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YIELD ESTIMATION THROUGHOUT THE GROWING SEASON

John R. Kruse and Darnell Smith*

The 1993 adverse weather and floods in the midwestern United States caused enormous damages. Apart from the impacts to urban areas, most of the ponding and flood damage in the upper midwest occurred on farmland with significant affects to agricultural yields and production.

Although public officials and policy makers knew that the agricultural damage was extensive during the summer of 1993, information was imprecise and because the setting of policy parameters, such as those relating to disaster assistance, emergency wetlands reserve, and the emergency conservation program, depended directly on expectations of harvested yields, intra-season quantification of weather induced impacts was required. Given this need, the Food and Agricultural Policy Research Institute (FAPRI) of Iowa State University was asked to estimate the extent of the flood damage in Iowa detailing the impacts on acreage, yields, prices, and farm income (see CARD BR 93-1). This experience of 1993 induced FAPRI to examine alternative procedures for estimating yields throughout the growing season and one of the more promising alternatives, in terms of parsimony and data availability, is presented in this paper.

The exploratory procedure illustrated in the study utilizes pooling of data and a maximum likelihood approach to incorporation of crop condition information into state level yield estimates as the growing season progresses. Initially, a weighting procedure was employed to create a crop condition index based on USDA's condition classification and the index then was used as an additional explanatory variable in pooled yield regressions. Using this technique, FAPRI estimated yields for corn in Iowa to average 111.9 bushels per acre, 3.1 bushels below USDA's yield estimate in their August crop production report with similar results obtained the remainder of the growing season (FAPRI estimates were consistently closer to actual average yields for Iowa corn that were ultimately under 90 bushel per acre). Because the results were encouraging, further evaluation of crop condition information utilization was warranted and this study describes the present phase of that research.

Many previous studies in yield estimation have concentrated on estimating yield as a function of biological constraints such as fertilizer, pesticides, plant population and other factors. However, these models have experienced difficulty in explaining extreme weather events (Wendland, 1987.) In addition, considerable data maintenance is required to support these models. This study attempts to combine a parsimonious approach with explanatory variables better able to reflect extreme conditions. Other studies have tried to estimate the relationship between yields and weather (Willimack, et al, 1985.) The principle limitations of such techniques is that they provide only one estimate of yield in time and are not parsimonious requiring site specific temperature and precipitation observations.

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THEORETICAL DEVELOPMENT

In general, the approach to estimating average ending yields based on crop conditions proceeds from the notion that there is one unique yield associated with each condition classification. This study uses crop conditions reported by USDA. USDA breaks crop conditions into five classifications: very poor, poor, fair, good, and excellent. Thus, theoretically, there exists some set of yields associated with each crop condition such that the following is true:

$$\sum_{i=V}^{E} y_i C_i = \bar{y}$$

where

- i = V, P, F, G, and E.
- V = Very Poor
- P = Poor
- F = Fair
- G = Good
- E = Excellent
- y_i = Yield for condition i.
- c_i = Percent of crop in condition i.
- $\bar{y}$ = Average yield

This approach can easily be extended to reflect average yield for any region. In this study, state level yields are evaluated, thus, a subscript s is added to denote the yield and set of weights or proportions for a particular state:

$$\sum_{i=V}^{E} y_{is} C_{is} = \bar{y}_s$$

Since the appropriate sets of yields corresponding to the crop conditions in each state are unknown, they must be estimated. Ordinarily it would be a simple matter to estimate the set of yields for each state by regressing state average yields on the percent of crop in each category. However, with only 8 years of annual observations on crop conditions there are not enough degrees of freedom fpr accurate estimation. Given that data on yields and crop conditions is available for major producing states, pooling cross sectional and time series data solves the degrees of freedom problem.

The pooled set of data consists of yields and crop conditions for each state. Since actual yield levels vary by state due to different soil types, fertilizer rates, pesticide rates, weather deviations, etc., the weights assigned to each crop condition category may also vary by state. For example, a corn crop in very poor condition in Iowa may yield an average of 80 bushels per acre, where as a corn crop in very poor condition in Georgia may yield an average of 30 bushels per acre. The fact that yield levels vary by state forces the inclusion of yield shifters unique to each state. However, if yield shifters for all five crop condition categories for each state are included, significant degrees of freedom are lost. An alternative is to estimate an average yield conditional upon a particular set of classification yields (y_{is}) for each crop condition type and the percent of crop in each crop condition type thus regressing actual yield on the calculated conditional yields for each state. Since the appropriate set of classification yields are unknown, the classification yields must be estimated. In order to let the sets of yields vary by state, dummy variables for n-1 states must also be included.

