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The ALMANAC model's sensitivity to input variables

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Abstract

Crop models often require extensive input data sets to realistically simulate crop growth. Development of such input data sets can be difficult for some model users. The objective of this study was to evaluate the importance of variables in input data sets for crop modeling. Based on published hybrid performance trials in eight Texas counties, we developed standard data sets of 10-year simulations of maize and sorghum for these eight counties with the Agricultural Land Management Alternatives with Numerical Assessment Criteria (ALMANAC) model. The simulation results were close to the measured county yields with bias values and root mean square errors less than 1.0 Mg ha^{-1} in each county. We then analyzed the sensitivity of grain yield to solar radiation, rainfall, soil depth, soil plant available water, and runoff curve number, comparing simulated yields with those with the original, standard data sets. Runoff curve number [US Department of Agriculture, Soil Conservation Service (1972) National Engineering Handbook, Hydrology Section 4, chapters 4–10] changes had the greatest impact on simulated maize and sorghum yields for all the counties. The next most critical input was rainfall, and then solar radiation for both maize and sorghum, especially for dryland conditions. For irrigated sorghum, solar radiation was the second most critical input instead of rainfall. The degree of sensitivity of yield to all variables was larger for maize than for sorghum except for solar radiation. Many models use a USDA curve number approach to represent soil water redistribution, so it will be important to have accurate curve numbers, rainfall, and soil depth to realistically simulate yields.
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Keywords: Sensitivity analysis; Crop modeling; Sorghum; Maize; Runoff curve number; Plant available water

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1. Introduction

While process-oriented crop models have great potential for assessing plant traits in different environments and aiding management decisions affecting grain yield, soil erosion, and water quality, potential users can be intimidated by extensive input data set requirements. Crop modeling, born about 30 years ago, has progressed considerably, with awareness not only of the limits to system behavior but also of the nature of the essential limiting factors (Sinclair and Seligman, 1996). Improved understanding of these factors can lead to simplification of models and model inputs. Crop models have progressed beyond just academic exercises quantitatively describing interactions between plants and the environment. Their future application depends on providing users with techniques to effectively, efficiently develop realistic input data sets.

Historically two groups have been interested in models: (1) researchers who develop and validate them for increased understanding of crop growth and development (Aggarwal et al., 1994; Carberry et al., 1989; Hoogenboom et al., 1993; Jamiesion et al., 1998; Porter et al., 1993) and (2) users interested in applications (Asare et al., 1992; Ives and Hearn, 1987; Weiss, 1990, 1994; Wullschleger et al., 1994). There have been more studies on calibration, validation and understanding crop models than on applications. Users interested in applications can be intimidated by the complexity of input data required to run models. Such input data include parameters for crops, soils, cultural management, and weather.

One such model requiring extensive inputs is Agricultural Land Management Alternatives with Numerical Assessment Criteria (ALMANAC) (Kiniry et al., 1992). ALMANAC includes subroutines and functions from the EPIC model (Environmental Policy Integrated Climate model; Williams et al., 1984), sharing components for simulating hydrology, soils, and crop growth. Likewise, the model Soil and Water Assessment Tool (SWAT; Arnold et al., 1998), Agricultural Policy/Environmental eXtender (APEX; Williams et al., 2002), and Agricultural Production Systems sIMulator (APSIM; Hammer, 1998) all share some components with ALMANAC. Thus response sensitivities of ALMANAC have some relevance for all these models.

The ALMANAC model simulates crop growth and the soil water balance. Processes simulated include light interception by leaves, biomass accumulation, partitioning of biomass into grain, water use, nutrient uptake, and growth constraints such as water, temperature, and nutrient stress. Grain yield is simulated based on harvest index (HI), which is the grain yield as a fraction of the total aboveground dry matter at maturity. The model simulates crop growth and competition for more than 20 crop species with different crop parameters. Drainage, irrigation, fertilization, furrow diking, and liming are simulated. There is a weather generator subroutine, based on concepts of the WGEN model (Richardson and Wright, 1984), capable of producing multiple years of daily weather. Competing crop species, such as weeds and crops, can be simulated. Soil, weather, tillage, and crop parameter data are needed. The Universal Text Integrating Language (UTIL; Taylor and Bryant, 1994) program designed for ALMANAC is a user-friendly interface for inputting data files, making data set development easier for new model users. The current version of ALMANAC (Kiniry et al., 1997) includes improvements on the extinction coefficient (k) based on row spacing (Flénet et al., 1996), and on radiation-use efficiency based on vapor pressure deficit (Stockle and Kiniry, 1990). To encourage more widespread application of this model, we investigated how to simplify ALMANAC's input data sets without losing simulation details.

