THE EFFECT OF CHANGES IN DAILY AND INTERANNUAL CLIMATIC VARIABILITY ON CERES-WHEAT: A SENSITIVITY STUDY

LINDA O. MEARNS
*National Center for Atmospheric Research**, *Boulder, CO, U.S.A.*

CYNTHIA ROSENZWEIG and RICHARD GOLDBERG
Goddard Institute for Space Studies and Columbia University, New York, NY, U.S.A.

Abstract. We investigate the effect of changes in daily and interannual variability of temperature and precipitation on yields simulated by the CERES-Wheat model at two locations in the central Great Plains. Changes in variability were effected by adjusting parameters of the Richardson daily weather generator. Two types of changes in precipitation were created: one with both intensity and frequency changed; and another with change only in persistence. In both types mean total monthly precipitation is held constant. Changes in daily (and interannual) variability of temperature result in substantial changes in the mean and variability of simulated wheat yields. With a doubling of temperature variability, large reductions in mean yield and increases in variability of yield result primarily from crop failures due to winter kill at both locations. Reduced temperature variability has little effect. Changes in daily precipitation variability also resulted in substantial changes in mean and variability of yield. Interesting interactions of the precipitation variability changes with the contrasting base climates are found at the two locations. At one site where soil moisture is not limiting, mean yield decreased and variability of yield increased with increasing precipitation variability, whereas mean yields increased at the other location, where soil moisture is limiting. Yield changes were similar for the two different types of precipitation variability change investigated. Compared to an earlier study for the same locations wherein variability changes were effected by altering observed time series, and the focus was on interannual variability, the present results for yield changes are much more substantial. This study demonstrates the importance of taking into account change in daily (and interannual) variability of climate when analyzing the effect of climate change on crop yields.

1. Introduction

There is considerable quantitative uncertainty concerning how agricultural crops respond to changes in climate variability, although it is known qualitatively that changes in variability can have serious effects. There have been noteworthy periods of climatic fluctuations in historical times, such as the 1930s in the central Great Plains, when the effects of climatic variability on agriculture were keenly experienced (Worster, 1979; Rosenberg, 1980). Agricultural vulnerability to climatic fluctuations has not decreased to any appreciable degree in more recent times (Anderson and Hazell, 1989). Moreover, in the face of possible climatic change from, for example, increased greenhouse gas concentrations in our atmosphere, there is mounting evidence that changes not only in climatic mean states but also

* The National Center for Atmospheric Research is sponsored by the National Science Foundation.

Climatic Change **32:** 257–292, 1996.

in their higher order moments will occur. Evidence for this is particularly strong in regard to precipitation (Gordon *et al.*, 1992; Whetton *et al.*, 1993; Mearns *et al.*, 1995a), and some evidence for changes in temperature variability has also come to light (e.g., Cao *et al.*, 1992; Mearns *et al.*, 1995b). Agricultural crops experience change in variability mainly through the frequency of climate extremes; it recently was demonstrated that change in variance has a larger effect on changes in extremes than does change in the mean of a given climate variable (Katz and Brown, 1992).

So far very little attention has been paid to possible impacts of changes in climatic variability in climate impacts assessments (e.g., Rosenzweig and Parry, 1994; Mendelsohn *et al.*, 1994). The effect of possible changes in high frequency (annual to daily time scales) climatic variability remains a significant uncertainty that has not received sufficient attention in the arena of integrated assessment of climate change. Here we present sensitivity experiments of the effect of changed daily and interannual variability of precipitation and temperature on crop yields generated by the CERES-Wheat model (Ritchie and Otter, 1985). Our objective is to determine the magnitudes of changes in variability, and temperature and precipitation variability important to wheat production in the U.S. Great Plains.

Mearns *et al.* (1992) (henceforth referred to as MR92) explored the effect of changes in (primarily) interannual variability of climate (temperature and precipitation) on simulated wheat yields, using a simple approach of altering the monthly year-to-year variances of observed time series. This approach, although producing informative results, was somewhat unrealistic in that changes in interannual variability were artificially isolated from changes in daily variability. For temperature daily variance was changed very little, but autocorrelation functions of daily time series were altered. For example, for maximum temperature with doubling of interannual variance daily variance is increased slightly (factor of 1.2) using this technique, as is the first order autocorrelation coefficient. The most substantial change, however, is in the autocorrelation function of the daily time series, which damps toward zero much more slowly than does the function of the original time series. For precipitation, frequency was not changed, but the mean and variance of daily intensity was altered somewhat.

In MR92 the relative variability of yield increased with increasing variability of both temperature and precipitation. Mean yields decreased with increasing variability of precipitation at a relatively wet location, but increased at a moisture limited location. The effects of variance changes of precipitation were greater than those of temperature. Results from this earlier study indicated that significant changes in simulated crop yields result from changes in climatic variability, and that such changes can be as important as changes in climatic means.

Here we continue this line of investigation using a stochastic simulation approach for generating time series of climate variables whereby daily variability is directly changed, which imposes changes in interannual variability. The same study area is used, the central Great Plains, in particular two locations in Kansas – Goodland a drier site in the northwest, and Topeka, a wetter site in the northeast.

This type of study contributes to a wide variety of research concerns. It serves as an important test of the crop models themselves, and can provide insights into the adequacy of their formulations for simulating crop response to climates. The study explores the basic nature of the interface between the atmosphere and biotic systems. The results may also provide useful information in a non-interactive mode for eventual interactive coupling of crop/ecosystem models with climate models.

In the next section we describe the CERES-Wheat model and the general study characteristics. In Section 3 we describe the weather generator used. The sensitivity experiments are described in Section 4 and Section 5 presents results, followed by concluding remarks in Section 6.

2. CERES Wheat Model and Study Characteristics

2.1. WHEAT MODEL

2.1.1. *General Description*

The CERES-Wheat model employs simplified functions to predict the growth and yield of wheat as influenced by plant genetics, weather, soil, and management factors (Ritchie and Otter, 1985). Climate input variables are daily solar radiation (MJ m^{-2} day^{-1}), minimum and maximum temperature (°C), and precipitation (mm day^{-1}). Model processes include phenological development (Hodges, 1991), vegetative and reproductive plant development stages, partitioning of photsynthates, growth of leaves and stems, senescence, biomass accumulation, and root system dynamics. Detailed descriptions of the model may be found in Ritchie and Otter (1985) and Rosenzweig (1990). Below we highlight certain aspects of the model that are particularly germane to our results.

Soil water. The soil water balance for a layered soil is calculated in CERES-Wheat in order to determine reduction in growth processes caused by soil and plant water deficits. For multi-year simulations, it also tracks the soil water when the wheat crop is not growing, enabling the calculation of soil moisture accumulation from the practice of fallowing. Evapotranspiration in the model (which is divided into transpiration and soil components) is driven by solar radiation and temperature, based on the equilibrium evaporation concept (Priestley and Taylor, 1972). A variable multiplier is applied to the calculated equilibrium evaporation to account for unsaturated air and for maximum temperatures greater than 24 °C and less than 0 °C. Root length density and distribution are used to calculate water absorbed for transpiration via a 'supply and demand' formulation. The water content of multiple soil layers is calculated based on changes in evaporation, root absorption, or flow to adjacent layers. Runoff is calculated using the USDA Soil Conservation Service Curve method (Williams *et al.*, 1982).

Four soil water deficit factors are defined based on layer water contents that are then used to modify root growth, photosynthesis and transpiration, leaf and stem extension growth, and tillering. We emphasize here soil water deficit factor

1 (SWDF1), which primarily affects photosynthesis and transpiration. It is defined as the ratio of total daily root water uptake from the soil plant system and potential plant evapotranspiration. Its value ranges from 0 (no stress) to 1 (maximum stress). This factor also modifies a number of other plant growth processes.

Crop failures. There are three types of crop failure in the CERES-Wheat model as formulated for this study: failure of germination; winter kill; and inadequate grains m^{-2}.

(1) Germination fails to occur if there is insufficient soil moisture for 90 days after planting. Sufficiency of soil moisture is defined as presence of extractable water in the top soil layer or the combined top two layers.

(2) Winter kill. We provide details on the winter kill submodel because the frequency of winter kill figures prominently in some of our results. Wheat plants can be killed or damaged by extremely low temperatures. This damage is also influenced by the degree to which the plants have adapted to the cold, known as hardening. In CERES-wheat the crown depth temperature, which is a function of maximum, minimum temperature and snow depth, is used to evaluate cold hardening and winter kill. Hardening is quantified using a hardening index (HI) whose value ranges from 0 to 2. Stage 1 hardening (HI 0–1) occurs when mean daily crown temperature is between -1 °C and 8 °C. Stage 2 occurs after Stage 1 while temperatures are below 0 °C, and is complete after 12 days. Damage is determined by the relative contrast between the crown temperature and the killing crown temperature, which is determined by the degree of hardening. For HI 0, 1, and 2, the killing crown temperatures are -6, -12, and -18 °C, respectively. Hence, less hardened plants, are susceptible to cold temperature extremes. The plant can also lose its hardening when crown temperatures rise above 8 °C and maximum temperature is above 10 °C.

(3) Inadequate grains per m^2 cause crop failure in growth stage 4 (anthesis to beginning of grain fill) if the number of kernels per m^2 drops below 100. This type of crop failure occurs when the stem weight of the simulated wheat is low, a plant variable which is primarily dependent on soil moisture via its effect on leaf area index (LAI) and biomass. Actual biomass increase depends on a soil water deficit factor; at times of maximum water deficit, the biomass increase is reduced to a very low value.

2.1.2. *Validation*

The CERES-Wheat model has been validated for production of yield at numerous locations (see Otter-Nacke *et al.*, 1986) and more recently for Goodland (MR92). Of interest here is how well the model reproduces year-to-year variability of yield. In MR92 it was found the model overestimated year-to-year variability, but part of this overestimation was due to the faulty comparison of point location simulated yield to county area actual yields. For this study we statistically compared the relationship between year-to-year variability of observed precipitation, observed year-to-year county yields and yield simulated using observed climate data for

Goodland. We found that the relationship of the simulated yields to annual crop season precipitation ($R^2 = 0.57$) was stronger than that of observed yields to annual crop season precipitation ($R^2 = 0.27$), and that the slope of the simple regression line (yield regressed on precipitation) was higher for the simulated yields. However, this comparison is also confounded by the lack of spatial compatibility between the point climate and the area observed yields, i.e., the point location misrepresents the area climate. This result was anticipated also since the crop model does not account for various factors (e.g., hail, insect pests, diseases) that can affect observed yield in any given year. The model does reproduce the fluctuations in yields for extreme weather years, for example the large drop in yield in Sherman country (Goodland) in 1956, which was a severe drought year. More work needs to be done in carefully validating the crop model specifically for reproduction of yield variability.

2.2. STUDY CHARACTERISTICS

The main difference in the climates of the two locations is the amount of precipitation received. Goodland, where annual average total precipitation is about 421 mm, is a relatively dry location, and summer fallowing is the common cultivation practive. Topeka, which receives on average 853 mm of precipitation annually, is relatively wet, which allows for continuous rainfed cropping.

The three generic soils used in the CERES-wheat model to represent low (S1), medium (S2), and high (S3) soil productivity levels at Goodland were deep sandy loam, deep silt loam, and shallow silty clay. At Topeka these were deep sandy loam, medium silt loam, and medium silty clay. The soils differ mainly on the basis of soil water holding capacity and depth.

The wheat cultivars grown at the two sites (Newton for Goodland and Scout 66 for Topeka) are similar. The largest difference between the two cultivars is that Newton has a longer duration of grain filling period, but this difference does not affect the results significantly.

Two types of management practices – continuous rainfed and fallow – were simulated by the model. For Topeka a crop was planted every fall for continuous rainfed production; and for Goodland every other fall for fallow production (two runs with alternate fallow years were averaged so that annual crop yields were reasonable). Soil moisture at planting was initialized for each soil type using the average soil moisture at planting from runs of the model using observed climate data.

3. Stochastic Weather Generator

3.1. DESCRIPTION OF THE MODEL

Richardson's (1981) stochastic weather generator simulates daily times series of maximum and minimum temperature, incident solar radiation, and precipitation.