One other problem arises with the pooled set of data. In addition to yield levels varying across states, the variance of yields across states is also different. This suggests that some method to account for the unequal variance among states must be used. A form of weighted least squares for pooled data will be used to correct this problem.

Note that the yields are also being estimated across time. With increases in technology such as new hybrids, better weed and pest control, and a wide variety of other factors some yield growth is to be expected. In addition, since some technologies are region specific, yields may grow at different rates in different states. To account for this varying change in technology, trend variables for each state should also be included in the regression.

The functional form for estimating final average yield is then described by:

$$\bar{y}_{st} = \beta_s \sum_{i=1}^{5} \gamma_i \, c_{ist} + A_s \, T + \sigma_s e_{st}$$

where

c_{ist} = Percent of crop in condition i
T = Time Trend
γ_{is} = Estimated yield associated with each crop condition classification.
e_{st} = White noise error term

This model is nonlinear in parameters but, conditional on the γ_i, it can be estimated using weighted least squares. Estimates of the γ_i were found using a grid search technique that indentifies the set of classification yields associated with the maximum value of the log likelihood function. An iterative programming procedure systematically varied the yields, regression parameters were estimated and the likelihood function was calculated at each iteration. (A grid search then locates the value of classification yield estimates that maximizes the likelihood, which in this case reduces to minimization of squared errors.) The pooled parameter estimator is given by:

$$\hat{\beta} = (X' \, \Omega^{-1} \, X)^{-1} \, X' \, \Omega^{-1} \, \bar{y}_s$$

Where the X matrix is:

$$
\begin{array}{cc}
 & \begin{array}{cccccccccc} T & TD1 & TD2 & \cdots & TD16 & CI & CID1 & CID2 & \cdots & CID16 \end{array} \\
X = & \begin{bmatrix}
1 & 0 & 0 & & 0 & C_{ywi} & 0 & 0 & & 0 \\
2 & 0 & 0 & & 0 & C_{ywi} & 0 & 0 & & 0 \\
\vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\
7 & 0 & 0 & & 0 & C_{ywi} & 0 & 0 & & 0 \\
1 & 1 & 0 & & 0 & C_{ywi} & C_{ywi} & 0 & & 0 \\
2 & 2 & 0 & & 0 & C_{ywi} & C_{ywi} & 0 & & 0 \\
\vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots & & \vdots \\
7 & 7 & 0 & & 0 & C_{ywi} & C_{ywi} & 0 & & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
1 & 0 & 0 & & 1 & C_{ywi} & 0 & 0 & & C_{ywi} \\
2 & 0 & 0 & & 2 & C_{ywi} & 0 & 0 & & C_{ywi} \\
\vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\
7 & 0 & 0 & & 7 & C_{ywi} & 0 & 0 & & C_{ywi}
\end{bmatrix}
\end{array}
$$

and Ω is a diagonal matrix to correct for group heteroskedasticity by state, TD1-TD16 is trend times dummy, CI is the calculated crop index for the appropriate year, week and condition classification yield estimates and CID1-CID16 is crop index times dummy.

ESTIMATION PROCEDURE

The Data

The crop condition data used in this study was taken from *Weekly Weather and Crop Bulletin* reports for 1986 through 1993. This included state level data on the percent of crop in each of five conditions: very poor, poor, fair, good, and excellent. The data on conditions were collected for corn and soybeans on a weekly basis. Data on state level corn and soybean yields were taken from monthly *Crop Production* reports and the January annual summary of *Crop Production*.

