January 2014

What Stages In The Phenology Of Corn Are The Most Correlated With Rainfed Corn Yields In The Corn Belt Using Remote Sensing?

Zachary Lee Braun

WHAT STAGES IN THE PHENOLOGY OF CORN ARE THE MOST CORRELATED WITH RAINFED CORN YIELDS IN THE CORN BELT USING REMOTE SENSING?

by

Zachary Lee Braun
Bachelor of Science, Minnesota State University-Mankato – 2012

A Thesis
Submitted to the Graduate Faculty

of the

University of North Dakota

in partial fulfillment of the requirements

for the degree of

Master of Science

Grand Forks, North Dakota
May 2014

This thesis, submitted by Zachary Lee Braun in partial fulfillment of the requirements for the degree of Master of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

Christopher Atkinson

Bradley Rundquist

Soizik Laguette

This thesis meets the standards for appearance, conforms to the style and format requirements of the Graduate School of the University of North Dakota, and is hereby approved.

Wayne Swisher
Dean of the Graduate School

Date

PERMISSION

Title: WHAT STAGES IN THE PHENOLOGY OF CORN ARE THE MOST CORRELATED WITH RAINFED CORN YIELDS IN THE CORN BELT USING REMOTE SENSING?

Department: Geography

Degree: Master of Science

In presenting this thesis in partial fulfillment of the requirements for a graduate degree from the University of North Dakota, I agree that the library of this University shall make it freely available for inspection. I further agree that permission for extensive copying for scholarly purposes may be granted by the professor who supervised my thesis work, or in his absence, by the chairperson of the department or the dean of the Graduate School. It is understood that any copying or publication or other use of this thesis or part thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the University of North Dakota in any scholarly use which may be made of any material in my thesis.

Zachary Lee Braun
May 2014

TABLE OF CONTENTS

LIST OF FIGURES vi

LIST OF TABLES viii

ACKNOWLEDGEMENTS ix

ABSTRACT x

CHAPTER

I. INTRODUCTION 1

II. LITERATURE REVIEW 7

Drought and Drought Indices 7

Corn Physiology, Growth, and Yield 9

Crop Yields and Climate 13

Biophysical Models 19

Crop Yields and Vegetation Indexes 20

III. METHODOLOGY 24

Study Area 24

Data 25

Land Cover 27

Calculations 30

IV. RESULTS 33

V. DISCUSSION 64

VI. CONCLUSION 68

BIBLIOGRAPHY 70

LIST OF FIGURES

Figure Page

1. 2012 United States Corn Belt 24

2. An example of a 16-km TCI Composite 27

3. 2007 Cropscape Corn Pixels for the 12 States 28

4. 2007 MIrAD-US 250 meter Irrigation Layer 29

5. Missouri as an example of the result of the majority resampling method 30

6. Methodology Flow Chart 32

7. Correlation graph of Illinois 34

8. Scatterplot of Illinois 35

9. Correlation graph of Indiana 36

10. Scatterplot of Indiana 37

11. Correlation graph of Iowa 38

12. Scatterplot of Iowa 39

13. Correlation graph of Kansas 40

14. Scatterplot of Kansas 41

15. Correlation graph of Michigan 42

16. Scatterplot of Michigan 43

17. Correlation graph of Minnesota 44

18. Scatterplot of Minnesota 45

19. Correlation graph of Missouri 46

20. Scatterplot of Missouri 47

21. Correlation graph of Nebraska 48

22. Scatterplot of Nebraska 49

23. Correlation graph of North Dakota 50

24. Scatterplot of North Dakota 51

25. Correlation graph of Ohio 52

26. Scatterplot of Ohio 53

27. Correlation graph of South Dakota 54

28. Scatterplot of South Dakota 55

29. Correlation graph of Wisconsin 56

30. Scatterplot of Wisconsin 57

31. Correlation graph of the Corn Belt 58

LIST OF TABLES

Table Page

1. 30 year annual averages of temperature and precipitation for the twelve states 25

2. Peak weeks of VCI and TCI correlation with yield for each state.................................59

3. Corresponding phenology stage of corn for the peak weeks of VCI and TCI correlation 60

4. Liner regression yield equations for each state...61

ACKNOWLEDGEMENTS

I wish to express my deepest gratitude to my committee for their support in helping me complete my thesis, especially Dr. Atkinson who has taken me “under his wing” as my advisor for the last four semesters. His guidance has helped me mature into a professional geographer. I would also like to extend my deepest gratitude to my fellow graduate students, not only in the Geography department but also in Atmospheric Sciences and Geology. Without their help and encouragement I would not have been able to finish in two years. I would also like to thank Felix Kogan and David Johnson for their expertise they provided when I contacted them for advice.

ABSTRACT

Two weekly and freely available remotely sensed vegetation indices, Vegetation Condition Index (VCI) and Temperature Condition Index (TCI), were assessed for state level corn yield correlation in the Corn Belt region of the United States for the years of 2007-2013. VCI and TCI were 16-km pixels which are derived from the Advanced Very High Resolution Radiometer (AVHRR). Corn pixels were identified by downloading yearly USDA Cropscape pixels for corn in each state. Irrigated corn pixels were removed by using the 2007 Irrigated Agriculture Dataset developed by Pervez and Brown (2010) as a mask. Corn pixels were then resampled to 16-km in ArcGIS 10.1, with only pixels with greater than 50% corn coverage being drawn. These corn pixels were then used to identify VCI and TCI corn pixels for each state. Weekly VCI and TCI corn pixel values were then averaged for each state and correlated with yield from the National Agriculture Statistics Service (NASS). For the Corn Belt as a whole, VCI had high positive correlation in Week 34 and TCI has high positive correlation in Week 28. The highest correlating VCI and TCI weeks for each state were then used for regression with yield. Seven of the 12 states had R^2 values greater than 0.7, meaning at least 70 percent of the variation in yield for seven of the states can be explained by VCI and TCI.

CHAPTER I

INTRODUCTION

As we experience the effects of a changing climate, a person who is concerned with agriculture must be concerned with its effects on yield. One way to help predict yields is through analysis of remotely-sensed data (Doraiswamy, et al. 2004, Kogan, et al. 2005). By using data retrieved from sensors carried on remote sensing platforms, it is possible to make accurate predictions of yield weeks or months ahead of harvest (Unganai and Kogan 1998). Being able to receive an early yield estimate can give a considerable advantage to a farmer by giving him or her more time to decide on the most profitable use for the crop. It also gives an advantage to policymakers by providing them an estimate of how much corn they may have to export for state profit.

In order to understand yield estimates, one must common extreme events in climate, such as droughts. Droughts occur from the interaction of natural events, such as periods without precipitation, and the interaction of the demand people have on the water supply (University of Nebraska-Lincoln 2014b). Human activities can also increase the effect of drought in an area. While the mechanisms behind drought are complicated, the definition of drought can be cumbersome as well. There are three common definitions of drought (NWS 2008), the first is meteorological drought which is when precipitation levels are below average or rain has not fallen for some time. The second is an agricultural drought, which includes factors such as precipitation, soil moisture and ground water level, and it affects crop health and irrigation. There are several physical characteristics crops give off signifying drought, namely corn. These include leaf rolling, where the leaf rolls inwards to expose less area to evapotranspiration, leaf loss where entire leaves are shed because of heat stress, and leaf scald where the leaves turn brown because of the plants inability to uptake water (Monsanto 2012). The third type of drought is hydrological drought, which is when below average precipitation levels affect water levels in lakes, reservoirs, and rivers. The effect of hydrological drought can extend the boundary of meteorological drought because of the loss of water flow to nearby areas (NWS 2008). The definition of drought can also depend upon the local climate, as an area that experiences precipitation frequently, such as a tropical rainforest, will have a vast difference in temporal frequency of rainfall compared to a desert climate (University of Nebraska-Lincoln 2014b). A week without precipitation may be considered a drought in a rainforest but hardly considered one in a desert.

There are microscopic short term responses plants take during drought stress, one of these is stomatal closing. Stomata, which are the openings in the leaf cells where water is transpired and CO_2 is exchanged with the atmosphere (Arve et al. 2011), are closed when plants suddenly encounter drought. By closing the stomata, water loss is lowered, allowing for a quick response to drought which increases water efficiency (Farooq et al. 2008). However, when the stomata is closed, the plants ability to dissipate heat is lowered at well, leading to a temperature increase in the plant (Farooq et al. 2008).

Climate change also has an effect on the occurrence of droughts. More warm temperature extremes in the 21st Century will occur because of an increase in global mean temperature (IPCC 2013, A Summary for Policymakers 2013). It is likely that land areas will have more frequent 20-year high temperature events and less 20-year low temperature events by the end of the 21st Century. In addition, rising global temperature has increased the total global area affected by droughts and the frequency of heat waves (NASA 2013). Likely future global trends due to rising global temperatures include melting of snow covered areas, increased frequency of warm temperatures, decreased precipitation in subtropical land regions, and decreased water resources in semi-arid areas (NASA 2013).

Drought is one of the costliest weather disasters (NWS 2008). With an average annual cost of droughts reaching $6 to $8 billion (Rumore 2011), an increase of the frequency and intensity in drought is a primary concern for climate scientists, agricultural producers, and policymakers (Rumore 2011). However, there have already been intense historical drought events in the U.S. that have been extremely costly. Perhaps the most famous drought was the “Dust Bowl” that occurred during the 1930s and was largely centered on the states of Colorado, Nebraska, Kansas, Oklahoma, Texas, and New Mexico. The Dust Bowl led to the emigration of about 400,000 people from the Southern Plains and cost an estimated $1 billion in governmental aid (University of Nebraska-Lincoln 2014a).

Drought and climate change are focused on in this thesis for multiple reasons. First, a major drought occurred during summer 2012, and affected farms in Southern Minnesota where the author’s family farms. Being able to see some of the devastation it caused had a profound impact on me. Another peculiar fact about the 2012 drought was its extensiveness. It was reported that about 80 percent of agricultural land in the U.S. experienced drought in 2012, making it the most widespread drought since the 1950s

(Crutchfield 2013). Another impact of the drought was the chain effect it had on food prices. For instance, while the Midwest was afflicted with drought in 2012, average corn yields decreased. These decreases in yield increased corn prices and caused higher prices for beef, pork, poultry and dairy. For the past 20 years, retail food prices have increased 2.5-3 percent every year; however, the prices were expected to increase 3-4 percent in 2013 because of the drought (Crutchfield 2013).

Corn was chosen for this study because of the tremendous value it has in the American economy. Around 80 million acres of corn are planted each year in the U.S., with the majority of them being planted in the Midwest (Capehart 2014). According to the National Agriculture Statistics Service (NASS), from 2002 to 2012, the acreage of corn planted has increased from 78 to 97 million acres (NASS 2013). This nearly 20 million acre increase proves the importance and value of this grain.

This dramatic increase in corn production is no accident, as certain drivers in America have increased corn's value such as ethanol, a longer growing season, and the advancement of hybrid seeds. The global production of ethanol increased from 30.8 billion liters in 2004 to 76 billion liters in 2009, which constitutes a growth rate of about 20 percent every year (Timilsina and Shrestha 2011). The boom in ethanol production in the U.S. starting in 2006 can be attributed to the phasing out of methyl tertiary-butyl ether (MTBE) as an octane enhancer, blender tax credits for ethanol, and rising oil prices (Energy Information Administration 2013). In 2012, ethanol production used 4.5 billion bushels of corn to produce 34.4 million metric tons of high-quality livestock feed and 13.3 billion gallons of ethanol (Renewable Fuels Association 2013). This increase of alternate fuel sources is one of the main contributors for the growth of corn acres planted in the U.S.

Demand for growing more cereal crops will continue to rise as global food demand increases with expanding human population. It is predicted that by 2030 global demand of cereal crops for food and animal feed will total 2.8 billion tons per year, 50 percent higher than in 2000 (Bruinsma 2003).

Another driver of corn production in the U.S. has been climate change and the extension of the growing season. Previously, it was impractical to plant corn in the most northern states because of short growing seasons. A general warming trend in the last century has changed farmers' planting options (Karlin 2013). For example, in North Dakota the growing season has increased by 12 days over the last century. There has also been a general increase in precipitation (Karlin 2013). These factors allow for planting of corn in places thought not practical decades ago. These changes in climate highlight the need for continuous study of corn yields and their relationship with climate.

It has not just been climate change that allows northern farmers to plant corn, but new seed varieties. Hardier genetically-modified seeds that survive in tougher conditions give farmers an upper hand over the elements (Fletcher 2013). Hybrid seeds also produce more yields per acre than ever before, encouraging northern farmers to plant corn in lieu of other crops. For example and to highlight increased corn acres planted, in 2013 wheat acreage in North Dakota was down 11 percent from 2003 (Fletcher 2013).

One way to monitor these changes in drought and corn coverage is remote sensing. Remote sensing is the science of studying an object from a distance (NOAA

2014). The main methods of remote sensing include in-person field data, aircraft, or satellite. Information about objects is retrieved by studying the objects interactions with energy across the electromagnetic spectrum (NOAA 2014). Some advantages of remote sensing include its ability to study a large area, its ability to study out of reach places, being able to quickly build base maps, and the analyzing of the images which can be done on a computer (Chulalongkorn University 1999). Some limitations include how it is not a direct sample and thus never an exact classification, the computer can easily mistake like objects for each other, and mixed pixels, which is when multiple land covers comprise a single pixel, creating noise in the measurement (Chulalongkorn University 1999).

My main research focus is to determine the best week of the year to get an accurate prediction of corn yield using National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) data over 12 states that make up the Corn Belt. A secondary focus is to determine the earliest time in the year that a prediction of yield can be made, which may not be the most accurate, but has a reasonable enough result to have validity.

CHAPTER II

LITERATURE REVIEW

Drought and Drought Indices

Drought can have a profound impact on crop production. For example, the lack of a surface snow cover of snow during winter can cause a hardening of the surface soil layers, harming root development in the spring and thus reducing yields (Al-Kaisi, et al. 2013). The period of when drought occurs during the development of the crop is also an important factor. In the early vegetative state of corn, a drought that causes four consecutive days of wilting can reduce yields 5-10 percent. If the four days of wilting occur during the silking stage of corn, yield can be decreased by 40-50 percent (Thelen 2012). During October of 2012, national yield forecasts conducted by the USDA revealed yield to be 24 percent less than the average national trend (Al-Kaisi, et al. 2013).

One major historical drought was during the 1950s. This drought lasted from 1951-1956 and empacted much of the southwestern U.S., especially Texas. It was noted that 75 percent of Texas had below normal rainfall with precipitation levels being about 40 percent lower than average. These low precipitation levels were made worse by high temperatures (NCDC 2003). When the drought ended, it cost Texas an estimated $22 billion in 2011 dollars. Farm laborers were also lost in the drought. In 1940, 29 percent of Texas workers were listed as farmers or farm workers. This fell to 12 percent in 1960, which some say led to more urbanization in Texas (Mashood 2011).

The last major drought in the U.S. came in the late 1980s. The 1987-1989 drought, while small and only covering about 39 percent of the U.S. mostly in the northern Great Plains, has been listed as one of the costliest natural disasters in U.S. history. The summed losses of energy, water, ecosystems and agriculture cost the U.S. an estimated $39 billion (NCDC 2003).

The drought of 2012 caused problems in the ethanol economy. With smaller yields because of the drought, corn prices rose, and this shrank the profit margins for ethanol production. This margin was reduced so much it forced several plants to shut down, reducing ethanol production by 10 percent (Al-Kaisi, et al. 2013).

Being able to measure the spatial distribution and strength of drought helps us to understand the event by giving a visual representation of their intensity. One popular method to estimate drought stress is the Palmer Drought Severity Index (PDSI) (Palmer 1965). The PDSI is a dimensionless number that typically ranges from -4 to 4, and although rare numbers can extend that range, with negative numbers representing shortage of water and positive numbers representing excessive moisture (Keyantash and Dracup 2002). The PDSI takes into account precipitation, evapotranspiration, and runoff. PDSI is calculated from a series of water-balance terms such as runoff, soil recharge, and evapotranspiration for a two-layer soil model and changes in a hypothetical moisture supply. Depending on observed meteorological conditions, the soil model is compared to a reference set of water balance terms. The PDSI has been shown to be accurate over longer time frames such as months and years, as compared to smaller time frames, such as weeks (Keyantash and Dracup 2002).

A second popular index to measure drought is the Standardized Precipitation Index (SPI). It is similar to the PDSI in that high negative numbers represent drought and high positive numbers indicate excessive wetness. However, it differs is it only takes precipitation into account. SPI is based on a probability factor of recorded precipitation occurring over time frames ranging from one-month to 24-months (NCDC 2013). High amounts of precipitation over a time frame increase the SPI value, while the lack of precipitation reduces SPI. SPI values typically range from -2 to +2, although they can rarely go past this range in extreme events.

Corn Physiology, Growth and Yield

Corn, or also known as maize, is a large grain plant that typically grows to be 8 feet tall, although some varieties when grown in enclosed environments have grown to be 34 feet tall (Karl 2013). Perhaps the most distinguishable part of the plant is the husk, which is a group of protective leaves which cover the kernels (Lerner 2000). These kernels are the seed of the plant. One ear of corn typically contains about 600 kernels, which are arranged into 16 rows (Iowa State University 2011). One bushel, a common unit of harvest measurement, contains around 7,280,000 corn kernels (Capehart 2014). This kernel has a variety of uses that include livestock feed, high fructose corn syrup, starch, corn oil, beverage alcohol, and ethanol.

There are two main stages in the growth cycle of corn: the vegetative stage (V stages), which is characterized by the number of leaf blades breaking away from the stalk (leaf collar), and the reproductive stages (R stages), which are separated by the development of the kernel (Abendroth and Elmore 2011).

The vegetative phase begins with emergence, or VE. This is when the shoot breaks through the soil surface. It can occur 4 to 5 days after planting in optimum conditions and up to two weeks in cool or dry conditions (Abendroth and Elmore 2011). Limiting factors during this period include flooding, seed decay, and early/late planting. The next major stage is V1, or when the first leaf collar is visible (Iowa State University 2012). After V1 a new leaf emerges every 4-5 days in May, 3-4 days in June, and two to three days in July (Abendroth and Elmore 2011). Because the plant is still small, at this stage it is still susceptible to flooding. The next milestone stage is V3, where the main root system, called the nodal roots, begin to take shape (Iowa State University 2012). Setbacks during this time largely depend on the condition of the soil. Non-optimum conditions such as excessive heat/cold or wetness/dryness of the soil can delay stage development (Iowa State University 2012). V7 is the next major vegetative stage. At this stage, rapid growth occurs above the soil, which includes development of the tassel, the pollen-producing flower, and the ear (Iowa State University 2012). Since more of the plant is exposed, it is now more vulnerable to above-ground damage such as hail, frost, and heat. Next, at V10, ear size, kernel size, and kernel number are determined. During this stage excessive heat and lack of nutrients can reduce yield (Lee 2011). More leaves are added every two to three days until there is about 20 leaf blades developed and the last stage of vegetative development is reached. The last major vegetative stage is VT, or when the last branch of the tassel has emerged and the silking stage has not started yet. The plant is tallest at this stage and can shed up to 500,000 pollen grains a day (Abendroth and Elmore 2011). Corn at this stage is extremely vulnerable to moisture deficiency and hail damage. Complete leaf loss at this stage will cause nearly 100 percent yield loss (Lee 2011).

