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Evaluating the Efficiency of Crop Index Insurance Products

By

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Evaluating the Efficiency of Crop Index Insurance Products

Abstract:

Index crop insurance products can eliminate the asymmetric information problem inherent in farm-level multiple peril crop insurance. Purchasers of index insurance products are, however, exposed to basis risk. This study evaluates the efficiency of various index insurance products to reduce farm yield loss for representative corn farms in southern Georgia. Index insurance products considered are based on county yields, cooling degree days, and predicted yields from a crop simulation model.

Key words: Yield Index Insurance, Risk Protection, Efficiency, Certainty Equivalent, DSSAT, CSM-CERES-Maize

Introduction

From its inception in 1938 the U.S. Federal Crop Insurance Program (FCIP) has provided Multiple Peril Crop Insurance (MPCI) policies that provide comprehensive protection against weather-related causes of loss and certain other unavoidable perils. Since the mid-1980s, MPCI yield guarantees have been based on the actual production history (APH) yield for the insured unit. In its most basic form, an APH yield is calculated as a rolling 4-10 year average of realized yields on the insured unit subject to no more than a 10% annual reduction. Under certain circumstances, the calculation of an APH yield becomes more complex. For example, in some cases the policyholder has the option of using 60% of the so called "transitional yield" in place of very low historical realized yields for purposes of calculating an APH yield.[1]

In recent years, various APH-based revenue insurance products have also been offered through the FCIP.[2] For 2005, APH-based insurance products (APH-based yield insurance, MPCI, and the various APH-based revenue insurance products) accounted for almost 90% of FCIP premiums. Several studies have noted that APH-based insurance products are subject to asymmetric information problem due to misclassification (adverse selection) and moral hazard problems (Just, Calvin, and Quiggin 1999; Coble et al. 1997; Smith and Goodwin 1996; Quiggin, Karaginannis, and Stanton 1994). In addition, APH-based insurance products have high transaction costs related to establishing and verifying APH yields and conducting on-farm loss adjustment.

Recent years have also witnessed increased discussion about index-based insurance products. Unlike conventional APH-based insurance products, the indemnity on index-based insurance products is not based on actual farm-level yield or revenue

losses. Rather, the indemnity is based on realizations of an index that is assumed to be correlated with actual farm-level yield or revenue losses. Since the indexes are based on objective and transparent sources of data, it is unlikely that informational asymmetries exist that can be exploited by index insurance contract purchasers. Thus, the inherent insurance problems of adverse selection and moral hazard (and the high transaction costs of attempting to address these inherent problems) can be largely ameliorated.

Area yield insurance is an example of an index-based insurance product that is less susceptible to many of the problems that plague APH-based insurance products. Area yield insurance is essentially a put option on the average yield for a production region. Indemnities are triggered by shortfalls in the area average yield rather than farm-level yields. For this reason, area yield insurance requires no farm-level risk classification. If the area is sufficiently large, area yield insurance is not susceptible to moral hazard problems since the actions of an individual farmer will have no noticeable impact on the area average yield. Area yield insurance also has relatively low transaction costs since there is no need to establish and verify APH yields for each insured unit nor is there any need to conduct on-farm loss adjustment.

Since 1993 an area yield insurance product called the Group Risk Plan (GRP) has been offered through the FCIP for selected crops and regions. In recent years, an area-based revenue insurance product called the Group Revenue Insurance Policy (GRIP) has also been offered for selected crops (all of which have exchange-traded futures contracts) and regions. Both GRP and GRIP areas are defined based on county political boundaries. GRP policies (and the yield component of GRIP policies) settle based on National Agricultural Statistics Service (NASS) estimates of county average yields.

Weather-based index insurance products are currently not available to agricultural producers in the U.S. However, potential agricultural applications have been discussed in the literature (Martin, Barnett and Coble 2001; Vedenov and Barnett 2004; Chen, Roberts, and Thraen 2003). Outside of the U.S., AGROASEMEX in Mexico and AGRICORP in Canada have used weather-based index insurance products. In addition, the World Bank has supported pilot programs in several developing counties.

While index-based insurance products have advantages in reducing adverse selection and moral hazard, purchasers are exposed to some degree of basis risk. For index-based insurance products, basis reflects the difference between the realized index and the farm-level yield. Because farm-level yields are not perfectly correlated with the insured index, purchasers of index-based insurance are exposed to some degree of basis risk. For instance, it is possible for the purchaser of an area yield insurance policy to experience production losses on his/her farm and yet not receive an indemnity because there has been no shortfall in the area average yield. Similarly, it is possible for a policyholder to receive an indemnity on an area yield insurance policy when no farm-level losses have occurred.

This article examines the relative performance of three different index-based insurance products. Specifically, the three indexes are based on: 1) area yields; 2) predicted yields from a model based on cooling degree days (CDD); and, 3) predicted yields from the Decision Support System for Agrotechnology Transfer (DSSAT) crop simulation model. The index insurance products are evaluated based on risk reduction for representative corn farms in five counties in South Georgia. The performance of the

index insurance instruments is then compared with that of an APH-like [3] yield insurance product.

The article is organized as follows. The next section reviews literature on index-based insurance. The next section describes the data and methods used to compare the risk protection generated by the three proposed index insurance products. Final sections discuss the empirical results and present concluding comments.

Literature Review

Miranda (1991) compared farm-level yield insurance (such as MPCI, the APH yield insurance) with area yield insurance for 102 soybean farms in western Kentucky. He found that on average, the purchase of optimal coverage area yield insurance reduced the variance of net yield more than the purchase of farm-level yield insurance.