Estimation

Weekly models for soybean and corn yields were estimated using weighted maximum likelihood estimation via the SAS Interactive Matrix Language. The equations for soybeans and corn were estimated according to specifications presented earlier. The key to the estimation process was the construction of the X matrix. As mentioned earlier the X matrix consisted of 38(34) columns with the first 19(17) columns associated with trend and trend shifters and the last 19(17) columns associated with conditional yield and conditional yield shifters for soybeans(corn). The X matrix included seven rows for each state and nineteen states in the case of soybeans and seventeen states in the case of corn. Conditional yields were determined by the percentage of the crop in each condition category and the associated yield estimate for each category. Thus, conditional yields were calculated by multiplying a matrix of crop conditions for each year and each state by a column vector of estimated yield weights for each crop condition. This created a column vector of conditional yields by year and by state.

Since the appropriate yield weights for the amount of crop in each condition type were unknown, numerous trials were performed in order to determine the appropriate yield weight. A nested do loop was programmed in SAS to vary the yield weights for each class. The only restriction placed on yield weights for each condition category was to insure that as yield weights varied from very poor to excellent, they increased in value. That is, the yield weight for the percent of crop in poor condition should be greater than or equal to the yield weight for very poor condition, and the yield weight for the percent of crop in fair condition should be greater than or equal to the yield weight for poor condition, and so on. For each set of yield weights a unique "regression" was performed. The value of the weighted maximum likelihood estimator was stored in a matrix along with the yield weights corresponding to that value for each yield weight interaction. Because the number of alternative yield weight combinations was infinitely large, yield intervals were first used to narrow the set of yield weight classifications. Once the appropriate set of yield ranges for each class of crop conditions was determined, the ranges were narrowed until a combined set of unique yields for each condition category was determined. For example, initially the range of weights for corn in very poor condition may be 0 to 80 in increments of 10, for the poor condition 40 to 120, for the fair condition 60 to 150, for the good condition 80 to 180 and for the excellent 100 to 200. The model procedure utilizes all possible combinations of weights form these ranges. The first such combination would be 0, 40, 60, 80, and 100 for each respective condition category. This set of yield weights would be used to construct the conditional yield vector in the X matrix. The model for this set of weights is then estimated and the value of the weighted maximum likelihood estimator is calculated. This value and the set of weights is placed in a matrix. We then increment to the next set of weights: 0, 40, 60, 80, and 120. The process continues until all combinations of weights are tried. SAS then performs a grid search on the matrix of maximum likelihood estimators. The maximum value of the likelihood estimate (in this case equivalent to sum of square error minimization) is selected along with the set of yield weights and parameter estimates corresponding to that value. If the yield weights are at any of the limits on the weight ranges, these ranges are expanded and the process is started over. Once the yields are narrowed to within a set of ranges, the increment is lowered. So in this example, the increment for corn may be lowered from 10 to 5. The process then begins again with the lower increment. The increments are narrowed until yield weights are within one bushel.

The complete process of determining the yield weights was performed on six specific weeks in the growing season for soybeans and corn. The six different weeks were selected based on data availability for all states considered. The weeks shown were in two week intervals from the week of July 3rd to July 9th to the week of September 11th through September 17th. Note that these weeks are neither the beginning of crop condition observations nor the final crop condition observations but do represent the set of weeks where conditions on all states for the years 1986-1992 are present. The results of the search for appropriate weights are present in Tables 1 and 2 at the end of this report.

RESULTS

Tables 1 and 2 indicate that as expected, both corn and soybean models do a better job of explaining final yield the closer crop conditions observations are to harvest as evidenced by consistently higher R^2, lower mean square errors, and lower mean absolute percent errors for weeks progressively closer to harvest (convergence in distribution). For the last week considered in this study, September 11th through September 17th, 91.9 percent of the variation in soybeans yields for all states is explained by the model and 94.6 percent of the variation in corn yields for all states is explained by the model. Note the remarkable jump in explanatory power of the corn model in going from the week of July 3rd through July 9th to the week of July 17th through July 23rd where R^2 increases from 77.5 percent to 90.3 percent and mean square error drops by more than half from 137.48 to 59.29. The increase in explanatory power for soybeans is more gradual. It is also interesting to note in Table 1 the tendency for soybean yield weights on the poor and very poor condition categories to be larger for weeks earlier in the growing season. This may reflect the greater ability of soybeans to recover from these conditions early in the season as opposed to late in the season. A similar pattern was not observable for corn.

