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Developing and Pricing Precipitation Insurance

**Steven W. Martin, Barry J. Barnett,
and Keith H. Coble**

Production agriculture and agribusiness are exposed to many weather-related risks. Recent years have seen the emergence of an increased interest in weather-based derivatives as mechanisms for sharing risks due to weather phenomena. In this study, a unique precipitation derivative is proposed that allows the purchaser to specify the parameters of the indemnity function. Pricing methods are presented in the context of a cotton harvest example from Mississippi. Our findings show a potential for weather derivatives to serve niche markets within U.S. agriculture.

Key words: cross-hedging, precipitation insurance, risk, weather derivative

Introduction

Production agriculture and agribusiness are exposed to many weather-related risks. Common examples include extremes of both precipitation and temperature. In the United States, the federally subsidized crop insurance program provides crop producers with protection against many weather-related risks. However, the program is plagued with moral hazard and adverse selection problems (Skees and Reed; Quiggin, Karagiannis, and Stanton; Smith and Goodwin; Coble et al.; Just, Calvin, and Quiggin). Further, federal crop insurance policies all contain deductibles that leave growers with some exposure to losses associated with extreme weather.

Livestock producers in the U.S. currently have no federally subsidized insurance, yet they are also exposed to weather risks. Extreme heat can cause increased death loss in broiler houses and/or higher electrical cost for cooling. Extreme cold can cause increased death loss for range-fed livestock. In 1999, Hurricane Floyd dramatically demonstrated that extreme precipitation can cause extensive problems with lagoon waste management systems for confinement livestock facilities (Barrett; Kilborn; Whitman). Many agribusinesses (input supply, transportation, storage, processing, marketing, etc.) are also indirectly affected by impacts of weather risk on production agriculture but have no federally subsidized insurance.

Recent years have witnessed an increased interest in weather-based derivatives as mechanisms for sharing risks due to weather phenomena. Since early 1997, market participants in the electricity and natural gas sectors have used temperature-based

Steven W. Martin is assistant extension economist at the Delta Research and Extension Center, Mississippi State University; Barry J. Barnett is associate professor, Department of Agricultural and Applied Economics, University of Georgia; and Keith H. Coble is assistant professor, Department of Agricultural Economics, Mississippi State University. This article is based on research conducted while Barnett was associate professor in the Department of Agricultural Economics, Mississippi State University. The authors express their appreciation for the helpful comments of J. Roy Black, Jerry R. Skees, and three anonymous referees. This research was funded by the Mississippi Agriculture and Forestry Experiment Station.

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derivatives to offset their exposure to extreme temperatures. Tailored over-the-counter derivatives are based on a specified temperature index such as cumulative heating degree days (HDD) or cooling degree days (CDD) for a given location over a specified period of time (Dischel 1998b). On September 22, 1999, the Chicago Mercantile Exchange began trading standardized monthly cumulative HDD and CDD futures and options contracts. Contracts are now traded for Atlanta, Chicago, Cincinnati, Dallas, Des Moines, Las Vegas, New York, Philadelphia, Portland, and Tucson.

In this article, we propose a unique precipitation derivative that allows the purchaser to specify the parameters of the indemnity function according to his/her risk management needs. While the proposed derivative has characteristics much like an option, we assume the highly tailored contracts and the relatively small dollar amounts of protection required by most retail purchasers would necessitate sales through traditional retail insurance channels. A cotton harvest example from Mississippi is employed to demonstrate the potential uses of such derivatives. We begin with a discussion of the rapidly growing market for weather derivatives.

Background on Weather Derivatives

Weather derivatives provide a mechanism for cross-hedging against variability in a firm's revenues or costs. If the firm's revenues or costs are sufficiently correlated with the underlying weather phenomenon, the weather derivative will provide a useful, though not perfect, mechanism for cross-hedging. For example, temperature extremes create problems for electric and natural gas utilities. During periods of extremely high temperatures, electric utilities may face levels of consumer demand in excess of generating capacity. To meet that demand, utilities purchase marginal quantities of electricity on spot markets. But, because extreme temperatures are often spatially correlated, a utility may find itself bidding against many other utilities for available spot market supplies of electricity. Spot-market prices can increase dramatically above long-run equilibrium levels. In June 1998, spot-market wholesale prices for electricity increased from \$35 per megawatt-hour to \$7,500 per megawatt-hour in a matter of days (Dischel 1998c). When summer temperatures are unusually mild, electric utilities are faced with reduced demand and lower revenues. Natural gas suppliers are also faced with temperature-related risks. Unusually mild winter temperatures reduce the demand for natural gas, and hence revenues of natural gas suppliers. Temperature derivatives allow utilities to shed the volumetric risk associated with extreme demand shifts.

