970: Estimating monthly streamflows within a region. Sacramento, Calif., Hydrologic Engineering Center, U.S. Army Corps of Engineers, Tech. Paper No. 18, 15 pp.

Benjamin, J.R. and C.A. Cornell, 1970: Probability, Statistics and Decision for Civil Engineers. New York, McGraw-Hill Book Co., 684 pp.

Benson, M.S. and N.C. Matalas, 1967: Synthetic hydrology based on regional statistical parameters. Water Resources Research, 3(4), 931-935.

Brooks, C.E. and N. Carruthers, 1953: Handbook of Statistical Methods in Meteorology. London, Her Majesty's Stationary Office, 412 pp.

Charnes, A. and W.W. Cooper, 1959: Chance-constrained programming. Management Science, 6(1), 73-79.

Chorafas, D.N., 1965: Systems and Simulation. New York, Academic Press, Chap. 15 and 21, 271-287 and 391-401.

Chow, V.T. (editor), 1964: Handbook of Applied Hydrology. New York, McGraw-Hill Book Co., Section 8-I and 8-II, 8-1 to 8-67.

_____, and D.D. Meredith, 1969: Water resources systems analysis- Part IV. Review of programming techniques. Univ. of Illinois, Hydraulic Engineering Series, 22, 70 pp.

Committee on Hydrometeorology, A.S.C.E., 1967: Hydrometeorological systems: progress report. J. Hydraul. Div., A.S.C.E., 93(HY4), 99-115.

Cressman, G.P., 1959: An operational objective analysis system. Mon. Wea. Rev., 87(10), 367-374.

Criddle, W.D., 1953: Consumptive use of water and irrigation requirements. J. Soil and Water Conserv., 8(5), 207-243.

Curry, G.L., J. Helm, and R.A. Clark, 1972: A model for a linked system of multi-purpose reservoirs with stochastic inflows and demands. College Station, Tex., Texas Water Resources Institute, Tech. Rep. No. 41, 57 pp.

Deininger, R.A., 1969: Linear programming for hydrologic analyses. Water Resources Research, 5(5), 1105-1109.

Dickson, R.R., 1967: The climatological relationship between temperatures of successive months in the U.S. J. Appl. Meteorol., 6(1), 31-38.

Eagleson, P.S., 1970: Dynamic Hydrology. New York, McGraw-Hill Book Co., 462 pp.

Eisel, L.M., 1970: Comments on 'The linear decision rule in reservoir management and design' by C. Revelle, E. Joeres, and W. Kirby. Water Resources Research, 6(4), 1239-1241.

Fiering, M.B., 1967: Streamflow Synthesis. Cambridge, Mass., Harvard Univ. Press, 135 pp.

_____, and B.B. Jackson, 1971: Synthetic Streamflows. Washington, D.C., American Geophysical Union, Water Resources Mono. 1, 98 pp.

Gardner, W.R., 1965: Rainfall and Runoff. Boston, Mass., Amer. Meteorol. Soc. Meteorol. Mono., 6(28), 138-148.

Hall, W.A. and J.A. Dracup, 1970: *Water Resources Systems Engineering*. New York, McGraw-Hill Book Co., 372 pp.

Hamon, W.R., 1961: Estimating potential evapotranspiration. *J. Hydraul. Div., A.S.C.E.*, 87(HY3), 107-120.

Hargreaves, G.H., 1968: Consumptive use derived from evaporation pan data. *J. Irrig. Drain. Div., A.S.C.E.*, 94(IR1), 97-105.

Hillier, F.S. and G.J. Lieberman, 1967: *Introduction to Operations Research*. San Francisco, Holden-Day Inc., 639 pp.

Hufschmidt, M.M. and M.B. Fiering, 1966: *Simulation Techniques for Design of Water Resource Systems*. Cambridge, Mass., Harvard Univ. Press, 212 pp.

Hydrologic Engineering Center, 1971: HEC-4. Monthly streamflow simulation. Sacramento, Calif., U.S. Army Corps of Engineers, 112 pp.

James, L.D., 1968: Economic derivation of reservoir operating rules. *J. Hydraul. Div., A.S.C.E.*, 94(HY5), 1217-1230.

Kohler, M.A., 1949: Double-mass analysis for testing the consistency of records and for making required adjustment. *Bull. Am. Meteorol. Soc.*, 188-189.

