Testing the Viability of Area Yield Insurance for Cotton and Soybeans in the Southeast

by

Xiaohui Deng, Barry J. Barnett, and Dmitry Vedenov

Author Affiliations: Xiaohui Deng is Ph.D. student and graduate assistant, Barry J. Barnett is associate professor, and Dmitry Vedenov is assistant professor, Department of Agricultural and Applied Economics, University of Georgia, Athens, GA.

Contact:
Xiaohui Deng
Department of Agricultural and Applied Economics
Conner Hall 306
University of Georgia
Athens, GA 30602

Phone: (706)542-0856
Fax: (706)542-0739
E-mail: sdeng@agecon.uga.edu

Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Tulsa, Oklahoma, February 18, 2004

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Abstract:

GRP is essentially a put option on the NASS estimate of the county average yield. Purchasers of GRP are exposed to geographic basis risk. This study uses farm- and county-level yield data to examine the viability of area yield insurance for cotton and soybean farms in the southeastern U.S.

Key words: area yield insurance, multiple peril crop insurance, risk reduction, certainty equivalent

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Background and objective

Recent years have witnessed much discussion about innovative agricultural insurance designs. Traditional agricultural insurance designs are often plagued with problems of asymmetric information and systemic risks (Miranda and Glauber 1997). Among the innovations being widely discussed are weather derivatives and area-based index contracts. Traditional crop insurance protects against farm-level yield or revenue losses. Weather derivatives protect against specific weather events that are often associated with farm-level losses. Area-based indexes contracts protect against yield or revenue losses measured, not at the farm level, but rather at an aggregate level such as the county.

Farm level loss adjustment is not necessary with weather derivatives or area yield contracts (Turvey). These innovations are also not subject to the asymmetric information problems that exist with traditional farm level crop insurance products. Indemnities are based on the realized value of transparent and objective indexes over which the policyholder has no control – weather events measured at a local weather station or aggregate area yields. However substantial basis risk can exist with these new innovations.

The Group Risk Plan (GRP) is an area yield insurance product being pilot tested within the Federal Crop Insurance Program. Group Risk Income Protection (GRIP) is a similar area revenue insurance product. Agricultural applications of weather derivatives have received significant attention and pilot tests are underway in several countries, though currently not in the U.S. (Miranda; Skees, Black and Barnett; Skees, Hazell, and Miranda; Turvey; Skees et al; Barnett et al; Chambers and Quiggin; Smith, Chouinard, and Baquet).

This study assesses the viability of GRP for cotton and soybean production in the southeast U.S. GRP performance is compared to that of traditional farm level Multiple Peril Crop Insurance (MPCI) for farms in Georgia and South Carolina. MPCI provides protection against yield losses, from a variety of natural sources, at the individual farm, or even sub-farm, level. GRP, on the contrary, provides protection against yield losses at the area (county) level. GRP premiums are typically much less expensive than MPCI premiums. GRP also is not subject to asymmetric information problems. GRP however is often criticized because of the potential for basis risk. In this context, basis risk means that farmers may not receive a GRP indemnity even though they have experienced farm level yield losses. This will occur if farm level yield losses are caused by a localized phenomenon that does not impact the overall county yield. This study compares MPCI and GRP at both the state and Crop Reporting District (CRD) levels. This is accomplished by utilizing both variance reduction and expected utility performance criteria.

Data

County level yield data are obtained from the National Agricultural Statistical Service (NASS). For Georgia and South Carolina these data were available over the 32 year period 1969-2000 for cotton and over the 27 year period 1974-2000 for soybeans. Scatter plots showed that the cotton yield data display an obvious time trend but the soybean data do not. Thus the cotton data were detrended and the predicted 2002-trended yield is used as the county yield expectation. Since there is no time trend in the soybean data, the in-sample average is used as the county yield expectation.

