AN INVESTIGATION OF AGRICULTURAL DROUGHT ON THE UNITED STATES CORN BELT USING SATELLITE REMOTE SENSING AND GIS TECHNOLOGY

by

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

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DEDICATION

This is dedicated to my wonderful parents Yaming Liu and Zhongchao Wu with gratitude and love.
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# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>List of Tables</td>
<td>vii</td>
</tr>
<tr>
<td>List of Figures</td>
<td>viii</td>
</tr>
<tr>
<td>List of Abbreviations</td>
<td>x</td>
</tr>
<tr>
<td>Abstract</td>
<td>xii</td>
</tr>
<tr>
<td>Chapter One: Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Effects of drought stress on crop plants</td>
<td>3</td>
</tr>
<tr>
<td>1.2 Limitation of traditional methods of agricultural drought monitoring</td>
<td>7</td>
</tr>
<tr>
<td>1.3 Objectives and scopes</td>
<td>8</td>
</tr>
<tr>
<td>1.4 Major data sources</td>
<td>8</td>
</tr>
<tr>
<td>Chapter Two: Literature review</td>
<td>12</td>
</tr>
<tr>
<td>2.1 Agricultural drought monitoring with meteorological data</td>
<td>12</td>
</tr>
<tr>
<td>2.2 Agricultural drought monitoring with satellite remote sensing</td>
<td>20</td>
</tr>
<tr>
<td>Chapter Three: Crop mapping with GIS technology</td>
<td>29</td>
</tr>
<tr>
<td>3.1 U.S. crop mapping</td>
<td>29</td>
</tr>
<tr>
<td>3.1.1 Crop production map</td>
<td>30</td>
</tr>
<tr>
<td>3.1.2 Crop yield map</td>
<td>32</td>
</tr>
<tr>
<td>3.2 Study area</td>
<td>33</td>
</tr>
<tr>
<td>3.3 Chapter summary</td>
<td>37</td>
</tr>
<tr>
<td>Chapter Four: Assessment of MODIS indices for agricultural drought monitoring</td>
<td>39</td>
</tr>
<tr>
<td>4.1 Identification of agricultural drought events</td>
<td>40</td>
</tr>
<tr>
<td>4.2 Comparisons of MODIS indices between 2012 and non-drought years</td>
<td>41</td>
</tr>
<tr>
<td>4.3 Comparative analysis of MODIS index anomalies and SPI</td>
<td>45</td>
</tr>
<tr>
<td>4.4 Comparisons of MODIS drought indices with USDM</td>
<td>52</td>
</tr>
<tr>
<td>4.5 Comparative analysis over irrigated areas</td>
<td>60</td>
</tr>
<tr>
<td>4.6 Chapter summary</td>
<td>67</td>
</tr>
<tr>
<td>Chapter Five: Model simulation and sensitivity analysis</td>
<td>69</td>
</tr>
</tbody>
</table>
5.1 Leaf and canopy radiative transfer models .................................................. 70
5.2 Field experiment and simulation setup ....................................................... 71
5.3 Sensitivity analysis of vegetation status and spectral indices ....................... 74
5.4 Anomaly analysis of leaf variables and vegetation indices ......................... 79
5.5 Chapter summary ....................................................................................... 82

Chapter Six: A new phenology-adjusted approach for agricultural drought monitoring. 83
6.1 Phenology-adjusted time series .................................................................. 84
6.2 Anomaly assessment of corn yield ............................................................. 89
6.3 Corn water use function and sensitivity of corn yield to water stress ........... 90
6.4 Phenology-Adjusted Drought Index (PADI) ............................................. 94
6.6 Chapter summary ....................................................................................... 96

Chapter Seven: Drought events assessment and PADI verification .................. 97
7.1 The 2012 drought over the Corn Belt ....................................................... 97
7.2 The 2005 drought over Illinois ................................................................. 103
7.3 Chapter summary ..................................................................................... 107

Chapter Eight: Conclusions and discussion ................................................... 109
8.1 Conclusions ............................................................................................. 109
8.1.1 Assessment of MODIS indices for agricultural drought monitoring ....... 110
8.1.2 Model simulation and sensitivity analysis ............................................ 111
8.1.3 A new phenology-adjusted approach for agricultural drought monitoring .. 112
8.2 Limitation of this work ........................................................................... 113
8.3 Future works .......................................................................................... 113

References ...................................................................................................... 115
LIST OF TABLES

Table | Page
-----|-----
Table 1 Spectral indices used for drought monitoring. | 27
Table 2 Percentage of agricultural sectors experienced severe or greater drought in 2012. | 36
Table 3 MODIS spectral indices evaluated in this study. | 40
Table 4 F statistics of ANOVA test. | 60
Table 5 Input parameters of PROSPECT and SAIL models in this study. | 74
Table 6 Estimated evapotranspiration and percentage of yield loss during corn-growing stages. | 91
Table 7 Average water use for corn. | 92
Table 8 Daily water uses for corn at 15 stages and corresponding weights for NDII6 anomaly in PADI. | 95
Table 9 Correlation coefficients of 2012 corn yield anomaly with PADI1, PADI2 and with four averaged MODIS index anomalies. | 101
Table 10 Correlation coefficients of 2005 corn yield anomaly with PADI and with four averaged MODIS index anomalies. | 106
LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1</td>
<td>The corn cover map developed based on Cropland Data Layer.</td>
<td>11</td>
</tr>
<tr>
<td>Figure 2</td>
<td>Typical reflectance and absorption characteristics of vegetation.</td>
<td>24</td>
</tr>
<tr>
<td>Figure 3</td>
<td>Corn production map for the United States (2006-2010).</td>
<td>31</td>
</tr>
<tr>
<td>Figure 4</td>
<td>U.S. corn yield map in 2011 and 2012.</td>
<td>33</td>
</tr>
<tr>
<td>Figure 5</td>
<td>Main area of the Corn Belt. Cropland land cover is shown in grey.</td>
<td>34</td>
</tr>
<tr>
<td>Figure 6</td>
<td>Time series of average temperature and precipitation over the Corn Belt for corn-growing season from 1990 to 2012.</td>
<td>35</td>
</tr>
<tr>
<td>Figure 7</td>
<td>USDM drought map.</td>
<td>37</td>
</tr>
<tr>
<td>Figure 8</td>
<td>Proportion of total area in each drought level for five key Corn Belt States.</td>
<td>41</td>
</tr>
<tr>
<td>Figure 9</td>
<td>Histograms of eight MODIS indices for corn-growing season.</td>
<td>44</td>
</tr>
<tr>
<td>Figure 10</td>
<td>Map of the Corn Belt showing locations of weather station.</td>
<td>47</td>
</tr>
<tr>
<td>Figure 11</td>
<td>6-month average SPI values at all stations from 2002 to 2012.</td>
<td>47</td>
</tr>
<tr>
<td>Figure 12</td>
<td>Correlation coefficient values between SPI and MODIS spectral index anomalies at three time steps and four time lags.</td>
<td>50</td>
</tr>
<tr>
<td>Figure 13</td>
<td>Scatter-plots of MODIS spectral index anomalies and SPI6.</td>
<td>51</td>
</tr>
<tr>
<td>Figure 14</td>
<td>Comparisons of weekly USDM maps with anomaly maps of eight MODIS indices during 2012 corn-growing season.</td>
<td>54</td>
</tr>
<tr>
<td>Figure 15</td>
<td>Boxplots of MODIS indices under USDM scheme for the week of July 10th, Aug 14th and Sep 11th.</td>
<td>59</td>
</tr>
<tr>
<td>Figure 16</td>
<td>The map of irrigated lands in Nebraska.</td>
<td>61</td>
</tr>
<tr>
<td>Figure 17</td>
<td>Scatter plot between corn yield change and proportions of irrigated cropland for major crop counties in Nebraska.</td>
<td>62</td>
</tr>
<tr>
<td>Figure 18</td>
<td>Time series of MODIS NDVI, NDII6 and LAI from 2001 to 2012 over irrigated and non-irrigated cropland.</td>
<td>64</td>
</tr>
<tr>
<td>Figure 19</td>
<td>Comparison of sensitivity of five MODIS spectral indices to irrigation presence in Nebraska for 2012.</td>
<td>66</td>
</tr>
<tr>
<td>Figure 20</td>
<td>Histogram of NDII6 over irrigated and non-irrigated regions in Nebraska.</td>
<td>67</td>
</tr>
<tr>
<td>Figure 21</td>
<td>Comparisons between USDM map, irrigated map and NDII6 anomaly map in eastern Nebraska.</td>
<td>67</td>
</tr>
<tr>
<td>Figure 22</td>
<td>Histograms of $C_{ab}$, $C_w$ and $C_m$ from laboratory measurements.</td>
<td>72</td>
</tr>
<tr>
<td>Figure 23</td>
<td>Schematic of the link between leaf and canopy models.</td>
<td>73</td>
</tr>
<tr>
<td>Figure 24</td>
<td>Simulated effects of $C_{ab}$ and $C_w$ on leaf reflectance.</td>
<td>76</td>
</tr>
<tr>
<td>Figure 25</td>
<td>Simulated reflectance of MODIS band 1 for varying $C_{ab}$ and simulated reflectance of MODIS band 6 for varying $C_w$.</td>
<td>77</td>
</tr>
</tbody>
</table>
Figure 26 Simulated effects of $C_{ab}$ on NDVI and effects of $C_w$ on NDI6 respectively within different LAI conditions. ................................................................. 78
Figure 27 Simulated effects of $C_{ab}$ on NDVI and relationship between $C_{ab}$ anomaly and NDVI anomaly within different LAI conditions. .................................................. 81
Figure 28 Simulated effects of $C_w$ on NDI6 and relationship between $C_w$ anomaly and NDI6 anomaly within different LAI conditions ................................................... 81
Figure 29 Corn growing progress ........................................................................................................ 85
Figure 30 Corn planting progress for five Corn Belt states from 2000 to 2012. .................. 86
Figure 31 Corn planting date for five Corn Belt states from 2000 to 2012. ....................... 87
Figure 32 Corn emergence date for five Corn Belt states from 2000 to 2012. ................. 87
Figure 33 MODIS data used for each corn-growing season from 2000 to 2012. .............. 88
Figure 34 MODIS data used for 2012 corn-growing season in state of Iowa. ................. 89
Figure 35 Comparison of original and de-trended corn yield data ................................................. 90
Figure 36 Average water use of corn for each week after emergence. ................................. 92
Figure 37 Correlation coefficient for corn yield anomaly versus NDI6 anomaly and accumulated NDI6 anomaly at 15 growing stages .................................................. 94
Figure 38 Scatter plots of 2012 corn yield anomaly and averaged anomalies of four MODIS indices during corn-growing season .......................................................... 98
Figure 39 Scatter plots of 2012 corn yield anomaly and PADI1 and PADI2 ....................... 99
Figure 40 Comparisons of PADI map at 500m resolution, county-level PADI map and corn yield anomaly map across the Corn Belt in 2012......................................... 102
Figure 41 Correlation coefficients of 2012 corn yield anomaly with PADI for counties in five Corn Belt states ................................................................. 103
Figure 42 USDM drought maps for Illinois in 2005 from June to September .................. 104
Figure 43 Comparisons of PADI map at 500m resolutions, county-level PADI map and corn yield anomaly map across Illinois in 2005. ......................................................... 105
Figure 44 Scatter plots of 2005 corn yield anomaly and PADI and averaged anomalies of four MODIS indices over corn-growing season for counties in Illinois................. 106
LIST OF ABBREVIATIONS

Abscisic acid.......................................................... ABA
Advanced Wide Field Sensor.................................. AWiFS
Advanced Very High Resolution Radiometer................. AVHRR
Climate Data Records ............................................. CDRs
Cropland Data Layer .............................................. CDL
Enhanced Thematic Mapper .................................... ETM
Fraction of Photosynthetically Active Radiation ............... FPAR
European Drought Observatory ................................... EDO
Geographic Information System .................................. GIS
Leaf Angle Distribution .......................................... LAD
Leaf Area Index ..................................................... LAI
Land Surface Temperature ........................................ LST
MODerate resolution Imaging Spectroradiometer .............. MODIS
National Agricultural Statistics Service ......................... NASS
Normalized Difference Infrared Index-band6 ..................... NDI6
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
Suomi National Polar-orbiting Partnership ...................... Suomi-NPP
Phenology-Adjusted Drought Index ............................... PADI
Palmer Drought Severity Index .................................... PDSI
Relative Sensitivity Index ......................................... RSI
Center for Sustainability and the Global Environment ........... SAGE
Scattering by Arbitrarily Inclined Leaves ......................... SAIL
Standardized Precipitation Index .................................... SPI
Shortwave Infrared .................................................. SWIR
Temperature Condition Index ...................................... TCI
Thematic Mapper ..................................................... TM
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
ABSTRACT

AN INVESTIGATION OF AGRICULTURAL DROUGHT ON THE UNITED STATES CORN BELT USING SATELLITE REMOTE SENSING AND GIS TECHNOLOGY

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Agriculture is often the first and most vulnerable sector to be affected by drought events. As a rapidly developing technology, remote sensing coupled with Geographic Information Science (GIS) provides great potential for rapid and spatial-explicit agricultural drought monitoring. The research presented in this dissertation is dedicated to promoting agricultural drought monitoring and impact assessment using satellite remote sensing and GIS technology.

Crop mapping with GIS technology provides a foundation for improving agricultural drought monitoring, with efforts focusing on intensive agricultural areas. In this study, U.S. Corn Belt, the major corn-production region of U.S. was identified and selected as study area. U.S. corn production and corn yield maps were generated and analyzed using GIS technology. With case study of the 2012 drought over the Corn Belt, the sensitivity of eight widely used indices to agricultural drought condition was assessed. Time series of these indices were generated from year 2000 to 2012 for the
study area and compared with the Standardized Precipitation Index (SPI)-a precipitation deficit/surplus indicator using pixel-to-weather station paired correlation approach. The anomaly of Normalized Difference Infrared Index-band6 (NDII6) presented the highest overall correlation with SPI at all time steps evaluated demonstrating good sensitivity to water stress over large agricultural areas. By comparing with U.S. Drought Monitor (USDM), the current advanced drought-monitoring tool, NDII6 anomaly demonstrated advantage of remote sensing in monitoring drought condition over irrigated land and showed the potential to advance fine-scale agricultural drought monitoring by providing more detailed spatial characterization of drought patterns.

In order to investigate the linkage between key vegetative variables and remote sensing vegetation indices, numerical simulation and sensitivity analysis were performed with the coupled leaf-canopy radiative transfer models based on field and laboratory measurements. Leaf Area Index (LAI), an important parameter of vegetation canopy, was found playing an important role in relationships between vegetation chlorophyll/water content and spectral indices but showing limited impact on the relationship between their anomalies. The results provide a physical basis for using index anomaly in agricultural drought monitoring.

Finally, a new agricultural drought indicator, the Phenology-Adjusted Drought Index (PADI) was proposed for assessing agricultural drought severity during growing season based on phenology information, NDII6 anomaly and corn water use function. The new method takes advantage of phenology-adjusted MODIS time series and unbalanced crop response to water stress during growing season. Since the PADI reflects
the cumulative effects of vegetation water content anomalies during corn-growing season, it provides a promising approach for agricultural drought monitoring from space at fine spatial scale. Verification with case studies of the 2012 drought over the Corn Belt and the 2005 drought over Illinois demonstrated the good capability of PADI for agricultural drought monitoring. Currently, the study is focusing on the Corn Belt, an intensive corn-growing region. Further studies will be conducted to investigate the performance of PADI to monitor agricultural drought condition over other corn-growing areas.
CHAPTER ONE: INTRODUCTION

Agricultural drought is one of the major natural hazards common all over the world. As a recurrent climate process, drought affects virtually all climatic regimes (Wilhite, 2000), affecting human activity and causing widespread economic consequences (Wilhite et al., 2007). Unlike other natural disasters such as hurricanes, floods and earthquake, drought is a slow-onset phenomenon, lacking highly visible and structural impacts (Guha-Sapir et al., 2012). In general, drought spread over a larger geographical area than damages brought by other natural hazards making it challenging to quantify the impacts (Karamouz et al., 2012).

Drought can be defined specifically as a deficit of water relative to normal conditions in one or a combination of stores (river, lake, soil moisture and ground water) or fluxes (precipitation, evapotranspiration and run-off) (Sheffield and Wood, 2011). The wide variety of sectors affected by drought, its diverse spatial and temporal distribution, and the many scales drought operates on make it difficult to develop both a single definition of drought and a universal drought measuring tool (Lake, 2011; WMO, 2006). Despite of variations in drought definition, drought has been broadly grouped into four categories: meteorological, hydrological, agricultural and socioeconomic (American Meteorological Society, 1997).
In this study, we focus primarily on agricultural drought, which has been defined as an interval of time, when there are insufficient soil moisture, precipitation and humidity during crop growing season to support healthy crop growth (Sheffield and Wood, 2011). Drought can greatly affect the quality of a crop as well as the yield. Deficient moisture at planting may hinder germination, leading to crop failure and a reduction of yield; dry weather and low humidity would also influence plant growth, photosynthesis and pollination. In 2012, a devastating drought, originated in the midst of a summer heat wave, profoundly affected the Corn Belt, an intensive agricultural region of the United States, causing widespread crop failure. The 2012 drought rapidly increased in severity during summer season and damaged large portions of the major field crops in top corn-producing states including Illinois, Indiana, Iowa, Nebraska and Ohio. It exceeds, in most measures, the 1988-1989 North American Drought, the most recent comparable drought (Kimery, 2012). The estimated 2012 corn yield in U.S. is 123.4 bushels per acre, 23.8 bushels below the 2011 yield. The total corn for grain production is estimated at 10.8 billion bushels, 13 percent below the production of 2011. The production loss also occurred in soybean for 2012, with totaled production 3.01 billion bushels, 3 percent below the 2011 production (USDA, 2013).

