Farmers' Subjective Perceptions of Yield and Yield Risk

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Using survey responses of Illinois corn farmers to differently framed yield questions, we examine their subjective information by relating stated yields and risk to the corresponding objective county measures. The results show that farm-level yields can be best characterized by soliciting probabilistic information, which provides more accurate yield assessments than an open-ended frame and consistent estimates of producers' subjective risk. Moreover, we find that overconfidence can be confused with differences in relevant information and that using recent data may be more appropriate in examining subjective risk statements. Our results are important for agricultural policy-makers and researchers, particularly those who work with surveys that include questions about producers' yields.

Keywords: probability elicitation, response format, subjective beliefs, yield distribution, yield perception, yield risk

Introduction

Farmers' individual yields are difficult to measure as accurate yield records are frequently unavailable for longer time periods. An alternative when long-term yield data is lacking is to use subjective yield information, which is particularly important in decision-making contexts. Obtaining subjective yield information however, presents a number of challenges. Which technique elicits yields most accurately? How are the individual elicited yields distributed? And how do farmers' elicited yields relate to the yields in their respective counties? Despite the relevance of these questions, only limited research exists on how producers perceive their individual yields. Yet, a better understanding of subjective yields is critical for both researchers and agricultural decision-makers. Producers' perceptions of yield and subjective probability functions not only determine their decision-making behavior in a number of contexts, but also constitute the basis of many simulation and utility maximization models employed by public policy-makers to determine optimal subsidy levels or to predict program participation rates.

In this paper, we evaluate two different techniques to elicit farm-level yields and estimate the functional form of farmers' subjective yield distributions. We then assess the accuracy of the subjective information by relating stated yields and risk to the corresponding objective county measures, and investigate how potential discrepancies between perceived and actual yields change if producers are confronted with different decision frames. Our analysis enhances the limited understanding of producers' subjective yield perceptions and contributes in several important dimensions. First, research in environmental economics indicates that the format for eliciting subjective information may have an impact on its accuracy. Frames where respondents are asked to assign probabilities tend to yield more accurate responses than direct frames (Ready, Navrud and Dubourg 2001; Champ and Bishop 2001). From the perspective of an agricultural producer this raises the question of whether such discrepancies also exist for subjective yield and yield risk perceptions. If so, results of studies examining objective and subjective yield measures may be affected by the format in which producers' subjective values are obtained. Here, we compare two different formats that are commonly used to recover subjective yield information and assess potential incongruence. Second, in contrast to Bessler (1980) and Eales et al. (1990) we do not aggregate farmers' subjective probability distributions, but instead assess perceived yields based on personalistic probabilities. This approach allows for a truly individual assessment of subjective yields because it incorporates the different uncertainty characteristics (e.g., soil, climate) inherent in each producer's operation. Finally, by relating farm-level yield perceptions to their corresponding county measures we quantify potential biases in yield perceptions and thus contribute to the limited research in this area (Pease 1992). Our results are important for agricultural decision- and policy-makers as well as researchers, particularly those who work with surveys that include questions about producers' yields.

Literature

Crop yield distributions have been investigated in numerous studies (e.g., Pease 1992; Moss and Shonkwiler 1993; Goodwin and Ker 1998) to aid producers in production and risk management planning and to assist decision-makers in pricing crop insurance or establishing subsidy levels. Although the factors influencing yields within a given year are well understood (soil productivity, agro-climatic factors, etc.), conflicting views exist about the functional form of crop yield distributions. Just and Weninger (1999) attribute this lack of consensus to insufficient farm-level yield observations and methodological shortcomings when modeling technological progress and reporting statistical significance. To address these issues, Sherrick et al. (2004) conduct an extensive analysis of corn and soybean yields. Using farm-level yield data from University of Illinois Endowment farms from more than 25 locations with at least 20 years of yield records during 1972-1999, they examine various polynomial trend models up to fifth order to account for non-random components in the yield distribution, but find little evidence for trend specifications beyond linear. Sherrick et al. (2004) then evaluate five alternative distributions to describe farm-level yields and conclude that the Weibull distribution provides the best fit followed by the beta whereas the normal and the log-normal specifications perform poorly. These results are consistent with an earlier study by Pichon (2002) who evaluates farm-level yields of several hundred Illinois corn producers with varying length of production records. Assuming but not testing for a linear trend, he identifies the Weibull distribution as the most appropriate functional form.