Both weather and soil data are important for crop yields, as they describe the basic energy, resources, and environment for crop growth. Within weather or soil data, there are many variables that differ in their relative importance for yield prediction. When developing input data sets, it is valuable to know which variables are most important for simulation accuracy. Users can then decide which variables need accurate values for their particular soil, location, or year and which can be input as more generic values, perhaps as monthly means for a region or as a general value for a soil texture.

Before users invest the time required to develop model input data sets, they need some assurance of the accuracy of the crop model. The ALMANAC model has been validated for maize (*Zea mays* L.) and sorghum [*Sorghum bicolor* (L.) Moench] yields in diverse environments (Kiniry et al., 1997; Kiniry and Bockholt, 1998; Yun et al., 2001). Realistic prediction of mean county yields is one criterion for evaluating crop models. Our objectives in this study were: (1) as a basis for sensitivity analysis, simulate the mean yield and variability around the mean for eight Texas counties over 10 years for maize and sorghum with the ALMANAC model; (2) test the sensitivity of simulated yield to selected weather and soil variables. With the results of the sensitivity analyses, we hoped to provide guidance as to the accuracy needed for selected inputs to obtain realistic simulations. These results should be helpful for future model applications involving management decisions and risk assessment and for applications on climate change and soil erosion.

2. Materials and methods

2.1. County yields

County yields were each simulated with a single management scenario, one soil, and one location's weather, as described later. Thus, we assumed heterogeneity within each county for these variables was not as great as variability among counties. This approach, while it should adequately simulate mean yield for a county, could fail to capture the dampening effect of multiple management scenarios, variable weather data, and variable soils within a county. Because of this, variation among years in simulated yields of a county could be larger than variability among years in reported yields.

While there are 10 climatic districts in Texas (NCDC, 1999), 80% of the sorghum area and 92% of the maize area are in only five. Area in each of these five districts ranged from 3% to 48% of the state total for maize and 6% to 36% of the state total for sorghum (Pietsch et al., 1998a,b). A readily available source of yearly grain yields within these districts are the county mean yields reported by NASS (1999). Within the five districts, eight representative counties were selected for each crop, each having a yield trial with maize, sorghum, or both (Pietsch et al., 1992a–1998b). We used yield trial sites as typical locations (Table 1) to simulate county yields for 1989–1998. Four yield trials were irrigated, and the rest were dryland. Within each of the seven counties, maize and sorghum had the same yield trial location. Daily maximum and minimum air temperatures and precipitation (NCDC, 1999) were from the weather station nearest the yield trial for each county. Daily solar radiation values were the monthly averages for 20 years from the nearest weather station having such data.

Accurate soil data is important for simulating crop growth but can be difficult to obtain for specific sites. Soil types and soil depths can change appreciably over short distances. Such soils can differ in water holding capacity, in available nutrients and in potential rooting depth. Basic soil parameter data are available for many soil types within the US for ALMANAC. Using USDA–NRCS (United State Department of Agriculture–Nature Resource Conservation Service) soil surveys, we determined the soil type with the largest extent of crop-land in each county. Soil parameters for each of these were derived from the soil database (Table 2). Management inputs, including planting and harvest date, planting density, row spacing, and irrigation amounts were determined according to the yield trials from 1991 to 1998 in each county (Table 3). In Moore county, the irrigation amount was set automatically by

Table 1
District percentage production of total Texas production of maize and sorghum in 1998

Districts	County	Area percentage		Plot test location	Weather station	
		Maize	Sorghum			
1. High Plains	Moore	48	36	Dumas	Dumas	Irrigated
	Lubbock	43	27	Lubbock	Lubbock	Irrigated
2. North Central	Dallas	5	9	Prosper	Dallas	Dryland
	Bell	14	23	Temple	Temple	Dryland
3. South Central	Medina	12	16	Castroville	Lytle	Irrigated
	Nueces	9	5	Corpus Christi (maize)	Corpus Christi	Dryland
	San Patricio	3	11	Gregory (sorghum)	Corpus Christi	Dryland
4. Upper Coast	Wharton	6	7	Wharton (maize)	Wharton	Dryland
				Danevang (sorghum)	Danevang	Dryland
5. Lower Valley	Hidalgo	3	13	Weslaco	Weslaco	Irrigated

ALMANAC, for testing the impact of rainfall or soil depth changes on the irrigation amount. The degree days from planting to maturity (PHU), which determined the crop development stage in ALMANAC, were 1600 for maize and 1500 for sorghum.