Daily precipitation occurrence is represented by a two-state first-order Markov chain model. It accounts for the stochastic dependence of the series of wet and dry days. Parameters estimated are two transition probabilities: P_{11} and P_{01}, the probability of a wet day following a wet day, and the probability of a wet day following a dry day. Rainfall amounts (x) are simulated for rain days using the gamma distribution:

$$f(x) = x^{\alpha-1}e^{(-x\beta^{-1})}/(\beta^{\alpha}\Gamma(\alpha)), x \geq 0, \tag{1}$$

where:

$$\begin{aligned} \alpha &= \text{the shape parameter;} \\ \beta &= \text{the scale parameter;} \\ \Gamma(\alpha) &= \text{the gamma function of } \alpha. \end{aligned}$$

The mean μ of the distribution is $\alpha\beta$ and the variance σ^2 is $\alpha\beta^2$.

Maximum and minimum temperature, and solar radiation are modeled as a multivariate first-order autoregressive process:

$$x_t(j) = Ax_{t-1}(j) + B\varepsilon_t(j), \tag{2}$$

where:

$x_t(j)$ = 3×1 matrix for day t for $j = 3$ elements, which are standardized values of maximum temperature ($j = 1$), minimum temperature ($j = 2$) and solar radiation ($j = 3$);

$\varepsilon_t(j)$ = 3×1 matrix for day t for j elements, of independent random normal components;

A, B = 3×3 matrices constructed from matrices of lag 0 and lag 1 correlations among the three j elements.
$A \simeq$ time dependence,
$B \simeq$ simultaneous correlations among the j elements.

Then the actual daily values of the j elements X_t are determined for $j = 1$, or $j = 3$ by:

$$X_{ti}(j) = x_{ti}(j) \times s_{ti}(j) + m_{ti}(j), \tag{3}$$

where:

$X_{ti}(j)$ = daily value of variable j on day t for precipitation occurrence state i, $i = 1$ for a wet day, $i = 0$ for a dry day;

$s_{ti}(j)$ = standard deviation of variable j on day t for state i;

$m_{ti}(j)$ = mean of variable j on day t for state i;

The seasonal cycle for the means and standard deviations of the j elements is determined by two-harmonic Fourier series. Since maximum temperature and solar radiation are conditioned on the occurrence of precipitation, separate models (including different harmonics, means, and variances) are used for values occurring on rain days and dry days, indicated by the i index. For $j = 2$, miminum temperature, there is no conditioning, and the index i in Eq. 3 is not used.

3.2. RELATIONSHIP BETWEEN ANNUAL AND DAILY VARIABILITY

Based on the stochastic model for precipitation occurrence and intensity, the variance of the monthly total precipitation is related to the characteristics of daily precipitation according to the following:

$$\sigma_I^2 \simeq N\pi\alpha\beta^2 \left[1 + \alpha(1-\pi)\frac{1+d}{1-d}\right] , \tag{4}$$

where:

σ_I^2 = year-to-year variance of monthly precipitation;
N = number of days in the time series;
π = unconditional probability of a wet day ($\pi = P_{01}/P_{10} + P_{01}$);
α, β = shape, scale parameters of the gamma distribution;
d = the persistence parameter for a first order Markov chain of precipitation occurrence($d = P_{11} - P_{01}$).

The relationship between interannual and daily variance of temperature is the following:

$$\mathrm{Var}(T) \simeq \frac{\sigma_d^2}{N}(1 + 2\sum_{k=1}^{\infty} \rho_k), \tag{5}$$

where:

$\mathrm{Var}(T)$ = interannual variance of monthly temperature ($^\circ C^2$);
σ_d^2 = variance of daily temperature ($^\circ C^2$);
ρ_k = autocorrelation coefficient of order k.

Since temperature is modeled as a first-order autoregressive process Eq. 5 is simplified to consider only ρ_1. It is important to note that these relationships are approximations.

As is the case with most weather generators, the Richardson model has some inadequacies which affect how well it simulates the climate. For example, the first-order autocorrelation coefficient of mean temperature can be misspecified (Katz, 1996). We rigorously validated the model for the locations we used (see Section 5.1.) and found it largely adequate for our purposes.

4. Sensitivity Tests

Approaches to changing the variability of stochastically generated climate time series was adumbrated by Mearns (1989) and described in more detail by Wilks (1992).

4.1. TEMPERATURE

We performed sensitivity tests at both locations for multiplicative changes of 0.33, 0.5, 2, and 3× the base temperature year-to-year variance, on a monthly time scale (Eq. 5). This was accomplished in the stochastic generator by altering $s_t(j)$ (for $j = 1, 2$) in Eq. 3 by the square roots of these variance change factors. This method changes the daily variance of minimum temperature exactly by the chosen factor, but only approximates it for maximum temperature.

Since maximum temperature is conditioned on the occurrence of precipitation and separate means and standard deviations are calculated in the Richardson model on the basis of this conditioning, the daily variance of the series, which is comprised of combining these separate models, is the following (Katz, 1996):

$$\sigma_d^2 = (1-\pi)\sigma_{d0}^2 + \pi\sigma_{d1}^2 + \pi(1-\pi)(\mu_1 - \mu_0)^2, \tag{6}$$

where:

σ_d^2 = variance of daily maximum temperature time series (°C^2);
σ_{d0}^2 = variance of daily maximum temperature on a dry day (°C^2);
σ_{d1}^2 = variance of daily maximum temperatureon a wet day (°C^2);
π = unconditional probability of a wet day;
μ_0 = mean daily maximum temperature on a dry day;
μ_1 = mean daily maximum temperature on a wet day.

Since the last term on the r.h.s. of Eq. 6 remains constant, then changing σ_{d0}^2 and σ_{d1}^2 by some factor, does not result in a change in σ_d^2 by this same factor. For example, by adjusting by a factor of two, the adjustment in variance of the time series is actually closer to 1.9 for Topeka, based on the average difference in the means of maximum temperature on a dry and a wet day of 2.4 and an average π of 0.25. For our purposes, these discrepancies are small and acceptable. We mention this here because in cases where relatively small changes in variance are made, the discrepancy could become important.

We chose the range of changes described above to overlap with the changes used in MR92, which included variance changes from 0.25 to 4× the current interannual variances, to facilitate comparison of the two sets of results. Additionally, in a recent regional climate model experiment of doubled CO_2, daily temperature variance changed by factors from 0.25 to 2.50 (Mearns *et al.*, 1995b). The 3× factor was included as an extreme change, which may be larger than could be expected under doubled CO_2 greenhouse-gas-induced climate warming. However, these changes are smaller than the seasonal ranges of changes found in observations for Kansas (Eder *et al.*, 1989), where the variance of winter is five times that of summer. For temperature variance changes thirty years of daily climate data were generated for each experiment.

4.2. PRECIPITATION

We constructed two different ways of changing the variance of precipitation. In both cases, changes are made in daily parameters in Eq. 4, such that interannual variability of precipitation is changed by a given factor. In the precipitation experiments 81 years of climate data (i.e., 80 years of crop yields) were generated for each case. Longer runs are desirable here because it takes longer time series for the precipitation statistics to converge to the values set by the parameters.

4.2.1. *Frequency and Intensity Changes (π and β)*

The first type of change involves changing the scale parameter of the gamma distribution (β), and the unconditional probability of precipitation (π), so that interannual variance of monthly total precipitation is changed by the following multiplicative factors: 0.33, 0.5, 2, and 3. Certain constraints were observed: mean total monthly precipitation ($N\pi\alpha\beta$) remains constant; the shape parameter α remains constant, as does persistence, *d*. Since $1/\sqrt{\alpha}$ is the coefficient of variation (c.v.) of the gamma distribution, then the c.v. of the precipitation intensity also remains constant. β is changed in Eq. 4 by a factor approximately the same as the interannual variance change factor, and π by approximately the inverse of that factor. For variance increase cases, β increases and π decreases; this results in an increase in both the mean and variance of the precipitation intensity. For variance decrease cases β decreases and π increases, thus reducing the mean and variance of precipitation intensity.

4.2.2. *Change in Persistence* (d)

In the second case only *d* in Eq. 4 is changed, to bring about changes in interannual variance of monthly total precipitation. Since $d = P_{11} - P_{01}$, both transition probabilities are changed. Variance increases by factors of 2 and 3 were simulated for Topeka and Goodland. Variance decreases are constrained by the physically plausible lower limit of $d = 0$, and *d* at these locations is quite low to begin with, in some months less than 0.2. Thus, we tried only one experiment at Topeka wherein the interannual variability was changed by a factor of 0.8.

4.3. TYPES OF COMPARISONS MADE

In discussing the results we compare changes in the mean and variability of yields, frequency of crop failure, and yield distributions. Two statistics are used, % base yield, and coefficient of variation of yield. In addition, we performed the Kolmogorov–Smirnov non-parametric two-sample test (Gibbons, 1985) to compare cumulative distributions of yield.

5. Results

5.1. BASE CLIMATE AND YIELD SIMULATIONS

5.1.1. *Climate Simulations*

We performed a series of climate simulations of various lengths (e.g., 30, 90, and 81 years) for each site. We report here the 81-year base climate simulations for Topeka and Goodland. The parameters for the weather generator were estimated from 30 years (1951–80) of observations for both sites. Observed mean daily precipitation is very well represented (Figs. 1a, 2a) by the simulated time series. Although the simulation of precipitation frequency is quite good at both locations (Figs. 1c, 2c) the mean intensity is sometimes overestimated in high rainfall months (Figs. 1b, 2b), which is partially due to bias in the method of estimation of α and β.

The results for the simulation of daily precipitation intensity for the two locations indicate ways in which the gamma distribution is a good, but less than perfect model of precipitation intensity for these locations. The medians of the distributions of intensity are almost always slightly high, even when the mean intensity is accurately reproduced (Fig. 3a–d). (We show results for May since it is one of the most important months for precipitation for producing final grain yield.) In addition, the lower quartile of the intensity distribution tends to be too high, indicating that there is an underestimation of very small rainfall events. The variability of daily intensity appears to be slightly underestimated, based on the standard deviation, but it is generally well represented as measured by the interquartile range. Maximum values (after controlling for difference in sample size between observed and simulated climate) are often too low.

Interannual variance of precipitation is also usually underestimated (Table I for Goodland), which follows directly from the simple daily precipitation model used (Wilks, 1989; Katz, 1996). These shortcomings notwithstanding, the reproduction of precipitation is generally quite good for these locations in the central Great Plains.

The estimates of mean and variance of daily maximum and minimum temperature are generally quite good (Table II for Topeka), but there are sometimes errors in the estimation of interannual variance. It is generally underestimated in summer months. The first-order autocorrelation coefficient (not shown) is often underesti-

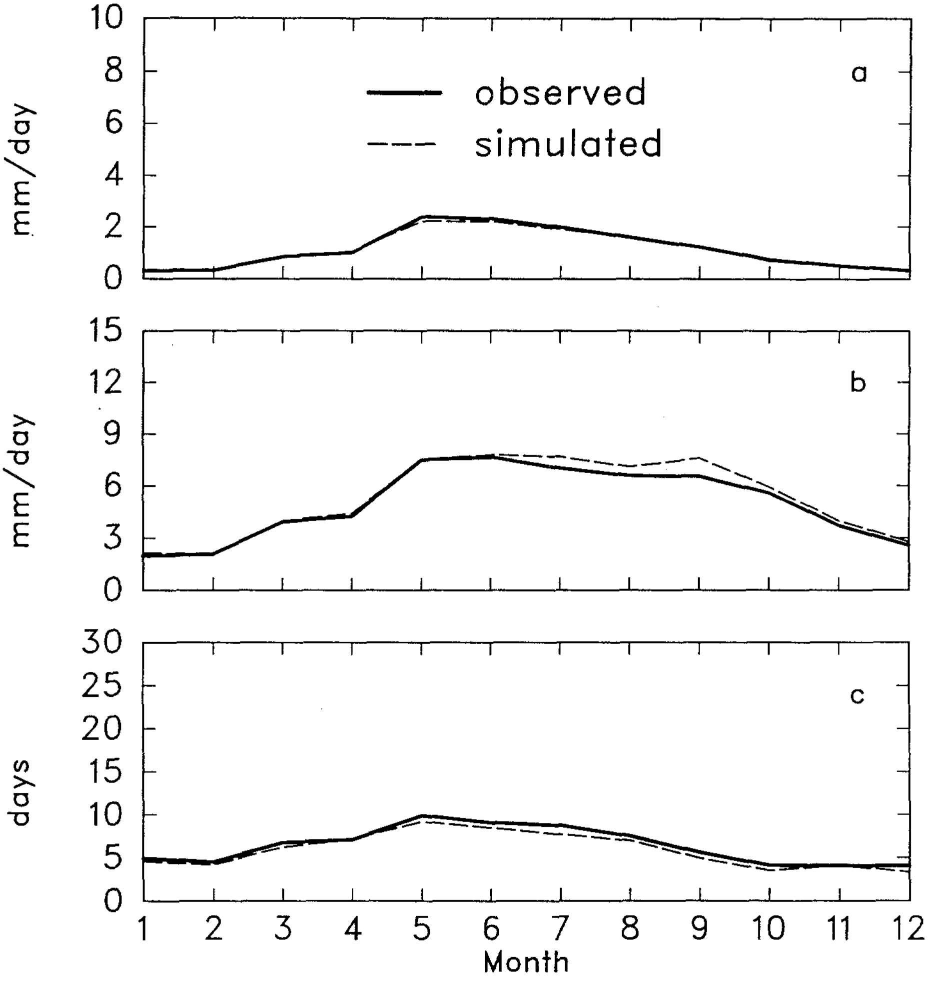

Figure 1. Goodland simulated (81 yr) versus observed (30 yr) precipitation mean monthly values. (a) Daily mean; (b) mean intensity; (c) frequency.

mated for maximum temperature. This error follows directly from the Richardson model structure (Katz, 1996).

