

More than Mean Effects: Modeling the Effect of Climate on the Higher Order Moments of Crop Yields

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Abstract. The objective of this article is to propose the use of moment functions and maximum entropy techniques as a flexible way to estimate conditional crop yield distributions. We present a moment based model that extends previous approaches in several dimensions, and can be easily estimated using standard econometric estimators. Upon identification of the yield moments under a variety of climate and irrigation regimes, we utilize maximum entropy techniques to analyze the distributional impacts from switching regimes. We consider the case of Arkansas, Mississippi, and Texas upland cotton to demonstrate how climate and irrigation affect the shape of the yield distribution, and compare our findings to other moment based approaches. We empirically illustrate several advantages of our moment based maximum entropy approach, including flexibility of the distributional tails across alternative irrigation and climate regimes.

The objective of this article is to propose the use of moment functions and maximum entropy techniques as a flexible way to estimate conditional crop yield distributions. This research contributes to the growing body of literature conditioning random agricultural output on input vectors such as management, pests, and weather (see Antle, 2010 and references therein). We apply this approach using both irrigated and dryland cotton yield data to demonstrate its flexibility in capturing the effects of climate change relative to other moment based approaches. Our application demonstrates this moment based maximum entropy approach's ability to capture climate-driven changes in the "fatness" of the yield distribution's tails, the importance of which was recently stressed in Nordhaus (2011), Pindyck (2011), and Weitzman (2011).

Two main lines of research have been employed in modeling yield variability in response to climate change. One is using stochastic weather generators to obtain climate scenarios with different variability characteristics and agricultural crop models to simulate effects on the mean and variability of crop yields. Examples of this line of research include Mearns et al. (1992, 1996, 1997), Wilks (1992), Barrow and Semenov (1995), Bindi et al. (1996), Peiris et al. (1996), Phillips et al. (1996), Riha et al. (1996), Semenov et al. (1996), Wolf et al. (1996), Olesen and Bindi (2002), Torriani et al. (2007), Xiong et al. (2009), Kapphan et al. (2011), and Wang et al. (2011) among others. One of the main findings of this line of research is that weather variable changes affect both the mean and variability of crop yields, with the magnitude of the effect depending on the crop and location used in the study. As noted in Schlenker and Roberts (2006, 2009a), the drawback of these simulation based models is that they do not take into account the adaptive behavior of producers.

The other line of research is a regression based framework that utilizes historical data to identify the effects of weather variables on both the mean and variability of yield. Examples of

this line of research include Adams et al., 2001, Chen et al., 2004; Isik and Devadoss, 2006; McCarl et al., 2008, Kim and Pang, 2009, Barnwal and Kotani, 2010, and Boubacar, 2010. The common aspect of these regression based studies is that they all use the Just and Pope (1978) stochastic production function, which Antle (1983) demonstrated as being overly restrictive in linking inputs to moments of the output distribution.

Another branch of relevant literature presents alternative modeling techniques for crop yield distributions. Gallagher (1987) utilized the Gamma distribution, Moss and Shonkwiler (1993) the inverse hyperbolic sine transformation, Goodwin and Ker (1998) demonstrate the usefulness of nonparametric models, and Ker and Coble (2003) develop a semi-parametric approach. More recently, Sherrick et al. (2004) considers several alternative parametric yield specifications that have been suggested as candidates by previous work or empirical evidence. Taken as whole, the main impetus of the crop modeling research is to minimize the possibility of *ex ante* specification errors, while maintaining empirical tractability and the ability to capture stylized features of the data.

Previous research suggests that non-zero skewness should be considered when considering crop yield modeling assumptions (Hennessy 2009a, 2009b). Day (1965) found that Mississippi delta cotton yields exhibited positive skewness, and both Nelson and Preckel (1989) and Moss and Shonkwiler (1993) found evidence of negative skewness for corn. Ramirez, Misra, and Field (2003) concluded that Corn Belt corn and soybean yields are negatively skewed and that Texas dryland cotton data exhibit positive skewness. Sherrick et al. (2004) conclude that distributions that permit negative skewness like the Weibull and beta best fit their samples. Our approach is in line with Nelson and Preckel's (1989) in that we model conditional distributions; however we provide a semi-parametric approach that does not require an *ex ante* distributional

assumption and admits both positive and negative skewness.

We present a moment based model based on the reduced form natural experiment specification employed in Schlenker and Roberts (2009a), and extend the model in several dimensions. Similar in spirit to Antle's (1983, 2010) FGLS estimation framework, we condition these moments on weather, irrigation, and technological change; however, we develop an approach that permits simultaneous identification of the moment functions and is robust to the type of specification errors that bias FGLS estimators. Upon identification of the yield moments under a variety of climate and irrigation regimes, we utilize maximum entropy techniques to analyze the distributional impacts from switching regimes. This information theoretic approach does not require an *ex ante* distributional assumption and to our knowledge has not been used in this context.

The next two sections present our moment based maximum entropy model and the data used to estimate it. The following section presents the empirical results, and includes a comparison of our model with other moment based approaches. The last section concludes.

Moment Based Maximum Entropy Model

Our empirical model has two components, and each is described in the following two subsections. First, we develop an extension of Antle's (1983) moment based approach to condition higher order moments of the yield distribution on weather and irrigation variables. The moment function specifications follow the reduced-form natural experiment approach laid out in Schlenker and Roberts (2006, 2009a), in which case these relationships can be considered causal. This model is then used to predict moments conditional on climate and irrigation regimes, which are in turn utilized as constraints within a maximum entropy framework. We refer to this

conditional distribution estimation technique as the Moment Based Maximum Entropy (MBME) approach.

Conditional Higher Order Moments

As with the Antle (1983, 2010) and Schlenker and Roberts (2006, 2009a) models, we begin by specifying some transformation of yield in period t , $g(y_t)$, as a parameterized function of conditioning variables \mathbf{x}_t , $f(\mathbf{x}_t; \boldsymbol{\beta})$, and a random error term,

$$(1) \quad g(y_t) = f(\mathbf{x}_t; \boldsymbol{\beta}) + \varepsilon_t.$$

In our empirical application below, we utilize $f(\mathbf{x}_t; \boldsymbol{\beta}) = \mathbf{x}_t' \boldsymbol{\beta}$ with \mathbf{x}_t a vector of weather and irrigation variables, but the approach is easily generalized to other conditioning variables and functional forms for $f(\cdot)$.¹ Under the assumption $E(\varepsilon_t | \mathbf{x}_t) = 0$, it follows that $E[g(y_t) | \mathbf{x}_t] = f(\mathbf{x}_t; \boldsymbol{\beta})$ which effectively links different types of conditional moments to the variables \mathbf{x}_t . For example, Antle (1983) utilized the identity function $g(y_t) = y_t$ while Schlenker and Roberts (2006, 2009a) utilized the natural logarithm $g(y_t) = \ln(y_t)$. In the former case, the model conditions the first raw moment on \mathbf{x}_t while the later conditions the first logarithmic moment on \mathbf{x}_t . Other natural candidates for $g(\cdot)$ include higher powers of the level, $g_j(y_t) = y_t^j, j \in \mathbb{N}$, which would condition higher order raw moments on \mathbf{x}_t ; higher powers of the log, $g_j(y_t) = [\ln(y_t)]^j, j \in \mathbb{N}$, which would condition higher order logarithmic moments on \mathbf{x}_t ; or more complicated transformations such as the partial moment formulations in Antle (2010).

As in Antle (1983, 2010), we extend (1) to a system of J equations

$$(2) \quad g_j(y_t) = f(\mathbf{x}_t; \boldsymbol{\beta}_j) + \varepsilon_{jt}, j = 1, \dots, J$$

which contains a different parameter vector $\boldsymbol{\beta}_j$ for each moment equation and we do not impose restrictions on the $\boldsymbol{\beta}_j$ either within or across equations. This insures that our modeling approach inherits the generality of the Antle (1983, 2010) approach with respect to the multiplicative error, additive error, and Just and Pope (1978) models. That is, equation (2) extends common approaches and is sufficiently general for testing restrictions on the moment function parameters within and across equations.

If we consider the specific case where $g_j(y_t) = y_t^j, j = 1, \dots, J$ and $f(\mathbf{x}_t; \boldsymbol{\beta}_j) = \mathbf{x}_t' \boldsymbol{\beta}_j$, then the system reduces to

$$(3) \quad y_t^j = \mathbf{x}_t' \boldsymbol{\beta}_j + \varepsilon_{jt}, j = 1, \dots, J$$

which is essentially Antle's (1983) Linear Moment Model (LMM) except that y_t^j replaces ε_{it}^j as the dependent variable in equations $j > 2$. This highlights a weakness of the LMM approach as identification of the higher order moments crucially relies on the error term of the first (mean) equation. This insures that any specification errors related to the mean equation will bias the other equations within the system. While the LMM focused on identifying centered moments versus the raw moments modeled here, this is a trivial distinction as any set of J centered moments can be expressed as functions of their raw moment counterparts, and vice versa. This implies that equation (3) is equivalent to the LMM in terms of characterizing the underlying probability function, and has the added feature of being robust to misspecification of the mean equation.

We include similar conditioning variables as in Schlenker and Roberts (2006, 2009a), and we directly control for the effect of irrigation. In discussing the research design proposed in

Mendelsohn, Nordhaus, and Shaw (1994), Schlenker, Hanemann, and Fisher (2005) note that pooling dryland and irrigated counties can produce bias in the coefficient estimates for precipitation since the structural relationship between precipitation and yield likely differs across irrigated versus dryland acreage.¹ Although Schlenker and Roberts (2009b) note that their results do not differ substantially when pooling cotton data across the 100th meridian, we directly control for irrigation and allow for the relationship between precipitation and yield to differ across irrigated and dryland acreage.

Our empirical model for the raw moments of the cotton yield distribution is,

$$(4) \quad y_{it}^j = \alpha_{ij} + \beta_{j1}low_{it} + \beta_{j2}med_{it} + \beta_{j3}high_{it} + \beta_{j4}p_{it} + \beta_{j5}p_{it}^2 + \beta_{ij6}irr_{it} + \beta_{j7}irr_{it}p_{it} + \beta_{j8}irr_{it}p_{it}^2 + \beta_{j9}t + \beta_{j10}t^2 + \varepsilon_{ijt},$$

where the dependent variable y_{it}^j is the j^{th} power of the yield variable y_{it} for county i in period t , α_{ij} is a county-by-equation fixed effect, low_{it} captures the intensity of low temperatures, med_{it} captures the intensity of medium temperatures, $high_{it}$ captures the intensity of high temperatures, and p_{it} and p_{it}^2 capture a quadratic effect of precipitation. We include a dummy variable irr_{it} to control for dryland ($irr_{it} = 0$) and irrigated ($irr_{it} = 1$) acreage, and account for differential irrigation effects across space by allowing the irrigation effect parameter to differ across counties. In addition, we allow for the effect of precipitation to differ across dryland versus irrigated acreage within a state by including interactions of the precipitation variables with the irrigation dummy. Finally, we also allow for equation specific quadratic trends that account for technological change over time.

