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Effect of Late Season Precipitation on Cotton Yield Distributions

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Introduction

Cotton is a tropical plant with an intermediate growth habit and extreme sensitivity to adverse environmental conditions. It is one of the major row crops produced in the US, and historically has been an important component of the Mississippi agricultural economy. However, Mississippi cotton production has seen a decline over recent years as a result of economic forces and changing climate conditions.

Current research on the effects of climate change on cotton production typically focuses on the effect of some aggregated measure of precipitation. Gwimbi and Mundoga (2010) measured impact of climate change for the entire growing season of cotton and found that cotton production levels declined as precipitation decreased and temperature increased. They further noted that although other factors such as soil fertility and farm management practices had an important influence on agriculture, climate remained the dominant factor influencing cotton production. AbdelGadir et al. (2012) investigated irrigation effect on cotton yield and found that irrigation significantly increased seed cotton yield in seasons with inadequate rainfall. However, the effect of climate change on cotton yields may not only depend on precipitation, but the precipitation occurring during specific growth stages (germination, fruiting, and maturation). Only a few studies (Parvin et al., 2005; Williford et al., 1995) have focused on the relationship between the effects of early- and late-season precipitation on cotton yields.

Cotton requires between 550 mm and 950 mm (22 to 37 in.) of precipitation during the season in a consistent and regular pattern (Doorenbos et al., 1984). However, untimely rainfall and/or irrigation as well as humid weather during the latter stages of cotton growth, primarily once the

bolts begin to open, may complicate defoliation, reduce yield and quality, lower the crop's ginning properties, or promote the attack of insect pests and disease organisms such as boll rot (Freeland et al., 2004; Williford, 1992; Boyd et al., 2004). Once the boll has opened, exposure of cotton lint to the environment causes withering and the fibers can become stained, spotted, dark, and dull (Freeland et al., 2006).

Of particular interest is the effect of rainfall during harvest. According to Riley (1961), excessive rain generates poor harvest conditions as mechanical equipment becomes inoperative when soils are water-logged. If rain persists, maturity may be delayed until the plants are caught by frost. In addition, excessive rain may generate periods of high humidity, which can in turn greatly reduce the quality of the cotton if it is picked while wet. Parvin et al. (2005) found that an additional centimeter of accumulated rainfall during harvest reduced yields by 0.10 kg, and Williford et al. (1995) found that each successive rain event during harvest also generated a reduction in yield.

Studies linking weather to yield outcomes may either be done through agronomy-based-simulation models, reduced-form regression analysis and/or reduced-form natural experiments (Schlenker and Roberts 2006; 2009a). The reduced-form natural experiment is the preferred approach as it combines the strengths of the reduced-form approach with those of crop-simulation models (Schlenker and Roberts 2006; 2009a). Modeling approaches for yield distributions may either be parametric, semi parametric and or nonparametric. Tack et al. (2012) asserts that in modeling yield variability in response to climate change, two main lines of research have been employed. The first combines stochastic weather generators as in with agricultural crop models to simulate effects on the mean and variability of crop yields (e.g. Wang

et al., 2011; Wilks, 1992), while the second relies on historical data to identify the effects of weather variables within a regression-based framework (e.g. Adams et al., 2001; Boubacar, 2010; Schlenker and Roberts, 2009a).

As noted earlier, research focusing on the effects of changing climate on cotton production has typically focused on the effect of aggregate intra-annual precipitation and temperature variables. Even if the underlying raw data contains observations at a more disaggregate level (ie daily/weekly/monthly), in practice they are aggregated up to an annual measure to match the observation-level of yields. This approach is potentially limiting as it artificially smooth over intra-season weather events and patterns that could have large production effects. While there are other likely intra-season events that have appreciable production effects, this research focuses on the effects of early- versus late-season precipitation. This distinction is important as heavy rains occurring near anticipated harvest dates might cause substantial reductions in realized yields.

The objective of this research is to use regression analysis to estimate the effect of late season precipitation on Mississippi cotton yields. While most studies investigating relationships between yield and climate focus on mean effects, we exploit the Moment Based Maximum Entropy (MBME) framework of Tack et al. (2012) to identify the effect of late season precipitation on the entire yield distribution. They report high temperatures and lack of irrigation concentrate yield outcomes toward the lower tail of the distribution, thus having significant implications for price variability, risk management, crop insurance, and other commodity support programs.

This research is relevant because our empirical findings will provide producers and policy makers with a better understanding of the relationship between production and climate. In addition, the proposed regression approach will provide a scientific framework for developing climate change forecasts that take into account the timing of precipitation events under different climatic scenarios. The remainder of this paper is as follows: Section 2 discusses the empirical model, while Section 3 describes the yield and climate data. Section 4 presents the empirical results and Section 5 concludes.

2. Empirical Framework

The MBME framework consists of two parts, the first of which is a moment model along the lines of Antle (1983, 2010). The moments of the yield distribution are expressed as parameterized functions of weather variables, and the parameters are empirically identified using historical data. The estimated parameters are then used to predict the moments under alternative climate scenarios. The second component uses these predicted moments to estimate the yield density using the principle of maximum entropy. A more detailed description of this approach and its advantages is available in Tack et al. (2012).

The MBME approach requires a distributional specification for yields, and we first considered using a normality assumption. The normality of crop yields has been a long standing issue in the literature (e.g. Day, 1965; Taylor, 1990; Ramirez, 1997; Harri et al, 2008). Whilst some researchers have reported negative skewness for certain crops others also reported positive skewness for these same crops. Using a single omnibus test for farm-level data, Just and Weninger (1999) reassessed the evidence for non-normality using the same data as previous

studies. They argue that these studies falsely rejected normality and reported that previous empirical literature did not provide enough evidence to conclude non-normality as previous research was plagued with misspecification errors and misreporting of statistical significance. For this study, the normality assumption generated densities with a large amount of probability mass over the negative real line. As crop yields are non-negative by definition, we took this as a major concern and utilized a lognormal assumption instead.

