A COMPARISON OF SUBJECTIVE AND HISTORICAL CROP YIELD PROBABILITY DISTRIBUTIONS

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Abstract

Forecast distributions based on historical yields and subjective expectations for 1987 expected crop yields were compared for 90 Western Kentucky grain farms. Different subjective probability elicitation techniques were also compared. In many individual cases, results indicate large differences between subjective and empirical moments. Overall, farmer expectations for 1987 corn yields were below those predicted from their past yields, while soybean expectations were above the historical forecast. Geographical location plays a larger role than crop in comparisons of relative variability of yield. Neither elicitation technique nor manager characteristics have significant effects on the comparisons of the forecasts.

Key words: subjective probability, probability elicitation, risk, decision support

Two principal uses of farm-level crop yield distributions are for representative farm simulation modeling and for individual decision support models. This research reports comparisons of yield distributions derived from farm records and from individual elicitation.

The accurate representation of farm-level yield risk is a primary concern of both policy/positive research and decision support efforts. For these purposes, there are four principal sources of data that can be used to construct yield representations:

1. County Yield Series. Annual production, acreage, and yield by county have been available in most states since at least the late 1950s. For risk analysis, the relationships between the statistical properties of probability distributions constructed from county series and those from individual farms are not generally known. Because of both measurement error and simple unavailability of data, it is usually not possible to construct structural models of county crop yields relating weather factors such as temperature and rainfall, and controllable management inputs such as fertilizer applications to realized yields. Eisgruber and Schuman discuss the problems associated with such aggregate data for risk applications. Nevertheless, the availability of county yield series continues to encourage their use in many research and decision support efforts.
2. Yield Series from Agronomic Experiments. Some experiment stations have maintained regular historical records of crop yields. Day provides the first extensive analysis of yield distributions for corn, cotton, and oats, using Mississippi Experiment Station data. Distributions constructed from such yield series have been used to calibrate plant growth models and thus to represent farm level yield variability. These distributions, however, tend to reflect unrepresentative management practices and are often characterized by expected values or variability of yields seldom achieved at the farm level. The clear advantage of these data is that controllable and uncontrollable inputs and management practices are usually reliably recorded, so that a structural model of crop yield may be developed. To date, there has been little comparative analysis of experimental and county yield data as proxies for farm level yield distributions.
3. Farm Level Historical Yield Series. Through public or private record keeping services, researchers in some states have access to farm level historical yield series of varying length and data quality. Given the opportunity, most researchers would prefer to develop both farm level and representative farm yield distributions from such historical series. Yet farm records are also not without their problems when used to forecast yield distributions. Farm yield series are often very short for statistical purposes (often less than 20 years). Controllable and uncontrollable inputs are generally not recorded at the farm level, so that it becomes impossible to relate factors such as fertilizer inputs, rainfall, tillage practices, or crop variety to yield. Nor is it generally possible to measure the effects of

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soil quality, crop rotations, rental/lease choices or government program participation on yield. It should be realized that crop yield on a particular farm for a given year is an average of production per acre on many dispersed fields, most of which are not recorded as growing the same crop from one year to the next.

4. Elicited Subjective Yield Forecasts. To represent manager perceptions of yield uncertainty (particularly for decision support purposes), many researchers have chosen to directly elicit forecast yield distributions from individual farm managers.[1] If an elicited forecast accurately represents the perceived yield uncertainty of the manager, there can be little doubt that this representation is best for use in models that take as their theoretical basis the Expected Utility Hypothesis. Nevertheless, agricultural economists are notably reticent in measuring subjective probability distributions for use in research and decision support models. The major factors inhibiting such applications are:
   (a) Elicitation of individual perceptions can be expensive and time-consuming. Resulting subjective probability distributions are strictly representative only of individual perceptions elicited at a particular moment.
   (b) Agricultural economists are sometimes uncomfortable with data that cannot be called 'objective', 'tangibly measured', or 'empirically based'. Cognitive perceptions, however measured, are considered to provide less credible data for economic research.
   (c) The methods and theories of cognitive psychology that form the basis for subjective probability elicitation are not well known to economists. Further, elicitation techniques abound, and economics researchers have little basis for choice of technique except ease of application. There is also considerable evidence suggesting that cognitive information processing limitations restrict the ability of individuals to avoid systematic biases while forming expectations (Tversky and Kahneman). Pease discusses results of psychological experiments which can aid economists to identify relevant differences in elicitation techniques and avoid elicitation biases.

