BIOMASS ASSESSMENT IN THE U.S. MIDWEST USING MODIS TIME-SERIES PRODUCTS

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by

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BIOMASS ASSESSMENT IN THE U.S. MIDWEST USING MODIS TIME-SERIES PRODUCTS

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ABSTRACT

Bioenergy becomes the largest source of renewable energy in the United States. Corn ethanol currently constitutes 99% of the country's biofuels in the U.S. Switchgrass, a type a Warm Season Grasses, has been regarded as alternative resources instead of annual crops for obtaining the bioenergy. The study is to delineate annual crops (corn, soybean, winter wheat and spring wheat) and perennial crops (Warm-Season Grasses and Cool-Season Grasses) in the U.S. Midwest based on MODIS time-series products and Cropland Data Layers (CDL) from 2000 to 2009. In addition, this study is to extract WSG biomass proximity by integral NDVI. Besides, based on Multiple Linear Regression, this study aims to identify the sensitive environmental factors that affect distributions of WSG. Major findings include: (1) the classification maps are relatively good for annual and perennial crops in the U.S. Midwest from 2000 to 2009. (2) In the U.S. Midwest, WSG biomass proximity of western states is lower than eastern states. (3) The precipitation in May shows dominantly higher influence on WSG biomass. Temperatures in April, June, and September have positive effects on WSG growth, and temperature in April has the

strongest effect than other months. However, temperatures in May and July have negative effects on WSG biomass. Land Capability Class of soil is less a control to WSG biomass than climate factors.

Key words: Biomass; Warm-season grasses; Time series analysis; Integral NDVI; MODIS

Chapter 1 Introduction and literature review

1.1 Bioenergy

1.1.1 Energy crops and biofuels

With global resources of fossil fuel dwindling, it is more prominent now than ever that we pay attention to sustainable energy and transformational technologies. Biofuels are renewable fuels that could be significant for reducing dependence of fossil fuels (Simpson, 2009; Schnepg & Yacobucci 2010), and offering America's farmers a new revenue opportunity (Paine LK et al., 1996; McLaughlin SB et al., 2006). Biofuels have a diverse range of alternatives, in which corn ethanol is currently the primary source and constitutes 99% of domestic biofuels in the U.S. (Farrell et al., 2006). Currently, corn is commonly utilized to produce ethanol in the U.S. Midwest (Solomon et al., 2007; Schnepg & Yacobucci, 2010). Other feedstock pathways from annual crops include soybean oil and crop residues. With advanced demand of biofuels, however, food shortages, food price increase, and environmental contamination become big concerns in major U.S. agricultural regions.

For this reason, the U.S. Department of Energy (DOE) has sponsored research to evaluate a wide variety of bioenergy alternatives since 1978 (Wright 1994). In the early 1990s, the DOE identified switchgrass (*Panicum virgatum* L.) as a model cellulosic energy crop (McLaughlin & Kszos 2005; Wright 2007). This type of

perennial grasses is easy to be established, provides great wildlife habitat, protects against soil and water nutrient losses, and thus has positive environmental effects. As shown in Table 1-1, among various biofuel resources, switchgrass will be able to provide 7.9 billion gallons of biofuel by 2022 (from United States Department of Agriculture (USDA) Biofuels Strategic Production Report, 2010). Switchgrass is one of the primary native, warm-season perennial grasses species in the pre-colonial tall-grass prairie, whose territory is mostly covered in the Midwest. The estimation of current biomass distribution of the warm-season grasses thus provides indispensable information in evaluating the potential of cellulosic bioenergy in the Midwest region.

Table1-1: USDA biofuels strategic report about energy crops assumption by 2022 (USDA Biofuels Strategic Production Report, 2010)

Type	**Amount (Billion Gallon)**
Switchgrass (perennial grass)	7.9
Soy biodiesel and corn oil	1.34
Crop residues (corn stover, includes bagasse)	5.5
Woody biomass (forestry residue)	0.1
Corn ethanol	15.0
Other (municipal solid waste (MSW))	2.6
Animal fats and yellow grease	0.38
Algae	0.1
Imports	2.2

Approximately 50% of the conterminous U.S. land is used either for crops or grazing and is well managed by the United States Department of Agriculture (USDA, 2000). For example, over 80% of the lands in Iowa are used for corn, soybean, and forage production for livestock (Burkart et al., 1994). Similar patterns are observed in most areas of the U.S. Midwest (National Agricultural Statistics Service [NASS], 2004). Currently, only a small fraction of agricultural output is utilized for energy production (Eidman et al., 2005). Spatial information on perennial grasses is far less recorded than annual crops in the United States. It is estimated that biomass supplies from perennial grasses feed only around 3% of the total domestic energy, mostly for heating, electricity and biofuel production (Perlack et al., 2005). Its growing areas, patterns and biomass amounts are not well recorded by any U.S. crop databases.

1.1.2 Remote sensing and spatial information analysis

Satellite remote sensing has become an main tool for measuring and monitoring ecosystem over large areas due to its wide coverage and relatively high spatial and temporal resolutions (Wylie et al., 2008; Zhang et al., 2010). Intensive efforts have been made to take advantage of satellite imagery that is capable of obtaining spatial distributions of various land covers and uses. A rich set of satellite products, such as those acquired by NOAA (National Oceanic and Atmospheric Administration)/AVHRR (Very High Resolution Radiometer), SPOT/ VEGETATION, TERRA, or AQUA/MODIS (Moderate Resolution Imaging Spectroradiometer), have

been utilized to detect land-use/cover changes and terrestrial ecosystems from local up to regional, continental and the global scales (Justice et al., 1985; Tucker & Sellers, 1986; Running & Nemani, 1988; IGBP, 1992; Reed et al., 1994; Myneni et al., 1997). This study thus focused on biomass assessment of warm-season perennial grasses (bioenergy crops) with various sources of satellite and environmental data sets.

1.2 Biomass assessment

1.2.1 Previous studies

The most common assessment of crop production and biomass supplies depends on statistical data that is from county-level survey and census (USDA National Agricultural Statistics Service (NASS) (http://www.nass.usda.gov/Data_and_Statistics/Quick_Stats/index.asp). The success of the census of agriculture is directly dependent upon the participation of America's farmers, ranchers and per-county records. Taking advantage of remote sensing technologies, satellite imagery provides a more efficient and spatially explicit approach on how the biomass is estimated on the basis of extracting detained spatial information. With satellite imagery, spatially resolved crop land-use and production in the U.S. are well documented from various projects such as the USDA Large Area Crop Inventory (Boatwright and Whitehead 1986) and the Crop Explorer by the USDA Foreign Agricultural Service (FAS 2009). The spatial and temporal resolutions are becoming finer to provide more accurate resources for biomass assessment. Since the 1970s, the

NASS has developed annual products of the Cropland Data Layers (CDL) and acreage estimations using medium-resolution (30–56 m) satellite images (NASS 2010b). However, warm-season native prairie grasslands have not been mapped specifically. Due to spectral similarities among perennial grass species, it is difficult to delineate warm-season bioenergy crops from other grass types with typical satellite-based classifiers that are commonly used in the above-mentioned crop databases. More advanced remote sensing techniques are thus needed to assess biomass supplies of perennial warm-season grasses.

1.2.2 Phenology-based time series analysis

Perennial bioenergy crops, dominated by switchgrass and other native prairie warm-season grasses (WSG), are phenologically different from cool-season grasses (CSG) that are introduced into the vast area of Midwestern pasturelands. Their phenology features can be revealed from satellite time series along a growing season. More specifically, the Normalized Difference Vegetation Index (NDVI) extracted from satellite imagery holds valuable information of vegetation bio-properties. The NDVI is widely used and is a great indicator of growth status, spatial density distribution (Sun et al., 1998; Purevdorj et al., 1998) and phenology of plant (Defnies et al., 1994; Derrein et al., 1992). Different phenological features could delineate WSG from CSG and other land covers. CSG have peak NDVI in May, while WSG turn to delay its peak values in July, as demonstrated in the Osage Plain in southwest

Missouri (Wang et al., 2010). In addition, they found the NDVI of WSG in summer-fall gradually fell, while CSG had a second NDVI peak.

As an early example, Reed et al., (1994) extracted phenological metrics to monitor vegetation changes. They calculated NDVI from AVHRR imagery to extract the onset of greenness, time of peak NDVI, rate of green up/senescence, maximum NDVI and integral NDVI. They found that these phenology metrics identified inter-annual variability of spring wheat, grassland and some forests. With the availability of coarse-resolution daily observations (e.g. AVHRR and MODIS), phenological features from NDVI time-series are analyzed to monitor cropland at regional scales (Schwartz 1999). More recently, Zhang et al. (2003) developed an approach to fitting the NDVI time-series curves into piecewise logistic functions that are well suitable for vegetation index. Their methodology provides a flexible means to monitoring vegetation dynamics relying on MODIS data at global (Zhang et al., 2006) and regional scales (Wardlow et al., 2007; Wardlow et al., 2008).