Using the data discussed in the following section, we consistently estimate these conditional moments using ordinary least squares with standard errors clustered by year to control for spatial correlations within each state. After reporting the empirical results, we

demonstrate how these equations can be used to trace out the effects of climate and irrigation on the distribution of cotton yields using maximum entropy.

Shape Implications for Cotton Yield Distributions

While the parameters in the previous section capture the relationship between weather, irrigation, and technological change with the higher order moments of the yield distribution, it is not immediately clear how these variables affect the overall shape of the distribution. The ability to predict the moments under different weather, irrigation, and technological change regimes does not in and of itself allow us to measure the effect of these regimes on the distribution of yield outcomes.

The inability of a finite set of moments to determine the entire density is referred to as the moments problem (Shohat and Tamarkin 1943), which arises as the result of trying to invert the mapping that takes a probability measure F to the sequences of moments

$$(5) \quad \mu_j = \int y^j dF(y), j = 1, \dots, J.$$

A practical solution to this problem is to apply the method of maximum entropy as in Stohs (2003) and Stohs and LaFrance (2004), who utilized this technique to generate de-trended unconditional yield distributions from sample moments for the purpose of premium determination. These studies identify the shape of the distribution through the error of the mean equation, thus our approach generalizes theirs in the same sense that our moment based approach generalizes the Antle (2003) framework. This section provides details of this procedure and considers some representative cases.

A brief review of the classical maximum entropy density estimation can be found in Wu and Wang (2011).² We follow the authors' discussion here. Given a continuous random variable Y with a density function f , the associated entropy is

$$(6) \quad H(f) = -\int f(y) \ln f(y) dy.$$

The principle of maximum entropy provides a method of constructing a density from known moment conditions. Suppose the density function f is unknown but a small number of moments of Y are given. There might exist an infinite number of densities satisfying the given moment conditions, however, Jaynes' (1957) Principle of Maximum Entropy suggests selecting the density, among all candidates satisfying the moment conditions, that maximizes the entropy.

Formally, the maximum entropy density is defined as

$$(7) \quad f^* = \arg \max_f H(f)$$

subject to the moment constraints

$$(8) \quad \int f(y) dy = 1, \int y^j f(y) dy = \mu_j, j = 1, \dots, J,$$

where $\mu_j = E(Y^j)$. The J constraints given in (8) can be thought of as moment constraints,

with μ_j being the population mean of the Y^j random variable. The associated Lagrangian is

$$(9) \quad L = -\int f(y) \ln f(y) dy - \left[\gamma_0 \int f(y) dy - 1 \right] - \sum_{j=1}^J \gamma_j \left[\int y^j f(y) dy - \mu_j \right].$$

The necessary conditions for an interior solution are given by

$$(10) \quad \begin{aligned} \frac{\partial L}{\partial f} &= -\ln f(y) - 1 = 0 \\ \frac{\partial L}{\partial \gamma_0} &= 1 - \int f(y) dy = 0 \\ \frac{\partial L}{\partial \gamma_j} &= \mu_j - \int y^j f(y) dy = 0, j = 1, \dots, J. \end{aligned}$$

The implied solution is the maximum entropy density and takes the form

$$(11) \quad f^*(y) = \frac{1}{\psi(\gamma^*)} \exp\left[-\sum_{j=1}^J \gamma_j^* y^j\right],$$

where $\psi(\gamma^*) = \int \exp\left[-\sum_{j=1}^J \gamma_j^* y^j\right] dy$ is the normalizing factor that insures the density integrates to unity.

The density in equation (11) is the well-known exponential family, which includes the normal, exponential, gamma, chi-square, beta, Dirichlet, Poisson, and many others as members. Given a specific set of moments, we estimate the γ parameters using predicted moments from equation (4) as the constraints.⁴ We estimate these maximum entropy distributions under alternative climate and irrigation regimes, thus allowing us to trace out distributional effects.

Data

Descriptive statistics for the data are reported in table 1. We include any county that has a full set of yield observations from 1972 to 2005.⁵ The reason for the relatively short time-period is discussed below. The data is a balanced panel of 84 counties across Arkansas (9 counties), Mississippi (11 counties) and Texas (64 counties). We have a total of 4,284 observations comprised of 476 observations from Arkansas counties, 612 from Mississippi, and 3,196 from Texas.

Yields for county-level upland cotton are collected from NASS, and are measured as 480 lb. bales per acre. We construct our yield measure as county-level production divided by planted acres. In 1972, NASS began distinguishing between irrigated and non-irrigated yields in Arkansas, Mississippi, and Texas. Since one of our main goals is to determine the effect of irrigation on the cotton yield distribution, we only include years in which this distinction is

made. Figure 1 demonstrates that there is significant spatial and temporal variation of the yield data within each state.

We use the same weather data as in Schlenker and Roberts (2009a), which spans 1950-2005 and is based on the rectangular grid system underling PRISM that covers the contiguous United States. The authors construct a distribution of temperatures within each day using a sinusoidal curve between minimum and maximum temperatures. They then estimate time in each 1°C temperature interval between -5 °C and 50 °C. The area-weighted average time at each degree over all PRISM grid cells within a county is constructed, which are then summed over the seven month cotton growing period from April through October.

The *low* measure of temperature is constructed as the number of degree days above 0°C minus the number of degree days above 14 °C, thus capturing the number of degree days within the interval. The *med* measure of temperature is constructed in the same way but with the bounds 15 °C and 31 °C. From table 1 we see that all three states have relatively similar exposure to low and medium temperatures on average, but the variation of these measures is much larger for Texas. Indeed, results from Bartlett tests of equal variance imply that variances of the weather variables are different across all pairwise combinations of states (all p-values less than 0.05). The *high* measure is the number of degree days above 32 °C. While relatively similar to Arkansas and Mississippi regarding low and medium temperature exposure, Texas cotton has twice the number of degree days within the high temperature category. In addition, Texas receives substantially less precipitation during the cotton growing season, both of which help explain the relatively low average yield compared to Arkansas and Mississippi. Figures 2 through 5 demonstrate that there is significant spatial and temporal variation of the weather data within each state. Interestingly, the intra-annual variation in all three temperature categories is

much larger for Texas suggesting a relatively large amount of weather variability across counties.

Empirical Results

Antle (1983) provides a convincing argument that focusing on the first three or four moments will provide a good approximation of the underlying distribution. We follow his approach and model the first three moments.

Since yield data is measured in per acre units, we include frequency weights based on planted acreage to control for differences across counties and irrigated versus dryland practices. One might suspect this approach introduces endogeneity, but we feel this is a minor concern for two reasons. First, the NASS distinction between irrigated and non-irrigated upland cotton data is determined by whether the acreage receives at least one application of water during the growing season (T. Gregory, Director of the MS NASS, personal communication, June 7, 2011). Thus, our dummy variable more reasonably controls for the availability of irrigation technology rather than the intensity of usage. Since installing this technology involves significant cost, the amount of irrigated acreage in a given year is likely uncorrelated with annual yield shocks. Second, even if a confluence of rare events led to wide spread non-usage of irrigation by farmers that had the technology available, the precipitation and weather variables included in the model would control for this type of event.

Another issue is whether the data can be pooled across states. To formally test this we estimate a version of equation (4) that allows for state specific parameters,

$$(12) \quad y_{ist}^j = \alpha_{ij} + \beta_{js1}low_{it} + \beta_{js2}med_{it} + \beta_{js3}high_{it} + \beta_{js4}p_{it} + \beta_{js5}p_{it}^2 + \beta_{ij6}irr_{it} \\ + \beta_{js7}irr_{it}p_{it} + \beta_{js8}irr_{it}p_{it}^2 + \beta_{js9}t + \beta_{js10}t^2 + \varepsilon_{ijt},$$

where the dependent variable y_{ist}^j is now the j^{th} power of the yield variable y_{ist} for county i in states s during period t . Using $s = 1, 2, 3$ to index the three states in our dataset, we pooled the data and tested null hypotheses of the form $H_0 : \beta_{j1k} = \beta_{j2k} = \beta_{j3k}$ for the first three moment equations $j = 1, 2, 3$.

We utilize the non-parametric block bootstrap p-value approach for testing multiple hypotheses outlined in Wooldridge (2010) to test whether the precipitation, temperature, and trend variables are the same across states. We re-sample whole years at a time to preserve correlation structures both within and across states. We construct 999 bootstrap samples and tested the null hypotheses

$$(13) \quad H_0 : \beta_{j1,1} = \beta_{j2,1} = \beta_{j3,1}, \beta_{j1,2} = \beta_{j2,2} = \beta_{j3,2}, \dots, \beta_{j1,10} = \beta_{j2,10} = \beta_{j3,10}$$

for each equation $j = 1, 2, 3$. The p-values for the three equations were 0.028, 0.022, and 0.086 respectively, suggesting that the model parameters should not be held constant across states.⁶ Thus, we estimate the parameters of the moment based model for each state separately.

Tables 2-4 reports parameter estimates of the first three moments of the yield distribution for Arkansas, Mississippi, and Texas using OLS with standard errors clustered by year to control for spatial correlation across counties. As in Schlenker and Roberts (2009a), exposure to low and medium temperatures have relatively minor effects on mean yields compared to temperatures above 32 °C. Extending their finding, we see that extreme heat continues to have a statistically significant effect on the higher order moments as well.

We find that irrigation is an important conditioning variable for all three of the moments. Of the eighty counties in our data, forty-two have both irrigated and dryland acreage. Using the average level of precipitation within each county, the county-level effect of irrigation on mean yield ranges from 0.39 to 0.52 bales per acre in Arkansas, 0.23 to 0.54 in Mississippi, and 0.33 to

0.78 in Texas. The associated p-values for the null hypothesis of a zero effect are all below 0.01. This pattern of statistical significance continues for the higher order moments, with the maximum p-value being 0.037.

The importance of the other conditioning variables is location and equation specific. For example, precipitation for dryland acreage does not appear to be an important conditioning variable in either Arkansas or Mississippi, but is for all three moments in Texas. Precipitation for irrigated acreage is important for only the first moment in Arkansas, but is important for all three in Mississippi. Again, technological change only appears to affect the first moment in Arkansas, but this finding does not generalize to Mississippi or Texas.

These findings have two immediate implications for modeling cotton yields. First, it is not sufficient to only allow the mean of the distribution to vary with weather, irrigation, and technological change; rather, a more holistic approach that takes into account the effects of these variables on higher order moments is warranted. Second, climate change research that focuses solely on the effect of climate on mean yields might not capture risk management implications.