The present research sought to compare and contrast forecasts based on farm-level yield series with forecasts based upon elicited expectations. The selection of one forecast method or the other depends upon the use of the resulting data. If the objective of research or decision support efforts is to reflect individual farmer uncertainty, then an accurate representation of subjective uncertainty is 'correct'. If the research objective is to choose the best data- or history-based forecast yield, then a statistical procedure utilizing historical yields would be preferable. Without attributing 'correctness', this research examined the correspondence of these forecasts. In addition, relative comparison was made between contrasting elicitation techniques. Specific objectives included the description of distributions based upon farm level historical series, comparison with subjective forecasts, and relative comparison of elicitation techniques in representing individual uncertainty.

FRAMEWORK OF THE STUDY

A sample of farm businesses was selected from lists of Kentucky Farm Business Analysis Association (FBA) members, using the criteria that selected farms had reliable yield records for corn and soybeans of at least ten years. Whole-farm average yields were recorded each year as part of the farm business analysis conducted by the Association. All interviews were conducted prior to planting in early 1987. The 98 farm managers interviewed were requested to express expectations for 1987 soybean and corn yields on a whole-farm average basis, as well as for a training random variable with known historical frequency.[2] The practice variable was always elicited first, followed in random succession by corn and soybean subjective probability distributions.

Selected farms were randomly pre-assigned to be interviewed using one of two elicitation techniques. The evaluated elicitation techniques were the Direct Cumulative Distribution Function method (DCDF) and the Conviction Weights method (CW). According to the direct-indirect taxonomy described by Norris and Kramer, these methods represent opposite poles of the spectrum of elicitation techniques.

The DCDF method requires respondents to express values of the random variable (in this case, yields) corresponding to pre-specified percentiles of its cumulative distribution function. It is assumed

[1] It is important to distinguish between 'elicited yield forecast' and 'subjective yield forecast'. The latter refers to 'true' subjective uncertainty as cognitively perceived, while the former is a measured representation of subjective uncertainty subject to measurement error.

[2] The practice variable was the expected maximum temperature on the forthcoming 4th of July.

that respondents can clearly understand and directly state their uncertainty judgements within the framework of formal probabilities. The DCDF method also requires that beliefs of assessors are consistent in the sense of mutually exclusive and exhaustive probabilities. The technique appears to be straightforward and easy to apply with individuals who have had probability training. Errors in assessing any particular value are not compounded, since all judgements are independent. The elicited distribution is not 'anchored' on any single value or probability.

The CW method is an indirect odds technique suggested by Nelson and Harris as useful for individuals without training in probability concepts. The technique relies upon pairwise comparison of relative uncertainty between a reference event and an exhaustive set of other possible events. In essence, respondents state odds they believe reflect the likelihood of occurrence of each yield range relative to a reference yield range. The modal event is designated as the reference event and assigned a 'score' of 100. The modal yield range (the interval with greatest probability density) is expected to be the easiest estimate for farm managers, and is less susceptible to cognitive bias. Subjects state 'scores' from 0 to 100 reflecting their perceived likelihood of each event relative to that of the mode. This elicitation technique also requires coherence of probability assessors, since probabilities for each yield range i are calculated as:

$$(1)\quad P_i = S_i \Big/ \sum_{i=1}^{n} S_i$$

where P_i is the subjective probability of the yield range and S_i is the score assigned by the subject to one of n yield ranges. Multiple modes and 'flat' sections of uniform probability are permitted for both methods.

Because previous experience and psychological research have indicated a common tendency towards overconfidence (distributions which are too 'tight' compared with an objective standard), particular emphasis was placed on urging respondents using either technique to carefully consider tail probabilities and endpoints. Both techniques were implemented within the framework of an interactive microcomputer program developed for subjective probability elicitation (Pease and Black) and a structured interview procedure (Spetzler and von Holstein). Prescribed interview procedures were carefully followed both to avoid measurement differences between interviews and to avoid (as much as possible) cognitive biases in probability assessment described in the cognitive science literature (von Winterfeldt and Edwards). Graphical and tabular output of assessed probabilities was displayed to each manager, and each was encouraged to modify elicited weights/probabilities if graph or table values caused them to doubt initial statements. Graphics display appears to be important for enlisting other perceptual abilities in the elicitation process, and respondents generally enjoyed examining the implications of the graphs. Other details of the interview procedure are detailed in Pease.