2.1 Modeling Lognormal Moments

It is well known that the lognormal is a member of the exponential family of distributions, and is characterized by the first and second logarithmic moments $E[\ln Y]$ and $E[(\ln Y)^2]$. To generate predicted values for these moments under alternative climate scenarios, we utilize the regression model

$$\begin{aligned} \ln(y_{it})^j = & \beta_{j0} + \beta_{j1}low_{it} + \beta_{j2}med_{it} + \beta_{j3}high_{it} + \beta_{j4}eprecip_{it} + \beta_{j5}lprecip_{it} \\ & + \beta_{j6}irr_{it} + \beta_{j7}trend_{it} + \varepsilon_{ijt}, \quad i = 1, \dots, N, t = 1, \dots, T, j = 1, 2 \end{aligned} \quad (1)$$

where the dependent variable $\ln(y_{it})^j$ is the j^{th} power of the log-yield variable for county i in period t , and α_{ij} is a county-by-equation fixed effect. We include the same low, medium and high temperature variables as in Schlenker and Roberts (2009a) and Tack et al. (2012), which capture the intensity of exposure to particular temperature intervals during the growing season. We include a dummy variable for irrigation to control for the most important source of intra-county production heterogeneity, and a trend to account for technological change over time. Departing from Schlenker and Roberts (2009a) and Tack et al. (2012), we split precipitation into $eprecip_{it}$ and $lprecip_{it}$ to differentiate the effect of early- versus late-season precipitation.

Under the assumption $E(\varepsilon_{ijt}) = 0$, equation 1 above can be thought of as directly formulating how weather, irrigation, and technological change affect moments of the crop yield distribution. Using the data discussed in the following section, we consistently estimated these moments using ordinary least squares with standard errors clustered at the county level.

2.2 Conditional Lognormal Densities

The density for the lognormal is given by

$$f(y; \mu, \delta) = \frac{1}{y\delta\sqrt{2\pi}} \exp\left(-\frac{(\ln y - \mu)^2}{2\delta^2}\right), \quad (2)$$

where μ is the location parameter and δ is the scale parameter. In general, if Y is distributed lognormal, then it can be defined by the transformation $\ln Y = \mu + \delta Z$ where Z is a standard normal variable with $E[Z] = 0$ and $E[(Z)^2] = 1$. This transformation implies that the first and second logarithmic moments are $E[\ln Y] = \mu$ and $E[(\ln Y)^2] = \mu^2 + \delta^2$, which can be inverted to obtain a mapping of the moments to the parameters. Solving these two equations for μ and δ yields

$$\mu = E[\ln Y] \text{ and } \delta = \sqrt{E[(\ln Y)^2] - E[\ln Y]^2}. \quad (3)$$

Thus, one can use the regression model given by equation (1) to obtain predicted moments, which can in turn be used to estimate the lognormal parameters according to equation (3).

3. Data

As in Tack et al. (2012), we use a panel of county level cotton yield data from 1972 to 2005; however, we restrict our attention to the 11 counties located in Mississippi. The yield data was obtained from the National Agricultural Statistics Service, and we defined yield as production

divided by planted acreage. The relatively short span of yield data is because NASS began distinguishing between irrigated and dryland yields in 1972. This distinction is crucial for the identification of precipitation effects, as the impact of an additional unit of naturally occurring rain likely differs across these production practices.

We use the same temperature data as in Schlenker and Roberts (2009a), which is constructed as degree days and distinguishes between low, medium, and high temperature intervals. Low temperature is constructed as the number of degree days between 0°C and 15°C, medium temperature is constructed in the same way but with bounds 15°C and 31°C, and high temperature measures degree days above 32°C. More detail on how these measures are constructed is available in Schlenker and Roberts (2009a).

The total amount of water applied to an acre of cotton consists of naturally occurring precipitation when considering non-irrigated dryland production systems and both farmer-controlled irrigation plus precipitation when considering irrigated systems. However, the actual amount of water applied via irrigation is typically unobservable, so we focus here on the effect of precipitation and allow this effect to vary across dryland and irrigated acreage as in Tack et al. (2012).

To allow for different effects across early- versus late-season precipitation during the May-October growing season, we utilize the underlying daily precipitation data to construct two measures of precipitation. Specifically, the early measure aggregates the daily records through the first five months of the growing season, while the late measure sums the daily records over

the final month of October. We are in the process of considering several alternative thresholds as the one used here is fairly arbitrary, thus we interpret our findings as preliminary results.

Descriptive statistics for the data are presented in Table 1. The data contains 612 total observations spanning 11 counties and 33 years. Four of these counties (Coahoma Holmes, Humphreys and Yazoo) only utilize dryland acreage, while the remaining seven counties (Bolivar, Leflore, Quitman, Sunflower, Tallahatchie, Tunica and Washington) utilize both dryland and irrigated. Overall, observations for irrigated acreage account for 38.9 percent of all observations and the remaining 61.1 percent account for dryland acreage of all observations.

