Revisiting Days Suitable for Fieldwork Relative to Global Climate Cycles

Tyler B. Mark, Assistant Professor
Department of Agricultural Economics
University of Kentucky
Lexington, KY, 40546
(859) 257-7283
Tyler.Mark@uky.edu

Jeremy M. D'Antoni, Research Economist[1]
Economic Research Service, USDA
Washington DC
JMDANTONI@ers.usda.gov

Terry W. Griffin, Ph.D., CCA
(501) 249-6360
Terry.Griffin@comcast.com

Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meetings, Dallas, TX, February 1-4, 2014

[1] The views expressed herein are those of the authors and do not necessarily represent those of the Economic Research Service or the US Department of Agriculture.

Revisiting Days Suitable for Fieldwork Relative to Global Climate Cycles

Abstract:
ENSO is a climatic phenomenon that influences global weather patterns. The objective of this paper is to assess the impact it has on DSFW. DSFW fluctuations impact an operator's equipment purchases, planting/harvesting decisions, and profitability. Results indicated that DSFW is inversely related to El Niño cycles for states analyzed.

Keywords: El Nino, La Nina, Climate, Fieldwork

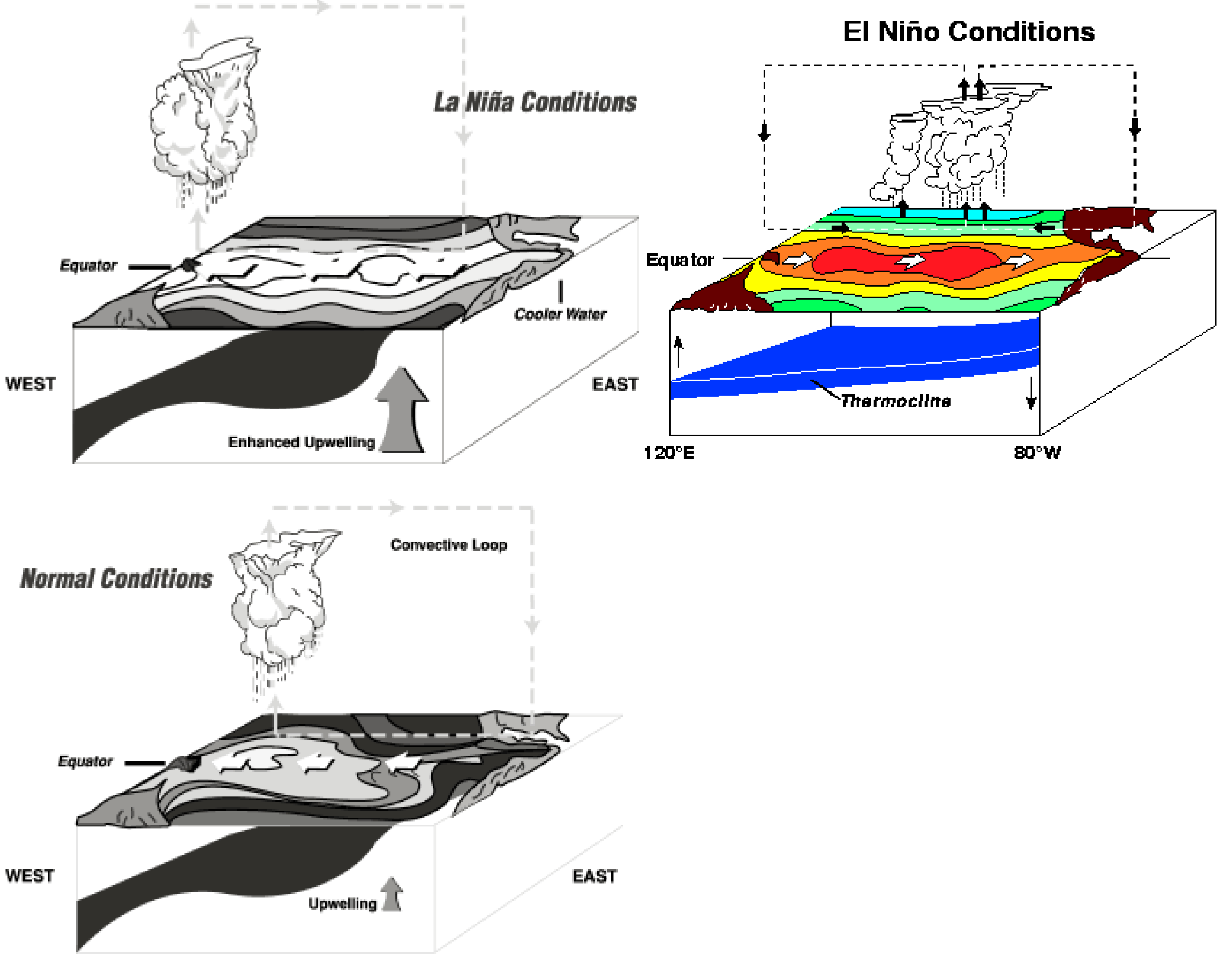
JEL Codes:

Introduction

Predicting the number days suitable for fieldwork (DSFW) and its implications on agricultural production has been a topic of discussion in agricultural literature for more than five decades (Rutledge, 1968) (Baier, 1973) (Dyer, 1979) (Rosenberg, 1982) (Rotz, 2005). It continues to be a topic of discussion as a result of the influence it has on timing of agricultural field operations, equipment purchases, and risk management. One relatively unexplored area of the literature is the influence of global weather patterns has on DSFW. Specifically, this paper investigates the influence El Niño Southern Oscillation (ENSO) has on DSFW.

ENSO is a global weather pattern that takes place in the Equatorial Pacific Ocean. Within the ENSO cycle there are three phenomenon observed: 1) El Niño, 2) Neutral or Normal and 3) La Niña (Figure 1). During El Nino the Equatorial Pacific ocean waters warm to temperatures above their neutral or normal temperatures as opposed to La Niña where the waters cool below normal temperatures. The warming and cooling of these waters influences global weather patterns (Ropelewski, 1987) (Adams R. C., 1999) (Zhang, 2012). Within the United States, during an El Niño cycle there is typically increased rainfall across the southern tier, especially from Texas to Florida. Additionally, during this period more intense storms tend to develop across the southeastern United States (Cook-Anderson, 2008). During the La Niña cycle, there is below normal precipitation across the southeast and higher than normal temperatures across the southeast (Graham, 1999).

Figure 1: Observed ENSO Cycles



Source: (NOAA, 2013) (Graham, 1999)

DSFW is typically determined by weather related events, such as rainfall and temperature, that affect the condition of soil in a field (Spurlock, Buehring, & Caillavet, 1995). As shown above, ENSO has implications for both rainfall and temperature depending on where the operation is located at in the United States. Farm decision makers are heavily dependent on weather risk for timing of applications, machinery management decisions and whole-farm planning. Widhalm (2013) setforth an outline for a Corn Forecast-Decision Cycle for meterologist and weather modeler to help them understand when decisions need to be made to optimize corn production in the Midwest. Within this cycle they prescribe that weather phenomenon such as ENSO need to be considered to optimize the production of corn. This prescribed cycle focuses on the farm remaining sustainable in an economically, biologically, and climatically volatile environment, field operations and machinery investment must be optimized.

The rationale for being concerned with DSFW is that during weather events that shorten DSFW, increased capacity from larger equipment or additional units of equipment are needed to achieve a timely planting or harvest of crops for a given number of acres. Uncontrollable factors include weather events that affect the ability to conduct field operations. Although uncontrollable factors such as weather are just that, uncontrollable, the influence of such events is somewhat predictable.

Conducting field operations such as tillage, planting, spraying and harvesting in a timely manner are important to obtain optimal yields to maximize whole-farm profitability. Too-early or too-late planting may adversely impact crop yields. Machinery management decisions such as choosing machine sizes relative to farm acreage should be made considering equipment efficiency and the likelihood of having sufficient days suitable to operate the machinery in the field. The farm decision maker has to evaluate the tradeoff between the added cost of machinery and completing field operations in a timely manner. Additional machinery requires increased capital investment while field operations conducted at non-optimal times lead to reduced yield and/or quality. Debate often arises relative to machinery sizing and being over or under equipped for a particular farming operation. Knowledge of these probabilities on days suitable for fieldwork, harvest progress, and yield penalties by harvest date is important for machinery management, acreage allocation and financing decisions; and ultimately how many acres can realistically be harvested with a given set of equipment. Being able to forecast structural changes in DSFW several months in advance would allow the initiated decision maker to adequately prepare by acquiring necessary equipment in years where DSFW is expected to decrease.

El Niño and La Niña cycles can have potentially damaging implications for the United States agricultural sector, accorrding to Solow et al., (1998) and Chen, McCarl, & Hill, (2002). Ubilava and Holt (2013) and Tack and Ubilava (2013) analyzed ENSO influence on world vegetable oil prices and United States corn yields, respectively. However, there is currently no literature on ENSO influence on DSFW. Changes in DSFW can have substantial implications for a producers income on a yearly basis. Producers who are under equiped in years when DSFW are decreased can encounter significant yield penalties as a result of untimely field operations. However, in years when DSFW increase over equiped producers are incurring additional costs because their equipment set is larger than needed. This has created the need for a deeper understanding of factors influencing DSFW.

The objective of this study is to investigate the impact of ENSO, precipitation index and drought severity on days suitable for fieldwork. To our knowledge, no other study has utilized these variables and evaluated there influence on DSFW. A deeper understanding of this relationship could increase the probability of farm profitability and decrease the probability of yield penalties as a result of untimely field operations. Thus, reducing the production risk due to weather and reducing the financial risk by not being unnecessarily over equipped during period when DSFW is increased.