The recent drought over crop areas reinforced the need for more accurate and practical approaches of agricultural drought monitoring so as to assist decision makers and the farming community in agricultural management and water resource utilization. Understanding the occurrence period, spatial distribution and severity is crucial to establish local/national agricultural drought strategies. The traditional methods for
agricultural drought monitoring are mostly based upon meteorological measurements that are usually limited in spatial and temporal coverage, especially in areas with sparse distribution of weather stations and areas in complex terrain (Caccamo et al., 2011).

As rapidly developing technology, remote sensing is now capable of estimating hydrological variables, such as precipitation, soil moisture, evapotranspiration, as well as vegetation status, health and crop productivity (Sheffield and Wood, 2011). Since vegetation abundance and development information are strongly related to environmental water stress, satellite observations of vegetation status can provide the basis for agricultural drought monitoring. When coupled with GIS, a valuable tool for spatial information management and analysis, remote sensing has the potential to provide a repetitive view of the earth surface, facilitating short- and long-term agricultural drought monitoring with higher spatial and temporal resolution.

1.1 Effects of drought stress on crop plants

The environmental stresses resulting from drought and high temperature affect crop growth and production at various levels of organizations and during all development stages (Alqudah et al., 2011; Joshi, 2010). The impact of drought on crop yield is quite complex, involving processes as diverse as reproductive organs, gametogenesis, fertilization, embryogenesis, and rhizogenesis (Barnabas et al., 2008). Crop plants under drought stress are likely to show stunted growth, wilting, reduced pollen viability, silk delay, shorter grain-filling duration, poor seed quality and lower individual grain weight (Alqudah et al., 2011; Smith et al., 2004).
The period of pollination and fertilization is the most important growing stage of crop because the success during this stage guarantee high crop yield. Water stress and high temperature can significantly influence crop pollination and yield potential during reproductive period. The drought stress limits crop pollination by reducing pollen grain viability (Trueman and Wallace, 1999) and increasing pollen grain sterility (Al-Ghzawi et al., 2009). Buitink et al. (2002) highlighted the close relationship between viability of corn pollen and drying condition of the environment. Corn pollen speed and survival rates also proved to be affected by relative water content (Aylor, 1999).

One of the ways drought stress affects pollen grain development is to increase level of Abscisic acid (ABA), an important factor causing pollen sterility (Boyer and Westgate, 2004). Pollen grain needs sufficient water and energy to complete development process in reproductive growth. Starch is considered an important energy source for pollen development and germination (Firon et al., 2012), hence the absence of starch may result in pollen sterility (Alqudah et al., 2011). Other energy sources for pollen development and germination include sugar and carbohydrate. Carbohydrates not only aid in pollen development as an energy source, but also are necessary for pollen wall biosynthesis (Goetz et al., 2001; Woo et al., 2008). Under drought stress, the sources of these energy reduced raising the possibility of pollen grain sterility, abnormal pollen grain and pollen grain abortion (Alqudah et al., 2011).

Following pollination and finishing at kernel maturity, grain-filling period normally lasts 60 days and is considered the critical time frame determining final output (Nielsen, 2011). During grain filling period, developing kernels is high priority sink for
photosynthate produced by corn (Nielsen, 2008). A grain-filling period in favorable environment can maximize the yield potential of a crop, while serious drought stress during the period may cause corn yield loss occurred from stand loss, incomplete kernel set, kernel weight reduction and premature plant death (Nielsen, 2011).

Drought stress is always a threat to crop yield. The 2012 drought greatly affected corn production across the Corn Belt. The drought-induced yield loss can be largely due to accelerated days to flowering, shorter grain-filling period and limited accumulation of dry matter (Alqudah et al., 2011). Corn yield generally depends on two components: the number of kernels reaches maturity and weights of those kernels (Smith et al., 2004). Both components can be affected by drought stress. Under water stress, ovary abortion or pollen sterility may occur leading to reduction in seed set (Boyer and Westgate, 2004). Even after successful pollination, fewer kernels may be developed due to high percentage of Abscisic Acid in generative organs of corn plant, which is considered as the major cause of kernel abortion (Liu et al., 2005). Drought during seed filling often leads to production of smaller corn seeds. The reasons for smaller seeds include smaller assimilate supply due to accelerated leaf senescence, lower sink capacity as a result of less cell volume and inhibition of storage product synthesis results from water stress (Smith et al., 2004). Drought-induced weight loss of individual grain is also associated with shorter grain-filling period and lower accumulation of dry matters in growing kernels (Alqudah et al., 2011; Samarah et al., 2009).

Water stress also influences root system of crop plants. Roots are considered as the very place where crops first encounter drought stress (Xiong et al., 2006). There are a
number of ways drought impacts on physical function of root including smaller root mass, change in root architecture, lower efficiency of root to extract water (Joshi, 2010; Xiong et al., 2006). Drought stress may also cause primary roots of crop plants to become thinner (Liang et al., 1997). During drought, soil becomes dry and loose. Increased soil temperature boost soil moisture evaporation making it more difficult for root system to access sufficient water since soil moisture is reduced. Corn plants, like other annual grass plants, have two distinct root systems: seminal and nodal roots (Nielsen, 2010). Nodal roots system play an important role in corn development process as it accesses water in soil and uptakes nutrient, providing anchorage to the plant through its entire life and supporting the plant’s developing structure (Wiebold, 2012). Although root elongation occurred in nodal roots helps crop plants to cope with shortage of water (Sharp et al., 2004), severe droughts may induce root shrinkage, reducing the development of nodal roots and further inhibiting the uptake ability of roots (Buljovic and Engels, 2001; North and Nobel, 1997).

The lack of soil moisture due to above normal temperature may lead to poor root development causing “Rootless corn syndrome” which occurs in many places extending from Nebraska to Indian during 2012 (Hoegemeyer, 2012). When water/heat stress occurs during summer, soil become loose, hot and dry that makes corn plants hard to form normal root systems. Drought affected root system may appear stubby and not anchored to the soil (Elmore and Abendroth, 2007). Without good root support, corn become easily lean or fall, as they grow taller. Abrasive action of heavy wind and
excessive rainfall may cause soil erosion and soil removal around root region that give rise to rootless corn.

1.2 Limitation of traditional methods of agricultural drought monitoring

Traditional agricultural drought monitoring is mostly based on hydrological data derived from ground-based measurements and thus lacks continuous spatial coverage. However, obtaining hydrological information at large scale is still challenging, especially at regions where the paucity of measurement stations prevents the development of a consistent picture of water cycle (Sheffield and Wood, 2011) and limits the fully assessment of drought at finer scale (Caccamoa et al., 2011; Rhee et al., 2010).

Limited by topographic conditions, it is not practical to set up an intensive weather-monitoring network over complex terrain. For example, for mountain regions, the network of weather stations is not as intensive as that for urban area (Ashcroft et al., 2009) and the network also lacks continuous spatial coverage in forested areas (Oldford et al., 2006). Furthermore, the data series are often incomplete for the available weather stations or not available in time to enable timely drought diagnosis and impact assessment. Spatial interpolation of drought index values over large area is the most common way in drought condition estimation. However, using interpolation to estimate meteorological variables often produces uncertainties particularly over complex terrain (Flannigan et al., 1998).

Furthermore, drought monitoring in different countries is limited by the technical and institutional capability of each country. Compared to developed countries that have mature weather monitoring systems, some countries like Afghanistan are just beginning
projects to establish drought monitoring systems and associated management policies and institutions (Thenkabail et al., 2004).

1.3 Objectives and scopes

The specific objectives of this dissertation are:

1) To assess the performance of popular remote sensing indices for agricultural drought monitoring.

2) To investigate the linkage between key vegetation variables and remote sensing vegetation indices based on our field experiments and model simulations.

3) To develop a new phenology-adjusted approach for agricultural drought monitoring and to validate the approach using crop data.

1.4 Major data sources

The major datasets employed in this study include precipitation data from the National Climatic Data Center (NCDC), MODIS data products from NASA Distributed Active Archive Centers (DAAC), agricultural data from USDA and map of irrigation lands in the U.S. from Center for Sustainability and the Global Environment (SAGE). More detailed specific datasets used are as follows:

1) MODIS 8-day surface reflectance (MOD09A1)

MODIS 8-day reflectance is a level-3 composite of daily surface reflectance. The dataset provides MODIS band 1-7 surface reflectance at 500 meters resolution. Each pixel is derived from the best possible L2G observation in an 8-day period. MOD09A1 for 13 years (2000-2012) are used in this study for selected study areas.
2) MODIS Land Cover Type (MCD12Q1)

MCD12Q1 is MODIS yearly land cover type data that 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 employed. The Land cover Type 2 identifies 13 land cover types including 10 natural vegetation classes, croplands and 2 non-vegetated land classes. The 8-day MODIS product has reduced cloud contamination and has less short-term fluctuations, providing sufficient temporal coverage in monitoring phenological variations of crops (Swain et al., 2011).

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) Leaf Area Index (LAI)

The MODIS LAI product was developed jointly by personnel at Boston University and the University of Montana under contract with the National Aeronautic and Space Administration. LAI is a dimensionless quantity that characterizes structural property of plant canopies. It is defined as one-sided leaf area per unit ground surface area (Myneni et al., 2003).

5) Fraction of Photosynthetically Active Radiation (FPAR)

Fraction of Photosynthetically Active Radiation (FPAR) is a physical based vegetation state indicator that measures the proportion of available radiation in the photosynthetically active wavelengths (0.4 to 0.7 mm) that a canopy absorbs (Myneni et
al., 2003). As an indicator of presence and state of vegetation cover, FPAR product has been widely used to calculate surface photosynthesis and quantitatively estimate plant productivity (Mackey et al., 2012). Given the importance that FPAR is an essential climate variable that related terrestrial vegetation, it has been used as a drought indicator (Gobron et al., 2005). The FPAR is one of the drought indicators recognized by the European Drought Observatory (EDO) that employed this index for drought monitoring and detection (Rossi and Niemeyer, 2012).

6) Cropland Data Layer (CDL)

Since the major interest of the study is agricultural drought, USDA cropland data layer (CDL) maps was employed to locate major crop regions in the Corn Belt (Figure 1). The USDA CDL is a geo-referenced and crop-specific land cover product covering the entire continental United States in 30m resolutions. Primarily produced during growing season, the CDL product is generated 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). Cornfield spatial information was extracted from 2012 CDL and reprojected from Albers Conical Equal Area to Sinusoidal projection to generate corn cover map at 500m resolution. The values from 0-1 represent the proportion of corn cover within the pixel.
7) Crop data

County-level corn yield data for major crop counties in the Corn Belt was collected from the USDA/NASS, which collects, summarizes and distributes useful agricultural statistics in service to U.S. agriculture.

8) Map of irrigation lands

The map of irrigated lands in the United States is generated by SAGE at the University of Wisconsin-Madison. The map provides fraction of irrigated area (0-100%) for each pixel at 500m resolution for the continental U.S.
CHAPTER TWO: LITERATURE REVIEW

2.1 Agricultural drought monitoring with meteorological data

One of the main goals of research on agricultural drought is to reduce the impact of this disaster, by improving accuracy and capability of drought monitoring tools. For the application of interest, there is a need for generating quantitative expression for the state of drought. Timely information about the onset of drought, its coverage, severity, duration, and impacts can limit suffering of millions, minimize economic losses and reduce damage to the environment.

The state of drought can be characterized by drought indices, which incorporate various related variables such as temperature, rainfall, evapotranspiration (ET), runoff and other existing drought indices. Drought indices allow scientists to compare droughts in various regions, to contrast current drought with those in history, to identify drought-prone area and to assess drought impact in terms of intensity, duration, and spatial coverage. Drought indices also provide an objective basis for agricultural producers and policymakers to analyze drought condition and make corresponding management and policy decisions (Sheffield and Wood, 2011).

As a single number, a drought index is more useful than raw data (Karamouz et al., 2012), as it provides a uniform characterization of drought that can be understood by diverse users. Usually thresholds are established for a drought index to classify a number
of categories of drought severity, such as ‘moderate’, ‘severe’ and ‘extreme’. However, because of the complexity of drought, no single index has been able to fully capture every trait of a drought and its potential impacts on diverse sectors.

Characteristics of drought can be quantitatively expressed using following methods and terminology (Sheffield and Wood, 2011): In general, a drought can be characterized in terms of a hydrological quantity $\theta$, which is expressed as a drought index, $q(\theta)$. A drought is then defined as a period of duration (D) with a value $q(\theta)$, less than a threshold $q_0(\theta)$ representing normal, followed by a value above this level.

The drought magnitude (M) is the departure below this level during the period of duration at any particular time (t):

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

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 obtained from the product of duration and intensity:

$$S = D \times I$$

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

The spatial extent of drought is defined as the ratio of the area in drought 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 (e.g., a model grid cell or pixel in satellite image) and \( N \) is the total number of units in the region of interest.

**Example of agricultural drought indices**

Ideally a drought index is expected to capture characteristics of drought and to make comparative study of the drought more reliable and more comprehensive (Lake, 2011). A large number of agricultural drought indices exist, each incorporating various variables and each providing different measures of drought. Among many agricultural drought indices, the Palmer Drought Severity Index (PDSI) (Palmer, 1965), the Standard Precipitation Index (SPI) (McKee et al., 1993), and the Crop Moisture Index (Palmer, 1968) are widely used measures of agricultural drought. The U.S. Drought Monitor (USDM), a current advanced tool of operational drought monitoring, incorporates information from multiple sources, having attracted increasing attentions in recent years.

**PDSI**

The Palmer drought severity index (PDSI) developed by Palmer (1965) was the first drought indicator developed for the United States. The PDSI algorithm is based on a two-layer soil water balance equation, which incorporates antecedent precipitation, moisture supply, and moisture demand (Palmer, 1965).

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

\[
D = P - Q
\]
Where $P$ is the total monthly precipitation and $Q$ is the precipitation value for existing conditions (Palmer 1965). $Q$ represents the water balance equation defined as:

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

Where $\overline{ET}$ is the evapotranspiration, $\overline{R}$ is the soil water recharge, $\overline{RO}$ is the runoff, and $\overline{L}$ is the water loss from the soil. The over bars signify that these are average values for the given month.

The Palmer moisture anomaly index ($Z$ index) is then defined as

$$Z = K \times D$$

And the PDSI for the month of interest is defined as

$$PDSI_i = 0.897PDSI_{i-1} + Z_i/3$$

Where $K$ is a climate-weighting factor and $i$ indicates the specific month. The resultant PDSI value ranges from -6.0 to + 6.0 and is classified into 11 groups. The closer the PDSI is to -6, the more severe the drought. The index is based on precipitation and temperature data as well as the local available water content of the soil. It takes the duration of a drought into consideration as well.

Despite the widespread acceptance of PDSI, the Palmer Index suffers from some inherent weakness (Heim, 2002). The index was specifically proposed for drought monitoring in semiarid or dry and sub-humid climatic regions where local precipitation is the main source of moisture (Doesken et al., 1991). When calculating PDSI, Palmer used a simplified two-layer lumped parameter model, which is a simplified method and may not be accurate for deriving drought conditions for single site. He also assumed an average water holding capacity of the top two soil layers for the region of interest.
However, in reality, soil properties vary widely at different locations, which make it difficult to spatially delineate a drought-affected region (Narasimhan and Srinivasan, 2005).

Some drawbacks of PDSI which are also described (Alley, 1984; Karl and Knight, 1985): 1) The values quantifying drought intensity were arbitrarily selected based on Palmer’s study of central Iowa and western Kansas which is not convincing; 2) Snowfall, and snow cover are not included in the index making the index value inaccurate in areas where snow occurs; 3) Palmer overlooked natural lag between the time precipitation falls and the resulting runoff.

In PDSI, potential evapotranspiration (PET) is calculated using Thornthwaite’s method, which is based on an empirical relationship between ET and temperature (Thornthwaite, 1948). However, Thornthwaite’s method showed the poorest performance among different methods that estimate ET in the study by (M E Jensen et al., 1990). There is also a concern that PDSI tends to underestimate drought severity because the method underestimates PET in humid regions (McKee et al., 1993; Rosenberg et al., 1983).

