# IRRIGATED AGRICULTURAL DECISION STRATEGIES

# FOR VARIABLE WEATHER CONDITIONS


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ABSTRACT

The primary purpose of this interdisciplinary research was to develop an irrigated agricultural decision-making model--including the development of a probabilistic precipitation prediction model, water-production functions, and an economic decision strategy dynamic programming model (DPM).

The primary findings were: The weather simulation model, which was a good estimator of yearly rainfall, tended to overestimate solar radiation but was satisfactory for other climate parameters. The irrigation scheduling model was generally consistant with the measured seasonal evapotranspiration (E) for corn but overpredicted seasonal evapotranspiration for wheat.

Comparison of the DPM with physically based irrigation models indicated that the DPM increased net returns per acre from $7 to $25 for corn with flood irrigation and $2 to $106 per acre for sprinkler systems. For wheat, the DPM increased net returns from $1 to $15 for flood irrigation and $20 to $38 for sprinkler systems. The DPM also estimated water demand functions for corn, sorghum, and wheat. These results indicated that the demand for water was inelastic for corn but elastic for wheat and sorghum. The DPM can be used by farmers with an on-farm microcomputer.

The results should lead to improved ground water management in the declining Ogallala aquifer and should help farmers and public agencies improve irrigation water management decisions.

Keywords: *irrigation scheduling, *water-production functions, *dynamic programming model, *water demand functions, irrigation, models, precipitation model, economic model, interdisciplinary, risk, uncertainty.

## SUMMARY

## IRRIGATED AGRICULTURAL DECISION STRATEGIES FOR VARIABLE WEATHER CONDITIONS

Steadily increasing production costs coupled with low crop prices have placed many farmers in a severe economic bind. For producers irrigating from deep wells, the sharply higher energy costs for pumping have increased the uncertainty for the future. The situation is particularly difficult in areas with declining water tables and low water yields per well such as those of the High Plains of eastern New Mexico and western Texas. Farmers in the southern High Plains have attempted to reduce irrigation water applications with disastrous yield results.

The primary purpose of this report was to develop a comprehensive irrigated agricultural decision-making model to evaluate the impact and provide a methodology for improving decision strategies under variable weather conditions in the southern High Plains. The analysis included the development and testing of a probabilistic precipitation prediction model, water-production functions, and an economic decision strategy model.

An interdisciplinary team approach was used to solve this complex problem of a declining source of ground water coupled with uncertainties of yields, increasing production costs, and effects of variable climatic factors. A probabilistic precipitation prediction model was utilized to simulate precipitation and other weather variables in the immediate future. In addition, experiments were conducted in the Clovis, New Mexico, area to measure crop yield response to various water application levels. The probabilistic precipitation prediction model and the crop-production function model were integrated into an economic decision

strategy model. An important component of this research effort was the inclusion of an information dissemination program to be conducted by a farm management specialist with the New Mexico Cooperative Extension Service.

The primary findings of this study are:

The weather simulation model is generally consistent with yearly measured rainfall, but tends to underestimate rainfall in the first part of the year and overestimate it in the last part. The model tends to overestimate solar radiation but is in good agreement with the other measured climate parameters.

The irrigation scheduling model is in good agreement with the measured seasonal evapotranspiration (E) and yield for corn when the maximum rooting depth in the model is set at 122 cm (4 ft.). When the model is run with the maximum rooting depth set at 106 cm (3.5 ft.) it accurately models measured wheat seasonal evapotranspiration and yields. The model tends to overpredict seasonal evapotranspiration when the maximum root depth of wheat is set in the model to 122 cm (4 ft.).

The economic component, a dynamic programming model (DPM), is a computer irrigation decision model which has the potential to improve High Plains agricultural profits and water efficiency. The advantage of the DPM is that the model output can easily be used by farmers with an on-farm microcomputer. The DPM has as output a decision matrix which returns the most profitable irrigation decision based on current conditions of soil moisture and water allocations.

The DPM operates on a mainframe computer which creates a file for downloading to a microcomputer diskette. Input data consist of soil type, irrigation system characteristics, crop price, and water pumping costs. This matrix can easily be loaded into a standard microcomputer diskette for operation with a soil moisture model.

Comparison of the DPM with a physically based irrigation model indicates that the DPM increases net returns per acre from $7 to $25 for corn with flood irrigation and a crop price of $3.57 per bushel (long-term average price). For sprinkler systems, the DPM increases corn net returns from $2 to $106 per acre. For wheat, with a price of $4.68/bu, the DPM increases net returns from $1 to $15 for flood irrigation and $20 to $38 for sprinkler systems.

Another major advantage of the DPM is its flexibility. The economic threshold for moisture stress changes with soil type, irrigation system, crop price, and water cost. Physically based models can achieve maximum profits but only under specific circumstances. The DPM adapts to a wide variety of different economic and physical conditions.

Other results of the DPM consist of a water demand function for corn, sorghum, and wheat. The results indicate that, for the Clovis, New Mexico area, the demand for water is inelastic for corn and elastic for wheat and sorghum, confirming their dryland capabilities. For a 100 percent increase in pumping costs, water consumption is reduced by 2 inches, or by 7 percent for corn. Sorghum has an elastic demand at low water prices reducing water consumption by 6 inches as pumping cost increases from $2 per acre-inch to $5 per acre-inch, but is inelastic at higher prices. Wheat has a similar elastic portion of demand. As water costs increase from $2 to $10, consumption declines from 38 acre-inches to 30 acre-inches. For water consumption below 28 inches, however, the demand function is inelastic.

The elasticity of demand indicates the potential water savings and economic viability of the various crops as water prices increase. For wheat and sorghum, substantial water savings occur (along with reduced yields) as water costs increase from modest levels. With corn, water cost increases do not encourage water savings, thus increased pumping costs will substantially decrease net returns, and possibly the crop will go out of production.

The results from this research effort should lead to improved ground water management in the declining Ogallala aquifer and should provide farmers and public agencies in the southern High Plains with information and techniques for improving decisions concerning the utilization of scarce resources.

TABLE OF CONTENTS

## LIST OF TABLES



## LIST OF APPENDIX TABLES

LIST OF FIGURES

## LIST OF APPENDIX FIGURES

# IRRIGATED AGRICULTURAL DECISION STRATEGIES FOR VARIABLE WEATHER CONDITIONS

## SECTION I

## INTRODUCTION

The southern High Plains of New Mexico contain productive, ground water irrigated agricultural areas (figure 1). These counties are rapidly depleting their irrigation water supply--ground water sources with little or no recharge. The Portales Valley in northern Roosevelt County, with irrigation predating statehood, already has felt the pinch of a declining water supply. Some irrigated cropland has been abandoned. Irrigation development has been more recent in the other counties. For example, there was no irrigation in Curry County in 1940, but by 1982 about 220,000 acres had been developed. During that same period, Lea County irrigated acreage increased from 2,000 to 120,000 and in Roosevelt County from 10,900 to 138,000 acres (Lansford et al., 1982). Some of the more recently developed areas also are discontinuing irrigation.

The ground water irrigated acreage of the southern High Plains region represents about 33 percent of the irrigated acreage in New Mexico (Lansford et al., 1982). It is estimated that in 40 years the irrigated acreage in the area will drop significantly (Lansford et al., 1982).

A series of regional "Citizens' Conferences on Water" was held throughout New Mexico. The conferences were sponsored by the New Mexico Water Resources Research Institute (Stucky et al., 1971). Participants discussed important water-related problems of the different regions. Participants in the southern High Plains region ranked the following

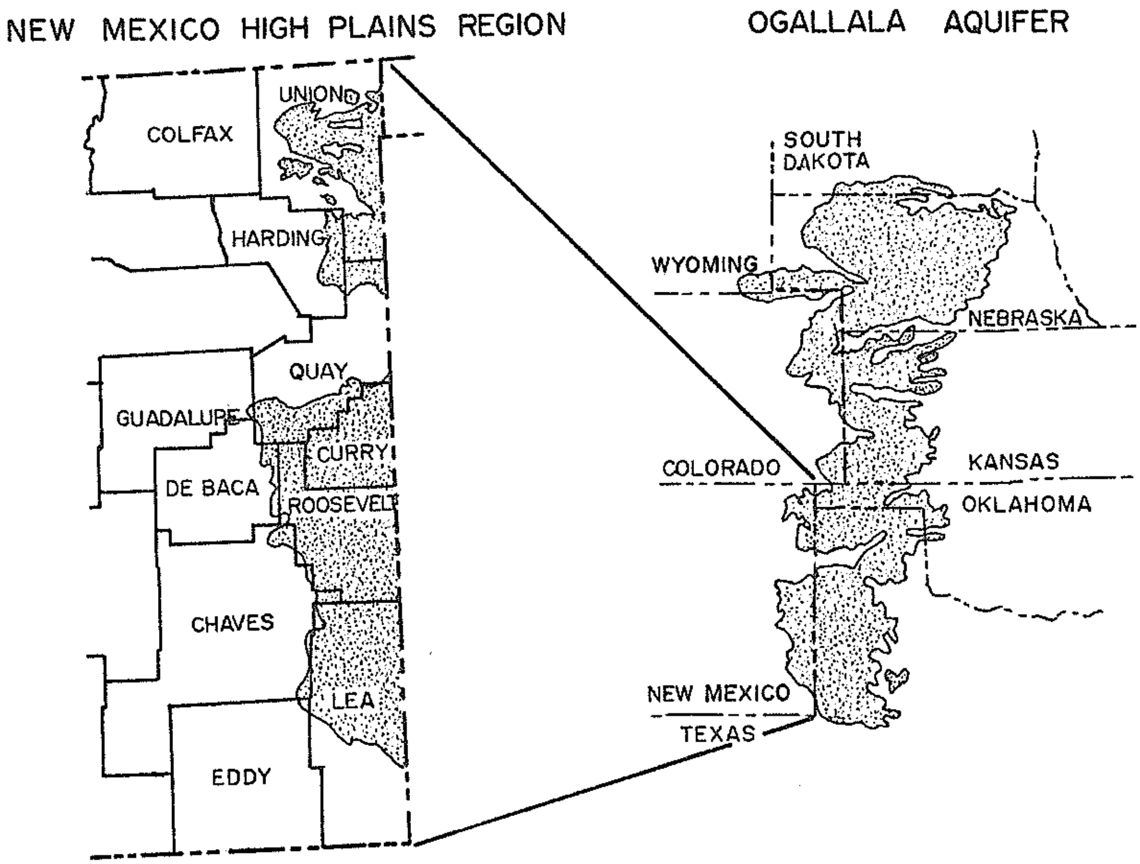


Figure 1. Ogallala aquifer region and New Mexico.

problem areas as being most important: (1) declining ground water table, (2) pollution of ground water, and (3) improvements in water-use efficiency in agriculture.

In the southern High Plains Basin (also referred to as the Texas Gulf Basin) of New Mexico, water withdrawals in 1975 were 755,000 acre-feet, or 17 percent of the total withdrawals of water in the state. In 1980, withdrawals were reduced to 577,300 acre-feet. About 98 percent of the withdrawals were from the ground water source (Sorensen, 1977 and 1982). Ground water depletions in the basin accounted for about 33.5 percent of the state total ground water depletions in 1975 and about 16 percent in 1980. Agricultural depletions in the three-county area (Curry, Roosevelt, and Lea) amounted to 551,760 acre-feet in 1975 and 413,500 acre-feet in 1980, all of which was from the ground water source. This was about 95 percent of the total ground water depletions in the three counties (Sorensen, 1977 and 1982).

Irrigation with ground water in the southern High Plains is an important part of agricultural production. However, it is still considered a supplemental source of the agricultural water supply. Precipitation, which occurs predominantly in the summer, is also an important component of the total water supply. With energy costs increasing, especially for pumping irrigation water, the dependence on precipitation has increased, while the dependence on ground water for irrigation has decreased to a supplemental level.

Steadily increasing production costs coupled with low crop prices have placed the farmer in a severe economic bind. For producers irrigating from deep wells (lifts of approximately 370 feet), the sharply higher energy costs for pumping have tightened their price-cost squeeze. The situation is particularly difficult in areas with declining water tables and low water yields per well.

A farm manager views his investment in an irrigation system, which is a very real expense, differently than he does the cash costs for operating the system during crop production. The manager can decide whether or not to incur future costs for fertilizer, fuel, and hired labor, but he cannot alter the cost he already has invested in the irrigation system. Generally, a farmer will continue to produce as long as he can cover these cash expenses and have something left to contribute toward past investments in machinery, irrigation systems, and land (fixed costs).

In years of average or above average precipitation, irrigating is limited to supplemental amounts; however, in drought years irrigating becomes imperative. The variation in precipitation leads to inefficiencies in production and resource use because farm planning decisions are based on expectations of average weather conditions.

Crops are established and investments in the operational side of the production process are made before precipitation expectations can be revised. In seasons when precipitation is above average, reductions in future pumping, in most cases, can be curtailed. However, other factors, such as fertilizer incorporation, are beyond adjustment. This may result in the inefficient utilization of fertilizer, which may influence yields. In drought years, considerably more irrigation water may be pumped than is economically feasible. This costly irrigation is necessary, however, to minimize the losses incurred as a result of previous investments.

Models capable of predicting seasonal precipitation before the crop production season will allow farmers to plan more effectively and to improve the efficiency of resource use. In years when drought conditions can be predicted, more water efficient crops and optimum water and fertilizer application levels can be selected. There is a need to know the impact that decreasing water supplies will have on agriculture and the economic value associated with a unit of water. Research has determined the maximum yield from the maximum evapotranspiration throughout the state (Hanson and Sammis, 1977). However, sufficient water is not always available to supply the needs for maximum evapotranspiration. Also, knowledge is needed concerning what yield reduction is associated with a unit reduction in applied irrigation water

(Arkley, 1963; DeWit, 1958). This information varies depending on the type of yield from the crop and whether it is produced for forage or lint. Research has been conducted in Arizona, Colorado, and California to derive production functions for selected crops (Hanks, Stewart, and Riley, 1976). The need exists to develop crop-production functions that have not been determined in other states. The development of a comprehensive water resources plan in the Southwest requires improved estimates of evapotranspiration and crop-production functions.

## Objectives

The primary purpose of this research is to develop a comprehensive irrigated agricultural decision-making model to evaluate the impact of weather variables on irrigation decisions and to provide a methodology for improving decision strategies under variable weather conditions in New Mexico's southern High Plains. The proposed analysis included the development and testing of a probabilistic precipitation prediction model, water-production functions, and an economic decision strategy model. The specific objectives are:

1. Probabilistic Precipitation Model

    a. To test the efficiency of probabilistic (Markov, Monte Carlo) precipitation predictions for operational decisions in supplemental irrigation.

    b. To develop and evaluate methods for integrating current weather data into the probabilistic predictions.

2. Crop-Production Functions (yield-water and fertilizer requirements)

    a. To measure crop yield response to various water and fertilized application levels.

    b. To test and evaluate crop-production function models for yield versus seasonal water application plus probable precipitation and nitrogen fertilizer application rates.

3. Economic Decision Strategy Model

   a. To develop economic base data in conjunction with the crop-production function models.

   b. To integrate the probabilistic precipitation prediction model, crop-production function models, and economic base data into the economic decision model.

   c. To test and evaluate the predictive models by utilizing the economic decision strategy model.

   d. To develop and evaluate alternative programs for Cooperative Extension Service application.

## SECTION II

## DESCRIPTION OF AN IRRIGATION SCHEDULING MODEL

An irrigation model was developed to determine the response of seasonal plant yield to irrigation timing and amount. The model is based on a model by Hanks (1974). The model determines the daily evapotranspiration (E) rate of a crop and accumulates the daily rate to the end of the season. It then enters the water-production function, the relationship between seasonal evapotranspiration and yield, and computes the corresponding yield resulting from the irrigation management for the season. The model also incorporates the effect of a nonuniform application of irrigation water over a field by modeling evapotranspiration at several locations within that field. It then weighs the output of the model according to the percentage of the field covered by that irrigation amount. The model structure is interactive in nature so that a predetermined date and amount of water can be applied. The model also can be programmed to stop at set time intervals specified by the user and to request that the user input the amount of irrigation water to be applied. Also, an economic decision map can be used to specify time and amount of water. The model provides information to the user showing how close the daily evapotranspiration is following a predetermined level of evapotranspiration and yield specified.

### Materials and Methods

The irrigation scheduling model (IRRSCH) was validated using a corn and wheat data set. The crops were grown under deficit irrigation. The study site was located 20 km (12 mi.) north of Clovis, New Mexico, at the Plains Branch Agricultural Experiment Station. The soil at the site was Pullman clay loam, a fine-loamy mixed Thermic Torretic Palenstall. The corn variety NKPX74 was planted April 10, 1980, in two plots that were furrow irrigated for stand germination. Subsequent irrigations were applied to the field using a sprinkler-line source. This technique provides adequate water throughout the growing season near the sprinkler line while applying a decreasing water application perpendicular to the line. Evapotranspiration (E) was determined at each irrigation level (figure 2) using a water balance equation where:

$$E = I + R - D \pm \Delta SM$$

and:

$I$ = irrigation mm

$R$ = rainfall mm

$D$ = drainage mm

$\Delta SM$ = change in soil moisture, mm

Irrigation was measured with catchment cans installed in the plot. The cans were read after each irrigation and raised as the crop grew so that they were 15 cm (6 in.) above the crop. Rainfall was measured with a standard U.S. Weather Bureau 20 cm (8 in.) rain gauge located next to the plots. Drainage was assumed to be negligible. Change in soil moisture was determined from neutron soil moisture readings. Climatic variables needed by IRRSCH were measured at a climatic station located less than 1 km from the plots.