Purchasers of weather derivatives are generally exposed to some degree of geographical basis risk. Weather derivatives are typically settled based on realized weather phenomena, measured by an objective party, at a given location. In the United States, the underlying index is normally based on National Oceanic and Atmospheric Administration (NOAA) measurements at a given weather station. In a world of complete weather derivative contracts, potential purchasers may be able to significantly reduce geographic basis risk by spreading their risk protection across derivatives based on several surrounding weather stations.

Weather derivatives are typically based on official NOAA measurements for at least two reasons. First, both parties can be confident of an objective measurement of the weather phenomenon on which the contract will be settled. Second, buyers (sellers) can base bid (offer) prices on an extended time series of data collected at the site. It is not

unusual for weather data to be available from a given weather station covering periods of 50 years or more. These data are made available via the internet by the National Climate Data Center, a NOAA subsidiary (Dischel 1998c).

Precipitation Insurance

Changnon and Changnon describe the process by which they established premium rate tables for short-term (1-72 hours) precipitation insurance. The policies were designed to provide protection against precipitation affecting outdoor events such as fairs or concerts. Data from 211 weather stations were used to calculate empirical hourly cumulative frequencies, averaged over calendar months, for six levels of precipitation (0.01, 0.05, 0.10, 0.25, 0.50, and 1.00 inches). The continental United States was divided into 17 rating regions, and the historical frequencies were then averaged across all the weather stations within each rating region.

Patrick presents estimated premium costs for a proposed rainfall insurance contract in the Mallee wheat-producing region of Australia. Though Patrick indicates premiums are derived from "reasonable [parametric] distributions of rainfall," no specifics are provided about distributional forms or parameters.

Sakurai and Reardon estimate the demand for a hypothetical "rainfall lottery" in Burkina Faso. The lottery, which is assumed to be administered by an insurance company, would make a lump-sum payment to lottery ticket-holders whenever annual rainfall, measured at a given weather station, is below some predetermined level.

The instruments described by Changnon and Changnon; Patrick; and Sakurai and Reardon are similar in that each uses weather station data to calculate premium rates. However, Changnon and Changnon set premium rates for a traditional precipitation insurance policy where loss adjustment would be based on realized precipitation at the event site. In contrast, Patrick, and Sakurai and Reardon, consider insurance policies which are effectively weather derivatives. Specifically, their studies describe put options with loss adjustment based on realized values of an underlying index of precipitation measured at a given weather station. Nevertheless, both Patrick, and Sakurai and Reardon characterize their proposed precipitation derivatives as insurance, because they assume the derivatives would be sold to farmers through retail insurance channels.

Turvey presents stylized European HDD, CDD, and precipitation options where the indemnity function is of the form

$$(1) \quad \text{indemnity} = \begin{bmatrix} 0 & \text{if } x > \text{strike}, \\ \text{strike} - x & \text{if } x \leq \text{strike} \end{bmatrix} \times \lambda$$

for puts, and

$$(2) \quad \text{indemnity} = \begin{bmatrix} 0 & \text{if } x < \text{strike}, \\ x - \text{strike} & \text{if } x \geq \text{strike} \end{bmatrix} \times \lambda$$

for calls, where *strike* is a choice variable, *x* is the cumulative realized value of the underlying index (HDD, CDD, or precipitation) during the contract period, and λ is some predetermined dollar value per unit of the index. Thus, for a precipitation put, if *x* is 2 inches, *strike* is 5 inches, and λ is \$100 per inch, the indemnity would be equal to \$300.

Skees and Zeuli propose a European precipitation put with an indemnity function of the form

$$(3) \quad \text{indemnity} = \begin{bmatrix} 0 & \text{if } x > \text{strike}, \\ \frac{\text{strike} - x}{\text{strike}} & \text{if } x \leq \text{strike} \end{bmatrix} \times \text{liability},$$

where *liability* is a choice variable that establishes the maximum possible indemnity. The brackets in equation (3) contain the loss cost function specifying the percentage of *liability* to be paid out as an indemnity conditional on the choice of *strike* and the realization of *x*. The indemnity function in equation (3) is analogous to that used by Skees, Black, and Barnett for Group Risk Plan area yield puts. Note, if $\lambda = \text{liability}/\text{strike}$, equation (3) is identical to equation (1).

