FORECASTING CORN YIELDS: A COMPARISON STUDY USING 1977 MISSOURI DATA

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ABSTRACT

Two different approaches to forecasting corn yields are compared using data collected in nine Missouri fields in 1977. One approach involves the use of nonlinear regression techniques to fit growth data to a logistic model. This approach requires the use of only current season data to produce biological grain yield forecasts. The report discusses several model variations free of least square model assumption violations. The second approach applies historically estimated linear regression parameters to current season data to calculate yield. Examination of the models shows similar forecasting abilities with acceptable forecasting errors one month before maturity. An upward bias is found in final estimates of net yield.

Key words: Corn, forecasting, regression, nonlinear, logistic, modeling, heteroscedasticity.

This paper was prepared for limited distribution to the research community outside the U.S. Department of Agriculture. The views expressed herein are not necessarily those of ESCS or USDA.

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*Carol C. House**

INTRODUCTION

It is a major responsibility of the Statistics Unit of the Department of Agriculture's Economics, Statistics and Cooperatives Service to forecast crop yields several months before the crop has matured. Tools used in making such forecasts include general linear regression models whose parameters have been estimated by use of historic data. These "between-year models" depend on a base period of time, usually three years, to supply data on the relationships of various plant measurements to final biological grain yield. An implied assumption is made that the present year is a part of the composite population which also includes these base period years. The model parameters that have been estimated are then used in conjunction with current year counts and measurements to forecast current year biological yield.

The Statistical Research Division has been involved in a continuing effort to improve these forecasts by exploring new models that eliminate the need for the assumption of homogeneity between growing seasons, employ the direct input of environmental variables such as rainfall and temperature, and/or are designed to give reliable forecasts earlier in the growing season. Since 1973 much of such work has centered around the use of a logistic growth model and the nonlinear regression techniques needed to estimate its parameters.

During the 1977 growing season, data were collected in nine corn fields in Missouri as part of the 1977 Corn Environment and Growth Study (CEGS). The data were used to evaluate the forecasting and estimating ability of this logistic growth model applied to corn production, and compare these results with forecasts and estimates produced by the currently used "between-year" linear models. Data were collected to allow field level estimates of the variables of interest, and were analyzed as nine replicates of a field level experiment. The nine corn fields in which data were collected were selectively chosen and not necessarily representative of the state as a whole. For this reason, strict statistical inferences to any population larger than the 9 fields would not be valid.

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The two types of models were evaluated and compared in two respects: their ability to forecast yield of an immature crop and the ability to estimate such yield at maturity. One hypothesis was that the within-year logistic model would be more responsive to current field conditions affecting the growing plants and therefore produce more accurate forecasts during the season. However, results were similar for both types of models. For yield estimation at maturity, the linear models reduced to a crop cutting procedure which required no model fitting or parameter estimation. Because of this, these models were expected to produce more accurate estimates. Check data of actual farmer production measured at an elevator after harvest was used to evaluate the models' estimation capabilities. Results again were similar for both model types. Unfortunately, both models were less accurate than expected.

A report of the 1977 CEGS project covering the data collection activities and analysis of the data is presented here. The objectives of this paper are to:

1) Describe the data collection and handling techniques involved in the study.

2) Present a discussion of the logistic growth model and the results from its use to forecast field level yields.

3) Discuss the between-year linear regression type models and the forecasts and estimates generated using this 1977 data set.

4) Present the techniques and results for estimating harvesting loss.

5) Compare the estimates from models in 3) and 4) above with each other and actual farmer production as measured at the elevator.

6) Summarize the conclusions from the analysis and make recommendations for future study.

Some additional data were collected in the research fields during this same time frame, consisting primarily of weather and environmental variables. These data could be of value in the recommended future analysis of the yield data, but they will not be discussed or analyzed in this report.

DATA COLLECTION

SAMPLE FIELD SELECTION

Nine fields were purposely selected throughout the major corn producing areas of Missouri. Each of the nine was located in a different geographical region of the state. In each region, the selected field was less than twenty-six acres and chosen such that it lay within 0.7 miles from an ASCS[1/] monitored weather station and within a reasonable driving distance from the home of the person collecting the data. Cooperating farm operators agreed to keep the research fields separated from other fields during harvest operations in order to obtain actual weight measurements at the elevator for all grain harvested.

Because of the nonrandom selection process in drawing the sample of fields, no effort was made to draw inference from the analysis in this report to the production of corn in the entire state of Missouri. Analysis was done at a field level, and yield forecasts only reflect the fields involved.

SELECTION OF PLOTS WITHIN A FIELD

In each quarter of a sample field, four pairs of "pre-harvest" and "post-harvest" plots were randomly selected. Each pre-harvest unit or plot consisted of two parallel row segments. One row segment was exactly 15 feet long while the other was of variable length and consisted of 50 consecutive corn plants. Each post-harvest plot consisted of two 15-foot parallel row segments and their row middles. For even-numbered plots, the post-harvest plot was located 4 rows and 12 paces further into the field than its associated pre-harvest plot. For odd-numbered plots, the post-harvest plot was located 4 rows and 12 paces closer to the starting corner.

Data collection was carried out in several overlapping phases: plot layout and plant population counts, silking observations, weekly sampling of ears to send to the laboratory for dry weight determination, monthly measurements of variables used in the operational objective yield program, laboratory measurements, elevator weights of final production, and post-harvest gleaning work for determining harvest loss. A basic description of data collection procedures follows. A more complete description can be found in the enumerators and laboratory manuals for this project. (XIII, XIV, XV)[2/]

1/ Agricultural Stabilization and Conservation Service of the U.S. Department of Agriculture. Local offices throughout the State participated in a weather monitoring network during the 1977 growing season.

2/ References to sources will be indicated by parenthesized Roman numerals which are associated with entries on the references page at the end of the report.

PLANT POPULATION COUNTS

During the first visit to each sample field, pre-harvest plots were laid out. Plants were counted in 30 feet of row in each plot. Row widths were measured at the end of the plot, so that plant population estimates could be made.

SILKING OBSERVATIONS

The purpose of this phase of data collection was to obtain the time of silk emergence for each of the 50 consecutive plants in the variable length row of each unit. Silk emergence for a plant was defined to have occurred when silk was first observed on any ear of the plant or its tillers. The silking date for a plant was set as the date midway between the date of the visit when silk emergence was first observed and the date of the previous visit. Observations were made for silk emergence every 3-4 days during peak silking periods, and weekly during less active silking periods. Silking date has been shown to be a good proxy for the date of pollination, i.e. the beginning of kernel growth in an ear. (XIX)

A yellow tag was placed on a plant when silking was first observed. Only plants with such tags were included in the remainder of the sampling process as plants not silking were assumed to have no grain producing capability.

WEEKLY SAMPLING OF EARS TO SEND TO THE LABORATORY

When approximately 50 percent of the plants in the variable length row had silked, the fourth phase of data collection began. These visits to the sample fields were made weekly and continued for 9 weeks or until harvesting of the field, whichever occurred first.

On each visit, two plants showing kernel formation were selected from each unit in the following manner. Blocks of 5 plants were independently ordered for sampling on the first through the ninth visit. One block of five plants was never sampled. On any given visit, plants in the selected block were observed in random order until two plants showing kernel formation had been sampled. A plant was considered to have kernel formation if any of its ears had such formation. Plants that did not silk were excluded from the population sampled for grain production.

The ears from these sampled plants were sent to a special laboratory for determination of dry matter weight. Great care was taken to maintain the identity of the ears so that the dry grain weight of a plant could be associated with its silking date.

MONTHLY MEASUREMENTS FOR BETWEEN-YEAR MODEL

The data collected from the second row segment in each plot (15 feet long) was used for the between-year type linear regression models. Data from this row were collected near the end of each month during the operational survey period. All measurements in a plot were nondestructive until the corn was judged to be mature. At this time the row segment was harvested and weighed. The following measurements were made on each visit:

1) Number of stalks

2) Number of stalks with ears or silked ear shoots

3) Number of ears or silked ear shoots

4) Number of ears with kernel formation

5) Number of stalks with ears having kernel formation

Additional measurements were made on certain visits depending on the maturity stage of the crop.

6) Average length of kernel rows on five ears

7) Length of cob for all ears

8) Weight of ears with grain

At maturity, when the row segment plants were harvested and the ears weighed, four ears were shipped to a laboratory for measurement of shelling fraction and moisture content.

POST-HARVEST GLEANINGS

As soon as possible after the farmer harvested the field, 16 post-harvest plots were laid out to estimate harvesting loss. All whole ears and pieces of ears lying inside the unit were picked up. In addition, all loose kernels were picked up in half the unit. This grain was sent to the laboratory for weights and moisture readings.

LABORATORY DETERMINATIONS

Laboratory work provided determinations needed for biological yield indications by the between-year and within-year models and the harvest loss estimates. Ears sampled weekly for the within-year application, were sent to the laboratory for determination of dry matter content. At the lab, two kernel rows were chosen randomly from each ear. The kernels in each selected row were carefully removed from the cob to prevent damage or puncturing and to prevent removal of cob parts with them. Kernels from each individual row were weighed after removal from the cob, and dried in an oven for 72 hours at a temperature of 150^{o}F to standardize moisture content. This temperature and drying period were selected because they were found to reduce moisture in grain at maturity to less than two percent, while not burning the immature grain coming into the laboratory early in the growing season. (XVI) Kernels were weighed after this drying process to determine dry matter content. Determinations from each of the two sampled kernel rows were averaged and expanded by the total number of kernel rows to compute a mean dry grain weight for the ear. Dry weight of multiple ears was then summed to the plant level.

Field measurements for the between-year model included the harvesting and weighing of ears from the row segment at maturity. At this time four of the harvested ears were sent to the laboratory. At the lab, each ear was weighed, shelled, and then a shelled weight taken. The shelled grain was tested in a moisture meter to give a reading of the percent moisture.

Post-harvest gleanings samples were also analyzed in the laboratory. The shelled grain was weighed and placed in a moisture meter to determine the percent moisture.

ELEVATOR WEIGHTS OF HARVESTED GRAIN

The farm operator agreed to get elevator weights of all grain harvested from the research field. The grain from this field was kept separate from all other grain until it was taken to an elevator where it was weighed and moisture tested.

LOGISTIC GROWTH MODEL

THE BASIC MODEL

The logistic growth model has been shown by previous studies to accurately describe a growth process in corn kernel formation. The model gives the relationship of kernel weight and development to the length of time the kernels have been growing by using repeated observations from the current year to estimate the parameters needed to predict the dependent growth variable at maturity.

The form of the logistic model and its graphical representation are given below:

$$Y_i = \frac{\alpha}{1 + \beta\rho^{t_i}} + \varepsilon_i \qquad i = 1, 2, \ldots, n$$

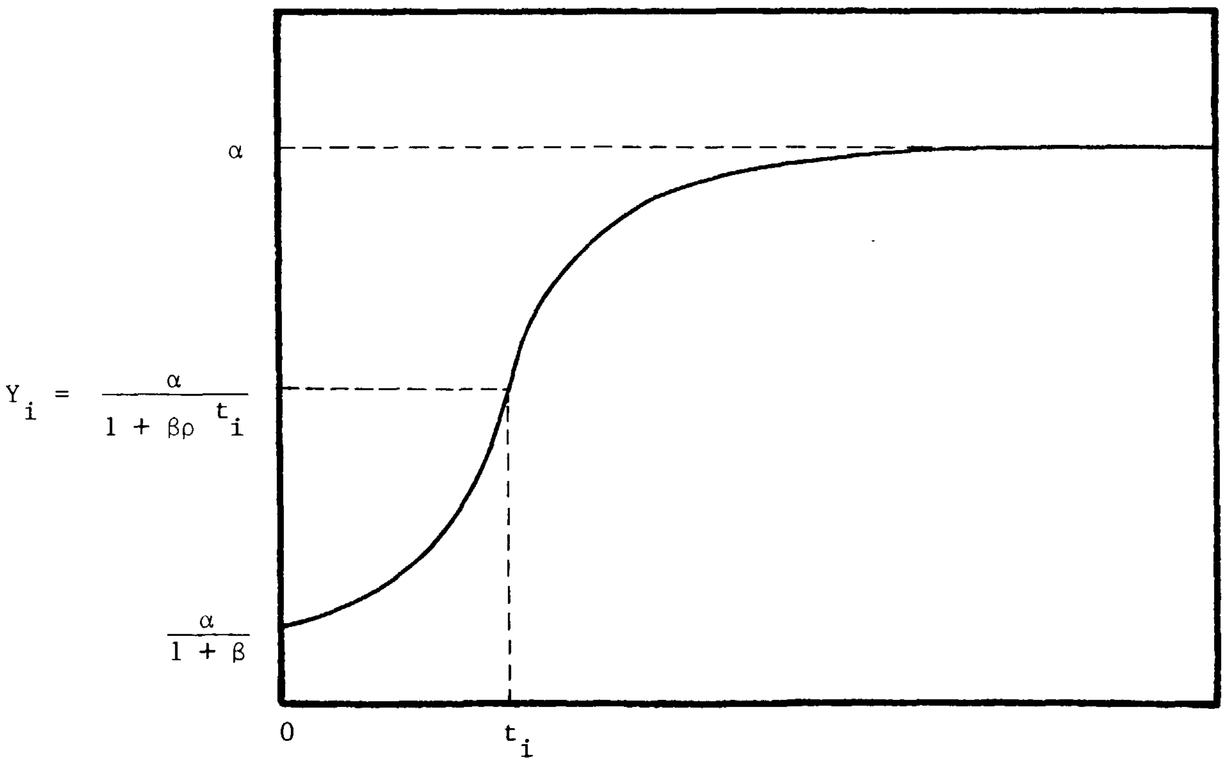
α, β, ρ nonnegative parameters

$0 < \rho < 1$

Y_i = dependent growth variable

t_i = independent time variable

ε_i = disturbance term



The logistic growth model hypothesizes that kernel weight accumulates slowly in a plant during the earliest stages of ear development, increases at an increasing rate for a period of time, and then increases at a decreasing rate approaching an asymptotic maximum value.

Previous research efforts (XIX) have discovered a workable combination of time and growth variables: "time since silking" and "dry kernel weight per plant." "Time since silking", the independent time variable, was defined as the estimated date of silk emergence (see section on Silking Observations) subtracted from the date when the plant was sampled.

The estimated dry kernel weight (in grams) for each ear of a plant processed in the laboratory was summed to provide an estimate of "dry kernel weight per plant." Plants with zero dry kernel weight were considered "non-survivors" and deleted, since weight per plant would be expanded by a "surviving" plant population to produce yield.

To avoid possible dependence between data points, data from all plants sampled from a plot on a particular visit were averaged to compute a mean dry kernel weight and a mean time since silking. These means were used as input variables in the logistic model. The model was fitted with data from an individual field. The process was repeated for each of the nine fields separately.

