Optimal Inter-Period Weighting of Cumulative Indices for Weather-Based Contingent Claims

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Abstract

Weather-based contingent claims to hedge against agricultural volumetric production risk typically rely on a cumulative index of the weather variable, such as rainfall. Frequently, the index is divided over the contract period and weighted to reflect the importance of timing in the weather-crop production relationship. This article reviews four alternative optimization methods and apply criteria for selecting among them to obtain an optimal and robust distribution of weights. The optimization methods are tested using crop reporting district yield and weather data for 45 years of corn production in Iowa. Results indicate that: (1) in very low-risk production environments derivative hedges are not efficient, and (2) an optimization method based on reducing the relative risk of revenue measured by the coefficient of variation performs somewhat better than other methods, although not appreciably more so than alternative methods.

Introduction

Of all risk factors affecting crop producers, adverse weather is typically the most significant and difficult to predict and mitigated against. The intra-temporal variation of large-area crop yields is mainly caused by weather variation and systemic risk explains a large portion of the variability of producer income. When speaking about weather in an agricultural setting, the most important single variable is most generally variation in rainfall during critical growing periods or time of mechanical field operations. For example, Rosenzweig and Binswanger utilize panel data from rural South India to measure the riskiness of farmers' investment portfolios in terms of their sensitivity to rainfall variation. Their results show that their asset position is significantly influenced by the degree of rainfall variability. Weather risk deeply affects producers' decision making behavior as documented by many studies (Anderson, Dillon and Hardaker; Hardaker, Huirne and Anderson; Robison and Barry) which suggests there is value in exploring opportunities to share systemic risk exposure in agriculture.

Weather-based derivative contracts initially developed in the energy sector are increasingly seen as a promising hedge tool against weather induced agricultural production risk both in developed and less developed countries. Agricultural applications have mostly focused on precipitation as the critical weather variable impacting crop production over a growing season, rather than on temperature, although a combined rainfall-temperature hedge is certainly possible.

A weather derivative is a type of parametric contingent claim contract where the payout is dependent on a measure of weather outcomes at a certain location (Hull). The instrument is parametric because the mechanism used to trigger payments is the realization of a predetermined weather index value rather than a direct measurement of financial loss. Weather derivatives for agriculture, as in the energy sector, are used to hedge against volumetric risk from adverse weather events (Müller and Grandi). Volume compensation can be viewed as payment for real losses that result from lower production output which is tied to specific weather patterns having a known relationship to production outcomes rather than direct measurement of output loss (Richards et al.).

Weather derivatives are considered exotic in part because the index on which payments are based is a cumulative measure of the weather variable over a specified period, such as total inches of rainfall over a five month growing season. In an agricultural setting, however, additional consideration needs to be given to index construction since the cumulative measure may not adequately reflect the importance of timing, or the inter-period incidence, of weather events over a growing season and fail to fully capture yield effects. A simple cumulative measure ignores or masks rainfall extremes of magnitude or duration that contribute to stress and yield loss if occurring during critical plant physiological growth stages or necessary field work periods.

Examples from the weather derivative literature recognize this issue and demonstrate several different approaches to weighting the cumulative index to account for the importance of rainfall over different periods of the growing season. That there are different approaches to the weighting problem suggests that there may be value in reviewing these methods in an attempt to ascertain if a generally preferred protocol can be identified. A second concern involves how different weighting methods perform in respect to data series of varying lengths. In many developing countries, a complete data series of weather and yield variables may be available for only a relatively short span, say fifteen to twenty years. It would be useful to know which method, if any, is robust in the sense that the distribution of weights over the index periods remain relatively unchanged when confronted with additional data.

Consequently, the objective of this article is to review several methods and apply criteria for selecting among them to obtain an optimal distribution of weather variable weights of a cumulative weather index. Five parts are included in this article. First, there is a brief review of the literature where weighting methods have been used in practice, and we give consideration to alternatives to the optimization criteria used in these studies. Second, the data used and adjustments made are presented. Third, four alternative optimization methods for determining a weighted weather index are formalized. Forth, results of the empirical analysis is provided. The methods and results are further evaluated in an out-of-sample framework to judge their stability over a shorter data series. Finally, a summary comments along with suggestions for additional work conclude.

Weighting Methods in Practice

Stoppa and Hess and Skees have recognized the need to weight the cumulative weather index to reflect the relative importance of rainfall during different periods of the growing season in agricultural risk analysis and derivative contract design. Both begin by dividing the indexed period into logical growth phase periods based on crop type and local growing conditions. Stoppa and Hess describe the design of a weather index insurance contract in Morocco to hedge against deficient rainfall. They determine the distribution of weights for the rainfall index for each period by first maximizing the correlation between the weighted cumulative rainfall and annual yield, and then make adjustments based on expert opinion. This method in effect seeks to minimize basis risk, which is the situation where local production outcomes are not well reflected in the terminal value of the cumulative index. While basis risk is of great concern, particularly in areas where heterogeneous micro-climates might exists, the solution of this problem does not necessarily mean the distribution of index weights reflects desirable revenue or income outcomes from the standpoint of the producer.

