MONITORING AGRICULTURAL DROUGHT USING GEOGRAPHIC INFORMATION SYSTEMS AND REMOTE SENSING ON THE PRIMARY CORN AND SOYBEAN BELT IN THE UNITED STATES

by

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A Dissertation
Submitted to the
Graduate Faculty
of
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in Partial Fulfillment of
The Requirements for the Degree
of
Doctor of Philosophy
Earth Systems and Geoformation Sciences

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DEDICATION

This is dedicated to my magnificent father Prof. Saleh Al Shomrany and to my family.

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It is an honor for me to express the sincere gratitude to the many people who have made this happen.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Advanced Very High Resolution Radiometer .... AVHRR
Cropland Data Layer .... CDL
Climatic or Crop Moisture Index .... CMI
Geographic Information System .... GIS
Geographically Weighted Regression .... GWR
Leaf Area Index .... LAI
Land Surface Temperature .... LST
MODerate Resolution Imaging Spectroradiometer .... MODIS
National Agricultural Statistics Service .... NASS
National Weather Service .... NWS
Normalized Difference Infrared Index-band6 .... NDII6
Normalized Difference Infrared Index-band7 .... NDII7
Normalized Difference Vegetation Index .... NDVI
Normalized Difference Water Index .... NDWI
Near Infrared .... NIR
Normalized Multi-band Drought Index .... NMDI
National Oceanic and Atmospheric Administration .... NOAA
Ordinary Least Square .... OLS
Palmer Drought Severity Index .... PDSI
Suomi National Polar-orbiting Partnership .... Suomi-NPP
Standardized Precipitation Index .... SPI
Soil Moisture Percentiles .... SMP
Shortwave Infrared .... SWIR
Temperature Condition Index .... TCI
Thematic Mapper .... TM
Tropical Rainfall Measuring Mission .... TRMM
U.S. Department of Agriculture .... USDA
U.S. Drought Monitor .... USDM
Vegetation Condition Index VCI
Vegetation Health Index .... VHI
Visible/Infrared Imager/Radiometer Suite .... VIIRS
World Agro-meteorological Information Service .... WAMIS
World Agricultural Outlook Board .... WAOB

ABSTRACT

MONITORING AGRICULTURAL DROUGHT USING GEOGRAPHIC INFORMATION SYSTEMS AND REMOTE SENSING ON THE PRIMARY CORN AND SOYBEAN BELT IN THE UNITED STATES

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Agricultural drought can be defined as inadequate soil water availability caused by low precipitation, and or high atmospheric water demand due to potential evapotranspiration which results in a reduction in crop yield. Agricultural drought serves as a major threat to food security and economic prosperity. In other words, the greater the drought, the greater the reduction of food production which leads to higher prices due to economic supply and demand.

Climate events caused by extreme weather has the potential to create disasters affecting agricultural production. Climate changes create various impacts when taking into consideration the ever increasing population of the planet, and thus the potential for food shortages caused by extreme weather events. As a result, it has become necessary to assess the potential impacts droughts and other climate events can have on the political and economic scales of the world. Such analysis and evaluation often requires

quantitative understanding.

The efforts of this research are focused on the Midwestern US, which is one of the major agricultural regions in the world, and comprises of 12 states: North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Illinois, Indiana, Michigan, Wisconsin, and Ohio. In the past decade, the Midwest has experienced many drought events. Remote sensing measurements over the primary Corn and Soybean regions of the United States were analyzed from 2000 to 2012, and the 2012 drought event was investigated as a particular case study.

The study aims to evaluate various remote sensing drought indices to assess those most fitting for monitoring agricultural drought. The objectives are (1) to assess and study the impact of drought effect on (corn and soybean) crop production by crop mapping information and GIS technology; (2) to use Geographical Weighted Regression (GWR) as a technical approach to evaluate the spatial relationships between precipitation vs. irrigated and non-irrigated corn and soybean yield, using a Nebraska county-level case study; (3) to assess agricultural drought indices derived from remote sensing (NDVI, NMDI, NDWI, and NDII6); (4) to develop an optimal approach for agricultural drought detection based on remote sensing measurements to determine the relationship between US county-level yields versus relatively common variables collected.

Extreme drought creates low corn and soybean production where irrigation systems are not implemented. This results in a lack of moisture in soil leading to dry land and stale crop yields. When precipitation and moisture is found across all states, corn and soybean production flourishes. For Kansas, Nebraska, and South Dakota, irrigation management methods assist in strong crop yields throughout SPI monthly averages. The data gathered on irrigation consisted of using drought indices gathered by the national agricultural statistics service website. For the SPI levels ranging between one-month and nine-months, Kansas and Nebraska performed the best out of all 12-states contained in the Midwestern primary Corn and Soybean Belt. The reasoning behind Kansas and Nebraska's results was due to a more efficient and sustainable irrigation system, where upon South Dakota lacked. South Dakota was leveled by strong correlations throughout all SPI periods for corn only. Kansas showed its strongest correlations for the two-month and three-month averages, for both corn and soybean.

Precipitation regression with irrigated and non-irrigated maize (corn) and soybean levels show yields as a function of precipitation. The GWR models predicted that yields were significantly better than OLS performances for maize (corn) and soybean. The OLS regression model when used showed a general trend of correlation between observed yields and long-term mean precipitation totals, with 84% and 63% of the variability in mean yield explained by the mean annual precipitation for the non-irrigated crops. The GWR technique performance in predicting yields was significantly better than OLS performances. For instance in the months of June, July, and August precipitations had greater impacts on maize (corn) yields than soybeans under non-irrigated conditions as a result of the greater sensitivity maize (corn) had to water stress.

SPI is capable of offering various time-scales enabling it to show initial warning signs of drought conditions and accompanying severity levels. SPI calculation techniques used for various locations are reflected upon the precipitation records acquired during those periods. Over the 3, 6, and 9-month periods, NDII6 performed the best out of all of the MODIS indices as shown in its results in monitoring vegetation moisture and drought detection. NDII6 performed the best due to its detection abilities. The 9-month SPI provides an indication of inter-seasonal precipitation patterns over medium timescale duration.

A new approach used is to average corn and soybean yields for all counties of the study area in comparison with average anomalies of the MODIS indices for the growing season between May through September from 2006-2012. There was a strong correlation between average corn yields versus MODIS NDII6 averages for these years with R^2 equaling 0.62. That means NDII6 is the best indicator to show drought conditions and vegetation moisture monitoring. There was a weak correlation with $R^2 = 0.16$ between averages of soybean yields and averages of precipitation. Irrigation and management systems, technological improvements from hybrids, producer management techniques, and other management practices have an impact on crop yield productions.

CHAPTER ONE: INTRODUCTION

Agricultural drought is defined as an insufficient amount of soil moisture, precipitation, and humidity during crop growing season, which in turn affects the healthy growth of crop and production. Agricultural drought links characteristics of meteorological drought to agricultural impacts. Precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced ground water or reservoir levels, and so forth. (Anderson, Martha C., Verdin, James P., Wardlow, Brian D. - James P. Verdin, 2012.). Plant water demand depends on prevailing weather conditions, biological characteristics of the specific plant, its stage of growth, and the physical and biological properties of the soil. Drought has been broadly grouped into four categories based on the American Meteorological Society (American Meteorological Society, 1997).

The environmental stresses resulting from drought and high temperature affects crop growth and production during all stages of development. Drought can be meteorological (reduced precipitation), agricultural (precipitation shortages, soil water deficits, reduced ground water and reservoir levels), or hydrological (reduced precipitation on water-supply resources). Drought in general affects all climatic systems and therefore has a heavy effect upon economic systems and society on a wide scale as shown in the (Figure 1) below.

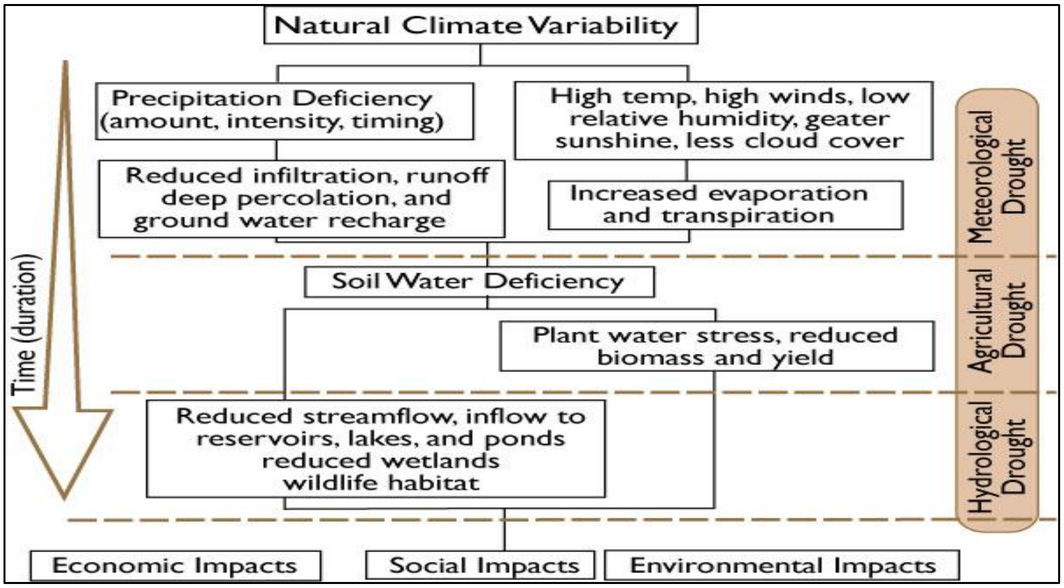


Figure 1 Physically Based Perspectives of Drought. Many of these impacts have the capacity to be monitored by remote sensing techniques. Data Source: Anderson, Martha C., Verdin, James P., Wardlow, Brian D. - James P. Verdin, 2012.

Agriculture is one of the most vulnerable sectors when it comes to drought impacts and effects. In 2012, a great drought had a drastic effect upon the Corn Belt region of the United States (Kimery, 2012). This led to crop production failures well below the previous year's crop production, for both corn and soybean (USDA, 2013).

Improvements in water and farming practices during the past few decades have positively mitigated drought impacts causing crop yield reductions during the crop growing season. Spatial and temporal variations of drought showed crop yield reductions in various cropping regions throughout the primary Corn and Soybean Belt. The 2012 corn yield in Illinois was 33.1% lower than in 2011, and the 2012 corn yield in Indiana was 32.2% lower than in 2011, but the 2012 corn yield in Minnesota was 6.5% higher than in 2011. Therefore, a more detailed spatial and temporal characterization of drought is necessary to assess the impacts of drought on crop yield.

In the USA specifically, drought has accounted for more than 14-billion dollars of economic loss annually (NCDC 2011). The factors that affect agricultural drought includes climate and weather such as precipitation, evaporation, temperature, humidity and wind, as well as soil types and moisture, crop types and stages of growth, water stress in crops, and irrigation. Weather stations, derived from ground-based measurements tend to lack continuous spatial coverage. The Palmer Drought Severity Index and other climate drought indices are used to monitor droughts effectively, as well as the standardized precipitation index, however large scale monitoring poses a challenge when using such methods (Sheffield and Wood, 2011). The challenge of accurately analyzing meteorological measurements at a regional level, rather than in unique areas, is significant. This is due to delay in obtaining timely information in certain areas containing complex terrains, such as mountainous regions or difficult to set up monitoring stations. (Ashcroft et al., 2009). The use of interpolation to estimate meteorological variables also produces uncertainties due to large data gaps over extended drought condition areas (Flannigan et al., 1998). These challenges in data collection and weather monitoring render the examination of regional drought areas difficult.

Drought monitoring is also limited by the technical aptitude and institutional capabilities in different countries. First world nations often have much more advanced methods and systems for monitoring weather, as opposed to third world countries which are in their beginning stages in acquiring and establishing drought monitoring systems and management institutions (Thenkabail et al., 2004). By using remote sensing techniques however, drought monitoring tools are able to assist in detecting drought onset, the duration of their severity, and they provide farmers and scientists with information of spatial coverage, which has encouraged the use of remote sensing capabilities over the recent past decades (Thiruvengadachari and Gopalkrishna, 1993). The makeup of such techniques consists of various remote sensing drought indices and weather indices, which utilize different portions of the atmospheric spectrum to provide the monitoring of drought and crop growth.

Agricultural drought mitigation is done through water management improvements and drought planning procedures. Information about the onset, magnitude and duration of droughts during the crop production cycle period gives important information as to which agricultural drought strategies are most suitable for use. Satellite observations of vegetative conditions which correlate to water stress environments provide a basis for agricultural drought monitoring (Marshall, Funk, and Michaelsen 2012; Sheffield and Wood 2011). Visible and infrared bands provide unique techniques for quantifying vegetation areas, including growth status, and leaf area coverage.

Crop growth is based upon various factors, from genetic crop cultivar, to soil, weather, and the cultivation practices involved. This includes the month and time of crop seeding, and the amount of irrigation and fertilizer used. Generally speaking, year to year yields have been modeled as a predictor by using empirical and crop simulation approaches. Multi-spectral sensors, such as those of visible and near-infrared, have provided yield models and have therefore played an important role in obtaining data onboard earth-observing satellites. Remote sensing gives accurate and timely crop growing condition estimations, and recent technologies in GIS have also allowed for the capture of and the storage and retrieval of modeling geographically linked data sets. Remote sensing data has an advantage when it comes to meteorological observations in that it is able to capture non-meteorological factors. Together, GIS and remote sensing are a powerful and effective means when it comes to monitoring and modeling crops at spatial distances and range-scales.

Crop growth and yield are determined by the potential of crop cultivar, weather, soil, and cultivation practices such as the date of sowing and the amount of irrigation and fertilizer used. Nevertheless, year-to-year yield variability has been modeled as a predictor using either empirical and crop simulation approaches. The ability to use multi-spectral (visible, near-infrared) sensors on polar orbiting earth observation satellites has served as an important factor for yield modeling. Remote sensing data provides accurate and objective estimations of crop growing conditions for issuing yield forecasts at a range of spatial scales. Remote sensing data has some advantages over meteorological observations for yield modeling, such as dense observational coverage, direct viewing and the ability to capture effects of non-meteorological factors. Recent developments in GIS technology allow for the capture, storage, retrieval, visualization, and modeling of geographically linked data. An integration of the three technologies - viz., crop simulation models, Remote sensing data and GIS provide an excellent solution for monitoring and modeling crops from various spatial scale ranges.

Remote sensing techniques can capture information over large areas through the use of sensors and spectral band satellites. Satellites orbiting planet earth are able to explore and capture the earth's surface at various intervals on a regular basis. The retrieved data provides a data layer for specific areas. Aircrafts used for monitoring on the other hand are able to capture detail-specific features in much smaller areas. The spectral bands used by these sensors cover spectral regions form visible and micro-wave portions of the spectrum. Advancements in computer science and GIS facilities consist of the analyzing and processing of remote sensing data observations from satellites. The integration of information derived from remote sensing techniques with other datasets - both in spatial and non-spatial formats fosters techniques for identification, monitoring, and assessment of agricultural drought.

Remote sensing has been adopted in many countries around the world. Studies on soil and water conservation using remote sensing and GIS have improved and procedures for pre-harvest estimations of major crops have also evolved and enhanced greatly. The key is to find specific remote sensing products that can be utilized in agricultural information systems for specific crops. Agricultural production encompasses various activities related to crops, climate, and the local weather of the region. Remote sensing technology has become operational in many other research environments where data integration has been applied. This includes the capturing of agricultural crop areas, growth conditions, and crop type identification. Understanding total production enables estimation for yields per unit areas. All of this has great potential in providing information on food-related security in times of environmental disasters.

Studies for estimating acreage production for different types of crops in various countries around the world show a near 90 percent accuracy level. (Das, H.P, 2000).

Production forecasting and crop-yield modeling, and crop-stress detection is all done using remote sensing data. Yield is affected and influenced by many different factors, including specific crop genotypes, soil characteristics, cultural and agricultural practices put to use, and the existence and impact of diseases and pests in such areas. Many approaches have been evaluated to determine the various parameters that affect crop growth and crop yielding. Such methods have been developed to assess crop growth, and from several sources of information; surveys of farm operators, crop condition reports from field surveys, and local weather information. Remote sensing technology is able to provide other spatial data in order to give timely information on crop conditions and their potential yields. The timely evaluation of potential yields is quite important due to the growing economic impact of agricultural production on economies across the world. The NDVI parameter is an important method of assessment for crop conditions and yield estimation when it comes to remote sensing techniques.

Various factors have resulted in frequent outbreaks of crop pests and diseases causing huge crop losses. This includes intensive cultivation, mono-cropping, changing weather conditions and the use of pesticides. Mono-cropping these losses is one way of enhancing grain production, and remote sensing tools have been useful in monitoring these large areas frequently, and in monitoring weather and ecological conditions favorable for crop pests and diseases. Weather conditions such as temperature, humidity (moisture), sunshine hours (light) and wind all influences the densities of pest population habitats. Remotely sensed meteorological parameters are temperature, soil moisture, moisture cloud, and precipitation. These parameters can also be used in the development of crop yield modes.

The lack of information on average precipitation levels and the consequent drought conditions which in turn affect agricultural productivity are natural calamities affecting crop production. Drought conditions may be monitored using data obtained by satellites. During agricultural drought, changes of vegetation may become apparent. Satellite sensors can show these changes by means of spectral radiance measurements and the manipulation of such measurements. Such indices are sensitive to the changes in vegetation affected by moisture stress. Visible and near infrared bands on satellites allow for the monitoring of vegetation greenness. Moisture stress in vegetation due to increased rainfall deficiency levels is shown by the lowering of vegetation index values. These decreases could also be caused by other stresses such as pest diseases, nutrient deficiency and soil geo-chemical effects. Reliable drought interpretation requires a Geographical Information System (GIS) based approach. This is because topography, soil type, spatial rainfall variability, crop type and variety, irrigation support, and management practices are all relevant parameters. In recent years, many investigations have demonstrated the capability of satellite-borne sensors to provide information on various drought indicators, which has helped to monitor agricultural drought more effectively.

1.1 Objectives and Scopes

The first objective is to assess and study the impact of drought effect on (corn and soybean) crop production by crop mapping information and GIS technology. This objective of the study will be focused on: (1) The assessment of drought impact effect on crop yields for corn and soybean; (2) The differences between separate irrigated and non-irrigated crops of corn and soybean; (3) The coefficient of determination (R^2) during growing season and yield of corn and soybean for the Midwestern US from 2000-2012.

The second objective is to use of Geographical Weighted Regression (GWR) to quantifying the spatial relationships of precipitation on irrigated and non- irrigated corn and soybean yield, using a Nebraska county level data for the case study.

The third objective is to use remote sensing indices to identify to evaluate drought detection among these indices. A time series of the indices will be created between the years 2000 to 2012 for the corn and soybean growing season (June -September), which will then be compared to the Standardized Precipitation Index (SPI), based on a pixel-to-weather station approach. A correlative relationship between SPI and the other remote sensing indices being utilized will be produced.

The fourth objective is to evaluate the connection between US county-level corn and soybean yields versus relatively common variables collected via remote sensing throughout the crop growing season months. The variables being assessed for both corn and soybean were a time series of NDVI, (NDII band 6 and band 7) based on information from both vegetation greenness and vegetation water content as derived by from EOS Terra MODIS sensor, and precipitation estimates from National Weather systems (NWS) Nexrad Doppler Weather radar system.

1.2 Major Data Sources

The datasets employed in this study includes data from the National Climatic Data Center (NCDC), MODIS data products from NASA DAAC (MODIS daily surface temperature, MODIS L3 surface reflectance products, and MODIS Land cover products), and agricultural data from USDA.

More Detailed Specific Datasets Used Include

1) MODIS 8-day surface reflectance(MOD09A1)

MODIS 8-day reflectance is a level-3 composite of daily surface reflectance. The datasets provide MODIS band 1-7 surface reflectance at 500m resolution. Each pixel is derived from the best possible L2G observation in an 8-day period. The L2G consists of gridded Level 2 data, and was developed to separate geo-locating from compositing and averaging. This format preserves data from the maps to a given pixel for observations at that pixel. Programs producing level 3 data are able to have all available data at each pixel to choose from without the need to geo-locate everything themselves. Level 2G-lite provides a minimal level of compositing daily level 2G data. However, MODIS surface reflectance data is found in the MOD09 series of data products. MOD09A1 for 13 years (2000-2012) is used in this study for selected study areas and were downloaded from the Land Processes Distributed Active Archive Center.

2) MODIS Land Cover Type (MCD12Q1)

MCD12Q1 is MODIS yearly land cover type data which describes land cover properties based on yearly input from Terra and Aqua. It contains multiple classification schemes. In this study land cover type 2 developed by the University of Maryland, was used which identifies 13 land cover types including 10 natural vegetation classes, croplands and 2 non-vegetated land classes.

3) MODIS land surface temperature (MOD11A2)

MODIS land surface temperature datasets provide per-pixel surface temperature. MOD11A2 is an 8-day MODIS level-3 product at 1 km resolution.

4) Crop data

Crop data is collected from the National Agricultural Statistics Service (NASS), which helps USDA to collect, summarize, analyze and publish agricultural information. In this study, acreage, yield of corn and soybean were collected for both crop mapping and the drought impact study.

5) United States Drought Monitor (USDM)

The US Drought Monitor produces weekly maps of drought conditions each Thursday morning, with map measurements based on climatic, hydrological and soil conditions taken from impacts and observations of more than 350 sources around the United States (Macon, 2014).

6) Precipitation data from the NOAA/ (National Weather Service (NWS) Advanced Hydrologic Prediction Service, Silver Spring, Maryland. (Seo, 1998: Seo, Breidenbach, and Johnson, 1999).

7) Precipitation data can be obtained from the High Plains Regional Climate Center automated weather data network (AWDN) for 64 AWDN stations distributed across the state of Nebraska.

8) Cropland Data Layer (CDL)

Cropland data layer (CDL) maps by the USDA were used to detect the major crop regions in the primary Corn and Soybean Belt. The USDA CDL is a crop-specific geo-reference product covering the whole continental United States in 30m resolutions. CDL is based on measurements from multi-date, multi-spectral Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+), and Advanced Wide Field Sensor (AWiFS) instruments (Swain et al., 2011). Corn and soybean crop spatial information was extracted from the 2012 CDL and re-projected from Albers Conical Equal Area to Sinusoidal projection to generate corn cover map at 500m resolution.

1.3 Study Area

The study area focuses on agricultural drought and its effect on the most intensive corn and soybean planting areas, the Midwestern region of the United States. Corn and soybean are the two dominant crops cultivated in 12 states of the Midwestern US region and they are also two major and minor crops areas common in this region as shown in the map (Figure 2) below: The study area consists of 12 Midwestern states and includes North and South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Illinois, Indiana, Michigan, Wisconsin, and Ohio. The study years range from 2000-2012.

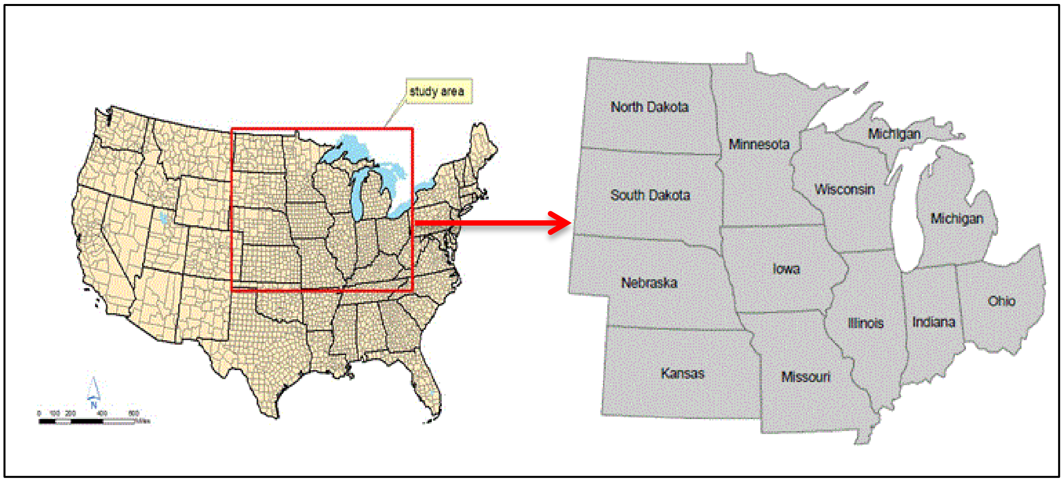


Figure 2 The study area of the Midwestern US comprises 12 states.

Corn and soybean production is influenced by the soil in the region, which is fertile and rich in organic material and nitrogen. The fertile land together with warm nights and well-distributed temperatures contribute to the ideal environment for raising corn and soybean. The Midwest region accounts for over 75% of the total national production and the major corn and soybean areas are in dark green and account for three-fourths of national production. The yellow numbers in the maps represent the percentage each state contributed to the total crop production between 2006 and 2010. Insignificant corn and soybean is depicted in the light green colors as shown in the maps below of (Figure 3).

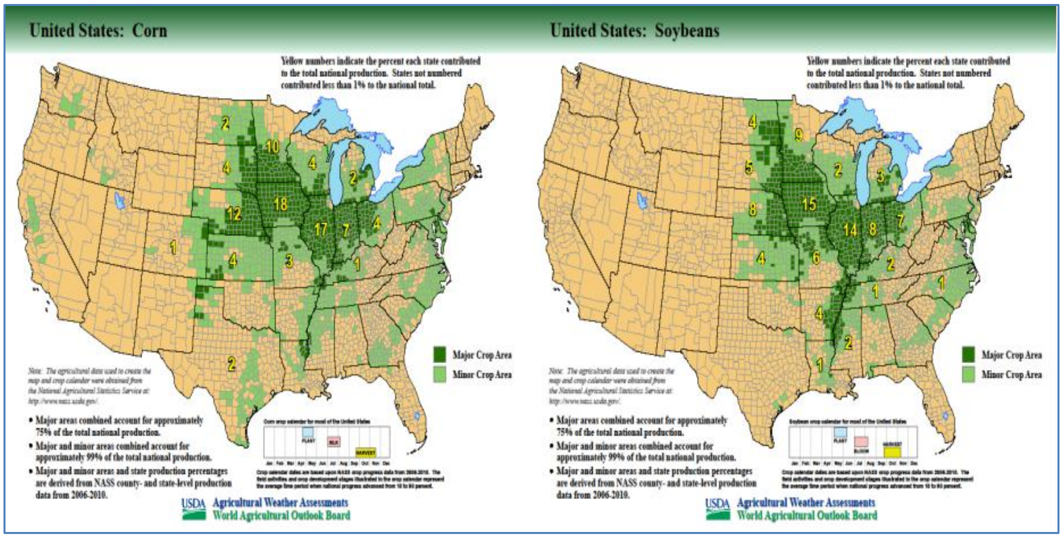


Figure 3 Corn and soybean production maps for the United States (2006-2010). (Data Source: USDA/WAOB).

Crop planting takes place in late April to June when soil temperatures are warm, often done two-weeks prior to soybean planting. Soil temperature can support or stall corn growth, and air temperature is one of the main factors influencing soil temperature. By late September the crops are fully matured and are then harvested throughout the month of October. Nearly half of all soybean production in the United States is exported to Europe, Mexico, South Korea, and Japan. Additionally, 40% of the corn is exported to nations outside of the US. Soybean seeds are usually planted between May and early June. Soybean then begins to bloom beginning in July and through to early August. Soybean is then harvested between late September and early November. Corn on the other hand is planted from late April to late May. The corn crop then blooms between July and mid-August. From late September to early November, corn yields are harvested.

1.4 Organization of Dissertation

The dissertation consists of six chapters. Chapter one is the introduction providing general information and the objectives and the scope as well as major data sources and the identified study area. Chapter two is the literature review, specifically touching upon agricultural drought monitoring with meteorological data, and satellite remote sensing. Chapter three addresses the impact of drought effect on corn and soybean crop production using crop mapping information and GIS technology, including the assessment of drought impact effect on crop yields for corn and soybean; the differences between separate irrigated and non-irrigated crops of corn and soybean yields; the coefficient of determination (R^2) for (time scales of 1, 2, 3, 6, and 9-month average SPI Values at all stations) during growing season and yield of corn and soybean for each of the 12 States of the Midwestern US from 2000-2012, and the chapter summary. Chapter four uses the use of GWR to evaluate relationships between precipitation vs. irrigated and non-irrigated corn and soybean yield, using a Nebraska County Level data as Case Study and followed by chapter summary. Chapter five assesses MODIS indices for agricultural drought monitoring and evaluates the use of Standard Precipitation Index (SPI) to assess MODIS drought indices using a percentage histogram and chapter summary. Chapter six is the new approach for agricultural drought detection based on remote sensing measurements to determine the relationship between US county-level yields versus relatively/common variables collected, as well as crop yield statistics, remote sensing of crop yields, study area, the development of a new approach for agricultural drought monitoring, phenology of crops for corn and soybean time series, and chapter summary.

Chapter seven focuses on the chapter summaries of previous chapters and gives limitations, originalities, and discussions upon future directions and constitutes the conclusion and the discussion.

CHAPTER TWO: LITERATURE REVIEW

2.1 Agricultural Drought Monitoring with Meteorological Data

The ability to identify the onset of drought, and the severity and duration of its existence allows us to understand the potential impact it may have, providing the ability to alleviate damage due to the environment and to minimize economic losses as a result. Reduction of drought impact comes from improving the accuracy of drought monitoring tools. Drought indices serve as useful indicators to identify related variables such as temperature, rainfall, evapotranspiration, and runoff. These indices give a holistic idea of the severity of the drought based upon past occurrences, allowing for scientists to compare and contrast droughts in various regions at different points in time in terms of intensity, duration, and spatial coverage. Such drought indices also provide a platform for evaluation by agricultural producers and policymakers alike who are able to take measured actions in dealing with such dilemma.

Drought indexes provide uniform characterizations of drought. Such indexes are classified through thresholds established for the sole purpose of rating a drought's severity on a scale between “moderate”, “severe” and “extreme”. Additionally, quantitative methods may be expressed through values seen in mathematical formulae.

The drought magnitude (M) level at any particular time (t): q and θ represent the drought index expressed.

$$M_t = q_0(\theta) - q(\theta)_t$$

The intensity (I) is the mean deficit over the drought duration

$$I = \frac{1}{D} \sum_{t=t_1}^{t_1+D-1} q_0\,(\theta) - q(\theta)_t$$

The severity of drought can be calculated based upon duration (D) and intensity:

$$S = D \times \mathrm{I}$$

$$S = \sum_{t=t_1}^{t_1+D-1} (q_0(\theta) - q(\theta)_t)$$

Regional drought characteristics include the spatial extent of drought which is defined as the ratio of the area in deficit to the total area of the region.

$$A = \frac{\sum_{i=1}^{N} A(i) \in (q(\theta) \leq q_0(\theta))}{\sum_{i=1}^{N} A(i)}$$

Where A (i) is the area of the elementary geographic unit of data values (e.g., a model grid cell or a river catchment) and N is the total number of units in the region of interest.

Drought indices were developed as a means to measure drought. A drought index accommodates data on rainfall, snow peak and melt, stream flow and other water –supply into a comprehensible picture. There are several indices that measure how much precipitation for a given period of time has deviated from historically norms. Some of the widely used drought indices include the Palmer Drought Severity Index (PDSI), Crop Moisture Index (CMI), the Standardized Precipitation Index (SPI), Palmer Moisture

Anomaly Index (Z-index), Soil Moisture Index (SMP),and Surface Water Supply Index (SWSI).

Example of Agricultural Drought Indices

A drought index is used to capture drought characteristics thereby contributing to reliable and comprehensive information (Lake, 2011). A large number of agricultural drought indices exist, each incorporating various variables and each providing different measures of drought. The Palmer Drought Severity Index (PDSI) is an example of agricultural drought indices. The Standard Precipitation Index (SPI) and the Crop Moisture Index are widely used (Palmer 1965; McKee et al., 1993). The U.S. Drought Monitor (USDM) is an advanced tool of operational drought monitoring which incorporates information from multiple sources, and has attracted increased attention in recent years.

The Palmer Drought Severity Index (PDSI):

The Palmer Drought Severity Index was the first indicator developed for the United States. Its algorithm is based on a two-layer soil water balance equation which includes precipitation, moisture supply and moisture demand variables (Palmer, 1965).

The index is a sum of the current moisture anomaly and a fraction of the previous index value. The moisture anomaly (D) can be defined as:

$$D = P - \mathrm{Q}$$

Where P is the total monthly precipitation, and Q is the precipitation value for existing conditions' (Palmer 1965). $\bar{P}$ represents the water balance equation defined as:

$$\mathrm{Q} = \overline{ET} + \bar{R} + \overline{RO} - \bar{L}$$

$\overline{ET}$ is the evapotranspiration, $\bar{R}$ is the soil water recharge, and $\overline{RO}$ defines the run off, and $\bar{L}$ is the water loss from soil. Overbars represent such figures as average values for any given month.

The palmer moisture index anomaly for Z index is

$$Z = K \times \mathrm{D}$$

K represents a climate-weighting factor. PDSI values range from -6.0 to +6.0 and is classified under 11 groups. A -6.0 PDSI signifies severe drought. The index is based on precipitation and temperature values. The time duration of a drought is also taken into consideration.

Despite the widespread acceptance of PDSI, the Palmer Index has faults of its own (HEIM, 2002). The index is used specifically for monitoring arid regions where precipitation is a main source of moisture (Doesken et al., 1991). When calculating the PDSI, one uses a simplified two-layer lumped parameter model which is not accurate for capturing drought conditions in a single site. An average water holding capacity of the top two soil layers is also cataloged for the region of interest, however with various soil properties at different locations, this makes it tough to spatially delineate a drought affected region.

Other drawbacks of PDSI include arbitrarily selected drought values being selected based upon Palmer's research in Iowa and Kansas. Snowfall and snow cover are also not included in the index, making the index value inaccurate in snowy conditions. Palmer also overlooked the natural lag time between precipitation and the resulting runoff.

Thornthwaite's method is used to calculate the potential evapotranspiration in PDSI. This is based on an empirical relationship between ET and temperature (Thronthwaite, 1948), which shows poor performance among various methods that estimate ET in a study carried out by ME Jensen et al., 1990. The fact that PDSI tends to underestimate drought severity due to underestimated evapotranspiration in humid regions is another concern (McKee et al., 1993; Rosenberg et al., 1983).

Standardized Precipitation Index (SPI):

SPI, which stands for the Standardized Precipitation Index, was developed to examine the impacts of precipitation deficiencies on soil moistures, ground water, stream flows, and snowpack (McKee et al., 1993). SPI is also better at measuring drought conditions than PDSI because it is able to represent long-term precipitation records at various locations. As rainfall measurements are strictly positives, the SPI fits the historical precipitation data uses a gamma probability distribution function and then transform the Gamma distribution to a normal distribution which has a mean of zero and a standard deviation of one (Edwards and McKee, 1997). Such transformation separate the rainfall measurements as above or below normal (SPI=0) situations.

As soil moisture quickly responds to drought while precipitation of ground water responds to longer time scale. SPI is classified into 7 different levels, which ranges from extreme wet to extreme drought conditions. Positive SPI values indicate greater than median precipitation and negative values indicate lower than median. Compared to PDSI, SPI is deemed a better representation of the water stress (Guttman, 1999; Rhee et al., 2010). SPI however does not account for the effect of soil nor temperature anomalies which are critical for agricultural drought monitoring (Narasimhan and Srinivasan, 2005). Soil moisture also greatly impacts the growth of crops more so than the natural rainfall that precipitates, therefore SPI lacks in that respect when such factors are at play.

Climatic or Crop Moisture Index (CMI):

Three years after PDSI was developed, Palmer (1968) developed the Crop Moisture Index (CMI) for agricultural drought monitoring (Heim, 2002). The CMI is based on a monthly mean temperature and precipitation, measuring evapotranspiration deficits and excessive wetness. The CMI measures short-term drought on a monthly basis and has been widely used to evaluate drought influences throughout growing seasons. The PDSI is a meteorological drought index that responds to weather conditions which have been abnormally dry or abnormally wet. The Crop Moisture Index (CMI) uses a meteorological approach to monitor week-to-week crop conditions (W.C. Palmer, 1968).

SPI is designed for short-term soil moisture demands of crops, and responds greatly to conditions quick to change. CMI is however inefficient in monitoring long-term drought and this creates misleading information regarding its ability to pick up quick response information to changing conditions (Nagarajan and Vloemans, 2010). CMI is unsuitable for additional reasons. When long-term drought monitoring is wanted, CMI begins and ends each growing season near zero. This limits CMI's reliability during the general growing season.

Soil Moisture Percentiles (SMP):

The SMP, soil moisture percentile, is used to calculate modeled and observed soil moisture data. It measures soil moisture reflecting hydrological input and output statistics for complex hydrological models (Sheffield, Wood; 2011). SMP is used often when it comes to mapping desertification and the ratio of actual-to-potential evaportranspiration which quantifies actual conditions on the ground (Sheffield and Wood, 2011).

Palmer Moisture Anomaly Index (Z-index):

The Palmer Z-index measures monthly moisture anomalies showing moisture conditions per month in comparison to normality. The Z-index is used as an intermediate for PDSI computation, not taking into account previous moisture conditions. When we compare the PDSI to the Z-index, the Z-index value varies more quickly from month to month. PDSI in itself varies slower because much of its value incorporates preceding conditions. As a result, data values of both PDSI and the Z-index differ (Quiring and Papakryiakou, 2003).

The Z-index is used to track agricultural drought due to its quick response to variations of soil moisture (Keyantash and Dracup, 2002). Z-index is deemed better than PDSI and more preferable when measuring agricultural drought and is likened to more than CMI when quantifying agricultural drought (Karl, 1986). With that said, the Z-index suffers from a complex formulation and computation which limits its usage due to specificity.

USA Drought Monitor (USDM):

The U.S Drought Monitor maps of current drought conditions have been issued weekly since 1999. The USDM is an index that combines information from various existing drought indicators, including PDSI and SPI. It also reports from state climatologists and observers across the nation. The USDM results from an active operation between the NDMC and the National Oceanic and Atmospheric Administration (NOAA). The U.S. Drought Monitor map provides a summary of drought conditions across the United States and the map is updated weekly by a variety of data-based drought indices and indicators that local experts input into a single composite drought indicator. The USDM is an advanced method for monitoring drought here in the US (Anderson et al., 2011). Furthermore, the USDM statistics are made available via inter-web. This centralization of data contributes more value to its usage and dependency. A D0-D4 scheme is used to classify droughts by their intensity from least to most intense with D0 reflectance showing abnormally dry conditions and D4 visuals indicating exceptional drought occurrences based on a ranked percentile approach as shown in (Figure 4).

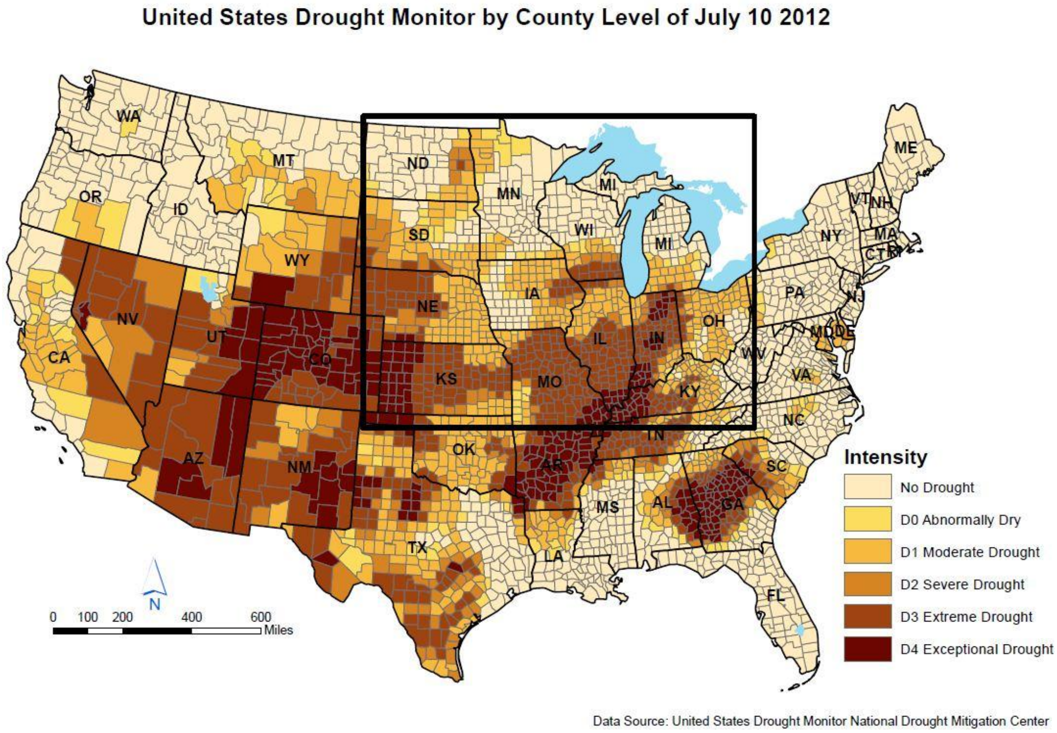


Figure 4 USDM drought map for July 10, 2012.The black box is the study area of the Midwestern US

2.2 Agricultural Drought Monitoring with Satellite Remote Sensing

Obtaining hydrological data from ground-based measurements remains a challenge in less developed regions where gauges are sparely distributed (Sheffield and Wood, 2011). To overcome this, the data obtained from remote sensing is able to provide a consistent visual of water cycles over a regional and global scale. Remote sensing has evolved to the point where it is now able to measure large numbers of hydrological variables ranging from precipitation, to soil moisture, to evapotranspiration, and water levels (Schmugge et al., 2002). Remote sensing is also able to provide useful information regarding biological variables such as plant productivity and health, and vegetative states.

As a result of such abilities, remote sensing has garnered popularity compared to traditional drought monitoring methods, and is used as a powerful tool for providing data and products when it comes to large-scale water cycle evaluations. Data acquired from multiple satellite sensors are used to quantify the characteristics of drought for hydrological and vegetative indices. High spatial resolution data obtained from satellites makes it an important tool for assessing droughts in areas where weather stations are lacking (Caccamoa et al., 2011; Ji and Peters, 2003; Peters et al., 1991). Remote sensing can also detect the onset of drought, its duration and its severity, and may provide agricultural producers and researchers with comprehensive pictures showing the development of drought (Figure 5) below from (Thenkabail et al., 2004) shows a schematic of the capability of remotes sensing in the visible / Infrared bands.

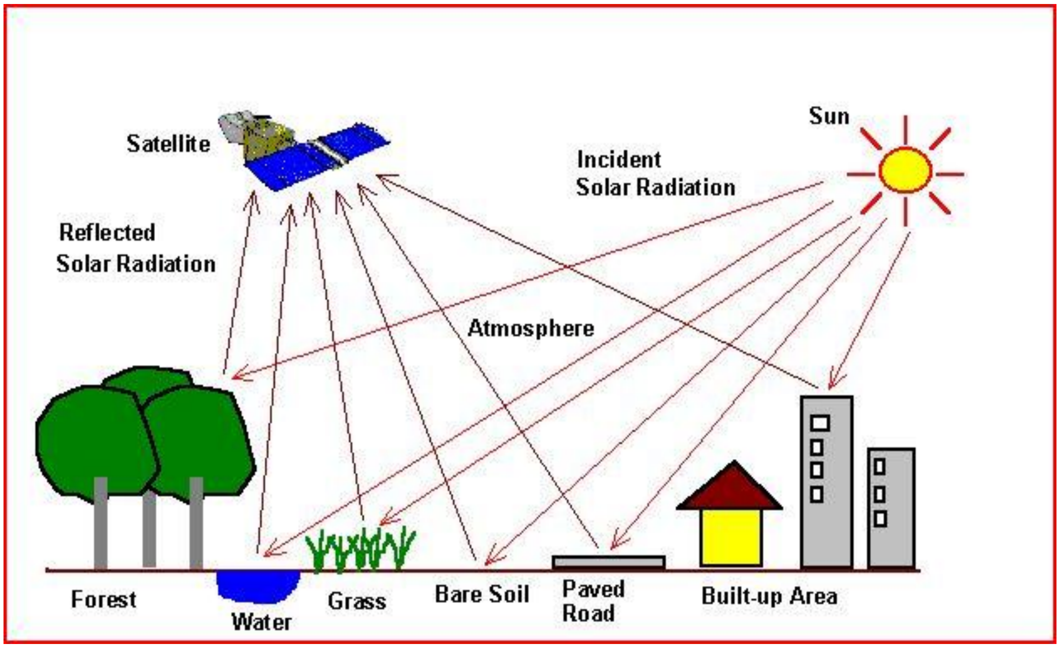


Figure 5 Optical remote sensing uses visible near infrared and short-wave infrared sensors by detecting the solar radiation reflected from targets on the ground. Data Source: Patel, Dhiren P., (1994).

The Advanced Very High Resolution Radiometer (AVHRR) onboard the National and Atmosphere Administration (NOAA)'s Polar-orbiting Operational Environmental Satellites (POES) has been frequently used for large-scale drought monitoring due to its global spatial coverage and relatively long time record. This scanning radiometer uses 6 detectors that collect Vis/ IR bands of radiation wavelengths. With the launch of Terra and Aqua platforms in 1999 and 2002, the Moderate Resolution Imaging Spector-radiometer (MODIS) instruments improves upon the heritage AVHRR in terms of its spatial resolution ranging from 250m to 500m and 1km. It also includes more spectral channels, more accurate geo-location, and improved atmospheric corrections (Fensholt and Sandholt, 2003).

Whereas AVHRR is utilized for large-area drought monitoring, MODIS improves upon the performance of AVHRR by providing higher spatial resolution and greater spectral resolution, enabling more detailed analyses of the study location (http://visibleearth.nasa.gov/view.php?id=54075).

Both Terra and Aqua satellites carry MODIS sensors. MODIS is a 36-band sensor and offers a total of 20 Reflective Solar Bands (RSB) (1-19 and 26) with narrower spectral bandwidths covering visible to shortwave infrared regions. These reflective bands along with thermal bands provide opportunity for studying vegetative conditions and variations. Agricultural drought monitoring with remote sensing measurements provides long-term availability and consistency of sensor data. The Visible Infrared Imaging Radiometer Suite (VIIRS) is developed for long-term continuity of AVHRR and MODIS. VIIRS is an instrument onboard the Suomi National Polar-orbiting Partnership (NPP) satellite that was launched in October, 2011. VIIRS has 22 bands between 0.4 um and 12.5 um. (Lee et al., 2006).

When comparing the MODIS bands in the VIS/NIR, the 16 MODIS bands have been replaced by 9 VIIRS bands. In the short-wave and mid-wave infrared (SWIR/MWIR), 11 MODIS bands have been replaced by 8 VIIRS bands (Murphy et al., 2001). Since VIIRS serves as a continuation of the MODIS data record, agricultural drought monitoring methods based on MODIS measurements may be migrated to VIIRS measurements through efforts on cross-sensor comparison.

Satellite observations of conditions showing vegetative states provides another basis for drought monitoring methods (Marshall et al., 2012) because the state of vegetation is generally representative of environmental water stress, especially in arid and semi-arid regions (Sheffield and Wood, 2011). Visible channels on the AVHRR were exploited for vegetation monitoring in research studies at varying scales (Tucker, 1979).

As a result of quick and direct responses of vegetation to drought, much vegetation in remote sensing indices have been developed for quantifying drought conditions at the regional, national, and global scale (Gu et al., 2007; Ji and Peters, 2003; F N Kogan, 1995b; Peters et al., 1991; Unganai and Kogan, 1998). Vegetation index is generated by spectral reflectance which is influenced by different mechanisms as shown in (Figure 6).

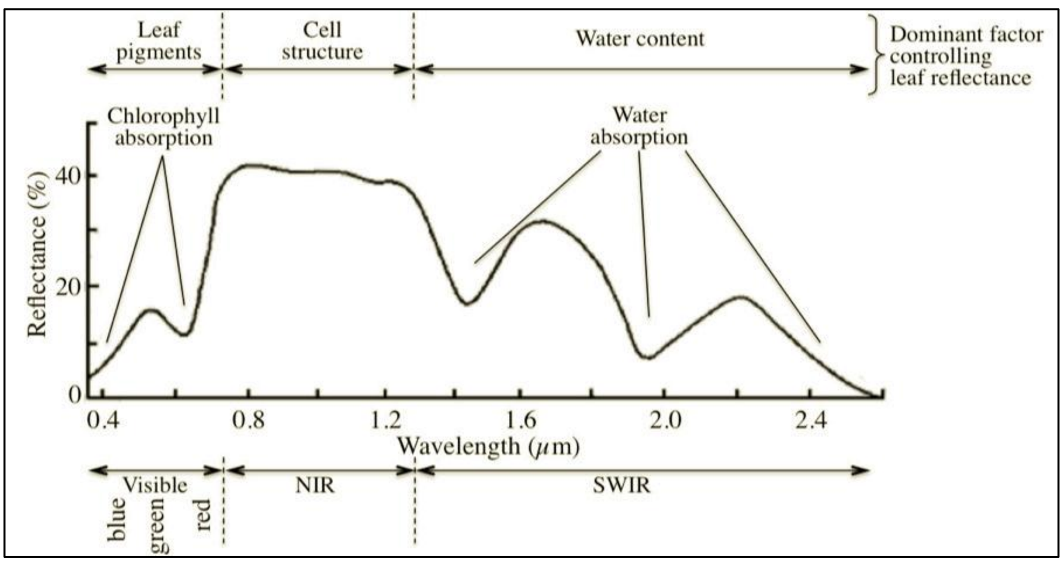


Figure 6 Typical reflectance and absorption characteristics of vegetation (Adapted from Jensen, 2000)

In regards to the reflectance of visible bands, chlorophyll and leaf pigments control such vegetative reflectance (Zarco-Tejada et al., 2000). High reflectance in the 0.7-1.2um regions is dominated by the cell structure of the vegetative materials (Hoffer, 1978). This reflectance of vegetation canopies in the red band and is inversely related to chlorophyll concentrations due to photosynthetic chlorophyll by vegetation in this region (Anyamba and Tucker, 2012). Red, NIR and SWIR bands are used more often than other bands when characterizing vegetation indices.

There are various spectral vegetation indices. The most widely known and used is the Normalized Difference Vegetation Index (NDVI) known as (NIR-Red)/ (NIR+Red) (R0.86 um -R0.66 um)/ (R0.86 um + R0.66 um). The reflectance value of the 0.86 µm channel (R0.86µm) is useful in discriminating pixels of crop production and the lack thereof. The red channel is located in the strong chlorophyll absorption region, while the near IR channel is located in the high reflectance of vegetation canopies. (Anyamba and Tucker, 2012).

To measure and map the density of green vegetation across the earth's landscapes, scientists use satellite sensors to observe distinct wavelengths of visible and near-infrared sunlight that is absorbed and reflected by plants. Calculating the ratio of the visible and near-infrared light reflected back up to the sensor yields a number between (-1) and (+1). The result of this calculation is called the Normalized Difference Vegetation Index. In addition, an NDVI value of zero means no green vegetation, whereas a close to +1 indicates the highest possible density of green leaves of vegetation.

Normalization allows NDVI to minimize directional reflectance and to reduce effects of sun-angles and shadows and topographic variations (Holben and Fraser, 1986). NDVI has been used in many studies for vegetation conditions and drought monitoring purposes (Gu et al., 2007; Tucker and Choudhury, 1987; Unganai and Kogan, 1998; Wan et al., 2004).

In light of NDVI, a number of NDVI-based vegetation indices have been proposed and used. The Vegetation Condition Index (VCI) "compares the current NDVI to the range of values observed in the same period in previous years. The VCI is expressed in % and gives an idea where the observed value is situated between the extreme values (minimum and maximum) in the previous years. Lower and higher values indicate bad and good vegetation state conditions, respectively" (http://land.copernicus.eu/global/products/vci). VCI is used for drought detection by scaling values of NDVI from [0-1]. Other vegetation indices applied include the Temperature Condition Index (TCI) and Vegetation Health Index (VHI), which combine VCI and TCI together for estimations of vegetation water stress levels. TCI outperforms NDVI and VCI in areas where soil has high moisture content due to excessive rainfall and persistent cloudiness (Liu and Kogan, 1996). Such vegetation indices present unique signatures of vegetation, including leaf area coverage and growth statuses, all of which provide for estimating vegetative conditions (Huete et al., 2002).

Other indices reflect SWIR bands, known as vegetation water indices and they are also used in drought study. An example is the Normalized Difference Water Index (NDWI) for remote sensing of vegetation liquid water from space., calculated as (NIR –

SWIR)/ (NIR + SWIR) ($R_{0.86}$-$R_{1.24}$)/ ($R_{0.86}$ + $R_{1.24}$), based on the fact that the 1.24µm band is on the edge of the vegetation liquid water absorption, while the 0.86µm band is insensitive to water content changes (Gao, 1996), which is sensitive to changes in liquid water content of vegetation.

The Normalized Difference Infrared Index (NDII) is able to monitor vegetation moisture content. Strong absorbance by water makes this band suitable for estimating the water content found in plants. Using the difference between two water absorption channels centered at 1640 nm and 2130 nm, the Normalized Multi-band Drought Index (NMDI) NIR-(Modis6-Modis7)/ (NIR+(Modis6-Modis7) was developed to provide both soil and vegetation moisture results (Wang and Qu, 2007). The NMDI utilizes 860 nm channels as the reference instead of using a liquid water absorption channel. However, it uses the difference between two liquid water absorption channels centered at 1640 nm and 2130 nm as the soil and vegetation moisture sensitive band. The information from multiple near infrared and short wave infrared channels has enhanced the sensitivity to drought severity and is suited to estimate soil and vegetation moisture.

Other water content indices in usage include the Global Vegetation Monitoring Index (GVMI) (Ceccato et al., 2002), and the Shortwave Infrared Water Stress Index (SIWSI (Fensholt and Sandholt, 2003). More remote sensing indices that are used can be seen in the (Table 1) below.

Table 1 Spectral indices used for drought monitoring

Index	Definition	Author
NDVI	(NIR-Red)/(NIR+Red)	(Tucker, 1979)
VARI	(Green-Red)/(Green+Red-Blue)	(Gitelson et al., 2002)
SR	NIR/Red	(Tucker, 1979)
EVI	2.5(NIR-Red)/(NIR+6Red-7.5Blue+1)	(Huete et al., 2002)
NDIIb6	(NIR-Modis6)/(NIR+Modis6)	(Hunt and Rock, 1989)
NDIIb7	(NIR-Modis7)/(NIR+Modis7)	(Hunt and Rock, 1989)
D1640	1- Modis6/(0.55NIR+0.55Modis7)	(Van Niel et al., 2003)
NDWI	(NIR-SWIR)/(NIR+SWIR)	(Gao, 1996)
NRV	(RVI – 1)/(RVI+1)	Baret and Guyot, 1991)
MSAVI	$\frac{2\mathrm{NIR}+1-\sqrt{(2\mathrm{NIR}+1)^2-8(\mathrm{NIR}-\mathrm{Red})}}{2}$	(Qi et al., 1994)
VCI	$(NDVI–NDVI_{min})/(NDVI_{max}–NDVI_{min})$	(Kogan, 1995b)
TCI	$(T_{max}–T)/ (T_{max}–T_{min})$	(Kogan, 1995b)
VHI	VHI $=\alpha$VCI $+(1-\alpha)$ TCI	(Kogan, 1995b)
NDDI	(NDVI-NDWI)/(NDVI+NDWI)	(Gu et al., 2007)
SAVI	(NIR-Red)(1+L)/(NIR+Red+L)	(Huete, 1988)
NMDI	$\frac{\mathrm{NIR}-(\mathrm{Modis6}-\mathrm{Modis7})}{\mathrm{NIR}+(\mathrm{Modis6}-\mathrm{Modis7})}$	(Wang and Qu, 2007)
VTCI	$(LST_{NDVImax}-LST_{NDVI})/(LST_{NDVImax}-LST_{NDVImin})$	(Wan et al., 2004)
VSWI	NDVI/T	(Carlson et al., 1990)

Data Source: Di, Wu (2014), An Investigation of Agriculture Drought on the United States Corn Belt Using Satellite Remote Sensing and GIS Technology.

Depending on the climatic region and surface type, the selection of the most appropriate remote sensing index for drought monitoring is considered. In the primary Corn and Soybean Belt using the MODIS time series from 2000 to 2012, four MODIS indices were used including NDVI, NDWI, NDII6, and NMDI. These indices particularly are sensitive to agricultural drought.

In summary, some advantages of remote sensing are that it is capable of providing information on a large number of hydrological variables such as precipitation, soil moisture, evapotranspiration and water levels. Satellite remote sensing provides cost-effective and rapid methods of acquiring up-to-date information over a big large geographical area. Remote sensing is also a practical way to obtain data from inaccessible areas as it is capable of continuous coverage. Satellite remote sensing also has standard tools and techniques which enables versatile usage. Repetitive coverage allows the monitoring of dynamic themes like water and agriculture. Satellite remote sensing provides useful information of biological variables such as vegetation state, plant productivity and health.

Some limitations of remote sensing are that some phenomena are cataloged with indirect measurements. It is also apt to finding interference from cloud cover and atmospheric particles, as well as encountering geometric issues, sensor calibration issues. There is a difference between satellite measurements and surface quantities which has an effect on hydrological and vegetative indices (Sheffield and Wood, 2011). Additionally earth radiances taken by satellite sensors require conversion to fit surface parameters that depict quantitative characterizations of drought. The method of retrieving using remote sensing is also imperfect due to land-atmosphere radiations. Cloud contamination is another limitation.

CHAPTER THREE: DROUGHT EFFECTS ON CORN AND SOYBEAN CROP PRODUCTIONS USING GIS TECHNOLOGY

This section of the study is focused on three parts of the research: (1) The assessment of drought impact effect on crop yields for corn and soybean; (2) The differences between separate irrigated and non-irrigated crops of corn and soybean; (3) The coefficient of determination (R^2) SPI and yield across several time scales of 1, 2, 3, 6, and 9-month average SPI values at all stations during growing season for corn and soybean, for all 12 States of Midwestern US study area from 2000-2012.

3.1 The Assessment of Drought Impact Effect on Crop Yields for Corn and Soybean

Geographical Information System (GIS) is a toot for organizing geographic data for analysis and presentation. In agriculture application, GIS helps in mapping features such as crops and the visualization of agricultural environments. GIS has continued to improve over the years and has begun to become utilized by scientists and researchers to map crop distributions and patterns, taking into account variables such as drought effects, flood effects, and hurricane effects on crop yields. GIS also helps in publishing crop data for sharing. Special organizations such as the National Agricultural Statistics Service (NASS) collect, summarize, and publish mass agricultural data sets. The World Agricultural Outlook Board (WAOB) is another organization that publishes maps of agricultural areas illustrating crop patterns and like features, using GIS spatial data layers.

This has enabled policy makers and analysts to observe evaluate, and decision make about weather and climate related impacts regarding agricultural trade and production.

GIS technology allows the development of maps which define major crop producing areas for the United States. As shown in (Figure 7) below, the major corn and soybean areas are in dark green and account for three-fourths of the total nation’s production. The yellow numbers in the maps represent the percentage each state contributed to the total crop production between 2006 and 2010. The minor corn and soybean is depicted in the light green colors. The two maps at the bottom were created using ArcGIS 10.4 from the United States Drought Monitor data source.

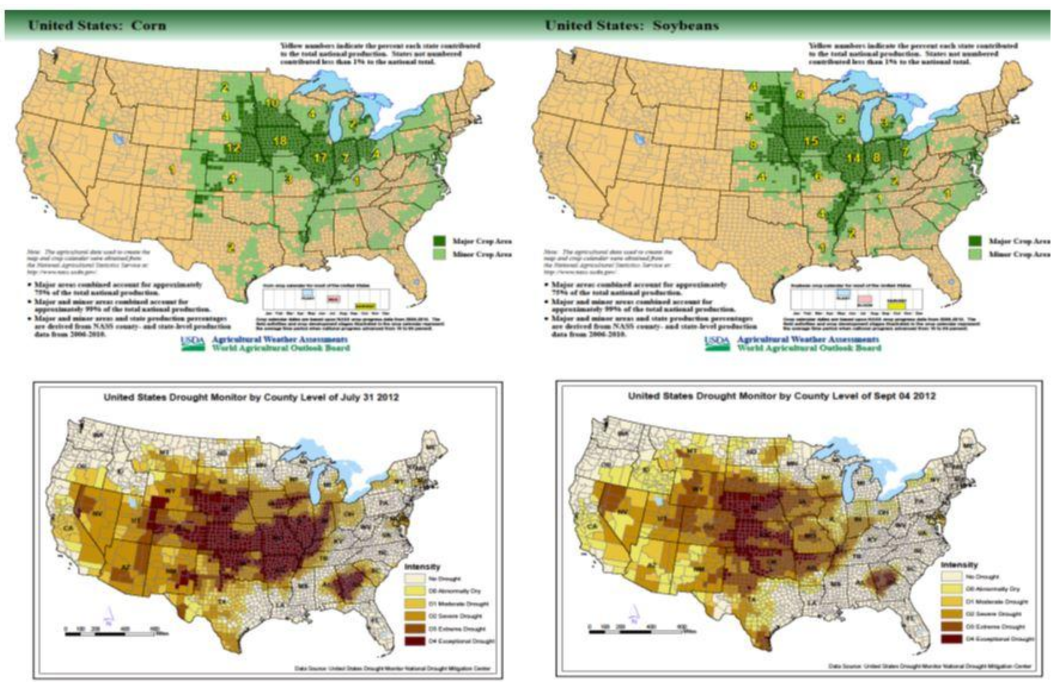


Figure 7 The top two maps show Corn and Soybean production from 2006 to 2010 (Data source: USDA/WAOB).

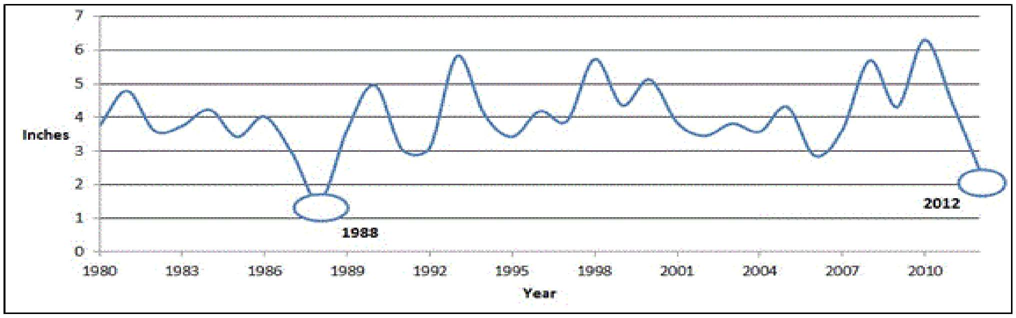
The two maps on top were acquired from the Agricultural Weather Assessment from the World Agricultural Outlook Board. The two maps on the bottom as shown in (Figure 7) above generated using ArcGIS for July and September 2012. These maps show that there is drought in the study area during this time period.

To better provide information for decision makers in agriculture, drought maps are created and updated at various time scales. Beyond addressing the spatial influence of drought upon crops, drought impact on crop production is also factorized into research. Drought events have had significant effects upon the United States, and in 2012 America's corn production reached a low point among its past decade.

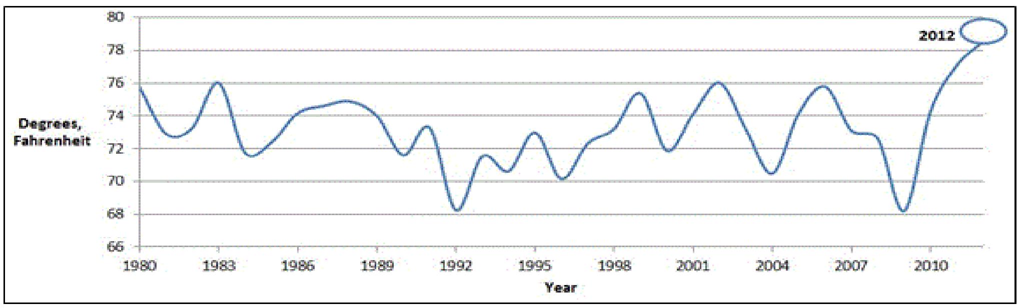
The effect of drought on corn and soybean yields shows a correlation between these two factors. Drought and high temperatures during the 2012 growing season affect agricultural productions in many regions of the United States. We generated maps using ArcGIS10.4 for July and September 2012 depicting the effects of the exceptional drought and high temperatures which afflicted the Midwest of the United States during this time period. A review of the drought and yields for 2012 were presented to better understand the effect of drought has on crop yields.

In (Figure 8) below, the extreme dry weather conditions of 2012 were similar to June 1988 that afflicted the growing season and illustrates the hot and dry results for July 2012 across the twelve selected corn and soybean producing states. The (Figure 8) data was acquired from the National Oceanic and Atmospheric Administration, Nation Climatic Data Center.

June precipitation, 12 States weighted average. June 2012 was dry, much like June 1988.



July average daily temperature, 12 States Weighted average July 2012 was very hot.



