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An Assessment of Weather-Related Risk Associated with Early Corn Planting in Mississippi

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An assessment of weather-related risk associated with early corn planting in Mississippi

By

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In central Mississippi, corn exposed to extreme temperatures and drought in summer months may result in reduced yields while corn planted early in the season may be susceptible to frost damage. This study performs an analysis and modeling of ideal planting dates using air and soil temperatures, daily precipitation, and January teleconnection indices to determine if early planting procedures may benefit corn grown in Mississippi. Resulting ideal planting dates vary annually, with early planting dates experiencing moderate harm and late planting dates experiencing severe harm. Additionally, models predicting ideal planting dates produce consistent R^2 values, but contain errors of 20–30 days. This research concludes that early planting dates are beneficial to production, as they are less likely to result in crop loss. Furthermore, January teleconnection patterns have an influence on ideal planting dates in Mississippi, indicating that long-term climate patterns may be responsible for changes in the growing season.

DEDICATION

I dedicate this work to my family that has supported me every step of the way. Dad, Mom, and Meso: thank you for all your encouragement!

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I would like to acknowledge my thesis advisor, Grady Dixon, and my committee members, Brien Henry and Andrew Mercer for all the help they have given me during this process.

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CHAPTER I

INTRODUCTION AND LITERATURE REVIEW

Introduction

The state of Mississippi produced 750,000 acres of corn in 2010 (Mississippi State University 2013) and acres are expected to rise in future years (Mississippi State University 2013). Unfortunately, heat and drought in the Southeast are often problematic for corn yields (Mississippi State University 2013). Extreme temperatures and drought during summer months reduce yields. Furthermore, if regional climate change enhances the frequency of excessive heat and drought, solutions to stabilize corn production are needed. This research evaluates climatologies and risk probabilities to determine if early-planting procedures may stabilize and potentially improve corn yields in the Southeast.

In Central Mississippi, producers typically plant corn between March 15 and April 20 (Mississippi State University 2013). The critical precipitation window (CPW) marks the beginning of the reproductive phase of corn growth and occurs approximately 60 days after planting (Kansas State University 2013). This is a period during which moisture is necessary to promote grain production. Corn planted in late April tassels in mid-June, when temperatures are much higher and precipitation is variable. Thus, crops that are planted at this time are often vulnerable to heat and drought that reduce yields. Moving the planting season forward two to three weeks earlier may result in tasseling during May, which typically has moderate temperatures, lower evaporation demands, and more consistent precipitation compared to June and July. By modifying the planting date, this may increase the probability of exposing plants to natural rainfall. This may, in turn, decrease reliance upon irrigation, allowing for conservation of water. However, planting earlier will also increase the likelihood of exposure to late-spring frosts. Therefore, it is important to consider the risks associated with each planting date to establish the optimal planting dates for corn production. This research uses temperature and precipitation data from 1982–2012 for three locations in Mississippi to identify total harm days and ideal planting dates for each year. Results are regressed against teleconnection indices to determine how global teleconnection patterns may influence growing seasons.

Literature Review

Planting

Corn is typically planted once soil temperatures reach 10–13 °C (Farnham and Marks 2001). This temperature range ensures that soils are warm enough to promote even germination. Seeds are planted approximately 38–51 mm deep, depending upon soil type and available moisture (Mississippi State University 2013). Estimated emergence above ground is calculated using Growing Degree Days (GDD). GDDs are values that identify crop maturity based upon temperature thresholds of the crop, calculated by subtracting a base temperature from the average daily temperature. In corn, the base temperature is set to 50 ºF (10 ºC). To eliminate values associated with a lack of growth, temperatures less than 50 ºF (10 ºC) are set to 50 ºF (10 ºC) while temperatures above 86 ºF (30 ºC) are set to 86 ºF (30 ºC) (Climate Prediction Center 2014) When calculating GDDs using soil temperatures, it takes approximately 119 GDDs from planting to emergence (Purdue University 2013). Plants exposed to warmer temperatures will emerge faster than those exposed to cooler temperatures. When faced with less-than-ideal conditions after planting, producers with freeze-damaged crops or uneven stands must decide whether to allow their seed to grow and risk negative impacts on yield or replant new seeds with associated expenses and risk exposure to the drought period of the summer.

Temperature

Corn requires an accumulation of specific heat units to germinate and grow properly. However, due to genetic variations in suboptimal temperature stress, optimal thermal conditions may vary (Greaves 1996). A temperature of 30 °C has been identified as optimal for growth processes (Warrington and Kanemasu 1983, Miedema et al. 1987) and photosynthesis (Vong and Murata 1977). Lower temperatures, between 21 ºC and 27 ºC, have also been associated with healthy growth (Shaw 1977) and high yields (Shaw 1983, Keeling and Greaves 1990). These previous results suggest that there may not be a precise ideal set of growing conditions, so, for the purposes of this study, "ideal" will be used to imply planting conditions with the least amount of harm to the crop.

Temperatures at and below freezing negatively impact corn (Aberg and Akerberg 1958, Dhillon et al. 1988, Greaves 1996). Aberg and Akerberg (1958) discovered that temperatures between 0 °C and -1.5 °C resulted in minimal damage to crop growth while Dhillon et al. (1988) found that temperatures between -2 °C and -3 °C produced extensive damage to the crop. Although planting earlier in the season increases the chances of experiencing late frosts, cool conditions may not drastically reduce yields. Cool temperatures are often less destructive if the plants are exposed while the growing point is still below the soil surface. Additionally, improvements in chill tolerance (Huang et al. 2013) may reduce the negative effects of freezing temperatures on corn.

Extreme heat is also responsible for yield loss in corn. Yield tends to increase with temperature up to a threshold of 30 °C, followed by a rapid decline in yield with temperatures above the threshold (Schlenker and Roberts 2006, Roberts and Schlenker 2011). Continued exposure to temperatures above 32 °C reduces germination in corn (Herrero and Johnson 1980). Periods above 35 °C, especially if combined with severe drought, may result in extensive yield loss.

Precipitation

Moisture is a key factor in corn growth across the United States (Nielsen et al. 2009, Nielsen et al. 2010, Ma et al. 2012). Nielsen et al. (2009) found that corn yields were higher if available soil moisture was greater at planting. However, these results depended strongly on the amount of precipitation falling roughly ten days prior to tasseling and into the middle of grain filling. The CPW, which marks the beginning of the reproductive phase, was identified as the most critical time to receive adequate precipitation to avoid water stress. Nielsen et al. (2010) produced similar results: corn exposed to abundant early-season soil moisture consistently produced higher yields than corn planted with low soil moisture. However, yields for both dry and moist soils were similar if precipitation received during the critical period was plentiful.

Drought is responsible for extensive crop loss in the United States. The 1930s' Dust Bowl era, 1988 Midwest drought, and 1993 Southeast drought reduced regional yields by 50%, 30%, and 90%, respectively (Warrick 1984, Rosenzweig and Hillel 1998). In 2012, 70–75% of US corn production was impacted by severe drought (USDA 2013). Because of corn's heavy reliance upon moisture, small variations in precipitation can produce drastic changes in plant growth and yield. A 10-day drought may result in minimal damage to plants while an extended 12-day drought can result in the loss of an entire crop (Mearns et al. 1996). Therefore, it is necessary to avoid drought, if possible.

Teleconnections

The El Niño-Southern Oscillation (ENSO) teleconnection pattern is a coupling of ocean-atmosphere processes in the equatorial Pacific. The neutral phase is identified by dominant easterly trade winds, with warm sea surface temperatures (SSTs) over the western Pacific and cool SSTs over the eastern Pacific. The La Niña (cold) phase is an intensification of neutral conditions, with stronger easterlies resulting in enhanced upwelling of cool water over the eastern Pacific. The El Niño (warm) phase is a reversal of normal conditions, where high pressure over the western Pacific and low pressure over the eastern Pacific allows warm water to encroach upon the eastern Pacific. ENSO is monitored in the Niño 3.4 region (Climate Prediction Center 2014), located in the central Pacific, as this is the region where the onset of ENSO is typically observed.

ENSO influences jet stream shifts, impacting temperature and precipitation patterns in the southeastern United States (Ropelewski 1986, Kurtzman 2006). Positive (warm phase) ENSO events have been linked to drought and decreased vegetation in southeast summers (Mennis 2001, Peters et al. 2003) while neutral phases are associated with increased vegetation (Peters 2003). Because of its strong impact on local weather patterns, ENSO also influences crop production (Hansen 1998, Adams 1999, Peters 2003). A study of Normalized Difference Vegetation Index (NDVI) conditions in the Southeast from 1989–1999 determined that neutral phases of ENSO provided optimum yields while warm and cold phases both produced poor vegetation condition (Peters 2003). Additional studies have focused specifically on ENSO's effects on corn production (Handler 1990, Carlson 1996, Hansen 1998). Hansen (1998) determined that corn in the southeastern United States (Alabama, Florida, Georgia, and South Carolina) responds strongly to ENSO events. Yield increased during La Niña years and dropped off in following years. Hansen (1998) attributes these yield increases to higher June precipitation caused by La Niña.

