Does Yield Risk Differ Across Soil Types? Evidence from Mississippi Variety Trials

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Abstract

As a critical growth factor, soil has a clear impact on crop yield. However, most existing studies focus on the effects of soil on the average yield (first moment), while the effects of soil on yield variability (higher moments) have seldom been researched. This study examines whether the yield variability (risk) changes with soil types by using the Mississippi Agricultural and Forestry Experimental Station annual corn variety trial data from 2000-2018. Our model follows Just-Pope production function that have been widely used to model production risk. Three different panel models: pooled, random effects, and fixed effects model are used for the estimation of the mean equations. The residuals of the mean equations are regarded as the measure of yield risk, and are used as dependent variables of the variance equations. It is found that loam soils have higher mean yield than clay soils, but the yield risk is also larger in loam soils. The study provides evidence of the role of soil in crop yield risk. As such, risk management agencies such as the RMA of the USDA may incorporate soil information in their rating procedures to achieve higher accuracy of crop insurance premium.

Key Words*: climate, production risk, moments, yield.*

Introduction

Crop yield is characterized by a high level of variability. The extent of such variability is largely influence by factors such as soil, pest and insect activities, and variations in weather that impact crop growth and yield. Extensive studies have reported the influence of these factors on the mean and variance of crop yield (see Schimmelpfennig, 2004, Schlenker & Roberts, 2006,Tack, Harri, & Coble, 2012; Isik & Devadoss, 2006 Anderson, Hazell, & Evans, 2002, Hazell, 2006). However, few have analyzed the role of soil on yield variability. As a critical growth factor, soil has a clear impact on yield and plays an important role in determining crop yield potential. These impacts have been well established in the agronomy literature(see Cox, Gerard, Wardlaw, & Abshire, 2010; Corwin, Lesch, Shouse, Soppe, & Ayars, 2003). In the Agricultural economics literature, most studies on the impact of soil have focused on soil's impact on the mean yield with few exceptions (see Woodard, 2016;Woodard & Verteramo-Chiu, 2017). Although the findings and conclusions of such studies are revealing, an analysis of how soil affects crop yield risk (higher moments of crop yield) have not been extensively researched in the agricultural economics literature.

The purpose of this research is to quantify the contribution of soil in addition to irrigation, trend, and weather conditions to corn yield. The major objective of the research is to investigate how different soil types affect the mean and variance of corn yield. The research would employ historical data on corn yield, soil type, irrigation, time variable as a proxy for technology gains, and rainfall variable from the Mississippi Agricultural and Forestry Experimental Station (MAFES) annual variety trial. Temperature data would be obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). This study would follow the specification in the Tack et al. (2012) moments model and employ a Just and Pope (1978) framework to determine the relationship between the input variables and corn yield. This research would contribute to the growing body of literature on yield modelling by estimating an econometric model to determine the impact of site-specific soil type, rainfall, irrigation, and time on the mean and variance of corn yield.

The results of this research would be useful to policy makers and producers since an estimation of first and second moments of the yield is an important component of farm level decision making. For crop producers, the results of the research would help to make informed risk management decisions. Since higher moments of the yield density in addition to the mean yield play an important role in determining crop insurance premium rates, policy makers such as the Risk Management Agency (RMA) of the Federal Crop Insurance Corporation (FCIC) can apply the results of this research in policies such as crop insurance pricing to achieve higher level of premium rates accuracy. A major issue faced by the Risk Management Agency (RMA) is the achievement of actuarially fair insurance premium rate. RMA is required by law to set crop insurance rates that are actuarially fair, that is expected insurance payment should be equal to insurance premiums (Woodard et al., 2012). The use of unfair insurance premium rates could lead to adverse selection. The current RMA rating methodology has come under serious criticisms (Goodwin 1994, Babcock et al.,2004, Skees and Reed 1986 and Coble et al. 2010) which point to significant flaws in the current RMA rating methodology. Among many ways suggested for improvement, Coble et al. (2010) recommend the use of risk related soil and weather variables in the rating methodology. Previous works by Woodard (2016) and Woodard and Chi (2017) have revealed significant improvement in the insurance premium when soil information is accounted for in the rating methodology. Based on these results, USDA/RMA proposes to define soil homogenous areas so that soil information could be incorporated in the rating methodology. This research, although does not directly model insurance, may provide a basis for such homogenous soil definition.

Literature Review

Research studies on yield vary by methodology, geographical location as well as their finding and conclusions. Most studies on yield have looked at the impact of weather variables such as temperature and precipitation on the mean and variability of crop yield. Other studies have also looked at the impact of site-specific characteristics such as acreage, fertilizer and chemical application, adoption of improved crop varieties, and geographical distribution on yield. Although these studies vary in their approaches, their finding point to significant impact of these variables on crop yield. The literature review is organized into three parts. The first part looks at the impact of weather on crop yield, followed by the impact of soil. The third provides a brief literature on modelling techniques on crop yield distribution.

Weather impact on yield

A significant amount of literature has focused on the impact of weather variables or climate on the mean and variability of yield with few of them analyzing the impact of such weather variables on the shape of the yield distribution (Tack, Harri, & Coble, 2012). The literature assessing the impact of climate on yield has been carried out in two main dimensions. There are those that use stochastic weather generators and agricultural crop models to simulate the effect of climate on yield (see Mearns, Rosenzweig, and Goldberg, 1997;Mearns, Rosenzweig, and Goldberg, 1992 ; Bindi et al.,1996 and Wang, Wang, and Liu, 2011). Mearns et al., (1992) uses sensitivity experiments with CERES wheat model to assess the response of yield to changes in mean and inter-annual variability of temperature and precipitation. The CERES wheat model uses a simplified function to predict growth and yield in response to plant genetics, weather, soil, and management factors. The study report that changes in temperature and precipitation have greater impact on the average of yields than changes in the variability of temperature and precipitation. Specifically, the research reports that a change in the variability of precipitation has significant impact on the yield variability as compared to a change in the variability of temperature. Bindi et al.(1996) studies the influence of climate on the mean and variability of grapevine yield, and report that a change in the variability of weather sequences has an insignificant effect on the average of grapevine yield but significantly affected variability of grapevine yield. The study however concludes that the predicted effect of climate change on the mean and variability of yield depends on the crop model selected, the variety of the grapevine chosen, and the introduction of changes in the climate variability.

