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Evaluation of Two Maize Models for Nine U.S. Locations

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ABSTRACT

Crop models can be evaluated based on accuracy in simulating several years' yields for one location or on accuracy in simulating long-term mean yields for several locations. Our objective was to see how the ALMANAC (Agricultural Land Management Alternatives with Numerical Assessment Criteria) model and a new version of CERES-Maize (Crop-Environment Resource Synthesis) simulate grain yield of rainfed maize (*Zea mays* L.). We tested the models at one county in each of nine states: Minnesota, New York, Iowa, Illinois, Nebraska, Missouri, Kansas, Louisiana, and Texas (MN, NY, IA, IL, NE, MO, KS, LA, and TX). Simulated grain yields were compared with grain yields reported by the National Agricultural Statistical Service (NASS) for 1983 to 1992. In each county we chose a soil commonly used in maize production, and we used measured weather data. Mean simulated grain yield for each county was always within 5% of the mean measured grain yield for the location. Within locations, measured grain yield was regressed on simulated grain yields and tested to see if the slope was significantly different from 1.0 and if the *y*-intercept was significantly different from 0.0, both at the 95% confidence level. Only at MN, NY, and NE for ALMANAC and at MN, NY, and TX for CERES was slope significantly different from 1.0 or intercept significantly different from 0.0. The CVs of simulated grain yields were similar to the those of measured yields at most sites. Also, both models were appropriate for predicting an individual year's yield for most counties. Values for plant parameters, such as heat units for development and the harvest index, and values for soil parameters describing soil water-holding capacity offer users reasonable inputs for simulating maize grain yield over a wide range of locations.

With the high economic risks of agriculture and increased public awareness of water quality, robust crop models offer hope as management tools. Such models help manage resources, maximize returns to producers, and reduce impacts on water quality. They can be used to optimize planting density, maturity type, fertilizer input, and irrigation across latitudes, soils, and rainfall zones. Models can help producers make decisions to alter inputs, maximize profits, reduce soil erosion and water pollution, and make replanting decisions.

Two process-level models that simulate maize grain yields are CERES-Maize (Jones and Kiniry, 1986) and ALMANAC (Kiniry et al., 1992c). These models simulate the processes of water balance, light interception by leaves, dry matter production, and partitioning of biomass into grain. CERES-Maize has been tested and used in the USA and around the world. Hodges et al. (1987) found that it accurately simulated maize grain yield in the northern U.S. Corn Belt. Researchers have adapted the model in Virginia (Molten et al., 1987), Michigan (Ritchie et al., 1989), Illinois (Kunkel et al., 1994), Kenya (Keating et al., 1988), and Australia (Hargreaves and McCown, 1988). The ALMANAC model simulates a range of crops and management options. The model includes subroutines and functions from the EPIC (Erosion Productivity Impact Calculator) model (Williams et al., 1984), with additional details for plant growth.

Although having similar components for evapotranspiration, soil water balance, and plant dry matter growth, ALMANAC and CERES differ in their simulation of grain yield production. ALMANAC simulates grain yield production based on harvest index (HI); potential grain yield is a set percentage of the aboveground dry matter at maturity. Stress near anthesis, from 45% of the growing season heat units until 60%, reduces simulated HI. Five days of severe drought in this interval reduces simulated maize HI to 0.30. Also, cessation of growth before maturity due to cold temperatures or drought reduces simulated yield. Conversely, CERES simulates production of seeds per plant based on growth per plant soon after silking. The model simulates seed mass production from a potential seed growth rate, a degree-day sum required for grain filling, and the amount of assimilate available for grain growth.