The Pacific Decadal Oscillation (PDO) is a 20–30-year teleconnection pattern similar to ENSO (Mantua and Hare 2002). The warm phase of the PDO is associated with above-average sea surface temperatures (SSTs) along the west coast of North America and below-average SSTs in the central Pacific while the cold phase is the opposite, with below-average SSTs along the west coast of North America and above-average SSTs in the central Pacific (Dixon et al. 2008). In the southeastern United States, the warm phase of the PDO results in below-average temperatures and above-average precipitation while the cold phase results in above-average temperatures and below-average precipitation (Mantua and Hare 2002). PDO phases have been known to influence ENSO anomalies; higher El Niño anomalies were found during the warm phase of the PDO from Louisiana to Florida (Kurtzman and Scanlon 2007).

Richman and Mercer (2012) identified eight January patterns in 500-mb height variability using principle component analysis (PCA). These patterns are the West Pacific/North Pacific Oscillation (WP/NPO), Subtropical Zonal Winter (SZW), Northern Asian (NA), Eastern Atlantic (EA), North Atlantic Oscillation (NAO), Pacific North American (PNA), Eurasian, and Tropical Northern Hemisphere (TNH). Together, these patterns account for 70% of January 500-mb height variability (Richman and Mercer 2012). These 500-mb teleconnection patterns can influence temperature and precipitation patterns across the United States by affecting the position of the jet stream and frequency of low-pressure systems. Of these eight patterns, the NAO is one of the most well known in 500-mb height variability. The positive phase of the NAO is associated with the enhancement of zonal westerly flow while the negative phase is associated with a blocking pattern that allows cold Arctic air to move southward into the continental U.S.

Climate Change

Changes in regional climate affect corn yields by altering characteristics of the growing season (Rosenzweig et al. 2001, Rosenzweig et al. 2002, Reilly et al. 2003, Lobell and Field 2007). Current corn production practices are acceptable for average conditions, but are not adequate for extreme events during which plants are most susceptible to moisture deficits. In addition to extreme temperature and drought, changes in climate can increase the vulnerability to pests, weeds, and disease (Rosenzweig et al. 2001) as well as the potential for flooding caused by excessive precipitation events (Rosenzweig et al. 2002). Adaptations to cropping systems in response to the effects of climate change have been addressed by previous studies (Fankhauser 1996, Smith and Lenhart 1996, Smit et al. 1999, Smit and Skinner 2002, Roberts and Schlenker 2011). Modifications in cropping strategy may lessen the negative impacts of climate change; this can potentially be accomplished by modifying planting techniques to address changes in local weather patterns (Smit and Skinner 2002).

CHAPTER II

DATA AND METHODOLOGY

Data

Weather patterns in the southeastern United States were analyzed to evaluate the benefits of planting corn earlier in the season. Daily summaries from Cooperative Observer Network (COOP) agricultural research stations were obtained from the National Climatic Data Center (NCDC) and Mississippi State University Delta Research and Extension Center (DREC) for the past 26 years (1982–2012) for Stoneville (excluding 1987,1989, 1991, 1994–1995), Verona (excluding 1990, 2011–2012), and Starkville (excluding 1990, 1998–2000, 2003–2012).

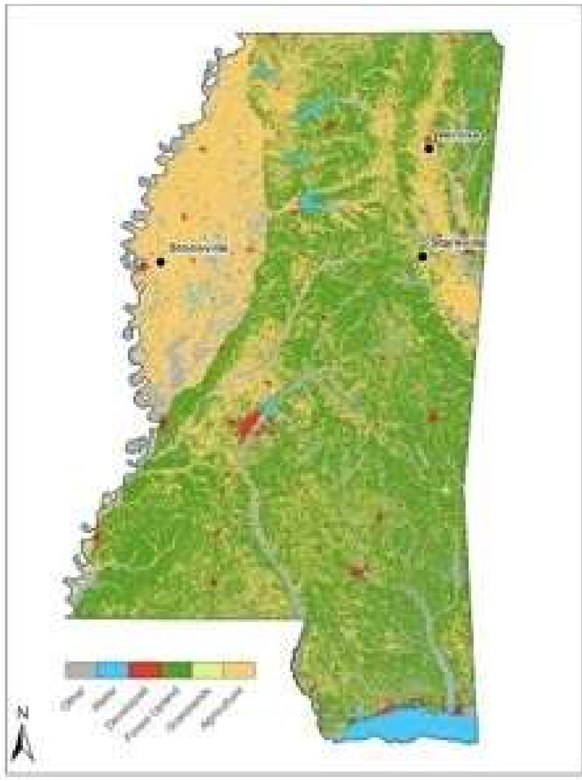

Figure 1 Map of Study Locations

Methods

To analyze harm associated with planting dates, it is necessary to split the risk analysis into pre-emergence and post-emergence. Prior to emergence, soil temperatures affect the growth of the crop. Therefore, risk associated with even germination and freezing soil before emergence was calculated in the pre-emergence category. Once emergence has occurred, air temperatures begin to affect the crop. Risk associated with frost after emergence and extreme heat was calculated in the post-emergence category. Drought was calculated equally in both pre- and post-emergence.

To predict emergence and tasseling, Growing Degree Days (GDDs) were calculated. GDDs were found by subtracting the base temperature of 50 ºF (10 ºC) from the average daily temperature. Limits on the maximum temperature (86 ºF) (30 ºC) and minimum temperature (50 ºF) (10 ºC) were imposed to ensure that only temperatures resulting in growth were considered (North Dakota Agricultural Weather Network 2014). Emergence was estimated using 119 GDDs, based upon the average value required for a plant to reach emergence (Purdue University 2013). A value of 1350 GDDs was used to estimate the beginning of the tasseling period. The end of tasseling was represented by a period of 14 days after the beginning of tasseling. The number of days required to reach emergence and tasseling for each potential planting date was then used to create loss probabilities associated with extreme heat, frost, and drought.

Each potential planting day in the study (February 1–April 30) was individually analyzed to determine acceptability for healthy growth. A binary analysis was performed to determine acceptability of each day based upon loss parameters. A day meeting any of the following criteria was deemed moderately harmful to plant growth:

1. maximum soil temperatures below 10 °C prior to emergence
2. minimum soil temperatures less than or equal to 0 °C while the growing point of the plant is below the soil surface
3. 10 days without adequate precipitation, with adequate precipitation being designated as 12.7 mm per day (Kranz et al. 2008)
4. minimum air temperatures less than or equal to 0 °C after plant emergence
5. maximum air temperatures greater than or equal to 32 °C

A second binary analysis was performed to account for extensive harm to the crop, with the following criteria deeming the day severely harmful to plant growth:

1. maximum soil temperatures below 10 ºC prior to emergence

2. minimum soil temperatures less than or equal to -2 ºC while the growing point of the plant is below the soil surface
3. 15 days without adequate precipitation, with adequate precipitation being designated as 12.7 mm per day (Kranz et al. 2008)
4. minimum air temperatures less than or equal to -2 ºC after plant emergence
5. maximum air temperatures greater than or equal to 35 ºC.

Days meeting any of the criteria for moderate (severe) harm were given a value of 1, identifying the day as a moderate (severe) harm day. Harm days were accumulated from the day of planting until the end of tasseling for each individual potential planting date. This produced a total number of moderate- and severe-harm days for each planting date. Using these totals, it was then possible to create various representations of the ideal planting date for each year. First, planting dates were ranked based upon the total number of moderate- and severe-harm days to find the average annual rank of each planting date. Second, the average harm-days count for each planting date was calculated. Lastly, the ideal planting date for each individual year was identified as the day with the minimum number of moderate- or severe-harm days each year. It was then possible to calculate the average ideal planting date for each location based upon both moderate and severe harm. In all analyses, the earliest date with ideal conditions was chosen as the ideal planting date to ensure that producers would be given the earliest possible option. This decision is supported by our results suggesting that severe harm is more likely later in the season.

An additional analysis was completed to determine what role global teleconnections play in altering the growing season. January indices for ten teleconnection patterns were used to predict the ideal planting date for each year. ENSO indices for the Niño 3.4 region were obtained from the Climate Prediction Center (CPC). PDO indices were obtained from the University of Washington. Indices for the WP/NPO, SZW, NA, EA, NAO, PNA, Eurasian Patterns, and TNH were also obtained for this analysis (Sparrow 2014). A stepwise regression was used to discover which teleconnections had the most influence on ideal planting date for moderate and severe harm. The stepwise multivariate regression was used to determine which predictor variables best describe the predicted variable. The stepwise output produced mean square error (MSE) and R^2 values. By using the variables that produced the highest R^2 values and lowest MSE values, it was possible to choose the teleconnections that best represented the planting dates. Teleconnections that reduced the MSE were retained for the regression analysis. Teleconnections that increased the MSE were removed from the regression analysis. The selected teleconnections were then used as predictors in a linear model that attempted to estimate ideal planting dates.

When models are assessed with the same data used to initially create the model, over-fitting can occur, leading to biased results. Therefore, it is important to use cross validation to assess how a model predicts on new data. In this study, cross validation was performed using a resampling method known as bootstrapping. Data was split into training and testing sets. The model was created using 80% of the data (training set) and model performance was tested using the remaining 20% of data that the model had not seen (testing set). The bootstrap used 1000 repetitions to measure model fit and prediction error.