Smith, Chouinard, and Baquet (1994) compared farm-level yield insurance to three different area-level yield insurance contracts for a sample of 123 dryland wheat farms in Chouteau County, Montana. Their overall findings indicated that the area-level yield insurance could provide effective risk protection for the farm producers.

Barnett et al. (2005) compared farm-level and area-level yield insurance for 66,686 corn farms in 10 states (Indiana, Illinois, Iowa, Kansas, Kentucky, Michigan, Minnesota, Nebraska, Ohio, and Texas) and 3,152 sugar beet farms in North Dakota and Minnesota. For corn, the area yield insurance contract performed well for all states except Nebraska and Michigan. For sugar beets, the area yield insurance contract did not perform well in the southern Red River Valley but did perform well in southwestern Minnesota. Results for the mid- and northern Red River Valley were mixed.

A number of empirical studies have also investigated potential agricultural applications of weather index insurance. Skees et al. (2001) found that a rainfall index insurance scheme could be feasible in Morocco and Argentina. AGROASEMEX, the state agricultural reinsurance company in Mexico has used weather index contracts to transfer part of its weather-related crop insurance risk into international capital markets. Martin, Barnett and Coble (2001) found that precipitation index insurance could provide effective protection against cotton yield and quality losses due to excess late-season precipitation in the delta region of Mississippi. Turvey (2001) examined the economics and pricing of weather index insurance in Ontario and suggested that temperature- and precipitation-based insurance contracts could be used to insure against yield losses for some crops. Vedenov and Barnett (2004) investigated the feasibility of using weather index insurance to protect against shortfalls in corn and soybean yields in Iowa and Illinois and cotton yields in Mississippi and Georgia. Their findings were mixed causing them to caution against "blanket assessments" of the feasibility of weather index insurance in agricultural applications. Cao (2004) proposed a predicted yield index insurance product, where the predicted yield index was a linear function of realized monthly cumulative cooling degree days (CDD) over specified months, for southern Georgia corn farmers. Her findings indicated that the effectiveness of risk protection provided by the predicted yield index was very limited.

An effective weather-yield model is critical to constructing satisfactory weather index insurance products. Bringing agronomic knowledge into a weather-yield model has the potential to improve the effectiveness of weather index insurance products. The Decision Support System for Agrotechnology Transfer (DSSAT) is a software package

combining crop, soil, and weather databases and programs to manage them, with crop models and application programs. It has been used for more than 15 years by researchers in over 100 countries to predict yield by integrating the effects of soil, crop phenotype, weather, and management options. The DSSAT package incorporates models of 27 different crops with tools that facilitate the creation and management of experimental, soil, and weather data files (ICASA).

To generate a predicted yield index via DSSAT, weather realizations are imported into the model while all other choice variables are held constant. Basis risk is still present with a DSSAT predicted yield index insurance since the predicted yields are not perfectly correlated with realized farm-level yields. It is hypothesized, however, that index insurance based on DSSAT predicted yields will have lower basis risk than index insurance based on a single weather variable, such as CDD, since DSSAT utilizes several weather variables and attempts to model interactions between the weather variables and other variables that affect realized yields.

Empirical Analysis

Data

Farm-level yield

Farm-level corn yield data were obtained from the USDA's Risk Management Agency (RMA). These data are the 4 to 10 year yield histories from 1991 to 2000 that were used to establish APH yields for 2001 MPCI purchasers. The data were aggregated to the level of an enterprise unit meaning that for a given year, the yield reflects all production in the county that is associated with a specific taxpayer identification number.

To be included in the analysis, each farm had to have yield data for at least the last 4 consecutive years of the period (i.e., 1997-2000).

County-level yield

Historical county-level yield data were collected from the National Agricultural Statistics Service (NASS). These data were collected from 1971 to 2004. All counties included in the study have less than 30% of the planted acreage under irrigation (see table 1).[4] These counties also have weather stations located within the county and daily weather data (with relatively few missing observations) available for the time period 1971-2004.

Regression analyses revealed statistically significant time trend in all county yields. To account for the temporal component, a simple detrending procedure was implemented by estimating a simple linear trend model:

(1) $$\tilde{y}_{jt} = \alpha_{j0} + \alpha_{j1} t + \varepsilon_{jt}$$

where *j* is the county, *t* is the year with *t* = 1971, 1972 , . . . 2004, $\tilde{y}_{jt}$ is the yield in county *j* and year *t*. Detrended county yields were then calculated as:

(2) $$y_{jt}^{det} = \frac{\tilde{y}_{jt}}{\hat{y}_{jt}} \hat{y}_{j2000}$$

where $\hat{y}_{jt}$ is the predicted county yield estimated from (1). The detrended county yields were then used to construct an *area yield index* insurance product.

Cumulative CDD Predicted Yield

Cao (2004) documented a linear relationship between detrended county-level corn yields and monthly cumulative CDD for six different counties in southern Georgia, including five counties selected for this study. Specifically, she found:

county	model	Pr>F	R^2	Adj. R^2
Appling	$\hat{y} = 272.647 - 0.1915 April - 0.1790 July - 0.3081 September$ (0.1535) (0.0773) (0.0037)	0.0015	0.4181	0.3557
Bulloch	$\hat{y} = 234.410 - 0.2855 April - 0.1450 July - 0.1696 September$ (0.0106) (0.0262) (0.0142)	0.0004	0.4144	0.3627
Coffee	$\hat{y} = 297.304 - 0.0746 June - 0.2728 July - 0.1317 September$ (0.3255) (0.0094) (0.0713)	<0.0001	0.5137	0.4651
Colquitt	$\hat{y} = 231.458 - 0.1282 June - 0.0839 July - 0.1644 September$ (0.1452) (0.3633) (0.0608)	0.0085	0.2950	0.2310
Pierce	$\hat{y} = 320.565 - 0.1473 June - 0.2035 July - 0.2062 September$ (0.1422) (0.1617) (0.0276)	0.0016	0.4393	0.3746

The left-hand side of the model is the predicted detrended county-level yield and each variable in the right-hand-side is the cumulative cooling degree days (CDD) for the indicated month in a give year. The numbers in parentheses are standard errors.