The reproductive stages are separated into six classes. The first, R1, is the silking stage that can be seen from silk emerging from the top of the husk. This silk captures pollen, and if receptive, will cause fertilization (Abendroth and Elmore 2011). The corn plant is most sensitive to drought at this stage as this is when it uses the most water, around 0.35 inches of day (Iowa State University 2009). Nutrient uptake is also very rapid at this time. R2, or the blister stage, is next and occurs 10 to 12 days after silking (Abendroth and Elmore 2011). It is called the blister stage because the kernel is white and translucent, resembling a blister. During this stage, the ear size is nearly complete, silk begins to dry, a small embryo develops, and starch begins to accumulate. Moisture content is at about 85 percent. If any stresses occur during this stage, kernels are aborted from the tip, downwards (Iowa State University 2012). R3, the milk stage, occurs 18 to 22 days after silking. The kernels are yellow on the outside with a creamy white inner fluid (Iowa State University 2012). The embryo continues to grow, more starch accumulates, and moisture content decreases slightly to 80 percent. The next stage R4, or the dough stage, begins 24 to 26 days after silking. The fluid has hardened to a more paste like substance, the embryo has again gained size, having now four embryonic leaves, and moisture content is at 70 percent (Abendroth and Elmore 2011). Kernels now have a dent at the base of the ear and any stresses reduce kernel weight, not number. R5, or the dent stage, occurs 31 to 33 days after silking. Now most kernels have a dent and are at 55 percent moisture (Lee 2011). During the denting stage, drying of the kernel has begun with the top of it becoming hard and yellow (Iowa State University 2012). Frost during this stage can slow down dry matter accumulation, delaying harvest operations. The final stage R6, or physiological maturity, occurs 66 to 70 days after silking. A black layer has accumulated at the bottom of the kernel signifying maturity, and moisture content is at 30 to 35 percent (Lee 2011). Kernels have reached their dry matter maximum and only external stress such as insect feeding can reduce yield (Abendroth and Elmore 2011).

Corn development largely depends on the accumulation temperature during the growth period. For corn, the optimal growth occurs between 50°F and 86°F. Growth rates decline when temperatures are warmer than 86°F (Gibson 2003). The growth rate of vegetation can be calculated and predicted by using these principles; this method is named Growing-Degree Days (GDD) (Gilmore and Rogers 1958). GDD is calculated by taking the average of the minimum and maximum temperature of the day and subtracting 50 from it, 50°F being the base temperature of vegetation growth. Any temperatures below 50°F are given a value of 50°F and any temperatures above 86°F are given the value of 86°F, this is because as temperatures approach 50°F, vegetation growth rate approaches zero, and as temperature approaches 86°F, vegetation growth reaches it maximum. As stated before, accumulation of GDD is strongly related to corn development. V2 begins at about 200 GDD, V12 at 870 GDD, VT at 1135 GDD, R1 at1400 GDD, and R6 at 2700 GDD (Lee 2011). The date a farmer plants can have a large influence on the speed of growth. For example, if corn was planted in Henderson, Kentucky, on May 1st, by August 31st it will have accumulated 2898 GDD, reaching R6 (physiological maturity). However, if planted in the same location on June 1st, by August

31^{st} it will have only accumulated 2325 GDD, only reaching the R4/denting stage (Lee 2011).

The yield potential of U.S. corn has changed dramatically over the last century. From 1866, the first year the USDA started measuring corn, to 1936, corn yield stayed nearly constant at about 26 bushels per acre (Nielson 2012). The first major leap in yield improvement came after the Dust Bowl in 1937 when hybrid corn growers began to emerge and yields increased about 0.8 bushels per acre per annum. The second advancement came in 1955 with the use of nitrogen fertilizer, improved genetics, pesticides, and improvements in technology. Since 1955, U.S. yields have increased by about 1.9 bushels per acre per year (Nielson 2012).

Crop Yields and Climate

Drought intensities are key parts of climate that affect agriculture. Crop and climate relationships can be used for predicting yield. Lobell and Field (2007) studied global climate-crop yield relationships, because the effects of climate change on yield are still unknown at the global scale. Their objective was to investigate the impact of climate trends on yield by developing new empirical/statistical models of global yield response to climate. They obtained yield data from the Food and Agriculture Organization (FAO) along with temperature and rainfall data from the Climate Research Unit (CRU), 1961-2002, at the 0.5 x 0.5 latitude/longitude degree spatial scale. For correlation, they used the first difference time series to detrend the data. They found 29 percent of the variance in year-to-year yield changes was explained by their predictors with rainfall being the most important for soybeans and rice and temperature being the most dominant for maize, barley, wheat, and sorghum. As specific examples, they found warming trends have decreased yields with maize, wheat and barley. They estimated without the warming trend production would have been approximately 2-3 percent higher for these crop covers. This generated a loss of about $4.8 billion for the three crops based on 2002 prices for the U.S. They cited, however, that this loss has been offset by the use of new farming methods such as changes in planting dates, the use of different cultivars, and the fertilization effect of CO_2 on crops. This was a landmark paper which showed the importance of understanding climate change and its future impact on crop yield.

Remote sensing data can also be used to assess vegetative health with climatic variables. Balaghi, et al. (2008) did a study in Morocco using the Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1973), rainfall, and temperature for the early

$$\mathbf{NDVI = (NIR - VIS)/(NIR + VIS)} \qquad \textbf{[1]}$$

prediction of wheat yields using data from the years of 1990-2005. Data sets for this study included wheat statistics from the Economic Services of the Ministry of Agriculture, weather data from the National Meteorology Direction, AVHRR images from the Monitoring Agricultural Resources Statistics (MARS-STAT) unit of the European Commission Join Research Centre, and land cover from the Global Land Cover 2000 for Africa map. For the land cover map, areas were defined as agriculture when 1 km pixels had more than 50 percent coverage of fields and/or pastures. Information was compiled for provinces and one national dataset. Rainfall, temperature, and NDVI were separated into dekads (10-day periods) from September to May. On the provincial level, they found high R^2 values, ranging from 72-98 percent using the independent variables of

NDVI, temperature, and precipitation, except for the provinces of Ouarzazate and Errachidia. They explained the two outliers were because the two provinces contained small total areas of wheat fields and irrigated agriculture in comparison to the other provinces. They concluded NDVI was the most important variable, especially for rainfed areas. But for arid and high-rainfall areas, temperature and precipitation were most important with precipitation being more relevant. For total production, NDVI explained 69.4 percent of yield (Balaghi, et al. 2008). This study showed me how pixels of vegetation indices can be selected based off a land cover dataset.

While crop models have been used to simulate current and future crop productions and although these methods have been thoroughly tested, not many have been tested under extreme temperature and precipitation scenarios. Niu, et al. (2009) set out to use the Environmental Policy Integrated Climate (EPIC) model on sorghum in the Great Plains to test EPIC in extreme climate scenarios and investigate uncertainties with non-site specific data. Soil data were acquired on-site using Soil Survey Geographic database (SSURGO) and State Soil Geographic Data Base (STATSGO) data. Weather data were collected from an on-site Automated Weather Data Network (AWDN) station, a neighboring AWDN station, a distant Cooperative Observer Network (COOP) station, a Partial-Local data model (recorded temperature and precipitation with modeled humidity, solar radiation, and wind speed), and a completely simulated dataset. Tillage dates were from field-observed data and a modeled dataset. They found that EPIC slightly overestimated yields for normal years and underestimated yields for years with extreme climates. EPIC produced an 87 percent probability predicting sorghum yields in the region. For extreme events, the best accuracy was with P-Wet (above average precipitation) and the worst was P-Dry (below average precipitation). For nitrogen treatments, when N-level declined, the model reliability became lower. For weather data, the best choice besides field data was the Partial-Data model. Niu, et al. (2009) also found completely simulated datasets were just as good as distant weather stations. Different soil datasets had little impact on accuracy. Simulated tillage had little impact as well. This study highlighted the many variables which impact the yield of crops.

Some crop models look at different climate scenarios. Wei, et al. (2009) looked to assess the effect of climate change on yield of rice, maize, and wheat with the change in water availability and other social stressors using the Crop Environment Resource Synthesis (CERES) model. The model was processed in 50 km x 50 km cells. First, climate change was constructed for China, then crop and hydrological models were run to simulate the effects of climate change on water availability and crop growth. Next, rainfed and irrigated production was totaled, followed by calculation of effects of the social drivers. Finally, results from three different adaptation policies were compared using the Intergovernmental Panel on Climate Change Fourth Assessment Report carbon dioxide burning scenarios. Wei et al. (2004) found yield increased under both carbon dioxide scenarios such as A2 (faster population growth and higher CO_2 levels) and B2 (slower population growth and lower CO_2 levels), yield increased in A2 more. Irrigated land area decreased, especially for rice paddies. Adding in future water availability reduced yields in the 2040s by 9 percent and 18 percent for B2 and A2 scenarios, respectively. Adding in the adaptation scenarios increased production, especially in agricultural technology. This study showed the human impact of socioeconomic factors on yields

Another study in China done by Zhang, et al. (2010) compared rice yield trends and climate change. They chose rice because it is a staple for the people of China. Also, they wanted to do an empirical test because of the lack of previous empirical work regarding rice yield responses in China. They had two main objectives. The first objective was to assess the responses of rice yields to climatic parameters at different spatial scales, and the second objective was to identify the major climatic drivers contributing to yield variations. Empirical data were gathered from 20 experiment stations run by the Chinese Meteorological Administration (CMA). For correlation, they used a first differences approach. What Zhang, et al. (2010) found was that rice yields were generally positively correlated with temperature and solar radiation levels (referred to as rads). Zhang, et al. (2010) also found a general negative relationship with precipitation. Going further, they found that yields in northern and northwest China had negative correlations with temperature and positive correlations with precipitation. They attributed these trends to rice being more prone to drought in those areas because of the lack of irrigation. They concluded rads are the main drivers of rice yields in China.

Spatial scale, the size of the study area, can also have an impact on yield responses to climate change. Li, et al. (2010) did a study in China looking at long-term observations between wheat yield and climate at different spatial scales. They specified studying wheat yield responses to climate change are important because the mean air temp in China increased 1.1°C in the last 50 years with 60 percent of the warming happening in the last 16 years. The overall negative trend in wheat yield per temperature warming is one of their concerns with this warming. Their main objective was to observe the relationship between wheat yield and climate under the current climate in China.

Correlations were found using the first difference time series between 1978 and 1995 at the scales of 0.5°, 2°/2.5°, and 4°/5°. While they found the yield increased over time, they attributed this to improvements in technology, institutional changes, and irrigation. Furthermore, they found the significance of the correlations was dependent on the scale of observation. Precipitation had a positive relationship with yield, better correlation at smaller scales, and decreased correlation at greater scales. This relationship is because of the variability in rainfall amounts across landscapes. Convection thunderstorms can develop and dissipate in less than an hour, precipitating over a small area, leaving surrounding areas dry. Temperature had an overall negative correlation with yield, with a stronger correlation at larger scales and lower correlation at small scales. These trends can be attributed to the continuous cover of temperature data, with small scale changes in temperature not affecting yield.

Previous studies have found that using different climate change scenarios can have an impact on model production. Weiss, et al. (2003) investigates the use of two different climate change scenarios on winter wheat in three cities in Nebraska, Alliance, Dickens, and Havelock, using a CERES-wheat model. Weiss, et al. (2003) also wanted to look at different management practices including sowing dates and cultivars. They found the two different climate scenarios produced different solar radiation, precipitation, and temperature patterns. Yield was also found to increase from west to east, as did kernel number (the density of corn on each ear harvested). They found the kernel nitrogen content decreased as the sowing date was delayed. The growth was also affected in the models as growth periods were shortened from increased temperatures and higher carbon dioxide levels. One interesting result was the mean water stress factor in Havelock, Nebraska was close to zero in all developmental stages. In Alliance and Dickens, Weiss et al. (2003) found that as yield increased, percent kernel nitrogen content decreased.

Biophysical Models

In addition to assessing the impact of climate change on crop yield, biophysical parameters can be added to models to help in yield predictions. Doraiswamy, et al. (2004) looked at canopy reflectance, Leaf Area Index (LAI), and top soil moisture to determine crop yields in nine Iowa counties. They discussed the problem with using operational satellite sensors such as AVHRR and its large-scale resolution making regional studies difficult. Doraiswamy, et al (2003) then decided to use the Moderate Resolution Imaging Spectroradiometer sensor (MODIS) because its 250-m resolution allowed them to study fields 25 ha and larger. Doraiswamy, et al. (2003) found their yield predictions were similar to those reported by NASS. For example, the predicted corn yield was only 3.12 percent less than NASS reported yield. They stated one of the errors in their data came from improper geometric, radiometric, and atmospheric correction in some of their images. These studies showed me some of the limitations of remote sensing which were stated by the authors.

Another biophysical model was used in northeastern China by Zhao, et al. (2013) to estimate corn growth and yield. The Python World Food Studies (PyWOFOST) model was used to first predict time of emergence to flowering. Then, by coupling LAI information derived from MODIS into the model, PyWOFOST predicted the yield based on input data from MODIS. Zhao, et al. (2013) found in every model, adding the MODIS biophysical data improved the R^2 value as compared to not including MODIS LAI.

Crop Yields and Vegetation Indexes

Instead of using direct climatological factors, some scientists use specifically-tailored vegetation and temperature indices, measures of vegetation health, derived from remote sensing platforms. Kogan (1995) describes two such indices: Vegetation Condition Index (VCI) and Temperature Condition Index (TCI). VCI is derived from NDVI values and TCI from Brightness Thermal (BT) values converted to temperature (T), where NDVI, NDVImax, and NDVImin are the smoothed weekly NDVI, its historical absolute maximum, and minimum, respectively, and T, Tmax, and Tmin are found using the same methods from BT.

$$\mathbf{VCI = 100(NDVI - NDVImin)/(NDVImax - NDVImin)} \qquad \mathbf{[2]}$$

$$\mathbf{TCI = 100(Tmax - T)/(Tmax - Tmin)} \qquad \mathbf{[3]}$$

When used in conjunction with each other, VCI and TCI provide a reliable method for detecting vegetation stress. VCI is based on Normalized Difference Vegetation Index (NDVI), while TCI is from Brightness Temperatures (BT). While VCI is a good indicator of stress, it does not include temperature and can give lower values when vegetation suffers from excessive moisture. TCI is then used to check temperatures of the fields to see if the crop is suffering from drought or too much moisture. VCI and TCI also can be used in the same model to produce a new index, the Vegetation Health Index (VHI). Kogan, et al. (2005) used VHI in Northern China to model corn production and found TCI had a stronger correlation in the model than VCI. These studies show how remotely sensed vegetation indices are strongly correlated with yields of crops.

VCI is a good indicator of crop health because it is derived from NDVI values. NDVI has been shown to be a sensitive indicator of chemical content (green biomass, green leaf area index, chlorophyll content) in vegetation (Gamon, et al. 1995). It also is positively correlated with maximum photosynthetic rates for grasslands and semideciduous shrubs (Gamon, et al. 1995). TCI is also a good indicator because it is derived from surface temperatures. As noted earlier in the paper, when plants become stressed by drought, they close their stomata, in turn raising their temperatures (Farooq, et al. 2008). Therefore, by using surface temperatures, one can get a direct indicator if the plant is being stressed by lack of moisture. This is what makes TCI a good measurement of current plant condition (Unganai and Kogan 1998).

In addition to VCI and TCI, NDVI has been modified to produce different methods to assess crop biomass in response to drought; one of them is called the Wide Dynamic Range Vegetation Index (WDRVI). Sakamoto, et al. (2013) found NDVI lost its sensitivity when LAI was greater than 2. A weighting parameter was then added to the numerator and denominator in calculating NDVI to help adjust for the excessive biomass. They also used a Shape Model Fitting (SMF) method that helped determine when corn was in its silking stage; silking stage is the time when corn is the most sensitive to drought. Sakamoto, et al. (2013) found WDRVI was most sensitive to corn yield 7-10 days before silking. However, WDRVI had overestimations for yield in fields fed by the Ogallala Aquifer, the downstream basin of the Mississippi, and southwestern Georgia. This research highlights the time frame of which NDVI is most strongly correlated with yield.

NDVI has also been correlated with the Standard Precipitation Index (SPI), an index based on total precipitation. Peters and Lei (2003) did a study in the Northern Great Plains to evaluate the relationship between NDVI and SPI. They found NDVI had the highest correlation with three-month SPI values. They attributed this to the lag time between precipitation and NDVI values. They also found the relationship depended on seasonality; the highest correlation was in the middle of the growing season, a time when most vegetation is in its reproductive stage. At this stage, vegetation is very sensitive to water availability. This was another study which highlighted the timing of the correlation between indexes and yield.

The time of the year is also an important factor when trying to estimate yield since crops have different sensitivities to water during different stages of their growth. Seiler, et al. (2000) conducted a study in Argentina where they used VCI and TCI to estimate corn yields. They found VCI had the highest correlation with yield 24-30 weeks after planting, while TCI had its highest correlation in week 29. Unganai and Kogan (1998) conducted a study in Zimbabwe using VCI and TCI to estimate crop yields. They found good estimations could be made six-13 weeks from harvest. Kogan, et al. (2005) found that when using VHI in Northern China, the best predictions for corn yield was found two to three weeks before the tasseling stage through two to three weeks after the tasseling stage. This study revealed how VCI and TCI can be used to accurately make predictions of corn yields.

Johnson (2014) also used vegetation indicies to make crop yield estimates for 10 states in the Midwest. He used 8-day MODIS NDVI, Daytime Land-Surface-Temperature (LST), precipitation data, and Nighttime LST values and correllated them with corn and soybean yields in the Midwest for the years 2006-2011. He only used MODIS pixels which could be covered by at least 90 percent of corn/soybean pixels that were downloaded from Cropscape. For both corn and soybeans, the highest correlation was with NDVI which peaked in late summer around the 0.7 correlation level. Daytime LST had a negative correlation in late summer with both crops, about -0.5 for soybeans and about -0.6 for corn. There was no significant correlation with nighttime LST and precipitation. He used the data for these years to create a model to predict 2012 yields based on NDVI and daytime LST. His model had a R^2 value of 0.77 for corn and 0.71 for soybeans. Johnson (2014) showed how Cropscape data can be used as a land cover to determine which remotely sensed pixels of vegetation indices should be used in a study.

CHAPTER III

METHODOLOGY

Study Area

While not having official boundaries, states traditionally comprising the Corn Belt include: Minnesota, Iowa, Nebraska, Wisconsin, Missouri, Illinois, and Indiana. Additionally, other states that have been included in this study are North Dakota, South Dakota, Kansas, Michigan, and Ohio. I will include these 12 states as my study area.

