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Potential impacts of climate change on the grain yield of maize for the midlands of KwaZulu-Natal, South Africa

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Abstract

The increase in atmospheric carbon dioxide concentration and changes in associated climatic variables will likely have a major influence on regional as well as international crop production. This study describes an assessment of simulated potential maize (*Zea mays*) grain yield using (i) generated weather data and (ii) generated weather data modified by plausible future climate changes under a normal planting date and dates 15 days earlier and 15 days later using CropSyst, a cropping systems simulation model. The analysis is for maize production at Cedara, a summer rainfall location within the midlands of KwaZulu-Natal, South Africa. Baseline weather data input series were generated by a stochastic weather generator, ClimGen, using 30 years of observed weather data (1971–2000). The generated baseline weather data series was similar to the observed for its distributions of daily rainfall and wet and dry day series, monthly total rainfall and its variances, daily and monthly mean and variance of precipitation, minimum and maximum air temperatures, and solar radiant density. In addition, Penman-Monteith daily grass reference evaporation (ET_o) calculated using the observed and generated weather data series were similar except that the ET_o values between 2 and 3 mm were less for the observed than for the corresponding generated values. Maize grain yields simulated using the observed and generated weather data series with different planting dates were compared. The simulated grain yields for the respective planting dates were not statistically different from each other. However, the grain yields simulated using the generated weather data had a significantly smaller variance than the grain yields simulated using the observed weather data series. The generated baseline weather data were modified by synthesized climate projections to create a number of climatic scenarios. The climate changes corresponded to a doubling of carbon dioxide concentration to 700 $\mu l\, l^{-1}$ without air temperature and water regime changes, and a doubling of carbon dioxide concentration accompanied by mean daily air temperature and precipitation increases of 2 °C and 10%, 2 °C and 20%, 4 °C and 10%, and 4 °C and 20%, respectively. The increase in the daily mean minimum air temperature was taken as three times the increase in daily mean maximum air temperature. Input crop parameters of radiation use and biomass transpiration efficiencies were modified for maize in CropSyst, to account for physiological changes due to increased carbon dioxide concentration. Under increased carbon dioxide concentration regimes, maize grain yields are much more affected by changes in mean air temperature than by precipitation. The results indicate that analysis of the implications of variations in the planting date on maize production may be most useful for site-specific analyses of possible mitigation of the impacts of climate change through alteration of crop management practices.

Keywords: Stochastic weather generation; Climate change; Crop simulation modelling; Maize yield

1. Introduction

An issue of global concern is the possible change in maize (*Zea mays*) production in response to different scenarios of climate change. Although tremendous progress is being made in providing data and the understanding needed for making yield predictions, there are still major uncertainties of the ability of agricultural systems to match the future demand for food. This is because, despite efforts to control environmental conditions and avoid artifacts in the experimental systems, it is not currently possible to create future ecosystems or the

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atmospheric and climatic conditions that will occur in the future. This, therefore, justifies the use of models for predicting and simulating crop responses to future conditions.

Crop production is variable, posing risks and uncertainties to the agricultural community. The main constraint in assessing risk from climate change is the lack of long-term weather data and man's inability to predict the future weather (Uehara and Tsuji, 1998). Crop simulation models use long-term weather data to account for weather variability in assessing risks involved with adopting alternative crop management strategies at a site of interest (Uehara and Tsuji, 1998). But the length of observed weather data record at most sites is insufficient for such analyses. This may prevent agricultural scientists and other potential users from using crop simulation models for assessing agricultural risks imposed by the long-term impact of weather on crop production.

Deterministic mathematical models that simulate time-series climatic variables (known as stochastic weather generators) have addressed this problem (Richardson and Wright, 1984). These models use observed historical weather data as inputs and generate synthetic weather data, which are statistically similar to the observed historical weather data records (Semenov and Jamieson, 1999). Weather generators need to be tested and validated for locations other than those for which they were developed and validated. ClimGen (Version 4.1.05) (Stöckle and Nelson, 1999; Stöckle et al., 2001) is a daily time step stochastic model developed to generate daily weather variables. It was tested at several locations in the world (Stöckle et al., 2001). Earlier versions of ClimGen were also tested for sites in South Africa representing a wide variety of climates (Clemence, 1997). The generated weather data could be used as data inputs for crop simulation models and offer agricultural scientists the opportunity to evaluate long-term effects of weather that are impossible to evaluate with a limited observed record of historical data (Richardson, 1985). Clemence (1997) used generated weather data from Cedara, a summer rainfall location in the midlands of KwaZulu-Natal, South Africa in which the present study is conducted, as an input to the CERES-maize crop growth model. There was generally good agreement between simulated grain yields using observed and generated weather data sets.

Agricultural crop production is significantly affected by climatic variables because photosynthetically active radiation, air temperature and water are the driving forces for crop growth (Rosenzweig et al., 1995; Rosenzweig and Hillel, 1998). In the coming decades, due to anticipated further increases in greenhouse gas concentrations (CO_2 being the most important gas), changes in climatic variables are predicted to increase the earth's mean surface temperature and would likely be accompanied by increased precipitation (Cubasch et al., 2001). Most plants that are grown under increased atmospheric [CO_2] conditions have shown an increased rate of photosynthesis and this manifests itself in higher biomass accumulation (Kimball, 1983). But there is uncertainty as to whether or not there is an increase in the rate of photosynthesis of C_4 plants, like maize, under such conditions. Based on surveys of published data, Poorter (1993), Kimball et al. (2002) and Poorter and Pérez-Soba (2002) found a growth response of about 11% on average for C_4 plants under increased atmospheric [CO_2] conditions. Young and Long (2000) hold the opinion that no direct effect of increased atmospheric [CO_2] should be expected in C_4 plants. However, there is a general consensus that under increased atmospheric [CO_2], the relative increase in the photosynthetic response of C_4 plants is greater for limiting than for abundant soil water conditions.