Significantly less research exists on producers' subjective probability beliefs of individual farm-level yields. Arguing that there is no reason to believe, a priori, that individual yield distributions should be similar, Bessler (1980) simply aggregates producers' elicited probability distributions and reports that one-period ahead ARIMA-forecasts based on historical yields agree with the aggregated elicited distributions. Pease (1992) in contrast elicits subjective yield probabilities of Kentucky corn and soybean farmers and computes their individual one-period ahead forecasts as the expected value of the elicited subjective distributions. Comparing this forecast to the mean of the linearly de-trended historical yields for each farm, he finds that farmers' subjective corn expectations were somewhat below and soybean expectations slightly above the corresponding objective means. Focusing on grain price forecasts, Eales et al. 1990 examine the subjective distributions of different groups of market participants and find that their means agree in most cases with subsequent futures prices. Overall, these studies indicate that elicited probabilities tend to provide reasonably accurate estimates of the objective mean. On higher order moments however, the evidence is less consistent. While Bessler (1980) observes equal or greater variability in the subjective forecasts than in forecasts generated from historical data, Pease (1992) and, to an even greater extent, Eales et al. (1990) report overconfidence in subjective variances.

When soliciting subjective information, the choice of the response format can have a sizable impact on the results. Recent research on contingent valuation, for example, shows that people's stated willingness to pay for particular goods or services differs with the survey method used (e.g. Brown et al. 1996; Ready, Navrud and Dubourg 2001). Answers where respondents are asked to assign probabilities tend to be closer to the actual underlying values than responses in more direct formats, regardless of question ordering (Ready, Navrud and Dubourg 2001; Champ and Bishop 2001). Pease (1992) uses two probabilistic elicitation methods and finds no differences, and neither Bessler (1980), Eales et al. (1990) nor Pease (1992) employ a direct open-ended frame. There hence appears to be no research analyzing the effects of different response frames on perceived yield and yield risk. Yet, information about potential biases arising from the response format is critical for designing and interpreting surveys.

Survey

Our empirical analysis is based on a crop yield risk survey administered at three Corn Farm Income meetings in Decatur, Rochelle and Mt. Vernon, Illinois, during the fourth quarter of 2001. The survey required voluntary and unassisted completion. Questions included the farm's primary location in the state (county), the size of operation (acres), and subjective yield information. Specifically, producers were asked to state their average corn yield, compare their yields to those of a typical farm in the county, and to describe their yield distribution.

Average corn yield: The average corn yield in a typical year, as the first subjective yield statement, is elicited as a response to a direct and open-ended question ("Enter your average corn yield in a typical year … (bu/acre)."). The directly-stated yield question should be relatively easy to answer, as it simply asks for producers' perceived average yield. Its format that is often used in surveys, particularly at the beginning, where a surveyor seeks information about age, size of operation, average yield etc. to the respondent's characteristics and production background.

Relative performance measures: Producers are next asked to compare their average yield and yield risk to those to a typical farm in their county ("We are interested in your corn yields relative to a typical farm in your county. Compared to a typical farm in your county, your average corn yield is (check box, fill in blank) …. higher, by … bu/acre, … lower, by … bu/acre, … about the same. Thinking about yield risk, compared to a typical farm in your county, would you say your average corn yield is (check box) …. more stable, … more variable, … same degree of variability?"). These questions were designed to assess how producers view themselves relative to others in their county.