The second line of research on the impact of weather variables on yields use regression approach to study the impact of weather on crop yields (see Isik & Devadoss, 2006 ;McCarl, Villavicencio, & Wu, 2008; Tack, Barkley, and Nalley 2015, Tack, Harri, and Coble 2012). Chen, McCarl and Schimmelpfennig (2004) studies the impact of climate on the mean and variability of corn, cotton, sorghum, soybean, and wheat. The study uses two specifications; a linear production model and a Cobb-Douglas production model for its analysis. Regression results report a significant negative effect of temperature on the average yield of corn, cotton and sorghum while precipitation had positive effect on the average yield of these crops, irrespective of the model specification. The effect of temperature was positive for average soybean yield and negative for average wheat yield Precipitation had a significant negative effect for the linear specification of soybeans and wheat yield while a positive effect was reported for the Cobb-Douglas specification. The variance results predicted a significant effect of weather on yield. The clearest results could be seen for the variability in the yield of corn, cotton and sorghum. For these crops, the results are independent of functional form. Increase in precipitation was found to decrease the variability of corn and cotton yield but increased sorghum yield. Variability of cotton and sorghum yields were found to be decreased by higher temperature, while variance of corn yield was found to be increased by higher temperature.

Isik & Devadoss (2006) analyze the impact of temperature and precipitation on the mean, variance and covariance of wheat, barely, potato, and sugar beets yield in Idaho and report that the impact of temperature and precipitation on crop yields differed by crop. Results from the study points to a significant impact of climate on the variability and covariance of yields. Using weather data from the Kansa weather library and wheat yield data from the Kansa Performance Test with winter wheat varieties, Tack, Barkley, & Nalley (2015) study the effect of warming temperature on wheat yield in the United states. The study reports that the impact of temperature on wheat yield varies across the September-May growing season and freezing temperature in the fall, and extreme heat in the spring is a major source of yield loss. Increased rainfall in the spring, however, was reported to offset the warming effect of temperature on yield. Tack, Barkley, & Nalley (2015) states that the predictive performance and forecasting of warming impacts from the study depends to a larger extent the the construction method for the measurement of temperature and exposure. Schlenker & Roberts (2006) also reports a non- linear relationship between temperature and corn yield with yield increasing with temperature for moderate temperature levels but decreasing significantly with temperature levels exceeding $30^{\circ}C$. Tack et al., (2012) finds consistent results as in Schlenker & Roberts (2009a) for mean yield and also report a significant effect of extreme heat on higher order moments. Extreme temperature was found to have significant effect on first and second moment of cotton yield in Arkansas but for all modelled moment of yield in Mississippi and Texas.

Soil impact on yield

The Soil Science Society of America defines soil as "The unconsolidated mineral organic material on the immediate surface of the earth that serves as a natural medium for the growth of land plants" (SSA,1936). It is a major input for plant growth and has significant impact on yield. Determining which soil type is most suitable for a crop is a complex process because soil interacts with other inputs to influence growth and yield. Different soil types would have different effects on crops. To be effective, an agricultural producer must address both soil variability and soil properties that have significant impact on yield. Different factors account for the variability soil. Interaction among parent material, cropping history, fertilization, vegetation, topography among others has been identified to account for the variability of soil on crop fields. Hence since fields contain different soil series and topographical characteristics, it is much common to have variability in soil properties within field boundaries(Cox et al., 2010).

In the field of agronomy, extensive research exists on the impact of soil on yield and variability in soil. Agbu and Olsen (1990) discovered a significant variation between soil physical properties within two small maps unit in Illinois. Topographical features have also been found to have a significant impact on yield and was found to explain about 6 to 54 percent of the variation in soybean and corn yield. A negative relationship was also found between yield and topography (Kravchenko and Bullock,2000). Other soil factors that affects crop yield assuming soil fertility is the soil productivity measure and soil properties such as porosity and water infiltration capacity (Hatfield et al. 2000) and soil available water capacity (Wassenar et al. 1999). Using a multiple regression approach, Majchrzat et al (2001) found that soil properties such as texture, bulk density and organic matter content explained about 76 percent of the variation in wheat yields. Cox et al. (2010) studies the variability of soil properties and their relationship with soybean yield using soybeans field on the Mississippi Research and Extension Black Belt Branch Experiment Station. The study reported clay content as a common factor that affects soybean yields on the selected fields. Areas with higher clay content were found to have higher soybean yields. This was attributed to the high-water holding capacity of clay that made water available during the dry periods of the growing season.

In the agricultural economics literature, research on the impact of soil on yield are limited and have focused on soil's impact on mean yield with few exceptions (see Woodard 2016 Woodard and Verteramo-Chiu 2017). In investigating the efficiency impacts of utilizing soil data in the pricing of the federal crop insurance program, Woodard and Verteramo-Chiu (2017) used soil type data from the National Resource Conservative Service (NRCS) SSURGO database and yield data from National Agricultural Statistical Service (NASS) and Farm Business and Farm Management Data (FBFM). Woodard and Verteramo-Chiu 2017 selected soil organic carbon,root zone depth, and available water storage as measure of soil productivity. Soil organic carbon (SOC) is an important determinant of soil fertility and root zone depth available water storage is the amount of plant available water that the soil can store. Regression results from the study reveal that soil organic carbon and root zone depth available water storage have significant impact on corn yield. Again, Woodard (2016) uses national county level data from the state of Illinois to estimate the effect of soil on yield. The objective of the study was to investigate the possibility of integrating soil into yield distributions and insurance rate-setting. The study reports a significant effect of soil productivity rating on mean yield and yield risk, but an insignificant non-linear effect of soil productivity rating on mean yield. The results of Woodard and Verteramo-Chiu (2017) and , Woodard (2016) on soil's impact on mean yield are consistent with the resulsts of Hurd (1994) which studies the impact of soil quality on cotton yield in California. Carew, Smith, and Grant