The method employed by Skees in a feasibility study of rainfall derivatives in

Romania puts the reduction of risk as the priority and seeks to maximize the reduction of relative risk in the optimal solution. This method finds the optimal combination of variable weights that maximize the reduction in relative risk given the observed yields with and without a contingent claims contract where the pure premium rate is held fixed at a certain value considered affordable in the local economy. Relative risk is measured as the coefficient of variation of producer revenues. This procedure however, may not adequately capture extreme downside risks associated with the underlying weather events.

Additional Criteria

For some risk averse producers, the priority when thinking about contingent claims contracts may be given to reducing the probability of suffering losses which threaten solvency. The 'safety first' criterion of Roy may therefore be an appropriate criteria when extreme downside risk is the primary concern. Under the safety first rule, a producer would seek to minimize the probability of ruin subject to a return threshold or maximize the expected return subject to maintaining a specified level of downside risk. The value at risk (VaR) is such a measure of downside risk and has received considerable attention from financial economists and may be a well suited criteria in the context of weather variability and production loss . The VaR determines the probability of a rate of return losing a certain amount in a given time period due to adverse market movements. Consider a random return R having a cumulative distribution function of F, then the $100 \cdot \alpha\%$ VaR equals the α-th quantile of R, so that $VaR = F^{-1}(\alpha)$ where $F^{-1}(\cdot)$ represents a quantile of the cumulative distribution of returns.

Lastly, the cost to a producer of a rainfall derivative is an important factor in the design of contingent claims contracts. This appears to be the concern justifying the fixing the premium rate by Skees in the coefficient of variation method. Bearing in mind that the writer of the contract will add a loading factor in percentage terms to the pure premium to cover costs of administration, risk bearing and profit, one objective may simply be to minimize the pure premium rate when determining the distribution of weights of the rainfall index.

Data

Data needs include a series of annual crop yield statistics and corresponding daily rainfall observations for a particular area. A suitably long series was also needed to allow for partitioning in later analysis. We use the Crop Reporting District (CRD) as the level of analysis which are statistical units that typically include eight to ten adjacent counties and provide for reasonable intermediate aggregation that would be consistent with systemic weather risk.

A dataset of historical county corn yields for Iowa, the top corn producing state in 2002, was obtained from the National Agricultural Statistics Service for forty-five years from 1956 to 2000. County level data was then aggregated to the CRD level, giving a total of nine CRD's. For each CRD, a centrally placed weather station was selected as the official source of weather data and daily rainfall measures where then obtained from the National Climate Data Center for the typical corn growing season lasting from 15 March to 15 August.

Adjusting Yield Trend

It is often necessary to detrend, or filter, the yield series in order to correct for heteroscedasticity and isolate yield volatility from systematic changes over the time series, such as that generated by improved technologies and management. The augmented Dickey Fuller and Phillips-Perron tests were first used to test for existence of a stochastic trend in each CRD. The yield series for each CRD was found to be trend instationary and the unit root was accepted at all cases. This suggests that a deterministic (linear) trend adjustment might not be appropriate for the yield data and the LOESS procedure was used instead to establish the trend (Cleveland, Devlin, and Grosse). The LOESS procedure allows for greater flexibility without the need for strick specification of the parametric form and is relative robust in the presence of outliers in the data. Similarly, the rainfall series of each CRD was checked for trend but adjustment was found not to be necessary.

Using the results of yield trend from the LOESS procedure, the detrended yields are found by the ratio method, rather than the difference method, since it adjusts trend in variance as well as the mean, and is given by: $adjusted\ yield_t = (actual\ yield_t / trend\ yield_t) * predicted\ 2000\ yield$.

Figure 1 provides an example of the actual yield per acre, the trend yield, and the detrended yield series for CRD D60 in East-central Iowa. The figure shows that actual yields increased remarkably from 1956 to 2000. The smooth line is the LOESS fit for the trend and shows, however, that the rate of yield increase is divided into two distinct periods over the forty-five year series.

Rainfall Index Division

There are a number of ways that the cumulative rainfall index can be divided into logical time periods over which weights are to be determined. The method used here was to aggregate the daily rainfall data into five critical growth periods based on corn physiology and climate conditions in Iowa. These are pre-planting, establishment, vegetative, pollination, and grainfilling. The specific time intervals are listed in Table 1. Alternative methods can include dividing the index into equal parts based on the maximum number of days that a particular crop cannot go without precipitation before suffering catastrophic yield loss, when one is concerned with deficient rainfall.

