WEATHER, CORN AND SOYBEAN YIELDS, AND TECHNOLOGY IN THE U.S. CORN BELT

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1. INTRODUCTION

Corn and soybean yields in the U.S. Corn Belt are primarily determined by weather and technology. Research on the relationship between weather, technology, and yields dates to the early 1900s, but the exact relationship remains a subject of debate. Although it is well recognized that summer precipitation and air temperature directly influences yield potential, other factors also affect corn and soybean yields. These include soil quality, planting date, disease, insects, and technological improvements from hybrids, fertilizers, and producer management techniques.

Despite decades of research relating weather and technology to corn and soybean yields, yields are sometimes unexpectedly high or low. For example, corn yields across Illinois in 2003 were much higher than expected despite a close following of growing season weather (Changnon and Hollinger 2004). The less than complete understanding of weather-technology-yield relationships is of particular concern given recent and expected increases in global temperature (NCDC, Climate of 2006 – Annual Report). Local and regional climate and weather could be altered by warmer global temperatures, yet the effect of the current climate and weather on yields is not fully understood (Wilbanks and Kates 1999). Climatological changes would further complicate important producer-level crop management decisions.

In recent years, there has been considerable speculation that the relationship between weather, technology, and corn yields has changed. Some research has concluded that a higher trend yield for corn was established in the mid-1990s. Seed companies attribute the yield increases to improved genetics and biotechnology (Fitzgerald 2006). Figure 1, adapted from Troyer (2006), is a typical example of the
“trend acceleration” interpretation of the history of U.S. corn yields since the mid-1990s. While higher yields might be due to a new trend, such claims should be treated with caution since weather can have a large effect on trend yields estimated over short periods of time (Nafziger 2004; Nielsen 2006). Soybean yields have received less attention because recent trend rates do not appear to have increased significantly.

These arguments are not unprecedented, as similar discussions surfaced a generation ago. Thompson (1975) examined the same issues after unfavorable weather caused unexpectedly low yields in 1974. Prior to 1974 there had been “… frequent reference in the early 1970’s to the fact that technology had advanced to such a level that weather was no longer a significant factor in grain production.” (p. 535) The following years showed that weather remained a very significant determinant of yields, as particularly severe corn and soybean yield losses occurred from unfavorable weather in 1983, 1988, and 1993. Historical considerations and current discussions provide ample motivation for additional inquiry into the relationship between weather, technology, and corn and soybean yields in the U.S. Corn Belt.

1.1 Background

Several methods can be used to estimate the relationship between weather, technology, and crop yields. Kaufmann and Snell (1997) categorize the various methods into two groups. The first group consists of crop weather models that directly assess the effects of weather and soil properties on plant physiology. These types of models are useful because they focus on the specific influences of known physiological and biological factors that affect plant development throughout its growth cycle. Despite the
usefulness of such models, they exclude the influence of technological advances over time and have somewhat poor explanatory power.

The second group consists of multiple regression models that estimate the relationship of weather and technology to crop yields. Multiple regression models have an advantage over crop weather models because they capture both weather and technological aspects of yield variation (Kaufmann and Snell 1997). Multiple regression models are limited by large spatial scales that may poorly reflect local weather, which in turn directly affects crop development and yields. However, the high explanatory power of multiple regression models and their ability to represent both weather and technology is particularly useful. Therefore, the following discussion focuses on studies that utilize regression methods.

Smith (1914) used simple correlations to determine the influence of rainfall and temperature on corn yields. July rainfall was shown to be the most dominant factor affecting yields in Ohio and the Midwest, as higher rainfall during this month would be expected to increase yields. However, Wallace (1920) disputed this finding by showing that July rainfall was not the most dominant factor in all areas, and that air temperature also played an important role. These studies were important to the advancement of agriculture and showed that summer weather was vitally important to corn production.

Subsequent studies utilized the increasing availability of computers and faster processing speeds to develop more sophisticated weather-technology-yield regression models. These culminated with several publications by Thompson (1962, 1963, 1969, 1970, 1985, 1986, and 1988), who developed regressions of the relationship between technology, monthly rainfall, monthly temperatures, and corn and soybean yields. His
most significant findings were: i) corn yields were particularly boosted by abundant rainfall during July and cooler-than-usual temperatures during August, ii) above-average July and August rainfall particularly boosted soybean yields, and iii) favorable weather in the early 1960s coincided with rapidly increasing corn yields, which provided evidence that technology was not solely responsible for observed yield increases.

While the previous studies pioneered the use of weather-yield-technology regression models, the models were not tested with modern diagnostics that are now available to identify autocorrelation, heteroskedasticity, mis-specification, and structural change. These tests are relatively simple to perform with statistical software packages that can be installed on personal computers. The diagnostics are important because they help to determine the reliability of regression output, which increases or decreases confidence in the output.

In 1975, Thompson noted that there had been minimal corn yield variability since the 1950s. This led to “more than usual” concern when unfavorable weather in 1974 led to low production at a time when ending stocks were already at 20-year lows. It discredited the theory that technology had increased such that weather was no longer important. In fact, considerable speculation developed that yields may have been leveling. Swanson and Nyankori (1979) showed that corn yields had not been leveling, and instead unfavorable weather years over 1950 through 1976 had reduced the trend yield. Garcia et al. (1987) also argued that corn yields had not been leveling, and instead appeared probable to continue to increase.

Few studies have examined data from the 1990s onward. Teigen (1991a and 1991b) developed weather-technology-yield regressions for corn and soybeans for
various areas of the U.S. Data included observations from 1950 through 1988. The models initially utilized similar monthly weather variables, but dropped insignificant variables to develop final regressions. The final regressions were then used to forecast yields from 1989 through 1991 and forecasts were compared to observed yields and official U.S. Department of Agriculture (USDA) crop production forecasts. Although the models performed “satisfactorily,” there were large errors across several regions. Teigen and Thomas (1995) updated the earlier studies by Teigen with data from 1950 through 1993, although 1993 was excluded for the Corn Belt due to historic summer flooding. Forecasts for 1994 missed corn and soybean yield observations by more than two standard errors, which led to the conclusion “… that yields in 1994 probably were not generated by the same process that operated during the 1950-93 estimation period.” (p. 19)

The aforementioned studies provided strong evidence that technology had not reduced the importance of weather. Evidence was verified by particularly low corn and soybean yields that were induced by weather in 1974, 1983, 1988, and 1993. However, the same topic has resurfaced today. In fact, there is widespread belief that today’s technology has made yields less dependent on weather. However, the issue of technology acceleration and its relation to weather has not been thoroughly evaluated with recent data. In addition, previous studies examined a very small number of forecasts, and therefore did not provide a consensus as to whether multiple regression models provided poor or useful yield forecasts. Finally, previous studies did not examine the possibility of combining regression model forecasts with USDA forecasts to develop superior composite forecasts.
1.2 Objectives

The potential usefulness of multiple regression models to estimate the influence of weather and technology on yields is compelling. Such models combine the physical and social aspects of yield modeling. Previous studies that used multiple regressions to estimate the effect of weather and technology on corn and soybean yields did not apply a rigorous set of diagnostic tests that are commonplace today. The diagnostics can help determine the validity of model output. Multiple regression models can also be used to determine possible reasons for recent yields that have seemingly outperformed the long-term trend. Finally, regression models can also be used to develop a set of forecasts that may be assessed relative to benchmarks.

The purpose of this research is to develop and estimate multiple regression models of the relationship between weather, technology, and corn and soybean yields in the U.S. Corn Belt. The models are based on specifications found in studies by Thompson (1962, 1963, 1969, 1970, 1985, 1986, and 1988). The models are applied to yield and weather observations from Illinois, Indiana, and Iowa over 1960 through 2006. Three key questions are addressed:

- Has the relationship between temperature, precipitation, technology, and corn and soybean yields in the U.S. Corn Belt changed since the last comprehensive studies? The null hypothesis is that the effect of technology and weather on yields will remain similar to earlier publications. The alternative hypothesis is that the effect of technology and weather on yields has changed.

- Has the trend rate of yield growth for corn accelerated since the mid-1990s? The null hypothesis is that the recent increase in corn yields is due to both
technological improvements and favorable weather. The alternative hypothesis is that the recent increase in corn yields is primarily due to favorable weather conditions.

• How do yield forecasts from the multiple regression models compare to benchmark forecasts? The null hypothesis is that regression yield forecasts will not outperform trend-only or USDA forecasts. The alternative hypothesis is that both trend and USDA yield forecasts outperform forecasts from the regression models.

1.3 Data and Methods

Regression models are developed for corn and soybean yields in Illinois, Indiana, and Iowa. These three states are chosen because: i) they represent over 40% of United States corn and soybean production from 2002 through 2006, ii) have fairly similar soil quality, and iii) experience similar weather. Modifications to Thompson’s original model are performed due to: i) changes in planting practices since the early 1960s, ii) patterns in the data, and iii) the desire to increase degrees of freedom for estimation.

Final corn and soybean yields for each year are obtained from the NASS Crop Production Annual Summary. This data is available electronically via the Internet (NASS, Quick Stats: Agricultural Statistics Data Base). Monthly weather observations are collected from each state’s climatologist office. Each office follows specific measurement and reporting procedures that are outlined by the National Climatic Data Center. This means that the weather observations are credible and reported with similar
methods and techniques. A descriptive analysis of weather and yield characteristics is presented.

Regression models of corn and soybean yields are developed with observations on: i) monthly precipitation, ii) monthly temperature, and iii) time to represent technology. Diagnostic tests for heteroskedasticity, autocorrelation, and mis-specification are performed on the models to assess the validity of model estimates. Coefficients of the estimated models are analyzed to determine the expected relationship between yields, technology, and weather. These results are compared to previous publications to determine if changes have occurred. Specifically, formal parameter stability tests are used to detect significant structural changes in the models over the sample period. The estimated models are also used to determine the effect of weather on trend yields. Weather since the mid-1990s is reviewed to assess if favorable weather has coincided with recently increased corn yields. Parameter stability tests are once again applied to determine if a significant change in trend yield growth occurred in the mid-1990s.

A monthly forecast competition is performed from 1980 through 2006. Out-of-sample forecasts are obtained from the weather-technology-yield models and compared to benchmarks represented by a trend-only version of the model and USDA forecasts issued in August, September, and October. The performance of the forecasts is assessed using standard accuracy measurements, such as mean absolute error and root mean squared error. Statistical significance of differences in forecast accuracy are assessed using the modified Diebold-Mariano test. Since the multiple regression model and USDA forecasts are obtained with different sets of inputs, modified Diebold-Mariano
tests are calculated to determine if significant improvement would occur if these forecasts were combined into composite forecasts.

1.4 Thesis Overview

To understand the weather-technology-yield relationship and the usefulness of weather and technology to forecast corn and soybean yields, the remainder of this thesis is divided into three chapters. Chapter 2 chronologically documents the literature that helped shape the general understanding of the relationship between weather, technology, and corn and soybean yields. This chapter is divided into three sections. The first section discusses earliest publications that unveiled the importance of weather and technology to yields. The second section discusses more advanced estimation techniques that used regressions and computer technology to aid statistical analyses.

Chapter 3 discusses the weather and yield data that is used in this thesis. Data sources and the methods used to generate the observations are discussed. Descriptive analyses of the trends and characteristics of the data are included.

Chapter 4 first reviews regression models developed by Thompson (1962, 1963, 1969, 1970, 1975, 1985, 1986, 1988) to estimate the relationship between corn and soybean yields and weather and technology. His model is modified to account for changes in planting practices since the 1960s and is applied to weather and yield observations from Illinois, Indiana, and Iowa over 1960 through 2006. Statistical tests are performed to assess the reliability of model output. The current relationship between weather, technology, and yields is also discussed, as well as the usefulness of the models.
to estimate yields. The possibility that technological improvements have increased trend yields is examined.

Chapter 5 assesses the usefulness of the regression model to forecast corn and soybean yields. Monthly trend-only forecasts and monthly yield forecasts from the USDA serve as benchmarks. Encompassing tests are performed, and the improvement in combining weather model and USDA forecasts into a single composite forecast is also examined.

Chapter 6 summarizes the current relationship between weather, technology, and corn and soybean yields in the United States Corn Belt. The impact of weather on trend yields and the usefulness of such models to forecast yields are discussed. Finally, the implication of this research for future studies is presented.
2. REVIEW OF LITERATURE

2.1 Introduction

Journal articles and publications are reviewed in this section of the thesis to gain a better understanding of the literature on the relationship between weather, technology, and corn and soybean yields in the U.S. Corn Belt. It will also help to develop the necessary background for the development and analysis of the weather-technology-yield regression model presented in the next chapter.

There are two major types of models used to estimate the effect of weather and technology on yields (Kaufman and Snell 1997). The first group consists of crop weather models that utilize knowledge of plant physiology, weather, and soil properties to estimate yields. The interaction of these factors during specific stages of crop development is used to estimate their influence on yields. However, the usefulness of these models are limited because they only incorporate the physical aspects of yield potential and fail to incorporate the technological factors that cause yields to steadily improve over time.

The second group consists of multiple regression models that utilize weather observations and technology to estimate yields. The models do not focus on specific stages of crop development and plant physiology, but typically use large spatial observations of monthly weather to relate to yields. This limits the ability of multiple regressions to assess the exact influence of weather during critical periods. However, a key advantage over crop weather models is that they include time or other measures to represent technological advances that cause annual yield increases.
A central focus of this thesis is to develop a model that accounts for both the physical and social aspects of yield variation. The multiple regression method best accomplishes this purpose. Therefore, the review of literature focuses on publications that utilized the regression method. The majority of the studies were collected from academic journals and government publications from 1914 to the present day. The studies were chosen because they significantly advanced knowledge about the relationship between weather, technology, and yields.

This section of the thesis is divided into two parts. The ‘Pioneer Studies’ section reviews articles published during the acquisition of basic weather-technology-yield knowledge from 1914 through the early 1950s. The ‘Modern Studies’ section reviews articles published from the late 1950s to the present time when advances in computer processing speeds allowed for more in-depth statistical analyses.

2.2 Pioneer Studies

Smith (1914) published the first statistical paper to determine the effect of weather on corn yields in the central United States. The study was built upon accepted theory that every plant had optimal air temperatures, moisture, soil qualities, and periods that most enhanced growth. The paper was deemed important because approximately 75% of world corn production occurred in the United States as of the publication date. Therefore, its importance to the economy and the lack of fundamental weather-yield knowledge led Smith to quantify the relationship. Several correlation coefficients were developed from various linear regressions to determine the impact of monthly rainfall and temperatures on yield. A time trend variable was also included to account for annual
yield increases due to technological improvements. However, the level of significance for each coefficient was not listed.

Ohio corn yields were analyzed with June, July, and August rainfall from 1854 through 1913. July rainfall had the highest correlation coefficient (r) of +0.59, though combined July and August rainfall had a higher coefficient of +0.67. He concluded “this makes it plain that the rainfall for the month of July has a far greater effect upon the yield of corn in Ohio than either June or August … but that the rainfall for July and August combined has a greater effect than for July alone.” (p. 80) Increased frequency of July rainfall events enhanced yield, as additional 0.25”, 0.50”, and 1.00” rains improved yield by 0.8, 1.2, and 2.3 bushels per acre, respectively. July rainfall of at least 3.00” appeared most beneficial because years with 2.50” to 3.00” averaged 29.8 bushels per acre, while years with 3.00”- 3.50” years averaged 4.3 bushels per acre more.

Various data sets for Ohio from 1891 through 1910 were also examined during 10-, 20-, 30-, 40-, and 50-day periods to determine when yield was most affected by weather. 10-day rainfall for Wayne County from July 11 through July 20 had a correlation coefficient of +0.71, which was the highest of all periods studied. However, results were “seriously doubted” because coefficients were 0.12 from July 1 through July 10, and 0.16 from July 21 through July 31. Therefore, the central Ohio counties of Franklin, Madison, and Pickaway were grouped to compare results. The 3-county combination had coefficients ranging from +0.49 to +0.60 for different lengths of period during July and August. Smith thereby concluded that rainfall from mid-July through mid-August most influenced yield, while impacts were minimal outside of July 1 through August 10. However, he noted that correlation coefficients should also be calculated for
other districts because different rainfall, temperature, or sunshine distributions could alter results.

Through the recognition that plants were unable to develop and grow at air temperatures below 6°C (43°F), Smith used “thermal constants” and “rainfall constants” to predict crop progress and yield. Thermal constants were calculated by summing daily mean temperature, and then subtracting 43°F. Negative values were omitted. Rainfall constants were calculated by summing daily rainfall during various periods. The data was provided by a local farmer who kept detailed records from 1883 to 1912 at Wauseon, Ohio.

Analysis of the data indicated that planting to emergence averaged 9 days and 143 thermal constants; emergence to tasseling 62 days and 1,599 thermal constants; and tasseling to ripening 50 days and 1,337 thermal constants. However, minimal relationship between thermal constants and yields were found. Correlations of rainfall constants and yields using these stages of growth showed little correlation to the early portion of the growing season, but correlated well thereafter. In particular, the highest rainfall-yield correlation of the entire publication was $r = +0.74$ from the blossoming phase to 10 days after. Furthermore, coefficients of +0.57 and +0.46 were shown from blossoming to 20- and 30-days after, respectively. Smith concluded “…rainfall immediately after blossoming has a very dominating effect upon the yield of corn of any period in the history of the plant.” (p. 84) Additionally, a simple x-y plot of July temperatures and rainfall from initial blossoming to 10 days after showed 1) wet weather most enhanced yield, 2) warm and dry weather particularly lowered yield, and 3) dry weather could be somewhat beneficial as long as temperatures were cool.
However, uncertainty remained regarding exactly how much rainfall per event would most benefit yield. For example, Smith noted that it was widely accepted that increased frequency of light rain events actually reduced yield because only the topsoil would wet. This would lead to shallow corn roots that were more susceptible to dry conditions. Therefore, he grouped the total number of rainfall events from June 21 through August 10 in increments of 0.01”+, 0.10”+, 0.20”+, 0.30”+, 0.40”+, 0.50”+, 0.60”+, 0.70”+, 0.75”+, 0.80”+, 0.90”+, and 1.00”+. It was determined that the number of 0.50”+ events best correlated to yield with $r = +0.70$ for Franklin County, and +0.64 for the group of central Ohio counties. It was noteworthy that correlation coefficients for increments under 0.50” ranged from +0.44 to +0.51 for central Ohio, but results “seem to show that one-half of an inch of rain is more beneficial than lesser amounts.” (p. 86)

Correlations using previous methods were also performed for the grouped combination of Illinois, Iowa, Indiana, and Missouri from 1888 through 1911 because they represented 30% of U.S. acreage. July rainfall most affected yield with a coefficient of +0.73, while July temperature was -0.61. The negative temperature correlation was attributed “to the fact that cool weather usually accompanies rain in July.” (p. 86)

Additionally, when these states were grouped with Iowa, Kansas, Kentucky, and Nebraska, the importance of July rainfall further increased with a coefficient of +0.78. The average yield for these states was 30 bushels per acre, but average yields decreased to 23 bushel per acre when July rainfall was at least 0.50” below average. Conversely, average yield increase to 33 bushels per acre when July rainfall was 0.50” above average. The yield difference represented 500 million bushels or $250 million with corn priced at
Therefore, July weather was clearly important to rural communities and the U.S. economy.

Smith concluded rainfall was the primary factor that influenced U.S. corn yields, particularly during July. The most important period of growth was relatively short and dominated by weather from blossoming to 10 days after. Reliable yield estimates appeared possible by August 10 through examination of previous weather. However, additional studies of critical growth periods and further advances in agricultural meteorology were required for weather yield estimates to be “of more practical value to the farmer”.

Wallace (1920) initially questioned conclusions by Smith (1914) that corn yields were most impacted by July rainfall. He believed that July rainfall may be the most significant weather variable impacting Ohio yields, but not in every state. Therefore, he analyzed monthly rainfall, temperature, and yield for Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, and Ohio to determine the impact of growing season weather on corn from 1891 through 1919. Correlation coefficients were developed from linear regressions and a time trend variable was included to account for annual yield increases.

Calculations indicated that rainfall influenced Ohio corn yields nearly identically as stated by Smith (1914), with July rainfall clearly the most explanatory variable. However, the impacts of rainfall and temperature on yields differed for each state. For example, July temperature had a larger impact than rainfall in Missouri. Iowa and Minnesota yields were not well correlated to July rainfall. Additionally, corn yields in Illinois were nearly equally impacted by July rainfall and temperature with coefficients of
+0.65 and -0.64, respectively. Therefore, Wallace determined it would be best to utilize each state’s three most important weather variables to develop models to forecast corn yields.

Multiple coefficients of correlation ranged from 0.86 for Kansas to 0.46 for Iowa. Significant discrepancies between actual and estimated yields existed. For example, Missouri yield in 1895 was estimated at 14% above average, though it was actually 33% above. The estimate for 1901 was 48% below average though it was actually 66% below. Since Iowa had a low multiple coefficient of correlation and its weather was deemed to differ across the state, site specific regressions were developed in place of the statewide model. Although the multiple correlation coefficient increased to 0.62, large improvements did not occur. However, the estimates were more accurate for Kansas, Missouri, and southern Illinois which led to the conclusion that weather-based corn yield prediction was “relatively simple” for the southern half of the Corn Belt.

Wallace theorized that the models were not useful yield estimators because 1) weather-yield relationships did not appear to be linear, 2) other factors could have significant effects on corn yield, 3) average monthly temperatures does not accurately reflect weather within months, 4) averaged monthly rainfall may be skewed due to rainfall’s localized nature, 5) averaged monthly rainfall does not account for runoff from high-intensity events, and 6) early frosts could reduce yields by 20% or greater regardless of previous weather. Therefore, he concluded “Each state is a specific problem in itself, and the probabilities are that each county in a state is a specific problem.” (p. 445)

Rose (1936) essentially built upon recommendations by Wallace (1920) and used 55 well-distributed counties to study rainfall- and temperature-yield relationships. Each
county was required to have a weather observation station and uniform soil. Various beginning dates were used, but all concluded in 1932. Variables beyond rainfall and temperature were not analyzed due to limited records. Over 2,000 correlation coefficients were calculated for each county with results plotted as isolines on a map of the central United States.

Rose quickly concluded that temperature correlated to yield more than previous studies had indicated. May temperature had correlation coefficients of at least +0.40 in northern Illinois and northeast Iowa, despite findings by Wallace (1920) that coefficients were +0.22 and +0.15 for Illinois and Iowa, respectively. Isolines showed warmer May weather was expected to increase yield in the northern half of Illinois, but yield was expected to decrease in the southern half with warmer temperatures. Therefore, he noted that statewide temperatures used in previous studies by Smith (1914) and Wallace (1920) covered too large an area and essentially hid its effect on yield.

Important impacts on corn yield were also shown across the western and far eastern Corn Belt. In these areas, the accumulated number of degrees greater than 90 degrees Fahrenheit (°F) each month had large impacts on yield. Portions of Kansas, Nebraska, South Dakota, and Minnesota experienced lowered yields in June, July, and August with increased accumulated degrees above 90°F. Spotty summer rainfall, low humidity, and shallow soil appeared probable to enhance the negative effects of hot weather in this region. The temperature-yield relationship was reversed but equally as important across northeast Indiana, eastern Michigan, and most of Ohio. Increased 90°F readings raised yield during summer months, which Rose theorized was because of climatologically higher absolute humidity.
July rainfall was deemed to have a “beneficial effect” on corn yield throughout the Corn Belt because the variable correlated positively in 49 of 55 counties. However, it was noted that coefficients were mostly less than +0.60. May, June, July, and August rainfall appeared to enhance yield for about 50% of the central U.S., particularly across Kansas, South Dakota, and Ohio during the mid-summer. Rose concluded rainfall-corn yield relationships were “by no means simple.”

Davis and Harrell (1942) believed that previous weather-yield studies may have been flawed because weather observations at specific locations were used to represent county-sized regions or larger. Therefore, they analyzed rainfall, temperature, and corn yield at plots located very close to a weather station. Weekly data were collected from May through August from experimental stations in Illinois, Kansas, Maryland, Missouri, Nebraska, Ohio, and Pennsylvania; field stations from the Bureau of Plant Industry in Colorado, Kansas, and Nebraska; and township corn yields and cooperative weather station observations in Iowa. Fisher’s (1925) method was used so that the impacts of rainfall and temperature were independent of other time periods.

Before analyses were performed, Davis and Harrell noted the impact of weather was likely affected by soil fertility. Rotations, fertilizer applications, and lime treatments probably affected the importance of rainfall timing. This appeared to be true at Wooster, Ohio where it was shown that the total amount of rainfall was important for yield, but the exact timing of rainfall was not as important. This was likely due to favorable soil properties at Wooster. Therefore, they noted that soil fertility may have been overlooked as a significant variable in previous studies.
Third-degree regressions (regressions that use linear, squared, and cubed variables) of average weekly rainfall were developed for each location to determine the expected impact of an additional inch of rain on corn yield. The multiple correlation coefficient at Wooster, Ohio was +0.47, but as mentioned the importance of rainfall timing was likely hidden by optimal production practices. Nonetheless, increased rainfall during July and early August would be expected to most improve yield at Wooster. The multiple correlation coefficient at Urbana, Illinois was +0.59. However, it was noted that corn was not rotated each year at the plot and that rainfall averaged lower than was optimal. This helped explain why the correlation was stronger and showed rain was particularly needed from the end of June forward. Western areas of Colorado, Kansas, and Nebraska indicated that dry conditions often prevailed and more total rainfall was needed. Additionally, severe thunderstorms accompanied by high soil runoff probably led to misrepresentative rainfall observations. At College Park, Maryland a strong rainfall-yield correlation was unidentifiable because rain amounts were nearly optimal each year. State College, Pennsylvania correlation results were not important which was theorized due to 4-year corn, oat, wheat, and hay rotations. A conglomerate of six western Iowa towns revealed the multiple correlation coefficient was only +0.28, though good soil fertility was believed to adequately retain moisture and possibly reduce the importance of rain. At Columbia, Missouri, rainfall was a statistically insignificant predictor of yield which differed from the conclusion by Wallace (1920) that corn yield prediction in the south was “relatively simple”. Instead, Davis and Harrell stated the rainfall-corn yield relationship “becomes increasingly difficult to express as we proceed from the western margin of the Corn Belt to the eastern margin”.
Third-degree regressions based on average weekly maximum temperature were also developed for each location to determine the expected impact of temperature on corn yield. At every location except Urbana, Illinois, a statistically significant amount of corn yield variation was explained by the temperature regressions. However, it is noteworthy that western areas were not examined due to limited data. Nonetheless, 90% of the variation in corn yield was explained by maximum temperature at Manhattan, Kansas; 76% in western Iowa, 72% at Lincoln, Nebraska; 58% at Columbia, Missouri, and 56% at Wooster, Ohio. However, extreme heat during 1934 and 1936 may have overestimated the true importance of temperature. Notably, July and August maximum temperatures were always too warm and it appeared that yield would increase with cooler temperature. June high temperatures were usually too warm as well, though warmer June weather would enhance yields at Wooster, Ohio and State College, Pennsylvania. May high temperatures were deemed less important than other months with Illinois, Kansas, and Nebraska too warm; Iowa neutral; and Maryland, Missouri, Ohio, and Pennsylvania too cool. However, Davis and Harrell noted that May rainfall probably reduced the impact of May temperature.

2.3 Modern Studies

Runge and Odell (1958) stated that previous weather-corn yield studies had been limited by small data sets, distances between weather stations and yield plots, and limited computational technology. Their study sought to reduce these issues by analyzing weather-technology-corn relationships at a fixed corn plot at Urbana, Illinois. The plot had been under relatively consistent management with data available from 1903 through
1956. However, it was necessary to convert open-pollinated yields during 1903 through 1939 to hybrid equivalents. Weather data was obtained from the official Urbana, Illinois station located 1.08 miles north of the plot.

Maximum temperature and precipitation during the growing season were used to develop a model that could explain corn yield variation. Different variations of first-, second-, third-, and fourth-degree regressions were developed to determine which was most representative. The growing season was given a maximum 112-day length that began on either May 12 or a silking-related beginning date. Each 112-day period was then divided into 14 eight-day and 56 two-day intervals. To determine the impact of length of period on the study, eight-day intervals were successively removed from the end of the growing season and re-regressed, followed by removal of the eight-day period from the beginning of the season and re-regressed. This process was continued until one eight-day period remained. A time trend variable was not initially included to limit multicollinearity between variables, but was added to the final model for comparisons.

Weather explained 67% of the variation in corn yield from 74 days before to 30 days after silking, as well as 50 days before to 14 days after silking. The latter was deemed the better model because of the shorter time period and a simpler second-degree equation (versus a fourth-degree equation). Higher than average precipitation was particularly beneficial to yield just before and during silking, while above average maximum temperatures during this time were most detrimental. Precipitation-temperature interactions appeared to exist because hot temperatures were often associated with dry weather, and cool temperatures with wet weather. When the linear time trend variable was introduced, the explanatory power of the regression increased from 67% to
75%. Runge and Odell concluded precipitation was most beneficial from one month before to during silking, and that future research should attempt to determine the economic feasibility of irrigation during this crucial period.

Given the rapid increase in soybean production across the central United States, Runge and Odell (1960) stated that although several studies were conducted to relate weather to corn yields, no study was known to exist which related weather and technology to soybean yields. Therefore, they explored the weather-technology-soybean relationship with the same methods as their previous weather-technology-corn yield study. A fixed beginning date of June 1 was used to develop the model. A model using a variable beginning date was not developed because reliable growth stage measurements were not available. Weather and yield data were obtained for the same plot used in their previous corn study in Urbana, Illinois. However, the time period included 1909 through 1957 as opposed to 1903 through 1956.

Maximum temperature and precipitation from June 25 to September 20 explained 68% of soybean yield variation. Maximum temperature throughout the entire period was too warm and decreased yield, though soybean-precipitation interactions appeared to be more complex than for corn. In particular, above-average June precipitation appeared to decrease yield while above average July precipitation greatly increased yield. This was apparently due to quick plant development during the month of July. However, above average precipitation during the first half of August decreased yield, as heavy rain may have prevented pods from maturing. Above average precipitation from mid-August through mid-September appeared to increase yield because it helped pods fill. But late-September precipitation decreased yield, as it probably caused pods to lodge and shatter.
Due to the lack of data regarding soybean development stages, Runge and Odell stated “More basic research relating soybean development to day length, degree days, etc., is necessary before it will be possible to satisfactorily estimate various developmental and physiological stages from planting dates and available weather data.” (p. 247) Although exact relationships were not concluded, the authors deemed the study useful because: 1) it showed that weather was important to soybeans, and 2) that the response of soybeans differed from corn.

