MEAN AND VARIANCE CHANGE IN CLIMATE SCENARIOS: METHODS, AGRICULTURAL APPLICATIONS, AND MEASURES OF UNCERTAINTY

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Abstract. Our central goal is to determine the importance of including both mean and variability changes in climate change scenarios in an agricultural context. By adapting and applying a stochastic weather generator, we first tested the sensitivity of the CERES-Wheat model to combinations of mean and variability changes of temperature and precipitation for two locations in Kansas. With a 2 °C increase in temperature with daily (and interannual) variance doubled, yields were further reduced compared to the mean only change. In contrast, the negative effects of the mean temperature increase were greatly ameliorated by variance decreased by one-half. Changes for precipitation are more complex, since change in variability naturally attends change in mean, and constraining the stochastic generator to mean change only is highly artificial. The crop model is sensitive to precipitation variance increases with increased mean and variance decreases with decreased mean. With increased mean precipitation and a further increase in variability Topeka (where wheat cropping is not very moisture limited) experiences decrease in yield after an initial increase from the 'mean change only' case. At Goodland Kansas, a moisture-limited site where summer fallowing is practiced, yields are decreased with decreased precipitation, but are further decreased when variability is further reduced. The range of mean and variability changes to which the crop model is sensitive are within the range of changes found in regional climate modeling (RegCM) experiments for a CO_2 doubling (compared to a control run experiment).

We then formed two types of climate change scenarios based on the changes in climate found in the control and doubled CO_2 experiments over the conterminous U. S. of RegCM: (1) one using only mean monthly changes in temperature, precipitation, and solar radiation; and (2) another that included these mean changes plus changes in daily (and interannual) variability. The scenarios were then applied to the CERES-Wheat model at four locations (Goodland, Topeka, Des Moines, Spokane) in the United States. Contrasting model responses to the two scenarios were found at three of the four sites. At Goodland and Des Moines mean climate change increased mean yields and decreased yield variability, but the mean plus variance climate change reduced yields to levels closer to their base (unchanged) condition. At Spokane mean climate change increased yields, which were somewhat further increased with climate variability change. Three key aspects that contribute to crop response are identified: the marginality of the current climate for crop growth, the relative size of the mean and variance changes, and timing of these changes. Indices for quantifying uncertainty in the impact assessment were developed based on the nature of the climate scenario formed, and the magnitude of difference between model and observed values of relevant climate variables.

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1. Introduction

Most climate change agricultural impact studies have analyzed the effects of mean changes of climate variables on crop production (e.g., Cooter, 1990; Mendelsohn et al., 1994; Rosenzweig and Parry, 1994). The focus on mean climate change has provided only limited information on how future changes in climate variability could affect agriculture. Few climate change scenarios formed for climate change impact analysis have considered detailed, explicit changes in variability (Mearns et al., 1992; Wilks, 1992; Mearns and Rosenzweig, 1994, 1997; Barrow and Semenov, 1995). This is partially because there is considerable uncertainty regarding how climate variability may change in the future, due to greenhouse warming or any other cause (Houghton et al., 1990, 1992, 1996). There is also quantitative uncertainty concerning how agricultural crops respond to changes in climate variability, but it is known that changes in variability can have serious effects on agricultural yield (Parry and Carter, 1985; Carter and Parry , 1986), though these effects vary regionally (Anderson and Hazell, 1989). One of the main means by which crops are affected is through changes in the frequency of extreme climate events (e.g., heat waves, Mearns et al., 1984); and changes in variance have a greater effect on the frequency of extremes than changes in the mean (Katz and Brown, 1992). The possible role of changes in variability is an important uncertainty in our knowledge of possible impacts of climate change. The need for research to determine possible effects of changes in climate variability on crops, is highlighted in the recent Intergovernmental Panel on Climate Change (IPCC) Working Group II Report (Reilly, 1996).

Most recently there has been a series of works exploring the sensitivity of crop models to changes in daily variability (Mearns, 1995; Semenov and Porter, 1995; Mearns et al., 1996; Riha et al., 1996). All these works share a common methodological background, i.e., climates with different variability characteristics are generated by manipulating the parameters of stochastic weather generators, such as that of Richardson (1981) and Richardson and Wright (1984). Semenov and Porter (1995), using a weather generator based on simulating dry and wet series and applying a crop model for wheat growth for locations in England and France found that changes in the variability of climate could have a more profound effect on yield than changes in mean climate. Mearns et al. (1996) and Riha et al. (1996), using modified versions of the Richardson (1981) weather generator, found a range of effects on several different crop models depending on the location and degree of change in variability. For example for a location in Georgia, using EPIC crop models Riha et al. (1996) found that simulated yields of corn and soybean increased with increasing precipitation variability. Mearns et al. (1996), using the CERES-Wheat model found, for example, large decreases in simulated yield with increased temperature variability at locations in Kansas.

Our current study is a continuation of the work presented in Mearns et al. (1996) (henceforth referred to as MRG96). In section 2, we provide a description of the

CERES-Wheat model. In section 3 we describe the stochastic weather generator used and in section 4 we summarize CERES-model sensitivity to variance change alone. We then present a sensitivity study of the effects of combined changes in both mean and variability of temperature and precipitation on the crop model response for the two locations studied in MRG96. We go on to develop climate change scenarios that include changes in both mean and second order moments of the variables of interest and apply these scenarios to the CERES-Wheat model at four sites in the United States. We use the control and doubled CO_2 runs from the National Center for Atmospheric Research (NCAR) regional climate model (RegCM) nested within a general circulation model (GCM) over the continental U. S. (Giorgi et al., 1994) for the scenario formation. Finally we discuss a method for quantifying uncertainties in the climate change scenarios based on the relative errors in the control run climate, and how these errors affect the crop model. We use this method to quantify uncertainty resulting from inclusion (or exclusion) of variability changes in climate change scenarios.

2. CERES-Wheat Model and Study Characteristics

2.1. WHEAT MODEL

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 biomass accumulation, phenological development (Hodges, 1991), partitioning of photosynthates, and soil moisture dynamics. 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.

2.1.1. *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 Number 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. Soil water deficit factor 1 (SWDF1), for example, 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.

2.1.2. *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. Wheat plants can be killed or damaged by extremely low temperatures. The amount of damage is 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. Precipitation in the model is converted to snow depth when the maximum temperature is less than or equal to 1 °C. Hardening is quantified using a hardening index (HI) whose value ranges from 0–2. 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 more susceptible to cold temperature extremes. The plant can also lose its hardening when crown temperatures rise above 8 °C and when 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. Biomass increase depends on a soil water deficit factor; at times of maximum water deficit, biomass increase is reduced to a very low value.

Table I
Observed climate (1951–1980) of the four stations

	Station							
	Goodland		Topeka		Spokane		Des Moines	
Latitude, longitude	39.2	101.4	39.1	95.6	47.6	117.5	41.5	93.6
January T_{max} (sd)	5.0	(8.6)	2.4	(8.0)	–0.4	(5.5)	–2.8	(7.7)
January T_{min} (sd)	–10.3	(6.4)	–9.0	(6.7)	–6.7	(6.9)	–12.4	(7.5)
July T_{max} (sd)	32.3	(4.5)	32.0	(4.0)	29.0	(5.0)	30.2	(3.8)
July T_{min} (sd)	16.2	(2.6)	19.7	(3.5)	12.9	(3.2)	18.8	(3.2)
GS total precip.	267.3		563.1		375.2		518.5	

Where: T_{max} = mean daily maximum temperature °C; T_{min} = mean daily minimum temperature °C; sd = standard deviation °C; GS total precip. = growing season (October–June) total precipitation (mm).