Description of yield distribution: A second subjective yield estimate and an assessment of individual risk are obtained by asking producers to assign probabilities into ten predefined yield categories given in figure 1 ("Please fill in the table with your best estimates of the probability of your yield being in the intervals listed, for example 15 times out of 100 is a 15% probability."). The sum of the probability column was already stated as 100%, indicating to respondents that their probabilities should add to 100%. Our procedure is similar to those employed by Bessler (1980) and Eales et al. (1990), yet we do not restrict the size of the weights – in our case probabilities. Because the probability assignment question is more challenging, it cannot be readily answered and hence requires participants to think more carefully. The answers to this question may therefore represent perceived yields that would be used in less immediate survey or decision contexts.

Methods

Directly Identified yields

Two subjective measures are elicited in the survey, directly-stated and indirectly-stated yields. The directly-stated measure is simply the producer's average corn yield in a typical year. The indirectly-stated measure is the value represented by the particular probabilities each producer has assigned to the different yield categories. It is computed by recovering the producer's subjective yield distribution and then calculating the implied mean. In contrast to simply summing the weighted category mid-points to obtain each respondent's mean, converting the discrete probabilities to a continuous function allows for more flexibility in determining indirectly-stated yields as the category mid-points are no longer binding.

The objective function used to recover the producers' yield distributions,

(1)

$$\min_{\theta_i} \sum_i \left[\left(p_{i1} - D(U_1 \mid \theta_i) \right)^2 + \sum_{j=2}^{9} \left(p_{ij} - \left[D(U_j \mid \theta_i) - D(U_{j-1} \mid \theta_i) \right] \right)^2 + \left(p_{i10} - \left[1 - D(U_9 \mid \theta_i) \right] \right)^2 \right]$$

simply minimizes the sum of squared differences between the stated probabilities and the fitted probabilities across all intervals and respondents. Here, p_{ij} denotes the stated probability of producer *i* for yield interval *j*, U_j refers to the upper bound of this interval, and *D(.)* is the cumulative distribution of farm-level yields. The functional form of *D(.)* is assumed to be the same for all producers. Solving (1) for θ_i returns a set of *i* *n*-dimensional parameter vectors (one for each respondent), where *n* represents the number of parameters required to describe *D(.)*.

To determine the functional form for *D(.)*, we examine the Weibull

(2) $$D(x) = 1 - e^{-(x/\beta)^{\alpha}}, \qquad 0 \le x < \infty,\ \alpha, \beta > 0,$$

and the beta distributions (3),

(3) $$D(x)=\frac{\int_0^x t^{\alpha-1}(1-t)^{\beta-1}\,dt}{\int_0^1 t^{\alpha-1}(1-t)^{\beta-1}\,dt}, \qquad 0\le x\le 1,\ \alpha,\beta>0,$$

as the most likely candidates. We also use the log-normal distribution (4),

(4) $$D(x)=\frac{1}{2}\left[1+erf\left(\frac{\ln(x)-\mu}{\sigma\sqrt{2}}\right)\right], \qquad 0\le x\le\infty,\ -\infty\le\mu\le\infty,\ \sigma>0,$$

where *erf* is the *erf*-function[1] and μ and σ are the mean and standard deviation of the variable's logarithm. Because Sherrick et al. (2004) find the log-normal distribution to be somewhat less accurate than (2) and (3) in describing farm-level yields, it is used here to check the consistency of the fitting results. The best suited functional form and the corresponding parameter vector θ_i are then used to obtain an implied mean yield μ_i and an implied standard deviation σ_i for each respondent. These values can be interpreted as the indirectly-stated average corn yield and the implied perceived yield risk.

County yields

The yield of a typical farm in a respondent's county is assumed to equal the average yield in that county. Because this average is based on historical observations, all county records are first de-trended to remove the effect of systematic yield increases due to changes in technology. Following Sherrick et al. (2004), we employ a linear trend model (equation 5). Because yields have not increased proportionally over time in the state, each county's yield data is de-trended individually to 2001 levels using

(5) $$Y_{adj,ct}=Y_{org,ct}+\gamma_c\left(2001-t\right)$$

Here, $Y_{adj,ct}$ is county c's yield in year t adjusted to 2001 levels and γ_c, is the slope coefficient from regressing county c's original yields $Y_{org,ct}$ on a linear time trend, t=1972, …, 2001.