(2016) studies the factors that aimfluencing wheat yeilds and variability of wheat yields in Manitoba. The study by Carew, Smith, and Grant (2016) quantifies the contribution of nitrogen fertilisers, time trends and insurance premium rates on mean and variance of wheat yields. Results from the study reveals a significant effect of soil quality on mean yield, which is consistent with the results of Woodard (2016) and Hurd (1994). The study employed the Just and Pope (1978,1979) production fucntion that allowed for the analysis of the effect of independent variables on the variance of wheat yields. The variance function estimates for the study found a significant negative relationship between soil quality and wheat yeilds. Soils with higher quality were associatied with lower yield variance and vice versa. Carew, Smith, and Grant (2016) also found nitrogen, potassium and sulfur fertilizers have also been identified to have identified to have an impact on yield variability.

Other conditioning variables

Other conditioning variables that have featured in most yield modelling literature are time trend, irrigation, prices, insurance premium rate, fertilizers among others. Time trend has been included in yield modelling studies to mostly examine the effect of technological change on crop yields. The impact of technology on yield has been modelled as either a deterministic or stochastic time trend that either accounts for heteroscedasticity adjustment. Time trend is assumed to have an impact on the mean of yield distributions. The possibility of shifts in the variance of yield distribution by time trend is made possible by accounting for heteroscedasticity and the impact of technological change goes beyond the first two moments of yield (Tolhurst & Ker, 2015). Tack et al.,(2012) report that technological change had a significant impact on the first moment of yield in Arkansas. Isik & Devadoss (2006) also report a positive relationship between trend and the mean and variance yield of the study crops. Carew, Smith, and Grant (2016) also found nitrogen, potassium and sulfur fertilizers and crop insurce premium rate to have significant impact on yield variability. Specifically, regions eith hgher crop insurance rate had hihger yield risk, a result which is consistent with the study by Carew and Smith (2006). Also higher nitrogen levels were associated with higher yield variance. This result is also consistent with the result of Smith, McKenzie and Grant (2003). Irrigation has also been identified to have an impact on yield variablity (Tack et al.,2012).

In modelling the effect of climate change on higher order moments of crop yield, Tack et al., (2012) reports the significant impact of irrigation on all three modelled moments of yield in Mississippi, Arkansas and Texas with the mean impact ranging from 0.39-0.52 bales per acre in Arkansas, 0.23-0.54 bales per acre in Mississippi and 0.13 – 0.78 in Texas. The study also reports that, the significance of other conditioning variables depends on the on the location and the equation in which they appear. In this regard, precipitation for dryland acreage was found to be insignificant for Arkansas and Mississippi but significant for all three moments in Texas and precipitation for irrigated locations is significant only for the first moment in Arkansas but insignificant for all moments of Mississippi.

While the literature assessing the impact of climate, soil and other conditioning variables presented here are not exhaustive, it is necessary to realize that most research have focused on the impact of climate on yield and yield variability with few assessing the impact of soil on yield variability. It is quite clear that the relationship between yield and climate has been well researched. Although previous studies employ different methods and different specification for their analysis, results from the studies point to a significant impact of weather and climate on yield. The results of these studies reveal that climate has significant impact on not only the mean of yield but on higher yield moments too. As such, climate studies that does not take into consideration the effect of weather variables on higher yield moment are unable to capture risk management implication (Tack et al., 2012b). Moreover, the studies that have evaluated the impact of soil on yield have used county level soil data. The problem of the county level soil data is the diminished variability in soil measure which is likely to lead to underestimation of soil effect on yield. A novelty of this research, as has been already emphasized in the introduction is the use of experimental trial soil data that gives an accurate representation on soil effect on yield and yield risk.

Yield Distribution

Another branch of research has focused on the distribution of yield of various crops. Approaches that have been used in modelling yield distribution are the parametric approach, semi-parametric approach and non- parametric approach. The parametric approach to modelling yield distribution assumes functional forms for a finite number of parameters. The approach has the advantage of making estimation and inference simple and offers a greater asymptotic efficiency under appropriate distributional assumptions. Frequently used parametric approach to yield estimation includes the Beta, lognormal and gamma distributions (Zhang 2017). Research works that employs the parametric approach include Ker and Coble (2003), Gallagher (1987), Moss and Shonkwiler (1993). Unlike the parametric approach, the non-parametric approach provides a form of optional flexibility to the modelling process. The data for the study form the basis for deciding an appropriate functional form. Estimates of non-parametric methods are generally biased, but then to be robust against functional form assumptions. Such works include the works of Goodwin and Ker (2000), Tack et al (2014**)**. Given the various approaches at modelling yield distributions, however, it is already accepted the crop yields are not normally distribution**.** Day (1965) analyzes the skewness of field crop distribution at different level of nitrogen application by using data on corn, cotton and oats from the Delta branch of Mississippi Experimental Station. Results from the research found positive skewness for all fertilizer level for the cotton series, negative skewness for the oats series and no significant deviation from the normal distributing for the corn series. Increased application of nitrogen beyond 45 pound decreased skewness and kurtosis of yield distribution (Day, 1965). This result is consistent with the result of Du, Hennessy, and Yu (2012) and Ramirez, Mizra and Field (2003). Weather inputs and response to weather has been found to play a role in determining the shape of the yield distribution. Evidence from the analysis of soybean has verified the importance of diminishing returns to weather. Declining returns to weather inputs of soybean has been found to have a negative distribution (Gallagher, 1987). Crop yield tend to be spatially correlated since geographical and weather variables in addition to other unobserved factors affects yields across neighboring counties (Annan et al. 2014 and Du, Hennessy, and Yu 2012) Swinton and King (1991) assert that the variability of yield over the passage of time have significant impact on estimation and inference.