Optimization Methods

This section specifies several methods of determining the optimal weights of the five period cumulative weather index when a weather derivative contract is used to hedge against insufficient rainfall that has volumetric consequences for yields. With the contract in place, the gross revenue position of the producer can be determined and compared to the situation where no derivative contract is purchased and producer income is fully exposed to yield variability. For the analysis, the whole CRD is chosen as the weather-based contingent claims buyer. We further assume that only production risk is considered and price is fixed at unity. The buyer is assumed to only use weather derivatives to hedge against production risk and does not purchase any other risk management instrument.

The cumulative rainfall index ($\tilde{w}$) over the five periods is first defined as

$$(1) \quad \tilde{w} = \sum_{i=1}^{5} w_i R_i$$

subject to

$$(2) \quad \tilde{w_i} \geq 0 \forall i \quad \text{and} \quad \sum_{i=1}^{5} w_i = 1$$

where R_i is the cumulative rainfall of the i-th period and w_i are the weights of each period.

For the design of the derivative contract, we use the specific form suggested by Skees, Black. and Barnett to protect a producers' revenue from downside risk. This contact form is essentially identical to a combination of a short and long European put option that describes a bear spread or a capped put option. However, the method described below of determining the derivative premium is referred to as the burn rate or historical burn and refers to actuarial or insurance-type techniques of weather derivative pricing using historical data to compute probabilities of future events (Hull; Müller and Grandi). This method is used in lieu of standard models of derivative pricing such as Black-Scholes since the basic assumptions of these techniques are not met. In particular they require a tradable underlying asset which a weather index is unable to satisfy.

The weather derivative contract can be described by the couple $[I(\cdot), P]$ where $I(\tilde{w})$ is the indemnity function, P is the pure premium, w_c is a predetermined index trigger value, and θ is the maximum liability value.

$$(3) \quad I(\tilde{w}) = \theta \cdot \max\Big(\Big[\frac{(w_c - \tilde{w})}{w_c}\Big], 0\Big)$$

$$(4) \quad P = E(I(\tilde{w})).$$

The trigger value w_c is calculated as 80% of the mean of the weighted rainfall index $\tilde{w}$, while the level of liability θ is determined to be the average of gross revenue obtained in the absence of a derivative contract. With the purchase of a rainfall derivative contract, and defining revenue as $\tilde{R} = \textit{yield} \cdot \textit{acres harvested}$ (recalling unit price), the corresponding gross revenue position is represented by:

$$(5) \quad \tilde{R}^{GR} = \tilde{R} + I(\tilde{w}) - P.$$

Correlation (Corr) Method

The Corr method is the previously described Stoppa and Hess method where the objective is to maximize the sample correlation between yield y and rainfall with respect to the index period weights $\tilde{w}_i$. The optimization problem is given by:

$$(6) \quad \max_{w_i} \mathrm{Corr}(\tilde{w}, y) = \left[\frac{\mathrm{Cov}(\tilde{w}, y)}{\sigma_{\tilde{w}} \cdot \sigma_y}\right]$$

subject to (1) and (2). The indemnity payment, premium, and gross revenue can be obtained from (5) based on the optimal index weights.

Coefficient of Variation (CV) Method

The CV method is essentially that employed by Skees as described previously where the objective is to minimize the relative risk, or the CV, of gross revenue except that the pure premium is not held fixed. The objective function of this optimization problem is given by:

$$(7) \quad \max_{w_i}(CV_1 - CV_2)$$

subject to

$$CV_1 = \frac{Std(\tilde{R})}{Mean(\tilde{R})}$$
$$CV_2 = \frac{Std(\tilde{R}^{GR})}{Mean(\tilde{R}^{GR})}$$

Conditions (1) to (5).

Value at Risk (VaR) Method

The VaR method specifically seeks to reduce downside revenue risk which can be thought of as a type of safety-first criteria in the optimization problem, as described previously. That is, the producer seeks to minimize the probability of ruin at some specified level of probability, α . Here, we assume the holder of the weather index contract is risk averse and has a preference for a low probability of ruin over weather events such that $\alpha = .30$. The objective of the optimization is to find those rainfall index weights that generates a revenue distribution that maximizes the quantile VaR. The model is constructed as:

$$(8) \quad \max_{w_i}(VaR_\alpha^1 - VaR_\alpha^0)$$

subject to

$$VaR_\alpha^1 = F^{-1}(\tilde{R}^{GR})$$
$$VaR_\alpha^0 = F^{-1}(\tilde{R})$$

Conditions (1) to (5).

Pure Premium (PP) Method

The objective of this method, as described previously, is to simply minimize the pure premium rate when determining the distribution of weights of the rainfall index. The pure premium rate is defined as the break-even price; that is:

$$(9) \quad PPR = \frac{P}{\bar{R}^{GR}}.$$

where P is the expected indemnities from (4) and $\bar{R}^{GR}$ is the average of gross revenues with the derivative contract. The objective function then chooses index weights to minimize the pure premium rate:

$$(10) \quad \min_{w_i} PPR \qquad \text{subject to conditions (1) to (5) and (9).}$$

Results and Evaluation

Results of the optimization methods applied to the data are given in Table 2, showing the derived weights of the weather index. The reader will first notice that results are reported for only four of the nine Iowa CRDs. The reason is that the excluded regions are nearly ideal corn producing areas involving relatively low production risk. This means that the gross revenue position of producers cannot be improved with a rainfall derivative hedge even at actuarially fair rates. This result highlights the predicament of U.S. Federal Crop Insurance proponents wishing to increase program participation: significant subsidies are required to induce producers in low risk production areas to purchase insurance. Consequently, we remove these observations and consider only those CRDs where a degree of weather risk does exist.