The corn plots were harvested with a combine, October 4, 1980. Each harvested subplot 1 m (3.5 ft.) wide by 28 m (90 ft.) long represented a different irrigation level. A complete description of the plot

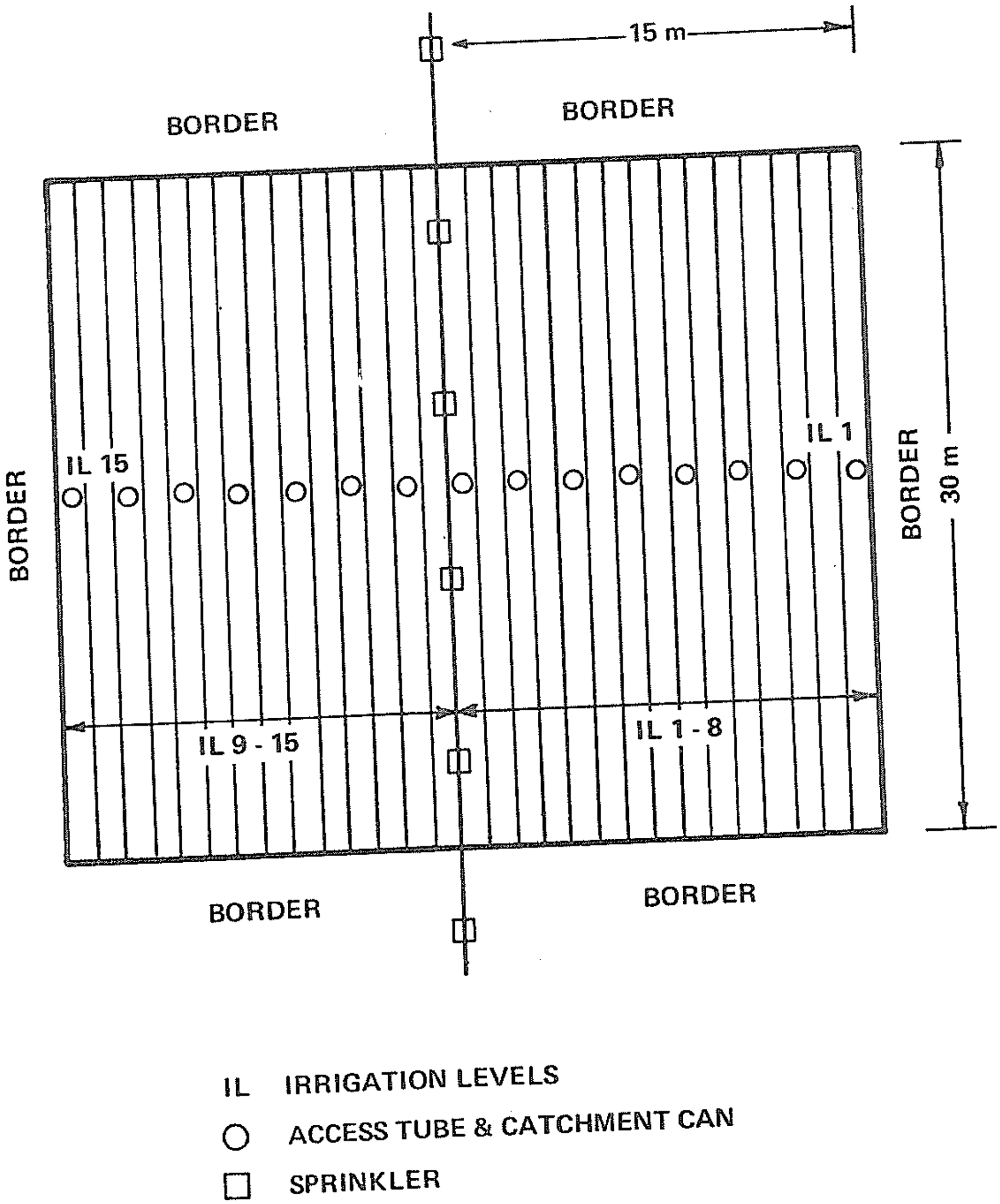


Figure 2. Details of the layout of the sprinkler-line source.

is given by Sammis et al. (1983). The water-production function used in the irrigation scheduling model was derived from the total data base of this experiment.

The IRRSCH model also was validated for a wheat crop grown under deficit irrigation at the same study site. Wheat was planted October 14, 1980 and 1981, and furrow irrigated for germination and subsequently irrigated using the sprinkler-line source. The plots were harvested with a combine June 23, 1981, and July 7, 1982. Harvest plots were 1 m (3.5 ft.) wide located on a bed and 28 m (90 ft.) long. Determination of evapotranspiration was derived as described by the corn experiment. The full data set of this experiment as described by Sammis et al. (1983) was used to derive the wheat water production function used in the irrigation scheduling model. A detailed description of the model structure is presented in appendix A.

## Results and Discussion

Table 1 presents the measured and modeled evapotranspiration and yield of corn for each irrigation level, two maximum rooting depths specified as input data, and two selected values of relative available water in the root zone at which daily evapotranspiration begins to decrease. The model predicts corn seasonal evapotranspiration within 2 percent of the measured values when the maximum rooting depth of corn is specified at 122 cm (4 ft.), and the reduction in evapotranspiration begins when the relative available water reaches 0.6 (table 2 and figure 3). Under these same conditions, the model tends to underestimate the yield (Y) under severe moisture stress conditions and overestimate yield under moderate stress conditions (figure 4). This vari-

Table 1. A comparison between measured and modeled evapotranspiration (E) and yield for corn grown at Clovis, New Mexico

| Irrigation Level | Seasonal E Measured | Seasonal E Modeled Version* 1 | Seasonal E Modeled Version* 2 | Seasonal E Modeled Version* 3 | Grain Yield Measured | Grain Yield Modeled Version 1 | Grain Yield Modeled Version 2 | Grain Yield Modeled Version 3 |
|---|---|---|---|---|---|---|---|---|
| | cm | | | | kg/ha | | | |
| Plot 1 | | | | | | | | |
| 1 | 39.3 | 42.2 | 40.6 | 47.2 | 103 | -776 | -980 | 170 |
| 2 | 44.3 | 47.2 | 47.0 | 53.8 | 116 | 174 | 232 | 1,389 |
| 3 | 57.5 | 59.2 | 60.5 | 64.0 | 610 | 2,482 | 2,323 | 3,265 |
| 4 | 69.5 | 70.9 | 72.1 | 74.7 | 3,543 | 4,517 | 4,243 | 5,225 |
| 5 | 87.4 | 89.2 | 90.7 | 91.7 | 8,197 | 7,840 | 7,303 | 8,357 |
| 6 | 96.5 | 98.0 | 100.1 | 99.8 | 9,763 | 9,536 | 8,815 | 9,838 |
| 7 | 98.6 | 96.8 | 98.3 | 98.6 | 9,573 | 9,240 | 8,509 | 9,591 |
| 8 | 100.5 | 98.0 | 99.8 | 99.6 | 9,556 | 9,499 | 8,783 | 9,792 |
| 9 | 97.8 | 97.5 | 99.3 | 99.8 | 9,219 | 9,407 | 8,697 | 9,818 |
| 10 | 91.1 | 89.9 | 91.7 | 93.0 | 8,234 | 8,004 | 7,447 | 8,550 |
| 11 | 75.1 | 78.7 | 80.3 | 82.0 | 5,402 | 5,970 | 5,549 | 6,539 |
| 12 | 64.7 | 66.3 | 67.8 | 70.4 | 2,835 | 3,678 | 3,505 | 4,397 |
| 13 | 53.1 | 55.4 | 55.4 | 59.3 | 1,024 | 1,658 | 1,498 | 2,386 |
| 14 | 46.4 | 43.9 | 44.7 | 50.0 | 256 | -395 | -255 | 683 |
| 15 | 36.7 | 39.1 | 38.4 | 44.2 | 101 | -1,306 | -1,294 | -386 |
| Plot 2 | | | | | | | | |
| 1 | 39.2 | 39.6 | 38.9 | 44.7 | 58 | -1,247 | -1,238 | -302 |
| 2 | 47.9 | 47.2 | 46.0 | 51.8 | 591 | 180 | 43 | 1,030 |
| 3 | 58.8 | 59.4 | 60.7 | 63.5 | 2,074 | 2,419 | 2,358 | 2,449 |
| 4 | 70.8 | 69.1 | 70.6 | 73.2 | 4,551 | 4,215 | 3,993 | 4,915 |
| 5 | 83.3 | 74.2 | 74.9 | 77.0 | 6,871 | 5,106 | 4,722 | 5,627 |
| 6 | 91.2 | 92.7 | 94.5 | 96.5 | 8,699 | 8,536 | 7,896 | 9,237 |
| 7 | 94.0 | 97.0 | 98.8 | 99.6 | 8,879 | 9,333 | 8,595 | 9,796 |
| 8 | 100.5 | 98.3 | 100.3 | 100.1 | 9,702 | 9,576 | 8,843 | 9,852 |
| 9 | 94.0 | 96.5 | 98.3 | 98.6 | 8,954 | 9,214 | 8,518 | 9,612 |
| 10 | 86.4 | 95.8 | 97.5 | 98.3 | 7,825 | 9,104 | 8,390 | 9,557 |
| 11 | 78.4 | 79.2 | 80.3 | 82.2 | 4,806 | 5,968 | 5,576 | 6,691 |
| 12 | 64.4 | 63.8 | 64.8 | 66.8 | 889 | 3,181 | 3,032 | 3,916 |
| 13 | 54.4 | 52.8 | 52.8 | 57.9 | 456 | 1,222 | 1,090 | 2,135 |
| 14 | 46.3 | 42.2 | 42.4 | 47.8 | 123 | -755 | -647 | 267 |
| 15 | 39.5 | 38.4 | 38.4 | 43.9 | 518 | -1,420 | -1,316 | -405 |

*

| Version | a | b | c | Maximum Root Depth |
|---|---|---|---|---|
| | | | | cm |
| 1 | -0.032 | 1.73 | 0.6 | 122 |
| 2 | 0 | 2.00 | 0.5 | 122 |
| 3 | 1.73 | 1.73 | 0.6 | 152 |

$T = T_{max}\ (a + bw)$ if $W \leq C$

$T = T_{max}$ if $W > C$

T = Transpiration

W = Relative available water in the root zone

Table 2. Linear regression equations compare modeled seasonal evapotranspiration ($E_m$) to measured E; and modeled yield ($Y_m$) to measured yield (Y) for corn and wheat

| Conditioning of Parameters in the Model a | b | c | R* | Equation | Coefficient of Determination |
|---|---|---|---|---|---|
| | | | cm | | |
| -0.032 | 1.73 | 0.6 | 122 | $E(cm) = 0.81 + 0.98\ E_m(cm)$ | 0.99 |
| | | | | $Y(kg/ha) = 295 + 0.93\ Y_m(kg/ha)$ | 0.94 |
| 0 | 2 | 0.5 | 122 | $E(cm) = 2.66 + 0.94\ E_m(cm)$ | 0.98 |
| | | | | $Y(kg/ha) = 325 + 1.00\ Y_m(kg/ha)$ | 0.94 |
| -0.032 | 1.73 | 0.6 | 152 | $E(cm) = -7.4 + 1.04\ E_m(cm)$ | 0.98 |
| | | | | $Y(kg/ha) = -581 + 0.98\ Y_m(kg/ha)$ | 0.93 |
| | | | | WHEAT 1980-1981 | |
| 0 | 2 | 0.5 | 91 | $E(cm) = -6.23 + 1.15\ E_m(cm)$ | 0.97 |
| | | | | $Y(kg/ha) = -159 + 1.07\ Y_m(kg/ha)$ | 0.86 |
| 0 | 2 | 0.5 | 122 | $E(cm) = -13.35 + 1.17\ E_m(cm)$ | 0.97 |
| | | | | $Y(kg/ha) = -669 + 1.09\ Y_m(kg/ha)$ | 0.87 |
| | | | | WHEAT 1981-1982 | |
| 0 | 2 | 0.5 | 91 | $E(cm) = -3.41 + 1.25\ E_m(cm)$ | 0.97 |
| | | | | $Y(kg/ha) = -535 + 1.58\ Y_m(kg/ha)$ | 0.90 |
| 0 | 2 | 0.5 | 122 | $E(cm) = -9.55 + 1.25\ E_m(cm)$ | 0.95 |
| | | | | $Y(kg/ha) = -1265 + 1.62\ Y_m(kg/ha)$ | 0.89 |
| | | | | COMBINED 1980-1982 | |
| 0 | 2 | 0.5 | 91 | $E(cm) = -1.79 + 1.13\ E_m(cm)$ | 0.84 |
| | | | | $Y(kg/ha) = -143 + 1.22\ Y_m(kg/ha)$ | 0.73 |
| 0 | 2 | 0.5 | 122 | $E(cm) = -7.82 + 1.13\ E_m(cm)$ | 0.83 |
| | | | | $Y(kg/ha) = -572 + 1.19\ Y_m(kg/ha)$ | 0.71 |
| | | | | FORCED THROUGH 0 | |
| 0 | 2 | 0.5 | 91 | $E(cm) = 1.09\ E_m(cm)$ | |
| | | | | $Y(kg/ha) = 1.16\ Y_m(kg/ha)$ | |
| 0 | 2 | | 122 | $E(cm) = 0.97\ E_m(cm)$ | |
| | | | | $Y(kg/ha) = 0.98\ Y_m(kg/ha)$ | |

*

| Version | a | b | c | Maximum Root Depth |
|---|---|---|---|---|
| | | | | cm |
| 1 | -0.032 | 1.73 | 0.6 | 122 |
| 2 | 0 | 2.00 | 0.5 | 122 |
| 3 | 1.73 | 1.73 | 0.6 | 152 |

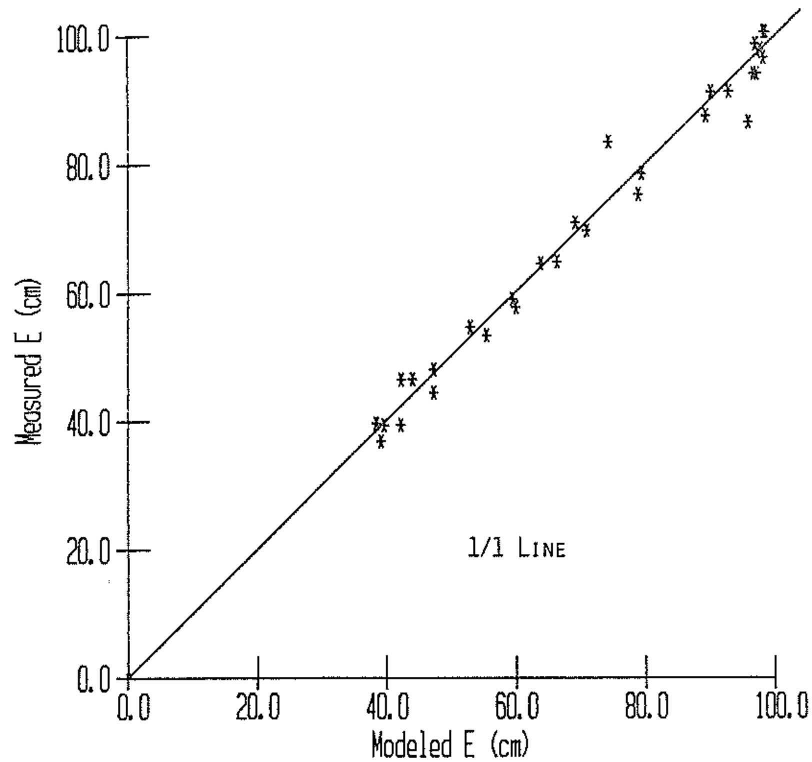


Figure 3. Comparison of modeled and measured seasonal evapotranspiration (E) of corn in 1980 at Clovis, New Mexico

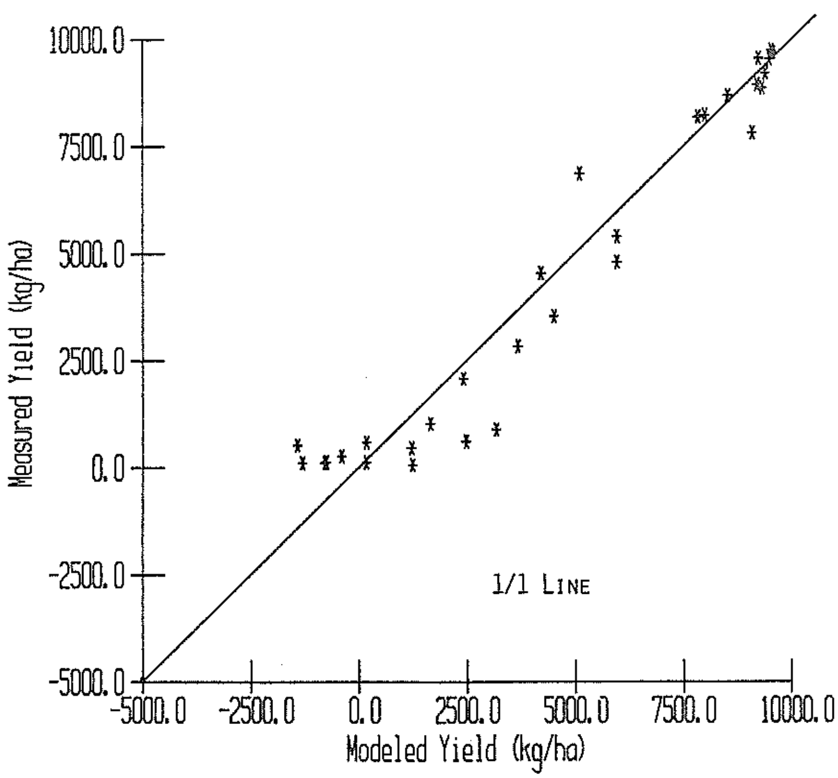


Figure 4. Comparison between measured and modeled grain yield of corn in 1980 at Clovis, New Mexico

ability is a result of the nonlinearity in the relationship measured in the field between evapotranspiration and yield that was not incorporated into the linear water-production function. When the maximum rooting depth is increased from 122 cm (4 ft.) to 152 cm (5 ft.), the model consistently overestimates the seasonal evapotranspiration by 7.4 cm (2.9 in.) as shown by the intercept of the linear regression of modeled versus measured evapotranspiration (table 2). This overestimate of seasonal evapotranspiration is due to the increase in the computed plant available water. This is due to the increased rooting depth, which allows more of the stored water to become available for plant growth throughout the growing season. Although the model overpredicts evapotranspiration, the prediction of yield compared to measured yield increases slightly under these conditions.

When the maximum rooting depth is set to 122 cm (4 ft.), but reduction in daily evapotranspiration is not allowed to occur until the relative available water reaches 50 percent, the model overpredicts the seasonal evapotranspiration. This can be seen from the slope of the regression between modeled and measured evapotranspiration. The slope of the regression equation decreased from 0.98 to 0.94. Some of this increase in modeled evapotranspiration was mitigated by the increase in the intercept to 2.66 cm (1.04 in). The model appears to be more sensitive to the selected maximum rooting depth than it does to the point at which reduction in daily evapotranspiration starts to occur. The model's sensitivity to rooting depth in predicting seasonal evapotranspiration also shows up in the verification of the model for wheat (table 3 and figures 5 and 6).

