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Estimating Corn Yield Response Models to Predict Impacts of Climate Change

Bruce L. Dixon, Steven E. Hollinger, Philip Garcia, and Viswanath Tirupattur

Projections of the impacts of climate change on agriculture require flexible and accurate yield response models. Typically, estimated yield response models have used fixed calendar intervals to measure weather variables and omitted observations on solar radiation, an essential determinant of crop yield. A corn yield response model for Illinois crop reporting districts is estimated using field data. Weather variables are timed to crop growth stages to allow use of the model if climate change shifts dates of the crop growing season. Solar radiation is included. Results show this model is superior to conventionally specified models in explaining yield variation in Illinois corn.

Key words: climate change, corn, growth stage, solar radiation, yield.

Introduction

The prospect of substantial climate change and its potentially serious impacts are being scrutinized by the scientific community.[1] In agriculture, the United States Environmental Protection Agency has sponsored studies to identify the effects of climate change on crop growth and yields (Rosenzweig). Clearly, the value of economic impact assessments in agriculture is highly dependent on appropriate yield response specifications and on the ability of such specifications to accurately predict yields in response to hypothesized climate change. The present study demonstrates that most previous yield response models based on field data have, in all likelihood, been misspecified. An alternative specification is presented and estimated which leads to more accurate yield predictions.

The present study modifies traditional crop yield response functions in several dimensions. Typically, temperature and precipitation are the only weather variables included. However, the three most important weather-related factors for plant growth and development are soil moisture, ambient air temperature, and solar radiation (Coelho and Dale). Precipitation and temperature data have been readily available. Only recently have estimates of solar radiation and soil moisture become accessible, which suggests the reason for their absence in previous yield response models. Agronomic studies using test plot data have identified solar radiation as an important yield determinant (Daughtry, Gallo, and Bauer). Hence, models estimated from field data without solar radiation are misspecified. Empirically, it is important to determine if including solar radiation results in different estimates of yield response model parameters and improved forecasts.[2]

Typically, corn yield response models estimated from field data have used monthly

The authors are, respectively, professor of agricultural economics and economics, University of Arkansas, Fayetteville; professional scientist, Illinois State Water Survey; professor of agricultural economics, University of Illinois at Urbana–Champaign; and graduate research assistant, Department of Agricultural Economics, University of Illinois at Urbana–Champaign.

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measurements of weather variables (see, among others, Huff and Neill; Offutt, Garcia, and Pinar). The choice of monthly measurements was largely a function of how the data were recorded. Because of the year-to-year variability of weather events and planting dates, the developmental stage of a crop during a particular month varies by location and year. As a result, the use of monthly data provides only a rough approximation of the weather effects on yields, and suggests that weather-related factors should be measured by growth stage of the crop.

Measuring weather-related factors by growth stage is particularly important for predicting yields under climate change. Suppose a greenhouse effect increases May precipitation and cloudiness (less solar radiation) in the midwest, delaying corn planting to June. Yield response models estimated from data for corn planted in May using weather-related variables measured by calendar month would be useless for determining the impact of that greenhouse effect on regional yields. However, yield response models based on weather-related variables measured by crop growth stage could be used for different planting dates.

In this article, two main hypotheses are investigated with respect to corn yield response functions. In the null form, the first hypothesis is: Variation in solar radiation levels is not an important factor for explaining the variability of observed corn yields from field data. The second hypothesis is: Measuring weather-related variables in relation to fixed calendar intervals is an acceptable approximation for explaining the variation in regional corn yields. One minor aspect of yield response modeling also is investigated. Observations of actual soil moisture are not recorded at regional levels. In this study, soil moisture observations are generated by a simulation model as described later. Since soil moisture observations are simulated, they are subject to modeling error. Precipitation is observed and more readily available to researchers than soil moisture levels. Thus, we investigate which of these two variables better explains yield variability.

The theory underlying the specification of the regression models is presented. Time-series, cross-sectional observations on corn yields from the nine crop reporting districts (CRDs) in Illinois for the years 1953 through 1990 are used to test the above hypotheses.