Individual farm level yields data are obtained from the Risk Management Agency (RMA). These data are the 4 to 10 year yield histories used to establish actual production history (APH) yields for MPCI purchasers. The data are for the 10-year period 1991-2000. Only farms which reported actual yields for the most recent consecutive 6-10 years were included in the study. As with the actual MPCI product, farm level yield data were not detrended and the APH yield was calculated as a simple average of the annual yields over each individual's sample period (6 to 10 consecutive years).

Counties must meet two criteria to be included in the study: (1) the county must have at least 20 available farm observations which meet the conditions indicated above; and, (2) the county can not have more than 3 consecutive years of missing county yield data and the total number of missing years of yield data could not exceed 6. The third column of table 1 lists the number of counties that meet these criteria. The fourth column lists the corresponding number of farms in those qualified counties within a specific state or CRD.

Methodology

Let $\tilde{y}_i$ be the realization of a stochastic yield on farm *i*, with $E(\tilde{y}_i) = \mu_i$. Similarly, let $\tilde{y}$ be the realization of a stochastic yield in the county where farm *i* is located, with $E(\tilde{y}) = \mu$. If $\tilde{y}_i$ is projected orthogonally on to $\tilde{y}$ then

(1) $\tilde{y}_i - \mu_i = \beta_i(\tilde{y} - \mu) + \tilde{\varepsilon}_i$

where

(2) $\beta_i = \text{cov}(\tilde{y}_i, \tilde{y}) / \sigma^2_{\tilde{y}} = \rho_i \dfrac{\sigma_{\tilde{y}_i}}{\sigma_{\tilde{y}}}$

(3) $E(\varepsilon_i) = 0;\ \ Cov(\tilde{y}, \tilde{\varepsilon}_i) = 0$

If insurance is actuarially fair then

(4) $\pi = E(\tilde{n})$

where π is the per acre insurance premium and $\tilde{n}$ is the per acre insurance indemnity. Ignoring price risk, the insurance contract can be evaluated by its impact on the variance of net yield

(5) $Var(\tilde{y}_i^{net}) = \sigma^2_{\tilde{y}i} + \sigma^2_{\tilde{n}} + 2Cov(\tilde{y}_i, \tilde{n})$

where

(6) $\tilde{y}_i^{net} = \tilde{y}_i + \tilde{n} - \pi$.

Purchasing insurance reduces farm level yield variability by

(7) $\Delta_i = Var(\tilde{y}_i) - Var(\tilde{y}_i^{net}) = -\sigma^2_{\tilde{n}} - 2Cov(\tilde{y}_i, \tilde{n})$.

Miranda showed that if $\tilde{\varepsilon}_i$ and $\tilde{y}$ are conditionally independent, then $\tilde{\varepsilon}_i$ and $\tilde{n}$ are uncorrelated and

(8) $Cov(\tilde{y}_i, \tilde{n}) = \beta_i \times Cov(\tilde{y}, \tilde{n})$.

If we define

$$(9)\ \beta_c = -\frac{\sigma_{\tilde{n}}^2}{2\operatorname{cov}(\tilde{y}, \tilde{n})}$$

and substitute (8) into (7) then equation (7) can be rewritten as

$$(10)\ \Delta_i = \sigma_{\tilde{n}}^2 \left[\frac{\beta_i}{\beta_c} - 1 \right].$$

Converting this into percentage terms

$$(11)\ \theta_i = \frac{\Delta_i}{\sigma_{\tilde{y}_i}^2} = \frac{\sigma_{\tilde{n}}^2}{\sigma_{\tilde{y}_i}^2}\left[\frac{\beta_i}{\beta_c} - 1\right] = \frac{\sigma_{\tilde{n}}^2}{\sigma_{\tilde{y}_i}^2}\left[\frac{\rho_i \dfrac{\sigma_{\tilde{y}_i}}{\sigma_{\tilde{y}}}}{\beta_c} - 1\right] = \rho_i \frac{\sigma_{\tilde{n}}^2}{\sigma_{\tilde{y}_i}\sigma_{\tilde{y}}\beta_c} - \frac{\sigma_{\tilde{n}}^2}{\sigma_{\tilde{y}_i}^2}\ .$$