Data and Methodology

Although the number of good days to conduct field operations varies each year, the influence of ENSO on the number of DSFW per month can be estimated. There are three primary data sources utilized in this estimation. First, data on DSFW is collected from USDA archives for eight states listed in Table 1. Currently, the two states with the most observations are Arkansas and Mississippi with 36 and 35 years of data, respectively. Second, data from the National Weather Service on historical ENSO cycles was utilized. Data on historical ENSO cycles goes back to 1950 and is broken down by month (National Weather Service, 2014). Within the data set, El Niño conditions account for approximately 24% of the observations, La Niña account for approximately 27% of the observations and the rest exhibit a normal condition. Third, data containing the precipitation index, temperature index, Palmer Drought Severity Index, and one, two, and three month standard precipitation index were collected at the state level from the National Oceanic and Atmospheric Administration (NOAA) (National Climatic Data Center, 2014). Descriptions of these variables are found in Table 2.

Table 1: DSFW Years Available by State

State	Years
Arkansas	1975-2011
Georgia	2006-2011
Louisiana	2005-2011
Mississippi	1976-2011
North Carolina	2010-2011
South Carolina	2007-2011
Tennessee	2006-2011
Virginia	2007-2011

DSFW is pooled and modeled using a two-limit tobit model followed by Blinder-Oaxaca decomposition for non-linear regression. DSFW is the dependent variable limited by 0 and 31 in the two-limit tobit model. Explanatory variables and descriptions can be found in Table ___. Constrains are developed within the model prohibiting DSFW from exceeding seven days in a week. The theoretical framework for the two-limit tobit model follows McMillen & McDonald (1990), where the model for latent variable y*, is observed only in the range (0,31), as shown below.

$$y_i^* = \beta_0 + \beta_1 x_i + \varepsilon_i = x_i\beta + \varepsilon_i \quad \varepsilon_i \sim N(0, \sigma^2) \tag{1}$$

$$y = 0 \; if \; y^* \leq 0 \tag{2}$$

$$y = y^* \; if \; 0 < y^* < 31 \tag{3}$$

$$y = 31 \; if \; y^* \geq 31 \tag{4}$$

As shown in Maddala (1983), the expected value of y is:

$$E(y_i) = \beta x_i[G_{2i} - G_{1i}] + \sigma[g_{1i} - g_{2i}] + [1 + G_{2i}]31 \tag{5}$$

where, G_{2i} is the value of the unit normal distribution evaluated at $(31 - \beta x_i)/\sigma$. $G_{1i}$is the value of the value of the unit normal distribution evaluated at $-\beta x_i/\sigma$. The terms g_{2i} & g_{1i}represent the values of the unit normal density at G_{1i} & G_{2i}. The last term $[1 + G_{2i}]31$is the probability that the dependent variable is at the upper limit times the value of the upper limit.

Therefore, the expected value for y between 0 and 31 can be found by:

$$E(y_i|0 < y_i^* < 31) = \beta x_i + \sigma[(g_{1i} - g_{2i})/(G_{2i} - G_{1i})] \tag{6}$$

Table 2: Variable Descriptions

Variable Name	Variable Description
enso	El Niño Southern Oscillation is a ocean-atmosphere phenomenon that causes global climate variability on interannual time scales. There are three different events that can happen: 1) La Niña, 2) El Niño, or 3) Normal.
niña	La Niña is the cooling of Equatorial Pacific Ocean water temperatures and is a dummy variable.
niño	El Niño is the warming of Equatorial Pacific Ocean water temperatures and is a dummy variable
pcp	Precipitation is rainfall sleet, snow, hail, etc. and is the state monthly average.
l_pcp	Lag of precipitation
pdsi	Palmer Drought Severity Index is based on the principles of a balance between moisture supply and demand. Irrigation is not considered in this calculation (National Climatic Data Center, 2007)
tmp	Temperature is a measure of the degree or intensity of heat present in the air on a monthly basis and is measured in Fahrenheit.
sp01	Standardized Precipitation Index is the probability of observing a given amount of precipitation in 1 month. (National Climatic Data Center, 2007)
sp02	Standardized Precipitation Index is the probability of observing a given amount of precipitation in 2 months. (National Climatic Data Center, 2007)
sp03	Standardized Precipitation Index is the probability of observing a given amount of precipitation in 3 months. (National Climatic Data Center, 2014)

The two-limit tobit is then decomposed by employing a Blinder-Oaxaca decomposition (Bauer and Sinning,2008). This allows for the decomposition of the difference in DSFW related to El Niño and La Niña into observable factors from the characteristics controlled for in the model and unobservable differences in the coefficients for La Nino and El Nino periods. The theoretical framework for this decomposition is represented below.

