IMPACT OF TEMPERATURE AND PRECIPITATION VARIABILITY ON CROP MODEL PREDICTIONS

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Abstract. Future climate changes, as well as differences in climates from one location to another, may involve changes in climatic variability as well as changes in means. In this study, a synthetic weather generator is used to systematically change the within-year variability of temperature and precipitation (and therefore also the interannual variability), without altering long-term mean values. For precipitation, both the magnitude and the qualitative nature of the variability are manipulated. The synthetic daily weather series serve as input to four crop simulation models. Crop growth is simulated for two locations and three soil types. Results indicate that average predicted yield decreases with increasing temperature variability where growing-season temperatures are below the optimum specified in the crop model for photosynethsis or biomass accumulation. However, increasing within-year variability of temperature has little impact on year-to-year variability of yield. The influence of changed precipitation variability on yield was mediated by the nature of the soil. The response on a droughtier soil was greatest when precipitation amounts were altered while keeping occurrence patterns unchanged. When increasing variability of precipitation was achieved through fewer but larger rain events, average yield on a soil with a large plant-available water capacity was more affected. This second difference is attributed to the manner in which plant water uptake is simulated. Failure to account for within-season changes in temperature and precipitation variability may cause serious errors in predicting crop-yield responses to future climate change when air temperatures deviate from crop optima and when soil water is likely to be depleted at depth.

1. Introduction

Air temperature and precipitation are major driving variables for crop simulation models. These models are usually developed and tested using data from several years and/or sites, and so implicitly respond both to changes in average temperature and precipitation, and to changes in within-season variability of temperature and precipitation. The sensitivity of these models to changes in average temperature (or precipitation) can be tested relatively easily, by adding (or multiplying) constant values to observed daily weather data. This approach has also been used to simulate effects of climate change on crop growth (e.g. Cohen, 1990; Nonhebel, 1993).

However, crop model predictions may also be affected by changes in the variability of temperature or precipitation, even if the means of these values change very little (Neild *et al.*, 1979; Mearns *et al.*, 1992, 1995; Semenov and Porter, 1995). This is because many of the relationships linking crop dynamics to atmospheric variables are nonlinear and interdependent, and because dynamic crop simulations can depend on the sequencing of weather events. Differences in climate from one location to another, as well as possible future climate changes, may involve changes

Climatic Change **32:** 293–311, 1996.

in climatic variability as well as changes in means (e.g. Rind *et al.*, 1989; Mearns *et al.*, 1990), and indeed variability changes may have the larger impact for some responses (Katz and Brown, 1992). A more thorough understanding of the response of crop models to such changes appears warranted. This understanding will also be relevant to evaluating the consequences for crop growth simulations of using daily climate data versus longer time averages (Bonan, 1993; Nonhebel, 1994).

Prerequisite to understanding the responses of crop simulations to changes in climatic means and variability jointly, is separate study of changes due to each of these two aspects of climate change. Mearns *et al.* (1992) approached this problem through adjustments to observed data series, although the different kinds of variability changes that can be achieved with this method are limited. The sensitivity of crop model predictions to changes in weather variability can be evaluated systematically using stochastic weather models ('synthetic weather generators'). These algorithms allow variability of temperature and precipitation to be manipulated while holding constant the respective climatic means. The purpose of this study was to explore the impacts of changes in temperature and precipitation variability on various aspects of the performance of several crop models in relation to the structure of the crop models and nonclimatic inputs, in order to evaluate the importance of accurately representing such variability.

2. Methods

2.1. LOCATIONS

Two locations are considered in these simulations: Redwood Falls, Minnesota and Tifton, Georgia. These sites were selected because they are near the northern and southern margins, respectively, of the corn-producing region of the United States. Corn and soybeans are the predominant crops of this region. Redwood Falls is in MLRA (major land resource area) 103, the central Iowa and Minnesota till prairies (Austin, 1972). Within MLRA 103, two contrasting soils were selected for study. The Ves loam (fine-loamy, mixed mesic Udic Haplustoll) is considered representative of the well-drained, loamy textured till prairie soils which are a major component of this MLRA. Ves soils have a high plant-available water capacity (approximately 20% by volume) throughout a deep rooting zone. In contrast, the Dickman sandy loam (sandy, mixed mesic Typic Hapludoll) is representative of soils in this region with relatively low plant-available water capacity. This capacity is approximately 14% by volume in the upper part of the rooting zone and decreases to 4% below about 90 cm. Tifton, Georgia is in MLRA 133A, on older, higher surfaces of the upper southern coastal plain. The Tifton loamy sand (fine-loamy, siliceous, thermic Plinthic Kandiudult) is extensive in this region. These soils have a relatively low plant-available water capacity of approximately 8% by volume in the upper part of the rooting zone, increasing to about 12% by volume below 90 cm (Sharpley and Williams, 1990b).

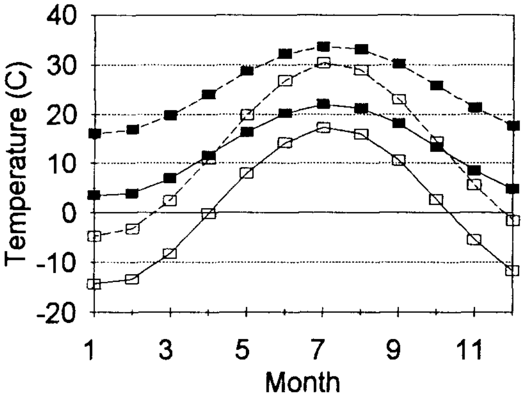

Figure 1. Smoothed (single Fourier harmonic) annual cycles of maximum (- - -) and minimum (—) temperature at Redwood Falls, MN (□) and Tifton, GA (■).

Smoothed (single Fourier harmonic) annual cycles of temperatures at the two sites are shown in Figure 1. Average (maximum, minimum) temperatures range from about 5 °C, −15 °C in winter to about 30 °C, 17 °C in summer at Redwood Falls, while the corresponding values at Tifton are 16 °C, 4 °C and 34 °C, 22 °C. Average precipitation at Redwood Falls ranges from around 15 mm per month in winter (December–February) to 90 mm per month in summer (June–August), while on average at Tifton the driest month is October ($\approx$55 mm) and the wettest is July ($\approx$130 mm).