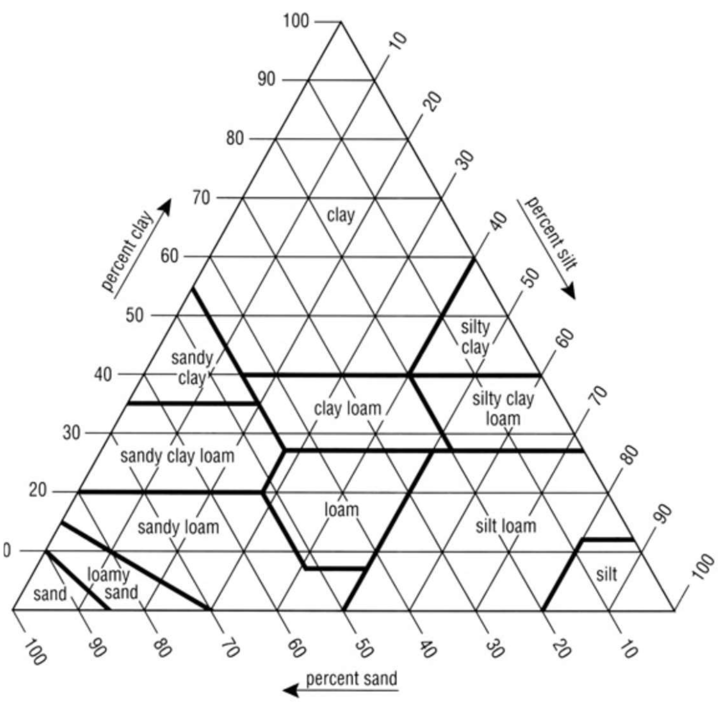
Data Descriptions and Sources

Corn yield, soil type, and rainfall data are obtained from the Mississippi Agricultural and Forestry Experimental Station's (MAFES) annual corn variety trial. The trial report yield for different corn hybrids for different locations for eighteen years (2000-2018). The experimental trials are conducted in about 3 to 8 different experimental stations or grower cooperator fields for each year. Yields of around 40 to 80 corn varieties are recorded for each location. The assumption is that the varieties are representative of what producers use in the real farming production. Field management practices such as fertilizer and herbicide application, planting date and harvest date changes across years. Each location-year is associated with a soil type and its associated soil-ph. The soil types include "Houston Clay", "Bosket very fine sandy loam", "Brooksville clay" among others. Some locations have constant soil type, but others have different soil types for different years. Descriptions of the various variables used for the study are presented below.

Soil

The United States Department of Agriculture (USDA) classifies soil into three main categories based on grain size distribution of the soil. This basis gives rise to three main soil types: sand, silt and clay. These three main classifications are further divided into twelve (12) classes. The classes are usually displayed on the USDA soil classification triangle. (see figure 1)

Fig.1



Source: USDA/NRCS

The MAFES variety trial report site specific soil type for each location. The soil types are the same for each location but differs for the various location. For the entire period of the trial, about twenty different soil types are reported based on the different locations. The soil types were grouped into two basic categories namely clay and loam. The reason behind this categorical grouping is attributed to the few sample observations to control for all the original soil types. As a result, there was the need to group the soil types into larger soil groups to make the modelling possible. The various soil types and their respective groups are presented in Table 1.

Yield

The yield variable is constructed as the average yield of all hybrid in a location during a time period of the trial. This is done due to the reason that, since the main aim of the trial was to test the yield capacity of various hybrids, the variability in yields would largely be influenced by different varieties. By taking the average yield of all corn varieties in a location, the effect of variety on yield variability would be minimized. Such operation is necessary to reduce the effect of variety on production risk given the many different varieties that are used in the trial for each year and location.

Weather

Variability in weather is a major contributor to historical yield variation. The study uses temperature and rainfall to measure weather. Monthly rainfall data are obtained from the MAFES variety trial. The trial reports monthly rainfall for each location from time of planting to time of harvest. Temperature data is obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). To be able to obtain an accurate effect of temperature on corn yields, the coordinates of the exact trial locations must be known. However, the MAFES trial does not provide these coordinates. As a result, the study matches the trial locations with their counties to obtain the county level temperature for each location. Daily maximum and minimum temperatures are obtained from time of planting to time of harvest for each location and year. The study then uses these daily temperatures to obtain the growing degree days for various locations and years. According to Schlenker & Roberts (2006, p. 392), " Growing degree days are typically defined as the sum of truncated degrees on a given day between two boundaries that are summed over the entire growing season." Different temperature bounds have been used by different studies. This study follows the Ritchie & Nesmith, (1991) temperature bounds of 8 ^{o}C and 32 ^{o}C, and computes the growing degree days for each location and year using this temperature threshold. The study also looks at the effects of monthly temperature and monthly rainfall of May, June, and July of the growing season. These months represents critical moments in the growing season, and temperature and precipitation during this time is more like to influence growth and yield. Table 2 gives the summary statistics for the various variables used in the study.

Table 1. Summary of Soil Groups.

Clay	Loam
Brooksville silty clay	Calloway silt loam
Commerce silty clay	Collins silt loam
Forestdale silty clay	Dubbs and Dundee silt loam
Vaiden silty clay	Mixture of Dundee and Dubbs loam
Brooksville and Vaiden silty clay	Dundee and Forestdale silt loam
Mixture of Dundee silt loam and Tensas silty clay	Loring silt loam, Memphis/Fayala silt loam
Houston clay	Memphis silt loam
Sharkey clay	Morganfield silt loam
Brooksville clay	Reidtown silt loam
	Dundee very fine sandy loam Bosket very fine sandy loam Commerce very fine sandy loam Bosket and commerce very fine sandy loam
	Prentis very fine sandy loam

