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RATING METHODOLOGY FOR NUTRIENT MANAGEMENT/BEST MANAGEMENT PRACTICE INSURANCE

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Abstract

The Agricultural Conservation Innovation Center submitted a Nutrient Management/Best Management Practices Insurance policy under section 508(h) of the Federal Crop Insurance Act to the Federal Crop Insurance Corporation (FCIC) Board of Directors. After review by several agricultural economists and actuaries, the FCIC Board authorized implementation of a Nutrient Management/Best Management Practice Insurance Endorsement pilot with reinsurance, risk subsidy, and administrative and operating subsidy beginning in 2003 for Iowa, Minnesota, Pennsylvania, and Wisconsin. This technical report documents the rating methodology used to determine premiums for this Nutrient Management/Best Management Practices Insurance. The FCIC Board reviewers and Dr. David Anderson have read the methodology and have suggested several useful improvements. However, the intent of this report is to document the method as originally submitted. Suggested improvements will be incorporated in later updates of the premiums.

Nutrient Management/Best Management Practices Insurance reduces the risk of yield loss as an impediment to adoption of nutrient management best management practices (BMPs). With this insurance, farmers who adopt approved practices receive compensation for yield losses due to BMP failure. The policy requires farmers to plant a check strip that receives the nutrient application associated with the non-BMP practice, while the rest of the field receives the nutrient BMP application. Indemnities are paid when the check strip yield sufficiently exceeds the yield on the remainder of the field.

The Agricultural Conservation Innovation Center (ACIC), a project of the American Farmland Trust, contracted with Dr. Paul Mitchell to develop premiums for Nutrient Management/Best Management Practices Insurance. This report documents the rating methodology he used to determine these premiums. The policy was submitted under section 508(h) of the Federal Crop Insurance Act to the Federal Crop Insurance (FCIC) Board of Directors for approval by the Risk Management Agency (RMA) of the U.S. Department of Agriculture. The policy was then subject to FCIC Board Review by several agricultural economists and consulting actuaries. At the December 12, 2001 meeting, the FCIC Board approved a Nutrient Management/Best Management Practices Insurance Endorsement pilot with reinsurance, risk subsidy, and administrative and operating subsidy beginning in 2003 for Iowa, Minnesota, Pennsylvania, and Wisconsin.

Recommendations made by the FCIC Board reviewers have not been incorporated into the rating process as reported here, since changes required for approval were not substantial. The intent of this technical report is to document the original method as submitted. These and other improvement are part of on-going research to improve the actuarial soundness of the policy. What follows is first a paragraph providing a brief overview of the rating method. The majority of the report consists of a lengthy description of the rating method and assumptions used, with several tables reporting premiums and the results of sensitivity analysis.

Various sources of information were utilized to determine premiums. These include experimental plot data provided to ACIC by academic researchers from several states, as well as research articles published in peer-reviewed journals and consultation with recognized academic experts and a consulting actuary. Analysis of the experimental data described below and various published articles indicated that nitrogen and phosphorus application rates at or above BMP rates have little or no impact on the mean and the variance of yields. As a result, any observed difference between the BMP yield and check strip yield depends largely upon year-to-year variability due to weather and within-field yield variability. As such, experimental or field plot data from a state or a location is not used to determine premiums. To determine the state premiums reported here, state average yields were used, a 30% coefficient of variation imposed, and a random correlation coefficient assumed for the correlation between the BMP and check strip yields. Sensitivity analysis indicates the impact of violations of these assumptions.

Impact of Nutrient BMP on the Yield Probability Density Function

Agronomists often estimate linear or quadratic response and plateau functions for the response of corn yield to the addition of nitrogen or phosphorus (Cerrato and Blackmer 1990; Binford et al. 1992; Cox 1992; McCollum 1991). With these functions, yield increases linearly or quadratically as nutrients are added until nutrient application reaches a critical level at which yield plateaus and no longer responds to additional applied nutrients. Typical application rates and recommended BMP rates are in the range of little or no response to additional nutrients. The data used for this analysis are consistent with this conclusion. Published agronomic studies typically do not test for differences in the variance between different nutrient application rates, but results of such analyses reported below indicate that reducing nutrient application rates to BMP recommended rates has an inconclusive impact on yield variance.

Nitrogen

Yields for each site-year combination were normalized to a proportion between zero and one by dividing each observed yield by the maximum observed yield at that site and year, regardless of the nutrient application rate. This converted yields from various locations, different years and different hybrids to comparable units. Table 1 summarizes the experimental data used for the analysis. ACIC personnel obtained these data from academic researchers in the various states. Some, but not all, of these data have been summarized in peer-reviewed journals articles.

The Iowa nitrogen data were the most comprehensive, with 10 application rates, three replications per rate, and a total of 103 site-years of data from locations around the state. Data from the other states are also from locations around the state, except for Minnesota, where data are from two locations—Waseca and Morris. Data from Wisconsin and Nebraska are side-by-side comparisons of various nutrient management practices. Similar data for Iowa were available (35 observations from alfalfa and manure crediting BMPs in 1999). For this type of data, only two observations for each site-year (the nutrient BMP and check strip) are available, which is insufficient to normalize yields by dividing the observed maximum. However, these data are used to estimate correlation coefficients between BMP and check strip yields and to provide a simple method of rating as a comparison (discussed below).

Tables 2 and 3 summarize the mean and standard deviation of the normalized yields (i.e. expressed as a proportion of the maximum observed yield at that site in that year) for the experimental data from some of the states. The tables do not include the Illinois data, since variable rates were used so that the data cannot be presented in this manner. Similarly, side-by-side field trial data from Iowa, Nebraska, and Wisconsin are not included, since nutrient rates were not experimentally controlled.

In these tables, the means generally become unresponsive to applied nitrogen at high application rates so that linear or quadratic response and plateau functions fit the data well. Using single-factor ANOVA indicates that no statistically significant difference in mean yields exists for the Indiana data for all rates at 80 lbs/ac or greater, or for the Pennsylvania data. For the Morris, MN data, mean yield does not statistically differ between a rate of 120 and 160 lbs/ac, or between 80 and 120 lbs/ac, but does significantly differ between 80 and 160 lbs/ac. For the Iowa data, no significant mean yield difference exists between 125 and 150 lbs/ac and between 200 and 300 lbs/ac, but mean yields do significantly differ between 150 and 200 lbs/ac, 200 and 250 lbs/ac, and 250 and 300 lbs/ac. This last case implies that the observed increase in mean yield when cutting from 300 to 250 lbs/ac is statistically significant. For the Waseca, MN data, all mean yields statistically differ at the different application rates.

The main point is that some data indicate that mean yields do not decrease when nitrogen fertilizer rates are reduced, while others indicate that they do, plus one case implies the opposite. A decrease in mean yield with adoption of the nutrient BMP is likely in some locations, as a result of the soil and other such site-specific factors that are difficult to predict. On the other hand, in other locations, no decrease in mean yields will occur as a result of the soil and other local site-specific factors. Premiums reported below assume that adopting the nutrient BMP has no mean effect, and sensitivity analysis is used to determine the impact if mean yield does decrease with the adoption of a nutrient BMP.

The variances of yield for the Iowa data fall into three groups. Using a two sample F test, the variances at 0 and 25 lbs/ac do not statistically differ from each other. Similarly, the variances at 50, 75, 100, 125, and 200 lbs/ac do not statistically differ and the variances at 150, 250,and 300 lbs/ac do not statistically differ. Any test between members from different groups indicates statistically different variances. As such, this seems to indicate that the standard deviation declines as nitrogen application increases, but only slightly. A grouping also occurs in the Indiana data, since the variances at 40, 120, and 200 do not statistically differ, nor do those at 80 and 160 lbs/ac. Strangely, the variance at 80 and 160 lbs/ac is lower than that at 40, 120, and 200 lbs/ac. The data for 60 and 180 lbs/ac were not included, since only 8 observations were available. The variances do not statistically differ for the Pennsylvania data and the Morris, MN data. For the Waseca, MN data, the variance show a decreasing trend as the application rate increases from 80 to 200 lbs/ac, with each variance statistically differing from the others.

The main implication is that the different data sets imply different relationships between the variance of yield and the nitrogen rate. Some imply no relationship (Pennsylvania and Morris, MN), while some provide weak (Iowa) or strong (Waseca, MN) support for a decreasing trend for yield variance as nitrogen increases. The Indiana data are difficult to interpret. It seems probable that the relationship depends on site-specific factors that are not completely understood and cannot be predicted. As such, the premiums reported below assume adopting the nutrient BMP has no variance effect, but uses sensitivity analysis to determine the impact if decreasing nutrient applications increases yield variance.

Phosphorus

Table 4 summarizes the phosphorus data. In Mallarino and Blackmer's (1992) analysis of corn yield response to phosphorus fertilizer, relative to the application of no phosphorous fertilizer, they find a statistically significant increase in mean yield at the 22 lbs/ac rate in only 6 of 25 sites. Relative to the 22 lbs/ac rate, the 45 and 67 lbs/ac rates did not result in statistically significant increases. They did not report results on possible differences in yield variance for each phosphorus fertilizer treatment. However, Table 4 summarizes their data, which they provided for this analysis. Using two-sample F tests to test for differences in variance indicated no statistically significant difference in yield variability conditional on the phosphorus application rate, even when the data is limited to sites with low soil test phosphorus (< 20 ppm P). These results are generally consistent with results reported for corn in North Carolina by Cox (1992) (his Figure 1) and McCollum (1991) (his Figures 7 and 8).

The main implication is that these phosphorus data and related publications indicate that reducing phosphorus applications as part of adopting a nutrient BMP has no statistically significant effect on the mean or variance of yields, which is consistent with the results of the analysis of the nitrogen data. As such, the premiums reported below assume adopting the nutrient BMP has no mean or variance effect, and then uses sensitivity analysis to determine the impact if adopting the nutrient BMP decreases mean yield and increases yield variance.