2.2. STUDY CHARACTERISTICS

The main difference in the climates of the four locations considered in our study is the amount of precipitation received (Table I). At Goodland and Spokane, two relatively dry locations, summer fallowing is the common cultivation practice. At moister sites Topeka and Des Moines continuous rainfed cropping is used. Although little wheat is currently grown at Des Moines we included it as an additional moist site to test possible cropping responses to climate change. The three Great Plains sites follow a summer maximum precipitation regime, whereas Spokane receives maximum precipitation in winter. Spokane and Des Moines experience cooler summers than the other two sites.

Three generic soils are used in the CERES-Wheat model for each location to represent low (S1), medium (S2), and high (S3) soil productivity levels. For example at Goodland these are deep sandy loam, deep silt loam, and shallow silty clay and at Topeka, 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 sites are those commonly used at each location: Newton for Goodland, Scout 66 for Topeka, Stephens for Spokane, and N. Plains for Des Moines.

CERES-Wheat has been validated at a number of locations in the United States (Otter-Nacke et al., 1986). In our earlier studies (Mearns and Rosenzweig, 1994; MRG96) we validated the model performance at Goodland and Topeka.

Two types of management practices – continuous rainfed and fallow – were simulated by the model. For Topeka and Des Moines a crop was planted every fall for continuous rainfed production; and for Goodland and Spokane, 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. Weather Generator

3.1. DESCRIPTION OF THE RICHARDSON MODEL

Richardson's (1981) stochastic weather generator simulates daily time 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:

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

where:

α = the shape parameter;
β = the scale parameter;
$\Gamma(\alpha)$ = the gamma function of α.

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:

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

where:

$x_t(j)$ = a vector for day t for 3 elements, which are standardized values of maximum temperature ($j = 1$), minimum temperature ($j = 2$) and solar radiation ($j = 3$);
$\epsilon_t(j)$ = a vector for day t for 3 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:

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

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 $j = 2$, minimum temperature, there is no conditioning, and the index i in Equation (3) is not used.

The Richardson model, or models very similar to it, have been evaluated as to how well they reproduce observed climate characteristics of particular locations (MRG96, Johnson et al., 1996; Katz, 1996). The model tends to underestimate interannual variability of precipitation, as well as the autocorrelation structure of daily temperature. However, we found that the model performed reasonably well for our purposes.

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 expression $N\pi\alpha\beta$ is the mean monthly total precipitation.

The relationship between interannual and daily variance of temperature is approximated by:

$$\mathrm{Var}(T) \simeq \frac{\sigma_d^2}{N}\frac{1+\rho_1}{1-\rho_1} , \tag{5}$$

where:

$$\begin{aligned}\mathrm{Var}(T) &= \text{interannual variance of monthly temperature } (^\circ\mathrm{C}^2);\\ \sigma_d^2 &= \text{variance of daily temperature } (^\circ\mathrm{C}^2);\\ \rho_1 &= \text{first order autocorrelation coefficient of daily temperature.}\end{aligned}$$

It is important to note that these relationships are approximations.

4. CERES-Wheat Sensitivity to Variance Change Alone

MRG96 analyzed the effect of daily (and interannual) variability change on the CERES-Wheat model (Ritchie and Otter, 1985) at Goodland and Topeka, Kansas. Daily temperature variability (on a monthly basis) was changed by factors of 0.33, 0.5, 2, and 3$\times$ the baseline (observed) variance. With increasing temperature variance, mean yields decreased and the relative variability of yield increased. The major cause of these yield changes was crop failure and damage due to extreme winter temperatures, which resulted in high incidence of winter kill.

For precipitation MRG96 constructed two different types of variance change. In both cases the mean total monthly precipitation ($N\pi\alpha\beta$) remained constant. In the first case, the frequency of precipitation and scale parameter of the gamma distribution (by which precipitation amounts are modeled, Equation (1)) were changed; and in the second only the persistence of precipitation occurrence (d) was changed. These parameters were changed such that interannual variability was changed by the factors 0.3, 0.5, 2, and 3. For the first type, β is changed approximately by the factor and π by the inverse of the factor to bring about the desired change. Interesting interactions of the precipitation variability changes with the contrasting base climates were found at the two locations. At Topeka, mean yield decreased and variability of yield increased with increasing precipitation variability, whereas mean yields increased at Goodland, where soil moisture is limiting and fallow production methods are used. Yield changes were similar for the two different types of precipitation variability change investigated. Changes in frequency proved particularly important in the first type of change. With variance decrease (when frequency increases) the amount of evaporation from the soil is high at both locations. At Goodland, the plants are stressed throughout the crop season. At Topeka, there is a sudden onset of stress late in the season, which strongly affects final yield, even though a high level of dry matter production is maintained during the growing season. These results are similar to those found by Mearns et al. (1992), when monthly observed time series were mechanically altered to bring about changes in (mainly) interannual variability of precipitation, but results in MRG96 were more extreme.

5. Sensitivity Analysis with Combined Mean and Variance Changes

5.1. FORMATION OF CLIMATE DATASETS WITH PRESCRIBED CHANGES

For the two locations discussed in MRG96, Goodland and Topeka, we present analyses of combined mean and variance changes of temperature and precipitation. The central research questions considered in the sensitivity analyses are: How does the crop model respond to the combined changes; and are the effects simply additive or are there complex interactions?

Climate time series (90 years in length) for the two locations were simulated for the following cases: (1) mean temperature increase of 2 °C and 4 °C, no change in variability; (2) mean temperature increase of 2 °C and 4 °C, daily and interannual variance doubled; (3) mean temperature increase of 2 °C and 4 °C, daily and interannual variance reduced by a factor of 0.5.

Given the very strong relationship that exists between mean and variance changes in precipitation (e.g., Waggoner, 1989) the construction of scenarios with only mean precipitation changes is highly artificial. For mean precipitation change we used the method employed in numerous climate change impacts studies (e.g., Smith and Tirpak, 1989). In this 'classic method' mean monthly (or daily) precipitation time series are multiplied by a fixed ratio. For example, to increase monthly precipitation by 20% the daily time series of precipitation is multiplied by a factor of 1.2. This, however, induces changes in the variance of the intensity process, roughly equivalent to changing β in the gamma distribution (Equation (1)) by a factor of 1.2. Since the variance of the gamma distribution is $\alpha\beta^2$, then the variance of the intensity process is changed by the factor 1.44. We note that in no impacts papers we surveyed was the fact that the variance of mean intensity of precipitation changes with this mean change method recognized and discussed. We changed the precipitation mean (and variance) (on a monthly basis) by increasing β by a factor of 1.2 or decreasing it by a factor of 0.8. These constituted the 'mean' change scenarios. We then further changed the variability for each mean change. For the mean increase we increased further the interannual variance (by a factor of 1.4) to make it double that of the base case. For the mean decrease case we further decreased the variance by the factor 0.78 such that the variance of monthly precipitation is one-half that of the base case. To further change the variance without further changing the mean, we used the method described in MRG96, whereby β is increased and unconditioned probability of precipitation (π) is decreased (Equation (4)).