By the early 1960s, large grain stock surpluses led Thompson (1962) to state that they were partially due to rapid corn yield increases from the mid-1930s through the 1950s. He also noted that belief existed within the agricultural community that much of the increase was due to an “explosion of technology.” However, he accredited some of this belief to a study by Ezekiel (1941) that incorrectly concluded that technology, as indicated by annual yield increases, was more important than summer temperatures and rainfall. Therefore, to determine the importance of weather and technology on corn yield, Thompson developed a multiple regression model to evaluate their effects. Variables included monthly rainfall and temperatures for June, July, and August that were separately modeled for Iowa, Illinois, Indiana, Missouri, and Ohio from 1935 through 1961. A single linear time trend variable was included to account for the: 1) adoption of hybrid corn in 1935, 2) introduction of nitrogen fertilizer in 1945, and 3) overall farming improvements. Yield and weather data was obtained from the USDA and monthly Climatological Data publications, with weather records converted from district-level to state-level through a weighting method.
Linear regressions explained 65% of the variation in corn yield in Iowa; 76% in Ohio; 82% in Indiana; 84% in Illinois; and 90% in Missouri. July rainfall was clearly the most important variable, as an additional inch of rain would be expected to increase corn yields approximately 2 to 3 bushels per acre in each state. The results for Ohio were similar to the conclusion by Wallace (1920) that July rainfall most significantly affected Ohio yields. August temperature was next most important, as readings 1°F cooler would be expected to increase yield 0.5 to 1.5 bushels per acre. However, the magnitude and significance of each weather variable varied across states. For example, June temperature was only significant in Iowa, and July temperature was insignificant in Indiana and Ohio. A new regression was calculated by omitting insignificant variables for each state. However, it only minimally changed the explained portion of yield variation.

The underlying assumption in the previous model was that increased departures from average had an equal effect on yield. However, it was known that this assumption was flawed. For example, too much rainfall could decrease yield due to flooding. The study by Ezekiel (1941) had indicated the usefulness of curvilinear regressions. Therefore, Thompson recalculated the model by using quadratic terms for all weather variables. This model improved and explained 89% of the variation in corn yield in Iowa; 90% in Ohio; 86% in Indiana; 89% in Illinois; and 95% in Missouri. Yields were usually larger than predicted during years with favorable weather, and less than predicted with unfavorable weather. However, autocorrelation in the error terms did not exist.

In attempt to separate the effects of weather and technology, trend yields for 1958, 1959, and 1960 were compared to actual yields. Favorable weather was shown to have increased corn yields 7.2% each year, which was approximately the same amount
stocks increased during this period. Thompson stated that “… weather factors were partially responsible for the build-up of feed grain surplus during the period 1958-1960. This concept is in contrast with the belief that an “explosion of technology” occurred during the decade of the 1950’s.” (p. 18) For comparison, a regression from 1950 through 1961 was developed which only included the time trend variable. The coefficient doubled, which could have led an observer to incorrectly conclude technology as having increased at twice the actual rate since 1950. Thus, it was shown that weather was a significant yield-affecting variable and that technology alone could not explain observed yield increases.

Thompson also examined the sudden corn yield increase from 1960 to 1961. This was particularly important because 1961 yields were 6 to 11 bushels per acre higher in each state than 1960. July rainfall and August temperature were more favorable for corn yields in 1961 than any year dating to 1935, with July rainfall ranging from 1.16” to 2.82” higher than 1960. Additionally, August temperature was 0.8°F to 2.9°F cooler in each state. By entering actual weather variables into the models and subtracting the effect of technology, it was shown that improved weather in 1961 accounted for approximately two-thirds of the yield increase. Technology accounted for the remaining one-third. However, technology accounted for an additional 2.1 to 3.8 bushels per acre, which was approximately twice the average rate. This was deemed plausible due to introduction of a feed grain program in 1961 which encouraged reduced acreage. Therefore, producers had responded by increasing plant population and fertilization rates.

Despite determining that a large amount of corn yield variation was explained by weather and technology, Thompson noted that unmeasured variables such as pre-season
precipitation, soil moisture, late season frosts, and distribution of weather within months were probably also affected yield. He also concluded results “… could be greatly improved if data of weekly or bi-weekly periods were used.” (p. 25)

Given conclusions from his previous study, Thompson (1963) updated it with additional data for corn and replicated the same techniques to determine the impact of weather on soybean yield. In particular, May temperature, pre-season precipitation, and monthly rainfall-temperature interaction variables were included in the regression. The interaction variables were added to reduce over- and underestimation of yields during particularly favorable and unfavorable weather scenarios. Weather and yield data were analyzed from 1930 through 1962, as opposed to a beginning date of 1935. This alteration was made because it had become apparent that the introduction of hybrids in 1930 was hidden by unfavorable weather. He stated the results of curvilinear multiple regressions would be considered more representative because “… it is now apparent that linear regression analyses are inadequate to measure the effects of either rainfall or temperature.” (p. 3)

For comparison purposes, linear corn yield regressions were estimated with variables for monthly rainfall and temperatures from June through August, May temperature, total “pre-season” precipitation from the previous September through May, and a time trend variable. The models explained 74% of the variation in corn yield in Iowa; 86% in Ohio; 88% in Indiana; 86% in Illinois; and 92% in Missouri. July rainfall was clearly the most important variable and was similar in magnitude as the 1962 study with each additional inch expected to increase yield two to three bushels per acre. August temperature was next most important as readings 1°F cooler would be expected to
increase yield 0.4 to 1.2 bushels per acre. This result was also similar to those found previously. May temperature was generally insignificant.

Quadratic multiple regressions were estimated with all variables because high-speed computing technology was available. The time trend variable remained linear, and the May temperature variable was dropped in Indiana, Iowa, and Ohio due to insignificance in the linear model. Results indicated that with average rainfall hot temperatures in August are more harmful to yields than heat in July, but that “weather can be too cool in August as well as too hot.” (p.23) However, Indiana and Ohio yields were less volatile than the remainder of the Corn Belt. Unusually high yields were noted in 1942, 1948, 1958, 1961, and 1962, which Thompson attributed to the possibility of unmeasured weather-fertilizer and soil moisture-nitrogen interactions during the most recent two years.

Optimal temperatures for maximum crop yields varied little across Illinois, Indiana, and Iowa as it appeared farmers chose varieties that were well adapted for local climate and soil conditions. However, ideal temperatures appeared to depend on the amount of rainfall. For example, the optimal temperature in Iowa rose as the amount of rainfall increased. However, it was known that increased temperatures and lower rainfall lowered Iowa yield as had been observed in 1934. Low corn yields occurred for the same reason for a majority of the Corn Belt in 1936, 1950, and 1951. Importantly, average monthly temperatures greater than 80°F appeared to be more damaging in August than July, but weather could also be too cool in August. It was concluded that the combined effect of temperatures and rainfall impact corn yields dependent on the magnitudes of each.
Thompson noted that soybeans had become a crop alternative for corn due to government programs initiated in 1934 that controlled available corn acreage. In turn, Iowa soybean acreage skyrocketed from 66,000 acres in 1930 to 3,405,000 acres by 1962. This led some to believe that soybean acreage controls would eventually be implemented. Therefore, Thompson examined the effects of weather and technology on soybean yield due to its increasing agricultural importance. The same variables as in the corn portion of the study were used.

Linear regressions explained 81% of the variation in soybean yield in Iowa; 85% in Ohio; 90% in Indiana; 86% in Illinois; and 94% in Missouri. August rainfall was the most important variable, as each additional inch would be expected to increase yields 0.3 to 0.7 bushels per acre. July rainfall was the next most important variable, as soybean yield would be expected to increase 0.2 to 1.2 bushels per acre with each additional inch. August temperature was third most important, as above average values would be expected to slightly reduce yields. Notably, it was shown that optimal June and July temperatures in Iowa, Indiana, and Ohio were above the average, while ideal Illinois and Missouri temperatures were approximately at the average.

Curvilinear regressions which included all variables indicated that favorable weather for soybeans was similar to corn, though differences were noted. August rainfall had a larger impact on soybean yields than July rainfall, as soybeans’ shallow roots suggested rain was needed later in the season to intake nitrogen from wet soils. Too much rain in June or July was noted to occasionally reduce soybean yield, though optimal June, July, and August temperatures were approximately the same for both crops. However, Thompson noted data that is more basic was needed regarding soybean plant
development. He theorized that weather was most important to soybeans during the
development stages that determined the: 1) number of flowers, 2) number of pods that
mature, and 3) seed size. Although soybean-yield relationships remained somewhat
obscure, it was concluded that “Weather variables are just as important in explaining
yield variations in soybeans as for corn.” (p. 46)

Runge (1968) built upon the idea that rainfall-temperature interactions had a
significant impact on corn yields. Therefore, he specifically attempted to quantify this
relationship with particular emphasis regarding the evolution of the interaction during the
growing season. He calculated rainfall-maximum temperature interaction variables for
each two-day and eight-day period from 1903 through 1956 using weather data from a
station in Urbana, Illinois. The same methodology from his 1958 and 1960 studies was
applied, with yield data also obtained from a plot under constant management in Urbana.

The regressions indicated that maximum temperatures 10°F above average or
rainfall 1.00” below average during eight-day periods did not necessarily reduce yield.
This was because favorable rainfall or temperatures under such conditions influenced
corn development. Furthermore, it was shown that weather was most important from 25
days before to 15 days after silking, or roughly June 30 through August 8. The largest
impact on yield occurred during the two-week period leading into silking. Importantly,
“… rainfall had very little effect on corn yield 25 days after silking because corn is
approaching physiologic maturity.” (p. 506) Rainfall appeared to have a larger yield
impact than temperature, though the combination of dry and warm weather was
particularly damaging.
Additionally, it was shown that meager rainfall and hot temperatures reduced yield more than abundant rainfall and cool temperatures increased it. For example, during the two-week period around anthesis (pollination) yield would be expected to increase 5% when rainfall was 1.00” below average with an average maximum temperature of 75°F. However, yield would be expected to decrease 5% if temperature increased to 90°F, and decrease 15% with a 100°F reading. Conversely, the combination of a temperature 10°F above average and 3.50” of rainfall during the same period would be expected to increase yield 5%. However, 5.00” of rain would be expected to increase yield 15%, while no rainfall would be expected to reduce yield 20%.

Although this study was performed at a specific plot, Runge stated its findings should apply to much of the Corn Belt – particularly at locations with similar weather and soils. From largest to smallest impact, he concluded highest corn yield should occur with growing season temperatures 5°F to 8°F above average and rainfall 3.00” to 5.00” above average, temperatures near average and rainfall 1.00” to 2.00” above average, temperatures 2°F to 3°F below average and rainfall at average, or temperatures 5°F to 8°F below average and rainfall 1.00” to 2.00” below average.

Thompson (1969) noted that his previous publications in 1962 and 1963 were criticized because of small data sets that limited the degrees of freedom in the regressions. To reduce this criticism he pooled each state’s data to develop a single regression that represented the Corn Belt as a whole. Yield and weather data were aggregated for the states of Illinois, Indiana, Iowa, Missouri, and Ohio from 1930 through 1967. Variables included monthly temperatures for June, July, and August, July rainfall, September through May “pre-season” precipitation, and a linear time trend. August
rainfall was not included as a variable because minimal correlation to yield existed after pooling.

Corn Belt yields were impacted by July rainfall as much as the other variables combined. Dry July weather was expected to decrease yield more than wet weather would improve it. Lower than average June rainfall would be expected to increase yield, which had been previously demonstrated by Smith (1914). Near to slightly below normal pre-season precipitation would be expected to increase yield, as it probably encouraged timely planting and reduced weeds. Average June temperature and below average July and August temperatures were ideal, with above average August temperature particularly harmful because seed filling was compromised (Houseman 1942; Thompson 1962). It was also shown that exceptionally high yield had occurred during years with above average July rainfall, average summer temperatures, and average pre-season precipitation.

Thompson noted that given normal weather, yields had doubled since 1930 from higher nitrogen fertilizer application rates. Additionally, nitrogen use increased roughly 500% from 1960 through 1967 versus 1950 through 1960. Although “The rate of increase in the use of Nitrogen on corn has been the factor most closely associated with the technology trend,” (p. 455) favorable weather also played a significant role. For example, July rainfall during the 1960s was 12% above average while temperatures were below average in July and August each year. Therefore, the rapid increase in yield also coincided with favorable weather. A general decrease in yield variability since the 1930s was also noted, though he cautioned this may have been from a favorable and cyclical long-term weather pattern not yet proven to exist.
Thompson (1970) believed that increased world demand for soybeans would allow its U.S. acreage to become equal to corn within 10 years. Therefore, a better understanding of weather-soybean yield relationships was needed. Total soybean production had jumped 1,200% from 1944 through 1968, but total Corn Belt acreage reduced from 84% of all U.S. production to 50%. This was primarily due to the influence of government land controls on cotton, which caused a southward production expansion of soybeans. Using the same methods and states as his previous study of corn in 1969, Thompson developed a single curvilinear soybean model. Pooled variables included monthly June and August temperatures, July and August rainfall, pre-season September through June precipitation, and a linear time trend variable from 1930 through 1968. July temperature was not included as a variable due to its low level of significance after pooling, and the regression model indicated a concave yield relationship which was not theoretically correct.

July rainfall appeared to have the largest impact on soybean yields with a coefficient of +0.51, while August rainfall had a much lower coefficient of +0.11. However, combined July-August rain totals had a coefficient value of +0.45. The regression indicated that raising average monthly rainfall 4.0 cm (1.57”) would be expected to increase yield 1.5 bushels from July weather and an additional 1.0 bushels per acre from August. Much above average August temperature greatly lessened yield, as hot weather probably increased respiration and reduced sugar storage. However, very cool conditions slowed pod growth and reduced yield. This showed that August weather was more important for soybeans than corn since much of the variation in corn yield was determined by July rainfall. Near to slightly above average pre-season precipitation
would be expected to increase soybean yield, particularly because June rainfall seemed to increase soil moisture for rapid plant growth in mid-July. At the same time, optimal June temperature was higher than average because it probably increased its development.

It was noted that exceptionally high yields had occurred in 1961 and 1968. Each of these years had above average July-August combined rainfall, average June and August temperatures, below average July temperature, and average pre-season precipitation. Thompson believed this specific set of variables was required for high yields, as similar July-August rainfall in 1950 and 1951 had lower yields due to cool summer temperatures. Furthermore, despite abundant July-August rainfall in 1954, 1956, and 1964, high yields were precluded by very warm weather. Therefore, near normal summer temperatures and above normal July and August rainfall appeared ideal. He stated southward expansion of soybeans would cease due to its unfavorable climate, and the highest acreage share would return to the traditional Corn Belt, or as he preferred, the “Corn and Soybean Belt.”

Thompson (1975) noted that minimal corn yield variability had occurred from the mid-1950s through 1973, and some again believed that technological improvements had reduced the importance of weather. However, that perception changed in 1974 when low yields occurred after a very wet spring, summer drought, and an early killing freeze in the central U.S. Grain stocks were already at 20-year lows, and the high grain prices led to liquidations of hog, cattle, and poultry with inflation of food prices a result. The large impact of 1974 weather on the economy led Thompson to review known weather-yield relationships. He also attempted to determine the impacts of increased weather variability and continued global cooling that began in the 1940s.
Thompson noted that highest grain yields had occurred with below average summer temperatures. This was apparently because cooler growing seasons increased photosynthate storage from lowered respiration rates. Furthermore, cool summers often coincided with above average rainfall. Optimal monthly average June through August temperatures for corn and soybeans were around 72°F, while highs greater than 86°F or lows below 50°F were unfavorable. Best corn yields had occurred with higher than average July and August rainfall, and average September through June precipitation. Ideally, twice the normal July precipitation was desired. Soybean yields were strongly related to July and August rainfall but could recover from dry Julys when August rainfall was adequate. This was deemed sensible because soybean pods continue to form in August.

Corn had been adversely affected by “severe” unfavorable departures from average weather from 1930 through 1940, as well as “significant” departures during the mid-1950s. 1960 through 1973 was “exceptionally” favorable with minimal weather and yield deviations from trend yields (a new trend began in 1960 due to rapidly increased nitrogen fertilizer rate). Corn regressions with technology held constant indicated weather variability was much higher from 1891 through 1955 than 1956 through 1973, with much of the yield trend since the 1930s “directly attributed to improved weather.” Similar soybean regressions also indicated weather was very favorable from 1956 through 1973. Thompson noted the latest USDA corn and soybean yield growth projections through 1985 were 2.2% per year, though he believed this was overly optimistic because favorable weather had coincided with technological improvements.
Furthermore, nitrogen fertilizer was widely used by 1974 would become “a limiting factor” in annual yield increases.

Thompson also noted that global cooling had been occurring since 1940. He stated that if the trend continued to 2000, mid-latitude yields would probably benefit due to cooler summers. However, it would be “detrimental” at higher latitudes because of the shorter growing season. Therefore, the corn and soybean belt would likely shift further south if climate cooling continued. However, larger impacts were expected if a shift to more variable weather developed – as had occurred during 1890 through 1955. If such a change occurred, he calculated that average corn yield would be expected to decrease 3%, assuming constant technology. Therefore, Thompson concluded that higher latitudes would be most affected by climate change, while any increase in weather variability would negatively affect grains and oilseeds.

Nelson and Dale (1978) noted that the combination of weather and technology had improved crop yields since the late 1950s. However, a “major problem” existed in modeling the relationship because the weather-technology interaction was very complex. Therefore, they developed and analyzed two types of models for Tippecanoe County in Indiana to predict yields. The same procedure was followed for six other Indiana counties, though it was noted that findings for Tippecanoe County were representative of the other areas.

The first models used a “Thompson approach” that developed multiple regressions to estimate and predict yields. Monthly weather observations from nearby observation stations beginning in 1941 were used to represent weather for the county. Linear and squared weather variables for the model included: 1) September through June
pre-season precipitation, 2) average June temperature, 3) July precipitation, 4) average July temperature, 5) August precipitation, and 6) average August temperature. The departure from average during the period of record was used instead of actual observations. Technology was represented by time in the first model, but a separate model removed the technology variable and substituted an estimate of applied nitrogen as a variable. Each model was estimated with all the aforementioned variables and with only variables that were significant in the all-variables model.

A second model developed a crop yield “Energy-Crop Growth” (ECG) model to predict yields. This model was analyzed for comparison to the Thompson approach. It used 84 daily values of: 1) solar radiation / potential for water evaporation, 2) a leaf-area index that represented the amount of radiation ingested by the corn canopy, and 3) a measure of soil-plant moisture stress. The 84 days began 42 days prior to 50% coverage of silked corn acreage, and ended 42 days afterward. The period of record was 1957 through 1975. Similar to the Thompson approach, two models were developed with a technology variable based on 1) time, and 2) nitrogen application. Although a beginning year of 1941 would have been more desirable for comparison to the Thompson-type models, solar radiation data was unavailable prior to 1957.

The Thompson models were estimated seven times with ending years from 1969 through 1975, while the ECG models used ending years from 1969 through 1974. After each model was estimated, out-of-sample forecasts were made for the following year by entering actual observations into the estimated model. Forecasts from the Thompson model predicted high yields in 1972 and 1973 when there was favorable weather, but were “much too high” in 1974 and “too low” in 1975. This exemplified that the addition
of one more year to the model had a large effect on the forecasts because the technology and weather coefficients were strongly affected by previous yields and weather. The model was also used to forecast yields by entering average weather to represent forecasts based on the trend variable alone. Predicted yields from the model that used time for technology fluctuated greatly as compared to nitrogen models. However, results shows that “… the last year included in the regression analysis has much significance in determining the regression equation and the following year’s yield estimate …“ (p. 930)

In general, the models that used nitrogen had better predictive ability than those that used time for technology. The Thompson and ECG models were “fairly similar” in their accuracy when nitrogen was used. The Thompson model was most accurate during the drought year in 1974, but the ECG models were more accurate in 1973 and 1975. Using nitrogen application as a representation of technology led to forecasts that only fluctuated by a few bushels per acre from year-to-year, while those that used time for technology tended to have large variations. This showed that the models were sensitive to the period of record used for regressions, and that it may be importance to find a better proxy than time to represent technology when developing models. However, the amounts of nitrogen applied to corn had to be represented by a government publication that only showed average state-level nitrogen application.

Swanson and Nyankori (1979) attempted to determine whether corn yields would level by the mid-1980s, as had been suggested by Thompson (1975). This was a topic of much speculation and other studies had also suggested that a flattening of the yield trend was possibly occurring – or was at least possible. They examined monthly weather and yields from 1950 through 1976 at the Allerton Trust Farm in central Illinois. The data
did not represent experimental plots, but instead actual farming outcomes in an effort to raise income for a local park and conference center. Regressions similar to those developed by Thompson (1969 and 1970) were used in the analysis.

Swanson and Nyankori assumed that technology was best represented by the yield trend during the period. However, they desired to determine whether the linear form was an accurate representation. Statistical tests showed that the linear trend from observed yields was statistically significant, which indicated that the linear trend was appropriate. Yields were also estimated through a weather-technology-yield model that was similar to Thompson’s regression models. The linear trend for the estimated weather-technology yields was also significant. It was further noted that the linear form fitted the data better than non-linear forms. When combined with the statistical evidence, they concluded that there was no evidence to suggest that corn and soybean yields were approaching a plateau. Instead, a linear and upward trend appeared to be occurring. Importantly, it was also shown that the weather-technology trend rate increased by a statistically significant amount, as compared to the observed trend rate. This showed that unfavorable weather had reduced the observed trend.

Additional determination as to whether yields were approaching a plateau was accomplished through comparison of corn and soybean yields at the Allerton Farms and associated county-level yields. Corn yields during the period averaged 13% higher at the Allerton Farms versus the same county, while soybean yields were 8.5% higher. Since the trend had been best represented linearly, and the Allerton farm was considered well managed, this provided evidence that well-managed farms had continued to adopt yield-increasing technology at the same rate. This provided further evidence that the trend
yield had not been slowing. A final task plotted the annual ratios of the Allerton Trust Farm yields to county yields, and then fitted the ratios with a line. The lines for both crops were statistically insignificant, which suggested that technology being used at the well-managed farms would eventually be utilized by other farms. This led to further conclusion that trend yields did not appear to be flattening.

By the mid-1980s, a large increase in weather variability was underway (Thompson 1985, 1986). This was exemplified by the 1974 scenario, as well as dry and hot summers in 1980 and 1983. Additional weather studies of Illinois and Iowa indicated that the decade of the 1970s had the highest number of heavy rain events during the century (Changnon 1984; Hillacker 1984). Furthermore, the highest frequency of record-breaking one-hour rainfall events in Iowa occurred during 1977 through 1982 compared to any period since 1916 (Hillacker 1984). Scientists had noted that global warming appeared to begin around 1880, followed by global cooling from 1940 through 1970. However, warming had returned during the 1980s. Carbon dioxide levels were agreed to have increased significantly since 1880, but a clear warming trend due to the gas was unidentifiable. Winters had been extremely cold and snowy across the central United States during the late 1970s, and interest in the impacts of climate change on corn and soybean yield variability had again increased.

The possible impacts of changed climate conditions and weather variability led Thompson (1985, 1986) to update and extend his 1975 study. Curvilinear corn and soybean weather-yield regressions were developed for Illinois, Indiana, Iowa, Missouri, and Ohio because 50% of production occurred in these states. The soybean model used data from 1930 through 1984 and the corn model used data from 1930 through 1983.
Weather variables were calculated as departures from average, and included linear and squared terms for average July and August rainfall, June, July, and August temperatures, as well as September through June pre-season precipitation. Three linear time trends were included to account for gradual yield increases from 1930 through 1959, rapid increases from 1960 through 1972, and steady increases from 1973 into the 1980s. After the model was estimated, average weather was then entered back into the model to “simulate” the expected yield each year with average weather. The “simulated” yield was then used as an independent variable in a final pooled regression, with the time trend variables and intercept dropped. Importantly, pooled data was weighted by the proportion of acreage dedicated to each crop in each state.

The first set of soybean regressions explained 96% of the variation in yield in Iowa, 93% in Ohio, 95% in Indiana, 96% in Illinois, and 94% in Missouri. The pooled regression indicated that highest soybean yields were expected with slightly above average June temperature and slightly below average July and August temperatures. Higher than average July and August rainfall were desirable, while slightly above average pre-season precipitation would also benefit yield. Simulated yields were 95% of normal yield or better from 1956 through 1973, particularly because July and August temperatures were at or below average through the entire period. Additionally, weather variability was the lowest during this time, and 9 of the 18 years produced above average yields. Increased weather variability was noted after 1973 with above average July-August temperatures from 1980 through 1983, and above average July-August rainfall from 1977 through 1982. Thompson concluded that warmer and drier summers due to
climate change would be expected to reduce soybean yield 3 bushels per acre, given an adjustment for technology.

The first set of corn regressions explained 96% of the variation in yield in Iowa, 96% in Ohio, 96% in Indiana, 97% in Illinois, and 93% in Missouri. The pooled regression explained 94% of the variation in corn yield. Highest yields occurred with above average July and August rainfall, below average July and August temperatures, and normal June temperatures and pre-season precipitation. Simulated yields were 95% of average or better from 1956 through 1973 due to unusually favorable weather. Simulated yields increased at a rate of roughly 0.4 bushels per acre from 1930 through 1972, particularly because July and August temperatures were 3.6°F cooler in the 1960s than the 1930s. However, simulated yields were much more variable after 1973 due to larger weather fluctuations and a clear yield trend was untenable. He concluded that if the most recent weather pattern were to continue, yield might fall if technology leveled. However, hybrid technology would likely improve to “… accommodate moderate climatic changes.”

Numerous technologies had improved to increase corn yields since the 1940s. However, there was little agreement regarding the change in the sensitivity of technology to weather. It was also unclear whether a yield plateau existed and was reachable in the near future. Without such information, the yield risk to producers was obscure. Therefore, Garcia, et al. (1987) examined these issues through regression analyses of yield-weather relationships at the local, district, and national levels. The University of Illinois Trust Farm was chosen as the local level, followed by nine Illinois Crop Reporting Districts (CRDs), and the U.S. aggregated as a whole.
It was recognized that the period of study could greatly influence the trend variable coefficient in the regressions. For example, local level yield was expected to increase 1.73 bushels per acre per year if data from 1955 through 1984 were used. However, the increase would drop to 1.26 bushels per acre per year if 1961 through 1984 were used. The difference was due to the impact of rapidly improved technology from the introduction of nitrogen fertilizer around 1960. Additionally, specific farmer decisions and isolated weather events were reflected in local yield data, though such effects would be smoothed at the district and national level. Therefore, careful selection was made to use a break point of 1960 given the rapid introduction of nitrogen fertilizer and its effect on yield. The initial regression consisted of monthly growing season weather variables from 1961 through 1982, though regressions for final analyses utilized only variables that were significant in the initial regressions.

Local, state, and national yield trends did not suggest that a plateau was being approached. However, absolute yield growth rate from 1961 through 1982 was lowest at the local farm level and higher at the district and national levels. Comparison between the trend in East CRD yields and Trust Farm yields (located within the East CRD) showed the difference in yields had lessened since 1961. During this time, the East CRD’s fertilizer application rate increased from 50% of the local level’s rate to 75%. This indicated that technological improvements were introduced more rapidly at the Trust Farm and it was sensible that district-level yields would continue to adapt. The difference between local- and national-level yields also decreased since 1961 though the magnitude was smaller. Garcia, et al. concluded that this “might be taken as evidence of tremendous potential for U.S. growth rates, if all U.S. corn land were of the quality of
that of central Illinois.” (p. 1098) However, it was cautioned that soil and land quality was not as high everywhere.

Final regressions explained 61% of the variation in corn yield at the local level, an average of 81% for the districts, and 89% at the national level. The variability in corn yield decreased from the local to national levels, as the larger spatial region removed the effects of randomness and specific weather events. Importantly, these results showed that yield risk was higher at the local level, and hence for individual producers, than district- or national-level analyses would suggest. Furthermore, studies of state- or national-level regions appeared to have similarly underestimated the importance of weather to yields.

When yield variability across the periods of 1931 through 1960 and 1961 through 1982 was examined with only a time trend variable, yield variability was higher from 1961 through 1982 at the national level and for 7 of the 9 CRDs. Increased use of marginal lands was theorized as the cause, particularly because southern Illinois districts had lower soil quality and it subsequently had the largest increase in yield variability. Inclusion of weather variables with the time trend regressions increased their explanatory power by approximately 50%, 20%, and 10% at the local, district, and national levels, respectively. Only 2 of the 9 Illinois districts now showed increased yield variability across the periods, and these were in the far southern portion which further suggested that lower land and soil quality may play a role in yield variability.

Although the inclusion of weather variables at the district level had increased the yield variation by 20% during 1961 through 1982, an increase of only 16% occurred during 1931 through 1960. The absolute magnitude of July temperature coefficients were higher in the most recent period, though coefficients for July precipitation were mixed.
The weather in each period was not the same, which made it difficult to determine if technology-weather relationships had actually changed. Garcia, et al. concluded additional research should focus on understanding “the interdependence of weather, input qualities, and technologies.”

The potential impact of climate change on U.S. corn and soybean production remained unclear. Thompson (1990) noted that rapid global warming had been occurring since 1980, though it had been preceded by global cooling from 1940 through 1970. During a severe drought in 1988, the possible connection between global warming and its relation to manmade greenhouse gasses was widely speculated. However, he noted that 1985 was much cooler and that it had occurred during the same buildup of man-made gasses. Therefore, he stated that such a rapid change from 1985 to 1988 could not be due to greenhouse gases, but instead to “… factors that have greater immediate effect than the greenhouse gasses.” (p. 88)

Beyond climate change, weather variability remained considerably higher since 1973. Droughts had occurred in 1974, 1977, 1980, 1983, and 1988, though “some of the most favorable weather of the past century” occurred in 1978, 1979, 1981, 1982, and 1985. Attention turned to the El Niño cycle, which is an occasional short-term warming of water in the equatorial Pacific. The relatively warm water shifts the position of the jet stream from its mean, which can affect global weather patterns. The La Niña cycle is similar but opposite, as abnormally cool water also impacts weather. The five Corn Belt droughts since 1973 occurred in the year after an El Niño cycle, though the 1983 drought happened toward the end of a strong El Niño. Most importantly, it was shown that not all droughts dating to 1891 had occurred during an actual El Niño year. Evidence also
seemed to suggest that clusters of quite favorable weather occurred every 18 to 19 years, and that if an El Niño developed during this time, the probability of drought was reduced. It was concluded that this information could be used “not to predict a drought but [as] a warning to watch for the signs.”

Despite a near-record U.S. average soybean yield of 34 bushels per acre in 1990, Teigen (1991a) noted that 11 states reported less than 25 bushels per acre and 4 states had over 40 bushels per acre. Only Delaware was exactly at 34 bushels per acre. However, the distribution and timing of weather varied greatly across soybean producing areas. Teigen examined the relationship between soybean yield, monthly precipitation, and monthly average temperature for 10 defined regions. Curvilinear regressions of monthly rainfall and temperature from 1950 through 1988 for Illinois, Indiana, Iowa, Missouri, Minnesota, and Ohio, as well as the multi-state regions of the 1) North Plains (North Dakota, South Dakota, Nebraska, and Kansas), 2) Delta States (Arkansas, Louisiana, and Mississippi), 3) Southeast (Alabama, Florida, Georgia, and South Carolina), and 4) remainder of the U.S.

Initial variables for the regressions included precipitation and temperatures for June, July, August, and September, as well as May precipitation. Interaction variables were used for June through August weather, with quadratics added for precipitation from May through August, as well as for temperatures in June and July. However, August temperature was used with linear and exponential variables. A linear time trend variable was used to represent “biological, chemical, political, and economic” changes through time. Detailed reasoning for model specification was not reported. Insignificant coefficients were then dropped from the initial regressions, with regressions recalculated.
using only significant variables. July and August precipitation were the only significant variables for every region.

Final regressions explained 85% of the variation in soybean yield in Iowa, 82% in Ohio, 90% in Indiana, 93% in Illinois, 80% in Missouri, and 82% to 93% in the remaining regions. All regions would be expected to have higher yields with above average July and August rainfall. Responses were greatest in Missouri and the North Plains and weakest in the Delta States and Southeast. Additional June precipitation would also be expected to aid Illinois, Indiana, and Ohio yields, while June temperature was insignificant in the central U.S.

