South Dakota State University
Open PRAIRIE: Open Public Research Access Institutional Repository and Information Exchange

Electronic Theses and Dissertations

2014

# A Comparison of Corn Yield Forecasting Models

Nicholas Jorgensen
*South Dakota State University*

Follow this and additional works at: https://openprairie.sdstate.edu/etd

Part of the Agricultural Economics Commons

## Recommended Citation

Jorgensen, Nicholas, "A Comparison of Corn Yield Forecasting Models" (2014). *Electronic Theses and Dissertations*. 339.
https://openprairie.sdstate.edu/etd/339

This Thesis - Open Access is brought to you for free and open access by Open PRAIRIE: Open Public Research Access Institutional Repository and Information Exchange. It has been accepted for inclusion in Electronic Theses and Dissertations by an authorized administrator of Open PRAIRIE: Open Public Research Access Institutional Repository and Information Exchange. For more information, please contact michael.biondo@sdstate.edu.

# A COMPARISON OF CORN YIELD FORECASTING MODELS

BY

NICHOLAS JORGENSEN

A thesis submitted in partial fulfillment of the requirements for the

Master of Science

Major in Economics

South Dakota State University

2014

A COMPARISON OF CORN YIELD FORECASTING MODELS

This thesis is approved as a creditable and independent investigation by a candidate for the Master of Science in Economics degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

Matthew Diersen, Ph.D.
Thesis Advisor Date

Eluned Jones, Ph.D.
Head, Department of Economics Date

Dean, Graduate School Date

# ACKNOWLEDGEMENTS

I wish to thank the Wheat Growers Scholar in Agribusiness Management for the graduate research funding I received. Without this contribution, my graduate education would not have been possible.

I would like to thank all of the staff of the Economics department and at SDSU who I have had to pleasure to learn from and work with during my time at the university.

I would especially like to express my gratitude to Dr. Matthew Diersen for his guidance as my thesis advisor. The knowledge and experience I have gained while working under Dr. Diersen will be one of the most beneficial things that I will take away from my college career.

I would also like to thank Dr. Larry Janssen for his four years of assistance as my undergraduate advisor.

Finally, I am grateful to all my committee members for helping me finish out the final part of my graduate education.

Nick Jorgensen

# CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# ABSTRACT

A COMPARISON OF CORN YIELD FORECASTING MODELS

NICHOLAS JORGENSEN

2014

The purpose of this research is to compare and analyze several different yield forecasting methods. The study analyzes corn yields in Ohio and South Dakota for the years 1986 through 2012. A base model, with a trend and state dummy variable is developed. Two competing models, one with objective variables and one with subjective variables, are then developed as additions to the base model. The competing objective model is developed by adding accumulated growing degree days (GDD) and accumulated rainfall variables. The competing subjective model is developed by adding a USDA crop conditions index (CCI) variable. The models are estimated weekly between weeks 24 and 36 of the calendar year.

The three models are compared using several different criteria. Examinations of adjusted $R^2$ values, F-test values, and root Mean Squared Error (MSE) values are conducted, as well as statistical tests of the competing model forecast errors.

The results show that the competing subjective (CCI) model performs the best at forecasting corn yield during the growing season. It outperforms the base and objective models for the entire study period. With a minimum MSE of 8 bushels per acre, it is over 7 bushels per acre more accurate at forecasting yield than its competitors.

# Chapter 1: INTRODUCTION

## 1.1 Introduction

Crop yield forecasts are an important piece of information to many members of the agricultural industry. These forecasts help industry members make decisions about production, influence futures market prices, and can even affect international trade. Given the importance of information like this, many researchers have set out to determine effective processes to model yield. Members of the fields of economics and agronomy have developed effective models for aggregate crop yields. The models produced by these fields are typically built differently and also used for different purposes.

The economic side of the literature tends to focus on developing models to study yield forecasts as a tool to estimate price changes. For example, Bain and Fortenbery (2013) develop a yield model to estimate how crop conditions reports affect the futures prices of wheat. Another example of economic corn yield forecasting is developing a model that forecasts yield with a time trend variable. Isengildina, Irwin, and Good (2013) use this type of trend model to compare corn yields over several years. Fackler and Norwood (1999) also use this process as part of their larger yield model. This type of model is used to quickly, and fairly accurately, obtain a yield forecast over time.

The agronomic body of literature that focuses on forecasting crop yields is much larger and broader in its purposes. For the most part, though, crop yield models are formulated to test the effectiveness of a new way to model yield, or to test a new variable that may have a significant effect on yield. Thompson (1963) studied how weather and technology affect corn and soybean yields. Tannura, Irwin, and Good (2008) set out to test and improve Thompson's model by simplifying it and adding technology variables.

Economic and agronomic models typically differ not only in the purposes for which they are used, but also in the factors that make up the yield estimation and forecasting models. Agronomic models often contain many weather, production, and geographic variables.  A common theme with most variables in agronomic models is that they are objective. They use measureable facts and data with little to no subjective adjustments. Economic models, on the other hand, are often parsimonious and are comprised of variables that are either dependent on subjective decision making or are subjectively adjusted.

For example, Kruse and Smith (1994) show that state level yield can be effectively forecasted using indices of crop conditions. Crop conditions reports are issued by the USDA and are based on subjective assessments made by evaluators in the field. Despite using less concrete data, these economic models still work well at explaining yield.  Fackler and Norwood (1999) conduct a similar study, using crop conditions indices to forecast corn yield throughout the growing season. Models that use crop conditions data as an explanatory variable for corn yield have not been studied heavily in prior research because of difficulties with the amount of data available. Crop conditions data has only been available since 1986, meaning that when Kruse and Smith conducted their 1994 study, they only had 7 years of state level crop conditions data (1986 through 1993). This limited amount of data forced them to focus on all states that have available crop conditions data to get the necessary degrees of freedom for a valid statistical study. Fackler and Norwood (1999) faced a similar problem with their 1999 study, studying only 13 years of crop conditions data.

Conducting a study of forecasting corn yield with crop conditions indices with the amount of data available today is more feasible. Over 25 years of crop conditions data exists as of 2012, and while this amount of data may limit the ability to study just one state, pooling only two states worth of crop conditions data will provide substantial degrees of freedom.

## 1.2 Crop Conditions and Crop Progress Report

During the growing season the USDA releases weekly reports outlining crop progress and crop conditions on a statewide level across the nation. Released each week from late April through November, the report is compiled from a sample of more than 5000 surveys that outlines the crop conditions in 18 major crop producing states for corn (USDA-NASS, 2010). There are also crop conditions reports produced for other crops such as soybeans and cotton. The surveys used in the report are based on the subjective analysis of county level surveyors that make visual observations and discuss the conditions of the crop as well as stages of planting and growth with local farmers. As stated above, this data is subjective and the USDA provides no exact formula to the public explaining how surveyors determine their estimates. This eliminates the ability to test for consistency in their estimates. The USDA does review the consistency of the reports with reports from prior weeks and from the surrounding areas. This review helps ensure a more confidents in their reports (USDA-NASS, 2010).

When surveyors rate the crop conditions, they use a 5 level scale. Below is the description of each of the 5 levels, sourced from the USDA (USDA-NASS, 2009).

- *Very Poor* - Extreme degree of loss to yield potential, complete or near crop failure.
- *Poor* - Heavy degree of loss to yield potential which can be caused by excess soil moisture, drought, disease, etc.
- *Fair* - Less than normal crop condition. Yield loss is a possibility but the extent is unknown.
- *Good* - Yield prospects are normal. Moisture levels are adequate and disease, insect damage, and weed pressures are minor.
- *Excellent* - Yield prospects are above normal. Crops are experiencing little or no stress. Disease, insect damage, and weed pressures are insignificant.

Several factors go into deciding what condition a crop in a certain area is in. Weather factors, agronomic conditions, pest and disease factors, and local farmers' opinions are all considered before the surveyor makes the final crop conditions assessment. The fact that this array of factors is considered makes it plausible to assume that crop conditions data would be a good candidate for a variable in a model that forecasts statewide yield during the growing season. This is because crop conditions data implicitly contain much of the information that has been subjectively combined together into one value. Assuming the surveyors and processes used to generate this data are valid, crop conditions data contain the effects of many variables that make up agronomic yield forecasting models. Therefore, using the crop conditions data in a yield forecasting model may possibly allow for a model much less complex than most yield forecasting models.

One common approach to using crop conditions data in a yield forecasting model is to build a crop conditions index (CCI). CCI's, as they have been used in prior research, are a summation of the individual percentages in each of the five conditions classes. Each of these five percentages is weighted by a certain factor and summed together to form an index. This version of this approach has been used by Kruse and Smith (1994), Fackler and Norwood (1999), and Bain and Fortenbery (2013). Lehecka (2013) studied both crop progress and crop conditions reports, in an attempt to see if the release of these reports had any major effect on futures prices around the time of the report release.

Crop progress data outlines the progress of planting or the physiological stage the corn plant is in during the growing season. This information is released in tandem with crop conditions data, once available, during the growing season. The reports published up until planting is completed contain planting progress information. Planting progress is expressed as the percent of the anticipated crop that is planted at the end of the week. After planting is completed, the percent of the corn crop in each of five physiological subsequent stages of growth (emergence, silking, dough, dent, and mature) is contained in the crop progress report (USDA-NASS, 2009).

## 1.3 Problem Statement and Objectives

While both economic (mostly subjective) and agronomic (mostly objective) models have been shown to be effective, no formal comparison of these methods has been done. Formally comparing these models would help determine strengths and weaknesses of both types of models, and could also help determine the proper situations to use either type of model. This research intends to use subjective and objective modeling processes to answer several questions.

The first hypothesis this research will examine is how effective both objective and subjective models are at forecasting yield throughout the growing season. Because the models used in this research do not have much prior research to provide expected results, it is difficult to estimate how they will perform. While most models that use objective data are complex and contain many variables, an objective model that uses only accumulated growing degree days and accumulated rainfall is tested. This type of model will be similar to that of the one used by Schlenker and Roberts (2006). The goal is to test if a simplified objective model or a crop conditions based model is useful at forecasting yield and for determining if one type of model is superior to the other. Previous research has shown that models based on crop conditions indices can effectively explain corn yield (Fackler and Norwood, 1999). A comparison between these two types of models is helpful in guiding researchers on what type of model would fit their objectives best. It also helps determine if one type of model is statistically superior to the other, or if there exists no major difference between the two types. Developing more intuitive models that are effective at forecasting yield gives the opportunity to forecast yield using relatively simple calculations.

The second hypothesis to examine is comparing how well these models perform against a basic trend-line yield model. Trend yield models are often used for yearly yield comparison and analysis, and pitting models against this benchmark type of model will indicate their overall usefulness. Once again, the small amount of prior research on concise yield models like the ones used in this research limits the ability to anticipate results. If a yield model using objective or subjective variables cannot explain yield as well as a trend model, it may not be very useful. This comparison will be made to show the effectiveness of objective or subjective variables compared to a baseline trend model. Many objective and subjective variables can take substantial time and effort to introduce properly into a model, while trend models are generally easy to formulate. If adding subjective or objective variables makes the baseline trend model only slightly better, the model builder may not be entirely better off, having spent an inordinate amount of time and effort in adding variables with little value as a result.

The third, and possibly most important, hypothesis is to test how well these models forecast yield within the growing season. Most other models that have been formally tested are not useful for forecasting yield during the growing season, and are only useful towards the end of or after the growing season. The models tested in this research are expected to be effective at forecasting yield from near the very beginning of the growing season, and continue to work even better as the growing season progresses. A formal affirmation of this hypothesis will provide yield forecasters justification to use models that are useful during a major part of the growing season instead of only the end of the growing season.

## 1.4 Qualifications

There are several benefits and drawbacks to conducting a study like this. There are gaps in this subject left by prior research, and while all of them cannot be filled by one study, several can be investigated. The usefulness of crop conditions data, the effectiveness of less complex models, and the possible ability to forecast yield during the growing season are all questions investigated in this research.

The first benefit of this research is that the models used are quite straightforward, and contain noticeably fewer variables than other yield models. For example, Thompson (1963) develops a yield model with over 20 variables. Other researchers have done work to show that using fewer variables is still effective, but their processes of variable elimination can still be complex. For example, Martinez, Baigorria, and Jones (2009) developed climate indices using principal component analysis (PCA) to model corn yield in the southeast United States. These indices are made up of only relevant variables, but the PCA process is statistically complex. The models proposed in this research contain a maximum of five variables, developed by accumulating temperature and rainfall data and indexing crop conditions data. Because many people in industry use some sort of yield model, justifying the effectiveness of less complex yield models will open up the opportunity for others to forecast yield on their own. For those that use complex models on a regular basis, this research may save them time and effort by justifying the use of simpler models.

