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**MODELING YIELD DISTRIBUTION IN HIGH RISK COUNTIES:
APPLICATION TO TEXAS UPLAND COTTON**

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***Selected Paper prepared for presentation at the American Agricultural Economics
Association Annual Meeting, Long Beach, California, July 23-26, 2006***

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Abstract

Very little attention has been given to the modeling of yield distribution for crops and regions in which yields exhibit irregular behavior. We undertake a statistical case study of Texas upland cotton and propose an alternative mixture distribution based on regime-switching model in which the conditional distribution of yield depends upon an observable drought index. The results show that the mixture distribution model provides a better fit to the data than conventional parametric distributions and produces higher implied premium rates than the current published Group Risk Plan insurance rates in more than two-thirds of Texas counties examined.

Key words: Crop insurance, adverse selection, semi-parametric mixture distribution, regime-switching model, yield distribution.

The modeling of crop yield distributions continues to receive considerable attention in the academic crop insurance and agricultural risk management literature. The importance of properly modeling yield distributions stems in part from the dramatic growth in participation in the U.S. crop insurance program and the introduction of a broad range of new crop insurance products after the enactment of the 2000 Agricultural Risk Protection Act (Goodwin, Vandever and Deal; Glauber). In 2004, total liability of all insurance contracts under the program reached \$46.6 billion, an increase of 67% over 1998 levels.

Accurate assessment of yield distributions, particularly their lower tails, is necessary for precise computation of crop insurance premium rates. Inaccurate rates can lead to adverse selection, in which producers whose rates are low relative to expected indemnities participate in greater proportion than producers whose rates are high relative to expected indemnities. Adverse selection raises the ratio of indemnities paid to the premiums collected, undermining the actuarial performance of the federal crop insurance and reinsurance program (Skees and Reed; Miranda; Goodwin). Concerns regarding the accuracy of crop insurance rates and rating methodologies have been voiced by critics of the U.S. crop insurance program, which during the period 1981-1993 experienced a loss ratio of 1.52 (Glauber).

Numerous studies have highlighted the challenges associated with the statistical modeling of yield for the rating of crop insurance (Day; Gallagher; Taylor; Goodwin and Ker; Just and Weninger; Ker and Goodwin; Ramirez, Misra and Field; Ker and Coble; Atwood, Shaik and Watts; Sherrick, *et al.*). Most published studies have developed statistical models of yields for crops and regions in which yield variation is relatively regular and for which crop abandonment is relatively rare (e.g., Iowa corn). In most of

these studies, standard parametric distribution methods are applicable and the discussion has centered on the appropriateness of one standard distributional form versus another (e.g., the normal versus the beta distribution) (Day; Gallagher; Taylor; Just and Weninger; Ramirez, Misra and Field; Atwood, Shaik and Watts; Sherrick, *et al.*).

However, very little attention has been given to the modeling of yield distributions for crops and regions in which yields exhibit irregular behavior. Of particular interest are crops and regions that exhibit high post-planting abandonment rates in years of unfavorable weather. In such regions, zero or near-zero individual and aggregate yields are observed with some frequency, making common unimodal continuous probability distributions inadequate for explaining yield variation. The correct choice of distributional form for the yields of such crops remains an unsettled but important question.

In this paper, we undertake a statistical case study of Texas upland cotton, which in recent years has exhibited poor actuarial performance under the U.S. crop insurance program. During the 1989-2004 period, indemnities paid to Texas cotton producers exceeded premiums collected in every year but 1994 (see Figure 1) and the typical insured Texas cotton producer received a \$2.79 of indemnity per dollar of premium paid. During this period, Federal subsidies and premium discounts to Texas cotton producers averaged \$116 millions per year, accounting for 12% of total subsidies provided by the federal crop insurance program nationally (RMA).

Texas upland cotton yields exhibit greater variation and irregularities than yields of other major crops. For example, between 1972 and 2004, the coefficient of variation of Texas county-level cotton yields was 38%, as compared to 19% for Iowa corn yields.

In addition, Texas cotton acreage abandonment rates averaged around 13%, as compared to 4% for Iowa corn. Thus, the conventional distributional forms used to model Iowa corn yields may not provide sufficient degrees of freedom in higher moments to accurately capture the idiosyncrasies of Texas cotton yields.

In this paper, we examine the performance of alternative distributional assumptions for the modeling of Texas county-level upland cotton yields. In order to establish a baseline, we fit conventional parametric distributions that have been widely used or have otherwise been proposed to rate crop insurance products: the normal, lognormal, and beta distributions. We then propose and estimate an alternative semi-parametric mixture distribution based on a regime-switching model in which the distribution of yield is conditioned on exogenous drought indices.

We also examine the implications of the various distributional forms for the computation of crop insurance rates. In particular, we compare the Group Risk Plan (GRP) fair premium rates implied by the various distributions and further compare them to the rates published by the Risk Management Agency (RMA).

The paper is organized as follows: in the next section, we discuss the Texas county-level upland cotton yield data used in the analysis and the methods used to extract exogenous secular trends from the data. In the subsequent section, we fit the detrended yield data to common parametric distributional forms. In the next section, we introduce and estimate a semi-parametric mixture distribution model for detrended yields. In the final section, the implications of distributional assumptions for the computation of GRP fair premium rates are analyzed. We summarize our findings and discuss the conclusions that may be drawn from the analysis.

Detrending of Yields

This research employs 1972-2004 Texas upland cotton county-level yields published by the National Agricultural Statistical Service (NASS). Cotton production practices in Texas include irrigated and non-irrigated (*i.e.* dryland) cotton. We focus on forty-five Texas counties where dryland practices are dominant. For each of these counties, thirty-three annual dryland yield observations, measured in pounds, are utilized.