Small errors in cross-correlations and serial correlations also result from using default correlation matrices in Eq. 2 generalized for the entire U.S. and for the entire year. Small errors based on departures from the correlations of the location-specific variables may exist. However, the differences in the temperature and solar radiation values generated from location-specific matrices compared to those generated using the general matrices are usually small (Richardson, 1982) and are trivial in their effects on simulated crop yields (Wilks, personal communication).

Since the solar radiation values used at these two locations were originally simulated from the weather generator, there was no need to evaluate them further in

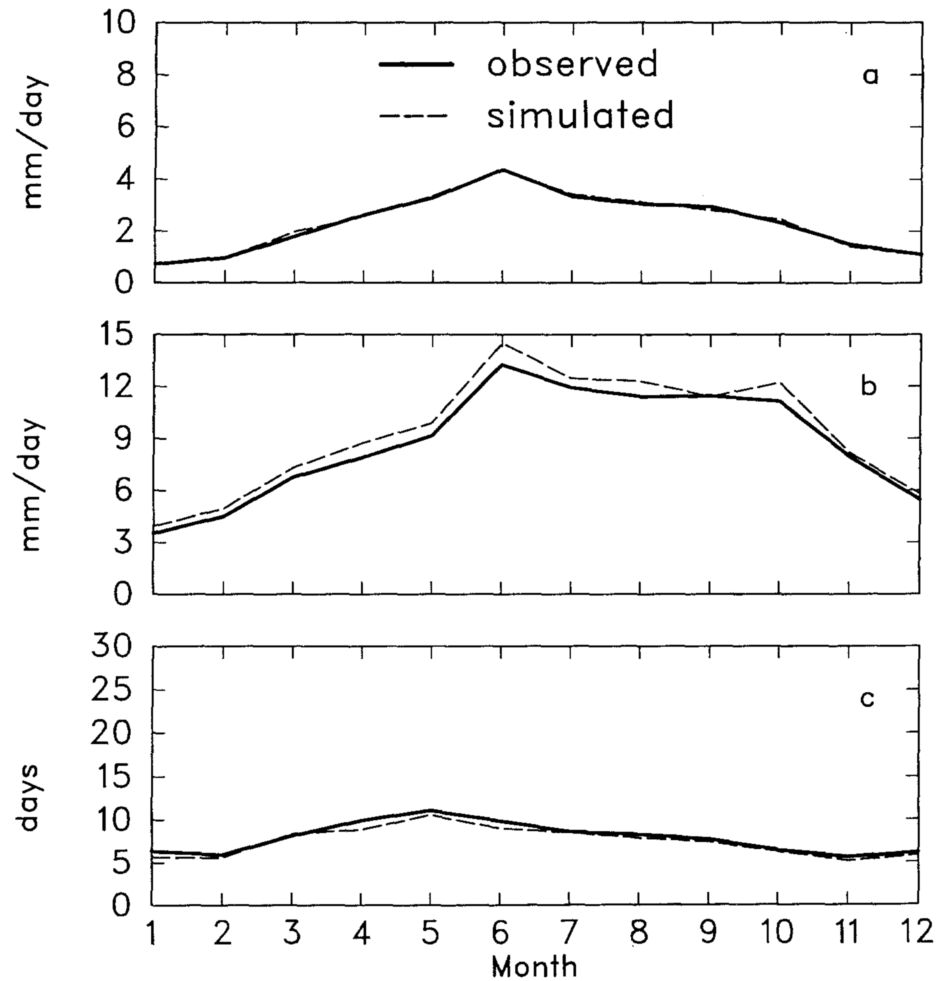

Figure 2. Topeka simulated (81 yr) versus observed (30 yr) precipitation mean monthly values. (a) Daily mean; (b) mean intensity; (c) frequency.

the baseline climate simulations. Moreover, the CERES crop models are relatively insensitive to variability errors in solar radiation (Richardson, 1985). Our results are not dissimilar from other validations of weather generators (Richardson, 1985; Johnson *et al.*, 1996).

5.1.2. *Yields Simulated from Stochastically Generated Baseline Climate*

We then compared the yields simulated using 30 years of observed climate data for each location and those simulated using the stochastically generated climate. Results were quite different at the two locations (Table III and Fig. 4). At Topeka, yields simulated from simulated climate ('Base yields') for three soil types, were very similar to those simulated from observed climate ('observed yields'). The

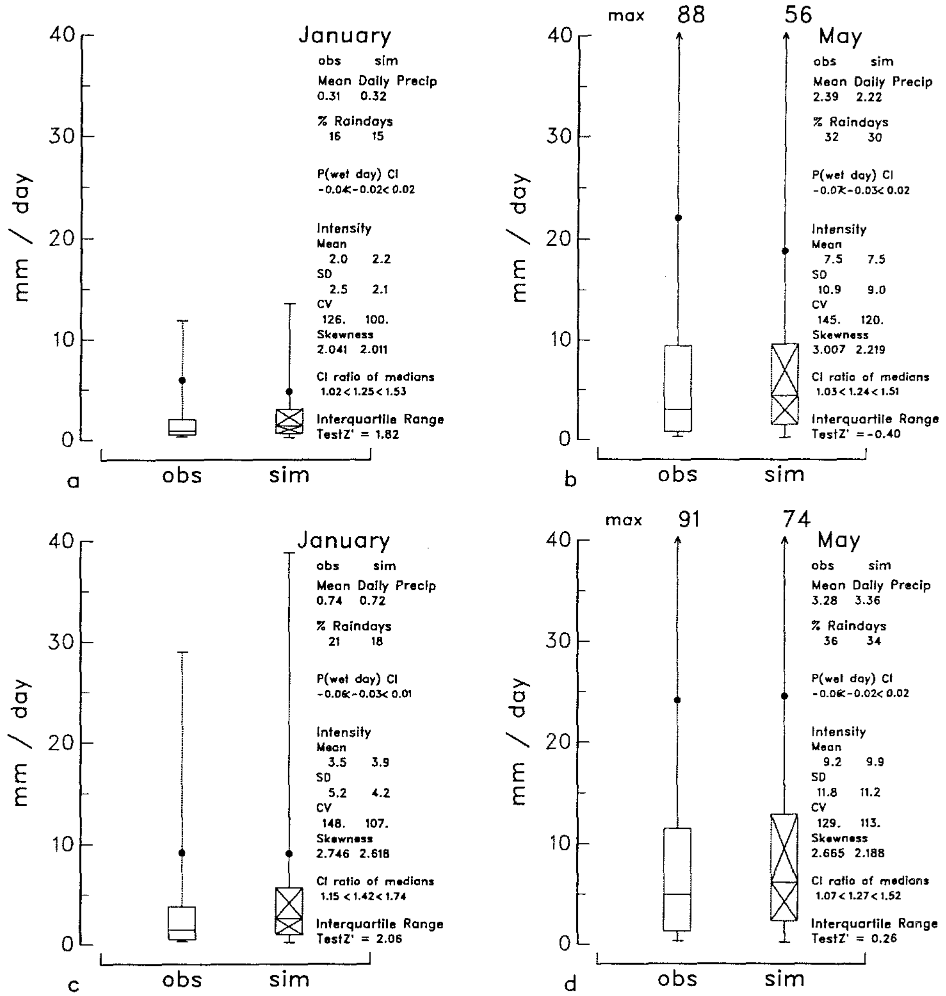

Figure 3. Box plots and statistics of observed (obs) vs. simulated (sim) intensity of daily precipitation. (a) Goodland January; (b) Goodland May; (c) Topeka January; (d) Topeka May. Solid dots on vertical lines extending from the boxes represent the 90th percentile. Numbers associated with arrows are maximum values. Prob. of wet day confidence interval (CI) means the 95% CI for the difference between simulated and observed unconditional probability of a wet day. The CI for the ratio of medians is the 95% CI for the ratio of sim/obs median precipitation intensity. Z is the Z value for the interquartile range test. The critical Z value for significant difference at the 0.05 level is ± 1.96.

differences in the cumulative frequency distributions were quite small (Fig. 4a and Table III).

At Goodland, where the climate is much more marginal for wheat growing, the simulation of yields is more sensitive to small errors in the simulation of climate than at Topeka (Table III and Fig. 4b). We simulated sets of yields, using several realizations of simulated climates of several different lengths. The most accurate realization (based on our statistical criteria) did not produce the most accurate

Table I

Variance (mm^2) of precipitation variance change cases base, PV.5, PV2, and PD2 cases
Goodland

	Winter	Spring	Summer	Fall	Annual
Base	132	2660	3575	1460	7276
Observed	271	3348	4851	1582	12452
ratio	0.49	0.79	0.74	0.92	0.56
PV.5	82	927	1567	578	4092
ratio	0.62	0.34	0.44	0.40	0.56
PV2	390	4810	6327	2971	16866
ratio	2.9	1.8	1.8	2.0	2.3
PD2	322	3779	6018	3058	14037
ratio	2.4	1.4	1.7	2.1	1.9

PV = variance change by altering π and β; for $PV > 1, \pi \downarrow \beta \uparrow$; for $PV < 1, \pi \uparrow \beta \downarrow$.
PD = variance change by altering persistence parameter (d).
ratio = ratio of precipitation change case variance to base variance except in first comparison, which is ratio of base to observed variance.

Table II

Topeka observed and simulated minimum daily temperature statistics

	January	April	July	October
Mean (°C)				
Observed	–9.0	5.9	19.7	6.7
Simulated	–9.1	5.8	19.7	7.4
Interannual variance (°C^2)				
Observed	8.0	2.8	2.3	4.1
Simulated	6.7	3.7	1.3	4.3
Daily variance (°C^2)				
Observed	45.4	29.3	12.3	33.5
Simulated	38.1	26.4	12.1	30.5

simulated yields (compared to yields generated by the 30-year observed climate). The realization that produced the most accurate yields actually overestimated the observed characteristics of precipitation. We combined these two 80-year simulated yield series to produce the baseline yield data set. Combining yields produced what we felt was the best compromise between using the best climate, but producing low yields, or using a climate that overestimated mean intensity of precipitation but produced a more 'accurate' yield series at Goodland (Table III and Fig. 4b).

Table III
Yields (kg/ha) simulated from observed climate vs. simulated climate

	Goodland fallow sim n = 160			Topeka rainfed sim n = 80		
	S1	S2	S3	S1	S2	S3
Observed (n = 30)						
mean	823	1735	1965	3728	4135	4581
sd	749	1099	1140	1459	1478	1340
cv (%)	91	63	58	39	36	29
Simulated						
mean	664	1295	1439	3602	3991	4401
sd	620	928	966	1498	1402	1251
cv (%)	93	72	67	42	35	28
D statistic	0.1287	0.2677	0.2489	0.0871	0.1228	0.1228
P value	0.70	0.05	0.07	0.96	0.54	0.76

n = sample size.
S = soil type.
Observed = yield simulated from observed climate.
Simulated = yield simulated from simulated climate.
sd = standard deviation.
cv = coefficient of variation (%).
D statistic = Kolmogorov–Smirnov 2-sample statistic, which is the maximum absolute difference between the empirical cumulative distribution functions for the observed and simulated yields.
P value = two-sided probability of attaining a larger *D* statistic under the null hypothesis of equal distributions. (i.e., the smaller the *P* value the more significant is the difference between the data sets).

A number of factors contribute to an underestimation of yield at Goodland. The underestimation of interannual variance of precipitation results in an underestimation of the frequency of high precipitation amounts on a monthly basis, which translates to smaller amounts on a daily basis and hence higher yields (generated from the observed climate) are underestimated (Fig. 4b). Since the yields are relatively low under current climate conditions, there is less of a response to the lower frequency of low precipitation years.

