Managing Crop Production Risk with Crop Index Insurance Products

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Xiaohui Deng, Barry J. Barnett, Yingzhuo Yu, and Gerrit Hoogenboom

Author Affiliations: Deng is Ph.D. student and graduate research assistant, Barnett is associate professor, Yu is Ph.D. student and graduate research assistant, Department of Agricultural and Applied Economics, University of Georgia, Athens, Georgia. Hoogenboom is professor, Department of Biological and Agricultural Engineering, University of Georgia, Griffin, Georgia.

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 Little Rock, Arkansas, February5-9, 2004

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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 examines the feasibility of various index insurance products for 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: multiple peril crop insurance, index crop insurance, risk reduction

Introduction

Crop production is a risky endeavor. Unfavorable weather conditions, among many other factors, can reduce both the quantity and quality of the crop produced. Production management decisions regarding irrigation, fertilizer application, pest control, and other factors can increase expected yields and/or reduce risk. However, not all sources of potential yield loss can be effectively controlled by production management decisions.

Crop insurance products can reduce the financial impacts of production losses. The traditional Federal Crop Insurance Program (FCIP) product, Multiple-Peril Crop Insurance (MPCI) is a farm-level, multiple-peril, crop yield insurance policy in which the coverage is based on the crop producer's actual production history (APH) for the insured unit. While MPCI is typically effective in mitigating the financial impacts of crop production losses, the actuarial performance of MPCI has been hampered by adverse selection and moral hazard problems. Correcting these problems would require significant additional investments in information gathering both prior to and after the sale of the policy.

Index insurance products such as the FCIP's Group Risk Plan (GRP) provide an alternative approach. GRP is, in essence, a put option on a county-yield index. The county-yield data, on which the index is based, are widely available. This greatly reduces problems such as adverse selection and moral hazard that are caused by information asymmetry. Similar index insurance products could be based on a variety of weather variables. Index insurance products are, however, subject to basis risk resulting from the imperfect correlation between the realized production loss and the realized shortfall in the underlying index.

This study compares the risk reduction provided by MPCI to that of three index insurance products for corn production in two southern Georgia counties. The first index insurance product is a hypothetical GRP (GRP is not currently offered for corn production in southern Georgia). The

second index insurance product is based on cooling degree days (CDD), a measure of cumulative temperatures above a specified threshold. The third index insurance product is based on the predicted yield from the Decision Support System Agrotechnology Transfer (DSSAT) crop simulation model. For this application, the DSSAT model is parameterized so that the only stochastic variables are those related to weather. It is hypothesized that index insurance based on predicted yields from the DSSAT model might have lower basis risk than index insurance based on a specific weather variable such as CDD.

Insurance Products

Multiple-Peril Crop Insurance (MPCI)

MPCI is the traditional crop insurance product provided through the FCIP that provides protection against yield losses due to a variety of natural causes at the farm, or even sub-farm, level. Though effective in mitigating the financial impacts of crop losses, MPCI is susceptible to asymmetric information problems. Stated simply, a policyholder will generally know more about his/her production than the insurance company. This asymmetric information provides opportunities for policyholders to use proprietary information to their advantage through adverse selection and moral hazard (Skees and Reed; Chambers; Smith and Goodwin; Coble et al.; Just, Calvin, and Quiggin). In response to large underwriting losses caused, in part, by adverse selection and moral hazard problems, MPCI premium rates were increased during the 1990s. As a result, for some potential policyholders, MPCI, even with federal subsidies, is cost prohibitive.

Group Risk Plan (GRP)

Index insurance products are not susceptible to moral hazard and adverse selection because the data used to construct the indices are objective, transparent, and widely-available. Compared to farm-level yield insurance products like MPCI, longer historical data series are available for most index insurance products. This leads to better estimates of the underlying distribution. Finally,

with index insurance products there is no need for farm-level loss adjustment so transaction costs are low.

GRP is an existing index insurance product that pays an indemnity whenever the realized county-level yield is below a pre-specified strike (Skees, Black, and Barnett). Basis risk exists because of the imperfect correlation between the county-level yield (the index) and a farmer's realized farm-level yield. For example, it is possible for a farmer to suffer a yield loss on his/her farm when the realized county yield is such that no GRP indemnity is triggered. It is also possible for a farmer to not suffer a yield loss and yet receive a GRP indemnity because of shortfalls in the realized county-level yield.