SPI

The Standardized Precipitation Index (SPI) was developed based on the varying impact of precipitation deficiency on the soil moisture, ground water, stream flow and snowpack (McKee et al., 1993). SPI provides a simpler way of drought condition measurement than PDSI, because it is computed based on the long-term precipitation record at any location, by fitting historical precipitation data to a Gamma probability
distribution function for a specific time period and location, and then transforming the Gamma distribution to a normal distribution with a mean of zero and standard deviation of one (Edwards and McKee, 1997).

The advantage of the SPI index is that it can be used to estimate precipitation shortage at multiple time scales. Soil moisture quickly responds to drought, while ground water responds to precipitation on a relatively long scale. For these reasons, McKee et al. (1993) originally calculated the SPI for 3-, 6-, 12-, 24-, and 48-month time scales.

Normally, SPI is classified into 7 groups that range from extremely wet to extremely drought. Positive SPI values indicate greater than median precipitation, and negative values indicate less than median precipitation. Compared to PDSI, SPI is more generally accepted in research and operational use (Guttman, 1999; Rhee et al., 2010). However, SPI does not account for the effect of soil, and temperature anomalies that are critical for agricultural drought monitoring (Narasimhan and Srinivasan, 2005). Also, soil moisture has a greater impact on crop growth than the total rainfall amount. So, in agricultural studies, a more comprehensive drought index is needed as a better indicator of agricultural drought.

**CMI**

Three years after the development of PDSI, Palmer (1968) developed the Crop Moisture Index (CMI), which is specifically designed for agricultural drought monitoring (Heim, 2002). The CMI was based on weekly mean temperature and precipitation, measuring both evapotranspiration deficits and excessive wetness. The CMI measures
short-term drought and has been widely used to evaluate drought influences on agriculture during growing season.

As it is designed for short-term soil moisture demand of the crops, CMI responds quickly to changing conditions. However, CMI is considered as a poor tool for monitoring long-term drought (Nagarajan and Vloemans, 2010) as the quick response to changing condition may convey misleading information about long-term drought (Mavi and Tupper, 2004). For example, a beneficial rainstorm during drought may allow CMI to indicate adequate soil moisture, even though an extended drought persists. Another reason CMI is not suitable for long-term drought monitoring is that CMI typically begins and ends each growing season near zero. This characteristic limits the use of CMI within the general growing season.

**Palmer Moisture Anomaly Index (Z-index)**

The Palmer Z-index is a measure of monthly moisture anomaly presenting how monthly moisture condition departs from normal (Palmer, 1965). The Z-index is actually an intermediate term in the computation of the PDSI, without the consideration of the moisture condition of previous months. Compared to PDSI, Z-index value varies more quickly from month to month (Quiring and Papakryiakou, 2003). On the other hand, the PDSI varies more slowly because two-thirds of its value incorporates antecedent conditions. Even if both PDSI and Z-index are derived from the same data, their values differ quite well (Quiring and Papakryiakou, 2003).

The Z index can be used to track agricultural drought, due to its quick response to the variations of soil moisture (Keyantash and Dracup, 2002). Z-index is considered more
appropriate as a measure of agricultural drought when compared with PDSI and more preferable for quantifying agricultural drought than CMI (Karl, 1986). However, like all other Palmer indices, Z-index suffers from a complex formulation and computation that limits its uses to some extent.

**U.S. Drought Monitor (USDM)**

Created in 1999, the U.S. Drought Monitor (USDM) is a composite index that combines information from many existing drought indicators, including the PDSI and the SPI, along with local reports from state climatologists and observers across the country. The Drought Monitor is the result of an active operation between the National Drought Mitigation Center (NDMC), Department of Agriculture’s Chief Meteorologist’s Office and the National Oceanic and Atmospheric Administration (NOAA). Based on the consideration that no single definition can fully describe drought and appropriate in all situations, the authors of USDM successfully integrates information from multiple sources to assess severity and spatial extent of drought in the United States on a weekly scale (Wilhite, 2009).

USDM is considered as the current advanced drought-monitoring tool for the United States (Anderson et al., 2011). The USDM is maintained on the website of NDMC (drought.unl.edu/monitor/monitor.html) and archived USDM statistics are available online to various users.

The USDM map uses a D0-D4 scheme to classify droughts by intensity from least to most intense with D0 reflecting abnormally dry condition and D4 indicating an exceptional drought. The map not only consists of a color map, showing spatial extent of
drought in various degrees but also includes accompanying label, describing dominant impacts of drought. The USDM uses the label “S” to indicate short-term drought impact and “L” to indicate long-term drought effect.

2.2 Agricultural drought monitoring with satellite remote sensing

Obtaining hydrological data from ground-based measurement remains a challenge at larger scale and in less developed regions with sparse distribution of gauges (Sheffield and Wood, 2011). To overcome this, data obtained from remote sensing have the potential to provide consistent picture of the water cycle over regional to global scale. Remote sensing is now capable of measuring a larger number of hydrological variables such as precipitation, soil moisture, evapotranspiration and water levels (Schmugge et al., 2002). Remote sensing can also provide useful information of biological variables such as vegetation state, plant productivity and health.

Compared to traditional drought monitoring methods, remote sensing has attracted increasing attentions in recent years as a powerful tool for providing data and products for observing large-scale water cycle. Data acquired from multiple satellite sensors have been used to quantify the state of drought in terms of hydrological and or vegetative indices. The high spatial resolution data obtained from satellite make it especially important for drought assessment in areas where weather stations are sparsely distributed (Caccamoa et al., 2011; Ji and Peters, 2003; Peters et al., 1991). Remote sensing can detect onset of drought, its duration, and severity (Thenkabail et al., 2004) providing agricultural producers and researchers with comprehensive picture of the development of drought.
The Advanced Very High Resolution Radiometer (AVHRR) onboard the National Oceanic and Atmospheric 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. With the launch of Terra and Aqua platforms in 1999 and 2002, the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments have been providing a potential for the more accurate and high-resolution global monitoring of drought. The MODIS outperforms AVHRR in that it provides observations with higher spatial resolutions (250m, 500m and 1km), more spectral channels, more accurate geolocation, and improved atmospheric corrections (Fensholt and Sandholt, 2003). Both Terra and Aqua satellites carry MODIS sensors, providing daily global observations and various products that are especially useful in drought monitoring applications. 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 the visible to shortwave infrared region. These reflective bands, coupled with thermal bands, provide a good opportunity to study vegetation conditions and variations.

An important concern in agricultural drought monitoring with remote sensing measurements is the long-term availability and consistency of sensor data. The AVHRR has been operating since the 1980s, and the MODIS instrument launched into the Earth orbit on board the Terra satellite in 1999. Visible Infrared Imaging Radiometer Suite (VIIRS) is designed for long-term continuity of spatial data series initiated by AVHRR and MODIS. The new generation of satellite technology will considerably improve drought detection method. VIIRS is an instrument onboard the Suomi National Polar-
orbing Partnership (NPP) satellite that was launched on 28 October 2011. VIIRS has 22 bands between 0.4 µm and 12.5µm (http://www.star.nesdis.noaa.gov/jpss/VIIRS.php). Like MODIS, VIIRS collects visible and infrared imagery and radiometric measurements of the Earth and improves upon the spectral measurements and image quality provided by AVHRR and MODIS (Lee et al., 2006). Compared to MODIS, in the VIS/NIR region, the 16 MODIS bands have been replaced by 9 VIIRS bands. And in the short-wave and mid-wave infrared (SWIR/MWIR) the 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 can be migrated to VIIRS measurements through some efforts on cross-sensor comparison.

Satellite observations of vegetation conditions have provided another basis for agricultural drought monitoring (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). Since late 1970, visible channels on the AVHRR were exploited for vegetation monitoring in research studies at varying scales (Tucker, 1979). High temporal frequency of observations from space facilitates monitoring of vegetation condition and seasonal pattern over time.

Due to quick and direct response of vegetation to drought, a number of vegetation remote sensing indices were developed as an indirect way for quantifying drought condition at 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 usually generated based on spectral reflectance of vegetation, which is influenced by different
physical mechanisms (Figure 2). Chlorophyll and leaf pigments control the vegetation reflectance in the visible bands (Zarco-Tejada et al., 2000) and the high reflectance in the 0.7-1.2µm regions is dominated by the cell structure of the vegetative materials (Hoffer, 1978). The reflectance of vegetation canopies in the red band is inversely related to chlorophyll concentrations due to photosynthetic chlorophyll by vegetation in this region (Anyamba and Tucker, 2012). In contrast, the energy in the NIR region is highly reflected by vegetation canopy due to leaf cellular structure. At the SWIR domain (1.2-2.5µm), vegetation reflectance curve is characterized by absorption due to leaf water content. The response of vegetation reflectance to water content is largest in spectral bands around 1.45, 1.95 and 2.50 µm (Carter and McCain, 1993). These characteristics drive the spectral response of plants vary with seasonal changes and/or stresses (e.g. drought). In practice, red, NIR and SWIR bands are more often applied than other bands for characterization of vegetation indices. Two or more bands in the solar-reflected optical spectrum (0.4-2.5µm) are often combined to enhance vegetative signals and minimize impacts of surrounding non-vegetation and effects of solar zenith angle.
There are a variety of spectral vegetation indices. The most widely used vegetation index is the Normalized Difference Vegetation Index (NDVI), which was introduced by Rouse et al. (1974). The NDVI is generated based on difference in reflectance between red band and near infrared band and has been considered as the most efficient and simple metric to monitor vegetation condition (Anyamba and Tucker, 2012). Normalization helps NDVI minimize directional reflectance and reduce the effect of sun-angle, shadow and topographic variation (Holben and Fraser, 1986). NDVI increases value with increasing biomass and response to favorable (e.g. appropriate temperature and precipitation) and unfavorable environmental conditions (e.g. drought). NDVI has been exploited in many studies for vegetation condition and drought-monitoring purposes (Gu et al., 2007; Tucker and Choudhury, 1987; Unganai and Kogan, 1998; Wan et al.,
2004). In the light of NDVI, a number of NDVI-based vegetation indices were proposed. The Vegetation Condition Index (VCI) was proposed (Kogan, 1995a) for drought detection by scaling NDVI values from 0 to 1 using the minimum and maximum NDVI for each site. Low VCI values indicate poor vegetation condition because of unfavorable weather condition and high values of VCI indicates healthy vegetation status. Compared to NDVI, VCI amplifies the long-term ecological signal and found to be more useful in seasonal and interannual comparisons of drought conditions (Anyamba and Tucker, 2012).

Other vegetation indices that have normally been applied in drought study include Temperature Condition Index (TCI) and Vegetation Health Index (VHI) (Kogan, 1995b; Unganai and Kogan, 1998), which combines VCI and TCI to estimate vegetation water stress. In some studies, TCI outperforms NDVI and VCI in areas where soil has high moisture content because of excessive rainfall and persistent cloudiness (Liu and Kogan, 1996). These vegetation indices present the unique signatures of vegetation, including biomass, growth status, and leaf area coverage and provide a basis for estimation vegetation condition (Huete et al., 2002).

In addition to the vegetation indices mentioned above, some remote sensing vegetation indices incorporate reflectance in SWIR bands due to strong absorption of leaf water content in this spectral region. These indices, known as vegetation water indices, provide an integrated measure of the amount of water contained in the foliage canopy and are also used in drought study. For example, the normalized difference water index (NDWI) calculated as \( \frac{R_{0.86}-R_{1.24}}{R_{0.86} + R_{1.24}} \) was suggested by Gao (1996) based on the fact that the 1.24\( \mu \)m 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 make NDWI sensitive to changes in liquid water content of vegetation canopies. Similar to NDWI, the normalized difference infrared index (NDII) can be derived (Ceccato et al., 2001; Hardisky et al., 1983) as \((R_{0.86} - R_{1.65})/(R_{0.86} + R_{1.65})\) to monitor vegetation moisture content. Strong absorbance by water around the 1.65µm region makes this band most suitable for the estimation of water content of plants. Using the difference between two water absorption channels centered at 1640 nm and 2130 nm, the Normalized Multi-band Drought Index (NMDI) was developed to provide signature of both soil and vegetation moisture (Wang and Qu, 2007). Other water content indices include Global Vegetation Monitoring Index (GVMI) (Ceccato et al., 2002) and the Shortwave Infrared Water Stress Index (SIWSI) (Fensholt and Sandholt, 2003). Table 1 lists some commonly used remote sensing indices that are applicable to agricultural drought monitoring.

The selection of the most appropriate remote sensing index for drought monitoring at different climatic region and surface type is frequently discussed in many studies (Caccamoa et al., 2011; Y Gu et al., 2008; Ji and Peters, 2003; Rhee et al., 2010; Thenkabail et al., 2004; Unganai and Kogan, 1998). The recent agricultural drought in the Corn Belt highlighted the necessity of fully assessment of popular remote sensing drought indices in the context of extreme drought. This study explored the applicability of remote sensing indices for agricultural drought monitoring in the Corn Belt using the MODIS time series from 2000 to 2012. Eight MODIS indices were assessed including NDVI, NDWI, NDII6, NMDI, VCI, VHI, LAI and FPAR.
Table 1 Spectral indices used for drought monitoring.

<table>
<thead>
<tr>
<th>Index</th>
<th>Definition</th>
<th>Author</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>(NIR-Red)/(NIR+Red)</td>
<td>(Tucker, 1979)</td>
</tr>
<tr>
<td>VARI</td>
<td>(Green-Red)/(Green+Red-Blue)</td>
<td>(Gitelson et al., 2002)</td>
</tr>
<tr>
<td>SR</td>
<td>NIR/Red</td>
<td>(Tucker, 1979)</td>
</tr>
<tr>
<td>EVI</td>
<td>2.5(NIR-Red)/(NIR+6Red-7.5Blue+1)</td>
<td>(Huete et al., 2002)</td>
</tr>
<tr>
<td>NDIb6</td>
<td>(NIR-Modis6)/(NIR+Modis6)</td>
<td>(Hunt and Rock, 1989)</td>
</tr>
<tr>
<td>NDIb7</td>
<td>(NIR-Modis7)/(NIR+Modis7)</td>
<td>(Hunt and Rock, 1989)</td>
</tr>
<tr>
<td>D1640</td>
<td>1- Modis6/(0.55NIR+0.55Modis7)</td>
<td>(Van Niel et al., 2003)</td>
</tr>
<tr>
<td>NDWI</td>
<td>(NIR-SWIR)/(NIR+SWIR)</td>
<td>(Gao, 1996)</td>
</tr>
<tr>
<td>NRV</td>
<td>(RVI – 1)/(RVI+1)</td>
<td>(Baret and Guyot, 1991)</td>
</tr>
<tr>
<td>MSAVI</td>
<td>(\frac{2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - Red)}}{2})</td>
<td>(Qi et al., 1994)</td>
</tr>
<tr>
<td>VCI</td>
<td>(\frac{(NDVI-NDVI_{\text{min}})}{(NDVI_{\text{max}}-NDVI_{\text{min}})})</td>
<td>(Kogan, 1995b)</td>
</tr>
<tr>
<td>TCI</td>
<td>(\frac{(T_{\text{max}}-T)}{(T_{\text{max}}-T_{\text{min}})})</td>
<td>(Kogan, 1995b)</td>
</tr>
<tr>
<td>VHI</td>
<td>VHI =(\alpha) VCI + (1 - \alpha) TCI</td>
<td>(Kogan, 1995b)</td>
</tr>
<tr>
<td>NDDI</td>
<td>(NDVI-NDWI)/(NDVI+NDWI)</td>
<td>(Gu et al., 2007)</td>
</tr>
<tr>
<td>SAVI</td>
<td>(NIR-Red)(1+L)/(NIR+Red+L)</td>
<td>(Huete, 1988)</td>
</tr>
<tr>
<td>NMDI</td>
<td>(\frac{NIR - (\text{Modis6} - \text{Modis7})}{NIR + (\text{Modis6} - \text{Modis7})})</td>
<td>(Wang and Qu, 2007)</td>
</tr>
<tr>
<td>VTCI</td>
<td>(\frac{(\text{LST}<em>{\text{NDVImax}}-\text{LST}</em>{\text{NDVI}})}{(\text{LST}<em>{\text{NDVImax}}-\text{LST}</em>{\text{NDVImin}})})</td>
<td>(Wan et al., 2004)</td>
</tr>
<tr>
<td>VSWI</td>
<td>NDVI/T</td>
<td>(Carlson et al., 1990)</td>
</tr>
</tbody>
</table>
Despite widespread applications of remote sensing for drought monitoring in recent years, limitations of using remote sensing data exist. In general, remote sensing provides an indirect way to capture drought signature by investigating environmental components (e.g. soil, vegetation) that are affected by drought. The disconnection exists between satellite measurements and surface quantities to characterize the state of drought in terms of hydrological and vegetative indices (Sheffield and Wood, 2011). Generally, the earth radiances measured by satellite sensors need to be converted into surface parameters that related to quantitative characterization of drought. The process of remote sensing retrieval is always challenging due to the complex transition of radiation through the land-atmosphere system. One of the limitations of satellite data is cloud contamination. Other factors influence satellite retrievals include 1) physical calibrations, spectral response functions, satellite geometry; 2) interference of atmospheric particles; and 3) inhomogeneous surface background. In addition, the lack of long-term data obtained from remote sensing limits the assessment of historic drought in climatic context and the comparison of the current drought with droughts in history.
CHAPTER THREE: CROP MAPPING WITH GIS TECHNOLOGY

As an application oriented technology, GIS is designed to capture, store, manage, analyze and present geographic data (Chang, 2010). When applied in agriculture, GIS assists in precision farming, crop mapping, and visualization of agricultural environment (Nahry et al., 2010; Wang et al., 2011). In this study, crop yield and crop production in the United States are delineated using GIS technology based on different sets of background data. These maps allow us to better identify agricultural areas and focus agricultural drought monitoring efforts on the most intensive crop regions in the U.S.