Using these experimental data indicates that at typical application rates the impact of nitrogen and phosphorus on the mean and variance of yield is highly site specific and variable from year to year, and hence unpredictable with any useful accuracy. As a result, the state specific data are not a tremendous aid for determining premiums, since the data do not include information on the site and year specific conditions, nor does the agronomic literature clearly indicate how to use such information if it were available. Therefore, premiums are determined for each state as described below. Furthermore, given the analysis above, the insurance does not distinguish between nitrogen and phosphorus, but determines premiums for a nutrient BMP that implies reduction of either nitrogen or phosphorus, or both in its implementation. As a result, the pertinent factors for determining premiums are the yield probability density function for a field and the correlation between check strip yield and BMP yield in a nearby strip.

Yield Probability Density Function

Examination of histograms indicated that normalized yields were unimodally distributed and negatively skewed. The beta density function, due to its flexibility, it is commonly used for estimating crop yields. Here since the normalized yields must be between zero and one, the support for the standard beta density function, assuming a beta density function for maximum likelihood estimation seemed particularly appropriate. Maximum likelihood parameter estimates for each state were estimated using only the yield data for the high application rates where the mean and standard deviation were assumed constant. Table 5 reports parameter estimates. Separate parameters were estimated in states where data for different previous crops were available. However, in all cases parameters did not differ statistically and so the data were pooled for parameter estimation. In Minnesota, parameters estimated for Morris and Waseca did statistically differ, so both pooled and separate estates are reported.

The implied means and coefficients of variation estimated with these experimental plot data probably overestimate the true mean and underestimate the true coefficient of variation. In general, experimental plot data are not as variable as farmer field data. Besides management differences between experimental plots and farmer fields, available experimental data do not provide information for the same field for several years to form a sufficiently long time series. Also, data for a year are usually from several smaller plots at a single site and measured yield variability for a site-year is a measure of intra-field yield variability not inter-year yield variability. In addition, pooling data from across a state reduces the variability. To illustrate, Table 5 reports a coefficient of variation of 17.7% for Iowa, while Hennessey, Babcock and Hayes (1997) report a coefficient of variation of 29.4% (their Table 2) as the average for 10 corn farms in Sioux County, IA. As a conservative estimate, premiums reported below assume for all locations a coefficient of variation of 30% for corn yields measured at the field level.

To determine premiums, the probability density function for actual yield is needed, not normalized yield. Again the beta density is used because of its flexibility. Four parameters are needed to specify the beta distribution—minimum, maximum, mean and standard deviation. Appropriate farmer field data were lacking and, as previously discussed, experimental plot data underestimate yield variability. As a result, USDA-NASS state average yields were used as estimates of the mean yield M for each state. State data were downloaded from the NASS website and the average of reported state averages for 1997-2000 was calculated and tabulated in Table 6. As previously mentioned, the coefficient of variation was assumed to be 30% for field level yield, which implies that the standard deviation S is 30% of the mean M. Minimum yield is assumed to be zero (i.e. total crop loss). The upper bound of the 95% confidence interval for the mean is used for the maximum yield. Because the standard deviation is 30% of the mean, the upper bound of the 95% confidence interval is the mean $M + 1.96S = M + (1.96)0.30M = 1.588M$. These values are reported in the last column of Table 6.

Given these four parameters for corn yields in each state, the implied beta random variable is rescaled to have a minimum of zero and maximum of one for a standard beta random variable. Since the original minimum is zero, the rescaled mean m and rescaled standard deviation s are the unscaled mean and the unscaled standard deviation each divided by the maximum. However, because the maximum is $1.588M$, the scaled mean is $m = M / 1.588M = 1/1.588 = 0.630$ and because the standard deviation is also a function of M, scaled standard deviation is $s = S/1.588M = 0.3M / 1.588M = 0.3/1.588 = 0.189$. These imply for each location that the mean is 63% of the maximum possible yield and the standard deviation 18.9% of this maximum.

Typically the standard beta density is specified in terms of two parameters—alpha and omega. Equations for alpha and omega as functions of the (rescaled) mean m and standard deviation s are (Evans et al. 1993):

$$\alpha = \frac{m^2(1-m) - ms^2}{s^2} \tag{1}$$

$$\omega = \frac{m(1-m)^2 - (1-m)s^2}{s^2}. \tag{2}$$

Substituting in the known values for m and s gives $\alpha = 3.484$ and $\omega = 2.049$.

Correlation between Nutrient BMP Yield and Check Strip Yield

The correlation between yields in the check strip with high nutrient application rates and the nearby nutrient BMP strips is an important determinant of the insurance premium. On-farm BMP plot data from Wisconsin and Iowa and experimental BMP comparison data from Nebraska provide data on this correlation. Table 7 reports correlation coefficients between the nutrient BMP and check strip yields for these three data sets. The high correlation for the Nebraska data is probably due to the greater degree of experimental control. Table 7 also reports estimated standard errors using Bartlett's approximation as reported in Box and Jenkins (1976, pp. 34-35): $s_{\hat{\rho}} = \left[(1-\hat{\rho}^2)/n\right]^{0.5}$, where $\hat{\rho}$ is the estimated correlation coefficient and n is the number of observations. The lower bound of the 95% confidence interval is calculated as the reported estimate minus 1.96 times this standard error.

As an alternative source of data, peer reviewed journal articles reporting results for site-specific yield studies were used. Jaynes and Colvin (1997) report estimated semivariograms for each of six years (1989-1994) for a 40 acre field in a corn-soybeans rotation in central Iowa (i.e., three semivariograms for corn and three for soybeans). Bakhsh et al. (2000) report estimated semivariograms for a 60 acre corn field in 1995 and 1996 in central Iowa. Both papers assume a second order stationary, isotropic spatial process—standard assumptions often used for analysis of spatial data (see Cressie 1993). These imply that the mean yield is constant throughout the field and that the covariance between yields at any two points in the field is a function of their separation distance, regardless of the direction. For both papers, yields at each sampling point were reduced to residuals using median polishing, then the spatial structure remaining in the residuals was analyzed. Both papers found that a spherical model for the semivariance function $\gamma(h)$ provided the best fit for these residuals. This implies $\gamma(h) = c_0 + c_s\left(1.5(h/a) + 0.5(h/a)^3\right)$ for any positive $h < a$ and $\gamma(h) = c_s$ for any $h > a$, where h is the separation distance in meters, c_0 is the estimated nugget, c_s is the estimated sill and a is the estimated range. Nugget effects were statistically insignificant, so c_0 was dropped from the estimation.

Given the assumed second order stationary and isotropic process, the semivariance can also be expressed as $\gamma(h) = \sigma^2 - c(h)$, where h is the separation distance in meters, σ^2 is within field yield variance, and $c(h)$ is the covariance function describing the covariance between residuals as a function of the distance between two points (Cressie 1993). Rearranging the equation gives $c(h) = \sigma^2 - \gamma(h)$. Given this covariance function for yield residuals, the covariance between yields at any two points is a function of their separation distance h, assuming a constant mean throughout the field. As such, the correlation between yields as a function of the separation distance is $\rho(h)$ = $c(h)/\sigma^2$ = $1 - \left(\gamma(h)/\sigma^2\right)$.

Using parameter estimates for the five semivariograms reported for corn yields, the correlation between yields was determined at separation distances of 5, 10 and 15 meters (16, 32, and 48 ft) as an estimate of the separation distance pertinent to this nutrient BMP insurance. Table 8 reports these correlations. Yield correlations at 5 meters are most consistent with those reported in Table 7.

Both papers find that yield correlations are highly variable between years, which is consistent with the findings of the other papers they cite. This year-to-year and location-to-location variability in the correlation between corn yields is an important factor in determining appropriate premiums, but cannot be controlled or accurately predicted. As such, the approach here is to assume that the correlation between the check strip and BMP yields is random. A similar approach is used in other Monte Carlo analyses when critical parameters are not known with certainty. The outcome in terms of the analysis here is an estimate of the distribution of the premiums, not just the estimated premium.

Based on the results reported in Tables 7 and 8, we assume the correlation coefficient is normally distributed with a mean of 0.90 and a standard deviation of 0.04. These parameters were chosen to be consistent with the mean and standard deviation reported in Table 8 for a 10 meter separation. These are meant to be more conservative than those based on a 5 meter separation, which are more consistent correlations reported in Table 7. The 95% confidence interval for the correlation coefficient with this mean and standard deviation is 0.978 to 0.822, which covers most of the range derived from the standard errors for the correlations reported in Table 8. With this mean and standard deviation, some probability exists for a randomly drawn correlation coefficient to exceed 1.0. As such, randomly drawn correlation coefficients are censored at 0.99. For these parameters, censoring is on average imposed on 1.2% of the random draws.

Probability of an Insurable Loss

When BMP yield is sufficiently low to trigger an MPCI insurance payment, farmers should not receive a nutrient BMP insurance payment that compensates them for the same loss. To prevent double indemnification for the same loss, if the BMP yield is such that an MPCI payment is made, the nutrient BMP insurance only compensates farmers for the difference between the check strip yield and the BMP yield down to the BMP yield at which the MPCI payments begin. The rest of the loss is covered by the MPCI indemnity. If Y_{APH} is the actual production history (APH) yield as determined for MPCI insurance and β is the level of MPCI coverage, then the BMP yield at which MPCI payments begin is $Y_{BMP} = \beta Y_{APH}$. For the purpose of determining the indemnity, define $\widetilde{Y}_{BMP}$ as the BMP yield censored from below at βY_{APH}:

$$(3) \qquad \widetilde{Y}_{BMP} = \begin{cases} \beta Y_{APH} & \text{if } Y_{BMP} \leq \beta Y_{APH} \\ Y_{BMP} & \text{if } Y_{BMP} > \beta Y_{APH} \end{cases}.$$

To impose a maximum level of liability, the check strip yield is censored from above at 35% above the APH yield. As such, define this censored check strip yield as $\widetilde{Y}_{Check}$:

$$(4) \qquad \widetilde{Y}_{Check} = \begin{cases} Y_{Check} & \text{if } Y_{Check} < 1.35 Y_{APH} \\ 1.35 Y_{APH} & \text{if } Y_{Check} \geq 1.35 Y_{APH} \end{cases}.$$

Given this, the maximum insured yield loss occurs when the BMP yield is at or below its allowed minimum of βY_{APH} and the check strip yield is at or above its allowed maximum of $1.35 Y_{APH}$.