Shape Implications under Maximum Entropy Distribution

To demonstrate the flexibility of this approach for generating county level yield distributions, we utilize the MBME approach to construct yield distributions under four different climate and irrigation regimes. The first two regimes represent historical climate conditions and distinguish between irrigated and dryland cotton acreage. These are referred to as the baseline distributions. The next two regimes consider the impact of a 1 °C uniform increase in temperature on the baseline distributions.

We report results for the two counties with the largest averages of dryland and irrigated acreage within each state. These counties are Craighead, AR, Mississippi, AR, Leflore, MS, Washington, MS, Dawson, TX, and Hale, TX. The baseline distributions are constructed for dryland and irrigated acreage by predicting the first three moments using the sample average of the data within each particular county and the estimated coefficients from tables 2-4. For each county-regime pair, this generates three predicted moments (m_1, m_2 , and m_3) which are then used in place of (μ_1, μ_2 , and μ_3) as constraints for the maximum entropy estimation.

We simulate the uniform shift in climate by creating new minimum and maximum daily temperature variables in the Schlenker and Roberts Stata do-file (<http://www.columbia.edu/~ws2162/dailyData/degreeDays.do>) that reflect a 1 °C increase. We do this for all years in the dataset and construct the corresponding degree day measures. The average of these new degree day measures across years of the simulated data represent the shift in climate. We do not consider a change in precipitation, but this could easily be accomplished in a similar manner. To be consistent with the baseline regimes, we hold all other variables constant at their sample averages.

Table 5 reports the estimated moments (m_1, m_2 , and m_3) under the four climate and irrigation regimes. Note that asterisks under the climate change regimes denote whether the predicted moment is statistically significantly different from its baseline counterpart. Similar to Schlenker and Roberts (2009b, see Table A5), we do not find strong statistical evidence of non-zero impacts under the 1 °C warming scenario for either dryland or irrigated cotton. The exception is Dawson, TX, where the effect is a reduction in mean yield of 0.101 bales (or 48 lbs) per acre and is significant at a five percent level. It is interesting to note that a significant effect on mean yield does not generally translate into a significant effect on the second and third

moments. For example, the climate change impacts suggest a mean-preserving spread for both Craighead and Mississippi, AR, as well as Washington, MS.

Figures 6-8 plot the associated maximum entropy distributions for the moments reported in Table 5, and several patterns emerge.⁷ First, the flexibility of the maximum entropy approach to capture mass points around zero is clearly demonstrated, especially with regard to Texas (Figure 8) where both dryland and irrigated acreage are susceptible to large scale crop losses. All baseline distributions in Texas have a non-zero probability of total crop loss, and the effect of climate change increases the probability of this outcome dramatically. Some of the shapes are peculiar and could be suggestive of distributional bimodality, in which case incorporating more higher order moments into MBME model could be warranted.

While the issue of an increased mass around zero does not appear to be a serious concern for Arkansas (Figure 6), there are distributional shape implications. Here, climate change has the effect of concentrating outcomes below the mean of the baseline distribution, but the implications for shallow versus deep losses are different. Specifically, the probability of outcomes just below the mean increases (more shallow loss events) but the probability of outcomes in the far left tail (deep losses) decreases. To what extent this trade-off actually effects producer welfare is not straightforward and warrants further consideration, however it should be noted that the overall trend is an exchange of upside risk for downside risk.

The results for dryland cotton in Mississippi (Figure 7) are interesting. Here we see that the effect of climate change on yields is indeed a mean preserving spread as suggested above, but the spread is *in reverse* as the outcomes become more concentrated around the mean of the distribution. While a more thorough analysis of the potential impact is surely warranted, the implication here is that if a producer values a reduction in downside risk substantially more than

an equivalent increase in upside risk, then Mississippi dryland producers might actually benefit from a 1 °C uniform increase in temperature. The results for Mississippi irrigated acreage are similar to the findings in Arkansas.

Comparison to other Approaches

A potential concern is whether the MBME approach developed here is preferable to other, simpler approaches. For example, one might consider combining the mean equation for each state s ,

$$(14) \quad y_{ist} = \alpha_i + \beta_{s1}low_{it} + \beta_{s2}med_{it} + \beta_{s3}high_{it} + \beta_{s4}p_{it} + \beta_{s5}p_{it}^2 + \beta_{s6}irr_{it} \\ + \beta_{s7}irr_{it}p_{it} + \beta_{s8}irr_{it}p_{it}^2 + \beta_{s9}t + \beta_{s10}t^2 + \varepsilon_{ist},$$

with the distributional assumption $\varepsilon_{ist} \sim N(0, \sigma_s^2)$. This would generate county-level conditional normal distributions that are homoskedastic within states, and the required parameters are easily estimated using a single OLS step. We will call this approach the Mean Based Gaussian (MBG) model. Alternatively, one could relax the homoskedasticity restriction and assume that $\varepsilon_{ist} \sim N(0, \sigma_s^2(\mathbf{x}_{it}))$, in which case the likely second stage FGLS specification for $\sigma_s^2(\mathbf{x}_{it})$ is the same as (14). We refer to this approach as the Mean Based Gaussian Heteroskedastic (MBGH) model, and note that it is essentially Antle's (1983) LMM model under a Gaussian distributional assumption.

Figures 9-14 compare the MBME, MBG, MBGH models under the four climate and irrigation regimes for each county. Looking at Figures 9 and 10, it is immediately clear that the Gaussian models do not have the flexibility to capture fat tails or skewness relative to the MBME model. Interestingly, when comparing the Baseline Dryland to the 1C Shift Dryland panels we see that the MBME model is capable of shifting from a non-normal distribution (Baseline panel)

to something very similar to a normal distribution (1C Shift Dryland) under the climate change scenario. Indeed, the Maximum Entropy approach essentially nests the entire exponential family of distributions, a very desirable property for modeling distributional impacts of climate change.

The strength of the MBME model to essentially nest the MBG and MBGH models is again displayed by the distributional plots for Mississippi (Figures 11 and 12). Interestingly, for the 1C Shift Dryland panels, we see that the MBG and MBGH tails are actually too thick relative to the MBME model. Not surprisingly, the MBG and MBGH models get the lower tails wrong for Texas yield distributions (Figures 13 and 14). The ability of the MBME model to include a bounded support insures that negative yields are probabilistically impossible, a convenient feature where large scale crop losses are not uncommon.

Conclusion

The proposed research provides a flexible method for linking weather and irrigation variables to the moments of yield distributions. The estimated moments can be used to construct estimates of the maximum entropy distributions, which allow one to trace weather and irrigation effects through to the shape of the distribution. We considered the case of Arkansas, Mississippi, and Texas upland cotton yields to demonstrate how climate change and irrigation affect the shape of the yield distribution. We illustrated several advantages of our moment based maximum entropy approach, including flexibility of the distributional tails across alternative irrigation and climate regimes.

Future extensions of this work should include forecasting the moments of the yield distribution under a variety of climate and irrigation scenarios. For example, one could use our empirical framework and results to forecast expected changes in yield variability under current

climate conditions and a, say, twenty percent reduction in irrigated acreage. Alternatively, one could forecast changes using climate predictions from the Hadley III model and hold current irrigated acreage constant. Finally, and perhaps most interestingly, one could forecast the long run effects of simultaneously changing both irrigation acreage and climate.

Footnotes

1. One can view our simple approach as providing a first order approximation of the relationship between the moment(s) and the conditioning variables. Perhaps a more exhaustive approach would consider nonlinearities in this relationship, in which case generalized additive models (Hastie and Tibshirani, 1986), multivariate adaptive regression splines (MARS) (Friedman, 1991), neural networks (Richards, Patterson, and Van Ispelen, 1998 apply this approach to tomato marketing margins), and projection pursuit regression (Friedman and Stuetzle, 1981) might prove useful.

2. The work of Schlenker, Hanemann, and Fisher (2005) contributed to a line of research debating the potential impact of global climate change on U.S. Agriculture. Related studies include Adams (1989); Kaiser et al. (1993); Mendelsohn, Nordhaus, and Shaw (1994); Adams et al. (1995); Schlenker and Roberts (2006); Schlenker, Hanemann, and Fisher (2006); Deschenes and Greenstone (2007); Schlenker and Roberts (2009a); Ashenfelter and Storchmann (2010); and Hertel and Rosch (2010).

3. Additional descriptions of the method of maximum entropy can be found in Jaynes (1982); Zellner and Highfield (1988); Golan, Judge, and Miller (1996), Mittelhammer, Judge, and Miller (2000), Ormoneit and White (1999), and Tagliani (1993).

4. To estimate the univariate maximum entropy distributions, we utilize the sequential updating method developed in Wu (2003). Matlab code for this approach is available on Ximing Wu's web page at <http://agecon2.tamu.edu/people/faculty/wu-ximing/>

5. The use of county-level data is common in the literature as it is the most disaggregate level where long time series are available. One could use farm-level data but then would have to confront issues related to the limited number of time series observations. On average, farm level variability will be greater than county variability.

6. To be fair to Schlenker and Roberts (2009a, 2009b), we did find evidence in favor of pooling the low, medium, and high temperature parameters across states for the mean equation (which is line with their approach).

7. An important caveat to note is that we do not include standard errors for the distributions. Since this is a two stage approach that combines both regression and maximum entropy estimators, and is applied to panel data, one must be very careful in identifying the appropriate sources of error when constructing estimates of the underlying conditional distributions. Perhaps block bootstrapping the underlying sample data by year and carrying each bootstrap iteration through to the maximum entropy distribution estimation would prove useful. As is, our findings in this section are merely suggestive.

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Table 1. Yield, Weather, and Irrigation Data: 1972-2005

Variable	Sample Mean (s.d.)	Min	Max	# of obs
Arkansas				
Upland Cotton Yield (480 lb. bales per acre)	1.263(0.4183)	0.2689	2.517	476
Low Temperature (degree days)	3063(38.27)	2947	3147	476
Medium Temperature (degree days)	1666(126.9)	1339	2127	476
High Temperature (degree days)	27.23(19.15)	4.000	118.5	476
Precipitation (10 centimeters)	6.905(1.320)	4.336	11.19	476
Irrigation (Yes = 1)	0.3571(0.4796)	0	1	476
Mississippi				
Upland Cotton Yield (480 lb. bales per acre)	1.541(0.3874)	0.4832	2.550	612
Low Temperature (degree days)	3095.5(30.50)	3013	3152	612
Medium Temperature (degree days)	1789(122.4)	1446	2154	612
High Temperature (degree days)	29.58(18.81)	4.177	94.01	612
Precipitation (10 centimeters)	7.354(1.596)	4.191	11.66	612
Irrigation (Yes = 1)	0.3888(0.4878)	0	1	612
Texas				
Upland Cotton Yield (480 lb. bales per acre)	0.7972(0.4780)	0.006599	3	3196
Low Temperature (degree days)	3052(84.94)	2808	3209	3196
Medium Temperature (degree days)	1760(304.0)	1139	2694	3196
High Temperature (degree days)	61.70(34.97)	4.118	207.2	3196
Precipitation (10 centimeters)	4.436(1.616)	0.9259	15.71	3196
Irrigation (Yes = 1)	0.4042(0.4908)	0	1	3196
Overall				
Upland Cotton Yield (480 lb. bales per acre)	0.9554(0.5381)	0.006599	3	4284
Low Temperature (degree days)	3059(76.84)	2808	3209	4284
Medium Temperature (degree days)	1754(271.9)	1139	2694	4284
High Temperature (degree days)	53.28(34.82)	4.000	207.2	4284
Precipitation (10 centimeters)	5.127(1.980)	0.9259	15.71	4284
Irrigation (Yes = 1)	0.3968(0.4892)	0	1	4284

Notes: Values reported for temperature and precipitation variables correspond to the April through October growing season. Low temperature measures degree days between 0C and 14C; medium temperature measures degree days between 15C and 31C; and high temperature measures degree days above 32C.