MODEL WEIGHTS AND ADJUSTMENTS

Estimates of the number of silked plants per acre for each plot were made by adjusting the plant population estimate by the proportion that had silked. Plot data of grain weight per plant were weighted by the plot estimate of silked plants per acre. The following weight was used.

$$W_i = \sqrt{\frac{\text{\# of silked plants per acre}}{10{,}000}} \qquad i = 1, 2, \ldots, n$$

The square root was incorporated to modify the effect of the weights for extreme values of plant population. (In reality, the estimates of plant population had small variances within field and thus the weighting had only a small effect on parameter estimation.)

The weighted model below was fitted to the data using the Marquardt nonlinear procedure in SAS (Statistical Analysis System). (I)

$$(W_i)\ (Y_i) = (W_i) \left[\frac{\alpha}{1 + \beta\rho^{t_i}} + \varepsilon_i \right] \qquad i = 1, 2, \ldots, n$$

This model will be referred to as the unadjusted model. An examination of the model residuals revealed that one of least squares' model assumptions was violated. The assumptions state that $W_i \varepsilon_i$ is normally distributed, with

$$E\,(W_i \varepsilon_i) = 0 \qquad \text{for all } i$$

$$\text{Var}\,(W_i \varepsilon_i) = \sigma^2 \qquad \text{for all } i$$

$$\text{Cov}\,(W_i \varepsilon_i,\ W_j \varepsilon_j) = 0 \qquad \text{for } i \neq j$$

In reality, the disturbance term $W_i \varepsilon_i$ has been observed to have a functional relationship with the independent variable. Thus

$$W_i \varepsilon_i = W_i \varepsilon_i (t_i)$$

$$\text{Var}\,(W_i \varepsilon_i) = \sigma^2_{\varepsilon(t_i)} \qquad \text{an increasing function of the time variable.}$$

This condition is referred to as heteroscedasticity.

To correct for the assumption violation, the following model was used.

$$\frac{(W_i)\ (Y_i)}{\hat{\sigma}_{u_i(t_i)}} = \left[\frac{W_i}{\hat{\sigma}_{u_i(t_i)}} \cdot \frac{\alpha}{1 + \beta \rho^{t_i}} \right] + \left[\frac{W_i}{\hat{\sigma}_{u_i(t_i)}} \cdot \varepsilon_i (t_i) \right]$$

where $\hat{\sigma}_{u_i(t_i)}$ is an estimate of the standard deviation of $u_i(t_i) = W_i \varepsilon_i (t_i)$

The disturbance term in this mdoel is:

$$\frac{u_i\ (t_i)}{\hat{\sigma}_{u_i(t_i)}}$$

with variance

$$\frac{\sigma^2_{u_i(t_i)}}{\hat{\sigma}^2_{u_i(t_i)}}$$

This model will be homoscedastic as long as the ratio remains constant over time. Several methods for estimating $\sigma_{u_i(t_i)}$ have been developed in earlier research. Results from the following will be presented in this report.

(1) Standard Error Adjustment Method

$\hat{\sigma}_{u_i(t_i)}$ was derived as a step function. The relevant range of the independent time variable was broken into two-day intervals and a sample standard deviation from the predicted value was computed for each interval. The assumption is made that within a small time period, $\varepsilon_i(t_i)$ changes so little that it can be assumed constant.

(2) Logistic Adjustment Method

An examination of the residuals from the regression of the unadjusted model suggested that $\sigma_{u(t)}$ itself could have a logistic structure. The absolute value of the residuals from the unadjusted regression were used in a nonlinear regression to fit the model

$$q_i = \frac{\mu}{1 + \nu\eta^{t_i}} + \delta_i \qquad i = 1, 2, \ldots, n$$

where δ_i has mean zero and small constant variance. Once these regression parameters μ, ν, η were estimated, the fitted equation

$$\hat{\sigma}_{u_i(t_i)} = \frac{\hat{\mu}}{1 + \hat{\nu}\hat{\eta}^{t_i}} \qquad i = 1, \ldots, n$$

was used as an estimate of $\sigma_{u_i(t)}$.

More discussion of these models can be found in an earlier paper, "A Within-Year Growth Model Approach to Forecasting Corn Yields". (V) Other methods of adjustment for heteroscedasticity in growth data were developed by Larsen using wheat data sets. (VII, VIII) Although these methods will not be discussed here, further work with these data will include an examination of these adjustment models when applied to corn growth.

Analysis of Forecasting Potential

When the nonlinear model is fitted, three parameters, α, β, ρ, are estimated. As discussed earlier, α is the dry kernel weight at maturity for the average plant. When the entire data set for a growing season is available for analysis, $\hat{\alpha}$ is an "estimate" of dry kernel weight per mature plant. This $\hat{\alpha}$ value is adjusted to the standard moisture level, expanded by the number of plants per acre with grain surviving at maturity, converted to a bushel figure, and adjusted for loss during the harvest process. This figure should then be compared to some type of check data to evaluate the model's ability to estimate yield, and to discover any biases that may exist. This comparison is described in the section below entitled "Analysis of Estimating Capability of Models."

The major purpose of this research was to develop and evaluate forecasting techniques. Therefore, it was important to consider how the logistic model, both unadjusted and with various adjustments, behaved when used to forecast yield at various points throughout the growing season. To make such a forecast, only data collected up to a certain date during the growing season were used in the regression model. The estimated $\hat{\alpha}$ based on the data for a portion of the growing season is the "forecasted" dry kernel weight per plant. The models were fitted to cumulative growth data each week as new data became available. These weekly forecasts for the unadjusted and two adjusted models are given for each field in Tables A1-A9 in the Appendix.

A number of criteria may be used to evaluate the forecasting performance of one of these three models and compare it with another. The five discussed here are of two distinct types. The first type can measure actual forecast error but requires data from the entire season to do it. The second type of criteria can <u>not</u> provide actual forecast error. Instead they provide measurements of the model fit to the data available at a particular period of time. They do not "forecast" the model fit. The value of this type of evaluation tool is that it can be used during a forecast period before criteria of Type 1 are available.

TYPE 1 - The following criterion was used in this analysis to measure forecast error:

1) The absolute percent deviation of the forecast from the estimate at maturity:

$$\left| \frac{\hat{\alpha}_w - \hat{\alpha}_m}{\hat{\alpha}_m} \right| \times 100$$

where $\hat{\alpha}_w$ is the forecasted α value for week w, $\hat{\alpha}_m$ is the estimate of α at maturity (using all weeks of data).

Criterion (1) provides the best indication of actual forecast error. It measures the ability of the model to produce a yield figure using early season data only, by comparing these forecasts with the estimate the model would make if it was fitted to the entire data set. It is the author's opinion that it is the most important of the criteria. The purpose of the model is to forecast crop yields. If the model fails to perform satisfactorily as a forecaster, it makes little difference what the size of the population variance is or whether the model is or is not homoscedastic. Its major disadvantage is that one must have final model estimates at maturity available to compute the deviations and so it is of limited use during the actual forecast period. For this reason criteria of Type 2 were examined.

TYPE 2 - These criteria were used to provide a measure of model fit and performance that is available during the forecast period:

2) The absence of model assumption violation, specifically heteroscedasticity.

3) The size of the residual mean square (RMS) from the regression.

4) The size of the regression coefficients of determination (R^2's).

5) The relative standard error of the primary parameter α:

$$\frac{\hat{\sigma}_{\hat{\alpha}}}{\hat{\alpha}} \times 100$$

where $\hat{\sigma}_{\hat{\alpha}}$ is the estimated standard deviation of $\hat{\alpha}$.

Criterion (2) uses the degree of observed heteroscedasticity to compare the models. This is important because the violation of least squares assumptions can make more traditional evaluation tools unreliable. Unlike criterion (1), the data can be checked for heteroscedastic errors whenever the model is fitted during the forecast period. Criteria (3) and (4) are traditionally used to evaluate how well an hypothesized model actually fits the data. They, also, can be computed during the forecast period before criterion (1) is available. This is their primary value in this analysis. The residual mean squares and R^2's from the model fit with early season data do not "forecast" the fit of the model at maturity, but merely supply information on the model fit with data available up to that point in time. Criterion (5) has been employed in earlier analyses (V, VII, VIII, IX, X, XI, XIX) as a primary indicator of model performance since it can be calculated during the forecast period. It is discussed here to provide continuity, but its value in the presence of varying degrees of heteroscedastic error is now questioned.

Each of these criteria is discussed in more detail in the text that follows. Tables providing additional information appear in the appendix.

The percent deviation of $\hat{\alpha}$ from the estimate at maturity was computed for all weeks in each field separately. These values are tabulated in the Appendix in Table A10.

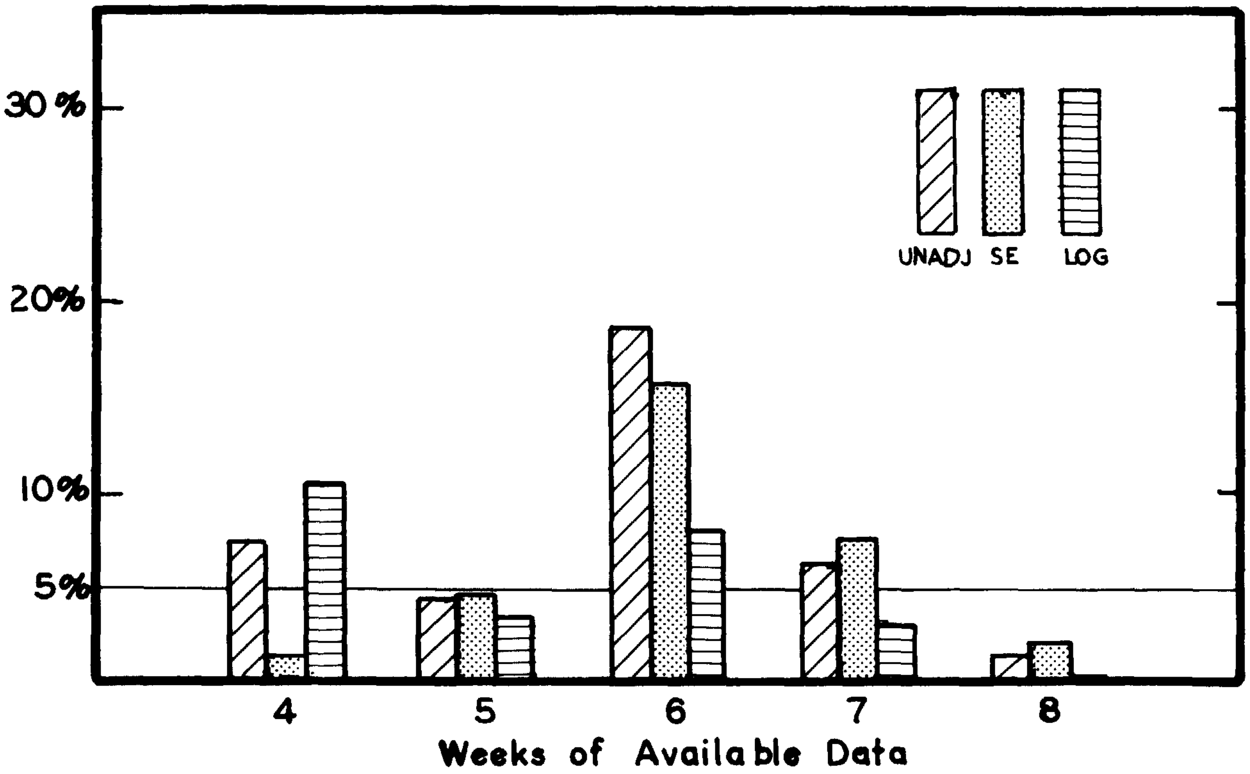
No upward trend in forecast levels was observed as the weekly forecasts approached maturity. For the past several years, such a trend has been observed in the weekly forecasts of corn yield generated by the logistic model. The data collected during these years was designed to run the model on a state or region-wide basis. One would suspect more variability in that type of data set than in data at the field level. As a part of this earlier analysis, simulated data that actually fit the model were generated through stochastic processes. When these data were used to generate weekly forecasts, this phenomenon of upward creeping forecast levels was not observed. (V, VI) The results from the simulated analysis and these new results obtained from field level fittings tend to suggest that the upward trend could be caused by trying to fit together into a single model data that more properly should be divided into several homogeneous groups, fit separately, and the results averaged together to compute state level forecasts. More research should be directed toward this problem using the earlier data sets.

The various patterns of convergence to the final estimated yield produced by the three models' forecasted values can be observed in the following bar graphs. They show by individual field the absolute value of the percent deviation from the final estimate of the forecasts produced with four to eight weeks of data. In analyzing the deviations between the forecasts and final estimate for each model, several points were considered individually for each field. We were interested in knowing 1) at what weekly visit did the deviation drop below the 5% level for the first time, 2) when did it drop permanently below the 5% level, and 3) finally what was the deviation for the last visit before September 1 (an important forecast date for our Agency). The results for each field are tabulated on the corresponding bar graph.

The 1977 growing season was earlier than usual in the Midwest. By the October 1 forecast date, all fields were mature and thus had zero deviation. For the September 1 forecast, all but one field had at least seven weeks of data with deviations well below the 5% level. In that one remaining field, the logistically adjusted model had a deviation just over 5%, while the standard error model's deviation was three times larger. The logistically adjusted model looked somewhat better than the standard error model when it came to the weekly visit with absolute deviation below 5%. It was smaller three out of nine times and equal to the other four times. For the visit when the 5% level was reached permanently, the standard error was earlier only twice. Week by week, over all fields, the absolute deviation of the logistic adjustment was smaller more often than the deviation of the standard error model.