Careful inspection of the distribution of weights will reveal a second anomaly. For CRD D20, the weights on the first period appear generally larger compared to the other CRDs. In fact, the rainfall relationship in this CRD showed a negative relationship with rainfall suggesting that corn production risk is related to excess, rather than insufficient, rainfall. In this case, the contract form was changed to a call option but otherwise used identical parameters as other CRDs. The generally heavier weights found in the first period make sense as excess moisture in the pre-planting period restricts suitable field days. Yield risk is reflected in delay in field preparation and planting.

Summary results of revenue distribution outcomes for the four alternative optimization methods and a scenario where no hedge product is purchased generated using Simtar$^{\text{TM}}$are contained in Table 3. For each CRD, the mean, standard deviation, and coefficient of variation for the revenue distribution is reported. Also included is the pure premium rate and the certainty equivalent based on a moderate risk aversion level and an exponential utility function. Finally, each optimization method is ranked for each CRD using the method of stochastic dominance of the resulting revenue distributions. The first observation is that it is somewhat difficult to identify a clearly superior method in all circumstances; however, the CV method appears to perform better relative to the alternatives. Even while the rankings are clearly ordinal, a graph of the cumulative distributions of revenue for one CRD given in Figure 2 shows that over much of the distribution it is difficult to make a judgement. It is likely that much of the distinction between methods is contained in the lower tail of the distribution, as might be expected when considering rainfall risk. To see this more closely, the cumulative distributions are truncated at Pr 30% and shown in Figure 3. In this region is is more clearly obvious how the CV method more often ranks higher than other methods followed by the Corr method. VaR generally performs least well but the difference between it and the PP method appear to be very slight.

Out-of-Sample Performance

While the results of the exercise appear to somewhat inconclusive, we hope that additional insight can be gained by examining the robustness, or stability, of the various methods. This is an important consideration since it is more common that available data, particularly in lesser developed countries, is of short duration. Model stability therefore becomes a criterion when considering which weather index weighting method may be preferred. Out-of-sample performance is used as the means to investigate model stability. The 45-year sample is partitioned into a fitting sample (in-sample, from 1956 to 1985) and a validation sample (out-of-sample, from 1986 to 2000). The whole set of optimized weights is generated by optimizing over the fitting sample with the out-of-sample performance determining rank. Table 4 gives the set of optimized weather index weights for the in sample partition while Table 5 gives the summary results of revenue for both the fitting and validation samples.

In only one CRD (D60) is the ranking of methods by stochastic dominance the same in both samples. Figures 4 and 5 show the cumulative revenue distribution truncated at Pr = 30% for each to get an idea of how methods change relative to one another in the lower tail. Once again, while it is difficult to generalize from these statistics, it appears there may be a slight advantage to the CV method over the alternatives.

Summary and Suggestions for Further Work

Of the four methods reviewed for finding the optimal distribution of weights of a weather derivative index, the CV and Corr method appear to be preferred over the VaR and PP methods, although the evidence is somewhat mixed. Conceptually, the CV method might be preferred to Corr on the grounds that producers make decisions based on their income distribution rather than basis risk. In some favorable production environments, weather derivatives are found to not be efficient even at actuarially fair premium rates such that producers would not seek insurance without subsidies.

Suggestions for further work are numerous. First, a clearer distinction might be found in production environments experiencing greater risk from weather events. Similarly, the level of aggregation to the CRD level may have been too large, excessively smoothing yield and revenue variability. Smaller units would also afford sufficient observations to allow meaningful statistical testing for differences between method results, then leading to a need for a conceptually appealing statistic for comparing out-of-sample performance.

References

Anderson, J.R., J.L. Dillon and J.B. Hardaker. Agricultural Decision Analysis. Ames, Iowa: Iowa State University Press, 1977.

Cleveland, W.S., Devlin, S.J., and Grosse, E., "Regression By Local Fitting," Journal of Econometrics, 37 (1988), 87– 114.

Hardaer, J.B., R.B.M. Huirne and J.R. Anderson. Coping With Risk in Agriculture. CAB International. 1997.

Hull, J.C. Fundamentals of Futures and Options Markets, 4th ed. Upper Saddle River: Prentice Hall. 2002.

Müller, A. and M. Grandi. "Weather derivatives: a risk management tool for weather-sensitive industries". The Geneva Papers on Risk and Insurance 25.2 (2000):273–87.