A further analysis of the usefulness of crop conditions data would be beneficial to those interested in yield forecasting. Many market analysts utilize crop conditions data, yet few formal studies have been conducted on the topic (Lehecka, 2013). The studies that have been done have had to deal with several issues because of few degrees of freedom. Conducting a crop conditions study today will be much simpler because enough data has been generated to study fewer states at a time. Using crop conditions data from two corn producing states, like South Dakota and Ohio, will be sufficient. Studying two states that are in different parts of the cornbelt in the United States, like South Dakota and Ohio, will allow for large weather events and regional bias to be eliminated. The benefits of testing the usefulness of crop conditions data to forecast yield will be to affirm that market analysts are in fact conducting reliable analysis.

Finally, the models used in this research are available for forecasting use throughout nearly all of the growing season. Rainfall and temperature data can be gathered from the day of planting until harvest, and crop conditions data can be analyzed weekly from around the time of general emergence in a given state. Trend models, which are also examined in this research, can be used to forecast yield before the crop has been planted. Typical yield forecasting models use variables that are not available until near the end of the growing season, rendering the models useless until that point. For example, Tannura, Irwin, and Good (2008) build a model that contains variables like the average temperature in August and total rainfall in August. Including this type of variable makes that model difficult to use until August has passed. Average or expected values can be entered into models like this, but doing this undoubtedly harms the accuracy of the model. Bypassing this problem, like this research does, allows the yield forecaster to generate reliable estimates during the growing season.

Despite potential benefits of this research, several drawbacks exist as well. The models studied are less complex and contain fewer variables than many other yield forecasting models. While this makes them easier to use, it may harm the overall effectiveness at explaining yield. That is not to say the models will not explain yield well, but explanatory power may be lost when a less complex model is developed. Also, while this research is plagued with fewer data availability issues than prior research on crop conditions data as a corn yield forecasting tool, a few problems still exist. There still is not yet enough crop conditions data available to study an individual state without concern over using too few degrees of freedom. This is the reason that South Dakota and Ohio are pooled together in this research. While this is a minor issue to overcome, studying an individual state is preferable if possible. Crop conditions data are also limited by not being reported any finer than at the state level. While it is collected at the county level, it is pooled together and issued at the state level. County level studies simply cannot be conducted with this type of data. The accumulated rainfall and growing degree data could be collected and studied at farm or county levels, but to allow comparison between the different models in this research, it is not.

## 1.5 Justification

Yield models play an important role in the agricultural industry. They are used to help estimate supply and demand for agricultural commodities, estimate prices, and determine agricultural productivity. Many different types of models are used to explain and forecast yield. Some models are only useable close to harvest, which limits their overall contribution to agricultural markets. Some models, though, are useable throughout the entire growing season. These models can be updated weekly or even daily, which can create major advantages for those who use them. Early season forecasts can help agribusinesses estimate crop volumes they may deal with during the coming growing season. Estimating crop volume can help these businesses make pricing decisions, guide decisions on when and where to build new storage locations, and help them determine input demands. Farmers and agricultural marketers can use the forecasts to make pricing decisions as well.

This research intends to test several yield forecasting models that can be used during the growing season. These models will be evaluated for accuracy and overall forecasting ability. By comparing these forecasting models directly against one another, the relative accuracy of these models can be determined. This information would be helpful for determining which type of model provides the best yield forecasts, helping avoid several potential problems. Take corn production in South Dakota for example. If this research finds that one type of in-season forecasting model is consistently 5 bushels per acre more accurate than another model currently used, major efficiencies can be gained from using the more accurate model. With nearly 6 million acres of corn in the state, a 5 bushels per acre accuracy improvement is equivalent to 30 million bushels of corn. This improvement in total estimated production can lead to better flow estimates, better pricing decisions, and better storage decisions that would have previously been guided by incorrect estimates. Ultimately, more efficient and beneficial decisions can be made by all members of the agricultural industry with more accurate yield forecasts.

# Chapter 2: LITERATURE REVIEW

This section evaluates yield forecasting approaches used in prior research to determine possible shortfalls or issues that new research can investigate. An overview of both objective and subjective modeling approaches provides examples of each type of model, which helps identify possible improvements this research can investigate.

## 2.1 Objective Models

Agronomic models can contain a vast array of variables, such as many types of weather variables, crop production variables (amount of fertilizer applied, planting date, etc.) and geographic variables. Nearly all variables included in these models are objective, built out of gathered facts about weather, production practices, and location. Occasionally variables are added that are derived from a subjective process, such as the Normalized Difference Vegetation Index (Teal, et al., 2006). Nonetheless, most variables in these models are objective. Boyer et al. (2013) model corn yield in several different cropping situations. They utilize a quadratic response plateau as their model for yield, where the crops response to nitrogen application is the variable used to explain yield in different rotations.

Most objective models are based mostly on weather related variables (Cai et al., 2013; Schlenker and Roberts, 2006; Tannura, Irwin, and Good, 2008). Some objective models can become very complex and can easily contain over 20 variables (e.g., Thompson, 1963). Often these terms are temperature and rainfall variables, plus squared values and interaction terms. Many of these models explain yield very well, depending on how they are specified. This is most likely because the model specifications are tested heavily to determine the best model formulation.

Thompson's model was based solely on weather related variables. The model included accumulated pre-season rainfall and monthly rainfall and temperature data from June to August. The monthly temperature and rainfall data are also squared, and several interaction variables between temperature and rainfall are included.

Previous research notes that models that contain quadratic specifications of temperature and rainfall often exhibit collinearity issues (Kaufmann and Snell, 1997). In 2008 several researchers set out to re-specify Thompson's model to eliminate any possible collinearity issues. The model was effective at explaining yield, most likely because so many variables are used in the equation. Tannura, Irwin, and Good (2008) reexamine and reformulate Thompson's model in their study and eliminate six of the variables. They ultimately develop a model similar to Thompson's model, eliminating the squared temperature and rainfall data, and the interaction terms.

Tannura, Irwin, and Good (2008) simplify an originally complex objective model by reducing the number of variables. This approach is similar to goals of other recent research. Cai et al. (2013) set out to model corn yield using climate indices. Using an index as a variable for explaining yield helps eliminate problems with degrees of freedom and over-specification. The approach they use is to take many commonly used weather variables and use Principal Component Analysis (PCA) to construct climate indices. Using PCA allows many weather variables to be used, while eliminating issues with multicollinearity, a problem that typically plagues weather models (Cai et al., 2013). While this approach is justified from the model building standpoint, eliminating multicollinearity and over-specification problems benefits the models from an economic standpoint as well. Eliminating these issues ultimately makes the models more intuitive, powerful and accurate. More accurate models lead to better yield estimates, which means better price and market condition estimates from an economic perspective.

The models discussed above are complex, either in the amount of variables included or the statistical processes used, but they explain corn yield well. However, these models only explain yield and do not forecast it. Given the nature of their specifications, they are used to explain the factors that affect yield, and are not always useful for forecasting yield. Nevertheless these models are useful for determining the time periods that rainfall and temperature have the greatest effect on corn yield, which can help guide the specification of other models. Therefore the objective models used in this research may lack similarity to these models, because they will be intended to be forecasting models.

Despite the amount of variables used in these models, factors like production practices are not included. This assumption implies that production practices do not have a major effect on yield. Several studies exist, though, that show production factors have a significant effect on yield.

For example, Westcott and Jewison (2013) develop a model for corn yield based on weather factors, as well as a planting date variable and a trend variable. This model is similar to Thompson (1963) and Tannura, Irwin, and Good (2008), but it includes a production practice variable. This model explained the variation in corn yield in the United States from 1988-2012 very well, with an $R^2$ of 0.964 (Westcott and Jewison, 2013). The performance of these models shows that very accurate yield estimates can be made by simply using the correct weather related variables and a few production practice variables.

Another example of a corn yield modeling process that is slightly less common than the processes above is a model using weather data and objective economic factors. Kaufmann and Snell (1997) develop a corn yield model based on several weather variables and economic and technological factors such as a measure of the CCC loan rate and the value of farm machinery. They argue, much like Tannura, Irwin, and Good (2008), that weather measured in calendar time periods is often ineffective. Alternatively, they measure rainfall amounts and temperatures during each of the physiological growth stages of the corn plant (Kaufmann and Snell, 1997). They add economic variables to account for the rationale that, depending on the economic climate, farmers may apply more or less inputs to their crop. They also proxy for the level of technology by including the value of farm machinery per acre to test the common assumption that technology has a major effect on corn yield (Kaufmann and Snell, 1997).

The models above use objective data to estimate yields. These models are generally very effective at explaining the variation in yield. Even though they are effective, these models are typically complex and can end up being rather un-intuitive. Often so many variables are added that the model becomes abstract and difficult to understand.

Another drawback of models that use objective data is that many of the variables used cannot be obtained until late in the growing season. For example, Westcott and Jewison (2012) use variables such as July temperature. By including this variable, the model itself simply is not useful until August, which is late into the growing season. The Tannura, Irwin, and Good (2008) model is not fully useable until even later in the season, because variables for August temperature and precipitation are included, rendering the model less effective until September. Climate averages could be used to get results from these models earlier in the growing season. However, using averages eliminates the unique variation in rainfall or temperatures that occur in a given month or year. These variations from average are most often the factors that drive major deviations from average yield, and eliminating them will reduce the effectiveness of the model. For example, using average rainfall during the summer months for a model to estimate corn yield in the drought year of 2012 would have greatly overestimated the amount of rainfall received in many states, and yield would have been overestimated. This type of possible error makes using these models for forecasting difficult.

Tannura, Irwin, and Good (2008) also note another shortfall of their model. When modeling weather on a monthly basis, events can be missed or the true effect of weather can be mis-represented (Tannura, Irwin, and Good, 2008). For example, the amount of rainfall in July can appear to be a sufficient amount that would be beneficial to corn yields. What can be missed by specifying it this way is that it is very possible that all of the rain fell in one event, and the rest of the month was dry. In this case, the amount of rainfall in July was not as beneficial to the crop as if it would have fallen in several events, and the true effect has been masked. This situation can also occur with temperatures.

## 2.2 Using Accumulated Growing Degree Days and Rainfall

One way to avoid the issues of not being able to use the models until late in the season and the misrepresentation of weather effects is to use accumulated growing degree days and accumulated rainfall as variables. Accumulated growing degree days and rainfall can be calculated on a daily basis, so a model can be estimated at any time during the growing season. This daily availability also eliminates the change of ignoring harmful or beneficial weather situations that do not occur on a monthly basis.

Teal et al. (2006) design a yield model that is related to mostly crop production or objective factors. Complex agronomic calculations such as Normalized Difference Vegetation Index (NDVI) were used to estimate yield potential. Their model initially contained no weather variables, but the researchers chose to normalize NDVI with growing degree days (GDD). GDD are calculated following Barger (1969):

$$GDD = \frac{T_{max} + T_{min}}{2} - 10℃\,,$$

where $T_{max}$ denotes the maximum temperature during the day and $T_{min}$ denotes the minimum temperature during the day. Accumulated GDD can be calculated by adding together every GDD from every day during the period being tested. Adding this variable essentially added the effects of weather into the model they used.

GDD is a variable that could be effectively used to proxy for weather in a yield model. GDD has not been utilized often in yield models. This is probably because other models developed by researchers use variables that show the same data as growing degree days. Temperature variables are similar to a GDD variable, and including both could result in collinearity problems. An exception is Schlenker and Roberts (2006), who develop a yield model based on a modified version of GDD, as well as a fixed location effect variable. They showed that corn yields show a strong, non-linear relationship to GDD.

## 2.3 Subjective Models

Subjective models for estimating yield are less common. Most subjective yield studies that have been done model yield to answer some economic question such as how yield changes may result in price changes, or how changes in prices or programs eventually affect yield. For example, Lehecka (2013) studies how the releases of crop progress and crop conditions reports affect the futures prices of corn and soybeans. Lehecka uses the work of Kruse and Smith (1994) and Fackler and Norwood (1999) as justification for assuming that changes in reported crop conditions change expected crop yields, and will therefore cause changes in crop prices. Kaufmann and Snell (1997) use a yield model that does contain economic variables, and some that are arguably developed by subjective processes. For example, they include a variable that measures the change in purchased inputs in their regression model. This variable is derived from marginal product theory, and is not directly measured. Unlike the Kaufman and Snell model, most economic models that have been developed typically use different variables than objective models.

Some economic models, though, estimate yield with objective variables to model price changes. Kantanantha et al. (2010) develop a model with a climate index formed using PCA, and use this index to model corn yield. They also include a GDP variable, and use this model to see how yield forecast changes affect futures prices.

One common trait among yield models is the use of de-trended yield data or the inclusion of a trend variable (Schlenker and Roberts, 2006). Despite this common theme, the approach of choosing when and how to de-trend the yield data or even whether or not to include a trend variable is an empirical and subjective decision. Some yield models used for analysis for historical yield are simply in-sample trend models. Isengildina, Irwin, and Good (2013) analyze corn yields by comparing actual corn yields to an in-sample trend model. This type of model is used very commonly by market analysts, as this type of model is easy to formulate and is useful for comparison.

Another example of an economic, subjective, yield model is a model that uses crop conditions data. Several studies have used the USDA's crop conditions reports to forecast corn yield such as Kruse and Smith (1994), Fackler and Norwood (1999), and Bain and Fortenbery (2013). While none of these studies have been published in academic journals, researchers such as Lehecka (2013) use their findings that crop conditions data can forecast yield to justify studying futures price changes after USDA report releases.