RESULTS

Historical Yield Series

Yield series for corn and soybeans on the investigated farms varied in length from 10 to 25 years, with an average of 17 years per farm. Most farm level series trended upward for both corn and soybeans. However, some farms exhibited very slight increases, while others had recently experienced a sequence of drought years with declining yields. Figures 1 and 2 display average yields for corn and soybeans among the sample farms over the period 1962-1986. Drought conditions caused extremely low corn yields in 1980 and 1983 and soybean yields in 1983.[3]

The simplest procedure for developing a 1987 forecast yield distribution for each farm is to remove systematic change from the series and adjust all residuals to 1987 levels. Two agronomic zones were identified by grouping counties with similar soil types in western Kentucky. Figure 3 indicates the counties grouped in each zone. The forecasting model constructed assumed that all farms within a zone experienced the same linear trend over the sample period, and that all farm yield distributions had the same dispersion but unique location (center). Analysis of individual and zone average yield series using the techniques outlined in Belsley et al. indicated that drought years exhibited extreme influence on the fitted trend (1980 and 1983 corn observations and 1983 soybean observations), and therefore these outlier years were not included for purposes of trend calculation.[4] No higher order formulation was significantly better than linear trend over the time period. The trend correction was calculated for each

[3] Among the sample farms, corn yields in 1980 averaged 76 percent of historical average yield, while 1983 corn yields were only 67 percent of average. For soybeans, 1983 yields were only 64 percent of historical average.

[4] Trend estimates using all data were lower by 29 percent and 52 percent for corn, and by 29 percent and 62 percent for soybeans in Zones 1 and 2, respectively.