2.2. WEATHER GENERATOR

Daily values for precipitation, maximum temperature, minimum temperature, and solar radiation are synthetically generated using the model of Richardson (1981). In this model, daily precipitation occurrence is represented as a two-state, first-order Markov chain, with parameters p_{01} (the probability of a wet day following a dry day) and p_{11} (the probability of a wet day following a wet day). In the following, it will be convenient to express these probabilities in terms of the two parameters

$$\pi = \frac{p_{01}}{1 + p_{01} - p_{11}}, \tag{1}$$

which is the unconditional (i.e., long-term climatological) probability of a wet day; and

$$d = p_{11} - p_{01}, \tag{2}$$

which is the lag-1 autocorrelation coefficient for the precipitation occurrences, and indexes the average lengths of series of wet and dry days. The precipitation amounts on wet days are drawn from gamma distributions with mean $\mu = \alpha\beta$ and variance

$\sigma^2 = \alpha\beta^2$, where α is the shape parameter and β is the scale parameter. Gamma distributions becomes more strongly skewed as the shape parameter becomes smaller, and for a given value of α the magnitudes of the generated precipitation amounts are directly proportional to β. Separate sets of the four precipitation parameters $(p_{01}, p_{11}, \alpha, \beta)$ were fit for each calendar month, using available climatic data from each of the two locations.

The temperature and radiation values are generated using the trivariate, first-order autoregression.

$$\begin{bmatrix} \tilde{x}_{\text{max}}(t) \\ \tilde{x}_{\text{min}}(t) \\ \tilde{x}_{\text{rad}}(t) \end{bmatrix} = [\mathbf{A}] \begin{bmatrix} \tilde{x}_{\text{max}}(t-1) \\ \tilde{x}_{\text{min}}(t-1) \\ \tilde{x}_{\text{rad}}(t-1) \end{bmatrix} + [\mathbf{B}] \begin{bmatrix} \epsilon_1(t) \\ \epsilon_2(t) \\ \epsilon_3(t) \end{bmatrix} \tag{3}$$

where the (3×3) parameter matrices $[\mathbf{A}]$ and $[\mathbf{B}]$ reflect the time- and cross-correlation structure of the three variables, the ϵ's are independent standard Gaussian variates, and the tildes indicate a standardization conditional on whether that day is simulated to be wet or dry,

$$\tilde{x}_i = \frac{x_i - \mu_{ij}}{\sigma_{ij}}, \quad i = 1, 2, 3; \;\; j = 0, 1. \tag{4}$$

That is, for each of the $i = 1, 2, 3$ variables, separate means and standard deviations are used for dry ($j = 0$) and wet ($j = 1$) days. The annual cycles of these means and variances, and of the correlations that are the basis of the matrices $[\mathbf{A}]$ and $[\mathbf{B}]$, are represented using single Fourier harmonics, again fit using available climatic data.

Sets of synthetic daily weather values exhibiting the same means as, but different variability from, the base climates were constructed using the approach presented in Wilks (1992). For the temperatures, adjusting the variances while maintaining the mean values is most easily achieved by changing the variances of the Gaussian forcing variables ϵ_1 and ϵ_2 in (3), while leaving constant the mean and standard deviation functions μ_{ij} and σ_{ij} in (4). In particular, forcing (3) with modified Gaussian random variables ϵ_1' and ϵ_2' having variances V_T yields synthetic temperature series with variances approximately equal to $V_T\sigma_T^2$, where σ_T^2 is the variance exhibited by temperatures in the model for the base climates. Actually, it is the conditional temperature variances given either that precipitation did or did not occur, that are changed by the factor V_T. Unless the respective two conditional means are equal, the effect on the variance of the whole (unconditional) temperature series will be somewhat less pronounced (Katz, 1996). The parameter V_T specifies relative temperature variability: for $V_T > 1$ the temperature series are more variable than in the base case, and for $V_T < 1$ the temperatures are less variable. In the limiting case of $V_T = 0$ only the climatological mean values (conditional on the precipitation state) of temperatures on a given day are simulated.

Parameter adjustments for precipitation are more complex. These are approached through expressions for the first two moments of the distribution of monthly total precipitation that are implied by the day precipitation process. In terms of the daily precipitation parameters, the long-term mean monthly precipitation is

$$\mu_p = N\pi\alpha\beta, \tag{5}$$

where N is the number of days in the month. The variance of the distribution of total monthly precipitation, reflecting year-to-year fluctuations, is well approximated by

$$\sigma_p^2 \approx N\pi\alpha\beta^2 \left[1 + \alpha(1-\pi)\frac{1+d}{1-d}\right] . \tag{6}$$

Different types of variability changes are produced by finding sets of new parameters π', d', α', and β' such that the resulting value of μ'_P in (5) is the same as the original value μ_P, but yielding a changed monthly variance specified by the relative precipitation variability factor V_P; i.e., $\sigma_P^{2'} = V_P\sigma_P^2$. Analogously to the situation for temperature, for $V_P > 1$ the modified synthetic precipitation series are more variable than in the base climate, and for $V_P < 1$ the precipitation exhibits less variability.

There are a number of ways to achieve changes in precipitation variability while preserving the mean monthly precipitation. The six types of changed precipitation variability that are used in this study are summarized in Table I. For Type I, the distribution of daily precipitation amounts is changed by increasing one of the gamma distribution parameters while decreasing the other, in such a way that their product is unchanged, i.e., $\alpha'\beta' = \alpha\beta$. For Type II only the parameter d changes, and this can be manipulated independently since it does not appear in (5). Type II changes affect only the pattern of rainfall occurrences, but not the average number of rain days, or the statistical distribution of rainfall amounts on rain days. In Types III and IV the variability changes are achieved by altering both the frequencies and intensities of daily precipitation. For Type IV the intensities are changed by adjusting the gamma distribution shape parameter, yielding different skewness of the daily precipitation distribution (the skewness of the gamma distribution is given by $2\alpha^{-1/2}$, so that symmetric distributions are approached for very large α). The probabilities of very large precipitation events are thus changed more in Type IV than in Type III, where it is the scale parameter that is allowed to change. In Types V and VI the variability changes are produced by simultaneously adjusting the frequencies, day-to-day correlations, and intensities of daily precipitation amounts. Again, since in Type VI the daily intensity changes result from changes in the skewness of the precipitation amount distributions, the frequencies of very large daily precipitation amounts are affected more strongly than for Type V, where the scale parameter changes. Mearns *et al.* (1996) investigated the response of crop yield to Types II and III precipitation variability changes, as defined here.