Forecasts using realized weather in 1989 and 1990 performed well for Iowa, Minnesota, the Southeast, the Delta States, and the remainder of the U.S. However, large forecast errors occurred across the major production regions in the Corn Belt. Significant yield overforecasts of 4.5, 5.3, and 5.4 bushels per acre occurred for Ohio, Indiana, and Missouri in 1989, respectively, though 1990 forecasts were within 1.3 to 3.0 bushels per acre. A production shift away from Nebraska and into South Dakota in the North Plains region likely created 4.5 and 5.8 bushel per acre over-estimates in 1989 and 1990, respectively. May 1990 precipitation in Illinois was three standard deviations above average, which caused the model to underestimate yield by 8.2 bushels per acre. However, the model for Illinois was deemed useful due to the unprecedented rainfall, which skewed the model. Despite limited predictive ability across several areas, Teigen stated the models performed “satisfactorily” and could be used with caution.

1991 forecasts were also developed with the model for comparison with USDA August and September estimates. Weather data through July and through August were
utilized and obtained through subjective interpretation of *Weekly Weather and Crop Bulletin* temperature and precipitation maps. May was shown as wet, June as warm and dry, July as dry, July as hot from the Ohio valley south, and August as warm and dry. Predictions were then compared to the yield estimates in USDA *Crop Production* releases. The July model forecast 1.90 billion bushels as compared to 1.87 billion bushels in the August production report, and the August model predicted 1.84 billion bushels as compared to 1.82 billion bushels from the September production report. The forecasts were within 1% of NASS estimates and Teigen concluded “crop forecasting and weather assessment should be easier with these equations”. However, he noted models could perform poorly due to: 1) low weather map resolutions, 2) large deviations from average temperature and rainfall, 3) weather events not reflected in monthly averages, 4) specific impacts of weather during critical growth stages, 5) technological improvements, and 6) acreage shifts. He also recommended that the models be updated in the future as residual errors increase.

In addition to studying weather-soybean yield relationships, Teigen (1991b) conducted a similar study of corn yields. He noted that unfavorable weather explained “much of the corn output shortfalls” during 1974, 1976, 1980, 1983, and 1988, while favorable weather helped explain high yields in 1971, 1972, 1978, 1979, 1981, 1982, 1986, and 1987. At the same time, corn yield variation was larger during the last 15 years than the previous 30. The same techniques and variables were used as in his soybean publication, with data collected from 1950 through 1988 for Illinois, Indiana, Iowa, Michigan, Missouri, Minnesota, Ohio, Wisconsin, and the multi-state regions of the 1) Central Plains (Colorado, Kansas, and Nebraska), 2) Dakotas (North Dakota and
South Dakota), and 3) the remainder of the U.S. September precipitation was not included as a variable in the initial regressions. July precipitation was the only significant in each state and region.

The percent of variation in corn yield explained by the regressions was not reported. Nonetheless, additional July rainfall would be expected to increase yield in all regions. Warmer July and August temperatures would be expected to decrease yield in all regions where it was a significant variable. Too much or too little May precipitation appeared to reduce yield from delayed planting or germination, respectively. Therefore, average May precipitation was considered ideal with average June precipitation preferred as well. Yield was expected to be less than average given average weather, but the negative impact of unfavorable weather was larger than the positive impact of favorable weather. For example, a yield of 3.5 bushels per acre less than average was expected in Missouri with a wet May, cool June, very wet July, and hot August. However, equal but opposite conditions reduced yield to 36.5 bushels per acre below average, primarily due to the reversal of July rainfall.

Forecasts using realized weather in 1989 and 1990 performed well for the Dakotas, Indiana, Michigan, Missouri, and Wisconsin. However, large errors occurred across the Central Plains, Illinois, Iowa, Minnesota, and Ohio. 1990 yields in Illinois and Indiana were underestimated by 17.4 and 10.4 bushels per acre, respectively, probably due to extreme May rainfall, which was 2.6 to 3.0 standard deviations above average. The 1990 yield in Iowa was 20.0 bushels overestimated because June and July were wet, which revealed model coefficients may be too large. 1990 Ohio yield was overestimated because July rainfall was 2.2 standard deviations above average. He stated models did
not perform well under extreme weather scenarios, though they performed “satisfactorily” under less extreme events.

Teigen further analyzed the possible effects of climate change on yield. Using the assumption that technology remained constant, a doubling of weather variability with no change in mean rainfall and temperature would be expected to reduce average corn yields 2 to 10 bushels per acre for each state. However, hotter, drier, and more variable weather was deemed “disastrous” as yields would be expected to decrease 20 to 50 bushels per acre. It was noted standard deviations for precipitation and temperature were only 1.00” to 1.50” and 2.0°F to 2.5°F. Therefore, a slight shift in climate could have major impacts on corn yield.

Despite several studies regarding weather-yield relationships, Hollinger and Changnon (1993) noted that no study existed in which the weather was controlled. They had particular interest in the possible benefit of cloud seeding to induce rain on Illinois crops. An experimental plot in Urbana, Illinois was created where rainfall could be controlled through the use of shelters. This allowed for the creation of various growing season weather scenarios that could be compared to yields under natural weather at the same location. The study was conducted during a five-year period from 1987 through 1991.

To create the experiment, the shelters were developed to block rainfall but utilize the ambient air temperature. Typically dry, average, and wet summer conditions were created through water applications. Application amounts for each condition were determined through calculations of rainfall during the 17 driest, average, and wettest years from 1901 through 1985 at a nearby weather station. Water was applied through
sprinklers during days and times most similar to those observed in east central Illinois. Additionally, at another sheltered plot, 25% more water was added to each simulated condition for comparison. The same scenarios were replicated for crops with different planting dates and densities in 1990 and 1991. Similarly, a plot of unsheltered crops was augmented by adding various amounts of water to each naturally occurring rainfall. These included adding: 1) 10%, 25%, and 40% more water to each rainfall, 2) 10%, 25%, and 40% more water to each rainfall from 0.10” to 1.00”, 3) 10% and 40% added to each rainfall over 1.00”, and 4) 40% to each rainfall under 0.10”.

Corn yields generally increased with higher summer rainfall and decreased with warmer temperatures. Unsheltered yields increased most dramatically when 40% water increases were added to events under 0.10” and over 1.00”, while 10% and 25% water increases generally improved yields. However, unsheltered results were mixed when water was added to every rainfall. Sheltered yields increased when water was added to dry, average, and wet conditions, which suggested: “that even in the wetter years in east-central Illinois, additional rainfall or irrigation could increase yields.” (p. 22) Temperature impacted corn yields more greatly than commonly believed. However, this result was expected since rainfall was controlled while ambient temperature fluctuated. Higher temperatures from planting to tassel initiation appeared to particularly reduce yield.

Water was particularly beneficial for corn from ear initiation to the end of the lag phase, which corresponded to late June through July. Plots with earlier planting dates of May 24 versus June 5 in 1990, and May 15 versus May 29 in 1991, had higher yields. Cooler temperatures during early growth appeared to be beneficial, but it was noted that
only two years of observations were not enough to conclude relationships regarding yield and planting. Varied plant populations in this experiment did not show a clear relationship to corn yields.

Relationships between rainfall and soybean yields were mixed and varied greatly between the sheltered and unsheltered plots. Sheltered, wet summer conditions with 25% more water added to each event averaged the highest yield, but the yield was similar to: 1) sheltered wet summer conditions without 25% more water, 2) average conditions, 3) average conditions plus 25% more water, and 4) dry conditions plus 25% more water. Soybean yields at the unsheltered plot were highest with no additional rainfall, 40% water added to 0.10” to 1.00” rains, and 25% added to each rainfall. Lowest yields occurred with 10% water added to heavy rainfall events, 40% added to all events, and 25% added to 0.10” to 1.00” rains. Therefore, the sheltered plots indicated that increased yield “should be expected with rainfall increases throughout the growing season”, though unsheltered locations appeared to indicate that “increasing rainfall had an insignificant effect on soybean yields.” Such varied results were possibly due to: 1) truly different responses of the plants, 2) an unaccounted variable, or 3) that sheltered soybeans were not rotated while unsheltered were. However, cooler summer temperatures were consistently shown to increase yields, as warm weather during the early growing season appeared to lower pod formation.

Hollinger and Changnon concluded that water applications that enhanced corn yields generally did not benefit soybeans. However, since most farms in Illinois had both crops, it was assessed that the best overall treatment for a producer would be to add at least 25% more water to each rain event, with a 40% increase most ideal. The usefulness
of cloud seeding to perform this task in the future was likely outweighed by limited yield benefits. However, better weather forecasts were noted as a possible tool to help producers determine the correct amount of additional water to apply.

Dixon et al. (1994) noted that there were “potentially serious” impacts of climate change on agriculture across the U.S., which increased the need to develop a yield response model for corn that could be used to predict yields under hypothetical changes in climate. Although previous studies examined this issue, they noted previous multiple regression weather-yield models were probably mis-specified because soil moisture and solar radiation observations were excluded but were critically important to yield potential. Since observations of soil moisture and solar radiation were increasingly available, they developed models that included this data for the nine crop reporting districts (CRDs) of Illinois. In particular, separate regression models were developed and based on: 1) calendar months, and 2) crop growth stages independent of calendar months. They then compared versions of these models to determine whether: 1) variations in solar radiation were important at explaining variations in corn yields, and 2) calendar months were a fair approximation to explain corn yields. The models were also used to produce and analyze out-of-sample forecasts.

Four linear models were developed that utilized weather and yield observations over 1953 through 1987 for estimation. The models were then used to produce out-of-sample forecasts for 1988 through 1990. The models differed through several variables including various measures of air temperature, precipitation, planting date, soil moisture, solar radiation, nitrogen applications, early-season frosts, and the effect of various soils and topography.
Weather, solar radiation, and soil moisture data were obtained from the Midwest Climate Center. Solar radiation for each district was computed from hourly observations of cloudiness, relative humidity, and air temperature. Soil moisture observations for each district was computed based on air temperature, modeled solar radiation, precipitation observations, and a soil moisture model. To develop models that were based on crop growth stages instead of calendar months, the development of corn was divided into four growth stages: 1) early vegetative growth, 2) ear development, 3) pollination and kernel set, and 4) grain fill. These were primarily determined through analysis of weekly USDA crop progress reports and the accumulation of growing degree days for each district.

Initial estimation results from each of the four models showed that coefficients within each district were dissimilar. Therefore, a test of homogeneity was performed, but it indicated the observations could be pooled to improve the reliability of the regression models. Pooling increased the number of significant variables and pooled data was utilized for the analysis. However, additional tests indicated that the pooled regressions were heteroskedastic and a generalized least regression method was required (as opposed to ordinary least squares regression).

Results showed the model that utilized crop growth stages, soil moisture, and solar radiation was not mis-specified. This meant that the linear form for all variables “...justifies excluding quadratic and interaction terms” (p. 64) However, not all of the variables were significant despite explaining 86% of the variation in yield. Additionally, collinearity was believed to be affecting the model and leading to potentially unreasonable estimates of the expected relationship between yields and solar radiation. However, the same model without solar radiation variables caused model mis-
specification and reduced the explanatory power of the model to 83%. This also led to changes in the significance of some of the coefficients and it was deemed the model that included solar radiation was superior.

The model that included solar radiation was then utilized to compare the usefulness of soil moisture versus precipitation variables. Therefore, the soil moisture variables were removed for various growth stages and precipitation variables were added. Results showed that the explanatory power of the model was similar with 85% of the variation in corn yield explained. However, none of the precipitation variables were significant. This was a notable contradiction to accepted weather-yield knowledge and was attributed to the possibility that precipitation and solar radiation were highly collinear. Although the difference between the soil moisture and precipitation models was small, it was deemed that using soil moisture was superior because some of the soil moisture variables were significant.

The regression model that utilized calendar months performed similarly to the model discussed above, though the explanatory power was slightly lower with an R-squared value of 84%. Encompassing tests suggested that the model that utilized crop growth stages was superior to the calendar months model, though the difference was small. Additionally, “numerous” coefficients had different signs and significance between the two models. Therefore, they concluded the crop growth model appears to have been superior for estimation and that “… the economic implications of yield response models estimated in the past with weather-related variables defined according to fixed calendar intervals can be questioned.” (p. 66)
Out-of-sample forecasts from the models were made for 1988 through 1990. Root mean squares error (RMSE) calculations were performed to determine the magnitude of the errors. The crop growth model had an RMSE of 19.4 bushels per acre, while the multiple regression with calendar months had an RMSE of 22.1 bushels per acre. Therefore, it was determined that the growth stage model produced superior forecasts and that such models should be “seriously considered” (p. 66). Furthermore, it was also concluded that solar radiation was a useful variable for estimating and forecasting the relationship between weather and yields.

Teigen and Thomas (1995) stated that “Weather is the single most important factor affecting crop production”. They examined the impacts of weather on corn, soybeans, and wheat, though only corn and soybeans are discussed in this review. Regressions were developed for each crop for Illinois, Indiana, Iowa, Minnesota, Missouri, Ohio, and the remainder of the U.S. Corn regressions were also developed for Michigan, Wisconsin, the Central Plains (Colorado, Kansas, and Nebraska), and the Dakotas. Soybean regressions were developed for Kansas, Nebraska, South Dakota, North Dakota, and the Delta States.

Methods were similar to Teigen’s 1991 studies with data covering 1950 through 1993. However, 1993 was excluded across much of the central U.S. due to extreme flooding in some areas. Initial regressions included monthly temperature and precipitation variables from May through September, as well as total pre-season precipitation from January through May. The quadratic form was used for all variables with interaction variables included from June through September. Exponential temperature functions were also included for June through August because the
specification allowed cooler weather to slightly add to yield, while hot weather would "subtract a lot." A linear variable to account for technological increase was also included. Final regressions for analyses excluded insignificant variables from the initial regressions. Note that July precipitation was significant for all states for both crops, with August precipitation significant for all states that produced soybeans.

The regressions explained 84% to 98% of the variation in corn yield with Iowa the lowest and Wisconsin the highest. From 78% to 95% of the variation in soybean yield was explained by the regressions, with South Dakota the lowest and the remainder of the U.S. the highest. The remainder of the U.S. also explained 97% of the variation in corn yield, which indicated that the effects of randomness were likely removed at such a large level as had been suggested by Garcia, et al. (1987).

Higher July precipitation was expected to increase corn yields for all areas, particularly when it was “hot”. However, precipitation 1.5 standard deviations above average or greater would be expected to reduce yields. July temperature was significant for both crops in roughly 60% of the states, while August temperature was significant for 4 of 11 soybean states and 9 of 11 corn states. For both July and August temperatures, cooler readings would be expected to increase yields. September precipitation was generally insignificant, as was January through May precipitation. However, increased September temperature appeared to increase yields by extending the growing season. January through May precipitation was only a significant factor for corn production in the Central Plains region, and for soybeans in Nebraska.

The annual increases in yield over time were around 1.8 and 0.4 bushels per acre per year for corn and soybeans, respectively. Highest trends rates were across Colorado,
Kansas, and Nebraska where irrigation had become a significant technological factor. Higher acreage was suggested as a possible reason for higher annual yield increases in the Dakotas, Illinois, and Ohio. Although contradictory to common belief, Teigen and Thomas theorized that larger farms utilized better technology, which offset the use of marginal land. Every Illinois census to 1969 confirmed that corn yields were 30 bushels per acre higher on 500 to 999 acre farms than farms of less than 15 acres. It appeared probable that “Lower acreage increases the proportion grown on small farms with lower yields.” (p. 7)

Forecasts for 1994 yields were performed to determine the accuracy of the models. Methods were similar to Teigen’s 1991 studies with weather data qualitatively interpreted from *Weekly Weather and Crop Bulletin* temperature and precipitation maps. Model forecasts were compared to estimates from the *World Agricultural Supply and Demand Estimates* report. June was warmer than average across the Corn Belt, with July and August cool for a majority of the U.S., and July slightly dry in Illinois and Indiana. Corn and soybean yields for the U.S. as a whole were under-forecast by 10.6 and 6.2 bushels per acre, respectively. Additionally, most of the state regressions missed final yields by at least two standard errors. Given such poor results, they concluded “… yields in 1994 probably were not generated by the same process that operated during the 1950 through 1993 estimation period.” (p. 19) It was noted that USDA yield-estimate methods may have changed over the past few years, or that “… plant populations, fertilizer use, or other input applications may help explain the outliers.” (p. 19)

Similar yield estimation problems continue to exist. Despite very favorable July weather in 2003, crop experts under-estimated yields by a large amount because August
was hot (Changnon and Hollinger 2004). A record high average corn yield of 164 bushels per acre occurred across in Illinois, with a particularly high average of 193 bushels per acre across a four-county region of west-central Illinois. A previous study had shown that weather explained 88% of the variation in corn yield in the four-county region (Changnon and Neill 1967). Changnon and Hollinger (2004) reviewed key studies and examined overlooked factors that led to the 2003 under-estimation. April through October weather data was collected from reports for the official station at Springfield, Illinois, as it was deemed representative of the area. Four-layer soil moisture data was available via the Illinois State Water Survey, with crop conditions and expected yield via Farm Week.

Examination of monthly weather variables showed June through August rainfall was above average, while April and May rainfall were below. Total rainfall for the six-month period was roughly 1.25” above average, while four of the six months had below average temperatures. However, August was warmer than July – an occurrence with the frequency of only once every ten years. Additionally, 2003 was the sunniest since records began in 1950 with total number of clear days higher than 30-year averages each month. Additionally, the number of partly cloudy days was near average. Each year there normally was 30 days greater than 90°F, but only 17 were recorded in 2003. Notably, eight of the 17 were in August, which was one more than usual.

A review of daily observations revealed more significant weather-yield clues. Generally dry and sunny weather from April 9-24 created favorable planting conditions with 90% planted by April 21. Early May was cloudy and rainy which increased top-level soil moisture for rapid emergence. Abundant sunshine for the last three weeks of
May reduced soil moisture, which led to deeper root development, but temperatures were near average with crop stress minimal. Quick plant growth occurred in early June due to 3.50” of rain over six of its first 13 days. This was followed by sunny conditions with near average temperatures for the remainder of the month. However, two rain events occurred at the end of the month – one of which one produced 2.81”. Sunshine continued through the first week of July, but moderate to heavy rain events of 0.47” to 1.69” occurred roughly every seven days through the month. Additionally, the number of clear days was twice the average, but temperatures were slightly below average so that crop stress was minimal during the critical tasseling phase. August was extremely dry with near average temperatures during the first 12 days, followed by hot conditions through the rest of the month. Interestingly, virtually no rain fell until August 27 when 3.27” occurred. Despite unfavorable August weather, a deep root system and abundant July rain events probably diminished heat’s effect so that seeds filled with low stress. Additional heavy rain on September 1 continued to replenish soil moisture, and dry and sunny weather through September 22 was ideal for drying and maximum kernel size. An early freeze on October 1 did not impact yields because the crop had matured, and October was otherwise typical.

The previous record corn yield in 1994 had averaged 173 bushels per acre for the four-county region. This converted to 182 bushels per acre when detrended to 2003 given a 1% annual increase from technological improvements. Monthly weather conditions were fairly similar during the six-month period, though important differences were noted. 97 sunny days occurred during the 2003 growing season, with a record 54 sunny days from June through August. In 1994, only 61 sunny days had occurred for
April through October. Therefore, sunshine probably led to a much higher photosynthesis rate in 2003. Additionally, there were only 17 90°F days in 2003 as compared to 27 in 1994. Therefore, crop stress from heat was likely lower in 2003.

Changnon and Hollinger concluded that optimal conditions in 2003 were due to:
1) adequate soil moisture, 2) a record numbers of sunny days, 3) limited heat, 4) no crop damage from severe storms, 5) well-timed July rains, and 6) heavy late-August rains. The primary differences between 2003 and 1994 were more sunshine and cooler temperatures in 2003. Experts appeared to have been surprised by high yields due to underestimating the effect on yield from early season weather, August soil moisture, and the number of sunny days.

2.4 Summary

This chapter reviewed literature about the relationship between weather, technology, and corn and soybean yields in the U.S. Corn Belt. Studies indicated that weather and technology were important factors and that a significant portion of yield variability could be explained by weather and technology.

Earliest weather-yield studies began with a publication by Smith (1914), which showed that July rainfall was the most dominant factor in Ohio and the Midwest. Higher rainfall increased yields, while lower rainfall decreased yields. Wallace (1920) further indicated that July rainfall was the most important variable for Ohio, but similar relationships did not necessarily exist in other states or locations. Instead, rainfall and temperatures during other months better explained yield variation. Since studies by Wallace and Smith had mostly examined state-level relationships, Rose (1936) quantified
weather-corn yield relationships at site-specific locations throughout the U.S. He showed that the effect of temperature on corn yields had been underestimated and played a much larger role than previously believed.

Weather-corn yield research dwindled following World War II because of abundant grain supplies and a shift in research funds toward weather forecasting and aerospace engineering (Thompson 1963). Interest returned in the late 1950s due to large grain ending stocks, the emergence of soybeans as a major commercial crop, and rapidly improved computer technologies. Runge and Odell (1958) showed that most of the variation in corn yield could be explained by time, rainfall, and temperature from 50 days before to 14 days after pollination. Runge and Odell (1960) also found that soybean yield variation was most likely explained by weather from June 25 to September 20.

Improved technology since 1930 led some to believe corn yield increases during the late 1950s and early 1960s were mainly attributable to the introduction of nitrogen fertilizers and improved hybrids (Thompson 1962). However, Thompson developed multiple regression models and showed that favorable weather coincided with much of the increase during in the early 1960s. July rainfall was clearly shown as the most significant factor impacting central U.S. yields with the magnitude of August temperatures the next most important. Thompson (1963) built upon his previous research to improve the model and apply it to soybeans. Soybean yields were most influenced by rainfall in August, followed by July rainfall. Runge (1968) specifically examined the impact of rainfall-temperature interactions and found that weather was most important for corn yields near pollination.
Thompson (1969) showed exceptional yields were observed with above average July rainfall, average summer temperatures, and average pre-season precipitation. Additionally, rapid increase in the use of nitrogen fertilizers meant annual yield increases in recent years were not solely due to technology. Thompson (1970) showed exceptional soybean yields had been observed with above average July-August rainfall, average June and August temperatures, below average July temperatures, and average pre-season precipitation. Thompson (1975) noted that a widespread belief developed that technology had reduced the importance of weather on corn yields. However, Thompson noted that a long period of very favorable weather from the mid-1950s through 1973 had created minimal variations in corn and soybean yields. A surprisingly low corn yield in 1974 from a wet spring, summer drought, and late-season freeze led Thompson to show that weather was still a significant factor in corn production.

Nelson and Dale (1978) attempted to resolve the weather-technology issue by using nitrogen application as a representation for technology. Different types of models were used to forecast yields, though it was shown that forecasts using multiple regressions could not be improved significantly at the county level. Swanson and Nyankori (1979) found that unfavorable weather in the 1970s had reduced the trend yield, and that average weather would be expected to lead to above average corn yields.

Thompson (1985, 1986) reaffirmed that weather variability had increased since the early 1970s and that soybean yields would be expected to be lower if warmer and increasingly variable weather continued, while the effect of such changes on corn yields was difficult to assess. However, since technology was likely to improve he concluded that undesirable weather would probably help to offset potential yield losses. Teigen
(1991a, 1991b) noted that weather and yield variability varied greatly across years and distances. He determined that multiple regression models could be used to forecast yields, though they performed somewhat poorly when weather was far from average. Teigen and Thomas (1995) updated these studies, but forecasts remained poor. Hollinger and Changnon (1993) showed that estimating the influence of weather was difficult – even with controlled conditions. Additionally, despite a close following of weather in 2003, record high corn yields took crop experts by surprise. Daily weather records showed that the record high yields were probably due to the unusual combination of record sunshine and favorably cool temperatures, as well as timely rains throughout the summer and dryness in late May (Changnon and Hollinger 2004). This reaffirmed findings by Dixon et al. (1994) that: 1) solar radiation was potentially important to forecast yields, and 2) analysis of weather during specific crop growth stages may provide better yield forecasts than those that utilized calendar months.

In conclusion, multiple regression models showed that weather and technology explain a majority of the variation in corn and soybean yields. The magnitudes of temperature and rainfall during July and August had the largest influence on each crop. Despite close following of weather and technological changes through time, unexpected corn yields occurred as recently as 2003. This exemplifies that the exact relationship between weather, technology, and yields remains difficult to assess. Additionally, only one study has been published that evaluates the usefulness of regressions to forecast yields with modern diagnostic tests. No study has examined whether the trend rate for corn yields has recently increased. The following chapters of the thesis evaluate the areas in which more research is needed.
3. DATA

3.1 Introduction

The multiple regression models developed by Thompson (1962, 1963, 1969, 1970, 1985, 1986, and 1988) used time and weather observations to explain variation in corn and soybean yields. Models developed in the next chapter utilize similar observations of time, weather, and yields to analyze the relationship between weather, technology, and yields in the U.S. Corn Belt. Therefore, a clear understanding of the weather and yield data is needed.

The purpose of this chapter is to review how the data was generated and to analyze its properties. This will help to understand and interpret the output generated by the models in the next chapter. Weather data is also analyzed to determine if upward or downward trends in precipitation or temperature have occurred over 1960 through 2006. A discussion on long-term weather forecasting is provided to determine whether observations used in this thesis are consistent with global warming and the possibility of weather cycles.

3.2 Weather and Yield Data

The first regression models developed by Thompson (1963) included monthly precipitation and temperature observations from 1930 through 1962. The modified models developed in the next chapter included monthly observations from 1960 through 2006. The data set used by Thompson was published, which made it possible to compare the data sets over 1930 through 1962. Weather observations were extremely similar and probably came from the same source.
As noted, corn yield, soybean yield, and monthly temperature and precipitation observations from 1960 through 2006 were used to modify and update Thompson’s original model. The states of Illinois, Indiana, and Iowa were chosen for the present study because they represented 43% to 45% of U.S. corn and soybean production from 2000 through 2006, as shown in Table 1. These states also have similar climate and planting dates. Consideration was given to including Minnesota and Nebraska since they often rank as top five corn and soybean production states. However, Minnesota was excluded because its northern climate is more susceptible to damaging early- and late-season frosts that may not be detected by monthly weather observations. Nebraska was excluded because a high proportion of its crops are irrigated, which skews weather-yield relationships.

Several publications noted that significant nitrogen fertilizer applications began around 1960 and coincided with an increase in corn yields (Thompson 1969, 1975, 1985, 1986, and 1988; Garcia, et. al 1987). Hence, a beginning date prior to 1960 is undesirable. Consideration was given to a starting year of 1974 since yield variability increased after 1973 (Thompson 1975, 1985, 1986, 1988). However, 1974 also marked the end of a favorable weather period that began in the early 1960s (Thompson 1975, 1985, 1986, 1988). Therefore, a beginning year of 1960 is used to develop models in the next chapter due to: 1) the increased use of nitrogen fertilizer around 1960, and 2) the addition of 15 more observations versus a beginning date of 1974.
3.3 Data Collection and Methods

State-level monthly precipitation and temperature observations were provided in electronic format from Jim Angel, State Climatologist for Illinois; the Indiana State Climate Office at Purdue University; and Harry Hillacker, State Climatologist for Iowa. To develop state-level observations, the National Climatic Data Center requires that each state is divided into “climatically quasi-homogeneous” climatic divisions (NCDC 2002). Climatic divisions do not necessarily coincide with USDA crop reporting districts.

To calculate statewide weather observations for a given month, precipitation and air temperature observations within each climate division are collected from a combination of the Cooperative Network, National Weather Service offices, and principal climatological stations (NCDC, *U.S. Climate Normals 1971-2000, Products*). Monthly precipitation for each climate division is calculated by averaging across observation sites the total amount of precipitation that occurred over a given month. Monthly temperature for each climate division is calculated by averaging the daily minimums and maximums over a month. State-level data is then derived by weighting values from each climate division by the fraction of land each represents. Data is not considered official until verified by the National Climatic Data Center.

Annual corn and soybean yields for each state were collected via the Internet (National Agricultural Statistics Service, *Quick Stats: Agricultural Statistics Data Base*). Corn and soybeans yields reflect the final average yield estimates provided in the NASS *Crop Production Annual Summary*. They are defined as the best estimate of total production divided by harvested acreage.
3.4 Descriptive Analysis

The weather and yield observations discussed in this chapter are used to develop weather-technology-yield models. Observations were collected from 1960 through 2006 for the states of Illinois, Indiana, and Iowa. Tables 2 and 3 show descriptive statistics for monthly precipitation and temperature, respectively. The arithmetic mean, median, maximum, minimum, range, standard deviation, and coefficient of variation are discussed. Correlations between monthly precipitation and temperature are presented in Tables 4 and 5. Table 6 shows annual corn and soybean yield observations detrended to 2006 technology. These descriptive statistics will provide a better understanding of the climate in each state and highlight similarities and differences.

3.4.1 Precipitation

Table 2 shows that Indiana is the wettest during the pre-season, which is defined as total precipitation from September through April. Illinois is drier by a small amount. However, Iowa averages approximately 6.00” to 8.00” less during the pre-season period. This is primarily due to considerably drier weather during the winter. Standard deviations are similar around 3.50”, which indicates that precipitation varies each year by approximately the same amount. However, pre-season precipitation is slightly more variable in Iowa as shown by a higher coefficient of variation.

Total precipitation during May was similar for each state. However, the range is higher in Illinois due to particularly wet conditions in 1995. Nonetheless, precipitation in May is similar across these states and averaged around 4.25” to 4.50”. Standard
deviations and coefficients of variation are similar, which indicates variability during the period was similar.

Precipitation during June in Illinois and Iowa both averaged around 4.00”, which was slightly drier than in May. However, Iowa averaged 0.50” more precipitation than in Illinois or Indiana, which was slightly wetter than in May. A review of the median also shows Iowa was the wettest during June. Illinois and Indiana have been much drier than Iowa in June with minimum values of 1.05” and 0.74”, respectively. However, coefficients of variation were somewhat similar, which suggests precipitation variability was similar.

July is wettest in Indiana with an average of 4.34”, though Illinois and Iowa are only drier by a few tenths of an inch. However, maximum precipitation in Iowa surpassed maximums in Illinois and Indiana precipitation by 3.23” and 1.85”, respectively. This was due to 10.50” in 1993. Interestingly, Iowa also experienced the driest July. This was reflected in a higher coefficient of variation and shows that July precipitation is somewhat more variable in Iowa than Illinois or Indiana.

August is the driest of the four main growing season months in each state. Iowa averages 4.01”, which is approximately 0.30” to 0.40” more than in Illinois or Indiana. Iowa has been considerably wetter and slightly drier than Illinois or Indiana, and has a notably higher coefficient of variation.

3.4.2 Temperature

Table 3 reveals that Illinois was the warmest of the three states throughout the growing season from May through August, while Iowa was always the coolest. The
month of May was the coolest with average temperatures around 62°F to 63°F, while July was the hottest with averages around 74°F to 75°F. Standard deviations in June, July, and August were very similar, around 2°F for each state, and coefficients of variation were very small compared to precipitation – sometimes more than 10 times smaller. This indicates that air temperatures are always within a typical and stable range, though differences can occur. For example, temperatures in Iowa have averaged as warm as 78.8°F and as cool as 66.2°F in August. May temperatures varied more than during June through August, but the standard deviations and coefficients of variation were only slightly higher.