Underlying Biological Hypotheses

Four growth stages of corn plant development are assumed. The length of a particular growth stage is specified as a fixed percentage of the total growing degree days (GDD) required for the crop to reach maturity (Hollinger).[3] The total accumulated GDD needed from planting to maturity are denoted GDDM. Table 1 provides definitions for the major plant activity during each growth stage as well as information as to how the beginning and ending dates of each growth stage are determined. The major plant activity in stage 1 is early vegetative growth, stage 2 is ear development, stage 3 is pollination and kernel set, and stage 4 is grain fill.

All the crop in a region does not reach a growth stage on the same day. We set the beginning of a growth stage to be when 50% of the crop reached that point. Growth stage 1 begins on the day 50% of the crop had been planted in a given CRD as determined from National Agricultural Statistics Service (NASS) weekly crop planting estimates. This planting date (*PDATE*) is estimated by linear interpolation between the two recorded dates bracketing the week when 50% of the crop was planted and is expressed in Julian days, i.e., number of days after January 1.

GDDM for each CRD is estimated by assuming the crop had received half of its GDDM when the crop tasseled (silked).[4] That was determined from weekly NASS estimates with linear interpolation between the two dates bracketing the week when 50% of the crop had tasseled (silked). GDDM is determined by doubling the accumulated GDD between *PDATE* and the date of tasseling (silking). Starting and ending dates defining the four growth stages for each observation are determined using the observed GDDM and the dates by which the proportion of GDDM for each stage (as outlined in table 1) had been accumulated.

Table 1. Definitions of Corn Growth Stages

Stage	Plant Activity	Date Entered	Date Exited
1	Early vegetative growth	Planting date	20% of GDDM* accumulated
2	Ear development	Exit date of stage 1 plus a day	48% of GDDM accumulated
3	Pollination and kernel set	Exit date of stage 2 plus a day	52% of GDDM accumulated
4	Grain fill	Exit date of stage 3 plus a day	Required GDDM attained; killing frost or October 31 reached—whichever is first

* GDDM denotes the total accumulated growing degree days (GDD) needed from planting to maturity.

Specification of the expected signs of the weather-related variable coefficients is necessary to validate the estimated regression models. Except for extreme weather conditions, the impacts on final yield of weather events during stages 1 and 2 are not well documented. Test plot experiments from Illinois have suggested a negative relationship between yield and temperatures in stages 1 and 2. Drier soils than typical in stage 2 can result in the plant having to send its roots deeper, benefiting the crop in stage 4 when the soil's top layers are dry.

Dry, hot weather leading into and continuing through stage 3 can result in decreased yields. Heat and moisture stress during stage 3 result in reduced yields because of poor pollination and kernel abortion. Dry, hot weather during the first two weeks of grain fill (stage 4) can result in additional kernel abortion, further reducing yield.

Solar radiation intercepted by the plant leaves provides the energy for photosynthesis. Daughtry, Gallo, and Bauer found a positive relationship between cumulative solar radiation intercepted throughout the season by the plant and final yield. The only data available for this study are estimates of solar radiation available for interception. As a result, the expected signs of the solar radiation coefficients cannot be definitively specified. Nonetheless, in stages 3 and 4, solar radiation and yield are expected to be positively related to yield because the plant's leaves, which intercept solar radiation, are fully developed. In stage 1, when the leaves are not fully developed, solar radiation does more to warm soils than to drive photosynthesis. If the temperature effect on yields in stage 1 is negative and the photosynthesis effect is positive, then the expected sign of the solar radiation variable is ambiguous.

Yield Response Function Specification and Data Sources

Following previous researchers, the crop response model is estimated in a single-equation framework (Gallagher; Huff and Neill; Offutt, Garcia, and Pinar). Various algebraic forms of the yield response regression have been estimated in prior yield response studies. Huff and Neill used linear specifications for precipitation and temperature and a quadratic trend variable. Thompson used an additive model with precipitation and temperature specified in linear and quadratic terms. Offutt, Garcia, and Pinar also used a linear specification for mean temperature, precipitation, and a trend variable. While there is no preferred form for entering weather variables into yield response models, the linear framework is most common. The previous studies cited above did not statistically test the validity of the linear specifications. Below, in the empirical section, the adequacy of a linear formulation is tested using a misspecification test.