1.2.3 WSG biomass proximity and environmental factors

<u>WSG biomass proximity assessment using NDVI</u>

NDVI is a good indicator of vegetation biophysical parameters including biomass, green leaf area index, percent green cover, and net primary production (Amri, et al., 2011; Weiss, et al., 2007). McNaughton et al. (1989) believes that above-ground net

primary production (ANPP) is an integrative estimate of ecosystem. In 1990s, remote sensing has proven to be a helpful and useful tool in the analysis of ANPP dynamics (Lloyd, 1990; Fischer, 1994a, b; Paruelo & Lauenroth, 1995). In particular, the integral NDVI, derived from satellite data, has been displayed to be strongly correlated to ANPP in grasslands (Tucker et al., 1985; Prince, 1991). Furthermore, Reed et al. (1994) analyzed the inter-annual variability of NDVI for different land-use categories in North America.

In addition, NDVI as an indicator of vegetation productivity is assessed using aboveground biomass measurements (Zhaoqin Li et al., 2012). Paruelo et al. (1997) found a significant positive relationship between the 4-year average integral of NDVI and the ANPP of nineteen grassland sites in central North America. In Olthof et al. (2007), vegetation productivity and biomass were monitored using long-term satellite earth observations and the extracted NDVI products. As there is no specific records of WSG yield in current crop databases, WSG biomass proximity is replaced by integral NDVI in this study.

NDVI and environmental factors

In recent years, many studies have been conducted to link vegetation dynamics to climate change using long-term NDVI products. Anyamba et al. (2001) reported that NDVI can be used to study vegetation response to climatic variation. They

demonstrate that NDVI had strong linear relationships with environmental variables such as precipitation and temperature. NDVI data have been widely used to study temporal (Lotsch, A. et al., 2003; Anyamba, A.et al., 2002) and spatial patterns (Nicholson, S.E. et al., 1994) of vegetation to climate fluctuations. For example, Gao, Dennis (2001) studied the temporal and spatial relationships between NDVI and climatological parameters in Colorado, U.S. Fang et al. (2006) reported NDVI increase as a representation of growth of temperate grasslands responding to climate changes in China. The relationship between NDVI and climatic variables has been widely validated across different regions of the world. At the regional scale, Nicholson et al. (1990) found that the spatial patterns of annually-integrated NDVI closely reflected mean annual precipitation in Sahel and East Africa from 1982 to 1985. Nicholson and Farrar (1994) demonstrate a linear relationship between precipitation and NDVI when precipitation was less than 50-100 mm/month in the semiarid Botswana. Additionally, Wang et al. (2003) researched temporal responses of NDVI to climate factors in the central Great Plains, Kansas and inferred that the relationship between precipitation and NDVI was strong and predictable.

At the global scale, Kawabata et al. (2001) analyzed inter-annual trends of vegetation affected by temperature and precipitation. Xiao and Moody (2005) mapped the geographical distribution of global greening trends and their climatic correlates. They found that temperature was the cardinal climatic factor associated with greening in the

northern high latitudes. However, in southern South America, southern Africa, and central Australia, both increase in temperature and decrease in precipitation were strongly correlated with greenness of vegetation.

Switchgrass yield varies with environmental conditions such as climate factors and soil type (Parrish DJ et al., 2005; Di Virgilio N et al., 2007). Dang et al. (2011) developed a statistical model to predict crop yield relied on a function of remote sensing-derived NDVI and found that soil constraint had an important effect on crop yield. Parrish and Fike (2005) illustrates that soil texture, with different amounts of sand, silt, and clay, affected soil water-holding capacity and thus had implications for seedling survival and yield. Furthermore, soil properties strongly affect the biomass of WSG, which grows best in deep, well-drained soil. In poorly drained sites switchgrass is more tolerant than other grasses. A pH of 6.0 or higher is better for WSG. This study conducts preliminary study to explore these environmental factors and their effects to WSG biomass in the study area.

1.3 Overall research objectives

This research aims to apply time-series satellite images to explore energy crop potential in the U.S. Midwest. To meet this goal, I will address the following objectives:

1) To map current distributions of primary crops (corn, soybean, winter wheat, spring

wheat, WSG, and CSG) owing to their different NDVI time-series of phenological features using MODIS data from 2000 to 2009 in the U.S. Midwest;

2) To extract biomass proximity and spatial distributions of WSG for assessment of its current bioenergy supplies in the Midwest;

3) To evaluate how WSG biomass responds to environmental factors such as climate and soil, and to identify the sensitive environmental factors that affect distributions of WSG.

In cropland mapping and biomass assessment, phenology-based time series analysis is performed to identify perennial energy crops and to assess their regional biomass. Then, a phenology-based decision tree is developed to map major crops, especially native prairie grasses in the U.S. Midwest. Finally, the integral NDVI in native prairie lands is extracted to represent the biomass of WSG. The accomplishment of this study objective will fill in the gap of perennial energy crops in current agricultural databases.

For environmental assessment, correlation analysis is performed the integral NDVI of WSG and a set of environmental factors. The outputs are used to identify the environmental variables that are sensitive to biomass of WSG. In this way the

environmentally sensitive lands can be outlined where annual crops could thus be effectively converted to WSG or bioenergy crops in the Midwest. Farmers may select where theses grasses could be substituted annual crops for WSG to gain higher profit. Establishment of perennial bioenergy crops also contributes to long-term carbon sequestration in soils, which has abundant environmental benefits (Marcelo Zeri et al., 2011). In this sense, my research will be helpful to decision making of advanced bioenergy policies.

Chapter 2 Study area and data collection

The twelve U.S. states in the Midwest (Ohio, Indiana, Illinois, Michigan, Minnesota, Wisconsin, Iowa, Missouri, Kansas, Nebraska, North Dakota, and South Dakota) compose the dominating biomass resource area in the United States. Known as the "breadbasket" of the United States, the Midwest is an important agricultural region for crop grains such as corn, soybean, and winter wheat. It also exports large amount of grains to the world. Specifically, corn export occupies around 40% of the world total (NCGA, www.ncga.com). As estimation by the Oak Ridge National Laboratory (ORNL) shows that the Midwest region covers more than 200 million acres of land that is suitable for energy crops production (Energy Information Administration, DOE, 2000). Among the national biomass feedstock, 74% of crop residues and 77% of switchgrass are currently in the Midwest region (Milbrandt 2005). In this research, the study area covers the whole Midwest region (Figure 2-1).

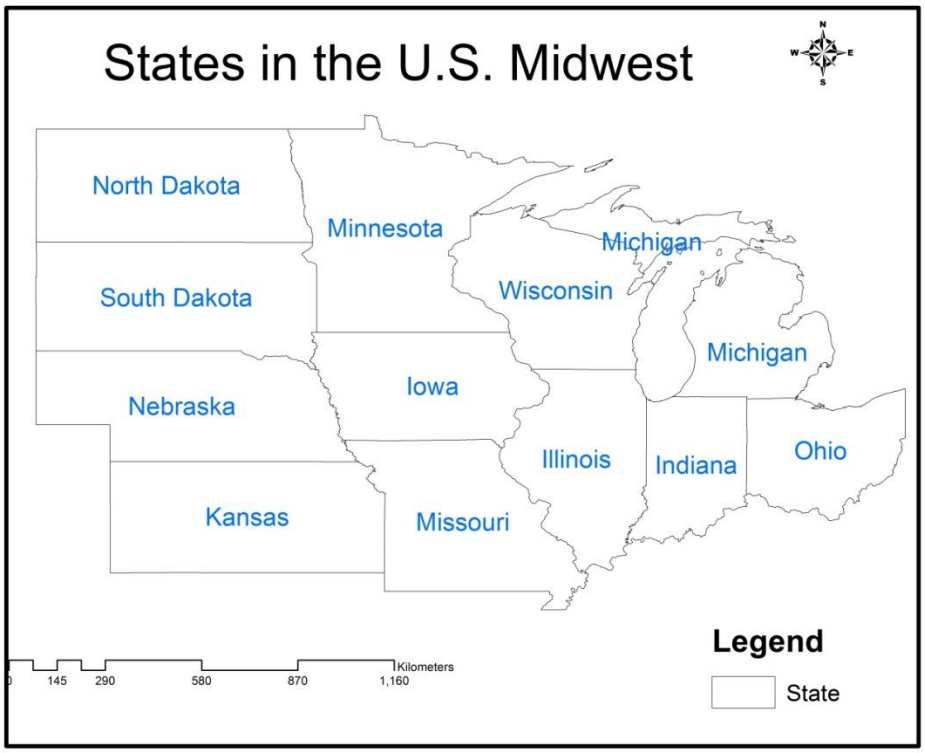


Figure 2-1: Study area of the U.S. Midwest

2.1 CDL Data

The Cropland Data Layer (CDL) products were initiated in 1971 when USDA National Agricultural Statistics Service (NASS) was involved in the LANDSAT 1 satellite program by the National Aeronautics and Space Administration (NASA) (Craig, 2010). During the late 1970s and the 1980s, NASS continued to utilize full LANDSAT scenes to assess major crops in important agricultural states. Full-state production began in 1991 and 1992 covering Arkansas, Mississippi, and Louisiana. By 2001, the CDL Partnership Program

had expanded to 15 to 20 agricultural states. In 2009, a partnership with the Environmental Protection Agency allowed NASS to extend the CDL program to forty-eight conterminous states.