Source: MAFES ‘s Annual variety trial report: 2000-2018

Table 2. Summary Statistics for Mississippi Corn, 2000-2018

Variable	Mean	Standard Deviation	Minimum	Maximum
Clay				
Yield (Bushels per acre)	172.9	47.30	53.23	263.3
Low Temperature (Degree Days)	1,177	99.50	904	1,406
Medium Temperature(Degree Days)	2,372	162.6	1,975	2,738
High Temperature(Degree Days	24.17	15.16	3.069	63.79
May Mean Temperature (^oC)	22.23	1.380	19.70	26.70
June Mean Temperature (^oC)	26.12	1.066	23.90	29.20
July Mean Temperature (^oC)	27.44	1.099	25	29.40
May Precipitation (Inches)	3.632	2.526	0.0200	11.05
June Precipitation (Inches)	3.657	2.509	0.360	13.20
July Precipitation (Inches)	3.480	2.386	0.240	12.45
Irrigation (Yes = 1, No =0)	0.446	0.501	0	1
Precipitation (Inches)	17.93	8.379	0	40.80
Previous Crop	1.813	0.531	1	3
Loam				
Yield (Bushels per acre)	175.8	52.15	67.25	254.8
Low Temperature (Degree Days)	1,212	97.33	974.8	1,497
Medium Temperature(Degree Days)	2,449	167.8	1,957	2,889
High Temperature(Degree Days	28.72	16.29	4.846	80.03
May Mean Temperature (^oC)	22.33	1.368	17.30	25.20
June Mean Temperature (^oC)	26.29	1.249	22.50	29.20
July Mean Temperature (^oC)	27.43	1.049	24.50	29.40
May Precipitation (Inches)	4.912	3.625	0.490	17.25
June Precipitation (Inches)	3.595	2.874	0.0200	12.45
July Precipitation (Inches)	4.264	3.101	0.240	15.87
Irrigation (Yes = 1, No =0)	0.479	0.503	0	1
Precipitation (Inches)	21.92	9.011	0	44.23
Previous Crop	1.871	0.563	1	3

Notes: Values reported for temperature and rainfall variables correspond to the March through October growing season. Previous crop has three categories: corn, cotton and soybean, and other.

Empirical Models

In predicting the impact of factors that affect crop yield and crop yield variability, some studies have resorted to the use of crop growth simulation models. The studies by Mearns et al. (1992, 1996, 1997); Wilks (1992); Barrow and Semenov (1995); Bindi et al. (1996); Peiris et al. (1996); Phillips, Lee, and Dodson (1996); Riha, Wilks, and Simoens (1996); Semenov et al. (1996); Wolf et al. (1996), among other have been carried out in this direction. Other studies have also used regression methods to study the impact of weather on yield. The works of Adams et al. (2001); Chen, McCarl, and Schimmelpfennig (2004); Isik and Devadoss (2006); McCarl, Villavicencio, and Wu (2008); Kim and Pang (2009); Barnwal and Kotani (2010); and Boubacar (2010) that focused on the impact of weather on yield variability have used regression analysis for their studies. The most common feature of the regression-based approach is their use of the Just and Pope (1978,1979) production function. The Just and Pope (1978,1979) production function can be decomposed into a mean response function and a heteroscedastic error term

$$y = f(x,\alpha) + h(x,\beta)\varepsilon \qquad (1)$$

where y is the crop yield, x is a set of explanatory variables, α and β are parameters to be estimated, $f(x,\alpha)$ is the mean response function which explains yield by the set of explanatory variables x. $h(x,\beta)\varepsilon$ is the variance function explained by the set of explanatory variables. Just -Pope (1978,1979) used both maximum likelihood estimation (MLE) and Feasible Generalized Least Squares (FGLS) for the estimation.

Even though the Just -Pope (1978,1979) production function has been more often estimated using the FGLS estimation approach, it has been shown by Saha et al (1997) the estimating the Just and Pope (1978,1979) using MLE provides unbiased and efficient estimates compared to the FGLS for small samples using Monte Carlo experiments. Antle (1983) has demonstrated the restrictiveness of the Just and Pope (1978) production function in linking inputs to moments of the yield distribution (Tack et al.,2012)

This study follows the Just and Pope (1978, 1979) specification of crop yield and production risk and employs the model specification used by Tack et al., (2012) method of higher moments with some modification. The Tack et al., (2012) methods builds on the methods of Antle (1983,2010) and Schlenker and Roberts (2006,2009a) models. Three different functional forms $y = f(x)$ are used for the analysis. The first model specification contains the degree days variables (low, medium, and high temperature), rainfall variable and its quadratic term, irrigation ($1 =$ irrigated, $0 =$ not irrigated), soil type ($0 =$ clay, $1 =$ loam), trend, and previous crop variable (categorical variable). The second model specification includes all the variables in model specification one in addition to the interaction of the irrigation with the rainfall and quadratic term of the rainfall variables. The third model specification includes irrigation, soil type, previous crop, and trend variables in addition to the monthly mean temperature and natural log of the monthly mean temperature of May, June, and July. Following the Tack et al. (2012) model, the empirical model of mean equation for corn yield is given as

$$y_{it} = \alpha_{ij} + \beta_1 low_{it} + \beta_2 med_{it} + \beta_3 high_{it} + \beta_4 p_{it} + \beta_5 p^2{}_{it} + \beta_6 irr_{it} + \beta_7 S + \beta_8 t_{it} + \varepsilon_{ijt} \qquad (2)$$

where the dependent variable y_{it} is yield variable for station i in time period t , α_{ij} is a station-by-location effect, $low_{it}, med_{it}, high_{it}$ captures the intensity of low, medium, and high temperatures respectively, p_{it} and $p^2{}_{it}$ captures the linear and quadratic effect of precipitation. Dummy variable irr_{it} is included to control for irrigated ($irr_{it} = 1$) and non-irrigated ($irr_{it} = 0$) stations, and S_i represents different soil types. The effect of precipitation can differ across irrigated versus non-irrigated locations by including interactions of the precipitation variable with the irrigation dummy. The yield variance function is given as follows:

$$e_{it}^{2} = \alpha_{ij} + \beta_1 low_{it} + \beta_2 med_{it} + \beta_3 high_{it} + \beta_4 p_{it} + \beta_5 p^2_{it} + \beta_6 irr_{it} + \beta_7 S + \beta_8 t_{it} + \varepsilon_{ijt} \qquad (3)$$

where the dependent variable e_{it}^{2} is the square of the residual from equation (2) for station i in period t, and all explanatory variables are as defined in Equation (2). To make the unit of yield variability measure more comparable to the mean, we take the square root of e_{it}^{2} in the model estimation.