Table 3. A comparison between measured and modeled evapotranspiration (E) and yield for wheat grown at Clovis, New Mexico

| Irrigation Level | Seasonal E Measured | Seasonal E Modeled Version* 1 | Seasonal E Modeled Version* 2 | Grain Yield Measured | Grain Yield Modeled Version 1 | Grain Yield Modeled Version 2 |
|---|---|---|---|---|---|---|
| | cm | cm | cm | kg/ha | kg/ha | kg/ha |
| **1980-1981** | | | | | | |
| 1 | 28.5 | 29.5 | 34.8 | 1,204 | 1,104 | 1,525 |
| 2 | 30.3 | 31.0 | 36.3 | 1,268 | 1,229 | 1,643 |
| 3 | 33.7 | 34.5 | 40.1 | 1,692 | 1,496 | 1,958 |
| 4 | 42.2 | 39.9 | 45.5 | 2,196 | 1,933 | 2,377 |
| 5 | 46.8 | 45.5 | 50.5 | 2,612 | 2,383 | 2,788 |
| 6 | 52.0 | 50.0 | 55.1 | 3,173 | 2,740 | 3,161 |
| 7 | 55.8 | 52.1 | 57.4 | 2,718 | 2,911 | 3,332 |
| 8 | 57.7 | 55.9 | 60.2 | 2,898 | 3,212 | 3,568 |
| 9 | 52.8 | 53.3 | 58.2 | 3,374 | 3,021 | 3,399 |
| 10 | 49.7 | 48.8 | 54.4 | 2,697 | 2,650 | 3,086 |
| 11 | 45.7 | 44.7 | 50.0 | 2,227 | 2,323 | 2,751 |
| 12 | 36.4 | 40.1 | 45.5 | 1,641 | 1,961 | 2,391 |
| 13 | 32.8 | 36.3 | 41.4 | 1,325 | 1,655 | 2,057 |
| 14 | 32.4 | 34.0 | 39.1 | 891 | 1,465 | 1,880 |
| **1981-1982** | | | | | | |
| 1 | 38.2 | 30.7 | 35.8 | 1,037 | 1,195 | 1,067 |
| 2 | 37.5 | 32.7 | 37.8 | 1,758 | 1,361 | 1,772 |
| 3 | 38.0 | 35.5 | 40.5 | 2,165 | 1,579 | 1,979 |
| 4 | 46.0 | 38.6 | 43.5 | 1,831 | 1,730 | 2,226 |
| 5 | 48.0 | 42.5 | 47.3 | 2,610 | 2,142 | 2,527 |
| 6 | 55.4 | 46.9 | 51.6 | 2,874 | 2,495 | 2,875 |
| 7 | 61.2 | 49.8 | 54.5 | 3,714 | 2,728 | 3,101 |
| 8 | 61.5 | 51.1 | 55.8 | 4,041 | 2,835 | 3,207 |
| 9 | 61.2 | 50.7 | 55.3 | 3,616 | 2,799 | 3,170 |
| 10 | 55.0 | 47.1 | 54.4 | 4,026 | 2,511 | 2,890 |
| 11 | 49.8 | 42.9 | 47.8 | 3,320 | 2,173 | 2,562 |
| 12 | 42.6 | 38.0 | 43.2 | 2,521 | 1,788 | 2,197 |
| 13 | 38.5 | 34.3 | 39.4 | 1,860 | 1,485 | 1,893 |
| 14 | 36.1 | 32.0 | 37.2 | 1,696 | 1,302 | 1,718 |
| 15 | 38.0 | 30.7 | 35.9 | 1,214 | 1,200 | 1,615 |

| * Version | a | b | c | Maximum Root Depth (cm) |
|---|---|---|---|---|
| 1 | 0 | 2 | 0.5 | 91 |
| 2 | 0 | 2 | 0.5 | 122 |

$T = T_{max}$ (a + bw) if $W \leq C$
$T = T_{max}$ if $W > C$
T = Transpiration
W = Relative available water in the root zone

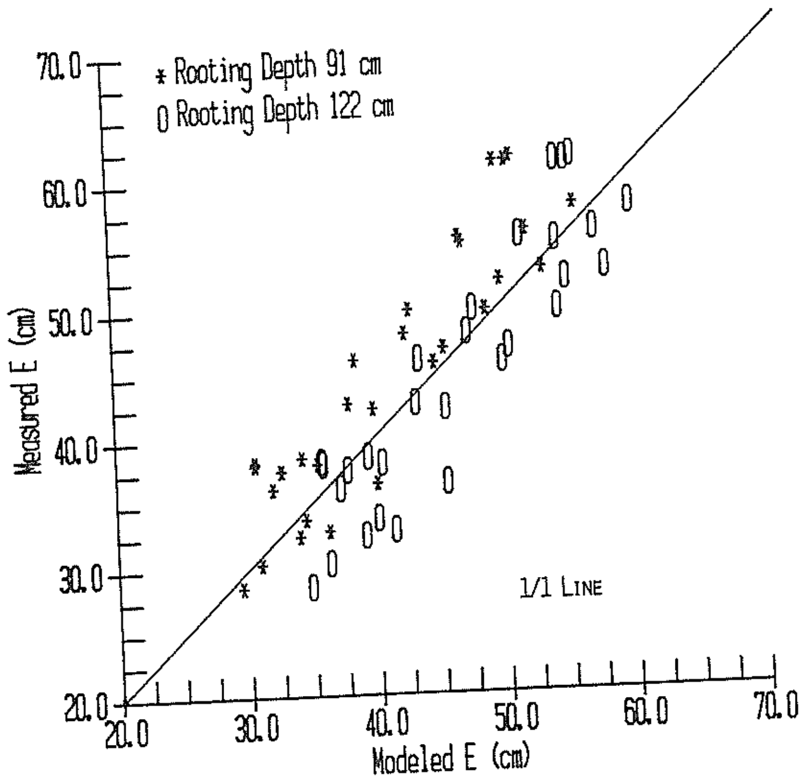


Figure 5. A comparison of two years of modeled and measured seasonal evapotranspiration (E) of wheat at Clovis, New Mexico

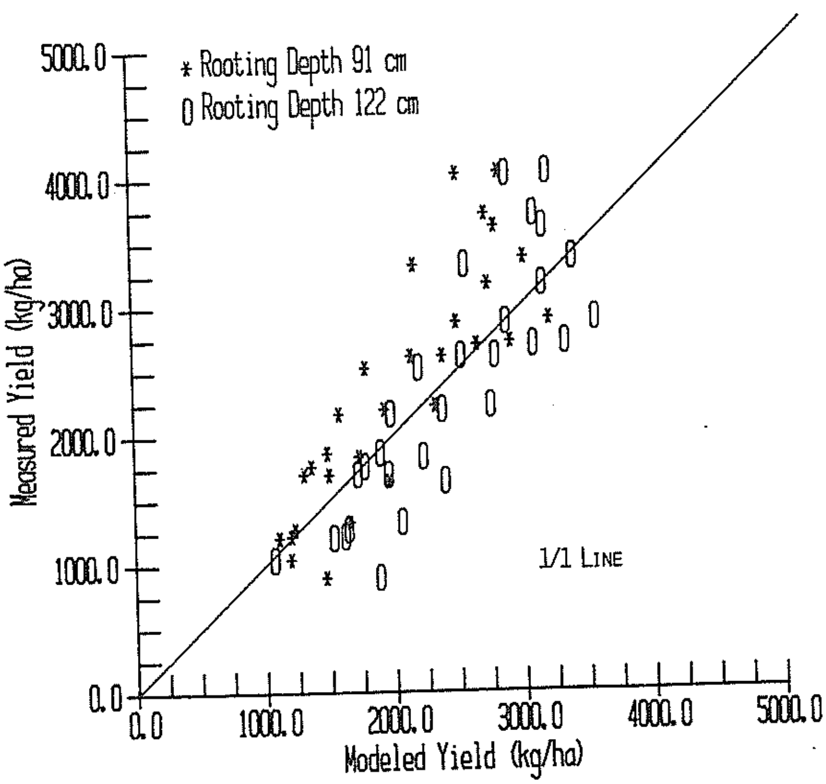


Figure 6. A comparison of two years of modeled and measured grain yield of wheat at Clovis, New Mexico

When the equations relating $E_m$ and E are forced through zero, the model based on wheat data underestimates seasonal evapotranspiration over the entire range of measured evapotranspiration by 9 percent when the maximum rooting depth is 91 cm (3 ft.), and overpredicts seasonal evapotranspiration by 3 percent when the maximum rooting depth is set at 122 cm (4 ft. [table 2]). The individual regression equations of modeled versus measured evapotranspiration for selected years and combined over years, but not forced through zero, show the same response to change in maximum rooting depth but in a slightly different manner. The intercept, but not the slope, changes indicating that the effect of the maximum rooting depth is uniform over the range of modeled evapotranspiration. The measured and modeled yield show the same picture as the seasonal evapotranspiration. The optimal rooting depth is located between 91 cm (3 ft.) and 122 cm (4 ft.) depths as indicated by figure 6, and the regression analysis in table 2. In order to model a rooting depth of 106 cm (3.5 ft.), the model would have to be modified to make intervals for rooting depth be equal to 15 cm (6 in.) instead of 30 cm (12 in.) as now used in the model.

## SECTION III

## WEATHER SIMULATION MODEL

The proper modeling of agricultural systems should include uncertainties due to the stochastic nature of weather. Because of the complexity of the interactions of meteorological and agricultural systems, analytical methods of the system's performance are not feasible (Matalas, 1967). A large number of realistic synthetic sequences can allow the planner to investigate the effect of different agricultural management strategies in the presence of weather variations. A stochastic computer simulation model, WTHSIM, was designed to provide the researcher with a large data base of daily weather profiles.

The model produces a stochastic representation of a given day's weather profile. This weather profile has eight components: rain occurrence (RO), rain amount (RA), maximum temperature (TX), minimum temperature (TN), maximum humidity (HX), minimum humidity (HN), solar radiation (SR), and wind (WI). This model is based on a model proposed by Richardson (1981). The approach is to generate rainfall occurrence and amount independently of the other variable, then generate the other variables conditioned on the wet or dry status of that day. While the precipitation components of the model are necessary for its use, the other variables are somewhat arbitrary. By suitable redefinition of the elements of the day's profile, different variables can be used. Because precipitation is generated independently of the other variables, a discussion of the model can be divided into two parts, precipitation and the other variables.

## Model Description

### Precipitation

The modeling of precipitation was done in two parts. A first order Markov model was used to determine the occurrence of precipitation and the amount of precipitation was treated as a deviate from a gamma distribution. The Markov model assumes that the occurrence of rain is dependent only on the previous day's state (wet or dry). Two parameters are needed to characterize this process, the probability that a day is dry given the previous day was dry (P[D/D]) and the probability that a day is dry given the previous day was wet (P[D/W]). A wet day is defined as a day receiving greater than or equal to 0.01 cm of rain. The probability of a wet day can be found by the equations:

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

$$P(W/W) = 1 - P(D/W).$$

To generate the value for occurrence or not, a uniform (0,1) deviate is drawn and compared with the respective parameter.

If a rainfall occurs, the distribution of rainfall amount (RA) is assumed to follow a gamma distribution function given by:

$$dF(RA) = (\Gamma(a)b^{a})^{-1} e^{-RA/b} (RA)^{(a-1)}$$

Two parameters (a, b) are needed to characterize this distribution.

To account for the seasonal variation of these parameters, separate values of P(D/D), P(D/W), a, and b are used for each week. (March 1 to March 7 = week 1.)

Temperature, Humidity, Solar Radiation and Wind

In order to model the other variables, it was desirable to include the interrelationship of these variables with precipitation, the interrelationships of these variables for both the same day and the previous day, and the seasonal variation. To accomplish this, a continuous multivariate time series model was used to produce "standardized" weather scores which were then transformed back to the raw scores conditioned on the week number and wet or dry status of that day. The time series component of this model requires that the series is weekly stationary (see Matalas, 1967); that is, every variable in the series has a constant mean and variance through time. To meet this requirement, some method of standardization of the data is necessary. This standardization should take into account the temporal variation of both the mean and variance, and the differences due to the occurrence of precipitation (Richardson, 1981).

The values are standardized by obtaining separate estimates of the mean and standard deviation for each week and rain event. To standardize the variables throughout the year, 104 (52 weeks x 2 rain events) values are needed for each variable. The standardized score is then the usual z-transform:

$$x_{t,i} = (w_{t,i} - u_{k,i,j}) / s_{k,i,j}$$

where the variables are:

x = standardized score

w = observed value

u = mean value

s = standard deviation and the indices refer to

t = time

i = weather parameter (i = TX, TN, HX, HN, SR, WI)

j = rain event (1 = dry, 2 = wet)

For example, the maximum temperature in Clovis, New Mexico, on April 10, 1980, was 27°C; also, no rain occurred on that day. The appropriate time period is 6. The needed parameters are:

$$u_{6,TX,1} = 22.85$$
$$s_{6,TX,1} = 4.76$$

The resulting standardized score is:

$$x_{41,TX} = (w_{41,TX} - u_{6,TX,1})/s_{6,TX,1} = (27-22.85)/4.76 = 0.802$$

The values of $x_{t,i}$ will have a mean of 0 and a variance of 1 regardless of the particular value of the indices; hence, they are the standardized scores that are used in the time series model.

Matalas (1967) presents a multivariate model that will characterize a historical sequence in terms of their lag 0 and lag 1 cross correlations. His model is based on the matrix equation:

$$x_t = Ax_{t1} = Be$$

where $x_t$ is a vector of length 6 whose ith element is the standardized score for the ith variable (i = TX, TN, HX, etc.) at time t, and e is a vector of length 6 whose ith element is a random number from a normal (0, 1) population; A and B are 6 x 6 matrices whose elements are designed so that the generated sequences have the desired lag 0 and lag 1 cross correlations. The individual elements of A ($a_{ij}$) can be thought of as the effect of the jth variable at time t-1 on the ith variable at time t. Likewise, $b_{ij}$ can be thought of as the effect of the jth variable at time t on the ith variable at time t.

Once the standardized value for a particular day is generated, the vector is transformed back to its raw values by the equation:

$$w_{t,i} = s_{k,i,j}(x_{t,i} + u_{k,i,j})$$

The result of this process is a sequence of variables that represents the historical sequence in terms of its mean, variance, lag 0, and lag 1 cross correlation coefficients. If one also can make the assumption that the variables in question are normally distributed, this process will produce a synthetic sequence that also will match the distribution of the historical sequence (Matalas, 1967).

## Estimation of Parameters

Estimation procedures have been previously published in various sources. For the Markovian submodel, only the probability of any given day being dry (P[D]) and the probability of a given day being dry given the previous day was dry (P[D/D]) are needed to completely specify the model. These estimates are obtained following the methods given by Heerman et al. (1971). The estimates of the gamma distribution parameters use asympotic approximations of the maximum likelihood estimators given by Thom (1947). These are:

$$\hat{a} = (1 + \sqrt{1 + 4A/3})/4A$$
$$\hat{b} = \overline{x} / \hat{a}$$

where

$$A = -\ln(\overline{x}) - (1/n)\Sigma \ln(x_i)$$

and $x_i$ is the daily amount of rainfall (if it occurs).

For the rest of the variables, estimates of their respective means and standard deviations are necessary. The mean and standard deviation for each category (ith variable, kth week, and jth rain event) are the usual estimates:

$$\hat{u}_{k,i,j} = (1/n_{k,i,j}) \quad \Sigma w_{k,i,j},$$
$$\hat{s}_{k,i,j} = ( (\Sigma w_{k,i,j} - n_{k,i,j}\ \hat{u}_{k,i,j})/(n_{k,i,j} - 1) )^{\frac{1}{2}}$$

The estimates of A & B are designed to produce a stationary sequence of variables that reproduce the desired lag 1 and lag 0 cross correlation coefficients. Because the standardized variables have a mean of zero and variance of 1, the individual lag 0 and 1 cross correlation coefficients are given by:

$$\hat{P}_0\ (j,k) = \sum_t x_{j,t}\ \ x_{k,t}$$
$$\hat{P}_1\ (j,k) = \sum_t x_{j,t}\ x_{k,t-1}$$

Where $P_1$ (j, k) is the correlation between variable j and variable k lagged one day. Matalas (1967) showed that the estimates of A & B satisfy the equations.

$$A = M_1 M_0^{-1} \qquad (1)$$
$$BB^T = M_0 - M_1\ M_0\ M_1^T \qquad (2)$$

Where $M_0$ is the matrix of lag 0 cross correlations ($E[x_t x_t]$) and $m_1$ is the matrix of lag 1 serial correlations ($E[x_t, x_{t-1}]$). In terms of this model, the matrices $M_0$ and $M_1$ have this form:

$$M_0 = (P_0(i,j))$$
$$M_1 = (P_1(i,j))$$

$M_0$ is the typical correlation matrix and is symmetric but $M_1$ is not symmetric since $P_1$ (j,k) is generally not equal to $P_1$ (k,j). The matrix B is any matrix that is a solution to equation 2. The Cholesky decomposition was used to compute B.

The total number of variables needed for this model is 889. The precipitation portion uses four variables for each week, the standardization portion uses 12 for each week, and the matrix A needs 36 parameters. Matrix B, if $BB^T$ is factorized into a triangular matrix, needs only 21 parameters since all elements above the main diagonal are 0.

Two subroutines have been provided to estimate and read the parameters into the proper arrays for WTHSIM'S use. SUBROUTINE SETPAR reads the parameters off of any unit and places the values in the proper arrays. PAREST estimates the parameters from weather data and places these estimates on a unit in such a way that SETPAR can be used directly. The routine PAREST is only run once for each location if the results are saved.

## Results and Discussion

Weather data for the New Mexico State University Agricultural Plains Branch Experiment Station near Clovis, New Mexico, were obtained from two sources. A cooperative weather station has been housed at the station since 1950 and data until 1979 was obtained from the U.S. Weather Service. Also, four years (1976-1977, 1980-1981) of data were collected by the New Mexico State University Agricultural Engineering Department in conjunction with their field experiments. The cooperative weather station did not routinely collect information on humidity, whereas the other site did. All of the other variables were present in both data sets.

Because of the large number of parameters needed for this model and the relative scarcity of complete weather records, some compromises had to be made to ensure good estimates of the parameters. Compounded with this is the relative aridity of the location, resulting in very few data on "wet" days. Because rain is treated separately in this model, the rain parameters were estimated from the U.S. Weather Service data and the other variables were estimated from the smaller data base. Only the Markovian model used weekly increments, all other parameters were done by four-week intervals.

The estimates of the precipitation components are presented in appendix B (table B-1) and graphically in figures B-1 and B-2. The estimates for the mean and standard deviations of the other variates are presented graphically in table B-2 and figures B-3, B-4, and B-5. The estimates of the lag 1 and lag 1 cross correlation coefficients are presented in table B-3.

Verification of this model utilized 20 years of simulated weather using WTHSIM, and various traits were graphed with their real counterparts. The cumulative distribution of rain amount for each of the 13 periods is shown in figures 7, 8, and 9.