For area yield insurance $\sigma_{\tilde{n}}^2$, $\sigma_{\tilde{y}}^2$, and β_c are invariant across individuals. Equation 11 demonstrates that ρ_i is positively related to the variance reduction from area yield insurance. That is, ceteris paribus, the higher the correlation between a producer's yield and the area-yield, the greater the yield risk reduction from area yield insurance. Though perhaps less intuitive, Miranda also demonstrates that $\sigma_{\tilde{y}_i}^2$ is positively related to the risk reduction that can be obtained from area yield insurance.

If we assume that indemnities are paid in units of production per acre, the GRP indemnity is calculated as

$$(12)\ \tilde{n} = \max\left(0, \frac{y_c - \tilde{y}}{y_c}\right) \times scale$$

where

$$(13)\ y_c = \mu \times coverage$$

and $70\% \leq coverage \leq 90\%$ in 5% increments and $90\% \leq scale \leq 150\%$.

The MPCI indemnity is calculated as

$$(14)\ \tilde{n} = \max(0, y_{ic} - \tilde{y}_i)$$

where

(15) $y_{ic} = \mu_i \times coverage$

and 50% ≤ *coverage* ≤ 85% in 5% increments. For MPCI, μ_i is a rolling 4 to 10 year average of historical farm yields.

Following Barnett, et al. we take the very conservative approach of assigning the same GRP coverage and scale value to all farmers in the same state or the same crop-reporting district (CRD). We then calculate the weighted average risk reduction across the group of farmers as

$$(16)\ \theta = \sum_{i=1}^{n} \frac{w_i \theta_i}{\sum_{i=1}^{n} w_i}$$

where θ is the weighted average percentage reduction in net yield variance, w_i is the ith farm's most recent years planted acres, and n is the total number of farms in the state or CRD.

Mean-Variance Criterion

Mean-Variance criterion, promoted by Markowitz, has been used in a wide range of financial decisions. Assume $\tilde{w}_f$ is a random variable with realizations when a decision-maker makes a decision. Then risk evaluation $V(\tilde{w}_f)$ is captured by $\tilde{w}_f's$ first two moments, expected return $E(\tilde{w}_f)$ and the variance $\sigma^2(\tilde{w}_f)$

$$(17)\ V(\tilde{w}_f) = f\left[E(\tilde{w}_f), \sigma^2(\tilde{w}_f)\right]$$

with

$$(18)\ f_E = \frac{\partial V(\tilde{w}_f)}{\partial E(\tilde{w}_f)} > 0\,.$$

The sign of

$$(19)\ f_{\sigma^2} = \frac{\partial V(\tilde{w}_f)}{\partial \sigma^2(\tilde{w}_f)}$$

however, is not universal. It could be negative, zero or positive depending on whether the individual is risk averse, risk neutral or risk loving. Further, if we apply the concept of an indifference curve, the ratio of the two partial derivatives measures the marginal rate of substitution (MRS) between expected return and the variance given a constant *V*, that is,

$$(20)\ MRS_{E,\sigma^2} = -\frac{dE(\tilde{w}_f)}{d\sigma^2(\tilde{w}_f)} = \frac{f_E}{f_{\sigma^2}}$$

MRS indicates how much expected return must increase to compensate the decision maker for an increase in variance if *V* remains constant. The sign of MRS shows that the indifference curve is upward-sloping, downward-sloping or horizontal depending on the sign of f_{σ^2} or the risk attitude of the decision maker.