July precipitation, 12-State weighted average (July 2012 was dry)

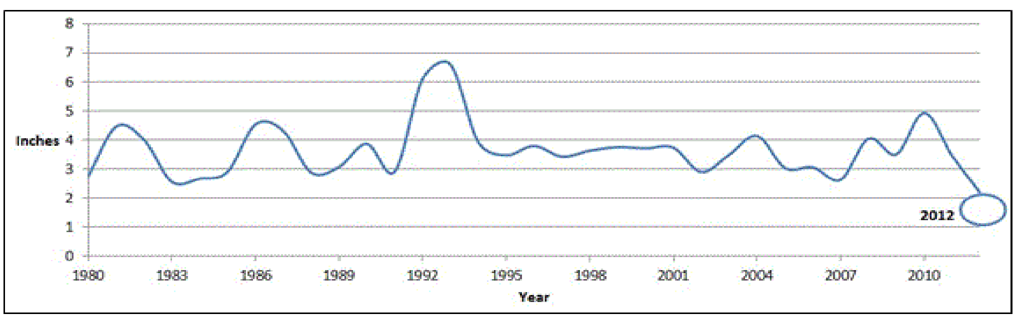


Figure 8 Shows June precipitation, July temperature and weighted-average precipitation levels for all 12-states.

Results of this unfavorable heat was seen in a sharp reduction of corn yield for 2012 - down to 123.4 bushels per acres, and a decrease of soybean yields to 39.6 bushels per acre as shown in the (Figure 9) below.

The 2012 drought increased in its effect during the summer season and negatively impacted great portions of the major field crops in the top corn-producing states including in Illinois, Indiana, Iowa, Nebraska, and Ohio. It exceeded, in most measures, the 1988-1989 North American Drought, used for comparison (Kimery 2012). Both corn and soybean yields therefore showed great reductions in 2012 according to the Crop Production 2012 Annual Report released by the USDA. (Figure. 9), acquired by the (USDA) National Agricultural Statistics Service (NASS) Quick Stats Database also shows the time series of USA corn and soybean yields from 1980 to 2012.

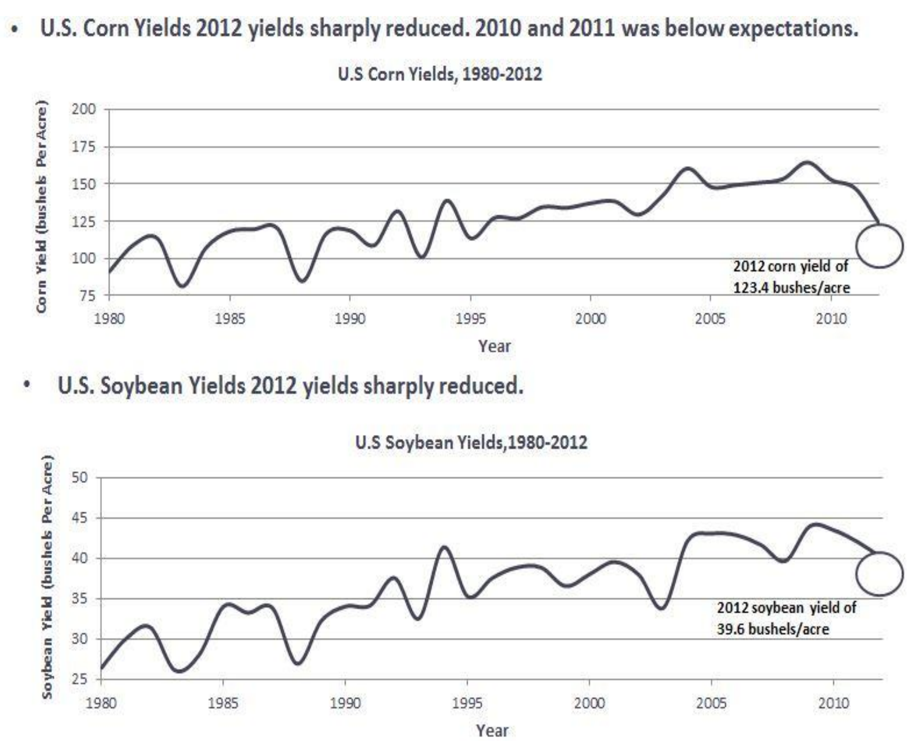


Figure 9 U.S. Corn and Soybean Yields with time series (1980-2012)

3.2 Differences between Separate Irrigated and Non-Irrigated Crops of Corn and Soybean Yields

The two states that were used to illustrate the irrigation and non-irrigation farming methods for corn and soybean productions were Nebraska and Kansas Midwestern US and were mapped for 2007. Because irrigation is unlikely to vary on a year-to-year basis, no change was assumed during the three years (from 2009 to 2011) as shown in (Figure 10). Various areas in both Nebraska and Kansas are heavily reliant on irrigation. Whether rain occurs or not, corn and soybean crops can still have adequate moisture as a result. Additionally, 2012 turned out to be an outlier year in terms of US weather in the Corn Belt (Fuchs, Brian A., Deborah A. Wood, and Dee Ebbeka, 2011). Nebraska is also a major corn producer, however much of its corn is irrigated using Ogallala Aquifer. The total corn planted in Nebraska in the year of 2012 was 10 million acres, among which nearly 6 million was irrigated.

NEBRASKA: Dry conditions allowed the drought to reach extreme levels. Various factors contributed to the warm temperatures during the winter season, including strong southerly winds, minor snow fall to the north, and a jet stream pattern keeping cold arctic air north of the state. Intense heat during the spring months caused a rapid decline in soil moisture conditions which were further propagated by hot and dry drought-like conditions. The continuation of heat and a lack of rainfall quickly led to the development of drought conditions. These conditions impacted various sectors from agriculture to infrastructure and water supplies.

KANSAS: Approaching the year 2012, Kansas in 2011 experienced a run-up to the extreme drought it experienced by the time May came around, caused by high temperatures and a lack of precipitation. As a result, the production of corn and soybean were all below normal. Low precipitation rates caused the impacts in the 2012 growing season. The livestock industry was affected by drought due to poor pasture conditions, high feeding costs, and low water availability, ultimately resulting in lower profit margins for farmers and producers alike due to high temperatures and humidity.

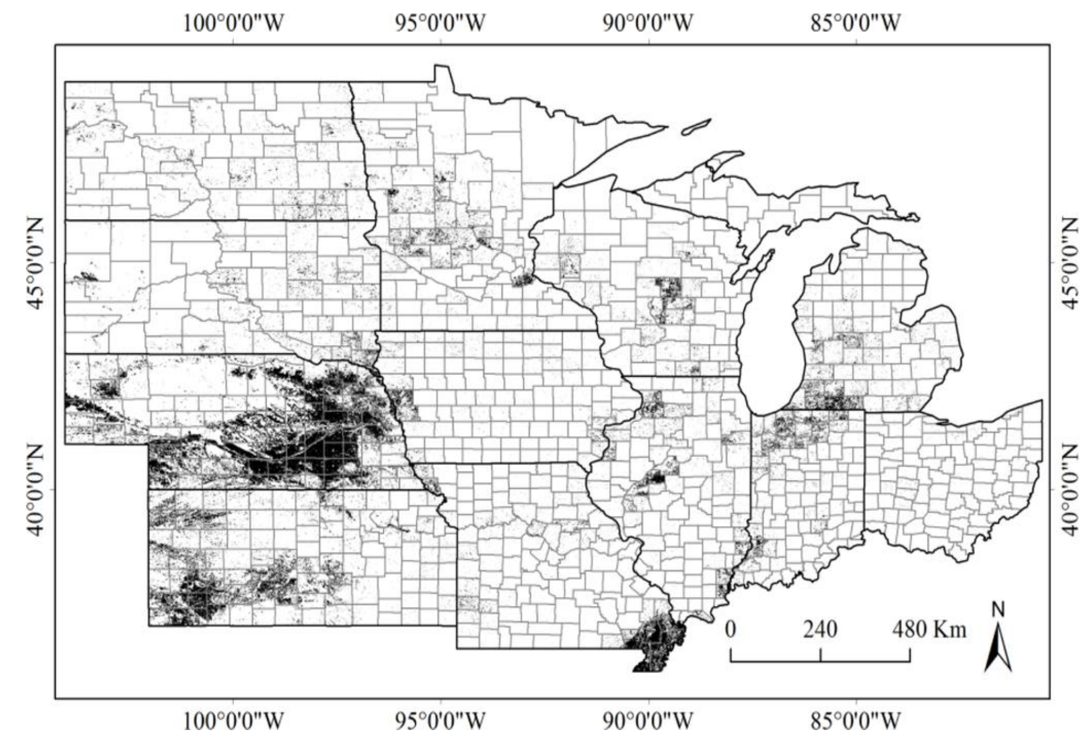


Figure 10 Irrigation of corn and soybean in Nebraska and Kansas for 2007. Data Source: Gong; Myneni; Chaoqing; Xin. (2013).

(Figures 11-18) were acquired from (USDA) National Agricultural Statistics Service (NASS) Quick Stats Database, and show irrigation and non-irrigation graphs for corn and soybean productions in Nebraska and Kansas states as shown below:

(Figure 11) shows soybean irrigated yield measured in (BU/Acre) for Nebraska state (1980-2012) as shown below. In 2012 irrigated crop yields reached a peak. The Irrigation ascending constantly from 1980 up until 2012, with some years showing decline, followed by increases on a consistent basis. There is a trend in the yield, which may be due to technological advances, fertilization, and improved farming methods. Since we do not have enough information about the impact of these advances, we will not attempt to model the effect here. Hence it should be noted the trend variance will become part of the follow-up studies.

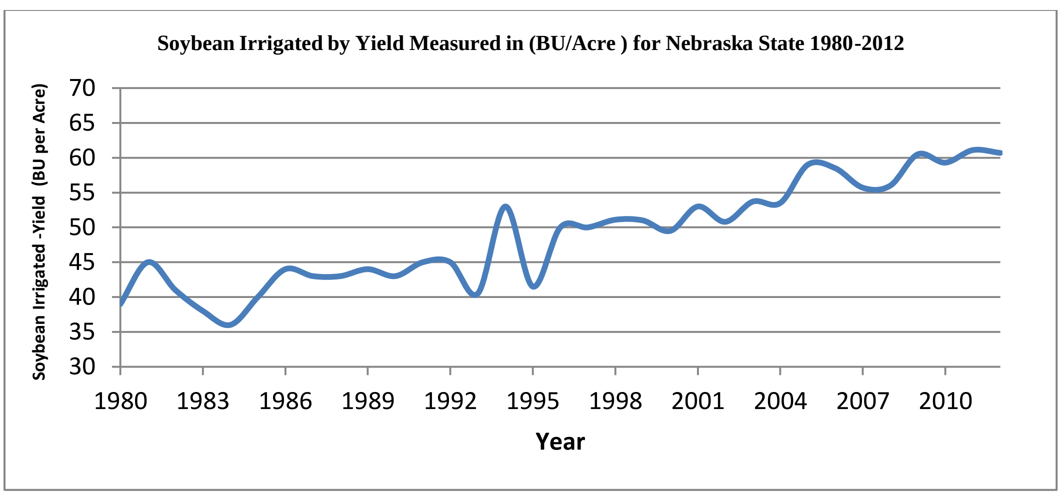


Figure 11 Soybean Irrigated by Yield Measured in (BU/Acre) for Nebraska State (1980-2012).

(Figure 12) shows soybean non- irrigated yield measured in (BU/Acre) for Nebraska state (1980-2012). There were non-irrigated yields for Nebraska from 1980 to 2012 and in 2012 there was no irrigation, similar to 1984 due to drought.

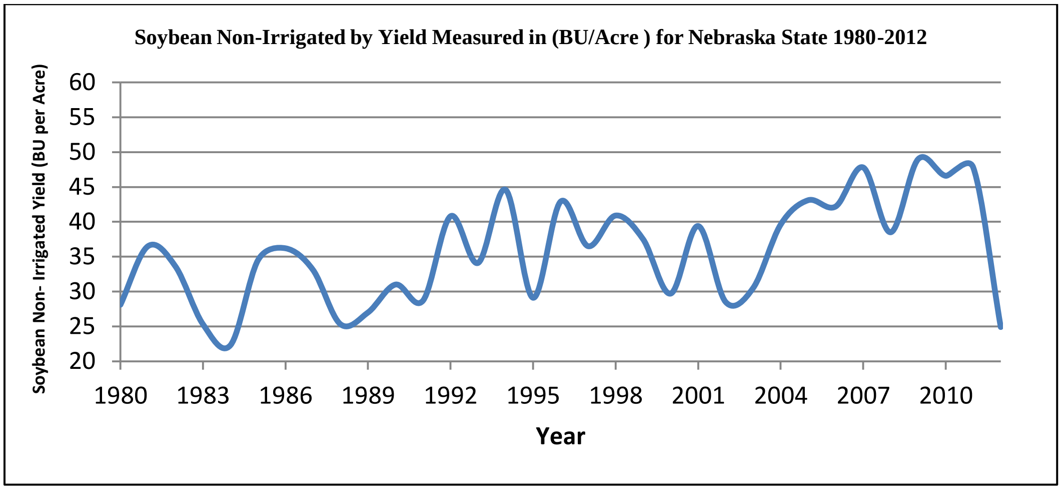


Figure 12 Soybean Non- Irrigated by Yield Measured in (BU/Acre) for Nebraska State (1980-2012).

(Figure 13) shows soybean irrigated yield measured in (BU/Acre) for Kansas state (1984-2009). The only data available above was between 1984 and 2009. In 2009, there was a sharp irrigation yield of soybean for Kansas.

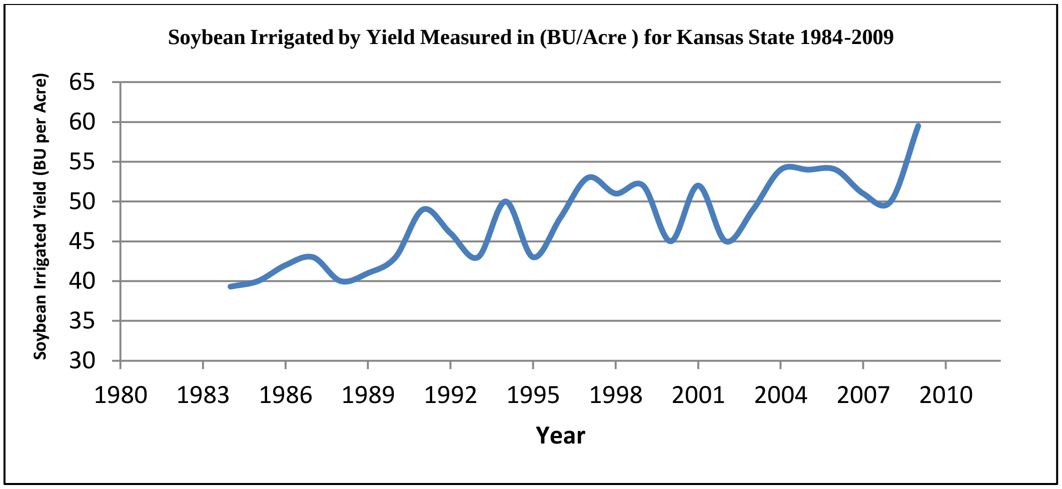


Figure 13 Soybean Irrigated by Yield Measured in (BU/Acre) for Kansas State (1984-2009).

(Figure 14) shows soybean non- irrigated yield measured in (BU/Acre) for Kansas state (1984-2009). The figure shows non-irrigated data and shows zero irrigation in 1984 with a decrease in irrigation occurring toward the end of 1999, followed by an increase and then a decline.

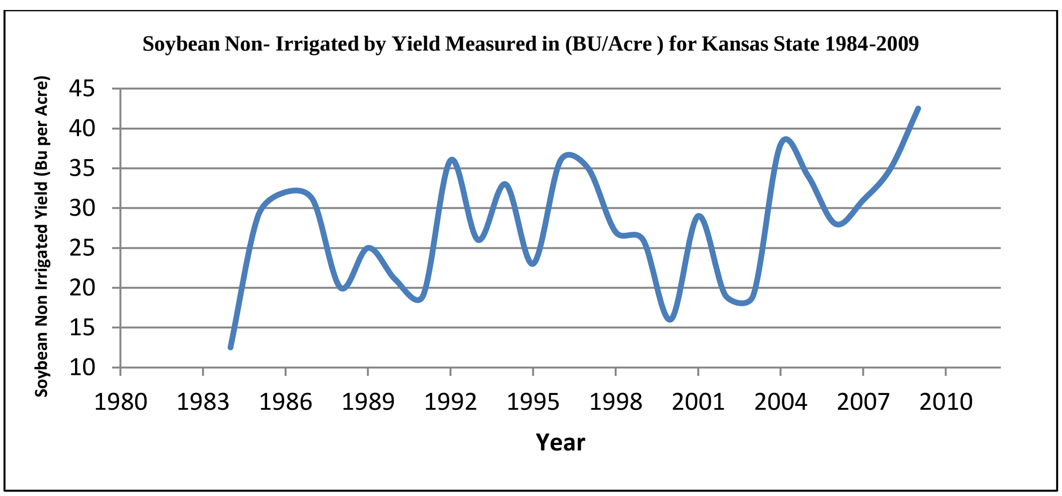


Figure 14 Soybean Non- Irrigated by Yield Measured in (BU/Acre) for Kansas State (1984-2009).

(Figure 15) shows corn irrigated yield measured in (BU/Acre) for Nebraska state (1980-2012). Corn irrigated yields increased between 1980 and 2012, although 1993 showed a sharp decline but quickly picked up the following couple of years, in 1994 and 1995.

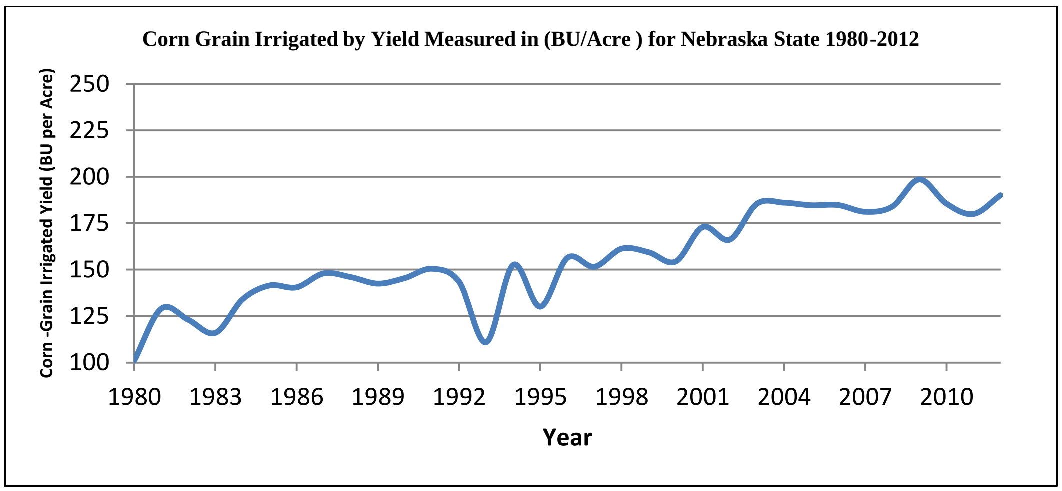


Figure 15 Corn Irrigated by Yield Measured in (BU/Acre) for Nebraska State (1980-2012).

(Figure 16) shows corn non-irrigated yield measured in (BU/Acre) for Nebraska state (1980-2012). Non-irrigation corn yields in 2012 showed no irrigation due to extreme drought.

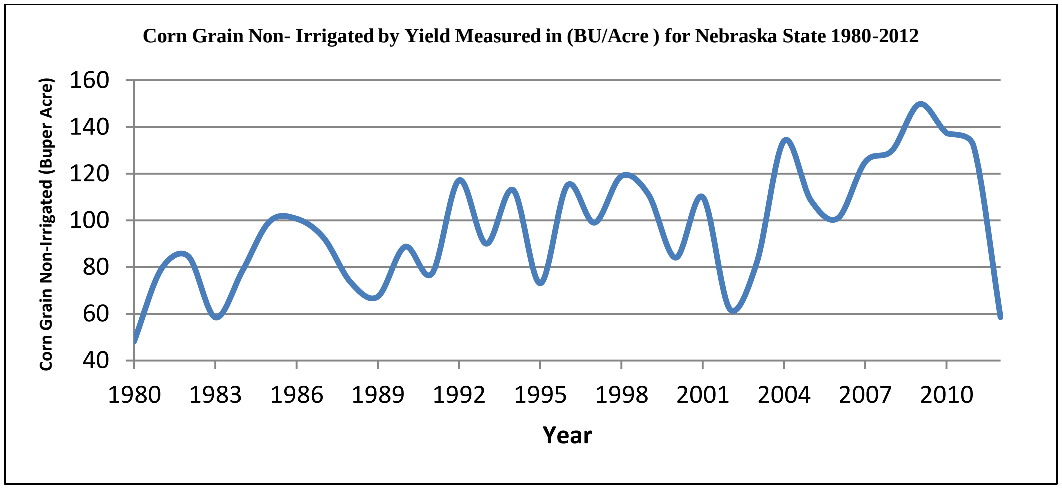


Figure 16 Corn Non- Irrigated by Yield Measured in (BU/Acre) for Nebraska State (1980-2012).

(Figure 17) shows corn irrigated yield measured in (BU/Acre) for Kansas state (1980-2012). Between 1980 and 2012, corn irrigated yields showed steady increase with maximum in 2004 and 2009.

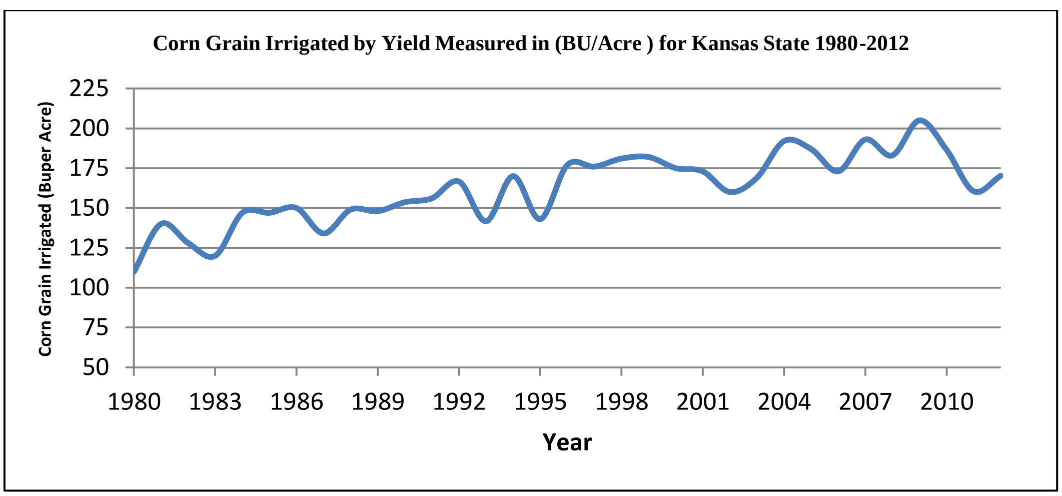


Figure 17 Corn Irrigated by Yield Measured in (BU/Acre) for Kansas State (1980-2012).

(Figure 18) shows corn non-irrigated yield measured in (BU/Acre) for Kansas state (1980-2012). Between 1980 and the data showed minimum in 1983 and 2012.

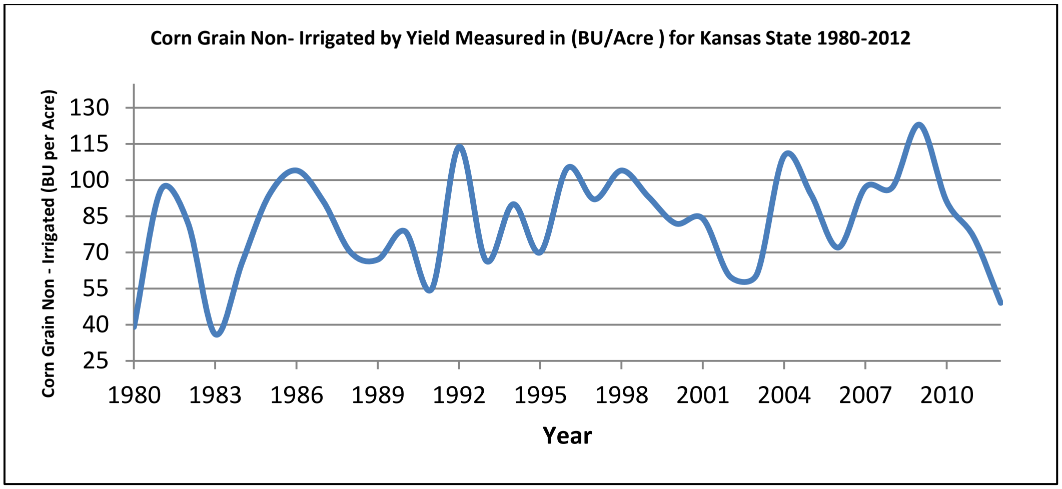


Figure 18 Corn Non- Irrigated by Yield Measured in (BU/Acre) for Kansas State (1980-2012).

3.3 The Coefficient of Determination (R^2) between Precipitation and Yield

The SPI over different months and time- scales are used as an index of rainfall excess of deficit or each state. Calculations were carried out for the 1-, 2-, 3-, 6-, and 9- month average SPI Values (growing season) and annual corn and soybean yield (see Appendix A)**.** The sum of SPI computed over for several time scales (1 month, 2 month, 3 month, 6 month, and 9 month) for the corn and soybean yield in growing season are shown in increasing order using the average SPI for all stations; this will give the average SPI per state for specific years from 2000 to 2012. Following this is the yield correlation of the SPI between the years 2000 and 2012.

Overall, there is an average of between 100-180 BU/Acre of corn-yield, and 30-50 BU/Acre for soybean-yield, both for many of the mid-western states during the five-month growing season. The correlations between averaged SPI and yield are computed.

The results for SPI 1-month, 2-month, 3-month, 6-month, and 9-month SPI show that as sample size increases, the more correlations will cluster around zero. Significance levels for Pearson's correlation using different sample sizes vary. Level of significance is based upon the likely and most unlikely determined observations according to percentage values. The most likely observations are based on a 95% probability density whereupon very unlikely observations are based upon the 0.025 area curve.

There was non-significant correlation in Kansas for corn SPI month 1 average and a strong correlation in Kansas for soybean SPI 1-month average, due to a well-established irrigation system installed, being $R^2 = 0.63$. For Nebraska SPI 1-month, there was a non-significant correlation for the corn and for South Dakota SPI 1-month, there was average correlation for the corn yield with an irrigation system, being $R^2 = 0.54$. For South Dakota SPI 1-month, there was a non-significant correlation for the soybean yield with an irrigation system due to due to ineffective realization, similar for the corn yield.

There was a significant correlation in Kansas for corn SPI 2-month average, with an irrigation system, being $R^2 = 0.47$. There was a significant correlation in Kansas for soybean SPI 2-month average, due to the irrigation system installed, being $R^2 = 0.67$. For Nebraska SPI 2-month, there was average correlation for the corn with an irrigation system, being $R^2 = 0.49$. For Nebraska SPI 2-month, there was a significant correlation for the soybean yield with an irrigation system, being $R^2 = 0.58$. For South Dakota SPI 2-

month, there was significant correlation for the corn yield with an irrigation system, being $R^2 = 0.60$. For South Dakota SPI 2-month, there was a non-significant correlation for the soybean yield with an irrigation system due to ineffective realization, being $R^2 = 0.34$.

There was a significant correlation in Kansas for corn SPI 3-month average, with an irrigation system, being $R^2 = 0.64$. There was a significant correlation in Kansas for soybean SPI 3-month average, due to the irrigation system installed, being $R^2 = 0.61$. For Nebraska SPI 3-month, there was average correlation for the corn with an irrigation system, being $R^2 = 0.47$, being $R^2 = 0.47$. For Nebraska SPI 3-month, there was an average correlation for the soybean yield with an irrigation system, being $R^2 = 0.52$. For South Dakota SPI 3-month, there was average correlation for the corn yield with an irrigation system, being $R^2 = 0.55$. For South Dakota SPI 3-month, there was a non-significant correlation for the soybean yield with an irrigation system due to ineffective realization, being $R^2 = 0.28$, due to drought conditions.

There was a significant correlation in Kansas for corn SPI 6-month average, with an irrigation system, being $R^2 = 0.51$. There was a non-significant correlation in Kansas for soybean SPI 6-month average, due to the irrigation system installed, being $R^2 = 0.36$. For Nebraska SPI 6-month, there was average correlation for the corn with an irrigation system, being $R^2 = 0.44$. For Nebraska SPI 6-month, there was an average correlation for the soybean yield with an irrigation system, being $R^2 = 0.47$. For South Dakota SPI 6-month, there was average correlation for the corn yield with an irrigation system, being $R^2 = 0.41$. For South Dakota SPI 6-month, there was a non-significant correlation for the soybean yield with an irrigation system due to ineffective realization, being $R^2 = 0.26$, due to drought conditions.

There was an average correlation in Kansas for corn SPI 9-month average, with an irrigation system, being $R^2 = 0.41$. There was a significant correlation in Kansas for Soybean SPI 9-month average, due to the irrigation system installed, being $R^2 = 0.32$. For Nebraska SPI 9-month, there was average correlation for the corn with an irrigation system, being $R^2 = 0.52$. For Nebraska SPI 9-month, there was an average correlation for the soybean yield with an irrigation system, being $R^2 = 0.53$. For South Dakota SPI 9-month, there was average correlation for the corn yield with an irrigation system, being $R^2 = 0.54$. For South Dakota SPI 9-month, there was a non-significant correlation for the soybean yield with an irrigation system due to ineffective realization, being $R^2 = 0.36$, due to drought conditions.

When there is extreme drought in the mid-western states that do not utilize irrigation systems, there is a low production of corn and soybean crops per Bu/Acre. However, when there is extreme drought in the states that do contain irrigation systems, Kansas, Nebraska, and South Dakota. Finally, when high- precipitation and moisture is found, there is a consistency in the amount of BU/Acre production that occurs in each of the states. The irrigation systems are only useful and show affect when drought is in effect. Otherwise, precipitation results in similar BU/Acre outputs of corn and soybean crops across all the Midwestern region states combined.

3.4 Chapter Summary

GIS technology was used to show maps and crop yields for the United States to identify major corn production areas. The corn maps illustrate corn-planting patterns presenting both major and minor corn and soybean areas. As the 2012 drought covered most of the US, the corn yield maps help us focus on the efforts on the most affected areas, the primary Corn and Soybean Belt, the most intensive agricultural region in the United States. Corn and soybean yield mapping serves as a useful tool for understanding climate variations of crop productivity. The 2012 devastating drought is demonstrated by comparing the yield map of 2012 with that of the previous year. Significant yield losses were noted across most areas of the primary Corn and Soybean Belt. Crop mapping with GIS technology provides a framework for better agricultural assessment activities. When used in conjunction with climate/weather products and satellite remote sensing products, the crop maps facilitate climate/weather fluctuations on agriculture and of water-stressed agricultural losses.

In conclusion, Chapter 3 demonstrates the utility of GIS in deterring the effects of drought on corn and soybean crop production. The first section of the chapter shows that GIS has improved in collecting and evaluating drought impact and the display of variables and patterns which accompany its effects during various time-scales (1, 2, 3, 6, and 9-month SPI). Section 3.2 examines the impact of water deficit for irrigated and non-irrigated crops of corn and soybean yields based on Nebraska and Kansas state level data. The livestock industry was affected by drought due to low water availability, poor pasture conditions, raising feeding costs, and ultimately resulting in lower profit margin for farmers and producers. The profit depends on the sale price/bushel. Usually when the yield/acre is low, the price per bushel goes up, and with government subsidy, farmers usually make money in low yield years.

Section 3.3 touches on the various time-scale SPI value impacts, upon which irrigation systems prove to be useful only when drought is in effect. For the SPI levels ranging between 1-month and 9-months, Kansas and Nebraska shows the highest coefficient of variance out of all 12-states contained in the Midwestern primary Corn and Soybean Belt. Kansas and Nebraska showed the strongest correlations due to irrigation system installations. South Dakota was leveled by strong correlations throughout all SPI periods for corn only. Average correlation yields resulted for all SPI levels for Nebraska for both corn and soybean yields. Kansas showed its strongest correlations for the 2-month and 3-month averages, for both corn and soybean, averaging out at an R^2 of 0.60. The lowest R^2 for Nebraska was found in its SPI 1-month correlation for corn with an R^2 = 0.39. Kansas showed similar low R^2 for its 1-month average SPI for corn, and its 6-month SPI average for corn. Extreme drought creates low corn and soybean production where irrigation systems are not implemented. The opposite is true for states such as Kansas, Nebraska, and South Dakota, where irrigation management methods assist in crop yields throughout much of the SPI-monthly averages. The "low $R^{2)}$ -levels during these SPI-months prove much stronger than are considered 'weak' yields for state SPI-levels for all of the other Midwestern belt states. When precipitation and moisture is found across all states, corn and soybean production flourishes.

CHAPTER FOUR: USE OF GWR TO EVALUATE RELATIONSHIPS BETWEEN PRECIPITATION VS. IRRIGATED AND NON- IRRIGATED CORN AND SOYBEAN YIELD

The relationship between spatial distribution of precipitation and crop yields on county, state, and regional scales while still taking into consideration spatial heterogeneity, assists managers to better evaluate long-term productivity trends in agriculture. This allows for accurately improved assessments in food security, policy making, the assessment of resources including water and land, and in managerial decision-making. The technique of Geographically Weighted Regression (GWR) gives us the ability to account for spatial non-stationarity with space. While its application is growing in other scientific disciplines (i.e., social sciences), such technique has not yet been established in agricultural settings. Geographic information systems (GIS), as well as GWR and the ordinary least square regression technique were utilized to analyze the relations found between precipitation categories and irrigated and non-irrigated maize (corn) and soybean yields for all counties in Nebraska from 2000 to 2012.

Using ArcGIS10.4, precipitation was spatially interpolated. GWR and OLS predicted fields, both measured, were correlated with annual (January 1 to December 31), seasonal (May 1 to September 30), and monthly (May, June, July, August, and September) precipitation for each county. Average annual precipitation in the state of Nebraska between the year of 2000 until 2012 was an average 24.6 inches (maximum:

32.3 inches; minimum: 14 inches). The average precipitation decreased from May to September during the growing season and the county's average yields follow a similar trend. The OLS regression model, when used, had a correlating trend between observed yield and the long-term average precipitation total with varying coefficients of determination. GWR's technique in predicting yields of spatially interpolated precipitation for irrigated and non-irrigated maize (corn) and soybean was much better than the performance of the OLS model. This significant improvement was based upon the GWR's ability to analyze the relationship between precipitation and yield, due to its ability to account for the heterogeneity spatial impact on the precipitation versus yield relationship.

Analogue data sources and manual processing has been the best means of this in the past. However, modern technological advances have led to an increase of computers and information technology enabling a wide array of ways to handle data of all sorts. Geographic Information Systems is an example used by various disciplines as tools for spatial data handling in a geographic environment. GIS consists of hardware, software, data and live-ware faculties. GIS is a very important tool when it comes to solving problems and dealing with geo-information. Spatial analysis plays an important role in GIS, as it provides the means to monitor spatial areas which in turn creates data-sets and features used for monitoring, analysis, and evaluation.

An important step for evaluating variations of yield on a regional scale is to understand the relationship between yield and surrounding environmental factors. Precipitation is one of the main drivers of crop productivity, and its variability in many agricultural production areas, such as in Nebraska, is significant for irrigated and also non-irrigated corn and soybean lands which comprise of significant portions of the total cultivated lands in the Midwestern US. Practical tools and methods for mapping and analysis are used for predicting irrigated and non-irrigated crop yields and to for also understanding the interactions between yield and primary climatic variables (i.e., precipitation) for decision makers allows for better planning, manning, and allocation of natural resources for crop production on large scales.

The relationship between precipitation and yield enables for greater understanding of present water needs, allowing for the evaluation of future water usage, and the evaluation of sustainability in production systems. Regional variations in yield can be large because of the differences in irrigated and non-irrigated productivity. Relationships between yield and climate variables on a spatial and temporal scale are extremely important when it comes to assessing food security, policies, and implementing land and water resource management decisions on large (watershed, statewide, regional) scales.

An improvement in the integration of GIS and spatial data analysis has come through the development of local spatial statistical techniques. One of the newer non-parametric modeling methods which has provided interpretable measures of sources of local variation and reduces variable co-linearity is the Geographically Weighted Regression (GWR) technique. GWR is among the new developments of local spatial analytical techniques. The Geographically Weighted Regression (GWR) allows variations in relationships between predictors and outcome variables (Fotheringham, Brunsdon, and Charlton 2002; National Centre for Geo-computation 2009). This means GWR is a local spatial statistical technique which relies on a form of kernel regression within a multiple linear regression framework to develop local relationships between the dependent and independent variables.

When modeling the spatial relationship between weather variables and crop and surface characteristics (e.g., precipitation vs. yield; precipitation vs. soil moisture, vegetation indices vs. radiation or temperature, etc.), the spatial heterogeneity of these relationships must be taken into account. Spatial non-stationarity is indicated when the measurement or estimation of the relationships among variables differs from location to location (Mennis, 2006). It shows that the relationship between variables vary from one location to another depending on physical factors of the environment, which are spatially auto correlated (Propastin et al., 2007).

The development of local spatial non-stationarity relationships between variables facilitates an exploratory analysis of the stationary assumption of a global multiple linear regression model. Commonly used regression models include conventional ordinary least squares, which is the most popular regression technique. It is the base level of spatial regression analysis and provides various models based on variables to create a single regression equation which does not account for the spatial non-stationarity of variables. Unlike OLS and other conventional regression models which provide a single regression equation to describe general relationships among explanatory and dependent variables, GWR generates spatial data that expresses spatial variations in relationships among variables. Maps generated from these analyses play a key role in describing and interpreting spatial non-stationarity between the variables (Mennis, 2006).

The objectives for the research in this chapter are to map the long-term spatial distribution of non-irrigated corn and soybean yields for all Nebraska counties using OLS, GWR, and GIS to assess the impact of precipitation on non-irrigated yields; to develop correlations between the months of May, June, July, August, and September, seasonal (May 1 to September 30), and annual (January 1 to December 31) precipitation and crop yields to determine the impact of non-irrigated and irrigated crop yields based on the three precipitation categories; and to evaluate the potential differences in using GWR over OLS in predicting crop yields on a county scale.

The utilization of geographic information systems to analyze correlations between precipitation categories and irrigation and non-irrigated maize (corn) and soybean yields for using a Nebraska State by county level as case study between 2000 and 2012 is proposed. Analyzing such correlations enables scholars and managers alike to make better decisions on food health, natural management plans, resource assessments, and land and water resources. GWR is an example of a technique which is able to take into account non-stationaries with space. This is a new method in agricultural setting.

4.1 Materials and Methods

Study Area

The study area of Nebraska (latitude 40° N to 43° N, longitude 95° 19′ W to 104° 3′ W) (Figures 19 and 20) below has 93 counties with a population of 1.7 million (mean population density of about 9 people km-2). Nebraska's water resources (ground and surface) are regulated by the Nebraska Dept. of Natural Resources and 23 districts. The state is one of the leading farming and ranching states in the U.S. with a total area of approximately 200,355 km2, and a mean elevation of 793 m above mean sea level. Nebraska's climate is mainly continental and is divided into an eastern and central park which are humid/sub-humid continental climate, and a western third which has arid climate.

Nebraska experiences a wide array of seasonal variations in terms of temperature and precipitation. The weather in Nebraska is influenced by cold dry continental air masses flowing from Canada in the winter and of warm air rising from the Gulf of Mexico during the summer. The high wind speeds that happen between January and early June, along with daily average wind speeds show significant fluctuations, with the lowest wind speeds occurring in the hot and humid summer months (Irmak, 2010).

Nebraska is divided into three broad environmental regions based upon environmental characteristics, climatic conditions and soil and topographic characteristics: the eastern region, the central region, and the western region. The eastern region has high amounts of precipitation with superior silt-loam soils rich in organic matter and high agronomic productivity. The central region is characterized by rich silt and loam soils with high organic matter with generally flat topography and moderate precipitation. The western region has less precipitation and soils with a lower potential for agronomic productivity as compared with the eastern and central regions (Searcy and Longwell, 1964).

The Sand Hills area consists of sand dunes and soils with sparse grasslands. The Sand Hills area covers 20+ counties in the north and north-central parts of the state.

Water availability is the dominant yield-reducing factor in Western Nebraska, where irrigation is necessary for producing average or high yields.

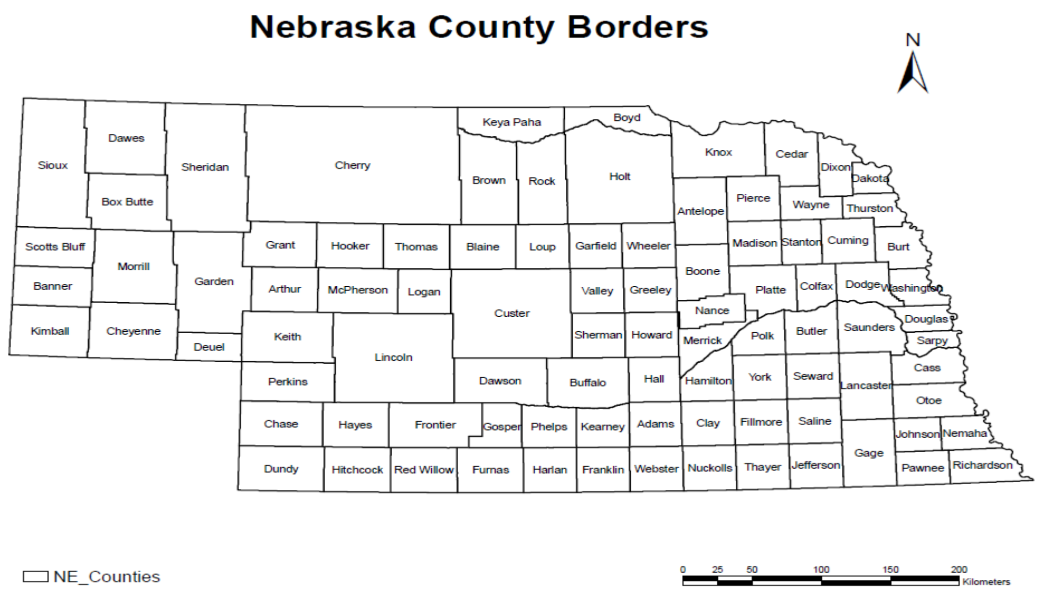


Figure 19 Nebraska county borders.

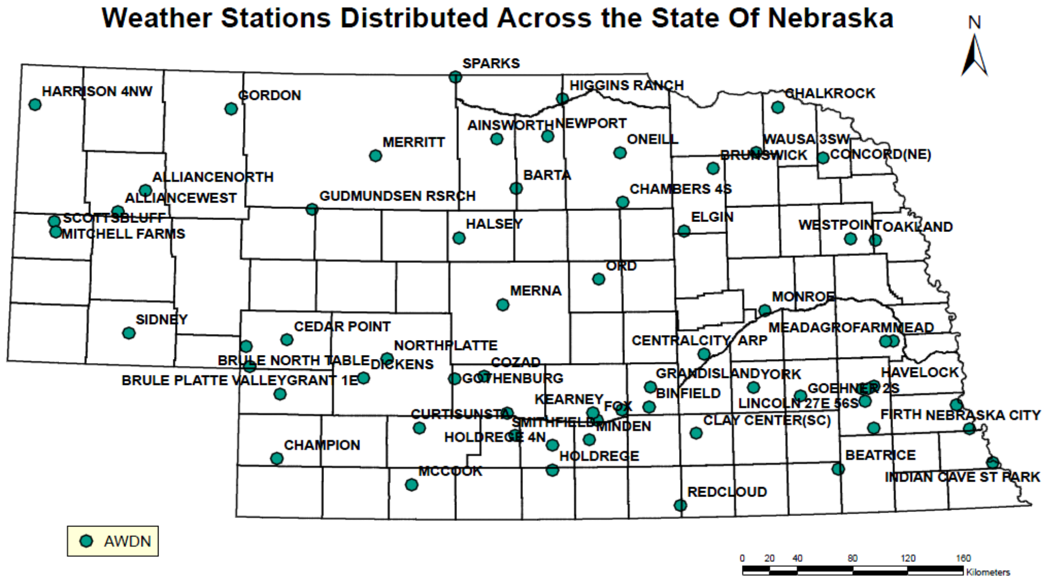


Figure 20 Weather Stations Distributed across the State of Nebraska by The High Plains Regional Climate Center Automated weather data network (AWDN).

Datasets

USDA- NASS Crop Yield Data

The USDA National Agricultural Statistical Service (www.nass.usda.gov) is an important source of information when it comes to gathering long-term yield data. The service provides yield data predictions almost for every county in the U.S. Yield data for irrigated and non-irrigated corn and soybean crops can be obtained for the counties of Nebraska from 2000 to 2012 from the USDA-NASS website. Yield is defined as the county average yield for either non-irrigated or irrigated crops which are reported. The USDA-NASS does not take into account the average irrigation amount applied per growing season, therefore irrigation and yield relationships were not included in this part of the study. County yield was averaged across the 12 years (2000 to 2012). Irrigated and non-irrigated crop yields were used as the dependent variables in the GWR model. The county yield can be defined as total harvested yield divided by the total area of harvested yield per year per county. Some of the counties in Nebraska did not report corn or soybean production from 2000-2012. In some parts of Nebraska (northwest and northern edge of the state near the sand hills), corn and soybean are not produced. In some counties, there were incomplete or missing yield data. Therefore, the counties with missing data were excluded from our analysis.

Precipitation Data

Precipitation data can be obtained from the High Plains Regional Climate Center (HPRCC; http://hprcc1.unl.edu/cgi-hpcc/home.cgi) automated weather data network (AWDN) for 64 AWDN stations distributed across the state of Nebraska (Figure 20) above. Precipitation data were defined into three categories: (1) long-term monthly (May, June, July, August, or September) average precipitation from 2000 to 2012, (2) long-term average seasonal (growing season) total precipitation from 2000 to 2012, and (3) long-term annual total precipitation from 2000 to 2012. Yield vs. precipitation relationship analyses can be conducted for all three categories to evaluate both irrigated and non-irrigated crop yield responses to the magnitudes of the three precipitation categories. The growing season can be considered from June 1 to September 30, which is typical for corn and soybean production in the region. The major assumption here is that the growing season can be assumed to be the same across the state. Other assumptions include similar corn hybrids and soybean varieties across Nebraska. Disease and weed pressure and other field management issues, such as nitrogen deficiency, that may cause yield reduction were not taken into account in this part of analyses.

GWR Model

The relationship between yield and precipitation is modeled using OLS regression and GWR. The model can be derived by OLS regression and can be applied globally to the entire study region from which measured data has been taken based on the assumption of spatial heterogeneity in the relationship between the variables under study (Foody, 2003). Spatial stationary assumes that statistical properties of an attribute are independent of a location and that the mean and variance of observed attribute values at different locations across the study region are constant. For example, precipitation might not vary across a small area. However, if there is spatial heterogeneity, then the global prediction of spatial relationships using OLS regression will misrepresent the relationship between precipitation and yield. Therefore, the relationship between these two variables is also examined with the GWR technique.

GWR is a local spatial statistical technique that can be used to analyze spatial non-stationarity when the input variable differs from location to location. It provides a local model to predict an independent variable or process (e.g., plant growth, yield) by fitting a regression equation to the available datasets of dependent variables. It enables identification of the yield stability of a region as well as the association of the independent environmental factors to the yield. The main advantage of GWR over OLS regression is its ability to deal with spatial non-stationarity (Propastin et al., 2007). Global regression techniques such as OLS may ignore local information and, therefore, indicate incorrectly that a large part of the variance in yield was unexplained.

GWR is useful for evaluating the spatial heterogeneity of a dependent variable. Spatial heterogeneity can exist when the structure of the process being modeled varies across the study area, whether it is county or state. The GWR method constructs separate equations by incorporating dependent and explanatory variables of features which are within the bandwidth distance of the target features. The shape and size of the bandwidth is dependent on the kernel type, bandwidth method, distance, and the number of features. Instead of calibrating a single equation, GWR generates a separate regression equation for each observation (i.e., spatially interpolated precipitation and yield) and thus allows parameter values to vary continuously in geographical space. Each equation is calibrated using a different weighting of the observations contained in the dataset. Because the regression equation is calibrated independently for each observation, a separate parameter prediction (*z*-value) and R^2 value are calculated for each observation. In GWR, a form of kernel regression and multi-linear regression can be used to build a model expressed as:

$$Y_i = \beta_{o(i)} + \beta_{1(i)} X_{1(i)} + \beta_{2(i)} X_{2(i)} + \beta_{3(i)} X_{3(i)} + K + \beta_{k(n)} X_{k(n)} + \varepsilon i$$

Where Y_i is the interpolated yield at location i (where i captures the coordinate location), β_o is the intercept, $\beta_{k(i)}$ is the kth local parameter prediction at the i th location (i.e., coefficient for the independent variable), $X_{k(i)}$ is the kth independent variable (precipitation) value at the ith location, and n represents the last location. In GWR, the weight assigned to each observation is based on a distance decay function centered on observation$i$. The distance decay function, which may take a variety of forms, is modified by a bandwidth setting at which distance the weight rapidly approaches zero (Mennis, 2006).

A spatial kernel provides geographical weightings in the models. A key coefficient in the kernel is the bandwidth which controls the size of the kernel. Bandwidths can be considered as smoothing functions of the local parameter predictions (Fotheringham, et al., 2002).

A fixed bandwidth is based on defined diameters of circular search neighborhoods, and diameter scalar units are the same as the various location variables with different choices being available. A GWR model depends upon the number of variables in the model and the bandwidth. Akaike Information Criterion (AIC) is better than the use of other bandwidths due to the interaction between the bandwidth and the complexity of the model.

Geographic weighting occurs when a bandwidth, kernel type, and regression model is chosen. The influence of data on the local parameter prediction is the basis for the geographic distance from the regression point. Locations that are close to the regression point of interest is weighted far heavier than points located further away (Fotheringham et al., 2002).

Statistical Analysis

The mean annual, growing season, and monthly precipitation values for each county are essential requirements of this part of the study. The zonal statistic can be used to calculate the precipitation values for each county defined by name (string attribute field) of the Nebraska county feature class based on the precipitation value from the precipitation raster dataset.

The Zonal statistics tool (Spatial Analyst tool of ArcGIS ver.10.4) calculates statistics on the value of a raster within the zone of another dataset. The zonal statistic tool summarizes the value of the precipitation raster within the county and reports the result as the mean, maximum, minimum, and range values.

4.2 Results and Discussion

The Results of Precipitation Amounts Distribution

The spatial distributions of long-term average annual (January 1 to December 31) precipitation and long-term average growing season (May 1 to September 30) total precipitation for all Nebraska counties are presented in (Figures 21a and 21b) respectively. Long-term monthly (May, June, July, August, and September) average precipitation for all counties is presented in (Figures 21c through 21g) respectively. The graduated circles display the quantitative values of precipitation found among each of the Nebraskan counties as arranged from smallest to largest. The precipitation data statistics are presented in (Table 2) below.

The precipitation across the state of Nebraska in inches between the years 2000 to 2012 shows the greatest amount of rain distribution in the most-eastern part of the state with limited to no amounts of precipitation depicted in western part of Nebraska.

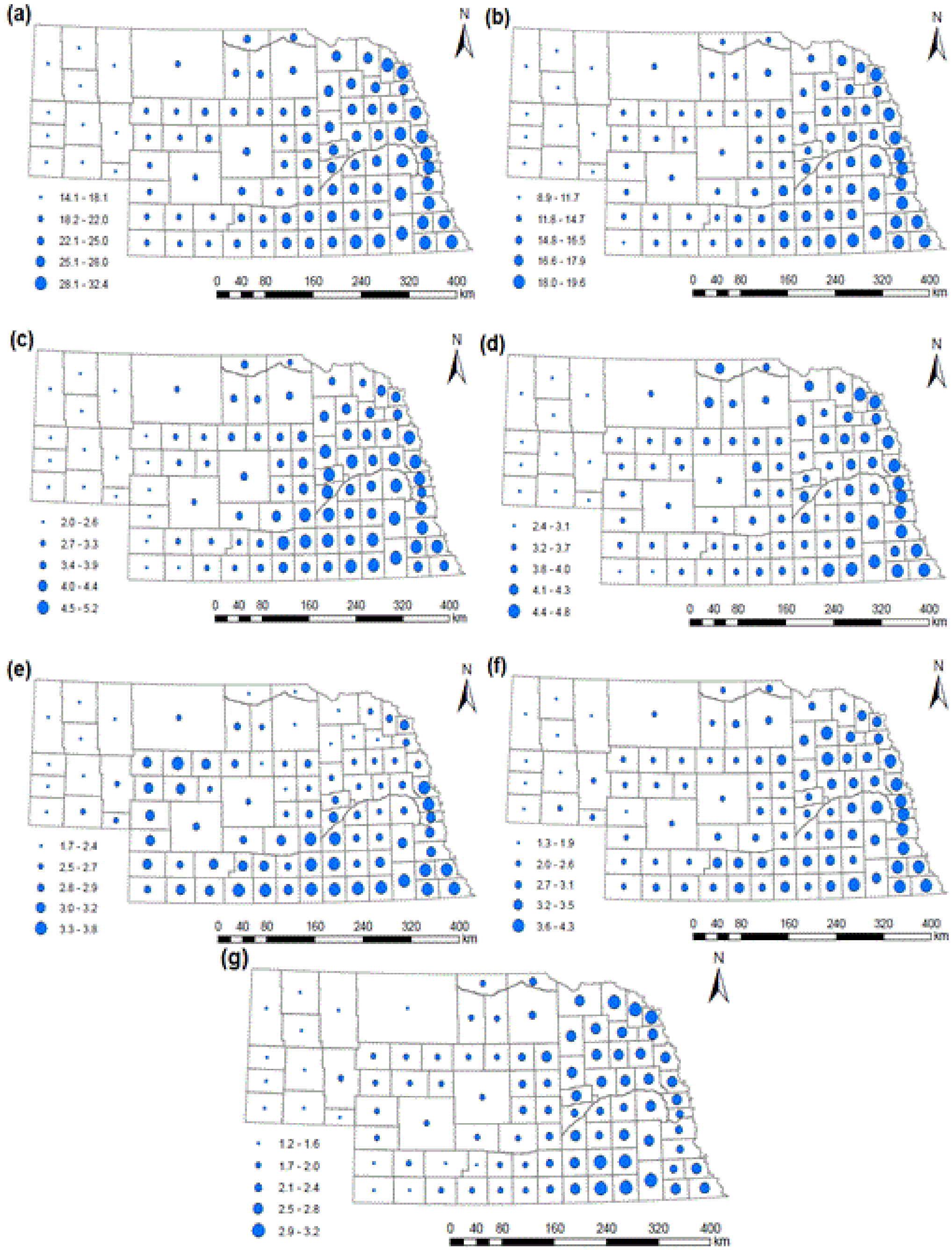


Figure 21 Variation of Long-Term Average (2000-2012) a- Annual, b- seasonal, c- May, d- June, e- July, f- August, and g- September Precipitation (inches) Across Nebraska. Data Source: The High Plains Regional Climate Center (AWDN).

Table 2 Precipitation (P) statistics for the observation period of 2000-2012 for the counties of Nebraska.

Parameter	Max(in)	Min(in)	Mean(in)	County with Max Precip	County with Min Precip
Long-term average annual P	32.4	14.1	24.6	Richardson	Scotts Bluff
Long-term average growing season P	19.6	8.9	15.4	Richardson	Scotts Bluff
Long-term average May P	5.2	2.0	3.7	Otoe	Scotts Bluff
Long-term average June P	4.8	2.4	3.8	Richardson	Banner
Long-term average July P	3.8	1.7	2.8	Richardson	Scotts Bluff
Long-term average August P	4.3	1.3	2.9	Nemaha	Sioux
Long-term average September P	3.2	1.2	2.1	Dixon	Kimball

The spatial trends presented in the table above and the map-graphs above show a gradual increase in precipitation from the eastern part of Nebraska to the western side of the state. The graphs show an estimated average annual difference of about 11 inches between the eastern and western counties throughout the years. During the seasonal growth months of the year (May, June, July, August, and September) there is a limiting factor of difference between the central counties of the states and the eastern borders. Between all other months, precipitation differences are vastly different between the west and the eastern parts of Nebraska. June and August show the least amount of precipitation in inches, while May, July, and September show substantial precipitation levels.

Soil types and the water-holding capacities as well as irrigation methods and other factors influencing irrigation practices vary significantly across the counties of the state. Crop irrigation requirements also vary, and since growing season precipitation varies, crop irrigation requirements also exhibit various variabilities.

The Results of Irrigated and Non-Irrigated Corn and Soybean Yields

The 13 year average non-Irrigated and irrigated corn and soybean yields are presented in (Figures 22, 23, 24, and 25) below. Summary statistics of historical crop yields are provided in (Table 3) below. The white-colored counties in figures below indicate counties with no data.

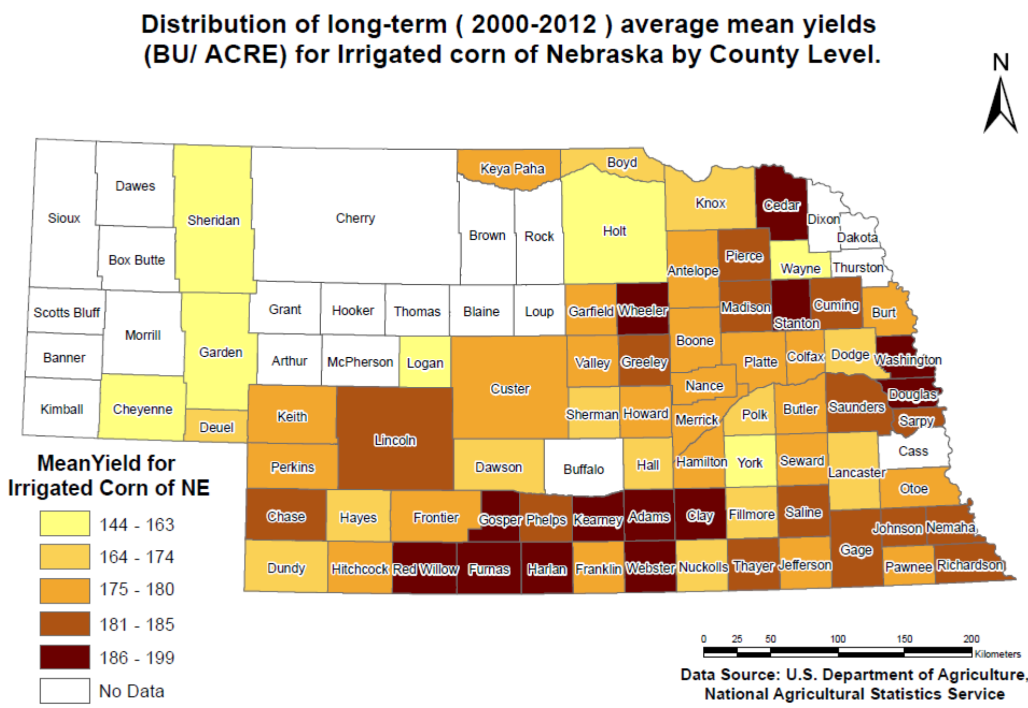


Figure 22 Distribution of long-term (2000-2012) average mean yields (BU/ ACRE) for Irrigated corn of Nebraska by County Level.

For the average mean yields for corn in the map -figure above, there is strong irrigation in the south (Gosper, Red Willow, Furnas, Harlan, Webster, Kearney, Adams, Clay) along with counties toward the eastern border of the state, such as Wheller, Washington, Douglas, Cedar, and Stanton.

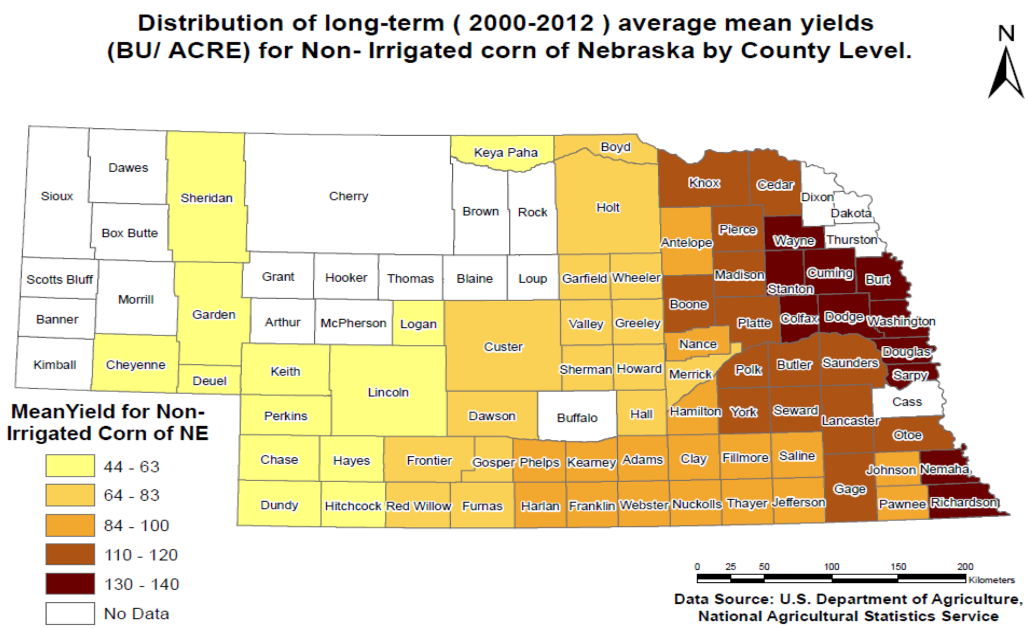


Figure 23 Distribution of long-term (2000-2012) average mean yields (BU/ ACRE) for Non-Irrigated corn of Nebraska by County Level.

For the non-irrigation map, there was much precipitation in the eastern part of Nebraska, touching on the counties of Wayne, Stanton, Colfax, Dodge, Burt, Washington, Douglas, Cuming, and Sarpy.

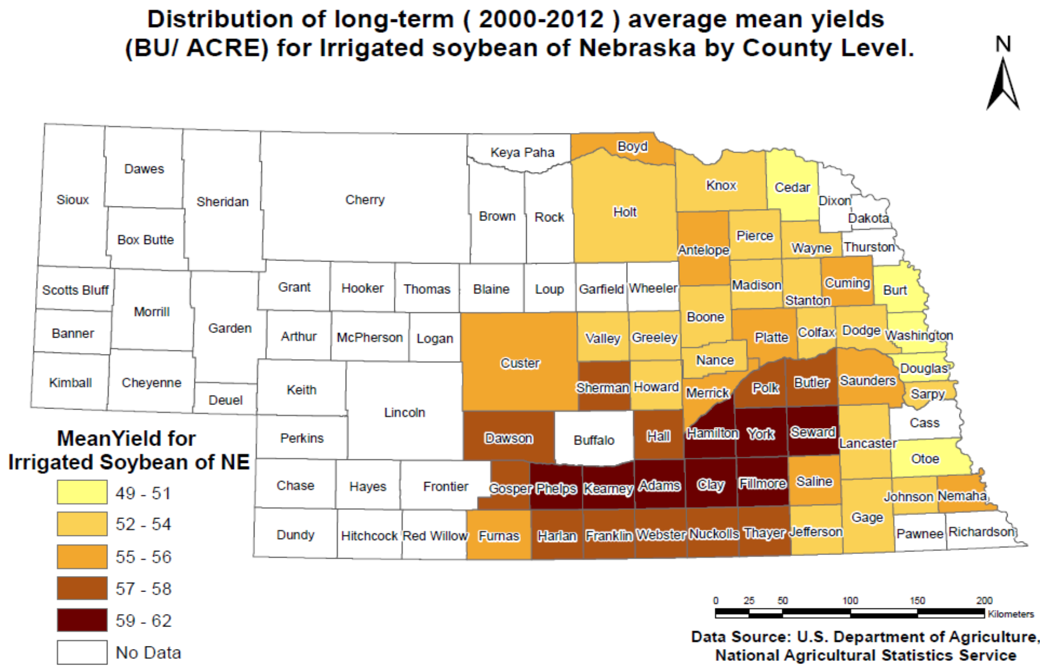


Figure 24 Distribution of long-term (2000-2012) average mean yields (BU/ ACRE) for Irrigated soybean of Nebraska by County Level.

The average mean yields for soybean in the map-figure above shows much irrigation occurring in the southern part of the state for the counties Phelps, Kearney, Adams, Clay, Fillmore, Hamilton, York, and Seward.

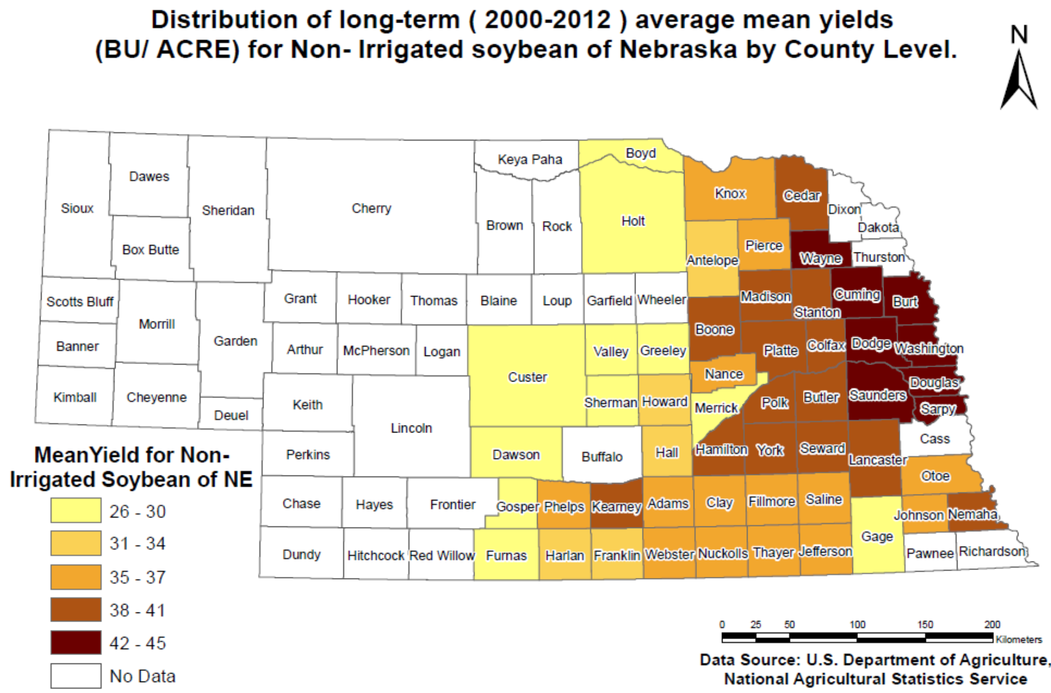


Figure 25 Distribution of long-term (2000-2012) average mean yields (BU/ ACRE) for Non- Irrigated soybean of Nebraska by County Level.

