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Abstract

The purpose of this study was to investigate the relationship between weather, technology, and corn and soybean yields in the U.S. Corn Belt. Corn and soybean yields, monthly temperature, and monthly precipitation observations were collected over 1960 through 2006 for Illinois, Indiana, and Iowa. Multiple regression models were developed based on specifications found in studies by Thompson (1962 1963 1969 1970 1985 1986 1988). Estimated models explained at least 94% and 89% of the variation in corn and soybean yields for each state, respectively.

Analysis of the regression results showed that corn yields were 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 appeared to be minimal. Soybean yields were most affected by technology and the magnitude of precipitation during June through August (and especially during August). Structural change tests were performed on each model to test for changes in any of the regression model parameters. Some breakpoints were identified, but were difficult to explain since the results were not consistent across states and crops. Additional tests for structural change were directed specifically at the trend variable in corn models. The tests did not indicate a notable change in the technology trend for corn since the mid-1990s.

Corn and soybean yield forecasts from the regression models on June 1 and July 1 were no more accurate then trend yield forecasts. Regression model forecasts for corn improved on August 1, while model forecasts for soybeans improved by September 1. U.S. Department of Agriculture (USDA) corn and soybean forecasts were always more accurate than those from the regression models. Nonetheless, encompassing tests showed that the accuracy of USDA yield forecasts could be significantly improved by the information contained in regression model forecasts. Across states and forecast months, combining regression model forecasts with USDA forecasts improved accuracy an average of 10% for corn and 6% for soybeans.

In sum, this research provided strong evidence that precipitation, temperature, and a linear time trend to represent technological improvement explained all but a small portion of the variation in corn and soybean yields in the U.S. Corn Belt. An especially important finding was that relatively benign weather for the development of corn since the mid-1990s should not be discounted as an explanation for seemingly “high” yields. The potential impact of this finding on the agricultural sector is noteworthy. Trend yield forecasts based on perceptions of a rapid increase in technology may eventually lead to poor forecasts. Unfavorable weather in the future may lead to unexpectedly low corn yields that leave producers, market participants, and policy-makers wondering how such low yields could have occurred despite technological improvements.

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Introduction

Weather and technology are the primary determinants of corn and soybean yields in the U.S. Corn Belt. 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 influence yield potential, other factors also affect corn and soybean yields. These include soil quality, planting date, disease, insects, and technological improvements from seed genetics, fertilizers, and producer management techniques.

Despite decades of research relating corn and soybean yields to weather and technology, yields are sometimes unexpectedly high or low. For example, corn yields across Illinois in 2004 were much higher than expected despite a close following of growing season weather (Changnon and Changnon 2005). The less than complete understanding of weather, technology, and yield relationships is of particular concern given recent and potential increases in global temperature (National Climatic Data Center 2007). Local and regional climate could be altered by warmer global temperatures yet the effect of current climate and weather on yields is not fully understood (e.g., Wilbanks and Kates 1999). Climatological changes would further complicate important producer-level crop management decisions.

There has been considerable speculation in recent years that a higher trend yield for corn was established in the mid-1990s. Many farmers, crop experts, and seed companies credit biotechnology-driven improvements in seed genetics for recent corn yield increases (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 (Offut, Garcia, and Pinar 1987; Nielsen 2006). Soybean yields have received less attention because recent trend growth rates do not appear to have increased significantly.

Several methods can be used to estimate the relationship between weather, technology, and crop yields. As Kaufmann and Snell (1997) and many others have observed, the various methods can be categorized into two groups. The first group consists of crop simulation 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. While such models have a strong foundation in biological theory and experimental data, they are nonetheless highly complex and difficult to generalize to aggregate areas such as crop reporting districts or states (Walker 1989).[1] This is a significant limitation when forecasting is the objective. Simulation models also tend to exclude the influence of technological advances over time and have somewhat poor explanatory power.

[1] See Duchon (1986) for an example of large-scale forecasting based on a crop simulation model.

The second group consists of multiple regression models that estimate the relationship of weather and technology to crop yields. One advantage of multiple regression models over crop simulation models is that regression models capture both weather and technological aspects of yield variation over time. Regression models are also relatively simple to specify and estimate for aggregate areas, a considerable advantage when forecasting is the objective (Walker 1989). However, aggregation also can create problems (Shaw 1964). For example, a monthly rainfall total of four inches can represent one inch of rain each week or one four inch rain in the first week of the month. These two scenarios may have markedly different implications for crop yields. In a related vein, averages over large spatial scales (crop reporting districts, states, or regions) may not adequately reflect local weather conditions that actually affect crop yields. Despite these limitations, multiple regression models have proven to be valuable in previous research due to their high explanatory power and ability to represent both weather and technology affects over time. Given these advantages and the difficulty of applying crop simulation models to aggregate areas, the focus henceforth is on regression models.

In a pioneering study, Smith (1914) used simple correlations to determine the influence of rainfall and temperature on corn yields.[2] 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 the first to show that summer weather was statistically important to corn production. Subsequent studies utilized the increasing availability of data and faster computer processing speeds to develop more sophisticated regression models (e.g., Davis and Harrell 1942; Runge and Odell 1958 1960; Nelson and Dale 1978). Several studies by Thompson (e.g., 1962 1963 1969 1970 1985 1986 1988) were particularly influential. He developed regression models of the relationship between technology, monthly rainfall, monthly temperatures, and U.S. corn and soybean yields. His most significant findings were: 1) corn yields were particularly boosted by abundant rainfall during July and cooler-than-usual temperatures during August, 2) above-average July and August rainfall particularly boosted soybean yields, and 3) 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.

Despite continuing interest in the relationship between weather, technology, and corn and soybean yields, only a few studies have estimated regression models using data from the 1990s onward (e.g., Schlenker and Roberts 2006; Lynch, Holt, and Gray 2007). Furthermore, earlier studies generally did not evaluate regression model estimates with modern diagnostic tests for autocorrelation, heteroskedasticity, mis-specification, and structural change.[3] These diagnostics are important because they help to determine whether statistical assumptions are violated. If violations are indicated, model results may be unreliable and alternative estimation methods may be required. In addition, only a handful of previous studies investigate the out-of-sample

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[2] See Baier (1977), Garcia et al. (1987), McKeown, Warland, and McDonald (2006), and Tannura, Irwin, and Good (2008) for reviews of the literature on regression models of weather, technology, and crop yields.

[3] Exceptions include the studies by Garcia et al. (1987), Offut, Garcia, and Pinar (1987), Dixon et al. (1994), and Lynch, Holt, and Gray (2007).

forecasting performance of weather and technology regression models (Teigen 1991a 1991b; Dixon et al. 1994; Teigen and Thomas 1995), and these studies evaluated very small forecast samples, at most three years. Hence, previous studies provide limited evidence on the forecasting performance of regression models. Finally, previous studies did not examine the possibility of combining regression model forecasts with U.S. Department of Agriculture (USDA) forecasts to develop superior composite forecasts.

Historical considerations and current debates provide ample motivation for additional study of the relationship between weather, technology, and corn and soybean yields. Therefore, the purpose of this study 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 1988). The regression models are applied to yield and weather observations from Illinois, Indiana, and Iowa over 1960 through 2006. Three key questions are addressed: 1) Has the relationship between temperature, precipitation, technology, and corn and soybean yields in the U.S. Corn Belt changed since the last comprehensive studies? 2) Has the trend rate of yield growth for corn accelerated since the mid-1990s? and 3) How does the accuracy of yield forecasts from the regression models compare to benchmark forecasts, such as those generated by the USDA?

Regression models are developed for corn and soybean yields in Illinois, Indiana, and Iowa. These three states are chosen because they represent over 40% of United States corn and soybean production in most years, experience similar weather, and have comparable planting dates. Modifications to Thompson's original model are performed due to changes in planting practices since the early 1960s, patterns in the data, and a desire to increase degrees of freedom for estimation. The regression models of corn and soybean yields include observations on monthly precipitation, monthly temperature, and 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 then analyzed to determine the relationship between yields, technology, and weather. Formal parameter stability tests are used to determine whether structural change occurred in model parameters over the sample period. Several tests are used to determine if a significant change in trend yield growth in corn occurred during the mid-1990s.

A monthly forecast competition is conducted over 1980 through 2006. Out-of-sample forecasts are obtained from the weather and technology regression 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 root mean squared error and mean absolute 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, encompassing tests are calculated to determine if significant improvement would occur if these forecasts were combined into a single composite forecast.

Data

The multiple regression models developed by Thompson (1962 1963 1969 1970 1975 1985 1986 1988 1990) used time and monthly weather observations to explain variation in corn and soybean yields. Models developed in this study utilize similar observations 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.

Weather and Yield Data

The regression models developed by Thompson (1963) included monthly precipitation and temperature observations from 1930 through 1962. The modified models developed in the next section 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 almost identical and probably came from the same source.

As noted above, 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 in the top five corn and soybean producing 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 (Kucharik and Ramankutty 2005).

Several publications noted that significant nitrogen fertilizer applications began around 1960 and coincided with an increase in corn yields (e.g., Thompson 1969 1975 1985 1986 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 may have increased after 1973 (Thompson 1975, 1985, 1986, 1988). A beginning year of 1960 is used to develop models in the next section due to the increased use of nitrogen fertilizer around 1960 and the addition of 14 more observations versus a beginning date of 1974.

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 be divided into "climatically quasi-homogeneous" climatic divisions (National Climatic Data Center 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 (National Climatic Data Center 2003). 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 are 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 *Quick Stats: Agricultural Statistics Data Base* (www.nass.usda.gov/QuickStats/), a website maintained by the National Agricultural Statistics Service (NASS). 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.

Descriptive Analysis

The weather and yield 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. Correlations between monthly precipitation and temperature are presented in Tables 4 and 5. Table 6 shows descriptive statistics for corn and soybean yield observations adjusted to a constant 2006 technology. These descriptive statistics provide a better understanding of the climate and yields in each state and highlight similarities and differences.

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, average precipitation in May is similar across these states, 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. At the extremes, 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 due to 10.50” of precipitation in July 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. At the extremes, Iowa has been considerably wetter and slightly drier than Illinois or Indiana, and has a notably higher coefficient of variation.

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.

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 monthly precipitation 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 for 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.

Corn and Soybean Yields

Yields are affected by a complex combination of factors, such as weather, soil quality, seed genetics, 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 Indiana 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 de-trended to 2006 technology for comparison independent of annual trend increases (trend yield).[4] In other words, yields over 1960 through 2006 were adjusted to the level of technology available in 2006. Iowa averaged the highest de-trended corn yield, 159.1 bushels per acre, followed by Illinois at 155 bushels per acre and Indiana at 149.6 bushels per acre, respectively. The range in corn yields was similar for Iowa and Illinois, but was nearly 20 bushels per acre lower in Indiana. Standard deviations show that the typical variation in de-trended corn yields was about 14-15 bushels annually. Iowa also averaged the highest de-trended soybean yield, 47.8 bushels per acre, followed by Indiana at 46.9 bushels per acre and Illinois at 46.0 bushels per acre, respectively. Standard deviations show that the typical variation

[4] De-trended yields were calculated as: $Y_t = y_t + b \cdot (47 - t)$ where Y_t = the de-trended yield in year t, y_t = the actual yield in year t, b = the estimated linear trend coefficient, and t is a time index running from 1 to 47.

in de-trended soybean yields was about 3.5-4.0 bushels annually. It is interesting to note the narrow range of coefficients of variation for both crops across all three states. This indicated that relative yield variability was similar across crops and states.

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 (National Climatic Data Center 2007). 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.

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 was not detected. The lack of a trend and earlier evidence of low month-to-month correlations support the view that monthly temperatures and precipitation from 1960 through 2006 were random. Finally, the fact that an upward trend in temperatures was not observed in Illinois, Indiana, or Iowa is not necessarily inconsistent with global warming, because the local effects of global warming on climate and weather are poorly understood (e.g., Wilbanks and Kates 1999).

Long-Term Weather Forecasting

Long-term weather forecasts refer to future periods on the scale of weeks, months, or longer. If long-term weather conditions can be forecast reliably, then this information should be incorporated into crop weather model predictions. There was considerable optimism about the potential for long-term weather forecasting in the early part of the 20th century, as it was thought that weather could be predicted by solving the systems of mathematical equations the govern the motion of air. However, Lorenz (1963) discovered that the mathematical equations used to forecast weather actually represented a ‘chaotic’ system. He noted the startling consequences for long-range weather forecasting:

> When our results concerning the instability of non-periodic flow are applied to the atmosphere, which is ostensibly non-periodic, they indicate that prediction of the sufficiently distant future is impossible by any method, unless the present conditions are known exactly. In view of the inevitable inaccuracy and

> incompleteness of weather observations, precise very-long-range forecasting would seem to be non-existent. (p. 141)

In other words, infinitesimally small changes in the initial conditions of the system will result in exponential changes in the forecasts, quickly rendering them useless from a practical standpoint. This is popularly known as the 'butterfly effect' (Lorenz 1993). One consequence is that attempts to forecast longer-term weather usually are 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." (Climate Prediction Center 2008). 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 10 years, 5) soil moisture anomalies, and 6) a multiple linear regression tool to utilize information from a "variety of sources" (Olenic 2007).

Long-lead forecasts based on El Niño or La Niña have had some success estimating future climates. For example, Mjelde, Hill, and Griffiths (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) identified only 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 (Olenic 2007).

As noted above, the complexity involved in long-term weather forecasting is daunting from a theoretical standpoint. 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, monthly precipitation and temperatures over 1960 through 2006 indicated that monthly weather observations in Illinois, Indiana, and Iowa were random and generally poor indicators of weather in future months. This limits the potential promise of Corn Belt weather in previous months and/or years to be used as predictors of weather in future months or years, absent the possible exception of strong El Niños or La Niñas. Hill and Mjelde perhaps best describe long-term climate forecasting as being "in its infancy" (p. 622).

Development of the Modified Thompson Model

Thompson (1963) modeled corn and soybean yields for Illinois, Indiana, Iowa, Missouri, and Ohio from 1930 through 1962. This set of states was chosen because the states cumulatively represented a significant portion of corn and soybean production at the time of the analysis. The model included linear and quadratic variables in an effort to improve upon his earlier linear-only version of the model (Thompson 1962).

Weather variables used in the Thompson (1963) study 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.[5] 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 formally specified as follows:

(1)
$$\begin{aligned}
(\text{yield})_t = {} & \beta_0 + \beta_1(\text{year})_t + \beta_2(\text{September through May precipitation})_t \\
& + \beta_3(\text{September through May precipitation})_t^2 + \beta_4(\text{June precipitation})_t \\
& + \beta_5(\text{June precipitation})_t^2 + \beta_6(\text{July precipitation})_t + \beta_7(\text{July precipitation})_t^2 \\
& + \beta_8(\text{August precipitation})_t + \beta_9(\text{August precipitation})_t^2 \\
& + \beta_{10}(\text{May temperature})_t + \beta_{11}(\text{May temperature})_t^2 + \beta_{12}(\text{June temperature})_t \\
& + \beta_{13}(\text{June temperature})_t^2 + \beta_{14}(\text{July temperature})_t + \beta_{15}(\text{July temperature})_t^2 \\
& + \beta_{16}(\text{August temperature})_t + \beta_{17}(\text{August temperature})_t^2 \\
& + \beta_{18}(\text{June precipitation} \times \text{June temperature})_t \\
& + \beta_{19}(\text{July precipitation} \times \text{July temperature})_t \\
& + \beta_{20}(\text{August precipitation} \times \text{August temperature})_t + \varepsilon_t
\end{aligned}$$

This model utilized 33 annual observations to estimate yields, while 21 parameters were required for the estimation. This only left 12 degrees of freedom, which is a relatively low number because it means that only 12 observations were "unrestricted." The goal of modeling is to capture important relationships with the minimum number of parameters in order to maximize the number of "free" observations. Therefore, a central goal in the development of the weather and technology regression models for this study is to adequately represent monthly weather, technology, and yield relationships for corn and soybeans while utilizing the smallest number of parameters.

Dixon et al. (1994) and others have argued that regression models based on weather during calendar months are 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 weekly variables keyed

[5] Pre-season precipitation was not included in his first study (Thompson 1962). In later studies (Thompson 1969 1970 1985 1986 1988), pre-season precipitation was defined as the total over September through June.

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) Dixon et al. showed limited loss of information in utilizing monthly weather variables versus variables based on crop stages, 2) Dixon et al. indicated 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 Changnon (2005) 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 was not used in the present study. Similar suggestions were also made to utilize soil moisture observations, but direct measurements are limited and not representative of the state level. Therefore, precipitation was used as a proxy for soil moisture.

Monthly weather from May through August was examined for inclusion in the modified model since it is widely understood that 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, Elmore and Abendroth (2006) showed that 50% of Iowa corn generally was planted by the end of April from 2000 through 2004, but the same amount of corn was not completed until May 10 from 1975 through 1979. The authors 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 5) that lower yields are more likely by planting too late than too early. In order to accommodate the shift to earlier planting dates over time, May precipitation was added as a variable and pre-season precipitation was re-defined as that occuring from September through April (as opposed to September through May in Thompson's original model).

The functional form of the variables included in the modified model 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.

Functional Form of 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 and 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, the existence of a quadratic relationship was exemplified in Iowa during 1993 when monthly summer precipitation was excessively high, leading to flooding, 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 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 reasonable to argue that corn and soybeans can recover from particularly low or high precipitation during May because weather during June through August has a much more significant impact on yield potential. Figures 15 and 16 confirmed this observation by showing a limited relationship between May precipitation and de-trended yields. Although the relationship was weak, May precipitation was included in the modified model because precipitation during the month affects planting date, root development, and initial growth. However, a linear form was used instead of a 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 was highly influential on 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 reflect the impact on yields from particularly favorable or unfavorable combinations of temperature and rainfall. Interaction variables were 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 for 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.

Functional Form of 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. Tables 2 and 3 show that 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. 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 in May and June and de-trended corn and soybean yields was weakly represented by a quadratic form, with both concave and convex relationships exhibited. However, Figures 30 through 33 show that the relationship between July and August temperatures and yields could be represented linearly and was strongly negative – especially for corn. This indicated that hot weather during these months was often associated with reduced yields, while cooler weather was often associated with increased yields. The lack of strong quadratic correlations early in the growing season and stronger linear relationships later in the season led to the specification of the linear form for all temperature variables. This eliminated another four variables from Thompson's original model.

Functional Form of Technology Variables

Corn and soybean yields have gradually increased since 1960. This is called "trend yield" and it is due to a variety of technological improvements that include seed genetics, fertilizers, and producer management techniques. 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 the linear form for time and 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 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.

Modified Model

Modifications to the Thompson (1963) model allowed a reduction of six variables from the original model. As discussed in 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. Because of these changes, the following modified model was used for a given state and crop:

$$
\begin{aligned}
(2) \qquad (\text{yield})_t = {} & \beta_0 + \beta_1(\text{year})_t + \beta_2(\text{September through April precipitation})_t + \\
& \beta_3(\text{May precipitation})_t + \beta_4(\text{June precipitation})_t + \beta_5(\text{June precipitation})_t^2 + \\
& \beta_6(\text{July precipitation})_t + \beta_7(\text{July precipitation})_t^2 + \beta_8(\text{August precipitation})_t \\
& + \beta_9(\text{August precipitation})_t^2 + \beta_{10}(\text{May temperature})_t + \beta_{11}(\text{June temperature})_t + \\
& \beta_{12}(\text{July temperature})_t + \beta_{13}(\text{August temperature})_t + \varepsilon_t
\end{aligned}
$$

The above model was also 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, the goal was to adequately represent weather-technology-yield relationships while maintaining the highest number of degrees of freedom possible. Therefore, the model developed in this section is argued 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). While ordinary least squares estimators are still unbiased and efficient under conditions of multicollinearity, the implications of multicollinearity in practice may be severe nonetheless, with parameters estimated with such imprecision that little is learned from the estimation exercise. 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 for May through August generally were negative as expected. However, the correlations were small, falling in the range of 0.01 to -0.37. The average and median values of all within-state correlations in Table 4 were 0.00 and 0.01, respectively. The highest pair-wise correlations in absolute value were 0.39, 0.44, and 0.43 for Illinois, Indiana, and Iowa, respectively (July-August temperature). Hence, multicollinearity problems were unlikely to be significant for the weather and technology regression models specified here.

Model Estimation Results

Summary statistics and estimated residuals for the corn models are presented in Table 8 and Figure 36, respectively. The same information is presented in Table 9 and Figure 37 for the soybean models. Diagnostic tests for autocorrelation, heteroskedasticity, and mis-specification were 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 publications, but help to determine if model output is reliable.

Model Fit and Residuals

R-squared values for corn were nearly equal for each state and showed 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 meant that weather and technology accounted for all but a small proportion of the variation in corn yields. 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 R-squared values were lower than for the corn models, weather and technology accounted for most of the variations in soybean yields. Regression F-statistics were significant at the 1% level for both crops in all three states, indicating that the independent variables in the regression models jointly explained a significant proportion of the variation in yields.

Figures 36 and 37 did not appear to show any obvious time pattern in the estimated residuals of the models. Hence, autocorrelation was unlikely. Heteroskedasticity also appeared unlikely because variability did 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 was the consistent under-forecasting of corn yields in Iowa since 2000.

Poorest yield estimates occurred when weather was less significant than usual, likely due to insects, diseases, and other unusual 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 aphids were particularly numerous (Cook and Estes 2003). These results were not surprising since the models were not designed to account for such diseases or insects.

Yield estimates were also poor when unusual weather occurred. This was exemplified by a frost-freeze in September 1974 that sharply 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* 1974). This led to large over-estimates because the model was not designed to account for such an unusual weather event, particularly one occurring outside of the main growing season.

Weather during consecutive months that deviated by a substantial amount and in the same direction from average 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. Although the models reduced yields because of the unfavorable June and July weather, the true effect on yields was more pronounced because the impact of the poor weather apparently cumulated over the two months. This 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 yields. Insect infestations, disease, unusual weather such as late-season frosts, and consecutive months with large deviations from average weather in the same direction also caused particularly poor yield estimates.

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 higher-order autocorrelations are included in the LM test. 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, which exists if the variance of the residuals increased or decreased in a systematic manner. In this study, heteroskedasticity is defined as the variance of the yield estimates increasing or decreasing from 1960 through 2006. Heteroskedastic observations would be problematic because the estimated standard error of coefficients would again 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. 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 biases 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 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 test statistics are presented in Tables 8 and 9 and none were significant, which indicated that the models were not mis-specified. Cubed tests are not presented, but were also insignificant.

Interpretation of Estimated Regression Coefficients

The focus of this section is to analyze the estimated 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 also are compared to studies by Thompson to determine if qualitative changes in the weather-technology-yield relationships occurred since his original publications.

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 slightly flattened the unconditional trend (unadjusted for the effects of weather). It also confirmed similar findings by Swanson and Nyankori (1979).

The impact of pre-season precipitation on yields was insignificant for Illinois and Indiana. However, it was significant in Iowa where each additional inch of pre-season precipitation was 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.

The impact of May precipitation on yields was highly significant in Indiana and Iowa. In these states, each one-inch above average would be expected to reduce yields two to three bushels per acre. Similarly, each one-inch below average would be expected to decrease 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 2007).

The impact of June precipitation on yields 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.

The impact of July precipitation on yields 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.

The impact of August precipitation on yields 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 one bushel per acre. The importance of August precipitation in Indiana may be a reflection of a large proportion of 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.

The impact of May and June temperatures on yields was 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.

The impact of July temperature on yields 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 had a highly significant impact on yield 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, the estimation results showed 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 true in Indiana, as precipitation during August was more influential on corn 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.

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. Similar to 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 again provides evidence that unfavorable weather slightly flatted the unconditional trend (unadjusted for the effects of weather) in soybeans.

The impact of pre-season precipitation on yields 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.

The impact of May precipitation on yields 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 observations that increased precipitation during May would probably delay planting and growth since soybean planting typically occurs in May.

The impact of June precipitation on yields 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.

The impact of July precipitation on yields 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 had an insignificant effect, which means that precipitation is more 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 temperature, 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, the estimation results showed that 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.

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 comparison of Thompson's results and this study's results was not possible because of specification differences. For example, the original model by Thompson (1963) used quadratics for all weather variables, so it was not possible to make direct comparisons of the expected effect of all precipitation and temperature variables on yields. In later studies (e.g., Thompson 1969 1970 1985 1986 1988), the definition of pre-season precipitation was changed from September-May to September-June, eliminating June precipitation as a stand-alone variable. The following discussion provides a qualitative rather than quantitative comparison to Thompson's estimation results (1962 1963 1969 1970 1985 1986 1988) 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 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 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 (Thompson 1969).

Thompson (1988) noted 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 soybeans 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 regression models estimated for this study were generally similar to results in the aforementioned Thompson publications. Both the current and previous studies showed that corn yields were strongly influenced by the magnitude of July precipitation and July and August temperatures. However, the current study indicated that June precipitation had a larger influence on corn yields than in Thompson's studies. As noted above, all but the first two of Thompson's publications defined pre-season precipitation as September-June precipitation, as opposed to September through April in the current study. 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 was minimal, as it appeared that corn can recover from unusually warm or cool conditions during its early developmental phases. Above-average pre-season precipitation was also suggested by the modified models to increase yield potential, but the effect of weather later in the growing season considerably outweighed 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 difference is that below-average temperatures in July and August appear to be the most ideal for soybean yields, although Thompson (1988) had suggested slightly above-average temperatures were the most ideal during this period. However, the models agreed 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.

The Effect of Average Weather on 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 levels of the temperature and precipitation variables over 1960 through 2006 were inserted into the estimated regressions for each crop and state. This generated hypothetical yield estimates over the sample period assuming 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 average weather trend yields and unadjusted trend yields over 1960 through 2006. For each state and crop, average weather trend yields were shifted higher and had slightly steeper slopes than 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.

Weather Indexes

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 the 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.[6] 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 assumes that the weather models are 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. Specifically, weather indexes for corn and soybeans were calculated as follows:

(3)
$$W_t = \frac{\hat{y}_t}{\hat{y}_t^{avg}} \cdot 100$$

where $\hat{y}_t$ is the predicted yield from the regression model with actual values for weather variables, and $\hat{y}_t^{avg}$ 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 favorable and higher values indicate weather that was more favorable. The mean of the weather indexes for each state and crop were 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. The worst weather year for corn in Illinois and Indiana was 1983, while historic rain made 1993 the worst weather year for Iowa corn yields. The most unfavorable year for soybean yields in Illinois and Indiana was 1983, while 1993 was the worst in Iowa.

[6] Doll (1967, p. 987) argues that the advantages of his weather index methodology are four-fold. First, the index is based on a functional relationship between yield and the meteorological variables and is thus freed of the vagaries of trend estimation. Second, the formulation of the model allows decreasing returns to meteorological variables within a time period and interactions among time periods. Third, the index can be estimated with readily available meteorological data. Fourth, because meteorological variables are included in the model, weather phenomena such runs and extremes are 'explained' by the meteorological model.

Previous research has identified a "benign" period favorable to producing corn starting in the mid-1950s and continuing through the early 1970s (Thompson 1975 1986; Carlson 1990; Baker, Rushy, and Skaggs 1993; Andresen et al. 2001). This period was characterized by above average rainfall and below average temperature during July and August, conditions clearly beneficial for corn production. Inspection of Figure 50 indicates that a similar period may have started in the mid-1990s. To investigate this issue further, average levels of the weather indexes for corn and soybeans were computed for three time periods: 1960-1972, 1973-1995, and 1996-2006. As shown in Table 10, there is a distinct pattern in the averages for corn across the three time periods. Average values were highest for the first sub-period, lowest for the second sub-period, and in between for the last sub-period. The drop in average values from the first to the second sub-period was especially sharp, averaging about five percentage points across the three states. It is also interesting to observe in Figure 50 that the period from the mid-1990s forward was quite stable for corn with no particularly bad weather years – especially in Iowa.

In contrast to the results for corn, averages for soybeans in Table 10 do not reveal any particular pattern across the sample. Average weather conditions for soybean production within each state were quite similar across the three sub-periods. Figure 51 does show that weather for soybeans was fairly tranquil during 1996-2006, although 2003 was rather unfavorable for soybeans in Iowa.

Structural Change

Structural change tests were 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 were performed on each model to identify if a structural break occurred. Dummy variables were then added to any models that show significant break points. This helped to identify the source of potential structural breaks. Potential sources of structural breaks were 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 was 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:

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

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. But, 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 11 shows that few of the variables for Illinois corn and Iowa corn were significant when dummy variables are included. Although the August precipitation dummy variables were significant at the 1% level in Illinois, this was 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 were significant at the 1% level for Iowa corn. However, many of the dummy variables for the soybean model were 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 were 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 12 shows that the dummy variables were significant. The magnitude of the August temperature dummy was sensible, as it indicated 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 illogical that increased August temperatures increased corn yields in the heart of the U.S. Corn Belt.

The results of the structural change tests were 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.

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 empirical evidence often used to support a conclusion 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 analyze 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.

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 was assessed by adding a dummy trend variable to the model at 1983. This model is presented in Table 13. Results show that the trend dummy was significant at the 5% level, but that the slope of the trend was 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 was fixed 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 were 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 any 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.[7] Results for these additional regressions are presented in Table 14 and they show that point estimates were very similar to the modified models originally presented in Table 7. The time trend variable over 1960 through 1995 ranged 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 only 0.09, -0.04, and 0.15 bushels per acre in Illinois, Indiana, and Iowa, respectively. Therefore, the models did not suggest a notable structural change in trends during the mid-1990s.[8]

The remaining issue is how to reconcile the lack of evidence for an increase in corn trend yields with the widespread perception that trend yields accelerated in the last decade. One

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[7] It is certainly plausible that structural change in the technology trend could occur smoothly over time, rather than in the segmented manner considered here. Lynch, Holt, and Gray (2007) estimated weather and technology regression models for corn yields in seven Corn Belt states and found that a segmented trend model generally was superior to a smooth transition trend model.

[8] The sensitivity of the results was examined by also fixing the breakpoint at 1994, 1995, 1997, or 1998. Estimation results were not sensitive to the alternative breakpoints.

possibility is that observers failed to recognize the impact of relatively favorable weather since the mid-1990s, and thereby, mistakenly attributed corn yield increases to technology. As shown in Table 10 and discussed earlier, average values for corn weather indexes were about three percentage points higher over 1996-2006 compared to 1973-1995. In addition, the period from the mid-1990s forward was quite stable for corn with no particularly bad weather years – especially in Iowa. 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. By any reasonable standard, weather since the mid-1990s has been relatively benign for corn development. If this fact is not well-understood or ignored, the relatively "high" yields since the mid-1990s can easily be attributed to technology instead of weather (see Figure 1).

Another possibility is that a shift to a higher trend in corn yields occurred in the last decade but the availability of a limited number of new observations prevented its detection. Two previous technological revolutions caused sharp jumps in trend yields (single cross hybrids in the 1930s and nitrogen fertilizers in the 1950s), so a shift would not be without historical precedent. As noted in the introduction, many farmers, crop experts, and seed companies credit biotechnology-driven improvements in seed genetics for recent corn yield increases (Fitzgerald 2006). Early experimental evidence provides some support for these views. For example, Below et al. (2007) report that triple-stack corn varieties containing the bt-rootworm trait have a large yield advantage over non-bt varieties, as large as 50 bushels per acre. The authors note that yield advantages conferred by the rootworm trait are difficult to attribute entirely to rootworm control and hypothesize that the trait alters the corn plant's efficiency of nitrogen use. It is important to recognize that the experimental results reported by Below et al. are based on only one site (Urbana, Illinois) for one year (2006). If these results are confirmed in further experiments, then widespread adoption of triple-stack corn varieties could well lead to an increase in trend yields.[9]

The pattern in estimated residuals for the corn regression models in recent years also provides some support for the view that trend yields have accelerated. As shown in Figure 36, residuals in recent years have had a tendency to be positive (actual yields greater than predicted yields). Specifically, estimated residuals for the Illinois corn model were positive four out of six years since 2001 and averaged +3.3 bushels. Residuals for the Indiana corn model were positive five out six years since 2001 and averaged +1.1 bushels. Residuals for the Iowa corn model were positive all six years since 2001 and averaged +6.9 bushels. While intriguing, these results should be viewed cautiously since positive or negative runs of such lengths can occur randomly and are not unprecedented. For example, estimated residuals for the Iowa corn model were positive every year over 1968-1973 and averaged +7.1 bushels. Additional observations will be needed before firm conclusions can be reached.

[9] The June 2007 *Acreage* report prepared by the National Agricultural Statistics Service of the USDA indicates that stacked trait hybrids were planted on 40%, 30%, and 37% of the corn acreage in Illinois, Indiana, and Iowa, respectively, in 2007. (http://usda.mannlib.cornell.edu/usda/current/Acre/Acre-06-29-2007.pdf)

As a final point, it is interesting to consider the possibility that history is simply repeating itself. Professor Louis Thompson ended his 1969 article on weather, technology, and corn production with this prescient statement:

> It is also significant that weather variability (affecting corn yields) has gradually decreased since 1930. As a consequence, there has been a decrease in year-to-year variations in corn yields. This trend in the improvement of weather and decrease in corn yield variability should be extrapolated with caution, however, because we may be near the end of a cool period occurring between periods of warmer than normal weather. Records in the U.S. Corn Belt indicate irregular cyclical weather, with periods of warmer summer weather alternating with periods of cooler summer weather. During this century, the decades of the teens, '30's, and '50's have been characterized by warm dry summers. If such a pattern persists, one might expect warmer and drier summers in the U.S. Corn Belt in the '70's and a temporary halt in the uptrend of corn yields. (p. 456)

Writing a few years later in 1975, Professor Thompson made the following observation of the importance of weather on crop yields:

> There has been more than usual attention in the press to weather and climatic change since mid-1974. The United States had so little variability in weather and grain production in the past two decades (until 1974) that an attitude of complacency had developed. 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)

More 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 Professor Thompson stating in 1990 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)

The obvious and highly pertinent question is whether a parallel should be drawn between weather patterns over 1960-1972 vs.1973-1995 and 1996-2006 vs. subsequent years. Without taking a position on the existence of long-term weather cycles or the potential impacts of global warming, history certainly suggests a good deal of caution in projecting recent and favorable weather patterns into the future.

Forecast Evaluation

The modified Thompson models provided valuable 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 timeseries 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 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 section is to develop a relatively large sample 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 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.

Yield Forecasting Competition

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 that result from being produced at different times.

The USDA publishes corn and soybean production forecasts 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 composed 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 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 regression models were assumed to be produced on the first day of each month. Forecasts were produced by regressing the model from 1960 through the year prior to the year being forecast. Then, actual weather values were entered into the model for the year being forecast. However, actual values were only entered for months prior to the current month. Average weather values were entered for remaining months to represent upcoming weather. This is consistent with USDA forecast assumptions and available evidence on the difficulty of making reliable long-term weather forecasts.[10] The average weather values were 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 were produced in the following manner:

1) The modified Thompson model was estimated 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.
2) May 1980 precipitation and May 1980 temperature values were entered into the model.
3) Average precipitation and temperature values from 1960 through 1979 were entered into the model for June, July, and August.
4) Yield forecasts for June 1, 1980 were calculated and saved.

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

Out-of-sample trend yield forecasts were produced in a similar manner to forecasts from the modified Thompson model. Trend yield forecasts were assumed to represent the best available yield forecast prior to the start of each growing season. These forecasts utilized previously observed yields to predict yields for the upcoming year, and they were 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 was used. However, trend yield forecasts did not change throughout the growing season since they were solely based on previous yield observations. Therefore, the trend yield forecasts were the same from June through October.