_____, and M.M. Richards, 1962: Multicapacity basin accounting for predicting runoff from storm precipitation. *J. Geophys. Res.*, 67(13), 5187-5197.

Krick, I.P., 1959: Long-range weather forecasting as a water supply tool. *J. Am. Water Works Assoc.*, 51(11), 1366-1376.

Linsley, R.K., M.A.Kohler, and J.L. Paulhus, 1958: *Hydrology for Engineers*. New York, McGraw-Hill Book Co., 340 pp.

Loucks, D.P., 1970: Some comments on linear decision rules and chance constraints. *Water Resources Research*, 6(2), 668-671.

Maass, A., M.M. Hufschmidt, R. Dorfman, H.A. Thomas, Jr., S.A. Marglin, and G.A. Fair, 1962: *Design of Water-Resource Systems*. Cambridge, Mass., Harvard Univ. Press, 443-493.

Maine, R. and D.J. Gauntlett, 1968: Modification to an operational numerical weather analysis system and application to rainfall. *J. Appl. Meteorol.*, 7(1), 18-28.

O'Connor, J.F., 1963: Extended and long-range weather forecasting. *J. Am. Water Works Assoc.*, 55(8), 1006-1018.

Paulhus, J.L. and M.A.Kohler, 1952: Interpolation of missing precipitation records. *Mon. Wea. Rev.*, 80(8), 129-133.

Portig, W.H., 1962: Atlas of the climates of Texas 1910-1959. Austin, Texas, University of Texas, 3-30.

ReVelle, C., E. Joeres, and W. Kirby, 1969: The linear decision rule in reservoir management and design. 1. Development of the stochastic model. *Water Resources Research*, 5(4), 767-777.

_____, and W. Kirby, 1970: Linear decision rule in reservoir management and design. 2. Performance optimization. *Water Resources Research*, 6(4), 1033-1044.

Sauer, S.P., 1970: Factors contributing to unusually low runoff during the period 1962-1968 in the Concho River basin, Texas. Texas District Open File Rep. No. 112, U.S.Geological Survey, Water Resources Division, 84 pp.

Schweig, Z. and J.A. Cole, 1968: Optimal control of linked reservoirs. *Water Resources Research*, 4(3), 479-497.

Sellers, W.D., 1965: *Physical Climatology*. Chicago, University of Chicago Press, 272 pp.

Sewell, W.R., 1968: *Human Dimensions of the Atmosphere*. Boulder, Colorado, National Science Foundation, 300 pp.

Solomon, S.L., J.P. Denouvilliez, E.J. Chart, J.A. Woolley, and C. Cadou, 1968: The use of a square grid system for computer estimation of precipitation, temperature and runoff. *Water Resources Research*, 4(5), 919-929.

Taha, H.A., 1971: *Operations Research, An Introduction*. New York, Macmillan Co., 703 pp.

Texas Water Development Board, 1967: Monthly reservoir evaporation rates for Texas 1940-1965. Austin, Tex., Rep. No. 64, 111 pp.

_____, 1970a: Systems simulation for management of a total water resource. Vol. 1. Introduction. Austin, Tex., Rep. No. 118, 83 pp.

Maunder, W.J., 1970: *The Value of the Weather*. London, Methuen and Co., Ltd., 388 pp.

McDonald, J.E., 1957: A note on the precision of estimation of missing precipitation data. *Trans. Am. Geophys. Union,* 38 (5), 657-661.

Namias, J., 1951: General aspects of extended-range forecasting. *Compendium of Meteorology*. Boston, Mass., Amer. Meteorol. Soc., 802-813.

_____, 1952: The annual course of month-to-month persistence in climatic anomalies. *Bull. Am. Meteorol. Soc.*, 33(7) 279-285.

_____, 1953: Thirty-Day Forecasting: a review of a ten-year experiment. Boston, Mass., Amer. Meteorol. Soc. *Meteorol. Mono*., 2(6), 83 pp.

_____, 1964: A 5-year experiment in the preparation of seasonal outlooks. *Mon. Wea. Rev*., 92(10), 449-464.

_____, 1966: Relation between fluctuations in United States climatic patterns and 1962-65 drought. *J. Am. Water Works Assoc*., 58(12), 1528-1548.

_____, 1968: Long-range weather forecasting - history, current status and outlook. *Bull. Am. Meteorol. Soc*., 49(5), 438-470.

National Oceanic and Atmospheric Administration, Climatological data by sections, 1919-1970.