To illustrate the contrast between Types III and IV precipitation variability changes (and, by extension Types V and VI), consider the following hypothetical example. If $\alpha = 1$ and $\beta = 1$ cm in the baseline climate, the probability of wet-day precipitation at least as large as 1 cm is about 0.37. If $p_{01} = 0.3$ and $p_{11} = 0.5$

Table I

Qualitative summary of precipitation parameter adjustments, which produce the six types of precipitation variability changes considered

Type	Description	$V_P \leq 1$	$V_P \geq 1$
I.	Changes in precipitation amounts only	$\alpha \uparrow, \beta \downarrow$	$\alpha \downarrow, \beta \uparrow$
II.	Changes in wet/dry spell lengths only	$d \downarrow$	$d \uparrow$
III.	More smaller, or fewer larger precipitation events	$\pi \uparrow, \beta \downarrow$	$\pi \downarrow, \beta \uparrow$
IV.	As III, but amounts change through changing skewness	$\pi \uparrow, \alpha \downarrow$	$\pi \downarrow, \alpha \uparrow$
V.	More frequent smaller and 'clumpier', or fewer larger and more uniformly distributed precipitation events	$\pi \uparrow, d \uparrow, \beta \downarrow$	$\pi \downarrow, d \downarrow, \beta \uparrow$
VI.	As V, but amounts change through changing skewness	$\pi \uparrow, d \uparrow, \alpha \downarrow$	$\pi \downarrow, d \downarrow, \alpha \uparrow$

(yielding $\pi = 0.375$ and $d = 1.50$), then for $V_P = 1.2$ (an increase in variability), holding (5) constant yields, through (6), $\beta' = 1.16$ cm (and $\alpha' = \alpha = 1$) for Type III. For Type IV, the corresponding results are $\alpha' = 1.42$ and $\beta' = 1$ cm). The probabilities of at least 1 cm of precipitation on wet days increase to approximately 0.42 and 0.64, respectively, for Types III and IV. Conversely, for $V_P = 0.8$ (a decrease in variability) the Type III changes yields $\beta' = 0.84$ cm, and the probability of at least 1 cm of precipitation drops to around 0.30; while for Type IV the change is $\alpha' = 0.58$, leading to the probability of at least 1 cm of precipitation on a wet day of only 0.19. In each of these cases the parameter π' moves in the opposite direction from either α' or β', in order that $\pi\alpha\beta = \pi'\alpha'\beta'$ (compare Eq. 5).

Since the mean values μ_{ij} in (4) depend on whether a wet or dry day is simulated, changing the average number of wet days (the parameter π) will lead to changes in mean values for simulated temperatures and radiation (Katz, 1996). In order to isolate completely the effects of precipitation variability changes in Types III–VI, corrections to these means are applied, which compensate for the increased or decreased frequency of wet days produced by $\pi' \neq \pi$. These adjusted means, which are then used in (4), are computed using

$$\mu'_{ij} = \mu_{ij} + (\pi' - \pi)(\mu_{i0} - \mu_{i1}). \tag{7}$$

Notwithstanding this correction, changes in the probability of a wet day also affect the daily temperature variance (as well as the autocorrelation function) (Katz, 1996), although for the present data this variance change was found to be quite small. In a climate impacts assessment, where physical consistency among the variables would be more important than isolating the effects of variability changes, it would probably be advisable not to use Eq. (7). Results in Mearns *et al.* (1996)

suggest that the adjustment is of little importance for temperature, but its effect is more substantial for radiation.

2.3. SOIL-CROP-ATMOSPHERE MODELS

The impact of climate variables on simulated crop yield depends on how other processes in the physical environment are simulated, and on how the physical environment, in turn, influences crop growth and development. The software used here to simulate crop growth incorporates models for corn (Stockle and Campbell, 1985; Moen *et al.*, 1994), wheat (Stockle and Campbell, 1989), and EPIC corn and soybeans (Sharpley and Williams, 1990a; Williams, 1995). All of these crop models access common routines for simulating potential evapotranspiration (PET), soil water flow and plant water uptake. This unified approach has the advantage of separating (to a large degree) the simulation of the effect of climate variables on important processes in the crop's physical environment from the simulation of the effect of that physical environment on the crop (Buttler and Riha, 1992). However, the crop and environment systems do interact, as the development of the crop canopy affects PET and the development of roots affects soil water uptake.

The Priestley–Taylor equation (Priestley and Taylor 1972) is used to specify potential evapotranspiration. Potential evapotranspiration is divided each day into potential evaporation and potential transpiration based on the leaf area index of the crop, with the specific dependency differing among the crop models.

All precipitation is assumed to infiltrate the soil surface (i.e. surface runoff was not simulated in this study). Soil water flow was modeled following the approach taken in the CERES models (Jones and Kiniry, 1986). Water is immediately transferred downward in the soil profile if the amount of water entering the layer exceeds the layer's saturated water content. Water will then continue to drain from a layer until a 'drained upper limit' (i.e. field capacity) is reached. Further water can be removed from the soil only through evaporation and transpiration. Soil evaporation is simulated by assuming a limiting water content to which soil evaporation can dry the soil, and that evaporative potential declines continuously as a function of soil depth.

Soil water uptake is calculated by first assuming that potential transpiration will be met through soil water being taken up by roots from each soil layer in proportion to the root density in that layer. However, there is a limiting soil water content below which the plant cannot take up water (lower limit or permanent wilting point). If potential transpiration cannot be met from a given soil layer, unsatisfied demand can be transferred to lower layers. This scheme is similar to the plant uptake simulation in the EPIC model, where, as in this study, root density is assumed to be decreasing exponentially with depth (Sharpley and Williams, 1990a; Williams, 1995). Soil characteristics were determined using the EPIC soil database (Sharpley and Williams, 1990b).

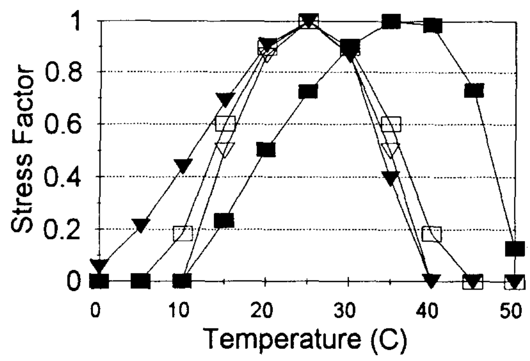

Figure 2. Dependency of photosynthesis or biomass accumulation on air temperature in the crop simulation models; corn (■), EPIC corn (□), wheat (▼) and EPIC soybean (▽).