For precipitation, *x* has a natural lower bound of zero. Thus, for puts, the maximum indemnity is $\lambda(\text{strike})$ for equation (1), and *liability* for equation (3). But there is no natural upper bound on *x*. Thus, for calls, there is no cap on the maximum indemnity.

We propose a more flexible form for European precipitation options. For brevity, we focus only on calls, though analogous presentations of puts are easily constructed. The indemnity function for calls is designated by

$$(4) \quad \text{indemnity} = \begin{bmatrix} 0 & \text{if } x < \text{strike}, \\ \frac{x - \text{strike}}{\text{limit} - \text{strike}} & \text{if } \text{limit} > x \geq \text{strike}, \\ 1 & \text{if } x \geq \text{limit} \end{bmatrix} \times \text{liability},$$

where *limit* is an additional choice variable. Again, the brackets contain the loss cost function for the option. By their choices of *strike* and *limit*, purchasers define the domain of *x* over which the option will pay an indemnity. For calls, $\text{limit} \geq \text{strike} \geq 0$. In addition to allowing purchasers to tailor the characteristics of precipitation options according to their risk management needs, the *limit* variable makes rating of precipitation calls more tractable.

For calls, when $\text{limit} > \text{strike}$, we can define a variable μ such that

$$(5) \quad \text{limit} = \text{strike} \left(1 + \frac{1}{\mu} \right),$$

where $0 < \mu < \infty$. Equation (4) can now be rewritten as

$$(6) \quad \text{indemnity} = \begin{bmatrix} 0 & \text{if } x < \text{strike}, \\ \frac{\mu(x - \text{strike})}{\text{strike}} & \text{if } \text{limit} > x \geq \text{strike}, \\ 1 & \text{if } x \geq \text{limit} \end{bmatrix} \times \text{liability},$$

where μ is an increasing payment factor. If $\mu = 1$, $\text{limit} = 2 \times \text{strike}$. If $\text{limit} > \text{strike} > 0$, μ determines how fast the maximum indemnity is paid relative to the base case of $\text{limit} = 2(\text{strike})$. Consider a call with the strike set at 6 inches over the contract period. If $\mu = 1$, limit will be equal to 12, so the maximum indemnity will be paid only when *x* is 6 inches above the strike. If $\mu = 2$, limit will be equal to 9, so the maximum indemnity

will be paid when x is only 3 inches above the strike. If $\mu = 3$, $limit$ will be equal to 8, so the maximum indemnity will be paid when x is only 2 inches above the strike. Thus, for calls with the same strike, the value for μ indicates how fast the option will pay the maximum indemnity relative to the base case of $\mu = 1$. If $\mu = 2$, the call will pay the maximum indemnity twice as fast as the base case; if $\mu = 3$, three times as fast, and so on.

Pricing Precipitation Insurance

Expected loss cost is the standard basis for establishing insurance premium rates (Skees and Barnett).¹ Loss cost is equal to indemnities divided by liability. Insurance actuaries calculate an expectation on future loss cost based on historical experience with the insurance product. Expected loss cost can be considered as an expected breakeven premium rate.

Using extended time series of weather data, historical loss costs can be simulated for stylized weather insurance instruments. An expected loss cost can then be estimated from the simulated historical loss costs.

We assume that requiring purchase sufficiently in advance of the contract period will prevent intertemporal adverse selection conditioned on precipitation forecasts (Luo, Skees, and Marchant). In general, advance purchase requirements will need to be set long enough such that an expectation on precipitation for the contract period conditioned on meteorological forecasts is likely no better than an unconditional expectation. For some areas, El Niño/Southern Oscillation (ENSO) phenomena may require very long advance purchase requirements (Ker and McGowan; Mjelde, Hill, and Griffiths; Podbury et al.). Alternatively, extensions of the procedures described here could be used to condition premium rates on ENSO phenomena.

Loss cost is the portion of the indemnity function enclosed in brackets in equations (4) and (6). The breakeven premium rate for the proposed precipitation insurance/option is simply the unconditional expectation of loss cost.