5.2. RESULTS OF COMBINED SENSITIVITY ANALYSES

5.2.1. *Temperature*

From the 90 years of simulated climate 89 years of yield were simulated. Mean temperature increase alone results in decreased simulated wheat yields and increased relative variability of yields (Table II), because of shortened growing periods, increased potential evapotranspiration, and failure of the plants to harden properly.

Table II
Yields (kg/ha) for soil 2 from temperature sensitivity tests

	Base	$T_{\text{mean}} + 2$	$t - v2$	$T + 2V2$	$t - v.5$	$T + 2V.5$
a. Goodland fallow						
Mean	1266	966		744		1418
SD	947	815		741		939
CV	75	84		99		66
P(F)	0.01	0.02		0.25		0.00
D statistic	n/a	0.2697	0.2472	0.4382	0.2809	0.1685
P-value	n/a	0.0020	0.0051	0.002	0.0009	0.1130
b. Topeka rainfed						
Mean	4208	3398		2470		3808
SD	1275	1350		1673		1254
CV	30	40		68		33
P(F)	0.00	0.03		0.19		0.00
D statistic	n/a	0.2697	0.2247	0.4382	0.1910	0.1685
P-value	n/a	0.0017	0.138	0.0000	0.0522	0.1127

Where: Base = base case yields simulated with simulated current climate (kg/ha); $T_{\text{mean}} + 2$ = case where maximum and minimum temperatures have been increased by 2 °C; $T + 2V2$ = case where maximum and minimum temperatures have been increased by 2 °C and daily variance doubled; $T + 2V.5$ = case where maximum and minimum temperatures have been increased by 2 °C and daily variance halved; Mean = mean yield (kg/ha); SD = standard deviation (kg/ha); CV = Coefficient of variation (%); P(F) = probability of crop failure; D statistic = Kolmogorov-Smirnov 2-sample statistic, (Gibbons, 1985) which is the maximum absolute difference between the empirical cumulative distribution functions for the base and experimental yields; P value = probability of attaining a larger D statistic (the smaller the P value the more significant is the difference between the data sets); n/a = not applicable; $T - v2$ = comparison (D statistic and P-value) between $T_{\text{mean}} + 2$ case and $T + 2V2$; $t - v.5$ = comparison (D statistic and P-value) between $T_{\text{mean}} + 2$ case and $T + 2V.5$.

Change in temperature variance modifies the effect of mean temperature increase (Table II, Figure 1). The yield decrease simulated at both locations with mean temperature increase is exacerbated by the doubling of variance, and the coefficient of variation (CV) is increased. The deleterious effect of variance increase is experienced by the crop through a very high incidence of crop failure due to winter kill. In the combined mean and increased variance cases the crop fails to harden properly, since it is not subjected to sufficiently cold temperatures due to higher mean temperatures; the variability increase subjects the crop to large fluctuations in temperatures, and thus greater frequency of temperature extremes at or below the killing crown temperature, which is not extremely low because of insufficient hardening (see section 2 and MRG96). In the present results the crop is so poorly hardened that it cannot cope with extremes at all.

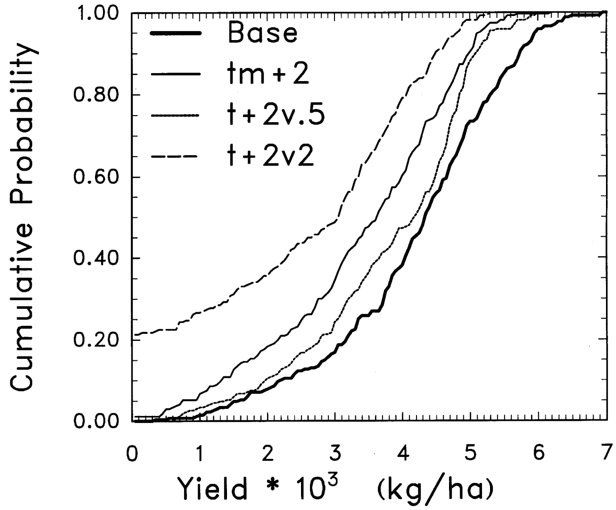

Figure 1. Cumulative distribution functions (cdfs) for temperature sensitivity analyses for Topeka continuous cropped rainfed. Yields for all three soil types for 89 years are included in each curve. Base = from 90 years of simulated observed climate; tm_2 = from 90 year time series with daily temperatures increased by 2 °C, no change in variance; $t + 2v.5$ = from 90-year time series with daily temperatures increased by 2 °C, daily variance reduced by one half; $t + 2v2$ = from 90-year time series with daily temperatures increased by 2 °C, daily variance doubled.

With a substantial reduction in variance, the yield reduction from increased mean temperature alone is greatly ameliorated. The crop is subject to many fewer extremes, and hence, even though it is not well hardened, it is subjected to very few killing temperatures. Incidence of crop failure at Goodland, due to winter kill is lower than in the base case (Table II), mean yield is higher and the relative variability (CV) lower. This result contrasts with the effect of variance decrease alone investigated in MRG96, where a halving of variance had little effect on mean or variability of yield at either location, except to somewhat reduce the coefficient of variation (CV) of yield at Goodland. The combination of a mean increase with variance decrease is clearly key in the present context. In general, we find complex interactions resulting from the combined mean and variances changes.

Results for mean temperature +4 °C and variance change cases are similar to those for the 2° case, except that probability of crop failure with increased temperature variance is lower (e.g., 0.12 for Topeka), and the improvement in yield with variance decrease is smaller.

These results also stand in contrast to those of Mearns et al. (1992) wherein a simple method was used to mechanically alter the observed time series directly to change interannual variability (but creating little change in daily variance). There was only a mild response to the combined variance and mean temperature change.

Table III
Yields (kg/ha) for soil 2 from precipitation sensitivity tests

	Base	$P1.2$	$P1.2 - v$	$P1.2V2$	$P.8$	$P.8 - v$	$P.8V.5$
a. Goodland fallow							
Mean	1266	2147		1998	691		436
SD	947	1343		1193	677		392
CV	75	63		60	98		90
P(F)	0.01	0.00		0.00	0.03		0.06
D statistic	n/a	0.3034	0.1124	0.3146	0.5056	0.2300	0.3034
P-value	n/a	0.0003	0.5072	0.0001	0.0000	0.0085	0.0003
b. Topeka rainfed							
Mean	4208	4761		4337	2982		2940
SD	1275	951		1304	1404		1451
CV	30	20		30	47		49
P(F)	0.00	0.00		0.00	0.00		0.02
D statistic	n/a	0.2697	0.1573	0.1461	0.4607	0.0899	0.4494
P-value	n/a	0.0017	0.1599	0.2216	0.0000	0.7561	0.0000

Where: $P1.2$ = case where mean monthly precipitation amounts have been increased by a factor of 1.2, by changing β in the γ distribution; $P1.2V2$ = same as $P1.2$, but variance further increased by increasing β and decreasing π so that variance is double that of base case. Mean remains as in $P1.2$; $P.8$ = case where mean monthly precipitation amounts have been β decreased by a factor of 0.8 by decreasing β in the γ distribution; $P.8V.5$ = same as $P.8$ but variance is further decreased by decreasing β and increasing π so that variance is one-half that of base case (Mean remains as in $P.8$); $P1.2 - v$ = comparison (D statistic and P-value) of $P1.2$ and $P1.2V2$; $P.8 - v$ = comparison (D statistic and P-value) of $P.8$ and $P.8V.5$; P(F), D statistic, and P-value defined as in Table II.