Exogenous secular trends in yields due to technical change pose a challenge for the modeling of yield distributions for the purposes of rating crop insurance products (Ker and Goodwin; Ker and Coble; Goodwin and Mahul; Ozaki, *et al.*). Lack of sufficient data compounds the problem, raising uncertainty about the exact form of the yield distribution (Goodwin and Mahul; Ozaki, *et al.*).

We initially considered several detrending methods suggested in literature, including first- and higher-ordered polynomials (Atwood, Shaik and Watts; Sherrick, *et al.*; Goodwin and Mahul; Oazki, *et al.*) and autoregressive integrated moving average models (Goodwin and Ker; Ker and Goodwin). However, none of these methods proved satisfactory, due primarily to overfitting problems.

For the purposes of this study, we elected to use a piecewise linear spline to model yields trends. This is the same method used to compute GRP insurance rates by the Risk Management Agency (Skees, Black and Barnett; Ker and Coble). The piecewise linear spline model allows up to two distinct linear trends in the data. In particular, the trend yield in period t , \hat{y}_t , is presumed to be a function of time:

$$(1) \quad \hat{y}_t = f(t) = y^* + \beta_1 \min(0, t - t^*) + \beta_2 \max(0, t - t^*)$$

The breakpoint t^* between linear segments and the slopes β_1 and β_2 of the linear segments are endogenously determined and estimated by nonlinear least squares. The piecewise linear spline model appeared to be free of the overfitting problems exhibited by more flexible models, but provided a necessary additional degree of flexibility not offered by a simple linear trend model. In this analysis, the breakpoint year occurs in the late 1980s in most counties.

Given the trend yields implied by the piecewise linear spline model, detrended county-level Texas upland cotton yields were computed by normalizing observed yields to 2004 equivalents as follows:

$$(2) \quad y_t^d = y_t \times \frac{\hat{y}_{2004}}{\hat{y}_t}$$

Here, y_t^d is the detrended yield in year t , y_t is the yield realized in year t and \hat{y}_t is the fitted trend yield in year t .

Table 1 shows descriptive statistics for detrended yields. Contradicting findings of negative skewness in most studies (Gallagher; Goodwin and Ker), the detrended Texas upland cotton yields exhibited positive skewness in 35 of 45 counties. The positive skewness implies that probability is amassed at lower tail of the yield distribution. Heteroscedasticity was also examined using White's test. Only 6 of 45 estimates rejected the hypothesis of homoscedasticity at a 5% significance level, indicating that heteroscedasticity is not a concern.

Parametric Distribution Models

In order to establish a baseline against which to evaluate the effectiveness of mixture distribution models for Texas county-level upland cotton yields, we begin by fitting common parametric distributions to the detrended county-level yields. The three parametric distributions examined are the normal, lognormal, and beta distributions.

Common parametric distributions often present problems for the modeling yield distributions, particularly in the rating of crop insurance products. The beta distribution, for example, is very sensitive to assumptions about the maximum and minimum possible yield, often producing unreasonable “U-shapes” when the data exhibits substantial variation (Ker and Coble; Goodwin and Mahul). The lognormal distribution is often criticized for possessing positive skewness, a property generally believed not be exhibited by yield distributions. And the normal distribution can be problematic for the rating of crop insurance because it allows negative yields.

Maximum likelihood estimates for the parameters and goodness-of-fit statistics for each of the three parametric distributions are presented in Table 2. To assess goodness-of-fit, we compute the Anderson-Darling statistic (A^2)

$$(3) \quad A^2 = -n - (1/n) \sum_{i=1}^n (2i-1) \left[\ln(\hat{F}(y_i)) + \ln(1 - \hat{F}(y_{n+1-i})) \right]$$

where $\hat{F}(y_i)$ is the fitted cumulative probability density of the specified distribution at a given observation and n is the sample size. The Anderson-Darling statistic allows one to test whether the yield data is generated by a specified distribution. An alternative to chi-square and Kolmogorov-Smirnov D tests, the Anderson-Darling statistic A^2 places more weight on the tail of the distribution.

As seen in Table 2, the beta distribution is rejected at 10% significance level for all 45 counties while the normal distribution is rejected in 8 counties. Based on the Anderson-Darling test, the parametric distributions may be ranked from best to worst fitting as follows: 1) normal distribution, 2) lognormal distribution and 3) beta distribution.

Figure 2 illustrates the selected Texas county-level upland cotton yield distribution. In the figure, the histogram represents the historical detrended yields and the plotted curves represent the fitted parametric distributions. This figure suggests bimodality of observed Texas upland cotton yields for Plain Regions, *i.e.* the northwest of Texas. This figure further suggests that parametric distribution provide a poor fit for the lower tails of the yield distribution.

Mixture Distribution Models

To address suspected misspecification problems associated with conventional parametric distributions, we estimate an alternative mixture distribution based on a regime switching model that is an extension of Quandt's λ -method and Goldfeld and Quandt's D -method. The basic idea underlying this approach is that the probability distribution of the detrended yield may be conditioned on exogenous environmental and economic condition or regimes. Under different regimes, the parameters of the conditional yield distribution may differ.

Specifically, we posit that the probability distribution of the detrended yield depends upon whether drought conditions exist. The detrended yield y_t is drawn from a normal distribution with mean μ_1 and variance σ_1^2 if drought condition exists, or from a

normal distribution with mean μ_2 and variance σ_2^2 , otherwise. Whether drought conditions exist depends upon a pair of exogenous random variables, one observable and the other unobservable. In particular, we assume that a drought occurs if, and only if, $z_t + \tilde{\varepsilon}_t < z^*$ where z_t is an observable index of drought conditions during the critical month of the growing season, z^* is an unknown critical threshold to be estimated, and $\tilde{\varepsilon}_t$ is an unobserved error term, assumed to be an i.i.d. normal random variable with zero mean and variance $\sigma_{\tilde{\varepsilon}}^2$.