CHAPTER III

RESULTS AND DISCUSSION

Analysis of Ideal Planting Dates

Average monthly maximum and minimum temperatures and average monthly precipitation for the months of May, June, and July were calculated for Stoneville (Table 1). Results show that May has the lowest average temperatures and the highest monthly precipitation. July has the highest average temperatures and the lowest monthly precipitation. This supports the hypothesis that planting corn earlier in the season would expose plants to cooler temperatures and more abundant precipitation. Corn planted late in the season would expose plants to higher temperatures and less precipitation. Considering that precipitation is most necessary during the CPW, it is important that corn be planted early enough for this period to fall in May and June when precipitation is more abundant. Verona's results (Table 2) show the same patterns, although the difference between June and July precipitation is smaller than in Stoneville's analysis. Starkville's results (Table 3) show the same patterns for temperatures, but they vary with precipitation. In this case, July has slightly more precipitation than June.

Table 1 Stoneville Monthly Temperature and Precipitation

	Average Monthly Maximum Temperature (ºC)	Average Monthly Minimum Temperature (ºC)	Average Monthly Precipitation (mm)
May	28.6	17.2	112.9
June	32.1	21.1	93.6
July	33.4	22.6	77.1

Table 2 Verona Monthly Temperature and Precipitation

	Average Monthly Maximum Temperature (ºC)	Average Monthly Minimum Temperature (ºC)	Average Monthly Precipitation (mm)
May	27.8	15.3	144.2
June	31.4	19.6	122.2
July	33.0	21.6	122.0

Table 3 Starkville Monthly Temperature and Precipitation

	Average Monthly Maximum Temperature (ºC)	Average Monthly Minimum Temperature (ºC)	Average Monthly Precipitation (mm)
May	27.5	15.2	121.6
June	31.0	19.3	102.8
July	32.8	21.7	105.0

Initially, it was hypothesized that dates between March 1 and March 15 would consistently be the ideal planting dates associated with each individual year. Instead, results for Stoneville (Fig. 3), Verona (Fig. 5), and Starkville (Fig. 7) show that annual ideal planting dates fluctuate between the earliest potential planting date (February 1) and the latest potential planting date (April 30). Stoneville has the longest period of record, giving this location the best representation of the spread of ideal planting dates. Roughly 25% of ideal planting dates for both moderate and severe harm in Stoneville occur before March 1. The highest percentage of ideal planting dates occurs after March 15 for all three locations. However, when considering only severe harm, the percentage of ideal planting dates occurring after March 15 decreases for all locations, and the percentage of ideal planting dates occurring before March 1 and from March 1–March 15 increases (Fig. 2). This shows that during severe-harm conditions, the ideal planting date shifts earlier in the season, implying that warm-season harm is more likely to be severe while cool-season harm is more likely to be moderate.

Graphs providing the number of harm days associated with each ideal planting date for Stoneville (Fig. 4), Verona (Fig. 6), and Starkville (Fig. 8) show that the number of harm days is relative to the year in question. For example, in Stoneville's analysis (Fig. 4), the ideal planting date for 1983 has only a few moderate-harm days and zero severe-harm days. However, five years later in 1988, the ideal planting date has roughly 60 moderate- and severe-harm days. Similar conclusions result from the Verona and Starkville analysis.