Changes in crop production in response to changing climatic variables could be studied using crop simulation experiments. CropSyst is a multi-year multi-crop simulation model developed to study the effect of cropping systems management on productivity and environment (Stöckle and Nelson, 2000; Stöckle et al., 2003). This model has been used to model the growth and development of several crops such as maize, wheat, barley, soybean and sorghum in the western USA, southern France, northern and southern Italy, northern Syria, northern Spain and western Australia with generally good results (Stöckle, 1996). CropSyst has also been used to investigate potential impacts of climate change on crop production (e.g., Tubiello et al., 2000; Donatelli et al., 2003). It was also calibrated and validated for the site under study using 5 years of maize grain yield and phenological data (Abraha, 2003).

Several attempts have been made to study the potential impacts of climate change on the grain yield of maize at different locations of the world: e.g., Muchena and Iglesias (1995) in Zimbabwe, Iglesias and Minguez (1995) in Spain, Delécale et al. (1995) in France, Tubiello et al. (2000) in Italy and Jones and Thornton (2003) for Africa and Latin America in general. Most of these studies used climate scenarios generated from global circulation models (GCM) and crop models. Muchena and Iglesias (1995) used synthetic climatic scenarios in addition to the GCM-generated scenarios.

The objective of this study was to investigate the effect of climate change on the grain yield of maize at an eastern seaboard location in South Africa. For this purpose, a daily time step stochastic weather generator, ClimGen was used to generate weather data from observed historical weather data. The generated weather data were modified by plausible projected future changes of climate variable means and variances. The modified generated weather data were then used as inputs to a crop simulation model, CropSyst, to assess the potential impact of climate change on the grain yield of maize.

2. Materials and methods

2.1. The ClimGen model

Stochastic models that generate a suite of long series synthetic weather data from observed weather data have become important to address the inadequacy of short-term observed weather data, for analysis of agricultural, hydrological, environmental and other weather-driven systems (Richardson, 1985; Annandale et al., 1999; Williams et al., 2001). ClimGen (Version 4.1.05) (Stöckle and Nelson, 1999; Stöckle et al., 2001), a daily time step stochastic model, generates daily precipitation (Pr), minimum and maximum air temperatures (T_n and T_x), solar radiant density (I_s), atmospheric humidity and wind speed data series with similar statistics to that of the historical weather data. The model requires inputs of daily series of these weather variables to calculate parameters used in the generation process for any length of period at a location of interest. ClimGen preserves, in the generated weather data, the correlation among the weather variables as well as the seasonal characteristics in the actual weather variable at the site of interest and, thus, does not take into account the climatic extremes and climatic variability that are expected to be increased in the future. Further information on ClimGen is well documented elsewhere (e.g., Castellvi and Stöckle, 2001; Castellvi et al., 2001; Stöckle et al., 2001).

2.2. Weather data generation using the ClimGen model

A 30-year data set of daily weather records (1971–2000) of precipitation (Pr), minimum and maximum air temperatures (T_n and T_x) and sunshine time for Cedara, KwaZulu-Natal (29°32′S, 30°17′E, altitude 1076 m) was used. The sunshine time for each day was converted to solar radiant density (I_s) using a method suggested by Reid (1986). A solar radiation model (Donatelli and Bellocchi, 2001) was also used to estimate I_s for days with missing sunshine time record (e.g., part of the year 1998). The 30-year weather data of Pr, T_n and T_x, and I_s were used to generate another 30-year weather data series (Table 1) using the ClimGen model. The generated weather data series was compared with the observed weather data series for its distributions of daily Pr and wet and dry day series, monthly total Pr and its variance, daily and monthly mean and variance of Pr, T_n and T_x, and I_s. The distributions were compared using the χ^2 test, and the mean and variance values were compared using the t-test and F-test, respectively.

Daily Penman-Monteith grass reference evaporation (ET_o) values (Allen et al., 1998), calculated by ClimGen for both the generated and observed weather data series, were compared for the generated and observed weather data series using cumulative and frequency distribution functions.

The 30-year observed and generated weather data series were used as inputs to the CropSyst model (Stöckle and Nelson, 2000; Stöckle et al., 2003) to simulate potential grain yields at Cedara. The grain yields simulated using both observed and generated weather data series were compared using a cumulative probability distribution. A Hutton, Doveton type soil (Soil Classification Working Group, 1991) and a highly productive maize cultivar PAN 6568 with plant row spacing of 0.75 m and plant population density of 44,000 plants ha^{-1} were used in the field and for the simulations. Base and cutoff temperatures of 8 and 30 °C, respectively, with thermal time for physiological maturity of 1530 °C day were used for the simulations. Planting dates were set to day of year (doy) 309, 5 November (as practiced by local farmers), and 15 days earlier (doy 294, 21 October) and later (doy 323, 19 November). After harvest, 40% of the maize residue was assumed to be left on the field to be incorporated later into the soil by tillage practices. The simulation period was for 30 continuous years in rotation along with fallow conditions. The soil water was initialized to near field capacity following a substantial amount of precipitation at the starting day of the simulation. A finite difference technique, for which water moves up and down depending on the soil water potential of adjacent layers, was used for the redistribution of water in the soil. The simulation runs were made for non-limiting soil fertility conditions.

2.3. Climatic scenarios

To simulate potential climate change impacts, the generated weather data was used as a baseline, and adjusted by hypothesized environmental projections of carbon dioxide concentration ([CO_2]), T_n and T_x, I_s and Pr to calculate potential grain yields of maize. A [CO_2] of 700 μl l^{-1} was assumed. Simulations with GCMs suggest that the projected increase in [CO_2] will modify the global climate by causing a surface warming and enhanced global mean hydrologic cycle (Cubasch et al., 2001). Worldwide observations for the period 1951–1990 have shown that the increase in the daily mean T_n of the global landmass is about three times that of the increase in the daily mean T_x, thus decreasing the daily air temperature range (Karl et al., 1993). Accordingly, T_n and T_x were modified in such a way that the increase in mean daily air temperature would be 2 and 4 °C. Ensembles of several climate change experiments used for an assessment of model projections of climate change by Cubasch et al. (2001) for an equivalent doubling of atmospheric [CO_2] were used as a guide in obtaining the 2 and 4 °C increases to the mean daily air temperature. The decrease in daily air temperature range is partially caused by increased cloud cover (Karl et al., 1993). Increased cloud cover would reduce I_s. The increase in cloud cover accompanied by a warmer atmosphere (which can hold more water vapour) could in turn result in increased Pr. Therefore, I_s was estimated under the modified T_n and T_x using the model of Donatelli and Bellocchi (2001), and an increase of 10% and 20% of Pr was assumed for the simulation of maize yield under current climate conditions. The climate change scenarios consider the effects of planting on doy 294, 309 and 323 corresponding to 21 October, 5 November and 19 November, respectively.