Under this assumption, the log likelihood of observing yield y_t in year t , conditional on contemporaneously observed drought index z_t , is

$$(4) \quad l(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, z^*, \sigma_{\tilde{\varepsilon}}^2 | y_t, z_t) \\ = \sum_{t=1}^T \log [F(z^* - z_t; 0, \sigma_{\tilde{\varepsilon}}^2) f(y_t; \mu_1, \sigma_1^2) + F(z_t - z^*; 0, \sigma_{\tilde{\varepsilon}}^2) f(y_t; \mu_2, \sigma_2^2)]$$

where F is the cumulative distribution function for a standard normal random variable and f is the normal probability density function.

We consider two alternative indices of drought conditions, both of which are published by the National Weather Service: 1) average rainfall throughout the climate division in which the county is located and 2) the Palmer Drought Index for the climate division in which the county is located. In all cases, the values of the indices during the critical third month of the cotton growing season are used to assess drought conditions. Since the month in which cotton is planted in Texas varies by geographic region, and may begin as early as February in South Texas and as late as June in Plain Region, the critical third month depends upon where the county is located.

A challenge arises in computing estimates for the regime switching model due to the highly irregularity of the likelihood function. In order to rule out the globally suboptimal local optima, an extensive grid search in both z^* and $\sigma_{\tilde{\varepsilon}}$. Maximum likelihood estimates for the two mixture distribution models are reported in Table 3 and 4. Hereafter the two mixture models are referred to as the “rainfall index”, and the “Palmer index” mixture models. In the two mixture models, the maximum likelihood estimates for $\sigma_{\tilde{\varepsilon}}$ are zero in most counties, which implies the two regimes are perfectly discriminated by the observed index variable.

In the previous section, the normal distribution was found to fit to Texas upland cotton yields best among all conventional parametric distributions. In order to evaluate the effectiveness of the semi-parametric mixture distribution model, we therefore limit the analysis to a comparison between the mixture model and the normal distribution model. Limiting the analysis to this comparison has the advantage that the normal distribution model may be viewed as a parametric restriction of the mixture model, allowing the comparison to be performed using the likelihood ratio test. The likelihood ratio is defined as

$$(5) \quad \lambda = \frac{L(\hat{\theta}_R)}{L(\hat{\theta}_U)}$$

where $\hat{\theta}_R$ is the maximum likelihood estimator under the restriction of normality and $\hat{\theta}_U$ is the maximum likelihood estimator obtained without the restriction. The likelihood ratio statistics, $-2 \ln \lambda$, is asymptotically a Chi-square statistic with 3 degrees of freedom.

Tables 3-4 present the likelihood ratio tests of the mixture distribution models against the alternative of a normal distribution. At the 5% significance level, the normal

distribution model may be rejected in favor of the rainfall index mixture model in 44 of 45 counties; and the normal distribution model may be rejected in favor of the Palmer index mixture model in 42 of 45 counties. These results suggest that in most Texas counties, a mixture distribution can explain the variation in Texas cotton yields significantly better than the normal distribution (see Figure 3 and 4).

Rating Crop Insurance Contract

This paper has been motivated by the need to compute accurate crop insurance rates, which depend largely upon how well the lower tail of the yield distribution is captured. Fair premium rates for GRP insurance computed using mixture distributions are now compared to the rates computed using common parametric distribution alternatives in order to assess potential systematic biases in these computations.

Under GRP insurance, an indemnity is paid if and only if the realized county yield \tilde{y} falls below a specified trigger yield, which is set equal to an elected coverage level α times the published expected area yield y^e . Specifically, per dollar of coverage,

$$(6) \quad \text{Indemnity} = \max \left\{ 0, \frac{\alpha y^e - \tilde{y}}{\alpha y^e} \right\}$$

Indemnities and premium rates are based on National Agricultural Statistics Service (NASS) county yield estimates, which is calculated by dividing the NASS estimates of crop production for specified practice in the county by the NASS estimates of planted or harvested acres for specified practice in the county.

Premium rates are set by computing the expected indemnity per dollar of coverage as

$$(7) \quad \pi = \frac{1}{\alpha y^e} \int_0^{\alpha y^e} (\alpha y^e - y) f(y) dy$$

where f is the probability density function of yield as estimated from historical county yield data. In addition, geographic smoothing methods are applied to GRP premium rates, rendering a final premium rate for each county that is as a weighted average of the raw premium rates for the county and its neighbors (Skees, Black and Barnett).

Table 5 provides the comparison of GRP 2006 rates versus the computed premium rates for the normal distribution, rainfall index mixture distribution, and Palmer index mixture distribution assuming a coverage level of 85 percent. In most counties, the mixture distribution models produce higher premium rates than the normal distribution. Among the 45 counties for which GRP rates are published by RMA, the rainfall index mixture model produces rates that are higher than the published rates in 32 counties and the Palmer index model produce rates that are higher than the published rates in 30 counties. In addition, the mixture distribution models produce higher premium rates than the normal distribution in more than one-half of Texas counties examined.

Summary and Conclusions

This research undertakes a statistical case study of Texas non-irrigated upland cotton, which has historically exhibited poor actuarial performance under the U.S. crop insurance program. Texas upland cotton yields exhibit greater variation and irregularities than yields of other crops in other parts of the country, suggesting that the poor actuarial performance of crop insurance for this cotton may be due in part to inadequacies in the conventional statistical models used to compute premium rates. A mixture distribution

conditioned on area drought condition is proposed for Texas county-level upland cotton yields and compared to conventional parametric models for the rating of crop insurance.