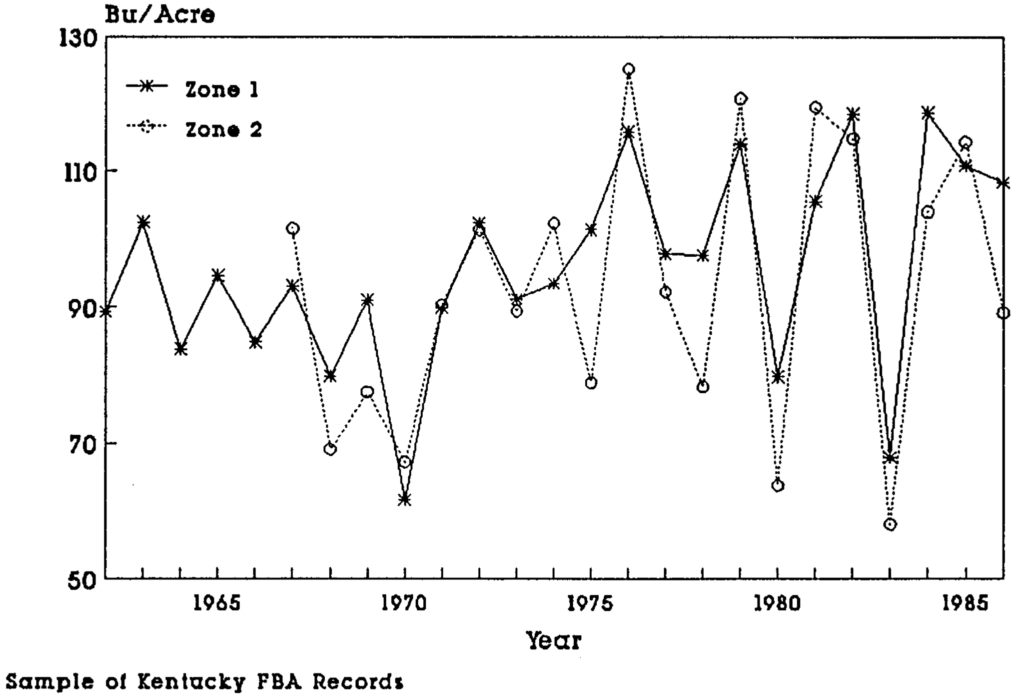


Figure 1. Mean Corn Yield, All Farms

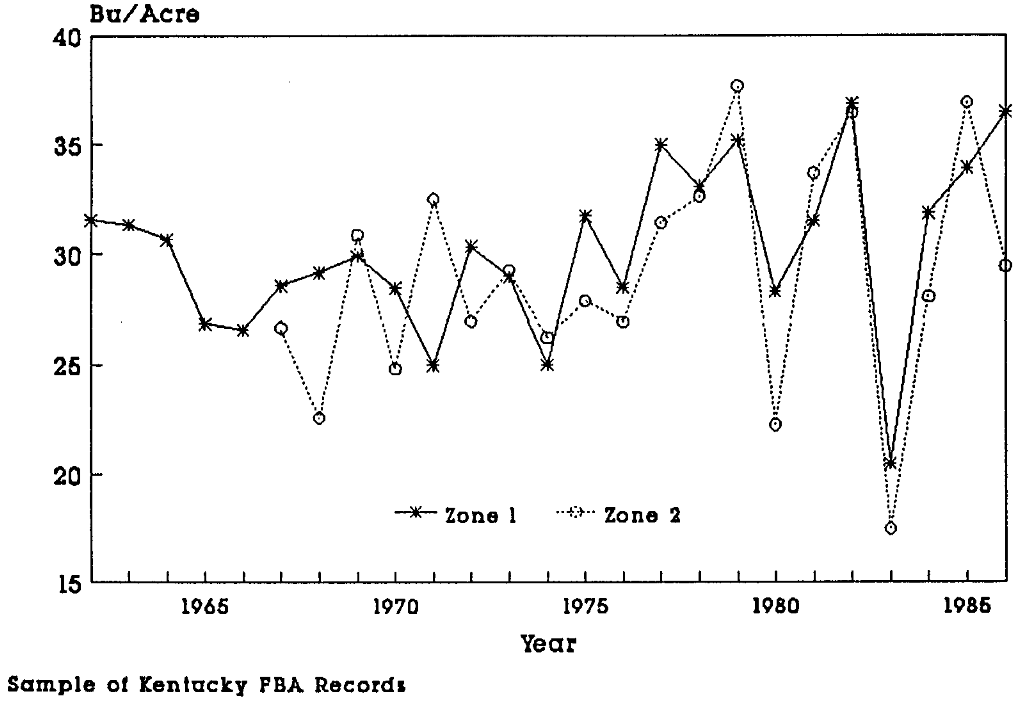


Figure 2. Mean Soybean Yield, All Farms

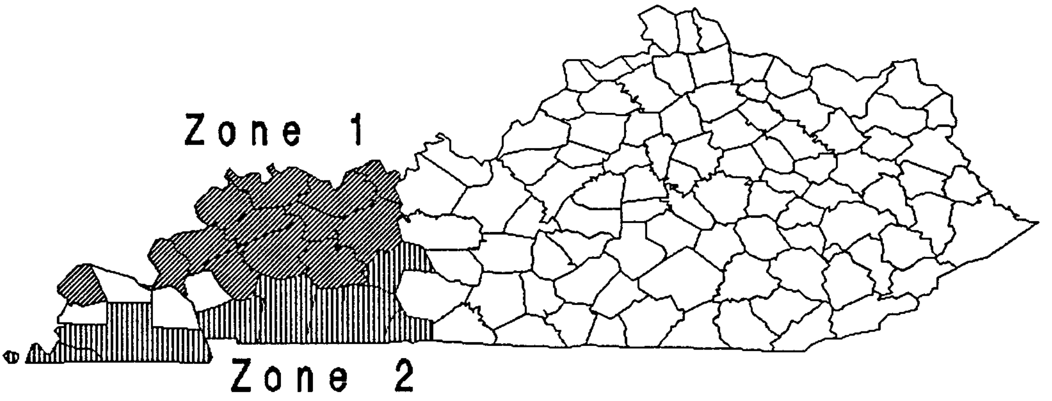


Figure 3. Study Zones, Kentucky

farm and added to each data point to obtain historical yields adjusted to the expected 1987 level. Estimated trend in bushels per year, mean yield, and relative variation for corn and soybeans over all farms in the two zones are presented in Table 1. Besides exhibiting lower mean yields for both corn and soybeans, Zone 2 farms are also seen to have experienced more variable yields than farms in Zone 1.

Analysis is considerably simplified if detrended yield distributions can be approximated by a normal distribution. When farm level distributions are examined individually, descriptive evidence showed consistent negative skewness for both corn and soybean distributions. Negative skewness was exhibited by 84 percent of historical corn and soybean distributions, while negative and positive kurtosis occurred in approximately equal proportions for both crops. Each empirical distribution was tested for significant departure from normality, using the Shapiro-Wilk W statistic. Among tests for goodness of fit to the normal distribution, Madansky found the W statistic to be most sensitive to departures from normality.