Some GCM simulations corresponding to a doubled atmospheric [CO_2] were made for South African conditions (Schulze and Perks, 2000; Hewitson, 2001). These simulations suggest a warmer climate in the future, but are less

Table 1
General statistical comparison of observed (1971–2000) and 30-year generated weather data series for Cedara, KwaZulu-Natal, South Africa

	January	February	March	April	May	June	July	August	September	October	November	December
Observed												
Wet day count	542	450	449	546	124	66	69	138	275	466	513	564
Dry day count	388	398	481	654	806	834	861	792	625	464	387	366
Pr												
Wet day mean	7.68	7.10	7.62	6.23	7.17	5.56	4.72	5.70	4.85	4.95	6.29	6.85
S.D.	10.36	9.33	9.65	7.42	10.41	7.18	6.21	6.54	7.02	6.33	8.25	9.26
Monthly mean	133.46	112.16	89.32	38.07	16.25	19.05	14.86	26.34	81.42	91.78	137.93	126.04
S.D.	53.82	54.41	63.39	27.68	24.96	33.06	13.12	26.10	99.20	48.45	78.95	43.51
T_n												
Mean	15.38	15.41	13.87	10.79	6.68	3.22	3.34	5.58	8.84	11.02	12.64	13.97
S.D.	2.28	2.20	2.54	2.96	3.23	2.93	2.70	3.08	3.23	2.87	2.66	2.33
T_x												
Mean	25.28	25.50	24.50	22.75	20.89	19.31	19.08	20.90	21.93	22.43	23.45	24.74
S.D.	4.38	4.26	4.33	4.03	4.02	3.67	3.80	5.08	6.24	5.78	5.24	4.86
I_s												
Mean	19.75	19.32	17.38	15.21	13.21	12.22	12.68	14.67	16.08	17.26	19.09	20.42
S.D.	6.94	6.45	5.53	4.16	2.78	1.92	2.10	3.59	5.10	6.36	6.82	6.83
Generated												
Wet day count	532	449	489	283	128	59	65	101	283	508	527	579
Dry day count	398	398	441	617	802	841	865	829	617	422	373	351
Pr												
Wet day mean	7.64	7.66	7.41	5.57	5.83	5.40	6.83	5.61	6.00	5.48	6.40	7.17
S.D.	11.59	10.52	10.22	8.16	8.91	7.92	12.03	7.56	21.39	7.66	11.66	11.16
Monthly mean	119.49	110.89	80.46	33.98	19.40	11.83	13.02	32.19	74.29	91.44	111.68	130.06
S.D.	47.66	42.19	43.05	24.37	18.69	14.79	13.20	21.65	51.82	36.61	41.93	52.18
T_n												
Mean	15.25	15.23	14.05	10.74	6.67	3.22	3.51	5.70	8.88	10.84	12.58	14.16
S.D.	2.19	2.18	2.36	2.87	3.02	2.87	2.70	3.08	3.23	2.87	2.65	2.29
T_x												
Mean	25.13	25.27	24.64	23.06	20.93	19.25	19.39	20.71	22.13	22.34	23.32	24.82
S.D.	4.58	4.30	4.19	4.00	3.97	3.58	3.95	5.08	6.17	5.89	5.38	4.73
I_s												
Mean	20.05	19.53	17.62	15.83	13.55	12.40	13.02	14.85	16.25	17.75	19.24	20.51
S.D.	7.17	6.66	5.76	4.55	3.28	2.35	2.62	3.94	5.54	6.73	7.11	7.00

Pr, precipitation (mm); T_n, minimum air temperature (°C); T_x, maximum air temperature (°C); I_s, solar radiant density (MJ m^{-2}); monthly mean, mean monthly total; S.D., standard deviation.

certain with regard to Pr. The GCM simulations from a regional model (PennState/NACR MM5) nested in a global model (UK Meteorological Office Unified Model) suggest that there will be an increase in atmospheric humidity, although translation of this change in terms of Pr is less clear (Hewitson, 2001). Simulation outputs from four GCMs (Hadley including and excluding sulphates, CSM and Genesis) indicate that there will be both a relative increase and decrease in Pr for the summer rainfall areas of South Africa in the future (Schulze and Perks, 2000). These GCM models have indicated an increase in Pr for the site of interest. Therefore, the present study is solely concerned with changes in potential maize grain yields under conditions of projected future climate with an increase in Pr.

The hypothesized scenarios in this study include:

(i) $[CO_2] = 700\ \mu l\ l^{-1}$ (Scenario A);

(ii) $[CO_2] = 700\ \mu l\ l^{-1}$ and an increment of 2 °C to the mean daily air temperature along with 10% increment to daily Pr (Scenario B);

(iii) $[CO_2] = 700\ \mu l\ l^{-1}$ and an increment of 2 °C to the mean daily air temperature along with 20% increment to daily Pr (Scenario C);

(iv) $[CO_2] = 700\ \mu l\ l^{-1}$ and an increment of 4 °C to the mean daily air temperature along with 10% increment to daily Pr (Scenario D);

(v) $[CO_2] = 700\ \mu l\ l^{-1}$ and an increment of 4 °C to the mean daily air temperature along with 20% increment to daily Pr (Scenario E).