In the present study, four different models are estimated. In each, yield per acre is a linear function of a set of independent variables. All the models include the price ratio of corn to soybeans, lagged one year (*PRATIOLG*), and pounds of applied nitrogen per acre (*NITR*). The price ratio is used to identify the quality of land planted to corn; the sign of this variable is expected to be negative.[5] Nitrogen is a critical, yield-determining input to corn. It is also highly correlated with time in the sample, with a correlation coefficient of .947. Nelson and Dale argue that nitrogen application rate is a better indicator of technological change than trend.

The four models differ by the weather-related variables included as regressors. They are planting date, temperature, precipitation, soil moisture, solar radiation, and two binary variables to account for unusual fall weather events. Planting date accounts for the experimentally observed phenomenon of yield decline associated with later planting dates (Illinois Cooperative Extension Service). The other weather-related variables, except for the two binaries, are measured by growth stage and by month, depending on the particular model specified.

The sample consists of annual time-series and cross-sectional observations. The crop reporting district is the observational unit. Data for computing the planting and tasseling (silking) dates were obtained from hand-recorded NASS records for 1953–76 and from various issues of the *Illinois Weather and Crops* (Illinois Agricultural Statistics Service) for 1977–90.

Of the four models estimated, three measure the weather-related variables relative to growth stage and the other model uses weather-related variables measured with respect to calendar months. The weather variables measured relative to growth stage are defined as:

TEM = Mean of daily high and daily low temperatures averaged over the days in growth stage s, $s = 1, 2, 3, 4$;

SOL = accumulated solar radiation available for interception in megajoules in growth stage s, $s = 1, 2, 3, 4$;

MOI = mean daily soil moisture measured as percentage of available water[6] in growth stage s, $s = 1, 2, 3, 4$; and

PRP = accumulated precipitation in inches during growth stage s, $s = 1, 2, 3, 4$.

When monthly measurements are used, the three-letter weather-related variable abbreviation is preceded by a three-letter abbreviation of the relevant month. For example, *JUNMOI* represents the average daily soil moisture during June. In preliminary estimation of models with weather-related variables measured by growth stage, solar radiation and precipitation were measured as mean daily accumulations. This approach had lower explanatory power than when solar radiation and precipitation were measured as accumulations within a growth stage.

Two binary variables account for unusual fall weather behavior. The variable *FALL* is 1 for observations when frost occurred before maturity, and 0 otherwise. For observations with *FALL* equal to 1, the weather variables for stage 4 were a function of weather that occurred from the beginning of growth stage 4 to the frost date. The variable *MATURE* is a binary variable indicating the crop did not accumulate the required GDDM by October 31. For such observations, *MATURE* equals 1 (0 otherwise), and the stage 4 weather variables were based on weather through October 31.

Climatic data were obtained from the Midwest Climate Center (Kunkel et al.). All reporting stations in a CRD with valid observations were used to compute the daily mean precipitation and temperature for each CRD. Daily solar radiation data from the Midwest Climate Center (MCC) were computed from hourly observations of cloud cover, relative humidity, and temperature. Daily soil moisture data were computed for each CRD using temperature, modeled solar radiation, precipitation data from the MCC, and a soil moisture model developed by Ritchie and adapted to the MCC system by Kunkel.