Anderson-Darling goodness-of-fit tests indicate that the beta distribution, which is widely utilized in the literature, is statistically rejected in modeling of upland cotton yields in all 45 counties while the normal distribution provides the best fit among other standard parametric distributions. Comparison of the proposed mixture distribution to the normal based on likelihood ratio tests are then used to establish that in most counties, the mixture distribution model provides a better fit to the data and produces higher implied GRP premium rates. The premium rates computed from the mixture distribution, moreover, are higher than the current published GRP rates in more than two-thirds of Texas counties examined, which suggests that current GRP rating methods underestimate the fair premium rate offering at least a partial explanation for the poor actuarial performance of the GRP program for upland cotton.

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**PRODUCER LOSS
RATIO**

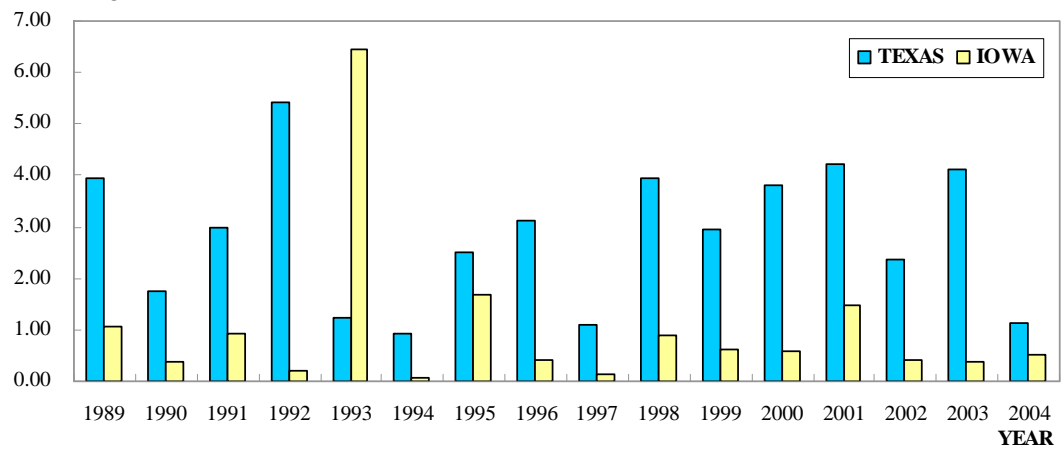


Figure 1. Producer Loss Ratios in Iowa Corn vs. Texas Upland Cotton

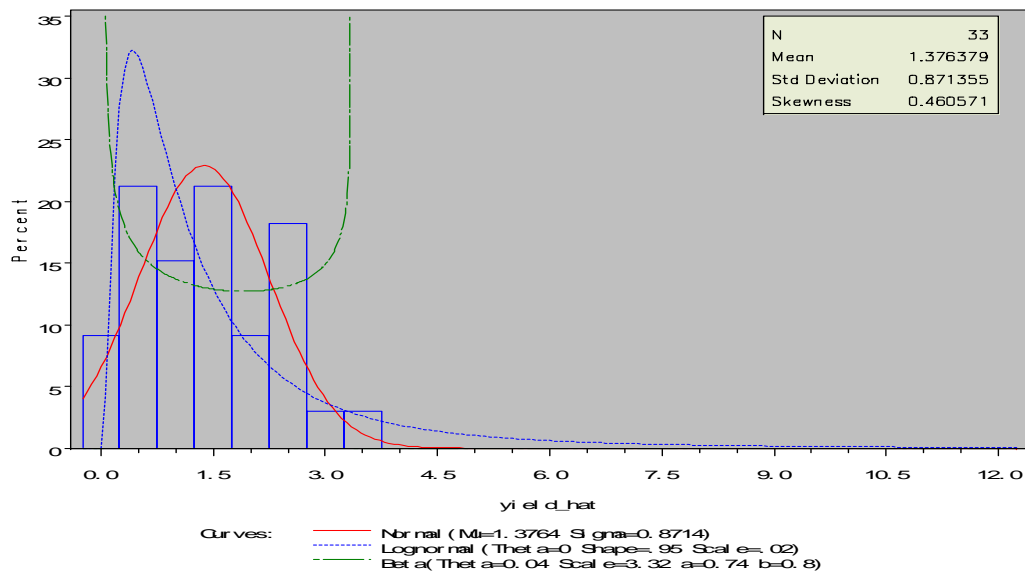


Figure 2. Parametric Distributions for Non-irrigated Upland Cotton in Yoakum County, Texas

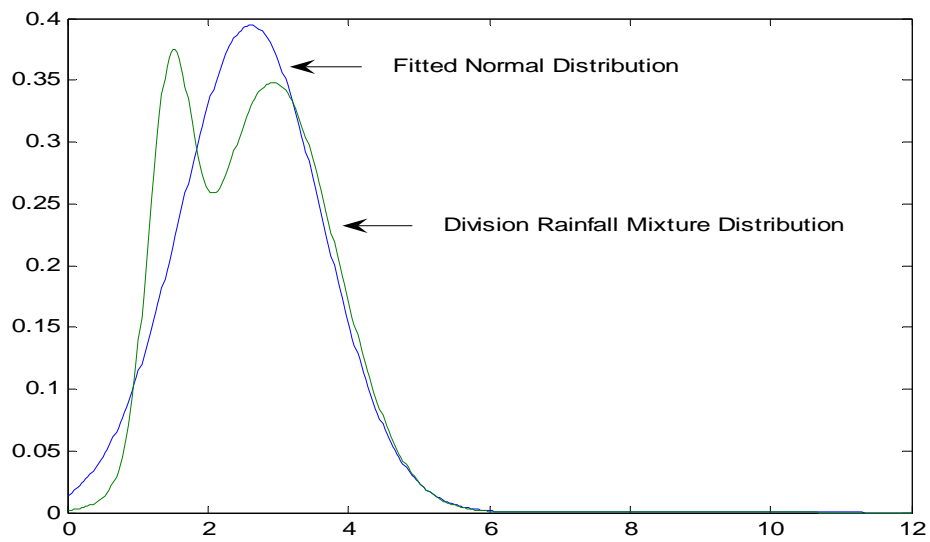


Figure 3. Yield Distributions for Non-irrigated upland cotton in Crosby County, Texas