Table 2
Soils selected and their parameters for background data sets in Texas

County	Soil type	%[a]	Soil depth (m)	PAW[b] (cm)	Runoff curve no.[c]
Moore	Sherm Silty Clay Loam	47	2.03	30	89
Lubbock	Olton Clay Loam	22	2.03	30	85
Dallas	Houston Black Clay	18	2.03	23	89
Bell	Houston Black Clay	12	2.03	23	89
Medina	Knippa Clay	7	1.52	22	85
Nueces	Victoria Clay	63	2.49	32	84
San Patricio	Victoria Clay	21	2.49	32	84
Wharton	Lake Charles Clay	23	2.03	27	89
Hidalgo	Hidalgo Clay Loam	15	2.03	24	78

[a] The percentage of soil extent to the total county land area.
[b] PAW, plant-available water (the difference between the field capacity and wilting point for the soil profile).
[c] Runoff curve numbers are based on soil hydrologic groups.

Table 3
Crop and management parameters for background data sets used in yield simulations in Texas for 1989 to 1998

County	Plant date	Harvest date	Plant density (plant/m^2)	Row space (m)	Irrigation amount (mm)
Maize					
Moore	22 April	1 October	7.2	0.76	Set automatically
Lubbock	20 April	24 September	7.5	1.02	89 mm/time, 4 times
Dallas	18 March	16 August	5.0	0.76	Dryland
Bell	2 March	30 July	5.2	0.97	Dryland
Medina	10 Mar	5 August	5.9	0.91	38 mm/time, 4 times
Nueces	17 February	10 July	5.0	0.97	Dryland
Wharton	17 March	1 August	5.5	1.02	Dryland
Hidalgo	17 February	7 July	6.3	0.76	51 mm/time, 2 times
Sorghum					
Moore	23 May	14 October	26	0.76	Set automatically
Lubbock	23 June	30 October	14	1.02	89 mm/time, 3 times
Dallas	26 March	15 August	14	0.76	Dryland
Bell	8 March	25 July	20	0.97	Dryland
Medina	12 March	25 July	25	0.91	38 mm/time, 4 times
San Patricio	5 March	8 July	21	0.97	Dryland
Wharton	18 March	20 July	19	1.02	Dryland
Hidalgo	18 February	1 July	22	0.76	51 mm/time, 4 times

2.2. Sensitivity analysis

The aforementioned data sets based on the actual conditions were the standard background crop parameters, soil data, and weather data. To analyze sensitivity of simulated yields to different variables, we simulated 10-year county mean crop yields by changing the input variables of solar radiation, rainfall, soil depth, plant available water in the soil, and runoff curve number US Department of Agriculture, Soil Conservation Service (1972). The data sets for sensitivity analysis were called scenario data sets. In each of them, only one variable was changed, and the others were kept the same as the original data sets. Each of these variables we chose to vary showed promise as having noticeable effects on crop growth. Of the four climatic factors needed in ALMANAC, rainfall had the greatest percentage difference among years and locations. However, it was also readily available at a large number of weather stations. Daily solar radiation was difficult to obtain for every location but contributed to the potential yields at each site. Maximum and minimum temperatures were available from the numerous weather stations in the state and changed relatively little among years. We tested the sensitivity of yield to rainfall and solar radiation in order to assess the relative importance for each input data. Soil depth, curve number, and plant available water (PAW) relate to terrain, soil texture, and the ability of soils to sustain crops during drought.

The amount of change in each variable was determined by the range found in the measured values of each (Table 4). The average daily solar radiation values for 1961–1990 were from National Solar Radiation Data Base Internet site for Amarillo, Lubbock, Fort Worth, Waco, Victoria, Corpus Christi, San Antonio, and Brownsville (http://rredc.nrel.gov/solar/)). Each year we calculated the mean daily solar radiations during the growing season for these locations. These values ranged from −11% to +10% of the mean for the 30 years. Thus, the range for each county was used to alter solar radiation of that county for all the simulation years to test the simulated yield's response to solar radiation. Rainfall was changed −20% and +20%, based on the average rainfall variance ratio [(rainfall−mean rainfall)/mean rainfall] from

Table 4
Variables changed in scenario data sets for sensitivity analysis. In each case, values are percentage changes. Rainfall for each county was changed ±20%