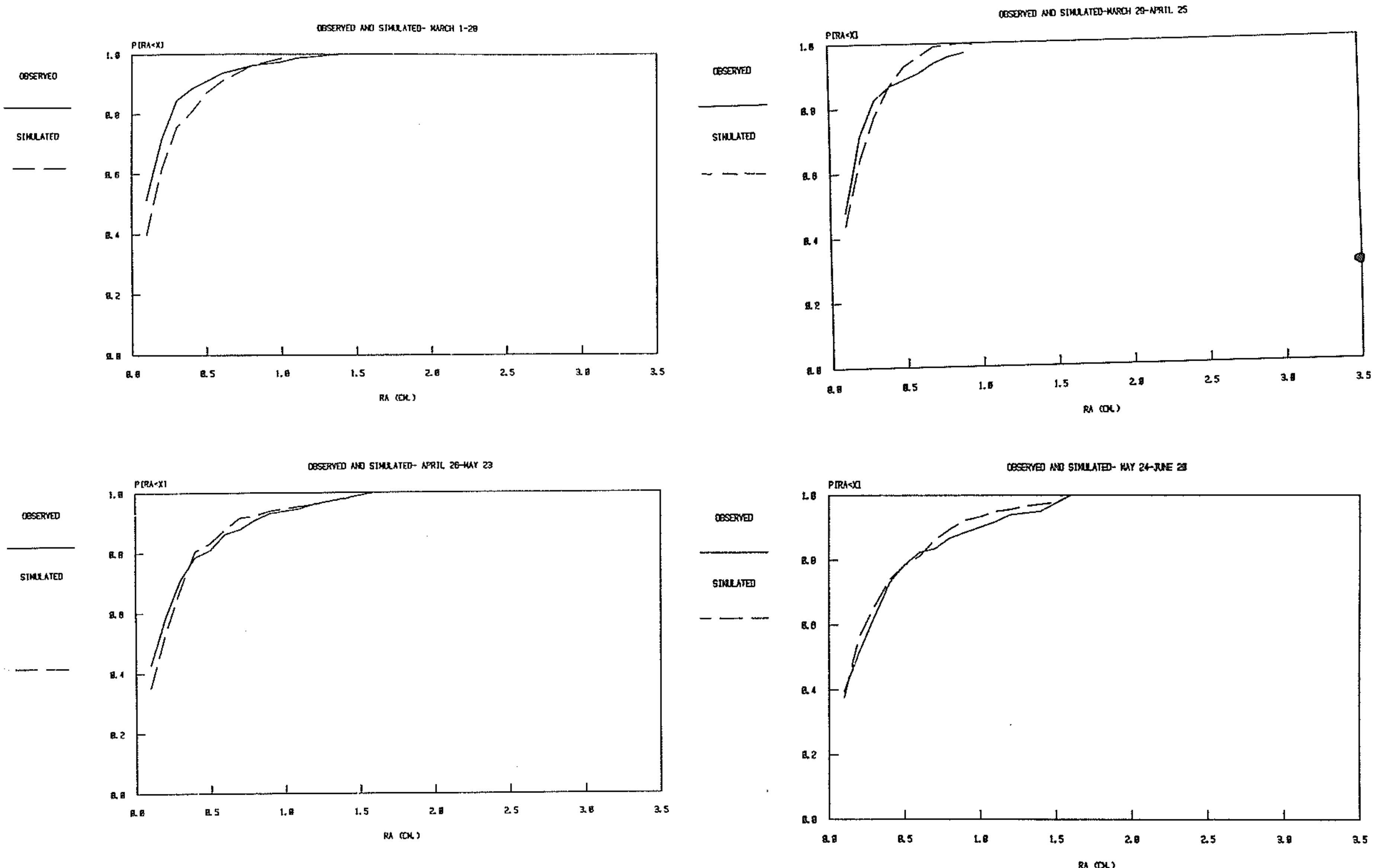


Figure 7. A comparison between observed and simulated cumulative distributions of rainfall amount (RA)

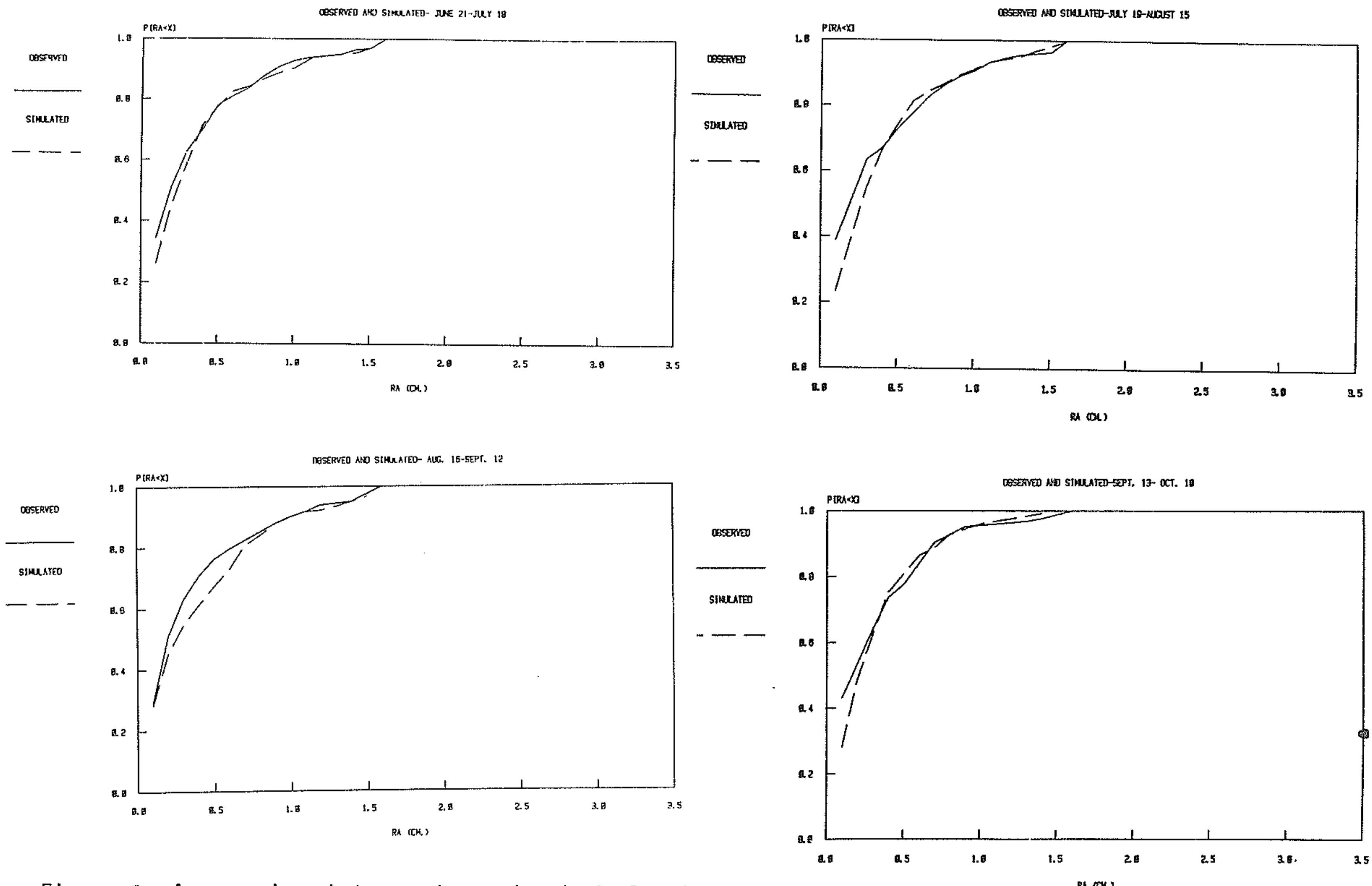


Figure 8 A comparison between observed and simulated cumulative distributions of rainfall amount (RA)

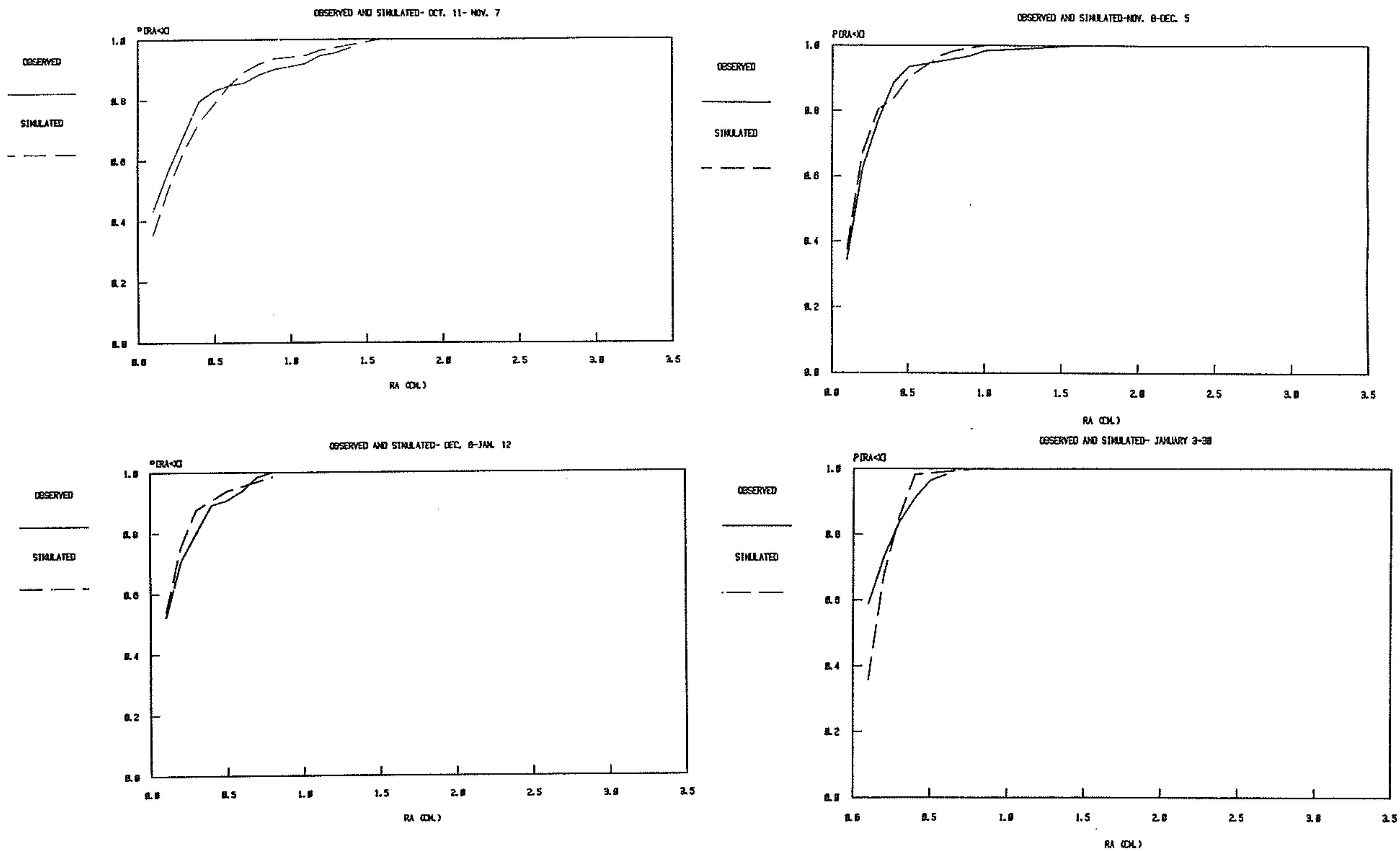


Figure 9. A comparison between observed and simulated cumulative distributions of rainfall amount (RA)

There seems to be a skewness in the actual distribution of precipitation that is not accounted for by a gamma distribution. This skewness tends to underestimate rain depth in the first part of the year and overestimate depth in the last part.

The model described above assumes that the standardized values of the weather variates are normally distributed and have a correlation structure similar to a first-order autoregressive process. The distribution of the actual standardized scores are compared to the simulated ed scores in figure B-6, appendix B. The modeled distributions compare well to the standard normal distribution. The serial coefficients for both observed and simulated sequences are shown in figures B-7 through B-10 in appendix B. Except for wind, the model seems to simulate the behavior of the system adequately. The serial coefficients of wind to the other variables probably could be considered 0. The serial correlation of wind to itself seems to be underestimated by the model. This is probably due to a persistence of wind through time that is not accommodated by a first order model. Perhaps a second order autoregressive model is more appropriate for wind sequences through time.

## SECTION IV

## ECONOMIC ANALYSIS OF IRRIGATION SCHEDULING IN THE HIGH PLAINS

Current irrigation scheduling models, while efficient in the engineering sense in the use of irrigation water, do not maximize net dollar returns from irrigation. These physically based models apply irrigation water only when the soil moisture content reaches a predetermined level independent of economic conditions. This level is generally the crop stress point (usually 50 percent of plant-available water in the root profile). The models do not consider the price of water, the value in use, or any ultimate pumping constraints that exist in some designated New Mexico water basins. Therefore, the use of technical water efficiency models by producers will not necessarily lead to profit maximization.

The dynamic programming model (DPM), presented in this section, has the express objective of maximizing net returns to water for corn and wheat. Although the model is based on the soil water balance concept and on crop-production functions used in physically based models, it makes an economic decision to irrigate only if the dollar benefits exceed the costs. The model simultaneously accounts for the probability of rainfall, the cost of pumping water, pumping restrictions, and the price of the crop.

The DPM also has the highly desirable characteristic in that the profitable irrigation plan can be utilized for actual on-farm use, through the use of a microcomputer. Initially, the DPM must be run on a large mainframe computer because of size and calculating requirements. Data on an individual farm, such as soil type, irrigation system, and pumping capacity, are entered into the model with a resulting decision matrix (DM) as output. The DM indicates whether or not a farmer should irrigate a particular crop at a given point in time by evaluating farm-specific data on soil moisture, remaining water allocation, and date. A farm microcomputer could execute a simple soil moisture accounting model and search for the appropriate irrigation decision. Unusual weather or delays in the irrigation schedule do not diminish the effectiveness of the decision map, although of course net income may be affected. The DPM determines an optimal (income maximizing) future irrigation schedule for all possible current conditions.

The decision matrix contains a large amount of data. A typical growing season for corn, for example, is 175 days. Each daily matrix consists of 1,100 different elements representing different possible soil moisture and water allocation positions. The entire seasonal matrix would contain 193,600 elements. At 2 computer bytes per element, this amounts to 387,200 bytes of data--the approximate size of a microcomputer diskette. The DM then would be useable on microcomputer diskettes for actual farm operations. The farmer could review the farm and irrigation characteristics with Cooperative Extension Service agents. The agent could then transmit the data to the university mainframe computer and receive the individualized DM diskette for actual operation.

## Procedures

Conceptually, the DPM, which is similar to that developed by Yaron et al., proceeds backward in time to parameterize the value of irrigation decisions. By parameterizing all possible future outcomes, the model decides which irrigation decision is optimal for a given time, water allocation, and soil moisture. The large number of possible outcomes requires considerable computer time and speed; and so the DPM is designed to work only on a mainframe computer. A mathematical description of the model follows. (Readers interested in dynamic programming should refer to Nemhouser [1977].)

Because of the complex dynamics of soil moisture and the probabilistic distribution of rainfall, conventional economic models such as linear programming are inadequate for irrigation decisions. Specifically, linear programming cannot deal with nonlinear functions. It also is more difficult to incorporate probabilistic functions into a linear programming model than a dynamic model. However, the major advantage of the DPM is the decision matrix output. A dynamic probabilistic linear programming model only operates as a unit. Therefore, if weather conditions do not follow expected patterns, the planned irrigation schedule becomes inadequate. The DPM with the decision matrix output automatically adjusts to current conditions. In short, the DPM is operational in a stochastic farm environment, while linear programming models would remain less operational.

## Mathematical Description

The DPM is conceptually divided into state equations describing the state of the system using equations and an objective function. The state equations describe the change in soil moisture from one time period (stage) to the next, based on evapotranspiration, irrigations, deep soil percolation, and precipitation. Defining percent soil moisture at time t as $M_t$, then:

$$M_{t+1}^{i} = M_t^i + \gamma_t(IRR_t + RAIN_t - ET_t^i) \quad (1)$$

where $M_t^i$ = percent soil moisture in the current root zone

$\gamma_t$ = a factor which transforms water volume (inches) into percent soil moisture. (Note as the root zone increases in depth over time, $\gamma$ decreases)

$IRR_t$ = an irrigation at time t (inches)

$RAIN_t$ = precipitation at time t (inches)

$ET_t^i$ = evapotranspiration at time t (inches)

There are two constraints placed on equation 1. Once the soil moisture is at capacity (depending on soil type), any additional moisture added to the profile will deep percolate, thus:

$$M_t^i \leq SC \text{ for all } t \quad (2)$$

where SC = soil water capacity as defined by Sammis et al. (1982) (percent)

Likewise, the moisture content of soils will only slowly drop below the permanent wilting point. To limit the number of calculations, it is convenient to place the restriction:

$$M_t^i \geq WP \text{ for all } t \quad (3)$$

where WP = the permanent wilting point

Changes in moisture occur from evapotranspiration, precipitation, and irrigation. Research has established that evapotranspiration is a function of soil moisture, leaf cover, and potential evapotranspiration. According to Sammis et al. (1983), evapotranspiration can be written as:

$$ET_t^i = (1 \div (PAV \times STR) \times (M_t^i - WP) \times K_t \times PET_t \quad (4)$$

where $ET_t^i$ = actual evapotranspiration under consistent irrigation practices

PAV = maximum plant-available water in the root zone (percent)

STR = soil moisture level when plant stress occurs (percent)

$K_t$ = empirical crop coefficient

PET = potential evapotranspiration (inches)

S.T. = $(1 \div (PAV \times STR) \times (M_t^i - WP) \leq 1$

This equation, while well documented, is valid only if the crop coefficient (K) is estimated from a consistent pattern of irrigations. The equation is less reliable for irrigation schedules with varying frequencies. To account for changes in irrigation frequency, evapotranspiration must be subdivided into three components, transpiration, energy limiting soil evaporation, and soil limiting evaporation. With frequent light irrigations or rainfall, evapotranspiration is not restricted by soil moisture or plant cover, and the relative proportions of energy limiting soil evaporation increases, thus equation number 4 understates the actual evapotranspiration. The dynamic programming model was modified to account for increased soil evaporation in the following manner:

$$ET_t^i = PET \times 2 \qquad (5)$$

where $ET_t^i$ = initially determined by equation 4

The factor (2) is used to account for the observation that a wet soil and plant cover (following a rain event or irrigation) evaporates at an unrestricted rate for approximately two days. The structure of the dynamic model does not allow for the incorporation of a two-day state variable without a large increase in model size--thus, twice the current potential evapotranspiration was used as an approximation. This procedure will slightly overstate the seasonal total evapotranspiration because the K coefficient was estimated to account for some soil energy limiting evaporation. The model will at time double count this. This may be corrected in future versions of the dynamic programming model, however, the estimated error caused by this does not significantly alter the deviation of the optimal irrigation schedule.

Precipitation is modeled as a stochastic event; various levels of possible precipitation amounts are assigned a probability of occurrence. Therefore, soil moisture has a range of possible outcomes proceeding from stage to stage. This is important for the objective function, but for any given precipitation amount, equation 1 holds. This equation is best considered a set of equations:

$$MT^{i}_{t+1} = M^{i}_{t} + \gamma_t(IRR_t + RAIN^{i}_{t} - ET^{i}_{t}) \qquad (6)$$

where $RAIN^{i}_{t}$ = a range of possible precipitation amounts, each assigned a probability

and

$$E(RAIN_t) = \sum_{i=1}^{n} PROB_t \times RAIN_t \qquad (7)$$

The implications for the objective function are outlined in a following section.

The amount of irrigation water applied for a flood system has two alternative decisions defined as 0 or 4 in of water. For a sprinkler irrigation system, there are three alternative decisions defined as 0, 2, or 4 in.

A second state equation accounts for the remaining water in the total water allocation. Pumping in a typical declared New Mexico water basin is legally restricted to 3.5 acre-feet per acre per year. Though this water can be diverted to other crops, typically this is not the management practice. Therefore, the DPM has a restriction of 42 acre-inches on water used during the season. With each irrigation, the cumulative water balance is reduced, restricting the water usage later in the season:

$$W_{t+1} = W_t - IRR_t \quad (8)$$

where $W_t$ = remaining water balance

and

$$0 \leq W_t \leq 42 \quad (9)$$

Immediate Loss Function

The objective of the DPM is to maximize the annual profits associated with a specified crop. The model accomplishes this by using an "immediate loss function" (ILF) in the ith period. The ILF is the cost of irrigation plus the economic value of yield loss associated with a particular moisture state relative to the ideal moisture state. This function is specified as follows:

$$LOSS_t^i = (PW_t \times IRR_t) + [(NET_t - ET_t^i) \div NET] \times PG_t \times PCROP \quad (10)$$

where $LOSS_t$ = the immediate loss

$PW_t$ = the cost of water ($ per inch)

$PG_t$ = the potential growth of the crop (lbs per acre) based upon an empirically based crop water production function

PCROP = the price of the crop in pounds

NET = non-stress evapotranspiration

## Recursive Dynamic Control Equations

Equations 1 through 11 describe the fundamental relationships in the dynamic control model. The core of the DPM is the recursive relationship defined as follows:

$$\Lambda_t(M_t,W_t) = \underset{IRR_t}{\text{Min}}\,[LOSS_t^i\ (M_t)] + \sum_{i=1}^{n}\ Prob_t \times \Lambda_{t+1}\ (M_{t+1}^i, W_{t+1})$$

$$\text{S.T. } W_{t+1} = W_t - IRR_t:\ M_{t+1}^i = M_t + \gamma_t\ (IRR_t + RAIN_t^i - ET_t^i) \qquad (11)$$

for $i = 1 \ldots n$

$$LOSS_t = PW_t \times IRR_t + [(NET_t - ET_t^i) \div NET)] \times PG_i \times PCROP$$

$$ET_t^i = [(1 \div (PAV \times STR) \times (M_t^i \div WP) \times K_t \times PET_t$$

$\Lambda_t(M_t,W_t)$ = the value of a node at a given stage

Conceptually, the model works backwards in time, assigning a value to all "nodes" in each time period where a node is a discrete level of the state variable. To value the current state node$^{(t)}$, the model calculates the (t+1) node positions derived from alternative irrigation decisions and looks up the value for those nodes (previously calculated). The loss function value is added to the expected value of these nodes. A discrete optimizing routine selects the optimal decision and simultaneously values the current node. With the two state variables and 50 different potential soil moisture levels,

$$(WP \ldots WP + \frac{PAV \times i}{50} \ldots SC) \text{ for } i=1 \ldots 50$$

and 22 different water resource levels:

$$(0 \ldots 42)$$

there are a total of 1,100 nodes per stage. The net return associated with each alternative irrigation decision is the cost of the irrigation subtracted from the expected value (based on anticipated rainfall through the remainder of the season) of the resulting nodes in stage i+1. (Each decision has a range of possible outcomes because of the probability distribution for precipitation.)