_____, Extended Forecast Div., National Weather Service, Average Monthly Weather Resume and Outlook, 1955-1970.

Naylor, T.H., J.L. Balintfy, D.S. Burdick, and K. Chu, 1968: *Computer Simulation Techniques*. New York, J. Wiley and Sons, 352 pp.

O'Connor, G.E., 1970: Probability distributions of hydrometeorological data for application to systems analysis of Texas Water resources. M.S. Thesis, Dept. of Meteorol., Texas A&M University, 95 pp.

_____, and R.A. Clark, 1971: Applications of climatology and meteorology to hydrologic simulation. College Station, Tex., Texas Water Resources Institute, Tech. Rep. No. 38, 127 pp.

______, 1970b: A completion report on stochastic optimization and simulation techniques for management of regional water resource systems. Vol. IIA. Sim-III Program Description. Austin, Tex., 118 pp.

______, 1971a: Stochastic optimization and simulation techniques for management of regional water resource systems. Austin, Tex., Rep. No. 131, 129 pp.

______, 1971b: Engineering data on dams and reservoirs in Texas. Part III. Austin, Tex., Rep. No. 126, 120 pp.

______, 1971c: Inventories of irrigation in Texas 1958, 1964, and 1969. Austin, Tex., Rep. No. 127, 204 pp.

Thornthwaite, C.W., and F.K. Hare, 1965: The loss of water to the air. Boston, Mass., Amer. Meteorol. Soc. Meteorol. Mono., 6(28), 163-180.

U.S. Geological Survey, Water Resources Data for Texas, Part 1. Surface Water Records, 1961-1970.

______, Surface Water Supply of the United States, Section 8, 1930-1960.

U.S. Soil Conservation Service, 1971: SCS National Engineering Handbook, Section 4, Hydrology. Washington, D.C., U.S. Government Printing Office, Chapters 9, 10 and 11.

U.S. Weather Bureau, 1961: Verification of the Weather Bureau's 30-day outlooks. Washington, D.C., U.S. Dept. of Commerce, Tech. Paper No. 39, 58 pp.

Van Hylckama, T., 1959: A nomagram to determine monthly potential evaporation. Mon. Wea. Rev., 87(3), 107-110.

Wade, J.C., A.O. Weiss, and L.R. Beard, 1971: Developing regional stochastic data bases. Tuscon, Arizona. Symposium on Statistical Hydrology, A.S.C.E., August, 25 pp.

Wolman, A., 1963: Status of water resources use, control and planning in the United States. J. Am. Water Works Assoc., 55(10), 1253-1272.

Appendix A

Contingency tables of 30-day meteorological forecast verification

REGION Concho MONTH ______

TEMPERATURE		OBSERVED			
		M Below/Below	N Normal	Above/M Above	
	M Below Below	# .XX	# .XX	# .XX	**
FORECAST	N Normal	# .XX	# .XX	# .XX	**
	Above M Above	# .XX	# .XX	# .XX	**
					++

$\chi^2 =$

PRECIPITATION		OBSERVED			
		Light	Moderate	Heavy	
	Light	# .XX	# .XX	# .XX	**
FORECAST	Moderate	# .XX	# .XX	# .XX	**
	Heavy	# .XX	# .XX	# .XX	**
					++

$\chi^2 =$

- number of observations.

.XX - probability of verification.

** - probability of a correct forecast for that category.

++ - probability of a correct forecast for all categories.

REGION Concho Annual

TEMPERATURE

OBSERVED

FORECAST		M Below/Below	N Normal	Above/M Above	
	M Below Below	96 .25	23 .06	34 .09	.63
	N Normal	42 .10	30 .08	32 .09	.29
	Above M Above	35 .09	28 .08	64 .16	.50
					.49

$\chi^2 \gg 30$

PRECIPITATION

OBSERVED

FORECAST		Light	Moderate	Heavy	
	Light	45 .12	46 .12	37 .10	.35
	Moderate	44 .12	75 .20	40 .10	.47
	Heavy	28 .06	38 .10	31 .08	.32
					.40

$\chi^2 > 30$

REGION Concho MONTH 1 Jan

TEMPERATURE OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below / Below	4 .25	4 .25	-	.50
N Normal	1 .06	2 .13	-	.67
Above / N Above	1 .06	2 .13	2 .13	.40
			χ^2= 11.27	.50