Simulation

Climatological research has supported the use of a gamma distribution to characterize the distribution of climatological variables (such as cumulative precipitation) exhibiting a physical lower bound of zero but no upper bound (Barger and Thom; Thom; Ison, Feyerherm, and Bark; McWhorter, Matthes, and Brooks; Wax and Walker). The probability density function for the gamma distribution is denoted by

$$(7) \quad f(x; \alpha, \beta) = \left(\frac{x}{\beta} \right)^{\alpha-1} \left[\frac{\exp\left(\frac{-x}{\beta}\right)}{\beta \Gamma(\alpha)} \right], \quad x \geq 0; \alpha, \beta > 0,$$

where x is the random variable (in this case, cumulative precipitation), α is the shape parameter, and β is the scale parameter. The mean of the distribution is $\alpha\beta$.

¹ While the proposed precipitation insurance is, in essence, an option, pricing based on standard options valuation models is problematic. Standard options valuation models require that one be able to construct (at least conceptually) a riskless portfolio consisting of both the option and the asset which forms the underlying index (Hull; Dischel 1998a). Yet, there is no actively traded forward market for precipitation.

To initiate the simulation, cumulative precipitation measures over the chosen contract period are calculated for each year in the historical data series. Maximum-likelihood estimation is then applied to these data to estimate the parameters on the gamma distribution. Because the natural log of zero is undefined, a statistical problem occurs if any of the cumulative precipitation observations in the historical data series are equal to zero. To address this problem, Wilks treats precipitation data as exhibiting type I censoring on the left. In the United States, precipitation amounts of less than 0.01 inch are not recorded in official measurements. If we designate the censoring point as C , where $0 < C < 0.01$, then a given set of cumulative precipitation data will contain N_C censored years in which cumulative precipitation over the contract period is recorded as zero, and N_W years with positive measured values. The total number of years in the data set will be equal to $N_C + N_W$. Wilks specifies the likelihood function for the parameters of the assumed gamma distribution as follows:

$$(8) \quad L(\alpha, \beta; x) = \prod_{j=1}^{N_C} F(C; \alpha, \beta) \prod_{i=1}^{N_W} f(x_i; \alpha, \beta) \\ = [F(C; \alpha, \beta)]^{N_C} \prod_{i=1}^{N_W} \frac{\left(\frac{x_i}{\beta}\right)^{\alpha-1} \exp\left(\frac{-x_i}{\beta}\right)}{\beta \Gamma(\alpha)},$$

where F is the cumulative distribution function,

$$(9) \quad F(C; \alpha, \beta) = \int_0^C f(x_j; \alpha, \beta) dx = \Pr\{x_j \leq C\}.$$

The log-likelihood function to be maximized is written as

$$(10) \quad \Lambda(\alpha, \beta; x) = N_C \ln[F(C; \alpha, \beta)] - N_W [\alpha \ln(\beta) + \ln[\Gamma(\alpha)]] \\ + (\alpha - 1) \sum_{i=1}^{N_W} \ln(x_i) - \frac{1}{\beta} \sum_{i=1}^{N_W} x_i.$$

Note that if $N_C = 0$, equation (10) reduces to the standard log-likelihood function for fitting the parameters of a gamma distribution.

Figure 1 presents estimated gamma probability density functions over cumulative daily precipitation for the weather station located at the Delta Research and Extension Center (DREC) in Stoneville, Mississippi. The probability density functions are based on data from 1936 through 1995. The associated parameter estimates and standard errors are found in table 1. All distributions exhibit positive skewness. Yet, as the time period lengthens, the distributions become more symmetric. This is consistent with findings reported in climatological literature suggesting more symmetric distributions may adequately characterize cumulative precipitation measured seasonally or annually, but are unlikely to be appropriate for shorter time periods. Climatologists prefer the gamma distribution because it is sufficiently flexible to adequately characterize cumulative precipitation over time periods of varying length (McWhorter, Matthes, and Brooks).

After fitting the parameters of the gamma distribution, the expectation of loss cost is calculated by integrating over the loss cost component of the indemnity function. For a call, the expectation of loss cost corresponding to equation (4) is given by