In this study, CDL data in 2007 is used as the reference for classification of perennial energy crops. Climate in this year was relatively normal according to weather records. The CDL map of each Midwestern state is downloaded from the NASS website (http: www.nass.usda.gov/research/Cropland/SARS1a.htm). In this year, the CDL maps were classified from the Indian ResourceSAT images at a spatial resolution of 56m. The overall accuracy of these state-level maps ranges between 80% and 90% (http://www.nass.usda.gov/research/Cropland/metadata/metadata_wa07). The downloaded maps were converted the same projection of North America Datum 1983 (NAD 1983), and mosaicked to create a single CDL layer of the Midwest region. With a user-defined decision tree, main crops including corn, soybean, winter wheat, spring wheat, and grass were remained in the map while other crops and non-crop covers were grouped into “non-crop” class. Majority analysis was applied to the new class map, which was finally re-sized to match the resolution of MODIS satellite images.

Figure 2-2 displays the general distribution of corn, soybean, winter wheat, spring wheat and grasses. The corn-soybean cropping practices dominate the “Corn Belt” in northern and central states. Grasses in this map contain a group of perennial classes in

the original CDL products including grassland herbaceous, pasture/hay, pasture/grass, and fallow/idle cropland. Grasses are popular in western and southern states. There is a large amount of winter wheat in Kansas while spring wheat primarily is distributed in the northwest. In Table 2-1, the percentages of main crops are calculated. Because of the spectral similarity of warm-season native prairie grasses (WSG) and cool-season forage grasses (CSG), the CDL products do not delineate these two grass types. Warm-season grasses (WSG) and their biomass quantities in the Midwest are the primary concern of this study.

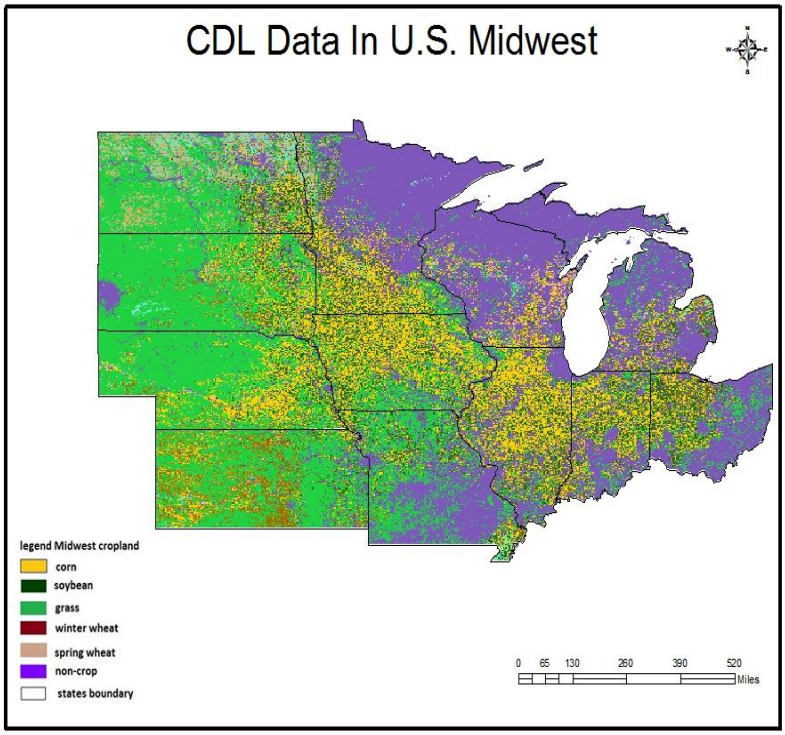


Figure 2-2: The 2007 CDL map. Only grasses and major annual crops are displayed in the map

Table 2-1: Areas of grasses and major annual crops according to the 2007 CDL product. Grasses include grassland herbaceous, pasturelands, hay fields, and other hays.

Type	Percentage
Corn & Soybean	24.59
Spring wheat	2.01
Winter wheat	2.80
Grass	31.98
Non-crop	33.10
Other crop	5.52

2.2 MODIS data

The MODIS acquires coarse-resolution, daily images all over the globe since satellite Terra was launched in 2000. The Midwest can be almost fully covered by four MODIS tiles: H10V04, H11V04, H10V05, and H11V05. In this study, the 500-meter, 8-day MODIS surface reflectance products (MOD09A1) from 2000 to 2009 are analyzed. MOD09A1 provides 13 bands at 500 meter resolution. For each MODIS tile, a total of forty-six MOD09A1 composites in each year were downloaded from the Land Processes Distributed Active Archive Center (http://lpdaac.usgs.gov). For each year, the downloaded images were re-projected to the North America Datum 1983 (NAD 1983).

NDVI, an index of the absorptive and reflective characteristics of vegetation, is a simple numerical indicator that has been widely used to analyze remote sensing

measurements. NDVI can be extracted from MODIS data to predict the growth situation of vegetation. It is calculated as:

$$NDVI = {(NIR - Red)}/{(NIR + Red)} \quad \text{(Eq. 2.1)}$$

Where NIR (846–885 nm) and Red (600–680 nm) denote surface reflectance in near infrared and red bands in the MODIS image.

For each year, the NDVI images are composed into time series, mosaicked and clipped Midwest region. A total of 46-scene NDVI time series in each year are developed, in which the NDVI time-series trajectory of each pixel has 46 points. Figure 2-3 is an example display of MODIS NDVI time series in the Midwest in 2007, in which red, green and blue are NDVI images on DOY 9, 113 and 281, respectively. As shown in this Figure, clusters with different colors reveal land covers that possess different growing trajectories along a growing season.

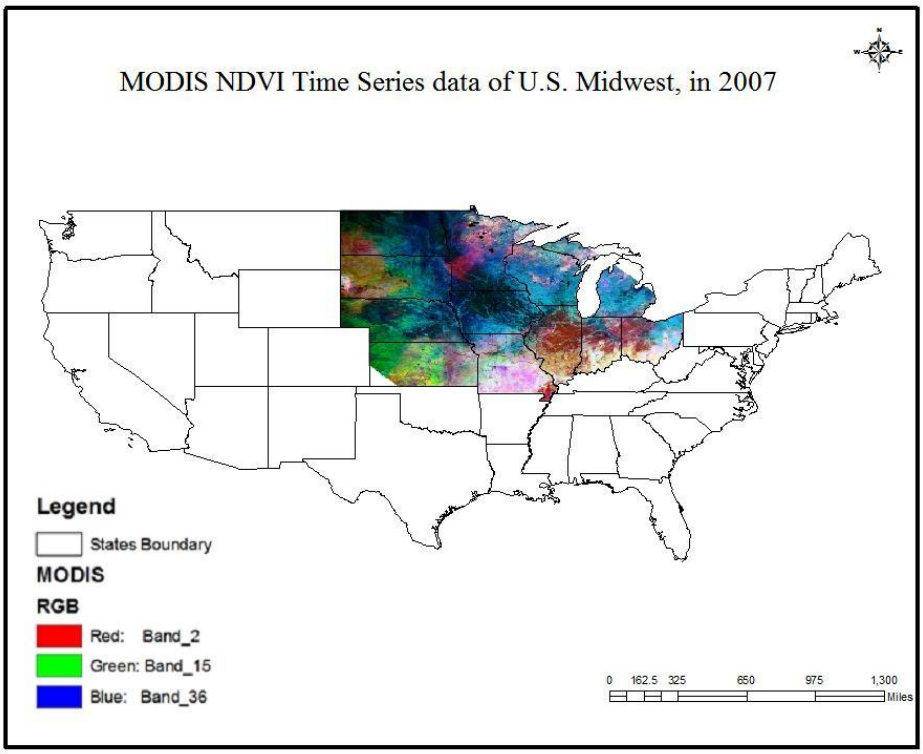


Figure 2-3: An example composition of MODIS NDVI series in the Midwest in 2007. Red: DOY 9; Green: DOY 113; Blue: DOY 281

2.3 Weather data

Climate factors can be leading determinants of crop yield. Weather data in this study was downloaded from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) website. PRISM is a unique knowledge-based system that uses point measurements of precipitation and temperature to produce continuous, digital grid estimates. The cell size of each grid is 4 by 4 kilometers. PRISM data is recognized as an optimal spatial weather data currently available in the U.S. territory. It also serves

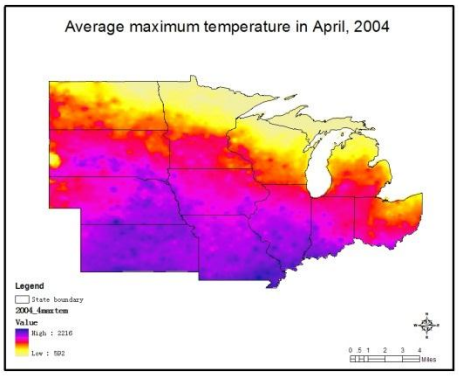
as the USDA's official climatological data (http://www.prism.oregonstate.edu).