Yield and Risk

An important prerequisite for comparing directly- and indirectly-stated yields to their objective measures is that relative yield risk is constant across farms. If producers with greater stated yields perceive greater relative risk than those with smaller yields, their subjective yield statements will be associated with relatively greater uncertainty, prohibiting direct comparisons between yields. In this case, all stated yields will need to be standardized before conducting the analysis. To test for independence of stated risk and yields, we use Equation 6

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[1] erf(z) is the error function encountered in integrating the normal distribution and defined as
$$erf(z)=\frac{2}{\sqrt{\pi}}\int_0^z e^{-t^2}\,dt.$$

(6) $\sigma_i = \alpha_0 + \alpha_1 Y_i$,

where σ_i denotes the standard deviation implied by producer *i*'s fitted farm-level yield distribution and Y_i his directly- or indirectly-stated mean yield.

Survey data

A total of 281 listed attendees participated in the three meetings and 134 completed questionnaires (48%). After excluding one farm manager, 3 out of state responses and 19 incomplete or inconsistent[2] forms, the final sample consisted of 111 usable surveys. These surveys represented relatively large farms with an average of approximately 1195 acres and a median of around 975 acres (table 1). Despite a few smaller operations, the respondents can be considered commercial scale. Spatial analysis revealed no geographical concentration of responses. The survey participants represented 50 different Illinois counties, and the top three counties accounted for only 13, 8 and 6 usable observations.

The probabilities assigned by each producer to the specific yield intervals are used in equation (1) to estimate the continuous density functions. Consistent with Sherrick (2004), the Weibull distribution provided the best overall fit by displaying the smallest sum of squared errors (13,225) across all surveys followed by the beta (14,014) and the log-normal (16,248) distribution. Figure 1 displays the assigned probabilities and the fitted Weibull yield distribution for one survey respondent as an example. The resulting Weibull parameters α_i and β_i are then used with equations (7) and (8),

(7) $\mu_i = \beta_i \Gamma\left(1+\alpha_i^{-1}\right)$,

(8) $\sigma_i = \sqrt{\beta_i^2\left[\Gamma\left(1+2\alpha_i^{-1}\right)-\left[\Gamma\left(1+\alpha_i^{-1}\right)\right]^2\right]}$,

where Γ is the gamma function, to recover each respondent's implied yield μ_i and standard deviation σ_i. Thus, each producers' mean and standard deviation are determined based on his best fitting set of parameters. The majority of the producers (70) had an implied mean yield between 140 and 160 bu/ac, with exactly half the observations above and half below the midpoint of the range, indicating that no potential bias resulted from the discrete nature of the yield intervals. Testing for independence of stated risk and yields (equation 6), we fail to reject the null hypothesis that the implied standard deviation is determined by either the directly- (p=0.581) or the indirectly-stated yield (p=0.155). Finally, the average yields in the counties represented in the survey are obtained by first de-trending the NASS county yields over the 1972-2001 period (equation 5)and then computing the arithmetic averages of the adjusted yields $Y_{adj,ct}$, t=1972, …, 2001, for each county *c*.

[2] Of the returned surveys, 115 or 86% had the probability section completed with no errors (summed to 100%, in density form, all between categories with positive probabilities), with 7 others usable by rescaling for rounding or summing errors that were 10% or less (e.g. if the assigned probabilities summed to 102%, then divide each individual entry by 102%). The remainder was irrecoverable and therefore excluded from the analysis.

Results and Discussion

Perceptions of relative performance

Tables 2-4 summarize the respondents' direct statements of their own mean yield and yield risk relative to a typical farm in their county. Most producers viewed themselves as attaining higher than average (44%) or similar yields (43%), and only 13% believed their yields to be below average (table 2). The majority of the producers also viewed their yield risk as lower than typical (44%) or about the same (41%), whereas 15% perceived greater yield variability (table 3). Combining and cross tabulating the information from tables 2 and 3 shows that about 87% of the respondents viewed their yields above average or average and about 85% viewed their yields to be of average or below average variability. Approximately 77% of the respondents thought they incurred both, better than or average yields with lower than or average variability. Overall, our results show that producers viewed their yield as "better-than-average" on average and may be overconfident when asked to assess their yield risk.