[10] For discussion of the latter point, see the section in this report on "Long-Term Weather Forecasting."

Forecast Accuracy Measures

Forecasts errors were defined as $e_t = ya_t - yf_t$, where ya_t = final average yield and yf_t = forecast yield. Root mean squared error (RMSE) is a standard measure of "average" forecast accuracy. Since errors were squared, RMSE weights large forecast errors relatively more than small forecast errors. Specifically, RMSE was calculated for each forecasting model as:

(5)
$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(ya_t - yf_t\right)^2}$$

where $n =$ number of forecasts. The root mean squared percentage error (RMSPE) is the same as RMSE, but it is calculated in percentage form. This allows equal cross-comparison of corn and soybean yield forecasts because results are independent of units (bushels per acre). RMSPE was calculated for each forecasting model as follows:

(6)
$$RMSPE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left[\left(\left(ya_t - yf_t\right)/ya_t\right)\cdot 100\right]^2}.$$

An alternative measure of "average" forecast error is mean absolute error (MAE). It represents the average absolute magnitude of the forecast errors in bushels per acre. In other words, all forecast errors were weighted equally. MAE was calculated for each forecasting model as follows:

(7)
$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\left(ya_t - yf_t\right)\right|.$$

The mean absolute percentage error (MAPE) is the same as the MAE, but it is calculated in percentage form. This again allows for equal cross-comparison of the corn and soybean yield forecasts. MAPE is calculated for each forecasting model as follows:

(8)
$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\left[\left(\left(ya_t - yf_t\right)/ya_t\right)\cdot 100\right]\right|$$

The modified Diebold-Mariano (MDM) test, developed by Harvey, Leybourne, and Newbold (1998), was used to determine whether differences in accuracy between two competing forecast models were statistically significant. The competing forecasts for each commodity were: 1) the modified Thompson regression model, and 2) trend yield or USDA forecasts. Before performing the MDM test, it was first necessary to compute the difference in squared forecast errors: $d_t = e_{1t}^2 - e_{2t}^2$, where e_{1t} = USDA or trend forecast error, and e_{2t} = modified Thompson model forecast error. The MDM test was then defined as:

(9)
$$\text{MDM} = \left[\frac{n+1}{n}\right]^{1/2}\left[n^{-1}\left(\gamma_0\right)\right]^{1/2}\bar{d}$$

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

Forecast Evaluation

Monthly corn and soybean yield forecasts from the modified Thompson models, trend yield models, and USDA were evaluated over 1980 through 2006 in Illinois, Indiana, and Iowa. All forecasts were compared to final average yields 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.

Stability of Relative Forecast Accuracy

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 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 were evaluated over 1980 through 2006 relative to USDA forecasts. To determine if the weather model improved relative to the USDA, d_t values were regressed on time for each state and crop. This showed 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_t 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 indicated that forecasts from the modified Thompson model improved relative to the USDA over 1980 through 2006. All slopes were 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_t 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 was not present over 1980 through 2006.

Corn Yield Forecast Accuracy

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. Forecasts for Iowa in 1993 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 were particularly poor when weather is cumulatively unfavorable. Forecasts in Iowa were consistently too low from 2001 through 2006, while Illinois had more 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 were 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, a two-to-one ratio of in-sample to out-of-sample errors is fairly typical for this type of forecasting exercise (Makridas and Winkler 1989). It is also important to note that weaker out-of-sample forecasting performance does not necessarily mean that the regression models did not have value in forecasting corn and soybean yields. The performance of alternative models may have been even weaker.

Statistical measures of accuracy for corn are presented in Table 16. Forecasts from the regression model were similar to trend yield forecasts on June 1 and July 1, and were within 19 to 21 bushels per acre of final average yields, or 18% to 21%. In fact, forecasts from the regression model were slightly better on June 1 than July 1. This provides evidence that knowledge of May and June weather was 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 were particularly poor in Illinois and Indiana in 1988 and for Iowa in 1993, years with a historic drought and flood in each state. If these were truly outlier events, then the accuracy of the regression model may have been understated.

Modified Thompson model forecasts improved 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 were accurate to within 15 to 17 bushels per acre of final average yields, or within 16% to 17%. This was an improvement from trend forecasts that were within 18% to 21% of final average yields. Regression model forecasts improved further for Illinois and Indiana on September 1, though forecasts for Iowa were slightly less accurate. By comparison, USDA forecasts on August 1 were 6 to 7 percentage points more accurate than the regression models and 7 to 9 percentage points more accurate on September 1. USDA forecasts further improved on October 1.

Modified Diebold-Mariano tests are presented in Table 17. Results show that USDA corn forecasts on August 1, September 1, and October 1 were significantly more accurate than forecasts from the modified Thompson models. This provides evidence that USDA forecasts were statistically superior to forecasts from the modified Thompson model, and became increasingly accurate relative to the regression models with each passing month.

Soybean Yield Forecast Accuracy

Final soybean yield forecast errors from the modified model are presented in Figure 57. Results showed that the standard deviation of the forecast errors ranged from around five to nine bushels per acre. The forecasts in 2003 were poor for Illinois, Indiana, and Iowa. This was probably due to the effects of an aphid infestation (Cook and Estes 2003). Forecast yields were too high 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 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 were 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 18. Regression model and trend forecasts for soybean yields on June 1 and July 1 were more accurate than the corn yield forecasts. Forecasts were accurate to within 12% to 15% of final average yields, as compared to 18% to 21% for the corn yield forecasts. Regression model and trend yield soybean forecasts were very similar on June 1 and July 1. This provides evidence that the regression models for soybeans in June and July did not lead to marked improvements over trend yield forecasts.

Modified Thompson model forecasts for soybeans improved for Illinois on August 1, but were slightly less accurate than earlier forecasts for Indiana and Iowa. RMSE values showed that regression model forecasts only improved by less than one percentage point for all states on September 1. Nonetheless, the improvement on September 1 was sensible because forecasts should improve on September 1 with the inclusion of weather observations during the important months of July and August. Surprisingly, RMSE values suggested that trend yield forecasts were more accurate for Iowa on September 1 and only slightly less accurate for Indiana. On the other hand, USDA forecasts were 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 17 indicated that the difference between regression model and USDA forecast were not significantly different for Illinois and Iowa on August 1, and remained insignificantly different on September 1. Forecasts on October 1 were statistically different as USDA forecasts improved.

Results for the soybean forecasts were similar to corn yield forecasts in that the modified Thompson model was no more accurate than trend yield forecasts early in the growing season. The difference in forecast accuracy between the regression model and USDA forecasts was only significant for Indiana on August 1. The difference was significant for all states on October 1.

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 were noticeably less accurate than USDA forecasts. This cast doubt on the usefulness of the regression models in forecasting 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 to determine if forecasts from the modified Thompson model and USDA can be combined to produce a superior forecast.[11] Harvey, Leybourne, and Newbold (1998) developed a forecast encompassing framework to estimate optimal weight that each forecast should be given. The weights can then be used to measure the amount of improvement that results from combining the two forecasts. The idea behind the test is that information contained in one forecast encompasses the information in an alternative forecast if the weight on the alternative forecast is zero. If it is not zero, then the alternative forecast provides useful information even if it less accurate. The reason is that the alternative forecast utilizes different information than the other forecast. Note that encompassing tests were 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 was based on the following regression:

(10) $$e_{1t} = \zeta_t + \lambda(e_{1t} - e_{2t})$$

where e_{1t} = USDA forecast error, and e_{2t} = modified Thompson model forecast error
The regression slope coefficient (λ) 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 contained different and useful information.

Results of the encompassing tests are presented in Table 19. There appeared 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 were 23% and 35% for corn and soybeans, respectively. Similarly, Indiana weights in August were 28% and 20% for corn and soybeans, respectively. Limited value was indicated for weighting corn and soybean forecasts in Iowa, with August model weights of 16% for corn and 8% for soybeans. Encompassing test statistics were 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 were insignificant.

There was a notable decline in regression 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 indicated that information in USDA forecasts improved sharply relative to modified Thompson models on October 1 – a logical result because USDA forecasts on October 1 reflected a larger availability of actual yield observations.

[11] It is interesting that Thompson suggested an investigation along these lines almost 40 years ago. While discussing the high in-sample correlation between USDA yield estimates and model estimates, he commented that, "…the high correlation suggests the possibility of using weather data as supplemental information in estimating crop size." (Thompson 1969, p. 456)

Results of the encompassing tests showed that a number of the modified Thompson models contained information that was not incorporated in USDA forecasts. However, encompassing tests did not address how much the regression 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 (λ) in Table 19, 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 regression model and USDA forecasts. Results of this evaluation are presented in Table 20 and indicated a substantial reduction in RMSE in a number of cases. Composite corn forecasts for Illinois and Indiana on September 1 improved by more than one bushel per acre versus the USDA forecast. This was an improvement in forecast accuracy of approximately 20%. Despite smaller model weights, composite corn forecasts for these states on October 1 improved by over a half bushel, or approximately 15%. Soybean forecasts in Illinois improved by a more modest 6% to 9%. Forecasts for corn and soybeans in Iowa improved by less than 2%. The soybean forecasts in Indiana improved by 5% or less. Overall, RMSE reductions across the three states and months averaged 10% for corn and 6% for soybeans.

The question remains as to whether the RMSE reductions discussed above were “large” or “small” relative to economic decision-making. A formal model of decision-making model 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 study. 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 20 were generally much higher than 2.9%. For example, the RMSE reduction for corn yield forecasts in Indiana was 20.8%. Therefore, it is plausible that composite yield forecasts resulted 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.

Summary and Conclusions

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 2004 in Illinois (Changnon and Changnon 2005). Understanding the weather-technology-yield relationship has increased importance given expectations for a continued increase in global temperatures (National Climatic Data Center 2007).

The purpose of this study 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 found in studies by Thompson (1962 1963 1969 1970 1985

1986 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). Three key questions were addressed: 1) Has the relationship between temperature, precipitation, technology, and corn and soybean yields in the U.S. Corn Belt changed since the last comprehensive studies? 2) Has the trend rate of yield growth for corn accelerated since the mid-1990s? and 3) How does the accuracy of yield forecasts from the regression models compare to benchmark forecasts, such as those generated by the U.S. Department of Agriculture (USDA)?

Corn and soybean yields, monthly temperature, and monthly precipitation observations were collected over 1960 through 2006 for Illinois, Indiana, and Iowa. 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. Descriptive analysis of the data showed that precipitation during September through April (pre-season) over 1960 through 2006 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 during 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. Observations of monthly weather were a poor indicator of weather in other months, although 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.

Corn yields increased most rapidly in Iowa, while soybean yield increases were fairly similar. De-trending yields to 2006 technology showed that Iowa averaged the highest corn and soybean yields, followed by Illinois and Indiana. Annual yield variability was similar for each state. This indicated that unusually high or low yields deviated by a similar percentage from average yields.

The original crop-weather model developed by Thompson (1963) was modified because of a steady shift to earlier planting since 1960 and patterns in scatter plots of weather and yield observations. A linear functional form was used to represent technology, precipitation, and temperature relationships, with the exception of June, July, and August precipitation, which were represented by quadratic functional forms. Estimated 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 levels typically considered to be “serious” (Gujarati 2003).

Analysis of the regression results showed that yields were reduced by unfavorable weather by a much larger amount than they were increased by favorable weather. Corn yields were 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 appeared to be minimal. Soybean yields were 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 was also important, but less so than precipitation. Although the models fit yields fairly well, they performed poorly when outside influences such as insects, diseases, and unusual weather occurred.

Structural change tests were performed on each model in corn and soybeans to test for changes in regression model 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 did not clearly reveal 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 and a general conclusion could not be made.

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 regression model showed corn yields were 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 since the mid-1990s.

The regression models explained a most 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 models for predicting yields (Armstrong 2001). Therefore, a forecasting competition was developed to analyze out-of-sample forecasts from the modified Thompson models. 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, August1, September 1, and October 1 over 1980 through 2006. This allowed for a relatively large sample of out-of-sample forecasts.

Corn and soybean yield forecasts from the regression models on June 1 and July 1 were no more accurate then trend yield forecasts. Regression model forecasts for corn improved on August 1, while model forecasts for soybeans improved by September 1. These results were sensible because forecasts from the modified Thompson models should improve as weather observations during the important months of July and August are included. USDA corn and soybean forecasts were always more accurate than those from the regression models. Nonetheless, encompassing tests showed that the accuracy of USDA yield forecasts could be significantly improved by the information contained in regression model forecasts. Across states and forecast months, combining regression model forecasts with USDA forecasts improved accuracy an average of 10% for corn and 6% for soybeans. The economic value of these improvements in accuracy is difficult to assess, but research in a similar context (Colino and Irwin 2007) suggests the reductions are economically non-trivial.

In sum, this research provided strong evidence that precipitation, temperature, and a linear time trend to represent technological improvement explained all but a small portion of the variation in corn and soybean yields in the U.S. Corn Belt. An especially important finding was that relatively benign weather for the development of corn since the mid-1990s should not be discounted as an explanation for seemingly “high” yields. The potential impact of this finding on the agricultural sector is noteworthy. Trend yield forecasts based on perceptions of a rapid increase in technology may eventually lead to poor forecasts (Lobell and Asner 2003). Unfavorable weather in the future may lead to unexpectedly low corn yields that leave producers, market participants, and policy-makers wondering how such low yields could have occurred despite technological improvements.

Several interesting directions could be considered in future research on weather, technology, and crop yields. Changnon and Changnon (2005) noted that Illinois corn yields in 2004 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. In addition, Dixon et al. included the ratio of corn and soybean prices to reflect the quality of land planted to each crop. Perrin and Heady (1975) and Lynch, Holt, and Grey (2007) used Palmer drought indexes in place of temperature and precipitation variables. Schlenker and Roberts (2006) modeled temperature in terms of cumulative growing degree days and found a non-linear relationship between corn yields and temperature in the U.S., a result they argued was more consistent with biological crop simulation models. It would be interesting to test whether the previous variables would significantly improve the models estimated in this study. Furthermore, average planting dates could be considered in the models to address arguments about the importance of the planting timeliness on corn and soybean yield potential (e.g., Nafziger 2007).

Lastly, USDA crop conditions ratings for corn and soybeans are widely used by market analysts, but few academic studies have formally investigated the use of the ratings in modeling crop yields (Kruse and Smith 1994; Fackler and Norwood 1999). The ratings may be useful because they represent direct – though subjective – assessments of the overall health of a crop on a weekly basis throughout the growing season. In theory, the ratings should reflect the effects of all variables on the health of a crop, including planting date, temperature, precipitation, solar radiation, insect infestation, disease, etc. Crop conditions ratings could be considered as additional variables in the weather and technology regression models. Alternatively, forecasts from crop conditions models could be compared to trend, modified Thompson model, and official USDA yield forecasts.

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Table 1. Corn and Soybean Production in the U.S. Corn Belt, 2000-2006

	Production (bushels)				Percent of U.S. Production			
Crop/Year	**Illinois**	**Indiana**	**Iowa**	**U.S.**	**Illinois**	**Indiana**	**Iowa**	**3-State Total**
Corn								
2006	1,817,450	844,660	2,050,100	10,534,868	17.3	8.0	19.5	44.7
2005	1,708,850	888,580	2,162,500	11,112,072	15.4	8.0	19.5	42.8
2004	2,088,000	929,040	2,244,400	11,807,086	17.7	7.9	19.0	44.6
2003	1,812,200	786,940	1,868,300	10,089,222	18.0	7.8	18.5	44.3
2002	1,471,500	631,620	1,931,550	8,966,787	16.4	7.0	21.5	45.0
2001	1,649,200	884,520	1,664,400	9,502,580	17.4	9.3	17.5	44.2
2000	1,668,550	810,300	1,728,000	9,915,051	16.8	8.2	17.4	42.4
Soybeans								
2006	482,400	284,000	510,050	3,188,247	15.1	8.9	16.0	40.0
2005	444,150	263,620	532,650	3,086,432	14.4	8.5	17.3	40.2
2004	495,000	284,280	497,350	3,123,686	15.8	9.1	15.9	40.9
2003	379,620	204,060	342,875	2,453,665	15.5	8.3	14.0	37.8
2002	453,650	239,455	499,200	2,756,147	16.5	8.7	18.1	43.3
2001	477,900	273,910	480,480	2,890,682	16.5	9.5	16.6	42.6
2000	459,800	252,080	464,580	2,757,810	16.7	9.1	16.8	42.7

Source: NASS, *Quick Stats: Agricultural Statistics Data Base*

Table 2. Precipitation Statistics (inches) for Illinois, Indiana, and Iowa, 1960 - 2006

Period/State	Mean	Median	Maximum	Minimum	Range	Standard Deviation	Coefficient of Variation
Preseason							
Illinois	22.83	22.98	30.80	15.87	14.93	3.64	0.16
Indiana	24.57	24.73	33.39	18.52	14.87	3.33	0.14
Iowa	16.47	16.85	24.29	9.67	14.62	3.53	0.21
May							
Illinois	4.32	4.36	8.71	1.25	7.46	1.73	0.40
Indiana	4.47	4.09	7.75	1.52	6.23	1.67	0.37
Iowa	4.27	4.02	7.86	1.75	6.11	1.55	0.36
June							
Illinois	4.00	3.80	7.67	1.05	6.62	1.46	0.37
Indiana	4.07	4.13	7.72	0.74	6.98	1.29	0.32
Iowa	4.57	4.38	8.67	1.72	6.95	1.67	0.37
July							
Illinois	3.96	3.58	7.27	1.75	5.52	1.32	0.33
Indiana	4.34	4.23	8.65	1.29	7.36	1.50	0.35
Iowa	4.19	3.99	10.50	0.95	9.55	1.73	0.41
August							
Illinois	3.60	3.38	6.92	1.69	5.23	1.33	0.37
Indiana	3.72	3.50	6.69	1.67	5.02	1.20	0.32
Iowa	4.01	3.82	8.24	1.04	7.20	1.71	0.43

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

Period/State	Mean	Median	Maximum	Minimum	Range	Standard Deviation	Coefficient of Variation
May							
Illinois	62.3	61.2	69.5	57.3	12.2	3.4	0.06
Indiana	61.4	60.1	68.3	56.0	12.3	3.6	0.06
Iowa	60.6	60.4	67.8	54.6	13.2	3.3	0.05
June							
Illinois	71.5	71.5	76.1	66.8	9.3	2.0	0.03
Indiana	70.4	70.7	74.3	66.4	7.9	2.0	0.03
Iowa	70.0	70.0	75.0	65.2	9.8	2.2	0.03
July							
Illinois	75.3	75.2	79.0	72.0	7.0	1.9	0.02
Indiana	74.1	73.8	78.0	71.2	6.8	1.8	0.02
Iowa	74.1	74.0	77.7	68.7	9.0	2.2	0.03
August							
Illinois	73.2	73.3	78.7	68.5	10.2	2.4	0.03
Indiana	72.2	72.0	77.9	67.8	10.1	2.3	0.03
Iowa	71.7	71.8	78.8	66.2	12.6	2.5	0.03

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

State	Variable	Preseason Precip	May Precip	June Precip	July Precip	August Precip	May Temp	June Temp	July Temp	Aug Temp
Illinois	Preseason Precipitation	1.00	0.07	0.12	-0.19	-0.12	-0.10	0.13	0.07	0.03
	May Precipitation		1.00	0.31	-0.14	-0.04	-0.25	-0.09	-0.02	0.16
	June Precipitation			1.00	0.10	0.14	0.03	-0.31	-0.02	0.06
	July Precipitation				1.00	-0.09	0.00	-0.21	-0.37	-0.32
	August Precipitation					1.00	0.29	-0.19	0.12	0.01
	May Temperature						1.00	-0.09	0.09	0.01
	June Temperature							1.00	0.04	0.20
	July Temperature								1.00	0.39
	August Temperature									1.00
Indiana	Preseason Precipitation	1.00	0.11	-0.03	-0.29	0.05	-0.16	0.16	0.16	0.06
	May Precipitation		1.00	0.21	-0.07	0.07	-0.32	-0.07	-0.11	0.16
	June Precipitation			1.00	0.04	0.16	0.03	-0.19	-0.12	0.02
	July Precipitation				1.00	-0.01	-0.03	-0.19	-0.30	-0.20
	August Precipitation					1.00	0.17	-0.25	0.05	0.12
	May Temperature						1.00	-0.09	0.09	0.05
	June Temperature							1.00	0.09	0.19
	July Temperature								1.00	0.44
	August Temperature									1.00
Iowa	Preseason Precipitation	1.00	0.38	0.02	0.30	-0.07	-0.10	-0.12	-0.03	0.04
	May Precipitation		1.00	0.12	0.09	-0.02	-0.08	-0.29	-0.04	0.02
	June Precipitation			1.00	0.06	-0.10	-0.28	-0.25	-0.15	0.08
	July Precipitation				1.00	0.17	0.01	-0.22	-0.33	-0.23
	August Precipitation					1.00	0.43	0.01	0.28	-0.08
	May Temperature						1.00	-0.04	0.16	-0.09
	June Temperature							1.00	0.18	0.14
	July Temperature								1.00	0.26
	August Temperature									1.00

Table 5. Across-State Weather Variable Correlations, Illinois-Indiana, Illinois-Iowa, and Indiana-Iowa, 1960-2006

State Pair	Variable	Preseason Precip	May Precip	June Precip	July Precip	August Precip	May Temp	June Temp	July Temp	Aug Temp
Illinois-Indiana	Preseason Precipitation	0.76	0.00	-0.08	-0.25	-0.04	-0.11	0.20	0.13	0.10
	May Precipitation	0.10	0.87	0.16	-0.23	0.01	-0.15	0.02	-0.03	0.23
	June Precipitation	0.03	0.25	0.75	-0.14	0.09	0.07	-0.20	-0.02	0.07
	July Precipitation	-0.28	0.00	0.17	0.70	-0.06	-0.01	-0.27	-0.31	-0.37
	August Precipitation	-0.03	0.02	0.17	-0.17	0.72	0.32	-0.23	0.15	0.10
	May Temperature	-0.18	-0.40	0.01	0.01	0.14	0.99	-0.08	0.09	0.02
	June Temperature	0.11	-0.14	-0.26	-0.13	-0.23	-0.13	0.95	0.08	0.16
	July Temperature	0.08	-0.13	-0.10	-0.27	0.03	0.08	0.05	0.96	0.45
	August Temperature	-0.01	0.10	0.00	-0.13	0.04	0.03	0.21	0.36	0.97
Illinois-Iowa	Preseason Precipitation	0.71	0.19	0.13	0.09	-0.04	-0.13	-0.05	-0.05	0.03
	May Precipitation	0.07	0.59	0.18	-0.12	-0.09	-0.43	-0.10	0.00	0.18
	June Precipitation	0.07	0.28	0.57	0.18	0.23	0.00	-0.45	-0.01	0.09
	July Precipitation	0.07	-0.07	0.02	0.72	0.04	0.00	-0.26	-0.48	-0.24
	August Precipitation	-0.20	-0.07	-0.15	-0.04	0.70	0.27	-0.06	0.18	-0.13
	May Temperature	-0.02	0.21	-0.22	0.05	0.42	0.92	-0.12	0.13	-0.12
	June Temperature	0.03	-0.23	0.08	-0.17	-0.06	-0.04	0.85	0.04	0.13
	July Temperature	0.13	-0.02	-0.12	-0.06	0.32	0.10	0.17	0.88	0.23
	August Temperature	0.03	0.06	0.01	-0.21	0.14	0.01	0.22	0.36	0.90
Indiana-Iowa	Preseason Precipitation	0.35	0.13	0.12	-0.07	-0.02	-0.23	0.01	0.00	-0.02
	May Precipitation	-0.02	0.40	0.19	-0.07	-0.10	-0.57	-0.14	-0.11	0.13
	June Precipitation	0.06	0.24	0.35	0.09	0.29	-0.03	-0.37	-0.08	0.01
	July Precipitation	0.03	-0.11	-0.19	0.49	-0.07	0.03	-0.10	-0.38	-0.11
	August Precipitation	-0.12	-0.13	-0.06	-0.08	0.51	0.15	-0.13	0.09	-0.04
	May Temperature	-0.02	0.28	-0.19	0.03	0.41	0.88	-0.15	0.13	-0.08
	June Temperature	0.04	-0.12	0.16	-0.25	-0.13	-0.04	0.74	0.09	0.16
	July Temperature	0.11	-0.05	-0.11	0.01	0.34	0.10	0.19	0.79	0.20
	August Temperature	0.05	0.09	0.01	-0.26	0.23	0.01	0.19	0.43	0.83

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

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

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

	Illinois				Indiana				Iowa			
Crop/Independent Variable or Statistic	**Linear Model**		**Quadratic Model**		**Linear Model**		**Quadratic Model**		**Linear Model**		**Quadratic Model**	
Corn												
Constant	76.09	***	79.87	***	72.23	***	76.01	***	69.55	***	77.54	***
	(4.60)		(7.13)		(4.22)		(6.53)		(4.50)		(6.84)	
Annual Time Trend	1.68	***	1.22	*	1.65	***	1.18	*	1.90	***	0.93	
	(0.17)		(0.69)		(0.15)		(0.63)		(0.16)		(0.66)	
Annual Time Trend²			0.01				0.01				0.02	
			(0.01)				(0.01)				(0.01)	
R^2	0.69		0.70		0.72		0.72		0.75		0.76	
Standard Error (bu. / acre)	15.52		15.60		14.22		14.29		15.20		14.97	
Soybeans												
Constant	26.55	***	27.05	***	25.00	***	25.90	***	26.42	***	26.62	***
	(1.05)		(1.63)		(1.07)		(1.65)		(1.19)		(1.85)	
Annual Time Trend	0.41	***	0.35	**	0.47	***	0.36	**	0.46	***	0.43	**
	(0.04)		(0.16)		(0.04)		(0.16)		(0.04)		(0.18)	
Annual Time Trend²			0.00				0.00				0.00	
			(0.00)				(0.00)				(0.00)	
R^2	0.72		0.72		0.76		0.77		0.71		0.71	
Standard Error (bu. / acre)	3.54		3.58		3.59		3.61		4.01		4.06	

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

	Coefficient Estimates					
Independent Variable or Statistic	**Illinois**		**Indiana**		**Iowa**	
Constant	292.02	***	262.65	***	363.46	***
	(80.52)		(84.21)		(82.81)	
Annual Time Trend	1.92	***	1.76	***	2.04	***
	(0.09)		(0.10)		(0.09)	
Preseason Precipitation	0.38		0.29		1.02	**
	(0.35)		(0.39)		(0.45)	
May Precipitation	-1.45	*	-2.43	***	-2.89	***
	(0.78)		(0.87)		(1.05)	
June Precipitation	14.04	***	16.82	***	8.93	*
	(4.89)		(4.25)		(5.02)	
June Precipitation^2	-1.50	***	-1.81	***	-0.82	*
	(0.52)		(0.50)		(0.48)	
July Precipitation	17.65	**	13.62	***	19.95	***
	(6.57)		(3.80)		(3.12)	
July Precipitation^2	-1.50	*	-1.06	***	-2.00	***
	(0.75)		(0.38)		(0.31)	
August Precipitation	2.88		15.85	**	4.37	
	(5.69)		(6.41)		(3.30)	
August Precipitation^2	-0.28		-1.78	**	-0.34	
	(0.71)		(0.79)		(0.35)	
May Temperature	0.28		0.19		-0.30	
	(0.38)		(0.36)		(0.48)	
June Temperature	0.19		-0.17		-0.68	
	(0.69)		(0.72)		(0.66)	
July Temperature	-1.65	**	-1.99	**	-2.23	***
	(0.79)		(0.78)		(0.74)	
August Temperature	-2.86	***	-2.02	***	-2.04	***
	(0.58)		(0.61)		(0.58)	
R^2	0.95		0.94		0.94	
Standard Error (bu. / acre)	7.57		7.62		8.75	
Regression F-statistic	44.64	***	40.54	***	39.42	***
LM test	10.51		18.18		6.28	
BPG test	11.02		13.02		11.81	
Ramsey RESET test	1.55		0.03		0.86	

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 test 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

Table 9. Modified Thompson Model Regression Estimates for Soybean Yields in Illinois, Indiana, and Iowa, 1960 - 2006

	Coefficient Estimates					
Independent Variable or Statistic	**Illinois**		**Indiana**		**Iowa**	
Constant	34.88		29.58		25.76	
	(25.42)		(27.87)		(27.83)	
Annual Time Trend	0.44	***	0.48	***	0.49	***
	(0.03)		(0.03)		(0.03)	
Preseason Precipitation	0.12		0.18		0.29	*
	(0.11)		(0.13)		(0.15)	
May Precipitation	-0.44	*	-0.71	**	-0.93	**
	(0.25)		(0.29)		(0.35)	
June Precipitation	2.21		5.13	***	2.56	
	(1.54)		(1.41)		(1.69)	
June Precipitaiton^2	-0.21		-0.52	***	-0.21	
	(0.17)		(0.16)		(0.16)	
July Precipitaiton	2.57		3.52	***	3.45	***
	(2.07)		(1.26)		(1.05)	
July Precipitation^2	-0.18		-0.33	**	-0.35	***
	(0.24)		(0.12)		(0.10)	
August Precipitation	3.16		3.95	*	4.42	***
	(1.80)		(2.12)		(1.10)	
August Precipitation^2	-0.29		-0.38		-0.37	***
	(0.23)		(0.26)		(0.12)	
May Temperature	0.07		0.08		-0.05	
	(0.12)		(0.12)		(0.16)	
June Temperature	0.34		0.03		0.38	
	(0.22)		(0.24)		(0.22)	
July Temperature	-0.20		-0.33		-0.34	
	(0.25)		(0.26)		(0.25)	
August Temperature	-0.58	***	-0.24		-0.34	*
	(0.18)		(0.20)		(0.19)	
R^2	0.91		0.91		0.89	
Standard Error (bu. / acre)	2.39		2.52		2.94	
Regression F-statistic	24.92	***	27.23	***	19.85	***
LM test	10.40		34.511		11.65	
BPG test	9.87		12.98		13.45	
Ramsey RESET test	0.72		1.00		0.57	

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 test 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. Average Values of Corn and Soybean Weather Indexes for Three Sub-Periods over 1960-2006

	Corn			Soybeans		
State	**1960-1972**	**1973-1995**	**1996-2006**	**1960-1972**	**1973-1995**	**1996-2006**
Illinois	99.2	93.7	94.2	97.9	96.6	96.0
Indiana	96.0	91.7	94.2	93.7	94.4	95.2
Iowa	95.5	90.1	95.2	94.1	92.7	93.7

Table 11. Modified Thompson Model Regression Estimates with Dummy Variables at Selected Breakpoints for Illinois Corn Yields, Iowa Corn Yields, and Iowa Soybean Yields, 1960-2006

	Coefficient Estimates					
Independent Variable Coefficients	**Illinois Corn (1988 Breakpoint)**		**Iowa Corn (1983 Breakpoint)**		**Iowa Soybeans (1988 Breakpoint)**	
Constant	312.20	***	215.93	**	18.75	
	(96.57)		(87.61)		(21.61)	
Annual Time Trend	1.82	***	2.39	***	0.49	***
	(0.20)		(0.29)		(0.05)	
Preseason Precipitation	0.79	*	0.23		-0.07	
	(0.44)		(0.71)		(0.15)	
May Precipitation	-2.82		-1.28		-0.64	
	(1.29)		(2.05)		(0.38)	
June Precipitation	5.07		8.72		1.34	
	(9.43)		(7.57)		(1.56)	
June Precipitaiton²	-0.67		-0.63		-0.14	
	(1.11)		(0.70)		(0.15)	
July Precipitaiton	8.56		11.45		-1.01	
	(9.32)		(7.40)		(1.65)	
July Precipitation²	-0.41		-0.95		0.25	
	(1.07)		(0.97)		(0.21)	
August Precipitation	1.97		2.81		1.67	
	(5.69)		(4.91)		(1.03)	
August Precipitation²	-0.02		-0.31		-0.12	
	(0.70)		(0.53)		(0.11)	
May Temperature	-0.22		-0.34		-0.11	
	(0.44)		(0.66)		(0.14)	
June Temperature	0.19		-0.10		0.32	*
	(0.78)		(0.96)		(0.18)	
July Temperature	-1.34		-2.56	***	-0.08	
	(0.95)		(0.81)		(0.20)	
August Temperature	-2.54	***	0.13		-0.08	
	(0.65)		(0.95)		(0.17)	
Annual Time Trend (Dummy)	0.93	**	0.34		0.31	**
	(0.38)		(0.38)		(0.13)	
Preseason Precipitation (Dummy)	0.65		1.53		0.71	**
	(1.18)		(0.38)		(0.27)	
May Precipitation (Dummy)	2.50		-1.48		-1.11	**
	(1.64)		(2.41)		(0.52)	
June Precipitation (Dummy)	10.26		-0.72		6.93	**
	(10.91)		(11.34)		(2.76)	
June Precipitaiton² (Dummy)	-1.08		-0.19		-0.59	**
	(1.25)		(1.10)		(0.28)	
July Precipitaiton (Dummy)	0.17		14.51		0.30	
	(14.44)		(8.61)		(2.62)	
July Precipitation² (Dummy)	0.12		-1.50		-0.14	
	(1.67)		(1.05)		(2.60)	
August Precipitation (Dummy)	55.53	***	-0.05		13.36	***
	(19.58)		(6.69)		(2.60)	
August Precipitation² (Dummy)	-8.14	***	0.10		-1.51	***
	(2.71)		(0.69)		(0.30)	
May Temperature (Dummy)	1.73	**	0.50		-0.16	
	(0.76)		(0.83)		(0.20)	
June Temperature (Dummy)	-1.16		0.23		-0.25	
	(1.35)		(1.14)		(0.29)	
July Temperature (Dummy)	-2.19		0.44		-0.77	*
	(1.42)		(1.43)		(0.38)	
August Temperature (Dummy)	-0.43		-2.06		0.31	
	(1.16)		(1.25)		(0.32)	
R^2	0.98		0.98		0.97	
Standard Error (bu. / acre)	6.11		6.94		1.78	

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

Table 12. Modified Thompson Model Regression Estimates with July and August Temperature Dummy Variables at 1983 for Iowa Corn Yields, 1960-2006

Independent Variable or Statistic	Coefficient Estimates	
Constant	278.29	***
	(68.17)	
Annual Time Trend	2.55	***
	(0.17)	
Preseason Precipitation	0.87	**
	(0.39)	
May Precipitation	-2.19	**
	(0.85)	
June Precipitation	4.00	
	(4.10)	
June Precipitaiton²	-0.28	
	(0.39)	
July Precipitaiton	17.83	***
	(2.50)	
July Precipitation²	-1.80	***
	(0.25)	
August Precipitation	2.35	
	(2.71)	
August Precipitation²	-0.26	
	(0.28)	
May Temperature	-0.11	
	(0.38)	
June Temperature	-0.41	
	(0.55)	
July Temperature	-2.98	***
	(0.65)	
August Temperature	2.64	
	(0.86)	
July Temperature (Dummy)	-0.26	***
	(0.69)	
August Temperature (Dummy)	-2.96	***
	(0.89)	
R^2	0.96	
Standard Error (bu. / acre)	6.89	

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

Table 13. Modified Thompson Model Regression Estimates with Annual Time Trend Dummy Variable at 1983 for Iowa Corn Yields, 1960-2006