CropSyst computes daily biomass accumulation as a function of intercepted solar irradiance and crop transpiration, using constant coefficients for radiation-use efficiency (Monteith, 1981), and biomass transpiration efficiency (Tanner and Sinclair, 1983). These coefficients were modified in CropSyst as summarized by Tubiello et al. (2000) to accommodate doubling levels of [CO_2].

3. Results and discussion

3.1. Comparison of observed and generated weather data

The seasonal distribution of wet and dry day series generated by ClimGen was compared with the observed weather data using the χ^2 statistical test at the 5% level of significance. Four out of 12 generated months were found to have a significantly different distribution from the observed data (Table 2). These months were March, April, August and October. In all of these months, with the exception of August, ClimGen generated a larger count of wet days than the observed weather data. Such incorrect distributions may obscure the effect of long dry spells on plants to be passed unnoticed especially when using crop models for growth simulation (Semenov and Jamieson, 1999). During these months, growth rates would be altered due to altered soil water conditions. For example, March corresponds to the grain filling stage of long season summer crops like maize at the site of interest and an altered Pr distribution during this month may lead to an incorrect estimation of grain yield. The generated daily Pr distribution was also compared with the observed weather data using the χ^2 distribution at the 5% level of significance. Four out of 12 generated months had a daily Pr distribution significantly different from the observed distribution (Table 2). The months that showed a significant difference were the same as for the distribution of wet and dry day series.

Table 2
Comparison of observed (1971–2000) and 30-year generated weather data for Cedara corresponding to a number of tests of 12 (the numbers in the column labeled "Rejected" indicate the number of months out of 12 that gave significant results at the 5% level of significance; a large number of significant results indicate poor performance of the model)

Variable	Rejected
Pr	
Wet and dry day series	4
Daily distribution	4
Monthly total	0
Monthly mean	0
Daily variance	1
Monthly variance	4
T_n	
Monthly mean	0
Daily variance	0
Monthly variance	0
T_x	
Monthly mean	0
Daily variance	0
Monthly variance	0
I_s	
Monthly mean	1
Daily variance	0
Monthly variance	0

Pr, precipitation; T_n, minimum air temperature; T_x, maximum air temperature; I_s, solar radiant density.

The *t*-test (5% level of significance) indicated that none of the generated months were significantly different from the observed data for monthly total Pr, monthly means of Pr, and T_n and T_x (Table 2). All months of the ClimGen-generated mean monthly I_s, but July, were not significantly different from the observed data series (Table 2). An F-test at the 5% level of significance was also conducted to compare daily variances between the generated and observed weather data series, and showed that the variability between the two data series was not significantly different for all the months except for Pr in September (Table 2). The variance of the generated means of the monthly T_n and T_x and monthly I_s was not significantly different from the observed for all months (Table 2). The monthly variance of Pr, however, gave 4 statistically significant results out of 12 indicating that the monthly variation of Pr was not reproduced well by ClimGen. The months for which the variance was significantly different included March, June, September and November. ClimGen consistently underestimated the monthly Pr variance for all 4 months. Therefore, great care should be exercised in interpreting impact assessment responses obtained from using such weather data as it may have uncertainties pertaining to the above statistics.

The ClimGen model also computed Penman-Monteith daily grass reference evaporation (ET_o) using the observed as well as the generated weather data. Cumulative probability of ET_o was calculated for both the observed and generated weather data series for 30 years. The agreement was good (Fig. 1a). The cumulative probability function may, however, obscure certain phenomena where the generated weather data may have either over- or under-reproduced certain values of ET_o. For this reason, a frequency distribution function of ET_o (Fig. 1b) was also calculated for both the observed and generated weather data series for the 30 years. The generated weather data followed the trend of the observed weather data series well except for ET_o values between 2 and 3 mm day^{-1} in which the generated weather data happens to produce a larger proportion of ET_o values. This could be attributed to a deficiency of the ClimGen model to reproduce extreme events of Pr in the observed weather data series, instead it reproduced Pr occurrences in-between the extremes more than they occurred in the observed weather data series.

3.2. Yield simulation using observed and generated weather data

The analysis of the implications of planting date on maize production may be most useful for site specific analyses of possible mitigation of the impacts of climate change through alteration of crop management practices.

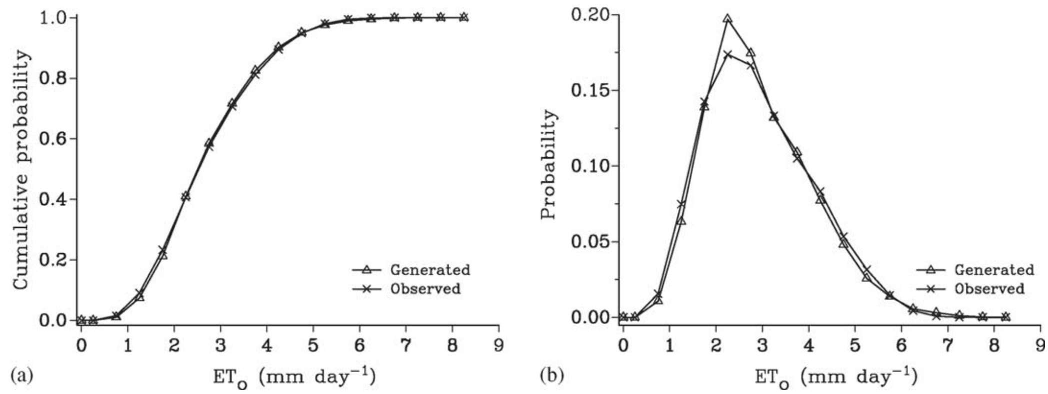

Fig. 1. (a) Cumulative and (b) frequency distribution plots of daily grass reference evaporation (ET$_o$) as calculated by ClimGen using the observed (1971–2000) and generated weather data series for Cedara, KwaZulu-Natal, South Africa.