Tables 1 and 2 may also suggest the possibility of another factor not considered in the study - maturity. It can be argued that because soybeans are planted later in the year, they are typically less mature for any given week than corn. Thus, the explanatory power of the soybean model naturally would be less than the corn model for any given week until soybeans maturity catches up with corn. This is what appears to be happening in Tables 1 and 2. This suggests the possibility of increasing model performance further with the addition of a maturity indicator.

Tables 3 and 4 present the results of holding yield weights at their September 11th through September 17th values. Note that the performance statistics worsen slightly with the imposed yield, but because the final yield weights are similar to the yields in previous weeks there is only a small loss in explanatory power. This demonstrates the robustness of the final yield weights and explains final yields throughout the season.

Tables 5 and 6 present the parameter estimates for soybeans and corn given the yield weights in Tables 1 and 2. A priori, we expected that the coefficient on condition yield index should be close to 1. For soybeans this coefficient is .915 and for corn this coefficient is 1.2. The dummy shifters for soybean conditional yields by state are significant at the $\alpha = .01$ level of significance for all states except Arkansas, Georgia, Kansas, Louisiana, North Carolina and Tennessee (the more marginal soybean producing states on average). In, addition, soybean trend yield shifters are significant at the $\alpha = .05$ level of significance for all states except Colorado, Georgia, Michigan, North Carolina, Ohio, South Carolina and south Dakota. The dummy shifters for corn conditional yields are all significant at the $\alpha = .01$ level of significance reflecting the diversity of corn yield weights among states. Only the corn trend yield shifters for Colorado, Michigan, North Carolina, and South Dakota are insignificant at the $\alpha = .01$ level of significance.

Tables 7 and 8 present the results of model simulation over 1993 for soybeans and corn by week and compares them with USDA estimations for the same weeks where available and final yields. The performance of the model compared with USDA estimates is mixed for both soybeans and corn. The model performs slightly better in predicting final yields than USDA in some states, but not as well as others. For example, in early September USDA estimated Indiana soybean yields to be 47 bushels per acre when this model suggested final soybean yields would be 45.8 bushels per acre. The actual yields for Indiana soybeans were 44 bushels per acre suggesting that the model performed better than USDA estimates for this state. However, for other states, USDA estimates were closer to actual yields. Overall, for soybeans USDA in the second week of September were closer in 12 of the 19 states than the model estimates. For corn, USDA estimates in the second week of September were closer in 13 of the 17 states. However, when comparing yield estimates for the week of July 31st to August 6th, model estimates were better than USDA in 8 of the 17 states.

The simulation of the model over 1993 is somewhat misleading in the respect that the model was not estimated over a period that contained a flood of any kind, not to mention a flood to the extent of 1993. Simulation of the model through 1994 should prove an interesting check of model performance. The incorporation of 1993 data into the estimation period may also improve predictability in flood situations in the future.

CONCLUSIONS

This paper presents an exploratory procedure for estimating state level crop yields throughout the growing season. The procedure utilizes pooling of data and a maximum likelihood approach incorporating information from USDA's crop condition reports. An iterative process was employed that systematically varied the implicit yield estimates associated with each condition classification, parameters were then re-estimated and the value of the likelihood function was calculated at each iteration. A subsequent grid search was performed that located the maximum value of the likelihood function and identified the estimated condition classification yields and parameter estimates associated with the maximum value of the likelihood function. The results were comparable to those provided by USDA and indicate that incorporation of crop condition information improves precision of yield estimates during the growing season and that gains to precision increase as the season progresses.

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Table 1. Estimated Average Soybeans Yields For Each Condition Catagory By Week

Week	Very Poor	Poor	Fair	Good	Excellent	R-Square	Mean Square Error	Mean Absolute Percent Error
Jul 3 - Jul 9	18	22	24	31	46	80.0%	9.97	7.7%
Jul 17 - Jul 23	15	22	24	29	49	84.9%	7.52	6.8%
Jul 31 - Aug 6	11	19	20	25	38	84.6%	7.71	6.7%
Aug 14 - Aug 2	16	19	20	28	35	86.3%	6.82	6.6%
Aug 28 - Sep 3	12	15	21	26	36	88.7%	5.65	6.0%
Sep 11 - Sep 17	8	18	23	30	38	91.9%	4.03	4.8%