These states were also natural choices for studying corn because of the amount of corn that is planted within them as compared to the rest of the country (Fig. 1).

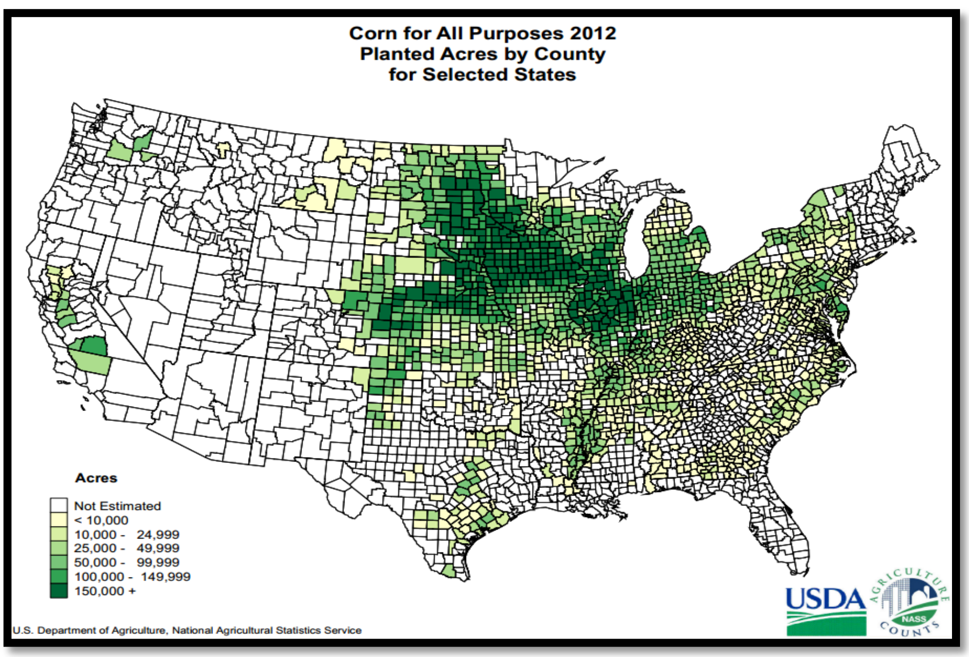

Figure 1. The United States Corn Belt as made visible by the high density of corn planted per county. Source: USDA.

The climate for each state differs as well. Table 1 below shows the annual average temperature and precipitation totals based off a 30-year average (1984-2013).

Table 1. 30 year annual averages of temperature and precipitation for the 12 states of the study, 1984-2013. Source: National Climatic Data Center.

State	Average Temperature (°C)	Precipitation Total (mm)
Illinois	10.9	951.7
Indiana	10.7	1009
Iowa	8.61	815.1
Kansas	12.3	687.3
Michigan	6.44	790.7
Minnesota	4.50	659.9
Missouri	12.5	1029
Nebraska	9.11	575.1
North Dakota	4.28	440.4
Ohio	10.2	972.6
South Dakota	7.00	484.4
Wisconsin	5.78	794.8

Data

I used weekly 16-km AVHRR VCI and TCI composites for 2007-2013. 16-km was used instead of the 4-km because of the recommendation of Dr. Felix Kogan (Braun 2013). I chose AVHRR over other remote sensing platforms for multiple reasons. First, AVHRR has broad-scale resolution. Mapping the entire Midwest using 30-m Landsat data would become cumbersome. Second, AVHRR images the entire Earth every day, while Landsat takes 16 days. Another reason for choosing AVHRR is the easy accessibility of obtaining AVHRR composites. Sixteen-km AVHRR VCI/TCI composites can be downloaded for free from the NOAA Center for Satellite Applications and Research (STAR) website.

TCI and VCI values were downloaded from the NOAA Global Vegetation Index (GVI) dataset. This dataset is created by taking daily 4-km pixels from AVHRR images and resampling them into 16-km weekly composite pixels. TCI and VCI are based on three bands in the AVHRR sensor: the visible band (Channel 1), near-infrared (Channel 2), and infrared (Channel 4). The visible and near-infrared bands are converted to reflectance values and are then used to create NDVI values. The infrared radiance values are converted to brightness temperature (T) (Kogan 1997). TCI (Fig. 2) and VCI values are then calculated from NDVI and BT, where NDVI, NDVImax, and NDVImin are the smoothed weekly NDVI, its historical absolute maximum, and minimum, respectively, and T, Tmax, and Tmin are found using the same methods from BT. See equations 2 and 3 earlier in the paper for the formulas. VCI captures vegetation greenness and TCI represents surface temperature. Both range from 0-100, where 0 represents severe vegetation stress and 100 is exceptional conditions for vegetation.

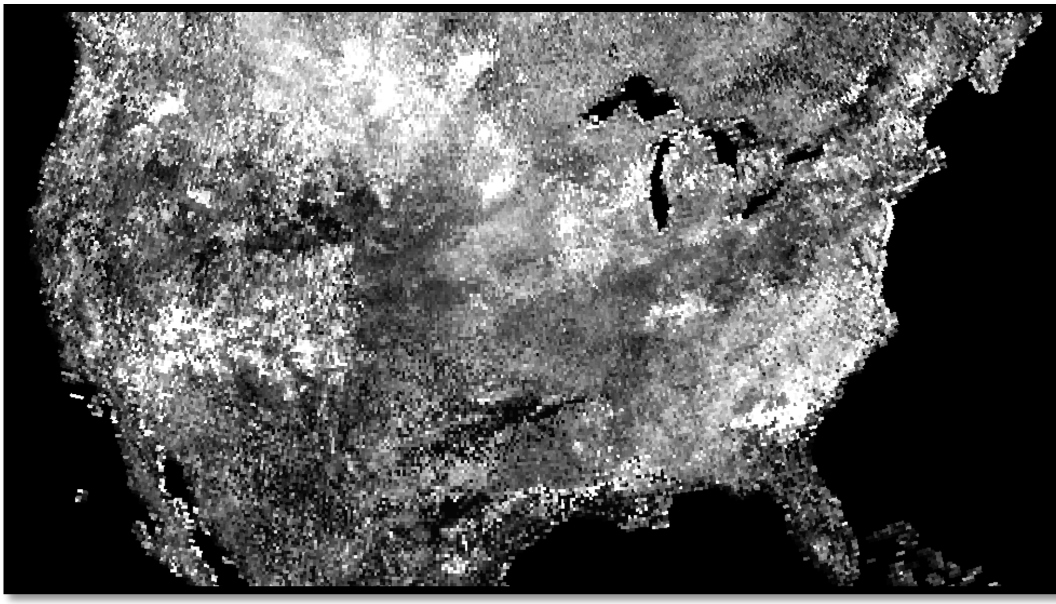

Figure 2. An example of a 16-km TCI composite of the U.S. Each pixel has a value ranging from zero (dark tones) to 100 (bright tones). Lower values represent non-optimal vegetation conditions and higher values represent optimal condition. Format for VCI is similar. Source: NOAA STARR.

Land Cover

I extracted the corn layers from Cropscape. Cropscape is a program that is run by the NASS where crop data can be displayed and downloaded at a 56m resolution. Cropscape data are created by using datasets from multiple satellite platforms: 1) Indian Remote Sensing (IRS)-P6; 2) Landsat 5, 6, and 8; and 3) the MODIS sensor. The pixels are then created by using a supervised classification. Ground truth data were gathered in cooperation with the Farm Service Agency (FSA). Accuracies varied for each crop and state; however, highly intensive agricultural areas such as the Corn Belt and Mississippi River Delta had higher accuracies. Dominant crops such as corn and soybeans had higher accuracies that typically exceeded 90% (Johnson and Mueller, The 2009 Cropland Data Layer 2010). I downloaded corn data files for seven years, 2007 (Fig.3) through 2013 for the Corn Belt. I can only download data as far back as 2007 as that is when data for most of the states in the Corn Belt became available.

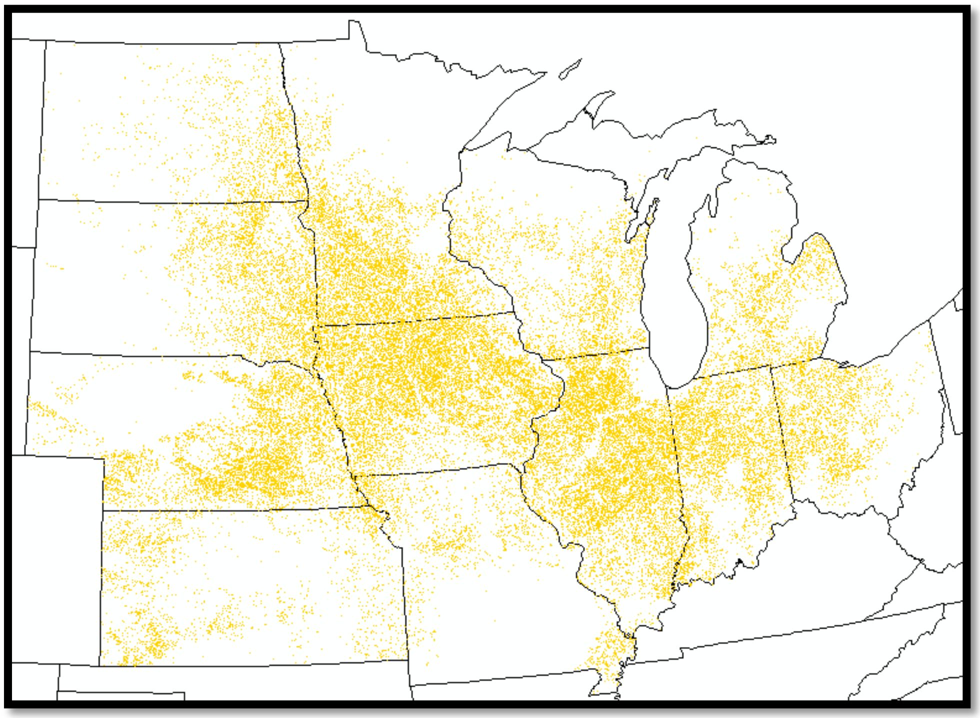

Figure 3. 2007 Cropscape Corn Pixels for the 12 states of the study. Each gold pixel represents a 52-m pixel Cropscape identified as corn. Source: USDA.

After extraction of the corn layers, I separated the non-irrigated corn from the irrigated corn. I did this because my research topic is about the timing of yield predictions on rainfed corn fields. Irrigated fields are unaffected by drought, thus possibly throwing off my data if I include irrigated fields in my study. To do this, I used a GRID file of irrigated fields at a 250-m level, generated by Pervez and Brown (2010), to remove pixels from my AVHRR composites (Fig. 4). Although there is not a well-established data set for irrigated fields in the U.S., Pervez and Brown (2010) were able to generate a map of irrigated lands using three main inputs: USDA county-level irrigation statistics for 2002, annual peak MODIS NDVI values, and the 2001 National Land Cover Dataset (NLCD).

First, Pervez and Brown (2010) masked out lands that only were identified or linked to agriculture at the county level. Next, they identified the annual highest MODIS NDVI pixels in each county. The area of these pixels were calculated and then compared to the USDA county-level irrigation statistics. If the area of the MODIS pixels were higher/lower than the USDA statistics, NDVI pixels were subtracted/added to the output map until the acreage matched the USDA acreage. By using this model, Pervez and Brown (2010) were able to obtain reasonable results for estimating irrigation totals with their results only 1.5 percent above the USDA agricultural census estimate.

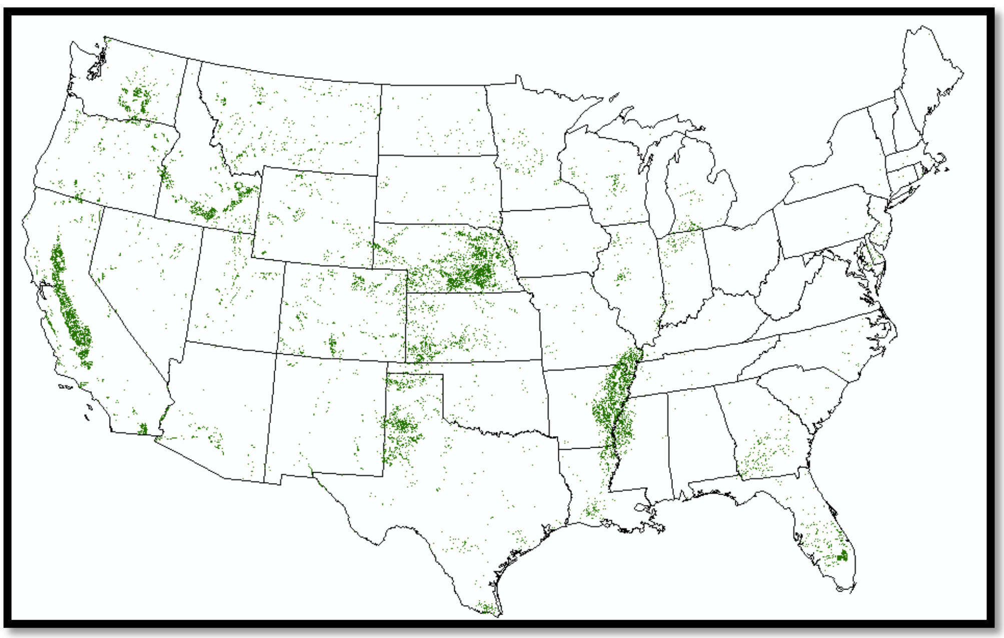

Figure 4. 2007 MIrAD-US 250 meter Irrigation Layer. Each green pixel represents a 250-m MODIS pixel MIrAD-US determined was irrigated. Source: Pervez and Brown (2010).

To reduce noise produced from mixed pixels, a threshold to separate AVHRR pixels that contained a majority of corn from those with little corn cover was established. This threshold represents the minimum percentage of a pixel that must be corn for it to be counted in my statistics. I used a minimum threshold of greater than 50 percent based on Balaghi, et al. (2008) in which they defined NDVI pixels as agricultural if they exceeded than 50 percent agricultural land cover within the pixel. This process was done in ArcGIS 10.1 (Environmental Systems Research Institute, Redlands, CA) by resampling the corn pixels to 16-km to match the vegetation indices. By using a "majority" resampling method, only 16-km corn pixels that contained more than 50 percent coverage by Cropscape corn pixels were drawn (Figure 5).

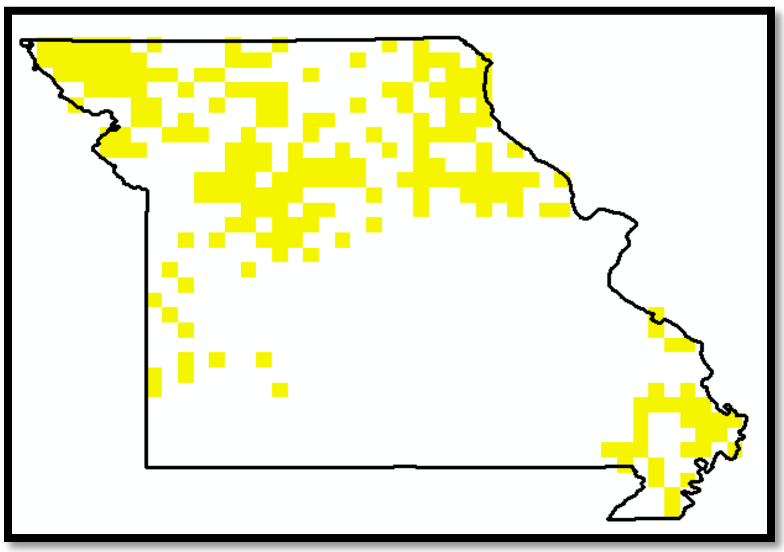

Figure 5. Missouri as an example of the majority resampling method. Each yellow pixel represents and 16-km pixel which has more than 50 percent corn cover. Source: USDA Cropscape.

Calculations

Weekly averages of the VCI and TCI were produced for each of the 12 states in my study area. This was done with the "Zonal Statistics" tool in ArcGIS 10.1. These values were then put into a Microsoft Excel 2010 (Microsoft Corporation, Redmond, WA) table for use in Statistical Product and Service Solutions 21 (SPSS) (IBM Corporation, Armonk, NY).

Weekly VCI and TCI values were correlated and regressed with yield data downloaded from NASS by using SPSS at the state scale level. The correlation scale ranges from -1 to +1. A positive correlation means the two values trend in the same direction (i.e. as one goes positive so does the other). A negative correlation means as one value goes positive, the other will trend towards negative and vice versa. The correlation values for weekly VCI and TCI with the yield were then graphed for each state and for the U.S. to show the change in correlation. Annual average yields were developed by a survey system, which typically contains a 27,000-farmer sample size for all agriculture in the U.S. NASS receives these surveys at the end of each harvest cycle by a number of different methods including mail surveys, telephone interviews, face-to-face interviews, and field observations. The correlation and regression statistics were done in SPSS 21.

The stage of phenology the corn is in when peak correlation occurs will be found by using the median usual planting date of corn for each state established by the USDA (USDA 2010b), and the growth rate for a 120-day corn hybrid (Hall 2006).A summary of my entire process in a flow chart form is found on the next page (Figure 6).