Table 1. Estimated Yield Trend and Descriptive Statistics of Yield Series, All Farms

Crop	Trend (Bushels / Acre / Year)	Expected 1987 Yield	CV[b]	Skew[c]
		Zone 1[a]		
Corn	1.84	110.3	0.20	-0.65
Soybeans	0.45	34.9	0.22	-0.47
		Zone 2		
Corn	1.30	106.9	0.25	-0.42
Soybeans	0.29	32.1	0.25	-0.38

[a]Farm Business Analysis Association records for Zone 1 farms begin in 1962, while those for Zone 2 begin in 1967. Mean yield and coefficients of variation are adjusted to 1987 expected yield levels.
[b]Coefficient of Variation
[c]Coefficient of Skewness

Table 2 presents results of these tests. As shown, there is substantial evidence that many corn and soybean yield distributions are not normally distributed. Pervasive negative skew is perhaps attributable to the production capacity process described by Gallagher.

Subjective Distributions

Descriptive statistics were also calculated for corn and soybean elicited forecast distributions. It should be noted that expected values were calculated from elicited probability distributions, and that managers did not explicitly estimate moments of their subjective probability distributions. For comparative purposes, Table 3 presents mean percent differences between subjective and historical moments. The expected values of corn subjective distributions were slightly lower than corresponding historical fore-

Table 2. Tests of Normality Hypothesis for Historical Yield Distributions (Number of Farms for which Hypothesis Rejected or Accepted at the 20 Percent Significance Level)[a]

	Corn	Soybeans
Accept	63	68
Reject	27	21

[a]The 20 percent significance level reflects the Type II error concern that a sample may be accepted as having been drawn from a normal population when in fact the hypothesis is false.

Table 3. Mean Percent Difference Between Subjective and Historical Moments[a]

	Zone 1			Zone 2		
	Mean	CV[b]	Skew[c]	Mean	CV[b]	Skew[c]
Corn	-1.0%	+3.6%	-55.4%	-2.9%	-15.2%	-19.0%
Soybeans	+6.4%	+6.7%	-59.6%	+4.4%	-10.1%	-42.1%

[a](Subjective moment - Historical Moment) / Historical Moment, averaged over all farms in the zone. Historical data is trend-adjusted to 1987 level.
[b]Coefficient of Variation
[c]Coefficient of Skewness

casts (on average, approximately 2 bushels). If the relationship between elicited and records-based expectations is interpreted as optimism or pessimism, farmers in both areas were very slightly pessimistic about expected corn yields in 1987. Pessimism may be partly attributable to the fact that corn yields had fallen on average in 1986 from 1985 levels (see Figure 1). Overall, 58 of 90 corn subjective means were less than the corresponding expected values based on historical data. Seventy-three percent of corn subjective means fell within +/-10 percent of historical values, and only two cases differed by more than 20 percent. Although the tendency was toward pessimism, deviations cancelled out to a surprising extent, resulting in near correspondence between historical and subjective forecasts in the aggregate.

In contrast, soybean subjective expected values averaged 5 percent (approximately 1.5 bushels) **above** corresponding historical forecasts. In other words, managers were more optimistic about soybean yields than their historical records would indicate. Such optimism may be attributable to a general pattern of increasing soybean yields in recent years. Figure 2 shows that, except for soybean yields in 1986 for Zone 2, yields had risen since 1983. Only 27 of 89 subjective means were less than historical means. Fifty-four percent of subjective means fell within +/-10 percent of historical values, while 13 percent of cases differed by more than 20 percent. The soybean subjective expected values thus reflected optimism relative to the historical record, and much less correspondence between subjective and historical values than for corn.

In contrast to the distinction by crop exhibited by relative means, the relationship between perceived and observed variability differed by area and not by crop. If high elicited relative variability is interpreted as under-confidence compared to the historical base, managers in Zone 1 were typically slightly under-confident, while Zone 2 managers were (to a much greater degree) over-confident. With reference to Table 1, Zone 1 historical yields were less variable, and the results may indicate that Zone 1 managers expected recent wide fluctuations to be reflected in 1987 yields. On the other hand, subjective Coefficients of Variation (CV) indicated that Zone 2 managers were much more confident about 1987 yields than either their historical records or comparison with Zone 1 variability would suggest.

Overall, corn subjective CVs averaged 5.8 percent below their historical counterparts, but this masks differing tendencies between zones and wide deviations in individual cases. Considering all corn distributions, only 30 percent of subjective CVs fell within +/-10 percent of the historical CV, while 42 percent of subjective CVs differed by more than 20 percent. Substantially more over-confidence was exhibited by managers overall than under-confidence. Thus, even though the data for corn indicated a pattern of general correspondence between subjective and historical expected values (and a slight tendency to underestimate relative to the historical record), there was no close correspondence between historical and subjective dispersion measures.