The nutrient BMP insurance only pays an indemnity when the BMP yield falls short of the check strip yield by more than the deductible. This condition can be expressed as:

$$(5) \qquad \widetilde{Y}_{BMP} < (1 - D)\widetilde{Y}_{Check},$$

where D is the deductible as a decimal and $\widetilde{Y}_{BMP}$ and $\widetilde{Y}_{Check}$ are the censored BMP and check strip yields respectively. For all results reported here, the deductible D is either 2.5% or 5%. The probability that an indemnity is paid (the probability of an insurable loss) is the probability that condition (5) is satisfied. Denote this probability as P_{Loss}. The Monte Carlo process described below estimates P_{Loss}.

Conditional Expected Value of Insured Losses

When an insurable loss occurs, the indemnity paid equals the percentage yield loss, minus the deductible, multiplied by the check strip yield and the price election. However, to cap the nutrient BMP insurance's liability and to prevent farmers from receiving payments for yield losses also covered by MPCI, the censored yields defined by (3) and (4) are used to determine indemnities. Express this indemnity succinctly as:

$$(6) \qquad \left((1-D)\tilde{Y}_{Check} - \tilde{Y}_{BMP}\right)P ,$$

where P is the price election. Use $E[L]$ to denote the expected value of (6), which is the expected indemnity paid when an insurable loss occurs. However, the expectation is conditional on condition (5) being satisfied. The Monte Carlo method described below estimates this conditional expectation needed for determining premiums.

Monte Carlo Simulations to Determine Premiums

A C++ program using numerical algorithms described in Press et al. (1992) was used to generate random numbers in order to use Monte Carlo methods to determine the probability of an insurable loss and the expected cost of such losses. First 1000 normal random variables are drawn for the correlation coefficient between check strip and BMP yield. For each correlation coefficient, 50,000 pairs of BMP and check strip yields are drawn as beta random variables with the proper correlation. Given these yield data, the probability of an insurable loss and the expected cost of these losses are determined.

Yield Distribution

To draw correlated beta random variables for the BMP and check strip yields, the weighted linear combination method of Johnson and Tenenbein (1981) is used. To generate a pair of correlated beta random variables, the method requires first drawing two independent random variables n_1 and n_2 from a common probability density. The standard normal density is used for results reported here. This pair of independent standard normal random variables is transformed to a pair of correlated uniform random variables u_1 and u_2 using the properly calculated weight c defined by equation (7) in the next paragraph. Using equations given in Johnson and Tenenbein's (1981) Table 1 for the standard normal gives $u_1 = \Phi(n_1)$ and $u_2 = \Phi(n_2 / \sqrt{c^2 + (1-c)^2})$. This pair is then transformed to a pair of standard beta random variables using the inverse of the beta cumulative density function parameterized with the appropriate α and ω as defined by equations (1) and (2). Lastly, this pair is then scaled to be within the minimum of 0 and the maximum of 1.588M, where M is the state level mean yield.

Johnson and Tenenbein (1981) specify the weight c as a function of Spearman's rank correlation coefficient. However, when two data vectors have no ties in rank, Spearman's rank correlation coefficient equals the typical Pearson's moment-based correlation coefficient (Freund 1992, p. 601). This analysis assumes that the two correlation coefficients are equivalent, the assumption implicitly used by Hennessy, Babcock, and Hayes (1997) in the empirical portion of their paper. As such, the weight c is determined by inverting the equation Johnson and Tenenbein (1981) give in their Table 2 when beginning with two uncorrelated standard normal random variables:

$$(7) \qquad c = \frac{\tau - \sqrt{\tau - \tau^2}}{2\tau - 1},$$

where $\tau = [2\sin(\rho\pi / 6)]^2$ and ρ is Pearson's moment based correlation coefficient.

In summary, for each randomly drawn correlation coefficient ρ, the weight *c* is calculated using equation (7), then 50,000 pairs of correlated beta random variables are drawn following the method of Johnson and Tenenbein (1981). Experimentation indicated that 50,000 pairs were needed for the yield mean, variance and covariance to converge to their parameterized values.

Yield Loss Probability

Because P_{Loss} depends on the randomly drawn correlation coefficient, P_{Loss} is random as well. For each randomly drawn correlation coefficient and crop insurance coverage level, the proportion of the randomly drawn check strip and BMP yield pairs that satisfies condition (5) is a Monte Carlo estimate of P_{Loss}, the probability of an insurable loss. The average and standard deviation of these proportions for each correlation coefficient is a Monte Carlo estimate of the mean and standard deviation of the distribution of P_{Loss}. Because each location has the same underlying beta density for yields (scaled up according to a location's mean yield) and the same normal density for the correlation coefficient, P_{Loss} has the same distribution for each location. However, because a different set of random variables is used for each location, the Monte Carlo estimates vary slightly. As such, Table 9 reports the average Monte Carlo estimated mean and standard deviation of P_{Loss} for all locations for each coverage level and both a 2.5% and 5% deductible. P_{Loss} decreases as the coverage level increases because the likelihood that BMP yield deficiencies are covered by crop insurance must increase with higher levels of crop insurance coverage. In addition, Table 9 reports the lower and upper bounds of the 95% confidence interval for the mean to indicate its probable range given the various sources of uncertainty.

Conditional Expected Yield Loss

The expected yield loss conditional on the occurrence of an insurable loss, i.e. the expected value of (6) conditional on (5) being satisfied, is $E[L]$. Note that $E[L]$ depends on the randomly drawn correlation coefficient ρ and as such is also random. However, unlike P_{Loss}, $E[L]$ depends on the mean yield and so its distribution changes for each location. Monte Carlo estimates of the mean of $E[L]$ were determined for each location as follows. Holding the deductible *D* constant at either 2.5% or 5%, for each randomly drawn correlation coefficient, the crop insurance coverage level β is set progressively at 0.65, 0.70, 0,75, 0.80 and 0.85. For all yield pairs satisfying (5) for each correlation coefficient and level of β, the insurable yield loss *L* (bu/ac) is:

$$(8) \qquad L = (1-D)\widetilde{Y}_{Check} - \widetilde{Y}_{BMP},$$

which is simply (6) without the price election *P*. For each coverage level, the average value of *L* for all yield pairs satisfying (5) is the Monte Carlo estimate of the mean of the distribution of $E[L]$.

Table 10 reports the estimates of the mean $E[L]$ for all locations and coverage levels as an indication of the yield losses for which indemnities will be paid after a 5% deductible. Table 11 reports the estimates of the mean $E[L]$ for all locations and coverage levels as an indication of the yield losses for which indemnities will be paid after a 2.5% deductible. Tables 10 and 11 do not report standard deviations for $E[L]$, but they ranged between 1.7 and 2.9 bu/ac with a 2.5% deductible and 1.6 and 2.9 bu/ac with a 5% deductible. The coefficient of variation ranged 20.4-23.1% with a 2.5% deductible and 21.7-24.2% with a 5% deductible, with no relationship in either case with mean yield.

Unconditional Expected Indemnities

Use $E[\lambda]$ to denote the unconditional expected yield loss minus the deductible when an indemnity is paid. Because no indemnity is paid when no insurable loss occurs, $E[\lambda] = P_{Loss} E[L]$. However, because both P_{Loss} and $E[L]$ are functions of the random correlation coefficient ρ, both are random and correlated with each other. Their randomness implies that $E[\lambda]$ is also random and their correlation implies that $E[\lambda]$ is not simply the product of the expected value of P_{Loss} and $E[L]$. Tables 10 (5% deductible) and 11 (2.5% deductible) report the average and standard deviation of $E[\lambda]$ for all random draws of the correlation coefficient ρ as Monte Carlo estimates of the mean and standard deviation of $E[\lambda]$ for each location and coverage level.

Premium Calculation

For each crop insurance coverage level and randomly drawn correlation coefficient, the pure premium is $E[\lambda]P$, where *P* is the price election. Note that this formulation assumes the price election is non-random, or if it is random, that it is not correlated with the probability of an insurable loss occurring, or with the expected magnitude of insurable losses when they occur. The analysis here assumes *P* is not random.

The premium is random since it depends on $E[\lambda]$, which is random because it depends on the correlation coefficient. The mean premium is simply the product of the mean $E[\lambda]$ and the price election *P*, while the premium's standard deviation is the product of the standard deviation of $E[\lambda]$ and the price election *P*. As such, the mean premium for any price election and crop insurance coverage level can be determined using the reported values for the mean $E[\lambda]$ in Tables 10 and 11. Similarly, a 95% confidence interval for the premium can also be determined using the reported values for the standard deviation of $E[\lambda]$ in Tables 10 and 11.

To summarize the use of Tables 10 and 11 for determining the pure premium, first find the state and crop insurance coverage level in the table appropriate for the chosen deductible. The pure premium is then the product of the mean $E[\lambda]$ for this state and coverage level and the chosen price election. For example, for a farmer in Wisconsin with 75% crop insurance coverage and a 5% deductible, the mean $E[\lambda]$ is 2.531, so that with a price election of \$2.00, the pure premium is 2.531*2.00 = \$5.06/ac. Similarly, for a farmer in Maryland with 80% crop insurance coverage and a 2.5% deductible, the mean $E[\lambda]$ is 2.631, so that with a \$2.00 price election, the pure premium is 2.631*2.00 = \$5.26/ac.

Sensitivity Analysis

Impact of Correlation Coefficient on Premium

For illustration, Table 10 assumes a 5% deductible and a price election *P* = \$2/bu. Table 11 does the same for a 2.5% deductible. Both tables report the mean premium and associated upper and lower bounds of the premium's 95% confidence interval. The 95%

confidence interval indicates the impact of uncertainty from year-to-year and field-to-field variability in the correlation coefficient. In general, the confidence interval is fairly wide and indicates the significant impact of the correlation coefficient on the premium. In years or fields with highly correlated yields, the correct premium is quite small, but in years or locations with less highly correlated yields, the correct premium is quite large. Unfortunately, the type of year that will occur or the type of field a farmer has cannot be predicted.