4. Results

We first use the historical data to estimate the parameters of equation (1). Given these estimates $\hat{\beta}$, we predict the logarithmic moments for each county i according to

$$\hat{E}[\ln(y_i)^j] = \hat{\beta}'_{ij} \bar{\mathbf{X}}_i, \quad (4)$$

where the regressors are held at their average sample values within each county, $\bar{\mathbf{X}}_i$. We do this separately for both dryland (irr set to 0) and irrigated (irr set to 1) produced, thus there are a total of 44 predicted moments corresponding to “average climate”, four for each county. Denote these as \hat{E}_{ijk}^a where a denotes average climate and $k = 0,1$ denotes dryland and irrigated acreage respectively. For each county, we then solve for the associated lognormal parameters using equation (3), denoted $\hat{\mu}_{ik}^a$ and $\hat{\delta}_{ik}^a$. These in turn generate the associated densities

$$f_{ik}^a \equiv f(y; \hat{\mu}_{ik}^a, \hat{\delta}_{ik}^a).$$

To evaluate the effect of late season precipitation on yields, we construct densities for both “drought” and “wet” climates. These alternative climates are defined in exactly the same way as in the average climate scenario, except that the late precipitation variable is held at a different value. Within each county, we use the historical late precipitation data to identify the 5th and 95th percentiles of the empirical distribution. To generate predicted moments for drought (wet) climate, we hold the late precipitation variable at the 5th (95th) percentile, and then generate the corresponding densities f_{ik}^d and f_{ik}^w as above. These densities are reported in Figures 1-6.

For each density, we calculate the mean, variance, downside risk, and upside risk according to

$$mean_{ik}^c = \int_0^{\infty} yf(y; \mu_{ik}^c, \delta_{ik}^c)dy, \quad c \in \{a, d, w\}, \quad (5)$$

$$var_{ik}^c = \int_0^{\infty} (y - mean_{ik}^c)^2 f(y; \mu_{ik}^c, \delta_{ik}^c)dy, \quad c \in \{a, d, w\}, \quad (6)$$

$$dside_{ik}^c = \int_0^{z_d} f(y; \mu_{ik}^c, \delta_{ik}^c)dy, \quad c \in \{a, d, w\}, \quad (7)$$

$$uside_{ik}^c = 1 - \int_0^{z_u} f(y; \mu_{ik}^c, \delta_{ik}^c)dy, \quad c \in \{a, d, w\}. \quad (8)$$

Note that we are using a fairly simplistic measure of down and upside risk here, the probability of an outcome below z_d for the former and the probability of an outcome above z_u for the latter.

For the results presented here, we set z_d to 10 percent below the mean under average climate and z_u to 10 percent above. We measure the impact of the drought and wet climates on the percentage change in the mean, variance, upside and downside risk by measuring the percentage change relative to average climate. These results are reported for dryland acreage in Table 2, and irrigated acreage in Table 3.

In general we find that late season drought reduces mean yields fairly homogenously across counties for both dryland and irrigated acreage, with the effect on dryland roughly 20 percent higher than the effect on irrigated. Interestingly, drought is associated with an overall reduction in variance, which implies that there is a shrinking of the uncertainty surrounding the negative mean impacts. This effect is significantly dampened by the use of irrigation, as the dryland variance impacts are roughly 70 percent larger on average. For both production types, the shift in variance is coupled with an exchange of upside risk for downside risk, thus implying that the variance reduction alone masks an important effect of the absence of late season precipitation. Surprisingly, this shift is much more pronounced for irrigated acreage.

In contrast to the drought findings, late season excessive rain has the exact opposite effect on the yield distribution. Our results for the wet climate scenario suggest increased mean yields across counties for both production types, with the effect being higher on dryland acreage compared to irrigated acreage. This is at odds with previous research that found that excessive late season precipitation reduced yields due to induced harvesting inefficiencies. It is possible that we are inappropriately measuring the late season, ie one full month might be too big of a window, or that the MBME model is inappropriately specified. Future work will address this issue by considering (i) alternative measurements of precipitation and (ii) alternative distributional assumptions.

5. Conclusions

Extending regression models of previous studies (Tack et al., 2012) and utilizing cotton yield data from 11 counties in Mississippi we estimate the impact of late season drought and excessive rain on the yield distribution. Specifically, we calculate the percentage changes in the

mean, variance, upside, and downside risk associated with both climate scenarios. Our results suggest that mean effects are rather small, but there is a considerable reallocation of risk across the tails of the distribution. Importantly, our results are highly preliminary at this point, as a multitude of robustness checks need to be analyzed.

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TABLES

Table 1. Summary Statistics of Dataset

Variable Name	Sample Mean (s.d)	Min	Max	# of obs
Yield (10lb.units per acre)	73.983(18.5965)	23.1936	122.400	612
Low Temperature (degree days)	2694.2(21.6355)	2611.7760	2742.174	612
Medium Temperature(degree days)	1676.6(115.327)	1343.843	2041.647	612
High Temperature (degree days)	29.576(18.8168)	4.1771	94.0123	612
Early Precipitation (centimeters)	50.554(13.7197)	25.0599	106.8535	612
Late Precipitation (centimeters)	9.33440(6.2174)	0 .0463	32.5355	612
Irrigation (Yes =1)	0.38880(0.4878)	0	1	612

Notes: Values reported for temperature and precipitation variables correspond to the May 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. Regression Results for Dry land

County Names	Drought				Wet			
	%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Bolivar	-1.568	-8.566	-15.082	9.739	1.944	11.335	17.932	-11.687
Coahoma	-1.693	-8.006	-10.117	6.693	3.162	16.127	17.917	-11.880
Holmes	-1.546	-7.778	-13.668	9.220	1.963	10.499	16.713	-11.337
Humphreys	-1.632	-15.975	-37.515	13.795	2.560	27.603	57.025	-25.144
Leflore	-1.520	-10.124	-21.504	12.424	1.723	12.282	23.493	-13.992
Quitman	-1.689	-7.620	-8.458	5.541	2.614	12.517	12.517	-8.204
Sunflower	-1.531	-10.997	-26.730	14.571	1.806	13.916	30.661	-17.523
Tallahatchie	-1.612	-7.723	-9.199	5.991	1.918	9.747	10.496	-6.835
Tunica	-1.687	-7.461	-8.712	5.820	2.116	9.747	10.513	-7.022
Washington	-1.580	-12.081	-31.951	16.348	2.067	17.095	41.044	-22.551
Yazoo	-1.491	-9.872	-35.585	20.973	2.220	15.774	53.761	-33.457

Note: %Mean for Dryland denotes percentage change in mean yield considering drought and wet impact respectively. %Variance(Var) for Dryland denotes percentage change in variance yield considering drought and wet impact respectively, %Upside(Up) and %Downside (Down) for Dryland denotes percentage change in the probability of upside and downside yield risk considering drought and wet impact respectively.