Figure 1--Absolute value of percent deviation of model forecasts from models' final estimates

Field 1

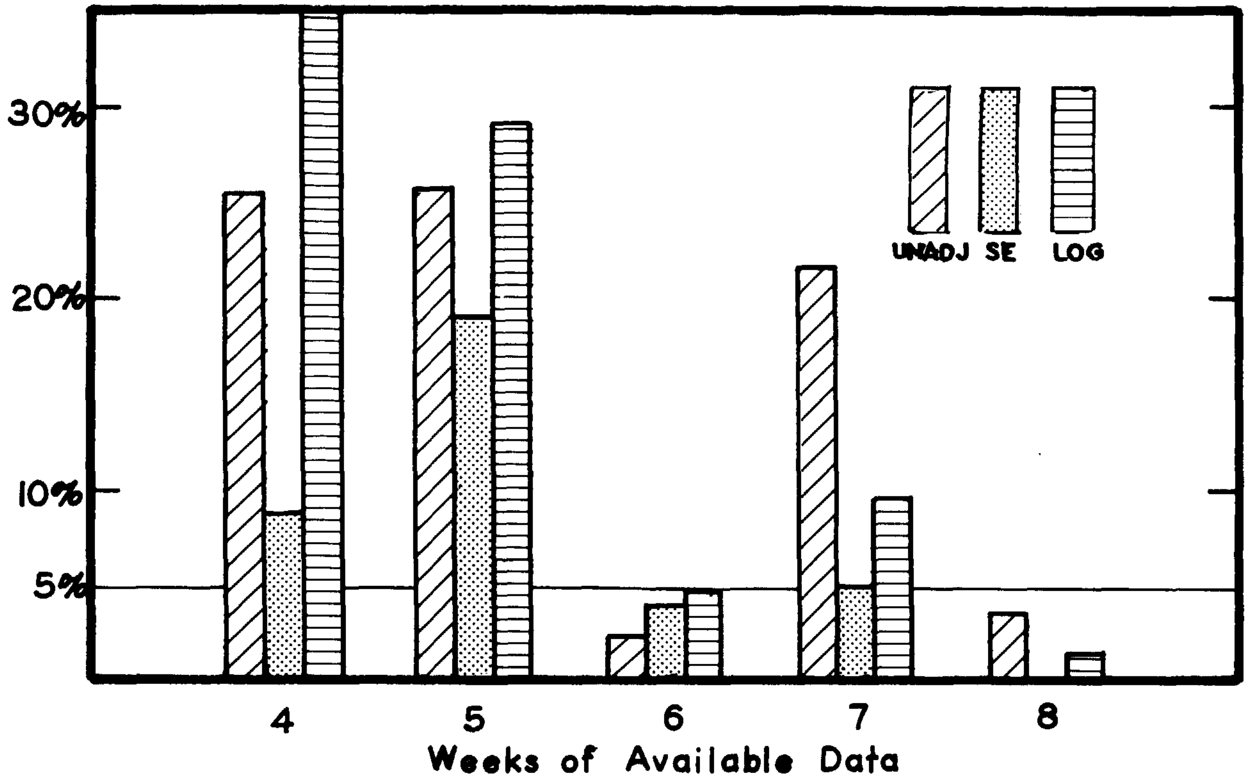


	Model	
	Standard Error Adjusted	Logistically Adjusted
Weekly Visit When Absolute Deviation Was ≤ 5%	4	5
Weekly Visit When Absolute Deviation Remained Permanently ≤ 5%	8	7
Absolute Deviation From Maturity For September 1 Forecast	2.1	.1

Weekly Visit For September 1 Forecast For Both Models Was 8 Weeks

Figure 2--Absolute value of percent deviation of model forecasts from models' final estimates

Field 2

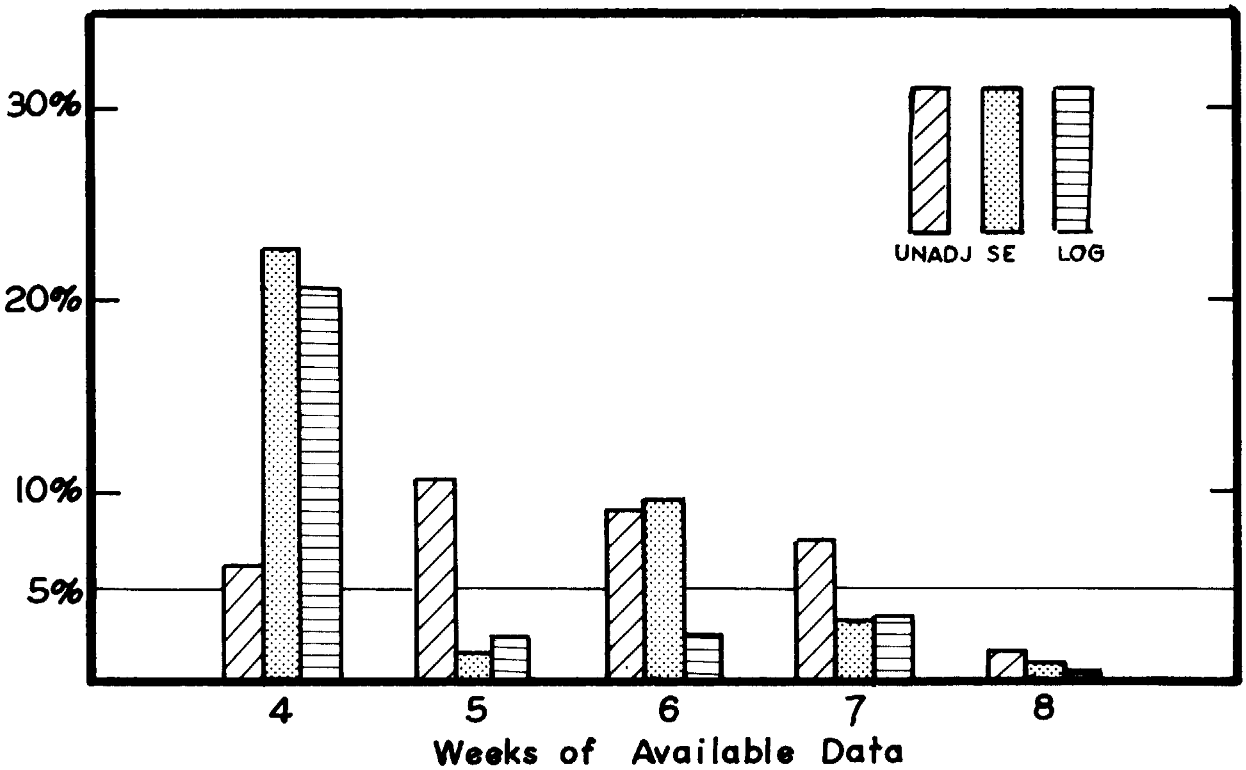


	Model	
	Standard Error Adjusted	Logistically Adjusted
Weekly Visit When Absolute Deviation Was ≤ 5%	6	6
Weekly Visit When Absolute Deviation Remained Permanently ≤ 5%	6	8
Absolute Deviation From Maturity For September 1 Forecast	0.0	1.4

Weekly Visit For September 1 Forecast For Both Models Was 8 Weeks

Figure 3--Absolute value of percent deviation of model forecasts from models' final estimates

Field 3

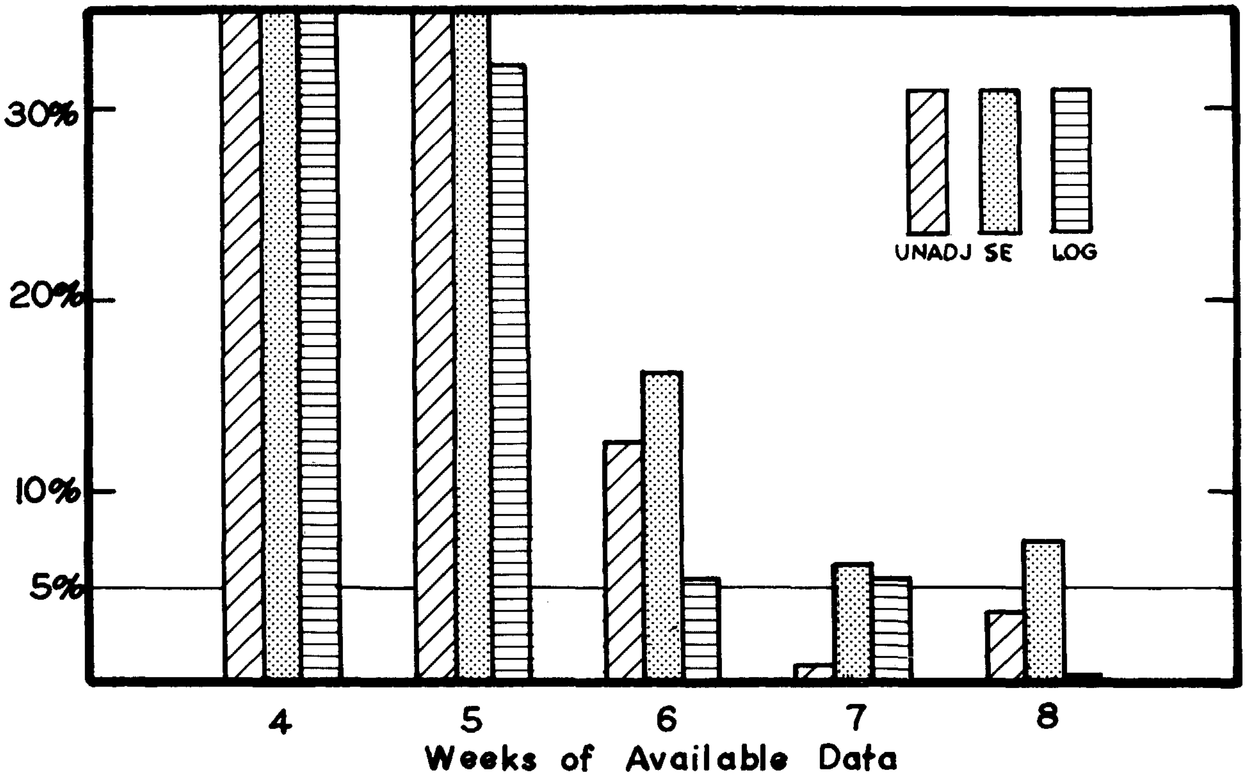


	Model	
	Standard Error Adjusted	Logistically Adjusted
Weekly Visit When Absolute Deviation Was ≤ 5%	5	5
Weekly Visit When Absolute Deviation Remained Permanently ≤ 5%	7	5
Absolute Deviation From Maturity For September 1 Forecast	1.2	0.6

Weekly Visit For September 1 Forecast For Both Models Was 8 Weeks

Figure 4--Absolute value of percent deviation of model forecasts from models' final estimates

Field 4

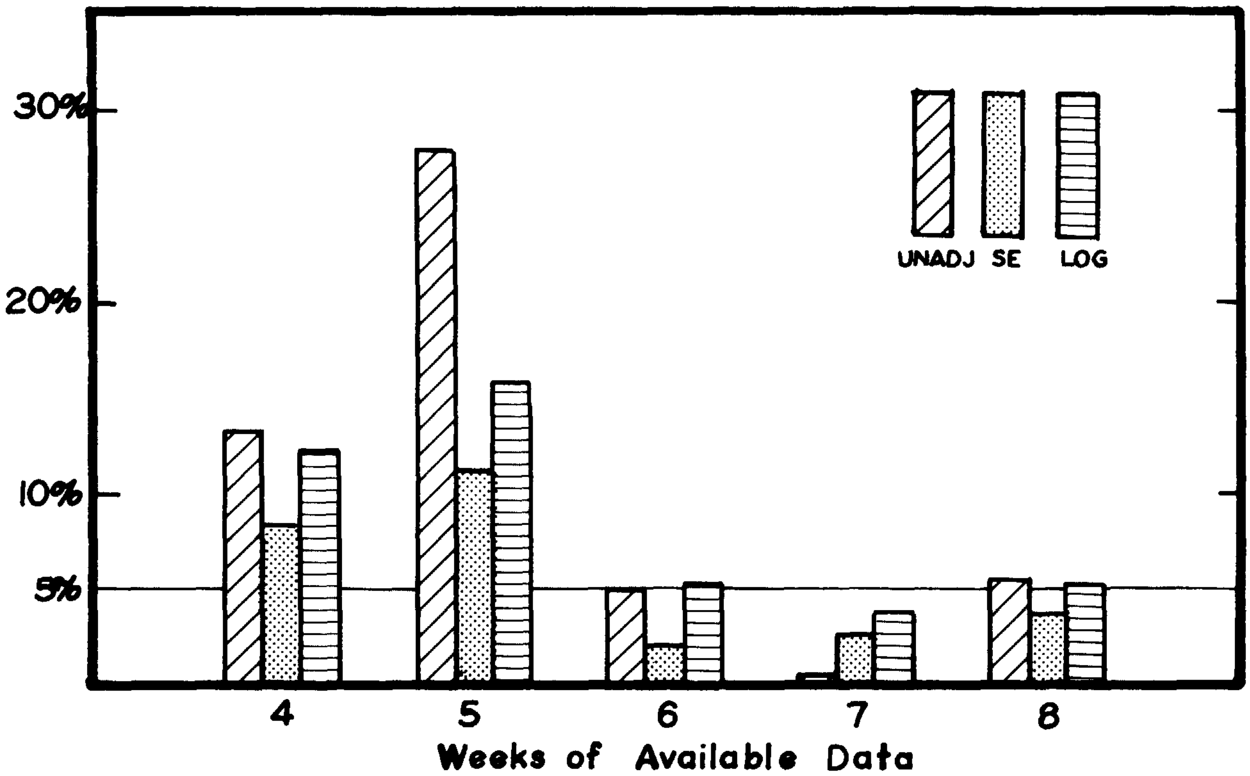


	Model	
	Standard Error Adjusted	Logistically Adjusted
Weekly Visit When Absolute Deviation Was ≤ 5%	9	8
Weekly Visit When Absolute Deviation Remained Permanently ≤ 5%	9	8
Absolute Deviation From Maturity For September 1 Forecast	16.2	5.3

Weekly Visit For September 1 Forecast For Both Models Was 6 Weeks

Figure 5--Absolute value of percent deviation of model forecasts from models' final estimates

Field 5

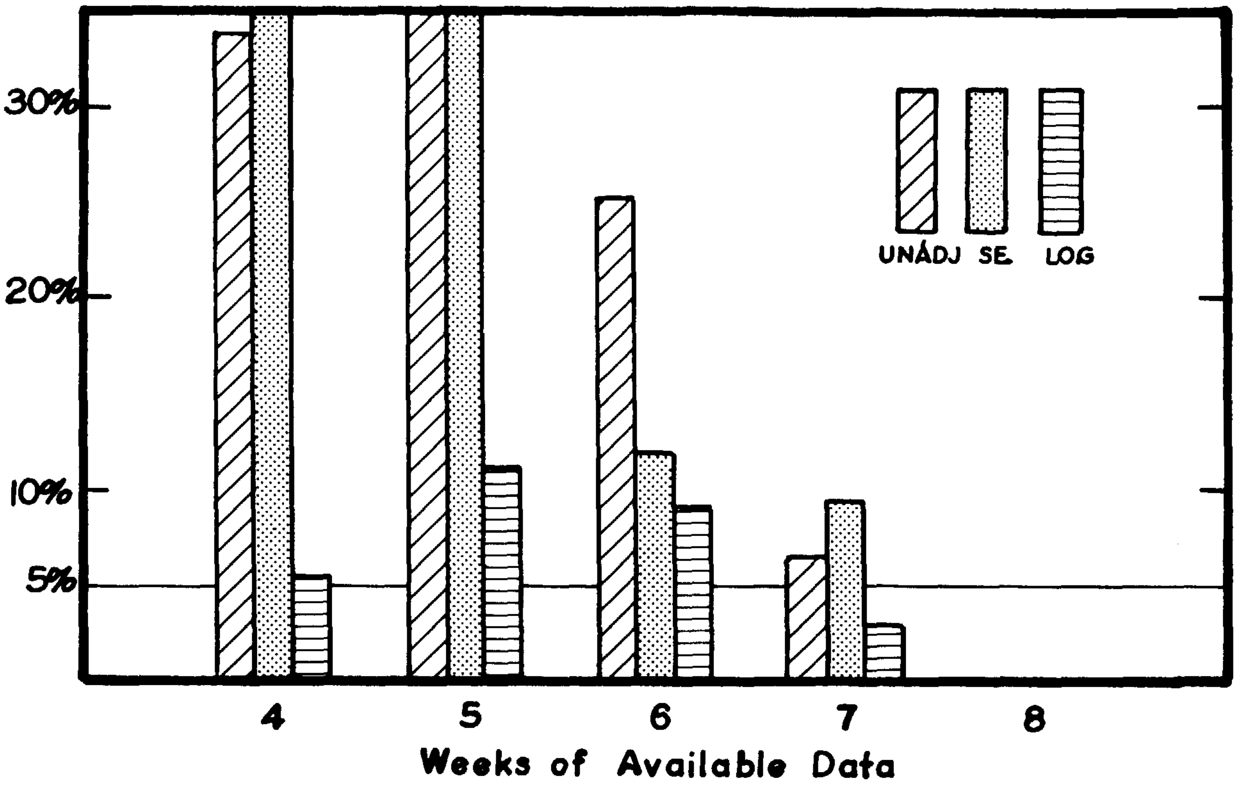


	Model	
	Standard Error Adjusted	Logistically Adjusted
Weekly Visit When Absolute Deviation Was ≤ 5%	6	7
Weekly Visit When Absolute Deviation Remained Permanently ≤ 5%	6	7
Absolute Deviation From Maturity For September 1 Forecast	2.6	3.7