Operation of the Model

The DPM is an APL program and is interactive model, the listing of the program is provided in Appendix C.

The model interactively prompts (asks the user) for the following data:

1. Soil capacity
2. Wilting point
3. Planting and harvest date
4. Crop type - corn sorghum or wheat
5. Crop stress point
6. Type of irrigation system - flood/irrigation
7. Cost of water - $/acre-inch
8. Price of the crop
9. Initial water allocation

Specific crop coefficients ($K_t$ and $\gamma_t$) are generated from equations in Sammis et al. (1983).

The DPM runs in one of two modes--deterministic or stochastic. The deterministic mode uses historical weather data for a particular year. Because the model conceptually moves backwards in time, and thus is able to forecast weather perfectly, the model is unrealistic. It is used only to test the operation of the model and to correlate results with empirical data.

The stochastic mode uses the previously outlined equation structure with a probability distribution for precipitation. Five alternative rain events were defined, each with an associated probability. This distribution was generated from an historical weather file. The rain event is a mean value of precipitation within a specified interval. For example in Clovis, New Mexico, the mean value of total precipitation between 0.3 and 0.6 inches for July 1-15 is .464; this event has a probability of occurrence of 2.65 percent. The distributions of the five alternative rain events in Clovis on this date are as follows:

| | | | | | |
|---|---|---|---|---|---|
| Mean rain value | 0 | 0.209 | .464 | .748 | 1.75 |
| Probability of occurrence | .861 | .066 | .027 | .026 | .020 |

DPM Output

The DPM has two types of output depending on mode of operation. The deterministic model results in an optimal irrigation and soil moisture time path, which can be verified empirically for accuracy.

The stochastic mode has as output the decision map. This decision map specifies an irrigation decision for any given data, soil moisture level, and water allocation. To use the map, it is only necessary to find the appropriate matrix element that corresponds to the data, soil moisture, and water allocation, and return the decision. For example, if on July 10 corn is in a field that has a soil moisture of 30 percent and there is a remaining water allocation of 22 inches, the DPM map would return a zero value, meaning do not irrigate. For the same water allocation and date, but at a field moisture level of 25 percent, the decision matrix element would return a value of 4, meaning irrigate 4 inches. The advantage of the map is that the decision on any date is not dependent on previous conditions, only the current value of the state variables. Therefore, for either wet or dry years, the model returns the appropriate irrigation decision.

A secondary output of the DPM is the value of water in production. The model can vary the initial water allocation at the start of the season and determine the corresponding expected net return. From this information, it is possible to value the water in use. For example, with an initial allocation of 36 acre-inches on corn, the net return might be -$150 (all values are in negative costs). With 32 acre-inches, the net return might be -$170, thus the (marginal) value of additional (intially allocated) water is $20 ÷ 4 or $5 per allocated acre-inch. The average cost of water for a furrow system in Clovis is $3.33 per acre-inch, implying that the incremental value in use exceeds costs and the profit maximizer should use the additional water.

DPM Performance Test

To be credible, the DPM must be economically superior to the physically based irrigation scheduling models currently available for use. Economic superiority is defined here as increased net returns to water (crop revenue minus water costs). Because of the lack of actual plot data, a test of the economic superiority was derived using the soil moisture and the weather simulation model of Sammis et al. described in Section III. The test statistically compared net returns of the DPM to three alternative physical irrigation strategies for 35 years of weather data. The comparison was made for both flood and sprinkler irrigation systems. The three alternative irrigation strategies applied water when soil moisture reached 40, 50, and 60 percent of maximum plant-available water. To prevent overwatering at the first of the season, the physical model was restricted to applying one irrigation during the first 30 days. The test consisted of statistically comparing the difference in means by a student-t distribution.

## Prices Used for the Test

Another major advantage of the DPM is its ability to adjust to varying crop and water prices. To fully test the DPM against the physically based model, prices were varied according to historical data. The past 20 years of corn prices, adjusted to 1982 dollars, have averaged $3.59 per bushel (6.4¢/lb) with a standard deviation of $.79/bu (1.4¢/lb). Three prices were used: $.05, $.064, and $.078, the average and a plus and minus standard deviation. For wheat, the price per bushel averaged $4.85 (8¢/lb) with a standard deviation of $1.47 (2.45¢/lb). For the test, $.055, $.08, and $.104 per pound were used.

Water costs in Curry County, New Mexico, are a function of type of well, depth to ground water, price of pump energy source, and type of irrigation system. It was assumed that the representative irrigation system consisted of a natural gas engine pumping 1,000 gallons per minute with 350 feet of pumping depth. Furrow irrigation used a free-flow system, and the sprinkler system required pressurization. Table 4 presents the price of water per acre-inch for labor, natural gas, and repairs for 1982 prices in Curry County.

## Other Parameters

Table 5 presents the values of other parameters used in the statistical comparison of the DPM on corn. Wheat used the same parameters except where noted.

Table 4. Specified water costs per acre-inch for furrow and sprinkler irrigation, clay loam soil, Clovis, New Mexico, 1982

| | Furrow ($/inch) | Sprinkler ($/inch) |
|---|---|---|
| Labor | .38 | .28 |
| Fuel | 2.75 | 4.16 |
| Repairs | .21 | .28 |
| Total | 3.34 | 5.21 |

Table 5. Model assumptions for statistical test on Dynamic Programing model for furrow and sprinkler irrigation, clay loam soil, Clovis, NM, 1982.

| Parameters | |
|---|---|
| Soil capacity* | 0.375 (by value) |
| Wilting point* | 0.176 (by value) |
| Planting date+ | 4/10 |
| Harvest date+ | 10/3 |
| Crop stress point# | .60 PAV |
| Initial water allocation | 42 inches |

* The soil type for this capacity and wilting point is clay loam.

+ The planting and harvest date for wheat is 10/1 - 6/23.

# The crop stress point for wheat is 50 percent PAV.

## Results and Discussion

Results of the DPM are presented in two sections: (1) the test of the DPM against physically based irrigation scheduling models, and (2) the demand analysis for water.

### Comparison of Dynamic Programing Model to a Physically Based Irrigation Scheduling Model

Table 6 presents the statistical comparison of the DPM used with a furrow irrigation system against the results of a physically based model using three threshold soil moisture levels to apply irrigations (40, 50, and 60 percent of plant-available water [PAV]). For corn, the point at which the crop comes under stress is 60 percent of plant-available water and for wheat the stress point is 50 percent. In all comparisons, average net revenues of the DPM exceed the physically based model. For the average price of corn of 6.4¢ per pound, the DPM increased net returns by $17 per acre over the nonstress, physically based model with the 60 percent threshold by achieving higher yields with less water. This would be the typical irrigation schedule for corn. It is apparent that some stress is optimal for the furrow system on this soil type because the 50 percent threshold level has a higher net return. Though the DPM was not greatly superior to the 50 percent threshold level, the results for corn are significant at the higher price levels. For wheat, the 50 percent threshold is the optimal for irrigation applications. The DPM is not significantly different in yield, water application, or net revenue.

With the sprinkler irrigation system (table 7), the optimal stress point for corn increases to the 60 percent level, i.e., the nonstress

Table 6. Per acre comparison of dynamic programing model (DPM) with standard irrigation scheduling model set at 40, 50 and 60% of plant available water (PAV), furrow irrigation for clay loam (averages of 35 years weather data).

| | | | | Irrigation Scheduling Model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DPM | | | 40% PAV | | | 50% PAV | | | 60% PAV | | |
| Price of Crop $/lb | Yield | Irrigated Water | Net Rev+ | Yield | Irrigation Water | Net Rev+ | Yield | Water | Net Rev+ | Yield | Water | Net Rev+ |
| | lb/ac | ac-in | $/acre | lb/ac | ac-in | $/acre | lb/ac | ac-in | $/acre | lb/ac | ac-in | $/acre |
| Corn .05/lb | 9735 | 34.4 | 372 | 8735 *** | 29.5 *** | 338 *** | 9639 | 34.9 | 366 | 9728 | 39.4 *** | 355 *** |
| .064/lb | 9764 | 35.1 | 509 | 8735 *** | 29.5 *** | 461 *** | 9639 | 34.9 | 502 * | 9728 | 39.4 *** | 492 *** |
| .078/lb | 9778 | 35.7 | 644 | 8735 *** | 29.5 *** | 584 *** | 9639 | 34.9 | 637 * | 9728 | 39.4 *** | 628 *** |
| Wheat .055/lb | 6942 | 35.2 | 265 | 6747 *** | 33.5 ** | 260 * | 6942 | 36.0 | 263 | 6911 | 39.5 *** | 248 *** |
| .08/lb | 6958 | 36.2 | 437 | 6747 *** | 33.5 *** | 429 * | 6942 | 36.0 | 436 | 6911 | 39.5 *** | 422 *** |
| .104/lb | 6955 | 36.3 | 603 | 6747 *** | 33.5 *** | 591 ** | 6942 | 36.0 | 603 | 6911 | 39.5 *** | 588 *** |

+ Net revenue is gross revenue minus water costs.
* 90% confidence level that the means are different.
** 95% confidence level that the means are different.
*** 99% confidence level that the means are different.

Table 7. Per acre comparison of dynamic programing model (DPM) with standard irrigation scheduling model set at 40, 50 and 60% of plant available water (PAV), sprinkler irrigation for clay loam (averages of 35 years weather data).

| Price of Crop $/lb | DPM | | | Irrigation Scheduling Model 40% | | | Irrigation Scheduling Model 50% | | | Irrigation Scheduling Model 60% | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Yield | Water | Net Rev + | Yield | Water | Net Rev + | Yield | Water | Net Rev + | Yield | Water | Net Rev + |
| | lb/ac | ac-in | $/acre | lb/ac | ac-in | $/acre | lb/ac | ac-in | $/acre | lb/ac | ac-in | $/acre |
| Corn .05/lb | 9770 | 33.0 | 317 | 7770 *** | 28.6 *** | 239 *** | 9391 *** | 32.7 | 299 *** | 9887 | 34.6 ** | 314 |
| .064/lb | 9822 | 33.5 | 454 | 7770 *** | 28.6 *** | 348 *** | 9391 *** | 32.7 | 430 *** | 9887 | 34.6 ** | 452 |
| .078/lb | 9830 | 33.5 | 592 | 7770 *** | 28.6 *** | 457 *** | 9391 *** | 32.7 | 562 *** | 9887 | 34.6 ** | 591 |
| Wheat .055/lb | 6980 | 35.0 | 201 | 6572 *** | 35.9 | 174 *** | 6909 | 37.5 *** | 185 *** | 6906 | 37.9 *** | 182 *** |
| .08/lb | 6990 | 35.0 | 377 | 6572 *** | 35.9 | 339 *** | 6909 | 37.5 *** | 357 *** | 6906 | 37.9 *** | 355 *** |
| .104/lb | 6990 | 35.0 | 544 | 6572 *** | 35.9 | 496 *** | 6909 | 37.5 *** | 523 *** | 6906 | 37.9 *** | 521 *** |

+ Net revenue is gross revenue minus water costs.
* 90% confidence level that the means are different.
** 95% confidence level that the means are different.
*** 99% confidence level that the means are different.

Table 8. Per acre comparison of dynamic programming model (DPM) with standard physically based irrigation scheduling model set at 40, 50 and 60% of plant available water (PAV) for sandy soil.

| | | | | Irrigation Scheduling Model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DPM | | | 40% PAV | | | 50% PAV | | | 60% PAV | | |
| Crop | Yield | Water | Net Rev+ | Yield | Water | Net Rev+ | Yield | Water | Net Rev+ | Yield | Water | Net Rev+ |
| | lb/ac | ac-in | $/acre | lb/ac | ac-in | $/acre | lb/ac | ac-in | $/acre | lb/ac | ac-in | $/acre |
| Corn | 8966 | 38.1 | 447 | 8844 *** | 37.4 *** | 442 ** | 8109 *** | 40 *** | 386 *** | 9960 *** | 40 *** | 375 *** |
| Wheat | 6481 | 37.3 | 394 | 6582 | 38.5 | 398 | 6167 *** | 40 *** | 360 *** | 6028 *** | 40 *** | 351 *** |

+ Net revenue is gross revenue minus water costs.
* 90% confidence level that the means are different.
** 95% confidence level that the means are different.
*** 99% confidence level that the means are different.

point. The DPM achieves a higher net revenue (though not statistically significant) with less yield and less water. For wheat, the optimal threshold remains at 50 percent. The DPM has significantly higher net returns, increasing profits by $20 per acre at the average price of 8¢ per pound. The increased profits again result from higher yield and reduced use of water.

The change in the optimal threshold for corn using a furrow versus a sprinkler irrigation suggests that soil type may be an important factor in the determination of the most economical soil moisture threshold. For the furrow irrigation with its 4-acre-inch water applications, a 60 percent nonstress threshold resulted in deep percolation. The sprinkler system with 2- or 4-acre-inch applications would not exceed the water capacity of soil and thus achieve a higher yield with less water. The DPM adjusts automatically to soil type as presented in table 8. As indicated in the table, the optimal soil stress threshold is now 40 percent for corn and wheat. Again, however, the DPM selected the optimal stress point and was significantly better than all physically based models.

## Demand Analysis

The DPM in the stochastic mode also can be used to construct water demand functions for individual crops. The demand function indicates the value of additional units of water in terms of extra net revenue. Figures 10, 11, and 12 present the demand functions for corn, sorghum, and wheat.

The demand functions also indicate the amount of expected water use given a price or cost for water. For instance with corn, at a pumping cost of $5.21, expected seasonal water usage is 32 acre-inches. What is apparent from the demand analysis is that the demand for water is very inelastic for corn and sorghum but elastic for wheat, indicating the dryland capability of this crop with rising prices/reduced allocations. The significance of the elasticity of demand is that corn is much less likely to be grown given a great increase in water costs, since it is not transferable to dryland status. Because the crop is limited in profitability, increases in water costs directly increase costs as opposed to resulting in water savings. Increases in water costs for wheat result in substantial savings of water enhancing the long-term viability of the crop and decreased water efficiency.

Sorghum has an elastic demand function at low prices but the function becomes more inelastic at higher prices. The amount of water required by sorghum is less, and so water costs are a smaller percentage of total operating costs. Increases in water costs initially result in water savings, and possibly result in a conversion to dryland production.

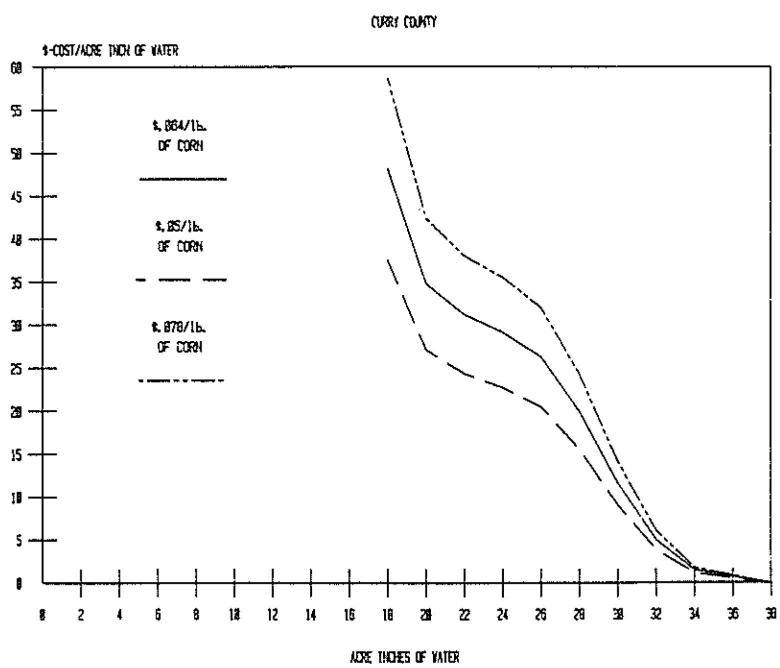


Figure 10. Demand for water in corn.

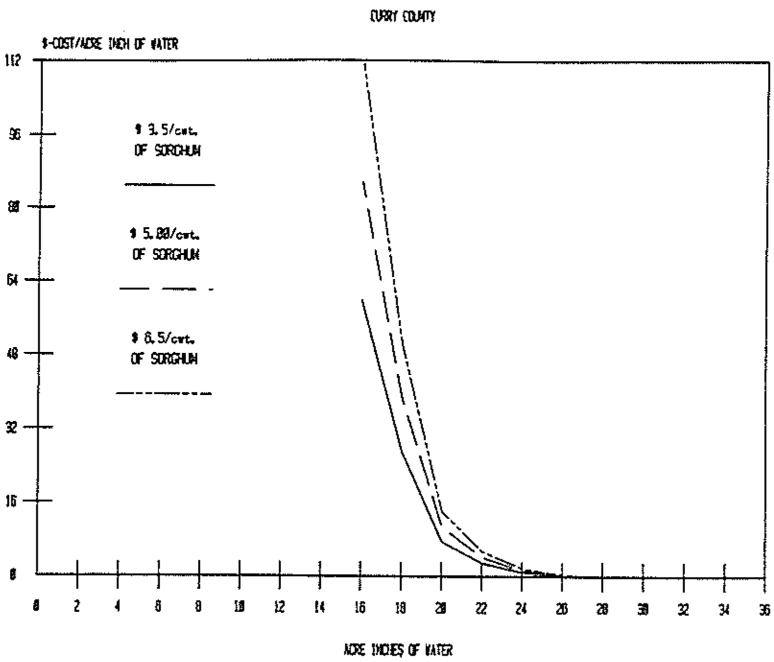


Figure 11. Demand for water in sorghum.

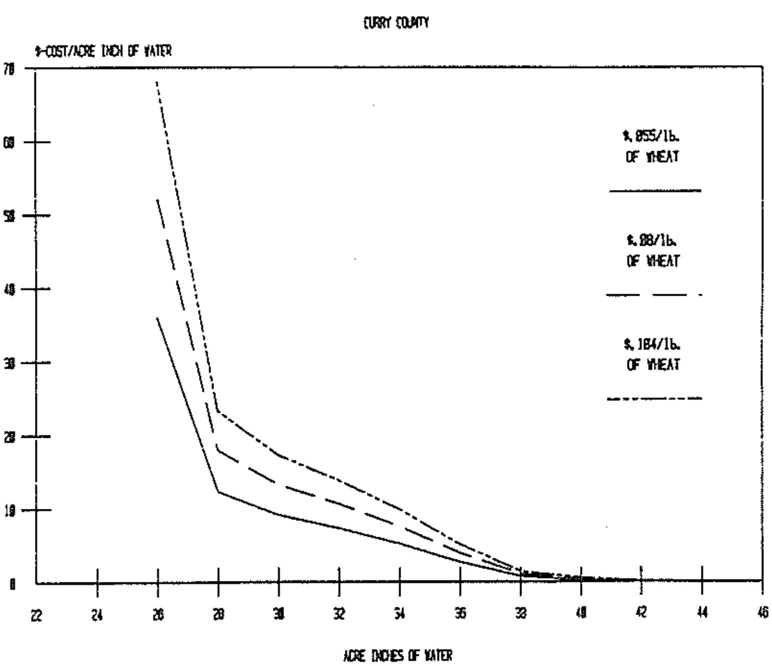


Figure 12. Demand for water in wheat.