To be widely accepted, crop models must accurately predict mean grain yields and describe much of the year-to-year variability in yields over a wide range of conditions. Accurate grain yield predictions allow application of models in making management decisions. Users also benefit from having realistic input parameters describing phenology, partitioning into grain, and soil water-holding capacity that allow yield simulations near their locations. This study included nine such data sets and compared maize grain yields simulated with ALMANAC and with an improved version of CERES-Maize to a comprehensive and standardized yield data set for U.S. counties (NASS, 1996). The data sets were chosen to represent the major maize production areas in the USA. This project was designed to provide a quantitative description of the accuracy of these models in this diverse group of regions. We wanted to develop data sets that are useful as typical inputs for many U.S. locations. Thus, the objective of this study was to demonstrate the capabilities of these two models at sites

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Abbreviations: HI, harvest index; LAI, leaf area index; NASS, National Agricultural Statistical Service; NOAA, National Oceanic and Atmospheric Administration; RMSE, root mean square error; RUE, radiation-use efficiency; VPD, vapor pressure deficit. *Where state names are abbreviated, U.S. postal codes are used.*

Table 1. Crop parameters used as inputs for CERES-Maize and ALMANAC models.†‡

	Input parameters					
	CERES				ALMANAC	
State	P1	P2	P5	G5	PHU	DMLA
	°C	d	°C	mg seed^{-1} d^{-1}	°C	m^2 m^{-2}
MN	150	0.3	685	7.8	1050	3.2
NY	215	0.5	685	5.2	1300	3.5
IA	200	0.5	685	7.8	1300	2.8
IL	220	0.5	725	7.8	1400	3.2
NE	220	0.5	725	6.8	1600	2.8
MO	220	0.5	725	6.3	1800	4.1
KS	220	0.5	725	8.6	1600	3.5
LA	220	0.5	725	8.5	1600	3.2
TX	220	0.5	880	6.3	1600	3.2

† P1, degree days (base 8°C) from seedling emergence to the end of the juvenile phase. P2, photoperiod sensitivity or days delay in tassel initiation per hour increase in photoperiod. P5, degree days (base 8°C) from silking to physiological maturity. G5, potential seed growth rate in mg seed^{-1} d^{-1}. PHU (physiological heat units), degree days (base 8°C) from planting to maturity. DMLA, potential leaf area index.
‡ The potential number of seeds^{-1} plant at low planting densities without stress (G3) is 500 for MN and NY, 450 for TX, and 600 for all other locations.

within several of the major maize production regions of the USA.

MODEL DESCRIPTIONS

CERES-Maize

Since the publication of CERES-Maize in 1986, three studies have provided new information about maize growth relationships described in the model. Functions derived from these studies are incorporated into the model version described herein.[1] These functions should improve accuracy of grain yield simulations across locations and planting densities.

Maize radiation-use efficiency (RUE) exhibited a wide range of values for data from several field locations with no apparent nutrient or drought limitations (Kiniry et al., 1989). Variations in vapor pressure deficit (VPD) accounted for 50% of this variability (Stockle and Kiniry, 1990). Thus, in the new version of CERES, RUE is 4.33 g dry matter per megajoule of intercepted photosynthetically active radiation for mean daily VPD < 1.0 kPa and is reduced by mean daily VPD > 1.0 kPa as

$$\text{RUE} = 5.05 - 0.72\ \text{VPD} \qquad [1]$$

This modification should increase the accuracy of biomass predictions across regions with widely different relative humidity. Similar responses derived for sorghum [*Sorghum bicolor* (L.) Moench] (Stockle and Kiniry, 1990), sunflower (*Helianthus annuus* L.) (Kiniry et al., 1992a), and potato (*Solanum tuberosum* L.) (Manrique et al., 1991) support the existence of such a response.

When drought stress forces plants to rely on stored assimilates during grain filling, the efficiency of use of these assimilates becomes critical for grain yield production. The original version of CERES-Maize assumed 100% efficiency; each gram of stored carbohydrate translocated out of vegetative organs produced 1.0 g of seed. Work with complete shading (Kiniry et al., 1992b) showed this efficiency to be much less, with only 0.26 g of seed produced per gram of carbohydrate lost from the stem and leaves. Respiration, energy costs of conversion, and translocation to roots consume the remainder of the stored carbohydrate. Incorporation of this lower conversion factor into the model causes simulated grain yields to be less buffered against late-season stresses.

