Changes in Producers' Perceptions of Within-Field Yield Variability after Adoption of Cotton Yield Monitors

Roderick M. Rejesus, Michele C. Marra, Roland K. Roberts, Burton C. English, James A. Larson, and Kenneth W. Paxton

This article investigates how information from cotton yield monitors influences the perceptions of within-field yield variability of cotton producers. Using yield distribution modeling techniques and survey data from cotton producers in 11 southeastern states, we find that cotton farmers who responded to the survey tend to underestimate within-field yield variability (by approximately 5–18%) when not using site-specific yield monitor information. Results further indicate that surveyed cotton farmers who responded to a specific question about yield monitors place a value of approximately $20/acre/year (on average) on the additional information about within-field yield variability that the yield monitor technology provides.

Key Words: precision farming, risk, spatial yield distributions, within-field variability yield monitor, yield perceptions, yield variability

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The widespread availability of satellite signals in 1995, together with the availability of Global Positioning System (GPS) technology, made it possible for farmers to locate yield data spatially using yield monitors (Lechner and Baumann,

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2000). Moreover, these geo-referenced data from yield monitors enabled farmers to create field maps to facilitate variable-rate (VR) application of inputs. Spatial information from yield monitors have implications for how farmers perceive yield variability in their fields and, consequently, for their management of inputs. Therefore, a detailed analysis of this issue is valuable.

With advances in yield monitor technology in the 1990s, the adoption of yield monitors in the United States spread rapidly over the next decade, especially for grain and oilseed crops (i.e., corn and soybeans). In 2000, for example, 30% of total corn area and 25% of total soybean area in the United States were already being harvested by machines with yield monitors (Daberkow, Fernandez-Cornejo, and Padgitt, 2002). In 2001, the total corn area harvested in the United States by such machines increased to 37%, whereas for soybean, it increased to 29% in 2002 (Griffin et al., 2004a). By 2006,

yield monitor adoption was estimated to be 42% of total corn acreage and 45% of total soybean acreage (Schimmelpfennig and Ebel, 2011). In comparison, less than 3% of the total cotton area of the United States was harvested by machines with yield monitors between 2000 and 2002. By 2005, that area had increased to only approximately 8%. More recent data for cotton farmers in the South indicate approximately a 10% adoption rate (Mooney et al., 2010).

The slower rate of adoption of yield monitors in cotton farming was initially constrained primarily by ineffective equipment (Durrence et al., 1999; Sassenrath-Cole et al., 1998; Searcy and Roades, 1998; Valco, Nichols, and Lalor, 1998). Early cotton yield monitors, first introduced in 1997, had many problems including poor accuracy, failure to maintain calibration, and sensors that became blocked by dust and other materials (Durrence et al., 1999; Roades, Beck, and Searcy, 2000; Wolak et al., 1999). Progress was made when cotton yield monitoring technologies became more reliable and, consequently, cotton growers became more receptive to adopting and using this technology (Perry et al., 2001).[1]

Given the more effective cotton yield monitors available today, it is important to determine how this technology influences producers' yield variability perceptions of their fields. This issue is important because how producers perceive within-field yield variability fundamentally affects their decision-making behavior, as explained further subsequently. (See Delavande, Gine, and McKenzie, 2009; Manski, 2004, for a summary of the literature on how subjective expectations or perceptions could affect economic decision-making in other contexts.)

In a precision farming context, for example, a farmer without yield monitoring technology may believe that the spatial yield variability in his or her field is low (i.e., believes the field is spatially more homogenous than it actually is) based on prior experience of farming the field. Thus, this particular farmer may decide not to invest in VR technology to apply inputs at variable rates across different sections of the field. As English, Mahajanashetti, and Roberts (2001) have shown, the economic viability of VR input application depends critically on the degree of the spatial variability of the farmer's fields; higher spatial variability results in higher returns from the use of VR application technologies. However, if the farmer's prior perception of spatial yield variability is lower than the true spatial yield variability, an error could be made in the grower's decision-making about whether or not to adopt VR technology. The farmer may decide to continue using a uniform-rate approach instead of implementing VR application of inputs, which presumably would provide higher economic returns. With the use of yield monitoring technology, the producer may be able to more accurately assess the spatial yield variability of farm fields and make better input allocation decisions to enhance farm returns.

The objective of this research is to determine how information from cotton yield monitors influences the within-field yield variability perceptions of producers. Cross-section survey data collected from cotton producers in the southeastern United States and yield distribution modeling techniques are used to achieve this objective. In addition, we use survey data to provide information on the "value" cotton producers place on the information derived from yield monitor technology.

A number of studies have investigated farmers' perceived temporal yield distributions (and temporal yield variability) (e.g., Bessler, 1980; Clop-Gallart and Juarez-Rubio, 2007; Egelkraut et al., 2006a, 2006b; Grissley and Kellogg, 1983; Pease, 1992; Smith and Mandac, 1995). Most of these studies, however, focus primarily on comparing a subjectively elicited temporal yield distribution with an objectively measured historical/temporal yield distribution (i.e., from county yields, historical individual yields from farm records, etc.). In general, this literature shows that mean yields that are

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[1] In contrast to grain yield monitors, one unique feature of cotton yield monitors is that yield information can be collected from individual rows (Griffin et al., 2004b). Cotton yield monitors use optical sensors that measure the bulk flow of cotton moving from the picking rotors to the basket in the vacuum tubes, which makes the yield measures more accurate. Grain yield monitors, on the other hand, use mass flow measures such that yield information cannot be collected from individual rows.

subjectively elicited tend to coincide with the objective measures, but higher moments from the subjective temporal yield distribution (including temporal yield variability) tend not to be as accurate. Subjectively elicited or perceived temporal yield variability tends to be lower than objective estimates (Clop-Gallart and Juarez-Rubio, 2007; Egelkraut et al., 2006a, 2006b; Pease, 1992), which implies an underestimation of temporal variability. This underestimation is consistent with what the behavioral finance literature calls "overconfidence" (see Smith and Mandac, 1995; Tversky and Kahneman, 1974).

Although a number of studies have examined perceived temporal yield variability as it compares to objective measures, to the best of our knowledge, none has empirically shown how information from yield monitoring technology affects farmers' perceived spatial yield variability using the empirical approaches used in this study. This article contributes to the literature in this regard. One directly related study (Larson and Roberts, 2004) showed, through regression techniques, that adoption of yield monitoring technology with GPS has a statistically significant positive effect (20%) on cotton farmers' perceptions of spatial yield variability. This result implies that farmers tend to be overconfident about spatial yield variability perceptions (i.e., perceived spatial yield variability tends to be lower than the yield variability based on the yield monitor data). Our study is different from Larson and Roberts (2004) in that we use yield distribution modeling techniques (rather than regression techniques) to examine the effect of yield monitoring information on spatial yield variability perception and we also show how this information affects the whole yield distribution (rather than just yield variability). Our study provides further empirical evidence on the existence of "overconfidence" in farmers' perceived yield variability and we specifically show this overconfidence in the spatial dimension of yield variability.

Empirical Strategy

Survey and Data Description

Data for this study were collected from a survey of cotton producers in 11 states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, and Virginia (Cochran et al., 2006). A mailing list of potential cotton producers for the 2003–2004 season was first obtained from the Cotton Board in Memphis, Tennessee. Based on this mailing list, 12,243 survey questionnaires were sent on January 28, 2005. Reminders and follow-up mailings were sent on February 4, 2005, and February 23, 2005, respectively. Of the 12,243 surveys mailed, 200 were returned either undeliverable or by farmers indicating they were no longer cotton producers, leaving a total of 12,043 farmers. Of the remaining cotton producers in the sample, 1,214 individuals provided data giving a 10% usable response rate.[2] Even with this relatively low response rate, the regional distribution of farmers in the survey closely follows the 2002 geographical distribution of cotton farmers based on the Census of Agriculture (Cochran et al., 2006). However, the respondents in our survey tend to have: 1) more cotton farmers in the middle age groups (45–64 years) relative to the 2002 Census; and 2) a greater proportion of farmers with larger acreages (greater than 500 acres) compared with the 2002 Census.