There is also a definitive positive trend in the observed annual precipitation time series (Fig. 5a), which is reflected in the simulated yield time series (Fig. 5b). The stochastically generated climate of course has no trend, reflecting a stationary series with the same mean as the observed precipitation time series. The high end of the observed time series produces very high yields that the stationary mean precipitation time series cannot reproduce. At the lower end, the lower precipitation values in the observed series do not produce yields as equally low as the high end yields are high. Hence, when the precipitation amounts are overestimated the yields

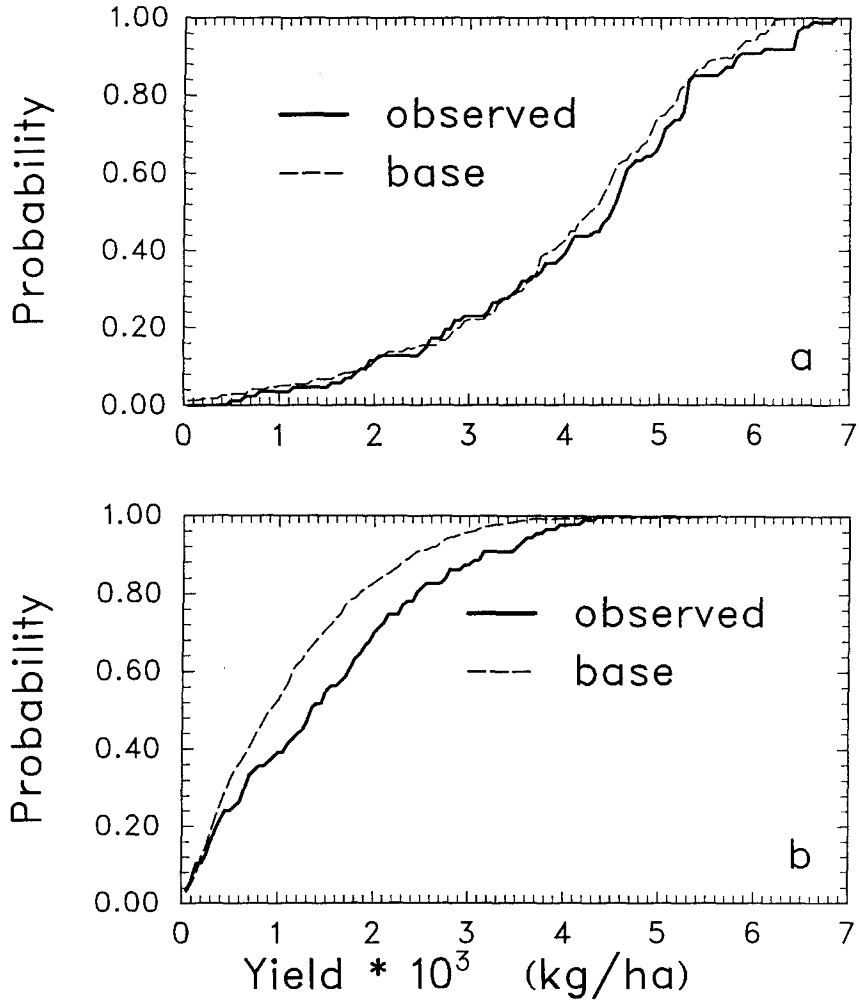

Figure 4. Cumulative distribution functions (CDFs) of wheat yields simulated from observed climate (labeled observed, $n = 29$) and stochastically generated climate (labeled base, $n = 80$) for (a) Topeka; (b) Goodland.

simulated from the generated climate are still lower than the yields simulated with the observed climate.

Another factor is the lack of year-to-year persistence in the annual time series of the stochastically generated climate. This problem is not very serious in the present context because there is very little persistence in the annual observed time series of precipitation at Goodland or Topeka. There is some autocorrelation, however, in the temperature times series. For example, the first-order autocorrelation of 0.31 at Goodland for annual mean temperature contrasts to that of the simulated time series value of -0.07. This may have a small additional effect on the simulation of a series of years of yields. The effect for temperature would most likely be less

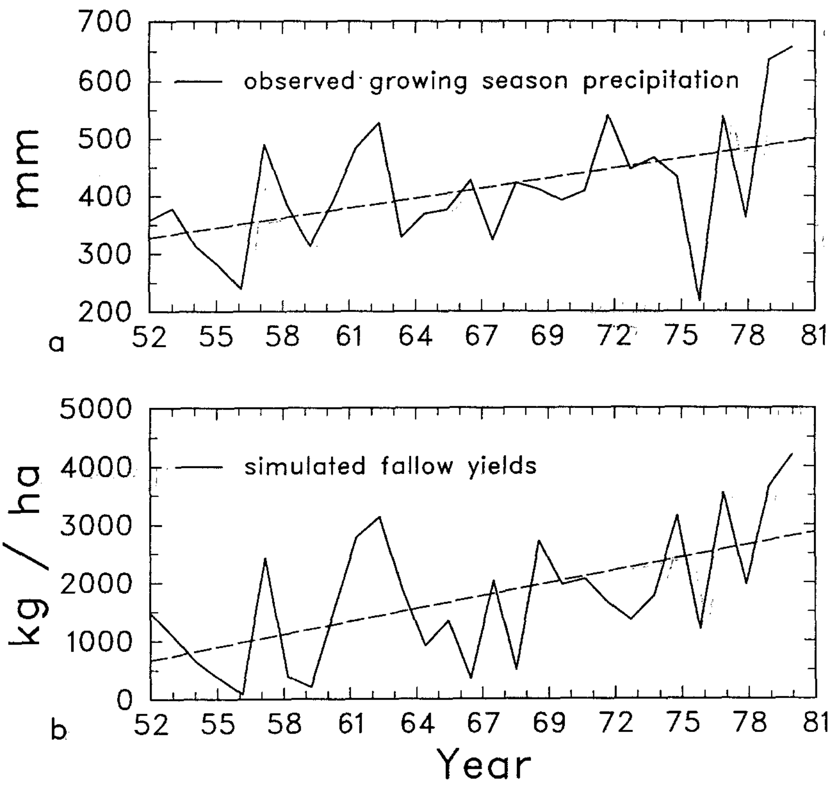

Figure 5. Goodland time series of (a) observed annual growing season precipitation (51–80); (b) fallow yields simulated from observed climate (52–80). Diagonal dashed lines are linear trend lines through the data.

than if there had been autocorrelation in the observed annual precipitation time series. It should be noted, however, that for locations where there is significant autocorrelation in the annual times series of precipitation, the stochastic weather generator would fail to reproduce this characteristic. This, consequently would also then contribute to the underestimation of interannual variance of the annual time series. This probably is one reason why the interannual variance of temperature is often underestimated by the Richardson model at both sites (Table II).

Since we are mainly interested in examining the way simulated yields change when climate variability changes, the 'errors' in simulated yield from the generated climate were not so large as to vitiate interpretation of the changes in yield caused by altered climate variability. The simulated climate at Topeka is not more accurate than that at Goodland, but the simulated yields are closer to observed there because the base precipitation is quite high, and deviations from the base precipitation have less effect on final yield calculations (Table II).

Table IV
Variances (°C^2) of Topeka simulated maximum temperature variance change cases

	January	April	July	October
Interannual				
Base	6.0	5.8	1.5	5.1
TV2	19.2	12.6	2.8	9.3
TV.5	4.9	3.4	0.7	2.4
Daily				
Base	57.6	42.9	14.0	34.3
TV2	100.4	87.0	25.5	68.0
TV.5	27.5	26.2	7.3	22.9

TV = temperature variance change.

5.2. TEMPERATURE CHANGE RESULTS

5.2.1. *Overview of Stochastically Generated Temperature Variance Change*

In general, approximately the correct ratio of variance change is simulated, on an interannual and daily basis, but there tend to be underestimations (Table IV). This is most likely due to how the variance is changed (Eq. 3) which only approximates the change in variance of the maximum temperature time series as described in Eq. 6. Sample size is also a consideration.

5.2.2. *Overview of Temperature Variance (TV) Yield Results*

The temperature sensitivity analyses show relatively large changes in the mean and relative variability of yield in response to changes in daily temperature variability at both locations (Figs. 6 and 7 for Topeka). Although the overall tendencies are similar to the changes seen in MR92 the results here are much more extreme. As in MR92, increases in temperature variability result in larger changes in yield than do decreases. The major factor responsible for the decreases in the mean and increases in variability of yield with increasing daily climate variability is the increased prevalence of crop failures due to winter kill at both locations (Fig. 7). The probability of crop failure for soil 2 is 0.21 for a doubling of daily temperature variance whereas with doubling of only interannual variance the sample estimated probability of crop failure approached 0.

Note that there is little difference in the response of the three soil types to the variance changes. This would be expected in this case, since soil water processes do not figure prominently in the crop responses to varied daily temperature.

5.2.3. *Variance Increases – Crop Failures Due to Winter Kill*

The effect of changes in daily variance may be concretely demonstrated by comparing two winter months with similar average temperatures (5.3 °C) but with very

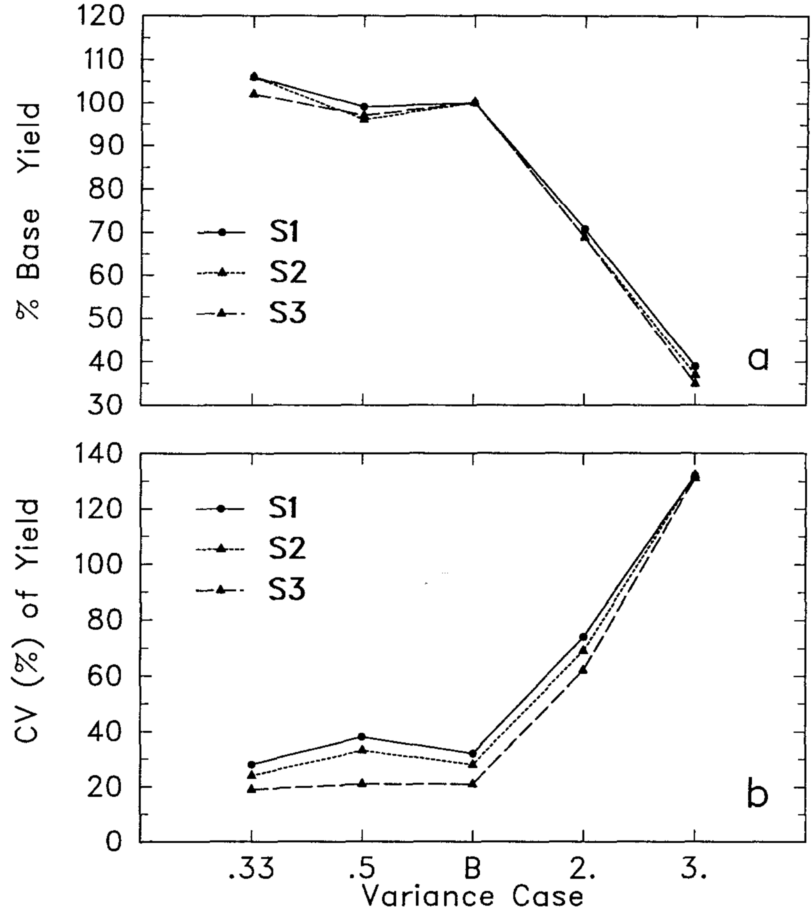

Figure 6. Topeka rainfed (a) % base yields, and (b) coefficient of variation (CV) for temperature variance change cases. S1, 2, and 3 refer to the three soil types. B on x-axis refers to the base case (no variance change).

different daily variances (Fig. 8). Each is taken from the Topeka time series wherein interannual variance of temperature has been doubled, but the former is from MR92, with little or no daily variance change and the latter from stochastically generated series that is based on changing the daily variance. In the first time series from MR92 with relatively low daily variability (Fig. 8a), the winter hardiness index increases through much of the month, whereas with higher daily variability (Fig. 8b), the rapid temperature vacillations prevent the plants from properly hardening. The hardiness index falls, rendering the plants less capable of surviving further extremes of cold, and the crop is finally killed. At Goodland, results are similar, but the probability of crop failure due to winter kill with a doubling of temperature variance is even higher (0.3 for soil 2). Wheat is more vulnerable to winter kill there, since there is greater moisture stress, and thus, on average,

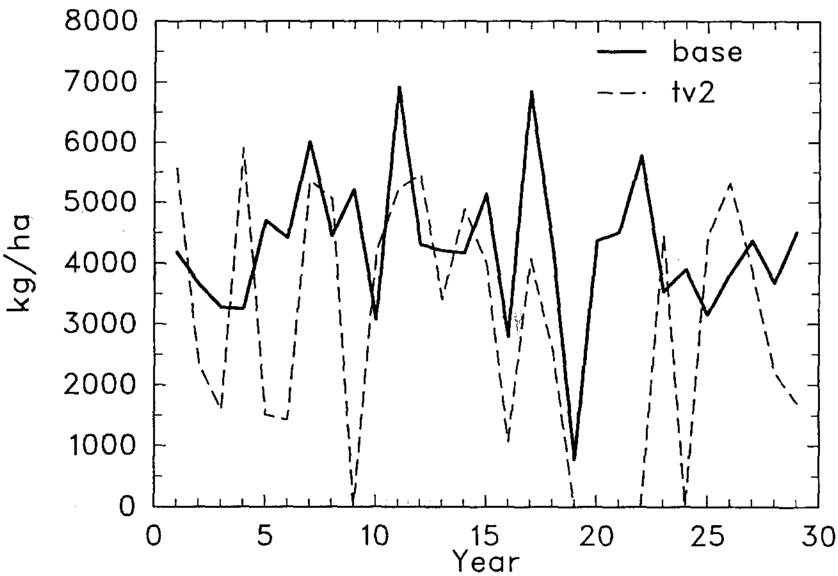

Figure 7. Topeka simulated yield time series for soil 2, Base and TV*2 cases.

fewer tillers per plant. In summary, the inclusion of increases in daily variability of temperature greatly increases the occurrence of winter kill, decreases mean yields, and increases yield relative and absolute variability.