The distribution of long-term average mean yields for soybean in the non-irrigated areas of Nebraska is found most along the eastern border of the state, in the counties Wayne, Cuming, Burt, Dodge, Washington, Saunders, Douglas, and Sarpy as shown in the figure above.

Table 3 Statewide average crop yield (BU/ACRE) statistics from 2000-2012 in Nebraska (N = number of counties; SD = standard deviation).

Crop type	N	Mean	Max	Min	SD	Median	Skewness
Irrigated maize (corn)	71	12388.9	13997.8	10613.6	834.9	12475.9	-0.338
Non-irrigated maize (corn)	71	6437.9	9427.1	2823.6	2823.6	6808.0	-0.457
Irrigated soybean	52	2792.5	3079.0	2494.1	2494.1	2766.0	-0.020
Non-irrigated soybean	52	1820.6	2442.0	1013.7	1013.7	1965.0	-0.460

A negative skewness displayed in (Table 3) above regards the yield distribution where the number of counties with a below mean yield exceeds the number of counties with above mean yields. Even though Nebraska has some of the best soil for agriculture in the whole country, the productivity of the land lacks in the skewness distribution displayed due to only a few of the counties producing its highest yields. The greater amount of marginal land is displayed in the western part of the state.

The reason for non-irrigated corn and soybean yields being lower in the western part of the state is due to the lack or irrigation methods and the low amount of precipitation as compared with the eastern and central portions. The soils in the western part of Nebraska are a combination of Tassel – Busher and rocky association which have weathered sandstone's that have lower water-holding capacities and organic content as compared with soils in the west central, and eastern portions.

The Results of Precipitation vs. Observed Yield Using OLS Regression

The coefficient of determination (R^2) between the observed yield and precipitation (using long-term average mean annual, seasonal, and monthly total precipitation for each county) for irrigated and non-irrigated maize (corn) and soybean using the OLS model are presented in (Table 4) below. The performance of the observed yield vs. long-term average mean annual total precipitation using OLS depicts a solid parallel for non-irrigated maize (corn) and soybean. For non-irrigated crops of maize (corn) and soybean, 84% for maize (corn) and 63% for soybean of the variability in mean yield is explained by the mean annual precipitation. About 38% and 30% of the variability in mean yield was explained by mean annual precipitation for irrigated maize (corn) and soybean, respectively. The R^2 was much lower for irrigated crops. As found with the annual total precipitation and yield, the correlation between seasonal precipitation and yield for non-irrigated crops was stronger than for irrigated crops (Table 4) between 2000 and 2012. When correlated to the yield, the annual precipitation may have an advantage in that it accounts for the seasonal precipitation that is also carried over and available to the crop as available soil moisture in the beginning of the growing season. In terms of individual-month total precipitation, the R^2 for non-irrigated maize (corn) ranged from 21% to 84%, and ranged from 13% to 62% for non-irrigated soybean. There was a strong correlation between seasonal precipitation and yield, but in the irrigated crops there was a weak and reverse correlation between precipitation and irrigated maize (corn) and irrigated soybean respectively, where the R^2 of individual-month total precipitation for irrigated maize (corn) ranged from 19% to 40%, and for irrigated soybean ranged from 37% to 24%. Level of significance is based upon the likely and most unlikely determined observations according to percentage values. The most likely observations are based on a 95% probability density whereupon very unlikely observations are based upon the 0.025 area curve.

Table 4 Relationships between observed yield vs. long-term average mean annual, seasonal, and monthly precipitation by OLS (N = number of counties).

		Coefficient of Determination (R^2)						
Crop	N	Annual	Seasonal	May	June	July	August	September
Non-irrigated maize (corn)	71	0.84	0.82	0.77	0.78	0.21	0.84	0.77
Non-irrigated soybean	52	0.63	0.60	0.52	0.53	0.13	0.62	0.49
Irrigated maize (corn)	71	0.38	0.38	0.32	0.28	0.39	0.40	0.19
Irrigated soybean	52	0.30	0.30	0.14	0.10	0.24	0.35	0.37

The Results of Long Term Average Annual Precipitation vs. Predated Yield Using GWR

The following two sections assess the connection between the long-term mean annual, seasonal total (May-September), and monthly precipitation levels contrasted with predicted non-irrigated maize (corn) and soybean yields for each county using the GWR model. The relationship between predicted yield and long-term average mean annual total precipitation and the residuals of the regression between predicted and measured yield for irrigated and non-irrigated maize (corn) and soybean are shown in (Figures 26 a through 26 d) below. The results of the GWR model showed good performance for non-irrigated maize (corn) and soybean. The statistics between measured and predicted yield are presented in (Table 5) below. For non-irrigated maize (corn) and soybean, about 96% and

67% of the variation in yield was explained by the mean annual precipitation alone. For irrigated maize (corn) and soybean crops, about 68% to 72% of the variation in yield was explained by the mean annual precipitation as shown in (Table 5).

The results of the standard deviation (SD) of the GWR predictions and the residual maps indicated that the residuals (observed-predicted yield) were within 2.5 of the SD. For all crops, less than 2% of the counties fell outside the 1.5 SD range. GWR analysis with the observed and predicted yields using mean annual precipitation presented a positive relationship at 5% significance level (Table 5). The t-test showed that the intercept and slope of the regression line were significantly different from unity ($p < 0.05$). Further analyses of the regression model showed that for most of the counties of the northeastern part of the state (including Dixon, Dakota, Wayne, Cuming, Thurston, and Burt), yields for non-irrigated crops were under predicted (higher value of residual SD) (Figures. 26a and 26b) even though precipitation is in the adequate range for crop production in those counties (Figure. 21a). This is because precipitation is not the only limiting factor driving crop yield, and other factors such as evapotranspiration, air temperature, solar radiation, soil type and water-holding capacity, organic matter content, pH, irrigation management, crop characteristics, disease and pests pressure, soil management, technological improvements from hybrids, fertilizers, producer managements techniques, and other management practices impact the yield thereby influencing the relationship between precipitation and irrigated and non-irrigated yields. Similarly for the irrigated crops, yield was under predicted for the counties in the central part of the state. Since precipitation is less in these counties as compared with the counties in the eastern part, irrigation has more influence on yield predictions. In general, the regression model over predicted the yield for high yielding conditions and under predicted for low yielding conditions. On a statewide average, the R^2 values were greater for non-irrigated maize (corn) and soybean than for irrigated maize (corn) and soybean (i.e., R^2 = 0.96, 0.67, 0.68, and 0.72 for non-irrigated maize (corn), non-irrigated soybean, irrigated maize (corn), and irrigated soybean, respectively; (Table 5) below. When compared to the OLS predictions, the GWR technique provided better predictions of yields for both irrigated and non-irrigated crops. When the R^2 values in (Table 4 and 5) are considered, the R^2 values for the GWR predictions were higher for irrigated maize (corn) and soybean than the R^2 values for the OLS regression.

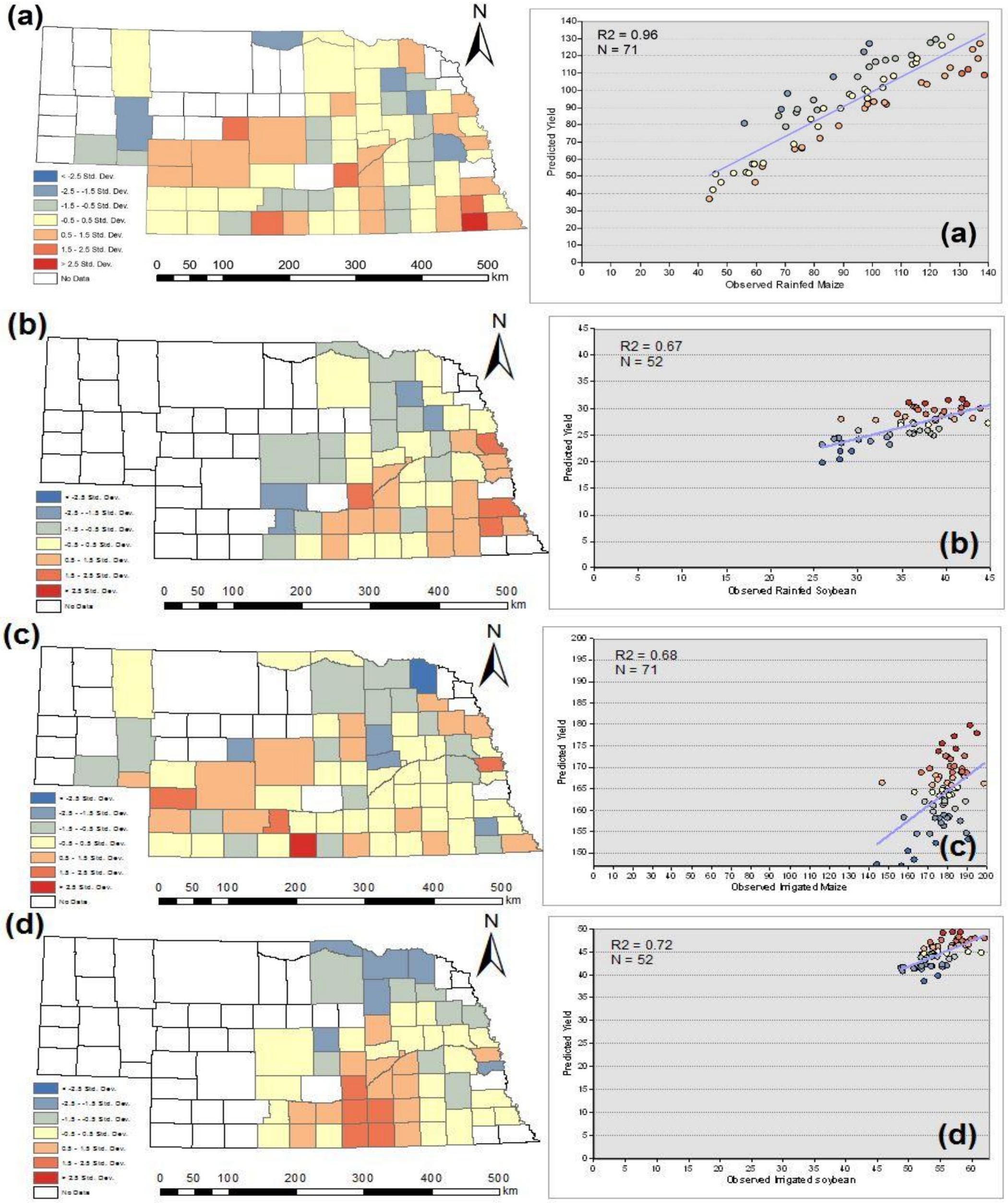


Figure 26 Predicted vs. (a) observed non-irrigated maize (corn), (b) non-irrigated soybean, (c) irrigated maize (corn), and (d) irrigated soybean yields across Nebraska using long-term average annual precipitation. Data points in each graph represent the yield of each county. Residual maps on the left side of each graph show counties where yield is under- or over predicted.

Table 5 Statistics for the state- average observed vs. predicted yields using GWR for the period of 2000-2012. Yield was predicted using mean annual precipitation (N = number of counties, SE = standard error, and DF = degrees of freedom).

Crop	N	R^2	SE	DF	F-Ratio	p > F
Non-irrigated maize (corn)	71	0.96	341	15	180.80	<0.0001
Non-irrigated soybean	52	0.67	42	40	115.30	<0.0001
Irrigated maize (corn)	71	0.68	410	40	66.40	<0.0001
Irrigated soybean	52	0.72	19	39	100.85	<0.0001

The Results of Long Term Average Seasonal Precipitation vs. Predicted Yield Using GWR

The measured and predicted maize (corn) and soybean yields for irrigated and non-irrigated conditions using seasonal total (May 1 to September 30) precipitation is presented in (Figures 27 a through 27 d). The statistical analyses are presented in (Table 6) below. For non-irrigated crops, there was a strong correlation between seasonal precipitation and yield, with R^2 of 0.94 and 0.74 for maize (corn) and soybean, respectively. The GWR SD residual maps indicate that the residuals were within the 2.5 SD ranges, which was higher than the SD with the annual precipitation. For all four crops, less than 2% of the counties fell outside the 1.5 SD range. The standard error of estimation for non-irrigated maize (corn) was higher when using seasonal precipitation than when using annual precipitation. The slopes of the regression line between precipitation and yield were significantly different from unity ($p < 0.05$). Slope is defined as the rise over the run, right? That is, the slope or steepness of a line (or hill) is equal to how fast it goes up with respect to how far it goes over. A line may have positive slope, negative slope, zero slopes, or undefined slope. Y is always equal to 1. All of the points on this line will have 1 as their y coordinate. The x-values can be any number, but y must always be 1. The null hypothesis represents the default, the status quo and relates to a statistical method of interpreting conclusions among a sample.

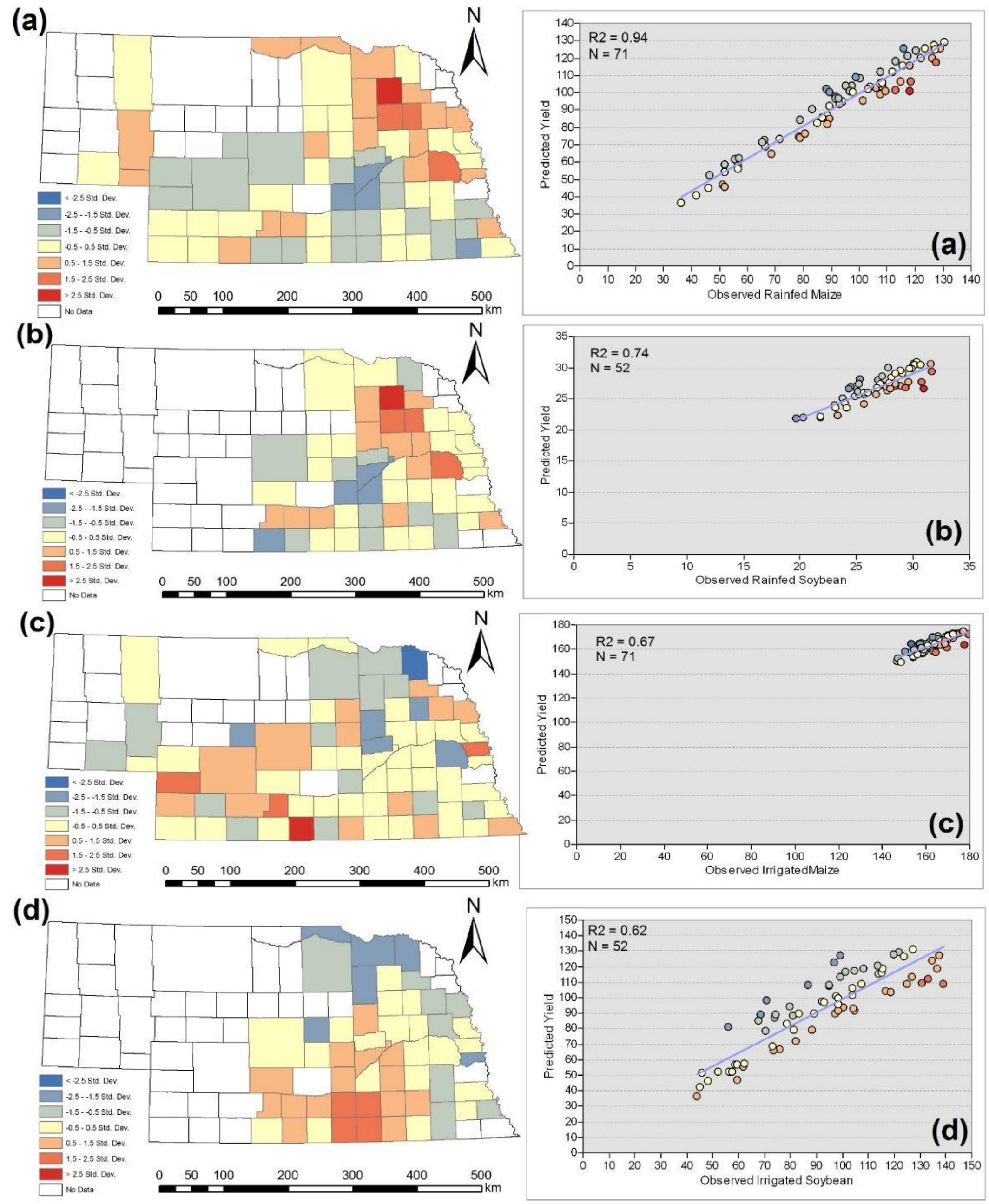


Figure 27 Predicted vs. (a) observed non-irrigated maize (corn), (b) non-irrigated soybean, (c) irrigated maize (corn), and (d) irrigated soybean yields across Nebraska using long-term average seasonal precipitation. Data points in each graph represent the yield of each county. Residual maps on the left side of each graph show counties where yield is under- or over predicted.

Table 6 Predicted yields for Nebraska counties for the observation period of 2000-2012 using mean seasonal total precipitation (N = number of counties, SE = standard error, and DF = degrees of freedom).

Crop	N	R^2	SE	DF	F-Ratio	p > F
Non-irrigated maize (corn)	71	0.94	364	55	246.6	<0.0001
Non-irrigated soybean	52	0.74	40	55	113	<0.0001
Irrigated maize(corn)	71	0.67	195	15	37.7	<0.0001
Irrigated soybean	52	0.62	20	17	140.7	<0.0001

The Results of Long Term Average Monthly Precipitation vs. Predicted Yield Using GWR

Correlations between long-term average monthly total precipitation for May, June, July, August, and September vs. long-term county average yield for non-irrigated maize (corn), non-irrigated soybean, irrigated maize (corn), and irrigated soybean are presented in (Figures 28 through 31). The R^2 values between monthly precipitation and yields are summarized in (Figure 32) below. The residual maps for yield vs. precipitation for each month (May, June, July, August, and September) for each county for non-irrigated maize (corn), non-irrigated soybean, irrigated maize (corn), and irrigated soybean are presented in (Figures 33, 34, 35, and 36), respectively.

The R^2 values ranged from 0.54 to 0.95 for non-irrigated crops and from 0.53 to 0.80 for irrigated crops. Differences appear regarding the impact of individual monthly total precipitation on crop yields across the state (i.e., R^2 between individual months' precipitation vs. yield varied from the eastern part to the western part). This is due to varying precipitations from east to west, in the impact of precipitation on yield which is also due to differences in the planting date across the state. In the eastern part, maize (corn) hybrids that have a longer maturity date (114 to 120 days) are planted. The maturity date of the maize (corn) hybrids in the central region is on average 112 days, and the maturity for those in the western portion of the state is on average 93 days. Depending on the location, seasonal date, climate conditions, and hybrid, the potential kernel development for maize (corn) normally begins in June, and tasseling in mid-July, with silking/pollination occurring in late July and grain fill occurring during early to mid-August throughout the study region.

The most important growth stage for maize (corn) occurs between tasseling and silking. During this stage, plant water stress can delay silking relative to pollen shedding and can reduce seed set. Usually, the water stress during the vegetative growth period is not as critical as the tasseling-silking stage, and the stress during the grain fill can be intermediate in terms of its impact on yield (Musick and Dusek, 1980). Maintaining healthy plants in all growth stages is important for achieving high yields.

What also causes spatial non-stationarity of the relationship between the yield and precipitation is the significant variable variations in tillage managements practiced by maize (corn) and soybean farmers in Nebraska. Based on the survey conducted by the USDA Natural Resources Conservation Service (USDA-NRCS, 2009), the tillage practices not only change with locations but also show great variability for the same location and same crop between farmers. For example, based on the assessment by the USDA-NRCS, a larger percentage of maize (corn) was planted on no-till in the eastern part of Nebraska than in the central and western parts. Madison, Douglas, Johnson, Sarpy, Gage, and Jefferson County in the eastern part of Nebraska had >77% of the planted maize (corn) as no-till. Banner was the only county, located in western Nebraska, that had more than 70% of the maize (corn) land area planted as no-till. For soybean, eastern Nebraska had a higher percentage of land planted on no-till than the central part. Soybean is not grown extensively in western and north-central Nebraska (USDA-NRCS, 2009).

There is a gradual decrease in maize (corn) and soybean no-till planting land area across the state of Nebraska, from east to west. For maize (corn), the percentage of no-till maize (corn) planting followed an opposite trend with precipitation. Disk-till is another tillage practice commonly used in central and west-central Nebraska. These practices impact the spatial non-stationarity relationships between precipitation and yield, as tillage practice influence the available soil water and precipitation relationship; depending on several factors, disk till fields, in general, may have greater soil evaporation than no-till fields.

July precipitation was the most critical for the high crop yield for both crops under-irrigated and non-irrigated conditions. This is due to the sensitivity of maize (corn) to water stress during critical growth stages (tasseling and silking), which usually occurs in July, depending on the location in the state. July precipitation had more impact on maize (corn) yield than on soybean under non-irrigated conditions. In all months and in both irrigated and non-irrigated treatments, yield was proportional to precipitation. For irrigated yields, July precipitation had more impact on soybean yield than on maize (corn).

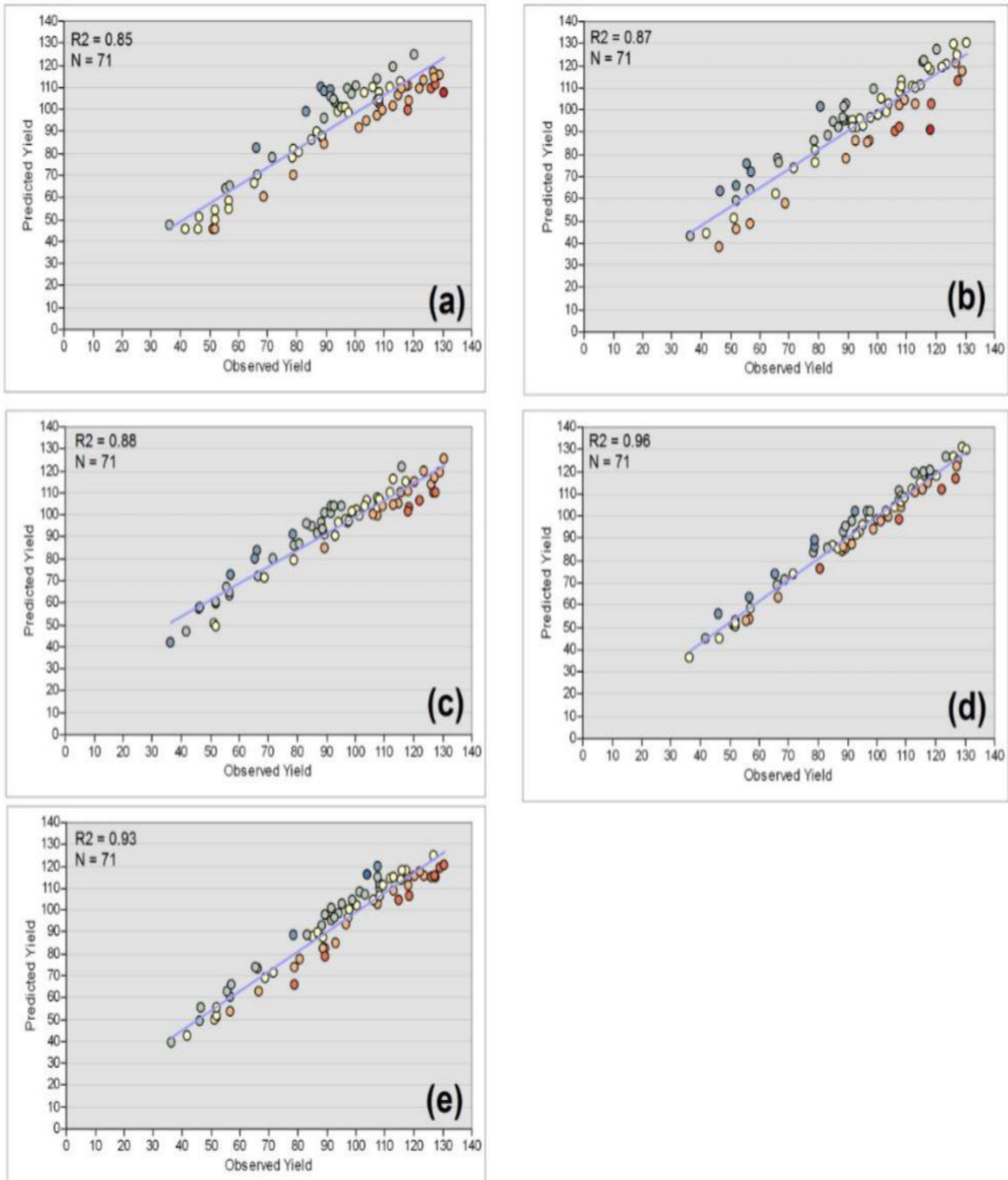


Figure 28 Predicted vs. observed non-irrigated maize (corn) yields across Nebraska using geographically weighted regression from mean monthly precipitation for (a) May, (b) June, (c) July, (d) August, and (e) September

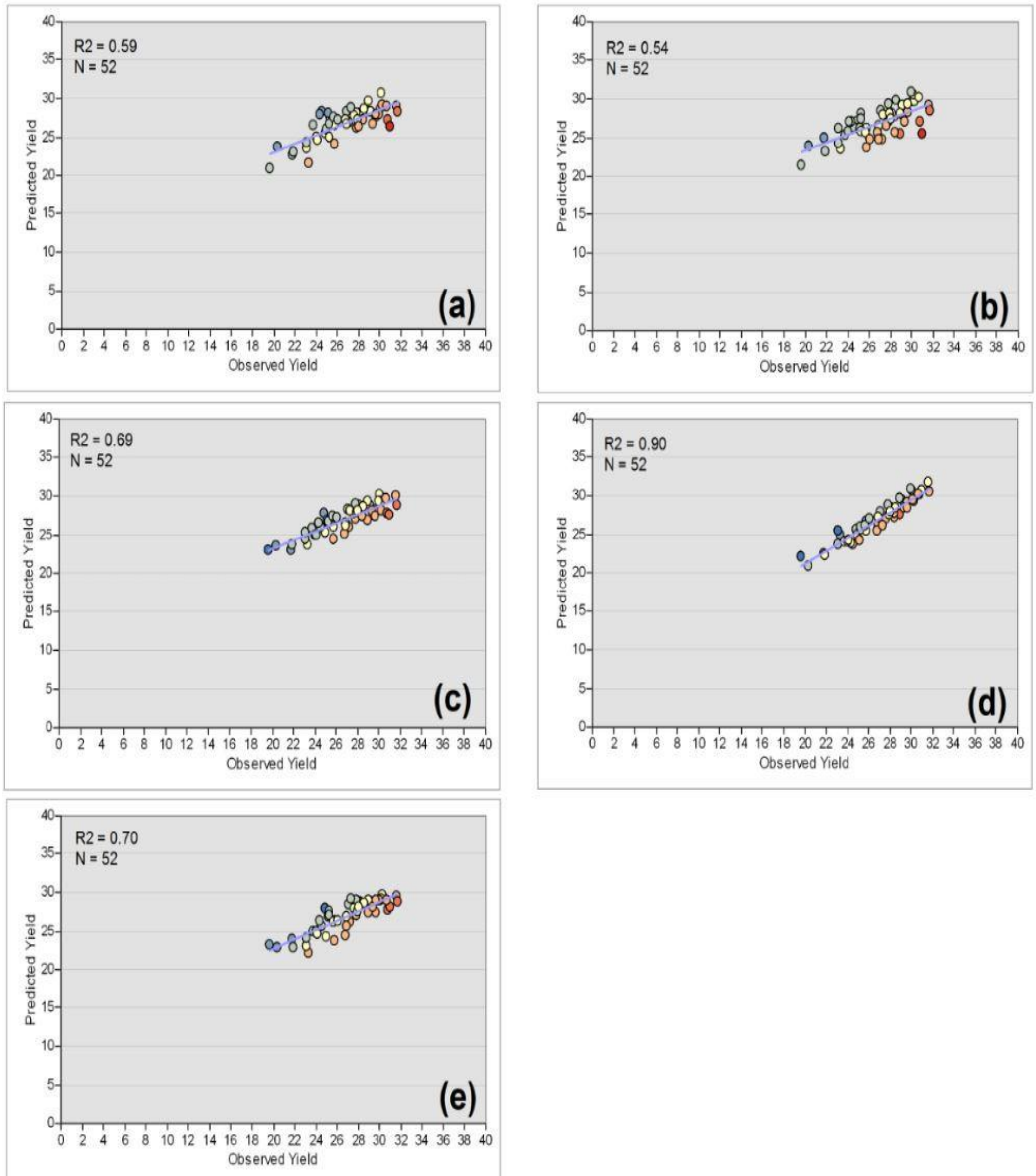


Figure 29 Predicted vs. observed non-irrigated soybean yields across Nebraska using geographically weighted regression from mean monthly precipitation for (a) May, (b) June, (c) July, (d) August, and (e) September

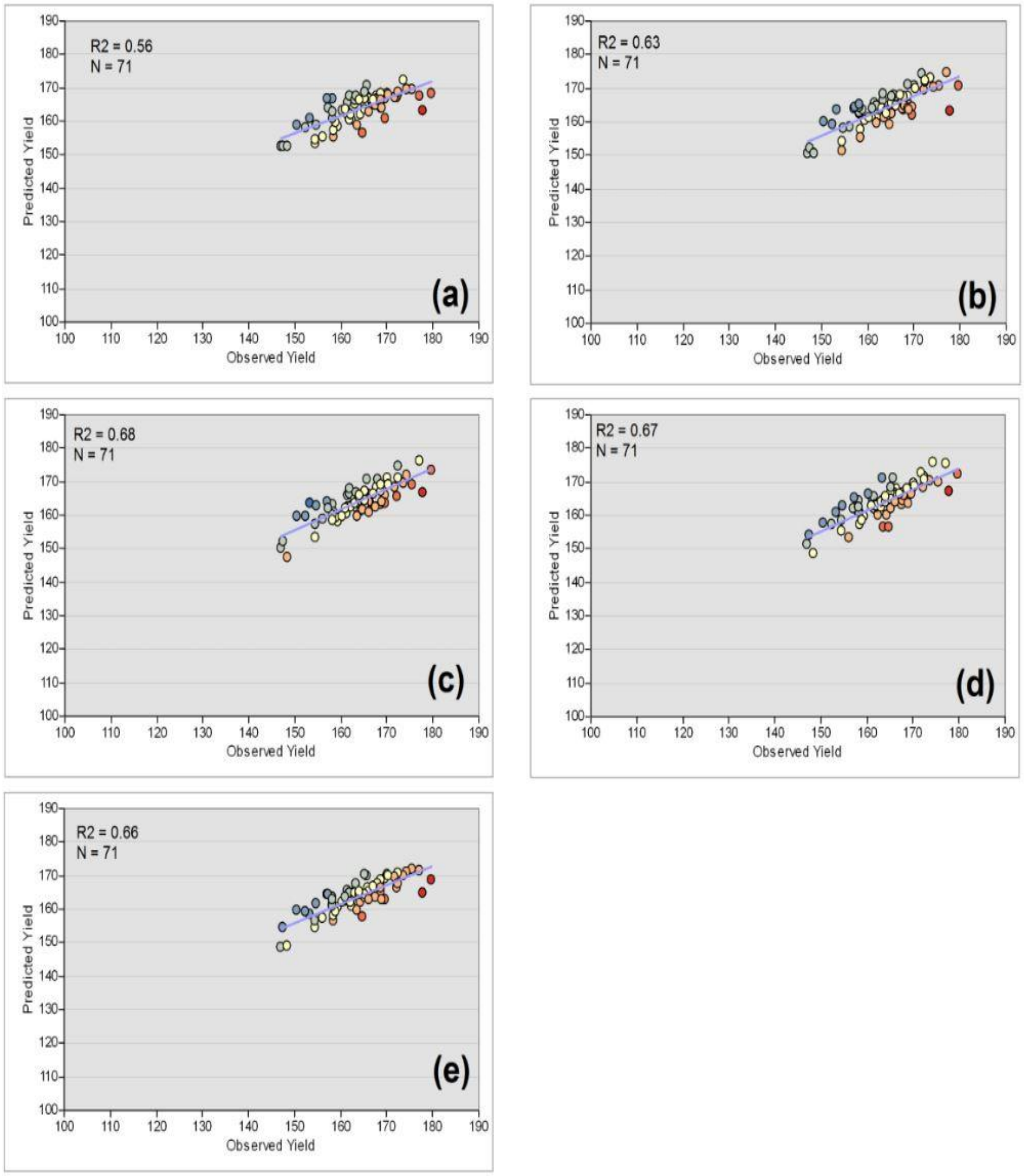


Figure 30 Predicted vs. observed irrigated maize (corn) yields across Nebraska using geographically weighted regression from mean monthly precipitation for (a) May, (b) June, (c) July, (d) August, and (e) September

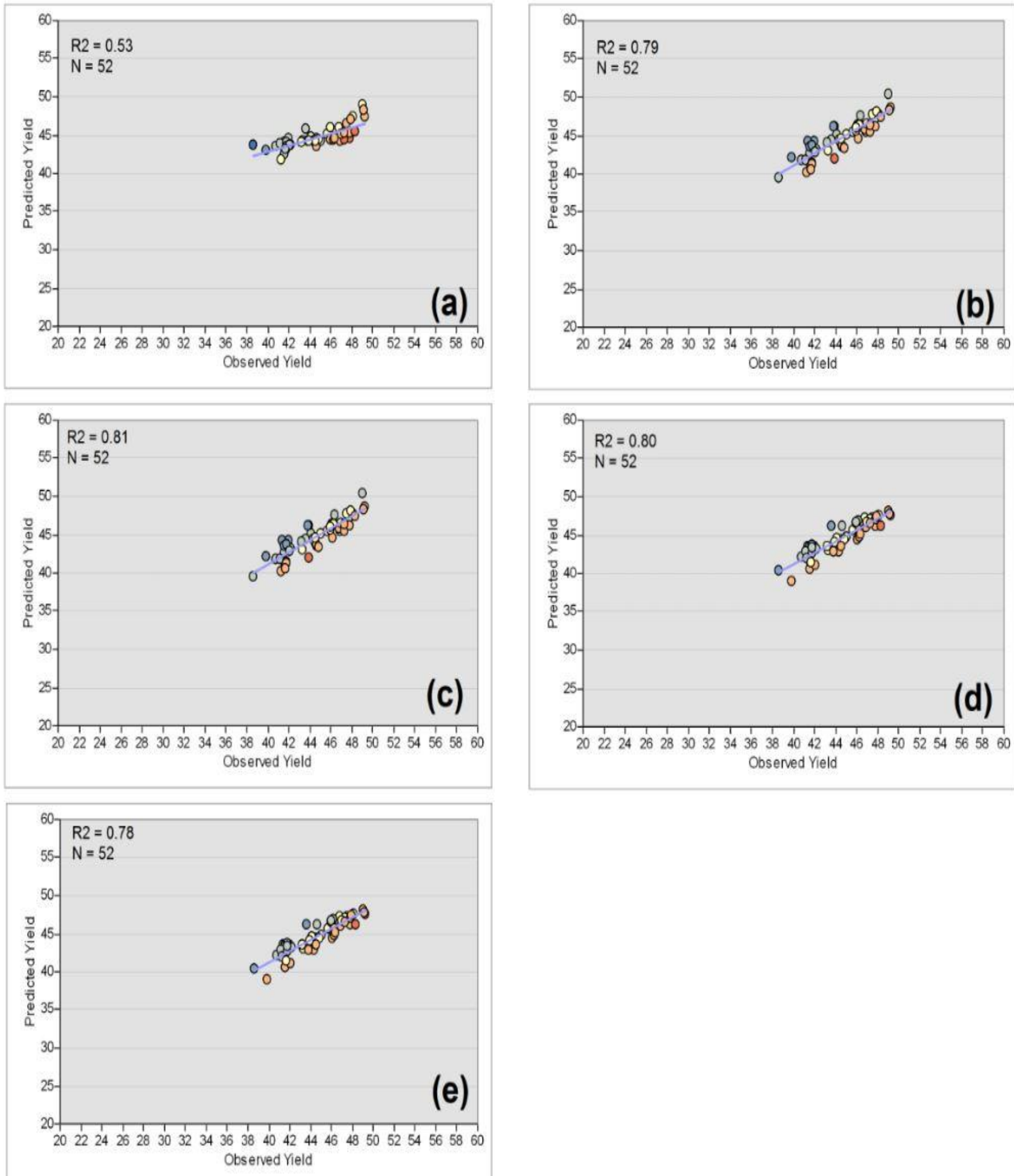


Figure 31 Predicted vs. observed irrigated soybean yields across Nebraska using geographically weighted regression from mean monthly precipitation for (a) May, (b) June, (c) July, (d) August, and (e) September

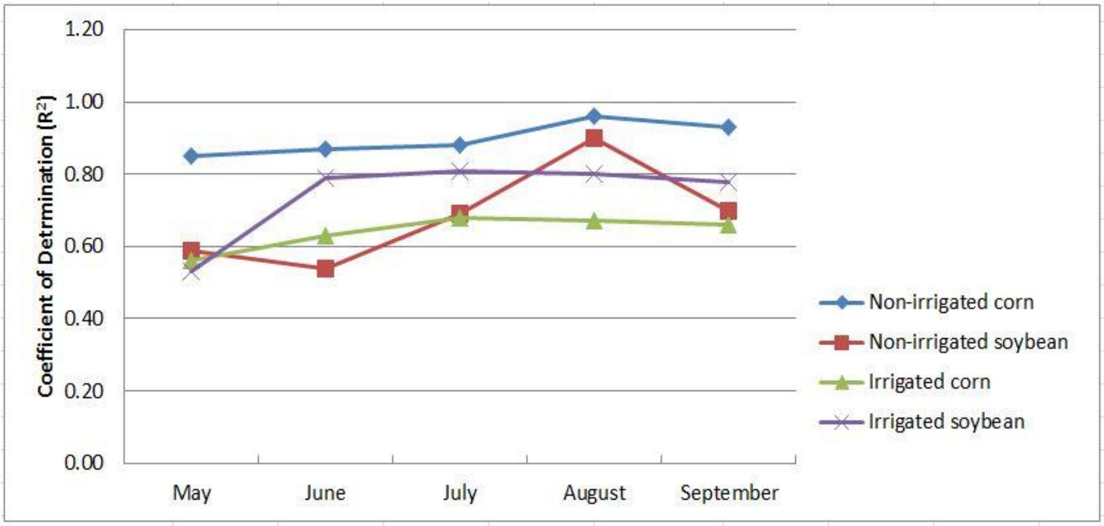


Figure 32 Coefficient of Determination (R^2) between observed and predicted irrigated and non-irrigated maize (corn) and soybean yields using GWR from mean monthly precipitation (May-September)

The R^2 values with standard error values are presented in (Table 7) below. For non-irrigated maize (corn), the initial precipitation in May is of importance for setting potential with regard to the number and size of kernels. On the other hand, precipitation in July is most important for yield potential. Counties with more July precipitation usually had higher yields, and findings are in agreement with those of other researchers who also reported that less precipitation during the months of July, August, and September in the Great Plains region may reduce yield (Robin and Domingo, 1953; Denmead and Shaw, 1960; Musick and Dusek, 1980; Schlenker and Roberts, 2006).

A field study of maize (corn) conducted in west-central Nebraska; Payero et al. (2009) resulted in data showing irrigations applied in July had the highest positive correlation with yield. This high correlation decreased considerably for irrigations applied in August, and became negative for irrigations in September. The best positive correlation between the soil water deficit factor and yield happened during weeks 12 through 14 of the "milk" and "dough" growth stages. Yield was poorly correlated to stress during weeks 15 and 16, and the correlation became negative after week 17. Reports showed that if water is limiting, then applying a larger proportion of the allocation in July is a good strategy, which supports the findings that, for both irrigated and non-irrigated maize (corn) and soybean, July precipitation had the strongest correlation with yield (Table 7) below, (Figure. 32) above.

Table 7 Predicted vs. observed yields for Nebraska counties for the period of 2000-2012 using mean monthly precipitation (May 1 to September 30). The intercept and slope were obtained from regression: Y = a + bx, where Y = predicted yield and x = precipitation.

Crop	N	Coefficient of Determination (R^2)					Standard Error				
		May	June	July	August	September	May	June	July	August	September
Non-irrigated maize (corn)	71	0.85	0.87	0.89	0.97	0.93	10.54	14.70	14.44	10.62	13.89
Non-irrigated soybean	52	0.60	0.54	0.70	0.90	0.70	3.07	3.68	3.82	2.09	2.95
Irrigated maize (corn)	71	0.57	0.64	0.68	0.68	0.66	5.14	6.95	6.54	6.92	8.89
Irrigated soybean	52	0.53	0.80	0.82	0.81	0.78	3.09	2.28	2.75	2.82	2.37

GWR standard deviation residual maps show that residuals were usually within the 1.5 SD ranges (Figures. 33 through 36). GWR analysis showed a significant relationship between observed and predicted yield in (Table 7) above. The t-test showed that the predicted values for intercept and slope of the regression line were significantly different from unity ($p < 0.05$). Similarly, for non-irrigated soybean, May precipitation is important for the initial potential pod development, and July precipitation is most important for maximum yield.

The R^2 values were lower for irrigated maize (corn) and soybean than for non-irrigated maize (corn) and soybean conditions for July. Counties with higher July precipitation had higher yields. The GWR SD residual maps indicate that the residuals for irrigated crops were usually within the 2.5 SD ranges (Figures.33 through 36). When all the months are considered, none of the counties fell outside the 2.5 SD range for July. Between observed and predicted yields, the relationship was significant ($p < 0.05$) (Table 8 below).

In many cases, the GWR model performed well in predicting county-average yields of precipitation across Nebraska, except for under-predicting the northeast part of the state. In general, the model over-predicted yields for high-yielding conditions and under predicted for low-yielding conditions.

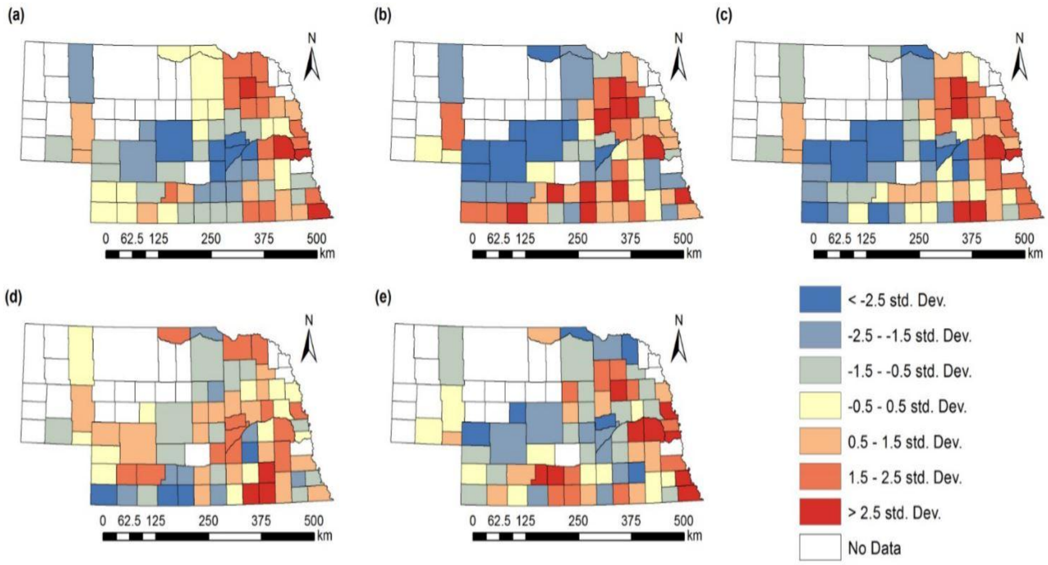


Figure 33 Residual maps for (a) May, (b) June, (c) July, (d) August, and (e) September for non-irrigated maize (corn) showing counties where yield is under- or over predicted based on the data presented in figure 28.

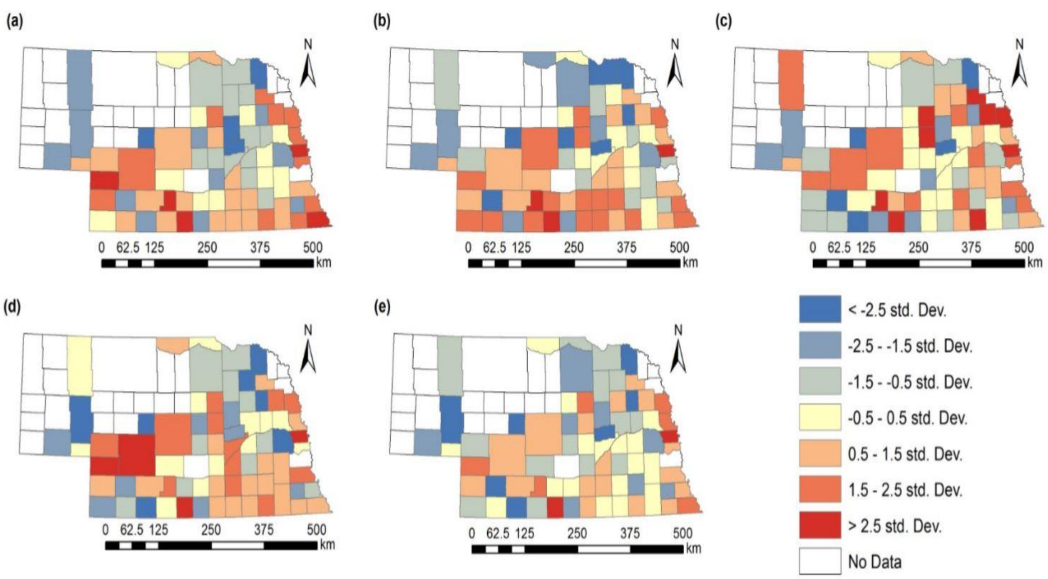


Figure 34 Residual maps for (a) May, (b) June, (c) July, (d) August, and (e) September for non-irrigated soybean showing counties where yield is under- or over predicted based on the data presented in figure 29.

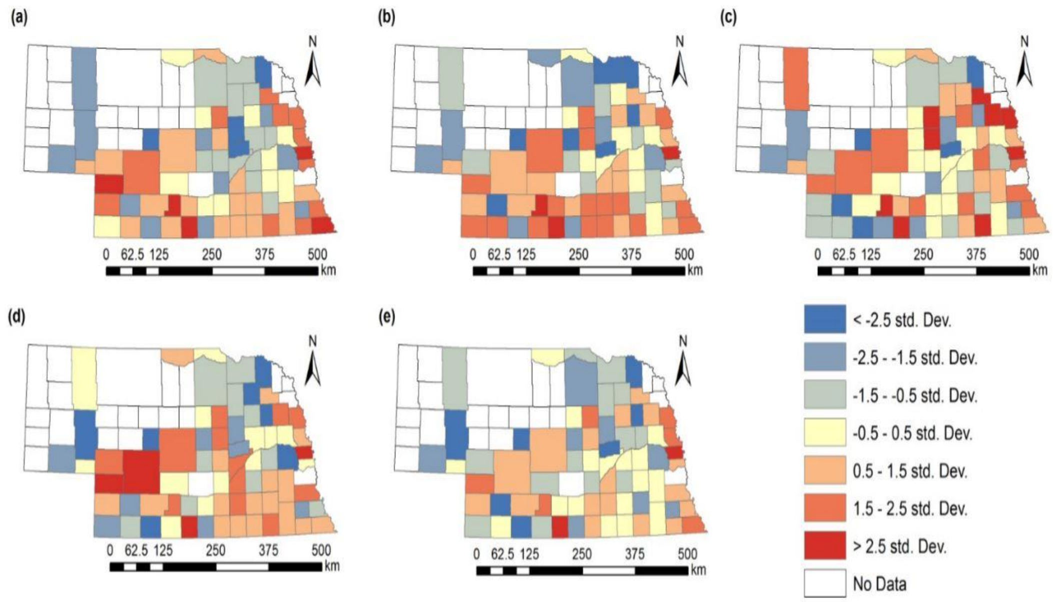


Figure 35 Residual maps for (a) May, (b) June, (c) July, (d) August, and (e) September for irrigated maize(corn) showing counties where yield is under-or over predicted based on the data presented in figure 30.

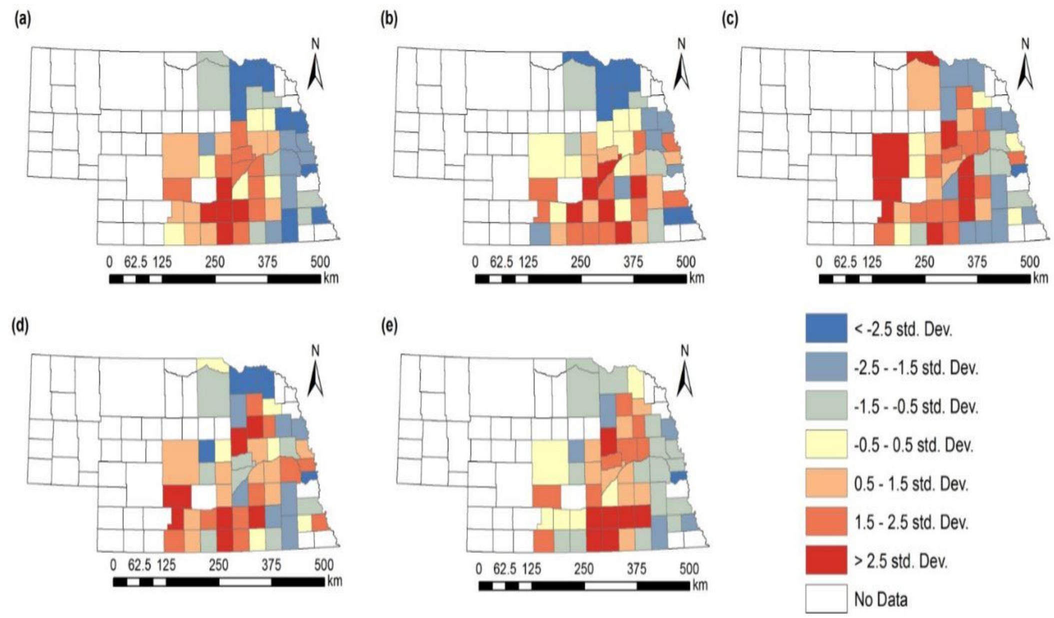


Figure 36 Residual maps for (a) May, (b) June, (c) July, (d) August, and (e) September for irrigated soybean showing counties where yield is under or over predicted based on the data presented in figure 31.

Table 8 F- ratio statistics of mean yields for observation period of 2000-2012 using mean monthly Precipitation (May 1 to September 30).

Crop	N	DF	F-Ratio					p > F
			May	June	July	August	September	
Non-irrigated maize (corn)	71	69	5.77	6.30	6.30	15.87	13.82	<0.0001
Non-irrigated soybean	52	50	4.58	3.63	10.86	9.68	8.79	<0.0001
Irrigated maize (corn)	71	69	5.77	6.30	9.39	10.99	13.82	<0.0001
Irrigated soybean	52	50	4.58	3.63	10.86	9.68	8.79	<0.0001

Evaluated analysis was completed for the irrigated and non-irrigated maize (corn) and soybean yield variations for Nebraska at the county level between 2000 and 2012. Geographically weighted regression (GWR) and ordinary least square (OLS) models correlated relationships between yield and precipitation levels. Yields for the county level and statewide average basis were conducted for point measurements and spatially interpolated stationary annual (January to December), seasonal (May to September) and monthly (May, June, July, August, September) precipitation levels for all of the counties.

Precipitation regression with irrigated and non-irrigated maize (corn) and soybean levels show yields as a function of precipitation. The GWR model's predicted yields were significantly better than OLS performances for maize (corn) and soybean. The OLS regression model when used showed a general trend of correlation between observed yields and long-term mean precipitation totals. 84% and 63% of the variability in mean yield was explained by the mean annual precipitation for the non-irrigated crops. Irrigated maize (corn) and soybean had 38% and 30% variability in mean yields with mean annual precipitation.

The GWR technique performance in predicting yields was significantly better than OLS performances and when the GWR technique was utilized, non-irrigated maize and soybean variation yields showed 68% and 72% variation levels with R^2 of 0.94 and 0.74 for maize (corn) and soybean. The annual mean total precipitation levels accurately predicted non-irrigated maize (corn) more so than non-irrigated soybean yields. The correlation between precipitation and yields were lower for irrigated maize (corn) and soybean, and irrigated yields had lower standard error of prediction than non-irrigated yields. On a statewide average, July precipitation had the highest correlation with yield for both maize (corn) and soybean. June, July, and August precipitations had greater impacts on maize (corn) yields than soybeans under non-irrigated conditions as a result of the greater sensitivity maize (corn) had to water stress than soybean. July precipitation levels had a greater impact on soybean yield than on maize (corn) for irrigated yields.

The superiority of the GWR technique over conventional OLS regression approach in analyzing the relation between yield and precipitation and predicting yields for irrigated and non-irrigated maize (corn) and soybean was depicted in the study. As a result, analysis can be used to show maize (corn) and soybean yields as a function of spatially interpolated monthly precipitation levels ahead of the harvest season. GWR's technique superiority is due to the accounting impact of the spatial non-stationarity of the precipitation versus yield relationships. Such attributes of the OLS model present a challenge in predicting yields on large scales. In addition to the precipitation, further application and evaluations of the relatively new GWR technique in similar agricultural research topics can improve the yield predictions by accounting for spatial non-stationarity of other climatic variables (i.e., radiation levels, air temperature, etc.), and management practices.

4.3 Chapter Summary

The use of GWR proves useful in evaluating spatial heterogeneity across various study areas between precipitation vs. irrigated and non-irrigated corn and soybean yield. The superiority of the GWR technique over conventional OLS regression approach in analyzing the relation between yield and precipitation and predicting yields for irrigated and non-irrigated maize (corn) and soybean was depicted in the study.

Long-term monthly (May, June, July, August, and September) average precipitation for all counties is presented among each of the Nebraskan counties. During the seasonal growth months of the year (May, June, July, August, and September) there is a limiting factor of difference between the central counties of the states and the eastern borders. Soil types and the water-holding capacities vary significantly across the counties of the state. The strongest irrigation results for corn were shown in the southern parts of Nebraska as well as with counties in the east. Non-irrigation results for corn were most relevant on the eastern side of Nebraska with mean yields reaching as high up as 110 BU/Acre and more. The greatest yields for irrigated soybean yields in Nebraska were found most in the south-central counties with mean soybean yields reaching as much as 62 BU/Acre. Non-irrigated soybean mean yields delivered the most in results at the eastern border of the state of Nebraska between the years 2000 to 2012.

The coefficient of determination (R^2) between the observed yield and precipitation (using long - term average mean annual, seasonal, and monthly total precipitation for each county) for irrigated and non-irrigated maize (corn) and soybean using the OLS model for the observed yield vs. long-term average mean annual, seasonal, and monthly precipitation statistics reached as much as 0.84 for non-irrigated maize (corn) and as low as 0.30 for irrigated soybean. The annual coefficient of determinants (R^2) coincided with the seasonal results for the respective months (May, June, July, August, September), with July having the lowest R^2 numbers and August the highest consistently.

The results of the GWR model showed very good performance for non-irrigated maize (corn) and soybean. GWR's technique superiority is due to the accounting impact of the spatial non-stationarity of the precipitation versus yield relationships. On a statewide average, the R^2 values were greater for non-irrigated maize (corn) and soybean than for irrigated maize (corn) and soybean. For non-irrigated maize (corn) and soybean, about 96% and 67% of the variation in yield was explained by the mean annual precipitation alone. For irrigated maize (corn) and soybean crops, about 68% to 72% of the variation in yield was explained by the mean annual precipitation. Precipitation is not the only limiting factor driving crop yield, as other factors contribute such as evapotranspiration, air temperature, solar radiation, soil type and water-holding capacity impact the yield thereby influencing the relationship between precipitation and irrigated and non-irrigated yields. For non-irrigated crops, there was a strong correlation between seasonal precipitation and yield, with R^2 of 0.94 and 0.74 for maize (corn) and soybean.

The R^2 values between monthly precipitation and yields show that the R^2 values ranged from 0.54 to 0.95 for non-irrigated crops and from 0.53 to 0.80 for irrigated crops.

Differences appear regarding the impact of individual monthly total precipitation on crop yields across the state (i.e., R^2 between individual months' precipitation vs. yield varied from the eastern part to the western part). This is due to varying precipitations from east to west, in the impact of precipitation on yield which is also due to differences in the planting date across the state. Depending on the location, seasonal date, climate conditions, and hybrid, the potential kernel development for maize (corn) normally begins in June, and tasseling in mid-July, with silking/pollination occurring in late July and grain fill occurring during early to mid- August throughout the study region. Western Nebraska had more than 70% of the maize (corn) land area planted as no - till. For soybean, eastern Nebraska had a higher percentage of land planted on no - till than the central part. There is a gradual decrease in maize (corn) and soybean no - till planting land area across the state of Nebraska. Disk-till is commonly used in central and west-central Nebraska, and impacts the spatial non-stationarity relationships between precipitation and yield, as it influences the available soil water and precipitation relationship depending on several factors. In general, disk-till fields has greater soil evaporation than no - till fields.

July precipitation was the most critical for the high crop yield due to the sensitivity of maize (corn) to water stress during critical growth stages (tasseling and silking). In all months and in both irrigated and non-irrigated treatments, yield was proportional to precipitation. For irrigated yields, July precipitation had more impact on soybean yield than on maize (corn).

CHAPTER FIVE: ASSESSMENT OF MODIS INDICES FOR AGRICULTURAL DROUGHT MONITORING

Among the various remote sensing drought indices, each use different bands, and most have been applied in prior drought studies (Caccamo et al., 2011; Gu et al., 2008; Ji and Peters, 2003; Kogan 1995; Tucker 1987; Wan et al., 2004). The happening of severe drought events increases the need for evaluating different remote sensing drought indices. Other than the AVHRR sensor, the Moderate Resolution Imaging Spectro-radiometer (MODIS) sensor is able to facilitate remote sensing applications with finer resolutions, particularly in the water sensitive spectrum bands; 1200nm, 1450nm, 1950nm). Many MODIS-based spectral indices have been used in past years for agricultural drought studies (Wang et al., 2007; Gu 2007; qin et al., 2008). In this study, popular MODIS drought indices are used to examine drought: NDVI, NDWI, NDII6, NDII7, and NMDI.

5.1 Use of Standard Precipitation Index (SPI) to Assess MODIS Drought Indices

The first method used is the traditional drought indicator SPI to assess MODIS indices. This is done by utilizing data from the USA drought monitor website to obtain GIS data in the archive to utilize the county level statistics for 2012. Dividing the data into five categories and creating a map in ArcGIS using abnormally dry, moderate drought, severe drought, extreme drought, exceptional drought categories.

The goal is to evaluate between remote sensing drought indices and the metrological-based SPI index. All remote sensing indices were related to SPI at various degrees. Choosing SPI over other drought indices is due to flexibility and the fact that it relies on precipitation information (Caccamo et al., 2011; Guttman, 1999). SPI can be computed for different time scales, and can provide early warnings of drought and can help assess drought severity. It is less complex than the Palmer Drought Index and many other indices. The SPI is designed to quantify the precipitation deficit for multiple timescales. These timescales reflect the impact of drought on the availability of the different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Groundwater, stream flow and reservoir storage reflect the long term precipitation anomalies. For these reasons, Mckee and others (1993) originally calculated the SPI for 1, 2, 3, 6, 9, 12, 24 and 48 moth timescales.

Finding the SPI calculation for a specific location is determined by the long-term precipitation records for a desired time-period. The long-term records are fitted to probability distribution so that the mean SPI for the location desired is zero by means of normal distribution (Edwards and Mckee, 1997). Positive SPI values show greater-than median precipitation and negative values specify less-than median precipitation. Because the SPI is normalized and wetter and drier climates can be represented in the same way, wet periods can also be monitored using SPI.

McKee and others (1993) in the SPI value in (Table 9) below, shows the SPI results for drought intensities. A criterion is also utilized to define a timescale for the drought event. This shows that a drought event takes place whenever the SPI reaches an intensity of -1.0 or less. The event ends when the SPI becomes positive. Each drought event is defined by a beginning and end and shows the intensity for each month that the event continues. The drought's "magnitude" is the positive sum of the SPI for all the months that a drought event happens.

Table 9 SPI values

2.0+	extremely wet
1.5 to 1.99	very wet
1.0 to 1.49	moderately wet
-.99 to .99	near normal
-1.0 to -1.49	moderately dry
-1.5 to -1.99	severely dry
-2 and less	extremely dry

Data Source: http://www.wamis.org/agm/pubs/SPI/WMO_1090_EN.pdf

Monthly precipitation uses weather station of Midwestern USA. The SPI is computed by NCEI for several time scales, ranging from one month to 24 months, to capture the various scales of both short-term and long-term drought. Here, the analysis includes 4 time intervals or time scales of 1-month or 2- month, 3 month, 6-month, and 9- month SPI for each weather station and each month in the corn and soybean - growing season from 2000 to 2012.

Longer timescales (e.g., SPI -12) was not incorporated in the analysis because precipitation integrated over such long timescales becomes less coupled with the current state of vegetation (Rossi and Niemeyer, 2012).

The Standardized Precipitation Index (SPI) is a probability index which calculates precipitation. The given amount of precipitation recorded is standardized so as to show average precipitation amounts. Negative represents a drought and positive represents wet conditions, based upon severity. SPI is computed for a range of time, typically spanning between one month and up to 24 months.

The figures below show the time series of 1-month, 2- month, 3-month, 6-month, and 9-month for several time scales of SPI based on spatially averaged data over the primary Corn and Soybean Belt.

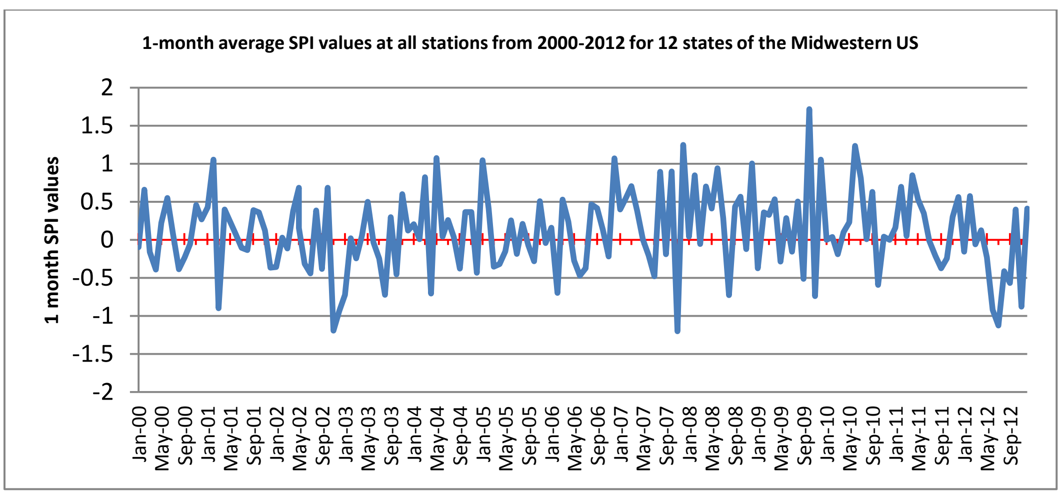


Figure 37 1 month average SPI Values at all stations from 2000-2012 for 12 states of the Midwestern US study area.

The 1-month SPI map is beneficial in summarizing the action of droughts, or lack thereof, on a 4-week average basis. The (Figure 37) above displays the 1-month average of SPI values at all stations between the years of 2000 and 2012 for 12 states of the

Midwestern US. Through the whole decade, there is a consistent ebbing and spiking of the graph characterizing consistent rains and consistent dry periods.

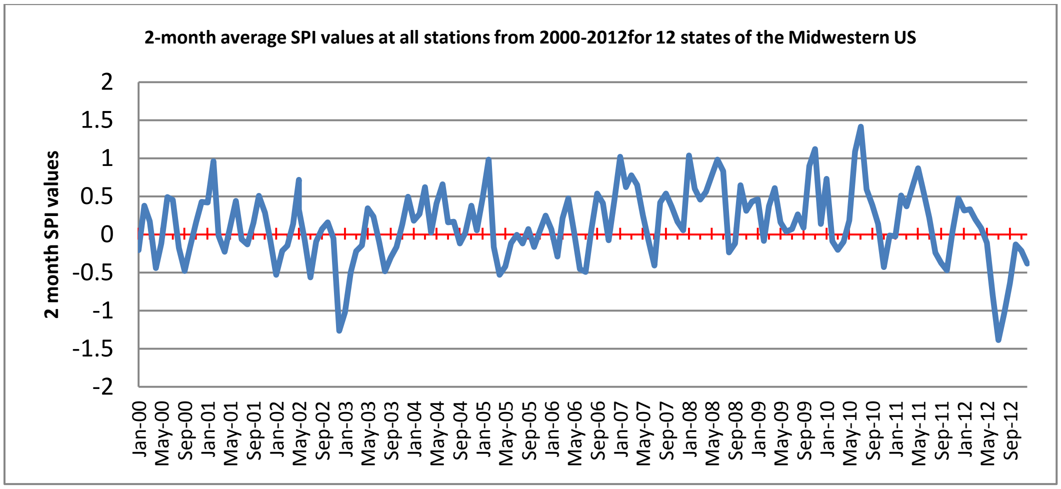


Figure 38 2 month average SPI Values at all stations from 2000-2012 for 12 states of the Midwestern US study area.