PRECIPITATION OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	2 .13	2 .13	1 .06	.40
Moderate	1 .13	2 .13	1 .06	.50
Heavy	3 .19	2 .13	2 .13	.29
			χ^2= 2.01	.38

REGION Concho MONTH 1 Feb

TEMPERATURE OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below / Below	4 .25	1 .06	-	.80
N Normal	4 .25	2 .13	1 .06	.29
Above / N Above	1 .06	2 .13	1 .06	.25
			χ^2= 10.53	.44

PRECIPITATION OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	2 .13	2 .13	3 .13	.29
Moderate	-	4 .25	3 .19	.57
Heavy	-	-	2 .13	1.00
			χ^2= 9.88	.50

REGION Concho MONTH 15 Jan

TEMPERATURE OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below / Below	4 .25	3 .19	3 .19	.40
N Normal	2 .13	2 .13	2 .13	.34
Above / N Above	-	-	-	---
			χ^2= 10.45	.38

PRECIPITATION OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	-	2 .13	2 .13	.00
Moderate	2 .13	2 .13	1 .06	.40
Heavy	1 .06	3 .19	3 .19	.43
			χ^2= 4.26	.31

REGION Concho MONTH 15 Feb

TEMPERATURE OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below / Below	6 .37	-	-	1.00
N Normal	2 .13	-	2 .13	.00
Above / N Above	3 .19	1 .06	2 .13	.33
			χ^2= 11.79	.50

PRECIPITATION OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	-	1 .06	1 .06	.00
Moderate	4 .25	5 .31	3 .19	.42
Heavy	-	1 .06	1 .06	.50
			χ^2= 14.35	.38

REGION Concho MONTH 1 Mar

TEMPERATURE

OBSERVED

FORECAST	M Below/Below	N Normal	Above/M Above	
M Below/Below	4 .25	2 .13	1 .06	.57
N Normal	2 .13	2 .13	2 .13	.34
Above/M Above	1 .06	-	2 .13	.67
			$\chi^2 = 5.64$	.50

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	1 .06	3 .19	.20
Moderate	2 .13	4 .25	-	.67
Heavy	3 .19	1 .06	1 .06	.20
			$\chi^2 = 8.62$	.38

REGION Concho MONTH 15 Mar

TEMPERATURE

OBSERVED

FORECAST	M Below/Below	N Normal	Above/M Above	
M Below/Below	5 .31	4 .25	1 .06	.50
N Normal	1 .06	-	1 .06	.00
Above/M Above	2 .13	-	2 .13	.50
			$\chi^2 = 11.05$	.44

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	4 .25	2 .13	2 .13	.50
Moderate	-	3 .19	-	1.00
Heavy	2 .13	2 .13	1 .06	.20
			$\chi^2 = 7.63$	.50

REGION Concho MONTH 1 Apr

TEMPERATURE

OBSERVED

FORECAST	M Below/Below	N Normal	Above/M Above	
M Below/Below	6 .37	1 .06	2 .13	.67
N Normal	-	1 .06	1 .06	.50
Above/M Above	-	2 .13	3 .19	.60
			$\chi^2 = 10.79$	.63

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	7 .43	2 .13	.10
Moderate	1 .06	1 .06	2 .13	.25
Heavy	1 .06	-	1 .06	.50
			$\chi^2 = 18.84$	.19

REGION Concho MONTH 15 Apr

TEMPERATURE

OBSERVED

FORECAST	M Below/Below	N Normal	Above/M Above	
M Below/Below	1 .06	1 .06	2 .13	.25
N Normal	2 .13	-	1 .06	.00
Above/M Above	3 .19	2 .13	4 .25	.45
			$\chi^2 = 3.94$	.31

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	2 .13	3 .19	2 .13	.29
Moderate	-	5 .31	1 .06	.83
Heavy	1 .06	-	2 .13	.67
			$\chi^2 = 10.99$	.56

REGION Concho MONTH 1 May

TEMPERATURE OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	4 .25	-	-	1.00
N Normal	3 .19	-	-	.00
Above/N Above	3 .19	-	6 .37	.67
				.63

$\chi^2 = 16.11$

PRECIPITATION OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	3 .19	-	.25
Moderate	2 .19	4 .25	3 .19	.44
Heavy	-	1 .06	2 .13	.67
				.44