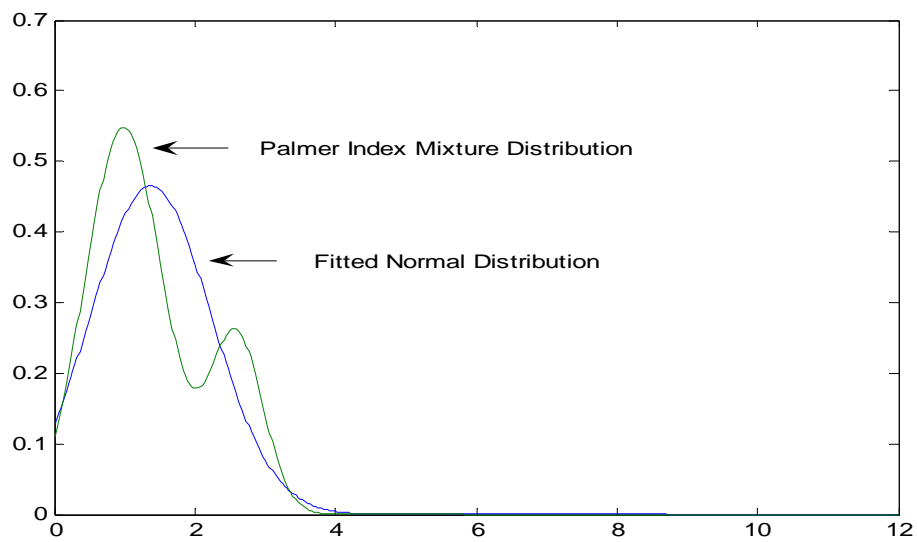


Figure 4. Yield Distributions for Non-irrigated upland cotton in Yoakum County, Texas

Table 1. Descriptive Statistics for Detrended Yields

COUNTY NAME	MEAN	STD DEV	MIN	MAX	SKEWNESS	KURTOSIS	CV
ANDREWS	126.90	84.06	15.81	319.29	0.83	22.61	66.24
BAILEY	153.65	106.65	14.21	436.36	0.81	0.47	69.41
BORDEN	189.74	115.36	11.67	482.62	0.30	-0.40	60.80
BRISCOE	163.85	82.66	45.26	354.88	0.56	-0.45	50.45
CAMERON	245.77	119.98	31.27	540.92	0.25	0.09	48.82
CHILDRESS	244.06	92.56	49.08	415.91	-0.02	-0.34	37.92
COCHRAN	179.91	129.38	7.28	488.03	0.88	0.34	71.91
COLLINGSWORTH	264.28	95.07	116.13	473.53	0.58	-0.20	35.97
CONCHO	241.71	115.91	4.25	585.38	0.54	1.35	47.96
COTTLE	199.80	80.55	36.95	376.42	-0.10	0.23	40.32
CROSBY	261.22	102.68	99.75	567.72	0.58	0.98	39.31
DAWSON	187.81	101.65	24.68	420.51	0.08	-0.70	54.12
DICKENS	274.81	114.87	77.42	638.79	0.89	2.25	41.80
DONLEY	260.21	97.32	86.76	454.47	0.07	-0.72	37.40
ELLIS	421.71	140.86	102.75	681.01	-0.13	-0.30	33.40
FISHER	233.30	117.34	6.11	431.24	0.05	-0.81	50.30
FLOYD	271.10	128.86	43.95	547.71	0.27	-0.43	47.53
GAINES	146.36	78.34	10.81	344.24	0.50	-0.07	53.52
GARZA	268.13	137.05	59.00	663.08	0.69	0.73	51.11
GLASSCOCK	83.09	52.33	12.93	256.58	1.15	2.25	62.98
HALE	294.87	143.88	37.71	590.15	0.36	-0.58	48.79
HALL	255.16	90.37	85.27	426.53	0.24	-0.74	35.42
HASKELL	250.82	109.20	24.43	457.52	-0.10	-0.45	43.54
HILL	489.75	159.64	215.04	845.12	0.67	0.09	32.60
HOCKLEY	211.62	108.34	7.32	512.42	0.83	0.75	51.20
HOWARD	139.44	86.65	13.35	344.07	0.04	-0.71	62.14
KNOX	247.06	104.69	28.33	489.37	-0.10	-0.01	42.38
LAMB	257.69	160.75	15.17	629.68	0.54	-0.51	62.38
LUBBOCK	265.59	125.15	53.28	629.74	0.53	0.74	47.12
LYNN	235.79	107.21	43.36	494.12	0.25	-0.05	45.47
MARTIN	143.30	90.64	8.12	293.73	-0.04	-1.39	63.26
MIDLAND	88.77	48.43	19.50	222.64	0.66	0.37	54.56
MITCHELL	219.38	126.19	2.53	450.82	-0.02	-0.72	57.52
MOTLEY	195.74	77.30	29.01	401.76	0.14	0.58	39.49
NAVARRO	426.41	133.20	200.44	740.82	0.65	0.31	31.24
NOLAN	206.21	106.63	14.12	394.54	-0.05	-0.81	51.71
PARMER	242.68	144.98	15.72	695.02	1.05	1.57	59.74
REFUGIO	593.53	220.88	77.70	1099.63	0.09	0.19	37.21
SAN PATRICIO	692.91	198.75	311.97	986.51	-0.27	-1.17	28.68
SWISHER	246.76	138.04	51.06	556.38	0.42	-0.51	55.94
TERRY	198.60	102.45	43.54	391.49	0.31	-0.86	51.59
TOM GREEN	191.77	82.55	7.70	475.18	0.93	3.57	43.05
WILLACY	397.15	172.15	40.34	824.80	-0.38	0.80	43.35
WILLIAMSON	509.80	119.91	220.16	748.47	0.03	-0.04	23.52
YOAKUM	137.64	87.14	3.68	335.62	0.46	-0.63	63.31

An asterisk (*) indicates statistical significance at the $\alpha = 0.05$ or smaller level.