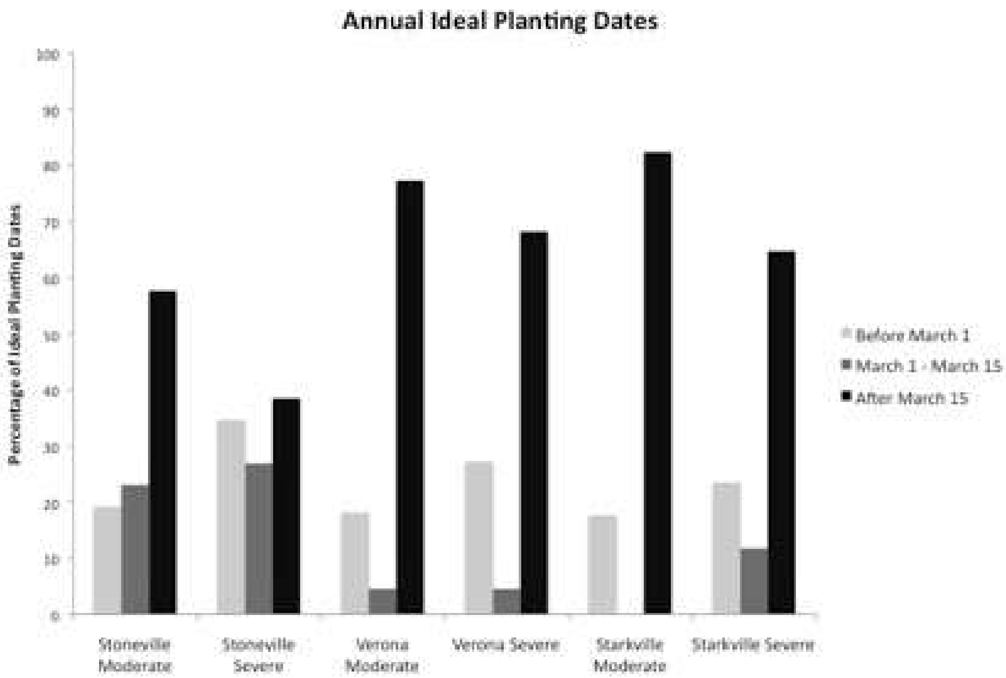

Figure 2 Histogram of Annual Ideal Planting Dates

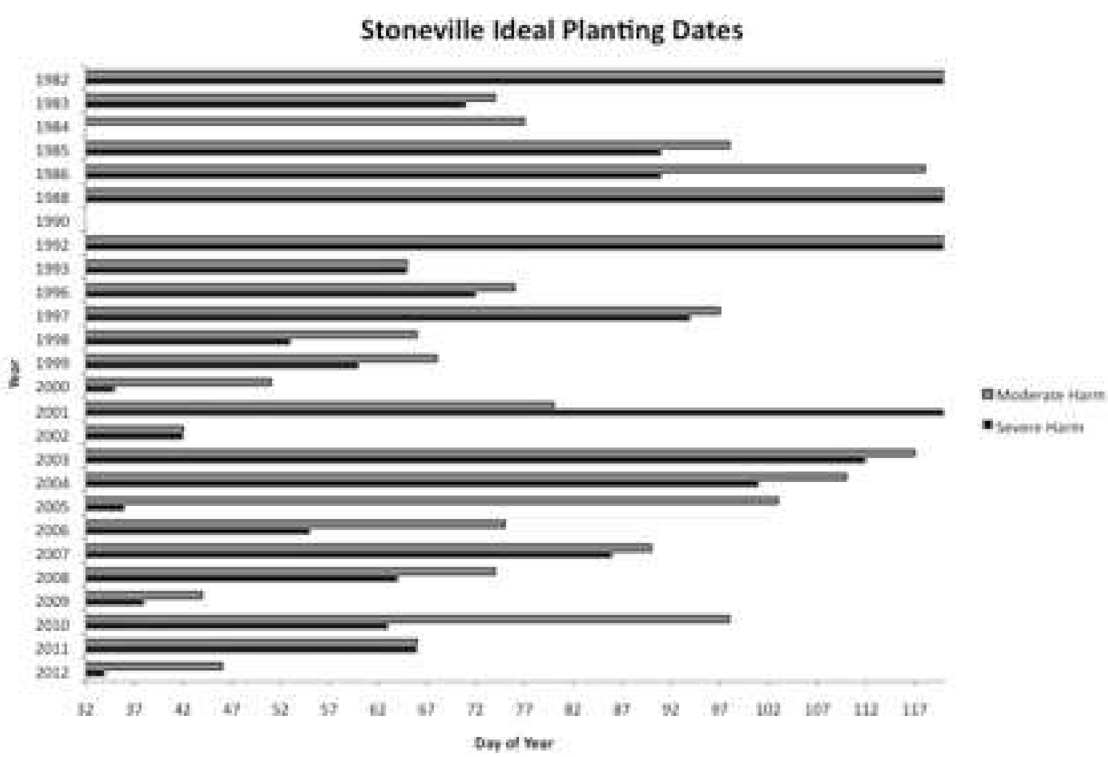

Figure 3 Stoneville Ideal Planting Dates

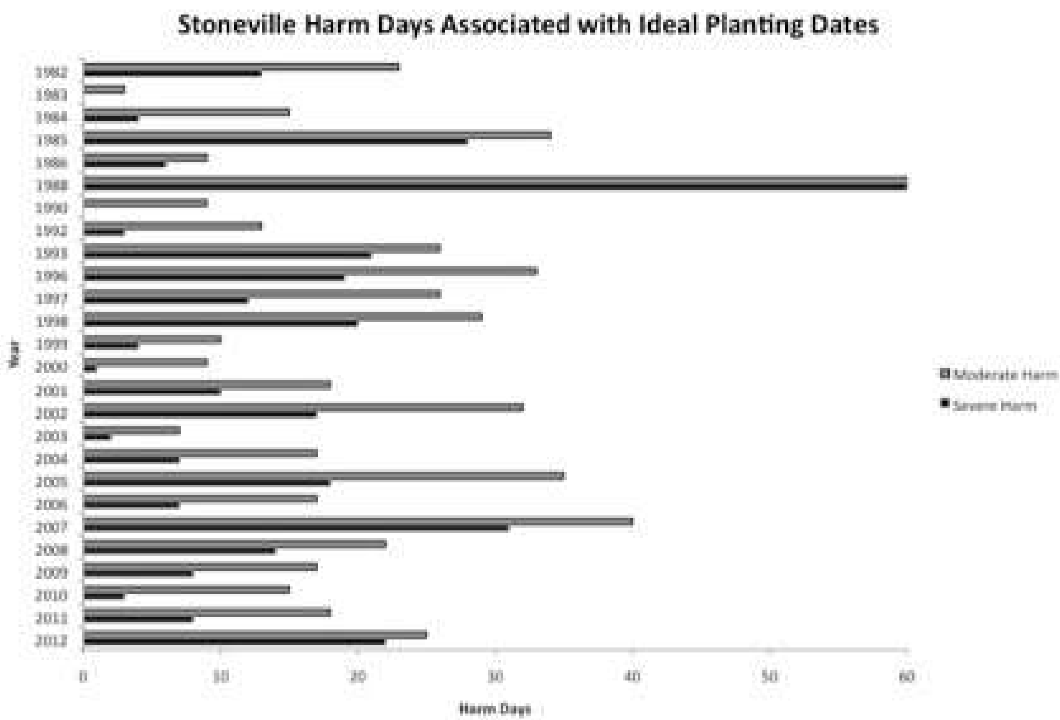

Figure 4 Stoneville Harm Days Associated with Ideal Planting Dates

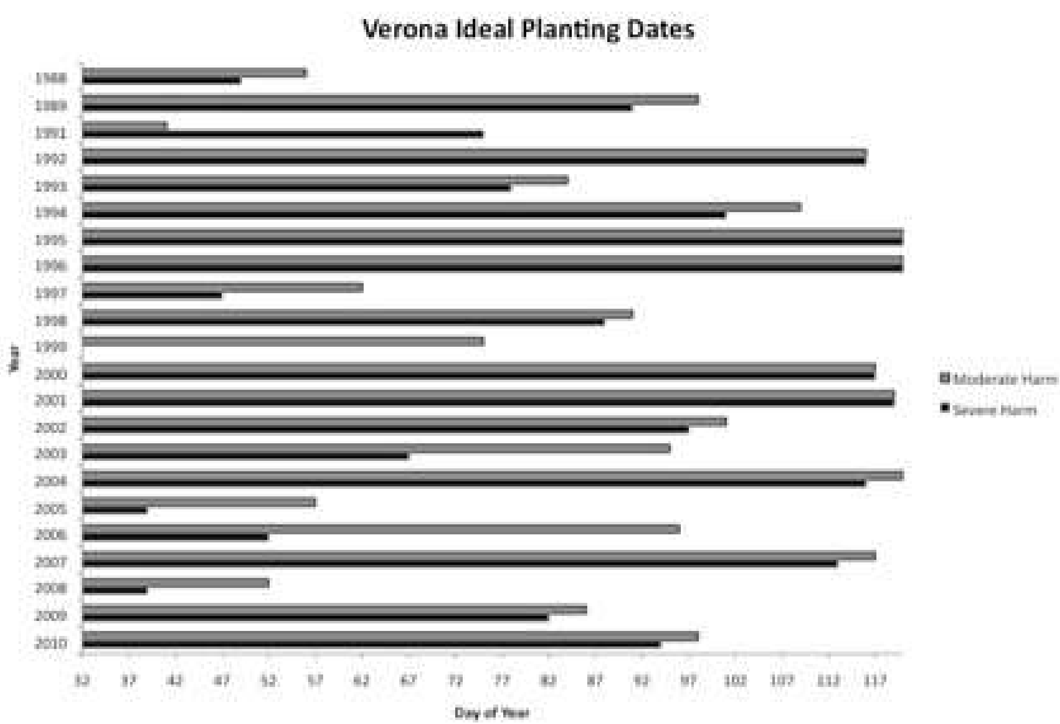

Figure 5 Verona Ideal Planting Dates

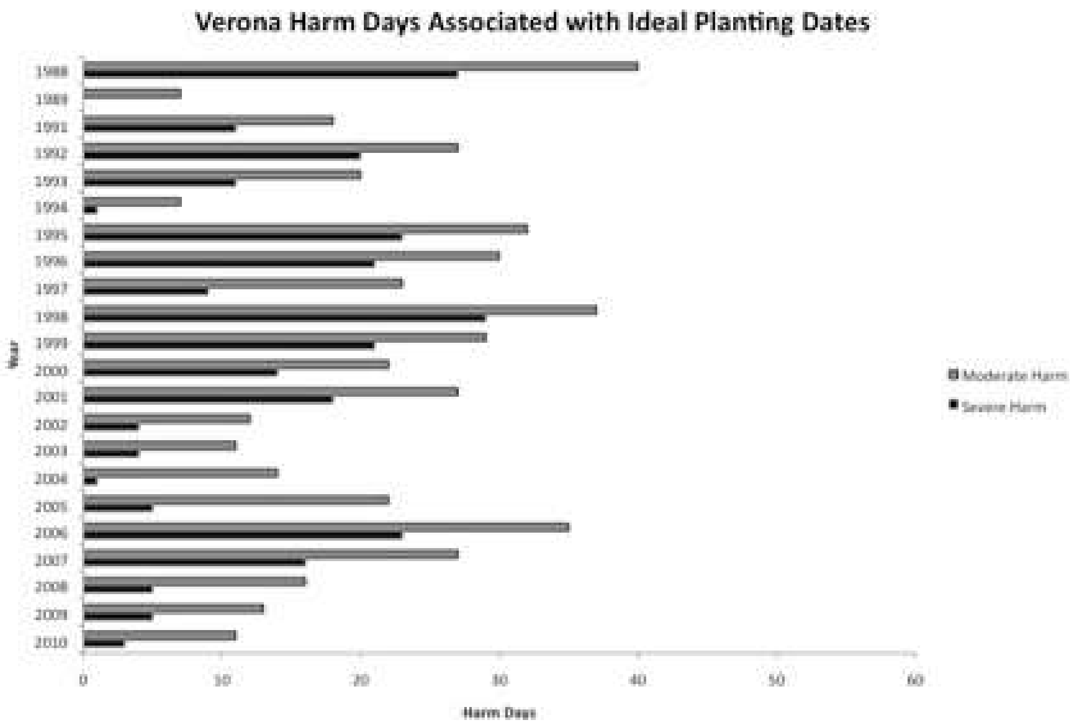

Figure 6 Verona Harm Days Associated with Ideal Planting Dates

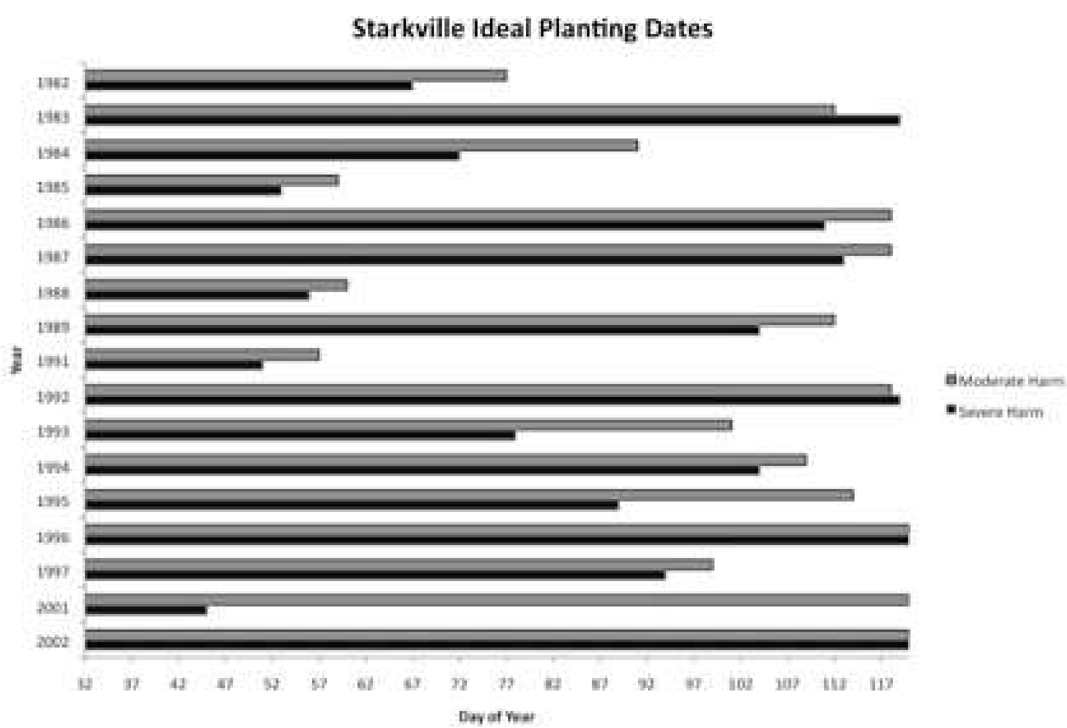

Figure 7 Starkville Ideal Planting Dates

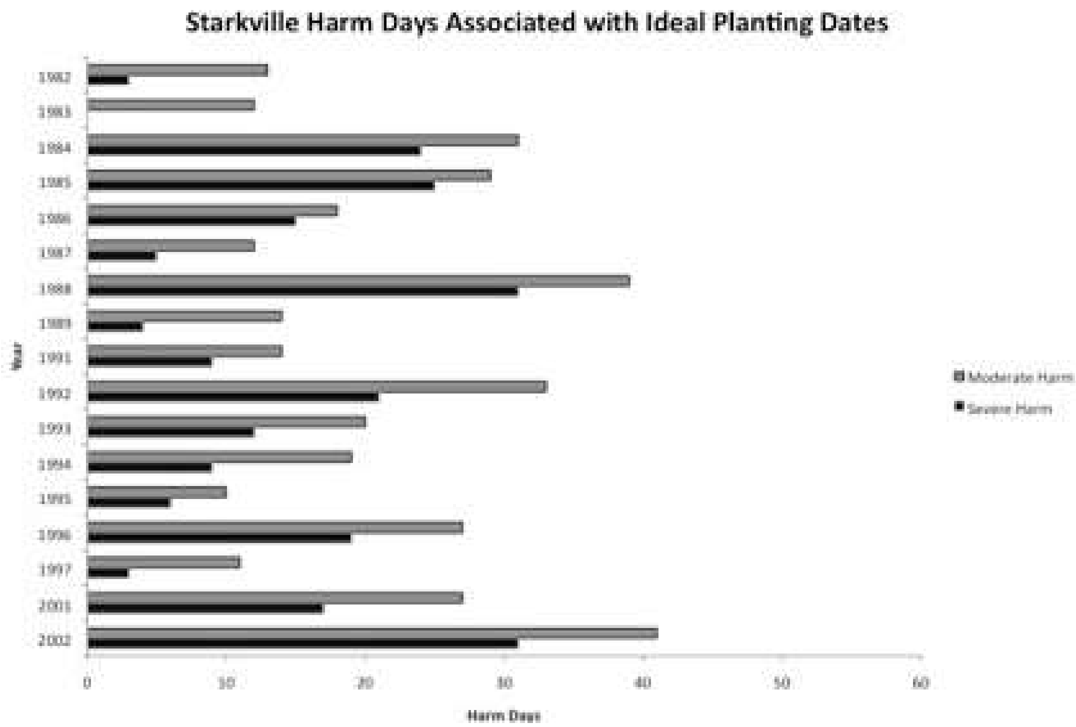

Figure 8 Starkville Harm Days Associated with Ideal Planting Dates

The average annual ideal planting dates at the 95% confidence interval (Table 5) show that late-season harm is more likely to be severe. The median ideal planting dates associated with moderate harm for Stoneville, Verona, and Starkville are March 23, April 2, and April 10, respectively. However, when considering severe harm, the median ideal planting dates shift 1–2 weeks earlier to March 13, March 25, and March 30, respectively. Although the ideal planting dates differ among the three locations, the number of harm days associated with the ideal planting dates remains fairly constant at the 95% confidence interval (Table 5). The median number of moderate-harm days for ideal planting dates in Stoneville, Verona, and Starkville are 21.462, 21.909, and 21.824, respectively. The median number of severe-harm days for ideal planting dates in Stoneville, Verona, and Starkville are 12.885, 12.227, and 13.647, respectively.

Table 4 Average Annual Ideal Planting Dates (95% C. I.)

Location	2.5%	50%	97.5%