Following Cao, we created a series of predicted yields for each county that were linear functions of the cumulative CDD variables. The predicted yields were then used to construct a *CDD yield index* insurance product.

DSSAT Predicted Yields

Cao's predicted yield indexes were based on very simple linear regression models that empirically estimated relationships between county yields and monthly CDD measures. More sophisticated models that account for other relevant explanatory variables could also be used to construct predicted yield indexes. Presumably, these indexes would have lower basis risk and thus provide more risk protection relative to the indexes generated with Cao's simpler models.

DSSAT is a software program package composed of parameterized deterministic plant growth models that simulate yield under specific weather conditions conditioned on a number of choice variables such as soil type, crop phenotype, planting date, level and

timing of fertilizer applications, irrigation, and etc. For this study, these choice variables were selected based on recommendations from crop scientists in the region. In each county, a specific corn cultivar PIO 31G98[5] was used to run the DSSAT CSM-CERES-Maize model under three planting dates, three soil types, irrigated and rainfed conditions, and two technology levels.[6] Thus, in each county, 36 scenarios associated with all possible combinations of the choice variable conditions were used to simulate the DSSAT yields. Under each scenario, the DSSAT simulated yield was based on variations in daily minimum and maximum temperatures, rainfall, and solar radiation throughout the growing season, with all choice variables held constant. Then a unique yield in each county was obtained as a weighted average across the 36 different scenarios. The simulated DSSAT yields from 1971 to 2004 were used to construct a *DSSAT yield index* insurance product.

Nonparametric Distribution

The 4 to 10 years of available farm yield data provide only limited information about the true underlying yield distribution for each farm. Low-frequency, high-magnitude yield losses may be underrepresented (or overrepresented) in the small sample of available farm yield data. To adequately assess the performance of various insurance instruments it is necessary to estimate farm-level yield distributions. To do this, farm yield is assumed to be multiplicatively conditioned on the geometric average of the three yield indexes for each of the 4 to 10 years s for which both farm and yield index data are available:

(3a) $$\tilde{y}_{is} = \sqrt[3]{\prod_x \tilde{y}_{js}^{x}} \times \varepsilon_{is} \quad i \,\forall\, j \; and \quad s = 1991, 1992, \ldots 2000$$

then,

(3b) $$\varepsilon_{is} = \frac{\tilde{y}_{is}}{\sqrt[3]{\prod_x \tilde{y}_{js}^x}}$$

For each farm i in county j, there are 4 to 10 observations of ε_{is} which can be thought of as farm-level idiosyncratic shocks relative to the yield indexes, x, which represent area yield index, CCD yield index, and DSSAT yield index, respectively. A large number of pseudo farm-level yields can then be calculated as all possible combinations of the available yield indexes and the 4 to 10 farm-level idiosyncratic shocks. Specifically,

(4) $$\mathbf{y}_i^{pseudo} = \sqrt[3]{\prod_x \mathbf{y}_j^x} \times \boldsymbol{\varepsilon}'$$

where $\prod_x \mathbf{y}_j^x$ is a $t \times 1$ column vector of the element-wise product of three yield indexes in county j, $\boldsymbol{\varepsilon}_i'$ is a $1 \times s$ row vector of idiosyncratic shocks for farm i located in county j, and $\mathbf{y}_i^{pseudo}$ is a $t \times s$ matrix of pseudo farm-level yields for farm i. Designate z as a counter variable for the pseudo farm-level yields with $z = 1, 2, \ldots Z$ and $Z = t \times s$. Then, each farm has pseudo farm-level yields record between $136 \leq Z \leq 340$. Considering the very limited number of farms in each county, all pseudo farm-level yields within a given county were then combined to form a representative farm for the county. Thus, the representative farm-level yields can be denoted as a vector of $\mathbf{y}_f^{pseudo}$ with $f \ \forall \ j$ and size of $R = Z \times N$, where N is number of qualified farms in county j (table 1).

Several studies have described procedures for estimating yield distributions from empirical data (Just and Weninger 1999; Sherrick et al. 2004). Some have fit parametric distributions with known attributes, such as the beta distribution or the log-normal distribution (Nelson and Preckel 1989; Tirupattur, Hauser, and Chaherli 1996). Others use non-parametric approaches (Ker and Goodwin 2000). For this analysis the

representative farm-level yield and yield indexes distributions were estimated non-parametrically using a kernel-smoothing approach. This approach was preferred to parametric estimation because it better preserves the information contained in the empirical data that could be lost if a parametric structure were imposed. Formally, if $\tilde{y}_{fr}$ with $r = 1, ..., R$, is used to designate each element of the matrix $\mathbf{y}_f^{pseudo}$ and each yield index $\tilde{y}_j^x$ is repeated for the corresponding element of $\mathbf{y}_f^{pseudo}$ so that the size of the yield index is also *R*, then the joint kernel density function of the representative farm *f* farm-level yield and a particular yield index is calculated as:

(5a) $$h(\tilde{y}_f, \tilde{y}_j^x) = \frac{1}{R\Delta_f \Delta_j^x} \sum_{r=1}^{R} K\left(\frac{\tilde{y}_f - \tilde{y}_{fr}}{\Delta_f}, \frac{\tilde{y}_j - \tilde{y}_{jr}^x}{\Delta_j^x} \right)$$

and the marginal density function of farm-level yield is calculated as:

(5b) $$h(\tilde{y}_f) = \int h(\tilde{y}_f, \tilde{y}_j^x) d\tilde{y}_j^x = \int \frac{1}{R\Delta_f \Delta_j^x} \sum_{r=1}^{R} K\left(\frac{\tilde{y}_f - \tilde{y}_{fr}}{\Delta_f}, \frac{\tilde{y}_j - \tilde{y}_{jr}^x}{\Delta_j^x} \right) d\tilde{y}_j^x$$

and the marginal density function of a particular yield index is calculated as:

(5c) $$h(\tilde{y}_j^x) = \int h(\tilde{y}_f, \tilde{y}_j^x) d\tilde{y}_f = \int \frac{1}{R\Delta_f \Delta_j^x} \sum_{r=1}^{R} K\left(\frac{\tilde{y}_f - \tilde{y}_{fr}}{\Delta_f}, \frac{\tilde{y}_j - \tilde{y}_{jr}^x}{\Delta_j^x} \right) d\tilde{y}_f$$

where $K(\cdot)$ is a joint kernel function and Δ_f, Δ_j^x are degrees of smoothness or bandwidths (Härdle 1992; SAS OnlineDoc 9.1.3) for the representative farm-level yield and yield index, respectively.

The estimated joint farm-level yield and yield index distributions were used to assess the performance of each insurance contract. The joint distributions are plotted in graph 1 and the descriptive statistics calculated from the estimated joint distributions are presented in table 2.

Premium Rating

In real APH yield insurance MPCI contracts, the APH yield is calculated as a rolling average of the realized yields over the most recent 4-10 years subject to no more than a 10% annual reduction. More complex calculation may be used under certain circumstances. The APH yield, an estimator based on a small sample size, can easily over/under estimate the central tendency of the underlying true but unknown farm-level yield distribution. In this study, evaluating the APH estimator is not our primary objective. We only use MPCI contract as a baseline to assess the relative risk protection offered by various index insurance products. Thus, for simplicity, we use the expectation of $h(\tilde{y}_f)$ as the APH yield for the representative farm. By doing this, we implicitly assume that the APH yield is a perfect estimator of the central tendency of the true but unknown farm-level yield distribution. This implies that our method may somewhat overstate the risk protection provided by the MPCI contract.

Three yield indexes contracts are considered in this analysis with MPCI with a 75% coverage level used as a baseline for purposes of comparison. The premium rates for all insurance products are assumed actuarially fair, which means that the premium is simply the expected indemnity. No additional cost is loaded on the premium.

MPCI indemnities are calculated as:

(6) $$\tilde{n}_f^{MPCI}(\tilde{y}_f \mid \text{coverage}) = \max(y_{fc} - \tilde{y}_f, 0)$$

where $\tilde{n}_f^{MPCI}$ is the MPCI indemnity per acre for the representative farm, $\tilde{y}_f$ is the realization of the stochastic yield, and $y_{fc} = \mu_f \times \text{coverage}$.[7] For MPCI, μ_f is the APH

yield, here calculated as the expectation of $h(\tilde{y}_f)$. The actuarially fair premium π_f^{MPCI} is the expectation of (6)

(7) $$\pi_f^{MPCI} = E\left(\tilde{n}_f^{MPCI}\left(\tilde{y}_f \mid \text{coverage}\right)\right) = \int \max\left(y_{fc} - \tilde{y}_f, 0\right) \times h\left(\tilde{y}_f\right) d\tilde{y}_f$$

where $h(\tilde{y}_f)$ is the marginal kernel density for yield on the representative farm *f* from (5b). The integral under the kernel density was calculated using numerical methods. Since the liability (i.e., the maximum possible indemnity) is y_{fc}, the actuarially fair premium rate ρ_f^{MPCI} is

(8) $$\rho_f^{MPCI} = \frac{\pi_f^{MPCI}}{y_{fc}}.$$

Premium rates of yield indexes were calculated in a way similar to those used for the actual GRP program as described by Skees, Black, and Barnett (1997).[8] Indemnities for a particular yield index are calculated as:

(9) $$\tilde{n}_f^x\left(\tilde{y}_j^x \mid \text{coverage, scale}\right) = \max\left(\frac{(y_{jc}^x - \tilde{y}_j^x)}{y_{jc}^x}, 0\right) \times yfcast \times scale$$

Where *yfcast* is calculated as the expectation of $h(\tilde{y}_j^x)$ and $y_{jc}^x = yfcast \times \text{coverage}$.