Yield data for 1953–90 were obtained from various issues of the *Illinois Agricultural Statistics* (Illinois Cooperative Crop Reporting Service). Prices of corn and soybeans for

1952–56 were drawn from the Illinois Cooperative Crop Reporting Service (1957), for 1957–59 from the U.S. Department of Agriculture's Crop Reporting Board, and for 1960–90 from the *Illinois Agricultural Statistics* (Illinois Cooperative Crop Reporting Service). Data on nitrogen applications were available by CRD for the period 1967–85, and by state for the periods 1953–66 and 1986–90, from the *Illinois Agricultural Statistics* (Illinois Cooperative Crop Reporting Service). The means of the 1967–76 CRD proportions are used to proportionately allocate state nitrogen applications to CRDs for 1953–66. Similarly, 1976–85 mean CRD proportions of state consumption are used to allocate state nitrogen consumption to CRDs for the years 1986–90.

Estimation and Interpretation

The 38 years of data are partitioned into estimation and prediction periods. The observations from 1953–87 are used for model specification and estimation. The observations from 1988–90 are used to test the model's out-of-sample predictive power. Model 1 is the model of primary interest. Models 2–4 are variants of model 1 and are used to investigate the various hypotheses posed earlier. Model 1 expresses yield per acre as a function of *PRATIOLG, NITR, FALL, MATURE, PDATE, TEM*1, *TEM*2, *TEM*3, *TEM*4, *SOL*1, *SOL*2, *SOL*3, *SOL*4, *MOI*1, *MOI*2, *MOI*3, and *MOI*4, and a binary variable denoted as *CRD*89. The variable *CRD*89 takes on a value of 1 if the observation is from either of the two southernmost CRDs. These two CRDs have soils and topographies that differ markedly from the seven northernmost CRDs. In what follows, a statistically significant result implies the .05 level unless otherwise indicated.

Preliminary estimation indicated possible differences in the slope coefficients across crop reporting districts, so the hypothesis of slope coefficient homogeneity was tested. The F-statistic testing for slope coefficient homogeneity across CRDs is not significant. Hence, the sample consists of nine CRDs as a pooled, cross-sectional, time series of data. Regressions for individual CRDs have insufficient regressor variability to clearly identify the impact of most independent variables. When using the pooled sample, more coefficients of the independent variables become significant. Finally, to test the structure of the error covariance matrix, tests of up to ninth-order autoregressive error terms were performed; the tests indicated autocorrelation was not a problem. This test was performed on each CRD separately.

Least squares was used initially to estimate models 1–4. Following Yang, Koo, and Wilson, the estimated models were tested for heteroskedasticity. All models demonstrated significant multiplicative heteroskedasticity (Judge et al., p. 439). Multiplicative heteroskedasticity assumes the variance of observation i, σ_i^2, and is explained as:

$$\sigma_i^2 = \exp(\underline{\alpha}'\underline{z}_i),$$

where $\underline{\alpha}$ is a vector of parameters and $\underline{z}_i$ is a vector of independent variables. The relevant independent variables in $\underline{z}_i$ for each model were selected using a least squares procedure. First, the residuals were obtained by estimating the original model by least squares. Then the logarithms of the squares of these residuals were regressed by least squares on the entire set of independent variables for a given model. Variables with significant coefficients were included in $\underline{z}_i$. The logarithms of the squared least squares residuals from the original model were regressed on only the significant independent variables to obtain an estimate of $\underline{\alpha}$. This estimate of $\underline{\alpha}$ was used to obtain a feasible generalized least squares estimate (FGLS) [Judge et al., equation (11.2.58)] of the models' slope coefficients.

Model with Solar Radiation and Timed Weather Variables

The FGLS estimates of model 1 are displayed in table 2. Model 1 was further checked for the existence of heteroskedasticity and none was evident using the Harvey test for multiplicative heteroskedasticity [Judge et al., equation (11.2.60)]. Likewise, Ramsey's