County	Solar radiation		PAW with different soil depth				PAW		Runoff curve no.	
			1.5 m	1.2 m	1.0 m	0.8 m				
Moore	−6	6	−25	−38	−47	−58	−14	13	−9	2
Lubbock	−4	5	−25	−40	−50	−60	−22	23	−8	4
Dallas	−8	7	−23	−36	−44	−55	−24	24	−9	2
Bell	−8	9	−23	−36	−44	−55	−24	24	−9	2
Medina	−11	8	0	−18	−31	−45	−25	24	−8	4
Nueces	−11	8	−37	−48	−56	−65	−25	26	−4	8
San Patricio	−11	8	−37	−48	−56	−65	−25	26	−4	8
Wharton	−7	7	−23	−37	−45	−54	−25	24	−9	2
Hidalgo	−10	10	−26	−39	−49	−58	−23	23	−9	4

1989 to 1998 for 10 weather stations (Table 1). The daily rainfall amounts were each changed by this ratio. The soil layer depths were set to 1.5, 1.2, 1.0, and 0.8 m for each soil. Ratliff et al. (1983) reported ranges of plant extractable water for different soil types. With their published values, we used plus or minus one standard deviation around the mean for plant extractable water to give the ranges of PAW for different soil types. For a given soil type, the highest and lowest curve numbers (Jones and Kiniry, 1986) were selected to test the simulated result's response to the curve number. Five scenario data sets were set up, in which only one variable was changed and others were kept the same as the background data sets: decreased solar radiation (Scenario 1a) and increased solar radiation (Scenario 1b), −20% rainfall (Scenario 2a) and +20% rainfall (Scenario 2b), soil depths of 1.5 m (Scenario 3a), 1.2 m (Scenario 3b), 1.0 m (Scenario 3c), and 0.8 m (Scenario 3d), 14–25% PAW decrease (Scenario 4a) and 13–26% PAW increase (Scenario 4b), and lowest (Scenario 5a) and highest (Scenario 5b) reported runoff curve numbers for each soil type (Table 4).

The relative sensitivity (Wilkerson et al., 1983) was used for determining the significance or sensitivity of variables to the simulated results:

$$\text{Relative sensitivity} = \left|((Y(X+\Delta X) - Y(X))/Y(X))/(\Delta X/\Delta X)\right|$$

where Y represented the simulated result (grain yield), X represented each variable, and ΔX represented the absolute change in variable X. The greater the relative sensitivity, the more sensitive the grain yield was to the variable. This gave some indication of how accurately the variable should be described to realistically simulate grain yields.

Mean county yields were simulated from 1989 to 1998 with background and scenario data sets respectively by addressing the following questions:

1. Could ALMANAC describe location differences in county mean grain yields of maize and sorghum with the background data sets? If measured county mean yields were regressed on simulated county mean yields, how close was the regression line to the 1:1 line and what was the r^2? For each county, how did the model's coefficient of variation (CV) compare with the CV for measured yields.
2. Comparing the simulated yields with different scenario data sets to that with background data sets, what were the differences among counties? Which variables were most critical for yield prediction?
3. What could be learned about the crop modeling process from our study for model users to apply the model, especially related to input data set development?

3. Results and discussion

3.1. County average yields

The ALMANAC model realistically simulated county mean yields for maize and sorghum for 10 years (Table 5). The mean error [(simulated yield−measured yield)/ measured yield] of mean simulated grain yields was 2.6% for maize, and −0.6% for

Table 5
Measured and simulated maize and sorghum grain yields and coefficients of variation (CV) for nine counties (10 years at each county)

County	Maize				Sorghum			
	Measured		Simulated		Measured		Simulated	
	Mean ($Mg\ ha^{-1}$)	CV (%)	Mean ($Mg\ ha^{-1}$)	CV (%)	Mean ($Mg\ ha^{-1}$)	CV (%)	Mean ($Mg\ ha^{-1}$)	CV (%)
Moore	9.2	14	9.8	9	5.1	10	4.4	9
Lubbock	6.4	19	6.3	39	3.3	15	3.3	14
Dallas	3.7	35	3.7	55	2.4	24	2.7	31
Bell	3.4	39	3.4	81	3.0	24	2.9	43
Medina	4.5	12	5.1	49	4.5	15	4.2	14
Nueces	3.1	43	3.4	63				
San Patricio					3.1	24	3.1	36
Wharton	4.6	22	4.5	69	4.1	17	4.2	11
Hidalgo	4.1	30	3.8	65	4.1	9	4.2	7

sorghum. Sorghum yields were slightly underpredicted and maize yields were slightly overpredicted. The overall mean simulated grain yields of all counties for both maize and sorghum were similar to the mean measured county yield. The mean CV values of simulated grain yields of each county for maize; 54% for all counties, 40% for irrigated counties, and 67% for dryland counties, were larger than the mean CV values of measured; 27, 18, and 35%, respectively. For sorghum, the mean CV values of simulated grain yields of each county; 21% for all counties, 11% for irrigated counties, and 30% for dryland counties, were similar to the mean CV for the measured grain yields; 17, 12, and 22%, respectively.