Independent Variable or Statistic	Coefficient Estimates	
Constant	342.62	***
	(79.68)	
Annual Time Trend	2.58	***
	(0.28)	
Preseason Precipitation	1.09	**
	(0.43)	
May Precipitation	-2.69	**
	(1.00)	
June Precipitation	6.79	
	(4.90)	
June Precipitaiton²	-0.60	
	(0.47)	
July Precipitaiton	19.55	***
	(2.98)	
July Precipitation²	-1.96	***
	(0.30)	
August Precipitation	5.02	
	(3.16)	
August Precipitation²	-0.47	
	(0.34)	
May Temperature	-0.23	
	(0.46)	
June Temperature	-0.44	
	(0.64)	
July Temperature	-2.25	***
	(0.71)	
August Temperature	-2.01	***
	(0.55)	
Annual Time Trend (Dummy)	-0.42	**
	(0.21)	
R^2	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 14. Modified Thompson Model Regression Estimates with Annual Time Trend Dummy Variable at 1996 for Corn Yields in Indiana, Illinois, and Iowa, 1960-2006

	Coefficient Estimates					
Independent Variable or Statistic	**Illinois**		**Indiana**		**Iowa**	
Constant	284.29	***	269.43	***	346.88	***
	(81.55)		(87.22)		(83.34)	
Annual Time Trend	1.83	***	1.80	***	1.90	***
	(0.14)		(0.15)		(0.15)	
Preseason Precipitation	0.46		0.27		1.10	**
	(0.37)		(0.40)		(0.45)	
May Precipitation	-1.44	*	-2.43	***	-3.10	***
	(0.78)		(0.88)		(1.05)	
June Precipitation	13.72	***	16.89	***	8.66	*
	(4.93)		(4.31)		(4.99)	
June Precipitaiton^2	-1.47	***	-1.81	***	-0.80	
	(0.53)		(0.49)		(0.47)	
July Precipitaiton	16.71	**	13.72	***	19.26	***
	(6.71)		(3.87)		(3.15)	
July Precipitation^2	-1.37	*	-1.08	***	-1.92	***
	(0.77)		(0.38)		(0.32)	
August Precipitation	2.54		15.63	**	4.48	
	(5.74)		(6.52)		(3.27)	
August Precipitation^2	-0.22		-1.77	**	-0.35	
	(0.72)		(0.80)		(0.35)	
May Temperature	0.28		0.19		-0.25	
	(0.38)		(0.36)		(0.48)	
June Temperature	0.25		-0.21		-0.51	
	(0.70)		(0.74)		(0.67)	
July Temperature	-1.63	**	-2.06	**	-2.23	***
	(0.80)		(0.81)		(0.74)	
August Temperature	-2.82	***	-2.01	***	-1.97	***
	(0.60)		(0.62)		(0.57)	
Annual Time Trend Dummy	0.09		-0.04		0.15	
	(0.11)		(0.10)		(0.12)	
R^2	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 15. Time Trend Coefficients for Relative Squared Errors (d_t) between Modified Thompson Model and USDA Forecasts of Corn and Soybean Yields in Illinois, Indiana, and Iowa, 1980 - 2006

Crop/State	August 1		September 1	October 1
Corn				
Illinois	16.8		22.2	20.2
	(14.3)		(17.1)	(17.4)
Indiana	19.9		40.5	39.7
	(15.5)		(24.0)	(23.9)
Iowa	9.2		22.6	18.7
	(7.2)		(30.2)	(31.7)
Soybeans				
Illinois	1.6	*	1.3	0.8
	(0.9)		(1.0)	(1.1)
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 16. Out-of-Sample Forecast Accuracy Statistics for Corn Yield Forecasts in Illinois, Indiana, and Iowa, 1980-2006

	June 1			July 1			August 1		September 1		October 1	
State/ Accuracy Measure	Regression Model	Trend Model	USDA	Regression Model	Trend Model	USDA	Regression Model	USDA	Regression Model	USDA	Regression Model	USDA
Illinois												
RMSE	20.3	19.5	NA	20.6	19.5	NA	15.3	10.8	12.8	7.9	12.8	4.7
RMSPE	22.5	20.9	NA	21.6	20.9	NA	16.2	9.3	12.6	5.7	12.6	3.3
MAE	15.3	14.5	NA	16.1	14.5	NA	11.7	8.4	9.6	6.2	9.6	3.5
MAPE	14.0	12.9	NA	14.2	12.9	NA	10.3	6.8	8.4	4.5	8.4	2.6
Indiana												
RMSE	19.5	17.8	NA	19.6	17.8	NA	14.9	9.8	12.5	6.7	12.5	4.7
RMSPE	21.4	18.3	NA	21.3	18.3	NA	16.1	9.0	12.8	5.2	12.8	3.8
MAE	13.4	14.5	NA	13.8	14.5	NA	9.5	8.0	8.5	5.1	8.5	3.6
MAPE	12.9	12.9	NA	13.1	12.9	NA	9.0	6.8	7.7	3.9	7.7	2.8
Iowa												
RMSE	19.8	18.5	NA	19.4	18.5	NA	16.7	11.8	17.1	9.7	17.1	6.1
RMSPE	22.1	18.9	NA	21.2	18.9	NA	17.4	11.8	18.0	9.3	18.0	6.6
MAE	12.5	13.6	NA	13.5	13.6	NA	12.5	8.4	12.5	5.1	12.5	3.7
MAPE	11.9	11.7	NA	12.5	11.7	NA	11.1	7.2	11.1	3.9	11.1	3.2

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 17. Modified Diebold-Mariano Test Results for Corn and Soybean Yield Forecasts in Illinois, Indiana, and Iowa, 1980-2006

	Regression Model vs. Trend Yield Forecasts		Regression Model vs. USDA Forecasts					
Crop/State	**June 1**	**July 1**	**August 1**		**September 1**		**October 1**	
Corn								
Illinois	-1.61	-1.50	-2.51	**	-3.61	***	-3.89	***
Indiana	-1.13	-0.73	-2.79	***	-3.11	***	-3.26	***
Iowa	-1.50	-1.60	-2.52	**	-2.58	**	-2.71	***
Soybeans								
Illinois	0.13	0.90	-1.80		-2.77	**	-3.63	***
Indiana	-0.65	0.66	-2.54	**	-2.89	***	-3.63	***
Iowa	0.08	-0.07	-0.83		-1.76		-2.51	**

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

Table 18. Out-of-Sample Forecast Accuracy Statistics for Soybean Yield Forecasts in Illinois, Indiana, and Iowa, 1980-2006

	June 1			July 1			August 1		September 1		October 1	
State/ Accuracy Measure	Regression Model	Trend Model	USDA	Regression Model	Trend Model	USDA	Regression Model	USDA	Regression Model	USDA	Regression Model	USDA
Illinois												
RMSE	4.1	4.2	NA	3.9	4.2	NA	3.7	3.3	3.4	2.9	3.4	1.3
RMSPE	13.1	12.7	NA	11.5	12.7	NA	9.8	8.0	9.3	6.7	9.3	3.2
MAE	2.9	3.2	NA	3.1	3.2	NA	2.7	2.6	2.6	2.3	2.6	1.1
MAPE	8.2	8.6	NA	8.4	8.6	NA	7.0	6.5	6.9	5.5	6.9	2.7
Indiana												
RMSE	4.5	4.4	NA	4.1	4.4	NA	4.5	3.1	4.3	2.9	4.3	1.4
RMSPE	13.0	12.1	NA	11.2	12.1	NA	11.9	7.5	11.6	7.1	11.6	3.8
MAE	3.8	3.6	NA	3.5	3.6	NA	3.5	2.6	3.3	2.4	3.3	1.1
MAPE	10.0	9.3	NA	9.0	9.3	NA	9.1	6.4	8.8	6.0	8.8	2.9
Iowa												
RMSE	5.1	5.1	NA	5.2	5.1	NA	5.9	4.6	5.8	3.7	5.8	1.9
RMSPE	15.2	14.5	NA	15.1	14.5	NA	17.8	11.8	17.7	8.8	17.7	4.9
MAE	3.5	3.7	NA	3.7	3.7	NA	3.8	3.5	3.8	2.4	3.8	1.6
MAPE	9.4	9.8	NA	9.8	9.8	NA	10.4	8.6	10.5	6.0	10.5	4.1

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 19. Encompassing Test Results for Modified Thompson Model and USDA Forecasts of Corn and Soybean Yields in Illinois, Indiana, and Iowa, 1980-2006

State/	Corn		Soybeans	
Forecast Month	Weight	p-value	Weight	p-value
Illinois				
August	0.23	0.12	0.35	0.10
	(0.14)		(0.20)	
September	0.28	0.00	0.33	0.04
	(0.09)		(0.15)	
October	0.16	0.01	0.13	0.07
	(0.06)		(0.06)	
Indiana				
August	0.28	0.02	0.20	0.17
	(0.11)		(0.14)	
September	0.24	0.00	0.19	0.16
	(0.07)		(0.13)	
October	0.16	0.01	-0.02	0.77
	(0.06)		(0.07)	
Iowa				
August	0.08	0.68	0.16	0.46
	(0.19)		(0.22)	
September	0.08	0.53	0.15	0.27
	(0.13)		(0.14)	
October	-0.04	0.59	-0.02	0.75
	(0.08)		(0.07)	

Note: The figures in parentheses are standard errors.

Table 20. Reduction in RMSE Associated with Optimal Composite Forecasts for Corn and Soybean Yields in Illinois, Indiana, and Iowa, 1980-2006

Crop/State/	RMSE			
Forecast Month	Regression Model	USDA	Composite	RMSE Reduction
		--- bushels per acre ---		
Corn				
Illinois				
August	15.3	10.8	10.3	5.0%
September	12.8	7.9	6.7	18.7%
October	12.8	4.7	4.1	15.1%
Indiana				
August	14.9	9.8	8.7	12.9%
September	12.5	6.7	5.6	20.8%
October	12.5	4.7	4.1	14.2%
Iowa				
August	16.7	11.8	11.8	0.3%
September	17.1	9.7	9.6	1.4%
October	17.1	6.1	6.1	0.7%
Soybeans				
Illinois				
August	3.7	3.3	3.1	6.8%
September	3.4	2.9	2.6	9.0%
October	3.4	1.3	1.2	6.3%
Indiana				
August	4.5	3.1	3.0	5.2%
September	4.3	2.9	2.8	4.9%
October	4.3	1.4	1.4	0.3%
Iowa				
August	5.9	4.6	4.6	0.2%
September	5.8	3.7	3.7	0.2%
October	5.8	1.9	1.9	0.7%

Note: RMSE denotes Root Mean Squared Error.

Figure 1. United States Corn Yields, 1960-2006

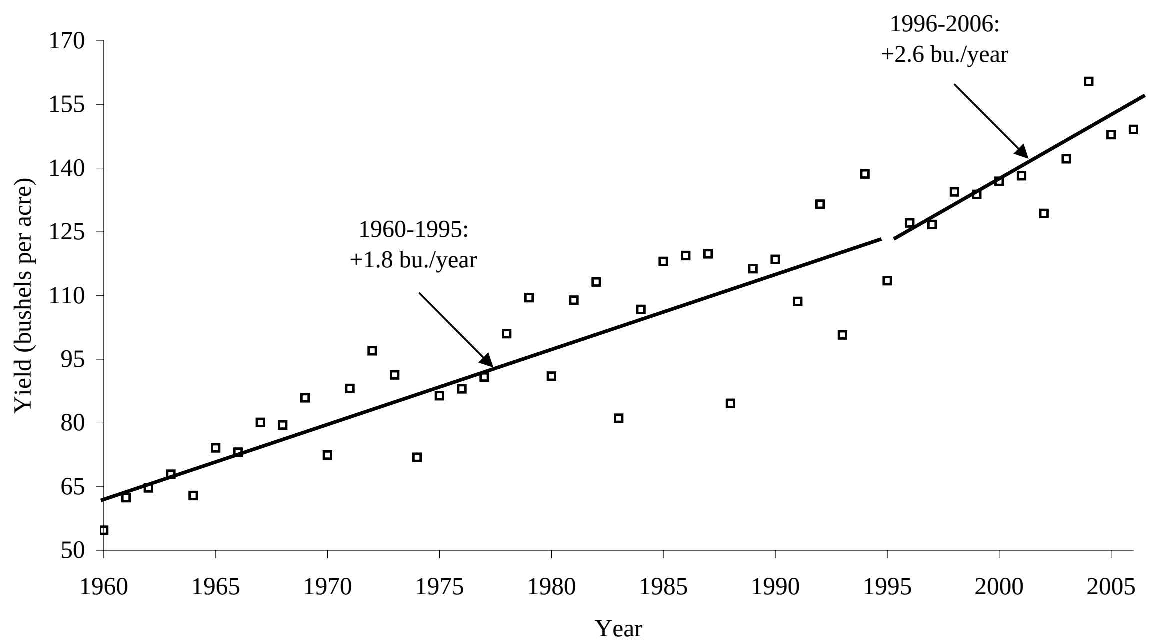
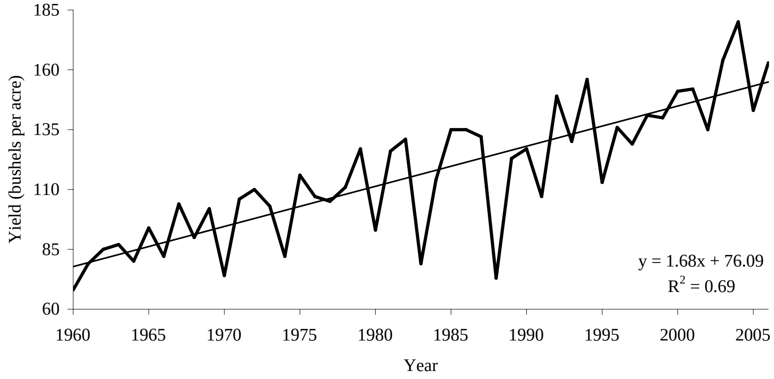
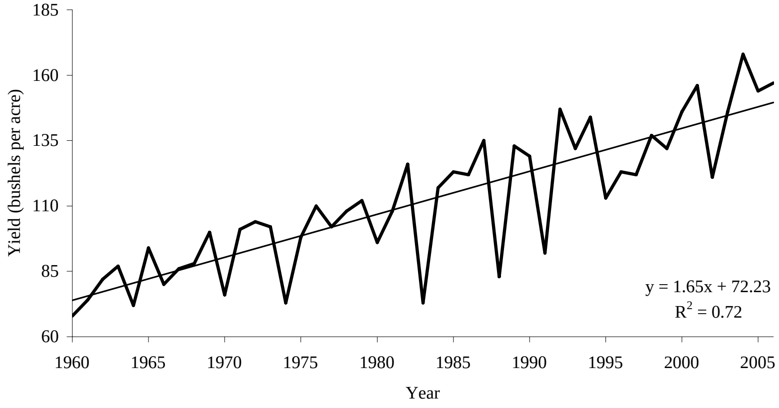


Figure 2. Corn Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

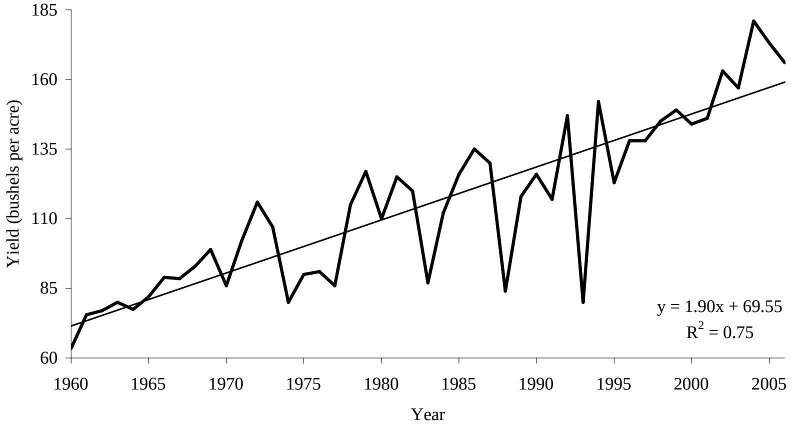


Figure 3. Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006

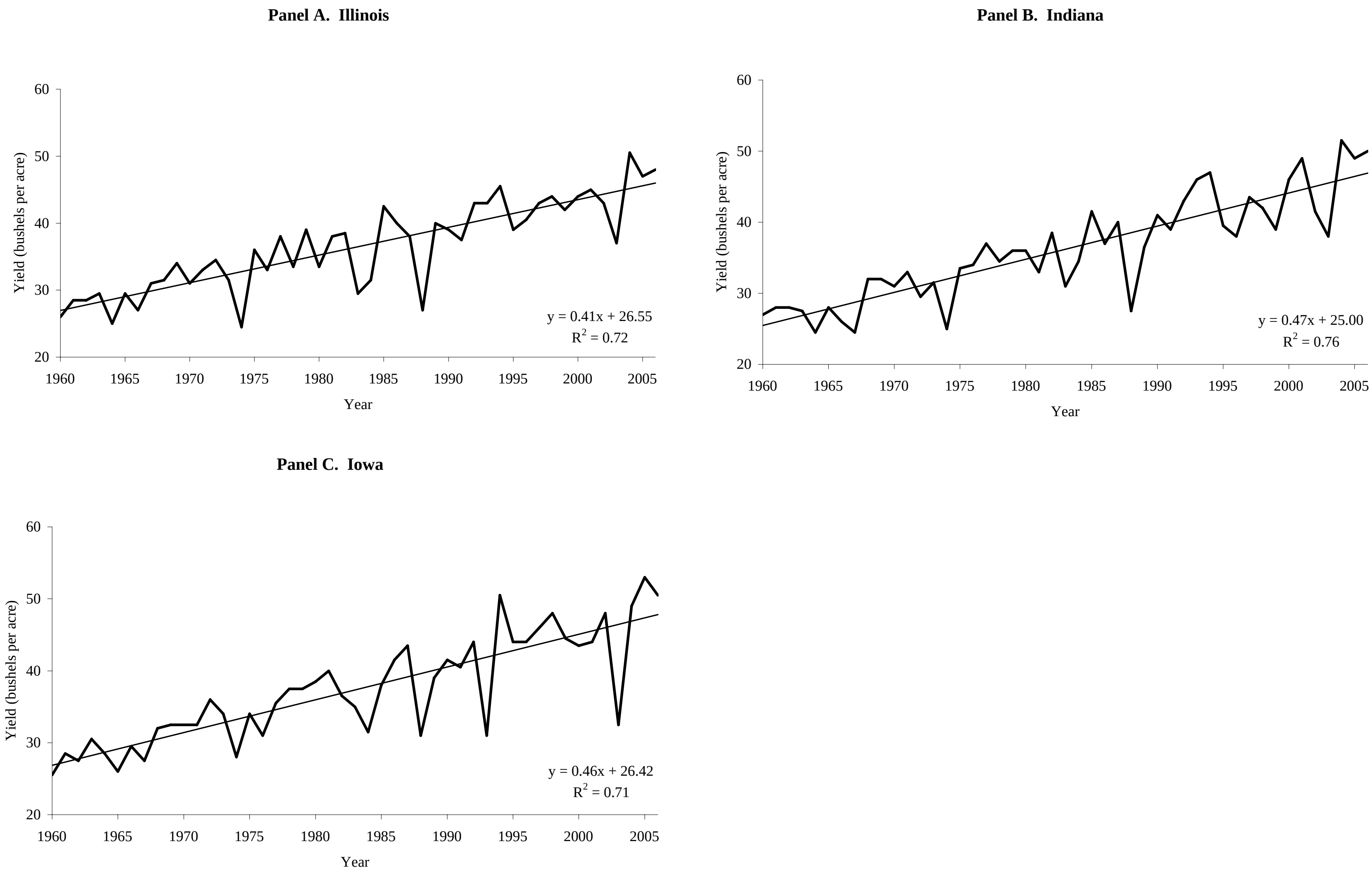


Figure 4. Pre-Season Precipitation in Illinois, Indiana, and Iowa (September-April), 1960-2006

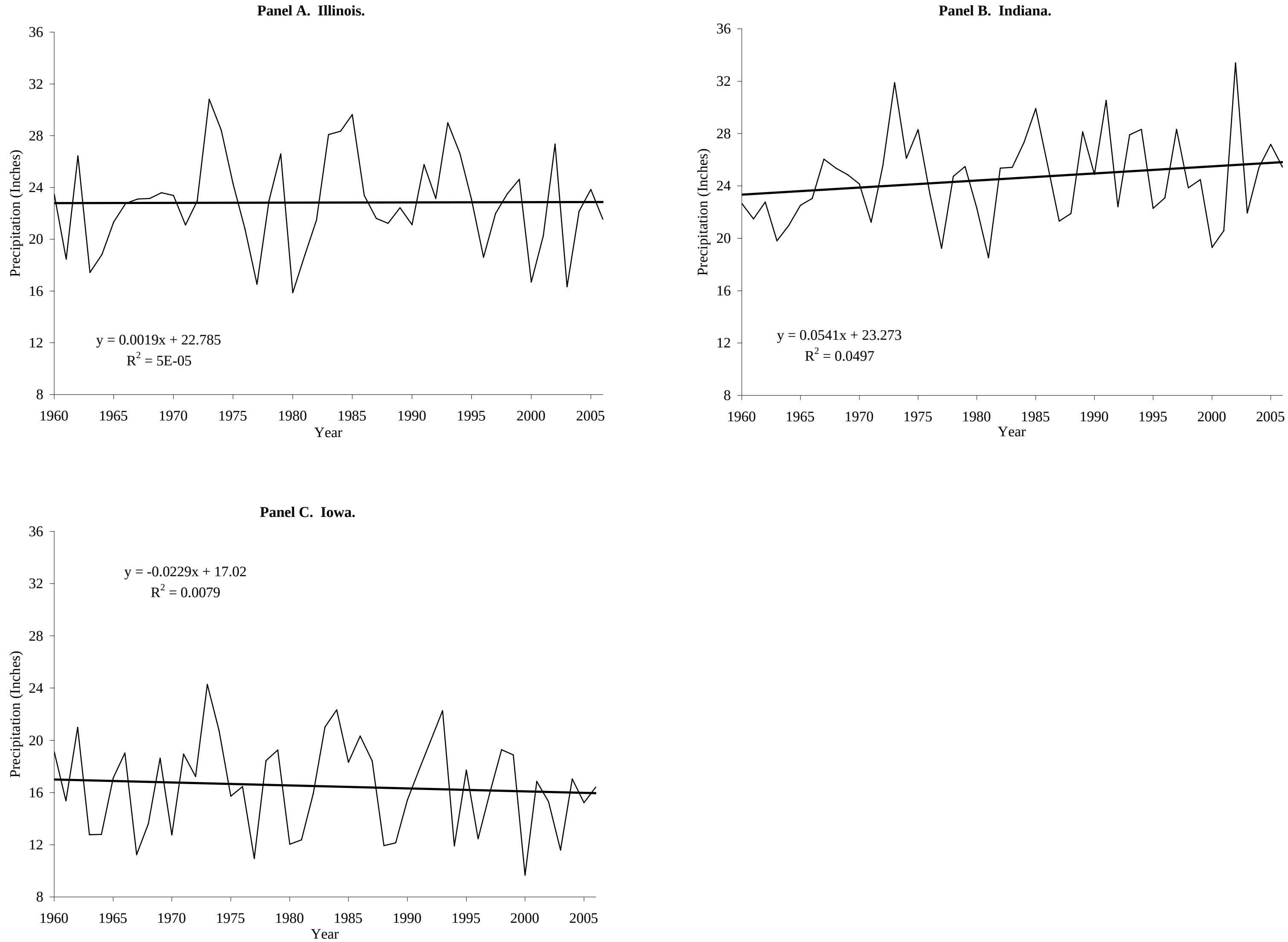
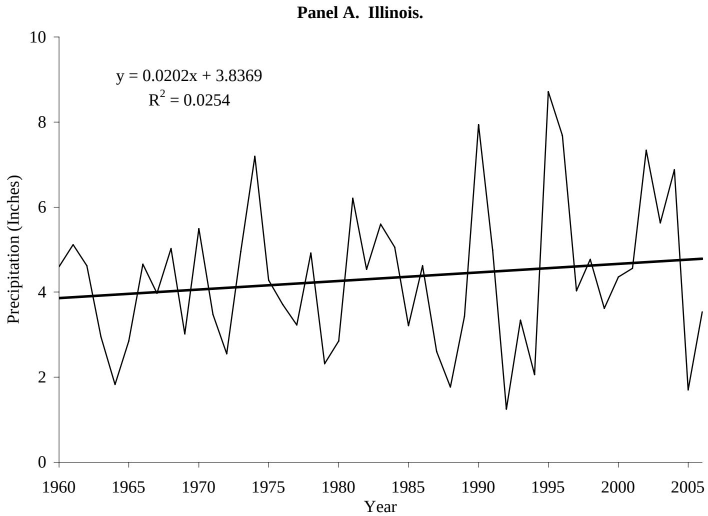
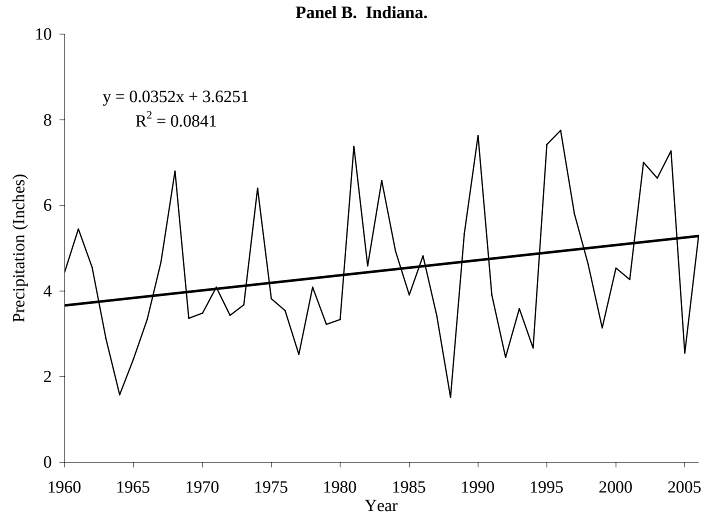


Figure 5. May Precipitation in Illinois, Indiana, and Iowa, 1960-2006





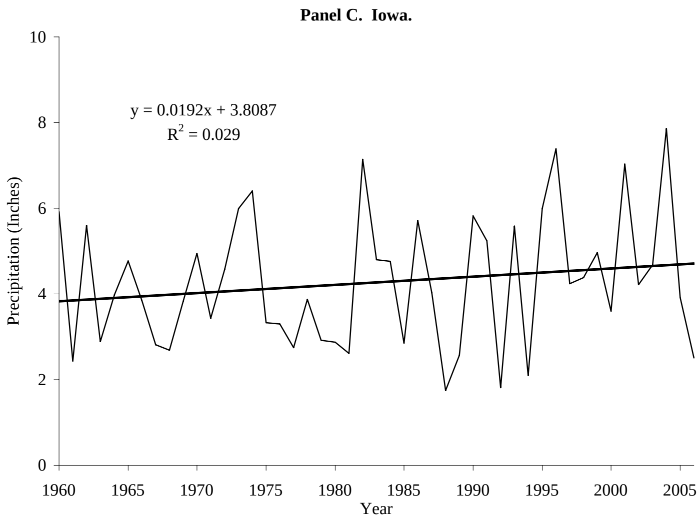


Figure 6. June Precipitation in Illinois, Indiana, and Iowa, 1960-2006

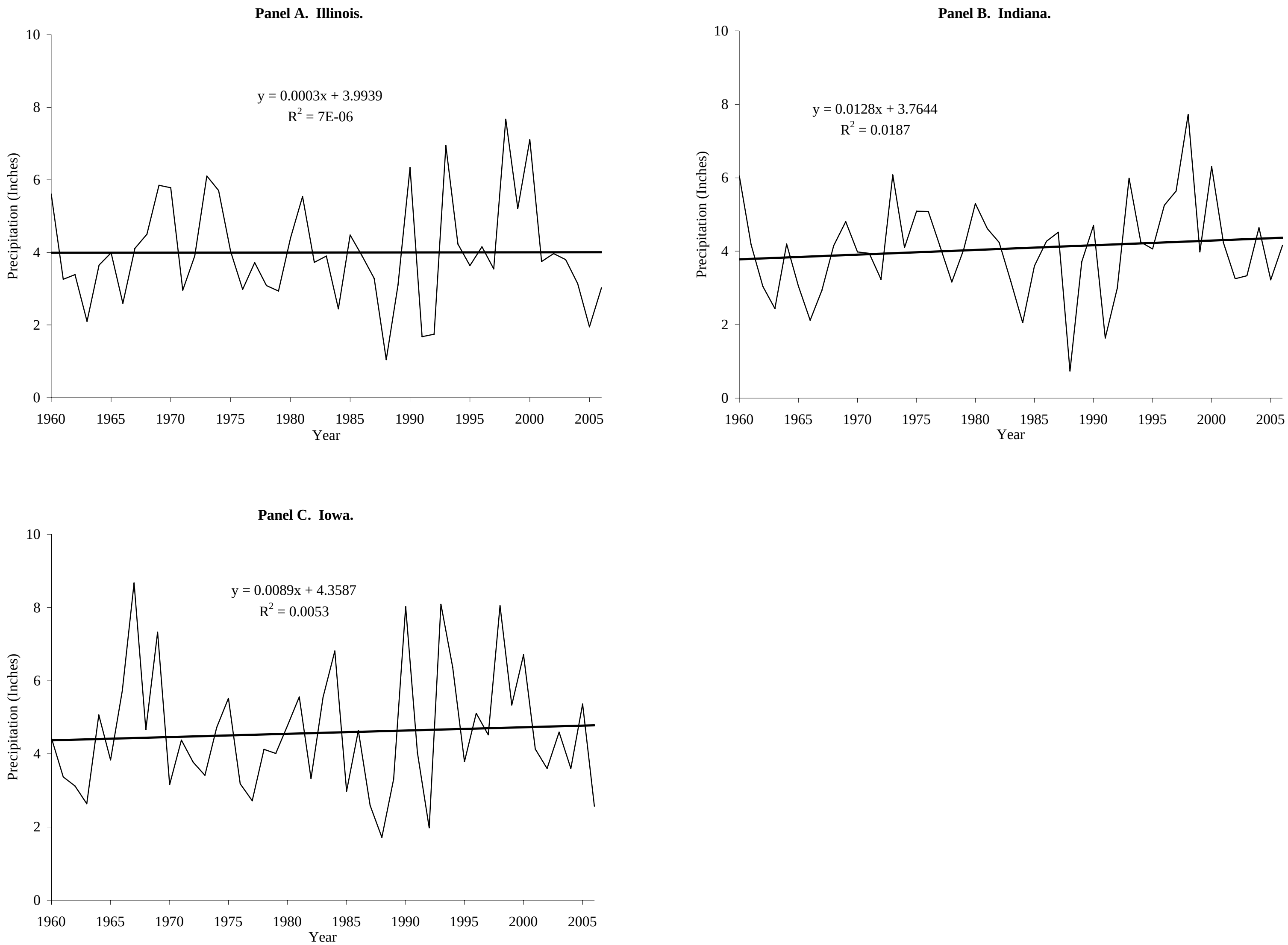
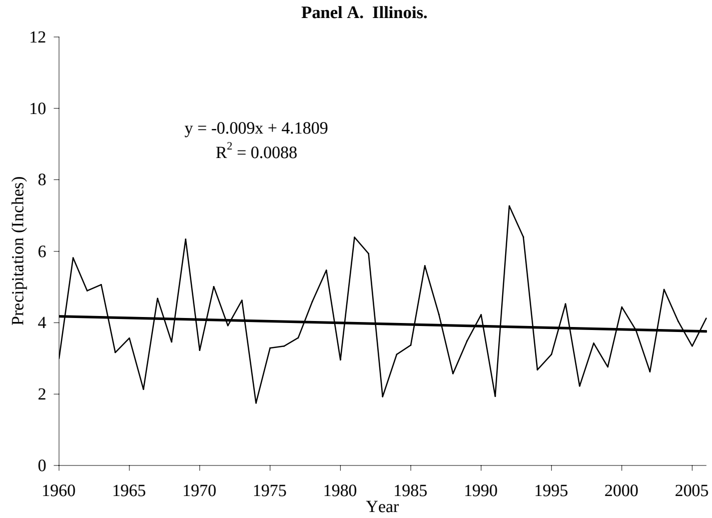
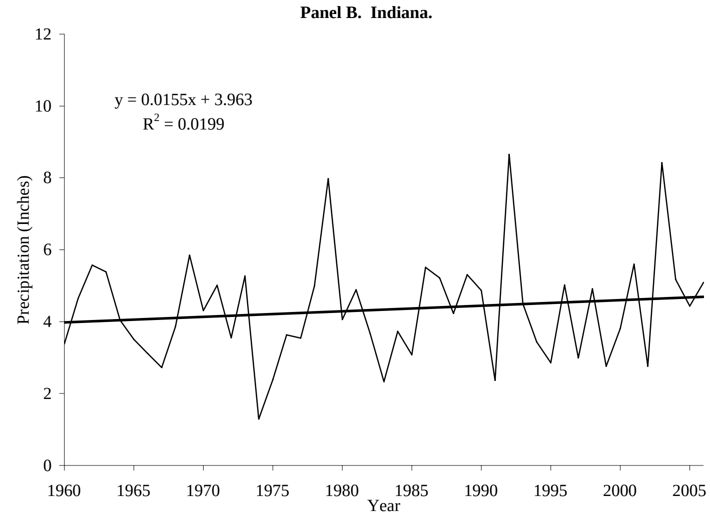


