Changes in Producers' Perceptions of Within-field Yield Variability Following Adoption of Cotton Yield Monitors

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ABSTRACT

This article investigates how information from cotton yield monitors influences the within-field yield variability perceptions of cotton producers. Using yield distribution modeling techniques and survey data from cotton producers in 11 Southeastern states, we find that cotton farmers tend to underestimate within-field yield variability (by about 10%-30%) when not utilizing site-specific yield monitor information. Survey results further indicate that cotton farmers in the Southeastern United States place a value of about $20/acre/year (on average) on the additional information about within-field yield variability provided by yield monitors.

Keywords: Precision Farming, Risk, Yield Monitor, Yield Variability, Yield Perceptions, Spatial Yield Distributions, Within Field Variability

JEL Codes: Q12; Q16

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Introduction

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, 2000). Moreover, these geo-referenced data from yield monitors enabled farmers to create field maps to facilitate variable-rate (VR) application of inputs.

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 et al., 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., 2004). By 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 about 8%.

The slower rate of adoption of yield monitors in cotton farming was initially constrained primarily by ineffective equipment (Searcy and Roades, 1998; Valco et al., 1998; Durrence et al., 1999; Sassenrath-Cole et al., 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 (Wolak et al., 1999; Durrence et al., 1999; Roades et al., 2000). 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).

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 (See Manski, 2004 and Delavande, Gine, and McKenzie, 2009 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/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 degree of the spatial variability of the farmer's fields – higher spatial variability results in higher returns from the use of VR application technologies. But, 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 utilize 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; Grisley and Kellog, 1983; Pease, 1992; Smith and Mandac, 1995; Egelkraut et al., 2006a and 2006b; Clop-Gallart and Juarez-Rubio, 2007). 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 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, which implies an underestimation of temporal variability. This underestimation is consistent with what the behavioral finance literature calls "overconfidence" (See Tversky and Kahneman, 1974; Smith and Mandac, 1995).

Even though 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 utilized in this study. This paper 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 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, 1,215 individuals provided data giving a 10% usable response rate.

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 utilize two survey questions that focus on perceptions about spatial yield variability. The first question was:

1. Since yields are likely to vary within a field, please estimate your cotton lint yields (lb/acre) for the following portions of your typical cotton field:

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

This question is used to establish a baseline distribution against which to measure changes in perceived spatial yield variability after yield monitoring information is obtained.[1] A total of 934 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 only answer the second question below 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.

[1] Given the cross-sectional nature of the data and the way the first question was asked, this "baseline" distribution 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 apply the changes in yield variability perception given in the proceeding question utilized in this study. The resulting distribution based on data from the full sample (i.e., includes yield monitor adopters and non-adopters) can be interpreted to reflect an average "base" distribution. In the analysis below we use this as the "base", but we also calculate a "base" based only on the sample respondents who answered the first and the second questions (i.e., the self-selected yield monitor users, see below).

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.

The information from the second question is used to determine the change in the perceived spatial variability and, ultimately, the change in the perceived subjective spatial yield distribution. A total of 81 cotton farmers answered question 2 above. 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 134 cotton farmers reported using a yield monitor. 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.

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 1/3 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).[2] The median values reported can then be used to divide each 1/3 portion of the field in half so that the normal distribution as a whole can be divided into 6 intervals (with 1/6 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

[2] Although a majority of the crop yield distribution literature argues that crop yields are distributed asymmetrically (i.e.,skewed) and are non-normal (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 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 due to yield monitor information.

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. Since the middle 4/6 of the distribution contains about 2/3 (or 67%) of the probability mass, one can estimate the standard deviation of the normal distribution as the yield range in the middle 2/3 of the distribution. The information and assumptions above can then be used to estimate the standard deviation of the perceived "base" yield distribution.

The standard deviation is estimated by first calculating the difference between the reported median value at the upper and lower 1/3 of the normal distribution. In Figure 1, this gives an estimate of the middle four intervals (4/6) of the normal distribution. Therefore, adding 1/3 of the value of the middle four intervals gives the range of the whole normal distribution (where range = maximum – minimum value). The range value can then be divided by four to get an estimate of the standard deviation of the distribution and the estimated variance is calculated as the square of this standard deviation value. The estimated variance and the reported median values in the average 1/3 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. These "average" values will serve as the two parameters needed to depict an "average" subjective normal yield distribution for the surveyed cotton farmers. This calculated distribution serves as our "base" normal yield distribution.