3.1 U.S. crop mapping

In recent years, GIS technology has been playing a more important role in agricultural management by providing efficient means for farmers, agricultural scientists and government agencies to spatially view crop distributions and growing patterns, and monitor natural disturbances (e.g. drought, floods, hurricanes) that affect crop productivity (Antwi-Agyei et al., 2012; Liu, 2009). GIS also aids in crop data publications, facilitating share of agricultural data between different agencies.

Part of the section is based on the project supported by the World Agricultural Outlook Board (WAOB) to develop latest U.S. crop production maps that delineate major crop producing areas for major U.S. crops. Serves as USDA's focal point for economic intelligence and the commodity outlook for U.S. and world agriculture, the WAOB has
produced crop maps to help illustrate cropping patterns and agricultural information in major agricultural areas. More than 150 maps are currently posted on the WAOB website, depicting agriculturally intensive areas in 27 countries and regions (http://www.usda.gov/oce/weather/pubs/Other/MWCACP/index.htm). However, many of the maps need to be updated with more recent data and some are not compatible with the leading GIS applications, and therefore limits the use of these maps. In order to generate updated U.S. crop maps, latest U.S. county-level crop data have been collected from National Agricultural Statistics Service (NASS), the statistical branch of U.S. Department of agricultural. NASS conducts agricultural surveys each year and publishes massive agricultural data (e.g. farm numbers, crop distributions, acreage, yield and stocks of grains) online allowing users to get useful agricultural statistics based upon requests.

3.1.1 Crop production map

Crop production maps were generated based the requirements and recommendations from WAOB. Multiple years of crop production data were averaged to represent normal crop production pattern and joined with base administrative shape file in ArcGIS 10, the most widely applied GIS platform for designing and organizing geographic information. At county-level, crop production data were sorted from the largest to the smallest values (i.e., from the most intensive to the least intensive agricultural areas). Production values that correspond to 75% and 99% of the country’s total production were identified. Major crop areas were defined to account for 75% of total national production and minor crop areas combined with major areas account for 99% of total production. Crop maps for 13 crops in the United States have been
generated, including barley, corn, American-pima cotton, upland cotton durum, flaxseed, peanuts, rice, sorghum, soybeans, spring wheat, sugar beets, sunflower seed, and winter wheat. Figure 3 shows average corn production map of United States from 2006 to 2010. Major corn areas plotted in dark green accounts for 75% of total national production, and minor corn areas are in light green combined with major areas account for 99% of total production. Yellow numbers on each state indicate the percentage each state contributed to the total crop production.

For each crop map, the crop calendar was plotted as a useful tool that provides crop-growing information including planting, sowing and harvesting periods of a certain crop species. This tool supports crop growers and agriculture researchers across the world in making proper decisions on crops and in guiding agricultural production and sowing period, respecting the agro-ecological dimension.

Figure 3 Corn production map for the United States (2006-2010). (Source: USDA/WAOB, http://www.usda.gov/oce/weather/pubs/Other/MWCACP/namerica.htm)
Corn production plays an important role in the U.S. economy. By far, the United States is the largest corn producer in the world, producing 32 percent of total world production of corn. As indicated by the corn production map, corn growth is dominated by central United States, consisting states like Iowa, Illinois, Indiana, Minnesota, Nebraska, Ohio and South Dakota. Among these states, Iowa is the largest producer of corn with 92 thousands corn farms on 30 million acres. Some minor corn states include Colorado, Kansas, Kentucky, Michigan, Missouri, Pennsylvania, Texas and Wisconsin. In 2012, the U.S. had 97.2 million acres of total area of corn planted for all purposes and 87.3 million harvested acres of corn for grain, producing 10.8 billion bushels of corn.

3.1.2 Crop yield map

Yield maps are one of the most important sources of spatial data for precision farming and agricultural management. Based on county-level yield data, U.S. corn yield maps were developed each year since 2000 to represent the output of corn yield. By comparing yield maps between different years, yield variations are known and can be used to investigate the existence of yield limiting factors. The widespread 2012 drought in U.S. significantly influenced the amount of corn yield loss. Figure 4 presents the comparison between corn yield map in 2011 and 2012. Most noticeable corn yield reduction occurred in eastern Nebraska, Illinois, Indiana, Iowa and Ohio. According to the Crop Production 2012 Annual Summary published by USDA/NASS, U.S. corn growers produced 10.8 billion bushels in 2012, 13 percent below the 2011 crop. The corn yield in 2012 is estimated at 123.4 bushels per acre, down from 147.2 in 2011.
GIS technology plays an important role to link data from different sources. When coupled with other weather/climate datasets, the resulting GIS-compatible crop mapping products can benefit agricultural policy makers, decision makers, and agricultural analysts by highlighting crop areas where weather and climate might have the greatest impact on agricultural production and trade.

### 3.2 Study area

Based on major crop area delineated in the corn map, this study is focusing agricultural drought study on the most intensive corn planting area, the Corn Belt, between 37°-43.5° N and 80°-103W° (Figure 5). The Corn Belt is geographically defined to include Iowa, Illinois, Indiana, and parts of Michigan, Ohio, Nebraska, Minnesota and Missouri (Hart, 1986). This region is characterized by deep and fertile soils rich in organic material and nitrogen. Like other parts of the country, topography of the Corn Belt varies from prairie in central Illinois and Iowa to the hilly regions along the Ohio River. The Corn Belt has favorable climate for corn growth with average annual rainfall...
ranges from 26 inches to 45 inches. Adequate rainfall often comes with a long, hot growing season that is usually associated with good corn yield. The fertile land together with warm nights and well-distributed temperature contribute to the ideal environment for raising corn.

Although a large percentage of corn in the Corn Belt grows for export outside the region, a big amount of the crop is produced for raising livestock, another basic farm enterprise in the Corn Belt. Besides corn, some other crops are also raised within the Corn Belt, for example, oat, wheat, and soybean-in most cases as part of a rotation with corn. The more productive areas lie in Iowa, northern and central Illinois, northern Indiana and western Ohio.

In the summer of 2012, warm and dry conditions persisted over the Corn Belt resulting in severe drought that caused widespread crop failure. The time series of temperature, precipitation were averaged over the Corn Belt for corn-growing season (Figure 6). The temperature of Corn Belt in year 2012, are among highest the since 1990,
only 0.6 Fahrenheit degrees lower than temperatures in 2002 and 2005, another two drought year in last decades. The precipitation of the 2012 has reach lowest level in last two decades with only 9.88 inches rainfall during corn-growing season, 4.38 inches lower than the 23-year average. The high temperature coupled with abnormally low rainfall making year 2012 the driest year during 1990-2012.

![Figure 6 Time series of average temperature and precipitation over the Corn Belt for corn-growing season from 1990 to 2012.](image)

Despite preliminary expectations of favorable corn-growing season due to mild winter and early planting, the 2012 summer drought damaged crops significantly (Adonizio et al., 2012). As the drought rapidly increased in severity in growing season, agricultural sectors are experiencing water stress in different degrees. Table 2 shows the progression of drought within the agricultural sector during 2012 summer. From mid-June to mid-August, the proportion of farms influenced by severe or greater drought increased from 16 percent to 43 percent. The percentage of affected cropland increased from 20 percent to 57 percent, while influenced total value of crops increased from 16 to
50 percent. As of September 30, only 25 percent of corn acreage was rated in good or excellent condition, compared with 52 percent during the same time in 2011.

| Table 2 Percentage of agricultural sectors experienced severe or greater drought in 2012. |
|-----------------------------------------------|---------------|---------------|---------------|
| Percentage of                               | June 19       | July 17       | August 14     |
| Farms                                        | 16            | 40            | 43            |
| Acres of Cropland                            | 20            | 51            | 57            |
| Value of Crops                               | 16            | 43            | 50            |

Source: Agricultural Resource Management Survey (ARMS) and U.S. Drought Monitor statistical data

As indicated by USDMA drought map, most central and western regions of the contiguous U.S. suffered drought in August 2012 (Figure 7). By August 2012, the entire Corn Belt was engulfed by the widespread drought with states such as Nebraska, Illinois, Indiana and Iowa experiencing the worst drought in 25 years (USDA, 2012). Unusually hot and dry weather along with limited rainfall worsened the drought and caused drought condition migrates northward from the South (Freedman, 2012). The 2012 drought had devastating effects on U.S. agriculture, destroying portions of the major crops in the Midwest and driving up food prices (USDA, 2012).
3.3 Chapter summary

In this chapter, GIS technology was employed for developing crop production maps and crop yield maps of the United States to identify major corn production areas. The corn maps illustrate corn-planting patterns presenting both major and minor corn areas. As 2012 drought covered most of the U.S, the corn maps help us focus agricultural drought monitoring efforts on the Corn Belt, the most intensive agricultural regions in the United States. Showing yield variability, corn yield mapping serves as a useful tool for understanding impacts of climate variations on crop productivity. The impact of devastating 2012 drought on U.S. corn yield was demonstrated by comparing yield map of 2012 with map of the previous year. Significant yield losses were noted across most
areas of the Corn Belt, which covers major corn-producing states including Nebraska, Illinois, Indiana, Iowa and Ohio.

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 measurements, the crop maps are expected to facilitate the impact assessment of climate/weather fluctuations on agriculture and the evaluation of water-stressed agricultural losses.
CHAPTER FOUR: ASSESSMENT OF MODIS INDICES FOR AGRICULTURAL DROUGHT MONITORING

The occurrence of the 2012 drought highlights the necessity for fully assessing current remote sensing drought indicators in the context of extreme drought. Although previous studies have compared the performance of some remote sensing indices for drought monitoring (Anderson et al., 2011; Caccamoa et al., 2011; Choi et al., 2013; Thenkabail et al., 2004), this study focused on comparison and in-depth time series analysis to assess the performance of the most commonly used remote sensing indices in agricultural drought monitoring across the Corn Belt.

The MODIS surface reflectance products were extracted for the pixels within crop regions in five key Corn Belt States: Illinois, Indiana, Iowa, Nebraska and Ohio. The analysis focused on the corn-growing season (June - September) and six MODIS spectral indices were assessed, including NDVI, NDWI, NDI\textsubscript{6}, NMDI, VCI and VHI (Table 3). The performance of two physically based vegetation indices Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation (FPAR) were also evaluated to identify relative strength of these indicators in drought context.
Table 3 MODIS spectral indices evaluated in this study.

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<td>Tucker (1979)</td>
</tr>
<tr>
<td>NDWI</td>
<td>$\frac{\text{Band 2} - \text{Band 5}}{\text{Band 2} + \text{Band 5}}$</td>
<td>Gao (1996)</td>
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<tr>
<td>NMDI</td>
<td>$\frac{\text{Band 2} - (\text{Band 6} - \text{Band 7})}{\text{Band 2} + (\text{Band 6} - \text{Band 7})}$</td>
<td>Wang and Qu (2007)</td>
</tr>
<tr>
<td>NDII6</td>
<td>$\frac{\text{Band 2} - \text{Band 6}}{\text{Band 2} + \text{Band 6}}$</td>
<td>Hunt and Rock (1989)</td>
</tr>
<tr>
<td>VCI</td>
<td>$\frac{(\text{NDVI} - \text{NDVI}<em>{\text{min}})}{(\text{NDVI}</em>{\text{max}} - \text{NDVI}_{\text{min}})}$</td>
<td>Kogan (1995)</td>
</tr>
<tr>
<td>VHI</td>
<td>$\text{VHI} = \alpha \text{VCI} + (1 - \alpha) \text{TCI}^*$</td>
<td>Kogan (1995)</td>
</tr>
</tbody>
</table>

*$\text{TCI} = \frac{(T - T_{\text{min}})}{(T_{\text{max}} - T_{\text{min}})}$, where $T$ is the temperature for each pixel, and $T_{\text{max}}$ and $T_{\text{min}}$ are maximum and minimum temperature, respectively, for each pixel and week during period 2000-2012.

4.1 Identification of agricultural drought events

Identification of drought events and selection of drought and normal years were based on weekly U.S. Drought Monitor statistics, which present percentage of total area of each state at each drought severity level (Figure 8). The USDM statistics indicate a clear separation between drought and non-drought affected years. Although the Corn Belt States experienced different degrees of drought stress in last 13 years, the growing seasons of 2002, 2005, 2012 were selected to represent drought years for five key Corn Belt states including Nebraska, Iowa, Indiana, Ohio and Illinois. The rest years were considered as normal years for Iowa, Indiana, Ohio and Illinois. Because the state of Nebraska have experienced more intense drought during last decades than other Corn Belt states as indicated by USDM, only year 2001, 2007, 2008, 2009, 2010 and 2011 were considered as normal years for Nebraska.
4.2 Comparisons of MODIS indices between 2012 and non-drought years

Eight 8-day MODIS indices were averaged over normal years for crop pixels in the Corn Belt to establish the normal growing conditions for corn during corn-growing season. Cropland cover mask was applied to mask out non-agricultural areas, such as forest, ranchland or bare soil in essence limiting the investigation to agricultural areas. With the normal vegetation condition defined by historical indices, current crop conditions could be assessed by comparing MODIS indices with normal conditions.

In Figure 9, histograms of eight MODIS indices were compared between 2012 data and normal-year average for corn-growing season (June-September). The histograms use lines instead of conventional bar charts to facilitate the analysis. Normal-year average, displayed as black line, is separated with 2012 data that is plotted as red. The
Histogram was based on valid crop pixels in the Corn Belt within the NDVI range (0, 1). Only two weeks of each month in the growing season was plotted for brevity.

Figure 9 demonstrated the impacts of drought on distributions of MODIS indices. In 2012, warm temperature in spring provided the opportunity for corn-growers to start 2012 corn planting earlier than normal. In the start of the 2012-growing season, the histograms of tested indices show similarities between 2012 and normal years. The normal-year average provides a standard reference for crop condition at a specific growing stage. Slightly larger values of indices were observed at earlier corn-growing season indicating well growing condition for corn during this period. However, with the 2012 drought gradually increased in severity since July, the 2012 data starts to skew to the left. The 2012 drought rapidly escalated early July and persisted into August. As a result, the drought impact stretched the distribution curve toward negative direction and lowered the peak. Index values demonstrated obvious decrease for the rest of growing season. The left shift of histograms of 2012 indicates a decrease in crop biomass, water content and leaf area following the drought. The shift amplitude reflects the impacts of the drought and is related to the sensitivity of these indices to agricultural drought impacts.

For spectral indices tested, NMDI presents smaller variations during drought compared to NDVI, NDWI, and NDII6, indicative of insensitivity of NMDI to agricultural drought. It is also noticed that histogram of NMDI right shifted at end of the 2012 growing season, unlike histograms of other indices. Both VCI and VHI provide an estimation of crop condition relative to the maximum and minimum interval of NDVI.
and temperature. Because the extremely unfavorable weather (dry and hot) in 2012, crop condition in most parts of the Corn Belt plummeted to the lowest minimum in 2012 during 2000-2012 period leading to increasing number of pixels with value close to zero in VCI and VHI with crop growth in 2012. The drought also causes the decrease in two physically based vegetation state indices, LAI and FPAR. The distribution of 2012 data has shown resemblance to that of normal-year data in FPAR until late July when water-stress aggravated. LAI presents the most obvious left-shifted histogram starting from early July 2012 among the tested indices indicating significant reduction in crop canopy area caused by the drought.
Figure 9 Histograms of eight MODIS indices for corn-growing season (bin size = 0.02).
In recent studies of drought monitoring, drought index anomalies have been attracted more attentions than index value because the ability of anomaly to isolate the variability in vegetation signal and to provide relative crop growing condition (Anyamba and Tucker, 2012). The MODIS crop maps over non-drought years provide a basis for generating baseline of normal growing condition based on which, MODIS index anomalies were generated. In next part, MODIS index anomalies were assessed over the Corn Belt by correlating anomalies with precipitation-based drought index.