Table 2. Maximum Likelihood Estimates for Parametric Distributions

COUNTY NAME	NORMAL			LOGNORMAL			BETA		
	Mean	Std Dev	A-sq	Scale	Shape	A-sq	Shape	Shape	A-sq
ANDREWS	1.27	0.84	1.000*	0.73	0.00	0.258	0.74	0.78	2.639*
BAILEY	1.54	1.07	0.498	0.95	0.10	1.135*	0.66	0.83	2.445*
BORDEN	1.90	1.15	0.494	0.87	0.37	1.234*	0.75	0.85	2.322*
BRISCOE	1.64	0.83	0.527	0.56	0.36	0.369	1.02	0.90	2.574*
CAMERON	2.46	1.20	0.462	0.68	0.73	1.801*	0.97	0.89	2.871*
CHILDRESS	2.44	0.93	0.192	0.48	0.80	0.931*	1.37	0.81	1.962*
COCHRAN	1.80	1.29	0.730*	1.00	0.24	0.933*	0.61	0.71	2.441*
COLLINGSWORTH	2.64	0.95	0.419	0.37	0.91	0.176	1.31	0.79	3.715*
CONCHO	2.42	1.16	0.272	0.84	0.69	2.484*	0.88	0.93	3.688*
COTTLE	2.00	0.81	0.486	0.55	0.58	1.905*	1.24	0.90	2.757*
CROSBY	2.61	1.03	0.361	0.42	0.88	0.665*	1.20	1.04	4.188*
DAWSON	1.88	1.02	0.436	0.73	0.42	1.413*	0.90	0.86	2.136*
DICKENS	2.75	1.15	0.715*	0.46	0.92	1.078*	1.09	1.03	4.823*
DONLEY	2.60	0.97	0.185	0.42	0.88	0.598	1.43	0.88	2.116*
ELLIS	4.22	1.41	0.217	0.41	1.37	0.804*	1.60	0.84	2.060*
FISHER	2.33	1.17	0.516	0.90	0.62	2.470*	0.89	0.65	1.341*
FLOYD	2.71	1.29	0.173	0.60	0.86	0.766*	1.05	0.83	2.241*
GAINES	1.46	0.78	0.308	0.70	0.20	0.797*	0.90	0.90	2.610*
GARZA	2.68	1.37	0.320	0.60	0.84	0.678*	0.92	0.95	3.537*
GLASSCOCK	0.83	0.52	0.593	0.71	-0.40	0.486	0.74	0.99	3.723*
HALE	2.95	1.44	0.480	0.62	0.93	0.742*	1.03	0.81	2.174*
HALL	2.55	0.90	0.328	0.39	0.87	0.274	1.41	0.76	2.605*
HASKELL	2.51	1.09	0.472	0.63	0.78	1.774*	1.15	0.80	1.895*
HILL	4.90	1.60	0.908*	0.33	1.54	0.490	1.54	0.89	3.761*
HOCKLEY	2.12	1.08	0.743*	0.73	0.58	1.492*	0.90	0.92	3.590*
HOWARD	1.39	0.87	0.773*	0.96	0.01	2.246*	0.72	0.82	2.136*
KNOX	2.47	1.05	0.187	0.60	0.77	1.636*	1.15	0.91	2.624*
LAMB	2.58	1.61	0.475	0.83	0.69	0.657*	0.76	0.80	2.085*
LUBBOCK	2.66	1.25	0.326	0.55	0.85	0.892*	0.99	0.98	3.693*
LYNN	2.36	1.07	0.232	0.56	0.73	1.019*	1.09	0.92	2.773*
MARTIN	1.43	0.91	0.836*	0.99	0.02	1.653*	0.73	0.65	0.891*
MIDLAND	0.89	0.48	0.415	0.62	-0.29	0.635*	0.91	0.98	3.015*
MITCHELL	2.19	1.26	0.242	1.17	0.43	2.763*	0.72	0.65	1.207*
MOTLEY	1.96	0.77	0.214	0.51	0.57	1.214*	1.22	1.00	3.443*
NAVARRO	4.26	1.33	0.472	0.32	1.40	0.236	1.58	0.93	3.848*
NOLAN	2.06	1.07	0.190	0.80	0.51	1.660*	0.91	0.70	1.192*
PARMER	2.43	1.45	0.582	0.73	0.68	0.574	0.76	0.93	3.762*
REFUGIO	5.94	2.21	0.248	0.50	1.69	1.177*	1.31	0.90	3.054*
SAN PATRICIO	6.93	1.99	0.613	0.32	1.89	0.890*	1.96	0.74	1.245*
SWISHER	2.47	1.38	0.418	0.68	0.71	0.945*	0.88	0.83	2.239*
TERRY	1.99	1.02	0.453	0.61	0.53	0.698*	0.98	0.74	1.797*
TOM GREEN	1.92	0.83	0.557	0.67	0.51	2.476*	0.97	1.02	4.965*
WILLACY	3.97	1.72	0.739*	0.74	1.20	3.613*	1.02	0.88	3.458*
WILLIAMSON	5.10	1.20	0.238	0.25	1.60	0.309	2.19	0.88	3.043*
YOAKUM	1.38	0.87	0.444	0.95	0.02	1.001*	0.74	0.80	1.782*

An asterisk (*) indicates statistical significance at the $\alpha = 0.10$ or smaller level.