Yield perceptions

The average of the directly-stated means in the 111 surveys is 152.60 bu/ac, which is 8.51 bu/ac greater than the average Weibull implied yield and 7.60 bu/ac greater than the NASS average (table 4). Using the Wilcoxon signed rank test, a non-parametric alternative when the distributional assumptions underlying the paired Student's t-test are not satisfied, we find that these differences are statistically significant ($p<0.001$ and $p<0.001$ respectively). This upward-bias in the direct yield statements is thus consistent with producers' perception of being "better-than-average." In contrast, yields from the probability assessment task are lower than those stated directly and about equal to the yields of a typical farm. The differences between Weibull implied and NASS yields, displayed in the histogram of figure 2, are small and not significant when examined with the Wilcoxon signed rank test ($p=0.570$). They show no evidence of a "better-than-average" effect. Table 4 also displays the producers' simple implied yield computed as the mean implied yield if the midpoint of each category is weighted by the probabilities assigned. The close agreement to the fitted mean both validates the fitting process and further indicates that farmers' responses in probability distribution form are centered below the direct responses about their mean yield. These results reveal a fundamental contrast between producers' beliefs when asked for a simple statement of average yield as opposed to assessing a complete probabilistic version of their yield distribution. Moreover, while upward-biased direct yield statements are consistent with producers' tendency to view themselves as "better-than-average" the effect disappears when respondents are asked for probabilistic yield information.

Our findings agree with Bessler (1980) and Eales et al. (1990) who report no significant differences between the implied means of producers' aggregate subjective yield distributions and the corresponding objective measures. More importantly, here we show that this result also holds for producers' individual subjective yield distributions, a much stricter test. Our results hence validate the assumptions of Bessler (1980) and Eales et al. (1990) and support Bessler's (1980) "hope that the aggregate representations of the macro variables 'look something like' their micro counterparts." The biased assessment of the direct open-ended frame is further consistent with the findings of

Ready, Navrud and Dubourg (2001) and Champ and Bishop (2001) in contingent valuation studies.

Producers may place greater weight on more recent years when stating their average yield directly than when assigning probabilities to particular yield categories, as the former task is cognitively easier and requires less careful thinking. Higher yields in the years immediately preceding the survey date then lead to greater directly-stated yields. We examine this hypothesis by computing the average farm yield in a respondent's county using only the last 5 and 10 years of NASS corn data. During the 1997-2001 (1992-2001) period the counties represented in the survey experienced yields substantially above their long-run average in two (four) years and yields substantially below their long-run average in only one (two) years, i.e. in both periods above-average yields outweighed poorer harvests two to one. As predicted the favorable yield environment is reflected in smaller discrepancies between producers' directly-stated yields and the county objective measures. However, although their differences reduce to 5.51 bu/ac and 4.62 bu/ac for the 5 and 10 year periods, they remain significant ($p<0.001$ and $p<0.00l$) and do not change the character of our findings.

Risk perceptions

Producers' perceived yield risk is examined by comparing their implied standard deviations to the standard deviations of the de-trended county-level yields. A frequency diagram of the paired differences of producer and county standard deviations is displayed in figure 3. The graph shows that the differences are about equally distributed. Moreover, the Wilcoxon signed rank test detects no significant differences between the average implied standard deviation of survey participants (19.39 bu/ac) and the average standard deviation of county level yields (19.44 bu/ac) (p=0.605). Because good and bad yields within one county offset each other to some degree, individual farm-level variability should exceed the variability of average county yields. Producers thus appear to understate their true yield variability. These results are consistent with the findings by Eales et al. (1990) and Pease (1992), although the degree of overconfidence displayed here differs. The ratio of perceived farm-level to countywide risk in our study (=1.00) is substantially larger than those computed from the results by Eales et al. (1990), particularly for soybean and more distant corn prices, which indicates that less biased risk assessments may result when producers have a closer relationship to the assessed subject matter. Farmers have, for example, more control over their individual yields than over market grain prices and hence tend to possess a somewhat more accurate perception of variability.