4.3 Comparative analysis of MODIS index anomalies and SPI

The comparative evaluation was conducted between MODIS index anomalies and the Standard Precipitation Index (SPI), a precipitation deficit/surplus indicator, to evaluate the timing of vegetation response to precipitation anomalies. To emphasize differences in moisture conditions between years, drought indicices were presented in form of anomaly with respect to multi-year average over a specific time period (Anderson et al., 2011). The anomaly generate negative values when moisture condition or vegetation status lower than normal. Due to the 8-day time step of the index anomaly, this method can rapidly capture changing patterns of crop and drought condition during the growing season. Following the approach of Anyamba et al. (2001), Lotsch (2005), Saleska et al. (2007) and Caccamoa et al. (2011), index anomalies (z-value) were developed as the departure from the long-term average for each pixels, standardized by the standard deviation (z-score) to provide a measure of deviation degree, reducing impact of spatially varying vegetation type (Caccamoa et al., 2011).
where, $Z_{ijk}$ is the variable anomaly for pixel $i$ in a period $j$ for year $k$; $\mu_{ij}$ is normal year average for pixel $i$ during time scale $j$ and $\sigma_{ij}$ is standard deviation for pixel $i$ during time scale $j$ over normal years.

The SPI uses observed precipitation as its only input. The value of SPI captures the accumulated rainfall deficit (SPI<0) or surplus (SPI>0) presenting the deviations of the precipitation totals from the mean (Naresh Kumar et al., 2009). Remote sensing vegetation indices are expected to relate to SPI because water availability influence vegetative condition and vegetation water content (Gu et al., 2007). SPI can be used to estimate precipitation deficiency at multiple time scales (ranging from 2 to 52 weeks) to detect both short- and long-term water stresses. The reason for choosing SPI over other drought indices is due to inherent flexibility of SPI that can be evaluated over multiple-time spans (Caccamo et al., 2011; Guttmann, 1999).

Monthly precipitation data were extracted from 129 weather stations within the Corn Belt to generate SPI time series (Figure 10). In this analysis, we included 1, 3, and 6 month SPI (referred to as SPI-1, SPI-3 and SPI-6, respectively) for each weather station and each month in the corn-growing season (June to September) from 2000-2012. 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). Figure 11 shows the time series of 6-month SPI based on spatially averaged gauge data over the Corn Belt, providing medium-term estimation of rainfall fluctuations. SPI values were positive in growing season (green
column in Figure 11) of 2004, 2007, 2008, 2009, 2010 and 2011 season and negative in 2002, 2005 and 2012, indicating varying rainfall distributions among years. In 2012, 6-month SPI values reached the minimum in corn-growing season since 2001 (mean SPI = -1.39) suggesting severe drought conditions across the Corn Belt (Figure 11).

Remote sensed response to both short period water deficiency (1-month SPI) and longer period water deficiency (3-month SPI, 6-month SPI) in corn areas was
investigated using pixel-to-weather station paired correlation approach. Possible time lag between rainfall patterns and vegetative response were considered by correlating SPI values of the current month with remote sensing indices of subsequent 0, 1, 2 and 3 months (Lag+0, Lag+1, Lag+2 and Lag+3).

Figure 12 shows the correlation coefficients between MODIS spectral indices anomaly and SPI values at three time steps (SPI-1, SPI-3 and SPI-6) and four time lags (Lag+0, Lag+1, Lag+2 and Lag+3). MODIS and SPI data from all available weather station pairs were pooled and averaged at all stations each month from June to September. In general, correlations obtained at 1-month time step were weaker than correlations obtained at 3- and 6-month time step for most of indices, which illustrates the cumulative impact of water deficiency on vegetation. Vegetation therefore responds not only to recent precipitation but also to precipitation in previous months. SWIR based spectral indices (NDII6 and NDWI) showed higher overall performance than other indices. The best correlations were found for NDII6 at 6-month SPI time steps (R=0.65). For the rest of tested indices, VHI and NDVI provided higher R-values (R=0.57) to VCI and outperformed the LAI and FPAR when no time lag was considered. NMDI provided the lowest correlation coefficients at all time steps and time lags. Although possible time lag was expected between rainfall patterns and vegetative response, the results showed that the strongest correlations were obtained at Lag+0 and weakest at lag+3 across all spectral indices. For each time step considered, the correlation between spectral indices and SPI decreased with the increment in time lag.
Figure 13 presents the scatter plots of MODIS spectral index anomalies on 6-month SPI values. 2012 data were plotted as triangle. Most MODIS indices provided a good discrimination between drought year of 2012 and other years (Figure 13). The 2012 observations clustered in the negative index anomaly/SPI domain, separated from observations from the rest years.

Caccamo et al. (2011) applied the pixel-to-weather station approach to assess the relationship between various remote sensing indices and SPI values in a high biomass system. The result showed that NDII6 best correlated with SPI among the indices tested and can be utilized as a suitable drought indicator for high biomass ecosystems. In this study, NDII6 presents the strongest correlation with SPI over corn area among eight MODIS indices and both NDII6 and NDWI outperformed other MODIS indices showing the good capability of the SWIR region (i.e., MODIS band 6 and band 7) to monitor drought conditions in agricultural areas. The performance of NDII6 for drought monitoring generally agrees with previous findings. NDII6 is found to be related to drought condition over forests and woodlands in Georgia (Wang et al., 2009). Yilmaz et al. (2008) considered NDII6 as a suitable spectral index for vegetation moisture monitoring and NDII6 presented best performance to detect drought in high biomass ecosystems in Australia (Caccamoa et al., 2011).
Figure 12 Correlation coefficient values between SPI and MODIS spectral index anomalies at three time steps and four time lags.
Figure 13 Scatter-plots of MODIS spectral index anomalies and 6-month SPI.
### 4.4 Comparisons of MODIS drought indices with USDM

Although USDM has been considered as a current advanced tool for drought monitoring due to its multiple inputs from many key drought indicators, satellite remote sensing is still being heavily relied upon to fill key informational gaps (e.g., crop growth conditions and soil moisture) and provide more spatially explicit information of drought variations.

Since the development of the first USDM map in 1999, the geographical depictions and classification of drought continue to improve as technology advances when more drought-related data available for the USDM inputs. At the same time, the capability of remote sensing to monitor key components of the hydrological cycle has been enhanced because of the launch of new sensors, improved calibration and more advanced techniques. Launched on board the Terra satellite in December 1999, the MODIS instrument provides several SWIR bands facilitating more accurate drought monitoring from space (Caccamoa et al., 2011).

The USDM map adopts a D0-D4 scheme to classify droughts by intensity from the least to the most intense with D0 reflecting abnormally dry condition and D4 indicating an exceptional drought. In previous study, remote sensing drought monitoring has been compared with USDM maps at varying spatial level. Tedessea et al. (2010) assessed vegetation condition based on Vegetation Outlook (VegOut), a remote sensing based drought-monitoring tool, and compare predicted result of VegOut with USDM over drought and non-drought years. Rhee et al. (2010) compared spatial distribution of MODIS based Scaled Drought Condition Index (SDCI) with USDM maps in agricultural
drought monitoring in both arid and humid regions. However few studies have statistically compared USDM drought classification and corresponding remote sensing variables.

The 2012 drought across the Corn Belt provides a good opportunity to compare the relationship between remote sensing drought indices and the USDM drought classification over large agricultural region. The maps of standardized anomalies in eight MODIS drought indices were compared with USDM maps over the 2012 growing season for the Corn Belt (Figure 14). The metrics displayed include USDM maps and anomalies in NDVI, NDWI, NDII6, NMDI, VCI, VHI, LAI and FPAR. These figures demonstrate the responsiveness of the various spectral indices to drought conditions, and the degree to which drought features are emphasized or missed in each index.
Figure 14 Comparisons of weekly USDM maps with anomaly maps of eight MODIS indices during 2012 corn-growing season.
As indicated by USD maps, the Corn Belt has experienced intensified drought over the growing season. At the early stage of the growing season (June), the Corn Belt was majorly affected by abnormally to moderate drought. Since July, severe to extreme drought conditions were shown toward the west, with increasing agricultural area under severe drought condition. The subsequent drought condition continued to intensify and geographically expanded over the Corn Belt. As indicated by Drought Monitor Archive statistics, by July 24, 2012, the entire Corn Belt was under extreme drought to exceptional drought, with approximately 57% of total area under extreme and exceptional drought. Unusually hot and dry weather combined with limited rainfall worsened the drought. Take Nebraska for example, by September 4, 2012, nearly 70% of total state’s area had experienced exceptional drought. In contrast, on September 6, 2011, only 18% of the state showed abnormally dry and the rest area showed no sign of drought.

All tested MODIS indices have shown significant value decrease in 2012 summer indicating prevailing severe drought condition during this time. Both MODIS maps and USD maps have captured the rapid intensification of drought condition since July, especially for August and September when exceptional drought occurred. As indicated by anomaly maps, a large portion of the Corn Belt presents two standard deviations below normal year during 2012 summer indicating very poor condition of corn crop. The abnormal crop condition stretched from east Nebraska to west Ohio where severe drought occurred for consecutive weeks. Among the tested indices, NMDI presents relatively mild dry condition with its value within normal range for most of the Corn Belt during early growing season. Compared with VCI, VHI anomaly presents the map that suggests
worse drought condition with nearly half cropland in exceptional drought in the early July. This is likely because spatial and temporal variations in VHI are due to variability in both surface temperature and vegetative status. The temperature component in VHI could possibly overstate the degree of drought condition. The discrepancies in remote sensing drought maps and USDM maps were also observed. For example, the south Iowa and north Missouri showed abnormally dry to moderate drought in June in the USDM map, while anomaly maps of most indices appear smaller than -1.5 which is indicative of extreme drought.

In this analysis, we are interested not only in how MODIS drought map spatially compared with USDM maps, but also how MODIS indices performed under each USDM classes. To facilitate the analysis, a one-way analysis of variance (ANOVA) was employed. As a particular form of statistical hypothesis testing, ANOVA provides a statistical test of whether the means of several groups are equal. It compares the means between the test groups and determines whether any of those means are significantly different from each other. Specifically, it tests the null hypothesis:

$$H_0: \mu_1 = \mu_2 = \mu_3 = \cdots = \mu_k$$

Where $\mu$ is group mean and $k$ is number of groups.

In this study, ANOVA were used to determine whether there are any significant differences between means of multiple MODIS indices in different USDM classes. Compared to multiple two-sample t-test, ANOVA reduces chances of committing a type I error, providing useful statistical analysis for three or more groups or variables.
Eight MODIS indices were extracted from cropland in five USDM classes (D0-D4) across the Corn Belt for three time groups in 2012: the week of July 10th, Aug 14th and Sep 11th. We recorded F-statistic of ANOVA (Table 3) and p-values for each group. The p-value returns from all test groups are smaller than 0.001, which is a strong indication that there are differences between means of MODIS indices under USDM classifications for tested groups. The Boxplots of MODIS indices in five USDM drought categories are presented in (Figure 15). The edges of the box are the 25th and 75th percentiles and whiskers extend to the most extreme data points not considered outliers. Although the observation supported the hypothesis that drought induced variations in remote sensing variables vary differently among some USDM classes, the separation between class 0 (abnormally dry), class 1 (moderate drought) and class 2 (severe drought) is challenging as some indices showed similar value distribution for these classes (e.g. NMDI in three time groups; NDII6, NMDI, VCI and FPAR in Aug 14th; NMDI and VHI in Sep 11th). FPAR, NDWI and VHI have smaller overlap of interquartile ranges in all five USDM classes than other indices in group Jul 10th, Aug 14th and Sep 11th separately.

Although MODIS indices demonstrate lower values in higher USDM drought classes, vegetation index-based drought monitoring cannot replace USDM by providing similar drought classes to USDM. Integrating multiple data sources, USDM is a composite index providing comprehensive picture of drought at large scale while remote sensing index-based drought monitoring provide indirect measurements of drought condition by monitoring water-stressed vegetation condition over large vegetative regions. The differences between remote sensing maps and USDM maps may due to
several reasons: 1) drought features provided by USDM come from multiple data sources, including: precipitation, temperature and many drought indicators; 2) the delayed vegetation response to water stress; 3) the poor vegetation condition may be the result of multiple factors, even though drought plays a key role; 4) irrigation and 5) uncertainties in USDM exist due to spatial interpolation of in-situ data.
Figure 15 Boxplots of MODIS indices under USDM scheme for the week of July 10th, Aug 14th and Sep 11th.
Table 4 F statistics of ANOVA test.

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<th>Jul 10th</th>
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4.5 Comparative analysis over irrigated areas

It is always a challenge for precipitation-based drought monitoring approach to accurately capture drought status over irrigated region because precipitation is not a proper surface drought indicator when irrigation applies. In this part, MODIS spectral indices were assessed over Nebraska in the context of extreme drought of 2012 to demonstrate the advantages of remote sensing approaches to monitor drought over irrigated regions.

The reason for the analysis over Nebraska is due to its large coverage of irrigated land. Nebraska has the second (after California) largest irrigated land in U.S. (Wihelmi and Whihite, 2002). As of 2007, Nebraska had 8.56 million irrigated acres. The state owns more than 100,000 registered irrigation wells and an additional 16,000 registered water wells (Johnson et al., 2011). Because Nebraska’s climate is more humid in the east than in the west, non-irrigated corn is mainly distributed in the eastern part of the state. In contrast, corn in the more arid western and central Nebraska is irrigated from both surface and ground water by using center-pivot irrigation system (Swain et al., 2011).
Between the 2002 and 2007 agricultural census years, the total irrigated land in Nebraska expanded by 934,000 acres (Johnson et al., 2011). The widespread irrigation system greatly reduces the impact of drought providing larger certainty with production than is possible with dry land farming.

In Nebraska, irrigated cropland is mainly distributed in the eastern region (Figure 16). Based on the map of irrigation, a cropland pixel was designated as irrigated if more than 70% of the pixel area was irrigated while a pixel was classified as non-irrigated if less than 30% of the total area was irrigated.

In 2012, most Nebraska crop counties showed decrease in corn yield. For 58% of the crop counties, corn yield in 2012 decreased by more than 20 percent compared to 2011. Although the devastating drought of 2012 greatly affected corn yield of Nebraska, the irrigation system makes possible the reduction of yield loss caused by the drought. Corn yield change between 2011 and 2012 was correlated with irrigated cropland percentage for major crop counties in Nebraska (Figure 17). Counties with higher
The percentage of irrigated cropland were less influenced by the drought than those without fully developed irrigation system. The study by Nebraska Farm Bureau Federation showed that the state’s irrigation system contributed to $11 billion in agricultural output during the 2012 drought (Hovey, 2013).

Figure 17 Scatter plot between corn yield change (2011-2012) and proportions of irrigated cropland for major crop counties in Nebraska.

Drought stresses during growing season can greatly affect growth and development of crops resulting in drastic fluctuations in crop vigor, and productivity. Under ideal condition, irrigation would be practiced when cropland under soil moisture stress. The basis of remote sensing of irrigated agriculture is that irrigated crops normally exhibit larger accumulated biomass than crops under deficit irrigation condition. The comparisons of averaged NDVI, NDII6 and LAI over irrigated (irrigated land > 70%) and non-irrigated (irrigated land < 30%) corn cropland from 2000 to 2012 are shown in
Figure 18. The irrigated and non-irrigated crops exhibit significant distinct profiles. Higher NDVI, NDII6 and LAI are observed on irrigated land than those with limited irrigation suggesting improved crop condition when irrigation applies. The year of 2002 and 2012 were climatologically typical drought years with below average precipitation across the continental U.S (Lott and Ross, 2010). This gives lower curves of vegetation indices in 2002 and 2012 growing season (Figure 18), indicating reduced biomass, vegetation water content and possibly sparser canopy cover for corn crop in these two years.
Ozdogan and Gutman (2010) examined the sensitivity of vegetation indices to irrigation presence using Relative Sensitivity Index (RSI):

\[
RSI = \frac{I_{irr} - I_{non}}{I_{non}(max) - I_{non}(min)}
\]

\(I_{irr}\) and \(I_{non}\) are the values of each index for irrigated and non-irrigated land. RSI is the difference of \(I_{irr}\) and \(I_{non}\) and normalized by the seasonal envelope (maximum–minimum) of non-irrigated values of each index. RSI provides the difference between...
irrigated and non-irrigated values for each spectral index compared to the seasonal amplitude in the same index’s non-irrigated value (Ozdogan and Gutman, 2008).

In the study by Ozdogan and Gutman (2010), Green Index (GI) presents the greatest sensitivity to irrigation presence during peak crop growth. GI, calculated as $\rho_{nir}/\rho_{green}$, was suggested by Gitelson et al. (2005) based on the evidence that green leaves have high reflectance in the green spectrum and absorption in the green spectrum is high enough to provide high sensitivity of GI to chlorophyll content but much lower than in the blue and red to avoid saturation (Gitelson et al., 2003).