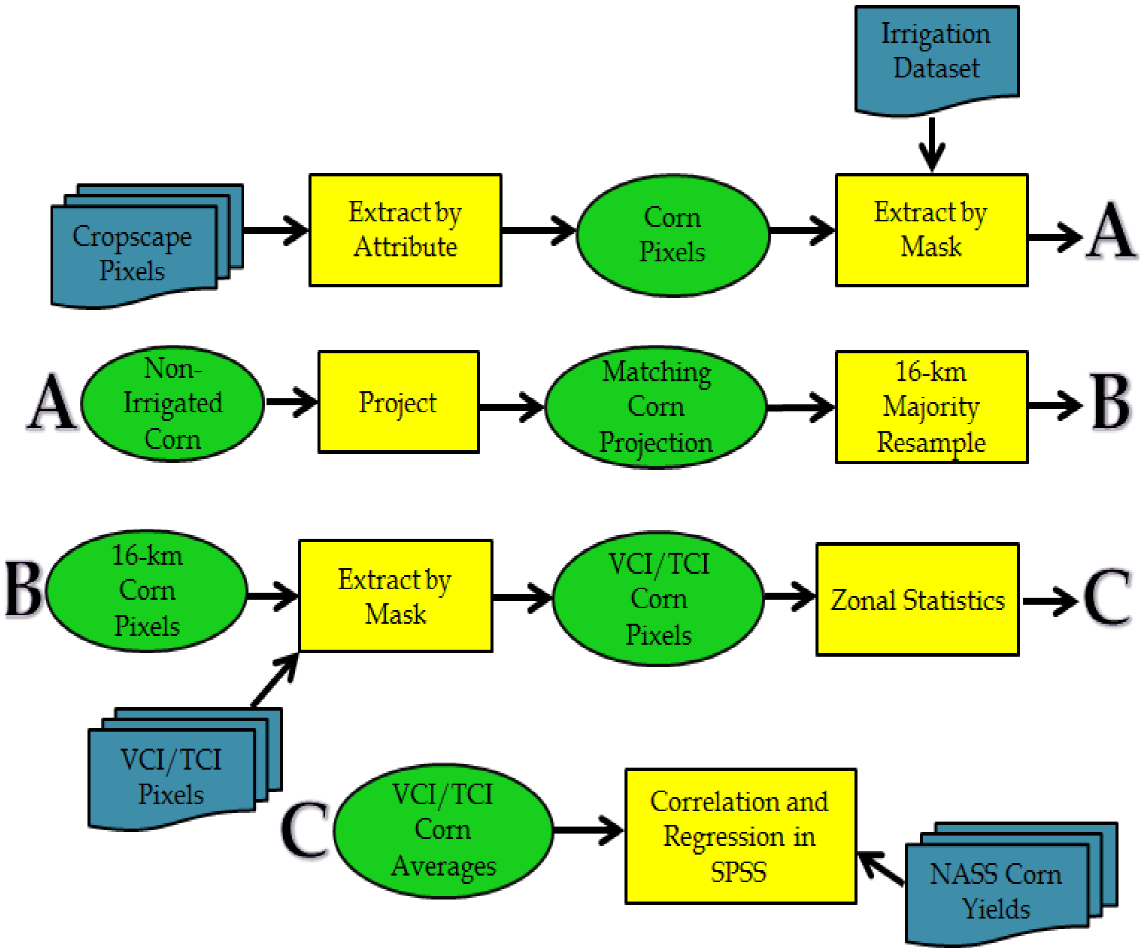

Figure 6. A flow chart diagram of each process aforementioned in my methodology. The blue items represent data inputs, the yellow items are processes, and the green items are the results of the processes.

CHAPTER IV

RESULTS

Having the databases built allowed for simple analysis to evaluate the correlation of corn yields and the vegetation indices. The Pearson correlation coefficient was used for the results for all 12 states, following the work of Kogan, et al. (2005) and Johnson (2014). The distribution of weekly correlation values to yield for each state and the national average can be seen in the graphs below. In most, there is a smooth, gradual curve in the correlation data. However, in some states such as Minnesota, the correlation curve is erratic and moves wildly. The high correlation of VCI was expected as VCI is based off NDVI values; this correlation has been shown as a good indicator of plant health (Kogan 1997). The high correlation with TCI was expected as well because the dependency of plant development, respiration and biological processes rely on temperature. Nonoptimal temperatures cause stress on crops and can decrease yields, or even speed plant development through the grain-filling stage (Unganai and Kogan 1998).

The highest week of correlation for VCI and TCI were then chosen as independent variables and regressed against yield as the independent variable for each state.

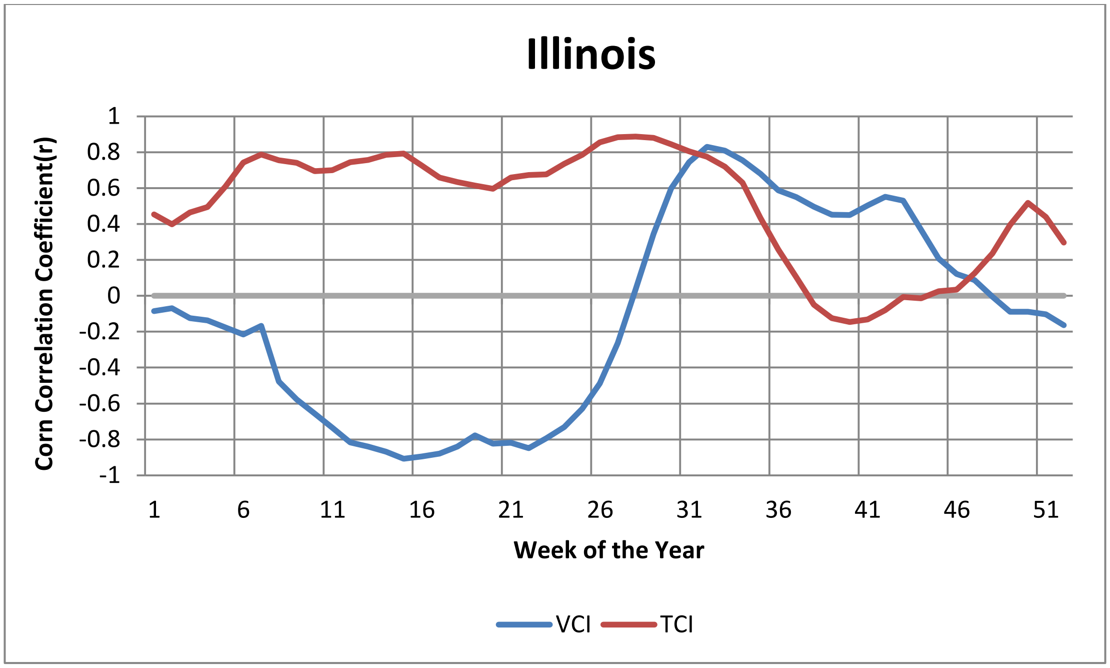

Figure 7. Correlation graph of Illinois. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

VCI in Illinois has a very large negative correlation in Weeks 11 through 23, which should be around planting time. Then, about Week 23 it dramatically increases to peak at 0.808 in Week 33, which is during the beginning of the reproduction stages. The Illinois graph shows a moderate correlation with TCI in the first few weeks of the year which increases to 0.8 in the weeks six through 11. TCI ultimately peaks in Week 28 before dropping off in week 40 to have no significant correlation. VCI peak correlation falls greatly into the R3 stage and TCI in the VT stage.

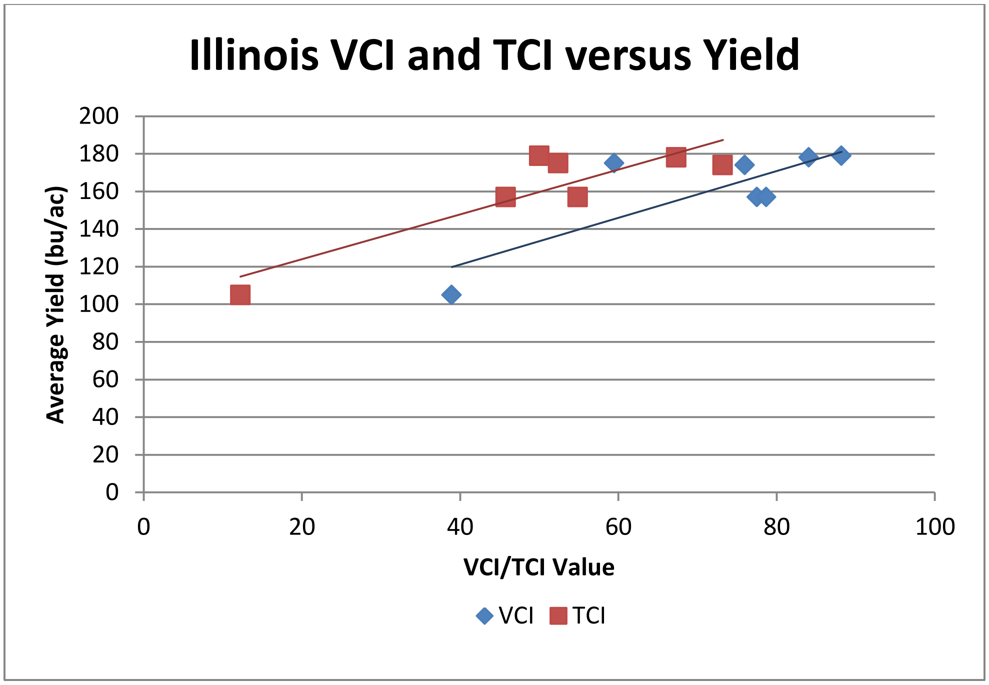

Figure 8. A scatterplot of Illinois VCI and TCI values vs Yield for 2007-2013. Peak VCI is week 33 and peak TCI is week 28. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS, it produced an equation of: Yield = 0.491(VCI33) + 0.866(TCI28) + 81.426. The adjusted R^2 of the model was 0.747 with an error of 3.539 bushels per acre. This means 74.7 percent of the variation in yield can be explained by VCI and TCI.

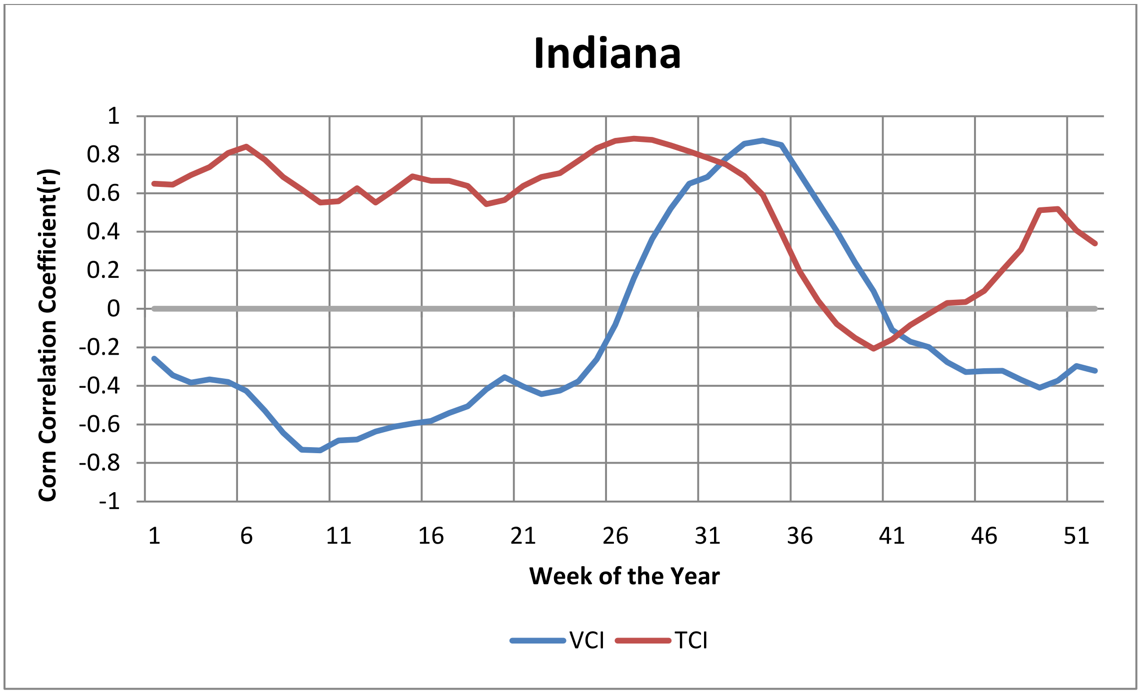

Figure 9. Correlation graph of Indiana. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

In Indiana, VCI has a negative correlation in the first half of the year before rising and peaking in correlation strength in Week 34 at 0.873. VCI correlation then drops around week 40. TCI maintains a moderately-high positive correlation during the first half of the year, peaking in Week 27 at 0.883. TCI then drops similarly to VCI at about Week 40. VCI peak correlation falls in the R3 stage and TCI in the V10 stage of development.

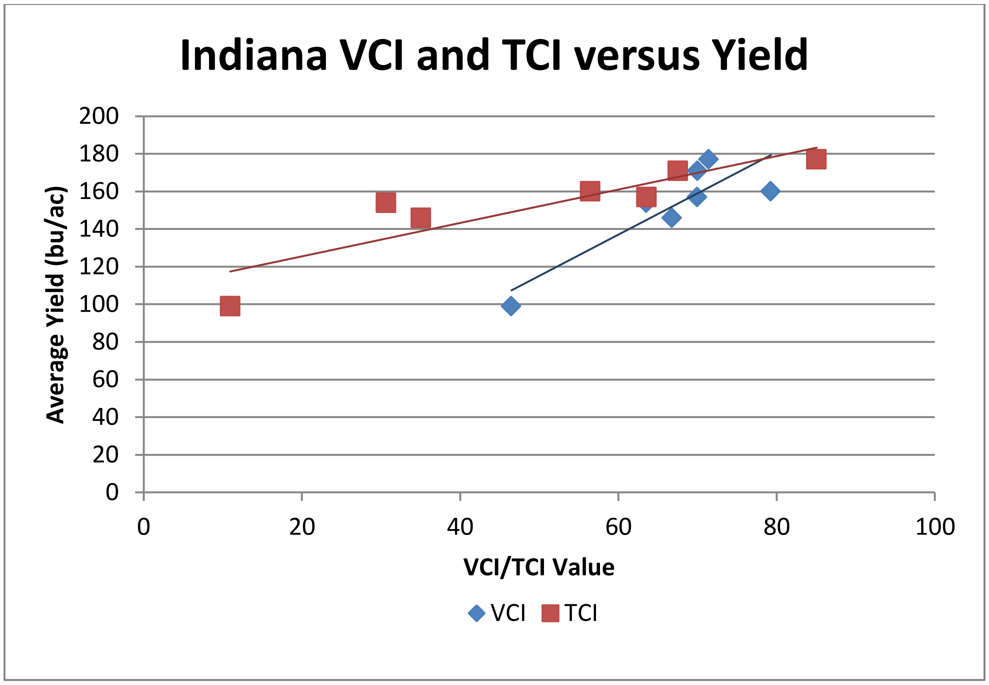

Figure 10. A scatterplot of Indiana VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 34 and TCI is week 27. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS it produced an equation of: Yield = 1.88(VCI34) + 0.541(TCI27) + 46.657. The adjusted R^2 of the model was 0.806 with an error of 4.507 bushels per acre. Meaning 80.6 percent of the variation in yield could be explained by this VCI and TCI.

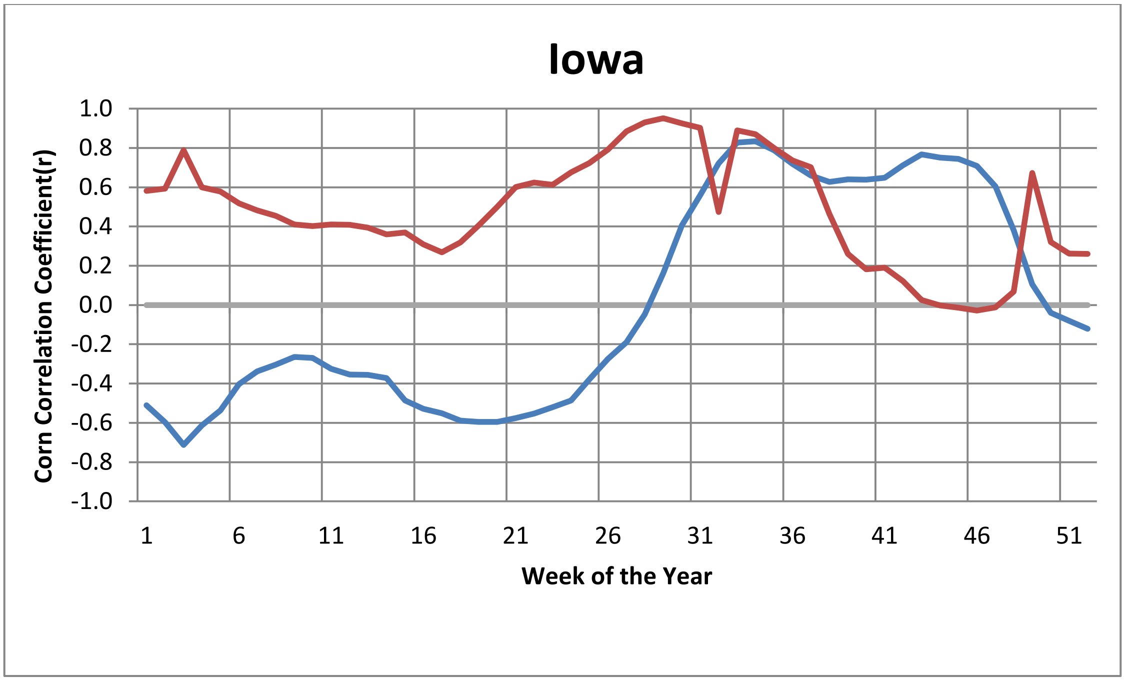

Figure 11. Correlation graph of Iowa. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

Iowa VCI, like Indiana and Illinois, is negative during the first half of the year and then increases until it peaks at Week 34 at 0.834, around the time of tasseling. It maintains moderately-high correlation before dropping off about Week 47. TCI has a moderately-high positive correlation in the first half of the year which peaks in Week 29 at 0.951. There is an anomaly in Week 32 where it drops dramatically and then increases. It then drops to no correlation at about Week 43. Based on median planting dates for Iowa and typical growth patterns of corn, VCI peak correlation falls into the R4 stage and TCI in the R1 stage.

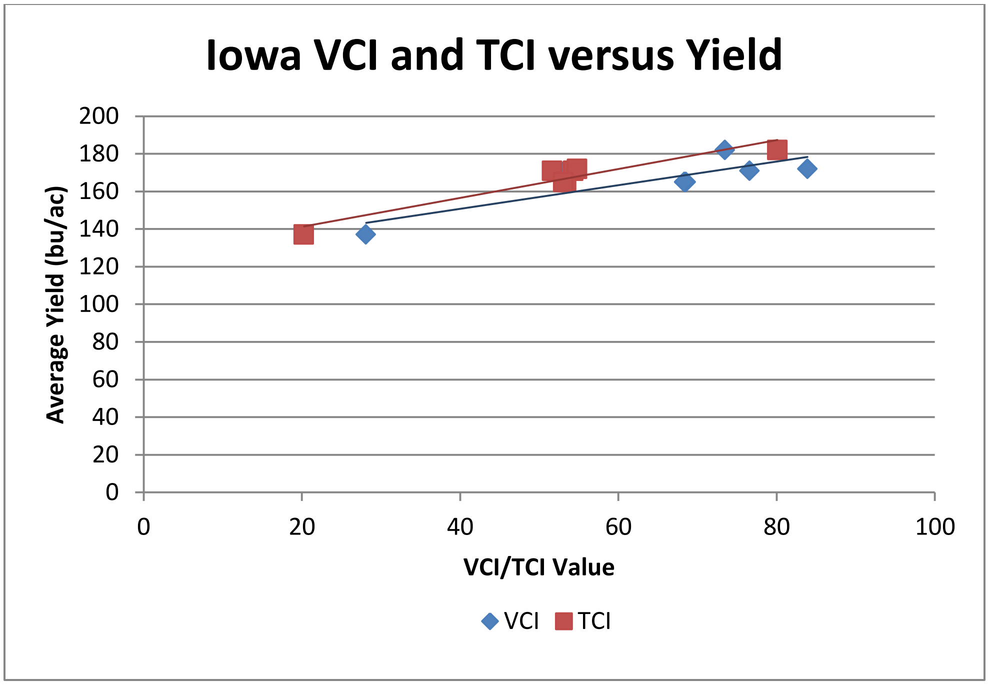

Figure 12. A scatterplot of Iowa VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 34 and TCI is week 29. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS they produced an equation of: Yield = 0.185(VCI34) + 0.616(TCI29) + 121.863. The adjusted R^2 for the model was 0.893 with an error of 4.586 bushels per acre. This means 89.3 percent of variation in yield can be explained by VCI and TCI.