Current research utilizing precision agriculture data (e.g. see Jaynes and Colvin 1997, Bakhsh et al. 2000, and papers they cite) indicates that the correlation coefficient is highly variable and accurate prediction is difficult. Indeed Bakhsh et al. (2000) find that the relationship between cumulative growing season rainfall and the parameters of the semivariogram for their data has a trend opposite to that found by Jaynes and Colvin (1997). (See Bakhsh et al. 2000, Figure 6 and discussion.) In the future it may be possible to offer more accurate premiums to farmers who make their long term yield monitor data available for analysis, if suitable algorithms can be developed.

The methodology for determining premiums accounted for this variability by assuming a distribution for the correlation coefficient. The mean premium is quite sensitive to the realized value of the correlation coefficient. Figure 1 illustrates the relationship between the realized correlation coefficient and the mean premium (assuming a $2/bu price election) for a 65%, 75% and 85% coverage level using the results of Monte Carlo simulations for Iowa. Plots for other states are similar. By drawing random correlation coefficients, the rating methodology averages across these curves for the premiums. Because the curvature is not strong, the standard deviation of the correlation coefficient will not greatly influence the mean premium, nor will the assumed distribution (as long as it is symmetric). However, the slope indicates that even a small decrease in the mean correlation coefficient implies a substantial increase in the mean premium. The rating methodology took a conservative approach by assuming a mean correlation coefficient of 0.9, rather than a higher value more consistent with the data from side-by-side field plots in Iowa, Nebraska, and Wisconsin (see Tables 7 and 8).

Impact of Mean Yield on Premium

Mean yield affects the magnitude of losses when they occur, so that both $E[L]$ and $E[\lambda]$ depend on mean yield. Figure 2 plots the mean premiums versus the mean yields for a 75% coverage level, using the data from all states presented in Table 10. The large horizontal gaps occur because no state average yields were in those ranges for the states analyzed (see Table 6). The plot indicates a linear relationship between mean yield and mean premium. Indeed estimating a linear regression yields an $R^2 > 0.99$, a highly significant slope parameter, and a zero intercept. As such, it should be possible to provide county specific premiums by using the county average yield from either USDA-NASS data or county crop insurance claim data, or even field (insured unit) specific premiums using APH yields for the insured unit. However, the yield variability matters as well, as discussed in the next section, and for this analysis the coefficient was held fixed at 30% because of a lack of information. Creating a county or unit specific premium schedule seems unwise without first getting better estimates of yield variability. If the insurance becomes a popular product, developing such a premium schedule would be sensible.

Impact of Yield Variability on Premium

Yield variability affects both the probability of losses and their magnitude, and thus the mean premium. For the analysis here, a 30% coefficient of variation was used as an estimate of field level yield variability, since estimates developed from the experimental data were suspected of being too low. To determine the impact of this assumption on estimated premiums, additional Monte Carlo simulations were conducted.

Holding the mean constant at 144.25, the mean used for estimating Iowa premiums, the assumed coefficient of variation was progressively set at 20%, 25%, 30%, 35% and 40%. Figure 3 plots the resulting estimate of the mean premium with a $2/bu price election versus the assumed coefficient of variation for 65%, 75%, and 85% crop insurance coverage levels.

Examining the numbers, the mean premium increases linearly with the coefficient of variation—a proportional increase in the CV implies a proportional increase in the mean premium. Figure 3 indicates the importance of assuming the correct coefficient of variation for the premium. Because the required data are not available for each location, the coefficient of variation was set at 30%. However, given the obvious linear relationship between the coefficient of variation and the mean premium, it seems that county or unit specific rates could be developed if the necessary data were available. As such, if this insurance becomes a popular product, developing such a premium schedule would be sensible.

Impact of Reducing Mean BMP Yield on Premiums

Based on analysis of experimental data, premiums were derived assuming that reducing nutrient applications from the higher non-BMP application rates to BMP recommended rates did not affect the mean or the variance of yield. Any mean reducing or risk increasing effect of reducing nutrient applications was considered unpredictable at typical application rates. This section evaluates the effect of BMP adoption reducing mean yield.

Monte Carlo simulations were conducted as described previously, but as a conservative estimate of a worse case scenario, the BMP yield mean was reduced 2% from the check strip mean yield. This change increases the probability of an insurable loss (P_{Loss}) and the conditional and unconditional expected magnitude of these loses ($E[L]$ and $E[\lambda]$), all of which work to increase the mean premium. Table 12 reports the resulting change in mean P_{Loss}. In general P_{Loss} increases about 18% from original levels with a 2.5% deductible and about 20% with a 5% deductible. Tables 13 and 14 report the impact on the mean premium for each state and coverage level. With a 5% deductible, the premium increase averages 22.8% and ranges between 21.4% and 24.8%. With a 2.5% deductible, the premium increase averages 22.0% and ranges between 20.8% and 23.5%.

In some fields in some years, adopting the nutrient BMP will reduce mean yields. Given this and the results of the sensitivity analysis, it may be sensible to increase premiums reported in Table 10 and Table 11 by an additional 22%, at least initially. This extra load would be to cover mean effects of BMP adoption not captured in the experimental data and published literature, such as farmer error while implementing the BMP and similar factors. As experience with the insurance develops, the associated loss data can be used to determine whether this adjustment is still justified.

Impact of Increasing BMP Yield Variance on Premiums

Monte Carlo simulations were conducted as for the previous analysis. However, a mean zero normal error was added to the BMP yield to increase its variance. The variance of this error was chosen so that the coefficient of variation of the BMP yield increased 5%. As with the mean BMP yield decrease, this increase in BMP yield variability increases the probability of an insurable loss (P_{Loss}) and the conditional and unconditional expected magnitude of these loses ($E[L]$ and $E[\lambda]$), all of which work to increase mean premiums. Table 12 reports the impact on P_{Loss} and Tables 13 and 14 report the impact on the mean premiums and the percentage change from original levels. P_{Loss} increases almost 15% for a 5% deductible and slightly more than 8% with a 2.5% deductible. For a 5% deductible, premiums increase on average about 36%, ranging between a minimum and maximum of about 31% and 40%. For a 2.5% deductible, premiums increase on average about 29%, ranging between a minimum and maximum of about 25% and 32%.

The increased variability of the BMP yield relative to the check strip yield effectively decreases the correlation between the BMP and check strip yields. For the simulations with increased variability, the mean correlation coefficient falls to 0.86 from the 0.90 assumed in the original simulations. Figure 1 shows that this decrease in correlation is the source of the associated substantial increase in premiums.

In some years in some fields, adopting the nutrient BMP does affect the variability of the BMP yields, but the experimental data show the variety of possible responses and indicate the unpredictable nature of such variance impacts. Assuming that reducing nutrient application does increase the variability of yield, this variance effect would appear as a lower correlation between the BMP and check strip yields. By choosing a conservative value for the mean correlation coefficient (less than that indicated by on farm BMP field trials) and randomly drawing the correlation coefficient, the analysis used to derive the premiums in Table 10 and Table 11 already takes this possible effect into account. As such, including an additional load to account for possible variance effects of BMP adoption does not seem warranted. However, given that the sensitivity analysis indicates that premiums are sensitive to the mean and variance of the correlation coefficient, as loss data from the insurance become available, it will likely be necessary to re-evaluate these assumed parameters.

Catastrophic Load

Determining an appropriate catastrophic load is difficult. However, the most likely cause for a catastrophic loss would be weather conditions or any other event that would reduce the mean yield of the BMP acres compared to the check strip. Thus, based on the results of the sensitivity analysis on the impact of reducing mean BMP yields, it is recommended that premiums be increased by 22%. As experience with the insurance product develops, a better catastrophic load can be determined from the loss data. Note that this catastrophic load is not included in the premiums reported in Table 10 and Table 11 (or Table 13). To include this load, simply divide the reported premium by 0.82.

Conclusion

This technical report summarized the rating methodology used to determine premiums for Nutrient Management/Best Management Practice Insurance. The intent was to document the method as originally submitted. The actual premiums approved by the RMA are likely to differ from these in the report, as the details of the policy for the pilot are still being finalized. However, these premiums for the pilot, when they become available, will be published on the RMA website. Several reviewers proposed useful improvements to the rating method and policy, and some have been incorporated as the policy and premium details are finalized. Remaining improvements will be incorporated as new premium rates are developed in consultation with the RMA, particularly after the actuarial data from the first few years of the pilot are available.

Table 1. Summary of experimental data used.*

State	Observations	Rates	Range of Years	Previous Crops
Nitrogen				
Illinois	450	0 - 274	1990-1992	corn, soybeans, alfalfa, wheat
Indiana	940	0 - 200	1991, 1992, 1994, 1995	corn
Iowa	2220	0 - 300	1986-1991	corn, soybeans
Minnesota	1857	0 - 200	1981-1989	corn
Nebraska	174	0 - 240	1987, 1988, 1992, 1993, 1996	corn
Pennsylvania	178	95 - 175	1976-1980	corn, legume
Wisconsin	320	NA	1989-1998	corn, soybeans, alfalfa
Phosphorus				
Iowa	100	0 - 67	1989-1990	corn, soybeans

* All data provided by ACIC.