Figure 7. July Precipitation in Illinois, Indiana, and Iowa, 1960-2006





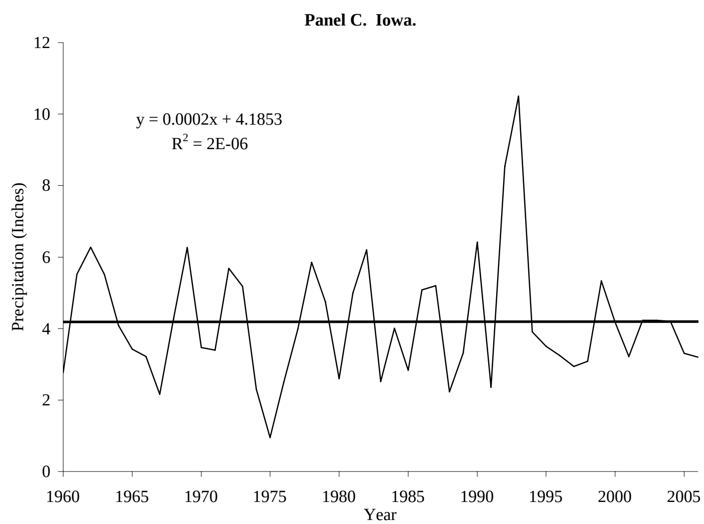


Figure 8. August Precipitation in Illinois, Indiana, and Iowa, 1960-2006

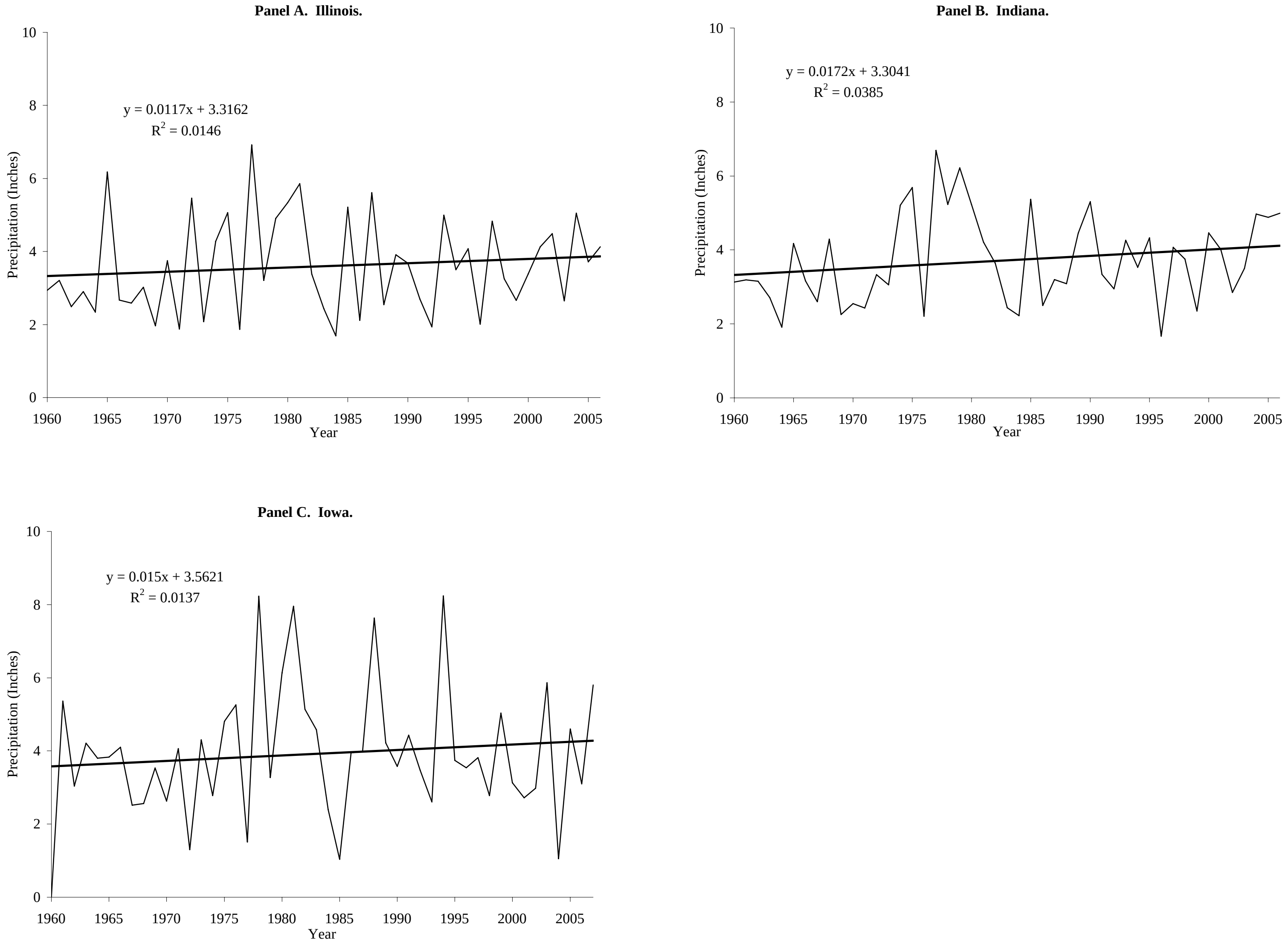
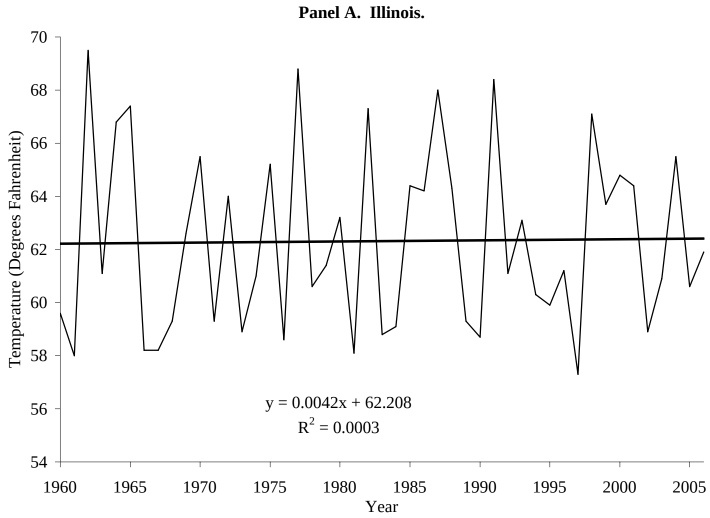
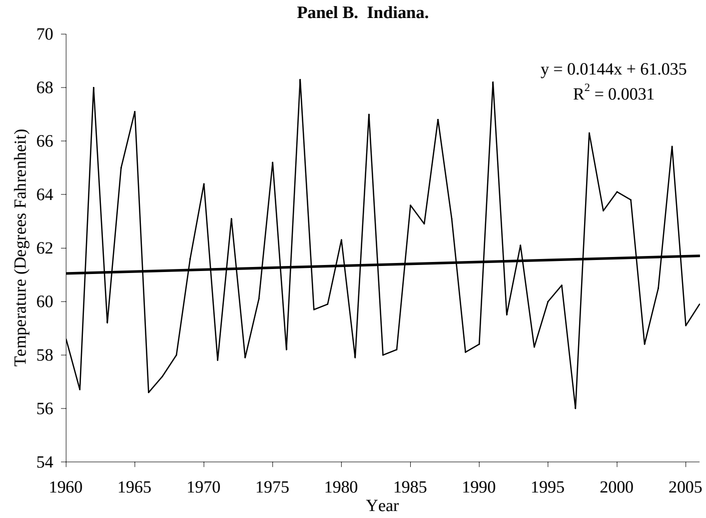


Figure 9. May Temperature in Illinois, Indiana, and Iowa, 1960-2006





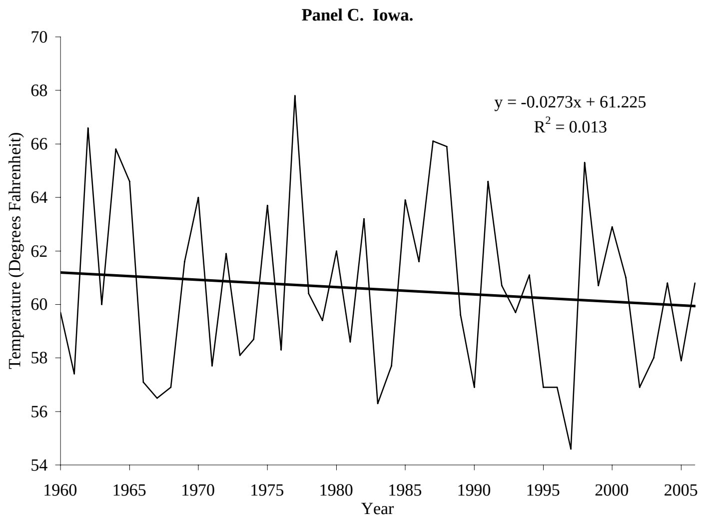
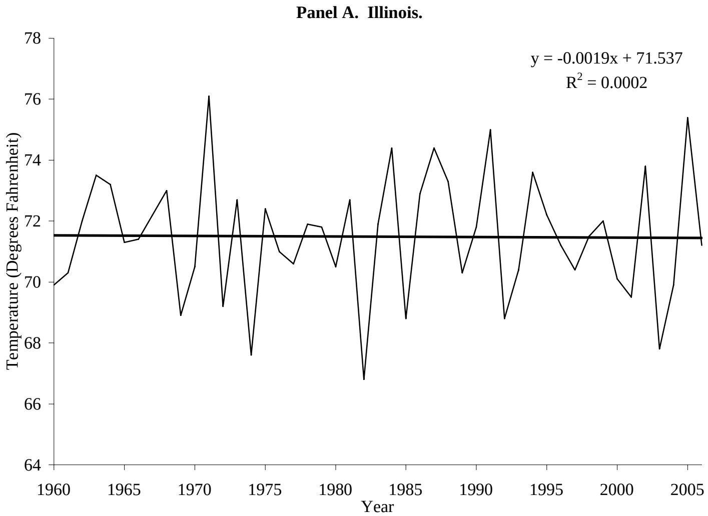
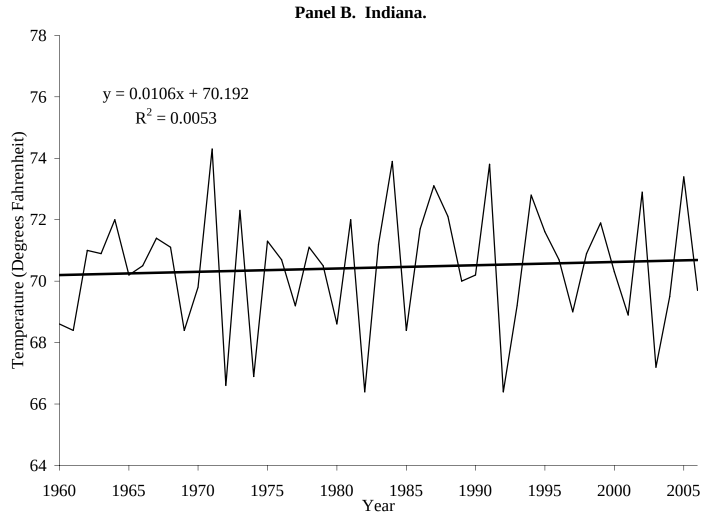


Figure 10. June Temperature in Illinois, Indiana, and Iowa, 1960-2006





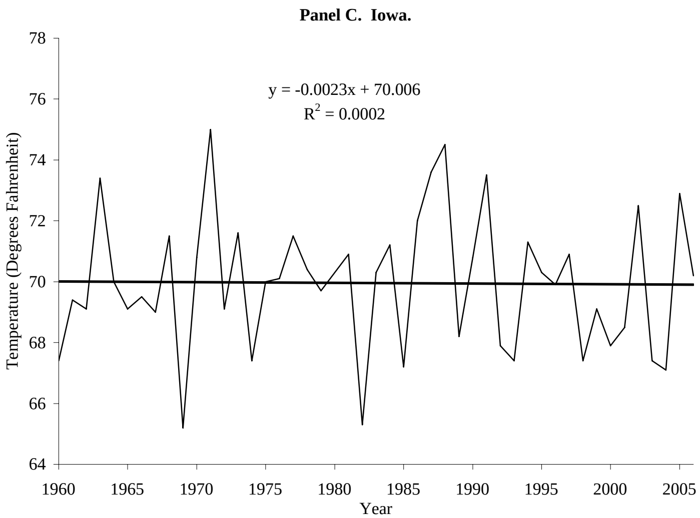


Figure 11. July Temperature in Illinois, Indiana, and Iowa, 1960-2006

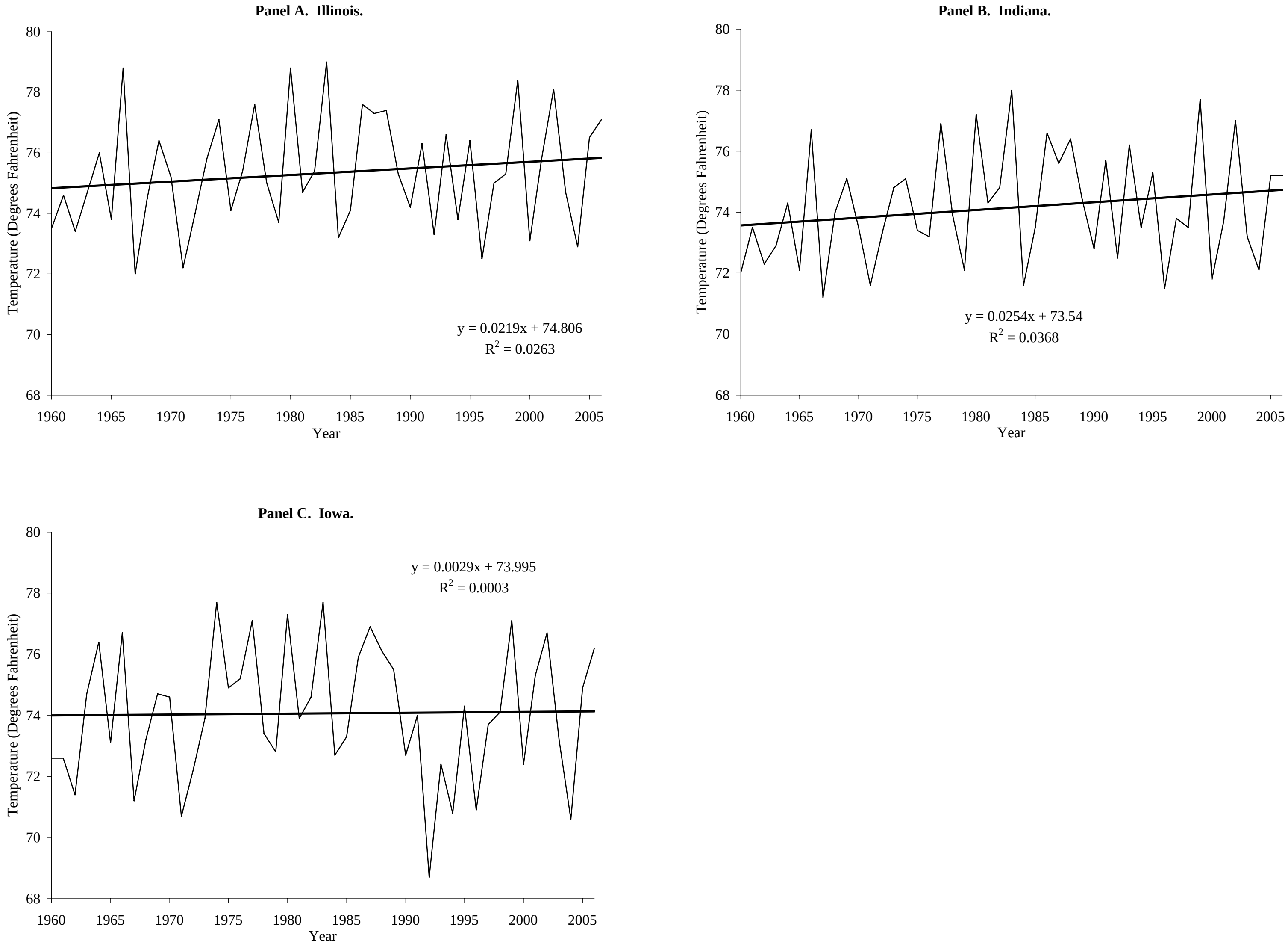
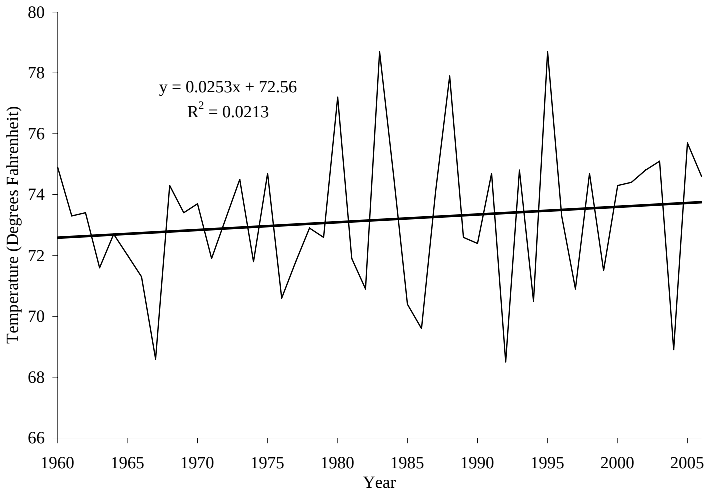
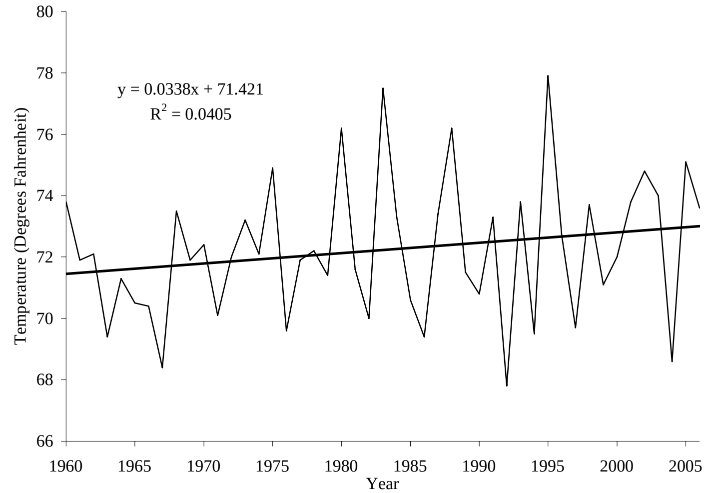


Figure 12. August Temperature in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois.



Panel B. Indiana.



Panel C. Iowa.

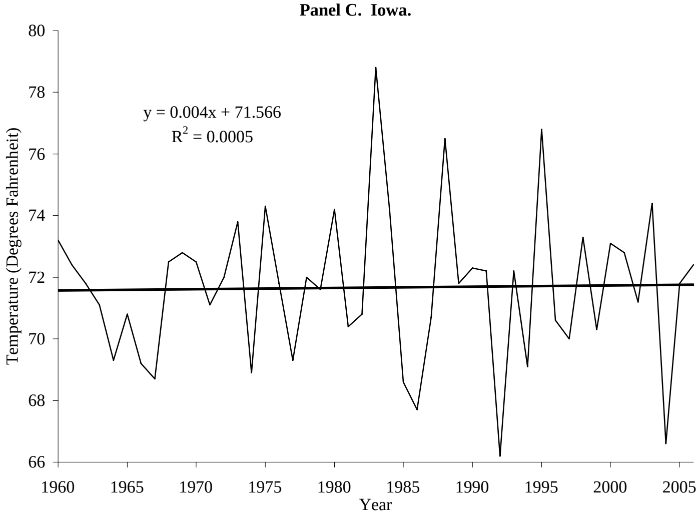
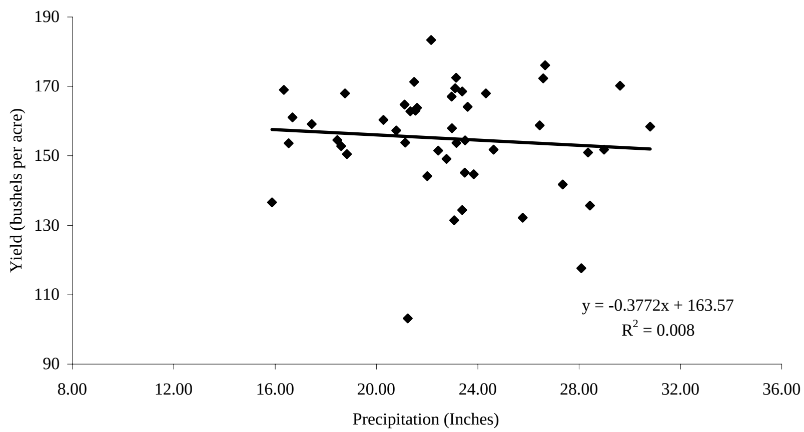
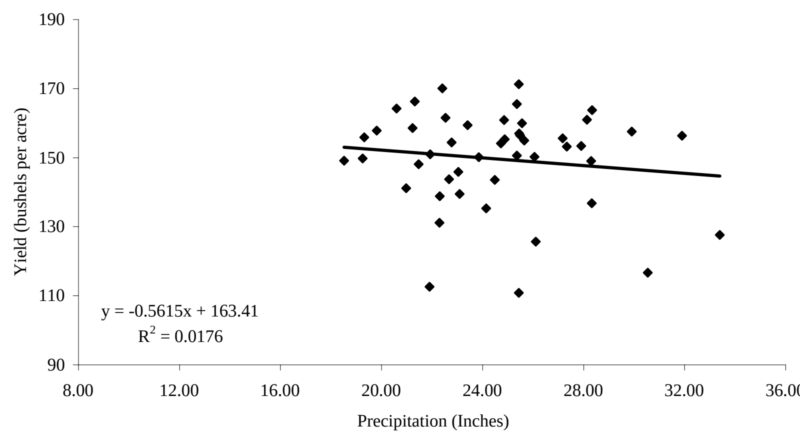


Figure 13. De-trended Corn Yields (to 2006) versus September-April (Pre-Season) Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

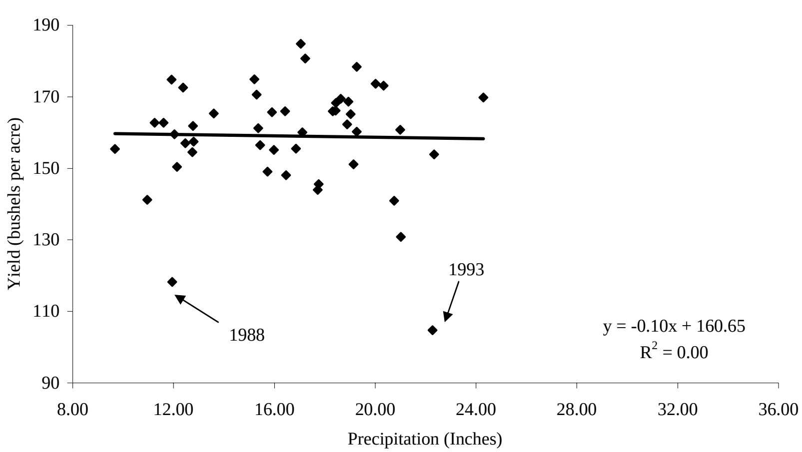
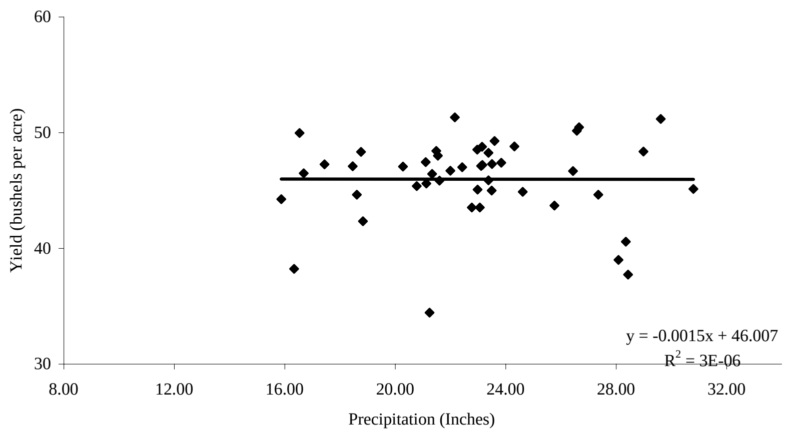
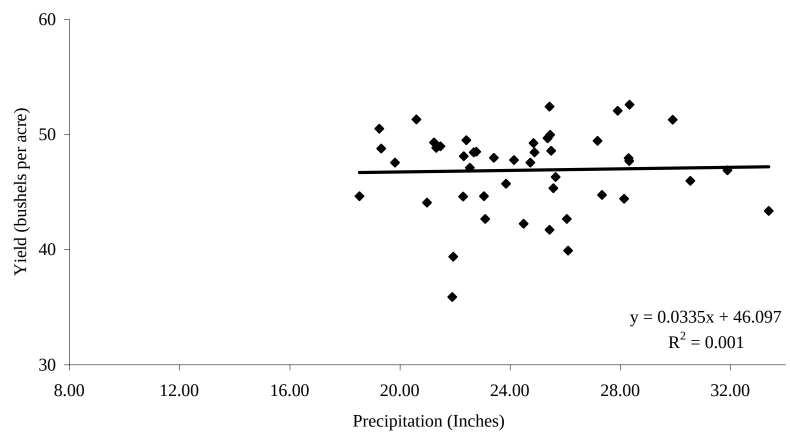


Figure 14. De-trended Soybean Yields (to 2006) versus September-April (Pre-Season) Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

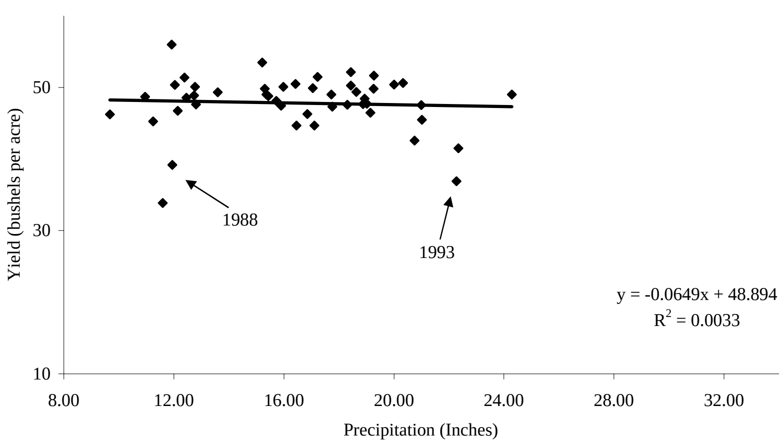


Figure 15. De-trended Corn Yields (to 2006) versus May Precipitation for Illinois, Indiana, and Iowa, 1960-2006

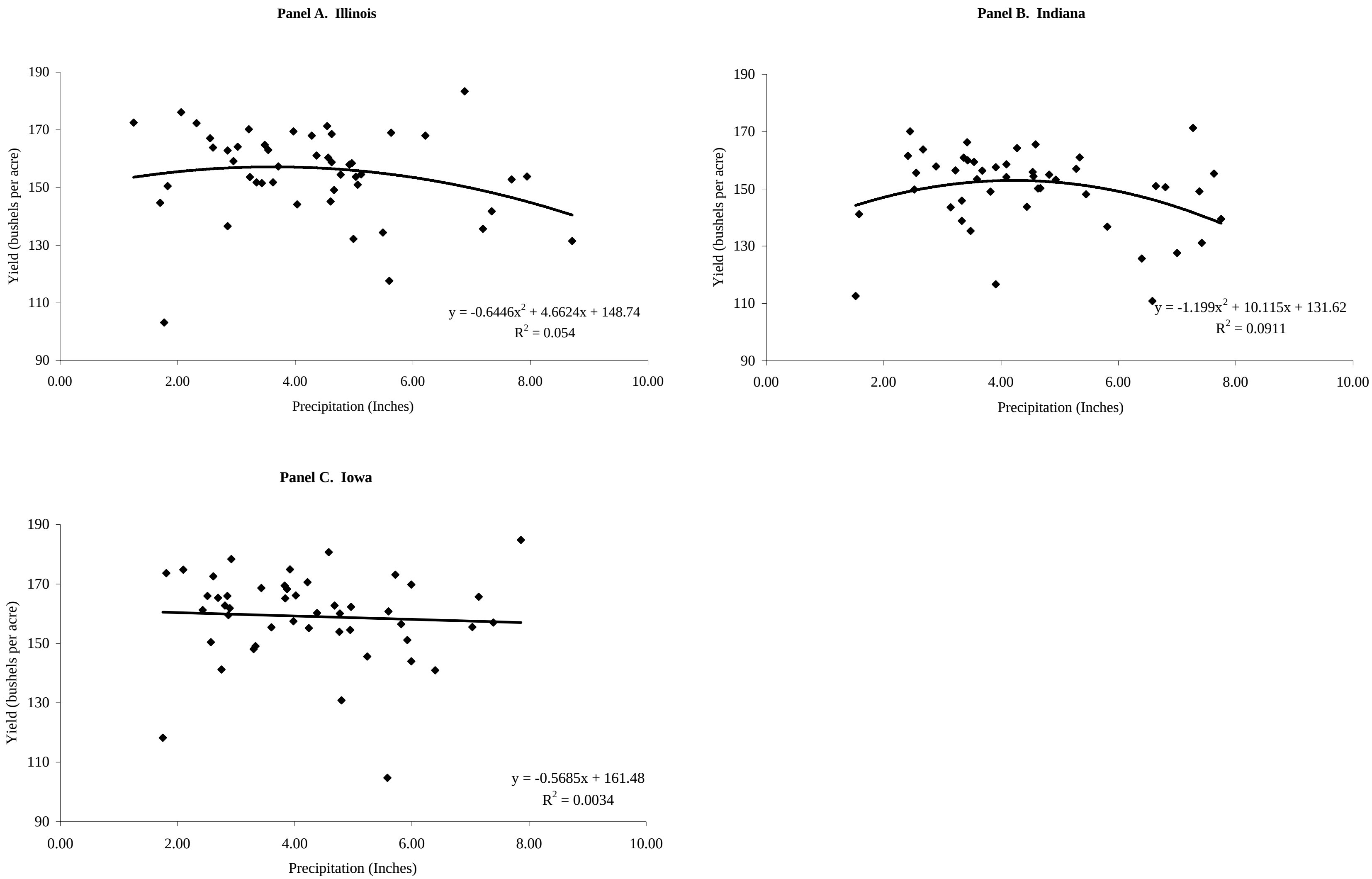


Figure 16. De-trended Soybean Yields (to 2006) versus May Precipitation for Illinois, Indiana, and Iowa, 1960-2006

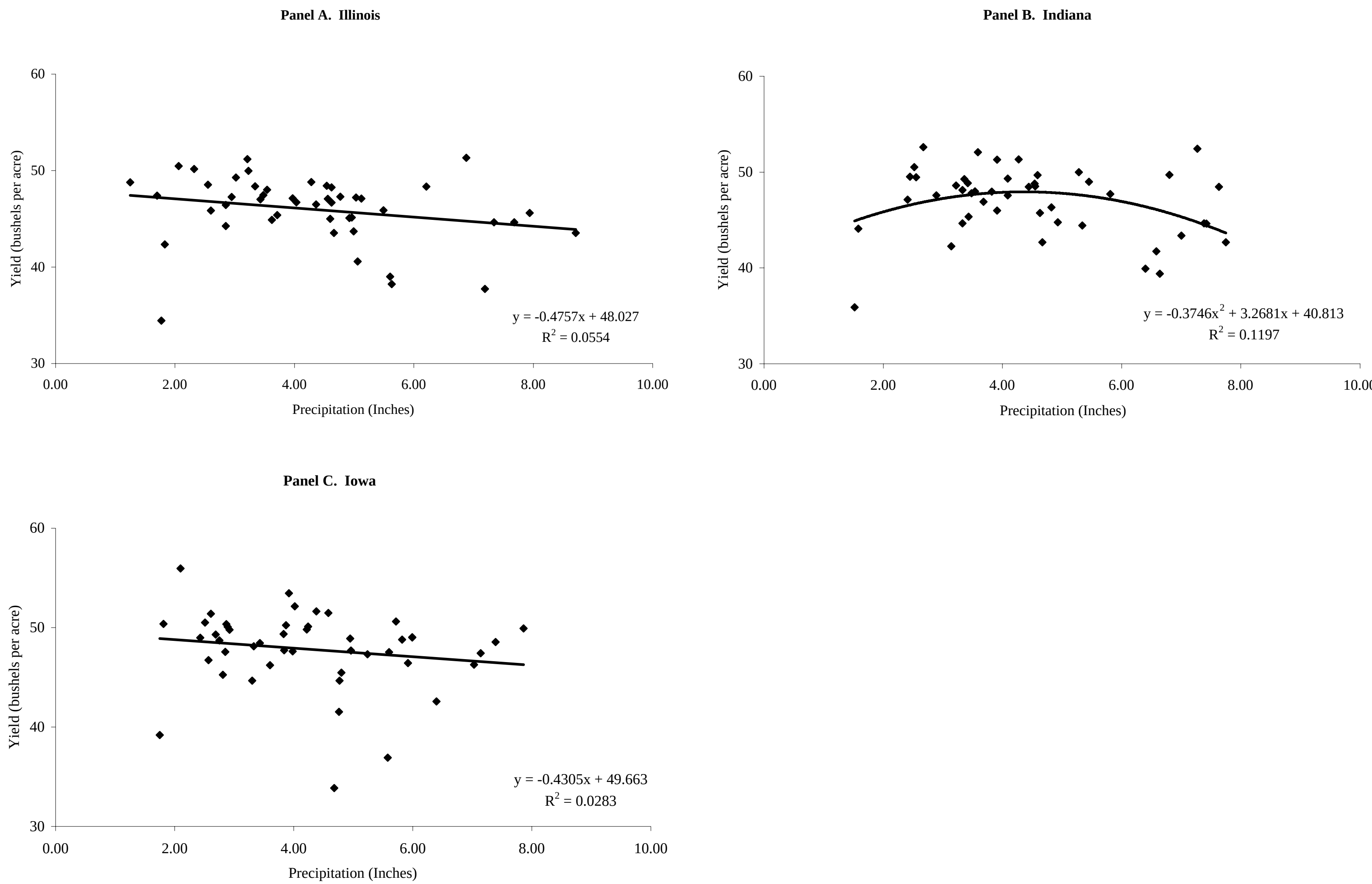


Figure 17. De-trended Corn Yields (to 2006) versus June Precipitation for Illinois, Indiana, and Iowa, 1960-2006