The ratio of actual transpiration (soil water uptake) to potential transpiration is used as the environmental indicator of water stress (deWit, 1958; Hanks, 1983, Nonhebel, 1993; Simane *et al.*, 1994) in all of the crop models. The functional relationship between water stress and a particular plant process, however, varies with the plant process and with the crop model. Since these functions affect plant growth and development, both potential transpiration (through the impact of leaf area development) and actual transpiration (through the impact of leaf area and rooting depth) can be dynamically influenced when water stress occurs.

All four crop models assume that temperature drives the phenological development of a crop, and therefore the total number of days over which growth can occur. In the corn model, the developmental stages of corn through the onset of grain filling are solely a function of accumulated heat units based on mean daily temperatures. The time required for the leaf area of the crop to completely senesce limits the length of the grain filling period, which in turn directly influences yield. Water stress occurring after the vegetative phase is assumed to accelerate the reduction in leaf area. Therefore, water stress during either the vegetative or the reproductive phases can reduce the time to physiological maturity, and thereby yield. The developmental stages in the spring wheat model (from emergence to physiological maturity) are determined solely as a function of thermal units calculated using a growing degree-day approach. In both the corn and wheat models, air temperature also impacts photosynthesis (which is calculated hourly) through a polynomial relationship (Fig. 2).

Water stress is assumed in both the corn and wheat models to affect growth by limiting photosynthesis in direct proportion to the ratio of actual to potential transpiration. A reduction in photosynthesis in turn limits dry matter accumulation and leaf area development. In addition, in the wheat model a water stress factor is accumulated during each of the developmental phases. Although this stress factor is always dependent on the ratio of actual to potential transpiration, the function relating this ratio to the stress factor varies with the developmental phase.

Ultimately, the stress factors from all the developmental stages impact the grain number, and thereby the grain yield.

In the EPIC crop model, the accumulated daily heat units needed for the crop to attain maturity is specified as an input to the model. The daily heat unit value is the average of the maximum and minimum temperature minus a base temperature, which is specified for each crop. Biomass accumulation in the EPIC model is the product of the energy-to-biomass conversion ratio (a constant) and intercepted photosynthetically active radiation (PAR). Intercepted PAR is a function of leaf area, whose development is dependent on accumulated heat units but can be slowed by temperature or water stress, whichever is more limiting. The temperature stress is symmetrical around an optimum temperature (Fig. 2). In the EPIC model, average daily soil surface temperature is used to determine temperature stress (Sharpley and Williams, 1990a), whereas in the simulations presented here, the mean of the daily maximum and minimum air temperature is used. Also, the ability of roots to take up water is affected by several soil conditions in the EPIC model, including soil temperature. These soil stress factors are not implemented in the simulations reported here.

In the EPIC crop model, yield is simulated as the product of accumulated biomass and the harvest index (ratio of grain to total dry matter). Water stress can reduce biomass accumulation, and therefore yield, when temperature stress is not more limiting. Water stress is the ratio of daily actual transpiration to daily potential transpiration. In addition to its impact on biomass accumulation, water stress can reduce the harvest index. When the ratio of accumulated actual transpiration to accumulated potential transpiration declines below 0.7, the optimum harvest index is decreased sigmoidally to a minimum level that is crop-dependent.

An assumption underlying all of the crop models as implemented in this study is that yield is only limited by light, temperature and water. Optimum fertility management and no pests or diseases are assumed. Also, yield reduction due to too much water (erosion, waterlogging, inability to cultivate, lodging) is not simulated. Therefore, the simulated yields represent potential crop yields rather than expected crop yields under standard management practices.

3. Results

3.1. BASELINE YIELD CHARACTERISTICS

Average yield is predicted using the four crop models (corn, wheat, EPIC soybean, EPIC corn) at each soil/site for 100 years of synthetic weather. All four models predict significantly lower yields on the Dickman compared to the Ves soil at the Minnesota site (Table II). Within a soil type, the two corn models predict similar average yields at the Minnesota site, whereas the EPIC corn model predicts slightly higher average yields at the Georgia site (Table II).

Table II
Average model yields (kg ha^{-1}, n = 100) and their standard deviations (in parentheses) in response to weather simulated using the unaltered climatic parameters

Crop model	Dickman/MN	Soil/location Ves/MN	Tifton/GA
Corn	7.7 (2.4)	9.2 (2.3)	7.3 (2.0)
EPIC corn	7.4 (1.5)	8.9 (1.3)	7.9 (0.9)
Wheat	3.3 (1.0)	3.8 (0.9)	3.1 (1.1)
EPIC soybeans	2.5 (0.4.)	3.1 (0.4)	3.2 (0.2)

The standard deviation of yield differs among crop models and sites (Table II). The standard deviation of yield predicted using the EPIC corn model is significantly less than the standard deviation of yield using the other corn model at all three soil/site combinations. These differences in standard deviation of yield are not surprising since the biophysical processes included in these models, as well as the complexity with which these processes are represented, do vary. Soil type does not affect the standard deviation of yield at the Minnesota site. Because average yields are different on the two soils, the coefficient of variation (CV = standard deviation/mean) of yield is lower for the Ves soil than the Dickman. These results may imply that a soil with relatively low plant available water capacity (Dickman) is likely to suppress yields in most years without amplifying the impact of interannual climatic variability on yield variations.

3.2. RESPONSE TO TEMPERATURE VARIABILITY

For the Minnesota soil and climate parameters, all four crop models predict decreasing average yields with increasing variability of temperature (Fig. 3a, b). The decreases are essentially linear as the temperature variance parameter, V_T, increases from zero to 1.9. This result contrasts with that for the Georgia site (Fig. 3c) where increasing temperature variability has little impact on average corn and soybean yields, while wheat yields decline about 50% less than at the Minnesota site. At both sites, the influence of temperature variability on the standard deviation (year-to-year fluctuation) of yield (not shown) was generally small, with the result that the CV increased with increasing temperature variability. The exception to this was the EPIC corn and soybean yield predictions for the Ves soil. The standard deviations decreased with increased temperature variability, which resulted in slight decreases in CV.

