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Effect of Late Season Precipitation on Cotton Yield Distributions

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Understanding the impact of late season precipitation on the distribution of cotton yields provides insight into managing yield risks. This research combines Linear Moment Models with historical weather data to assess the impact of late season precipitation extremes on cotton production and revenue.The empirical analysis suggests that late season drought reduces both mean yield and variance. The shift in variance is coupled with an exchange of upside risk for downside risk implying that the variance reduction alone masks an important effect on producer's risk. Revenue impacts suggest high revenue for irrigated acreage as compared to dryland acreage, and the late season drought impact on revenue shows that the use of irrigation causes increases in revenue as compared to dryland acreage.

Keywords: Yield Distributions, Revenue, Late Season Precipitation

DEDICATION

I would like to dedicate this research to my parents, Mr. C.T Amonoo and Mrs. Beatrice Araba Hagan, my best friend Emmanuel Arthur and my siblings, Aso, Kay, Ebo and Kafui.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

This chapter presents a brief background of the cotton plant and Mississippi cotton production through the years, cotton water requirements, a general problem statement, research objectives and the organization of the remainder of research.

Background

Cotton is a major cash crop grown on large scales across the world. The major cotton producers are China, India, and the United States, respectively. China uses almost all of the cotton it produces domestically, and the United States has been the largest exporter for many years. Mississippi and Georgia are the largest cotton producing states in the mid-south and south-east regions of the United States.

As an important agricultural cash crop, cotton generates income and serves as a source of employment throughout its production process. Universally, the lint is used as a textile raw material and the cotton seed is the second most important source of vegetable oil. The cotton seed cake is a rich source of quality protein for incorporation in animal feeds. Also the waste after ginning is used for products such as paper and cardboard (Freeland et al, 2006).

Cotton is a tropical plant with an indeterminate growth habit and extreme sensitivity to adverse environmental conditions. According to the National Cotton Council (2012), cotton requires a growing season of 150 and 180 days. Cotton production begins with germination and emergence as the first stage, seedling establishment as the second stage, leaf area and canopy development as the third, flowering and boll development as the fourth stage and maturation as the last stage of the cycle. (National Cotton Council of America, 2012).

Over the years, the cotton plant has been genetically modified to improve its resistance to pests and diseases and to exhibit better resistance to weed control. However, the cotton plant's ability to withstand the scarcity and untimely availability of precipitation has not received much attention as research in this area is challenging due to changing climates. Generally, it is difficult to factor the amount and timing of precipitation as farmers' control over inputs do not extend to weather variables because the amount and distribution of water from precipitation is random each year.

Recent climate change evidence and predictions show increasing temperatures, drought frequency, and shifting rainfall patterns. As indicated in the proceedings of the Intergovernmental Panel on Climate Change (IPCC, 2000), the combination of increasing temperature and shifting rainfall amounts and patterns has the potential to negatively impact agriculture. Climatic variables such as temperature and precipitation in appropriate amounts and timing positively influence the yield of cotton. However, empirical results (Freeland et. al., 2010) show that extremely high temperatures and excessive precipitation during sensitive growth stages (e.g., germination, fruiting, maturation, harvesting) cause decreases in the quality and quantity of yield (National Cotton Council of America, 2012).

Problem Statement

Cotton is one of the major row crops produced in the US, and historically it has been an important component of the Mississippi agricultural economy. Mississippi is among the top five cotton producing states in the nation. The highest yield was recorded in 1997 at 901 pounds of lint per acre and the lowest yield per acre occurred in 1866 at 86 pounds of lint per acre. The highest recorded acreage occurred in 1930 with 4,136,000 acres and lowest recorded acreage occurred in 1982 at 680,000 acres. The highest production occurred in 1937 at 2,692,000 bales and the lowest production occurred in 1866 at 320,000 bales. Despite previous production trends, Mississippi cotton production has seen a decline in recent years due to economic forces and changing climate conditions. According to Mississippi cotton and corn statistics compiled, for land that was planted cotton in 2006, 31.5 percent was planted to corn in 2007 and 10.3 percent was planted to corn between 2007 and 2008. More recently, total cotton production in 2011 was 1,200,000 bales, but this amount declines in 2012 with a production of 993,000.

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 the 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 effects 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 total precipitation, but the precipitation occurring during specific growth stages (i.e., germination, fruiting, and maturation). In this regard, 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 Water Requirement

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 bolls 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 caused 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 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 (i.e., 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 smooths 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.

Objectives

The general objective of this research is to use regression analysis to estimate the effect of late season precipitation on Mississippi cotton yield distributions. The specific objectives of this research are the following:

1. Similar to previous studies, we are interested in looking at the mean and the variance yield impacts. Additionally, we explore downside and upside risk impact given the increasing interest in agricultural risk and its associated insurance policies. We define downside risk impact as the probability of a negative outcome below the mean and upside risk as the probability of a positive outcome above the mean.
2. We utilize estimated impacts from (1) to calculate yield densities for average drought and wet climates and compare drought and wet climate to the average climate. While average climate captures the average precipitation, drought climate captures low late-season precipitation outcomes and wet climate captures high late-season precipitation outcomes.
3. We utilize current cotton price data to convert yield impacts into revenue impact for major cotton producing counties in Mississippi.

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.

Organization of Study

The remainder of this research is organized as follows. Chapter two reviews the literature, chapter three presents the empirical model and describes the yield and climate data, chapter four reports the empirical results, and chapter five concludes.

CHAPTER II

LITERATURE REVIEW

This section discusses previous research relevant to the study under three main categories. The first part discusses yield distributions as a result of uncertainties in weather variables. The second part discusses the choice of a specific regression specification. The third part discusses how the regression framework can be used to infer yield distributions.

Yield Distribution

The need for proper modeling of yield distributions stems in part from the dramatic growth in participation by farmers in the US 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 et al., 2004; Glauber 2004).

Tack et al. (2012) posited that in modeling yield variability in response to climate change, two main lines of research have been employed. First, the use of 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. Research of this type includes 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 changes in weather variables 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 (Tack et al., 2012). As noted in Schlenker and Roberts (2006, 2009), the drawback of these simulation-based models is that they do not take into account the adaptive behavior of producers. Specifically, this process requires the use of large numbers of parameters, making estimations complex; and considers farmers' production systems and nutrient applications as exogenous variables; The second line of research is the use of the regression-based framework (e.g. Adams et al., 2001; Chen et al., 2004; McCarl et al., 2008; Boubacar, 2010), which utilizes historical data to identify the effects of weather variables on the mean and variability of yield (Tack et al, 2012).

Empirical studies also present alternative modeling assumptions for crop yield distributions. Gallagher (1987) utilized the gamma distribution, and Moss and Shonkwiler (1993), the inverse hyperbolic sine transformation. Others have used the beta distribution (e.g., Nelson and Preckel 1989; Tirupattur, Hauser, and Chaherli 1996), the log-normal distribution (e.g., Stokes 2000; Sherrick et al. 2004), the hyperbolic tangent function transformation (e.g., Taylor 1990), the inverse hyperbolic sine transformation (e.g., Moss and Shonkwiler 1993; Ramirez, Moss and Boggess 1994; Ramirez 1997, and Wang et al. 1998), and the Wiebull distribution (Chen and Miranda 2004). Goodwin and Ker (1998) demonstrated the usefulness of non-parametric models.

They used the nonparametric density estimation approach to evaluate county-level crop yield distributions. They argued in their study that the nonparametric technique, unlike conventional parametric techniques, does not assume a particular known functional form. They opined that using adequate data, nonparametric estimates can be improved for insurance purposes. Ker and Coble (2003) developed a semi-parametric approach.

Sherrick et al. (2004) considered several alternative parametric yield specifications that have been suggested as candidates by previous works or based on empirical evidence. For their research, they utilized farm-level data for corn and soybeans that span a period of 27 years. They estimated five distributions (i.e., normal, lognormal, logistic, beta, and Weibull,), which formed the basis for comparisons of the economic impacts across various distributions. The estimated yield distributions were ranked and compared based on goodness-of-fit tests, and they found the beta and Weibull distributions provided the best fit for their sample data.

Distributional assumption of normality of yield distributions has been a long-standing issue among previous studies (e.g., Day, 1965; Harri et al, 2008; Taylor, 1990; Ramirez, 1997). While some researchers have reported negative skewness for certain crops, others also reported positive skewness for these same crops. Day (1965), a major proponent of nonnormality, used yield distributions from a controlled experiment with seven different fertilizer levels for Mississippi cotton, corn and oats. His data spans from 1921 to 1957 for cotton and corn and from 1928 to 1957 for oats. He found significant positive skewness for cotton, significant negative skewness for oats and no significant skewness for corn. However, as reported in Just and Weninger (1999), Taylor (1990) estimated multivariate nonnormal probability distributions by fitting hyperbolic tangent transformations of normal varieties and using Pearson, Geary and Wike-Shapiro tests for normality. He reports significant skewness for corn, soybean and wheat yields from 1945-1987 in Macoupin County, Illinois. Hence no consensus has been established as to the best approach to estimate yield distributions.

Just and Weninger (1999), using a single omnibus test for region-wide and farm specific yield data, reassessed the evidence for nonnormality of yield research using the same data as previous studies. They argued that these studies falsely rejected normality of crop yield data and reported that previous empirical literature did not provide enough evidence to conclude nonnormality of yield distribution since the data and analysis were plagued with the misspecification of the nonrandom components of the yield distribution, misreporting of statistical significance and the use of aggregate time series data to represent farmland yield distributions. For instance, using the same data as used by Gallagher (1987), who analyzed U.S soybean yield from 1941-1948 and accounted for soybean variability by correcting yield model for heteroskedasticity and variation in deterministic component, concluded a non-rejection of normality.

Harri et al., (2009) ascertained the validity of nonnormality of yield distribution, using the R-test and multivariate test for normality on 3852 crop/county combinations of corn, cotton, soybean and wheat. The authors reported that normality rejection rates differ in previous studies by as much as 15% depending on the trend specification. They further concluded that a high percentage of county yield data in the Corn Belt region for corn and wheat appeared to be nonnormally distributed but less so for soybeans and cotton. As reported, results for cotton show that for the majority of the counties, normality could not be rejected.

According to Coble and Barnett (2008), the effect of climate change on yield risk is much less clear from relatively few studies that provide quantified results. Earlier research asserted that late-season rainfall seemed to result in a greater yield reduction than the same amount of rainfall during the early season. Williford et al. (1995) examined replicated weekly harvest treatments for reductions in yield and quality during 1991, 1992, and 1993 from research plots at Stoneville, Mississippi. He argues that cotton yield varied considerably by years as yields were 1528, 1110 and 909kg of lint per hectare for the 3 years, respectively. The three-year period provided different environments that were reflected in production. The authors estimated different intercepts for the yield for effective comparisons. Employing regression analysis, they showed a negative relationship between crop yield and harvest rainfall.

Similarly, Parvin et al., (1990) collected hand-harvested data on the relationship between yield and growing period for commercial cotton at 22 locations in the Delta area of Mississippi. They hypothesized that decreases in yield could be explained by increases in time and rainfall. Using regression analysis and because there could be problems of multicollinearity (the correlation between rainfall and trend since their data were time series data), several models were run to ascertain this. Results indicated a correlation between rainfall and time. They concluded a negative relationship between crop yield and harvest rainfall. This is in line with the conclusions of Crowther (1925) and Crowther (1933) who over a period of 23 years showed a relationship between seasonal yield and weather for cotton grown under irrigation in the Sudan Gezira. They concluded cotton yields were negatively correlated with the amount of early-May and June rainfall. Increase in total rainfall during the period of cotton cultivation resulted in a decline in yield at the oldest trial farm. Cotton yields were also negatively correlated with late rainfall and rainfall in the preceding year.

Chen et al. (2004) investigated how changes in climate result in yield variability of crops such as sorghum, soybeans, wheat, corn and cotton. Their results showed that an increase in rainfall decreases the variability of cotton and corn yields. Higher temperatures decrease the variance of cotton and sorghum yields.

Tack et al, (2012) linked weather and irrigation variables in a moment based maximum entropy framework to trace the shape of yield distribution based on higher moments, considering the case of Arkansas, Mississippi, and Texas upland cotton yields. Their results suggested that high temperature and lack of irrigation concentrated yield outcomes toward the lower tail of the distribution. They further explained that high temperature is mean enhancing for all counties under study, variance enhancing for three of the six counties and generates more positively skewed distributions for all but one of the counties while lack of irrigation is mean enhancing for all counties under study and variance enhancing for four of the six counties. The lower tail distribution subsequently has significant implications for price variability, risk management, and crop insurance (Tack et al., 2012).

Production Function Specification

Empirical studies (e.g., Just and Pope, 1977, 1979; Antle, 1983, 2010) indicate that it is not enough to consider risk analysis (effect of weather on yield) under uncertainty of production on the mean effect of inputs on output. This posit is a result of the limitations of a previous stochastic production function specification and how it affects coefficient estimates of variance and other higher moments and consequently how ineffectively these models capture risk. They argued that for instance, when one considers "overcapitalization" in grain harvesting, the use of large harvesting equipment as opposed to small equipment usually leads to less variability of output as a result of random weather conditions that can destroy a ripe crop before harvest (Just and Pope 1979). Thus in such instances increased input use results in a reduction in variability of output.

Just and Pope (1977, 1979) argued that a useful production function for such studies should possess sufficient flexibility so that the effect of input on the deterministic component of production is different from the effect on the stochastic component. Unlike the conventional production function specification

$$y = A(\prod_{i=1}^{n} X_i^{\alpha i})e^{\varepsilon} \quad , \tag{2.1}$$

where y is output, X_i is a factor input $\left(X_i > 0\right)$ and ε is a stochastic disturbance with $E(\varepsilon) = 0$ and $V(\varepsilon) > 0$ where E denotes expectations operator and V denotes variance, a production function when explicitly written should be of the form

$$y = f\left(X\right) + h\left(X\right)\varepsilon \ \ , E\left(\varepsilon\right) = 0 \quad V\left(\varepsilon\right) = 1 \tag{2.2}$$

By this specification, the presence of, $h(X)$ which is a function of input, when expressed in its additive form "perturbs the effects of the disturbance in such a way that relationships of inputs with risk are not determined solely by the relationships of inputs with expected output" Just and Pope (1979). Therefore, the expectation and variance of $E(y) = f(X)$ and $V(y) = h(X)$ respectively implies independent effect on mean and variance of output.

Several studies (e.g., Antle (1983, 2010); Nelson and Preckel (1989); Tack et al 2012) have conditioned moments on weather, irrigation and technological change. Unlike the conventional production function approach to modeling crop yield, which involves parameterizing a deterministic production function and appending an error term to it, the moment based approach begins with a general parameterization of the moment of the probability distribution of output. More flexible representations of output distributions can be obtained using the moment based approach. Antle (1983) outlines motivations for the choice of a moment based model over the conventional method, and I follow the author's discussions here.

1. Unlike the conventional estimation of only the mean output as a function of input, the probability distribution of output is a unique function of its moment, thus the moment based approach allows an establishment of the relationship between input and these moments.
2. Using a flexible moment based approach for testing the stochastic structure of production Antle (1983) shows that the conventional econometric models that are based on ad hoc appending of additive or multiplicative random error terms to a deterministic production function are not adequate representations of the probability distribution due to the imposition of arbitrary restrictions on the moment of the output. Just and Pope (1978) and Kramer (1979) have shown error misspecification to have economic implications since conventional production function models do not permit testing of restrictions.

3. Thirdly, empirical evidence from Day (1965), Anderson (1973), Roumasset (1976), Just and Pope (1979), Nikiphoroff 1981, Antle and Goodger (1982) indicates that the second, third and fourth moments of output may be functions of inputs and these relationships should be accounted for in the theory of decision making under uncertainty.

Empirical evidence indicates a firm's behavior under production uncertainty can therefore always be defined in terms of the moments of the probability distribution of output. Antle (1983) opined that to minimize the arbitrary restrictions when using the conventional stochastic function, the moment based approach begins with a general representation of the moment functions that describe a stochastic technology.

Linking Moments to Distributions

After obtaining the moments of yield distributions, one can use the estimated moments to infer distributions using the following approaches. The first approach involves making a distributional assumption and Antle (1983, 2010) model along these lines. The second approach employs the use of Moment Based Maximum Entropy framework and a study employing this method includes Tack et al, (2012). In the Moment Based Maximum Entropy approach, estimated predicted moments are used in a maximum entropy framework after assuming a particular distribution to generate densities. The advantage this approach has over conventional methods of estimating densities is its ability to predict the entire yield density when the only information available is predicted moments.

Yield Price and Revenue

Farmers are vulnerable to many possibilities that influence the risk exposure of their activities. Although they have control over some of their inputs (cultivar type), their inability to control weather is a major challenge to their operations as weather forms an integral part of the inputs used for crop production. Empirical studies indicate that wide swings in the farm revenue can result from variances of weather, yields and prices.

Studies relating yield outcomes to weather variables have established that recent changes in the weather (precipitation, temperature) tend to increase the risk associated with farming activities. A farmer's revenue is dependent on yield and price, and knowledge of yield cannot be isolated from weather.

CHAPTER III

EMPIRICAL MODEL

This chapter presents the econometric model and framework employed for the research. The empirical model used extends the linear moment modeling approaches of Antle (1983, 2010) and utilizes cotton weather data of Schlenker and Roberts (2006, 2009a) combined with a normal distributional assumption. However, to relax the symmetry assumption, the lognormal distributional assumption is also utilized to generate densities.

Linear Moment Model Approach

The Linear Moment Model (LMM) framework is a data based estimation technique attributed to Antle (1983). 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, which can then be used to estimate yield densities under the assumption of normality.

Antle (1983) considers a multiplicative error model that has the advantage of being transformed into an additive error model by taking its natural logarithm. Expressing moments as parameterized functions of inputs, this model is of the functional form

$$Q = m(x, \beta)e^u \tag{3.1}$$

where Q denotes the output, $x = (x_1, \ldots, x_n)$ as a vector of inputs, β is a parameter vector and u is a random variable. Using equation 3.1 above, the expectations of the mean and variance are given as

$$\mu_1 = E[Q] = m(x, \beta)\, E[e^u] \tag{3.2}$$

$$\mu_2 = E[Q - E(Q)]^2 = m(x, \beta)^2\, E[e^u - E(e^u)]^2 \tag{3.3}$$

Similarly by the above equations the general *i*th centered moment about the mean is expressed as

$$\mu_i = E[Q - E(Q)]^i = m(x, \beta)^i\, E[e^u - E(e^u)]^i \tag{3.4}$$

implying that mean and other higher moments of the probability distribution of output are functions of inputs through the function $m(x, \beta)$.

Following and extending the stochastic production function discussed in Antle (1983) and Schlenker and Roberts (2006, 2009a), this research expresses yield in period t as a parameterized function of the conditioning weather variables and a random error term. The moment model is of the form

$$\begin{aligned} y_t &= f(x_t, \beta_1) + \varepsilon_{1t} \\ \ln(\varepsilon_{1t}^2) &= f(x_t, \beta_2) + \varepsilon_{2t} \end{aligned} \tag{3.5}$$

where y_t denotes yield, x_t denotes a vector of weather variables and ε_{1t} and ε_{2t} denote random error terms. Under the assumptions $E(\varepsilon_{1t} \mid x_t) = E(\varepsilon_{2t} \mid x_t) = 0,$ 3.5 implies

$$E(y_t \mid x_t) = f\left(x_{t,}\beta_1\right)$$
$$E((y_t - E(y_t \mid x_t)^2 \mid x_t) = e^{f(x_t,\beta_2)} E(e^{\varepsilon_{2t}} \mid x_t) \tag{3.6}$$

as conditional mean and conditional variance respectively. The above equation (3.6) indicates that for the different moment's equation the parameter vector β_j is different, avoiding the imposition of arbitrary restrictions across equations.

As discussed in Tack et al (2012), Maximum Entropy provides a rationale for generating densities from a set of moments. They opine that maximum entropy is flexible for approximating densities as it nests a whole family of generalized exponential distributions including the exponential, pareto, normal, lognormal, gamma and beta distribution as special cases (Jaynes 1982). Therefore, utilizing the parameters in the equation (3.8) we establish a relationship of weather variables, irrigation and technological change with the mean and variance of the yield distribution. They further argue that "the ability to predict moments under different climatic conditions does not in and of itself allow us to measure the effect of these climatic conditions on the entire distribution of yield outcome". This condition as asserted by Shohat and Tamarkin (1943) is termed the moment problem and occurs when a finite set of moments is unable to determine the entire density.

This shortcoming can be improved using the maximum entropy concept (Stohs, 2003; Tack et al, 2012). According to Jaynes (1982), the maximum entropy (MAXENT) distribution is "uniquely determined as the one which is maximally noncommittal with regards to missing information and it agrees with what is known but expresses maximum uncertainty with respect to all other matters". The normal distribution is the maximum entropy distribution under the assumption that the mean and variance are sufficient statistics for the distribution. In the empirical application, we maintain that this is the case but also evaluate the robustness of the findings when log normality is maintained.

Modeling Conditional Normal Moments

The normal distribution is a continuous probability distribution and is characterized by the first and second moments $\mu_N = E\left[Y \mid X\right]$ and $\sigma_N^2 = E\left[(Y-\mu)^2 \mid X\right]$. To generate predicted values for these moments under alternative climate scenarios, this research extends equation (3.7) and utilizes the regression models

$$\begin{aligned} y_{it} &= \beta_{i0} + \beta_1 low_{it} + \beta_2 med_{it} + \beta_3 high_{it} + \beta_4 eprecip_{it} + \beta_5 lprecip_{it} \\ &\quad + \beta_6 irr_{it} low_{it} + \beta_7 irr_{it} med_{it} + \beta_8 irr_{it} high_{it} + \beta_9 trend_{it} + \varepsilon_{1it}, \\ &\quad i = 1,\ldots,N,\ t = 1,\ldots,T \end{aligned} \tag{3.7}$$

$$\begin{aligned} \ln \varepsilon_{1it}^2 &= \beta_{i0} + \beta_1 low_{it} + \beta_2 med_{it} + \beta_3 high_{it} + \beta_4 eprecip_{it} + \beta_5 lprecip_{it} \\ &\quad + \beta_6 irr_{it} low_{it} + \beta_7 irr_{it} med_{it} + \beta_8 irr_{it} high_{it} + \beta_9 trend_{it} + \varepsilon_{2it}, \\ &\quad i = 1,\ldots,N,\ t = 1,\ldots,T \end{aligned} \tag{3.8}$$

where the dependent variable y_{it} is the yield for county i in period t, β_{i0} is a county-by-equation fixed effect and $\ln \varepsilon_{1it}^2$ denotes the squared errors of equation 3.8. Research includes the same low, medium and high temperature variables as in Schlenker and Roberts (2009a) and Tack el 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 also include interactions with the temperature variables to allow temperature effects to vary across dryland and irrigated acreage. A trend is estimated to account for technological change over time. Departing from Schlenker and Roberts

(2009a) and Tack et al. (2012), I split precipitation into $eprecip_{it}$ and $lprecip_{it}$ to differentiate the effect of early- versus late-season precipitation.

Conditional Normal Densities

Estimating the normal densities involves the following steps. First, using the above equations (3.8), where yield is regressed on precipitation variables while controlling for temperature, irrigation and technological change over time, we obtain parameter estimates $\hat{\boldsymbol{\beta}}_1$ and residuals. The square of the residuals from the first regression estimation is taken and its natural logarithm estimated. The second step involves regressing the natural logarithm of the squared residuals from step 1 on the same explanatory variables while still controlling for irrigation and technological change over time as depicted in equation 3.9 to obtain $\hat{\boldsymbol{\beta}}_2$. $\hat{\boldsymbol{\beta}}_1$ and $\hat{\boldsymbol{\beta}}_2$ can then be used to predict the conditional mean and variance of the normal distribution.

This moments-model approach thus provides a mechanism by which 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. The conditional density of a normal distribution is given as

$$f(y \mid x; \mu, \sigma) = \left\{ \frac{1}{\sigma\sqrt{2\pi}} \exp^{-\frac{(y-\mu)^2}{2\sigma^2}} \right\}, \tag{3.9}$$

where μ and σ^2 are the conditional mean and variance respectively. Thus given estimates of these parameters $\hat{\mu}$ and $\hat{\sigma}^2$, densities can be estimated using

$$f(y \mid x; \hat{\mu}, \hat{\sigma}) = \left\{ \frac{1}{\hat{\sigma}\sqrt{2\pi}} \exp^{-\frac{(y-\hat{\mu})^2}{2\hat{\sigma}^2}} \right\}, \tag{3.10}$$

Conditional Lognormal Densities

Since symmetry is imposed for a normal distribution automatically, we relax this assumption by assuming a lognormal distribution. The conditional density of a lognormal distribution is given as

$$f_{\ln}(y \mid x; \mu_{\ln}\sigma_{\ln}^2) = \left\{ \frac{1}{y\sigma_{\ln}\sqrt{2\pi}} \exp^{-0.5\left(\frac{(\ln y - \mu_{\ln})}{\sigma_{\ln}}\right)^2} \right\}, \tag{3.11}$$

where $\mu_{\ln}$ is the location parameter and $\sigma_{\ln}$ is the scale parameter. In general, if Y is distributed lognormal, $LN(\mu_{\ln}, \sigma_{\ln}^2)$ then it can be defined by the transformation $\ln Y = X$ where X is distributed $N(\mu_N, \sigma_N^2)$. This transformation implies that the lognormal parameters can be written as a function of normal parameters,

$$\mu_{\ln} = \ln \mu_N - \frac{1}{2}\sigma_{\ln}^2 \quad \text{and} \quad \sigma_{\ln} = \sqrt{\ln\left(1 + \frac{\sigma_N^2}{\mu_N^2}\right)} \tag{3.12}$$

These equations imply that parameter estimates from the previous subsection $\hat{\mu}_N$ and $\hat{\sigma}^2_N$, can be used to estimate the lognormal parameters $\hat{\mu}_{\ln}$ and $\hat{\sigma}_{\ln}$. This in turn allows one to estimate the conditional lognormal densities using

$$f_{\ln}(y \mid x; \hat{\mu}_{\ln} \, \hat{\sigma}_{\ln}^{2}) = \left\{ \frac{1}{y \hat{\sigma}_{\ln} \sqrt{2\pi}} \exp^{-0.5\left(\frac{(\ln y - \hat{\mu}_{\ln})}{\hat{\sigma}_{\ln}}\right)^2} \right\} \tag{3.13}$$

The data used for these estimations are discussed in the subsection that follows.

Data Source

Research used a panel of county level upland cotton yield data from 1972 to 2005; however, I restrict my attention to the 11 counties located in Mississippi with 612 observations. The yield data were obtained from the National Agricultural Statistics Service, and yield is defined as production divided by planted acreage. This measure rather than production divided by harvested acres allows us to better capture the effect of weather outcomes. 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.

This research utilizes the same temperature data as in Schlenker and Roberts (2009a) and Tack et al (2012), which is constructed as degree days and distinguishes between low, medium, and high temperature intervals. The weather data spans 1950-2005 and is based on the rectangular grid system underling PRISM that covers the contiguous United States. The data contains daily temperature and precipitation information, which is crucial for distinguishing between early- and late-season conditions. A distribution of temperatures is constructed within each day, using a sinusoidal curve between minimum and maximum temperatures, which permits estimation of the 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 six month active cotton growing period from May to October

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. Schlenker and Roberts (2009a) found out that depending on the crop, yield growth increases gradually with temperature up to 29-32°C but decreases sharply for all three crops used for the study. Critical threshold temperatures were 29°C, 30°C and 32°C for corn, soybeans and cotton respectively. Tack et al. (2012), utilizing the same temperature data, found that exposure to low and medium temperature have relatively minor effects on mean yields compared to temperatures above 32°C.

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, this study utilizes the underlying daily precipitation data to construct three measures of precipitation. Specifically for the first option, the early measure aggregates the daily records through the first five months of the growing season thus May through September, while the late measure sums the daily records over the final month of October. In the second precipitation measure, early precipitation is divided into two sub-seasons. Here early measure aggregates the daily records from May through June and mid precipitation measure as July to October. This research maintains late measure as the sum of the daily records over the final month of October.

Although empirical results (Crowther, 1925) show a negative correlation between yield and the preceding year's rainfall, recent studies have not given much attention to the isolation of the amount of moisture existing in the soil prior to the start of a new crop production season. Importantly, since irrigation systems are not utilized prior to planting, the amount of soil moisture is reasonable measured by precipitation. Thus the third measure of precipitation considers the following demarcations: the amount of precipitation prior to planting, which comprises aggregated daily precipitation records for the month of April and amount of precipitation during the season, which is aggregated daily precipitation records from May through October.

State level cotton prices were also obtained from NASS. Although yield data used for the studies spans 33 years, price data obtained from NASS and used to examine the impact of drought and wet climate on a farmer's revenue span 7 years (2005-2012). The relatively short span of price data used in this analysis is a result of recent declination of cotton production although yield keeps increasing. Plots for cotton production have been allotted for corn and other agricultural crops production. For effective analysis with the yield data measured in 10lb units, the price data used were of the same units.

CHAPTER IV

RESULTS AND DISCUSSIONS

This chapter presents and discusses the empirical results of the research. The first subsection presents summary statistics of the data; the second subsection presents and discusses the estimation of moments used for generating densities; the third subsection is devoted to the discussion of results of the effect of drought and wet climates on these densities. The last subsection discusses how current cotton prices are used to convert yield impact into revenue impacts.

Descriptive Statistics of Data

Descriptive statistics for the county-level yield data obtained from NASS are presented in Table 4.1. The data contains 612 total observations spanning 11 counties and 33 years. Four of these counties (Coahoma Holmes, Humphreys and Yazoo) only report dryland acreage, while the remaining seven counties (Bolivar, Leflore, Quitman, Sunflower, Tallahatchie, Tunica and Washington) report irrigated acreage. 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.

Table 4.1 Summary statistics of dataset

Variable Name	*Sample Mean(s.d)*	*Min*	*Max*	*# of Obs*
Yield (10lb.units per acre)	73.93(18.59)	23.19	122.40	612
Low Temperature (degree days)	2694.2(21.64)	2611.78	2742.17	612
Medium Temperature (degree days)	1676.60(115.33)	1343.84	2041.65	612
High Temperature (degree days)	29.58(18.82)	4.18	94.01	612
Early Precipitation (centimeters)	50.55(13.72)	25.05	106.85	612
Late Precipitation (centimeters)	9.33(6.23)	0 05	32.54	612
Irrigation (Yes=1)	0.39(0.49)	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

The normalized measure of dispersion of a probability distribution is called the coefficient of variation (CV) and is derived as a ratio of the standard deviation to the non-zero mean and may be expressed in percentages. From table 4.1, the coefficient of variation of the county yield data used for the study is approximately 25 percent. The early precipitation variable records a CV of approximately 27 percent and late precipitation variable records approximately 67 percent as coefficient of variation. It is interesting to note from the table the variable late precipitation is more variable than early precipitation and yield when their coefficient of variation is used as criteria for making analysis.

Estimation of Moments and Densities

This study first utilizes the historical data to estimate the parameters of equation (3.8). Given these estimates $\hat{\boldsymbol{\beta}}_1$ and $\hat{\boldsymbol{\beta}}_2$, we predict the conditional mean and variance for each county i according to

$$\begin{aligned} \hat{E}[(y_i \mid x)] &= \hat{\boldsymbol{\beta}}_i' \overline{\mathbf{X}}_i \\ \hat{E}[((y_i - \hat{E}[(y_i \mid x)^2 \mid x)] &= \hat{\boldsymbol{\beta}}_i' \overline{\mathbf{X}}_i , \end{aligned} \tag{4.1}$$

where the regressors are held at their average sample values within each county, $\overline{\mathbf{X}}_i$. This study considers dryland (irr set to 0) and irrigated (irr set to 1) production separately, thus there are a total of 44 predicted moments corresponding to "average climate", four for each county. Denote these as μ_{ik}^a and σ_{ik}^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. These in turn generated the associated conditional densities $\hat{f}_{ik}^a \equiv f(y; \hat{\mu}_{ik}^a, \hat{\sigma}_{ik}^a)$.