5.2.2. *Precipitation Change*

Mean precipitation increase, as expected, increases yield at both locations, although more so at Goodland where the crop is often moisture-limited under base conditions (Table III). With further variance increase (but no further increase in mean), the yields at Topeka are reduced from the mean change highs, returning to the level of the base case (Figure 2a). Hence, as was demonstrated using a simpler method in Mearns et al. (1992), and in MRG96 at Topeka, variance increases in precipitation tend to reduce yields. This is largely a function of the relatively wet base climate. With further variance increase, very little more can be gained in yield in the high precipitation years, and mainly yield losses are experienced in the low precipitation years. Thus, the yield gains with a mean precipitation increase can be effectively lost depending on the surrounding variability conditions. A doubling of precipitation variance with a mean increase of 20% is not beyond the range of changes found in climate change experiments (Mearns et al., 1995a). At the drier site Goodland with further variance increase, yields decrease slightly from the mean change case (Table III).

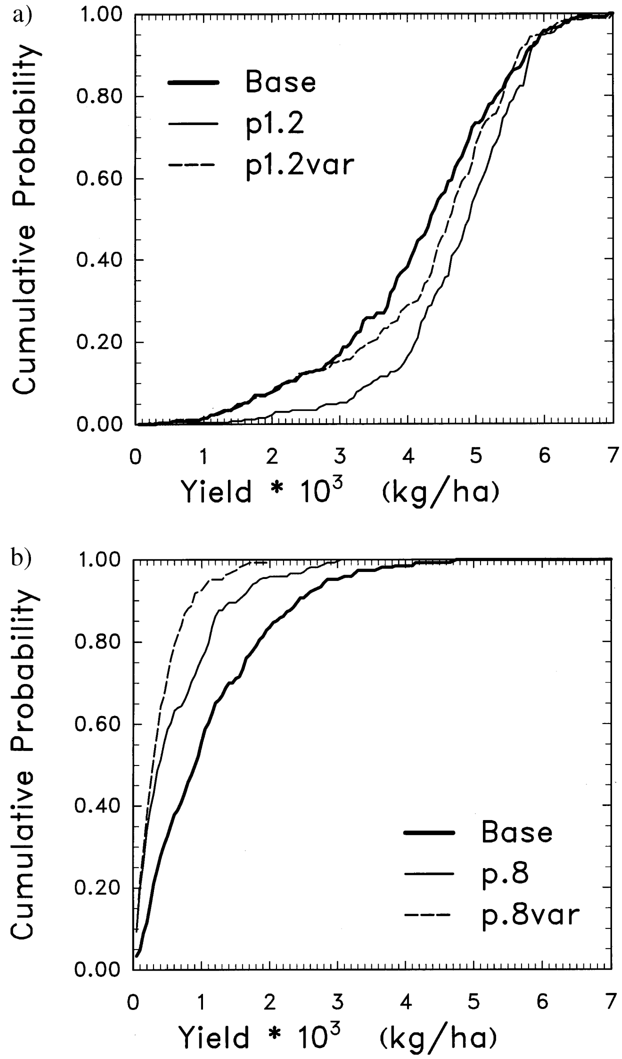

Figure 2. Cumulative distribution functions (cdfs) of simulated yield for precipitation sensitivity cases for (a) Topeka, cases of precipitation increase of 20% (p.1.2) and precipitation increase of 20% with variance increase; (b) Goodland for precipitation decrease of 20% (p.8) and precipitation decrease with variance decrease (p.8var). Base is defined in Figure 1. Yields for all three soil types for 89 years are included in each curve.

With mean precipitation decrease, both sites experience yield decreases and CV increases. With further variance decrease Goodland experiences few years with adequate moisture (Figure 2b), and the probability of crop failure (due to insufficient grains/m^2) doubles. This result is similar to that of MRG96 when variance was decreased. At Topeka, where moisture conditions are better, the response is muted, but varies with soil type. A relatively large difference is seen only for highly productive soils (for soil 3, 261 kg/ha less than the mean decrease case).

6. Changes in Variability in the RegCM

We used the climate model experiments reviewed below (Giorgi et al., 1994) for our climate change scenarios because of their high spatial (and temporal) resolution, which can be of particular importance when considering changes in variability. Second order moments of climate variables change rapidly with spatial resolution. The use of high resolution regional model results eliminates some of the problems that occur when using coarse resolution GCM results (Robock et al., 1993).

The nested regional model technique consists of using the output of general circulation model global simulations to provide driving initial and time-dependent lateral boundary conditions for high-resolution simulations over selected regions of interest. In this manner the regional climatic effects of sub-GCM forcings, (e..g, complex topography) can be represented in a physically based way (Giorgi and Mearns, 1991). This method has the advantage over empirical downscaling techniques that have frequently been used to increase resolution of climate model results (e.g., Lettenmaier, 1995) in that the resulting higher resolution climate is physically based, and the assumption of constancy of derived empirical relationships between large scale and local climate conditions under perturbed climate conditions need not be made.

Giorgi et al. (1994) used a regional climate model (RegCM) to generate two continuous $3\frac{1}{2}$ year-long high resolution climate simulations over the continental United States, one for present-day conditions and one for conditions under doubled carbon dioxide concentration. The regional model was nested within the GENESIS version of the NCAR Community Climate Model (CCM) (Thompson and Pollard, 1995a,b). The regional model was run at 60 km grid point spacing.

Detailed analysis of the regional climate model runs was performed in order to evaluate the quality of the control run and to determine the magnitude and direction of variability change (Giorgi et al., 1994; Mearns et al., 1995 a,b). In the regional model control run estimated precipitation was too low in the eastern half of the U. S. and too high in the western half. In addition there was a consistent overestimation of the frequency of precipitation, throughout the domain, even when the mean precipitation was underestimated. Smallest errors were found in the Pacific northwest, where even variability of precipitation was well reproduced. Mean daily temperature was overestimated in the Great Lakes region but was relatively well reproduced in the central Plains. Diurnal range, however, was consistently underestimated as was daily variance (of both maximum and minimum temperature) throughout the domain.

Changes in the variance of daily temperature, comparing the three year control run to the three year doubled CO_2 run were quite substantial. Large decreases in variance occurred throughout the winter and early spring. In late spring and early summer some regions (such as the central Plains) exhibited sharp increases in variance. This latter result is particularly interesting, since it indicates that increases in the frequency of extreme high temperatures in summer might be larger than assumed when only considering mean increases in temperature.