It is not immediately clear whether temperature variability affects simulated yields primarily through the functions relating photosynthesis or biomass accumulation and leaf area development, through the effect of temperature on the length of crop growth, or as a consequence of both these processes. In the case of the corn

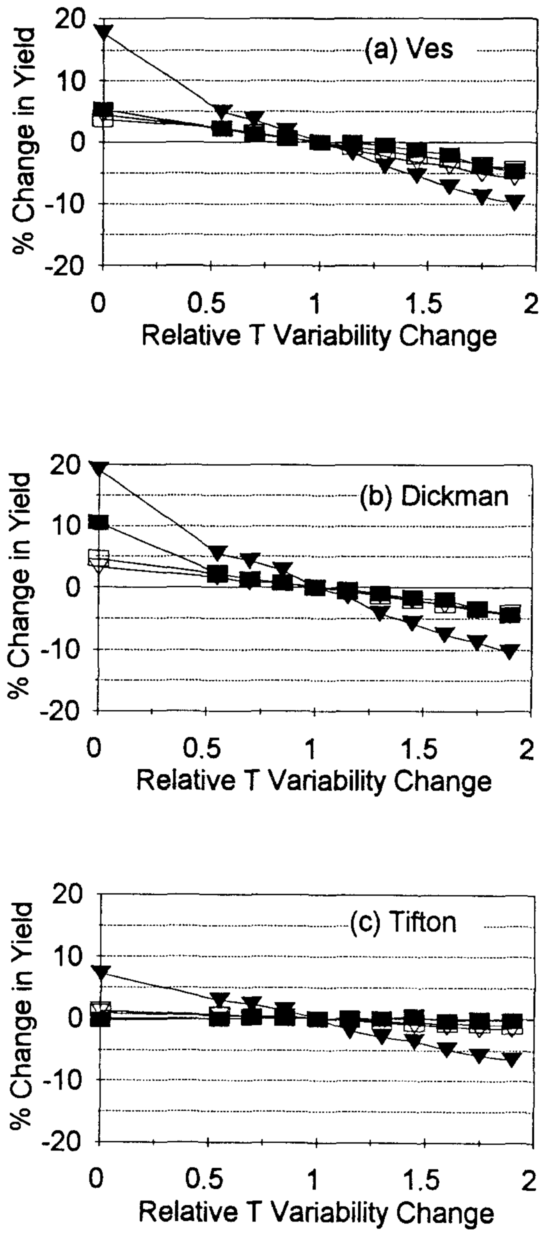

Figure 3. Percentage changes in average yields as a function of the relative temperature variability change, V_T, at Redwood Falls, MN (Ves and Dickman soil) and Tifton, GA (Tifton soil); corn (■), EPIC corn (□), wheat (▼) and EPIC soybean (▽).

model, average days to maturity decrease with increasing temperature variability at the Minnesota site (not at the Georgia site), but in this model the length of the growing season is influenced by photosynthesis through its effect on leaf area development. Therefore, a series of simulations were implemented in which photosynthesis was made independent of temperature. In these simulations increasing temperature variability had no impact on average corn yield at either site. Evidently, the temperature dependency of photosynthesis (Fig. 2) is responsible for the simulated yield response to temperature variability of the corn model.

In the case of the wheat model, the influence of temperature variability on average days to maturity is small at both sites. As with the corn model, a series of simulations were implemented in which photosynthesis was not allowed to vary with temperature. When this is done, average yields and standard deviations do not change appreciably with changes in temperature variability at either site. This result indicates that an analogous mechanism for the suppression of average yield by increasing temperature variability is operating in the corn and wheat models.

For the EPIC soybean model, increasing temperature variability does not alter the average days to maturity at either site, although there is an increase in the variance in days to maturity with increasing temperature variability. When the temperature stress function for biomass accumulation and leaf area development (Fig. 2) is not implemented, increasing temperature variability does not alter average yield. Using the EPIC corn model, increasing the temperature variability decreases the average days to maturity at the Minnesota site, but not at the Georgia site (by 5 days from $V_T = 0$ to $V_T = 1$ and by 1 day from $V_T = 1$ to $V_T = 1.9$). As is the case with the other three crop models, when the temperature stress function is not implemented, there is no effect of temperature variability on average yield.

The differences among the crop models and among sites in simulated average yield responses to changing temperature variability can be explained primarily by how the air temperatures over the growing season relates to the dependencies of photosynthesis or biomass accumulation on temperature. The models behave similarly at the Minnesota site because the air temperatures are near or below the optimum range for much of the growing season (Fig. 1). Since the functions decline rapidly at low temperatures and change more gradually around the optima (Fig. 2), increasing temperature variability at this site would be expected to negatively impact crop growth. In contrast, at the Georgia site air temperatures are closer to the optima, and increasing temperature variability therefore has less effect.

The cumulative water stress index (the summation of 1 – actual transpiration/potential daily transpiration) is greater for all crops grown on the Dickman versus the Ves soil. However, in all cases, the stress index and variability of the stress index changes very little with increasing temperature variability.

3.3. RESPONSES TO PRECIPITATION VARIABILITY

In addition to influencing average yield (Table II), soil type noticeably mediates the response of predicted yields to changes in precipitation variability for most of the cases examined (Fig. 4). Interestingly, average yield on the Dickman soil, which has less water-holding capacity than the Ves soil, in general responds less to changes in precipitation variability than does yield on the Ves soil. Average yields increase on the Ves soil wherever increasing precipitation variability increases the probability of days with high rainfall, even if this means fewer days with rain (Types III and IV) or fewer rain days and dry spells (Types V and VI). The other aspects of precipitation variability change among Types III–VI appear to be less important than the changes in π. In the case of Type I, variability of the daily rainfall amounts increases as V_P increases while the number of rain days and the length of dry and wet spells are held constant. This implies that there are fewer large rainfall events for $V_P < 1$, which favors yields on the Dickman and suppresses yields on the Ves. The amount of water transpired in the Dickman simulations of the corn, EPIC corn and EPIC soybean models increased at $V_P = 0.7$ in Type I precipitation variability change, relative to greater levels of precipitation variability ($V_P \geq 1$). As dry and wet spells increase from shorter to longer (V_P increasing in variability change Type II over the range considered here) there is no impact on average yield for crops grown in the Ves soil and only a slight decline in average yield for crops grown on the Dickman.

The ranges for the parameter V_P shown in Figures 4 and 5 are limited by the feasible solutions that can be obtained from (6), while holding (5) constant, for different months at the two locations. That is, without allowing the mean precipitation to change (which is strongly related to precipitation variance in observed data; Waggoner, 1989), increasing or decreasing V_P beyond some limit produces nonsense solutions; such as negative α, β or π; or π or d greater than one. Some of the parameter changes used here, however, do constitute quite strong departures from the base climates, as is illustrated by the example in Section 2.2.