Economic models that utilize only a CCI and maybe a few more variables have obvious drawbacks as well. A model with only one variable or few variables can seem overly simplistic, especially when some models that exist for similar purposes can contain up to 20 variables. Also, crop conditions data are subjective, and therefore cannot be verified or tested for accuracy. Positively, though, using a CCI model is intuitive. It is easy to access the necessary data, and the model can be built in less time than may be necessary to build a more complex model. Kruse and Smith (1994) and Fackler and Norwood (1999) found that this method of estimation can produce statistically valid and effective forecasts of corn yield.

## 2.4 Controlling for Trend Yield

As mentioned in the introduction, a way to forecast corn yield is to estimate a trend yield over time (Isengildina, Irwin, and Good, 2013). This process is used in almost all research that models yield, although trend yield is not estimated specifically. Nearly all corn yield forecasting models, either subjective or objective, contain a control variable for time. This is because corn yields typically face a very strong upward trend over time (Zhu, Goodwin, and Ghosh, 2011). For example, the objective models above contain yearly control variables. Similarly, the CCI models also control for yearly changes in corn yield by estimating "deviations from trend yield" instead of simply estimating yield (Fackler and Norwood, 1999; Kruse and Smith, 1994). Deviations from trend yield are calculated by first estimating a trend yield model, and then using the difference from trend yield and actual yield as the dependent variable in their final model.

Controlling for time trends in corn yield models is necessary because over time general changes in the practices and technology used in corn production have caused a strong annual increasing trend in yield (Tannura, Irwin, and Good, 2008). The failure to control for this trend will render the results of most models incorrect.

## 2.5 Accelerated Technological Change

A consideration that has appeared in recent research is that since the mid-1990's the trend of corn yield growth has accelerated. Previous research seems to provide evidence of this phenomenon (Troyer, 2006). This is commonly attributed to technological improvements and vastly improved practices over the last several decades that have been adopted and driven faster growth in yield. For example, new corn varieties introduced since this time period, such as "Triple-Stack" hybrids, have shown increased yields (Below et al., 2007). This increase in the trend yield of corn over time has led researchers to accept that changes since the mid-1990's may need to be accounted for.

Tannura, Irwin, and Good (2008) test this common assumption in their research. They test for structural changes in the corn yield trend in the mid-1990's in Illinois, Indiana, and Iowa. They find no significant evidence that a clear change occurs during this time period. While this change may well have occurred over the course of several years, they find that no need exists to control for a specific technological change during this time (Tannura, Irwin, & Good, 2008).

## 2.6 CCI Formulation and Use

The studies that use crop conditions information to forecast crop yields convert the crop conditions numbers into a CCI. Crop conditions reports contain five levels of data, percentages of the crop that is in each of the five categories, and can easily be converted into an index that consists of just one number. Kruse and Smith (1994) sought to determine an average yield value associated with each of the five categories of crop conditions. They associate yield values with the conditions, and weight each state with a different time trend constant to account for spatial differences in yield. Because the study was done in 1994 and only 8 years of crop conditions reports existed, there were not enough observations to study only one or two states. Because such a limited sample existed then, they had to analyze crop conditions in every state. This added a degree of complexity that studies using crop conditions data today can avoid, because only one or two states need to be analyzed to get a significant amount of observations. Their results showed that a CCI can be used to accurately forecast yield during the corn growing season, and that the explanatory power of the model increases as the CCI used gets closer to harvest.

Fackler and Norwood (1999) utilize a similar process in their study of corn yield forecasting, with slight additions to the Kruse and Smith model. Notably, in addition to the variables Kruse and Smith use, they adjust for abandoned acres. Their rationale is that a larger fraction of corn in “very poor” condition leads to more acres that are likely to be abandoned. If this abandonment is not accounted for, the final yield can possibly be understated (Fackler & Norwood, 1999).

Bain and Fortenbery (2012) develop a CCI to model yield that is similar to the work done in prior research on the subject of CCI models. In prior research, average yields for each conditions category are determined and used as weights in the CCI model. Instead of determining average yields in each condition category, they simply weight each condition category by a scalar. This forms a CCI from which the final value is not equivalent to a yield, but rather the overall condition percentage of the crop.

The weights on each category decrease by increments of 0.25 as the quality decreases, from the weight on excellent at 1. Setting the weight on corn in very poor condition to zero eliminates any bias that could come from abandoned acres, assuming only corn in very poor condition is abandoned (Fackler and Norwood, 1999). This type of index is easier to formulate than that of the other CCI’s noted in the literature. The models of Kruse and Smith (1994) and Fackler and Norwood (1999) are quite different from the model of Bain and Fortenbery (2012). The earlier models generate CCI’s that are essentially overall condition of the corn crop in the states studied. The CCI used by Bain and Fortenbery is essentially the overall condition of the corn crop.

# Chapter 3: RESEARCH DESIGN

A research problem with respect to yield forecasting models has been identified and prior research on the subject has been evaluated. In this chapter, sources of the appropriate data to continue research on yield forecasting models are discussed, and data sources utilized in the research are outlined. Model specifications are developed. Possible specification issues are investigated. Finally, a framework for analyzing the results of the models is discussed.

## 3.1 Crop Conditions Data

The USDA has released crop conditions data for 18 states since 1986 for several crops, including corn. Therefore, 27 years (1986 through 2012) of useable data exist. Since there are slightly too few years to use crop conditions from one state, two states or several states can be combined to produce statistically robust analysis. The two states used in this research are South Dakota and Ohio. The reason for choosing states that are not in the same region is to eliminate any regional overlap and to show the effect of crop conditions reports on yield. For example, if two states such as South Dakota and North Dakota were used, it is highly possible that the same weather event could affect both states, and since weather variables are not specifically included in the analysis, their effect could bias the true effect of corn conditions reports on yield. Choosing two states that are far apart decreases the likelihood that the same weather events affect yields, therefore eliminating any bias that common events could cause.

Crop conditions reports are generally released between week 19 of the calendar year, which typically ends on May 16$^{th}$, and week 46, which typically ends on November 15$^{th}$. The earliest week that both South Dakota and Ohio have reports for every year is week 24, which typically ends around June 15th. The latest week that both South Dakota and Ohio have reports for every year is week 36, which typically ends around September 10th. Therefore, only the weeks 24 through 36 are analyzed in this research. Crop conditions data are available for every week for weeks 24 through 36 and every year from 1986 to 2012 for both South Dakota and Ohio.

### 3.2 Weather Data

Weather data for South Dakota and Ohio is available from the National Climatic Data Center (NCDC) website on a daily basis for the entire time period from 1986 to 2012 (NOAA, 2013). Maximum and minimum temperatures are available, which are the only two pieces of information needed to formulate growing degree days. Daily rainfall is also available.

To get a measure of state-level growing degree days and rainfall for South Dakota and Ohio, weather data from 3 locations in each state are used. The locations were chosen based on their location within the major corn producing regions of each state, which gives a representative sample of the weather that affects the corn crop in each state. In South Dakota, these three locations are Aberdeen, Brookings, and Yankton. Aberdeen is located on the northern end of the major corn producing region of South Dakota. Brookings is located on the east central end and Yankton is located at the southern end of the corn producing region of South Dakota. In Ohio, the three locations used are Columbus, Sidney, and Bowling Green. Columbus is located on the south-eastern edge of the major corn producing region in Ohio. Sidney is located on the west central edge of the major corn producing region and Bowling Green is located on the northern edge of the major corn producing region in Ohio.

From 1986 to 2012, all three locations in South Dakota have complete weather data for each year. However, several years in Ohio are missing data from the weather stations in Sidney and Bowling Green. In 1992, the weather data from Bowling Green is missing many days during the growing season, and is unusable. Therefore, in 1992 only weather data from Sidney and Columbus are analyzed. In 2008, data from both Bowling Green and Sidney are unusable. To get a more representative sample of weather data in 2008, weather data from Findlay is added into the analysis. Findlay is located between Bowling Green and Sidney, and is analyzed with Columbus for 2008.

The minimum and maximum temperature data for each location from the NCDC is denoted in tenths of degrees Celsius, which is converted to degrees Fahrenheit. This conversion will make model results easier to interpret. The rainfall data for each location from the NCDC is denoted in tenths of millimeters. The data are converted to inches for easier model interpretation for those familiar with the US standard measurement system.

Accumulated GDD and accumulated rainfall data are calculated for each location in both states and then aggregated together by state. The average of all three locations in each state is taken for both GDD and rainfall to get state-level measures of GDD and rainfall.

## 3.3 Calculation of a CCI

The method used for computing the CCI for a given week is:

$$CCI = (\%Excellent) * 1 + (\%Good) * 0.75 + (\%Fair) * 0.5 + (\%Poor) * 0.25 + (\%Very\ Poor) * 0$$

This CCI is the one proposed and used by Bain and Fortenbery (2013). This CCI ranges in value from 0 to 100, where a CCI of 100 indicates that 100% of the crop is in excellent condition and a CCI of 0 indicates that 100% of the crop is in very poor condition (Bain and Fortenbery, 2013). The CCI is calculated on a weekly basis between weeks 24 and 36 for South Dakota and Ohio.

## 3.4 Calculation of Accumulated Growing Degree Days and Rainfall

The formula used for calculating growing degree days is:

$$GDD = \frac{T_{max} + T_{min}}{2} - T_{Base} \text{ ,}$$

from McMaster and Wilhelm (1997). This formula is a more general calculation of growing degree days than the one used by Teal et al. (2006), and can be used with temperatures in either Celsius or Fahrenheit. This formula, while including base temperature, leaves out a temperature threshold, which is a key factor in GDD for corn. Typically, corn GDD are bounded by a maximum temperature threshold, $U_T$. Adding this maximum threshold changes the equation to:

$$GDD = \frac{T_{max}+T_{min}}{2} - T_{Base}\ if\ T_{max} < \ U_T\ or\ GDD = \frac{U_T+T_{min}}{2} - T_{Base}\ if\ T_{max} \geq \ U_T.$$

Similarly, GDD are also typically bounded by a minimum temperature threshold, $L_T$. $L_T$ and $T_{Base}$ are equivalent. Adding this minimum threshold changes the equation to:

$$GDD = \frac{T_{max}+T_{min}}{2} - T_{Base}\ if\ T_{min} > \ L_T\ or\ GDD = \frac{T_{max}+L_T}{2} - T_{Base}\ if\ T_{max} \leq \ L_T.$$

The minimum and maximum temperatures are typically 50°F and 86°F respectively (NDAWN, 2013). This temperature threshold varies for crops, but 50-86°F is the commonly used threshold for corn. Outside of this range temperatures become stressful on the corn plant. Schlenker and Roberts (2006) affirm the fact that temperatures above 86°F are stressful on a corn plant.

After growing degree days are calculated, they are accumulated for each year at each location. They are accumulated daily after the approximate date that 50% of the corn crop has been planted. Once each location has been accumulated for the growing season, they are averaged with the other locations in each state.

Accumulated rainfall at each location is calculated similarly. Starting at the approximate date that planting is 50% completed, each rainfall event is added together throughout the growing season. Once the entire growing season is accumulated at each location, all locations in each state are averaged together.

### 3.5 Calculating the Approximate Mid-planting Date

Crop progress and conditions reports are released on a weekly basis. Despite this, planting takes place on a daily basis. This makes it highly likely that the date on which 50% of the corn crop has been planted in a state will not fall on a report release date. In these cases, the mid-planting date falls between two consecutive reports. Therefore, the date at which 50% of the corn crop is planted has to be approximated.

The reports surrounding the mid-point were identified for each year by state. It was assumed that planting progress was constant during those weeks. Daily planting progress was then added to the starting week's date until 50% planting progress was achieved. Then the day in the week closest to the interpolated midpoint, a calendar date, was used as a starting point to record accumulated weather variables.

### 3.6 Specification of a Trend Model

The first step in the modeling process in this research is to develop a trend yield forecasting regression model:

$$Yield_{si} = \alpha_0 + \alpha_1 * Trend_i + \alpha_2 * SD_s + e_{0t} \ ,$$

where $Yield_{si}$ is the final corn yield for state $s$ in year $i$, specified as a function of an intercept term, the trend value in year $i$, $Trend_i$, and the dummy variable for state $s$, $SD_s$. $SD$ equals zero for South Dakota and one for Ohio. Year $i$ takes on a value of 1 in 1986. The USDA has collected state-level yield data for a much longer period than crop conditions data, but for direct comparison with the other models in this research, the same time period is used. Therefore, 26 years of data is used for the trend model. A comparison between the trend model and the CCI will still show the relative usefulness of each model. The coefficients are the effects each variable has on yield. A model specification very similar to this will be used for the CCI and weather models in the rest of the research. Note that the CCI and climate models specified below are variations on this trend model. The CCI and climate models are designed to estimate how CCI and climate variables can explain corn yield deviations from trend.