In this study, we assume that all farmers are risk averse with negative f_{σ^2} and upward-sloping indifference curve. That presumes that when facing two strategies resulting in the same expected return, farmers will choose the one with smaller variance. Initally, we construct both MPCI and GRP premiums to be actuarially-sound in sample. Thus, we evaluate the performance of the insurance contracts by comparing how much they reduce the variance of the farm level net yield.

Since the farm level yield data are available for only 6-10 years, we follow the conservative approach utilized by Barnett et al. in optimizing GRP coverage and scale at the state or CRD level rather than the individual farm level. To find the optimal coverage and scale, Barnett et al first set scale at its optimal level by solving for β_l, where *l* indicates a given state or CRD. They then find the optimal coverage level by fixing the optimal scale and searching across all possible coverage levels for the one that generates the largest reduction in net yield risk. In this study, however, we solve for optimal scale and coverage simultaneously using the BFGS algorithm. The BFGS algorithm is a specific case of a Quasi-Newton method in solving finite-dimensional optimization. It is extremely effective among the most widely used gradient methods. It overcomes a potential problem in the

Newton method by replacing the inverse of the Hessian with its estimate, which is constructed symmetric and negative definite as must be true of the inverse Hessian at a local maximum. The negative definiteness of the Hessian estimate guarantees that the objective function value increases in the direction of the Newton step (Greene, Miranda and Fackler). After solving for the optimal coverage and scale for each state or CRD, every farm in the state or CRD is assigned the region-wide optimal coverage and scale.

Three MPCI scenarios and two GRP scenarios are modeled. MPCI is modeled at 65%, 75% and 85% coverage levels. The first GRP scenario has coverage set at 90% and scale at 100%. The second GRP scenario applies the optimal coverage and scale.

Expected Utility Criteria

Expected utility defined over the domain of ending wealth is

$$(21)\ V(\tilde{w}_f) = \int_{w_f} U(\tilde{w}_f) f(\tilde{w}_f) d\tilde{w}_f$$

where $\tilde{w}_f$ is ending wealth and $U' = dU / d\tilde{w}_f$ (the marginal utility of $\tilde{w}_f$) is strictly positive. The certainty equivalent is that level of wealth which would yield a decision-maker with utility function U the same level of satisfaction as the random $\tilde{w}_f$. If we donate the certainty equivalent by $w*$ then its formal definition is:

$$(22) U(w*) = \int_{w_f} U(\tilde{w}_f) f(\tilde{w}_f) d\tilde{w}_f \ .$$

Taking advantage of the fact that the utility function, being monotonic, has an inverse function, $w*$ could be solved as

$$(23)\ w* = U^{-1}(U(w*)) = U^{-1}\left(\int_{w_f} U(\tilde{w}_f) f(\tilde{w}_f) d\tilde{w}_f\right).$$

Following Arrow and Pratt, the coefficient of absolute risk aversion is defined as $A_a = -\frac{U''(C)}{U'(C)}$, and the coefficient of relative risk aversion is defined as $A_r = -C\frac{U''(C)}{U'(C)}$, where U is a utility function defined over wealth, C. Merton suggested that the assumption of constant relative risk aversion over wealth was more plausible than constant absolute risk aversion. In our study we assume the utility function reflects constant relative risk aversion and borrow a HARA-class utility function specified as $U = \frac{w^{1-r}}{1-r}$ when $r \neq 1$ and $U = \log(w)$ when r = 1 (Hanna, Gutter and Fan). If we discretize (22) and assume that the ending wealth of each year is uniformly distributed, the expected utilities for different scenarios are:

(24a) $E(U_{ior}) = \sum_{t=1}^{m_i} \frac{y_{ito}^{net}}{m_i(1-r)}, \quad r \neq 1$

(24b) $E(U_{ior}) = \sum_{t=1}^{m_i} \frac{1}{m_i} \log(y_{ito}^{net}), \quad r = 1$

where r is the coefficient of constant relative risk aversion and the subscript o refers to the insurance scenario (different coverage levels for MPCI and different coverage and scale levels for GRP). The corresponding certainty equivalent of ending wealth for the i^{th} farm is denoted by:

(25a) $CE_{ior} = [(1-r)E(U_{ior})]^{\frac{1}{1-r}}, \quad r \neq 1$

(25b) $CE_{ior} = e^{E(U_{ior})}, \quad r = 1$.