The model realistically simulated trends in mean yields among locations (Fig. 1–3). The regression of mean simulated yields to mean county yields for maize was:

$$\mathrm{MYIELD} = 0.92\ \mathrm{SYIELD} + 0.24, \qquad r^2 = 0.99 \tag{1}$$

where MYIELD is the mean measured county yield ($Mg\ ha^{-1}$) for each county, and SYIELD is the mean simulated yield for each county. For sorghum yields simulated, the regression equation was:

$$\mathrm{MYIELD} = 1.23\ \mathrm{SYIELD} + 0.75, \qquad r^2 = 0.91 \tag{2}$$

For maize and sorghum pooled, the regression equation was:

$$\mathrm{MYIELD} = 0.94\ \mathrm{SYIELD} + 0.25, \qquad r^2 = 0.97 \tag{3}$$

All the regressions were significant ($\alpha = 0.01$). The y-intercepts were not significantly different from zero and the slopes were not significantly different from 1.0.

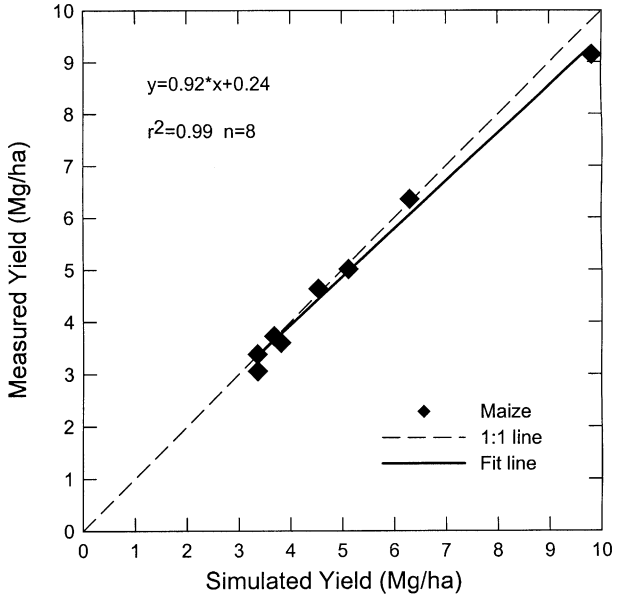

Fig. 1. Maize simulations with ALMANAC in eight counties of Texas. The solid line is the regression and the dashed line is the line with a slope of 1.0, through the origin. Each point represented one county. The measured and simulated yields were mean county yields for 10 years from 1989 to 1998 in each county.

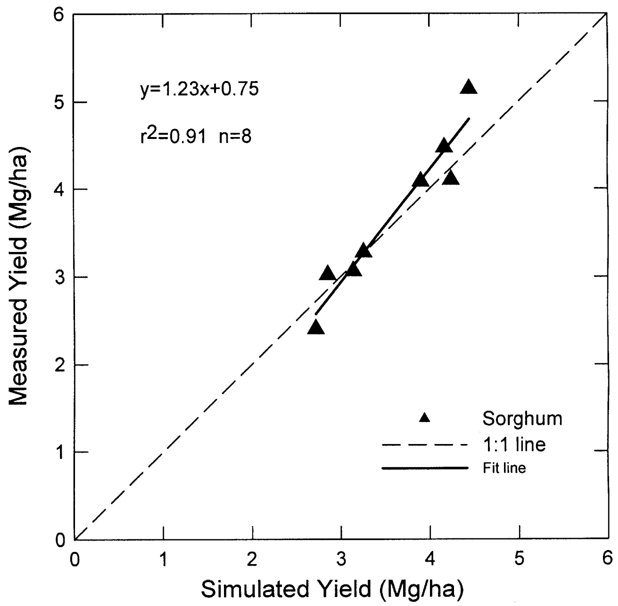

Fig. 2. Sorghum simulations with ALMANAC in eight counties of Texas. The solid line is the regression and the dashed line is the line with a slope of 1.0, through the origin. Each point represented one county. The measured and simulated yields were mean county yields for 10 years from 1989 to 1998 in each county.