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 p^{th} percentiles of the empirical distribution. To generate yield densities across a range of late season precipitation values, we hold the late precipitation variable at the p^{th} percentile for $p \in \{1,5,10,15,85,90,95,99\}$, and then estimate the corresponding parameters $\hat{\mu}_{ik}^p$ and $\hat{\sigma}_{ik}^p$ and densities $\hat{f}_{ik}^p$

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

$$mean_{ik}^{p} = \int_{0}^{\infty} yf(y;\hat{\mu}_{ik}^{p},\hat{\sigma}_{ik}^{p})dy, \tag{4.2}$$

$$var_{ik}^{p} = \int_{-\infty}^{\infty} (y - mean_{ik}^{p})^{2} f(y;\hat{\mu}_{ik}^{p},\hat{\sigma}_{ik}^{p})dy, \tag{4.3}$$

$$dside_{ik}^{p} = \int_{-\infty}^{z_d} f(y;\hat{\mu}_{ik}^{p},\hat{\sigma}_{ik}^{p})dy, \tag{4.4}$$

$$uside_{ik}^{p} = 1 - \int_{-\infty}^{z_u} f(y;\hat{\mu}_{ik}^{p},\hat{\sigma}_{ik}^{p})dy. \tag{4.5}$$

for each county – irrigation combination *ik* and late-season percentile $p \in \{1,5,10,15,85,90,95,99\}$. This study uses a fairly simplistic measure of downside and upside risk, 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.

Normal and Lognormal Results

This subsection discusses generated densities, yield and revenue impacts as influenced by average, drought and wet climates. Results presented comprise the three different measures for precipitation discussed earlier and referred to as Models 1, 2 and 3.

For each model, the study considers densities followed by yield impacts and then revenue impacts for normal distribution and subsequently lognormal distribution.

Model 1 results under normality

In the first model, precipitation variables included in regression equations are early and late precipitation. Early precipitation aggregates daily precipitation records from May through September and late precipitation captures the last month, October. Following the empirical method, research generates densities and discusses results across counties used in the study.

Figures 4.1 – 4.11 present normal density distributions for model 1. Normal densities presented hold late precipitation variable for drought climate at the 1st percentile (most severe drought) and wet climate at 99th percentile (most severe moisture). From the densities, we observe there is not much difference in the means of the average, drought and wet climate distributions. In general, the figures qualitatively suggest that drought generates a slight reduction in the mean and variance, while excessive rainfall is associated with a slight increase in mean and a rather large increase in variance. Tables 4.2 - 4.9 quantify the qualitative impact from figures 4.1- 4.11.

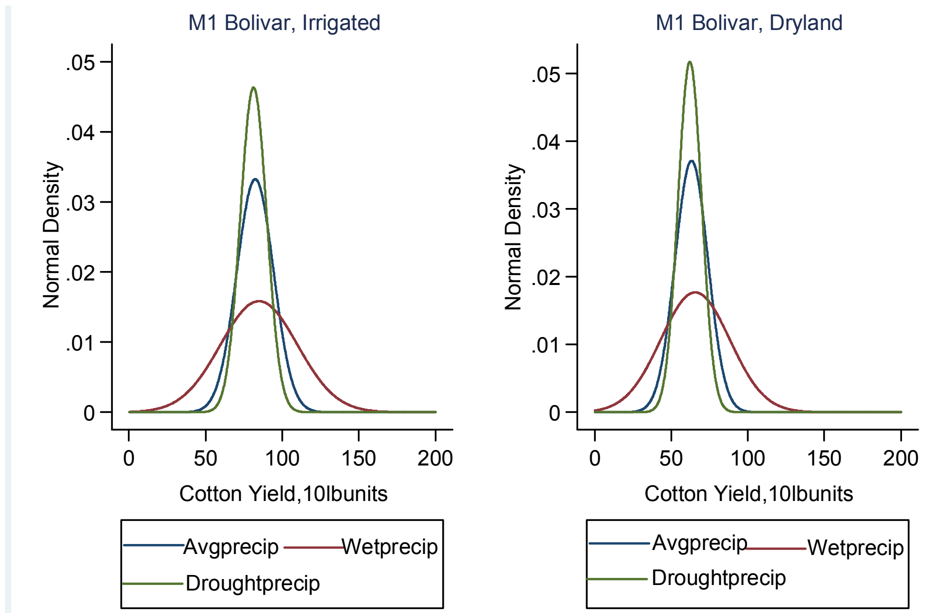

Figure 4.1 Irrigated and dryland normal yield distribution for Bolivar, (model 1)

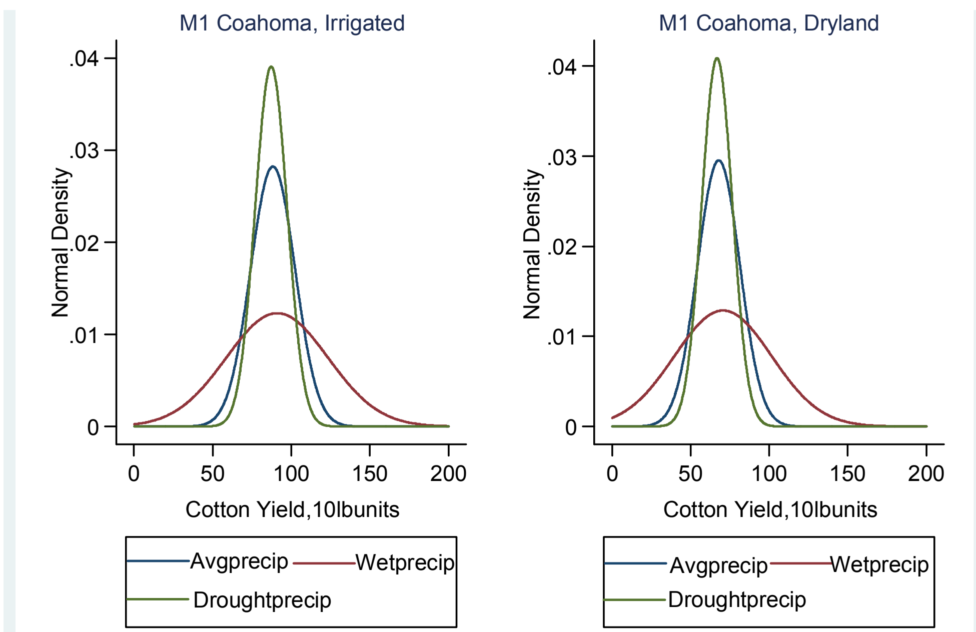

Figure 4.2 Irrigated and dryland yield distribution for Coahoma, (model 1)

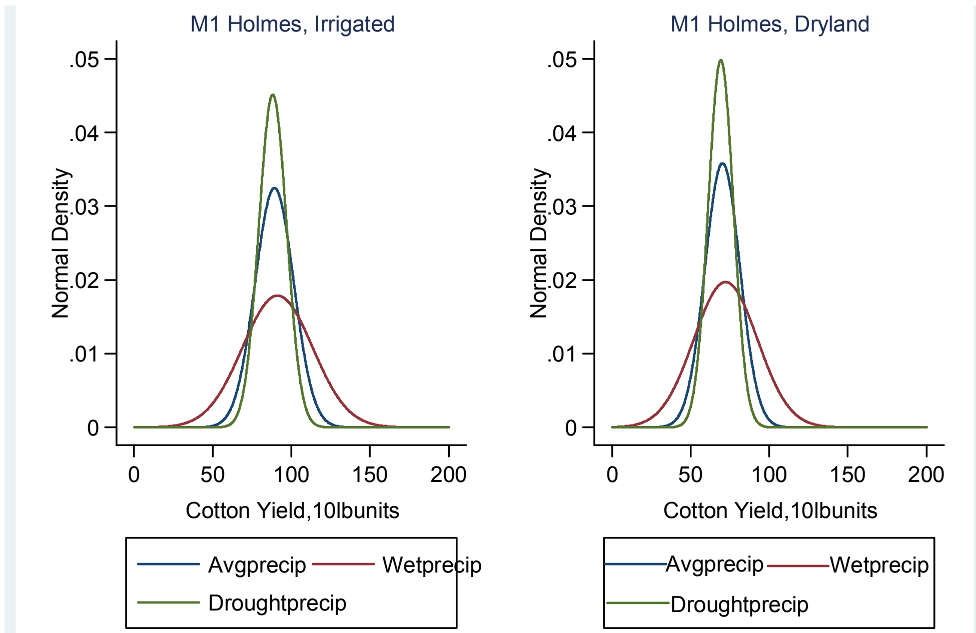

Figure 4.3 Irrigated and dryland yield distribution for Holmes, (model 1)

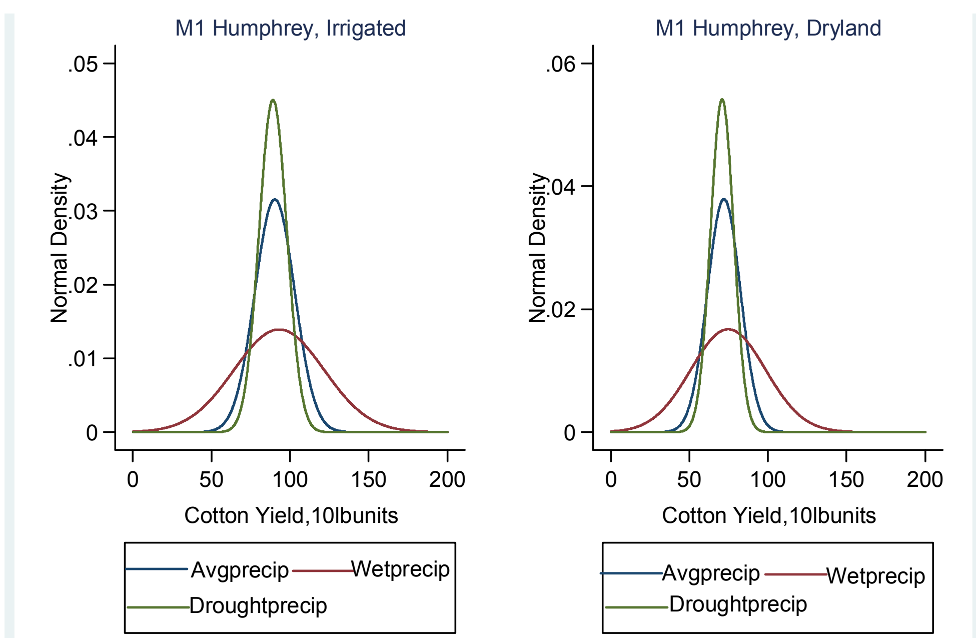

Figure 4.4 Irrigated and dryland normal yield distribution for Humphrey, (model 1)

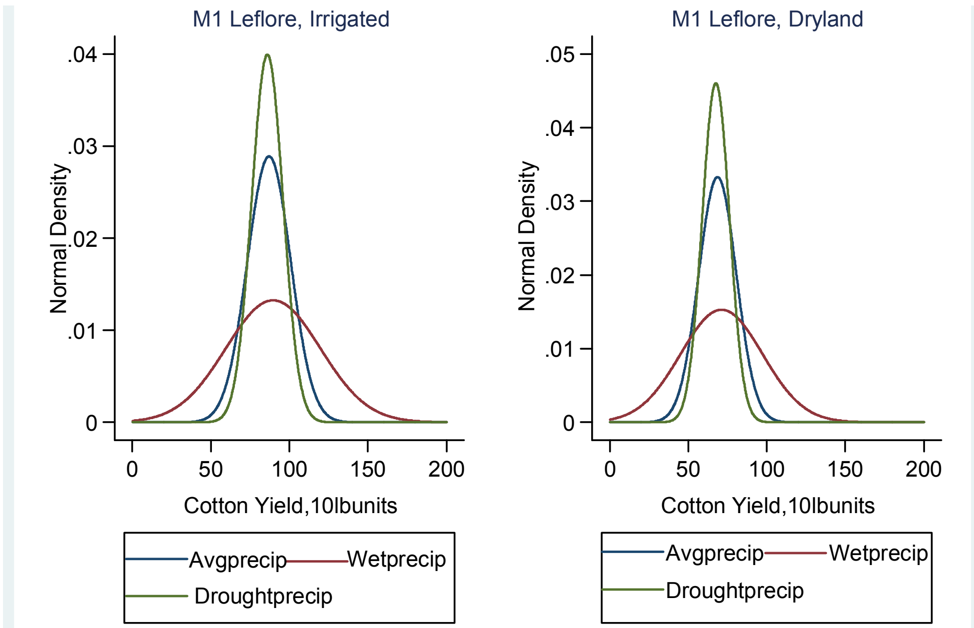

Figure 4.5 Irrigated and dryland normal yield distribution for Leflore, (model 1)

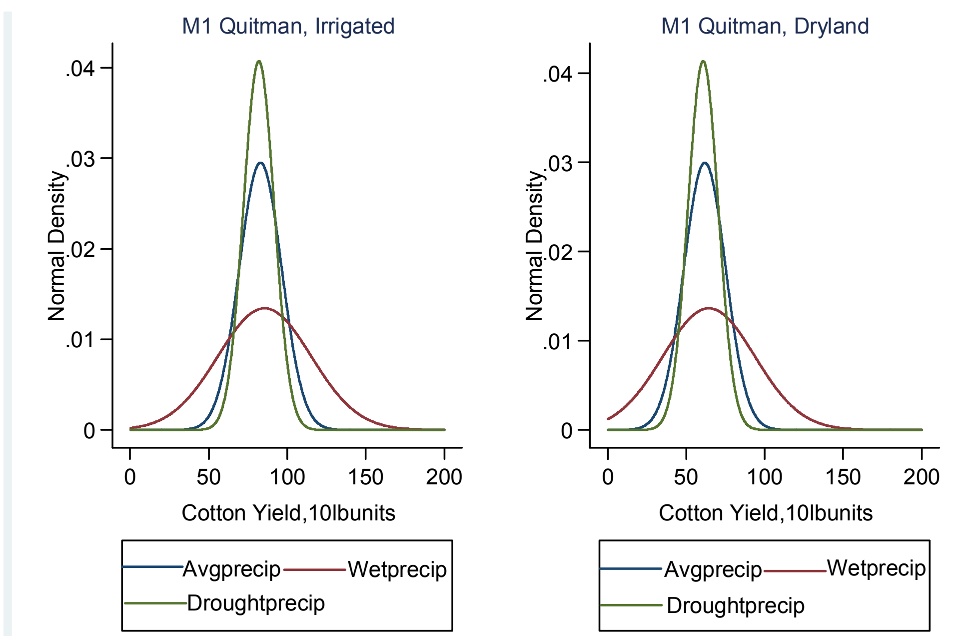

Figure 4.6 Irrigated and dryland normal yield distribution for Quitman, (model 1)

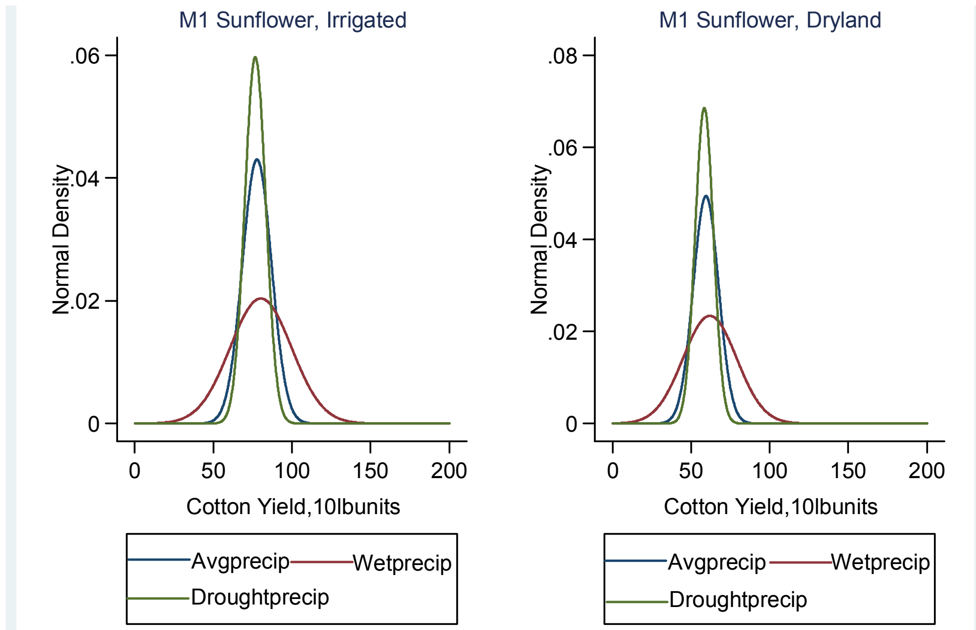

Figure 4.7 Irrigated and dryland normal yield distribution for Sunflower, (model 1)

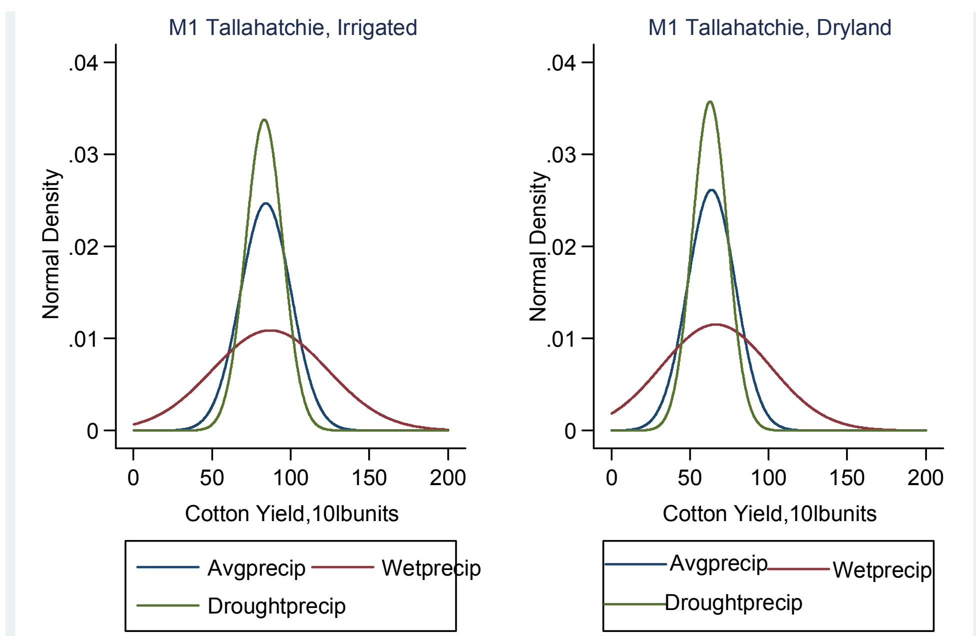

Figure 4.8 Irrigated and dryland normal yield distribution for Tallahatchie, (model 1)

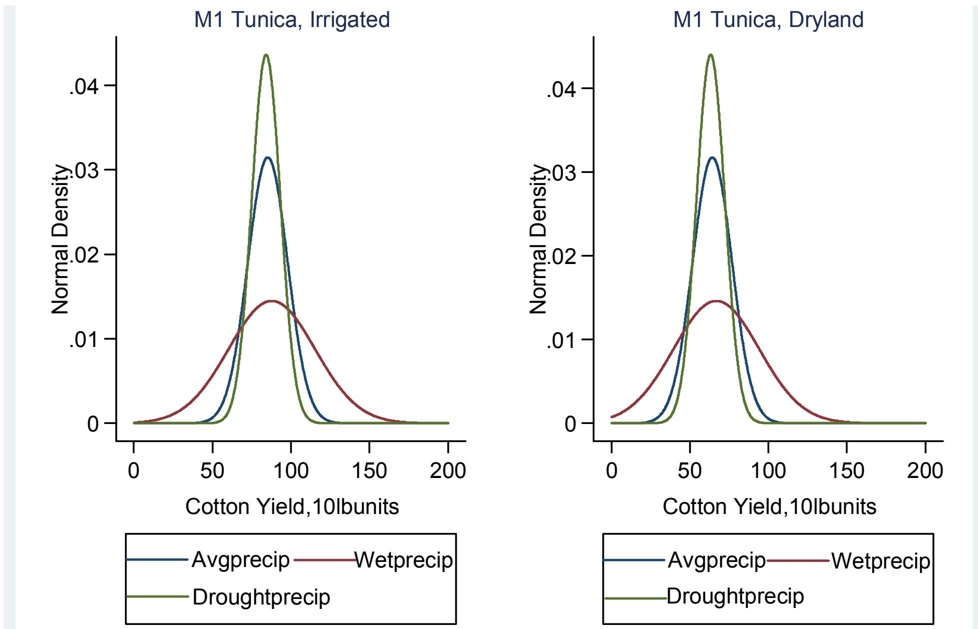

Figure 4.9 Irrigated and dryland normal yield distribution for Tunica, (model 1)

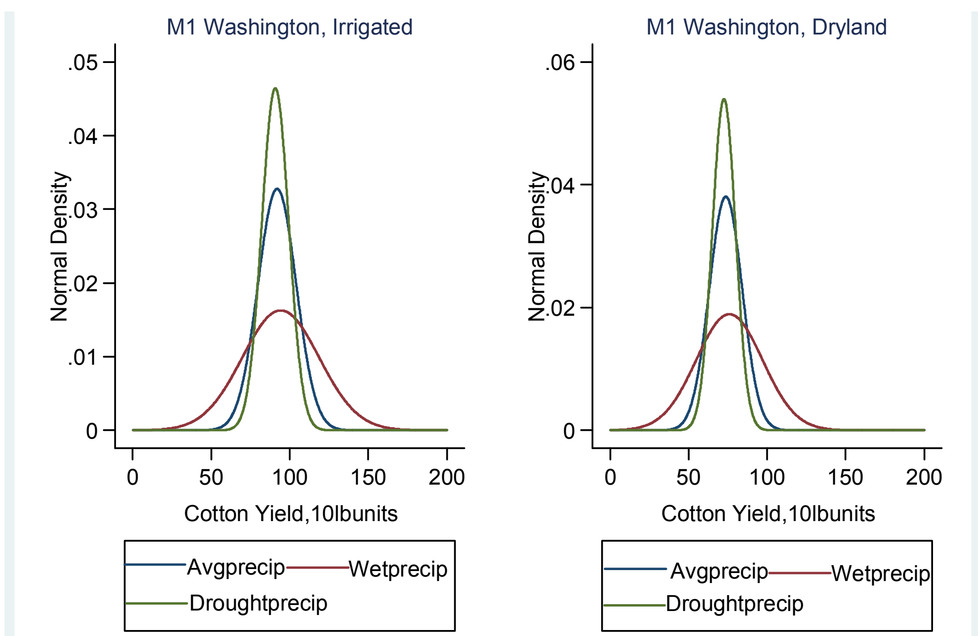

Figure 4.10 Irrigated and dryland normal yield distribution for Washington, (model 1)

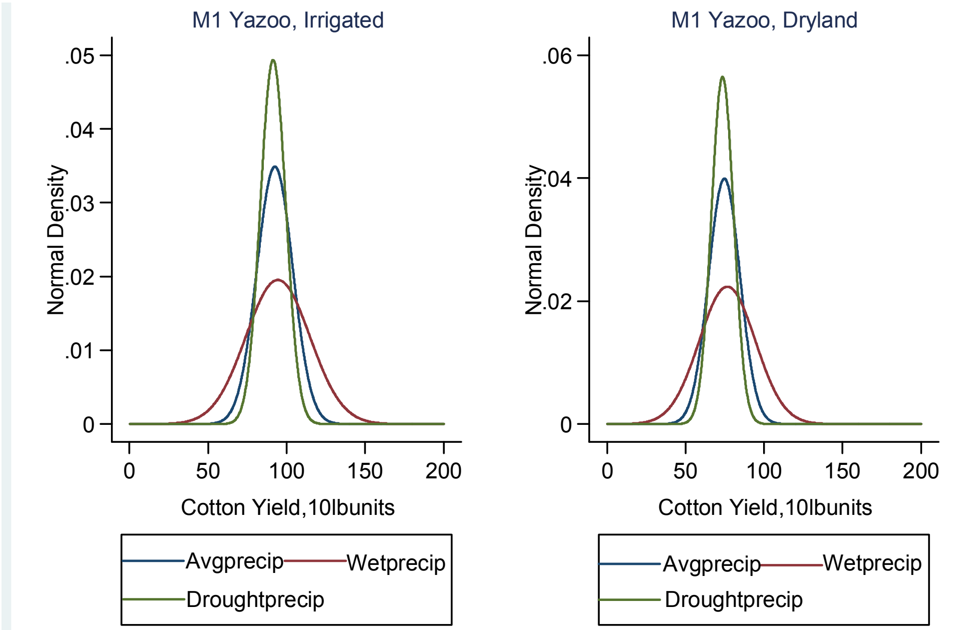

Figure 4.11 Irrigated and dryland normal yield distribution for Yazoo, (model 1)

Yield impact

Research also considers the impact of drought and wet climates on the mean, variance, upside and downside risk. Drought impact is constructed as $100 \times [F_i^{drought}(y_i^*) - F_i^{average}(y_i^*)] / F_i^{average}(y_i^*)$ while wet impact is constructed as $100 \times [F_i^{wet}(y_i^*) - F_i^{average}(y_i^*)] / F_i^{average}(y_i^*)$. This research considers drought and wet impact for a range of late precipitation variables and reports results in Tables 4.2 – 4.21 below. For each table, I discuss average results associated with drought and wet climate. From table 4.2, the acreage weighted average of the drought climate county level impact on mean (variance) yields are -1.63% (-47.52%) and -1.27 % (-47.72%) for dryland acreage and irrigated acreage respectively. Interestingly, severe late-season drought does not have a major impact on mean yields, but the variance surrounding this effect has narrowed substantially. The results suggest that irrigation provides some protection against the mean yield effect but the variance effect is equivalent across production methods. This research defines upside and downside risk as the probability of an outcome from the upper and lower tail of the distribution. The acreage weighted average of the drought climate county level impact on upside risk (downside risk) yields are -11.91 % (-39.53%) for dryland and -18.42 % (-43.25%) for irrigated acreage. Thus severe drought is associated with a large reduction in variance, and this reduction is spread disproportionately across upside and downside risk. On the other hand, the acreage weighted average of wet climate impact on the mean (variance) yields are 3.77% (333.94%) and 2.82 % (344.21%) while impact on upside risk (downside risk) yields are 24.96% (57.91%) and 36.91% (66.87%). Thus, a small increment in the means and a rather large increment in the variances for both production methods subsequently cause upside and downside risk to increase with much impact on irrigated acreage.

Table 4.2 Yield impact results, normal distribution (model 1)

System	County	Drought 1%				Wet 99%			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-1.73	-47.46	-10.65	-39.71	3.88	337.87	24.95	56.21
	Coahoma	-1.58	-47.20	-9.33	-31.75	4.20	391.04	19.62	49.47
	Holmes	-1.54	-47.29	-13.40	-41.09	2.80	232.90	24.61	52.18
	Humphreys	-1.63	-49.72	-16.29	-48.23	3.75	415.35	37.02	72.55
	Leflore	-1.56	-46.94	-11.32	-36.66	3.77	366.19	25.85	54.84
	Quitman	-1.71	-46.82	-7.16	-29.43	4.42	345.79	14.49	44.62
	Sunflower	-1.82	-46.26	-12.36	-50.46	4.15	354.94	34.12	80.89
	Tallahatchie	-1.62	-46.06	-6.42	-24.98	4.78	345.90	9.02	43.43
	Tunica	-1.67	-47.22	-8.72	-32.97	4.07	351.65	19.26	47.92
	Washington	-1.56	-49.02	-16.70	-48.33	3.13	309.14	33.65	68.33
	Yazoo	-1.53	-48.74	-18.71	-51.21	2.56	222.57	31.99	66.52
	Average	**-1.63**	**-47.52**	**-11.91**	**-39.53**	**3.77**	**333.94**	**24.96**	**57.91**
Irrigated	Bolivar	-1.33	-47.67	-17.31	-43.61	2.97	342.30	36.05	66.76
	Coahoma	-1.21	-47.26	-16.10	-37.60	3.03	414.77	34.91	60.83
	Holmes	-1.22	-47.46	-19.68	-44.84	2.21	233.02	33.65	61.36
	Humphreys	-1.30	-50.10	-21.21	-47.62	2.97	413.81	43.63	74.05
	Leflore	-1.23	-47.13	-15.88	-37.97	2.93	370.27	33.35	59.11
	Quitman	-1.28	-46.84	-14.82	-36.98	3.13	377.09	31.90	57.75
	Sunflower	-1.39	-46.70	-21.44	-53.99	3.17	353.40	50.07	96.09
	Tallahatchie	-1.23	-46.12	-11.80	-29.75	3.08	379.36	23.66	48.66
	Tunica	-1.26	-47.23	-17.10	-41.24	3.00	372.20	36.78	65.17
	Washington	-1.25	-49.33	-22.43	-49.36	2.51	308.34	41.82	73.33
	Yazoo	-1.24	-49.05	-24.83	-52.81	2.06	221.74	40.18	72.42
	Average	**-1.27**	**-47.72**	**-18.42**	**-43.25**	**2.82**	**344.21**	**36.91**	**66.87**

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

In Tables 4.3 to 4.5 below, yield impacts are reported for less severe drought and less excessive rain scenarios. In general, we see a trend of drought being associated with reduction in mean, variance, upside and downside risk under both production methods.

Conversely, wet climate has been associated generally with an increment in mean, variance upside and downside risk. However, when drought and wet climates are generated holding late precipitation at 85th and 15th percentiles, (Table 4.5) we see a reverse of drought and wet impact on the mean, variance, upside and downside yield risk. From the table, the acreage weighted average of the drought climate county level impact on mean (variance) yields are 0.98% (50.44%) for dryland and 0.76 % (50.39%) for irrigated acreage. This increment in variance causes an increment in upside risk (downside risk) of 7.96% (20.91%) and 11.30 % (23.68%) respectively. On the other hand, acreage weighted average of wet climate impact on the mean (variance) yields are -1.01% (-33.14%) and -0.78% (-33.22%), which subsequently causes reduction in upside risk (downside risk) yields as -7.63% (-24.19%) and -11.49 % (-26.66%) for dryland and irrigated acreage.