The extent of producers' overconfidence may further be related to the relatively greater number of years with adverse weather conditions in the early part of the 1972-2001 period. The last significant drought affecting the entire state of Illinois occurred in 1988. Since then other areas have been hit by floods or droughts, but the effects have been less widespread and less severe. Including only post-1988 county yields into the analysis, we find, as expected, a decrease in the average standard deviation of county level yields to 16.34 bu/ac. Comparing this value to the average producer implied standard deviation of 19.39 bu/ac, the Wilcoxon signed rank test rejects the hypothesis of equality (p=0.010). The survey respondents hence no longer appear overconfident but provide subjective risk assessments consistent with the notion that variability of individual farm yields should be greater than county yield variability. This suggests that farmers pay close attention in their observing to the most recent information, which is consistent with findings in psychology (Wyer and Srull 1981; Kahnemann, Slovic and Tversky 1982).

An important question that arises in this context is whether the observed bias between directly-stated yields and objective yield measures can be explained by producers' perceived risk and other characteristics such as farm size. Farmers who are less overconfident in their individual risk assessment may also provide less biased direct yield statements. Moreover, farm size may be an indicator of long-term term success and experience in agriculture, which may cause producers to be more objective when directly stating their yields. Examining these hypotheses in a regression framework with perceived risk and farm size as explanatory variables, we find that none of the coefficient estimates are significant during the 1972-2001 and the post-1988 data periods, indicating that there may be other factors such as age or risk aversion (Kahneman and Lovallo, 1993) that may explain the observed biases in producers' direct yield statements.

Conclusion

Using the survey responses of Illinois corn farmers to questions about their farm's primary location and yields, we evaluate farmers' perceived yields and risk and how differences between perceived and actual past yield distributions change if producers are confronted with different decision frames. Overall, the results show that farm-level yields can be best characterized by soliciting probabilistic information. The probability assignment task not only provides more accurate yield assessments than an open-ended frame but also consistent estimates of producers' subjective risk. These findings are in partial contrast to previous studies that report consistent subjective means (Bessler 1980; Eales el al. 1990) but overconfidence in subjective variances (Eales el al. 1990; Pease 1992). We find that overconfidence can be confused with differences in relevant information and that using recent data may be more appropriate in examining subjective risk statements to account for this effect. Our results further indicate that random variables where farmers have repeated experiences such as yields may be easier to determine than variables over which producers have less control and information such as prices (Eales et al. 1990). Future researchers need to be aware of these issues when evaluating and using subjective variance assessments, particularly in modeling and predicting producers' behavior, as well as when eliciting information about producers mean yields.

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Table 1. Number of Usable Survey Responses and Farm Size of Respondents

Location	Usable surveys	Farm size			
		Average	Median	Min	Max
		acre	*acre*	*acre*	*acre*
Decatur	41	1219	900	65	4000
Rochelle	46	1025	845	15	3000
Mt. Vernon	24	1479	1200	240	4000
All	111	1195	975	15	4000

Table 2. Producers' Perceived Average Yield Relative to a Typical Farm in Their County

Survey Location	Higher		About the same	Lower	
	Yield	… by	Yield	Yield	… by
	%	*bu/ac*	*%*	*%*	*bu/ac*
Decatur	37	10.5	56	7	15.0
Rochelle	50	10.0	35	15	16.0
Mt. Vernon	46	17.9	37	17	11.9
All	44	11.9	43	13	14.6

Table 3. Producers' Perceived Yield Variability Relative to a Typical Farm in Their County

Survey Location	More Stable Yield	Same Yield Variability	More Variable Yield
	%	*%*	*%*
Decatur	49	41	10
Rochelle	43	33	24
Mt. Vernon	38	54	8
All	44	41	15

Table 4. Producers' Perceived Average Yield, Weibull Implied Mean Yield and Yield of a Typical Farm in Their County