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# APPENDIX A

## Description of IRRSCH

The IRRSCH (irrigation scheduling model) consists of a main program and a series of subroutines. In the main program, the model first calls STARTR, which initializes the arrays in a simulation weather subroutine. Subroutine Input reads in the basic information about the soils, crop, and irrigation. The model then initiates iterations 1 through 7 where the first irrigation is read and becomes the mean value. The subsequent irrigations are ±1, 2, and 3 standard deviations of that applied irrigation water. The model resets the initial conditions each time it comes back to a new computation of the irrigation amount. The model then reads the maximum rooting depth for the particular crop and asks whether to use a simulated weather file or a read-in weather file. Subroutine Climate is called to read a weather file or subroutine Simulate, which simulates weather for a year's time period. The model prints out the weather and potential evapotranspiration ($E_0$). The operator is asked if he desires to enter the irrigation amounts and then through the interacting process the model asks the operator to input the amount of irrigation. If the interactive part is not activated, then the model uses the input irrigation amounts and dates read in subroutine input.

The main program calls subroutine E, which calculates evapotranspiration (E), based on Penman's equation and then the main program in the model adds up and prints out the total possible yield based on nonstressed E, the total amount of irrigation in inches, the total amount of rainfall in inches, the deep drainage in inches, and the amount of evaporation due to transpiration (T) and due to soil evaporation ($E_s$).

The model also has a series of subroutines described below, which calculate and print out in the main program the following data: (1) date; (2) root zone 1-10, each representing one-foot depth; (3) the growing-degree-days; (4) a crop coefficient that reduces potential E to actual E; (5) $E_0$; (6) nonmoisture stress transpiration; (7) soil evaporation; (8) accumulated nonmoisture stress E; (9) projected daily E, the E that is needed for uniform moisture stress throughout the growing season and will result in the projected yield specified as input by the users; (10) actual E, which is the resulting E based on soil moisture stress; (11) accumulated actual E; (12) difference between the projected and actual E; (13) difference between the projected and actual yield based on the difference between the projected and actual E; and (14) the difference between the nonstress E and the actual E.

## Description of the Various Subroutines

### Subroutine Input

1. Title.
2. Number of iterations if operator desires to put on more than one set of irrigation conditions for the field.
3. Elevation.
4. Temperature code centigrade or Fahrenheit.
5. Input which controls echo print of the climate data.
6. Number of depths in which the model will run for a maximum of 10 compartments of the soil reservoir.

7. Soil types for each one of the depths with the codes being:

   1 = sandy

   2 = sandy loam

   3 = loam

   4 = clay loam

   5 = silty clay

   6 = clay

8. Field number and the crop by:

   1 = alfalfa

   2 = corn

   3 = sorghum

   4 = wheat

   5 = pecans

   6 = barley

9. Planting date, emergence date, harvest date.

10. Growing-degree-day code which is equal to 1 if the GDD calculation is desired in deriving the crop coefficients (K), otherwise, the value is 0 and the crop coefficients are computed based on a time determined function.

11. The projected yield for the growing season.

12. Initial soil moisture content percentage by volume, if the initial values equal 0, then the initial soil moisture content will be determined by the field capacity and the soil type. The model writes out the initial moisture content in the soil profile.

13. The minimum level of the plant-available water which will be used to force an irrigation and the amount in inches of that which

forces irrigation. Any percentage over 50 percent will be reset to 50 percent.

14. The Christian uniformity is converted to the proper units of a normal distribution function and the distribution of the application for the water over the field is assumed to be normally distributed from both center pivot and flood type irrigation systems.

Subroutine Soil

Subroutine soil determines the field capacity and permanent wilting point for the designated soil type determined from subroutine Input (Hanson, Isradson, Stringham, 1980).

Subroutine Julian

Subroutine Julian returns a Julian date with an input of month/day/year, a correction is made for leap year.

Subroutine NOSTRS

Subroutine NOSTRS computes a nonstressed daily E based on potential E using Penman's equation described by function POTET and a crop nonstressed coefficient (K) Sammis et al. (1979). Function POTET computes the potential evapotranspiration ($E_0$) using Penman's equation. The function represents potential evapotranspiration over a short green grass and uses the data and equations described by Sammis et al. (1979). The relationship between net and solar radiation used in computing POTET is described by Alla A. Abder-Jabbar (1983). The necessary data to compute potential evapotranspiration is maximum temperature, minimum temperature, maximum humidity, minimum humidity, solar radiation, and wind. The computed potential evapotranspirations are stored in the eighth position on the climate array.

Subroutine Climate

Subroutine Climate reads the climate data from a file. It searches for the planting date and then places that data in the first position in the climate array and continues to read the file to the harvest data. The climate array is in column 1; maximum temperature, column 2; minimum temperature, column 3; maximum relative humidity, column 4; minimum relative humidity, column 5; solar radiation in langley/day, column 6; wind in miles per day, column 7; pan evaporation inches per day, column 8; computed potential evapotranspiration, column 9; the irrigation amounts in inches, read previously, and column 10; the precipitation in inches. The climate array echo prints the climate file.

Function ETyLd: calculates the yield reduction or addition in lbs/acre from the projected and maximum yield based upon the slope of the water production functions. The functions are described by Sammis (1979) for sorghum, Sammis (1983) for wheat, and Sammis (1983) for corn.

Subroutine Coefficient. Subroutine coefficient computes the crop coefficient (K). It reduces potential evapotranspiration to nonstressed actual evapotranspiration based upon GDD; Sammis et al. (1979).

Subroutine Coefficient 2. Subroutine coefficient 2 accomplishes the same objective based upon the Julian date; Sammis et al. (1979).

Function Irrigation: computes the amount of irrigation water that is applied to other portions of the field based on ±1, 2, and 3 standard deviations of the mean application using Christian's uniformity (1942). to describe the mean and standard deviation of a normal distribution.

Subroutine ET

Subroutine ET returns the daily E computed based upon the effect of soil moisture stress on the nonstressed E. The model first computes the rooting depth based upon a time dependent crop coefficient that is in a data statement, based upon the crop ID. Moisture accounting is then accomplished from the surface to the maximum rooting depth. Rainfall and irrigation water is applied, filling the first depth with the remainder going to fill subsequent depths. Deep drainage is the amount of water that passes below the maximum rooting depth. The irrigation efficiency or rainfall efficiency is that percent of deep drainage that occurs. The model subtracts yesterday's T from the soil rooting depth based upon the 40 percent, 30 percent, 20 percent, and 10 percent rooting extraction pattern in the fourth quarter of the rooting depth. Consequently, if there is only one depth containing roots, all of the T is extracted from that depth. If the roots are two feet deep, 70 percent is extracted from the top and 30 percent from the second depth. If the roots are three feet deep, 50 percent is extracted from the top foot, 35 percent from the second foot, and 15 percent from the third foot, etc. Evaporation is subtracted form the top foot. Evaporation (E) and transpiration (T) are separated into the component parts based upon the following equations:

$$T = T_{max}(a + bW) \text{ if } W \leq c \qquad (1)$$

$$T = T_{max} \text{ if } W > c \qquad (2)$$

$$W = SWS/AW$$

$$T_{max} = KE_o$$

where:

$T_{max}$ = maximum Transpiration

K = 0.9 K a crop coefficient derived form lysimeter data, Sammis et al. (1979)

SWS = soil water stored in the root zone cm between permanent wilting point and field capacity

AW = available water in the root zone equal to the difference between water content and permanent wilting point

c = some level of W less than one

$E_o$ = potential evapotranspiration based on Penman's equation (1948)

$$\int E_s dt = E_{scum} = C\ (T-T_p) \text{ if } SWS\ (1)/AW(1) \leq 0.8 \qquad (3)$$

where:

$T_p$ = the time when $E = E_p$ which occurs when $\lfloor SWS(1)/AW(1) \rfloor$ equals 0.8

T = Time in days

SWS (1) = the soil water greater than permanent wilting point stored in the first foot of soil cm

AW (1) = the available soil water in the first foot of soil cm

c = an empirical constant for a given soil type, Jensen (1978).

$$E_s = E_o - T_{max} \text{ if } SWS(1)/SW(1) > 0.8 \qquad (4)$$

When rainfall amounts do not bring the first foot of soil to greater than 80 percent of available water, then that day's evaporation is described by equation 4 or the amount of rain, whichever is smallest.

The current daily E is the sum of the evaporation and transpiration. After subtracting the computed E and T from the soil reservoir, the model checks to see if a forced irrigation is necessary because relative available water (W) has fallen below the specified amount.

Subroutine Growing-Degree-Days. This subroutine computes the growing-degree-days (GGD) based upon the following function:

GDD = (max temp - min temp)/2 - base temp

where:

max temp is set to the upper limit if max exceeds this temperature

min temp is set to lower limit if it decreases below this limit

The value of maximum cutoff temperature, the minimum cutoff temperatures, and base temperature by crops are given in Table A-1.

Subroutine WTHSIM. Subroutine provides a day's weather profile for output. The variables passed to WTHSIM are as follows:

DSEED-An integer in double precision form used as a seed for generation of random numbers.

WTHR(7)-Array containing the previous day's weather profile on input or output and the generated profile for that day.

Each element of the array is:

1 TX (centigrade)

2 TN (centigrade)

3 HX (percent)

4 HN (percent)

5 SR (langelies)

6 WI (miles/day)

7 Precipitation (centimeters)

If WTHR(7) is 999, it is assumed that the previous day's profile is missing.

Table A-1. Maximum, minimum, and base temperatures used to compute growing-degree-days for selected crops.

| Crop | Maximum Temp. | Minimum Temp. | Base Temp. |
|---|---|---|---|
| | °C | °C | °C |
| Alfalfa | - | - | 5 |
| Corn | 30 | 10 | 10 |
| Sorghum | - | - | 7 |
| Wheat | - | - | 0 |
| Barley | 30 | 5 | -5 |

DAY--Integer with the value of the current day (Day 1 = March 1).

IER--Counter telling how many random draws were made before a profile was created that was within the limits set.

In addition to the passed variables, there are five arrays placed in a common area with name PAR. These arrays contain the parameters used in the simulation model. They are:

MUVARS (L, J, K)--The mean for the jth weather variable conditioned on the kth week and presence (L = 2) of rain. J is the variable index which is, TX, TN, HX, HN, SR, WI.

The last part is necessary due to the nature of the deviates. They are all normally distributed and have a range of the entire real line. It is, therefore, possible for the program to generate unrealistic numbers. This is due to the nature of the normal distribution and the large variances typically seen in weather parameters. The following six limits are checked by the program:

1. TX < TN

2. HX < HN

3. HX > 100

4. SR < 0

5. WI < 0

6. HN < 0

If any one of the limits is exceeded, the standard scores for that day are regenerated, and the limits are checked once more. This process repeats itself until a profile within the limits is obtained. The number of iterations depends on the values of the parameters used. For parameters estimated using the data of Clovis, New Mexico, it was found that about 15 percent of the generations fall outside of the given limits.

As a final aside, the parameters, other than rain, are only arbitrary definitions of the elements of a matrix equation. This model was constructed to fill the needs of a crop production model but it is not limited to just that. For example, Richardson (1981) developed a model involving the simulation of temperature and evaporation, in addition to precipitation. This model can accommodate such a simulation by redefining the elements of the weather array. The only changes in the program would be in the last section which checks the limits.

# APPENDIX B

# WEATHER SIMULATOR MODEL

# COMPONENTS AND STATISTICAL COMPARISONS

Table B-1. Parameters used to simulate precipitation patterns at the New Mexico State University Plains Branch Agricultural Experiment Station, Clovis, New Mexico

| | Data Used For Weather Simulation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Week | P(D) | P(D/D) | Gamma | Beta | Week | P(D) | P(D/D) | Gamma | Beta |
| 1 | 0.909523 | 0.932714 | 0.888329 | 0.219361 | 27 | 0.847925 | 0.866462 | 0.850838 | 0.466548 |
| 2 | 0.928571 | 0.948186 | 0.888329 | 0.219361 | 28 | 0.806451 | 0.827260 | 0.850838 | 0.466548 |
| 3 | 0.899999 | 0.922391 | 0.888329 | 0.219361 | 29 | 0.838709 | 0.867221 | 0.804668 | 0.381104 |
| 4 | 0.890476 | 0.899498 | 0.888329 | 0.219361 | 30 | 0.783409 | 0.840234 | 0.804668 | 0.381104 |
| 5 | 0.923809 | 0.936723 | 0.911923 | 0.216182 | 31 | 0.880184 | 0.927031 | 0.804668 | 0.381104 |
| 6 | 0.866666 | 0.902966 | 0.911923 | 0.216182 | 32 | 0.921659 | 0.931870 | 0.804668 | 0.381104 |
| 7 | 0.857142 | 0.894345 | 0.911923 | 0.216182 | 33 | 0.894009 | 0.929458 | 0.762110 | 0.413438 |
| 8 | 0.885714 | 0.925475 | 0.911923 | 0.216182 | 34 | 0.847925 | 0.923382 | 0.762110 | 0.413438 |
| 9 | 0.871428 | 0.906938 | 0.769312 | 0.396504 | 35 | 0.843317 | 0.889194 | 0.762110 | 0.413438 |
| 10 | 0.866666 | 0.896920 | 0.769312 | 0.396504 | 36 | 0.894009 | 0.909934 | 0.762110 | 0.413438 |
| 11 | 0.800000 | 0.849855 | 0.769312 | 0.396504 | 37 | 0.921659 | 0.930214 | 1.037782 | 0.220678 |
| 12 | 0.838095 | 0.876296 | 0.769312 | 0.396504 | 38 | 0.898617 | 0.918110 | 1.037782 | 0.220678 |
| 13 | 0.790476 | 0.837772 | 0.749705 | 0.486704 | 39 | 0.967741 | 0.972032 | 1.037782 | 0.220678 |
| 14 | 0.757142 | 0.791767 | 0.749705 | 0.486704 | 40 | 0.930875 | 0.936326 | 1.037782 | 0.220678 |
| 15 | 0.752381 | 0.798649 | 0.749705 | 0.486704 | 41 | 0.935484 | 0.951043 | 0.965400 | 0.170338 |
| 16 | 0.832676 | 0.868126 | 0.749705 | 0.486704 | 42 | 0.926266 | 0.940674 | 0.965400 | 0.170338 |
| 17 | 0.800767 | 0.843498 | 0.827848 | 0.437222 | 43 | 0.935483 | 0.941632 | 0.965400 | 0.170338 |
| 18 | 0.801843 | 0.830412 | 0.827848 | 0.437222 | 44 | 0.925652 | 0.926856 | 0.965400 | 0.170338 |
| 19 | 0.746543 | 0.798231 | 0.827848 | 0.437222 | 45 | 0.914285 | 0.926366 | 1.024297 | 0.158224 |
| 20 | 0.746543 | 0.788438 | 0.827848 | 0.437222 | 46 | 0.947618 | 0.954216 | 1.024297 | 0.158224 |
| 21 | 0.718893 | 0.775352 | 0.779442 | 0.477656 | 47 | 0.928571 | 0.938316 | 1.024297 | 0.158224 |
| 22 | 0.732718 | 0.769549 | 0.779442 | 0.477656 | 48 | 0.942857 | 0.955794 | 1.024297 | 0.158224 |
| 23 | 0.783409 | 0.812197 | 0.779442 | 0.477656 | 49 | 0.904761 | 0.931520 | 0.933058 | 0.172175 |
| 24 | 0.732718 | 0.761937 | 0.779442 | 0.477656 | 50 | 0.919047 | 0.923326 | 0.933058 | 0.172175 |
| 25 | 0.718893 | 0.775880 | 0.850838 | 0.466548 | 51 | 0.909523 | 0.927046 | 0.933058 | 0.172175 |
| 26 | 0.788018 | 0.832284 | 0.850838 | 0.466548 | 52 | 0.904761 | 0.917229 | 0.933058 | 0.172175 |