To test the sensitivity of remote sensing spectral indices to irrigation presence, GI was compared with four indices, NDVI, NDWI, NDII6 and NMDI using RSI (Figure 19). Each index was generated from an averaged 8-day response of irrigated and non-irrigated cropland in Nebraska for 2012. Although GI is more sensitive to irrigation presence than NDVI, NDWI, NMDI, the comparative analysis indicated that NDII6 has the largest RSI during peak corn-growing season among the tested indices. In essence, NDII6 captures salient temporal features of irrigation and outperforms other four spectral indices in detecting irrigation presence.
Due to irrigation, agricultural areas receive full or partial sources of water supply to offset rainfall shortfalls under drought conditions. This makes it challenging to accurately monitor agricultural drought on irrigated land for precipitation-based drought monitoring methods. Histogram of NDII6 for irrigated cropland compared to that of NDII6 for non-irrigated cropland shows that NDII6 acquired over irrigated areas had higher value and greater disparity than that for non-irrigated areas (Figure 20). Figure 21 presents the comparisons between USDM and NDII6 anomaly map in eastern Nebraska for the week of August 7th. It has been observed that NDII6 anomaly has smaller fluctuation in NDII6 on irrigated land. Although USDM map is adjusted each week to reflect real-world conditions over many regions based on suggestions from experts throughout the country (Nghiem, 2007), it shows weakness to provide accurate localized depiction of agricultural drought conditions over irrigated land. Compared with USDM
map, the MODIS-based NDII6 anomaly provides 8-day agricultural drought information with higher spatial details on cropland with supplemental water sources.

![Histogram of NDII6 over irrigated and non-irrigated regions in Nebraska.](image1)

**Figure 20** Histogram of NDII6 over irrigated and non-irrigated regions in Nebraska.

![Comparisons between USDM map, irrigated map and NDII6 anomaly map in eastern Nebraska.](image2)

**Figure 21** Comparisons between USDM map, irrigated map and NDII6 anomaly map in eastern Nebraska.

### 4.6 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,
NMDI, VCI, VHI, LAI and FPAR products. The correlation between anomalies in MODIS indices and precipitation–based SPI data was examined across the Corn Belt to evaluate the relative performance of each MODIS index to detect agricultural drought that 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 1-month SPI and 3-month SPI suggesting these anomalies are reflective of agricultural drought condition caused by median-scale rainfall deficiency. Among the tested indices, NDII6 showed highest overall correlations with SPI, 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 condition. Comparisons between remote sensing drought maps and the USDM drought maps have been conducted to better understand the complementary drought information that MODIS drought indices can provide. The maps of index anomalies provided more spatial details at fine scale, while agreed to the changes of USDM maps quite well at large spatial scale.

MODIS spectral indices were also assessed over irrigated areas to demonstrate the advantages of remote sensing approaches to monitor drought over irrigated regions. NDII6 outperformed other four tested indices showing highest sensitivity to irrigation presence. Compared with USDM, the map of NDII6 anomaly provided more accurate localized depiction of drought conditions over irrigated land. Thus, anomaly of NDII6 has the potential for agricultural drought monitoring at high spatial resolution.
CHAPTER FIVE: MODEL SIMULATION AND SENSITIVITY ANALYSIS

Drought poses serious threats to agriculture. Water stress can cause physiological changes in crop, affecting vegetation abundance and development, which in turn causes variations in vegetation spectral signatures (Wang et al., 2008). Based on spectral characteristics, remote sensing vegetation indices using reflectance from visible to SWIR channels have been proposed to provide indication of drought occurrence, development and distributions from a local to global scale. In recent studies of drought monitoring, drought index anomalies are frequently used because anomaly is considered to isolate the variability of vegetation signal and to provide relative vegetation condition in historic context (Anyamba and Tucker, 2012). In last chapter, NDII6 anomaly has demonstrated great potential for agricultural drought monitoring. However, few studies have studied the physical linkage between anomaly of vegetation variables and anomaly of vegetation indices. This study proposed a novel approach to the problem, focusing on investigation of the relationship between anomalies of vegetation chlorophyll and water content and anomalies of spectral indices through model simulation. Field and laboratory measurements were conducted to identify the physical properties of corn leaves first, then leaf models and canopy models were applied to simulate canopy reflectance, and finally sensitivity analysis for two anomaly pairs (chlorophyll content-NDVI and leaf water content-NDII6) was performed to investigate quantitative linkage between anomalies in
key vegetative parameters and anomalies in both vegetation greenness index and vegetation water index. It is found that although the relationships between leaf chlorophyll/water content and vegetation indices are LAI dependent, the relationships between their anomalies are not sensitive to LAI, a critical parameter of vegetation canopy structure. So, physically, the anomalies of vegetation indices are more robust for vegetation greenness/water content monitoring and agricultural drought detection. This chapter discusses the main conclusions of this research, as well as future directions.

5.1 Leaf and canopy radiative transfer models

The leaf- and canopy- level radiative transfer models used in this study are PROSPECT and Scattering by Arbitrarily Inclined Leaves (SAIL) MODEL respectively. PROSPECT was developed by Jacquemoud and Baret (1990) to simulate leaf-level reflectance from 400nm to 2500nm. The PROSPECT model describes a leaf as consisting of N homogeneous layers and leaf reflectance and transmittance are calculated based on absorption coefficient and refractive index at various wavelength for leaf layer. The model employed in this study is PROSPECT version 4, which requires four input parameters: leaf structure parameter N which is the number of compact layers indicating the average number of cell walls interfaces within the mesophyll (Jacquemoud et al., 2009); leaf water content \( C_w \, \text{g/cm}^2 \), leaf chlorophyll a and b concentrations \( C_{ab} \, \mu\text{g/cm}^2 \), and leaf dry matter content \( C_m \, \text{g/cm}^2 \).

Widely used in remote sensing community, the SAIL Model is proposed to simulate the spectral reflectance at canopy level from uniform homogeneous vegetation canopies (Verhoef and Bunnik, 1981). It is based on the 1-D model developed by Suits
(1972) to simulate the bidirectional reflectance of turbid medium plant canopies, by solving the scattering and absorption of four upward/downward radiative fluxes. The model used in this study was the version rewritten in June of 2003 by USDA-ARS, Hydrology and Remote Sensing Laboratory, for implementation on windows platform. As a turbid medium model, SAIL approximates canopy as an infinitely extended plane-parallel medium that constitutes randomly oriented scattering phytoelements. SAIL allows users to simulate canopy-level reflectance by adjusting multiple input variables including LAI, leaf angle distribution (LAD), soil background properties and the solar and sensor geometry.

The coupled PROSPECT and SAIL models combined with laboratory measurements allowed us to study the impacts of changing key leaf parameters (water content and chlorophyll concentrations) on leaf and canopy reflectance. MODEL simulations can help quantify the contribution of leaf variables one by one to leaf reflectance (Jacquemoud et al., 2006). In order to further discover the linkage between leaf variables and vegetation indices, the SAIL model assist to generate reflectance at canopy level based on which vegetation indices were derived. The study links spectral vegetation indices with the variations of leaf biochemical contents, which causes spectral variation of canopy reflectance allowing better understanding of drought induced variations of canopy biophysical variables by using remote sensing vegetation indices.

5.2 Field experiment and simulation setup

In order to derive accurate leaf-level reflectance, input parameters for PROSPECT should be set to value range expected in the real world. With the exception of N, all other
leaf parameters can be physically measured. Based on previous studies (Ceccato et al., 2001; Wang et al., 2008), a reasonable value 1.3 was assigned to parameter N. The rest of leaf parameters employed in this study were based on field and laboratory measurements.

A field sampling campaign in USDA ARS cornfields was conducted during late vegetative stage of corn on July 19, 2009, a year with normal annual fall of rain. 36 leaf samples were randomly collected from 4 sites in the cornfield. Corn leaf variables were then measured in laboratory including fresh and dry weight, content of water and chlorophyll from corn leaf samples. Figure 22 presents histograms of measured leaf chlorophyll a and b concentrations ($C_{ab}$), leaf water content ($C_w$) and leaf dry matter content ($C_m$).

![Figure 22 Histograms of $C_{ab}$, $C_w$ and $C_m$ from laboratory measurements.](image)

The default values for N, $C_{ab}$, $C_w$ and $C_m$ were set to 1.3, 37, 0.016 and 0.0046 respectively based on average values of field experiment result. $C_{ab}$ and $C_w$ were adjusted separately over their normal range of variation: Leaf chlorophyll concentrations from 1-67 ($\mu$g/cm$^2$) and water content from 0.001-0.04 (g/cm$^2$).

The inputs of SAIL were tied with leaf reflectance/transmission from PROSPECT simulation and reflectance of background soil. The simulated leaf reflectance from
PROSPECT is served as the input of SAIL. Figure 23 illustrates the simulation process. The main input parameters of the integrated simulation are listed in Table 5. Five discrete values of LAI were employed (LAI = 0.5, 1.0, 2.0, 3.0, 4.0). The model allows users to select different predefined Leaf Angle Distributions (LAD). In this analysis, the canopy of corn was assumed to have erectophile LAD, a typical canopy simulation of corn.
Table 5 Input parameters of PROSPECT and SAIL models in this study.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>PROSPECT</th>
<th>SAIL</th>
</tr>
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<tbody>
<tr>
<td>N</td>
<td>1.3</td>
<td>LAI</td>
</tr>
<tr>
<td>$C_{ab}$ ($\mu g/cm^2$)</td>
<td>1-67</td>
<td>LAD Erectophile</td>
</tr>
<tr>
<td>$C_w$ (g/cm$^2$)</td>
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<td>Solar zenith angle 30</td>
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<tr>
<td>$C_m$ (g/cm$^2$)</td>
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<td>Fraction Direct Solar 0.8</td>
</tr>
<tr>
<td>View angle</td>
<td></td>
<td>Nadir</td>
</tr>
</tbody>
</table>

5.3 Sensitivity analysis of vegetation status and spectral indices

It is true that the leaf biochemical and biophysical variables are not independent (Wang et al., 2008) indicating that variations in leaf water content may give rise to changes in chlorophyll content and leaf internal structure (Jacquemoud, 1993). However, to better quantify the relative influence of each parameter, the reflectance spectra were obtained by adjusting each parameter separately in a given range while keeps other parameters the default values.

Figure 24 presents a simulation based on PROSPECT model intended to show how sensitive the leaf reflectance is to variations of $C_{ab}$ from 12 to 60$\mu g/cm^2$ and to $C_w$ from 0.01 to 0.03$\mu g/cm^2$. The variations of chlorophyll concentration $C_{ab}$ only affects wavelength range from 400 to 700nm (Figure 24a). An increase of $C_{ab}$ induces a decrease of reflectance in visible domain. Only MODIS visible band 1, 3 and 4, are influenced by variations in $C_{ab}$ and MODIS NIR and SWIR bands are insensitive to the change of chlorophyll content. Among bands affected by $C_{ab}$, MODIS band 2 presents the largest variations. The effect of $C_w$ presents entirely different behavior with $C_{ab}$ on leaf
reflectance. It is observed that an increase of $C_w$ induces a decrease of leaf reflectance in wavelength range from 900 to 2500nm, but this occurs with no noticeable effects in the visible domain (Figure 24b). Contrary to MODIS visible bands, where effects of $C_w$ on leaf reflectance are rather limited, MODIS SWIR bands 5, 6 and 7 are very sensitive to variations of $C_w$. Figure 24 also illustrates how spectral vegetation indices based on VIS, NIR and SWIR wavebands of optical sensors make use of these properties. For example, both NDVI and NDII6 were developed based on combination of two bands that have different sensitivity to change of chlorophyll or water content. The NDVI was developed based on difference in reflectance between red band and near infrared band; And NDII6 uses the strong liquid water absorption band centered at 1629nm and NIR band centered at 857nm that is insensitive to water content change.
We performed sensitivity analysis on MODIS band 1 (centered at 646nm) and 6 (centered at 1629nm) separately with different LAI values to illustrate effects of $C_{ab}$ on red band and $C_{w}$ on SWIR band (Figure 25). In each case, an increase of $C_{ab}$ or $C_{w}$ is connected with a decrease in reflectance. However, the reflectance reduction induced by the increment of $C_{ab}$ or $C_{w}$ has different characteristics. The reflectance of red band decreases significantly when $C_{ab}$ increases to 20µg/cm² while reflectance of SWIR band shows relatively gentle decrease with increase of leaf water content. Not only $C_{ab}$ and $C_{w}$ affect the canopy reflectance, but also leaf area index is an important driver. Figure 25
illustrates simulated canopy reflectance with LAI range from 0.5 to 4. An increase in LAI induces a decrease of reflectance for both red and SWIR bands.

![Figure 25](image.png)

Figure 25 (a) Simulated reflectance of MODIS band 1 for varying $C_a$ and LAI. (b) Simulated reflectance of MODIS band 6 for varying $C_w$ and LAI.

The study further investigated the effects of changing chlorophyll content and leaf water content on widely used vegetation greenness index NDVI and vegetation water index NDII6, which were constructed using canopy-level simulated reflectance of MODIS bands 1, 2 and 6 (centered at 646, 857 and 1629 nm). Based on combination of two bands that have different sensitivity to change of chlorophyll or water content, both
NDVI and NDII6 were successful attempts to quickly identify vegetation conditions based on satellite measurements. Compared to another widely used vegetation water index NDWI, NDII6 uses SWIR band centered at 1629nm which has stronger liquid water absorption than band centered at 1240nm (Ceccato et al., 2001; Hardisky et al., 1983). The use of strong water absorption band makes NDII6 more suitable for the estimation of plant water content (Wang et al., 2008).

When NDVI and NDII6 were modeled with the varying $C_{ab}$ and $C_w$ and within an LAI range from 0.5 to 4, it is noticeable that both indices increase with larger leaf biochemical variables (Figure 26). NDVI shows the largest variations when $C_{ab}$ changes from 0 to 20$\mu$g/cm$^2$ in contrast of relatively flat increase of NDII6. NDVI has slight variation when $C_{ab}$ over 30$\mu$g/cm$^2$ at each LAI value. The figure also presents an instructive simulation of coupled model intended to show how sensitive the vegetation indices are to variation in LAI from 0.5 (bare soil) to 4 (relative dense vegetation). The simulation study illustrates the large effect of LAI on vegetation indices and both NDVI and NDII6 are highly sensitive to the LAI variations. At higher LAI range, both indices

![Figure 26 Simulated effects of $C_{ab}$ on NDVI and effects of $C_w$ on NDII6 within different LAI conditions.](image-url)
are still sensitive to changes in $C_{ab}$ and $C_w$, and compared with NDII6, NDVI is more easily saturated with LAI>2. When $C_{ab}$ increases from 1 to 20, the simulated NDVI value increases from 0.2 to 0.815 with LAI value 4, in contrast of NDVI increment from 0.2 to 0.42 with LAI value 0.5. The simulation presents the impacts of $C_{ab}$ on NDVI and $C_w$ on NDII6 at varying LAI conditions and shows that both NDVI and NDII6 are highly sensitive to the canopy structural parameter LAI. The results suggest that LAI need to be taken into account for estimation of $C_{ab}$ and $C_w$ from vegetation indices. It also demonstrates the difficulties of using absolute index values to determine leaf parameters due to the impact of LAI.

### 5.4 Anomaly analysis of leaf variables and vegetation indices

Since the relationships between vegetation indices and vegetation biochemical/biophysical parameters are LAI dependent, it is necessary to investigate more robust approaches to determine vegetation biochemical/biophysical parameters. For agricultural drought monitoring, we are more interested in comparing vegetation status with normal conditions, i.e. the anomaly of vegetation biochemical/biophysical parameters. So, we focused on the analysis of anomalies of vegetation indices and intend to derive relationship between vegetation index anomalies and leaf parameter anomalies.

In order to generate anomalies for two leaf parameters $C_{ab}$ and $C_w$, the averaged value from laboratory measurement ($C_{ab}=38 \mu g/cm^2$ and $C_w=0.016 g/cm^2$) were employed as the normal value for chlorophyll content and leaf water content and we allowed two parameters to fluctuate in their normal range ($C_{ab}$ from 12 to 60 $\mu g/cm^2$ and to $C_w$ from 0.01 to 0.03$\mu g/cm^2$) and construct data series of $C_{ab}$ and $C_w$, based on which anomalies in
$C_{ab}$ and $C_w$ were developed as the value departure from the normal value, standardized by the standard deviation of each data series. For each $C_{ab}$ and $C_w$ in the data range, we calculated corresponding NDVI and NDII6 respectively at each LAI conditions and generate NDVI anomaly and NDII6 anomaly under each LAI condition the same way $C_{ab}$ and $C_w$ were created.

Figure 27 presents comparisons of two relationships ($C_{ab}$-NDVI and $C_{ab}$ anomaly-NDVI anomaly). The simulation shows that NDVI is highly sensitive for each LAI category, obtaining nearly 80% variation when NDVI is modeled with $C_{ab}=60 \mu g/cm^2$ and LAI changes from 0.5 to 4, demonstrating the large dependency of NDVI on LAI. The relationship between NDVI anomaly and $C_{ab}$ anomaly was also studied within different LAI conditions. An interesting pattern is noticed that the plots of NDVI anomaly on $C_{ab}$ anomaly at varying LAI condition were almost coincided with each other. Similar pattern is found in plot of NDII6 on $C_w$ and plot of NDII6 anomaly on $C_w$ anomaly (Figure 28). Changes of LAI generate different impact on $C_w$-NDII6 relationship showing that an increase in LAI is connected with an increase in the NDII6 for each $C_w$ value. NDII6 changes from 0.02 to 0.58 responding to LAI values from 0.5 to 4 when $C_w=0.03 g/cm^2$. However, the changing LAI has very limited impact on $C_w$-NDII6 anomaly relationship. Also shown in Figure 28 is the nearly linear relationship between NDII6 anomaly and $C_w$ anomaly. Plots of NDII6 anomaly on $C_w$ anomaly at varying LAI condition were almost coincided with each other in the middle of the plot. The study demonstrates limited impact of LAI on relationship between anomaly in spectral vegetation indices and
anomaly in leaf variables. So, anomalies of spectral indices are more robust in vegetation status monitoring.