Table 2. Effect of Weather and Irrigation on Cotton Yield Moments, Arkansas

Dependent variable:	1 Yield	2 Yield ²	3 Yield ³
Low Temperature	-0.000648 [0.00183]	-0.000538 [0.00581]	0.00103 [0.0148]
Medium Temperature	0.000754 [0.000645]	0.000791 [0.00193]	-0.000153 [0.00470]
High Temperature	-0.0109*** [0.00309]	-0.0227** [0.0102]	-0.0399 [0.0252]
Precipitation	0.112 [0.164]	0.184 [0.428]	0.280 [0.920]
Precipitation Squared	-0.00882 [0.0103]	-0.0162 [0.0271]	-0.0283 [0.0586]
Irrigation*Precipitation	-0.458* [0.247]	-1.171 [1.086]	-2.569 [3.504]
Irrigation*Precipitation Squared	0.0304* [0.0170]	0.0761 [0.0744]	0.161 [0.239]
Trend	0.0297** [0.0143]	0.0395 [0.0407]	0.00162 [0.101]
Trend Squared	-0.000285 [0.000424]	0.000361 [0.00130]	0.00314 [0.00336]
County Fixed Effects	Y	Y	Y
County Specific Irrigation Effects	Y	Y	Y
Mean of Dependent Variable	1.263882	1.772074	2.702048
N	476	476	476
R-sq	0.749	0.711	0.654

Notes: Table shows results of regressing yield, yield², and yield³ on weather, trend, and irrigation variables. Weather variables are aggregated for the months April-October. Planted acre frequency weights are included. Clustered standard errors by year are in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 3. Effect of Weather and Irrigation on Cotton Yield Moments, Mississippi

Dependent variable:	1 Yield	2 Yield ²	3 Yield ³
Low Temperature	-0.000941 [0.00210]	-0.00322 [0.00662]	-0.00835 [0.0165]
Medium Temperature	0.00167** [0.000655]	0.00402** [0.00193]	0.00800 [0.00473]
High Temperature	-0.0121*** [0.00283]	-0.0331*** [0.00902]	-0.0727*** [0.0229]
Precipitation	0.252 [0.158]	0.701 [0.447]	1.564 [1.035]
Precipitation Squared	-0.0156 [0.00953]	-0.0432 [0.0268]	-0.0958 [0.0615]
Irrigation*Precipitation	-0.424** [0.192]	-1.267* [0.634]	-2.943 [1.740]
Irrigation*Precipitation Squared	0.0266** [0.0123]	0.0819* [0.0414]	0.196* [0.115]
Trend	0.0315** [0.0127]	0.0772** [0.0356]	0.149* [0.0851]
Trend Squared	-0.000634 [0.000399]	-0.00138 [0.00120]	-0.00226 [0.00302]
County Fixed Effects	Y	Y	Y
County Specific Irrigation Effects	Y	Y	Y
Mean of Dependent Variable	1.541315	2.525506	4.348466
N	612	612	612
R-sq	0.641	0.606	0.559

Notes: Table shows results of regressing yield, yield², and yield³ on weather, trend, and irrigation variables. Weather variables are aggregated for the months April-October. Planted acre frequency weights are included. Clustered standard errors by year are in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 4. Effect of Weather and Irrigation on Cotton Yield Moments, Texas

Dependent variable:	1 Yield	2 Yield ²	3 Yield ³
Low Temperature	-0.000362 [0.00120]	-0.000697 [0.00211]	-0.00110 [0.00354]
Medium Temperature	0.000244 [0.000660]	0.000576 [0.00111]	0.00117 [0.00177]
High Temperature	-0.00449** [0.00169]	-0.00663** [0.00283]	-0.0102** [0.00471]
Precipitation	0.221*** [0.0659]	0.303*** [0.102]	0.439** [0.174]
Precipitation Squared	-0.0216*** [0.00507]	-0.0292*** [0.00732]	-0.0414*** [0.0120]
Irrigation*Precipitation	-0.360*** [0.105]	-0.447** [0.200]	-0.494 [0.385]
Irrigation*Precipitation Squared	0.0301*** [0.0109]	0.0342 [0.0220]	0.0314 [0.0447]
Trend	-0.0122 [0.0148]	-0.0286 [0.0260]	-0.0621 [0.0450]
Trend Squared	0.000646 [0.000436]	0.00151* [0.000820]	0.00311** [0.00149]
County Fixed Effects	Y	Y	Y
County Specific Irrigation Effects	Y	Y	Y
Mean of Dependent Variable	0.797274	0.8641389	1.153844
N	3196	3196	3196
R-sq	0.553	0.519	0.450

Notes: Table shows results of regressing yield, yield², and yield³ on weather, trend, and irrigation variables. Weather variables are aggregated for the months April-October. Planted acre frequency weights are included. Clustered standard errors by year are in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 5. Distributions for Climate and Irrigation Scenarios

Scenario	m₁	m₂	m₃
Baseline Dryland			
<i>Craighead, AR</i>	1.125590	1.430990	2.017554
<i>Mississippi, AR</i>	1.239172	1.707981	2.555988
<i>Leflore, MS</i>	1.396610	2.080046	3.281212
<i>Washington, MS</i>	1.568801	2.561124	4.333720
<i>Dawson, TX</i>	0.5531182	0.3960293	0.324448
<i>Hale, TX</i>	0.5478938	0.4068280	0.3861314
Baseline Irrigated			
<i>Craighead, AR</i>	1.593657	2.808411	5.278339
<i>Mississippi, AR</i>	1.617925	2.819924	5.121613
<i>Leflore, MS</i>	1.764068	3.274664	6.286099
<i>Washington, MS</i>	1.799910	3.419940	6.750760
<i>Dawson, TX</i>	1.256312	1.801851	2.864571
<i>Hale, TX</i>	1.090115	1.383261	1.917055
Climate Change Dryland			
<i>Craighead, AR</i>	1.026941	1.124128*	1.290311*
<i>Mississippi, AR</i>	1.157627	1.435100	1.885012*
<i>Leflore, MS</i>	1.381632	1.934819	2.792643
<i>Washington, MS</i>	1.546785	2.397130	3.804814*
<i>Dawson, TX</i>	0.4519883**	0.2738109	0.1774388
<i>Hale, TX</i>	0.4807599	0.3331543	0.3134910
Climate Change Irrigated			
<i>Craighead, AR</i>	1.495009	2.501549*	4.551096*
<i>Mississippi, AR</i>	1.536380	2.547043	4.450636*
<i>Leflore, MS</i>	1.749090	3.129437	5.797530
<i>Washington, MS</i>	1.777894	3.255946	6.221853*
<i>Dawson, TX</i>	1.155182**	1.679633	2.717562
<i>Hale, TX</i>	1.022982	1.309588	1.844415

Notes: This table reports the estimated moments for the Maximum Entropy estimator of the yield distribution for under baseline climate and a 1 C uniform increase in daily temperature. For the climate change regimes, we include asterisks to denote statistically significant differences relative to each county's baseline counterpart. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