Richards, T.J., M.R. Manfredo and D.R. Sanders. "Weather derivatives: managing risk with market-based instruments". Presented at the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 22–23 April, St. Louis, MI. 2002.

Robison, L.J. and P.J. Barry. The Competitive Firm's Response to Risk. Macmillan, New York, 1987.

Rosenzweig, M.R., and H.P. Binswanger. . "Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments." The Economic Journal. Volume 103, Issue 416(Jan., 1993): 56–78.

Roy, A.D., "Safety First and the Holding of Assets." Econometrica. 20(1952): 431–49.

Skees, J.R, "Alternatives for Financing Catastrophic Yield Risks in Romanian Agriculture", Working Report to USAID, May 8, 2003.

—., J.R. Black and B.J. Barnett. "Designing and Rating an Area-yield Crop Insurance Contract." American Journal of Agricultural Economics 79(1997):430–38.

Stroppa, A., and U. Hess., "Design and Use of Weather Derivatives in Agricultural Policies: the Case of Rainfall Index Insurance in Morocco", Contributed Paper Presented at the International Conference "Agricultural Policy Reform and the WTO: Where are We Heading?" Capri (Italy), June 23–26, 2003.

Table 1: Critical Corn Production Intervals of the Weather Index

	Critical Growth Period	Time Span
1	Pre-Planting	March 15 –April 14
2	Establishment	Apr 15-May 12
3	Vegetative	May 13-June 2
4	Pollination	June 3 – June 28
5	Grainfilling	June 29 – August 15

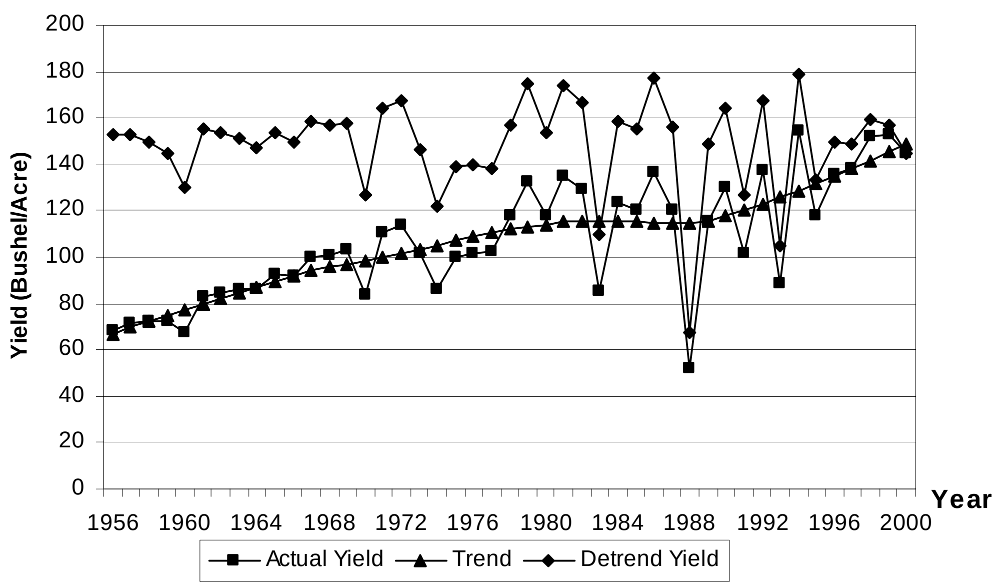

Figure 1: Actual and Detrended Yields for Corn in Crop Reporting District D60

Table 2: Optimized Weights of the Weather Index for Iowa CRDs

		w1	w2	w3	w4	w5
D20	R_Corr	0.5779	0.2568	0.1423	0.0231	0.0000
	R_CV	0.0900	0.2326	0.2124	0.1749	0.2902
	R_VaR	0.1510	0.1195	0.2859	0.1713	0.2723
	R_PP	0.2596	0.0291	0.2970	0.1766	0.2377
D30	R_Corr	0.0000	0.0000	0.3535	0.3556	0.2909
	R_CV	0.0000	0.3139	0.0000	0.3123	0.3737
	R_VaR	0.0537	0.4233	0.1656	0.1737	0.1837
	R_PP	0.0173	0.4133	0.1671	0.1965	0.2058
D60	R_Corr	0.0000	0.0000	0.0000	0.6464	0.3536
	R_CV	0.1392	0.0000	0.2905	0.1855	0.3848
	R_VaR	0.5116	0.1153	0.1687	0.0448	0.1595
	R_PP	0.5046	0.0813	0.2028	0.0328	0.1785
D90	R_Corr	0.0000	0.0000	0.0839	0.6531	0.2630
	R_CV	0.0000	0.1926	0.4933	0.1485	0.1656
	R_VaR	0.1884	0.2057	0.2271	0.2549	0.1238
	R_PP	0.3327	0.0934	0.2411	0.1739	0.1589