Once the "base" normal yield distribution is characterized, the paired responses to question 2 are used to quantify the average change in perceived spatial yield variability due to the availability of yield monitor information (for the whole sample). 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 new variance for each individual in the sample and calculate the change in within-field yield variability for each individual producer. Averaging these changes in perceived spatial yield variability across respondents allows calculation of an average change in farmers' perceptions of within-field yield variability for the sample. Using this new variance, a new normal yield distribution can be graphically depicted (as in Figure 2) to reflect the average change in the perceived within-field yield distribution due to the yield monitor information.

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

The limitation of the analysis above 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 a perceived yield distribution is based on a beta distribution. The beta distribution is used in this study because, relative to other non-normal 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 (e.g., Ramirez, Misra, and Field, 2003; Field, Misra, and Ramirez, 2003; Chen and Miranda, 2008) shows that temporal cotton yield distributions tend to be right-skewed, which can be easily accommodated by the beta distribution. 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 first task is to determine the four parameters needed (i.e., minimum, maximum, and two shape parameters) to estimate a "base" spatial beta yield distribution that is perceived by the sample of cotton producers:

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

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. We can use a yield of zero (i.e., lowest possible cotton yield) as the minimum of our perceived beta distribution and, from question 2 (and Table 1), the maximum observed data point of the "Most Productive 1/3" variable (i.e. in this case, 2,060 lb/acre) as the maximum of our perceived beta distribution. The two shape parameters are estimated using the Method of Moments (MoM) formulas for the beta distribution expressed as follows:

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

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

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

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

where *a* and *b* are the minimum and maximum values, and *m* is the mode. Therefore, to implement (4) and (5) above, we use the minimum and maximum values as discussed above (i.e. minimum = 0 and maximum =2,060 lbs/acre) 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 (4) and (5) can then be plugged into equation (2) and (3) to complete the four parameters needed to characterize the average perceived "base" spatial beta yield distribution for the sample.

As with the empirical approach for the normal distribution above, the average change in within-field yield variability perception is quantified using the responses to 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 calculate the new 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 added to the "base" perceived variance). The new variance estimate, together with the previously estimated "base" mean make it possible to re-calculate the two shape parameters and graphically depict the change in the perceived "base" spatial beta yield distribution due to the yield monitor information's effect on the farmer's within-field yield variability perceptions (as in Figures 3 and 4).

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

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

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 sub-section 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 due to 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.

The Value of Yield Monitor Information

The survey questionnaire also directly elicited information about whether or not 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 non-adopters. Hence, we compare the value a yield monitor adopter attaches to this technology versus the value a non-adopter 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 25 lbs/acre (or 12.4%), on average, for the 66 respondents who answered both question 1 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. Figure 2B also graphically shows the effect of yield monitor information on cotton producers' perceptions of within-field yield variability. But in this case we use the average standard deviation of all 934 respondents who answered question 1 to calculate the initial perceived base distribution (i.e., 178 lbs/acre instead of 202 lbs/acre). With this change in base variability comes a more dramatic increase in the perceived yield variability (48 lbs/acre or 27.5% increase).

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, when the beta distribution is assumed 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 44.97 lbs/acre (or about 10.69%) 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.

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

The perceived base 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 more pronounced change in within-field yield variability perception relative to using the triangular distribution formulas.

Perceived within-field yield variability increases by 17.7 lbs/acre (or 31.4%) after information from yield monitoring technology becomes available (Figure 4). The magnitude of this increase relative to perceived within-field yield variability is higher than the ones in Figure 3, but is close in magnitude to the spatial variability increase of 27% observed in Figure 2B. Nevertheless, the results in Figure 4 provide further evidence of the overconfidence of cotton producers with regards to within-field yield variability perceptions and this result is robust across the different distributional assumptions used in this study.