Table 2. Summary of Regression Estimates for Models 1-4

	Timed Variable Models			Monthly Variable Model	
Variable	Model 1 (Full)	Model 2 (No Solar)	Model 3 (Precipitation)	Variable	Model 4 (Monthly)
*TEM*1	.350	.705	.253	*MAYTEM*	1.20
	(.784)	(2.58)	(.519)		(7.50)
*TEM*2	−2.01	−1.16	−2.29	*JUNTEM*	.794
	(−6.73)	(−4.57)	(−7.15)		(3.55)
*TEM*3	−.667	−.807	−.967	*JULTEM*	−1.23
	(−3.68)	(−4.53)	(−4.81)		(−3.73)
*TEM*4	−.916	−.938	−.890	*AUGTEM*	−2.74
	(−2.95)	(−3.97)	(−2.62)		(−9.34)
*SOL*1	−.041		−.033	*MAYSOL*	−.0004
	(−3.10)		(−2.31)		(−.030)
*SOL*2	−.087		−.106	*JUNSOL*	.006
	(−7.54)		(−9.34)		(.314)
*SOL*3	−.083		−.136	*JULSOL*	−.057
	(−2.52)		(−3.41)		(−2.82)
*SOL*4	.014		.011	*AUGSOL*	.023
	(1.77)		(1.24)		(1.23)
*MOI*1	−.002	−.224		*MAYMOI*	−.111
	(−.029)	(−2.38)			(−1.33)
*MOI*2	−.202	−.158		*JUNMOI*	−.134
	(−3.00)	(−2.01)			(−1.79)
*MOI*3	.086	.238		*JULMOI*	.206
	(1.80)	(5.07)			(.452)
*MOI*4	.098	.026		*AUGMOI*	.165
	(3.15)	(.793)			(5.13)
*PRP*1			−.306		
			(−.959)		
*PRP*2			.041		
			(.124)		
*PRP*3			.694		
			(.664)		
*PRP*4			.071		
			(.376)		
PRATIOLG	−72.5	−54.2	−78.2	*PRATIOLG*	−55.4
	(−6.48)	(−4.24)	(−6.55)		(−4.93)
NITR	.207	.253	.184	*NITR*	.251
	(14.7)	(15.4)	(13.1)		(18.9)
FALL	−2.77	−10.7	−.248		
	(−1.23)	(−3.55)	(−.121)		
MATURE	−8.61	−14.0	−5.04		
	(−1.29)	(−2.57)	(−1.08)		
PDATE	−.921	−.406	−.948		
	(−7.78)	(−3.73)	(−7.27)		
*CRD*89	−16.7	−21.7	−12.7	*CRD*89	−22.5
	(−9.36)	(−10.5)	(−7.40)		(−11.5)
INTERCEPT	563	332	633	*INTERCEPT*	290
	(14.5)	(12.0)	(16.1)		(8.92)
R^2	.855	.825	.850		.839
Adj. R^2	.847	.817	.840		.831
Harvey[a]	19.2	14.5	24.2		11.9
RESET[b]	2.35	7.96	.332		5.22

Note: Asymptotic *t*-ratios are in parentheses.
[a] Harvey's test for heteroskedasticity, distributed as χ^2. The respective critical values at .05 are: model 1, 28.9; model 2, 23.7; model 3, 28.9; and model 4, 25.0.
[b] Second, third, and fourth powers of predicted dependent variable, distributed as *F*. The critical value at .05 for all models is 2.64.

RESET test for omitted explanatory variables was performed, and no significant misspecification was detected.[7] Harvey's test of coefficient stability also was not significant, indicating stable coefficient values over the sample.

Not all of the coefficients in model 1 are significant. This is not surprising, since the model's regressors are collinear. The highest conditioning index on the untransformed variables is 329, with four of the indices in excess of 100.[8] The coefficient signs in model 1 are largely in agreement with prior expectations. *PRATIOLG* is negative, *NITR* is positive, and the two weather binaries are negative. The six weather variables hypothesized to have particular signs (*TEM*3, *TEM*4, *MOI*3, *MOI*4, *SOL*3, and *SOL*4) all have their expected signs except *SOL*3.