Table 3: Summary Results of Revenues and Rank of Alternative Optimization Methods

		R	R_Corr	R_CV	R_VaR	R_PP
D20	Mean	224.51	224.51	224.51	224.51	224.51
	Std	41.14	51.37	38.07	38.43	38.92
	CV	18.32	22.88	16.96	17.12	17.34
	PP	N/A	0.0750	0.0246	0.0216	0.0214
	CE	117.65	142.82	130.56	131.22	131.28
	Rank	5	1	4	3	2
D30	Mean	183.78	183.78	183.78	183.78	183.78
	Std	43.77	43.13	41.36	42.98	42.88
	CV	23.81	23.47	22.50	23.39	23.33
	PP	N/A	0.0432	0.0305	0.0165	0.0163
	CE	99.33	110.98	113.31	110.23	110.25
	Rank	5	2	1	4	3
D60	Mean	192.98	192.98	192.98	192.98	192.98
	Std	39.06	37.33	34.56	39.67	39.58
	CV	20.24	19.34	17.91	20.56	20.51
	PP	N/A	0.0701	0.0438	0.0222	0.0214
	CE	82.01	120.34	125.41	108.46	115.63
	Rank	5	2	1	4	3
D90	Mean	116.02	116.02	116.02	116.02	116.02
	Std	29.62	27.56	26.51	28.45	30.40
	CV	25.53	23.75	22.85	24.52	26.20
	PP	N/A	0.0794	0.0608	0.0488	0.0405
	CE	42.54	60.14	62.30	55.19	37.84
	Rank	4	2	1	3	5

PP: Pure Premium Rate; CE: Certainty equivalence at the moderate risk level

Table 4: In Sample Optimized Weights of the Weather Index for Iowa CRDs

		In Sample (1956 to 1985)				
		w1	w2	w3	w4	w5
D20	R_Corr	0.7253	0.0479	0.2268	0.0000	0.0000
	R_CV	0.6510	0.0000	0.1795	0.0849	0.0846
	R_VaR	0.3244	0.0907	0.2400	0.1337	0.2112
	R_PP	0.3289	0.1367	0.2300	0.1032	0.2012
D30	R_Corr	0.0000	0.0000	0.0000	0.4470	0.5530
	R_CV	0.0000	0.3212	0.0000	0.1954	0.4834
	R_VaR	0.4116	0.2290	0.0149	0.1512	0.1932
	R_PP	0.2284	0.2086	0.0545	0.3163	0.1921
D30	R_Corr	0.0012	0.0000	0.0000	0.4392	0.5596
	R_CV	0.1841	0.0000	0.2662	0.2067	0.3429
	R_VaR	0.6116	0.0000	0.1448	0.0205	0.2231
	R_PP	0.6270	0.0000	0.1318	0.0411	0.2001
D90	R_Corr	0.0000	0.0582	0.0000	0.5972	0.3446
	R_CV	0.0000	0.1733	0.5216	0.1539	0.1513
	R_VaR	0.1294	0.2782	0.3579	0.1054	0.1290
	R_PP	0.2946	0.1206	0.2849	0.1305	0.1694

Table 5: In and Out-of-Sample Summary Results of Revenues and Rank of Alternative Optimization Methods

		In Sample (1956 to 1985)						Out of Sample (1986 to 2000)				
		R	R_Corr	R_CV	R_VaR	R_PP		R	R_Corr	R_CV	R_VaR	R_PP
D20	Mean	218.04	218.04	218.04	218.04	218.04	Mean	237.44	237.44	237.44	237.44	237.44
	Std	36.86	35.07	31.94	37.06	36.88	Std	47.29	62.53	45.50	34.15	34.97
	CV	16.90	16.08	14.65	17.00	16.91	CV	19.91	26.33	19.16	14.38	14.73
	PP	N/A	0.0434	0.0264	0.0025	0.0004	PP	N/A	0.1134	0.0778	0.0456	0.0484
	CE	135.88	174.76	178.47	137.88	135.79	CE	117.10	97.24	142.83	166.23	165.57
	Rank	4	2	1	3	5	Rank	4	5	3	1	2
D30	Mean	173.77	173.77	173.77	173.77	173.77	Mean	203.81	203.81	203.81	203.81	203.81
	Std	41.13	40.03	39.59	41.56	42.52	Std	43.26	40.09	39.53	41.70	39.07
	CV	23.67	23.04	22.78	23.92	24.47	CV	21.23	19.67	19.40	20.46	19.17
	PP	N/A	0.0437	0.0386	0.0047	0.0047	PP	N/A	0.2178	0.0413	0.0493	0.0553
	CE	113.05	115.49	116.38	110.76	112.24	CE	98.78	104.44	109.96	108.31	107.09
	Rank	3	2	1	5	4	Rank	5	4	1	2	3
D60	Mean	192.53	192.53	192.53	192.53	192.53	Mean	193.87	193.87	193.87	193.87	193.87
	Std	37.15	37.73	36.42	38.90	39.39	Std	44.01	32.85	31.57	44.91	45.13
	CV	19.29	19.60	18.91	20.21	20.46	CV	22.70	16.94	16.28	23.16	23.28
	PP	N/A	0.0403	0.0279	0.0191	0.0170	PP	N/A	0.1170	0.0587	0.0484	0.0464
	CE	118.07	140.41	142.81	122.00	119.71	CE	81.47	110.64	121.94	98.09	95.80
	Rank	5	2	1	3	4	Rank	5	2	1	3	4
D90	Mean	119.27	119.27	119.27	119.27	119.27	Mean	109.52	109.52	109.52	109.52	109.52
	Std	29.27	27.35	26.76	28.78	31.79	Std	30.26	30.26	27.39	27.15	27.51
	CV	24.54	22.93	22.44	24.13	26.65	CV	27.63	27.63	25.00	24.78	25.12
	PP	N/A	0.0541	0.0479	0.0387	0.0329	PP	N/A	0.1287	0.0905	0.0751	0.0581
	CE	42.34	80.49	81.80	64.46	38.42	CE	49.08	54.71	58.89	60.57	62.43
	Rank	4	2	1	3	5	Rank	5	4	3	2	1