Cotton producers were asked questions about the extent to which precision agriculture technologies were used on their farms as well as information on the general structure and characteristics of their farming operations. They were also asked about the profitability of precision agriculture in their operations as well as the outlook on the future prospects of precision farming in general.

For this study, we primarily use two survey questions that focus on perceptions about spatial yield variability. The first question was:

1. Because yields are likely to vary within a field, please estimate your cotton lint yields

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[2] The data used in this study are more than 5 years old (by the time of publication). Nevertheless, the unique features of the data make it relevant even with the age of the data set and allows for a detailed investigation of the topic in the study, which heretofore was not possible because no data were available on yield variability perceptions and yield monitor use.

(lb/acre) for the following portions of your typical cotton field:

Least productive 1/3___ Average productive 1/3___ Most productive 1/3 ___.

A total of 933 farmers gave an estimate for all three field segments requested in the question. The second survey question used in this study applies only to those who already adopted yield monitors (i.e., the questionnaire provides instructions to answer the second question only if they had adopted yield monitors) and directly asks how the yield monitor information changed their perception of yield variability:

2. How did the yield information you obtained from yield monitoring change your perception of the yield variability within your typical cotton field? Circle the statement that best matches your findings.

A. Substantially increased my perception; my yields appear to be at least 50% more variable than I thought.
B. Somewhat increased my perception; my yields appear to be from 25–50% more variable than I thought.
C. Slightly increased my perception; my yields appear to be from 1–25% more variable than I thought.
D. Did not change my perception; my yields appear to be the same as I originally thought.
E. Slightly decreased my perception; my yields appear to be from 1–25% less variable than I thought.
F. Somewhat decreased my perception; my yields appear to be from 25–50% less variable than I thought.
G. Substantially decreased my perception; my yields appear to be at least 50% less variable than I thought.

A total of 81 cotton farmers answered question 2. However, only 66 producers answered both questions 1 and 2 (i.e., of the 81 farmers who answered question 2, 15 of them did not answer question 1). Note that a total of 191 cotton farmers indicated using a yield monitor (of the 933 farmers who answered question 1), but only 66 of them answered both questions 1 and 2.

Descriptive statistics for question 1 are presented in Table 1 and a frequency distribution of the responses in question 2 is shown in Table 2. The figures in Table 2 indicate that over 80% of the farmers who answered question 2 think that yield monitor information increased their perceived within-field spatial variability. This response implies that surveyed cotton farmers who did not use yield monitors do tend to be overconfident about their within-field variability (i.e., they believe that their within-field variability is less than the actual value). These responses also provide a crude indication of the magnitude of overconfidence. However, the response to this question per se does not provide information about other perceived distributional impacts of yield monitor information (i.e., skewness and kurtosis) and whether or not the magnitude of overconfidence differs under varying assumptions about the producers' perceived distribution (i.e., normal vs. a beta, for example). The proceeding analysis aims to shed more light on these issues.

Deriving the 'Base' and the 'New' Within-Field Yield Distributions

Data from the two survey questions are used to construct a "base" distribution and a resulting "new" distribution as a result of changes in perceived spatial variability. First, we use the responses from the first question to calculate a "base" spatial variability measure for those 742 producers that indicated that they have not adopted yield monitors. Then we compare this with another spatial variability measure calculated based on the remaining 191 farmers that reported using yield monitors. This is essentially a "with–without" comparison and the difference in the perceived variability measures (and the resulting spatial yield distribution) is assumed as a result of yield monitor adoption.

Given the cross-sectional nature of the data and the way the first question was asked, the "base" distribution from the nonadopters does not necessarily reflect the actual perceived distribution before yield monitor information was used. However, this distribution can still serve as a "base" for which to compare the perceived variability of the yield monitor adopters. The implicit assumption in this case is that the nonadopters and adopters of yield monitors should

Table 1. Summary Statistics of Responses to Survey Question 1: Estimated Yields (lb/acre) for the Least, Average, and Most Productive Fields ($n = 934$)

Estimated Yields from:	Mean	Standard Deviation	Minimum	Maximum
Least productive one-third of field	600.27	201.54	100	1,300
Average productive one-third of field	847.08	194.82	200	1,650
Most productive one-third of field	1135.96	256.12	300	2,060

have similar characteristics such that the differences in perceived spatial distribution can be attributed to yield monitor adoption (i.e., no selection issues).[3]

Examining some sociodemographic characteristics of the yield monitor adopters vis-à-vis no-adopters suggests that their sociodemographic profiles tend to be very similar. For example, the mean age, farming experience, and years of education for the yield monitor adopters are 50, 27, and 15 years, respectively. For the nonadopters, the mean age, farming experience, and years of education are 49, 26, and 14 years, and these values are not statistically different (at the 5% level) from the values reported for the adopters. However, cotton farmers with yield monitors tend to have mean farm sizes (1,913 acres) that are larger than the nonadopters (1,521 acres) and these yield monitor adopters tend to be slightly more likely to adopt computers for farm management (i.e., 64% vs. 57% for nonadopters). The characteristics of these two groups should be taken note of when interpreting the results from the analysis using the full sample.

The second approach used in the study to construct a "base" distribution and a resulting "new" distribution is based on the 66 observations that answered both questions 1 and 2.

These producers are all yield monitor adopters and their responses to question 1 can be regarded as the perceived spatial variability "after adoption" of yield monitors (i.e., they answered this question with information from the yield monitors in mind). Hence, this can be regarded as the "new" distribution and the responses in question 2 can be used to calculate a "base" distribution (see discussion for more details). For example, if a producer answered A in question 2 (i.e., say, yield monitors increased perception by exactly 50%), then we can reduce the spatial variability calculated from the response in question 1 by 50% to compute (or "back out") a "base" variability measure before adoption of yield monitors.[4]

Because only 66 observations are used in this second approach, one issue that needs to be addressed here is whether the 66 farmers who responded to questions 1 and 2 have a different sociodemographic profile than the rest of the yield-monitor adopters ($n = 191-66 = 125$). We examined this issue and found that the 66 observations used tend to be slightly younger, slightly less experienced, have more years of education, have larger farm sizes, and are more likely to use computers in farm management than the remaining 125 observations that adopted yield monitors but did not answer question 2. The mean age, farming experience, years of education, farm size, and likelihood of using a computer for management are as follows for the 66 observations: 48 years, 23 years, 15 years, 2288 acres, and 87%. On the other hand, the mean values for the rest of the sample are as follows: 51 years, 27 years, 14 years, 1473 acres, and 51%. The 66 observations have fairly

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[3] Larson and Roberts (2004) used a regression (or conditional means) approach to investigate the yield monitor effect on perceived variability and control for the different characteristics of adopters and nonadopters. In this approach, they controlled for observable characteristics and their results are consistent with the results of the present study. Other regression (or conditional mean) approaches can be used to analyze the issue of interest in this study and at the same time account for selection issues (i.e., simultaneous equations framework and/or instrumental variable type models), but we believe this may require additional data and could be a topic for future work.

[4] As compared with the first approach, this second approach can be thought of as a comparison "before and after" yield monitor adoption (for the same individual). We thank one referee for suggesting this specific approach to the analysis.