Weather-Based Index Insurance

Indices based on weather variables can also be used to develop index insurance products that are conceptually analogous to GRP. Weather-based index insurance, to date, has not been widely used in agriculture, although previous research has suggested some potential applications in crop production (Turvey; Skees et al.; Varangis, Skees, and Barnett, Martin, Coble, and Barnett; Vedenov and Barnett). Weather-based index insurance is currently not available in the U.S. but is being tested in counties such as Canada, Mexico, Argentina, Morocco, and Mongolia.

Insurance on weather indices can be constructed as either a put or a call option depending upon the relationship between the index and yield losses. If the weather index and crop yields co-vary positively, the insurance would be constructed as a put option, otherwise it would be constructed as a call option. Turvey proposed a number of hypothetical weather-based index insurance instruments for corn and soybean producers in Ontario. Specifically, he proposed precipitation-based put options to protect against insufficient precipitation and temperature-based heat unit (cumulative temperatures above 50 degrees Fahrenheit) put (call) options to protect against insufficient (excessive) heat over specified periods. Martin, Barnett, and Coble designed a

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precipitation index insurance product as a call option to protect against cotton yield and quality losses due to excess late-season precipitation in the delta region of Mississippi. Cao proposed a predicted yield index insurance product for southern Georgia corn farmers where the predicted yield was a linear function of realized CDD over specified months. Since the index was denominated in yield, the insurance product was designed as a put option.

Index Insurance Based on Crop Simulation Model

A proposed alternative insurance product is based on an index of predicted yields simulated from the Decision Support System for Agrotechnology Transfer (DSSAT) crop simulation model. DSSAT has been used and applied for more than 15 years by researchers in over 100 countries to predict yield when inputs, such as soil type, crop phenotype, weather and management options are imported to the model.

To generate a predicted yield index for the insurance product, weather realizations are imported into the model while all other choice variables are held constant. Basis risk is still present with 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.

Indemnity Functions

For simplicity, assume a corn price of $1 per bushel. This simplification causes no loss of generality and allows indemnities to be denominated in either dollars or bushels per acre. For a given insurance unit, the MPCI indemnity function is

$$(1) \qquad \tilde{n}_t = \mathbf{max}(strike - \tilde{y}_t, \quad 0)$$

where t indicates a specific crop year, $\tilde{n}_t$ is the indemnity per acre, $\tilde{y}_t$ is the realization of the random yield per acre, and *strike* is calculated as

$$ (2) \qquad\qquad strike = \mu \times coverage $$

with $65\% \leq coverage \leq 85\%$ in 5% increments. The APH yield, μ, is measured as the rolling 4 to 10 year historical average yield for the insurance unit in crop year t. The breakeven premium is simply the expectation of $\tilde{n}_t$.

The indemnity function for an index insurance product could be designed similar to MPCI as:

$$ (3) \qquad\qquad \tilde{n}_t = \mathbf{max}(strike - \tilde{I}_t, \quad 0) $$

for a put option, and

$$ (4) \qquad\qquad \tilde{n}_t = \mathbf{max}(\tilde{I}_t - strike, \quad 0) $$

for a call option, where $\tilde{n}_t$ is the indemnity per acre and $\tilde{I}_t$ is the realization of the random index in crop year t. *Strike* is calculated as

$$ (5) \qquad\qquad strike = E\!\left(\tilde{I}_t\right) \times coverage $$

The index insurance products constructed for this study are based on the slightly different indemnity function used for GRP. Further, all of the index insurance products used in this study are constructed as put options. The indemnity function is

$$ (6) \qquad\qquad \tilde{n}_t = \mathbf{max}\!\left(\frac{strike - \tilde{I}_t}{coverage}, \quad 0 \right) \times scale $$

where *scale* is a policyholder choice variable that increases or decreases the amount of protection per acre.

Assuming that the underlying index is stationary, the breakeven premium for index insurance products that are constructed as put options is

$$(7) \qquad \pi = E(\tilde{n}_t) = \int_0^{strike} \left(\frac{strike - \tilde{I}_t}{coverage} \right) f(\tilde{I}) d\tilde{I}$$

where $f(\tilde{I})$ is the probability density function of the index.

Risk Reduction Analysis

The various insurance products are compared based on the extent to which they generate

risk reduction for two representative farms. Risk reduction is measured as the percentage reduction

in the variance of net yield (realized yield net of insurance premiums and indemnities) from

purchasing the insurance product relative to the yield variance without any insurance purchasing.