Similar results were obtained for soybeans. Overall, subjective CVs averaged only 1.8 percent below paired historical CVs. However, only 29 percent of subjective CVs fell within +/-10 percent of historical CVs, and 42 percent of cases differed by more than +/-20 percent.

With respect to skewness, a high proportion of elicited distributions had negative skew (86 percent of corn subjective distributions and 73 percent of soybean distributions). Similar proportions of historical skewness coefficients were negative. The tendency was for subjective skew to be smaller in absolute magnitude than historical skew. Subjective skewness was very similar on average between zones, with soybean subjective skewness statistics averaging approximately one-third less than corn subjective skew (-0.21 for soybeans vs. -0.31 for corn). Zone 1 managers perceived less skewness than did Zone 2 managers relative to their historical yield series. Managers in both zones seemed to perceive a negatively skewed yield generation process, but not as skewed as their historical records suggest.

This description of relative moments of subjective and historical distributions did not answer the statistical question of whether subjective and historical distributions were significantly different. In order to determine whether observed differences were significant, it was necessary to carry out pairwise statistical tests of equality between subjective and historical distributions.

Are Subjective and Historical Distributions Significantly Different?

The statistical question to be addressed was whether significant differences existed between subjective distributions and forecast distributions formulated from historical data. If the underlying yield generation process can be approximated by a normal distribution, comparison of the first two moments is sufficient to determine equality between subjective and objective distributions. As indicated above, there was cause to doubt the adequacy of the normality approximation. Thus, non-parametric tests were used to test pairwise goodness of fit between empirical and subjective probability distributions. The assumed statistical model was characterized by a random yield generation process which was stable over time. Therefore, the null hypothesis was that empirical distributions have been drawn from a population identical to the elicited distribution.

Several goodness of fit tests exist which can be utilized to test for equality between distributions. The Kolmogorov-Smirnov (KS) test is sensitive to a wide range of departures in location, scale, and higher moments between distributions, and is independent of the form of the underlying distribution (Gibbons).[5] The two-tailed KS test statistic is determined by the maximum absolute deviation between subjective and empirical cumulative distribution functions. For illustrative purposes, Figures 4 and 5 display the aggregate cumulative distribution functions for corn and soybeans, respectively. Table 4 displays results of KS tests.

Overall, approximately two-thirds of soybean empirical distributions did not differ significantly from the corresponding subjective distribution, while three-fourths of corn empirical and subjective distributions did not differ significantly. Nevertheless, a substantial proportion of empirical distributions differed significantly from corresponding subjective distributions in location or higher moments. There were relatively fewer significant deviations between subjective and empirical corn distributions than between corresponding pairs of soybean distributions, and there were fewer deviations in Zone 2 than in Zone 1. Managers who placed greater weight on recent disaster corn yields might have had 1987 expectations that follow the observed pattern. On the other hand, there was no obvious indication why subjective soybean expectations would not follow the same pattern. Fewer rejections in Zone 2 might have been affected by sample size, because yield series were shorter in that area. Differences between area results may also have been masked by education and experience characteristics of managers, and a closer examination of the deviations between subjective and empirical forecasts was indicated. Specifically, the following questions were examined: (1) Did either elicitation technique provide better correspondence between subjective and historical distributions?, and (2) Did socio-economic characteristics such as education and experience affect correspondence?

Table 4. Goodness of Fit Tests Between Empirical and Subjective Distributions: Proportion of Rejections of Null Hypothesis of Identity[a]

	Corn	Soybeans
Zone 1	28.9% (45)	36.4% (44)
Zone 2	20% (45)	31.1% (45)
All Farms	24.4% (90)	33.7% (89)

[a]Kolmogorov-Smirnov One-sample Goodness of Fit Test Ho : Farm level empirical distribution identical to corresponding subjective distribution, significance level = 5%. Number of cases given in parentheses.