Table 2. Frequency Distribution of Responses to Survey Question 2: Estimated Effect of Yield Monitor Information on Spatial Variability Perception of the Field ($n = 66$)

Response	Frequency	Percent	Cumulative Percent
A. Substantially increased my perception; my yields appear to be at least 50% more variable than I thought.	11	16.67	16.67
B. Somewhat increased my perception; my yields appear to be from 25–50% more variable than I thought.	24	36.36	53.03
C. Slightly increased my perception; my yields appear to be from 1–25% more variable than I thought.	20	30.30	83.03
D. Did not change my perception; my yields appear to be the same as I originally thought.	10	15.15	98.48
E. Slightly decreased my perception; my yields appear to be from 1–25% less variable than I thought.	1	1.52	100.00

Note: (1) Of the $n = 66$ respondents who answered questions 1 and 2, none chose "F. Somewhat decreased my perception; my yields appear to be from 25–50% less variable than I thought." or "G. Substantially decreased my perception; my yields appear to be at least 50% less variable than I thought."

similar age, experience, and education, but their farm size and likelihood of computer use tend to be different relative to the rest of the sample. Like in the first approach, these characteristics should be kept in mind when interpreting the results from the analysis.

Change in Perception of Spatial Yield Variability Assuming a Normal Yield Distribution

One way to interpret and use the answers from question 1 is to assume that the response for each one-third portion of the field is the median value for that particular part of the field. With this interpretation, we can characterize the perceived yield distribution of the cotton farmer to be symmetric and normally distributed (Figure 1).[5] The median values reported

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[5] Although a majority of the crop yield distribution literature argues that crop yields are distributed asymmetrically (i.e., skewed) and are nonnormal (see Harri et al., 2009, for a recent summary of this literature), other studies maintain that the normality assumption is reasonable for modeling crop yield distributions (see Claasen and Just, 2011; Just and Weninger, 1999). Hence, we still consider the normal distribution a plausible distribution to assume when studying changes in within-field yield variability perceptions. We also investigate this issue using an asymmetric distribution (i.e., beta) in the next section. The normal distribution is considered a "starting point" for the analysis of the change in perceived within-field yield variability as a result of yield monitor information.

can then be used to divide each one-third portion of the field in half so that the normal distribution as a whole can be divided into six intervals (with one-sixth allocated to each interval). Under the assumption of normality, the median value reported for the "Average Productive 1/3" of the field can be interpreted as the mean of the distribution and we know from basic statistics that one standard deviation from the mean in each direction contains approximately 68% of the probability mass. Because the middle four-sixths of the distribution contains approximately two-thirds (or 67%) of the probability mass, one can estimate the standard deviation of the normal distribution as the yield range in the middle two-thirds of the distribution. The information and assumptions can then be used to estimate the standard deviation of the perceived spatial yield distribution.

The general approach here is to first use the individual responses to question 1 and then calculate the parameters (e.g., mean and standard deviation) of a normal distribution at the individual producer level. Based on these individual level estimates, the average values of these parameter estimates are then computed in the second step (i.e., the average mean and average standard deviation) to produce an "average" normal distribution. At the individual level (i.e., the first step), the standard deviation is estimated by first calculating the difference between the reported median value at the upper and lower

one-third of the normal distribution. In Figure 1, this gives an estimate of the middle four intervals (four of six) of the normal distribution. Therefore, adding one-third of the value of the middle four intervals gives the range of the whole normal distribution. The range value can then be divided by four to get an estimate of the standard deviation of the distribution. We use this approach to calculate the standard deviation to assure that the two middle one-third sections of the distribution are equidistant from the mean (to conform to a normal). The estimated variance is then calculated as the square of this standard deviation value.

The estimated variance and the reported median values in the average one-third of the field (which is also the mean in the normal) for the sample would then allow one to calculate an average mean and an average variance for the yield monitor adopters and nonadopters, respectively.[6] Consistent with the first approach described in the previous subsection, these "average" values can serve as the two parameters needed to depict an "average" subjective normal yield distribution for cotton farmers that did not adopt yield monitors (i.e., the "base" normal yield distribution in this case) and those that adopted yield monitors (i.e., the "new" normal yield distribution after using information from yield monitors).

To operationalize the second approach to constructing a "base" and "new" distribution, we use data from the 66 observations that answered both questions 1 and 2. The paired responses to question 2 are used to quantify the average change in perceived spatial yield variability after the availability of yield monitor information. If the response is A or G (i.e., increase/decrease variability perception by at least 50% or more), we assume the perceived variance increases or decreases by 50%. If the response is B or F (i.e., increase/decrease variability perception by 25–50%), we assume the perceived variance increases or decreases by 37.5%. If the response is C or E (i.e., increase/decrease variability perception by 1–25%), we assume the perceived variance increases or decreases by 12.5%. Lastly, if the response to question 2 is D, the new variance is the same as the "base" variance. These transformed quantitative responses allow us to calculate the "base" variance for each of the 66 yield monitor adopters in the sample, as described in the previous subsection. Recall that for the 66 yield monitor adopters here, the perceived variability calculated from the response to question 1 is the "new" within-field variability measure (after yield monitor adoption) because these farmers may have used the information from the yield monitor when answering the question. Hence, the transformed responses to question 2 would allow one to derive the "base" perceived variability measure before yield monitor adoption. Moreover, this approach would allow one to directly calculate the change in within-field yield variability for each of the 66 producers. Averaging these changes in perceived spatial yield variability across these respondents allows calculation of an average change in farmers' perceptions of within-field yield variability for the sample. Using the calculated "base" and "new" variance, normal yield distributions can be graphically depicted (as in Figure 2) to reflect the average change in the perceived within-field yield distribution resulting from the yield monitor information.

Change in Perception of Spatial Yield Variability Assuming a Beta Yield Distribution

The limitation of the analysis is the symmetry assumption implied by the use of a normal distribution. We address this limitation by examining the effect of yield monitor information on the within-field yield variability perception assuming the perceived yield distribution that is based on a beta distribution. The beta distribution

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[6] As suggested by a reviewer, we also calculated an "average" variance (and standard deviation) by first calculating the average response for the least productive one-third and most productive one-third of the field. This is in contrast to the approach described in which we first individually calculate a variance and a standard deviation for each observation (based on each farmer's response to the least productive one-third and most productive one-third) and then we take the average of these individual variances/standard deviations. These two approaches provide the same results. The results from the alternative approach described in this footnote are available from the authors on request.
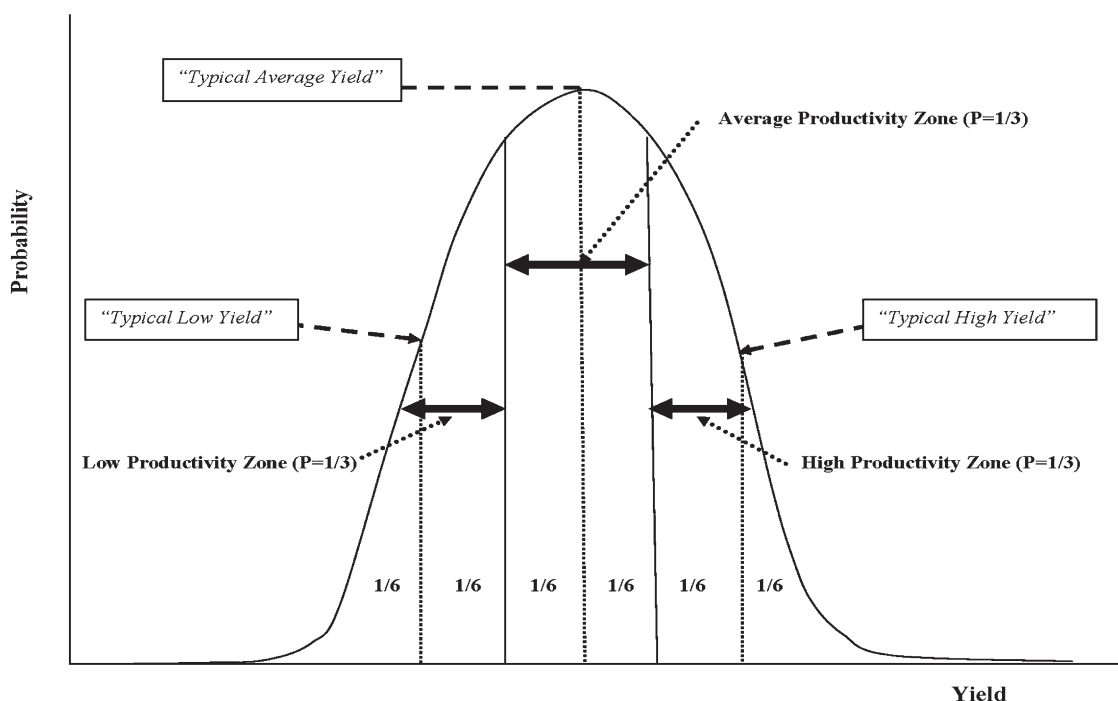
Figure 1. Probability Distribution Showing the Productivity Zones and "Typical" Values: Normal Distribution