Table 3. Parameter Estimates, Rainfall Index Mixture Distribution Model

COUNTY NAME	μ_1	μ_2	σ_1^2	σ_2^2	z^*	$\sigma_{\tilde{\epsilon}}$	Likelihood Ratio
ANDREWS	0.72	1.60	0.09	0.75	1.79	0.44	17.090*
BAILEY	1.62	0.18	1.05	0.00	4.15	0.00	16.546*
BORDEN	1.85	2.59	1.34	0.00	3.86	0.00	22.938*
BRISCOE	1.00	2.03	0.10	0.60	1.70	1.30	9.566*
CAMERON	1.81	2.50	0.00	1.46	0.23	0.00	10.567*
CHILDRESS	1.47	2.81	0.37	0.52	0.87	0.00	18.814*
COCHRAN	1.01	2.01	0.42	1.73	1.20	0.00	7.722
COLLINGSWORTH	2.67	2.42	0.99	0.00	3.70	0.48	21.087*
CONCHO	1.98	2.94	0.59	1.66	2.91	0.00	10.690*
COTTLE	1.11	2.33	0.33	0.33	0.87	0.00	21.135*
CROSBY	1.45	2.92	0.09	0.81	1.20	0.00	22.680*
DAWSON	0.59	2.26	0.04	0.65	1.15	0.75	17.733*
DICKENS	1.76	3.12	0.55	1.05	0.87	0.00	12.313*
DONLEY	1.93	2.99	0.43	0.79	1.35	0.00	12.383*
ELLIS	2.85	4.73	1.29	1.20	1.20	0.00	14.948*
FISHER	1.49	2.70	0.76	1.14	0.94	0.00	9.211*
FLOYD	1.77	2.96	0.23	1.68	1.20	0.00	12.443*
GAINES	1.04	1.86	0.35	0.50	2.03	0.00	11.404*
GARZA	1.33	3.19	0.32	1.44	0.87	0.00	21.182*
GLASSCOCK	0.40	1.03	0.03	0.25	1.44	1.14	9.565*
HALE	3.00	2.23	2.10	0.00	4.15	0.00	18.841*
HALL	1.79	2.99	0.32	0.54	1.35	0.00	19.012*
HASKELL	1.58	2.91	0.84	0.75	0.94	0.00	13.057*
HILL	3.43	5.45	0.85	1.97	1.20	0.00	15.032*
HOCKLEY	1.34	2.17	0.00	1.17	0.52	0.00	26.092*
HOWARD	0.36	1.81	0.05	0.39	1.37	0.82	20.515*
KNOX	1.65	2.83	0.97	0.68	0.94	0.00	11.140*
LAMB	1.12	2.84	0.13	2.48	0.77	0.00	15.198*
LUBBOCK	1.21	2.89	0.00	1.37	0.61	0.95	18.992*
LYNN	1.55	2.82	0.53	0.87	1.67	0.00	14.231*
MARTIN	0.37	1.92	0.04	0.40	1.47	0.81	27.483*
MIDLAND	0.41	1.10	0.02	0.17	1.46	0.82	17.048*
MITCHELL	1.86	3.23	1.38	0.64	3.05	0.00	9.898*
MOTLEY	1.13	2.27	0.26	0.35	0.87	0.00	19.362*
NAVARRO	3.06	4.72	0.53	1.42	1.20	0.00	15.261*
NOLAN	1.31	2.95	0.49	0.37	1.96	0.85	14.635*
PARMER	1.07	2.51	0.02	2.04	0.52	0.00	9.342*
REFUGIO	4.03	6.13	0.02	4.80	0.97	0.00	16.258*
SAN PATRICIO	4.54	7.17	0.06	3.58	0.97	0.00	14.349*
SWISHER	1.72	3.26	1.22	1.29	2.28	0.00	12.765*
TERRY	0.73	2.35	0.04	0.71	0.95	1.23	13.690*
TOM GREEN	1.84	2.48	0.31	2.83	5.20	0.00	15.979*
WILLACY	0.55	4.44	0.02	1.44	0.06	1.26	20.814*
WILLIAMSON	4.34	5.48	0.36	1.48	1.31	0.00	13.493*
YOAKUM	0.71	1.79	0.18	0.64	1.80	0.72	10.409*

An asterisk (*) indicates statistical significance at the $\alpha = 0.05$ or smaller level.