3.4.3 Precipitation-Temperature Correlations

Table 4 shows that correlations of monthly precipitation across months within Illinois, Indiana, and Iowa were low. For example, the highest correlation in Illinois was between May and June precipitation with a coefficients of only 0.31. The highest correlation in Indiana (in absolute value) was between pre-season and July precipitation with a coefficient of -0.29. The highest correlation in Iowa was between pre-season and May precipitation with a coefficient of 0.38. The average correlation between precipitation variables was 0.02, 0.02, and 0.10 for Illinois, Indiana, and Iowa, respectively. This indicates that monthly precipitation was a poor indicator of future precipitation for other months within each state.

Correlations of monthly temperatures within each state were also generally low. The average correlation between temperature variables was 0.11, 0.13, and 0.10 for Illinois, Indiana, and Iowa, respectively. However, July and August temperatures showed
a moderately positive correlation within each state with coefficients of 0.39, 0.44, and 0.26 in Illinois, Indiana, and Iowa, respectively. This indicates that monthly temperatures during the growing season were generally poor indicators of temperatures in future months, although temperatures in July and August showed a tendency to deviate in the same direction from average.

Precipitation and temperature correlations within each state were always negative in May, June, and July. This means that temperatures tended to increase as precipitation decreased. The relationship was most notable in July when precipitation-temperature correlations ranged from -0.30 to -0.37 within Illinois, Indiana, and Iowa. Moderate correlations were noted in Illinois and Iowa during June with coefficients of -0.31 and -0.25, respectively. However, the relationship was less correlated in June in Indiana at -0.19. The relationship between August temperature and precipitation was less clear with coefficients of 0.01 in Illinois, 0.12 in Indiana, and -0.08 in Iowa. These results indicate that July precipitation and temperatures are somewhat correlated within each state as warm-dry and cool-wet scenarios tend to occur in tandem.

Table 5 shows that precipitation and temperature observations during the same month across states were strongly correlated between Illinois and Indiana. For example, temperatures across the same months were closely correlated with May, June, July, and August correlation coefficients ranging from 0.95 to 0.99. However, the coefficients across the same months only ranged from 0.85 to 0.92 between Illinois-Iowa, and 0.74 to 0.88 between Indiana-Iowa. Precipitation across the same months was also closely correlated between Illinois and Indiana with pre-season, May, June, July, and August
correlation coefficients ranging from 0.70 to 0.87. However, precipitation across the same periods between Illinois-Iowa was less correlated with coefficients ranging from 0.57 to 0.72. Precipitation between Indiana-Iowa was much lower with correlation coefficients from 0.35 to 0.51. In fact, with the exception of July precipitation, weather observations during the same months in Illinois and Indiana were always more highly correlated than either state correlated to Iowa. Iowa temperatures during May, June, and July were moderately correlated to Illinois and Indiana precipitation during the same months with coefficients from -0.37 to -0.57. This indicates that warm (or cool) weather in Iowa during May, June, or July is often associated with dry (or wet) weather in Illinois and Indiana. Illinois temperatures were weakly correlated with Indiana precipitation during the same months of May, June, and July with coefficients from -0.26 to -0.40, though Indiana temperatures did not correlate as well with Illinois precipitation.

3.4.4 Corn and Soybean Yields

Yields are affected by a complex combination of factors, such as weather, soil quality, seed, farm size, and producer-level management techniques. Despite this complexity, yields tend to show a general increase over time, which is commonly referred to as the “trend yield.” Figure 2 shows that corn yields increased at the fastest rate in Iowa with annual increases of 1.9 bushels per acre per year. Trend yields in Illinois and Iowa were slightly lower at 1.7 bushels per acre. Figure 3 shows that soybean yields increased at a constant rate of approximately 0.5 bushels per acre in Indiana and Iowa, though Illinois lagged at 0.4 bushels per acre.
Yields were detrended to 2006 technology so that they could be compared independently of the annual trend increases (trend yield). In other words, yields over 1960 through 2006 are transformed as if all the yields occurred in 2006. De-trended yields are calculated as follows:

\[ Y_t = y_t + b \cdot (47 - t) \]

Where \( Y_t \) = the de-trended yield in year \( t \), \( y_t \) = the actual yield in year \( t \), \( b \) = the trend coefficient, and \( t \) is the time index running from 1 to 47. Iowa averaged the highest detrended corn and soybean yields, while Illinois and Indiana lagged by 4 and 8 bushels per acre, respectively. Although Indiana averaged the lowest detrended corn yield with 149.6 bushels per acre, it had slightly higher detrended soybean yields than Illinois. The range in corn yields was similar for Iowa and Illinois, but was nearly 20 bushels per acre lower in Indiana with lower maximum and minimum yields, as well. Detrended corn and soybean yields varied by approximately 15 and 5 bushels per acre, respectively. However, coefficients of variation were very similar for both crops, which indicates that annual yield variability of each crop was relatively similar during 1960 through 2006.

3.5 Long-Run Weather Trends

The National Climatic Data Center (NCDC) states that global temperatures have risen at a rate of 0.06°F during the last one-hundred years, and the rate has increased to 0.18°F during the past three decades (NCDC, Climate of 2006 – Annual Report). Although global warming cannot be fully linked to man-induced rises in greenhouse gases, they note that increased temperature rates during the last several decades have been consistent with computer model projections for the upcoming one-hundred years.
Such increases have the potential to alter worldwide weather patterns, which could have a dramatic effect on yield potential if hotter temperatures occurred during sensitive periods of crop development. Therefore, it is worthwhile to review temperature and precipitation observations to determine if trends or patterns in the data exist, and whether such information might be usable to forecast future weather.

3.5.1 Weather Trends

Monthly charts of growing season precipitation and temperatures from 1960 through 2006 are presented in Figures 4 through 12 for Illinois, Indiana, and Iowa. Trend regressions were estimated for each set of monthly weather observations to determine whether a significant upward or downward trend in precipitation and temperature occurred over the sample period. All tests were insignificant at the 5% level. This indicates that monthly precipitation and temperatures during sensitive periods of crop development were stable across the sample period. Although precipitation and temperature observations showed large year-to-year variability, a clear trend is not detected. Instead, it appears that weather was random with occasional outliers during various years. However, a graphical review of the outliers does not appear to suggest a pattern. The lack of a trend and annual variations in weather support the view that monthly temperatures and precipitation from 1960 through 2006 were random.

The fact that an upward trend in temperatures was not observed in Illinois, Indiana, or Iowa may still be consistent with global warming because the local effects of global warming on climate and weather are poorly understood (Wilbanks and Kates...
This helps to explain why weather variables appeared to be random in light of global warming.

### 3.5.2 Long-Term Weather Forecasting

Long-term weather forecasts refer to future periods on the scale of weeks, months, or longer. However, meteorologists “… do not consider day-to-day forecasts more than a week or 10 days ahead to be possible …” (USA Today, *Long-Term Weather Outlooks*). Therefore, attempts to forecast longer-term weather are usually presented in general terms.

The Climate Prediction Center (CPC) is the division of the U.S. National Weather Service that focuses on long-term weather forecasting. The CPC is well-known in the weather community as the primary source for long-term forecasts, and are self-ascribed to be “best known for its United States Climate forecasts based on El Niño and La Niña conditions in the tropical Pacific.” (CPC, *Who We Are*). The Center uses a number of tools to subjectively forecast long-term weather based on: 1) climate and weather models, 2) correlations of global surface-level ocean temperatures, mid-level atmospheric winds, and rainfall and temperature during the previous year, 3) equatorial Pacific Ocean temperatures (warmer-than-average is referred to as an El Niño; colder than average is referred to as La Niña), 4) long-term seasonal trends in temperature and precipitation during the past ten years, 5) soil moisture anomalies, and 6) a multiple linear regression tool to utilize information from a “variety of sources” (CPC, *Long-Lead Forecast Tool Discussion and Analysis*).
Long-lead forecast based El Niño or La Niña have some successes at estimating future climates. For example, Mjelde et al. (1998) noted that long-range weather forecasts across various agricultural areas of Peru, Brazil, and Australia have benefited producer-level decisions. However, studies of El Niño-precipitation relationships by Ropelewsi and Halpert (1986, 1987, 1989) only identified the Great Basin region across the southern Rocky Mountains as the area of the U.S. where strong relationships exist. Hill and Mjelde (2002) noted that climate relationships may be correlated to various areas of the world from: 1) water temperatures across the northern Atlantic Ocean (North Atlantic Oscillation), 2) fluctuations in the Indian monsoon season, 3) air pressure differences between the equator and North America (Pacific North America Index), and 4) longer-scale observations of water temperatures in the northeast and tropical Pacific (Pacific Decadal Oscillation). The CPC has found that their in-house long-term forecasts of temperature are most accurate across the continental U.S. during the late winter and late summer, though precipitation forecasts are less accurate except when a “strong El Niño and La Niña” exists (CPC, Long-Lead Forecast Tool Discussion and Analysis).

The complexity involved in daily and long-term weather forecasting is large. Ocean temperatures across various areas of the world have shown some promise at climate forecasting. However, correlations are weak across the U.S. Corn Belt. Additionally, observed monthly precipitation and temperatures over 1960 through 2006 suggests monthly weather in Illinois, Indiana, and Iowa was random and generally poor indicators of weather in future months. This limits the potential promise of weather in previous months and-or years to be used as predictors of weather in future months across
the U.S. Corn Belt, absent the possible exception of strong El Niños or La Niñas. Hill and Mjelde perhaps best describe climate forecasting as being “in its infancy” (p. 622).

3.6 Summary

Observations of precipitation, temperature, and corn and soybean yields over 1960 through 2006 for Illinois, Indiana, and Iowa were presented in this chapter. These states were chosen because they have similar weather and crop development timescales, and they represent nearly half of U.S. corn and soybean production. 1960 was used as a beginning year because it marked a rapid increase use in the use of nitrogen fertilizer as part of common producer-level management. Weather data was collected via state climatologist offices, while yield data was collected electronically from NASS.

Precipitation during September through April (pre-season) was markedly drier in Iowa than Illinois or Indiana. However, precipitation was fairly similar from May through August, though it was slightly more variable in Iowa in July and August. Monthly temperatures from May through August were much less variable than precipitation. May was the coolest month and July was the hottest, and Illinois on average was warmer than Indiana and Iowa.

Monthly precipitation within each state was a poor indicator of future precipitation within each state, and monthly temperatures were also poor indicators of future temperatures. However, July and August temperatures tended to deviate in the same direction from average. Monthly precipitation and temperatures tended to deviate in the opposite direction from average in May and June, but especially in July. This indicated that cool-wet and warm-dry scenarios tend to occur in tandem, though
correlations were not strong. Weather during the same months was very closely correlated between Illinois and Indiana, but less correlation was shown between these states and Iowa. Nonetheless, weather across states tended to deviate from average in the same direction during the growing season.

Corn yields increased the most rapidly in Iowa, while soybean yield increases were fairly similar. Detrended yields to 2006 technology showed that Iowa averaged the highest corn and soybean yields, respectively followed by Illinois and Indiana. However, annual yield variability was relatively similar for each state. This indicated that unusually high or low yields deviate in a similar percentage from the mean.

Global warming is occurring, though the reason for the increase in global temperatures is debatable. Precipitation and temperature observations during 1960 through 2006 were not shown to significantly increase or decrease. This may still be consistent with global warming because localized effects may not necessarily be observable at regional levels. Several tools are available that link large-scale weather observations to future climate in various areas of the world, but climate forecasting is relatively new and improvements are needed for better long-term forecasts in U.S. Corn Belt.

In conclusion, observations of precipitation, temperature, and corn and soybean yields appear to be consistent with expectations of the meteorological and agricultural communities. This suggests the weather and yield data will be useful for investigating the relationship between weather, technology, and yields in the next chapter.
4. EMPIRICAL RESULTS

4.1 Introduction

The publication by Louis Thompson (1963) provided in-depth regression analysis of the relationships between weather, technology, and corn and soybean yields in the U.S. Corn Belt. He showed that corn yields across various states were particularly influenced by the amount of July rainfall and the magnitude of August air temperature, and that soybean yields seemed to be most related to July and August rainfall.

This section of the thesis develops and statistically analyzes a modified version of Thompson’s original weather-technology-yield model. Modifications to Thompson’s original model are necessary due to changes in planting practices since its publication, observable patterns in monthly weather-yield scatter plots, and the desire to increase degrees of freedom for estimation. Detailed reasoning behind the development and modifications to the original model are presented.

The modified models are then fit to corn and soybean yields for Illinois, Indiana, and Iowa with weather and yield observations over 1960 through 2006. The models are tested for autocorrelation, heteroskedasticity, and mis-specification to determine whether model assumptions are consistent with sample data. Coefficients of the models are utilized to determine the relationship between weather, technology, and corn and soybean yields. Results of the analysis are compared to publications by Thompson (1963, 1969, 1970, 1985, 1986, and 1988) to determine if changes in the weather-technology-yield relationships have occurred. The effect of average weather on trend yields is also assessed and weather indexes for each crop and state are developed to quantify the relative favorability of weather during the period. Finally, the models are tested for
structural breaks that might indicate changes in the relationship between weather, technology, and yields.

Observations over 1960 through 2006 show that corn yields have often outperformed the long-term trend since the mid-1990s. This has led to speculation that the mid-1990s mark the beginning of a new and higher trend in corn yields. Comprehensive analyses of the trend variable are performed with weather-technology-yield models to determine whether the yield trend increases are statistically significant. Several tests are performed to determine the potential significance and change in magnitude of the trend since the mid-1990s. Weather indexes are also used to assess the favorability of weather and its possible influence on corn yields since the mid-1990s.

4.2 Development of the Modified Thompson Model

Thompson (1963) estimated corn and soybean yields for Illinois, Indiana, Iowa, Missouri, and Ohio from 1930 through 1962. Those states were chosen because they represented a significant portion of corn and soybean production at the time of the analysis. The model included linear and quadratic variables that were based on his early linear-only version of the model (Thompson 1962).

The purpose of this section is to develop a modified version of the original Thompson (1963) model. Modifications are necessary due to changes in planting practices and production. The process and models used by Thompson for his weather-technology-yield regression models are presented. Observations of precipitation, temperature, and corn and soybean yields during 1960 through 2006 are reviewed to determine the most representative functional form for use in the modified model. Finally,
the “modified Thompson model” that is used throughout the remainder of this thesis is presented.

4.2.1 The Thompson Model

Weather variables that were used in the full Thompson model included monthly rainfall and temperature for June, July, and August, temperature-precipitation interaction variables for June through August, September through May “pre-season precipitation” to represent soil moisture, and a time index (time trend) variable to represent technological improvements. However, it is notable that the terms for May temperature were excluded for Indiana, Iowa, and Ohio because they were deemed insignificant from analysis of the linear-only model. He reasoned that using linear and quadratics for all variables was acceptable because “with the development of high speed computers, there is less need to eliminate the less important variables.” (p. 9) The original Thompson (1963) model was as follows:

\[
\text{yield}_i = \beta_0 + \beta_1 \text{(year)}_i + \\
\beta_2 \text{(September through May precipitation)}_i + \\
\beta_3 \text{(September through May precipitation)}^2_i + \\
\beta_4 \text{(June precipitation)}_i + \beta_5 \text{(June precipitation)}^2_i + \\
\beta_6 \text{(July precipitation)}_i + \beta_7 \text{(July precipitation)}^2_i + \\
\beta_8 \text{(August precipitation)}_i + \beta_9 \text{(August precipitation)}^2_i + \\
\beta_{10} \text{(May temperature)}_i + \beta_{11} \text{(May temperature)}^2_i + \\
\beta_{12} \text{(June temperature)}_i + \beta_{13} \text{(June temperature)}^2_i + \\
\beta_{14} \text{(July temperature)}_i + \beta_{15} \text{(July temperature)}^2_i + \\
\beta_{16} \text{(August temperature)}_i + \beta_{17} \text{(August temperature)}^2_i + \\
\beta_{18} \text{(June precipitation} \times \text{June temperature)}_i + \\
\beta_{19} \text{(July precipitation} \times \text{July temperature)}_i + \\
\beta_{20} \text{(August precipitation} \times \text{August temperature)}_i +
\]
The original Thompson model utilized 33 annual observations to estimate yields, while 21 parameters were required for the estimation. This only leaves 12 degrees of freedom, which is a relatively low number because it means that only 12 observations are “unrestricted”. The essence of modeling is to capture the relationship with the lowest number of parameters in order to maximize the number of “free” observations. Therefore, a central goal in the development of the weather-technology-yield model in the next section is to utilize the smallest number of parameters in order to increase the degrees of freedom.

### 4.2.2 Modifications to the Thompson Model

The goal of this section is to develop a model that adequately represents monthly weather, technology, and yield relationships for corn and soybeans. In particular, it is desirable to reduce the number of independent variables in Thompson’s original models while creating a model that can be applied across crops and states for comparison. As a result, careful consideration was given to devising a model such that the same variables and functional forms can be used across states and crops.

Dixon et al. (1994) argued that regression models based on weather during calendar months were potentially less useful in estimating and forecasting yields than models based on weather during specific stages of crop development. However, results of their study showed that the improvement in crop weather models from using variables keyed to crop development was marginal and the measurement of variables was considerably more complex. Dixon et al. (1994) also utilized weather and yield observations at the crop district level, but homogeneity tests indicated that observations
could be pooled at a state level. The modified Thompson models in this study will use monthly weather variables at the state level because: 1) previous research shows limited loss of information in utilizing monthly weather variables versus variables based on crop stages, 2) previous research suggests state-level data provides reasonable results, and 3) this will allow a direct comparison to Thompson’s original models. Dixon et al. (1994) and Changnon and Hollinger (2004) suggested that solar radiation (sunshine) might prove to be useful, but real-time measurements representative of the state level do not exist over the full sample period (1960 through 2006) for Illinois, Indiana, and Iowa. Therefore, solar radiation is not consistent. Similar suggestions were also made to utilize soil moisture observations, but direct measurements are extremely limited and not representative of the state level. Therefore, precipitation is used as a proxy for soil moisture.

Monthly weather from May through August was examined for inclusion in the modified model since weather during these months most influences growth and yield potential. Monthly weather during these months was also used in Thompson’s original model, but modifications were necessary due to changes in planting dates. For example, the Iowa State University Agronomy Extension office shows that 50% of Iowa corn was generally planted by the end of April from 2000 through 2004, but the same amount of corn during 1975 through 1979 was not completed until May 10 from 1975 through 1979 (Iowa State University Agronomy Extension, Planting Date Trends). They further explain that planting has shifted earlier and earlier due to a combination of: 1) machinery that can plant wider rows, 2) hybrids that are more tolerant to cold stress, 3) better seed treatments, 4) reduced tillage production systems, and that 5) lower yields are more likely
by planting too late than too early. The shift in planting made it necessary to add May precipitation as a variable and to redefine pre-season precipitation as that which occurs from September through April (as opposed to September through May).

Specification of parameters for the models was determined through a review of patterns in the data. As will be discussed in the following sections, this was accomplished through a review of plots of monthly weather observations versus yields de-trended to 2006 technology. Yields are de-trended so that they can be compared from 1960 through 2006 as if technology had been constant at the 2006 level (see Section 3.4.4).

4.2.2.1 Precipitation Variables

The relationship between precipitation and yields was believed to be quadratic because precipitation could be too high or too low for maximum yield potential, but an ideal amount between extreme dryness and wetness probably exists. For example, limited rainfall would stress corn and soybean crops due to a lack of soil moisture. Yields would be lower as a result. Additionally, too much rainfall would lead to flooding and reduced yields. While the effect of dryness is well known to reduce yields, the existence of a quadratic relationship was exemplified in Iowa in 1993 by monthly summer precipitation that was excessively high, led to flooding and reduced sunlight, and significantly reduced yields.

Figures 13 and 14 show plots of pre-season precipitation versus de-trended corn and soybean yields. The relationship appears to be fairly random, as a quadratic or linear relationship is not readily apparent. However, pre-season precipitation was believed to
be important because it serves as a proxy for initial soil moisture level. Therefore, it was included as a linear term in the modified model. This reduced one variable from the original Thompson model.

It is believed that corn and soybeans could recover from particularly low or high precipitation during May because weather during June through August was known to have a much more significant impact on yield potential. Figures 15 and 16 confirmed this observation by showing that the relationship between May precipitation and de-trended yields was weakly linear. Although the relationship was weak, May precipitation was included in the modified model because precipitation during the month affect planting date, root development, and initial growth. However, the linear term was used instead of the quadratic form because a clear relationship was not exhibited. This reduced one variable from Thompson’s original model.

Figures 17 through 22 show that plots of precipitation versus de-trended yields clearly exhibited quadratic relationships in June, July, and August. As expected, precipitation during these months appeared to most influence yields – especially in July. Therefore, similar to Thompson’s original model, June through August precipitation variables were included in the modified model in the quadratic form.

Recall that Thompson’s original model used interaction variables to boost yields positively or negatively from particularly favorable or unfavorable combinations of temperature and rainfall. Interaction variables are created by multiplying monthly precipitation by monthly temperature. Figures 23 through 25 plot the interaction variables versus de-trended yields for corn in June, July, and August. These were compared to plots of precipitation versus de-trended corn yields in Figures 15 through 17.
Comparisons showed that interaction variables were nearly identical in form and explanatory power to the precipitation-only plots. Additionally, the correlation coefficients between precipitation and interaction variables for the respective months of June, July, and August were all higher than 0.995 within each state. Therefore, the inclusion of interaction variables would introduce severe multicollinearity into the modified models, and the interaction variables were excluded. This reduced three more variables from Thompson’s original model.

### 4.2.2.2 Temperature Variables

Similar to precipitation, the relationship between temperature and yields was believed to be quadratic. In other words, temperatures could be too cool or warm for maximum yield potential, though an ideal temperature exists. However, monthly temperatures have a much lower range and standard deviation than monthly precipitation. This is exhibited in Tables 2 and 3 that show the coefficients of variation for May through August temperatures were markedly lower than the precipitation variables. This meant that monthly temperatures from May through August were substantially less variable than precipitation variables. This is sensible, as extremely hot or cold average temperatures are not expected during the summer – although precipitation can be excessively high or low. The narrow range of observed average temperatures during May through August suggests that a linear form for temperature variables may better reflect actually temperature-yield relationships than a quadratic form.

Figures 26 through 29 show that the relationship between temperature and de-trended corn and soybean yields in May and June were weakly represented with the
4.2.2.3 Technology Variable

Corn and soybean yields have gradually increased each year since 1960. This is called “trend yield” and is due to a variety of technological improvements that include improved seed genetics, technological advances, and producer management techniques. These improvements cause yields to gradually increase each year, though debate exists as to whether the rate is constant, accelerating, or flattening.

Figures 34 and 35 present both linear and quadratic trends. Visual inspection of the plots reveals minimal difference between the two trend models in all cases. Separate statistical tests of corn and soybean yields versus time were also performed for each state and crop with: 1) the linear form for time, and 2) the quadratic form for time. Table 7 shows that the constant and linear terms of the linear-only models were significant at the 1% level for all states and crops. However, the quadratic terms were insignificant in the quadratic models for all states and crops and the linear terms were less significant. These results do not necessarily mean that a breakpoint in the unadjusted trend did not occur in
the mid-1990s (see Figure 1). Instead, results simply show that the trend yield over the sample period can be adequately represented in linear terms. Therefore, the linear form was used in the modified model to represent technological increases through time. This was the same form specified in Thompson’s original model.

4.2.3 The Modified Thompson Model

Modifications to the Thompson model allowed a reduction of six variables from the original model. As discussed in the previous sections, squared terms for May through August temperatures were eliminated from the model. Precipitation-temperature interaction variables were also eliminated to reduce multicollinearity. May precipitation was added as a linear variable due to the earlier shift in planting dates, and pre-season precipitation was redefined as that which occurs from September through April. As a result of these changes, the following model is used throughout the remainder of the thesis:

\[
(\text{observed yield})_i = \beta_0 + \beta_1 (\text{year})_i + \\
\beta_2 (\text{September through May precipitation})_i + \\
\beta_3 (\text{May precipitation})_i + \\
\beta_4 (\text{June precipitation})_i + \beta_5 (\text{June precipitation})^2_i + \\
\beta_6 (\text{July precipitation})_i + \beta_7 (\text{July precipitation})^2_i + \\
\beta_8 (\text{August precipitation})_i + \beta_9 (\text{August precipitation})^2_i + \\
\beta_{10} (\text{May temperature})_i + \\
\beta_{11} (\text{June temperature})_i + \\
\beta_{12} (\text{July temperature})_i + \\
\beta_{13} (\text{August temperature})_i 
\]

The above model was also regressed and compared to a version that included quadratics for all precipitation and temperature variables. The quadratic version had a
lower number of significant variables, though it explained a similar amount of the variation in yield. The version presented in this section (with a combination of both linear and quadratic terms) had a higher number of significant variables and often explained a higher amount of the variation in yields. As noted previously, a goal of this section is to adequately represent the weather-technology-yield relationship while maintaining the highest number of degrees of freedom as possible. Therefore, the model developed in this section is believed to be superior to a model that includes quadratics for all weather variables.

In a review of similar Thompson-type models, Kaufmann and Snell (1997) noted that “… a high degree of collinearity probably exists among variables because temperature and rainfall are highly correlated …” (p. 180). Gujarati (2003) suggests that multicollinearity is a “serious problem” when pair-wise correlations are in excess of 0.80 (p. 359) A review of Table 4 shows that within-state pair-wise correlations of precipitation and temperature are small and usually much less than an absolute value of 0.40. In fact, the average and median values of the within-state collinearity were 0.00 and 0.01, respectively. Additionally, the highest pair-wise correlations in absolute value were 0.39, 0.44, and 0.43 for Illinois, Indiana, and Iowa, respectively. Therefore, multicollinearity issues are unlikely with the weather-technology-yield models specified in this thesis.

4.3 Model Performance and Diagnostic Tests

Before a full analysis of the modified model is performed, it is necessary to review the summary statistics and residuals of the models. Summary statistics and model
residuals for the corn models are presented in Table 8 and Figure 36, while the same information is presented in Table 9 and Figure 37 for the soybean models. Diagnostic tests for autocorrelation, heteroskedasticity, and mis-specification are also performed to determine whether significant violations of the underlying model assumptions are present. Some of these statistical tests were not available at the time of Thompson’s original publication, but help to determine if model output is reliable or unreliable.

### 4.3.1 Model Fit and Residuals

R-squared values for corn were nearly equal for each state and show that 94% to 95% of the variation in yield was explained by the models. This translated into standard errors of approximately 8 to 9 bushels per acre. This means that weather and technology accounted for all but a small proportion of the variation in corn yield. R-squared values for soybean models were slightly lower than the corn models and show that 89% to 91% of the variations in yields were explained by the models. This translated into standard errors from 2.4 to 2.9 bushels per acre. Although these values were lower than the corn models, it still shows that weather and technology accounted for most of the variations in soybean yield. Regression F-statistics were significant at the 1% level for both crops in all three states.

Figures 36 and 37 do not appear to show any obvious time pattern in the estimated residuals of the models. Hence, autocorrelation is unlikely. Heteroskedasticity also appears unlikely because variability does not appear to be increasing or decreasing. Yield estimates were poor during several years, but the poorest estimates often differed
across states and years. One notable result is the consistent underforecasting of corn yields in Iowa since 2000.

Poorest yield estimates occurred when weather was less significant than usual due to insects, diseases, and other non-traditional factors. For example, model performance was particularly poor in 1970 in Illinois and Indiana. This was due to a corn blight epidemic that dramatically reduced yields by as much as 50%. In fact, it was deemed “very severe” in Illinois, Indiana, and eastern Iowa (Ullstrup 1972). Similarly, an aphid infestation in 2003 caused significant soybean yield over-estimates – especially across Illinois and Iowa where the insects were particularly numerous (DeWitt and Tollefson, Soybean Aphids Making A Mark and The Pest Management and Crop Development Bulletin, Soybean Aphid Story: 2003). These results are somewhat expected since the model is not designed to account for such diseases or insects.

Yield estimates were also poor when unaccountable weather occurred. This was exemplified by a frost-freeze in September 1974 that particularly reduced corn yields in Iowa and soybean yields in Illinois. Several sub-freezing nights around September 21 caused especially widespread damage to the northern two-thirds of Iowa’s production (Weekly Weather and Crop Bulletin, October 1, 1974). This led to large over-estimates because the model was not designed to account for specific weather events, and weather that occurred outside of the main growing season.

Weather that deviated in the same direction from average during consecutive months also led to poor estimates. For example, 1988 corn and soybean yields were over-estimated for all states. This year had a particularly prolonged dry and hot growing season that greatly reduced yields. The models performed poorly because they accounted
for monthly weather independently of other months. For example, dry weather in June was unfavorable for yield potential. Dry and hot weather in July was also unfavorable. Although the model reduced yields because of the unfavorable June and July weather, the true effect on yields was more pronounced because weather and yield potential are likely cumulative. This appears to have caused the models to over-estimate yields by a relatively large amount.

In summary, the models estimated yields reasonably well but performed poorly during some years. The years of poorest performance often differed across states because of different sets of conditions that influenced estimates. Insect infestations, disease, unaccountable weather such as late-season frosts, and consecutive months with similar deviations from average weather also caused particularly poor yield estimates.

4.3.2 Diagnostic Tests

Residuals of each regression model were tested for autocorrelation. Autocorrelation exists if there is a time pattern in the residuals of a model. This is not desired because it would lead to a bias in the standard error estimates for the coefficients. In other words, the significance of the intercept, technology, and weather variables could be overstated. The Breusch-Godfrey test, also known as the Lagrange Multiplier (LM) test was used to test for autocorrelation. This test is more powerful than the Durbin-Watson test because it tests for more than first-order correlations. For full details of the LM test, see Gujarati (2003 p. 472).

Results indicated that the only model with statistically significant autocorrelation was the soybean yield model for Indiana. The model was re-estimated using a first-order
autoregressive error model to account for the autocorrelation. The magnitude and significance of the point estimates were very similar to the OLS regression. Therefore, the model without correction for autocorrelation was used because it was similar to the corrected version, and its output can be directly compared with the other models.

Residuals of each regression model were tested for heteroskedasticity. Heteroskedasticity exists if the variance of the residuals increase or decrease in a systematic manner. In this thesis, heteroskedasticity exists if the variance of the yield estimates increased or decreased from 1960 through 2006. Heteroskedastic observations would be problematic because the estimated standard error of coefficients would be biased. The Breusch-Pagan-Godfrey (BPG) test is used. For a full explanation, see Gujarati (2003 p. 411). Results indicated that no model exhibited statistically significant heteroskedasticity.

Only one previous study tested for mis-specification (Dixon et al., 1994), yet this is a potentially critical issue when using multiple regression models to estimate yields with weather and technology. Mis-specification can result in biased parameter and standard error estimates – a particularly concerning outcome. As one example, crop development does not necessarily follow the human calendar, but the multiple regression method is based on specific time periods, such as months. This means that multiple regressions used to estimate the effect of weather on crop yields may be mis-specified because the effect of weather may occur on a continuum without regard to human-defined calendars. Mis-specification can also occur through the omission of important variables, such as those for yield-affecting insects, late-season freezes, and solar radiation. Additionally, the incorrect functional form or utilizing periods such as months
versus weeks or days can also cause models to be mis-specified (see Chapter 1 for more information regarding various types of models that can be used to estimate the effect of weather and technology on yields). However, since particular growth stages tend to occur in the same months across the U.S. Corn Belt, multiple regression models that utilize monthly weather may nonetheless provide useful results. However, it is necessary to test for mis-specification before determining whether mis-specification skews regression output.