is used in this study because, relative to other nonnormal parametric distributions used in the literature (i.e., the gamma or Weibull), it is "flexible" enough to accommodate a wider range of skewness and kurtosis values and, thus, allows for varying degrees of asymmetry, which is not possible with the normal or other less flexible parametric distributions. Previous literature shows that temporal cotton yield distributions tend to be right-skewed, which can be easily accommodated by the beta distribution (e.g., Chen and Miranda, 2008; Field, Misra, and Ramirez, 2003; Ramirez, Misra, and Field, 2003). In addition, most of the empirical literature in agricultural economics over the past decade has used the beta distribution to model temporal crop yields (e.g., Babcock, Hart, and Hayes, 2004; Goodwin, 2009).

The approach here is to derive a beta distribution based on the sample of 66 yield monitor adopters who answered both questions 1 and 2. Consistent with the analysis of this sample in the previous subsection (i.e., the "second" approach), the responses to question 1 are used to construct the "new" distribution. Then, using the answers to question 2, the "base" distribution can be calculated (i.e., "backed out") from the "new" beta distribution. The first task, therefore, is to determine the four parameters needed (i.e., minimum, maximum, and two shape parameters) to estimate a spatial beta yield distribution that is perceived by the sample of 66 cotton yield monitor adopters:

$$(1) \quad f(y) = \frac{1}{B(\alpha,\beta)} \cdot \frac{(y-a)^{\alpha-1}(b-y)^{\beta-1}}{(b-a)^{\alpha+\beta-1}},$$

where y is the random variable of interest (i.e., yields in our case), α and β are shape parameters, a and b are the minimum and maximum (respectively), and $B(\cdot)$ is the beta function.

To derive the beta distribution based on question 1, we can use a yield of zero (i.e., lowest possible cotton yield) as the minimum of our perceived beta distribution and, from the data on question 1, the maximum observed data point of the "Most Productive 1/3" variable (i.e., in this case,

2,000 lb/acre[7] as the maximum of our perceived beta distribution. The two shape parameters are estimated using the Method of Moments formulas for the beta distribution expressed as follows:

$$(2) \quad \alpha = \left(\frac{\bar{y}-a}{b-a}\right)\left(\frac{\left(\frac{\bar{y}-a}{b-a}\right)\left(1-\frac{\bar{y}-a}{b-a}\right)}{\left(\frac{\sigma_y^2}{(b-a)^2}\right)} - 1\right),$$

$$(3) \quad \beta = \left(1-\frac{\bar{y}-a}{b-a}\right)\left(\frac{\left(\frac{\bar{y}-a}{b-a}\right)\left(1-\frac{\bar{y}-a}{b-a}\right)}{\left(\frac{\sigma_y^2}{(b-a)^2}\right)} - 1\right),$$

where α and β are the two shape parameters of the beta distribution, $\bar{y}$ is the estimated mean, σ_y^2 is the estimated variance, and a and b are the minimum and maximum values.

To estimate the shape parameters in equations (2) and (3), one ideally should have a spatial yield data series for each cotton farmer's field in the sample (i.e., having a perceived yield for each grid/section of the farmer's field). This type of data series allows for calculation of the mean and variance of their perceived within-field yield distribution and, consequently, the two shape parameters that account for the potential asymmetry in the distribution (i.e., skewness). However, we are limited by the fact that the subjective yield data we have for each cotton producer in the sample is only based on their responses to question 1. To overcome this limitation, we take advantage of the empirical insight from Johnson (1997) who showed that a triangular distribution is a good proxy for the beta distribution, implying that the mean and the variance parameters estimated from a triangular distribution are good approximations of the mean and variance for a beta distribution. Thus, they can be used to estimate the shape parameters of the beta distribution (using equations [2] and [3]).

The mean and variance parameters from a triangular distribution can be calculated using the following formulas:

$$(4) \quad \bar{y} = \frac{a+b+m}{3}$$

$$(5) \quad \sigma_y^2 = \frac{a^2+b^2+m^2-ab-am-bm}{18},$$

where a and b are the minimum and maximum values and m is the mode. Therefore, to implement equations (4) and (5), we use the minimum and maximum values as discussed previously (i.e., minimum = zero and maximum = 2,060 lbs/acre)[8] and also we take the most frequent response to the "Average Productive 1/3" category as the mode (i.e., in this case 1,000 lbs/acre). The resulting mean and variance from equations (4) and (5) can then be plugged into equations (2) and (3) to complete the four parameters needed to characterize the average perceived spatial beta yield distribution after yield monitor adoption.

Like with the empirical approach for the normal distribution (using the 66 observations), the average change in within-field yield variability perception is quantified using the paired responses of the 66 yield monitor adopters who answered question 2. In this case, we first calculate the average percent change in the variance using the quantified version of the responses to question 2. We use this average change in variance to "back out" the "base" perceived within-field yield variance (i.e., the average percent change is multiplied by the variance estimate in equation [5] and the resulting value is used to calculate the "base" perceived variance). This variance estimate, together with the previously estimated mean, make it possible to recalculate the two shape parameters and graphically depict the change in the perceived "base" spatial beta yield distribution resulting

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[7] A reviewer pointed out that this maximum value estimate used in fitting the beta distribution may be underestimated. Hence, we conducted a sensitivity analysis that increased the magnitude of this maximum value by 257 lbs/acre (i.e., the standard deviation of the responses for the most productive field) for the sample of 66 farmers and we found that the results are qualitatively similar to the results in which a 2000-lbs/acre maximum is assumed. Results of this sensitivity analysis are available from the authors on request.