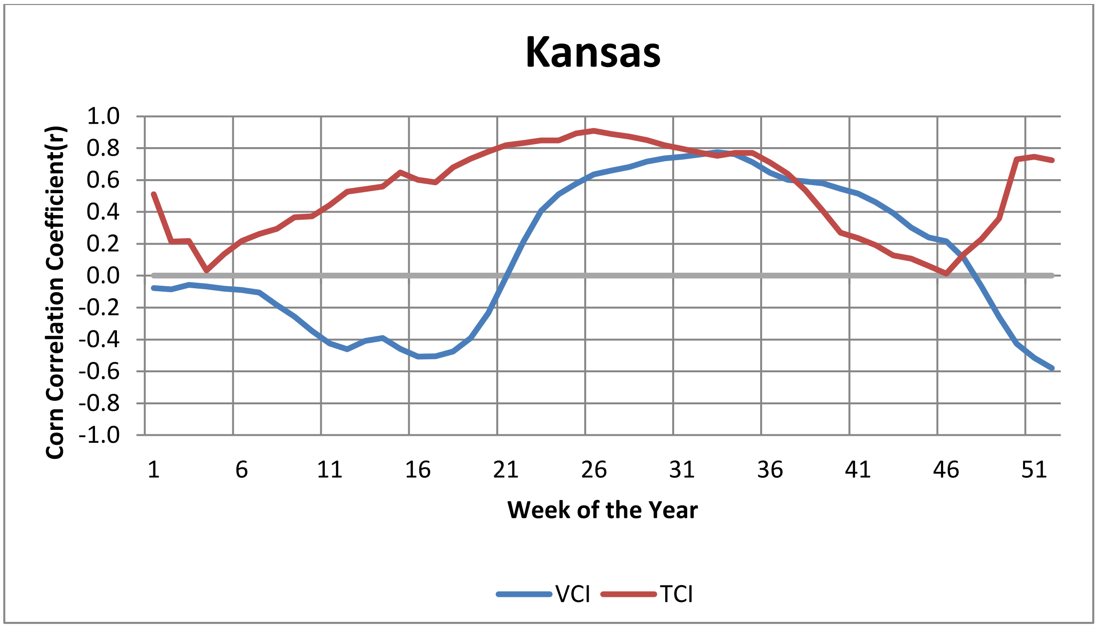

Figure 13. Correlation graph of Kansas. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

VCI correlation in Kansas starts the year with little correlation before dropping to have a moderately strong negative correlation around planting season during Week 16. VCI correlation then rises to peak at Week 34 at 0.763, before lowering to no strong correlation near the end of the year. TCI correlation begins the year dropping quickly to little correlation in Week Five before gradually increasing to a peak in Week 26. TCI then drops to small correlation in Week 46 before rising again at the end of the year. Based on median planting dates for Kansas and average corn growth rates, VCI peak correlation lands in the R4 stage and TCI in the V10+ stage.

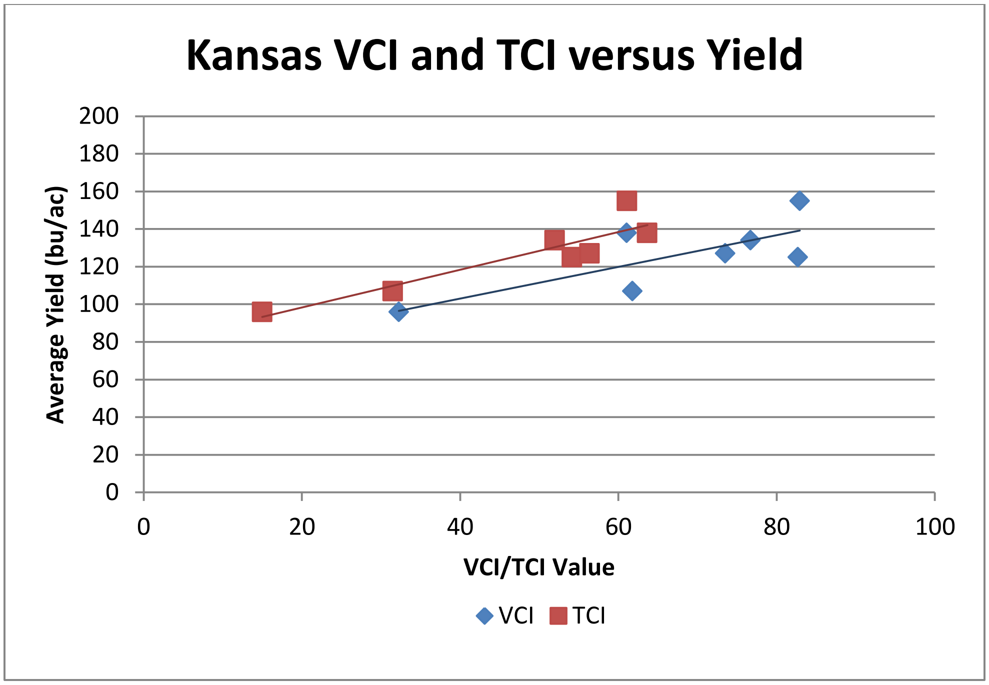

Figure 14. A scatterplot of Kansas VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 34 and TCI is week 26. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks of peak correlation of VCI and TCI were regressed in SPSS they produced an equation of: Yield = 0.089(VCI34) + 0.930(TCI26) + 75.689. The adjusted R^2 for the model was 0.742 with an error of 9.996 bushels per acre. This means 74.2 percent of variation in yield data can be explained by VCI and TCI.

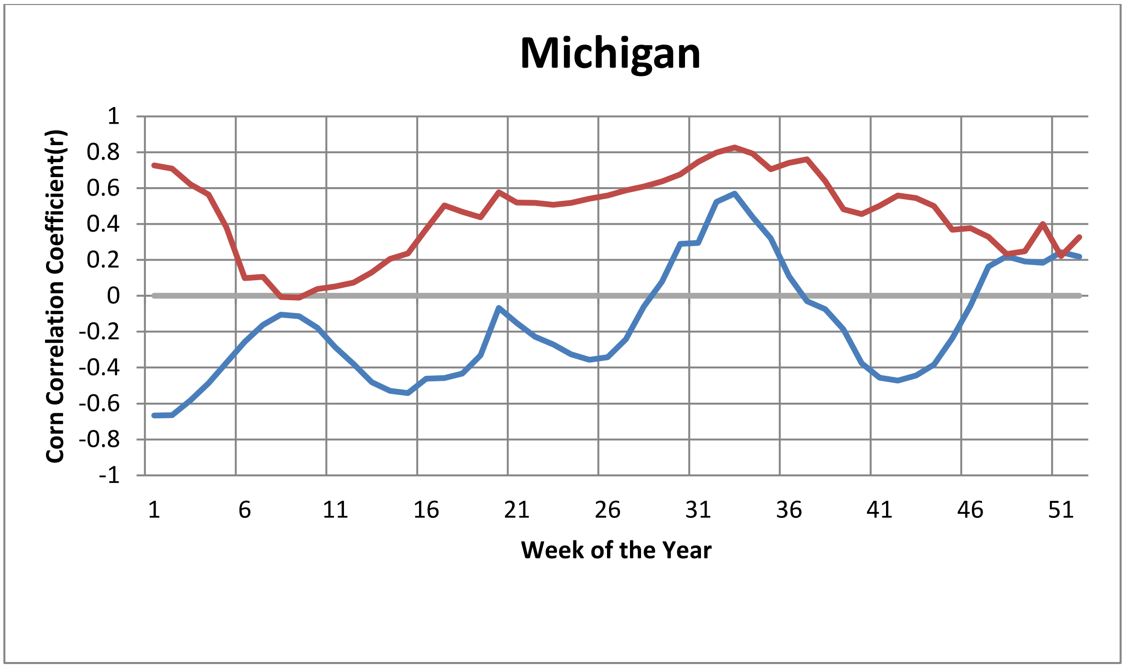

Figure 15. Correlation graph of Michigan. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

Michigan corn yield correlation with VCI starts the year with a moderatly negative correlation which decreases in strength and increases and lowers multiple times before it becomes positive and peaks in Week 33 at 0.569. It then drops off similarly to the previous states. TCI correlation has a similar curve to the previous states where it starts positive, drops to little correlation, then gradually increases to peak in Week 33 at 0.826 before dropping in strength again. For Michigan both the VCI and TCI correlation values peak in the R2 stage of corn reproduction development.

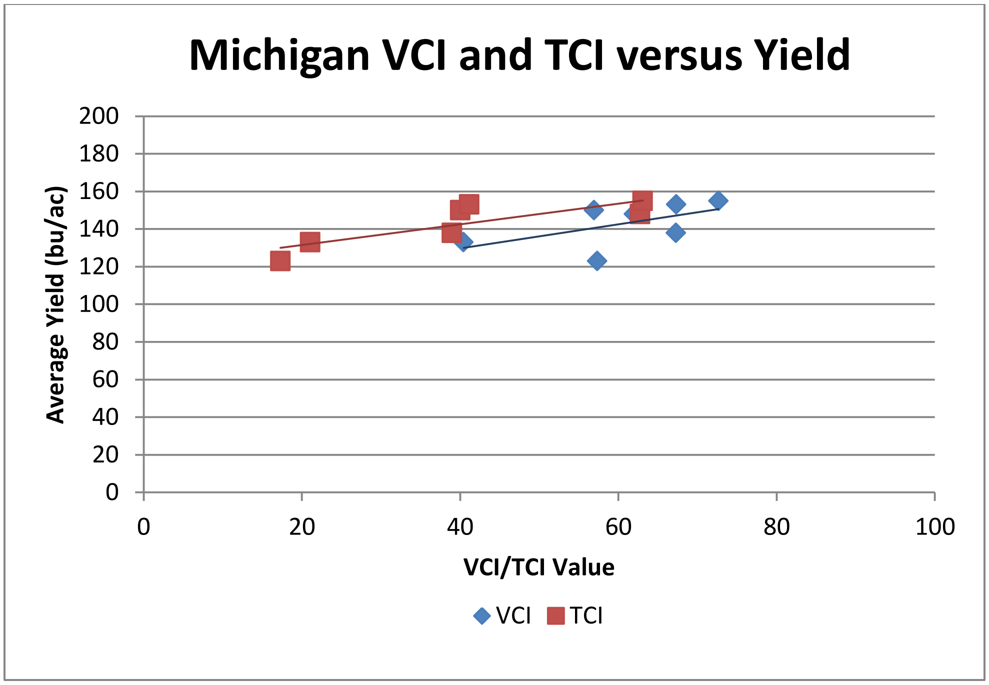

Figure 16. A scatterplot of Michigan VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 33 and TCI is week 33. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS they produced an equation of: Yield = 0.021(VCI33) + 0.538(TCI33) + 119.752. The adjusted R^2 for the model was 0.523 with an error of 8.182 bushels per acre. This means 52.3 percent of the variation in the yield data can be explained by VCI and TCI.

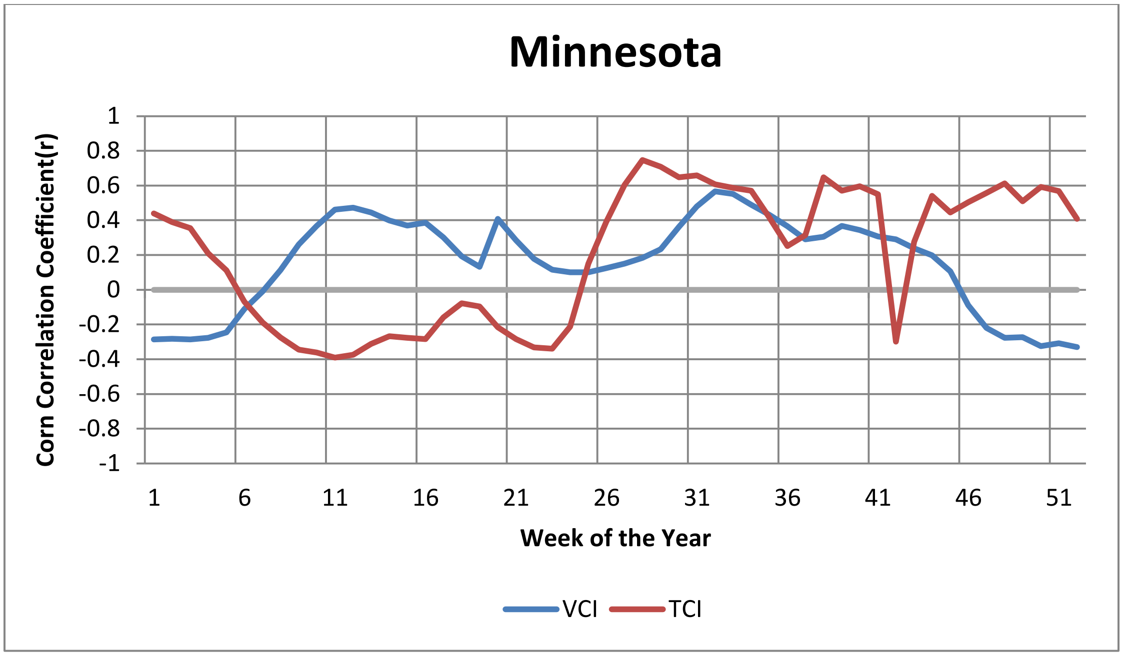

Figure 17. Correlation graph of Minnesota. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

VCI correlation in Minnesota has an erratic nature to its curve, but has similar peak values like the previous states. It starts negative in the beginning of the year before increasing and peaking in Week 32 at 0.566. TCI starts positive, but then drops quickly to be negative in the first half of the year before increasing again and peaking at Week 28 at 0.826. It then stays positive except for an anomaly in Week 42 where it drops quickly and rises up again. VCI peaks in the R2 stage and TCI peaks in the VT stage.

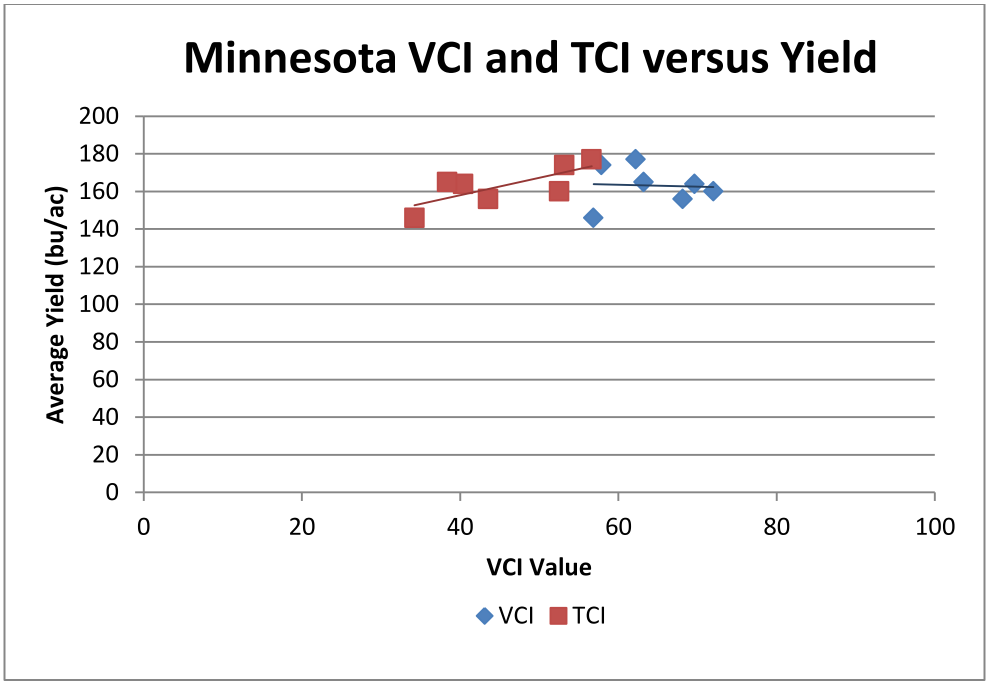

Figure 18. A scatterplot of Minnesota VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 32 and TCI is week 28. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS they produced an equation of: Yield = 0.308(VCI32) + 0.769(TCI28) + 108.125. The adjusted R^2 for the model was 0.486 with an error of 7.658 bushels per acre. This means 48.6 percent of the variation in yield data can be explained by VCI and TCI.

.

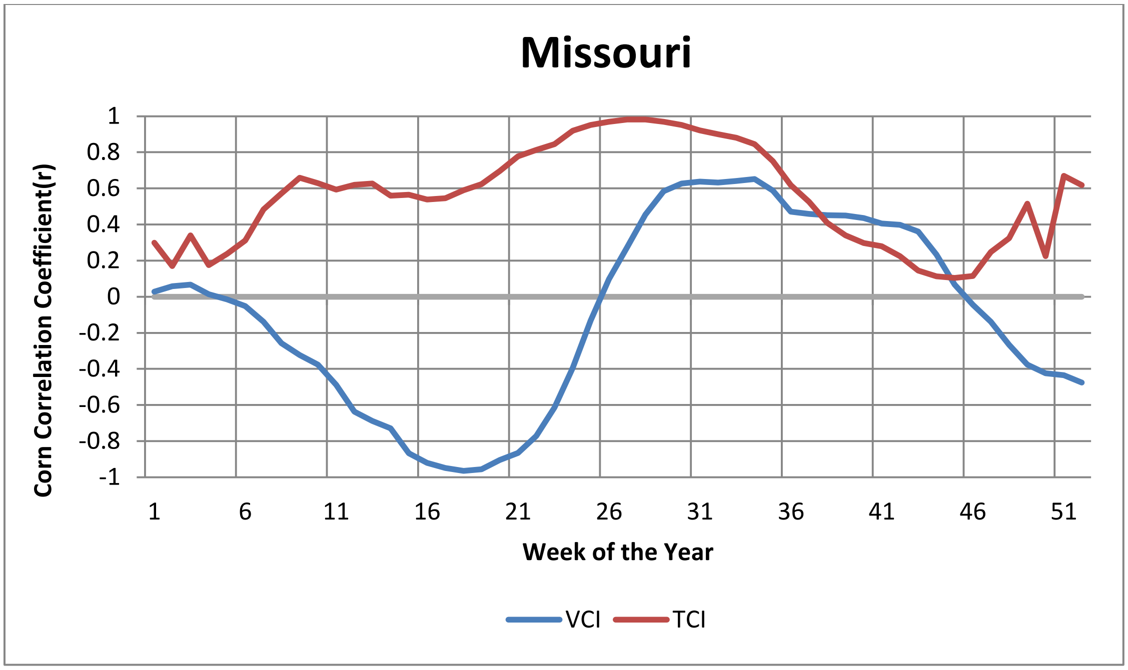

Figure 19. Correlation graph of Missouri. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

Missouri VCI correlation starts with no strong correlation before dropping greatly and having a strong negative correlation in Week 17 before increasing and peaking in Week 34 at 0.652. VCI then drops off again towards the end of the year. TCI starts positive and gradually increases to peak in Week 27 at 0.982 before decreasing afterwards. Based on the median planting dates for Missouri and the average growth rate of corn, VCI peaks in the R4 stage reproduction and TCI peaks in the V10+ vegetative stages.