$$\overline{Y_A} - \overline{Y_B} = (\overline{X_A} - \overline{X_B})\widehat{\beta_A} + \overline{X_B}(\widehat{\beta_A} - \widehat{\beta_B}) \quad (7)$$

The first term $\overline{Y_A} - \overline{Y_B}$ is the difference in the outcome between two different groups (i.e. La Niña and El Niño). The second term $\overline{X_A} - \overline{X_B}$, allows for the observable attributes between the two groups to be determined. The final term $\widehat{\beta_A} - \widehat{\beta_B}$, allows for the differences in the unobservable effects to be determined. This decomposition will lead to erroneous predictions if the goal is to analyze the observable corner solution. Therefore, assuming homoscedastic and normally distributed error terms ε_{ig}, the conditional expectations of Y_{ig}given X_{ig}consists of the respective conditional expectations and probability of observations α_1, $\alpha_2$or a value between α_1 and α_2.

$$E\left[Y_{ig}\middle|X_{ig}\right] = \alpha_1\Phi_1(\beta_g, X_g, \vartheta_g) + \alpha_2\Phi_2(\beta_g, X_g, \vartheta_g) + \Lambda(\beta_g, X_g, \vartheta_g) * \left[X_{ig}\beta_g + \vartheta_g(\frac{\lambda(\beta_g,X_g,\vartheta_g)}{\Lambda(\beta_g,X_g,\vartheta_g)})\right]$$

(8)

where: $\lambda(\beta_g, X_g, \vartheta_g) = \Phi\left[\frac{(\alpha_1 - X_{ig}\beta_g)}{\vartheta_g}\right] - \Phi\left[\frac{(\alpha_2 - X_{ig}\beta_g)}{\vartheta_g}\right]$ (9)

In equation 9, Φ is the standard normal density function.

$$\Lambda(\beta_g, X_g, \vartheta_g) = \Phi_2(\beta_g, X_g, \vartheta_g) - \Phi_1(\beta_g, X_g, \vartheta_g) \quad (10)$$

$$\Phi_1(\beta_g, X_g, \vartheta_g) = \Phi[\vartheta_g^{-1}(\alpha_1 - X_{ig}\beta_g)] \quad (11)$$

$$\Phi_2(\beta_g, X_g, \vartheta_g) = 1 - \Phi[\vartheta_g^{-1}(\alpha_2 - X_{ig}\beta_g)] \quad (12)$$

Using equations 10-12, equation 8 can be rewritten in terms of a sample:

$$S(\widehat{\beta_g}, X_{ig}, \widehat{\vartheta_g}) = \frac{1}{N}\sum_{i=1}^{N} \alpha_1\Phi_1(\widehat{\beta_g}, X_{ig}, \widehat{\vartheta_g}) + \alpha_2\Phi_2(\widehat{\beta_g}, X_{ig}, \widehat{\vartheta_g}) + \Lambda\alpha_1\Phi_1(\widehat{\beta_g}, X_{ig}, \widehat{\vartheta_g}) *$$

$$\left[X_{ig}\widehat{\beta_g} + \widehat{\vartheta_g}\left(\frac{\lambda(\widehat{\beta_g}, X_{ig}, \widehat{\vartheta_g}}{\Lambda(\widehat{\beta_g}, X_{ig}, \widehat{\vartheta_g})}\right)\right] \quad (13)$$

This allows for the single parts of the decomposition equation to be estimated by equation 14.

$$\widehat{\Delta} = [S(\widehat{\beta_A}, X_{iA}, \widehat{\vartheta_A}) - S(\widehat{\beta_A}, X_{iB}, \widehat{\vartheta_A})] + [S(\widehat{\beta_A}, X_{iB}, \widehat{\vartheta_A}) - S(\widehat{\beta_B}, X_{iB}, \widehat{\vartheta_B})] \quad (14)$$

However, equation 7 is not appropriate for the observed outcome variable of the tobit model because of the conditional expectation in the tobit model depends on standard errors ϑ_g. This will not impact the signs of the marginal effects, but will impact their magnitude. However, if the dependent variable is not truncated then equation 14 will reduce to the original Blinder-Oaxaca decomposition as stated in equation 7.

When estimating the decomposition in STATA the decomposition is performed for two different weighting matrices or Omega 1 and Omega 2. Omega 1follows Reimers (1983) and the weight Ω is treated as a scalar matrix. Therefore weight is found by:

$$\Omega = (0.5)\mathrm{I} \tag{15}$$

where I is an identity matrix. Omega 2 follows Cotton (1988) and the weight Ω is again treated as a scalar matrix. Therefore the weight is found by:

$$\Omega = s\mathrm{I} \tag{16}$$

where I is an identity matrix and s is determined by the relative sample size of the majority group.