The nature of these yield responses to changes in precipitation variability, and the fact that the different crop models behave fairly similarly, is attributable to the manner in which water uptake is modeled in these simulations. The water stress indicator, although applied at different times and to different components of the crop models, is calculated in a similar manner in all the models; it is the ratio of soil water uptake (actual transpiration) to potential transpiration. The simulation of soil water uptake is shared by all the crop models, and is proportional to the fraction of total root density at a given depth. If there is not enough water in surface layers to meet the demand for water, this demand is passed downward to deeper layers. Once the soil dries at depth, even if the soil is rewetted at the surface, there will be unmet demand in proportion to the amount of roots that are in dry soil. The result is that water uptake will be less than the potential evapotranspiration, producing water stress in the crop models.

Since potential transpiration is generally greater than growing-season precipitation in the Minnesota climate, crops must rely on stored soil water to meet transpiration demands. The Ves soil has a higher water-holding capacity than the Dickman soil and, as expected, the amount of water transpired and predicted average yield of all crops are higher on the Ves than on the Dickman soil. Crops grown on the Ves soil are less subject to water stress. However, as stored water is depleted

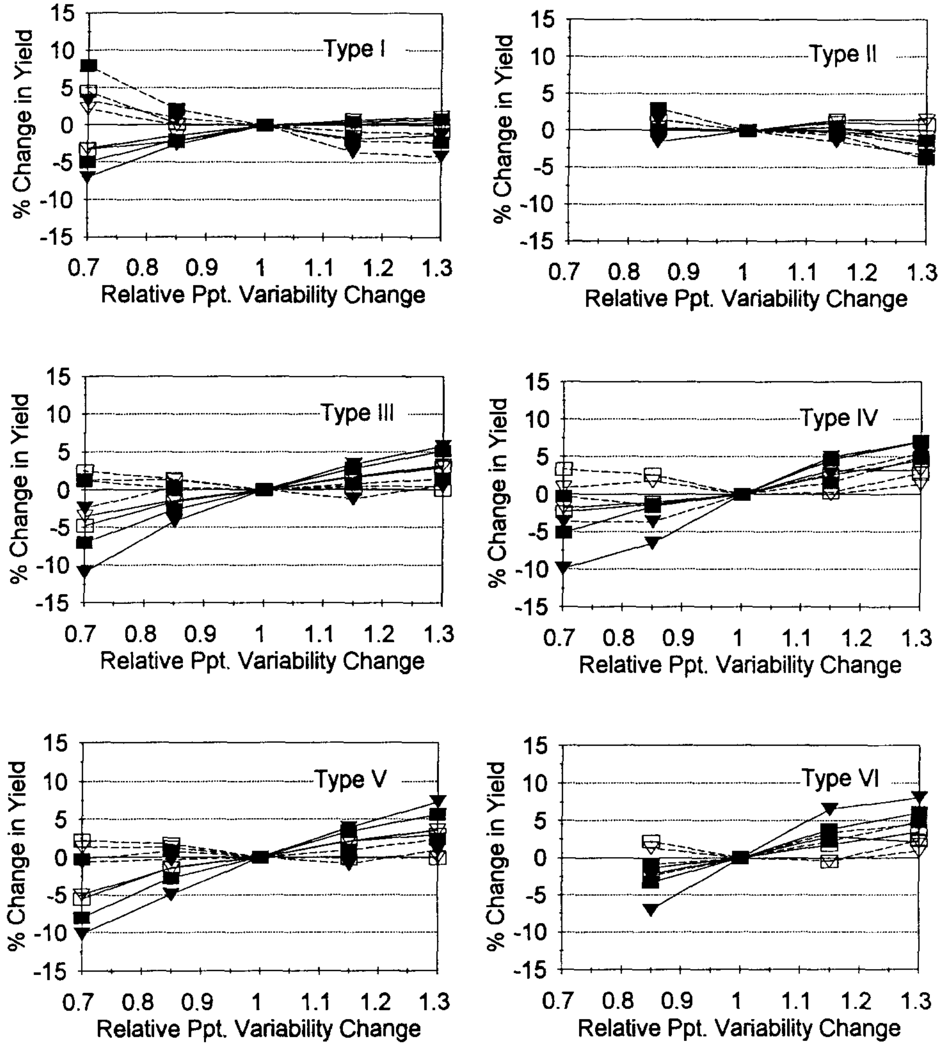

Figure 4. Percentage change in average yields at Redwood Falls, MN as a function of the magnitude of relative variability change, V_P, for the six types of change in precipitation variability. Ves (—) and Dickman (- - -) soils; corn (■), EPIC corn (□), wheat (▼) and EPIC soybean (∇).

deeply in the Ves soil, larger rainfall events are required to recharge this soil at depth than are required to recharge the Dickman. Without this recharge, some stress will still occur. Thus, simulated crop growth on the Ves soil, with a larger water-holding capacity, is more sensitive to variability of precipitation amount distribution than simulated crop growth on the Dickman soil, while at the same time simulated crop growth is less subject to stress on the Ves soil. There is some indication in Fig. 4 of greater yield increase on Ves for Type IV vs. Type III, and for Type VI vs. Type V variability changes, for $V_P = 1.3$.