The major interest is to determine the yield risk, which is measured by the yield variance equation. The yield variance equation would be used as a measure of risk. For instance, if one soil type is associated with higher conditional yield variance, it would be regarded as the soil type associated with a higher risk.

Results and Discussion

For the mean yield equation, three different panel models are used: pooled model, random effects, and fixed effects models. Due to the time invariant nature of the soil variable, the estimation of the mean equations by the fixed effect approach did not include the soil variable. Tables 3, 4, and 5 gives the mean yield parameter estimates for the pooled, random effects, and fixed effect models respectively.

The results reveal the negative effects of extreme temperatures on corn yield. Temperatures above 32 ^{0}C are found to reduce corn yields significantly. This result is consistent with the results of Schlenker & Roberts (2006) which report the negative effect of extreme temperatures on corn yield, and Tack et al., (2012) which also finds similar results for extreme temperature on cotton yields. Average temperatures in June and July are also found to have significant negative impact on corn yields as revealed by the pooled, random, and fixed effect models. The negative effect of average temperature on corn yield is consistent with the result of Chen, McCarl and Schimmelpfennig (2004).

Irrigation and time trend were also found to impact corn yields for the pooled and random effect models, irrespective of the functional form, but not for the fixed effect model. However, the magnitude of these effects differed by functional form. The interaction of irrigation and precipitation, and precipitation had no significant effect on corn yield for the pooled, random, and fixed effect model. However, the quadratic term of the precipitation variable had a significant effect on corn yield in Model 2 for the fixed effect model. The effects of irrigation and trend on mean corn yield is consistent with the literature (See Tack et al.,2012; Isik & Devadoss 2006).

The effect of previous crop was model and functional form specific. For the pooled regression, previous crop (Cotton and Soybean) was significant only in the Model 3, while previous crop (Other) had no significant effect. For the random effect model, both categories of previous crop (Cotton and Soybean, Other) had no significant effect on corn yield for all the three functional form specification. For the fixed effect model, previous crop (Other) was significant in both Models 1 and 2, but insignificant for Model 3 while previous crop (Cotton and Soybean) had no significant effect for all three functional forms.

Loam soil was found to be positively impacting mean corn yield (for the pooled model and the random effects model) irrespective of functional form, but the effect was statistically insignificant. Carew, Smith, & Grant (2016) find similar results on the effect of soil on mean wheat yield in Manitoba, Canada.. The effect of the loam soil in this study is in contrast with the result of Woodard (2016) and Woodard & Verteramo-Chiu, (2017a) whose results points to the significant effect of their soil variables on mean corn yields. A reason for this conflicting results could be attributed to the form of variable used for the study. While this study uses a qualitative variable, Woodard (2016) and Woodard & Verteramo-Chiu, (2017a) use quantitative variables, some of which are soil quality proxies. However, the effect of loam soil on corn yield is consistent with literature. Studies have found corn yield to be lower in silty clay soils than in sandy loam soils during warmer and wetter years (See Samson et al., 2019)

Table 3. Mean Yield Effects Estimates for Mississippi Corn, 2000-2018 (Pooled Data Models)

Variable	Model 1	Model 2	Model 3
Low Temperature	0.04657	0.05194	
	(0.053)	(0.053)	
Medium Temperature	0.04154	0.03303	
	(0.029)	(0.029)	
High Temperature	-0.86598***	-0.82041***	
	(0.245)	(0.250)	
Precipitation	0.28239	2.08927	
	(1.453)	(2.018)	
Precipitation Squared	-0.02571	-0.05359	
	(0.031)	(0.039)	
Irrigation	60.06469***	90.31046***	66.07955***
	(6.528)	(33.232)	(6.882)
Loam Soil	6.57651	6.29931	9.62172
	(6.561)	(6.663)	(6.543)
Trend	2.01824***	2.11806***	2.85964***
	(0.639)	(0.643)	(0.668)
Previous Crop (Cotton and Soybean)	10.56958	11.28947	12.83433*
	(7.365)	(7.359)	(7.612)
Previous Crop (Other)	17.87778	15.58969	4.80685
	(13.004)	(13.057)	(13.250)
Irrigation*Precipitation		-1.77399	
		(3.384)	
Irrigation*Precipitation Squared		0.00918	
		(0.083)	
May Mean Temperature			1.04836
			(2.608)
June Mean Temperature			-8.42393**
			(3.534)
July Mean Temperature			-6.26806*
			(3.465)
May Precipitation			-0.01109
			(3.574)
June Precipitation			6.36337
			(3.859)
July Precipitation			-7.32865*
			(4.318)
Constant	-10.10057	-22.14182	474.24005***
	(50.354)	(51.535)	(106.472)
Observations	134	134	134
R-squared	0.553	0.563	0.544

Notes: Base group for the soil type variable is clay, and that of previous crop is corn. Weather variables are aggregated for the months, March – October. Values in parentheses are standard error. *, **, *** denotes significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Mean Yield Effects Estimates for Mississippi Corn, 2000-2018 (Random Effects Models)