5.2.4. *Variance Decreases*

Decreases in the variance of temperature have much less effect on simulated yields than increases (Fig. 6). In general, critical thresholds related to the various parabolic functions making up the crop model are mainly crossed when variance is increased. For example the photosynthetic reduction factor, which acts to reduce the effective transformation of PAR into carbohydrate, is a function of daytime temperature. At the optimum temperature (18 °C) no reduction occurs, but at the temperature extremes (−3 °C and 37 °C) maximum reduction occurs and no carbohydrate is produced. The slope of the function increases towards these extremes. In both the base and decreased variance cases, these thresholds are not crossed and so results tend to be more similar. There is little gain from being farther away from the extreme thresholds, when the mean temperatures of the base climate are close to the optima for crop growth as prescribed in the model.

There is one effect of decreased daily temperature variability: at Goodland the relative variability of yield (CV) decreases from 70% (3 soil average) to 60% with a halving of daily temperature variability. Comparing the temperatures at Goodland and Topeka, mean monthly maximum temperatures are similar, but the daily variance is higher at Goodland. Topeka minimum temperatures are higher than those at Goodland. Temperatures for many functions are more suboptimal at Goodland (compared to Topeka) and so reduced variability both decreases the

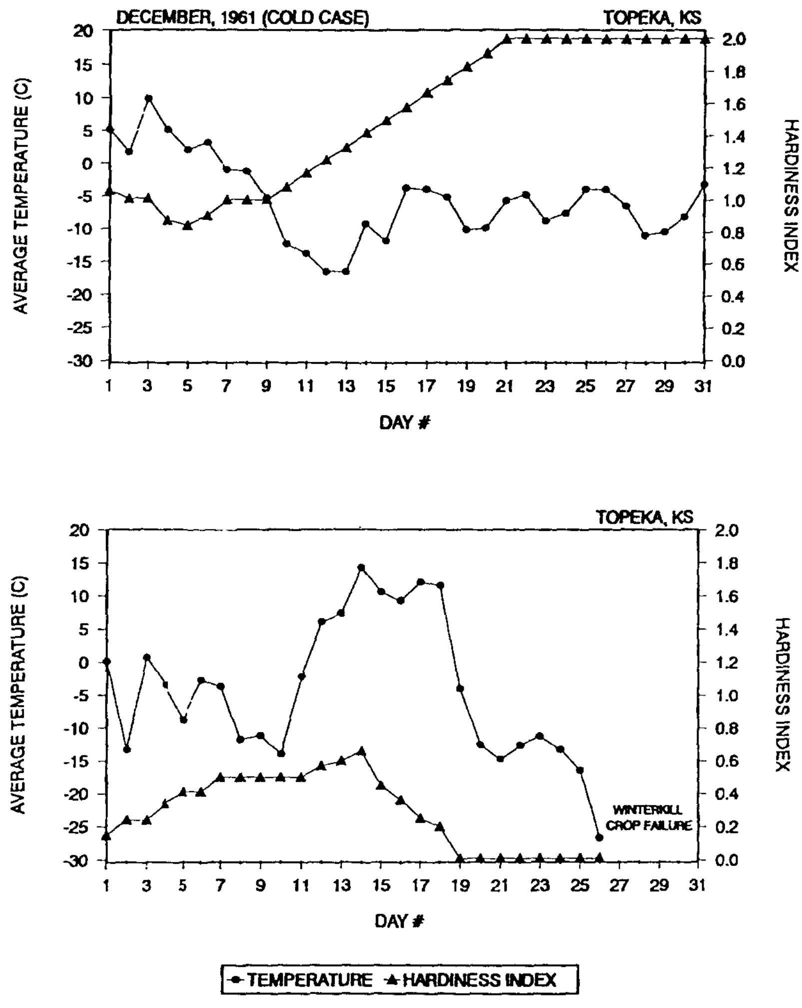

Figure 8. Topeka daily mean temperature and Hardiness Index for a sample December (cold) from (a) MR92, where mainly interannual variance is changed and (b) stochastically generated case with changes in daily (and interannual) variance.

extreme high and low temperatures enough such that yield variability decreases somewhat.

5.2.5. *Senescence Due to Cold Temperatures*

Cold damage is prevalent with temperature variance increase even when winter kill does not occur (Fig. 7). Figure 9 presents seasonal daily average values of leaf area indexes (LAIs) for base, TV.5, and TV2 yields runs for Topeka. The averages in the LAI graph only include years without crop failures. Even when winter kill does not lead to crop failure, there is still severe senescence due to cold temperatures in the TV2 case. Although there is an advantage for the reduced temperature variability

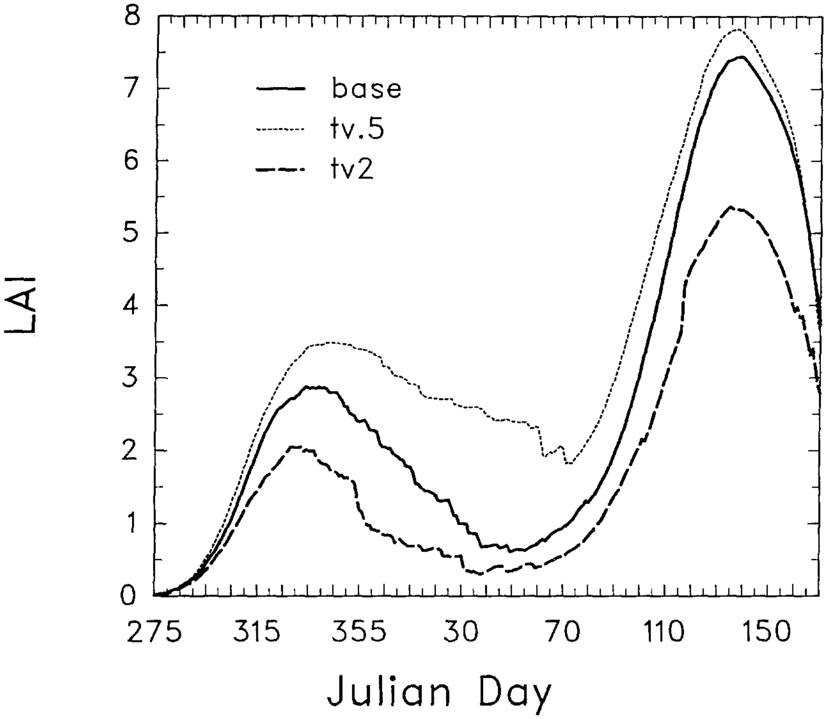

Figure 9. Topeka daily average leaf area index (LAI) during growing season for the three indicated temperature cases.

case in winter for accumulating LAI, this advantage is less in the spring, and final LAI (and yields) are very similar to the base case. Similar results are also seen for the TV.33 and TV3 cases.

5.3. PRECIPITATION RESULTS

5.3.1. *Changes in Frequency and Intensity (PV Changes)*

(a) Description of changes in precipitation statistics. Figure 10 displays sample times series of daily precipitation for Goodland for three different precipitation variance cases: (a) π is increased, β decreased (one-third times the base variance, PV.33); (b) the Base case (simulated current climate); and (c) π is decreased, β increased (three times the base variance, PV3). When precipitation frequency is changed, because of the conditioning of maximum temperature and solar radiation on precipitation occurence, these two variables are changed as well. Although Katz (1993, 1996) demonstrated a method whereby maximum temperature could be altered in the Richardson model so that it would not change with frequency, we do not adopt that method here. The changes in maximum temperature that occur at our stations when we change precipitation frequency are relatively small and have

Table V
Daily precipitation intensity and frequency for Goodland doubled precipitation variance cases

Case	January		July	
	Mean (mm/day)	Variance (mm^2/day)	Mean (mm/day)	Variance (mm^2/day)
Intensity				
Observed	2.0	6.25	7.0	88.36
IV2	2.2	8.41	7.1	116.64
PV2	4.0	24.01	13.7	179.56
π				
Observed	16		28	
IV2	16		28	
PV2	8		15	

IV2 refers to the time series as changed for MR92.
PV2 refers to time series as changed for present study.
π = the unconditional probability of precipitation (%).

only a trivial effect on results. (see Section 5.3.1.c). Moreover, it could be argued that it would be inconsistent to accept the changes in solar radiation resulting from changes in precipitation frequency but not those of temperature. Table II compares the interannual variance of monthly precipitation, Base vs. PV2 vs. PV.5 for Goodland. There are under and overestimations of change in interannual variance, but the overall average changes are generally correct.

There are several ways in which the PV changes and interannual precipitation variance changes in MR92 differ. In the earlier study, precipitation frequency was not altered (Table V). Although mean and variance of precipitation intensity were altered, the changes were relatively small compared to those made in PV changes (Table V). The change in year-to-year variance of precipitation on a monthly time scale are basically the same, although more exact in MR92 since mechanical alteration of the observed time series was made.

(b) Overview of PV change yield results. Yields respond substantially to changes in daily and interannual variability of precipitation. Changes in frequency prove to be particularly important. As in MR92, at Topeka yields decrease and relative variability increases with increasing precipitation variability (Fig. 11), but results are more complex at Goodland (Fig. 12). At Topeka, the slopes of the lines are steeper than in the MR92 study. For example, with a variance doubling in MR92, yields dropped on average to 95% of the base yield, but in the current study, the decrease is to approximately 85% of the base yield. Relative variability of yield also changes more rapidly with change in precipitation variance compared to MR92. At both locations changes in mean yield diminish (or change direction) between PV2 and PV3, which appears to be a threshold for the trends in changes seen. At

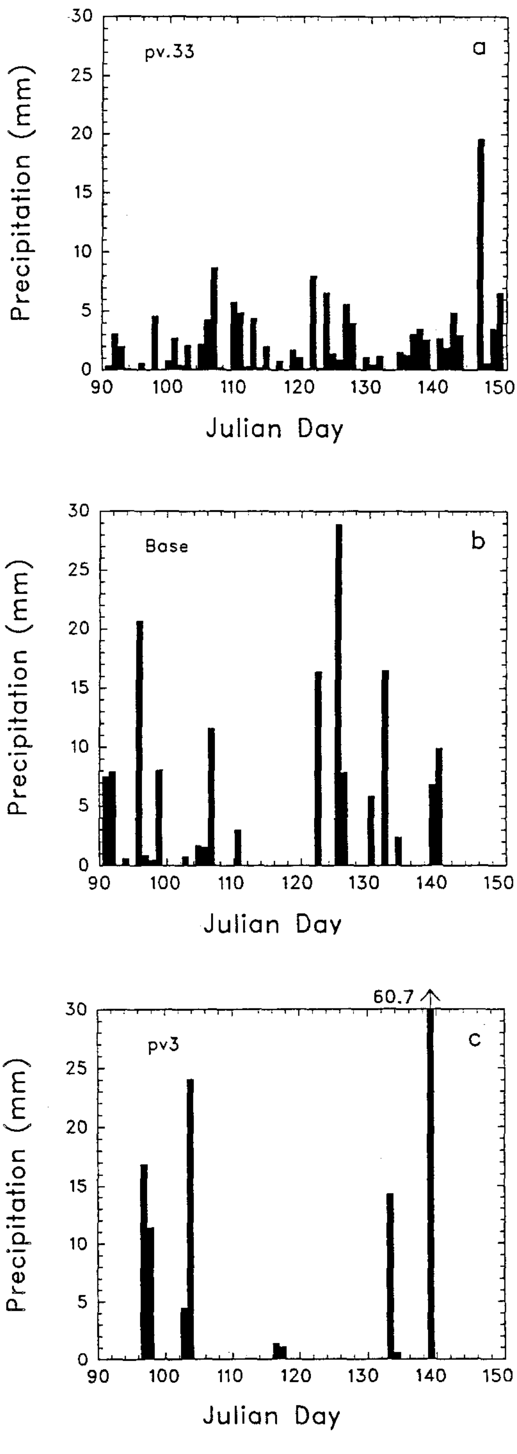

Figure 10. Sample daily time series of simulated precipitation (May–June) for (a) PV.33; (b) Base; and (c) PV3 for Goodland, for years when total May–June precipitation amount in each case was approximately 75 mm.