The average certainty equivalent of ending wealth of all farmers in a given state or CRD is calculated as:

(26) $\overline{CE}_{or} = \frac{1}{n}\sum_{i=1}^{n} CE_{ior}$.

Then the average certainty equivalents are compared for each of the scenarios over various degrees of relative risk aversion.

Results

Mean-Variance Criteria

For cotton, results for each of the GRP and MPCI scenarios described earlier are presented in Table 1. For each scenario the table presents the weighted average percentage of variance reduction together with the corresponding coverage and scale levels.

For Georgia, all three coverage levels of MPCI generate more risk reduction than restricted GRP in every region expect for CRD 70, whose restricted GRP generates more risk reduction than 65% MPCI. When GRP is free to optimize coverage (70%-150%) and scale (70%-150%), it generates more risk reduction than 65% MPCI expect for the northern 6 counties of CRD 80. It also performs better than 75% MPCI for CRD 70 and CRD 50. MPCI with 85% coverage generates more risk reduction than any of the GRP scenario.

For South Carolina, GRP performs better than in Georgia. Restricted GRP performs better than 65% MPCI and the unrestricted GRP reduces risk more than 75% MPCI for every region studied. AS with Georgia, 85% MPCI generates more risk reduction than any of the GRP scenario.

For soybeans, table 2 is constructed similarly to table 1. Results show that GRP performs very poorly. Even the unrestricted GRP reduces net yield variance less than 65% MPCI. For CRD 30, the restricted GRP actually increases net yield risk.

For the crops and regions examined here, GRP performance is poor compared to the study by Barnett et al. of corn production in the Midwest and Sugar Beet production in the Red River Valley. Since GRP works best in relatively homogeneous production regions, this result implies that Georgia and South Carolina cotton and soybean production may be too heterogeneous for GRP to provide adequate risk protection.

Interestingly, the poor GRP performance corresponds to a lower scale level but a higher coverage level. For all unrestricted GRP, when the optimal variance reductions are less than 25%, the optimal scale levels are less than 80% while the coverage levels are around 140% (except for CRD 70 Georgia). However previous results by Barnett et al. for more homogeneous production regions generate much higher (most above 40%) risk reduction with higher level of scale and lower level of coverage. Intuitively, one might conclude that in more heterogeneous production regions, optimal scale will be lower due to the low correlation between farm level yield and county level yield. Maximum risk reduction then requires higher levels of coverage to compensate for the relatively low levels of scale. Results from a Monte-Carlo simulation further support this conclusion.[1] Table 5 shows that GRP works poorly even at very high coverage levels in more heterogeneous production regions. On the contrary, GRP performs well in more homogeneous production regions with much lower optimal coverage levels.

Expected Utility Criteria

Next, we switch to the results using the Expected Utility Criteria. Under constant risk aversion, monotonic transformation of the net yield (wealth) will not change farmers' risk preferences. So considering the possibility of negative net yields, we take advantage of constant relative risk aversion and assign an initial wealth of 150 lbs in cotton and 20 bu in soybean to each individual. Table 3 and Table 4 provide certainty equivalents for each of the scenarios mentioned above over various degrees of relative risk aversion. At each risk aversion level, higher coverage levels are always associated with higher certainty equivalents for MPCI and optimal scale and coverage level always renders higher certainty equivalents for GRP. Comparing MPCI and GRP at each risk aversion level, even the lowest coverage 65% MPCI performs better than the optimal GRP, which is different from the results based on Mean-Variance criterion.

[1] Simulation steps refer to Appendix.