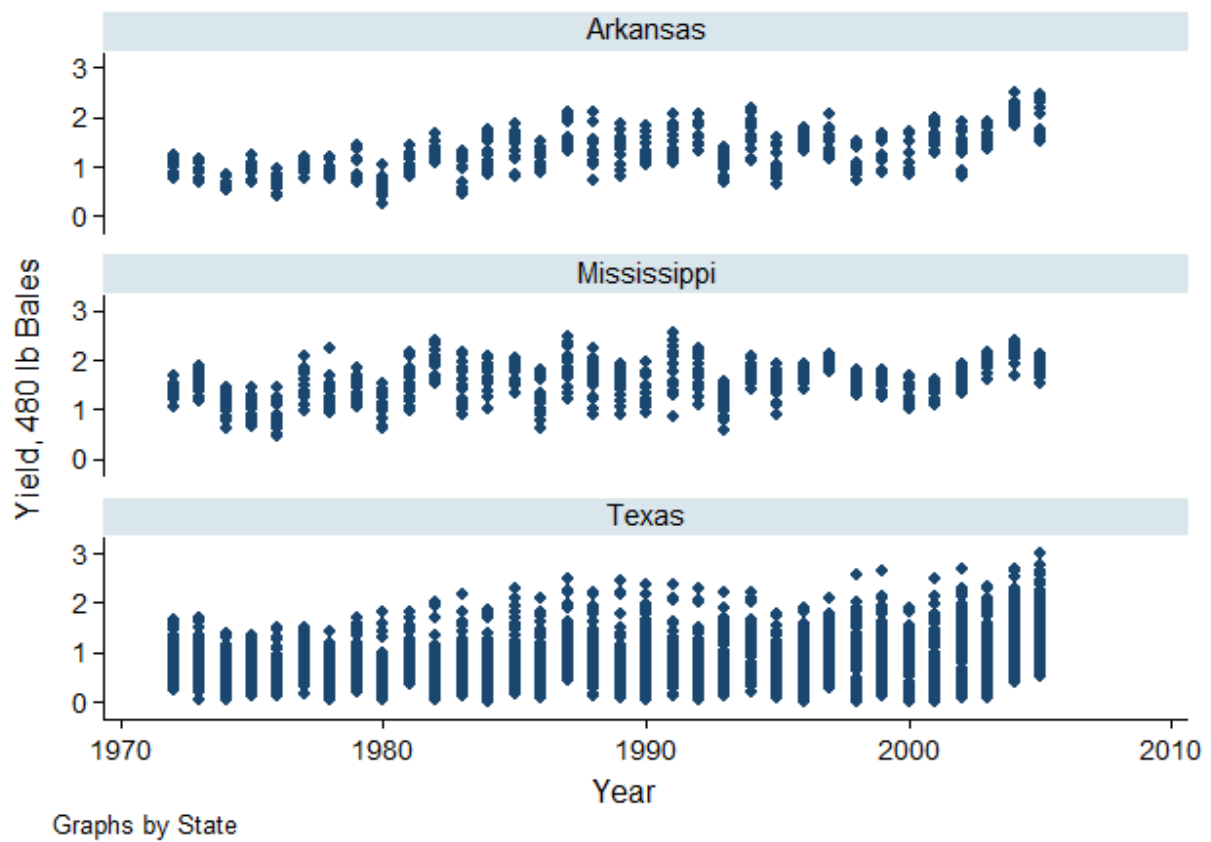


Figure 1. County Level Variation in Yield, by State

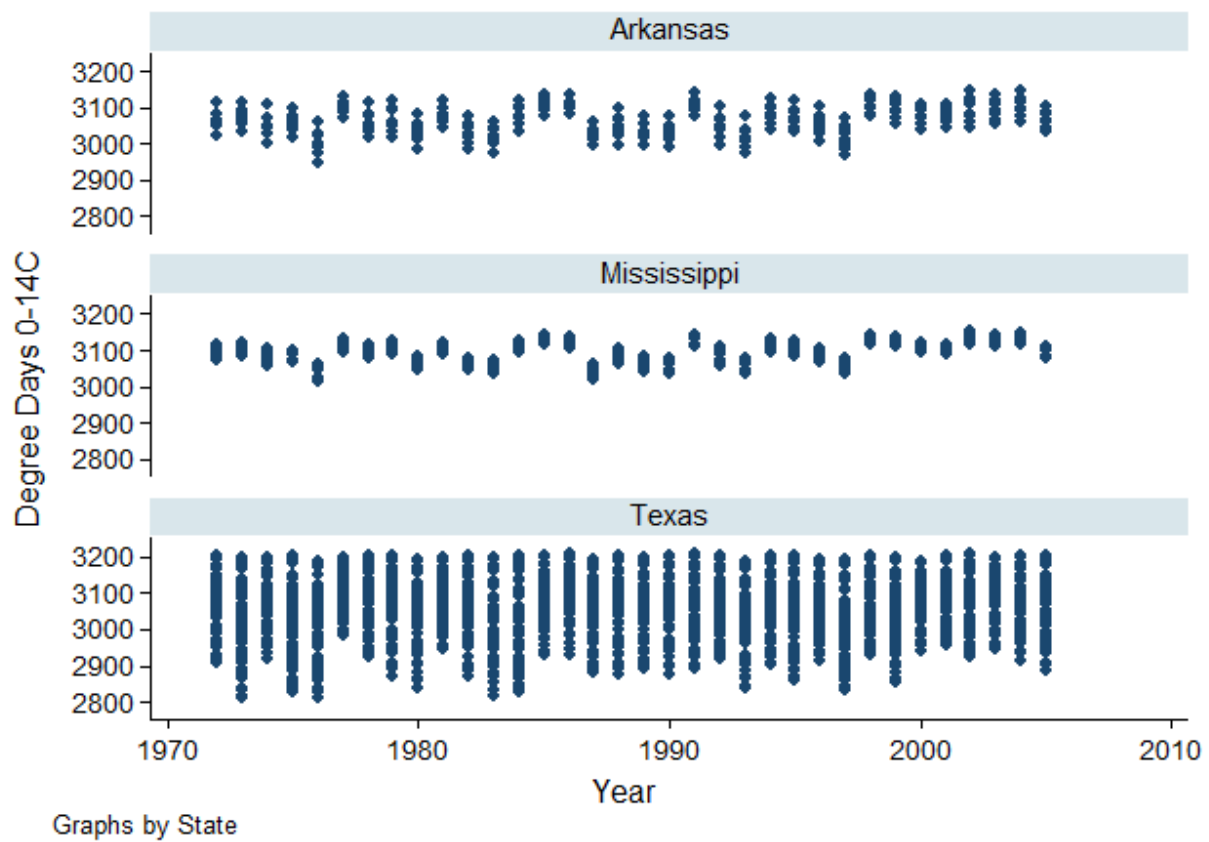


Figure 2. County Level Variation in Low Temperature, by State

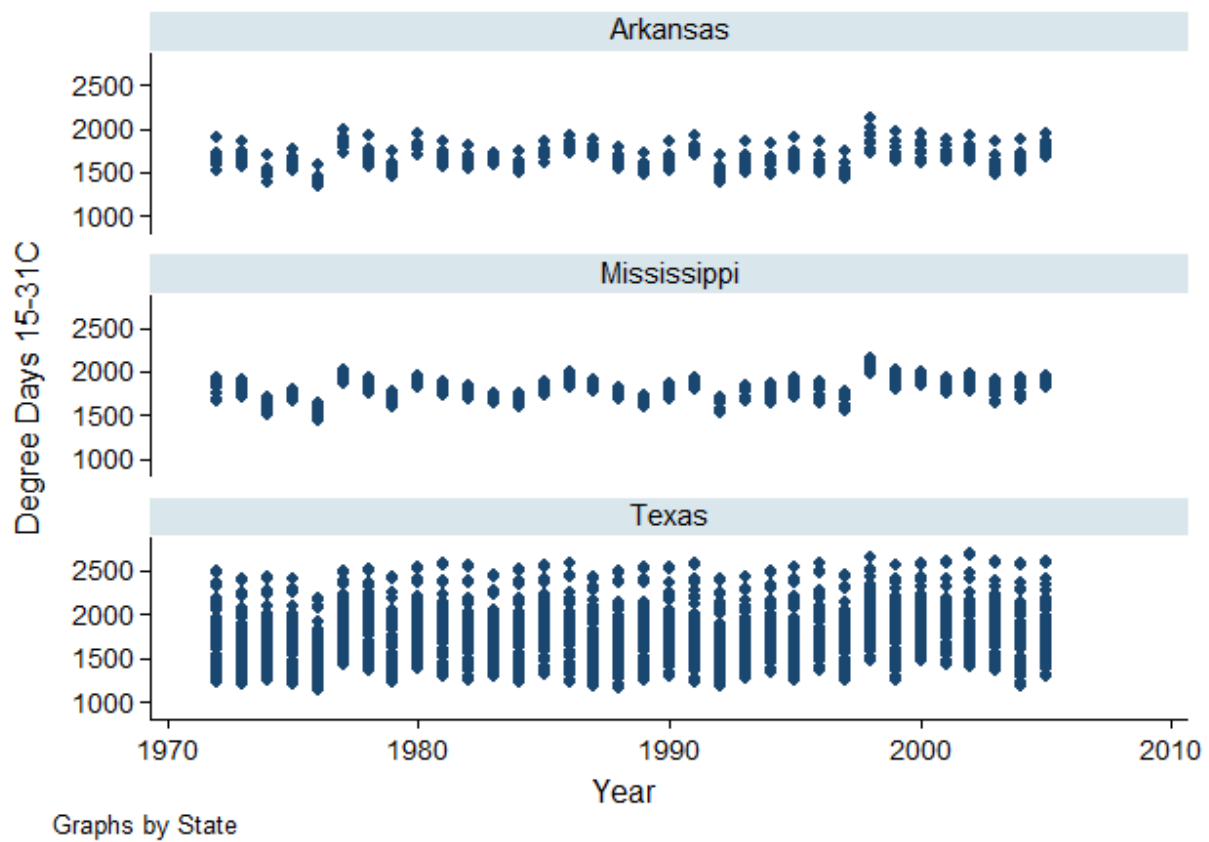


Figure 3. County Level Variation in Medium Temperature, by State

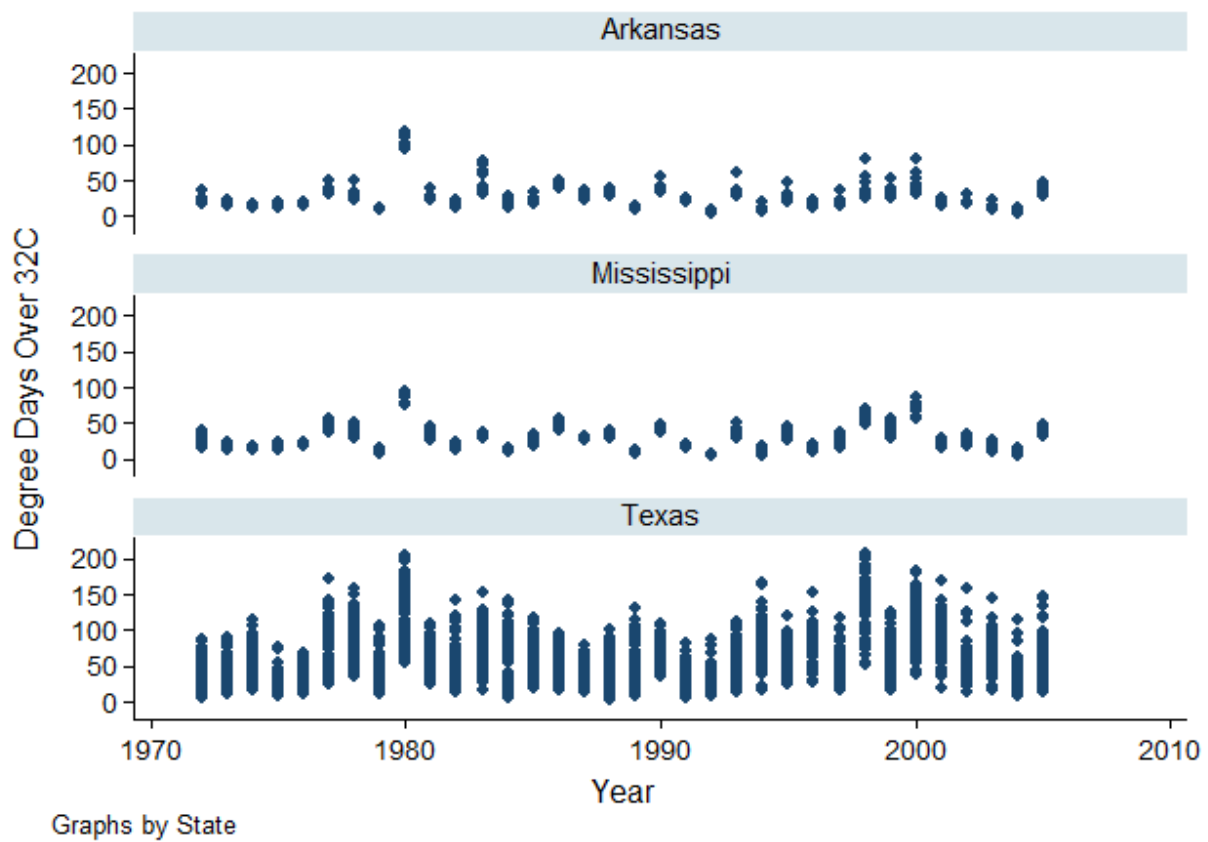


Figure 4. County Level Variation in High Temperature, by State