In the first three stages, solar radiation is negatively signed and significant. The negative signs in stages 1 and 2 are not surprising; during these stages, the plant's interception capabilities are not fully developed, and high solar radiation levels are associated with elevated soil temperatures which might cause decreased yields. Also, in all four stages, each solar radiation variable and its same-period temperature variable are associated with strong linear dependencies, indicating problems with collinearity (Belsley, Kuh, and Welsch). Thus, projections of climate change impacts where the variations in temperature and solar radiation differed from those in the sample should be interpreted cautiously.[9]

The unexpected negative sign of *SOL*3 could be due to the shortness of stage 3 (mean of 4.3 days) and the imprecision in determining the beginning and ending of the stage. As expected, *SOL*4 is positive and significant. In this stage, the plant's solar radiation interception capability is fully developed. In stage 4, solar radiation has a positive coefficient and temperature has a negative coefficient. Thus, warmer and cloudier weather in the last stage of development would decrease yield. It also is clear that the earlier a crop is planted, the better. The negative coefficient of *PDATE* indicates about a bushel loss for each day planting is delayed within the bounds of the observed data.

On the basis of the above discussion, model 1 is a tenable model of corn yield response to economic and weather variables. An asymptotically efficient estimator in the presence of heteroskedasticity is used, most coefficients have their expected signs, the coefficients are stable, and the Ramsey RESET test does not reject the hypothesis of a correctly specified model. This latter result justifies excluding quadratic and interaction terms. Of course, the actual underlying process may be nonlinear, but apparently not sufficiently so to reject the estimated model. The failure to reject linearity also suggests more extreme levels of the regressors would be necessary to make diminishing returns observable.

Impact of Omitting Solar Radiation

Model 2 includes the same independent variables as model 1, except the four solar radiation variables are omitted. The in-sample explanatory power, as measured by the adjusted coefficient of determination (adjusted R^2), drops by .03 as a result of omitting the solar radiation variables. Moreover, the RESET statistic for model 2 rejects the hypothesis of a correctly specified model.

There also is considerable change among the coefficient estimates of common variables in the two regressions. *TEM*1, *MOI*1, *MOI*3, *FALL*, and *MATURE* become significant in model 2, and *MOI*4 becomes insignificant. There is considerable change in three of the *MOI* coefficients. As shown in table 3, model 2's forecasting ability as measured by Theil's U_1 statistic and root mean square error (RMSE) is distinctly inferior to that of model 1. Thus, the omission of solar radiation is nontrivial. This is especially true in predicting the effect of a particular weather variable on crop yield. For example, the differences in implications of changes in soil moisture between models 1 and 2 are considerable.

Substituting Precipitation for Soil Moisture

Model 1 uses soil moisture as a measure of water available to the crop. Model 3 substitutes precipitation, the *PRP* variables, for the *MOI* variables. Coefficient magnitudes of vari-

Table 3. Forecasting Performance of Models

	Model			
	1	2	3	4
Theil[a] U_I	.360	.449	.353	.410
Bias	.014	.040	.034	.000
Regression	.055	.110	.015	.163
Disturbance	.931	.850	.951	.837
RMSE[b]	19.4	25.2	18.7	22.1

Notes: These statistics are computed on the basis of 27 observations. The observations cover the years 1988–90 for each of the nine crop reporting districts.

[a] The Theil U_I can lie between zero and plus infinity. The figures associated with bias, regression, and disturbance are the proportion of the mean square error that can be attributed to these three sources, as discussed in Maddala (1977, p. 345).

[b] RMSE is the root mean square error where the error is defined as the predicted value less the actual value, in bushels.

ables common to both models do not differ markedly. Somewhat surprisingly, precipitation is insignificant in each growth stage. This contradicts conventional wisdom on precipitation's impact on yield. The lack of significance of the *PRP*s may be a result of collinearity with the *SOL*s. When the *SOL*s are deleted, the *PRP* coefficients have larger asymptotic t-ratios.

The in-sample explanatory power of model 3 as measured by R^2 is marginally lower than that of model 1. The RESET statistic for model 3 does not indicate a misspecified model. As shown in table 3, model 3 has a slightly lower RMSE than model 1 in predicting observations in the prediction sample.