For any given crop year, net yield is the realized farm-level yield plus the indemnity and less

the premium,

$$(8) \qquad \tilde{y}_t^{net} = \tilde{y}_t + \tilde{n}_t - \pi$$

The variance of net yield is measured as

$$(9) \qquad \mathbf{var}(\tilde{y}_t^{net}) = \mathbf{var}(\tilde{y}_t) + \mathbf{var}(\tilde{n}_t) + 2\,\mathbf{cov}(\tilde{y}_t, \tilde{n}_t)$$

Insurance purchasing reduces the farmer's yield risk by

$$(10) \qquad \Delta = - \,\mathbf{var}(\tilde{n}_t) - 2\,\mathbf{cov}(\tilde{y}_t, \tilde{n}_t)$$

Converting this into percentage terms, the variance reduction due to the insurance product is

$$(11) \qquad \theta = \frac{\Delta}{\mathbf{var}(\tilde{y}_t)}$$

Scenario 1: Identical Breakeven Premium Rates

Risk reduction is assessed under two scenarios. In the first scenario, premium rates are both

breakeven and identical for all insurance products. For the various index insurance products, *scale*

is constrained to be 1.00 and *coverage* is set at the level that generates the breakeven premium rate

calculated for MPCI.

Solving for *coverage* in equation (5) and substituting into equation (7) yields

$$(12) \qquad \pi = E\!\left(\tilde{I}_t\right) \times \int_0^{strike} \left(\frac{strike - \tilde{I}_t}{strike}\right) f(\tilde{I})d\tilde{I}$$

The integral in equation (12) is the breakeven premium rate. Further, equation (12) indicates that for a given index insurance product, the premium rate is solely a function of *strike*. Inversing equation (12) to solve for *strike* yields

$$(13) \qquad strike = \left(E\!\left(\tilde{I}_t\right) \times \int_0^{strike} \left(\frac{strike - \tilde{I}_t}{strike}\right) f(\tilde{I})d\tilde{I} \right)^{-1}$$

For each of the representative farms we first calculate the in-sample breakeven premium rate for MPCI at the 65%, 75% and 85% coverage levels. Equation (13) is then used to solve for the *strike* on the index insurance product that yields the same in-sample breakeven premium rate as that for the MPCI insurance (at a given coverage level). The percentage risk reduction for each insurance product is calculated as in equation (11).

Scenario 2: Optimal Coverage and Scale

In the second scenario, risk reduction for each index insurance product is maximized by solving for the optimal levels of both *coverage* and *scale*. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) iterative algorithm is used to simultaneously solve for the level of *scale* and *coverage* that generate the maximum percentage risk reduction for each of the three index insurance products. The BFGS algorithm is a specific case of a Quasi-Newton method for solving finite-dimensional optimization problems. It is among the most widely used gradient methods since 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).

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Data

Comparisons of risk reduction were conducted for hypothetical representative farms in Bulloch county and Coffee county in southern Georgia. These counties both have weather stations located within the county and daily weather data (with relatively few missing observations) available for the time period of 1961-2003. In both counties, less than 25% of the planted corn acreage is irrigated.

County-Level Yields

Annual county-level corn yield data for Bulloch and Coffee counties were obtained from the National Agricultural Statistical Service (NASS). The county-level yield data were detrended to account for systemic changes in yields over time.

Simulated Farm-Level Yield

Limited farm-level yield data for the two counties were obtained from the Risk Management Agency APH records for insured farmers. These data are for farms with at least 6 years of documented yield data between 1991 and 2000. Farm yields are assumed to be conditioned on county yields for all years where both farm and county yield data are available. Following Miller, Barnett, and Coble, a bootstrapping technique was used to simulate 43 years of annual farm level yields (1961-2003) based on the longer time-series of available county yields and the relationship between farm yields and county yields for the years when both are available. For each year between 1961-2003, 20 possible yields are simulated. Thus each representative farm has 860 total simulated yields.

Cumulative CDD Predicted Yield

Cao documented a linear relationship between county-level corn yields and monthly cumulative CDD for six different counties in southern Georgia, including Bulloch and Coffee counties. Specifically, she found:

county	model	Pr>F	R^2	Adj. R^2
Bulloch (14)	$y = 234.410 - 0.2855\,April - 0.1450\,July - 0.1696\,September$ $\quad\quad\quad\quad (0.0106)\quad\quad (0.0262)\quad\quad\quad\quad (0.0142)$	0.0004	0.4144	0.3627
Coffee (15)	$y = 297.304 - 0.0746\,June - 0.2728\,July - 0.1317\,September$ $\quad\quad\quad\quad (0.3255)\quad\quad (0.0094)\quad\quad\quad\quad (0.0713)$	<0.0001	0.5137	0.4651

where the left-hand side of the model is the county average yield and each variable in the right-hand-side is the cumulative CDD for the month indicated.