Potential Implications for Temporal Yield Variability and Yield Risk Perceptions

To this point we have talked about how yield monitor information could influence farmer's perceived *spatial* or *within-field* yield variability, but not on how changes in spatial yield variability perception could possibly translate to changes in *temporal* yield variability perception or the more traditional notion of yield risk perception. Note that temporal variance (or standard deviation) is the typical measure used to define risk. Hence, if the change in spatial variability perception influences temporal variability perception, then it can be argued that yield risk perceptions are also directly affected by change in spatial yield variability perception. In the foregoing discussion, we explore how changes in spatial yield variability perceptions could possibly affect farmer's yield risk perceptions and its implications for risk management decisions.

Intuitively, it seems fairly straightforward how changes in spatial variability perceptions of yield can affect the temporal variability perceptions (Lowenberg-Deboer, 1999). First assume that there are two sources of shocks that influence the temporal variability of yields – weather

across time (that influences the whole field the same way at each point in time) and the degree of spatial heterogeneity of the field from year-to-year. Presumably, if a field is perceived to be more heterogeneous, then there are perceived low-yielding areas that represent the lower tail of the perceived temporal yield distribution. Therefore, if the perceived low-yielding areas are "eliminated" (i.e., say, the yield monitor shows less spatial variability and low-yield areas are really closer to having average yields), then it may be reasonable to anticipate that the probability mass in the lower tail of the perceived temporal distribution should also be reduced, *ceteris paribus* (i.e., assuming the temporal shocks are still the same). The converse should also hold true when the perceived spatial variability is higher than originally thought.

More formally (and without loss of generality), assume a field only has two sections – a high-yielding section (*H*) and a low-yielding section (*L*) – and we are only considering a two year case (*t* = 1, 2). Let δ_i (*i* = *H*, *L*) be the proportion of the field in the ith section such that $\sum \delta_i = 1$. The yield for the whole field in each year *t* can then be expressed as:

(8) $$Y_F = \delta_H Y_H + \delta_L Y_L ,$$

where Y_F is the yield for the whole-field, Y_H is the yield for the high-yielding section and Y_L is the yield for the low-yielding section. Let the yields Y_H and Y_L not be know with certainty (i.e., perceptions are not perfect or the presence of measurement errors) such that they can be characterized as random variables with means $\overline{Y}_H$, $\overline{Y}_L$ and variances σ_H^2, σ_L^2. Based on (8) and the standard variance decomposition formula (Greene, 2003 p. 862-863), spatial variability (or variance) of the whole field (σ_F^2) can then be written as:

(9) $$\sigma_F^2 = \delta_H^2 \sigma_H^2 + \delta_L^2 \sigma_L^2 + 2\delta_H \delta_L \rho_{HL} \sigma_H \sigma_L$$

where σ_H and σ_L are the standard deviations of Y_H and Y_L, and ρ_{HL} is the correlation coefficient between Y_H and Y_L. Given the spatial variability of the whole field in (9) and since the whole-field yields in years 1 and 2 are random variables, the temporal variability for the whole-field for our two-year time period is:

(10) $$\sigma_T^2 = \sigma_{F,1}^2 + \sigma_{F,2}^2 + 2\rho_{12}\sigma_{F,1}\sigma_{F,2}$$

where $\sigma_{F,1}^2$ and $\sigma_{F,2}^2$ are the spatial variances of the whole-field in years 1 and 2 respectively, ρ_{12} is the correlation coefficient of the whole-field yields in years 1 and 2, and $\sigma_{F,1}$, $\sigma_{F,2}$ are the whole-field standard deviations for years 1 and 2, respectively.

Taking the first derivative of the temporal variability equation in (10) with respect to the spatial standard deviations ($\sigma_{F,1}$ and $\sigma_{F,2}$) gives:

(11a) $$\frac{\partial \sigma_T^2}{\partial \sigma_{F,1}} = 2\sigma_{F,1} + 2\rho_{12}\sigma_{F,2},$$

(11b) $$\frac{\partial \sigma_T^2}{\partial \sigma_{F,2}} = 2\sigma_{F,2} + 2\rho_{12}\sigma_{F,1}.$$

If ρ_{12} is positive (i.e., positive autocorrelation), then the signs of (11a) and (11b) are unambiguously positive. This indicates that changes in spatial yield variability perceptions are positively related to changes in temporal yield variability perceptions (or yield risk). With our finding above that a cotton farmer who does not use a yield monitor tends to be overconfident (i.e., perceives less spatial variability), we can then posit that the use of yield monitor information would increase the perceived spatial variability such that perceived σ_F^2 without yield monitor information is less than perceived σ_F^2 when yield monitor information is utilized