The reason why the two criteria lead to different results in comparing 65% MPCI and optimal GRP lies in the different assumptions inherent in each criterion. The Mean-Variance criterion, although widely used, is technically applicable only if either the utility function is quadratic in its argument (wealth) or the argument is normally distributed (Barnett). In this study, the assumed utility function ($U = \frac{w^{1-r}}{1-r}$ when $r \neq 1$ and $U = \log(w)$ when r=1) is a power function or a log function but not a quadratic function and the net yield (wealth) from different scenarios are somewhat skewed. So it is not surprising that the two criteria give slightly different results.

Discussion

The study compares the risk reducing performance of GRP and MPCI on cotton and soybeans in Georgia and South Carolina. Compared to previous empirical analyses (e.g., Barnett et al), under both Mean-Variance and Expected Utility criteria, GRP performs poorly. This is likely due to more heterogeneity in the production regions being considered for this study. Based on this, one might conclude that the potential demand for cotton and soybean GRP in Georgia and South Carolina is low.

Further study will abandon the assumption of an actuarially-fair premium and instead use actual MPCI and GRP premiums. For areas where GRP is not currently offered, premiums will be calculated using GRP rating procedures. Expected utility analysis will be used to compare preferences for MPCI and GRP both with and without federal premium subsidies. In addition, further research could also extend to other crops and regions to determine how robust the findings, particularly those crops and regions that are not well served by the MPCI product.

Appendix

Monte-Carlo Simulation Steps:

1. a series of 50 years county yield $\{\tilde{y}_c\}$ is generated, normally distributed with $N(700,180)$.

2. 500 series of 50 years individual yield $\{\tilde{y}_i\}^\rho$ are generated at 3 different correlation levels with $\{\tilde{y}_c\}$. The three correlations are 0.3, 0.5, 0.7, respectively.

3. At each correlation level, ρ, θ_i^ρ could be iteratively computed using Quasi-Newton optimization technique.

4. repeat procedures 1-3 50 times and average θ_i^ρ within each correlation level and present $\bar{\theta}^\rho$.

In order to avoid to hit the ceiling of coverage or scale level, both scale and coverage levels are free to move between 0%-300%.

Table 1. Corn Percentage Variance Reduction Under GRP and MPCI Scenarios by State and Crop Reporting Districts

St	CRD	No.of counties	Total farmers	GRP			MPCI		
				Restricted Coverage & Scale	Optimal Coverage & Scale ($\bar{\theta}_{js}$)	Optimal Coverage & Scale	coverage		
				C=90%, S=100%	C∈(70%, 150%) S∈(70%, 150%)	C∈(70%, 150%) S∈(70%, 150%)	65%	75%	85%
GA	All	27	1516	16.81%	25.89%	140.80%, 87.41%	20.59%	30.08%	43.13%
	80	13	935	13.23%	21.45%	138.76%, 78.71%	17.22%	27.10%	41.04%
	Northern 80 (7)	6	421	8.54%	19.61%	140.08%, 77.66%	21.38%	30.58%	43.32%
	Southern 80 (7)	7	514	17.28%	23.05%	144.09%, 82.34%	13.64%	24.10%	39.07%
	70	3	160	18.56%	24.17%	127.39%, 74.51%	10.85%	19.87%	34.15%
	60	7	275	26.86%	39.27%	137.48%, 117.21%	36.15%	45.32%	55.13%
	50	4	146	12.16%	34.24%	150.00%, 87.67%	17.10%	25.40%	39.07%
SC	All	7	237	17.46%	37.84%	148.08%, 100.13%	15.32%	26.43%	42.34%
	50	3	110	15.44%	37.77%	139.75%, 100.77%	14.97%	24.61%	38.02%
	30	4	127	20.68%	37.97%	150.00%, 98.42%	15.54%	27.57%	45.06%

Table 2. Soybean Percentage Variance Reduction Under GRP and MPCI Scenarios by State and Crop Reporting Districts