The 2-month average shows drought in much of the beginning of the decade, followed by steady precipitation periods throughout the end of the decade starting mid-way through. Then very heavy drought strikes again between the mid and end of the year 2012 as shown in the (Figure 38) above.

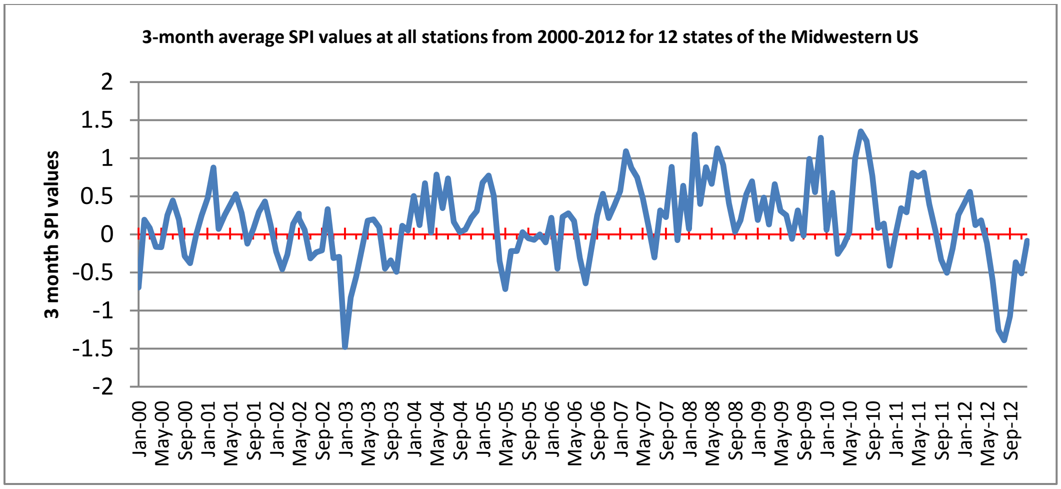


Figure 39 3 month average SPI Values at all stations from 2000-2012 for 12 states of the Midwestern US study area.

The 3-month average for SPI values at all stations from 2000-2012 displays much drought in the beginning of the decade followed by averaging precipitation in the middle of the decade leading into heavy precipitation between 2007 and 2011, by which time drought comes back effect during the 2012 year as shown in the (Figure 39) above.

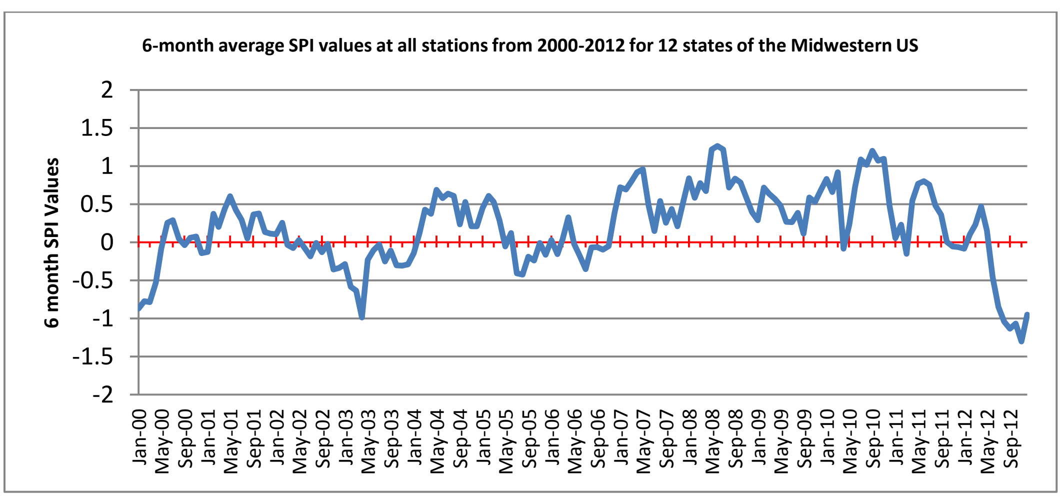


Figure 40 6 month average SPI Values at all stations from 2000-2012 for 12 states of the Midwestern US study area.

The 6-month average SPI values in (Figure 40) above show heavy sways through this historical period. Seasonal to medium-term trends in precipitation is indicated. Heavy drought extends from the beginning of the decade and at the end of the decade with the average SPI showing much precipitation throughout the middle years of this timespan.

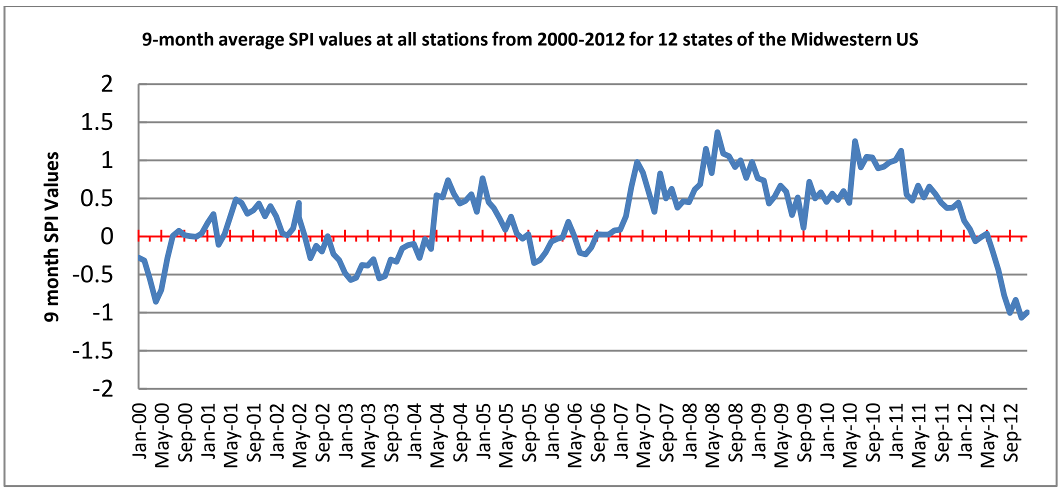


Figure 41 9 month average SPI Values at all stations from 2000-2012 for 12 states of the Midwestern US study area.

The 9-month SPI provides an indication of inter-seasonal precipitation patterns over medium timescale duration. Droughts usually take a season or more to develop, and the 9-month interval shows a consistency in precipitation throughout the decade with much of the positive SPI values being found toward the mid-end rear of the (Figure 41) above.

The research in the corn and soybean agricultural areas display remotely sensed data for short-term water deficiencies of 1-month SPI, 2-month SPI, and 3-month SPI, and longer-periods of water deficiencies for approximately 6-month SPI, and 9-month SPI.

The figures below present scatter plots of MODIS spectral index anomalies (NDVI, NDWI , NDII6 ,NDII7, and NMDI) on 3, 6, and 9 month SPI values for corn and soybean growing season (May – Sep) from 2000 to 2012.

(Figure 42 and 43 and 44) below represent the scatter plots of the MODIS spectral index anomalies on a 3-month, and 6-month, and 9-month SPI scale respectively. In Figures below, the best indicator used to show these drought conditions was the NDII6, which outperformed all of the MODIS indices for vegetation moisture monitoring and for detecting drought, over the pro-longed periods of 3, 6, and 9-months, out-performing all of the other MODIS indices, portraying drought conditions as most affected for the years of 2005 and 2006 and extreme drought in 2012. Among the various MODIS spectral indices used, analysis showed important differences in their relationships with SPI. The spectral indices that correlated best with SPI were in the SWIR water absorption region which showed that changes in vegetation water content were more pronounced than the changes found in the greenness properties of high biomass ecosystems.

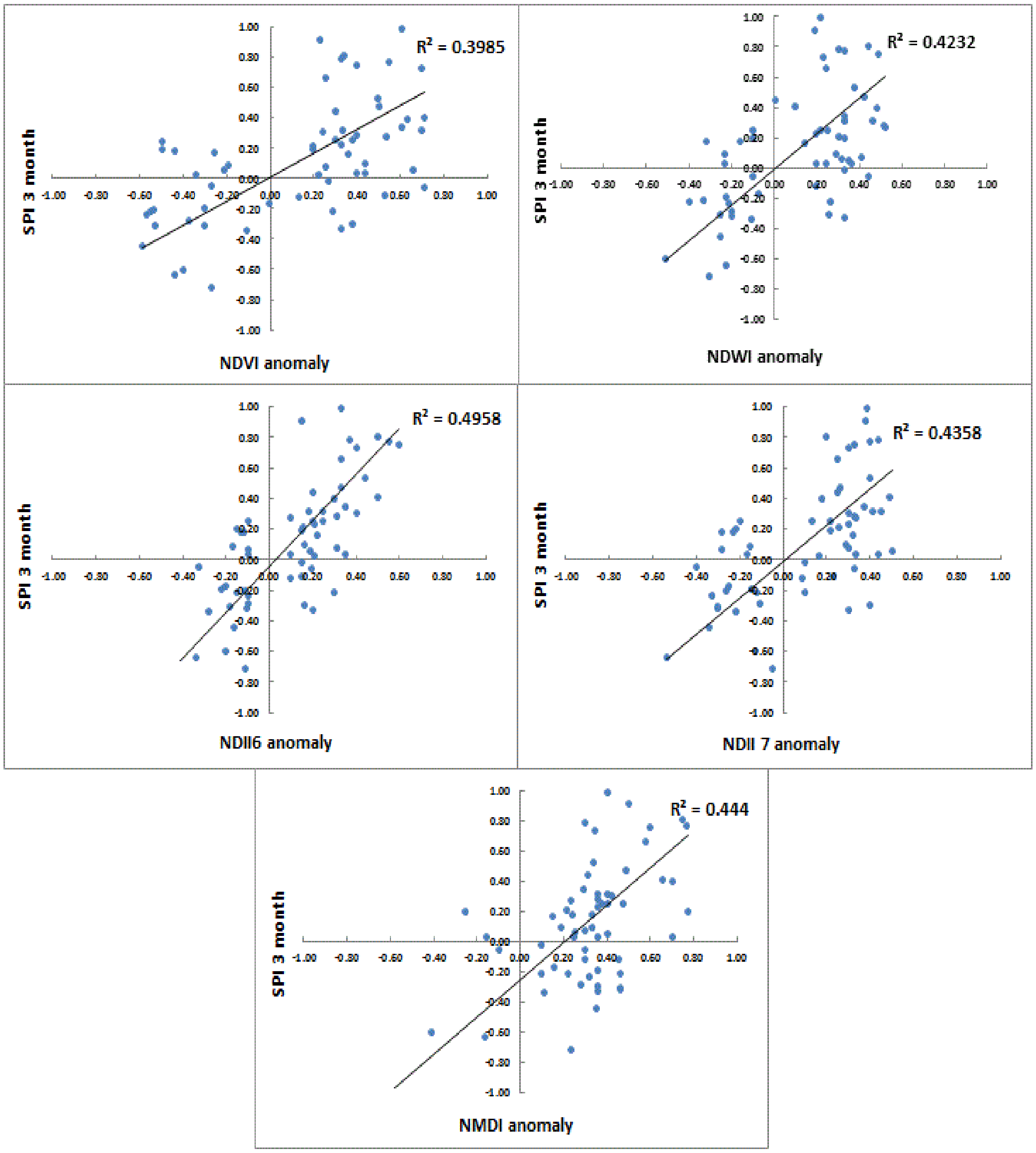


Figure 42 Scatter plots of MODIS spectral index anomalies and 3- month SPI for corn and soybean- growing season from 2000 to 2012.

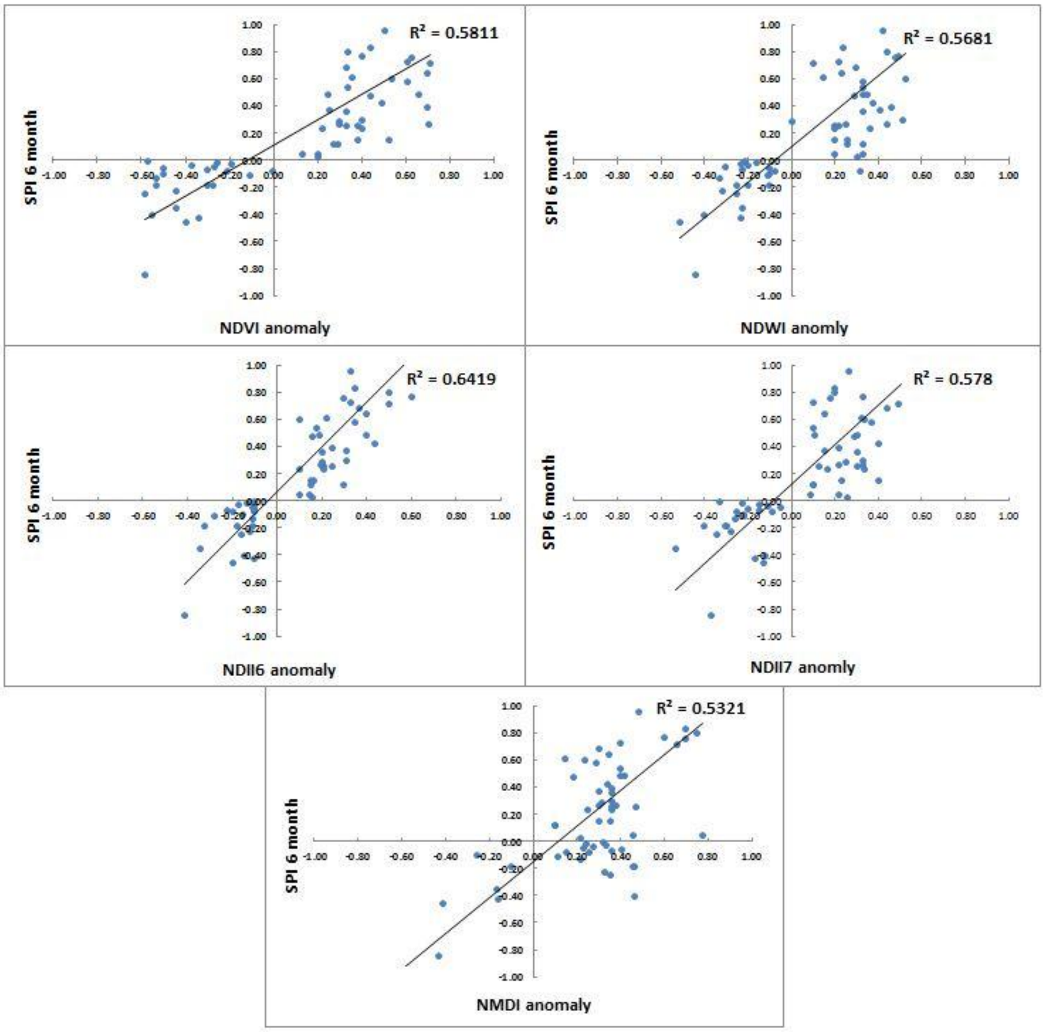


Figure 43 Scatter plots of MODIS spectral index anomalies and 6- month SPI for corn and Soybean- growing season from 2000 to 2012.

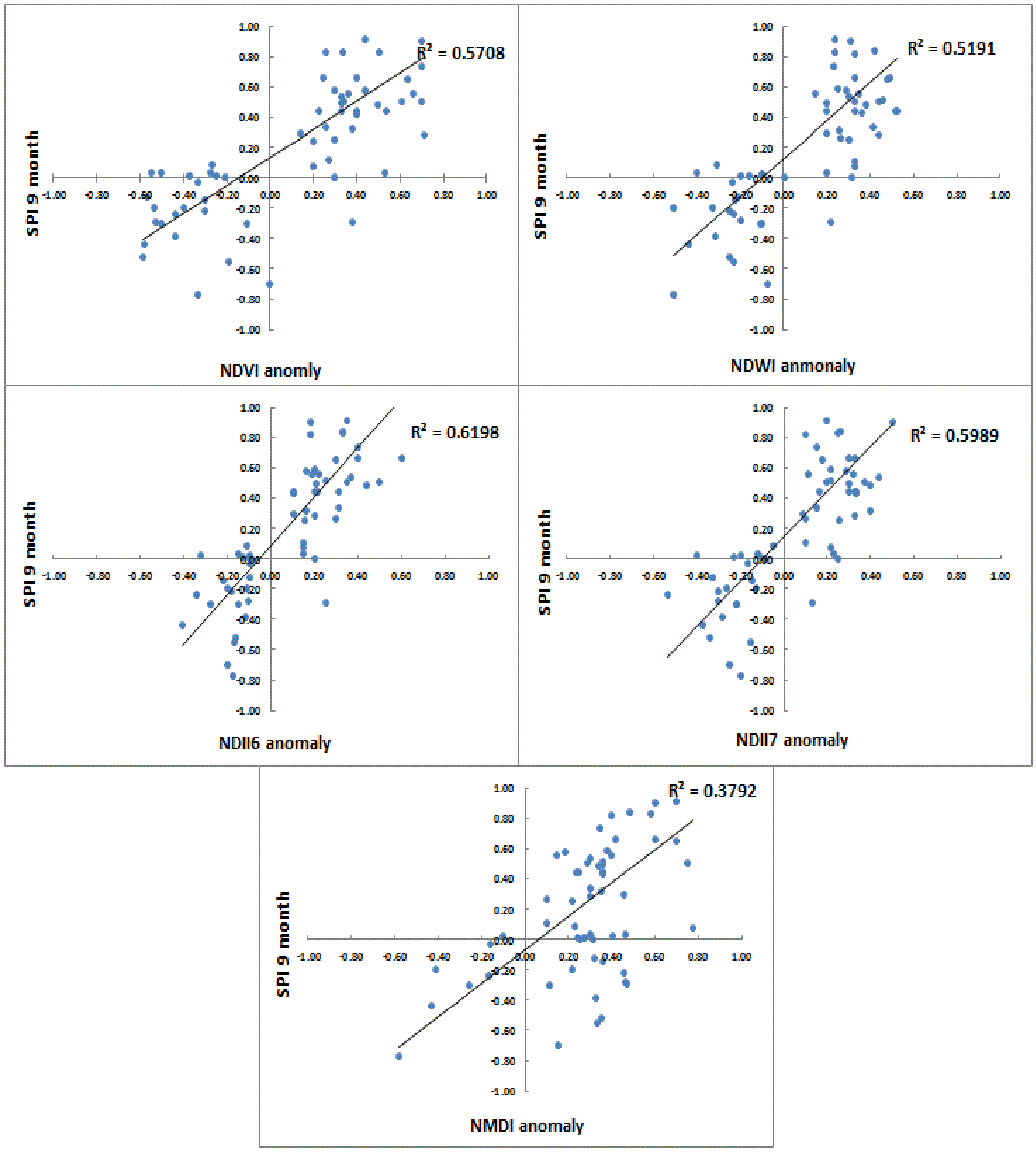


Figure 44 Scatter plots of MODIS spectral index anomalies and 9- month SPI for corn and soybean- growing season from 2000 to 2012.

5.2 Assessing MODIS Drought Indices Using a Percentage Histogram

Histograms of a drought index are a graphical representation showing visual impressions of the distribution of index values from which performance is evaluated. For the preliminary tests, 4 MODIS drought indices will be assessed as shown in the (Table 10) below.

Four indices are used because they are sensitive to capturing features of agricultural drought as shown in the (Table 10) below. Similar information can be gathered using MODIS by means of investigating agricultural drought using MODIS-based drought indices such as NDVI and LST (land surface temperature) data.

Table 10 MODIS spectral indices evaluated in this study.

NDVI	$\frac{\text{Band 2} - \text{Band 1}}{\text{Band 2} + \text{Band 1}}$	**Tucker (1979)**
NDWI	$\frac{\text{Band 2} - \text{Band 5}}{\text{Band 2} + \text{Band 5}}$	**Gao (1996)**
NMDI	$\frac{\text{Band 2} - (\text{Band 6} - \text{Band7})}{\text{Band 2} + (\text{Band 6} - \text{Band7})}$	**Wang and Qu (2007)**
NDII6	$\frac{\text{Band 2} - \text{Band 6}}{\text{Band 2} + \text{Band 6}}$	**Hunt and Rock (1989)**

Data Source: Di, Wu (2014), An Investigation of Agriculture Drought on the United States Corn Belt Using Satellite Remote Sensing and GIS Technology

The identification of drought events and selections of drought and normal years are based on weekly USDM statistics, which present percentages of total areas within each state at specific drought severity levels. The USDM statistics indicate a clear separation between drought and non-drought affected years. The primary Corn and Soybean Belt states which serve as the study area, from 2000 to 2012, showed in 2012 major dry months during the growing season.

Local agricultural systems suffered from water-deficiency which adversely impacted the drought. Corn and soybean suffered big losses as a result of the drought. Toward the end of August 2012, the main drought areas in the US included moderate to exceptional drought stretching from the central Rockies into Mississippi and the Ohio valleys and southern great lakes. A contracting area of moderate to exceptional drought in the southeast and areas of moderate to severe droughts in the mid-Atlantic existed.

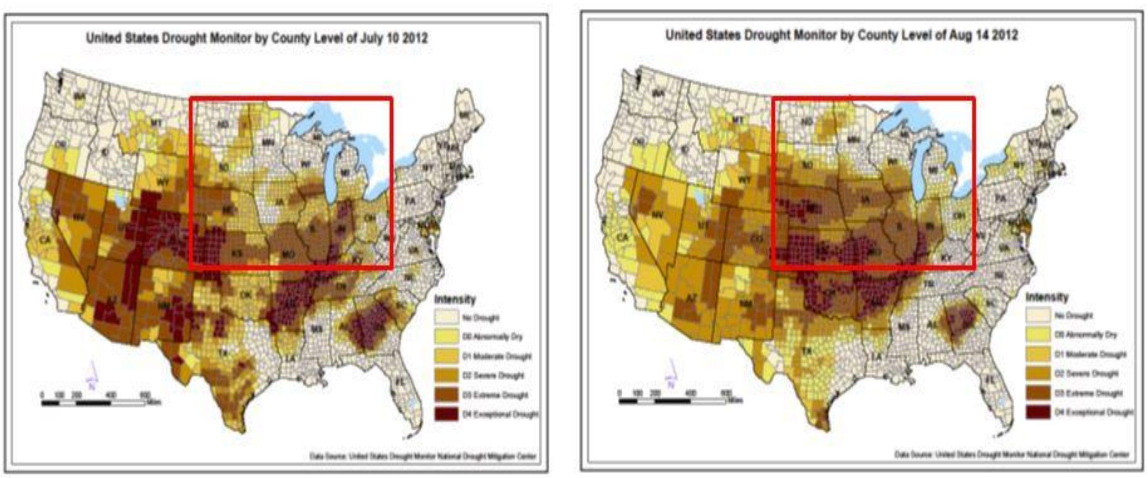


Figure 45 USDM drought maps for July 10, 2012 on the left side and August 14, 2012 on the right side.

The Maps in (Figure 45) depict results between July 2012 - Aug of 2012 for the entire US and with Midwestern study-area states being the most stressed. The 2012 drought tells of the necessity to fully assess remote sensing drought indicators when considering extreme droughts. Despite previous studies comparing the performances of remote sensing indices for drought monitoring, the study focuses on the comparison between in-depth time series analysis to assess the performance of remote sensing indices in agricultural drought monitoring across the primary Corn and Soybean Belt.

MODIS surface reflectance products were extracted for the 12 states making up the primary Corn and Soybean Belt study area. The analysis focuses on the corn and soybean growing season from June to September, and the 4 MODIS spectral indices that were used: NDVI, NDWI, NDII6, and NMDI.

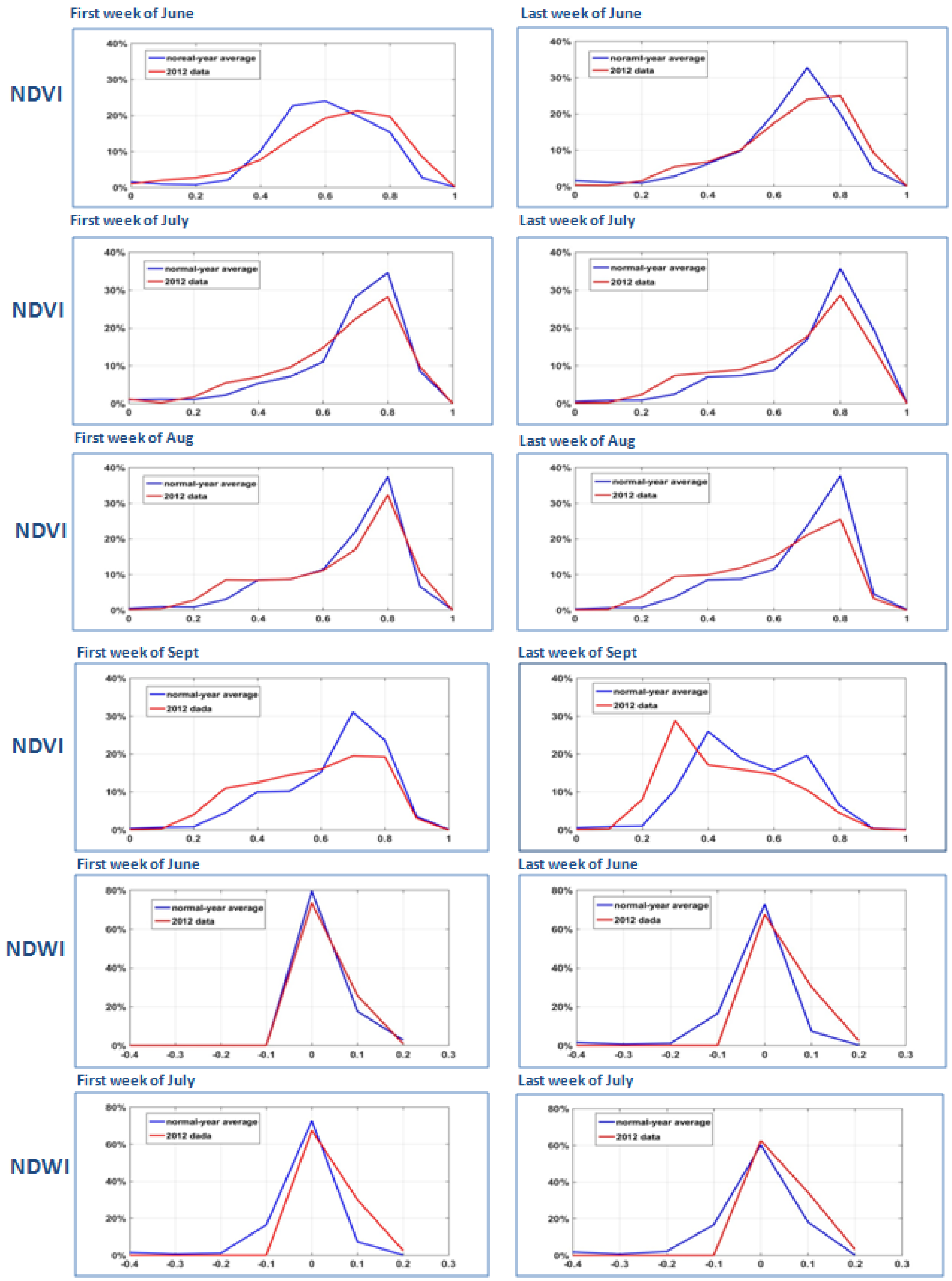
Comparisons of MODIS Indices between 2012 and Non-Drought Years (2000-2011)

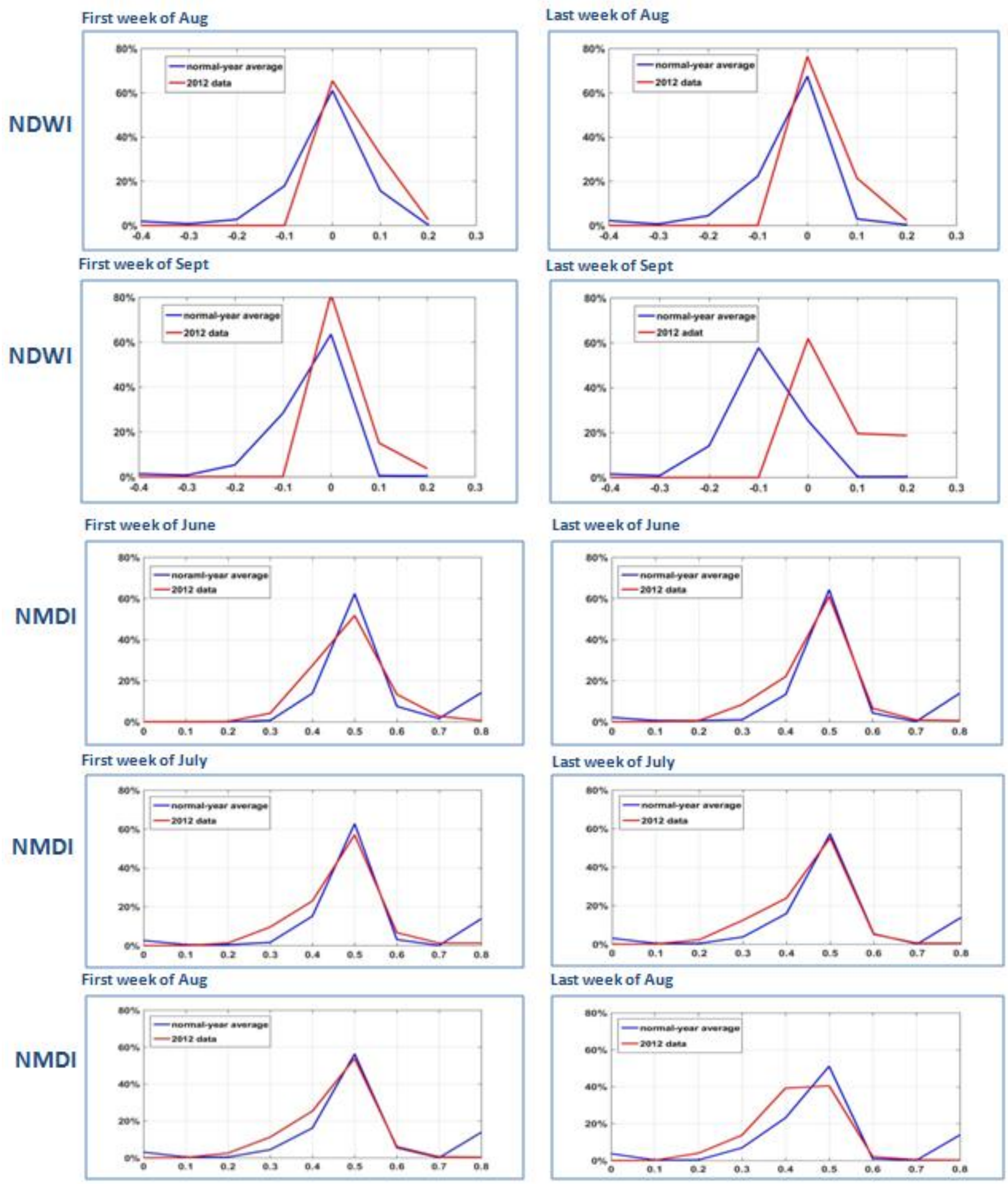
The 8-day, 500-m MODIS surface reflectance products (MOD09A1) from 2000-20012 are the primary satellite data in this study. The Midwestern US can be almost fully covered by four MODIS tiles. For each MODIS tile, all MOD09A1 scenes from 2000 to 2012 for the growing season were downloaded from the Land Processes Distributed Active Archive Center for four tiles (h10v04, h10v05, h11v04, and h11v05) covering the study area.

By averaging the eight day MODIS indices over normal years for crop pixels in the primary Corn and Soybean Belt, the normal growing condition for corn and soybean during their respective growing seasons is established. Mosaic and re-projection (the North America Datum 1983) are used for resampling, for each of the 8-day periods to get data for the study area. The MODIS Tool was used to import four files constituting the research study area. Using Mosaic reduces the study area scope making it much easier to view, analyze, and evaluate, to then configure the coordinates using latitude and longitude points.

Using normal vegetative conditions from historical indices, MODIS indices with normal conditions are able to assess current crop conditions. As seen in (Figure 46) below in the histograms showing the MODIS indices, these show data for the normal-year average (2000-2011) of the corn and soybean growing seasons, from June to September. The normal-year average is shown as a blue line, and the 2012 data is shown as a red line. The red signifies the drought, and the blue signifies the normal years. The histograms use lines instead of conventional bar charts to facilitate the analysis.

The histogram created is based upon crop pixels in the primary Corn and Soybean Belt within the NDVI range from [0 to 1] of each month. The remote sensing data reflectance is from the first week and last week of each month during the growing season.


First week of June
Last week of June
NDVI
noreal-year average
2012 data
noraml-year average
2012 data
First week of July
Last week of July
NDVI
normal-year average
2012 data
First week of Aug
Last week of Aug
NDVI
First week of Sept
Last week of Sept
NDVI
2012 dada
First week of June
Last week of June
NDWI
First week of July
Last week of July
NDWI


First week of Aug
Last week of Aug
NDWI
normal-year average
2012 data
First week of Sept
Last week of Sept
NDWI
normal-year average
2012 data
2012 adat
First week of June
Last week of June
NMDI
noraml-year average
normal-year average
2012 data
First week of July
Last week of July
NMDI
normal-year average
2012 data
First week of Aug
Last week of Aug
NMDI
normal-year average
2012 data

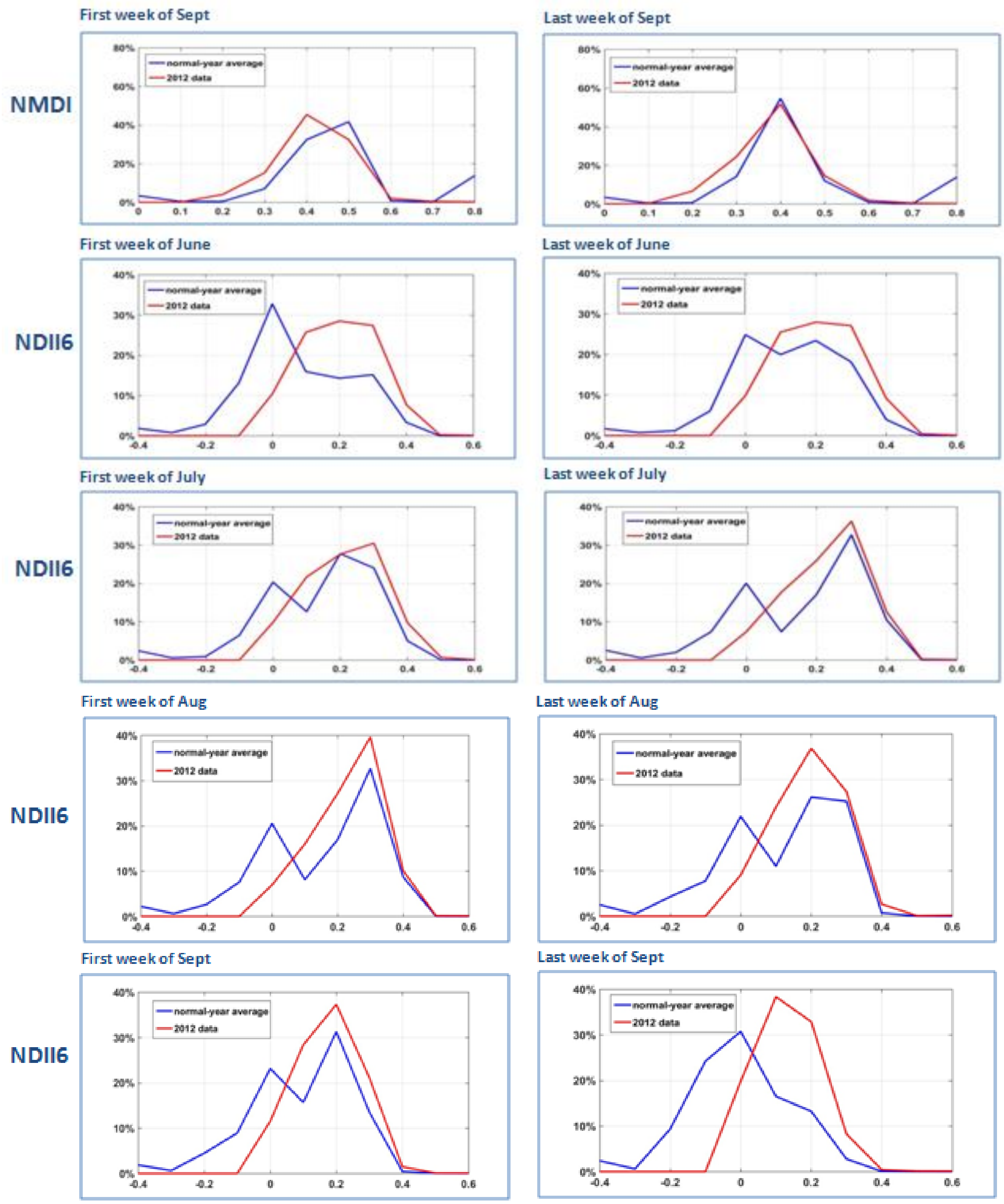


Figure 46 Histograms of four MODIS drought indices were compared between 2012 data and normal-year average for corn and soybean-growing season.

(Figure 46) shows graphs articulating details about the indices used in the research. The significance of these graphs in is showing the impact each index has in displaying the data acquired using them, showing positive and negative trends for each one. The histograms also show the impact of drought on distributions of MODIS indices. In 2012, warm temperatures during the months of April and May allowed corn and soybean growers to begin their planting season early. In the 2012 growing season, the histograms of such tested indices showed similarities between 2012 and normal years.

Generally speaking, the normal year (2000-2011) average gives a standard reference of crop conditions at specific growing stages. In the earlier corn and soybean - growing seasons, indices reported larger values indicating greater conditions for corn and soybean production. However, the 2012 drought season increased in severity starting in July, and persisted into August as shown by the data skewing to the left toward a negative direction and lowering in peak. Index values showed decreases for the rest of the growing season, including in crop biomass, water content, and leaf areas, all after-effects of the drought.

The increase in value among the x-axis shows that healthy vegetation exists in the reflectance spectrum. If the value on the x-axis is toward the lower end of the value system, then there is stressed vegetation reflectance.

The X-axis represents the bin size which represents which cells are created to specifically identify the area of the range; the range represents the study area. For example, the number of zeros divided by the total of square cells multiplied by 100 = the percentage. Finding the number of zeros divided by the total, and multiplied by 100 gives a percentage reflectance of the NDVI and the same thing as the rest of indices. The y axis represents the reflectance.

The range minimum is 0 (-1) and the maximum is 1 for NDVI. NDVI stands for Normalized Difference Vegetation Index. This is a commonly used remote sensing technique to help identify vegetation and to provide a measure of its health and vitality. The NDVI is based upon a spectral signature of vegetation, using an x-axis and y-axis used for portraying reflectance of vegetation. High NIR reflectance and Low Red reflectance portrays healthy vegetation. Less NIR reflectance and more or high (red visible) reflectance signifies unhealthy and sparse vegetation levels. NDVI combines NIR and red bands into a single value by subtracting the reflecting in the red spectral band from that in the near infrared band. NDVI has been used for agricultural mapping and monitoring (Maselli et al., 1992).

NDVI is a simple two band mathematical transformation that capitalizes on the differential response of chlorophyII absorption and internal spongy mesophyll layer reflectance from pant levers in the visible red and near infrared (NIR) spectral regions, respectively.

The launch of MODIS, with an increased number of land related spectral bands and expanded spectral coverage into the shortwave –infrared region (SWIR) led to the development of several new VIS incorporating SWIR observations. MODIS has two SWIR bands that are sensitive to changes in plant (Band 6: 1628-1652nm) and soil (Band 7: 2105-2155nm) water content.

NDWI stands for Normalized Difference Water Index and portrays surface water bodies and the differential response of the NIR (i.e., high reflectance by intercellular spaces) and SWIR reflectance (i.e., high absorption by plant water content) in healthy vegetation. NDWI produces an image where positive values are characterized as open-water areas, and negative values are portrayed as non-water features, such as terrestrial vegetation and bare soil cover areas. Like NDVI, NDWI has a native scaling of -1 to +1. (NDVI= 0 to 1) and (NDWI=-0.4 to 0.2).

With regard to spectral indices testing, NMDI shows peak average at .5 for both normal year and 2012 data during the first and last months of June, July, and August. NMDI presents a smaller variation during drought when compared to NDVI, NDWI, and NDII6, portraying NMDI insensitivity to agricultural drought. The NMDI shows a right-skewed shift at the end of the 2012 growing season, unlike the histograms of other indices above. The NMDI range goes from 0 to 0.8 NMDI and is used to detect and monitor the moisture of vegetation and soil over large areas (Lingli Wang and John J Qu, 2007). The NMDI band stands for Normalized Multi-band Drought Index, which incorporates data from MODIS "SWIR bands, as well as the NIR band. NMDI utilizes the differences between the two SWRI bands, which are sensitive to soil and plant water content. The relative difference between these two SWIR bands changes according to fluctuation in both soil and plant water content.

NDII6 is able to capture variations of normal year averages and 2012 data values. The skew extends towards the right, indicating a positive trending. The NDII6 band ranges from -0.4 – 0.6. The greater the value among the x-axis, the healthier vegetation reflectance there is. If the value on the x-axis is negative, then there is stressed vegetation reflectance. The NDII6 index is a normalized difference infrared index that integrates both the NDVI and NDWI indices and is able to be derived to monitor vegetation moisture content. Strong absorbance by water makes this band suitable for estimating the water content found in plants. NDII6 is able to capture variations of normal year averages and 2012 data values. The skew extends towards the right, indicating a positive trend. Lastly, Normalized Difference Infrared Index (NDII) is a widely-used index to remotely sense Equivalent Water Thickness (EWT) of leaves and canopies. Considering that MODIS has three SWIR bands at 500 m resolution, two of which have been used in NDWI and NDII respectively, we apply the last SWIR band 7 to generate the similar calculation: R_{860} nm-R_{2130} nm / R_{860} nm + R_{2130} nm. NDII7 is used in this study.

5.3 Chapter Summary

This study has evaluated the capability of MODIS measurements in agricultural drought monitoring through analysis of time series of 13-year NDVI, NDWI, NDII6 and NDII7, NMDI products. The correlation between anomalies in MODIS indices and precipitation-based SPI data was examined across the primary Corn and Soybean Belt to evaluate MODIS index to detect agricultural drought caused by precipitation deficits. The SPI values calculated at different timescale were also examined to evaluate vegetation response to precipitation anomalies at different time steps. The results showed that the index anomalies were better correlated with the 6-month SPI than 3-month SPI and 9-month SPI suggesting these anomalies are reflective of agricultural drought conditions caused by median-scale rainfall deficiency. Among the tested indices, NDII6 showed the highest overall correlation with all SPI over 3, 6, and 9-months, demonstrating good sensitivity of NDII6 to water stress over large agricultural areas and therefore has potential for application as a suitable index to monitor agricultural drought conditions.

CHAPTER SIX: A NEW APPROACH FOR AGRICULTURAL DROUGHT DETECTION USING REMOTE SENSING MEASUREMENTS

6.1 Crop Yield Statistics

The basis of this objective is to analyze and evaluate the relationship between US county-level averages of corn and soybean yields versus common variables collected through the entire crop growing season by remote sensing measurements. Crop yield statistics is to highlight natural events such as weather and climatic condition. Additionally, the statistics show strategies playing out and identify regions that are chronically underperforming. These strategies include planting irrigation, fertilizer and pesticide uses.

The statistics are gathered from the National Agricultural Statistics Service (NSAA) and from the United States Department of Agriculture (USDA) to establish state and national level yield estimates. Corn and soybean are the two largest commodities grown by land area and the planted acreage has steadily expanded in reach by about 25% over the last couple of decades (USDA/NASS Quick Stats) and yield trends for these two crops have been increasing. They are both high value commodities for the global export market of the United States.

6.2 Remote Sensing of Crop Yield

Specific crop focuses have been emphasized on corn and soybeans. These two crops have been studied often partly due to the widespread quintiles of geography, and also due to other potential crops. With regard to remote sensing technologies which have been progressed, there is a newer and more sophisticated sensor called the Moderate Resolution Imaging Spectroradiometer (MODIS), which improves on AVHRR in terms of spectral responses, spatial resolutions, and greater emphasis placed on land related observations (Justice et al., 2002). MODIS is aboard two earth science research oriented satellites, Terra and Aqua, launched in 1999 and 2002. MODIS carries about 36 spectral bands with most having a nadir ground resolution of about 1 km, similar to AVHRR. Two of the key bands for land observations, the red and NIR, have finer resolutions of about 500 m.

Additionally, remote sensing techniques being used to derive precipitation data gives context to yields considering rainfall rates vary based upon locations. To measure rainfall amounts, the Tropical Rainfall Measuring Mission (TRMM) has been established to provide accurate spatial details. TRMM does not monitor the Corn Belt region of the United States however. This is because its orbit around planet earth is positioned for it to focus only on the equatorial tropics and subtropics, so it does not capture imagery beyond 35 degrees north and south. Within the US however, there is an alternative option, the NWS part of the NOAA operates a ground based remotely sensed data set with coverage provided Doppler radars by which precipitation levels can be estimated (Seo, 1998).

6.3 Study Area

The 12 states focused on are geographically contiguous, relatively flat and level, and have very fertile soils. These twelve states make up more than three-fourths of the US corn and soybean production, and therefore constitute the study area from which yield surveying satellites obtain data from as shown in (Figure 47) below.

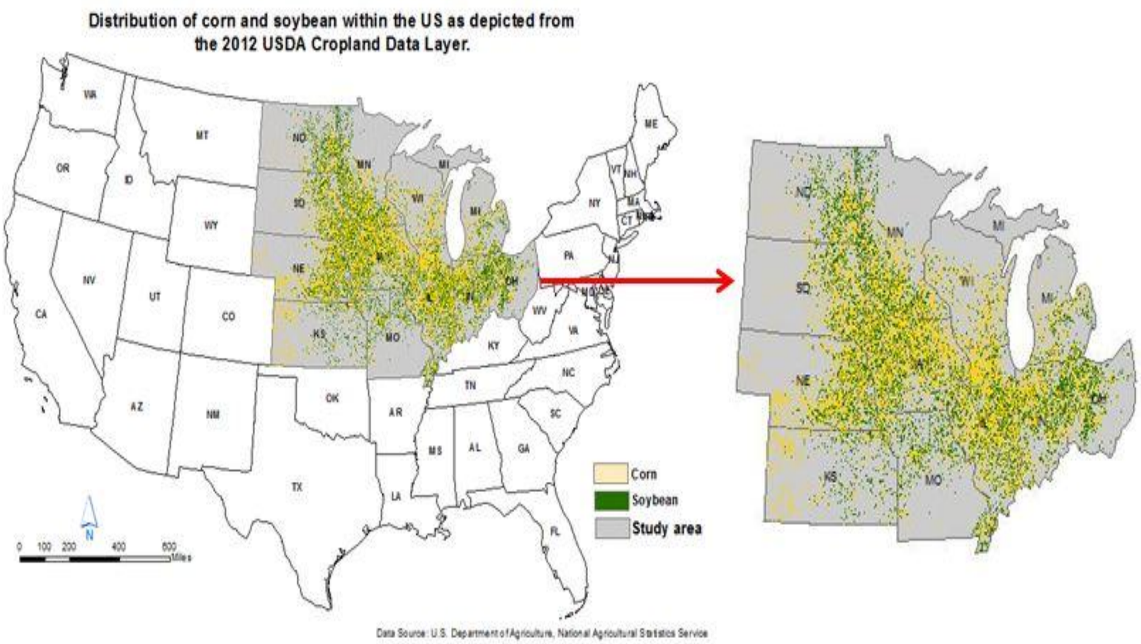


Figure 47 Distribution of corn and soybean within the US as depicted from the 2012 USDA Cropland Data Layer. Deeply shaded states are those that were used in analysis.

6.4 Developing a New Approach for Agriculture Drought Monitoring

The main objective is to firmly understand the relationship between US county-level average corn and soybean yields versus relatively common variables collected throughout the entire crop growing season (May - September) via remote sensing over all of the years (2006-2012) by the Pearson coefficient of determination (R^2).

The results are shown in (Figures 48, 49, 50, and 51) for soybean and (Figures 52, 53, 54, 55) for corn respectively. The variables assessed were a time series of the NDVI, NDII6, and NDII7 as derived by the Terra MODIS sensor, and precipitation estimates produced from the NWS Nexrad Doppler weather radar system. The Nexrad precipitation datasets were both considered novel in regard to what has been researched previously for predicting crop yields. Also, equal importance to corn and soybeans was given whereas in many studies only a single crop type is analyzed.

This new approach involves datasets taken from NDVI, NDII6, NDII7, and Precipitation. The datasets detail spatial characteristics and enable the modeling of crop field levels. The NDVI and NDII6, NDII7 resolution is 500 m. The precipitation is about 4 km. Temporal revisit times are also high with all of these products as raw input data for each are collected daily. On any given date cloud cover impacts quality of imagery from remote sensing satellites and MODIS composite products help simplify data management and processing. The precipitation dataset is also produced and distributed but not impacted by cloud cover due to the penetrating ability of radar used. The entire data series time window was only to cover the primary Corn and Soybean Belt crop growing season typically from May through September during the years of 2006 to 2012.

The dependent variables for which remote sensing dataset were compared and came from annual county level corn and soybean yields as published by the USDA NASS and an annual average yield for each county for both corn and soybeans across the primary Corn and Soybean Belt, years 2006-20012 was gathered.

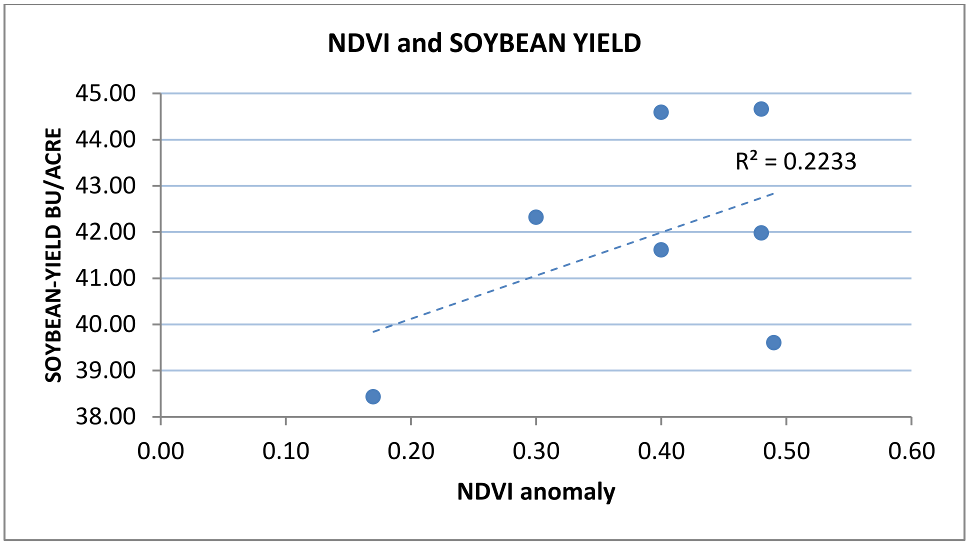


Figure 48 Scatter plots of 2006 -2012 for average of soybean yield for all counties of the study area versus average anomalies of MODIS index for NDVI during growing season from May through Sep for each year from 2006-2012.

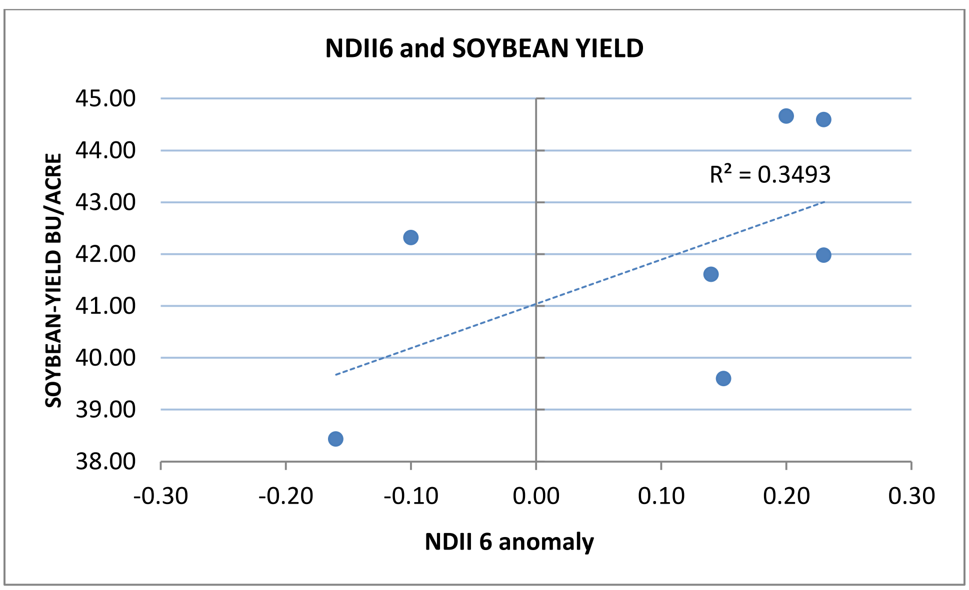


Figure 49 Scatter plots of 2006 -2012 for average of soybean yield for all counties of the study area versus average anomalies of MODIS index for NDII6 during growing season from May through Sep for each year from 2006-2012.

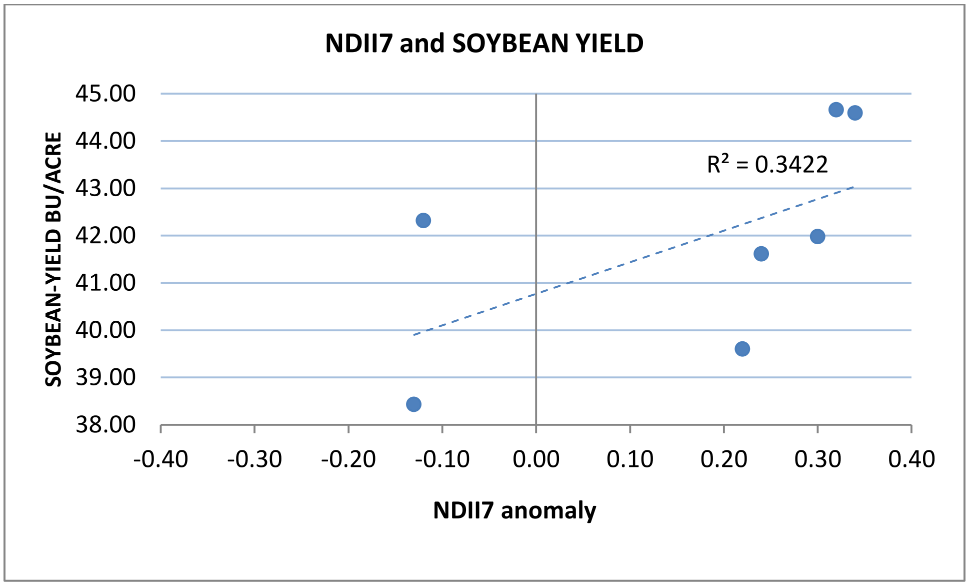


Figure 50 Scatter plots of 2006 -2012 for average of soybean yield for all counties of the study area versus average anomalies of MODIS index for NDII7 during growing season from May through Sep for each year from 2006-2012.

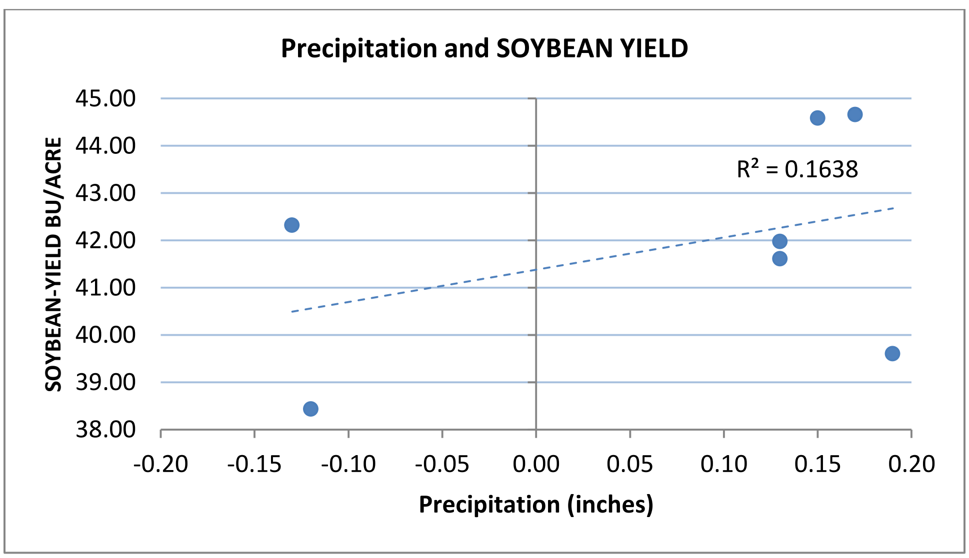


Figure 51 Scatter plots of 2006 -2012 for average of soybean yield for all counties of the study area versus average of precipitation in inches during growing season from May through Sep for each year from 2006-2012.

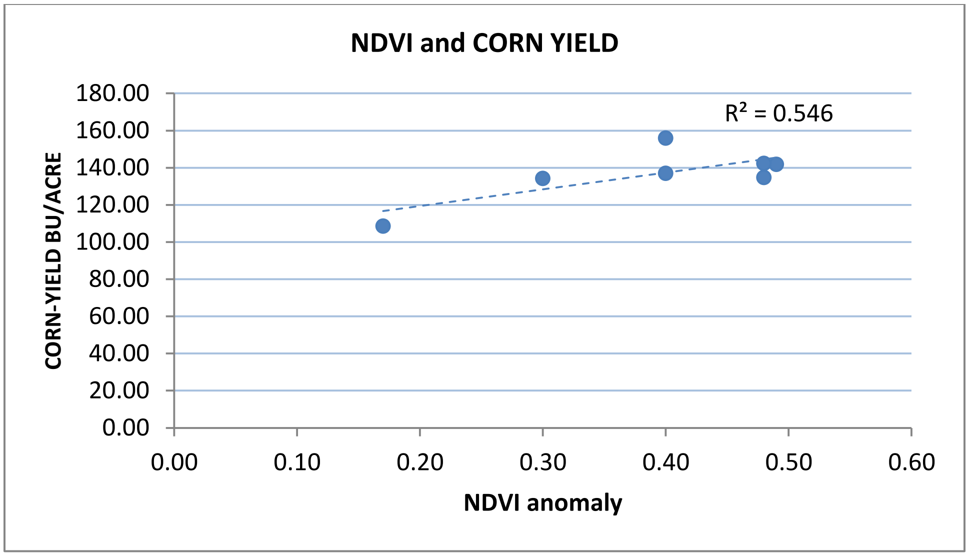


Figure 52 Scatter plots of 2006 -2012 for average of corn yield for all counties of the study area versus average anomalies of MODIS index for NDVI during growing season from May through Sep for each year from 2006-2012.

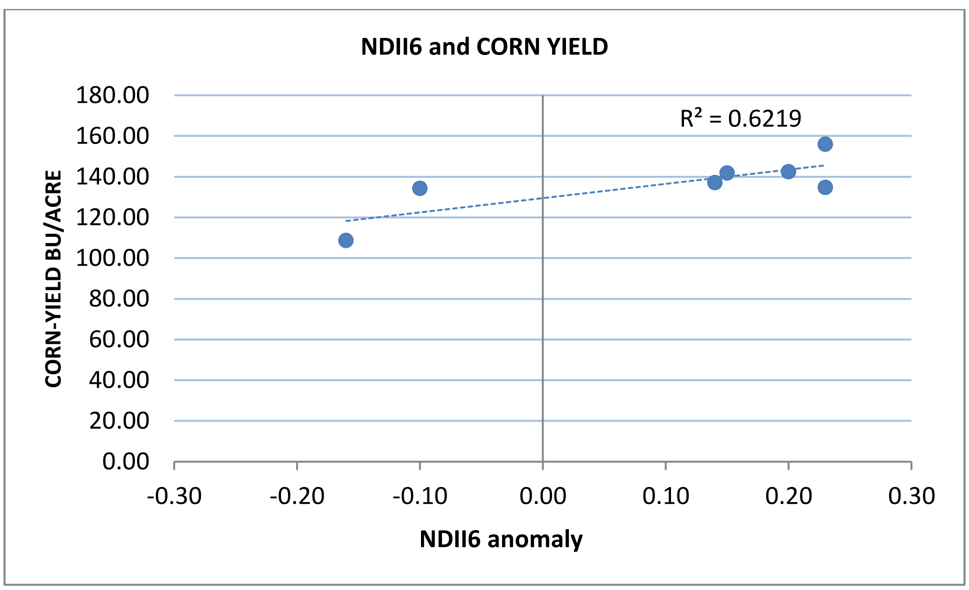


Figure 53 Scatter plots of 2006 -2012 for average of corn yield for all counties of the study area versus average anomalies of MODIS index for NDII6 during growing season from May through Sep for each year from 2006-2012.

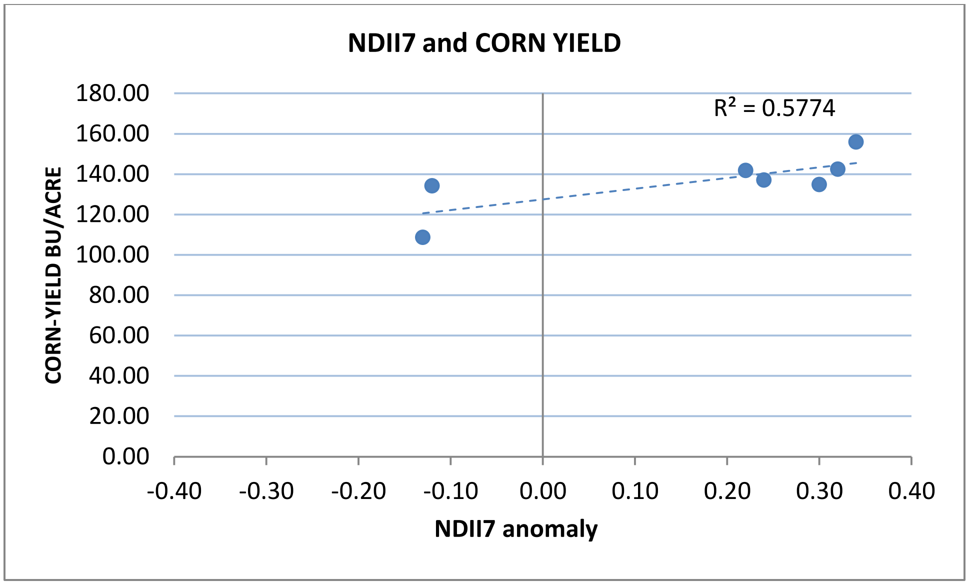


Figure 54 Scatter plots of 2006 -2012 for average of corn yield for all counties of the study area versus average anomalies of MODIS index for NDII7 during growing season from May through Sep for each year from 2006-2012.

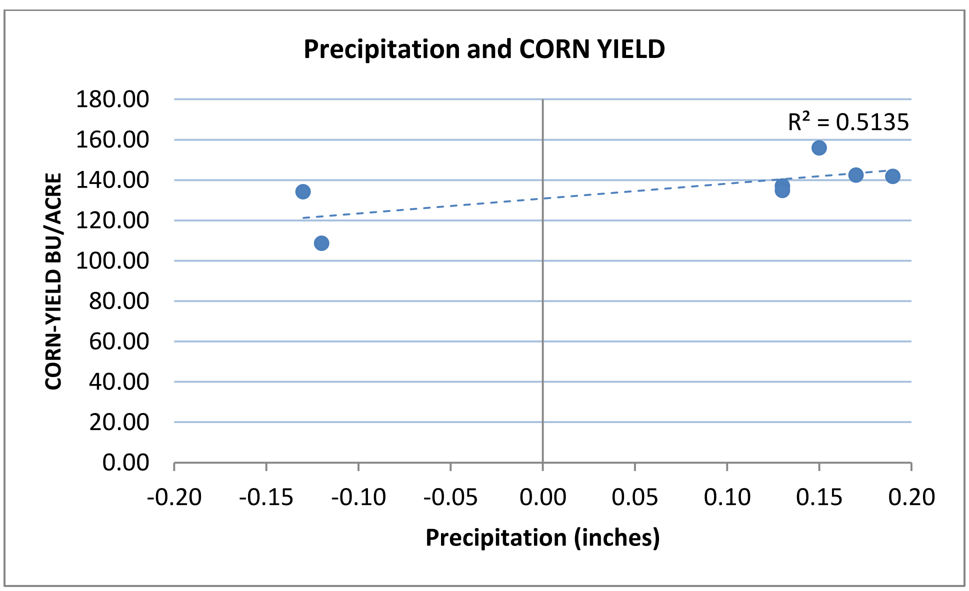


Figure 55 Scatter plots of 2006 -2012 for average of corn yield for all counties of the study area versus average of precipitation in inches during growing season from May through Sep for each year from 2006-2012.

The approach used is the average of corn and soybean yields for all counties of the study area versus average anomalies of the MODIS indices for the growing season between May through Sep for each year. The focus of the research extends to a six-year period, with drought beginning in 2006 up until 2012, whereupon extreme drought effects were experienced in this year.