Table 2. Estimated Average Corn Yields For Each Condition Catagory By Week

Week	Very Poor	Poor	Fair	Good	Excellent	R-Square	Mean Square Error	Mean Absolute Percent Error
Jul 3 - Jul 9	5	68	80	109	126	77.5%	137.48	7.1%
Jul 17 - Jul 23	60	65	72	121	124	90.3%	59.29	4.8%
Jul 31 - Aug 6	50	58	73	114	115	93.8%	37.95	4.1%
Aug 14 - Aug 2	41	64	89	120	139	94.1%	35.87	3.9%
Aug 28 - Sep 3	55	55	94	126	143	93.7%	38.32	3.9%
Sep 11 - Sep 17	32	72	90	133	157	94.6%	33.08	3.5%

Table 3. Soybean Regression Performance Imposing Final Week's Estimated Yields

Week	Very Poor	Poor	Fair	Good	Excellent	R-Square	Mean Square Error	Mean Absolute Percent Error
Jul 3 - Jul 9	8	18	23	30	38	77.5%	11.24	8.1%
Jul 17 - Jul 23	8	18	23	30	38	82.6%	8.71	7.5%
Jul 31 - Aug 6	8	18	23	30	38	83.0%	8.51	7.3%
Aug 14 - Aug 2	8	18	23	30	38	85.1%	7.44	6.9%
Aug 28 - Sep 3	8	18	23	30	38	88.5%	5.77	6.0%
Sep 11 - Sep 17	8	18	23	30	38	91.9%	4.03	4.8%

Table 4. Corn Regression Performance Imposing Final Week's Estimated Yields

Week	Very Poor	Poor	Fair	Good	Excellent	R-Square	Mean Square Error	Mean Absolute Percent Error
Jul 3 - Jul 9	32	72	90	133	157	77.0%	140.25	7.2%
Jul 17 - Jul 23	32	72	90	133	157	88.3%	71.47	5.2%
Jul 31 - Aug 6	32	72	90	133	157	92.6%	45.20	4.4%
Aug 14 - Aug 2	32	72	90	133	157	93.6%	39.26	3.8%
Aug 28 - Sep 3	32	72	90	133	157	93.4%	40.42	4.0%
Sep 11 - Sep 17	32	72	90	133	157	94.6%	33.08	3.5%

Table 5.
Soybean Parmeter Estimates, Final Week

Variable	Parameter Estimate	Standard Error	T-Ratio
TREND	-0.057	0.420	-0.136
DUMTDAR	0.840	0.624	1.346
DUMTDGA	0.392	0.583	0.673
DUMTDIA	0.599	0.559	1.072
DUMTDIL	0.936	0.555	1.687
DUMTDIN	1.193	0.560	2.129
DUMTDKS	0.919	0.522	1.760
DUMTDKY	0.829	0.583	1.422
DUMTDLA	1.297	0.558	2.322
DUMTDMI	0.508	0.570	0.891
DUMTDMN	0.655	0.544	1.204
DUMTDMO	0.638	0.563	1.133
DUMTDMS	1.447	0.619	2.337
DUMTDNC	0.085	0.589	0.144
DUMTDNE	1.445	0.535	2.699
DUMTDOH	0.550	0.555	0.991
DUMTDSC	0.258	0.575	0.448
DUMTDSD	-0.314	0.559	-0.561
DUMTDTN	0.650	0.617	1.052
CY	0.915	0.076	12.108
DUMCYAR	-0.000	0.112	-0.001
DUMCYGA	-0.053	0.103	-0.508
DUMCYIA	0.431	0.095	4.525
DUMCYIL	0.325	0.095	3.405
DUMCYIN	0.326	0.098	3.341
DUMCYKS	-0.037	0.089	-0.417
DUMCYKY	0.186	0.103	1.802
DUMCYLA	-0.096	0.100	-0.961
DUMCYMI	0.227	0.097	2.352
DUMCYMN	0.344	0.096	3.582
DUMCYMO	0.235	0.101	2.329
DUMCYMS	-0.157	0.116	-1.352
DUMCYNC	0.047	0.102	0.466
DUMCYNE	0.222	0.094	2.350
DUMCYOH	0.389	0.098	3.983
DUMCYSC	-0.157	0.101	-1.563
DUMCYSD	0.133	0.095	1.395
DUMCYTN	0.089	0.111	0.804