($\sigma^2_{F,\text{ no yield monitor}} < \sigma^2_{F,\text{ with yield monitor}}$). In this case, the higher (but more accurate) spatial yield variability perception when using yield monitor information would directly translate to higher temporal variability perceptions and an increase in yield risk perceptions. If ρ_{12} is negative, then the signs of (11a) and (11b) are ambiguous and will depend on the relative magnitudes of $\sigma_{F,1}$ and $\sigma_{F,2}$. In this case, the unambiguous relationship between spatial yield variability and temporal yield variability perceptions discussed above would only be true if (11a) and (11b) are positive.

If the conditions for positive (11a) and (11b) hold, more accurate spatial variability perceptions may have a direct impact on temporal yield variability (or yield risk perceptions). Consequently, improved perceptions about temporal variability, or yield risk, would aid cotton producers in making risk management decisions (Egelkraut et al., 2006b). Producers would be more able to choose the appropriate risk management instruments that fit the risks of their operation better. A producer would better determine the best crop insurance plans, insurance coverage levels, and marketing strategies for the farm. This, in turn, would provide more adequate risk protection for his/her operation and this added protection would likely lower the taxpayer costs from government provided disaster payments (Egelkraut et al., 2006b). In summary, our discussion above shows that improved within-field variability perceptions from the use of yield monitors may have more wide-ranging implications to the more traditional notion of yield risk (i.e., temporal yield variability) and risk management decision-making.

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 $21.67/acre/year, while non-adopters perceive a lower, but similar value of $20.40/acre/year. The statistical comparison of these two means using t-tests indicate that the mean information value of adopters are not significantly different from 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 non-significant difference in the yield monitor information value provided by adopters and non-adopters suggest that non-adopters can also accurately assess the value of yield monitor information even without actually using technology. Both adopters and non-adopters place the same marginal value on the yield monitor information, but the non-adopters may just have decided not to use the technology (i.e., their cost-benefit calculations indicate that the value of the information may not be enough to cover the costs in the non-adopters' case). However, if the non-adopters have access to yield monitor information, 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 utilized. Results from various yield distribution modeling analyses (under different assumptions) show that cotton farmers in the Southeastern United States tend to underestimate within-field yield variability by about 10%

to 30%, compared with the more objective spatial yield variability estimates from yield monitoring. Survey results further indicate that cotton farmers in the Southeastern United States place a value of about $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. We also discuss how the changes in spatial (or within-field) yield variability perceptions may translate to changes in temporal yield variability perceptions (or yield risk perceptions) and influence risk management decision-making.

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). But 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).

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Table 1. Summary Statistics of Responses to Survey Question 1 (n=934)

Estimated Yields from:	Mean	St. Dev.	Min.	Max.
Least Productive 1/3 of field	600.27	201.54	100	1300
Average Productive 1/3 of field	847.08	194.82	200	1650
Most Productive 1/3 of field	1135.96	256.12	300	2060

Table 2. Frequency Distribution of Responses to Survey Question 2 (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.”

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

Variable	Mean	St. Dev.	Min.	Max
(i) Value placed on yield monitor information for producers who have adopted yield monitor technology (n=50)	21.67	30.08	0	150
(ii) Value placed on yield monitor information for producers who have not adopted yield monitor technology (n=433)	20.40	28.72	0	200

Notes: (1) The summary statistics reported in this table are for the sample who found yield monitor information to be valuable. For (i), 80 yield monitor adopters (out of 104) indicated that yield monitor information is valuable and 50 of those placed a value on it. For (ii), 642 producers who did not adopt yield monitors (out of 866) indicated that yield monitor information is valuable and 433 of those placed a value on it.