Weekly Visit For September 1 Forecast For Both Models Was 7 Weeks

Figure 6--Absolute value of percent deviation of model forecasts from models' final estimates

Field 6

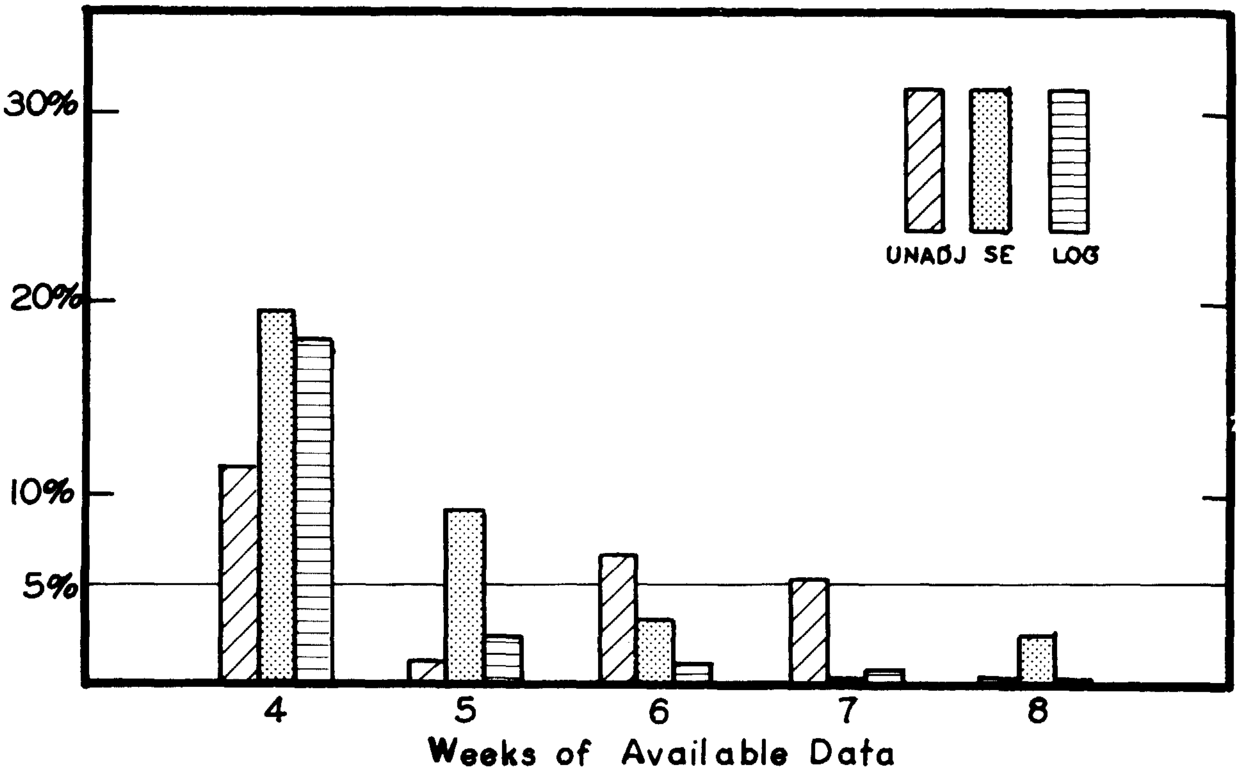


	Model	
	Standard Error Adjusted	Logistically Adjusted
Weekly Visit When Absolute Deviation Was ≤ 5%	8	7
Weekly Visit When Absolute Deviation Remained Permanently ≤ 5%	8	7
Absolute Deviation From Maturity For September 1 Forecast	0.0	0.0

Weekly Visit For September 1 Forecast For Both Models Was 8 Weeks

Figure 7--Absolute value of percent deviation of model forecasts from models' final estimates

Field 7

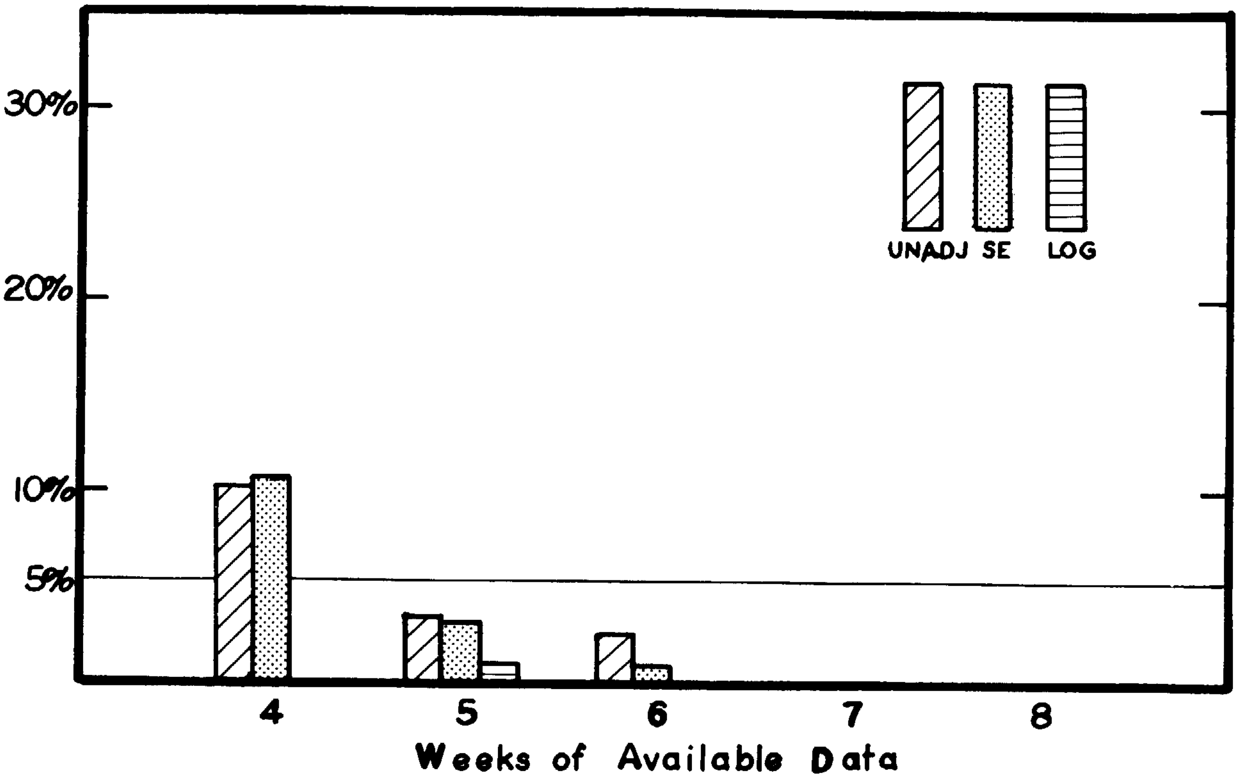


	Model	
	Standard Error Adjusted	Logistically Adjusted
Weekly Visit When Absolute Deviation Was ≤ 5%	6	5
Weekly Visit When Absolute Deviation Remained Permenently ≤ 5%	6	5
Absolute Deviation From Maturity For September 1 Forecast	0.4	1.0

Weekly Visit For September 1 Forecast For Both Models Was 7 Weeks

Figure 8--Absolute value of percent deviation of model forecasts from models' final estimates

Field 8

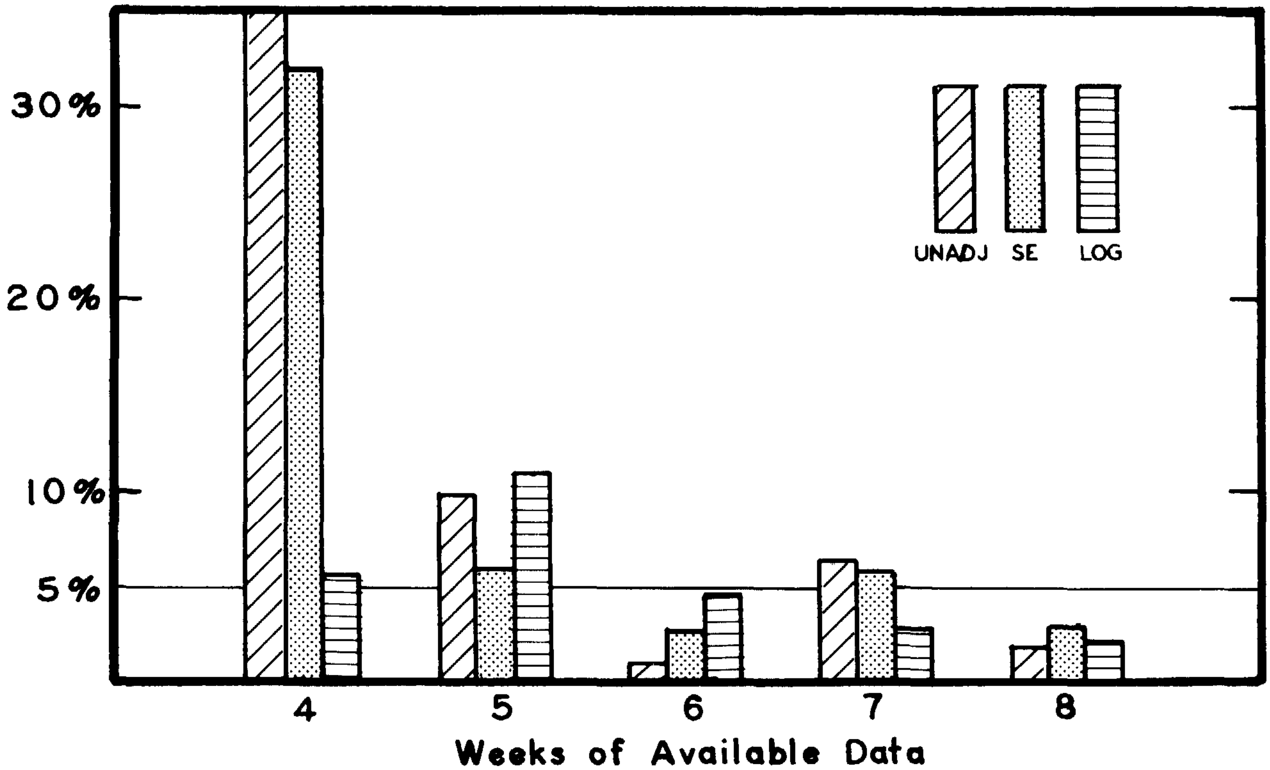


	Model	
	Standard Error Adjusted	Logistically Adjusted
Weekly Visit When Absolute Deviation Was ≤ 5%	5	5
Weekly Visit When Absolute Deviation Remained Permanently ≤ 5%	5	5
Absolute Deviation From Maturity For September 1 Forecast	0.0	0.0

Weekly Visit For September 1 Forecast For Both Models Was 7 Weeks

Figure 9--Absolute value of percent deviation of model forecasts from models' final estimates

Field 9



	Model	
	Standard Error Adjusted	Logistically Adjusted
Weekly Visit When Absolute Deviation Was ≤ 5%	6	6
Weekly Visit When Absolute Deviation Remained Permanently ≤ 5%	7	6
Absolute Deviation From Maturity For September 1 Forecast	2.9	2.2

Weekly Visit For September 1 Forecast For Both Models Was 8 Weeks

A paired t-test was run to test the difference of the two mean absolute deviations. (The test assumed a normal distribution of both samples with equal but unknown variance.) The results showed that no significant difference existed at any significance level above 50%. Thus we found that in a comparison of the two adjusted models by means of criterion #1, the logistic adjustment appeared on the surface to be somewhat better, but the two models were not different enough to draw any statistical conclusions.

The second criterion for model comparison is the absence of model assumption violations, specifically regarding the assumption of constant variance over time. Examining the residuals from the fit of the original data with the logistic model showed this assumption was violated, so the two adjusted models were then fitted. The first indication that these adjusted models had alleviated the problem came in the residual mean squares. The RMS is an estimate of σ^2. The estimates for the unadjusted model increased as more data were added, indicating the later season data possessed a larger amount of variability. The RMS's of both adjusted models remained relatively constant with the addition of later season data. To quantify this change more precisely for the purpose of comparing the adjusted models, two additional statistics were generated. $R(r,t)$ is the correlation coefficient between the absolute value of the regression residuals and the independent time variable. Prob $>|R(r,t)|$ gives the probability that the random sample correlation coefficient will be greater than the computed value for this set of data. The probability is computed under the null hypothesis that the correlation between the two variables is zero. Thus low values would correspond to the rejection of the null hypothesis while large value would lead to a failure to reject. Both of these statistics are tabulated in the Appendix. For the unadjusted model, the correlations were in the range of 0.4 or 0.5, and the computed probability always led to a rejection of the hypothesis of zero correlation. To compare the adjusted models, Prob $>|R(r,t)|$ was used to determine how often each model would reject the hypothesis of zero correlation with 95% confidence. In six of the nine fields, the two models behaved in a similar manner, rejecting the null hypothesis for at most one weekly run of the model. In two of the remaining fields, the logistically adjusted model failed to eliminate the heteroscedasticity more than two-thirds of the time, while the standard error model performed as it did in the other six fields. However, the decision to reject or fail to reject the null hypothesis was often borderline. If one were to use 90% confidence, the logistically adjusted model would have rejected it only once more often than the standard error in one of the fields and twice in the other. Results from the final field were very different. The standard error model worked well to eliminate the heteroscedasticity, while the logistic adjustment did no better than the unadjusted. On this field, there was difficulty getting convergence in the regression fitting the absolute value of the residuals to a logistic curve. This could account for the failure in the logistic adjustment.

The estimate of the population variance (the residual mean square) was examined for each nonlinear regression run. These figures appear in the Tables A1-A9 in the Appendix. In examining several model fittings of the same data set, the residual mean square can be used as an indicator of "goodness-of-fit." A smaller RMS means that more of the variation in the data points can be explained by the model. It is important to emphasize here that care must be taken before any comparison of RMS's is made between two distinct data sets. Adjusting the original data for heteroscedasticity is equivalent to fitting the logistic model to a data set with inherently less variability. Thus a comparison of the RMS from the unadjusted model and either of the two adjusted models would not be appropriate. However, it is appropriate to compare the RMS's of the two adjusted models since the data sets in question were formed in a similar manner. They merely used different estimates of $\sigma(t)$ to try to achieve a population variance equal to one.