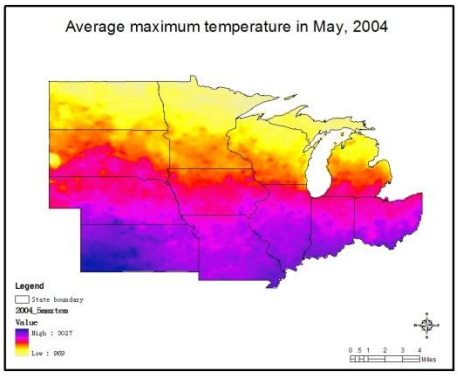
In this study, the PRISM data in 2004 were analyzed, because this is a relatively mild year in the Midwest. Based on NOAA information, no extreme weather records exist in the U.S. Midwest in 2004 (http://climvis.ncdc.noaa.gov/cgi-bin/cag3/state-map-dis

play.pl). Owing to time-consuming, weather data just were analyzed in 2004. After climate records are downloaded, the files are converted to raster and clipped to the Midwest in ArcGIS environment. The cell values in these raster data represent the corresponding climate factors. In this study, weather data that are used in environmental assessment include:

1) Monthly maximum temperature (from April to September):

Only records in growing (April-October) are downloaded. The temperature unit is centigrade degree with a scale factor of 100. Figure 2-4 displays the distribution of monthly maximum temperature in each month in 2004. Apparently, the northern areas are colder than southern areas in Midwest region.





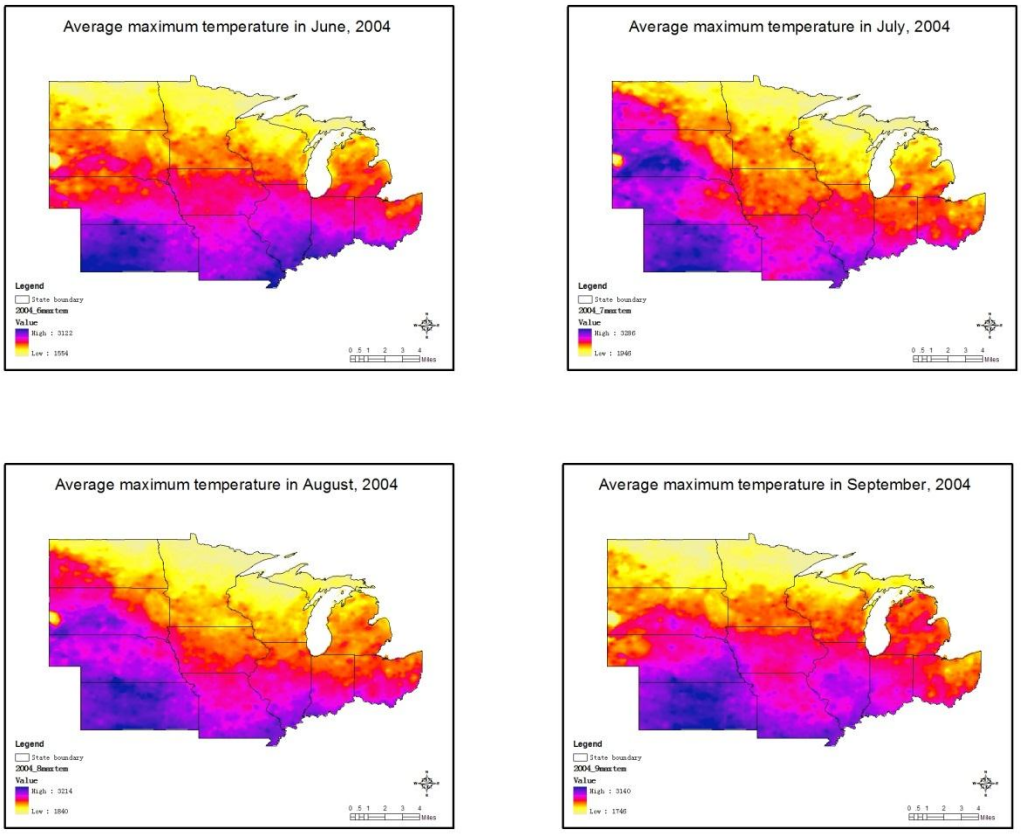


*Figure 2-4: Average maximum temperature of April- September in 2004 (The unit is centigrade*100)*

2) Monthly precipitation (from April to September):

The precipitation unit is millimeters with a scale factor of 100. Figure 2-5 displays the distribution of precipitation of growing-season months in 2004. There are no obvious 1st -order geographic trends about precipitation in the Midwest, although it varies dramatically in both spatial and temporal dimensions.

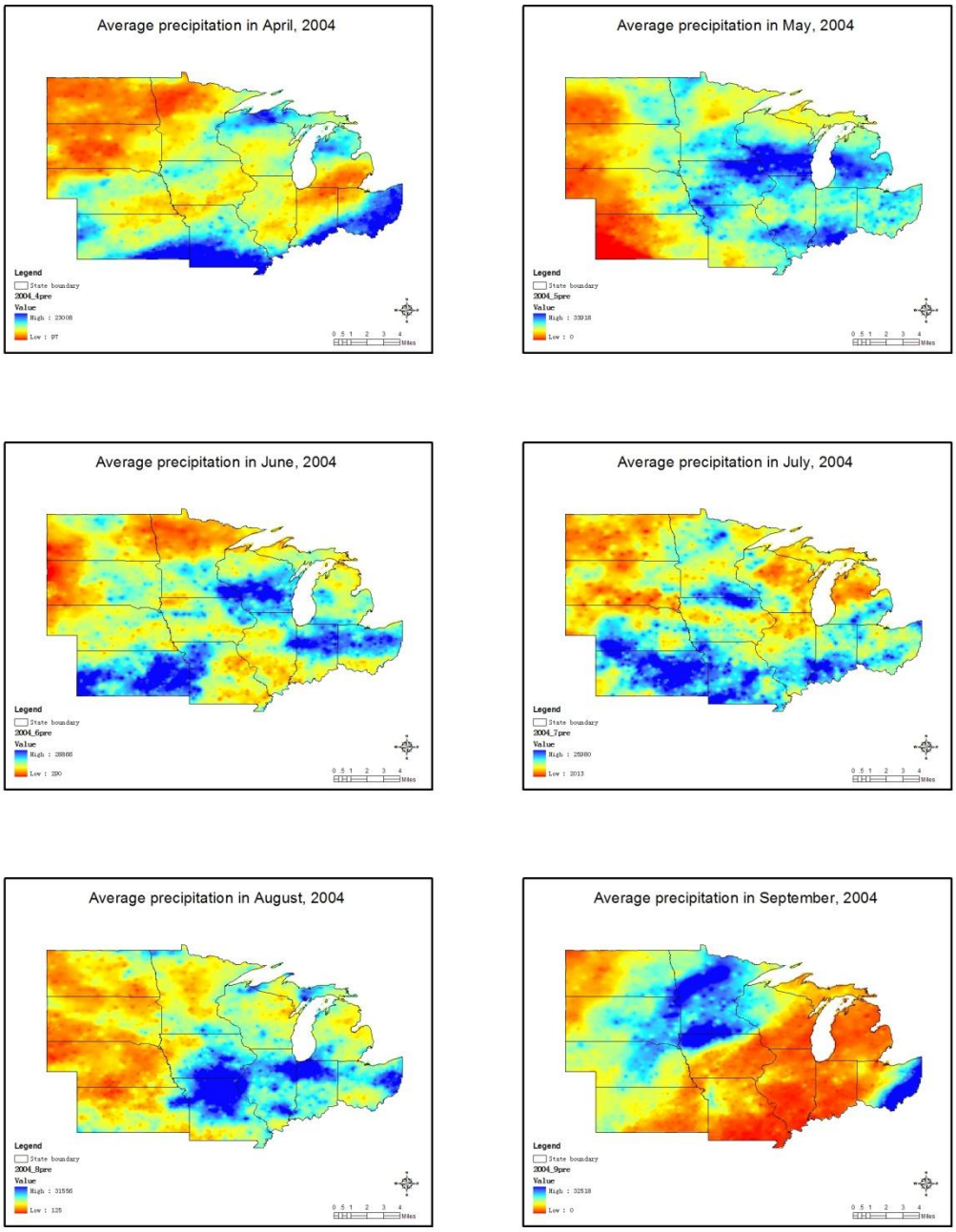


*Figure 2-5: Monthly precipitation of April- September in 2004 (The unit is millimeter*100)*

2.4 Soil data

Soil is an important controlling factor for crop growth and biomass production. This study applied the STATSGO soil data published by the National Cooperative Soil Survey program in 1978, as a joint effort of USDA and National Resource Conservation Service (NRCS). In the STATSGO database, soil type could be represented by 8 classes in the Land Capability Classification scheme, each class standing for a group of soil with similar capabilities for agricultural cultivation. Class 1 is most suitable for high-production annual crops, while class 8 represents soil with severe limits in crop production. The risk of soil damage or limitations in use becomes progressively greater from class 1 to class 8. Table 2-2 gives the list and detailed description of the 8 classes. In the USDA/NRCS National Soil Survey Handbook, part 622, it is reported that soils in the first four classes are capable of producing adapted plants, such as the commonly cultivated annual crops and pasture plants. Soils in classes 5, 6, and 7 are suited to growing native plants. Besides, some soils in classes 5 and 6 adapted to produce specialized crops such as distinct fruits. Soils in class 8 do not return benefits for inputs of management for crops, grasses or trees without major reclamation.