Accurate prediction of seed number is vital to simulating grain yield responses to plant density and selecting planting rates to achieve optimum grain yield. The original version of CERES-Maize (Jones and Kiniry, 1986) used the nonlinear function of Edmeades and Daynard (1979) to predict seeds per plant as a function of plant growth rate soon after silking. Potential seed number per plant is a cultivar-specific input. Seed set is determined early in seed development following silking, as shown with shading (Kiniry and Ritchie, 1985) and drought stress (Grant et al., 1989) studies. The version of CERES-Maize used in this study predicts seed number as a linear function of plant growth rate (GROWTH), with the slope and potential seed number being genotype-specific (Kiniry and Knievel, 1995). Thus, number of seeds per plant (SEEDS) is calculated from GROWTH (g plant^{-1} d^{-1}) from silking to the beginning of grain growth as:

$$\text{SEEDS} = 165 + 58.7\ \text{GROWTH} \qquad [2]$$

A similar linear function (Keating et al., 1988) accurately predicted grain yields of rainfed and irrigated maize in Kenya for 1 to 9 plants m^{-2}.

The plant densities used as inputs in the CERES simulations were based on common dryland densities for the counties. Values were 45 000 plants^{-1} ha in MO, TX, LA, KS, and NE; 50 000 in MN, IA, and IL; and 64 000 in NY. Crop parameters described common commercial hybrids for each location (Table 1). Potential seed number (G3) was 500 seeds plant^{-1} for the two northernmost locations (MN, NY), 450 for TX, and 600 seeds plant^{-1} for all others.

The ALMANAC Model

The ALMANAC model simulates plant growth using leaf area index (LAI) and, as in CERES-Maize, radiation-use efficiency sensitive to VPD. The model uses input plant density to adjust potential LAI. Maximum simulated LAI is 6.0 at high densities of a full-season hybrid, with reduced values for

[1] These models and the data sets used for validation are available from the corresponding author at no charge. Send three high-density (1.44 Mb) diskettes with the request.

Table 2. Values for maize harvest index (HI) reported in the literature.

	HI		
Location	Mean	SD	References
New York, USA	0.46	0.04	Francis et al., 1978
Colorado, USA	0.47	0.05	Fairbourn et al., 1970
Ontario, Canada	0.47	0.04	Daynard and Muldoon, 1981 (highest 9 trials)
Hungary	0.50	—	Zoltán, 1988, 1990
Florida, USA	0.50	0.03	Bennett et al., 1989 (highest 4 treatments)
Minnesota, USA	0.56	0.04	Voorhees et al., 1989
Argentina	0.57	—	Sobriano and Ginzo, 1975
Georgia, USA	0.58	0.05	Brown et al., 1970
Nebraska, USA	0.58	0.02	Raun et al., 1989

Table 3. Data sets used in simulations for 1983 to 1992.

Town	County	Lat N, Long W	Weather Stn.	Planting date	Mean annual rainfall†
					mm
Morris, MN	Stevens	45°21′, 95°33′	St. Cloud	1 May	534
Aurora, NY	Cayuga	42°26′, 76°26′	Aurora	22 Apr.	911
Ames, IA	Story	42°01′, 93°22′	Ames	16 May	892
Nickerson, NE	Dodge	41°30′, 96°00′	Lincoln	10 May	735
Urbana, IL	Champaign	40°04′, 88°07′	Urbana	16 May	1056
Columbia, MO	Boone	38°34′, 92°12′	Columbia	1 May	1023
Hiawatha, KS	Brown	39°51′, 95°32′	Atchison	28 Apr.	922
St. Joseph, LA	Tensas	31°33′, 91°08′	Jonesville	5 Mar.	1479
Temple, TX	Bell	31°04′, 97°13′	Temple	14 Feb.	981

† Calculated for 1983 to 1992.

early-maturity hybrids and lower planting densities. The input potential LAI values in the nine counties varied between 2.8 and 4.1 (Table 1). Simulated LAI was often reduced by stress.