Results

In 2012, these states produced crops that accounted for over $24 billion dollars in value and there are approximately 365,000 operators in this region (National Agricultural Statistics Service, 2014). Changes in DSFW substantially influence the farm management decision making strategy. This research expands the literature on DSFW by analyzing the influence of ENSO on DSFW. This study focuses on states in the Southeastern United States, except for Alabama and Florida (Table 1 and Figure 2). In general, producers in this region will face the same general climatic conditions on an annual basis for a given ENSO cycle. This allowed for the data from all of these states to be pooled and a two-limit tobit model to be estimated.

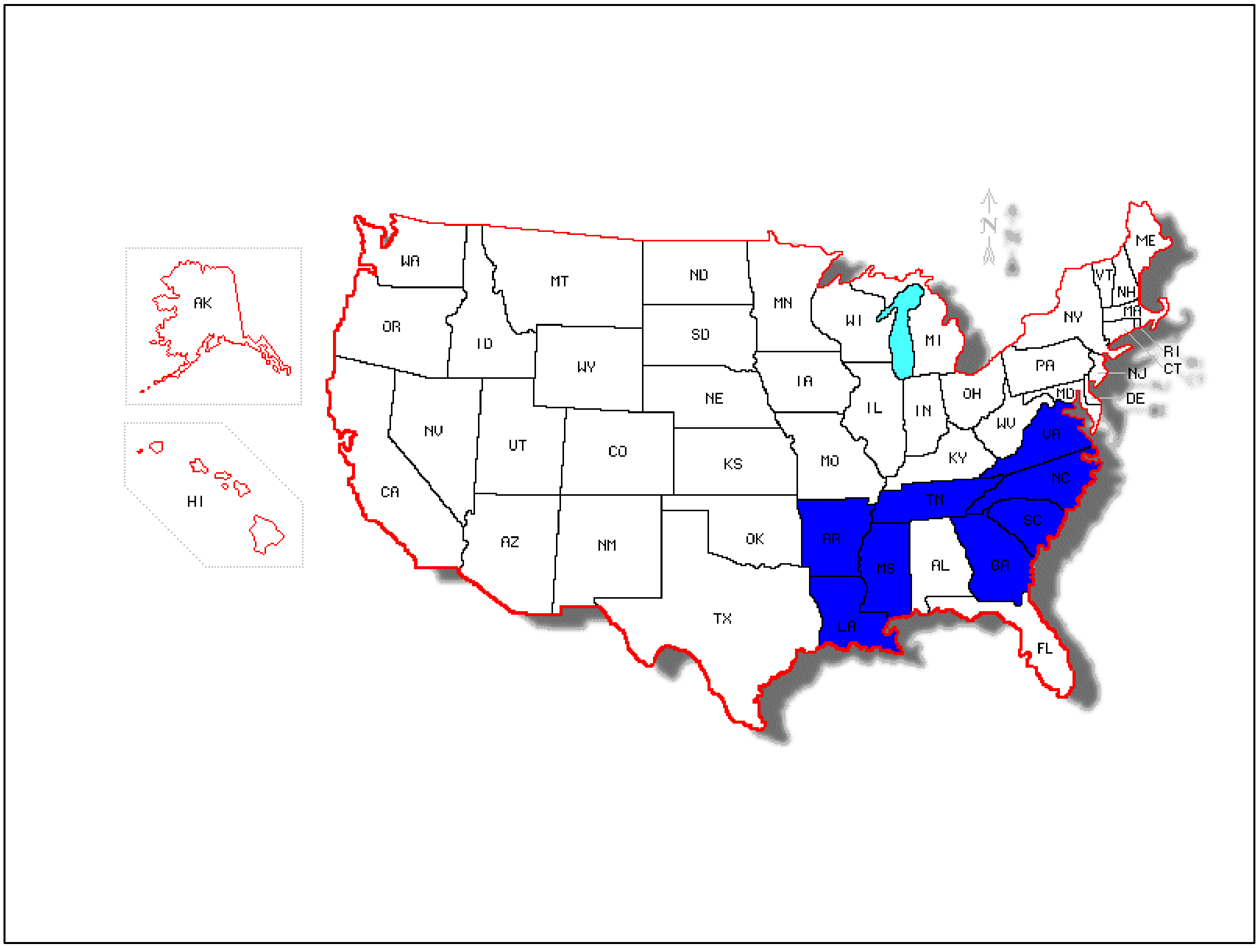


Figure 2: Map of States Included in Study:

The results from the two-limit tobit model indicate that El Niño cycles have an inverse impact on DSFW and La Niña cycles have a positive impact on DSFW (Table 3). This is consistent with expectations for these two cycles, given that during an El Niño cycle rainfall across the southern portion of the United States increases. According to the model, 1.12 fewer DSFW per month in El Niño cycle.. On the surface this may not appear to be a big decision influencer for producers. However, applying this to a simple example more clearly illustrates the issue that producers face is shown in Appendix. The impact of the El Niño is further amplified because the additional precipitation encountered during this cycle further decreases the DSFW available per month. A decrease in DSFW has the most significant influence on farm operators during planting and harvesting, as producers are trying to avoid yield penalties. Those pivotal months for this region would be April-Mid June and August-October.