[8] Note that the assumptions made here are meant to make the empirical analysis tractable. The assumed minimum value of zero (in the beta distribution analysis) implicitly accounts for the producer estimates in the lower third of the field (i.e., producer responses are not ignored). We acknowledge that the lowest response for the question on the least productive third is 100 lbs/acre and we could have used this minimum in the beta analysis. However, we found it reasonable to assume a zero value as the smallest possible yield instead. The inferences are the same regardless of whether a zero or 100 lbs/acre is assumed to be the minimum.
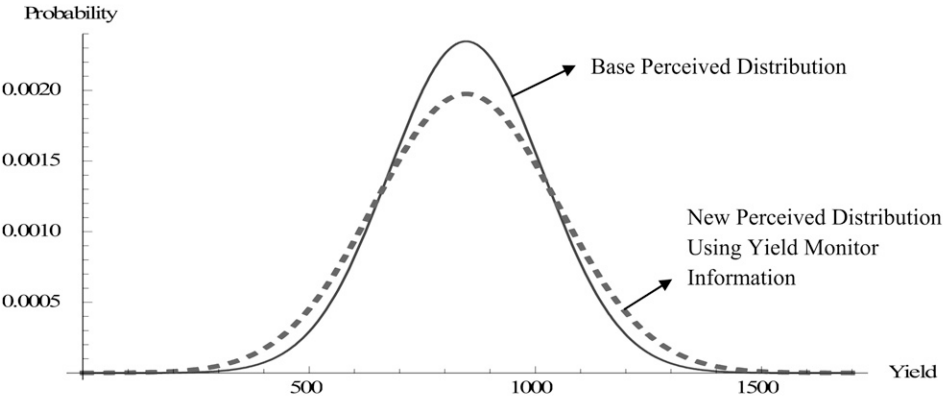
A. Base Distribution Mean= 847 lbs/acre and St. Dev.=170 lbs/acre
New Distribution Mean= 847 lbs/acre and St. Dev.=202 lbs/acre
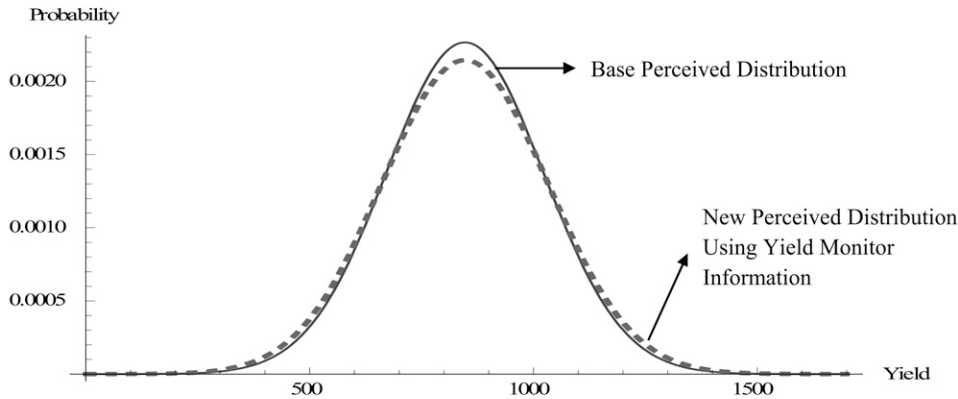
B. Base Distribution Mean= 847 lbs/acre and St. Dev.=176 lbs/acre
New Distribution Mean= 847 lbs/acre and St. Dev.=186 lbs/acre

Figure 2. Change in Perceived Yield Distribution Resulting from Yield Monitor Information: Normal Distribution Assumption

Notes: (1) Figure 2A assumes the base and new distribution are based on the sample that answered questions 1 and 2 ($n = 66$).

(2) Figure 2B assumes the base distribution is based on the sample of nonadopters ($n = 742$) and the new distribution is based on the sample of yield monitor adopters ($n = 191$).

from the yield monitor information's effect on the farmer's within-field yield variability perceptions (as in Figures 3 and 4).

Robustness Check 1: Using the PERT Approximation to Estimate the Beta Distribution

Another approach to overcome the limitation of the yield perception data is to use the mean and variance formulas found in the PERT (Program Evaluation and Review Technique) literature to approximate the mean and variance of the perceived beta yield distribution. Malcolm et al. (1959) and Moskowitz and Bullers (1979) showed that a pragmatic, or shorthand, way to estimate the mean and variance of a beta distributed random variable is:

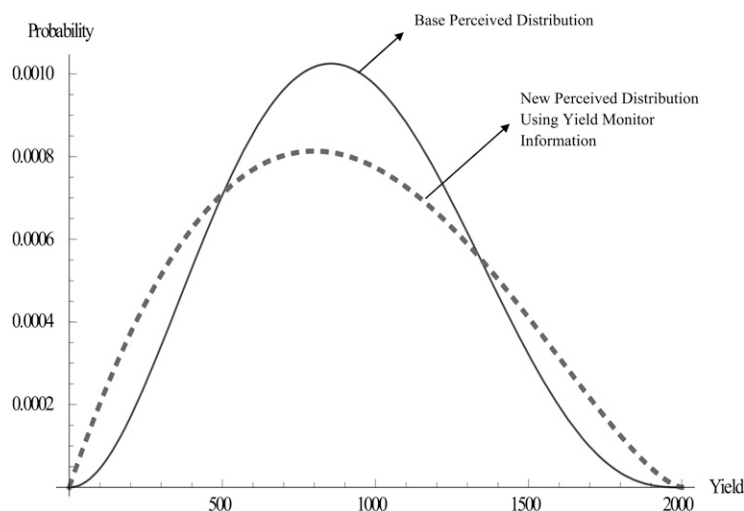$$(6) \quad \bar{y} = \frac{a + b + 4m}{6}$$

Figure 3. Change in Perceived Yield Distribution Resulting from Yield Monitor Information: Beta Distribution/Triangular Distribution

Notes: (1) The parameters of the base beta distribution above are calculated from the estimated mean and variance derived from the moment equations of a triangular distribution.
(2) Parameters of the base beta distribution are: $\bar{y}$ = 1000, σ_y = 352.21, α = 2.00, and β = 2.5. Skewness = 0.09, kurtosis = –0.61.
(3) Parameters of the new beta distribution are: $\bar{y}$ = 1000, σ_y = 408.24, α = 3.03, and β = 3.53. Skewness = 0.16, kurtosis = –0.76.

$$(7) \quad \sigma_y^2 = \frac{(b-a)^2}{36}.$$

This method has also been used by Clop-Gallart and Juarez-Rubio (2007) to evaluate the reliability of subjectively elicited temporal crop yield probability distributions. The estimated mean and variance parameters from equations (6) and (7) are used in equations (2) and (3), respectively, to estimate beta shape parameters. The procedures presented in the previous subsection are then used to calculate the average change in within-field yield perception variability and to graphically depict the change in the perceived beta yield distribution resulting from yield monitor information. The results using these PERT estimates of mean and variance are compared with the results using the mean and variance estimated using the triangular distribution to evaluate the robustness of our results.

Robustness Check 2: Tests Comparing Mean Perceived Yield Variability of Adopters vs. Nonadopters

To compare and further check the robustness of the results from the yield distribution modeling

techniques, we also conduct statistical tests (t tests) to determine whether the mean yield variability perceptions of yield monitor adopters are statistically different from those of nonadopters. First, we use the standard deviation variability measure in this normality case as a measure of spatial yield variability perceptions. The mean value of the estimated standard deviations for: 1) the 191 yield monitor adopters, i.e., not necessarily all 191 answered question 2; and 2) the 66 yield monitor adopters who answered questions 1 and 2 are then compared against the remaining nonadopters (n = 742) in the sample.

Second, we also conduct tests based on the perceived within-field spatial variability measure in Larson and Roberts (2004) calculated as follows:

$$(8) \quad \begin{aligned} WFSV_i = \Big[&\tfrac{1}{3} \times \left(Y_i^{least} - Y_i^{avg}\right)^2 \\ &+ \tfrac{1}{3} \times \left(Y_i^{mid} - Y_i^{avg}\right)^2 \\ &+ \tfrac{1}{3} \times \left(Y_i^{most} - Y_i^{avg}\right)^2 \Big]^{0.5} \end{aligned}$$