### 3.7 Specification of the CCI Model

Prior research has shown that a CCI can explain the variation in final corn yields (Kruse and Smith, 1994; Fackler and Norwood, 1999; Bain and Fortenbery, 2013), and this result is quite intuitive. A crop that is evaluated to be in mostly “very good” condition is expected to have a higher final yield than a crop that is in mostly “poor” condition. Given the intuition that crop conditions should have an effect on yield, the year to year variation in crop conditions should add explanatory power to a trend yield forecasting model. Therefore, adding a CCI variable to a corn yield trend model will be tested to examine how much explanatory power is added to the model. The CCI regression model is specified as

$$Yield_{si} = \alpha_0 + \alpha_1 * Trend_i + \alpha_2 * SD_s + \beta_1 * CCI_{sij} + e_{1t}$$

where $Yield_{si}$, $Trend_i$, and $SD_s$ are specified as they were in the initial trend model. $CCI_{sij}$ is the crop conditions index for state *s* in week *j* of year *i*. Week *j* ranges from 24-36, which is the set of weeks that has available crop conditions reports for each state in each year. A regression will be estimated for each week between weeks 24 and 36, with only the CCI in the week of estimation being used. The effect of the CCI on corn yield, $\beta_1$, will be the effect of concern in this model. This value will show whether the overall effect of the CCI used in this model significantly explains part of the variation in corn yield. The expected sign on the CCI coefficient is positive, as a higher CCI should indicate a higher final yield.

## 3.8 Specification of the Climate Model

The work of Schlenker and Roberts (2006) shows GDDs have an effect on overall corn yield. Prior research that uses objective models to explain corn yield utilizes temperature related variables (Cai et al., 2013; Schlenker and Roberts, 2006). Therefore, accumulated GDDs can be added to a trend yield model to test how it improves explanatory power. Rainfall is another variable that can be justified for use in a corn yield forecasting model. As with temperature related variables, many prior objective models use rainfall data as a variable to explain corn yield (Martinez, Baigorria, and Jones, 2009; Tannura, Irwin, and Good, 2008). Therefore, accumulated rainfall is also added to the trend yield model. This leads to a regression model specification:

$$Yield_{si} = \alpha_0 + \alpha_1 * Trend_i + \alpha_2 * SD_s + \beta_2 * GDD_{sij} + \beta_3 * Rain_{sij} + e_{2t},$$

where $Yield_{si}$, $Trend_i$, and $SD_s$ are specified as in the first equation. $GDD_{sij}$ is the accumulated growing degree days for state *s* as of week *j* of year *i*. $Rain_{sij}$ is the accumulated rainfall for state *s* as of week *j* of year *i*. The coefficients, once again, are the effects that each variable has on final corn yield. $\beta_2$ and $\beta_3$ are the effects of concern in this model, to determine if growing degree days and rainfall have a significant effect on corn yield.

The expected sign of the coefficients is difficult to estimate, as little previous research is available for direct guidance. Schlenker and Roberts (2006) find that temperature has a non-linear effect on corn yield, with yield increasing as temperature increases until the threshold of 30°C (86°F) is reached. Once this temperature is surpassed, they find that the heat becomes harmful to the corn plant and its yield (Schlenker and Roberts, 2006). Because the GDD formula used is structured to omit temperatures above 86°F, the sign on $\beta_2$ is expected to be positive. This is because only temperatures that are beneficial to the corn plant are measured. The expected sign of $\beta_3$ is positive, as more rain over the course of the growing season should increase final corn yield. Schlenker and Roberts (2006) determined that any rainfall above 26 inches during the growing season can become harmful. Nonetheless, rainfall amounts during the season larger than this are uncommon, and therefore the positive effect of rainfall should be shown in the model.

## 3.9 Comparison of Forecasting Models

The trend model is estimated for each year from 1986 through 2012. The CCI and climate models are estimated for weeks 24 through 36 for both South Dakota and Ohio from 1986 to 2012. Both models in each week have a total of 54 observations, or 27 years for both states. Given that both the CCI model and weather model are estimated over the same time period and using the same dependent variable, it is relatively easy to compare the two. The models for each week can be compared to see if one model is better at explaining yield throughout the entire growing season. Time periods over which both models are effective at explaining yield will also be determined. This analysis may show which type of model is superior for a given forecasting horizon. Given that the CCI and climate models do not exist outside of weeks 24 to 36 of the growing season, the trend model is expected to be the best option for forecasting yield before that time period. Once in the week 24 to 36 time period, model explanatory power will guide which model will be the most appropriate for forecasting yield during the growing season.

Several methods of comparison will be used to evaluate the three models tested in the study. The first will be a comparison of adjusted $R^2$. The model with the highest adjusted $R^2$ explains the most variation in state level corn yield of the models. The other test that will be conducted is an examination of the mean squared error (MSE) of the regression models. The MSE determines by how many bushels per acre each model is incorrect on average. The MSE can be interpreted in the same units as the dependent variable, which is corn yield, so the MSE from each of the models can be compared directly. A stronger or more accurate model will have a smaller MSE.

A method of comparing the MSE of the three models will be to graph them through time. Given that the trend model is only estimated once for the growing season and the CCI and weather models are estimated weekly, a depiction of the models throughout the growing season will be helpful to show the performance across models. Figure 1 depicts a representation of what this test will be assumed to look like graphically.

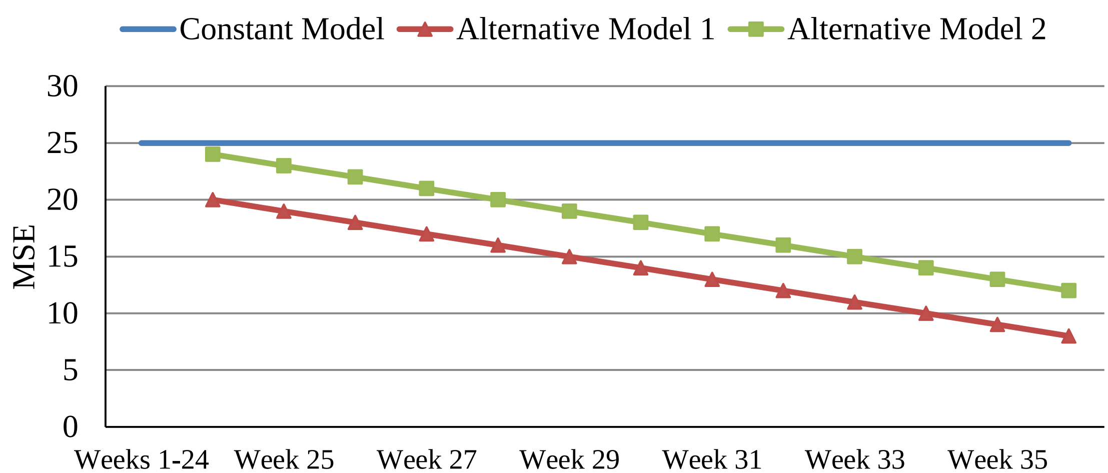


Figure 1. Depiction of Model Dominance.

The constant model represents a model like the trend yield estimation model used in this research (Figure 1). The expected constant shape for the trend model across the time period is because no additional information is added to the model and it is only estimated once, meaning the results will not change. Alternatives 1 and 2 represent models like the CCI and weather models. The general downward slope of the alternative models' MSE is based on assumptions about the behavior of the models as time progresses (Figure 1). As the growing season progresses, new data are produced that should allow the alternative models to improve in their forecasting accuracy.

A lot of information can be gleaned about the dominance of one model over the others through time. Whichever model has the lowest MSE on the graph at any given point in time indicates it is the most accurate. Depicting this through time makes it possible to evaluate which model is the best at a certain point throughout the growing season, and the degree to which it is better can also be determined.

In Figure 1, the MSE lines from each model type never cross. This makes observations about which model is the best at any given point in time easy to determine, because alternative 2 is always superior to alternative 1, which is always superior to the constant model. Problems could arise, though, when making assumptions of model dominance based on a graph if the MSE appears differently than in Figure 1. In Figure 2, for instance, there are several points in time when one model crosses another. There is a lack of clear dominance in this setting. This possible situation makes it nearly impossible to definitively say which model is better than another only by examining a graph. In

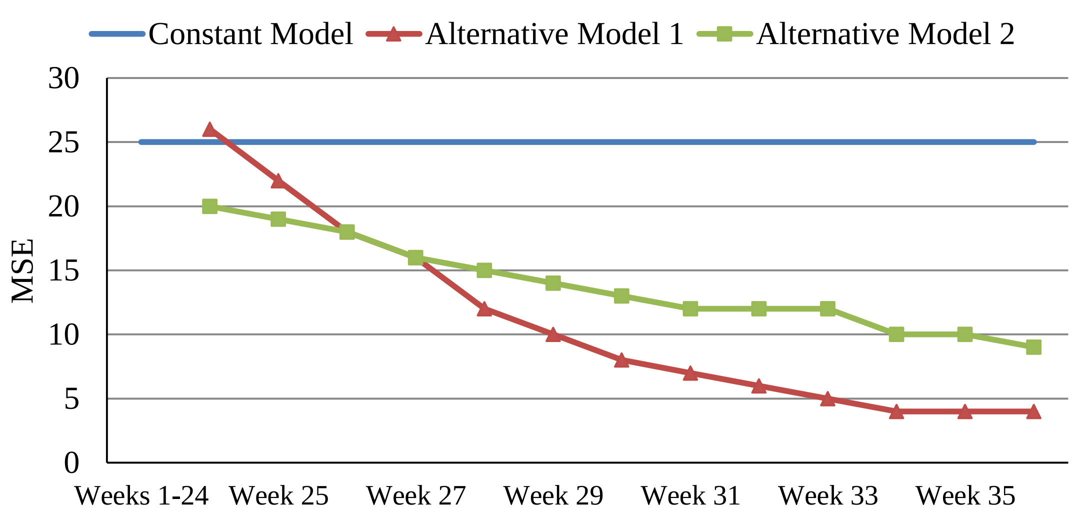


Figure 2. Alternative Depiction of Model Dominance.

essence, the MSE is inconclusive about the superiority of the three models, and additional statistical testing must be conducted.

### 3.10 The DM and MDM statistic

One statistical method that can answer the question of forecast dominance is the use of the DM or MDM statistic. The DM statistic was designed by Diebold and Mariano (1995) as a statistic that can be evaluated by a t-test. The approach uses an error differential, $d_t$, defined as:

$$d_t = (e_{1t} - e_{2t}) * e_{1t},$$

using the residuals from two competing models, $e_{1t}$and $e_{2t}$. $d_t$ is calculated for each forecasted period. The next step is to take the average of $d_t$ across all forecasted periods and divide it by its standard error. This gives the DM statistic. The statistic is useful for forecasting models that only forecast one period, or horizon, ahead.

For models that exceed one forecasting horizon, adjustments need to be made. Harvey, Leybourne, and Newbold (1997) proposed a modification to the DM statistic that adjusts for multiple forecasting horizons, creating the MDM statistic. The MDM is calculated as:

$$MDM = n^{-1/2}[n + 1 - 2h + n^{-1}h(h - 1)]^{1/2} * DM ,$$

where n is the number of observations, h is the number of forecasting horizons, and DM is the Diebold-Mariano statistic. This statistic can be compared to a critical value on the $t_{n-1}$ distribution. If the MDM statistic exceeds the critical value, then there is a statistically significant difference between the forecasting errors of the two competing models. Colino and Irwin (2007) use this statistic to evaluate the forecast error differentials between hog and cattle outlooks and futures prices. This research will use the MDM statistic to compare the forecast errors from the CCI and weather models.

## 3.11 Encompassing Forecast Testing

Another statistical method that compares forecasting models is the encompassing forecast test. Developed by Harvey, Leybourne, and Newbold (1998), the encompassing forecast test is a regression based test formulated as:

$$e_{1t} = \alpha_3 + \lambda(e_{1t} - e_{2t}) + \varepsilon_t,$$

where, similar to the DM and MDM statistics, $e_{1t}$ and $e_{2t}$ are the out-of-sample forecasting errors from two competing forecasting models. After estimating the regression, the coefficient of concern is λ. The null hypothesis of this test is that $\lambda=0$, meaning that model 2 adds no additional information to the forecasting model and model 1 encompasses it. Therefore, if λ is not statistically significant, then forecasting model 2 is encompassed by forecasting model 1. However if λ is statistically significant, it is implied that forecasting model 2 contains information that forecasting model 1 does not, and is not encompassed by it. Manfredo and Sanders (2004) use this encompassing forecast test to compare the forecasting ability of futures markets forecasts made with implied volatility and other types of models. This research will use the forecast encompassing test developed by Harvey, Leybourne, and Newbold (1998) to evaluate the forecasting ability of the CCI and weather models.