Changes in precipitation varied a great deal seasonally and regionally. In the central Plains precipitation decreased in the fall, and increased in early spring. There was a high degree of spatial variability in the plains, such that, for example, western Kansas experienced a large increase in precipitation in the summer, but eastern Kansas saw a decrease. In July, mean precipitation increased, intensity increased, but frequency decreased in the region near Goodland. In the northwest precipitation increased in most months.

7. Climate Change Scenarios from RegCM

We formed two scenarios from the RegCM runs: one incorporating only mean changes in climate variables and the other incorporating both mean and variability changes. It should be noted that the results of these climate model experiments, although quite interesting, do not necessarily contain information regarding climate change that is of any higher quality than other climate model experiments. However, the scenario is spatially detailed (60 km horizontal resolution), and the time step used in the model for dynamic calculations (i.e., 6 minutes) was of an order such that some greater confidence may be placed in the output on a daily time scale. The central research question considered in this analysis is: do the changes in variability predicted by the climate model have significant effects on final yield and other components simulated by the crop model?

7.1. MEAN CHANGES ONLY

We applied what we have referred to as the ‘classic’ scenario formation technique (e.g., Smith and Tirpak, 1989). Differences ($2 \times CO_2$-control) in monthly mean maximum and minimum temperature, were calculated for the grid locations roughly corresponding to the locations Goodland, Topeka, Des Moines and Spokane (Table IV). Differences range from a low of 1.63 °C for minimum temperature in May for Goodland to a high of 7.0°C for March minimum temperature at Topeka. Average annual differences for all sites are about 4 °C for both maximum and minimum temperatures. Monthly mean differences were then added to the daily observational time series of maximum and minimum temperature for the 30 years of observed data. These procedures result in a change only in the mean of the temperature – daily (and interannual) variability remains the same as for the observations.

We calculated the ratios (r) of $2 \times CO_2$ to control mean monthly precipitation from the regional model output for the four grids, and then the observed daily

Table IV
Ratios and differences defining mean changes in climate

	1	2	3	4	5	6	7	8	9	10	11	12
Topeka												
Max T	4.33	4.23	6.77	3.23	2.13	4.27	2.97	3.43	4.43	4.90	4.87	5.87
Min T	4.67	4.20	7.00	2.93	3.20	4.17	3.07	4.00	4.73	3.70	4.20	4.80
Precip.	0.75	0.42	3.43	0.65	0.82	1.60	0.78	1.41	0.86	0.74	0.89	0.86
SR	1.01	1.02	0.93	1.01	0.99	0.99	1.05	0.99	1.02	0.99	0.99	1.00
Goodland												
Max T	3.27	4.03	5.33	2.20	2.33	3.90	2.90	5.67	4.80	4.30	4.40	5.97
Min T	3.87	4.00	6.07	2.33	1.63	3.60	1.67	3.37	3.67	2.87	3.83	5.23
Precip.	1.17	0.76	2.75	0.83	1.10	0.97	2.60	0.28	1.15	0.70	0.59	0.74
SR	0.97	1.00	0.91	0.96	1.01	1.00	1.08	1.04	1.05	1.03	0.99	0.98
Spokane												
Max T	3.73	5.73	4.50	2.10	3.00	3.97	2.80	4.13	3.47	2.47	3.70	3.90
Min T	4.00	5.90	4.50	2.30	3.40	3.03	3.50	4.00	6.33	4.00	4.73	3.10
Precip.	1.13	1.49	0.77	1.35	0.71	1.12	1.28	0.78	4.43	2.02	0.77	1.24
SR	0.95	0.96	1.02	1.00	0.99	1.03	0.97	0.98	0.90	0.92	0.96	1.02
Des Moines												
Max T	6.43	5.67	7.70	3.83	2.57	3.60	3.47	3.37	4.90	4.23	4.83	5.37
Min T	6.60	5.97	6.53	3.40	3.77	4.27	3.80	4.03	5.20	3.17	4.07	4.43
Precip.	0.43	0.91	1.27	1.22	1.07	2.43	1.07	2.82	1.55	0.86	1.09	0.57
SR	1.04	0.96	0.97	0.99	0.96	0.98	1.03	0.97	1.01	1.04	1.00	1.06

Month: 1 = January, 2 = February, etc.; Max T = Maximum temperature (difference between $2 \times CO_2$ and control from RegCM); Min T = Minimum temperature (difference between $2 \times CO_2$ and control from RegCM); Precip. = Precip.itation (ratio of $2 \times CO_2$ to control from RegCM); SR = incident solar radiation (ratio of $2 \times CO_2$ to control from RegCM).

precipitation values were multiplied by these ratios. The mean monthly total precipitation is thus changed, but as described in section 3, so is the daily intensity and its variance. The mean intensity changes by the ratio (r), and the variance of the intensity by r^2. The frequency of precipitation (unconditional probability of precipitation, π), generally remains as in the observations, except when the application of the ratio results in a daily precipitation amount less than 0.1 mm. Under such circumstances small changes in frequency result. For solar radiation, we also used the ratio approach. In general, changes in solar radiation were small (Table IV), and the CERES-Wheat model is relatively insensitive to small changes in solar radiation compared to the changes in other climate variables. Hence, we do not discuss further changes in solar radiation.

We then estimated the parameters for the weather generator for this mean altered dataset and generated several realizations of 90 years each. This became the ‘mean change only’ climate (MC). Due to sampling errors, the characteristics of the simulated dataset vary slightly from those of the altered observational dataset.

Maximum and minimum temperatures increase each month, whereas precipitation exhibits contrasting increases and decreases. Topeka experiences an overall decrease in precipitation for the year, whereas Spokane and Des Moines see relatively large increases (Table IV). There is a smaller increase at Goodland, but much of it occurs in spring.

7.2. MEAN AND VARIANCE CHANGES

To generate scenarios with mean and variability changes (MVC), we calculated the parameters for the weather generator for the control and $2 \times CO_2$ output from the regional model, and then took the ratio or difference of these parameters, whichever was most appropriate. Wilks (1992) recommended using changes in interannual variability and then selecting among possible alternatives for how to change daily parameters. Here we follow an approach modified from that suggested by Mearns and Rosenzweig (1994), and Mearns (1995) wherein changes in daily parameters are determined, which impose changes in interannual variability according to Equations (4) and (5). For precipitation, the ratios of the α and β parameters were calculated, and then α and β calculated from the observed climate were multiplied by the ratios to form new parameter values. Ratios of π and d were similarly calculated and new parameters determined again from multiplying the parameters generated from the observed data by these ratios. From the new π and d, new transition probabilities P_{11} and P_{01} were determined according to the relations presented earlier for Equation (4).

This method differs from that described in Mearns and Rosenzweig (1994) and Mearns (1995) in how the new transition probabilities are determined. In the earlier works, ratios of the transition probabilities themselves were calculated from the control and $2 \times CO_2$ values, and these ratios were then used to modify the observed transition probabilities. When the transition probabilities are changed directly, a different value for unconditional probability of precipitation is produced, and mean monthly precipitation in the two scenarios can differ. The way transition probabilities are changed in the current study results in the mean monthly precipitation change being almost the same for the two scenarios, that is, for each month,

$$N\pi'\alpha'\beta' \approx N\pi\alpha\beta\,, \tag{6}$$

where the prime indicates parameters for the variance change precipitation and the non prime, those for the mean change precipitation.