Table 2. Mean, standard deviation, and coefficient of variation (CV) of corn yield (as proportion of observed site-year maximum yield) for Indiana and Iowa data for different nitrogen application rates.*

State	Application Rate	Mean	St. Dev.	CV	Observations
Indiana	0	0.778	0.170	21.9	158
	40	0.821	0.139	16.9	152
	60	0.763	0.162	21.2	8
	80	0.856	0.111	13.0	152
	120	0.842	0.141	16.8	159
	160	0.856	0.110	12.9	151
	180	0.779	0.091	11.7	8
	200	0.851	0.135	15.9	152
Iowa	0	0.491	0.168	34.2	222
	25	0.570	0.160	28.0	222
	50	0.663	0.149	22.5	222
	75	0.742	0.141	19.0	222
	100	0.798	0.140	17.6	222
	125	0.833	0.141	16.9	222
	150	0.843	0.125	14.8	222
	200	0.874	0.141	16.2	222
	250	0.900	0.118	13.1	222
	300	0.878	0.116	13.2	222

* All data provided by ACIC.

Table 3. Mean, standard deviation, and coefficient of variation (CV) of corn yield (as proportion of observed site-year maximum yield) for Pennsylvania and Morris and Waseca, Minnesota data for different nitrogen application rates.*

State	Application Rate	Mean	St. Dev.	CV	Observations
Pennsylvania	95	0.807	0.121	15.0	59
	130	0.820	0.132	16.1	59
	175	0.832	0.125	15.0	59
Waseca, MN	0	0.566	0.127	22.5	170
	40	0.748	0.116	15.5	170
	80	0.854	0.120	14.0	170
	120	0.924	0.072	7.8	170
	160	0.951	0.058	6.1	170
	200	0.962	0.049	5.1	170
Morris, MN	0	0.383	0.152	39.6	168
	40	0.609	0.162	26.5	167
	80	0.693	0.161	23.2	168
	120	0.705	0.163	23.1	167
	160	0.731	0.153	20.9	168

* All data provided by ACIC.

Table 4. Mean, standard deviation, and coefficient of variation (CV) of corn yield for Iowa data for different phosphorus application rates.*

Phosphorus Rate	Mean	St. Dev.	CV	Observations
0	142.8	31.9	22.3	25
22	148.6	29.7	20.0	25
45	149.2	30.7	20.6	25
67	150.2	30.5	20.3	25

* All data provided by ACIC.

Table 5. Maximum likelihood parameter estimates for the constant mean and standard deviation of normalized corn yields for each state or location.

State	Observations	Nitrogen Rate	Mean	Error	St. Dev.	Error	CV
Iowa	915	>124	0.875	0.0050	0.155	0.0054	17.7
Illinois	205	> 99	0.958	0.0045	0.065	0.0069	6.8
Indiana	469	>119	0.859	0.0072	0.159	0.0071	18.5
Minnesota	844	>119	0.874	0.0063	0.190	0.0073	21.7
Waseca, MN	510	>119	0.950	0.0042	0.095	0.0070	10.0
Morris, MN	334	>119	0.745	0.0114	0.212	0.0078	28.5
Pennsylvania	177	> 94	0.828	0.0116	0.156	0.0098	18.8

Table 6. Four-year (1997-2000) average of average state yield as reported by USDA-NASS and implied standard deviation assuming a 30% coefficient of variation and implied maximum yield calculated as mean plus 1.96 standard deviations.

State	Mean	Standard Deviation	Maximum
Delaware	114.00	34.2	181.0
Illinois	140.25	42.1	222.7
Indiana	134.50	40.4	213.6
Iowa	144.25	43.3	229.1
Kansas	140.25	42.1	222.7
Kentucky	113.25	34.0	179.8
Maryland	111.75	33.5	177.5
Michigan	120.50	36.2	191.4
Minnesota	145.00	43.5	230.3
Missouri	117.25	35.2	186.2
Nebraska	135.50	40.7	215.2
New York	105.75	31.7	167.9
North Dakota	108.75	32.6	172.7
Ohio	137.00	41.1	217.6
Pennsylvania	101.50	30.5	161.2
South Dakota	110.50	33.2	175.5
Virginia	100.25	30.1	159.2
Wisconsin	136.00	40.8	216.0

Table 7. Correlation coefficient, estimated standard error, and implied lower bound on the 95% confidence interval for side-by-side on farm (IA, WI) or experimental (NE) nutrient BMP and check strip yields.

State	Correlation Coefficient	Standard Error	Lower Bound
Iowa	0.961	0.0470	0.868
Nebraska	0.990	0.0188	0.953
Wisconsin	0.954	0.0237	0.907

Table 8. Correlation coefficient for corn yields at various separation distances using semivariogram parameter estimates in the cited papers.

		Correlation Coefficient		
Source	Year	5 meters	10 meters	15 meters
Jaynes and Colvin 1997	1989	0.924	0.849	0.777
	1991	0.937	0.875	0.814
	1993	0.970	0.940	0.911
Bakhsh et al. 2000	1995	0.938	0.877	0.820
	1996	0.970	0.941	0.914
	Mean	0.948	0.897	0.847
	St. Dev.	0.021	0.042	0.062

Table 9. Monte Carlo estimated mean and standard deviation of the probability of an insurable loss (P_{Loss}) for each crop insurance coverage level, plus associated lower and upper bounds of the 95% confidence interval for the mean.

Deductible	Coverage	Mean	Standard Deviation	Lower Bound	Upper Bound
2.5%	65%	0.325	0.027	0.272	0.377
2.5%	70%	0.311	0.027	0.258	0.364
2.5%	75%	0.295	0.027	0.243	0.348
2.5%	80%	0.277	0.027	0.225	0.329
2.5%	85%	0.258	0.026	0.207	0.309
5%	65%	0.257	0.038	0.182	0.332
5%	70%	0.244	0.038	0.170	0.318
5%	75%	0.229	0.037	0.157	0.301
5%	80%	0.213	0.036	0.143	0.283
5%	85%	0.195	0.034	0.128	0.262

Table 10a. With a 5% deductible, estimated mean $E[L]$, mean and standard deviation $E[\lambda]$, premiums for a \$2 price election, and lower and upper 95% confidence interval bounds on the premiums for each crop insurance coverage level in each state.

State	MPCI Coverage	Mean $E[L]$	Mean $E[\lambda]$	St. Dev. $E[\lambda]$	Premium	Lower Bound	Upper Bound
Delaware	65%	9.35	2.459	0.823	4.92	1.69	8.14
	70%	9.14	2.289	0.773	4.58	1.55	7.61
	75%	8.90	2.097	0.716	4.19	1.39	7.00
	80%	8.61	1.884	0.652	3.77	1.21	6.32
	85%	8.26	1.658	0.583	3.32	1.03	5.60
Illinois	65%	11.76	3.125	1.011	6.25	2.29	10.22
	70%	11.48	2.903	0.951	5.81	2.08	9.53
	75%	11.13	2.650	0.880	5.30	1.85	8.75
	80%	10.75	2.381	0.799	4.76	1.63	7.89
	85%	10.34	2.095	0.711	4.19	1.40	6.98
Indiana	65%	11.19	2.970	1.006	5.94	1.99	9.88
	70%	10.96	2.759	0.941	5.52	1.83	9.21
	75%	10.70	2.529	0.870	5.06	1.65	8.47
	80%	10.36	2.279	0.793	4.56	1.45	7.67
	85%	9.96	2.010	0.710	4.02	1.24	6.80
Iowa	65%	12.08	3.205	1.074	6.41	2.20	10.62
	70%	11.80	2.981	1.008	5.96	2.01	9.91
	75%	11.47	2.727	0.933	5.45	1.80	9.11
	80%	11.10	2.451	0.848	4.90	1.58	8.23
	85%	10.70	2.166	0.757	4.33	1.36	7.30
Kansas	65%	11.76	3.125	1.011	6.25	2.29	10.22
	70%	11.48	2.903	0.951	5.81	2.08	9.53
	75%	11.13	2.650	0.880	5.30	1.85	8.75
	80%	10.75	2.381	0.799	4.76	1.63	7.89
	85%	10.34	2.095	0.711	4.19	1.40	6.98
Kentucky	65%	9.48	2.501	0.834	5.00	1.73	8.27
	70%	9.26	2.323	0.783	4.65	1.58	7.72
	75%	9.01	2.129	0.725	4.26	1.42	7.10
	80%	8.73	1.920	0.660	3.84	1.25	6.43
	85%	8.43	1.700	0.590	3.40	1.09	5.71
Maryland	65%	9.28	2.444	0.833	4.89	1.62	8.15
	70%	9.08	2.275	0.782	4.55	1.49	7.61
	75%	8.82	2.086	0.725	4.17	1.33	7.01
	80%	8.51	1.874	0.660	3.75	1.16	6.34
	85%	8.17	1.647	0.588	3.29	0.99	5.60
Michigan	65%	9.96	2.646	0.900	5.29	1.76	8.82
	70%	9.73	2.459	0.845	4.92	1.61	8.23
	75%	9.47	2.251	0.781	4.50	1.44	7.57
	80%	9.16	2.024	0.712	4.05	1.26	6.84
	85%	8.77	1.781	0.636	3.56	1.07	6.05
Minnesota	65%	12.08	3.200	1.056	6.40	2.26	10.54
	70%	11.80	2.966	0.989	5.93	2.06	9.81
	75%	11.46	2.705	0.912	5.41	1.83	8.98
	80%	11.11	2.427	0.827	4.85	1.61	8.10
	85%	10.69	2.138	0.737	4.28	1.39	7.16

Table 10b. With a 5% deductible, estimated mean $E[L]$, mean and standard deviation $E[\lambda]$, premiums for a \$2 price election, and lower and upper 95% confidence interval bounds on the premiums for each crop insurance coverage level in each state.