Temperature and the One Month Standardized Precipitation Index influence DSFW. DSFW tend to increase as temperature increases as observed in 2012 as a La Niña cycle started; temperatures soared and 78% of the U.S. corn production area experienced drought (Rippey, 2012). An increase in the average temperature is good for increasing DSFW and increases the probability of timely field operation. However, during La Niña cycles producers could run into increased costs as a result of increased need for irrigation. The last significant factor that influences DSFW is sp01. The Standardized Precipitation Index has the opposite sign of what was expected. This measurement is indexed such that 0 is the median historical precipitation, positive values indicate periods of wetness, and negative values indicate periods of dryness . It was expected that this should be negative so that as the probability of receiving above median precipitation should decrease DSFW and vice versa.

Table 3: Results of Tobit Model

Variables	Coefficients
enso	0.7337*
	(0.434)
nina	1.1468***
	(0.358)
nino	-1.1219***
	(0.369)
Pcp	-1.4292***
	(0.238)
l_pcp	-0.1437
	(0.159)
pdsi	0.2234
	(0.249)
Tmp	0.3050***
	(0.082)
sp01	1.3565**
	(0.529)
sp02	-1.5747
	(1.284)
sp03	0.3595
	(0.699)
cons	7.4822
	(5.791)

N: 180
Pseudo R2: 0.129
Log psuedolikelihood: -491.9

Notes: Standard Errors in parentheses. *significant at 10%; ** significant at 5%; ***significant at 1%

The tobit results revealed that ENSO cycles do influence DSFW. A closer examination of specifically the El Niño phenomenon, through the usage of a Blinder-Oaxaca Decomposition, allows for the observed and unobserved impacts to be examined. Results for the decomposition indicate approximately 87% of the variation in DSFW is explained by observable characteristics, primarily El Niño (Table 4). The results also indicated that there is little difference between the Omega 1 and Omega 2 weighting matrices utilized in the decomposition see Sinning, Hahn, & Bauer (2008) for more detail on weighting matrices).

Table 4: Results EL Niño Blinder-Oaxaca Decomposition

Results	Coefficient	Percentage
Omega = 1		
Characteristic	-3.3723	86.73%
Coefficient	-0.5069	13.27%
Omega = 0		
Characteristic	-3.365	86.56%
Coefficient	-0.5223	13.43%
Raw	-3.888	100%

Discussion

Even if used as efficiently as possible, planters, harvesters, and other equipment have theoretical limits less than 100%. This means that while farm equipment is committed to a field operation, only a portion of that time does the equipment actually conduct the operation it is intended to do. Even with sufficient understanding of the optimum timing to plant and harvest a crop, making farm management decisions such as machinery management and acreage allocation without information on DSFW may lead to unsuccessful farming operations.

This paper illustrates the importance incorporating ENSO cycles into the operating decision making process. Findings reveal that during the El Niño cycle there will be decreased DSFW that can result in the need for different or additional equipment requirements than in years where La Niña or Normal cycles dominate. Additionally, operators may have increased operating costs during La Niña periods as a result of increase irrigation needs because of reduced rainfall across the region.

Overall, ENSO climatic cycles have a significant influence both positive and negative on DSFW. Operators who fail to recognize the influence of these weather patterns could find themselves operating at less than efficient levels. Operating at non optimal levels could lead to non-sustainable profit levels and jeopardize the long term viability of the operation. However, each operation will be impacted differently and further investigation into how each state is impacted specifically by these weather phenomenon. There are also other minor weather patterns that could also be incorporated in that would help to further explain DSFW.

References

Adams, R. C. (1999). The Economic Consequences of ENSO Events for Agriculture. *Climate Research, 13*(3), 165-172.

Adams, R., Chen, C., McCarl, B., & Weiher, R. (1999). The Economic Consequences of ENSO Events for Agriculture. *Climate Research, 13*(3), 165-172.

Baier, W. (1973). Estimation of Field Workdays in Canada from the Versatile Soil Moisture Budget. *Canadian Agricultural Engineering, 15*(2), 84-87.

Bauer, T., & Sinning, M. (2008). An Extension of the Blinder-Oaxaca Decomposition to Nonlinear Models. *Advances in Statistical Analysis, 92*(2), 197-206. doi:10.1007/s10182-008-0056-3

Chen, C., McCarl, B., & Hill, H. (2002). Agricultural Value of ENSO Information Under Alternative Phase Definition. *Climate Change, 54*(3), 305-325.