For the other climate variables, parameters include annual values of mean and standard deviation of solar radiation, maximum, and minimum temperatures with separate values calculated for rain days and dry days for maximum temperature and solar radiation. Differences in these mean annual quantities were calculated. The other parameters of the Fourier series were altered by transforming the harmonics to their trigonometric forms (of amplitudes and phase angles) and then ratios ($2 \times CO_2$/control) of amplitudes and phase angles were taken. The amplitudes and phase angles from the observations were then multiplied by the ratios. Then the resulting new amplitudes and phase angles were transformed back to the Fourier series form used in the Richardson weather generator. We then compared the MC and the mean and variance change (MVC) climates for the four locations.

7.3. COMPARISON OF CHANGED CLIMATES

Table Va shows daily temperature characteristics for four sample months for simulated time series for the current simulated climate (SIM OBS), the MC climate, and the MVC climate for the four locations. Daily and interannual variance of temperature does not change in the MC case, only in the MVC case. In the MVC scenario, for Topeka and Des Moines in general there were temperature variance decreases in the winter and increases in the summer. Little change in temperature variability occurred at Spokane, and changes at Goodland were similar to those of Des Moines and Topeka, but less pronounced.

For precipitation (Table Vb, seasonal comparison) the scope of variability change (MC versus MVC) varies greatly from season to season and among the sites. Goodland clearly experiences the largest changes in variability as measured by the coefficient of variation, with variability increases occurring in all seasons, the largest in summer and fall. Topeka experiences little change through the year. Spokane and Des Moines experience variability change only in the fall. Variability change is more complex than portrayed in Table Vb, however, since values change for each month, and the interannual variability changes seen in the table result from changes in the frequency, mean and variance of the daily intensity process. Although the mean precipitation amounts for the two scenarios are close as they are constrained to be, the frequency and intensity statistics differ, i.e., in Equation (6), $\alpha' \neq \alpha$, etc. In the MVC case, since α changes, the coefficient of variation of daily intensity $(1/\sqrt{\alpha})$ changes, whereas it remains constant in the MC case. The fewest changes in precipitation frequency occur at Spokane and Topeka while Goodland experiences the greatest number.

Given the shortness of the RegCM model runs (three years control and three years $2 \times CO_2$), changes in the ratios of particularly the precipitation parameters may not be very stable. This exercise should be viewed as a test application of our method and in no way as a scenario that has significant ‘predictive’ meaning.

8. Effects on Simulated Yields

For all sites, for both the MC and MVC change cases, growing season period is decreased by between 17 and 25 days (compared to the base cases) due to hastened phenology, thus reducing the amount of time for growth, biomass accumulation, and grain filling. Changes in variance do not affect the length of the growing period. At Goodland and Des Moines, there are relatively large differences in the

Table V

Comparison of simulated observed, mean change, and mean + variance change climates

a. Mean daily temperature (°C)	Month			
	January	April	July	October
i. Goodland				
SIM OBS				
Mean	–2.8	9.0	24.4	11.4
Variance °C^2	37.5	33.4	11.0	30.1
MC				
Mean	0.7	11.2	26.7	14.7
Variance	41.3	32.9	13.0	32.8
MVC				
Mean	0.5	11.2	26.4	15.1
Variance	33.6	32.0	11.0	22.8
ii. Topeka				
SIM OBS				
Mean	–3.6	12.2	25.8	14.0
Variance °C^2	40.0	28.6	10.5	28.0
MC				
Mean	0.6	15.3	28.7	18.3
Variance	34.3	29.0	10.6	29.1
MVC				
Mean	1.0	15.4	28.6	18.3
Variance	19.5	25.6	12.5	19.0
iii. Spokane				
SIM OBS				
Mean	–3.7	7.4	20.7	8.9
Variance °C^2	24.1	14.8	14.9	20.6
MC				
Mean	0.2	10.0	23.7	11.9
Variance	24.7	14.1	15.5	21.8
MVC				
Mean	–0.1	9.8	24.1	11.7
Variance	22.9	15.0	15.0	18.2
iv. Des Moines				
SIM OBS				
Mean	–7.5	10.0	24.6	12.6
Variance °C^2	40.5	36.5	10.4	30.7
MC				
Mean	–0.9	13.4	28.0	16.1
Variance	40.6	34.0	10.5	32.9
MVC				
Mean	–1.0	13.8	28.1	16.9
Variance	19.5	31.9	14.6	19.9

Table V
(Continued)

b. Seasonal precipitation	Season			
	DJF	MAM	JJA	SON
i. Goodland				
SIMS OBS				
Total	29.7	131.9	183.3	73.9
Variance	183	1832	3193	1612
CV	46	33	31	54
MC				
Total	25.7	180.3	222.4	70.4
Variance	105	3275	7061	1161
CV	40	32	38	48
MVC				
Total	24.5	170.3	233.0	60.7
Variance	143	3967	11891	1147
CV	49	37	47	60
ii. Topeka				
SIM OBS				
Total	79.4	241.0	335.6	199.8
Variance	1838	4764	8827	6439
CV	52	29	27	40
MC				
Total	53.6	313.2	426.0	168.0
Variance	489	10631	22077	4201
CV	41	33	35	38
MVC				
Total	49.2	308.0	422.0	163.0
Variance	442	10547	18371	3933
CV	43	34	32	38
iii. Spokane				
SIM OBS				
Total	157.8	100.1	64.1	96.8
Variance	2334	753	573	986
CV	32	27	37	32
MC				
Total	204.0	92.9	60.7	173.7
Variance	2091	645	541	4681
CV	22	27	38	39
MVC				
Total	202.0	88.9	65.6	170.0
Variance	1900	770	735	6566
CV	22	31	41	48

Table V
(Continued)

b. Seasonal precipitation	Season			
	DJF	MAM	JJA	SON
iv. Des Moines				
SIM OBS				
Total	90.2	237.5	380.0	172.9
Variance	891	4637	6760	4099
CV	33	29	27	37
MC				
Total	51.3	276.7	619.5	213.2
Variance	408	6476	35951	5606
CV	39	29	31	35
MVC				
Total	52.0	285.0	609.5	216.7
Variance	322	6981	23748	11007
CV	35	29	25.3	48

OBS = 90-year simulated current climate time series; MC = 90-year simulated climate with mean changes only; MVC = 90-year simulated climate with mean and variance changes; DJF = December, January, February; MAM = March, April, May; JJA = June, July, August; SOW = September, October, November; Total = total mean precipitation for season (mm); Variance = variance of total (mm^2); CV = coefficient of variation (%).

yields generated from the two different climate change scenarios, while at Spokane the yields differ somewhat, but very little contrast in yields is obtained at Topeka (Table VI). At Goodland and Des Moines, yields generated from the MVC climates return to levels closer to the base case after having been increased by the MC climates (Figure 3a, b). Only at Spokane do the variance changes result in further increases in yield, from a 96% increase to a 118% increase (from the base yield). At Goodland, and Spokane, where soil moisture tends to be limiting, the crop is likely more sensitive to changes in precipitation variability. At Topeka, changes in precipitation variability are less extreme (Table Vb), and the crop is less sensitive to such changes since soil moisture is not an important limiting factor. At Des Moines, where soil moisture is also not very limiting, there are relatively large differences between the scenarios, mainly because variability changes in precipitation are larger than at Topeka (Table Vb). Goodland experiences the largest contrast in yield (as percentage change) between the MV and MVC scenarios and experiences the largest changes in interannual variability of precipitation.