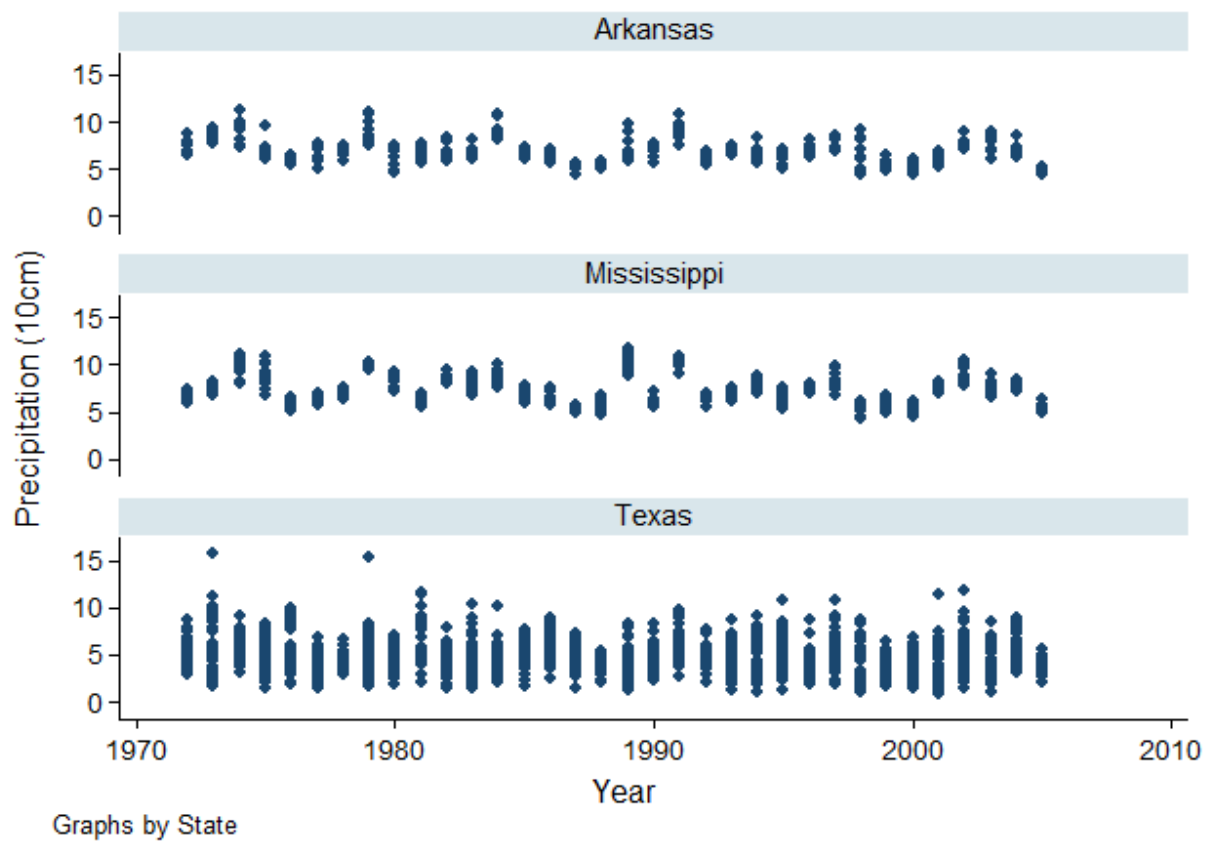


Figure 5. County Level Variation in Precipitation, by State

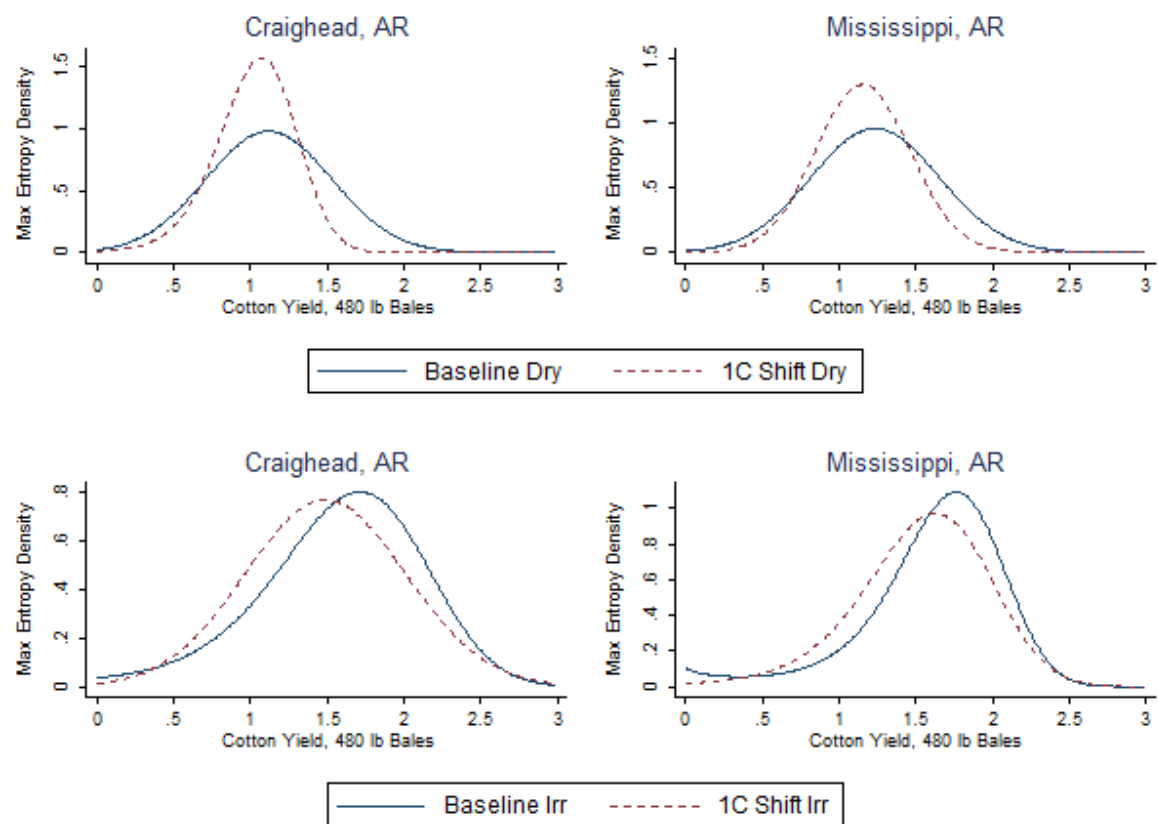


Figure 6. Maximum Entropy Distributions under Four Climate and Irrigation Regimes, Arkansas

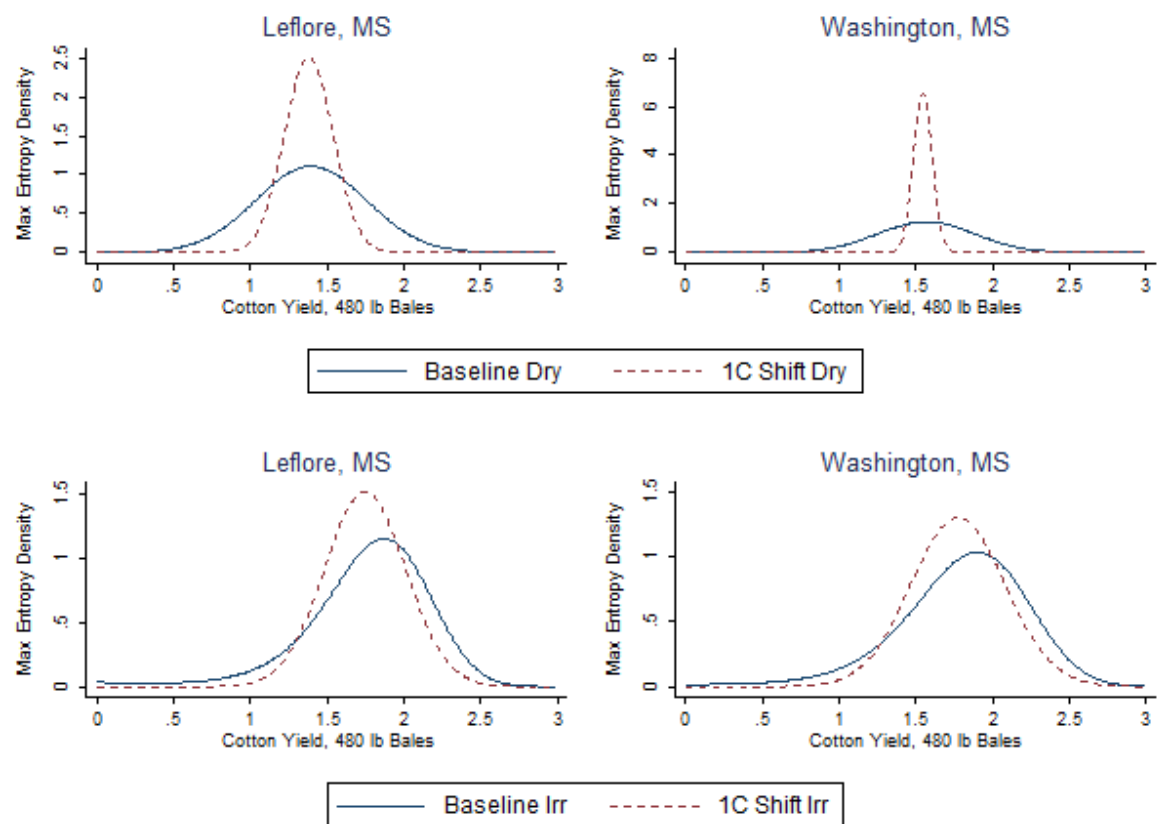


Figure 7. Maximum Entropy Distributions under Four Climate and Irrigation Regimes, Mississippi