Stoneville Moderate	March 12	March 23	April 2
Verona Moderate	March 22	April 2	April 13
Starkville Moderate	March 30	April 10	April 21
Stoneville Severe	March 2	March 13	March 25
Verona Severe	March 12	March 25	April 6
Starkville Severe	March 18	March 30	April 12

Table 5 Average Harm Days Associated with Ideal Planting Dates (95% C. I.)

Location	2.5%	50%	97.5%
Stoneville Moderate	17.500	21.462	26.887
Verona Moderate	17.864	21.909	25.959
Starkville Moderate	17.057	21.824	26.647
Stoneville Severe	8.384	12.885	18.194
Verona Severe	8.636	12.227	16.091
Starkville Severe	9.410	13.647	18.296

The average number of harm days for Stoneville's earliest 16 years from 1982–2002 (Fig. 9, Fig. 10) shows that the average number of moderate- and severe-harm days is highest on the first potential planting date (February 1). As the season continues, the average number of both moderate- and severe-harm days drops and levels out near mid-

March before beginning to increase again late in the season. When comparing this analysis to the most recent ten years (2003–2012), a similar pattern is witnessed. However, the average number of both moderate- and severe-harm days is lower in the early-season and higher in the late-season. This change cannot be attributed to any form of regional climate change in Stoneville because the median of the past ten years (2003–2012) falls within the range of the 95% confidence interval of 1982–2002.

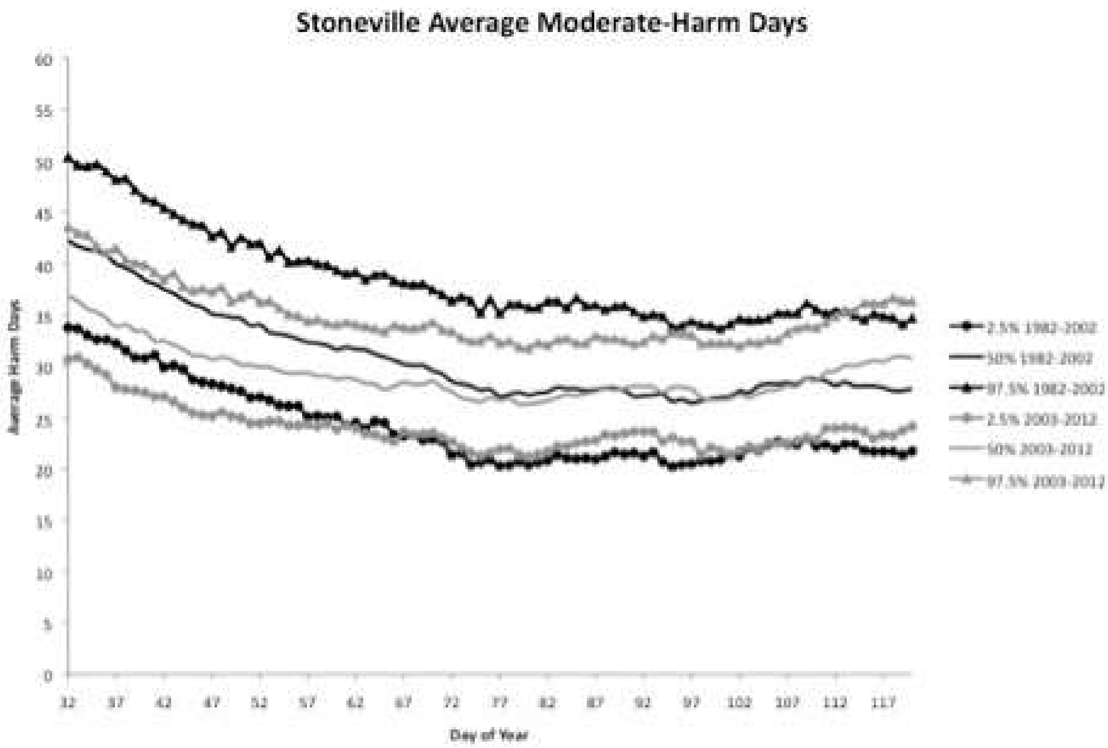

Figure 9 Stoneville Average Moderate-Harm Days 1982–2002 and 2003–2012 "(95% C. I.)

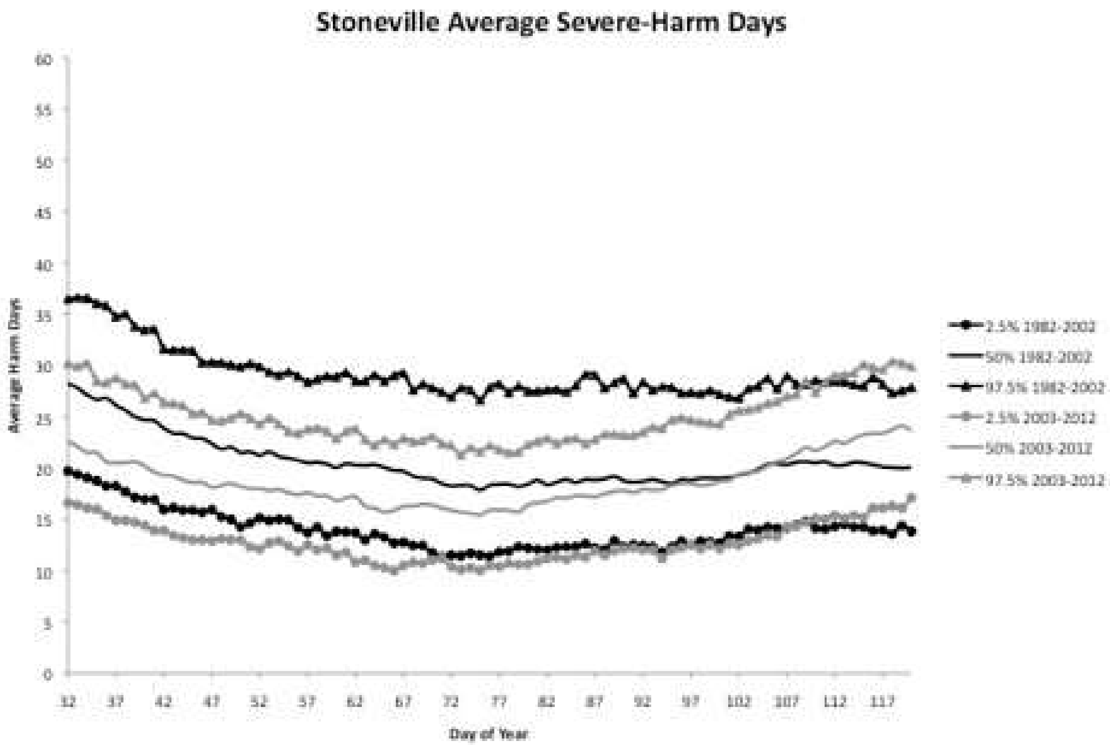

Figure 10 Stoneville Average Severe-Harm Days 1982–2002 and 2003–2012 (95% C. I.)