Table 4.3 Yield impact results, normal distribution (model 1)

System	***County***	***Drought 5%***				***Wet 95%***			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	1.59	-44.89	-9.89	-36.47	1.97	114.58	13.28	34.40
	Coahoma	-1.56	-46.91	-9.25	-31.44	2.94	228.10	16.61	38.30
	Holmes	-1.42	-44.57	-12.35	-37.60	1.80	116.44	16.07	37.21
	Humphreys	-1.47	-46.36	-14.76	-43.44	2.30	175.72	23.68	51.90
	Leflore	-1.43	-44.33	-10.48	-33.61	1.63	97.67	12.19	29.40
	Quitman	-1.70	-46.54	-7.11	-29.15	2.65	165.94	11.46	30.45
	Sunflower	-1.68	-43.90	-11.57	-46.80	1.98	106.30	16.06	46.77
	Tallahatchie	-1.58	-45.24	-6.27	-24.27	1.89	104.04	7.42	20.69
	Tunica	-1.64	-46.62	-8.58	-32.31	2.06	124.16	11.42	29.09
	Washington	-1.40	-45.59	-15.09	-43.45	1.83	128.48	20.22	45.93
	Yazoo	-1.32	-44.02	-16.23	-44.31	1.96	145.59	24.78	54.28
	Average	**-1.53**	**-45.36**	**-11.05**	**-36.62**	**2.09**	**137.00**	**15.75**	**38.04**
Irrigated	Bolivar	-1.22	-45.07	-15.99	-40.19	1.52	114.38	19.39	40.41
	Coahoma	-1.20	-46.96	-15.95	-37.25	2.24	233.95	27.02	48.67
	Holmes	-1.12	-44.71	-18.08	-41.17	1.41	116.24	22.20	43.29
	Humphreys	-1.17	-46.67	-19.13	-42.92	1.83	174.98	28.38	52.54
	Leflore	-1.13	-44.50	-14.64	-34.87	1.28	97.50	15.83	31.53
	Quitman	-1.27	-46.57	-14.69	-36.64	1.97	170.40	21.49	41.52
	Sunflower	-1.28	-44.27	-19.91	-50.24	1.51	105.78	24.50	54.11
	Tallahatchie	-1.19	-45.30	-11.50	-28.94	1.42	106.81	12.76	25.65
	Tunica	-1.24	-46.63	-16.79	-40.47	1.56	124.86	20.33	40.27
	Washington	-1.12	-45.85	-20.18	-44.46	1.47	128.06	25.53	48.77
	Yazoo	-1.06	-44.25	-21.46	-45.85	1.58	145.08	31.33	58.75
	Average	**-1.18**	**-45.53**	**-17.12**	**-40.27**	**1.62**	**138.00**	**22.61**	**44.14**

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

Table 4.4 Yield impact results, normal distribution (model 1)

System	*County*	*Drought 10%*				*Wet 90%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-1.31	-38.98	-8.26	-29.70	1.51	79.51	10.17	27.58
	Coahoma	-1.19	-38.51	-7.14	-23.39	0.96	48.58	5.84	15.31
	Holmes	-1.31	-42.07	-11.44	-34.57	1.48	89.08	13.30	31.71
	Humphreys	-1.24	-41.23	-12.60	-36.73	1.85	125.96	19.15	43.73
	Leflore	-1.30	-41.23	-9.52	-30.20	1.19	64.37	8.93	22.46
	Quitman	-1.18	-35.57	-5.08	-19.53	1.28	61.51	5.78	16.71
	Sunflower	-1.48	-40.14	-10.34	-41.28	1.29	59.94	10.29	32.09
	Tallahatchie	-1.36	-40.54	-5.45	-20.51	1.11	53.40	4.59	13.15
	Tunica	-0.92	-29.95	-4.95	-17.23	0.74	33.78	4.14	11.98
	Washington	-1.21	-40.98	-13.07	-37.37	1.47	94.43	16.34	38.33
	Yazoo	-1.14	-39.71	-14.15	-38.46	1.92	141.02	24.27	53.37
	Average	**-1.24**	**-38.99**	**-9.27**	**-29.91**	**1.35**	**77.42**	**11.16**	**27.86**
Irrigated	Bolivar	-1.01	-39.10	-13.20	-32.94	1.16	79.37	14.99	32.21
	Coahoma	-0.92	-38.54	-12.16	-28.03	0.74	48.60	9.43	19.28
	Holmes	-1.03	-42.19	-16.70	-37.96	1.17	88.93	18.46	36.74
	Humphreys	-0.99	-41.46	-16.23	-36.31	1.47	125.47	23.12	44.12
	Leflore	-1.02	-41.36	-13.24	-31.38	0.94	64.26	11.68	23.99
	Quitman	-0.88	-35.58	-10.24	-25.00	0.95	61.75	10.74	22.68
	Sunflower	-1.13	-40.42	-17.63	-44.55	0.98	59.72	15.94	36.72
	Tallahatchie	-1.03	-40.59	-9.89	-24.58	0.84	53.98	7.75	16.37
	Tunica	-0.69	-29.96	-9.43	-22.22	0.56	33.79	7.51	16.21
	Washington	-0.97	-41.16	-17.40	-38.33	1.18	94.15	20.74	40.56
	Yazoo	-0.92	-39.88	-18.65	-39.92	1.55	140.53	30.70	57.74
	Average	**-0.96**	**-39.11**	**-14.07**	**-32.84**	**1.05**	**77.32**	**15.55**	**31.51**

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

Table 4.5 Yield impact results, normal distribution (model 1)

System	*County*	*Drought 15%*				*Wet 85%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	1.15	56.17	7.74	21.75	-1.16	-35.48	-7.35	-26.06
	Coahoma	0.56	26.15	3.43	9.37	-0.92	-31.30	-5.52	-17.60
	Holmes	1.11	60.93	9.97	24.61	-0.95	-32.93	-8.38	-24.73
	Humphreys	1.03	57.41	10.74	26.41	-1.04	-35.95	-10.56	-30.46
	Leflore	0.87	43.88	6.55	16.99	-0.99	-33.49	-7.32	-22.64
	Quitman	1.01	46.35	4.59	13.62	-0.98	-30.55	-4.24	-15.89
	Sunflower	1.20	55.03	9.59	30.16	-1.25	-35.51	-8.91	-35.01
	Tallahatchie	0.89	41.07	3.70	10.79	-0.94	-30.23	-3.81	-13.61
	Tunica	0.67	29.77	3.70	10.81	-0.83	-27.42	-4.47	-15.39
	Washington	1.18	69.94	13.07	31.48	-1.13	-38.93	-12.22	-34.83
	Yazoo	1.14	68.09	14.45	34.00	-0.89	-32.77	-11.10	-29.92
	Average	**0.98**	**50.44**	**7.96**	**20.91**	**-1.01**	**-33.14**	**-7.63**	**-24.19**
Irrigated	Bolivar	0.89	56.08	11.49	25.28	-0.89	-35.57	-11.68	-29.02
	Coahoma	0.43	26.15	5.59	11.72	-0.71	-31.32	-9.33	-21.27
	Holmes	0.87	60.85	13.91	28.36	-0.75	-32.99	-12.13	-27.39
	Humphreys	0.82	57.26	13.15	26.49	-0.83	-36.10	-13.53	-30.15
	Leflore	0.69	43.82	8.62	18.09	-0.78	-33.57	-10.09	-23.61
	Quitman	0.75	46.46	8.57	18.41	-0.73	-30.56	-8.47	-20.48
	Sunflower	0.92	54.84	14.89	34.46	-0.96	-35.72	-15.03	-37.99
	Tallahatchie	0.68	41.39	6.26	13.42	-0.71	-30.27	-6.79	-16.46
	Tunica	0.50	29.78	6.74	14.60	-0.62	-27.42	-8.48	-19.90
	Washington	0.94	69.76	16.66	33.22	-0.90	-39.09	-16.25	-35.76
	Yazoo	0.92	67.92	18.45	36.46	-0.72	-32.87	-14.57	-31.18
	Average	**0.76**	**50.39**	**11.30**	**23.68**	**-0.78**	**-33.22**	**-11.49**	**-26.66**

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

Revenue impact

To convert yield impacts into revenue impacts, the average for state level cotton price data is estimated. The value obtained is then used to estimate mean revenue values by multiplying average price by the mean of the lognormal distribution. To estimate the upper and lower revenues, we use the variance of the lognormal density. First we estimate the standard deviation by taking the square root of the lognormal density variance and construct upper revenue as average price by one standard deviation above the mean. Similarly, we construct the lower revenue as average price by one standard deviation below the mean. In other to examine how drought (wet) climate impact on revenue ranges as we consider distribution from a severe drought (excessive moisture) scenario to less drought (less moisture) scenario, we generate revenue impact for a range of late precipitation values.

Figures 4.12 - 4.22 are revenue range plots with high and low revenues plotted on the y-axis against drought and wet late precipitation values as the distribution moves from less climate conditions toward excessive climate conditions. The climate condition includes drought, mean and wet respectively. Drought climate ranges from the 1st percentile, which is considered the severe drought scenario through the 25th percentile, which is the less severe drought scenario. On the same graph, Wet climate ranges from the 75th percentile (less moisture) through the 99th percentile (excessive drought). Results are compared to the mean revenue, which holds late precipitation variable for both drought and wet climate at the 50th percentile. Graphs are presented for dryland and irrigated acreage. We discuss results for all 11 counties in Mississippi used for the studies.

Figures 4.12- 4.22 present revenue impact results across counties for model 1. We observe that for all counties in model 1, there are less distributional differences in revenue for drought percentiles 1, 5, 10, 15 and 20. However, we see a distributional difference moving from the 20th percentile to the 25th percentile. Comparing drought revenues to mean revenues, we observe that revenue distribution under drought is slightly lower to the mean revenue. However on the same graph for wet climate scenario, we observe slight distributional differences moving from less moisture to excessive moisture scenarios with obvious distributional difference seen from the 95th percentile to the 99th percentile. Similarly, for irrigated results placed side by side with dryland results, we see a similar pattern of revenue distributions for drought and wet precipitation values. There are less distributional differences in revenue range for drought late precipitation values and observable distributional differences in revenue for wet climate. Although cotton quality and cost associated with irrigation are not factored in the analysis, the presence of irrigation causes revenue under irrigated acreage to increase when results are compared to dryland acreage results

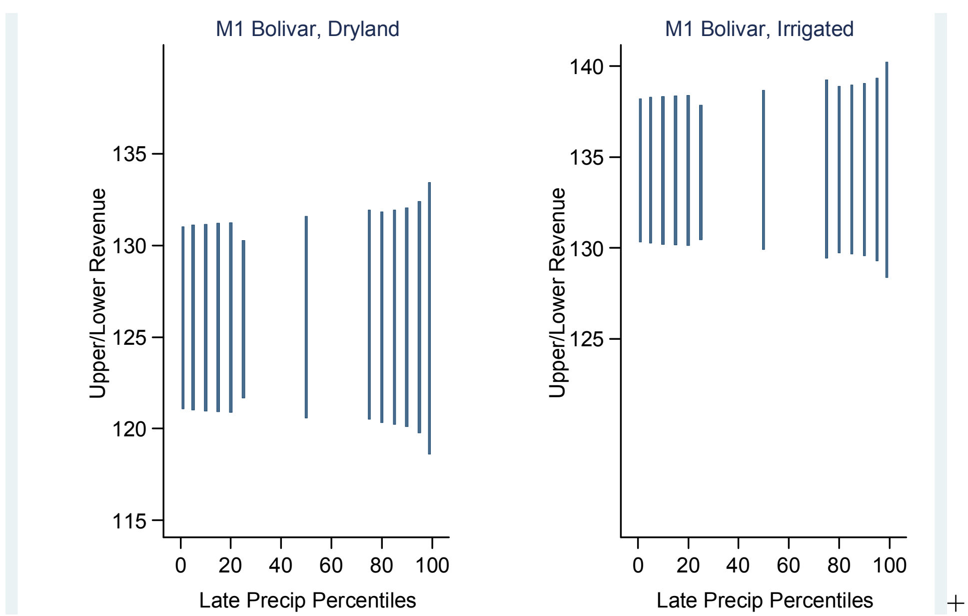

Figure 4.12 Dry and irrigated land revenue impact for Bolivar, (model1)

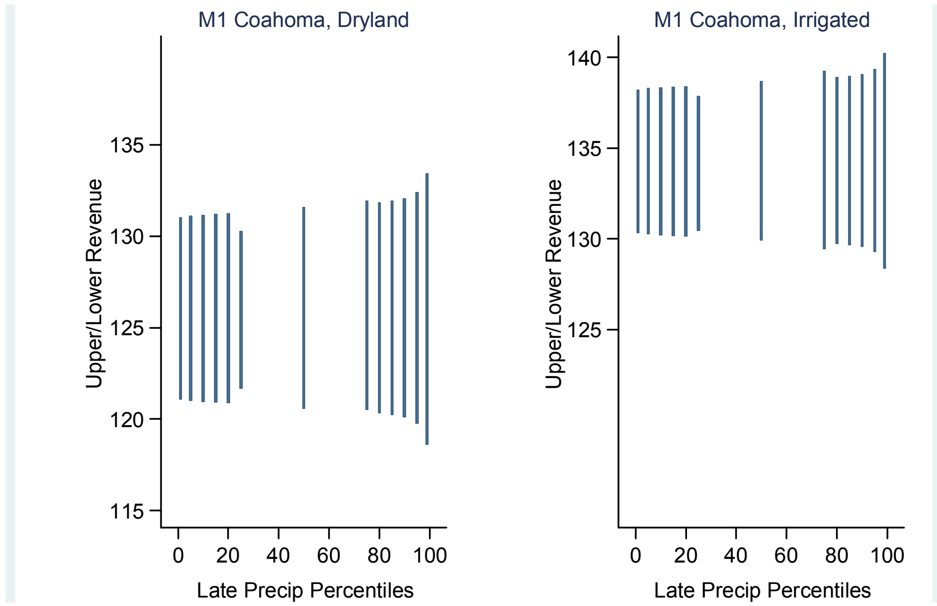

Figure 4.13 Dry and irrigated land revenue impact for Coahoma, (model1)

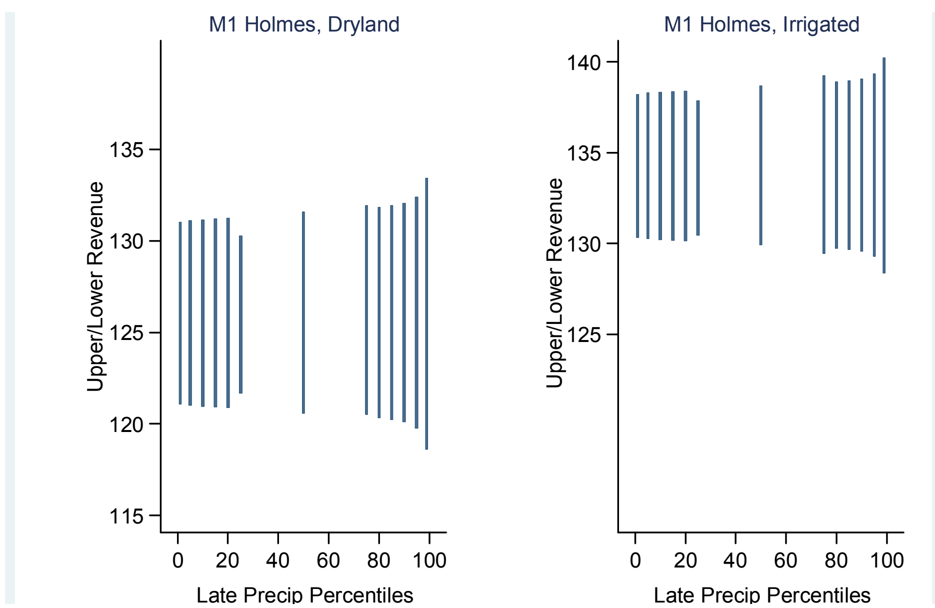

Figure 4.14 Dry and irrigated revenue impact for Holmes, (model 1)

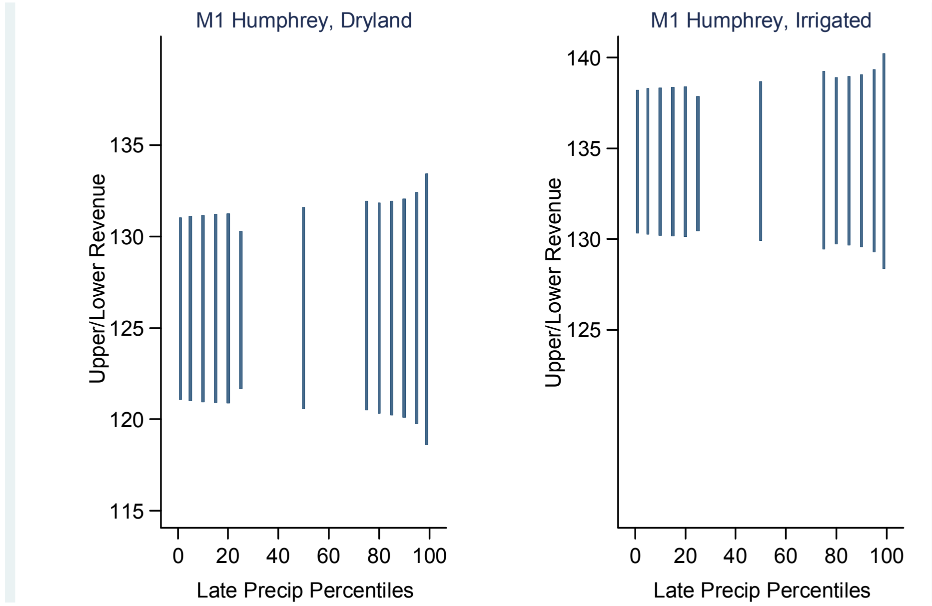

Figure 4.15 Dry and irrigated land revenue impact for Humphrey, (model 1)

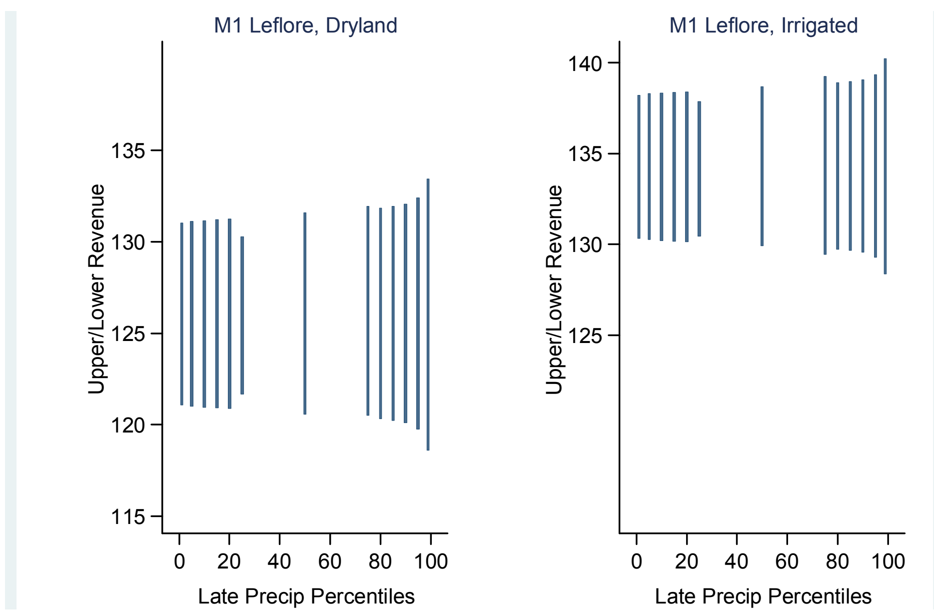

Figure 4.16 Dry and irrigated land revenue impact for Leflore, (model 1)

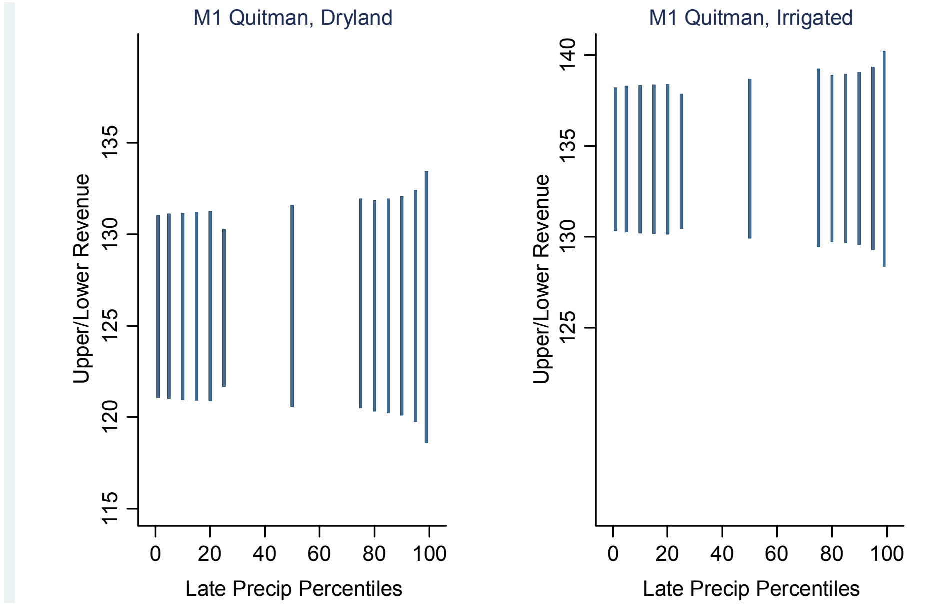

Figure 4.17 Dry and irrigated land revenue impact for Quitman, (model 1)

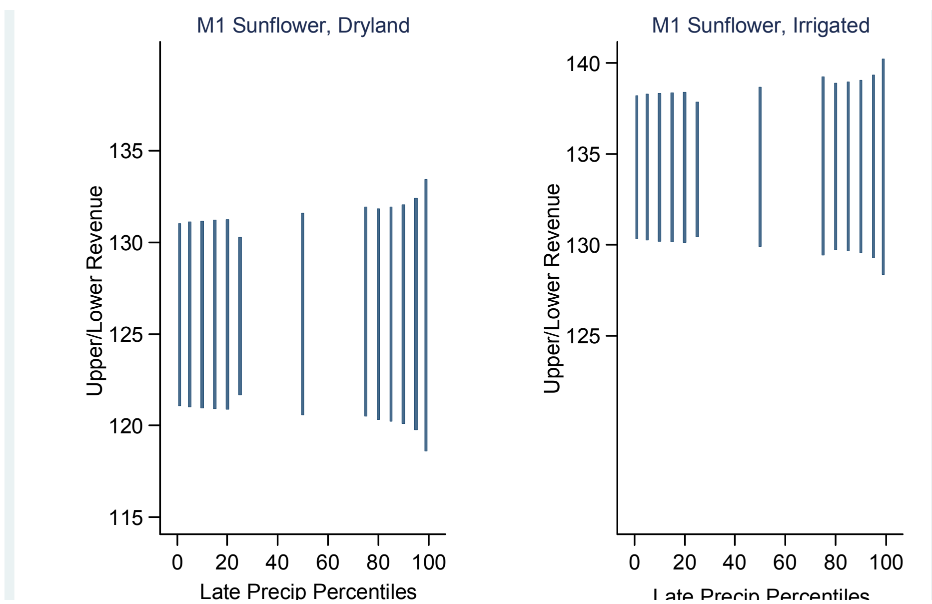

Figure 4.18 Dry and irrigated land revenue impact for Sunflower (model 1)

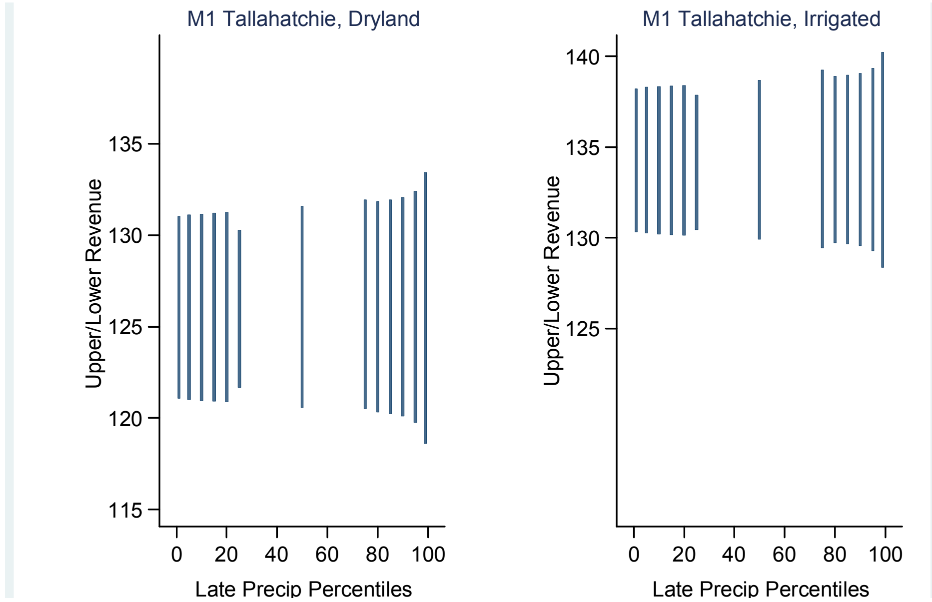

Figure 4.19 Dry and irrigated land revenue impact for Tallahatchie (model 1)

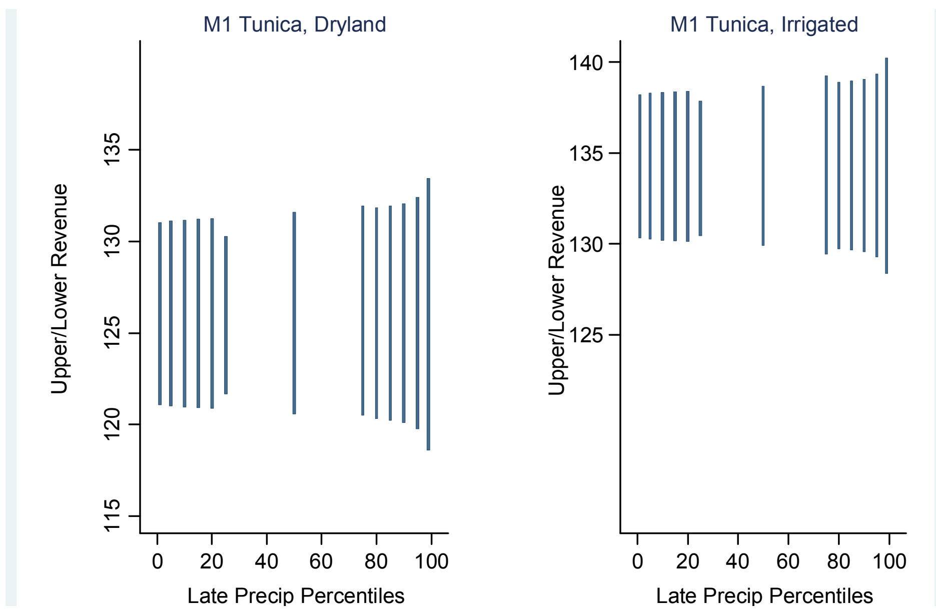

Figure 4.20 Dry and irrigated land revenue impact for Tunica (model 1)

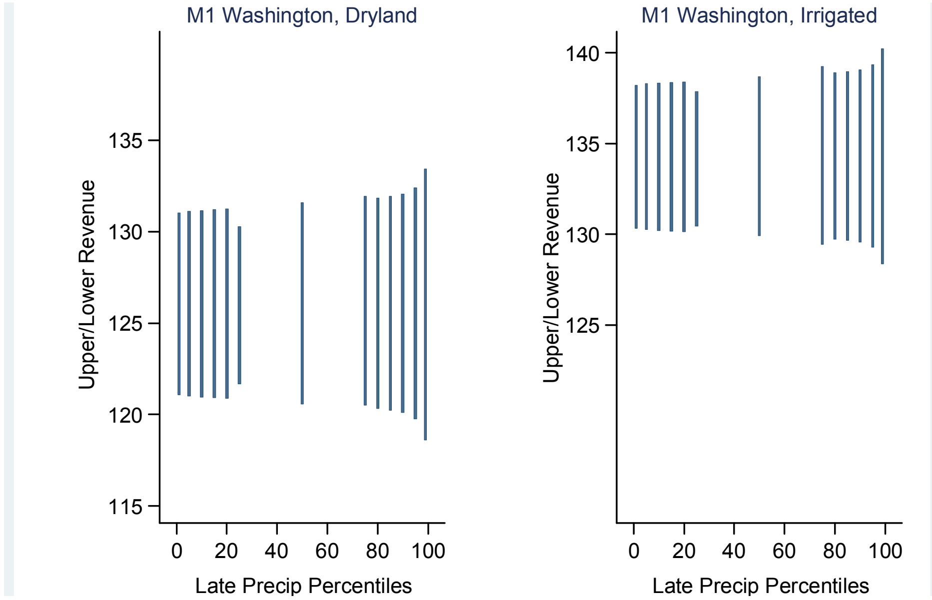

Figure 4.21 Dry and irrigated land revenue impact for Washington (model 1)

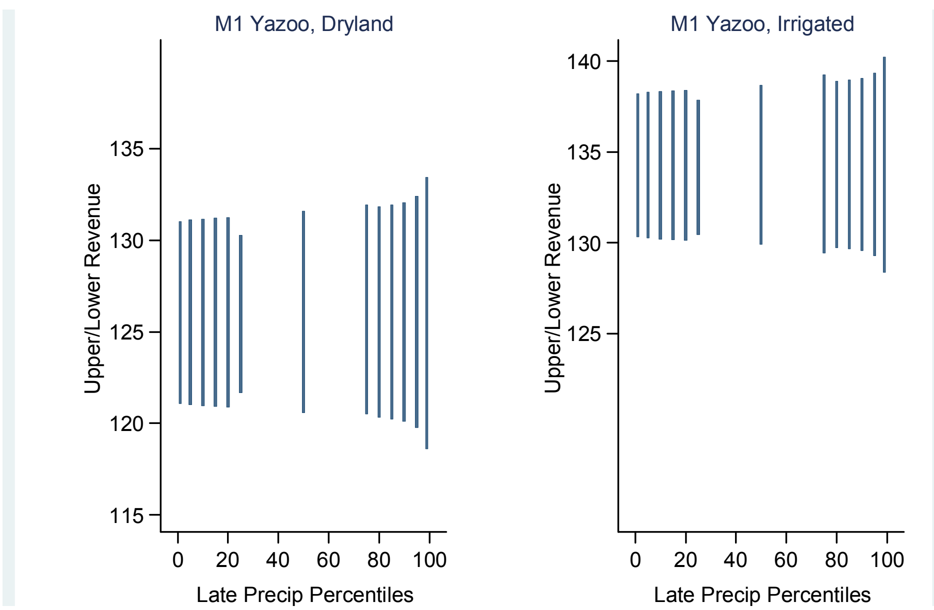

Figure 4.22 Dry and irrigated land revenue impact for Yazoo (model 1)

Generally, the symmetric distribution renders normality as a poor assumption as there is evidence of skewness when log normality is assumed. Additionally, some counties (Bolivar, Quitman and Tallahatchie) generated densities that have some amount of their probability massed over the negative real line. At severe drought and excessive moisture percentile values, drought (wet) is associated with a reduction (increment) in mean variance, upside and downside risk. Conversely at lower percentiles, the reverse occurs. Revenue impacts results under irrigated acreage imply that excessive moisture plays a significant role in revenue distribution.

Model 1 results under log normality

Assuming lognormal distribution is necessary to relax the symmetry assumption and serves as a source of robustness check of the normality assumption. Additionally, crop yields are non-negative by definition, hence the use of lognormal distributional assumption. Holding late precipitation variable for drought climate at the 1st percentile (severe drought) and that for wet climate at the 99th percentile (excessive moisture), Figures 4.23 – 4.33 present lognormal densities for model 1. Lognormal densities presented show evidence of skewness with extreme cases in Quitman and Tallahatchie counties. Evidence of skewness is more pronounced on dryland acreage than can be observed on an irrigated acreage. From the distributions we observe, there is not much difference in the means of the average, drought, and wet precipitation distributions.