The results shown in (Figure 53) above show a strong correlation between average corn yields versus MODIS NDII6 averages for the years 2006-2012 between May to September. This is as R^2 equals 0.62, and NDII6 is the greatest indicator to show drought conditions and vegetation moisture monitoring over the Corn Belt region. There is also great correlation between precipitation and corn yields affected on the Corn Belt regions for the year 2012 due to extreme drought as shown in (Figure 55). The best results are shown in (Figure 49) and (Figure 50), whereupon correlations show soybean yields for all counties of the study area in comparison with MODIS NDII6 and NDII7 results between May to September for 2006 to 2012. The weak correlation between $R^2 = 0.16$ averages of soybean yields as shown in (Figure 51) means that there are irrigation and management systems and practices in place. Solar radiation, soil type and water-holding capacity, organic matter content, crop characteristics, disease and pests pressure, soil management, technological improvements from hybrids, producer management techniques, and other management practices that have an impact on crop yield productions on a consistent basis.

6.5 Phenology of Crop for Corn and Soybean Time Series

The (Figure 56) below shows the national average corn-growing progress during the important growing stages of the year, between April and November, between the years 2008 to 2012. The chart below shows the timeline in which the corn crops were planted began emerging, silking, doughing, and then became dented, matured, and finally harvested. Emerged refers to the visibility of the plant from the soil. Silking follows after the tassel emerges. Dough then establishes in all kernels as a dough-like substance. Dent happens when all kernels are dented and the ear is firm and solid, with no milk present in the majority of the kernels. Mature is considered safe from frost with shucks opening and green foliage presented. Soybean phenological stages take place similarly with emerged blooming setting pods, and dropping leaves taking place. Figures below acquired by https://www.nass.usda.gov/Publications/National_Crop_Progress/

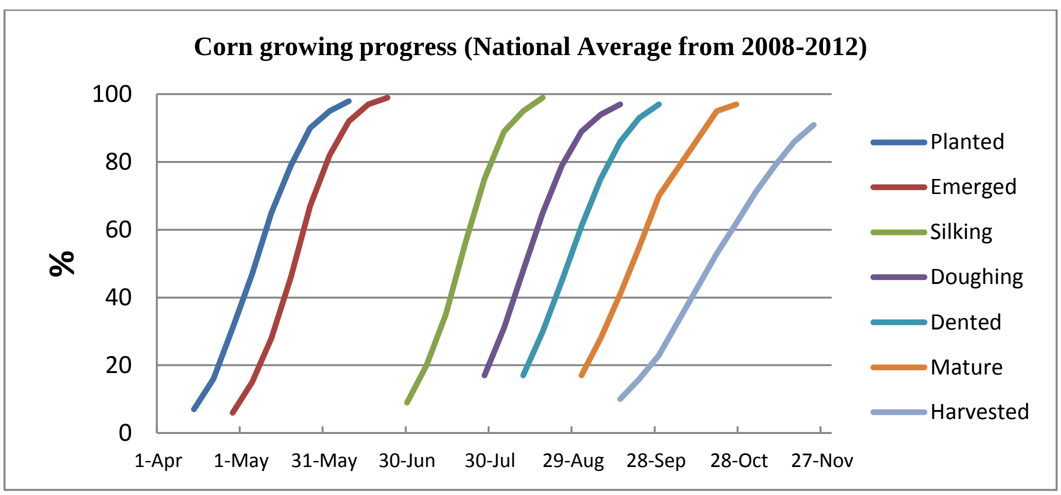


Figure 56 Corn growing progress (national average from 2008-2012)

The (Figure 57) below shows the national average corn-growing progress during the important growing stages of the year, between May and November from 2008 to 2012.

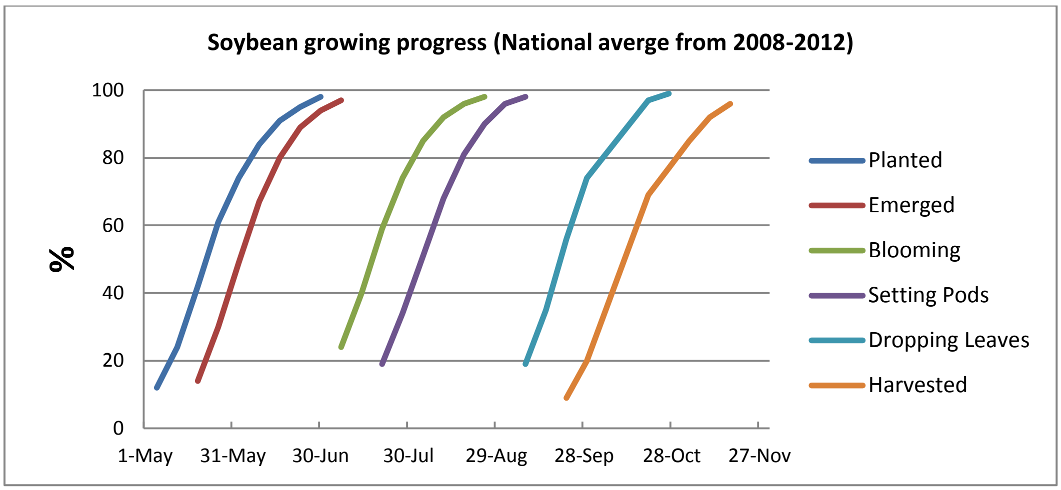


Figure 57 Soybean growing progress (national average from 2008-2012)

The (Figure 58 and 59) show the percentage the progress of crop development given during the phenological stages during the corn and soybean production for each state. The percentages relate to the percentage of plants within a given acre currently in a given phenological stage. Half the expected acreage equates to 50 percent to be used. A figure of 100 percent, weather permitting, gives the time when planting ceases. 50 percent distinguishes when a given field has reached a particular stage, for both corn and soybean crops.

(Figure 58) below gives corn-planting progress for the twelve mid-western corn producing states between the years 2000-2012 from April to mid-June. Also, the (Figure 59) below gives soybean-planting progress of the twelve mid-western soybean producing states between the years 2000-2012 from the end of April to mid-June.

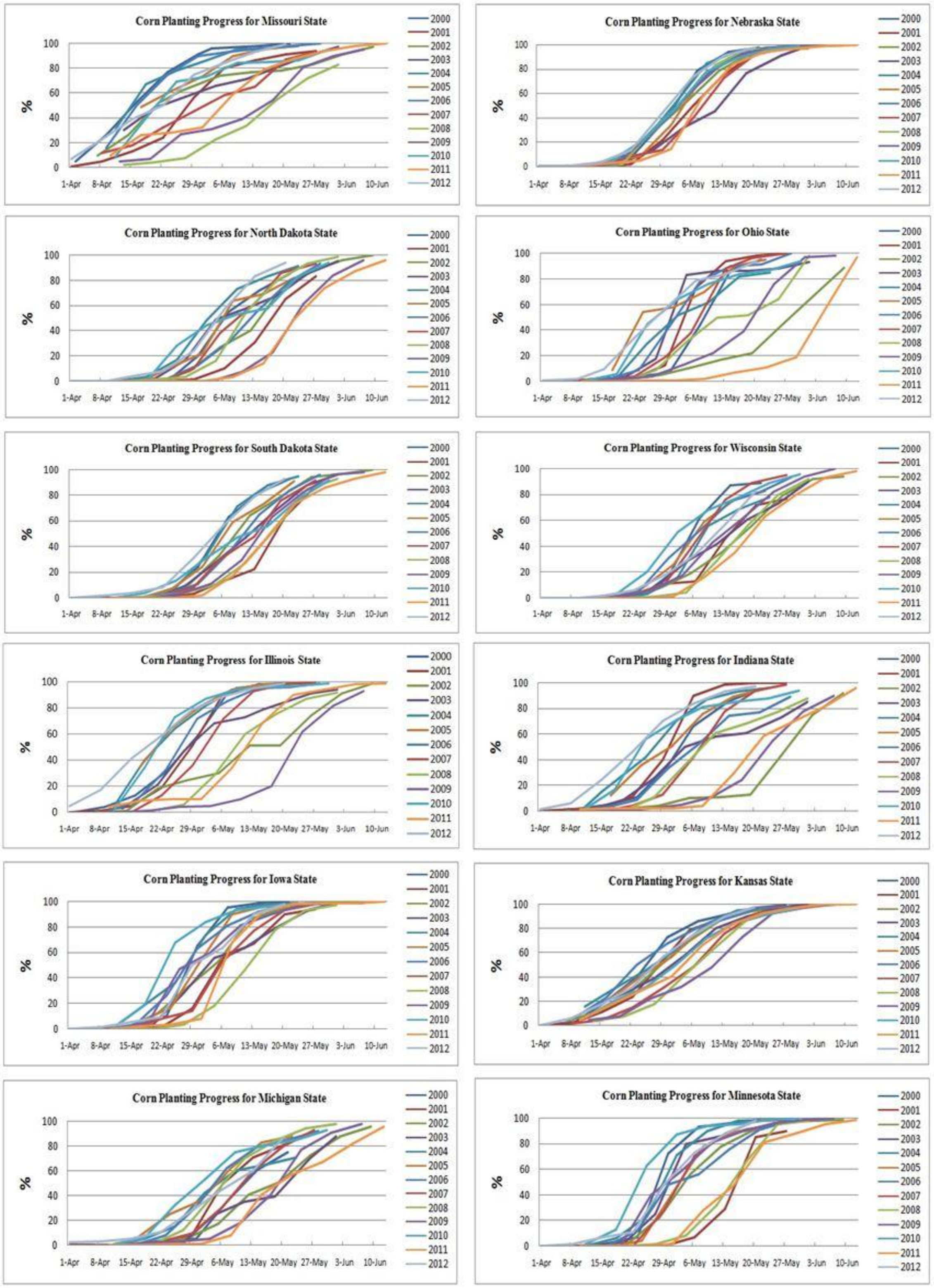


Figure 58 Corn Planting Progress for 12 States of Midwestern US from 2000-2012.

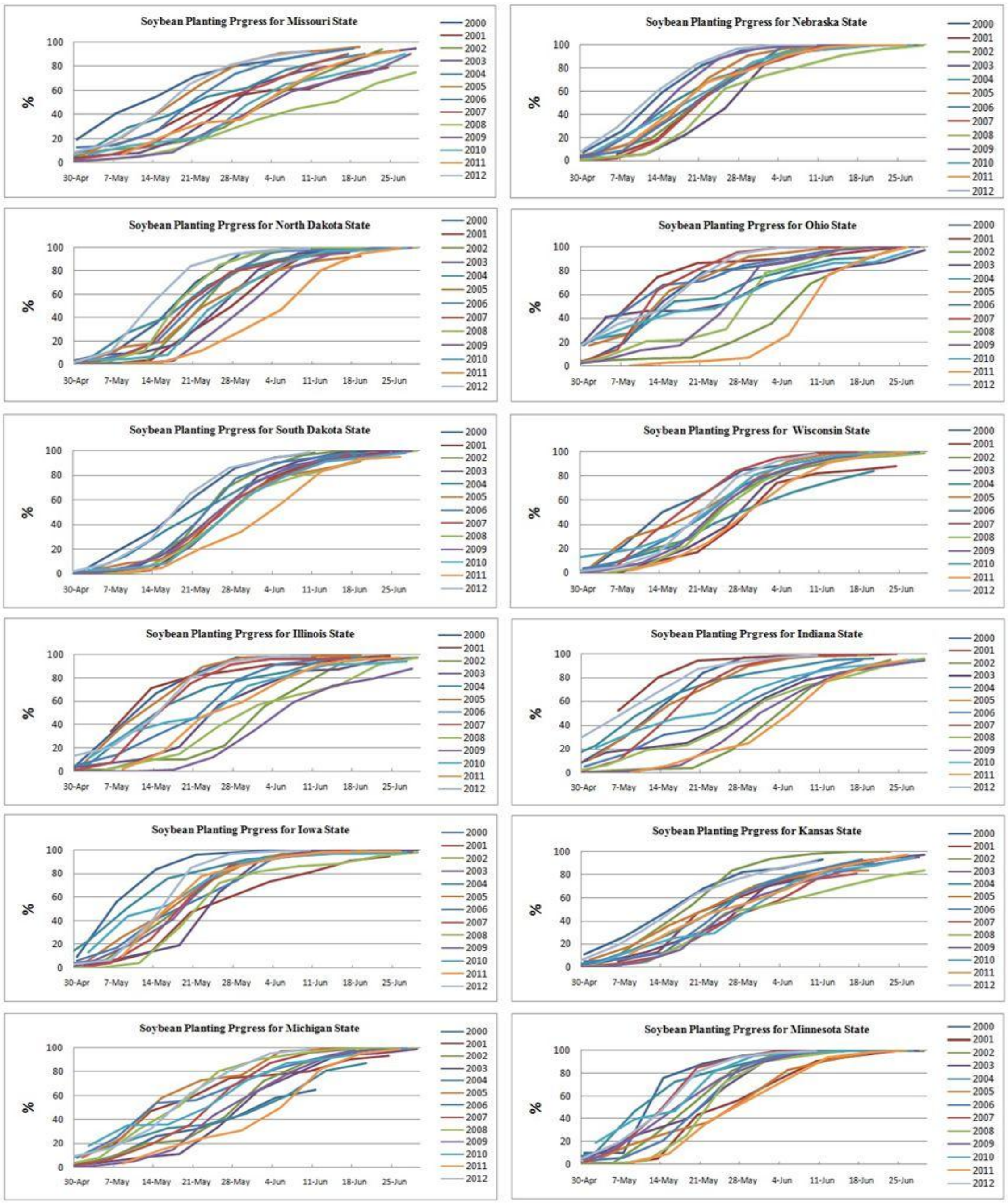


Figure 59 Soybean Planting Progress for 12 States of Midwestern US from 2000-2012.

6.6 Chapter Summary

In summary, four datasets were used to forecast models of county level corn and soybean yields across the US primary Corn and Soybean Belt. The datasets tested included NDVI, NDII6, and NDII7 gathered from space-borne MODIS sensors and precipitation using the NWS Nexrad weather monitoring system. There was a strong correlation between the average corn yields versus MODIS NDII6 averages for the years 2006-2012 between May to September. NDII6 proved itself as the most suitable and efficient indices for showing drought conditions and vegetation moisture monitoring over the primary Corn and soybean Belt. County-level data from NASS between the years 2006 - 2012 was used to verify explanatory power throughout the growing season.

In conclusion, chapter 6 touches upon the approaches used for drought detection. The adequacy of various remote sensing techniques applied to derive precipitation data gives context to yields considering rainfall rates vary depending on the location attributes considered. The various phenological stages are also covered in this section, with details of production during each state of development showing results. There is a strong correlation between average corn yields versus MODIS NDII6 averages for the years 2006-2012 between May to September. There was also strong correlation between precipitation and corn yields affected on the Corn Belt regions for the year 2012 due to extreme drought.

CHAPTER SEVEN: CONCLUSION AND DISCUSSIONS

The dissertation explores the possible applications of remote sensing and GIS technology to agriculturally monitor corn and soybean in the Midwest. With the impact of the 2012 drought over the primary Corn and Soybean Belt, the usage of four indices for monitoring agricultural drought was analyzed. In assessing agricultural drought, the remote sensing drought indices used were NDVI, NDWI, NDII6 and band 7 and NMDI. NDII6 proved to be the most useful for analysis as a result of its ability to capture agricultural yielding under various circumstances. Remote sensing measurements from multiple optical channels were used to monitor soil and vegetation drought based on the spectral reflectance change responding to vegetation and soil moisture variations.

7.1 Conclusion

The main achievements of this research included: 1) Kansas and Nebraska as having performed the best results contained in the Midwestern primary Corn and Soybean belt. The reasoning behind Kansas and Nebraska's results was due to a more efficient and sustainable irrigation system, where upon South Dakota lacked. 2) Precipitation regression with irrigated and non-irrigated levels had high correlations and greater impacts in the month of July. 3) SPI proved itself to offer the best means of using data from the various time-scales with the 3, 6, and 9-month NDII6 performing the strongest. NDII6 performed the best due to its detection abilities. 4) The new approach used is the corn and soybean average for all counties between May and September with the results showing strong correlations between average corn yields versus MODIS NDIII6 averages.

7.1.1 Assessment of the Impact of Drought Effect on Crop Production Using GIS Technology

GIS captures, stores, manages, analyzes, and presents geographic data as a technology. When used toward agricultural means, GIS enables accurate crop mapping and visualization of agricultural environments. In this study, crop yielding and crop production delineates using GIS technology based on different sets of background data. Such maps allow us to better identify agricultural areas and focus on drought monitoring efforts on the most intensive crop yields.

Over the recent years, GIS as a technology has played a critical role in enabling farmers, scientists, and government agencies to view crop patterns and distributions affecting productivity. GIS also aids in crop data publications, facilitating agricultural data between various agencies.

Crop production maps were produced based upon World Agricultural Outlook Board standards. Consistent years of crop production data were used to depict crop patterns using the ArcGIS 10.4 software platform. Crop production data at the county level was sorted from the most intensive agricultural areas to the least intensive areas. Major crop regions identified made up for 75% of the total national production crop areas combined. Crop maps for 13 crops in the US were generated to show corn and soybean. For the corn and soybean crop calendar, there was useful tool provided portraying crop-growing information including planting, sowing and harvesting periods of certain crop species. This support crop growth of agricultural researchers across the world made proper decisions on crops and in guiding agricultural production and sowing periods, respecting agro-ecological dimensions.

Yielding crop maps serve as important sources in illustrating precise farming and agricultural data. The corn and soybean yield maps based on county level data was developed for each year since 2000 to depict the corn output. By comparing yield maps throughout the years, variations in the maps are used to evaluate existing factors that contribute to yield limitations.

GIS technology links data from various sources, and when coupled with weather and climate datasets, benefits agricultural policy makers and analysts by highlighting crop areas where weather and climate might have the greatest impact on agricultural productions and trade.

GIS technology was used to show maps and crop yields for the United States to identify major corn production areas. Corn and soybean yield mapping serves as a useful tool for understanding climate variations of crop productivity. When used in conjunction with climate/weather products and satellite remote sensing measurements, the crop maps facilitate climate/weather fluctuations on agriculture and of water-stressed agricultural losses. During the growing season months of May, June, July, August and September, through the primary Corn and Soybean Belt, Kansas and Nebraska showed the strongest correlations as a result of implemented irrigation systems. South Dakota had strong correlations throughout all SPI periods only for corn, and not soybean.

7.1.2 The Use of GWR to Evaluate Precipitation vs. Irrigated and Non-irrigated Corn and Soybean Yield

GWR proved useful in evaluating spatial heterogeneity study areas between precipitation vs. irrigated and non-irrigated corn and soybean yield. The strongest irrigation results for corn were shown in the southern parts of Nebraska as well as with counties in the east. Non-irrigation results for corn were most relevant on the eastern side of Nebraska with mean yields reaching as high up as 110 BU/Acre and more. The greatest yields for irrigated soybean yields in Nebraska were found most in the south-central counties with mean soybean yields reaching as much as 62 BU/Acre. The results of the GWR model showed very good performance for non-irrigated maize (corn) and soybean. Precipitation is not the only limiting factor driving crop yield; other factors such as evapotranspiration, air temperature, solar radiation, soil type and water-holding capacity impact yielding. In all months and in both irrigated and non-irrigated treatments, yield was proportional to precipitation.

7.1.3 Assessment of MODIS Indices for Agricultural Drought Monitoring

The 2012 drought in the primary Corn and Soybean Belt assisted in assessing the four MODIS indices used: NDVI, NDWI, NDII6, and NMDI to detect drought over agricultural areas. This study evaluated the capability of remote sensing indices in agricultural drought monitoring using 13-year observations.

The results show that index anomalies were better correlated with the 6-month SPI than 3-month SPI and 9-month SPI. This is the result of agricultural drought conditions caused by median-scale rainfall deficiency. Among the tested indices, NDII6 showed the highest overall correlation with all SPI over 3, 6, and 9-months, demonstrating good sensitivity of NDII6 to water stress over large agricultural areas with potential for application as a suitable index to monitor agricultural drought conditions.

The various remote sensing maps and drought maps have been conducted to better understand the complementary drought information that MODIS drought indices can provide. Although the discrepancies in spatial-temporal drought patterns captured by remote sensing maps and USDM maps existed, both MODIS drought maps and USDM maps depict rapid intensifications of drought conditions

7.1.4 An Agricultural Drought Detection Approach Using Remote Sensing to Determine the Correlation between US County-Level Yields

The adequacy of various remote sensing techniques applied to derive precipitation data gives context to yields considering rainfall rates vary depending on the location attributes considered.

There is a strong correlation between average corn yields versus MODIS NDII6 averages for the years 2006-2012 between May to September. There was also strong correlation between precipitation and corn yields affected on the Corn Belt regions for the year 2012 due to extreme drought. The best results were shown in the correlations of soybean yields for all counties of the study area in comparison with MODIS NDII6 and NDII7 results between May to September for 2006 to 2012.

7.2 Limitations of This Work

The Geographically Weighted Regression (GWR) allows variations in relationships between predictors and outcome variables. This means GWR is a local spatial statistical technique which relies on a form of kernel regression within a multiple linear regression framework to develop local relationships between the dependent and independent variables. The geographical weighted regression result is great for spatial heterogeneity with space. GWR is among the new developments of local spatial analytical techniques. GIS is a very important tool when it comes to solving problems and dealing with geo-information. Spatial analysis plays an important role in GIS. An improvement in better integration of GIS and spatial data analysis has come through the development of local spatial statistical techniques. GIS and GWR were used to analyze relations found between precipitations and irrigated and non-irrigated corn and soybean yields between 2000 and 2012 for Nebraska. GWR was good because it showed irrigated and non-irrigated corn and soybean yields. GWR's technique in predicting yields of spatially interpolated precipitation for irrigated and non-irrigated maize and soybean was much better than the performance of the OLS model. The OLS regression model, when used, had a correlating trend between observed yield and the long-term average precipitation total with varying coefficients of determination. An improvement in better integration of GIS and spatial data analysis has come through the development of local spatial statistical technique.

The development of a new approach for Agricultural Drought Monitoring is for the purpose of understanding the relationship between US county-level average corn and soybean yields versus relatively common variables collected throughout the entire crop growing season (May - September) via remote sensing over all of the years (2006-2012) by the Pearson coefficient of determination (R^2). The approach used is the average of corn and soybean yields for all counties of the study area versus average anomalies of the MODIS indices for the growing season between May through September for each year. The focus of the research extends to a six-year period, with drought beginning in 2006 up until 2012, whereupon extreme drought effects were experienced in this year.

There was a strong correlation between average corn yields versus MODIS NDII6 averages for the years 2006-2012 between May to September, with R^2 equaling 0.62. There is also great correlation between precipitation and corn yields affected on the Corn Belt regions for the year 2012 due to extreme drought. The best results showed correlations of soybean yields for all counties of the study area in comparison with MODIS NDII6 and NDII7 results between May to September for 2006 to 2012.

There was a weak correlation with $R^2 = 0.16$ between averages of soybean yields and averages of precipitation. That means there are irrigation and management systems, technological improvements from hybrids, producer management techniques, and other management practices that have an impact on crop yield productions on a consistent basis.

With regard to remote sensing, it plays a major role in applications of soil moisture and drought monitoring. Remote sensing based estimations of soil and vegetation moisture has shown a lot of promise for drought monitoring in this study. The cost effectiveness and the easy availability of remote sensing data with higher spatial and temporal solutions in near real time make remote sensing based operational systems for drought monitoring very practical. This has not been thoroughly investigated here, and would be a key direction for the future work.

7.3 Future Works

With GIS application, further work of application and evaluations of the relatively new GWR technique in similar agricultural research topics can improve the yield predictions by accounting for spatial heterogeneity of other climatic variables except precipitation which was done by this study (i.e., air temperature, solar radiation, etc.) and management practices.

The next generation of MODIS sensor, the Visible and Infrared Scanner (VIRS) provides the ability to monitor weather and climate. Additional research will be able to integrate multiple satellite sensors to establish climate data records for more effective drought climate study over agricultural regions. Different satellite sensors have different spectral, spatial and temporal specifications, cross-sensor calibration and validation is essential to generate long term CDRs (climate recording data), critical for monitoring and assessing drought as well as other natural hazards.

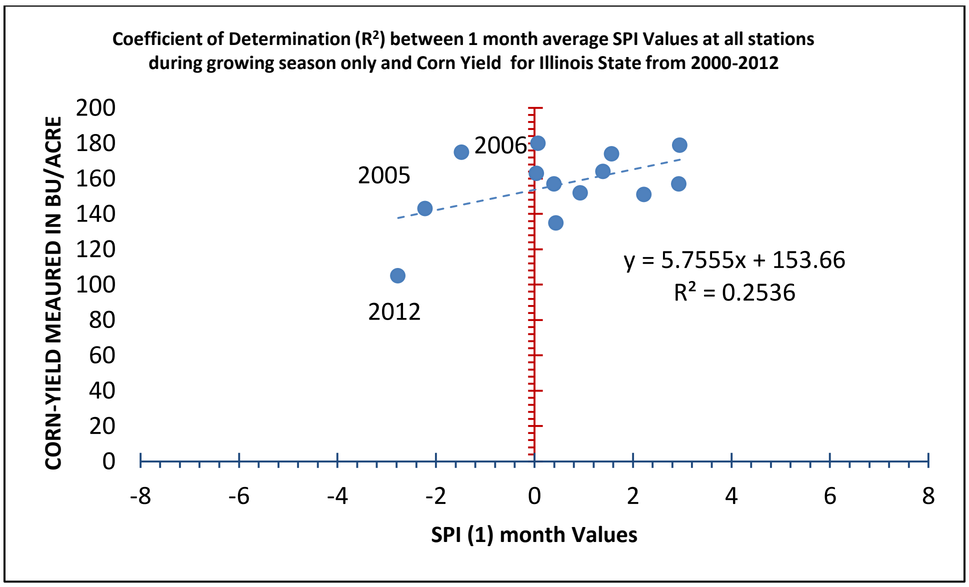
This study illustrated a new approach for agricultural drought monitoring, and additional research can be conducted for corn and soybean areas in the world with different climatic regions using MODIS remotely sensed variables for further evaluation and validation; crop yields of cotton, potatoes, wheat, and barley to name a few.

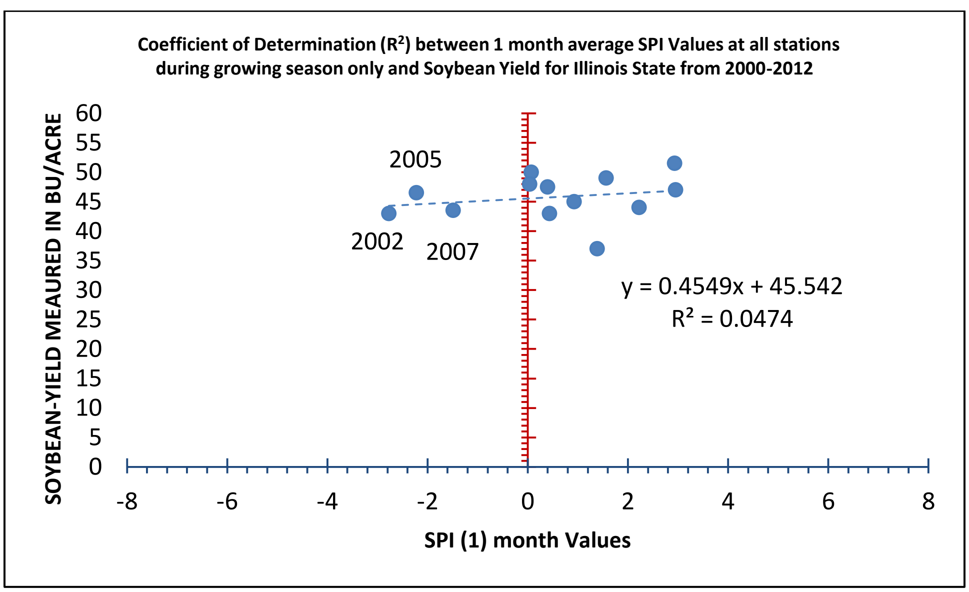
In identifying corn and soybeans phonological profiles using remote sensing, we are able to accurately assess a stage by stage development of crop yield and fruition.

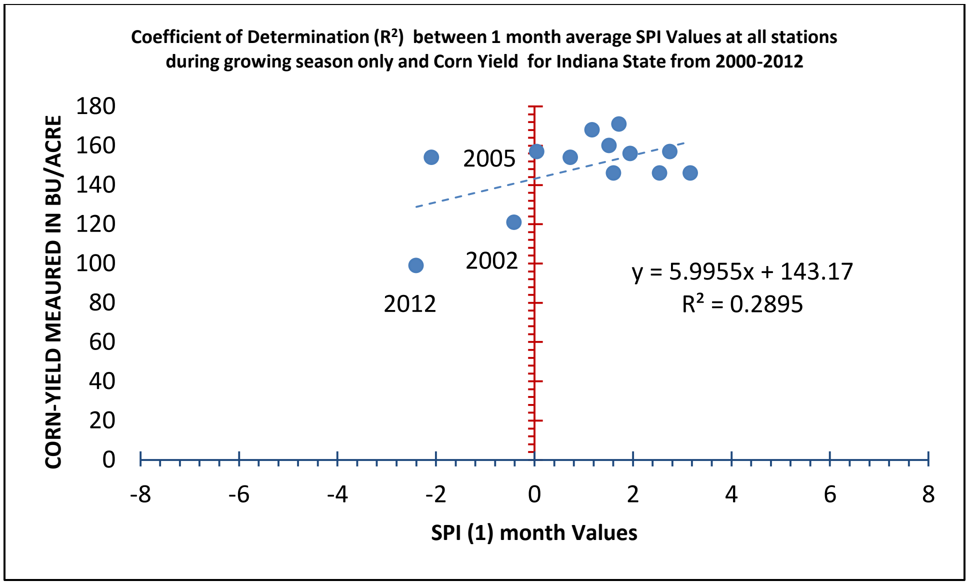
Precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, and reduced ground water or reservoir levels are all examples. These assessments enable early identification, which may also be applied to remote sensing applications, using the electromagnetic spectrum to capture earth features reflecting and emitting energies from earth's surface. Such advances in remote sensing techniques provide the potential to greatly improve agricultural drought detection and assessment.

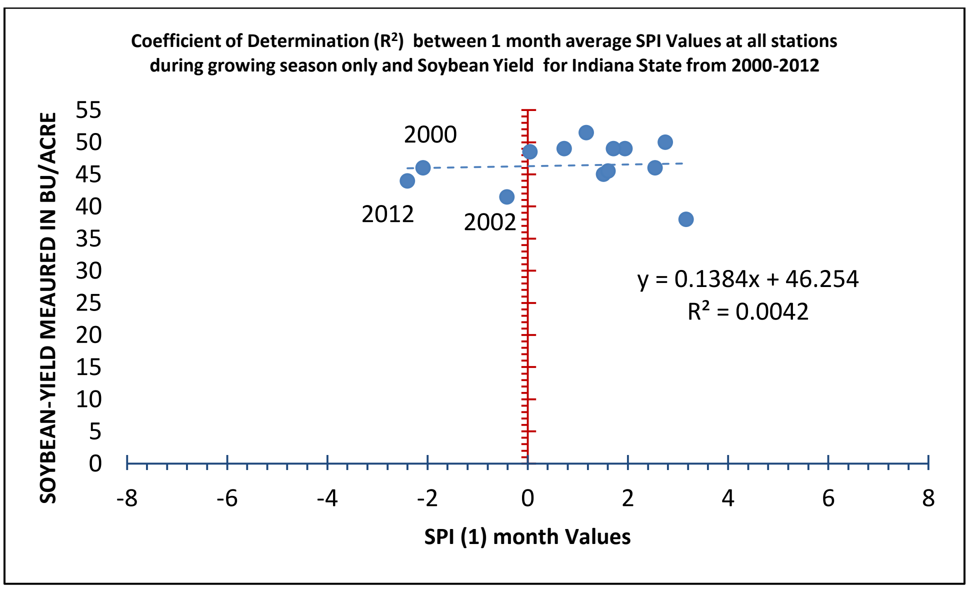
APPENDIX A

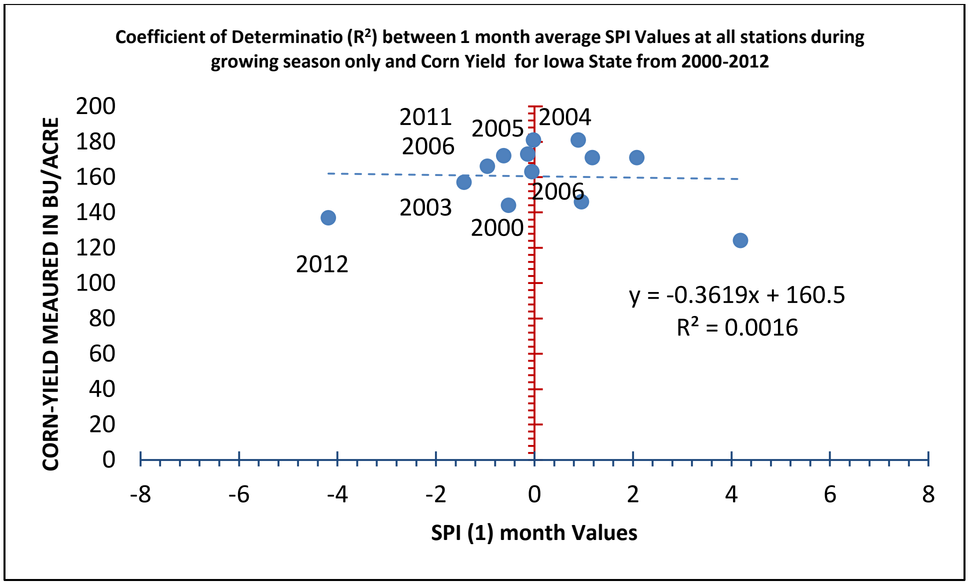
Coefficient of Determination (R^2) between Corn and Soybean Yield with SPI 1 Month



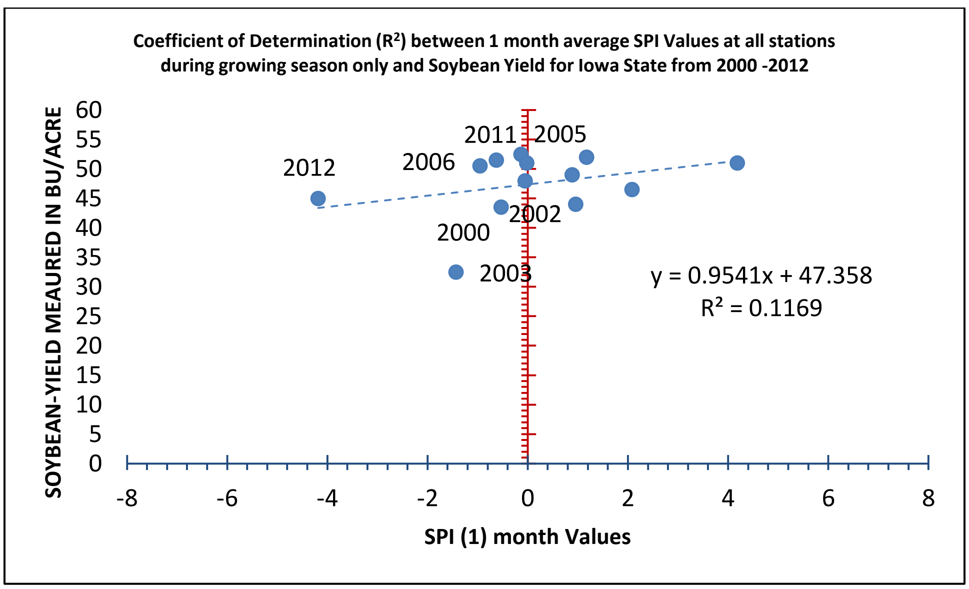



Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Corn Yield for Indiana State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8
SPI (1) month Values
2005
2002
2012
y = 5.9955x + 143.17
R² = 0.2895

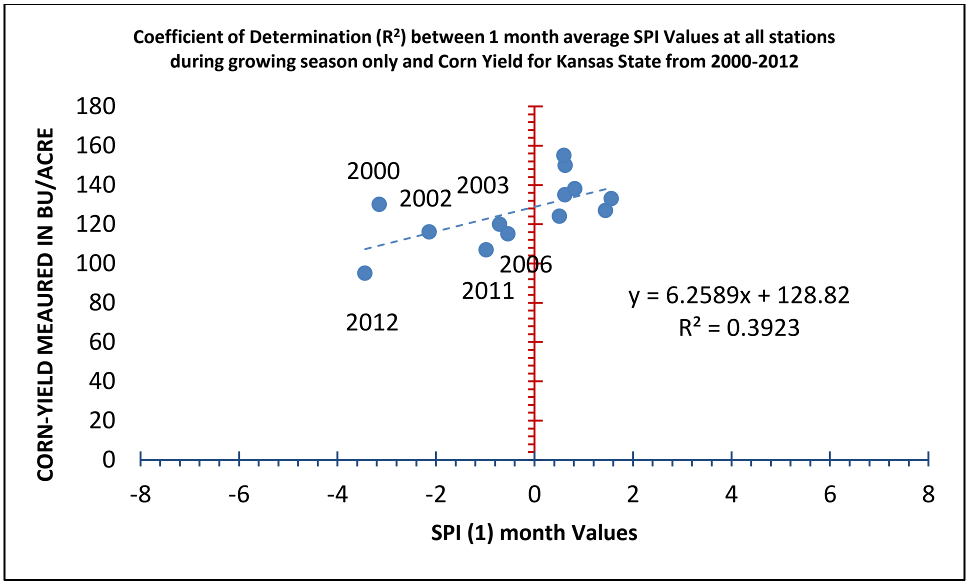

Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for Indiana State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
55
50
45
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8
SPI (1) month Values
2000
2012
2002
y = 0.1384x + 46.254
R² = 0.0042

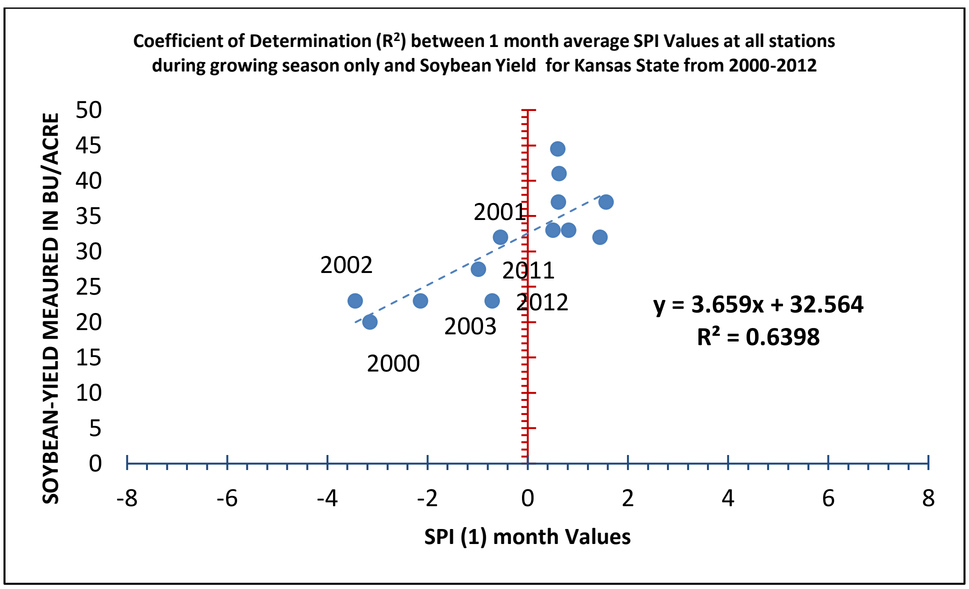


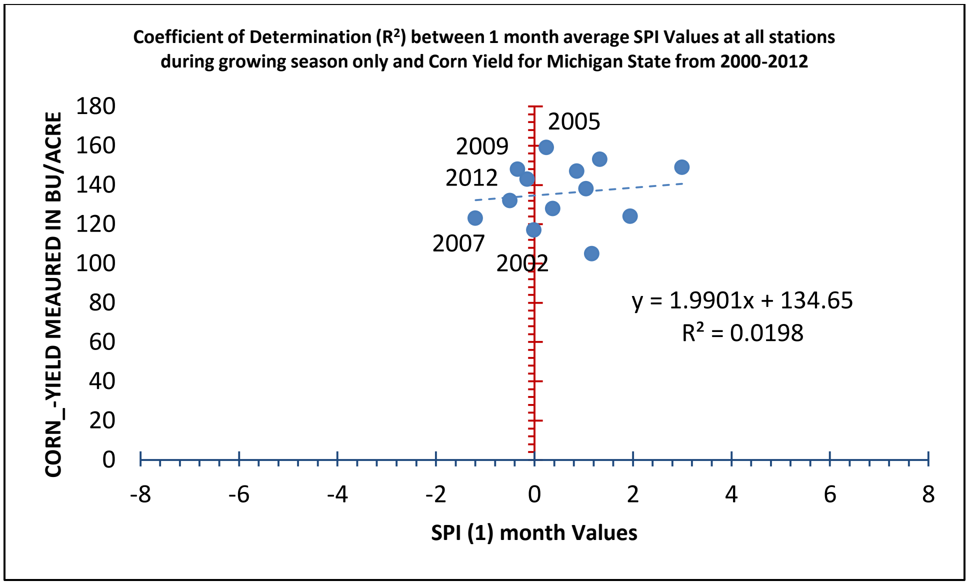
Coefficient of Determinatio (R²) between 1 month average SPI Values at all stations during growing season only and Corn Yield for Iowa State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2011
2005
2004
2006
2003
2000
2006
2012
y = -0.3619x + 160.5
R² = 0.0016



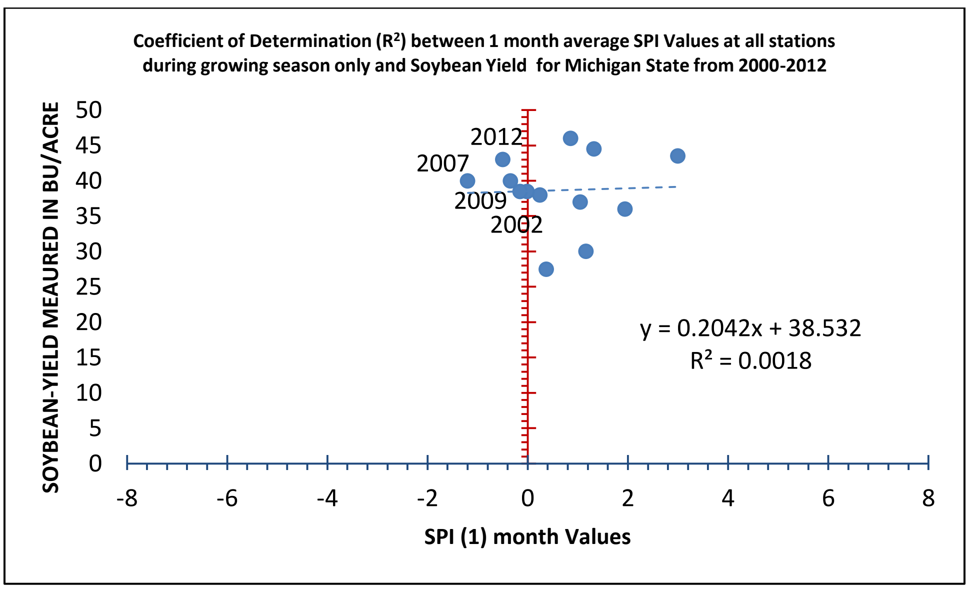
Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for Iowa State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2011
2005
2012
2006
2002
2000
2003
y = 0.9541x + 47.358
R² = 0.1169


Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Corn Yield for Kansas State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2000
2002
2003
2006
2011
2012
y = 6.2589x + 128.82
R² = 0.3923

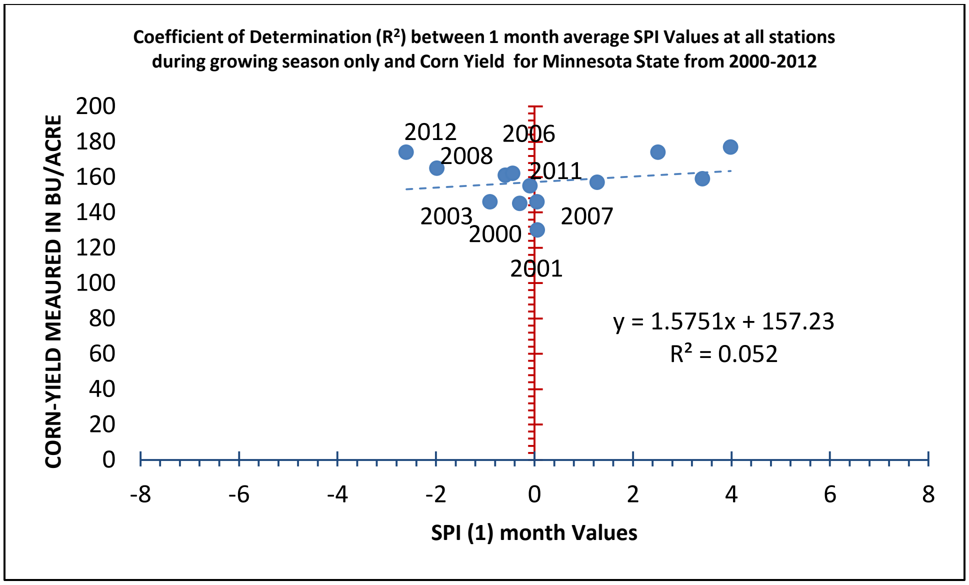

Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for Kansas State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2001
2002
2011
2012
2003
2000
y = 3.659x + 32.564
R² = 0.6398

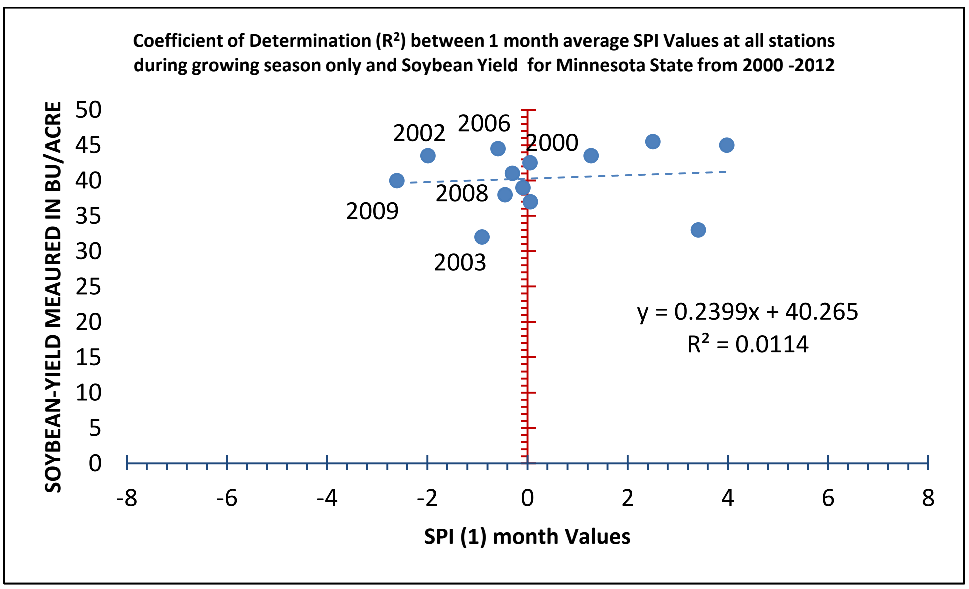


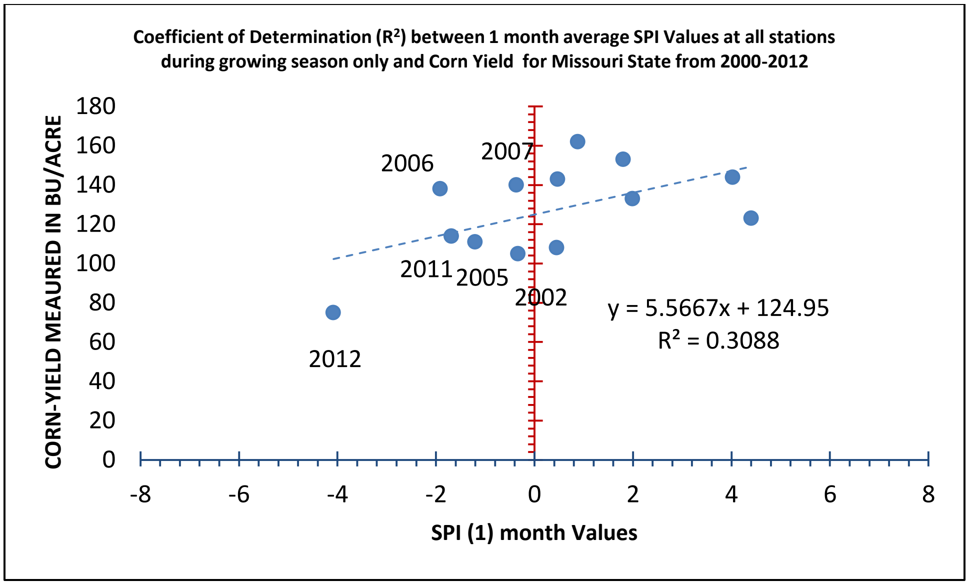
Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Corn Yield for Michigan State from 2000-2012
CORN_-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
2005
2009
2012
2007
2002
y = 1.9901x + 134.65
R² = 0.0198
-8
-6
-4
-2
0
2
4
6
8
SPI (1) month Values

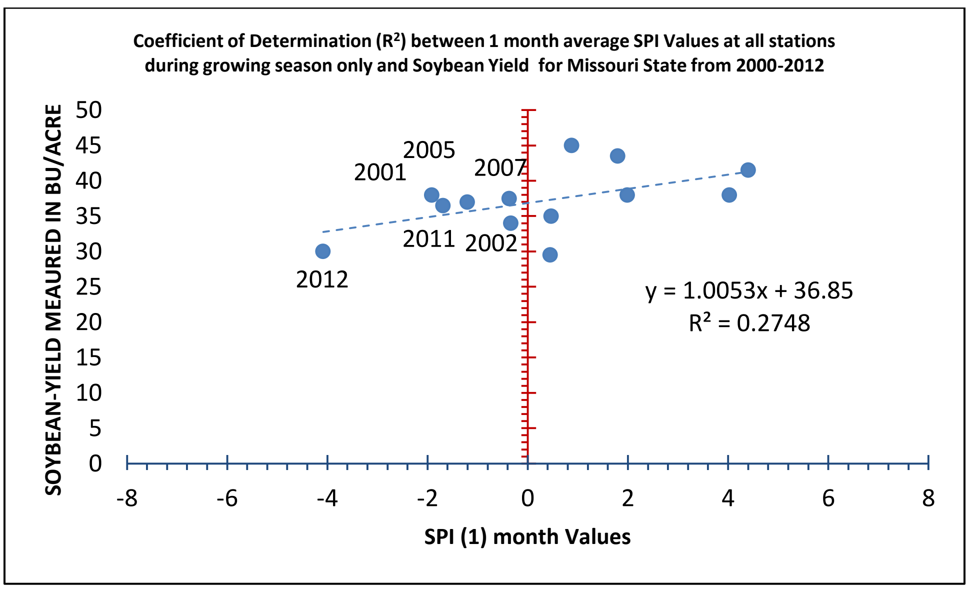


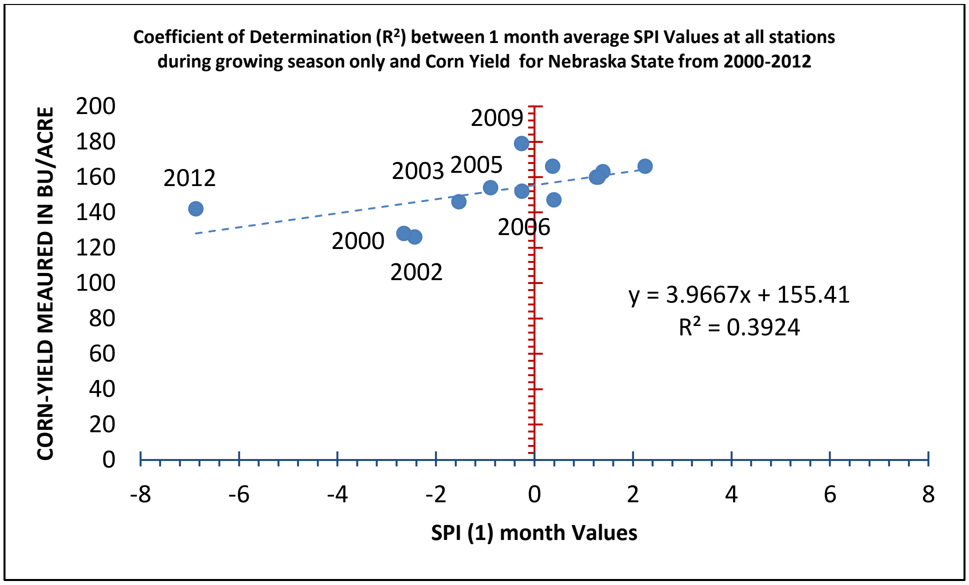
Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for Michigan State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
50
45
40
35
30
25
20
15
10
5
0
2012
2007
2009
2002
y = 0.2042x + 38.532
R² = 0.0018
-8
-6
-4
-2
0
2
4
6
8
SPI (1) month Values


Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Corn Yield for Minnesota State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2012
2006
2008
2011
2003
2000
2007
2001
y = 1.5751x + 157.23
R² = 0.052
200
180
160
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8

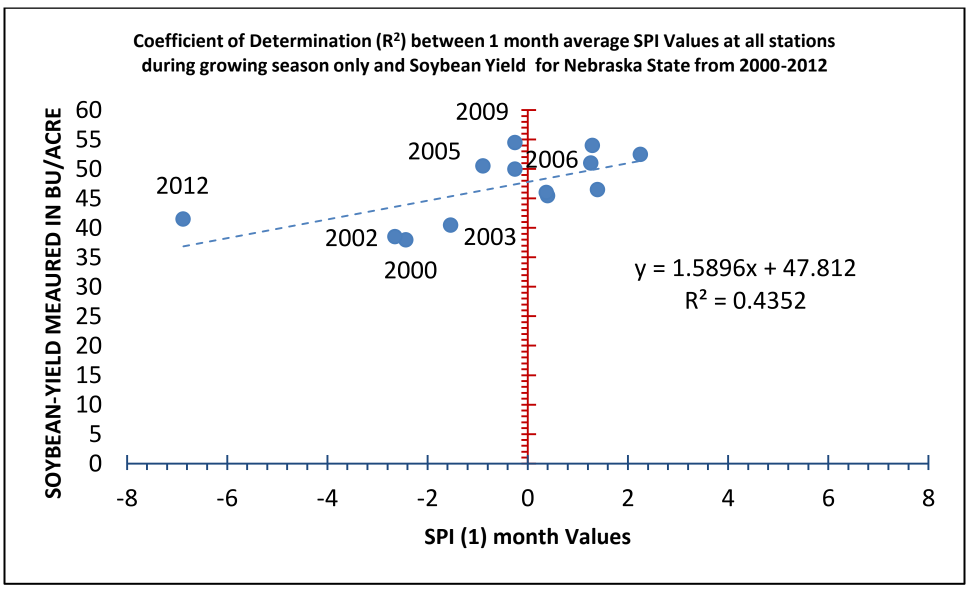

Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for Minnesota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2002
2006
2000
2008
2009
2003
y = 0.2399x + 40.265
R² = 0.0114
50
45
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8


Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Corn Yield for Missouri State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2006
2007
2011
2005
2002
2012
y = 5.5667x + 124.95
R² = 0.3088

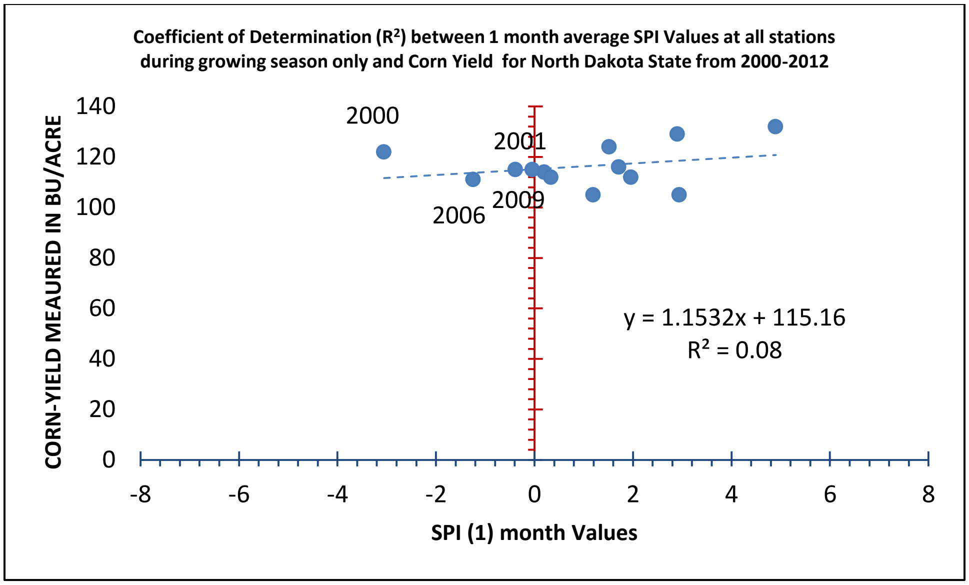

Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for Missouri State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2005
2001
2007
2011
2002
2012
y = 1.0053x + 36.85
R² = 0.2748

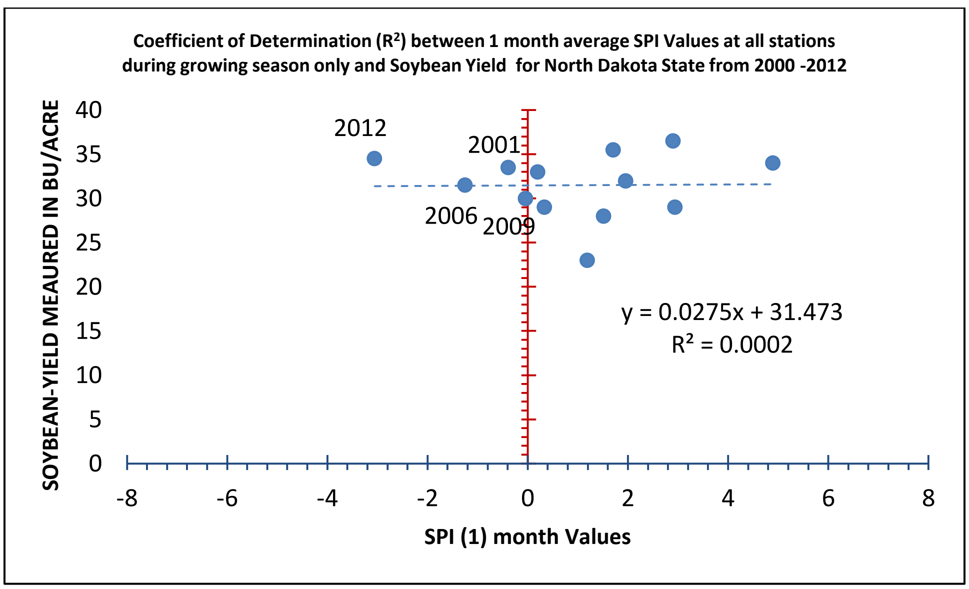


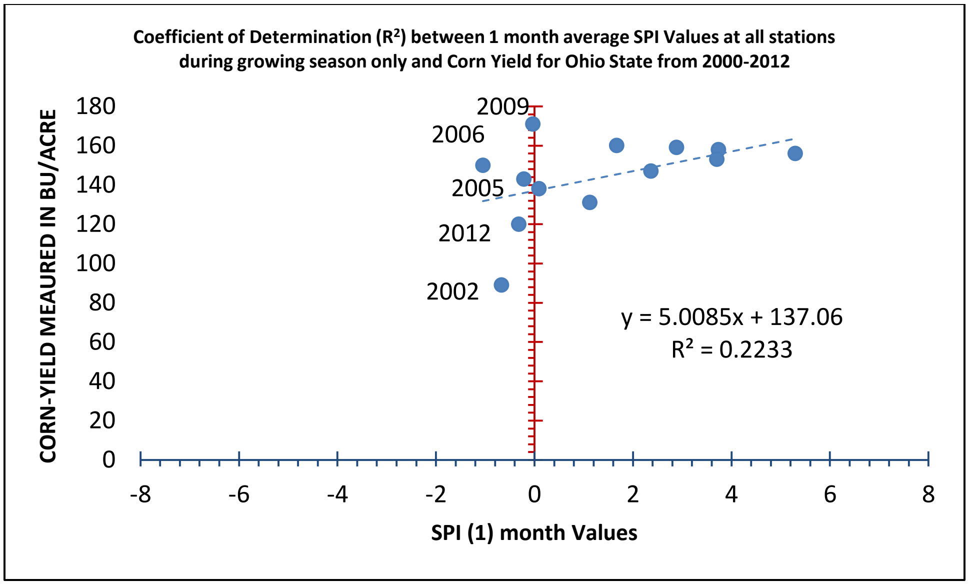
Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Corn Yield for Nebraska State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
200
180
160
140
120
100
80
60
40
20
0
2009
2003
2005
2012
2000
2002
2006
y = 3.9667x + 155.41
R² = 0.3924
-8
-6
-4
-2
0
2
4
6
8
SPI (1) month Values

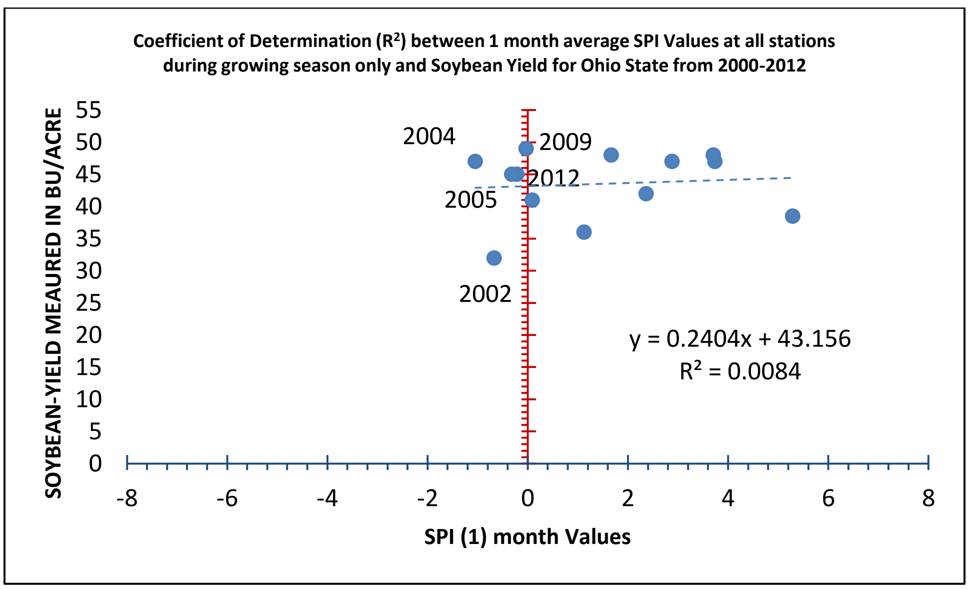


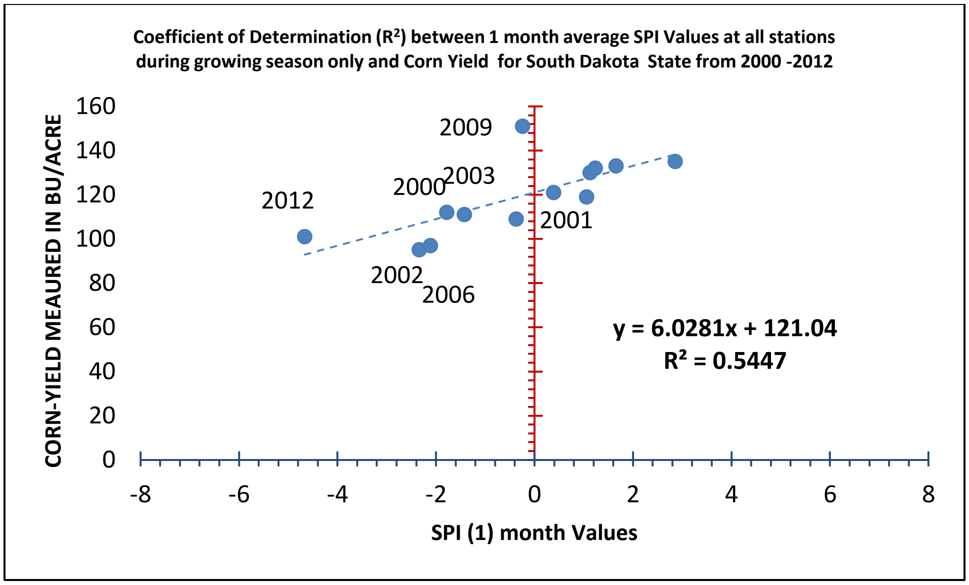
Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for Nebraska State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
60
55
50
45
40
35
30
25
20
15
10
5
0
2009
2005
2006
2012
2002
2003
2000
y = 1.5896x + 47.812
R² = 0.4352
-8
-6
-4
-2
0
2
4
6
8
SPI (1) month Values


Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Corn Yield for North Dakota State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8
SPI (1) month Values
2000
2001
2006
2009
y = 1.1532x + 115.16
R² = 0.08