Coverage and *scale* are bounded as the actual GRP with 70% ≤ *coverage* ≤ 90% and 90% ≤ *scale* ≤ 150%. The actuarially fair premium is the expectation of (9)

(10) $$\pi_f^x = E\left(\tilde{n}_j^x\left(\tilde{y}_j^x \mid \text{coverage, scale}\right)\right) = \int \max\left(\frac{(y_{jc}^x - \tilde{y}_j^x)}{y_{jc}^x}, 0\right) \times yfcast \times scale \times h\left(\tilde{y}_j^x\right) d\tilde{y}_j^x$$

where $h(\tilde{y}_j^x)$ is the marginal kernel density for a particular yield index in the county *j* where the representative farm *f* is located. Similar as π_f^{MPCI}, the integral under the

kernel density was calculated using numerical methods. The actuarially fair premium rate ρ_f^x is

(11) $$\rho_f^x = \frac{\pi_f^x}{yfcast \times scale}$$

Decision Criterion

Premium rates for all yield indexes products and the baseline 75% MPCI, were by construction, actuarially fair in-sample. Thus, the insurance products could be compared by simply considering the resulting variance of net yield (net of insurance premiums and indemnities). However, a simple comparison of variance reduction ignores the higher moments of the yield distribution and thus may affect the rankings of the various insurance products.

For this reason, we compare the various insurance products based on certainty equivalents. For any realization of $\tilde{y}_f$ and insurance scenario *k*, the yield net of insurance premiums and indemnities is

(12) $$\tilde{y}net_f^k = \tilde{y}_f - \pi_f^k + \tilde{n}_f^k$$

where *k* is either MPCI, one of the three yield index insurance products, or no insurance purchasing, π_f^k is premium, and $\tilde{n}_f^k$ is indemnity. In the case of no insurance purchasing $\tilde{y}net_f^k = \tilde{y}_f$. Revenue is calculated as

(13) $$R_f^k = p \times \tilde{y}net_f^k$$

where R_f^k is revenue for the representative farm *f* at insurance scenario *k* and *p* is a constant price for corn in bushel.[9] Certainty-equivalent revenues (CER) were calculated from the constant relative risk aversion (CRRA) utility function

(14) $$U\left(R_f^k\right) = \frac{(R_f^k)^{1-\gamma}}{1-\gamma}$$

where R_i^k is as defined in (13) and γ is the measure of relative risk aversion. Myers (1989) estimated that for a representative U.S. crop farmer $1 \leq \gamma \leq 3$. Based on that finding, and also following Wang et al. (1998), γ is here set equal to 2. Then the CER was calculated as

(15) $$CER_f^k = \left[\int U\left(R_f^k\right) h\left(\tilde{y}_f\right) d\tilde{y}_f\right]^{-1}$$

where $U\left(R_i^k\right)$ is from (14) and $h\left(\tilde{y}_f\right)$ is the marginal kernel yield density for the representative farm *f*.

For each of the index insurance products, *coverage* and *scale* were optimized within the constraints 70% ≤ *coverage* ≤ 90% and 90% ≤ *scale* ≤ 150% to maximize the differences between the CER with yield index insurance and the CER with no insurance. The optimal *scale* and *coverage* were found simultaneously using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (Greene 2000; Miranda and Fackler 2002).

Results

Table 2 presents descriptive statistics calculated from the estimated joint kernel density functions for the representative farm yield and area yield index, the representative farm yield and DSSAT yield index, and the representative farm yield and cumulative CDD yield index. The coefficients of variation for both the CDD and DSSAT yield indexes are consistently relatively smaller since they do not account for other stochastic factors that can affect yield realizations.

Table 3 presents the Pearson pair-wise correlations among the simulated representative farm yield, the area yield index, the DSSAT yield index, and the

cumulative CDD yield index. All correlations are statistically significant. In every county, the correlation between the simulated representative farm yield and each yield index is always small (less than 0.3), which likely indicates that none of the proposed yield indexes can provide effective farm-level risk protection.

Table 4 presents the optimal *coverage* and *scale* levels of the three proposed yield index insurance contracts when these choice variables are restricted as in the existing GRP policy. Out of the 15 cases of county/index insurance combinations, there are 6 cases when the optimal *coverage* is at the upper limit of 90%, another 6 cases when it is at the lower limit of 70%, and 3 cases in between. In most cases the optimal *scale* is at the lower limit of 90%. In only 3 cases does it exceed 90%.

Actuarially fair premium rates are also shown in table 4. The actuarially fair premium rates for 75% MPCI are also presented for comparison. In every case, the yield index insurance products have lower premium rates than the 75% MPCI insurance product.

Table 5 presents changes in certainty equivalent revenues (CER) for various index insurance contracts per acre. The table shows CER without insurance and then the change in CER with restricted optimal index insurance contracts. CER corresponding to MPCI at 75% *coverage* is presented for comparison purpose. Positive (negative) changes imply that producers are better (worse) off as a result of purchasing the specific insurance contract.

In general, the three yield index insurance products do not provide risk protection that is comparable to that provided by the actuarially fair MPCI policy at 75% coverage. For Appling County, none of the index insurance products provided effective risk

protection for the representative farm. In fact, purchasing any of the yield indexes actually made the farm worse off. For Bulloch County, both the area yield index and the DSSAT yield index provided some risk protection but the CDD yield index did not. For the other counties, all three index insurance products provided some degree of risk protection. Considering only the four counties where at least one of the index insurance products provided some risk protection, the area yield index and the DSSAT yield index each provided the most risk protection for two counties. While The CDD yield index provided some risk protection in three counties, at least one of the other two index insurance products always provided more risk protection.

Conclusion

This study evaluated the risk reduction performance of three proposed index insurance products for corn in South Georgia. The regions considered are characterized by heterogeneity in production factors such as soil quality and drainage and thus, in principal, should not be well suited to simple index insurance products based on area yields or weather events. This analysis tested whether a more sophisticated index insurance product based on the DSSAT crop production model would provide more risk reduction than simple products based on area yields or weather variables. The study also compared the performance of the various index insurance products to that of an actuarially fair MPCI policy at 75% coverage.