Maize grain yield was simulated by the CropSyst model using the observed and generated weather data series. In Fig. 2a a simple line graph, and in (b) a cumulative probability plot, represent a comparison of the grain yields simulated from the observed and generated weather data for planting date fixed to the doy 309 (5 November). Table 3 also presents a statistical comparison of simulated grain yield from the observed and generated weather data for planting dates on doy 294 (21 October), 309 and 323 (19 November). The statistical results indicate that the mean grain yields simulated using the observed and generated weather data series are similar for the respective planting dates. A t-test conducted at the 5% level of significance indicated that the respective means are not statistically different. But the grain yields produced from the observed weather data series had a wider range than the grain yields from the generated weather data series with the respective planting dates. This can be seen either from Fig. 2a (the relative extension of yield along the ordinate) and (b) (the relative extension of the yield along the abscissa) or Table 3 (minimum and maximum grain yields and standard deviation from the generated weather data). An F-test was conducted at the 5% level of significance to test the equality of variances of the grain yields simulated from the observed and generated weather data series and indicated that the variance of the two simulated grain yields for the respective planting dates were statistically different. The lack of reproducing the extreme Pr events by the ClimGen model resulted in underestimation of the variability of the growing season Pr in the generated weather data series, and hence less variability in the simulated grain yields as compared to the yield simulated from the observed weather data series. The very low yields for some of the observed weather data reflect drought years with low growing season rain at the site.

The grain yield generally followed the trend of the amount of Pr received during the growing season both in the observed and generated weather data series (Fig. 3a and b). Grain yields were highest when simulated for the early planting date (doy 294) followed by the locally practiced planting date (doy 309) and late planting date (doy 323) for both the observed and generated weather data series with the exception of a few cases for the observed weather data series. In a few incidences, the observed weather data series with the early planting date resulted in simulations of grain yields that were less than the yields simulated using the locally practiced and late planting dates, especially for

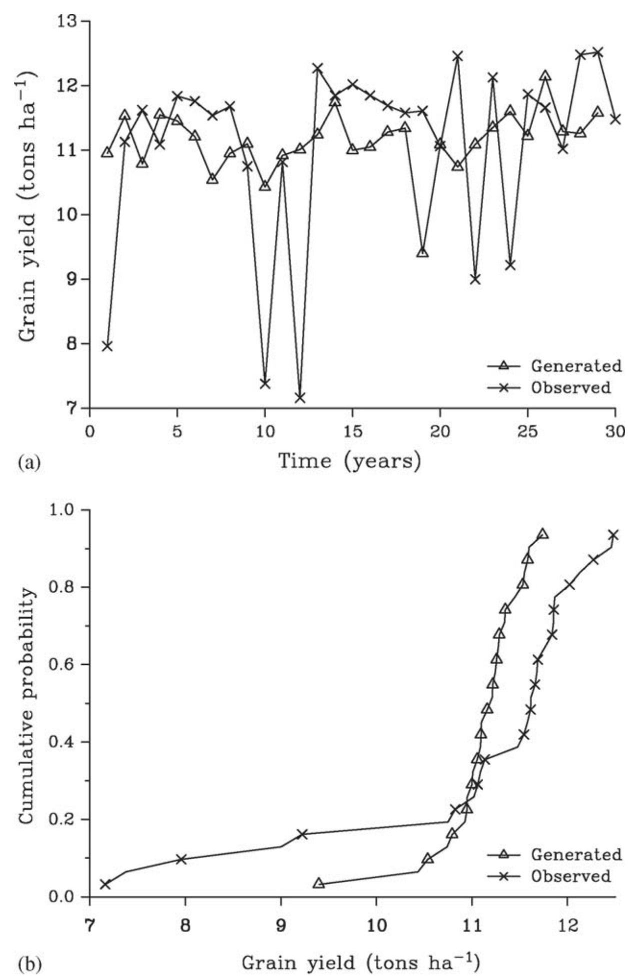

Fig. 2. Maize grain yield comparisons over a 30-year period as simulated by CropSyst using observed (1971–2000) and generated weather data series (a) simple line graph and (b) cumulative probability plots, for Cedara.

Table 3
Maize grain yield (tonnes ha^{-1}) as simulated by the CropSyst model using observed (1971–2000) and generated weather data series of 30 years using different planting dates for Cedara

Day of planting	Weather data	Mean yield	Standard deviation	Maximum yield	Minimum yield
294 (21 October)	Observed	11.17	1.70	12.60	6.54
	Generated	11.23	0.56	12.37	10.73
309 (5 November)	Observed	11.08	1.45	12.52	7.16
	Generated	11.13	0.48	12.14	9.40
323 (19 November)	Observed	10.85	1.46	12.35	5.74
	Generated	10.88	0.41	11.73	10.12

growing seasons with lower Pr amounts. In all these incidences, the Pr amount received by the crop during the growing season for the early planting date was greater than or equal to that for the locally practiced or late planting date. The reason for the lower simulated yield is that in the case of the early planting date for these years, most of the little Pr received at the early growing stage was consumed during the vegetative growth leaving no or little soil water for the sensitive flowering and grain filling stages that largely determine final yield. The local and late planting dates, planted 14 and 28 days after the early planting date, respectively, have the advantage of retained soil water from earlier Pr before planting, not used up by plants. It should also be recalled that 40% of the maize residue from previous season is left on the field which would create a buffer between the soil and atmosphere to moderate soil evaporation and retain much of the soil water.