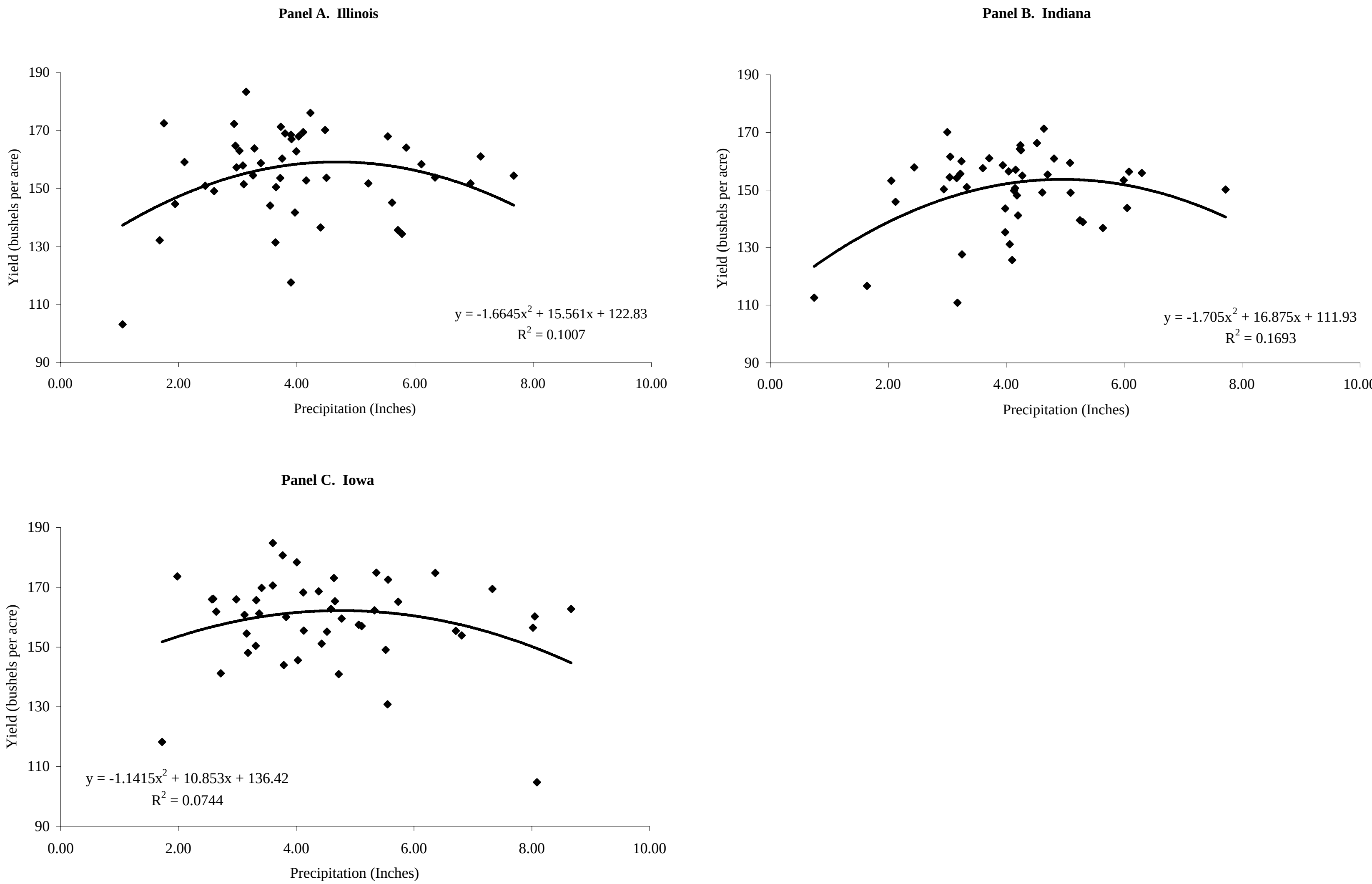
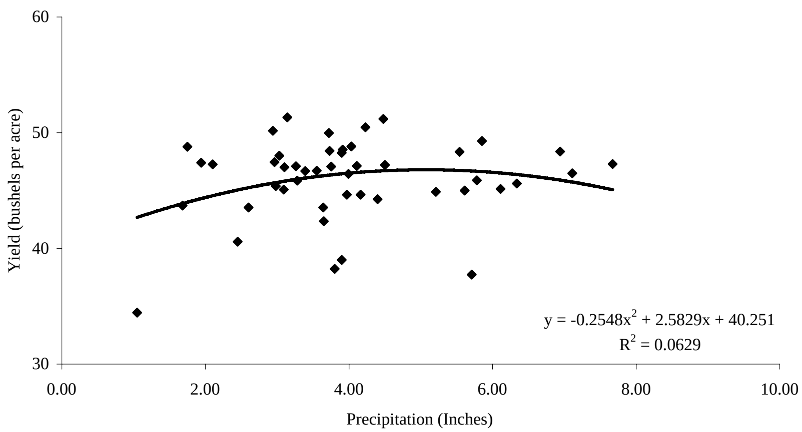
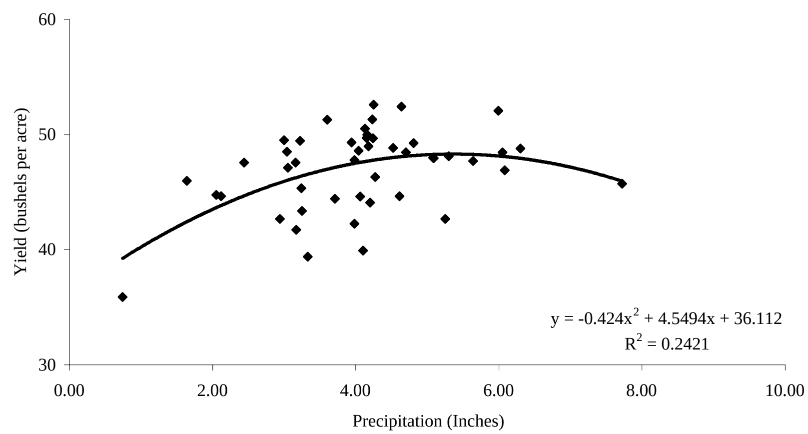


Figure 18. De-trended Soybean Yields (to 2006) versus June Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

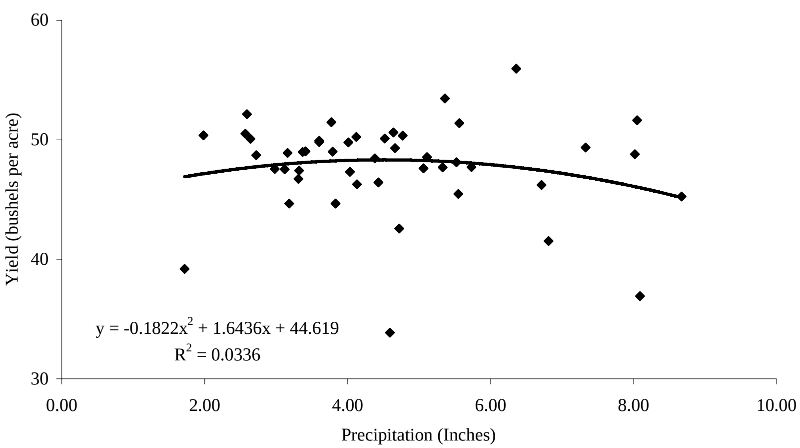


Figure 19. De-trended Corn Yields (to 2006) versus July Precipitation for Illinois, Indiana, and Iowa, 1960-2006

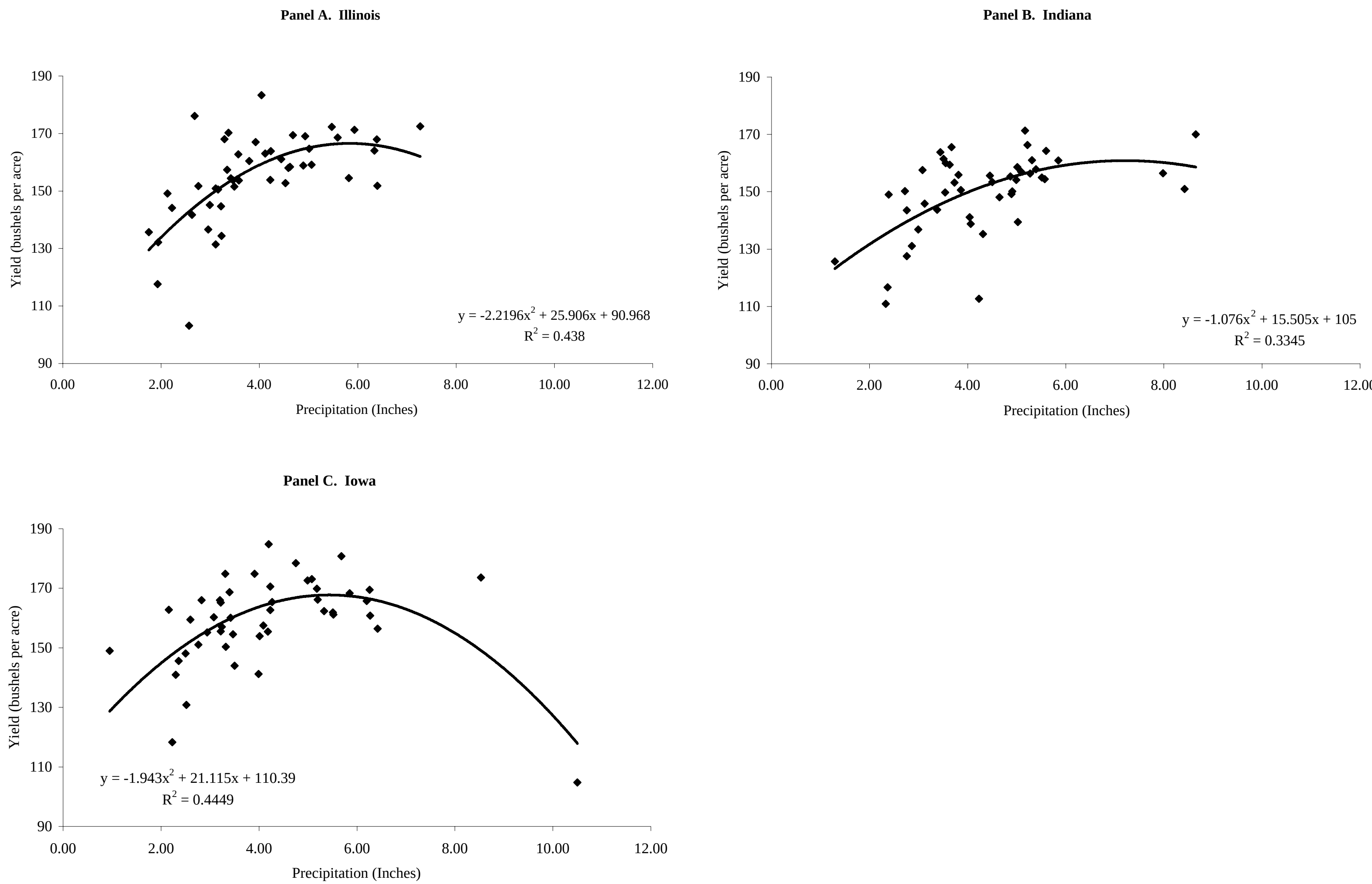


Figure 20. De-trended Soybean Yields (to 2006) versus July Precipitation for Illinois, Indiana, and Iowa, 1960-2006

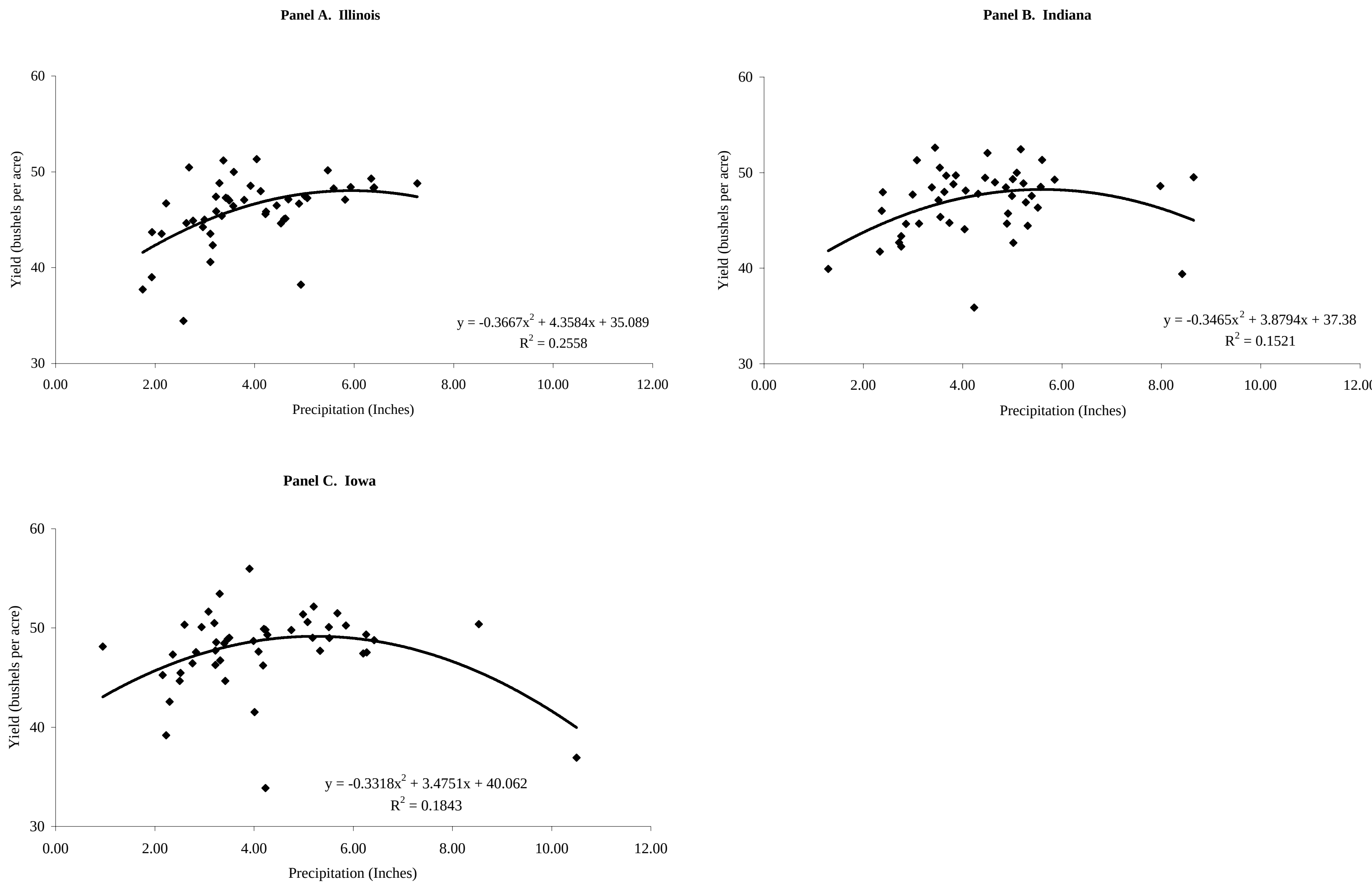
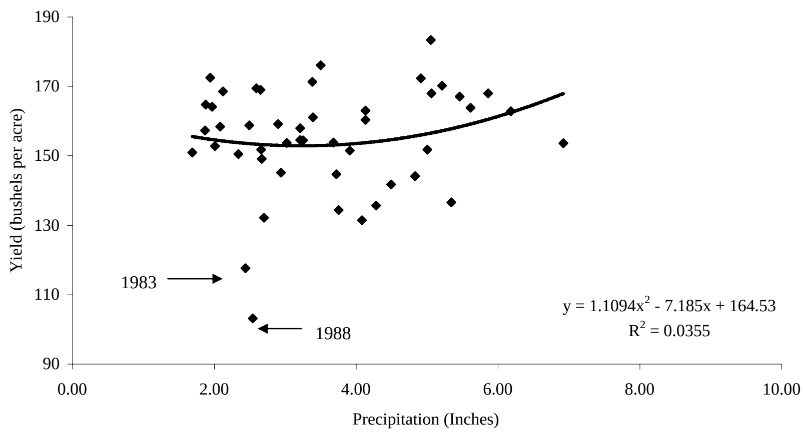
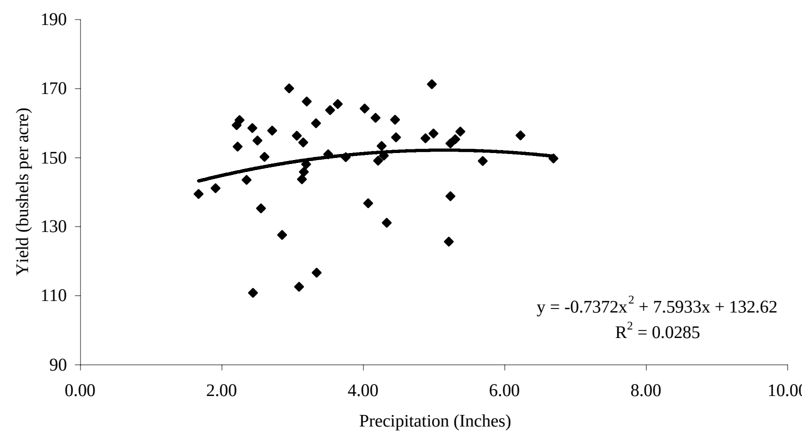


Figure 21. De-trended Corn Yields (to 2006) versus August Precipitation for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

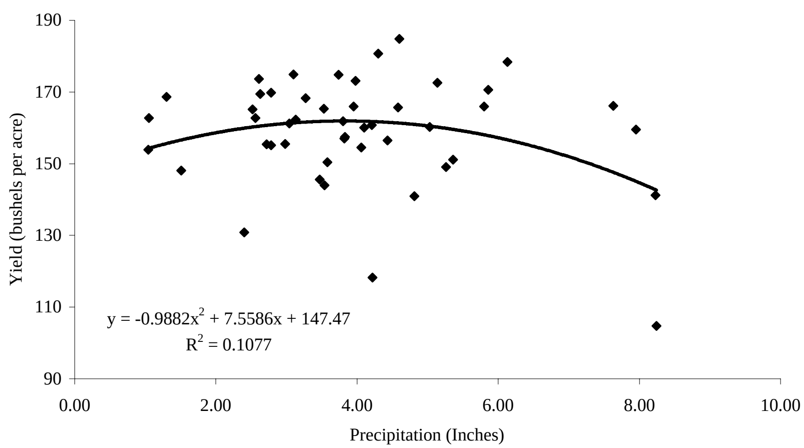


Figure 22. De-trended Soybean Yields (to 2006) versus August Precipitation for Illinois, Indiana, and Iowa, 1960-2006

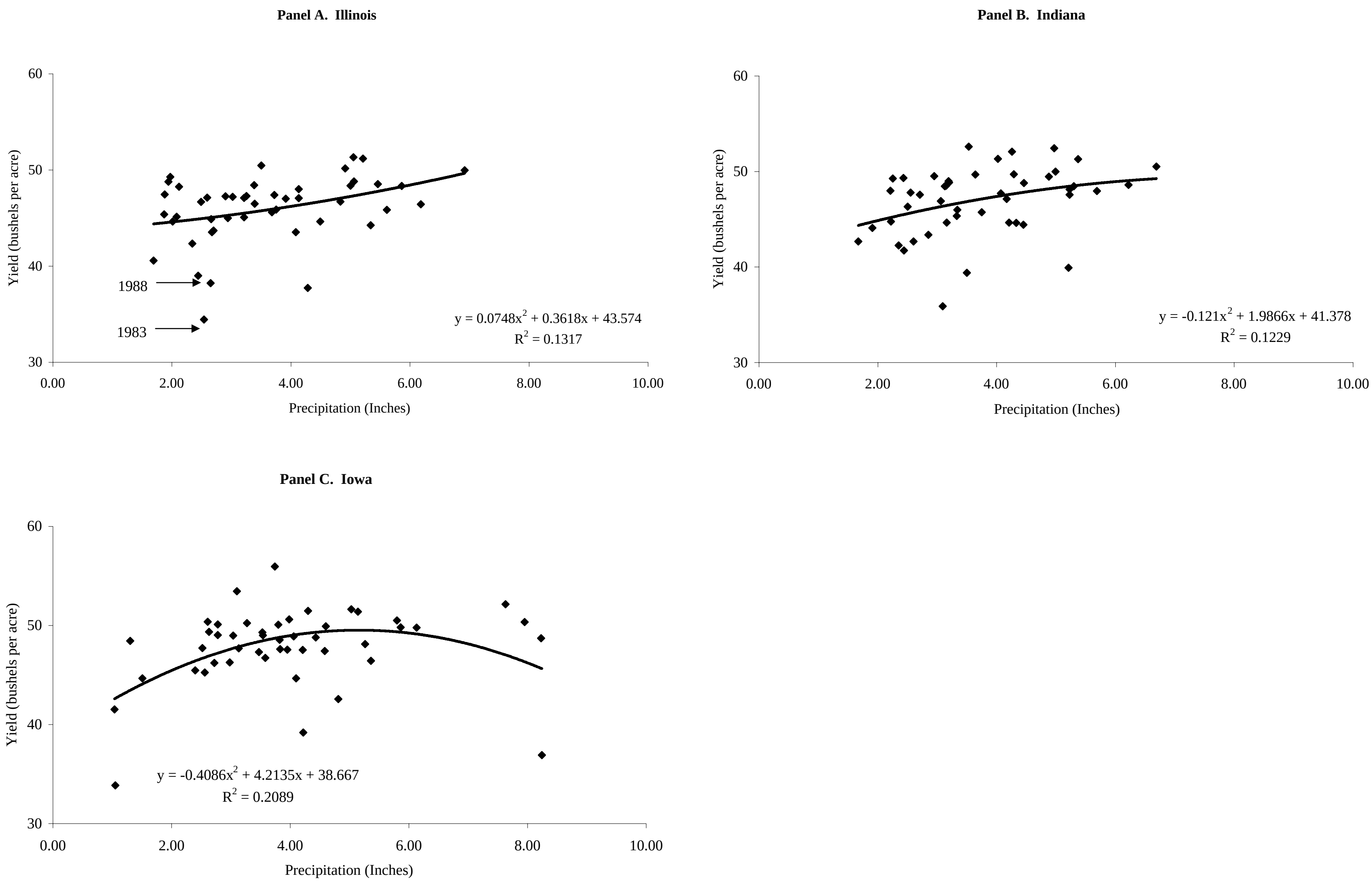
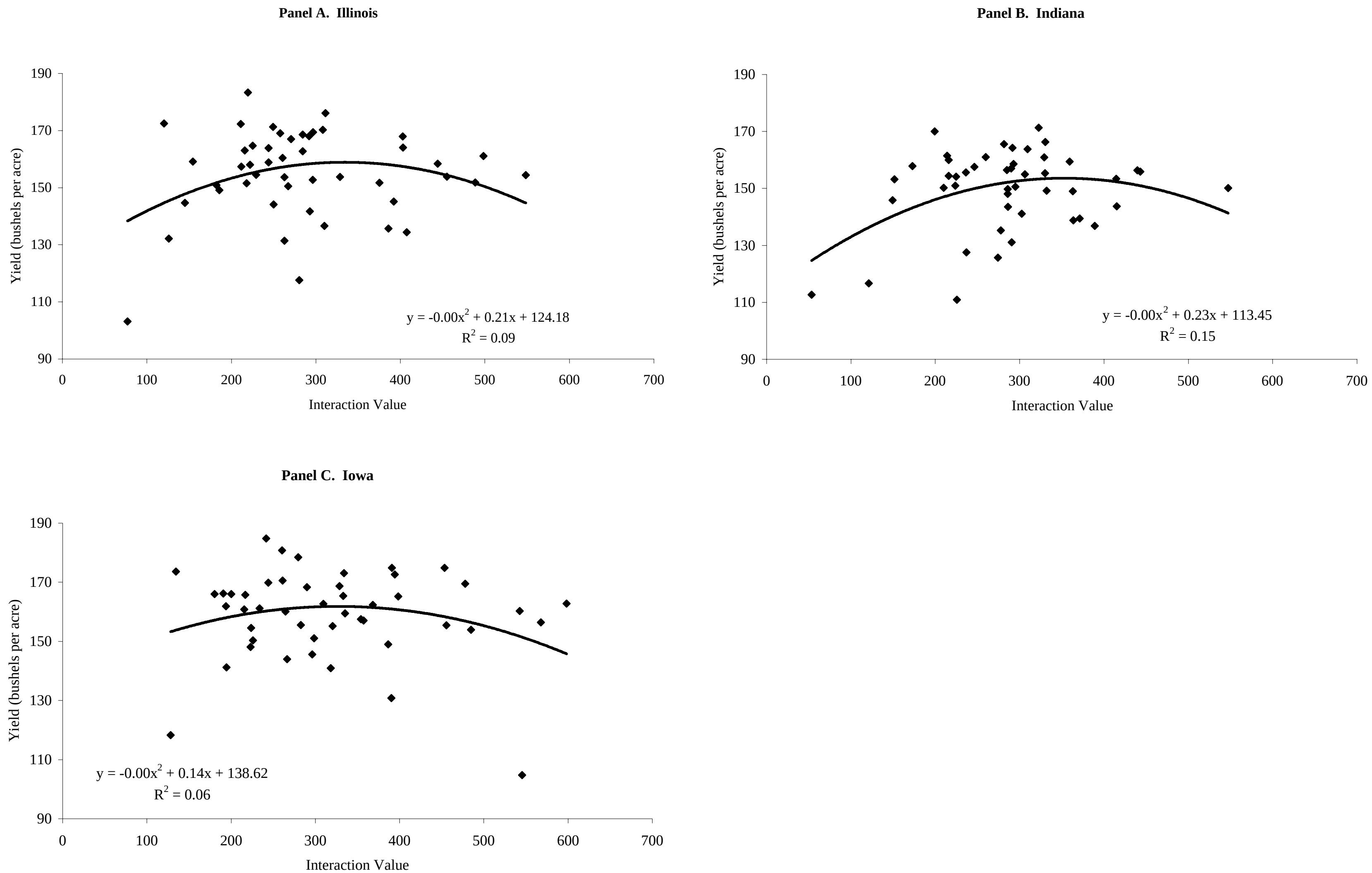
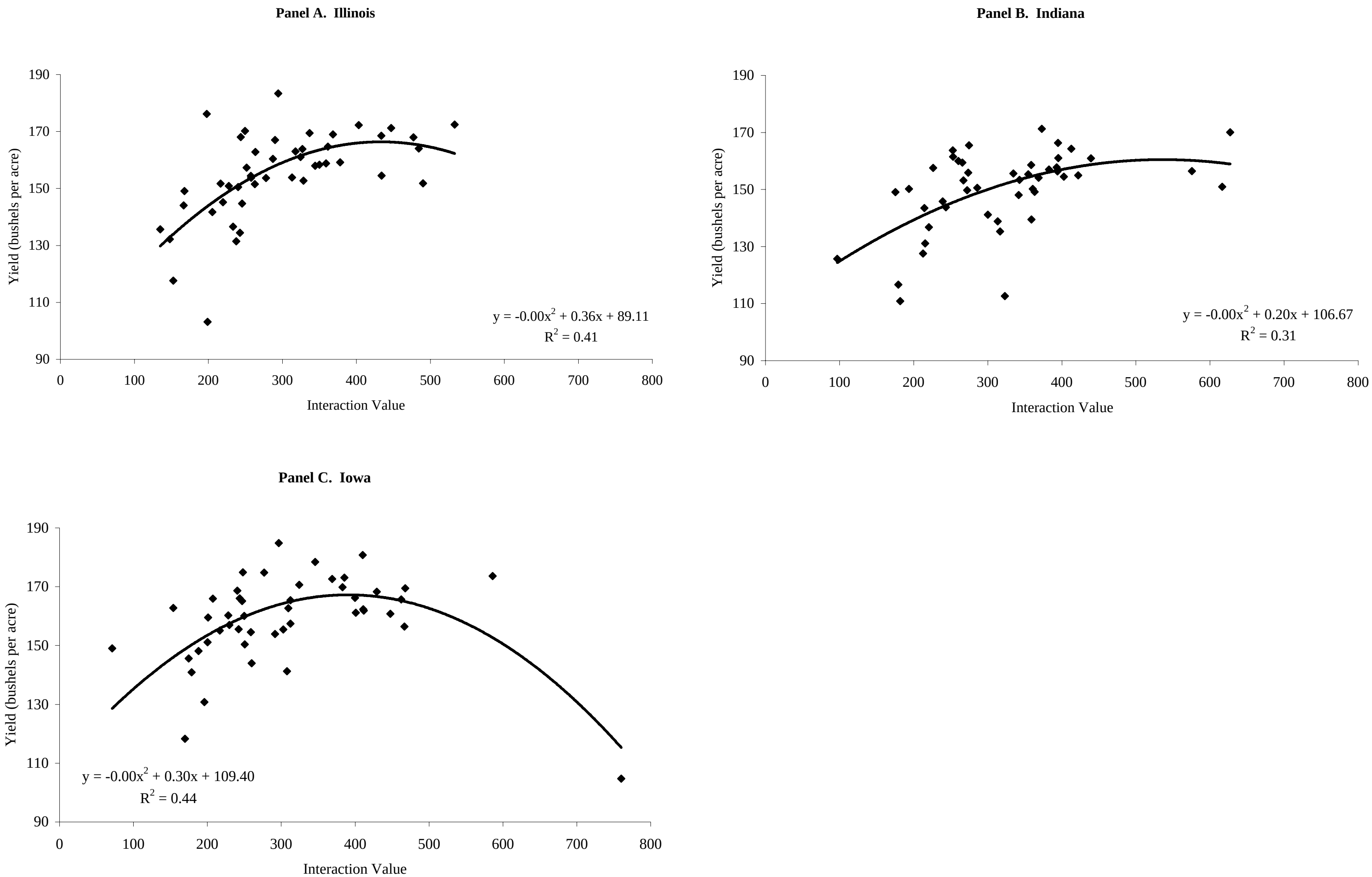


Figure 23. De-trended Corn Yields (to 2006) versus June Precipitation-Temperature Interaction Value for Illinois, Indiana, and Iowa, 1960-2006



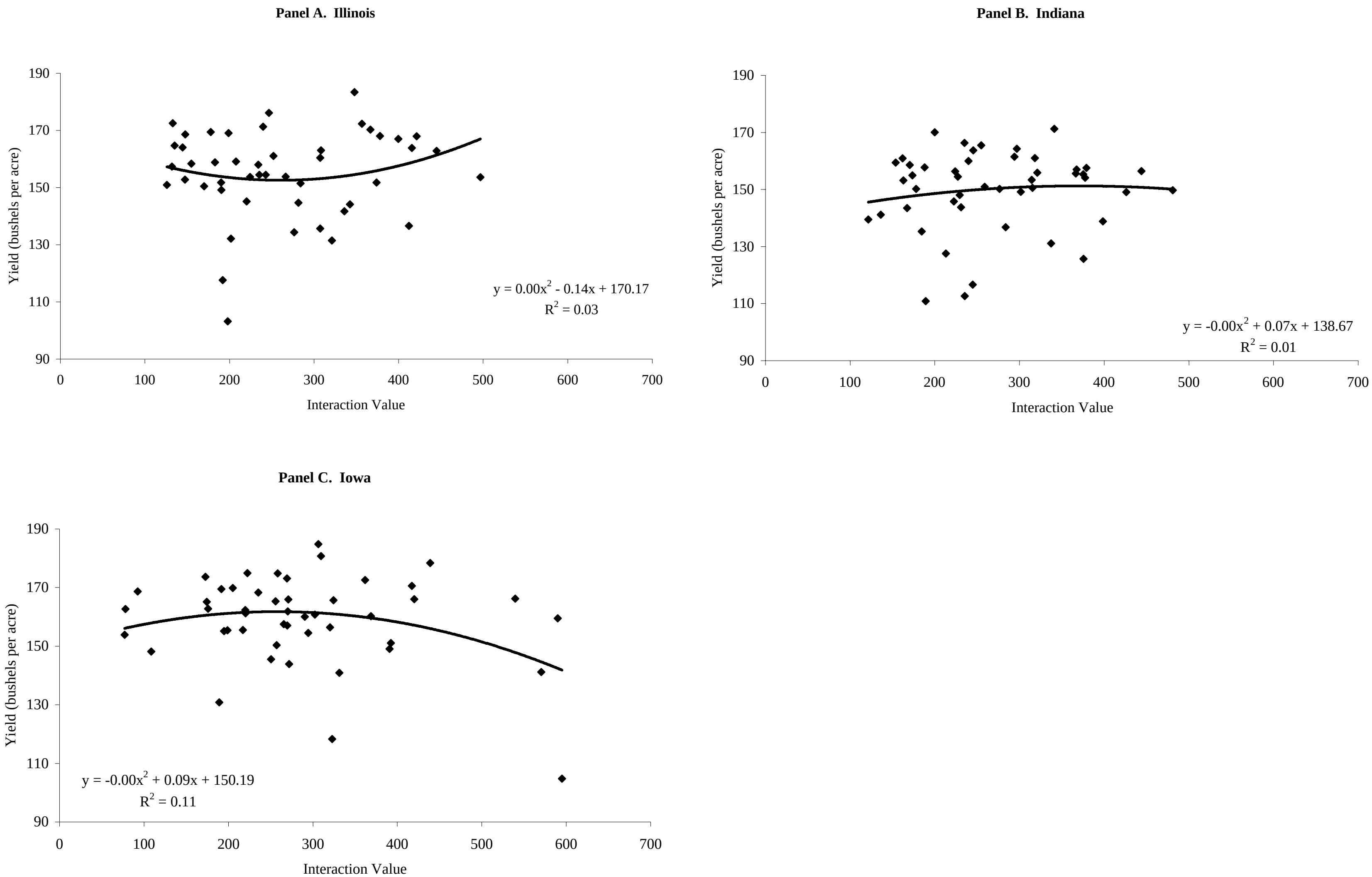
Note: Interaction Value = June Temperature x June Precipitation

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



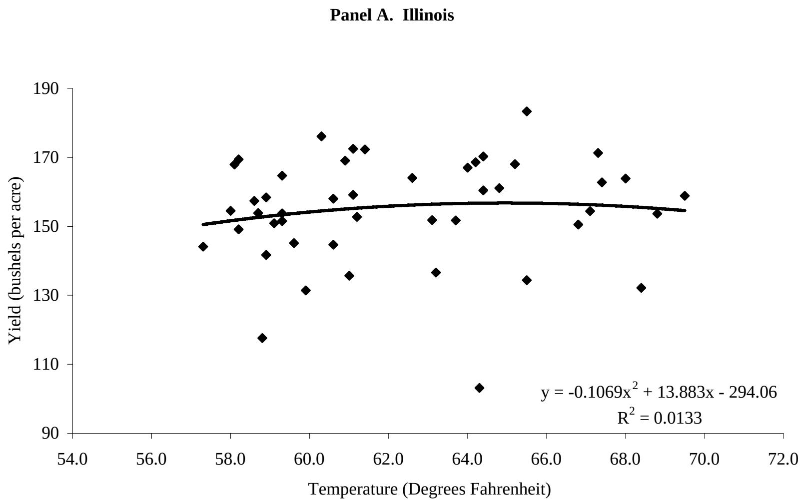
Note: Interaction Value = June Temperature x June Precipitation

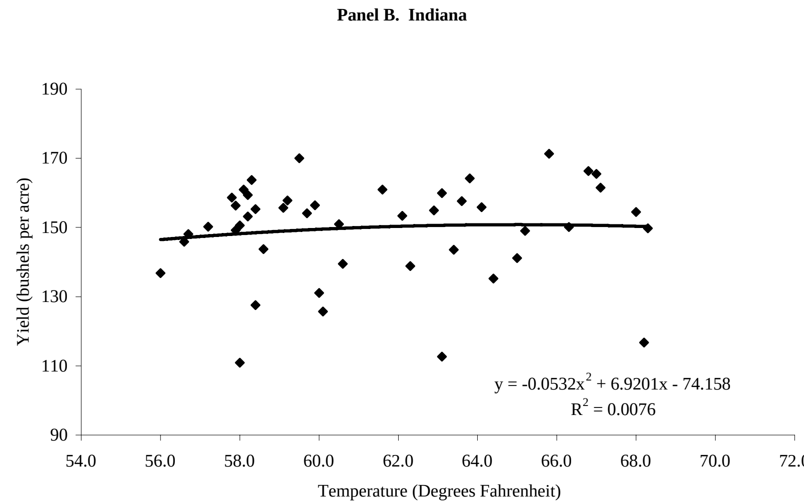
Figure 25. De-trended Corn Yields (to 2006) versus August Precipitation-Temperature Interaction Value for Illinois, Indiana, and Iowa, 1960-2006



Note: Interaction Value = June Temperature x June Precipitation

Figure 26. De-trended Corn Yields (to 2006) versus May Temperature for Illinois, Indiana, and Iowa, 1960-2006