None of the index insurance products provided risk protection comparable to the MPCI policy. Among the index insurance products, area yield index and DSSAT yield index products generally performed better than the CDD yield index insurance product.

A limitation of this analysis is that it cannot account for losses due to prevented planting, replanting, or poor quality. These losses are covered to some extent by MPCI but are not studied in this analysis. Data limitation required that long-term farm-level yields be simulated based on short-term (4 to 10 years) common data between farm-level yields and the yield indexes. It is unclear how robust the findings would be across alternative data sources or alternative procedures for simulating farm-level yields. Analyses based on additional crops, longer series of farm-level yields, and other regions are required to test the consistency and robustness of these results.

Endnotes

[*] More details about the calculation of APH yields can be found at http://www.rma.usda.gov/FTP/Publications/directives/18000/pdf/05_18010.pdf.

[2] APH-based revenue insurance products are generally offered only for crops with exchange-traded futures contracts. Indemnities are triggered by realizations of the product of farm-level yield losses and a price index based on futures market prices.

[3] Description of the MPCI-like insurance product is provided in the section of Empirical Analysis.

[4] The irrigation percentage of the harvested cropland is based on data obtained from the 2002 census of agriculture.

[5] PIO 31G98 is very common in Georgia, characterized as a high yield, short- to mid-season hybrid.

[6] Details about the choices of the three planting dates, three soil types and the acreage percentages, irrigation acreage percentages, two technology levels for irrigation and rainfed applications will be provided upon request.

[7] Without loss of generality, assume that insurance indemnities and premiums are paid in units of production per acre. In practice, a price, that is established when the contract is initiated, is used to convert units of production per acre into monetary units per acre. The price is a constant that acts as a simple scaling factor.

[8] Unlike actual GRP premium rating procedures no geographic smoothing of premium rates was imposed.

[9] The Price used for corn was the 2004 Chicago Board of Trade June daily average price on the July contract.

Table 1: Selected Counties in the Study

Counties Selected	Number of Farms Included	2002 % of Harvested Cropland that was Irrigated*
Appling	7	14.1
Bulloch	25	23.3
Coffee	12	22.0
Colquitt	10	29.0
Pierce	18	21.6

* Source: USDA 2002 Census of Agriculture

Table 2: Descriptive Statistics for the Representative Farm-level Yield and Three Yield Indexes Calculated from the Estimated Joint Kernel Density Functions

Yield	Mean (bu/acre)	Standard Deviation	Coefficient of Variation (%)
	Appling		
Farm-level Yield	57.06	31.43	55.08
Area Yield Index	62.22	23.68	38.06
DSSAT Yield Index	62.10	17.76	28.60
CDD Yield Index	96.83	22.82	23.57
	Bulloch		
Farm-level Yield	69.44	36.51	52.58
Area Yield Index	78.22	22.89	29.26
DSSAT Yield Index	49.54	14.58	29.43
CDD Yield Index	69.00	16.48	23.88
	Coffee		
Farm-level Yield	91.49	34.88	38.12
Area Yield Index	103.81	26.84	25.85
DSSAT Yield Index	73.10	18.24	24.95
CDD Yield Index	70.34	17.99	25.58
	Colquitt		
Farm-level Yield	93.61	26.94	28.78
Area Yield Index	102.47	22.46	21.92
DSSAT Yield Index	71.25	13.61	19.10
CDD Yield Index	67.44	13.18	19.54
	Pierce		
Farm-level Yield	119.94	51.60	43.02
Area Yield Index	107.29	29.01	27.04
DSSAT Yield Index	55.32	15.14	27.37
CDD Yield Index	67.90	21.75	32.03

Table 3: Pearson Pair-wise Correlations among Simulated Farm-level Yield and Three Realized Yield Indexes

		fy_rep	cytrend	dyield	y_cdd
Appling	fy_rep	1.00			
	cytrend	0.23	1.00		
	dyield	0.19	0.53	1.00	
	y_cdd	0.17	0.44	0.31	1.00
		fy_rep	cytrend	dyield	y_cdd
Bulloch	fy_rep	1.00			
	cytrend	0.29	1.00		
	dyield	0.27	0.66	1.00	
	y_cdd	0.23	0.48	0.28	1.00
		fy_rep	cytrend	dyield	y_cdd
Coffee	fy_rep	1.00			
	cytrend	0.26	1.00		
	dyield	0.20	0.31	1.00	
	y_cdd	0.26	0.55	0.31	1.00
		fy_rep	cytrend	dyield	y_cdd
Colquitt	fy_rep	1.00			
	cytrend	0.27	1.00		
	dyield	0.17	0.02	1.00	
	y_cdd	0.27	0.54	0.01	1.00
		fy_rep	cytrend	dyield	y_cdd
Pierce	fy_rep	1.00			
	cytrend	0.28	1.00		
	dyield	0.28	0.37	1.00	
	y_cdd	0.32	0.39	0.42	1.00

Note: fy_rep represents the simulated farm-level yield
cytrend represents the realized detrended county-level yield
dyield represents the predicted yield from DSSAT CSM-CERES-Maize model
y_cdd represents the predicted yield from cumulative CDD-yield model

Table 4. Restricted Optimal Coverage and Scale levels, and The Actuarially Fair Premium Rates of Three Yield Index Insurance Contracts