Graphs showing the average number of moderate- and severe-harm days for Verona (Fig. 11) and Starkville (Fig. 12) share a similar pattern to Stoneville's analysis. Early-season harm starts out high and begins to decrease as the season continues. However, the increase in late-season harm is not as apparent. Verona begins to see a slight increase in late-season harm near mid-April, but drops off again in late-April. Starkville's results show a downward trend with no evident increase in late-season harm. Additionally, because the period of record is limited for these locations, no analysis was completed to determine if regional climate change occurred.

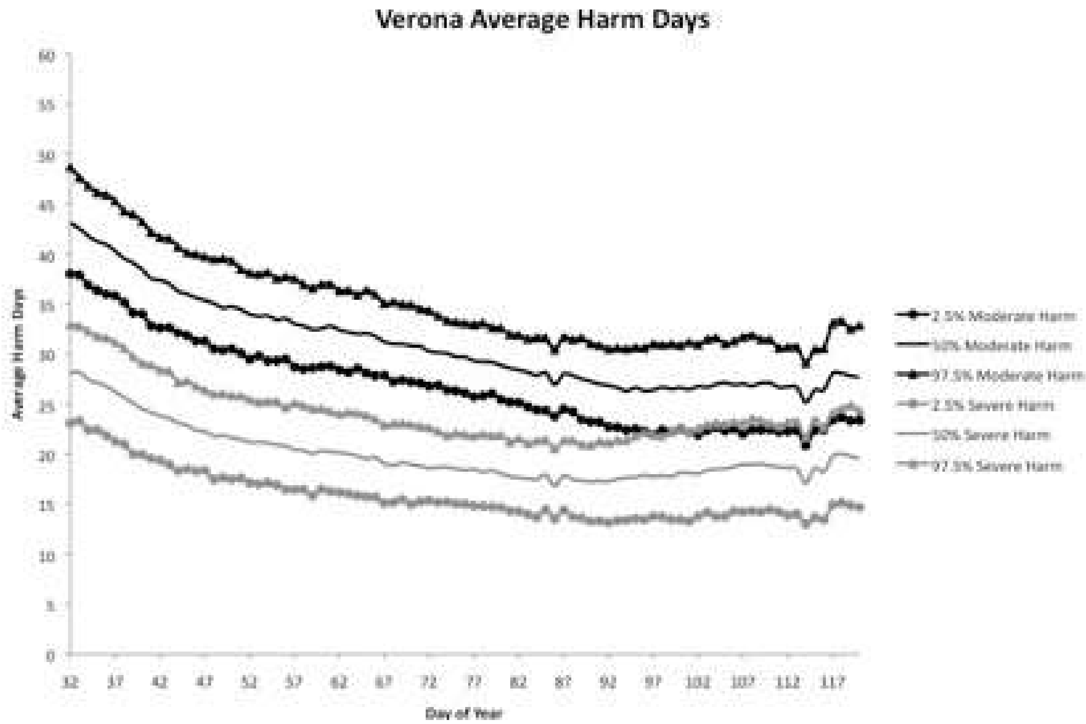

Figure 11 Verona Average Harm Days 1988–2010 (95% C. I.)

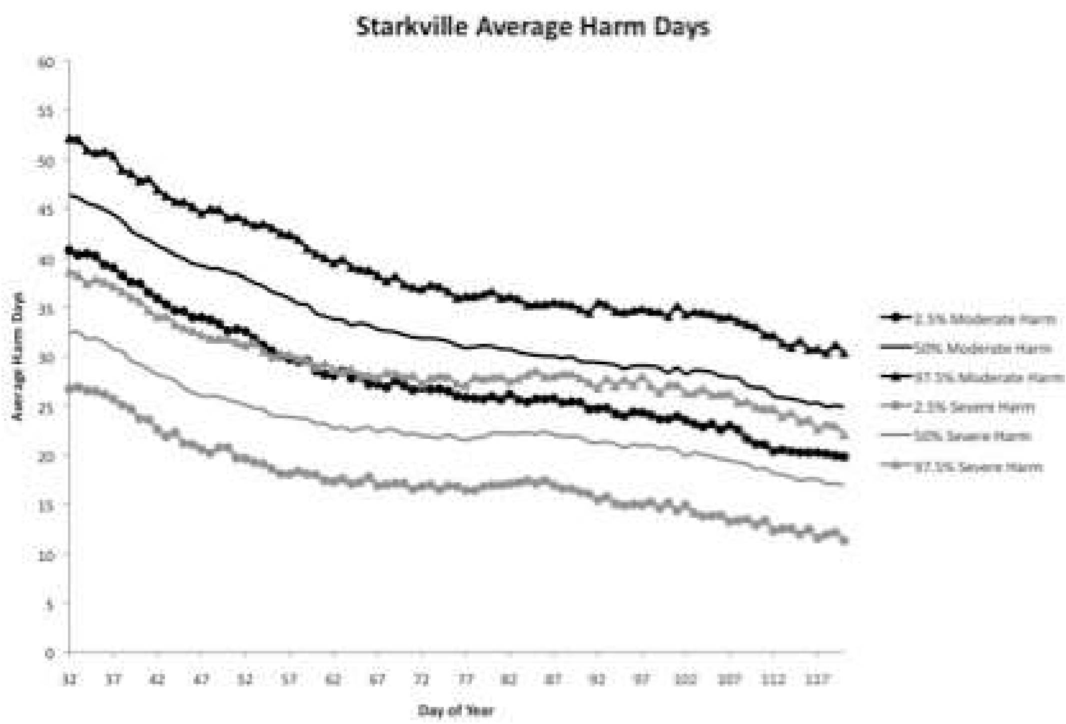

Figure 12 Starkville Average Harm Days 1982–2002 (95% C. I.)

It was expected that a relationship between ideal planting date and number of harm days would be found. In theory, an earlier planting date is expected to have fewer harm days than a later planting date. However, the resulting correlations (Table 6) show no statistically significant relationship between the two with either moderate or severe harm. Instead, the number of harm days seems to be an interannual fluctuation based upon weather patterns. For example, in Stoneville's moderate-harm analysis, the latest hypothetical planting date (April 30) is identified as the ideal planting date for 1982, 1988, and 1992. Moderate-harm days associated with each ideal planting date are 23, 60, and 13, respectively. In comparison, the earliest ideal planting dates found for Stoneville include February 1, February 11, and February 13, occurring in 1990, 2002, and 2009, respectively. Moderate-harm days associated with these dates are 9, 32, and 17, respectively. This shows that the total number of harm days associated with each ideal planting date is a relative value. A specific number of harm days could be associated with either an early or late planting date, depending on the year in question. For example, it cannot be assumed that a planting date with 30 harm days will always be ideal. For a given year, a value of 30 could signify early planting. In another given year, a value of 30 may represent a day much later than the ideal planting date.

Table 6 Correlation Values: Ideal Planting Date vs Harm Days

	Ideal Planting Date vs Harm Days Correlation
Stoneville Moderate Harm	0.181
Stoneville Severe Harm	0.242
Verona Moderate Harm	-0.023
Verona Severe Harm	0.030
Starkville Moderate Harm	-0.099
Starkville Severe Harm	-0.184

Model Performance

The stepwise regression produced r-squared values (Table 7) for the relationship between January teleconnection indices and ideal planting dates. Stoneville's planting dates produce the highest R^2 values with 0.604 for moderate harm and 0.553 for severe harm. This implies that the chosen teleconnections explain roughly 60% of the variability in moderate-harm planting dates and 55% of the variability in severe-harm planting dates. Less variability was explained with the remaining locations. Starkville's planting dates produce the next-highest R^2 values with 0.359 for moderate harm and 0.415 for severe harm. Verona produces the lowest R^2 values with 0.197 for moderate harm and 0.127 for severe harm.

Table 7 R^2 Values: Ideal Planting Dates vs January Teleconnection Indices

	R^2 Values
Stoneville Moderate Harm	0.604
Stoneville Severe Harm	0.553
Verona Moderate Harm	0.197
Verona Severe Harm	0.127
Starkville Moderate Harm	0.359
Starkville Severe Harm	0.415

The stepwise regression also identified which teleconnections had the most influence on predicting planting dates (Tables 8–13). When predicting Stoneville's moderate- and severe-harm planting dates, the three most prominent teleconnections are the PDO, NAO, and NA. Also included in the results are the WP/NPO, ENSO, and Eurasian Patterns. Verona's results are mixed: moderate harm is best explained by the NAO, WP/NPO, and Eurasian Patterns while severe harm is best explained by the NAO and PDO. Starkville's results produce different teleconnection patterns: moderate harm is explained by the TNH and ENSO while severe harm is explained by the TNH, EA, and PNA.