where $WFSV_i$ is the perceived within-field standard deviation for producer i, Y_i^{least} is the
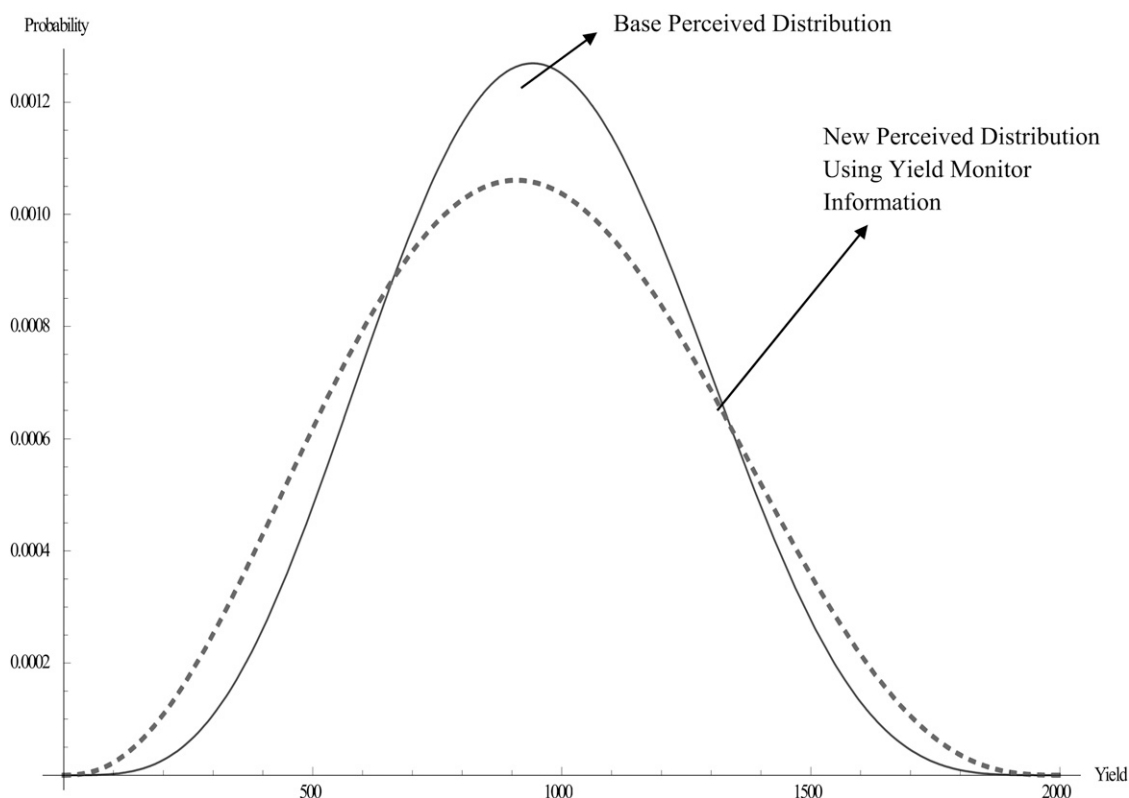
Figure 4. Change in Perceived Yield Distribution Resulting from Yield Monitor Information: Beta Distribution/PERT Estimates

Notes: (1) The parameters of the base beta distribution are calculated from the estimated mean and variance derived from the moment equations in the PERT literature.
(2) Parameters of the base beta distribution are: $\bar{y}$= 1000, σ_y = 287.57, α = 5.04, and β = 5.54. Skewness = 0.05, kurtosis = –0.44.
(3) Parameters of the new beta distribution are: $\bar{y}$= 1000, σ_y = 333.33, α = 3.50, and β = 4.00. Skewness = 0.08, kurtosis = –0.56.

yield reported by producer i for the least productive one-third of the field, Y_i^{avg} is the yield reported by producer i for the average productive one-third of the field, Y_i^{most} is the yield reported by producer i for the most productive one-third of the field, and Y_i^{mid} is calculated as follows: $Y_i^{mid} = (3 \times Y_i^{avg}) - Y_i^{least} - Y_i^{most}$. Again, the mean $WFSV_i$ for yield monitor adopters is tested against nonadopters to determine whether there is a statistically significant difference between them (i.e., all of the 191 yield monitor adopters vs. the 742 nonadopters, and the 66 yield monitor adopters who answered questions 1 and 2 vs. the 742 nonadopters). If it is found that the mean of the perceived variability

for yield monitor adopters is statistically different (i.e., higher) than for nonadopters, then this supports the presence of "overconfidence" behavior by nonadopters.

The Value of Yield Monitor Information

The survey questionnaire also directly elicited information about whether the yield variability information from the yield monitor is valuable to the farmer:
  3. Do you think the additional information about within-field variability you obtain from your cotton yield monitor is valuable to you? Yes _____ No _____

4. If yes, what value do you place on the additional information you obtain from your cotton yield monitor? $_____ acre/year.

These two questions were asked separately for both self-declared yield monitor adopters and nonadopters. Hence, we compare the value a yield monitor adopter attaches to this technology vs. the value a nonadopter attaches to it.

Results and Discussion

Change in Spatial Yield Variability Perception Assuming a Normal Yield Distribution

Assuming normality, perceived spatial variability (i.e., the standard deviation) increases by 32 lbs/acre (or 18.8%), on average, for the 66 respondents who answered both question 1e and 2. This increase is graphically depicted in Figure 2A where the use of yield monitor information resulted in a more dispersed normal yield distribution. The estimated standard deviation for the 66 cotton respondents before yield monitor adoption is 170 lbs/acre, and after using yield monitor information, the standard deviation is 202 lbs/acre (where the difference is statistically significant at the 1% level). Figure 2B also graphically shows the effect of yield monitor information on cotton producers' perceptions of within-field yield variability. However, in this case, we use the average standard deviation of the 742 nonadopter respondents (from question 1) to calculate the initial perceived base distribution and the responses of the 191 yield monitor adopters to serve as the distribution after using yield monitor information. In Figure 2B, there is a less dramatic increase in the perceived yield variability (10 lbs/acre or 5.6% increase), but the increase is still statistically significant (at the 5% level). Nevertheless, the main inference based on both Figures 2A and 2B is still the same (i.e., there is an increase in perceived within-field variability after yield monitor adoption); only the magnitudes differ.

Results from Figures 2A and 2B support the general notion of "overconfident" perceptions of spatial yield variability. Assuming a normal yield distribution, cotton farmers in our sample tend to underestimate the spatial yield variability in their fields. Yield monitor information allows them to more accurately discern the within-field yield variability.

Change in Spatial Yield Variability Perception Assuming a Beta Yield Distribution

Figure 3 shows the change in the perceived within-field yield distribution after obtaining yield monitor information. The beta distribution is assumed in this figure, and the mean and variance of the triangular distribution are used to calculate the shape parameters. In this case, perceived within-field yield variability increases by 56 lbs/acre (or ≈16%) after yield monitor information is obtained by cotton producers.

This result is again supportive of the behavioral expectation that cotton producers relying solely on judgment from experience tend to underestimate within-field yield variability. Thus, perceived spatial yield variability tends to be lower than a more objective measure of spatial yield variability such as variability information coming from a yield monitor.

In addition, the beta yield distribution analysis gives information about the effect of yield monitor information on the skewness and kurtosis of the perceived within-field distribution. Based on Figure 3, we see that using yield monitor information made the perceived yield distribution more right-skewed and flatter (i.e., wider-peaked, or more platykurtic). This implies that probability of experiencing within-field yields below 300 lbs/acre is actually higher than what was initially perceived without the yield monitor. Again, this supports the notion of overconfidence when yield monitor information is not used.

Robustness Check 1: Using the PERT Approximation to Estimate the Beta Distribution

The resulting distribution using the PERT formulas to estimate the shape parameters of the beta distribution is tighter than the one using the triangular distribution formulas (Figure 4). Using the PERT formulas resulted in a less pronounced change in within-field yield variability

perception relative to using the triangular distribution formulas. However, perceived within-field yield variability still increases by 45.76 lbs/acre (or 16%) after information from yield monitoring technology becomes available (Figure 4).

Moreover, the degree of increase in right-skewness and flatness (or being wide-peaked) resulting from the use of yield monitors is also less evident in Figure 4 compared with Figure 3. Nevertheless, these results provide further evidence of the likely overconfidence of cotton producers with regard to within-field yield variability perceptions. This result is robust to the different approximations used in calculating the shape parameters of the beta distribution and even across distributional assumptions (beta vs. normal).