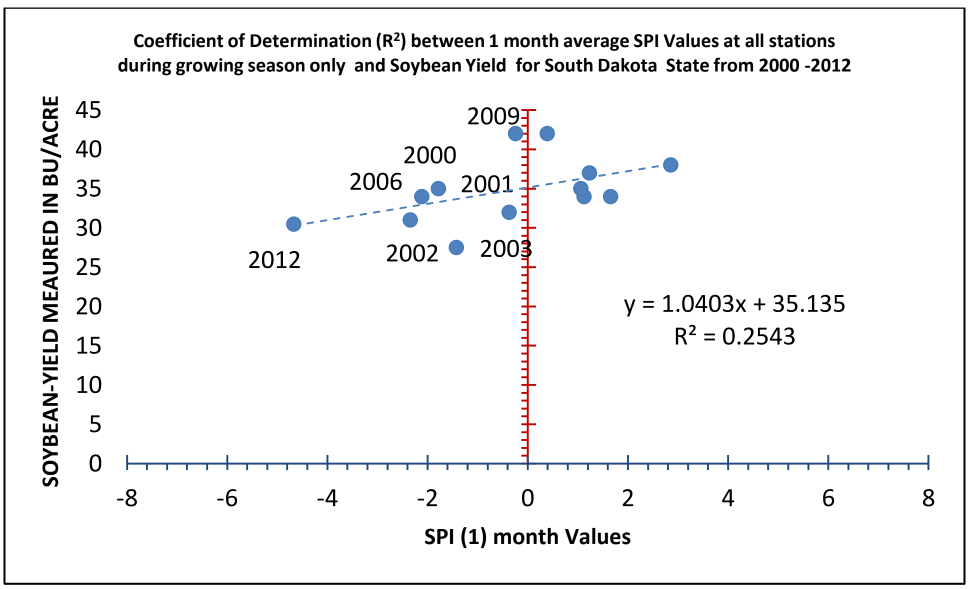

Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for North Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8
SPI (1) month Values
2012
2001
2006
2009
y = 0.0275x + 31.473
R² = 0.0002


Coefficient of Determination (R^2) between 1 month average SPI Values at all stations during growing season only and Corn Yield for Ohio State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2009
2006
2005
2012
2002
y = 5.0085x + 137.06
R² = 0.2233

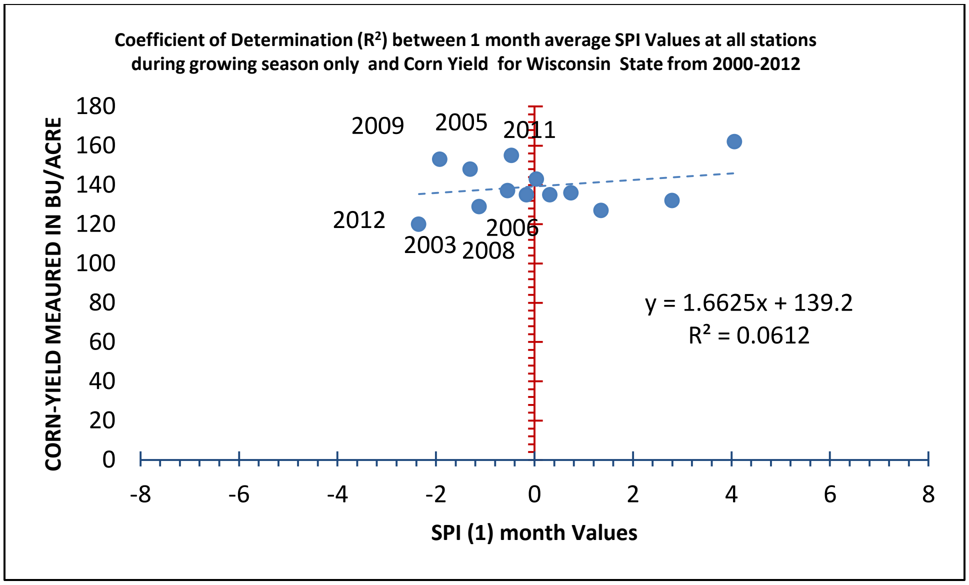

Coefficient of Determination (R^2) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for Ohio State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2004
2009
2012
2005
2002
y = 0.2404x + 43.156
R² = 0.0084

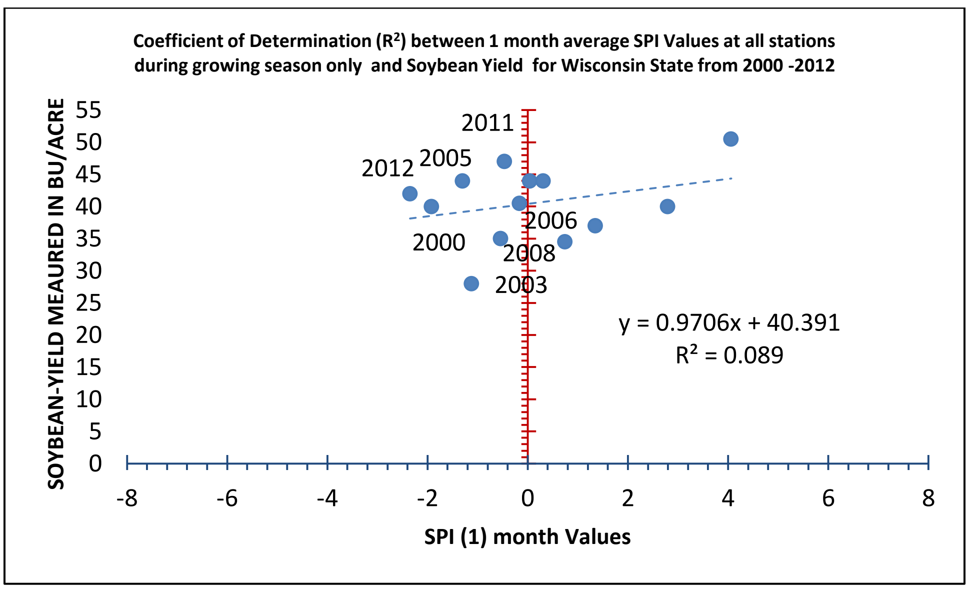


Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Corn Yield for South Dakota State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2009
2000
2003
2012
2001
2002
2006
y = 6.0281x + 121.04
R² = 0.5447

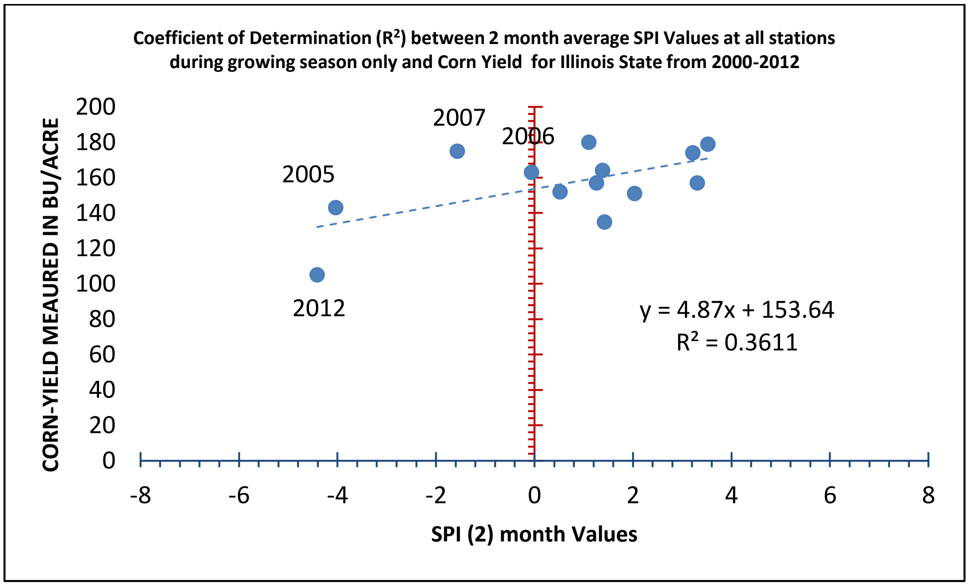


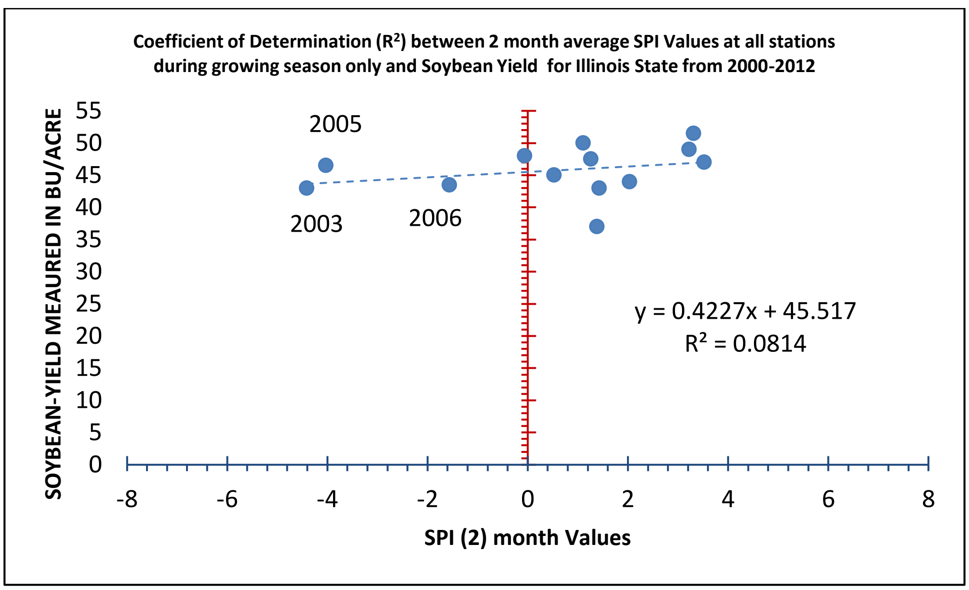
Coefficient of Determination (R²) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for South Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2009
2000
2006
2001
2012
2002
2003
y = 1.0403x + 35.135
R² = 0.2543

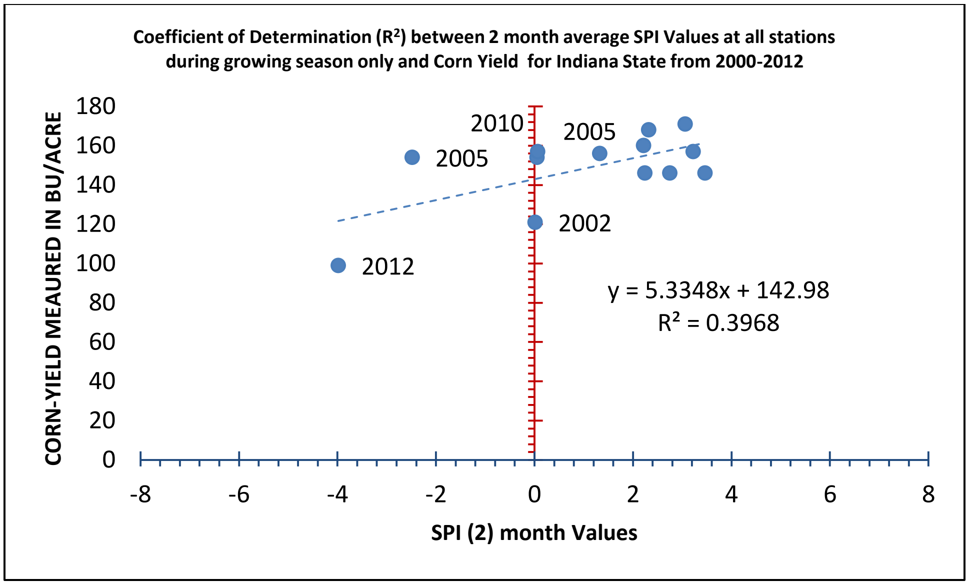

Coefficient of Determination (R^2) between 1 month average SPI Values at all stations during growing season only and Corn Yield for Wisconsin State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2009
2005
2011
2012
2006
2003
2008
y = 1.6625x + 139.2
R^2 = 0.0612

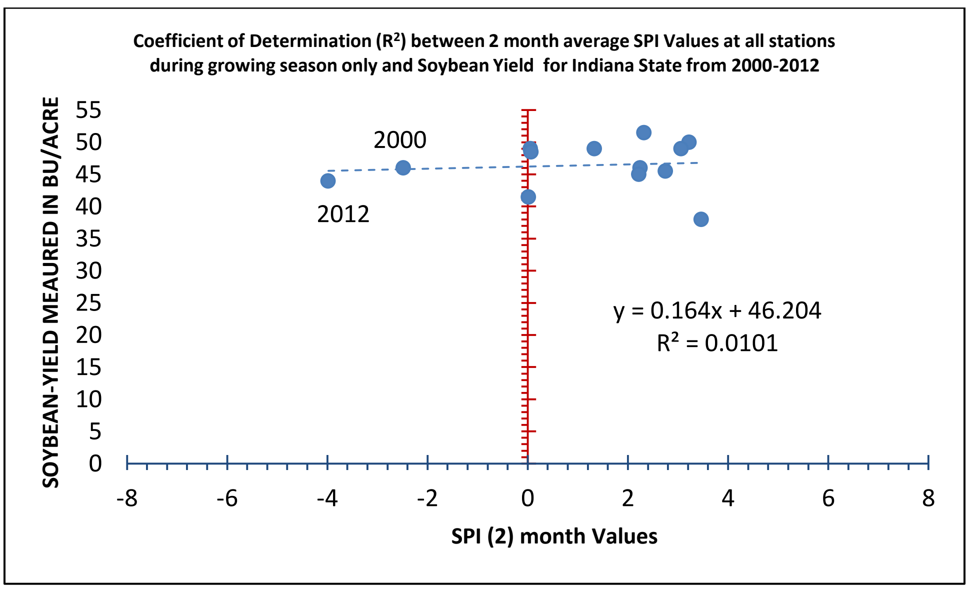

Coefficient of Determination (R^2) between 1 month average SPI Values at all stations during growing season only and Soybean Yield for Wisconsin State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (1) month Values
2011
2012
2005
2006
2000
2008
2003
y = 0.9706x + 40.391
R^2 = 0.089

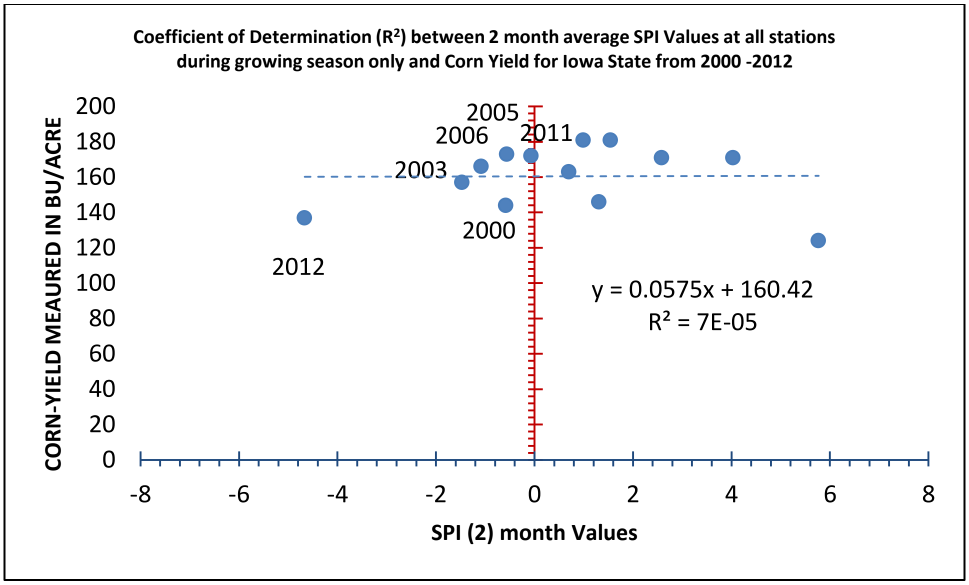
Coefficient of Determination (R^2) between Corn and Soybean Yield with SPI 2 Month

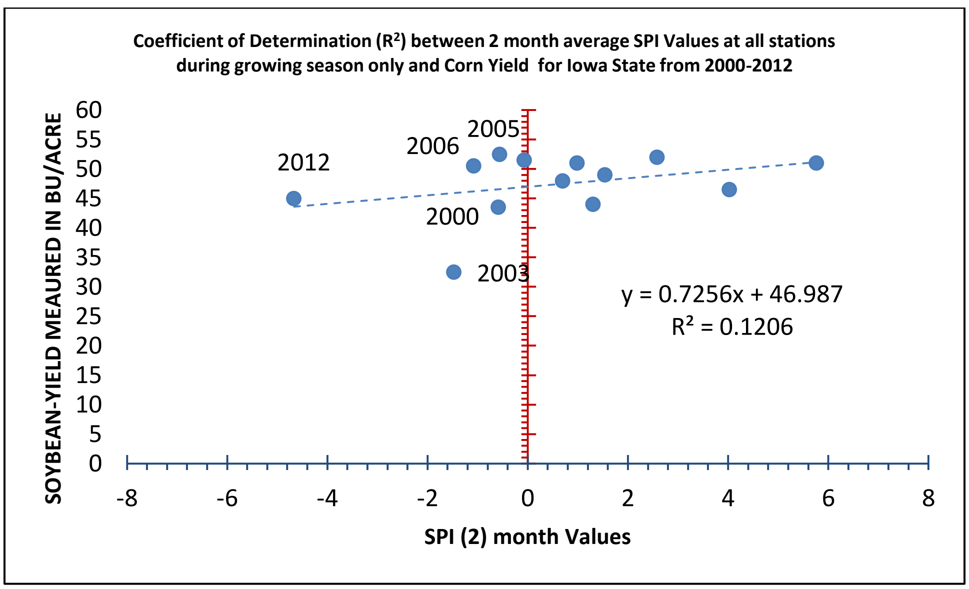


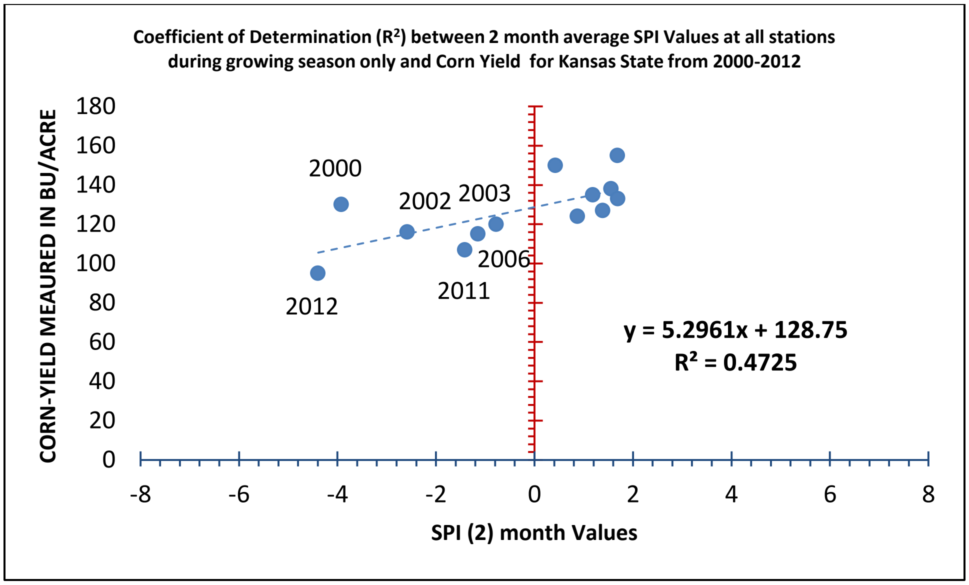


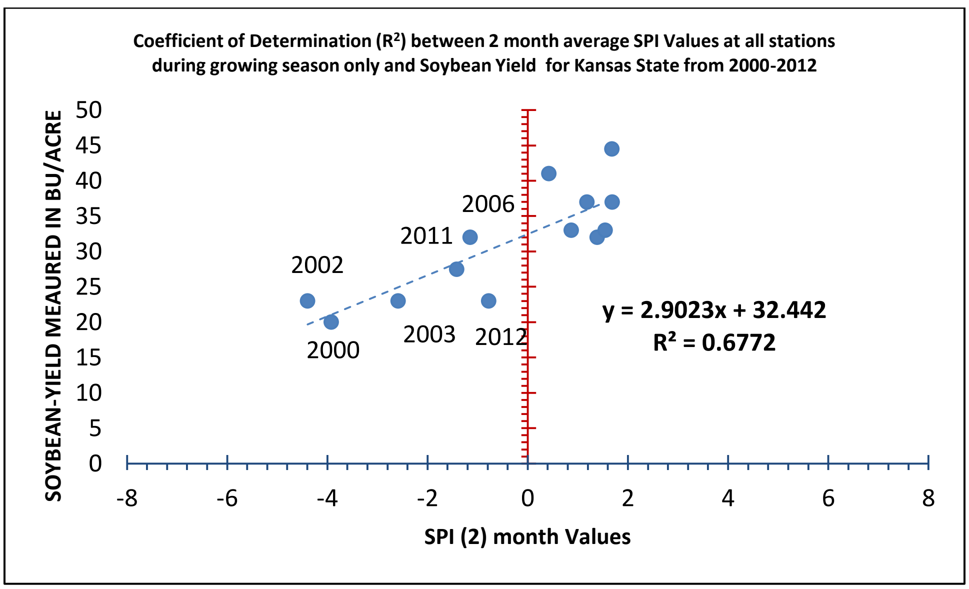

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Indiana State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
2010
2005
2005
2002
2012
y = 5.3348x + 142.98
R² = 0.3968
-8
-6
-4
-2
0
2
4
6
8
SPI (2) month Values

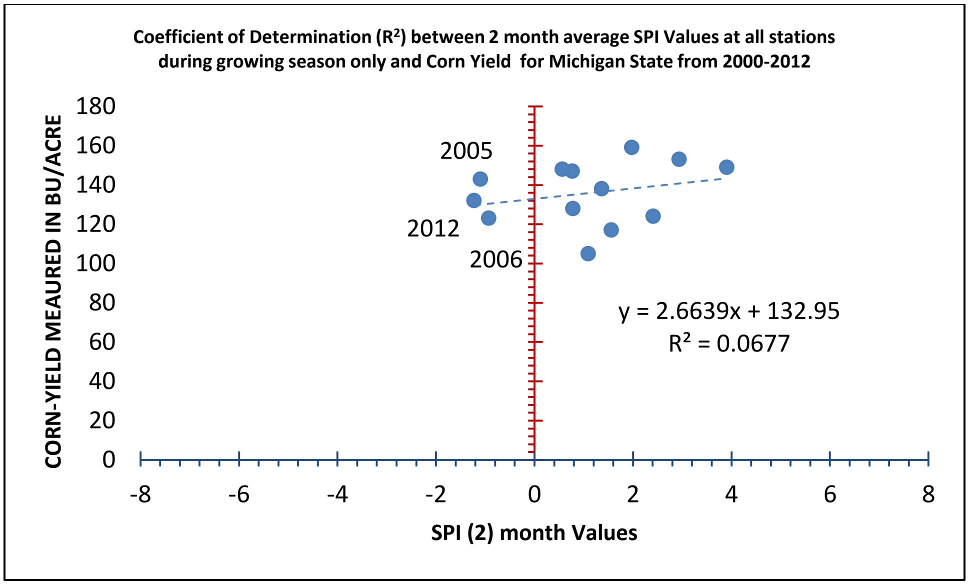

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for Indiana State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
55
50
45
40
35
30
25
20
15
10
5
0
2000
2012
y = 0.164x + 46.204
R² = 0.0101
-8
-6
-4
-2
0
2
4
6
8
SPI (2) month Values

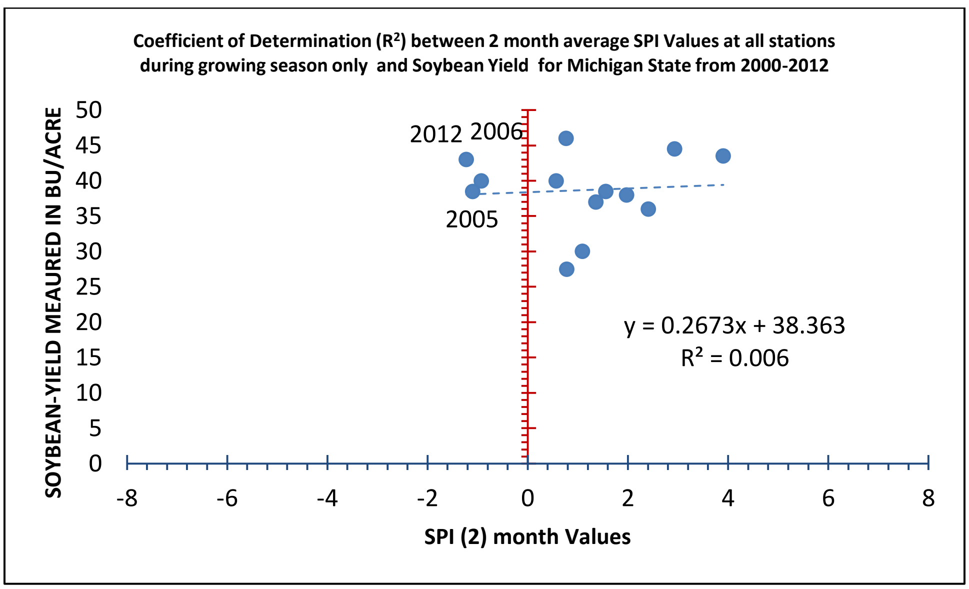

Coefficient of Determination (R^2) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Iowa State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2005
2006
2011
2003
2000
2012
y = 0.0575x + 160.42
R^2 = 7E-05

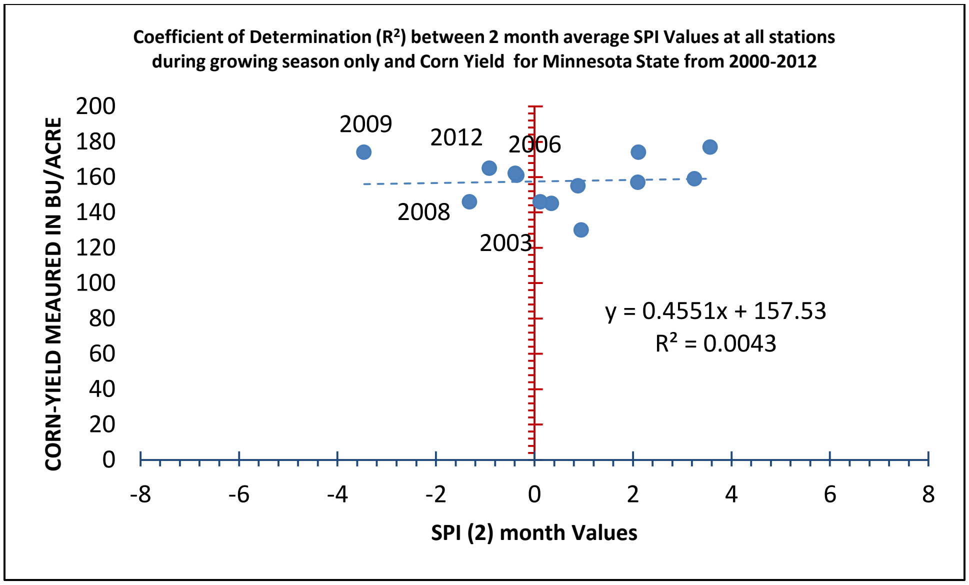

Coefficient of Determination (R^2) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Iowa State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2005
2006
2012
2000
2003
y = 0.7256x + 46.987
R^2 = 0.1206

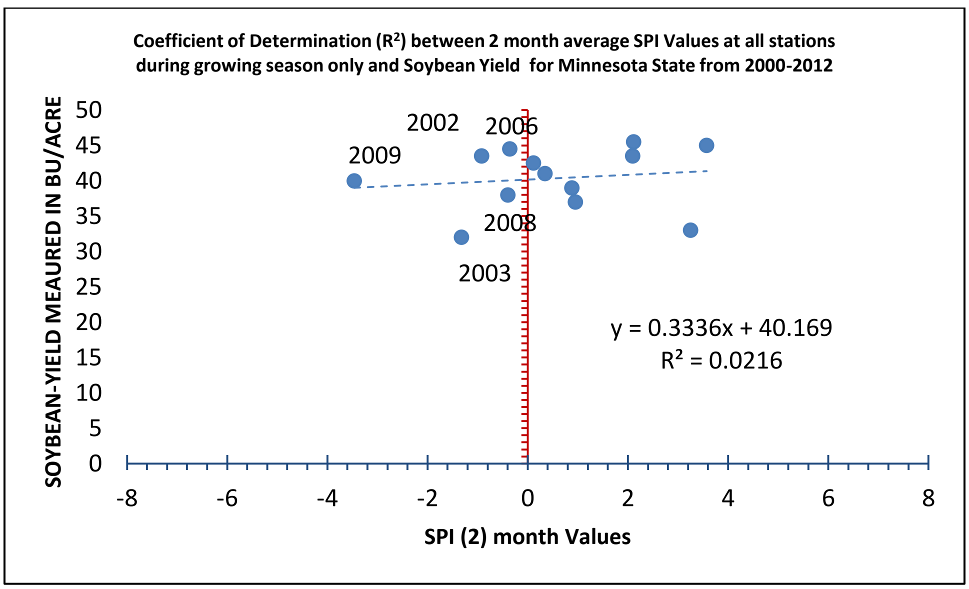

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Kansas State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
y = 5.2961x + 128.75
R² = 0.4725
2000
2002
2003
2006
2011
2012
180
160
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8

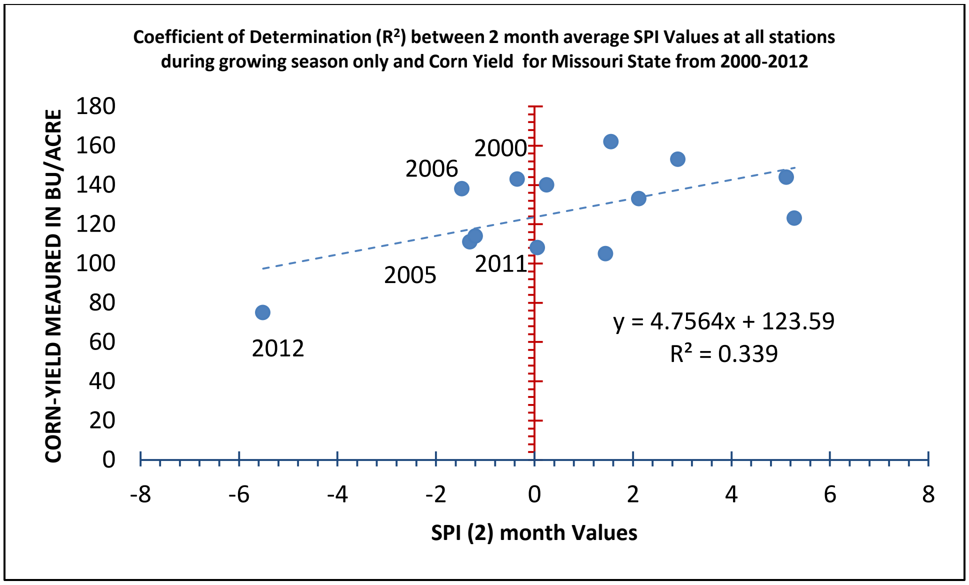

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for Kansas State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
y = 2.9023x + 32.442
R² = 0.6772
2006
2011
2002
2003
2012
2000
50
45
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8

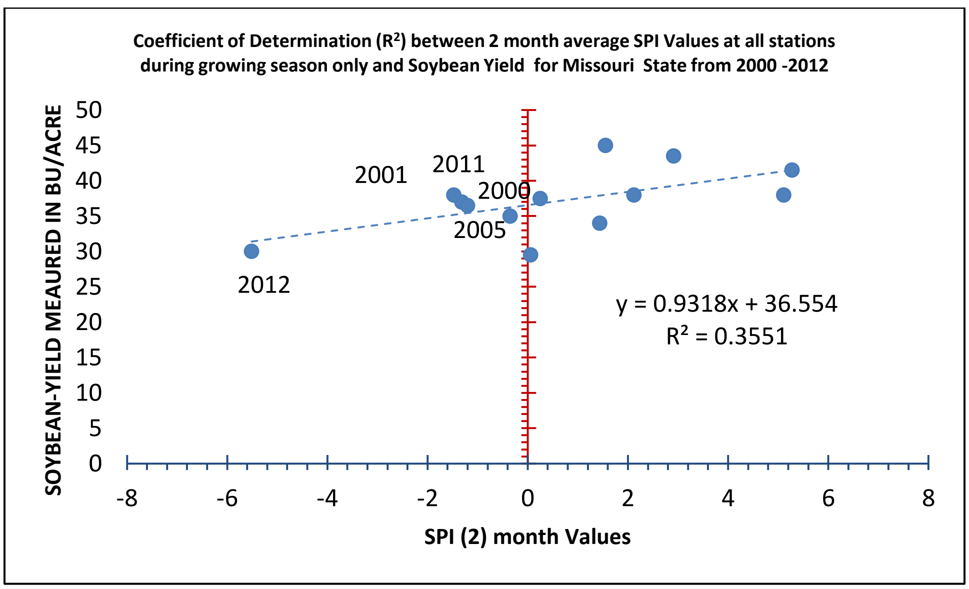

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Michigan State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8
2005
2012
2006
y = 2.6639x + 132.95
R² = 0.0677
SPI (2) month Values

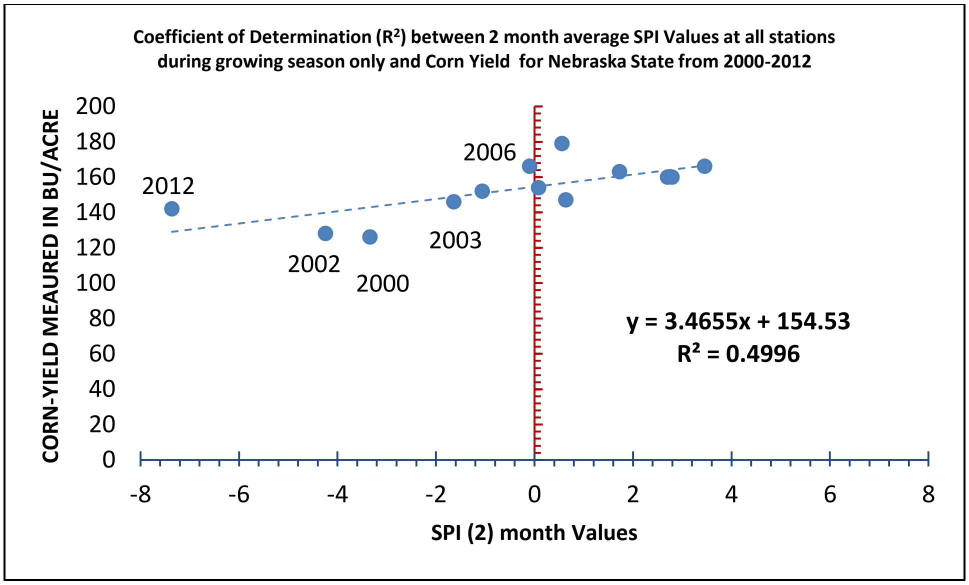

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for Michigan State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
50
45
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8
2012
2006
2005
y = 0.2673x + 38.363
R² = 0.006
SPI (2) month Values

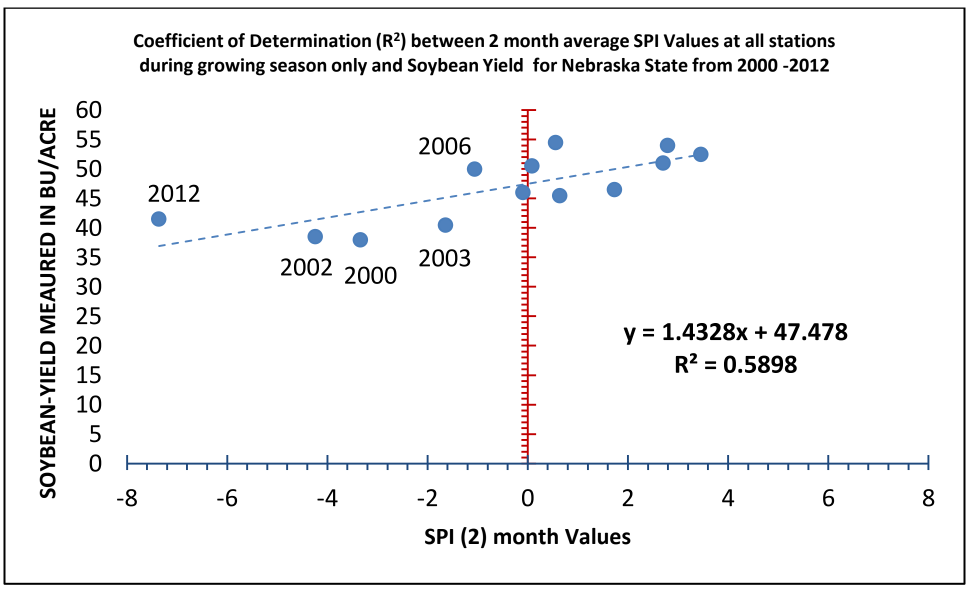

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Minnesota State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2009
2012
2006
2008
2003
y = 0.4551x + 157.53
R² = 0.0043

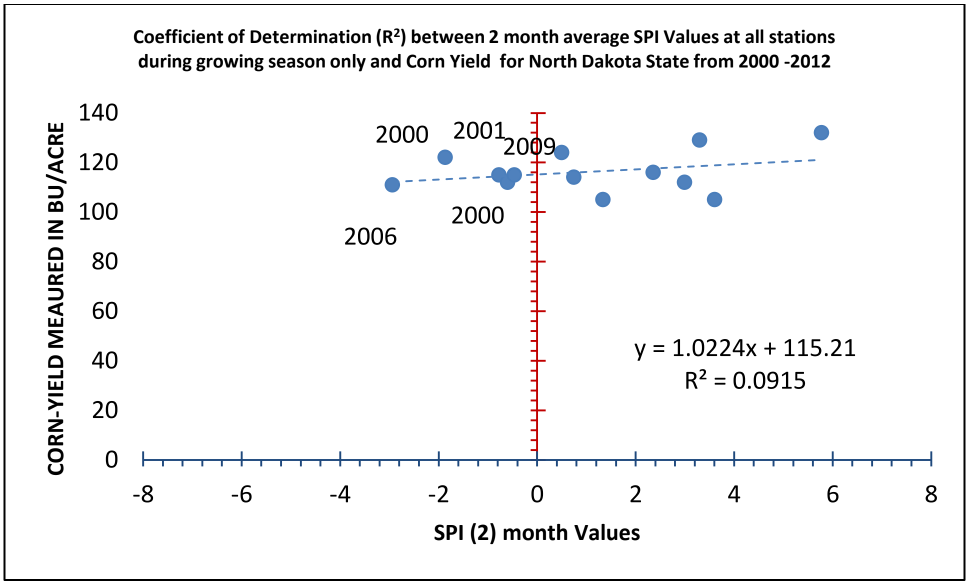

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for Minnesota State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2002
2006
2009
2008
2003
y = 0.3336x + 40.169
R² = 0.0216


Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Missouri State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8
SPI (2) month Values
2006
2000
2005
2011
2012
y = 4.7564x + 123.59
R² = 0.339

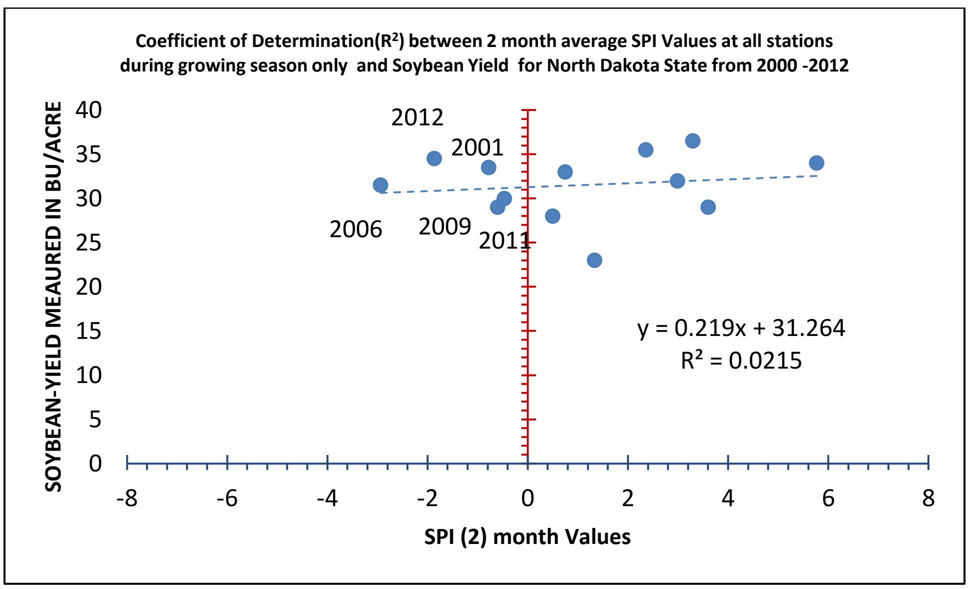

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for Missouri State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
50
45
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8
SPI (2) month Values
2001
2011
2000
2005
2012
y = 0.9318x + 36.554
R² = 0.3551


Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Nebraska State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2012
2002
2000
2003
2006
y = 3.4655x + 154.53
R² = 0.4996

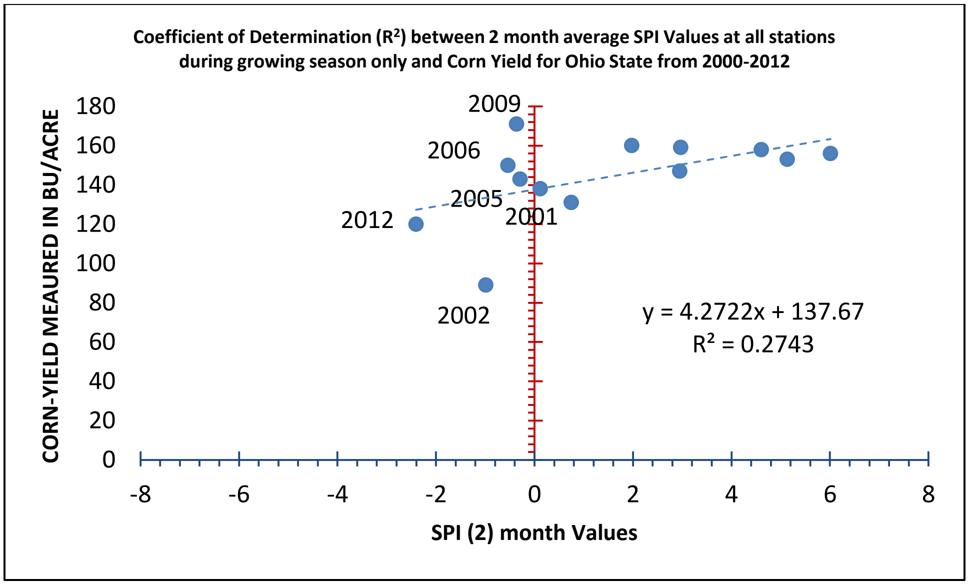

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for Nebraska State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2012
2002
2000
2003
2006
y = 1.4328x + 47.478
R² = 0.5898

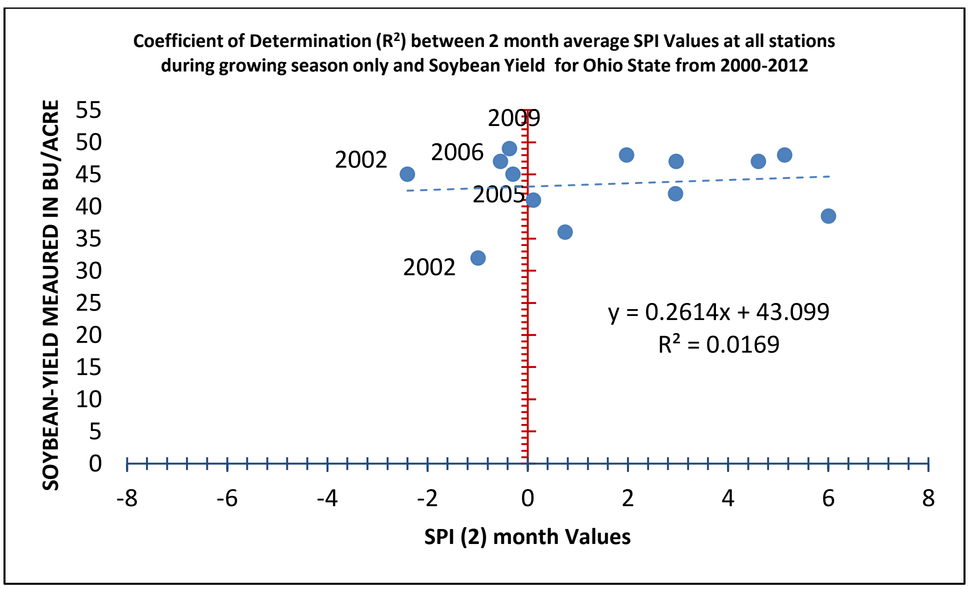


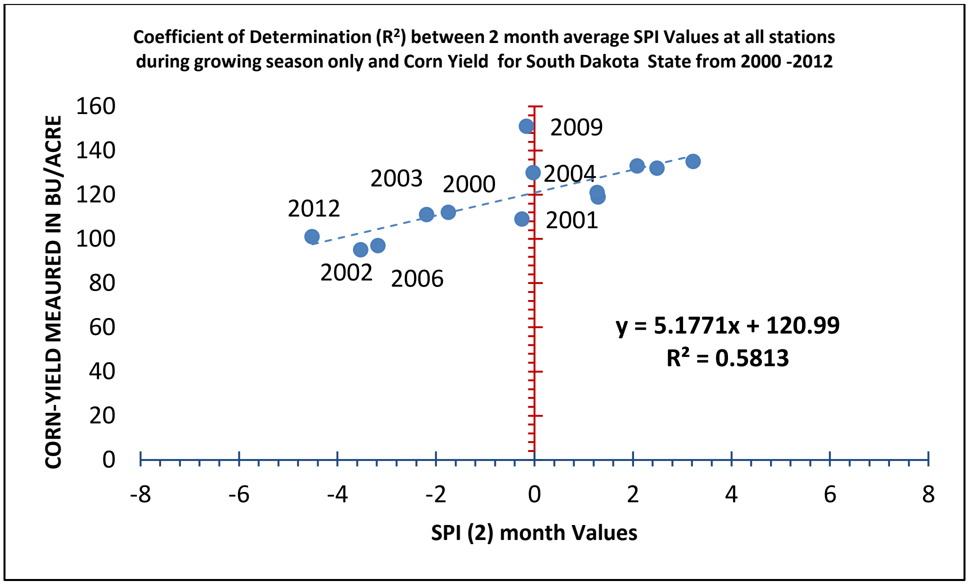
Coefficient of Determination (R^2) between 2 month average SPI Values at all stations during growing season only and Corn Yield for North Dakota State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
140
120
100
80
60
40
20
0
2000
2001
2009
2000
2006
y = 1.0224x + 115.21
R^2 = 0.0915
-8
-6
-4
-2
0
2
4
6
8
SPI (2) month Values

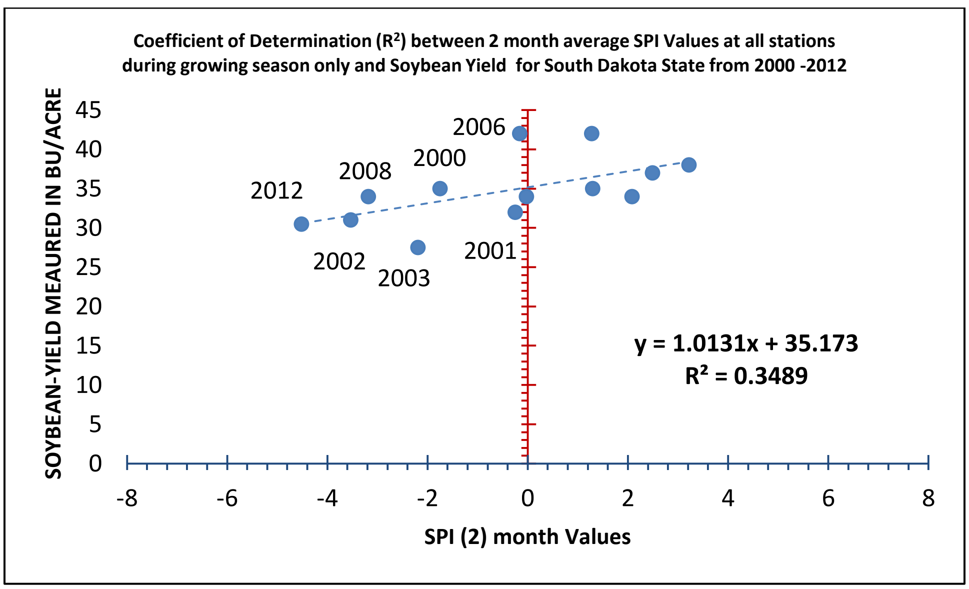


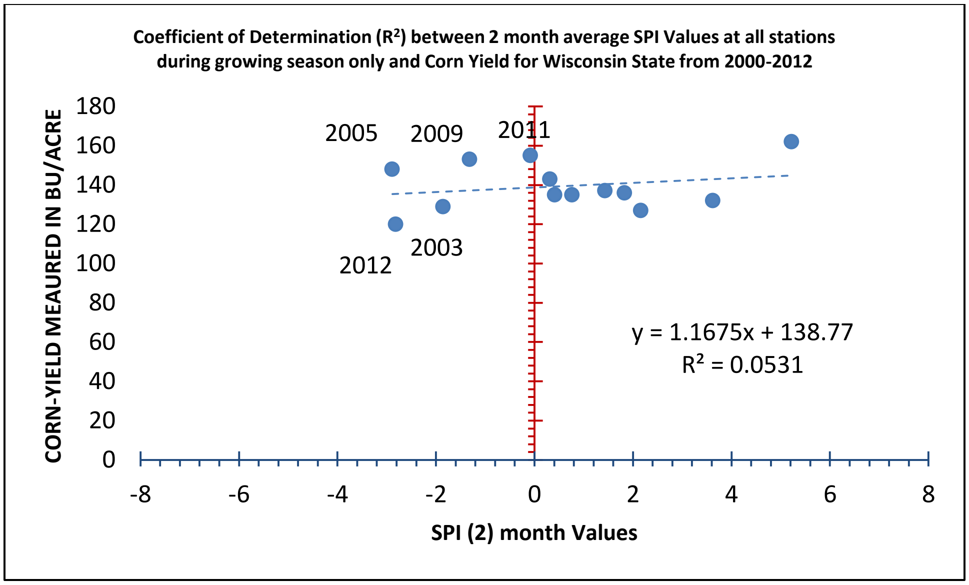
Coefficient of Determination(R^2) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for North Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
40
35
30
25
20
15
10
5
0
2012
2001
2006
2009
2011
y = 0.219x + 31.264
R^2 = 0.0215
-8
-6
-4
-2
0
2
4
6
8
SPI (2) month Values

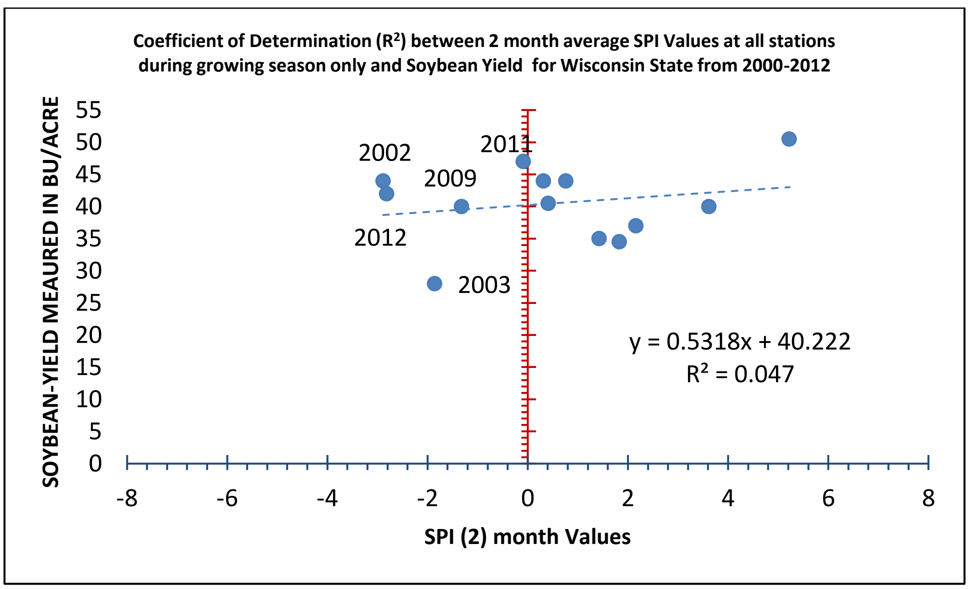

Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Ohio State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
2009
2006
2005
2012
2001
2002
y = 4.2722x + 137.67
R² = 0.2743
-8
-6
-4
-2
0
2
4
6
8
SPI (2) month Values


Coefficient of Determination (R²) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for Ohio State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
55
50
45
40
35
30
25
20
15
10
5
0
2009
2002
2006
2005
2002
y = 0.2614x + 43.099
R² = 0.0169
-8
-6
-4
-2
0
2
4
6
8
SPI (2) month Values

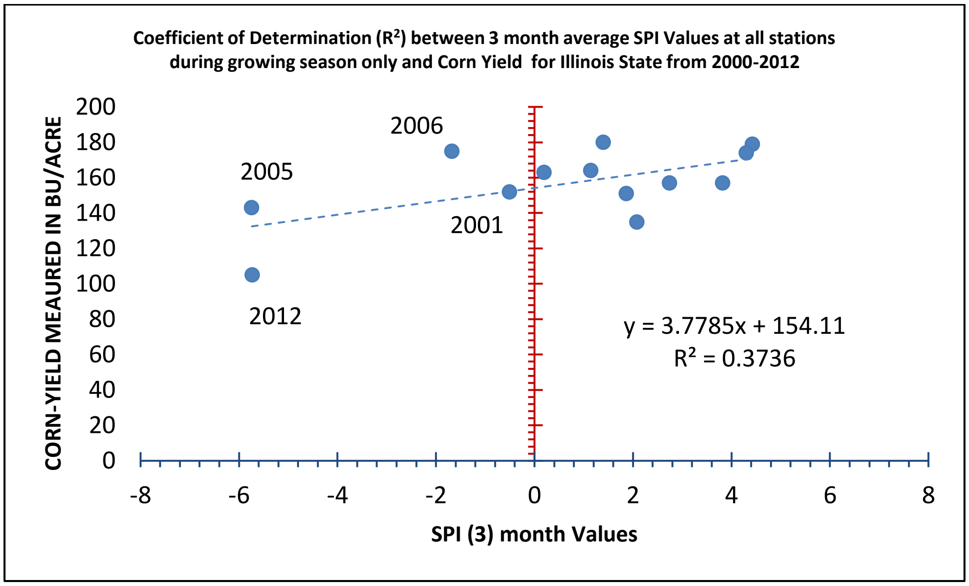

Coefficient of Determination (R^2) between 2 month average SPI Values at all stations during growing season only and Corn Yield for South Dakota State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2009
2004
2003
2000
2012
2001
2002
2006
y = 5.1771x + 120.99
R^2 = 0.5813

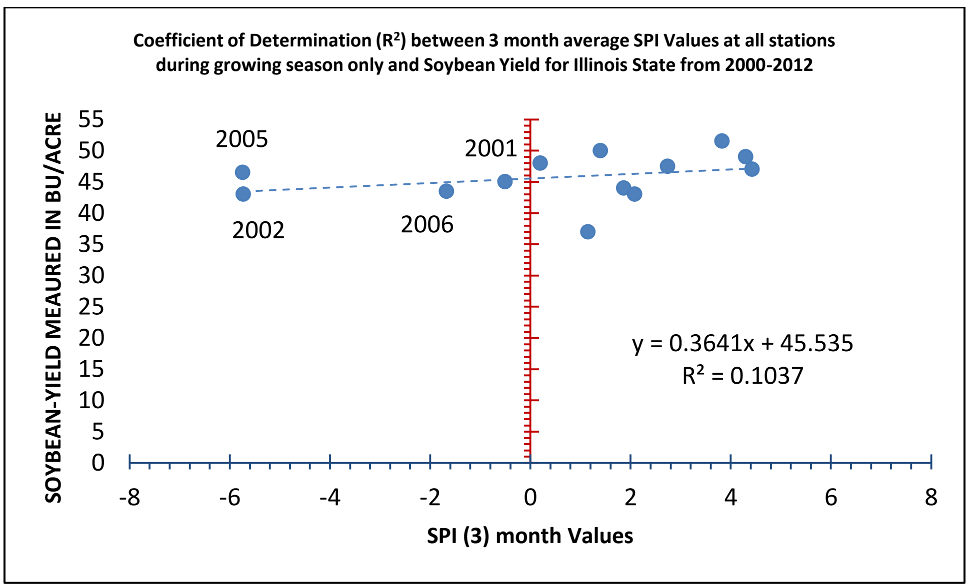

Coefficient of Determination (R^2) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for South Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2006
2008
2000
2012
2001
2002
2003
y = 1.0131x + 35.173
R^2 = 0.3489

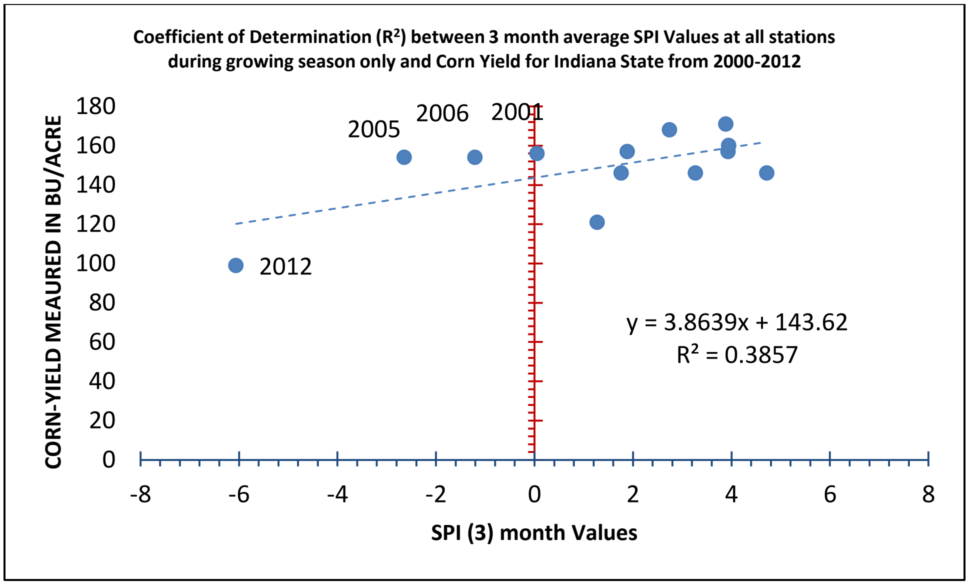

Coefficient of Determination (R^2) between 2 month average SPI Values at all stations during growing season only and Corn Yield for Wisconsin State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2005
2009
2011
2012
2003
y = 1.1675x + 138.77
R² = 0.0531

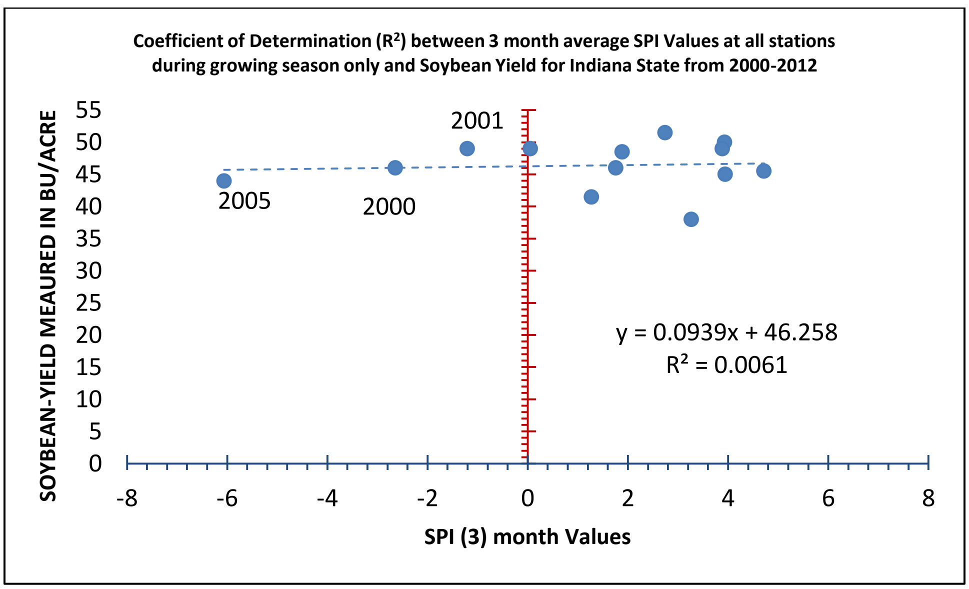

Coefficient of Determination (R^2) between 2 month average SPI Values at all stations during growing season only and Soybean Yield for Wisconsin State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (2) month Values
2002
2011
2009
2012
2003
y = 0.5318x + 40.222
R² = 0.047

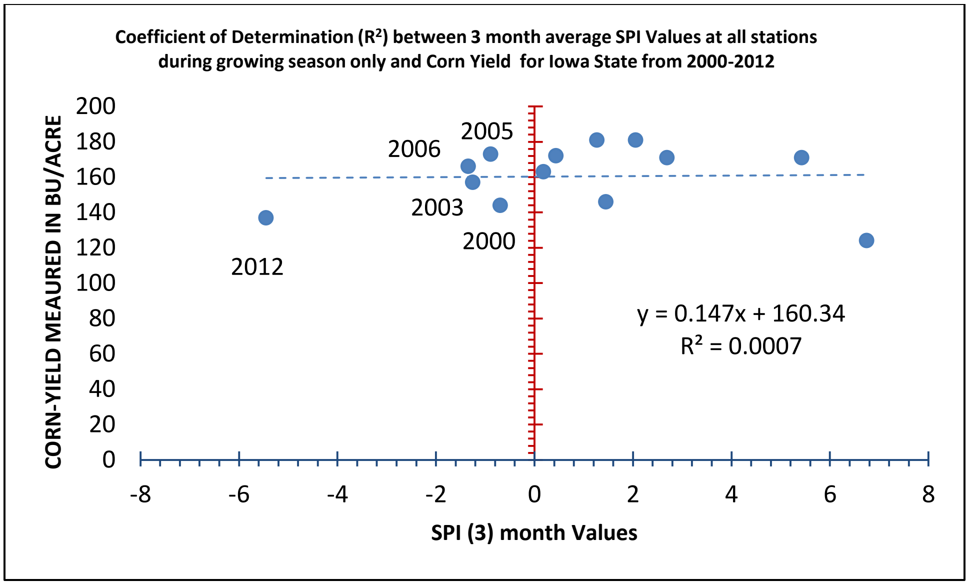
Coefficient of Determination (R^2) between Corn and Soybean Yield with SPI 3 Month