Survey Location	Directly-Stated Average Yield	Simple Implied Mean Yield	Weibull Implied Mean Yield	County Average Yield	Directly-Stated Minus Typical Yield[a]	Directly-Stated Minus Weibull Implied Yield[a]
	bu/ac	*bu/ac*	*bu/ac*	*bu/ac*	*bu/ac*	*bu/ac*
Decatur	163.66	154.76	155.88	152.49	11.17[*]	7.78[***]
Rochelle	154.00	142.80	144.17	148.27	5.73[***]	9.83[***]
Mt. Vernon	131.08	124.35	123.86	126.00	5.08[***]	7.22[***]
All	152.61	143.23	144.10	145.01	7.60[*]	8.51[***]

[a] Significantly greater than zero at $p<0.0500$ (*), $p<0.010$ (**) and $p<0.001$ (***).

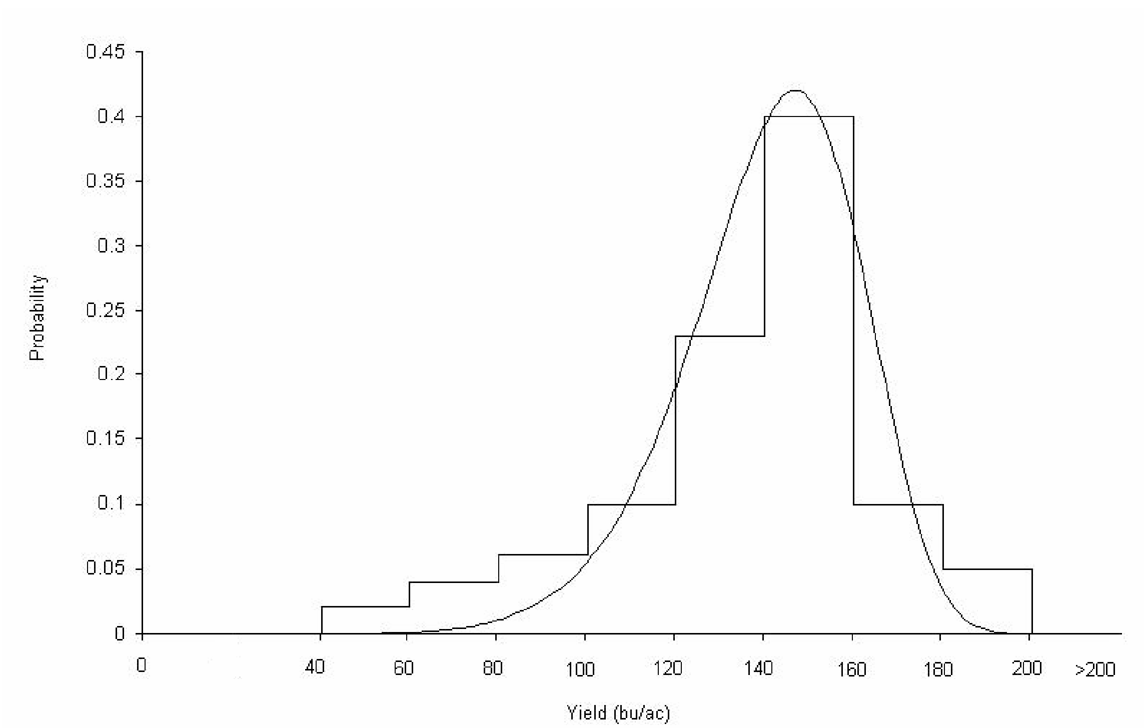

Figure 1. Yield probabilities assigned by one survey respondent and fitted Weibull yield distribution.