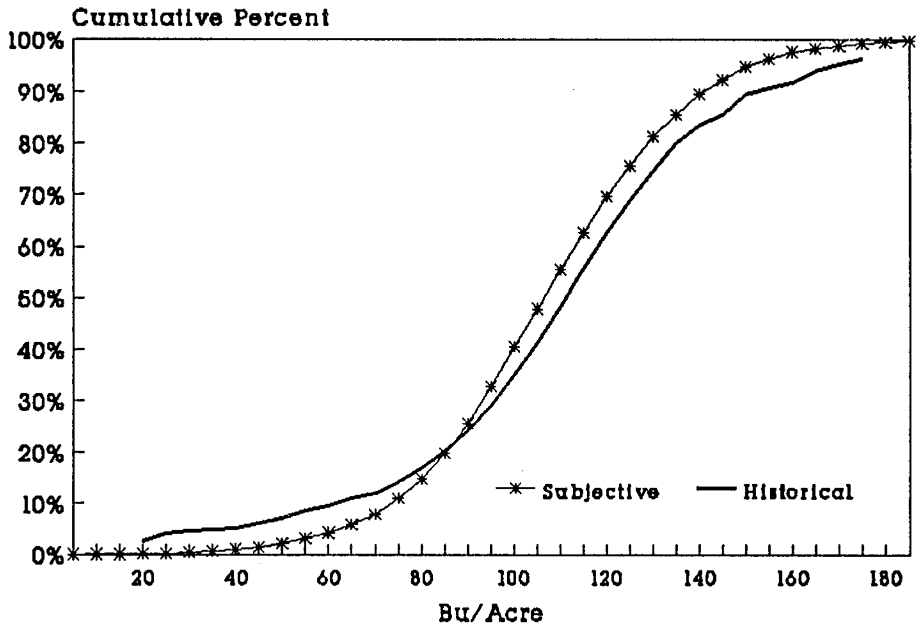
Table 4 indicates that a substantial proportion of empirical forecasts differed from their paired subjective forecast. Controlling for the experimental elicitation method may serve to explain some portion of the observed deviations. Ludke measured error scores (Π) as deviations between subjective and objective probability distributions, utilizing six elicitation techniques. The error scores were calculated as the sum of absolute percentage differences between subjective and objective quantiles:

$$(2)\quad \Pi_{ik} = \left| \sum_{i} \sum_{j} (S_{ij} - O_{ij}/O_{ij}) \right|$$

where:

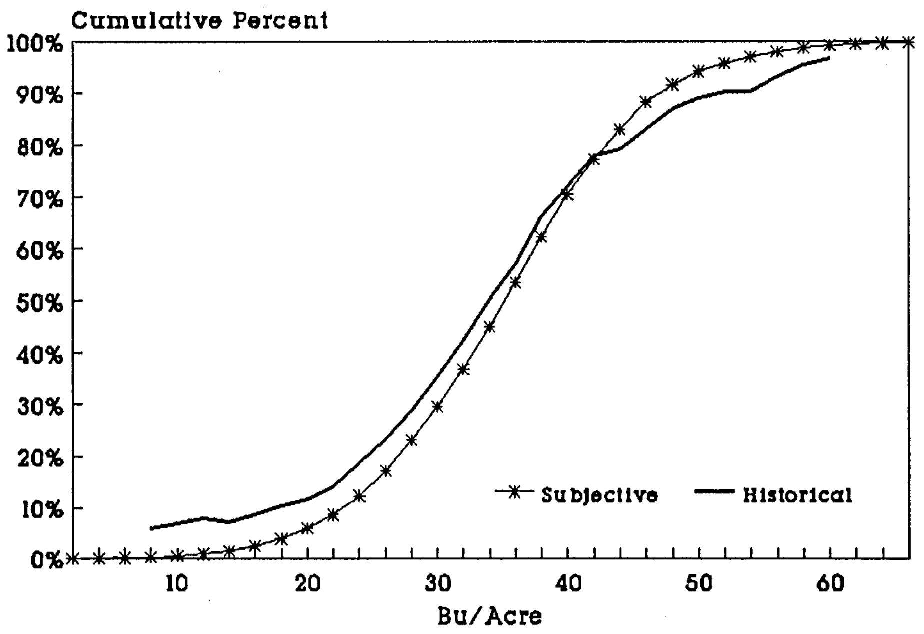
S_{ijk}=Subjective cumulative percentile at quantile i for individual j, distribution k, and

[5] A one-sample test was appropriate because only historical yields were randomly drawn from a population distribution. Subjective distributions in this formulation are analogous to theoretical distributions in goodness-of-fit tests, against which empirical samples may be tested.



Mean Percentiles at Indicated Yield

Figure 4. Corn: Aggregate Subjective and Historical Cumulative Distributions



Mean Percentiles at Indicated Yield

Figure 5. Soybeans: Aggregate Subjective and Historical Cumulative Distributions.

O_{ijk}=Objective cumulative percentile at quantile i for individual j, distribution k.

Ludke regressed error scores on elicitation techniques used for each individual and on the individual's socio-economic characteristics. He concluded that elicitation technique had a significant impact, but that the relative ranking of elicitation techniques depended upon the shape of the probability distribution.

