5.1. Model Requirements for Weather Data

Crop growth, grain yield, fertilizer recovery, and the processes affecting them vary greatly from year to year in any location as well as from location to location. The overwhelming determinant of this spatial and temporal variability is weather. In wheat-growing regions temperature dictates the length of the growing season and the rate of crop development, and hence, the type of wheat grown. Precipitation and stored soil moisture are key parameters influencing agronomic practices involved in dryland wheat cultivation and also determine the length of the effective growing season. Solar radiation influences rates of photosynthesis and evaporation and will thus influence growth processes and water balance. The rates of nutrient transformation occurring in the soil are influenced by soil moisture and temperature.

To evaluate differing cropping and fertilizer strategies in any location, it would be desirable to have experiments conducted over many years to capture the variability due to weather which occurs. Long-term data of this type are seldom available, but where long-term weather records exist a model can be run to provide a more complete picture of crop growth and fertilizer response variations over time.

Long-term weather data, particularly daily rainfall, temperature, and radiation, are frequently required in modelling studies where crop growth or response patterns are studied over a period of years. Hydrology models such as CREAMS (Knisel, 1980) and the Representative Basins Model (Body and Goodspeed, 1979) frequently require long runs of weather data to be able to capture the effects of infrequent events such as high intensity thunderstorms. The erosion-productivity model EPIC (Williams et al., 1983) also requires access to long-term weather records to evaluate the long-term consequences of differing tillage practices and crop rotation sequences on productivity. Models designed to provide "best-bet" solutions for optimizing sowing time of pastures (Dowling and Smith, 1976) or crops (Stapper, 1984) also require long-term weather records.

Frequently, these long-term weather data are not available or the records are incomplete. An alternative is to utilize stochastic time-series modelling procedures to generate a sequence of weather data with stastical properties indistinguishable from historical sequences. To produce these sequences a short run of weather data is used to determine some coefficients describing the data, and the coefficients in turn are used to generate a longer sequence of data. If such procedures can reliably be used to generate climatic data for use with stochastic models, an added bonus is that a small file of climatic parameters can be maintained to describe a site rather than maintaining a large data base with daily observations, thus reducing computer storage requirements and cost.

This chapter describes some attributes of the Australian climate and reviews some of the various generation techniques available and evaluates the procedures described by Richardson and Wright (1984) for locations within the Australian wheat belt.

5.2. Nature of Australian Climates

Australia is the driest continent on earth with one-third of the continent receiving an average of 250 mm per annum or less. Rainfall, or the lack of it, is thus the most important single factor determining land use and rural productivity. This dryness is largely a function of latitude. Australia lies within an area of predominantly high pressure between the regular paths of tropical rain-bearing influences in the north and temperate rain-bearing influences in the south. A more detailed discussion of the climatology may be found in Gentilli (1971).

The distribution of rainfall throughout the year thus varies from the north to the south of the continent and from the eastern to the western coasts. In all regions of the continent rainfall declines with distance from the coast such that the 750 mm annual rainfall isohyet seldom extends more than 250 km inland (Fitzpatrick and Nix, 1970). Regions of winter rain occur in the south and the most pronounced winter maxima occur in the southwest of Western Australia. Tropical monsoons produce a marked summer maximum of rainfall in the north. The middle latitudes of Australia, except on the east coast, are dry or have erratic rainfall because they lie outside the paths of these two rain-bearing influences.

Testing the rainfall component of any weather generator against data from Australian wheat belt locations is a particularly challenging exercise since the degree of variability of Australian rainfall generally exceeds that for crop-growing regions in other areas of the world (Leeper, 1973). Figure 5.1 illustrates the extent to which annual rainfall deviates from long term mean annual rainfall on the Australian continent. For most of the wheat-growing regions of Australia, this variability is at least 10% greater than for corresponding areas of the world at the same latitude. Only locations in the southern fringe of the wheat belt (those with a Mediterranean-type

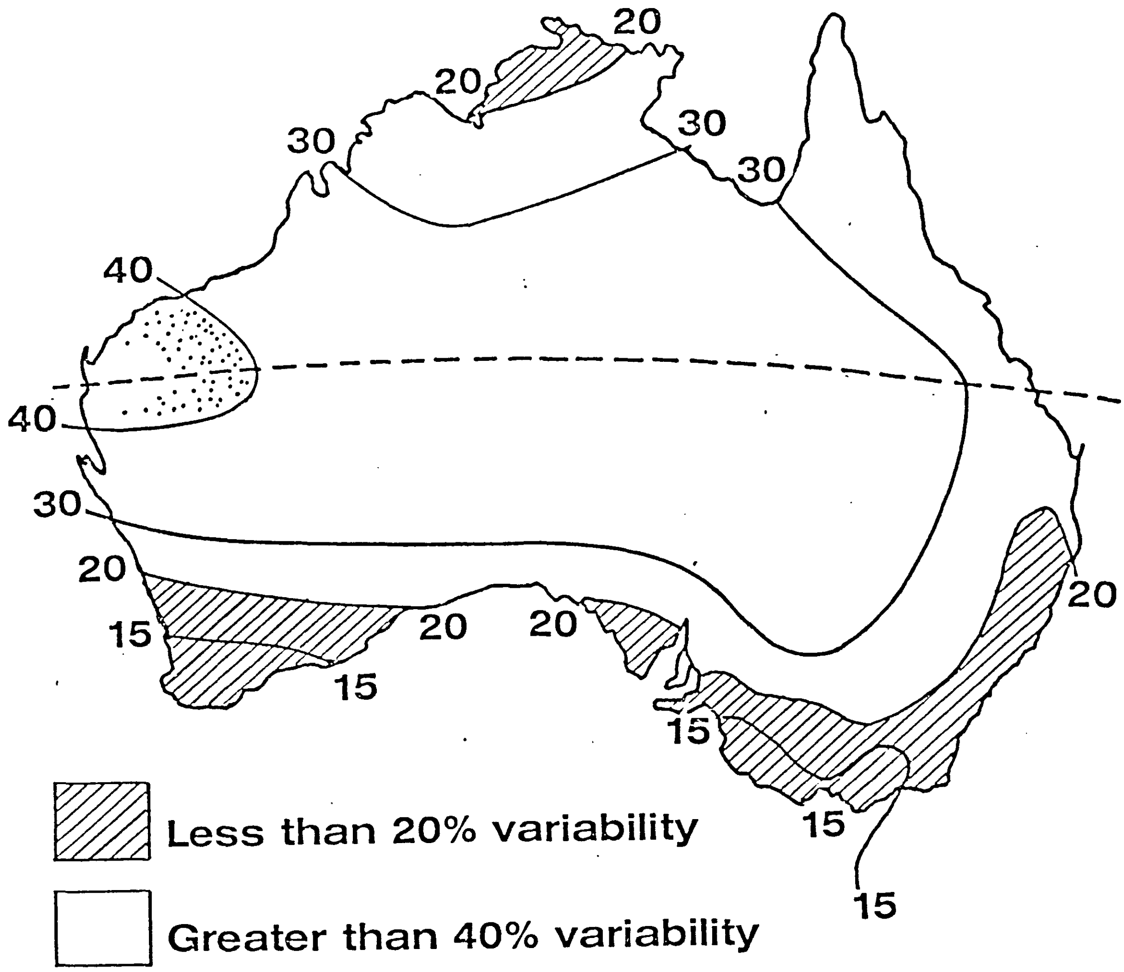


Figure 5.1. Percentage Mean Variability From Annual Mean Rainfall for Locations in Australia (redrawn from Leeper, 1973).

climate) experience rainfall with equal or less variability than other locations in the world receiving the same amount of annual rainfall.

Modest relief and the insular nature of the landmass tend to produce smaller extremes of temperature compared to areas of other continents with similar latitudes. Isotherms for January maxima and July minima and their ranges are plotted in Figure 5.2. In the far north of the continent the hottest month is November, further south toward the Tropic of Capricorn, December is the hottest month, and in most of the subtropical area, January is the hottest month (Anon, 1983). Within the wheat belt (Figure 5.4) frosts are common in winter but are never severe or prolonged, but late frosts periodically cause damage to crops (Marcelles and Single, 1975).

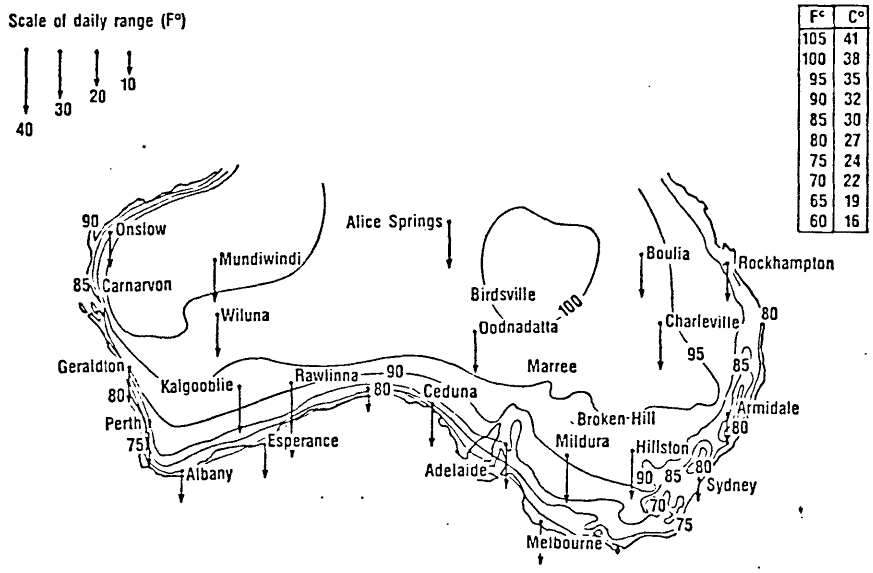
Average daily solar radiation exceeds 25 MJ/m^2 over most of the continent in January (Fitzpatrick and Nix, 1970). Latitude greatly influences solar radiation receipts in the winter months with daily values declining as rainfall increases with increase in latitude.

5.3. General Structure and Review of Weather Generators

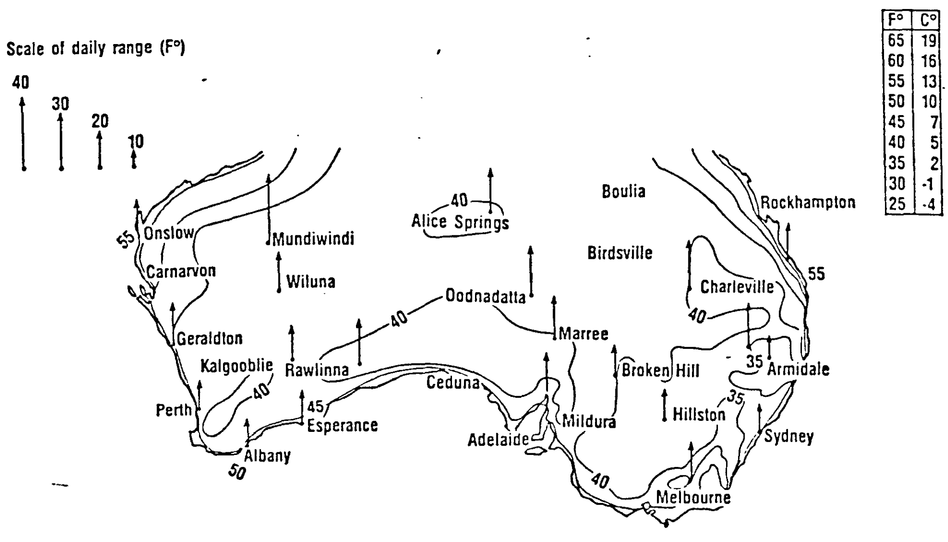
5.3.1. Techniques for Generating Daily Rainfall Data

Many models have been proposed for simulating daily precipitation. Most techniques consist of two steps. The first is to determine the sequence of wet and dry days and the second is to determine the amount of precipitation on wet days.

Various methods exist for the simulation of wet and dry day occurrences. One simple method is to consider wet and dry days as independent events. However, Gabriel and Neuman (1962), using rainfall data from Tel Aviv, Israel, found that daily rainfall events are not independent but depend on the wet or dry status of the previous day.



(a). January Maximum Temperature (deg. F).



(b). July Minimum Temperature.

Figure 5.2. Isotherms for Southern Australia. (Modified after Fitzpatrick and Nix, 1970)

Consequently, models which ignore this dependence have often been unsuccessful (for example, Smith and Schreiber, 1973; Cole and Sheriff, 1972; Buishand, 1978).

Thus, the probability of rain occurring on a day is conditioned by the wet or dry status of the previous day. This type of model based on conditional probabilities is referred to as a Markov chain model. Since the work of Gabriel and Neumann this technique has become the most widely adopted for predicting rainfall occurrences. Table 5.1 indicates some of the diversity of rainfall environments where the technique has been successfully employed.

Markov chain models may be described by their "order" and "state." "Order" refers to the number of days preceding a day that affects the weather on that day. For example, a first order Markov chain uses a probability conditioned on the weather of the previous day and a second order Markov chain uses a probability conditioned by the events of the previous two days. The "state" of the chain refers to the categories used to describe an event. For precipitation a two-state chain uses the occurrence or nonoccurrence of rainfall as states. Multistate models utilize various rainfall amounts as states. In defining a wet day a small threshold amount of rainfall is usually used. Richardson (1981) and Haan et al. (1976) use 0.25 mm as this threshold, whereas Stern et al. (1981) use small but differing threshold amounts for differing locations.

The simplest form of Markov chain employed is the first order two-state chain with the states being "wet" or "dry." In most of the studies cited previously (Table 5.1), this level of complexity proved satisfactory to describe the rainfall sequence reliably. In some circumstances this has proven unsatisfactory and techniques to determine the appropriate chain order length have been devised (Gates and Tong, 1976).

Table 5.1. Studies Employing a Markov Chain Technique for Predicting Rainfall Occurrence

Author	Location
Haan et al., 1976	Kentucky, United States
Bruhn et al., 1980	Geneva, New York, United States
Gates and Tong, 1976	Israel and United Kingdom
Coe and Stern, 1982	Jordan, Niger, Botswana, and Sri Lanka
Srikanthan and McMahon (1983, 1984)	Australia (various locations)
Chin (1977)	United States (various locations)
Buishand (1978)	Netherlands, Indonesia, India
Richardson (1981)	United States (various locations)
Dennett et al. (1984)	Syria
Stern (1980a)	Nigeria
Stern (1980b)	Nigeria, India
Smith and Schreiber (1973)	Arizona, United States
Weiss (1964)	United States
Garbutt et al. (1980)	Various locations in West Africa
Jones et al. (1972)	State College, Mississippi, United States
Larsen and Pense (1982)	United States (various locations)

Lawler (1983) described a useful technique where rainfall data can be coded with a 0 for a dry day and a 1 for a wet day. The possible sequences of wet and dry days over a two-day period are:

0	0	dry day followed by a dry day
0	1	dry day followed by a wet day
1	0	wet day followed by a dry day
1	1	wet day followed by a wet day.

The conditioned or transition probabilities for a two state first order Markov chain may be calculated by (a) totalling the number of occurrences of 00, 01, 10, 11 in the data; (b) summing the number of occurrences of 00 and 01 to give TOTAL 1, and similarly for 10 and 11 to give TOTAL 2; (c) dividing the number of occurrences of 00 by TOTAL 1 to give P_{00}; dividing the number of occurrences of 10 by TOTAL 2 to give P_{10}; dividing the number of occurrences of 11 by TOTAL 2 to give P_{11}.

These transition probabilities can be written in the form of a matrix:

$$\begin{matrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{matrix}$$

$P_{11} + P_{01} = 1$ and $P_{10} + P_{11} = 1$

This matrix is known as the transition probability matrix (TPM) and is a convenient method of describing the probability of rainfall occurrences. Further description of the theory of Markov chains can be found in Haan (1977).

The appropriate chain order length may vary from location to location and throughout the year (Chin, 1977; Bruhn et al., 1980; Lawler, 1983). Use of a higher order chain and a multi-state chain is necessary when modelling rainfall amount as distinct from rainfall occurrence. Haan et al. (1976) have developed a stochastic model using a first order seven state chain. The states employed were various rainfall amounts.

Srikanthan and McMahon (1983) used the transition probability matrix (TPM) method with up to seven states to describe daily rainfall at 12 locations within Australia. The seven states employed ranged from zero or dry for the first state to rainfall amounts greater than 31 mm for the seventh state. To improve the model's ability to predict isolated large rainfall events, Srikanthan and McMahon employed a transformation procedure (Box and Cox, 1964) on rainfall amounts falling within this last class which reduced the skewness of the distribution. In order to accommodate all 12 stations, the number of states for each station was systematically varied depending on the maximum observed rainfall and the average number of wet days in a particular month. The actual number of states employed varied from 2 to 7, depending on month and station.

A number of models have been proposed for the distribution of precipitation amounts occurring on wet days. Plots of the frequency of rainfall events against daily rainfall amount (Figure 5.3) indicate that smaller amounts of rainfall occur more frequently than larger amounts. Todorovic and Woolhiser (1975) and Richardson (1982b) have used a 1-parameter exponential distribution to approximate this curve. A 2-parameter gamma distribution has been used by Buishand (1978), Stern (1980a, b), Dennett et al. (1984), Coe and Stern (1982), Garbutt et al. (1980), Ison et al. (1971), Katz (1977), and Larsen and Pense (1982). A 3-parameter mixed exponential distribution has been used by Woolhiser and Pegram (1979), and a skew-normal distribution by Nicks (1974).

The 2-parameter gamma was found to be superior to the simple exponential when applied across a range of sites (Richardson, 1982b).

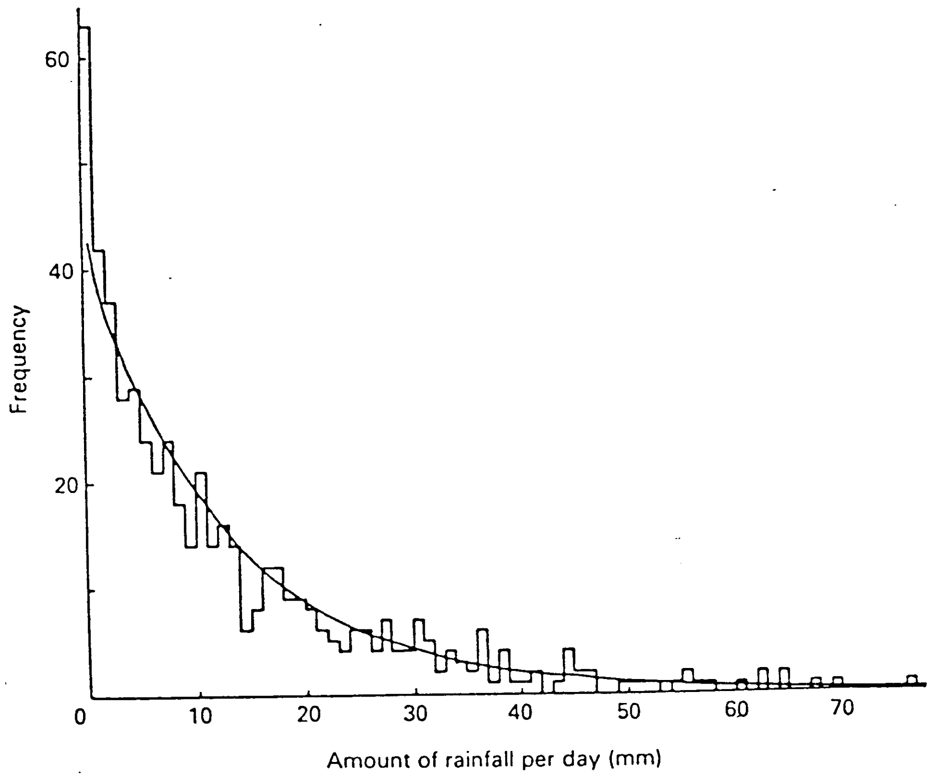


Figure 5.3. Observed Frequency Distribution of Rainfall Amounts on Rainy Days in June at Kano, Nigeria (1916-75), With a Fitted Exponential Distribution (Mean = 12.95 mm). (From Stern et al., 1982).

The general form of the density function of the gamma distribution is:

$$f(p) = \frac{\beta^{\alpha} p^{\alpha-1} e^{-\beta p}}{\Gamma\ (\alpha)},\ p>0$$

where: (i) α is a shape parameter

(ii) β is a scale parameter

(iii) $\Gamma\ (\alpha)$ is a gamma function of α

(iv) ρ is an ordinate of the probability density function

Procedures for estimating α and β have been reported by Haan (1977), Stern (1980b), Garbutt et al. (1981) and Richardson and Wright (1984).

A rainfall generator program can be constructed by using a random number generator on a computer to produce a random variate. This random variate is then used with the TPM to determine if a day is wet or dry. If it is wet then another random variate can be used with the probability distribution for rainfall amount to estimate the amount of rain which falls.

Combining the models for rainfall occurrence and rainfall amount yields a tool which can provide valuable information pertinent to the agronomy of crops in certain areas. Stern et al. (1982b) and Stern et al., (1981) have employed the technique to determine the mean starting date for the rainy season and the variability of this start in areas with a monsoonal climate. The probability of an n-day dry spell after an initial rain can also be estimated which would assist in planting date and crop species selection decisions. Garbutt et al. (1981) examined the rainfall climates of eleven sites in West Africa along an approximate longitudinal transect using the Markov-gamma model. The technique showed that most of the variation in rainfall in the region could be explained by differences in the probability of rain falling and not on the amount of rain per rainy day.

In their review of generation procedures Srikanthan and McMahon (1983) found the TPM technique to be superior to the first order 2-state Markov-gamma procedure for Australian rainfall data but concluded that all the procedures examined "reasonably reproduced" mean annual and monthly rainfall.

5.3.2. Techniques for Generating Temperature and Solar Radiation Data

Rainfall is usually regarded as the most basic of weather variables, and thus, most generation procedures for other weather variables rely on some form of dependence on the rainfall status. Jones et al. (1972) used a regression procedure to generate daily temperature data from rainfall data and the time of the year. A separate relationship for each of wet and dry days was used. The model generated sequences of weather data from State College Mississippi reliably. This type of model, however, cannot account for such sequences of weather data as a string of consecutive hot days. These sequences, known as persistence patterns, have been shown (Richardson, 1982a) to have some degree of serial dependence. This means that today's temperature is a function of yesterday's temperature and so on. Richardson (1982a) has also demonstrated that weather variables tend to be cross correlated as well as having these patterns of serial dependence.

This means that today's maximum temperature is related to today's solar radiation and today's minimum temperature may be related to today's maximum temperature.

Several different approaches to incorporating these patterns of serial correlation and cross correlation into weather generators have been used. Bruhn et al. (1980) modified the Jones et al. (1972) model to predict maximum temperature as a function of the month of the year, the rainfall occurrence on the previous day, and the previous day's maximum temperature. The functions for minimum temperature also incorporated the rainfall status of the previous day. Minimum temperature was found to be a function of the current day's maximum temperature. Their functions may be expressed as:

$$\text{Maximum temperature} = f(M, R_{t-1}, TMAX_{t-1}, RN)$$

$$\text{Minimum temperature} = f(M, R_{t-1}, TMAX_{t}, RN)$$

$$\text{Total solar radiation} = f(M, R_{t}, RN)$$

where:

M = month being simulated

R_{t-1} = rainfall occurrence on the previous day

R_t = rainfall occurrence on the current day

$TMAX_{t-1}$ = maximum temperature on the previous day

$TMAX_t$ = maximum temperature on the current day

RN = random variable with a normal probability distribution

The model worked satisfactorily at both Geneva, New York and at Fort Collins, Colorado.

Nicks and Harp (1980) developed a model for generating a sequence of temperature and solar radiation data dependent on the sequence of wet and dry days. For each variable (temperature or solar radiation), four equations corresponding to the four rain conditions: (1) a dry day after a dry day, (2) a wet day after a wet day, (3) a dry day after a wet day, and (4) a wet day after a wet day were developed. The technique preserved the persistence pattern in temperature and solar radiation appropriately conditioned for the wet or dry day status of day and the previous day, but it did not consider the cross correlation of the variables. Larsen and Pense (1982) developed a weather generator which incorporated components describing serial dependence within temperature data and solar radiation data. Procedures were incorporated to describe cross correlations between maximum and minimum temperatures, but no attempt to describe cross correlation of temperature with solar radiation was made.

The performance of each of these generators will depend greatly on the location where they are tested. The generators using regression techniques (Bruhn et al., 1980; Jones et al., 1972) require a separate series of regression equations for each month of the year and could conceivably become unwieldy if used at a multitude of sites. The cross correlations of temperature with solar radiation within generated weather data will be important in crop simulation models. Deviations from observed patterns of these variables may affect photosynthesis, evapotranspiration, and growth processes differently.

The WGEN generator (Richardson and Wright, 1984) attempts to preserve the dependence structure within generated weather data and is readily adaptable to inclusion into crop or hydrology models. WGEN is the subject of evaluation in this study. A brief description of the method used for generating temperature and solar radiation data follows.

Maximum temperature, minimum temperature, and solar radiation are generated depending on the wet or dry status of each day. Only the current day wet/dry status is considered in the model (cf. Nicks and Harp, 1980). The basic form of the generating function for each of maximum temperature, minimum temperature, and solar radiation is:

$$y_i(N) = X_i(N) \cdot \sigma_i(N) + \bar{y}_i(N)$$

where:

$y_i(N)$ = daily value of maximum temperature (N=1), minimum temperature (N=2), or solar radiation (N=3)

$\sigma_i(N)$ = standard deviation for day i

$\bar{y}_i(N)$ = mean for day i

$X_i(N)$ = 3 x 1 matrix for day i of residuals

The means and standard deviations for each of wet and dry days for each N=1, 2, or 3 are interpolated from a Fourier series describing their seasonal variation. These Fourier coefficients are thus required as inputs for the generator.

The matrix of residuals is derived from the serial coefficients of each of maximum and minimum temperature and solar radiation and cross correlation coefficients between each of the weather variables. The cross correlation coefficients used to derive this matrix are both lag zero (i.e., cross correlations between the variables on a day) and lag one (i.e., cross correlations between a variable on one day and another variable on the previous day). Further details of this correlation matrix are given by Richardson and Wright (1984).

The magnitude of the serial correlation coefficients and the cross correlation coefficients used to calculate the elements of this matrix were found to be very consistent across 31 locations examined by Richardson (1982a). If we assume that this matrix is consistent for all locations, the only parameters required to generate temperature and solar radiation are the Fourier coefficients describing the annual variation in temperature and solar radiation on wet and dry days.

5.3.3. Overview of Richardson Weather Generator Program WGEN

The program generates a sequence of daily rainfall data by using four precipitation parameters:

(i) P(W/W) the probability of a wet day given the previous day was wet

(ii) P(W/D) the probability of a wet day given the previous day was dry

(iii) the shape coefficient of the gamma distribution

(iv) the scale parameter of the gamma distribution

These parameters depend on the month of the year. The program operates by accessing a random number generator and, based on the value of the random variate, the previous day's wet or dry status, and the first two coefficients, determines whether this day is wet or dry. If it is wet a second random variate is used with the third and fourth parameters to determine the amount of rainfall.

Daily maximum and minimum temperatures and solar radiation are determined based on a Fourier series describing the change in their mean values and coefficient of variation throughout the year for each of wet and dry days. The simulated values are thus conditioned on the wet or dry status of the day and are adjusted according to an assumed matrix of serial and cross correlation coefficients. This matrix preserves patterns of temperature persistence and ensures that simulated daily values of temperatures and solar radiation are appropriately correlated. This should minimize the possibilities of simulating a very hot dry day but with low solar radiation.