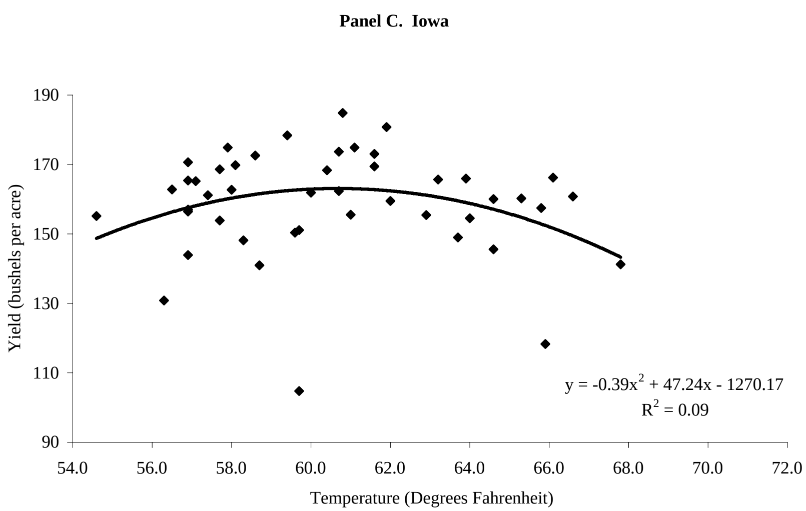
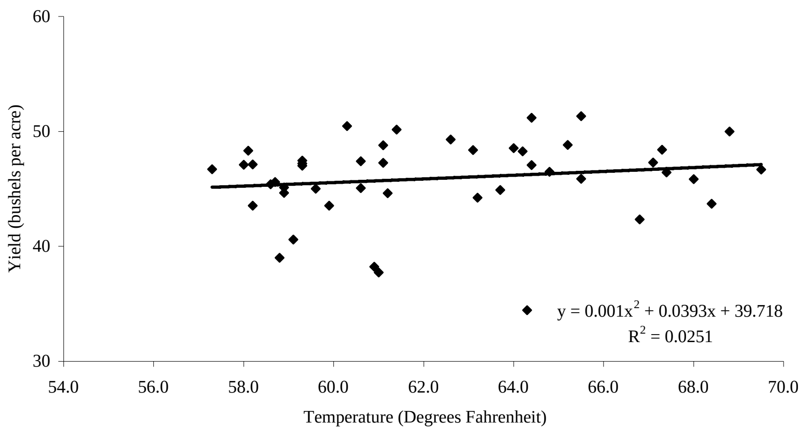
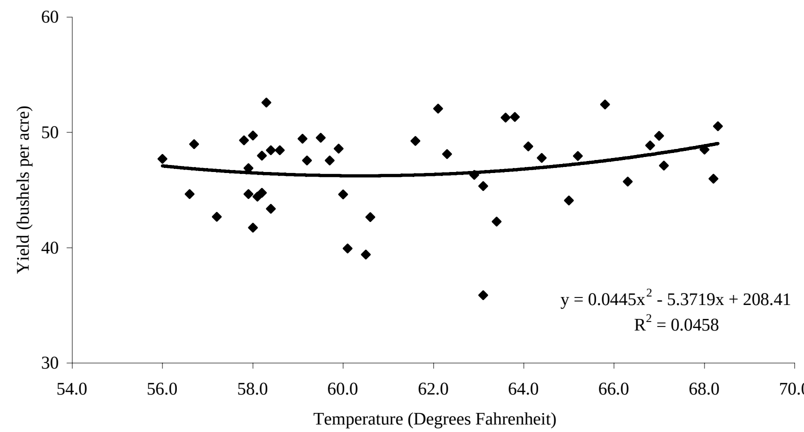


Figure 27. De-trended Soybean Yields (to 2006) versus May Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

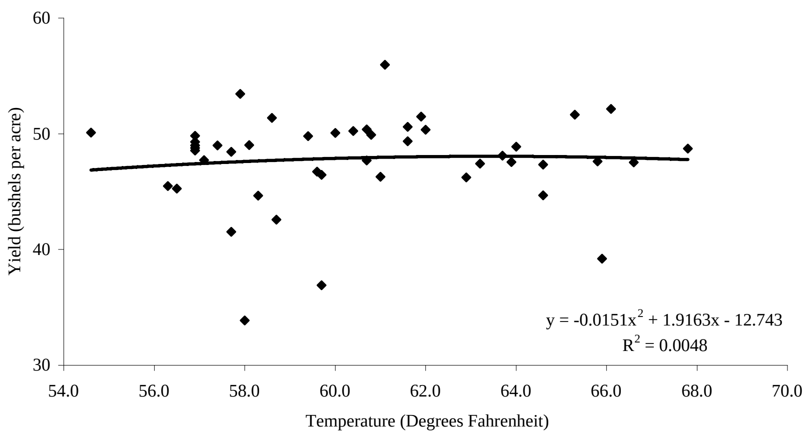


Figure 28. De-trended Corn Yields (to 2006) versus June Temperature for Illinois, Indiana, and Iowa, 1960-2006

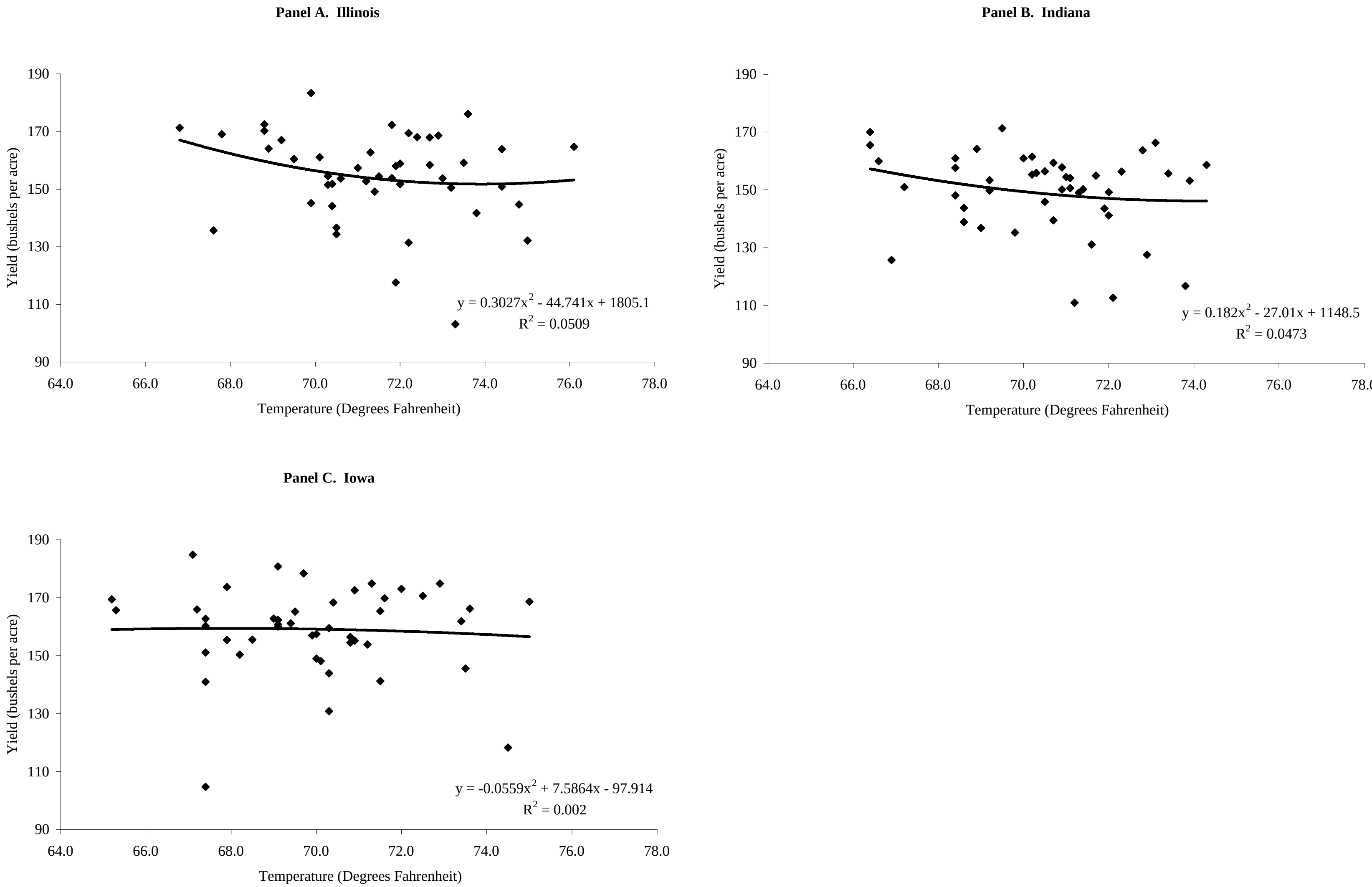
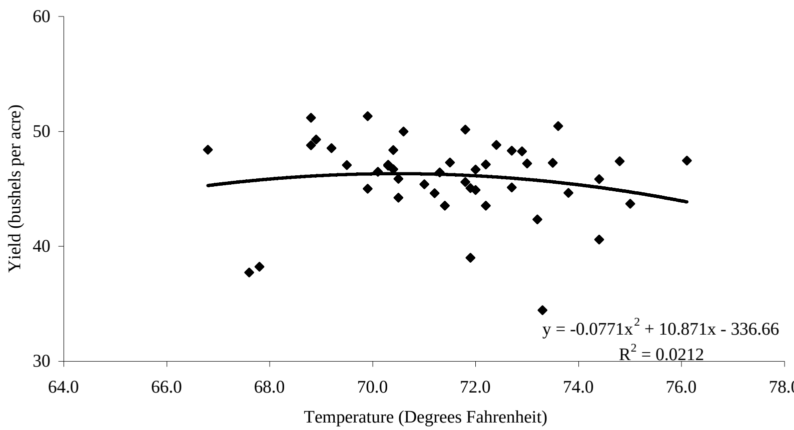
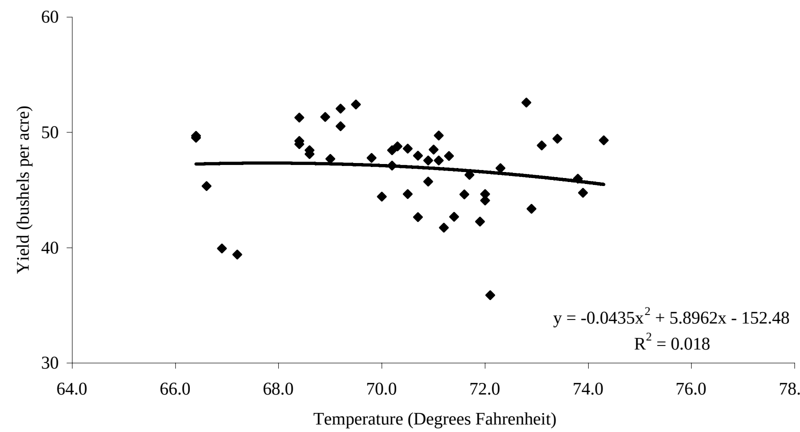


Figure 29. De-trended Soybean Yields (to 2006) versus June Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

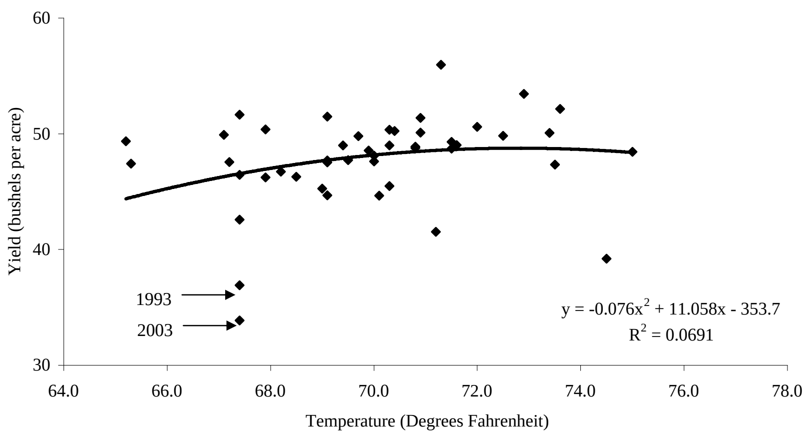
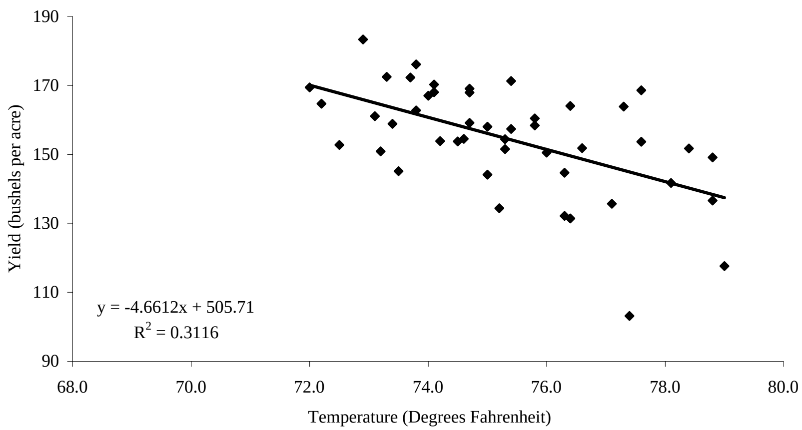
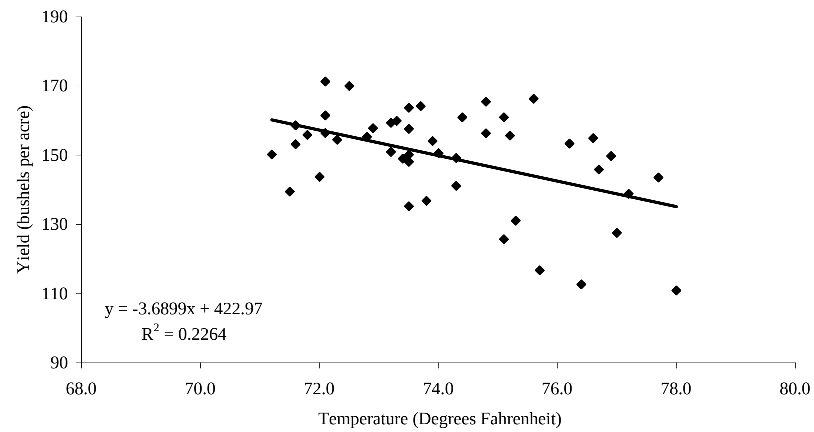


Figure 30. De-trended Corn Yields (to 2006) versus July Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

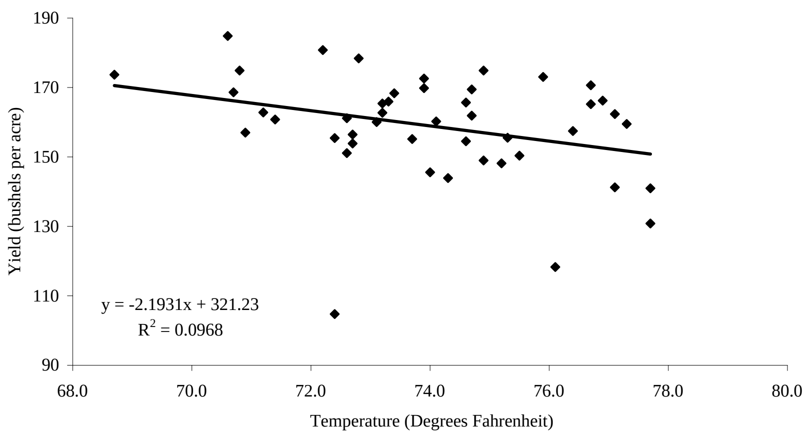
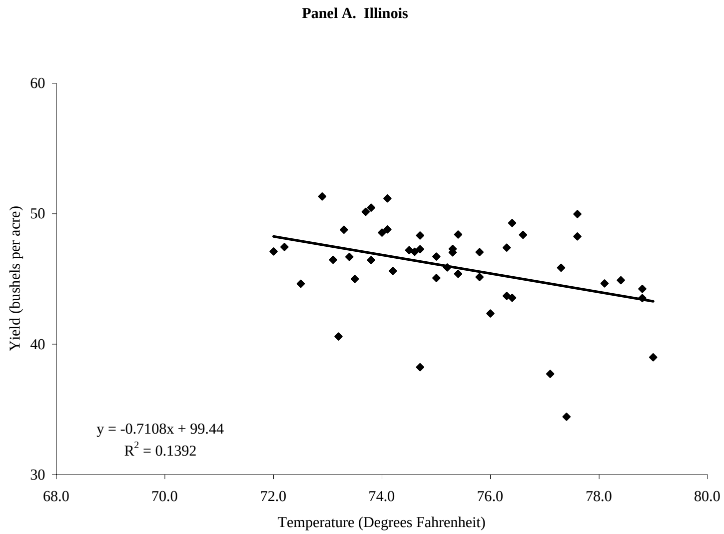
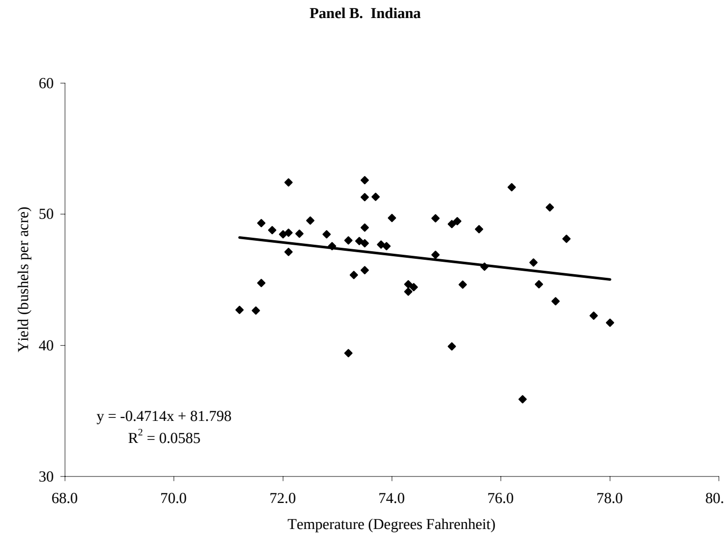


Figure 31. De-trended Soybean Yields (to 2006) versus July Temperature for Illinois, Indiana, and Iowa, 1960-2006





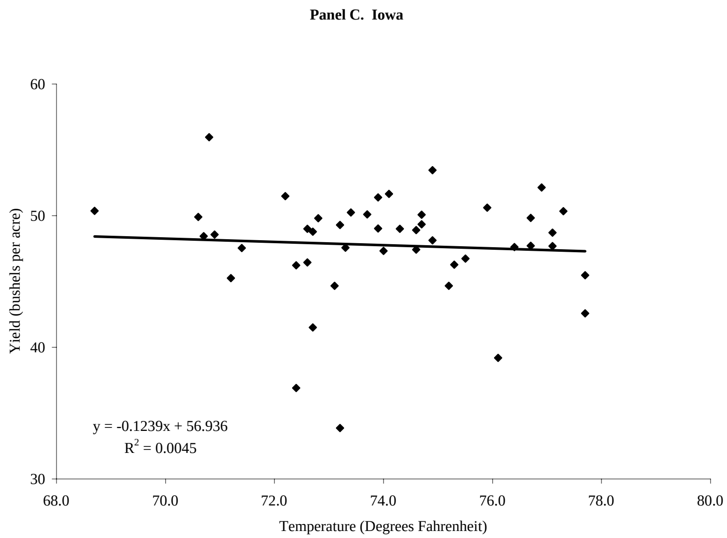
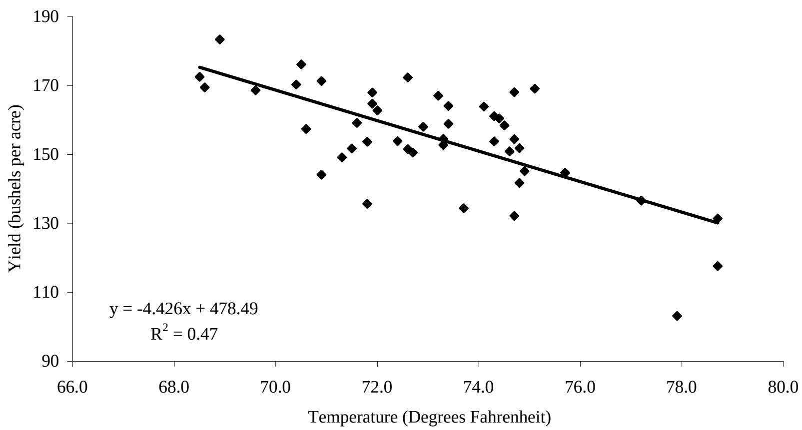
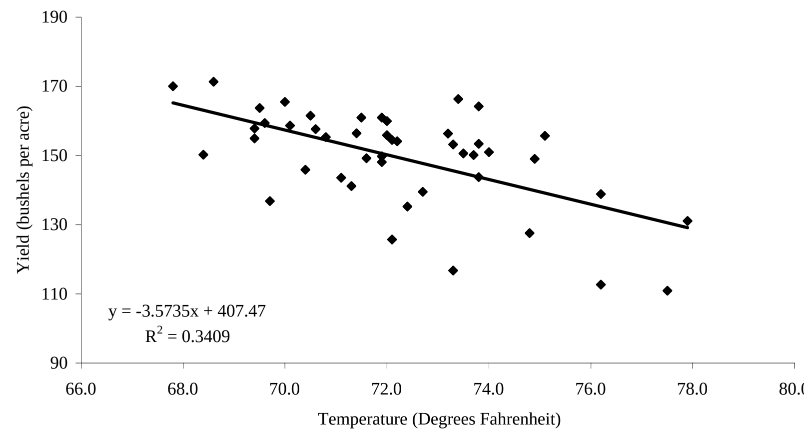


Figure 32. De-trended Corn Yields (to 2006) versus August Temperature for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

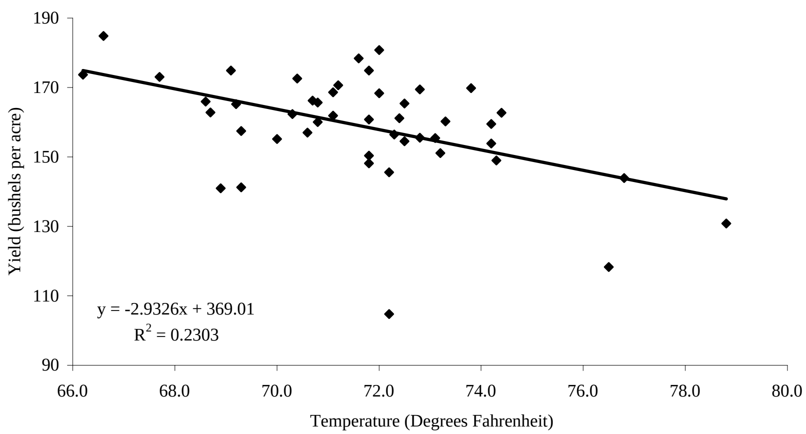


Figure 33. De-trended Soybean Yields (to 2006) versus August Temperature for Illinois, Indiana, and Iowa, 1960-2006

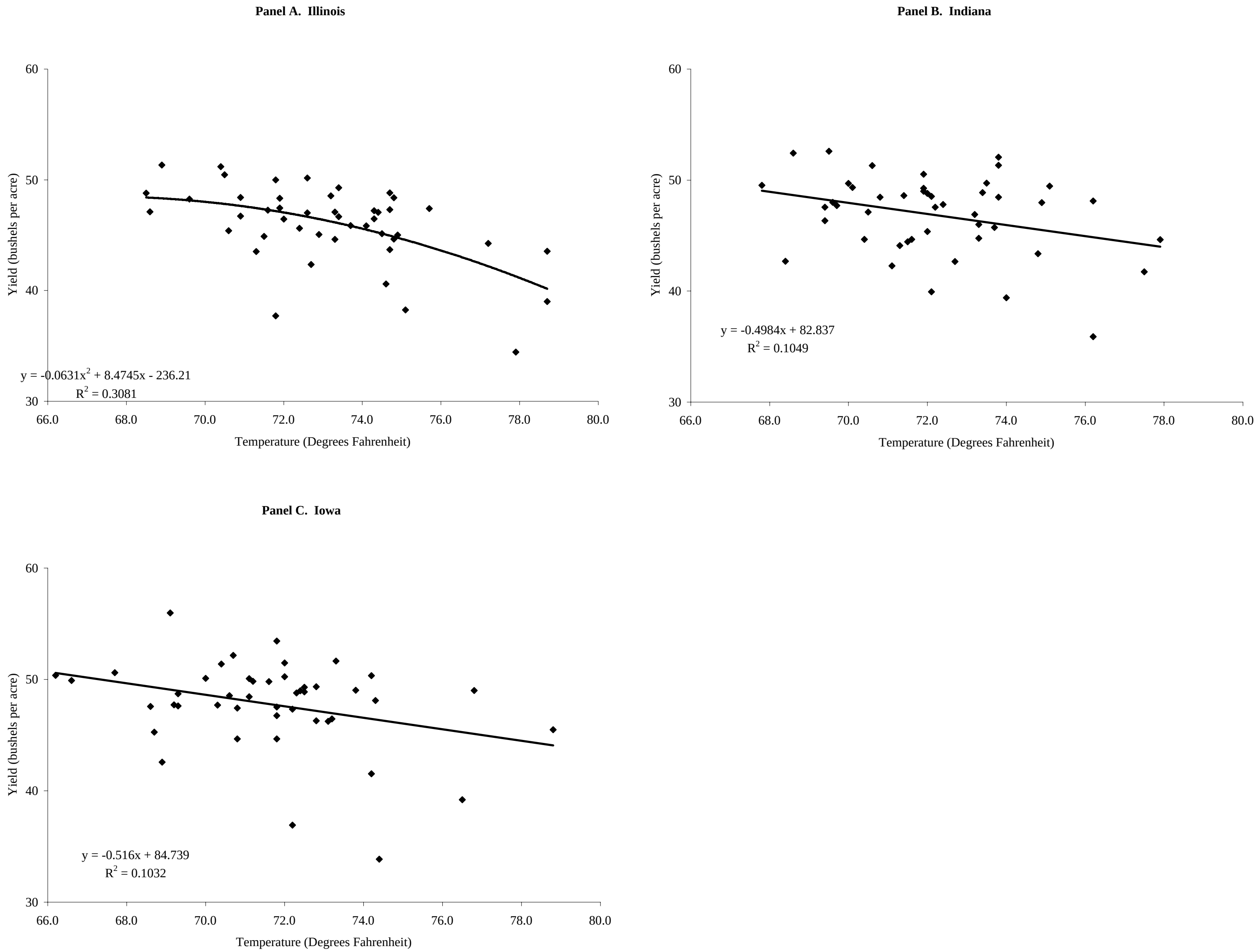
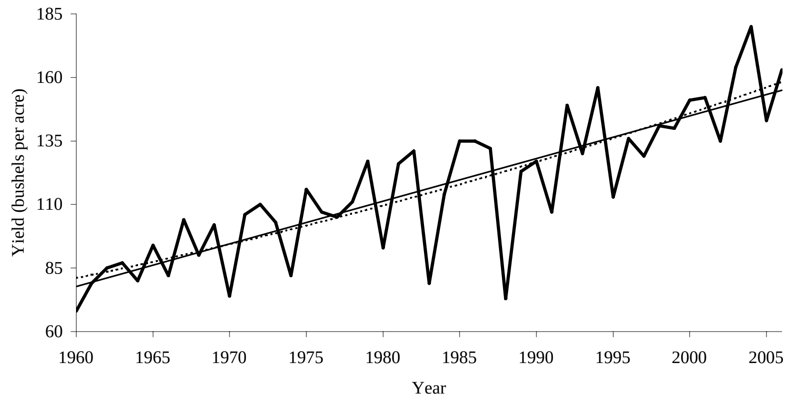
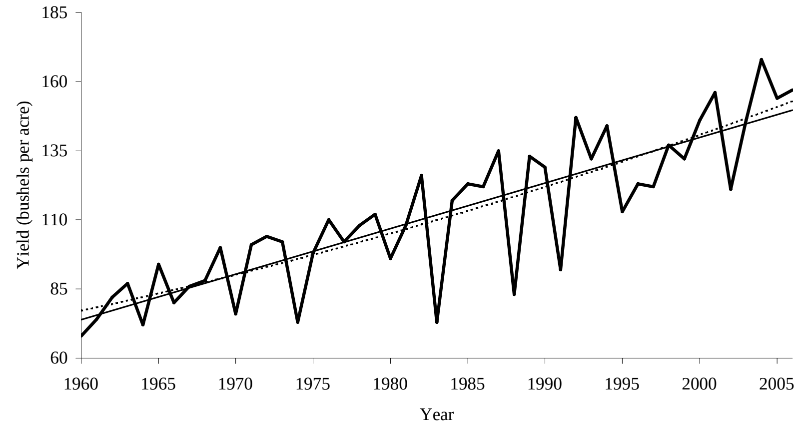


Figure 34. Alternative Trend Models for Corn Yields in Illinois, Indiana, and Iowa, 1960-2006

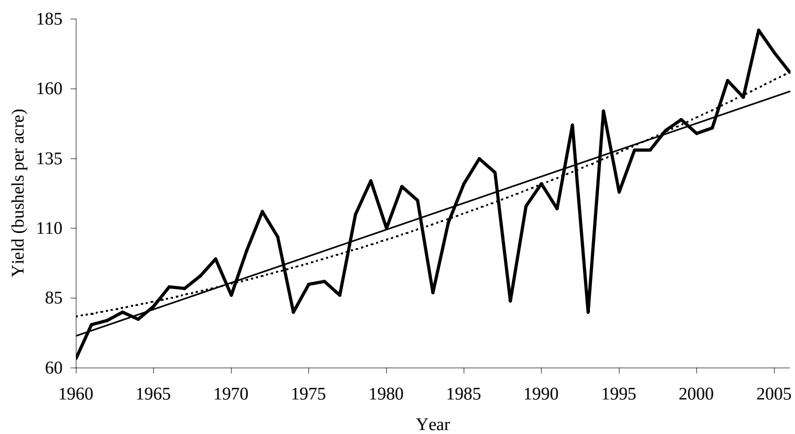
Panel A. Illinois



Panel B. Indiana



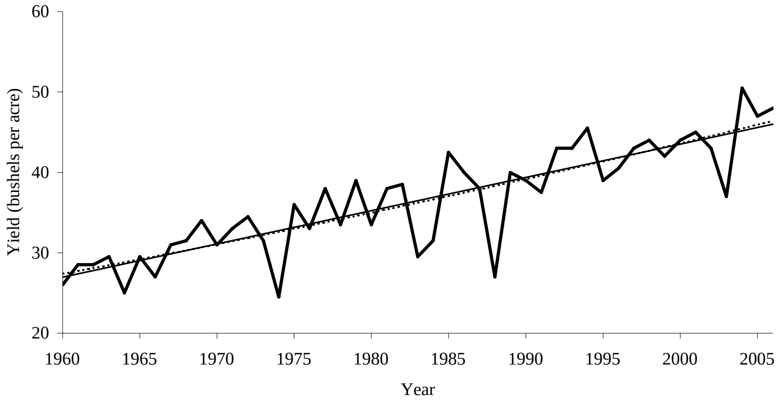
Panel C. Iowa



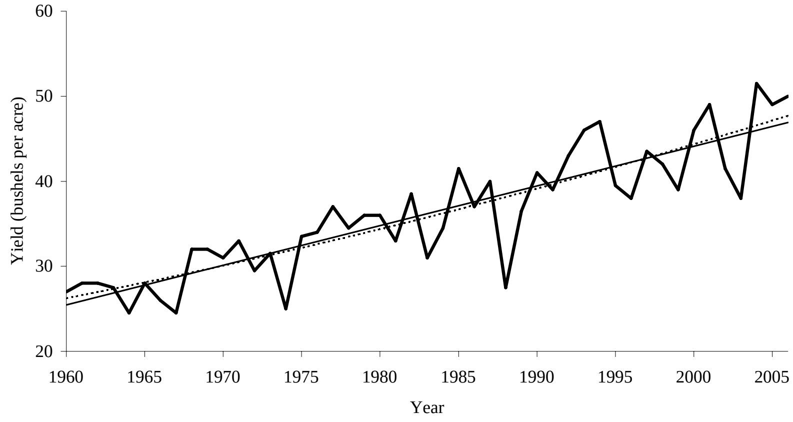
Note: The quadratic model is the dashed and the linear model is the solid line.

Figure 35. Alternative Trend Models for Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006

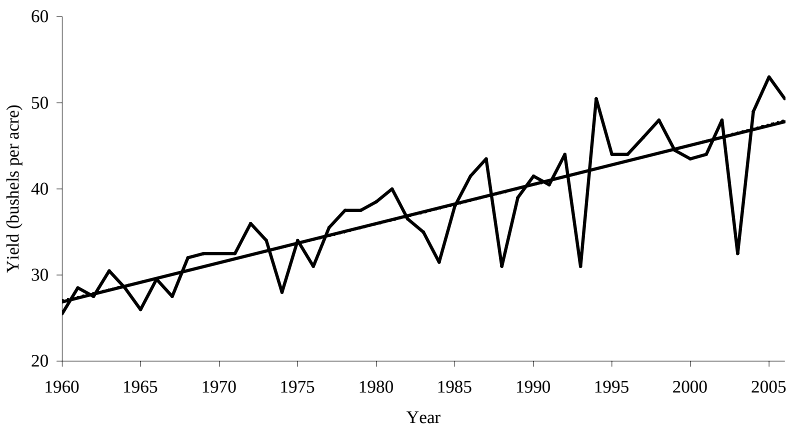
Panel A. Illinois



Panel B. Indiana



Panel C. Iowa



Note: The quadratic model is the dashed and the linear model is the solid line.