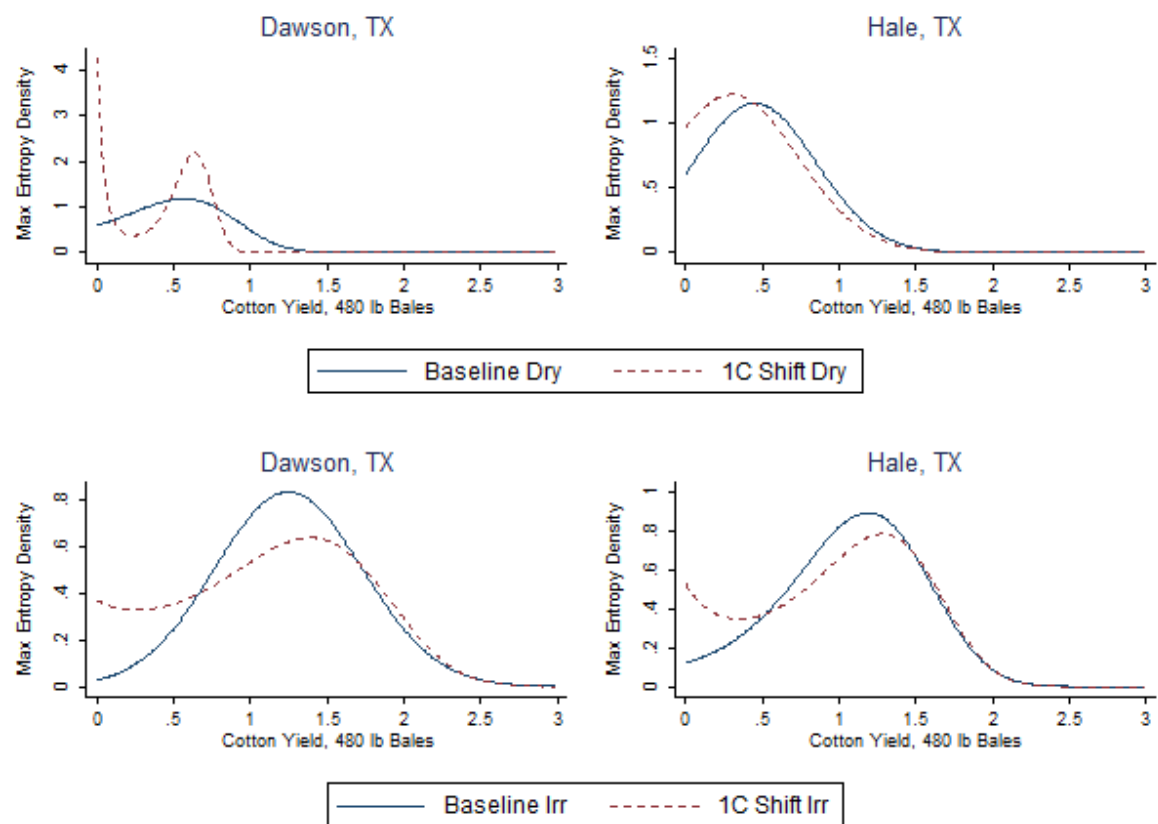


Figure 8. Maximum Entropy Distributions under Four Climate and Irrigation Regimes, Texas

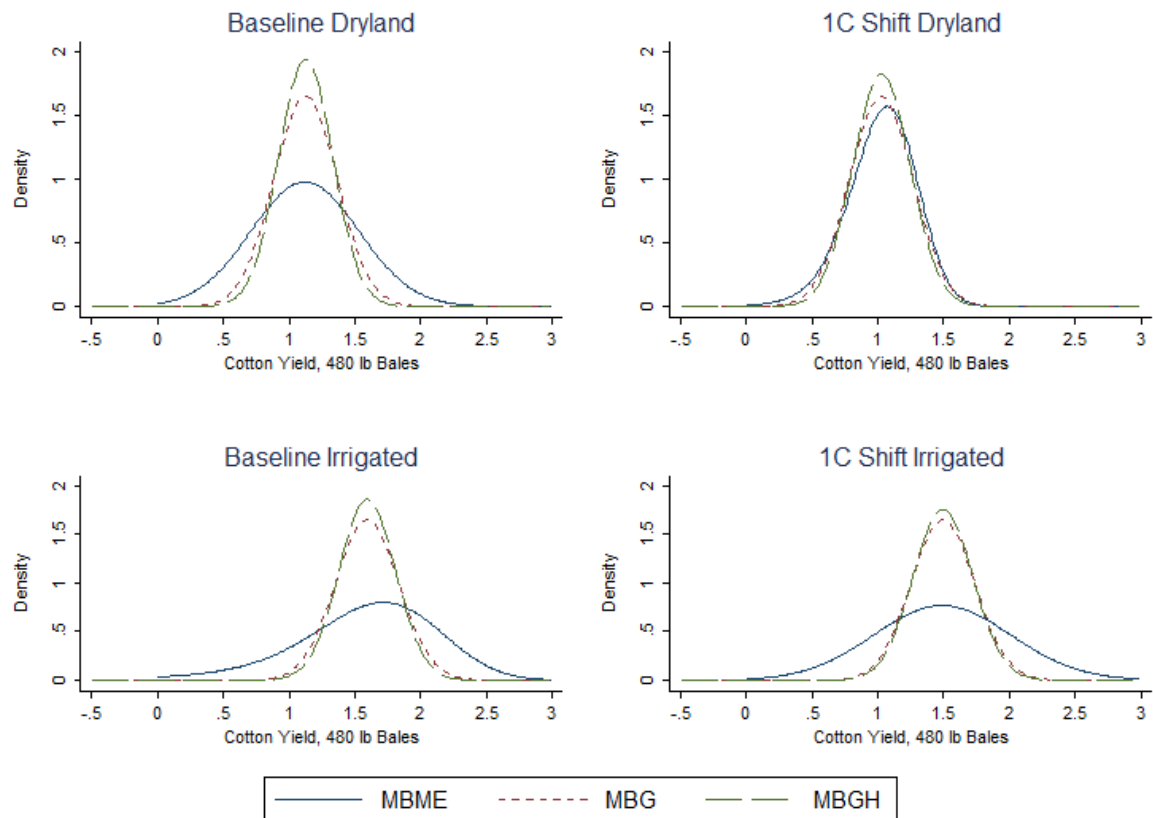


Figure 9. Distributions from the Moment Based Maximum Entropy (MBME), Mean Based Gaussian (MBG), and Mean Based Gaussian Heteroskedastic (MBGH) Models for Craighead, Arkansas

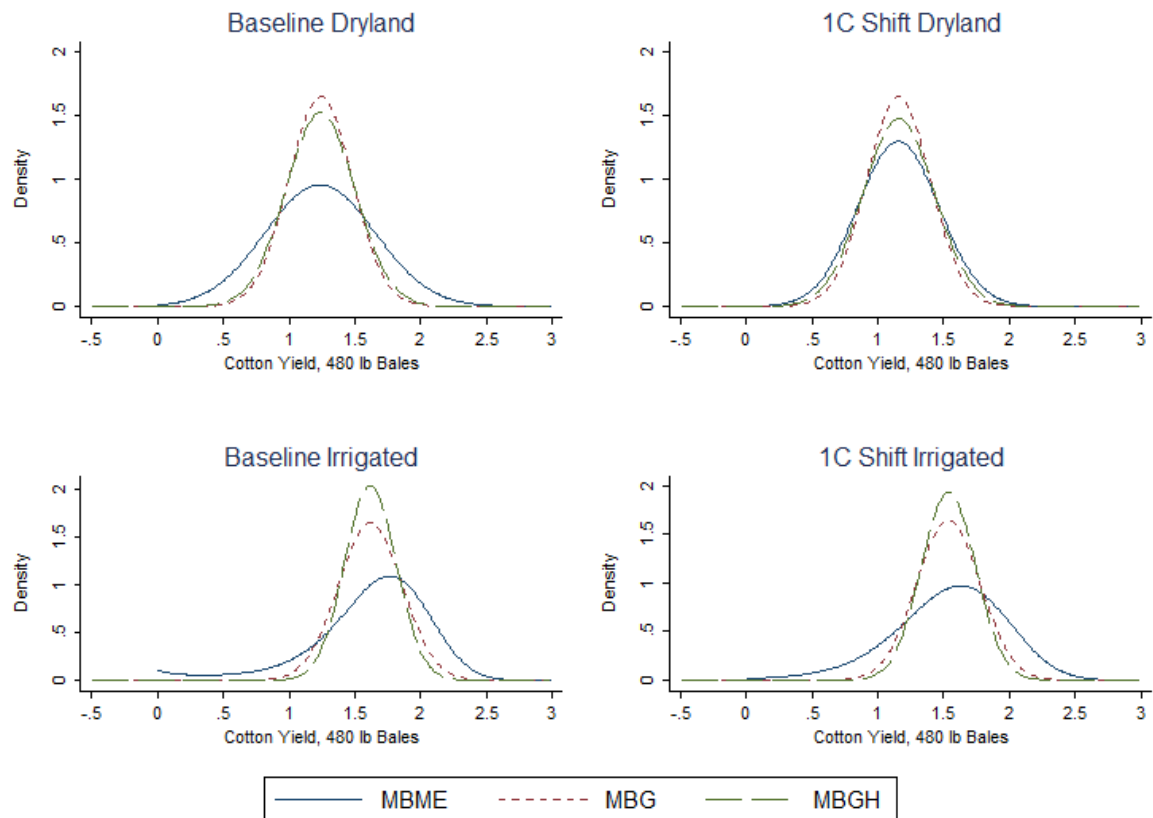


Figure 10. Distributions from the Moment Based Maximum Entropy (MBME), Mean Based Gaussian (MBG), and Mean Based Gaussian Heteroskedastic (MBGH) Models for Mississippi, Arkansas

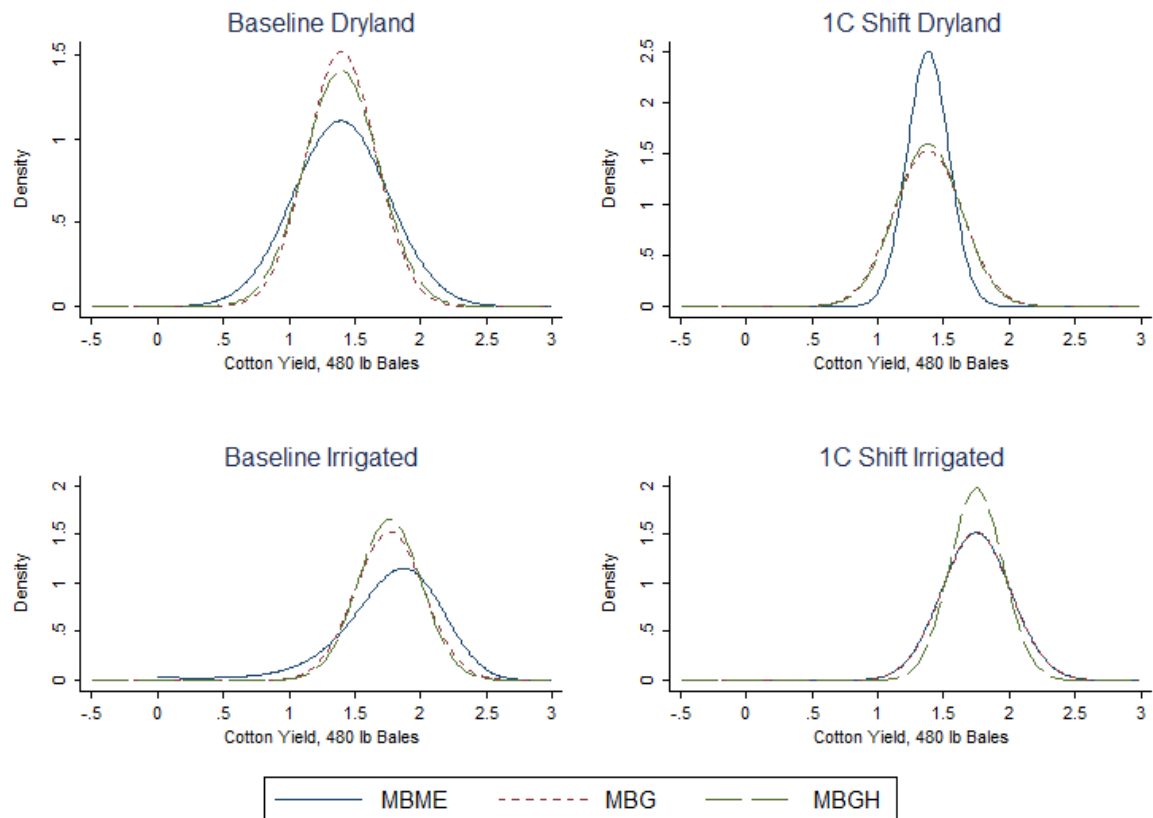


Figure 11. Distributions from the Moment Based Maximum Entropy (MBME), Mean Based Gaussian (MBG), and Mean Based Gaussian Heteroskedastic (MBGH) Models for Leflore, Mississippi