5.4. Data and Programs Used to Evaluate the Richardson Weather Simulator

5.4.1. Weather Data

Weather data of two forms were obtained from the Australian Bureau of Meteorology. Daily rainfall data from 52 locations either within or on the periphery of the wheat belt were used. These data were screened to discard years with missing observations. The mean annual rainfall calculated for each location and the number of years of "clean" record are tabulated below (Table 5.2).

Secondly, Australian Meteorological Bureau daily surface climate data which contain elements for rainfall, temperature, barometric pressure, wind, rain, and sunshine hours and various phenomena codes were used for calculation of temperature-related coefficients. In contrast to the rainfall data described above, these data sets had only a short period of record and often had many missing observations. The data were screened to determine where gaps in the record existed and to check that recorded temperatures fell within the bounds of -20° to 50°C. Any year with more than five consecutive missing observations was discarded. A Fourier series with three harmonics relating long-term mean weekly maximum or minimum temperature to day of the year was fitted for each location. The Fourier series has the form:

$$X = \alpha + \sum_{i=1}^{3} \beta_i(\cos(\frac{it}{2\pi})) + \gamma_i (\sin(\frac{it}{2\pi}))$$

Table 5.2. Locations Used for Development of Rainfall Generator Parameters and Subsequent Testing

Location	State	Latitude (°S)	Longitude (°W)	Mean Annual Precipitation (mm)	Number of Years of Record
Barraba	NSW	30.22	150.36	689	100
Bathurst	NSW	33.25	149.35	622	120
Bendigo	VIC	36.46	144.17	548	111
Biloela	QLD	24.24	150.35	700	59
Clare	SA	33.25	143.55	633	117
Cobar	NSW	31.30	145.49	347	81
Condobolin	NSW	33.05	147.09	442	100
Coonabarabran	NSW	31.16	149.17	724	102
Coonamble	NSW	30.57	148.23	499	100
Cowra	NSW	33.50	148.41	600	76
Dalby	QLD	27.11	151.16	688	96
Dalwallinu	WA	30.17	116.40	358	65
Dubbo	NSW	32.15	148.36	581	97
Esperance	WA	33.51	121.53	697	63
Euroka	NSW	30.01	148.07	426	77
Forbes	NSW	33.23	148.01	522	106
Geraldton	WA	28.46	114.36	456	68
Gilgandra	NSW	31.42	148.39	555	87
Griffith	NSW	34.17	146.02	409	55
Hamilton	VIC	37.45	142.02	695	100
Horsham	VIC	36.43	142.13	446	102
Jondaryan	QLD	27.2	151.3	647	84
Kadina	SA	33.58	137.43	392	100
Kerang	VIC	35.44	143.55	368	99
Kybybolite	SA	36.54	141.00	553	77
Lignum (Gunnedah)	NSW	30.59	150.15	601	29
Loxton	SA	34.27	140.35	274	72
Merbein	VIC	34.11	142.04	282	64
Miles	QLD	26.40	150.41	655	96
Moora	WA	30.39	116.00	462	73
Moree	NSW	29.28	149.51	575	87
Muresk	WA	31.45	116.40	455	55
Nhill	VIC	36.20	141.39	411	99
Northam	WA	31.39	116.40	442	75
Nuriootpa	SA	34.29	139.00	509	31
Orange	NSW	33.17	149.06	867	95
Parkes	NSW	33.08	148.11	584	42
Pittsworth	QLD	27.43	151.38	698	94
Quirindi	NSW	31.31	150.41	681	96
Rutherglen	VIC	36.03	146.28	592	85
Springsure	QLD	24.07	148.05	674	95
Temora	NSW	34.26	147.32	518	69
Trangie	NSW	32.02	147.59	496	82
Waite Institute	SA	34.58	133.38	634	53
Walgett	NSW	30.01	148.07	472	97
Walpeup	VIC	35.08	142.02	347	46
Warialda	NSW	29.32	150.34	687	105
Warooka	SA	35.00	137.24	442	100
Wellington	NSW	32.33	148.57	599	79
West Wyalong	NSW	33.55	147.13	448	84
Wongan Hills	WA	30.53	116.42	345	48
Young	NSW	34.19	148.18	643	105

where:

α = mean of maximum or minimum temperature

γ_i, β_i = amplitude of the harmonics

t = day of the year measured from January 1

X = maximum or minimum temperature

Missing daily observations for periods up to 5 consecutive days were interpolated from these curves. This technique would reduce the observed variance in temperature for periods where data were missing, but it was considered to be a more viable alternative than discarding whole years and diminishing the length of record substantially. Many of the missing observations arose because records were often not taken on weekends or holidays. The resulting length of record varied for each location (Table 5.3) but was at most 40 years with some locations having as few as 6 years. Rainfall data from this data set were utilized only to determine temperature relations for wet and dry days. The length of record was considered too short for many of the locations for reliable characterization of rainfall generator parameters. In many instances, rainfall data were recorded as accumulated totals for a period of several days together with the number of days of accumulation. This would make accurate prediction of rainfall per rain day very difficult.

Since the records for daily solar radiation or hours of sunshine from which it may be calculated were so sparse, the weekly mean solar radiation data estimated by Fitzpatrick and Nix (1970) were used as a substitute. Fitzpatrick and Nix used an empirical procedure to estimate solar radiation from the latitude, time of year, and mean

Table 5.3. Locations Used for Calculation of Weather Generator Parameters for Temperature and Solar Radiation

Location	State	Number of Years	Temperature, °C January Minimum	Temperature, °C January Maximum	Temperature, °C July Minimum	Temperature, °C July Maximum
Bathurst	NSW	17	12.7	27.5	0.0	11.3
Bendigo	VIC	23	14.0	28.7	3.6	11.3
Cambooya	QLD	14	16.3	30.0	2.3	18.6
Clare	SA	23	13.8	30.2	3.0	12.4
Cobar	NSW	20	21.1	34.3	4.9	15.5
Condobolin	NSW	16	19.2	33.5	3.7	14.9
Coonabarabran	NSW	24	11.6	31.2	0.5	15.5
Cowra	NSW	18	16.1	30.9	3.5	12.8
Dalby	QLD	23	19.3	32.6	5.1	19.3
Dalwallinu	WA	26	17.7	34.7	6.0	16.2
Dubbo	NSW	26	19.9	32.8	2.9	15.1
Esperance	WA	18	14.4	28.4	6.0	15.4
Forbes	NSW	23	17.1	32.5	2.7	14.0
Geraldton	WA	40	18.6	31.8	8.5	18.9
Gilgandra	NSW	6	16.1	31.4	2.7	16.1
Goondiwindi	QLD	24	20.1	34.1	5.5	18.7
Hamilton	VIC	18	10.0	25.8	3.7	9.9
Horsham	VIC	22	13.5	29.9	3.7	14.1
Kadina	SA	21	15.3	30.2	5.7	14.5
Kyabram	VIC	18	14.0	30.5	2.3	11.8
Kybybolite	SA	15	11.2	28.4	4.2	11.5
Loxton	SA	15	15.0	31.8	4.0	15.3
Manjimup	WA	20	13.2	27.5	6.6	12.9
Merbein	VIC	10	16.1	31.6	4.3	14.0
Merredin	WA	12	17.0	33.8	4.9	15.4
Miles	QLD	13	20.4	33.6	4.3	20.3
Moree	NSW	18	20.3	34.1	4.3	18.3
Mudgee	NSW	18	15.1	30.6	1.6	14.6
Muresk	WA	15	15.8	33.7	4.1	14.9
Nhill	VIC	24	13.2	30.5	3.4	12.4
Nuriootpa	SA	20	12.8	28.7	4.0	12.3
Nyngan	NSW	19	20.2	34.7	4.0	16.7
Orange	NSW	7	12.4	26.4	1.1	8.2
Parkes	NSW	23	17.8	31.7	4.8	14.2
Pittsworth	QLD	6	17.7	30.4	5.7	18.6
Quirindi	NSW	14	17.5	32.6	2.1	16.5
Rutherglen	VIC	18	13.2	31.8	1.8	11.9
Tamworth	NSW	26	18.3	32.0	3.5	15.6
Temora	NSW	15	15.3	31.5	1.6	12.7
Trangie	NSW	14	18.6	32.8	2.9	15.6
Wagga	NSW	7	15.9	30.6	3.3	12.7
Waite Institute	SA	14	17.4	29.2	8.3	13.6
Walgett	NSW	24	20.7	35.5	4.7	18.9
Walpeup	VIC	15	15.4	32.2	4.4	13.6
Warooka	VIC	12	15.3	27.5	7.4	14.3
Warwick	QLD	19	17.5	30.2	2.8	17.4
Wellington	NSW	18	17.1	32.3	2.0	15.1
Wongan Hills	WA	15	17.1	33.5	5.6	15.4
Young	NSW	18	14.0	31.4	1.1	12.6

monthly relative humidity. To enable calculation of weather generator parameters, a Fourier series with three harmonics was fitted to these weekly estimates of radiation and daily values interpolated from them using the procedure described above for temperature. The location of the data sets used for calculation of weather generator parameters is shown in Figure 5.4.

5.4.2. Programs

Calculation of Rainfall Generation Parameters

A FORTRAN program (Appendix 5) was developed to read the daily rainfall data and calculate the conditional probabilities P(W/W) and P(W/D) used in the Markov chain component of the generator and the coefficients (α, β) of the gamma distribution for rainfall amount for each month of the year. The subroutine PCRAIN responsible for these calculations was obtained from Richardson (pers. comm.). The program also has options to calculate the coefficients required for two alternative distributions for rainfall amount, the simple exponential (Richardson, 1981), and a skewed distribution (Nicks, 1983). These alternatives are provided in subroutine PPRAIN also obtained from Richardson. The resultant values of P(W/W), P(W/D), α and β for each of the stations are appended (Appendix 6).

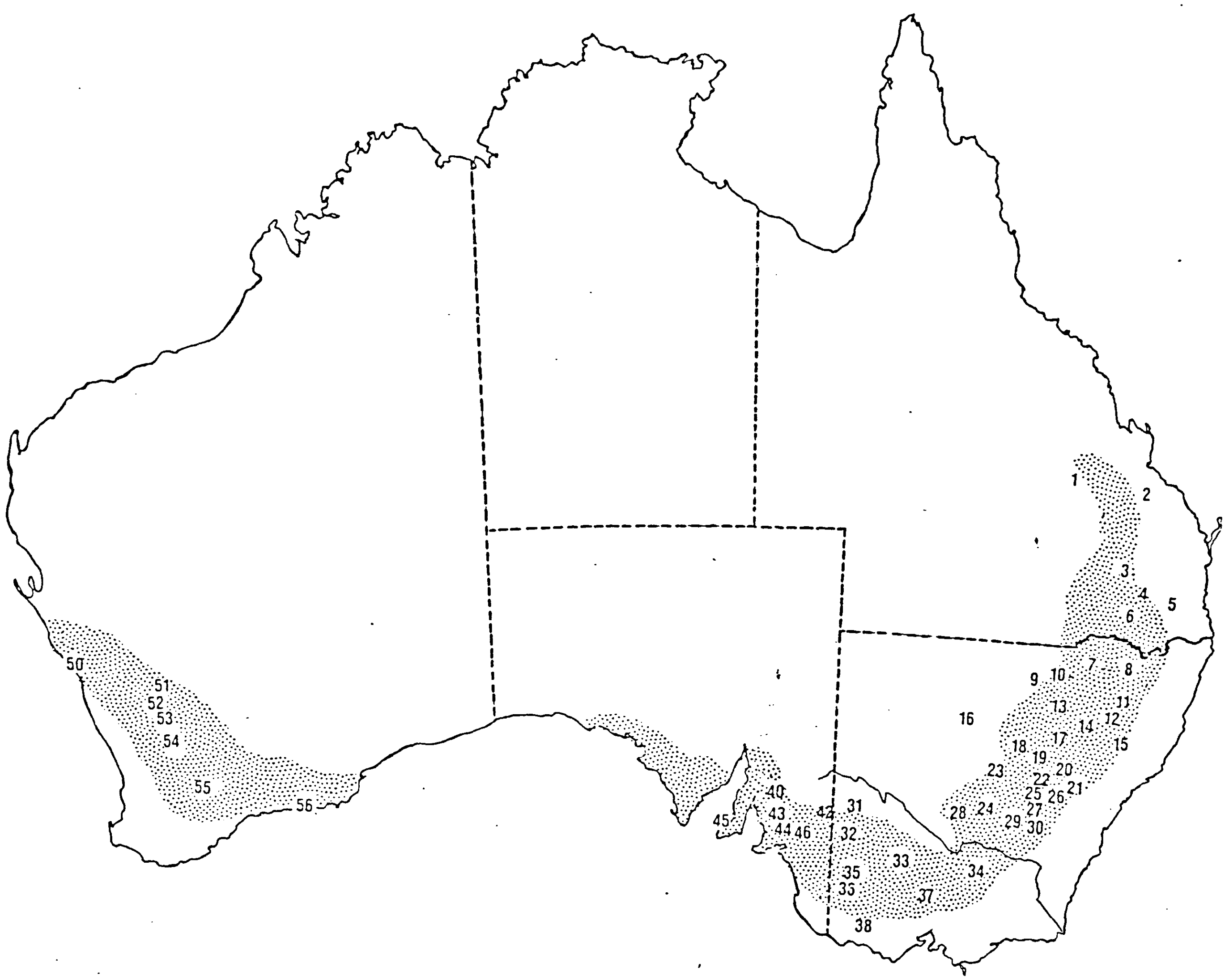
The program also calculates several statistics to describe the daily rainfall data and to provide a basis for comparison of observed and generated data. Means and the four moments (standard deviation, variance, skewness, and kurtosis) for each of the following were calculated:

Figure 5.4. Locations Within the Australian Wheat Belt Used for the Development of the Weather Generator Parameters and Subsequent Testing. Sites Listed are in Approximate Latitudinal Sequence for Each State:

1	Springsure	28	Griffith
2	Biloela	29	Temora
3	Miles	30	Young
4	Dalby		
5	Jondaryan	31	Merbein
		32	Walpeup
6	Pittsworth	33	Kerang
7	Moree	34	Rutherglen
8	Warialda	35	Nhill
9	Walgett	36	Horsham
10	Euroka	37	Bendigo
11	Barraba	38	Hamilton
12	Lignum (Gunnedah)		
13	Coonamble	40	Clare
14	Coonabarabran	41	Kadina
15	Quirindi	42	Loxton
16	Cobar	43	Nuriootpa
17	Gilgandra	44	Waite Institute
18	Trangie	45	Warooka
19	Dubbo	46	Kybybolite
20	Wellington		
21	Orange	50	Geraldton
22	Parkes	51	Dulwullins
23	Condobolin	52	Moora
24	West Wyalong	53	Wongan Hills
25	Forbes	54	Northam
26	Bathurst	55	Muresk
27	Cowra	56	Esperance

Additional Sites Used for Temperature Generation Not Located on the Map are Listed Below, Together With the Nearest Rainfall Station Code.

6	Cambooya
4,7	Goondiwindi
34	Kyabram
20,24	Mudgee
18	Nyngan
12	Tamworth
29	Wagga Wagga
6	Warwick



1. Springsure
2. Biloela
3. Miles
4. Dalby
5. Jondaryan
6. Pittsworth
7. Moree
8. Warialda
9. Walgett
10. Euroka
11. Barraba
12. Gunnedah
13. Coonamble
14. Coonabarabran
15. Quirindi
16. Cobar
17. Gilgandra
18. Trangie
19. Dubbo
20. Wellington
21. Orange
22. Parkes
23. Condobolin
24. West Wyalong
25. Forbes
26. Bathurst
27. Cowra
28. Griffith
29. Temora
30. Young
31. Merbein
32. Walpeup
33. Kerang
34. Rutherglen
35. Nhill
36. Horsham
37. Bendigo
38. Hamilton
40. Clare
41. Kadina
42. Loxton
43. Nuriootpa
44. Waite Institute
45. Warooka
46. Kybybolite
50. Geraldton
51. Dalwallinu
52. Moora
53. Wongan Hills
54. Northam
55. Wagin
56. Esperance

1. Monthly total rainfall.
2. Number of wet days per month.
3. Rainfall per rain day for each month.
4. Length of run of consecutive wet days for each month.
5. Number of daily rainfall events greater than 10 mm for each month.
6. Number of daily rainfall events greater than 25 mm for each month.

In addition to this, the means and moments for the total number of dry spells per 3-month period and the length of dry spells in each 3-month period were calculated.

For each month, cumulative probability density functions (CPDF) for monthly rainfall and rain per rain day using the procedure described in Chapter 7 were estimated. Points representing each decile were also interpolated from these CPDFs. Deciles for the length of the longest dry spell on an annual basis were also determined as was the length of the longest dry spell for the period of record. These calculations for rainfall statistics are performed in subroutine WSTATS and related subroutines called from within WSTATS. A sample output for one location is appended (Appendix 7).

Rainfall Generator

The WGEN generator of Richardson and Wright (1984) was modified to generate only rainfall using the monthly values of P(W/W) and P(W/D), α and β as inputs. Details of the operations performed and a listing of the programs are provided by Richardson and Wright. The same routines developed to compute the statistics from the observed data were added to this program to calculate statistics from the generated data. The generator was set to generate 99 years of daily rainfall.

Rainfall Comparison Program

A FORTRAN program was developed to compare the observed and generated rainfall parameters listed above. Monthly means were compared with a Student's t distribution using the method of unequal variances (p. 106, Steele and Torrie, 1980). Steele and Torrie note that when t is computed using this method it is not strictly distributed according to t but is a close approximation. Comparisons were made at the 5% significance level.

Observed and generated monthly variances were compared using a two-tailed F test (p. 117, Snedecor and Cochran, 1967). For this test, the hypothesis is that the two samples are independent random samples from a normal population with the same variance σ^2 (this is reasonable since the simulated data are presented for the same area and from the same sample data). In cases where zero values existed for the variance (e.g., some months may have had no rainfall events greater than 25 mm), variance ratios could not be computed and no comparison was made.

Skewness of distributions was compared as below:

$$R = \frac{\sqrt{b_1} - \sqrt{b_2}}{\frac{b_1}{n_1} + \frac{b_2}{n_2}}$$

where:

$\sqrt{b_1}$ = skewness of observed population = $m_3/(m_2\sqrt{m_2})$

$\sqrt{b_2}$ = skewness of generated population = $m_3/(m_2\sqrt{m_2})$

n_1 = number of observed years

n_2 = number of generated years.

m_2 = second moment about the mean = $\Sigma(x-\bar{x})^2/n$

m_3 = third moment about the mean = $\Sigma(x-\bar{x})^3/n$

The ratio R will approximate σ^t distribution as it is assumed that m_2 corresponds to the population variance for the two samples. If the resulting R values were greater than 1.96 (the 5% level of significance value), then the two populations were differently skewed. Differences in kurtosis were not examined.

The mean number, and length of dry spells per 3-month period were compared using the Student's t procedure described above.

It should be noted that for the above calculations to be legitimate the assumption that observations were drawn from a normal population has to be made. The distinction is made here between comparing monthly values, drawn from a population of years; and daily values. Daily rainfall amounts form a highly skewed distribution since there is always a large number of small observations and a small number of large observations. Since rainfall is accumulated over a longer period, monthly rainfall amounts should not be so highly skewed and the population should approach a normal distribution. In a preliminary analysis of some sample locations using a Shapiro-Wilks procedure (Anderson, 1983) the distribution of monthly rainfall totals was found to be approximately normal.

The program produces plots comparing the observed and generated distributions of monthly rainfall amount and rain per rainday. The 9th and 1st deciles are plotted to compare the tails of the distributions and the median is also plotted (see Figure 5.5). A sample output of the statistical comparison is appended (Appendix 8).

Calculation of Temperature and Solar Radiation Parameters

A FORTRAN program was developed to extract the "clean" data from the data sets listed above and to compute generator parameters for temperature and solar radiation using the procedures described by (Richardson and Wright, 1984). This program calculates parameters describing the rainfall, maximum and minimum temperature, and solar radiation, which can later be used as inputs to the weather generator program.

For consistency and subsequent ease of use; in later studies (Chapters 6 and 7) the daily mean interpolated values for solar radiation were used to calculate the solar radiation coefficients. It should be noted that this will lead to erroneous values for these parameters since the same mean interpolated value is used for dry days and wet days occurring on the same day of the year. The resultant error for crop simulation purposes will probably be small (Richardson, 1985).

Richardson (1982) describes the seasonal change in the mean and coefficient of variation for temperature and solar radiation with a function:

$$u_i = \bar{u} + C \cos \frac{2\pi}{365} (i - T), \; i = 1,365$$

where

u_i = the value of the mean or coefficient of variation on day i.

$\bar{u}$ = the mean of u_i.

C = amplitude of the harmonic.

T = position of the harmonic in days from January 1.

The program calculates the values of $\bar{u}$ and C for the mean and coefficient of variation for each of maximum temperature, minimum temperature, and solar radiation for both wet and dry days. Richardson (1981) found that for locations in the contiguous United States, T was close to the 200th day of the year for temperature for all locations and near the 172nd day of the year for solar radiation. These values are obviously incorrect for the southern hemisphere and procedures were developed to estimate T. A Fourier series was fitted to the observed data for maximum temperature and minimum temperature on each of wet days, dry days, and wet and dry days combined and the T values were determined as the day on which these functions reached a maximum. The values obtained are tabulated (Table 5.4) and the means obtained from all locations were used in the program. Due to the nature of the solar radiation data the calculation was considered inappropriate and a value of T = 355 days assumed (172 + 365/2).

Table 5.4. Values of "T" for Maximum and Minimum Temperatures on Wet and Dry Days

T1 = T for maximum temperature on dry days.
T2 = T for maximum temperature on wet days.
T3 = T for minimum temperature on dry days.
T4 = T for minimum temperature on wet days.

Station	T1	T2	T3	T4
Bathurst	24	27	27	35
Bendigo	26	26	31	36
Cambooya	19	19	28	27
Clare	27	29	28	34
Cobar	23	24	25	34
Condobolin	25	26	26	32
Condobolin	23	23	25	32
Coonabarrabran	21	19	24	29
Cowra	25	25	25	26
Cowra	25	29	29	36
Dalby	17	12	25	29
Dalwallinu	25	26	32	31
Dubbo	21	23	26	31
Esperance	30	26	39	34
Forbes	24	26	26	31
Geraldton	42	36	38	38
Gilgandra	21	19	27	33
Goondiwindi	21	18	26	31
Hamilton	34	39	41	44
Horsham	28	29	30	37
Kadina	29	28	31	32
Kyabram	26	25	33	38
Kybybolite	31	33	38	41
Loxton	25	25	27	33
Manjimup	28	30	36	34
Merbean	27	28	31	31
Merredin	22	22	29	31
Miles	17	5	24	24
Moree	22	19	26	29
Mudgee	23	25	29	32
Muresk	22	24	31	34
Nhill	27	27	31	36
Nuriootpa	26	29	30	35
Nyngan	20	22	24	32
Orange	25	24	29	28
Parkes	23	26	27	32
Pittsworth	19	25	29	25
Quirindi	23	26	25	32
Rutherglen	26	28	33	37
Tamworth	21	23	25	33
Temora	24	26	30	36
Walpeup	25	24	32	36
Trangie	19	19	27	27

(Continued)

Table 5.4. Values of "T" for Maximum and Minimum Temperatures on Wet and Dry Days (Continued)

Station	T1	T2	T3	T4
Wagga Wagga	25	26	32	37
Waite Institute	30	37	38	41
Walgett	18	11	23	26
Warooka	31	27	42	39
Warwick	16	20	30	28
Wellington	22	23	28	31
Wellington	23	21	26	29
Wongan Hills	23	23	33	31
Young	26	29	32	38
Mean	24.4	24.7	29.5	32.9
Std. Deviation	4.5	5.8	4.6	4.2

The WGEN PAR program calculated the following for each of the locations:

TXMD = annual mean of maximum temperature (TMAX) on dry days.

ATX = amplitude of TMAX on wet or dry days.

CVTX = mean coefficient of variation of TMAX on wet or dry days.

ACVTX = amplitude of coefficient of variation of TMAX on wet or dry days.

TXMW = annual mean of TMAX on wet days.

TN = annual mean of minimum temperature (TMIN) on wet days.

ATN = amplitude of TMIN on wet or day days.

CVTN = mean of coefficient of variation of TMIN on wet or dry days.

ACVTN = amplitude of coefficient of variation of TMIN on wet or dry days.

RMD = annual mean solar radiation on dry days.

AR = amplitude of solar radiation on dry days.

RMW = annual mean solar radiation on wet days.

The resulting values for each location which are used as inputs to the generator are appended (Appendix 9).

The program also calculates several statistics to describe the temperature data and to enable comparisons with generated temperature data. Means and moments for each of the following are calculated.

1. Monthly average minimum temperature.
2. Monthly average maximum temperature.
3. Number of days per month with maximum temperatures exceeding 40°.
4. Number of days per month with maximum temperatures exceeding 35°.

5. Number of days per month with minimum temperatures less than 5°.
6. Number of days per month with minimum temperature less than 0°.
7. Monthly average maximum temperature on dry days.
8. Monthly average maximum temperature on wet days.
9. Monthly average minimum temperature on dry days.
10. Monthly average minimum temperature on wet days.

The Weather Generator Program

Additions to the WGEN program were made to accommodate the "T" values described previously and to compute the summary statistics noted above. The program is attached (Appendix 10).

Temperature Comparison Program

A program to compare the means and moments above was developed using similar test criteria to those outlined for the rainfall generator program. The program also plots the simulated and observed mean maximum and minimum temperatures on wet and dry days.

5.5. Evaluation of the Simulator

5.5.1. Rainfall

In almost all instances the rainfall generator faithfully reproduced sequences of rainfall data with the same mean monthly values of: total rainfall, number of wet days, rainfall per rain day, and the length of run of consecutive wet days. At 13 sites the simulated annual rainfall significantly differed ($p \geqq 0.05$) from the observed annual rainfall. These 13 sites were: Cobar, Dubbo, Kerang, Lignum, Loxton, Moree, Northam, Pittsworth, Trangie, Waite Institute, Walgett, Walpeup, and Wellington. While these differences may have been statistically significant they represented at most a 3.13% departure from the mean annual rainfall. At these sites and all others simulated mean monthly rainfall did not differ significantly from observed monthly mean rainfall.