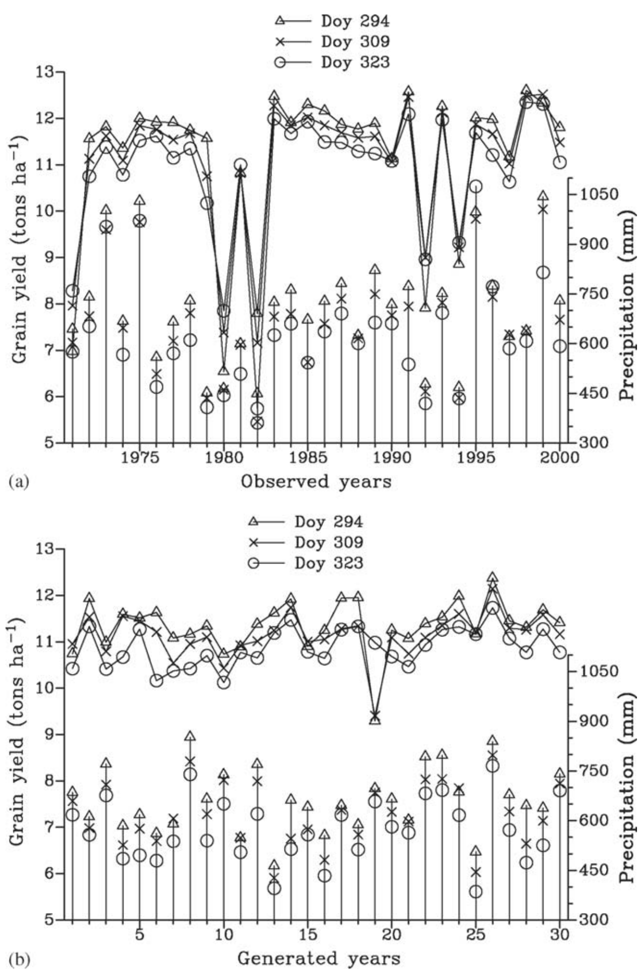

Fig. 3. Grain yield of maize (line graph) as simulated by the CropSyst model using (a) observed (1971–2000) and (b) generated weather data series for planting days of the year 294 (October 21), 309 (November 5) and 323 (November 19) and precipitation (needle graph) received during the growing period at Cedara.

When using the observed weather data series, the early planting date, which resulted in the highest simulated mean yield, also resulted in the greatest variability compared with either the locally accepted or late planting date (Table 3). The difference was mainly due to the distribution and amount of Pr received during the growing season; early rain and a large amount of seasonal Pr resulted in high yields but early rain and low amount of seasonal Pr resulted in low yields. This had the effect of increasing the yield variability for the early planting date.

A *t*-test showed that the simulated grain yield for the early planting date was not statistically greater at the 5% level, than that for the locally practiced planting date using the observed weather data. All the above arguments make early planting risky for farmers and lead to a conclusion that the locally practiced planting date for maize using the observed weather data is most suitable.

ClimGen generally produced more wet days than observed (Table 1); and it also produced more wet days followed by wet days (eliminating the occurrence of long dry spells) during the months of October, November and December than observed in the real weather data. These could be the reasons for the increased grain yield simulated from the generated weather data. A *t*-test indicated that the mean grain yield simulated from the generated weather data using the early planting date was significantly greater, at the 5% level of significance, than the yield for the locally practiced and late planting dates. The early planting date that resulted in greater simulated grain yield might have the advantage of capturing early Pr which leads to vigorous vegetative growth during the active growing stage. This could result in an increased leaf area for photosynthesis. The generated weather data using the early and locally practiced planting dates also simulated an abnormally low yield for the 19th generated year as depicted in Fig. 3b. During the early stages of the early and local planting dates of this period, there was generally frequent but very little (less than 5 mm) rain. Thus the atmospheric evaporation demand of the crop was not met which resulted in a high crop water stress index. There were also high air temperatures and increased solar irradiances particularly during the grain filling stage which resulted in increased evapotranspiration, and increased crop water and temperature stress indices. All these contributing factors could have been the reasons for the abnormally low yield. In addition, the high air temperatures could have the effect of reducing the time for grain filling, and hence reduced yield. The late planting date also experienced high temperatures but only during its vegetative stage and hence grain yield was less affected. The late planting date also had the advantage of enhanced soil water reserves and timely Pr.

3.3. Yield simulation under different climatic scenarios

The CropSyst model was also used to simulate grain yield of maize for a generated baseline weather data and hypothesized scenarios created from the generated weather data.

The mean and standard deviation of the simulated grain yields, for the baseline and all scenarios, are presented in Table 4 and the cumulative probability distribution of the simulated mean grain yields along with the adopted planting dates are presented in Fig. 4. The 20% increment of daily Pr resulted in a very minor change in simulated grain yield as compared to the 10% increment of Pr (because the simulated water status of the maize crop was found to be non-limiting at 10% Pr increase under equivalent doubling of atmospheric [CO_2]). Hence graphs depicted for scenarios with 10% Pr increment would suffice to represent the 20% increment as well.

Equivalent doubling of atmospheric [CO_2] (Scenario A) (Table 4), unaccompanied by air temperature or water regime changes, caused an increase in simulated grain yield of maize for all planting dates by an average of 16.40% as compared to the baseline grain yield (Table 4; Fig. 4). The increase in simulated grain yields was 15.59%, 16.98% and 16.63% for the early, local and late planting dates, respectively. The amount of Pr received during the growing season, as generated by ClimGen, was greater for the early planting date, followed by that for the local and late planting dates. Keeping this in mind, the local and late planting dates were relatively more efficient in utilizing the available Pr per unit biomass accumulation under conditions of equivalent doubling of atmospheric [CO_2] although the early-planted simulated yield was still greater. The relative increase of crop yields under conditions of increased atmospheric [CO_2] tends to be greater under water-limited growing conditions, while the actual yields may still be greater for non-stressed conditions (Chaudhuri et al., 1990).

For Scenario B, the simulated grain yield was less than the grain yield simulated with the equivalent doubling of atmospheric [CO_2] alone but it was still greater than the baseline simulated yield. Simulated yield increments were 9.69%, 9.70% and 10.01% for the early, local and late planting dates, respectively, as compared to the baseline simulated grain yield. This indicates that the photosynthesis of Scenario B was still greater than for the baseline climate. The relative increase of the simulated grain yield was greater for the late planting date which had relatively less Pr.