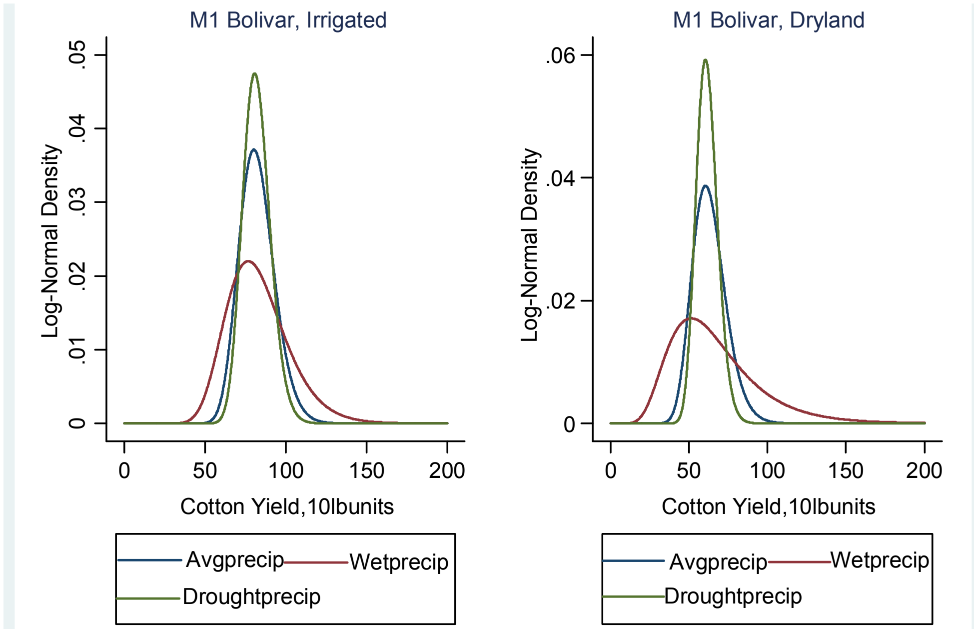

Figure 4.23 Irrigated and dryland lognormal yield distribution for Bolivar, (model 1)

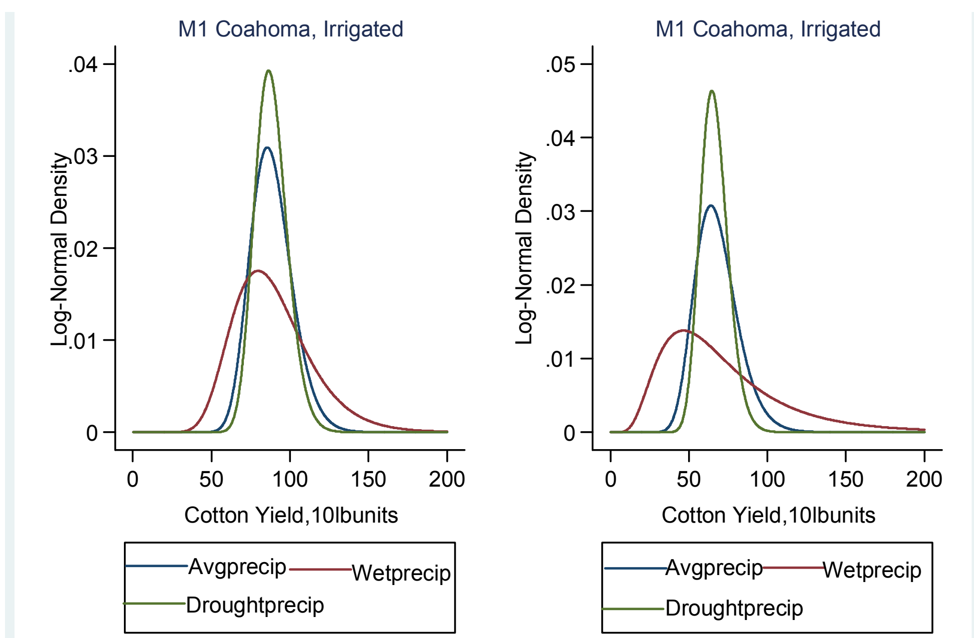

Figure 4.24 Irrigated and dryland lognormal yield distribution for Coahoma, (model 1)

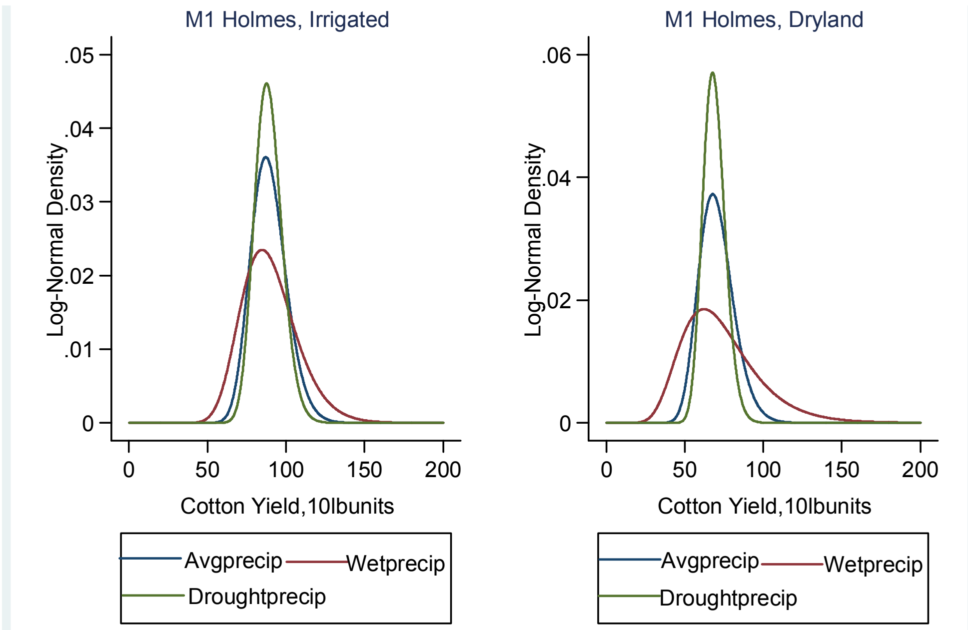

Figure 4.25 Irrigated and dryland lognormal yield distribution for Holmes, (model 1)

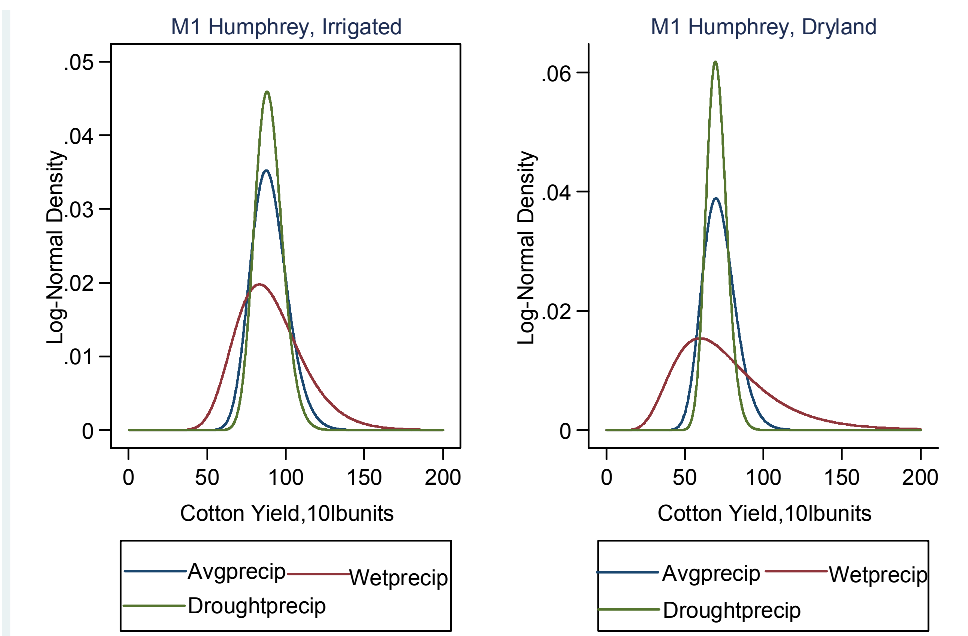

Figure 4.26 Irrigated and dryland lognormal yield distribution for Humphrey, (model 1)

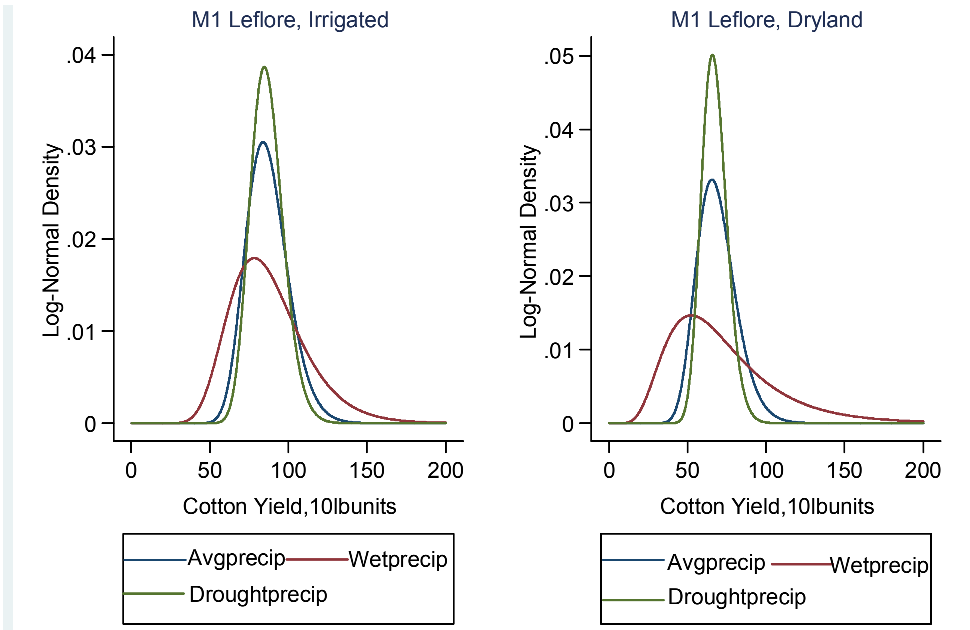

Figure 4.27 Irrigated and dryland lognormal yield distribution for Leflore, (model 1)

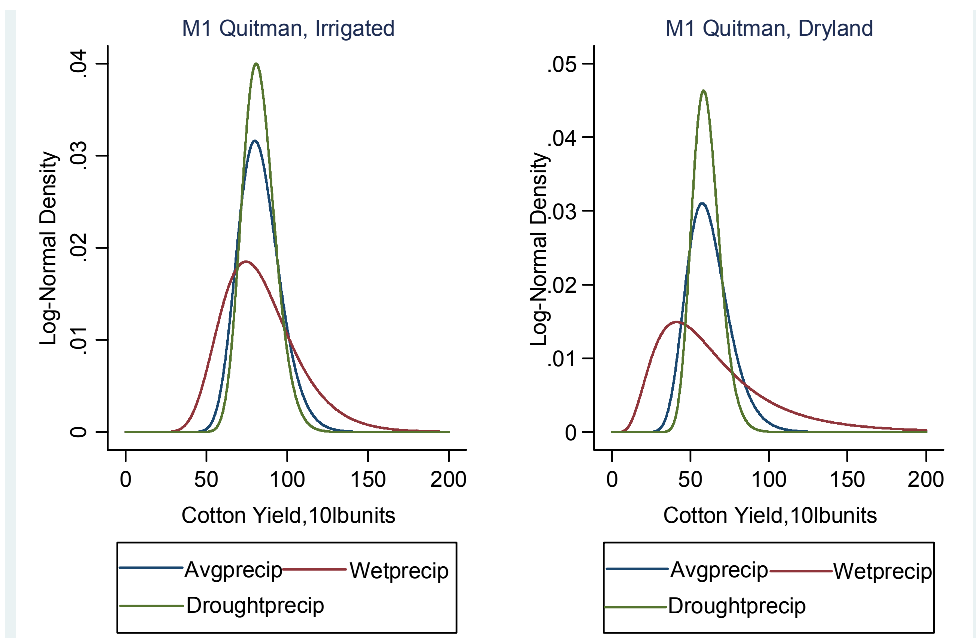

Figure 4.28 Irrigated and dryland lognormal yield distribution for Quitman, (model 1)

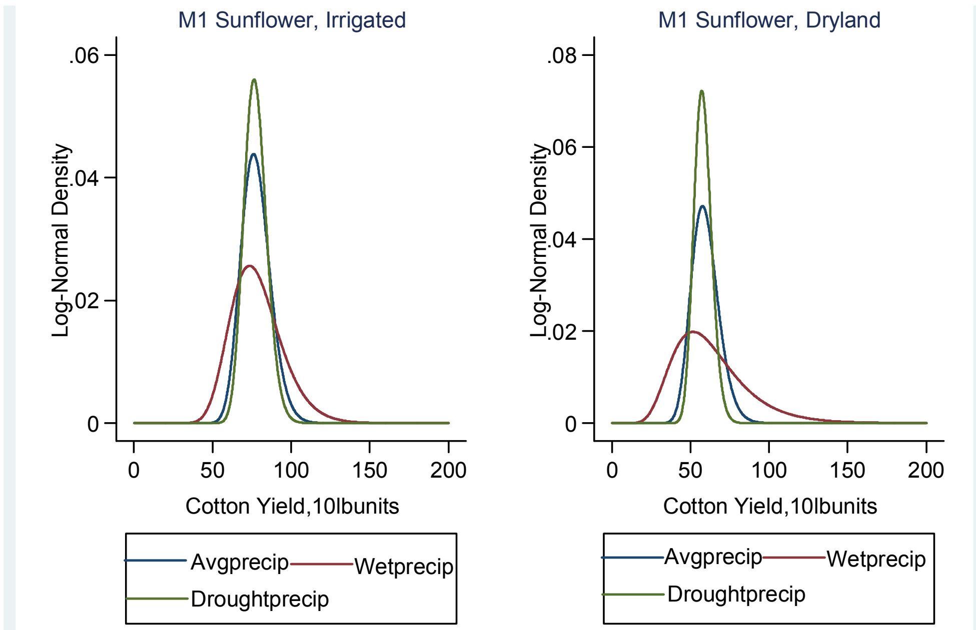

Figure 4.29 Irrigated and dryland lognormal yield distribution for Sunflower, (model 1)

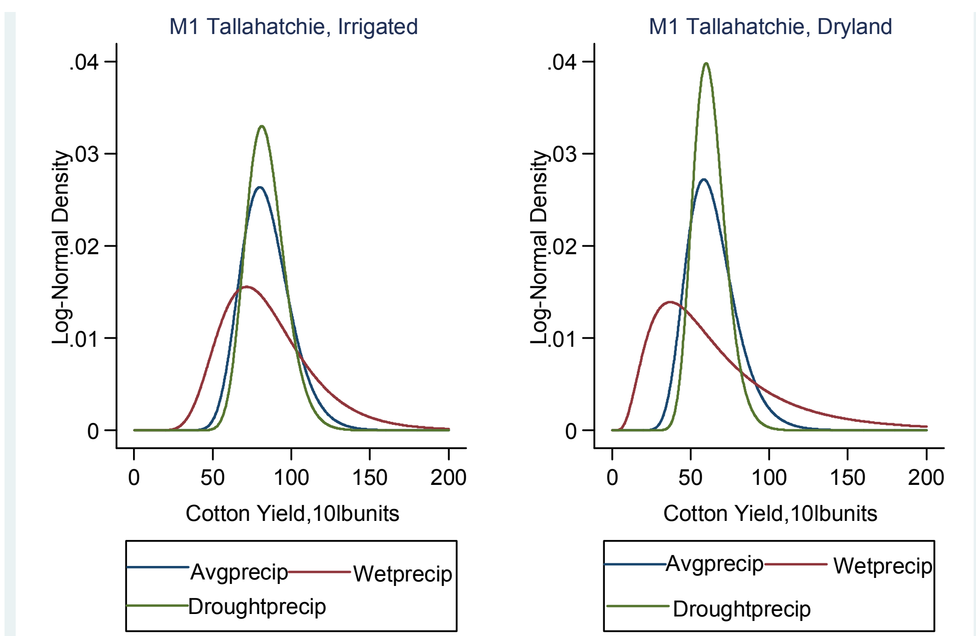

Figure 4.30 Irrigated and dryland lognormal yield distribution for Tallahatchie, (model 1)

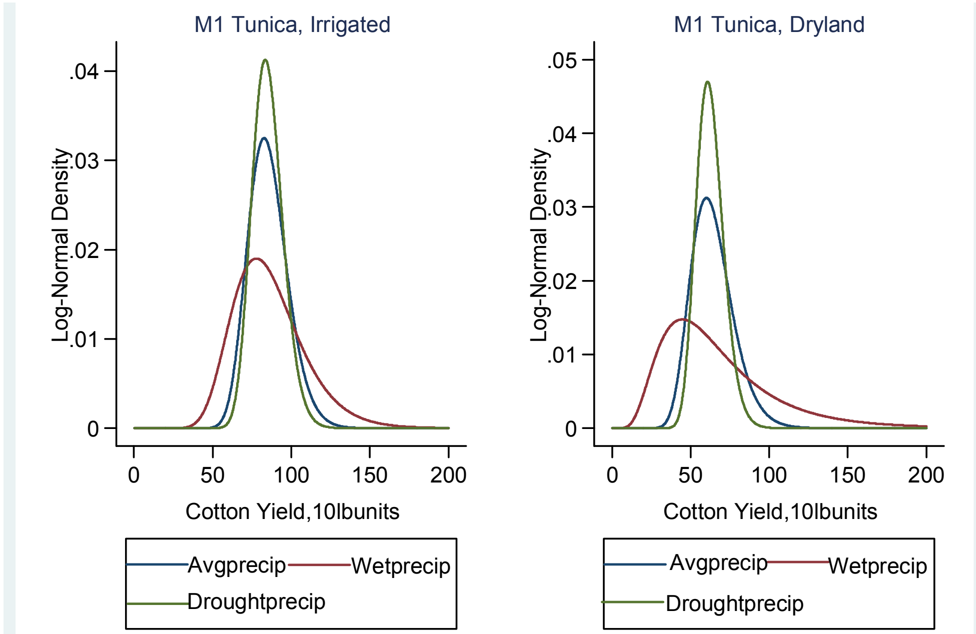

Figure 4.31 Irrigated and dryland lognormal yield distribution for Tunica, (model 1)

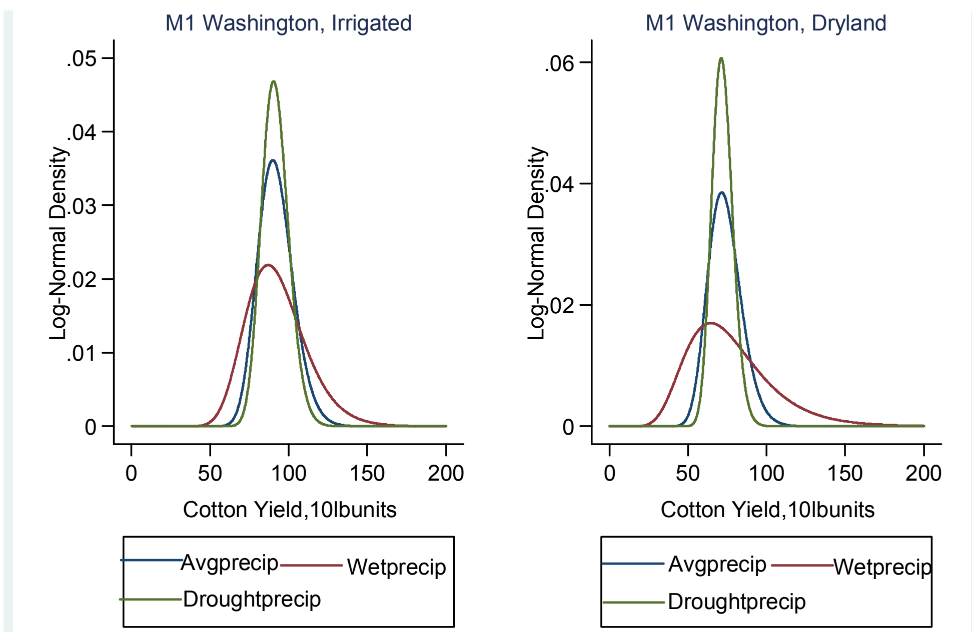

Figure 4.32 Irrigated and dryland lognormal yield distribution for Washington, (model 1)

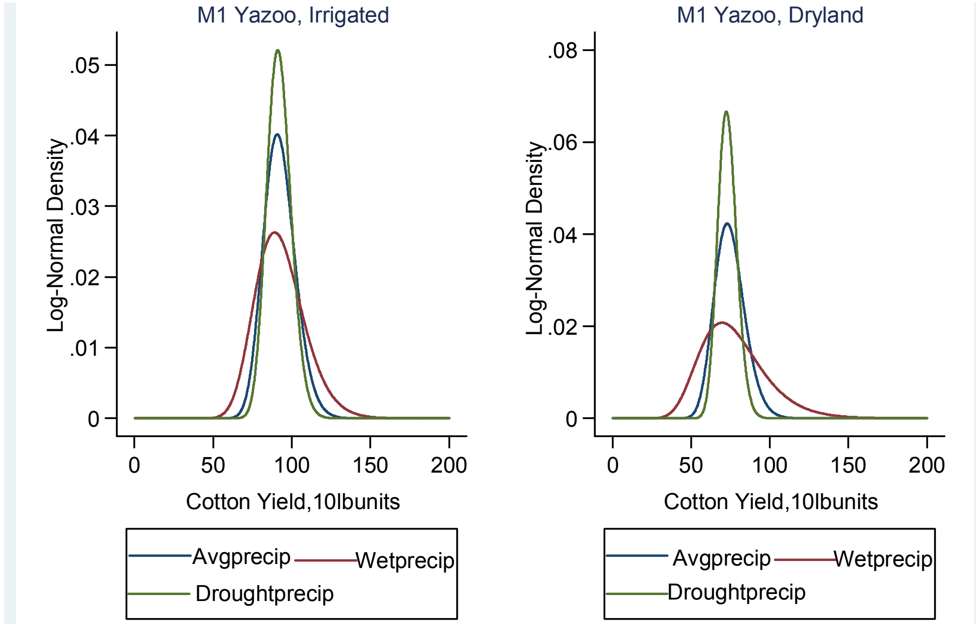

Figure 4.33 Irrigated and dryland lognormal yield distribution for Yazoo, (model 1)

Yield impact results when lognormal distribution assumption is used follows the same results pattern as when normal distribution is used. Drought (Wet) is associated with reduction (increment) in mean, variance, upside and downside risk at higher percentiles and the reverse occurs at lower percentiles. The values presented for lognormal yield impact are slightly above the values presented for normal distribution. Yield impacts presented for lognormal distributed are shown in Tables 4.6 - 4.9 below. Revenue impact results are the same as the revenue impact results for normal distribution and hence not reported. Therefore relaxing the skewness constraint by utilizing a log normal distribution assumption is important to clearly bring out skewness in the cotton yield densities. Since the use of normal distribution assumption appears to limit the entire shape of the distribution, the rest of the within season precipitation effect focuses on the lognormal distributional assumption.

Table 4.6 Yield impact results, lognormal distribution (model 1)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-2.47	-56.84	-14.15	-50.87	4.74	591.49	46.31	47.37
	Coahoma	-2.25	-57.02	-13.61	-40.31	0.37	565.98	46.33	30.36
	Holmes	-2.20	-56.74	-17.92	-52.80	3.81	394.17	41.44	50.32
	Humphrey	-2.33	-59.05	-21.85	-60.78	3.95	716.03	64.54	62.44
	Leflore	-2.22	-56.69	-15.14	-44.72	2.59	571.61	47.43	39.02
	Quitman	-2.45	-56.66	-10.71	-36.94	1.61	522.90	39.11	25.27
	Sunflower	-2.59	-55.34	-14.85	-59.71	5.77	650.07	54.65	67.42
	Tallahatchie	-2.31	-56.02	-10.16	-30.65	-2.61	447.53	38.14	16.74
	Tunica	-2.40	-57.12	-11.95	-38.96	1.84	523.05	40.46	27.94
	Washington	-2.23	-58.42	-22.38	-59.97	4.00	534.86	56.01	61.83
	Yazoo	-2.19	-57.73	-26.10	-66.18	3.62	381.36	54.29	72.44
	Average	**-2.33**	**-57.06**	**-16.26**	**-49.26**	**2.70**	**536.28**	**48.06**	**45.56**
Irrigated	Bolivar	-0.39	-39.74	-24.13	-27.74	0.85	210.96	50.10	43.82
	Coahoma	-0.35	-39.18	-21.12	-23.02	0.64	246.68	48.37	37.08
	Holmes	-0.35	-39.52	-25.94	-29.31	0.64	149.91	44.87	41.29
	Humphrey	-0.38	-41.96	-27.48	-31.00	0.82	247.72	58.50	49.63
	Leflore	-0.36	-39.09	-19.87	-21.98	0.66	222.34	42.83	33.54
	Quitman	-0.37	-38.85	-19.54	-21.64	0.77	228.63	43.02	33.32
	Sunflower	-0.41	-39.31	-27.00	-32.06	0.93	215.04	59.45	55.51
	Tallahatchie	-0.36	-38.04	-15.54	-16.38	0.02	223.60	36.09	23.60
	Tunica	-0.37	-39.28	-21.20	-23.88	0.77	224.45	45.63	37.29
	Washington	-0.36	-41.29	-28.79	-32.51	0.72	191.67	55.06	49.60
	Yazoo	-0.36	-41.10	-33.15	-37.25	0.60	143.34	55.93	53.15
	Average	**-0.37**	**-39.76**	**-23.98**	**-26.98**	**0.68**	**209.48**	**49.08**	**41.62**

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

Table 4.7 Yield impact results, lognormal distribution (model 1)

System	***County***	***Drought 1%***				***Wet 99%***			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-2.28	-54.23	-13.32	-46.71	2.82	179.53	22.13	36.02
	Coahoma	-2.23	-56.72	-13.51	-39.90	3.06	361.28	32.62	30.81
	Holmes	-2.02	-53.94	-16.68	-48.34	2.56	182.60	25.81	39.89
	Humphrey	-2.10	-55.71	-20.03	-54.93	3.26	289.89	38.57	52.91
	Leflore	-2.04	-53.96	-14.14	-40.87	2.30	149.64	19.42	28.54
	Quitman	-2.43	-56.36	-10.64	-36.57	3.37	265.44	23.25	25.04
	Sunflower	-2.39	-52.96	-14.08	-55.40	2.82	164.80	23.88	46.81
	Tallahatchie	-2.25	-55.14	-9.96	-29.71	2.38	157.66	15.47	17.03
	Tunica	-2.35	-56.49	-11.78	-38.14	2.85	193.16	19.63	24.61
	Washington	-2.00	-54.97	-20.43	-54.04	2.61	203.80	31.91	47.73
	Yazoo	-1.88	-53.04	-22.97	-57.85	2.80	235.33	41.10	62.31
	Average	**-2.18**	**-54.87**	**-15.23**	**-45.68**	**2.80**	**216.65**	**26.71**	**37.43**
Irrigated	Bolivar	-0.36	-37.33	-22.25	-25.49	0.44	78.72	26.52	26.01
	Coahoma	-0.35	-38.91	-20.93	-22.80	0.61	150.03	35.94	30.13
	Holmes	-0.33	-36.98	-23.82	-26.82	0.41	79.92	29.33	28.66
	Humphrey	-0.34	-38.75	-24.76	-27.81	0.54	116.05	37.11	34.75
	Leflore	-0.33	-36.69	-18.28	-20.12	0.37	67.96	19.54	18.07
	Quitman	-0.37	-38.59	-19.37	-21.44	0.57	113.31	27.90	24.32
	Sunflower	-0.37	-37.00	-25.00	-29.61	0.44	72.86	29.22	30.47
	Tallahatchie	-0.35	-37.30	-15.14	-15.92	0.38	73.56	16.74	13.82
	Tunica	-0.36	-38.73	-20.80	-23.41	0.45	85.32	24.64	23.03
	Washington	-0.33	-38.03	-25.90	-29.13	0.43	87.33	33.09	32.30
	Yazoo	-0.31	-36.63	-28.71	-32.12	0.46	97.81	43.26	42.48
	Average	**-0.35**	**-37.72**	**-22.27**	**-24.97**	**0.46**	**92.99**	**29.39**	**27.64**

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

Table 4.8 Yield impact results, lognormal distribution (model 1)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-1.88	-47.95	-11.40	-37.91	2.16	119.93	16.60	30.07
	Coahoma	-1.70	-47.66	-10.72	-29.27	1.36	70.38	9.95	16.26
	Holmes	-1.87	-51.31	-15.57	-44.44	2.12	135.78	21.07	34.99
	Humphrey	-1.78	-50.36	-17.35	-46.51	2.64	199.43	30.63	46.54
	Leflore	-1.85	-50.62	-12.97	-36.57	1.69	95.12	13.93	22.81
	Quitman	-1.69	-44.37	-7.94	-23.95	1.82	90.78	10.51	16.68
	Sunflower	-2.11	-49.03	-12.83	-48.84	1.83	88.16	14.90	33.70
	Tallahatchie	-1.94	-50.04	-8.81	-24.77	1.55	77.86	8.82	12.33
	Tunica	-1.32	-37.90	-7.18	-19.58	1.06	47.93	6.61	11.85
	Washington	-1.72	-50.12	-17.91	-46.49	2.10	144.75	25.43	41.15
	Yazoo	-1.63	-48.52	-20.25	-50.52	2.74	226.99	40.20	61.47
	Average	**-1.77**	**-47.99**	**-12.99**	**-37.17**	**1.92**	**117.92**	**18.06**	**29.80**
Irrigated	Bolivar	-0.29	-31.96	-18.31	-20.79	0.34	56.06	20.49	20.60
	Coahoma	-0.27	-31.36	-15.91	-17.07	0.21	35.30	12.31	11.79
	Holmes	-0.30	-34.69	-21.98	-24.68	0.34	62.36	24.34	24.20
	Humphrey	-0.29	-34.01	-20.99	-23.41	0.43	85.76	30.10	28.98
	Leflore	-0.30	-33.87	-16.51	-18.06	0.27	46.01	14.40	13.72
	Quitman	-0.26	-28.81	-13.40	-14.52	0.28	44.31	13.86	13.20
	Sunflower	-0.33	-33.43	-22.04	-25.99	0.29	42.71	19.12	20.56
	Tallahatchie	-0.30	-33.10	-12.98	-13.48	0.24	38.93	10.09	8.87
	Tunica	-0.20	-24.02	-11.57	-12.66	0.16	24.88	9.10	9.20
	Washington	-0.28	-33.78	-22.33	-24.97	0.34	65.75	26.80	26.69
	Yazoo	-0.27	-32.68	-24.99	-27.85	0.45	95.01	42.37	41.71
	Average	**-0.28**	**-31.97**	**-18.27**	**-20.32**	**0.31**	**54.28**	**20.27**	**19.96**

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

Table 4.9 Yield impact results, normal distribution (model 1)

System	*County*	***Drought 1%***				***Wet 99%***			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	1.65	82.30	12.41	24.42	-1.66	-44.07	-10.27	-33.17
	Coahoma	0.80	36.70	5.73	10.35	-1.31	-39.45	-8.45	-21.73
	Holmes	1.58	89.82	15.53	28.03	-1.35	-41.20	-11.69	-31.62
	Humphrey	1.47	84.25	16.61	30.12	-1.48	-44.58	-14.74	-38.53
	Leflore	1.24	63.16	10.07	17.79	-1.41	-41.96	-10.18	-27.07
	Quitman	1.44	67.05	8.21	14.00	-1.40	-38.58	-6.73	-19.27
	Sunflower	1.71	80.44	13.84	31.85	-1.79	-44.00	-11.26	-41.33
	Tallahatchie	1.26	58.98	6.99	10.44	-1.34	-38.27	-6.36	-15.95
	Tunica	0.95	41.99	5.89	10.78	-1.18	-34.89	-6.52	-17.37
	Washington	1.68	104.23	20.10	34.66	-1.61	-47.90	-16.84	-43.32
	Yazoo	1.62	101.41	23.19	41.57	-1.27	-40.87	-16.14	-39.47
	Average	**1.40**	**73.67**	**11.54**	**23.09**	**-1.44**	**-41.43**	**-10.84**	**-29.89**
Irrigated	Bolivar	0.26	40.40	15.71	16.09	-0.26	-28.85	-16.18	-18.28
	Coahoma	0.13	19.42	7.28	7.15	-0.21	-25.14	-12.20	-12.92
	Holmes	0.25	43.66	18.30	18.57	-0.22	-26.62	-15.96	-17.70
	Humphrey	0.24	41.23	17.03	17.18	-0.24	-29.29	-17.49	-19.37
	Leflore	0.20	31.96	10.62	10.33	-0.23	-27.07	-12.54	-13.52
	Quitman	0.22	33.80	11.06	10.70	-0.21	-24.51	-11.06	-11.87
	Sunflower	0.27	39.40	17.87	19.29	-0.28	-29.19	-18.72	-21.95
	Tallahatchie	0.19	30.23	8.14	7.28	-0.21	-24.22	-8.87	-9.00
	Tunica	0.15	22.02	8.16	8.28	-0.18	-21.89	-10.39	-11.33
	Washington	0.28	49.67	21.49	21.75	-0.26	-31.94	-20.85	-23.26
	Yazoo	0.27	48.40	25.23	25.83	-0.21	-26.54	-19.56	-21.66
	Average	**0.22**	**36.38**	**14.63**	**14.77**	**-0.23**	**-26.84**	**-14.89**	**-16.44**

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

Model 2 results under normal distribution

A more general approach to Model 1 is to break up the 5-month early season of model 1into two sub-seasons. That is, we divide the season from May to June as early, July to September as mid and October as late. Therefore, the regression model is generalized to include early precipitation, mid precipitation and late precipitation. Research estimates model 2 as a robustness check for model 1. As in the first model, we hold late precipitation variable for drought climate at the 1st percentile (most severe drought) and wet climate at 99th percentile (most severe moisture). Generated normal densities results follow a similar pattern as in the first model 1 and hence are not presented. Hence, for yield densities, additional complexity in regression specification is unwarranted.

Model 2 results under lognormal distribution

Under lognormailty and still holding late precipitation variables at extreme scenarios, generated yield impacts follow a similar pattern, and these are presented in tables 4.10-4.13. Yield impacts are then converted into revenue impact and results are presented in Figures 4.34-4.44. Although revenue impacts follow a similar pattern, there exist slight distributional differences when compared to the revenue impact of model 1. Once again from these graphs we see that under irrigated acreage, revenue impacts are higher than dryland acreage. Thus the use of irrigation buffers the revenue distribution because revenue impacts are shifted up when compared to dryland acreage.