The Ramsey RESET (REgression Specification Error Test) was performed on each model to determine if there was significant evidence of mis-specification. The first step of the test is to run the original regression and save the predicted yields. The second step is to re-run the regression model with the squared or cubed predicted values added as independent variables to the original regression. The idea is that non-linear versions of the predicted values should not be able to explain the yield observations if the model is specified correctly. For a full explanation, see Gujarati (2003 p. 521). The squared tests are presented in Tables 8 and 9 and show that the Ramsey RESETs were insignificant, which indicated that the models are not mis-specified. Cubed tests are not presented, but were also insignificant.

4.4 Interpretation of Regression Results

The focus of this section is to analyze the relationship between weather, technology, and corn and soybean yields. Coefficients of the regression models are reviewed to determine how weather and technology affect corn and soybean yield potential. Results are compared to studies by Thompson (1963, 1969, 1970, 1985, 1986,
and 1988) to determine whether changes in the weather-technology-yield-relationship occurred. The performance of the regressions as predictors of yields is discussed to identify scenarios in which the models perform particularly well or poorly. The effect of weather on trend yields is discussed and weather indexes for corn and soybeans are developed to identify the favorability of weather on each crop since 1960. Structural change tests are performed to determine if a statistical break in relationships occurred.

### 4.4.1 Corn Yields, Weather, and Technology

The trend variable to account for technological improvements was highly significant in each state. Point estimates showed that corn yields were expected to increase 1.8 to 2.0 bushels per acre per year. A review of Figure 2 shows that these rates were consistently and slightly higher than unadjusted trend increases from 1960 through 2006, which ranged from 1.7 to 1.9 bushels per acre per year. This provides evidence that unfavorable weather obscured the yield-weather-technology relationship by flattening the trend unadjusted for the effects of weather. It also confirms similar findings by Swanson and Nyankori (1979).

Pre-season precipitation was insignificant for Illinois and Indiana. However, it was significant in Iowa where each additional inch of pre-season precipitation would be expected to increase yields by approximately one bushel per acre. A review of Table 2 suggests the significance of pre-season precipitation may be pronounced in Iowa because of its markedly lower average than Illinois or Indiana. It provides some evidence that pre-season precipitation in Illinois and Indiana is usually adequate, and that these states may initially have a comparative soil moisture advantage. However, Table 2 also shows
that the standard deviation in Iowa’s pre-season precipitation is around 3.50” inches, which means that it would typically be expected to affect yield by only +/- 3.5 bushels per acre. The importance of precipitation on yield potential during other months is much greater.

May precipitation was highly significant in Indiana and Iowa. In these states, each one-inch increase from average would be expected to reduce yields two to three bushels per acre. Similarly, each one-inch decrease would be expected to increase yields by the same amount. The same effect would be expected in Illinois, but by a lower magnitude. These results are sensible because wet weather in May would delay planting, slow growth, and possibly encourage an unfavorably shallow root system. Unfavorably shallow roots can lead to a variety of problems including: 1) “floppy corn” that is susceptible to high winds early in the season, 2) roots that are extremely sensitive to soil moisture and temperature fluctuations, and 3) the necessity to harvest as soon as possible to avoid the likelihood of lodging problems at maturity (Thomison, Conditions Favorable for "Rootless, Floppy Corn").

June precipitation was statistically significant in all three states at the 10% level or less. Panel A of Figure 38 shows the expected contribution to corn yields from June precipitation. Yield response is similar in each state and shows that an ideal amount of June precipitation exists. This means that higher or lower amounts than the ideal amount would be expected to reduce yields. Figure 39 shows that average precipitation is around 0.75” lower than ideal. However, Figures 40 and 41 show that increasing amounts by 0.75” would only be expected to increase yield by less than one bushel per acre, while decreasing precipitation by 0.75” from average would be expected to reduce yields by
two to three bushels per acre. This means that dry weather would be expected to lower yields more than equally wet weather would be expected to increase yields.

July precipitation was also significant in each state. Panel B of Figure 38 shows the expected contribution to corn yields from July precipitation. Yield response patterns are similar to June, but July precipitation contributes more to corn yields than precipitation during any other period. Figure 39 shows that approximately 2.00” higher average would increase yield up to five bushels per acre in Illinois and Indiana. However, Figure 41 shows that 2.00” less than average would be expected to reduce yields by 18 to 22 bushels per acre. The response in Iowa was less dramatic with 0.75” more than average in Iowa expected to increase yield approximately one bushel per acre, while 0.75” less than average would be expected to decrease yield around five bushels per acre. This means that unfavorably dry weather would be much more damaging to yields than favorably wet weather would be helpful.

August precipitation was insignificant in Illinois and Iowa, but was significant in Indiana. Panel C of Figure 38 shows that the response of Indiana’s yield to August precipitation is very similar to June precipitation. Figure 39 shows that around 0.75” more than average would be expected to be ideal for Indiana. However, June and July precipitation contribute more to Indiana’s yield potential. Although above average August precipitation would also be expected to increase corn yields in Illinois and Iowa, Figure 40 shows that the expected contribution is less than 1 bushel per acre. The importance of August precipitation in Indiana may be further reflection of its sandier soils that have less ability to retain moisture than in Illinois and Iowa. As a result, this
provides evidence that moderately higher-than average precipitation in August would have a more beneficial effect on corn yields in Indiana than in Illinois or Iowa.

May and June temperatures were insignificant in all states. Panels A and B of Figure 42 show that slopes of the coefficients are close to zero, which means that above-average or lower-than average-temperatures would not be expected to have a large influence on corn yields. However, recall that May and June precipitation were significant. This suggests that initial crop growth and development are much more dependent upon early-season precipitation than temperature, as corn can probably recover from unfavorable coolness or warmth in its beginning phases. This means that dry weather in May and seasonably wet weather in June would be the most ideal for corn yields during the first half of the growing season.

July temperature was significant in all states. Panel C of Figure 42 shows that each one-degree increase in temperature above average would be expected to reduce yields by approximately two bushels per acre. Similarly, each one-degree decrease in temperature from average would be expected to increase yields by two bushels per acre. Table 3 shows that the standard deviation in July temperature is around two degrees Fahrenheit, which means that it would typically be expected to affect yield by +/- 4 bushels per acre. Although this is a notable percentage of yield potential, it shows that the amount of July precipitation is considerably more important.

August temperature was the only weather factor that was highly significant in each state. Panel D of Figure 42 shows that each one-degree increase in temperature from average would be expected to reduce yields by approximately two to three bushels per acre. Similarly, each one-degree decrease in temperature from average would be
expected to increase yields by two to three bushels per acre. Table 2 shows that the
standard deviation in August temperature is around 2.4 degrees Fahrenheit, which means
that August warmth would typically influence yield potential by +/- 5 to 6 bushels per
acre. This means that hot August temperatures can reduce yields by a notable amount,
while cooler weather can increase yields. However, recall that the amount of August
precipitation is more important than the August temperature in Indiana.

In summary, it was shown that unfavorably dry weather during the summer
months decreased corn yields more than favorable wet weather increased it. The
magnitude of July precipitation had the largest influence on yield potential, and the
amount of June precipitation was also very important. In each state, moderately higher-
than-average precipitation throughout June through August would be expected to produce
the highest yields. This was particularly exhibited in Indiana, as precipitation during
August is influential to its yield. Above-average temperatures in July and August
reduced yields, though it was less important than the magnitude of June or July
precipitation. Otherwise, warm and dry weather in May was best for yield potential,
while the influence of pre-season precipitation was small.

### 4.4.2 Soybean Yields, Weather, and Technology

The trend variable to account for technological improvements was highly
significant in each state. Point estimates showed that soybean yields were expected to
increase 0.4 to 0.5 bushels per acre per year. As was exhibited in the corn models, a
review of Figure 3 shows that these rates were consistently and slightly higher than
unadjusted trend increases from 1960 through 2006, but by less than 0.03 bushels per
acre per year. This provides some evidence that unfavorable weather obscured the yield-technology relationship in soybeans by flattening the trend component unadjusted for the effects of weather.

Pre-season precipitation was insignificant for Illinois and Indiana. However, it was significant in Iowa where each additional inch of pre-season precipitation would be expected to increase yields by approximately 0.3 bushel per acre. As noted in the previous section, the significance of pre-season precipitation may be pronounced in Iowa because of its markedly lower average than Illinois or Indiana. Table 2 shows that the standard deviation in Iowa’s pre-season precipitation is around 3.50” inches, which means that it would typically be expected to affect soybean yield by +/- 1.0 bushel per acre each year. Similar to corn yields, the importance of precipitation on the yield potential of soybeans is much greater during other months.

May precipitation was significant for all states, and especially Indiana and Iowa. Each one-inch increase in May precipitation would be expected to reduce yields 0.4 to 0.9 bushels per acre. Similarly, each one-inch decrease in May precipitation would be expected to increase yields 0.4 to 0.9 bushels per acre. These results are consistent with knowledge that increased precipitation during May would probably delay planting and growth since soybean planting typically occurs in May.

June precipitation was highly significant in Indiana, but insignificant in Illinois and Iowa. Panel A of Figure 43 shows the expected contribution to soybean yields from June precipitation. Yield response is similar in each state and shows above-average precipitation would be expected to maximize yield potential. Figure 44 shows that around 1.00” more than average would be the most ideal, though Figure 45 shows it
would only contribute approximately 0.5 bushels per acre. However, Figure 46 shows decreasing June precipitation by around 1.00” from average would be expected to reduce yields by 0.7 to 1.4 bushels per acre. This means that drier weather would be expected to lower yields more than equally wet weather would be expected to increase it.

July precipitation was highly significant in Indiana and Iowa, but was insignificant in Illinois. Panel B of Figure 43 shows the expected contribution to soybean yields from July precipitation. The relationship in Iowa and Indiana was nearly identical, while the model showed that considerably more rain would be needed in Illinois to maximize yields. Figures 44 and 43 show that around 0.75” more than average would be the most ideal for Indiana and Iowa, and it would only contribute an additional 0.2 to 0.3 bushels per acre. However, Figure 46 shows 0.75” less than average would be expected to reduce yields by 0.6 to 1.0 bushels per acre. This indicates that dry weather in July is much more harmful to yield potential that wet weather is helpful.

August precipitation had the largest impact on the yield potential of soybeans in Illinois and Iowa. Although it was only significant in Iowa, Figure 43 shows that the yield response was similar in each state. Figures 44 and 45 show that 1.50” to 1.75” more than average would be expected to increase yield by 0.8 to 1.3 bushels per acre more than if typical precipitation occurred. However, Figure 46 shows the same amount less than average would be expected to reduce soybean yields 2.4 to 4.0 bushels per acre per year. This shows that the amount of precipitation during August is particularly important and has a dominating effect on yield potential.

Panels A through D of Figure 47 show the expected effect on soybean yields from temperatures for May through August. May temperature was insignificant, which means
that May precipitation is most influential during planting. June temperature also had
minimal impact in Indiana, though warmer than average weather would be expected to
increase yields in Illinois and Iowa. When combined with June precipitation, this means
that warm and wet weather in June would be favorable, while dry and cool conditions
would lower yield potential. The opposite was observed in July and August, as each one-
degree increase in temperature from average would be expected to reduce yields by 0.2 to
0.3 bushels per acre in July, and 0.3 to 0.6 bushel per acre in August. Table 3 shows that
the typical variation in temperatures is higher during August than July. Since the effect
of August temperature on yields is equally or more pronounced than July, this shows that
the magnitude of temperature during August has a greater effect on soybean yields.
However, the amount of precipitation during these months has a much larger influence.

In summary, unfavorably dry weather during the summer decreased soybean yield
more than favorably wet weather increased it. Dry weather during the early portion of
the growing season would be the most ideal, though above-average precipitation
thereafter would be expected to maximize yield. The amount of August precipitation had
the largest influence on yield potential in Illinois and Iowa, though it was not quite as
important as June precipitation in Indiana. Cooler weather during July and August would
be expected to lead to highest soybean yields, while warmer weather in June would be
ideal if rainfall is sufficient. This means that a transition from dry to wet conditions and
from relative warmth to coolness would be the most ideal for soybean yields from May
through August.
4.4.3 Comparison to Thompson’s Results

The purpose of this section is to review how the expected relationship between weather, technology, and corn and soybean yields has changed relative to previous publications by Thompson. Direct comparisons of the models are not possible because of specification differences. For example, the original model by Thompson (1963) used quadratics for all weather variables. Therefore, it was not possible to make direct comparisons of the expected effect of pre-season precipitation, May precipitation, and temperatures on yields. The following discussion provides a qualitative rather than quantitative comparison to Thompson’s estimation results due to differences in model specification and variable forms.

Thompson (1963) noted that, “The most significant weather variables in the production of corn and soybeans are July rainfall and August temperature” (p. 49) In particular, above-average rainfall in July and lower-than-average temperature in August was ideal for production, while August rainfall had a larger influence on soybeans than corn. He furthered noted that rainfall during August was “not significant” for corn production, though above-average rainfall in July and August was the best for high soybean production (Thompson 1969 and 1970). Both crops were also concluded to have highest yields with near-average June temperature and below-average July and August temperatures. Subsequent studies (Thompson 1985 and 1986) showed that soybean yields generally produced highest yields with near-average temperatures during June, July, and August and above-average July and August rainfall, while the effect of weather on corn yields was similar to previous findings in 1969.
Final conclusion by Thompson (1988) showed that highest corn yields were associated with: 1) above-average July rainfall, 2) below-average temperatures in July and August (though August could be too cool), 3) average pre-season precipitation (September through June), 4) slightly above-average June temperature, and 4) slightly above-average August rainfall (though August could be too wet). Highest soybean yields were associated with: 1) above-average July and August rainfall (especially important in August), 2) slightly above-average June and July temperatures, 3) average August temperature, and 4) average pre-season precipitation. This showed that corn was “…more sensitive than soybean to high temperature in August as well as in July“ (p. 23), while August could be too cool and wet for ideal corn production.

Results from the modified Thompson model were similar to results in the aforementioned publications, though several differences exist. Both the current and previous studies showed that corn yields are strongly influenced by the magnitude of July precipitation and July and August temperatures. However, June precipitation was shown to have a larger influence on corn yields than previously indicated by Thompson. That being said, it should be noted that Thompson’s publications defined pre-season precipitation as that which occurred from September through June, as opposed to September through April in the thesis. Therefore, inclusion of the June variable showed that the magnitude of June precipitation is more important than indicated previously – especially if the month is considerably drier than average because it can quickly reduce potential corn yields. Additionally, Figure 47 suggests the effect of May and June temperature are minimal, as it appears corn can recover from unusually warm or cool conditions during its early developmental phases. Above-average pre-season
precipitation is also suggested by the modified models to increase yield potential, but the effect of weather later in the growing season considerably outweighs the magnitude of precipitation prior to May.

Several differences were also found to exist with regard to relationships between weather and soybean yields. As also noted with respect to corn, June precipitation is more important to soybean yield potential than previously indicated. Although the amount of August and July precipitation is particularly important – especially during August – the magnitude of July precipitation is also high. This suggests that above-average precipitation throughout June, July, and August is best for soybean yields – as opposed to only July and August. The main other difference is that below-average temperatures in July and August appear to be the most ideal for soybean yields, though Thompson (1988) had suggested slightly above-average temperatures were the most ideal during this period. However, the models agree that above-average warmth in June may be the most ideal for soybeans. Therefore, the magnitude of July and August temperatures may be more closely related to soybean yields than previously suggested, although the effect of precipitation is clearly more important.

4.4.4 The Effect of Average Weather on Unadjusted Trend Yields

The slopes of unadjusted trend yields over 1960 through 2006 were lower than the slopes of the weather-adjusted trend yields produced by the models. These results are consistent with findings by Swanson and Nyankori (1979). It occurs because unfavorable weather lowers yields much more than favorable weather increases yields. As a result, the weather-adjusted trend yields are steeper (higher) than the unadjusted trend yields.
This raises an important issue because it would be useful to know what the trend yield might be if neither favorable of unfavorable weather occurred. In other words, what might trend yields be if weather had been average each month and year?

Average temperature and precipitation observations over 1960 through 2006 were plugged into the estimated regressions. This allowed for hypothetical yield estimates from 1960 through 2006 as if exactly average weather occurred each month and year. This made it possible to compare the average weather trend yield to the unadjusted trend yield. Figures 48 and 49 show that the average weather trend yields and unadjusted trend yields over 1960 through 2006. For each state and crop, the average weather trend yields were shifted higher and had steeper slopes than the unadjusted trend yields. In particular, the average weather yield estimates for corn in 2006 were 11 to 12 bushels per acre higher than the unadjusted trend yields. This means that the unadjusted trend yields were 7% to 8% lower than would be expected if average weather occurred in Illinois, Indiana, and Iowa. Similarly, 2006 average weather yield estimates for soybeans ranged from two to three bushels per acre higher than the unadjusted trend yields. This means the unadjusted soybean trend yields were respectively 4%, 5%, and 7% lower than would be expected if average weather occurred in Illinois, Indiana, and Iowa, respectively. This provides strong evidence that the unadjusted trend yields over 1960 through 2006 were sharply reduced by yield losses from unfavorable weather – especially in 1974, 1983, 1988, and 1993. It further suggests that unfavorable weather reduces yields much more than favorable weather increases yields.
4.4.5 Weather Indexes to Explain the Effect of Weather on Yields

It is useful to quantify the level of favorableness or unfavorableness of weather on corn and soybeans each year with a single index number. This would provide an objective measurement of how “good” or “bad” weather for corn and soybean yields was during a particular year. Doll (1967) developed weather indexes “… as the ratio of the yield predicted for the actual weather that occurred during the year to they yield predicted had average weather occurred in the year.” (p. 87) The same methodology can be used to compare weather indexes for corn and soybeans each year for Illinois, Indiana, and Iowa over 1960 through 2006. Results for each year determine how “good” or “bad” weather was during a particular year for corn or soybeans. The strength of this method is that the weather index is an objective quantification of weather that affects crop development. Notably, it implies that the weather models were correctly specified and that predicted yields represent yields that would have occurred if outside factors such as disease, insects, specific weather events, and weather outside of the main growing season had not affected yields. In this thesis, weather indexes for corn and soybeans are calculated as follows:

\[ W_t = \frac{\hat{y}_t}{\hat{y}_{t, \text{avg}}} \times 100 \]

where \( \hat{y}_t \) is the predicted yield from the regression model with actual values for weather variables, and \( \hat{y}_{t, \text{avg}} \) is the predicted yield from the regression model with average values for weather variables.
Weather indexes are plotted in Figures 50 and 51. A value of 100 means that exactly average weather occurred for corn and soybean yields, while lower values represent weather that was less than average and higher values indicate weather was better than average. The mean of the weather indexes for each state and crop are all lower than 100. This reinforces the earlier conclusion that unfavorable weather reduces yields more than favorable weather increases yields. In general, the mid-1970s through the mid-1990s had many years that were particularly unfavorable for corn and soybeans. 1983 was the worst weather year for corn in Illinois and Indiana, while historic rain made 1993 the worst weather year for Iowa corn yields. 1983 was the most unfavorable for soybean yields in Illinois and Indiana, while 1993 was also the worst in Iowa.

The period from the mid-1990s and forward appears to have been the most stable for corn with no particularly bad weather years – especially in Iowa. Weather for soybeans was also fairly tranquil during this period, though 2003 was rather unfavorable for soybeans in Iowa. However, as noted earlier, aphids had a large effect on soybean yields in 2003 and the models may attribute this to poor weather. Similarly, weather in Illinois in 1970 for corn yields was near average, but the very low yield observations shows the impact of the blight.

4.4.6 Structural Change

Structural changes tests are performed on each corn and soybean model for Illinois, Indiana, and Iowa to determine if the relationship between weather, technology, and yields changed at some point over 1960 through 2006. This is an important task because previous studies did not examine the possibility of structural change. In
particular, unknown break point tests are performed on each model to identify if a structural break occurred. Dummy variables are then added to any models that show significant break points. This will help to identify the source of potential structural breaks. Potential sources of structural breaks are further identified by limiting breakpoint tests to time trend, precipitation, and temperature variables.

The unknown breakpoint test of Quandt (1960) and Andrews (1993) is used to determine whether the relationship between weather, technology, and yields changed over the sample. The null hypothesis is that no model parameter changed over the sample period. This is the most general structural change hypothesis that can be tested. Significant change in a single parameter is sufficient to reject this null.

Computation of the test is straightforward. The first step is to run Chow tests of structural change for all feasible sample breakpoints after trimming a percentage of sample observations from the end of each sample. Trimming improves the power of the test. Andrews (1993) recommends trimming a total of 30%. However, 62% trimming is actually used since structural change tests cannot be performed prior to 1975 and after 1992 because 15 observations and are required to run each of the regressions for the Chow test. Each Chow test statistic is calculated as follows:

$$\text{Chow} = \frac{(SSE_p - SSE_1 + SSE_2) / k}{(SSE_1 + SSE_2) / (n_1 + n_2 - 2k)}$$

where $SSE_p$ = Sum of squares error of pooled regression, $SSE_1$ = Sum of squares error of regression number 1, $SSE_2$ = Sum of squares error of regression number 2, $k =$ number of estimated parameters (13), $n_1 =$ number of observations in regression 1, and $n_2 =$ number of observations in regression 2. The second step is to determine the
maximum F-statistic of the various break points, which is the Quandt Likelihood Ratio-Statistic (QLR-Statistic). The highest QLR-statistic is then used to determine if statistically significant structural change occurred at the indicated breakpoint. Note that the QLR statistic does not follow the standard F-distribution. Simulated tables of critical values are found in Stock and Watson (2007, p. 568)

Figures 52 and 53 plot the QLR tests for structural change over 1975 through 1992. Results show that structural change was insignificant for corn in Indiana and soybeans in Illinois and Indiana. However, structural change was significant at the: 1) 10% level in 1988 for Illinois corn, 2) 1% level in 1983 for Iowa corn, and 3) 1% level in 1988 for Iowa soybeans. One possible reason for structural changes in Iowa might be due to extreme rainfall and flooding in 1993. However, Panel D of Figures 52 and 53 show that removing 1993 observations did not eliminate the structural break point for either crop. Therefore, a separate attempt to resolve this issue was made by removing 2003 from the Iowa data sets since unfavorable weather and an aphid-related problem particularly reduced soybean yields in Iowa. However, Panel E of Figures 52 and 53 show that removing 2003 observations did not alter the structural change results. A final attempt was made by removing both 1993 and 2003 observations. Panel F of Figures 52 and 53 show that structural change remained significant and possible reasons for structural change in Iowa were inconclusive.

To better assess possible reasons for structural change, dummy variables were added to all models at the identified break points for Illinois corn, Iowa corn, and Iowa soybeans. Table 10 shows that few of the variables for Illinois corn and Iowa corn are significant when dummy variables are included. Although the August precipitation
dummy variables are significant at the 1% level in Illinois, this is inconsistent with earlier findings in Table 8 that showed August precipitation was insignificant for Illinois corn yields. Additionally, only the time trend and July temperature variables are significant at the 1% level for Iowa corn. However, many of the dummy variables for the soybean model are significant for Iowa. In particular, the dummy variables for trend, pre-season precipitation, May precipitation, and June precipitation were significant at the 5% level. Nonetheless, the results of these tests are inconclusive due to the lack of an obvious reason for the identification of structural change.

Possible sources of structural changes were further examined by testing specific variables for structural change. The time trend variable, grouped precipitation variables, and grouped temperature variables were each tested separately using the unknown breakpoint QLR tests. Results failed to identify that time trend, precipitation, or temperatures alone led to significant structural change for Illinois corn and Iowa soybeans. However, the July and August temperature variables in the Iowa corn model exhibited a significant structural break at the 5% level in 1983. This suggests that July and August temperature likely affected the Iowa corn model. A review of Panel C in Figures 11 and 12 shows this is feasible, as much cooler temperatures occasionally occurred after 1983 in Iowa. Therefore, dummy variables for July and August temperatures were added to the Iowa corn model at the 1983 breakpoint. Table 11 shows that the dummy variables are significant. The magnitude of the August temperature dummy is sensible, as it indicates the each one-degree increase in temperature would be expected to lower corn yield by 2.96 bushels per acre per year over 1983 through 2006 versus 1960 versus 1982. However, the non-dummy August temperature variable shows
that corn yields would be expected to increase 2.64 bushels per acre per year over 1960 through 1982. This latter result is unreasonable, as it is logical that increased August temperatures reduce corn yields in the U.S. Corn Belt.

The results of the structural change tests are inconclusive and difficult to explain. Tests for structural change were significant for Iowa corn and soybeans, but only weakly significant for Illinois corn. However, Illinois soybeans and Indiana corn and soybeans did not exhibit structural change. These states have similar weather, climate, soils, and utilize similar production techniques. Therefore, if a true structural change in the relationship between weather, technology, and yields occurred over 1960 through 2006, it would be expected that all or none of the states would exhibit structural change for either corn or soybeans. The addition of dummy variables to the regression models that exhibited structural change was also inconclusive. Although structural break point tests identified specific years in which the relationship between weather, technology, and yields occurred, the lack of consistent evidence precludes a general conclusion.

4.5 Technology Acceleration and Corn Yields

There has been considerable discussion in the agricultural community that improved technology has caused corn yields to increase at an increasing rate in recent years. Figure 1, adopted from Troyer (2006), provides an example of the belief that corn yields since the mid-1990s have increased at an increasing rate relative to prior decades. As a result, there has been fairly widespread acceptance that yields will continue to outperform the long-term unadjusted trend and that a new trend beginning in the mid-1990s should be used as a starting point for estimating trend yields. At the same time,
Figure 3 shows that soybean yields since 1996 have increased at a similar rate to the 1960 through 2006 unadjusted trend. Therefore, soybean yields have been given less attention and this section will examine whether technology has recently improved for corn, or if recent increases in corn yields can be explained by weather.

The previous section focused on general tests for structural change on all variables, including the time trend for technology. Results were inconclusive and did not indicate an obvious structural break occurred in corn over 1975 through 1992. However, the previous section did not test for structural breaks in the mid-1990s due to regression degrees of freedom limitations. The mid-1990s is an important period to research because belief exists that a new trend began in the mid-1990s. Therefore, this section focuses solely on structural change in the trend variable.

The technology acceleration hypothesis will be tested in two ways. The first is to perform QLR unknown breakpoint tests on the trend variable of the corn models. This will help to determine if a significant change in the weather-adjusted trend occurred over 1968 through 1998. The date range follows the recommendation by Andrews (1993) to utilize 30% trimming, which also allows for the possibility of a structural break in the mid-1990s. The second test assumes that the trend did increase in the mid-1990s and assesses the significance and magnitude of any change. In particular, this analysis performs a Chow test on the trend variable with the break fixed at 1996 to determine if a significant change in the weather-technology-yield relationship occurred. Then, the magnitude of the weather-adjusted trend coefficient before and after 1996 is examined. The favorability of weather since the mid-1990s is also reviewed.
QLR tests for structural change on the trend variable at an unknown year indicated that a significant change in the trend variable did not occur in Illinois and Indiana, but that a significant change occurred at the 5%-level in Iowa in 1983. The magnitude of the change in the trend variable for Iowa is assessed by adding a dummy trend variable to the model at 1983. This model is presented in Table 12. Results show that the trend dummy is significant at the 5% level, but that the slope of the trend is expected to be 0.42 bushels per acre per year lower – not higher – over 1983 through 2006 compared to 1960 through 1982.

QLR unknown breakpoint tests failed to identify the mid-1990s as a period in which a significant break in trend yields for corn occurred in Illinois, Indiana, or Iowa. However, unknown breakpoint tests are less powerful than tests where the breakpoint is known. Therefore, 1996 is chosen as a breakpoint because it is near the middle of the 1990s, when trend yields for corn are commonly believed to have increased. Additionally, yields are near trend levels in 1996, which avoids potential distortions introduced by selecting an earlier ear, such as 1995, when yields were abnormally low. This is the most favorable test of the hypothesis that trend yields for corn have increased since the mid-1990s because it directly measures the magnitude and significance of the change in trend at 1996.

Dummy variables were added to each model at 1996 to determine the significance and magnitude of the any change in the time trend. Results of the regression are presented in Table 13 and show that point estimates are very similar to the modified model originally presented in Table 7. The time trend variable over 1960 through 1995 ranges from 1.8 to 1.9 bushels per acre per year. The dummy variables were insignificant.
and indicated that the trend since 1996 had changed by a magnitude of 0.09, -0.04, and 0.15 bushels per acre per year in Illinois, Indiana, and Iowa, respectively. Therefore, the models do not suggest a notable change in the trend.

Results of the structural breakpoint tests did not provide compelling evidence of an increase in trend yields for corn in the mid-1990s. However, Figure 1 (adopted from Troyer 2006) shows that trend yields at the national level appear to have increased since the mid-1990s. As noted above, the increase in unadjusted trend has led to the common belief that trend yields have increased at an increasing rate in recent years. Although these results are contradictory, Nafziger (2004) points out that “… at least over a period of a few years, weather has a larger effect on yields of corn and soybean than management.” (p. 1) Therefore, weather since the mid-1990s is reviewed to assess its possible effect on corn yields for Illinois, Indiana, or Iowa.

Figure 50 shows that weather indexes for corn were fairly stable since the mid-1990s. In fact, the 1970s through the mid-1990s in each state had at least five years in which weather was less favorable for the development of corn than any year from 1996 through 2006. This suggests that recent weather was relatively benign for corn development. Additionally, Figure 48 shows that corn yields since the mid-1990s were often higher than the unadjusted trend, but were not particularly high when viewed with respect to the average weather trend. Since weather was relatively close to average from 1996 through 2006, recent corn yields may be outperforming the unadjusted trend because unfavorable weather in prior years shifted the unadjusted trend downward. Recall that the unadjusted trend is shifted downward because unfavorable weather lowers yields much more than favorable weather increases yields. Therefore, observers may be
mistakenly attributing corn yield increases to improvements in technology by failing to recognize: 1) the effects of unfavorable weather during the 1970s, 1980s, and 1990s on unadjusted trend yields, and 2) relatively benign weather since 1996.

It is also possible that the mid-1990s marked the beginning of a new trend, but the relatively small number of new observations is preventing its detection. Many farmers, crop experts, and major seed companies credit a combination of improved genetics, agronomic practices, and biotechnology for recent corn yield increases (Fitzgerald 2006). However, historical considerations cannot be ignored. After unexpectedly poor corn yields due to unfavorable weather in 1974, Thompson (1975) discussed the importance of weather on yields because, “There was frequent reference in the early 1970’s to the fact that technology had increased to such a level that weather was no longer a significant factor in grain production.” (p. 535) As shown in Figure 50, unfavorable weather for the development of corn eventually followed in 1980, 1983, and 1988. This further identified the 1960s through the early-1970s as a favorable period for corn with Thompson (1990) stating that, “The trend was very steep from 1960 to 1972 because the favorable weather each year resulted in excellent response to increasing technology.” (p. 89) Therefore, it is also possible that higher-than-expected yields since the mid-1990s may be due to a combination of favorable weather and improving technology.