The increase in air temperature reduced the growing season by an average of 30 days as compared to the baseline and Scenario A (which had equal growing season length) as simulated by CropSyst. This shorter season left less time for grain and biomass accumulation and is one reason for the reduction of simulated yield as compared to the grain yield simulated from Scenario A. The I_s for this simulation was also computed as a function of daily air temperature range. The 2 °C increment in mean daily air temperature is achieved by increasing the T_n by as much as three times the T_x increment. This had a reducing effect on the daily range of air temperature observations, and hence a reduced I_s. There is a strong linear correlation between the accumulation of intercepted solar radiant energy and dry biomass production with the concept of radiation use efficiency (Monteith, 1981). Therefore, the reduced I_s received by the crop during the

Table 4
Simulated maize grain yields (30-year mean and standard deviation) for baseline (generated weather data) and hypothesized climatic scenarios for Cedara

	Scenarios					
	Baseline	A	B	C	D	E
[CO_2] ($\mu l\ l^{-1}$)	350	700	700	700	700	700
Mean temperature (T_{av})	Baseline T_{av}	Baseline T_{av}	+2 °C	+2 °C	+4 °C	+4 °C
Solar radiant density (I_s)	Baseline I_s	Baseline I_s	Generated from daily air temperature range	Generated from daily air temperature range	Generated from daily air temperature range	Generated from daily air temperature range
Precipitation (Pr)	Baseline Pr	Baseline Pr	+10%	+20%	+10%	+20%
Planting date	Grain yield (tonnes ha^{-1})					
Early	11.35 ± 0.56	13.12[a] ± 0.65	12.45[a] ± 0.40	12.46[a] ± 0.40	10.55[b] ± 0.42	10.55[b] ± 0.42
Local	11.13 ± 0.48	13.02[a] ± 0.49	12.21[a] ± 0.40	12.22[a] ± 0.41	10.32[b] ± 0.48	10.32[b] ± 0.48
Late	10.88 ± 0.41	12.69[a] ± 0.48	11.97[a] ± 0.38	11.98[a] ± 0.38	10.09[b] ± 0.47	10.09[b] ± 0.47

[a] Simulated mean grain yield significantly greater than the mean baseline grain yield.
[b] Simulated mean grain yield significantly less than the mean baseline grain yield.

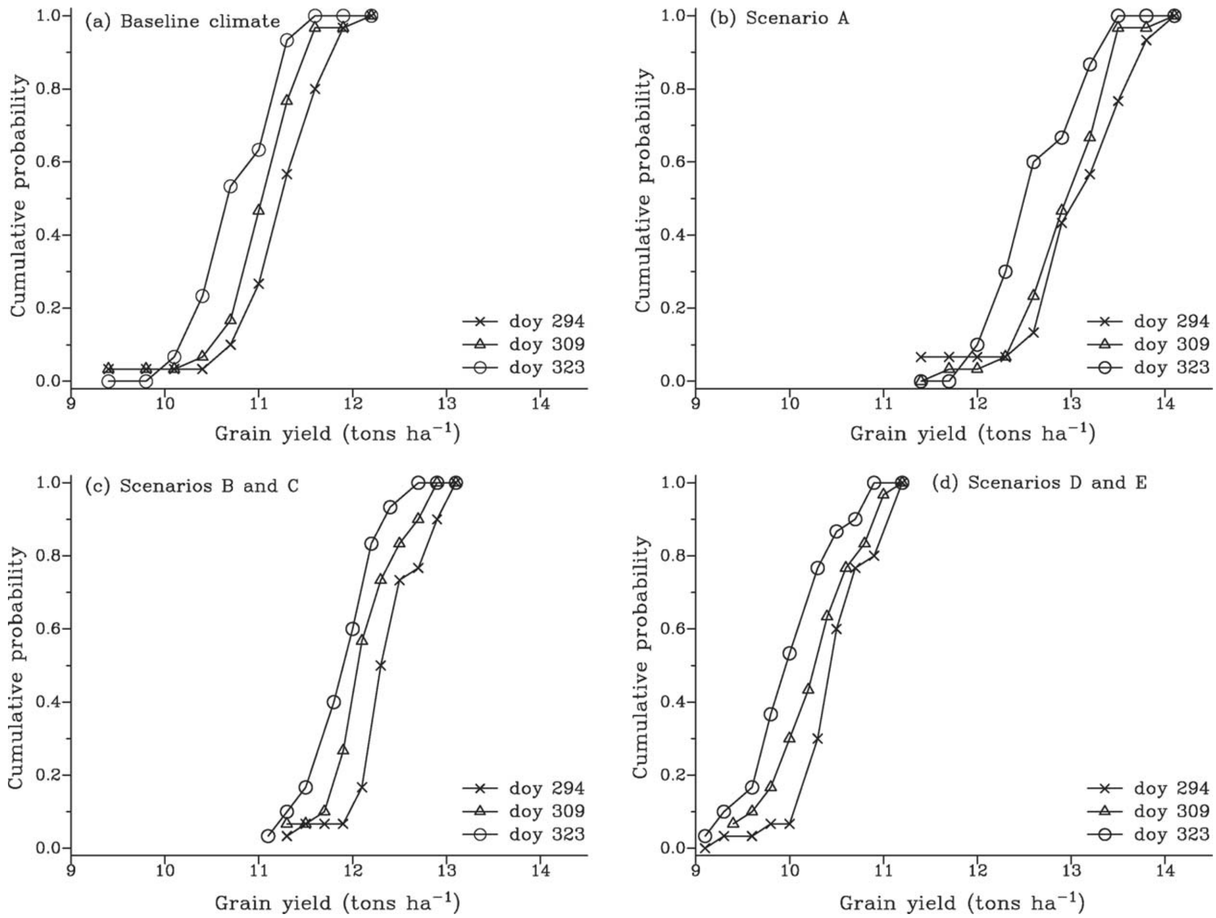

Fig. 4. Cumulative probability distribution of maize grain yields under (a) baseline climate, (b) equivalent doubling of [CO_2]—Scenario A, (c) equivalent doubling of [CO_2], 2 °C increment to the mean daily air temperature along with 10 (20%) increment to daily precipitation—Scenarios B and C, (d) equivalent doubling of [CO_2], 4 °C increment to the mean daily air temperature along with 10 (20%) increment to daily precipitation for early, locally practiced and late planting dates—Scenarios D and E.

growing season is another cause of the reduction in yield under Scenario B (Table 4). Increasing Pr by 20% (Scenario C) did not result in any significant grain yield increase for the simulated years except in 1 or 2 years out of the 30-simulation years for each planting date (Table 4).