Des Moines and Topeka experience large decreases in temperature variability in winter. This results in less damage in winter from temperature extremes but this initial advantage does not contribute to greater yield at maturation. The different effects of the damage due to cold temperatures for Des Moines for the three cases

Table VI
Simulated yield (kg/ha) for soil 2 from different climate change scenarios

	Case			
	Base	MC	MVC	MVC-MC
a. Goodland fallow				
Mean	1266	2121	1744	
SD	947	1098	1263	
CV	75	52	72	
D statistic	n/a	0.3078	0.1910	0.2360
P-value	n/a	0.0000	0.0522	0.0085
b. Topeka rainfed				
Mean	4208	4038	4014	
SD	1275	1322	1366	
CV	30	33	34	
D statistic	n/a	0.1011	0.1011	0.0787
P-value	n/a	0.6308	0.6308	0.8676
c. Spokane fallow				
Mean	837	1643	1831	
SD	667	895	1075	
CV	80	54	59	
D statistic	n/a	0.4381	0.5281	0.1124
P-value	n/a	0.0000	0.0000	0.5072
d. Des Moines rainfed				
Mean	4211	4624	4424	
SD	1100	637	720	
CV	26	14	16	
D statistic	n/a	0.2697	0.1685	0.2472
P-value	n/a	0.0017	0.1127	0.0051

Where: Base = base yields simulated with simulated current climate (kg/ha); MC = yields simulated with MC climate; MVC = yields simulated with MVC climate; Mean = mean yield (kg/ha), $n = 89$; SD = standard deviation (kg/ha); CV = Coefficient of variation (%).
D statistic, P-value defined as in Table II.
MVC-MC – D statistic and P values in this column compare the MVC and MC simulated yields.

is clearly seen in seasonal average daily values for Leaf Area Index (Figure 4). Relatively high LAIs are obtained in winter for only the MVC case. To clarify this effect we calculated changes in the frequency of some key extreme temperatures related to winter kill and crop damage due to low temperatures. For example, at Des Moines the probability of the mean daily temperature (roughly equivalent to the crown temperature) falling below the threshold crown killing temperature for HI $= 0.0$ (–6.0 °C) is 0.45 for the base case, 0.15 for the MC case and 0.07 for the

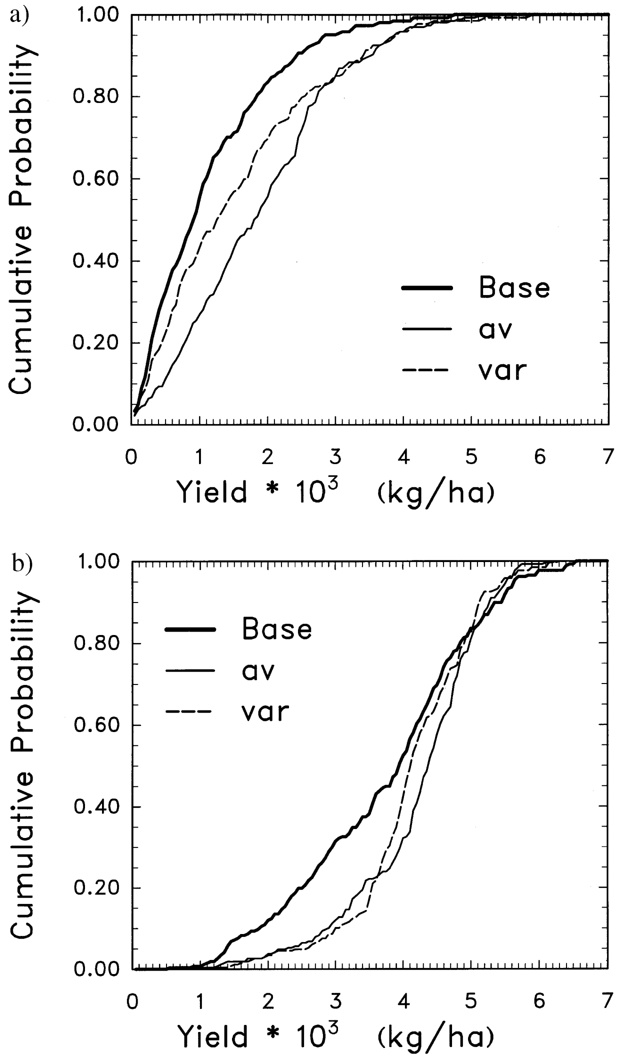

Figure 3. Cumulative distribution functions (cdfs) for base, MC (av) and MVC (var) yields, for (a) Goodland fallow and (b) Topeka rainfed. Yields for all three soil types for 89 years are included in each curve.

MVC case. Since the hardening index is in general much higher than 0.0 for the base case, the high frequency of this event is not problematic. However, in the MC and MVC cases, the HI is often close to 0.0, and maintaining temperatures above this threshold is critical to the crops' survival.

The increased LAI is not necessarily a positive condition for obtaining a high yield, however. Similar conditions for the MVC (var) case are found at Topeka, but as at Des Moines further yield increases do not occur. The added vegetative growth is more of a liability than advantage later in the growing season, since it requires

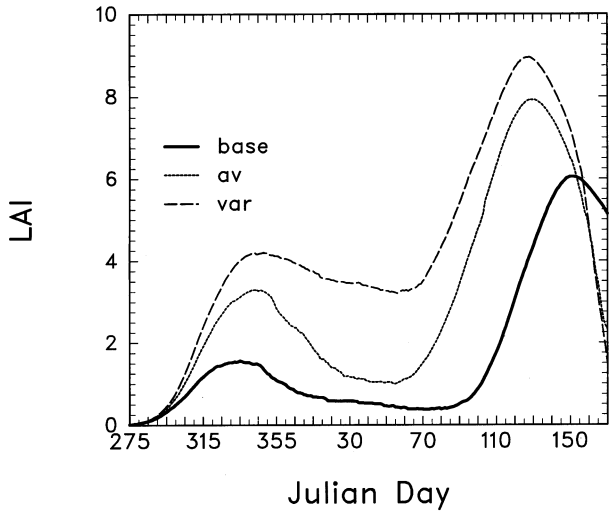

Figure 4. Leaf area index (LAI) average daily values during the growing season for Des Moines rainfed Soil 2 for the Base case, MC (av) case, and MVC (var) case.

more water to maintain. The MVC (var) case has the highest LAI throughout the growing season, but not the highest yield. The lack of substantial yield difference between the scenarios at Topeka, which experiences a relatively large change in temperature variability in winter but little change in variability of precipitation throughout the year, suggests that for these scenarios, the effect of the precipitation variability change dominates over that of temperature regarding determination of final yield.