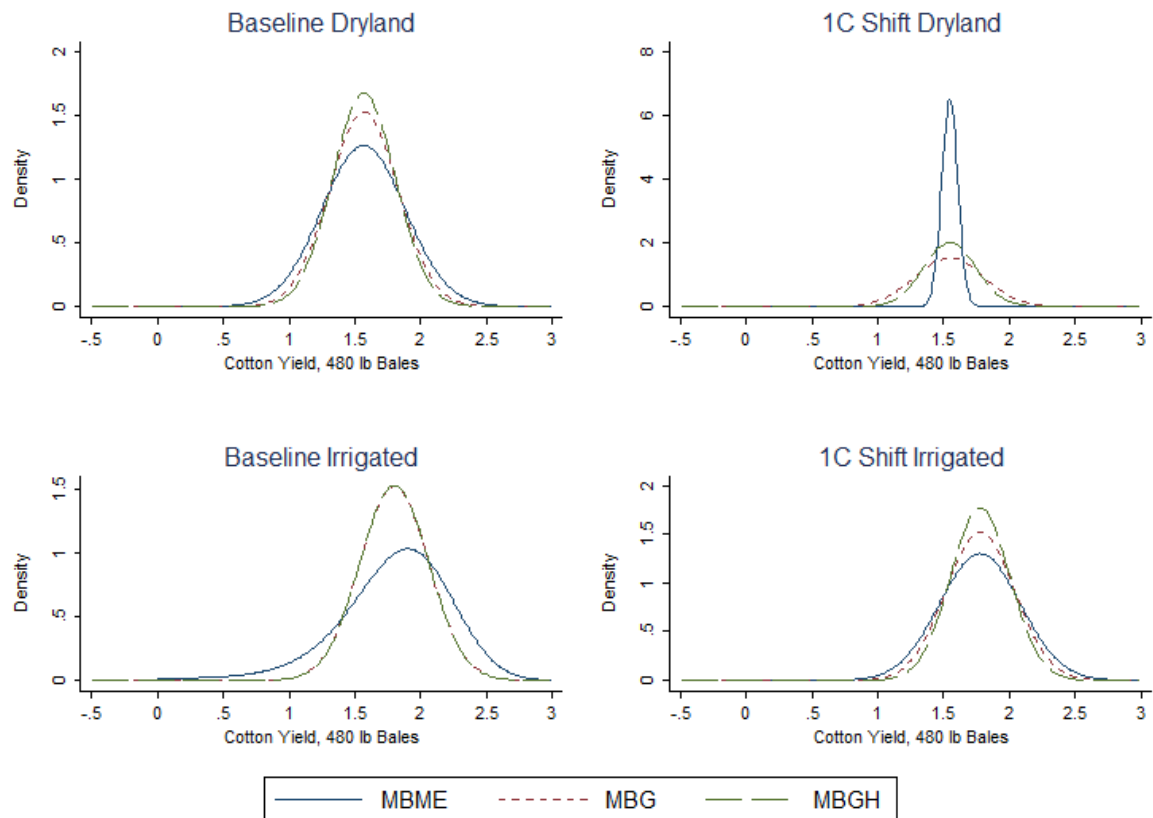


Figure 12. Distributions from the Moment Based Maximum Entropy (MBME), Mean Based Gaussian (MBG), and Mean Based Gaussian Heteroskedastic (MBGH) Models for Washington, Mississippi

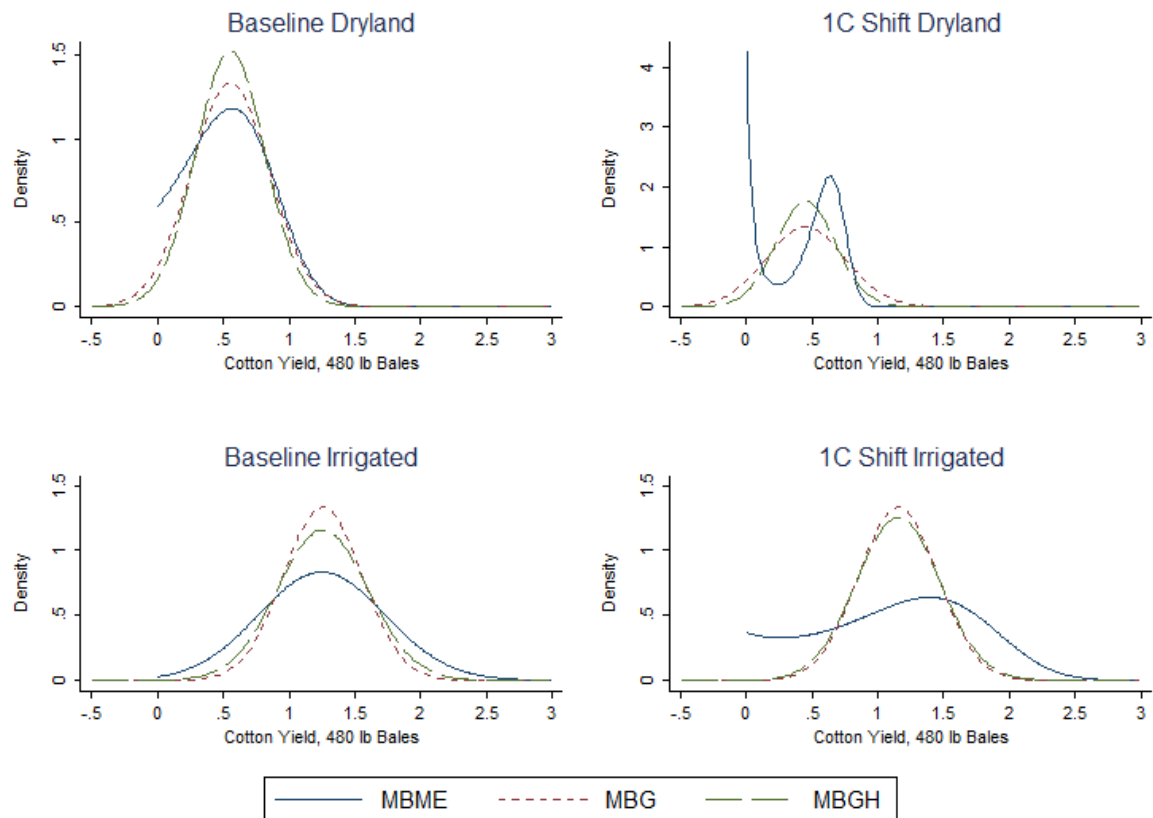


Figure 13. Distributions from the Moment Based Maximum Entropy (MBME), Mean Based Gaussian (MBG), and Mean Based Gaussian Heteroskedastic (MBGH) Models for Dawson, Texas

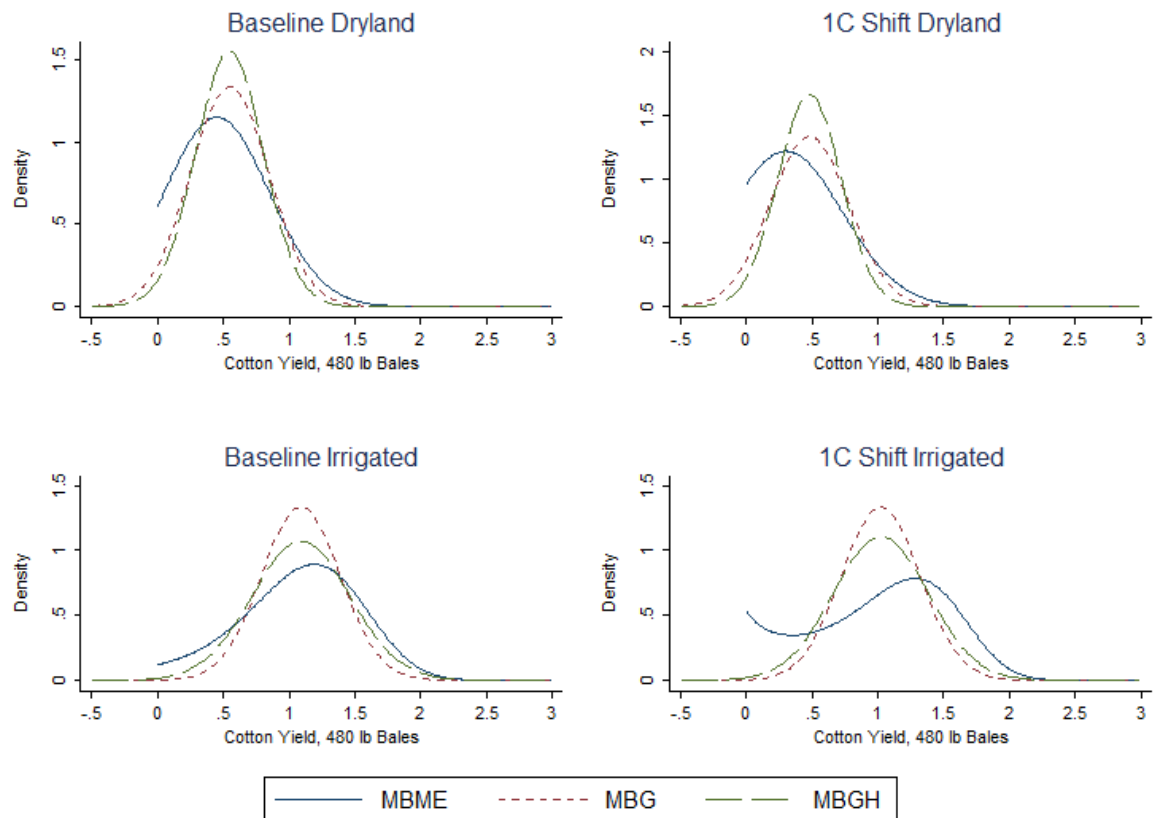


Figure 14. Distributions from the Moment Based Maximum Entropy (MBME), Mean Based Gaussian (MBG), and Mean Based Gaussian Heteroskedastic (MBGH) Models for Hale, Texas