Table 4.10 Yield impact results, lognormal distribution (model 2)

System	County	Drought 1%				Wet 99%			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-2.74	-56.53	-11.68	-53.32	5.36	604.37	45.31	50.21
	Coahoma	-2.50	-57.06	-11.38	-40.57	0.13	548.61	43.98	29.29
	Holmes	-2.45	-56.39	-15.74	-56.19	4.28	403.17	40.95	55.10
	Humphrey	-2.58	-58.88	-18.23	-61.16	4.19	711.61	60.51	60.78
	Leflore	-2.46	-56.69	-12.41	-44.83	2.63	561.61	44.35	37.57
	Quitman	-2.72	-56.80	-8.63	-35.70	0.81	486.19	36.52	22.03
	Sunflower	-2.87	-54.99	-11.11	-60.81	6.37	659.73	51.03	67.58
	Tallahatchie	-2.56	-56.03	-8.78	-32.50	-1.91	458.73	37.55	18.50
	Tunica	-2.66	-57.00	-10.06	-41.51	2.60	538.71	39.66	30.67
	Washington	-2.48	-57.50	-21.38	-67.34	4.74	561.72	60.64	77.68
	Yazoo	-2.42	-56.56	-25.43	-73.50	4.04	391.73	59.52	90.58
	Average	**-2.59**	**-56.77**	**-14.08**	**-51.58**	**3.02**	**538.74**	**47.28**	**49.09**
Irrigated	Bolivar	-1.06	-23.10	-2.96	-23.42	2.37	86.87	11.17	45.34
	Coahoma	-0.97	-23.00	-3.15	-17.55	2.46	99.50	11.73	35.46
	Holmes	-0.98	-22.98	-4.02	-24.34	1.77	65.30	10.40	40.17
	Humphrey	-1.05	-24.53	-4.50	-26.68	2.41	99.44	15.55	53.72
	Leflore	-0.98	-22.89	-3.08	-18.58	2.36	91.67	11.03	36.31
	Quitman	-1.02	-22.80	-2.37	-15.96	2.49	92.49	9.26	30.51
	Sunflower	-1.11	-22.56	-2.15	-27.59	2.54	89.40	10.99	57.76
	Tallahatchie	-0.98	-22.33	-2.34	-13.65	2.52	96.24	9.33	26.92
	Tunica	-1.01	-23.00	-2.90	-18.76	2.39	91.33	10.62	36.31
	Washington	-1.00	-23.94	-5.59	-30.50	2.00	80.91	15.96	58.36
	Yazoo	-0.99	-23.61	-6.38	-35.00	1.66	63.82	14.97	60.33
	Average	**-1.01**	**-23.16**	**-3.59**	**-22.91**	**2.27**	**87.00**	**11.91**	**43.74**

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

Table 4.11 Yield impact results, lognormal distribution (model 2)

System	County	Drought 1%				Wet 99%			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-2.53	-54.00	-11.12	-49.03	3.13	182.15	21.13	38.16
	Coahoma	-2.48	-56.76	-11.31	-40.16	3.22	357.54	30.65	30.11
	Holmes	-2.24	-53.68	-14.76	-51.57	2.84	185.39	25.16	43.55
	Humphrey	-2.33	-55.62	-16.85	-55.25	3.60	293.47	35.60	52.07
	Leflore	-2.27	-53.99	-11.67	-40.94	2.55	151.13	17.66	28.01
	Quitman	-2.69	-56.51	-8.58	-35.34	3.49	260.07	21.38	22.78
	Sunflower	-2.66	-52.70	-10.70	-56.45	3.13	167.18	21.58	47.35
	Tallahatchie	-2.49	-55.17	-8.63	-31.51	2.69	160.12	14.87	18.29
	Tunica	-2.61	-56.39	-9.94	-40.64	3.19	196.27	18.82	26.66
	Washington	-2.22	-54.27	-19.69	-61.23	2.91	207.77	33.95	58.97
	Yazoo	-2.09	-52.23	-22.62	-65.15	3.11	240.34	44.63	77.39
	Average	**-2.42**	**-54.67**	**-13.26**	**-47.93**	**3.08**	**218.31**	**25.95**	**40.30**
Irrigated	Bolivar	-0.98	-21.58	-2.78	-21.58	1.21	37.25	5.02	24.80
	Coahoma	-0.96	-22.82	-3.13	-17.38	1.79	64.95	8.06	27.20
	Holmes	-0.90	-21.37	-3.75	-22.34	1.14	37.73	6.26	26.66
	Humphrey	-0.94	-22.48	-4.13	-24.03	1.48	52.44	8.81	34.92
	Leflore	-0.91	-21.34	-2.88	-17.08	1.03	32.44	4.24	17.43
	Quitman	-1.01	-22.63	-2.36	-15.81	1.57	50.86	5.34	20.71
	Sunflower	-1.03	-21.14	-2.05	-25.54	1.21	35.04	4.32	29.20
	Tallahatchie	-0.96	-21.84	-2.29	-13.29	1.13	34.93	3.63	13.55
	Tunica	-0.99	-22.65	-2.86	-18.41	1.24	39.77	4.94	20.52
	Washington	-0.90	-21.89	-5.11	-27.48	1.17	41.05	8.66	35.40
	Yazoo	-0.85	-20.87	-5.63	-30.38	1.27	45.72	11.05	46.70
	Average	**-0.95**	**-21.88**	**-3.36**	**-21.21**	**1.29**	**42.93**	**6.39**	**27.01**

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

Table 4.12 Yield impact results, lognormal distribution (model 2)

System	***County***	***Drought 1%***				***Wet 99%***			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-2.08	-47.86	-9.72	-39.90	2.40	121.49	15.71	31.86
	Coahoma	-1.89	-47.78	-9.14	-29.42	1.51	71.00	9.07	16.14
	Holmes	-2.07	-51.12	-13.86	-47.51	2.35	137.66	20.43	38.17
	Humphrey	-1.97	-50.35	-14.75	-46.75	2.92	201.99	28.10	45.94
	Leflore	-2.05	-50.69	-10.79	-36.61	1.87	96.08	12.56	22.47
	Quitman	-1.88	-44.54	-6.61	-23.00	2.00	91.29	9.46	15.53
	Sunflower	-2.34	-48.87	-9.96	-49.80	2.04	89.23	13.26	34.19
	Tallahatchie	-2.15	-50.12	-7.73	-26.31	1.73	78.74	8.38	13.20
	Tunica	-1.46	-37.99	-6.34	-20.98	1.18	48.39	6.18	12.79
	Washington	-1.91	-49.65	-17.44	-53.23	2.34	147.22	26.88	50.60
	Yazoo	-1.81	-47.96	-20.11	-57.51	3.04	231.77	43.62	76.31
	Average	**-1.96**	**-47.90**	**-11.49**	**-39.18**	**2.13**	**119.53**	**17.60**	**32.47**
Irrigated	Bolivar	-0.80	-18.24	-2.38	-17.72	0.93	27.36	3.71	19.28
	Coahoma	-0.73	-18.03	-2.48	-13.13	0.59	17.69	2.36	9.76
	Holmes	-0.83	-19.94	-3.50	-20.60	0.94	30.15	5.06	22.21
	Humphrey	-0.80	-19.51	-3.59	-20.35	1.19	40.19	6.89	28.50
	Leflore	-0.82	-19.56	-2.64	-15.40	0.75	22.68	3.00	12.95
	Quitman	-0.71	-16.46	-1.74	-10.84	0.76	21.86	2.35	10.64
	Sunflower	-0.90	-18.97	-1.90	-22.51	0.79	21.38	2.60	19.23
	Tallahatchie	-0.82	-19.16	-2.02	-11.35	0.67	19.40	2.05	8.35
	Tunica	-0.55	-13.54	-1.73	-10.14	0.45	12.70	1.62	7.77
	Washington	-0.77	-19.27	-4.48	-23.73	0.94	31.77	6.81	28.71
	Yazoo	-0.74	-18.48	-4.97	-26.50	1.24	44.56	10.79	45.75
	Average	**-0.77**	**-18.29**	**-2.86**	**-17.48**	**0.84**	**26.34**	**4.29**	**19.38**

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

Table 4.13 Yield impact results, lognormal distribution (model 2)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	1.17	47.36	7.22	17.77	-1.75	-42.55	-8.51	-33.16
	Coahoma	0.75	30.47	4.35	8.86	-1.34	-37.25	-6.80	-19.94
	Holmes	1.64	82.75	13.88	28.87	-1.31	-37.19	-9.37	-29.38
	Humphrey	1.29	62.78	11.75	24.56	-1.46	-41.16	-11.43	-34.32
	Leflore	1.25	56.49	8.15	16.21	-1.36	-37.88	-7.59	-23.14
	Quitman	0.96	36.03	4.23	8.52	-1.54	-38.61	-5.64	-18.36
	Sunflower	1.60	65.18	10.18	27.99	-1.85	-41.87	-8.48	-39.21
	Tallahatchie	1.38	58.55	6.51	11.04	-1.36	-35.97	-5.29	-15.40
	Tunica	0.91	35.31	4.67	10.14	-1.25	-33.70	-5.54	-17.67
	Washington	1.46	75.60	16.24	34.53	-1.70	-45.96	-15.75	-47.38
	Yazoo	1.62	89.28	22.16	46.74	-1.39	-40.24	-16.02	-45.04
	Average	**1.28**	**58.16**	**9.94**	**21.38**	**-1.48**	**-39.31**	**-9.13**	**-29.36**
Irrigated	Bolivar	0.71	20.18	2.74	14.85	-0.71	-16.36	-2.15	-15.64
	Coahoma	0.34	10.00	1.35	5.82	-0.56	-14.23	-1.95	-10.02
	Holmes	0.70	21.69	3.68	16.78	-0.60	-15.02	-2.64	-14.91
	Humphrey	0.66	20.56	3.63	16.27	-0.67	-16.63	-3.05	-16.94
	Leflore	0.55	16.12	2.15	9.61	-0.63	-15.37	-2.08	-11.65
	Quitman	0.60	16.97	1.83	8.54	-0.58	-13.85	-1.47	-8.91
	Sunflower	0.74	19.82	2.40	17.99	-0.77	-16.43	-1.69	-19.10
	Tallahatchie	0.54	15.28	1.62	6.77	-0.57	-13.70	-1.45	-7.70
	Tunica	0.40	11.30	1.44	6.98	-0.50	-12.27	-1.57	-9.09
	Washington	0.75	24.54	5.33	23.03	-0.72	-18.15	-4.22	-22.17
	Yazoo	0.74	24.06	6.03	27.20	-0.58	-14.84	-3.97	-20.80
	Average	**0.61**	**18.23**	**2.93**	**13.99**	**-0.63**	**-15.17**	**-2.39**	**-14.27**

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

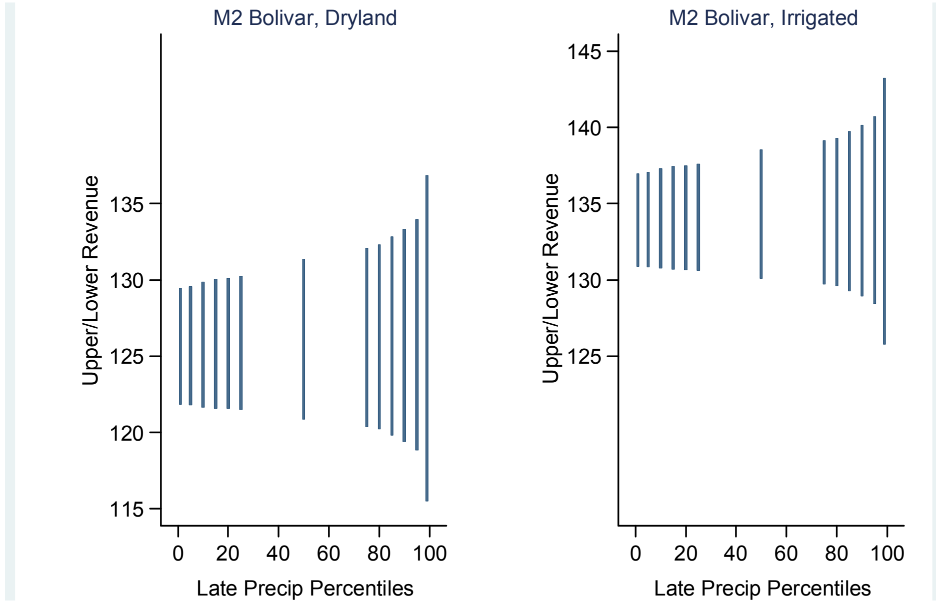

Figure 4.34 Dry and irrigated land revenue impact for Bolivar, (model 2)

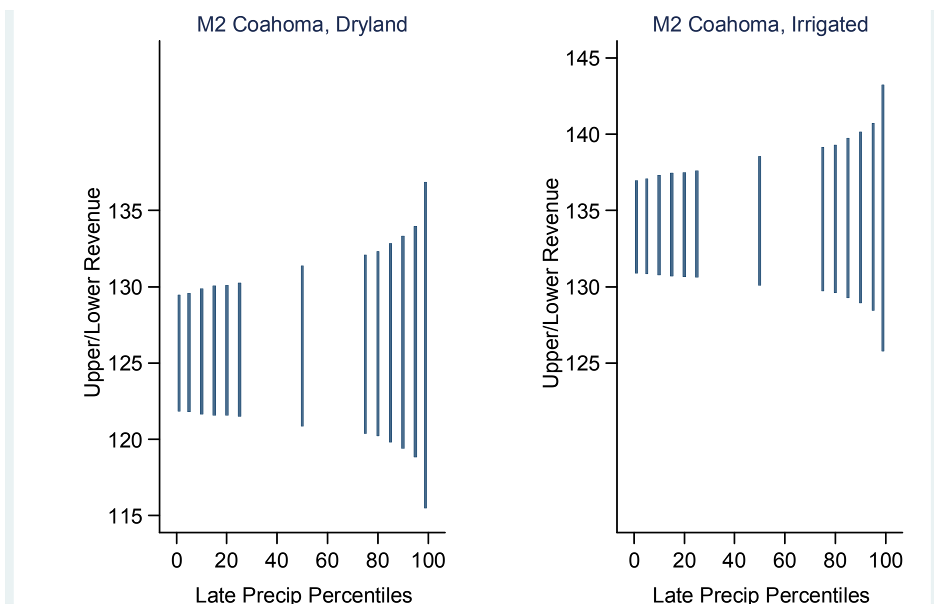

Figure 4.35 Dry and irrigated land revenue impact for Coahoma, (model 2)

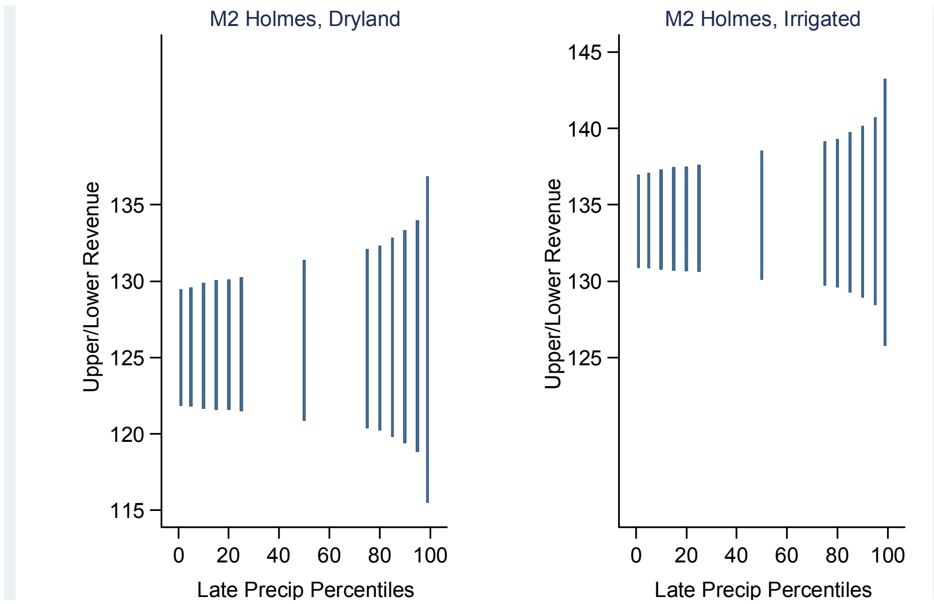

Figure 4.36 Dry and irrigated land revenue impact for Holmes, (model 2)

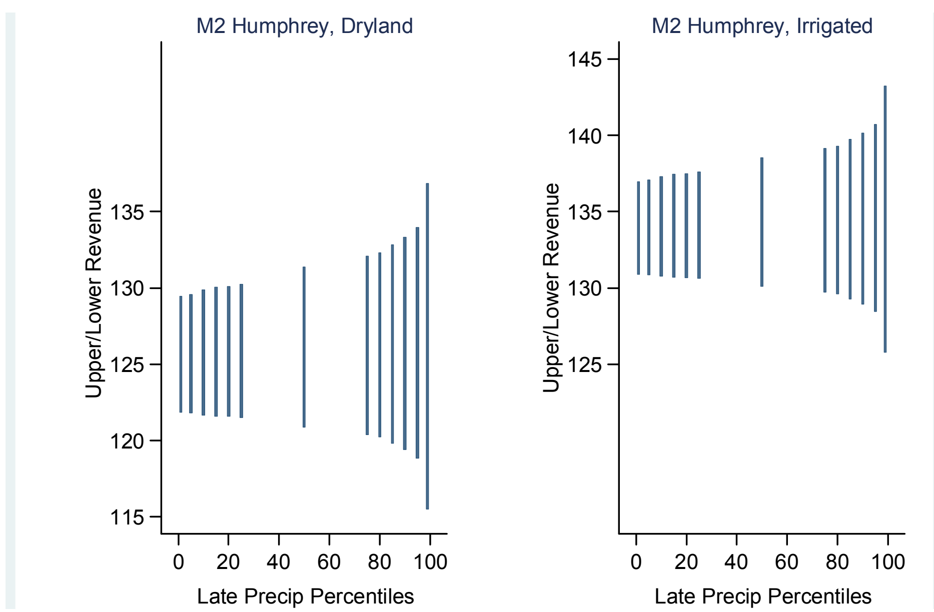

Figure 4.37 Dry and irrigated land revenue impact for Humphrey, (model 2)

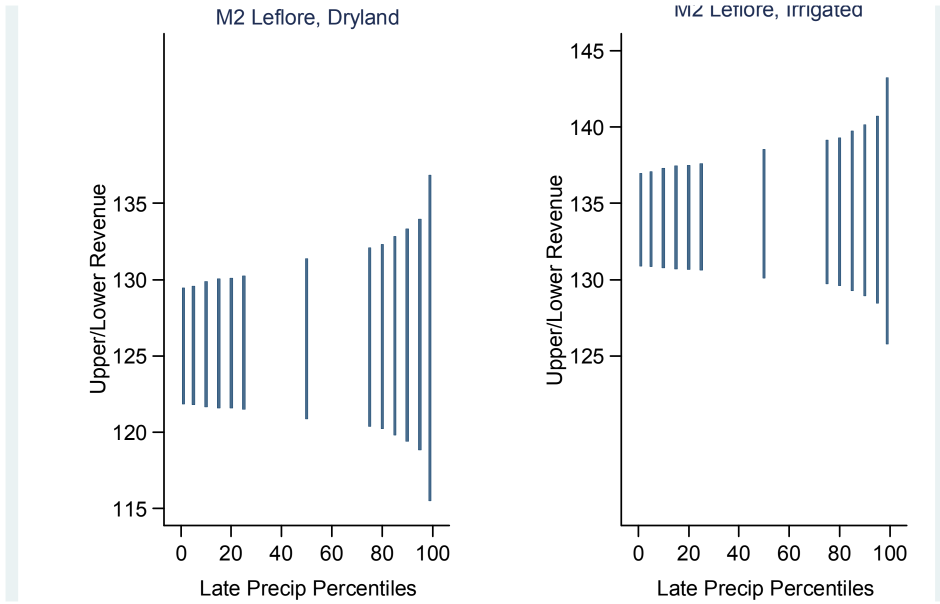

Figure 4.38 Dry and irrigated land revenue impact for Leflore, (model 2)

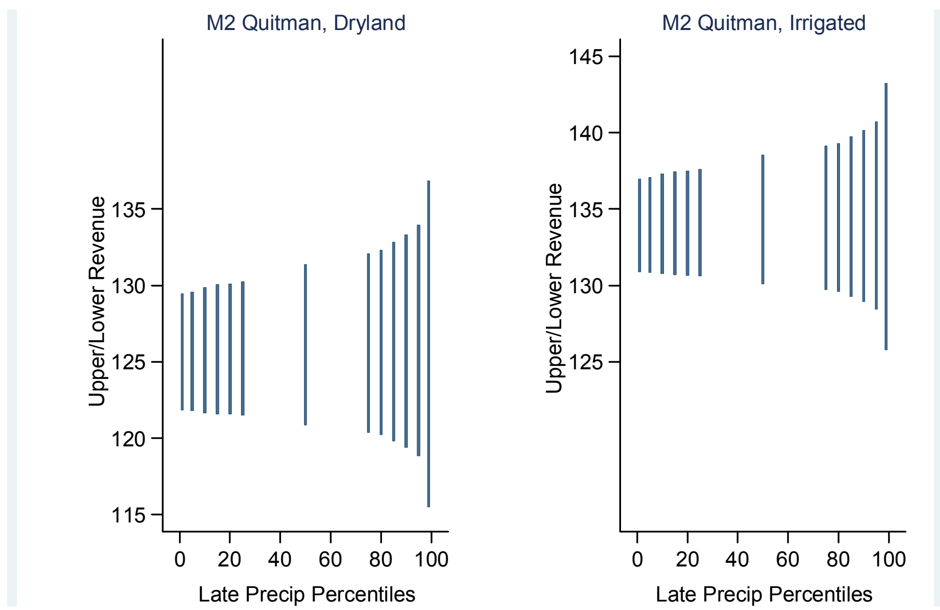

Figure 4.39 Dry and irrigated land revenue impacts for Quitman, (model 2)

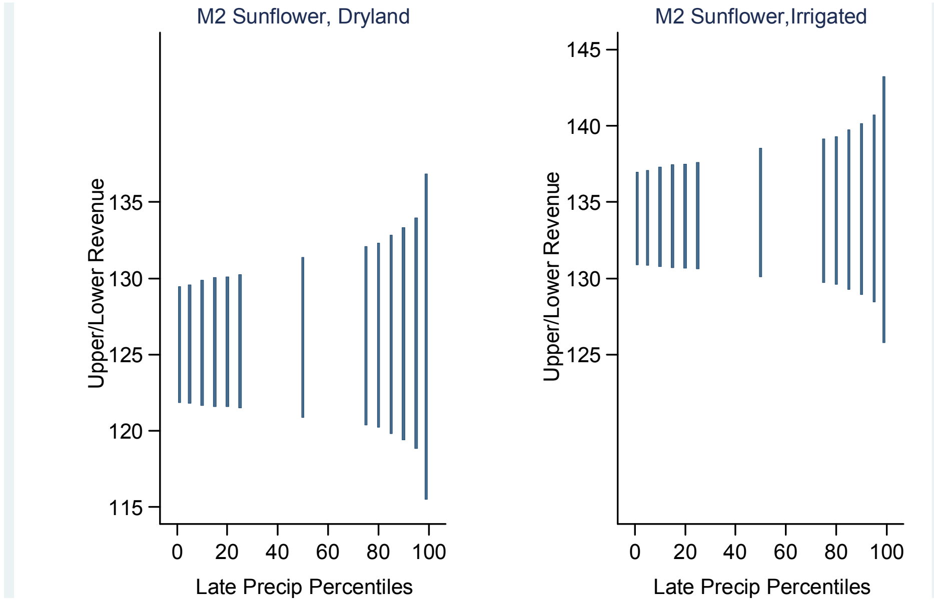

Figure 4.40 Dry and irrigated land revenue impact for Sunflower, (model 2)

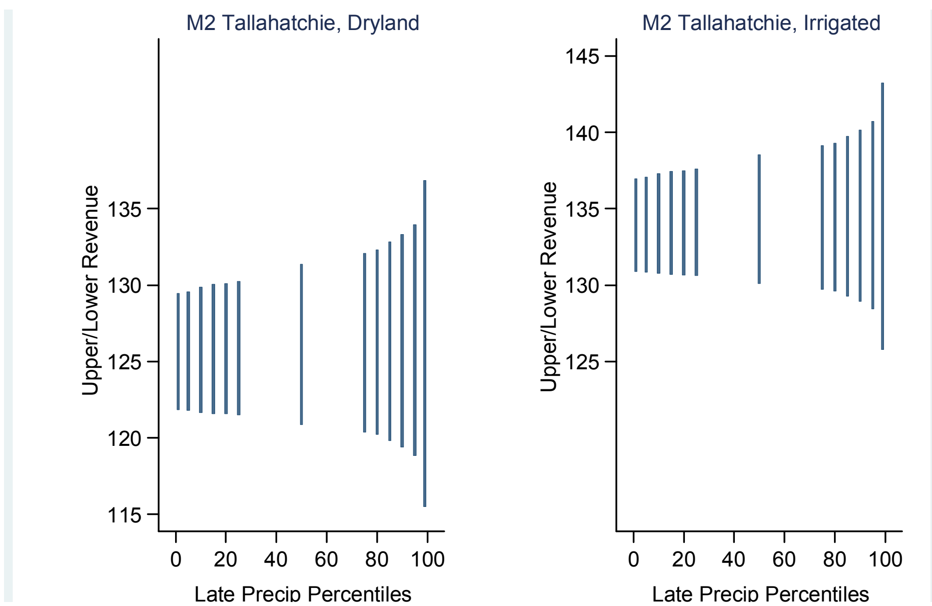

Figure 4.41 Dry and irrigated land revenue impact for Tallahatchie, (model 2)

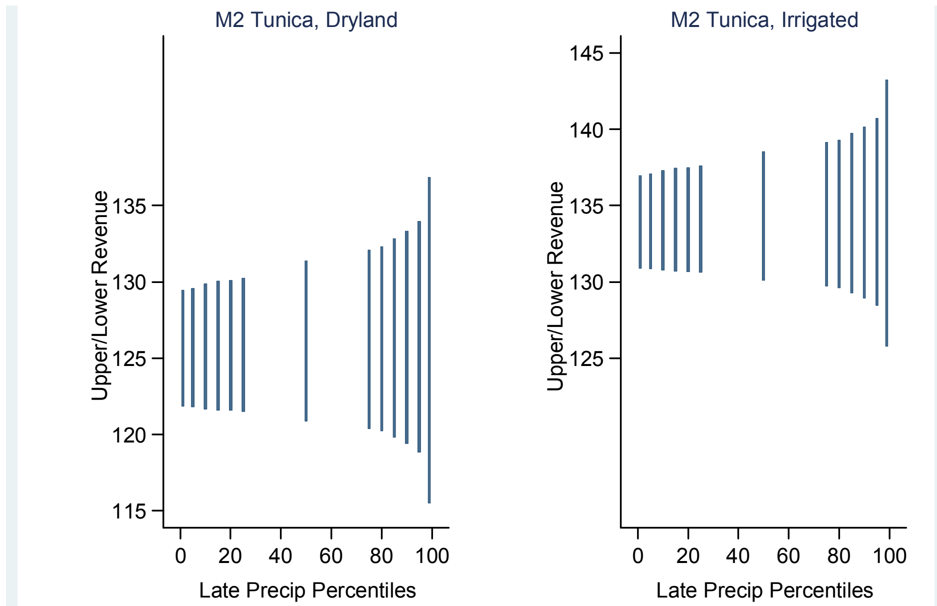

Figure 4.42 Dry and irrigated land revenue impact for Tunica, (model 2)

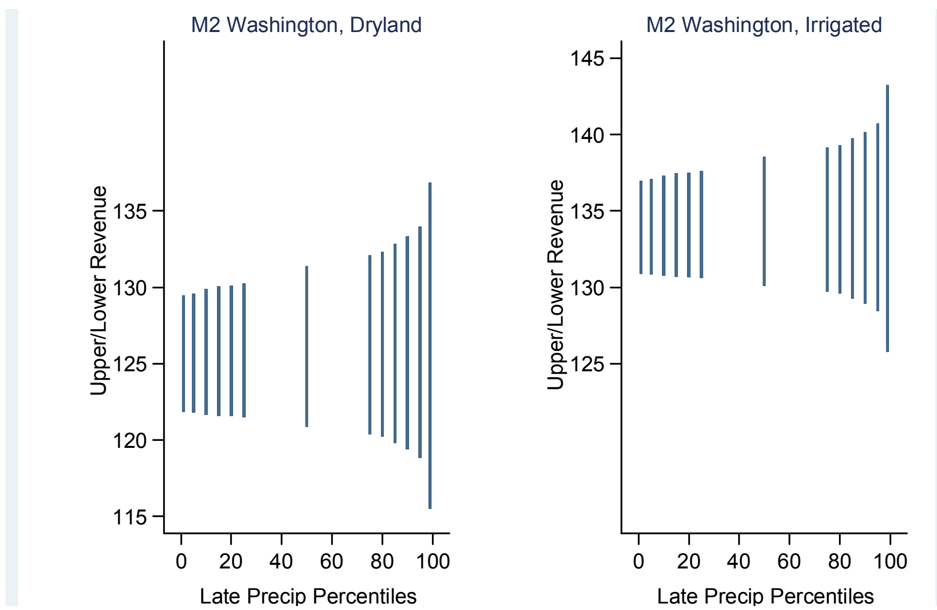

Figure 4.43 Dry and irrigated land revenue impact for Washington, (model 2)

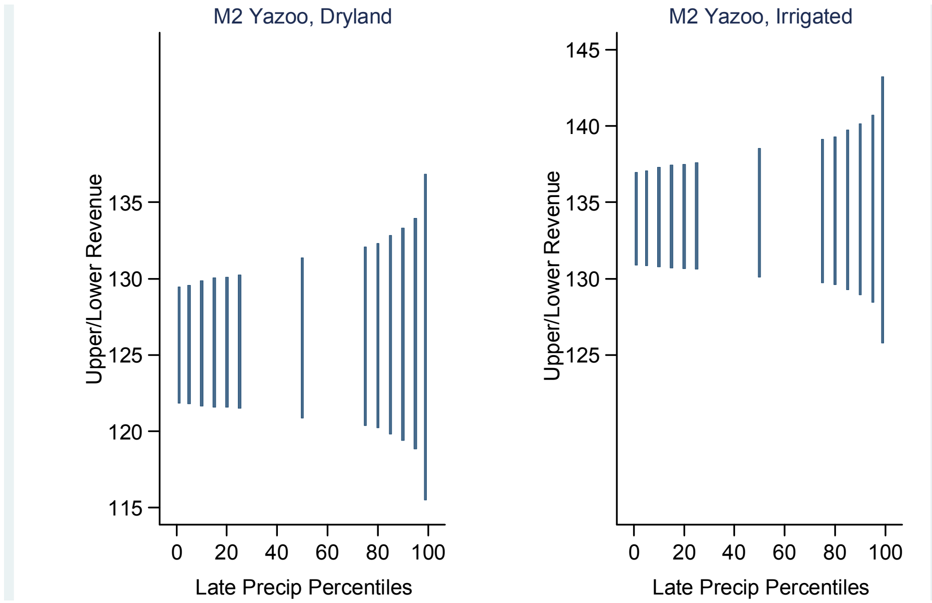

Figure 4.44 Dry and irrigated land revenue impact for Yazoo, (model 2)

It is possible from the revenue impacts presented that breaking early precipitation into two sub-seasons gives way for the differences in graphs when model 2 revenue impacts is compared to model 1 revenue impact. In short, normal distribution is not a good distributional assumption because there exists positive skewness under lognormality. Therefore evidence of positive skewness and negative yields in model 1 holds, and we can conclude that model 1 is robust to alternative definition of within-precipitation effect.

Model 3

No studies investigating Mississippi climate impact on cotton yield have accounted for existing moisture in the soil prior to production. Therefore, our third model seeks to find if there exists any relationship between existing soil moisture and actual growing period precipitation. This moves studies from a within season precipitation effect to a pre-season precipitation effect. We account for moisture existing in the soil prior to the start of a new crop production season by isolating the last month (April) before the start of a new cotton season as prior precipitation. Therefore in our third model, precipitation variables are generalized to include prior precipitation and actual precipitation. Actual precipitation is the summation of daily precipitation from May to October while prior precipitation is the summation of daily precipitation in the month of April. As with the within precipitation effect, we present and discuss results for normal densities, yield and revenue impacts. As a robustness check, we consider and present results for lognormal distribution by relaxing the skewness assumption.

Model 3 results under normality

Normal densities are estimated and results are presented in Figures 4.45- 4.55. From these figures we observe that for all counties, there exist no differences in the means of the average, drought, and wet precipitation densities. Additionally, there exist negative yields.