Table 6.
Corn Parmeter Estimates, Final Week

Variable	Parameter Estimate	Standard Error	T-Ratio
TREND	-0.828	1.109	-0.746
DUMTDGA	2.348	1.717	1.367
DUMTDIA	3.170	1.511	2.098
DUMTDIL	3.900	1.474	2.647
DUMTDIN	3.614	1.473	2.454
DUMTDKS	5.236	1.494	3.504
DUMTDKY	2.599	1.590	1.634
DUMTDMI	1.533	1.584	0.968
DUMTDMN	3.528	1.470	2.401
DUMTDMO	3.183	1.503	2.118
DUMTDNC	0.135	1.756	0.077
DUMTDNE	4.840	1.474	3.283
DUMTDOH	3.157	1.491	2.118
DUMTDPA	3.325	1.495	2.224
DUMTDSD	1.494	1.520	0.983
DUMTDTX	2.375	1.545	1.538
DUMTDWI	2.701	1.481	1.824
CY	1.206	0.000	31.234
DUMCYGA	-0.523	0.001	-8.020
DUMCYIA	-0.277	0.001	-5.159
DUMCYIL	-0.289	0.001	-5.477
DUMCYIN	-0.255	0.001	-4.771
DUMCYKS	-0.346	0.001	-6.709
DUMCYKY	-0.374	0.001	-6.349
DUMCYMI	-0.366	0.001	-6.386
DUMCYMN	-0.263	0.001	-4.837
DUMCYMO	-0.340	0.001	-6.084
DUMCYNC	-0.414	0.001	-6.013
DUMCYNE	-0.295	0.001	-5.628
DUMCYOH	-0.246	0.001	-4.445
DUMCYPA	-0.455	0.001	-8.354
DUMCYSD	-0.579	0.001	-10.450
DUMCYTX	-0.442	0.001	-8.307
DUMCYWI	-0.388	0.001	-7.424

Table 7. Comparison of Actual Soybean Yields and Model Yield Estimates For 1993 By State

State	Jul 3 - Jul 9 Model	Jul 3 - Jul 9 USDA	Jul 17 - Jul 23 Model	Jul 17 - Jul 23 USDA	Jul 31 - Aug 6 Model	Jul 31 - Aug 6 USDA	Aug 14 - Aug 20 Model	Aug 14 - Aug 20 USDA	Aug 28 - Sep 3 Model	Aug 28 - Sep 3 USDA	Sep 11 - Sep 17 Model	Sep 11 - Sep 17 USDA	Final Yields
Alabama	23.2	NA	22.1	NA	20.0	24.0	20.7	24.0	21.7	24.0	21.6	24.0	24.0
Arkansas	34.6	NA	33.0	NA	31.8	27.0	30.6	27.0	30.4	26.0	29.2	26.0	25.0
Georgia	24.8	NA	22.0	NA	18.3	19.0	18.9	19.0	17.2	17.0	18.5	17.0	17.0
Iowa	38.6	NA	35.1	NA	37.2	35.0	36.5	35.0	38.9	35.0	36.7	35.0	30.0
Illinois	44.1	NA	43.1	NA	44.6	42.0	43.8	42.0	45.0	44.0	44.0	44.0	43.0
Indiana	44.3	NA	43.4	NA	45.4	45.0	46.1	45.0	44.3	47.0	45.8	47.0	44.0
Kansas	31.3	NA	30.7	NA	28.7	29.0	31.5	29.0	31.4	29.0	32.5	29.0	28.0
Kentucy	36.1	NA	34.7	NA	35.8	32.0	37.0	32.0	36.5	33.0	34.8	33.0	33.0
Louisianna	32.6	NA	30.7	NA	31.1	28.0	30.8	28.0	30.2	25.0	28.9	25.0	23.0
Michigan	36.3	NA	35.6	NA	37.0	36.0	36.8	36.0	37.1	36.0	37.3	36.0	38.0
Minnesota	28.9	NA	28.8	NA	28.9	27.0	30.2	27.0	29.3	25.0	29.8	25.0	22.0
Missouri	35.3	NA	32.0	NA	31.2	33.0	33.2	33.0	33.5	35.0	33.3	35.0	33.0
Mississippi	30.6	NA	31.1	NA	28.7	25.0	28.6	25.0	27.4	25.0	27.9	25.0	22.0
North Carolina	23.7	NA	24.6	NA	24.9	24.0	23.9	24.0	21.5	24.0	22.4	24.0	24.0
Nebraska	36.3	NA	35.5	NA	34.6	35.0	39.3	35.0	44.5	36.0	45.2	36.0	35.0
Ohio	39.2	NA	41.2	NA	42.8	41.0	41.3	41.0	37.8	39.0	38.2	39.0	38.0
South Carolina	20.2	NA	18.1	NA	17.4	17.0	16.0	17.0	14.5	15.0	16.5	15.0	15.0
South Dakota	21.4	NA	19.9	NA	20.3	22.0	21.4	22.0	24.3	22.0	22.4	22.0	21.0
Tennessee	35.7	NA	34.1	NA	30.3	28.0	30.5	28.0	31.2	28.0	29.1	28.0	31.0