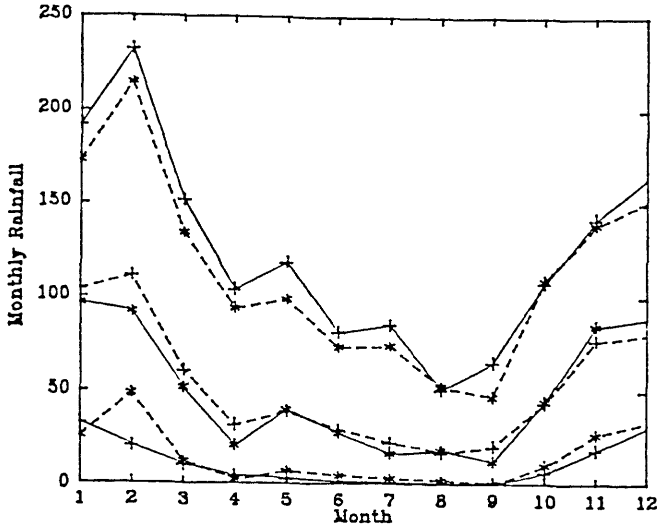
Further indications of the performance of the simulator at predicting monthly rainfall totals can be gleaned by comparison of median (5th decile) monthly rainfall amounts from the simulated and observed data (Fig. 5.5). The generator predicts median monthly rainfall equally well in the summer dominant rainfall areas (Fig. 5.5A) as in the winter dominant rainfall areas (Fig. 5.5D and 5.5E) and those with a more even distribution (Fig. 5.5B and 5.5C). Upon more close examination of Fig. 5.5 it can be seen that generally the 1st and 9th deciles for simulated monthly rainfall amount lie within those for observed rainfall amounts. This is particularly evident in individual months in some cases at some locations (e.g., Pittsworth month 6 [Fig. 5.5A3], Walgett month 2 [Fig. 5.5A5]) and for more lengthy periods in some of the Victorian locations (e.g., Hamilton [Fig. 5.5C1], Rutherglen [Fig. 5.5C3], and Walpeup [Fig. 5.5C4]). These differences indicate that the range of predicted monthly rainfall is less than that observed. This implies that the generator is adequate over most of the range of possible monthly rainfall totals but does not predict extreme rainfall amounts of both the high and low tails of the distribution with sufficient frequency. Further evidence of this shortcoming is provided by the fact that the variance of simulated monthly rainfall totals is, in almost all instances (months and locations), significantly less than that calculated from

Figure 5.5. Comparison of Observed and Simulated Monthly Rainfall (mm) For:

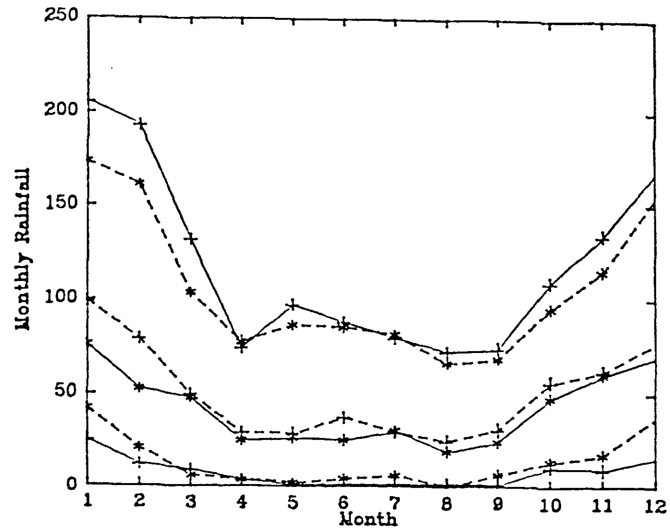
A1.	Biloela	QLD
A2.	Miles	QLD
A3.	Pittsworth	QLD
A4.	Jondaryan	QLD
A5.	Walgett	NSW
A6.	Quirindi	NSW
B1.	Coonabarabran	NSW
B2.	Barraba	NSW
B3.	Dubbo	NSW
B4.	Cobar	NSW
B5.	Bathurst	NSW
B6.	Orange	NSW
B7.	Forbes	NSW
B8.	Temora	NSW
C1.	Hamilton	VIC
C2.	Horsham	VIC
C3.	Rutherglen	VIC
C4.	Walpeup	VIC
C5.	Kerang	VIC
C6.	Griffith	NSW
D1.	Clare	SA
D2.	Waite Institute	SA
D3.	Kybybolite	SA
D4.	Warooka	SA
D5.	Kadina	SA
D6.	Loxton	SA
E1.	Geraldton	WA
E2.	Esperance	WA
E3.	Wongan Hills	WA
E4.	Northam	WA
E5.	Muresk	WA
E6.	Moora	WA

Lines marked (+) indicate deciles calculated from observed data, lines marked (*) indicate deciles calculated from simulated data. Upper lines are ninth decile rainfall amount, middle lines fifth decile, and lowest lines first decile rainfall amount.

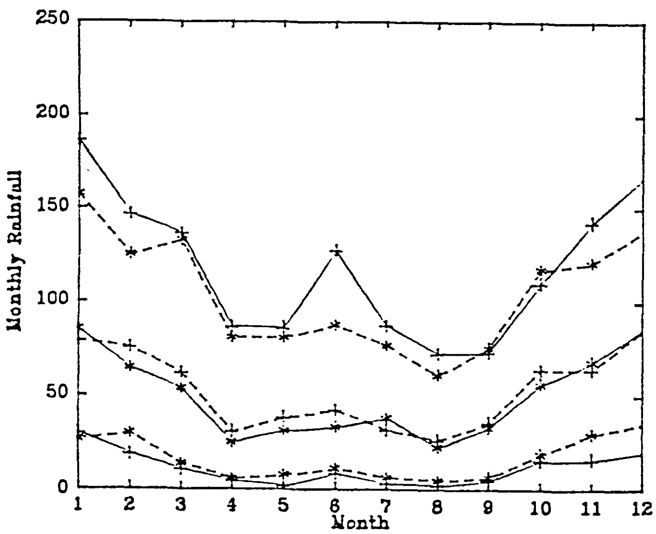
A1. BILOELA



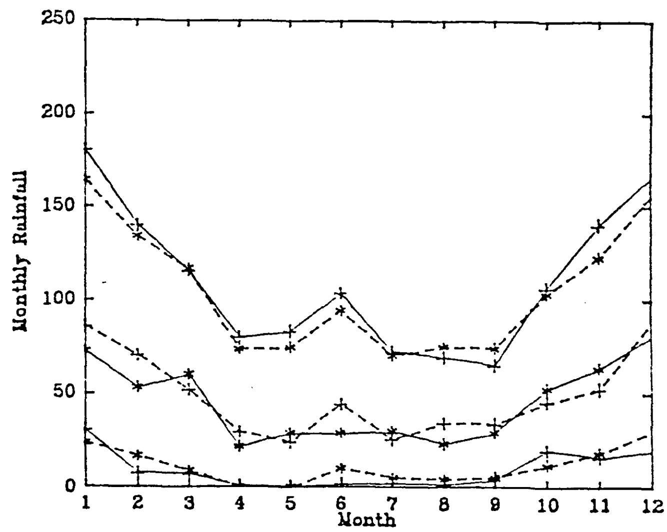
A2. MILES



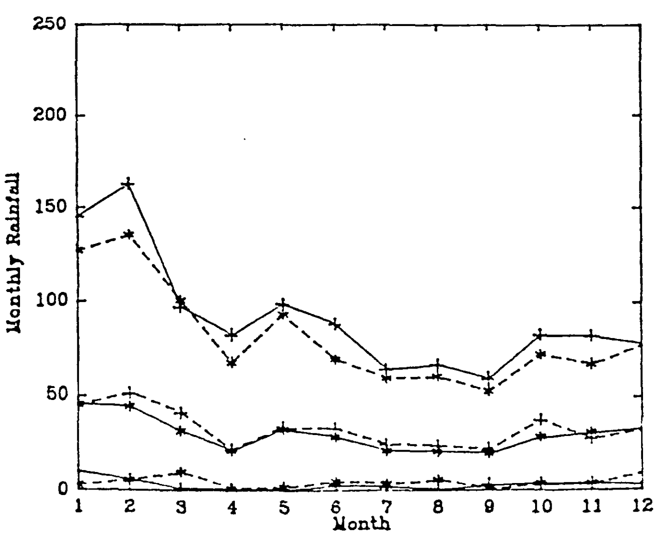
A3. PITTSWORTH



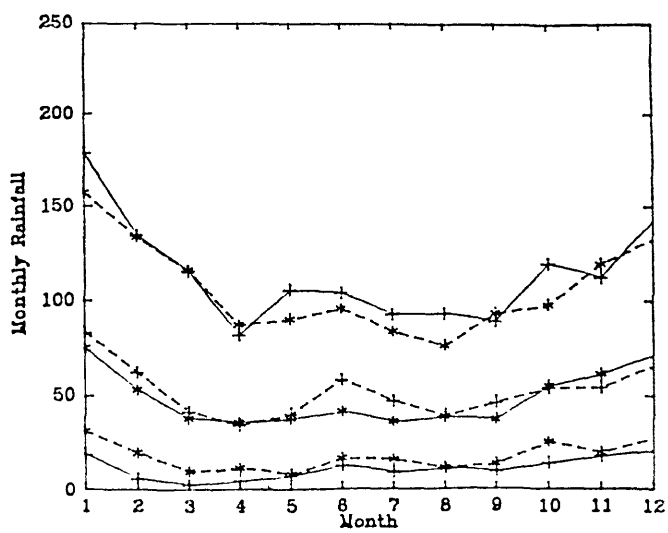
A4. JONDARYAN



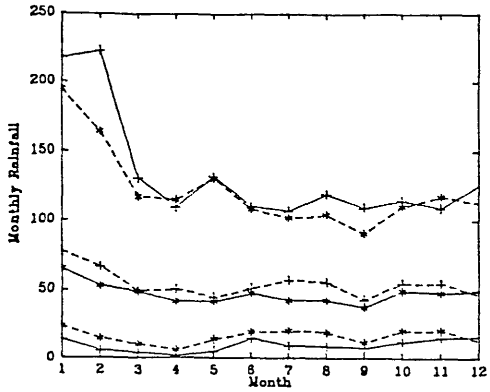
A5. WALGETT



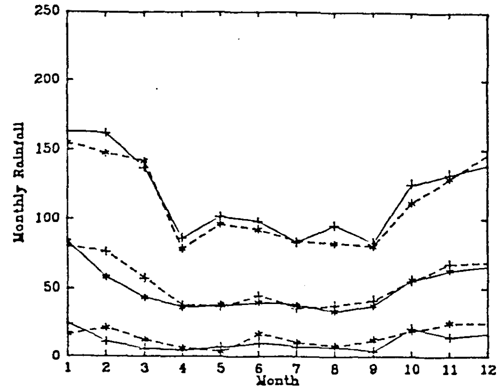
A6. QUIRINDI



B1. COONABARABRAN



B2. BARRABA



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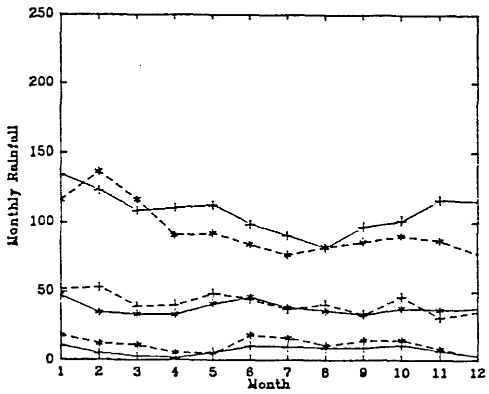
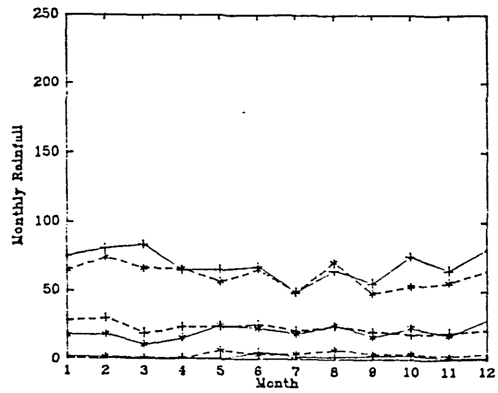
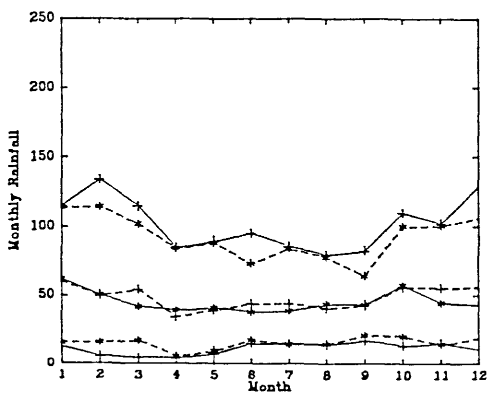