Table 3. Regression Results for Irrigated land

County Names	Drought				Wet			
	%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Bolivar	-1.935	-15.231	-9.858	4.022	2.402	20.655	10.744	-4.514
Coahoma	-2.078	-15.692	-9.742	4.058	3.874	32.766	15.452	-6.651
Holmes	-1.907	-14.488	-9.368	3.946	2.42	20.035	10.523	-4.544
Humphreys	-2.022	-17.622	-11.877	4.313	3.188	31.09	15.676	-6.026
Leflore	-1.882	-15.369	-10.168	3.987	2.139	19.028	10.177	-4.123
Quitman	-2.083	-15.442	-9.287	3.895	3.226	26.449	12.47	-5.373
Sunflower	-1.897	-15.403	-10.289	4.089	2.245	19.882	10.691	-4.387
Tallahatchie	-1.981	-15.245	-9.323	3.806	2.358	19.794	9.777	-4.094
Tunica	-2.075	-15.026	-9.186	3.932	2.601	20.573	10.185	-4.451
Washington	-1.959	-15.875	-10.703	4.243	2.571	22.895	12.201	-5.015
Yazoo	-1.849	-14.153	-9.596	4.063	2.758	23.141	12.584	-5.015

Note: %Mean for Wetland denotes percentage change in mean yield considering drought and wet impact respectively. %Variance (Var) for Wetland denotes percentage change in variance yield considering drought and wet impact respectively and %Upside (Up) and %Downside (Down) Wetland denotes percentage change in the probability of upside and downside yield risk considering drought and wet impact respectively.

2. FIGURES

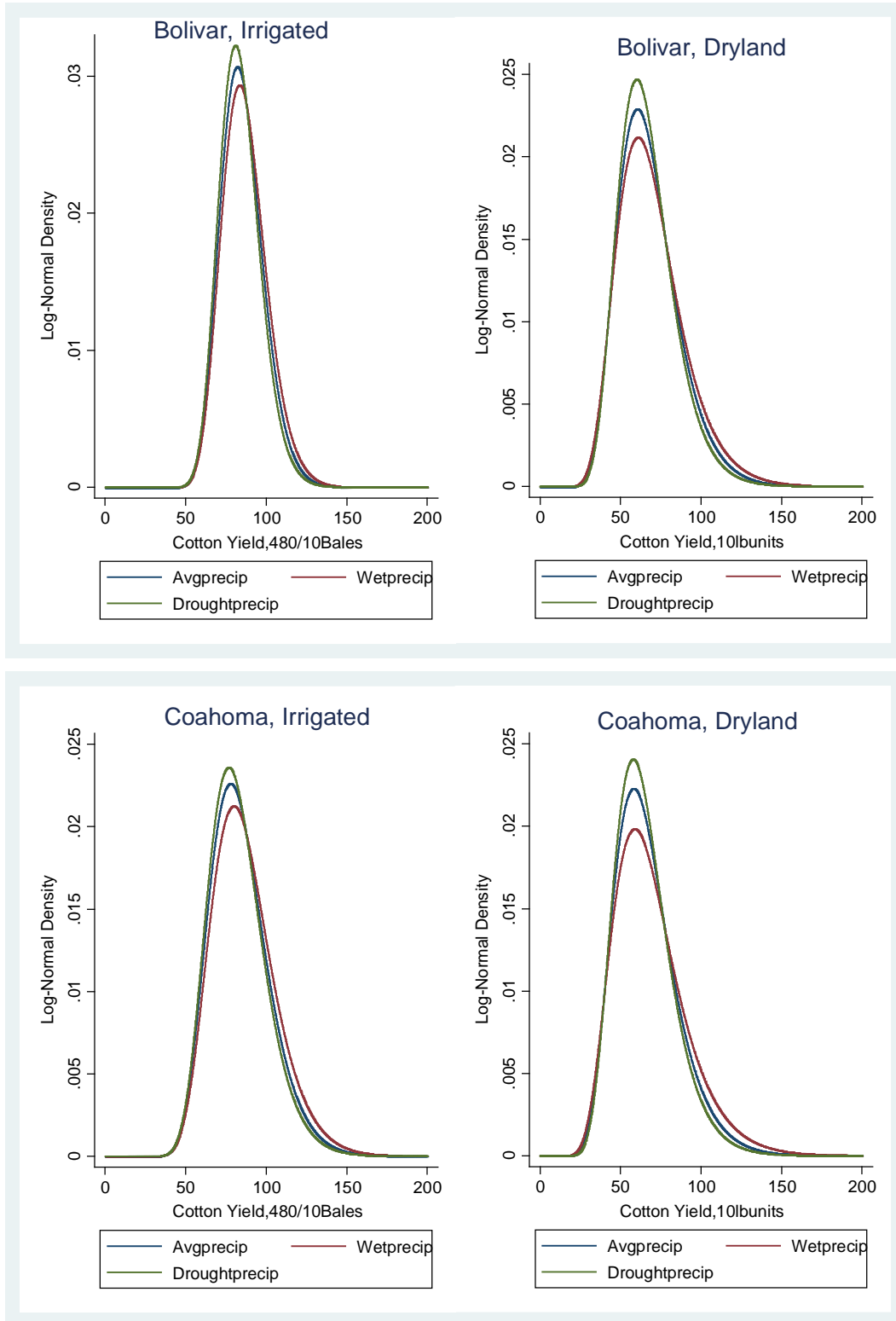


Figure 1. Irrigated and Dry land Cotton Yield distribution for Bolivar and Coahoma, MS