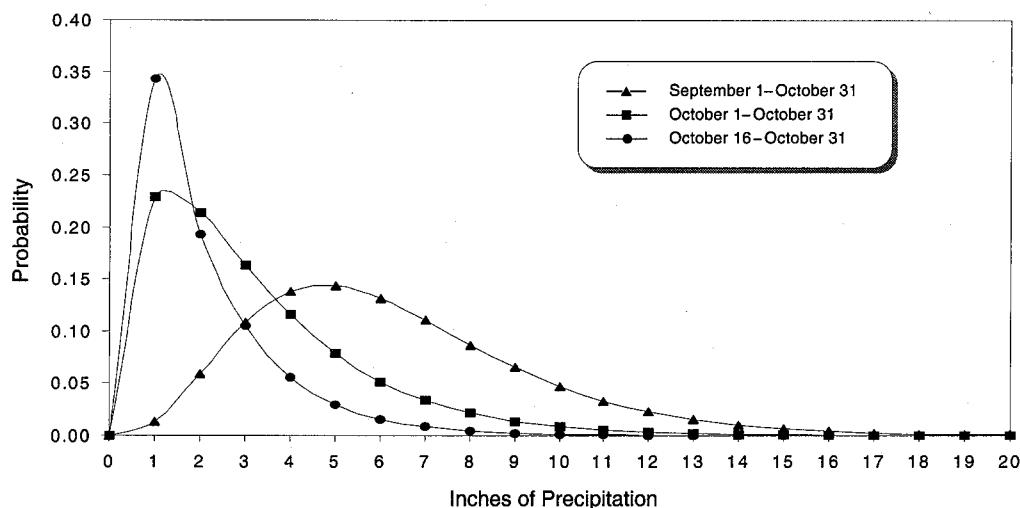


Figure 1. Estimated gamma probability density functions for precipitation at the Delta Research and Extension Center, based on daily precipitation data, 1936–1995

$$(11) \quad E(\text{loss cost}) = \int_{\text{strike}}^{\text{limit}} \left(\frac{x - \text{strike}}{\text{limit} - \text{strike}} \right) f(x) dx + \int_{\text{limit}}^{\infty} f(x) dx,$$

where $f(x)$ is the gamma density. This expression can be rewritten to correspond to equation (6) as follows:

$$(12) \quad E(\text{loss cost}) = \int_{\text{strike}}^{\text{limit}} \left(\frac{\mu(x - \text{strike})}{\text{strike}} \right) f(x) dx + \int_{\text{limit}}^{\infty} f(x) dx.$$

No indemnity is paid if $x < \text{strike}$.

Results

A cotton harvest example is used to illustrate the procedure described above. In the mid-South, cotton harvest generally occurs during the period from mid-September until the end of October. Growers in the region typically defoliate the crop when approximately 70% of the bolls are open. However, precipitation between the time cotton bolls open and harvest can cause significant reductions in revenue. These losses occur due to lost yield and reduced quality.

Using data from DREC test plots, Williford et al. estimate per acre revenue losses between defoliation and harvest due to various discrete levels of precipitation. They assume a 650 pound per acre expected yield and an expected price of \$0.60 per pound. We fit a quadratic function to these data to obtain the continuous loss function:

$$(13) \quad \begin{aligned} \text{loss per acre} &= -5.02 + 15.0757z - 0.3166z^2 \\ &\quad (2.07) \quad (0.60) \quad (0.04) \\ &R^2 = 0.997, \end{aligned}$$

Table 1. Gamma Distribution Parameter Estimates Based on Daily Precipitation Measurements

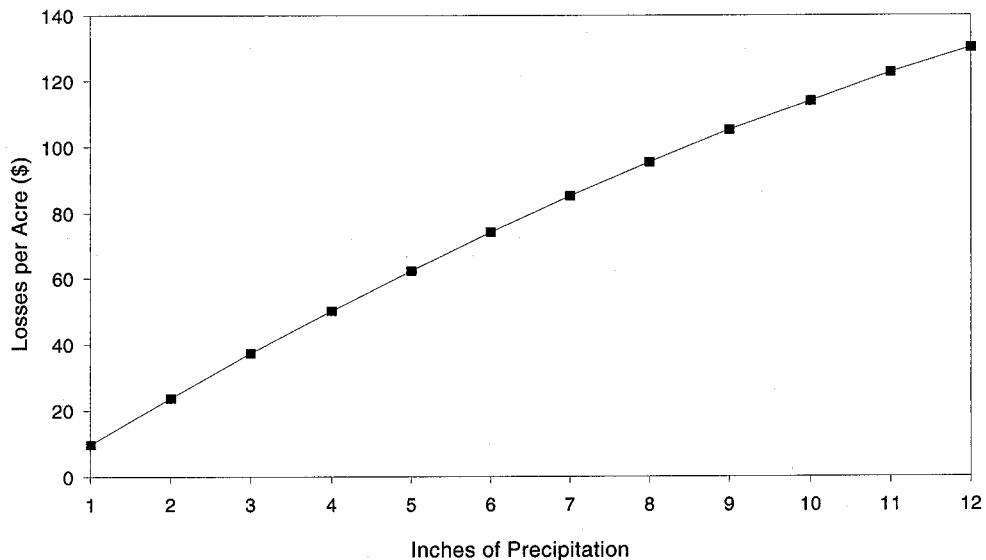
Weather Station	Shape Parameter, α (Standard Error)	Mean, $\alpha\beta$ (Standard Error)
Delta Research & Extension Center, Stoneville, Mississippi September 1–October 31 (1936–1995)	4.24 (0.766)	6.41 (0.413)
Delta Research & Extension Center, Stoneville, Mississippi October 1–October 31 (1936–1995)	1.88 (0.327)	3.25 (0.314)
Delta Research & Extension Center, Stoneville, Mississippi October 16–October 31 (1936–1995)	1.19 (0.201)	1.94 (0.250)
Greenville, Mississippi October 1–October 31 (1936–1995)	1.21 (0.199)	2.89 (0.339)
Cleveland, Mississippi October 1–October 31 (1936–1988)	1.25 (0.219)	3.19 (0.392)