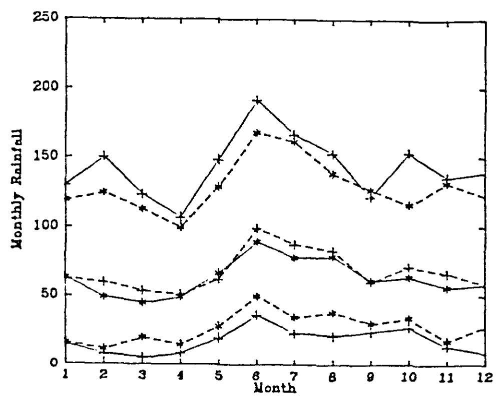
B4. COBAR



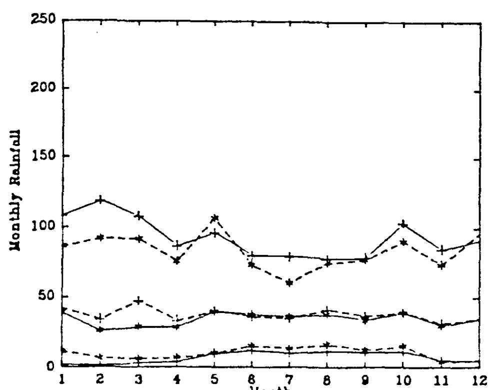
B5. BATHURST



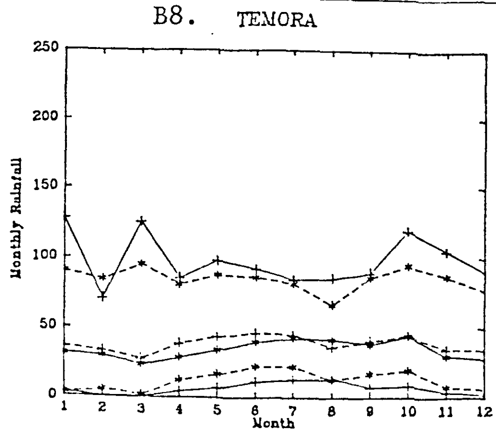
B6. ORANGE



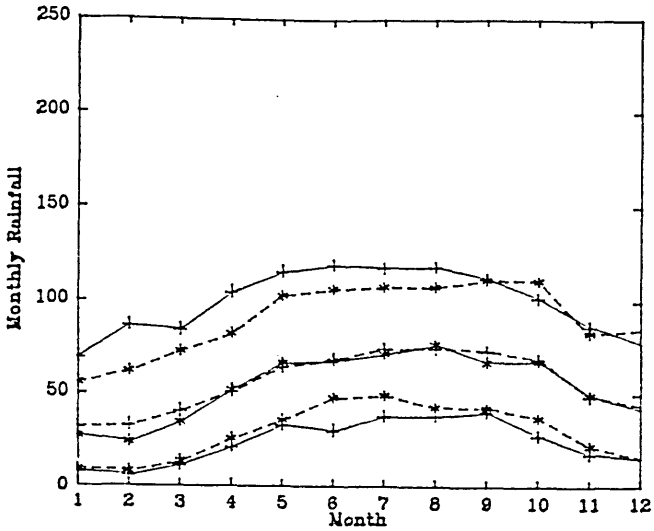
B7. FORBES



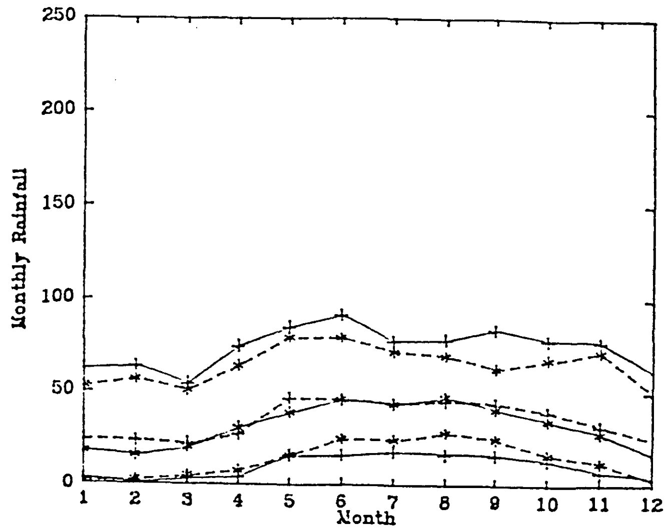
B8. TEMORA



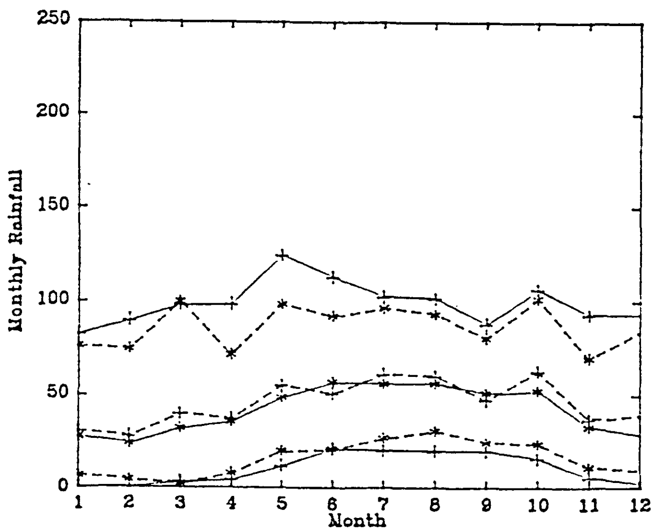
C1. HAMILTON



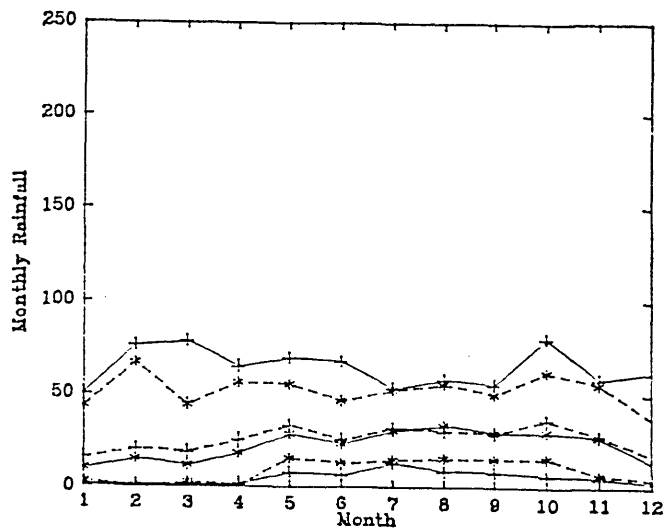
C2. HORSHAM



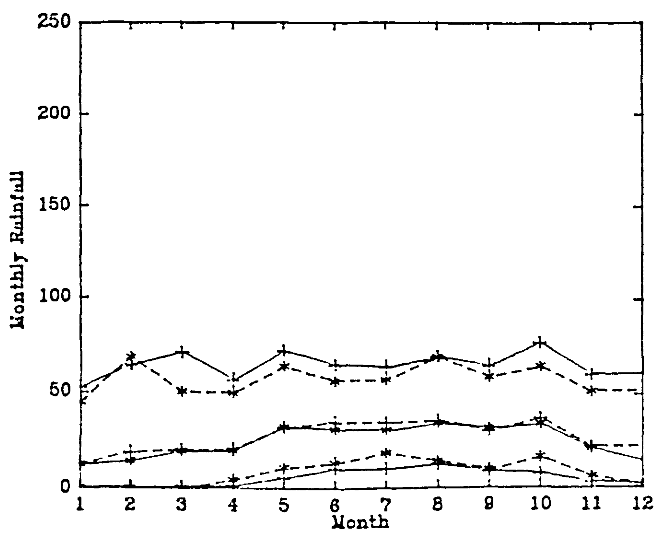
C3. RUTHERGLEN



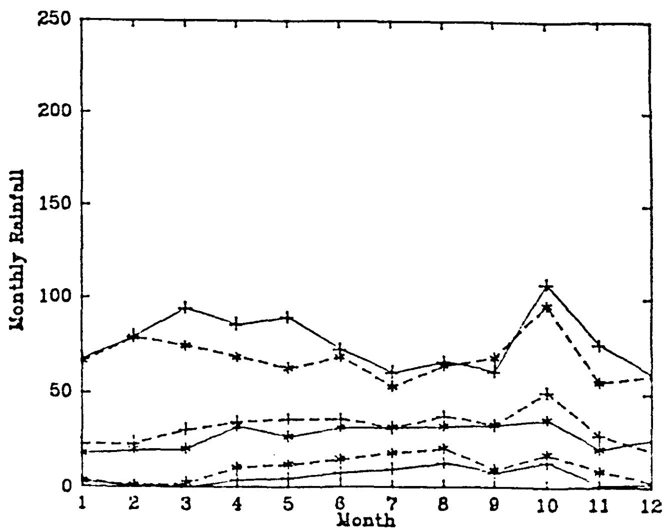
C4. WALPEUP



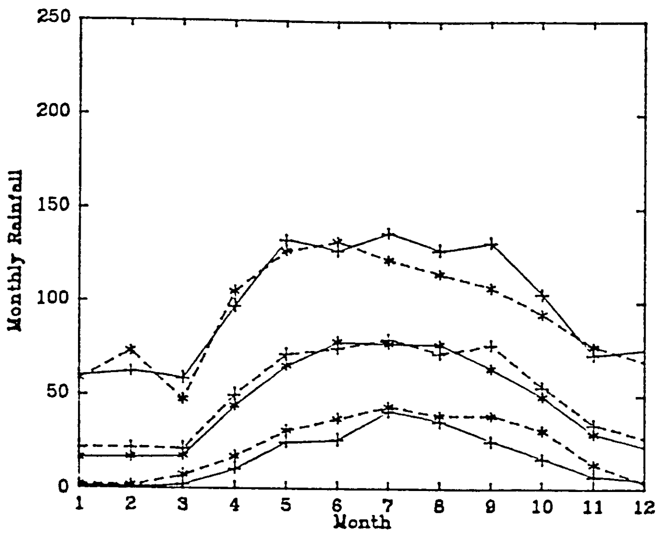
C5. KERANG



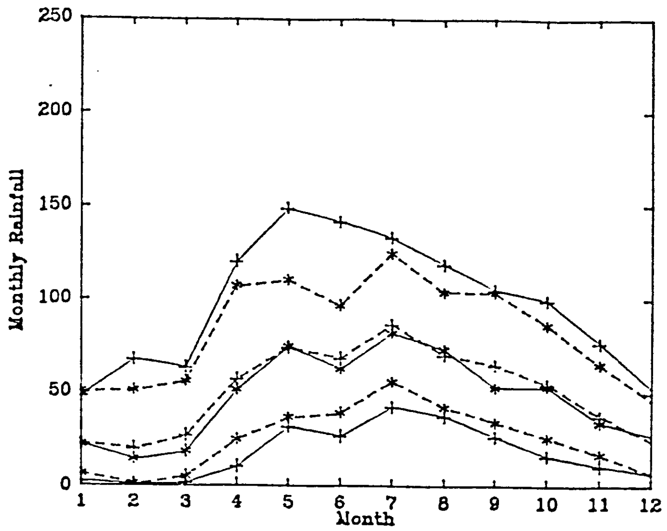
C6. GRIFFITH



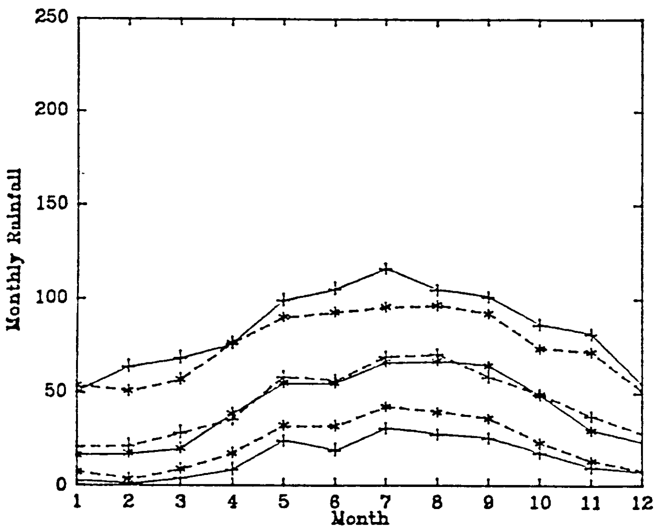
D1. CLARE



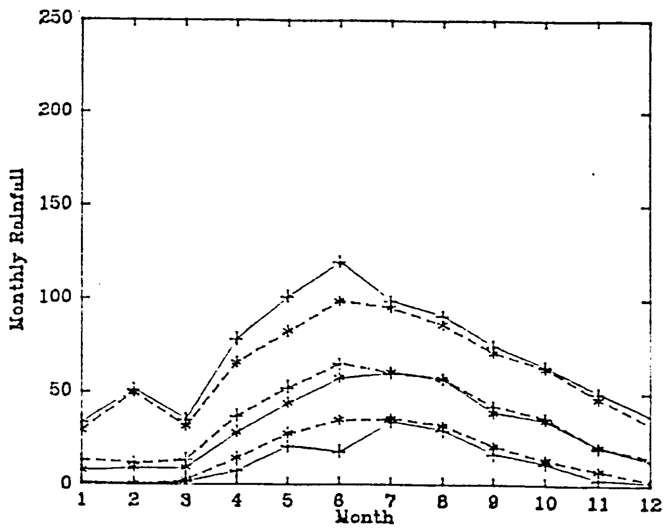
D2. WAITE INSTITUTE



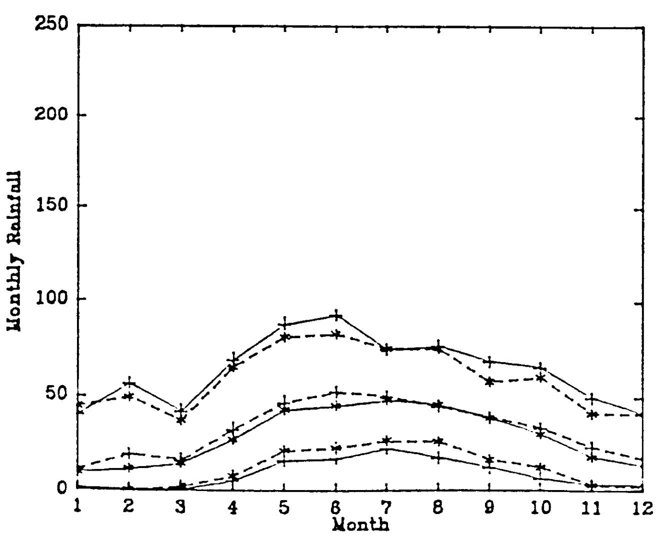
D3. KYBYBOLITE



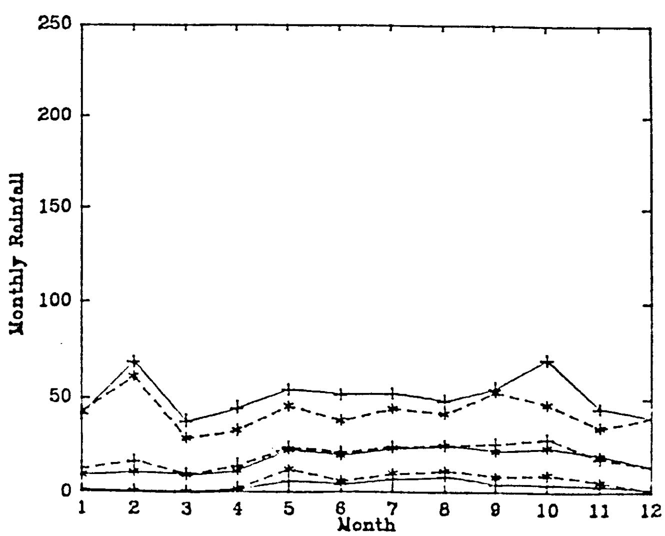
D4. WAROOKA



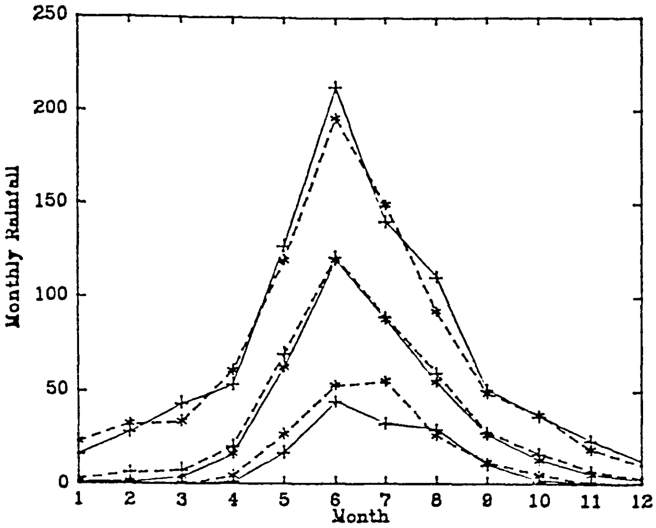
D5. KADINA



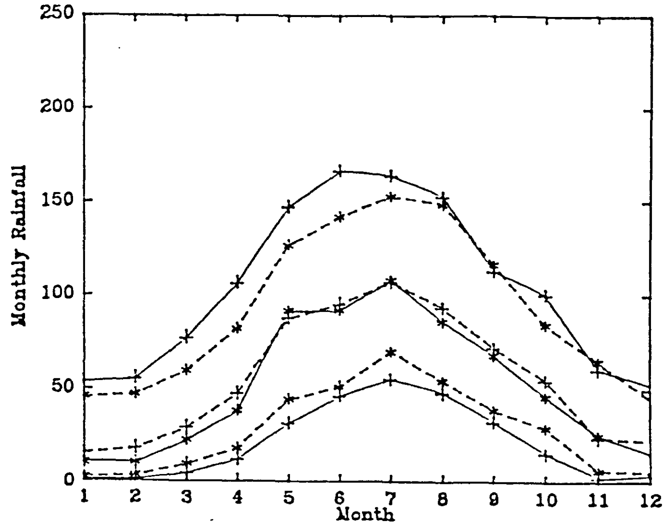
D6. LOXTON



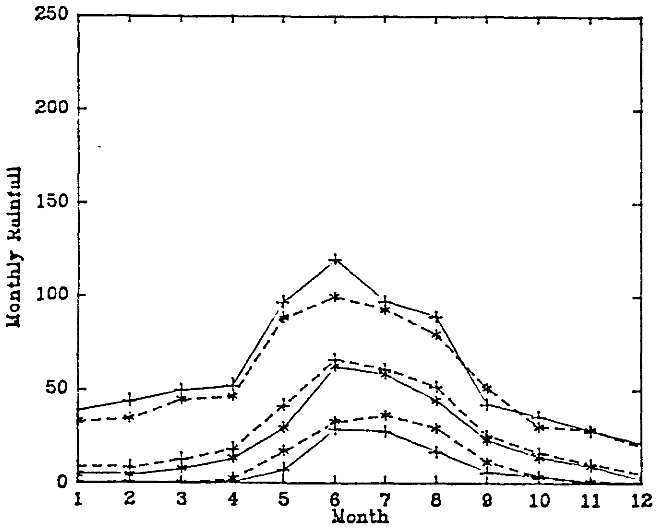
E1. GERALDTON



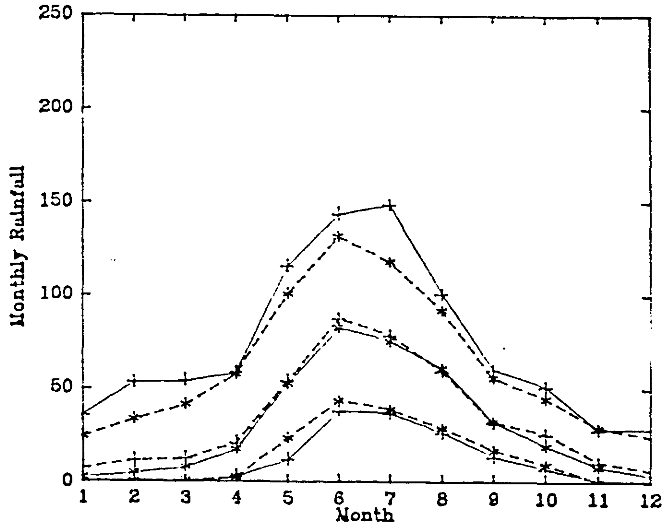
E2. ESPERANCE



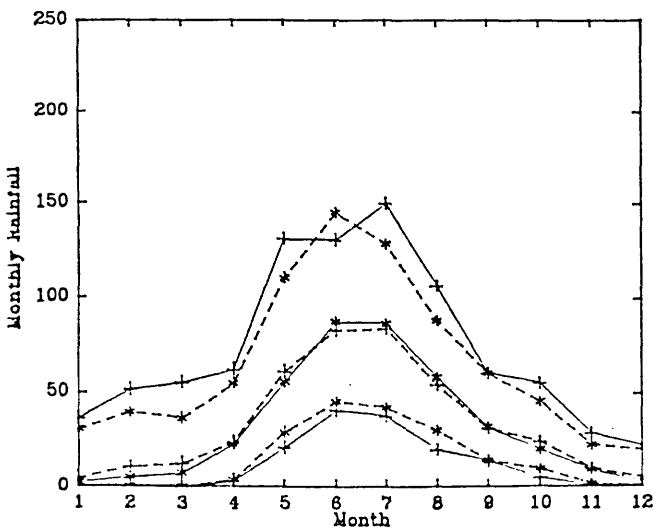
E3. WONGAN HILLS



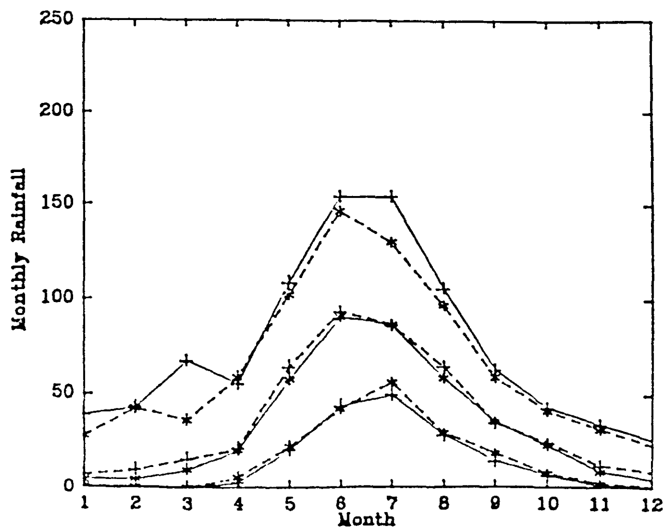
E4. NORTHAM



E5. MURESK



E6. MOORA



the observed data. No consistent annual pattern is evident from the standard deviation of monthly rainfall amounts tabulated (Tables 5.5 to 5.11). When the coefficients of variation for rainfall amount are plotted (Fig. 5.6) it becomes more apparent that the generator is unable to mimic the extremes of variability that occur during the dry season (April to September in Biloela and November to April in Geraldton). During these dry periods the coefficient of variation rises markedly, presumably due to isolated storm events in occasional years and during the wetter months the coefficient is markedly lower. It is during these periods of lesser variability that the generator produces a sequence of rainfall data with variability more closely matching that from observed data. It should be noted, however, particularly in the areas with a Mediterranean-type climate (e.g., Geraldton) that, while these differences in coefficient of variation are large during the dry months, the mean monthly rainfall is quite small (see Fig. 5.5A1 and 5.5E1) and the absolute value of the error is very small.

For further evaluation of generator performance in predicting monthly rainfall amounts it is appropriate to examine both the number of wet days/month and the rainfall per rain event. This provides insights as to the generator's capability of predicting rainfall occurrence as well as event size. In all data sets studied the generated values for these two parameters were not significantly different from the observed. In the more southern locations (winter dominant rainfall) increasing monthly rainfall can be attributed to a large increase in the number of wet days/month and a smaller increase in the amount of rain per rain day (see Tables 5.7, 5.9, and 5.12).

Table 5.5. Comparison of Observed and Simulated Rainfall Parameters for Bathurst

	January	February	March	April	May	June	July	August	September	October	November	December	Year
Monthly Rainfall													
Observed means	65.8	59.9	52.1	43.0	45.5	45.7	44.5	45.3	46.9	60.2	55.5	57.7	622.1
Generated means	61.7	58.9	56.3	40.0	43.4	44.1	45.8	44.9	43.9	60.0	56.7	57.5	613.0
Observed S.D.	44.7	49.6	45.1	31.3	32.2	32.5	28.4	28.2	26.8	35.3	39.0	44.4	
Generated S.D.	38.6	38.6	33.4	28.6	28.3	23.1	24.6	25.6	23.0	31.5	33.8	32.8	
Number of Wet Days/Month													
Observed means	6.5	6.0	6.0	5.9	7.3	8.7	8.9	8.7	8.3	8.2	6.9	6.4	
Generated means	6.3	5.8	6.4	5.7	7.2	8.6	9.2	8.4	8.0	8.1	7.0	7.1	
Observed S.D.	3.2	3.2	3.4	3.4	3.4	3.9	3.7	3.8	3.2	3.5	3.1	3.3	
Generated S.D.	2.8	2.5	2.6	2.8	3.5	3.2	3.2	3.1	2.8	3.0	3.0	2.8	
Rain Per Rain Day													
Observed means	10.0	9.0	7.8	7.1	6.2	5.2	5.1	5.3	5.8	7.1	7.7	8.5	
Generated means	9.5	10.1	8.7	6.6	5.9	5.0	4.8	5.3	5.6	7.3	8.0	8.4	
Observed S.D.	5.7	5.1	4.9	4.3	4.0	2.6	2.6	2.9	2.7	3.6	3.7	4.7	
Generated S.D.	4.5	5.4	3.6	3.9	2.8	2.0	1.8	2.3	2.5	3.0	3.5	4.5	
Number of Consecutive Wet Days													
Observed means	4.1	3.7	3.6	3.4	4.0	4.6	4.8	4.9	4.9	4.8	4.2	4.1	
Generated means	4.0	3.7	3.9	3.3	4.1	4.7	4.9	4.8	4.9	4.6	4.2	4.4	
Observed S.D.	1.6	1.7	1.6	1.7	1.5	1.6	1.6	1.6	1.7	1.7	1.5	1.8	
Generated S.D.	1.7	1.4	1.5	1.4	1.6	1.6	1.4	1.5	1.6	1.5	1.6	1.6	
Number of Falls > 10 mm													
Observed means	2.3	2.1	1.6	1.5	1.4	1.4	1.3	1.3	1.5	2.0	1.9	1.9	20.1
Generated means	2.1	2.0	2.0	1.3	1.5	1.2	1.3	1.3	1.3	2.1	2.0	2.1	20.2
Observed S.D.	1.7	2.0	1.5	1.2	1.3	1.4	1.2	1.1	1.2	1.5	1.5	1.6	
Generated S.D.	1.4	1.4	1.5	1.4	1.4	1.1	1.3	1.2	1.1	1.4	1.4	1.5	
Number of Falls > 25 mm													
Observed means	0.7	0.6	0.5	0.3	0.3	0.2	0.2	0.2	0.2	0.4	0.4	0.6	4.4
Generated means	0.6	0.6	0.4	0.2	0.2	0.1	0.1	0.1	0.1	0.3	0.4	0.4	3.6
Observed S.D.	0.8	0.9	0.8	0.6	0.6	0.4	0.4	0.5	0.4	0.7	0.6	0.8	
Generated S.D.	0.7	0.8	0.6	0.5	0.4	0.3	0.2	0.4	0.4	0.6	0.6	0.6	

Table 5.6. Comparison of Observed and Simulated Rainfall Parameters for Biloela

	January	February	March	April	May	June	July	August	September	October	November	December	Year
Monthly Rainfall													
Observed means	106.6	110.7	65.7	39.6	46.0	33.8	27.8	22.1	22.8	51.6	79.0	94.6	700.3
Generated means	104.9	122.1	66.5	40.1	47.0	35.8	31.6	22.6	22.2	50.4	77.7	87.3	708.3
Observed S.D.	64.1	81.3	51.3	48.3	48.1	29.0	32.5	20.9	25.3	38.4	47.4	62.8	
Generated S.D.	63.3	63.3	45.5	33.7	38.8	29.0	28.9	19.6	18.4	38.6	40.3	46.0	
Number of Wet Days/Month													
Observed means	9.8	8.9	7.0	4.5	4.8	4.5	4.2	3.9	3.6	6.2	7.4	8.5	
Generated means	9.6	9.6	6.9	4.2	5.1	4.6	4.4	3.9	3.6	6.4	7.3	8.0	
Observed S.D.	3.6	4.4	3.9	2.5	3.3	2.6	3.2	2.5	2.3	2.8	3.2	3.5	
Generated S.D.	3.6	3.5	3.4	2.4	2.9	2.5	2.6	2.4	2.4	3.2	2.8	3.2	
Rain Per Rain Day													
Observed means	10.7	12.2	9.2	8.1	8.6	7.4	6.1	4.8	5.0	8.2	10.2	11.2	
Generated means	10.4	12.8	9.4	8.4	9.0	7.4	6.6	5.5	5.8	7.4	11.3	11.3	
Observed S.D.	6.2	7.6	6.9	7.8	6.7	7.3	6.8	3.5	4.5	5.8	5.6	6.3	
Generated S.D.	4.4	4.8	5.5	6.0	5.3	5.1	4.6	4.3	5.0	4.0	7.1	5.4	
Number of Consecutive Wet Days													
Observed means	4.8	4.3	4.0	2.7	2.8	2.5	2.5	2.6	2.3	3.6	4.4	4.6	
Generated means	4.7	4.4	3.9	2.6	2.9	2.5	2.7	2.6	2.3	3.7	4.3	4.6	
Observed S.D.	1.2	1.5	1.6	1.2	1.5	1.2	1.4	1.5	1.4	1.2	1.8	1.6	
Generated S.D.	1.5	1.3	1.5	1.4	1.3	1.2	1.2	1.2	1.4	1.5	1.4	1.4	
Number of Falls > 10 mm													
Observed means	3.2	3.0	2.0	1.1	1.3	1.1	0.9	0.8	0.7	1.7	2.5	2.8	21.0
Generated means	3.5	3.9	2.2	1.4	1.6	1.2	1.0	0.6	0.7	1.8	2.7	2.9	23.6
Observed S.D.	1.9	2.2	1.6	1.4	1.3	1.0	1.1	0.9	0.9	1.6	1.7	1.7	
Generated S.D.	2.3	2.0	1.5	1.2	1.6	1.1	1.1	0.8	1.0	1.7	1.6	1.7	
Number of Falls > 25 mm													
Observed means	1.2	1.4	0.7	0.4	0.5	0.3	0.2	0.1	0.2	0.5	0.9	1.1	7.6
Generated means	1.1	1.6	0.6	0.4	0.6	0.3	0.2	0.1	0.1	0.3	0.8	1.0	7.2
Observed S.D.	1.1	1.3	0.8	0.8	0.8	0.5	0.5	0.3	0.5	0.7	0.8	1.1	
Generated S.D.	1.1	1.2	0.8	0.6	0.8	0.5	0.5	0.4	0.3	0.7	0.9	1.0	

Table 5.7. Comparison of Observed and Simulated Rainfall Parameters for Clare

	January	February	March	April	May	June	July	August	September	October	November	December	Year
Monthly Rainfall													
Observed means	25.5	25.6	26.5	49.8	74.9	79.1	81.4	78.7	71.4	56.7	35.7	27.9	633.1
Generated means	26.5	28.6	23.9	53.8	76.4	80.4	81.0	77.2	76.3	59.1	39.2	29.8	652.2
Observed S.D.	29.0	29.7	28.3	43.7	45.3	40.0	37.0	33.3	38.6	36.1	27.9	26.5	
Generated S.D.	21.6	27.4	15.6	33.2	35.3	34.2	28.7	29.8	27.7	27.8	23.6	23.8	
Number of Wet Days/Month													
Observed means	4.3	4.0	5.0	8.2	11.9	13.8	15.1	14.5	12.4	10.3	7.1	5.1	
Generated means	4.3	4.2	4.7	8.5	12.1	13.9	15.3	14.4	12.8	11.0	7.5	5.6	
Observed S.D.	2.5	2.6	2.9	4.3	4.3	4.2	3.9	4.1	3.7	3.5	3.3	2.7	
Generated S.D.	2.7	3.0	2.4	4.1	4.0	4.3	4.0	4.2	3.3	3.4	3.5	3.2	
Rain Per Rain Day													
Observed means	5.3	5.2	4.7	6.2	6.1	5.5	5.3	5.4	5.6	5.3	4.8	5.2	
Generated means	5.8	6.4	5.1	6.2	6.3	5.8	5.3	5.4	6.0	5.4	5.3	5.0	
Observed S.D.	6.4	4.8	3.8	4.1	2.8	2.1	2.0	1.7	2.2	2.4	2.6	3.9	
Generated S.D.	4.2	5.5	3.0	3.0	2.3	1.8	1.5	1.5	1.6	2.0	2.6	2.9	
Number of Consecutive Wet Days													
Observed means	2.7	2.4	3.0	3.8	4.6	5.1	5.5	5.6	5.4	5.0	3.9	3.1	
Generated means	2.8	2.3	3.0	3.9	4.5	5.1	5.6	5.3	5.4	5.3	4.2	3.3	
Observed S.D.	1.4	1.3	1.5	1.5	1.5	1.6	1.3	1.5	1.4	1.5	1.5	1.3	
Generated S.D.	1.4	1.1	1.2	1.4	1.3	1.3	1.4	1.4	1.2	1.3	1.4	1.7	
Number of Falls > 10 mm													
Observed means	0.7	0.8	0.7	1.5	2.4	2.4	2.4	2.4	2.3	1.8	1.1	0.9	19.4
Generated means	0.8	1.0	0.7	1.8	2.7	2.5	2.3	2.4	2.7	1.8	1.1	0.9	20.5
Observed S.D.	0.9	1.0	1.0	1.5	1.9	1.8	1.7	1.6	1.7	1.4	1.2	1.0	
Generated S.D.	0.9	1.1	0.8	1.5	1.7	1.7	1.6	1.5	1.6	1.3	1.0	1.1	
Number of Falls > 25 mm													
Observed means	0.2	0.2	0.2	0.3	0.5	0.3	0.3	0.3	0.3	0.3	0.1	0.2	3.1
Generated means	0.1	0.2	0.1	0.3	0.3	0.2	0.2	0.1	0.2	0.2	0.1	0.1	2.1
Observed S.D.	0.5	0.4	0.5	0.7	0.8	0.6	0.5	0.5	0.7	0.6	0.4	0.5	
Generated S.D.	0.4	0.5	0.2	0.6	0.5	0.5	0.4	0.3	0.4	0.5	0.4	0.3	

Table 5.8. Comparison of Observed and Simulated Rainfall Parameters for Cobar

	January	February	March	April	May	June	July	August	September	October	November	December	Year
Monthly Rainfall													
Observed means	31.8	33.1	29.9	25.0	28.0	30.6	23.1	29.6	23.5	30.2	28.2	34.6	347.6
Generated means	31.4	35.7	26.1	28.0	27.3	30.0	23.7	31.6	25.2	25.8	25.9	28.4	339.0
Observed S.D.	40.1	37.2	43.3	31.8	23.4	25.1	18.6	23.7	20.5	27.3	30.2	33.1	
Generated S.D.	25.1	32.6	26.1	23.2	19.3	22.7	16.9	23.7	21.0	20.4	22.4	23.1	
Number of Wet Days/Month													
Observed means	3.6	4.3	3.6	3.4	4.8	5.6	5.3	5.3	4.3	4.8	4.2	4.0	
Generated means	3.5	4.2	3.5	3.6	4.8	5.2	5.5	5.3	4.2	4.5	4.1	3.8	
Observed S.D.	2.7	3.1	3.0	2.4	3.3	3.1	3.0	3.2	2.4	2.9	2.7	2.6	
Generated S.D.	2.1	2.7	2.7	2.5	2.9	2.7	3.0	2.6	2.6	2.7	2.5	2.4	
Rain Per Rain Day													
Observed means	7.8	6.6	6.5	6.1	5.9	5.2	4.1	5.3	5.1	6.2	5.8	7.8	
Generated means	8.2	7.6	6.7	7.3	6.0	5.3	4.3	5.7	5.6	5.8	5.8	7.2	
Observed S.D.	7.3	5.9	7.6	7.1	5.7	3.8	2.5	3.7	3.8	4.9	4.8	6.1	
Generated S.D.	6.0	4.5	5.5	5.5	4.3	3.3	2.3	2.9	3.2	3.5	3.6	4.5	
Number of Consecutive Wet Days													
Observed means	2.3	2.5	2.2	2.2	2.8	3.3	3.3	3.3	3.0	3.0	2.8	2.6	
Generated means	2.2	2.4	2.2	2.3	2.9	3.2	3.4	3.3	2.9	3.1	2.6	2.6	
Observed S.D.	1.4	1.5	1.6	1.5	1.7	1.6	1.6	1.7	1.4	1.5	1.5	1.4	
Generated S.D.	1.3	1.4	1.3	1.4	1.4	1.4	1.4	1.5	1.5	1.3	1.3	1.4	
Number of Falls > 10 mm													
Observed means	0.9	1.0	0.8	0.8	0.9	0.9	0.6	0.9	0.7	1.0	0.9	1.1	10.4
Generated means	1.1	1.2	0.9	1.0	0.8	0.9	0.6	1.0	0.8	0.8	0.9	1.0	11.2
Observed S.D.	1.2	1.1	1.4	1.2	1.0	1.2	0.7	1.0	1.0	1.1	1.1	1.2	
Generated S.D.	1.0	1.2	1.1	1.0	0.9	1.0	0.9	1.2	1.0	1.0	1.1	1.0	
Number of Falls > 25 mm													
Observed means	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.3	0.3	2.7
Generated means	0.3	0.3	0.2	0.2	0.1	0.1	0.0	0.1	0.1	0.1	0.1	0.2	1.7
Observed S.D.	0.7	0.7	0.5	0.6	0.4	0.4	0.3	0.4	0.4	0.5	0.6	0.6	
Generated S.D.	0.5	0.5	0.5	0.4	0.3	0.4	0.0	0.3	0.3	0.2	0.4	0.5	

Table 5.9. Comparison of Observed and Simulated Rainfall Parameters for Geraldton

	January	February	March	April	May	June	July	August	September	October	November	December	Year
Monthly Rainfall													
Observed means	6.4	9.7	14.5	23.6	70.4	121.9	89.1	62.5	29.2	17.3	7.9	4.0	456.5
Generated means	6.7	10.9	12.2	26.6	72.1	122.3	93.3	58.6	28.6	19.0	8.3	4.1	462.8
Observed S.D.	13.9	20.8	26.8	24.3	53.6	60.5	40.1	37.6	19.4	14.5	9.2	6.0	
Generated S.D.	9.2	14.0	13.5	21.2	35.4	51.7	37.2	25.3	14.4	12.8	6.6	5.4	
Number of Wet Days/Month													
Observed means	1.5	2.0	2.7	5.0	10.2	13.8	13.7	11.9	8.7	6.0	3.1	1.6	
Generated means	1.7	2.2	2.5	5.1	10.6	14.3	14.0	11.8	8.2	6.1	3.1	1.4	
Observed S.D.	1.5	1.8	2.1	3.1	4.4	3.9	4.5	3.8	3.7	2.7	2.4	1.6	
Generated S.D.	1.5	1.9	1.9	3.3	4.1	4.0	4.1	4.0	3.0	2.7	1.8	1.5	
Rain Per Rain Day													
Observed means	3.0	2.7	3.8	4.1	6.7	8.7	6.5	5.3	3.3	2.7	2.3	1.9	
Generated means	3.2	3.5	4.0	5.3	6.9	8.6	6.7	5.0	3.5	3.1	2.7	2.1	
Observed S.D.	5.4	4.3	5.0	3.3	3.4	3.4	2.4	2.7	1.7	1.9	2.3	3.2	
Generated S.D.	4.8	3.7	4.2	3.5	2.4	2.8	1.9	1.8	1.2	1.7	2.1	2.4	
Number of Consecutive Wet Days													
Observed means	1.2	1.4	1.8	2.7	4.4	5.2	5.2	5.2	4.7	3.9	2.2	1.3	
Generated means	1.3	1.6	1.8	2.8	4.6	5.1	5.0	4.9	4.7	4.0	2.2	1.1	
Observed S.D.	1.1	1.2	1.1	1.6	1.4	1.4	1.6	1.4	1.6	1.7	1.4	1.1	
Generated S.D.	1.0	1.2	1.2	1.3	1.4	1.3	1.3	1.3	1.4	1.6	1.2	1.1	
Number of Falls > 10 mm													
Observed means	0.2	0.3	0.4	0.6	2.2	4.0	2.8	1.8	0.6	0.3	0.2	0.0	13.3
Generated means	0.2	0.3	0.4	0.8	2.4	4.5	3.0	1.6	0.4	0.2	0.1	0.0	13.9
Observed S.D.	0.5	0.7	0.9	0.8	2.0	2.3	1.7	1.5	0.8	0.5	0.5	0.2	
Generated S.D.	0.4	0.7	0.7	1.1	1.4	2.4	1.7	1.3	0.6	0.4	0.3	0.2	
Number of Falls > 25 mm													
Observed means	0.0	0.1	0.2	0.1	0.5	1.1	0.6	0.2	0.1	0.0	0.0	0.0	2.9
Generated means	0.0	0.0	0.0	0.1	0.3	0.9	0.5	0.2	0.0	0.0	0.0	0.0	2.1
Observed S.D.	0.2	0.2	0.4	0.4	0.8	1.1	0.7	0.5	0.3	0.2	0.1	0.0	
Generated S.D.	0.1	0.1	0.2	0.2	0.5	1.0	0.7	0.4	0.1	0.1	0.0	0.0	