4.6 Summary

The original crop-weather model developed by Thompson (1963) is presented in this chapter. It was modified due to changes in planting and patterns in monthly weather-yield scatter plots. Notably, the linear form to represent the time trend for technology
was determined to be the best representation of increased yields. Precipitation, temperature, and corn and soybean yield observations from Illinois, Indiana, and Iowa over 1960 through 2006 were then utilized to estimate the regression models. Results indicated that at least 94% of the variation in corn yields is explained by weather and technology, while these factors explain at least 89% of the variation in soybean yields. Diagnostic tests indicated that the models generally did not exhibit autocorrelation, heteroskedasticity, or mis-specification.

Analysis of the regression results showed that yields are reduced by unfavorable weather by a much larger amount than they are increased by favorable weather. Corn yields are particularly affected by technology, the magnitude of precipitation during June and July, and the magnitude of temperatures during July and August. The effect of temperatures during May and June appear to be minimal. Soybean yields are most affected by technology and the magnitude of precipitation during June through August (and especially during August). The magnitude of July and August temperatures on soybean yields is also important, but less so than precipitation. Although the models estimated yields fairly well, they performed poorly when outside influences such as insects, diseases, and unusual weather occurred. Additionally, the cumulative effects from weather that deviated in the same direction from average during consecutive months also created poor estimates.

The modified models showed that the relationship between weather, technology, and corn and soybean yields was similar to the relationships estimated by Thompson (1963, 1969, 1970, 1985, 1986, and 1988). However, some differences exist. Temperatures during May and June appear to have little effect on corn yields, and
temperatures during June through August appear to have a larger effect on soybean yields. Additionally, the magnitude of June precipitation was shown as more important to corn and soybean yields than suggested by Thompson. Soybean yields also appear to be more influenced by the magnitude of precipitation during June through August, though August precipitation remains the main driver of soybean yields.

Average weather would be expected to lead to yields that are higher than the unadjusted trend, and would also lead to a higher but constant rate of yield increase. This indicates that unfavorable weather over 1960 through 2006 shifted the unadjusted trend downward and also flattened its slope. Therefore, average weather would be expected to lead to yields that outperform the unadjusted trend.

Weather indexes for corn and soybeans showed that the mid-1970s through the mid-1990s had several unfavorable years for the development of each crop. 1983 was the worst year for corn and soybeans in Illinois and Indiana, while 1993 was the worst for each crop in Iowa. Weather since the mid-1990s was not particularly unfavorable, with Iowa having particularly benign conditions for corn.

Structural break tests failed to identify a significant change in the relationship between weather, technology, and yields for Indiana corn and soybeans and Illinois soybeans. However, structural breaks were indicated at 1988 for Illinois corn, 1983 for Iowa corn, and 1988 for Iowa soybeans. Reasons for these results are difficult to assess. This is because a true structural break appears somewhat unlikely to have occurred because breaks should be observed in all states since weather, crop development phases, soil qualities, and geography are relatively similar across Illinois, Indiana, and Iowa.
The common belief that corn yields have increased at an accelerated rate since the mid-1990s was explored. Structural break tests failed to identify the mid-1990s as period in which trend yields increased. However, observations that corn yields were often higher than the unadjusted trend could not be ignored. Weather from 1996 through 2006 was shown to be relatively benign for the development of corn with many years from the mid-1970s through 1995 unfavorably hot, dry, cool, or wet. Therefore, it was deemed possible that favorable weather had caused yield increases. However, it was also possible that trend increases were occurring but were not detectable due to a lack of new observations. Historical considerations also suggest that a combination of favorable weather and improved technology may be causing higher-than-expected yields in recent years.

In conclusion, the multiple regression method produced useful models to estimate the relationship between weather, technology, and corn and soybean yields in the U.S. Corn Belt. Although the relationship remains inexact, it is apparent that the models provide useful information that helps to explain recently increased corn yields. Comparisons of unadjusted trend yields to average-weather trend yields clearly show that the unadjusted trend has been shifted downward with a flatter slope. This indicates that unfavorable weather lowers yields much more than favorable weather increases yields, and indicates that periods of favorable weather can cause periods of what appears to be much higher-than-expected yields. These results were assessed through a review of in-sample estimates. It is also interesting to determine the usefulness of the models to forecast out-of-sample corn and soybean yields – a task which is covered in the next chapter.
5. THE MODIFIED THOMPSON MODEL AS A FORECASTING TOOL

5.1 Introduction

The modified Thompson models developed in the previous chapter provided useful results regarding the relationship between weather, technology, and corn and soybean yields in Illinois, Indiana, and Iowa over 1960 through 2006. The amount of variation in yields explained by each model was high, around 90%, and coefficients helped to determine the expected effect of weather and technology on yields. However, previous results only assessed the usefulness of the models with in-sample data. While the models explained all but a small part of the in-sample variation in corn and soybean yields, Armstrong (2001) noted much research shows, “…that the fit of a model to time-series data provides a poor way to assess predictive validity.” (p. 461) Weaker performance in out-of-sample prediction can be due to a variety of factors, including data-mining induced over-fitting, structural breaks and parameter instability, inclusion of irrelevant variables, and omission of relevant variables (e.g., Clements and Hendry, 2002). Therefore, usefulness of the models in out-of-sample forecasting is assessed in this chapter.

Previous studies by Teigen (1991a and 1991b) and Teigen and Thomas (1995) utilized multiple regressions to forecast corn and soybean yields across various areas of the U.S. However, forecasts were only made for a small number of years and the measure of accuracy of the models to forecast yields was somewhat subjective. A study by Dixon et al. (1994) only provided out-of-sample forecasts for three years. Therefore, a central goal of this chapter is to develop a large set of forecasts that can be assessed with conventional tests of forecast accuracy. While this type of analysis is considered
standard in the forecasting literature, a comprehensive out-of-sample evaluation of yield forecasts from regression models has not been conducted to date.

A forecasting competition is developed in this chapter to assess the usefulness of the models to predict yields. In particular, a competition is developed through utilization of forecasts from: 1) the modified Thompson models, 2) trend models, and 3) the USDA. A method is developed to create monthly out-of-sample corn and soybean yield forecasts for Illinois, Indiana, and Iowa with the modified Thompson models. These forecasts are compared to trend yield and USDA forecasts that serve as benchmarks. The methodology used by the USDA to produce their monthly forecasts is presented, and all forecasts are evaluated with respect to final average yields. Statistical measures of forecast accuracy are presented. The evaluation will help to identify the usefulness of weather and technology to forecast yields while the growing season is in progress. Finally, forecasts from the modified Thompson model and USDA will be combined to produce and evaluate a single forecast for each crop and state.

5.2 Development of a Yield Forecasting Competition

This section of the thesis develops a forecasting competition to create and compare monthly yield forecasts for Illinois, Indiana, and Iowa. Monthly out-of-sample corn and soybean yield forecasts from 1980 through 2006 are produced from June through October with the modified Thompson models. The forecasts are compared to benchmarks that are represented by: 1) out-of-sample trend yield forecasts in June and July, and 2) USDA Crop Production forecasts in August, September, and October. The various forecasts are evaluated for usefulness in the next section. The forecasting
competition is devised such that the varying forecasts do not have information advantages by being produced at different times. Therefore, it is necessary to gain an understanding of how the forecasts are generated such that they can be fairly compared.

The USDA publishes its corn and soybean production forecast in August, September, October, and November with final average yield estimates released in January. Good and Irwin (2006) explain that the production forecasts are based on planted and harvest acreage estimates and yield forecasts. The yield forecasts are based on: 1) a farmer-reported survey conducted via a “list frame” that is a composition of farmers names, addresses, and phone numbers, and 2) an independent “area frame” where fields are randomly chosen from the land area used to produce corn or soybeans (see Good and Irwin (2006) for full details). The forecasts are based on results of the list frame and area frame during the end of the previous month and into the first few days of the month being forecast. Therefore, forecasts represent conditions as of the beginning of the release month forecast and assume that average weather occurs for the remainder of the growing season. For fair comparison to the USDA forecasts, modified Thompson model forecasts must: 1) utilize precipitation and temperature observations that are only available at the beginning of each month, and 2) assume average weather follows for the remainder of the growing season. Trend yield forecasts already fit these qualifications because they are independent of weather observations.

Out-of-sample yield forecasts from the models are assumed to be produced on the first day of each month. Forecasts are produced by regressing the model from 1960 through the year prior to the year being forecast. Then, actual weather values are entered into the model for the year being forecast. However, actual values are only entered for
months prior to the current month. Average weather values are entered for remaining months to represent upcoming weather. The average weather values are based on data from 1960 through the year prior to the year being forecast. This method assumes perfect knowledge of weather variables through the first day of each month. For example, yield forecasts for June 1, 1980 are produced in the following manner:

1) The modified Thompson model is regressed with data from 1960 through 1979.
2) Pre-season precipitation is entered into the model by summing total precipitation from September 1979 through April 1980.
3) May 1980 precipitation and May 1980 temperature values are entered into the model.
4) Average precipitation and temperature values from 1960 through 1979 are entered into the model for June, July, and August.
5) Yield forecasts for June 1, 1980 are calculated and saved.

Forecasts for July 1, 1980 are produced by repeating this process and using actual June 1980 precipitation and temperature values. This process is repeated for August 1 and September 1. The same methodologies are repeated until all forecasts are created through 2006. Note that September 1 and October 1 forecasts are the same since the modified Thompson model does not utilize weather information from September and October to forecast yields.

Out-of-sample trend yield forecasts are produced in a similar manner to forecasts from the modified Thompson model. Trend yield forecasts are produced because they are assumed to represent the best available yield forecast prior to the start of each growing season. These forecasts utilize previously observed yields to predict yields for
the upcoming year, and they are created by regressing observed yields on time. To produce the out-of-sample trend yield forecasts, the same process used to create forecasts from the modified Thompson model is used. However, trend yield forecasts do not change throughout the growing season since they are solely based on previous yield observations. Therefore, the trend yield forecasts are the same from June through October.

5.3 Methods of Evaluation

Methods used to analyze forecasts in the remainder of this chapter are defined in this section. This will help to familiarize the reader with the techniques that are used to assess the usefulness of the models as predictors of yields. In particular, the calculation and importance of Root Mean Square Errors (RMSE), Root Mean Square Percentage Errors (RMSPE), Mean Average Error (MAE), and Mean Average Percentage Errors (MAPE) are discussed.

Forecasts errors provide the main input for the assessment of forecast accuracy. The magnitude of the error indicates the difference between the forecast yield and the observed yield. The errors can then be used in other types of analyses for this chapter. Specifically, forecasts errors area defined as follows:

\[ e_i = y_{a_i} - y_{f_i} \]

where \( y_{a_i} \) = final average yield, and \( y_{f_i} \) = forecast yield

Root mean squared error (RMSE) is the square root of the average of the squared errors. Since the errors are squared, the RMSE weights poor forecasts relatively more than good forecasts. Specifically, the RMSE is calculated for each model as follows:
The root mean squared percentage error (RMSPE) is the same as the RMSE, but it is calculated in percentage form. This allows for equal cross-comparisons of the corn and soybean yield forecasts because results are independent of units (bushels per acre). Lower RMSPE values represent better forecasts. Specifically, the RMSPE is calculated for each model as follows:

$$RMSPE = \frac{1}{n} \sqrt{\sum_{t=1}^{n} \left( \frac{ya_t - yf_t}{ya_t} \times 100 \right)^2}$$

The mean absolute error (MAE) is the average of the absolute value of the forecast errors. It represents the absolute magnitude of the forecast errors in bushels per acre. It is different from the RMSE because all of the forecasts are weighted equally. In other words, poor forecasts are weighted equally with good forecasts. Lower MAE values represent better forecasts. Specifically, the MAE is calculated for each model as follows:

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| ya_t - yf_t \right|$$

The mean absolute percentage error (MAPE) is the same as the MAE, but it is calculated in percentage form. This allows for equal cross-comparisons of the corn and soybean yield forecasts because results are independent of the large difference in their average yields. It represents the absolute magnitude of the forecast errors in percentage form. Lower MAPE values represent better forecasts. Specifically, the MAPE is calculated for each model as follows:
\[ MAPE = \frac{1}{n} \sum_{t=1}^{n} \left( \frac{ya_t - yf_t}{ya_t} \right) \times 100 \]

The modified Diebold-Mariano (MDM) test developed by Harvey, Leybourne, and Newbold (1998) is used to determine whether differences in accuracy between two competing forecasts are statistically significant. The competing forecasts in this thesis are the: 1) weather model, and 2) trend yield or USDA forecasts. The MDM test is more useful than the common paired t-test because errors from the competing forecasts tend to move in the same direction. In other words, poor or good yield forecasts from each model usually occur during the same year because weather is such a large determinant of yield. Before performing the MDM test, it is first necessary to measure the difference in squared forecast errors as follows:

\[ d_t = e_{1t}^2 - e_{2t}^2 \]

where \( e_{1t} \) = USDA or trend forecast error, and \( e_{2t} \) = modified Thompson model forecast error. The MDM test is then defined as follows:

\[ MDM = \left[ \frac{n+1}{n} \right]^{1/2} \left[ n^{-1} \gamma_0 \right]^{1/2} \bar{d} \]

where \( n \) = number of forecasts, \( \gamma_0 = n^{-1} \sum_{t=1}^{n} \left( d_t - \bar{d} \right)^2 \), and \( \bar{d} \) = mean of \( d_t \)

5.4 Forecast Stability

Yield forecasts from the regression models may have been disadvantaged in the 1980s relative to those produced in the 1990s and 2000s. This is because the data sets used to make the forecasts only began in 1960, which means that forecasts in the 1980s utilized a much smaller number of observations than those in the 1990s and 2000s. In
other words, the number of degrees of freedom utilized by the models to estimate yields was smaller in the 1980s than in the 2000s. By the 2000s, the degrees of freedom increased and yield forecasts may have improved. To determine whether forecasts from the modified Thompson models steadily improved over 1980 through 2006, forecasts are evaluated over 1980 through 2006 relative to USDA forecasts. To determine if the weather model improves relative to the USDA, $d_i$ values are regressed on time for each state and crop. This shows whether there was a significant increase or decrease between the relative size of squared forecast errors from 1980 through 2006.

To demonstrate the results of this test, $d_i$ values of forecasts produced on September 1 for corn and soybeans are presented in Figures 54 and 55, respectively. A positive slope of the trend line indicates that forecasts from the modified Thompson model improved relative to the USDA over 1980 through 2006. All slopes are slightly positive except for Iowa soybeans. The average position of the trend lines is below the zero line, which indicates that forecasts from the USDA were usually more accurate than forecasts from the modified Thompson model. Estimated time trend coefficients for $d_i$ on August 1, September 1, and October 1 are presented in Table 14. While all but two of trend line slopes were positive, only forecasts from the Illinois soybean model improved significantly. Hence, a discernable trend in the accuracy of regression model forecasts relative to USDA forecasts generally is not present over 1980 through 2006.

5.5 Forecast Evaluation

Monthly corn and soybean yield forecasts from the modified Thompson models, trend yield models, and USDA are evaluated over 1980 through 2006 in Illinois, Indiana,
and Iowa. All forecasts are analyzed versus final average yields that are reported in January after each growing season in the USDA *Crop Production Annual Summary* publication. Where applicable, results are presented in bushels per acre and in percentage form for cross-commodity evaluations of the corn and soybean yield forecasts.

### 5.5.1 Corn Yield Forecast Errors

Final corn yield forecast errors from the modified model are presented in Figure 56. Results show that the standard deviation of the forecast errors ranged from around 15 to 19 bushels per acre. Errors exceeded one standard deviation by a large amount in several years. For example, 1988 was over-forecast by 28 and 41 bushels per acre in Illinois and Indiana, respectively. 1993 forecasts for Iowa were over 53 bushels per acre too high. Both 1988 and 1993 were characterized by unfavorable weather in successive months, which further suggests that forecasts are particularly poor when weather is cumulatively unfavorable. Forecasts in Iowa were consistently underforecast from 2001 through 2006, while Illinois had typical error fluctuations during these years and Indiana forecasts were quite accurate.

A review of Table 8 shows that the out-of-sample standard deviations of forecast errors are more than twice the in-sample standard error of models estimated over 1960 through 2006. This is not a surprising result given the relatively simple model specifications and the inherent complexity in yield, weather, and technology relationships. In addition, it is important to note in this regard that weaker out-of-sample forecasting performance does not necessarily mean the regression models do not have value in forecasting yields. The performance of alternative models may be even weaker.
Statistical measures of accuracy are presented in Table 15. Forecasts from the trend model are similar to trend yield forecasts on June 1 and July 1, and are within 19 to 21 bushels per acre of final average yields, or 18% to 21%. In fact, forecasts from the weather model are slightly better on June 1 than July 1. This provides evidence that perfect knowledge of May and June weather is not particularly useful in improving upon trend yield forecasts. This is likely due to later weather over-riding the smaller effects of weather early in the growing season. However, it is notable that forecasts are particularly poor in Illinois and Indiana in 1988 and for Iowa in 1993. 1988 was characterized by a historic drought and Iowa experienced a historic flood in 1993. Therefore, the usefulness of the weather model may be understated.

Modified Thompson model forecasts improve on August 1, which is sensible because August 1 forecasts include weather observations for July that have a large effect on corn yields. RMSE values on August 1 are accurate to within 15 to 17 bushels per acre of final average yields, or within 16% to 17%. This is an improvement from trend forecasts that are within 18% to 21% of final average yields. Weather model forecasts improve further for Illinois and Indiana on September 1, though forecasts for Iowa are slightly less accurate. However, USDA forecasts on August 1 are 6 to 7 percentage points more accurate than the weather models and 7 to 9 percentage points more accurate on September 1. USDA forecasts further improve on October 1.

Modified Diebold-Mariano tests are presented in Table 16. Results show that USDA corn forecasts on August 1, September 1, and October 1 are significantly more accurate than forecasts from the modified Thompson models. This provides evidence that USDA forecasts are statistically superior to forecasts from the modified Thompson
model, and become increasingly accurate relative to the regression models with each passing month.

5.5.2 Soybean Yield Forecasts

Final soybean yield forecast errors from the modified model are presented in Figure 57. Results show that the standard deviation of the forecast errors ranged from around five to nine bushels per acre. 2003 forecasts were poor for Illinois, Indiana, and Iowa. This was probably due to the effects of an aphid infestation (DeWitt and Tollefson, Soybean Aphids Making A Mark and The Pest Management and Crop Development Bulletin, Soybean Aphid Story: 2003). Yields were over-forecast in Illinois and Indiana in 1991, and especially in Indiana in 1992. However, the poorest forecast clearly occurred in 1993 in Iowa when the model over-forecast its yield by nearly 21 bushels. A pattern in the forecasts errors was not visually detectable, and it appears that forecasts for Illinois were particularly stable since 1980.

Similar to the corn models, a review of Table 9 shows that the standard deviations are more than twice the in-sample standard error of the regression models over 1960 through 2006. As noted in the previous section, this is not a surprising result given the relatively simple model specification and the inherent complexity in yield-weather-technology relationships.

Statistical measures of accuracy are presented in Table 17. Weather model and trend forecasts for soybean yields on June 1 and July 1 are more accurate than the corn yield forecasts. Forecasts are accurate to within 12% to 15% of final average yields, as compared to 18% to 21% for the corn yield forecasts. Weather model and trend yield
soybean forecasts are very similar on June 1 and July 1. This provides evidence that the weather models for soybeans in June and July do not lead to marked improvements over trend yield forecasts.

Modified Thompson model forecasts for soybeans improve for Illinois on August 1, but are slightly less accurate than earlier forecasts for Indiana and Iowa. RMSE values show that weather model forecasts only improve by less than one percentage point for all states on September 1. Nonetheless, the improvement on September 1 is sensible because forecasts should improve on September 1 with the inclusion of weather observations during the important months of July and August. In fact, RMSE values suggest that trend yield forecasts are more accurate for Iowa on September 1 and only slightly less accurate for Indiana. On the other hand, USDA forecasts are 2 to 6 percentage points more accurate than the weather model on August 1, 3 to 9 percentage points more accurate on September 1, and 6 to 13 percentage points more accurate by October 1. However, the modified Diebold-Mariano tests in Table 16 indicate that the difference between weather model and USDA forecast are not significantly different for Illinois and Iowa on August 1, and remain insignificantly different on September 1. Forecasts on October 1 are statistically different as USDA forecasts improve.

Results for the soybean forecasts are similar to corn yield forecasts in that the weather model is no more accurate than trend yield forecasts early in the growing season. The difference in forecast accuracy between the weather model and USDA forecasts was only significant for Indiana on August 1, though the difference was significant for all states on October 1.
5.6 Encompassing Tests

The previous section showed that forecasts from the modified Thompson model began to improve on August 1 for corn and September 1 for soybeans. However, the models were no more accurate than trend yield forecasts on June 1 and July 1. Additionally, the models are noticeably less accurate than USDA forecasts. This casts doubt on the usefulness of the regression models to forecast corn and soybean yields for Illinois, Indiana, and Iowa. However, Granger and Newbold (1973) pointed out that a forecast can still prove to be useful despite being less accurate than an alternative forecast.

An encompassing test is used in this chapter to determine if forecasts from the modified Thompson model and USDA can be combined to produce a superior forecast. Harvey, Leybourne, and Newbold (1998) developed a forecast encompassing test to determine the appropriate weight that the inferior forecast should be given. The results can then be used to measure the amount of improvement that occurs. The idea behind the test is that information contained in one forecast encompasses the information in an alternative forecast if the weight is zero. If it is not zero, then the inferior forecast still provides useful information because it utilizes different information than the more accurate forecast. Note that encompassing tests are not performed on forecasts from the modified Thompson model and the trend model because the time trend is a component of the modified Thompson model.

The encompassing test based on the following regression:

\[ e_{ir} = \zeta + \lambda(e_{ir} - e_{2ir}) \]

where \( e_{ir} = \) USDA forecast error, and \( e_{2ir} = \) modified Thompson model forecast error.
The regression slope coefficient ($\lambda$) represents the weight that should applied to the modified Thompson model forecast and $1 - \lambda$ is the weight that should be used on the USDA forecast. The null hypothesis is that $\lambda = 0$, which means that there is zero covariance between $e_{1t}$ and $e_{1t} - e_{2t}$. This would imply that the USDA forecasts encompass the information in the modified Thompson model forecasts. If $\lambda \neq 0$, this implies that two forecasts contain different and useful information.

Results of the encompassing tests are presented in Table 18. There appears to be considerable value in weighting the forecasts for corn and soybeans in Illinois and Indiana. For example, Illinois weights for the modified Thompson models in August are 23% and 35% for corn and soybeans, respectively. Similarly, Indiana weights in August are 28% and 20% for corn and soybeans, respectively. Limited value is indicated for weighting corn and soybean forecasts in Iowa, with August model weights of 16% for corn and 8% for soybeans. Encompassing test statistics are significant in two of three cases for Illinois corn, and all three cases for corn in Illinois and soybeans in Indiana. However, the three encompassing tests for Iowa corn and soybeans and Indiana soybeans are insignificant.

There is a notable decline in model weights from August 1 to October 1. For example, corn weights in Illinois decreased from 28% to 16% from September 1 to October 1, and soybean weights dropped from 33% to 13%. These results indicate that information in USDA forecasts improved sharply relative to modified Thompson models on October 1 – a logical result because USDA forecasts on October 1 reflect a larger availability of actual yield observations.
Results of the encompassing tests show that a number of the modified Thompson models contain information that is not contained in the USDA forecasts. However, encompassing tests do not address how much the model forecasts could improve the accuracy of USDA forecasts. To determine the magnitude of improvements in forecasts accuracy, modified Thompson model and USDA forecasts over 1980 through 2006 were combined into a single composite forecast based on the weights from the encompassing regressions. More specifically, the mean of the respective forecast errors over 1980 through 2006 was first added to each forecast. Then, the modified Thompson model forecasts were multiplied by the weight ($\lambda$) in Table 18, and the USDA forecasts were multiplied by the remaining weight ($1-\lambda$). The RMSE of the composite forecasts was then compared to RMSE values for the weather model and USDA forecasts. Results of this evaluation are presented in Table 19 and indicate a substantial reduction in RMSE in a number of cases. Composite corn forecasts for Illinois and Indiana on September 1 improve by more than one bushel per acre versus the USDA forecast. This is an improvement of approximately 20%. Despite smaller model weights, composite corn forecasts for these states on October 1 improve by over a half bushel, or approximately 15%. Soybean forecasts in Illinois improve by a more modest 6% to 9%. Forecasts for corn and soybeans in Iowa improve by less than 2%. The soybean forecasts in Indiana improve by 5% or less. Overall, RMSE reductions across the three states and months average 10% for corn and 6% for soybeans.

The question remains as to whether the RMSE reductions discussed above are “large” or “small” relative to economic decision-making. A formal model of decision-making under risk for corn and soybean market participants in each state is required to
answer this question rigorously. Such a task is beyond the scope of this thesis. However, Colino and Irwin (2007) analyzed a similar situation with respect to composite forecasts and RMSE reductions for cattle and hog prices. They determined that a 2.9% RMSE reduction in price forecasts resulted in marked and “non-trivial” economic value for hog producers. RMSE reductions in Table 19 are generally much higher than 2.9%. For example, the RMSE reduction for corn yield forecasts in Indiana is 20.8%. Therefore, it is plausible that composite yield forecasts result in economically significant RMSE reductions. Although the Colino and Irwin study was based on price and this study was based on corn and soybean supply (yield) – supply is known to be an integral portion of price discovery for corn and soybeans.

5.7 Summary

The modified Thompson models presented in Chapter 4 explained a majority of the in-sample variation in corn and soybean yields. However, Armstrong (2001) noted that in-sample explanatory power is not necessarily a good indicator of the ability of a model to produce out-of-sample forecasts. Although previous studies by Teigen (1991a and 1991b), Teigen and Thomas (1995), and Dixon et al. (1994) analyzed forecasts from similar types of multiple regression models, they did not analyze a large number of forecasts.

To assess the usefulness of the modified Thompson models as predictors of yields, a forecasting competition was developed to produce and compare forecasts from: 1) the modified Thompson model, and 2) USDA and trend forecasts that served as benchmarks. Forecasts were produced on June 1, July 1, August 1, September 1, and
October 1 for each year. The first day of each month was chosen for fair comparisons
given USDA forecasts are representative of the first day of each month. Several
statistical methods of evaluation were presented.

Corn yield forecasts from the modified Thompson model and trend model on June
1 and July 1 were similar, which indicated that perfect knowledge of weather early in the
growing season would not lead to marked improvements in trend-yield forecasts.
However, model forecasts improved substantially on August 1 with RMSE values
showing that forecasts were within 16% to 17% of final average yields. However, USDA
corn forecasts were 6 to 7 percentage points more accurate than the model forecasts on
August 1. In fact, modified Diebold-Mariano tests showed that USDA forecasts were
always statistically superior to those from the modified Thompson model.

Soybean forecasts on June 1 and July 1 were more accurate than the corn yield
forecasts, but were still close to trend forecasts. This further suggested that perfect
knowledge of weather early in the growing season did not greatly improve yield
predictions. Iowa soybean forecasts on September 1 were less accurate than trend
forecasts, and Indiana forecasts were only slightly more accurate than trend. Although
USDA forecasts were more accurate from August 1 through October 1 than those from
the weather models, modified Diebold-Mariano tests showed that USDA forecasts did not
significantly outperform model forecasts until October 1.

The modified Thompson models were less accurate at forecasting yields than the
USDA. However, this did not necessarily mean that the modified Thompson models did
not provide useful results. Encompassing tests were performed to determine if forecasts
from the modified Thompson models and USDA: 1) utilized different information, and 2)
could provide economic value by being combined into single composite forecasts. Results showed that some of the forecasts utilized different information and that composite forecasts could produce significant accuracy improvements. For example, composite corn forecasts for Illinois and Indiana improved the accuracy of USDA forecasts by around 20% and 15% on September 1 and October 1. Illinois soybean forecasts could be improved by 6% to 9%. However, corn and soybean forecasts for Iowa could not be greatly improved, and neither could Indiana soybean forecasts. Colino and Irwin (2007) showed that RMSE reductions of just 2.9% were able to provide non-trivial economic value in forecasting cattle and hog prices. RMSE reductions presented in this chapter are much larger and suggest that a significant improvement in yield forecasts is possible – especially for corn. Since yields are one of the main drivers of supply-side economics for corn and soybeans, it is plausible that there may be noted economic value in the use of composite forecasts to improve USDA forecasts.
6. CONCLUSIONS

6.1 Summary and Review

Weather and technology are the main drivers of corn and soybean yields in the U.S. Corn Belt. Despite nearly a century of research on the relationship between weather, technology, and yields, the exact relationship remains debatable. In fact, corn yields were unexpectedly high as recently as 2003 in Illinois (Changnon and Hollinger 2004). Understanding the weather-technology-yield relationship has increased importance given expectations for a continued increase in global temperatures (NCDC, *Climate of 2006 – Annual Report*).

Speculation has developed that technological improvement since the mid-1990s altered the relationship between technology and weather for corn. This is commonly used to explain why corn yields have often out-performed the long-term trend over the past 10 years. Seed companies attribute the yield increase to genetic and biotechnology improvements (Fitzgerald 2006). However, Nafziger (2004) and Nielsen (2006) note that weather can have a large effect on yields over short periods and that caution should be used before reaching such a conclusion. Thompson (1975) indicated that similar thinking existed in the early-1970s, but unfavorable weather in 1974, 1983, and 1988 showed that the corn yield increases were due to a combination of improved technology and favorable weather (Thompson 1990). Soybean yields have received less attention because recent yields have not been notably higher than expected.

The purpose of this thesis was to investigate the relationship between weather, technology, and corn and soybean yields in the U.S. Corn Belt. Multiple regression models were developed based on specifications indicated in studies by Thompson (1962,
1963, 1969, 1970, 1985, 1986, and 1988). This type of model was considered best for this investigation because it captured the effects of both weather and technology, while models based on physiological and biological properties typically exclude technology and are highly complex (Kauffman and Snell 1997). Corn and soybean yields, monthly temperature, and monthly precipitation observations were collected over 1960 through 2006 for Illinois, Indiana, and Iowa to estimate the regression models. 1960 was used as the beginning year because it coincided with a marked increase in nitrogen fertilizer application and was supported by previous studies of Corn Belt yields (Thompson 1969, 1975, 1985, 1986, and 1988; Garcia, et. al 1987).

Analysis of the data showed that state-level monthly precipitation in Illinois, Indiana, and Iowa over 1960 through 2006 was similar, though pre-season precipitation was notably lower in Iowa. Monthly temperatures averaged the warmest in Illinois, followed by Iowa and Indiana, respectively. Observations of monthly weather were a poor indicator of weather in other months, though correlations of in-state precipitation and temperatures showed that they tended to move in opposite directions in May and June, and especially in July. This indicated that cool-wet and warm-dry scenarios occasionally occurred in tandem. Additionally, monthly weather across Illinois, Indiana, and Iowa tended to deviate from average in the same direction during the growing season, which indicated that similar weather patterns often affected all three states. Precipitation and temperature observations did not increase or decrease significantly over the sample, which was not necessarily inconsistent with the possible effects of global warming at the state level. Otherwise, corn yields in Iowa increased at the fastest rate over 1960 through 2006, while soybean yield increases were similar across states.
Modifications to the original model developed by Thompson (1963) were made because of a steady shift to earlier planting since 1960 and patterns in scatter plots of weather and yield observations. A linear form was used to represent technology because it was shown to be the best representation of trend yields over 1960 through 2006. The models explained at least 94% and 89% of the variation in corn and soybean yields for each state, respectively. Diagnostic tests of each model generally failed to show significant levels of autocorrelation, heteroskedasticity, and mis-specification. Multicollinearity was not a notable issue because in-state correlations of weather variables were much lower than the 0.80 collinearity threshold defined by Gujarati (2003).