where z is precipitation between defoliation and harvest, and the numbers in parentheses are standard errors. The loss function is shown in figure 2. On a hypothetical 1,000-acre cotton farm, 4 inches of cumulative precipitation cause an estimated loss of approximately \$50,200; 6 and 8 inches of cumulative precipitation cause estimated losses of approximately \$74,000 and \$95,300, respectively.

Suppose, prior to planting, this grower purchased a buy-up insurance policy covering 65% of the actual production history (APH) yield at 100% of the expected price (the most common selections on buy-up policies). For simplicity, assume the APH yield is equal to the expected yield of 650 pounds per acre. Also assume a price selection equal to the expected price of \$0.60 per pound. The expected revenue on the crop is \$390,000. Yet, because of the 35% deductible, the grower is responsible for the first \$136,500 of yield or quality losses (realized yield is adjusted for quality losses on crop yield insurance policies). Suppose further that in late September the crop is on target to meet the 650 pound per acre yield expectation. The grower is concerned about potential losses due to precipitation prior to harvest. At this time, the crop yield insurance policy provides essentially no financial protection because of the deductible. Historical data from 1936–1995 reveal mean cumulative precipitation for October at the DREC of 2.96 inches, with a range from 0.03 to 10.99 inches. Twelve inches of precipitation, higher than any occurrence in the historical record, would generate an estimated \$130,300 in losses, all of which would fall under the grower's deductible. Even with a 75% coverage level, a crop yield insurance policy would not pay an indemnity until over 8 inches of precipitation had caused almost \$100,000 in losses. If, in late September, the expected yield on the crop is higher (lower) than the APH yield, higher (lower) losses due to precipitation would be required to trigger a crop yield insurance indemnity.

We construct a precipitation call for the period October 1–October 31, with the underlying index being precipitation measured at the DREC. Table 2 presents breakeven premium rates for various strikes and limits.

For different choices of *strike* and *limit*, and different realizations of x , table 3 reports the cost and indemnity for a call with *liability* equal to \$100,000. Various combinations of *strike* and *limit* would provide protection against the estimated losses. Breakeven premium costs range from \$30,200 for *strike* = 1 and *limit* = 8, to \$5,400 for *strike* = *limit* = 8.



Source: Adapted from Williford et al.

Figure 2. Estimated losses per acre on cotton due to precipitation between defoliation and harvest

While various combinations are possible, consider a few examples. If realized precipitation is 6 inches, total losses would be approximately \$74,000. A \$100,000 call with a *strike* of 4 inches and a *limit* of 6 inches would have a breakeven cost of \$17,900. With the realized precipitation of 6 inches, the call would pay an indemnity of \$100,000. This would more than cover the estimated loss. A \$100,000 call with a *strike* of 4 inches and a *limit* of 8 inches would have a breakeven cost of \$13,100 and, given the same realized precipitation, would pay an indemnity of \$50,000, covering only about two-thirds of the estimated loss.