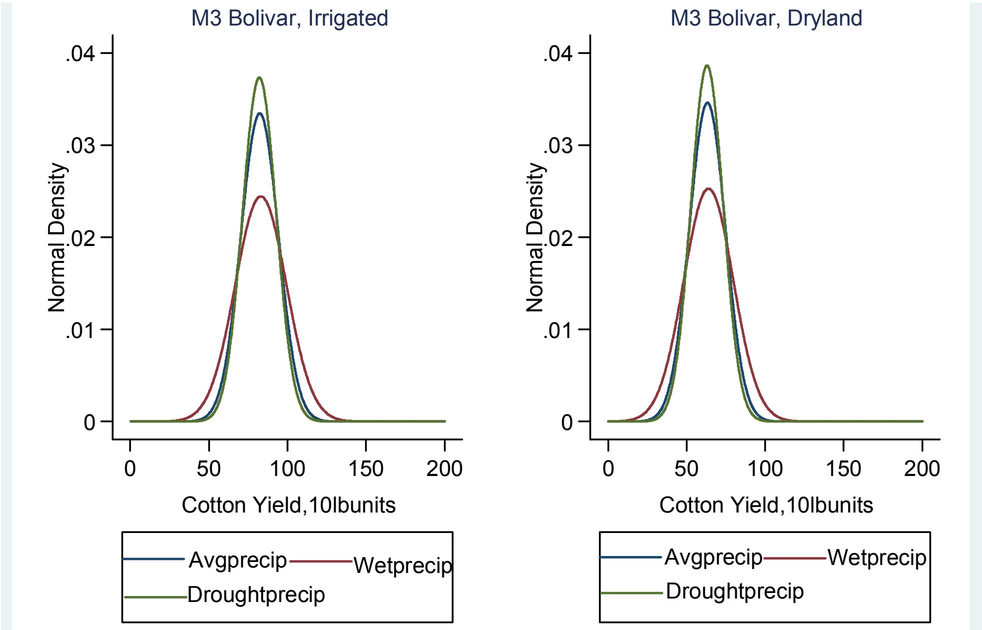

Figure 4.45 Irrigated and dryland normal yield distribution for Bolivar, (model 3)

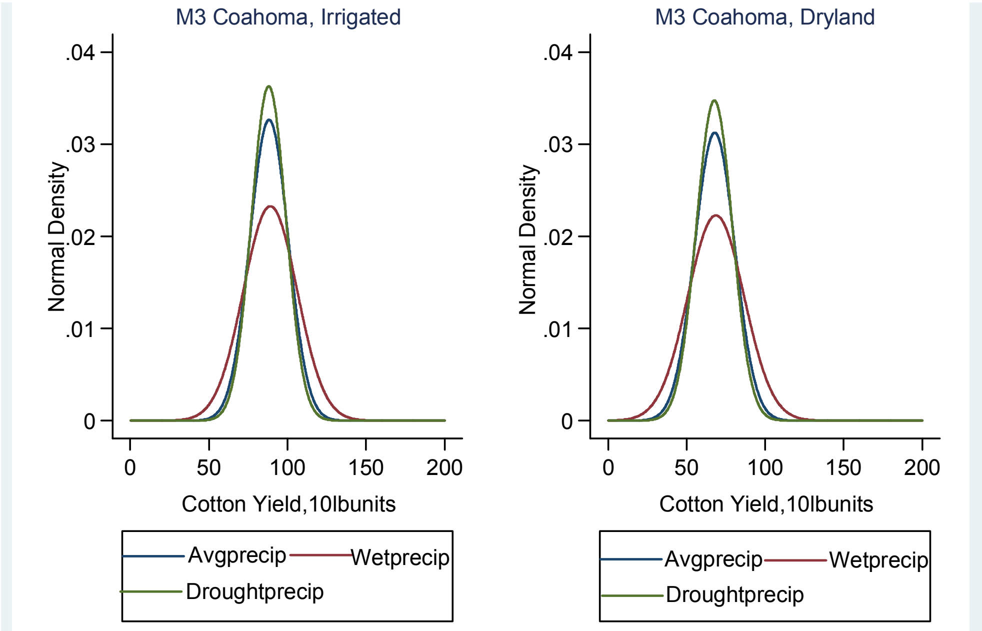

Figure 4.46 Irrigated and dryland normal yield distribution for Coahoma, (model 3)

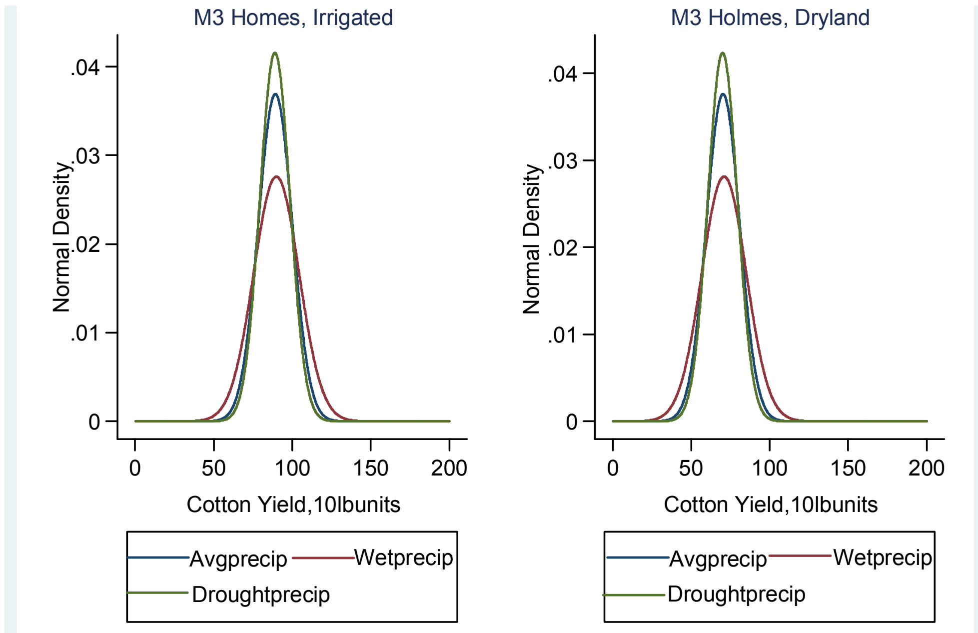

Figure 4.47 Irrigated and dryland normal yield distribution for Holmes, (model 3)

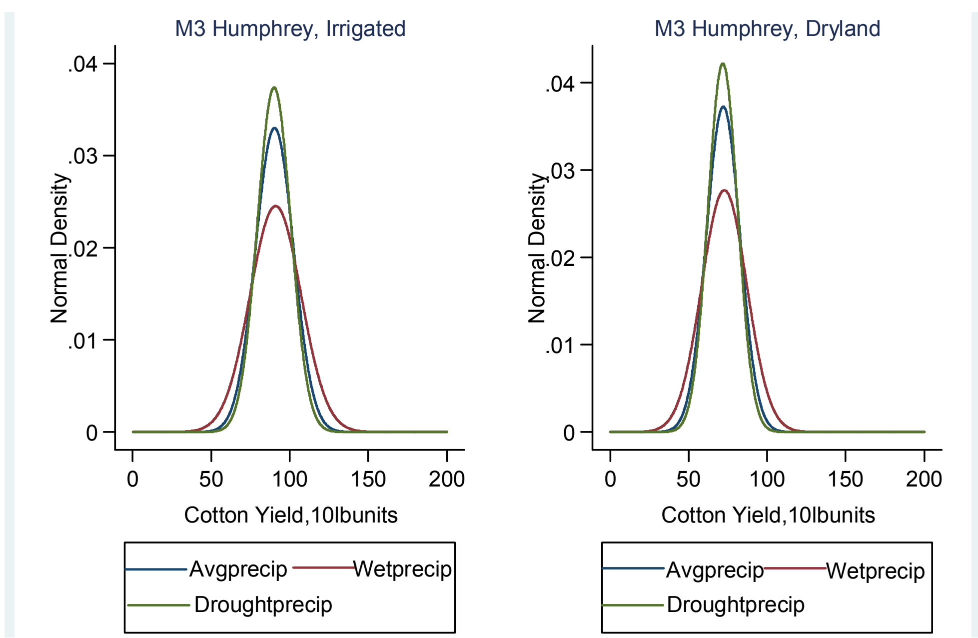

Figure 4.48 Irrigated and dryland normal yield distribution for Humphrey, (model 3)

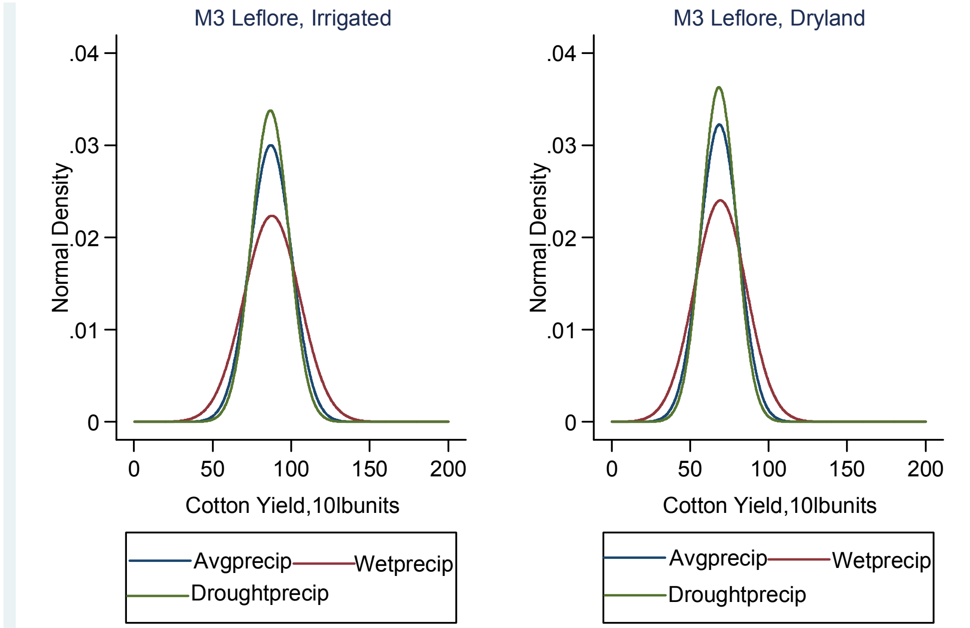

Figure 4.49 Irrigated and dryland normal yield distribution for Leflore, (model 3)

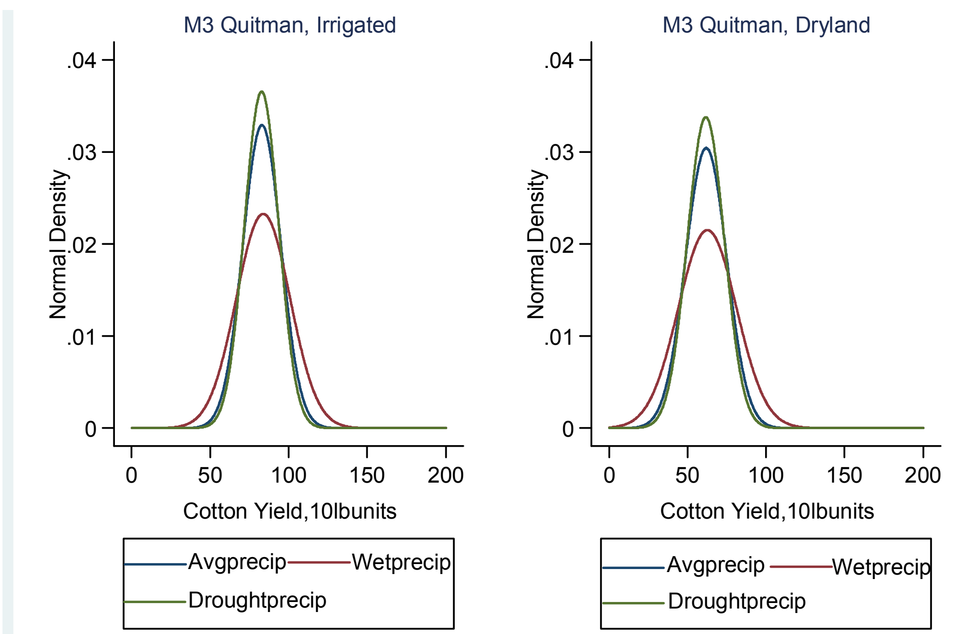

Figure 4.50 Irrigated and dryland normal yield distribution for Quitman, (model 3)

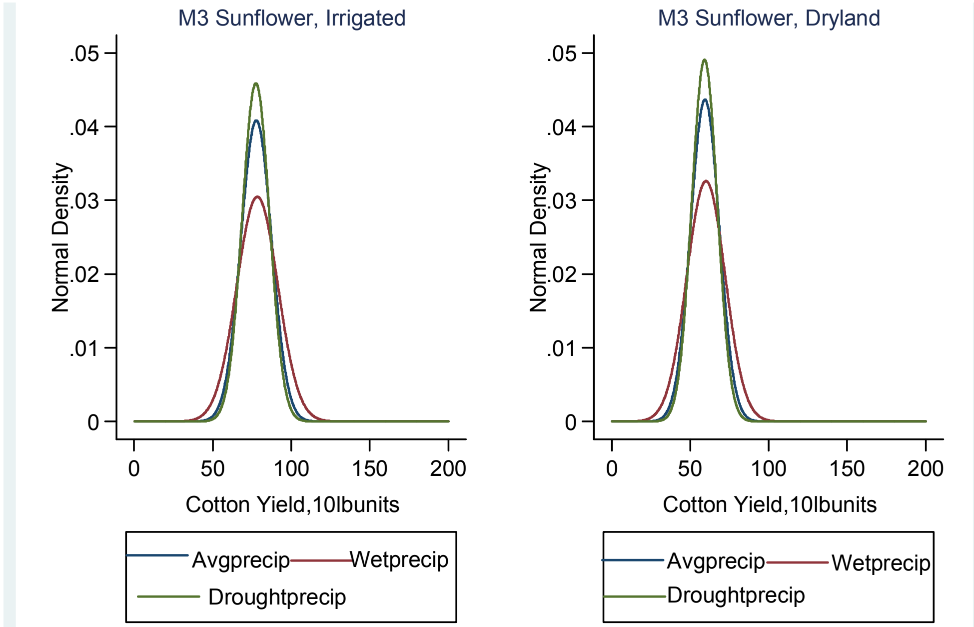

Figure 4.51 Irrigated and dryland normal yield distribution for Sunflower, (model 3)

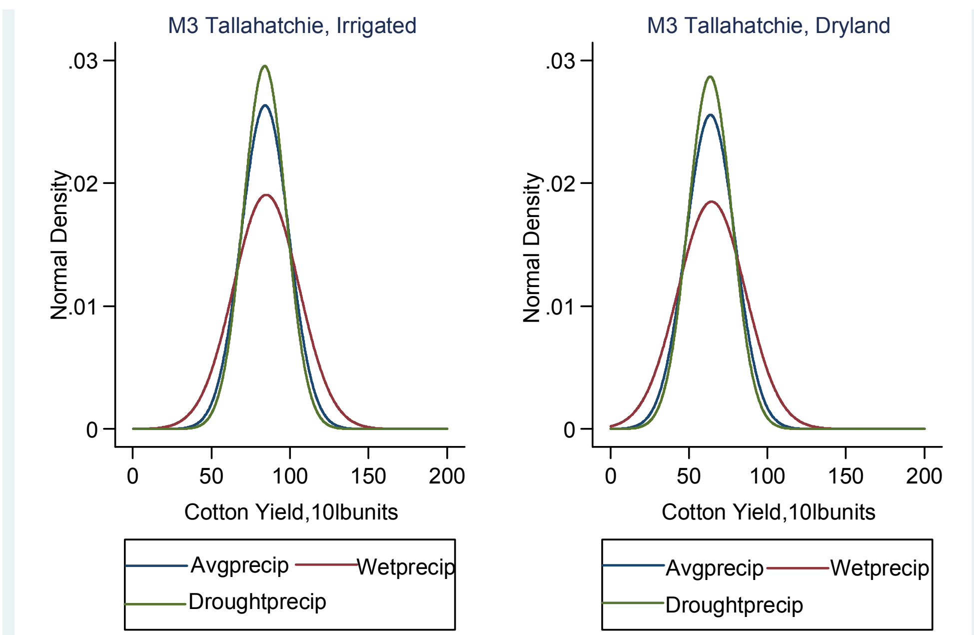

Figure 4.52 Irrigated and dryland normal yield distribution for Tallahatchie, (model 3)

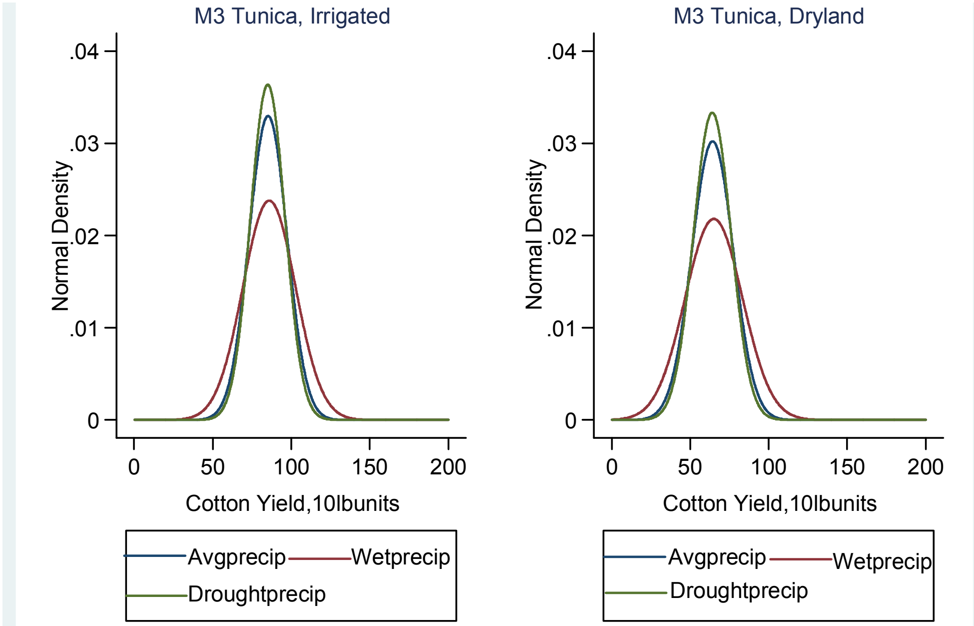

Figure 4.53 Irrigated and dryland normal yield distribution for Tunica, (model 3)

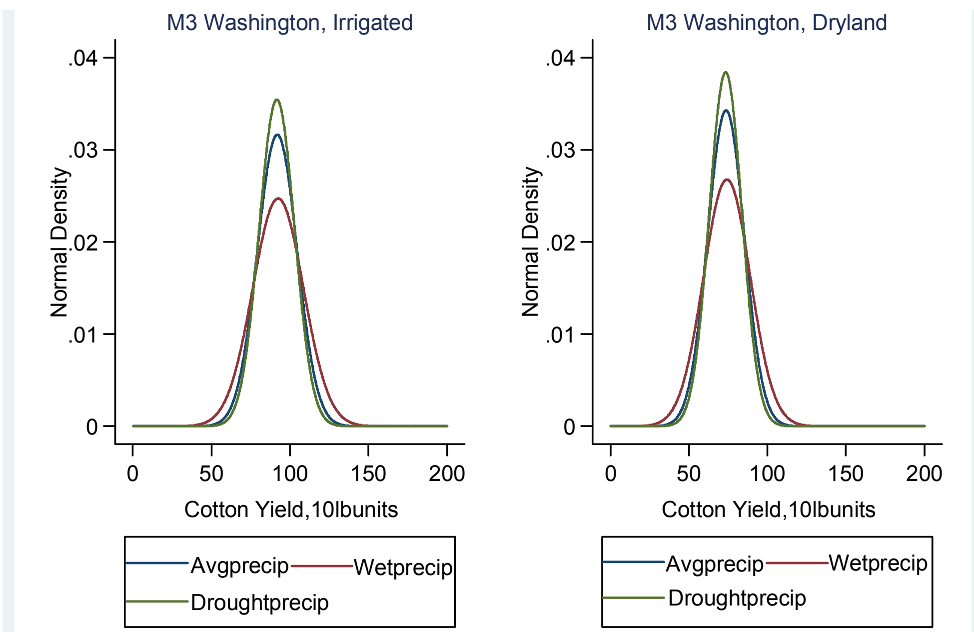

Figure 4.54 Irrigated and dryland normal yield distribution for Washington, (model 3)

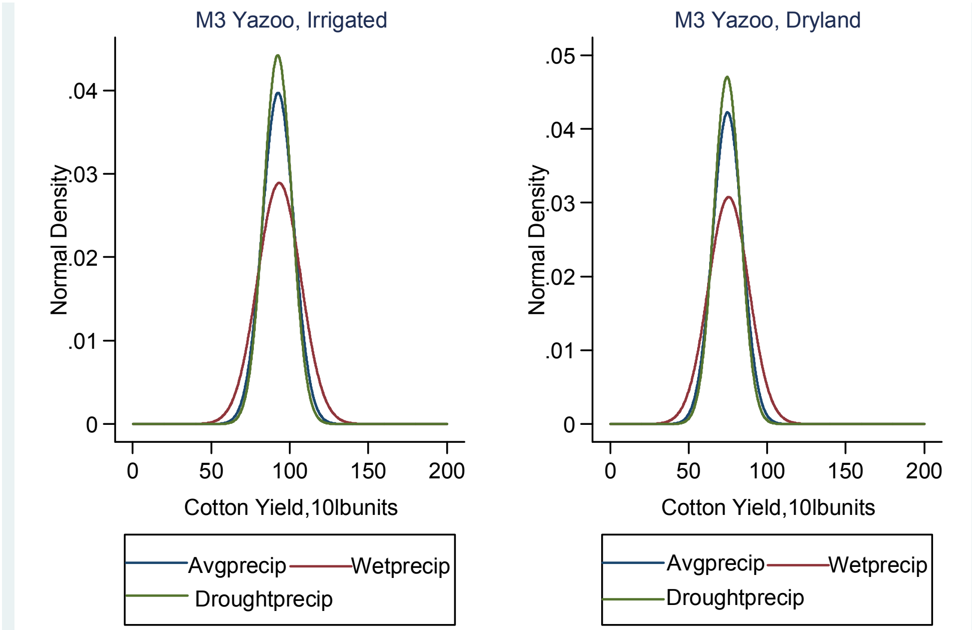

Figure 4.55 Irrigated and dryland normal yield distribution for Tunica, (model 3)

Model 3 yield impacts

Considering a pre-season precipitation effect scenario, prior precipitation is held at 1st and 99th for drought and wet climates respectively and yield impact results are discussed as follows. The acreage weighted average of the drought climate county level impact on mean (variance) yields are -0.38% (-20.01%) for dryland acreage and -0.29 % (-20.02%). An approximately equal reduction in variance (20%) causes reduction in upside risk and downside risk across production methods with effects higher on irrigated acreage as compared to dryland acreage. Thus, acreage weighted average of the drought climate county level impact on upside risk (downside risk) yields are -5.37% (-11.10%) and -8.10% (-14.01%) dryland and irrigated acreage respectively.

Conversely, for wet climate, the acreage weighted average impact on mean (variance) yields are 1.05% (85.39%) and 0.81% (85.78%) while impact on upside risk (downside risk) yields are 13.68% (25.48%) and 20.99% (33.98%). A relatively small increment in mean and subsequently a rather large increment in variance cause upside and downside risk to increase with pronounced effect on irrigated acreage. The values for upside risk (downside risk) include 13.68(25.48) and 20.99(33.98) respectively for dryland and irrigated acreage.

Table 4.14 Yield impact results, normal distribution (model 3)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-0.40	-19.73	-4.65	-10.16	1.13	87.66	12.48	23.93
	Coahoma	-0.35	-19.02	-4.43	-9.16	1.13	97.03	13.13	23.98
	Holmes	-0.38	-21.10	-6.89	-13.65	0.94	79.26	15.99	28.79
	Humphrey	-0.39	-22.01	-7.39	-14.52	0.94	81.50	16.65	29.78
	Leflore	-0.39	-20.94	-5.31	-10.82	0.97	80.45	12.42	22.60
	Quitman	-0.38	-18.86	-3.50	-7.92	1.28	99.57	10.71	21.04
	Sunflower	-0.44	-20.67	-5.80	-13.49	1.12	80.01	14.15	29.02
	Tallahatchie	-0.41	-20.47	-3.27	-7.24	1.16	88.42	8.12	16.58
	Tunica	-0.35	-17.75	-3.49	-7.62	1.15	91.95	10.81	20.72
	Washington	-0.35	-20.32	-6.21	-12.16	0.76	64.10	12.76	23.01
	Yazoo	-0.33	-19.24	-8.14	-15.41	0.96	89.32	23.23	40.84
	Average	**-0.38**	**-20.01**	**-5.37**	**-11.10**	**1.05**	**85.39**	**13.68**	**25.48**
Irrigated	Bolivar	-0.30	-19.73	-7.14	-12.92	0.87	87.72	19.06	31.89
	Coahoma	-0.27	-19.02	-7.58	-12.88	0.87	97.26	22.69	35.80
	Holmes	-0.30	-21.10	-10.18	-17.29	0.74	79.25	23.93	38.60
	Humphrey	-0.31	-22.02	-9.41	-15.93	0.75	81.42	21.12	33.64
	Leflore	-0.31	-20.95	-7.29	-12.67	0.77	80.46	16.93	27.30
	Quitman	-0.29	-18.86	-6.80	-11.98	0.95	100.58	20.94	33.84
	Sunflower	-0.34	-20.68	-9.06	-16.67	0.85	79.95	21.99	37.89
	Tallahatchie	-0.31	-20.49	-5.67	-10.07	0.87	91.08	14.53	23.50
	Tunica	-0.26	-17.74	-6.62	-11.53	0.87	92.52	20.65	33.34
	Washington	-0.28	-20.33	-8.30	-14.01	0.61	64.07	17.06	27.33
	Yazoo	-0.26	-19.25	-11.01	-18.14	0.78	89.25	31.97	50.65
	Average	**-0.29**	**-20.02**	**-8.10**	**-14.01**	**0.81**	**85.78**	**20.99**	**33.98**

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

In Tables 4.15 - 4.17, yield impacts are reported for the less severe drought and excessive rain scenarios. Similar to the results pattern for within season precipitation effects (model 1 and 2), we see a trend of drought (wet) being associated with reduction (increment) in mean, variance, upside and downside risk and these results are presented in tables 4.15 and 4.16 for model 3. However, when prior precipitation variable is held at the 85th and the 15th percentiles for drought and wet climates respectively, we see a reverse of drought and wet impact on the mean, variance, upside and downside yield risk. Results are presented in Table 4.17 and we observe from the table that, acreage weighted average of the drought climate county level impact on mean (variance) yields are 0.20% (12.58%) for dryland and 0.15% (12.58) for irrigated land. Thus indicating drought increment for dryland and irrigated land. It is interesting to note that an equal increment in variance for the two production methods causes a relatively small increment in upside and downside risk, and this effect is higher on irrigated acreage. Conversely, excessive moisture causes a very small reduction in mean and relatively high reduction in variance across tables, and this reduction subsequently causes a reduction in upside and downside risks. Excessive moisture generates acreage weighted average impact on mean (variance) yields as -0.25% (-13.75%) and -0.19% (-13.76%) and impact on upside (downside) yields as -3.53% (-7.23%) and -5.35 % (-9.21%).

Table 4.15 Yield impact results, normal distribution (model 3)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-0.33	-16.68	-3.85	-8.36	0.52	33.46	5.88	11.90
	Coahoma	-0.29	-15.75	-3.58	-7.38	0.48	33.03	5.74	11.08
	Holmes	-0.35	-19.56	-6.32	-12.50	0.56	41.59	9.71	18.03
	Humphrey	-0.37	-20.72	-6.89	-13.53	0.50	37.09	9.01	16.70
	Leflore	-0.36	-19.29	-4.84	-9.82	0.41	27.92	5.35	10.22
	Quitman	-0.32	-15.85	-2.88	-6.48	0.42	25.78	3.72	7.80
	Sunflower	-0.37	-17.59	-4.84	-11.20	0.47	28.04	6.06	13.15
	Tallahatchie	-0.32	-16.54	-2.57	-5.65	0.52	33.91	3.96	8.14
	Tunica	-0.33	-17.22	-3.38	-7.36	0.60	40.93	5.86	11.74
	Washington	-0.34	-19.73	-6.00	-11.75	0.42	31.65	7.22	13.39
	Yazoo	-0.33	-19.24	-8.14	-15.40	0.55	43.63	13.41	24.30
	Average	**-0.34**	**-18.01**	**-4.84**	**-9.95**	**0.50**	**34.28**	**6.90**	**13.31**
Irrigated	Bolivar	-0.25	-16.68	-5.91	-10.67	0.40	33.46	9.01	15.62
	Coahoma	-0.22	-15.74	-6.14	-10.41	0.37	33.04	9.88	16.19
	Holmes	-0.28	-19.56	-9.34	-15.86	0.44	41.58	14.49	23.85
	Humphrey	-0.29	-20.73	-8.78	-14.86	0.40	37.06	11.46	18.71
	Leflore	-0.28	-19.29	-6.63	-11.52	0.32	27.92	7.31	12.21
	Quitman	-0.24	-15.84	-5.60	-9.84	0.31	25.82	7.22	12.25
	Sunflower	-0.28	-17.60	-7.56	-13.89	0.36	28.03	9.45	16.84
	Tallahatchie	-0.24	-16.56	-4.46	-7.88	0.40	34.23	6.88	11.58
	Tunica	-0.25	-17.21	-6.40	-11.14	0.46	40.99	11.15	18.58
	Washington	-0.27	-19.74	-8.03	-13.54	0.34	31.64	9.66	15.78
	Yazoo	-0.26	-19.24	-11.01	-18.13	0.44	43.61	18.38	29.72
	Average	**-0.26**	**-18.02**	**-7.26**	**-12.52**	**0.38**	**34.31**	**10.44**	**17.39**

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

Table 4.16 Yield impact results, normal distribution (model 3)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-0.29	-15.05	-3.44	-7.45	0.29	17.87	3.38	6.98
	Coahoma	-0.27	-14.90	-3.37	-6.93	0.35	23.60	4.29	8.37
	Holmes	-0.33	-18.48	-5.93	-11.71	0.36	25.40	6.38	12.02
	Humphrey	-0.31	-17.84	-5.82	-11.39	0.35	24.78	6.37	11.94
	Leflore	-0.32	-17.80	-4.42	-8.96	0.32	21.24	4.20	8.09
	Quitman	-0.30	-15.16	-2.75	-6.16	0.35	21.09	3.11	6.57
	Sunflower	-0.35	-16.62	-4.55	-10.50	0.32	18.49	4.18	9.17
	Tallahatchie	-0.31	-15.98	-2.47	-5.43	0.32	19.39	2.44	5.07
	Tunica	-0.28	-14.49	-2.79	-6.05	0.28	17.06	2.74	5.64
	Washington	-0.23	-13.97	-4.09	-7.94	0.35	25.14	5.92	11.03
	Yazoo	-0.30	-17.90	-7.51	-14.21	0.36	27.08	8.94	16.38
	Average	**-0.30**	**-16.20**	**-4.28**	**-8.79**	**0.33**	**21.92**	**4.72**	**9.21**
Irrigated	Bolivar	-0.23	-15.05	-5.28	-9.51	0.23	17.87	5.19	9.10
	Coahoma	-0.21	-14.90	-5.78	-9.79	0.27	23.61	7.38	12.17
	Holmes	-0.26	-18.48	-8.77	-14.88	0.29	25.40	9.51	15.79
	Humphrey	-0.25	-17.85	-7.41	-12.53	0.28	24.77	8.10	13.33
	Leflore	-0.26	-17.81	-6.06	-10.51	0.25	21.24	5.75	9.65
	Quitman	-0.23	-15.16	-5.33	-9.36	0.26	21.12	6.04	10.29
	Sunflower	-0.27	-16.63	-7.10	-13.03	0.25	18.48	6.51	11.68
	Tallahatchie	-0.24	-16.01	-4.29	-7.58	0.24	19.51	4.22	7.19
	Tunica	-0.21	-14.49	-5.29	-9.19	0.21	17.07	5.19	8.81
	Washington	-0.19	-13.97	-5.47	-9.19	0.28	25.14	7.92	12.98
	Yazoo	-0.24	-17.91	-10.16	-16.74	0.29	27.07	12.22	19.90
	Average	**-0.23**	**-16.20**	**-6.45**	**-11.12**	**0.26**	**21.93**	**7.09**	**11.90**

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

Table 4.17 Yield impact results, normal distribution (model 3)

System	***County***	***Drought 1%***				***Wet 99%***			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	0.22	12.84	2.49	5.18	-0.26	-13.55	-3.06	-6.62
	Coahoma	0.10	6.14	1.22	2.44	-0.24	-13.54	-3.04	-6.23
	Holmes	0.28	18.61	4.83	9.16	-0.24	-13.97	-4.35	-8.55
	Humphrey	0.19	13.16	3.58	6.79	-0.24	-14.26	-4.54	-8.86
	Leflore	0.27	17.70	3.57	6.89	-0.23	-13.21	-3.18	-6.40
	Quitman	0.11	6.24	0.99	2.14	-0.26	-13.42	-2.40	-5.37
	Sunflower	0.24	13.67	3.16	6.98	-0.26	-12.80	-3.42	-7.85
	Tallahatchie	0.18	10.44	1.38	2.89	-0.29	-14.88	-2.29	-5.01
	Tunica	0.13	7.39	1.25	2.61	-0.27	-14.00	-2.69	-5.82
	Washington	0.21	14.53	3.61	6.80	-0.21	-12.62	-3.66	-7.10
	Yazoo	0.25	17.63	6.08	11.23	-0.25	-15.03	-6.19	-11.70
	Average	**0.20**	**12.58**	**2.92**	**5.74**	**-0.25**	**-13.75**	**-3.53**	**-7.23**
Irrigated	Bolivar	0.17	12.84	3.83	6.74	-0.20	-13.55	-4.71	-8.47
	Coahoma	0.08	6.14	2.10	3.51	-0.19	-13.54	-5.21	-8.81
	Holmes	0.22	18.60	7.19	11.98	-0.19	-13.97	-6.44	-10.91
	Humphrey	0.16	13.15	4.56	7.56	-0.19	-14.27	-5.79	-9.76
	Leflore	0.21	17.70	4.88	8.21	-0.19	-13.21	-4.36	-7.53
	Quitman	0.08	6.24	1.93	3.33	-0.20	-13.42	-4.67	-8.18
	Sunflower	0.19	13.67	4.93	8.88	-0.20	-12.81	-5.34	-9.78
	Tallahatchie	0.13	10.49	2.38	4.09	-0.22	-14.90	-3.96	-6.99
	Tunica	0.09	7.39	2.37	4.05	-0.20	-13.99	-5.09	-8.84
	Washington	0.17	14.53	4.83	7.96	-0.17	-12.62	-4.90	-8.22
	Yazoo	0.20	17.63	8.30	13.57	-0.20	-15.04	-8.39	-13.82
	Average	**0.15**	**12.58**	**4.30**	**7.26**	**-0.19**	**-13.76**	**-5.35**	**-9.21**

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

Model 3 revenue impact

Following the same revenue estimation procedure as discussed for model 1 under normality, yield impacts are converted into revenue impacts and results discussed as follows for all counties used in the study. Figures 4.55 – 4.65 show plots of revenue impacts for model 3. On each plot region, there are separate graphs for dryland acreage and irrigated acreage. On the y-axis for each graph are upper and lower revenue ranges, and on the x- axis is a range of prior precipitation values. For each of the graphs, the first six bars indicate drought percentiles, the middle single bar denotes mean percentile and the last six bars denote the wet percentiles. The first six bars move from severe drought (1^{st} percentile) to less severe drought (25^{th} percentile) while the last six bars move from less excessive moisture to excessive moisture. The mean bar is at the 50^{th} percentile, and we compare severe drought and excessive moisture impact to it. It can be seen that there is not much distributional difference from severe drought percentiles to less drought percentiles, and drought impacts on revenue ranges are below the mean revenue distributions for dryland acreage. On the other hand, there exist observable distributional differences as wet climate moves from less moisture to excessive moisture plus revenue ranges are either equal or above the mean revenue for dryland acreage. Results for irrigated acreage follow the same pattern with major differences across production systems lying in the upper and lower revenue boundaries. Thus for irrigated acreage, irrigation provides a buffer for the revenue impact.