The ALMANAC model simulates maize grain yield with a modified HI approach. For maize, we used a HI value of 0.53, assuming that severe stress near midseason could reduce it to 0.30. The 0.53 value was the mean for 12 hybrids grown with adequate soil moisture in 1991 and 8 hybrids in 1992 (Kiniry, unpublished data). In this study, HI showed no response to population density or to maturity type. Values reported for temperate regions usually vary between 0.46 and 0.58, and have a mean of 0.52 (Table 2). Similar mean HI values, 0.50 and 0.55, were measured in 1991 and 1992 in NY (Cox and Otis, 1993) with several plant densities. The value of 0.30 was the HI of the most severe drought stressed treatment in a Missouri field study (Griffin, 1980). Similarly, severe drought reduced HI to 0.27 in Brazil (Costa et al., 1988) and to 0.31 in Argentina (Sobriano and Ginzo, 1975). For simulations in two counties, grain yields were assumed to be more source-limited than at other sites. Thus, potential HI was 0.45 in LA and 0.30 in TX. Values of HI in the tropics have similarly been reported to be lower than those in temperate regions, with 0.37 in Mexico (Yamaguchi, 1974) and 0.39 in Brazil (Costa et al., 1988). In NY, the simulated HI was more stable and the minimum value was set to 0.52.

MODEL EVALUATION: DEMONSTRATION DATA SETS

Data were collected annually through statistically representative farmer surveys. For each county, data included hectares planted and harvested, and total production by separate categories of dryland and irrigated hectares. For this study we used dryland grain yields and used one county for each of the nine states. These are major maize producing counties for the states. The data are available publicly from USDA-NASS online servers (NASS, 1997).

Locations from which data sets were taken represent a wide range in latitude, duration of growing season, and annual rainfall (Table 3). New York and MN have short-season hybrids and lower values for degree days to maturity (PHU). The TX and LA sites represent extremes in the probability of drought-induced yield reductions. Within the Midwest, MO and KS sites are low yielding, whereas the IL and IA sites are high yielding. Although annual rainfall sums were similar among the four Midwestern sites, the greater runoff curve numbers (Table 4) for MO and KS caused greater runoff and less soil water during the season.

Soils in the nine sites differed greatly in their ability to store water (Table 4). Soils with the highest plant available water in the profile at field capacity were in MN, IA, NE, IL, and KS. The NY soil and one of the two LA soils (Sharkey) had the lowest plant available water. The LA county contained two very different areas for maize production. Thus, we simulated the primary soil for each of these areas and calculated the mean simulated yields.

Daily NOAA weather station data for 1983 to 1992 were used for each county. Solar irradiance values used as input were the mean monthly long-term means for each county (NOAA, 1993). We used 10 recent years of NASS grain yields, to avoid comparing simulation results with yields of older hybrids. With ALMANAC, fertilizer quantities of 150 kg N ha^{-1} yr^{-1} and 65 kg P ha^{-1} yr^{-1} were applied except in LA. Fertilizer in LA consisted of 224 kg N and 70 kg P, to simulate common applications for that county (H.J. Mascagni, personal observation).

The two models were evaluated by addressing three questions:

1. Can these models describe location differences in mean yields? If mean measured yields are regressed on mean

Table 4. Demonstration data sets.