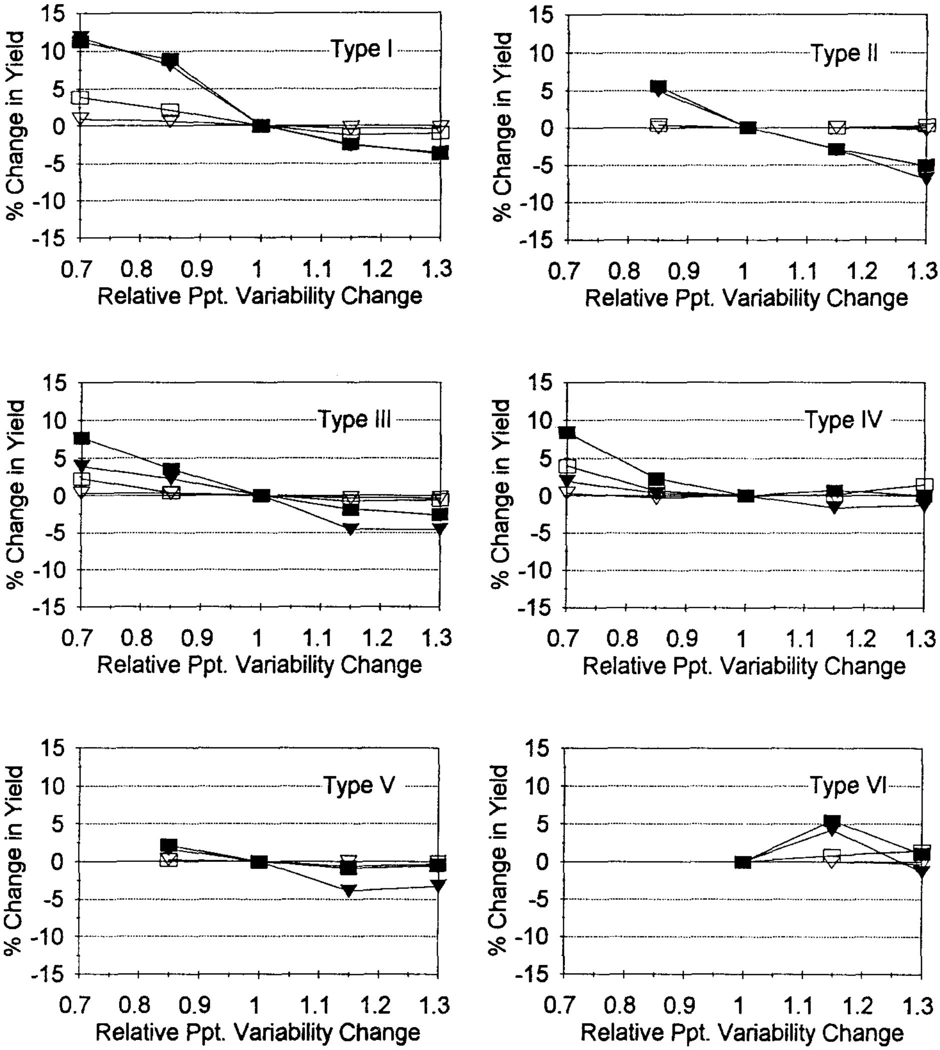

Figure 5. Percentage change in average yields at Tifton, GA as a function of the magnitude of the relative variability change, V_P, for the six types of change in precipitation variability; corn (■), EPIC corn (□), wheat (▼) and EPIC soybean (▽).

The response at the Tifton site is similar to the results for the Dickman soil (Fig. 5). The low water-holding capacity of the soil combined with higher growing-season precipitation result in this soil/site being relatively insensitive to changes in variability of precipitation, although wheat and corn yields are increased when the variability of daily rainfall amounts decrease (Type I–IV, Fig. 5). At the Tifton site, the change in yield predicted using the EPIC corn and soybean models was smaller than change in yield predicted using the corn and wheat models, though the direction of change was usually similar (Fig. 5). This difference is probabily due to the more complex representation of corn and wheat responses to climatic factors contained in the corn and wheat models compared to the EPIC model.

4. Discussion and Conclusions

The results of this study suggest that increasing variability of temperature produces smaller average yield where growing-season temperatures are outside the optimum range for photosynthesis or growth. Other studies using winter wheat models to examine the impact of within-year temperature variability on crop yield have also reported decreasing yield with increasing temperature variability (Mearns *et al.*, 1996; Semenov and Porter, 1995). In the Mearns *et al.* study, larger decreases in predicted winter wheat yields occurred as temperature variability increased than occurred for the crops simulated in this study. Mearns *et al.* (1996) attributed the effect of increasing within-year temperature variability on winter wheat yields primarily to increased likelihood of winter damage while this study has focused on crop production during a frost-free growing season. The smaller impact of increasing within-year temperature variability on winter wheat yields reported by Semenov and Porter (1995) is consistent with the present results in suggesting that increasing within-year temperature variability will have the greatest effect on yield where growing season temperatures are outside the optimum for growth. However, an assumption inherent in all the crop models used in this study is that temperature dependency of photosynthesis or biomass accumulation remains constant over the growing season. Whether this is a realistic assumption may be open to question (Berry and Bjorkman, 1980).

The findings of this study suggest that where temperature optima for plant growth are similar to growing-season air temperatures, weekly or monthly air temperature data could be used as input to a crop simulation model with little impact on predicted yields. In other cases, crop models using summary air temperature data may overpredict yield (Nonhebel, 1994).

Increasing the within-year (and, accordingly, interannual) variability of temperature generally increases the CV of crop yields. In this study, these increases were in the range of 1–5% over the range of temperature variability examined. In other studies using winter wheat models, the CV in year-to-year yield has also been found to increase with increasing variability of temperature (Mearns *et al.*, 1996; Semenov and Porter, 1995). The larger increase in CV found by Mearns *et al.* (1996) was attributed to the increased likelihood of winter damage. In contrast, in the Semenov and Porter (1995) study, doubling the daily variance of temperature had much less effect on the CV of yield. Again, it is likely that increasing within-year temperature variability will have a more pronounced effect on the CV of yield as growing season temperatures are further from optimal.

Changing precipitation variability has been reported to both increase and decrease average simulated yields, depending on the climate and soil type (Mearns *et al.*, 1992, 1996; Nonhebel, 1994; Semenov and Porter, 1995). The present results indicate that the sign of the relationship between precipitation variability and average yield may be mediated by the nature of the soil in which the plants are grown. Furthermore, the strength of the relationship, and sometimes even its sign as well, appears to depend on the qualitative nature of the change in precipitation variability, with different variability types sometimes yielding quite different responses to the same level of interannual variance change. However, in this study, the main differences in responses to variability change appeared to be between those types in which the average frequency of rain days (the parameter π) was changed (III–VI), versus those where it was held constant (I and II).

For soils with relatively large water-holding capacities but subject to occasional low growing-season rainfall, increasing precipitation variability in a manner that increases the likelihood of larger rainfall events generally resulted in greater average yields, while decreasing this variability lowered simulated yields. Simulated yields on soils with low water-holding capacities were not as much affected by such changes in precipitation variability, but showed average yield decreases in response to increasing precipitation variability when the average number of rain days was held constant. This was also the case where stress due to soil moisture status was relatively low for initial climate simulations. These results are generally consistent with those reported by Mearns *et al.* (1996) for simulated yield of winter wheat.

The large differences in response between soils with high and low water-holding capacities are seen to derive from the (commonly assumed) modeled mechanism of water uptake from depth in the soil profile. The present results suggest that the robustness of this mechanism should be the subject of further investigation.