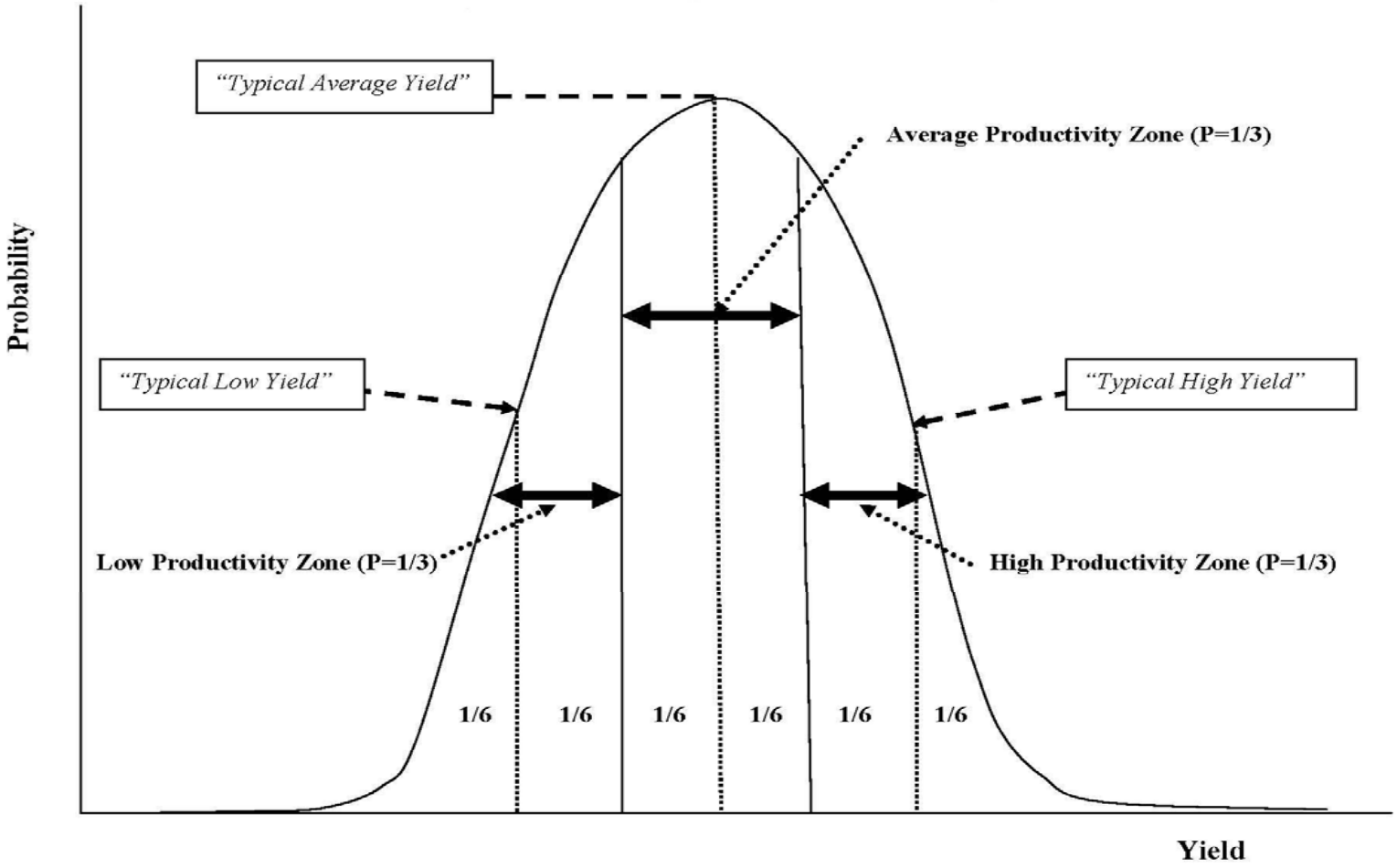
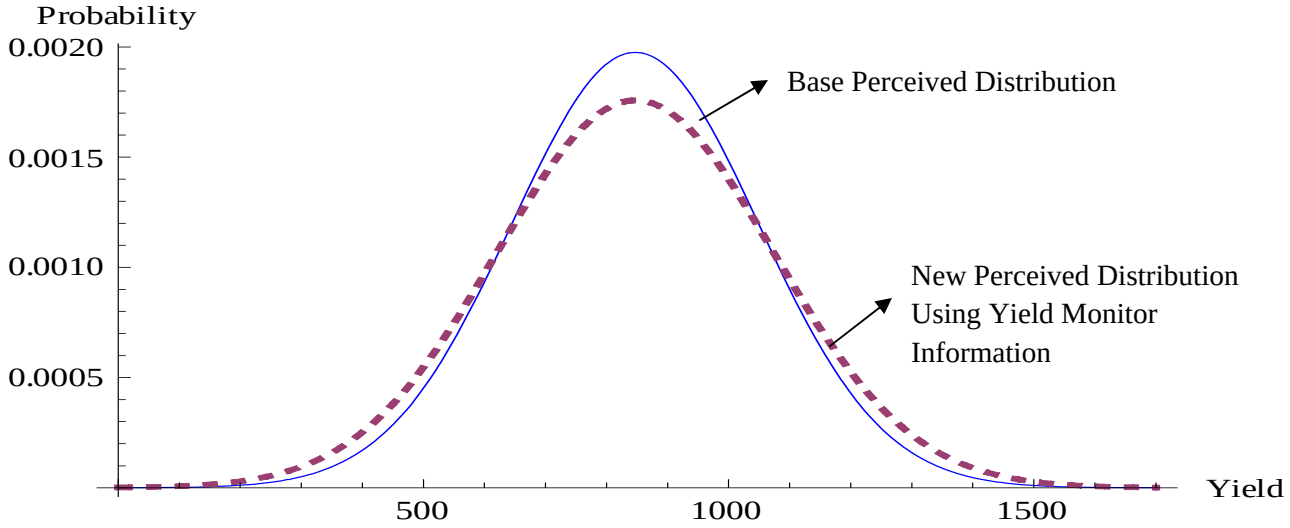