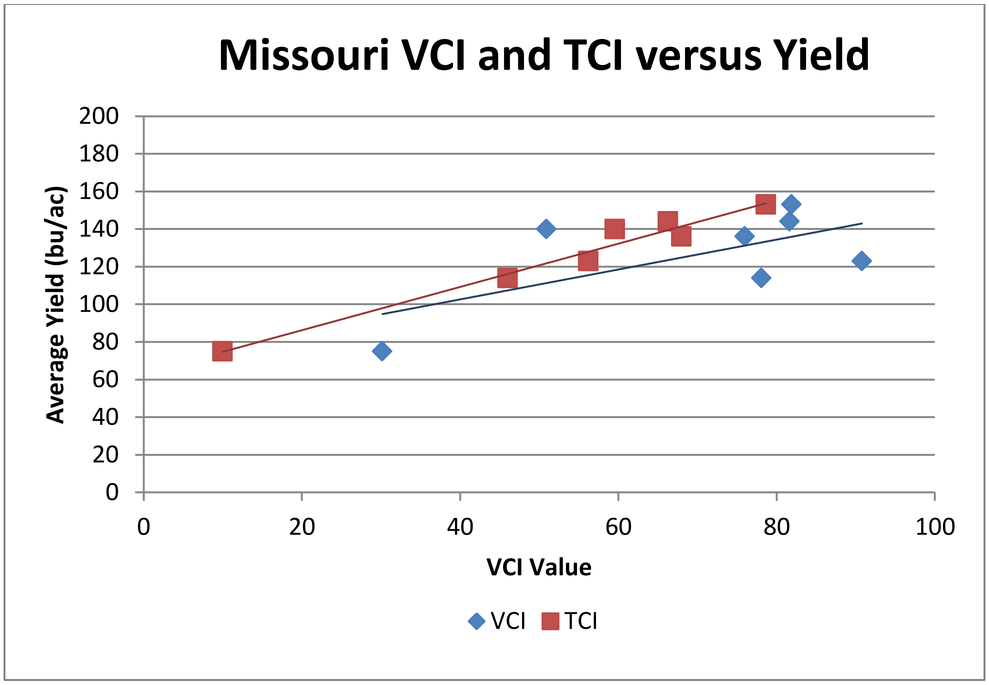

Figure 20. A scatterplot of Missouri VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 34 and TCI is week 27. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS they produced an equation of: Yield = -0.228(VCI34) + 1.315(TCI27) + 70.103. The adjusted R^2 for the model was 0.969 with an error of 4.573 bushels per acre. This means 96.9 percent of the variation in the yield data can be explained by VCI and TCI.

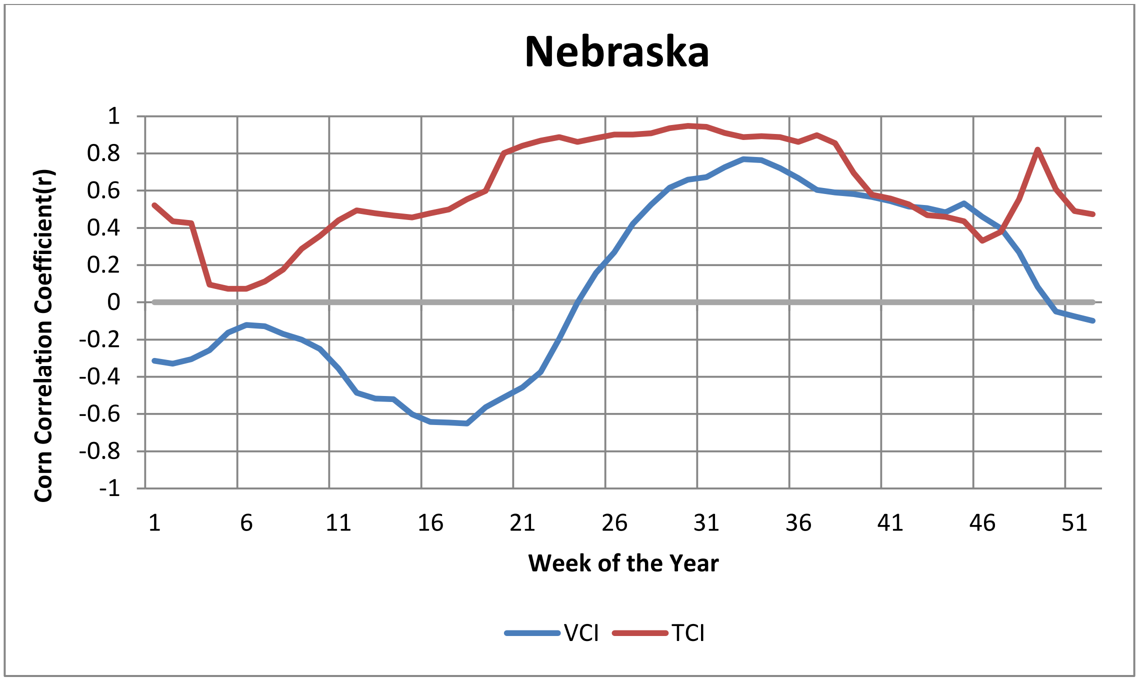

Figure 21. Correlation graph of Nebraska. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

Nebraska VCI correlation follows a similar pattern to previous states where it has a negative correlation in the first half of the year before rising to peak in Week 33 at 0.769, then decreasing in correlation until the end of the year. TCI follows the same suit as previous states, starting positive and gradually increasing to peak in Week 31 at 0.943, then decreases. There is an anomaly at Week 48 where it rises quickly, and then drops back down again. Based on the median planting date for corn in Nebraska and the average growth rate of corn, VCI correlation peaks in the R4 reproductive stage and TCI peaks in the R2 reproductive stage.

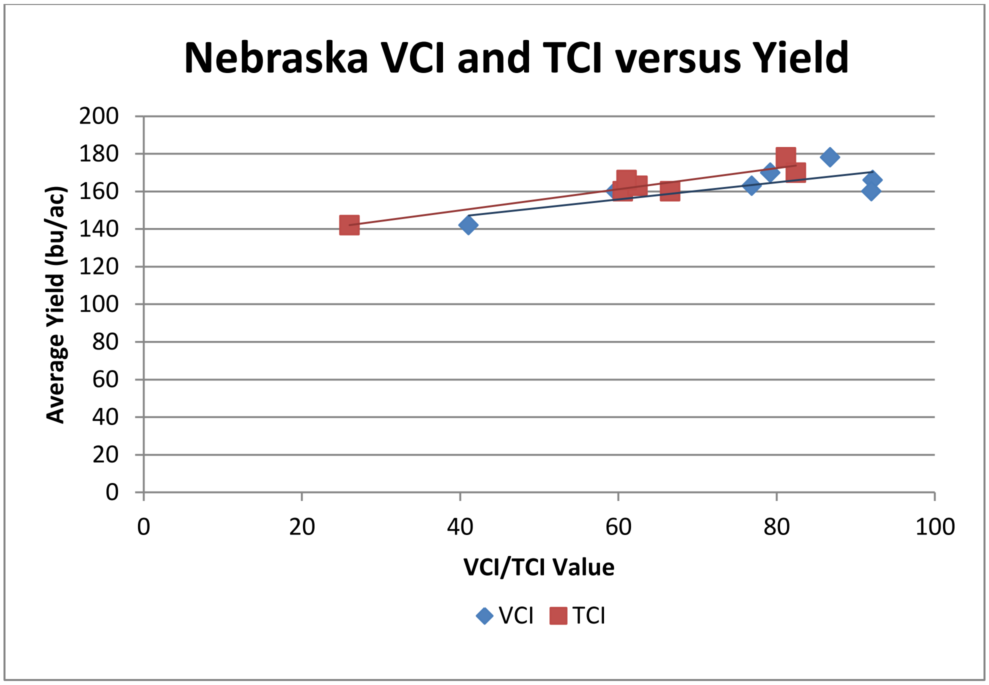

Figure 22. A scatterplot of Nebraska VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 33 and TCI is week 31. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS they produced an equation of: Yield = 0.069(VCI33) + 0.507(TCI31) + 125.605. The adjusted R^2 for the model was 0.842 with an error of 4.417 bushels per acre. This means 84.2 percent of the variation in yield data can be explained by VCI and TCI.

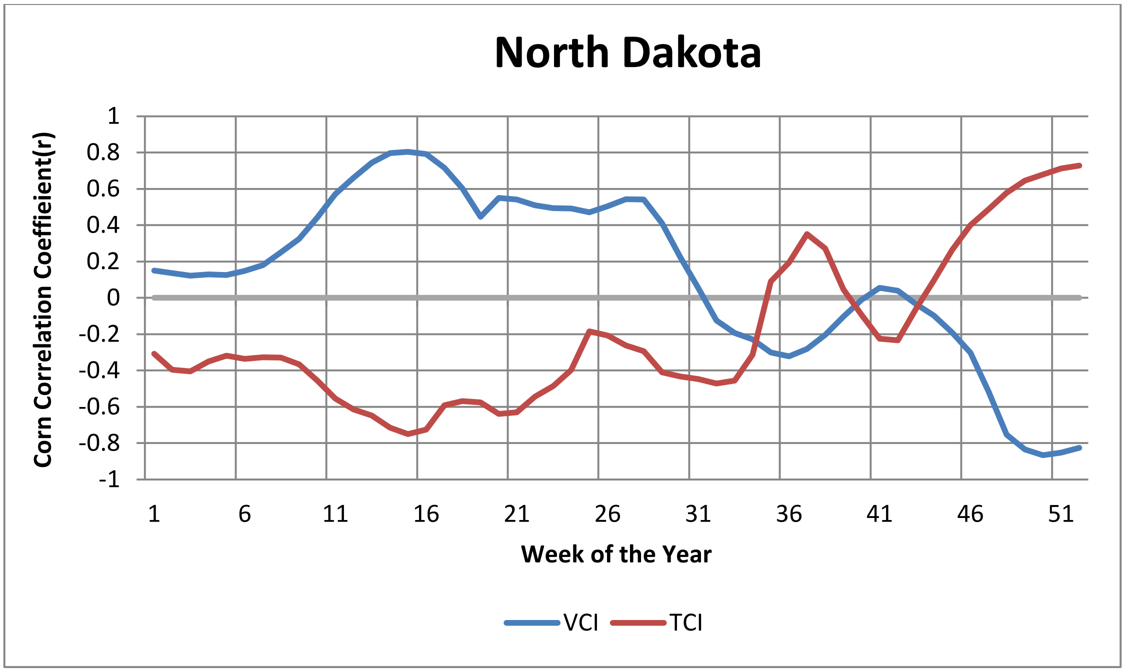

Figure 23. Correlation Graph of North Dakota. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

North Dakota has a unique correlation curve as VCI starts positive and peaks in Week 15 before dropping and having a strong negative correlation at the end of the year. TCI starts negative and has its strongest correlation in Week 15 having a negative correlation value of -0.751 before increasing to the end of the year. By using the median date of corn planting in North Dakota and the average growth rate of corn, both VCI and TCI correlation peak in the V7 stage of vegetative development.

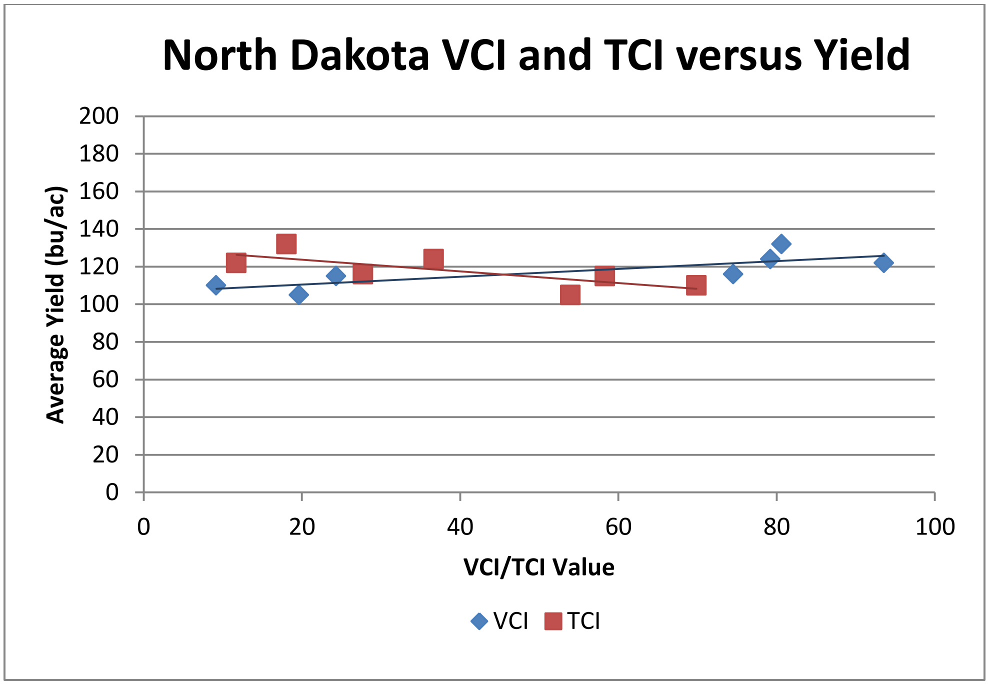

Figure 24. A scatterplot of Nebraska VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 15 and TCI is week 15. Notice the weak trends of VCI and TCI with yield. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS they produced an equation of: Yield = 0.258(VCI15) + 0.085(TCI15) + 102.546. The adjusted R^2 for the model was 0.475 with an error of 6.570 bushels per acre. This means 47.5 percent of the variation in the yield data can be explained by VCI and TCI.

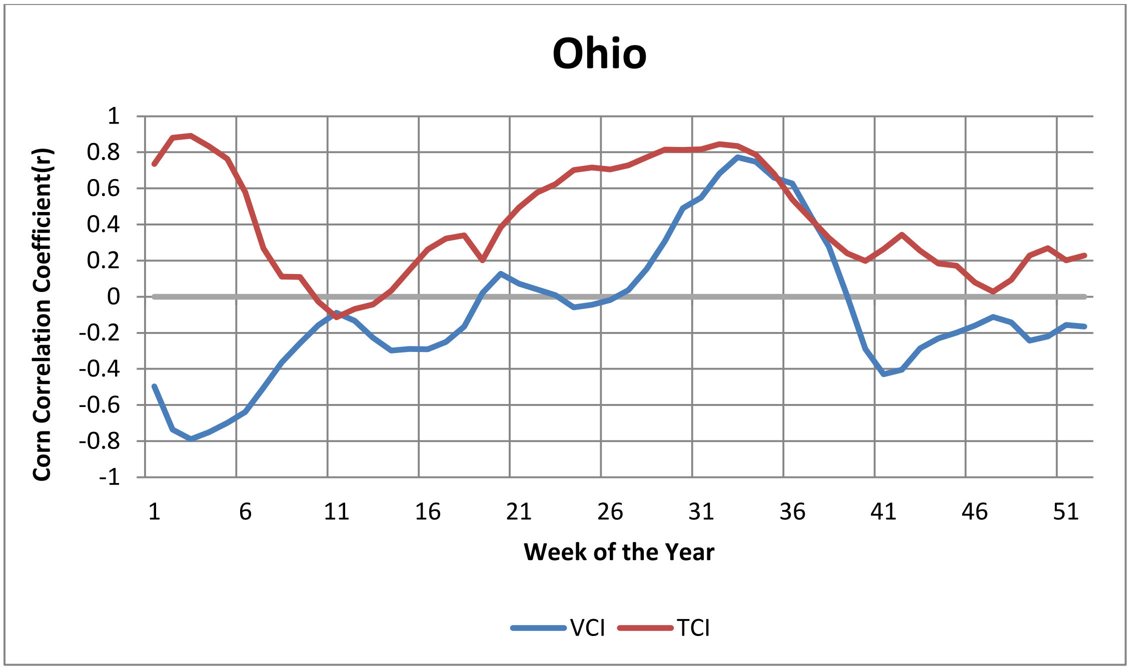

Figure 25. Correlation graph of Ohio. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

Ohio correlation curves follow similar patterns to previous states. VCI starts negative in the beginning of the year, gradually increasing to peak in Week 33 at 0.773. TCI is different from other states in that the strongest correlation in is Week 3 at 0.891. It then falls to around 0 at about Week 10, then increases, reaching another high correlation around Week 34. It then falls towards the end of the year. Bases on the median planting date of corn in Ohio and the average growth rate of corn, VCI correlation peaks in the R3 stage of development. TCI peaks well before corn is planted since it peaks in Week 3 of the year.

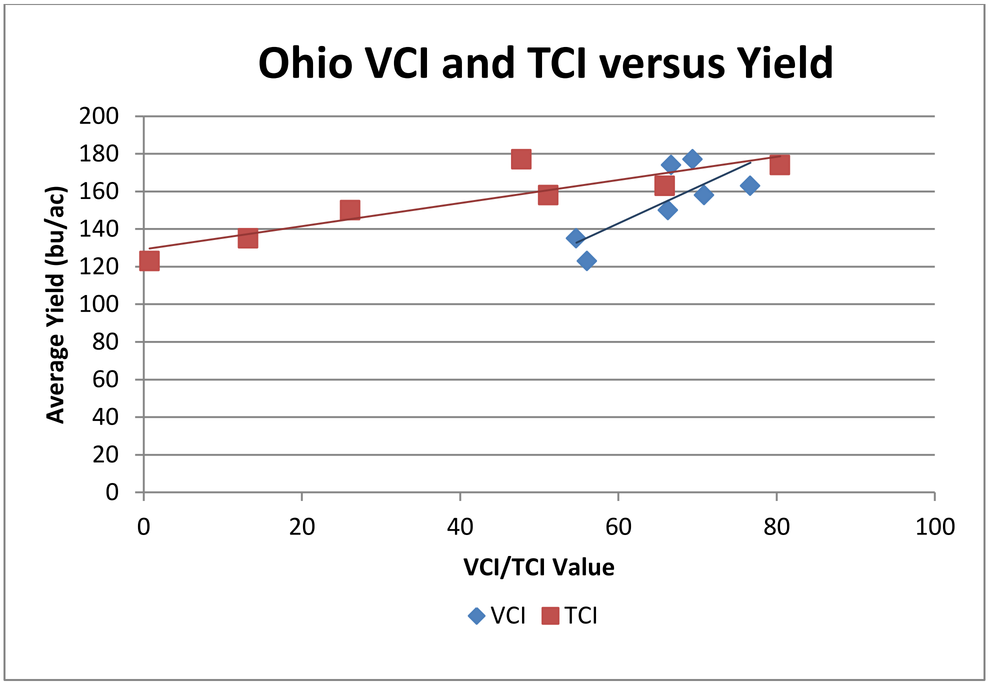

Figure 26. A scatterplot of Ohio VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 33 and TCI is week 3. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS they produced an equation of: Yield = 0.467(VCI33) + 0.515(TCI3) + 102.546. The adjusted R^2 for the model was 0.711 with an error of 10.661 bushels per acre. This means 71.1 percent of the variation in the yield data can be explained by VCI and TCI.