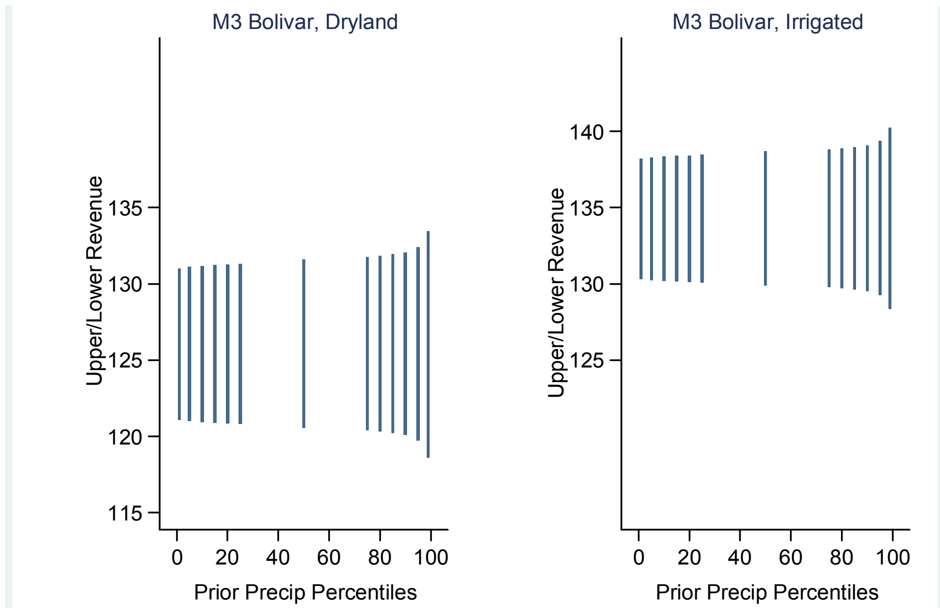

Figure 4.56 Dry and irrigated land revenue impact for Bolivar, (model 3)

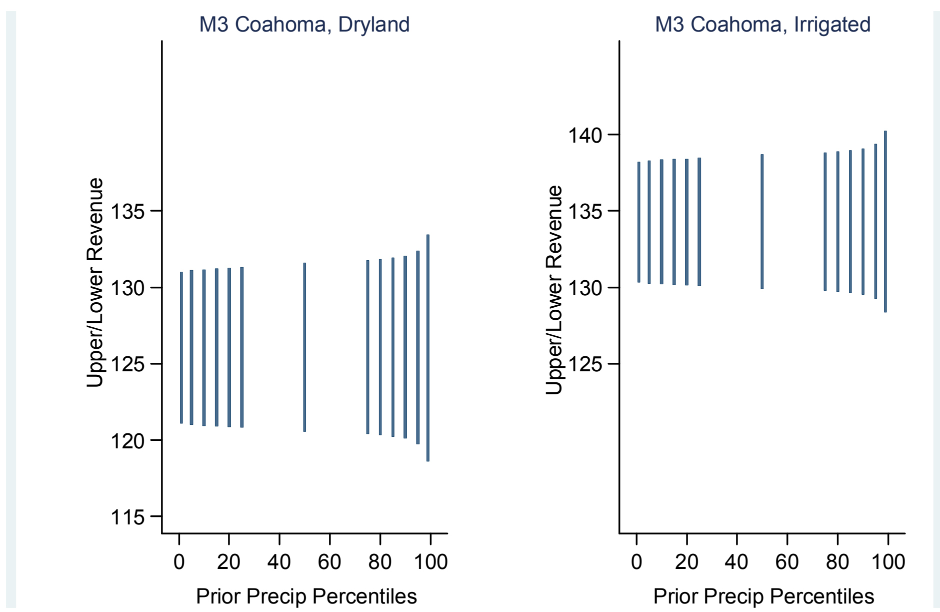

Figure 4.57 Dry and irrigated land revenue impact for Coahoma, (model 3)

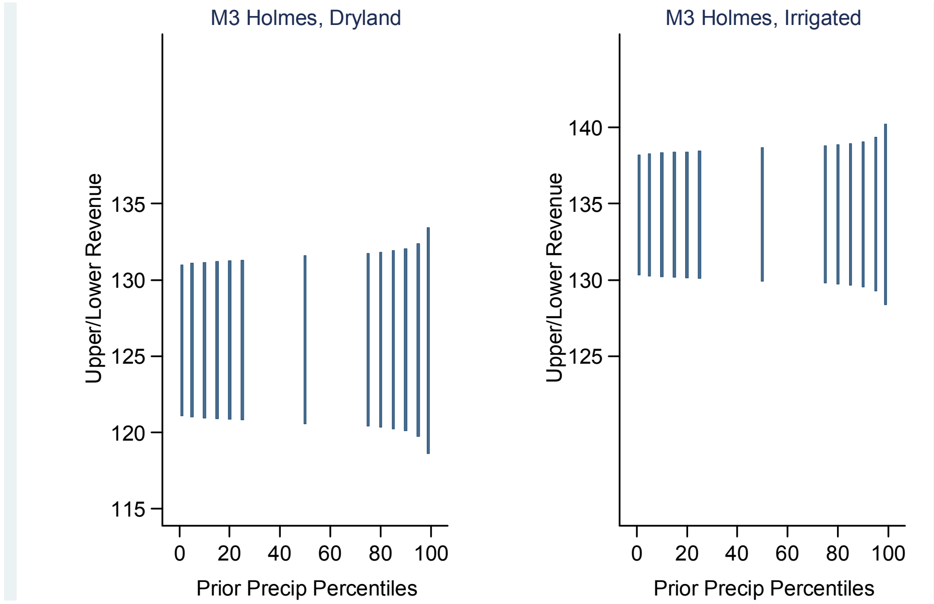

Figure 4.58 Dry and irrigated land revenue impact for Holmes, (model 3)

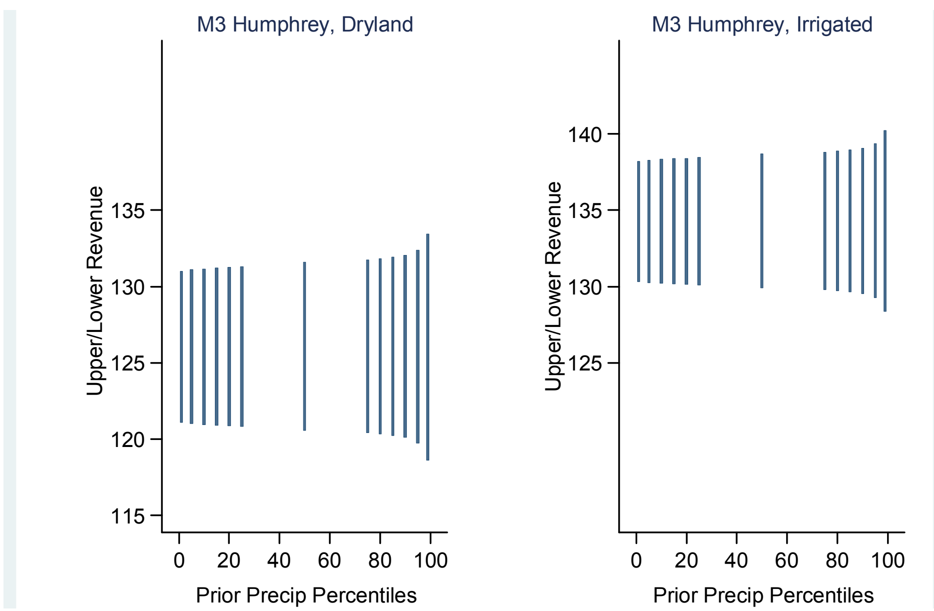

Figure 4.59 Dry and irrigated land revenue impact for Humphrey, (model 3)

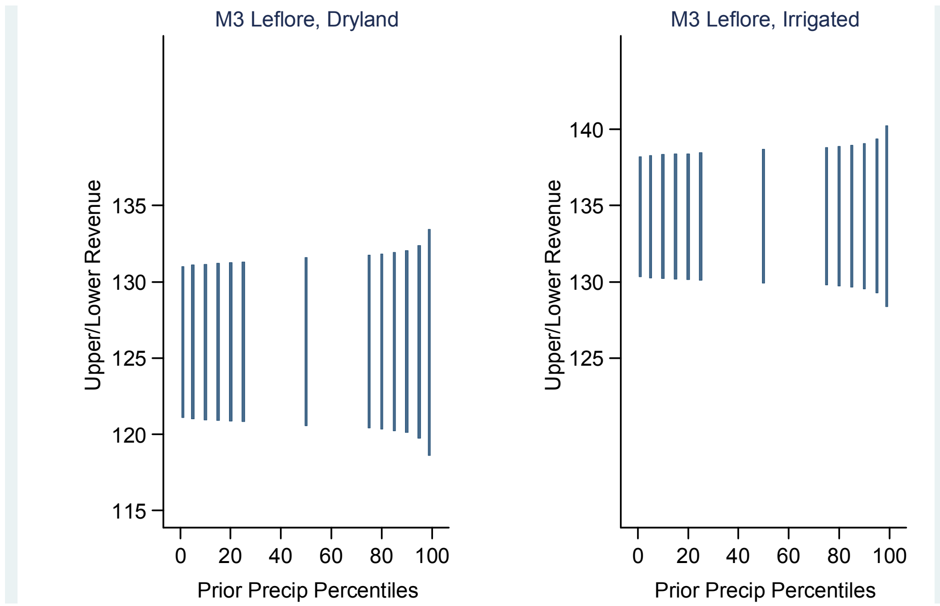

Figure 4.60 Dry and irrigated land revenue impact for Leflore, (model 3)

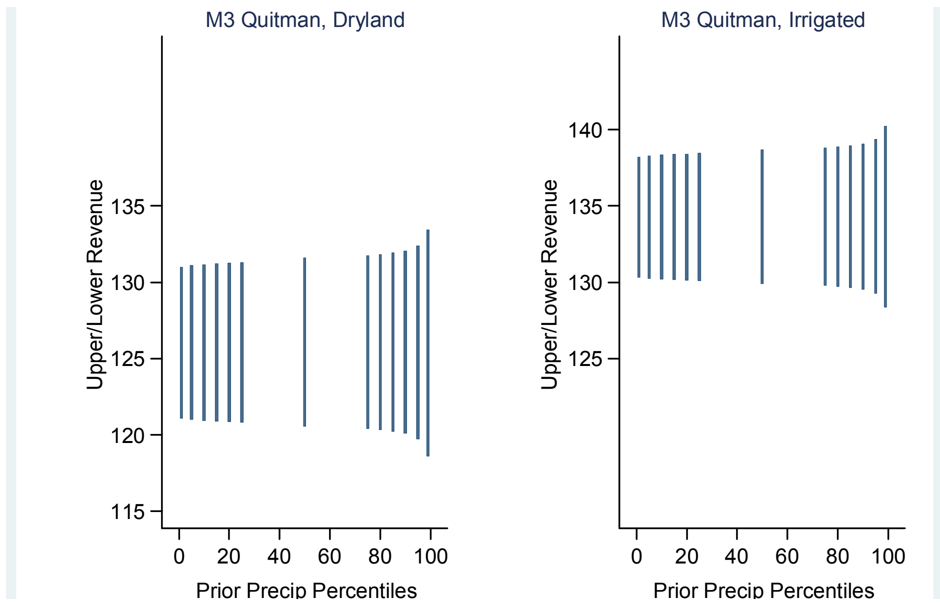

Figure 4.61 Dry and irrigated land revenue impact for Quitman, (model 3)

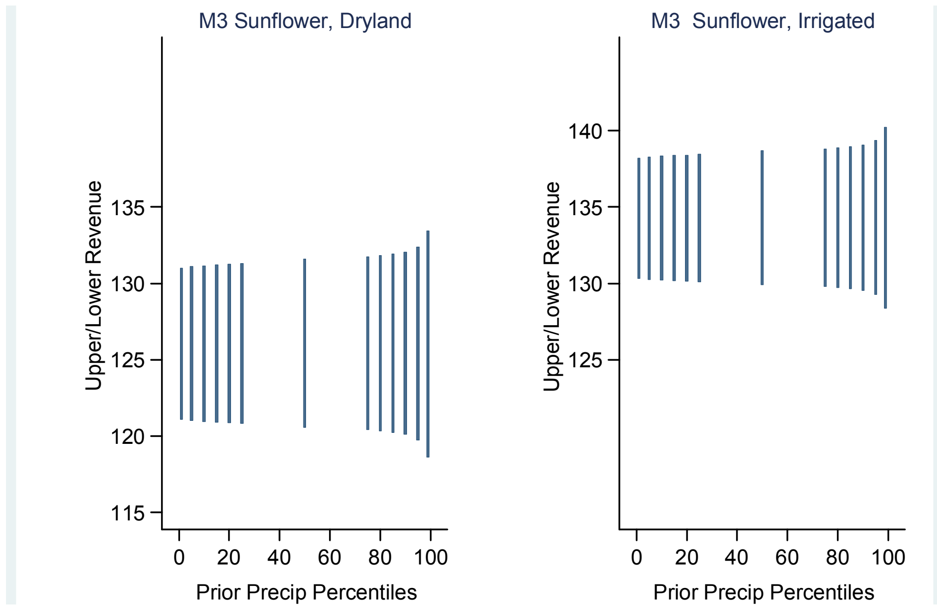

Figure 4.62 Dry and irrigated land revenue impact for Sunflower, (model 3)

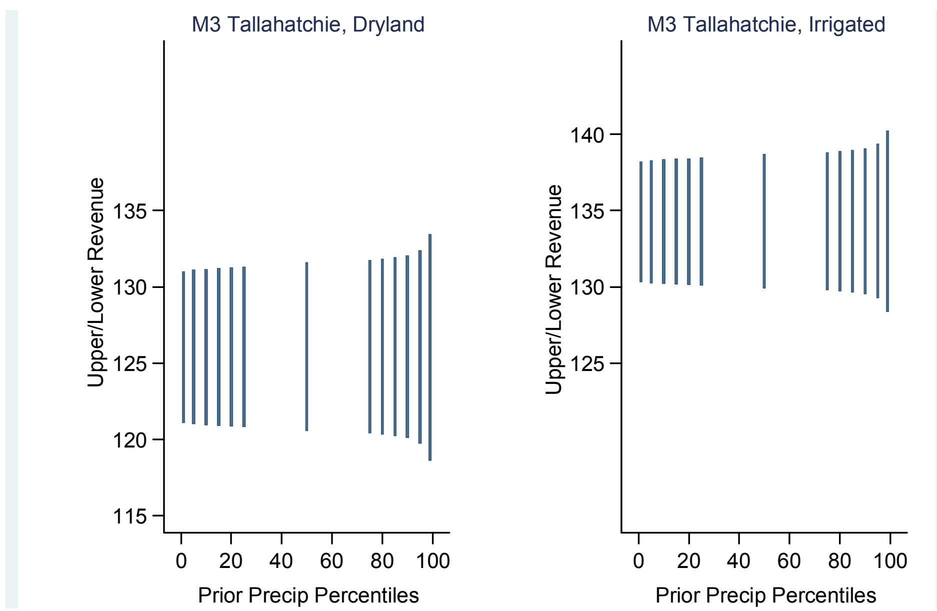

Figure 4.63 Dry and irrigated land revenue impact for Tallahatchie, (model 3)

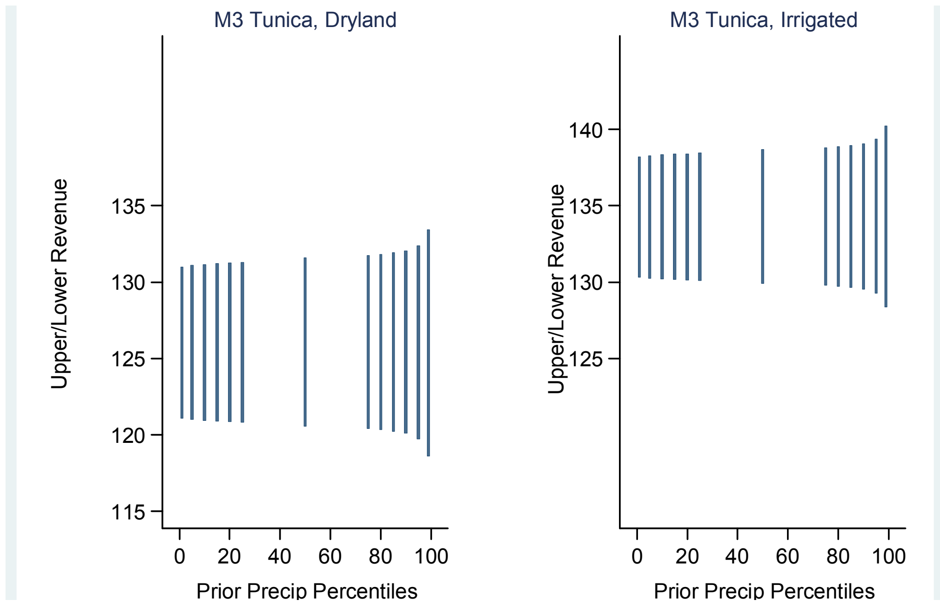

Figure 4.64 Dry and irrigated land revenue impact for Tunica, (model 3)

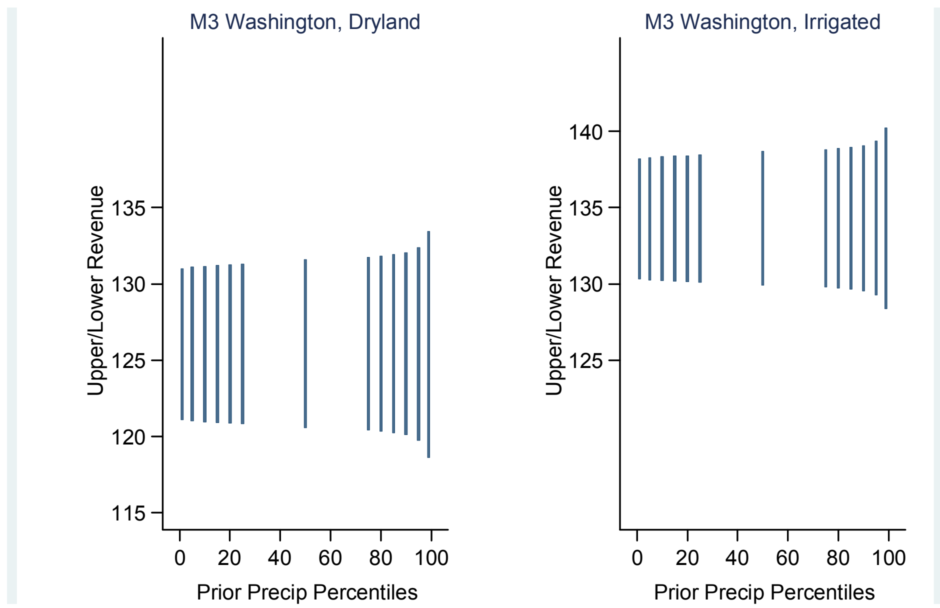

Figure 4.65 Dry and irrigated land revenue impact for Washington, (model 3)

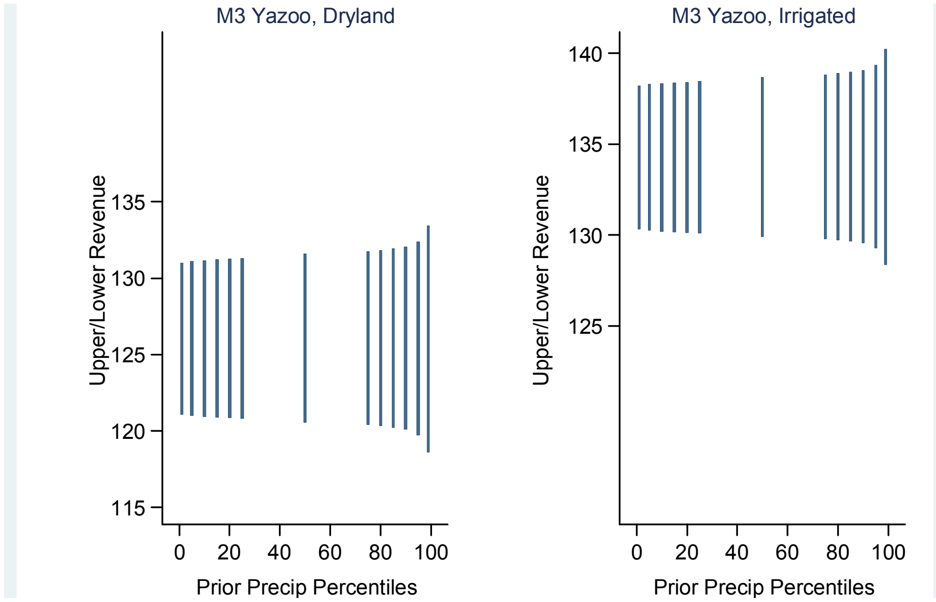

Figure 4.66 Dry and irrigated land revenue impact for Yazoo, (model 3)

Model 3 results under lognormality

Here again, we relax the normality assumption as a robustness check by holding prior precipitation variables at the 1^{st} and the 99^{th} percentiles for drought and wet climate respectively. Under lognormality assumption, generated densities show positive skewness and some distributional differences in the variance of dryland acreage average, drought, and wet precipitation density results.

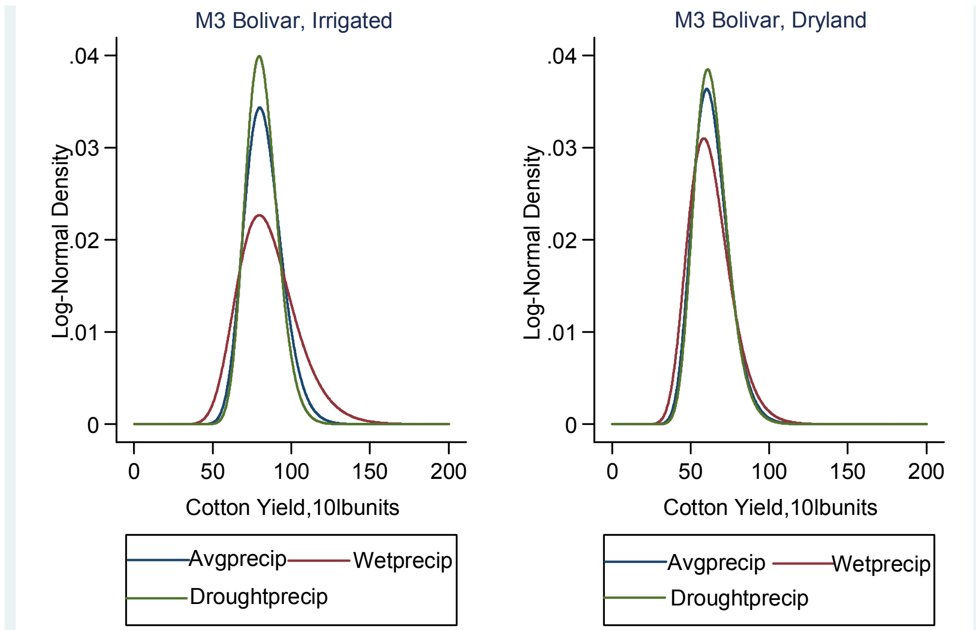

Figure 4.67 Irrigated and dryland lognormal yield distribution for Bolivar, (model 3)

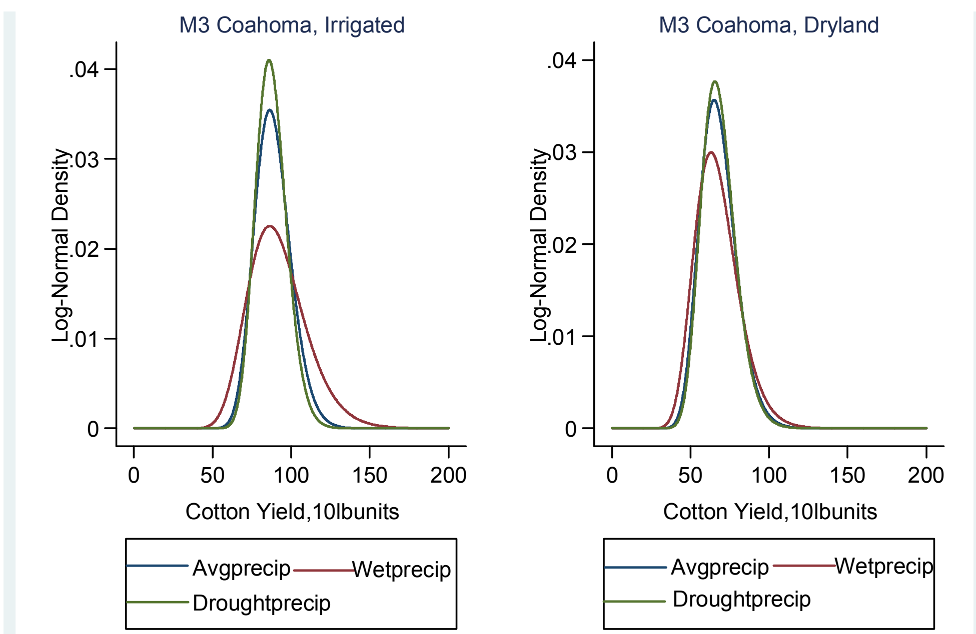

Figure 4.68 Irrigated and dryland lognormal yield distribution for Coahoma, (model 3)

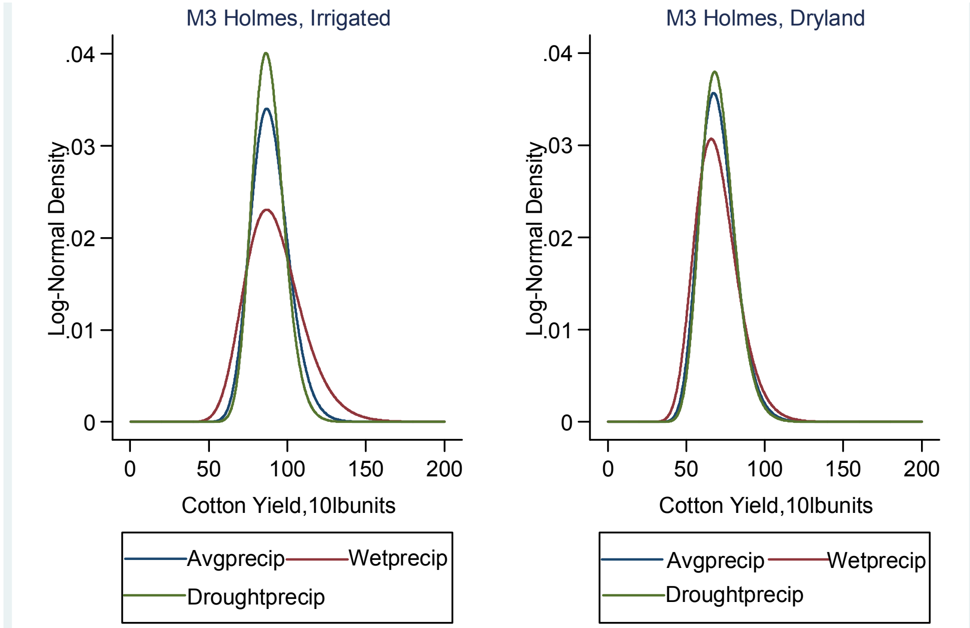

Figure 4.69 Irrigated and dryland lognormal yield distribution for Holmes, (model 3)

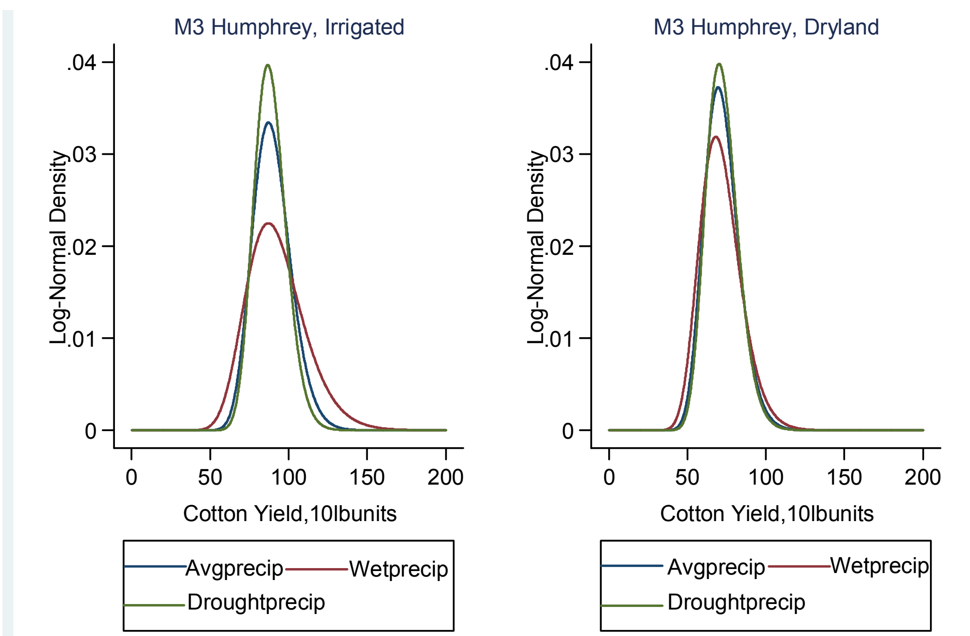

Figure 4.70 Irrigated and dryland lognormal yield distribution for Humphrey, (model 3)