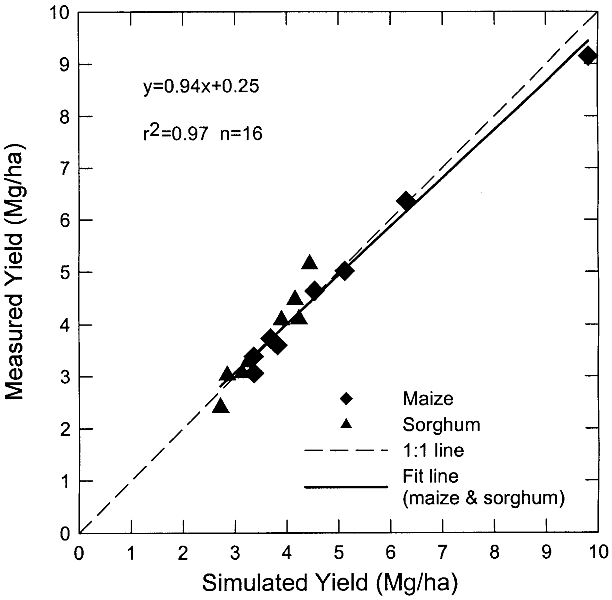

Fig. 3. Maize and sorghum simulations with ALMANAC in nine counties of Texas. The solid line is the regression and the dashed line is the line with a slope of 1.0, through the origin. Each point represented one county. The measured and simulated yields were mean county yields for 10 years from 1989 to 1998 in each county.

The model's bias values (simulated minus measured) and the root mean square error (RMSE) values were similar across locations (Table 6). For each county, bias values and values for root mean square error were <1.0 Mg ha^{-1} for both maize and sorghum. The simulated results were similar to the measured yields for both maize and sorghum, but sorghum simulations were more stable than maize.

Table 6
Bias (simulated minus measured grain yields) and root mean square error (RMSE) (Mg ha^{-1}) for 10 years at nine counties in Texas

County	Maize		Sorghum	
	Bias (Mg ha^{-1})	RMSE (Mg ha^{-1})	Bias (Mg ha^{-1})	RMSE (Mg ha^{-1})
Moore	0.67	0.21	−0.70	0.12
Lubbock	0.06	0.53	−0.02	0.07
Dallas	−0.04	0.61	0.31	0.26
Bell	−0.02	0.64	−0.17	0.31
Medina	0.11	0.52	−0.31	0.17
Nueces	0.31	0.46		
San Patricio			0.08	0.26
Wharton	−0.10	0.86	0.14	0.15
Hidalgo	0.22	0.59	0.11	0.16
Mean	0.14	0.55	−0.07	0.19

3.2. Sensitivity analyses

Changes in solar radiation had different effects on yield for the two crops. Increasing solar radiation decreased yields for dryland maize and sorghum (Table 7). For irrigated maize, both increases and decreases in solar radiation showed a decrease in mean yields. For irrigated sorghum, yields increased with increasing solar radiation. The effect of changing solar radiation on the yields was small. The decreases and increases in solar radiation resulted in a changes less than 7% in the overall mean dryland maize yields and less 3% in overall mean dryland sorghum yields. With irrigation, decreases and increases in solar radiation resulted in less than 2% changes in overall mean maize yields and less than 8% changes in overall mean sorghum yields. Increased solar radiation resulted in increased water stress for dryland

Table 7
Relative per cent change[a] in simulated maize and sorghum grain yields with changes in solar radiation (Scenario 1), rainfall (Scenario 2), soil depth (Scenario 3), soil plant available water (Scenario 4), and runoff curve number (Scenario 5)