Table 2-2: Land Capability Classification (LCC) of soil and definition (referred USDA/NRCS National Soil Survey Handbook, part 622)

Classes	Definition	Land Suited to Cultivation and Limitation of Soil
Class 1	Slight imitations that restrict their use.	Suited to cultivated crops, pasture, range, woodland, and wildlife.
Class 2	Moderate limitations that reduce the choice of plants or require moderate conservation practices.	Suited to cultivated crops, pasture, range, woodland, or wildlife food and cover. Limitations maybe results from (1) gentle slopes, (2) moderate susceptibility to wind or water erosion or moderate adverse effects of past erosion, (3) less than ideal soil depth, (4) somewhat unfavorable soil structure and workability, (5) slight to moderate salinity or sodium easily corrected but likely to recur, (6) occasional damaging overflow, (7) wetness correctable by drainage but existing permanently as a moderate limitation, and (8) slight climatic limitations on soil use and management.
Class 3	Severe limitations that reduce the choice of plants or require special conservation practices, or both.	Suited to cultivated crops, pasture, woodland, range, or wildlife food and cover. Limitations maybe results from (1) moderately steep slopes, (2) high susceptibility to water or wind erosion or severe adverse effects of past erosion, (3) frequent overflow accompanied by some crop damage, (4) very slow permeability of the subsoil, (5) wetness or some continuing waterlogging after drainage, (6) shallow depths to bedrock, hardpan, clay pan that limit the rooting zone and the water storage, (7) low moisture-holding capacity, (8) low fertility not easily corrected, (9) moderate salinity or sodium, or (10) moderate climatic limitations.
Class 4	Very severe limitations that restrict the choice of plants or require very careful management, or both.	Suited to crops, pasture, woodland, range, or wildlife food and cover. Limitations maybe results from (1) steep slopes, (2) severe susceptibility to water or wind erosion, (3) severe effects of past erosion, (4) shallow soils, (5) low moisture-holding capacity, (6) frequent overflows accompanied by severe crop damage, (7) excessive wetness with continuing hazard of waterlogging after drainage, (8) severe salinity or sodium, or (9) moderately adverse climate.

Class 5	Little or no hazard of erosion but has other limitations.	Limit their use mainly to pasture, range, forestland, or wildlife food and cover. Limitations maybe results from (1) soils of the bottom lands subject to frequent overflow that prevents the normal production of cultivated crops, (2) nearly level soils with a growing season that prevents the normal production of cultivated crops, (3) level or nearly level stony or rocky soils, and (4) ponded areas where drainage for cultivated crops is not feasible but where soils are suitable for grasses or trees. Because of these limitations, cultivation of the common crops is not feasible but pastures can be improved and benefits from proper management can be expected.
Class 6	Severe limitations.	Unsuited to cultivation and that limit their use mainly to pasture, range, forestland, or wildlife food and cover. Limitations maybe results from (1) steep slope, (2) severe erosion hazard, (3) effects of past erosion, (4) stoniness, (5) shallow rooting zone, (6) excessive wetness or overflow, (7) low moisture capacity, (8) salinity or sodium, or (9) severe climate. Because of one or more of these limitations, these soils are not generally suited to cultivated crops. They may be used for pasture, range, woodland, or wildlife cover or for some combination of these.
Class 7	Very severe limitations.	Unsuited to cultivation and that restrict their use mainly to grazing, forestland, or wildlife. Limitations maybe results from (1) very steep slopes, (2) erosion, (3) shallow soil, (4) stones, (5) wet soil, (6) salts or sodium, (7) unfavorable climate, or (8) other limitations that make them unsuited to common cultivated crops. They can be used safely for grazing or woodland or wildlife food and cover or for some combination of these under proper management.
Class 8	Limitations that preclude their use for commercial plant production and limit their use to recreation, wildlife, or water supply or for esthetic purposes.	Cannot be expected to return significant on-site benefits from management for crops, grasses, or trees, although benefits from wildlife use, watershed protection, or recreation may be possible. Limitations maybe results from (1) erosion or erosion hazard, (2) severe climate, (3) wet soil, (4) stones, (5) low moisture capacity, and (6) salinity or sodium.

In short, the CDL can serve as reference of classification while MODIS data provides phenological features of annual and perennial crops. To evaluate the dependency of WSG production in different environments, it is necessary to examine the WSG biomass and various environmental factors such as growing-season temperature, precipitation and LCC of soil properties.

Chapter 3 Approaches

In this study, major annual (corn & soybean, winter wheat, spring wheat) and perennial (WSG, CSG) crops are first classified based on MODIS and CDL data. WSG areas were calculated from 2000 to 2009. A multivariate regression analysis is then performed to examine the relationship between WSG biomass proximity and a set of environmental factors. Factors that significantly influence WSG production are finally identified that may be used to assess biomass proximity potentials in the U.S. Midwest. Figure 3-1 is overview of the methodological steps in this study.

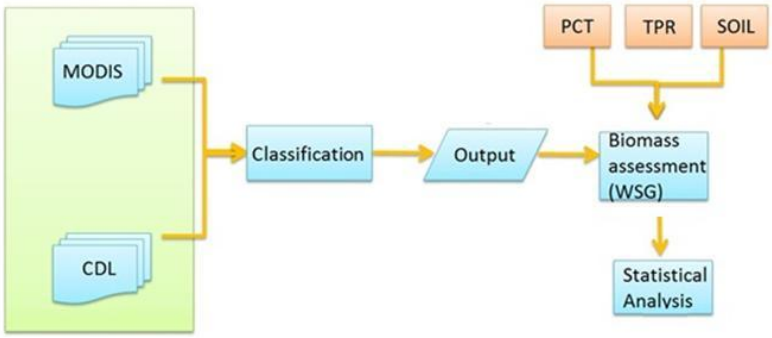


Figure 3-1: The workflow of this study. (PCT-Precipitation, TPR-Temperature, SOIL-LCC)

3.1 Time-series analysis and phenological metrics

The flowchart of MODIS classification is shown in Figure 3-2. After extracting NDVI time-series and smoothing the data, phenological metrics are extracted using the TIMESAT program. The training data of each crop are selected from CDL maps and

published literatures. Finally, a phenology-assisted decision tree is developed to classify major annual and perennial crops.

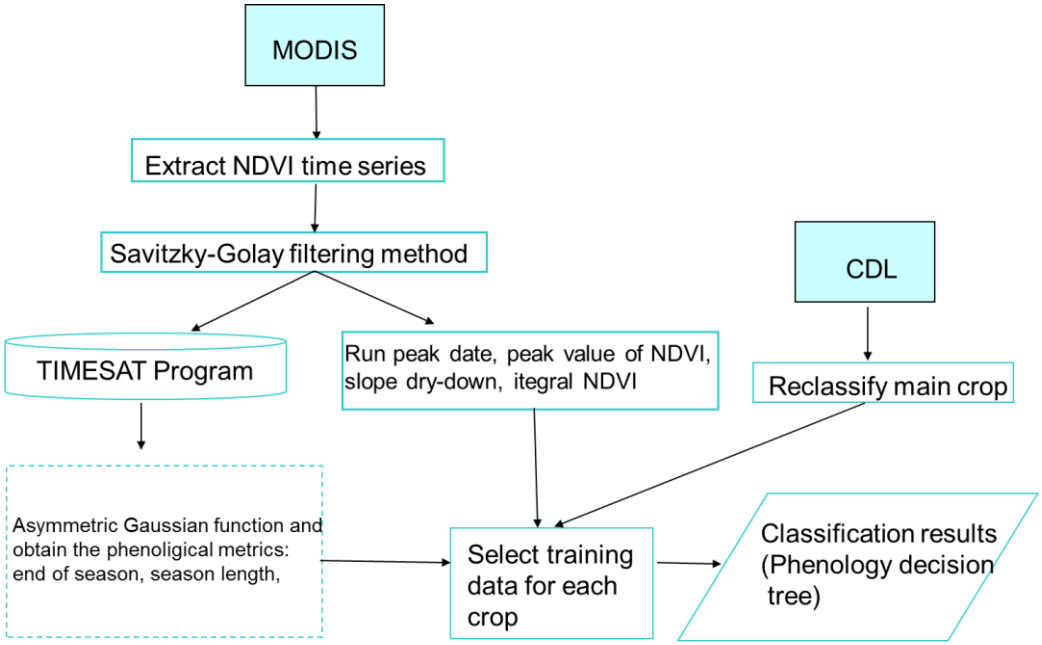


Figure 3-2: Flowchart for classification of annual and perennial crops with MODIS and CDL data

3.1.1 Phenological differences of crops

There are distinct trajectories of annual and perennial crops. Figure 3-3 displays the crops trajectories after Smooth procedure, which is based on NDVI variation of crops in the tall-grass prairie (Wang et al., 2011). The example of trajectory is extracted MODIS data in 2005. Vertical axis is NDVI value*100; Horizontal axis is 46 points at 8-day interval. They are the fundamental references of phenological features.