Cook-Anderson, G. (2008, January 28). *El Nino at Play as Source of More Intese Regional U.S. Wintertime Storms.* Retrieved from NASA's Goddard Space Flight Center: http://www.nasa.gov/centers/goddard/news/topstory/2008/elnino_winter.html

Cotton, J. (1988). On the Decomposition of Wage Differentials. *Review of Economics and Statistics*, 236-243.

Dyer, J. a. (1979, December). Weather-Based Estimation of Field Workdays in Fall. *Canadian Agricultural Engineering, 21*(2), 119-122.

Graham, S. (1999, April 27). *The Cold Counterpart to El Nino is Known as La Nina.* Retrieved from NASA Earth Observatory: http://earthobservatory.nasa.gov/Features/LaNina/

Griffin, T. (2009). Acquiring and Applying Days Suitable for Fieldwork for your State. *Journal of the American Society of Farm Managers and Rural Appraisers, 72*, 35-42.

Griffin, T., & Kelley, J. (2009). *Days Suitable for Fieldwork in Arkansas.* Little Rock: University of Arkansas Extension. Retrieved from http://www.uaex.edu/Other_Areas/publications/PDF/FSA-33.pdf

Maddala, G. (1983). *Limited Dependent and Qualitative Variables in Econometrics.* New York: Cambridge University Press.

McMillen, D., & McDonald, J. (1990, August). A Two-Limit Tobit Model of Suburban Land-Use Zoning. *Land Economics, 66*(3), 272-282.

National Agricultural Statistics Service. (2013). *United States Department of Agriculture.* Retrieved from Crop Progress Report.

National Agricultural Statistics Service. (2014, January 15). *Quick Stats Tools.* Retrieved from United State Department of Agriculutre: http://www.nass.usda.gov/Quick_Stats/index.php

National Climatic Data Center. (2007). *Time Bias Corrected Divisional Temperature-Precipitation-Drought Index.* NOAA. Retrieved from http://www7.ncdc.noaa.gov/CDO/DIV_DESC.txt

National Climatic Data Center. (2014, January). *NOAA Satellite and Information Service*. Retrieved from http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp

National Weather Service. (2014, January 6). *Cold & Warm Episodes by Season*. Retrieved from NOAA/National Wather Service: http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml

NOAA. (2013, January 9). *El Nino Theme Page*. Retrieved from http://www.pmel.noaa.gov/tao/elnino/el-nino-story.html

Reimers, C. (1983). Labor Market Discrimination Against Hispanic and Black Men. *Review of Economics and Statistics*, 570-579.

Rippey, B. (2012, 7 12). *Agricultural Weather and Drought Update.* Retrieved January 2014, from United States Department of Agriculture: http://blogs.usda.gov/2012/07/12/agricultural-weather-and-drought-update-%E2%80%93-71212/

Ropelewski, C. a. (1987). Global and Regional Scale Precipitation Patterns Associated with El Nino/Southern Oscillation. *Monthly Weather Review, 115*(8), 1606-1626.

Rosenberg, S. C. (1982). *Prediction of Suitable Days for Field Work.* St. Joseph, Michigan: ASAE.

Rotz, C. a. (2005). Predicting Suitable Days for Field Machinery Operations in a Whole Farm Simulation. *Applied Engineering in Agriculture, 21*(4), 563-571.

Rutledge, P. a. (1968). The Influence of the Weather on Field Tractability in Alberta. *Canadian Agricultural Engineering, 10*(2), 70-73.

Sinning, M., Hahn, M., & Bauer, T. (2008). The Blinder-Oaxaca Decomposition for Nonlinerar Regression Models. *The Stata Journal, 8*(4), 480-492.

Solow, A., Adams, R., Bryant, K., Legler, D., O'Brien, J., B., M., . . . Weiher, R. (1998). The value of Improved ENSO Prediction to US Agriculture. *Climate Change, 39*(1), 47-60.

Spurlock, S., Buehring, N., & Caillavet, D. (1995). *Days Suitable for Fieldwork in Mississippi.* Mississippi Agricultural & Forestry Experiment Station.

Stiles, S., & Griffin, T. (2009). *Estimating Farm Machinery Costs.* Little Rock: University of Arkansas Extension. Retrieved from http://www.uaex.edu/Other_Areas/publications/PDF/fsa-21.pdf

Ubilava, D., & Holt, M. (2013). El Nino Southern Oscillation and its Effects on World Vegetable Oil Prices: Assessing Asymmetrics Using Smooth Transition Models. *The Australian Journal of Agricultural and Resource Economics, 57*, 273-297.