Another less complex method of seeing if one type of forecasting model encompasses another is to combine the two models together, making a composite model. In the case of this research, the composite model would be formulated as

$$Yield_{si} = \alpha_0 + \alpha_1 * Trend_i + \alpha_2 * SD_s + \beta_1 * CCI_{sij} + \beta_2 * GDD_{sij} + \beta_3 * Rain_{sij}$$

This composite model contains all of the variables being investigated. Estimating this regression model at selected weeks during the study period and examining changes in model fit and accuracy, and coefficient signs and significances can lend insight as to whether the variables from one model contain the information of the variables from another. This composite model will only be estimated for select weeks, the beginning and end of the study period, assuming that results in between will follow a pattern between the terminal points.

# Chapter 4: RESULTS

## 4.1 Yield Data

Yield data was accessed from USDA/NASS. State level yield data from 1986 to 2012 was obtained for both South Dakota and Ohio. Descriptive statistics of this yield data show a large increase in the average corn yield over the 26 year time period in both states. Figure 3 shows the yield data from both states over the studied time period.

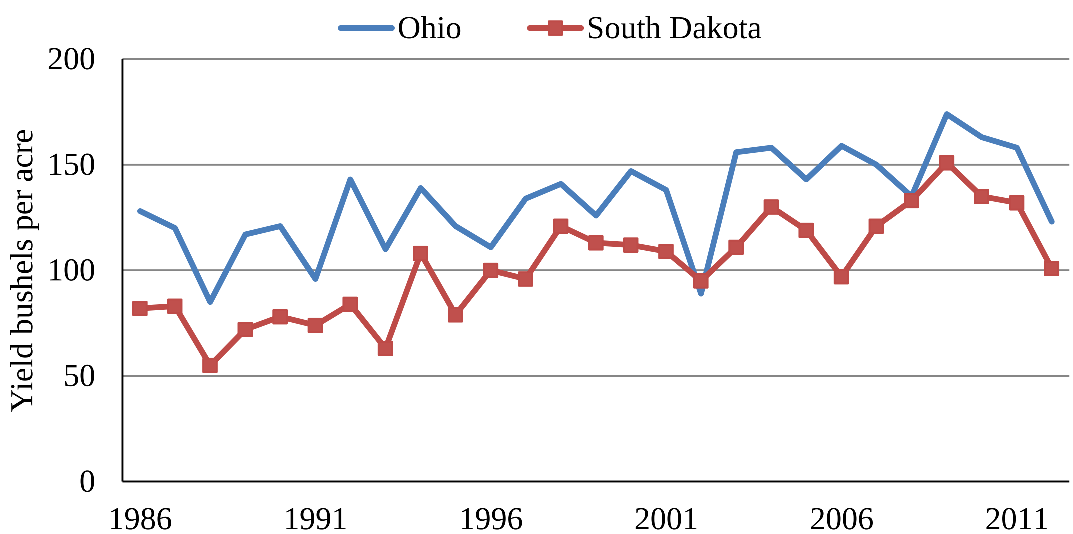


Figure 3. State Level Corn Yield 1986-2012.

It is immediately obvious that the year to year variation in yield in both states follows a very similar pattern. South Dakota and Ohio where chosen to be evaluated because of the assumption that their distance apart would lead to small similarities in weather and production related effects, leading to variations in yield that were as different as possible. It seems, though, that weather or production related effects that take place are often on a large scale that affects both areas, despite their distance apart. For example, predominate weather patterns may very well impact both states. Major changes in production practices may also occur in both states simultaneously.

The low yield for South Dakota during the time period was 55 bushels per acre in 1988. The low yield for Ohio during the time period was 85 bushels per acre in 1988. The high yield in South Dakota and Ohio both occurred in 2009, with the yield in South Dakota being 151 bushels per acre and the yield in Ohio being 174 bushels per acre. On average, yields in Ohio have been increasing at about 2.5% per year, while yields in South Dakota have been increasing at about 3.5% per year during the time period.

Table 1. Ohio and South Dakota Corn Yield Statistics.

| Bushels per Acre | Ohio | South Dakota |
|---|---|---|
| Mean | 132.78 | 102 |
| St. Dev. | 22.67 | 24.22 |
| Min | 85 | 55 |
| Median | 135 | 101 |
| Max | 174 | 151 |

Table 1 outlines several other descriptive statistics of the yield data. Another interesting statistic is the standard deviation of yield in both states. The standard deviation of yield in South Dakota is higher, suggesting that yield is more variable in South Dakota than in Ohio.

## 4.2 Crop Conditions Data

Crop conditions data were accessed from the USDA/NASS. Data from 1986 to 2012 were studied. Weeks 24 through 36 were studied for each state, as weeks outside of this range had missing observations from one or both states. As noted in the research design, the crop conditions data were transformed into an index. The index was a combination of each of the five crop conditions ratings, each of which was multiplied by a scalar.

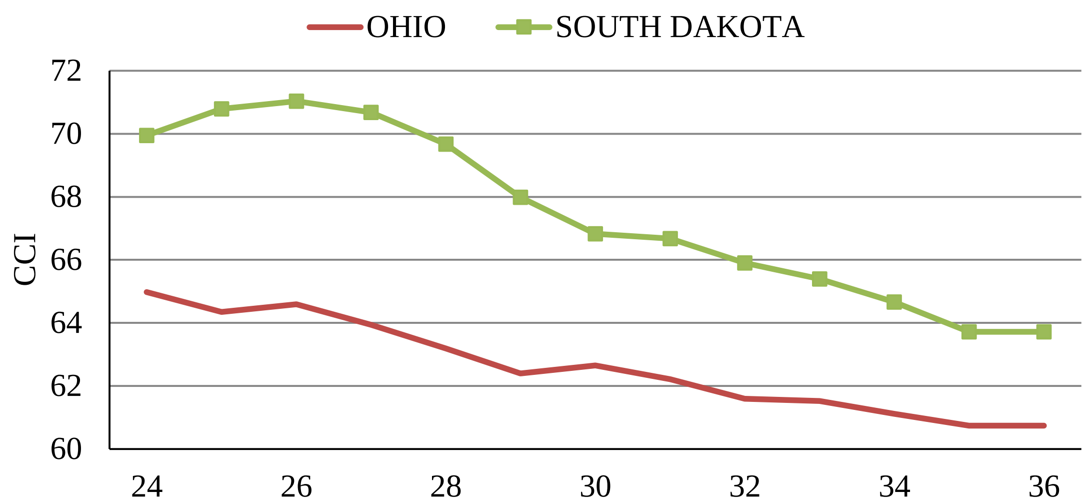


Figure 4. Average CCI Values Weeks 24-36.

Figure 4 shows the average level of the CCI throughout the studied weeks for both states. There is a clear downward trend in the CCI values throughout the growing season. This is mostly likely because crop condition initial estimates of the corn crop are optimistic and fade throughout the season. This is also justifiable, as it is difficult to estimate crop conditions while the corn plant is in its early physiological stages. As the growing season progresses and the crop becomes more mature, surveyors can more accurately gauge the condition of the corn crop, which becomes worse off than they initially estimate. Another interesting point to recognize is the marked difference between the average CCI in South Dakota and Ohio. South Dakota's crop ratings are on average higher than in Ohio. Despite this, yields in Ohio are almost always higher. This observation leads to an interesting conclusion about crop conditions surveyors in different states. While a crop condition rating may be higher in South Dakota than in Ohio, that does not necessarily mean a higher yielding corn crop in South Dakota than in Ohio. This finding is similar to the findings of Kruse and Smith (1994) and Fackler and Norwood (1999).

## 4.3 Weather Data

Weather data for each location chosen in South Dakota and Ohio was obtained from the National Climatic Data Center (NCDC) website. Temperature and rainfall data from 1986 to 2012 were examined. Similar to the crop conditions data, only weeks 24 through 36 were studied. The temperature data was converted into average accumulated GDDs in both South Dakota and Ohio. The rainfall data was converted into average accumulated rainfall (in inches) in both states as well.

Table 2. Ohio and South Dakota Accumulated GDD.

| | Ohio | South Dakota |
|---|---|---|
| Average Week 24 | 596.45 | 473.76 |
| Average Week 36 | 2446.12 | 2176.19 |

Table 2 outlines the averages of the accumulated GDD data in both states. On average, Ohio has more accumulated GDDs than South Dakota by week 24. Similarly, Ohio also has more accumulated GDDs by week 36 than South Dakota. These differences in GDD patterns between the two states may be able to explain the yield differences.

Table 3. Ohio and South Dakota Accumulated Rainfall.

| Inches | Ohio Rainfall | South Dakota Rainfall |
|---|---|---|
| Average Week 24 | 5.07 | 4.06 |
| Average Week 36 | 15.75 | 12.65 |

Table 3 outlines averages of the accumulated rainfall data in both states. On average, accumulated rainfall at week 24 is higher in Ohio than it is in South Dakota. Similarly, accumulated rainfall is typically higher at week 36 in Ohio than in South Dakota. Once again, these differences in rainfall amounts may be able to explain the differences in yield.

4.4 Trend Model Results

A regression model to explain yield using trend information was estimated for the years 1986 through 2012 in South Dakota and Ohio. The results of this model are outlined in Table 4.

Table 4. Trend Model Results.

| | Intercept | SD | Trend |
|---|---|---|---|
| Coefficient | 72.46 | 30.78 | 2.11 |
| S.E. | 5.16 | 4.51 | 0.29 |
| T-Test | 14.04 | 6.82 | 7.28 |
| Prob(t) | 0.00 | 0.00 | 0.00 |
| Model adjusted $R^2$ | 0.65 | | |
| Model F-Test | 49.78 | | |
| Model MSE | 16.58 | | |

All variables in the trend yield model were significant at the 99% confidence level. The intercept in this case is the corn yield in South Dakota at the beginning of the study period. The coefficient on the state dummy variable of 30.78 indicates that corn yields in Ohio are typically 31 bushels per acre higher than corn yields in South Dakota. This is a significant difference, and indicates that the more favorable weather conditions in Ohio have a beneficial effect on yield in the state. The coefficient on the trend variable of 2.11 suggests that both states have seen a yield increase of about 2 bushels per acre per year since 1986. This indicates a relatively strong upward trend in yields during the time period.

The model has an adjusted $R^2$ of 0.65, indicating that this trend model explains nearly 65% of the variation in corn yield in South Dakota and Ohio. This result shows that although the model only utilizes three variables as regressors, it still explains much of the variation in South Dakota and Ohio corn yields. The F-test of this model is 49.78, which indicates that overall the model is significant, and its estimations of yields are statistically different from zero. While a high adjusted $R^2$ value and a high F-test value are positive signs for this model, a very important test is still to examine the MSE. The MSE of this model is 16.58, meaning that this model typically estimates yield within 17 bushels per acre. While that may seem like quite a large error, considering that this model can be estimated months or even years before a corn crop in a given year is harvested reveals that this model is quite useful.

## 4.5 CCI Model Results

A regression model developed to forecast corn yields in South Dakota and Ohio using a CCI is estimated. The model is estimated for the years 1986 through 2012, weekly from week 24 through week 36. While 13 regression models are estimated, Table 5 only displays the results from week 24 and week 36.

Table 5. CCI Regression Model Results for Selected Weeks.

| Weeks 24 | Intercept | Trend | SD | CCI |
|---|---|---|---|---|
| Coefficient | 2.13 | 2.06 | 35.82 | 1.02 |
| S.E. | 24.56 | 0.27 | 4.55 | 0.35 |
| T-Test | 0.087 | 7.59 | 7.87 | 2.92 |
| Prob(t) | 0.93 | 0.00 | 0.00 | 0.00 |
| Model adjusted $R^2$ | 0.69 | | | |
| Model F-Test | 40.93 | | | |
| Model MSE | 15.48 | | | |
| | | | | |
| Week 36 | Intercept | Trend | SD | CCI |
| Coefficient | -8.37 | 2.42 | 34.34 | 1.2 |
| S.E. | 6.60 | 0.14 | 2.17 | 0.09 |
| T-Test | -1.27 | 13.19 | 17.28 | 15.83 |
| Prob(t) | 0.21 | 0.00 | 0.00 | 0.00 |
| Model adjusted $R^2$ | 0.92 | | | |
| Model F-Test | 203.78 | | | |
| Model MSE | 7.91 | | | |

The intercept term in both selected weeks is not significant even at the 90% confidence level, and therefore is not considered statistically different from zero. The coefficient on the trend variable is significant at the 99% confidence level in both weeks. The coefficients are between 2 and 3 bushels per acre, similar to the coefficient in the trend model of 1.9 bushels per acre. The state dummy variable in both regressions was also significant at the 99% confidence level, with values in the 34 to 36 bushels per acre range. This finding is also consistent with the trend model. The coefficient on the CCI variable is significant at the 99% confidence level, indicating that a CCI is a useful variable for forecasting yield. The coefficients were 1 to 1.2, indicating at a one unit increase in the CCI in South Dakota and Ohio typically leads to over a 1 bushel per acre increase in corn yield.

Table 6 shows the regression coefficients and their significance for all thirteen weeks. All coefficients in the CCI regression model are significant at the 95% confidence level for all thirteen weeks, except for the intercept term. The intercept term is never statistically significant.