$\chi^2 = 8.75$

REGION Concho MONTH 15 May

TEMPERATURE OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	5 .31	-	1 .06	.83
N Normal	-	2 .13	1 .06	.67
Above/N Above	1 .06	2 .13	4 .25	.57
				.69

$\chi^2 = 9.12$

PRECIPITATION OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	1 .06	3 .19	.20
Moderate	-	6 .37	-	1.00
Heavy	1 .06	3 .19	1 .06	.20
				.50

$\chi^2 = 16.60$

REGION Concho MONTH 1 Jun

TEMPERATURE OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	2 .13	-	3 .19	.40
N Normal	5 .31	1 .06	-	.13
Above/N Above	2 .13	-	3 .19	.60
				.38

$\chi^2 = 13.23$

PRECIPITATION OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	1 .06	1 .06	.34
Moderate	1 .06	3 .19	2 .13	.50
Heavy	1 .06	6 .37	-	.00
				.25

$\chi^2 = 14.35$

REGION Concho MONTH 15 Jun

TEMPERATURE OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	3 .19	-	2 .13	.60
N Normal	1 .06	1 .06	1 .06	.34
Above/N Above	3 .19	2 .13	3 .19	.43
				.44

$\chi^2 = 2.79$

PRECIPITATION OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	3 .19	3 .19	1 .06	.43
Moderate	4 .25	2 .13	1 .06	.29
Heavy	1 .06	1 .06	-	.00
				.31

$\chi^2 = 7.62$

REGION Concho MONTH 1 Jul

TEMPERATURE

OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	-	-	1 .06	.00
N Normal	1 .06	1 .06	2 .13	.25
Above/N Above	4 .25	2 .13	5 .31	.46
				.38

$\chi^2 = 9.60$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	-	2 .13	.34
Moderate	5 .31	3 .19	2 .13	.30
Heavy	2 .13	1 .06	-	.00
				.25

$\chi^2 = 11.99$

REGION Concho MONTH 15 Jul

TEMPERATURE

OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	4 .25	-	-	1.00
N Normal	1 .06	-	-	.00
Above/N Above	1 .06	2 .13	8 .51	.73
				.75

$\chi^2 = 35.74$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	4 .25	3 .19	1 .06	.50
Moderate	1 .06	1 .06	2 .13	.25
Heavy	2 .13	2 .13	-	.00
				.31

$\chi^2 = 6.50$

REGION Concho MONTH 1 Aug

TEMPERATURE

OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	3 .19	-	-	1.00
N Normal	1 .06	3 .19	1 .06	.60
Above/N Above	2 .13	1 .06	5 .31	.63
				.69

$\chi^2 = 11.90$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	4 .25	-	3 .19	.57
Moderate	3 .19	3 .19	1 .06	.47
Heavy	-	-	2 .13	1.00
				.56

$\chi^2 = 11.00$

REGION Concho MONTH 15 Aug

TEMPERATURE

OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	3 .19	-	1 .06	.75
N Normal	1 .06	2 .13	2 .13	.40
Above/N Above	-	5 .31	2 .13	.29
				.44

$\chi^2 = 14.16$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	5 .31	2 .13	.12
Moderate	-	3 .19	3 .19	.50
Heavy	-	2 .13	-	.00
				.25

$\chi^2 = 12.24$

REGION Concho MONTH 1 Sep

TEMPERATURE

OBSERVED

FORECAST	M Below/Below	N Normal	Above/M Above	
M Below / Below	3 .19	-	1 .06	.75
N Normal	1 .06	3 .19	1 .06	.60
Above / M Above	2 .13	1 .06	4 .25	.57
				.63

$\chi^2 = 8.27$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	2 .13	1 .06	.25
Moderate	2 .13	3 .19	3 .19	.38
Heavy	1 .06	1 .06	2 .13	.50
				.38

$\chi^2 = 4.13$

REGION Concho MONTH 15 Sep

TEMPERATURE

OBSERVED

FORECAST	M Below/Below	N Normal	Above/M Above	
M Below / Below	6 .37	-	2 .13	.75
N Normal	-	1 .06	1 .06	.50
Above / M Above	3 .19	-	3 .19	.50
				.63

$\chi^2 = 11.45$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	1 .06	-	.50
Moderate	3 .19	6 .37	1 .06	.60
Heavy	-	3 .19	1 .06	.25
				.50