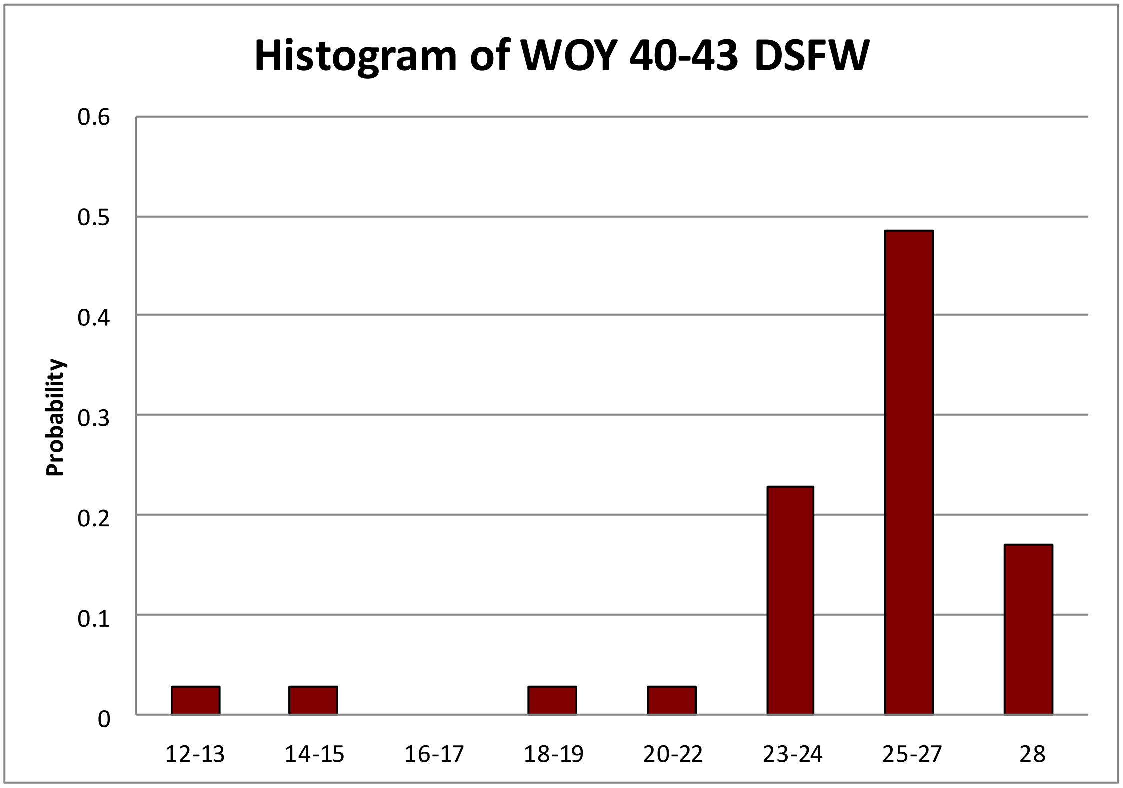
Widhalm, M. (2013). Climate Forecasts for Corn Producer Decision-Making. *Earth Interactions*. doi:10.1175/2013EI000541.1

Zhang, Y. Y. (2012). ENSO Anomalies over the Weste4rn United States: Present and Future Patterns in Regional Climate Simulations. *Climatic Change, 110*(1), 315-346.

Appendix

During the one-month time period of 40th to 43rd weeks of the year, there is nearly a 50% chance of having between 25 and 27 days suitable for fieldwork during; the time period considered most crucial for harvesting cotton in the southeastern United States. There is an 89% chance of having between 23 and 28 days suitable during this time period. A ‘bad’ year with respect to days suitable occurs when 22 or fewer days suitable are observed. During this time period it is expected that cotton harvest progresses from 15% to 70% (National Agricultural Statistics Service, 2013).

A hypothetical multi-crop farm may have 1,000 acres of cotton and one cotton picker with a working rate of 5.8 acres per hour for 8 hours per day (Stiles & Griffin, 2009). The goal is to complete harvest by end of week 43. Under the best conditions, 46.4 acres can be harvested each day (5.8 acres per hour multiplied by 8 hours per day). It will take 21.6 days to complete harvest (1,000 acres dived by 46.4 acres per day). The minimum and average number of days suitable for fieldwork recorded in the 1995 to 2007 dataset for Arkansas was 12.1 days and 23.2 days, respectively. The minimum number of days observed were 9 full days less than needed and the average year had 23.2 days suitable, which is 1.6 days more than needed. Therefore even a slightly worse than average year could cause the farm decision maker to not be able to meet their goals of a timely harvest. The impact of a El Nino year reducing days suitable by 1.2 days per month forces this hypothetical farm decision maker to not meet their goals or to consider expanding equipment capacity for the given scenario (Griffin & Kelley, 2009) (Griffin T. , 2009).


Histogram of WOY 40-43 DSFW
Probability
0.6
0.5
0.4
0.3
0.2
0.1
0
12-13
14-15
16-17
18-19
20-22
23-24
25-27
28

349