Figure 36. Modified Thompson Model Residuals for Corn Yields in Illinois, Indiana, and Iowa, 1960-2006

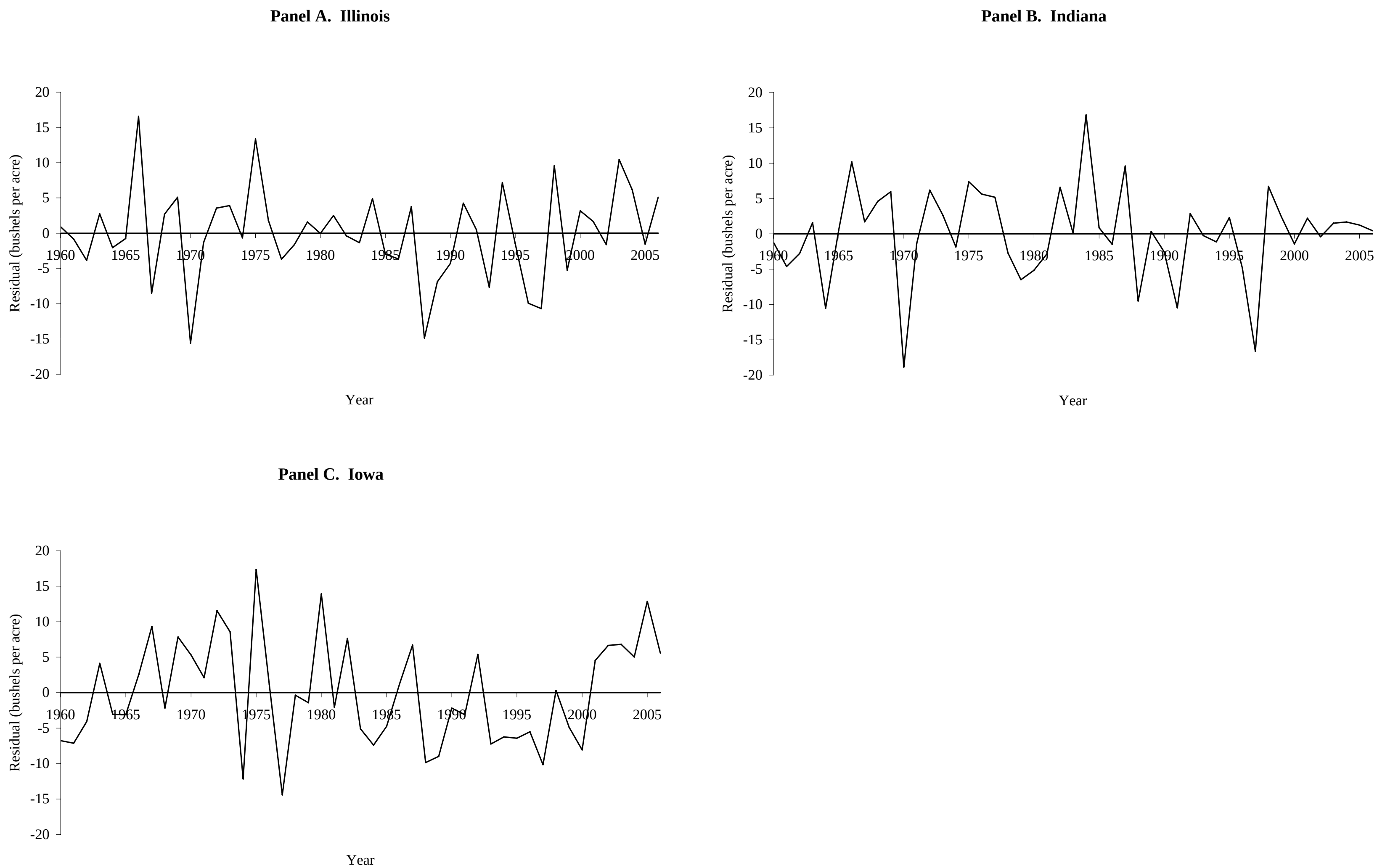


Figure 37. Modified Thompson Model Residuals for Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006

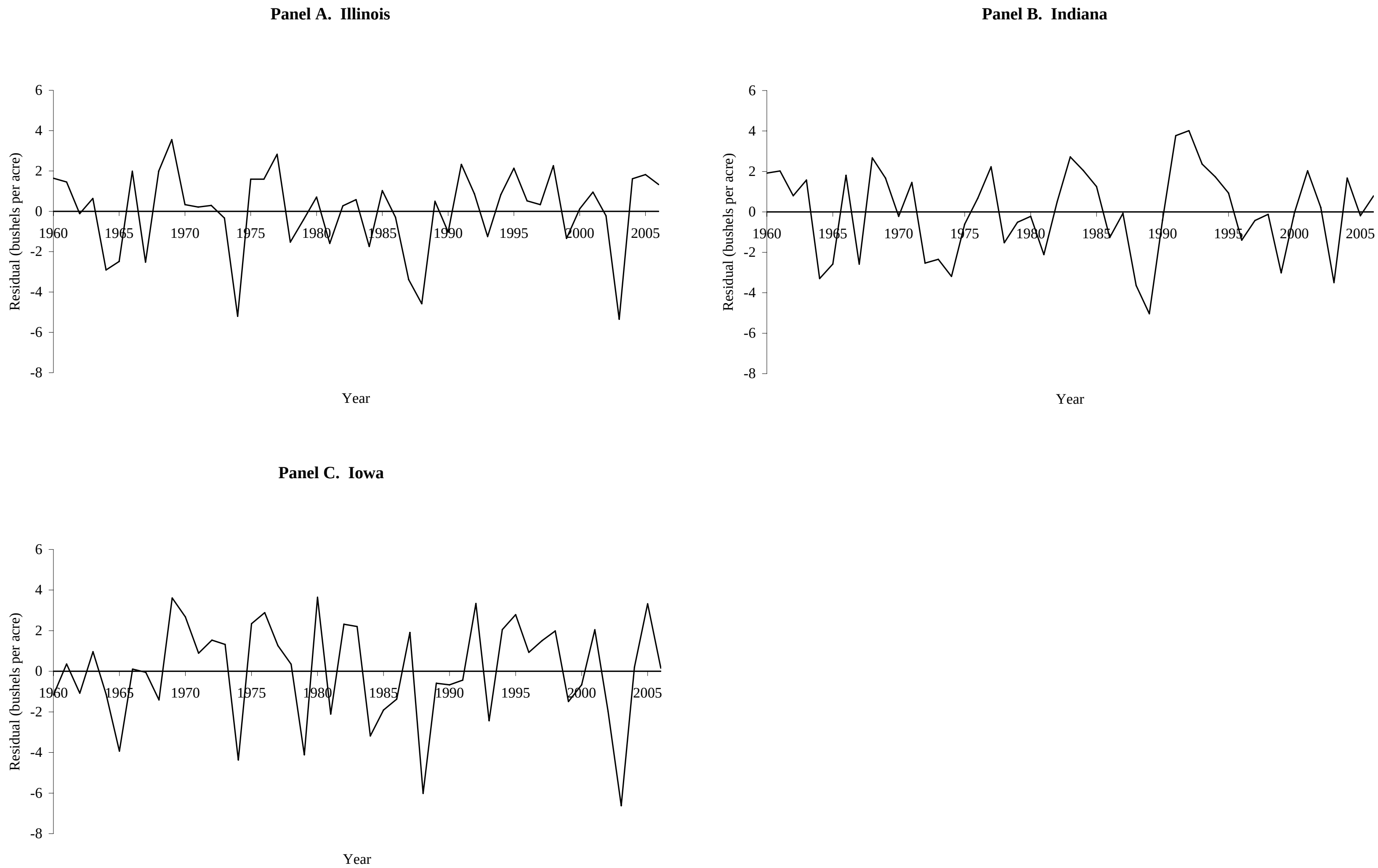
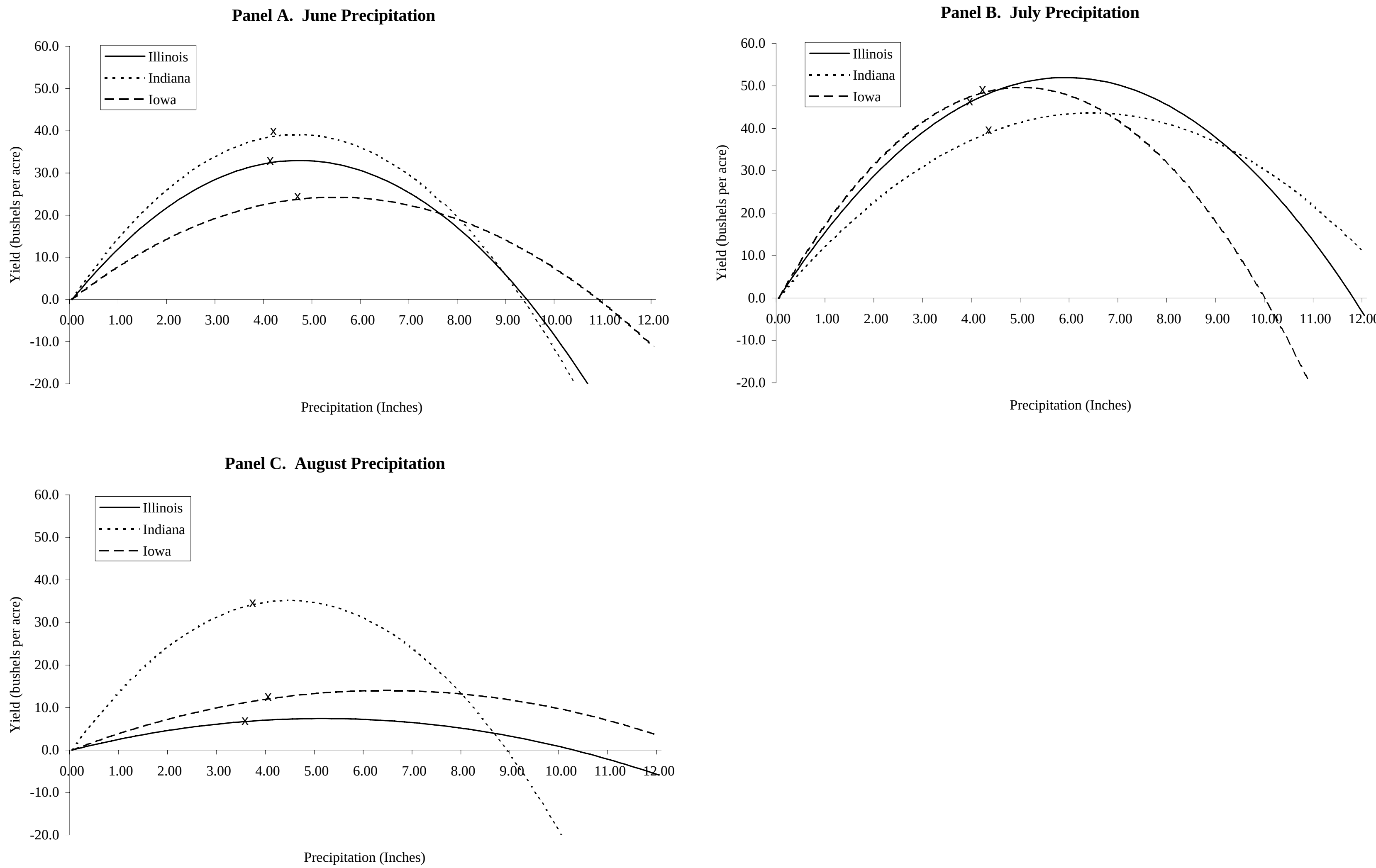


Figure 38. Expected Change in Corn Yields from Monthly Precipitation in Illinois, Indiana, and Iowa, 1960-2006



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

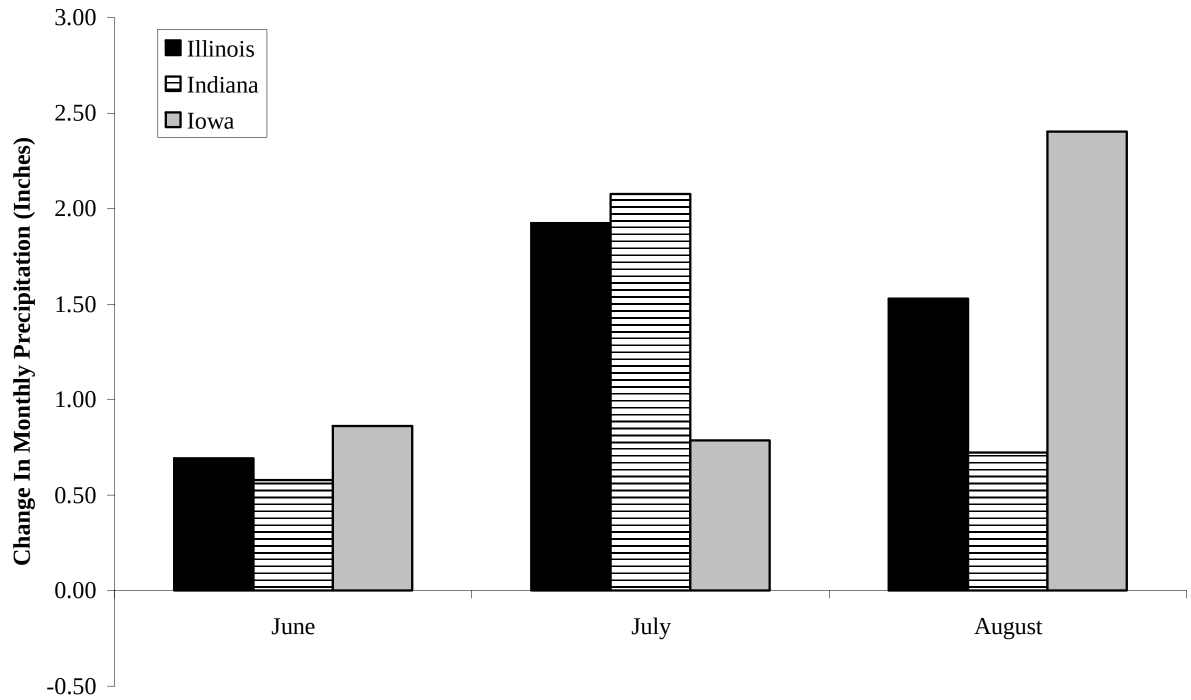


Figure 40. Change In Corn Yields By Increasing Precipitation from Average to Optimum in Illinois, Indiana, and Iowa, 1960-2006

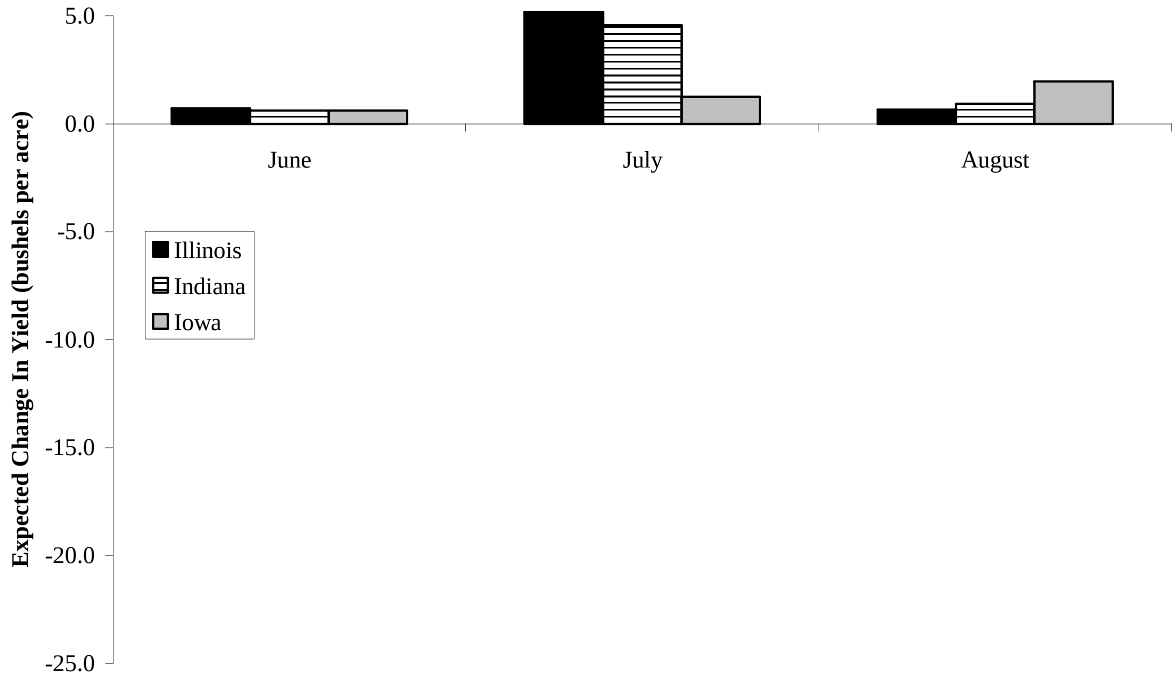


Figure 41. Change In Corn Yields By Decreasing Precipitation from Average to Optimum in Illinois, Indiana, and Iowa, 1960-2006

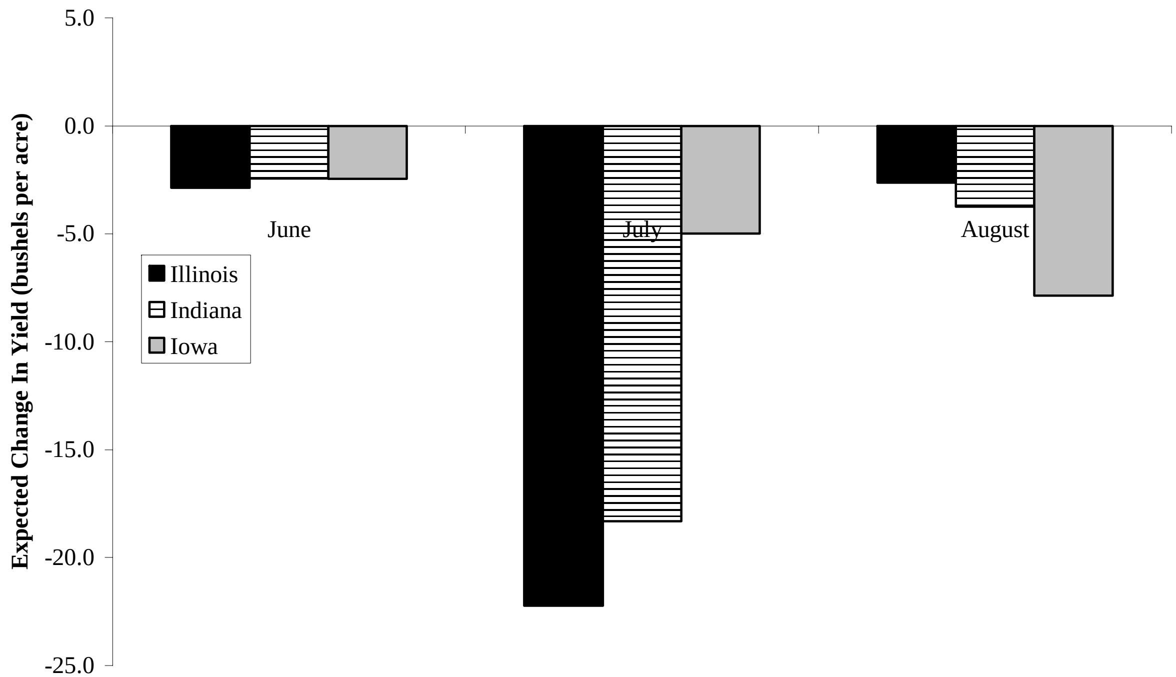


Figure 42. Expected Change in Corn Yields from Monthly Temperature in Illinois, Indiana, and Iowa, 1960-2006

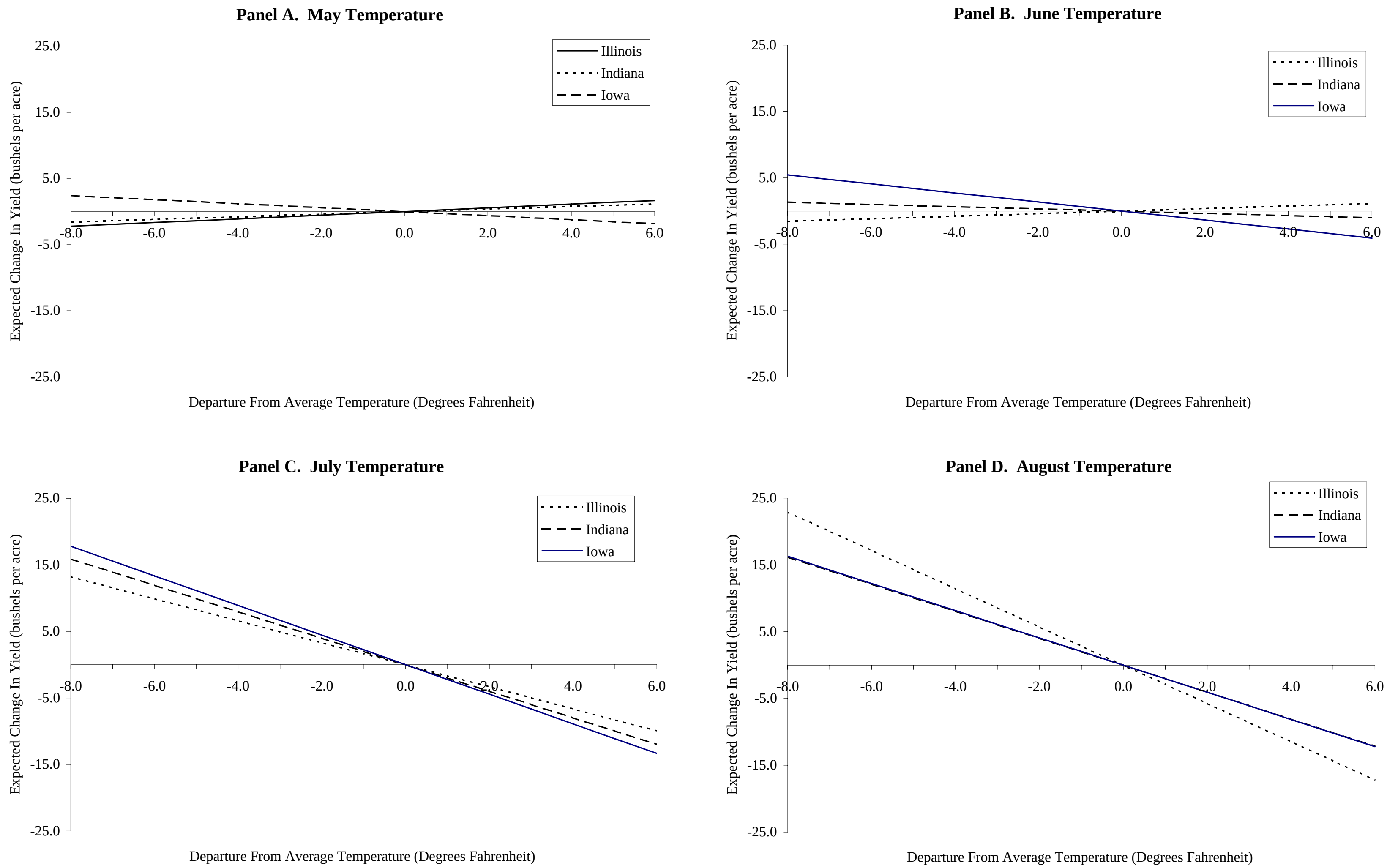
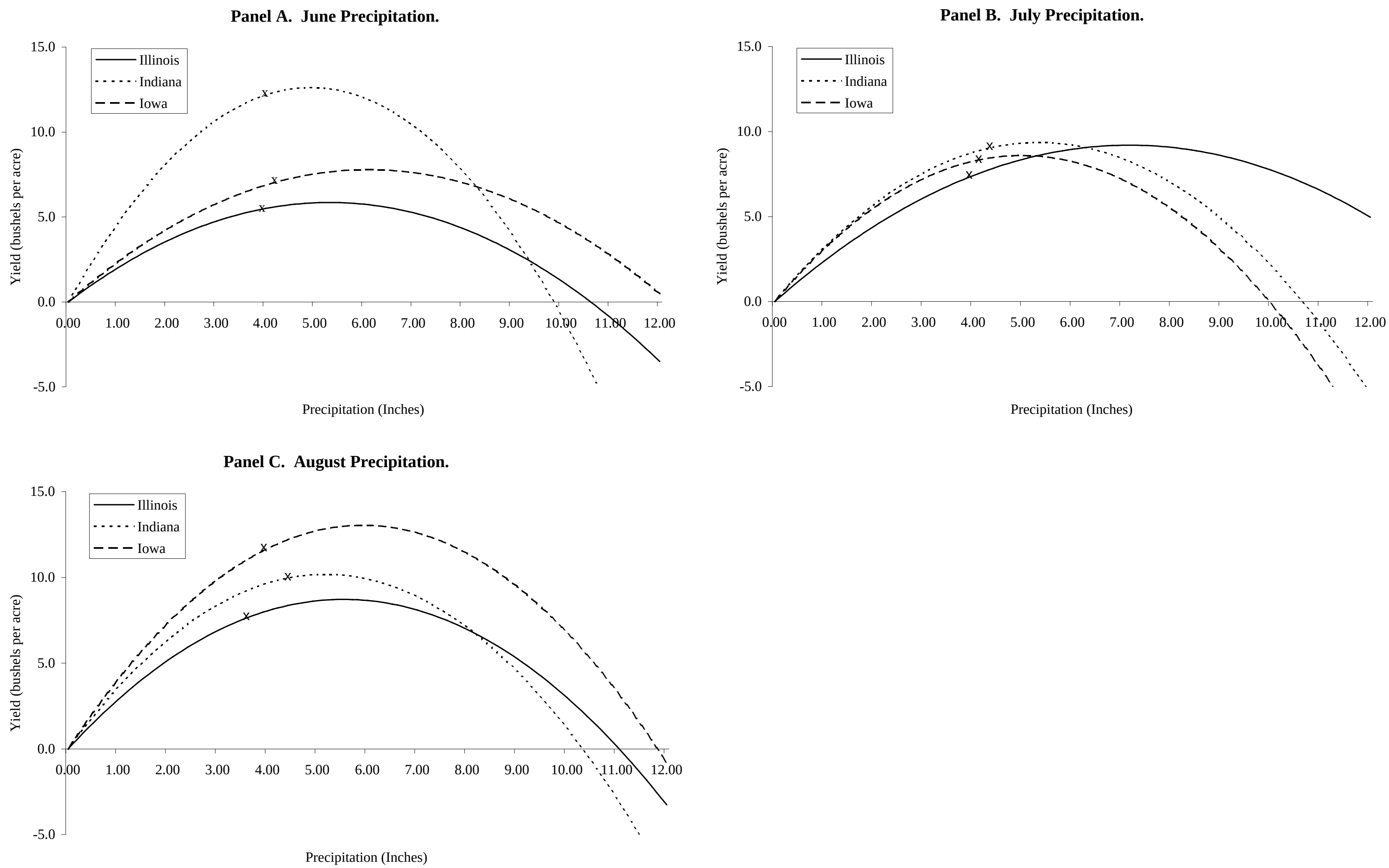


Figure 43. Expected Change in Soybean Yields from Monthly Precipitation in Illinois, Indiana, and Iowa, 1960-2006



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

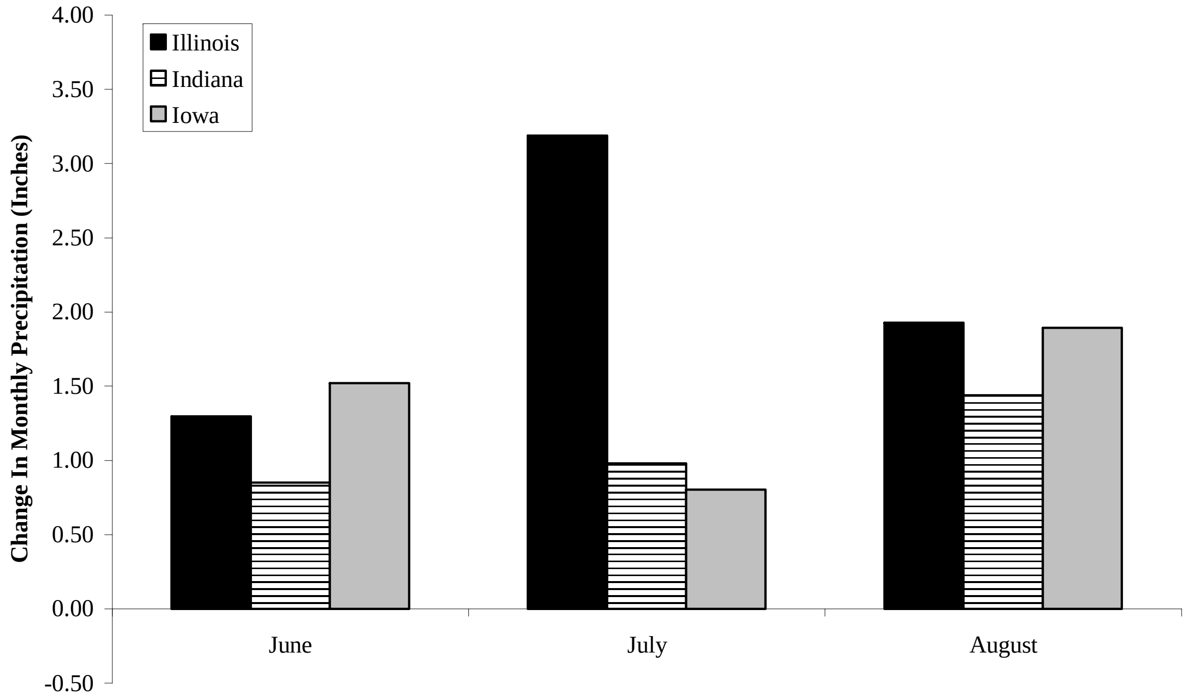


Figure 45. Change In Soybean Yields By Increasing Precipitation from Average to Optimum in Illinois, Indiana, and Iowa, 1960-2006

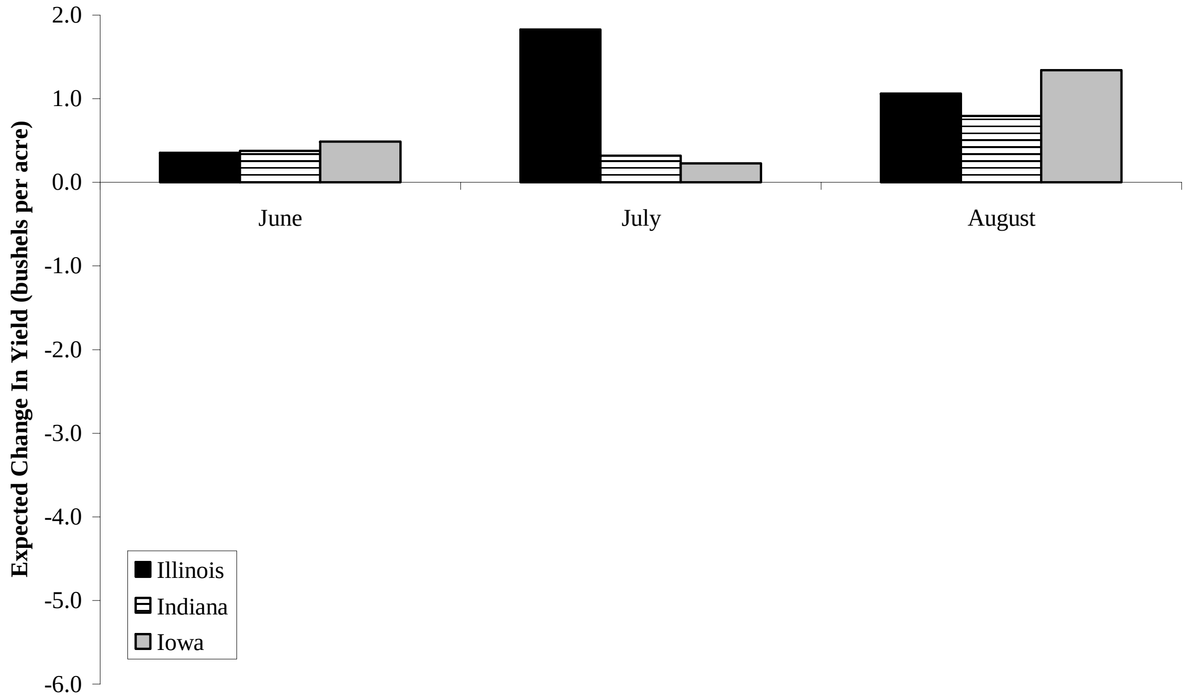


Figure 46. Change In Soybean Yields By Decreasing Precipitation from Average to Optimum in Illinois, Indiana, and Iowa, 1960-2006

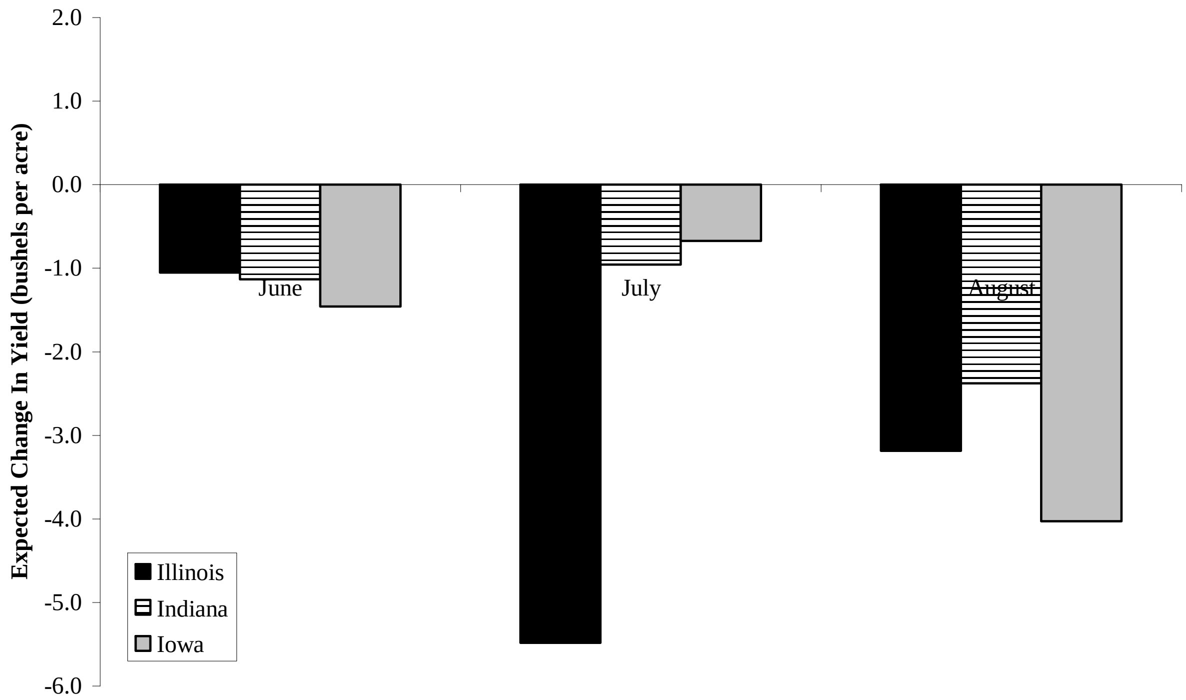


Figure 47. Expected Change in Soybean Yields from Monthly Temperature in Illinois, Indiana, and Iowa, 1960-2006

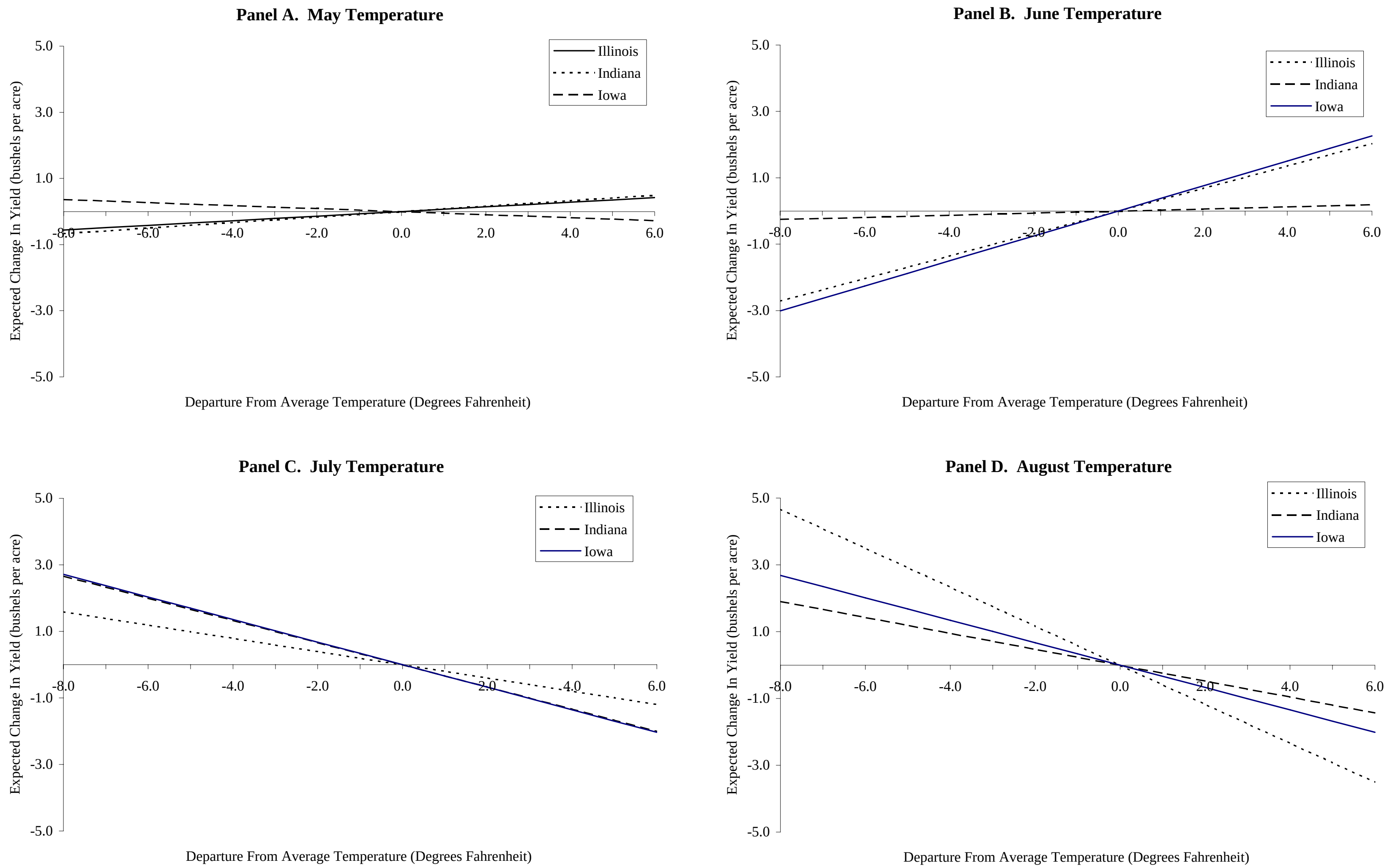
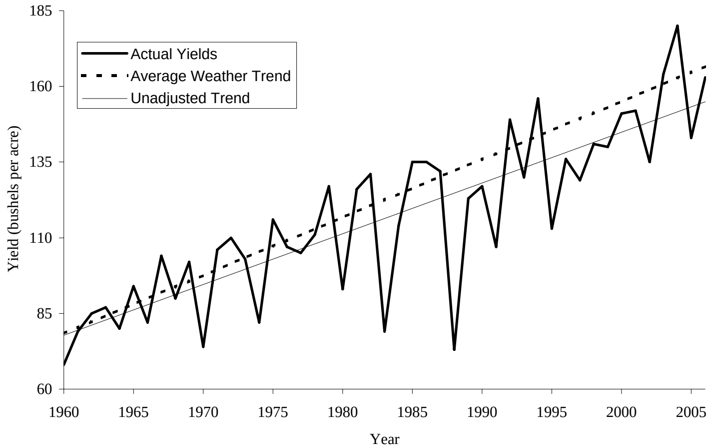
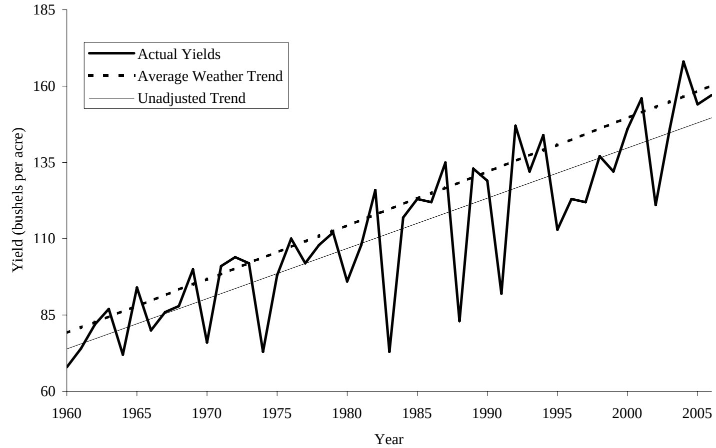