Town	Soil series†	Soil depth	PAW‡	Runoff curve no.§
		m	cm	
Morris, MN	Webster clay loam (fine-loamy, mixed, mesic Typic Endoaquolls)	1.5	25	75
Aurora, NY	Honeoye silt loam or loam (fine-loamy, mixed, mesic Glossoboric Hapludalfs)	1.0	19	71
Ames, IA	Nicollet loam (fine-loamy, mixed, mesic Aquic Hapludolls)	1.5	26	75
Nickerson, NE	Moody silty clay loam (fine-silty, mixed, mesic Udic Haplustolls)	1.5	29	75
Urbana, IL	Drummer silty clay loam (fine-silty, mixed, mesic Typic Endoaquolls)	1.5	28	75
Columbia, MO	Mexico silt loam (fine, smectitic, mesic Aeric Vertic Epiaqualfs)	1.5	22	81
Brown County, KS	Grundy silt loam (fine, smectitic, mesic Aquertic Argiudolls)	1.8	32	82
St. Joseph, LA	Sharkey clay (very-fine, smectitic, nonacid, thermic Vertic Haplaquepts)	1.5	14	82
	Commerce silty clay loam (fine-silty, mixed, nonacid, thermic Aeric Fluvaquents)	1.5	22	82
Temple, TX	Houston Black clay (fine, smectitic, thermic Udic Haplusterts)	1.6	22	91

† Soil classification as of early 1997; several have been reclassified in recent years.
‡ PAW, plant available water (the difference between the drained upper limit and the lower limit throughout the profile).
† Runoff curve numbers are based on soil hydrologic groups and assume contouring with good hydrologic condition.

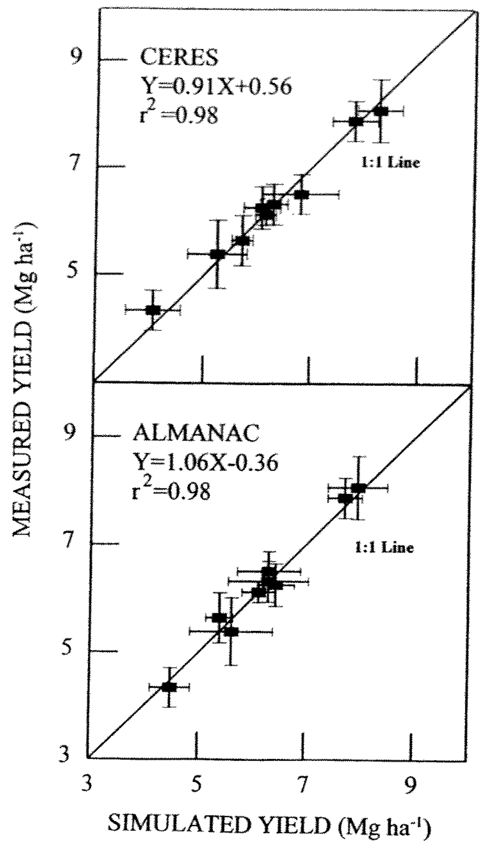

Fig. 1. Comparison of mean simulated and mean measured maize grain yields for nine locations. Each data point represents the mean of 10 yr. Error bars represent SE.

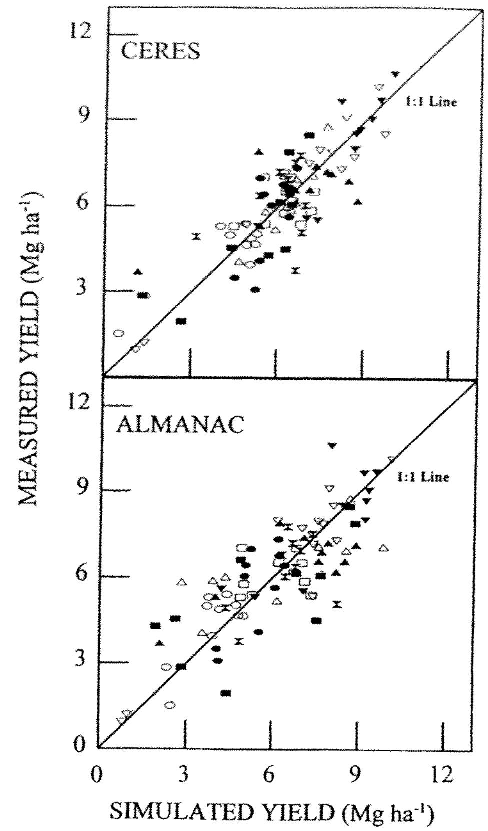

Fig. 2. Comparisons of yearly maize grain yields simulated by ALMANAC or CERES-Maize with measured yields for 1983 to 1992. Symbols indicate locations (states). *Open symbols:* oval, TX; rectangle, NY; triangle up, NE; triangle down, IA. *Solid symbols:* oval, MO; rectangle, KS; triangle up, MN; triangle down, IL; hourglass, LA.

simulated yields, how close is the regression line to the 1:1 line and what is the r^2?
2. At each location, how does each model's coefficient of variation (CV) compare with the CV for measured yields?
3. How well do the models account for the variability in measured data at each site?