Corn yields were primarily determined by technology, the magnitude of precipitation in June and July, and the magnitude of temperature in July and August. Soybean yields were primarily determined by technology, precipitation during June through August (especially August), and temperature in July and August. Above-average precipitation and below-average temperature during the key growing months would be expected to lead to highest yields. For example, 1.93 inches more precipitation than average in July for Illinois was optimal to maximize corn yields and would be expected to increase yields by six bushels per acre more than if average weather occurred. Similarly, 1.93 inches more than average precipitation in August was optimal to maximize soybean yields and would be expected to increase yields by one bushel per acre. The coolest August (8°F cooler than average) would be expected to increase corn and soybean yields in Illinois by up to 23 and 5 bushels per acre, respectively. However, precipitation was more important to corn and soybean yields and unfavorable weather
decreased yields to a much larger degree than favorable weather increased yields. Using the same examples, 1.93 inches less than average in July for Illinois would be expected to decrease corn yields by 22 bushels per acre more than if average weather occurred. 1.93 inches less than average in August would be expected to reduce Illinois soybean yields by three bushels per acre.

While models generally estimated yields well, they performed poorly during years in which insects, diseases, or unusual weather occurred. Models also estimated yields poorly during years in which monthly weather cumulatively deviated in the same direction from average. Coefficients of the models were used to show that average weather would be expected to lead to yields that are higher than the unadjusted trend. This provided evidence that unfavorable weather shifted the unadjusted trend downward and flattened its slope. In-sample yield estimates over 1960 through 2006 were used to develop weather indexes to determine the favorability of weather over the sample. Results indicated that 1983 and 1988 were the worst weather years for corn and soybeans in Illinois and Indiana, though 1993 was the worst for each crop in Iowa. Weather since the mid-1990s was generally benign – especially as it related to Iowa corn yields.

Comparisons of regression results over the sample to those estimated by Thompson (1963, 1969, 1970, 1985, 1986, and 1988) showed that the relationship between weather, technology, and yields was similar. However, temperatures in May and June appear to have less effect on corn yields than previously suggested, and temperatures from June through August appear to be more important for soybean yields than previously indicated. The amount of June precipitation is more influential to corn
yield potential, and soybean yields appear to need significant rain events during June, July, and August.

Structural change tests were performed on each model in corn and soybeans to test for changes in any of the parameters. Breakpoints were identified as significant in 1988 for Illinois corn and Iowa soybeans, while 1983 was identified for Iowa corn. However, it was expected that all states and crops would show similar results since weather, crop development, soil, and geography were similar. The addition of dummy variables at the break points failed to explain the cause of the structural breaks. Therefore, the technology variable, grouped precipitation variables, and grouped temperature variables were tested separately for structural change, but results remained difficult to explain. Therefore, a general conclusion could not be made.

Degrees of freedom limitations prevented the structural change tests discussed above from determining whether the mid-1990s was a period in which the relationship between weather, corn yields, and technology changed. However, the mid-1990s is the most important period to analyze because it is when the trend yield for corn is commonly believed to have increased relative to the long-term trend. Therefore, additional tests for structural change were specifically performed on the trend variable. The first analysis was based on unknown breakpoint tests limited to the trend variable. A significant break was identified in Iowa for 1983, but the addition of a trend dummy variable to the modified Thompson models showed corn yields would be expected to decrease – not increase – each year over 1983 through 2006 in Iowa (relative to 1960 through 1982). The second analysis specified 1996 as a specific breakpoint and conducted conventional Chow tests for structural change for each of the modified Thompson models. Dummy
variables were insignificant and indicated that the trend over 1996 through 2006 changed by only 0.09, -0.04, and 0.15 bushels per acre per year in Illinois, Indiana, and Iowa, respectively (versus 1960 through 1995). Therefore, the models did not suggest a notable change in the trend.

A review of weather indexes for corn suggested weather from 1996 through 2006 was relatively benign in each state. Therefore, favorable weather likely led to corn yields that were higher than the trend. That being said, a lack of new observations could also be obscuring a new trend and preventing statistical detection.

The modified Thompson models explained a majority of the in-sample variation in corn and soybean yields, but in-sample variation is not necessarily a good indicator of the accuracy of the model for predicting yields. Therefore, a forecasting competition was developed to analyze out-of-sample forecasts from the modified Thompson model. These were compared to USDA and trend yield forecast that served as benchmarks. The competition was developed such that forecasts were made on June 1, July 1, August 1, September 1, and October 1 over 1980 through 2006. This allowed for a relatively large number of forecasts to analyze.

Corn and soybean yield forecasts on June 1 and July 1 were not notably more accurate then trend yield forecasts, which indicated that perfect knowledge of weather early in the growing season would not lead to model forecasts that are more accurate than trend forecasts. Corn yield forecasts improved on August 1, while soybean yield forecasts improved more notably on September 1. These results are sensible because forecasts from the modified Thompson models should improve as weather observations during the important months of July and August are included. However, USDA corn
forecasts were always more accurate than those from the modified Thompson model. USDA soybean forecasts were not significantly more accurate until October 1 when actual yield observations were included by the USDA.

Although USDA forecasts were more accurate than forecasts from the modified Thompson models, the development of single composite forecasts could still prove to be useful if the forecasts utilized different information. Encompassing tests were significant and showed that the accuracy of USDA corn yield forecasts could be improved in Illinois and Indiana by around 20% and 15% on September 1 and October 1, respectively. Illinois soybean forecasts could also be improved by 6% to 9% on August 1, September 1, and October 1. The economic value of these improvements is difficult to assess, but research in a similar context (Colino and Irwin 2007) suggests the reductions are economically non-trivial.

The key questions of this thesis can now be answered:

- Has the relationship between temperature, precipitation, technology, and corn and soybean yields in the U.S. Corn Belt changed since the last comprehensive studies? June precipitation appears to be more influential to corn yields than previously assessed, while temperatures in May and June as less influential. Soybean yields appear to be more influenced by temperatures during June, July, and August, as well as significant precipitation during June, July, and August – though August precipitation still has the largest influence on yields. Technology still appears to be best represented linearly with a beginning year of 1960.
• Has the trend rate of yield growth for corn accelerated since the mid-1990s?
  The trend rate of yield growth for corn has not accelerated for corn since the mid-1990s. Instead, the trend yield for corn is best represented linearly with a beginning year of 1960.

• How do yield forecasts from the multiple regression models compare to benchmark forecasts? Forecasts from the modified Thompson models generally are equal to or less accurate than benchmark forecasts. However, economically significant improvement in USDA forecasts may exist for some states and crops through the development of single composite forecasts.

6.2 Implications

The first implication of this thesis is that drier-than-average weather during weather-sensitive times of development for corn and soybeans is much more detrimental to yield potential than wet weather is helpful. For corn, this mainly corresponds to the precipitation during June and July. For soybeans, this corresponds to precipitation during June, July, and August. Slightly higher-than-average rainfall during these times is expected to produce highest yields, but below-average departures from average can quickly lower yields. Therefore, closer attention should be given to precipitation and the magnitude of statewide dryness during these months. Less attention should be given to temperatures in May and June since precipitation and weather that follows over-rides the importance of growing season temperatures early in the period, and the crops can recover from the effects of below- or above-average temperatures.
The second implication of this thesis is that the magnitude of temperatures during July and August has a smaller effect on corn and soybean yields than the magnitude of precipitation during these months. Warmer-than-average temperatures during these months are expected to reduce corn yields, though soybean yields are less responsive. Nonetheless, the expected effect related to warmer monthly temperatures during these months is much lower than the expected effect of reduced monthly precipitation.

The third implication of this thesis is that corn yields since the mid-1990s may not be improving relative to the unadjusted trend due to rapid improvements in technology alone. This is because several structural break tests and the addition of dummy variables to the modified Thompson models for corn failed to show that a new trend began in the mid-1990s. Instead, relatively benign weather form 1996 through 2006 may be resulting in increased corn yields and/or coinciding with improved technology. This is supported by particularly unfavorable weather for corn in 1974, 1983, 1988, and 1993 that shifted the unadjusted trend yield downward and flattened its slope. The benign weather period that followed may be leading to misperceptions because it helps to increase corn yields well beyond the unadjusted trend in some years. Thompson (1975) noted that similarly widespread beliefs existed in the early-1970s and that technology had supposedly greatly lessened the importance of weather. Unfavorable weather that followed from the mid-1970s through the early-1990s disproved that thinking. It is plausible that a similar scenarios currently exists where technology is improving, but favorable weather is enhancing yield improvements and leading to yields that consistently out-perform the unadjusted trend.
The fourth implication of this thesis is that the modified Thompson models cannot be used to improve trend yield forecasts early in the growing season. This supports the idea that weather later in the growing season has a much larger effect on yields that earlier weather. It further suggests that corn and soybeans can overcome unfavorable weather and conditions prior to their key growing period in July and August. Notably, these results imply that the influence of weather during planting in April and May is far less influential than weather that follows.

The fifth implication of this thesis is that the modified Thompson models can be used to substantially improve the accuracy of USDA forecasts for: 1) corn in Illinois, 2) corn in Indiana, and 3) soybeans in Illinois. Although it is clearly evident that the USDA forecasts are more accurate on a stand-alone basis, they can be combined with modified Thompson model forecasts to develop more accurate composite forecasts.

6.3 Limitations and Extensions

A limitation is that statewide weather observations did not necessarily represent weather that equally affected corn and soybean production. This is because monthly precipitation and temperature observations at the state level are weighted by area and not by crop production. Therefore, it may be useful to conduct a similar study with a weighting scheme based on crop distribution – though such a task becomes notably more complex. Additionally, different results may be provided by developing a model based on crop phases instead of calendar months.

Broadening this study to relationships between weather, yields, and technology for other states, regions, and crops could prove to be useful. For example, use of the
multiple regression method to estimate the relationship between weather, technology and various types of wheat would be useful since wheat is the most widely produced crop in the world. Similar research could be performed on other corn and soybean states, or sub-regions of states, as well.

The usefulness of additional variables to assess the relationship between yields, weather, and technology could also prove to be useful. For example, Hollinger and Changnon (2004) stated that Illinois corn yields in 2003 may have been unexpectedly high because of the unusual combination of favorable coolness in July and August and higher-than-usual sunshine. Dixon et al. (1994) also noted that the amount of solar radiation was a key factor in plant development and they developed a proxy for solar radiation for use in regression analysis. Therefore, solar radiation is likely the most notable variable missing from the models and it would serve as a useful beginning point for exploration. Furthermore, the incorporation of planting dates into the modified Thompson models should also be explored to prove or disprove their influence and significance on corn and soybean yield potential.

As a final note, it would be interesting for future research to utilize USDA Crop Progress corn and soybean condition reports to develop multiple regression models to estimate and predict yields. The reports could be useful because they represent direct—though subjective—assessments of the overall health of each crop on a weekly basis throughout the growing season. The assessment process was standardized in 1986 and is based on a 5-point scale ranging from “very poor” to “excellent”. This information could be utilized to develop multiple regression models for each state, and value could exist because the reports should reflect the effects of all variables on the health of the crop,
including weather, technology, insects, diseases, planting date, solar radiation, and any and all other factors. These forecasts could then be assessed relative to benchmark forecasts represented by trend, modified Thompson models, and the USDA in a forecasting competition similar to that performed in Chapter 5.

6.4 Concluding Remarks

This thesis provided strong evidence that precipitation, temperature, and a simple time trend to represent technological improvements explains most of the variation in corn and soybean yields in the U.S. Corn Belt. This is a powerful finding because it shows that the development of relatively simple multiple regression models can be an important tool in understanding weather-technology-yield relationships when backed by rigorous fundamental analyses. Results of the analyses can then help to prove and disprove widespread perceptions in the agricultural community.

The use of multiple regression models in this thesis showed that corn and soybean yields are best represented with a linear trend beginning in 1960 – despite: 1) numerous and significant technological improvements over the past five decades, and 2) widespread belief that the trend for corn is accelerating in recent years. Recent observations of increased global temperatures are not reflected in monthly temperature and precipitation observations in Illinois, Indiana, and Iowa during key growing-season months – a fact that: 1) suggests global warming does not necessarily mean hotter and drier summers can be expected, and 2) is consistent with the possible effects of global warming at the state level. Multiple regression models can also be used to improve USDA forecasts, even though USDA forecasts are clearly more accurate on a stand-alone basis. This result
could prove to be important because USDA forecasts serve as market benchmarks and immediately influence cash and futures prices upon their release.

As a final note, it is important that lessons of history are not forgotten. Despite the common belief that corn yields are increasing due to improved technology, this thesis provided strong evidence that benign weather for the development of corn since the mid-1990s cannot be discounted as an explanation for seemingly “high” yields. The potential impact of this finding on the agricultural community is large. Trend yield forecasts based on perceptions of an increased trend yield may eventually lead to poor production forecasts. Unfavorable weather during an upcoming year may lead to unexpectedly low corn yields that leave producers, market participants, agricultural economists, seed companies, and end users wondering how very low yields could have occurred despite technological improvement. A strikingly low corn yield occurred under the veil of similar perceptions in 1974, and this scenario may well be repeated if an improved understanding of trend yields and the complex relationship between weather, technology, and yields is not widely understood.
Table 1. Corn and Soybean Production in the U.S. Corn Belt, 2000-2006

<table>
<thead>
<tr>
<th>Crop / Year</th>
<th>Illinois</th>
<th>Indiana</th>
<th>Iowa</th>
<th>U.S.</th>
<th>Illinois</th>
<th>Indiana</th>
<th>Iowa</th>
<th>3-State Total</th>
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<td>2,050,100</td>
<td>10,534,868</td>
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<td>8.0</td>
<td>19.5</td>
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</tr>
<tr>
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<td>888,580</td>
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Source: NASS, Quick Stats: Agricultural Statistics Data Base
Table 2. Precipitation Statistics (inches) for Illinois, Indiana, and Iowa, 1960 - 2006

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<th>Period / State</th>
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<th>Maximum</th>
<th>Minimum</th>
<th>Range</th>
<th>Standard Deviation</th>
<th>Coefficient of Variation</th>
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</table>

Source: Monthly weather observations were collected from each state’s climatologist office
Table 3. Temperature (degrees Fahrenheit) Statistics for Illinois, Indiana, and Iowa, 1960 - 2006

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<thead>
<tr>
<th>Period / State</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Range</th>
<th>Standard Deviation</th>
<th>Coefficient of Variation</th>
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<td>61.2</td>
<td>69.5</td>
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<td>71.5</td>
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<td>2.0</td>
<td>0.03</td>
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<td>74.3</td>
<td>66.4</td>
<td>7.9</td>
<td>2.0</td>
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</tr>
<tr>
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<td>70.0</td>
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<td>65.2</td>
<td>9.8</td>
<td>2.2</td>
<td>0.03</td>
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Source: Monthly weather observations were collected from each state’s climatologist office
Table 4. Within-State Weather Variable Correlations, Illinois, Indiana, and Iowa, 1960-2006

<table>
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<tr>
<th>State / Variable</th>
<th>Preseason Precip</th>
<th>May Precip</th>
<th>June Precip</th>
<th>July Precip</th>
<th>August Precip</th>
<th>May Temp</th>
<th>June Temp</th>
<th>July Temp</th>
<th>Aug Temp</th>
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<td>-0.12</td>
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<td>0.07</td>
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<td></td>
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</tr>
<tr>
<td>June Temperature</td>
<td>1.00</td>
<td>0.18</td>
<td>0.14</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>July Temperature</td>
<td>1.00</td>
<td>0.26</td>
<td></td>
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</tr>
<tr>
<td>August Temperature</td>
<td>1.00</td>
<td></td>
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<table>
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<tr>
<th>State / Variable</th>
<th>Preseason Precip</th>
<th>May Precip</th>
<th>June Precip</th>
<th>July Precip</th>
<th>August Precip</th>
<th>May Temp</th>
<th>June Temp</th>
<th>July Temp</th>
<th>Aug Temp</th>
</tr>
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<tbody>
<tr>
<td>Preseason Precip</td>
<td>0.76</td>
<td>0.10</td>
<td>0.03</td>
<td>-0.28</td>
<td>-0.03</td>
<td>-0.18</td>
<td>0.11</td>
<td>0.08</td>
<td>-0.01</td>
</tr>
<tr>
<td>May Precip</td>
<td>0.00</td>
<td>0.87</td>
<td>0.16</td>
<td>0.25</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.05</td>
<td>0.10</td>
</tr>
<tr>
<td>June Precip</td>
<td>-0.08</td>
<td>-0.23</td>
<td>0.75</td>
<td>0.70</td>
<td>-0.17</td>
<td>0.42</td>
<td>0.04</td>
<td>0.03</td>
<td>0.48</td>
</tr>
<tr>
<td>July Precip</td>
<td>-0.25</td>
<td>0.01</td>
<td>-0.14</td>
<td>-0.06</td>
<td>0.27</td>
<td>0.02</td>
<td>0.10</td>
<td>0.03</td>
<td>0.48</td>
</tr>
<tr>
<td>August Precip</td>
<td>-0.04</td>
<td>0.09</td>
<td>0.09</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.15</td>
<td>0.08</td>
<td>0.05</td>
<td>0.45</td>
</tr>
<tr>
<td>May Temperature</td>
<td>-0.11</td>
<td>0.02</td>
<td>-0.17</td>
<td>0.72</td>
<td>0.32</td>
<td>0.15</td>
<td>0.08</td>
<td>0.05</td>
<td>0.45</td>
</tr>
<tr>
<td>June Temperature</td>
<td>0.20</td>
<td>0.13</td>
<td>0.14</td>
<td>0.99</td>
<td>0.95</td>
<td>0.15</td>
<td>0.08</td>
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</tr>
<tr>
<td>July Temperature</td>
<td>0.13</td>
<td>0.00</td>
<td>0.00</td>
<td>0.31</td>
<td>0.46</td>
<td>0.15</td>
<td>0.08</td>
<td>0.05</td>
<td>0.45</td>
</tr>
<tr>
<td>August Temperature</td>
<td>-0.02</td>
<td>0.02</td>
<td>-0.02</td>
<td>-0.26</td>
<td>-0.06</td>
<td>0.22</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Note: Rows represent the first state in a pair and columns represent the second state in a pair.
Table 6. De-trended Yield (bushels per acre) Statistics for Illinois, Indiana, and Iowa, 1960 - 2006

<table>
<thead>
<tr>
<th>Crop / State</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Range</th>
<th>Standard Deviation</th>
<th>Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Corn</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Illinois</td>
<td>155.0</td>
<td>157.3</td>
<td>183.4</td>
<td>103.2</td>
<td>80.2</td>
<td>15.3</td>
<td>0.10</td>
</tr>
<tr>
<td>Indiana</td>
<td>149.6</td>
<td>153.4</td>
<td>171.3</td>
<td>110.9</td>
<td>60.4</td>
<td>14.1</td>
<td>0.09</td>
</tr>
<tr>
<td>Iowa</td>
<td>159.1</td>
<td>161.2</td>
<td>184.8</td>
<td>104.8</td>
<td>80.1</td>
<td>15.0</td>
<td>0.09</td>
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<tr>
<td><strong>Soybeans</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Illinois</td>
<td>46.0</td>
<td>46.7</td>
<td>51.3</td>
<td>34.4</td>
<td>16.9</td>
<td>3.5</td>
<td>0.08</td>
</tr>
<tr>
<td>Indiana</td>
<td>46.9</td>
<td>47.8</td>
<td>52.6</td>
<td>35.9</td>
<td>16.7</td>
<td>3.6</td>
<td>0.08</td>
</tr>
<tr>
<td>Iowa</td>
<td>47.8</td>
<td>48.7</td>
<td>56.0</td>
<td>33.9</td>
<td>22.1</td>
<td>4.0</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Note: Yields are de-trended to 2006 using linear time trend regressions over 1960 - 2006
### Table 7. Trend-Only Regression Models for Corn and Soybean Yields in Illinois, Indiana, and Iowa, 1960 - 2006

<table>
<thead>
<tr>
<th>Independent Variable or Statistic</th>
<th>Illinois Linear Model</th>
<th>Illinois Quadratic Model</th>
<th>Indiana Linear Model</th>
<th>Indiana Quadratic Model</th>
<th>Iowa Linear Model</th>
<th>Iowa Quadratic Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Corn</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>76.09 ***</td>
<td>79.87 ***</td>
<td>72.23 ***</td>
<td>76.01 ***</td>
<td>69.55 ***</td>
<td>77.54 ***</td>
</tr>
<tr>
<td></td>
<td>(4.60)</td>
<td>(7.13)</td>
<td>(4.22)</td>
<td>(6.53)</td>
<td>(4.50)</td>
<td>(6.84)</td>
</tr>
<tr>
<td>Annual Time Trend</td>
<td>1.68 ***</td>
<td>1.22 *</td>
<td>1.65 ***</td>
<td>1.18 *</td>
<td>1.90 ***</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.69)</td>
<td>(0.15)</td>
<td>(0.63)</td>
<td>(0.16)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>Annual Time Trend²</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.69</td>
<td>0.70</td>
<td>0.72</td>
<td>0.72</td>
<td>0.75</td>
<td>0.76</td>
</tr>
<tr>
<td>Standard Error (bu. / acre)</td>
<td>15.52</td>
<td>15.60</td>
<td>14.22</td>
<td>14.29</td>
<td>15.20</td>
<td>14.97</td>
</tr>
<tr>
<td><strong>Soybeans</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>26.55 ***</td>
<td>27.05 ***</td>
<td>25.00 ***</td>
<td>25.90 ***</td>
<td>26.42 ***</td>
<td>26.62 ***</td>
</tr>
<tr>
<td></td>
<td>(1.05)</td>
<td>(1.63)</td>
<td>(1.07)</td>
<td>(1.65)</td>
<td>(1.19)</td>
<td>(1.85)</td>
</tr>
<tr>
<td>Annual Time Trend</td>
<td>0.41 ***</td>
<td>0.35 **</td>
<td>0.47 ***</td>
<td>0.36 **</td>
<td>0.46 ***</td>
<td>0.43 **</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.16)</td>
<td>(0.04)</td>
<td>(0.16)</td>
<td>(0.04)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Annual Time Trend²</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.72</td>
<td>0.72</td>
<td>0.76</td>
<td>0.77</td>
<td>0.71</td>
<td>0.71</td>
</tr>
<tr>
<td>Standard Error (bu. / acre)</td>
<td>3.54</td>
<td>3.58</td>
<td>3.59</td>
<td>3.61</td>
<td>4.01</td>
<td>4.06</td>
</tr>
</tbody>
</table>

Note: one, two, and three stars denote statistical significance at the 10%, 5%, and 1% levels, respectively.
### Table 8. Modified Thompson Model Regression Estimates for Corn Yields in Illinois, Indiana, and Iowa, 1960 - 2006

<table>
<thead>
<tr>
<th>Independent Variable or Statistic</th>
<th>Coefficient Estimates</th>
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<tr>
<td>Constant</td>
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</tr>
<tr>
<td></td>
<td>(80.52)</td>
</tr>
<tr>
<td>Annual Time Trend</td>
<td>1.92 **</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
</tr>
<tr>
<td>Preseason Precipitation</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>(0.35)</td>
</tr>
<tr>
<td>May Precipitation</td>
<td>-1.45 *</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
</tr>
<tr>
<td>June Precipitation</td>
<td>14.04 ***</td>
</tr>
<tr>
<td></td>
<td>(4.89)</td>
</tr>
<tr>
<td>June Precipitation²</td>
<td>-1.50 ***</td>
</tr>
<tr>
<td></td>
<td>(0.52)</td>
</tr>
<tr>
<td>July Precipitation</td>
<td>17.65 **</td>
</tr>
<tr>
<td></td>
<td>(6.57)</td>
</tr>
<tr>
<td>July Precipitation²</td>
<td>-1.50 *</td>
</tr>
<tr>
<td></td>
<td>(0.75)</td>
</tr>
<tr>
<td>August Precipitation</td>
<td>2.88</td>
</tr>
<tr>
<td></td>
<td>(5.69)</td>
</tr>
<tr>
<td>August Precipitation²</td>
<td>-0.28</td>
</tr>
<tr>
<td></td>
<td>(0.71)</td>
</tr>
<tr>
<td>May Temperature</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
</tr>
<tr>
<td>June Temperature</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>(0.69)</td>
</tr>
<tr>
<td>July Temperature</td>
<td>-1.65 **</td>
</tr>
<tr>
<td></td>
<td>(0.79)</td>
</tr>
<tr>
<td>August Temperature</td>
<td>-2.86 ***</td>
</tr>
<tr>
<td></td>
<td>(0.58)</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>Illinois</th>
<th>Indiana</th>
<th>Iowa</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.95</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td>Standard Error (bu. / acre)</td>
<td>7.57</td>
<td>7.62</td>
<td>8.75</td>
</tr>
<tr>
<td>Regression F-statistic</td>
<td>44.64 ***</td>
<td>40.54 ***</td>
<td>39.42 ***</td>
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<td>LM test</td>
<td>10.51</td>
<td>18.18</td>
<td>6.28</td>
</tr>
<tr>
<td>BPG test</td>
<td>11.02</td>
<td>13.02</td>
<td>11.81</td>
</tr>
<tr>
<td>Ramsey RESET</td>
<td>1.55</td>
<td>0.03</td>
<td>0.86</td>
</tr>
</tbody>
</table>

Note: one, two, and three stars denote statistical significance at the 10%, 5%, and 1% levels, respectively. The LM test denotes the LaGrange Multiplier Test for autocorrelation, the BPG test denotes the Breusch-Pagan-Godfrey test for heteroskedasticity, and the Ramsey RESET is the test for mis-specification. The LM statistic follows a χ² distribution with p degrees of freedom, where p is the highest order of autocorrelation in the test. The BPG statistic follows a χ² distribution with K-1 degrees of freedom, where K is the number of estimated parameters. The Ramsey RESET statistic follows a t-distribution with N-K degrees of freedom, where N is the number of sample observations.

<table>
<thead>
<tr>
<th>Independent Variable or Statistic</th>
<th>Illinois</th>
<th>Indiana</th>
<th>Iowa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>34.88</td>
<td>29.58</td>
<td>29.58</td>
</tr>
<tr>
<td></td>
<td>(25.42)</td>
<td>(27.83)</td>
<td>(27.87)</td>
</tr>
<tr>
<td>Annual Time Trend</td>
<td>0.44 ***</td>
<td>0.48 ***</td>
<td>0.49 ***</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Preseason Precipitation</td>
<td>0.12</td>
<td>0.18</td>
<td>0.29 *</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.13)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>May Precipitation</td>
<td>-0.44 *</td>
<td>-0.71 **</td>
<td>-0.93 **</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.29)</td>
<td>(0.35)</td>
</tr>
<tr>
<td>June Precipitation</td>
<td>2.21</td>
<td>5.13 ***</td>
<td>2.56</td>
</tr>
<tr>
<td></td>
<td>(1.54)</td>
<td>(1.41)</td>
<td>(1.69)</td>
</tr>
<tr>
<td>June Precipitation²</td>
<td>-0.21</td>
<td>-0.52 ***</td>
<td>-0.21</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.16)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>July Precipitation</td>
<td>2.57</td>
<td>3.52 ***</td>
<td>3.45 ***</td>
</tr>
<tr>
<td></td>
<td>(2.07)</td>
<td>(1.26)</td>
<td>(1.05)</td>
</tr>
<tr>
<td>July Precipitation²</td>
<td>-0.18</td>
<td>-0.33 **</td>
<td>-0.35 ***</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.12)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>August Precipitation</td>
<td>3.16</td>
<td>3.95 *</td>
<td>4.42 ***</td>
</tr>
<tr>
<td></td>
<td>(1.80)</td>
<td>(2.12)</td>
<td>(1.10)</td>
</tr>
<tr>
<td>August Precipitation²</td>
<td>-0.29</td>
<td>-0.38</td>
<td>-0.37 ***</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.26)</td>
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<td>May Temperature</td>
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<td>0.08</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.12)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>June Temperature</td>
<td>0.34</td>
<td>0.03</td>
<td>0.38</td>
</tr>
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<td>(0.22)</td>
<td>(0.24)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>July Temperature</td>
<td>-0.20</td>
<td>-0.33</td>
<td>-0.34</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.26)</td>
<td>(0.25)</td>
</tr>
</tbody>
</table>
| August Temperature               | -0.58 ***| -0.24   | -0.34 *
|                                  | (0.18)   | (0.20)  | (0.19)|

<table>
<thead>
<tr>
<th></th>
<th>Illinois</th>
<th>Indiana</th>
<th>Iowa</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.91</td>
<td>0.91</td>
<td>0.89</td>
</tr>
<tr>
<td>Standard Error (bu. / acre)</td>
<td>2.39</td>
<td>2.52</td>
<td>2.94</td>
</tr>
<tr>
<td>Regression F-statistic</td>
<td>24.92 ***</td>
<td>27.23 ***</td>
<td>19.85 ***</td>
</tr>
<tr>
<td>LM test</td>
<td>10.40</td>
<td>34.511</td>
<td>11.65</td>
</tr>
<tr>
<td>BPG test</td>
<td>9.87</td>
<td>12.98</td>
<td>13.45</td>
</tr>
<tr>
<td>Ramsey RESET</td>
<td>0.72</td>
<td>1.00</td>
<td>0.57</td>
</tr>
</tbody>
</table>

Note: one, two, and three stars denote statistical significance at the 10%, 5%, and 1% levels, respectively. The LM test denotes the LaGrange Multiplier Test for autocorrelation, the BPG test denotes the Breusch-Pagan-Godfrey test for heteroskedasticity, and the Ramsey RESET is the test for mis-specification. The LM statistic follows a \( \chi^2 \) distribution with \( p \) degrees of freedom, where \( p \) is the highest order of autocorrelation in the test. The BPG statistic follows a \( \chi^2 \) distribution with \( K-1 \) degrees of freedom, where \( K \) is the number of estimated parameters. The Ramsey RESET statistic follows a \( t \)-distribution with \( N-K \) degrees of freedom, where \( N \) is the number of sample observations.
### Table 10. Modified Thompson Model Regression Estimates with Dummy Variables at Selected Breakpoints for Illinois Corn Yields, Iowa Corn Yields, and Iowa Soybean Yields, 1960-2006