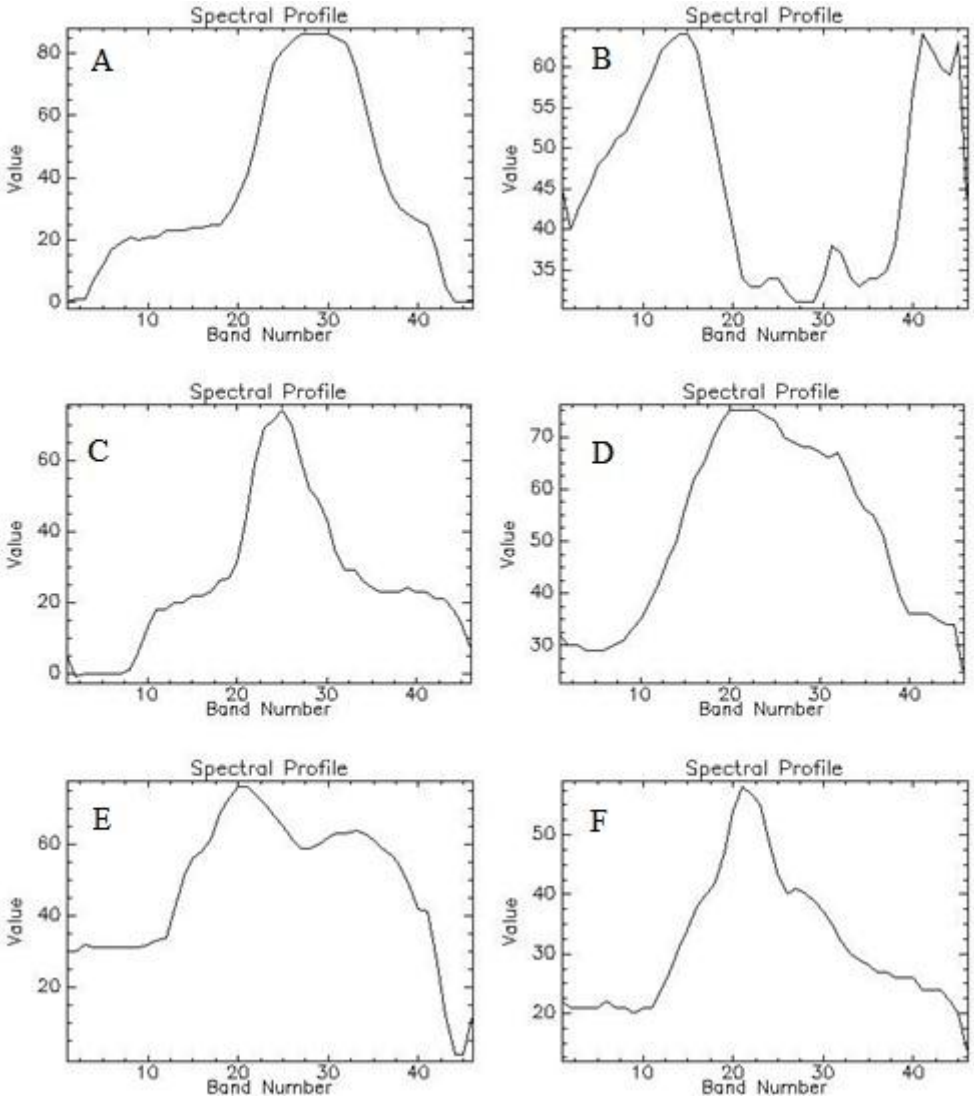


*Figure 3-3: Crops trajectories after smoothing. The trajectory is extracted MODIS data in 2005. Vertical axis is NDVI value*100; Horizontal axis is 46 points at 8-day interval. A-Corn; B-Winter wheat; C-Spring wheat; D-WSG, E-CSG; F-Short-grass*

Figure 3-4 illustrates the phenology differences between WSG and CSG. Wang et al. (2010) report that CSG have peak NDVI in spring (May), while WSG turn to delay its peak values in early summer (July) in the Osage Plain, southwest Missouri. The

NDVI of WSG in summer-fall gradually falls, while a 2nd NDVI peak could be observed for CSG. These differences provided prominent information to delineate WSG from CSG and annual crops.

Figure 3-4: Crop calendar-the growth changes for WSG and CSG (Source: Wang et al., 2010)

3.1.2 Smoothing NDVI time series

In growing season, NDVI from MODIS surface reflectance can be heavily impacted by cloud residuals, atmospheric and sun-sensor illumination conditions, and viewing geometry. A myriad of smoothing algorithms have been developed to reduce noise from atmospheric effects and to reconstruct high-quality NDVI time series (Chen et al., 2004). For instance, Reed et al. (1994) used a nonlinear median smoother to remove cloud contaminated NDVI values. Savitzky and Golay (1964) proposed a least-square-fit convolution for smoothing and processing a set of consecutive values.

In this study, the Savitzky-Golay filtering method was applied to smooth the NDVI time-series curves for further analysis. Firstly, a five-point median filter was applied to remove spikes of NDVI values. Secondly, a polynomial fit of the Savitzky–Golay filtering method was used to smooth the time-series curves. Figure 3-5 displays an example NDVI trajectory before and after smoothing procedure in 2004.

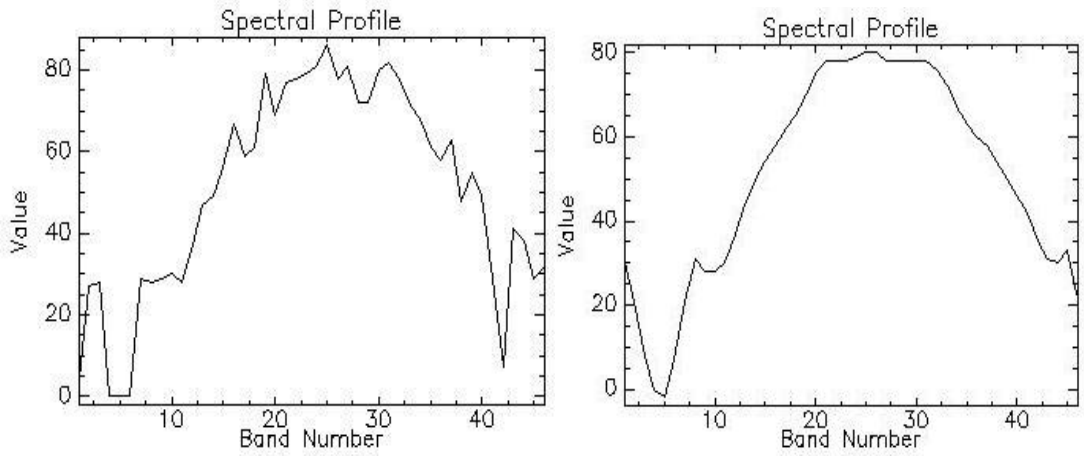


Figure 3-5: Comparison of an example NDVI time-series curve before and after Smooth procedure. The trajectory is extracted from a pasture field in 2004 (with 46 points at 8-day interval)

3.1.3 TIMESAT Program

Phenology of vegetation with temporal development reveals its dynamic growth properties. Among various phenology extraction algorithms, the approach is threshold-based and Best Index Slope Extraction (BISE) algorithm (Viovy et al., 1992). It has been used to extract seasonal metrics of vegetation phenology (e.g. Reed et al., 1994) and to classify vegetation or land cover types (Lovell & Graetz, 2001;

Xiao et al., 2002). Another approach is the Fourier-based fitting method (Cihlar, 1996; Roerink et al., 2000; Sellers et al., 1994), which has been applied to derive terrestrial biophysical parameters (e.g. Sellers et al., 1994). Each approach possesses its own merits and has been successfully implemented to NDVI time-series preprocessing for specific applications. More recently, an asymmetric function fitting method was developed to fit original NDVI time series into theoretical simulation to extract seasonality information for phenological researches (Jonsson & Eklundh 2002). In a comparative analysis of the abovementioned methods, Chen et al. (2004) found that the Asymmetric Gaussian function-fitting approach was more flexible and effective in obtaining a high-quality NDVI time series.

The TIMESAT program (Jonsson and Eklundh, 2004) fits the smoothed NDVI time-series curves in an Asymmetric Gaussian function. TIMESAT is a software package for analyzing time series of satellite data and extracting seasonality information. The processes follow these steps: In the first place, the number of seasons and their approximate timing are defined. Then, by least-squares fitted Asymmetric Gaussian simulation, the time-series data is filtered. Finally, phenological seasonality metrics are extracted from the filtered time series. Common outputs of phenology metrics include start of season, end of season, length of season, base value, position of middle of season, maximum value of fitted data, amplitude, left derivative, large integral, and small integral. Figure 3-6 shows these outputs that TIMESAT

extracts from an example time-series satellite trajectory. Table 3-1 illustrates the definitions of phenological metrics of TIMESAT.

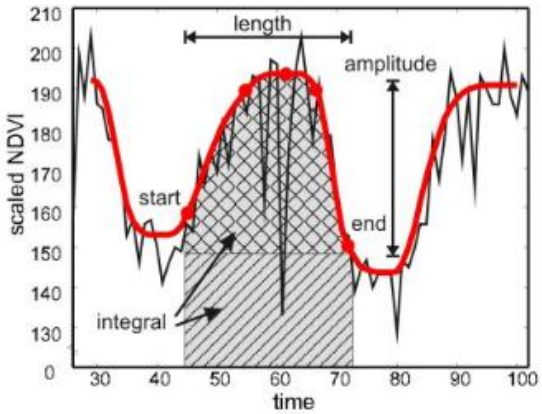


Figure 3-6: The TIMESAT extracted phenology metrics based on time-series satellite data.