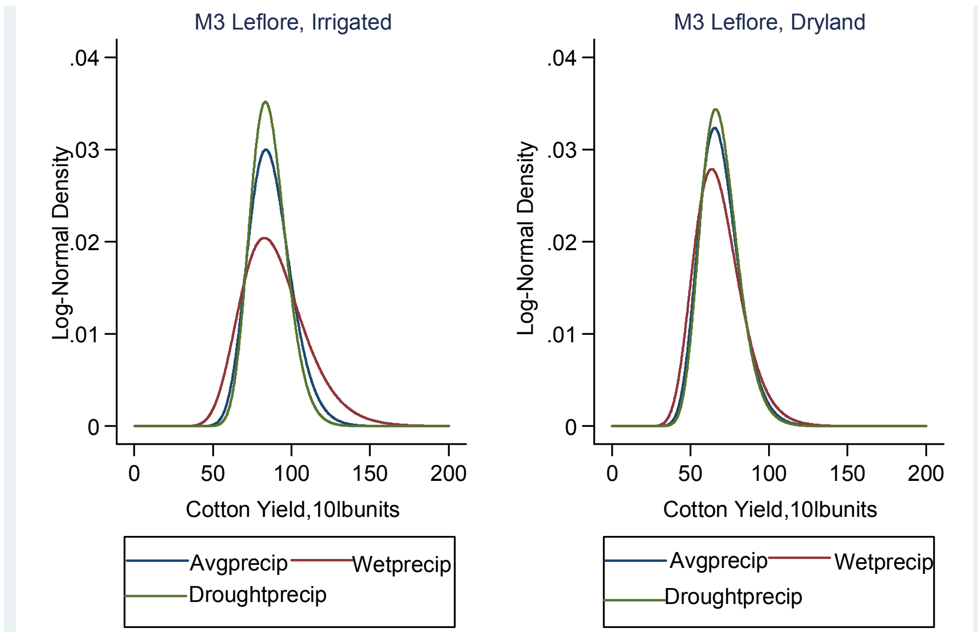

Figure 4.71 Irrigated and dryland lognormal yield distribution for Leflore, (model 3)

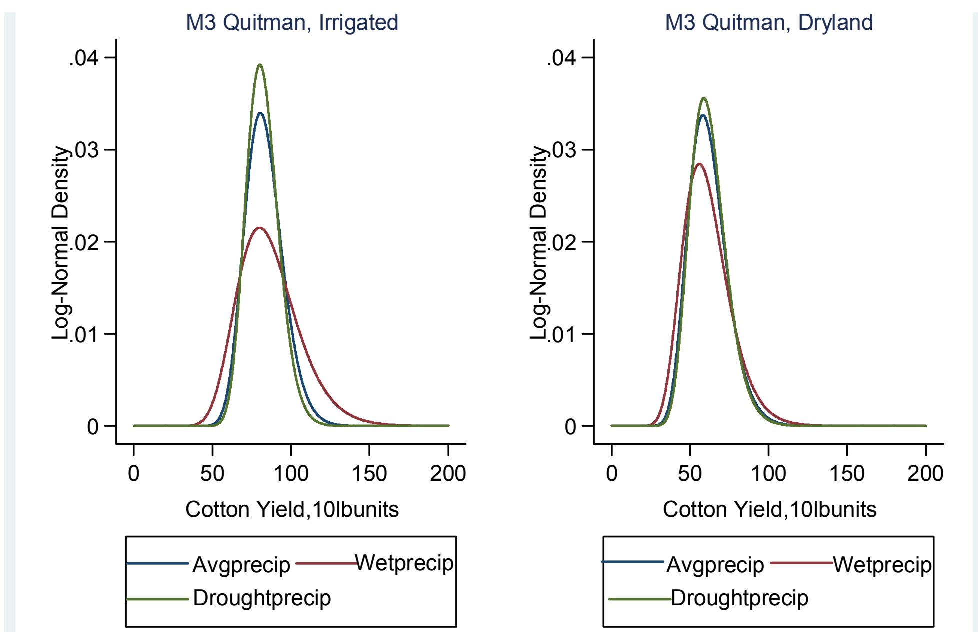

Figure 4.72 Irrigated and dryland lognormal yield distribution for Quitman, (model 3)

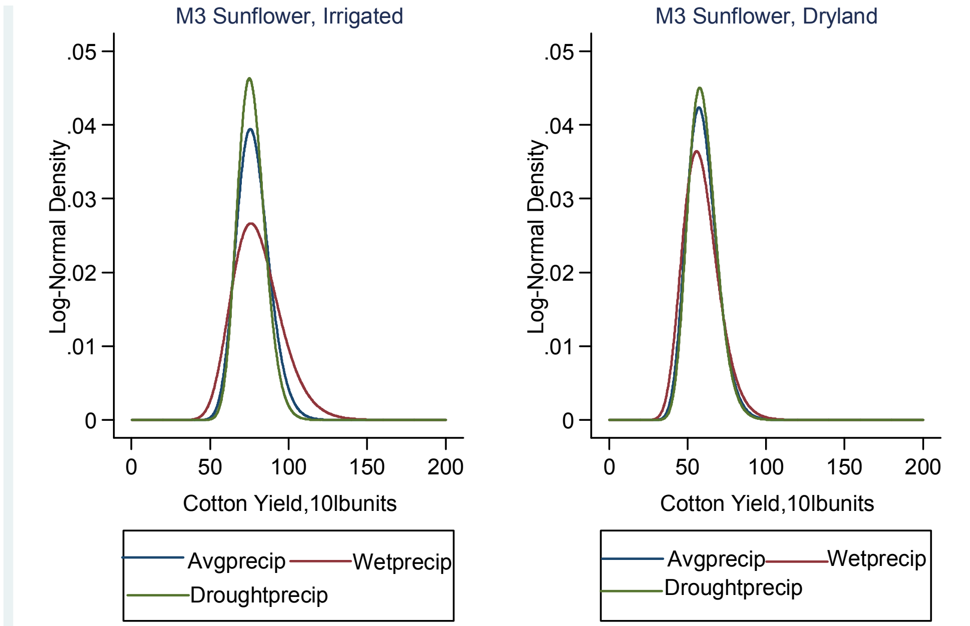

Figure 4.73 Irrigated and dryland lognormal yield distribution for Sunflower, (model 3)

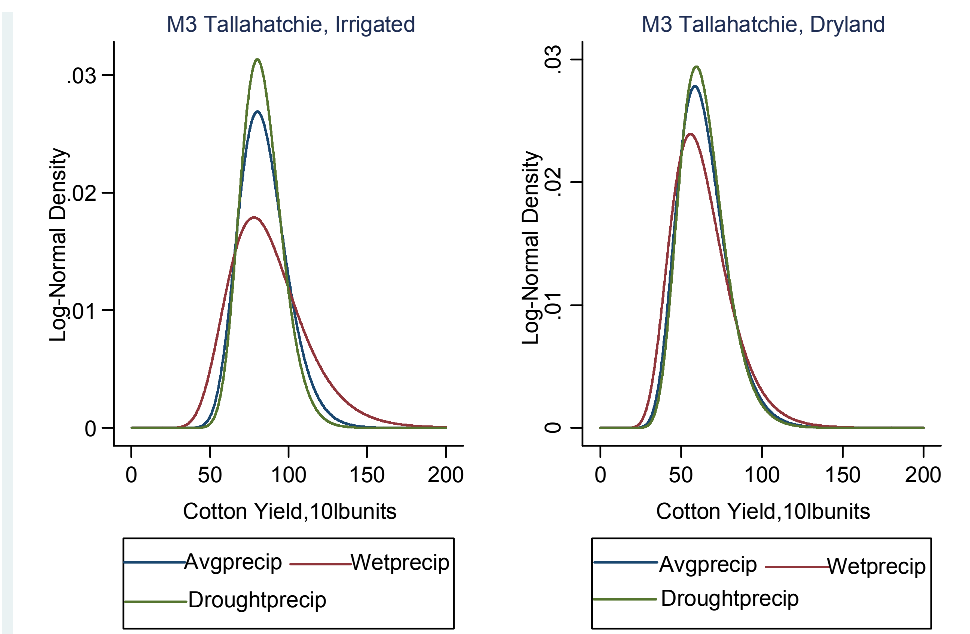

Figure 4.74 Irrigated and dryland lognormal yield distribution for Tallahatchie, (model 3)

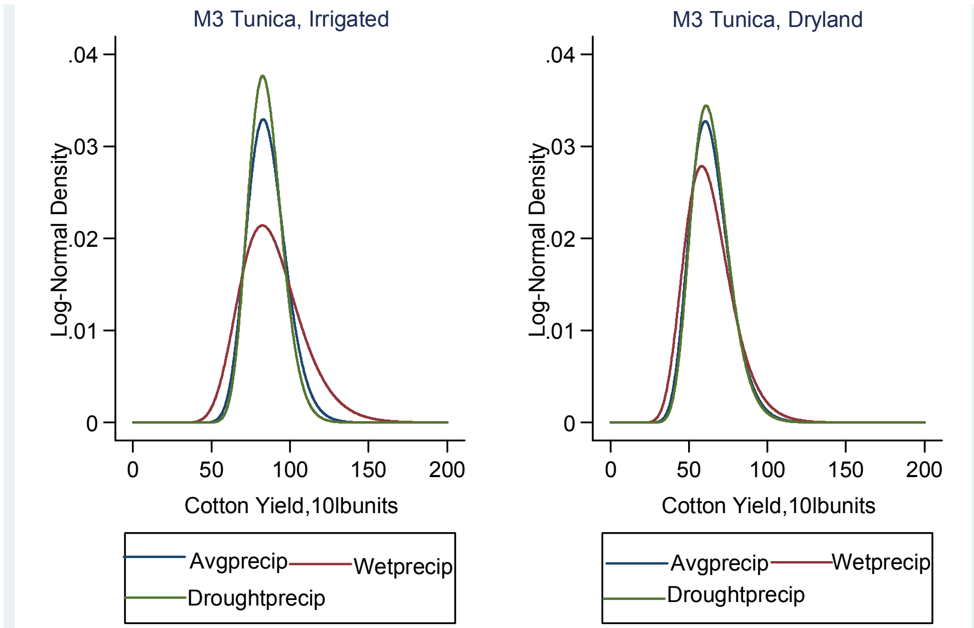

Figure 4.75 Irrigated and dryland lognormal yield distribution for Tunica, (model 3)

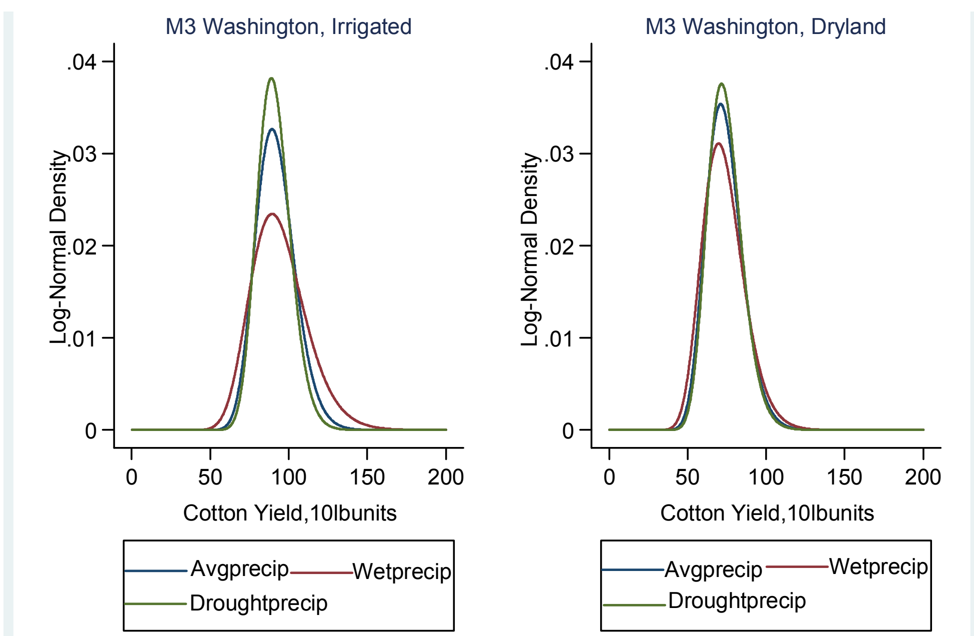

Figure 4.76 Irrigated and dryland lognormal yield distribution for Washington, (model 3)

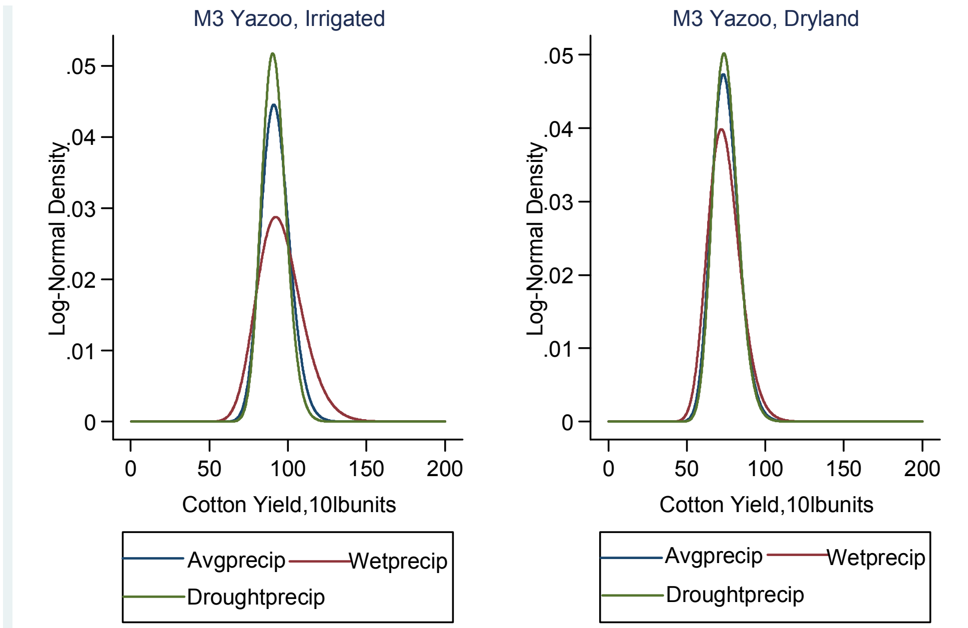

Figure 4.77 Irrigated and dryland lognormal yield distribution for Yazoo, (model 3)

For yield impact, acreage weighted average of the drought climate county level impact on mean (variance) yields are 0.32% (-11.84%) for dryland and -1.23 % (-26.5%) for irrigated land. Surprisingly, we see that severe drought is associated with a small increment of about (0.32%) in mean yield and excessive moisture is associated with a small reduction of (0.89) in mean yield for dryland result but the sign reverts under irrigated land, a deviation from the within season models already discussed when holding precipitation variable at range of late precipitation percentiles. The acreage weighted average of the drought climate county level impact on upside (downside) yields are -7.84% (-1.62%) for dryland and -3.32 % (-25.39%) for irrigated acreage. From Table 4.18, acreage weighted average of wet climate impact on the mean (variance) yields are -0.89% (41.88%) and 3.37% (146.53%) while impact on upside (downside) yields are 20% (4.15%) and 17 % (55.6%) for dryland and wet climate respectively. It is interesting to note for dryland results that wet is associated with a small reduction of approximately 0.9 percent in mean yields.

Table 4.18 Yield impact results, lognormal distribution (model 3)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	0.33	-11.66	-7.22	-1.27	-0.95	42.78	18.94	3.41
	Coahoma	0.30	-11.21	-7.27	-1.51	-0.96	46.85	21.45	4.54
	Holmes	0.32	-12.52	-8.41	-1.92	-0.79	39.06	19.15	4.43
	Humphrey	0.33	-13.08	-9.70	-2.38	-0.79	40.07	21.64	5.41
	Leflore	0.33	-12.41	-7.17	-1.38	-0.82	39.60	16.51	3.18
	Quitman	0.33	-11.12	-6.05	-0.82	-1.08	48.19	18.21	2.47
	Sunflower	0.37	-12.25	-8.82	-1.47	-0.94	39.43	20.64	3.65
	Tallahatchie	0.35	-12.13	-5.35	-0.50	-0.98	44.04	13.69	1.09
	Tunica	0.29	-10.43	-5.66	-0.85	-0.98	44.77	17.30	2.57
	Washington	0.30	-12.03	-8.47	-2.13	-0.64	32.30	17.35	4.41
	Yazoo	0.28	-11.35	-12.17	-3.60	-0.81	43.61	35.51	10.54
	Average	**0.32**	**-11.84**	**-7.84**	**-1.62**	**-0.89**	**41.88**	**20.04**	**4.15**
Irrigated	Bolivar	-1.27	-26.15	-2.47	-23.76	3.62	150.60	15.11	51.38
	Coahoma	-1.14	-25.22	-3.51	-25.57	3.63	169.96	20.39	64.21
	Holmes	-1.27	-27.82	-3.97	-27.48	3.09	134.09	16.75	53.74
	Humphrey	-1.32	-28.94	-4.15	-28.30	3.14	138.06	17.06	53.19
	Leflore	-1.29	-27.83	-3.10	-22.28	3.19	134.32	13.80	41.27
	Quitman	-1.20	-25.10	-2.53	-22.52	3.95	175.56	17.47	55.05
	Sunflower	-1.42	-27.03	-1.63	-28.85	3.58	137.32	13.31	58.74
	Tallahatchie	-1.30	-27.40	-2.39	-18.01	3.44	149.14	12.86	34.35
	Tunica	-1.09	-23.76	-2.61	-20.67	3.61	159.08	16.39	51.85
	Washington	-1.18	-26.95	-4.28	-25.43	2.55	105.48	14.27	45.27
	Yazoo	-1.10	-25.02	-5.85	-36.42	3.27	158.21	29.51	102.45
	Average	**-1.23**	**-26.48**	**-3.32**	**-25.39**	**3.37**	**146.53**	**16.99**	**55.59**

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

Tables 4.20 - 4.22 below report yield impact results for the less severe drought and excessive rain scenarios. Contrary to the earlier discussed model 3 normal yield impact results, in Figure 4.22 when prior precipitation is held at the 15th and the 85th percentiles for drought and irrigated acreage, drought generates extremely small reduction in mean yields (0.17), a small increment in variance (6.90), which causes upside risk to increase by 4.17 percent and downside risk to increase by 0.91 percent. On the other hand, wet generates an extremely small increment in mean yield of about 0.21 and rather a relatively large reduction in variance (-8.01), which causes a reduction in upside and downside risk of about -5.18 percent and -1.07 percent respectively for dryland acreage. On irrigated acreage however, drought causes a small increment in mean (0.64%) and a relatively large increment in variance (18.67%), which causes a slight increment in upside risk (2.56) and an increment in downside risk of about 12.89 percent. Conversely, wet causes a reduction in mean yields by 0.82% percent and a rather large reduction in the variance of about 18.66 percent, which subsequently causes a small reduction in upside risk (-16.76) and a rather large reduction in downside risk.

Table 4.19 Yield impact results, lognormal distribution (model 3)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	0.28	-9.78	-5.97	-1.05	-0.44	17.70	9.00	1.61
	Coahoma	0.24	-9.21	-5.88	-1.22	-0.40	17.50	9.38	1.98
	Holmes	0.30	-11.56	-7.71	-1.76	-0.47	21.69	11.68	2.69
	Humphrey	0.31	-12.27	-9.05	-2.22	-0.42	19.50	11.75	2.92
	Leflore	0.30	-11.38	-6.52	-1.26	-0.34	14.91	7.14	1.38
	Quitman	0.27	-9.27	-4.97	-0.68	-0.36	13.84	6.33	0.87
	Sunflower	0.31	-10.34	-7.34	-1.23	-0.40	14.98	8.99	1.56
	Tallahatchie	0.27	-9.70	-4.20	-0.39	-0.44	18.05	6.47	0.56
	Tunica	0.28	-10.11	-5.47	-0.82	-0.51	21.40	9.39	1.41
	Washington	0.29	-11.66	-8.19	-2.06	-0.36	16.80	9.83	2.49
	Yazoo	0.28	-11.34	-12.17	-3.60	-0.46	22.74	20.39	6.03
	Average	**0.28**	**-10.60**	**-7.04**	**-1.48**	**-0.42**	**18.10**	**10.03**	**2.14**
Irrigated	Bolivar	-1.05	-22.39	-2.19	-19.61	1.66	52.05	5.69	27.13
	Coahoma	-0.92	-21.17	-2.98	-20.71	1.53	51.45	7.14	31.25
	Holmes	-1.16	-25.96	-3.73	-25.19	1.85	65.77	9.00	35.07
	Humphrey	-1.24	-27.40	-3.94	-26.39	1.67	58.04	8.00	31.38
	Leflore	-1.18	-25.79	-2.90	-20.23	1.35	42.65	4.87	20.03
	Quitman	-0.99	-21.35	-2.21	-18.47	1.31	39.44	4.45	22.03
	Sunflower	-1.19	-23.34	-1.55	-24.04	1.51	43.33	4.25	27.99
	Tallahatchie	-1.02	-22.44	-2.01	-14.00	1.65	52.61	4.91	18.70
	Tunica	-1.05	-23.10	-2.55	-19.97	1.90	64.66	7.38	31.03
	Washington	-1.14	-26.22	-4.17	-24.58	1.42	48.91	7.21	27.28
	Yazoo	-1.10	-25.01	-5.85	-36.41	1.86	70.72	14.83	62.15
	Average	**-1.10**	**-24.01**	**-3.10**	**-22.69**	**1.61**	**53.60**	**7.07**	**30.37**

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

Table 4.20 Yield impact results, lognormal distribution (model 3)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	0.25	-8.79	-5.33	-0.94	-0.25	9.73	5.20	0.93
	Coahoma	0.23	-8.69	-5.53	-1.15	-0.30	12.71	7.01	1.48
	Holmes	0.28	-10.89	-7.23	-1.65	-0.31	13.63	7.69	1.77
	Humphrey	0.26	-10.49	-7.63	-1.88	-0.29	13.31	8.31	2.06
	Leflore	0.27	-10.47	-5.95	-1.15	-0.27	11.48	5.62	1.09
	Quitman	0.26	-8.85	-4.73	-0.65	-0.30	11.42	5.30	0.73
	Sunflower	0.29	-9.75	-6.89	-1.16	-0.27	10.05	6.21	1.07
	Tallahatchie	0.26	-9.37	-4.04	-0.38	-0.27	10.57	3.97	0.35
	Tunica	0.23	-8.45	-4.52	-0.68	-0.24	9.30	4.40	0.66
	Washington	0.20	-8.13	-5.57	-1.41	-0.29	13.50	8.05	2.04
	Yazoo	0.25	-10.52	-11.23	-3.32	-0.31	14.51	13.55	4.00
	Average	**0.25**	**-9.49**	**-6.24**	**-1.30**	**-0.28**	**11.84**	**6.85**	**1.47**
Irrigated	Bolivar	-0.94	-20.33	-2.02	-17.47	0.95	26.78	2.95	16.15
	Coahoma	-0.87	-20.10	-2.84	-19.48	1.14	35.94	5.07	23.73
	Holmes	-1.09	-24.64	-3.55	-23.62	1.20	38.76	5.49	23.78
	Humphrey	-1.05	-23.87	-3.47	-22.24	1.17	37.73	5.34	22.74
	Leflore	-1.08	-23.94	-2.71	-18.43	1.05	31.96	3.69	16.00
	Quitman	-0.94	-20.48	-2.13	-17.58	1.09	31.89	3.60	18.62
	Sunflower	-1.12	-22.16	-1.51	-22.57	1.04	27.86	2.68	19.66
	Tallahatchie	-0.99	-21.73	-1.95	-13.46	1.00	29.13	2.76	11.95
	Tunica	-0.87	-19.64	-2.20	-16.45	0.87	25.49	2.99	15.23
	Washington	-0.78	-18.98	-3.03	-16.67	1.16	38.29	5.74	22.63
	Yazoo	-1.02	-23.45	-5.49	-33.76	1.23	42.09	9.20	41.89
	Average	**-0.98**	**-21.76**	**-2.81**	**-20.16**	**1.08**	**33.26**	**4.50**	**21.12**

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

Table 4.21 Yield impact results, lognormal distribution (model 3)

System	*County*	*Drought 1%*				*Wet 99%*			
		%Mean	%Var	%Up	%Down	%Mean	%Var	%Up	%Down
Dryland	Bolivar	-0.18	7.06	3.83	0.68	0.22	-7.88	-4.75	-0.84
	Coahoma	-0.08	3.42	2.00	0.42	0.21	-7.88	-4.98	-1.04
	Holmes	-0.23	10.11	5.83	1.34	0.21	-8.14	-5.30	-1.21
	Humphrey	-0.16	7.23	4.68	1.16	0.21	-8.31	-5.96	-1.47
	Leflore	-0.23	9.63	4.77	0.92	0.20	-7.68	-4.28	-0.83
	Quitman	-0.09	3.47	1.70	0.23	0.22	-7.81	-4.14	-0.57
	Sunflower	-0.21	7.50	4.71	0.81	0.22	-7.44	-5.17	-0.87
	Tallahatchie	-0.15	5.78	2.24	0.20	0.24	-8.70	-3.73	-0.35
	Tunica	-0.11	4.11	2.01	0.30	0.23	-8.15	-4.35	-0.65
	Washington	-0.18	7.96	4.91	1.24	0.18	-7.32	-4.99	-1.26
	Yazoo	-0.21	9.61	9.20	2.71	0.21	-8.78	-9.28	-2.74
	Average	**-0.17**	**6.90**	**4.17**	**0.91**	**0.21**	**-8.01**	**-5.18**	**-1.07**
Irrigated	Bolivar	0.70	18.99	2.08	12.04	-0.84	-18.41	-1.85	-15.54
	Coahoma	0.32	8.91	1.28	6.94	-0.78	-18.37	-2.60	-17.54
	Holmes	0.91	27.91	4.01	18.23	-0.80	-18.95	-2.76	-17.28
	Humphrey	0.66	19.46	2.81	13.08	-0.82	-19.35	-2.83	-17.32
	Leflore	0.89	26.41	3.06	13.69	-0.78	-18.05	-2.08	-13.14
	Quitman	0.35	9.05	1.02	6.13	-0.83	-18.25	-1.92	-15.35
	Sunflower	0.78	20.32	1.92	15.02	-0.84	-17.35	-1.28	-16.93
	Tallahatchie	0.56	15.34	1.46	6.92	-0.91	-20.31	-1.83	-12.40
	Tunica	0.40	10.76	1.27	7.08	-0.84	-19.01	-2.13	-15.83
	Washington	0.70	21.56	3.31	14.08	-0.70	-17.23	-2.75	-14.90
	Yazoo	0.83	26.66	5.96	28.59	-0.84	-20.00	-4.69	-28.11
	Average	**0.64**	**18.67**	**2.56**	**12.89**	**-0.82**	**-18.66**	**-2.43**	**-16.76**

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

For a pre-season precipitation effect, normality was still a poor distributional assumption as there is evidence of positive skewness when symmetry assumption was relaxed by assuming a lognormal distribution. Generally it can be observed that severe drought generates extremely small increment in mean and relatively high reduction in variance, which causes a reduction in upside risk and very small reduction in downside risk for dryland acreage. Excessive moisture on the other hand causes a small reduction in mean and a rather high increment in variance, which causes a very small impact on the downside risk for dryland acreage. On irrigated acreage, however, severe drought causes a small reduction in mean and a high reduction in variance, and this reduction causes approximately the same reduction in downside risk. Excessive moisture causes an increment in mean and very high increment in variance, which causes a relatively high increment in downside risk. Generalizations from model 3 show that relaxing the skewness constraint affects density results. For yield impacts, results show that with the exception of mean, drought (wet) is associated with a reduction (increment) in variance, upside and downside risk for higher percentiles but at lower percentiles the reverse occurs.

CHAPTER V

CONCLUSIONS

With recent declination in cotton production as a result of changing climate and other economic forces, this study generally uses regression analysis to examine the effect of late season precipitation on cotton yield distribution. The study is motivated by the fact that rainfall occurring near anticipated harvest dates might cause substantial reductions in realized yields.

The empirical model used in this research extends regression models of previous studies Antle (1983, 2010) and Tack et al., (2012) by using Antle's Linear Moment Model (LMM) and Schlenker and Roberts' (2006 2009a) weather data. Differently from these studies, the precipitation variable is split into early and late season in order to isolate late-season effect. County level upland cotton yield data is obtained from NASS that spans 1972-2005 from 11 counties in Mississippi. The relatively short time series yield data is because NASS began distinguishing between irrigated and non-irrigated acreage in 1972, and the differences allow us to measure irrigation effects across the two production methods. The modeling process establishes a relationship between yield, weather, irrigation variables and trend. In order to estimate the variation in yield caused by late precipitation, the impact of the trend was eliminated from the data by including the trend variable in the regression model.

Utilizing a normal distribution assumption and a lognormal distribution as a robustness check, we estimate the first two moments and use these moments as constraints in a maximum entropy framework to generate densities. Late season drought and late season wet climates are generated by holding all estimated parameters at their means except the late precipitation variable (for within season precipitation effect) and prior precipitation (pre-season precipitation effect) variable at specific percentiles for a range of precipitation values. Normality is not a good distributional assumption for generated densities as there was evidence of skewness under lognormality.

This research estimates the impact of late season drought and excessive rain on the yield distribution considering mean, variance, upside, and downside risk and report effects on only dry and irrigated acreage.

In general for both within season and pre-season precipitation effect, we find that late season drought reduces mean yields fairly homogenously across counties for both dryland and irrigated acreage, with the effect on dryland 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 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 (i.e., one full month might be too big of a window) or that the LMM model is inappropriately specified. Future work will address this issue by considering

1. alternative measurements of precipitation e.g. biweekly
2. alternative distributional assumptions e.g. beta distribution
3. the agronomy and morphology of the cotton plant

Additionally we find that the values at which late precipitation variable is held in order to create the drought and wet scenarios influence their impact on mean variance upside and downside risk. At severe drought (1^{st}) and excessive moisture (99^{th}) percentile drought (wet) is associated with a reduction (increment) in mean variance upside and downside risk. However, at the 15^{th} (85^{th}) percentile for drought (wet), drought impact were positive while wet impacts were negative on mean, variance, upside and downside yield risk; although generally drought (wet) is associated with a reduction (increment) in mean, variance, upside and downside yield risk.

Yield impacts are converted to revenue impacts using the mean and variance of lognormal distribution. We find that there are no distributional differences moving from severe drought to less drought and slight distributional differences moving from less moisture to excessive moisture. Revenue impact on irrigated acreage is higher than revenue impact on dryland acreage. It is interesting to note that this study did not consider yield quality and cost of irrigation in the modeling process. In any case, this analysis makes no claim to finality but is intended to direct some attention to some promising lines of further research.

The findings from this research have important empirical and policy implications for accurate modeling of yield distributions for risk management purposes. First, the framework of this research will help guide future studies that seek to link late precipitation events to cotton and other agricultural crop production. This research also adds to the existing body of literature that asserts that it is not enough to solely rely on the variance for estimating insurance policy as we demonstrate in yield impact estimation that reduction in variance affect upside and downside risks values.

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______[NASS] National Agricultural Statistics Service (NASS) of United States Department of Agriculture (USDA).

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APPENDIX A

EFFECTS OF WEATHER AND IRRIGATION ON COTTON YIELD MOMENTS

Dependent Variable:	Yield	Log(Errors)
Early Precipitation	-0.0191	0.0329***
	[0.0706]	[0.0102]
Mid Precipitation	-0.0823	-0.00102
	[0.0841]	[0.0134]
Late Precipitation	0.190	0.0985***
	[0.119]	[0.0167]
Irrigation* Early Precipitation	0.0193	-0.0212
	[0.109]	[0.0200]
Irrigation* Mid Precipitation	-0.255*	-0.00135
	[0.135]	[0.0245]
Irrigation* Late Precipitation	-0.0941	-0.0687**
	[0.166]	[0.0322]
Low Temperature	-0.0435	-0.0329***
	[0.0443]	[0.00556]
Medium Temperature	0.0840***	0.00347*
	[0.0122]	[0.00197]
High Temperature	-0.678***	-0.0171**
	[0.0642]	[0.00813]
Irrigation* Low Temperature	0.0369***	0.000188
	[0.00977]	[0.00165]
Irrigation* Medium Temperature	-0.0483***	0.000372
	[0.0153]	[0.00267]
Irrigation* High Temperature	0.260***	0.00214
	[0.0840]	[0.0141]
Trend	0.523***	0.0137
	[0.0568]	[0.0105]
County Fixed Effects	Y	Y
Mean of Dependent Variable	73.983	3.781
Number of observations	612	612
R-squared values	0.5740	0.1051

Notes: Tables shows results of regressing yield and lnyield on weather, trend and irrigation variables clustered at the county level are in brackets. *, ** and *** denotes significance at the 10% 5% and 1% levels.