The RMS's for the two adjusted models revealed that the standard error model was consistently lower (and closer to one) than the logistic adjustment, usually by .5 or .6. A paired t-test showed that the differences were significant at the .01 level.

The next criterion for model comparison is the size of the regression R^2s. These were computed by week and field for each model. The standard error model had slightly higher correlations than either of the other two, although correlations from all models where high (consistently $\geq$ .85 and often $\geq$ .9). This showed that the model fit was good for all models. The small differences between models were not judged of sufficient importance to allow discrimination.

The relative standard error, $\hat{\sigma}_{\hat{\alpha}}/\hat{\alpha}$ of the primary parameter, α, was computed for each regression run. This estimate was used as an indicator of the confidence one can place on $\hat{\alpha}$ at the specific point in time that data were available to run the regression. It is important to keep in mind that this estimate of variability does not include a forecasting error, and late season changes in field growing conditions could shift the final estimate of α outside a confidence interval determined by $\hat{\sigma}_{\hat{\alpha}}/\hat{\alpha}$ and $\hat{\alpha}$. The results of the calculations are given in the Appendix in Tables A1-A9.

The presence of heteroscedasticity in a data set affects the standard errors of the parameters, and the estimates of those standard errors. Draper and Smith conclude that "if weighted least squares analysis were called for but an ordinary least squares analysis were performed, the estimates obtained ... would not have minimum variance." (II, p. 80) On the other hand, Goldberger states that estimates of such variances may be understated when heteroscedasticity is present. (III) Thus, two methods of reducing the presence of heteroscedasticity within a data set could affect the estimates of the standard error such that the more heteroscedastic adjustment appeared to more precisely estimate α while the true standard error of $\hat{\alpha}$ would be lower for the more homoscedastic adjustment. Because of this, it would be risky to use such estimates as a basis for comparison between adjusted models.

The analysis above failed to produce a clear-cut decision on which of the adjusted models was best overall. Each adjusted model provided some information and desirable characteristics not provided by the other. An attempt was made to utilize both outputs by employing a weighted average of the two $\hat{\alpha}$ forecasts. Initially, each model was given equal weight.

$$\hat{\alpha} = \left[\hat{\alpha}_{se} + \hat{\alpha}_{log}\right]/2$$

The results on Table 1 show the averaged $\hat{\alpha}$ value and its percent deviation from the final averaged estimate. When considered across fields, the averaged $\hat{\alpha}$ forecasts seemed to deviate from the final estimate to a lesser degree than the logistically adjusted model (recall that this did slightly better than the standard error) but a paired t-test showed no significant difference between the absolute deviation from the two different methods. The average difference was 1.07%.

It is of course possible to devise a large number of different weighting schemes to combine the results of the logistic and standard error adjustment models into a single indication of crop yield. Several have been examined by the author. The schemes, having less theoretical basis than a straight average and showing poor results, were uninteresting. Future research should include additional attempts to produce more satisfactory weighting schemes.

Table 1--Grain dry matter per plant at maturity: weighted forecasts and their percent deviations from final estimates

Weeks of Data		Field 1	2	3	4	5	6	7	8	9
4	Forecast (grams)	156.9	192.4	110.4	99.3	117.3	190.9	161.6	176.3	164.2
	Deviation (%)	5.9	24.9	-21.6	-20.7	-10.1	-20.4	-18.8	-8.3	-19.0
5	Forecast (grams)	154.2	190.2	140.3	182.0	113.0	199.0	187.1	196.4	219.5
	Deviation (%)	4.0	23.5	-0.4	45.4	-13.4	25.5	-5.9	2.1	8.3
6	Forecast (grams)	165.6	154.6	149.5	131.9	125.8	175.3	196.7	195.6	200.6
	Deviation (%)	11.7	0.4	6.1	5.4	-3.6	10.5	-1.1	1.7	-1.0
7	Forecast (grams)	158.4	165.3	145.7	125.6	126.4	168.2	200.3	192.3*	211.4
	Deviation (%)	6.9	7.3	3.4	0.3	-3.1	6.1	0.7		4.3
8	Forecast (grams)	149.9	152.9	142.1	130.0	124.8	158.6*	196.3		197.4
	Deviation (%)	1.1	-0.7	0.9	3.8	-4.4		-1.3		-2.6
9	Forecast (grams)	148.2*	154.0*	140.9*	125.2*	130.5*		198.9*		202.5*

* Final estimate

BETWEEN-YEAR LINEAR MODELS

These procedures are used in the current operational program to forecast and estimate yields during the growing season from fruit measurements and plant counts made in the field. The models used are simple linear regression models, with different models used to forecast various components of yield. In order to forecast yield, this procedure depends on a base period of years to supply data to compute the relationships between the various components of biological yield and the field measurements of plant growth and development. These base period data were fit to the linear models, estimating the parameters. The assumption was then made that the current year is a member of the composite population of these base years, and thus the relationships between vegetative measurements and biological yield that existed during the base years continued to exist during the current growing season. Data collected during the current year were combined with the parameters previously estimated in an algebraic expression to compute yield. No new regression was run with the current data. At maturity, the use of these estimated parameters was no longer needed to estimate yield. At this time corn was harvested and the actual counts and weights were used to expand a plot estimate to the acre level.

The two primary components of yield used were the number of ears with grain and the weight per ear at maturity. Once forecasts or estimates of number of ears and weight per ear were calculated, these two variables were multiplied together at the unit level with a conversion factor that expanded the area of the unit to an acre and converted pounds to bushels. These unit level forecasts were averaged across a field to provide the field level forecast, as well as estimates of field level yield variability.

Data collection for this part of the study was done on a monthly basis until harvest, providing a forecast of yield on August 1, September 1, and October 1. The resulting forecasts and estimates appear in the Appendix in Tables A11 through A19.

MODELS TO FORECAST NUMBER OF EARS

Two models were used to forecast the number of ears. Model 1 forecasted the number of ears with grain at maturity based upon the current count of stalks made in the plot. Model 2 used the ratio of stalks with ears or ear shoots to total stalks to predict the ratio of ears present to the expected number of ears with evidence of kernel formation at maturity. The forecasted number of ears could be determined by this ratio.

Table 2--Models to forecast number of ears

Maturity Category	Model 1/
1) No ears	$Y = a_1 + b_1 \text{ (stalks)}$
2) Pre-Blister	$Y = \omega_{21}\left[a_2 + b_2(\text{stalks})\right] + \omega_{22}\left[\dfrac{\#\text{ ears}}{e_2 + f_2\ (\frac{\text{stalks with ears}}{\text{stalks}})}\right]$
3) Blister	$Y = \omega_{31}\left[a_3 + b_3(\text{stalks})\right] + \omega_{32}\left[\dfrac{\#\text{ ears}}{e_3 + f_3\ (\frac{\text{stalks with ears}}{\text{stalks}})}\right]$
4) Milk	$Y = \omega_{41}\left[a_4 + b_4(\text{stalks})\right] + \omega_{42}\left[\dfrac{\#\text{ ears}}{e_4 + f_4\ (\frac{\text{stalks with ears}}{\text{stalks}})}\right]$
5) Dough	$Y = (\#\text{ ears with grain})$
6) Dent	$Y = (\#\text{ ears with grain})$
7) Mature	$Y = (\#\text{ ears with grain})$

1/ Model parameters estimated with historic data are a_i, b_i, e_i, f_i for $i = 1, 2, 3, 4$.

Model weights determined by historically based expected precision are ω_{ij} for $i = 2, 3, 4$ and $j = 1, 2$.

Model 2 has historically provided better forecasts for corn varieties with multiple ears per stalk, while Model 1 is better suited to the situation where there is one ear per stalk.[1/] Predictions for each model were weighted together to derive the forecasted number of ears. The weights used were dependent on the expected precision of each model judged by historically based correlations.[1/] Models 1 and 2 were used exclusively for forecasting when plants were in early maturity stages (milk stage or earlier). When the crop reached dough stage, the actual field count of ears with grain was used for the forecast. At these later stages it could be assumed that the developed ears counted would be the same ears that would be counted at harvest.

Table 2 summarizes the models discussed above.

MODELS TO FORECAST WEIGHT PER EAR

Several models were used to forecast and estimate grain weight per ear, depending on the maturity of the crop at the time of the forecast. Ear weight was given in pounds of shelled grain per ear adjusted to 15.5 percent moisture.

For plots where ears were not yet present or had no actual kernel growth, a straight historical average weight per ear was used. Model 1 was based on the average length of kernel row on five ears sampled outside the unit. Model 2 used the average length of cob measurements made nondestructively over the husks. Models 1 and 2 were weighted together to provide a single forecast for maturity stages three through six. When a unit was judged to be mature, the ears were harvested and weighed. Four ears were sent to the laboratory to estimate shelling fraction and moisture percent. These measurements were used to make a direct estimate of yield with no reliance on parameters estimated with historical data.

Table 3 summarizes.

ANALYSIS OF FORECASTING POTENTIAL

To compute a yield figure from the between-year linear models, historical parameter estimates and weights were needed. The theory suggests that data from each of the research fields should be collected for three years to provide the historical base to estimate parameters. This was not available, and generally would not be available because of crop rotation. Therefore, a substitution was made.

1/ Unpublished research. Methods Staff, Estimates Division, Economics, Statistics and Cooperatives Service, U.S. Department of Agriculture.

Table 3--Models to forecast weight per ear

Maturity Category	Model 1/
1) No ears	$Y = \text{Historic average}$
2) Pre-Blister	$Y = \text{Historic average}$
3) Blister	$Y = \omega_{31}\left[a_3 + b_3 \left(\begin{smallmatrix}\text{average kernel}\\ \text{row length}\end{smallmatrix}\right)\right] + \omega_{32}\left[c_3 + d_3\left(\begin{smallmatrix}\text{average kernel}\\ \text{row length}\end{smallmatrix}\right)\right]$
4) Milk	$Y = \omega_{41}\left[a_4 + b_4 \left(\begin{smallmatrix}\text{average kernel}\\ \text{row length}\end{smallmatrix}\right)\right] + \omega_{42}\left[c_4 + d_4\left(\begin{smallmatrix}\text{average kernel}\\ \text{row length}\end{smallmatrix}\right)\right]$
5) Dough	$Y = \omega_{51}\left[a_5 + b_5 \left(\begin{smallmatrix}\text{average kernel}\\ \text{row length}\end{smallmatrix}\right)\right] + \omega_{52}\left[c_5 + d_5\left(\begin{smallmatrix}\text{average kernel}\\ \text{row length}\end{smallmatrix}\right)\right]$
6) Dent	$Y = \omega_{61}\left[a_6 + b_6 \left(\begin{smallmatrix}\text{average kernel}\\ \text{row length}\end{smallmatrix}\right)\right] + \omega_{62}\left[c_6 + d_6\left(\begin{smallmatrix}\text{average kernel}\\ \text{row length}\end{smallmatrix}\right)\right]$
7) Mature	$Y = \dfrac{\left(\begin{smallmatrix}\text{average field}\\ \text{weight per ear}\end{smallmatrix}\right)\left(\begin{smallmatrix}\text{shelling}\\ \text{fraction}\end{smallmatrix}\right)\left(\begin{smallmatrix}\text{dry matter}\\ \text{fraction}\end{smallmatrix}\right)}{\left(\begin{smallmatrix}\text{adjustment fraction to}\\ \text{convert to 15.5\% moisture}\end{smallmatrix}\right)}$

1/ Model parameters estimated with historic data are a_i, b_i, c_i, d_i for $i = 3, 4, 5, 6$.

Model weights determined by historically based expected precision are ω_{ij} for $i = 3, 4, 5, 6$ and $j = 1, 2$.

The parameter estimates used were based on the three previous growing seasons for the entire state of Missouri. This required the assumption that the nine fields in the study were similar to the average field in Missouri in terms of the relationships between the predictor variables and final yield.

The suitability of this assumption should be the subject of future research. This research should include the following:

1) Use the combined data from all fields for this single growing season to estimate parameters that will then be used on the individual field level. This procedure is somewhat artificial since it could not be done in a real forecasting situation. It would, however, tell what these models are capable of under nearly ideal conditions, and will give an indication of how much departures from the earlier assumption of homogeneity with the entire state might hurt the forecasting capabilities.

2) Compare the relationships between yield and predictor variables in these nine fields with relationships from the entire state (analysis can be done with data collected in the operational program).

It is important to reemphasize that any problem with the use these parameters estimates applies only to the forecasting models. The yield estimates at maturity were made by standard crop cutting and expansion methods that involved only the data collected at that time. Such estimates should be unbiased with variability controlled primarily by sample size.

One of the first things that was noticed during the analysis was a high degree of variability in obtaining field level estimates. The standard deviations were computed between plots in a single field. The average standard deviation for biological yield was just under a 20 bushel per acre for the August 1 forecast. The minimum value was 11.1 bushels and maximum was 33.5. These estimates of the standard deviations at the field level appear to increase for later forecasts. A paired t-test was run to compare the estimated standard deviations of biological yield forecasted at August 1 with the standard deviations from the final estimates to see if there was a significant increase over time. With eight degrees of freedom, the $|t| = 2.03$ was significant at the 90% confidence level. To determine which components of yield were contributing to this increase in variation, a paired t-test was run for the estimates of the standard deviation for both the number of ears and the weight per ear. The largest contributor was average weight per ear, with $|t| = 4.4$ which was significant at the 99% level. The "number of ears" seemed to contribute less, with a t-value that was significant with 80% confidence but not with 90%.

These results were not surprising. Model produced variables (the early season forecasts) in general tend to be less variable than the population on which they are based since the models tend to average small variations in the data. Other factors that could contribute to this increase in measured variability as the season progresses are: the possibility that there existed little variation in the input variables during the early part of the season, measurement errors that tend to eliminate variability, and environmental conditions later in the season that tend to influence yield inconsistently throughout the field.

Whichever of these factors contributed, the situation exists that the reliability of early forecasts is overstated. Also, growing condition changes in later season could easily invalidate any earlier confidence in the estimates. Results show that for the nine fields in this study, six estimates of final yield lay outside one standard deviation of the August 1 forecast.

The actual percent deviation from the final estimates are given in Table 4 on the following page. For the August 1 forecast, the average deviation (absolute) across fields was 15%. By September 1, the average deviation for those fields not harvested was about 7% with only two fields outside the 5% level. Thus using the absolute percent deviation from the final estimate as a gauge to evaluate the forecasting potential of the between-year models, they seemed to do well one month before the final estimate, but poorly when two months away.