$\chi^2 = 16.60$

REGION Concho MONTH 1 Oct

TEMPERATURE

OBSERVED

FORECAST	M Below/Below	N Normal	Above/M Above	
M Below / Below	5 .31	1 .06	2 .13	.63
N Normal	4 .25	1 .06	1 .06	.16
Above / M Above	-	1 .06	1 .06	.50
				.44

$\chi^2 = 10.94$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	-	1 .06	1 .06	.00
Moderate	4 .25	3 .19	2 .13	.33
Heavy	2 .13	2 .13	1 .06	.20
				.25

$\chi^2 = 6.50$

REGION Concho MONTH 15 Oct

TEMPERATURE

OBSERVED

FORECAST	M Below/Below	N Normal	Above/M Above	
M Below / Below	6 .37	2 .13	1 .06	.67
N Normal	1 .06	1 .06	2 .13	.25
Above / M Above	2 .13	1 .06	-	.00
				.44

$\chi^2 = 9.83$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	1 .06	-	1 .06	.50
Moderate	4 .25	4 .25	2 .13	.40
Heavy	1 .06	1 .06	2 .13	.50
				.44

$\chi^2 = 8.80$

REGION Concho MONTH 1 Nov

TEMPERATURE

OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	4 .25	2 .13	3 .19	.44
N Normal	2 .13	1 .06	4 .25	.14
Above/N Above	-	-	-	---
				.31

$\chi^2 = 12.12$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	3 .19	3 .19	-	.50
Moderate	-	1 .06	3 .19	.25
Heavy	-	2 .13	4 .25	.67
				.50

$\chi^2 = 11.00$

REGION Concho MONTH 15 Nov

TEMPERATURE

OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	5 .31	2 .13	1 .06	.63
N Normal	3 .19	2 .13	1 .06	.34
Above/N Above	-	-	2 .13	1.00
				.56

$\chi^2 = 10.59$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	2 .13	-	3 .19	.40
Moderate	1 .06	5 .31	1 .06	.72
Heavy	3 .19	1 .06	-	.00
				.44

$\chi^2 = 12.11$

REGION Concho MONTH 1 Dec

TEMPERATURE

OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	2 .13	-	4 .25	.33
N Normal	3 .19	2 .13	2 .13	.29
Above/N Above	1 .06	1 .06	1 .06	.34
				.31

$\chi^2 = 6.95$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	3 .19	2 .13	1 .06	.50
Moderate	3 .19	2 .13	2 .13	.29
Heavy	1 .06	1 .06	1 .06	.34
				.38

$\chi^2 = 3.13$

REGION Concho MONTH 15 Dec

TEMPERATURE

OBSERVED

FORECAST	N Below/Below	N Normal	Above/N Above	
N Below/Below	7 .43	-	3 .19	.70
N Normal	1 .06	-	3 .19	.00
Above/N Above	-	1 .06	1 .06	.50
				.50

$\chi^2 = 17.48$

PRECIPITATION

OBSERVED

FORECAST	Light	Moderate	Heavy	
Light	6 .37	1 .06	1 .06	.76
Moderate	1 .06	-	1 .06	.00
Heavy	2 .13	2 .13	2 .13	.34
				.50

$\chi^2 = 13.33$

Appendix B

A review of rainfall-runoff prediction equations considered but not used in this study

I. Multicapacity basin accounting

II. Soil Conservation Service storm rainfall

III. Rational formula

IV. Multiple-linear correlation equations

I. Multicapacity basin accounting

Kohler and Richards (1962) present a method that weighs simultaneous observations of atmospheric and soil parameters to provide information to determine surface runoff. Gardner (1965) also presented a summary of this method where runoff is determined by

$$Q = (P^N + D^N)^{1/N} - D \quad .$$

Q is surface runoff, P is precipitation, and D is called the moisture deficiency which considers antecedent soil moisture conditions. N is a parameter related to the moisture deficiency by

$$N = C + (K) (D) \quad .$$

C and K are coefficients which can be estimated by 2.0 and 0.5 as a first approximation, respectively. Their method involves the concept that surface runoff will not occur until the moisture deficit of the soil is satisfied. Such a concept may or may not be valid because some observations demonstrate that surface runoff occurs before this deficiency has been satisfied, especially when the <u>rate</u> of precipitation exceeds the <u>rate</u> of percolation. Also, this method does not consider storm characteristics or measureable soil properties, because the values of D are determined by multi-linear regression of meteorological and soil properties.