Table 8 Stoneville Moderate-Harm Regression Results

Variable	MSE	R-Squared
PDO	500.004	0.307
NA	450.245	0.376
NAO	429.197	0.431
EA	415.81	0.473
Eurasian	404.81	0.512
WP/NPO	369.001	0.577
ENSO	364.957	0.604
TNH	382.959	0.607
PNA	404.789	0.609
SZW	429.625	0.611

Table 9 Stoneville Severe-Harm Regression Results

Variable	MSE	R-Squared
NAO	762.885	0.200
PDO	642.745	0.326
NA	593.029	0.405
WP/NPO	494.292	0.527
Eurasian	490.201	0.553
PNA	500.745	0.566
ENSO	520.334	0.573
EA	546.776	0.576
TNH	580.238	0.577
SZW	618.828	0.577

Table 10 Verona Moderate-Harm Regression Results

Variable	MSE	R-Squared
NAO	627.888	0.062
WP/NPO	592.588	0.115
Eurasian	565.817	0.197
EA	575.599	0.226
NA	565.951	0.281
SZW	588.912	0.296
PDO	621.08	0.304
TNH	662.858	0.307
ENSO	709.817	0.311
PNA	768.403	0.311

Table 11 Verona Severe-Harm Regression Results

Variable	MSE	R-Squared
NAO	864.796	0.099
PDO	837.88	0.127
ENSO	844.499	0.164
WP/NPO	839.211	0.213
Eurasian	825.518	0.269
NA	854.373	0.288
PNA	906.069	0.292
SZW	970.587	0.292
TNH	1045.174	0.292
EA	1132.253	0.292

Table 12 Starkville Moderate-Harm Regression Results

Variable	MSE	R-Squared
TNH	416.216	0.264
ENSO	362.494	0.359
WP/NPO	368.911	0.391
PDO	378.956	0.419
Eurasian	371.791	0.474
NA	376.769	0.511
PNA	368.484	0.565
EA	398.371	0.577
SZW	440.664	0.584
NAO	495.925	0.591

Table 13 Starkville Severe-Harm Regression Results

Variable	MSE	R-Squared
TNH	675.833	0.149
EA	594.173	0.252
PNA	497.918	0.415
Eurasian	502.091	0.452
PDO	438.622	0.558
NA	446.987	0.587
NAO	472.207	0.604
SZW	504.991	0.619
WP/NPO	545.439	0.634
ENSO	622.909	0.634

Correlation values between Stoneville moderate-harm planting dates and January teleconnection indices show that PDO, Eurasian, ENSO, and WP/NPO values have the highest correlation (Table 14). Correlation values for all four teleconnection patterns are positive, indicating that a stronger positive index results in a later ideal planting date. For Stoneville's severe-harm planting dates (Table 15), the NAO and PDO have the highest correlations. Relationships are positive for both teleconnection patterns, indicating that a stronger positive index results in a later ideal planting date. Verona's moderate-harm and severe-harm correlations (Table 16, Table 17) show the strongest relationship with NAO. The relationship is positive for both forms of harm, indicating that a stronger positive index results in a later ideal planting date. Starkville's moderate-harm and severe-harm correlations (Table 18, Table 19) show the TNH has the strongest relationship. For this location, relationships are negative, indicating that a stronger positive index results in an earlier ideal planting date.

Table 14 Correlation: Stoneville Moderate-Harm Planting Dates vs January Teleconnection Indices

	Correlation
PDO	0.554
NA	-0.164
NAO	0.275
EA	-0.065
Eurasian	0.338
WP/NPO	0.335
ENSO	0.337

Table 15 Correlation: Stoneville Severe-Harm Planting Dates vs January Teleconnection Indices

	Correlation
NAO	0.448
PDO	0.379
NA	-0.229
WP/NPO	0.035
Eurasian	0.201

Table 16 Correlation: Verona Moderate-Harm Planting Dates vs January Teleconnection Indices

	Correlation
NAO	0.249
WP/NPO	-0.088
Eurasian	0.223

Table 17 Correlation: Verona Severe-Harm Planting Dates vs January Teleconnection Indices

	Correlation
NAO	0.315
PDO	-0.067

Table 18 Correlation: Starkville Moderate-Harm Planting Dates vs January Teleconnection Indices

	Correlation
TNH	-0.513
ENSO	0.060

Table 19 Correlation: Starkville Severe-Harm Planting Dates vs January Teleconnection Indices

	Correlation
TNH	-0.386
EA	-0.279
PNA	0.095

Each location produced two models to predict ideal planting dates. The first predicts moderate-harm planting dates while the second predicts severe-harm planting dates. The R^2 boxplot shows the variability in ideal planting dates that is described by teleconnection patterns. The root mean square error (RMSE) boxplot shows the error associated with the model.

Stoneville's moderate-harm model produces a median R^2 value of approximately 0.65 (Fig. 13). Outliers are present both above and below the whiskers, indicating that some of the values deviate from the sample. Stoneville's moderate-harm model produces a median RMSE value of approximately 24 days (Fig. 15). Outliers above the whiskers have an RMSE value of 40–50 days. Outliers below the whiskers have an RMSE value of 5–10 days. Stoneville's severe-harm model (Fig. 14) produces a median R^2 value of approximately 0.58. Fewer outliers are present in the severe-harm sample than in the moderate-harm sample. The model produces a median RMSE value of approximately 26 days (Fig. 16). Many outliers are present above the whiskers, with RMSE values greater than 40 days. A few outliers are also present below the whiskers, with RMSE values less than 10 days.

Verona's moderate-harm model produces a median R^2 value of approximately 0.2 (Fig. 13). However, many outliers are present above the whiskers with values above 0.5. The model produces a median RMSE value of approximately 28 days (Fig. 15). Many outliers are found above the whiskers with RMSE values above 50 days. Verona's severe-harm model produces a median R^2 value of approximately 0.12 (Fig. 14). A large number of outliers are present above the whiskers. The model produces a median RMSE value of approximately 30 days (Fig. 16). A few outliers are present above the whiskers with RMSE values above 50 days.

Starkville's moderate-harm model produces a median R^2 value of approximately 0.38 (Fig. 13). Outliers are found both above and below the whiskers. The model produces a median RMSE value of approximately 20 days (Fig. 15). One outlier is present above the whiskers, with a value near 40 days. Starkville's severe-harm model produces a median R^2 value of approximately 0.45 (Fig. 14). Two outliers are found above the whiskers with values above 0.70. The model produces a median RMSE value of approximately 26 days (Fig. 16). One outlier has a value near 53 days.

Overall, the models produced consistent R^2 values, indicating that there is a relationship present between teleconnection patterns and the growing season. However, the models also produced high RMSE values, indicating that the models' predictions are not accurate. Median RMSE values were fairly consistent for each location, typically falling between 20–30 days. In a study period of only three months, the current error of roughly one month is too high for the models to be reliable. With an increase in the amount and quality of data, the models could potentially lead to more accurate predictions.