Table 8. Comparison of Corn Yields Estimated by the Model With USDA Estimates and Final Yields for 1993 by State

State	Jul 3 - Jul 9 Model	Jul 3 - Jul 9 USDA	Jul 17 - Jul 23 Model	Jul 17 - Jul 23 USDA	Jul 31 - Aug 6 Model	Jul 31 - Aug 6 USDA	Aug 14 - Aug 20 Model	Aug 14 - Aug 20 USDA	Aug 28 - Sep 3 Model	Aug 28 - Sep 3 USDA	Sep 11 - Sep 17 Model	Sep 11 - Sep 17 USDA	Final Yields
Colorado	165.0	NA	163.3	NA	158.2	140.0	147.5	140.0	149.9	140.0	138.1	140.0	120.0
Georgia	84.7	NA	73.2	NA	70.1	65.0	71.1	65.0	71.9	65.0	69.8	65.0	70.0
Iowa	121.3	NA	103.0	NA	105.0	115.0	109.4	115.0	112.8	112.0	105.3	112.0	80.0
Illinois	141.7	NA	134.8	NA	140.7	140.0	141.7	140.0	142.3	140.0	143.9	140.0	130.0
Indiana	140.4	NA	138.3	NA	143.1	140.0	140.4	140.0	142.7	136.0	143.2	136.0	132.0
Kansas	155.4	NA	145.2	NA	150.2	140.0	149.0	140.0	150.4	135.0	148.7	135.0	120.0
Kentucky	120.5	NA	111.1	NA	111.3	102.0	107.3	102.0	110.7	100.0	106.3	100.0	104.0
Michigan	110.3	NA	113.9	NA	110.6	110.0	113.3	110.0	113.1	110.0	112.2	110.0	110.0
Minnesota	86.9	NA	85.3	NA	87.4	90.0	92.4	90.0	93.1	85.0	93.7	85.0	70.0
Missouri	121.0	NA	112.3	NA	107.8	112.0	112.3	112.0	107.8	105.0	106.2	105.0	90.0
North Carolina	77.3	NA	77.2	NA	66.8	55.0	63.1	55.0	59.8	55.0	54.9	55.0	65.0
Nebraska	140.1	NA	131.4	NA	129.0	124.0	136.9	124.0	145.6	122.0	146.1	122.0	104.0
Ohio	133.5	NA	137.9	NA	138.8	128.0	134.9	128.0	123.5	115.0	121.5	115.0	110.0
Pennsylvania	114.2	NA	109.7	NA	106.8	98.0	104.8	98.0	103.6	94.0	104.8	94.0	96.0
South Dakota	66.6	NA	65.9	NA	68.8	69.0	69.3	69.0	75.6	67.0	70.6	67.0	63.0
Texas	119.4	NA	114.8	NA	114.5	121.0	103.3	121.0	109.7	115.0	108.6	115.0	115.0
Wisconsin	97.7	NA	94.6	NA	99.4	105.0	98.2	105.0	108.5	105.0	106.8	105.0	92.0