A grower may wish to spread his/her *liability* across multiple options. Continuing our example, a grower could purchase a \$50,000 call with a *strike* of 4 inches and a *limit* of 6 inches, and a \$50,000 call with a *strike* of 4 inches and a *limit* of 8 inches. This combination would have a breakeven cost of \$15,500 and would pay an indemnity of \$75,000 for 6 inches of realized rainfall. By spreading *liability* across multiple options with different combinations of *strike* and *limit*, options purchasers can attempt to better match indemnities to anticipated losses over the domain of potential precipitation.

We conduct an expected utility analysis to test the efficacy of these instruments in protecting against precipitation-induced cotton losses prior to harvest. Our hypothetical 1,000-acre farm, located at the Delta Research and Extension Center, is assumed to have an initial wealth of \$400,000. Using the loss function in equation (13), pre-harvest losses are estimated for each year from 1936 through 1995 based on cumulative precipitation from October 1–31. Table 4 presents mean ending wealth and the standard deviation of ending wealth under three scenarios: (a) no purchase of precipitation derivatives, (b) purchase of a \$100,000 call for DREC with a *strike* of 4 inches and a *limit* of 8 inches, and (c) purchase of a \$100,000 call for DREC with a *strike* of 1 inch and a *limit* of 8 inches.

Table 2. Breakeven Premium Rates on Precipitation Calls for October 1–31, Based on DREC Precipitation Measurements

Inches of Precipitation		Breakeven Premium Rate	Inches of Precipitation		Breakeven Premium Rate
strike	limit	(%)	strike	limit	(%)
1	8	30.2	6	6	11.9
4	4	25.7	6	8	8.2
4	6	17.9	6	10	5.9
4	8	13.1	8	8	5.4
5	5	17.6	8	10	3.7
5	6	14.6	11	11	1.6
5	8	10.4			

Table 3. Cost and Indemnity of Various Precipitation Calls with \$100,000 liability, October 1–31, Based on DREC Precipitation Measurements

Inches of Precipitation			Cost (\$)	Indemnity (\$)	Inches of Precipitation			Cost (\$)	Indemnity (\$)
strike	limit	x			strike	limit	x		
1	8	5	30,200	57,143	1	8	7	30,200	85,714
4	4	5	25,700	100,000	6	6	7	11,900	100,000
4	6	5	17,900	50,000	4	8	7	13,100	75,000
4	8	5	13,100	25,000	6	8	7	8,200	50,000
1	8	6	30,200	71,429	1	8	8	30,200	100,000
6	6	6	11,900	100,000	4	8	8	13,100	100,000
4	6	6	17,900	100,000	6	8	8	8,200	100,000
4	8	6	13,100	50,000	8	8	8	5,400	100,000

The grower's expected utility over wealth is assumed to be characterized by a utility function with constant relative risk aversion:

$$(14) \quad E(U_{sr}) = \sum_{j=1}^m \frac{W_{js}^{1-r}}{m(1-r)}, \quad r \neq 1,$$

$$E(U_{sr}) = \sum_{j=1}^m \frac{1}{m} \ln(W_{js}), \quad r = 1,$$

where U is utility, W is annual ending wealth, s is the scenario, j is the year, and r is the coefficient of constant relative risk aversion. The corresponding certainty equivalent of ending wealth is denoted by

$$(15) \quad CE_{sr} = (1-r)E(U_{sr})^{1/(1-r)}, \quad r \neq 1,$$

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

Table 5 provides certainty equivalents for each of the three scenarios over various degrees of relative risk aversion. The scenario involving purchase of a call with a *strike* of 4 and a *limit* of 8 generates the highest certainty equivalents. For $r > 1$, both scenarios

Table 4. Summary Statistics on Ending Wealth Assuming Purchase of October 1–31 Precipitation Calls, Based on DREC Precipitation Measurements

Call Scenario	Ending Wealth (\$)	
	Mean	Std. Deviation
No Purchase	364,633	30,136
<i>strike</i> = 4, <i>limit</i> = 8	364,854	16,082
<i>strike</i> = 1, <i>limit</i> = 8	363,264	4,580

Table 5. Certainty Equivalents Assuming Purchase of October 1–31 Precipitation Calls, Based on DREC Precipitation Measurements

Constant Relative Risk Aversion	Call Scenario		
	No Purchase	<i>strike</i> = 4, <i>limit</i> = 8	<i>strike</i> = 1, <i>limit</i> = 8
----- Certainty Equivalents (\$)			
1.0	363,338	364,504	363,236
1.5	362,662	364,328	363,222
2.0	361,966	364,152	363,208
2.5	361,251	363,976	363,194
3.0	360,517	363,800	363,179
4.0	358,988	363,447	363,151

involving purchase of a precipitation call generate higher certainty equivalents than the scenario with no purchase. The certainty equivalent for a purchase scenario is less than that of a no-purchase scenario only when $r = 1$ and the call has a *strike* of 1 and a *limit* of 8.