Robustness Check 2: Tests Comparing Mean Perceived Yield Variability of Adopters vs. Nonadopters

Based on the standard deviation measures from the normality case, we find that the average standard deviation for yield monitor adopters ($n = 191$) is 186 lbs/acre, whereas it is 176 lbs/acre for nonadopters ($n = 742$). The average standard deviation for the yield monitor adopters is statistically higher (at the 5% level of significance) than the average standard deviation for the nonadopters (p value = 0.05). Moreover, the average standard deviation of the 66 yield monitor adopters who answered questions 1 and 2 (202 lbs/acre) is also statistically higher (at the 5% level) than the average standard deviation of the 742 farmers (176 lbs/acre) that did not adopt yield monitors (p value = 0.005). Again, these results suggest that within-field variability perceptions of farmers tend to be lower before the adoption of yield monitors, which is supportive of the overconfidence behavior.

The mean $WFSV_i$ (from equation [8]) for all yield monitor adopters ($n = 191$) is 247 lbs/ac, whereas for nonadopters, it is 233 lbs/ac. The $WFSV_i$ for the adopters is statistically higher than the nonadopters (p value = 0.05). In addition, the mean $WFSV_i$ for the 66 yield monitor adopters who answered questions 1 and 2 is 268 lbs/acre, whereas the $WFSV_i$ for the 742

nonadopters is 233 lbs/acre. The difference between these two mean $WFSV_i$ measures (35 lbs/acre) is also statistically significant at the 5% level of significance (p value = 0.012). The results of the statistical tests above point to an approximately 5–15% higher perceived spatial variability for yield monitor adopters as compared with the nonadopters. This magnitude is within the range of the estimates seen in the yield distribution modeling ($\approx$5–18%), providing further evidence with regard to the robustness of our results (i.e., presence of overconfidence behavior). Moreover, all these estimates of overconfidence are fairly consistent with the 20% overconfidence figure provided in Larson and Roberts (2004).

The Value of Yield Monitor Information

The information in Table 3 addresses the question of whether the aforementioned correction in overconfidence derived from yield monitor information translates into perceived value to the producer. The average value perceived by yield monitor adopters is $21.39/acre/year, whereas nonadopters perceive a lower but similar value of $19.31/acre/year.[9] The statistical comparison of these two means using t tests indicated that the mean information value of adopters is not significantly different from that of the non-adopters (i.e., the null hypothesis of equality of means is not rejected; t-statistic = 0.2935 with a p value of 0.7692). Finding similar mean values was somewhat unexpected given that yield monitor adopters have actually used the technology to collect spatial information and may have more information to more accurately value the yield monitor information. Nonetheless, the nonsignificant difference in the yield monitor information value provided by adopters and nonadopters suggests that nonadopters can also accurately assess the value of yield monitor information even without actually using technology. Both adopters and nonadopters place

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[9] The way questions 3 and 4 were structured, we believe the values reported by producers are best interpreted as "gross" values rather than "net" values (i.e., net of costs). This interpretation is consistent with how we explain the proceeding statistical result.

Table 3. Summary Statistics: Self-reported Value ($/acre/year) of Yield Monitor Information

Variable	Mean	Standard Deviation	Minimum	Maximum
(i) Value placed on yield monitor information for producers who have adopted yield monitor technology ($n = 44$)	21.39	29.26	0	150
(ii) Value placed on yield monitor information for producers who have not adopted yield monitor technology ($n = 324$)	19.31	25.75	0	200

Note: (1) The summary statistics reported in this table are for the sample who found yield monitor information to be valuable. For (i), 81 yield monitor adopters (out of 191) indicated that yield monitor information is valuable and 44 of those placed a value on it. For (ii), 709 producers who did not adopt yield monitors (out of 742) indicated that yield monitor information is valuable and 324 of those placed a value on it.

the same marginal value on the yield monitor information, but the nonadopters may just have decided not to use the technology. It could be that their cost–benefit calculations indicate that the value of the information may not be enough to cover the costs in the nonadopters' case. For example, the transactions cost of learning how to interpret and make use of the spatial yield information plus the actual cost of the technology itself may be higher than the value of the information. However, if the nonadopters have access to yield monitor information (and its interpretation), say, provided as a demonstration by a salesman, their decision calculus may change in favor of adoption.

Conclusions and Implications

Using survey data from cotton producers in 11 states in the southeastern United States, we empirically examine the effect of yield monitor information on farmers' perceptions about within-field yield variability. We find that cotton farmers tend to underestimate within-field yield variability when site-specific yield monitor information is not used. Results from various yield distribution modeling analyses (and other robustness checks) show that cotton farmers who responded to the survey questions on yield monitor perception effects tend to underestimate within-field yield variability by approximately 5% to 18% compared with the more objective spatial yield variability estimates from yield monitoring. Surveyed farmers tend to be overconfident about the probability of having lower yields when relying only on experience to evaluate their spatial within-field variability. Survey results further indicate that cotton farmers who responded to a specific question about yield monitors place a value of approximately $20/acre/year (on average) on the additional information about within field yield variability provided by yield monitors.

The underestimation of spatial yield variability is consistent with the existing literature in the sense that farmers tend to be "overconfident" with respect to perceptions about yield variability. However, the empirical evidence in the literature typically pertains only to overconfidence about temporal yield variability. This study provides evidence that the overconfidence about yield variability is also present in the spatial dimension. Future work may focus more on using regression (or conditional mean) approaches that control for selection issues to better tease out the effect of yield monitor information on perceived spatial yield variability (see discussion in footnote 3). A richer data set may be required for this type of study.

The findings in this study provide important implications for input use and risk management. A farmer's subjective view of within-field yield variability fundamentally affects input application decisions. In the absence of spatial yield monitor information, it is possible that farmer overconfidence (i.e., underestimating within-field yield variability) could influence the decision to adopt variable rate application technologies. Without yield monitor information, the farmer would perceive more spatially homogenous yields and be less likely to use variable rate input application techniques (English, Mahajanashetti, and Roberts, 2001; Larson and Roberts, 2004).

However, more accurate yield monitor information that shows higher within-field variability would increase the likelihood of a perceived benefit from using variable rate input application techniques. Yield monitor information gives a more precise "signal" about the true nature of the within-field variability and could be used by farmers to make better input application decisions (Bullock et al., 2009). This insight can also have implications for dealers of variable rate technologies. If dealers can provide more accurate within-field yield variability information through inexpensive yield monitoring, farmers may be encouraged to purchase variable rate application technologies (especially when the true variability is substantially higher than initial perceptions).

In addition, better perceptions of within-field spatial variability would likely allow producers to be more aware of the areas in the fields that are lower-yielding and proactively find solutions to improve yields in those areas through better crop management. If the producer was "overconfident" about the spatial variability of his or her field, then he or she might not recognize that there are lower-yielding areas where management adjustments may be needed to improve performance. The producer would be more cognizant of the "lower" tail of the spatial distributions of yields when he or she knows that the within-field yield variability may be bigger than what was previously thought.

References

Babcock, B.A., C.E. Hart, and D.J. Hayes. "Actuarial Fairness of Crop Insurance Rates with Constant Rate Relativities." *American Journal of Agricultural Economics* 86,3(2004):563–75.

Bessler, D.A. "Aggregated Personalistic Beliefs on Yields of Selected Crops Estimated Using ARIMA Processes." *American Journal of Agricultural Economics* 62,4(1980):666–74.

Bullock, D.S., M.L. Ruffo, D.G. Bullock, and G.A. Bollero. "The Value of Variable Rate Technology: An Information-Theoretic Approach." *American Journal of Agricultural Economics* 91,1(2009):209–23.

Chen, S.L., and M.J. Miranda. "Modeling Texas Dryland Cotton Yields, with Application to Crop Insurance Actuarial Rating." *Journal of Agricultural and Applied Economics* 40, 1(2008):239–52.

Claasen, R., and R.E. Just. "Heterogeneity and Distributional Form of Farm-Level Yields." *American Journal of Agricultural Economics* 93,1(2011):144–60.