First we tested to see if each regression model was significant ($P < 0.05$). With a *t*-test, we then tested measured grain yield as a function of simulated yield, to see if the slope was significantly different from 1.0 and if the *y*-intercept was significantly different from 0.0 (95% confidence level). Bias values and RMSE values were calculated as described by Retta et al. (1996).

Table 5. Measured and simulated maize grain yields and coefficients of variation (CV) for nine locations (10 yr at each location).

	Grain yield					
	Measured		CERES		ALMANAC	
State	Mean	CV	Mean	CV	Mean	CV
	Mg ha^{-1}	%	Mg ha^{-1}	%	Mg ha^{-1}	%
MN	6.5	18	6.5	32	6.8	30
NY	6.1	10	6.2	10	6.1	16
IA	7.9	15	7.8	17	7.7	13
IL	8.1	23	8.3	16	8.0	22
NE	6.3	19	6.3	13	6.3	38
MO	5.6	26	5.7	11	5.4	15
KS	5.3	37	5.2	34	5.6	44
LA	6.3	20	6.1	18	6.4	17
TX	4.3	27	4.1	39	4.5	26
Mean	6.3	22	6.2	21	6.3	25

RESULTS AND DISCUSSION

Both models were appropriate for simulating mean grain yields in the nine locations across the USA (Fig. 1). For all counties, the models' mean simulated grain yields were within 5% of mean measured yields. The regression equation for CERES was

$$\text{MYIELD} = 0.91\ \text{SYIELD} + 0.56, \quad r^2 = 0.98 \quad [3]$$

where MYIELD is the mean measured grain yield (Mg ha^{-1}) for each location and SYIELD is the mean simulated grain yield for each location. For ALMANAC, this equation was

$$\text{MYIELD} = 1.06\ \text{SYIELD} - 0.36, \quad r^2 = 0.98 \quad [4]$$

Both CERES and ALMANAC had significant ($P < 0.05$) regression models for MYIELD as a function of SYIELD. The *y*-intercepts were not significantly different from zero and slopes were not significantly different from 1.0.

CERES and ALMANAC were similar in their ability to simulate within-site variability as shown by the CVs of mean grain yields (Table 5). The overall mean simulated grain yields of CERES and of ALMANAC were similar to the mean measured grain yield. The overall mean CV of simulated grain yields of each model was also similar to the overall mean CV for the measured grain yields. Both models overestimated the CV for MN relative to the CV of measured grain yields. For the other

Table 6. For CERES, measured maize yields as a function of simulated yields for nine locations (10 yr at each location).†

State	Slope Estimate	Slope SE	y-Intercept Estimate	y-Intercept SE	r^2	Bias	RMSE
			Mg ha^{-1}			Mg ha^{-1}	
MN	0.39*	0.14	3.97*	0.93	0.50	0.03	1.52
NY	0.22*	0.33	4.74	2.07	0.05	0.04	0.78
IA	0.78	0.17	1.81	1.31	0.73	−0.10	0.69
IL	1.23	0.23	−2.09	1.90	0.79	0.19	0.92
NE	1.36	0.24	−2.24	1.52	0.80	−0.02	0.61
MO	1.60	0.59	−3.52	3.39	0.48	0.08	1.11
KS	0.92	0.22	0.51	1.23	0.68	−0.09	1.13
LA	0.29	0.39	4.51	2.40	0.06	−0.17	1.42
TX	0.64*	0.12	1.72*	0.54	0.77	−0.28	0.85

* Slope significantly different from 1.0 or y-intercept significantly different from zero at the 95% confidence level.
† Values of SE are the standard errors of the estimates. Bias values are the means of simulated minus measured grain yields. Each RMSE value is calculated from the bias values (see text).

eight counties, ALMANAC had a CV closer to the measured CV for three counties, CERES's CV was closer to measured for four counties, and for both models the CVs were 2% different from the measured CV for IA.