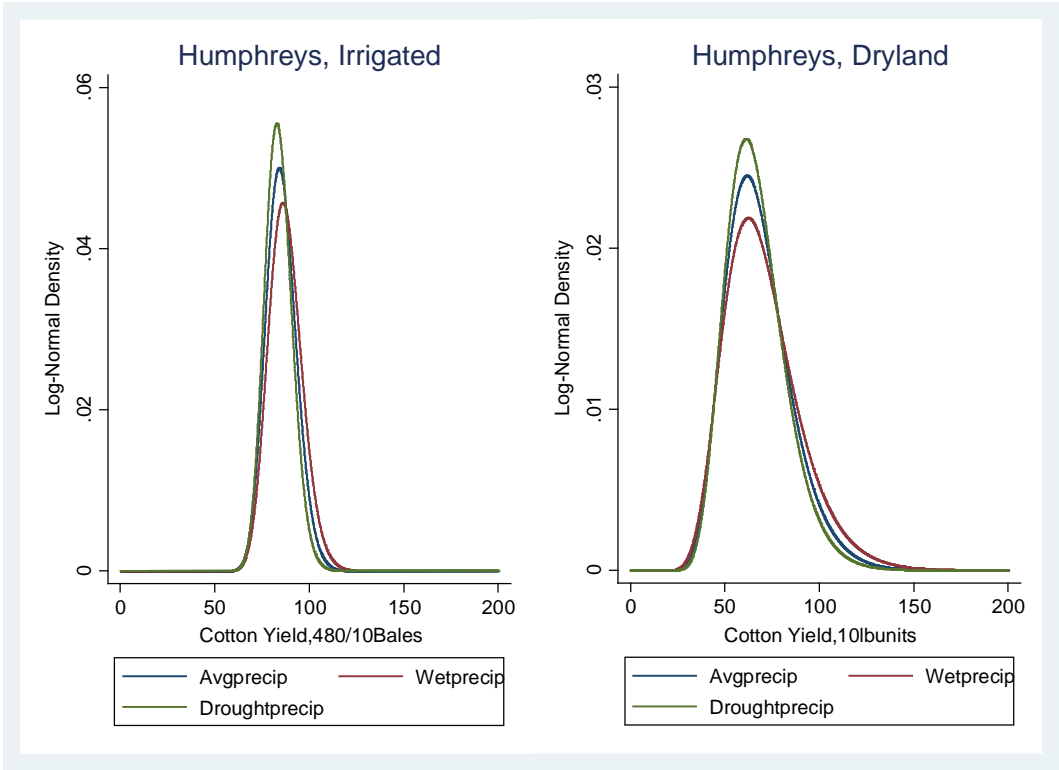
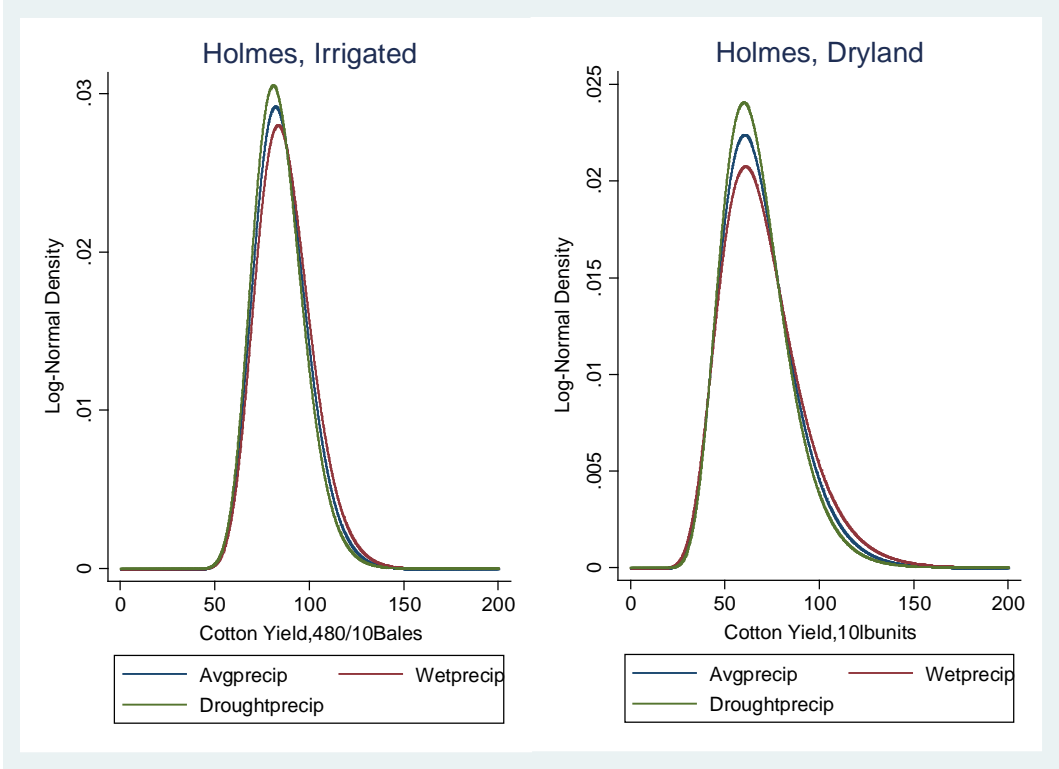


Figure 2. Irrigated and Dry land Cotton Yield distribution for Holmes and Humphreys, MS