II. Soil Conservation Service storm rainfall

The U.S. Soil Conservation Service (1971) presents a method which involves a term that attempts to account for surface storage, soil permeability, and antecedent soil water content. The equation is of the form

$$Q = \frac{(P - Ia)^2}{P - Ia + S} \quad ,$$

where Q is surface runoff, P is rainfall, Ia is the amount of rainfall that must occur before surface runoff will occur, and S is defined as the potential maximum soil-water retention. S is a parameter used to represent the type of vegetation and soil conditions for a river basin. The factors affecting surface runoff are interception, infiltration, and surface storage, which generally take place before there is any surface runoff. The relationship considers a 20 percent potential maximum retention, S, where the initial abstraction, Ia, is represented by

$$Ia = 0.2S \quad .$$

By substitution, surface runoff is approximated by

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

Studies of various river basins have resulted in graphs of Ia versus S for different basins representing the hydrologic relationship between soil and vegetation. The runoff curve number, or CN, can be used to determine S by

$$S = \frac{1000}{CN} - 10 \quad .$$

A family of runoff curves is obtained for each basin from studies of land use, land treatment, hydrologic conditions, and hydrologic soil group. Surface runoff then can be estimated by establishing curve numbers for the entire river basin or sections having similar soil and vegetation characteristics.

III. Rational formula

Linsley and Kohler (1958) and Chow (1964) present a very simple empirical relationship called the rational formula, given by

$$Q = C\ I\ A \quad .$$

Q is the peak discharge, C is a runoff coefficient dependent upon the river basin characteristics, I is the rainfall intensity in inches per unit time, and A is the basin drainage area in acres. The equation assumes:

1. a linear relationship between Q and I, and
2. the same C for different storms, basin conditions, and rainfall intensities.

It is called the rational formula because of the numerical consistency of the units of each of the variables. Although C is assumed to be a constant for a given basin, it actually varies from year-to-year, and month-to-month because of varying climatic and soil conditions. Also, the two assumptions listed normally are not valid.

IV. Multiple-linear correlation equations

Beard (1962) presented a method of multi-variable linear regression where the relationship between the dependent and all independent variables are assumed to be linear. Under ordinary conditions, runoff does not exhibit a linear relationship to rainfall. Usually, the logarithm of runoff is very nearly a linear function of rainfall, thus making it suitable to obtain a linear correlation of logarithms. The transformation of a linear equation to logarithms yields

$$\log Y = a_1 \log X_1 + a_2 \log X_2 + \ldots + a_n \log X_n + \log B ,$$

or transformed the equation can be written as

$$Y = B X_1^{a_1} X_2^{a_2} \ldots X_n^{a_n} .$$

Y is the independent variable such as streamflow, X_n represents the dependent variables, a_n are the regression coefficients, and B is a constant. This equation is known as a learning curve, generating function, or "Cobb-Douglas" function. It can be obtained by doing a multiple-linear regression on the logarithms of various parameters considered to influence surface runoff.

Appendix C

Glossary of terms

Acre-foot: The quantity of water required to cover an acre to the depth of one foot.

Algorithm: A prescribed set of well-defined rules or processes for the solution of a problem in a finite number of steps.

Chance-constrained programming: A mathematical means of converting a probabilistic problem into its deterministic equivalent.

Climate: A representation by the statistical collective of the weather conditions in a region during a specified interval of time in terms of average or extremes of atmospheric parameters.

Conditional probability: The probability or likelihood that event A has occurred or will occur given the knowledge that event B has occurred.

Critical period: The period of time in which a reservoir system is most critical with respect to the demands upon the system.

Cube-root-normal distribution: The cube-root-normal probability distribution.

Data error: Uncertainty inherent in a scientific observation.

Decision-making: The process whereby a complex problem with conflicting interests is divided into component parts or subproblems, and then logically combined into a "best course of action" for the original problem.

Deterministic: The situation where the parameters which describe a physical system cannot be random but are represented by an exact mathematical relationship.

Dynamic meteorology: The study of atmospheric motions as solutions of the fundamental equations of hydrodynamics or other systems of equations appropriate to a special situation.

Expected value: The single value which may characterize a random variable and its probability distribution.

Extended-range forecast: A forecast of weather conditions for a period extending beyond two days from the time issued.

Goodness-of-fit: The verification of whether or not a data set can be described by a specified probability distribution, usually expressed as a level of significance or percentage of time when the data set will not conform to the distribution.