Table 6. CCI Model Coefficients Weeks 24-36.

| | Intercept | Trend | SD | CCI |
|---|---|---|---|---|
| Week 24 | 2.13 | 2.06* | 35.82* | 1.02* |
| Week 25 | -4.69 | 2.07* | 37.84* | 1.10* |
| Week 26 | -14.78 | 2.16* | 38.64* | 1.22* |
| Week 27 | -4.22 | 2.14* | 38.04* | 1.08* |
| Week 28 | -4.89 | 2.29* | 37.75* | 1.08* |
| Week 29 | -2.06 | 2.37* | 36.98* | 1.03* |
| Week 30 | 1.07 | 2.33* | 35.05* | 1.02* |
| Week 31 | 0.17 | 2.34* | 35.41* | 1.04* |
| Week 32 | 0.001 | 2.30* | 35.34* | 1.06* |
| Week 33 | -2.88 | 2.29* | 35.10* | 1.11* |
| Week 34 | -6.91 | 2.40* | 34.91* | 1.16* |
| Week 35 | -5.48 | 2.31* | 34.26* | 1.17* |
| Week 36 | -8.37 | 2.42* | 34.34* | 1.20* |

* Significant at the 95% level

MSE is used to show how the model's accuracy changes through the growing season. Figure 5 displays the MSE of the CCI model for all 13 regressions as it progresses throughout the study period. As the growing season progresses, the overall model accuracy increases. The MSE of the model decreases from above 15 bushels per acre at week 24 to below 8 bushels per acre at week 36. This is a forecasting accuracy increase of 7 bushels per acre. A similar increase is also noticeable in the adjusted $R^2$ of the CCI model. The model not only becomes more accurate, but gains more explanatory power as the growing season progresses.

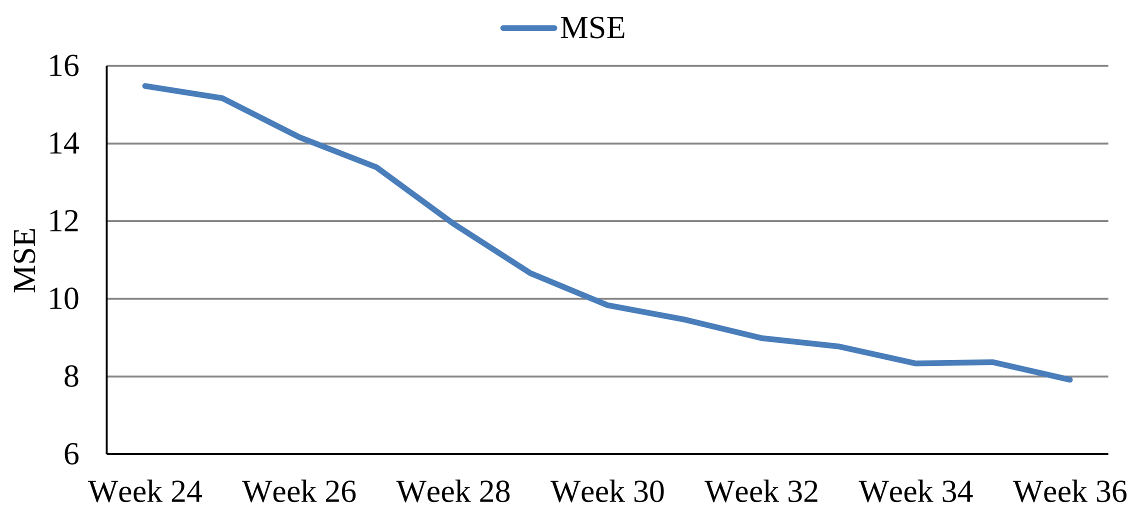


Figure 5. MSE of the CCI Model.

The results of the CCI model suggest that crop conditions data can be used to develop powerful and accurate yield forecasting models. The accuracy and explanatory power of the model increases throughout the growing season. This is a vast improvement over many yield forecasting models, which are typically not useful until near the end of the growing season. While the CCI model does produce its best results near the end of the growing season, it is already useful for forecasting yield in week 24.

4.6 Weather Model Results

A regression model developed to forecast corn yields in South Dakota and Ohio using weather variables is estimated. The model is estimated for weeks 24 through 36 for each year from 1986 through 2012. As with the CCI yield model, 13 regressions are estimated for the weather model. Table 7 summarizes the results of the weather yield model for weeks 24 and 36.

Table 7. Weather Regression Model Results for Selected Weeks.

| Week 24 | Intercept | Trend | SD | GDD | Rain |
|---|---|---|---|---|---|
| Coefficient | 75.17 | 2.08 | 31.46 | -0.02 | 1.94 |
| S.E. | 8.4 | 0.29 | 4.79 | 0.02 | 0.10 |
| T-Test | 8.95 | 7.25 | 6.57 | -1.39 | 1.94 |
| Prob(t) | 0.00 | 0.00 | 0.00 | 0.17 | 0.06 |
| Model adjusted $R^2$ | 0.67 | | | | |
| Model F-Test | 27.30 | | | | |
| Model MSE | 16.18 | | | | |
| | | | | | |
| Week 36 | Intercept | Trend | SD | GDD | Rain |
| Coefficient | 98.87 | 2.25 | 31.98 | -0.02 | 1.51 |
| S.E. | 20.83 | 0.27 | 5.07 | 0.01 | 0.54 |
| T-Test | 4.75 | 8.33 | 6.31 | -2.4 | 2.83 |
| Prob(t) | 0.00 | 0.00 | 0.00 | 0.02 | 0.01 |
| Model adjusted $R^2$ | 0.72 | | | | |
| Model F-Test | 34.76 | | | | |
| Model MSE | 14.84 | | | | |

The intercept term for both selected weeks is significant at the 99% confidence level, and it increases significantly from week 24 to week 36. The coefficients on the trend variable are significant for both weeks at the 99% confidence level, and vary from 2.08 to 2.25 bushels per acre. This is similar to the trend coefficient in the base model. The state dummy variable coefficients are significant at the 99% confidence level for both weeks, and vary slightly around 31 bushels per acre. This is also similar to the state dummy variable coefficient in the trend model.

The statistical significance of the GDD variable varies throughout the growing season. Table 8 shows the weather regression model coefficients and their significance for all 13 weeks.

Table 8. Weather Model Coefficients Weeks 24-36.

| | Intercept | Trend | SD | GDD | Rain |
|---|---|---|---|---|---|
| Week 24 | 75.17* | 2.08* | 31.46* | -0.02 | 1.94 |
| Week 25 | 74.41* | 2.05* | 32.16* | -0.02 | 2.5* |
| Week 26 | 79.04* | 2.08* | 32.7* | -0.02 | 1.99* |
| Week 27 | 83.21* | 2.13* | 32.96* | -0.03* | 2.08* |
| Week 28 | 82.68* | 2.17* | 32.81* | -0.02* | 1.96* |
| Week 29 | 80.40* | 2.23* | 31.81* | -0.02 | 2.14* |
| Week 30 | 81.37* | 2.22* | 30.89* | -0.02 | 2.02* |
| Week 31 | 82.81* | 2.21* | 30.50* | -0.02 | 1.95* |
| Week 32 | 86.45* | 2.22* | 31.29* | -0.02 | 1.77* |
| Week 33 | 90.14* | 2.24* | 31.98* | -0.02* | 1.70* |
| Week 34 | 94.77* | 2.24* | 32.13* | -0.02* | 1.66* |
| Week 35 | 97.83* | 2.26* | 31.94* | -0.02* | 1.64* |
| Week 36 | 98.87 | 2.25* | 31.98* | -0.02* | 1.51* |

* Significant at the 95% level

The GDD coefficient ranges from not significant at the 90% confidence level at week 24 to significant at the 95% confidence level at week 36. This indicates that temperature effects have a less significant effect on corn yield early in the growing season, and become more significant as the growing season progresses. The coefficient on the GDD variable remains relatively similar throughout the growing season at around -0.02. This coefficient means that a one unit increase in GDD leads to a 0.02 bushels per acre decrease in yield in South Dakota and Ohio. This is a curious result, as one would expect that more favorable temperatures, would lead to higher corn yields.

There are several explanations as to why the result is opposite of what was initially expected. The first is that the true effect of GDD on corn yield is being misrepresented by the model. The second is that while GDD are meant to value weather favorable for corn growth, it does not mean that temperatures always are favorable. The GDD formula used in this research is maximized at 86°F, therefore temperatures higher than that are simply counted as 86°F. No GDD discount for unfavorable weather is included in the GDD formula. Therefore, the negative effect of unfavorable weather for corn growth may be showing up in the GDD term.

The statistical significance of the rainfall variable throughout the growing season also changes, similar to the GDD variable. At week 24 it is statistically significant only at the 90% confidence level, and by week 36 is significant at the 99% confidence level. This is most likely because weather has an increasingly more important effect on corn yield as the growing season progresses. The coefficient on the rainfall variable also varies throughout the growing season, but always remains positive. This positive effect was expected, showing that more cumulative rainfall has a positive effect on corn yield. The coefficient varies from 1.9 bushels per acre at week 24, to 2.1 bushels per acre at week 29, to 1.5 bushels per acre at week 36.

Figure 6 shows the MSE of the weather model from weeks 24 through 36.

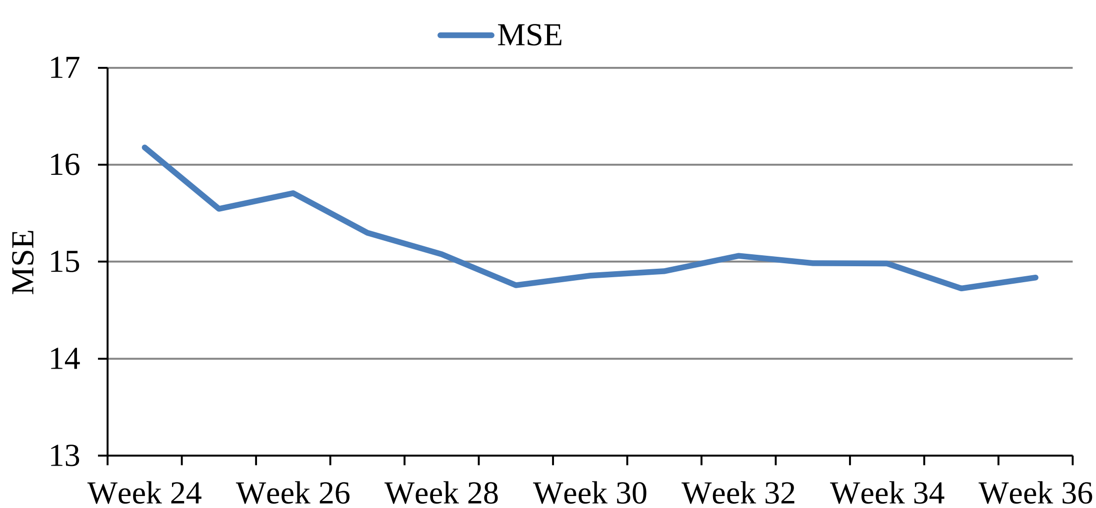


Figure 6. MSE of the Weather Model.

As with the CCI model, there is a general downward trend in the MSE of the weather model. The MSE of the model at week 24 is above 16 bushels per acre, and it decreases to below 15 bushels per acre at week 36. From week 24 to week 29, the MSE of the model decreases at a fast rate, similar to the pattern of the MSE of the CCI model. Once week 29 is reached though, the MSE of the model holds steady and actually increases slightly at a few times. This is unlike the pattern of the MSE of the CCI model, which continued to decrease through week 36.

## 4.7 Model Comparisons

Several methods can be used to compare the usefulness of the different regression models. Comparisons of adjusted $R^2$, F-tests, and MSE of the models can aid in determining which model is the most effective at forecasting corn yields. Table 9 summarizes the adjusted $R^2$ statistics, F-test statistics, and MSE values of the three models for three selected weeks.

Table 9. Comparison of Model Results.

| | Trend | CCI | | | Weather | | |
|---|---|---|---|---|---|---|---|
| | | Week 24 | Week 30 | Week 36 | Week 24 | Week 30 | Week 36 |
| Adj. $R^2$ | 0.65 | 0.69 | 0.88 | 0.92 | 0.67 | 0.72 | 0.72 |
| F-Test | 49.78 | 40.93 | 126.06 | 203.78 | 27.30 | 34.64 | 34.76 |
| MSE | 16.58 | 15.48 | 9.83 | 7.91 | 16.18 | 14.86 | 14.84 |

Analysis of the adjusted $R^2$ shows that at week 24, the first week that the CCI and weather models are estimated, all of the models have relatively comparable explanatory power. At week 30, the CCI model becomes superior in terms of explanatory power. From week 30 on, the CCI model is superior to all other models in terms of explanatory power. The trend model has the lowest adjusted $R^2$ of all three models in all weeks during the study period.

The MSE, as noted before, is reported in the same units as the dependent variable, meaning in this case in bushels per acre. It reveals how many bushels per acre each model is off on its in-sample forecasts, on average. Analysis of the MSEs provided in Table 9 shows that the CCI model has the lowest MSE for the entire study period, and is therefore more accurate at forecasting yield throughout the growing season. By week 36, the MSE of the CCI model is below 8 bushels per acre, meaning that the model estimates yield within 8 bushels per acre of actual yield. This is significantly better than the trend and weather models at week 36.