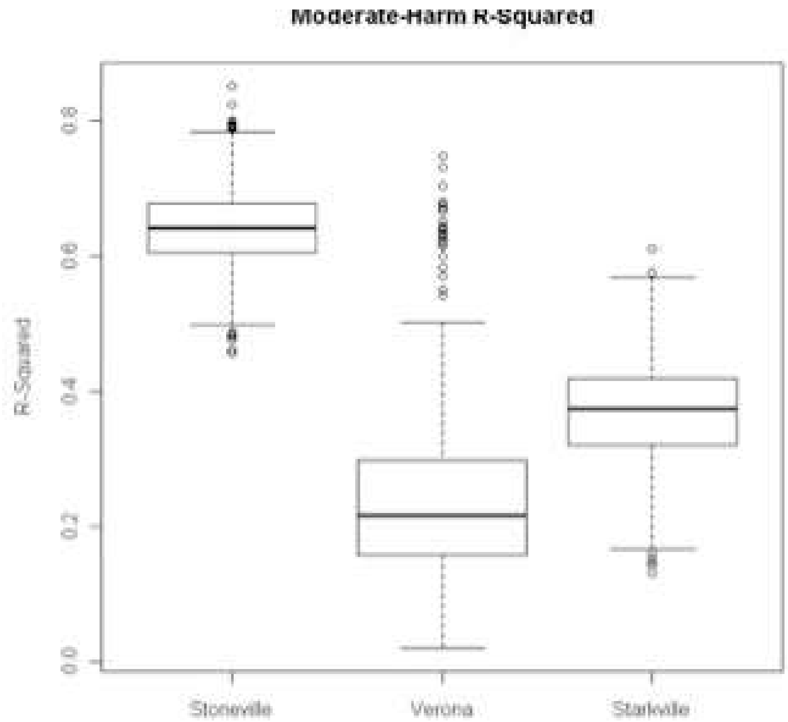

Figure 13 Moderate-Harm R^2 Boxplots

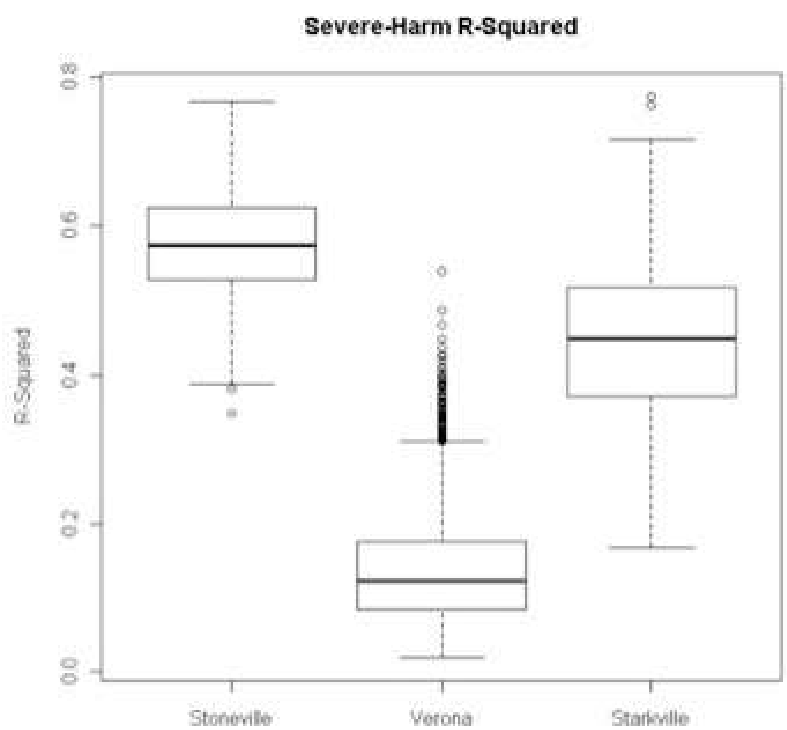

Figure 14 Severe-Harm R^2 Boxplots

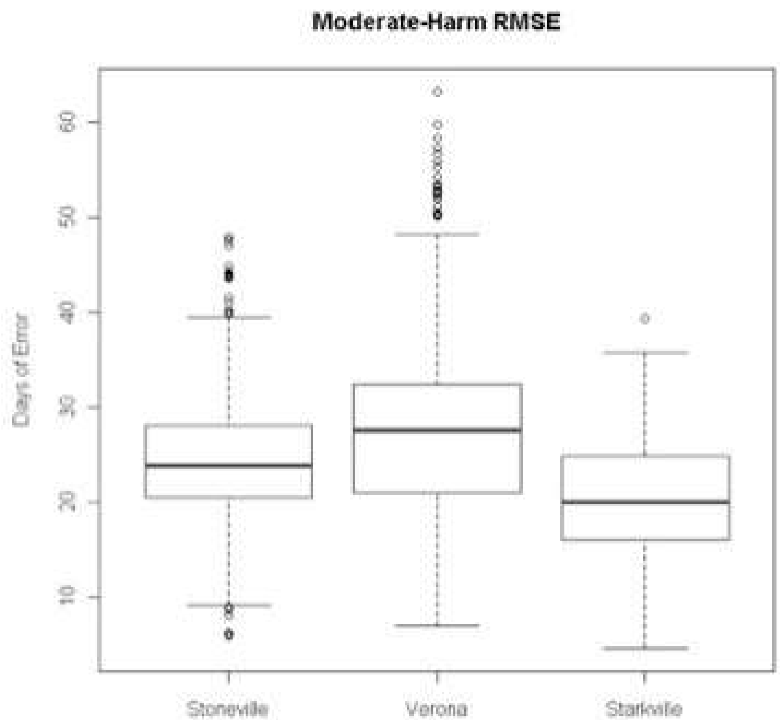

Figure 15 Moderate-Harm RMSE Boxplots

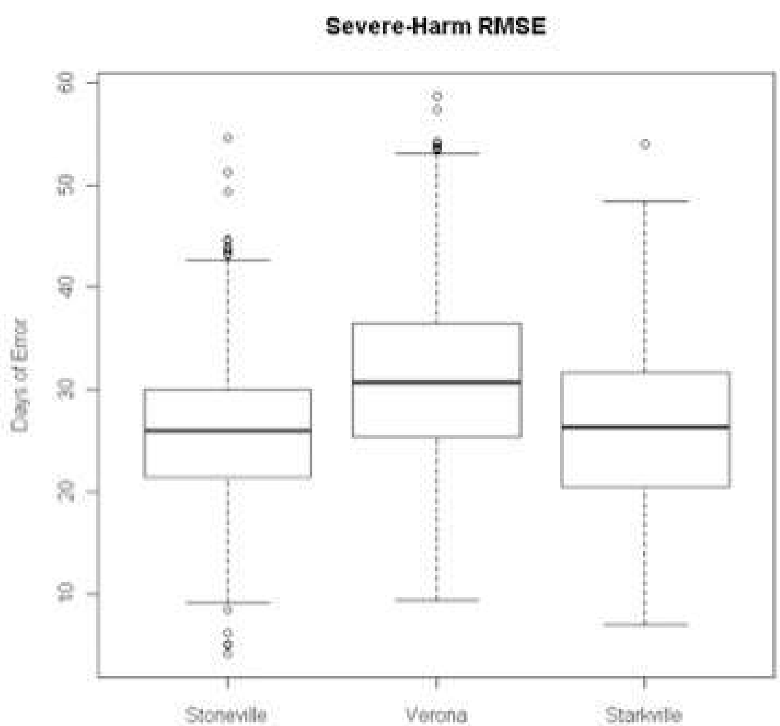

Figure 16 Severe-Harm RMSE Boxplots

Limitations

A significant limitation of this study is the short period of record for weather stations in northern Mississippi. Many of these stations do not have consistent daily weather summaries until the early 1980s. Most stations that have a longer period of record lack soil temperature data, which is necessary for this analysis. The combination of short period of record and lack of soil temperature data limited this study to only a few locations in Mississippi. Additionally, the period of record and years included in the study varies for each location. Therefore, it is difficult to accurately compare results between the three locations.

Second, emergence and tasseling had to be estimated based upon the calculation of Growing Degree Days. While our estimations are representative of the average number of GDDs required to reach emergence and tasseling, corn will reach these stages at different times based upon various factors. Third, our study does not incorporate characteristics of various breeds of corn. With an increase in the success of genetic engineering in agriculture, some breeds of corn have become more resilient to damage associated with frost, heat, and drought. Future studies could benefit from the analysis of multiple breeds to determine how breed type may influence ideal planting dates.

Fourth, not all harm is equal in terms of crop damage. For example, a day with a minimum temperature of -10 ºC and a day with a minimum temperature of -5 ºC are both considered a severe-harm day in this study. However, a minimum temperature of -10 ºC is more harmful than a minimum temperature of -5 ºC. Additionally, there was no distinction made between early-season harm and late-season harm. However, corn responds differently to weather conditions during specific periods in the plant's growth process. With regards to moisture, it is most important for the plant to receive adequate precipitation during the CPW. Drought conditions during the CPW produce more extensive damage than during any other period. Therefore, it is expected that a more complex ranking system would produce a more accurate depiction of the ideal planting date. Future research may include values of 2, 0, and -2 for optimum, neutral, and poor growing conditions (Moeletsi, Moopisa, and Tsubo 2013) to further determine thresholds for optimum growth.

Fifth, this study does not differentiate between stratiform and convective precipitation. Stratiform rainfall spread evenly over multiple days is typically preferred for agriculture, as it is allowed to gradually infiltrate into the soil and become available to the crops. Convective rainfall is often heavier and falls quicker, leading to soil erosion and field flooding.

Lastly, soil moisture was not taken into account for this analysis. Soil moisture plays a significant role in the overall production of crops as well as the resiliency of crops to extreme conditions. Excessive heat occurring when soil is dry will be more detrimental to crops than heat occurring when soil moisture is sufficient. Therefore, a day classified as harmful in this study could potentially be less harmful if adequate soil moisture is available for the plant. Additionally, this study assumes that no irrigation has been implemented to increase water availability to crops. Future studies focusing on ideal planting dates should consider the above limitations and alter research methods to best model real observations.

CHAPTER IV

SUMMARY AND CONCLUSION

The analysis of annual ideal planting dates for three locations in Mississippi shows that there is no specific range of planting dates that is consistently best for each year. Therefore, it cannot be stated that corn producers should always plant before a specific date. However, perhaps most important is the result that early planting dates are more likely to experience moderate harm while late planting dates are more likely to experience severe harm. This supports the theory that late-season corn planting is more harmful to crops due to extreme heat and drought. Planting dates in early March may limit exposure to extreme heat and drought in summer months, limiting crop loss and stabilizing yields. Additionally, considering planting dates in the early growing season gives producers more time to decide when to plant corn based upon current field and weather conditions.

No relationship was found between ideal planting dates and total number of harm days. However, severe-harm characteristics produced significantly fewer harm days than moderate-harm characteristics. It is important to note that harm days analyzed in this study may not necessarily result in crop death, but are representations of risk associated with exposing crops to less-than-ideal weather conditions.

No evidence of regional climate change was found for Stoneville, Mississippi during this study period. Although the average number of harm days over the past 10 years has varied from the previous 16 years, the results are not statistically significant. This indicates that changes experienced in the growing season over the past ten years are likely due to natural variations in weather patterns that fall well within the confidence interval of the previous 16 years. Future research may wish to address this topic again once more data becomes available for analysis.

This study does support the hypothesis that global teleconnection patterns may influence the timing of the growing season in Mississippi. Results from the linear models show that regressions between January teleconnection indices and ideal planting dates produce consistent R^2 values, signifying a relationship between teleconnection patterns and the growing season. However, RMSE values between 20 and 30 days prove that the models are unable to accurately predict ideal planting dates. Due to the high amount of error, there is currently no operational value to these models. However, this is an area of research that may be useful in future climate change scenarios. Future research could extend this analysis to include other regions of the United States, longer periods of record, and more complex ranking systems to identify risk periods.

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