Following Cao, we use equations (14) and (15) to create a single predicted yield index for each county that is a linear function of the cumulative CDD variables.

DSSAT Predicted Yields

Cao's predicted yield indexes are based on very simple linear regression models that empirically estimated relationships between county average 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, increase risk reduction relative to the indexes generated with Cao's simpler models.

DSSAT is a parameterized deterministic plant growth model that simulates 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, etc. For this study, these choice variables were selected based on recommendations from crop scientists. The planting date is assumed to be March 15th. Nitrogen is applied at a rate of 25 pounds per acre prior to planting and a side-dress application of 120 pounds per acre 30 days after planting. Corn production is assumed to be under dryland conditions on Tifton Loamy Sand soil in Bulloch County and Pelham Loamy Sandy soil in Coffee County. Both of these soils are light, textured soils with relatively low water holding capacity. The DSSAT model is used to predict corn yields based on variations in daily minimum and maximum temperatures, rainfall, and solar radiation throughout the growing season,

with all other variables held constant. The index of DSSAT predicted corn yields is created using realized daily values for the relevant weather variables over the period 1961-2003.

Results

Descriptive Statistics

Table 1 presents descriptive statistics for the representative farm simulated yield, county-level yield, the cumulative CDD predicted yield, and the DSSAT model predicted yield for Bulloch and Coffee counties. The coefficient of variation for both the CDD and DSSAT predicted yields is relatively narrow since these models do not account for other stochastic factors that can affect yield realizations.

In Bulloch County, the correlation between the county level yield and the CDD predicted yield is 51.32%. The correlation between the county-level yield and the DSSAT predicted yield is 47.27% . For Coffee County, the two correlations are 60.13% and 53.90%, respectively.

Scenario 1: Identical Breakeven Premium Rates

In this scenario, premium rates are both breakeven and identical for all insurance products. The in-sample breakeven premium rate is calculated for MPCI at the 65%, 75%, and 85% coverage levels. For the index insurance products, *scale* is constrained to be 1.00 and *coverage* is set at the level that generates the breakeven premium rate calculated for MPCI.

Table 2 presents the risk reduction (in percentage terms) and the corresponding coverage levels for each of the insurance products for the representative farms in Bulloch and Coffee Counties. MPCI always generates the most risk reduction. Among the index insurance products, GRP performs the best. The CDD predicted yield and DSSAT predicted yield index insurance products generate significantly lower levels of risk reduction with the DSSAT predicted yield index performing slightly better than the CDD predicted yield index.

Scenario 2: Optimal Coverage and Scale

In the second scenario, *coverage* and *scale* are optimized to generate the largest risk reduction. Thus, premium rates are no longer identical across products. For the GRP index insurance product that is currently available for some crops and regions of the U.S., *coverage* is restricted to be between 70% and 90% and *scale* must be set between 90% and 150%. Table 3 presents results for the three index insurance products when *coverage* and *scale* are optimized within these restrictions. In most cases, the restricted optimization of *coverage* and *scale* does not improve the risk reduction generated by the index insurance products compared to the first scenario. One reason for this is that in the first scenario, *scale* is fixed at 100% while *coverage* is allowed to freely adjust to exhaust the breakeven premium rate calculated for the corresponding MPCI product. As a result, in the first scenario, the index insurance products frequently take on *coverage* levels in excess of the 90% maximum allowed for the restricted optimization.

Table 4 presents risk reduction results when *coverage* and *scale* levels are unrestricted. Relaxing these restrictions generates a significant improvement in risk reduction from GRP in both counties. Risk reduction is also greatly improved for the CDD and DSSAT predicted yield index insurance products in Coffee County. However, the resulting in-sample breakeven premium rates are prohibitively high. The CDD and DSSAT predicted yield index insurance products for Bulloch County have more reasonable premium rates but do not significantly improve risk reduction for the representative farm.

Conclusion

Due to the asymmetric information problems inherent in farm-level crop insurance products, researchers have, in recent years, conducted analyses on the feasibility of a variety of index insurance products. In the U.S., the GRP county-level yield index insurance product is now available for some crops and regions. Agricultural applications of other index insurance products,

including those based on weather variables or plant growth simulation models, are still under consideration.