While analyzing selected weeks throughout the growing season gives a picture about which models are the most effective, an examination of all the weeks estimated in this research will help determine when changes occur in the accuracy of the models throughout the growing season. In a format similar to that depicted in Figure 1, the MSEs of the three models are shown in Figure 7.

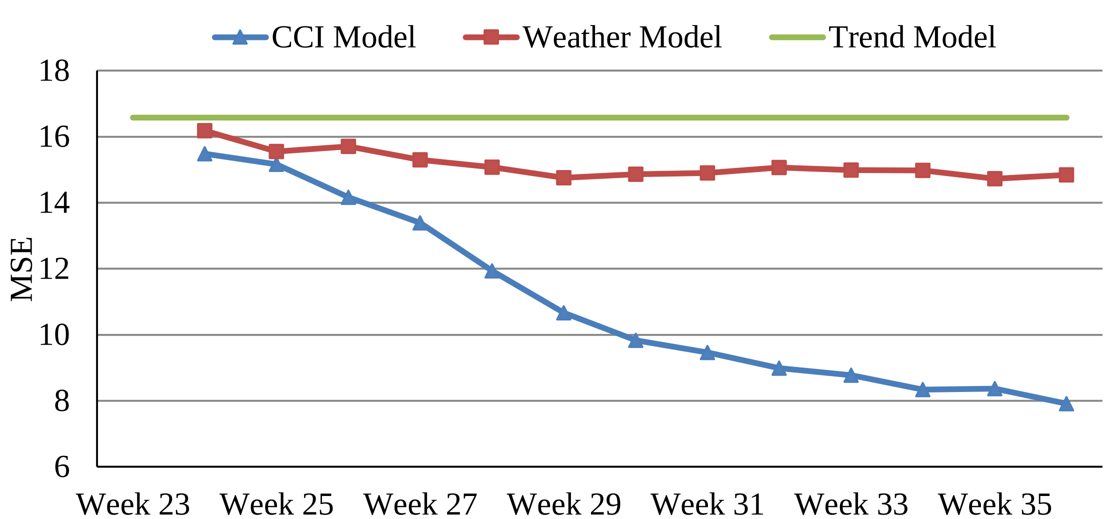


Figure 7. MSE Throughout the  Growing Season.

Upon examination of Figure 7, it is immediately clear that the CCI model is superior to the trend and weather models in terms of model accuracy throughout almost the entire growing season. In the early weeks, though, all three models have MSEs within about 1 bushel per acre of each other. So while the CCI model is superior to the other two models, it is difficult to say by looking at the graph if there is a statistical difference between them.

## 4.8 Composite Model Test

As noted in the research design, an examination of the MSEs of the yield forecasting models is useful, but in cases where models are comparable or cross one another in accuracy over time, further analysis is needed. Using the MDM statistic, encompassing forecast test, and composite model test, deeper insight into the true superiority of one model may be determined.

The first test completed was the composite model test. The CCI and weather regression models were combined, and the composite model was estimated at weeks 24 and 36. Table 10 outlines the adjusted $R^2$, MSE, and model coefficients.

Table 10. Composite Model Results.

| Week | Adj. $R^2$ | MSE | Intercept | Trend | SD | GDD | Rain | CCI |
|---|---|---|---|---|---|---|---|---|
| 24 | 0.71 | 15.04 | 7.77 | 2.0* | 38.3* | -0.03* | 1.27 | 1.06* |
| 36 | 0.92 | 8.07 | -9.62 | 2.4* | 34.09* | 0.00 | 0.04 | 1.20* |

* Significant at the 95% level

The results at week 24 are not as easy to evaluate as the results at week 36. At week 24 the CCI and accumulated GDD variables are statistically significant, but accumulated rainfall is not. The intercept behaves similarly to the intercept of the CCI model, in that it is statistically insignificant. The main purpose of estimating a composite model is to see whether or not more information is gained from a composite model than in the individual models. At week 24 the adjusted $R^2$ of the composite model is 0.71, which is slightly higher than the adjusted $R^2$ of the individual CCI and weather models at week 24, 0.69 and 0.67 respectively. Essentially, combining these models created a better model than the individual models, with 2 to 4 percent more variation in yield explained.

At week 36 the results of the composite model clearly show that the CCI model is superior to the weather model. The weather model coefficients are statistically insignificant, and the coefficients on the remaining variables are nearly the same as the coefficients for the CCI model at week 36. The composite model adjusted $R^2$ value of 0.92 is also exactly the same as the CCI model adjusted $R^2$ value at week 36. No information is added by using weather model variables, and the composite model essentially becomes the CCI model at week 36.

4.9 Encompassing Forecast Test

While using a composite model to make general conclusions about the information contained in the CCI and weather models during certain periods of time is useful, a more formal statistical test helps lend more assurance to the conclusions. The use of the encompassing forecast test developed by Harvey, Leybourne, and Newbold (1998) will formally test whether one forecasting model encompasses the other. To estimate the regression model necessary execute this test, true forecast information must be available. While the main goal of this research is not to conduct out-of-sample forecasting, some was done to evaluate the models.

The CCI and weather models were estimated from 1986 to 2002, and the model coefficients were used to generate out-of-sample forecasts for 2003. The process was repeated for each year through 2012, where the models were estimated from 1986 through 2011 and the coefficients were used to forecast 2012. The result was 10 years (2003 through 2012) of out-of-sample forecasts. Forecast errors one horizon out can be determined and used to run the encompassing forecast and MDM tests. The results of the encompassing forecast test are outlined in Table 11 for three selected weeks during the growing season.

Table 11. Encompassing Forecast Test.

| Week | CCI λ | Weather λ |
|---|---|---|
| 24 | -0.027 | 1.03* |
| 30 | -0.20 | 1.20** |
| 36 | -0.16 | 1.16** |

* Significant at the 90% level
** Significant at the 95% level

The encompassing forecast test was estimated for both the weather model and the CCI model. The weather model regression specification is:

$$e_{Wt} = \alpha_3 + \lambda(e_{Wt} - e_{CCIt}) + \varepsilon_t,$$

where $e_{Wt}$ are the out-of-sample forecast errors for the weather model and $e_{CCIt}$ are the out-of-sample forecast errors for the CCI model. The CCI model regression specification is:

$$e_{CCIt} = \alpha_3 + \lambda(e_{CCIt} - e_{Wt}) + \varepsilon_t \, ,$$

where the out-of-sample forecast errors for each model are specified as above. The CCI model encompasses the weather model at the 90 to 95% confidence level. The null hypothesis of this test is that λ=0, meaning the competing model adds no additional information to the other models forecast. Therefore, the statistical insignificance of the

CCI model's λ means that the competing (weather) model adds no additional information to the CCI forecast at any of the three weeks examined. Alternatively, the statistical significance of the weather model's λ means that the competing (CCI) model does add additional information to the weather model forecasts at all three weeks examined. The two tests convey the same results: the CCI model encompasses the weather model at every week in the study period.

4.10 The MDM Test

The MDM test will help to further affirm the superiority of one forecasting model over the other. As with the encompassing forecast test, out-of-sample forecast data was needed. Out-of-sample forecast data for 2003-2012 was used to calculate the MDM statistic and evaluate its significance. Table 12 shows the MDM statistic for three weeks in the growing season.

Table 12. MDM Test.

| Week | MDM statistic |
|---|---|
| 24 | 0.34 |
| 30 | 0.66 |
| 36 | 0.45 |

* Significant at the 95% level

As table 12 shows, the results of the MDM test show that, at all three weeks examined, there is no statistical difference in the forecast errors of the CCI and weather models. This is a perplexing result for several reasons. All model statistics point to the CCI model as being superior to the weather model. It consistently has higher in-sample statistics, such as adjusted $R^2$ and MSE. The out-of-sample tests, the encompassing forecast test and the composite model test, both show that the weather model adds no additional information that the CCI model does not already contain. The fact that there is no statistical difference in the forecast errors of these two models is perplexing. It is most likely related to the fact that both models over-predict and under-predict yield, and ultimately the average of the errors is the same. Figure 8 shows a graphical representation of this in the forecast errors for week 36.

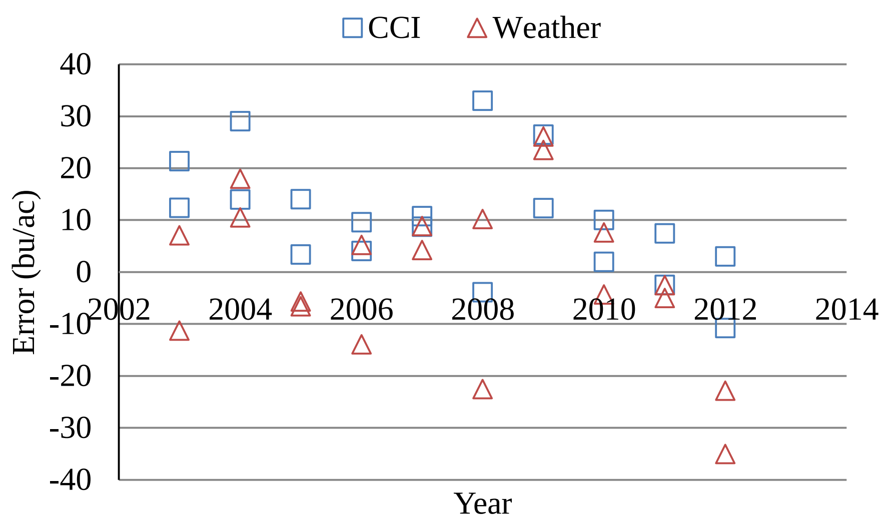


Figure 8. Model Forecast Errors at Week 36.

Upon examination of figure 8, it becomes obvious why the MDM tests fail to find any statistical difference between the two models. The errors often cross one another, with the CCI model sometimes being more accurate, and the weather model sometimes being more accurate. The errors for neither model are consistently positive or negative, meaning both average somewhere near zero.

4.11 Model Specification Tests

Certain specifications in the models used in this research have competing justifications in the literature that warrants examination. Tannura, Irwin, and Good (2008) evaluate the need to account for the possibility of accelerated technological change in the last 20 years. Kaufmann and Snell (1997) maintain that models that are estimated on a calendar basis, like the ones used in this research, are less effective than models that are based on the physiological progress of the corn plant. Both of these points are examined in the following section.

### 4.11.1 Accelerated Technological Change

Tannura, Irwin, and Good (2008) find literature that exist to support controlling for accelerated technological change, e.g. Troyer (2006). Therefore, testing a variable to control for this possible change in the trend of corn yields in the mid-1990s will lend further insight into the differing conclusions in previous research. Empirical results will need to be evaluated to see if it is appropriate to control for this factor in this research. The variable, $1996\ Dummy_i$, is a dummy variable that equals zero in years before 1996 and equals one in the years from 1996 on. The year 1996 is chosen to follow the work done by Tannura, Irwin, and Good (2008), who tested whether or not a true change occurred in the corn yield trend. To estimate its effect over time, this variable will be interacted with the time trend variable. This variable, $1996\ Dummy_i * Trend_i$, equals zero before 1996 and equals the value of the trend variable in years 1996 on. The significance of the accelerated technological change control variable in the models in this research will determine if it truly has a significant effect on yields. While Tannura, Irwin, and Good (2008) found no significant trend change, several more years of data related to this subject exist and more data alone could result in different findings. The model will be specified as:

$$Yield_{si} = \alpha + \beta_1 * Trend_i + \beta_2 * 1996\ Dummy_i * Trend_i + \beta_3 * SD_s$$

After running the trend model specified above, initial results show that when trend yield is forecasted for South Dakota alone, this variable is significant and should be included. South Dakota shows a significant change (increase) in the yield trend in 1996. However, when the model forecasts trend yield for Ohio alone, the accelerated technological change has no significant effect. In Ohio it is apparent that no significant change in trend corn yield occurred in 1996. Finally, when the initial model is used to forecast yield for Ohio and South Dakota together, the accelerated technological change control variable is statistically insignificant.

These mixed results show that in some cases it may be necessary to control for the recent acceleration in technological change, such as when forecasting trend yield for South Dakota. It appears, though, that when forecasting yield over a larger area, such as across multiple states, the acceleration in trend-line corn yields no longer takes place in 1996. This could be due to several reasons. First, the change could have occurred in Ohio at a different time than in South Dakota. It is reasonable to assume that this is possible. Because the states are in different regions, technologies may have been adopted sooner in Ohio than in South Dakota. Second, the change could have occurred over the course of several years in Ohio and not in one year like in South Dakota. Another plausible option is corn yields in Ohio have always historically been higher than in South Dakota, and the increase in yields gained from better technology in the mid-1990s did not increase yield as much in Ohio as it did in South Dakota.

Statistical evidence does not show any proof of existence of accelerated technological change in the combined South Dakota and Ohio model. Therefore, an accelerated technological change variable is not included in yield forecasting regressions that are similar to the ones used in this research.