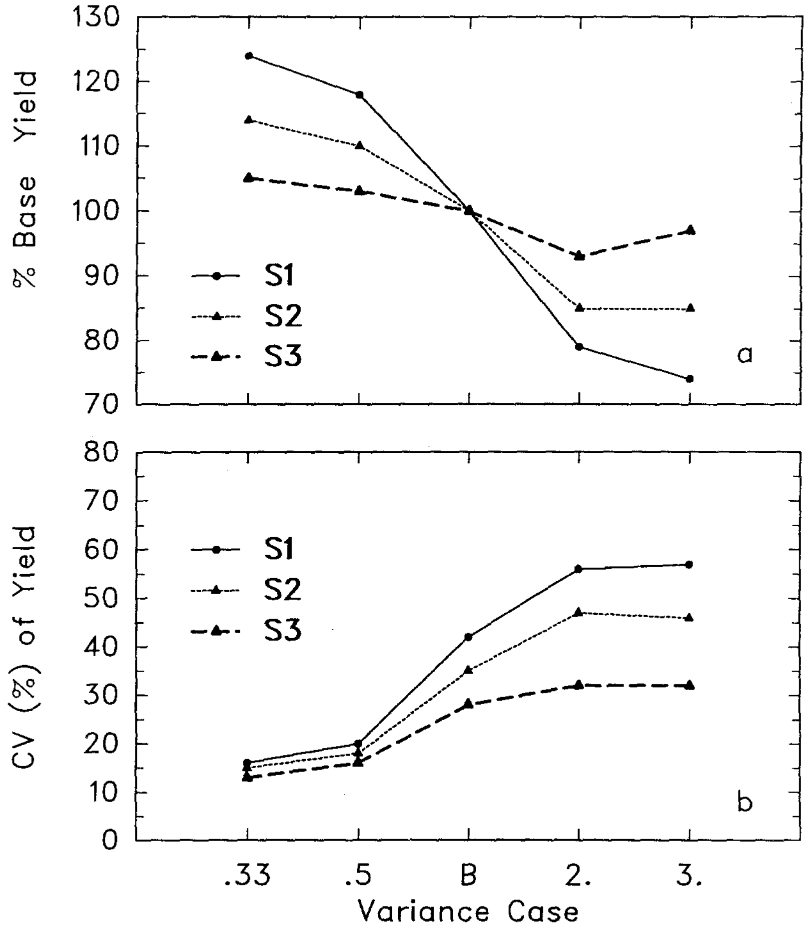

Figure 11. Topeka (a) % base yields and (b) CV for precipitation variance (PV) change cases.

Goodland, relative variability of yield increases with both increased and decreased variability of precipitation (Fig. 12b). Absolute variability (as measured by the standard deviation), however, increases only with increasing PV (Table VI). In the earlier study CV increased monotonically with increasing precipitation variability.

There are clear differential effects of yield change based on soil type. In general, largest changes in mean and relative variability of yield occur on the least productive soils (Figs. 11, 12). The overall directions of change are similar for all soil types. At Goodland there is a clear separation between magnitude of response for Soil 1 and the other two soils, which reflects the relative difference in the base yields (Table II).

At Topeka the increased mean and decreased variability in the PV.5 case results from having a lower frequency of low yields, but the upper range does not appreciably change (Fig. 13a). In the PV2 case the yield distribution changes shape with

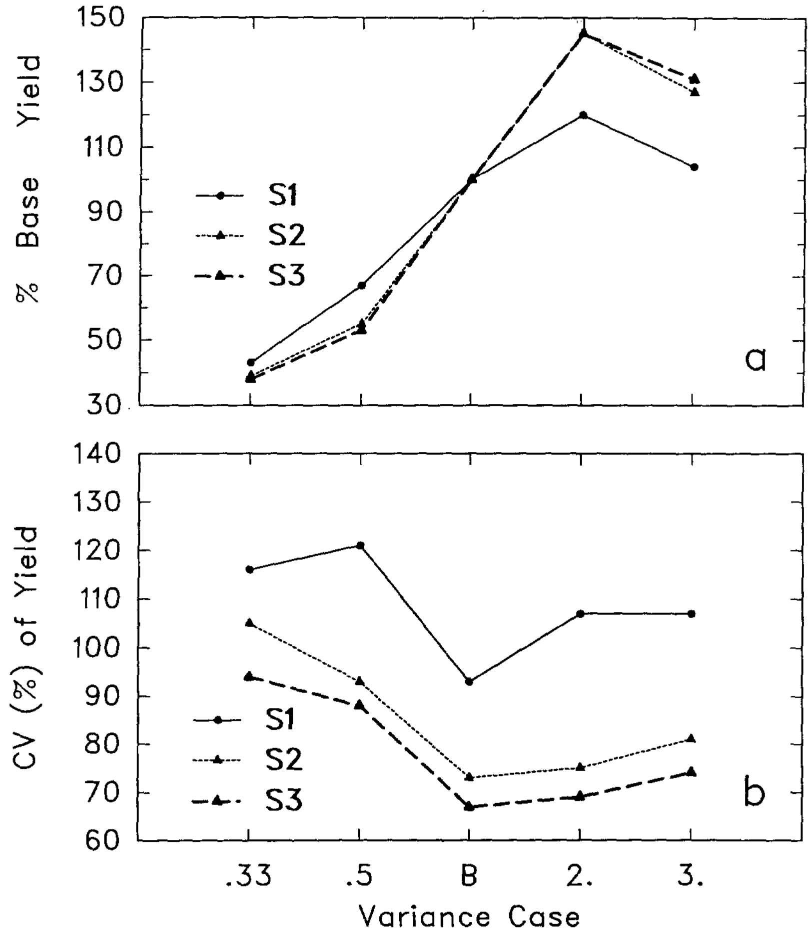

Figure 12. Goodland (a) % base yields and (b) CV for precipitation variance (PV) change cases.

a greater frequency of low yields (Fig. 13a). The overall range, however, does not change. At Goodland the shapes of the distributions do not appreciably change, but higher frequencies are noted at the low end in the PV.5 case and at the high end in the PV2 case (Fig. 13b).

Essentially the same physical processes (e.g, variations in evaporation from soil) are responsible for the yield results at Goodland and Topeka for variance increase or decrease in precipitation, but the interactions of the variance changes with the different base climates results in the different tendencies at the two locations.

(c) Goodland. Change in precipitation variance (with changes in frequency) affects soil evaporation significantly, particularly in the spring (Fig. 14a). With roughly the same aggregate amount of precipitation on average for each case, the soil evaporation is much higher in the PV.33 case than in the Base and PV3 cases.

Table VI
Simulated yields (kg/ha) of precipitation variance change cases

	Base	PV.33	PV.5	PV2	PV3	PD.8	PD2	PD3
(a) Topeka rainfed soil 2 n = 80								
Mean	3991	4553	4406	3388	3377	4229	3694	3210
sd	1402	670	812	1609	1559	1153	1570	1491
D statistic	na	0.3125	0.213	0.300	0.2875	0.1000	0.1750	0.2750
P value	na	0.000	0.03	0.001	0.001	0.69	0.12	0.003
(b) Goodland fallow soil 2 n = 80[a]								
Mean	1275	503	707	1847	1624	na	1922	1508
sd	928	526	658	1389	1322	na	1342	1304
D statistic	na	0.4562	0.3500	0.1987	0.1188	na	0.275	0.131
P value	na	0.00	0.00	0.03	0.38	na	0.00	0.27

[a] except the base, where n = 160.
sd = standard deviation (kg/ha).
D statistic = Kolmogorov–Smirnov 2-sample *D* statistic comparing base yields with variance change yields (see definition in Table II).
P value = (see definition in Table II).
na = not applicable.

This difference occurs for two reasons. Decreased variance (i.e., increased frequency) brings many days with small precipitation amounts (Fig. 10a); more precipitation evaporates immediately and hence does not infiltrate to increase available soil moisture. Low precipitation variance increases crop moisture stress through the season as indicated by the stress factor SWDF1 (Fig. 14b). More rain days also results in reduced solar radiation and potential evapotranspiration. The reduced water demand, however, is greatly overshadowed by the greater soil moisture loss through evaporation. These contrasts are also evident in actual evapotranspiration (Fig. 14c) and leaf area index (Fig. 14d). There are large differences in LAI that persist throughout the growing season, and in this case LAI is highly correlated with final yield (Table VI).

The second reason for the contrasts in soil evaporation and other plant growth components with decreased variability is the reduced interannual variability of total monthly precipitation. The reduced frequency of high precipitation months results in a lower incidence of high soil moisture months (and years). The fact that there is also a reduced frequency of low precipitation months has less of a mitigating effect.

In order to examine more fully the effects of reduced precipitation variance we ran the crop model using isolated components of the PV.33 climate. This included a case where the PV.33 precipitation time series were used but all other variables were held the same as in the Base case. While this destroys the cross-correlations of the climate variables, it provides us with insights into the relative importance of different variables. Interestingly, the highest LAI values (and yield) result from

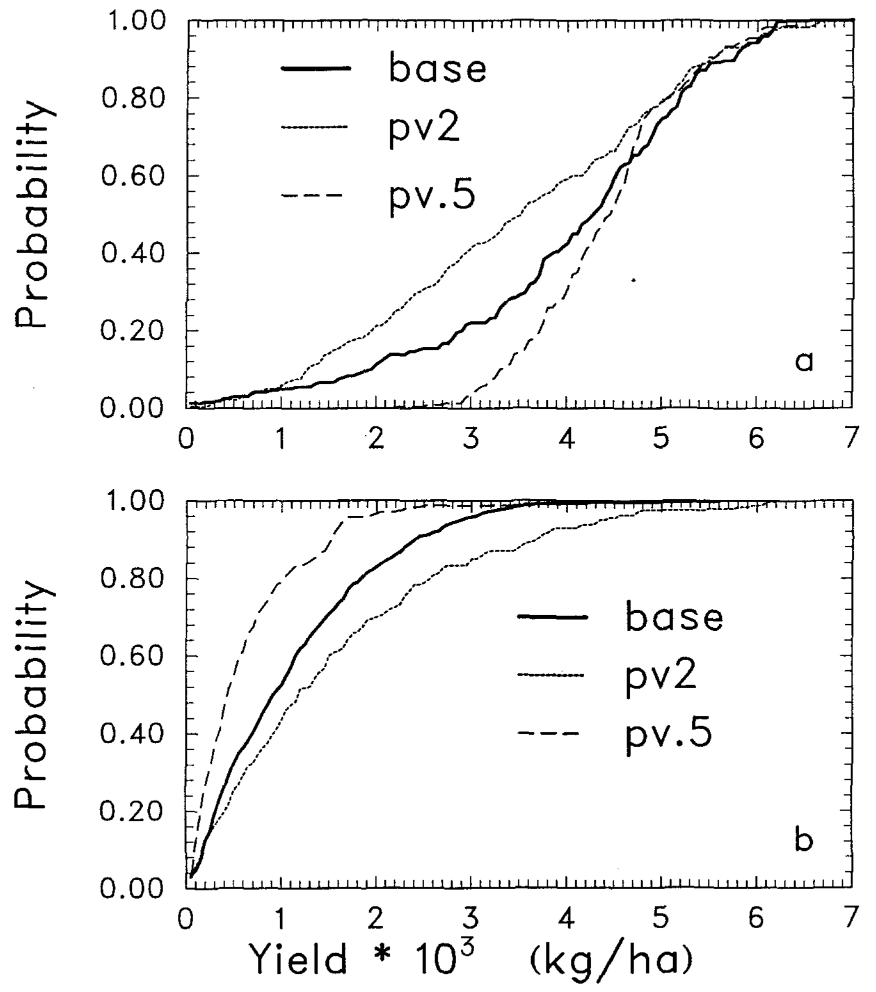

Figure 13. Cumulative distribution functions (CDFs) for Base, PV.5 and PV2 cases for (a) Topeka; and (b) Goodland.

the solar radiation only change (Fig. 15). The decreased solar radiation reduces the photosynthetic rate of the crop, but it also reduces the potential evapotranspiration. Lower moisture demand earlier in the season proves advantageous later in the season, since the reduced LAI and reduced potential evapotranspiration results in less water stress later in the season when yield is forming. On the other hand, the case where precipitation changes are isolated from changes in solar radiation and all other variables results in the greatest decrease in LAI (and yield), with no mitigating effect of solar radiation decrease on water stress. Note that the isolated effect of the temperature change that attends increased precipitation frequency is small.