St	CRD	No.of counties	Total farmers	GRP			MPCI		
				Restricted Coverage & Scale	Optimal Coverage & Scale ($\bar{\theta}_{js}$)	Optimal Coverage & Scale	coverage		
				C=90%, S=100%	C∈(70%, 150%) S∈(70%, 150%)	C∈(70%, 150%) S∈(70%, 150%)	65%	75%	85%
SC	All	7	268	2.09%	8.59%	145.12%, 70%	20.31%	29.67%	43.42%
	50	3	123	4.58%	10.78%	144.10%, 77.16%	23.55%	32.30%	45.38%
	30	4	145	-0.35%	6.59%	150%, 70%	17.14%	27.08%	41.50%

Table 4. Cotton Certainty Equivalence Under GRP and MPCI Scenarios by State and Crop Reporting Districts

South Carolina	**C=0.9 S=1.0**	**Optimal scale and coverage**	**0.65**	**0.75**	**0.85**
all					
1	831.02063	835.50198	835.6779	839.09483	842.69478
2	804.59644	814.01459	816.9109	824.09277	831.35593
3	778.07206	792.56568	799.35734	810.43873	821.27736
50					
1	810.01472	814.68679	813.12944	816.68317	820.42638
2	784.03181	793.51758	792.89717	800.24633	807.70014
3	758.50754	772.41315	774.5457	785.67951	796.63823
30					
1	849.21472	853.5408	855.20805	858.50651	861.98237
2	822.40832	831.86621	837.71019	844.74717	851.84519
3	795.0177	809.99308	820.84775	831.88372	842.61833
Georgia					
all					
1	791.67426	795.26489	799.27094	803.05814	806.9847
2	759.13429	765.78835	777.83053	785.58554	793.3988
3	728.30064	737.45238	758.59965	770.16945	781.60666
80					
1	808.45836	811.22509	814.73198	818.12088	821.78003
2	779.60878	784.68472	795.14524	802.12629	809.43327
3	752.08051	758.89123	777.35786	787.8742	798.63722
70					
1	877.97976	878.51309	880.91901	883.81405	886.9954
2	856.39758	857.34957	864.06213	870.10161	876.53125
3	835.58326	836.82967	848.29953	857.51441	867.10236
60					
1	717.02631	726.13832	729.97402	735.36361	740.2863
2	669.65332	689.02843	701.87532	712.93476	722.77258
3	624.36144	653.93869	676.88611	693.25024	707.59631
50					
1	730.20963	738.11577	741.3044	745.60187	750.18164
2	689.96642	704.92073	715.51113	723.87864	732.63711
3	654.21763	675.12777	694.08126	705.94782	718.25025

Table 4. Soybean Certainty Equivalence Under GRP and MPCI Scenarios by State and Crop Reporting Districts

South Carolina	**C=0.9 S=1.0**	**Optimal scale and coverage**	**0.65**	**0.75**	**0.85**
all					
1	43.122943	43.261922	43.600416	43.682816	43.767262
2	42.145433	42.41605	43.141286	43.310906	43.481274
3	41.1799	41.56871	42.700746	42.959299	43.214866
50					
1	43.938997	44.046923	44.403578	44.488778	44.575402
2	42.959813	43.166324	43.934269	44.110901	44.286669
3	41.991001	42.280114	43.478576	43.749459	44.014536
30					
1	42.430705	42.595323	42.919113	42.999138	43.081736
2	41.454614	41.778957	42.468618	42.63229	42.798077
3	40.491862	40.965444	42.040932	42.289025	42.536525

Table 5. simulated variance reduction under GRP at different correlation levels

correlation	Variance reduction	Optimal coverage	Optimal scale
0.3	0.0866253	2.7784623	0.7892088
0.5	0.243711	1.9966503	0.9625752
0.7	0.4820727	1.6423642	1.1271478

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