Table 5.10. Comparison of Observed and Simulated Rainfall Parameters for Temora

	January	February	March	April	May	June	July	August	September	October	November	December	Year
Monthly Rainfall													
Observed means	44.0	32.8	41.3	42.0	44.4	49.3	45.6	46.1	42.4	50.6	41.8	38.0	518.4
Generated means	43.4	38.5	37.3	43.9	47.3	50.4	48.9	39.1	47.2	51.3	41.1	36.9	525.3
Observed S.D.	45.3	27.7	48.0	42.0	36.0	32.6	26.3	28.5	27.7	37.3	36.4	36.7	
Generated S.D.	39.5	28.8	33.1	26.3	27.5	24.6	22.7	21.2	27.3	32.1	31.4	27.3	
Number of Wet Days/Month													
Observed means	4.0	3.6	3.8	5.0	5.9	8.3	8.8	8.4	6.7	6.6	4.7	4.0	
Generated means	3.9	3.9	3.6	5.2	6.2	8.3	9.1	7.9	7.2	6.7	4.9	4.0	
Observed S.D.	2.6	2.4	2.9	3.1	3.4	3.7	3.7	4.0	2.8	3.1	2.9	3.0	
Generated S.D.	2.4	2.3	2.4	2.6	2.6	3.2	3.0	3.1	2.6	2.8	2.3	2.2	
Rain Per Rain Day													
Observed means	9.4	8.4	8.8	7.6	7.2	5.9	5.1	5.4	6.2	7.1	8.7	8.3	
Generated means	10.6	9.8	9.7	8.8	8.1	6.0	5.5	5.0	6.5	7.9	8.0	9.2	
Observed S.D.	6.7	6.3	6.8	5.5	4.1	2.9	2.7	2.4	3.3	3.7	6.8	6.2	
Generated S.D.	7.7	6.9	7.6	5.1	5.0	2.3	2.1	2.1	3.0	3.8	4.7	6.9	
Number of Consecutive Wet Days													
Observed means	2.8	2.5	2.7	3.2	3.6	4.7	4.6	5.2	4.3	4.3	3.1	2.9	
Generated means	2.7	2.7	2.5	3.3	3.7	4.6	4.7	4.8	4.6	4.3	3.3	2.8	
Observed S.D.	1.5	1.3	1.6	1.7	1.7	1.6	1.8	1.9	1.6	1.9	1.6	1.8	
Generated S.D.	1.5	1.4	1.4	1.4	1.3	1.5	1.4	1.6	1.4	1.6	1.3	1.4	
Number of Falls > 10 mm													
Observed means	1.4	1.3	1.4	1.3	1.4	1.5	1.4	1.3	1.3	1.5	1.3	1.1	16.3
Generated means	1.4	1.3	1.4	1.6	1.6	1.7	1.5	1.0	1.6	1.8	1.4	1.3	17.6
Observed S.D.	1.5	1.2	1.6	1.4	1.4	1.3	1.3	1.2	1.3	1.6	1.3	1.3	
Generated S.D.	1.3	1.2	1.4	1.3	1.3	1.3	1.3	1.0	1.3	1.5	1.2	1.2	
Number of Falls > 25 mm													
Observed means	0.5	0.3	0.4	0.3	0.3	0.3	0.2	0.2	0.3	0.4	0.4	0.4	3.9
Generated means	0.5	0.4	0.4	0.3	0.2	0.2	0.1	0.1	0.2	0.3	0.3	0.3	3.4
Observed S.D.	0.8	0.5	0.8	0.6	0.7	0.6	0.4	0.4	0.5	0.6	0.6	0.6	
Generated S.D.	0.8	0.6	0.6	0.6	0.5	0.4	0.3	0.2	0.5	0.5	0.6	0.6	

Table 5.11. Comparison of Observed and Simulated Rainfall Parameters for Quirindi

	January	February	March	April	May	June	July	August	September	October	November	December	Year
Monthly Rainfall													
Observed means	84.5	69.0	52.6	41.8	45.8	51.2	46.0	44.4	45.7	60.1	63.2	76.7	680.9
Generated means	87.2	66.7	54.9	42.3	44.6	56.9	48.7	41.0	50.0	57.4	61.3	74.1	685.0
Observed S.D.	57.0	58.4	50.2	36.0	35.6	37.8	34.1	30.5	32.9	38.0	38.8	48.9	
Generated S.D.	47.9	43.1	41.4	31.3	32.1	33.4	28.5	24.3	32.8	28.9	37.7	46.6	
Number of Wet Days/Month													
Observed means	6.7	5.8	4.7	4.7	5.6	7.0	6.7	6.5	6.1	6.9	6.5	6.5	
Generated means	7.0	5.7	4.8	4.8	5.8	7.2	6.8	6.6	6.3	6.4	6.3	6.7	
Observed S.D.	2.9	3.2	2.9	2.7	3.2	3.7	3.1	3.0	2.9	3.3	2.9	2.8	
Generated S.D.	2.8	3.0	2.6	2.6	3.3	3.0	2.9	2.9	3.1	2.7	2.8	2.7	
Rain Per Rain Day													
Observed means	12.4	11.3	10.5	8.5	8.0	7.4	6.4	6.8	7.2	8.7	9.6	11.4	
Generated means	12.3	11.6	11.3	8.9	7.3	7.9	7.3	6.2	7.9	9.4	9.4	11.3	
Observed S.D.	7.2	8.3	9.1	6.6	4.9	4.7	3.3	3.8	3.8	4.3	4.8	5.9	
Generated S.D.	4.8	5.9	6.6	6.0	4.0	3.8	3.6	3.2	4.2	4.8	4.0	6.3	
Number of Consecutive Wet Days													
Observed means	4.0	3.5	3.1	2.8	3.3	3.9	4.2	4.1	3.8	4.4	4.1	4.3	
Generated means	4.2	3.5	3.1	2.8	3.2	3.8	4.0	4.1	3.8	4.4	3.9	4.3	
Observed S.D.	1.4	1.6	1.6	1.5	1.4	1.7	1.8	1.7	1.6	1.6	1.6	1.6	
Generated S.D.	1.5	1.4	1.4	1.3	1.4	1.4	1.4	1.6	1.5	1.4	1.4	1.6	
Number of Falls > 10 mm													
Observed means	2.5	2.1	1.7	1.4	1.5	1.7	1.5	1.4	1.5	2.1	2.3	2.6	22.3
Generated means	3.1	2.3	2.0	1.5	1.6	2.0	1.7	1.5	1.8	2.2	2.3	2.6	24.6
Observed S.D.	1.6	1.7	1.5	1.4	1.4	1.4	1.3	1.3	1.3	1.5	1.7	1.7	
Generated S.D.	1.7	1.5	1.6	1.3	1.5	1.5	1.4	1.3	1.5	1.3	1.7	1.7	
Number of Falls > 25 mm													
Observed means	1.1	0.7	0.5	0.4	0.4	0.4	0.3	0.2	0.3	0.5	0.6	0.9	6.5
Generated means	1.0	0.7	0.6	0.3	0.2	0.4	0.3	0.2	0.3	0.4	0.5	0.7	5.7
Observed S.D.	1.1	1.0	0.8	0.7	0.6	0.7	0.6	0.5	0.6	0.7	0.8	0.9	
Generated S.D.	1.0	0.8	0.8	0.6	0.5	0.6	0.5	0.4	0.6	0.6	0.7	0.9	

Table 5.12. Comparison of Observed and Simulated Rainfall Parameters for Rutherglen

	January	February	March	April	May	June	July	August	September	October	November	December	Year
Monthly Rainfall													
Observed means	36.1	38.2	44.2	43.0	54.9	62.3	59.6	58.5	52.7	57.1	43.1	40.9	590.6
Generated means	35.1	36.2	45.9	40.9	57.6	55.8	60.2	61.7	50.3	60.8	39.8	43.3	587.6
Observed S.D.	36.8	47.9	43.4	35.6	37.7	35.4	33.7	29.3	27.9	35.2	35.8	39.8	
Generated S.D.	26.8	31.5	35.7	27.0	29.5	27.2	26.3	23.8	22.2	30.1	24.6	28.2	
Number of Wet Days/Month													
Observed means	4.1	3.8	4.8	5.9	8.4	9.9	11.3	11.0	8.9	8.1	5.9	4.7	
Generated means	4.1	3.4	4.6	5.7	8.5	9.3	11.6	11.4	8.6	8.2	5.5	5.0	
Observed S.D.	2.6	2.5	3.1	3.6	3.9	3.8	3.6	3.7	2.8	3.6	2.8	2.7	
Generated S.D.	2.4	2.1	3.0	2.8	3.2	2.9	3.9	3.5	2.8	3.2	2.5	2.5	
Rain Per Rain Day													
Observed means	7.6	8.1	7.9	6.9	6.2	6.4	5.2	5.2	5.9	6.9	6.6	7.7	
Generated means	8.6	10.5	9.6	6.9	6.9	5.9	5.2	5.5	6.0	7.6	7.0	8.7	
Observed S.D.	6.4	7.9	5.1	3.9	3.1	3.1	2.4	1.8	2.5	3.4	4.4	5.6	
Generated S.D.	5.5	8.2	6.4	3.7	2.9	2.1	1.6	2.0	2.2	3.3	3.4	5.7	
Number of Consecutive Wet Days													
Observed means	2.8	2.5	3.0	3.5	4.5	5.0	5.7	5.8	5.3	4.9	4.0	3.4	
Generated means	2.9	2.4	3.0	3.5	4.6	5.2	5.8	5.8	5.3	4.8	3.7	3.4	
Observed S.D.	1.6	1.4	1.7	1.8	1.8	1.6	1.5	1.6	1.6	1.8	1.6	1.6	
Generated S.D.	1.6	1.2	1.6	1.5	1.6	1.5	1.5	1.3	1.4	1.4	1.4	1.4	
Number of Falls > 10 mm													
Observed means	1.2	1.2	1.5	1.3	1.8	2.0	1.7	1.7	1.6	1.9	1.3	1.3	18.5
Generated means	1.3	1.1	1.7	1.4	2.0	1.8	1.8	1.7	1.6	2.3	1.4	1.6	19.6
Observed S.D.	1.4	1.3	1.7	1.3	1.6	1.6	1.5	1.3	1.3	1.4	1.3	1.3	
Generated S.D.	1.2	1.1	1.5	1.1	1.3	1.3	1.2	1.3	1.1	1.6	1.1	1.3	
Number of Falls > 25 mm													
Observed means	0.3	0.4	0.3	0.3	0.3	0.4	0.3	0.2	0.3	0.4	0.3	0.4	3.8
Generated means	0.3	0.4	0.4	0.3	0.3	0.2	0.1	0.2	0.1	0.3	0.2	0.3	3.0
Observed S.D.	0.6	0.8	0.7	0.6	0.6	0.6	0.5	0.4	0.5	0.6	0.7	0.6	
Generated S.D.	0.5	0.6	0.6	0.5	0.5	0.5	0.4	0.4	0.4	0.5	0.4	0.5	

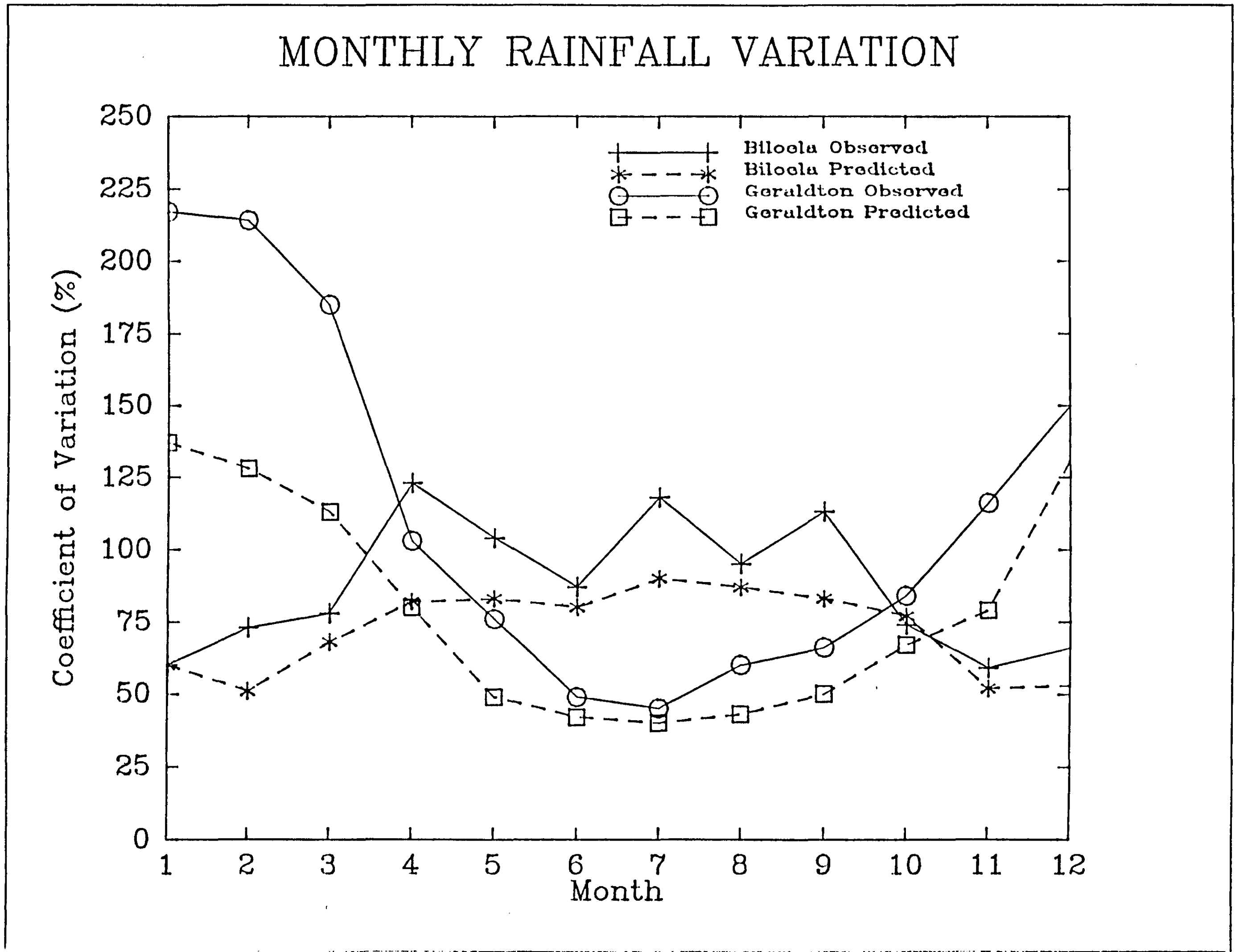


Figure 5.6. Comparison of the Coefficient of Variation for Monthly Rainfall Amount Calculated From Observed and Predicted Rainfall at Biloela and Geraldton.

In the more northern locations increasing monthly rainfall is more due to an increase in rain per rain day than to an increase in the frequency of rainfall (Table 5.6). Intermediate locations in the wheat belt with more evenly distributed rainfall have higher relative monthly rainfall totals associated with increases in both parameters. The plotted rainfall event size data (Figure 5.7) and tabulated event frequency data (Tables 5.5 to 5.12) illustrate that the generator is appropriately mimicking these differences.

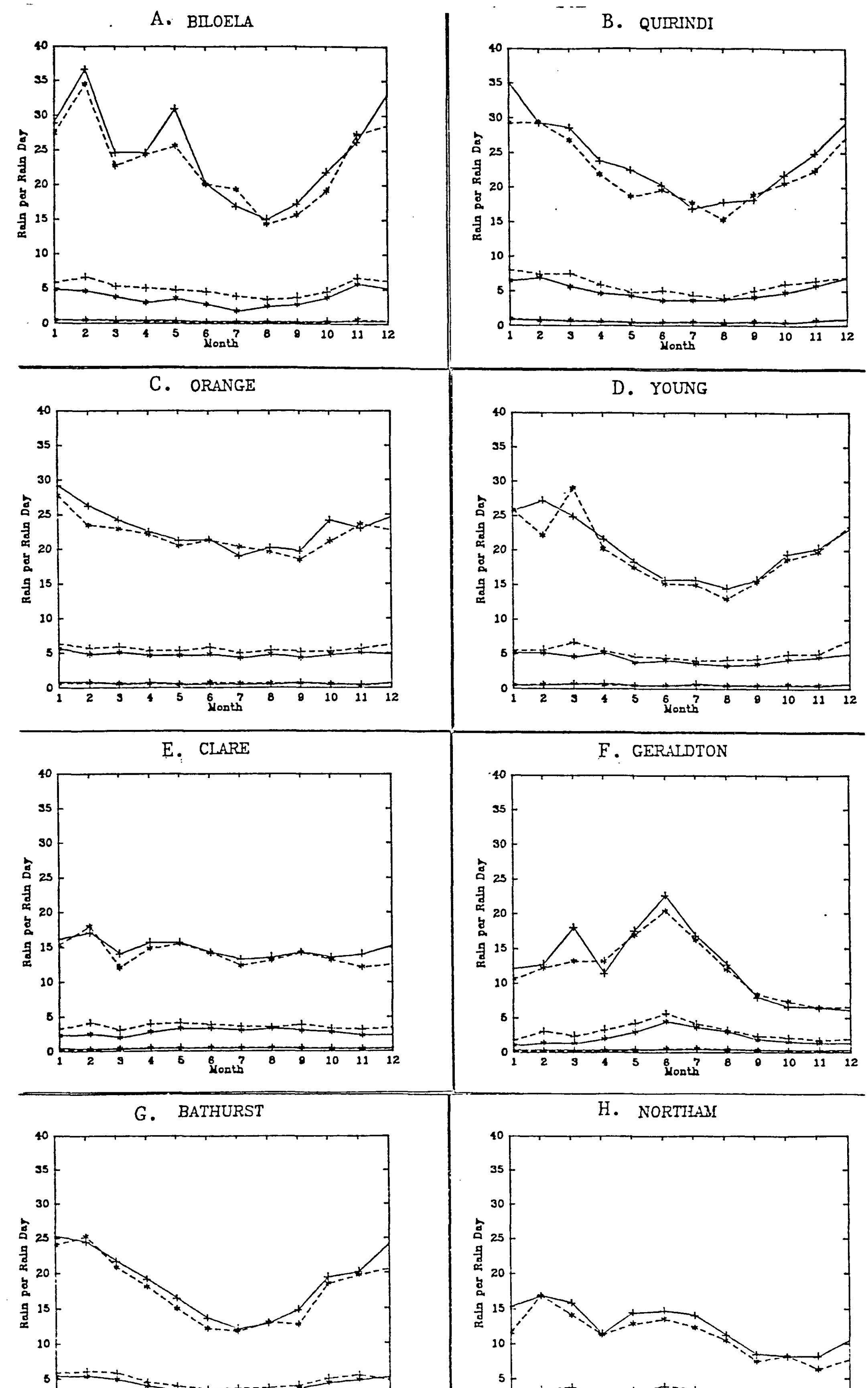
These changes in simulated rainfall occurrence throughout the year are associated with increases in P(W/W) and P(W/D) during the wet months (Appendix 6) for Esperance and due to large increases in the scale parameter (β) of the gamma distribution which determines rainfall amount at Biloela. The variance of rainfall per event and number of wet days per month were in almost all instances significantly less than those calculated from the observed data. This difference in "spread" of the distribution for rainfall amount per event (Fig. 5.7) is less obvious than for the monthly rainfall totals (Fig. 5.5).

The ability of the generator to capture the mean effects but to miss some of the extremes is also exemplified by the frequency of large rainfall events. At all sites tested except Barraba, Biloela, Coonabarabran, Cowra, Jondaryan, Springsure, and Warialda in at least 1 month of the year the model significantly underpredicted the number of daily rainfall events of over 25 mm. In 13 of the stations tested the model significantly underpredicted the number of daily rainfall events of greater than 10 mm in at least 1 month of the year. It should be noted, however, that the inability of the generator to simulate the extremes of rainfall distribution was by far the exception

Figure 5.7. Comparison of Observed and Simulated Rainfall (mm) Per Rainy Day for Eight Locations.

A.	Biloela	QLD
B.	Quirindi	NSW
C.	Orange	NSW
D.	Young	NSW
E.	Clare	SA
F.	Geraldton	WA
G.	Bathurst	NSW
H.	Northam	WA

Lines marked (+) indicate deciles calculated from observed data, lines marked (*) indicate deciles calculated from simulated data. Upper lines are ninth decile rainfall amount, middle lines fifth decile rainfall amount, and lowest lines are first decile rainfall amounts.


A. BILOELA
B. QUIRINDI
C. ORANGE
D. YOUNG
E. CLARE
F. GERALDTON
G. BATHURST
H. NORTHAM
Rain per Rain Day
Month
0
5
10
15
20
25
30
35
40
1
2
3
4
5
6
7
8
9
10
11
12

rather than the rule. Significant differences in the number of rainfall events greater than 10 mm were observed in only 17 cases of a total of 624 location month combinations.

Examining the length of dry spells (consecutive days without rain) and wet spells (consecutive wet days) tests the model's ability to predict persistence. In all locations studied the model reproduced the mean monthly number of consecutive wet days in a manner not significantly different from the data observed. One problem which occurs in this type of analysis is that frequently wet spells cross month boundaries and thus the wet spell length may not be a true wet spell length, particularly in locations with many wet days per month. The generator very closely simulated the number of periods without rain as indicated by the number of dry spells per year (Table 5.13). The simulator for most sites underpredicted the length of the longest dry spell by an average margin of 11.5 days and at worst (Condobolin, Table 5.13), 82 days. The 9th decile lengths of dry spells for simulated and observed were very similar, indicating that only in extreme cases (less than 10% of cases) was the simulator unable to reproduce sequences of dry days.

5.5.2. Temperature

In most locations the simulator reliably reproduced temperature sequences similar to those observed. Several months at some of the locations (Table 5.14) had simulated temperatures significantly different from the means calculated from the observed data. Consistent underestimates of minimum temperature occurred at some locations (e.g., Geraldton and Tamworth in Figure 5.8) but consistent patterns of inaccuracies in simulation were not discernable at most locations. The generator performed equally on dry days as on wet days.

Table 5.13. Comparison of Observed and Simulated Dry Spells for Selected Locations

Station	Mean Number of Dry Spells Per Year		Longest Dry Spell		Mean Length of Dry Spells	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
			- - - - - - - - - -(days)- - - - - - - - - -			
Bathurst	52.2	52.3	91.0	56.0	5.8	5.6
Biloela	42.7	42.8	70.0	80.0	8.0	7.9
Cobar	36.0	35.7	132.0	87.0	10.2	9.8
Condobolin	42.8	43.2	135.0	53.0	8.1	7.7
Cowra	47.4	46.6	71.0	64.0	6.8	6.7
Dalby	43.2	42.6	80.0	69.0	7.8	7.6
Dubbo	44.3	44.0	78.0	64.0	7.3	7.0
Esperance	58.7	58.8	50.0	45.0	4.6	4.5
Geraldton	40.5	40.4	111.0	126.0	10.1	9.9
Griffith	47.9	48.7	101.0	78.0	7.0	6.5
Kadina	50.7	50.7	110.0	100.0	6.7	6.7
Kybybolite	54.6	54.7	59.0	61.0	4.6	4.6
Loxton	45.9	44.9	75.0	86.0	8.0	8.0
Muresk	43.2	41.9	105.0	102.0	8.6	9.0
Pittsworth	48.4	48.5	62.0	67.0	6.7	6.6
Quirindi	47.1	47.1	58.0	61.0	6.8	6.7
Rutherglen	51.8	51.6	64.0	88.0	6.3	6.3
Walgett	36.1	35.9	102.0	76.0	9.6	9.4
Wongan Hills	41.8	43.1	103.0	81.0	10.0	8.9
Young	49.6	49.1	78.0	58.0	6.4	6.2

The generator performed poorly in estimation of the frequency of extreme temperatures in months where these are rare events. During the summer months the generator did not simulate the occurrence of cold days (minimum temperatures less than or equal to 5°C) sufficiently frequently and tended to simulate too many cold days in the winter months (Table 5.14). This phenomenon was particularly apparent at the high altitude site Coonabarabran. This error in temperature estimation during the summer months would have little impact on the simulation of the wheat crop since this is outside the growth period.

Table 5.14. Comparison of Observed and Predicted

(i) Daily maximum temperatures for each month
(ii) Daily minimum temperatures for each month
(iii) Number of days per month with maximum temperatures exceeding 35°C
(iv) Number of days per month with minimum temperature less than or equal to 5°C

Parameter	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
A. Dalby												
Daily minimum (°C)												
Observed mean	18.75	18.09	15.59	11.44	7.19	5.16	4.94	6.60	10.18	14.10	15.62	18.18
Generated mean	19.35	18.39	16.29	12.35	9.19	6.11	4.97	6.03	8.63	12.39	15.87	18.22
Daily maximum (°C)												
Observed mean	31.51	30.64	28.53	25.32	20.87	18.86	19.45	21.45	25.24	28.18	30.94	31.39
Generated mean	32.83	31.92	30.01	26.38	23.18*	20.39*	19.52	20.29	22.65*	26.13*	29.44	31.67
Number of days > 35°C												
Observed mean	5.32	3.18	0.32	0.09	0.00	0.00	0.00	0.00	0.14	1.36	4.64	4.82
Generated mean	7.71*	4.78*	2.06*	0.04	0.00	0.00	0.00	0.00	0.00	0.10	1.02	4.43
Number of days ≦ 5°C												
Observed mean	0.00	0.00	0.00	1.41	11.14	16.14	17.23	12.73	3.18	0.14	0.00	0.00
Generated mean	0.00	0.00	0.00	1.41	5.65*	11.80*	15.69	12.41	6.43*	1.65*	0.08	0.00
B. Cobar												
Daily minimum (°C)												
Observed mean	20.63	19.22	15.73	11.61	7.55	5.34	5.18	7.04	10.20	13.68	16.81	19.24
Generated mean	20.25	19.40	16.59	12.78	8.43	6.13	4.97	6.17	8.68	12.39	16.09	18.96
Daily maximum (°C)												
Observed mean	33.79	32.19	28.57	23.55	18.03	15.91	16.42	18.83	22.88	26.83	30.74	33.02
Generated mean	34.05	33.07	29.83	25.12	20.26*	17.25	16.03	17.18	20.36*	24.71	29.50	32.63
Number of days > 35°C												
Observed mean	13.58	7.47	1.74	0.00	0.00	0.00	0.00	0.00	0.21	1.68	6.84	11.32
Generated mean	12.96	9.31	3.29*	0.24	0.00	0.00	0.00	0.00	0.00*	0.35*	2.90*	8.65*
Number of days ≦ 5°C												
Observed mean	0.00	0.00	0.00	1.32	7.11	14.74	16.11	9.16	2.95	0.11	0.00	0.00
Generated mean	0.00	0.00	0.06	0.82	5.71	10.43*	15.49	10.63	4.84*	1.06*	0.10	0.00

(Continued)

Table 5.14. Comparison of Observed and Predicted (Continued)

(i) Daily maximum temperatures for each month
(ii) Daily minimum temperatures for each month
(iii) Number of days per month with maximum temperatures exceeding 35°C
(iv) Number of days per month with minimum temperature less than or equal to 5°C

Parameter	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
C. Coonabarrabran												
Daily minimum (°C)												
Observed mean	15.90	14.23	10.81	6.17	2.92	1.11	0.57	2.60	5.42	9.41	12.17	14.79
Generated mean	15.58	14.37	12.19	7.61	3.41	1.20	0.32	1.46	3.70	7.70	11.17	14.81
Daily maximum (°C)												
Observed mean	30.98	29.36	26.74	22.30	17.51	15.57	15.76	17.96	21.42	25.17	29.43	30.78
Generated mean	31.92	30.68	28.32	23.91	19.66*	16.60	15.54	16.63	19.43	23.28	27.50	30.40
Number of days > 35°C												
Observed mean	5.65	1.26	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.70	3.13	5.74
Generated mean	5.45	3.29*	1.27*	0.02	0.00	0.00	0.00	0.00	0.00	0.02*	0.51*	2.96*
Number of days ≦ 5°C												
Observed mean	0.00	0.00	2.04	13.00	22.22	24.22	26.70	23.61	15.43	4.91	0.74	0.09
Generated mean	6.82*	4.47*	2.45	11.98	16.92*	22.29	30.39*	23.18	15.78	12.45*	4.02*	2.88*
D. Geraldton												
Daily minimum (°C)												
Observed mean	19.01	18.15	16.25	13.58	11.46	9.77	8.96	9.00	10.38	12.63	15.67	17.66
Generated mean	18.77	17.88	16.07	13.43	11.04	9.01	8.66	9.29	10.92	13.35	15.82	17.55
Daily maximum (°C)												
Observed mean	31.87	31.29	28.55	24.88	21.56	19.78	19.59	21.22	23.73	25.70	29.01	30.76
Generated mean	32.08	31.24	28.72	25.67	22.38	19.68	19.30	20.39	22.40	25.78	28.56	30.60
Number of days > 35°C												
Observed mean	9.00	7.31	3.23	0.49	0.00	0.00	0.00	0.00	0.67	1.62	5.28	7.44
Generated mean	8.96	6.92	3.12	0.39	0.00	0.00	0.00	0.00	0.00*	0.43*	2.51*	5.76*
Number of days ≦ 5°C												
Observed mean	0.00	0.00	0.00	0.00	0.59	1.72	3.10	2.26	0.77	0.15	0.00	0.00
Generated mean	0.00	0.00	0.00	0.16	0.71	2.24	2.43	1.80	0.57	0.04	0.00	0.00