County	Scenario 1		Scenario 2		Scenario 3				Scenario 4		Scenario 5	
	a	b	a	b	a	b	c	d	a	b	a	b
Maize												
Moore	−12	3	−13	−20	−6	−6	−8	−31	−3	4	−6	−3
Lubbock	−1	2	−11	7	−1	−4	−12	−20	1	−2	9	−7
Dallas	5	−3	−27	26	−8	−14	−26	−30	−7	2	54	−14
Bell	1	−1	−32	20	−9	−15	−21	−23	−7	2	58	−15
Medina	11	−7	−22	31	0	1	−10	−23	8	6	43	−19
Nueces	17	−8	−32	54	−13	−22	−11	−17	7	32	39	−55
Wharton	1	−6	−26	29	−7	−21	−14	−20	6	−15	127	−21
Hidalgo	−3	3	−9	41	−7	−15	−19	−21	−5	10	11	−6
Dryland mean	6	−4	−29	33	−9	−18	−18	−22	0	13	70	−26
Irrigated mean	−1	−1	−14	15	−4	−6	−12	−24	0	4	14	−9
Combined mean	2	−3	−22	24	−7	−12	−15	−23	0	9	42	−18
Sorghum												
Moore	−11	11	−4	−12	1	2	2	−11	3	6	−7	3
Lubbock	−2	2	−6	6	−2	−8	−22	−51	−3	0	10	−4
Dallas	3	−10	−32	16	−8	−15	−19	−25	−11	−5	31	16
Bell	1	−1	−25	21	−7	−10	−14	−16	−5	5	42	−16
Medina	−5	4	−11	6	0.0	−3	−6	−14	0	2	6	−9
San Patricio	0	−1	−25	23	−11	−17	−3	−9	10	15	18	−52
Wharton	−4	3	−13	6	−8	−13	−16	−23	−3	4	6	−29
Hidalgo	−10	11	0	0	−2	−3	−5	−9	−1	1	0	0
Dryland mean	0	−2	−24	16	−9	−14	−13	−18	−2	5	24	−20
Irrigated mean	−7	7	−5	0	−1	−3	−8	−21	0	2	2	−3
Combined mean	−4	3	−15	8	−5	−9	−11	−20	−1	4	13	−12

For Scenarios 1, 2, 4 and 5, "a" was a decrease and "b" was an increase in the variable (see text). For Scenario 3, soil depth was progressively decreased from a to d.

[a] Relative per cent = (simulation with scenario data set−simulation with background data set)/simulation with background data set.

maize and sorghum simulations. Water stress decreased biomass product per unit light intercepted, in agreement with Chapman et al. (1993). Maize production was more sensitive to drought stress than sorghum, so the water stress effect was more obvious for maize.

Maize was more sensitive to the rainfall changes than sorghum. Likewise, rainfall changes had greater effects on dryland yields than irrigated, as expected. For dryland conditions, the 20% decrease and increase in rainfall resulted in proportionately greater changes of simulated mean yields for maize. Simulated changes for dryland sorghum were proportionately similar to the rainfall change. In Moore county, where irrigation was automatically applied in the model to keep the similar yields with different rainfall, there was 3% greater irrigation with decreased rainfall and 8% less with increased rainfall than in the original data for maize, and 5% greater and 6% less than the original data for sorghum. There was little response to irrigation water demand compared with the 20% rainfall changes.

Similar to response to rainfall changes, the simulated yields of maize were more sensitive to soil depth changes than yields of sorghum. Simulated maize and sorghum yields decreased with decreasing soil depth because plant available water in the soil profile was reduced. Compared with the original soil depth of about 2.0 m, mean plant available water of the soils with 1.5, 1.2, 1.0, and 0.8 m depth was reduced by 23, 37, 46, and 56% (Table 4). The mean simulated yields decreased progressively as depth decreased, for both maize and sorghum.

Changing plant available water by altering upper and lower limits resulted in little change in simulated yields. A 23% decrease and increase in plant available water resulted in less than 10% changes in mean maize yields and less than 5% changes in mean sorghum yields. As expected, maize yields were more sensitive to plant available water than sorghum, especially under dryland conditions.

Jones and Kiniry (1986) gave the different runoff curve numbers for different hydrologic soil groups and tillage practice for row crops. Such changes in curve number greatly impacted simulated yields. An 8% decrease (lowest curve number) and a 4% increase (highest curve number) in curve number resulted in large changes for mean maize yields. Mean changes for sorghum yields were less than for maize, but still proportionately greater than the curve number changes. Under dryland conditions, decreased curve number increased the mean maize yields nearly three fold as much as it increased the mean sorghum yields. Increased curve number for dryland locations decreased mean maize and sorghum yields by similar percentages. Many models of soil–crop systems use a USDA curve number approach to calculate runoff (Connolly, 1998). Therefore, accurate values of curve number in input data sets are essential to realistically simulate yields, especially in dryland conditions.