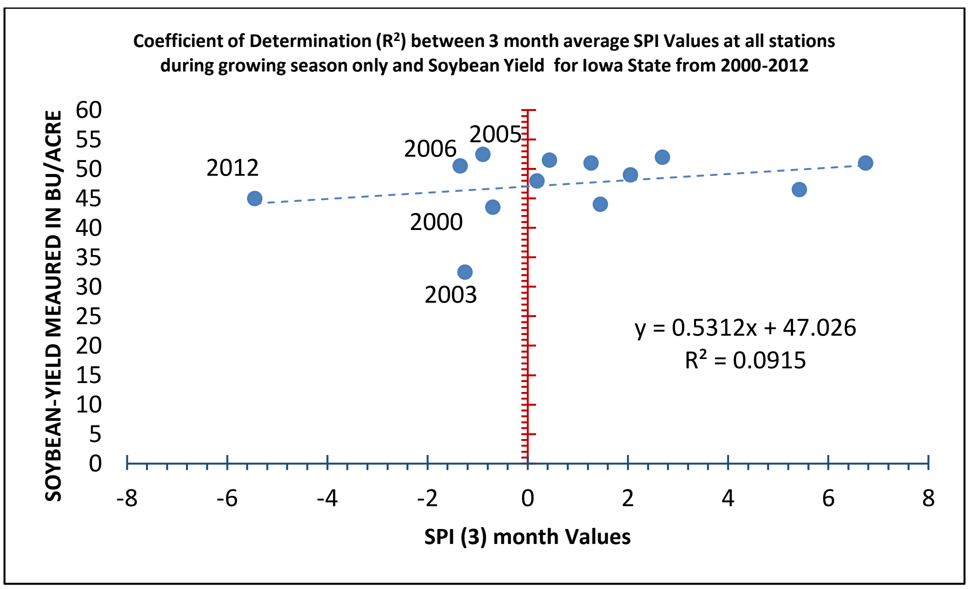


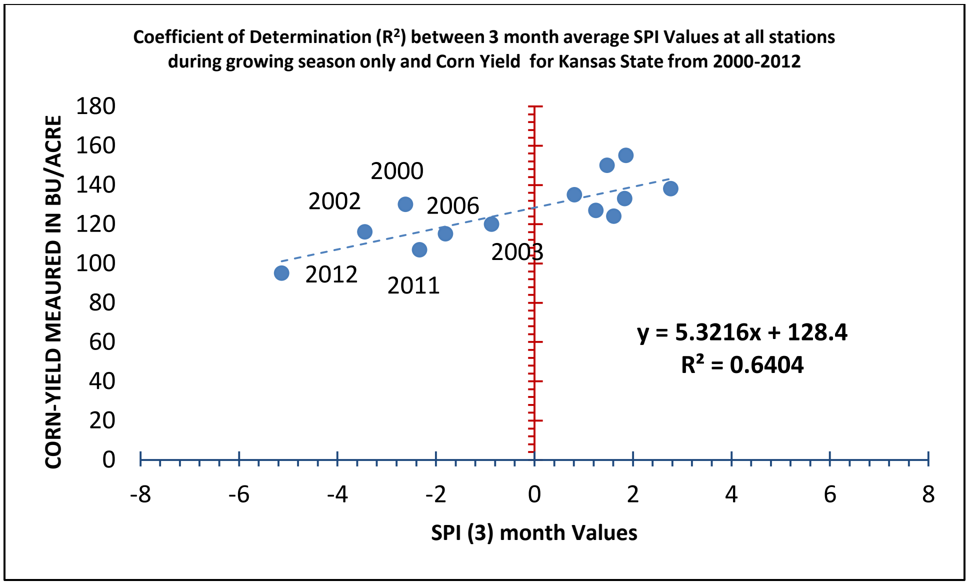


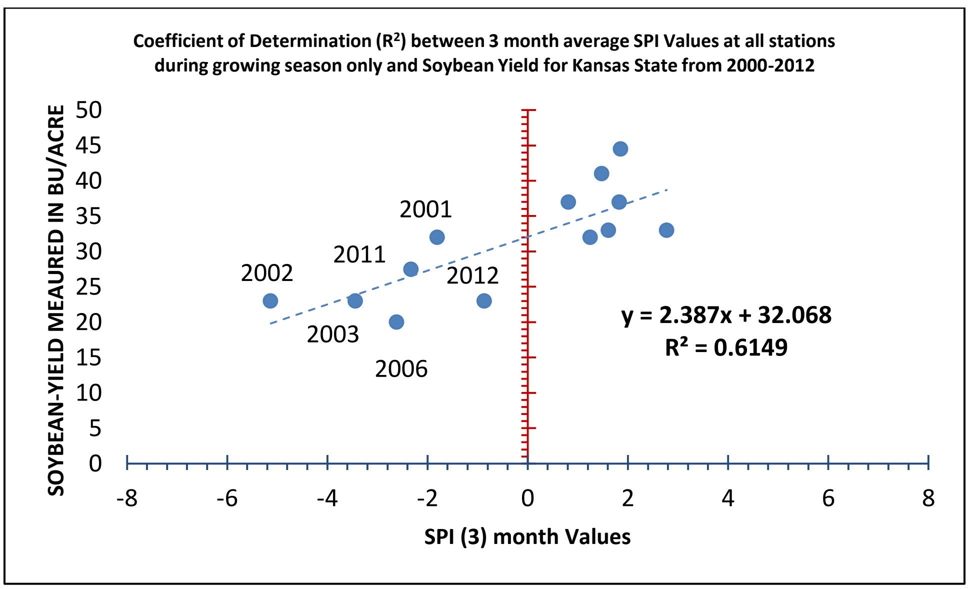

Coefficient of Determination (R²) between 3 month average SPI Values at all stations during growing season only and Corn Yield for Indiana State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2005
2006
2001
2012
y = 3.8639x + 143.62
R² = 0.3857

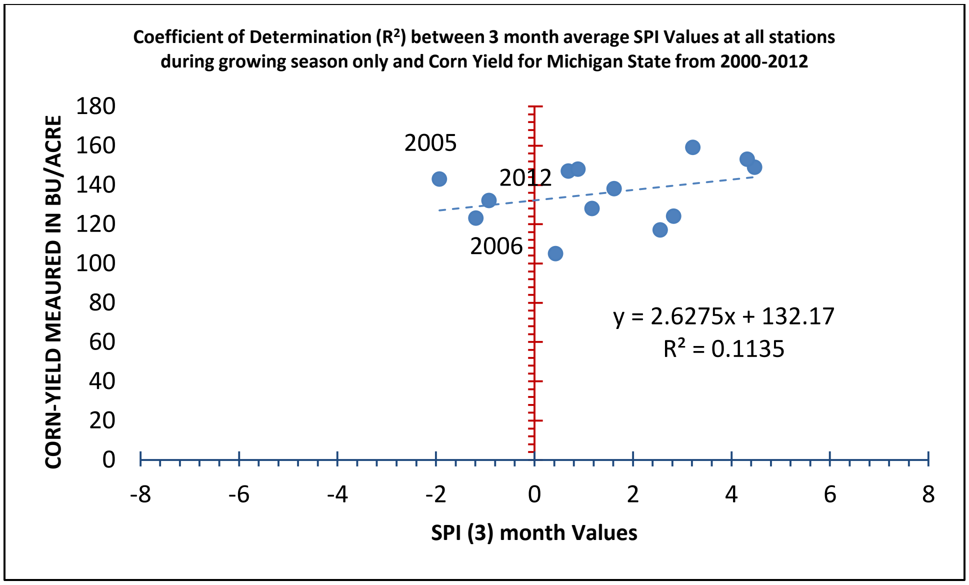

Coefficient of Determination (R²) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for Indiana State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2001
2005
2000
y = 0.0939x + 46.258
R² = 0.0061

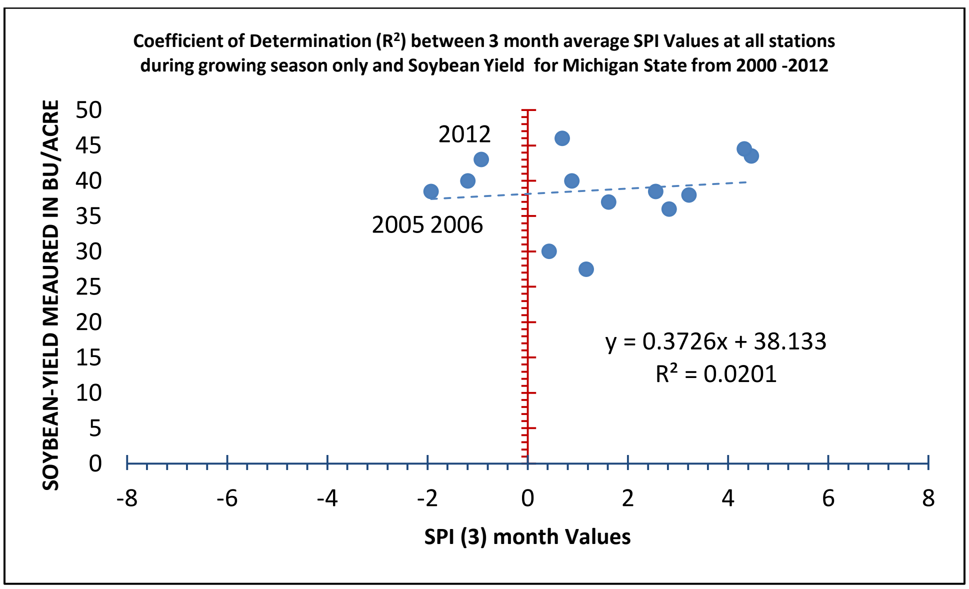

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Corn Yield for Iowa State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2005
2006
2003
2000
2012
y = 0.147x + 160.34
R^2 = 0.0007

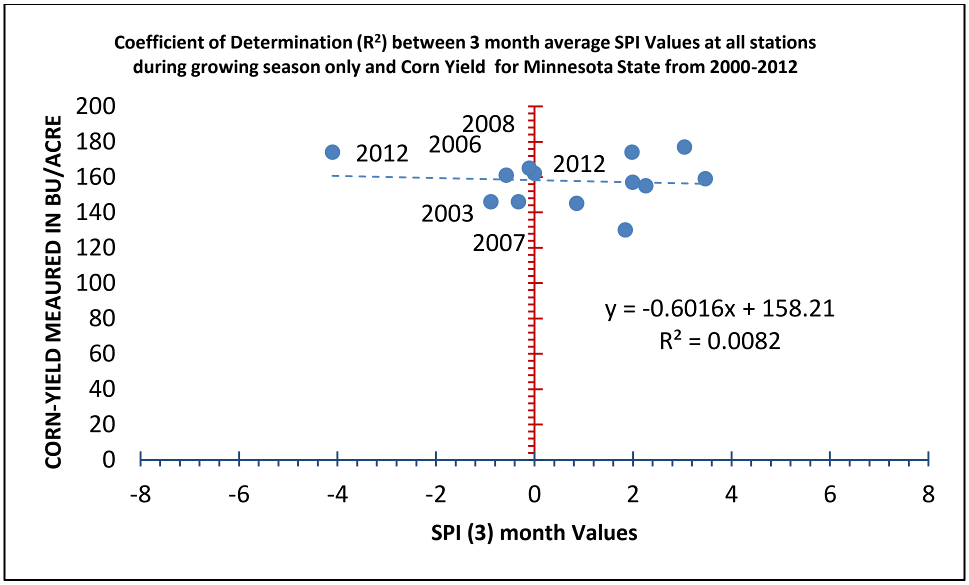

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for Iowa State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2006
2005
2012
2000
2003
y = 0.5312x + 47.026
R^2 = 0.0915

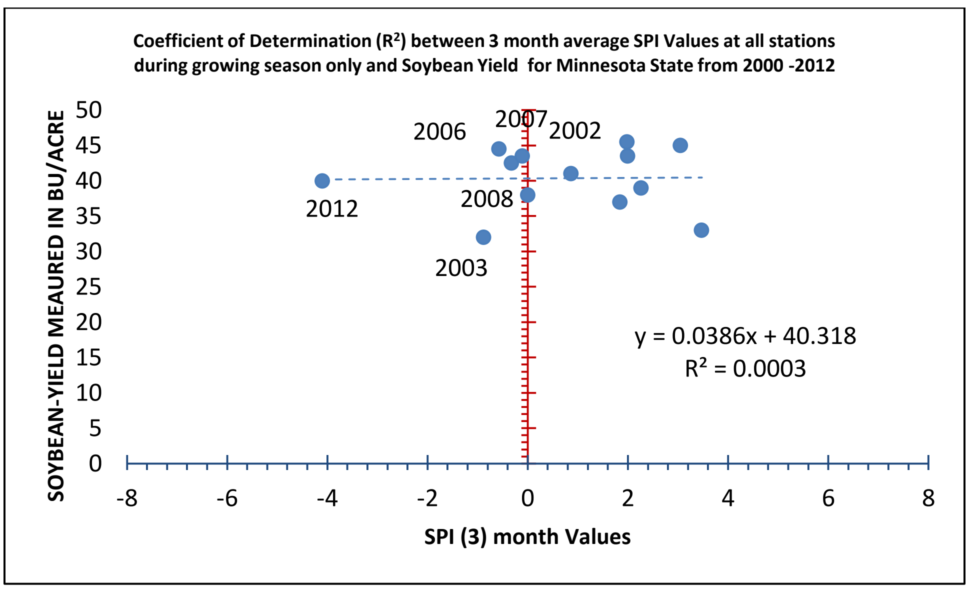

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Corn Yield for Kansas State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2000
2002
2006
2003
2012
2011
y = 5.3216x + 128.4
R² = 0.6404

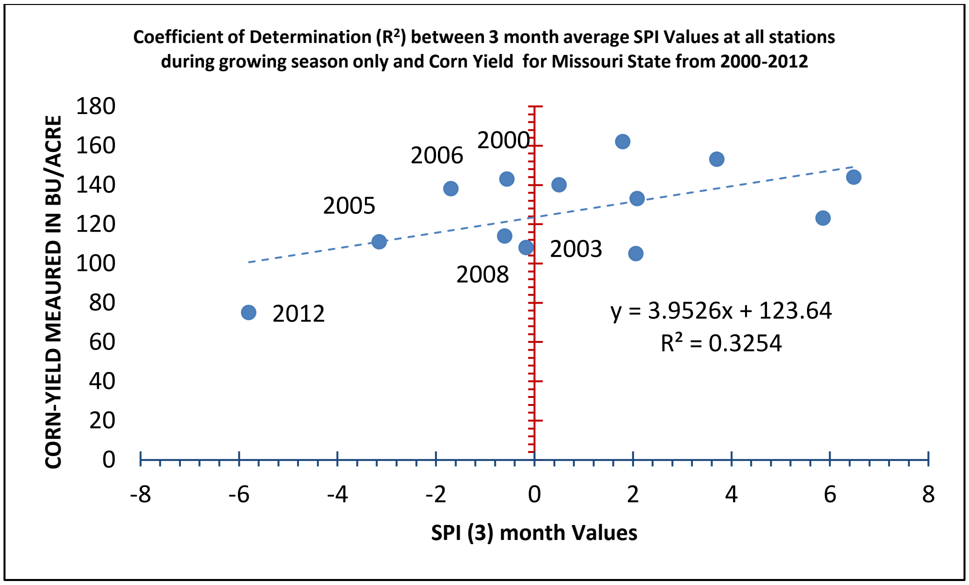

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for Kansas State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2001
2011
2002
2012
2003
2006
y = 2.387x + 32.068
R² = 0.6149

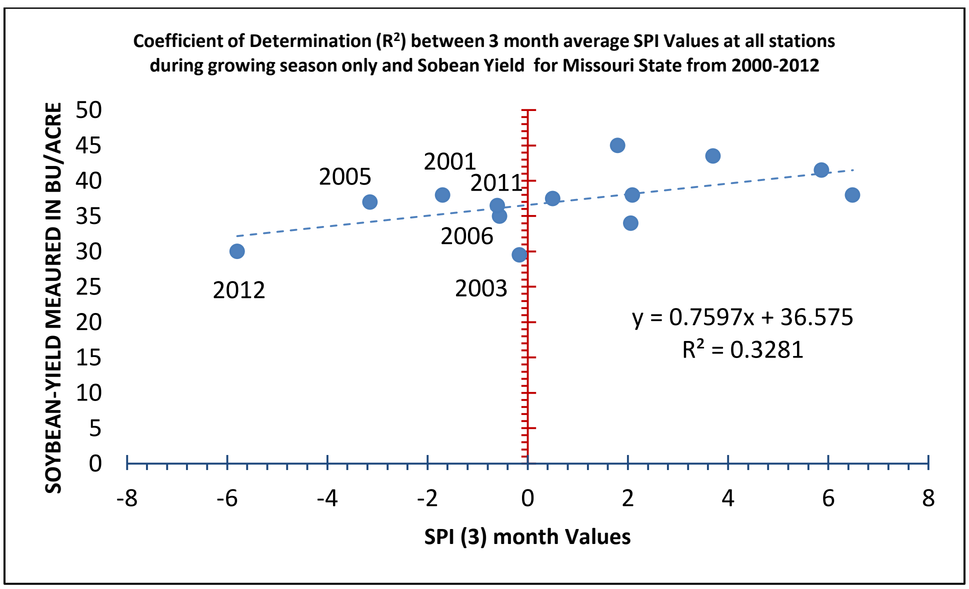

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Corn Yield for Michigan State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
2005
2012
2006
y = 2.6275x + 132.17
R^2 = 0.1135
-8
-6
-4
-2
0
2
4
6
8
SPI (3) month Values

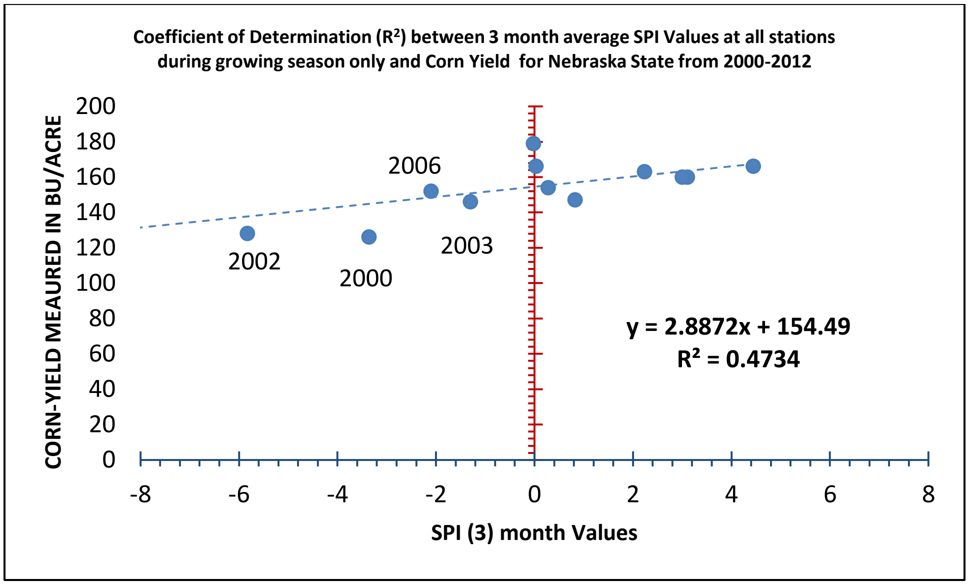

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for Michigan State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
50
45
40
35
30
25
20
15
10
5
0
2012
2005 2006
y = 0.3726x + 38.133
R^2 = 0.0201
-8
-6
-4
-2
0
2
4
6
8
SPI (3) month Values

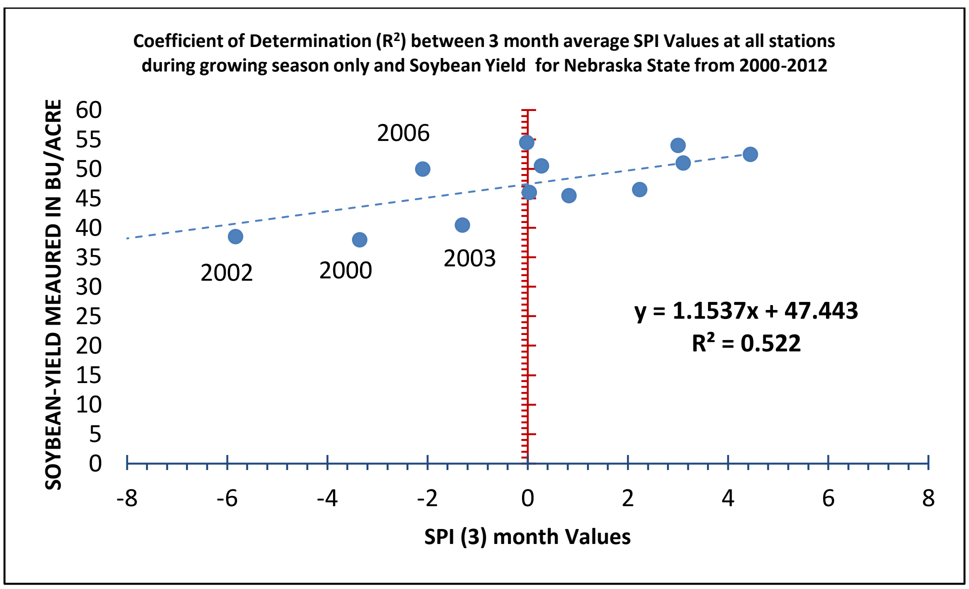

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Corn Yield for Minnesota State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2008
2006
2012
2012
2003
2007
y = -0.6016x + 158.21
R^2 = 0.0082

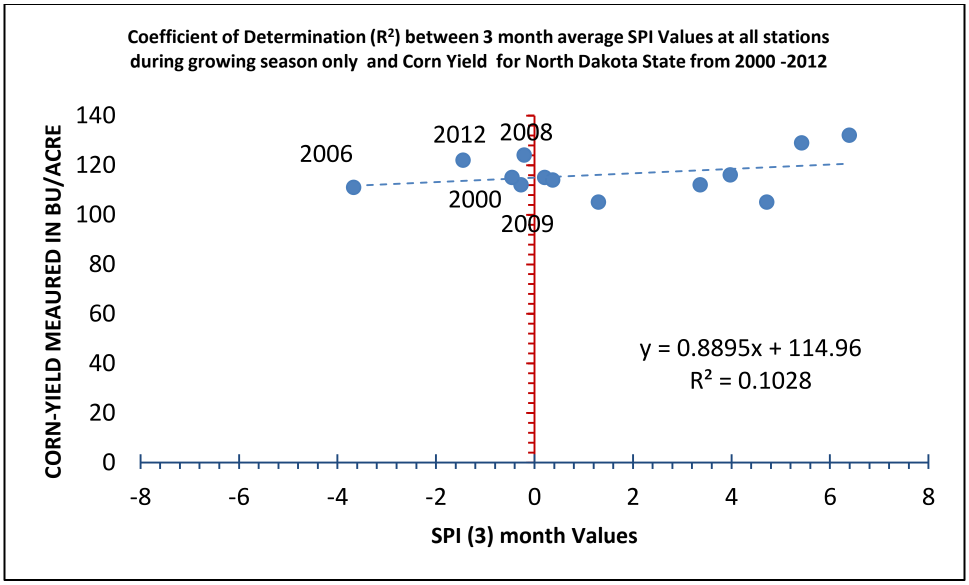

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for Minnesota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2006
2007
2002
2012
2008
2003
y = 0.0386x + 40.318
R^2 = 0.0003

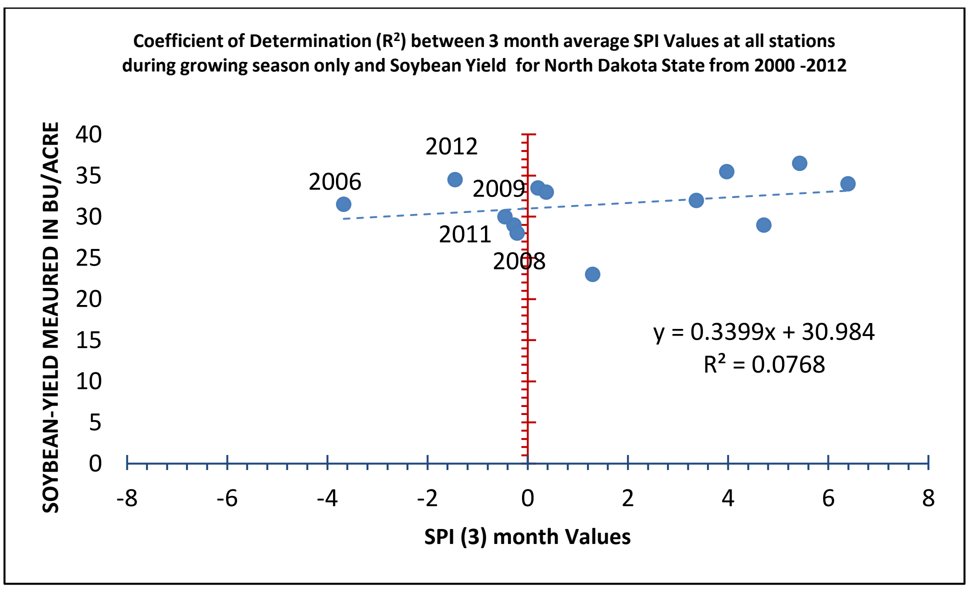

Coefficient of Determination (R²) between 3 month average SPI Values at all stations
during growing season only and Corn Yield for Missouri State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8
SPI (3) month Values
2000
2006
2005
2003
2008
2012
y = 3.9526x + 123.64
R² = 0.3254

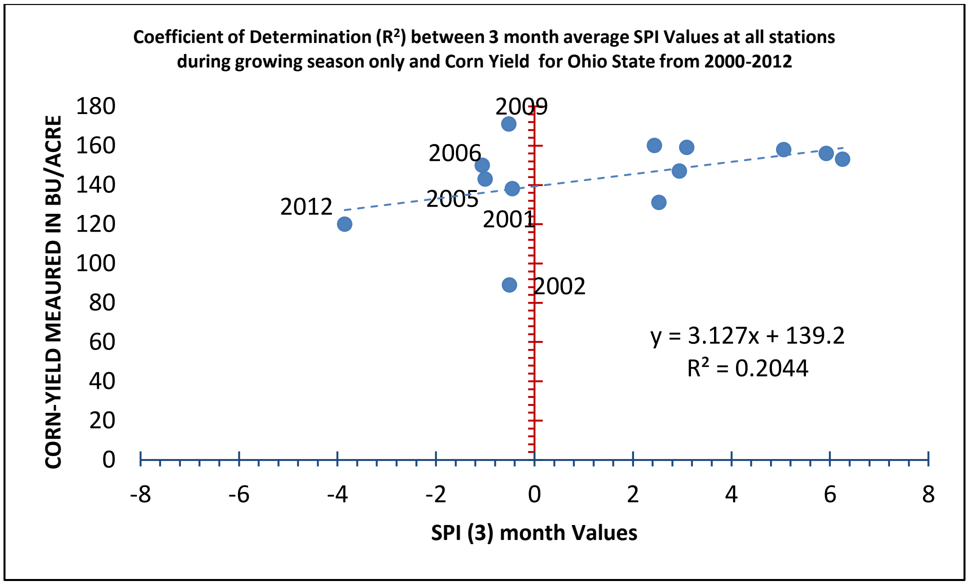

Coefficient of Determination (R²) between 3 month average SPI Values at all stations
during growing season only and Sobean Yield for Missouri State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
50
45
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8
SPI (3) month Values
2005
2001
2011
2006
2012
2003
y = 0.7597x + 36.575
R² = 0.3281

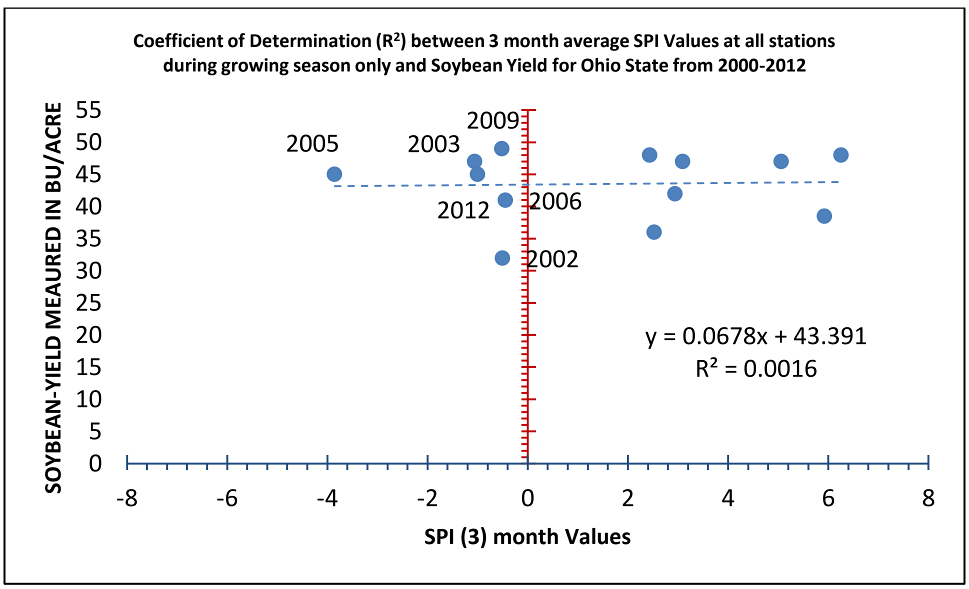

Coefficient of Determination (R²) between 3 month average SPI Values at all stations during growing season only and Corn Yield for Nebraska State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
200
180
160
140
120
100
80
60
40
20
0
2006
2002
2000
2003
y = 2.8872x + 154.49
R² = 0.4734
-8
-6
-4
-2
0
2
4
6
8
SPI (3) month Values

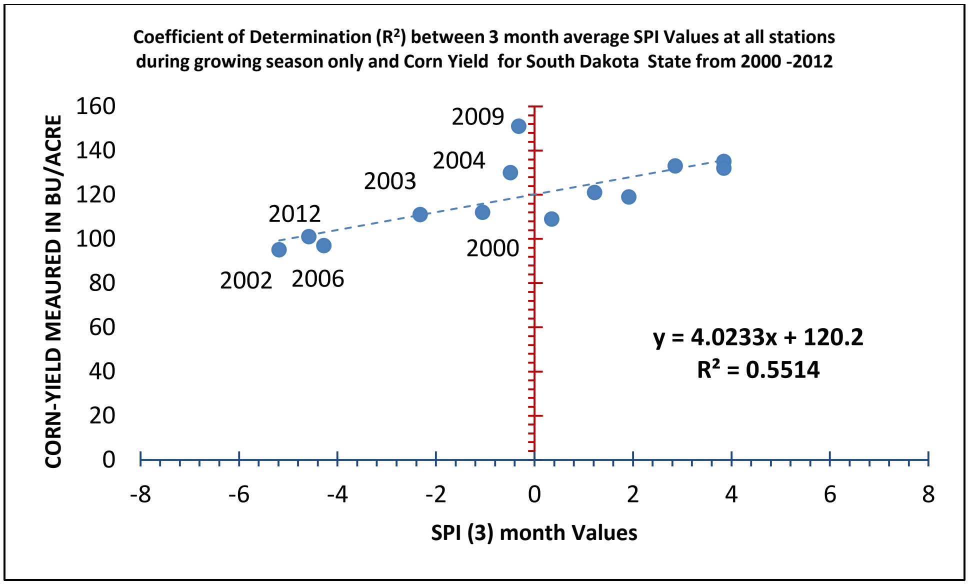

Coefficient of Determination (R²) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for Nebraska State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
60
55
50
45
40
35
30
25
20
15
10
5
0
2006
2002
2000
2003
y = 1.1537x + 47.443
R² = 0.522
-8
-6
-4
-2
0
2
4
6
8
SPI (3) month Values


Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Corn Yield for North Dakota State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8
SPI (3) month Values
2006
2012
2008
2000
2009
y = 0.8895x + 114.96
R^2 = 0.1028

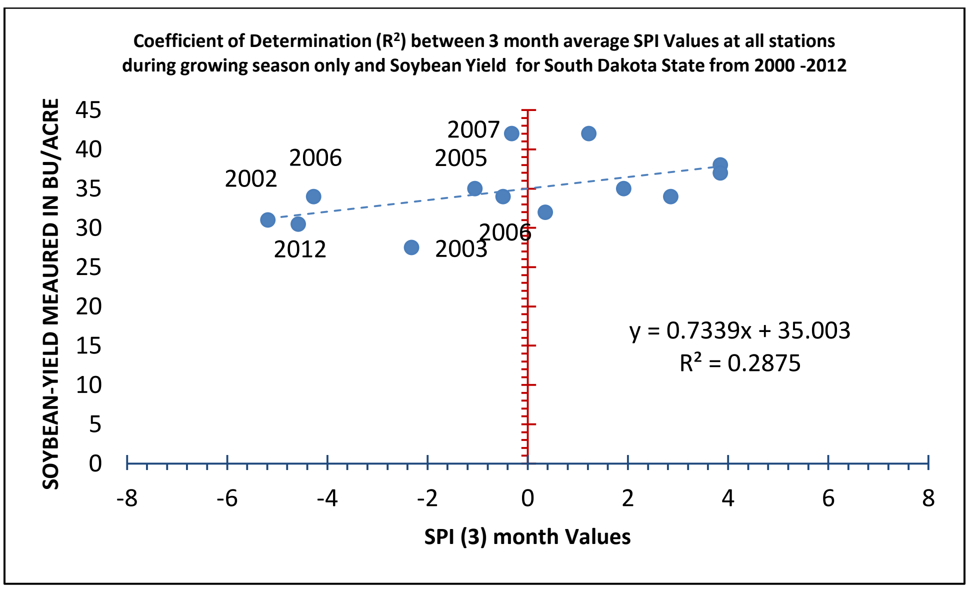

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for North Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8
SPI (3) month Values
2012
2006
2009
2011
2008
y = 0.3399x + 30.984
R^2 = 0.0768


Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Corn Yield for Ohio State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2009
2006
2005
2012
2001
2002
y = 3.127x + 139.2
R^2 = 0.2044

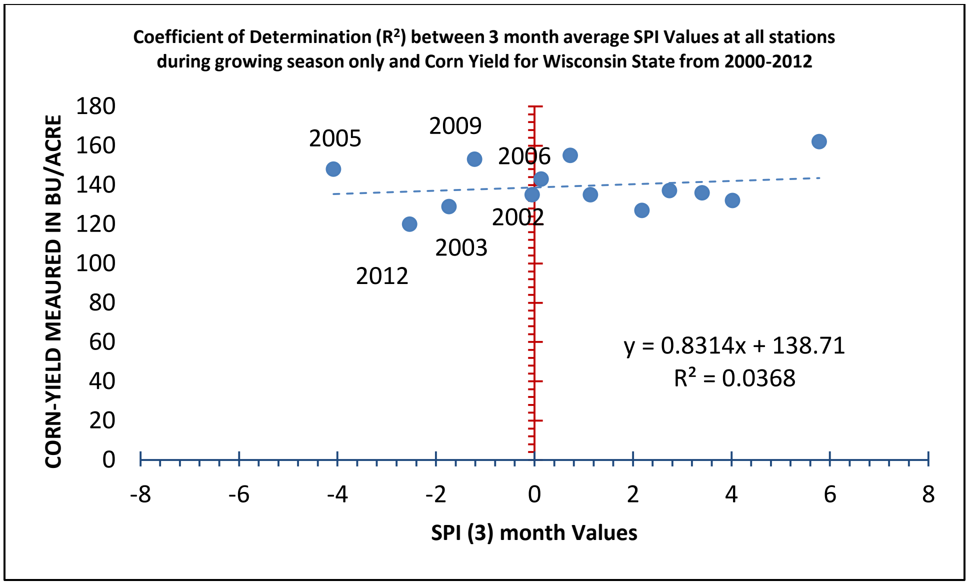

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for Ohio State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2009
2005
2003
2012
2006
2002
y = 0.0678x + 43.391
R^2 = 0.0016

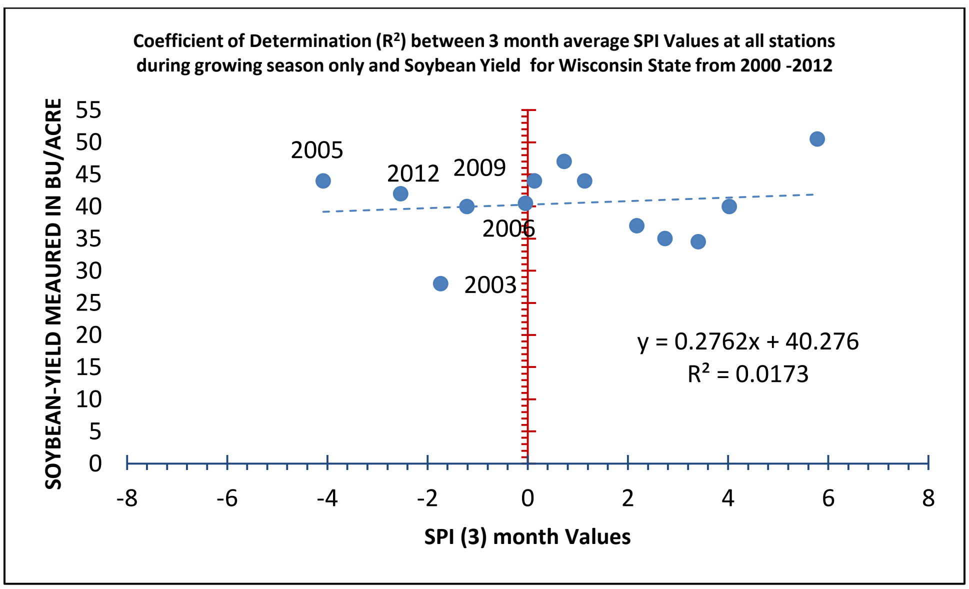


Coefficient of Determination (R²) between 3 month average SPI Values at all stations during growing season only and Corn Yield for South Dakota State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2009
2004
2003
2012
2000
2002
2006
y = 4.0233x + 120.2
R² = 0.5514

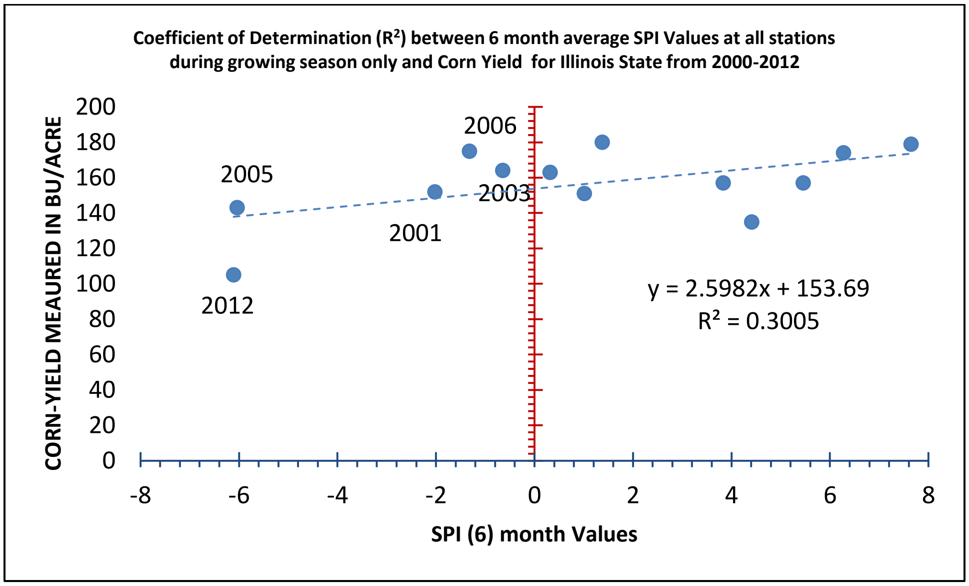


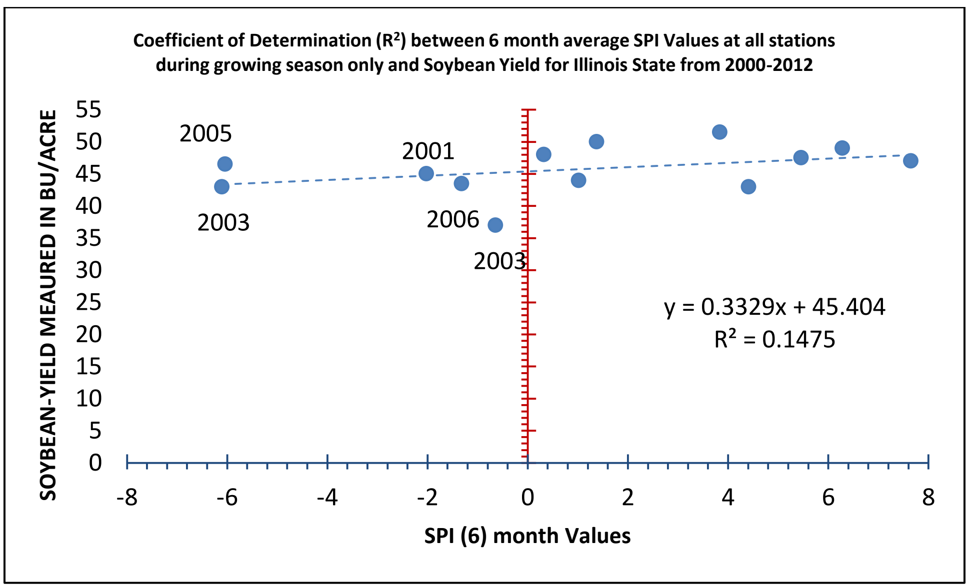
Coefficient of Determination (R²) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for South Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2007
2006
2005
2002
2012
2003
2006
y = 0.7339x + 35.003
R² = 0.2875

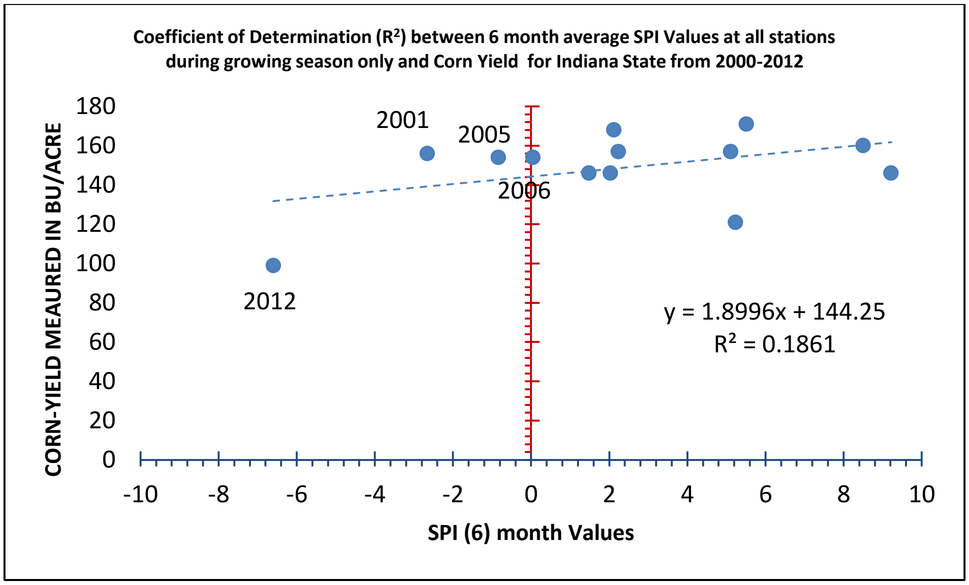

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Corn Yield for Wisconsin State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2005
2009
2006
2002
2003
2012
y = 0.8314x + 138.71
R^2 = 0.0368

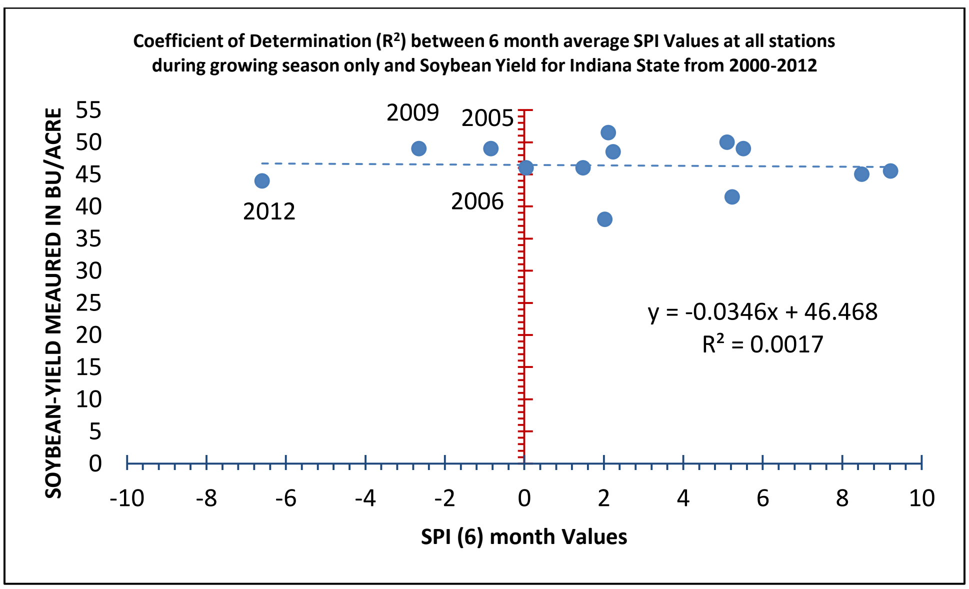

Coefficient of Determination (R^2) between 3 month average SPI Values at all stations during growing season only and Soybean Yield for Wisconsin State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (3) month Values
2005
2012
2009
2006
2003
y = 0.2762x + 40.276
R^2 = 0.0173

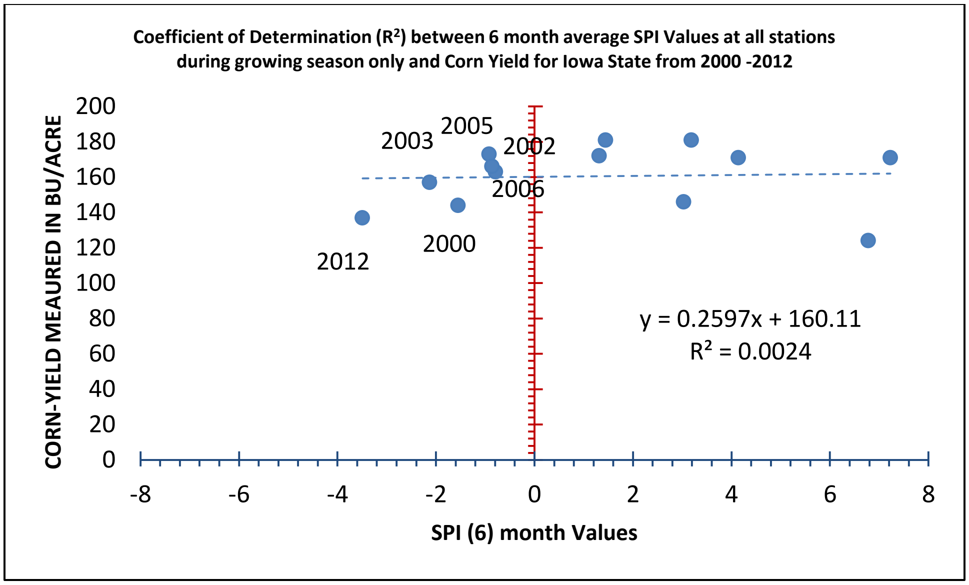
Coefficient of Determination (R^2) between Corn and Soybean Yield with SPI 6 Month

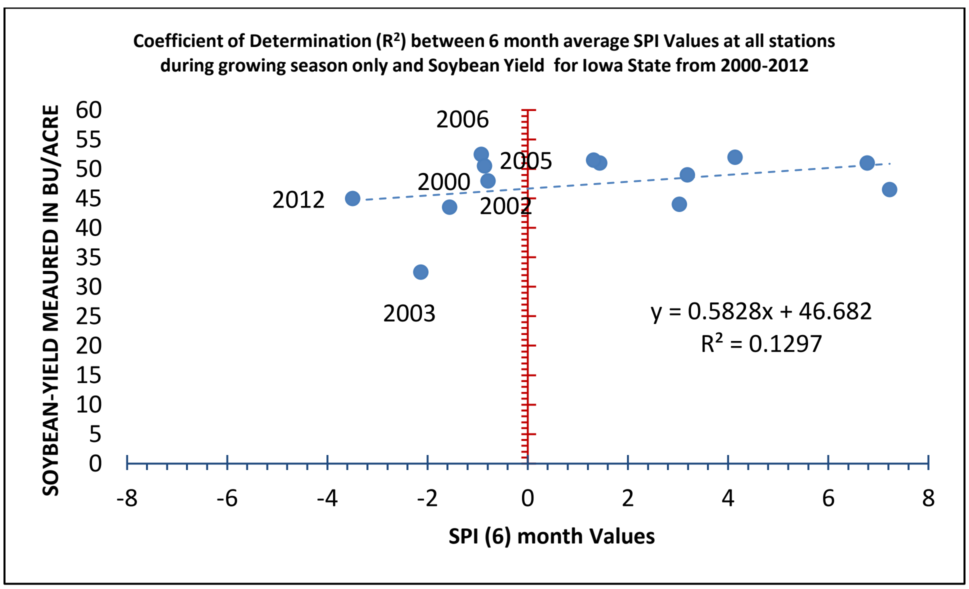


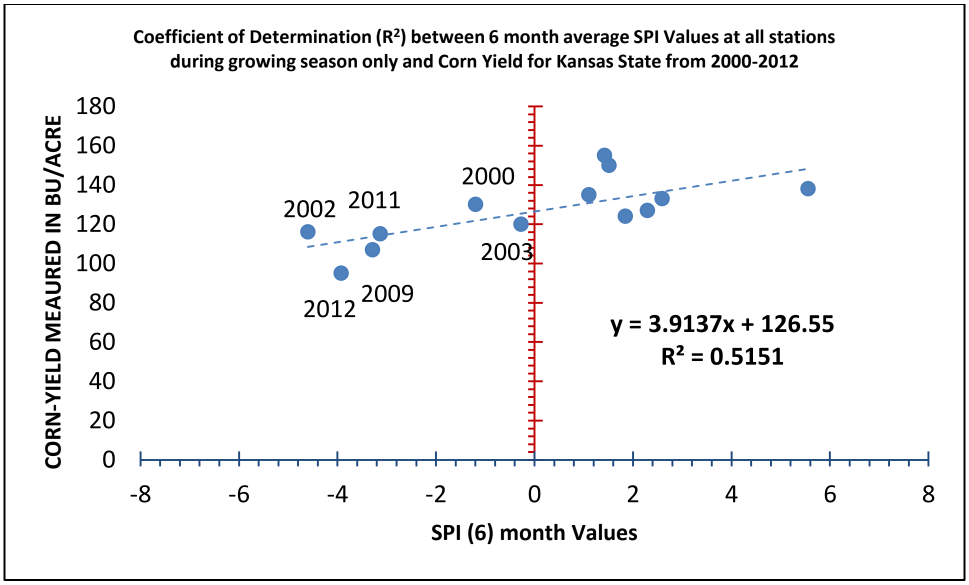


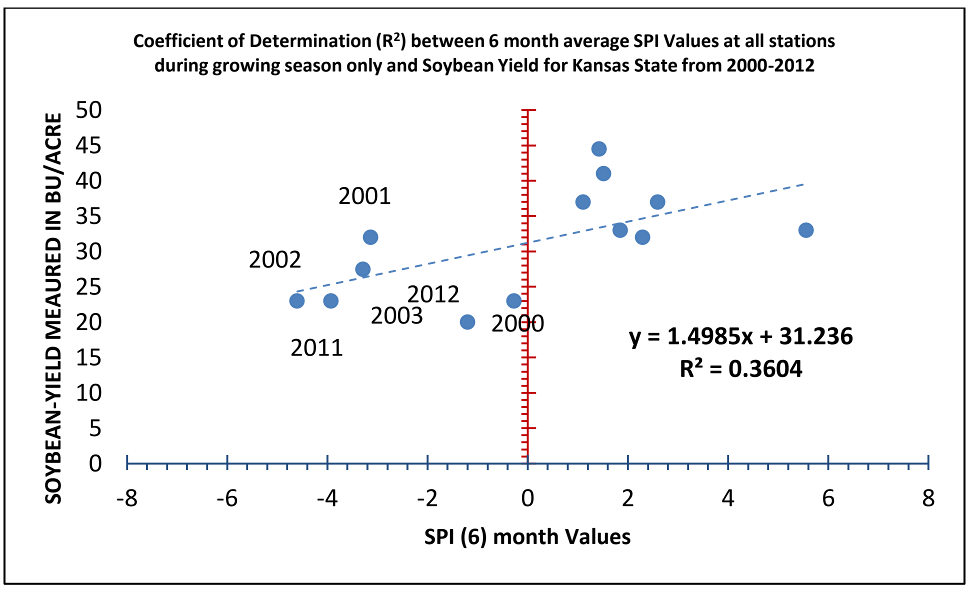

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Corn Yield for Indiana State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2001
2005
2006
2012
y = 1.8996x + 144.25
R² = 0.1861
180
160
140
120
100
80
60
40
20
0
-10
-8
-6
-4
-2
0
2
4
6
8
10

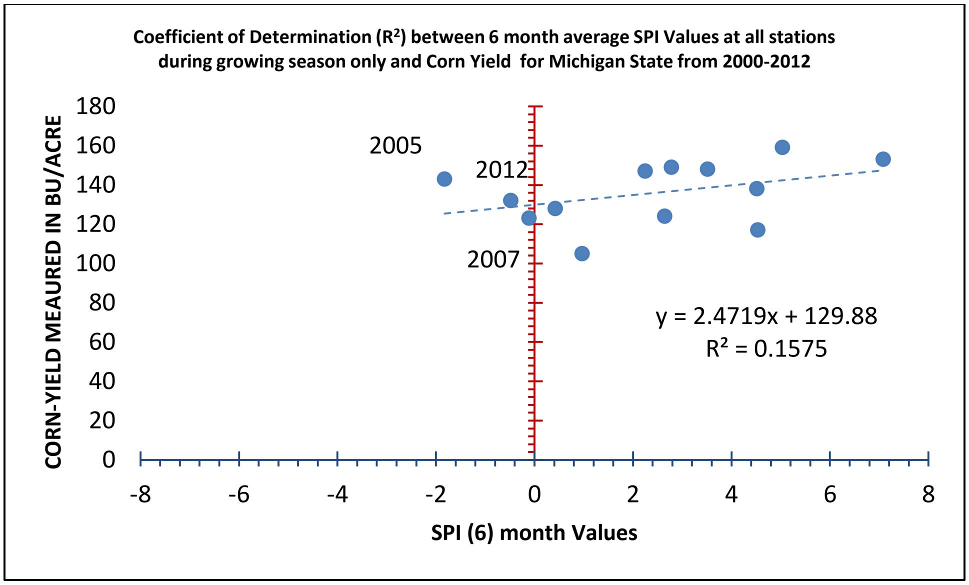

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for Indiana State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2009
2005
2006
2012
y = -0.0346x + 46.468
R² = 0.0017
55
50
45
40
35
30
25
20
15
10
5
0
-10
-8
-6
-4
-2
0
2
4
6
8
10

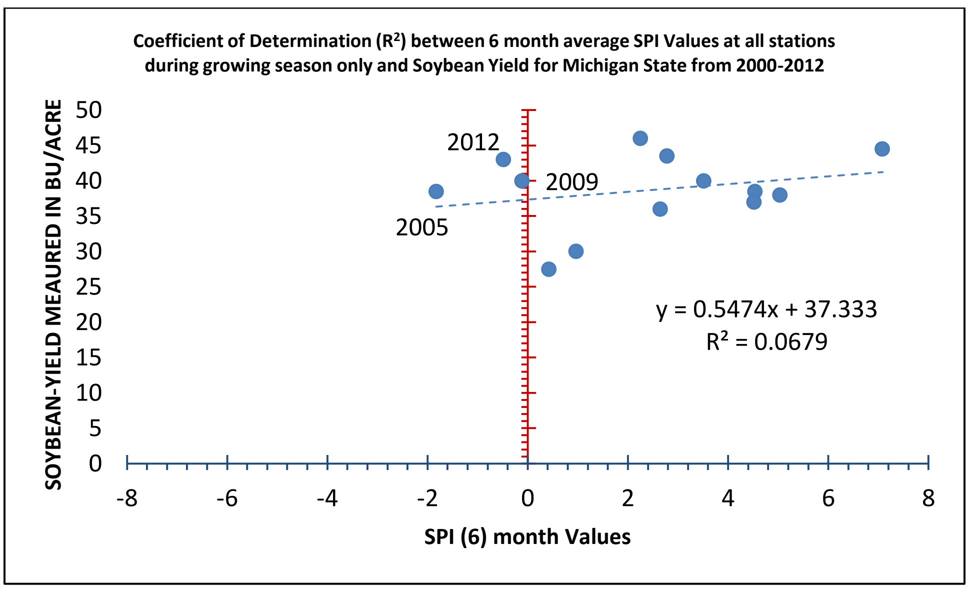

Coefficient of Determination (R^2) between 6 month average SPI Values at all stations during growing season only and Corn Yield for Iowa State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2003
2005
2002
2006
2000
2012
y = 0.2597x + 160.11
R^2 = 0.0024

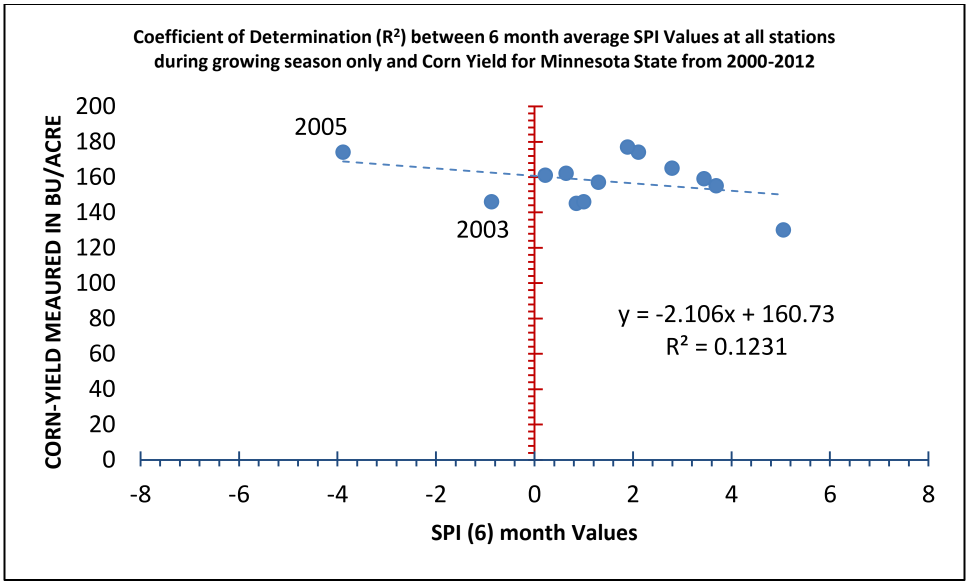

Coefficient of Determination (R^2) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for Iowa State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2006
2005
2000
2002
2012
2003
y = 0.5828x + 46.682
R^2 = 0.1297

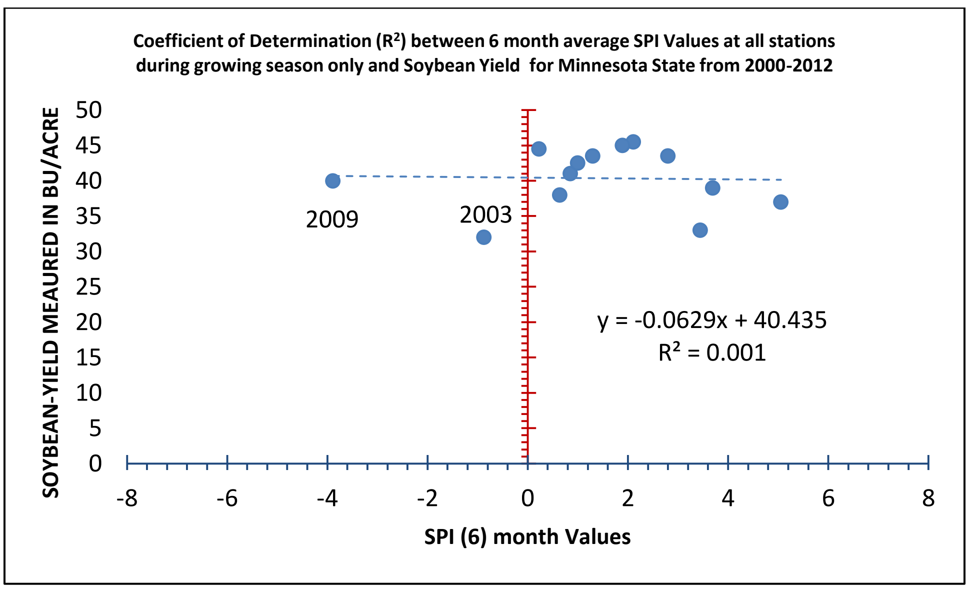

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Corn Yield for Kansas State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2002
2011
2000
2003
2012
2009
y = 3.9137x + 126.55
R² = 0.5151

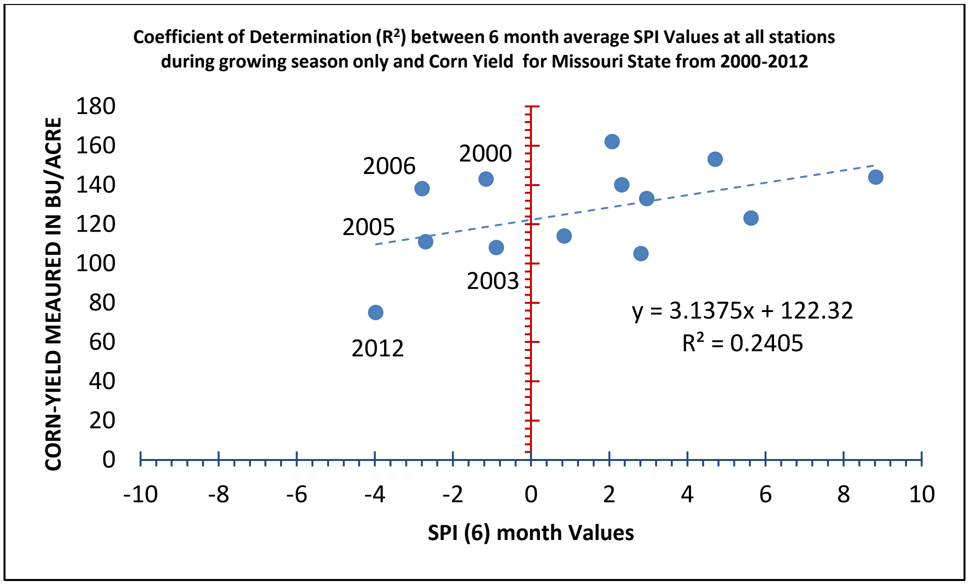

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for Kansas State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2001
2002
2012
2003
2000
2011
y = 1.4985x + 31.236
R² = 0.3604

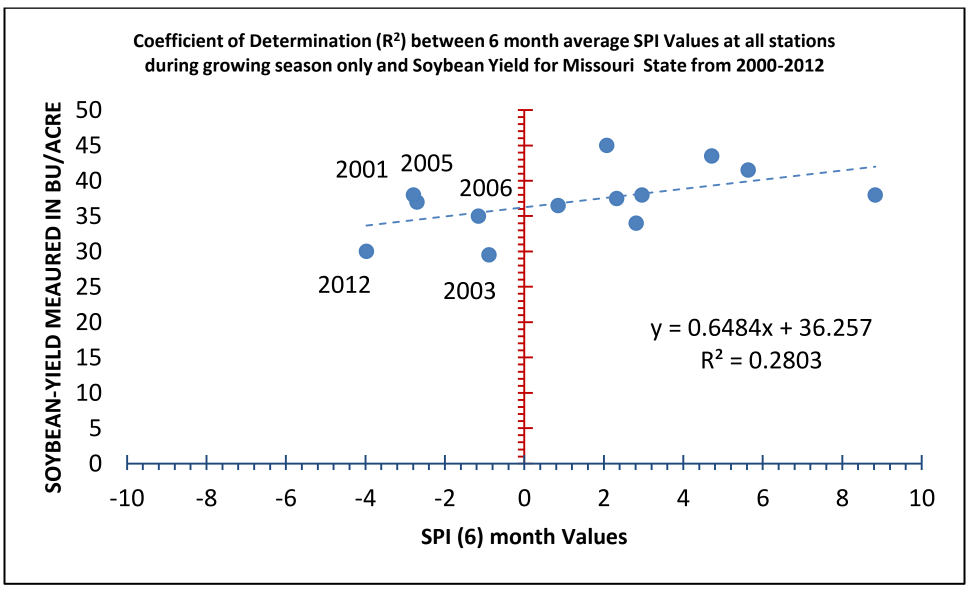

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Corn Yield for Michigan State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
2005
2012
2007
y = 2.4719x + 129.88
R² = 0.1575
-8
-6
-4
-2
0
2
4
6
8
SPI (6) month Values

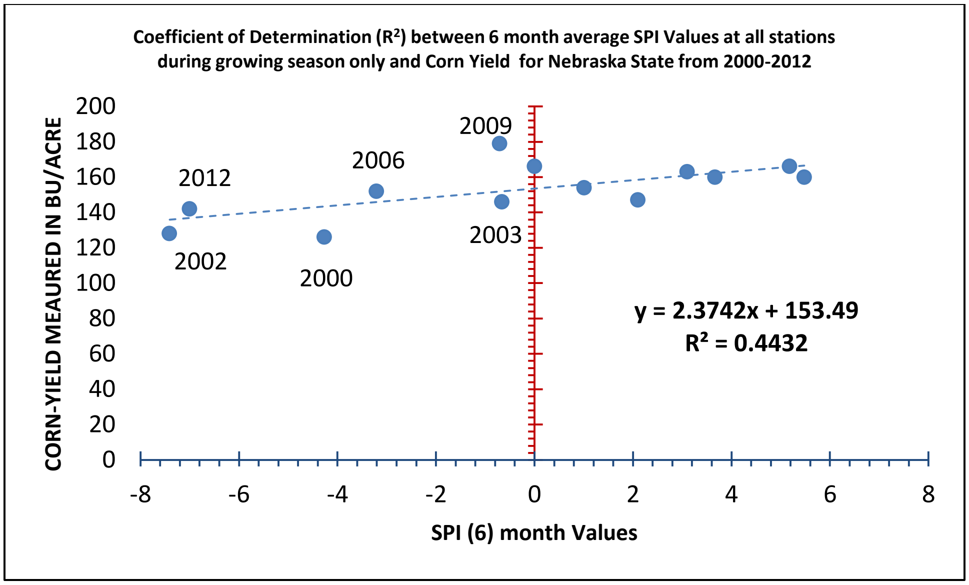

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for Michigan State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
50
45
40
35
30
25
20
15
10
5
0
2012
2009
2005
y = 0.5474x + 37.333
R² = 0.0679
-8
-6
-4
-2
0
2
4
6
8
SPI (6) month Values


Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Corn Yield for Minnesota State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2005
2003
y = -2.106x + 160.73
R² = 0.1231

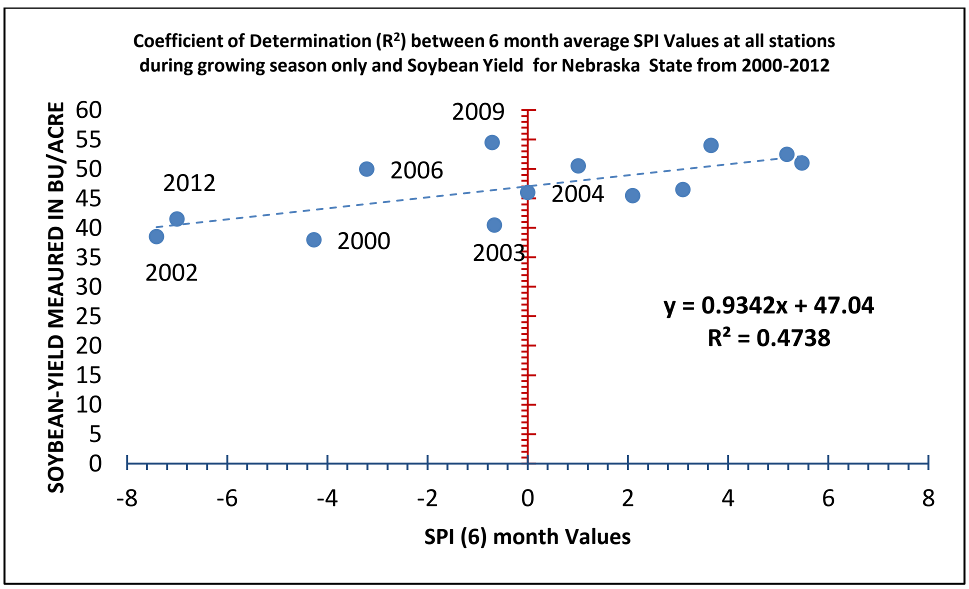

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for Minnesota State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2009
2003
y = -0.0629x + 40.435
R² = 0.001