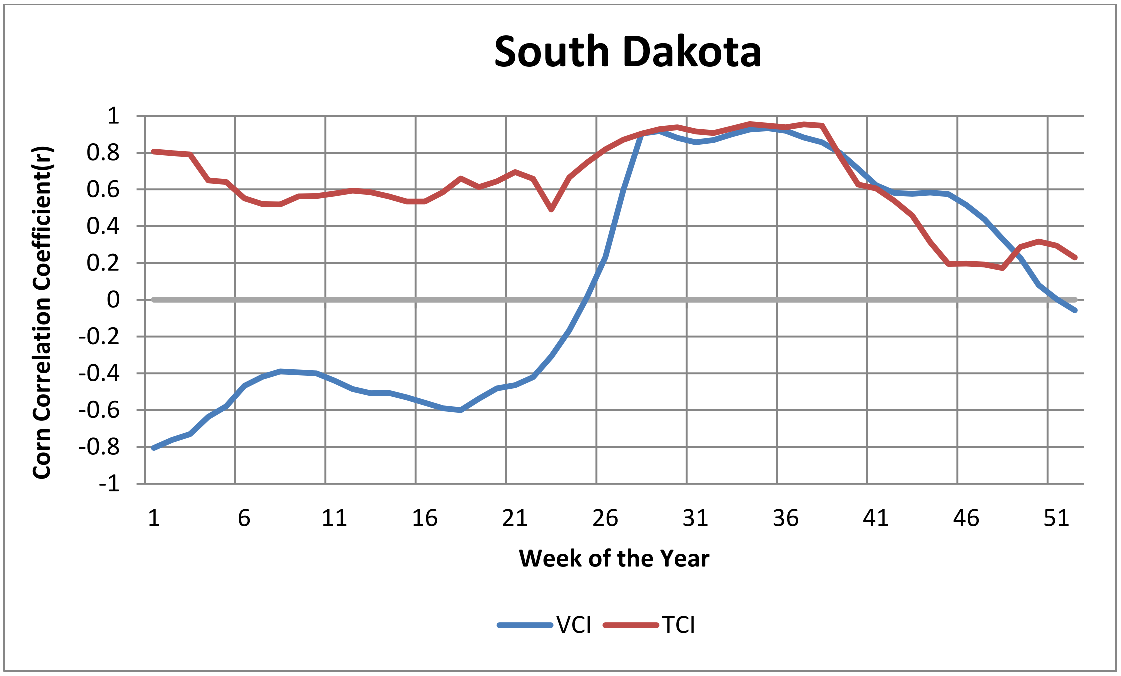

Figure 27. Correlation graph of South Dakota. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

South Dakota VCI starts strongly negative, and then sharply increases in Week 23 to peak in Week 35 at 0.934, where it then slowly decreases to the end of the year. TCI starts strongly positive and stays positive, peaking in Week 34 at 0.955. At about Week 38 TCI correlation decreases until the end of the year. Based on the median planting date of corn in South Dakota and the average growth rate of corn, VCI correlation peaks in the R4 reproductive stage and TCI in the R3 reproductive stage.

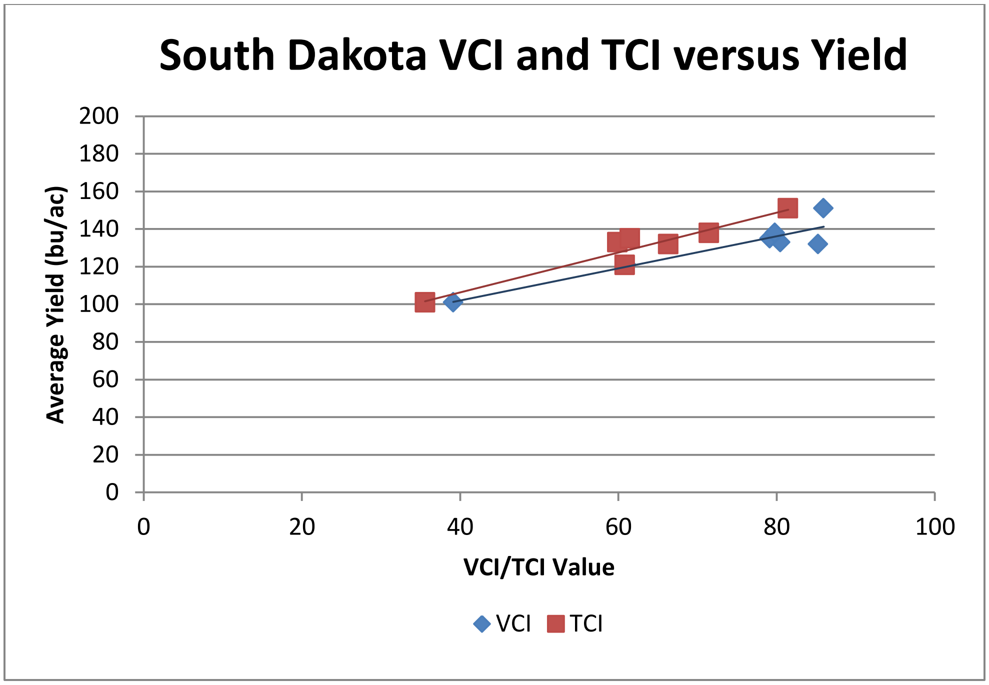

Figure 28. A scatterplot of South Dakota VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 35 and TCI is week 34. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS they produced an equation of: Yield = 0.385(VCI35) + 0.652(TCI34) + 61.362. The adjusted R^2 for the model was 0.930 with an error of 4.125 bushels per acre. This means 93.0 percent of the varitation in the yield data can be explained by VCI and TCI.

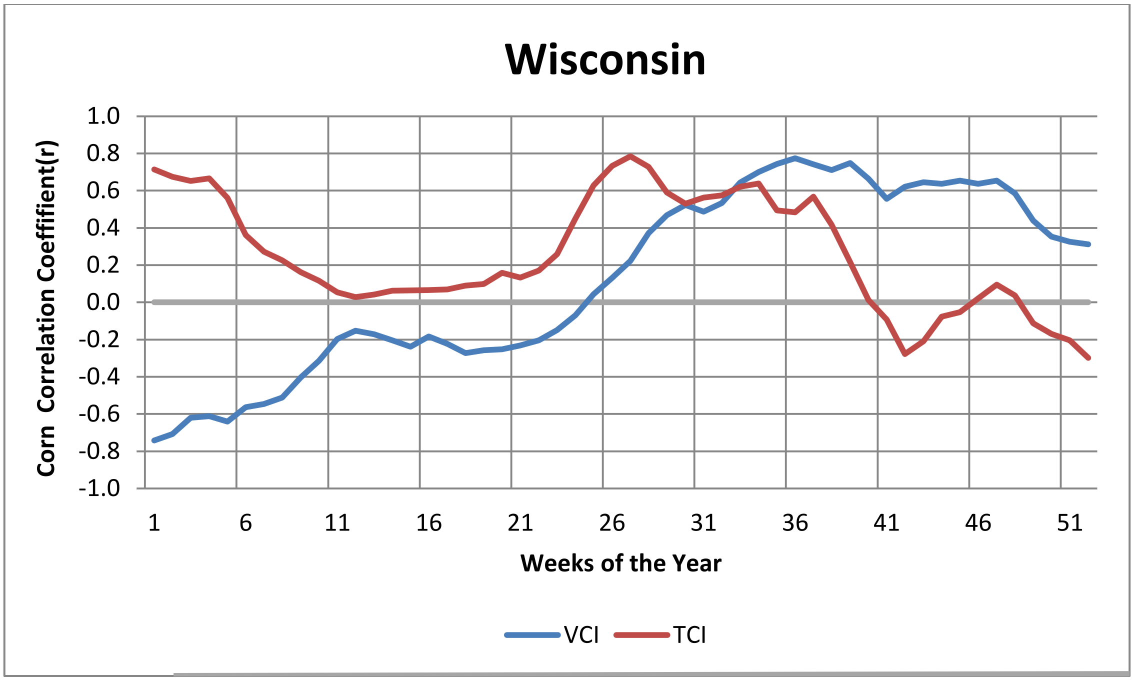

Figure 29. Correlation graph of Wisconsin. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

Wisconsin VCI correlation curves start strongly negative, which gradually increase to peak in Week 36 at 0.775, before dropping slightly at the end of the year. TCI curves start strongly positive, drop during the planting season, and increase to peak at Week 27 at 0.785. TCI then drops towards the end of the year. Based on the median planting date of corn in Wisconsin and the average growth rate of corn, VCI peaks in the R4 reproductive stage and TCI in the V10 vegetative stage.

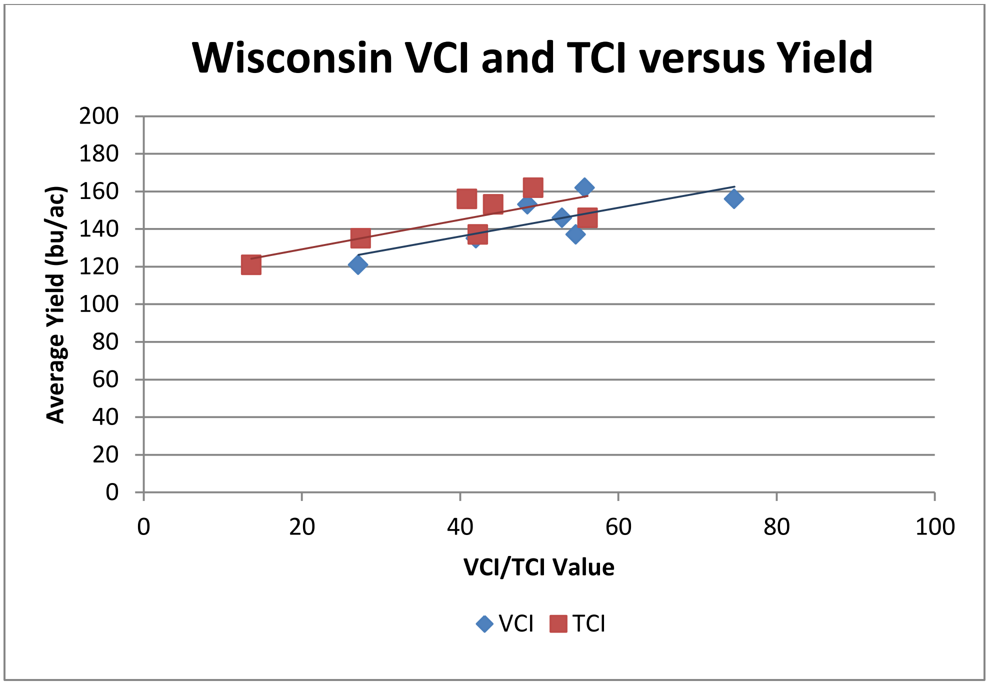

Figure 30. A scatterplot of Wisconsin VCI and TCI values vs Yield for the years of 2007-2013. VCI is week 36 and TCI is week 27. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

When these two weeks were regressed in SPSS they produced an equation of: yield = 0.443(VCI36) + 0.479(TCI27) + 103.053. The adjusted R^2 for the model was 0.590 with an error of 9.102 bushels per acre. This means 59.0 percent of the variation in the yield data can be explained by VCI and TCI.

My main research focus was to find the best time of the year for each state's yield by correlating yield with the vegetation indices of VCI and TCI. It is evident by comparing the graphs that the best time for predicting crop yield using VCI and TCI is in the weeks of late 20s through the early 30s as many of the states have their strongest correlations fall within this time period. These dates mark the beginning of July through early August and are typically during the beginning of the reproductive stages of corn, also known as silking (Johnson 2014).There were exceptions however for two states, North Dakota and Ohio. In North Dakota both indexes were highest correlated in Week 15, before planting even begins in North Dakota. This could be attributed to the little correlation VCI and TCI seem to have with yield. As you can see in the North Dakota scatter plot for Week 15 VCI and TCI (Figure 23), there is somewhat horizontal trend with yield and VCI/TCI. More annual data may be needed for North Dakota. In Ohio, TCI is highest correlated in Week 3. This is most likely because of coincidence, with that week following yield patterns by chance. If you follow the correlation graph for Ohio (Figure 24), you can see Week 32, which is around the reproductive stage in corn growth, also has a high correlation with yield. In the future with more data for Ohio, this high correlation in Week 3 should diminish.

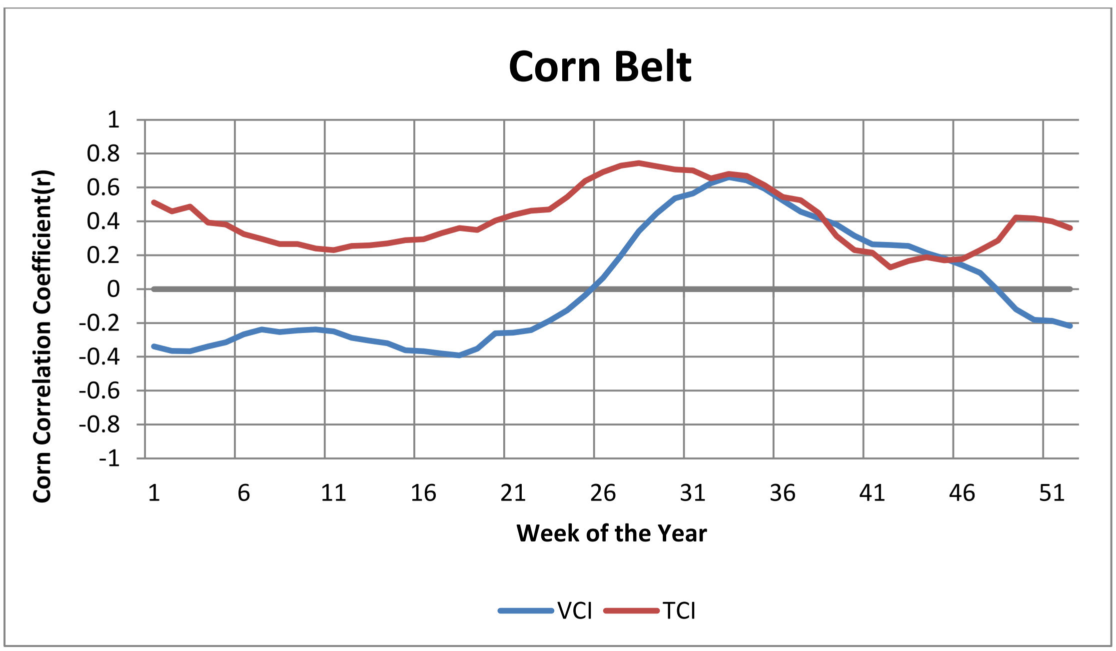

Figure 31. Correlation graph of the Corn Belt. Source: NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

This graph shows the VCI and TCI curves which have been averages for the entire Corn Belt between the years of 2007 through 2013. The VCI curve is nearly identical to the NDVI curve created by Johnson (2014), which is not surprising as VCI is an index derived from NDVI values. VCI correlation peaks in Week 33. TCI has a largely positive correlation over the course of the year, peaking at about Week 28.

The results for the highest correlated weeks of VCI and TCI correlation for each state are shown in Table 2 below. The highest correlation value was chosen because this represents the week with the strongest relationship with average yield for that state.

Table 2. The highest weekly Pearson Correlation values for each state. Each weeks number is the week number of the year. Possible correlation values range from -1 (strong inverse relationship) to +1 (strong positive relationship). NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

State	**VCI Correlation Value**	**TCI Correlation Value**
Illinois	Week 33 = 0.808	Week 28 = 0.887
Indiana	Week 34 = 0.873	Week 27 = 0.883
Iowa	Week 34 = 0.834	Week 29 = 0.951
Kansas	Week 34 = 0.763	Week 26 = 0.909
Michigan	Week 33 = 0.569	Week 33 = 0.826
Minnesota	Week 32 = 0.566	Week 28 = 0.826
Missouri	Week 34 = 0.652	Week 27 = 0.982
Nebraska	Week 33 = 0.769	Week 31 = 0.943
North Dakota	Week 15 = 0.804	Week 15 = -0.751
Ohio	Week 33 = 0.773	Week 3 = 0.891
South Dakota	Week 35 = 0.934	Week 34 = 0.955
Wisconsin	Week 36 = 0.775	Week 27 = 0.785

The summarized results for the stages of phenology for VCI and TCI peak correlation is shown in Table 3 below. The stages in phenology were selected by using the median planting date for each state and the average growth rate of corn.

Table 3. The corresponding phenology stage for the peak weeks of VCI and TCI correlation in each state. Source: ISU; UNL.

State	**VCI Peak Correlation Phenology Stage**	**TCI Peak Correlation Phenology Stage**
Illinois	R3	VT
Indiana	R3	V10
Iowa	R4	R1
Kansas	R4	V10+
Michigan	R2	R2
Minnesota	R2	VT
Missouri	R4	V10+
Nebraska	R4	R2
North Dakota	V7	V7
Ohio	R3	Pre-Planting
South Dakota	R4	R3
Wisconsin	R4	V10

The summarized results for the regression are shown in Table 4 below. The adjusted R^2 value gives a percent of how much of the variation in the yield can be explained by VCI and TCI. For example, Illinois has an adjusted R^2 value of 0.831. This means 83.1% of the variation in the yield can be explained by using weeks 33 (VCI) and 28 (TCI) averages.

Table 4 below summarizes the equations for yield in each state, the adjusted R^2 value, and the standard error of the estimate of yield in bushels per acre. The equations were found by using linear regression in SPSS 21.

Table 4. The twelve states and their yield equation, corresponding regression values, and standard error of the estimate from their two highest weeks of VCI and TCI. All values were derived from SPSS. NOAA STAR; Pervez and Brown, 2010; USDA Cropscape; and, USDA NASS.