To test whether elicitation technique had an impact on subjective assessments, univariate regression models were estimated, regressing error scores (calculated as in the Ludke analysis for corn and soybean distributions) on the elicitation technique employed with each individual. In addition, the joint distribution of error scores was also regressed on elicitation technique by estimating the multiple dependent variable formulation:

$$(3)\ \Pi_{ic} ; \Pi_{is} = f(\ METHOD_j\ )$$

where:

Π_{ic} = Corn error score for individual i,

Π_{is} = Soybean error score for individual i, and

$METHOD_j$ = CW or DCDF.

Table 5 results indicate no significant differences between error scores of individuals using different elicitation techniques. These results are at odds with earlier findings by Ludke and other researchers. However, previous elicitation research by psychologists has been carried out in controlled laboratory conditions, with subjective assessments compared against objective frequencies. There is no doubt in such a context as to the 'correct' result. The current research has had the more modest aim of comparing correspondence of subjective assessments with an admittedly uncertain and unstable historical yield series. Our conclusion that farmer-assessors are not 'accurate' holds only if the forecast distribution based upon historical yields is accepted as the 'correct' forecast of future yields.

A second caveat to these results must also be considered. This research has taken great pain to implement a carefully organized elicitation procedure. It may well be discovered upon further examination (as has been suggested by researchers such as Spetzler and von Holstein) that careful implementation of the assessment procedure is more important than choice of technique.

Pingali and Carlson elicited subjective probability distributions for predicted fruit damage from a group of North Carolina orchardists using the triangular distribution elicitation method. They compared these subjective distributions against expert opinion and historical observations by regressing the absolute error of subjectively predicted fruit damage on a set of demographic and management variables. Ninety-four percent of the variation in absolute errors was explained by variables reflecting education, age, size of orchard, scouting, and extension education. For the current study, error scores as described above were also regressed on demographic characteristics of subjects, with a categorical variable for zone. Table 6 indicates that such variables provided virtually no explanatory power for observed deviations between subjective and historical distributions in the current study. In general, no formulation explained more than 5 percent of the variation in error scores. It is not clear why the current results are inconsistent with the Pingali and Carlson results. It does not seem reasonable to conclude that the triangular distribution better represents subjective uncertainty, as only three points along the distribution are elicited. It is possible that insect damage is less variable and more predictable than crop yield.

Table 5. Regressions of Error Scores on Elicitation Technique, F-test Results[a]

Dependent Variable(s)	F-statistic	Degrees of Freedom	Observed Pr(F>)
Π_{ic}	.65	1,89	.42
Π_{is}	.49	1,89	.49
Π_{ic}, Π_{is}	.92	2,88	.40

[a]Dependent variables regressed on categorical variable $METHOD_j$ using ANOVA and MANOVA procedures. Multivariates F-test uses Wilk's Lambda.

CONCLUSIONS

This research focused on the correspondence between records-based and subjective crop yield probability distributions. It was found that in many individual cases, large and significant differences exist between subjective and empirical moments. Some differences were observed in expected values,

Table 6. Regressions of Error Scores on Socio-economic Characteristics, F-Test Results[a]

Dependent Variable(s)	F-Statistic	Degrees of Freedom	Observed Pr(F>)
Π_{ic}	.08	2,88	.92
Π_{is}	.96	2,88	.39
Π_{ic}, Π_{is}	.55	4,174	.70

[a]Multivariate F-test uses Wilk's Lambda. Independent variables measuring socio-economic characteristics include:

YRSFAR: Number of years farming experience
EDLEVEL: Highest educational level achieved
ZONE: Categorical variable for zone.

with subjective forecasts tending to underestimate forecasts derived from historical corn yields and (conversely) to overestimate historically-based soybean forecasts. Wide individual differences were observed in measures of relative dispersion, with recent regional experiences seeming to play a more important role than crop. The skewness of empirical yields was more pronounced than would have been implied by individual estimates. Again, it should be noted that the 'errors' implied in subjective forecasts depend upon the assumption that forecasts derived from historical yields were 'correct'.

No significant effects were observed for the influence of either elicitation technique or proxies for managerial capacity. The experience of carefully designing and executing elicitation interviews in accordance with principles found in the psychological literature leads the research team to suggest that careful control of the elicitation interview process may be more important than choice of elicitation technique in obtaining accurate measures of subjective uncertainty. However, this issue cannot be decided within the context of single period elicitation research. Only calibration of subjective assessments over several years against the best regression forecasts of farm yields can determine whether subjective probability distributions better predict farm level yields.

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