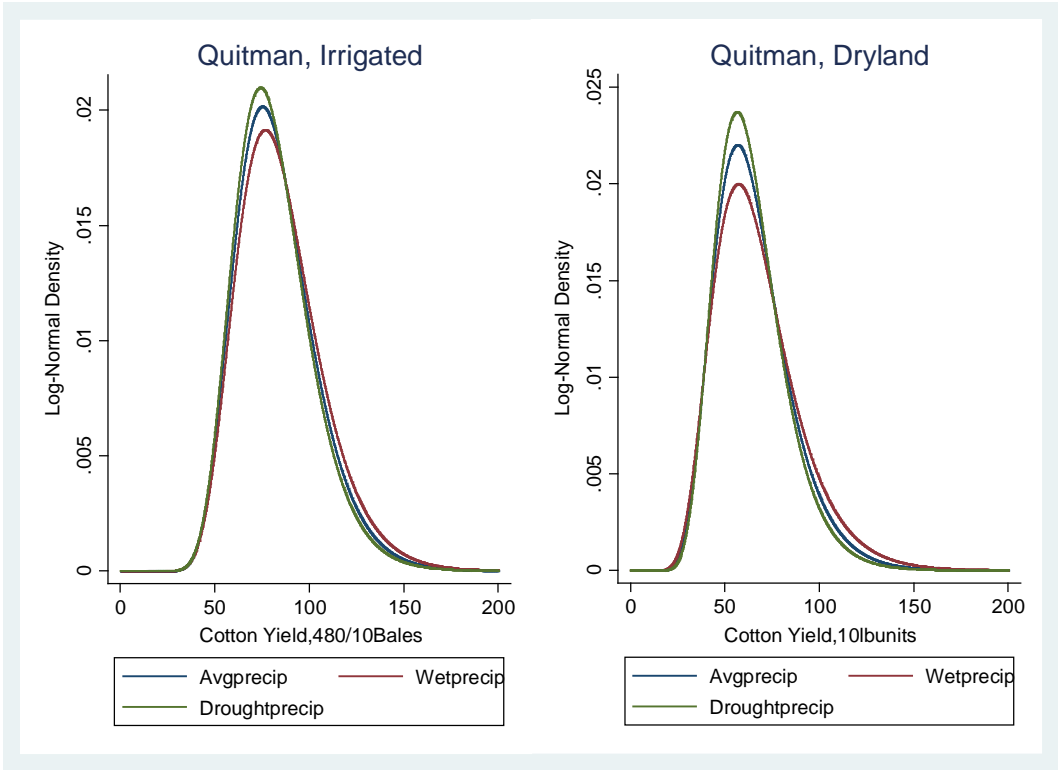
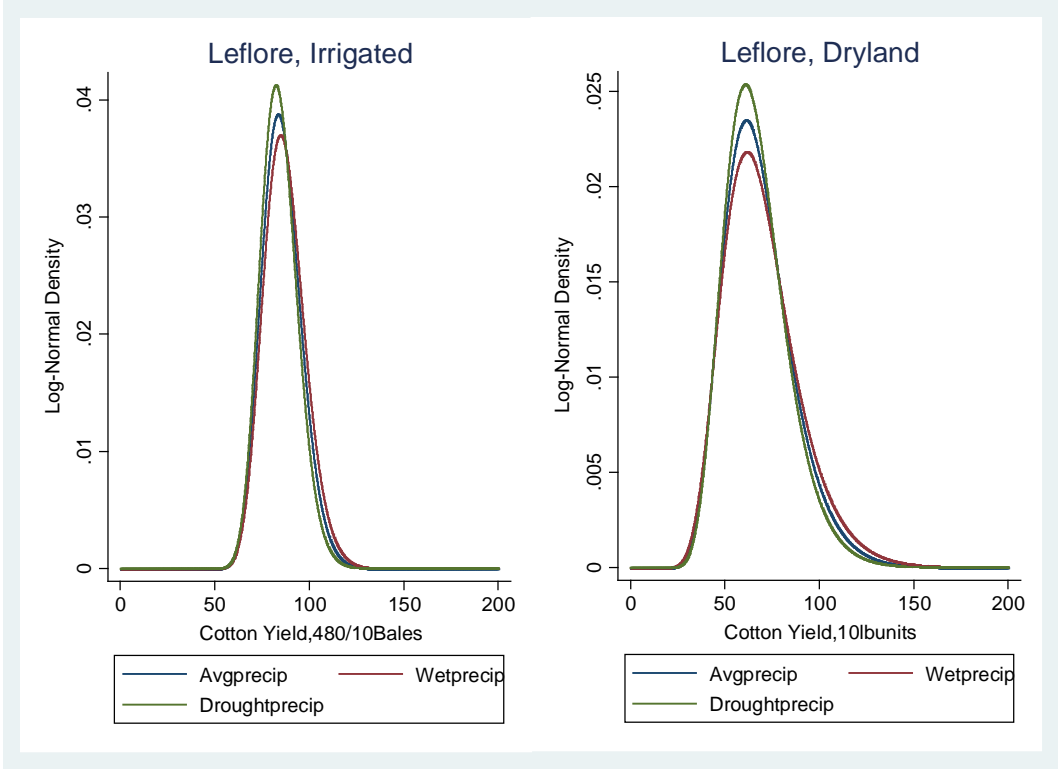


Figure 3. Irrigated and Dry land Cotton Yield distribution for Leflore and Quitman, MS