(Source: http://www.nateko.lu.se/TIMESAT/timesat.asp)

Table 3-1: Phenological metrics of TIMESAT (Source: Jonsson & Eklundh, 2004)

Phenological metrics	Definition	Used phenological metrics of this study
Time for the start of the season	Time for which the left edge has increased to a user defined level (often 20% of the seasonal amplitude) measured from the left minimum level	
Time for the end of the season	Time for which the right edge has decreased to a user defined level measured from the right minimum level	Time for the end of the season
Length of the season	Time from the start to the end of the season	Length of the season
Base level	Given as the average of the left and right minimum values	
Time for the mid of the season	Computed as the mean value of the times for which, respectively, the left edge has increased to the 80 % level and the right	

	edge has decreased to the 80 % level	
Largest data value for the fitted function during the season		
Seasonal amplitude	Difference between the maximal value and the base level	
Rate of increase at the beginning of the season	Calculated as the ratio between the values evaluated at the season start and at the left 80 % level divided by the corresponding time difference	
Rate of decrease at the end of the season	Calculated as the ratio between the values evaluated at the season end and at the right 80 % level divided by the corresponding time difference	
Large seasonal integral	Integral of the function describing the season from the season start to the season end	
Small seasonal integral	Integral of the difference between the function describing the season and the base level from season start to season end	

3.2 Training data and crop mapping

3.2.1 Collecting training data

Training points of perennial crops (WSG and CSG) were collected from various published research results.

Wang et al. (2010) found that native prairie grasses dominated large prairie remnants such as Prairie State Park and Osage Prairie in southwestern Missouri. Furthermore, in Kansas, there are 80% WSG in the Flint Hills grassland and 90.05% WSG in the Tall-grass Prairie National Preserve (TPNP). Based on the previous studies in the

Midwest, there are additional proofs to support WSG/CSG classification in the study region. Peterson et al. (2002) discriminated cool season and warm season grassland cover types in northeastern Kansas. Their results show that tall-grass prairies are heavily dominated by WSG species such as big bluestern (*Andropogon gerardii Vitman*) and switchgrass (*Panicum virgatum L.*). In their research results, WSG also dominate Douglas County in Kansas. In addition, there are dominant WSG in the semiarid grasslands of the Sandhills grassland, Nebraska (Eggemeyer et al., 2006).

In this study, training data of WSG and CSG are extracted from these published resources (Table 3-2). It should be noted, however, these data points hold high uncertainty due to the lack of spatial details in publications. Based on the phenological features of WSG and CSG, twenty points of WSG and twenty points of CSG in the U.S. Midwest were randomly selected in the previously studies area in the U.S. Midwest.

Table 3-2: WSG and CSG data sources in previous studies

Type	**Location**
Warm-season Grasses	Douglas County, in northeastern Kansas (D. L. Peterson et al., 2002)
Warm-season Grasses	Montgomery County, in West-central Indiana (Rex A Omonode et al., 2006)

Warm-season Grasses	Nebraska National Forest (NNF), Halsey, Nebraska (Kathleen D. Eggemeyer et al., 2006)
Switchgrass (Warm-season Grasses)	Southern Iowa (R. Lemus et al., 2002)
Cool-season grasses	Naturalized grassland in southern Iowa (Sara E. Florine et al., 2005.)
Warm-season grassland, Cool-season grasses	Missouri prairie, (Wang et al., 2010)
Warm-season grass, Cool-season grasses	Southwestern Wisconsin (Julie E. Doll et al., 2011)

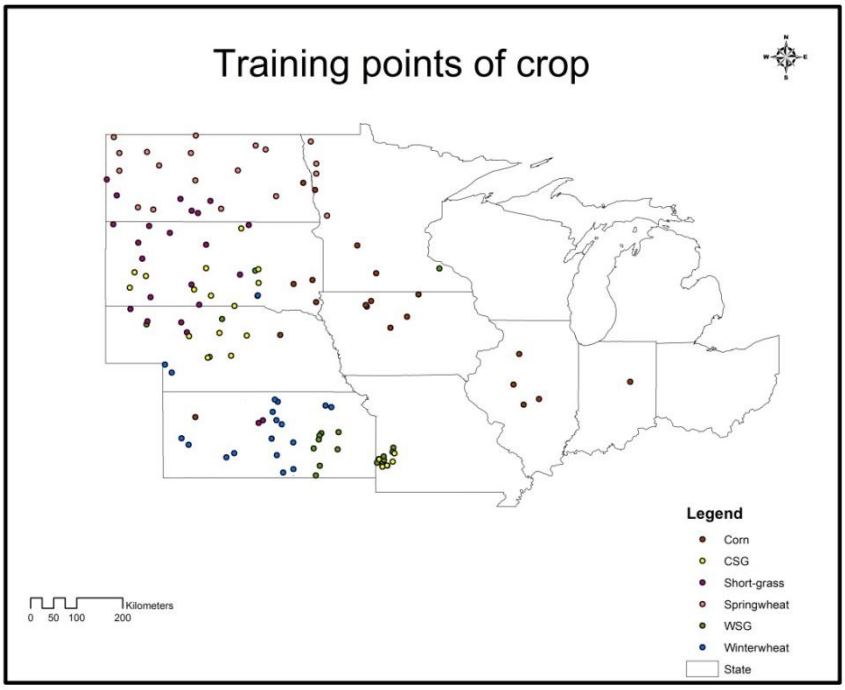


Figure3-7: Training data points of annual and perennial crops

Training data of major annual crops (corn, soybean, winter wheat and spring wheat) are selected based on CDL data in 2007 and supplementary evidence from the general crop calendars such as planting, silk and harvest accessed at the USDA website (http://www.usda.gov/nass/). To reduce uncertainties from shift planting of annual crops, in each year, these points were double checked depending on their specific phenological features in accordance with crop calendars (Wang et al., 2011). As shown in Figure 3-7, approximately 20 points for each annual crop are randomly collected as training data in each year. In addition, to acquire relatively accurate classification, Short-grass WSG and Short-grass CSG, that mostly grow in Shortgrass prairies in western states, were also classified in this study. Past research (Risser et al., 1981) outlined the boundaries of tall grass prairie, the mixed and short-grass prairie regions in the High Plains. Upon historical records, short-grass species can be observed in western Kansasand southwestern Nebraska. Training data of short-grass is primarily collected according to Risser et al. (1981).

3.2.2 Phenology-assisted decision tree approach

3.2.2.1 Analysis of phenology metrics

Based on phenological metrics of training data of WSG, CSG and annual crops, statistical properties illustrated that two metrics had significant differences for the main crops including corn, soybean, winter wheat, spring wheat, CSG, WSG, Shortgrass WSG, and Shortgrass CSG:

(1) End of season, which represents the date when NDVI has decreased to 20 percent of the amplitude after peak NDVI.

(2) Season length, which represents the dates from the start of season (when NDVI has increased to 20 percent of the amplitude) to the end of season.

Other metrics, such as start of season, tend to be overlaid among different crops and therefore, are not useful in crop classification in this study.

Annual crops display apparent temporal differences in peak NDVI over the course of a growing season, reflecting their variation in growth development. Wang et al. (2011) defined three growing stages in order to quantify these differences: Early (Day of Year [DOY] 1–161); Middle (DOY145–193); and Late (DOY 161–313). To improve the accuracy of classification an additional set of phenology metrics that are not explored in TIMESAT are extracted in ENVI software. These metrics include the integral NDVI, peak value, peak date and summer dry-down:

(1) Peak date, which indicates the date when peak NDVI falls.

(2) Summer dry-down, which represents the decrease of NDVI in the early-middle stages if the peak NDVI falls in the early stage (Wang et al. 2011). It is especially useful for winter wheat identification.

(3) Integral of NDVI, or cumulative growth, which is calculated as the integral of NDVI from April to October.

3.2.2.2 Decision tree approach

The phenology metrics above are put in a decision tree to identify annual and perennial crops in the U.S. Midwest. Winter wheat is first identified because of its early peak season (early spring) and dramatic summer dry-down (dramatic decrease of NDVI) after harvest in early summer. Spring wheat is more commonly grown in northern states. Figure 3-8 demonstrates the decision tree in 2009. In general, corn and soybean in the prairie often have an early end of season (before DOY 305), shorter season length (<180 days) and less cumulative NDVI (< 9.0). Corn and soybean have similar phenology features. They are not further separated because the primary concern was native perennial grasses in this study. After annual crops are extracted, WSG are delineated with a shorter growing length (< 223 days) than CSG.

These thresholds in the decision tree are selected based on statistical analysis of collected training data. Due to inter-annual variations, different thresholds of decision rules are developed for each year. Table 3-3 lists the thresholds in 10 years. Finally, if peak NDVI of a pixel is less than peak value of Short Grass and its peak date is greater than peak date of Short-grass, it is classified as Short-WSG. Otherwise it is classified as Short-CSG. If a pixel's length of season is longer than length of tall grass, the result would be WSG. Conversely, it should be CSG. Pixels with Peak NDVI less than 0.2 are categorized as barren and shrub lands.

Zhang et al. (2003) demonstrated that temporal shifts of onset of greenness for both natural vegetation and agricultural lands are around two days per latitude degree along the 40°–45°N latitude transect. In Wang et al. (2011), an approximate shift of two days of peak date was observed in annual crops and 3 days of peak date in grasslands. In this study, a lag factor of peak date is added to annual crops and grasses, respectively. The lag factors are calculated as:

$$Lag_{annual\ crop} = 2.0 * (Latitude_{[i,j]} - 38.0) \quad \text{(Eq. 3.1)}$$

$$Lag_{grass} = 3.0 * (Latitude_{[i,j]} - 38.0) \quad \text{(Eq. 3.2)}$$

Non-crop land covers (e.g., forest, wetland, water, urban) and other crops (e.g., durum wheat, sorghum, and pasture/hay) are extracted from the CDL product and are masked out of the process. The outputs of the decision tree include classes of WSG, CSG, corn/soybean, spring wheat and winter wheat. In post classification process, the classes are smoothed with as majority filter analysis (3*3 cells) to remove isolated classes in the study region.