Table 4--Percent deviations of crop cutting forecasts of yield and components of yield from final estimates

Field	Forecast Date	Biological Yield	Weight Per Ear	Number of Ears
	Percent Deviations			
1	August 1	23.1	-6.8	32.2
	Sept. 1	-4.9	-7.6	2.5
2	August 1	-18.0	-22.0	3.1
	Sept. 1	-18.2	-21.3	2.5
3	August 1	16.5	-3.6	19.9
	Sept. 1	0.0 1/	0.0 1/	0.0 1/
4	August 1	17.0	7.0	8.0
	Sept. 1	3.7	3.5	1.8
5	August 1	22.0	6.7	14.5
	Sept. 1	7.6	7.6	0.0
6	August 1	4.7	6.3	-2.1
	Sept. 1	0.0 1/	0.0 1/	0.0 1/
7	August 1	-1.4	-2.2	-0.9
	Sept. 1	0.0 1/	0.0 1/	0.0 1/
8	August 1	-16.8	-17.7	0.0
	Sept. 1	0.0 1/	0.0 1/	0.0 1/
9	August 1	17.1	-0.3	17.9
	Sept. 1	-0.1	0.0	0.0
Average (Absolute)	August 1	15.2	8.1	11.0
	Sept. 1 2/	6.9	8.0	1.4

1/ Field was judged mature at Sept. 1 visit.

2/ Fields harvested on Sept. 1 visit were excluded from average.

HARVEST LOSS ESTIMATION

After each field was harvested, sixteen plots were laid out in the field to make measurements of the reduction in yield due to grain loss during harvesting procedures. These post-harvest plots were paired with the pre-harvest plots, and an attempt was made to make all observations within two to three days after harvest. The actual grain found on the ground inside the unit was picked up and sent to the lab for weights and moisture testing. The figure for harvest loss was found by expanding the weight of the grain found in this area to an acre basis and adjusting for moisture percent. No historical parameters were used for this estimate.

$$HL = \left[\begin{pmatrix} \text{weight of grain} \\ \text{from ears} \end{pmatrix} + (2) \begin{pmatrix} \text{weight of loose} \\ \text{grain on ground} \end{pmatrix} \right] \begin{pmatrix} \text{conversion} \\ \text{factor} \end{pmatrix}$$

where the grain weight was adjusted to 15.5% moisture, expanded to the acre level, and expressed in bushels. The multiplier (2) was used for weight of loose grain since it was collected in only half the unit.

The harvest loss procedures gave an estimate of visible grain left on the ground after harvest. This does not necessarily constitute all of harvest loss, the portion of biological yield produced by the plants that was not measureable by the farm operator after harvest. Measurement errors as well as field conditions would tend to increase the differences in the two concepts and can lead to an underestimation of actual harvest loss. Some of these conditions are:

1) Mud or snow on ground such that grain is no longer visible.

2) Bird or animal destruction of grain. This can be substantially reduced by timely collection of data.

3) Powdering of grain by the combine. Once the kernels are crushed, grain lost in this way cannot be measured.

Table 5 on the following page shows the estimates of harvest loss for all nine fields.

Table 5--Estimates of harvest loss and variation in bushels per acre

Field	Mean Harvest Loss in Bushels	Standard Deviation in Bushels
1	21.1	8.4
2	7.7	4.7
3	4.0	2.8
4	10.8	7.1
5	24.7	5.7
6	1.7	2.1
7	6.1	4.6
8	0.9	0.3
9	6.2	4.2
Average	9.2	4.4

A nested analysis of variance was run across all fields. The within-field variation accounted for only 23% of the total variation, with 77% occurring between fields. The average harvest loss pooled over all fields was 9.3 bushels per acre with standard deviation of 4.6 bushels per acre. This produced a high CV of 50% for the grain recovered after harvest.

Using the above estimate of variability, calculations were made to determine the within-field sample sizes needed for the given precision at 95% confidence.

Table 6--Harvest loss sample size estimates

Maximun allowable error in bushels at 95% confidence	1	3	5	8	10	12
Sample size needed	82	10	4	2	1	1

The results show that estimates of harvest loss could have been affected by a 2 to 3 bushel error due to sampling.

This harvest loss estimate was available for use in adjusting the final biological yield estimates for each field, but was not available for any of the forecasts since it could only be calculated after harvest was completed. For these, a historical statewide average of percent of biological yield actually harvested was used to adjust for harvest loss. This average, like the other historically based parameters, was computed from the three year base data for the entire state of Missouri. For the 1977 growing season in these nine fields, the historical average underestimated the actual harvest loss.

ANALYSIS OF ESTIMATING CAPABILITY OF MODELS

Both the "between-year" linear models and the "within-year" growth models were examined to analyze their forecasting capability. To do this, the forecasts from the models were compared with the final estimates produced by the models at maturity. The second part of examining a forecasting model is to use some type of check data to tell if there were any biases in the model estimates of final yield and to estimate the variability present.

The check data used were the farmer harvested production for the field as weighed at the elevator. This total production weight adjusted to standard moisture, was divided by the farmer estimate of field acreage to produce a yield per acre figure. Data collection procedures for obtaining the elevator weights worked well and seemed to provide a reliable source of check data for field level estimates. One possible problem that could affect the yield figure from the elevator weights is the farmer's estimate of field acreage. An overestimate of acreage, i.e. a fencepost to fencepost type estimate, would produce an underestimate of yield. Future research should examine such a possibility.

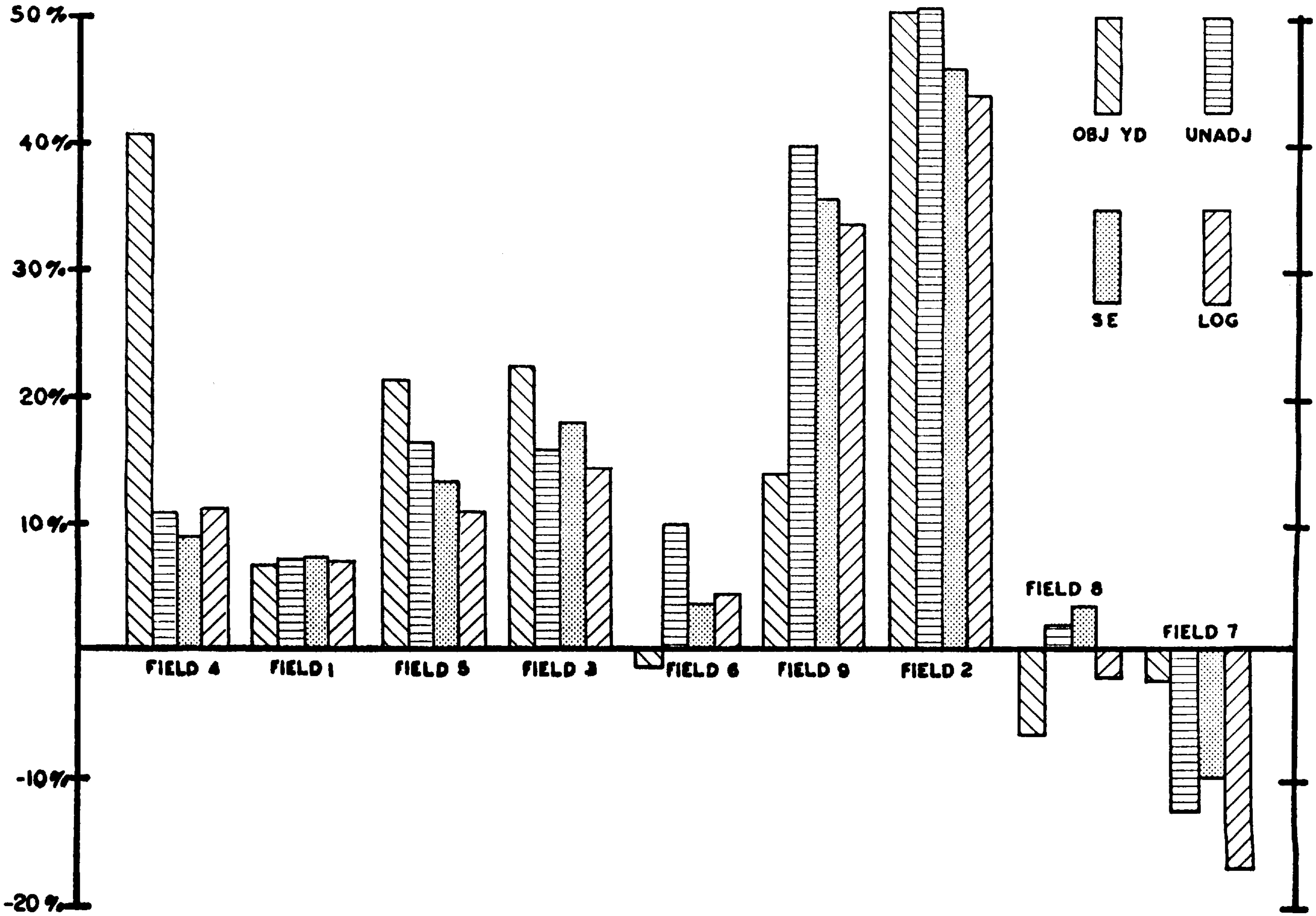
Table 7 shows the yield based on grain weighed at the elevator and the final estimates from the models adjusted by the harvest loss estimates for all fields. The bar graph (Figure 10) shows each model's percent deviation from the elevator yield figure. The final estimates from the "between-year" (objective yield) procedures were made by a direct expansion of crop cutting measurements.

The bar graph is arranged by fields with increasing yield (as measured at the elevator). It shows a wide range of deviations of all models from the check data. The largest deviation, over 50%, occurred in field 2. The smallest deviation was approximately one percent. In all fields, the deviation was over 5% from at least one model. Field 8 had all growth models under 5% absolute deviation but the linear model deviation was over 6%. It was interesting to note that although all model estimates seemed to deviate greatly from the yield figure determined at the elevator, there was less evidence of such deviation among themselves within a field. All three growth model estimates remained relatively consistent in relationship to each other. The crop cutting estimates in all but two fields were close to the growth model estimates. In one of these two fields the crop cutting estimate was 20 to 30 percentage points lower while in the other field it was about 30 points higher.

Table 7--Final yield estimates and percent deviations from elevator check data

Model		Field 1	2	3	4	5	6	7	8	9	Average
Unadjusted Logistic	Estimate	73.1	135.3	82.8	50.0	80.8	87.8	109.1	112.1	112.2	
	Deviation	7.3	50.2	16.0	10.9	16.4	10.0	-12.5	1.1	39.7	15.5
Standard Error Logistic	Estimate	73.2	131.2	84.3	49.2	78.8	82.9	112.4	113.6	108.9	
	Deviation	7.5	45.6	18.1	9.1	13.5	3.9	-9.9	2.4	35.6	14.0
Logistically Adjusted Logistic	Estimate	72.9	129.1	81.7	50.0	77.0	83.3	103.7	107.9	107.1	
	Deviation	7.0	43.3	14.4	10.9	11.0	4.4	-16.8	-2.7	33.4	11.7
Crop Cutting	Estimate	72.7	135.3	87.5	63.4	84.2	78.9	122.0	103.1	91.5	
	Deviation	6.8	50.2	22.5	40.6	21.3	-1.1	-2.2	-7.0	13.9	16.2
Elevator Check Data	Estimate	68.1	90.1	71.4	45.1	69.4	79.8	124.7	110.9	80.3	

Figure 10--Deviations of final yield estimates from elevator check data



The deviations from the check data were much larger than desirable. Given the assumption that the check data were valid there were several possibilities why the deviations might be large:

1) The variability within a field was too great to estimate field yield accurately with only sixteen plots per field.

2) There was an overestimation of the precision of the estimators.

3) The variability was correctly estimated but some type of bias existed.

These three possibilities can be better addressed by looking at the crop cutting estimates made by the between-year procedures. These techniques are very simple and straightforward, and thus any biases should be easier to locate than in the growth models. The other reason to concentrate less on the within-year models at this point is that it was not practical to make plot level runs of the logistic models for all fields. This was due to the computer costs involved and the problems with convergence that were experienced when trying to fit the logistic model to a very small number of data points. Thus most of the analysis concentrated on the crop cutting estimates, and results were transferred to the growth model estimates when it appeared appropriate.

To check out the first possibility, the estimates of the standard deviations for the final "biological yield" figures for crop cutting were examined. (Analysis of harvest loss has already shown that it contributed only a small percentage of within field variability). These biological yield estimates do indeed show a great deal of variability on the field level. An analysis of variance was run to calculate a variance within fields across all fields. (This requires the assumption that variance within a field is equal for all fields.) The estimated mean was 102.4 bushel per acre with standard deviation 22.8. The analysis of variance showed slightly more variation within fields than between fields, an unexpected result. However, the between field variation was based on a nonrandom sampling procedure. The following table gives the within field sample size to obtain estimates within a 95% confidence interval of various lengths. To get within ± 5 bushels would have required over 80 units in the research field. Twenty units would have gotten within ± 10 bushels. These estimates came from fields of 26 acres or less. Using larger fields in the future could easily increase the within field variability.

Table 8--Biological yield (by crop cutting techniques) sample size estimates

Maximum allowable error in bushels at 95% confidence	1	3	5	8	10	12	15	20
Sample size needed	2003	223	81	32	20	14	9	5

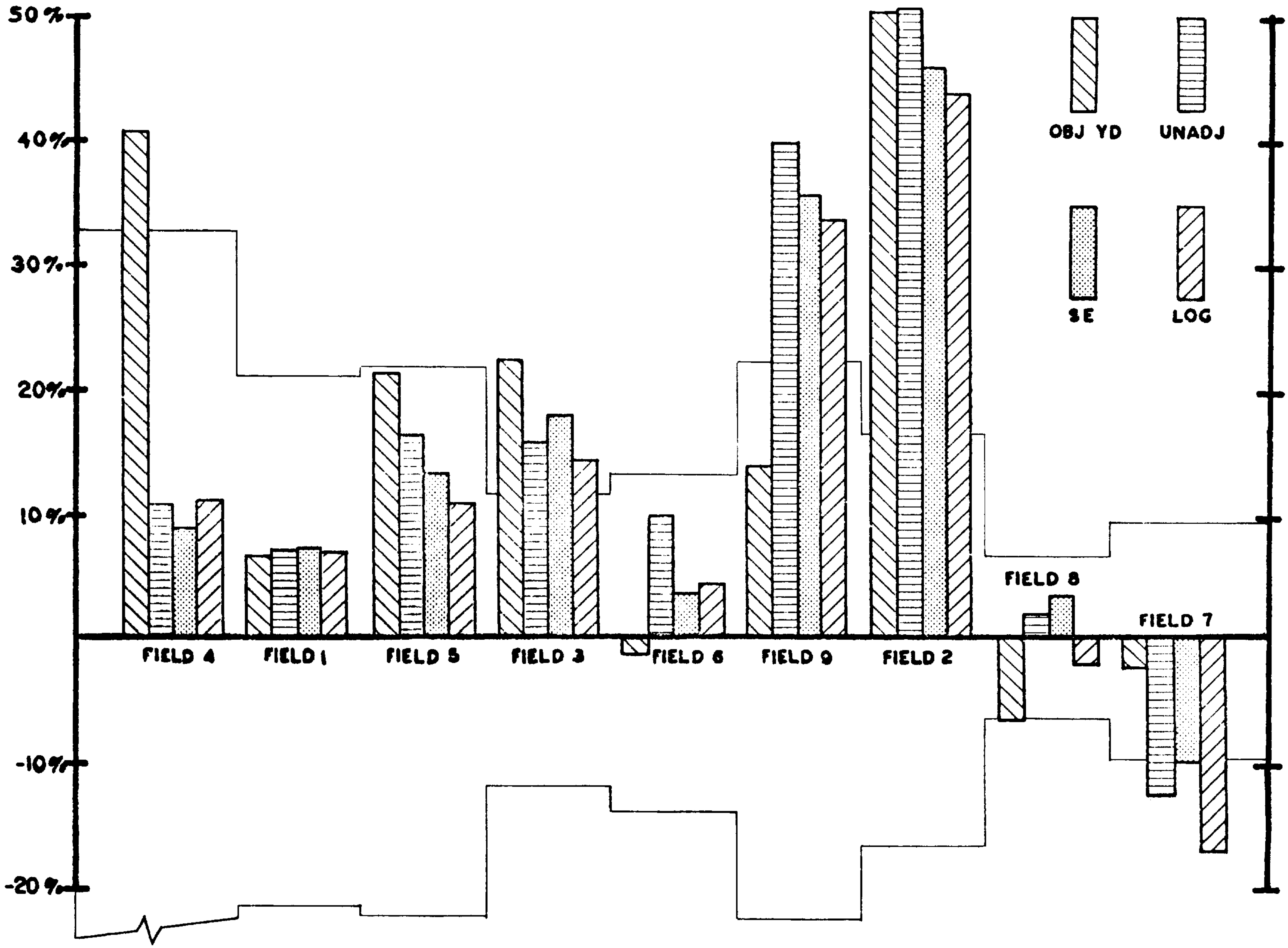
Given our sample size of sixteen units per field, it now appeared unrealistic to have looked for even unbiased estimates to have absolute deviation from the true value within 5% or even 10%. To examine what could be expected from the model estimates if no bias existed, 95% confidence intervals for harvested yield were calculated using the within field estimate of variance $\hat{\sigma}^2$, from each field. Half the interval width, $\hat{\sigma}(2.131)/\sqrt{16}$, is given in Table 9 for eac field. The bar graph has been repeated showing the confidence intervals.