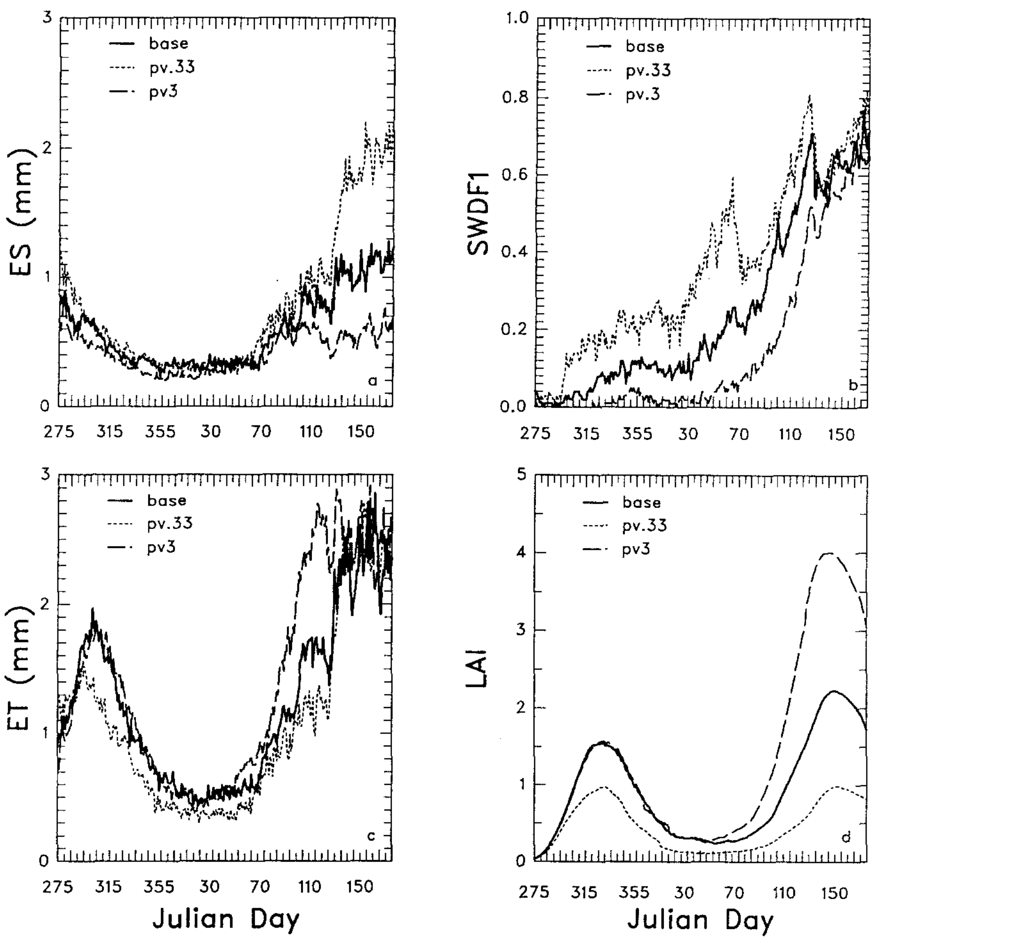

Figure 14. Goodland, Soil 2, for PV.33, Base, and PV3 cases, daily average values during the growing season of: (a) soil evaporation (ES); (b) soil water deficit factor 1 (SWDF1); (c) actual evapotranspiration (ET); and (d) leaf area index (LAI).

In the case of increased variability, frequency of rain events decreases while both the mean and variance of daily precipitation intensity increase (Fig. 10c). With fewer but larger rainfall events, soil evaporation decreases, infiltration of precipitation increases and hence available soil moisture (Fig. 14a–c). Runoff, though small at Goodland, increases as well. Increased solar radiation brings both increases in crop photosynthetic rate and in potential ET. However, the increases in these factors are not as great as their decreases in the PV.33 case, because there are naturally occurring upper limits to the amount that solar radiation can increase. The determining factor for yield is the decrease in soil water deficit, (Fig. 14b) and thus, compared to the base and PV.33 cases, both LAI (Fig. 14d) and yield (Table VI) are higher.

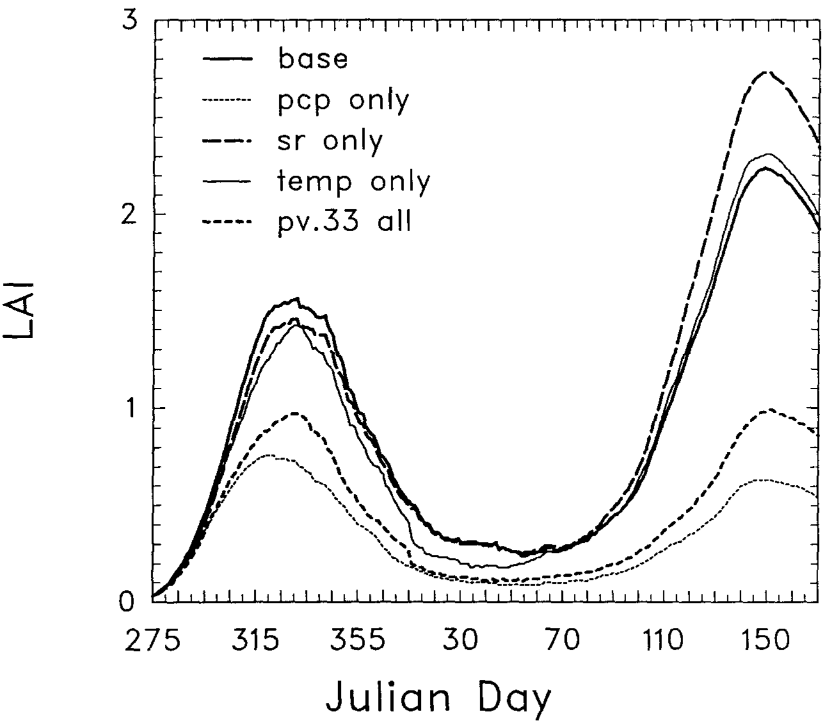

Figure 15. Goodland Soil 2 seasonal LAI values for different subcases of the PV.33 case. In each subcase, time series from the base case are used except for the climate element listed, which is the time series for that element from the PV.33 case: pcp = precipitation, sr = solar radiation, temp = temperature.

The decrease in average daily SWDF1 is also a function of the increased interannual variability of precipitation. The high precipitation years naturally reduce soil moisture stress. And although there is a higher frequency of low precipitation years as well, there is less room for further increase of stress, since soil moisture stress is relatively high under current conditions. At Goodland, the changes in interannual and daily variance components of precipitation complement each other, leading to larger changes in yield than in MR92.

(d) Topeka. The wetter conditions for wheat growth at Topeka result in different responses to changed precipitation variability. As at Goodland, increasing precipitation variability brings increased potential evapotranspiration and decreased soil evaporation (Fig. 16a). There are critical contrasts, however, in SWDF1 (Fig. 16b) and actual evapotranspiration (Fig. 16c). At Topeka, increased precipitation variability causes the soil water deficit factors to increase rather than to decrease, for the cropping season as a whole, and particularly during May and June (Fig. 16b). Since soil moisture stress is relatively low in the Base case, there is little to gain by further increasing available soil water. Actual evapotranspiration, with increased

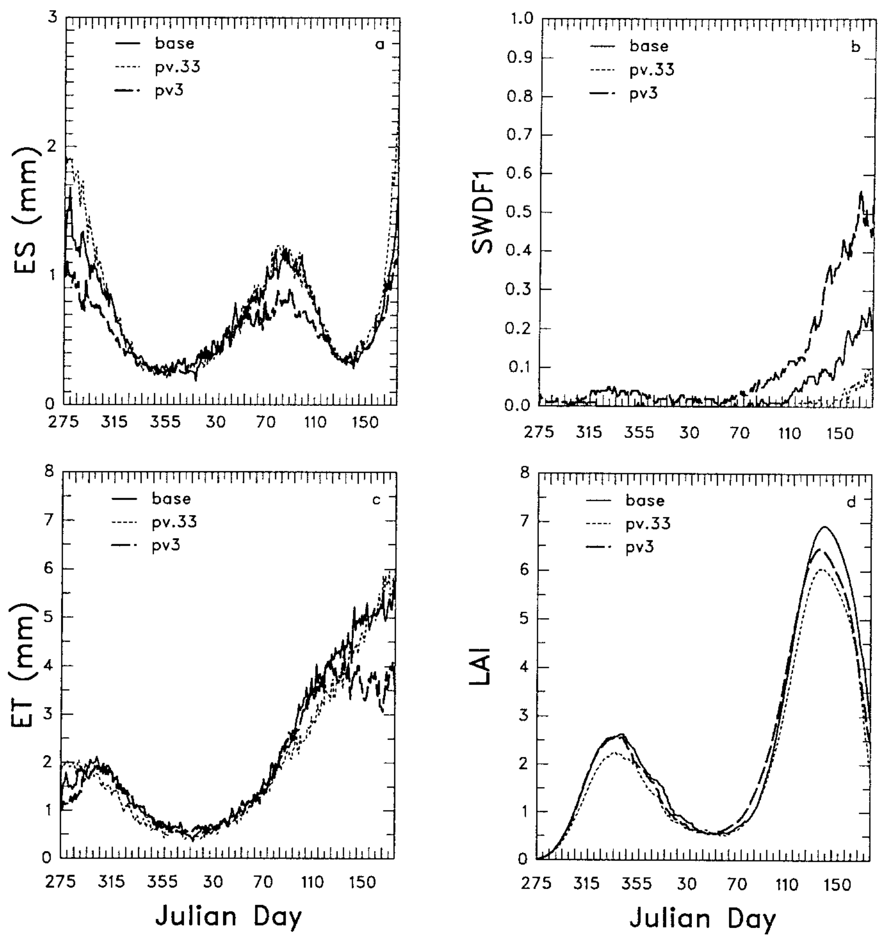

Figure 16. Topeka rainfed, Soil 2, for PV.33, Base, and PV3 cases, daily average values during the growing season of: (a) soil evaporation (ES); (b) soil water deficit factor 1 (SWDF1); (c) actual evapotranspiration (ET); and (d) leaf area index (LAI).

variability is initially higher than in the PV.33 case, but falls to lower values in May and June, as soil moisture stress for all cases becomes fairly high (Fig. 16c).

A critical difference at Topeka is the much higher LAI values attained throughout the season, and particularly at the LAI peak in May and early June (cf. Figs. 14d and 16d). At that same time soil evaporation drops, reflecting the high transpiration demand associated with high LAI and insolation (Fig. 16a). Actual evapotranspiration reflects the large differences in actual transpiration at Topeka (Fig. 16c). In the PV increase cases, actual evapotranspiration falls off abruptly (Fig. 16c) due to moisture stess (reflected in the high SWDF1 values, Fig. 16b) during May and June, and grain yield (even though LAI is never dramatically reduced) suffers. Whereas LAI and final yield values are positively correlated at Goodland, this is not the case at Topeka. Although LAI remains high in the PV2 and PV3 cases, this becomes a burden from a water demand point of view later in the season when yield is forming. Hence, the greater soil moisture stress resulting from the much higher demand (which is partially a function of LAI) results in lower final grain yield.