PP: Pure Premium Rate; CE: Certanty equivalence at the moderate risk level

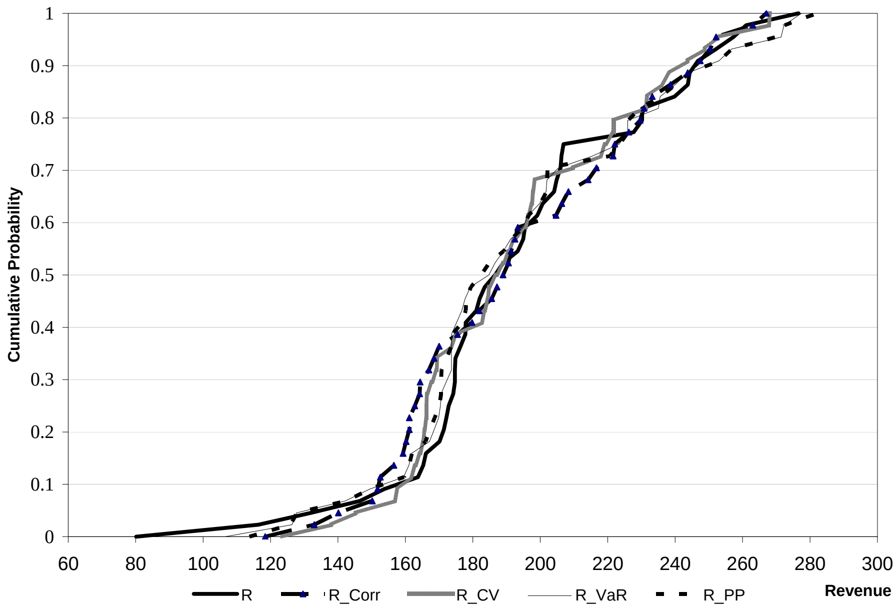

Figure 2: CDFs of Revenue in Crop Reporting District D60 Under Four Optimization Methods.

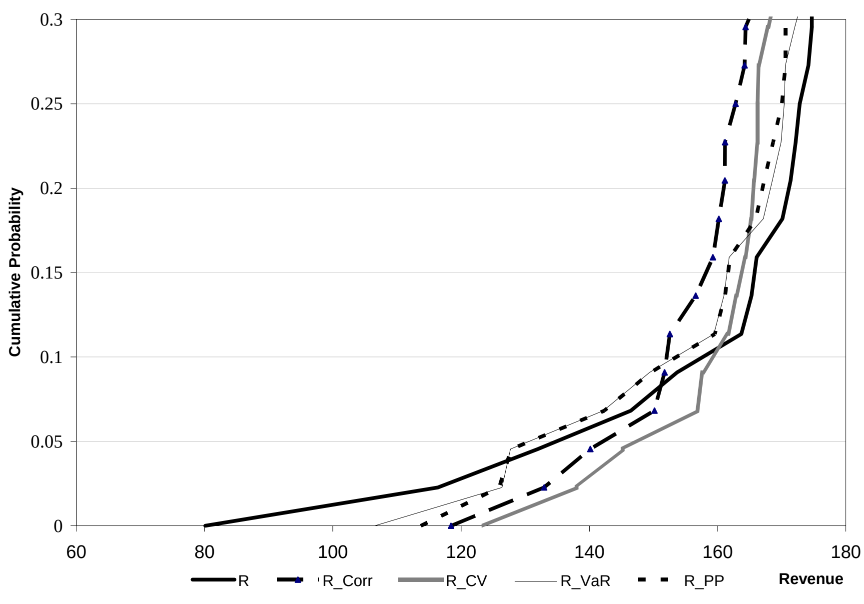

Figure 3: CDFs of Revenue in Crop Reporting District D60 Under Four Optimization Methods at Pr=30%.