Table 9--$\hat{\sigma}(2.131)/\sqrt{16}$ used in construction of 95% confidence intervals for deviations of final yield estimates (in bushels and percent)

	Field								
	1	2	3	4	5	6	7	8	9
Bushels	14.1	15.3	8.5	15.1	15.1	10.7	12.0	7.4	17.8
% Of elevator yield figure	20.7	17.0	11.9	33.5	21.8	13.4	9.6	6.6	22.2

Only three of the nine fields had the estimates from all models within the confidence band. The crop cutting estimate was inside the band for only five fields. Thus for almost one half of the fields, the estimates lay outside the 95% confidence interval, even though estimates of within field variation had made these intervals quite large. In fact, estimates from two of the fields did not even lie in a 99.9% confidence interval. Such outcomes were highly unlikely if the estimates were in fact unbiased, therefore one must conclude that variation due to sample size did not adequately explain the large deviation in the model estimates.

Figure 11--Deviations of final yield estimates from elevator check data shown with 95% confidence interval



We are left with the other two possibilities cited: the estimates were unbiased but the variability within fields was greatly underestimated, or the estimates were biased.

The bar graph in Figure 11 not only shows large deviations from the true value, but also that those deviations are in fact almost always in the positive direction, overestimating the true yield. If the estimates were unbiased, one would expect to see both over and underestimation of the true yield.

It is the author's conclusion that the four models being evaluated tended to consistently overestimate the true yield figure. Averaging the percent deviation for the four models across the nine fields gave some indication of the size of this bias.

The results are tabulated in Table 7. The average deviation across fields ranged from a low of 11.7 bushels per acre from estimates produced by the logistically adjusted growth model to a high of 16.2 bushels produced by the between-year crop cutting model. In six of the nine fields, deviations produced by estimates from all models were positive, while Field 7 was the only field in which all models underestimated yield. Yield in Field 2 was overestimated by 40% to 50% by all of the models. The overestimation of yield differed considerably from field to field, but the bias was consistent for different models within the same field. Future research efforts should be undertaken to quantify this bias and pinpoint its sources.

SUMMARY AND RECOMMENDATIONS

The logistic growth models were evaluated to determine their forecasting abilities. The 1977 growing season in Missouri was earlier than usual, allowing seven weeks of data to be available to run the models for the September 1 forecast date. With this much data available, all forecasts (with the exception of one field) were within 5% of the model's final estimate. This was considered a good September 1 forecast. If fewer weeks of data had been available, the forecast would have been less reliable.

As data from each field were run to produce weekly forecasts of yield, there was no evidence of an upward creeping effect of the forecasts as maturity was approached. This effect has been noticed in growth data collected since 1975, and was considered a serious problem. The data collected in these years were fitted for state level forecasts and so one would expect more variability in that type of data than in data collected at the field level. These results tend to suggest that the upward trend could be caused by trying to fit together into a single model data which actually fit several models with distinct parameters. The possibility of running more than one model per state for these earlier data sets should be explored. Data could be aggregated based on criteria using weather conditions, agricultural practices, etc.

Two different adjustments to the model were made to alleviate heteroscedasticity. The unadjusted model and the two adjusted models were compared. The analysis failed to produce a clear-cut decision on which of the adjusted models was best overall. The standard error model came out ahead in terms of smaller residual mean squares and less heteroscedasticity. The logistically adjusted model had smaller deviations of forecasts from the final model estimates, although the differences were not large enough to be statistically significant. At this time, two recommendations are made:

1) Future analysis of these data should involve the use of the techniques discussed by Larsen in his analysis of wheat growth data to try other adjustments for heteroscedasticity. It is hoped that such an analysis may produce a model which is best overall for corn growth.

2) Until further research is completed, it is the author's opinion that an equal weighted average of the forecasts from the two adjusted models provides the most information.

The between-year linear regression models were run with the data collected and evaluated as to their forecasting potential. Parameters used in the models were historically derived for the entire state of Missouri. This may have affected their forecasting performance. Results from the analysis indicated that within-field variability was understated for early forecasts. In six of the nine fields, the final yield estimate produced by the models was outside one standard deviation of the August 1 forecast. By the September 1 forecast the average deviation from the final estimate was approximately 7%, similar to results with the within-year growth model.

The final estimates (adjusted for harvest loss) from both the between-year linear models crop cutting techniques and the within-year growth models were compared to each other and to independent check data on total field production as measured at an elevator. The within-year growth model and the crop cutting techniques gave similar estimates of field biological yield. Neither did consistently better than the other. Estimates of within field variability obtained from the crop cutting estimates were very high. The pooled estimate of the standard deviation was 22.8 bushels per acre. Thus a large sample size would be necessary to get precise field level estimates.

A more disturbing result from this analysis was that all of the models examined were estimating something quite different from harvested yield per acre as measured by elevator weight of grain and the farmer's estimate of field size. As reported above, all models produced similar field level estimates of yield. Using the estimates of within field variability obtained from the crop cutting procedures, a 95% confidence region was calculated about the elevator yield figure for each field.

Only three of the nine fields had estimates from all models within the confidence band. The objective yield estimate was inside the interval for only four fields, while estimates from two of the fields even lay outside a 99.9% confidence interval. The biases in the estimates seemed to consistently overestimate the elevator yield figure, with average deviation running from 11% to 17%, depending on the model. The deviations of the crop cutting procedures were largest.

Research should be undertaken to identify the sources of such biases, especially those that exist in such straightforward techniques such as crop cutting. Possible sources of bias that should be examined include:

1) Underestimation of harvest loss.

2) Estimation procedures for determining percent moisture and shelling fraction. This would only affect the bias in the objective yield model.

3) Possible errors in obtaining elevator data.

4) The possibility that the location of field plots may not be random.

5) The accuracy of the farmer's estimate of field size.

6) The accuracy of field scales in weighing harvested ears. Again, this would only affect a bias in the objective yield model.

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APPENDIX

Table A1--Estimates at cutoff dates - field 1

Model	Weeks Of Data	$\hat{\alpha}$	$\sigma_{\hat{\alpha}}/\hat{\alpha}$	RMS	R^2	R(r,t)	P> |R(r,t)|
Unadjusted	2*						
	3	146.9	74.1	328.6	.926	.468	.0008
	4	159.2	19.2	557.4	.929	.611	.0001
	5	154.6	9.6	925.1	.923	.637	.0001
	6	175.2	10.2	1409.0	.913	.519	.0001
	7	157.1	6.0	1987.8	.895	.588	.0001
	8	150.3	5.2	2425.7	.884	.638	.0001
	9	148.3	3.9	2390.4	.892	.532	.0001
Standard Error Adjustment	2*						
	3	177.6	38.3	1.4	.921	.108	.4630
	4	150.8	10.9	1.4	.940	.138	.2764
	5	155.4	3.1	1.4	.972	.041	.7197
	6	171.5	6.3	1.3	.971	-.005	.9633
	7	159.7	5.0	1.4	.935	.026	.7829
	8	151.7	4.5	1.4	.923	.072	.4193
	9	148.6	3.6	1.4	.924	.070	.4023
Logistic Adjustment	2*						
	3	470.8	181.8	2.4	.881	.022	.880
	4	163.0	22.4	2.6	.878	-.104	.4136
	5	153.0	11.2	2.6	.877	-.121	.2846
	6	159.6	8.1	2.5	.878	-.078	.4500
	7	152.2	6.5	2.2	.875	-.018	.8535
	8	148.1	5.5	2.0	.879	.062	.4861
	9	147.9	5.0	2.5	.866	-.164	.0499

* Convergence not obtained

Table A2--Estimates at cutoff dates - field 2

Model	Weeks Of Data	$\hat{\alpha}$	$\sigma_{\hat{\alpha}}/\hat{\alpha}$	RMS	R^2	R(r,t)	P> |R(r,t)|
Unadjusted	2*						
	3*						
	4	114.6	27.1	257.7	.912	.629	.0001
	5	192.9	20.6	408.0	.939	.641	.0001
	6	157.2	8.2	791.2	.926	.544	.0001
	7	186.5	9.6	1374.7	.909	.513	.0001
	8	148.3	5.3	1979.4	.883	.586	.0001
	9	153.6	4.6	2344.8	.882	.599	.0001
Standard Error Adjustment	2*						
	3*						
	4	170.6	46.1	1.5	.880	.078	.5403
	5	185.2	15.9	1.6	.912	.082	.4691
	6	150.7	3.0	1.5	.982	-.016	.8773
	7	164.7	3.1	1.3	.967	.153	.1070
	8	156.8	4.8	1.5	.924	.020	.8256
	9	156.8	4.0	1.5	.922	.067	.4249
Logistic Adjustment	2*						
	3*						
	4	214.2	75.4	2.9	.850	-.120	.3444
	5	195.2	19.5	2.5	.891	-.061	.5935
	6	158.4	8.7	2.4	.901	.112	.2788
	7	165.8	6.9	2.2	.888	.121	.2020
	8	149.0	6.6	2.8	.864	-.073	.4158
	9	151.1	5.4	2.4	.871	.027	.7480

* Convergence not obtained

Table A3--Estimates at cutoff dates - field 3

Model	Weeks Of Data	$\hat{\alpha}$	$\hat{\sigma}_{\hat{\alpha}}/\hat{\alpha}$	RMS	R^2	R(r,t)	P> |R(r,t)|
Unadjusted	2	48.0	11.9	105.4	.930	.580	.0005
	3	111.1	45.7	380.3	.880	.559	.0001
	4	131.8	18.9	377.4	.937	.400	.0011
	5	155.5	11.5	489.3	.948	.387	.0004
	6	153.3	7.0	873.4	.933	.376	.0002
	7	150.8	4.9	944.1	.939	.375	.0001
	8	142.7	3.6	1086.6	.936	.387	.0001
	9	140.5	3.1	1278.3	.930	.450	.0001
Standard Error Adjustment	2	63.7	29.2	1.3	.927	.326	.0683
	3	85.3	18.6	1.2	.927	.269	.0643
	4	110.7	6.0	1.3	.957	.220	.0807
	5	145.5	6.4	1.4	.961	.230	.0398
	6	156.8	5.0	1.4	.963	.076	.4606
	7	148.0	3.2	1.4	.968	.106	.2670
	8	144.8	2.6	1.4	.966	.046	.6083
	9	143.1	2.4	1.4	.962	.052	.5395
Logistic Adjustment	2	64.0	24.4	1.8	.927	.326	.0686
	3	75.7	16.2	1.8	.902	.241	.0991
	4	110.0	7.9	2.0	.931	.140	.2699
	5	135.1	6.7	2.0	.938	.237	.0340
	6	142.1	6.1	2.3	.923	.137	.1833
	7	143.4	4.5	2.3	.929	.121	.2020
	8	139.4	3.7	2.3	.928	.087	.3262
	9	138.6	3.6	2.2	.924	.082	.3266

Table A4--Estimates at cutoff dates - field 4

Model	Weeks Of Data	$\hat{\alpha}$	$\sigma_{\hat{\alpha}}/\hat{\alpha}$	RMS	R^2	R(r,t)	P> |R(r,t)|
Unadjusted	2*						
	3	126.5	60.1	70.9	.909	.433	.0021
	4	187.4	45.3	130.3	.929	.529	.0001
	5	251.5	35.5	208.8	.950	.521	.0001
	6	141.9	11.1	862.9	.870	.368	.0002
	7	127.4	6.6	916.2	.883	.400	.0001
	8	130.6	5.6	1083.7	.883	.427	.0001
	9	126.1	4.6	1318.3	.872	.478	.0001
Standard Error Adjustment	2*						
	3	220.3	55.2	.9	.994	-.006	.9664
	4	191.8	35.9	.9	.940	.012	.9275
	5	197.1	15.8	.9	.949	.134	.2354
	6	144.3	6.7	1.0	.938	-.018	.8583
	7	131.9	4.7	1.0	.935	.016	.8643
	8	133.6	3.7	.9	.934	.071	.4227
	9	124.2	3.9	1.0	.921	.047	.5770
Logistic Adjustment	2*						
	3	50.2	78.9	44.2	.849	-.490	.0004
	4	6.8	44.1	3813.5	.842	-.504	.0001
	5	166.8	16.8	3.0	.907	-.237	.0346
	6	119.4	30.5	46.1	.851	-.431	.0001
	7	119.3	20.0	29.4	.854	-.412	.0001
	8	126.3	9.9	8.0	.864	-.340	.0001
	9	126.1	5.1	1.9	.859	.085	.3115