Under Scenario D, grain yield further decreased compared to Scenarios B and C. The simulated grain yield was 7.05%, 7.28% and 7.26% for the early, local and late planting dates, respectively, below the baseline simulated grain yield. The 4 °C increment in mean daily air temperature reduced the growing season by an average of 50 days, and hence a loss of potential in accumulation of biomass. The existing air temperature has become limiting to the point that the increase in atmospheric [CO_2] could not compensate for the yield loss incurred due to the increase in air temperature. The daily air temperature range that was calculated under Scenarios D and E was so narrow that the resulting I_s was greatly reduced as compared to the baseline as well as compared to Scenarios A–C. This greatly reduced I_s could be a major cause for the reduction of simulated yield under Scenarios D and E created with 4 °C increment. Once again, increasing Pr by 20% did not result in any significant change in simulated grain yield for all the simulations. The lack of a different response with 10% versus 20% changes in precipitation signifies that the simulated water status of the maize crop was non-limiting under both Pr regimes.

Early planting allows the crop to escape the hot weather of a future environment if the currently practiced growing season were to be used. The simulated grain yield from the early planting date was greater by 1.97% and 4.01% within Scenarios B and C (2 °C increment) and 2.23% and 4.56% within Scenarios D and E (4 °C increment) than the local and late planting dates, respectively. A *t*-test indicated that the mean grain yield from the early planting date was significantly greater than that for the local and late planting dates within the respective scenarios. The effectiveness of early planting resulting in increased grain yield was apparent for scenarios with increased mean daily air temperatures. This can be seen from the relative increase of grain yields within each scenario for the different planting dates. The early planting date had the effect of prolonging the crop's growing season by about 2 and 4 days as compared to the local and late planting dates within the respective scenarios. Early planting also had the advantage of a higher I_s load under the reduced daily air temperature range (from which I_s was calculated) as compared to local and late plantings. These could be the reasons for the yield difference between the different planting dates within each scenario (Table 4).

Muchena and Iglesias (1995) in Zimbabwe, Iglesias and Minguez (1995) in Spain and Delécale et al. (1995) in France conducted maize yield simulations using climate scenarios generated from three GCMs for a doubled atmospheric [CO_2] and the CERES-Maize crop model. Air temperature was predicted to increase at all locations but Pr was predicted to decrease in Zimbabwe, and increase in Spain and France. The simulated maize yield was significantly reduced for the sites in Zimbabwe and Spain, but 7–9% increases were found for France as compared to the baseline climate yield. For the latter, the scenario agrees well with ours and the findings fall within the range of ours. Muchena and Iglesias (1995) also made simulations for scenarios of equivalent doubling of atmospheric [CO_2] only, and with 2 and 4 °C increase to the mean daily air temperature with no change in Pr at three sites in Zimbabwe. The simulated maize yields increased by 11.03% under equivalent doubling of atmospheric [CO_2] only and decreased by 1.82% and 18% for the additional 2 and 4 °C increases to the mean daily air temperature as compared to the baseline climate yield. This compares well with our work although the magnitude of the change was slightly larger in our case in the positive direction. This could be due to the difference in the assumption of the behaviour of Pr in the scenarios but also partly due to the choice of a higher yielding variety used in our simulations.

Jones and Thornton (2003) also predicted a 10% decrease in maize production in 2055 in Africa and Latin America using climate scenarios generated using a GCM and the CERES-Maize crop model. Tubiello et al. (2000) predicted a 13% decrease in simulated maize yield at two locations in Italy using climate scenarios generated from two GCMs for an equivalent doubling of atmospheric [CO_2] and the CropSyst model. Air temperature and Pr were predicted to increase and early planting was included as a means of adaptation to prevent yield loss.

It is a common phenomenon for the mean daily air temperature to increase under generated future climatic scenarios but some GCMs used in the above studies predicted drastic temperature increases. Large increases to the mean daily air temperature may result in underestimation of simulated maize grain yield predictions, and hence some of the simulated yield predictions from the above-mentioned literature may have been underestimated.

4. Conclusions and recommendations

This study showed that representative long-term weather data of precipitation, minimum and maximum air temperatures and solar radiant density could, in general, be generated from historical weather data using a stochastic weather generator for yield assessment purposes. Some weather variables were not reproduced well by the model and as a result simulated maize grain yield may have been under- or overestimated in some cases. This signifies that caution should be exercised in the interpretation of the responses from impact assessments when using generated weather data.

Where water is not limiting, under equivalent doubling of atmospheric [CO_2] and increased mean daily air temperature, the change in simulated grain yield is a balance between the beneficial effects of increased atmospheric [CO_2] on yield and the yield reducing effects of an increased mean daily air temperature. Simulated maize grain yields increased under equivalent doubling of atmospheric [CO_2], and upon addition of 2 °C to the mean daily air temperature but decreased when the mean daily air temperature is increased by 4 °C as compared to the baseline climate yield. Simulated maize grain yield did not change in response to 10% versus 20% increase in precipitation under increased atmospheric [CO_2]; the simulated water status of the maize crop was non-limiting under such conditions.

Early planting dates for all scenarios resulted in increased yields and could serve as possible means of mitigating impacts of climate change. All scenarios also resulted in increased yields except for the 4 °C increment to the mean daily air temperature. For this scenario, either other adaptation techniques should be sought to resume cultivation of maize in this region without yield reductions or a shift to other crops with a higher thermal time requirement is necessary.

While the synthetic scenarios did enable us to explore what would happen if certain climatic variables were to change, they do not provide information about the timing of the projected climate changes, and hence results from transient GCMs which involve time-dependent projections should be employed for more realistic assessments. Furthermore, these scenarios do not consider the negative effects of pests, diseases and weeds on simulation of maize grain yield under increased atmospheric [CO_2] and assume present cultural practices and current varieties.

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