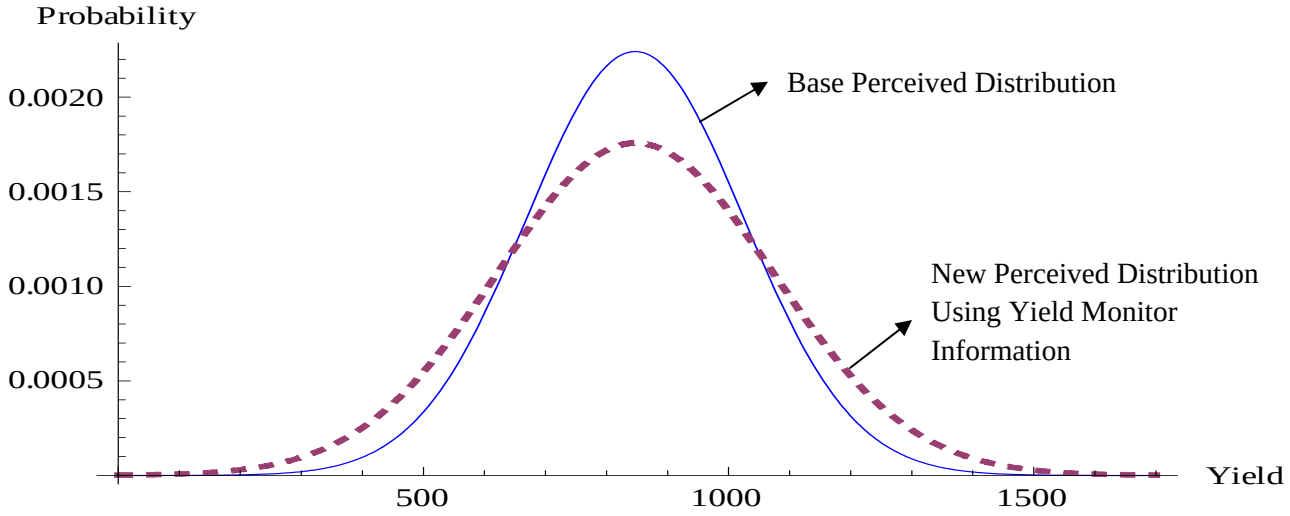