This study compared risk reduction from various insurance products for representative corn farms in two southern Georgia counties. In addition to the standard MPCI farm-level yield insurance product, three index insurance products were considered. The first was GRP county-level yield index insurance. The second was a predicted yield index insurance product based on an underlying linear model of corn yields as a function of cumulative CDD measured over selected months. The third was a predicted yield index insurance product based on the DSSAT crop simulation model. For each of the representative farms, the risk reduction generated by each of the index insurance products was simulated.

None of the index insurance products generated risk reduction comparable to MPCI. Among the index insurance products, GRP generally performed much better than either the cumulative CDD predicted yield index insurance or the DSSAT predicted yield index insurance.

Analyses based on additional crops and regions are required to test the consistency and robustness of these results. In addition, further extensions of this work will employ out-of-sample analyses of risk reduction.

Table 1: Descriptive Statistics

Bulloch	Mean	Standard Deviation	Coefficient of Variance	Minimum	Maximum
Representative Farm Yield	77.0093	50.0143	0.6495	9.3450	177.1407
County Yield	87.7307	22.8525	0.2605	42.6281	123.9985
C-CDD Predicted Yield	77.0541	16.6963	0.2167	22.5728	99.6256
DSSAT Predicted Yield	67.2337	9.2539	0.1376	46.5713	83.9479

Coffee	Mean	Standard Deviation	Coefficient of Variance	Minimum	Maximum
Representative Farm Yield	113.0305	59.9331	0.5302	26.4496	239.4699
County Yield	101.0563	26.5652	0.2629	32.7059	156.1892
C-CDD Predicted Yield	81.7604	22.5361	0.2512	32.4514	137.5246
DSSAT Predicted Yield	77.5382	9.0925	0.1173	43.5379	88.7552

Table 2: Risk Reductions for Different Insurance Products at Identical Breakeven Premium Rates at Different Locations

Bulloch

	Breakeven Premium Rate					
	11.3452%		7.6107%		4.7334%	
	Risk Reduction	Coverage	Risk Reduction	Coverage	Risk Reduction	Coverage
MPCI	42.8528%	85%	32.5175%	75%	22.7480%	65%
GRP Index	24.0824%	100%	18.9689%	87%	13.7965%	77%
DSSAT Predicted Yield Index	7.2018%	116%	7.2003%	107%	6.2028%	100%
C-CDD Predicted Yield Index	8.4189%	108%	6.5450%	98%	3.7068%	87%

Coffee

	Breakeven Premium Rate					
	5.1107%		2.6693%		1.2432%	
	Risk Reduction	Coverage	Risk Reduction	Coverage	Risk Reduction	Coverage
MPCI	32.6488%	85%	20.4425%	75%	11.3494%	65%
GRP Index	27.9691%	90%	17.8581%	80%	10.3037%	69%
DSSAT Predicted Yield Index	13.4638%	106%	10.0231%	98%	5.5825%	87%
C-CDD Predicted Yield Index	10.4462%	92%	6.3849%	77%	4.5759%	61%

Table 3: Risk Reduction for Representative Farms Using Different Index Insurance Products with Coverage and Scale Restricted

Bulloch County	Coverage 70%-90%	Scale 90%-150%	Risk Reduction	Premium Rate
GRP Index	90.00%	147.42%	22.37%	12.39%
DSSAT Predicted Yield Index	90.00%	119.63%	3.23%	3.47%
C-CDD Predicted Yield Index	90.00%	90.00%	4.74%	4.88%

Coffee County	Coverage 70%-90%	Scale 90%-150%	Risk Reduction	Premium Rate
GRP Index	90.00%	150.00%	34.73%	7.73%
DSSAT Predicted Yield Index	90.00%	150.00%	8.50%	2.79%
C-CDD Predicted Yield Index	90.00%	102.46%	9.63%	4.83%

Table 4: Risk Reduction for Representative Farms Using Different Index Insurance Products with Unrestricted Coverage and Scale

Bulloch County	Coverage	Scale	Risk Reduction	Premium Rate
GRP Index	141.69%	128.91%	31.24%	41.45%
DSSAT Predicted Yield Index	109.95%	107.75%	8.01%	12.52%
C-CDD Predicted Yield Index	109.41%	86.29%	8.62%	10.19%

Coffee County	Coverage	Scale	Risk Reduction	Premium Rate
GRP Index	163.14%	182.06%	65.14%	58.04%
DSSAT Predicted Yield Index	147.53%	194.94%	18.92%	60.36%
C-CDD Predicted Yield Index	179.41%	155.75%	23.56%	52.53%

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