Variable	Model 1	Model 2	Model 3
Low Temperature	0.00215	0.04839	
	(0.052)	(0.053)	
Medium Temperature	0.05064*	0.03378	
	(0.029)	(0.029)	
High Temperature	-0.92851***	-0.83082***	
	(0.237)	(0.249)	
Precipitation	1.18874	2.11504	
	(1.442)	(2.013)	
Precipitation Squared	-0.04489	-0.05429	
	(0.031)	(0.039)	
Irrigation	52.34351***	89.36868***	62.95885***
	(11.699)	(33.214)	(9.372)
Loam Soil	8.89487	6.44858	7.47706
	(10.083)	(6.824)	(8.529)
Trend	1.30564**	2.07957***	2.50873***
	(0.657)	(0.643)	(0.674)
Previous Crop (Cotton and Soybean)	10.57265	11.09244	10.32422
	(7.500)	(7.360)	(7.682)
Previous Crop (Other)	25.34332*	16.09346	7.37148
	(12.932)	(13.041)	(13.238)
Irrigation*Precipitation		-1.68719	
		(3.379)	
Irrigation*Precipitation Squared		0.00683	
		(0.082)	
May Mean Temperature			0.95237
			(2.534)
June Mean Temperature			-8.35372**
			(3.469)
July Mean Temperature			-6.23155*
			(3.325)
May Precipitation			0.06882
			(3.486)
June Precipitation			5.90204
			(3.859)
July Precipitation			-6.52620
			(4.165)
Constant	23.46557	-19.15077	480.54547***
	(52.924)	(51.531)	(109.211)
Observations	134	134	134

Notes: Base group for the soil type variable is clay, and that of previous crop is corn. Weather variables are aggregated for the months, March – October. Values in parentheses are standard errors. *, **, *** denotes significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Mean Yield Effects Estimates for Mississippi Corn 2000-2018 (Fixed Effects Models)

Variable	Model 1	Model 2	Model 3
Low Temperature	-0.01316	-0.00483	
	(0.055)	(0.056)	
Medium Temperature	0.04698	0.03510	
	(0.032)	(0.033)	
High Temperature	-0.80831***	-0.77491***	
	(0.246)	(0.249)	
Precipitation	1.56491	2.83895	
	(1.533)	(2.013)	
Precipitation Squared	-0.04894	-0.06550*	
	(0.032)	(0.039)	
Irrigation	18.70571	42.63498	28.58940
	(26.495)	(43.422)	(27.294)
Trend	0.83940	1.05740	1.57175**
	(0.733)	(0.743)	(0.759)
Previous Crop (Cotton and Soybean)	11.14455	10.64894	7.13139
	(8.067)	(8.071)	(8.143)
Previous Crop (Other)	28.80415**	25.29909*	11.74821
	(13.613)	(13.741)	(13.725)
Irrigation*Precipitation		-0.39808	
		(3.463)	
Irrigation*Precipitation Squared		-0.02594	
		(0.083)	
May Mean Temperature			-0.48603
			(2.588)
June Mean Temperature			-7.73640**
			(3.546)
July Mean Temperature			-5.66515*
			(3.288)
May Precipitation			0.67872
			(3.503)
June Precipitation			4.45895
			(4.365)
July Precipitation			-4.66401
			(4.282)
Constant	64.35885	59.72545	510.04440***
	(58.991)	(59.317)	(117.693)
Observations	134	134	134
R-squared	0.156	0.176	0.159

Notes: Base group for the soil type variable is clay, and that of previous crop is corn. Weather variables are aggregated for the months, March – October. Values in parentheses are standard errors. *, **, *** denotes significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Yield Risk Effects Estimates for Mississippi Corn, 2000-2018 (Pooled Data Models)

Variable	Model 1	Model 2	Model 3
Low Temperature	0.01094	0.00298	
	(0.030)	(0.029)	
Medium Temperature	-0.01790	-0.01264	
	(0.017)	(0.016)	
High Temperature	-0.00124	-0.00527	
	(0.140)	(0.138)	
Precipitation	0.55322	-0.21881	
	(0.833)	(1.112)	
Precipitation Squared	-0.01544	-0.00272	
	(0.018)	(0.022)	
Irrigation	-7.99398**	-29.97782	-7.47477*
	(3.741)	(18.309)	(3.921)
Loam Soil	8.29786**	7.23423*	6.78705*
	(3.760)	(3.671)	(3.728)
Trend	0.06630	0.14916	-0.03226
	(0.366)	(0.354)	(0.380)
Previous Crop (Cotton and Soybean)	4.17624	3.63837	2.31741
	(4.221)	(4.054)	(4.337)
Previous Crop (Other)	2.18672	1.14947	-4.46655
	(7.453)	(7.193)	(7.549)
Irrigation*Precipitation		1.31490	
		(1.864)	
Irrigation*Precipitation Squared		-0.01115	
		(0.045)	
May Mean Temperature			-0.53731
			(1.486)
June Mean Temperature			-3.85749*
			(2.013)
July Mean Temperature			2.84916
			(1.974)
May Precipitation			-2.53596
			(2.036)
June Precipitation			-1.12565
			(2.199)
July Precipitation			4.89032**
			(2.460)
Constant	48.63233*	56.31297**	58.80288
	(28.860)	(28.393)	(60.661)
Observations	134	134	134
R-squared	0.089	0.129	0.159

Notes: Base group for the soil type variable is clay, and that of previous crop is corn. Weather variables are aggregated for the months, March – October. Values in parentheses are standard errors. *, **, *** denotes significance at the 10%, 5%, and 1% levels, respectively. Dependent variable is the square root of the squared residuals estimated from the pooled model of mean yield equation.