Figure 27 Simulated effects of $C_{ab}$ on NDVI and relationship between $C_{ab}$ anomaly and NDVI anomaly within different LAI conditions.

Figure 28 Simulated effects of $C_w$ on NDII6 and relationship between $C_w$ anomaly and NDII6 anomaly within different LAI conditions.

The index anomalies are more robust than absolute index values in assessing water-stressed vegetation condition and drought condition in that: 1) anomalies provide relative vegetation condition with respect to what is normal within a vegetative region based on baseline which is established from historical average; 2) anomalies better describe water-stressed vegetative variability over larger area than absolute indices do and give a frame of reference that allow more meaningful comparisons between locations.
and more accurate calculations of trend; 3) compared with absolute index value, index anomaly shows little dependence on LAI, providing a measure of deviation degree, which is suitable for assessment of crop status and agricultural drought conditions at different phenological phases. The sensitivity analysis in this chapter provides a physical basis demonstrating advantages of using index anomaly in vegetation monitoring.

5.5 Chapter summary

In order to investigate the relationship between key vegetation variables and vegetation indices, sensitivity study has been conducted by using laboratory measurements and the coupled leaf-canopy reflectance model. The study has illustrated that chlorophyll and water content have different effects on canopy reflectance, and demonstrated how remote sensing vegetation indices respond to these two vegetation variables respectively.

The sensitivity analysis demonstrated that LAI plays an important role in the relationship between vegetation indices and vegetation variables. However, LAI has very limited impact on both $C_{ab}$-NDVI and $C_{w}$-NDII anomaly relationships. Although the relationships between leaf variables and vegetation indices are LAI dependent, the relationships between their anomalies are less sensitive to LAI. The sensitivity analysis in this chapter provided a physical basis of using index anomaly in vegetation monitoring. Compared with absolute index value, index anomaly shows little dependence on LAI, providing a measure of deviation degree of vegetation status, which is suitable for assessment of relative crop status and agricultural drought conditions.
CHAPTER SIX: A NEW PHENOLOGY-ADJUSTED APPROACH FOR AGRICULTURAL DROUGHT MONITORING

For agricultural drought monitoring over large crop areas, a few studies have considered the phonological variations between years. Varying corn-planting dates set a challenge to compare crop conditions of a certain growing stage between years and generate baseline of normal growing condition for different growing stages. In previous sections, SWIR band based NDII6 demonstrated good sensitivity to water stress over large agricultural area and NDII6 anomaly was identified as a suitable remote sensing variable to describe drought-stressed vegetative variability. In order to derive more phenologically meaningful index anomaly, this study made efforts to generate phenology-adjusted MODIS time series, based on which NDII6 anomalies for each 8-day period within corn-growing season were calculated.

As an accumulated process, drought stress is a major factor limiting crop growth and production (Whitmore and Whalley, 2009). In light of this, the accumulated NDII6 anomaly throughout the growing season is expected to better capture water-stressed crop status and agricultural drought condition. It is also noted that water stress in varying crop growing stages affects crop productivity at different degrees. Corn yield is most sensitive to water stress during reproductive stage, followed by grain-filling, and finally vegetative growth stages (Payero et al., 2006). In this chapter, a new agricultural drought indicator, the Phenology-Adjusted Drought Index (PADI) was proposed based on crop phenology,
NDII6 anomaly and crop water use function to assess agricultural drought condition throughout the growing season and two schemes of PADI were put forward. Further study and verification of PADI were conducted in next chapter.

6.1 Phenology-adjusted time series

Because the changing crop-planting dates set a challenge of comparing crop growing condition at a specific phenological stage among years, the study takes into account the timing of crop planting, which is highly dependent on soil moisture and temperature conditions as well as agricultural decisions (Sakamoto et al., 2010). Currently, the best information about crop planting progress is the Crop Progress Reports developed by USDA/NASS, which provide weekly crop progress information, including the percentage of a specific crop reaching a certain crop growing stage (e.g., silking, doughing or maturing) at state level. Figure 29 presents the national averaged (2007-2011) corn-growing progress for important growing stages. Figure 30 gives corn-planting progress of five major corn states in the Corn Belt from 2000-2012. In 2012, unusually warm temperature in spring drives growers across the Corn Belt to plant earlier than usual. From USDA reports, as of May 7th 2012, 89% of the corn had been planted in Illinois, while only 27% of the corn planted at the same time in 2011 (USDA, 2012). The date at which 50% of corn in total is being planted and emerged, as indicated in the USDA's weekly crop progress report, is one reliable measures of how early or late the crop is planted. We plotted 1%, 50% and 99% corn-planting date (Figure 31) and corn-emergence date (Figure 32) for five states in the Corn Belt (Illinois, Indiana, Iowa, Nebraska and Ohio). The solid back line shows the date 50% of corn in total planted. The
whiskers show the dates 1% (left) and 99% (right) of corn is being planted. In 2012, all these states show the earliest sign of corn planting since 2000. USDA provides first corn planting estimate on April 1, estimating proportion of corn in total at 5% being planted for Illinois and 1% for Indiana, Ohio and Nebraska. Three states have the earliest dates of 50% corn planted since 2000, including Illinois, Indiana and Nebraska. Illinois was reported completion of corn planting as of May 20. Ohio and Nebraska was at 98%, while Indiana was at 97%. Ohio was the most behind in five states with 94% corn planted by the date.

Figure 29 Corn growing progress (national average from 2007-2011).
Figure 30 Corn planting progress for Illinois, Indiana, Iowa, Nebraska and Ohio from 2000 to 2012.
First, we derive the start of the season (SOS) and end of the season (EOS) for corn from 2000 to 2012 in five corn states. The SOS is generally the start of the crop vegetative stage, which in this study is defined as the date 90% corn emerged from soil based on NASS Crop Progress Report. Then, EOS is identified as the date corn matures, normally 120 days after corn emergence. For each state and individual year, the 8-day
MODIS data between SOS and EOS were obtained for the period of analysis (grey bar in Figure 33).

Figure 34 shows the MODIS eight-day data that were used to represents corn-growing season since emergence for the state of Iowa in 2012. Each corn-growing period contains 15 8-day MODIS data that divide corn-growing season period into 15 individual 8-day stages.
6.2 Anomaly assessment of corn yield

Long-term corn yield fluctuations are often associated with climatic variability such as temperature and precipitation (Lobell and Asner, 2003). However, not only climate factors, but also human factors influence corn production, including institutional and technological changes (Sun et al., 2007). When linking drought index anomalies with crop yield data, it is important to remove trend in corn yield that considered being unrelated to climate factors. Removing trend from the data enables us focus our analysis on the fluctuations of yield that due to extreme weather and climate events. Corn yield data has been processed in many studies to remove influence from technology advancement including seed genetics and fertilizer (Lobell and Asner, 2003; Malone et al., 2009; Sun et al., 2007). However there is no standard theoretical basis for choosing one de-trending method over the other. In this study, county-level corn yield were de-trended by subtracts the best straight-fit line from 1970-2012 yield time series. Figure 35 presents the comparison of original and de-trended corn yield data for county Knox, Nebraska. Red line shows crop yield data that has been de-trended.
6.3 Corn water use function and sensitivity of corn yield to water stress

Water used by the crop, known as evapotranspiration (ET), is the water removed from the soil by evaporation from the soil surface and transpiration by the plant (Kranz et al., 2008). Approximately 70 percent of crop water use comes from corn transpiration. However, corn does not extract water uniformly from soil throughout its growing period.

Rhoads and Bennett (1990) measured field corn evapotranspiration and estimate yield loss per stress day during differing growing stage (Table 6). At the early growing stage, corn extract small amount of water because of limited root zone and leaf area. The greatest daily water use usually occurs from tassel to pollination in mid-July when corn roots fully developed and sufficient water is needed for nutrient uptake and transport. As grain filling nears completion, crop water use declines quickly as corn approach maturity. Evapotranspiration increases as corn grows until Blister stage that usually occurs about
10-14 days after silking. The estimated peak evapotranspiration of corn reaches to 0.33 inches per day from end of vegetative stage to Blister.

<table>
<thead>
<tr>
<th>Growth stage</th>
<th>Evapotranspiration (inches/day)</th>
<th>Percent yield loss per stressed day (min-average-max)</th>
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<tr>
<td>1-4 leaf</td>
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<tr>
<td>4-8 leaf</td>
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<td>8-12 leaf</td>
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<tr>
<td>12-16 leaf</td>
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<tr>
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</tbody>
</table>

Table 6 Estimated evapotranspiration and percentage of yield loss during corn-growing stages.

Adapted from Rhoads and Bennett (1990)

The amount of water used by corn is dependent on factors including stage of growth, weather parameters, management and environmental conditions (Allen et al., 1998; Fritz et al., 2010). High temperature, low humidity, clear skies and high wind speed will cause high water demand for corn (Kranz et al., 2008). Table 7, taken from the University of Minnesota Extension Bulletin Irrigation Scheduling (FO-1322), provides estimated averaged daily water use for each week after emergence. The curves of daily water use are presented in Fig 36.

It has been shown that the water demand for corn does not evenly distributed throughout the growing season and the daily water use peaks in period from week 10 to 11 after emergence.
<table>
<thead>
<tr>
<th>Week after emergence</th>
<th>Water use for corn (inches/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.03</td>
</tr>
<tr>
<td>2</td>
<td>0.05</td>
</tr>
<tr>
<td>3</td>
<td>0.07</td>
</tr>
<tr>
<td>4</td>
<td>0.09</td>
</tr>
<tr>
<td>5</td>
<td>0.13</td>
</tr>
<tr>
<td>6</td>
<td>0.15</td>
</tr>
<tr>
<td>7</td>
<td>0.2</td>
</tr>
<tr>
<td>8</td>
<td>0.2</td>
</tr>
<tr>
<td>9</td>
<td>0.22</td>
</tr>
<tr>
<td>10</td>
<td>0.24</td>
</tr>
<tr>
<td>11</td>
<td>0.24</td>
</tr>
<tr>
<td>12</td>
<td>0.22</td>
</tr>
<tr>
<td>13</td>
<td>0.21</td>
</tr>
<tr>
<td>14</td>
<td>0.17</td>
</tr>
<tr>
<td>15</td>
<td>0.14</td>
</tr>
<tr>
<td>16</td>
<td>0.11</td>
</tr>
<tr>
<td>17</td>
<td>0.09</td>
</tr>
<tr>
<td>18</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Figure 36 Average water use of corn for each week after emergence.
In chapter 5, MODIS NDII6 anomaly was found to be a suitable index to monitor crop water content and drought conditions. To test the relationship between NDII6 anomaly and yield variations at each corn-growing stage and to identify critical phase in the corn-growing period, NDII6 anomaly were correlated with the corresponding 2012 corn yield anomaly at county level for 15 corn-growing stages. The NDII6 anomaly at each 8-day growing stage presents the relative crop condition as compared to the normal. When accumulated over corn-growing season, NDII6 anomaly is expected to provide the estimation of water stressed crop condition. Corn yield and MODIS data from 405 crop counties in the Corn Belt were used in the analyses. Figure 37 shows the dynamics of the correlation coefficients for corn yield anomaly versus NDII6 anomaly and accumulated NDII6 anomaly at 15 growing stages. Based on the assumption that the departure of drought index is representative of water stress, the correlation analysis identifies important phase in the corn life cycle when yield variations is highly correlated with index anomaly. According to Figure 37, yield anomaly is highly correlated with NDII6 anomaly from stage 8 to stage 10 (late-July to mid-August), when corn has high water demand. The period is known as reproductive period, which determines the actual number of kernels that will form in the spikes. The best correlation coefficient 0.8 occurs at stage 9 indicating the most sensitive stage in growing season to water stress. The accumulated NDII6 shows increasing correlation coefficient with corn yield anomaly as corn grows (Figure 37). The correlation analysis indicates that water deficiency at each growing stage exerts varying-degree impact on corn yield (Kogan et al., 2005) and the sensitivity of corn to water stress peaks during reproductive phase.
Figure 37 Correlation coefficient for corn yield anomaly versus NDII6 anomaly and accumulated NDII6 anomaly at 15 growing stages.

6.4 Phenology-Adjusted Drought Index (PADI)

Drought has accumulated impacts on corn production throughout the growing season. To better estimate the cumulative impact of drought on crop and assess agricultural drought condition during growing season, a new agricultural drought indicator, the Phenology-Adjusted Drought Index (PADI), was proposed. The PADI was calculated as cumulative weighted NDII6 anomaly over corn-growing season. Due to unbalanced crop response to water stress during growing season, weights of NDII6 anomaly were assigned for each 8-day growing stage based on curve of corn water use. To derive weights for NDII6 anomaly at each 8-day stage, we use quadratic polynomial function (y) to fit the water use curve and generate daily water use of corn (x) at each 8-day stage:

\[ y = -0.054x^2 + 0.054x - 0.003 \]
Weights are then calculated by normalizing daily water use at each stage by the sum (Table 8).

<table>
<thead>
<tr>
<th>8-day stages after emergence</th>
<th>Daily water use (inches/day)</th>
<th>Weights of NDII6 anomaly</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.01</td>
<td>0.005</td>
</tr>
<tr>
<td>2</td>
<td>0.05</td>
<td>0.023</td>
</tr>
<tr>
<td>3</td>
<td>0.10</td>
<td>0.046</td>
</tr>
<tr>
<td>4</td>
<td>0.14</td>
<td>0.065</td>
</tr>
<tr>
<td>5</td>
<td>0.17</td>
<td>0.078</td>
</tr>
<tr>
<td>6</td>
<td>0.19</td>
<td>0.088</td>
</tr>
<tr>
<td>7</td>
<td>0.21</td>
<td>0.097</td>
</tr>
<tr>
<td>8</td>
<td>0.22</td>
<td>0.101</td>
</tr>
<tr>
<td>9</td>
<td>0.22</td>
<td>0.101</td>
</tr>
<tr>
<td>10</td>
<td>0.21</td>
<td>0.097</td>
</tr>
<tr>
<td>11</td>
<td>0.19</td>
<td>0.088</td>
</tr>
<tr>
<td>12</td>
<td>0.17</td>
<td>0.078</td>
</tr>
<tr>
<td>13</td>
<td>0.14</td>
<td>0.065</td>
</tr>
<tr>
<td>14</td>
<td>0.10</td>
<td>0.046</td>
</tr>
<tr>
<td>15</td>
<td>0.05</td>
<td>0.023</td>
</tr>
</tbody>
</table>

We proposed two schemes of PADI to estimate relative crop water condition, one of which are cumulative NDII6 anomalies and the other only considers NDII6 anomalies that are negative.

\[
PADI_1 = \sum_{i=1}^{t} w_i \cdot \Delta \text{NDII6}_i
\]

\[
PADI_2 = \sum_{i=1}^{t} w_i \cdot \Delta \text{NDII6}_i \quad (\Delta \text{NDII6} = 0, \text{if} \Delta \text{NDII6} > 0)
\]
Where $w_i$ is the weight for ndii6 anomaly at growing stage $i$, and $t$ is the current growing stage. In next chapter, the performance of both PADI\textsubscript{1} and PADI\textsubscript{2} in agricultural monitoring will be assessed and compared in two case studies in next chapter.

### 6.6 Chapter summary

NDII6 anomaly has been justified in previous chapters as a suitable remote sensing variable to assess agricultural drought. Because drought has cumulative impacts on crop production, the accumulated NDII6 anomaly is expected to provide a good assessment of water-stressed crop condition and serve as an ideal agricultural drought indicator. In order to generate phenologically meaningful NDII6 anomaly, this study adjusted MODIS time series for each corn-growing season from 2000 to 2012 based on USDA Crop Progress Report. As the sensitivity of crop to water deficiency varies throughout the growing season, different weights were assigned to NDII6 anomaly at varying growing stages based on corn water use function. Based on phenology information, NDII6 anomalies and crop water use function, a new agricultural drought-monitoring index, the Phenology-Adjusted Drought Index (PADI) was proposed. At the end of this chapter, two schemes of PADI were put forward and will be examined in the next chapter.
CHAPTER SEVEN: DROUGHT EVENTS ASSESSMENT AND PADI VERIFICATION

Although crop yield may be affected by a variety of factors, water stress during growing season may result in drastic changes in crop greenness, vigor and productivity (Unganai and Kogan, 1998). As a result, yield loss can be served as a water stress indicator, providing an indirect way to assess severity of agricultural drought and validate satellite-based drought monitoring.