The two crops showed different rankings for the relative sensitivity of input factors. For all the sites, runoff curve number had the highest relative sensitivity for both maize and sorghum (Table 8). For both irrigated and dryland maize, the relative significance ranking was: curve number, rainfall, solar radiation, soil depth, and plant available water. Sorghum ranking of significant variables differed between irrigated and dryland conditions. The order of the significant variables was the same as the maize for dryland sorghum, but for irrigated sorghum, the ranking was: curve

Table 8
Relative sensitivity of simulated maize and sorghum yield to solar radiation (SR), rainfall (R), soil depth (SD), soil plant available water (PAW), and curve number (CN) (10 year at each county)

County	SR	R	SD	PAW	CN
Maize					
Moore	1.21	0.82	0.27	0.24	0.90
Lubbock	0.31	0.44	0.18	0.07	1.54
Dallas	0.53	1.33	0.47	0.18	6.03
Bell	0.08	1.30	0.42	0.17	6.56
Medina	0.91	1.32	0.22	0.28	5.24
Nueces	1.28	2.16	0.32	0.76	8.78
Wharton	0.52	1.37	0.39	0.42	11.80
Hidalgo	0.31	1.25	0.35	0.33	1.35
Dryland mean	0.60	1.54	0.40	0.38	8.29
Irrigated mean	0.69	0.96	0.26	0.23	2.26
Combined mean	0.65	1.25	0.33	0.31	5.28
Sorghum					
Moore	1.76	0.38	0.08	0.30	1.08
Lubbock	0.41	0.29	0.39	0.07	1.22
Dallas	0.87	1.18	0.41	0.33	5.37
Bell	0.17	1.14	0.30	0.20	5.99
Medina	0.46	0.43	0.16	0.04	1.70
San Patricio	0.08	1.19	0.22	0.48	5.65
Wharton	0.48	0.47	0.37	0.13	6.77
Hidalgo	1.04	0.02	0.10	0.04	0.01
Dryland mean	0.40	1.00	0.32	0.29	5.95
Irrigated mean	0.92	0.28	0.18	0.11	1.00
Combined mean	0.66	0.64	0.25	0.20	3.48

number, solar radiation, rainfall, soil depth, and plant available water. Maize was more sensitive to water stress than sorghum, and thus the factors related to water supply such as curve number, rainfall, soil depth, and plant available water affected simulated yields more for maize than for sorghum. Comparing values of relative sensitivity between maize and sorghum, maize had greater sensitivity for all the variables except solar radiation with irrigated sorghum. For irrigated sorghum, solar radiation was the second most sensitive variable.

4. Conclusion

The ALMANAC model realistically simulated mean county yields for maize and sorghum and had small values for bias and for root mean square errors. As discussed earlier, the use of a single scenario data set for each county for maize resulted in the expected result of greater variability among simulated yields for each county, than among measured yields. This was not as evident for the sorghum simulations.

Thus using such a simplification appears to be adequate for simulating mean maize yield of a county but may have difficulties when simulating individual year maize yields for a county. Using the scenario data sets with changing solar radiation, rainfall, soil depth, PAW, and curve number, the simulated yields changed for both maize and sorghum, but maize was more sensitive to changes than sorghum. Accurate estimates of curve number and rainfall are important for both maize and sorghum yield simulations, especially for dryland conditions. If water supply is adequate for sorghum growth, accurate values of solar radiation are critical. The fact that the simulated yields differed in their sensitivity to variables gave some basic ideas on input data sets for future model users.

Based on our sensitivity analyses, an efficient way to develop input data files for crop modeling is as follows. First, curve numbers should be estimated accurately according to the hydrologic group, row configuration or terraces, and terrain. Next, the closest weather station should be selected for weather data, especially rainfall. Once the closest available rainfall station is chosen, long-term average monthly solar radiation values could be used without measurement. To simulate a county's yields, the cropland soil type having the largest extent in the county should be selected from the soil survey. This soil can be used with soil depth changed according to the actual soil profiles in the field. Crop and management parameters can be set up based on the users' experience or common cultural system features.

This type of sensitivity analysis of variables provides guidance for the process of creating input data sets for crop modeling. Such analysis is also valuable for risk assessment with extreme climatic conditions and different soil features. When developing data sets, it is necessary not only to estimate accurate values of curve number, but also to determine the accurate rainfall data and soil depth for a location. The fact that simulated mean county grain yields of maize and sorghum reasonably changed with the different scenario data sets gave us increased confidence to simulate effects of these factors on crop growth and to predict yields in extreme environments. In addition, it is realistic that rainfall can vary 20%, and soil depth can vary from 1.5 to 0.8 m in actual situations. Thus yield responses we have reported for data sets with such changes in rainfall or soil depth should be helpful to future users developing data sets for their locations.

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