On balance, the results are mixed. Conceptually, the soil moisture variables, which reflect an interaction between soil type and precipitation, should provide a more accurate reflection of the factors influencing yields. However, little difference in explanatory power exists between the two specifications, with model 1 performing slightly better in-sample and model 3 slightly better out-of-sample. Two of the four *MOI* coefficients are significant and none of the *PRP* coefficients are significant. This suggests that using soil moisture variables is more precise for predicting the impact of weather events on yields. In this context, the use of soil moisture variables seems valuable, but further study is required before a more definitive statement can be made regarding the relative usefulness of soil moisture variables in specifying yields at the CRD level.

Impact of Measuring Weather Variables by Calendar Month

The second hypothesis states that the conventional approach of measuring weather-related variables according to fixed calendar months is an adequate approximation to measuring weather-related variables by crop growth stage. Model 4 is a conventional specification using monthly weather-related variables.[10] It contains *PRATIOLG, NITR,* and observations on May, June, July, and August temperature, solar radiation, and soil moisture.

Results from model 4 have both similarities with and differences from model 1. In-sample explanatory power as measured by R^2 is slightly higher for model 1, and the Theil U_I statistic and RMSE for the prediction observations are lower for model 1. The decomposition of the mean square error of prediction indicates slightly better forecasting performance for model 1.

Another way of investigating the appropriateness of model 4 as an approximation to model 1 is through the use of an encompassing principle test. An encompassing test examines whether a particular model can account for salient features of a rival model. In the context of the second hypothesis, the question becomes: Does model 4 encompass model 1? Following Mizon and Richard, the second hypothesis can be tested by combining all the variables common to both models 1 and 4 into one model and using a Wald test to determine if those variables unique to model 1 have at least one coefficient different from zero. In effect, the two nonnested models become nested within one formulation.

The Wald statistic rejects the null hypothesis that model 4 explains the salient features of model 1. In a broader context, as with other nonnested procedures, the test also can be performed to assess whether model 1 encompasses model 4. This null hypothesis also is rejected, indicating that not all features of model 4 are explained by model 1. Model 1 does a better job of encompassing model 4 than vice versa. Including model 4's unique variables in model 1 results in three of the 12 monthly weather-related variables being significant, and a .014 increase in the adjusted R^2. Including model 1's variables in model 4 results in eight of the 12 timed weather-related variables being significant, and an increase in the adjusted R^2 of .029. Hence, within the context of the second hypothesis, the encompassing test suggests that using calendar measurements of weather-related variables is inferior to measuring weather-related variables by crop growth stage.

The differences in coefficient signs and significance between models 1 and 4 are numerous with respect to the weather-related variables. Early season temperatures in model 4 (*MAYTEM* and *JUNTEM*) have positive, significant coefficients. But *TEM*1 has an insignificant coefficient and *TEM*2 has a negative, significant coefficient in model 1.[11] Solar radiation is highly significant for three of the four stages in model 1, but significant for only one stage in model 4. Soil moisture is significant only in August in model 4, whereas soil moisture is significant in two of model 1's stages.

The coefficient of *PRATIOLG* in model 1 is 31% larger than in model 4. This margin is narrowed if *PDATE* is included in model 4. Therefore, the yield impact of the economic variable *PRATIOLG* is quite sensitive to model specification. Moreover, the economic implications of yield response models estimated in the past with weather-related variables defined according to fixed calendar intervals can be questioned.

It is now possible to evaluate the second hypothesis concerning the importance of measuring weather-related variables relative to crop growth stage. Model 4, with monthly observations on weather-related variables, explains less in-sample yield variation than model 1, with weather-related variables timed to crop development stage. The model with monthly variables does not forecast as well as the model with variables timed to growth stage. Model 1 is not rejected by the RESET test and model 4 is. The encompassing tests provide evidence that model 1 is superior to model 4. The signs and significance of many weather-related variables differ by the time frame used to measure these variables. Thus, our results suggest that in assessing the impact of future climate changes, corn yield response models estimated using weather-related variables measured relative to crop growth stages should be seriously considered because they provide potentially more defensible models and improved forecasts.