* Convergence not obtained

Table A5--Estimates at cutoff dates - field 5

Model	Weeks Of Data	$\hat{\alpha}$	$\sigma_{\hat{\alpha}}/\hat{\alpha}$	RMS	R^2	R(r,t)	P> |R(r,t)|
Unadjusted	2*						
	3	183.8	67.8	175.7	.940	.602	.0001
	4	117.4	16.7	366.1	.934	.358	.0037
	5	172.9	29.6	906.7	.902	.483	.0001
	6	142.1	9.5	1064.6	.917	.499	.0001
	7	134.8	5.9	1321.1	.916	.486	.0001
	8	128.0	4.2	1497.7	.914	.459	.0001
	9	135.4	3.9	1713.1	.916	.426	.0001
Standard Error Adjustment	2*						
	3	198.7	46.7	1.9	.950	.010	.9452
	4	121.1	8.2	2.0	.978	-.094	.4611
	5	117.2	10.1	1.6	.943	.322	.0035
	6	129.2	6.1	1.7	.946	.225	.0272
	7	128.6	4.7	1.7	.944	.185	.0511
	8	127.3	3.8	1.8	.945	.135	.1277
	9	132.0	3.0	1.8	.946	.151	.0716
Logistic Adjustment	2*						
	3	166.7	39.6	2.5	.935	.164	.2667
	4	113.4	10.8	3.4	.939	-.027	.8352
	5	108.7	9.6	2.5	.894	.343	.0018
	6	122.4	6.3	2.6	.905	.236	.0209
	7	124.2	5.0	2.7	.906	.188	.0468
	8	122.3	4.2	2.8	.906	.154	.0824
	9	129.0	3.7	2.8	.907	.173	.0381

* Convergence not obtained

Table A6--Estimates at cutoff dates - field 6

Model	Weeks Of Data	$\hat{\alpha}$	$\sigma_{\hat{\alpha}}/\hat{\alpha}$	RMS	R^2	R(r,t)	P> |R(r,t)|
Unadjusted	2	75.5	27.4	241.8	.884	.739	.0001
	3	153.8	19.3	303.8	.944	.348	.0154
	4	224.2	24.3	788.4	.915	.414	.0007
	5	268.0	30.2	1322.0	.902	.456	.0001
	6	209.7	12.7	1678.3	.902	.508	.0001
	7	178.3	7.1	1965.9	.898	.467	.0001
	8	167.6	5.1	2176.8	.895	.441	.0001
	9**						
Standard Error Adjustment	2	69.9	22.6	1.3	.905	.084	.6486
	3	140.3	7.8	1.2	.968	.025	.8685
	4	214.0	7.4	1.1	.964	.090	.4807
	5	220.8	9.7	1.1	.941	.086	.4478
	6	177.1	7.5	1.2	.904	.118	.2528
	7	172.9	4.6	1.2	.919	.092	.3343
	8	158.2	3.0	1.2	.933	.107	.2286
	9**						
Logistic Adjustment	2	75.5	80.0	61.5	.869	-.658	.0001
	3*						
	4	167.7	14.0	1.8	.897	.196	.1203
	5	176.7	10.7	1.6	.882	.181	.1090
	6	173.5	7.5	1.6	.884	.138	.1813
	7	163.4	5.6	1.7	.884	.090	.3436
	8	159.0	4.7	1.8	.884	.063	.4773
	9**						

* Convergence not obtained
** Field harvested

Table A7--Estimates at cutoff dates - field 7

Model	Weeks Of Data	$\hat{\alpha}$	$\sigma_{\hat{\alpha}}/\hat{\alpha}$	RMS	R^2	R(r,t)	P> |R(r,t)|
Unadjusted	2	153.0	29.3	286.9	.952	.410	.0199
	3	137.1	10.3	513.4	.948	.331	.0217
	4	176.1	11.9	1060.6	.931	.369	.0027
	5	203.4	8.5	1217.6	.943	.340	.0020
	6	214.5	7.6	1812.8	.932	.360	.0003
	7	212.0	6.5	2554.2	.917	.338	.0003
	8	202.8	4.7	2921.8	.913	.343	.0001
	9	200.8	4.1	3260.4	.908	.293	.0004
Standard Error Adjustment	2	155.6	19.3	1.3	.948	-.054	.7699
	3	135.6	3.7	1.3	.977	-.078	.5994
	4	166.7	5.2	1.2	.970	.105	.4102
	5	188.1	4.7	1.2	.971	.136	.2305
	6	199.8	4.9	1.2	.968	.085	.4127
	7	207.8	2.9	1.2	.972	.048	.6125
	8	201.5	2.6	1.2	.970	.040	.6517
	9	207.0	2.6	1.2	.965	-.028	.7354
Logistic Adjustment	2	173.6	41.4	2.4	.930	.016	.9295
	3	138.5	9.6	2.8	.924	-.213	.1464
	4	156.4	8.5	2.1	.925	.125	.3238
	5	186.0	6.5	2.1	.935	.151	.1820
	6	193.5	6.0	2.2	.926	.153	.1379
	7	192.7	5.0	2.2	.914	.135	.1562
	8	191.1	4.3	2.3	.911	.055	.5383
	9	190.8	3.8	2.3	.907	.027	.7501

Table A8--Estimates at cutoff dates - field 8

Model	Weeks Of Data	$\hat{\alpha}$	$\sigma_{\hat{\alpha}}/\hat{\alpha}$	RMS	R^2	R(r,t)	P> |R(r,t)|
Unadjusted	2	133.4	54.6	297.8	.928	.378	.0329
	3	173.7	14.6	306.3	.968	.240	.0998
	4	174.8	6.5	526.9	.967	.316	.0111
	5	201.3	6.0	701.5	.968	.257	.0215
	6	189.8	4.3	1226.0	.952	.418	.0001
	7	194.6	3.3	1279.3	.957	.367	.0001
	8**						
	9**						
Standard Error Adjustment	2	115.8	23.5	1.4	.951	-.127	.4896
	3	166.3	7.7	1.4	.985	.012	.9333
	4	176.3	4.6	1.3	.981	.042	.7411
	5	203.6	3.7	1.2	.981	.043	.7056
	6	195.6	3.8	1.3	.976	.000	.9978
	7	197.2	2.9	1.2	.974	.052	.5826
	8**						
	9**						
Logistic Adjustment	2*						
	3*						
	4*						
	5	189.1	4.7	2.5	.962	.111	.3256
	6*						
	7	187.4	3.5	2.4	.953	.082	.3904
	8**						
	9**						

* Convergence not obtained
** Field harvested

Table A9--Estimates at cutoff dates - field 9

Model	Weeks Of Data	$\hat{\alpha}$	$\sigma_{\hat{\alpha}}/\hat{\alpha}$	RMS	R^2	R(r,t)	P> |R(r,t)|
Unadjusted	2*						
	3*						
	4	129.5	14.2	209.9	.944	.534	.0001
	5	231.0	20.5	384.3	.940	.482	.0001
	6	212.6	12.4	638.0	.938	.562	.0001
	7	224.0	7.0	813.4	.949	.581	.0001
	8	206.5	5.0	1177.2	.940	.540	.0001
	9	210.5	4.0	1394.5	.941	.507	.0001
Standard Error Adjustment	2*						
	3*						
	4	138.9	13.0	1.3	.936	-.016	.8973
	5	216.4	7.4	1.2	.980	.045	.6902
	6	209.5	3.4	1.1	.981	.128	.2151
	7	216.0	5.3	1.1	.953	.201	.0338
	8	198.3	3.9	1.1	.949	.149	.0926
	9	204.2	3.0	1.1	.952	.191	.0216
Logistic Adjustment	2*						
	3*						
	4	189.5	27.4	2.2	.918	.086	.5007
	5	222.6	18.7	3.0	.930	-.252	.0241
	6	191.7	8.8	1.8	.921	.240	.0184
	7	206.8	5.9	1.7	.931	.281	.0027
	8	196.4	4.6	1.8	.925	.217	.0138
	9	200.9	3.7	1.8	.928	.186	.0260

* Convergence not obtained

Table A10--Percent deviations of logistic model forecasts from final (9 week) estimates

Weeks Of Data	Model	Field 1	2	3	4	5	6	7	8	9
4	Unadjusted	7.3	-25.4	-6.2	48.6	-13.3	33.8	-12.3	-10.2	-38.5
	Standard Error	1.5	8.8	-22.6	54.4	-8.3	35.3	-19.5	-10.6	-32.0
	Logistic	10.2	41.8	-20.6	-94.6	-12.1	5.5	-18.0	*	-5.7
5	Unadjusted	4.2	25.6	10.7	99.4	27.7	59.9	1.3	3.4	9.7
	Standard Error	4.6	18.1	1.7	58.7	-11.2	39.6	-9.1	3.2	6.0
	Logistic	3.4	29.2	-2.5	32.3	-15.7	11.1	-2.5	.9	10.8
6	Unadjusted	18.1	2.3	9.1	12.5	4.9	25.1	6.8	-2.5	1.0
	Standard Error	15.4	-3.9	9.5	16.2	-2.1	11.9	-3.5	-.8**	2.6
	Logistic	7.9	4.8	2.5	-5.3	-5.1	9.1	1.4	*	-4.6
7	Unadjusted	5.9	21.4	7.3	1.0	-.4	6.4	5.6		6.4
	Standard Error	7.5	5.0	3.4	6.2	-2.6	9.3	.4		5.8
	Logistic	2.9	9.7	3.5	-5.4	-3.7	2.8**	1.0		2.9
8	Unadjusted	1.3	-3.5	1.6	3.6	-5.5		1.0		-1.9
	Standard Error	2.1	0.0	1.2	7.5	-3.6		-2.7		-2.9
	Logistic	.1	-1.4	.6	.2	-5.2		.2		-2.2

* Convergence not obtained

** Field harvested

Table A11--Forecasts and estimates of yield, components of yield, and variation generated by the objective yield models ----- field 1

Variable		Aug. 1	Sept. 1	Oct. 1
Wt. Per Ear	Mean	.354	.351	.380
	S.D.	.025	.046	.084
Number of Ears	Mean	15.6	12.1	11.8
	S.D.	2.7	2.3	2.3
Biological Yield	Mean	115.5	89.2	93.8
	S.D.	20.8	20.4	26.2
Harvested Yield Historic Harvest Loss	Mean	107.4	82.9	87.3
	S.D.	19.3	19.0	24.4
Harvested Yield Current Harvest Loss	Mean	94.3	68.1	72.7
	S.D.	23.5	22.7	26.5

Table A12--Forecasts and estimates of yield, components of yield, and variation generated by the objective yield models ----- field 2

Variable		Aug. 1	Sept. 1	Oct. 1
Wt. Per Ear	Mean	.330	.333	.423
	S.D.	.015	.017	.087
Number of Ears	Mean	16.8	16.7	16.3
	S.D.	2.2	2.9	3.2
Biological Yield	Mean	117.3	117.0	143.1
	S.D.	14.0	19.5	26.9
Harvested Yield Historic Harvest Loss	Mean	109.1	108.8	133.1
	S.D.	13.0	18.1	25.0
Harvested Yield Current Harvest Loss	Mean	109.5	109.3	135.3
	S.D.	14.0	19.9	28.7

Table A13--Forecasts and estimates of yield, components of yield, and variation generated by the objective yield models ----- field 3

Variable		Aug. 1	Sept. 1	Oct. 1 *
Wt. Per Ear	Mean	.348	.361	
	S.D.	.017	.043	
Number of Ears	Mean	18.1	15.1	
	S.D.	2.1	2.6	
Biological Yield	Mean	106.7	91.6	
	S.D.	11.1	15.0	
Harvested Yield Historic Harvest Loss	Mean	99.3	85.2	
	S.D.	10.3	14.0	
Harvested Yield Current Harvest Loss	Mean	102.7	87.5	
	S.D.	11.1	16.0	

* Field harvested

Table A14--Forecasts and estimates of yield, components of yield, and variation generated by the objective yield models ----- field 4

Variable		Aug. 1	Sept. 1	Oct. 1
Wt. Per Ear	Mean	.368	.356	.344
	S.D.	.081	.033	.068
Number of Ears	Mean	12.2	11.5	11.3
	S.D.	3.9	3.8	3.6
Biological Yield	Mean	75.6	67.0	64.6
	S.D.	33.5	21.7	26.0
Harvested Yield Historic Harvest Loss	Mean	70.3	62.3	60.0
	S.D.	31.1	20.2	24.2
Harvested Yield Current Harvest Loss	Mean	68.2	63.3	63.4
	S.D.	31.0	25.4	28.4

Table A15--Forecasts and estimates of yield, components of yield, and variation generated by the objective yield models ----- field 5

Variable		Aug. 1	Sept. 1	Oct. 1
Wt. Per Ear	Mean	.349	.352	.327
	S.D.	.030	.040	.072
Number of Ears	Mean	19.0	16.6	16.6
	S.D.	2.3	2.4	2.7
Biological Yield	Mean	132.9	117.2	108.9
	S.D.	19.7	22.1	27.8
Harvested Yield Historic Harvest Loss	Mean	123.6	109.0	101.3
	S.D.	18.3	20.6	25.9
Harvested Yield Current Harvest Loss	Mean	108.2	92.5	84.2
	S.D.	19.9	22.1	28.3

Table A16--Forecasts and estimates of yield, components of yield, and variation generated by the objective yield models ----- field 6

Variable		Aug. 1	Sept. 1	Oct. 1 *
Wt. Per Ear	Mean	.374	.352	
	S.D.	.032	.063	
Number of Ears	Mean	14.0	14.3	
	S.D.	1.9	2.5	
Biological Yield	Mean	84.4	80.6	
	S.D.	14.6	19.5	
Harvested Yield Historic Harvest Loss	Mean	78.5	74.9	
	S.D.	13.6	18.1	
Harvested Yield Current Harvest Loss	Mean	82.7	78.9	
	S.D.	15.6	20.0	

* Field harvested

Table A17--Forecasts and estimates of yield, components of yield, and variation generated by the objective yield models ----- field 7

Variable		Aug. 1	Sept. 1	Oct. 1 *
Wt. Per Ear	Mean	.359	.367	
	S.D.	.027	.072	
Number of Ears	Mean	21.8	22.0	
	S.D.	3.2	3.2	
Biological Yield	Mean	126.4	128.2	
	S.D.	21.3	21.7	
Harvested Yield Historic Harvest Loss	Mean	117.5	119.2	
	S.D.	19.9	20.2	
Harvested Yield Current Harvest Loss	Mean	120.3	122.0	
	S.D.	23.2	22.5	

* Field harvested

Table A18--Forecasts and estimates of yield, components of yield, and variation generated by the objective yield models ----- field 8

Variable		Aug. 1	Sept. 1	Oct. 1 *
Wt. Per Ear	Mean	.371	.451	
	S.D.	.027	.067	
Number of Ears	Mean	14.2	14.2	
	S.D.	2.0	2.0	
Biological Yield	Mean	86.5	104.0	
	S.D.	12.5	13.7	
Harvested Yield Historic Harvest Loss	Mean	80.4	96.7	
	S.D.	11.6	12.8	
Harvested Yield Current Harvest Loss	Mean	85.6	103.1	
	S.D.	12.6	13.8	

* Field harvested

Table A19--Forecasts and estimates of yield, components of yield, and variation generated by the objective yield models ----- field 9

Variable		Aug. 1	Sept. 1	Oct. 1
Wt. Per Ear	Mean	.388	.389	.389
	S.D.	.029	.042	.049
Number of Ears	Mean	18.4	15.6	15.6
	S.D.	4.6	4.1	4.7
Biological Yield	Mean	114.3	97.5	97.6
	S.D.	27.3	28.4	32.2
Harvested Yield Historic Harvest Loss	Mean	106.3	90.7	90.8
	S.D.	25.4	26.4	29.9
Harvested Yield Current Harvest Loss	Mean	108.2	91.4	91.5
	S.D.	28.0	30.3	33.3