State	MPCI Coverage	Mean $E[L]$	Mean $E[\lambda]$	St. Dev. $E[\lambda]$	Premium	Lower Bound	Upper Bound
Missouri	65%	9.82	2.590	0.830	5.18	1.93	8.43
	70%	9.59	2.405	0.778	4.81	1.76	7.86
	75%	9.32	2.202	0.720	4.40	1.58	7.22
	80%	9.03	1.983	0.655	3.97	1.40	6.53
	85%	8.70	1.753	0.585	3.51	1.21	5.80
Nebraska	65%	11.05	2.939	0.976	5.88	2.05	9.70
	70%	10.78	2.728	0.916	5.46	1.87	9.04
	75%	10.48	2.489	0.845	4.98	1.66	8.29
	80%	10.14	2.233	0.766	4.47	1.46	7.47
	85%	9.76	1.965	0.681	3.93	1.26	6.60
New York	65%	8.79	2.362	0.763	4.72	1.73	7.71
	70%	8.58	2.195	0.717	4.39	1.58	7.20
	75%	8.37	2.008	0.662	4.02	1.42	6.61
	80%	8.10	1.806	0.603	3.61	1.25	5.97
	85%	7.77	1.588	0.538	3.18	1.07	5.29
North Dakota	65%	9.02	2.425	0.783	4.85	1.78	7.92
	70%	8.81	2.253	0.734	4.51	1.63	7.38
	75%	8.56	2.062	0.679	4.12	1.46	6.79
	80%	8.27	1.853	0.617	3.71	1.29	6.13
	85%	7.97	1.633	0.550	3.27	1.11	5.42
Ohio	65%	11.36	3.017	1.022	6.03	2.03	10.04
	70%	11.13	2.800	0.955	5.60	1.86	9.34
	75%	10.83	2.560	0.881	5.12	1.67	8.57
	80%	10.49	2.303	0.801	4.61	1.47	7.75
	85%	10.12	2.035	0.715	4.07	1.27	6.87
Pennsylvania	65%	8.50	2.260	0.734	4.52	1.64	7.40
	70%	8.32	2.105	0.690	4.21	1.51	6.91
	75%	8.08	1.930	0.640	3.86	1.35	6.37
	80%	7.83	1.738	0.582	3.48	1.19	5.76
	85%	7.55	1.536	0.520	3.07	1.03	5.11
South Dakota	65%	9.31	2.477	0.787	4.95	1.87	8.04
	70%	9.11	2.307	0.740	4.61	1.71	7.51
	75%	8.88	2.115	0.685	4.23	1.54	6.92
	80%	8.57	1.907	0.626	3.81	1.36	6.27
	85%	8.26	1.685	0.561	3.37	1.17	5.57
Virginia	65%	8.50	2.252	0.718	4.50	1.69	7.32
	70%	8.31	2.096	0.674	4.19	1.55	6.83
	75%	8.07	1.919	0.625	3.84	1.39	6.29
	80%	7.79	1.725	0.570	3.45	1.21	5.69
	85%	7.49	1.518	0.509	3.04	1.04	5.03
Wisconsin	65%	11.13	2.971	1.021	5.94	1.94	9.94
	70%	10.90	2.760	0.955	5.52	1.78	9.26
	75%	10.63	2.531	0.883	5.06	1.60	8.52
	80%	10.30	2.280	0.803	4.56	1.41	7.71
	85%	9.94	2.016	0.718	4.03	1.22	6.85

Table 11a. With a 2.5% deductible, estimated mean $E[L]$, mean and standard deviation $E[\lambda]$, premiums for a \$2 price election, and lower and upper 95% confidence interval bounds on the premiums for each crop insurance coverage level in each state.

State	MPCI Coverage	Mean $E[L]$	Mean $E[\lambda]$	St. Dev. $E[\lambda]$	Premium	Lower Bound	Upper Bound
Delaware	65%	10.15	3.327	0.927	6.65	3.02	10.29
	70%	9.96	3.132	0.877	6.26	2.83	9.70
	75%	9.73	2.907	0.819	5.81	2.60	9.02
	80%	9.46	2.653	0.753	5.31	2.35	8.26
	85%	9.14	2.382	0.682	4.76	2.09	7.44
Illinois	65%	12.70	4.205	1.136	8.41	3.96	12.86
	70%	12.43	3.951	1.075	7.90	3.69	12.12
	75%	12.11	3.658	1.004	7.32	3.38	11.25
	80%	11.75	3.340	0.923	6.68	3.06	10.30
	85%	11.34	2.997	0.833	5.99	2.73	9.26
Indiana	65%	12.08	3.999	1.137	8.00	3.54	12.45
	70%	11.86	3.756	1.072	7.51	3.31	11.71
	75%	11.61	3.486	0.998	6.97	3.06	10.88
	80%	11.30	3.190	0.919	6.38	2.78	9.98
	85%	10.91	2.868	0.833	5.74	2.47	9.00
Iowa	65%	13.09	4.308	1.210	8.62	3.87	13.36
	70%	12.84	4.051	1.144	8.10	3.62	12.58
	75%	12.52	3.756	1.068	7.51	3.32	11.70
	80%	12.17	3.430	0.982	6.86	3.01	10.71
	85%	11.79	3.086	0.887	6.17	2.69	9.65
Kansas	65%	12.70	4.205	1.136	8.41	3.96	12.86
	70%	12.43	3.951	1.075	7.90	3.69	12.12
	75%	12.11	3.658	1.004	7.32	3.38	11.25
	80%	11.75	3.340	0.923	6.68	3.06	10.30
	85%	11.34	2.997	0.833	5.99	2.73	9.26
Kentucky	65%	10.26	3.364	0.944	6.73	3.03	10.43
	70%	10.06	3.159	0.892	6.32	2.82	9.82
	75%	9.82	2.933	0.833	5.87	2.60	9.13
	80%	9.55	2.687	0.767	5.37	2.37	8.38
	85%	9.26	2.421	0.695	4.84	2.12	7.57
Maryland	65%	10.04	3.294	0.942	6.59	2.90	10.28
	70%	9.85	3.100	0.890	6.20	2.71	9.69
	75%	9.63	2.879	0.832	5.76	2.50	9.02
	80%	9.33	2.631	0.767	5.26	2.26	8.27
	85%	9.01	2.357	0.693	4.71	2.00	7.43
Michigan	65%	10.79	3.571	1.016	7.14	3.16	11.12
	70%	10.57	3.356	0.961	6.71	2.95	10.48
	75%	10.33	3.113	0.896	6.23	2.71	9.74
	80%	10.05	2.844	0.825	5.69	2.46	8.92
	85%	9.68	2.554	0.747	5.11	2.18	8.04
Minnesota	65%	13.10	4.303	1.191	8.61	3.93	13.28
	70%	12.83	4.034	1.124	8.07	3.66	12.48
	75%	12.50	3.730	1.047	7.46	3.35	11.56
	80%	12.16	3.400	0.960	6.80	3.04	10.56
	85%	11.77	3.050	0.866	6.10	2.71	9.50

Table 11b. With a 2.5% deductible, estimated mean $E[L]$, mean and standard deviation $E[\lambda]$, premiums for a \$2 price election, and lower and upper 95% confidence interval bounds on the premiums for each crop insurance coverage level in each state.

State	MPCI Coverage	Mean $E[L]$	Mean $E[\lambda]$	St. Dev. $E[\lambda]$	Premium	Lower Bound	Upper Bound
Missouri	65%	10.59	3.488	0.935	6.98	3.31	10.64
	70%	10.37	3.274	0.883	6.55	3.09	10.01
	75%	10.12	3.038	0.824	6.08	2.85	9.31
	80%	9.84	2.780	0.757	5.56	2.59	8.53
	85%	9.53	2.503	0.686	5.01	2.32	7.69
Nebraska	65%	12.03	3.980	1.102	7.96	3.64	12.28
	70%	11.78	3.737	1.042	7.47	3.39	11.56
	75%	11.49	3.458	0.971	6.92	3.11	10.72
	80%	11.16	3.155	0.890	6.31	2.82	9.80
	85%	10.79	2.830	0.803	5.66	2.51	8.81
New York	65%	9.56	3.182	0.860	6.36	3.00	9.73
	70%	9.36	2.992	0.814	5.98	2.79	9.17
	75%	9.14	2.772	0.759	5.54	2.57	8.52
	80%	8.89	2.533	0.698	5.07	2.33	7.80
	85%	8.58	2.272	0.631	4.54	2.07	7.02
North Dakota	65%	9.81	3.271	0.879	6.54	3.10	9.99
	70%	9.63	3.073	0.830	6.15	2.89	9.40
	75%	9.40	2.851	0.774	5.70	2.67	8.74
	80%	9.12	2.605	0.712	5.21	2.42	8.00
	85%	8.82	2.339	0.642	4.68	2.16	7.20
Ohio	65%	12.25	4.067	1.159	8.13	3.59	12.68
	70%	12.02	3.816	1.090	7.63	3.36	11.91
	75%	11.76	3.535	1.015	7.07	3.09	11.05
	80%	11.43	3.231	0.932	6.46	2.81	10.12
	85%	11.07	2.907	0.843	5.81	2.51	9.12
Pennsylvania	65%	9.18	3.043	0.828	6.09	2.84	9.33
	70%	9.01	2.866	0.783	5.73	2.66	8.80
	75%	8.79	2.662	0.733	5.32	2.45	8.20
	80%	8.55	2.435	0.674	4.87	2.23	7.51
	85%	8.28	2.192	0.610	4.38	1.99	6.78
South Dakota	65%	10.04	3.329	0.886	6.66	3.18	10.13
	70%	9.85	3.133	0.839	6.27	2.98	9.55
	75%	9.63	2.910	0.783	5.82	2.75	8.89
	80%	9.36	2.666	0.723	5.33	2.50	8.17
	85%	9.05	2.398	0.656	4.80	2.22	7.37
Virginia	65%	9.18	3.022	0.805	6.04	2.89	9.20
	70%	9.02	2.843	0.761	5.69	2.70	8.67
	75%	8.80	2.638	0.711	5.28	2.49	8.06
	80%	8.52	2.410	0.656	4.82	2.25	7.39
	85%	8.22	2.162	0.594	4.32	2.00	6.65
Wisconsin	65%	12.08	4.020	1.156	8.04	3.51	12.57
	70%	11.85	3.777	1.090	7.55	3.28	11.83
	75%	11.60	3.508	1.016	7.02	3.03	11.00
	80%	11.27	3.210	0.935	6.42	2.76	10.09
	85%	10.93	2.891	0.846	5.78	2.47	9.10

Table 12. Change in mean P_{Loss} when mean BMP yield is 2% less than check strip mean yield (mean effect) and BMP yield coefficient of variation is 5% greater than check strip yield coefficient of variation (variance effect).