Recently, many studies have been conducted attempting to associate remote sensing vegetation indices with yield of agricultural crops. Previous works have presented connections between NDVI, VHI and LAI and crop biomass accumulation that has in turn been associated with crop yield (Mkhabela et al., 2011; Salazar et al., 2007; Shanahan et al., 2001; Unganai and Kogan, 1998; Zhang et al., 2006). In this chapter, PADI is further investigated using crop yield data and compared with other existing remote sensing approaches in two case studies.

7.1 The 2012 drought over the Corn Belt

The study further investigated PADI by performing correlation analysis between PADI$\text{1}$, PADI$\text{2}$ and corn yield anomaly in 2012 to evaluate the ability of PADI in assessment of yield losses due to water stress. Corn yield anomaly was also correlated
with average anomaly of MODIS-based NDVI, VHI, LAI and NDII6 over growing season, a commonly used way to assess crop-growing condition, for comparison.

The analyses were done for total 405 major crop counties in five corn-growing states (Illinois: 88 counties; Indiana: 74 counties; Iowa: 97 counties; Nebraska: 80 counties; Ohio: 65 counties). PADI$_1$, PADI$_2$ and anomalies in NDVI, NDII6, LAI and VHI were calculated for each county to be correlated with county yield data.

![Figure 38 Scatter plots of 2012 corn yield anomaly and averaged anomalies of four MODIS indices during corn-growing season for counties in Illinois, Indiana, Iowa, Nebraska and Ohio.](image)
Figure 39 Scatter plots of 2012 corn yield anomaly and PADI1 and PADI2 for counties in Illinois, Indiana, Iowa, Nebraska and Ohio.
Figure 38 and Figure 39 show scatter plots of the county-level 2012 corn yield anomaly versus two sets of PADI and four MODIS drought indicators respectively for five corn states. Table 9 presents the correlation coefficient between crop yield anomalies and tested indices. The highest correlation coefficient (0.87) occurs in Indiana between 2012 crop yield anomaly and PADI$_2$. The correlation is less significant in Illinois compared with other four states. All tested indices have smallest correlation coefficient in Illinois except VHI. Two forms of PADI outperform others in explaining corn yield variations due to 2012 drought. The PADI$_2$, shows better correlation coefficient than PADI$_1$, the cumulative weighted NDII6 in all five states except Indiana. The significant losses in corn yield during 2012 are successfully captured by the index and the correlation analysis justifies the use of PADI$_2$ to measure relative corn growing condition in water stress. Based on the analysis, PADI$_2$ was chosen as optimum agricultural drought index that outperforms other tested indices in evaluating water-stressed corn yield variations. Although PADI$_2$ does not measure drought directly, by measuring relative water condition of crop, PADI$_2$ provide a good way to estimate agricultural drought condition throughout the growing season. And PADI$_2$, instead of PADI$_1$, was named PADI. The PADI maps in 2012 at both 500m resolutions and county-level are shown in Figure 40. 2012 Corn yield anomalies were plotted as comparison (Figure 40(c)). As indicated by PADI drought map, severe droughts were scattered over the region and southern area of Illinois and Indiana are the worst drought-affected regions across the Corn Belt. Severe drought during growing season could have damaging impacts on corn production. The drought pattern indicated by PADI results was consistent with corn yield information that
large areas of corn yield reduction were observed at southern Illinois and Indiana. Regression analysis was performed between PADI and 2012 corn yield anomaly for all crop counties in five Corn Belt states (Figure 41). The correlation coefficient (R) achieved for PADI and corn yield anomaly was 0.86 showing statistically significant result (p-value<0.001).

<table>
<thead>
<tr>
<th></th>
<th>PADI&lt;sub&gt;1&lt;/sub&gt;</th>
<th>PADI&lt;sub&gt;2&lt;/sub&gt;</th>
<th>∆NDVI</th>
<th>∆NDII6</th>
<th>∆LAI</th>
<th>∆VHI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Illinois</td>
<td>0.73</td>
<td>0.75</td>
<td>0.58</td>
<td>0.65</td>
<td>0.42</td>
<td>0.61</td>
</tr>
<tr>
<td>Indiana</td>
<td>0.87</td>
<td>0.87</td>
<td>0.80</td>
<td>0.85</td>
<td>0.68</td>
<td>0.87</td>
</tr>
<tr>
<td>Iowa</td>
<td>0.78</td>
<td>0.81</td>
<td>0.81</td>
<td>0.81</td>
<td>0.82</td>
<td>0.83</td>
</tr>
<tr>
<td>Nebraska</td>
<td>0.77</td>
<td>0.78</td>
<td>0.75</td>
<td>0.77</td>
<td>0.62</td>
<td>0.71</td>
</tr>
<tr>
<td>Ohio</td>
<td>0.77</td>
<td>0.79</td>
<td>0.74</td>
<td>0.70</td>
<td>0.74</td>
<td>0.53</td>
</tr>
</tbody>
</table>

Table 9 Correlation coefficients of 2012 corn yield anomaly with PADI1, PADI2 and with four averaged MODIS index anomalies.
Figure 40 Comparisons of PADI map at (a) 500m resolution, (b) county-level PADI map and (c) corn yield anomaly map across the Corn Belt in 2012.
Figure 41 Correlation coefficients of 2012 corn yield anomaly with PADI for counties in five Corn Belt states.

7.2 The 2005 drought over Illinois

In 2005, Illinois suffered extreme drought conditions during summer season. The rainfall during this time ranked 10\textsuperscript{th} lowest of the past 113 years (Zhang et al., 2006). During the corn-growing season in 2005, with the exception of southern area, a large portion of the state’s area experienced extreme drought condition as indicated by the USDM maps in Figure 42. The overall corn yield estimated by the Illinois Agricultural Statistics Service was 145 bushels per acre, which is seven percent below the previous five-year average.
PADI drought map for the 2005 corn-growing season were illustrated in Figure 43. Severe drought conditions were observed over northern Illinois, which could have detrimental impacts on local agriculture with the potential to affect Illinois corn production. As indicated by 2005 corn yield anomaly map (Figure 43), northern Illinois counties demonstrate significant corn yield losses. Based on USDA estimates, the harvested statewide average corn yield was 143 bushels/acre, 37 bushels less than yield of 2004. The spatial distribution of 2005 corn yields revealed differences across the state. Although southern counties of Illinois presented above average corn yield in 2005, large corn yield reduction was observed in the North. In order to further test the performance of PADI in agricultural drought monitoring, corn yield anomaly was correlated with PADI and anomalies in NDVI, NDII6, LAI and VHI for major crop counties in Illinois in 2005.
(Figure 44). All tested indices demonstrate good correlation (above 0.82) with yield anomaly; PADI showed the strongest correlation (0.86) and VHI anomaly provided a slightly lower R-value (0.85) (Table 10).

Figure 43 Comparisons of (a) PADI map at 500m resolutions, (b) county-level PADI map and (c) corn yield anomaly map across Illinois in 2005.
Figure 44 Scatter plots of 2005 corn yield anomaly and PADI and averaged anomalies of four MODIS indices over corn-growing season for counties in Illinois.

Table 10 Correlation coefficients of 2005 corn yield anomaly with PADI and with four averaged MODIS index anomalies.

<table>
<thead>
<tr>
<th>Correlation coefficient with 2005 corn yield anomaly</th>
<th>PAD</th>
<th>∆NDVI</th>
<th>∆NDII</th>
<th>∆LAI</th>
<th>∆VHI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Illinois</td>
<td>0.86</td>
<td>0.83</td>
<td>0.83</td>
<td>0.82</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Compared with USDM map and other drought monitoring tools based on ground measurements, the PADI map focuses on agricultural drought monitoring and provides a more detailed way by identifying corn-growing regions under water stress. Because of the potentially huge agricultural lost caused by extreme drought, PADI provides a promising tool to evaluate water-stressed yield losses. It is also noted that the pixel level analysis can be temporal integrated or spatial aggregated for drought detection at different temporal-spatial scales. PADI can also be integrated with other information (population, food price, agricultural area, etc.) for assessing regional food security.
This study employed long time-series corn yield data for validating the new approach. The results showed that the performance of PADI was fairly robust to assess drought-stressed corn yield losses over large corn-planting area. Based on phenology-adjusted time series and crop water use function, PADI provides a new way to assess agricultural drought and can be used as a drought-stressed yield loss indicator. By using 8-day MODIS product, PADI is expected to provide timely information of crop conditions across large geographic areas, which can be used by experts in drought and agriculture to quickly identify most stressed crop area and gain insight into the variations in corn production due to water stress.

7.3 Chapter summary

The widespread 2012 drought in the Corn Belt and 2005 drought in Illinois were used to investigate and compare PADI, NDVI, NDII6, NDWI and NMDI for agricultural drought monitoring. Under drought stress, variations in crop yield provide a good way to assess the drought severity. Taking advantage of adjusted phenological information and weighted NDII6 anomaly, PADI best correlated with corn yield anomaly in two case studies and demonstrated the highest overall performance in agricultural drought monitoring among tested methods.

Compared with precipitation-based drought maps, the 500m PADI drought map offered a detailed way by looking at specific crop region under water stress. It is also noted that the pixel level analysis can be temporal integrated or spatial aggregated at different administrative levels for decision-making purposes. The PADI can also be
coupled with other information (population, food price, agricultural area, etc.), for applications in food security assessment.

The successful applications of PADI for agricultural drought monitoring across the Corn Belt demonstrated that PADI could be applicable in large corn-growing areas. Showing a strong correlation with yield fluctuations, PADI has also provided the potential as a good corn yield indicator. A more thorough evaluation of the PADI as an agricultural drought-monitoring tool and yield indicator for other agricultural areas will be conducted in the near future.
CHAPTER EIGHT: CONCLUSIONS AND DISCUSSION

The dissertation has explored the potential applications by integrating remote sensing measurements and GIS technology for agricultural drought monitoring in the U.S. Corn Belt. With case study of the 2012 drought over the Corn Belt, the sensitivity of eight widely used indices for monitoring agricultural drought condition was analyzed. The NDII6 anomaly demonstrated good sensitivity to water stress over large agricultural areas. Parameterization with field and laboratory experiments and simulation with coupled leaf-canopy radiative transfer models further demonstrated the physical linkage between NDII6 anomaly and vegetation water content variation. Then, a new proposed agricultural drought indicator PADI was investigated and tested over the U.S. Corn Belt in this dissertation to reflect the cumulative status of crop water content anomaly and assess agricultural drought severity over the corn-growing areas. The PADI was based on NDII6 anomaly, time series of phenology-adjusted MODIS data products, and corn water use function. Verification based on case studies of the 2012 drought over the Corn Belt and 2005 drought over Illinois demonstrated the capability of PADI for agricultural drought monitoring over the corn-growing regions, and showed the potential to advance fine-scale agricultural drought monitoring with remote sensing technology.

8.1 Conclusions
The main achievements of this research included: 1) found that NDII6 is a suitable remote sensing index for agricultural drought monitoring through time series analysis and comparison of eight commonly used indices; 2) discovered that NDVI and NDII6 anomalies provide a more robust way to monitor vegetation greenness and water content than absolute index value based on field experiments and model simulations; 3) developed a new approach for assessing agricultural drought status based on phenology information, NDII6 anomaly and corn water use function.

8.1.1 Assessment of MODIS indices for agricultural drought monitoring

The 2012 drought in the Corn Belt provided a good opportunity to assess the capability of six popular MODIS spectral indices (NDVI, NDWI, NDII6, NMDI, VCI and VHI) and two MODIS products (LAI and FPAR) to detect drought over extensive agricultural areas. This study evaluated the capability of remote sensing indices in agricultural drought monitoring using time series of 13-year MODIS observations.

MODIS indices were correlated with SPI, a commonly used precipitation-based index, to evaluate the relative performance of each MODIS index to detect drought condition that caused by precipitation deficits. NDII6 outperformed the other tested indices and presented the highest overall correlation with SPI at all time steps evaluated. All tested indices showed highest correlation with SPI when no time lag was considered, indicating quick responses of these indices to precipitation deficiency. The tested indices were better correlated with the SPI6 than SPI1 and SPI3 suggesting that median-scale precipitation deficiency is more detectable by MODIS-based indices.
The comparisons between remote sensing anomaly maps and the USDM drought maps have been conducted to better understand the complementary drought information that MODIS drought indices can provide. Although the discrepancies in spatio-temporal drought patterns captured by remote sensing drought map and USDM map existed, both MODIS drought maps and USDM maps have captured the rapid intensification of drought condition since July.

Finally, sensitivity analysis of remote sensing spectral indices to irrigated areas was conducted. The result indicated that NDII6 was more sensitive to irrigation presence than other tested indices. Traditional precipitation-based drought monitoring shows weakness to describe drought condition over irrigated land. Compared with USDM map, the map of NDII6 anomaly provided more accurate localized depiction of crop conditions over irrigated land. Therefore, NDII6 anomaly has the potential to advance fine scale drought monitoring by providing more detailed characterization of crop water stress.

Based on 8-day MODIS data, NDII6 anomaly can be used to assess corn water stress status at different corn growing stages and gain insight into the possible near-term trend in vegetation conditions.

**8.1.2 Model simulation and sensitivity analysis**

Based on field and laboratory measurements and simulations with the coupled leaf-canopy radiative transfer models, sensitivity analyses were performed to investigate the relationship between vegetative biochemical and biophysical variables and vegetation indices. Specifically, the relationship between chlorophyll content and NDVI and the relationship between leaf water content and NDII6 were analyzed. LAI, an important
parameter of vegetation canopy, was found playing a critical role in relationship between vegetative variables and remote sensing vegetation indices. It has been shown that the relationships between leaf variables and vegetation indices are LAI dependent, while the relationships between their anomalies are not sensitive to LAI. So, NDVI and NDII6 anomalies are more robust for vegetation greenness and water content monitoring. Model simulation and sensitivity analyses provided a physical basis for using NDII6 anomaly for vegetation water stress assessment and agricultural drought monitoring.

### 8.1.3 A new phenology-adjusted approach for agricultural drought monitoring

Using phenology information, NDII6 anomaly and crop water use function, a new agricultural drought-monitoring index, the Phenology-Adjusted Drought Index (PADI) was proposed to reflect the cumulative status of vegetation water content anomaly and assess agricultural drought severity during crop growing season.

The performance of PADI in agricultural drought monitoring was investigated in two case studies: the 2012 drought over the Corn Belt and the 2005 drought in Illinois. Regression analyses were performed to correlate PADI, NDVI, NDII6, NDWI and NMDI with corn yield anomaly. As severe drought stress during growing season is a major factor leading to yield loss, crop yield variations provide a reasonable way to assess degrees of drought stress and validate satellite-based agricultural drought monitoring. In both cases, PADI was best correlated with corn yield anomaly demonstrating the highest overall performance in agricultural monitoring among tested remote sensing methods. Because of strong correlation between PADI and corn yield fluctuations, PADI can also serve as potential indicator of water-stressed corn yield variations. By using 8-day 500m
MODIS product, PADI has demonstrated the great potential to characterize agricultural drought conditions over large corn-growing regions at high spatial resolution.

8.2 Limitation of this work

One of the achievements of this research is PADI, the proposed new index for monitoring agricultural drought conditions over corn-growing areas and corn yield variations based on corn phenology and water use function. Currently, the study area and PADI applications are limited to the U.S. Corn Belt, where corn is intensively planted. For areas with moderate corn-growing density, which are common conditions found in reality, the performance of PADI in agricultural drought monitoring has not been examined.

When plant density is low, satellite-measured surface reflectance is combined response from vegetation and soils. Uncertainties may arise in estimation of vegetation condition using remote sensing vegetation indices because they cannot fully remove the background soil effects (Gao, 1996). Further studies are required to extend and investigate the proposed techniques under different circumstance.

8.3 Future works

Although this study illustrated the potential of PADI for assessing agricultural drought and water stressed corn condition, more extensive validations are necessary. The expanded test of PADI will be conducted over other corn-growing areas in the world within different climatic regimes.
The next generation of MODIS sensor, VIIRS will continue to provide critical data products for global weather and climate monitoring. This newly developed index can also be applied to VIIRS measurements for future agricultural drought monitoring. In the near future, additional research will be conducted to integrate multiple satellite sensors (e.g. MODIS and VIIRS) to establish long-term Climate Data Records (CDRs) for more effective drought climate study over agricultural regions. While different satellite sensors have different spectral, spatial and temporal specifications, cross-sensor calibration and validation are essential to generate long term CDRs, which are critical for monitoring and assessing drought as well as other natural hazards.
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Zhang, P., T. A. Bruce, and R. Myneni (2006), Monitoring 2005 Corn Belt Yields From Space, in *Eos*, pp. 150-151, Wiley Online Library.
Di Wu was born in Nanjing, P. R. China. He received his Bachelor of Science in Geographic Information System from Nanjing University in 2008. He joined the Ph.D. program of Earth Systems and Geoinformation Sciences at George Mason University in 2008. He was employed for five years as a graduate research assistant under the instruction of Dr. John J. Qu. His research area at the time of this dissertation is about integrated GIS and remote sensing for monitoring agricultural drought.