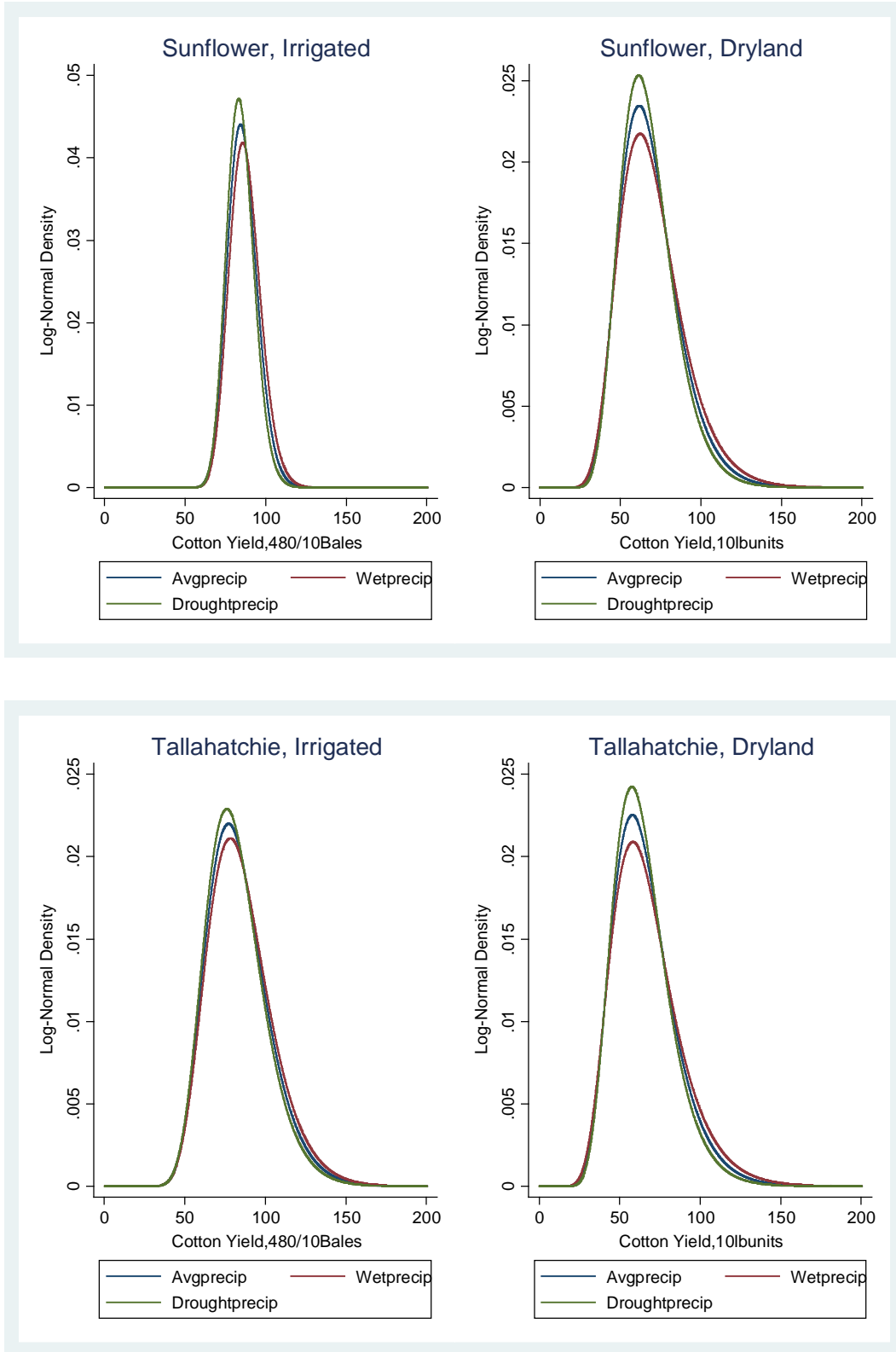


Figure 4. Irrigated and Dry land Cotton Yield distribution for Sunflower and Tallahatchie, MS