Both models simulated grain yield trends for all the data pooled (Fig. 2). Neither model tended to noticeably underestimate or overestimate grain yields in years with low measured grain yields. Similarly, the models showed no consistent bias for years with relatively high measured grain yields.

The models reasonably simulated grain yields for the 10 years for most counties. Regression models for measured yields as a function of simulated yields were not significant for CERES at NY and LA and for ALMANAC at NY, IA, and LA. Bias values for both models were always within 0.4 Mg ha^{-1} and RMSE values were always less than 1.8 Mg ha^{-1} (Tables 6 and 7). For each model, slopes were not significantly different from 1.0 and y-intercepts were not significantly different from zero for six counties. Excluding NY and LA, the r^2 was greater for CERES at five locations and was greater for ALMANAC at two locations. The inability of the models to account for reported grain yields among years at NY and LA may relate to the cause of the variability. Models predicting grain yield reductions based largely on drought stress may predict little difference among years at locations with consistently adequate rain. In addition, actual daily solar irradiance data (which was not available for our nine counties) might increase simulation accuracy in the absence of drought.

Model applications dictate which performance criteria are most important. For users predicting actual measured yields for individual years, the measured:simulated yield regression across years for a location should have a high r^2 and a slope close to 1.0. Thus, with these data, the two models were adequate for most of the sites, with CERES usually superior as indicated by the r^2 values. Causes of model failure at some sites are worthy of further study. Accurate mean yield simulations and accurate CVs of yields are vital when evaluating long-term factors such as tillage effects on long-term yield trends. Models with reasonable mean yields and reasonable CVs are probably best for risk assessment involving maturity type or planting density. These two models had similar CV values and both should be valuable for such applications.

Inputs to the models used at some locations raised questions that need further research. The lower HI values for ALMANAC in LA and TX implied that reported grain yields for these counties probably were restricted by something not captured in the model. The more stable HI for NY implied that environmental stress was less than the model simulated. Values for grain filling rate in CERES need to be investigated further to determine whether they are realistic for these regions. Similarly, potential LAI for ALMANAC should be evaluated further with independent field data.

Based on our analyses, both models appeared reasonable at most sites for applications involving management decisions requiring reasonable long-term mean grain yields and reasonable variations around the mean. Both models also simulated yield trends for most of the counties.

Table 7. For ALMANAC, measured maize yields as a function of simulated yields for nine locations (10 yr at each location).†

State	Slope Estimate	Slope SE	y-Intercept Estimate	y-Intercept SE	r^2	Bias	RMSE
			Mg ha^{-1}			Mg ha^{-1}	
MN	0.43*	0.13	3.57*	0.89	0.60	0.31	1.42
NY	0.09*	0.23	5.54*	1.41	0.02	0.01	1.06
IA	0.71	0.35	2.37	2.76	0.34	−0.16	1.03
IL	0.83	0.22	1.49	1.81	0.64	−0.12	1.15
NE	0.36*	0.13	4.03*	0.84	0.51	−0.01	1.73
MO	1.28	0.44	−1.26	2.39	0.52	−0.25	1.06
KS	0.57	0.20	2.15	1.22	0.51	0.27	1.77
LA	0.56	0.35	2.64	2.29	0.24	0.19	1.18
TX	0.85	0.21	0.56	1.00	0.67	0.13	0.71

* Slope significantly different from 1.0 or y-intercept significantly different from zero at the 95% confidence level.
† Values of SE are the standard errors of the estimates. Bias values are the means of simulated minus measured grain yields. Each RMSE value is calculated from the bias values (see text).

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