Figure 48. Average Weather Trend and Unadjusted Trend for Corn Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

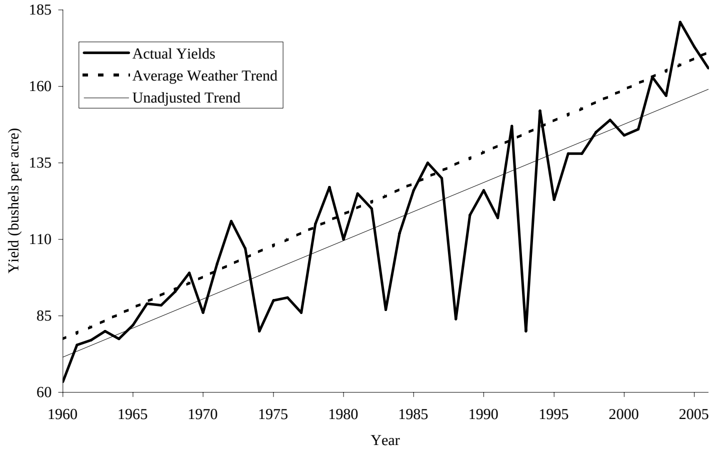
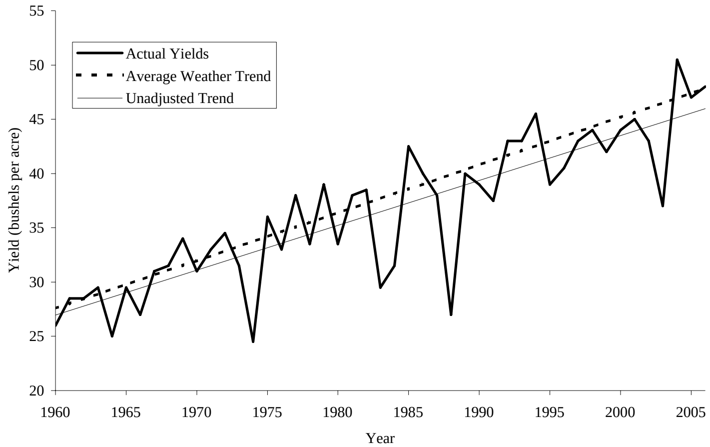
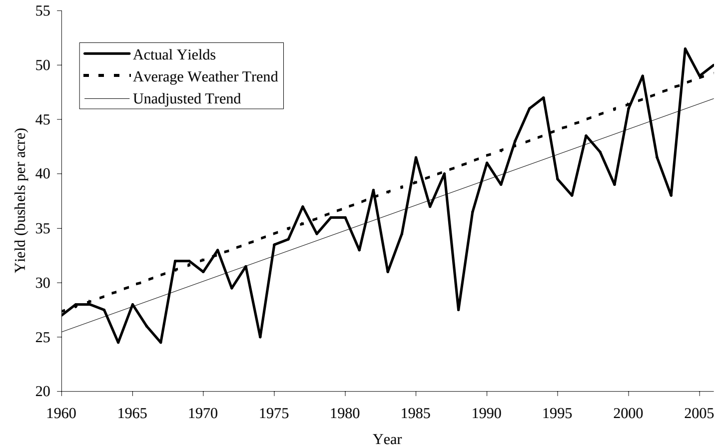


Figure 49. Average Weather Trend and Unadjusted Trend for Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

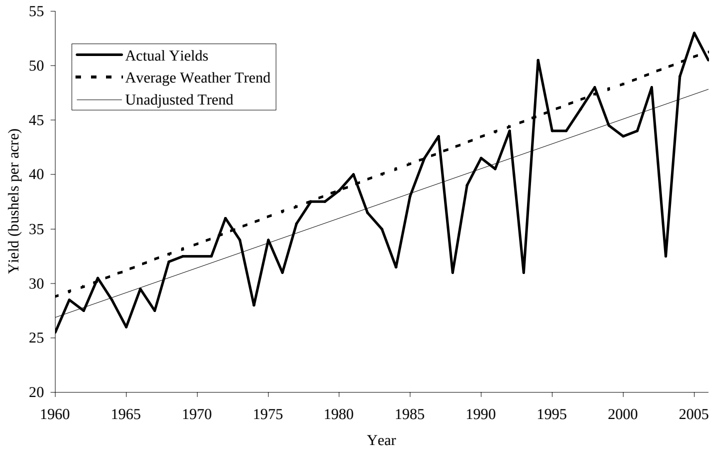
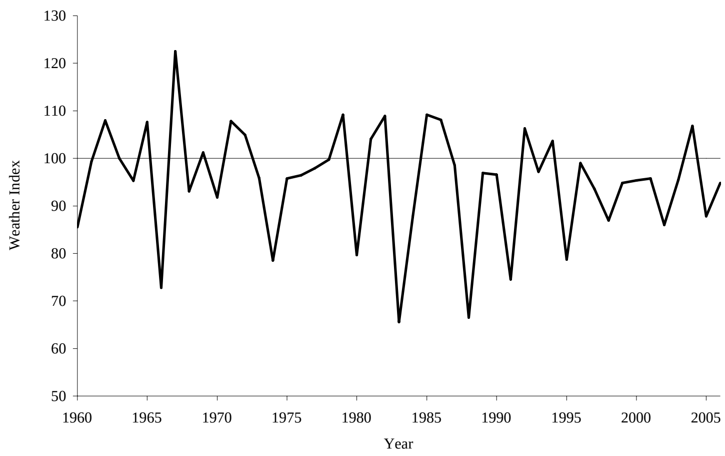
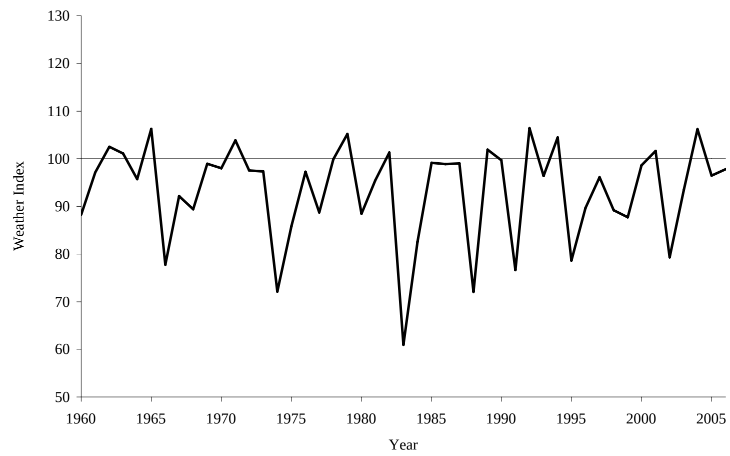


Figure 50. Corn Weather Indexes for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

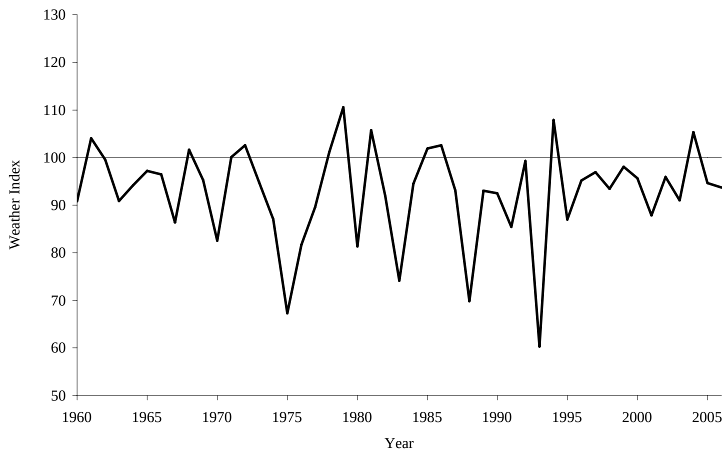
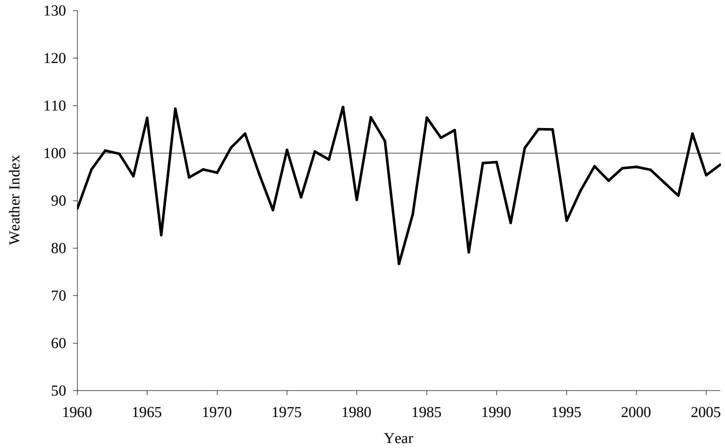
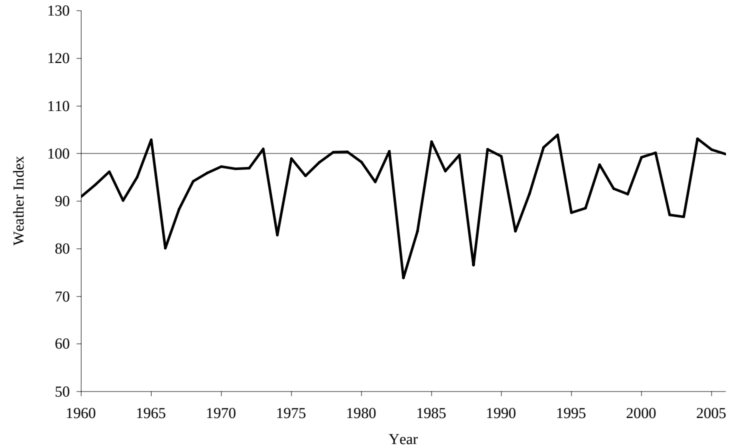


Figure 51. Soybean Weather Indexes for Illinois, Indiana, and Iowa, 1960-2006

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

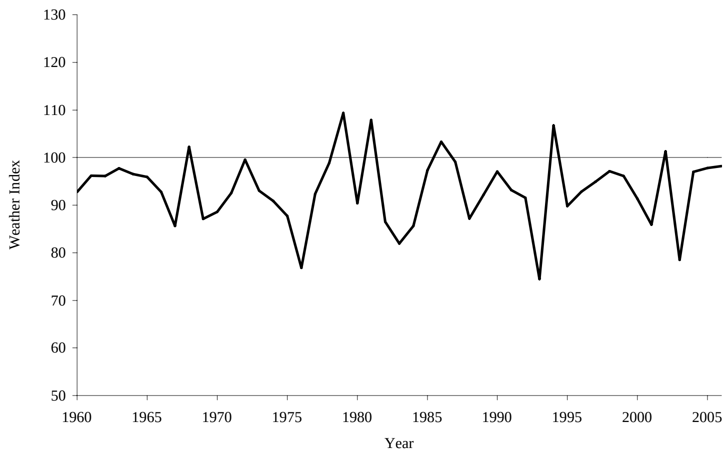
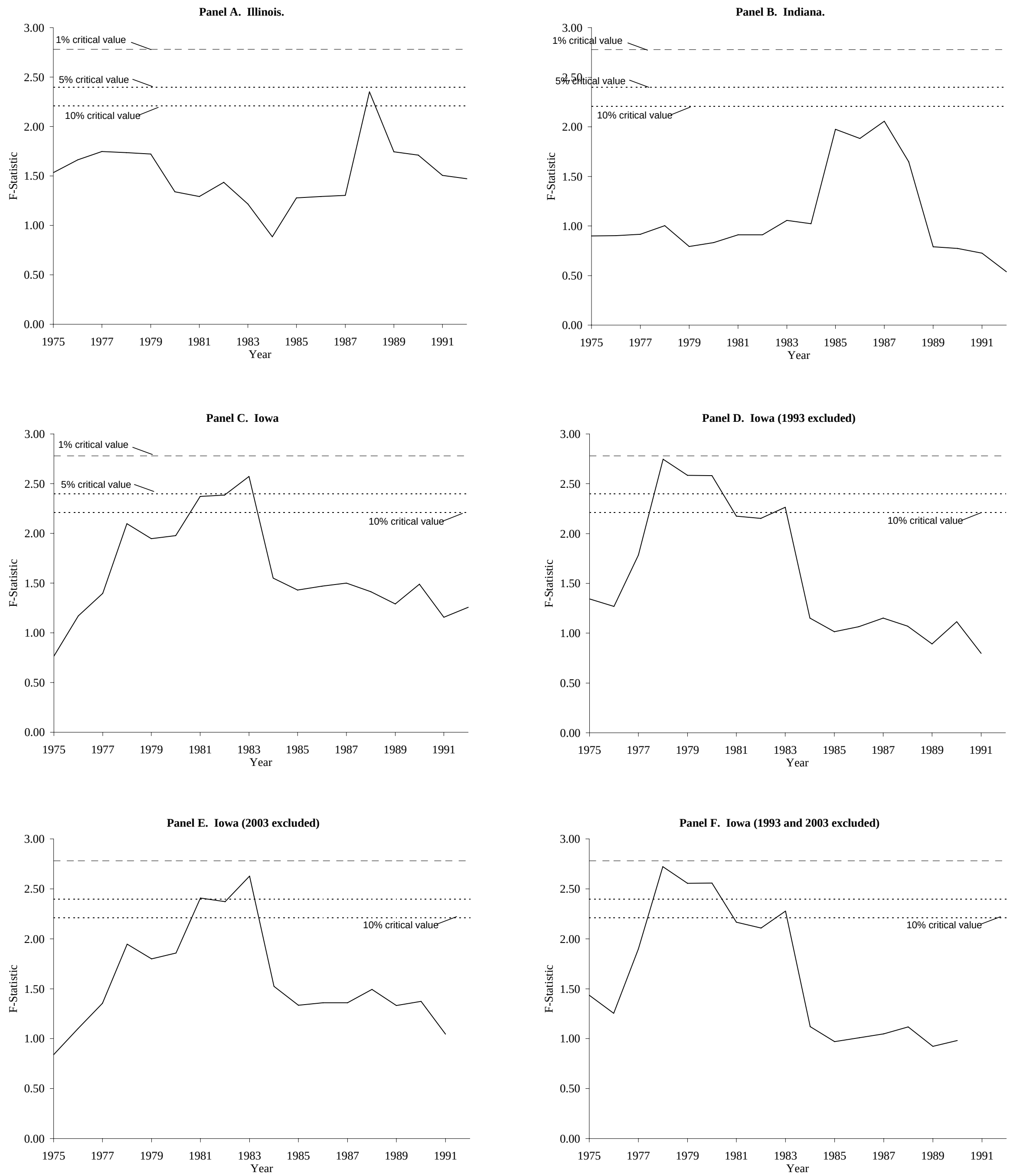
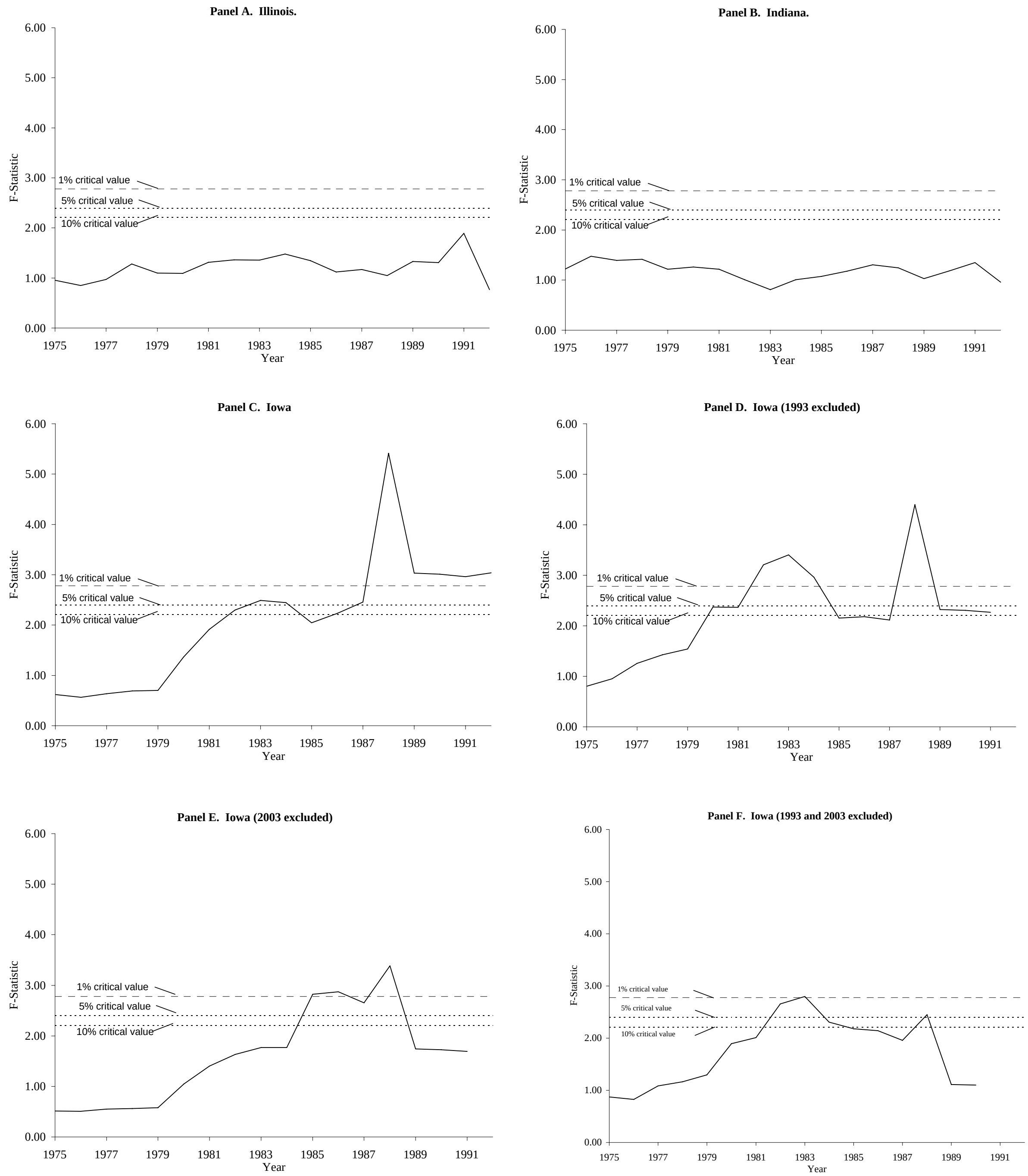


Figure 52. QLR Tests for Structural Change in Modified Thompson Models for Corn Yields in Illinois, Indiana, and Iowa, 1960-2006



Note: Dashed lines show the QLR-Statistic

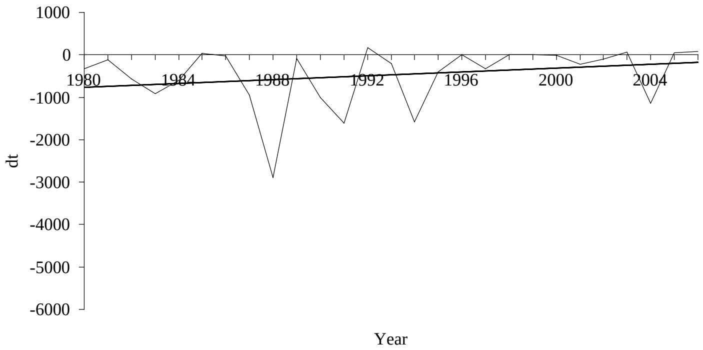
Figure 53. QLR Tests for Structural Change in Modified Thompson Models for Soybean Yields in Illinois, Indiana, and Iowa, 1960-2006



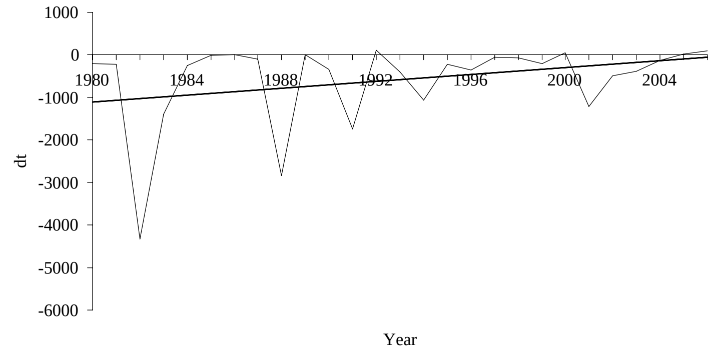
Note: Dashed lines show the QLR-Statistic

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

Panel A. Illinois



Panel B. Indiana



Panel C. Iowa

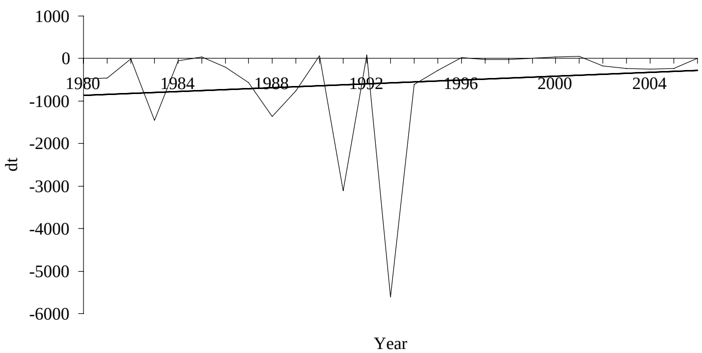


Figure 55. Relative Size of Squared Forecast Errors (d_t) for Modified Thompson Models and the USDA on September 1 for Soybean Yields in Illinois, Indiana, and Iowa, 1980-2006

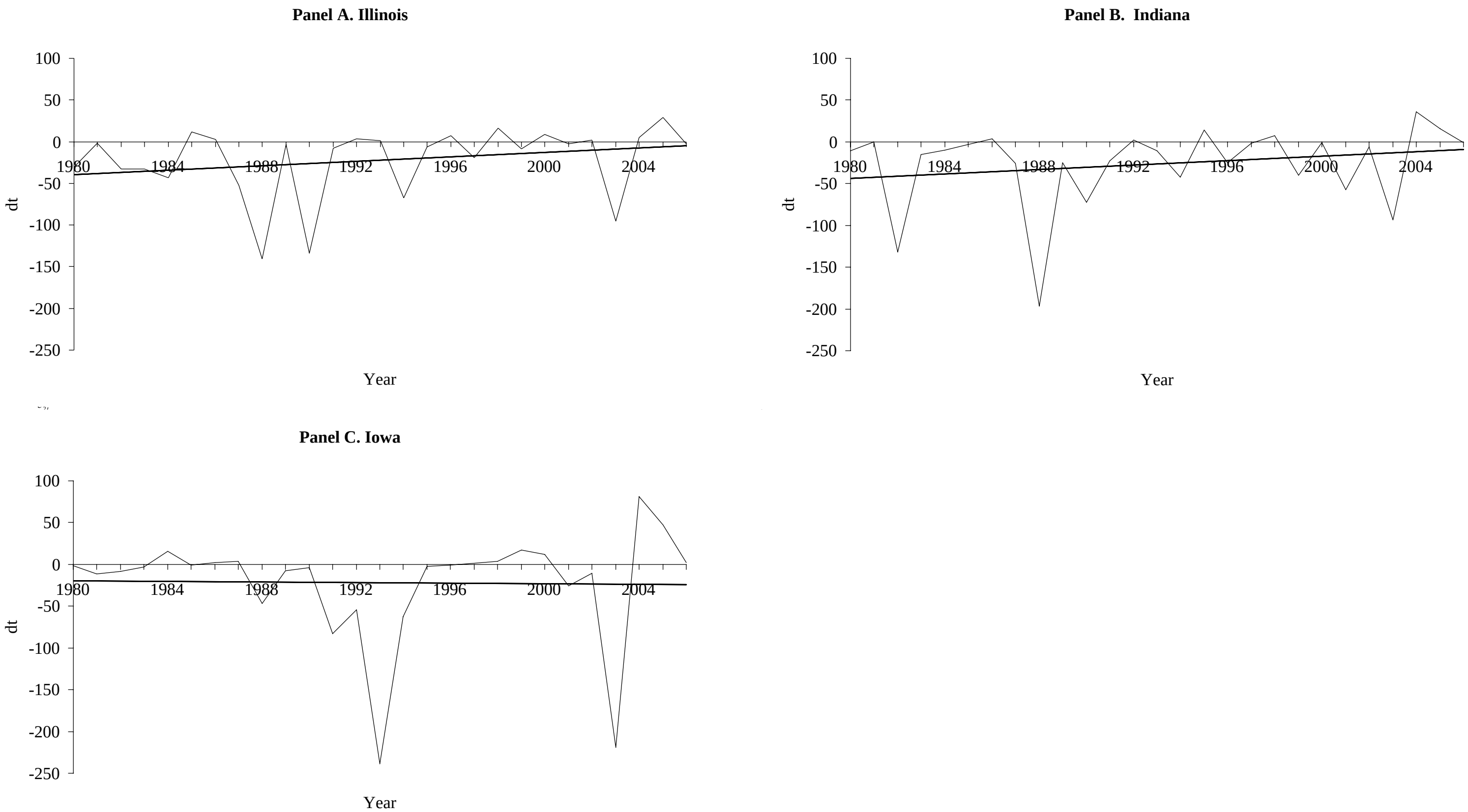
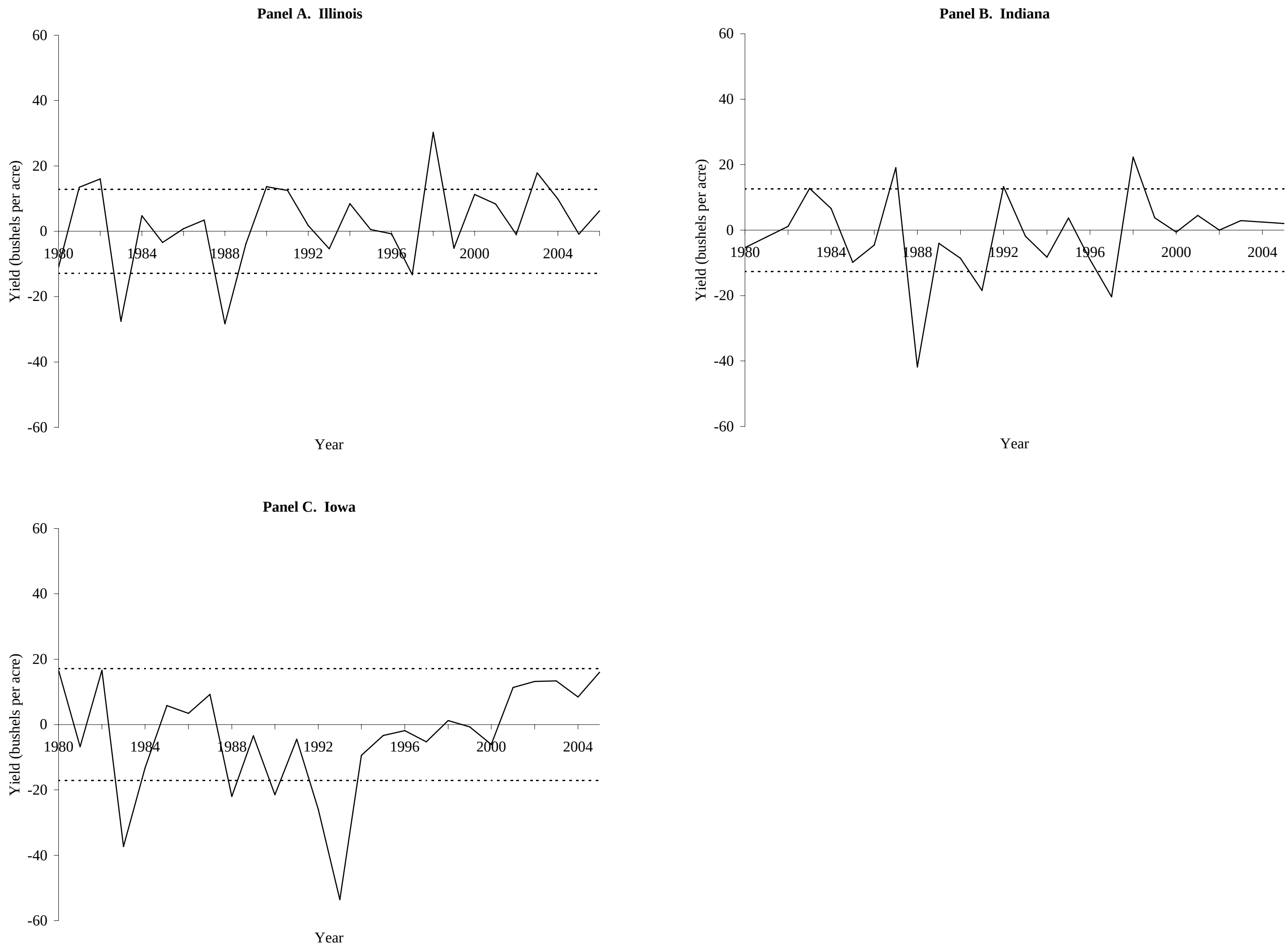
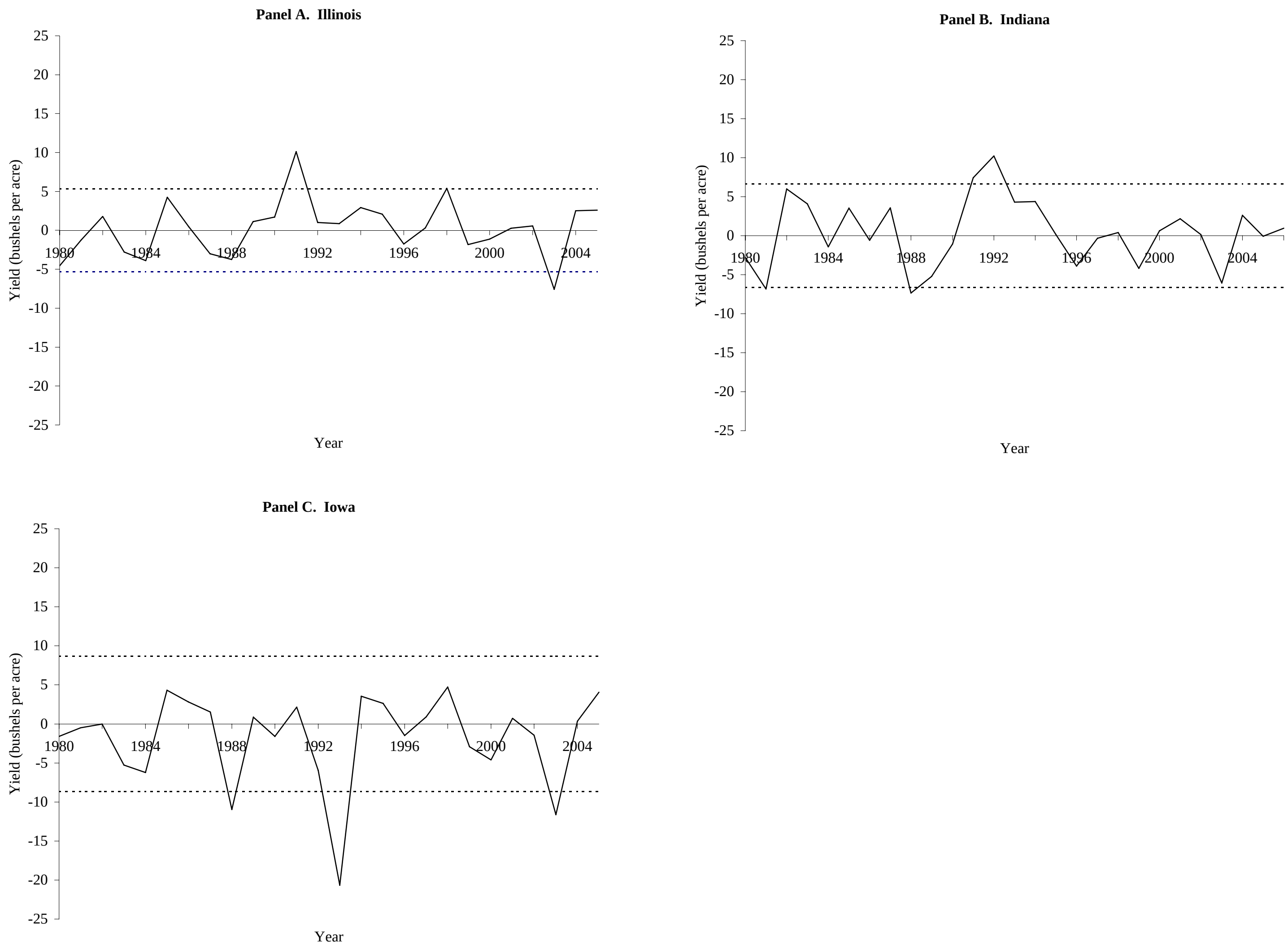


Figure 56. Out-of-Sample Forecast Errors for Modified Thompson Models of Corn Yields in Illinois, Indiana, and Iowa, 1980-2006



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



Note: dashed lines indicated the standard deviation of the forecast errors