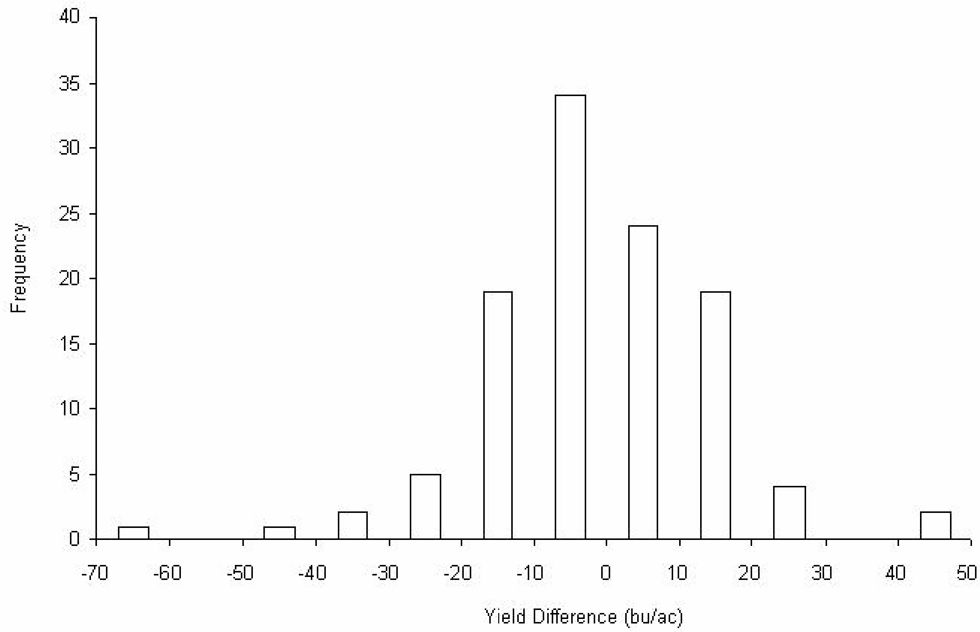

Figure 2. Frequency diagram of paired differences between Weibull implied and 1972-2001 county mean yields.

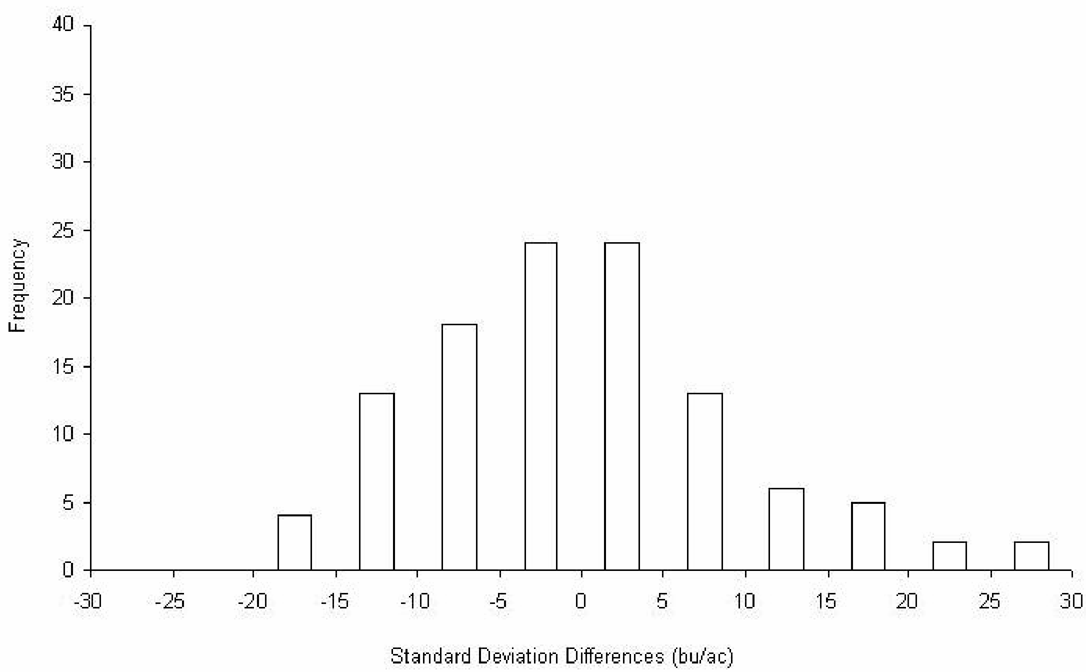

Figure 3. Frequency diagram of paired differences between Weibull implied and 1972-2001 county standard deviations.