Table 7 Yield Risk Effects Estimates for Mississippi Corn, 2000-2018 (Random Effect Models)

Variable	Model 1	Model 2	Model 3
Low Temperature	0.00654	0.00485	
	(0.027)	(0.029)	
Medium Temperature	-0.01470	-0.01352	
	(0.015)	(0.016)	
High Temperature	-0.07231	-0.00131	
	(0.125)	(0.137)	
Precipitation	0.46392	-0.16733	
	(0.743)	(1.102)	
Precipitation Squared	-0.01373	-0.00324	
	(0.016)	(0.022)	
Irrigation	-9.63410***	-28.59772	-7.84189**
	(3.340)	(18.156)	(3.566)
Loam Soil (Loam)	6.97033**	7.19871*	5.88031*
	(3.356)	(3.640)	(3.390)
Trend	-0.19052	0.15059	0.00266
	(0.327)	(0.351)	(0.346)
Previous Crop (Cotton and Soybean)	2.96629	3.50945	1.46145
	(3.768)	(4.020)	(3.945)
Previous Crop (Other)	4.41452	1.06260	-2.91048
	(6.653)	(7.133)	(6.866)
Irrigation*Precipitation		1.19781	
		(1.849)	
Irrigation*Precipitation Squared		-0.00929	
		(0.045)	
May Mean Temperature			-0.48942
			(1.351)
June Mean Temperature			-4.26578**
			(1.831)
July Mean Temperature			2.43869
			(1.796)
May Precipitation			-2.87997
			(1.852)
June Precipitation			-0.58330
			(2.000)
July Precipitation			4.67425**
			(2.238)
Constant	50.69569*	55.06151*	78.46836
	(25.762)	(28.155)	(55.172)
Observations	134	134	134
R-squared	0.126	0.129	0.189

Notes: Base group for the soil type variable is clay, and that of previous crop is corn. Weather variables are aggregated for the months, March – October. Values in parentheses are standard errors. *, **, *** denotes significance at the 10%, 5%, and 1% levels, respectively. Dependent variable is the square root of the squared residuals estimated from the random effect model of mean yield equation.

Table 8. Yield Risk Effects Estimates for Mississippi Corn, 2000-2018 (Fixed Effects Models)

Variable	Model 1	Model 2	Model 3
Low Temperature	0.00560	0.00730	
	(0.027)	(0.026)	
Medium Temperature	-0.01299	-0.01438	
	(0.015)	(0.014)	
High Temperature	-0.08521	-0.07530	
	(0.124)	(0.122)	
Precipitation	0.34997	0.35592	
	(0.734)	(0.987)	
Precipitation Squared	-0.01115	-0.00890	
	(0.016)	(0.019)	
Irrigation	-8.77010***	-13.41931	-5.93544*
	(3.296)	(16.262)	(3.460)
Loam Soil	5.43165	3.95557	1.78566
	(3.313)	(3.260)	(3.290)
Trend	-0.41151	-0.21464	-0.13317
	(0.323)	(0.314)	(0.336)
Previous Crop (Cotton and Soybean)	1.40467	1.12422	-1.49487
	(3.719)	(3.601)	(3.828)
Previous Crop (Other)	7.23652	5.23191	0.84802
	(6.566)	(6.389)	(6.662)
Irrigation*Precipitation		0.28360	
		(1.656)	
Irrigation*Precipitation Squared		-0.00428	
		(0.040)	
May Mean Temperature			-1.26237
			(1.311)
June Mean Temperature			-3.53348**
			(1.777)
July Mean Temperature			1.98649
			(1.742)
May Precipitation			-2.10967
			(1.797)
June Precipitation			-0.52275
			(1.941)
July Precipitation			4.23706*
			(2.171)
Constant	51.90342**	51.54906**	91.19066*
	(25.425)	(25.218)	(53.535)
Observations	134	134	134
R-squared	0.130	0.141	0.164

Notes: Base group for the soil type variable is clay, and that of previous crop is corn. Weather variables are aggregated for the months, March – October. Values in parentheses are standard errors. *, **, *** denotes significance at the 10%, 5%, and 1% levels, respectively. Dependent variable is the square root of the squared residuals estimated from the fixed effect model of mean yield equation.

The idiosyncratic residuals (e) from the three mean equations are used for the variance equations respectively. We use the square root of the squared of the residuals as the dependent variables for the variance equations. The variance equations are estimated all by pooled data model because the location-specific effects have already been taken out from the idiosyncratic residuals.

Few of the variables in the model have a significant impact on corn yield risk. Low, medium and high temperatures, precipitation and its quadratic term, trend, and previous crop had impact on corn yield risk but these impacts were not significant (Tables 6,7, and 8). Average monthly temperatures in May and July, and monthly precipitation in May and June had no significant impact on corn yield risk (Tables 6, 7, and 8). The clearest results are seen for irrigation, average monthly temperature for June, and precipitation in July. Irrigation was found to have negative effect on corn yield variance in model 1 and model 3 (Tables 6,7, and 8). Average temperature in the month of June had a significant positive effect on corn yield variance while precipitation in the month of July had significant negative effect on corn yield variance (Tables 6,7, and 8). In contrast to the results of Tack et al.(2012), interaction between irrigation and precipitation had no significant effect on corn yield variance.

The most interesting finding is the effect of soil types on corn yield risk. As shown in Tables 6, 7, and 8, compared to clay soils, loam soil is found to have a positive significant effect on corn yield variance. This result is statistically significant for the pooled and random effects model residuals (Tables 6 and 7), while insignificant but still positive for the fixed effects model residuals. This result is consistent with studies that examine the effect of soil on crop yield variance (See Woodard, 2016; Woodard & Verteramo-Chiu, 2017; Carew et al., 2016). This finding provides evidence that soil type matters for corn yield risk after controlling for weather and management factors. Though loam soil leads to higher yield, it also brings more yield instability. Therefore, a direct policy implication is that, clay and loam soils should be rated separately when making crop insurance premium rating.

Conclusion

The objective of this research was determine the impact of soil, weather, irrigation, and trend on corn yield by using data from the Mississippi Agricultural and Forestry Experimental station. A Just-Pope production function is employed to quantify the impact of these variables on corn yield. Three panel models which are pooled model, random effect model, and fixed effect model are used. Different functional forms are used for these panel models. The results obtained need to be viewed in the context of the functional forms and variables included. Results from the research points to a significant impact of extreme temperature, irrigation, and trend on mean corn yield. Irrigation, average monthly temperature in June, and precipitation in July were also found to have significant impact on corn yield variance. Compared to clay soils, loam soils had significant positive effect on corn yield variance. These results point to the significant impact of soil on corn yield risk and reveal the need to account for soil information in crop risk analysis. As such, the Risk Management Agency (RMA) could incorporate soil information into the crop insurance rating methodology to improve efficiency.

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