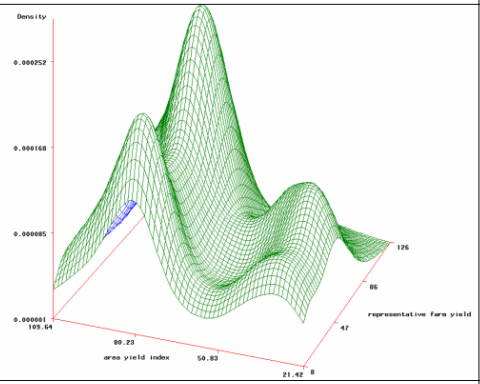
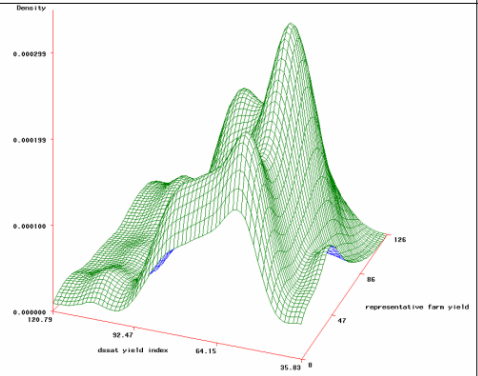
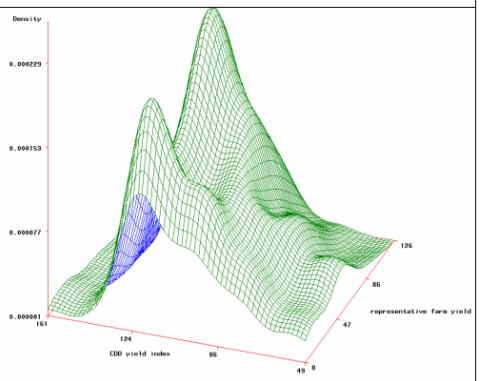
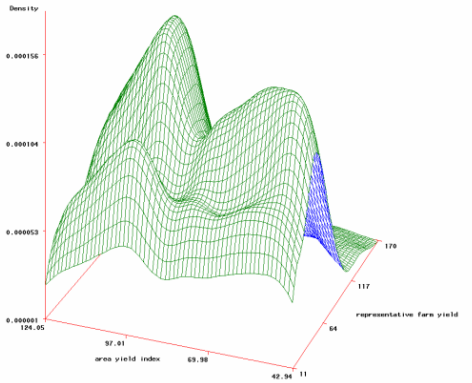
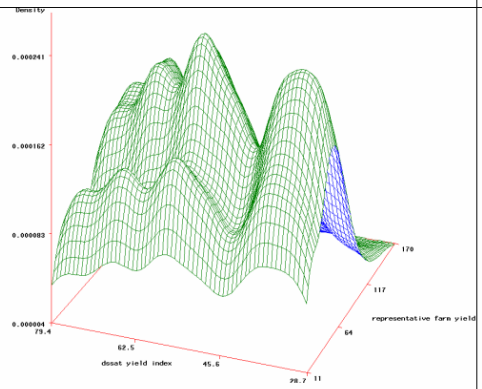
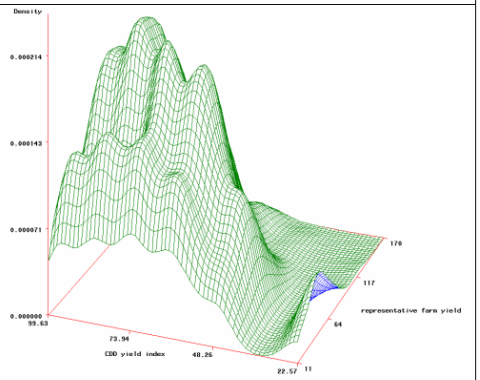
County	*Coverage* (70% - 90%)	*Scale* (90% - 150%)	Premium Rates (%)	75% MPCI Premium Rates (%)
	Area Yield Index Insurance			
Appling	70	90	4.2	11.54
Bulloch	70	90	1.16	9.95
Coffee	90	90	4.36	5.31
Colquitt	90	90	3.07	5.43
Pierce	70	90	2.88	7.97
	Dssat Yield Index Insurance			
Appling	70	90	0.36	11.54
Bulloch	80	90	2.43	9.95
Coffee	90	100	2.57	5.31
Colquitt	90	121	1.43	5.43
Pierce	90	104	3.09	7.97
	CDD Yield Index Insurance			
Appling	70	90	0.81	11.54
Bulloch	70	90	1.08	9.95
Coffee	86	90	3.45	5.31
Colquitt	90	138	2.17	5.43
Pierce	87	90	6.17	7.97