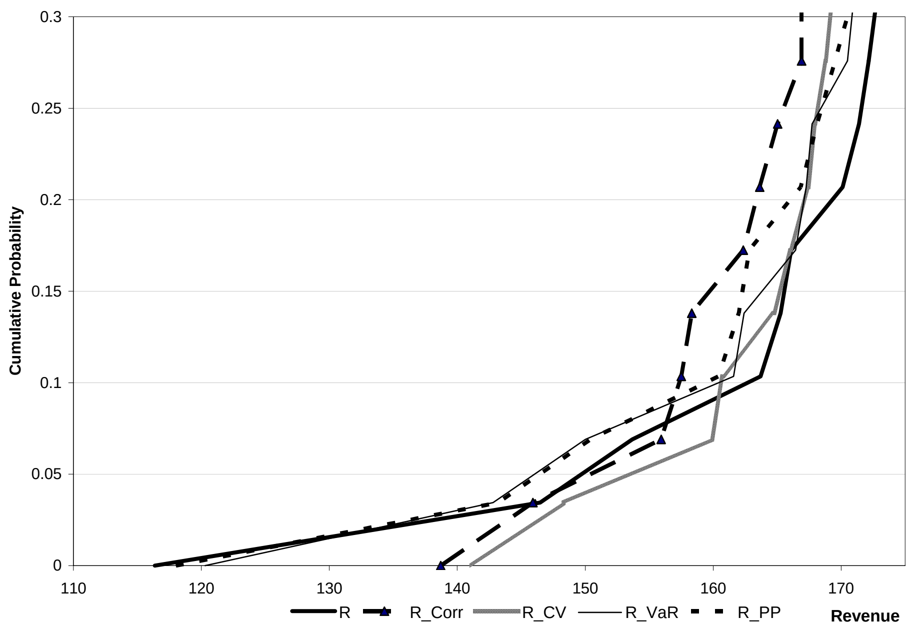

Figure 4: In Sample CDFs of Revenue in Crop Reporting District D60 Under Four Optimization Methods at Pr=30%.

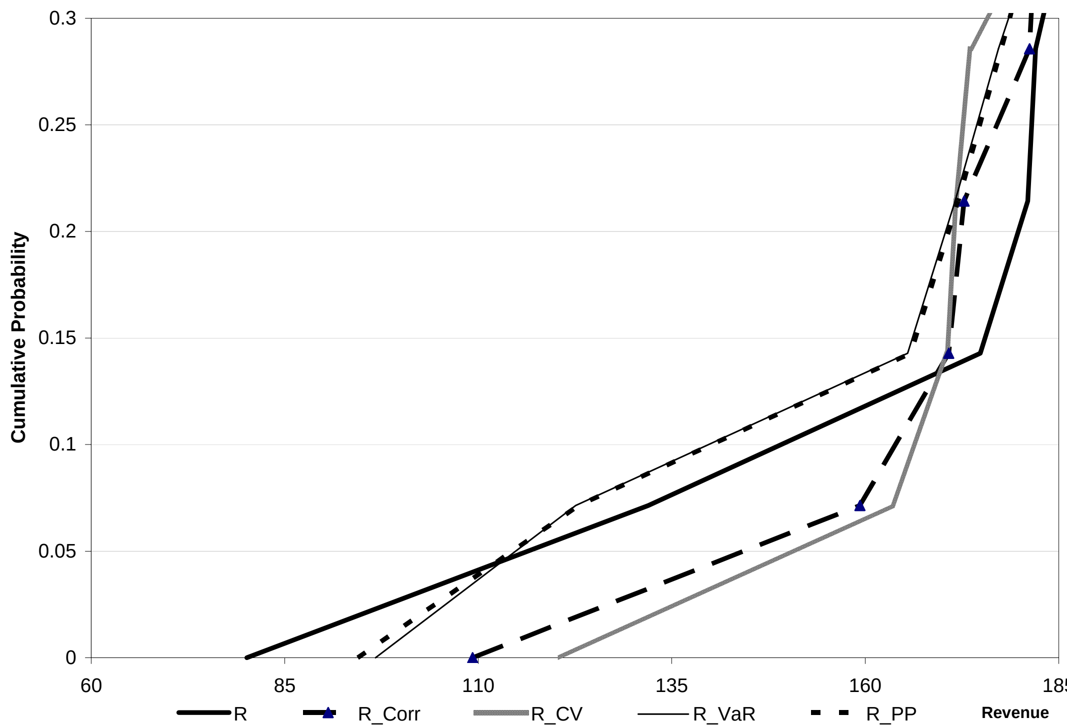

Figure 5: Out-of-Sample CDFs of Revenue in Crop Reporting District D60 Under Four Optimization Methods at Pr=30%.