Deductible	Coverage	Original	Mean Effect	% Change	Variance Effect	% Change
2.5%	65%	0.325	0.382	17.6%	0.351	8.0%
2.5%	70%	0.311	0.367	17.9%	0.336	8.1%
2.5%	75%	0.295	0.349	18.2%	0.320	8.3%
2.5%	80%	0.277	0.329	18.6%	0.301	8.4%
2.5%	85%	0.258	0.307	19.1%	0.280	8.7%
5%	65%	0.257	0.305	18.8%	0.293	13.9%
5%	70%	0.244	0.291	19.2%	0.279	14.2%
5%	75%	0.229	0.274	19.6%	0.263	14.5%
5%	80%	0.213	0.256	20.2%	0.245	15.0%
5%	85%	0.195	0.235	20.8%	0.225	15.5%

Table 13a. Change in mean premium when mean BMP yield is 2% less than check strip mean (mean effect) and BMP yield coefficient of variation is 5% greater than check strip yield coefficient of variation (variance effect) for a 5% deductible and $2 price election.

State	Coverage	Original	Mean Effect	% Change	Variance Effect	% Change
Delaware	65%	4.92	6.01	22.2%	6.77	37.6%
	70%	4.58	5.62	22.6%	6.28	37.2%
	75%	4.19	5.16	23.1%	5.75	37.1%
	80%	3.77	4.66	23.8%	5.18	37.5%
	85%	3.32	4.13	24.6%	4.57	37.9%
Illinois	65%	6.25	7.60	21.6%	8.39	34.2%
	70%	5.81	7.08	22.0%	7.79	34.1%
	75%	5.30	6.50	22.7%	7.13	34.5%
	80%	4.76	5.87	23.4%	6.42	34.8%
	85%	4.19	5.20	24.1%	5.67	35.4%
Indiana	65%	5.94	7.22	21.6%	8.12	36.7%
	70%	5.52	6.74	22.1%	7.55	36.8%
	75%	5.06	6.20	22.6%	6.93	36.9%
	80%	4.56	5.61	23.2%	6.25	37.1%
	85%	4.02	4.98	23.9%	5.53	37.6%
Iowa	65%	6.41	7.79	21.5%	8.72	36.1%
	70%	5.96	7.27	22.0%	8.11	36.1%
	75%	5.45	6.68	22.5%	7.44	36.5%
	80%	4.90	6.04	23.2%	6.72	37.0%
	85%	4.33	5.37	23.9%	5.94	37.2%
Kansas	65%	6.25	7.60	21.6%	8.39	34.2%
	70%	5.81	7.08	22.0%	7.79	34.1%
	75%	5.30	6.50	22.7%	7.13	34.5%
	80%	4.76	5.87	23.4%	6.42	34.8%
	85%	4.19	5.20	24.1%	5.67	35.4%
Kentucky	65%	5.00	6.08	21.5%	6.89	37.7%
	70%	4.65	5.67	22.0%	6.40	37.7%
	75%	4.26	5.22	22.6%	5.87	37.9%
	80%	3.84	4.73	23.3%	5.29	37.9%
	85%	3.40	4.21	23.9%	4.68	37.7%
Maryland	65%	4.89	5.95	21.8%	6.70	37.0%
	70%	4.55	5.56	22.3%	6.22	36.7%
	75%	4.17	5.12	22.8%	5.70	36.6%
	80%	3.75	4.62	23.4%	5.14	37.0%
	85%	3.29	4.09	24.2%	4.54	38.0%
Michigan	65%	5.29	6.45	21.9%	7.20	36.1%
	70%	4.92	6.02	22.4%	6.69	36.1%
	75%	4.50	5.53	22.9%	6.13	36.2%
	80%	4.05	5.00	23.5%	5.53	36.5%
	85%	3.56	4.43	24.3%	4.88	37.0%
Minnesota	65%	6.40	7.77	21.5%	8.72	36.3%
	70%	5.93	7.23	21.9%	8.10	36.5%
	75%	5.41	6.63	22.5%	7.40	36.8%
	80%	4.85	5.98	23.2%	6.65	37.1%
	85%	4.28	5.30	23.9%	5.86	37.1%

Table 13b. Change in mean premium when mean BMP yield is 2% less than check strip mean (mean effect) and BMP yield coefficient of variation is 5% greater than check strip yield coefficient of variation (variance effect) for a 5% deductible and $2 price election.

State	Coverage	Original	Mean Effect	% Change	Variance Effect	% Change
Missouri	65%	5.18	6.30	21.6%	6.99	34.9%
	70%	4.81	5.87	22.2%	6.50	35.1%
	75%	4.40	5.40	22.7%	5.96	35.3%
	80%	3.97	4.89	23.4%	5.38	35.5%
	85%	3.51	4.35	24.1%	4.75	35.6%
Nebraska	65%	5.88	7.18	22.2%	8.12	38.1%
	70%	5.46	6.69	22.7%	7.54	38.3%
	75%	4.98	6.14	23.3%	6.91	38.9%
	80%	4.47	5.54	24.1%	6.23	39.5%
	85%	3.93	4.90	24.8%	5.51	40.1%
New York	65%	4.72	5.75	21.8%	6.37	34.7%
	70%	4.39	5.37	22.2%	5.91	34.6%
	75%	4.02	4.93	22.8%	5.41	34.8%
	80%	3.61	4.45	23.3%	4.88	35.2%
	85%	3.18	3.94	24.1%	4.32	35.9%
North Dakota	65%	4.85	5.91	21.8%	6.58	35.7%
	70%	4.51	5.51	22.3%	6.11	35.6%
	75%	4.12	5.07	22.9%	5.59	35.5%
	80%	3.71	4.58	23.6%	5.02	35.6%
	85%	3.27	4.06	24.4%	4.43	35.6%
Ohio	65%	6.03	7.34	21.7%	8.30	37.5%
	70%	5.60	6.84	22.2%	7.70	37.5%
	75%	5.12	6.28	22.7%	7.04	37.5%
	80%	4.61	5.69	23.4%	6.33	37.4%
	85%	4.07	5.05	24.2%	5.58	37.1%
Pennsylvania	65%	4.52	5.50	21.7%	6.06	34.0%
	70%	4.21	5.14	22.2%	5.62	33.5%
	75%	3.86	4.73	22.7%	5.14	33.2%
	80%	3.48	4.29	23.3%	4.63	33.2%
	85%	3.07	3.81	24.0%	4.09	33.1%
South Dakota	65%	4.95	6.02	21.5%	6.56	32.3%
	70%	4.61	5.63	21.9%	6.09	31.9%
	75%	4.23	5.18	22.5%	5.57	31.6%
	80%	3.81	4.70	23.1%	5.01	31.3%
	85%	3.37	4.17	23.8%	4.43	31.4%
Virginia	65%	4.50	5.47	21.4%	5.97	32.6%
	70%	4.19	5.11	21.8%	5.55	32.5%
	75%	3.84	4.70	22.3%	5.09	32.6%
	80%	3.45	4.24	23.0%	4.59	33.0%
	85%	3.04	3.75	23.6%	4.06	33.6%
Wisconsin	65%	5.94	7.26	22.1%	8.14	37.0%
	70%	5.52	6.77	22.6%	7.57	37.1%
	75%	5.06	6.24	23.2%	6.94	37.0%
	80%	4.56	5.65	23.8%	6.25	37.1%
	85%	4.03	5.02	24.6%	5.54	37.3%

Table 14a. Change in mean premium when mean BMP yield is 2% less than check strip mean (mean effect) and BMP yield coefficient of variation is 5% greater than check strip yield coefficient of variation (variance effect) for a 2.5% deductible and $2 price election.

State	Coverage	Original	Mean Effect	% Change	Variance Effect	% Change
Delaware	65%	6.65	8.08	21.4%	8.72	31.0%
	70%	6.26	7.63	21.8%	8.18	30.6%
	75%	5.81	7.10	22.2%	7.57	30.3%
	80%	5.31	6.51	22.7%	6.91	30.3%
	85%	4.76	5.87	23.3%	6.21	30.4%
Illinois	65%	8.41	10.18	21.1%	10.80	28.4%
	70%	7.90	9.59	21.4%	10.12	28.1%
	75%	7.32	8.92	21.9%	9.38	28.2%
	80%	6.68	8.19	22.5%	8.57	28.2%
	85%	5.99	7.38	23.2%	7.70	28.4%
Indiana	65%	8.00	9.68	21.1%	10.44	30.5%
	70%	7.51	9.13	21.5%	9.80	30.5%
	75%	6.97	8.50	22.0%	9.09	30.4%
	80%	6.38	7.81	22.4%	8.32	30.4%
	85%	5.74	7.06	23.0%	7.49	30.5%
Iowa	65%	8.62	10.42	20.9%	11.19	29.9%
	70%	8.10	9.82	21.3%	10.51	29.8%
	75%	7.51	9.14	21.7%	9.76	29.9%
	80%	6.86	8.39	22.2%	8.93	30.1%
	85%	6.17	7.59	22.9%	8.03	30.1%
Kansas	65%	8.41	10.18	21.1%	10.80	28.4%
	70%	7.90	9.59	21.4%	10.12	28.1%
	75%	7.32	8.92	21.9%	9.38	28.2%
	80%	6.68	8.19	22.5%	8.57	28.2%
	85%	5.99	7.38	23.2%	7.70	28.4%
Kentucky	65%	6.73	8.14	21.0%	8.84	31.4%
	70%	6.32	7.67	21.4%	8.30	31.3%
	75%	5.87	7.15	21.9%	7.70	31.2%
	80%	5.37	6.58	22.4%	7.04	31.0%
	85%	4.84	5.95	23.0%	6.33	30.7%
Maryland	65%	6.59	7.98	21.2%	8.62	30.9%
	70%	6.20	7.54	21.6%	8.08	30.4%
	75%	5.76	7.02	22.0%	7.49	30.1%
	80%	5.26	6.44	22.5%	6.85	30.2%
	85%	4.71	5.80	23.1%	6.16	30.7%
Michigan	65%	7.14	8.66	21.3%	9.27	29.8%
	70%	6.71	8.17	21.7%	8.70	29.6%
	75%	6.23	7.60	22.1%	8.06	29.4%
	80%	5.69	6.98	22.7%	7.37	29.5%
	85%	5.11	6.30	23.3%	6.62	29.6%
Minnesota	65%	8.61	10.41	20.9%	11.22	30.3%
	70%	8.07	9.79	21.3%	10.52	30.3%
	75%	7.46	9.09	21.8%	9.73	30.5%
	80%	6.80	8.32	22.4%	8.87	30.5%
	85%	6.10	7.51	23.0%	7.95	30.4%

Table 14b. Change in mean premium when mean BMP yield is 2% less than check strip mean (mean effect) and BMP yield coefficient of variation is 5% greater than check strip yield coefficient of variation (variance effect) for a 2.5% deductible and $2 price election.