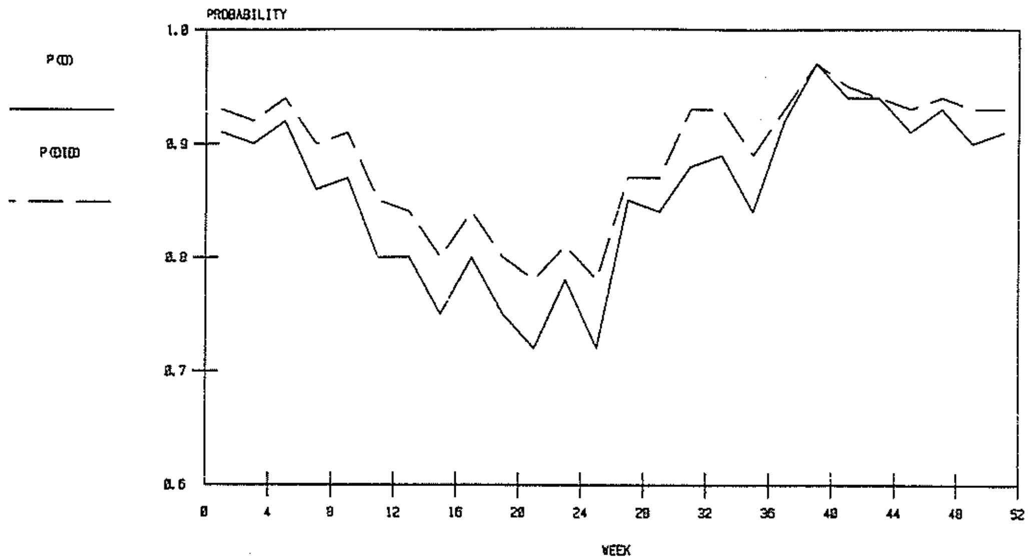



Figure B-1. Markov probability parameters over time

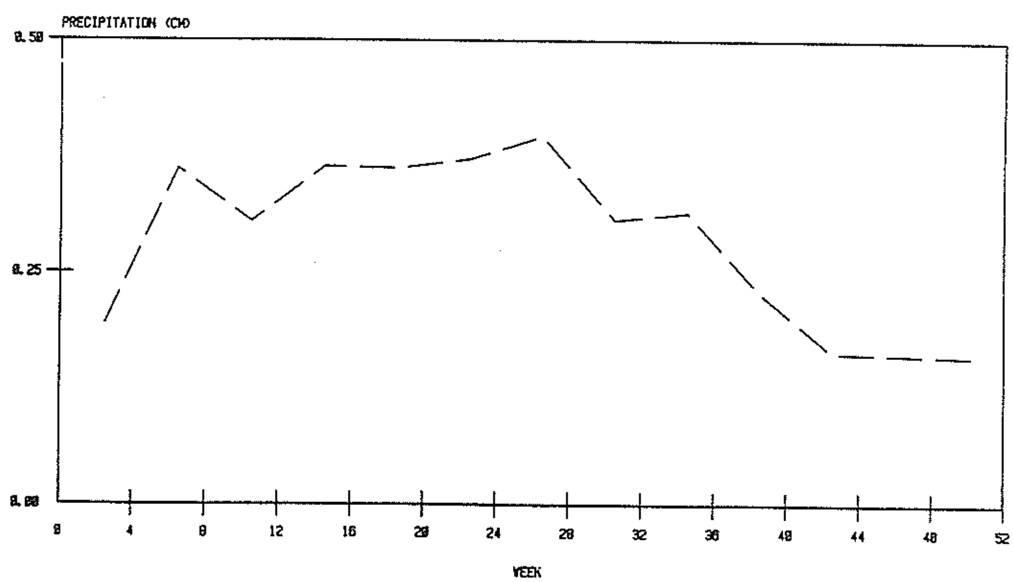



Figure B-2. Average depth of a single rain event over time

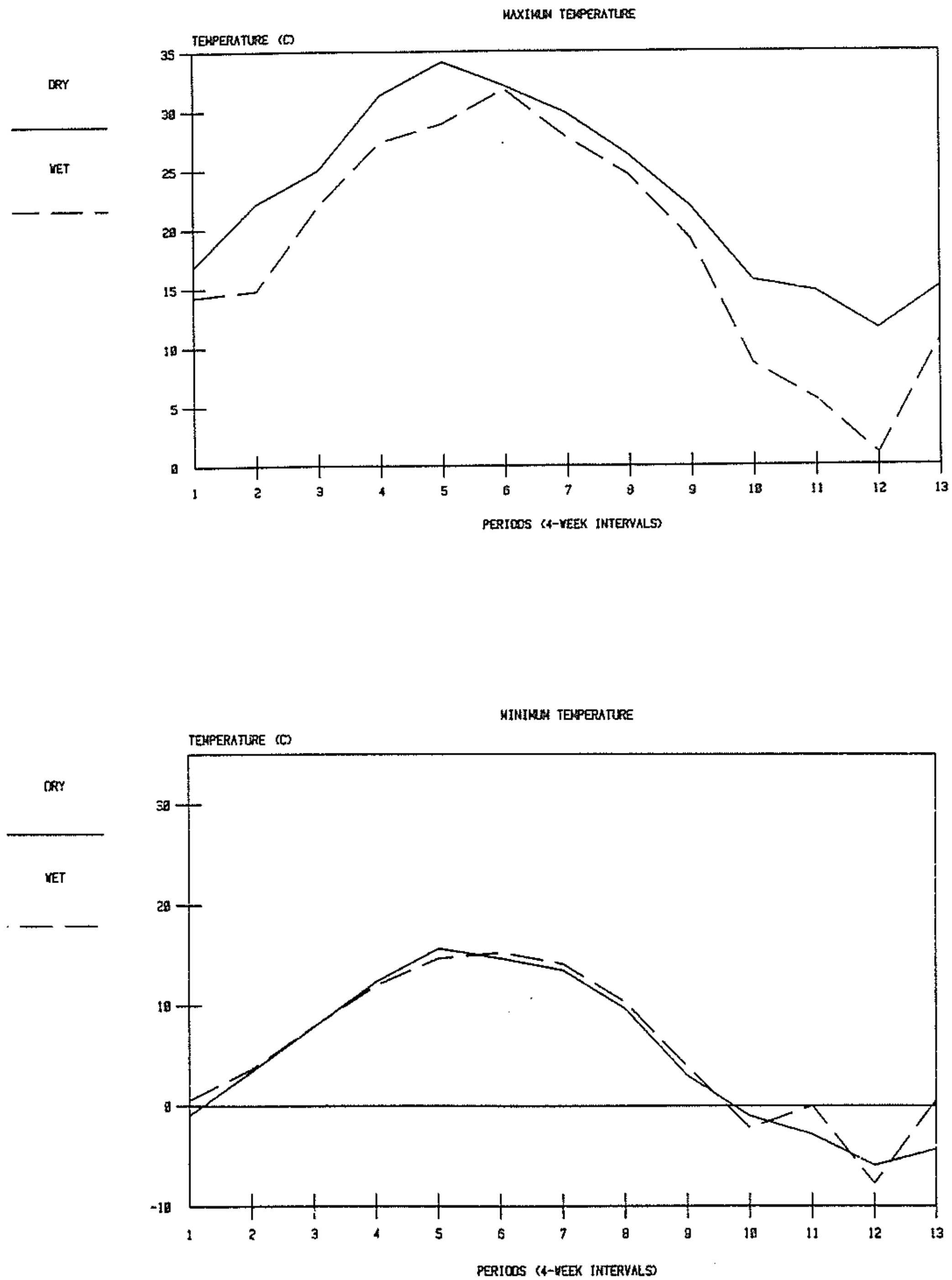
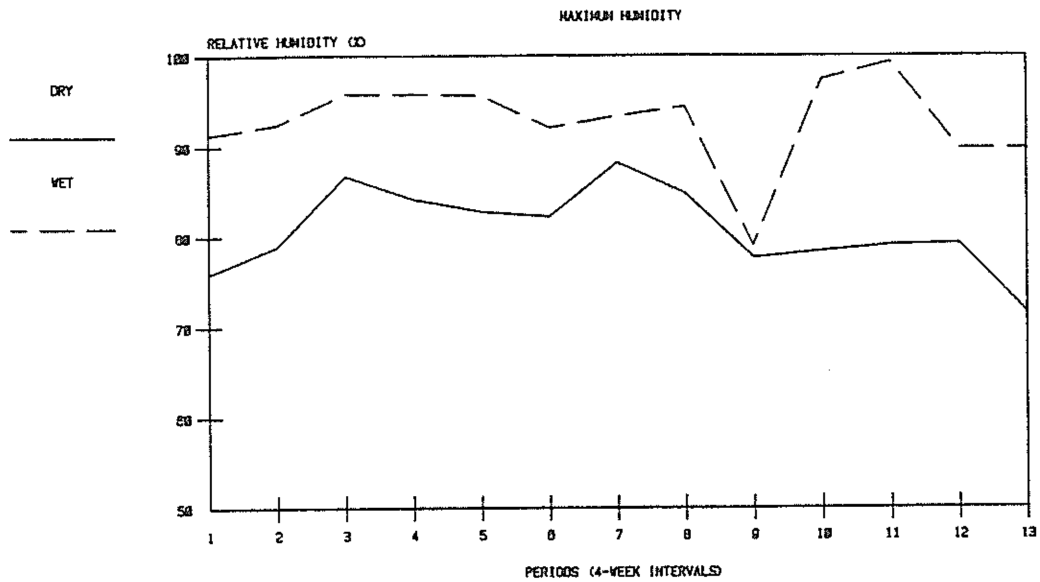



Figure B-3. Mean values of the weather variates for both dry and wet days over time

Table B-2. Means and standard deviations of weather parameters by four-week periods at the Plains Branch Agricultural Experiment Station, Clovis, New Mexico.

| | Maximum Temperature | | | | Minimum Temperature | | | | Solar Radiation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Dry | | Wet | | Dry | | Wet | | Dry | | Wet | |
| Period | Mean | S.D.* | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| 1 | 16.824 | 5.683 | 14.284 | 4.902 | -0.964 | 3.73 | 0.555 | 3.255 | 450.44 | 94.29 | 331.85 | 108.68 |
| 2 | 22.190 | 4.751 | 14.859 | 5.36 | 3.409 | 4.301 | 3.657 | 4.920 | 531.57 | 108.91 | 295.52 | 115.45 |
| 3 | 25.059 | 4.111 | 22.045 | 3.783 | 7.891 | 3.562 | 7.953 | 3.169 | 562.24 | 125.13 | 447.16 | 120.04 |
| 4 | 31.335 | 5.209 | 27.385 | 5.240 | 12.393 | 3.576 | 12.025 | 1.873 | 627.37 | 96.37 | 477.49 | 150.51 |
| 5 | 34.117 | 2.855 | 28.923 | 8.231 | 15.654 | 2.362 | 14.688 | 4.067 | 595.62 | 75.30 | 493.38 | 128.75 |
| 6 | 32.107 | 6.256 | 31.825 | 3.137 | 14.644 | 5.096 | 15.264 | 2.644 | 564.69 | 92.34 | 462.65 | 124.77 |
| 7 | 29.786 | 6.957 | 27.748 | 4.256 | 13.470 | 3.486 | 14.123 | 2.286 | 505.28 | 62.88 | 374.77 | 137.43 |
| 8 | 26.282 | 7.268 | 24.618 | 4.934 | 9.665 | 4.261 | 10.347 | 3.928 | 438.88 | 105.22 | 291.45 | 119.38 |
| 9 | 21.298 | 4.839 | 19.168 | 3.537 | 2.965 | 4.123 | 3.886 | 0.782 | 354.27 | 87.99 | 230.90 | 72.26 |
| 10 | 15.610 | 7.695 | 8.557 | 11.089 | -1.056 | 4.603 | -2.222 | 3.766 | 271.65 | 75.30 | 139.88 | 56.81 |
| 11 | 14.700 | 6.513 | 5.556 | 6.736 | -2.893 | 4.947 | 0.0010 | 7.220 | 223.21 | 46.40 | 129.73 | 110.38 |
| 12 | 11.527 | 3.985 | 0.973 | 7.207 | -5.96 | 4.145 | -7.763 | 7.058 | 262.18 | 69.94 | 185.67 | 105.90 |
| 13 | 15.129 | 6.012 | 10.694 | 2.501 | -4.315 | 4.792 | 0.555 | 4.466 | 321.36 | 84.81 | 303.00 | 85.00 |
| | Wind | | | | Maximum Humidity | | | | Minimum Humidity | | | |
| 1 | 311.88 | 152.59 | 216.00 | 106.65 | 75.910 | 17.025 | 91.280 | 4.070 | 20.393 | 17.845 | 39.000 | 16.233 |
| 2 | 269.40 | 118.18 | 312.08 | 82.01 | 78.950 | 15.610 | 92.400 | 6.239 | 15.649 | 10.701 | 42.333 | 21.987 |
| 3 | 253.00 | 94.35 | 243.05 | 77.77 | 86.736 | 11.822 | 95.789 | 3.909 | 23.567 | 16.256 | 40.368 | 18.184 |
| 4 | 227.91 | 73.27 | 241.05 | 89.82 | 84.180 | 14.929 | 95.764 | 4.380 | 19.904 | 12.732 | 36.176 | 17.903 |
| 5 | 225.94 | 72.46 | 299.25 | 95.08 | 82.776 | 14.187 | 95.625 | 39.937 | 27.955 | 8.354 | 39.937 | 15.004 |
| 6 | 231.87 | 68.38 | 184.23 | 50.19 | 82.216 | 11.949 | 92.050 | 8.360 | 27.966 | 7.339 | 35.619 | 16.910 |
| 7 | 195.63 | 93.85 | 205.31 | 81.66 | 88.230 | 8.293 | 93.368 | 5.133 | 28.064 | 12.678 | 44.000 | 15.616 |
| 8 | 207.33 | 97.39 | 234.50 | 108.38 | 84.806 | 13.368 | 94.400 | 3.202 | 26.850 | 16.300 | 41.000 | 16.089 |
| 9 | 211.41 | 92.53 | 306.50 | 60.10 | 77.676 | 14.160 | 79.000 | 16.970 | 22.806 | 11.055 | 22.500 | 17.677 |
| 10 | 237.27 | 110.11 | 282.80 | 60.01 | 78.372 | 17.355 | 97.400 | 3.577 | 29.280 | 16.529 | 66.400 | 22.678 |
| 11 | 284.96 | 155.29 | 231.66 | 82.03 | 79.075 | 15.165 | 99.333 | 1.154 | 29.943 | 12.654 | 64.000 | 28.618 |
| 12 | 253.38 | 133.13 | 277.25 | 151.15 | 79.211 | 14.865 | 89.750 | 4.272 | 28.313 | 16.717 | 77.000 | 11.357 |
| 13 | 265.89 | 141.22 | 254.25 | 149.54 | 71.527 | 17.214 | 89.750 | 3.201 | 17.473 | 13.506 | 54.666 | 16.502 |

* Standard Deviation



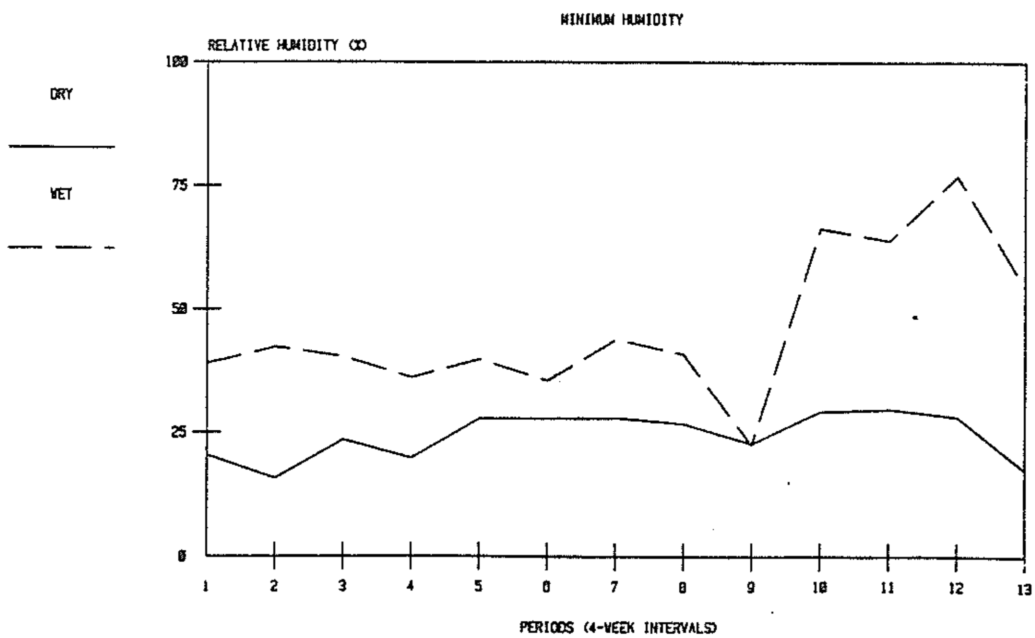
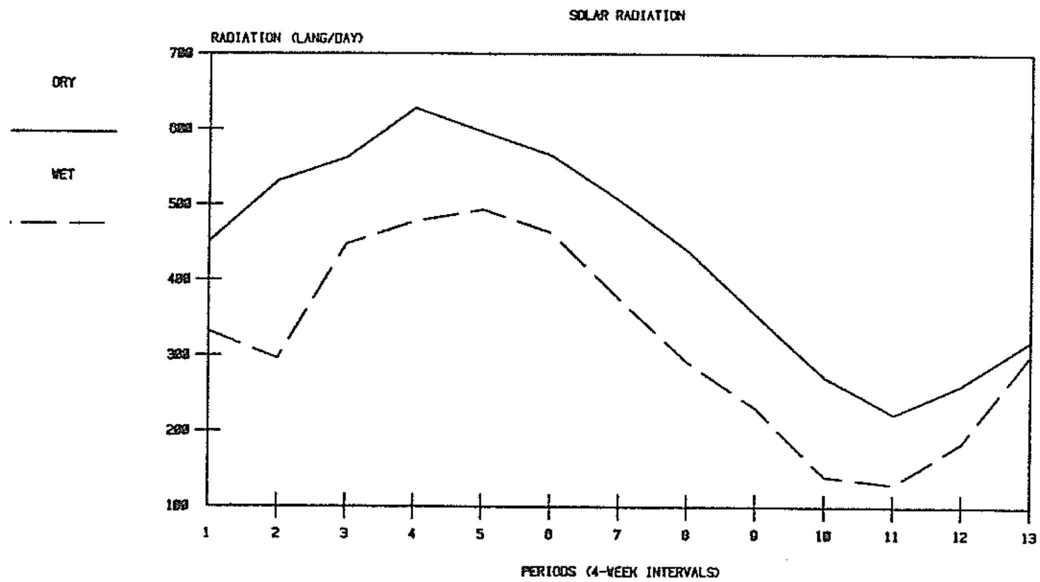




Figure B-4. Mean values of the weather variates for both dry and wet days over time



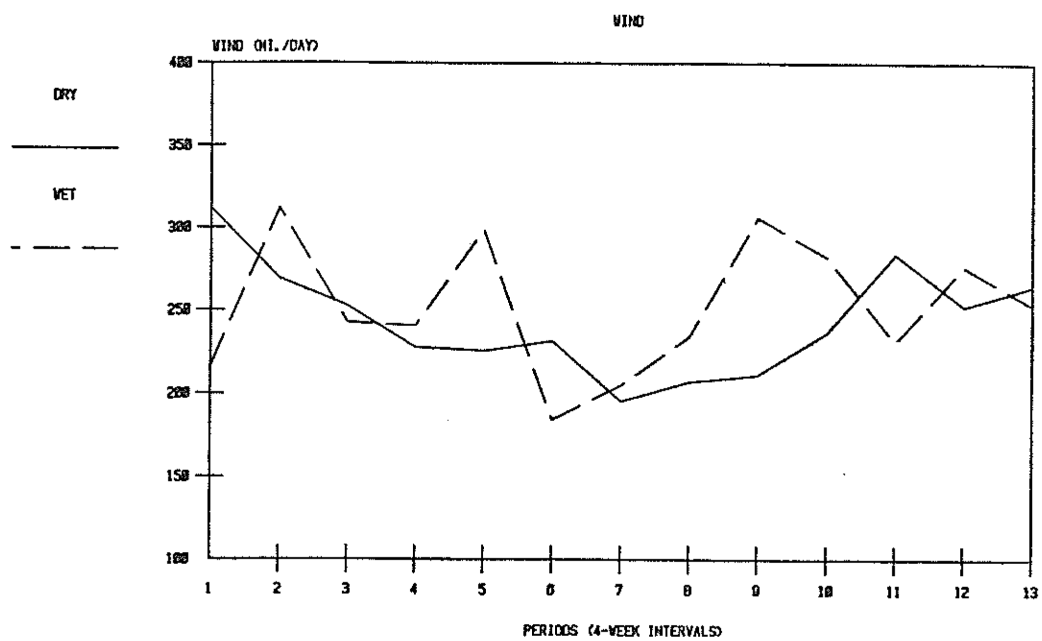




Figure B-5. Mean values of the weather variables for both dry and wet days

Table B-3. Estimates of the lag 0 and lag 1 cross correlations coefficients for Plains Branch Agricultural Experiment Station, Clovis, New Mexico.