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>312.20 ***</td>
<td>215.93 **</td>
<td>18.75 **</td>
</tr>
<tr>
<td></td>
<td>(96.57)</td>
<td>(87.61)</td>
<td>(21.61)</td>
</tr>
<tr>
<td>Annual Time Trend</td>
<td>1.82 ***</td>
<td>2.39 **</td>
<td>0.49 ***</td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.29)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Preseason Precipitation</td>
<td>0.79 *</td>
<td>0.23</td>
<td>-0.07</td>
</tr>
<tr>
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<td>(0.44)</td>
<td>(0.71)</td>
<td>(0.15)</td>
</tr>
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<tr>
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<td>(2.05)</td>
<td>(0.38)</td>
</tr>
<tr>
<td>June Precipitation</td>
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<td>8.72</td>
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<td>(9.43)</td>
<td>(7.57)</td>
<td>(1.56)</td>
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<td>-0.67</td>
<td>-0.63</td>
<td>-0.14</td>
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<tr>
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<td>(1.11)</td>
<td>(0.70)</td>
<td>(0.15)</td>
</tr>
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<td>8.56</td>
<td>11.45</td>
<td>-1.01</td>
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<td>(9.32)</td>
<td>(7.40)</td>
<td>(1.65)</td>
</tr>
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<td>July Precipitation²</td>
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<td>-0.95</td>
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</tr>
<tr>
<td></td>
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<td>(0.97)</td>
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<td>(4.91)</td>
<td>(1.03)</td>
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<td>-0.12</td>
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<td>(0.53)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>May Temperature</td>
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<td>-0.34</td>
<td>-0.11</td>
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<td>(0.66)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>June Temperature</td>
<td>0.19</td>
<td>-0.10</td>
<td>0.32 *</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
<td>(0.96)</td>
<td>(0.18)</td>
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<td>July Temperature</td>
<td>-1.34</td>
<td>-2.56 ***</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>(0.95)</td>
<td>(0.81)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>August Temperature</td>
<td>-2.54 ***</td>
<td>0.13</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>(0.65)</td>
<td>(0.95)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Annual Time Trend (Dummy)</td>
<td>0.93 **</td>
<td>0.34</td>
<td>0.31 **</td>
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<td>(0.38)</td>
<td>(0.38)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Preseason Precipitation (Dummy)</td>
<td>0.65</td>
<td>1.53</td>
<td>0.71 **</td>
</tr>
<tr>
<td></td>
<td>(1.18)</td>
<td>(0.38)</td>
<td>(0.27)</td>
</tr>
<tr>
<td>May Precipitation (Dummy)</td>
<td>2.50</td>
<td>-1.48</td>
<td>-1.11 **</td>
</tr>
<tr>
<td></td>
<td>(1.64)</td>
<td>(2.41)</td>
<td>(0.52)</td>
</tr>
<tr>
<td>June Precipitation (Dummy)</td>
<td>10.26</td>
<td>-0.72</td>
<td>6.93 **</td>
</tr>
<tr>
<td></td>
<td>(10.91)</td>
<td>(11.34)</td>
<td>(2.76)</td>
</tr>
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<td>-1.08</td>
<td>-0.19</td>
<td>-0.59 **</td>
</tr>
<tr>
<td></td>
<td>(1.25)</td>
<td>(1.10)</td>
<td>(0.28)</td>
</tr>
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<td>0.17</td>
<td>14.51</td>
<td>0.30</td>
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<td>(14.44)</td>
<td>(8.61)</td>
<td>(2.62)</td>
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<td>-0.14</td>
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<td>(1.05)</td>
<td>(2.60)</td>
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<td>-0.05</td>
<td>13.36 ***</td>
</tr>
<tr>
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<td>(19.58)</td>
<td>(6.69)</td>
<td>(2.60)</td>
</tr>
<tr>
<td>August Precipitation² (Dummy)</td>
<td>-8.14 ***</td>
<td>0.10</td>
<td>-1.51 ***</td>
</tr>
<tr>
<td></td>
<td>(2.71)</td>
<td>(0.69)</td>
<td>(0.30)</td>
</tr>
<tr>
<td>May Temperature (Dummy)</td>
<td>1.73 **</td>
<td>0.50</td>
<td>-0.16</td>
</tr>
<tr>
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<td>(0.76)</td>
<td>(0.83)</td>
<td>(0.20)</td>
</tr>
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<td>-1.16</td>
<td>0.23</td>
<td>-0.25</td>
</tr>
<tr>
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<td>(1.35)</td>
<td>(1.14)</td>
<td>(0.29)</td>
</tr>
<tr>
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<td>0.44</td>
<td>-0.77 *</td>
</tr>
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<td>(1.42)</td>
<td>(1.43)</td>
<td>(0.38)</td>
</tr>
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<td>-2.06</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>(1.16)</td>
<td>(1.25)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.98</td>
<td>0.98</td>
<td>0.97</td>
</tr>
<tr>
<td>Standard Error (bu. / acre)</td>
<td>6.11</td>
<td>6.94</td>
<td>1.78</td>
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</table>

Note: one, two, and three stars denote statistical significance at the 10%, 5%, and 1% levels, respectively.
Table 11. Modified Thompson Model Regression Estimates with July and August Temperature Dummy Variables at 1983 for Iowa Corn Yields, 1960-2006

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<tr>
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<td>Constant</td>
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<tr>
<td></td>
<td>(68.17)</td>
</tr>
<tr>
<td>Annual Time Trend</td>
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</tr>
<tr>
<td></td>
<td>(0.17)</td>
</tr>
<tr>
<td>Preseason Precipitation</td>
<td>0.87 **</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
</tr>
<tr>
<td>May Precipitation</td>
<td>-2.19 **</td>
</tr>
<tr>
<td></td>
<td>(0.85)</td>
</tr>
<tr>
<td>June Precipitation</td>
<td>4.00</td>
</tr>
<tr>
<td></td>
<td>(4.10)</td>
</tr>
<tr>
<td>June Precipitation²</td>
<td>-0.28</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
</tr>
<tr>
<td>July Precipitation</td>
<td>17.83 ***</td>
</tr>
<tr>
<td></td>
<td>(2.50)</td>
</tr>
<tr>
<td>July Precipitation²</td>
<td>-1.80 ***</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
</tr>
<tr>
<td>August Precipitation</td>
<td>2.35</td>
</tr>
<tr>
<td></td>
<td>(2.71)</td>
</tr>
<tr>
<td>August Precipitation²</td>
<td>-0.26</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
</tr>
<tr>
<td>May Temperature</td>
<td>-0.11</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
</tr>
<tr>
<td>June Temperature</td>
<td>-0.41</td>
</tr>
<tr>
<td></td>
<td>(0.55)</td>
</tr>
<tr>
<td>July Temperature</td>
<td>-2.98 ***</td>
</tr>
<tr>
<td></td>
<td>(0.65)</td>
</tr>
<tr>
<td>August Temperature</td>
<td>2.64</td>
</tr>
<tr>
<td></td>
<td>(0.86)</td>
</tr>
<tr>
<td>July Temperature (Dummy)</td>
<td>-0.26 ***</td>
</tr>
<tr>
<td></td>
<td>(0.69)</td>
</tr>
<tr>
<td>August Temperature (Dummy)</td>
<td>-2.96 ***</td>
</tr>
<tr>
<td></td>
<td>(0.89)</td>
</tr>
<tr>
<td>R²</td>
<td>0.96</td>
</tr>
<tr>
<td>Standard Error (bu. / acre)</td>
<td>6.89</td>
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</table>

Note: one, two, and three stars denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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<th>Coefficient Estimates</th>
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<tr>
<td>Constant</td>
<td>342.62 ***</td>
</tr>
<tr>
<td></td>
<td>(79.68)</td>
</tr>
<tr>
<td>Annual Time Trend</td>
<td>2.58 ***</td>
</tr>
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<td></td>
<td>(0.28)</td>
</tr>
<tr>
<td>Preseason Precipitation</td>
<td>1.09 **</td>
</tr>
<tr>
<td></td>
<td>(0.43)</td>
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<tr>
<td>May Precipitation</td>
<td>-2.69 **</td>
</tr>
<tr>
<td></td>
<td>(1.00)</td>
</tr>
<tr>
<td>June Precipitation</td>
<td>6.79</td>
</tr>
<tr>
<td></td>
<td>(4.90)</td>
</tr>
<tr>
<td>June Precipitation²</td>
<td>-0.60</td>
</tr>
<tr>
<td></td>
<td>(0.47)</td>
</tr>
<tr>
<td>July Precipitation</td>
<td>19.55 ***</td>
</tr>
<tr>
<td></td>
<td>(2.98)</td>
</tr>
<tr>
<td>July Precipitation²</td>
<td>-1.96 ***</td>
</tr>
<tr>
<td></td>
<td>(0.30)</td>
</tr>
<tr>
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</tr>
<tr>
<td></td>
<td>(3.16)</td>
</tr>
<tr>
<td>August Precipitation²</td>
<td>-0.47</td>
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<td></td>
<td>(0.34)</td>
</tr>
<tr>
<td>May Temperature</td>
<td>-0.23</td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
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<tr>
<td>June Temperature</td>
<td>-0.44</td>
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<tr>
<td>July Temperature</td>
<td>-2.25 ***</td>
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<tr>
<td></td>
<td>(0.71)</td>
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<tr>
<td>August Temperature</td>
<td>-2.01 ***</td>
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<tr>
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<td>(0.55)</td>
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<tr>
<td>Annual Time Trend (Dummy)</td>
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<tr>
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<td>(0.21)</td>
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</table>

| R²                                | 0.95                  |
| Standard Error (bu. / acre)       | 8.35                  |

Note: one, two, and three stars denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Independent Variable Coefficients</th>
<th>Coefficient Estimates</th>
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</tr>
<tr>
<td>Constant</td>
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</tr>
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<td>(81.55)</td>
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<td>Annual Time Trend</td>
<td>1.83</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
</tr>
<tr>
<td>Preseason Precipitation</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
</tr>
<tr>
<td>May Precipitation</td>
<td>-1.44</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
</tr>
<tr>
<td>June Precipitation</td>
<td>13.72</td>
</tr>
<tr>
<td></td>
<td>(4.93)</td>
</tr>
<tr>
<td>June Precipitation²</td>
<td>-1.47</td>
</tr>
<tr>
<td></td>
<td>(0.53)</td>
</tr>
<tr>
<td>July Precipitation</td>
<td>16.71</td>
</tr>
<tr>
<td></td>
<td>(6.71)</td>
</tr>
<tr>
<td>July Precipitation²</td>
<td>-1.37</td>
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<td>(0.77)</td>
</tr>
<tr>
<td>August Precipitation</td>
<td>2.54</td>
</tr>
<tr>
<td></td>
<td>(5.74)</td>
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<tr>
<td>August Precipitation²</td>
<td>-0.22</td>
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<td></td>
<td>(0.72)</td>
</tr>
<tr>
<td>May Temperature</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
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<td>June Temperature</td>
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<td>(0.70)</td>
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<td>July Temperature</td>
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<td>(0.80)</td>
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<td>(0.60)</td>
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<tr>
<td>Annual Time Trend Dummy</td>
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<tr>
<td></td>
<td>(0.11)</td>
</tr>
</tbody>
</table>

| R²                                 | 0.95      | 0.94     | 0.94      |
| Standard Error (bu. / acre)        | 7.62      | 7.73     | 8.69      |

Note: one, two, and three stars denote statistical significance at the 10%, 5%, and 1% levels, respectively.
Table 14. Time Trend Coefficients for Relative Squared Errors ($d_t$) between Modified Thompson Models and the USDA for Corn and Soybean Yields in Illinois, Indiana, and Iowa, 1980 - 2006

<table>
<thead>
<tr>
<th></th>
<th>August 1</th>
<th>September 1</th>
<th>October 1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Corn</strong></td>
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<td></td>
<td></td>
</tr>
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<td>Illinois</td>
<td>16.8</td>
<td>22.2</td>
<td>20.2</td>
</tr>
<tr>
<td></td>
<td>(14.3)</td>
<td>(17.1)</td>
<td>(17.4)</td>
</tr>
<tr>
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<td>19.9</td>
<td>40.5</td>
<td>39.7</td>
</tr>
<tr>
<td></td>
<td>(15.5)</td>
<td>(24.0)</td>
<td>(23.9)</td>
</tr>
<tr>
<td>Iowa</td>
<td>9.2</td>
<td>22.6</td>
<td>18.7</td>
</tr>
<tr>
<td></td>
<td>(7.2)</td>
<td>(30.2)</td>
<td>(31.7)</td>
</tr>
</tbody>
</table>

| **Soybeans** |        |          |           |
| Illinois     | 1.6     | *        | 1.3       |
|              | (0.9)   |          | (1.0)     |
| Indiana      | 0.9     | 1.3      | 0.9       |
|              | (1.0)   | (1.2)    | (1.2)     |
| Iowa         | 1.2     | -0.2     | -1.5      |
|              | (1.3)   | (1.7)    | (1.7)     |

Note: The figures in parentheses are standard errors. One, two, and three stars denote statistical significance at the 10%, 5%, and 1% levels, respectively.
<table>
<thead>
<tr>
<th>State / Accuracy Measure</th>
<th>June 1</th>
<th>July 1</th>
<th>August 1</th>
<th>September 1</th>
<th>October 1</th>
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<td>USDA</td>
<td>Weather Model</td>
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<td>15.3 10.8</td>
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<tr>
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<td>21.6 20.9</td>
<td>NA</td>
<td>16.2 9.3</td>
</tr>
<tr>
<td></td>
<td>MAE 15.3</td>
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<td>NA</td>
<td>11.7 8.4</td>
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<tr>
<td></td>
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<td>14.2 12.9</td>
<td>NA</td>
<td>10.3 6.8</td>
</tr>
<tr>
<td>Indiana</td>
<td>RMSE 19.5</td>
<td>17.8 NA</td>
<td>19.6 17.8</td>
<td>NA</td>
<td>14.9 9.8</td>
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<tr>
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<td>MAE 13.4</td>
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<td>13.8 14.5</td>
<td>NA</td>
<td>9.5 8.0</td>
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<td></td>
<td>MAPE 12.9</td>
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<td>12.5 11.7</td>
<td>NA</td>
<td>11.1 7.2</td>
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</tbody>
</table>

Note: RMSE denotes Root Mean Squared Error, RMSPE denotes Root Mean Squared Percentage Error, MAE denotes Mean Average Error, MAPE denotes Mean Average Percentage Error.
Table 16. Modified Diebold-Mariano Test Results for Corn and Soybean Yield Forecasts in Illinois, Indiana, and Iowa, 1980-2006

<table>
<thead>
<tr>
<th></th>
<th>Corn</th>
<th>Soybeans</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>June 1</td>
<td>July 1</td>
</tr>
<tr>
<td><strong>Weather Model vs. Trend Yield Forecasts</strong></td>
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</tr>
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<td>-1.50</td>
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Note: One, two, and three stars denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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Note: RMSE denotes Root Mean Squared Error, RMSPE denotes Root Mean Squared Percentage Error, MAE denotes Mean Average Error, MAPE denotes Mean Average Percentage Error
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Note: The figures in parentheses are standard errors.

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Figure 1. United States Corn Yields, 1960-2006

- 1960-1995: +1.8 bu./year
- 1996-2006: +2.6 bu./year
Figure 2. Corn Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = 1.68x + 76.09 \]

\[ R^2 = 0.69 \]

Panel B. Indiana

\[ y = 1.65x + 72.23 \]

\[ R^2 = 0.72 \]

Panel C. Iowa

\[ y = 1.90x + 69.55 \]

\[ R^2 = 0.75 \]
Figure 3. Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = 0.41x + 26.55 \]
\[ R^2 = 0.72 \]

Panel B. Indiana

\[ y = 0.47x + 25.00 \]
\[ R^2 = 0.76 \]

Panel C. Iowa

\[ y = 0.46x + 26.42 \]
\[ R^2 = 0.71 \]
Figure 4. Pre-Season Precipitation in Illinois, Indiana, and Iowa (September-April), 1960-2006

Panel A. Illinois.

\[ y = 0.0019x + 22.785 \]
\[ R^2 = 5 \times 10^{-5} \]

Panel B. Indiana.

\[ y = 0.0541x + 23.273 \]
\[ R^2 = 0.0497 \]

Panel C. Iowa.

\[ y = -0.0229x + 17.02 \]
\[ R^2 = 0.0079 \]
Figure 5. May Precipitation in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.

\[ y = 0.0202x + 3.8369 \]
\[ R^2 = 0.0254 \]

Panel B. Indiana.

\[ y = 0.0352x + 3.6251 \]
\[ R^2 = 0.0841 \]

Panel C. Iowa.

\[ y = 0.0192x + 3.8087 \]
\[ R^2 = 0.0290 \]
Figure 6. June Precipitation in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.

\[ y = 0.0003x + 3.9939 \]
\[ R^2 = 7 \times 10^{-6} \]

Panel B. Indiana.

\[ y = 0.0128x + 3.7644 \]
\[ R^2 = 0.0187 \]

Panel C. Iowa.

\[ y = 0.0089x + 4.3587 \]
\[ R^2 = 0.0053 \]
Figure 7. July Precipitation in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.

\[ y = -0.009x + 4.1809 \]
\[ R^2 = 0.0088 \]

Panel B. Indiana.

\[ y = 0.0155x + 3.963 \]
\[ R^2 = 0.0199 \]

Panel C. Iowa.

\[ y = 0.002x + 4.1853 \]
\[ R^2 = 2E-06 \]
Figure 8. August Precipitation in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.

\[ y = 0.0117x + 3.3162 \]

\[ R^2 = 0.0146 \]

Panel B. Indiana.

\[ y = 0.0172x + 3.3041 \]

\[ R^2 = 0.0385 \]

Panel C. Iowa.

\[ y = 0.015x + 3.5621 \]

\[ R^2 = 0.0137 \]
Figure 9. May Temperature in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.

\[ y = 0.0042x + 62.208 \]
\[ R^2 = 0.0003 \]

Panel B. Indiana.

\[ y = 0.0144x + 61.035 \]
\[ R^2 = 0.0031 \]

Panel C. Iowa.

\[ y = -0.0273x + 61.225 \]
\[ R^2 = 0.013 \]
Figure 10. June Temperature in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.

\[ y = -0.0019x + 71.537 \]
\[ R^2 = 0.0002 \]

Panel B. Indiana.

\[ y = 0.0106x + 70.192 \]
\[ R^2 = 0.0003 \]

Panel C. Iowa.

\[ y = -0.0023x + 70.006 \]
\[ R^2 = 0.0002 \]
Figure 11. July Temperature in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.
\[ y = 0.0219x + 74.806 \]
\[ R^2 = 0.0263 \]

Panel B. Indiana.
\[ y = 0.0254x + 73.54 \]
\[ R^2 = 0.0368 \]

Panel C. Iowa.
\[ y = 0.0029x + 73.995 \]
\[ R^2 = 0.0003 \]
Figure 12. August Temperature in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.

\[ y = 0.0253x + 72.56 \]

\[ R^2 = 0.0213 \]

Panel B. Indiana.

\[ y = 0.0338x + 71.421 \]

\[ R^2 = 0.0405 \]

Panel C. Iowa.

\[ y = 0.004x + 71.566 \]

\[ R^2 = 0.0005 \]
Figure 13. De-trended Corn Yields (to 2006) versus September-April (Pre-Season) Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -0.3772x + 163.57 \]
\[ R^2 = 0.008 \]

Panel B. Indiana

\[ y = -0.5615x + 163.41 \]
\[ R^2 = 0.0176 \]

Panel C. Iowa

\[ y = -0.10x + 160.65 \]
\[ R^2 = 0.00 \]
Figure 14. De-trended Soybean Yields (to 2006) versus September-April (Pre-Season) Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[
y = -0.0015x + 46.007 \\
R^2 = 3E-0630
\]

Panel B. Indiana

\[
y = 0.0335x + 46.097 \\
R^2 = 0.001
\]

Panel C. Iowa

\[
y = -0.0649x + 48.894 \\
R^2 = 0.0033
\]
Figure 15. De-trended Corn Yields (to 2006) versus May Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -0.6446x^2 + 4.6624x + 148.74 \]

\[ R^2 = 0.054 \]

Panel B. Indiana

\[ y = -1.199x^2 + 10.115x + 131.62 \]

\[ R^2 = 0.0911 \]

Panel C. Iowa

\[ y = -0.5685x + 161.48 \]

\[ R^2 = 0.0034 \]
Figure 16. De-trended Soybean Yields (to 2006) versus May Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -0.4757x + 48.027 \]

\[ R^2 = 0.0554 \]

Panel B. Indiana

\[ y = -0.3746x^2 + 3.2681x + 40.813 \]

\[ R^2 = 0.1197 \]

Panel C. Iowa

\[ y = -0.4305x + 49.663 \]

\[ R^2 = 0.0283 \]
Figure 17. De-trended Corn Yields (to 2006) versus June Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois
\[ y = -1.6645x^2 + 15.561x + 122.83 \]
\[ R^2 = 0.1007 \]

Panel B. Indiana
\[ y = -1.705x^2 + 16.875x + 111.93 \]
\[ R^2 = 0.1693 \]

Panel C. Iowa
\[ y = -1.1415x^2 + 10.853x + 136.42 \]
\[ R^2 = 0.0744 \]
Figure 18. De-trended Soybean Yields (to 2006) versus June Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -0.2548x^2 + 2.5829x + 40.251 \]
\[ R^2 = 0.0629 \]

Panel B. Indiana

\[ y = -0.424x^2 + 4.5494x + 36.112 \]
\[ R^2 = 0.2421 \]

Panel C. Iowa

\[ y = -0.1822x^2 + 1.6436x + 44.619 \]
\[ R^2 = 0.0336 \]
Figure 19. De-trended Corn Yields (to 2006) versus July Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -2.2196x^2 + 25.906x + 90.968 \]

\[ R^2 = 0.438 \]

Panel B. Indiana

\[ y = -1.076x^2 + 15.505x + 105 \]

\[ R^2 = 0.3345 \]

Panel C. Iowa

\[ y = -1.943x^2 + 21.115x + 110.39 \]

\[ R^2 = 0.4449 \]
Figure 20. De-trended Soybean Yields (to 2006) versus July Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -0.3667x^2 + 4.3584x + 35.089 \]

\[ R^2 = 0.2558 \]

Panel B. Indiana

\[ y = -0.3465x^2 + 3.8794x + 37.38 \]

\[ R^2 = 0.1521 \]

Panel C. Iowa

\[ y = -0.3318x^2 + 3.4751x + 40.062 \]

\[ R^2 = 0.1843 \]
Figure 21. De-trended Corn Yields (to 2006) versus August Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = 1.1094x^2 - 7.185x + 164.53 \]

\[ R^2 = 0.0355 \]

Panel B. Indiana

\[ y = -0.7372x^2 + 7.5933x + 132.62 \]

\[ R^2 = 0.0285 \]

Panel C. Iowa

\[ y = -0.9882x^2 + 7.5586x + 147.47 \]

\[ R^2 = 0.1077 \]
Figure 22. De-trended Soybean Yields (to 2006) versus August Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = 0.0748x^2 + 0.3618x + 43.574 \]
\[ R^2 = 0.1317 \]

Panel B. Indiana

\[ y = -0.121x^2 + 1.9866x + 41.378 \]
\[ R^2 = 0.1229 \]

Panel C. Iowa

\[ y = -0.4086x^2 + 4.2135x + 38.667 \]
\[ R^2 = 0.2089 \]
Figure 23. De-trended Corn Yields (to 2006) versus June Precipitation-Temperature Interaction Value for Illinois, Indiana, and Iowa*, 1960-2006

Panel A. Illinois

\[ y = -0.00x^2 + 0.21x + 124.18 \]
\[ R^2 = 0.09 \]

Panel B. Indiana

\[ y = -0.00x^2 + 0.23x + 113.45 \]
\[ R^2 = 0.15 \]

Panel C. Iowa

\[ y = -0.00x^2 + 0.14x + 138.62 \]
\[ R^2 = 0.06 \]

*Interaction Value = June Temperature x June Precipitation
Figure 24. De-trended Corn Yields (to 2006) versus July Precipitation-Temperature Interaction Value for Illinois, Indiana, and Iowa*, 1960-2006

Panel A. Illinois

\[ y = -0.00x^2 + 0.36x + 89.11 \]
\[ R^2 = 0.41 \]

Panel B. Indiana

\[ y = -0.00x^2 + 0.20x + 106.67 \]
\[ R^2 = 0.31 \]

Panel C. Iowa

\[ y = -0.00x^2 + 0.30x + 109.40 \]
\[ R^2 = 0.44 \]

*Interaction Value = July Temperature \times July Precipitation
Figure 25. De-trended Corn Yields (to 2006) versus August Precipitation-Temperature Interaction Value for Illinois, Indiana, and Iowa*, 1960-2006

Panel A. Illinois

\[ y = 0.00x^2 - 0.14x + 170.17 \]

\[ R^2 = 0.03 \]

Panel B. Indiana

\[ y = -0.00x^2 + 0.07x + 138.67 \]

\[ R^2 = 0.01 \]

Panel C. Iowa

\[ y = -0.00x^2 + 0.09x + 150.19 \]

\[ R^2 = 0.11 \]

*Interaction Value = July Temperature x July Precipitation
Figure 26. De-trended Corn Yields (to 2006) versus May Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -0.1069x^2 + 13.883x - 294.06 \]

\[ R^2 = 0.0133 \]

Panel B. Indiana

\[ y = -0.0532x^2 + 6.9201x - 74.158 \]

\[ R^2 = 0.0076 \]

Panel C. Iowa

\[ y = -0.39x^2 + 47.24x - 1270.17 \]

\[ R^2 = 0.09 \]
Figure 27. De-trended Soybean Yields (to 2006) versus May Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = 0.001x^2 + 0.0393x + 39.718 \]
\[ R^2 = 0.0251 \]

Panel B. Indiana

\[ y = 0.0445x^2 - 5.3719x + 208.41 \]
\[ R^2 = 0.0458 \]

Panel C. Iowa

\[ y = -0.0151x^2 + 1.9163x - 12.743 \]
\[ R^2 = 0.0048 \]
Figure 28. De-trended Corn Yields (to 2006) versus June Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = 0.3027x^2 - 44.741x + 1805.1 \]

\[ R^2 = 0.0509 \]

Panel B. Indiana

\[ y = 0.182x^2 - 27.01x + 1148.5 \]

\[ R^2 = 0.0473 \]

Panel C. Iowa

\[ y = -0.0559x^2 + 7.5864x - 97.914 \]

\[ R^2 = 0.002 \]
Figure 29. De-trended Soybean Yields (to 2006) versus June Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -0.0771x^2 + 10.871x - 336.66 \]

\[ R^2 = 0.021230 \]

Panel B. Indiana

\[ y = -0.0435x^2 + 5.8962x - 152.48 \]

\[ R^2 = 0.018 \]

Panel C. Iowa

\[ y = -0.076x^2 + 11.058x - 353.7 \]

\[ R^2 = 0.0691 \]
Figure 30. De-trended Corn Yields (to 2006) versus July Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -4.6612x + 505.71 \]
\[ R^2 = 0.3116 \]

Panel B. Indiana

\[ y = -3.6899x + 422.97 \]
\[ R^2 = 0.2264 \]

Panel C. Iowa

\[ y = -2.1931x + 321.23 \]
\[ R^2 = 0.0968 \]
Figure 31. De-trended Soybean Yields (to 2006) versus July Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -0.7108x + 99.44 \]

\[ R^2 = 0.1392 \]

Panel B. Indiana

\[ y = -0.4714x + 81.798 \]

\[ R^2 = 0.0585 \]

Panel C. Iowa

\[ y = -0.1239x + 56.936 \]

\[ R^2 = 0.0045 \]
Figure 32. De-trended Corn Yields (to 2006) versus August Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

\[ y = -4.426x + 478.49 \]

\[ R^2 = 0.47 \]

Panel B. Indiana

\[ y = -3.5735x + 407.47 \]

\[ R^2 = 0.3409 \]

Panel C. Iowa

\[ y = -2.9326x + 369.01 \]

\[ R^2 = 0.2303 \]
Figure 33. De-trended Soybean Yields (to 2006) versus August Temperature for Illinois, Indiana, and Iowa, 1960-2006

**Panel A. Illinois**

\[ y = -0.0631x^2 + 8.4745x - 236.21 \]

\[ R^2 = 0.3081 \]

**Panel B. Indiana**

\[ y = -0.4984x + 82.837 \]

\[ R^2 = 0.1049 \]

**Panel C. Iowa**

\[ y = -0.516x + 84.739 \]

\[ R^2 = 0.1032 \]
Figure 34. Alternate Trend Models for Corn Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa

Note: The quadratic model is dashed and the linear model is solid.
Figure 35. Alternate Trend Models for Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa

Note: The quadratic model is dashed and the linear model is solid.
Figure 36. Modified Thompson Model Residuals for Corn Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa
Figure 37. Modified Thompson Model Residuals for Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa
Figure 38. Expected Change in Corn Yields from Monthly Precipitation in Illinois, Indiana, and Iowa, 1960-2006

Note: "x" denotes average precipitation over 1960 through 2006 for each state.
Figure 39. Change from Average Monthly Precipitation to Maximize Corn Yields in Illinois, Indiana, and Iowa, 1960-2006
Figure 40. Change in Corn Yields By Increasing Precipitation from Average to Optimum in Illinois, Indiana, and Iowa, 1960-2006

Figure 41. Change in Corn Yields By Decreasing Precipitation from Average to Optimum in Illinois, Indiana, and Iowa, 1960-2006
Figure 42. Expected Change in Corn Yields from Monthly Temperature in Illinois, Indiana, and Iowa, 1960-2006

Panel A. May Temperature

Panel B. June Temperature

Panel C. July Temperature

Panel D. August Temperature
Figure 43. Expected Change in Soybean Yields from Monthly Precipitation in Illinois, Indiana, and Iowa, 1960-2006

Panel A. June Precipitation.

Panel B. July Precipitation.

Panel C. August Precipitation.

Note: "x" denotes average precipitation over 1960 through 2006 for each state.
Figure 44. Change from Average Monthly Precipitation to Maximize Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006
Figure 45. Change in Soybean Yields By Increasing Precipitation from Average to Optimum in Illinois, Indiana, and Iowa, 1960-2006

Figure 46. Change in Soybean Yields By Decreasing Precipitation from Average to Optimum in Illinois, Indiana, and Iowa, 1960-2006
Figure 47. Expected Change in Soybean Yields from Monthly Temperature in Illinois, Indiana, and Iowa, 1960-2006

Panel A. May Temperature

Panel B. June Temperature

Panel C. July Temperature

Panel D. August Temperature
Figure 48. Average Weather Trend and Unadjusted Trend for Corn Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa
Figure 49. Average Weather Trend and Unadjusted Trend for Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa
Figure 50. Corn Weather Indexes for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa
Figure 51. Soybean Weather Indexes for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa
Figure 52. QLR Tests for Structural Change in Modified Thompson Models for Corn Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.

Panel B. Indiana.

Panel C. Iowa

Panel D. Iowa (1993 excluded)

Panel E. Iowa (2003 excluded)

Panel F. Iowa (1993 and 2003 excluded)

Note: Dashed lines show the QLR Statistic
Figure 53. QLR Tests for Structural Change in Modified Thompson Models for Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.

Panel B. Indiana.

Panel C. Iowa

Panel D. Iowa (1993 excluded)

Panel E. Iowa (2003 excluded)

Panel F. Iowa (1993 and 2003 excluded)

Note: Dashed lines show the QLR-Statistic
Figure 54. Relative Size of Squared Forecast Errors ($d_t$) for Modified Thompson Models and the USDA on September 1 for Corn Yields in Illinois, Indiana, and Iowa, 1980-2006
Figure 55. Relative Size of Squared Forecast Errors ($d_t$) for Modified Thompson Models and the USDA on September 1 for Soybean Yields in Illinois, Indiana, and Iowa, 1980-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa
Figure 56. Out-of-Sample Forecast Errors for Modified Thompson Models of Corn Yields in Illinois, Indiana, and Iowa, 1980-2006

Note: dashed lines indicated the standard deviation of the forecast errors
Figure 57. Out-of-Sample Forecast Errors for Modified Thompson Models of Soybean Yields in Illinois, Indiana, and Iowa, 1980-2006

Panel A. Illinois

Panel B. Indiana

Panel C. Iowa

Note: Dashed lines indicated the standard deviation of the forecast error.
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