We have demonstrated here that the changes in climatic variability determined by climate model experiments of doubled CO_2 can have significant effects on (simulated) crop yields. But, in most cases it is difficult to untangle the different causes of the changes in yield, since the means and variances of several different variables are changing simultaneously, from month to month, and some of the changes can obviously have compensating effects. It is clear, however, that how marginal the observed cropping climate is, and the size of variability changes in relation to mean changes are key in anticipating the magnitude of effects from variability change. The time during the crop growing period when the variability changes occur is also of importance. For this winter grown crop, change in variability in temperature in summer, for example, will have little if any effect.

9. Impact Uncertainty Indices

While including variability changes in climate change scenario development may be considered an advance in methods, the underlying problem of accounting for the effects of errors in the climate model remains. In climate change impacts analyses

Table VII

Yield ratio	Location			
	Spokane	Goodland	Topeka	Des Moines
a. Integrated climate model validation using crop models				
Y_o/Y_{c1}	0.34	0.65	14.3	17.0
b. Yield uncertainty parameter (YUP)				
$(Y_c - Y_o)/(Y_{c2} - Y_{c1})$	0.56	3.1	2.1	0.75
c. YUP with variance changes				
$(Y_{cv} - Y_o)/(Y_{c2} - Y_{c1})$	0.70	1.74	2.36	0.38

See text for precise variable definitions.

errors in GCM control run simulations of current climate make the direct use of output from climate models unfeasible (Cohen, 1990; Robock et al., 1993); and these errors are precisely why methods, such as those presented in this study, have been developed to account for the climate change without distorting the scenario through inclusion of the climate model errors. And, given these errors, whether the climate model responds 'correctly' to external forcings, such as increased green house gases, becomes an important uncertainty. Little research has been performed in quantifying this uncertainty. Here we develop two indices that summarize the quantitative impacts of errors in the climate control run on the assessment of the climate change impact.

The first approach is to provide an integrated validation of the control run by making use of the direct output from the climate model. We calculate the ratio of mean yield simulated by the CERES-Wheat model from observed climate data (Y_o) to mean yield simulated from the control run of the climate model (Y_{c1}): Y_o/Y_{c1}. This is an integrated validation in that the total effect of the errors in the control run on the impact model is determined.

Table VIIa shows the integrated validation results for the four locations considered in this study. The farther the ratio is from 1.0, the greater is the effect of the control run errors on the impacts model. Note the very large difference between the ratios at Goodland and Topeka. The error in underestimating precipitation increases very quickly between these locations, which mainly accounts for the large differences in the ratios. From the point of view of the crop model, these results indicate that the control run of RegCm does not estimate the current climate well.

This simple method of course cannot account for compensating errors in the control run that might lead to the impact model results looking 'good' even though the climate model climatology has serious errors. Another important consideration is whether the time series of observed data used truly represents the control run of the climate model, which usually does not correspond to any specific series of years of observations.

Table VIIb presents 'yield uncertainty parameters' (YUP), by which we measure the effect of the climate model errors on the uncertainty of the climate change scenario and hence, the uncertainty of assessment of the climate change impact. YUP is also a ratio:

$$YUP = (Y_c - Y_o)/(Y_{c2} - Y_{c1}) \tag{7}$$

where:

Y_c = mean yield simulated from 'classic method' climate change scenario (mean differences appended to observed data);
Y_o = mean yield simulated from observed climate data;
Y_{c2} = mean yield simulated from climate model 2 $\times$ CO_2 run output; and
Y_{c1} = mean yield simulated from climate model control run output.

This ratio combines the integrated validation ratio with estimates of the climate change impact. The numerator and denominator represent two different ways of calculating differences in yield between a perturbed climate and a baseline climate. The effect of changes in variability are automatically included in the denominator, since the direct climate model outputs are used. Again, the farther the ratio is from 1.0, the larger is the uncertainty in the impact assessment. For two locations YUP is greater than 1.0, double that in the case of Topeka, which we interpret as substantial uncertainty in the impact. In the case of Des Moines, the value is much closer to 1.0, reflecting the fact that the two ways of calculating changes in yield give similar results. However, from Table VIIa, we see large errors in its control run. Thus, both indices are needed to characterize impact uncertainty.

One can also measure the effect of including changes in variability in Equation (7), by replacing Y_c with, say Y_{cv}, yield simulated with stochastically generated times series that include changes in climate variability from the climate model. We calculated this modified YUP for our stations, listed in Table VIIc. These values are quite different from those of Table VIIb. The contrast between the two sets of values may be viewed as a measure of uncertainty due to consideration of changes in climatic variability in the impacts analysis.

Arguments can be made that errors in the absolute values of climate variables compared to point observations is not the best way to determine the quality of a climate model. The overall spatial pattern correlation for a large area or the entire earth may be more important than absolute value errors at one location. We present these indices as simple initial steps toward quantifying uncertainty in climate change scenarios and impacts analysis.

10. Summary and Discussion

In our exploration of the combined effects of mean and variability change of climate on crops we have identified three key aspects of the changed climate that contribute to the crop response: the marginality of the current climate for crop growth, the relative size of the mean and variance changes, and timing of these changes. Substantial differences in the evaluation of the impact of climate change on crop yields can evolve depending upon how the scenario is formed, to what degree changes in variability are taken into account, and the nature of the base climate for a particular location. The results we have presented are based on results from only one set of climate model experiments. Scenarios incorporating changes in variability from other climate model results will naturally generate different responses in other crop models (e.g., Barrow and Semenov, 1995; Semenov and Barrow, 1996).

One aspect of variability change that our method does not consider is changes in the persistence of important interannual events such as El Niño and La Niña events; and the importance of these events for agricultural production has been demonstrated (e.g., Cane et al., 1994; Rosenzweig, 1994; Adams et al., 1995). Since the weather generator does not reproduce the autocorrelation structure of the variables on interannual time scales, changes in the persistence of these important events are not captured by our method. One way of capturing these autocorrelations and then changes in persistence is to condition the weather generator on different states, (e.g., El Niño versus normal years). Then, by superimposing a first (or higher order) Markov chain on the weather generator, different sequences of states (with different daily characteristics) could be generated. The success of conditioning to improve the simulation of current climate has been demonstrated (Wilks, 1989; Wang and Conner, 1996).

In this study we have attempted to advance the state of art of climate change scenario formation by evaluating the effect of incorporating climate variability change on the resulting assessment of climate change impacts in an agricultural context. Obviously, this type of scenario would be useful in evaluating the effect of climate change in any number of contexts, such as human mortality and morbidity (where daily extreme events are quite critical), water resources, and unmanaged ecosystems. Our method of including variability change is only one of several possible. It is striking in the evolution of climate change impacts research and its recent incorporation in the framework of integrated assessment how little attention has been given to improvement of climate change scenario development, especially from climate models, as well as efforts to analyze the effects of climate model errors on scenario formation. For example, much attention (rightfully) has recently been focussed on issues such as possible adaptation (of agricultural systems) to climate change (Kaiser et al., 1993; Rosenzweig and Parry, 1994; Mendelsohn et al., 1994). Yet what type of climate agricultural systems will be confronted with in the future remains vague and highly uncertain, and more research efforts should be aimed at scenario development. Indeed appropriate adaptations to high frequency variability change could well be different from those to a slowly evolving mean change. We trust our study serves as a useful start in rectifying this imbalance in integrated assessment and climate change impacts research in general.

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