State	Coverage	Original	Mean Effect	% Change	Variance Effect	% Change
Missouri	65%	6.98	8.44	21.0%	8.99	28.9%
	70%	6.55	7.96	21.5%	8.44	28.9%
	75%	6.08	7.41	22.0%	7.83	28.9%
	80%	5.56	6.81	22.6%	7.16	28.9%
	85%	5.01	6.16	23.1%	6.44	28.7%
Nebraska	65%	7.96	9.66	21.4%	10.44	31.2%
	70%	7.47	9.10	21.8%	9.80	31.1%
	75%	6.92	8.46	22.3%	9.09	31.4%
	80%	6.31	7.75	22.9%	8.31	31.7%
	85%	5.66	6.99	23.5%	7.46	31.9%
New York	65%	6.36	7.70	21.0%	8.18	28.5%
	70%	5.98	7.26	21.3%	7.67	28.2%
	75%	5.54	6.75	21.8%	7.11	28.2%
	80%	5.07	6.19	22.3%	6.49	28.2%
	85%	4.54	5.58	22.9%	5.84	28.6%
North Dakota	65%	6.54	7.92	21.0%	8.45	29.1%
	70%	6.15	7.46	21.4%	7.92	28.9%
	75%	5.70	6.95	21.9%	7.34	28.7%
	80%	5.21	6.38	22.4%	6.69	28.5%
	85%	4.68	5.76	23.1%	6.00	28.3%
Ohio	65%	8.13	9.86	21.2%	10.66	31.0%
	70%	7.63	9.28	21.6%	9.99	31.0%
	75%	7.07	8.63	22.0%	9.25	30.8%
	80%	6.46	7.92	22.6%	8.43	30.5%
	85%	5.81	7.17	23.2%	7.56	30.1%
Pennsylvania	65%	6.09	7.37	21.1%	7.79	28.0%
	70%	5.73	6.96	21.5%	7.30	27.5%
	75%	5.32	6.49	21.8%	6.76	27.0%
	80%	4.87	5.96	22.4%	6.17	26.8%
	85%	4.38	5.39	23.0%	5.55	26.5%
South Dakota	65%	6.66	8.05	20.9%	8.45	26.9%
	70%	6.27	7.60	21.3%	7.92	26.4%
	75%	5.82	7.08	21.7%	7.33	26.0%
	80%	5.33	6.52	22.2%	6.69	25.5%
	85%	4.80	5.89	22.8%	6.01	25.4%
Virginia	65%	6.04	7.30	20.8%	7.69	27.3%
	70%	5.69	6.89	21.1%	7.22	27.0%
	75%	5.28	6.41	21.6%	6.69	26.9%
	80%	4.82	5.89	22.1%	6.12	27.0%
	85%	4.32	5.30	22.7%	5.50	27.2%
Wisconsin	65%	8.04	9.76	21.4%	10.47	30.3%
	70%	7.55	9.20	21.8%	9.83	30.2%
	75%	7.02	8.58	22.2%	9.12	29.9%
	80%	6.42	7.88	22.8%	8.33	29.8%
	85%	5.78	7.14	23.4%	7.50	29.7%

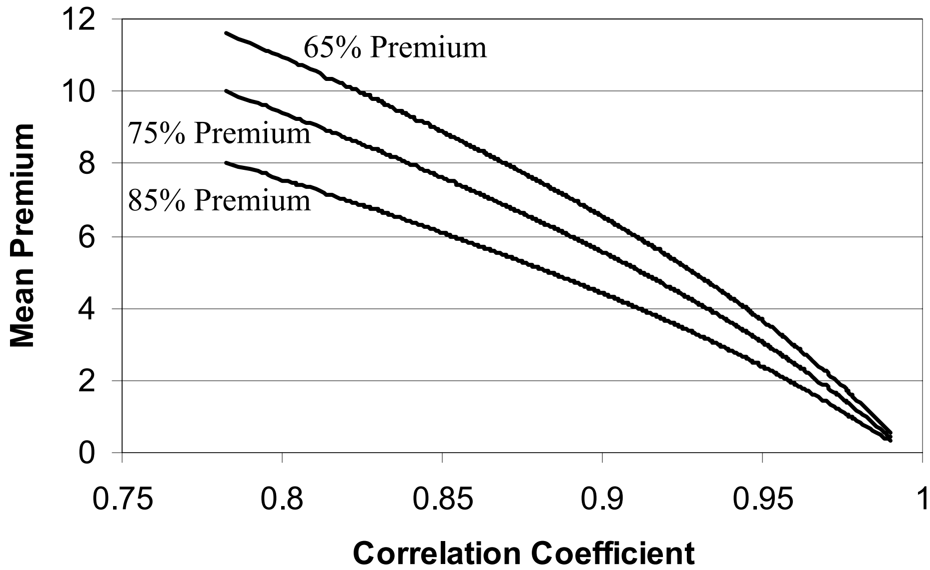

Figure 1. Impact of correlation coefficient on mean premium in Iowa for a $2 price election and a 5% deductible.

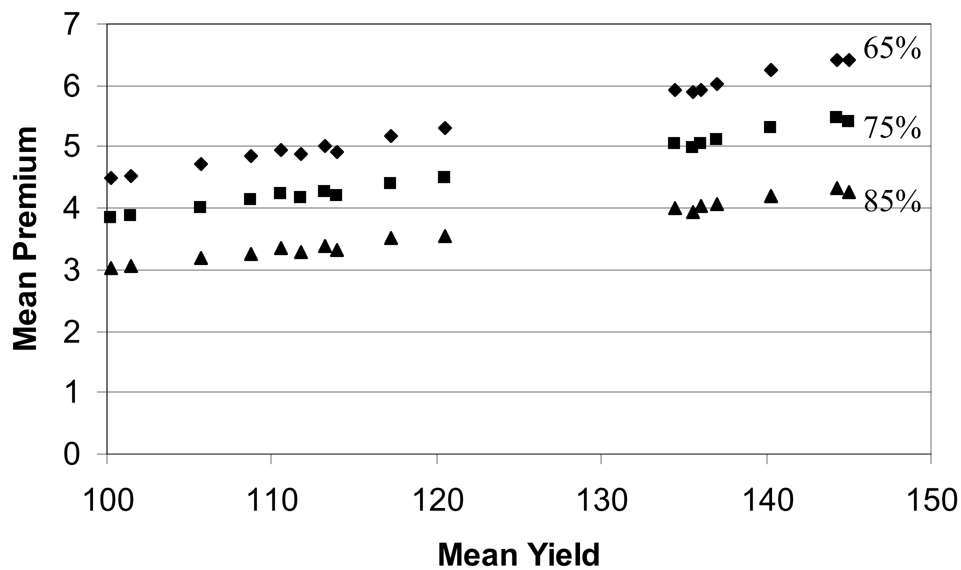

Figure 2. Impact of mean yield on mean premium for 65% (diamonds), 75% (squares) and 85% (triangles) crop insurance coverage level with a 5% deductible.

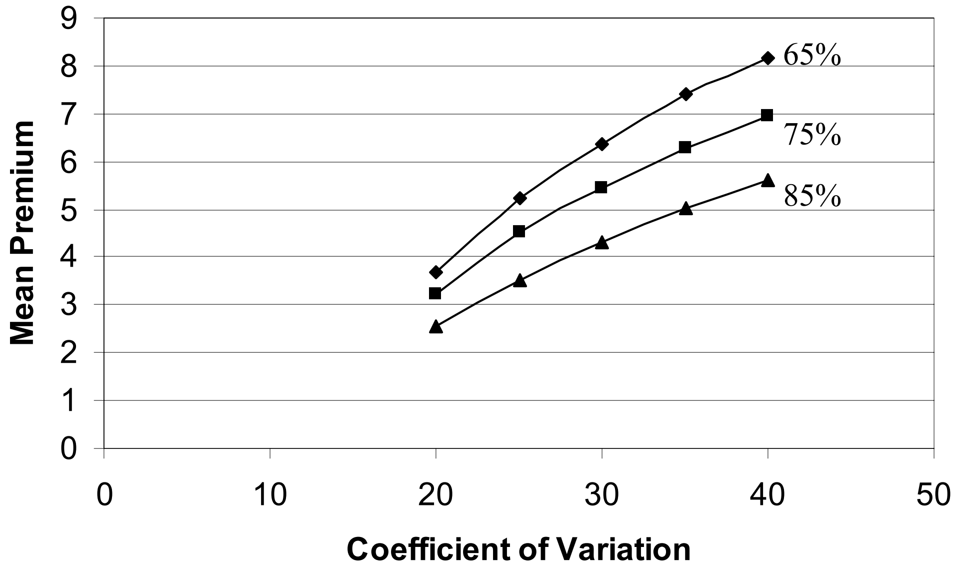

Figure 3. Impact of the yield coefficient of variation on the mean premium with a 5% deductible for Iowa and a 65% (diamonds), 75% (squares), and 85% (triangles) crop insurance coverage level.

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