(Continued)

Table 5.14. Comparison of Observed and Predicted (Continued)

(i) Daily maximum temperatures for each month
(ii) Daily minimum temperatures for each month
(iii) Number of days per month with maximum temperatures exceeding 35°C
(iv) Number of days per month with minimum temperature less than or equal to 5°C

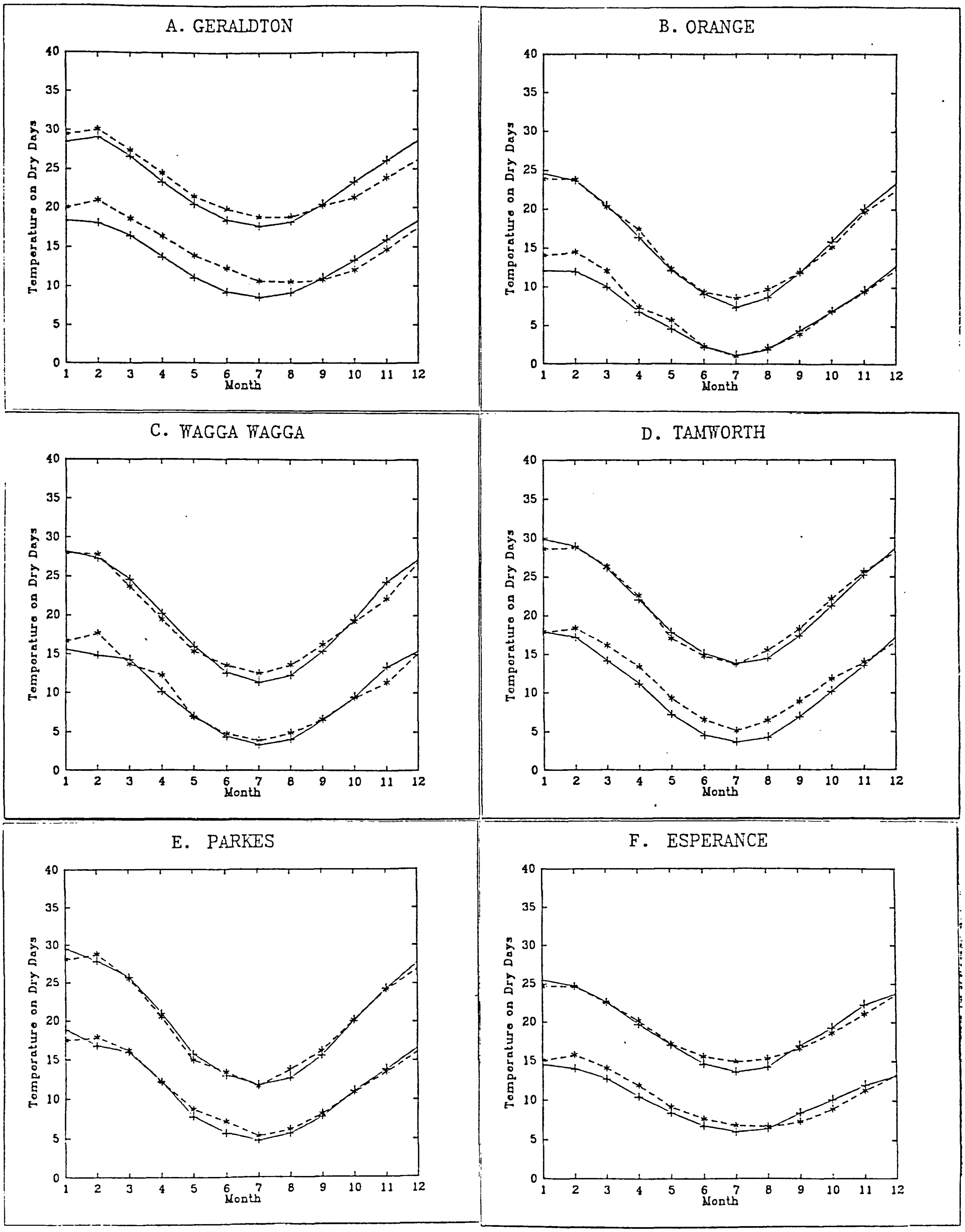
Parameter	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
E. Esperance												
Daily minimum (°C)												
Observed mean	14.40	14.85	12.89	10.99	8.34	7.02	6.31	6.56	7.53	9.32	11.55	13.30
Generated mean	14.27	13.69	12.54	10.29	8.15	6.91	5.93	6.61	7.96	10.20	12.04	13.51
Daily maximum (°C)												
Observed mean	28.56	27.73	25.30	21.93	18.29	16.44	16.08	17.11	19.24	22.02	24.71	27.45
Generated mean	28.35	27.08	25.84	22.11	18.79	16.67	15.61	16.38	18.33	21.91	25.17	26.93
Number of days > 35°C												
Observed mean	5.47	3.59	1.06	0.06	0.00	0.00	0.00	0.00	0.12	0.41	1.76	3.94
Generated mean	3.82*	2.04*	1.29	0.06	0.00	0.00	0.00	0.00	0.00*	0.02*	0.61*	2.04*
Number of days ≦ 5°C												
Observed mean	0.00	0.00	0.06	0.47	3.18	6.12	9.41	8.35	5.29	2.06	0.18	0.00
Generated mean	0.02	0.02	0.12	1.08	2.76	5.29	10.47	7.06	3.27	1.04*	0.14	0.02
F. Bathurst												
Daily minimum (°C)												
Observed mean	13.72	12.66	9.29	5.09	2.60	0.83	0.00	1.51	3.89	6.86	9.09	11.73
Generated mean	13.64	13.20	10.47	5.79	3.00	1.20	0.00	0.98	3.13	6.28	8.46	11.19
Daily maximum (°C)												
Observed mean	27.58	25.91	23.32	19.21	13.92	11.52	11.68	13.23	16.89	20.05	24.16	26.33
Generated mean	27.54	26.66	23.62	19.87	15.90	12.36	11.22	12.01	14.95	18.74	23.51	25.74
Number of days > 35°C												
Observed mean	1.19	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.63
Generated mean	0.55	0.49	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04*	0.22
Number of days ≦ 5°C												
Observed mean	0.13	0.13	5.44	15.44	23.19	25.25	29.06	26.00	19.63	10.44	4.44	1.00
Generated mean	0.24	0.23	3.24	13.65	16.71*	25.55	31.00*	27.67*	17.69	9.48	4.02	0.92

* Generated mean significantly different from observed mean at 5% level.

Figure 5.8. Comparison of Observed and Simulated Monthly Mean Maximum and Minimum Temperatures on Dry Days at Six Locations.

A.	Geraldton	WA
B.	Orange	NSW
C.	Wagga Wagga	NSW
D.	Tamworth	NSW
E.	Parkes	NSW
F.	Esperance	WA

Lines marked (+) are values calculated for observed data, lines marked (*) are values calculated from simulated data. Upper lines are maximum temperatures and lower lines are minimum temperatures.


A. GERALDTON
B. ORANGE
C. WAGGA WAGGA
D. TAMWORTH
E. PARKES
F. ESPERANCE
Temperature on Dry Days
Month
0
5
10
15
20
25
30
35
40
1
2
3
4
5
6
7
8
9
10
11
12

Overestimating the frequency of cold days during winter months may result in simulation of a wheat crop growth duration longer than is appropriate. Late frosts occasionally cause crop failure in Australian wheat crops. The simulator reliably predicted the frequency of days with minimum temperatures less than zero degrees during the spring months.

5.6. Examination of Length of Record Used

A further investigation was undertaken to determine the appropriate length of historical rainfall records to use for calculating rainfall generator parameters. The analysis also examined whether differences existed in choice of period of record used for the calculation of parameters. In this analysis nine sets of the generator parameters [P(W/W), P(W/D), α and β] were calculated using the following historical daily rainfall data:

(1) 50 years of data, where possible, spanning the years, 1930-1980

(2) 40 years of data, 1940-1980

(3) 30 years, 1950-1980

(4) 20 years, 1960-1980

(5) 10 years, 1930-1940

(6) 10 years, 1940-1950

(7) 10 years, 1950-1960

(8) 10 years, 1960-1970

(9) 10 years, 1970-1980

The analyses were performed for seven sites of approximately equivalent annual rainfall but with differing rainfall patterns. The sites examined were: (in decreasing order of latitude and therefore, in increasing order of summer dominance of rainfall) Esperance, Hamilton, Young, Bathurst, Quirindi, Barraba, and Biloela. Due to gaps in the more recent records the 50-year period 1920-1970 was used for Hamilton and the period 1911-1960 was used for Esperance.

Comparisons were made between parameters calculated from long-term observed data for the whole of the length of record (as in 5.5) and parameters calculated from a 99-year sequence of rainfall generated using the generator input coefficients calculated from the differing sequences of historical record. The parameters studied in these comparisons were identical to those listed for the whole of record comparison (see 5.5.2).

In all cases as the length of record was shortened the ability to predict the long-term monthly means was weakened. The generator simulated monthly rainfall at Esperance well with only 30 years of daily data used to determine the input parameters. The ability of the generator to reproduce rainfall sequences at Esperance with a shorter record for parameter characterization is possibly indicative of the much lower rainfall variability (coefficient of variation for annual rainfall 18%) at this site. The selection of different sequences from within the period of length of record may yield different results. At Biloela (Table 5.15), if the 50-year sequence (1931-1980) and the 30-year sequence (1951-1980) were used to characterize the generator parameters, a reliable simulation of the whole of length of record resulted. If, however, the 40-year period (1941-1980) was used, significant differences in monthly rainfall totals were obtained in 2 months. Selection of the different decades produced highly variable results. A noticeable trend of simulating on average wetter years when more recent decades were chosen was apparent.

by the Vertisol is higher and the drainage rate coefficient (SWCON) is lower, the nitrate redistribution within the Vertisol would be expected to be lower. Thus fertilizer nitrogen is more likely to be concentrated closer to the placement zone in the Vertisol than in the Alfisol.

The range of outcomes for the upper placement depths was small at the Waite Institute (Figures 6.10 and 6.11), particularly for the Alfisol. Alston's (1980) data indicated no significant response to fertilizer placement on an Alfisol at this location. The simulation suggests that for placement depths to 60 cm this outcome would be the most frequent.

Due to the nature of the seasonal differences in rainfall distribution pattern, soil water relations at the two locations would probably be very different at the time of fertilizer application. At the Waite Institute there is a high probability of winter rainfall and thus more frequent opportunities for fertilizer nitrate to be redistributed within the profile from the placement zone. At Jondaryan in some years dry periods would render surface-placed fertilizer unavailable as the upper portion of the profile dried. It is in these years that positive responses to deep placement are most apparent, provided there is sufficient moisture initially to encourage root growth toward the placement zone. There is, however, a low frequency of large responses to deep placement (to 90 cm) on both soils at both sites since, if there is insufficient water to move nitrate from the upper layers, then there is generally insufficient water for crop growth.

From the analysis it is apparent that the longer the period of record chosen to determine the parameters the more reliable is the simulation of rainfall. Further evaluation of the appropriate length of record to use is beyond the scope of this thesis.

5.7. Discussion and Conclusions

How closely a stochastic weather simulation model needs to represent the real system depends on the application. The WGEN simulator produced simulated data which were statistically comparable to the real world in various measures of central tendency (means and 5th deciles). Some small shortcomings were observed when comparisons were made using measures of dispersion and distribution. The few occurrences (extreme rainfall amounts or extremely long dry periods) where the simulator did not perform well may have some consequences for the simulation of wheat growth, but these were very infrequent. The accurate simulation of monthly rainfall amount in almost all instances was associated with the correct simulation of the number of wet days per month and rainfall per rain event. This should ensure a reliable simulation of soil water balance and should help to reduce errors in simulation of soil moisture dependent nitrogen transformation rates.

If the simulator was to be used in conjunction with an erosion model where potentially erosive rainfall events are important, the inability to simulate the infrequent extreme rainfall amounts may be a problem. Modifications to the generator to accommodate these rare events would come at the cost of increased complexity (Srikanthan and McMahon, 1983). Larsen and Pense (1982) argued that there must be a balance between complexity and the foreseen use of the model, otherwise the extra effort may be largely wasted or of academic interest only. The EPIC model (Williams et al., 1983) which simulates erosion utilizes the Nicks (1984) rainfall simulator. This differs from the Richardson simulator in that a skew-normal distribution for rainfall amount rather than a gamma distribution is used. The simulator uses the same number of parameters as the Richardson generator and uses the same Markov chain procedure for predicting rainfall occurrence. The performance of the EPIC model at simulating erosion in a diversity of environments has been excellent (Williams et al., 1983) and thus suggests a simplified rainfall generator model may also be adequate for this task.

Small modifications to WGEN parameter characterization program which may yield slight improvements could be investigated. One of these would involve varying threshold rainfall amounts. Increasing the threshold would reduce the frequency of small rainfall amounts and thus increase the "weight" of larger rainfall amounts. Further analysis of the rainfall data would be required to choose a different threshhold. Smoothing of data between months by fitting a Fourier series to the monthly values of P(W/W), P(W/D), α and β may be a worthwhile further refinement. Rather than using constant values of the parameters for a month, a daily value could be interpolated from the Fourier series. This could be particularly helpful in areas such as Esperance with a marked start and end to the dry season which may not necessarily coincide with month boundaries. Garbutt et al. (1981), Stern (1980a), and Stern et al. (1981) used this technique to predict the start and end of the wet season in seasonal rainfall locations. This would only require minor modifications to the code and would also reduce the input parameters required by the generator.

For most of the locations examined the model reliably simulated temperature. At some locations, however, prediction of minimum temperature was consistently incorrect and the frequency of occurrence of simulated temperature extremes was too low. One possible modification to the temperature generating functions would be to adjust the "T" value, the position of the harmonic (days) for the seasonal change in the means and coefficient of variation of temperature. The generator uses a fixed value of "T", but examination of the data reported in Table 5.4 shows a latitudinal variation in "T". A minor modification to the simulator to reflect this could incorporate the following relationships as determined from these data:

$$T1 = 0.95 * LAT - 55.35 \quad (r = 0.317)$$

$$T2 = 1.40 * LAT - 70.35 \quad (r = 0.418)$$

$$T3 = 0.79 * LAT - 55.01 \quad (r = 0.213)$$

$$T4 = 1.15 * LAT - 70.39 \quad (r = 0.529)$$

where T1, T2, T3, T4 = position of the harmonic (days) as defined in Table 5.4. LAT = degrees S latitude. This modification would enable a minor shift in the phase angle used in the generation of temperature sequences and may yield a minor improvement in temperature simulation for only a small cost in added complexity. This may not greatly affect simulation of temperature extremes.

Another refinement which may improve temperature simulation would be to compute the matrix of residuals used in the temperature simulation for each location separately. To do this requires determination of the serial and cross-correlation coefficients for maximum and minimum temperature as described by Richardson (1981).

When this was done (Appendix 11) some differences between the values observed and those reported by Richardson were obtained. Further investigation is required to determine whether recalculation of the matrix of residual using either Australian mean correlation data or data from individual locations would yield any improvement.

It should be noted that these possible areas for refinement may yield only limited improvement. The generator in its existing form generates sequences of daily temperature and rainfall data quite adequate for the simulation of crop growth. Richardson (1985) was able to demonstrate that the distribution of simulated wheat yields generated by the CERES-WHEAT model was the same regardless of whether simulations were performed using actual solar radiation data or monthly mean solar radiation for Oklahoma City. This supports the methodology for generating solar radiation data reported in this chapter which should be satisfactory for crop simulation purposes.

Table of Contents

6.1 Introduction and Principles of Sensitivity Analysis

Sensitivity analysis is a procedure carried out on a completed and validated (at least partly) model (Dent and Blackie, 1979). Since the technique involves exploring the operation and performance of the model, it should become an integral part of model evaluation and it may lead to further enhancement of the model. Dent and Blackie (1979) describe the technique as:

> In successive 'runs' of the model under identical environmental conditions, the value of a parameter may be changed. The resultant modification in model-output will be analyzed to determine whether or not the changed parameter values are of material consequence. A sensitive parameter is one which causes a major change in model-output; the model is said to be sensitive to such a parameter. A similar, though in practice more complex, procedure can be envisaged to isolate sensitive subsystems and relationships.

Whisler (1983a) evaluated the sensitivity of a multiple crop rice based simulation model, IRRIMOD by independently changing various crop and management variables up or down 20% and examining the effect on simulated yield. A guide to the accuracy required in collection of weather data was also obtained by Whisler (1983b) by performing similar sensitivity analyses on model input weather variables. Similarly, Stapper (1984) examined, with the SIMTAG model, the impact of changing each of the climatic input parameters (daily rainfall, temperature, and solar radiation) up or down 20% on simulated wheat yields for various locations in Syria. Rainfall proved to be the most sensitive parameter, but considerable variation across sites and seasons was found. Singh (1985) has reported the sensitivity of the CERES-MAIZE model to changes in solar radiation and temperature on sites where water was not limiting.

Maas and Arkin (1980a) performed a sensitivity analysis on key variables in the SORGF sorghum model and reported sensitivities as "S" values. "S" is defined as the change in system output per unit change in system input. As well as the weather data, percent extractable soil water, plant population density, row spacing, maximum leaf area, and maximum leaf number were varied to determine their relative sensitivity. France and Thornley (1984) describe the same procedure for testing sensitivity.

Larsen (1981) has reported the results of an extensive sensitivity analysis of two wheat models to climatic data inputs, soil water inputs, and genetic parameters. The two models examined were an early progenitor of CERES (1980 version) and TAMW (Texas A&M University Wheat Model developed by Maas and Arkin, 1980b). The TAMW model is structured along similar lines to the CERES model. Both models were being evaluated as key elements in a large area yield forecasting system employing real time weather data and space satellite acquired data on crop area and development. In evaluating the forecasting system, the researchers were required to know with what precision starting estimates of soil water availability had to be made, as well as the sensitivity to the real time climatic data which would be applied to the models.

Larsen's method of examining sensitivity was to adjust the various selected parameters sequentially up or down and to examine the frequency and magnitude of responses in model output. The frequency data were obtained by running the model with a 30-year sequence of climatic data (i.e., simulating 30 crops). Sensitivity was reported as a "probability sensitivity measure." These multiple-year analyses were performed only at one location, Columbia, Missouri.

Single-year sensitivity analyses were also examined for five other locations in the midwest of the United States. To determine when a particular parameter was sensitive, the analyses were performed separately for each of the growth stages identified by the model.

The analyses yielded valuable information concerning several key components of the soil water balance submodel and plant growth submodel. The CERES model was found to be particularly sensitive to perturbation of some of these soil water inputs while the TAMW model was very sensitive to perturbation of the temperature data. Information resulting from these analyses has greatly assisted model developers and thus the current version of CERES has evolved with significant changes from the 1980 version. Since the current CERES model has global application, sensitivity analyses on the current version of the model should be performed in a diversity of wheat-growing environments.

Other examples of sensitivity analyses reported for crop growth models may be found in Whisler (1983c) for various variables in the rice crop simulation model RICEMOD, van Keulen et al. (1981) for ARIDCROP model, Iwaki (1977) for photosynthesis and light interception in a rice model, and Lambert and Reicosky (1977) for various parameters describing water movement through maize plants in the TROIKA model.

6.2 Examination of Key Coefficients

6.2.1 Method

Fertilizer efficiency, N uptake, grain yield, and the processes affecting them are ultimately influenced by climate. Since weather is the most variable of the environmental components affecting the soil-crop system, a full sensitivity analysis of parameters in the model should be carried out across many years of climatic data. For this exercise the CERES-WHEAT model, coupled with the WGEN weather generator (described in Chapter 5), was used to simulate N dynamics and crop growth in three diverse wheat-growing environments. The three locations used, soil characteristics, and wheat varieties used (Table 6.1) were selected to span the range of global wheat-growing regions.

Table 6.1. Initial Conditions and Resultant Means Used in Sensitivity Analysis Simulations. Where Indicated Standard Errors are Calculated From 20 Years of Simulation

Parameter	Wongan Hills	Wichita	Rothamsted
Generated mean annual rainfall (mm)	357	847	717
Latitude	30.5°S	37.7°N	51.7°N
Variety	Condor	Newton	Maris Hobbit
Planting date	May 20	October 2	October 2
Mean simulated growing season length (days)	165 ± 5	251 ± 5	271 ± 9
Mean growing season rainfall (mm)	278 ± 38	409 ± 102	515 ± 54
Soil type	Red-brown earth (Rhodustalf)	Silt loam (Haplustoll)	Brown earth (Eutrochrept)
Extractable water (cm)	14.1	37.2	29.0
Mean simulated extractable water at harvest (cm)	2.4	6.9	6.1
Mean simulated unfertilised yield ± S.E.	1,384 ± 312	1,953 ± 965	3,920 ± 1,014
Mean simulated fertilised yield ± S.E.	2,086 ± 795	2,222 ± 1,062	7,897 ± 1,711

The model utilized 20 years of generated daily climatic data representative of each of the sites, and it commenced simulation in each of these years with the same initial conditions of soil fertility, planting date, and management inputs. The extractable soil water present at planting in each of the 20 years was that simulated with a fallow period running from the end of the past crop to planting time. In wetter locations and in wet years at dry locations, this will approach the drained upper limit (DUL) throughout the profile. In years with a dry period immediately before planting, however, initial soil moisture may be less.

Reference simulations for each of the sites were obtained by running the model with the 20 years of climatic data and with a fertilizer input of 50 kg N/ha at Wongan Hills, 50 kg N/ha at Wichita, and 100 kg N/ha at Rothamsted. A further set of reference simulations was obtained by running the model with the 20 years of climatic data for the three sites but with no fertilizer applied. Grain yield, biomass, and N uptake from these reference simulations were compared with those produced when each of certain model parameters were varied.

Several problems can arise in this type of analysis. First, it may be biologically or physically unreasonable to change one variable without correspondingly changing some other variables. For example, in many instances at one site it would be unlikely to envisage an increase in solar radiation without a corresponding increase in temperature. A second problem concerns the magnitude of the perturbation used. For some variables which have a large reported variability (e.g., root length to weight ratio) a perturbation of only 20% will not adequately reflect the variability and a sizeable impact on yield or N uptake may not be evident. For some other variables which can either be determined more accurately or which remain relatively constant, a 20% perturbation may be abnormally high. A further problem concerns the integrity of the model.

Perturbation of one variable alone may lead to an upset in a mass or energy balance calculation which would never occur under normal simulation and may lead to catastrophic consequences for model output. Given that these problems can occur, the analysis is still valid in order to identify the most sensitive parameters and indeed to test the structural integrity of the model.

Each of 26 variables identified as having a possible impact on model output was in turn perturbed up or down 5%, 10%, and 20%. The model was then run with the 20 years of climatic data and the output compared to the reference simulations. These procedures were adopted for each of fertilized and unfertilized cases.

The first run was structured such that the first variable was perturbed while the remaining variables maintained their input or default values. The second run reset the first variable to its original value, perturbed the second variable, and held the remaining variables to their original values. For each site and for each of the two fertilizer treatments (0 kg N/ha and the rate described above), the analysis involves a total of:

20 years x 6 perturbation levels x 26 variables = 3,120 simulations

Three different classes of variables were identified as having a potential impact on model output. First, variables which form part of the input data set for the model were examined (Table 6.2a). The variables chosen were those where it could be perceived that an error in measurement could easily be made. One of the aims of this sensitivity analysis is thus to examine the requirement for accuracy in describing the input data. The variables considered are the four weather variables, variables describing the water storage and drainage rate of the soil

Table 6.2. Variables Examined in a Sensitivity Analysis of the CERES-WHEAT Model

a. Model Input Variables

Variable Name	Subroutine	Function
Rain	Main	Daily rainfall amount (mm/day)
TEMPMX TEMPMN	Main	Daily maximum and minimum temperatures (Degrees C)
SOLRAD	Main	Daily solar radiation (MJ/m^2)
BD(L)	SOILNI	Soil bulk density (g/cc)
LL(L)	SOILRI	Lower limit soil water content for soil layer L (volume fraction)
DUL(L)	SOILRI	Drained upper limit soil water content for layer L (volume fraction)
SAT(L)	SOILRI	Field saturated water content in layer L (volume fraction)
SWCON	SOILRI	Coefficient for determining whole profile drainage rate
INO3(L)	SOILNI	Initial extractable soil nitrate in layer L (ppm)
IOC(L)	SOILNI	Initial soil organic carbon in layer L (%)
SCN	SOILNI	Initial C:N ratio of added straw

profile, the initial amounts of nitrate present in the profile, and two variables which may affect the supply of N from mineralization of organic matter (IOC and SCN). Maximum and minimum temperatures were varied simultaneously.

Secondly, variables (Table 6.2b) directly affecting the nitrogen components of the model were also examined. These analyses are intended to help answer questions such as: if the model under/over predicts the rate of nitrification by x percent, what are the consequences for the accuracy of simulated yield, N uptake, and efficiency of N utilization?

Table 6.2. Variables Examined in a Sensitivity Analysis of the CERES-WHEAT Model (Continued)

b. Variables Pertaining to the Nitrogen Components of the Model

Variable Name	Subroutine	Function
DMOD*	NTRANS	Maximum rate of decomposition of organic matter (1/day)
RNTRF(L)	NTRANS	Calculated rate of nitrification of ammonium in layer L per day (kg N/ha/day)
CNI(L)	NTRANS	Capacity for nitrification index (zero to unity dimensionless factor)
DNRATE(L)	NTRANS	Calculated denitrification rate (kg N/ha/day)
LEACH*	NFLUX	Calculated loss of nitrate from layer L (kg N/ha/day)
FNO3	NUPTAK	Unitless soil nitrate supply index used in N uptake calculations
MAXUL*	NUPTAK	Maximum uptake of N per unit length of root (mg N/cm/day)
RNFAC(L)	WATBAL	Zero to unity factor describing mineral N availability effect on root distribution
NFAC	NFACTO	Zero to unity factor describing N status of the plant
NDEF1	NFACTO	Zero to unity N deficiency factor for photosynthetic rate
NDEF2	NFACTO	Zero to unity N deficiency factor for expansion growth
NDEF3	NFACTO	Zero to unity N deficiency factor for tiller number
NDEF4	NFACTO	Zero to unity N deficiency factor for leaf senescence
GNP	GROSUB	N concentration in daily increment of grain growth (g N/g grain dry matter)

*Listed as a coefficient in the model without an associated variable name.