Conclusions

Corn yield response models estimated using field data traditionally have been based on fixed calendar intervals and have lacked solar radiation variables. We conclude such models have a reduced usefulness for predicting the yield impacts of climate change. The models estimated here indicate that solar radiation variables are important. In their absence, the corn yield model was misspecified, substantial changes occurred in coefficient magnitudes, and forecasting performance was reduced.

Timing related weather variables to growth stages also is important for examining the impact of weather variation on crop yields. The corn yield model based on fixed monthly intervals for measuring weather events was misspecified, demonstrated less predictive power, and was encompassed by the model with weather-related variables timed to growth stages. In addition, marked changes in the corn-to-soybean price ratio coefficient estimates indicate that precise definitions of time intervals for measuring weather events are important for developing economic models that use weather events as exogenous variables. Moreover, assuming climate change alters growing season dates, yield forecasts will need to be based on models with weather variables timed to growth stages.

The findings have implications for further research. The impact of solar radiation and timing the weather variables to growth stages for other crops should be explored. Solar radiation data are currently available for the midwest (Kunkel et al.) and should be included in initial specifications of yield response models for this region. Future research would benefit by the availability of regional observations on the percentage of solar radiation intercepted by a crop at various points in time. In addition, data on when crops enter into their various growth stages would obviate the need to use interpolation methods to establish crop growth stage beginning and ending dates.

Finally, further research and data are needed to more clearly identify the relative usefulness of precipitation-type variables at the CRD level. While the use of soil moisture variables did provide more precise estimates of the effects of precipitation on yields, their use in lieu of precipitation variables did not increase the explanatory power of the model or improve forecasting ability.

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Notes

[1] See Houghton and Woodwell; Rind; and the list of studies in MacLean for research related to the effects of climate change in a general context. See Adams et al.; Lewandrowski and Brazee; Liverman; and Kokoski and Smith for examples of studies related to agriculture.

[2] Solar radiation has been used in physiological simulators that approximate individual corn plant yields (Reetz). Andresen et al. also use solar radiation to formulate an energy-crop growth index to explain field corn yields in various Indiana counties. However, their analysis provides no assessment of the comparative forecasting ability of this approach to traditional methods, nor do they examine the usefulness of solar radiation at higher levels of spatial aggregation.

[3] GDD is the number of degrees the daily mean air temperature exceeds a threshold of 50°F. If minimum air temperature was less than 50°F, minimum temperature was set to 50°F. If maximum air temperature exceeded 86°F, maximum temperature was set to 86°F.

[4] It is assumed that NASS did not distinguish between tasseling and silking in recording when one or the other event occurred, since they occur in relatively rapid succession.

[5] An alternative to *PRATIOLG* is the ratio of acres of corn harvested to acres of soybeans harvested. (A complete data series of planted acres was not available. However, in those periods when planted acres were available, planted acres were highly correlated with harvested acres.) In preliminary regressions, the ratio of acres harvested was highly insignificant and therefore discarded in favor of *PRATIOLG.*

[6] Percentage of available water is the ratio of the current water in the soil that the plant can use, divided by the maximum water the soil can hold that the plant can use.

[7] The RESET is a test for omitted variables, incorrect functional form, and simultaneous equations bias. The RESET is discussed in Ramsey; Maddala (1992); and Fomby, Hill, and Johnson.

[8] Belsley, Kuh, and Welsch indicate values over 100 usually imply serious collinearity problems. No attempts were made to lower collinearity levels. Antidotes popular in the literature, such as ridge regression, omission of some collinear variables, use of extraneous parameter estimates, or principal components, may introduce more problems than they cure (Maddala 1992).

[9] As *TEM* rises, the length of stage s will shorten, so *SOL* will decline, *ceteris paribus.*

[10] Including *PDATE* in model 4 negligibly improves the model's explanatory power. It is omitted since it has not been typically included in prior studies using field data.

[11] The mean *PDATE* for the estimation sample was May 16. Stages 2, 3, and 4 had mean beginning dates of June 16, July 19, and July 24, respectively.

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