Table 4. Parameter Estimates, Palmer Index Mixture Distribution Model

COUNTY NAME	μ_1	μ_2	σ_1^2	σ_2^2	z^*	$\sigma_{\tilde{\epsilon}}$	Likelihood Ratio
ANDREWS	0.46	1.37	0.00	0.68	-2.44	0.78	13.916*
BAILEY	1.20	2.13	0.47	1.65	1.44	0.00	12.989*
BORDEN	0.55	2.48	0.06	0.69	-1.54	0.00	44.448*
BRISCOE	0.68	1.73	0.04	0.62	-2.40	0.00	10.465*
CAMERON	0.46	2.73	0.01	0.96	-2.73	0.37	24.626*
CHILDRESS	1.60	2.96	0.33	0.43	-0.54	0.82	20.335*
COCHRAN	0.23	1.90	0.00	1.56	-2.51	0.00	19.022*
COLLINGSWORTH	2.23	3.14	0.29	1.12	1.23	0.00	16.193*
CONCHO	1.76	2.79	0.51	1.36	-1.34	0.00	10.253*
COTTLE	1.54	2.49	0.42	0.39	0.68	0.00	14.555*
CROSBY	2.15	3.10	0.52	1.09	0.50	0.00	10.612*
DAWSON	1.46	2.60	0.79	0.55	1.44	0.00	12.303*
DICKENS	2.36	3.52	0.59	1.78	1.79	0.00	13.483*
DONLEY	2.14	3.04	0.50	0.92	0.32	0.00	9.853*
ELLIS	3.29	4.56	2.22	1.37	-1.75	0.00	6.818
FISHER	1.36	2.97	0.48	0.88	-0.36	0.00	21.840*
FLOYD	2.23	3.22	0.81	1.96	0.50	0.00	8.572*
GAINES	1.17	2.04	0.42	0.45	1.86	0.00	10.955*
GARZA	1.40	3.24	0.52	1.36	-1.54	0.00	19.273*
GLASSCOCK	0.64	1.16	0.14	0.32	1.44	0.00	11.486*
HALE	1.38	3.11	0.04	1.94	-2.40	0.00	13.165*
HALL	2.18	3.38	0.51	0.43	1.95	0.19	14.305*
HASKELL	1.44	2.97	0.55	0.71	-1.54	0.00	18.653*
HILL	4.92	4.80	3.01	0.14	3.09	0.55	8.219*
HOCKLEY	1.76	2.83	0.54	1.57	1.86	0.00	12.807*
HOWARD	1.00	2.09	0.54	0.31	1.44	0.00	16.585*
KNOX	1.86	2.98	0.79	0.72	-0.19	0.00	11.423*
LAMB	2.10	3.53	1.53	3.11	1.86	0.00	8.511*
LUBBOCK	0.86	2.77	0.11	1.39	-2.51	0.00	8.105*
LYNN	1.93	3.25	0.66	0.86	1.95	0.42	11.747*
MARTIN	0.98	2.22	0.57	0.22	1.44	0.00	22.360*
MIDLAND	0.39	0.94	0.00	0.22	-2.40	0.00	18.879*
MITCHELL	0.65	2.77	0.31	0.79	-1.63	0.27	25.902*
MOTLEY	1.34	2.23	0.43	0.40	-1.54	0.00	11.217*
NAVARRO	4.27	4.13	1.83	0.00	3.58	0.00	10.349*
NOLAN	0.90	2.57	0.33	0.60	-1.54	0.00	25.973*
PARMER	1.86	2.64	0.50	2.45	-1.56	0.00	8.253*
REFUGIO	5.99	5.39	5.15	0.17	3.70	0.00	7.354
SAN PATRICIO	3.75	7.25	0.23	3.08	-2.52	0.00	15.000*
SWISHER	2.17	3.07	1.35	2.30	1.86	0.00	4.487
TERRY	0.74	2.33	0.05	0.74	-1.75	0.84	17.014*
TOM GREEN	1.40	2.26	0.33	0.59	-1.01	0.00	11.575*
WILLACY	0.55	4.44	0.02	1.43	-2.72	0.37	36.230*
WILLIAMSON	3.62	5.43	0.58	0.98	-2.29	0.68	11.063*
YOAKUM	0.99	2.59	0.30	0.14	2.95	1.50	22.274*

An asterisk (*) indicates statistical significance at the $\alpha = 0.05$ or smaller level.

Table 5. Parametric and Mixture GRP Premium Rates¹

COUNTY NAME	GRP06	DIVISION	PALMER	NORMAL
ANDREWS	9.68	21.54*	23.13*	22.60*
BAILEY	20.88	24.57*	21.83*	24.03*
BORDEN	18.15	20.49*	22.71*	20.15*
BRISCOE	12.87	15.19*	15.97*	15.55*
CAMERON	12.83	14.47*	15.72*	14.83*
CHILDRESS	8.60	10.68*	10.75*	10.10*
COCHRAN	22.12	24.72*	25.69*	25.16*
COLLINGSWORTH	7.60	8.58*	7.84*	9.27*
CONCHO	11.15	13.28*	13.89*	14.45*
COTTLE	10.19	11.92*	11.38*	11.12*
CROSBY	10.66	11.31*	10.03	10.69*
DAWSON	19.99	18.65	17.61	17.18
DICKENS	8.10	11.89*	10.30*	11.76*
DONLEY	11.48	9.73	9.41	9.88
ELLIS	6.56	8.63*	8.40*	8.19*
FISHER	15.39	15.55*	15.93*	15.48*
FLOYD	12.87	13.85*	13.39*	14.26*
GAINES	17.37	16.76	16.77	16.91
GARZA	13.50	16.46*	16.34*	15.84*
GLASSCOCK	22.98	21.20	19.91	21.13
HALE	13.98	14.41*	15.18*	14.82*
HALL	9.06	9.24*	8.99	9.04
HASKELL	12.13	12.91*	13.12*	12.52*
HILL	6.90	7.93*	7.42*	7.86*
HOCKLEY	13.70	15.78*	14.30*	15.88*
HOWARD	22.83	22.69	21.58	20.76
KNOX	8.33	12.36*	12.26*	12.01*
LAMB	20.44	21.26*	19.86	20.86*
LUBBOCK	14.08	14.77*	14.45*	14.08*
LYNN	14.19	13.46	12.94	13.36
MARTIN	25.34	23.52	22.69	21.26
MIDLAND	13.28	18.11*	17.75*	17.37*
MITCHELL	19.10	19.28*	20.50*	18.69
MOTLEY	9.63	11.41*	11.07*	10.77*
NAVARRO	7.56	7.26	7.16	7.30
NOLAN	15.64	17.31*	17.33*	16.11*
PARMER	10.60	19.88*	18.55*	19.68*
REFUGIO	10.22	9.73	9.28	9.80
SAN PATRICIO	8.54	6.43	6.71	6.26
SWISHER	14.87	18.17*	17.46*	17.98*
TERRY	16.97	17.46*	17.43*	16.05
TOM GREEN	9.65	9.64	12.11*	12.31*
WILLACY	11.03	13.60*	13.25*	12.43*
WILLIAMSON	4.59	3.57	4.58	4.25
YOAKUM	21.91	21.25	20.93	21.28

An asterisk (*) indicates computed premium rates are equal or smaller than published GRP rate.

1/ The premium rates are calculated at 85 percent coverage level.