State	**SPSS Yield Equation**	**VCI and TCI adjusted R^2 Value**	**Standard Error of the Estimate (Bushels per Acre)**
Illinois	0.491(VCI33) + 0.866(TCI28) + 81.426	0.747	3.539
Indiana	1.88(VCI34) + 0.541(TCI27) + 46.657	0.806	4.507
Iowa	0.185(VCI34) + 0.616(TCI29) + 121.863	0.893	4.586
Kansas	0.089(VCI34) + 0.930(TCI26) + 75.689	0.742	9.996
Michigan	0.021(VCI33) + 0.538(TCI33) + 119.752	0.523	8.182

Minnesota	0.308(VCI32) + 0.769(TCI28) + 108.125	0.486	7.658
Missouri	- 0.228(VCI34) + 1.315(TCI27) + 70.103	0.969	4.573
Nebraska	0.069(VCI33) + 0.507(TCI31) + 125.605	0.842	4.417
North Dakota	0.258(VCI15) + 0.085(TCI15) + 102.546	0.475	6.570
Ohio	0.467(VCI33) + 0.515(TCI3) + 102.546	0.711	10.661
South Dakota	0.385(VCI35) + 0.652(TCI34) + 61.362	0.930	4.125
Wisconsin	0.443(VCI36) + 0.479(TCI27) + 103.053	0.590	9.102

The regression values were strong for the majority as eight of the 12 states had R^2 values greater than 0.7, meaning in eight of the states, about 80 percent and above of the variance in the yield can be explained by these two indexes. Eleven of the twelve also had standard errors less than 10 bushels per acre. With the 2013 national average corn yield being 123.4 bushels per acre, this gives me an error of less than 10 percent in those states. This shows how critical vegetative health and optimal temperature becomes during the reproductive stages of corn and how well VCI and TCI can be used as predictors of yield.

CHAPTER V

DISCUSSION

The optimal time during the growing season to predict yield was not surprising since, on average, over the Corn Belt corn is planted from mid-April through mid-May. Following corn growth, Weeks 28-34 marked the beginning of the tasseling stage in corn to begin in July to August, where the correlation was strongest. This follows previous studies as Kogan (2005). He also found the tasseling stage to be the most opportune time for correlating yield to VCI and TCI values in corn.

My second research focus was to find the earliest time one could make a prediction of yield with reasonable accuracy. A surprising result of this focus was the largely negative correlation many of the states had in the beginning weeks of the year (Weeks 1-16), mainly with VCI. A slight negative trend was expected because of the results which Johnson (2014) had with NDVI in the Corn Belt. With VCI being an index derived from NDVI values, similar results were expected. However, Johnson (2014) only showed his national average, which was about -0.3 in April. This study showed a national average also around -0.3 in April, but when the states are compared independently, a large variation of VCI correlation is observed early in the year. For example, the states of Missouri and Illinois have correlation with VCI about -0.9 in April, a stark difference from Wisconsin and Ohio which have correlations of about -0.2. The contrasts in these states occur during early planting. The higher correlation could be because of the southern states planting earlier and having more canopy cover. This result could also indicate the significance of overall vegetative health condition indicated by remote sensing before planting could result in better initial growth.

Contrary to VCI, TCI had a largely positive correlation in the beginning weeks of the year with the exception of South Dakota, going as high as 0.891 in week 3 for Ohio. Not only were there high correlations in the beginning of the year, TCI had peak correlations typically one to two weeks before peak VCI correlations. This result leads to the conclusion that in the late vegetative stages, V10, VT, and the beginning stages of the reproductive phases in corn, R1, R2, and R3, also known as silking, blister, and milk, optimal temperature is a better indicator rather than vegetative health. This could be attributed to the measure of VCI compared to TCI. There is a lag effect in the response of corn greenness to the crop condition, which is what is measured by NDVI. Thus VCI, which is derived from NDVI, is a measure of the condition of corn with about two weeks of stress. TCI, which is derived from temperature, is a more immediate measure of the condition of the corn, as corn closes its stomata in response to stress quickly.

Using the two peak weeks for these two indices, a prediction of yield can be made about four weeks ahead of harvest, with some states such as Minnesota where a prediction can be made about eight weeks before harvest, during the early/nid reproduction stages. However, this is if you only use the peak weeks as indicated in the table above. In most states there is a gently sloping correlation curve surrounding the peak week. If you were to use data two to three weeks prior to the peak week, albeit using a slightly weaker correlation, you could make reasonable predictions a few weeks earlier.

These results run similar to the results of Unganai and Kogan (1998) of corn in South Africa where they found on average a prediction could be made six weeks before harvest.

There were a few other noteworthy observations to pull from the VCI and TCI correlation. The first being TCI values outperformed VCI in nearly every state. This was a surprising result as I was expecting results more similar to what Unganai et al. (1998) found in South Africa, a more even distribution of highest values between VCI and TCI.

The second noteworthy observation was the erratic nature of the correlation curves in some states, namely Minnesota. An observation of the wild curves reveals that most of them occur during later parts of the year. While the weeks of the year of the abrupt changes in the curves may be significant, it is more likely because of the low amount of years used in the study. Once more years become available for use in Cropscape the more accurate the correlations and the curves should become thereby reducing the erratic nature in some of the graphs. The scale could also be brought down to the county level to improve accuracy. Another reason for the erratic nature of some of the curves were the tight groupings of the VCI and TCI values for Minnesota and other states. Compared to other states which had smoother correlation curves, such as Illinois, Minnesota's VCI and TCI scatter point plots were grouped closer together, perhaps making correlation calculations harder for SPSS. Once again this could be fixed by using more years of study.

Another result was the dates of the peak weeks of correlation of VCI and TCI. The planting date varies by about three weeks between the southern states and the northern states. For example, the average date of corn planting begins on April 5th in

Kansas (~Week 14), and the average date for Minnesota is April 22nd (~week 17) (USDA 2010a). One would expect the peak weeks of correlation for VCI and TCI to follow the same pattern of planting dates, because of the nearly three week difference between planting in Missouri and Minnesota, but this was not the case in my results. Going back to the two aforementioned states, VCI and TCI peak correlation weeks in Kansas were 34 and 26, respectively, and Minnesota's were 32 and 28, respectively. The rest of the states follow this pattern of about week 34 +/- 1 week for VCI, or around early to mid-reproductive stages. There is a weak trend for TCI going south to north with Kansas' peak correlation at Week 26 and South Dakota's and Michigan's at Week 34 and 33 respectively. This is broken by Minnesota's at Week 28 and Wisconsin's at Week 27. This independence of VCI and TCI peak correlations from planting date is a peculiar result and could be because of having a broader scale resolution of using state averages. If broken down further, to the county level, these differences could become more apparent. Another option would be to include more southern states, such as Texas or Louisiana.

As for the R^2 values, the states which generally had more statewide planting of corn (Figure 1), generally had higher R^2 values for their models calculated by SPSS. Once again, this could be fixed by bringing the scale down to the county level which should help improve accuracy of the correlations.

CHAPTER VI

CONCLUSION

The results of this study suggest that at a 16-km scale, statewide averages of VCI and TCI for areas of corn, can be used to predict yield about four, and, in some cases, six weeks ahead of harvest in the late vegetative stages or early reproductive stages using a cost effective method of simple correlation and regression. The weeks of prediction can be pushed back further if neighboring weeks of VCI and TCI data are used, albeit at a slightly smaller accuracy.

Both VCI and TCI were found to have strong correlations in every state, with some states having stronger correlations than others. TCI had a higher peak correlation in every state than VCI. While surprising, VCI is a direct indicator of vegetative health. The higher correlation with TCI makes sense as temperature, especially during the tasseling stage can damage yield or speed up grain development too quickly, not allowing enough time for the grain to fill to its greatest potential.

The results of correlating the vegetative indices of VCI and TCI were largely a success with many states having high correlation values of these indices with yield. There were some discrepancies in some states such as Minnesota which had erratic correlation patterns; however, this result may be explained by the abbreviated study period, tight groupings of VCI and TCI values, and having the indices averaged over the state corn areas. In addition, the week of peak levels of corn correlation with VCI and TCI were not found to be directly related to planting date. This could be attributed to only using seven years of data because of the lack of current historical crop data from Cropscape.

Despite the promising results of this study, it can still be improved. State level averages of VCI and TCI, although broken down to only areas with 50 percent or greater corn cover, could be delineated further to the county-level as NASS provides county-level yields. The significance of the data can also become increased in the future as more years of Cropscape become available. The growth rate of corn for each state could be assessed instead of using one general standard by using the average state daily temperature and calculating GDD. Spatial scale could be scaled down as well, since NOAA STARR does provide the 16-km and 4-km VCI and TCI AVHRR data already calculated and rectified. The algorithm for calculating VCI and TCI could be taken and applied to MODIS imagery, resulting in 250-m pixel size. Knowing that improvements to research data could always be upgraded in terms of detail, the results of this study seem to strongly suggest that AVHRR still provides high-quality regional corn condition data that can help farmers predict yield in advance of harvest.

Bibliography

Abendroth, Lori J., and Roger W. Elmore. 2011. *Iowa State University* "Corn Growth and Development." http://www.ipm.iastate.edu/ipm/files/03%20Corn%20Growth%20and%20Development.pdf

Al-Kaisi, Madhi M.. 2013. "Drought impact on crop production and the soil environment: 2012 experiences from Iowa." *Journal of Soil and Water Conservation*: 19-24.

Arve, L. E., S. Torre, J. E. Olsen, and K. K. Tanino. 2011. *Abiotic Stress in Plants - Mechanisms and Adaptations.*

Balaghi, Riad, Bernard Tychon, Herman Eerens, and Mohammed Jibene. 2008. "Empirical regression models using NDVI, rainfall and temperature data for the early prediction of wheat grain yields in Morocco." *International Journal of Applied Earth Observation and Geoinformation* 10:438-452.

Braun, Z. L., interview by F. Kogan. 2013. *Email between Felix Kogan and Zachary Braun*

Bruinsma, J. 2003. "World Agriculture: Towards 2015/2030: An FAO Perspective."

Capehart, Thomas. 2014. *Corn.* http://www.ers.usda.gov/topics/crops/corn/background.aspx#.U1cD6PldXc0.

Chulalongkorn University. 1999. *Advantages of remote sensing for land evaluation.* http://www.sc.chula.ac.th/courseware/2309507/Lecture/remote23.htm.

Crutchfield, Steve. 2013. *U.S. Drought 2012: Farm and Food Impacts.* http://www.ers.usda.gov/topics/in-the-news/us-drought-2012-farm-and-food-impacts.aspx#.UWYup5PqnlR.

Doraiswamy, Paul, J. L. Hatfield, T. J. Jackson, B. Akhmedov, J. Prueger, and A. Stern. 2004. "Crop condition and yield simulations using Landsat and MODIS." *Remote Sensing of Environment* 92 4:548-559.

Energy Information Administration. 2013. *U.S. ethanol production and the Renewable Fuel Standard RIN Bank*. http://www.eia.gov/todayinenergy/detail.cfm?id=11551.

Farooq, M., A. Wahid, N. Kobayashi, D. Fujita, and S. M.A. Basra. 2008. "Plant drought stress: effects, mechanisms and management." *Agronomy for Sustainable Development* 185-212.

Fletcher, Owen. 2013 *U.S. Corn Belt Expands to North.* http://online.wsj.com/news/articles/SB10001424127887324904004578539352566317388.

Gamon, John A. 1995. "Relationships between NDVI, canopy structure, and photosynthesis in three Californian vegetation types." *Ecological Applications* 5 1:28-41.

Gibson, Lance R. 2003. *Growing degree-day calculation.* http://agron-www.agron.iastate.edu/Courses/agron212/Calculations/GDD.htm.

Gilmore, E. C., and J. S. Rogers. 1958. "Heat units as a method of measuring maturity in corn." *Agronomy* 611-615.

Hall, R. G. 2006. "Corn growth stages with estimated calendar days and growing-degree units." *South Dakota State University*. http://www.sdstate.edu/ps/extension/crop-mgmt/corn/upload/Corn-growth-stage-day-and-GDU-calendar10.pdf.

Iowa State University. 2009. "Corn Field Guide." *Iowa State University.* http://www.agronext.iastate.edu/corn/docs/corn-field-guide.pdf.

---. 2011. *Common Corn Questions and Answers.* http://www.agronext.iastate.edu/corn/corn-qna.html.

---. 2012. "Corn Growth Stage Development." *University of Nebraska Lincoln.* http://weedsoft.unl.edu/documents/growthstagesmodule/corn/corn.htm#.

"IPCC 2013, A Summary for Policymakers." 2013.

Johnson, David M. 2014. "An assessment of pre- and within-season remotely sensed variables for forecasting corn and soybean yields in the United States." *Remote Sensing of Environment* 141:116-128.

Johnson, David M, and Richard Mueller. 2010. "The 2009 Cropland Data Layer." *Photogrammetric Engineering and Remote Sensing* 1201-1205.

Karl, J. R. 2013. "The maximum height of the maize subspecies; data." *Maize Genetics Cooperation Newsletter* 2-3.

Karlin, Joel. 2013. *Favorable Climate Change in North Dakota Encourages Increased Corn Plantings.* http://www.dtnprogressivefarmer.com/dtnag/common/link.do?symbolicName=/ag/blogs/template1&blogHandle=agfundamental&blogEntryId=8a82c0bc3d53d661013d8d7d0e280249.

Keyantash, John, and A. John Dracup. 2002. "The Quantification of Drought: An Evaluation of Drought Indices." *Bulletin of of the American Meteorlogical Society* 1167-1180.

Kogan F. 1995. "Application of vegetation index and brightness temperature for drought detection." *Advances in Space Research* 15 11:91-100.

---. 1997. "Global Drought Watch From Space." *Bulletin of the American Meteorlogical Society* 82:1949-1964.

Kogan, F., Y. Bangjie, G. Wei, P. Zhiyuan, and J. Xianfeng. 2005. "Modelling corn production in China using AVHRR-based vegetation health indices." *International Journal of Remote Sensing* 26 11:2325-2336.

Lee, Chad. 2011. *University of Kentucky.* "Corn Growth and Development." http://www.uky.edu/Ag/GrainCrops/Presentations/CornGrowthStages_2011.pdf.

Lerner, Rosie. 2000. *Corn-Ears.* http://www.hort.purdue.edu/ext/senior/vegetabl/corn1.htm.

Li, Sanai, Tim Wheeler, Andrew Challinor, Erda Lin, Hui Ju, and Yinlong Xu. 2010. "The observed relationships between wheat and climate in China." *Agricultural and Forest Meteorology* 150:1412-1419.

Lobell, David B., and B. Christopher Field. 2007. "Global scale climate-crop yield relationships and the impacts of recent warming." *Environmental Research Letters* 2 014002

Mashood, Farzad. 2011. *Current drought pales in comparison with 1950s 'drought of record'.* http://www.statesman.com/news/news/local/current-drought-pales-in-comparison-with-1950s-d-1/nRdC5/.

Monsanto. 2012. *Agronomic Alert.* Monsanto Technology Development & Agronomy.

NASA. 2013 *Global Climate Change.* http://climate.nasa.gov/effects.

NASS. 2013. *Quick Stats.* USDA.

NCDC. 2003. *20th Century Drought.* http://www.ncdc.noaa.gov/paleo/drought/drght_history.html.

---. 2013, *Climate of 2013 - April U.S. Standardized Precipitation Index.* http://www.ncdc.noaa.gov/oa/climate/research/prelim/drought/spi.html.

Nielson, R. L. 2012. *Historical Corn Grain Yields for Indiana and the U.S.* http://www.agry.purdue.edu/ext/corn/news/timeless/YieldTrends.html.

Niu, Xianzeng, William Easterling, Cynthia J. Hays, Allyson Jacobs, and Linda Mearns. 2009. "Reliability and input-data induced uncertainty of the EPIC model to estimate climate change impact on sorghum yields in the U.S. Great Plains." *Agriculture, Ecosystems, and Environment* 129:268-276.

NOAA. 2014. *What is remote sensing?* http://oceanservice.noaa.gov/facts/remotesensing.html.

NWS. 2008. "Drought: Public Fact Sheet." *National Weather Service.* http://www.nws.noaa.gov/om/brochures/climate/DroughtPublic2.pdf.

Palmer, Wayne C. 1965. "Meteorlogical Drought." Washington D.C.

Pervez, S., and J. Brown. 2010. "Mapping irrigated lands at 250-m scale by merging MODIS data and National Agricultural Statistics." *Remote Sensing* 2:2388-2412.

Peters, Albert J., and J. Lei. 2003. "Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices." *Remote Sensing of Environment* 87 (1):85-98.

Renewable Fuels Association. 2013. *Ethanol Facts: Agriculture.* http://www.ethanolrfa.org/pages/ethanol-facts-agriculture.

Rouse, J. W., R. H. Haas, J. A. Schell, and D. W. Deering. 1973. "Monitoring vegetation systems in the Great Plains with ERTS." *Third ERTS Symposium, NASA* 309-317.

Rumore, Danya. 2011. *Study: U.S. drought risk to increase with climate change.* http://web.mit.edu/newsoffice/2011/drought-risk-climate-change.html.

Sakamoto, Toshihiro, Anatoly A. Gitelson, and Timothy J. Arkebauer. 2013. "MODIS-based corn grain yield estimation model incorporating crop." *Remote Sensing of Environment* 131 (15): 215-231.

Seiler, R. A., F. Kogan, and G. Wei. "Monitoring Weather Impact and Crop Yield from NOAA Avhrr Data in Argentina." *Advances in Space Research* 26, (7):1177-1185.

Thelen, Marilyn. *Effects of Drought-Stress on the Corn Plant.* July 6, 2012. http://farmprogress.com/story-effects-drought-stress-corn-plant-9-61217.

Timilsina, Govinda R., and Ashish Shrestha. 2011. "How much hope should we have for biofuels?" *Energy* 36 (4):2055-2069.

Unganai, Leonard S., and F. N. Kogan. 1998. "Drought Monitoring and corn yield estimation in Southern Africa from AVHRR Data." *Remote Sensing of Environment* 63 (3):219-232.

University of Nebraska-Lincoln. 2014a. *Economics of the Dust Bowl.* http://drought.unl.edu/DroughtBasics/DustBowl/CopingandRecovering.aspx.

---. *What is Drought?* 2014b. http://drought.unl.edu/DroughtBasics/WhatisDrought.aspx.

USDA. 2010a. *Field Crops Usual Planting and Harvesting Dates.* USDA

---. 2010b. *Cornell.* "Field Crops: Usual Planting and Harvesting Dates." http://usda01.library.cornell.edu/usda/current/planting/planting-10-29-2010.txt.

Wei, Xiong. 2009. "Future cereal production in China: The interaction of climate change, water availability and socio-economic scenerios." *Global Environmental Change* 19:34-44.

Weiss, Albert, Cynthia J. Hays, and Jaepil Won. 2003. "Assesing winter wheat responses to climate change scenerios: A simulation study in the U.S. Great Plains." *Climatic Change* 58:119-147.

Zhang, Tianyi, Jiang Zhu, and Reiner Wassmann. 2010. "Responses of rice yields to recent climate change in China: An empirical assesment based on long-term observations at different spatial scales (1981-2005)." *Agricultural and Forest Meteorology* 150 1128-1137.

Zhao, Yanxia, Sining Chen, and Shuanghe Shen. 2013. "Assimilating remote sensing information with crop model using Ensemble Kalman Filter for improving LAI monitoring and yield estimation." *Ecological Modeling* 270:30-42.