Lag 0 Cross-Correlations Between Standardized Variates

| | TX | TN | HX | HN | SR | WI |
|---|---|---|---|---|---|---|
| TX | .90 | .51 | -.20 | -.40 | .25 | -.02 |
| TN | | .87 | -.10 | -.13 | -.02 | -.06 |
| HX | | | .87 | .27 | -.03 | -.06 |
| HN | | | | .75 | -.26 | .04 |
| SR | | | | | .95 | .08 |
| WI | | | | | | .94 |

Lag 1 Cross-Correlations Between Standarized Variates

| | TX | TN | HX | HN | SR | WI |
|---|---|---|---|---|---|---|
| TX | .29 | .14 | -.15 | -.21 | .10 | -.10 |
| TN | .30 | .29 | -.03 | -.09 | -.03 | -.09 |
| HX | -.23 | -.06 | .34 | .35 | -.08 | -.02 |
| HN | -.16 | .06 | .13 | .24 | -.09 | .02 |
| SR | .03 | -.02 | .02 | -.03 | .27 | .04 |
| WI | 0.1 | -.12 | -.03 | .04 | -.01 | .44 |

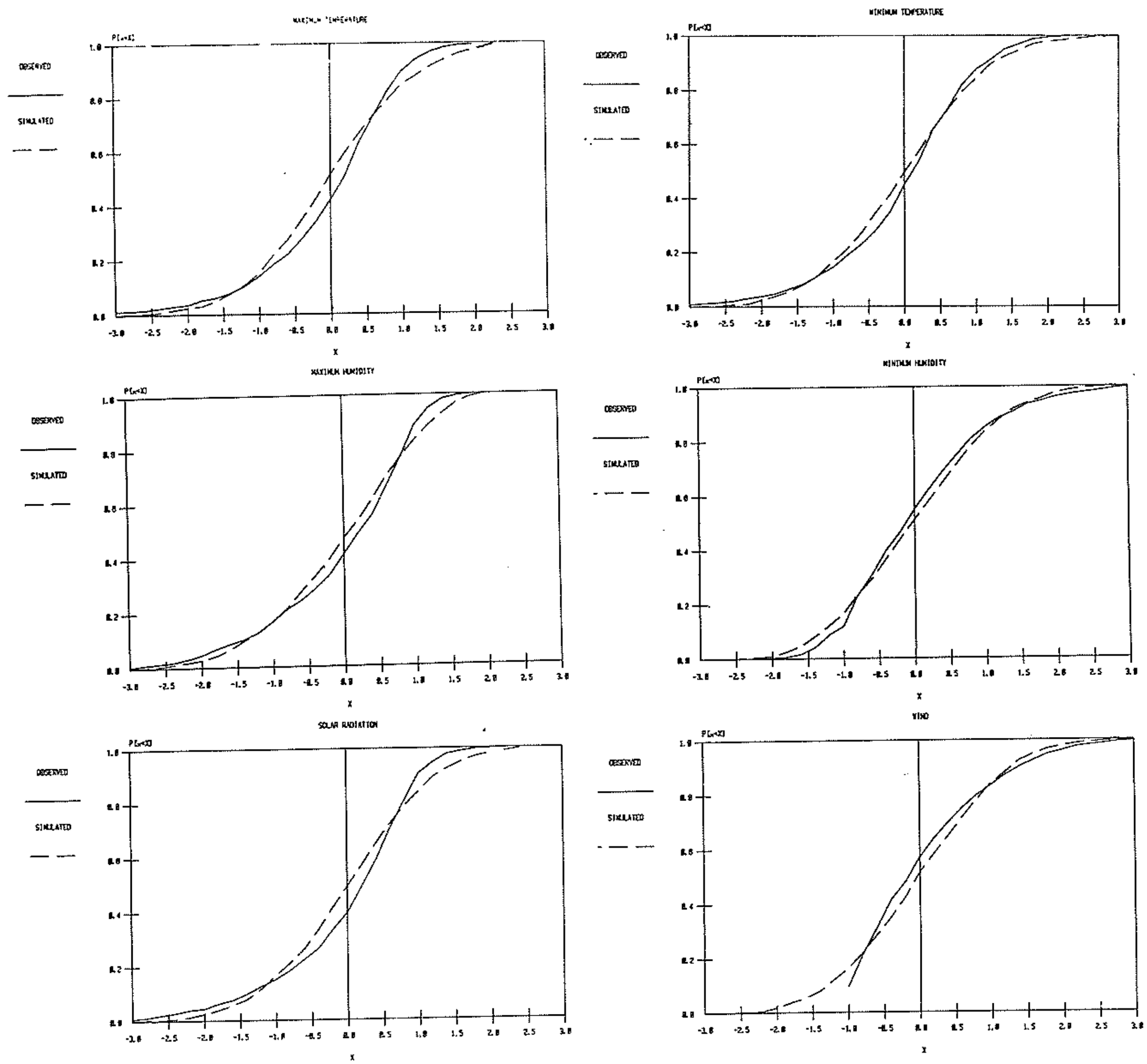



Figure B-6. A comparison of observed (solid line) and simulated (dashed line) cumulative distributions of the standardized weather variates

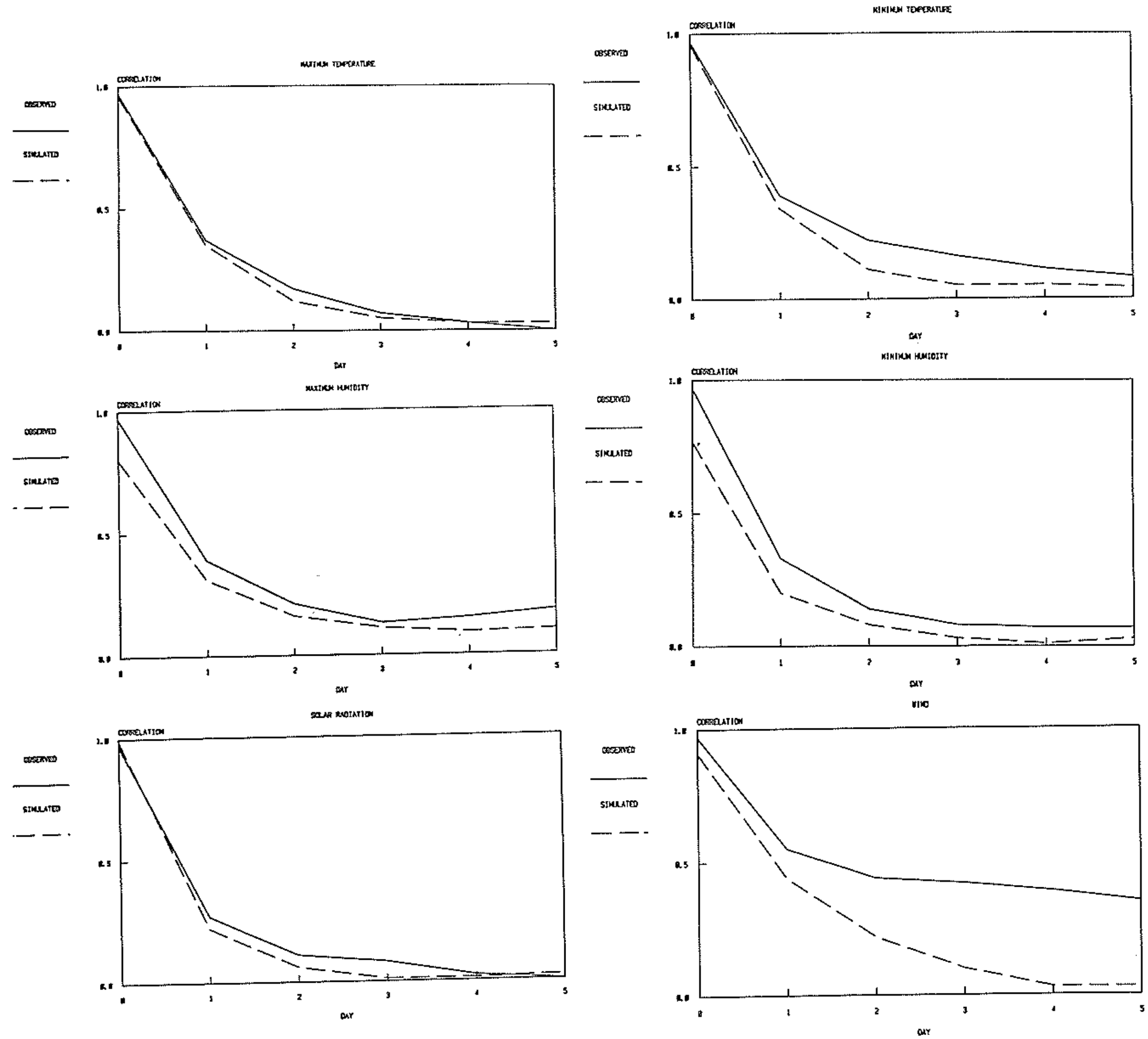



Figure B-7. Serial correlation coefficients of the six weather variables, observed (dashed line) and simulated (solid line)

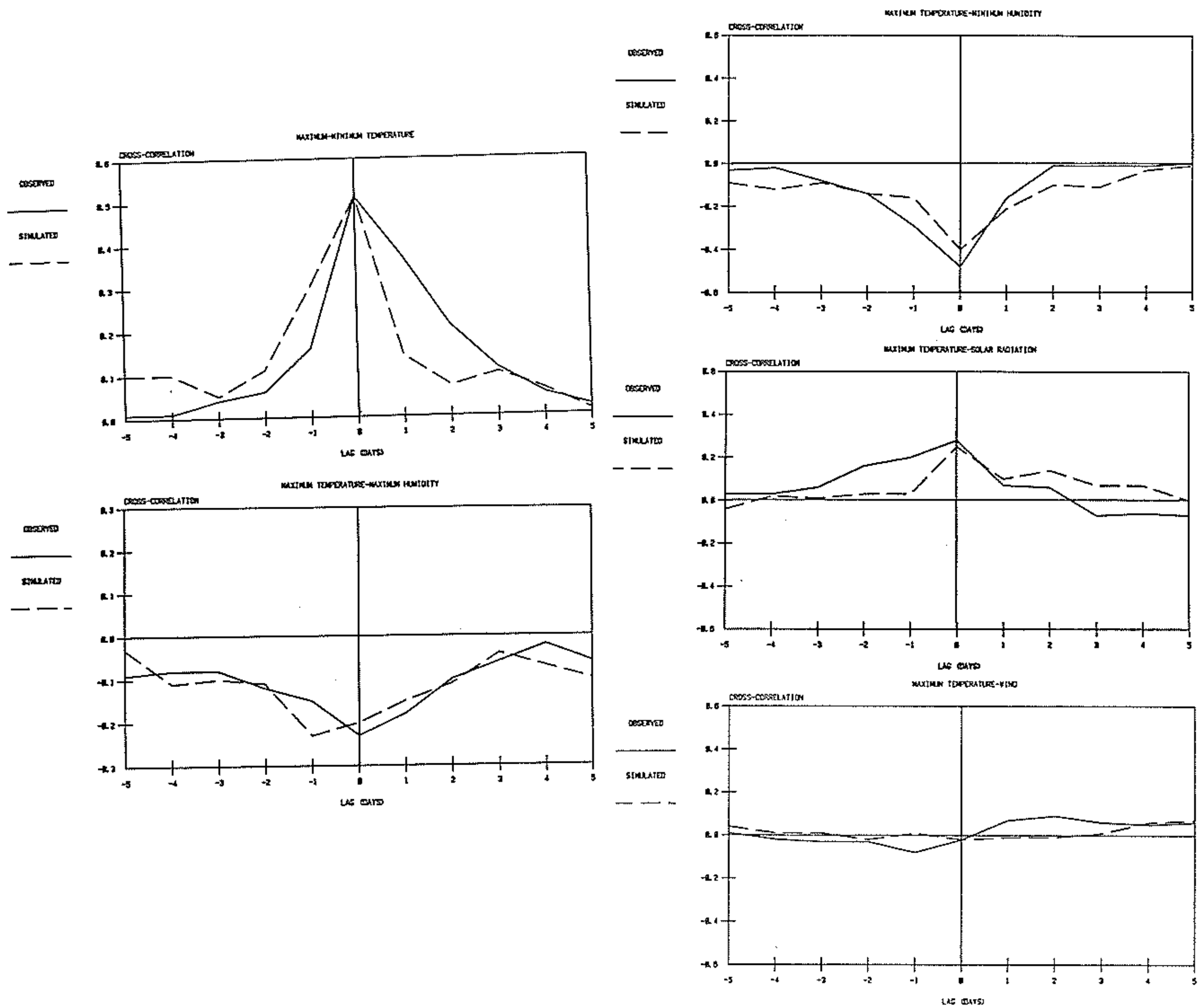



Figure B-8. A comparison of observed and simulated cross correlation coefficients for maximum temperature (TX), minimum temperature (TN), maximum humidity (HX), minimum humidity (HN), solar radiation (SR), and wind (WI)

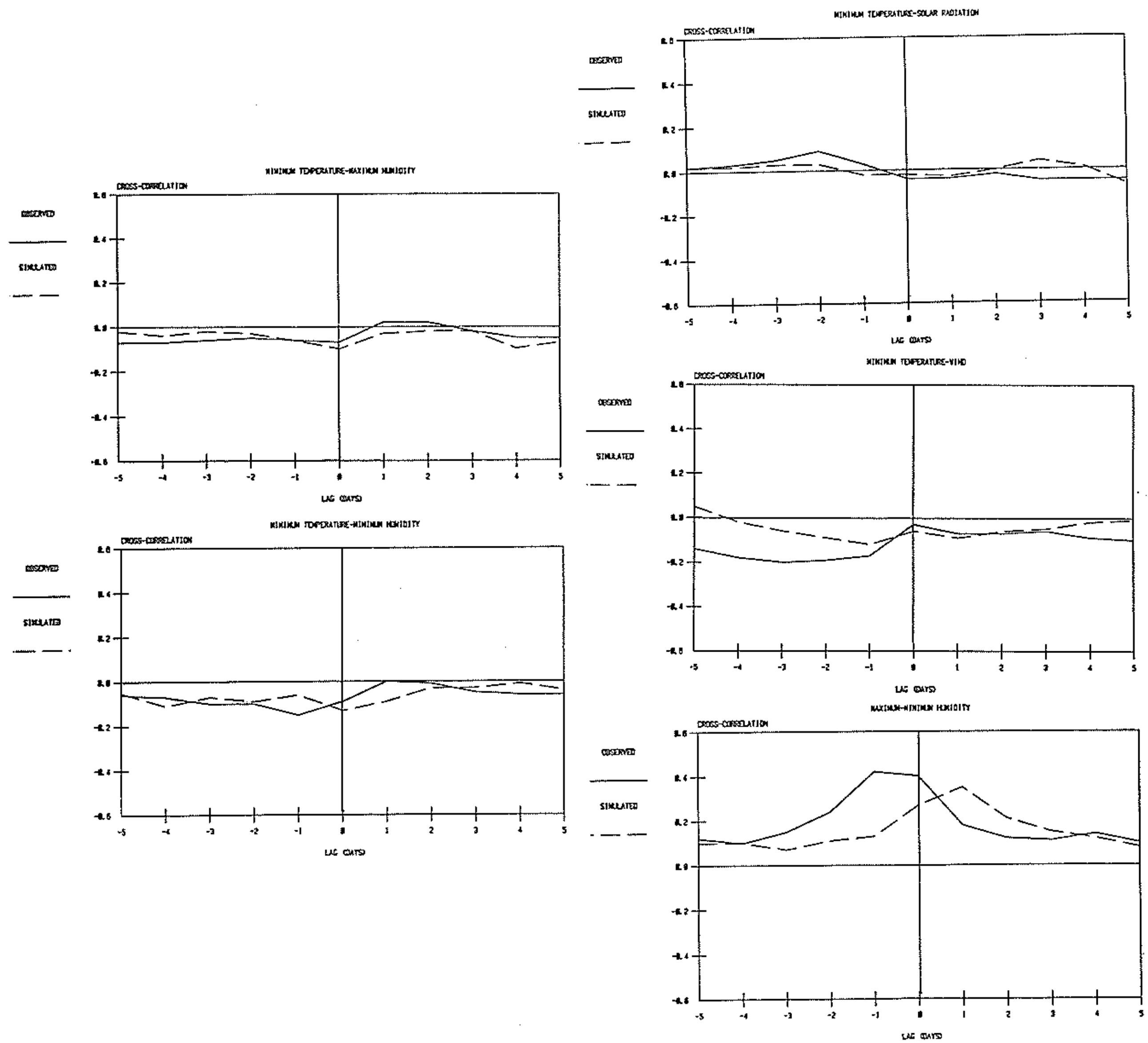



Figure B-9. A comparison of observed and simulated cross correlation coefficients for maximum temperature (TX), minimum temperature (TN), maximum humidity (HX), minimum humidity (HN), solar radiation (SR), and wind (WI)

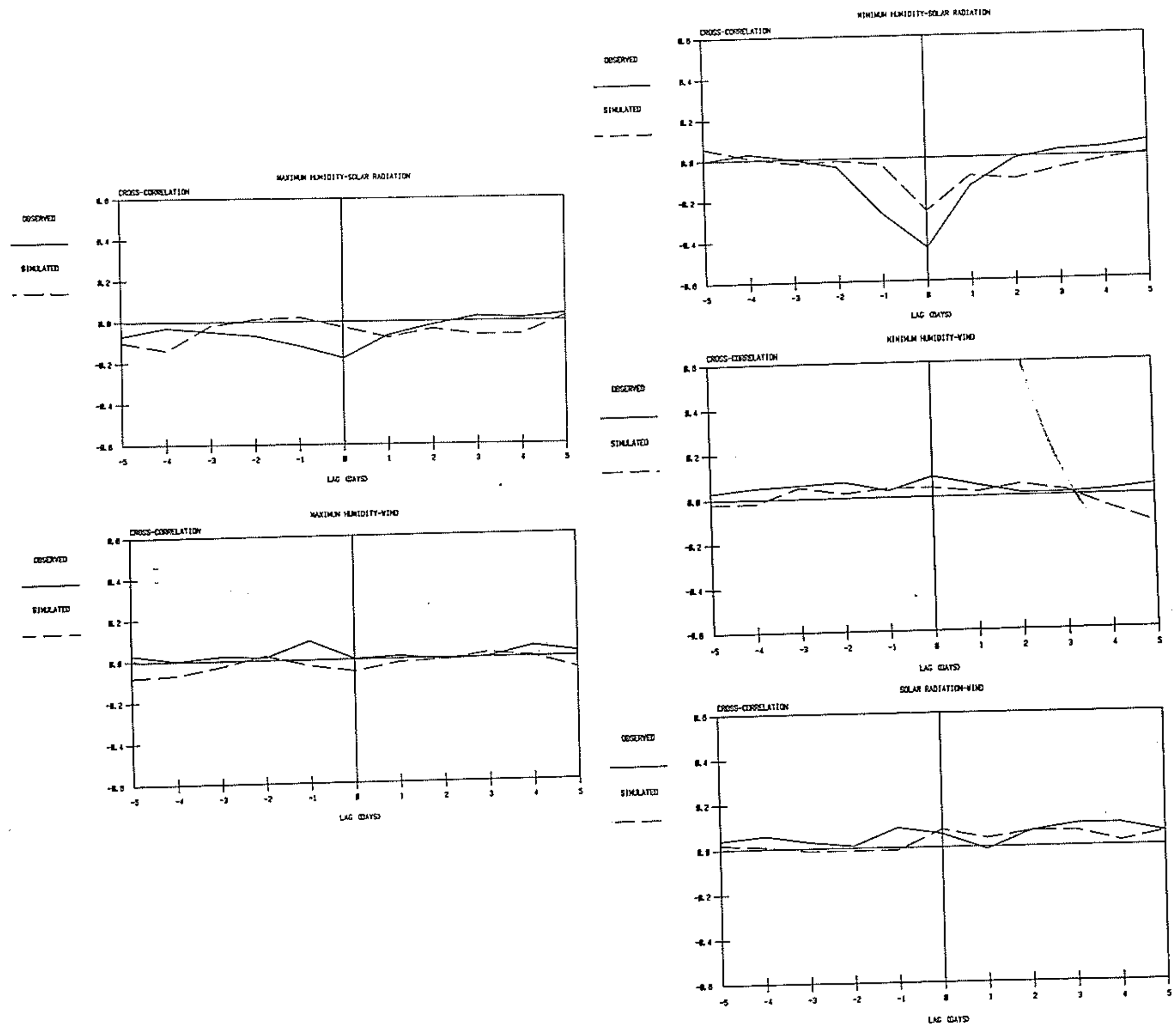



Figure B-10. A comparison of observed and simulated cross correlation coefficients for maximum temperature (TX), minimum temperature (TN), maximum humidity (HX), minimum humidity (HN), solar radiation (SR), and wind (WI)