Clop-Gallart, M.M., and F. Juarez-Rubio. "Elicitation of Subjective Crop Yield PDF." *Spanish Journal of Agricultural Research* 5,1(2007): 16–24.

Cochran, R.L., R.K. Roberts, B.C. English, J.A. Larson, W.R. Goodman, S.R. Larkin, M.C. Marra, S.W. Martin, K.W. Paxton, W.D. Shurley, and J.M. Reeves. *Precision Farming by Cotton Producers in Eleven States: Results from the 2005 Southern Precision Farming Survey.* Research Series No. 01-06, University of Tennessee Agr. Exp. Sta., Dept. of Agr. Econ., Knoxville, TN, 2006.

Daberkow, S.G., J. Fernandez-Cornejo, and M. Padgitt. 2002. "Precision Agriculture Technology Diffusion: Current Status and Future Prospects." Proceedings of the 6th International Conference on Precision Agriculture, 2002, pp. 1668–81.

Delavande, A., X. Gine, and D. McKenzie. "Measuring Subjective Expectations in Developing Countries: A Critical Review and New Evidence." Policy Research Working Paper, Development Economics Research Group, The World Bank, Washington, DC, 2009.

Durrence, J.S., D.L. Thomas, C.D. Perry, and G. Vellidis. "Preliminary Evaluation of Commercial Cotton Yield Monitors: The 1998 Season in South Georgia," Proceedings of the Beltwide Cotton Conference, 1999, pp. 366–72.

Egelkraut, T.M., B.J. Sherrick, P. Garcia, and J.M.E. Pennings. "Farmers' Subjective Perceptions of Yield and Yield Risk." Selected Paper presented at the 2006 NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, MO, April 17–18, 2006a.

Egelkraut, T.M., P. Garcia, J.M.E. Pennings, and B.J. Sherrick. "Producers' Yield and Yield Risk: Perceptions versus Reality and Crop Insurance Use." Selected Paper presented at the AAEA Meetings, Long Beach, CA, July 23–26, 2006b.

English, B.C., S.B. Mahajanashetti, and R.K. Roberts. "Assessing Spatial Break-Even Variability

in Fields with Two or More Management Zones." *Journal of Agricultural and Applied Economics* 33,3(2001):551–65.

Field, J.E., S.K. Misra, and O.A. Ramirez. "Evaluating Crop and Revenue Insurance Products as Risk Management Tools for Texas Cotton Producers." *Journal of Agricultural and Applied Economics* 35,1(2003): 39–52.

Goodwin, B.K. "Payment Limitations and Acreage Decisions under Risk Aversion: A Simulation Approach." *American Journal of Agricultural Economics* 91,1(2009):19–41.

Griffin, T.W., J.M. Lowenberg-DeBoer, D.M. Lambert, J. Peone, T. Payne, and S.J. Draberkow. "Precision Farming: Adoption, Profitability, and Making Better Use of Data." Paper presented at the Triennial North Central Farm Management Conference, Lexington, KY, July 14–16, 2004a.

Griffin, T.W., D.M. Lambert, J.M. Lowenberg-DeBoer, and B.J. Erickson. "Using Cotton Yield Monitor Data for Farm-level Decision Making." *Site-specific Management Center (SSMC) Newsletter*. West Lafayette, IN: Purdue University, October 2004b.

Grissley, W., and E.D. Kellogg. "Farmers' Subjective Probabilities in Northern Thailand: An Elicitation Analysis." *American Journal of Agricultural Economics* 65,1(1983):74–82.

Harri, A., C. Erdem, K.H. Coble, and T.O. Knight. "Crop Yield Distributions: A Reconciliation of Previous Research and Statistical Tests for Normality." *Rev. of Ag. Econ* 31,1(2009):163–82.

Johnson, D. "The Triangular Distribution as a Proxy for the Beta Distribution in Risk Analysis." *The Statistician* 46,3(1997):387–98.

Just, R.E., and Q. Weninger. "Are Crop Yields Normally Distributed?" *American Journal of Agricultural Economics* 81,2(1999):287–304.

Larson, J.A., and R.K. Roberts. "Farmers' Perceptions of Spatial Yield Variability as Influenced by Precision Farming Information Gathering Technologies." Selected Paper presented at the SAEA Annual Meetings, Tulsa, OK, February 14–18, 2004.

Lechner, W., and S. Baumann. "Global Navigation Satellite Systems." *Computers and Electronics in Agriculture* 25,1–2(January 2000): 67–85.

Malcolm, D.G., J.H. Rosenboom, C.E. Clark, and W. Fazer. "Application of a Technique for Research and Development Program Evaluation." *Operations Research* 7,5(1959):646–69.

Manski, C.F. "Measuring Expectations." *Econometrica: Journal of the Econometric Society* 72,5(2004):1329–76.

Mooney, D.F., R.K. Roberts, B.C. English, D.M. Lambert, J.A. Larson, M. Velandia, S.L. Larkin, M.C. Marra, S.W. Martin, A. Mishra, K.W. Paxton, R. Rejesus, E. Segarra, C. Wang, and J.M. Reeves. *Precision Farming by Cotton Producers in Twelve Southern States: Results from the 2009 Southern Cotton Precision Farming Survey*. Research Series 10-02. Knoxville, TN: Department of Agricultural and Resource Economics, University of Tennessee, 2010.

Moskowitz, H., and W.I. Bullers. "Modified PERT versus Fractile Assessment of Subjective Probability Distributions." *Organizational Behavior and Human Performance* 24,2(1979): 167–94.

Pease, J.W. "A Comparison of Subjective and Historical Crop Yield Probability Distributions." *Southern Journal of Agricultural Economics* 24,2(1992):23–32.

Perry, C.D., G. Vellidis, N. Wells, and C. Kvien. 2001. "Simultaneous Evaluation of Multiple Commercial Yield Monitors in Georgia," Proceedings of the Beltwide Cotton Conference, 2001, pp. 328–39.

Ramirez, O.A., S.K. Misra, and J.E. Field. "Crop-Yield Distributions Revisited." *American Journal of Agricultural Economics* 85,1(2003): 108–20.

Roades, J.P., A.D. Beck, and S.W. Searcy. "Cotton Yield Mapping: Texas Experiences in 1999," Proceedings of the Beltwide Cotton Conference, 2000, pp. 404–407.

Sassenrath-Cole, G.F., S.J. Thomson, J.R. Williford, K.B. Hood, J.A. Thomasson, J. Willams, and D. Woodard. "Field Testing of Cotton Yield Monitors," Proceedings of the Beltwide Cotton Conference, 1998, pp. 364–66.

Searcy, S.W., and J.P. Roades. "Evaluation of Cotton Yield Mapping," Proceedings of the Beltwide Cotton Conference, 1998, pp. 33–35.

Schimmelpfennig, D., and R. Ebel. *On the Doorstep of the Information Age: Recent Adoption of Precision Agriculture*. EIB-80, US Dept. of Agriculture, Economics Research Service, Washington, DC, August 2011.

Smith, J., and A.M. Mandac. "Subjective versus Objective Yield Distributions as Measures of

Productive Risk." *American Journal of Agricultural Economics* 77,1(1995):152–61.

Tversky, A., and D. Kahneman. *Judgement under Uncertainty: Heuristics and Biases.* D. Kahneman, P. Slovic, and A. Tversky, eds. Cambridge, MA: Cambridge University Press, 1974.

Valco, T.D., R.L. Nichols, and W.F. Lalor. "Adopting Precision Farming Technology for Cotton Nutrition," Proceedings of the Beltwide Cotton Conference, 1998, pp. 627–29.

Wolak, F.J., A. Khalilian, R.B. Dodd, Y.J. Han, M. Keshkin, R.M. Lippert, and W. Hair. "Cotton Yield Monitor Evaluation, South Carolina—Year 2," Proceedings of the Beltwide Cotton Conference, 1999, pp. 361–64.