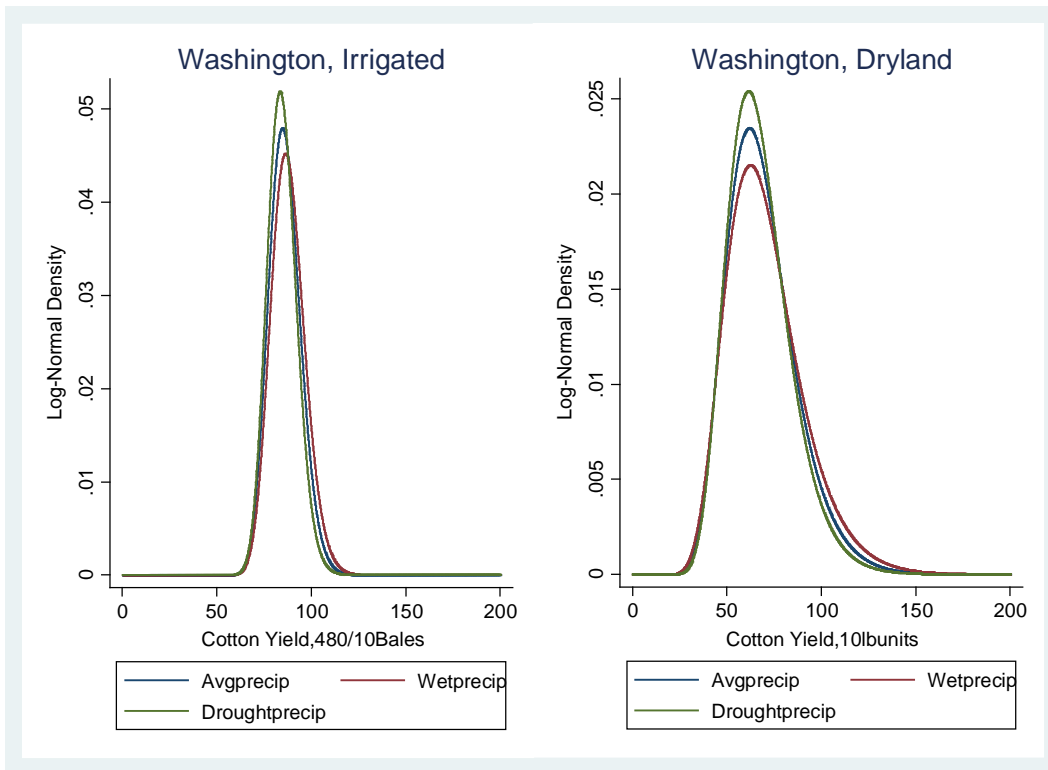
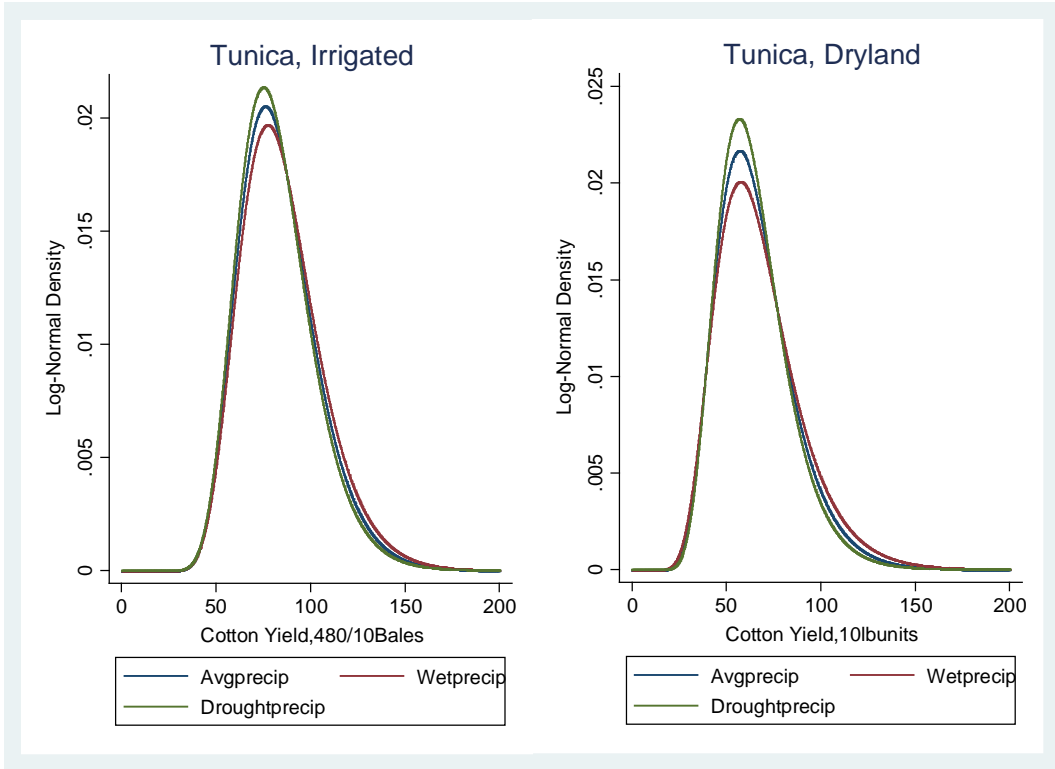


Figure 5. Irrigated and Dry land Cotton Yield distribution for Tunica and Washington,

MS

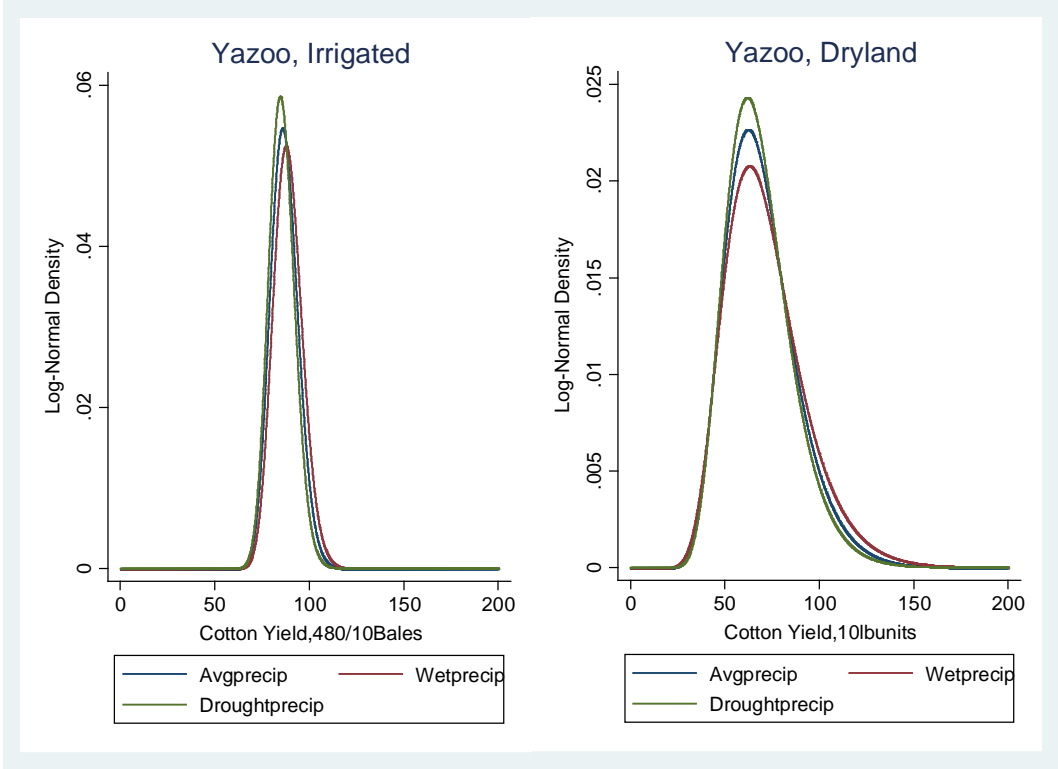


Figure 6. Irrigated and Dry land Cotton Yield distribution for Yazoo, MS