The variables chosen are the major rate variables involved with each of the processes of mineralization, nitrification, denitrification, leaching, and N uptake. The description of plant N dynamics is also subjected to scrutiny by examination of the N deficiency indices and GNP, the variable determining the concentration of N in the grain.

As part of an additional study not reported here, a third class of variables which affect the soil water balance, photosynthetic efficiency, leaf area development, and assimilate partitioning were also examined.

Comparisons with the reference simulations were made by determining % change as below for each simulation.

$$C_J = \frac{Y_{P,J} - Y_{U,J}}{Y_{U,J}} \times 100$$

where,

C_J = Percent change in yield in Year J.

$Y_{P,J}$ = Yield for Year J when a variable is perturbed.

$Y_{U,J}$ = Yield from reference simulation in Year J.

Thus for each variable perturbed, and for each perturbation level, 20 values of C were obtained. It should be noted that in some instances an increase of 5% in the value of a variable may increase simulated yields in some years and decrease simulated yields in other years. These 20 elements of C (C(j), j=1,20) were ranked from smallest to largest and the following elements extracted for graphical representation.

C(20) = largest effect of change.

C(18) = 9th decile outcome (i.e., change occurring in 90% of years will be less than this amount).

C(10) = median change.

C(3) = 1st decile outcome (i.e., change occurring in 10% of years will be less than this amount).

C(1) = smallest effect of change (may be largest negative effect).

The difference between C(20) and C(1) reflects the maximum possible range of outcomes and the difference C(18) to C(3) reflects the range of outcomes in 80% of years. In the strict sense 1st and 9th deciles were calculated by fitting a linear segmented function to the frequency distribution of outcomes and interpolating the 10% and 90% probability points from these functions. This technique is described more fully in Chapter 7 and will not be elaborated upon here. Using these five values of C, a plot (Figure 6.1) can be developed which provides information on both the frequency and magnitude of responses to perturbation. Illustrative figures for each of the perturbation levels, variables and locations were developed (Figure 6.2).

"S" values (Maas and Arkin, 1980a) across the range of perturbations were obtained by fitting a simple linear regression for each of the variables as below:

$$\Delta Y = S\ \Delta V$$

where: ΔY = Mean % change in yield from 20-year simulation caused by perturbation of variable V

ΔV = % perturbation of variable V

The values were obtained for each of the three sites and for the combination of the three sites (Table 6.3 and 6.4).

6.2.2 Results

Figure Interpretation--In the following figure (Figure 6.2) the relative sensitivity to perturbation of the variables can be gauged by comparing column lengths. Using the case of input variables perturbed +5% at Wongan Hills (Figure 6.2a), the variables DUL and INO3 can be seen to have a greater range of sensitivity to perturbation than IOC since their column lengths are greater. The IOC range (+2% to -2%) can be seen to be particularly small since the upper portion

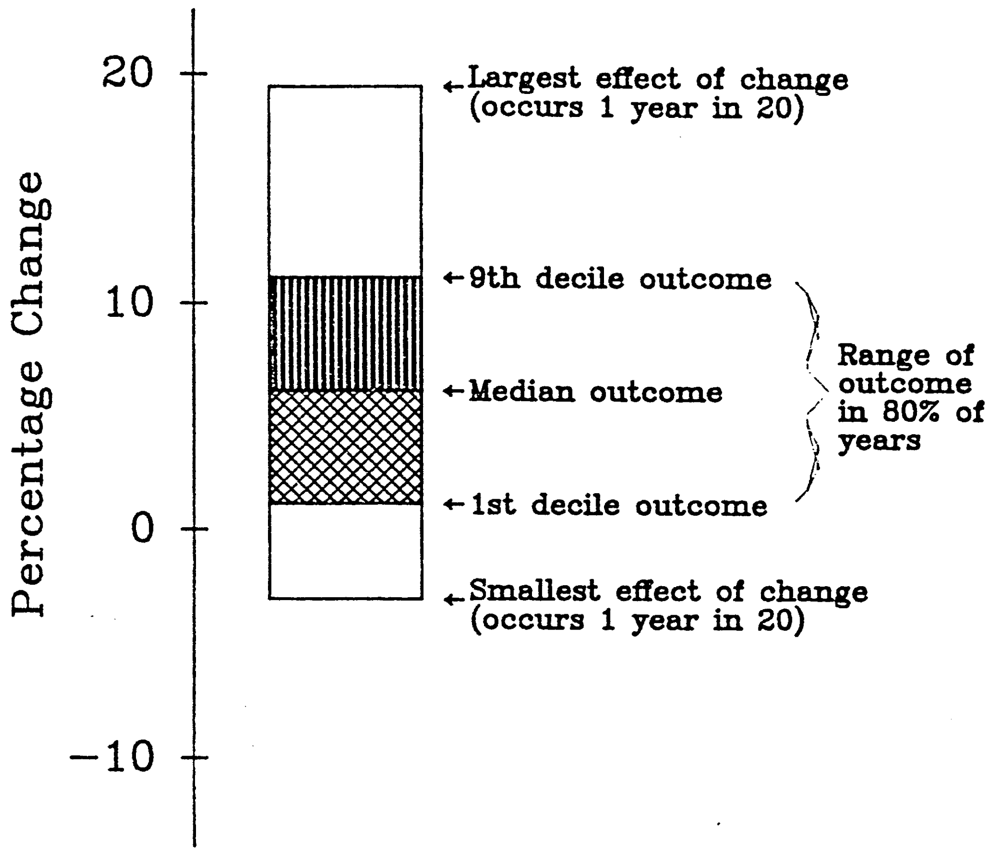


Figure 6.1. Figure Illustrating Hypothetical Range of Simulated Effects on Yield When a Model Variable is Perturbed.

Figures 6.2. Range and Frequency of Yield Outcomes as the Result of Perturbations of Various Variables. Zero Indicates No Departure From the Yields Generated in the Reference Simulation. The Column Lengths Indicate the Magnitude of the Range of Outcomes With the Frequencies Indicated as Described in Figure 6.1.

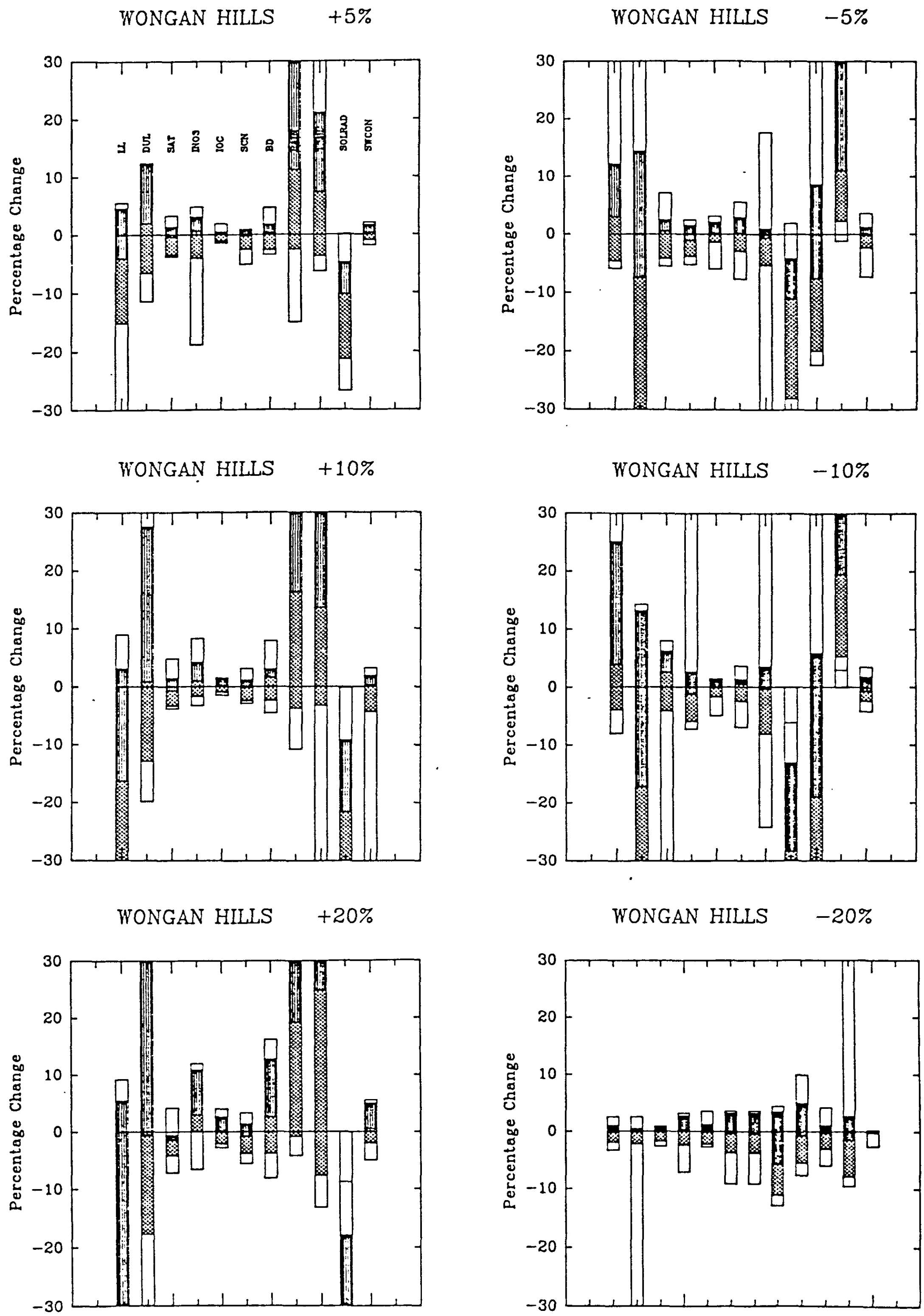


Figure 6.2a. Perturbation of Input Variables at Wongan Hills.

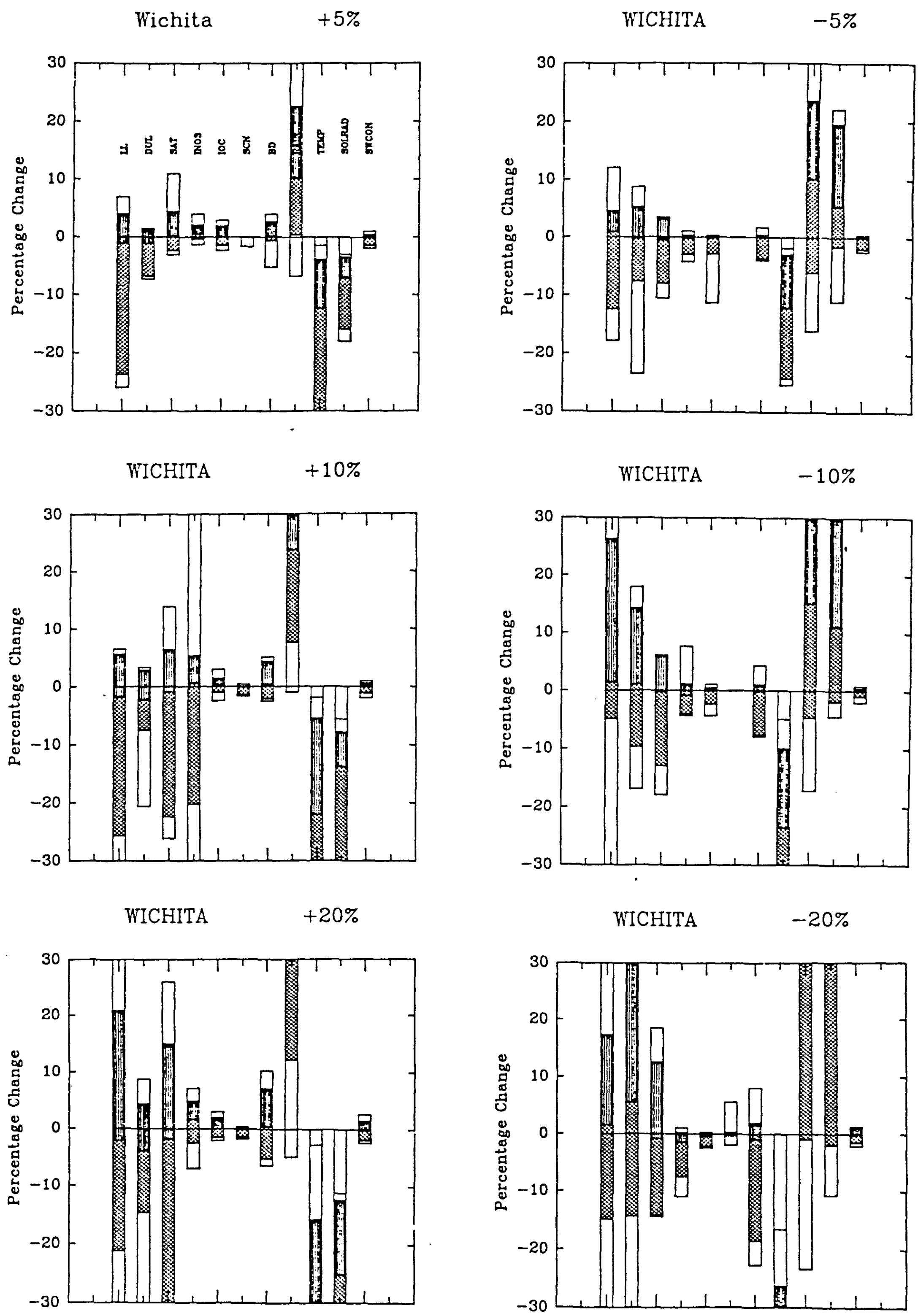


Figure 6.2b. Perturbation of Input Variables at Wichita.

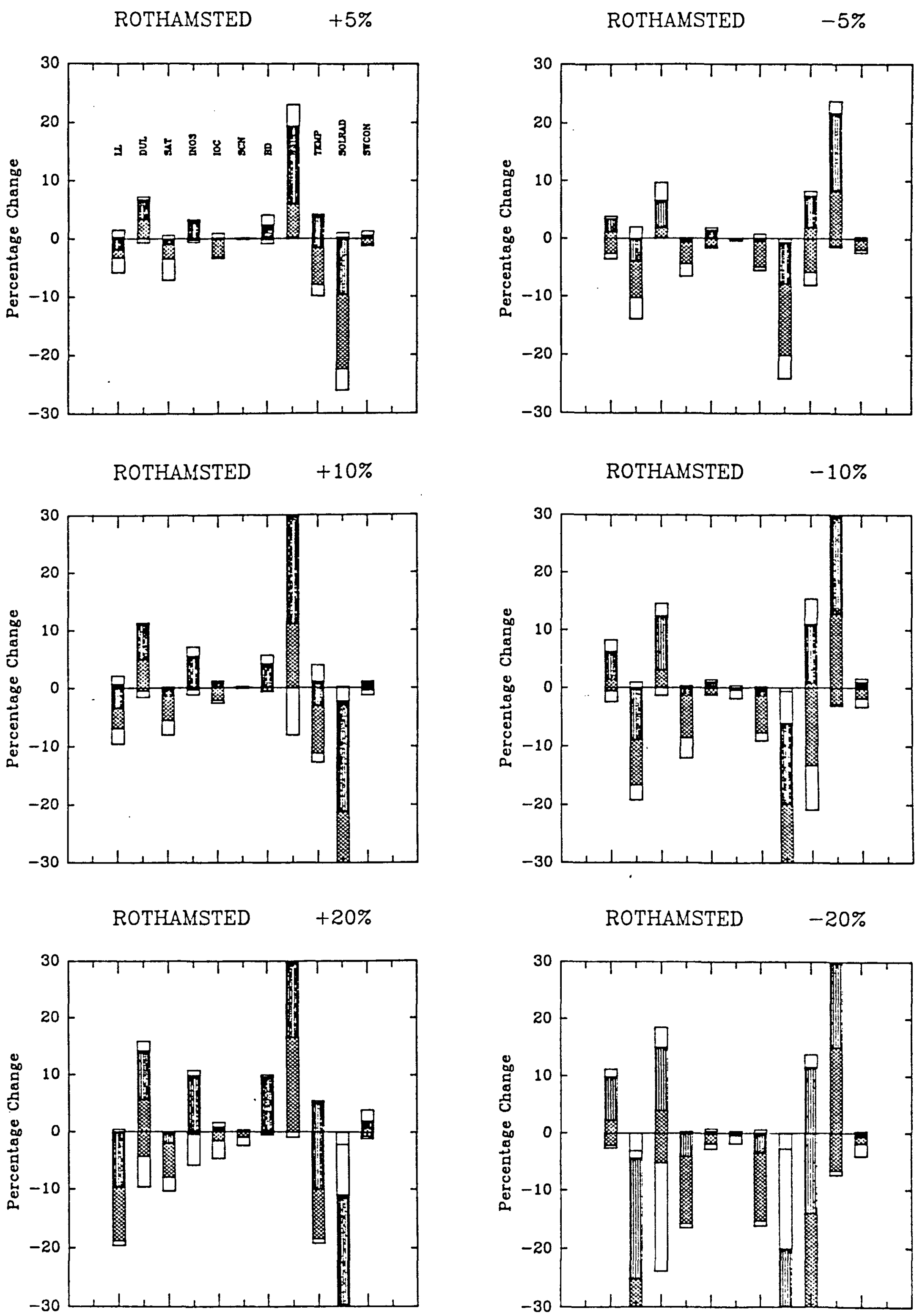


Figure 6.2c. Perturbation of Input Variables at Rothamsted.

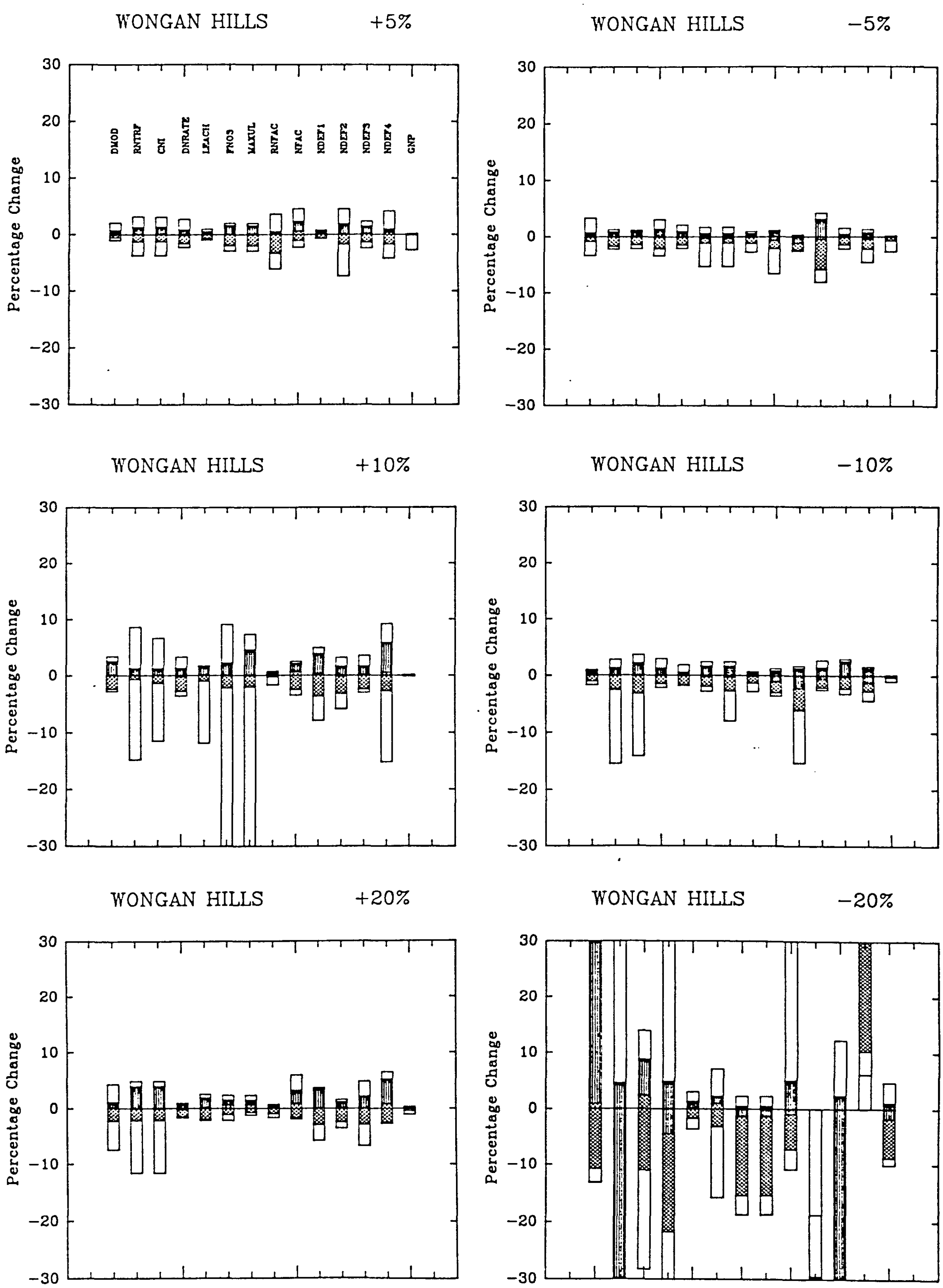


Figure 6.2d. Perturbation of N-Component Variables at Wongan Hills.

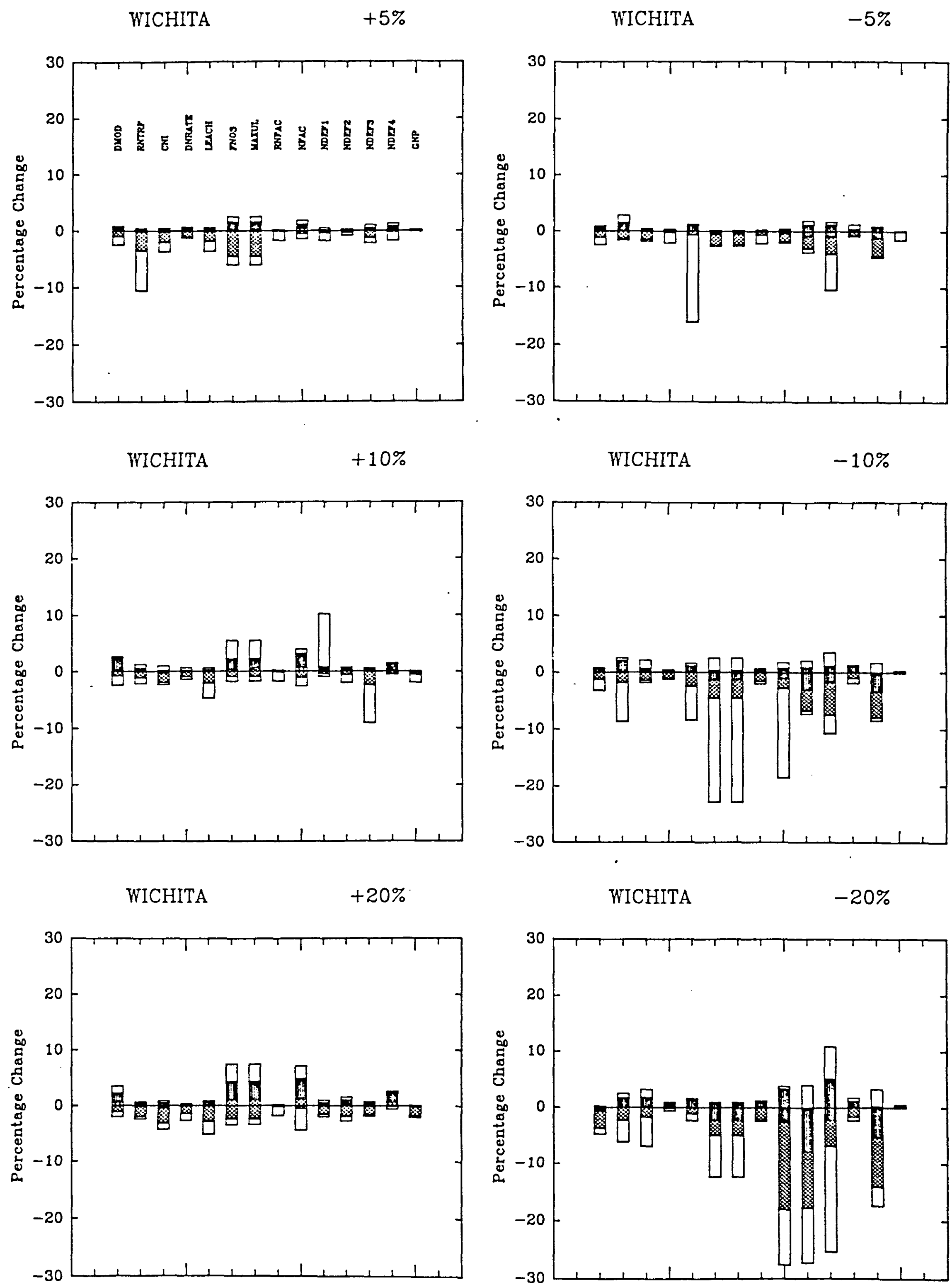


Figure 6.2e. Perturbation of N-Component Variables at Wichita.

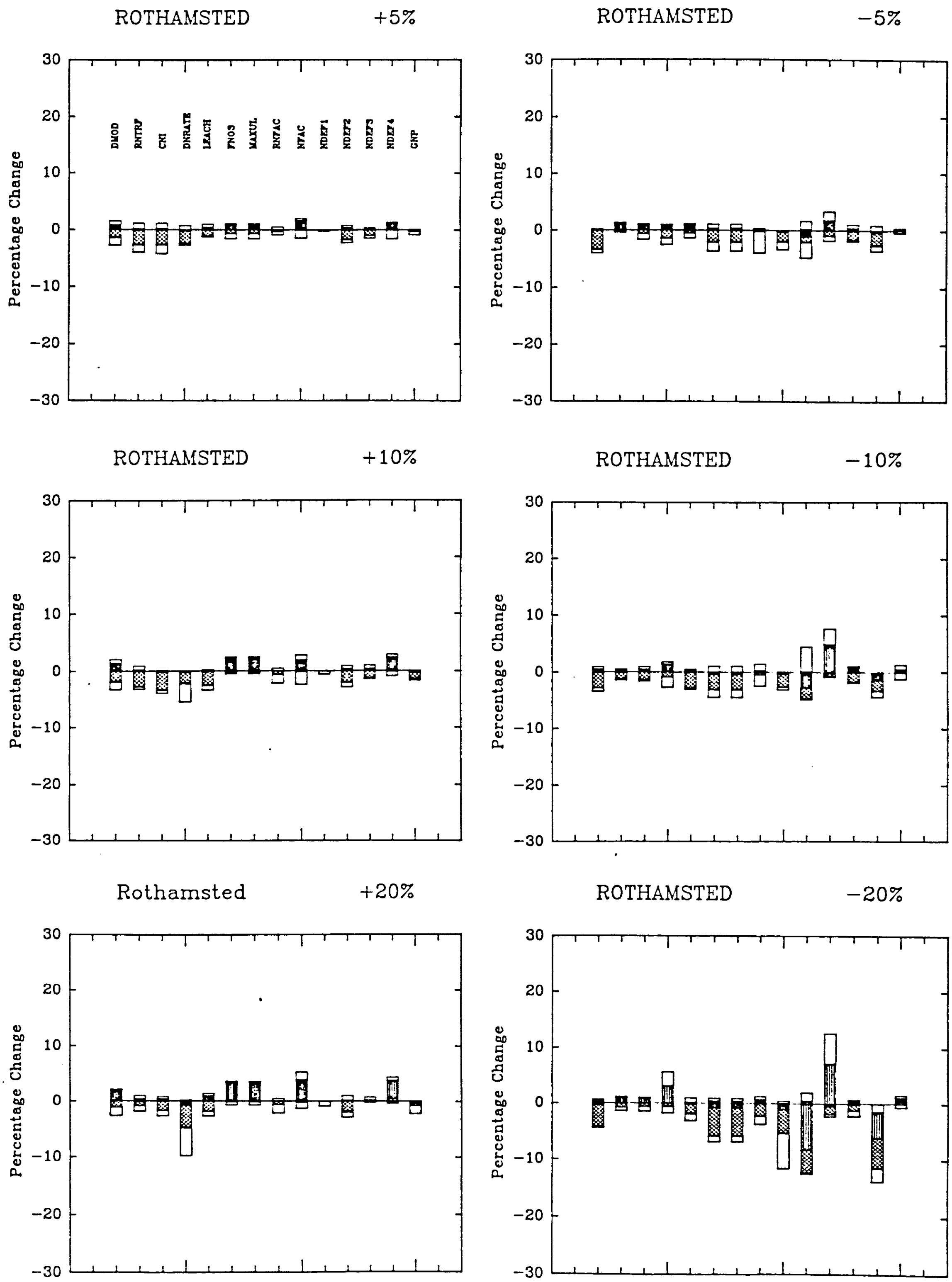


Figure 6.2f. Perturbation of N-Component Variables at Rothamsted.