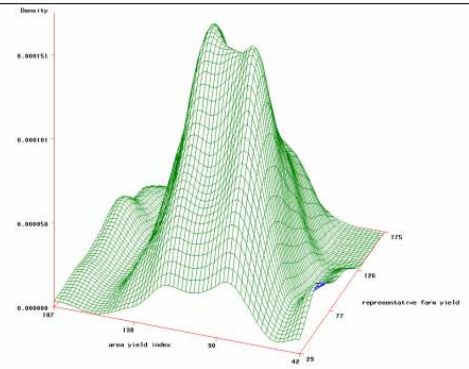
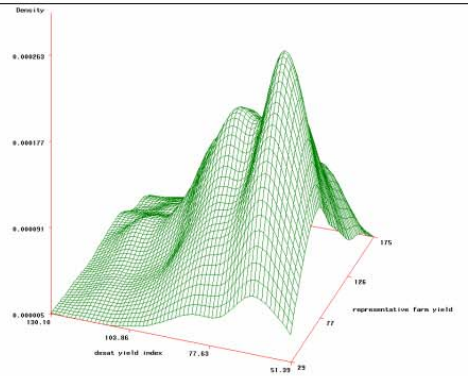
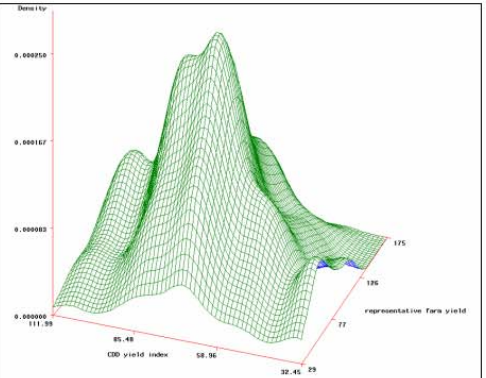
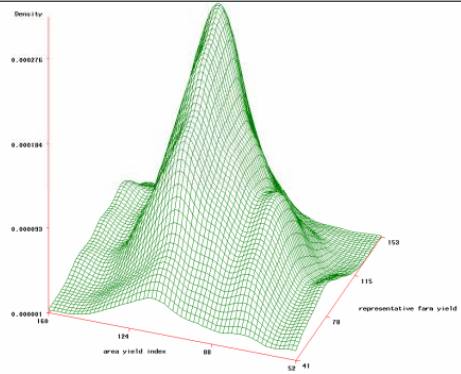
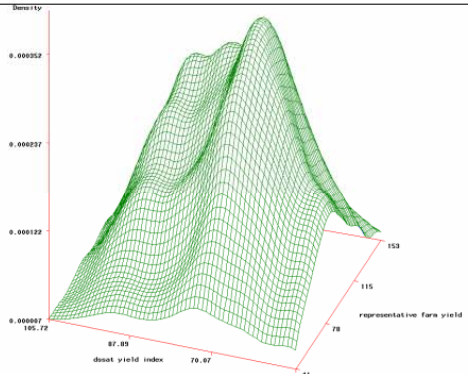
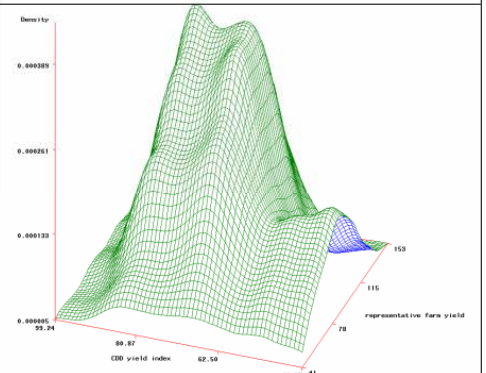
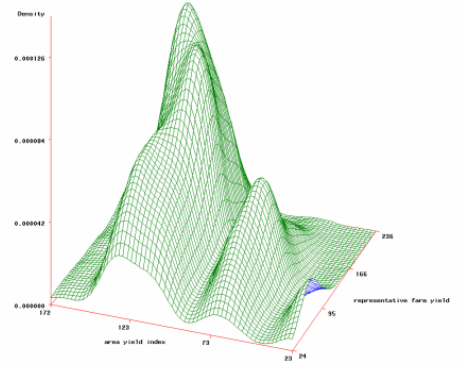
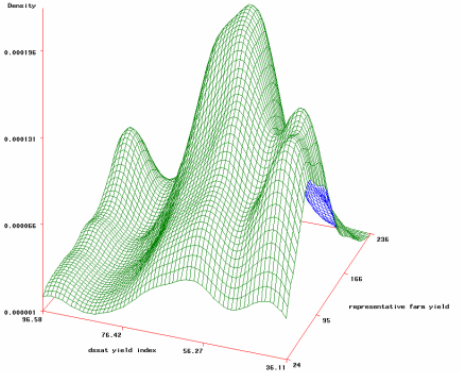
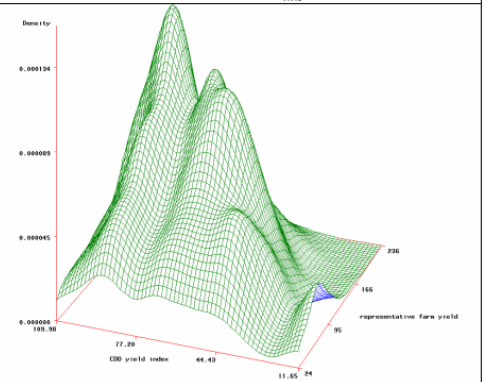
Table 5: Changes in Certainty Equivalent Revenues (CER) with Different Insurance Contracts

County	CER	Change in CER with Insurance			
	Without Contract	Area Yield Index	Dssat Yield Index	CDD Yield Index	MPCI 75%
Appling	136.91	(2.30)	(3.29)	(7.28)	50.11
Bulloch	172.47	3.23	1.49	(3.22)	44.57
Coffee	259.80	4.45	7.30	6.14	19.61
Colquitt	292.80	4.38	2.69	4.08	17.44
Pierce	314.76	2.69	16.99	8.36	51.92

Note: Brackets imply negative values. Certainty equivalent revenues are denoted in Dollar/Acre and are based on a constant relative risk aversion utility function with a risk aversion coefficient of 2.

Graph 1: Estimated Joint Kernel Density Functions of Farm-Level Yield and Yield Indexes

County	Joint Density between Representative Farm Yield and Area Yield Index	Joint Density between Representative Farm Yield and DSSAT Yield Index	Joint Density between Representative Farm Yield and CDD Yield Index
Appling			
Bullock			

Coffee			
Colquitt			
Pierce			

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