Coefficient of Determination (R^2) between 6 month average SPI Values at all stations during growing season only and Corn Yield for Missouri State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2006
2000
2005
2003
2012
y = 3.1375x + 122.32
R^2 = 0.2405

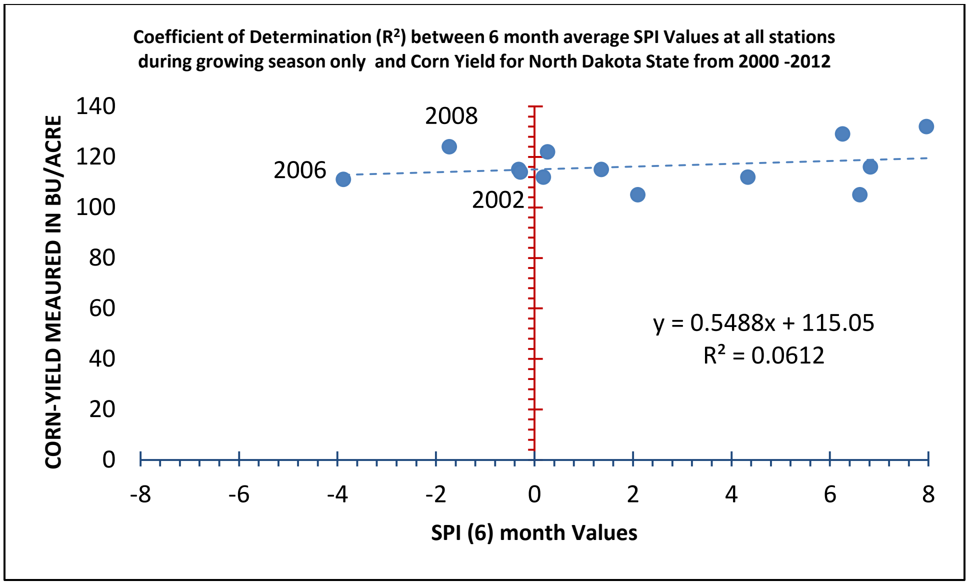

Coefficient of Determination (R^2) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for Missouri State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2001
2005
2006
2012
2003
y = 0.6484x + 36.257
R^2 = 0.2803

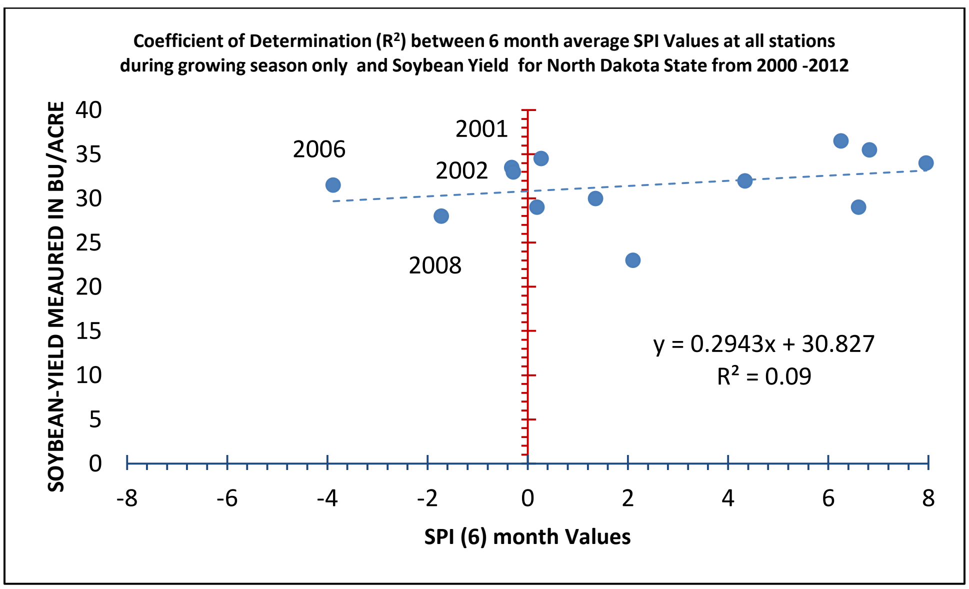


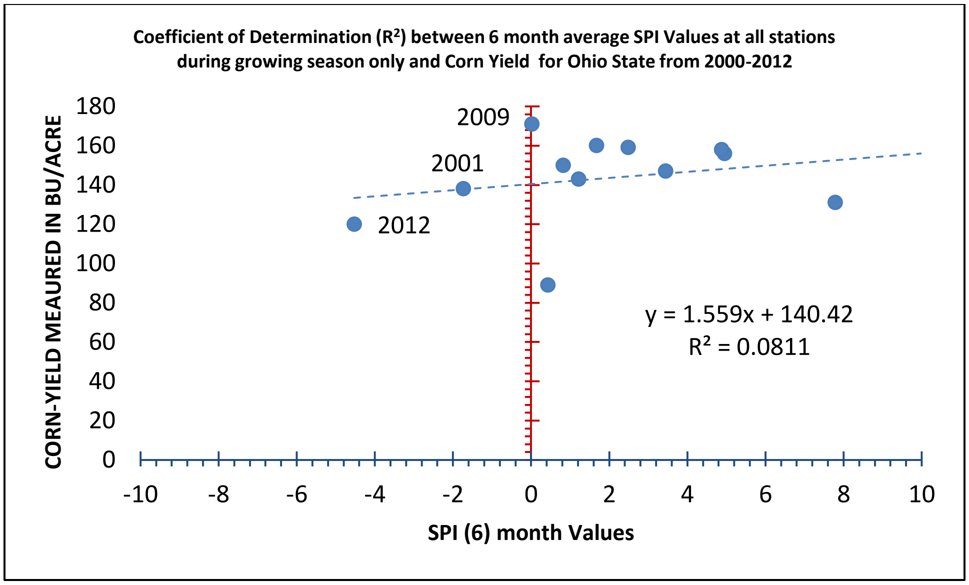
Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Corn Yield for Nebraska State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2009
2006
2012
2003
2002
2000
y = 2.3742x + 153.49
R² = 0.4432

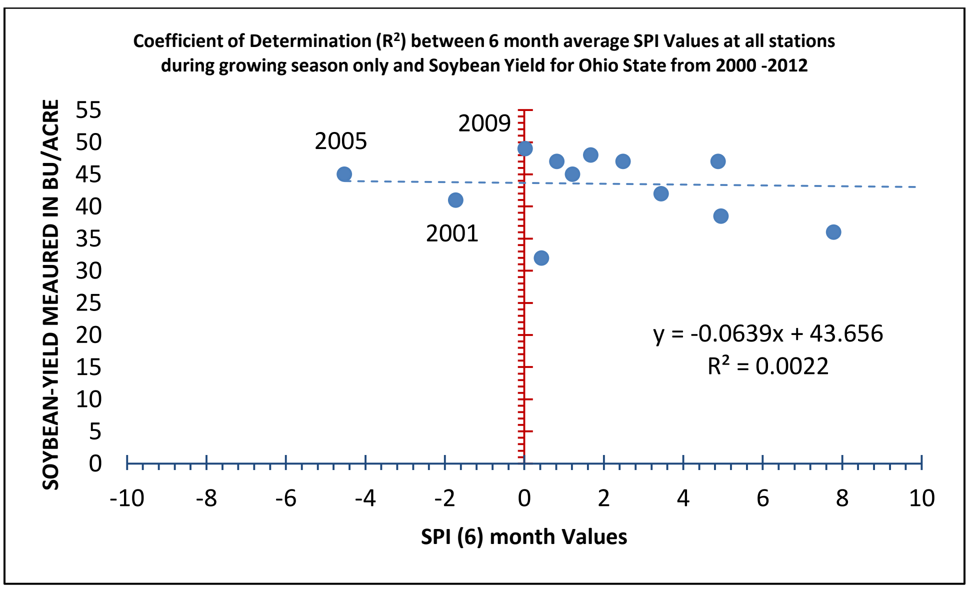


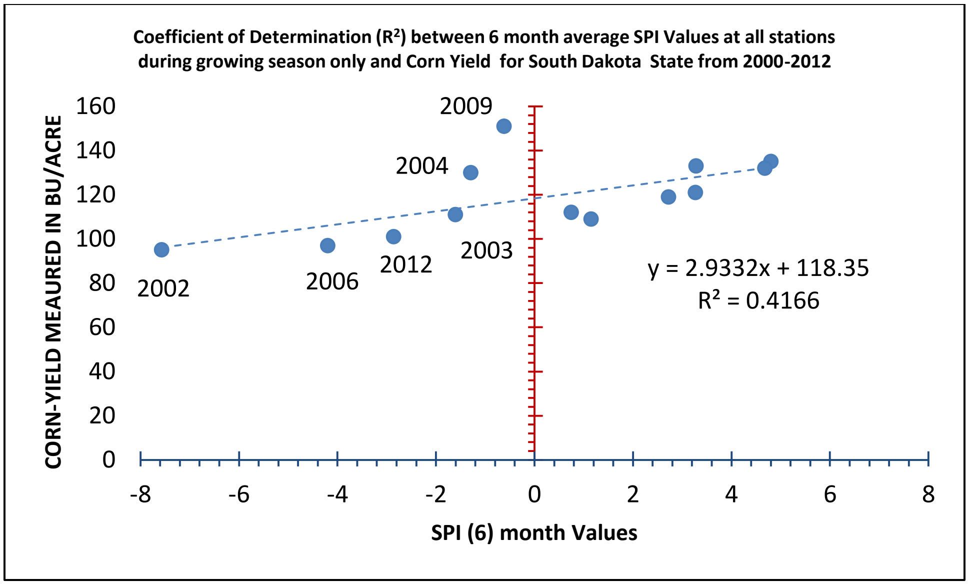
Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for Nebraska State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2009
2006
2012
2004
2000
2003
2002
y = 0.9342x + 47.04
R² = 0.4738

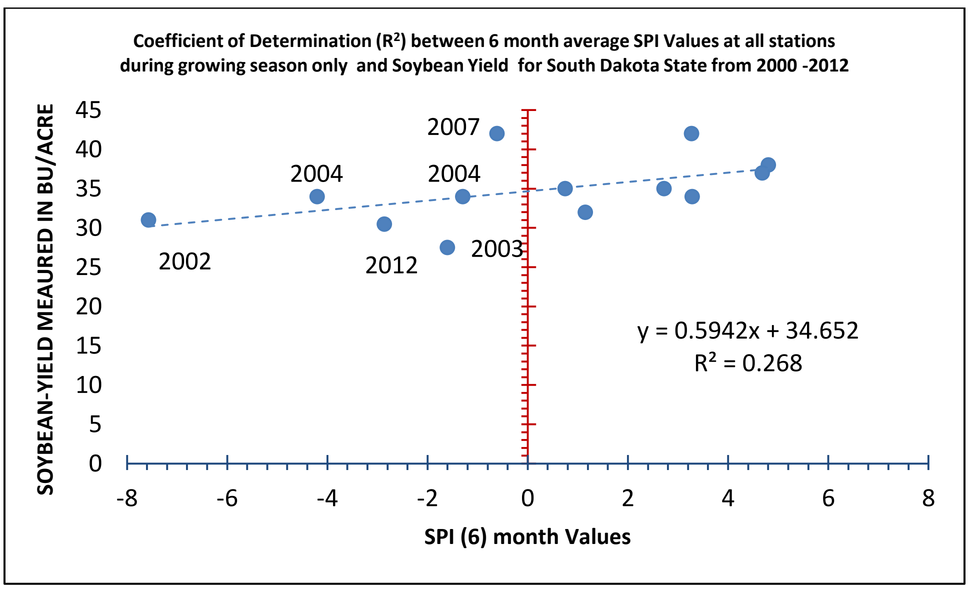

Coefficient of Determination (R^2) between 6 month average SPI Values at all stations during growing season only and Corn Yield for North Dakota State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
140
120
100
80
60
40
20
0
2008
2006
2002
y = 0.5488x + 115.05
R^2 = 0.0612
-8
-6
-4
-2
0
2
4
6
8
SPI (6) month Values

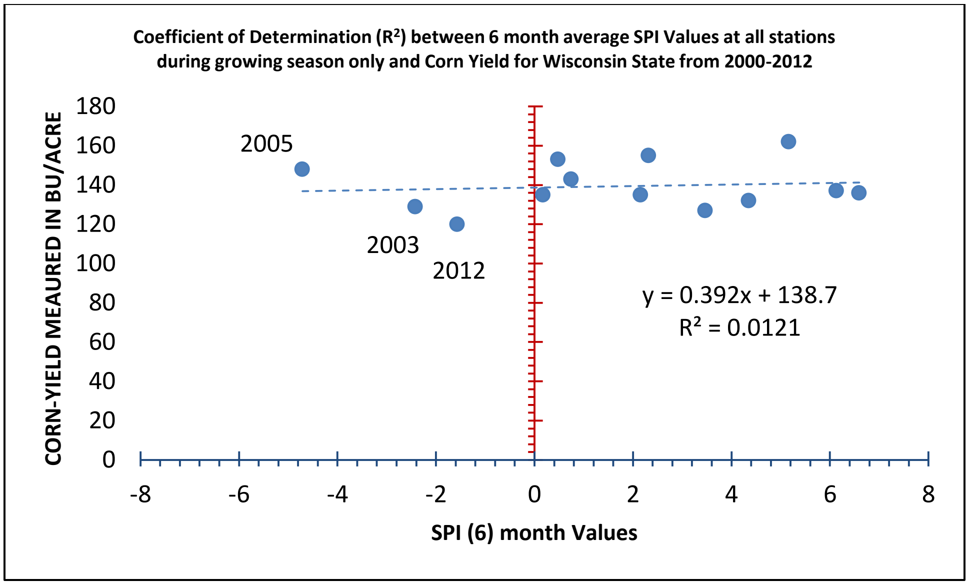

Coefficient of Determination (R^2) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for North Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
40
35
30
25
20
15
10
5
0
2006
2001
2002
2008
y = 0.2943x + 30.827
R^2 = 0.09
-8
-6
-4
-2
0
2
4
6
8
SPI (6) month Values

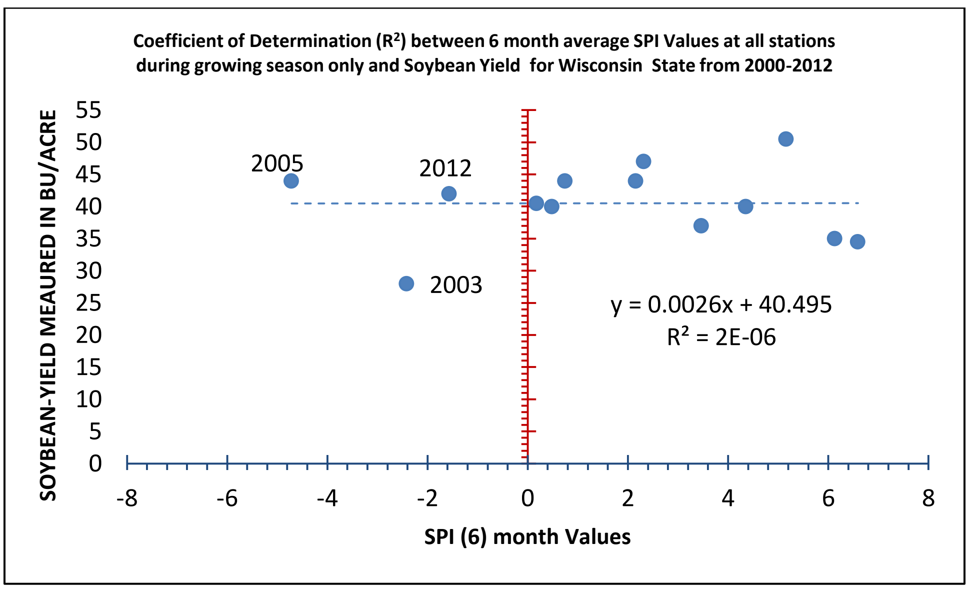

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Corn Yield for Ohio State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2009
2001
2012
y = 1.559x + 140.42
R² = 0.0811


Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for Ohio State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2009
2005
2001
y = -0.0639x + 43.656
R² = 0.0022

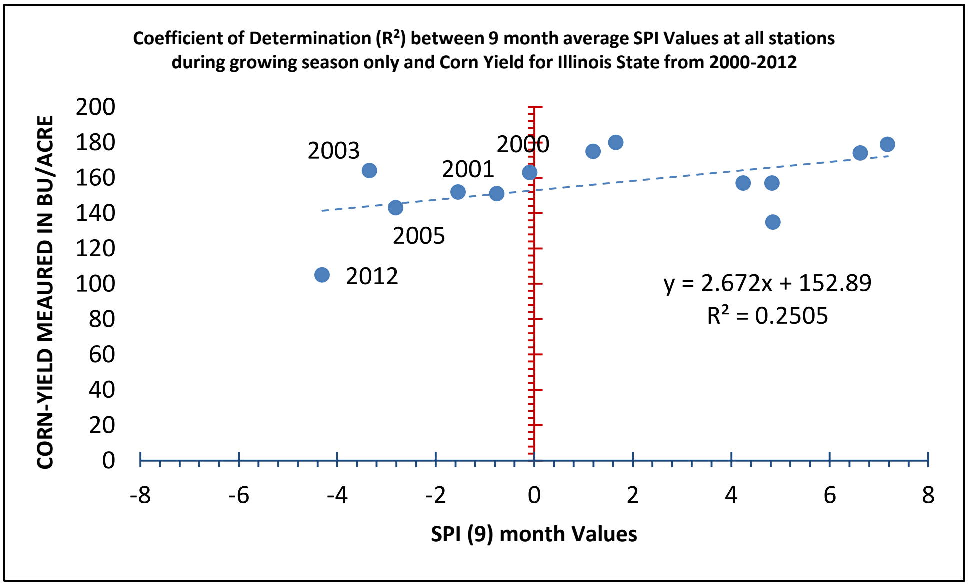

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Corn Yield for South Dakota State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2009
2004
2003
2002
2006
2012
y = 2.9332x + 118.35
R² = 0.4166

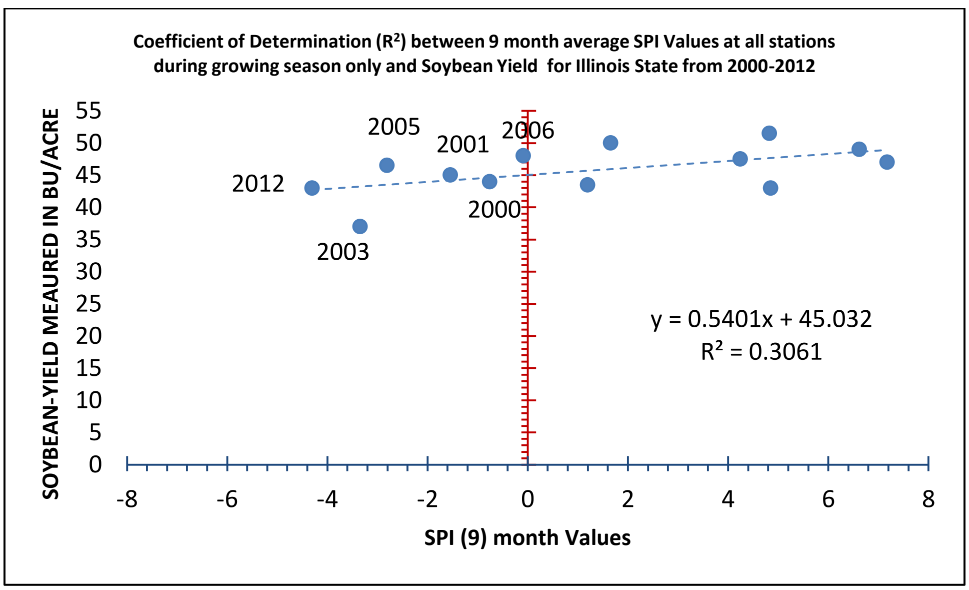

Coefficient of Determination (R²) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for South Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2007
2004
2004
2003
2002
2012
y = 0.5942x + 34.652
R² = 0.268

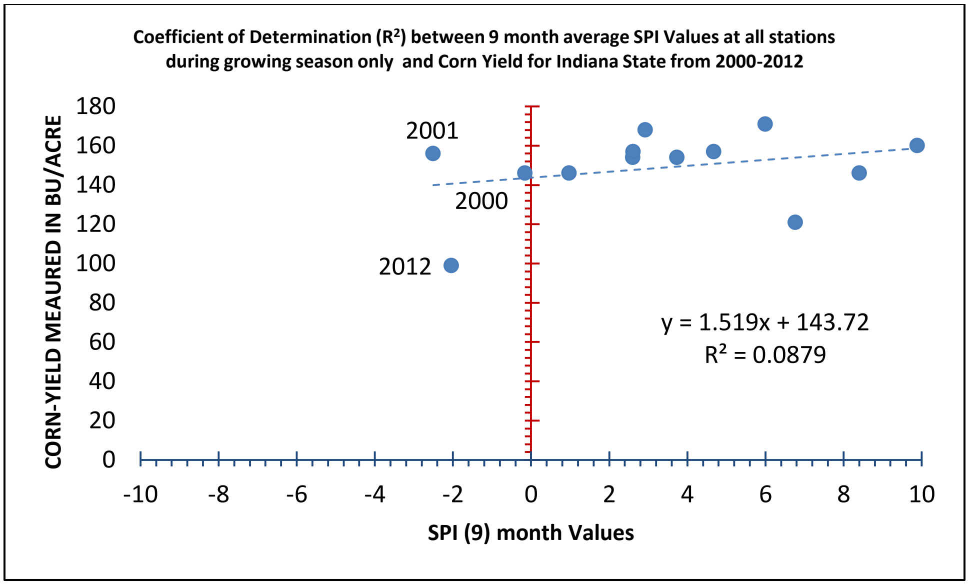

Coefficient of Determination (R^2) between 6 month average SPI Values at all stations during growing season only and Corn Yield for Wisconsin State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2005
2003
2012
y = 0.392x + 138.7
R^2 = 0.0121


Coefficient of Determination (R^2) between 6 month average SPI Values at all stations during growing season only and Soybean Yield for Wisconsin State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (6) month Values
2005
2012
2003
y = 0.0026x + 40.495
R^2 = 2E-06

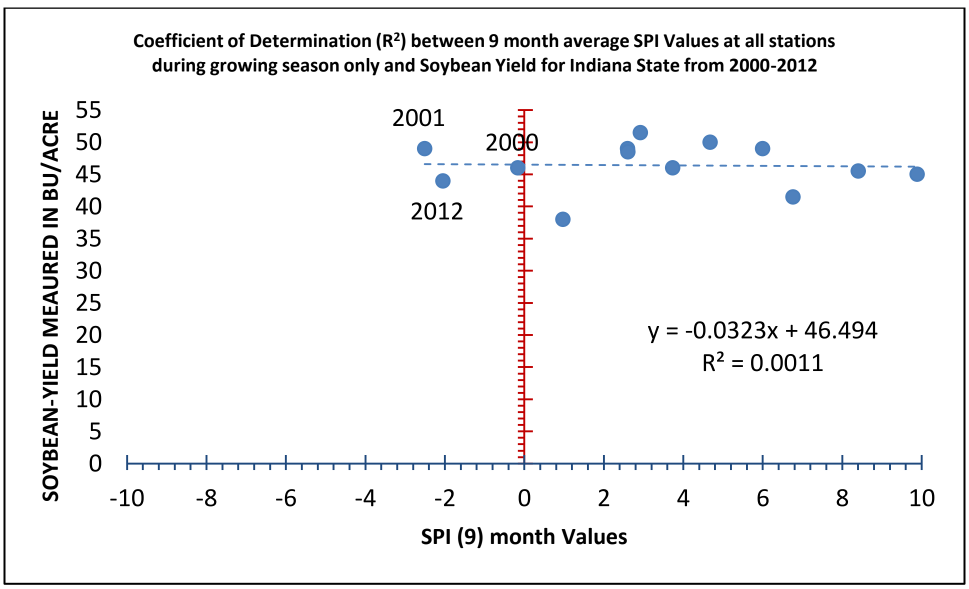
Coefficient of Determination (R^2) between Corn and Soybean Yield with SPI 9 Month



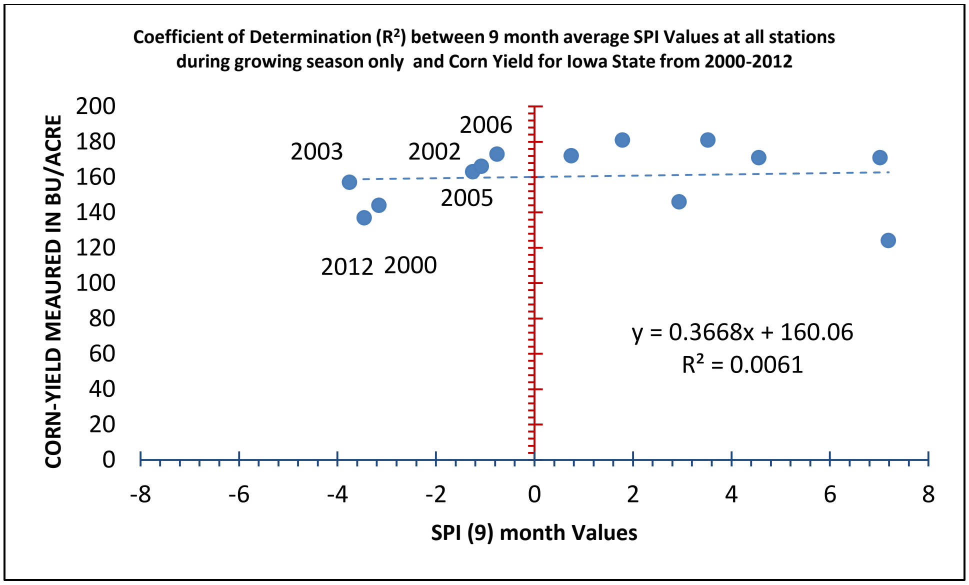


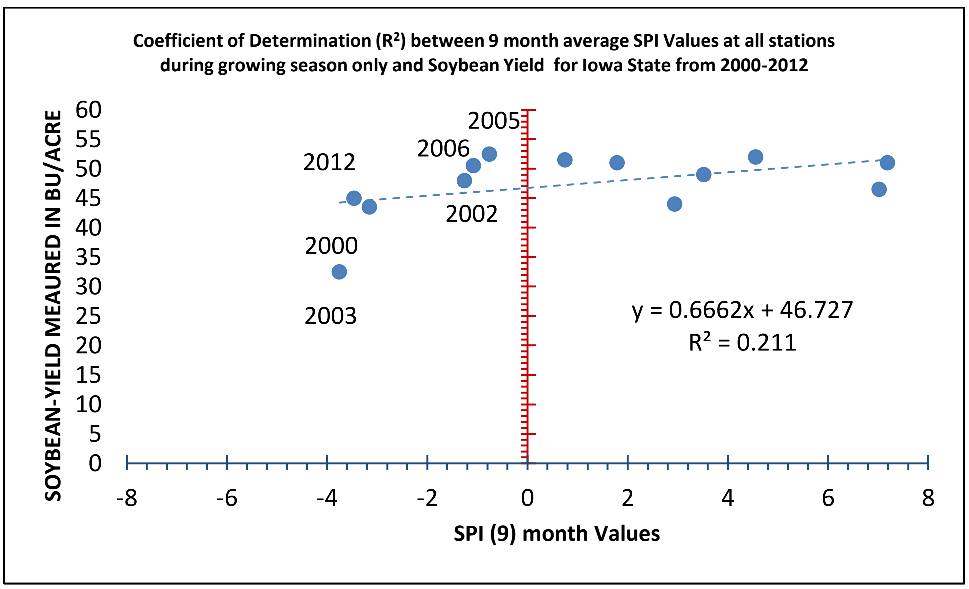


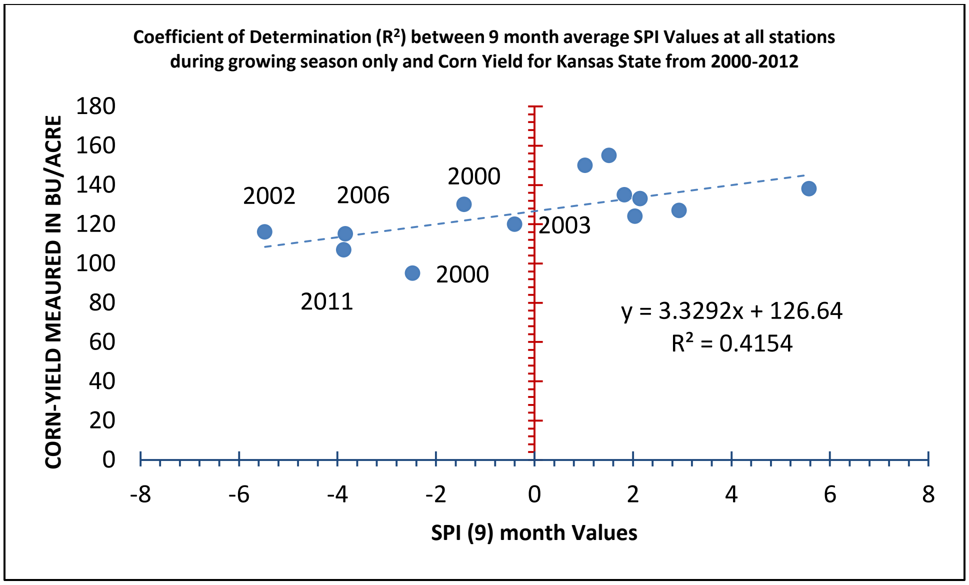
Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Corn Yield for Indiana State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2001
2000
2012
y = 1.519x + 143.72
R² = 0.0879

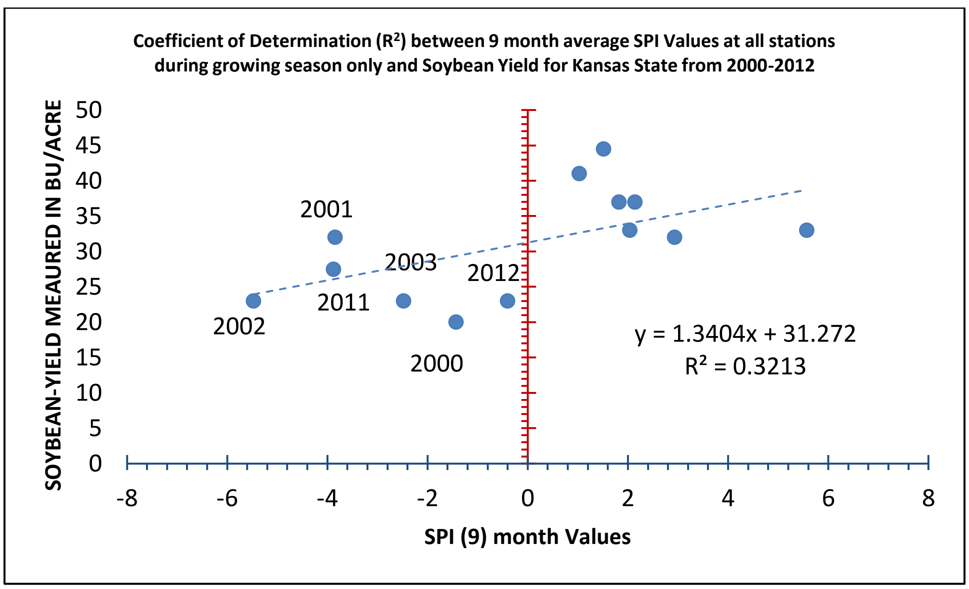


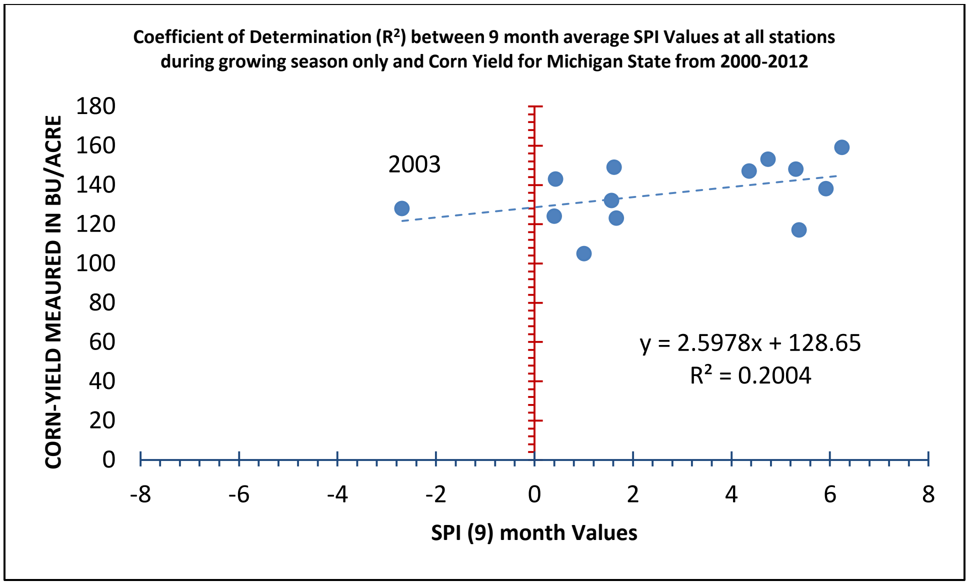
Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for Indiana State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2001
2000
2012
y = -0.0323x + 46.494
R² = 0.0011

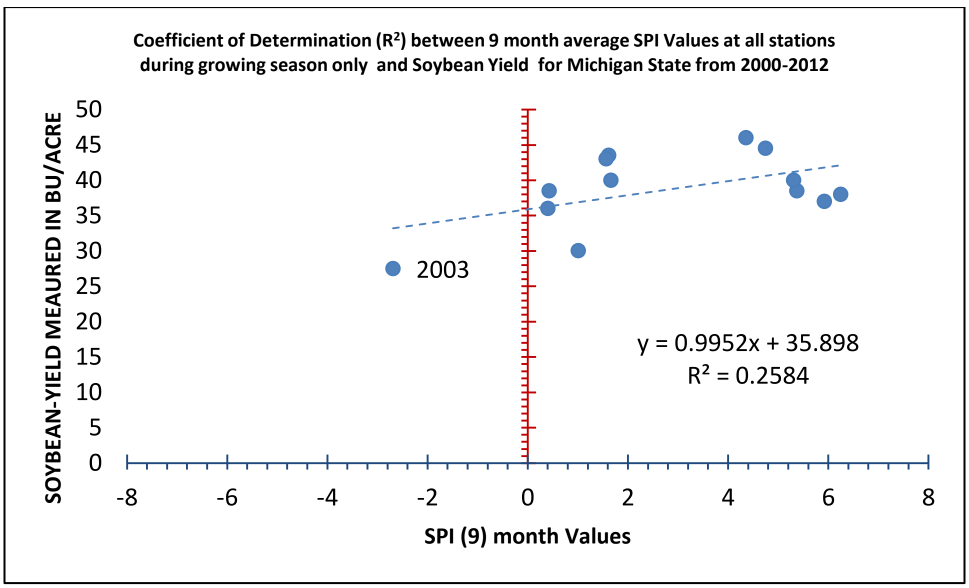

Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Corn Yield for Iowa State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2006
2003
2002
2005
2012
2000
y = 0.3668x + 160.06
R² = 0.0061

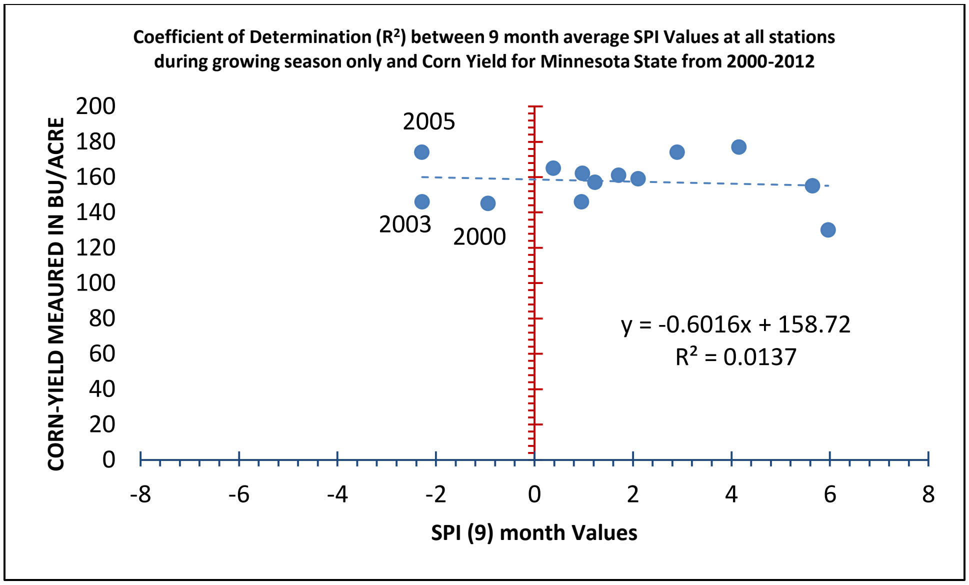

Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for Iowa State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2005
2006
2012
2002
2000
2003
y = 0.6662x + 46.727
R² = 0.211

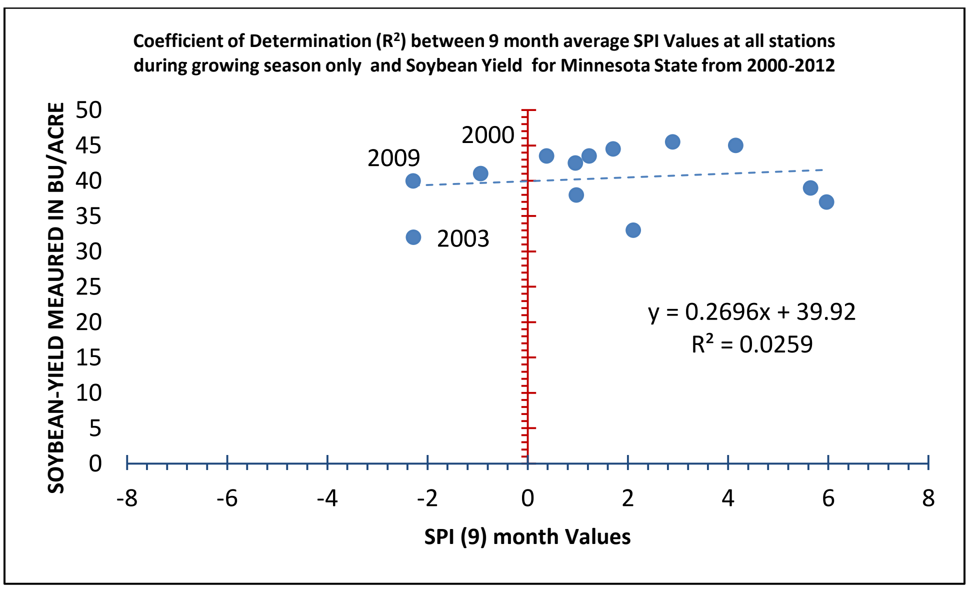

Coefficient of Determination (R^2) between 9 month average SPI Values at all stations during growing season only and Corn Yield for Kansas State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2002
2006
2000
2003
2000
2011
y = 3.3292x + 126.64
R^2 = 0.4154

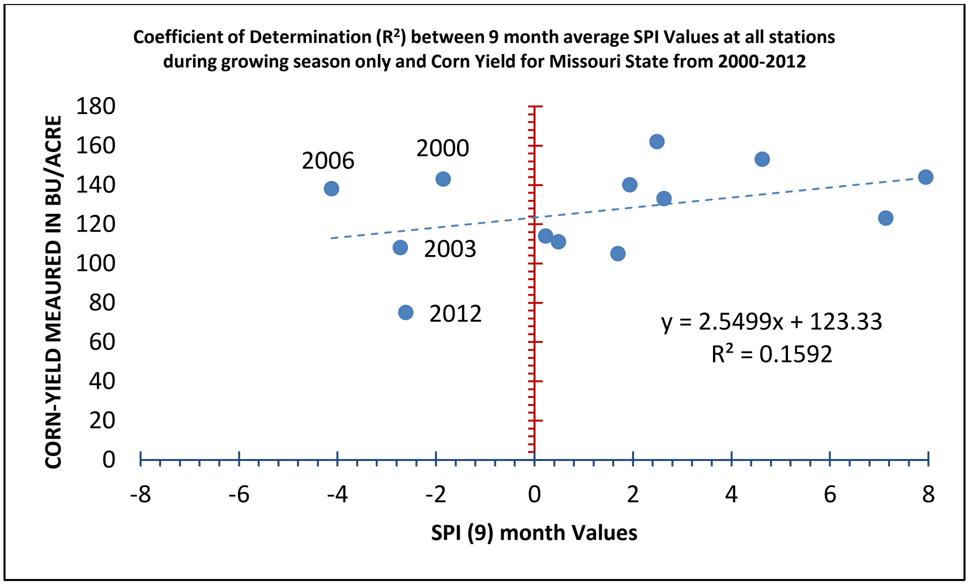

Coefficient of Determination (R^2) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for Kansas State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2001
2003
2012
2011
2002
2000
y = 1.3404x + 31.272
R^2 = 0.3213

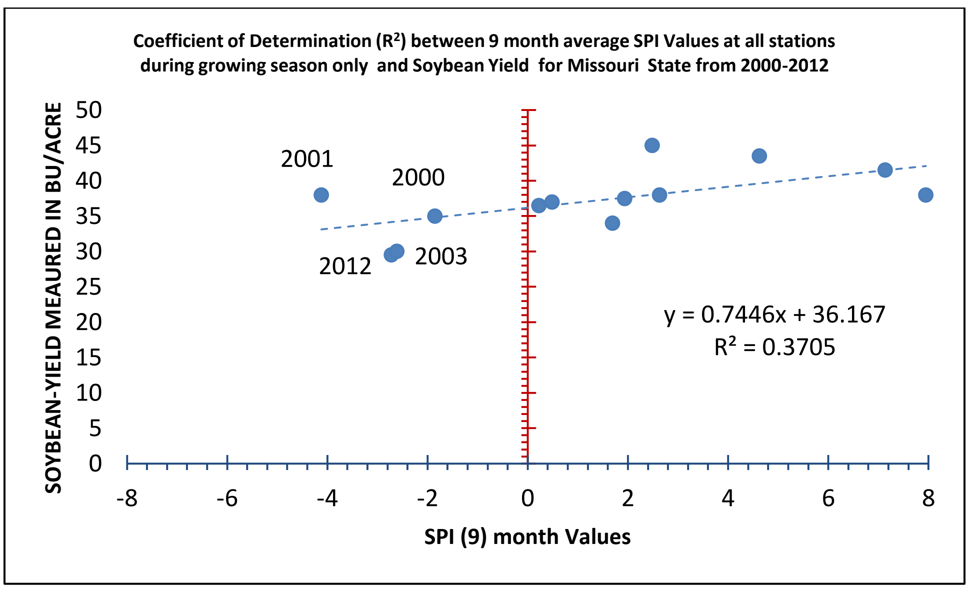

Coefficient of Determination (R^2) between 9 month average SPI Values at all stations during growing season only and Corn Yield for Michigan State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8
SPI (9) month Values
2003
y = 2.5978x + 128.65
R^2 = 0.2004

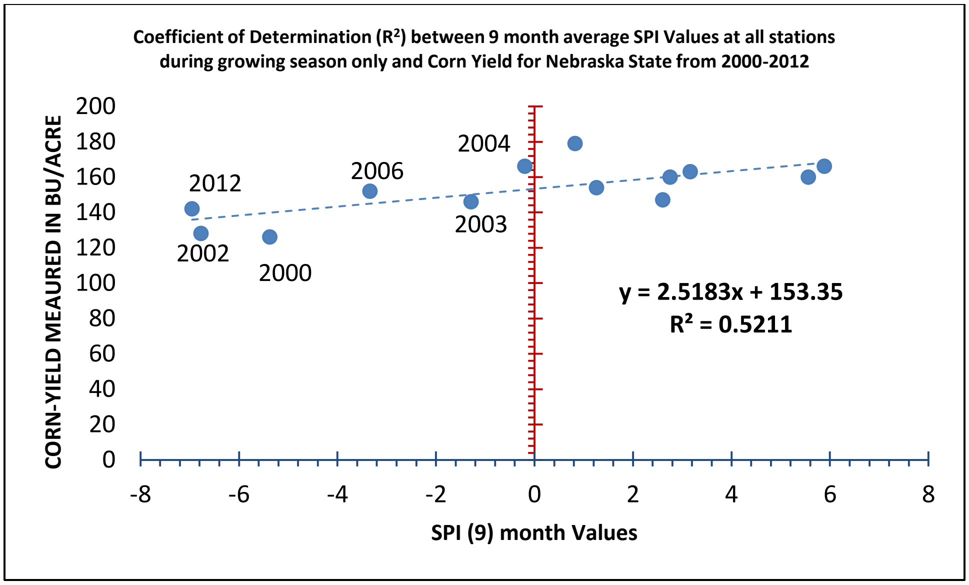

Coefficient of Determination (R^2) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for Michigan State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
50
45
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8
SPI (9) month Values
2003
y = 0.9952x + 35.898
R^2 = 0.2584

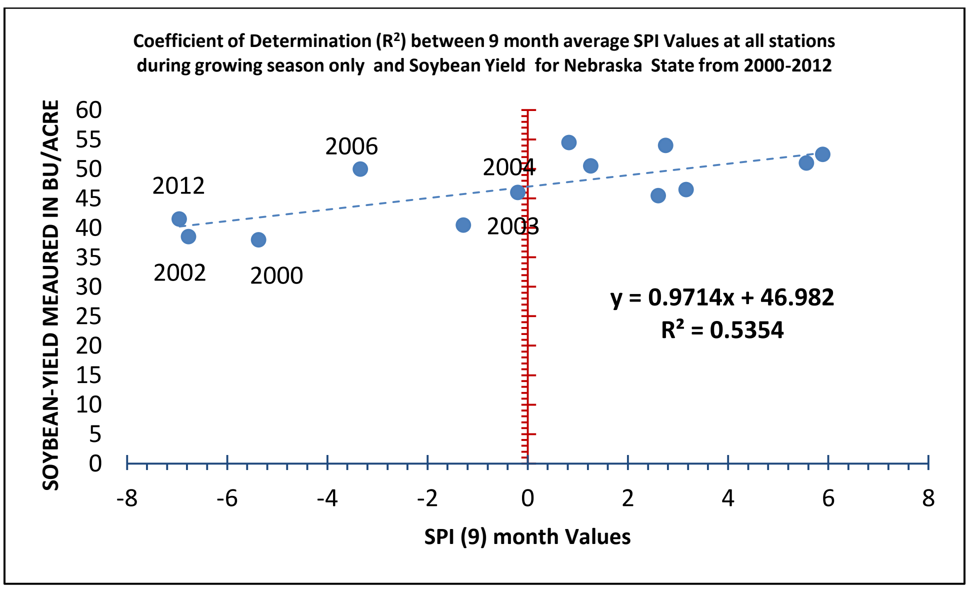

Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Corn Yield for Minnesota State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2005
2003
2000
y = -0.6016x + 158.72
R² = 0.0137

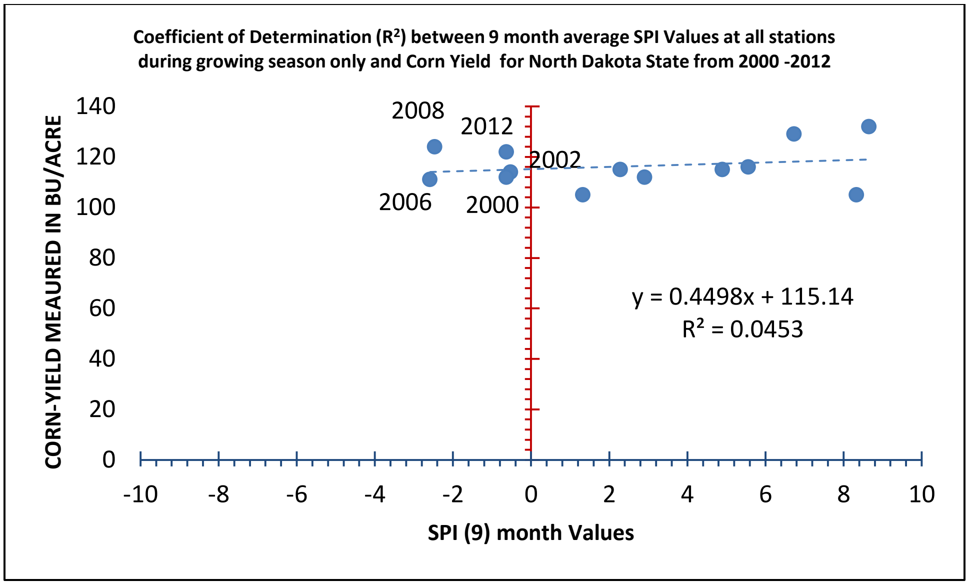

Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for Minnesota State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2000
2009
2003
y = 0.2696x + 39.92
R² = 0.0259

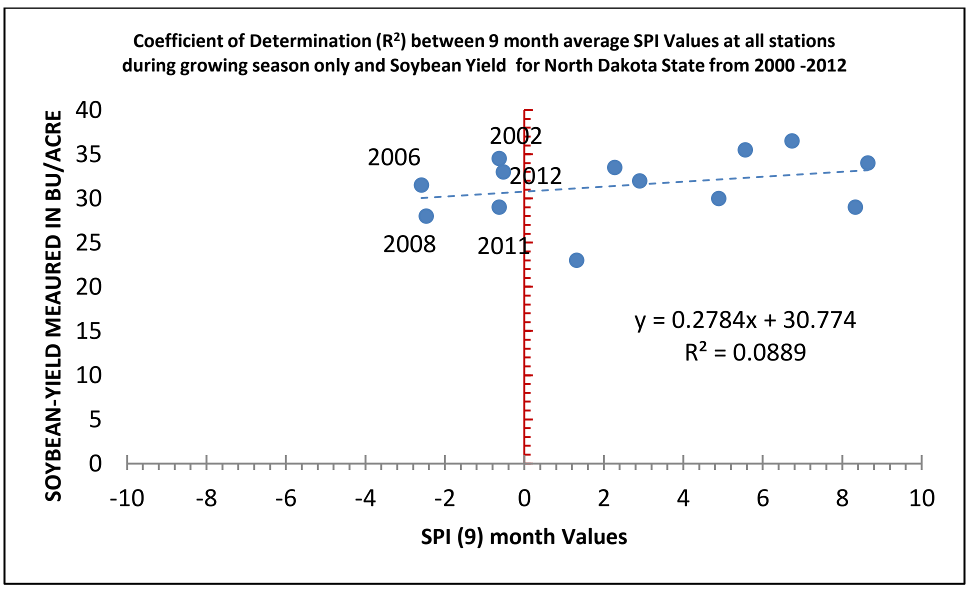

Coefficient of Determination (R^2) between 9 month average SPI Values at all stations during growing season only and Corn Yield for Missouri State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2006
2000
2003
2012
y = 2.5499x + 123.33
R^2 = 0.1592

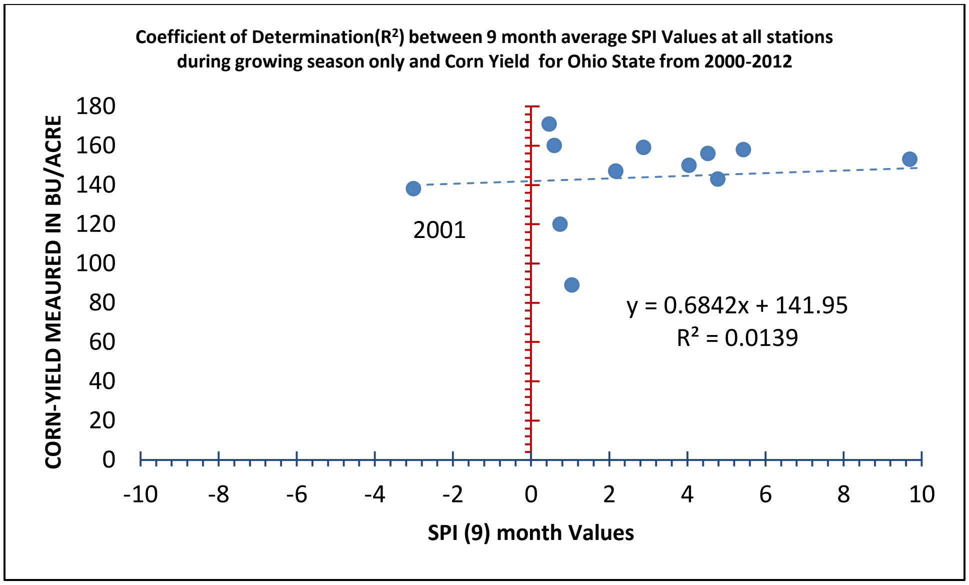

Coefficient of Determination (R^2) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for Missouri State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
SPI (9) month Values
2001
2000
2012
2003
y = 0.7446x + 36.167
R^2 = 0.3705

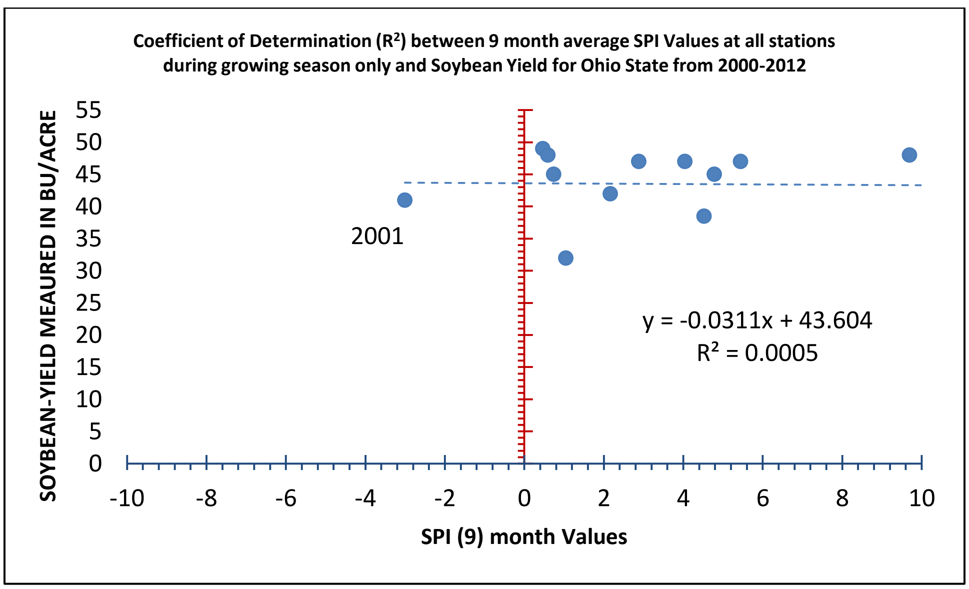

Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Corn Yield for Nebraska State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
200
180
160
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8
SPI (9) month Values
2012
2002
2000
2006
2004
2003
y = 2.5183x + 153.35
R² = 0.5211

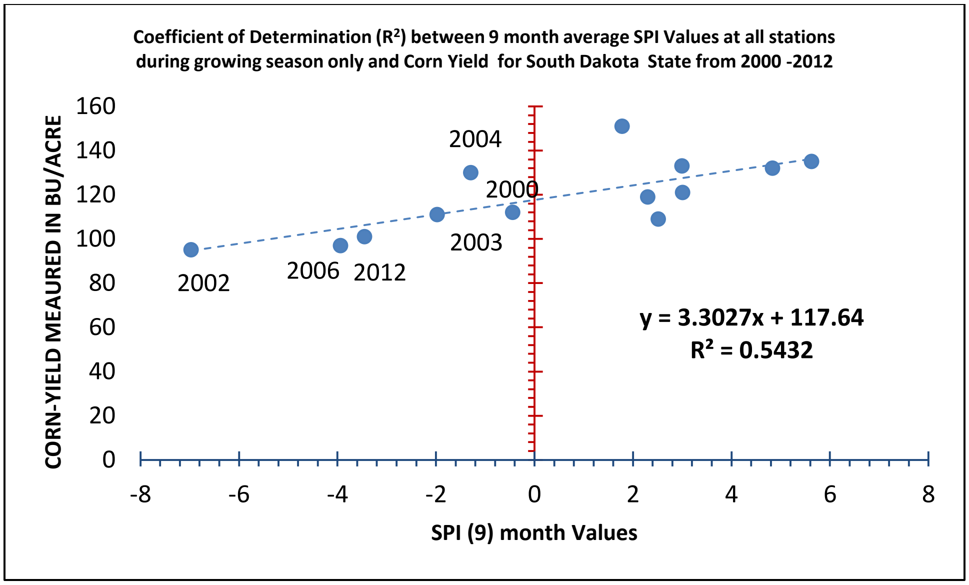

Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for Nebraska State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
60
55
50
45
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8
SPI (9) month Values
2012
2002
2000
2006
2004
2003
y = 0.9714x + 46.982
R² = 0.5354


Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Corn Yield for North Dakota State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
140
120
100
80
60
40
20
0
-10
-8
-6
-4
-2
0
2
4
6
8
10
SPI (9) month Values
2008
2012
2002
2006
2000
y = 0.4498x + 115.14
R² = 0.0453

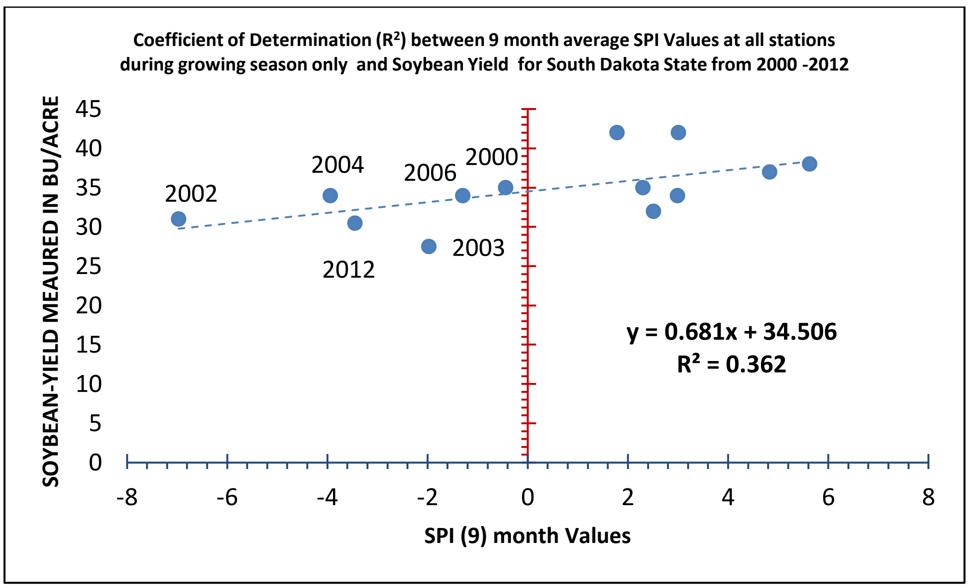

Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for North Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
40
35
30
25
20
15
10
5
0
-10
-8
-6
-4
-2
0
2
4
6
8
10
SPI (9) month Values
2006
2002
2012
2008
2011
y = 0.2784x + 30.774
R² = 0.0889


Coefficient of Determination(R²) between 9 month average SPI Values at all stations during growing season only and Corn Yield for Ohio State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
-10
-8
-6
-4
-2
0
2
4
6
8
10
SPI (9) month Values
2001
y = 0.6842x + 141.95
R² = 0.0139

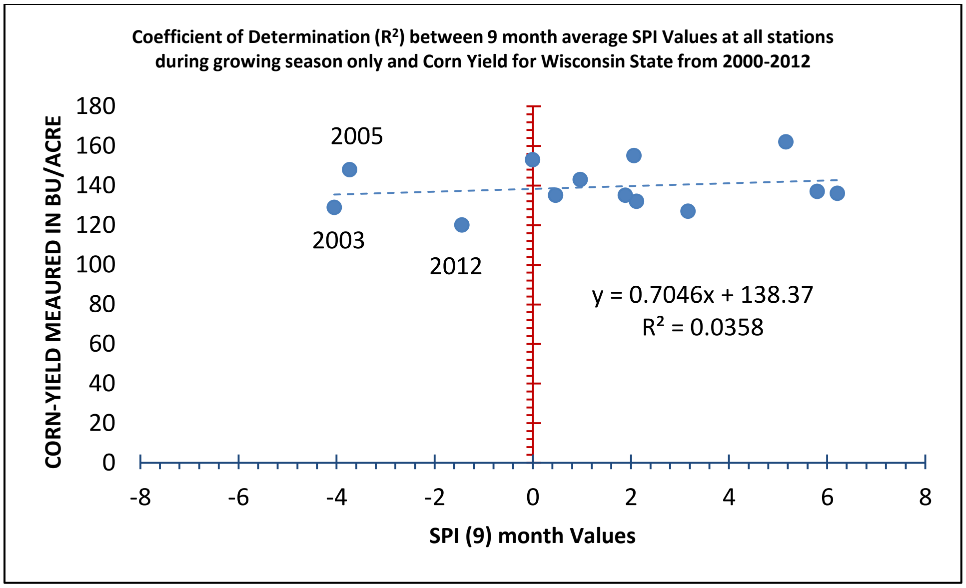

Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for Ohio State from 2000-2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
55
50
45
40
35
30
25
20
15
10
5
0
-10
-8
-6
-4
-2
0
2
4
6
8
10
SPI (9) month Values
2001
y = -0.0311x + 43.604
R² = 0.0005

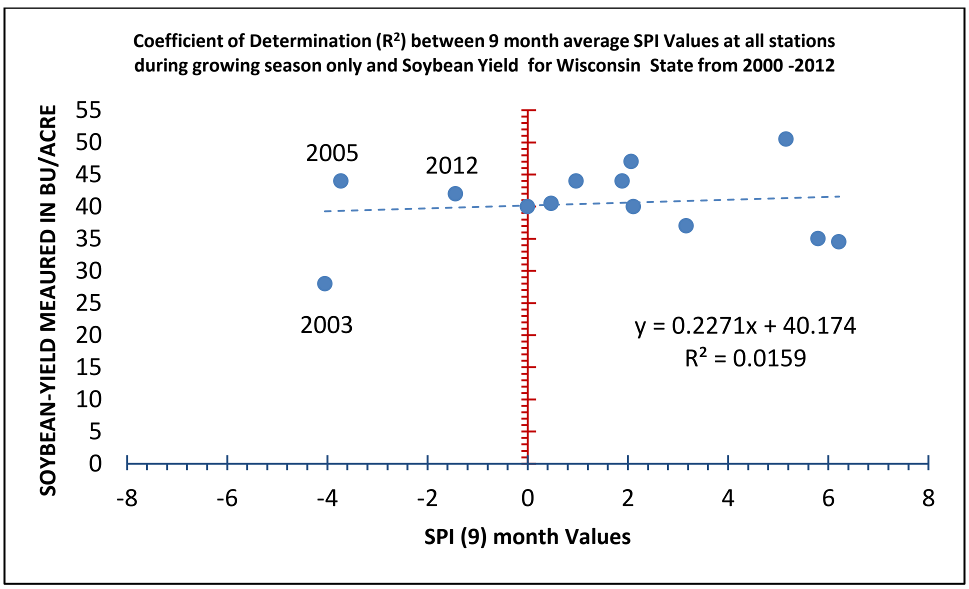


Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Corn Yield for South Dakota State from 2000 -2012
CORN-YIELD MEAURED IN BU/ACRE
160
140
120
100
80
60
40
20
0
-8
-6
-4
-2
0
2
4
6
8
SPI (9) month Values
2004
2000
2003
2002
2006
2012
y = 3.3027x + 117.64
R² = 0.5432



Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for South Dakota State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
45
40
35
30
25
20
15
10
5
0
-8
-6
-4
-2
0
2
4
6
8
SPI (9) month Values
2002
2004
2006
2000
2003
2012
y = 0.681x + 34.506
R² = 0.362


Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Corn Yield for Wisconsin State from 2000-2012
CORN-YIELD MEAURED IN BU/ACRE
180
160
140
120
100
80
60
40
20
0
2005
2003
2012
y = 0.7046x + 138.37
R² = 0.0358
-8
-6
-4
-2
0
2
4
6
8
SPI (9) month Values


Coefficient of Determination (R²) between 9 month average SPI Values at all stations during growing season only and Soybean Yield for Wisconsin State from 2000 -2012
SOYBEAN-YIELD MEAURED IN BU/ACRE
55
50
45
40
35
30
25
20
15
10
5
0
2005
2012
2003
y = 0.2271x + 40.174
R² = 0.0159
-8
-6
-4
-2
0
2
4
6
8
SPI (9) month Values

REFERENCES

Alley, W. M (1984), The Palmer Drought Severity Index: Limitations and assumptions, Journal of Climate and Applied Meteorology, 23, 1100-1109.

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