Table 6.3. "S" Values for Yield Sensitivity Determined From Regression of Mean Yield Response (% Deviation From Control) on Perturbation Percentage for 26 Variables When Fertilizer Was Applied

Variable	Wongan Hills	Wichita	Rothamsted	Combined
LL	-1.074*	-0.235*	-0.342	-0.550*
DUL	0.964*	-0.131*	0.930*	0.588*
SAT	-0.054*	-0.043	-0.359	-0.152*
INO3	0.105	0.048*	0.175	0.109*
IOC	0.007	0.029	0.208*	0.082*
SCN	-0.030	0.001	0.055	0.009
BD	0.019	0.029	0.360*	0.136*
RAIN	2.646*	2.441*	1.678*	2.255*
TEMP	1.345*	-2.019*	0.197	-0.159
SOLRAD	-2.542*	-1.646*	-1.776*	-1.988*
SWCON	0.031	-0.001	-0.045	-0.005
PSE	0.657*	0.789*	0.056	0.500*
DMOD	0.002	0.002	0.004	0.000
RNTRF	0.049	-0.010	-0.038	-0.038
CNI	0.007	-0.006	-0.116	-0.031
DNRATE	-0.008	-0.004	-0.080	0.043
LEACH	0.002	-0.028	0.155	0.002
FNO3	0.008	0.054*	-0.055	0.006
MAXUL	0.019	0.054*	-0.055	0.024
RNFAC	0.016	0.005	0.050	0.065
NFAC	0.092*	0.097*	0.008	0.059
NDEF1	0.133	0.104	-0.060	-0.063
NDEF2	0.011	0.026*	-0.225	0.029*
NDEF3	0.012	0.027*	0.048	0.032
NDEF4	-0.016	0.061*	0.051	-0.027*
GNP	0.001	0.016	-0.067*	0.136*

* Indicates coefficient of determination for the regression significant at the 5% level.

Table 6.4. "S" Values for Yield Sensitivity Determined From Regression of Mean Yield Response (% Deviation From Control) on Perturbation Percentage for 26 Variables When Fertilizer Was Not Applied

Variable	Wongan Hills	Wichita	Rothamsted	Combined
LL	-1.025*	0.152	-0.317*	-0.397*
DUL	1.453*	-1.015	0.607*	0.348
SAT	-0.068	-0.416	-0.135	-0.206
INO3	0.796*	0.130*	1.003*	0.643*
IOC	0.220*	0.038	0.094*	0.117*
SCN	-0.267	0.009	-0.023	-0.094
BD	0.663*	0.168*	1.251*	0.694*
RAIN	1.264*	3.676*	0.031	1.657*
TEMP	0.202	-2.656*	0.772*	-0.561
SOLRAD	-0.916*	-2.784*	-0.482*	-1.394*
SWCON	-0.194	-0.003	0.025	-0.057
DMOD	0.143	0.018	0.195*	0.118*
RNTRF	-0.017	0.119*	0.137*	0.080*
CNI	-0.049	0.035	0.180*	0.055
DNRATE	-0.038	-0.003	-0.108*	-0.050
LEACH	-0.049	-0.010	0.004	-0.018
FNO3	0.100	0.057*	0.098	0.085
MAXUL	0.100	0.057*	0.098	0.085
RNFAC	0.038	0.003	-0.005	0.012
NFAC	0.133	0.022	0.034	0.063*
NDEF1	-0.104	-0.023	-0.314	-0.147*
NDEF2	0.027	-0.166	-0.123*	-0.087
NDEF3	0.026	-0.195	0.033	-0.045
NDEF4	-0.019	-0.079	0.403*	0.102
GNP	-0.043	-0.009*	-0.132*	-0.061*

* Indicates coefficient of determination for the regression significant at the 5% level.

of the column (+0.5% to +2%) indicates the 2% increase in yield only occurred 1 year in 20. Thus in 80% of years, perturbation of IOC by +5% will result in only a (+0.5% to -1.8%) range of effects on yield. The median effect is zero. In the case of the variable INO3 most of the range of outcomes (+6% to -18%) is dominated by "outliers." In this case, in 80% of years yield changes will be in the range of -4% to +3%, but 1 year in 20 5% perturbation of INO3 will cause simulated yield to be reduced by 18%, and also 1 year in 20 simulated yield will be increased by 6%. The median effect of perturbation of both INO3 and IOC is, however, approximately the same. Perturbation of the variable RAIN causes a large range of possible yield outcomes and the median effect (+11%) is larger than for most other variables. Column heights and position of the within column boundaries thus display both magnitude and frequency of response to perturbation.

Input Variables

LL and DUL--These two variables determine the range of extractable soil water. An increase in LL or a decrease in DUL would cause a decrease in the amount of soil water available (ESW) to the crop. At the driest site (Wongan Hills) S values for grain yield (Tables 6.3 and 6.4) of approximately -1 were obtained for LL. This implies that a 1% overestimation of LL will result in a 1% underestimation in yield. Similar values but of opposite sign were obtained for DUL. The model was much less sensitive to perturbations of LL and DUL at Wichita presumably because the ESW was much larger due to both a greater profile depth and a wider range between LL and DUL throughout the profile.

Relative to other variables the range of possible outcomes is large (Figure 6.2). In most years an increase in LL causes a decrease in yield (Figures 6.2a,b,c), but in some years a 5% increase in LL resulted in a small increase in yield. Similar increases in yield with reductions in DUL were apparent. This apparent anomaly may arise when increased water stress early in the growing season reduces crop growth and thus conserves water for later in the season. Fischer and Kohn (1966) have defined a period of moisture stress around anthesis as being the most critical for yield determination. Thus conservation of water until this period may have a beneficial effect on yield.

The large range in possible outcomes and large (relative to other variables) S values indicates that parameters determining soil water storage are very sensitive and therefore input values must be estimated with some precision. This sensitivity is apparent since soil water status is used to modify the rates of various plant growth processes directly as well as determining the rates of all the major N transformations. The effects of increases in LL are not necessarily paralleled by the effects of decreases in DUL because the magnitude of DUL affects storage of water above DUL (i.e., toward saturation) as well as ESW. This water between DUL and SAT (saturation) can readily drain. Decreasing DUL can thus increase the proportion of water in the profile which drains. In some years this could act as a short-term extra buffer for water storage, but in other years decreases in DUL may affect the rate of nitrate leaching.

The effects of perturbation of LL and DUL on biomass (see Table 6.5) were similar to those on grain yield. Perturbation of DUL also had similar effects on N uptake as on biomass and grain yield, but N uptake was not greatly affected by perturbation of LL when fertilizer was applied.

Table 6.5. "S" Values for Biomass and N Uptake Sensitivity From Regression of Response (% Deviation From Control) on Perturbation Percentage for 26 Variables When Fertilizer Was or Was Not Applied. The "S" Values Are From the Combined Analysis of All Sites

Variable	Biomass (0 kg N/ha)	Biomass (fertilised)	N Uptake (0 kg N/ha)	N Uptake (fertilised)
LL	-0.326*	-0.221*	-0.231*	-0.005
DUL	0.370	0.204	0.238	0.249
SAT	-0.071	-0.047	-0.033	-0.081
INO3	0.610*	0.184*	0.523*	0.272*
IOC	0.091*	0.017*	0.069	0.094
SCN	-0.081	-0.028*	-0.091*	-0.021
BD	0.586*	0.134*	0.557*	0.343*
RAIN	1.157*	1.419*	1.066*	0.863*
TEMP	-0.031	-0.379	0.211	0.000
SOLRAD	-0.854*	-0.899*	-0.989*	-0.691*
SWCON	-0.029	0.007	-0.017	0.021
DMOD	0.096*	0.023*	0.058	0.063
RNTRF	0.033	0.001	0.073	0.051
CNI	0.012	-0.011*	0.054	0.188
DNRATE	-0.032*	-0.026*	0.001	-0.047
LEACH	-0.007	-0.002	-0.026	0.038
FNO3	0.084*	0.058*	0.104*	0.939
MAXUL	0.084*	0.059*	0.104*	0.939
RNFAC	0.005	0.002	0.010	0.118*
NFAC	0.067*	0.085*	0.136*	0.025
NDEF1	0.015	0.167*	-0.005	-0.189
NDEF2	0.021	0.044*	0.097*	0.096
NDEF3	0.009	0.002	0.067*	-1.753
NDEF4	0.081*	0.083*	0.064	0.031
GNP	-0.025*	-0.006*	0.178*	-0.018

* Indicates coefficient of determination for the regression significant at the 5% level.

Potential N uptake from a layer is calculated as a function of the ESW as shown below:

SMDFR = SW/ESW

Potential N uptake = MAXUL * RLV * SMDFR * SMDFR * FNO3 * UCF

where: MAXUL = Maximum N uptake per cm of root.

RLV = Rooting density in the layer cm root/cm^3 soil.

SMDFR = Soil moisture deficit factor.

FNO3 = Zero to unity nitrate supply index.

UCF = Unit conversion factor.

Increases in LL or decreases in DUL would appear to increase potential N uptake since ESW would be reduced and hence SMDFR increased. Decreases in water storage, however, would also tend to force SW to the lower end of the ESW range thus reducing uptake. The resulting sensitivity, or lack thereof, on N uptake is due to a counterbalancing of these two opposing effects. A further confounding of this effect is that when fertilizer is applied, increased plant growth would tend to lower SW, which may contribute to the differing sensitivities when fertilized or unfertilized.

SAT and SWCON--SAT determines the amount of water above the DUL which the profile can hold. Increases in SAT will cause potential increases in the amount of water moving through the profile with drainage. Increases in SAT will thus result in increases in nitrate leaching if there is sufficient rainfall to frequently cause drainage events. When fertilizer was applied the greatest sensititivity was evident at the wettest site (Rothamsted) (Figure 6.2c). When no fertilizer was applied the largest sensitivity was observed at Wichita (Figure 6.2b), the site with the largest ESW. Since SAT determines the maximum amount of water the soil can hold, increases in SAT may result in improved water relations in the dry periods between profile recharge events. Thus at the drier sites (Wongan Hills and Wichita) there is a higher frequency of positive effects on yield associated with increases in SAT than at Rothamsted (Figures 6.2a,b). Very little sensitivity to SAT on N uptake or biomass was evident (Table 6.5).

SWCON proved to be a fairly insensitive parameter. Increases in SWCON on the average produced small increases in yield at Wongan Hills when fertilizer was applied (Figure 6.2a) and small decreases when no fertilizer was applied (Table 6.4). Increases in yield associated with increases in SWCON could be the result of increased water flux to deeper layers in dry years leading to improved water relations. Decreases in yield associated with increases in SWCON may be associated with increases in leaching caused by the increased water flux through the profile. Very little sensitivity to SWCON on N uptake or biomass was evident (Table 6.5).

INO3--When no fertilizer was applied (Table 6.4) the sensitivity to INO3 was high (overall $S = 0.643$). When fertilizer was applied sensitivity to INO3 was very much lower, but some sensitivity was still apparent (Figures 6.2a,b,c). The sensitivity to INO3 for simulation of biomass and N uptake was similar to that for grain yield. In most cases increases in INO3 were associated with increases in yield. In some years increases in INO3 caused decreases in yield. This is possible when an increased growth early in the season resulted in an early exhaustion of the water supply with a consequent reduction in grain filling rate. Such water/nitrogen interactions have been reported by Storrier (1965) and Fischer and Kohn (1966). The analysis suggests that under conditions of low N supply, the amounts of nitrate (and by analogy ammonium) that are supplied as input data to the model must be estimated with some precision.

IOC--The initial supply of "stable" soil organic N is estimated in the model by assuming a C:N ratio of 10 in bulk soil. Thus an increase in IOC would imply an increase in potentially mineralizable N. There was little sensitivity to IOC at Wongan Hills and Wichita when fertilizer was applied. At both these sites frequent low soil moisture availability in the upper layers would result in a low mineralization rate and hence reduce sensitivity. When fertilizer was not applied IOC was a much more sensitive parameter at both sites suggesting that under low N supply the N supplied from mineralization of "stable" organic N is important. The analysis suggests that estimates of IOC provided to the model must be made with some precision when N supply is limited. N uptake was not sensitive to perturbation of IOC.

SCN--The model was found to be fairly insensitive to the C:N ratio of the added crop residue. Each of the simulations was run with an added crop residue of 1,500 kg of straw dry matter/ha with a C:N ratio of 60. If all the N contained in this residue were to mineralize during the growing season the contribution to the mineral N supply would be 10 kg N/ha. If errors were made in the estimation of the C:N ratio of + or - 20% this contribution would become 8.3 or 12.5 kg N/ha, respectively. When fertilizer is applied these small differences in N supply, particularly when spread over a growing season, would be masked. Similar calculations reveal a minor importance of errors in estimation of SCN as they would affect the rate of N immobilization when fertilizer is applied. Some sensitivity was found at Wongan Hills (S = 0.267) when no N was applied. This site had the lowest initial N supply and the shortest growing season over which to mineralize any previously immobilized N. These factors may have contributed to this sensitivity. Some increased sensitivity may be expected at higher rates of straw application and with materials with a higher C:N ratio. In most instances where N supply is not very limiting the sensitivity is low.

BD--Bulk density is used in the calculation converting soil N input data from a concentration basis (ppm) to a mass basis (kg N/ha). It is also used in the calculation of porosity which is subsequently used to calculate saturation moisture content. Thus increases in BD will cause increases in INO3 and INH4 (initial KCl extractable ammonium) and will cause a decrease in SAT. Reflecting the changes in initial N supply, there was a large sensitivity to BD when fertilizer was not applied. When fertilizer was applied little sensitivity was apparent at the two dry sites but some was apparent at Rothamsted. The sensitivity was equivalent (though of opposite sign) to that for SAT at Rothamsted, suggesting that the sensitivity to BD may be as a result of changing porosity. When fertilizer was not applied the sensitivity to BD approximated that of INO3, indicating that modification of the initial N supply is the probable cause of the sensitivity.

The analysis suggests that estimates of BD supplied to the model must have reasonable precision at low rates of N supply.

RAIN--The perturbation performed was to the size of generated daily rainfall events in a multiplicative manner. This means the frequency of rainfall events remained unchanged but the magnitude of each event was changed. This proved to be the most sensitive of all parameters tested. The magnitude of the sensitivity to RAIN is indicated by the large range of possible outcomes (Figure 6.2) in yield. The effects on biomass and N uptake were equally large. The sensitivity was much greater at the drier sites than at Rothamsted. The relative sensitivity to RAIN at the three sites differed markedly with fertilizer treatments. Figure 6.2 indicates a 5% increase in RAIN may cause more than a 30% increase in yield in more than 10% of years at Wongan Hills and Wichita and in 5% of years at Rothamsted. Increases in RAIN infrequently were associated with decreases in yield at Wongan Hills, due possibly to either leaching or to early growth of a large biomass which may prematurely exhaust the water supply later in the season. Decreases in yield with increases in RAIN were more frequent at Wichita and Rothamsted. Thus the accuracy of simulations of crop growth, nitrogen dynamics, and yield will be greatly prejudiced by the accuracy of supplied rainfall data.

TEMP--Temperature was a highly sensitive parameter at Wongan Hills and at Wichita but not at Rothamsted when fertilizer was applied. When no fertilizer was applied there was less sensitivity at Wongan Hills and more at Rothamsted. Increases in temperature at Wongan Hills were associated with increases in yield (positive mean S) whereas increases in temperature were associated with decreases in yield at Wichita. The large range of possible outcomes (Figure 6.2) masks some of the mean effect. At Wongan Hills, with a marked winter dominant rainfall, soil moisture is usually in short supply during the late spring and early summer period when grain filling is occurring.

Increases in mean temperature will speed the development of the crop and it may thus avoid the periods of moisture stress. Increased temperature will of course increase rates of evaporation which in some years may lead to additional moisture stress. This effect of increased temperature on speeding the development rate was more marked at Wongan Hills than at the other two sites (Table 6.6) because the mean temperatures experienced during the crop growth period are higher than those at the other two sites. The small amount of vernalization required by the spring wheat variety Condor used in the simulation is obviously still satisfied despite the rises in temperature. The reduction in yield with increased temperature at Wichita is most probably associated with increases in evaporation leading to moisture stress. In several years at Wichita increased perturbation of temperature would lead to increased rates of defoliation and plant death due to winter killing. This occurs since the perturbation is multiplicative and not additive and so a low negative temperature is made lower when the perturbation factor is increased. Mid-winter temperatures at this location are sufficiently low to cause some winter kill in many years but not at the other two locations. The effects of perturbation of temperature were less apparent on simulated biomass and N uptake. Since temperature is a major driving variable in many crop growth processes and nitrogen transformations, its perturbation can cause many interacting effects. Among these effects are effects on crop duration, evaporation, severity of winter killing, and effects on nitrogen supply processes.

Table 6.6. Effect of Temperature Perturbation on the Simulated Mean Duration of Crop Growth (days)

Perturbation (%)	Wongan Hills	Wichita	Rothamsted
0	165	251	270
+5	161	249	265
+10	156	246	261
+20	148	242	253
-5	171	254	275
-10	177	257	282
-20	190	264	298

SOLRAD--In the model solar radiation is used to predict the potential evaporation and, together with leaf area, the potential rate of crop photosynthesis. The model partitions the potential evaporation between soil and crop components and uses the two stage method described by Ritchie (1972) to predict actual evaporation from this potential. The effect of SOLRAD on evaporation is more powerful than the effect on photosynthesis since simulated net photosynthesis rate is also dependent upon prevailing temperature, water and nitrogen stresses, and on the size of the crop biomass (respiration requirement). Thus the primary impact of SOLRAD on crop yield will be via the effect on evaporation rather than on photosynthesis. In every year simulated when SOLRAD was increased, yield reductions occurred, except during 1 year at Rothamsted when SOLRAD was increased 20%. When SOLRAD was decreased occasional years showed a decrease in yield but most years showed an increase in yield. The analysis suggests the primary impact is via evaporation and the large sensitivity implies that solar radiation used as input to the model must be reliably estimated.

In a separate study, perturbation of the coefficient determining the efficiency of conversion of solar radiation into biomass indicated a high degree of sensitivity. This would suggest that sensitivity to solar radiation in the photosynthesis component of the model exists and this is overridden by larger effects of solar radiation on evapotranspiration.

N-Component Variables

DMOD--Biomass and N uptake were very little affected by perturbation of the mineralization rate when fertilizer was applied and the sensitivity for grain yield was the lowest obtained for all parameters (S = 0.000). When fertilizer was not applied and the N supply more severely limited plant growth, increased sensitivity to mineralization rate perturbation was apparent (S = 0.118). The sensitivity was lowest at Wichita. This soil had the largest amount of organic N present. The greater sensitivity at the other two sites reflects the lower availability of N for plant growth. Small errors in the estimation of the mineralization rate of crop residue as distinct from "stable organic matter" will have little influence on predicted yields, biomass, or N uptake due to the small contributions residues make to the N supply in these simulations as discussed earlier (see SCN). Had a larger mass of residue with a more favorable composition (lower C:N ratio) for decomposition been used in the simulations, greater sensitivity to this coefficient may have been apparent. Similarly, if a large mass of material with a large C:N ratio had been added, leading to substantial immobilization, greater sensitivity may have also been apparent. Thus, small errors in the mineralization/immobilization components of the model are unlikely to influence predicted yields greatly unless the soil N supply is very limited.

RNTRF and CNI--These two variables influence the rate of nitrification. When fertilizer was applied at Rothamsted and Wichita upward or downward perturbation of these variables always caused only small changes in yield (Figure 6.2d,e,f). Larger changes were apparent in some years at Wongan Hills. Sensitivity was higher when fertilizer was not applied, but sensitivity overall was not high. Restriction of the nitrification rate would maintain a greater proportion of the soil mineral N in the ammonium form rather than the nitrate form. Since nitrification is generally a rapid process, the 20% downward perturbation of RNTRF may have only slowed the conversion a few days, thus exhibiting little sensitivity over a whole growing season. Perturbation of CNI may extend this period of reduced nitrification a little longer, since this variable is concerned with determining the buildup in nitrification capacity once conditions for nitrification become favourable. Thus, in some instances higher sensitivity to CNI may be exhibited. Sensitivity to nitrification is further discussed in Section 6.6. In most instances small errors in simulation of the nitrification rate will not be detectable in grain yield, biomass, or N uptake.

DNRATE--Overall, little sensitivity to DNRATE was observed. Denitrification was expected to be an infrequent phenomenon at Wongan Hills since prolonged periods of saturation in the upper part of the profile are rare events. Figure 6.2d indicates that the range of effects on yields of perturbing DNRATE is very small, perhaps indicative of either the low frequency of denitrification events or their small size when they do occur. Reductions in DNRATE of 10% and 20% resulted in a 20% yield increase in 1 or 2 of the 20 years simulated. At Rothamsted denitrification would be a more frequent phenomenon due to the prevailing moisture regime. In almost all years simulated at Rothamsted (Figure 6.2f) upwards perturbations of DNRATE resulted in reductions in yield (albeit small). The converse, where DNRATE was perturbed downward, did not lead to frequent yield increases. The S values obtained over all sites indicate that small errors in denitrification rate will rarely affect the simulated yields, biomass, or N uptake.

LEACH--In this case the variable affecting the rate of nitrate movement from every layer was perturbed. The model was insensitive to changes in the rate of leaching of nitrate under low N supply and at the drier sites (Wongan Hills and Wichita). At the dry sites many years occur when there is insufficient moisture to substantially redistribute nitrate within the profile. In these years there is high probability there is also insufficient moisture for crop growth. The greatest sensitivity to perturbation of this variable was experienced at the wettest site (Rothamsted) (S = 0.155) when fertilizer was applied. In this case, increasing the leaching rate led on average to increases in yield. Figure 6.2f, however, indicates that there are as many years when yields were decreased by upwards perturbation of LEACH as there were years when yields were increased. Since perturbation was to the nitrate movement from all layers, this may be more indicative of redistribution of nitrate within the profile than losses from the root zone. A more appropriate means of testing sensitivity to leaching would have been to perturb only the LEACH from the bottom layer. In some instances, if nitrate is relocated to layers where there is a greater likelihood of water being present, short-term nutritional droughts may be avoided.

Since large leaching losses have been recorded at Rothamsted (Whitmore and Addiscott, 1986), further investigation of the nature of the sensitivity of the model to leaching is required. This is addressed to some extent in Section 6.3.

FNO3 and MAXUL--Both these variables potentially affect the daily rate of N uptake. Potential N uptake is calculated as a function of the supply index (FNO3), a moisture index (SMDFR), the root length density, and the maximum uptake of N per unit length of root (MAXUL). When fertilizer was applied very little sensitivity was seen in grain yield response at any of the sites. Slightly more sensitivity was displayed when fertilizer was not applied, but the sensitivity remained very low. Similar responses in sensitivity were recorded for biomass. N uptake was found to be highly sensitive to both variables when fertilizer was applied. Since MAXUL and FNO3 are multiplied together in the potential uptake equation their sensitivities for N uptake are identical. The greater sensitivity for N uptake compared to grain yield or biomass suggests that on many occasions N uptake was affected in the simulations with little effect on the growth processes. This can occur when there are relatively high concentrations of N within the plant, as may occur with high rates of fertilizer addition.

The high sensitivity to perturbation of these two variables for N uptake when fertilizer is applied is somewhat surprising since an overestimation of N uptake on one day will lead to a diminished supply, thereby causing a reduction in FNO3 the following day thus lowering uptake. The high sensitivity does indicate that the functions in the model concerned with calculation of uptake rate need to be reliably estimated for the simulation of N uptake but not necessarily for yield.

RNFAC--Root distribution in the model is simulated by using a rooting preference function WR (supplied as input) as the primary driving variable. The distribution of new root growth is modified according to the prevailing moisture and N availability conditions. Very little sensitivity to perturbation of RNFAC was exhibited by grain yield, biomass accumulation, or N uptake at any of the sites.

NFAC, NDEF1, NDEF2, NDEF3, NDEF4, and GNP--Together these variables control the mechanisms by which the plant adjusts to changes in tissue N concentration. NDEF1, NDEF2, NDEF3, and NDEF4 are all calculated from NFAC. NFAC is calculated from the tissue concentrations as below:

NFAC = 1.0 - (TANC-TMNC)/(TCNP-TMNC)

Where TANC = Actual vegetative shoot N concentration.

TMNC = Minimum vegetative shoot N concentration.

TCNP = Critical vegetative shoot N concentration.

As the plant ages, TMNC and TCNP fall. Thus, if TANC is maintained at a constant level, as the plant ages the crop will change from a period of deficiency to a period of sufficiency.

When deficiency occurs a low value of NFAC causes a reduction in growth via its effect on growth processes (by way of the four N deficiency factors). With reduced growth, N concentration will tend to remain constant since less dilution is occurring. Thus, as the plant ages it tends to grow out of deficiency. In practice, however, if the soil N supply remains limited, reduced uptake will compensate for the reduction in growth and may cause NFAC to also remain low. This very dynamic nature of the feedback mechanisms involved within the model may mask some of the effects of perturbation of the deficiency indices and NFAC. Had the perturbation been growth stage dependent as in the case of Larsen's (1981) perturbation of environmental variables, some greater sensitivity may have been evident.

Given that these compensating effects can occur, sensitivity to the deficiency indices can occasionally be very marked. Figures 6.2d,e indicate that when fertilizer is applied there are some years when a 10% or 20% reduction in these indices will substantially affect grain yields at Wongan Hills and Wichita. Overall high sensitivity to NDEF1 and NDEF4 for grain yields was evident at Rothamsted when fertilizer was not applied. GNP rarely influenced yields. Very high sensitivity to NDEF3 for N uptake was found when fertilizer was not applied.

The difficulty in obtaining a precise indication as to the sensitivity of these indices indicates that further work on the model is warranted in more clearly defining the concentration/growth process relationships. Further sensitivity analyses with the model running in a deterministic mode, together with comparisons with observed concentration and growth data, may help clarify responses to N deficiency.

6.3 Sensitivity to Fertilizer Rate and Timing

The sensitivity of the model to various fertilizer management strategies is evident from some of the validation studies outlined in