Thus at Topeka, in contrast to Goodland, relatively abrupt changes in soil moisture stress and evapotranspiration toward the end of the cropping season have the largest effect on final yield, whereas at Goodland water stress throughout the season determines final conditions (Figs. 14b and 16b). With increased precipitation variability, at Topeka, where base level precipitation is high, there is little advantage to further increases in soil moisture in the high precipitation years, but large losses in soil moisture and final yield occur in the low precipitation years.

5.4. CHANGES IN PERSISTENCE (PD CHANGES)

Variability changes brought about by changing the persistence of precipitation affects simulated wheat growth in ways similar to changes in frequency/intensity described above. At Topeka, mean yields decrease with increasing persistence (and interannual variance), and relative variability of yield increases (Table VI), whereas at Goodland both mean and relative variability of yield increase with increasing persistence (Table VI).

Changes in some processes related to plant growth are distinctly different from those of the PV change cases. Daily average potential evapotranspiration through the growing season does not change as persistence is varied, and changes in runoff are relatively small. Soil evaporation, however, decreases slightly as persistence increases at Topeka, and is similar in magnitude to the PV changes cases. At Goodland, the changes in soil evaporation are smaller than in the PV cases, but the direction of change is the same (decreased soil evaporation with increased precipitation variability). LAI is much lower in the PD3 case than in the PV3 case (peak values in May of 2.5 m^2/m^2 versus 4.0 m^2/m^2, respectively).

One may infer from these contrasting results that changes in daily frequency and intensity have a decided effect on soil evaporation at Goodland, whereas they are less significant at Topeka. The similarity to the PV changes at Topeka is likely a result largely of the relative abundance of soil moisture in the base climate, such that there is less sensitivity to differences in the daily sequencing and/or frequency of precipitation. Thus, when soil moisture is adequate the change in interannual variability of precipitation basically drives the changes in yields for the different case. Although there are differences in growth processes, these do not lead to large differences in the final response of the crop (i.e., yield formation) compared to the PV change cases at Topeka. At Goodland, the PV3 yield (soil 2) is 150 kg/ha greater than that of PD3, consistent with the difference in LAI, but this is relatively small.

6. Summary and Concluding Remarks

The effect of changes in daily and interannual variability of temperature and precipitation on simulated yields can be significant. At both locations increased temperature variability substantially decreased mean yields and increased their variability owing chiefly to increased frequency of crop failure due to winter kill. Increased precipitation variability effects were location-specific. Where soil moisture was limited, increased precipitation variability increased mean and variability of yields, but where soil moisture was plentiful, mean yields declined but variability increased. Magnitudes of these yield changes were significantly affected by soil type.

These variability change effects are significantly larger when changes in both variability times scales are appropriately taken into account. This is more realistic since variability on these time scales are physically (and statistically) related. Climate change will naturally bring about simultaneous changes on both time scales. Therefore, a stochastic simulation approach to altering variance of time series allows for greater flexibility and physical meaning in making changes, compared to the approach in MR92 of directly altering observed time series for bringing about variance changes on a (primarily) daily time scale. The limitations of the earlier study notwithstanding, some of its overarching conclusions were confirmed here, such as the differential effect of baseline moisture conditions on the direction of change of mean yield with changes in precipitation variability.

This study analyzes how the CERES-Wheat model responds to changes in variability and, as such, the study is most clearly a test of the crop model, and caution must be used in inferring from these results possible effects on actual yields. More rigorous testing of crop models in regard to their ability to respond accurately to year-to-year climate variability is needed as well as model development to simulate more realistic response to climate extremes. For example, crop models do not successfully simulate crop losses due to excess precipitation, which can result in water logging and lodging. Some of the higher yields estimated in this study in response to precipitation increases would in reality probably result in decreases.

The changes in variability examined in this paper are relatively large and should be viewed as representing variability changes possible under conditions of climatic change caused by external forcing of the climate system, such as increasing greenhouse gases. They fall within the range of changes that have recently been found in the regional climate model experiments discussed in the introduction. In that regard they are not overly extreme.

Our results both complement and contrast with those of the study by Riha *et al.* (1996), in which several crop models were subjected to changes in temperature and precipitation variability, also using a stochastic weather generation approach. The effect of increased temperature variability on mean wheat yields basically agrees with their results, but yield variability results differ. For precipitation, our results contrast with theirs, but interpretation is difficult since their ranges of precipitation variance changes do not overlap with ours and their sites have substantially different soil moisture regimes. Our results for effect of change in temperature variability are similar to those of Semenov and Porter (1995) where a stochastic weather generator was used to investigate changes in simulated wheat yields with climate variability change at two European locations, but our results are somewhat more extreme. Their comparisons of the effect of mean and variability changes of climate further confirmed our earlier results (MR92).

The investigation of possible effects of climate variability change on resource systems such as agriculture is a new endeavor, one that requires further development. One research task is to incorporate changes in variability in climate change scenarios, since the absence of such changes could be an important uncertainty in integrated assessments of climate change. Mearns (1995), and Mearns and Rosenzweig (1994) in a pilot investigation, have indicated that incorporating such changes can indeed alter one's assessment of the possible impact of climatic change on agriculture. Further development of techniques for such incorporation is currently underway.

Acknowledgements

We thank Larry McDaniel for assistance with graphics and statistical computing; Dan Wilks for providing an additional means of estimating gamma variates, information on location specific correlation matrices, as well as very useful review comments, and Rick Katz for general advice and comments on an earlier draft. We also thank an additional anonymous reviewer for useful comments. This research was partially supported by a grant from the EPA Global Climate Change Division.

References

Anderson, J. R. and Hazell, P. B.R. (eds.): 1989, *Variability in Grain Yields*, Johns Hopkins University Press, Baltimore, 395 pp.

Cao, H. X., Mitchell, J. F. B., and Lavery, J. R.: 1992, 'Simulated Diurnal Range and Variability of Surface Temperature in a Global Climate Model for Present and Doubled CO_2', *J. Climate* **5**, 920–943.

Eder, B. K., Truppi, L. E., and Finkelstein, P. L.: 1989, *A Climatology of Temperature and Precipitation Variability in the United States*, U.S. EPA Project Report, Atmospheric Research and Exposure Assessment Laboratory, Research Triangle Park, NC, 43 pp.

Gibbons, J. D.: 1985, *Nonparametric Statistical Inference*, Marcel Dekker Inc., New York, 408 pp.

Gordon, H. B., Whetton, P. H., Pittock, A. B., Fowler, A. M., and Haylock, M. R.: 1992, 'Simulated Changes in Daily Rainfall Intensity Due to the Enhanced Greenhouse Effect: Implications for Extreme Rainfall Events', *Climate Dynamics* **8**, 83–102.

Hodges, Tom: 1991, *Predicting Crop Phenology*, CRC Press, Boca Raton, 233 pp.

Johnson, G. L., Hanson, C. L., and Ballard, E. B.: 1996, 'Stochastic Weather Simulation: Overview and Analysis of Two Commonly Used Models', *J. Appl. Meteorol.*, in press.

Katz, R. W.: 1993, 'Toward a Statistical Paradigm for Climate Change', *Climate Res.* **2**, 167–175.

Katz, R. W.: 1996, 'The Use of Stochastic Models to Generate Climate Change Scenarios', *Clim. Change* **32**, 237–255 (this issue).

Katz, R. W. and Brown, B. G.: 1992, 'Extreme Events in a Changing Climate: Variability is More Important than Averages', *Clim. Change* **21**, 289–302.

Mearns, L. O.: 1989, 'The Simulation of Meteorological Time Series for Climate Change Scenario Development', Paper presented at the *U.S. EPA Meeting on Climate Change Scenario Development* at Boulder, 31 August, 1989. (Summarized in Scenarios Advisory Meeting Summary Report, December 1989, U.S. EPA, Washington, DC).

Mearns, L. O.: 1995, 'Research Issues in Determining the Effects of Changing Climatic Variability on Crop Yields', in Rosenzweig, C. (ed.), *Climate Change and Agriculture: Analysis of Potential International Impacts*, American Society of Agronomy Special Publication No. 58, ASA, Madison WI, chap. 6, pp. 123–143.

Mearns, L. O. and Rosenzweig, C.: 1994, 'Use of a Nested Regional Climate Model with Changed Daily Variability of Precipitation and Temperature to Test Related Sensitivity of Dynamic Crop Models', in *Preprints of the AMS Fifth Symposium on Global Change Studies*, January 23–28, 1994, American Meteorological Society, Boston, pp. 142–155.

Mearns, L. O., Rosenzweig, C., and Goldberg, R.: 1992, 'The Effect of Changes in Interannual Climatic Variability on CERES-Wheat Yields: Sensitivity and $2\times CO_2$ Studies', *J. Agricul. Forest Meteorol.* **62**, 159–189.

Mearns, L. O., Giorgi, F., Shields Brodeur, C., and McDaniel, L.: 1995a, 'Analysis of the Variability of Daily Precipitation in a Nested Modeling Experiment: Comparison with Observations and $2\times CO_2$ Results', *Global and Planetary Change* **10**, 55–78.

Mearns, L. O., Giorgi, F., Shields, C., and McDaniel, L.: 1995b, 'Analysis of the Diurnal Range and Variability of Daily Temperature in a Nested Modeling Experiment: Comparison with Observations and $2\times CO_2$ Results', *Climate Dynamics* **11**, 193–209.

Mendelsohn, R., Nordhaus, W. D., Shaw, D.: 1994, 'The Impact of Global Warming on Agriculture: A Ricardian Analysis', *Amer. Econ. Rev.* **84**, 753–771.

Otter-Nacke, S., Goodwin, D. C., and Ritchie, J. T.: 1986, *Testing and Validating the CERES-Wheat Model in Diverse Environments*, AGRISTARS YM-15-00407 JSC 20244, Johnson Space Center, Houston.

Priestley, C. H. B. and Taylor, R. J.: 1972, 'On the Assessment of Surface Heat and Evaporation Using Large-Scale Parameters', *Mon. Wea. Rev.* **100**, 81.

Riha, S. J., Wilks, W., and Simoens, P.: 1996, 'Impact of Temperature and Precipitation Variability on Crop Model Predictions', *Clim. Change* **32**, 293–311 (this issue).

Richardson, C. W.: 1981, 'Stochastic Simulation of Daily Precipitation, Temperature, and Solar Radiation', *Water Res. Res.* **17**, 182–190.

Richardson, C.W.: 1982, 'Dependence Structure of Daily Temperature and Solar Radiation', *Trans. Amer. Soc. Agricul. Engineers* **25**, 735–739.

Richardson, C. W.: 1985, 'Weather Simulation for Crop Management Models', *Trans. Amer. Soc. Agricul. Engineers* **28**, 1602–1606.

Ritchie, J. T. and Otter, S.: 1985, 'Description and Performance of CERES-Wheat: A User-Oriented Wheat Yield Model', in Willis, W. O. (ed.), *ARS Wheat Yield Project*, ARS-38, U.S. Department of Agriculture–Agricultural Research Service, pp. 159–175.

Rosenberg, N. J.: 1980, *Drought in the Great Plains: Research on Impacts and Strategies*, Water Resources Publications, Littleton, Co.

Rosenzweig, C.: 1990, 'Crop Response to Climate Change in the Southern Great Plains: A Simulation Study', *Professional Geographer* **42**, 20–39.

Rosenzweig, C. and Parry, M. L.: 1994, 'Potential Impact of Climate Change on World Food Supply', *Nature* **367**, 133–137.

Semenov, M. A. and Porter, J. R.: 1995, 'Climatic Variability and Modelling of Crop Yields', *Agricult. Forest Meteorol* **73**, 265–283.

Whetton, P. H., Fowler, A. M., Haylock, M. R., and Pittock, A. B.: 1993, 'Implications of Climate Change Due to the Enhanced Greenhouse Effect on Floods and Droughts in Australia', *Clim. Change* **25**, 289–317.

Wilks, D. S.: 1989, 'Conditioning Stochastic Daily Precipitation Models on Total Monthly Precipitation', *Water Res. Res.* **25**, 1429–1439.
Wilks, D. S.: 1992, 'Adapting Stochastic Weather Generation Algorithms for Climate Change Studies', *Clim. Change* **22**, 67–84.
Worster, D.: 1979, *Dust Bowl: The Southern Plains in the 1930s*, Oxford University Press, New York, 277 pp.
Williams, J. R., Dyke, P. T., and Jones, C. A.: 1982, 'EPIC – A Model for Assessing the Effects of Erosion on Soil Productivity', *Proc. Int. Conf. on State-of-the-Art in Ecol. Modelling*, Colorado State Univ., May 24–28, 1982.

(Received 7 February 1995; in revised form 18 October 1995)