Figure 1. Probability Distribution Showing the Productivity Zones and "Typical" Values



A. Base Distribution Mean= 847 lbs/acre and St. Dev.=202 lbs/acre
New Distribution Mean= 847 lbs/acre and St. Dev.=227 lbs/acre



B. Base Distribution Mean= 847 lbs/acre and St. Dev.=178 lbs/acre
New Distribution Mean= 847 lbs/acre and St. Dev.=227 lbs/acre

Figure 2. Change in Perceived Yield Distribution due to 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 that answered question 1 (n=934) and the new distribution is based on the sample that answered questions 1 and 2 (n=66).

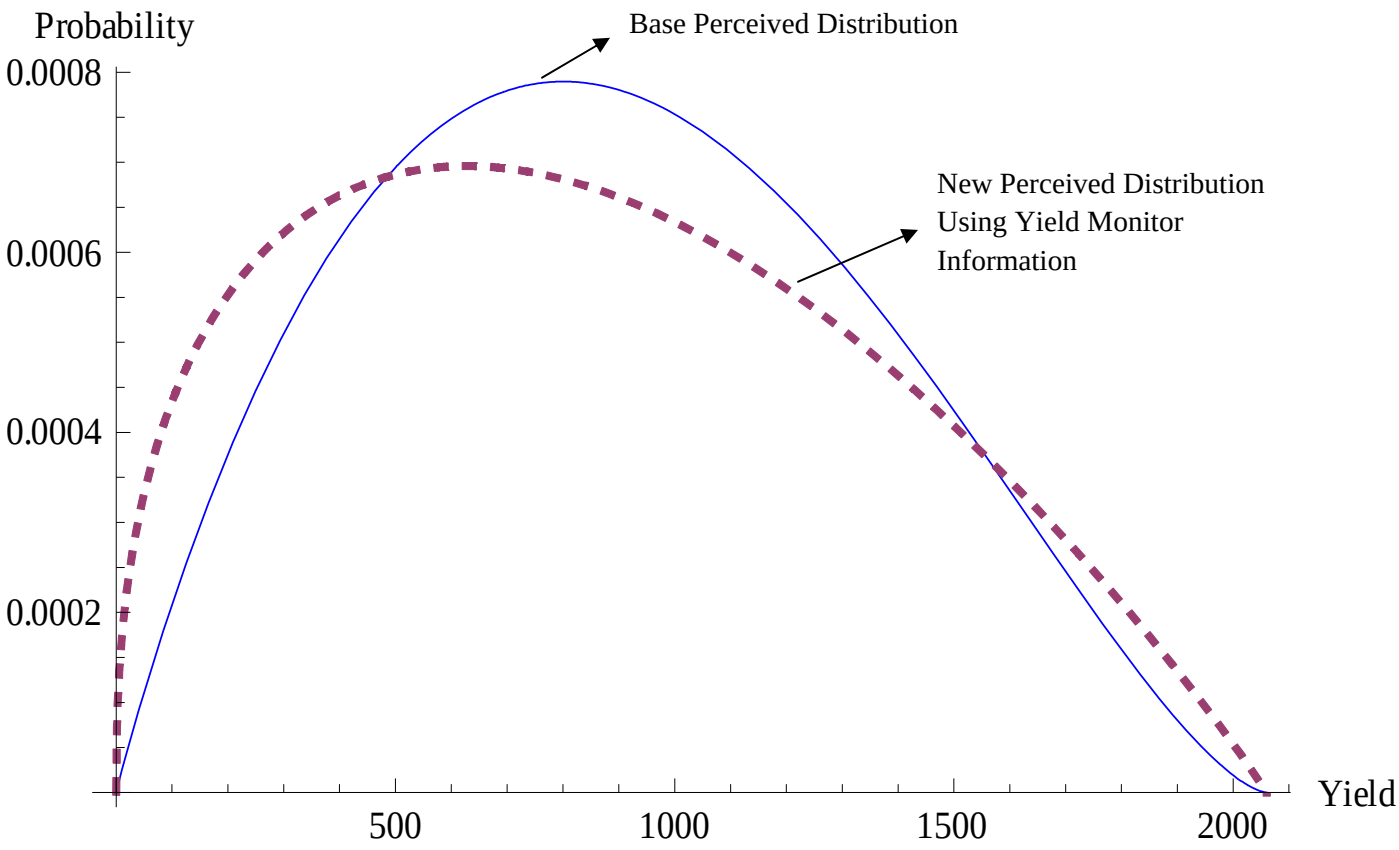


Figure 3. Change in Perceived Yield Distribution due to Yield Monitor Information: Beta Distribution/Triangular Distribution

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: $\bar{y}$ =1020, σ_y =420.55, α =1.96, and β =2.51.

(3) Parameters of the new beta distribution are: $\bar{y}$ =1020, σ_y =465.52, α =1.42, and β =1.96.