To assess the impact of geographic basis risk, the same scenarios are tested with the calls based on weather stations located in Greenville and Cleveland, Mississippi (tables 6 and 7). Greenville, Mississippi, is located approximately 11 miles west and slightly south of DREC. Cleveland, Mississippi, is situated approximately 31 miles north and slightly east of DREC. Daily precipitation data were available for 1936–95 for Greenville and 1936–88 for Cleveland. (Parameter estimates for the underlying gamma distributions are shown in table 1.)

Table 6 reports mean ending wealth and the standard deviation of ending wealth for calls based on Greenville and Cleveland, Mississippi, and table 7 presents certainty equivalents for the calls. For every value of r , the certainty equivalents of the purchase scenarios exceed those of the no-purchase scenario. The calls based on DREC and Greenville generate lower standard deviations of ending wealth than those based on Cleveland. However, the calls based on Cleveland cost less than those based on DREC and Greenville. As a result, the highest certainty equivalents generally occur with the purchase of calls based on Cleveland—the location farthest away from the hypothetical farm. The only exception is for the call with *strike* = 4 and *limit* = 8 at the higher levels of r . In this case, calls based on DREC generate higher certainty equivalents than those based on Cleveland. Thus, for these examples, basis risk does not significantly undermine the benefits of purchasing precipitation calls.

Table 6. Summary Statistics on Ending Wealth Assuming Purchase of October 1–31 Precipitation Calls, Based on Greenville and Cleveland, Mississippi, Precipitation Measurements

Weather Station/Call Scenario	Ending Wealth (\$)	
	Mean	Std. Deviation
Greenville: <i>strike</i> = 4, <i>limit</i> = 8	364,610	17,788
Greenville: <i>strike</i> = 1, <i>limit</i> = 8	364,629	12,818
Cleveland: <i>strike</i> = 4, <i>limit</i> = 8	365,284	19,470
Cleveland: <i>strike</i> = 1, <i>limit</i> = 8	364,936	14,483

Table 7. Certainty Equivalents Assuming Purchase of October 1–31 Precipitation Calls, Based on Greenville and Cleveland, Mississippi, Precipitation Measurements

Constant Relative Risk Aversion	Greenville Call Scenarios		Cleveland Call Scenarios	
	<i>strike</i> = 4, <i>limit</i> = 8	<i>strike</i> = 1, <i>limit</i> = 8	<i>strike</i> = 4, <i>limit</i> = 8	<i>strike</i> = 1, <i>limit</i> = 8
----- Certainty Equivalents (\$)				
1.0	364,181	364,408	364,767	364,655
1.5	363,966	364,297	364,505	364,514
2.0	363,750	364,187	364,241	364,373
2.5	363,534	364,076	363,975	364,231
3.0	363,318	363,966	363,706	364,090
4.0	362,885	363,746	363,162	363,808

Conclusion

Interest in weather derivatives is growing rapidly. To date, most applications in the United States have been in nonagricultural industries. However, several other countries are attempting to use weather derivatives in agricultural applications. While the current federal crop insurance program crowds out some demand, weather derivatives could possibly serve niche markets within U.S. agriculture.

We propose a flexible precipitation insurance/option instrument that allows the purchaser to specify various parameters of the indemnity function. We also present a proposed rating method based on simulation procedures. The choice variable, *limit*, allows buyers to define a layer of protection over the domain of potential precipitation. This feature can alternatively be characterized as an increasing payment factor reflecting the rate at which the maximum indemnity will be paid relative to a base case. The *limit* variable has numerous potential applications beyond precipitation options. For example, its adoption would likely improve the efficiency of other index options such as federal crop insurance Group Risk Plan contracts.

Further research could address the potential for reducing geographical basis risk by spreading *liability* across contracts purchased on several surrounding weather stations.

Alternatively, insurers, or other weather brokers, could use geographical smoothing techniques to base indemnities and premiums on some algebraic combination of weather-station measurements. Further research is also required to determine appropriate advance purchase requirements for different climatological regions. Should meteorologists develop procedures that accurately predict ENSO occurrences on a consistent basis, the rating procedures described here could be modified to allow for conditional expectations on loss cost.

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