That the yield response to changes in precipitation variability can depend on the qualitative nature of the variability change presents a substantial challenge to modelers of the impacts of climate changes. Current atmospheric general circulation models (GCMs) yield inconsistent results concerning changes in mean precipitation at particular locations, and the sign and magnitude of any change in interannual variability is even less clear. Since GCMs reproduce the current statistics of daily precipitation rather poorly (Mearns *et al.*, 1990; Reed, 1986; Rind *et al.*, 1989; Wilson and Mitchell, 1987), GCM results concerning the nature of these variability changes (e.g., Gordon *et al.*, 1992) must be regarded as speculative. However, the present results suggest that the qualitative nature of these changes may be a significant determinant of important agricultural impacts.

Acknowledgements

This research was supported by the National Science Foundation under grant BSR-9213883, and by the U.S. Department of Agriculture under grant 91-34244-5917.

References

Austin, M. E.: 1972, 'Land Resource Regions and Major Land Resource Areas of the United States', *Agricultural Handbook* 296, USDA/SCS, 82 pp.

Berry, J. A. and Bjorkman, O.: 1980, 'Photosynthetic Response and Adaptation to Temperature in Higher Plants', *Annu. Rev. Plant Phys.* **31**, 491–543.

Bonan, G.: 1993, 'Do Biophysics and Physiology Matter in Ecosystem Models?' *Climatic Change* **24**, 281–285.

Buttler, I. W. and Riha, S. J.: 1992, 'Water Fluxes in Oxisols: A Comparison of Approaches', *Water Resources Res.* **28**, 221–229.

Cohen, S. J.: 1990, 'Bringing the Global Warming Issue Closer to Home: The Challenge of Regional Impact Studies', *Bull. Amer. Meteorol. Soc.* **71**, 520–526.

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* **7**, 83–102.

Hanks, R. J.: 1983, 'Yield and Water-Use Relationships: An Overview', in Taylor, H. M., Jordan, W. R., and Sinclair, T. R. (eds.), *Limitations to Efficient Water Use in Crop Production*, Am. Soc. of Agron., Madison, WI, pp. 393–411.

Jones, C. A. and Kiniry, J. R. (eds.): 1986, *CERES – Maize: A Simulation Model of Maize Growth and Development*, Texas A&M Univ. Press, College Station, 194 pp.

Katz, R. W.: 1996, 'Use of Stochastic Models to Generate Climate Change Scenarios', *Climatic 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', *Climatic Change* **21**, 289–302.

Mearns, L. O., Schneider, S. H., Thompson, S. L., and McDaniel, L. R.: 1990, 'Analysis of Climatic Variability of General Circulation Models: Comparison with Observations and Changes in Variability of 2X-CO_2 Experiments', *J. Geophys. Res.* **D95**, 20469–20490.

Mearns, L. O., Rosenzweig, C., and Goldberg, R.: 1992, 'Effects of Change in Interannual Climatic Variability on CERES – Wheat Yields: Sensitivity and 2XCO_2 General Circulation Model Scenarios', *Ag. For. Meteorol.* **62**, 159–189.

Mearns, L. O., Rosenzweig, C., and Goldberg, R.: 1996, 'The Effect of Changes in Daily and Interannual Variability on CERES – Wheat: A Sensitivity Study', *Climatic Change* **32**, 257–292 (this issue).

Moen, T. N., Kaiser, H. M., and Riha, S. J.: 1994, 'Regional Yield Estimation Using a Crop Simulation Model: Concepts, Methods and Validation', *Agricul. Systems* **46**, 79–92.

Neild, R. E., Richman, H. N., and Seeley, M. W.: 1979, 'Impacts of Different Types of Temperature Change on the Growing-Season for Maize', *Agr. Meteorol.* **20**, 367–374.

Nonhebel, S.: 1993, 'Effects of Change in Temperature and CO_2 Concentration on Simulated Spring Wheat Yields in The Netherlands', *Climatic Change* **24**, 311–329.

Nonhebel, S.: 1994, 'The Effects of Use of Average Instead of Daily Weather Data in Crop Growth Simulation Models', *Agricul. Systems* **44**, 377–396.

Priestley, C. H. B. and Taylor, R. J.: 1972, 'On the Assessment of Surface Heat Flux and Evaporation Using Large-Scale Parameters', *Monthly Weather Rev.* **100**, 81–92.

Reed, D. N.: 1986, 'Simulation of Time Series of Temperature and Precipitation over Eastern England by an Atmospheric General Circulation Model', *J. Climatol.* **6**, 233–253.

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

Rind, D., Goldberg, R., and Ruedy, R.: 1989, 'Change in Climate Variability of the 21st Century', *Climatic Change* **14**, 5–37.

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

Sharpley, A. N. and Williams, J. R. (eds.): 1990a, *EPIC – Erosion/Productivity Impact Calculator: 1. Model Documentation*, U.S. Dept. of Agric., AgricResearch Serv. Tech. Bull. No. 1768.

Sharpley, A. N. and Williams, J. R. (eds.): 1990b, *EPIC – Erosion/Productivity Impact Calculator: 2. User Manual*, U.S. Dept. of Agric., Agric. Research Serv. Tech. Bull. No. 1768.

Simane, B., van Keulen, H., and Stol, W.: 1994, 'Application of a Crop Growth Model (SUCROS-87) to Assess the Effect of Moisture Stress on Yield Potential of Durum Wheat in Ethiopia', *Agricul. Systems* **44**, 337–352.

Stockle, C. O. and Campbell, G. S.: 1985, 'A Simulation Model for Predicting Effect of Water Stress on Yield:An Example Using Corn', *Advan. Irrigation* **3**, 283–323.

Stockle, C. O. and Campbell, G. S.: 1989, 'Simulation of Crop Response to Water and Nitrogen: An Example Using Spring Wheat', *Trans. ASAE* **32**, 66–74.

Waggoner, P. E.: 1989, 'Anticipating the Frequency Distributions of Precipitation if Climate Change Alters Its Mean', *Agricul. Forest Meteorol.* **47**, 321–337.

Wilks, D. S.: 1992, 'Adapting Stochastic Weather Generation Algorithms for Climate Change Studies', *Climatic Change* **22**, 67–84.

Williams, J. R.: 1995, 'The EPIC Model', in V. P. Singh (ed.), *Computer Models of Watershed Hydrology*, 909–1000.

Wilson, C. A. and Mitchell, J. F. B.: 1987, 'Simulated Climate and CO_2-Induced Climate Change over Western Europe', *Climatic Change* **10**, 11–42.

deWit, C. T.: 1958, *Transpiration and Crop Yields*, Agric. Research Paper 64.6 Pudoc, Wageningen, 88 pp.

(Received 15 November 1994; in revised form 11 October 1995)