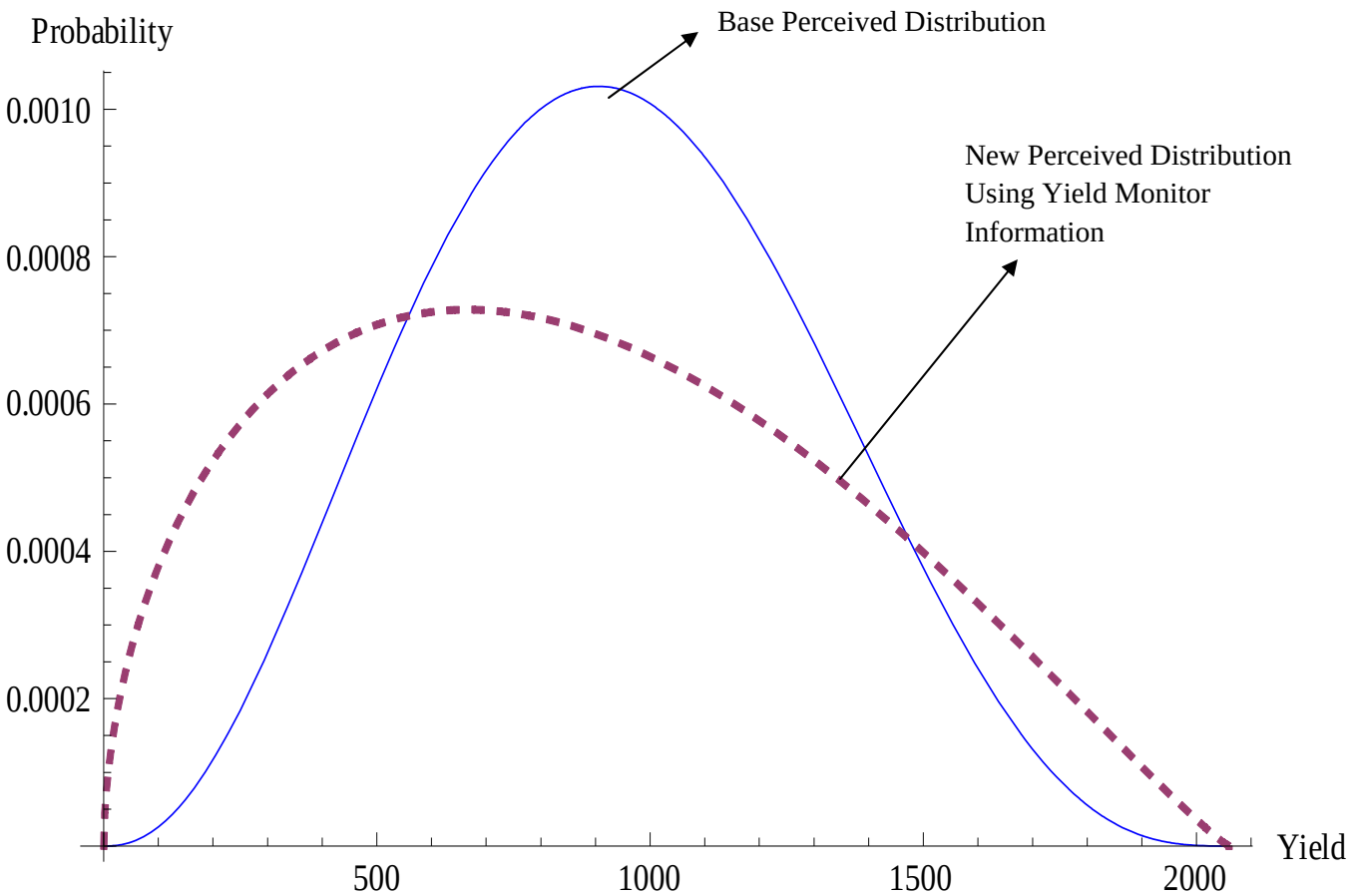


Figure 4. Change in Perceived Yield Distribution due to Yield Monitor Information: Beta Distribution/PERT Estimates

Notes: (1) The parameters of the base beta distribution above 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: $\bar{y}$ =1010, σ_y =343.33, α =3.41, and β =4.07.

(3) Parameters of the new beta distribution are: $\bar{y}$ =1010, σ_y =451.03, α =1.55, and β =2.15.