4.11.2 Calendar versus Physiological Stage Estimation

The models in this research are estimated on a calendar year basis. Previous research has made the point that this may not be the most ideal model specification. Kaufmann and Snell (1997) argue that this type of specification is a failure of typical regression models that estimate or forecast corn yields. They argue that the plants growth is not governed by the chronology of the human calendar, and that its physiological stages do not occur on a consistent calendar basis. Therefore, they believe models that estimate or forecast corn yield should be estimated at peak times during corn plant stages of growth instead of on a calendar basis.

Testing this type of physiological specification can be done using data from the USDA's Crop Progress reports. Casual observation shows that the CCI model's explanatory power increases faster before silking occurs, and then increases more slowly after silking occurs. Using this casual observation as a starting point, obtaining a CCI for the weeks that silking is 50% completed, or closest to 50% completed, in both South Dakota and Ohio and estimating yield with this data will create a model based not on a calendar basis, but on a physiological basis.

This model will be specified as:

$$Yield_{si} = \alpha + \beta_1 * Trend_i + \beta_2 * SD_s + \beta_3 * CCI_{sij},$$

the same as the initial CCI model, except that week $j$ is now specified as the week that silking is 50% complete in state $s$ of year $i$. So, instead of the model being ran week to week as it is with the CCI data, it is now ran at selected weeks during the growing season when physiological changes in the corn plant occur.

Running both the calendar based and physiological based CCI models and comparing their explanatory power shows either type of specification works equally well. There is no significant difference in the explanatory power or the variable coefficients or significance in either type of model, with the explanatory power of the physiologically based model being slightly lower. This is determined by taking the average of the weeks that silking is 50% complete in South Dakota and Ohio, which is week 30, and comparing the adjusted $R^2$ of the calendar based CCI model at week 30 to the 50% silking model.

Given that either type of model specification is effective, several reasons can be given for using a calendar based model. First is that the calendar based model is slightly more effective. Second is that there are 13 weeks of data to run the calendar based CCI model, while only 5 points exist to estimate the physiologically based model. These points are emergence, silking, doughing, denting, and mature. To obtain useful parameters for a physiologically based model, 50% dates for each of the growth stages must be estimated. At 50% emergence, crop conditions reports are not typically reported. Therefore, only four reliable model estimation points, silking, doughing, denting, and maturity will be available each year.

Much like the CCI model, the argument Kaufmann and Snell (1997) make for modeling according to physiological stage and not by the calendar applies to the climate model as well. For reasons and justifications very similar to the CCI model, the climate model is estimated on a calendar basis. While all 5 points in the physiological growth stage can be estimated in the weather model, because the data is daily and not weekly, a calendar year specification is still used. This is to maintain consistency between the CCI and climate models, so they can be compared directly against each other.

# Chapter 5: SUMMARY AND CONCLUSIONS

The purpose of this research was to examine and compare different methods of yield forecasting. To do this effectively, three objectives were set to be tested. The first was to empirically test objective (weather) and subjective (CCI) yield forecasting models. The second was to compare their effectiveness. The third was to examine how well these models forecasted yield within the growing season.

The first goal was to test the two competing types of yield forecasting models. This was done using the USDA’s crop conditions information to create a subjective yield forecasting model and using climate data to construct an objective yield forecasting model. South Dakota and Ohio corn yields were examined between the years 1986 to 2012. Both model formulations effectively explained yield within both states during the time period. Each model was based on a trend-line model formulation, with either the objective or subjective variable added to the model specifications. This process leads to model formulations that contain relatively few variables. Previous objective, or weather based, models typically contain upwards of 20 variables. Models here both contained less than 5 variables. Despite this simplification, the models still forecasted yield well, with a maximum MSE of 16 bushels per acre, and a minimum of 8 bushels per acre. This verifies that less complex model formulations can still lead to accurate yield forecasts.

The second goal of the research was to compare the competing models against one another, and also against a trend-line yield model. When compared against the trend-line yield model, both the weather and the CCI model performed at least slightly better than the trend-line model. Overall, the trend-line and weather models performances are very similar, with MSE’s that are very similar. The CCI model performs better than both of the other models. It has a lower MSE and a higher adjusted $R^2$ than the other models. At its best, the CCI model has a MSE of only 8 bushels per acre, compared to the lowest MSE of the weather model of around 15 bushels per acre. Therefore, the CCI model is typically 7 bushels per acre more accurate than the weather or trend models. While 7 bushels per acre may not seem like a very large difference, apply it to corn production in South Dakota. Assuming around 5.5 million acres of corn are planted in the state in a given year, this implies that the CCI model will account for 38.5 million bushels of production that the weather or trend models will either over-account or under-account for. This is a large discrepancy, and shows that using CCI information to forecast yield is much more accurate and useful than a trend model or weather model formulated as in this research.

The third goal of this research was to see how both the weather and CCI models performed throughout the growing season. A major benefit of formulating the models as they were in this research was to be able to estimate them for 13 weeks during the growing season. Many yield forecasting models in the literature do not have this ability, and are not useful until late in the growing season. Both the weather and CCI models perform rather poorly early in the growing season, with MSEs of around 15-16 bushels per acre. The weather model's MSE hovers around 15 bushels per acre throughout the entire growing season, with variation of typically less than 1 bushel per acre between weeks. As stated before, this is marginally, if at all, better than the trend-line. The CCI model, though, increases drastically in its yield forecasting accuracy, with an MSE of around 10 bushels per acre by mid-July and an MSE of 8 bushels per acre by mid-September. This shows that while the CCI model is more useful at forecasting yield during the growing season than the trend or weather models, it still performs its best at the end of the growing season. By mid-July, though, the forecaster has the ability to use the CCI model to forecast yield fairly accurately.

This work builds on the works of Kruse and Smith (1994) and Fackler and Norwood (1999) and shows that the method of forecasting yield with crop conditions data is a valid and accurate option for the yield forecaster. The weather model, which was formulated based on the findings of Schlenker and Roberts (2006), does not perform as well. Forecast encompassing tests show that the addition of accumulated GDD and accumulated rainfall data does not add any additional information to a yield forecasting model that crop conditions data does not already contain. This is not to say that using GDD and rainfall data is not effective, but rather that the way these variables were formulated did not work as well as was anticipated.

Further extensions of this research could do several things. Further research can approach building a better weather model with GDD and rainfall data formulated in a similar manner, which would be beneficial to the forecaster in that weather data could possibly be used during the growing season to forecast yield, giving the forecaster more options than just crop conditions data or a trend model. A further investigation into the second order dominance (MDM and forecast encompassing tests) could lend more insight into the statistical dominance of an in-season weather or CCI yield forecasting model. MDM and forecasting encompassing tests could be run at more points during the growing season to get a better sense of when one model becomes dominant over the other. An investigation into the problematic results of the MDM test could also be conducted, to help determine if there is a statistical difference between the out-of-sample forecast errors of the models used in this research. A deeper examination into the concept of accelerated technological change may be prudent, as new methods of modeling may need to be developed if the phenomenon has truly occurred. Deeper investigation into estimating these in-season forecasting models at periods related to the physiological development of the crop may lend insight into findings like that of Kaufmann and Snell (1997).

In conclusion, this research developed several in-season yield forecasting models that vary in their usefulness. It was shown that crop conditions information is very useful as a variable for forecasting yield, with model MSEs below 10 bushels per acre. This is more accurate than a trend or weather based model, and this increased accuracy may lead to better pricing and storage decision for producers and agribusiness firms.

# REFERENCES


Bain, R., & Fortenbery, T. R. (2013). Impacts of Crop Conditions Reports on National and Local Wheat Markets. *NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management*, (pp. 1-27). St. Louis.

Barger, G. L. (1969). Total Growing Degree Days. *Weekly Weather Crop Bulletin, 56*(18): 10.

Below, F. E., Uribelarrea, M., Ruffo, M., Mosse, S. P., & Becker, A. W. (2007). Triple-Stacks, Genetics, and Biotechnology in Improving Nitrogen Use of Corn. *North Central Extension- Industry Soil Fertility Conference.* Des Moines.

Boyer, C. N., Larson, J. A., Roberts, R. K., McClure, A. T., Tyler, D. D., & Zhou, V. (2013). Stochastic Corn Yield Response Fuctions to Nitrogen for Corn after Corn, Corn after Cotton, and Corn after Soybeans. *Journal of Agricultural and Applied Economics, 45*(4): 669-681.

Cai, R., Mullen, J. D., Bergstrom, J. C., Shurley, D. W., & Wetzstein, M. E. (2013). Using a Climate Index to Measure Crop Yield Response. *Journal of Agricultural and Applied Economics, 45*(4): 719-737.

Colino, E. V., & Irwin, S. H. (2007). Outlook vs. Futures: Three Decades of Evidence in Hog and Cattle Markets. *American Journal of Agricultural Economics, 92*(1): 1-15.

Diebold, F. X., & Mariano, R. S. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics, 13*(3): 253-263.

Fackler, P. L., & Norwood, B. (1999). Forecasting Crop Yields and Condition Indices. *NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management*, (pp. 1-18). Chicago.

Harvey, D., Leybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting, 13*(2): 281-291.

Harvey, D., Leybourne, S., & Newbold, P. (1998). Tests for Forecast Encompassing. *Journal of Business and Economic Statistics, 16*(2): 254-259.

Isengildina, O., Irwin, S. H., & Good, D. L. (2013). Do Big Crops Get Bigger and Small Crops Get Small? Further Evidence on Smooting in U.S. Department of Agriculture Forecasts. *Journal of Agricultural and Applied Economics, 45*(1): 95-107.

Kantanantha, N., Serban, N., & Griffin, P. (2010). Yield and Price Forecasting for Stochastic Crop Decision Planning. *Journal of Agricultural, Biological, and Environmental Statistics, 15*(3): 362-380.

Kaufmann, R. K., & Snell, S. E. (1997). A Biophysical Model of Corn Yield: Integrating Climatic and Social Determinants. *American Journal of Agricultural Economics, 79*: 178-190.

Kruse, J. R., & Smith, D. (1994). *Yield Estimation Throughout the Growing Season.* Ames: Center for Agricultural and Rural Development.

Lehecka, G. V. (2013). The Reaction of Corn and Soybean Futures Markets to USDA Crop Progress and Condition Information. *Southern Agricultural Economics Association*, (pp. 1-24). Orlando.

Manfredo, M. R., & Sanders, D. R. (2004). The Forecasting Performance of Implied Volatility From Live Cattle Options Contracts: Implications for Agribusiness Risk Management. *Agribusiness, 20*(2): 217-230.

Martinez, C. J., Baigorria, G. A., & Jones, J. W. (2009). Use of climated indices to predict corn yields in southeast USA. *International Journal of Climatology, 29*: 1680-1691.

McMaster, G. S., & Wilhelm, W. (1997). *Growing degree-days: one equation, two interpretations.* Lincoln, NE: USDA-ARS.

NDAWN. (2013). *Corn Growing Degree Days*. Retrieved 2013, from NDAWN Center: http://ndawn.ndsu.nodak.edu/help-corn-growing-degree-days.html

NOAA. (2013). *National Climatic Data Center*. Retrieved 2013, from National Oceanic and Atmospheric Association: http://www.ncdc.noaa.gov/

Schlenker, W., & Roberts, M. J. (2006). Nonlinear Effects of Weather on Corn Yields. *Review of Agricultural Economics, 28*(3): 391-398.

Tannura, M. A., Irwin, S. H., & Good, D. L. (2008). *Weather, Technology, and Corn and Soybean Yields in the U.S. Corn Belt.* Department of Agricultural and Consumer Economics.

Teal, R. K., Tubana, B., Girma, K., Freeman, K. W., Arnall, D. B., Walsh, O., et al. (2006). In-Season Prediction of Corn Grain Yield Potential Using Normalized Difference Vegetation Index. *Agronomy Journal, 98*: 1488-1494.

Thompson, L. M. (1963). *Weather and Technology in the Production of Corn and Soybeans.* Center for Agricultural and Rural Development.

Troyer, A. F. (2006). Adaptedness and Heterosis in Corn and Mule Hybrids. *Crop Science, 46*(2): 528-543.

USDA-NASS. (2009, August 25). *National Crop Progess- Terms and Definitions*. Retrieved September 18, 2013, from Publications: http://www.nass.usda.gov/Publications/National_Crop_Progress/Terms_and_Definitions/index.asp

USDA-NASS. (2010, October 28). *Crop Progress and Condition Metadata*. Retrieved September 18, 2013, from Charts and Maps:

http://www.nass.usda.gov/Charts_and_Maps/Crop_Progress_&_Condition/Metadata/index.asp

Westcott, P. C., & Jewison, M. (2013). *Weather Effects on Expected Corn and Soybean Yields.* USDA.

Zhu, Y., Goodwin, B. K., & Ghosh, S. K. (2011). Modeling Yield Risk Under Technological Change: Dynamic Yield Distributions and the U.S. Crop Insurance Program. *Journal of Agircultural and Resource Economics, 36*(1): 192-210.