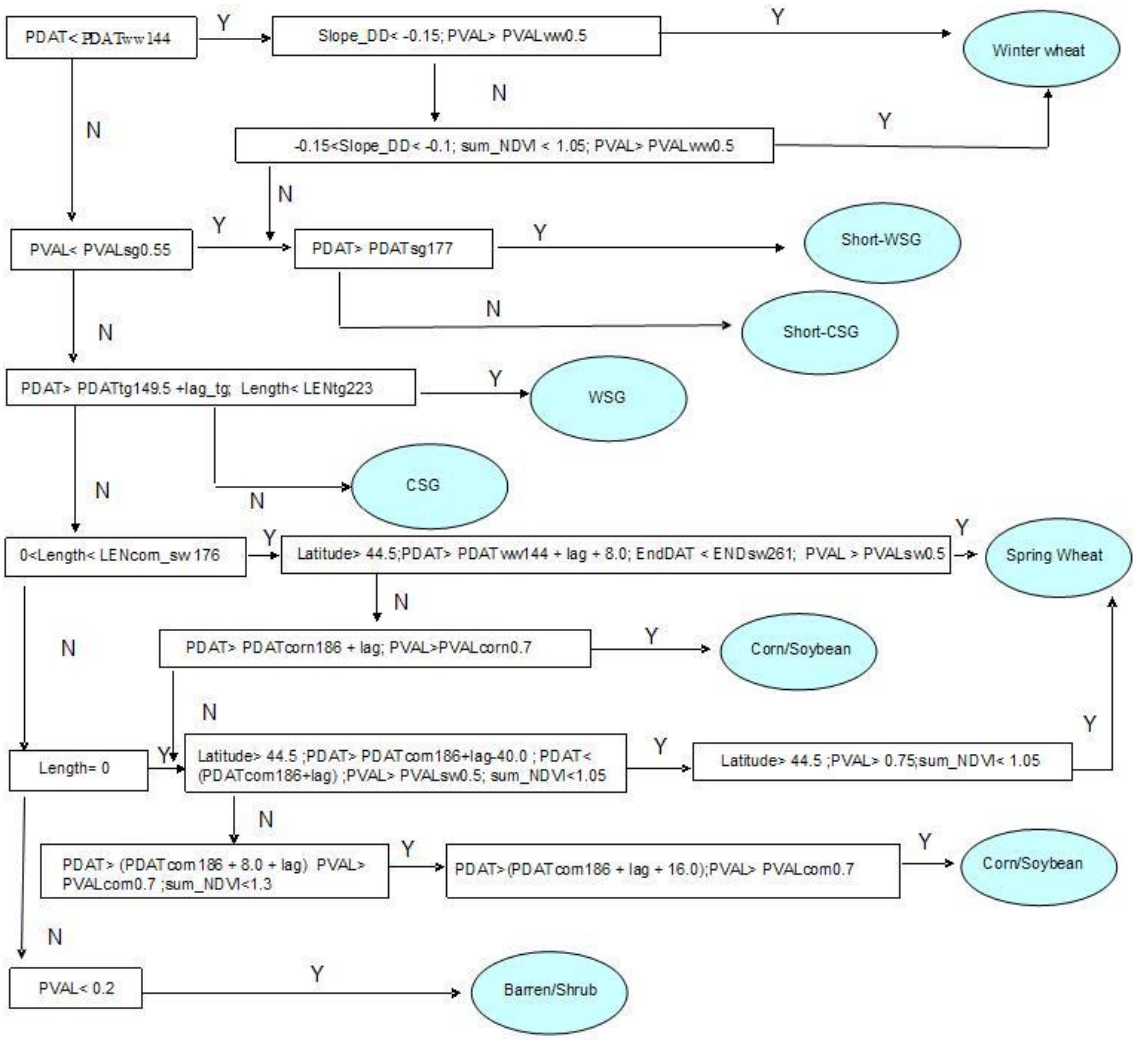


Figure 3-8: Flowchart of phenology-assisted decision tree in 2009. (PDAT = peak date; PDATww=peak date winter wheat; Slope_DD=Slope_dry down; PVAL=peak value; PVALww=peak value winter wheat; PVALsg= peak value of short-grass; PDATsg= peak date short-grass; PDATtg= peak date of tall grass; LENtg=season length of tall grass; ENDsw= End day of spring wheat)

Table 3-3: Phenological thresholds of decision rules in the decision tree in 2000-2009

Input thresholds	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009

PDATww	144	136	144	136	144	144	144	144	144	144
PVALww	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5
LENsw	192	176	192	184	184	184	184	184	176	176
ENDsw	261	261	261	261	261	261	261	261	261	261
PVALsw	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5
PDATcorn	186	178	178	178	186	186	186	186	186	186
PVALcorn	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
PVALsg	0.5	0.55	0.42	0.55	0.48	0.52	0.45	0.55	0.47	0.55
PDATsg	161	177	201	153	177	169	169	153	225	177
LENtg	218	243	224	241	235	238	222	248	224	223
PDATtg	149.5	149.5	149.5	149.5	149.5	149.5	149.5	149.5	149.5	149.5
PVALtg	0.6	0.6	0.6	0.6	0.6	0.6	0.5	0.6	0.6	0.6

3.3 Statistical analysis of environmental influences on WSG

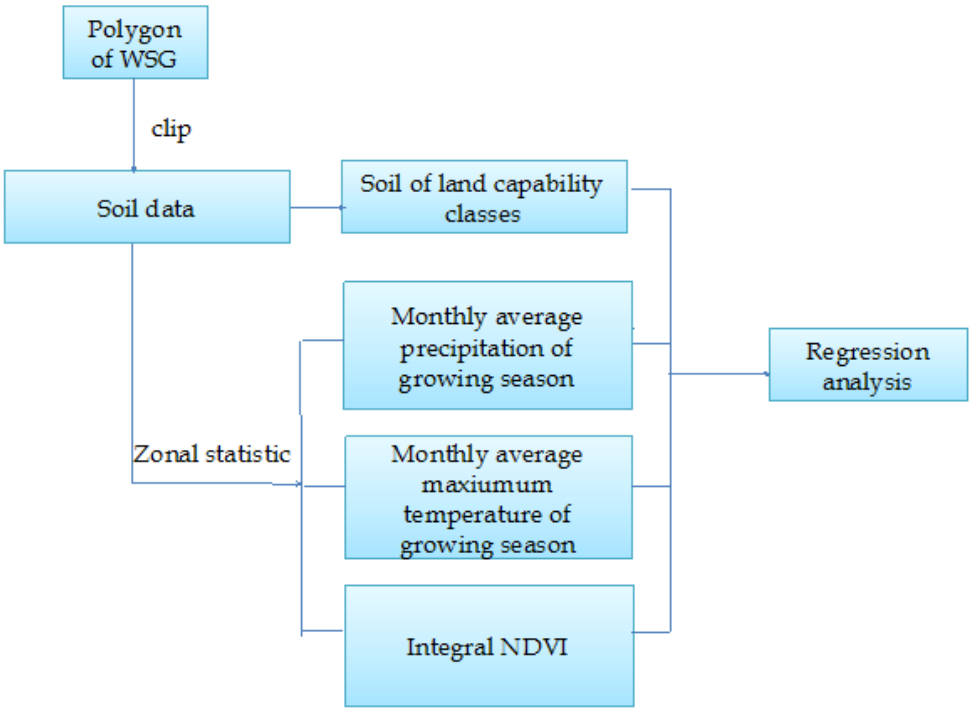


Figure 3-9: Flowchart for environmental assessment of WSG in the study region

The flowchart in Figure 3-9 demonstrates the steps of processing data of environmental parameters (climate, soil) and their relationships with WSG biomass. In the class maps, WSG fields are identified by overlaying with STATSGO soil polygons. In ArcGIS, zonal statistic is performed for WSG polygons to summarize environmental factors of monthly precipitation and monthly average maximum temperature in a growing season (April to September). Finally, multivariate regression analysis is implemented among WSG biomass, monthly precipitation and temperature, and land capability classes of soil, to identify the environmental factors that WSG

production is most sensitive with.

3.3.1 WSG polygons and biomass approximation

Pure WSG fields are rare and often fragmented except in reserved grasslands such as Flint Hills in Kansas and Sand Hills in Nebraska. Due to intensive grazing managements, WSG and CSG often grow in mixed conditions. In certain years CSG species may grow better while in other years WSG favors. Therefore, it is reasonable that WSG and CSG are misclassified to each other in the period of 2000-2009. In this case, we define a pixel as WSG when it is classified as WSG in 6 of the 10 years. This important step is strong support for WSG classification of perennial crops, since it reduces commission errors (classifying a pixel as WSG while there is more CSG species in field) in environmental assessment. The refined WSG areas are overlaid with the STATSGO soil polygon data and split a set polygons, in which each polygon possess the same soil properties. Polygons with areas higher than 1500m*1500m (3 by 3 pixels) are finally selected. As Figure 3-10 shown, these are the WSG polygons that are used in next process.

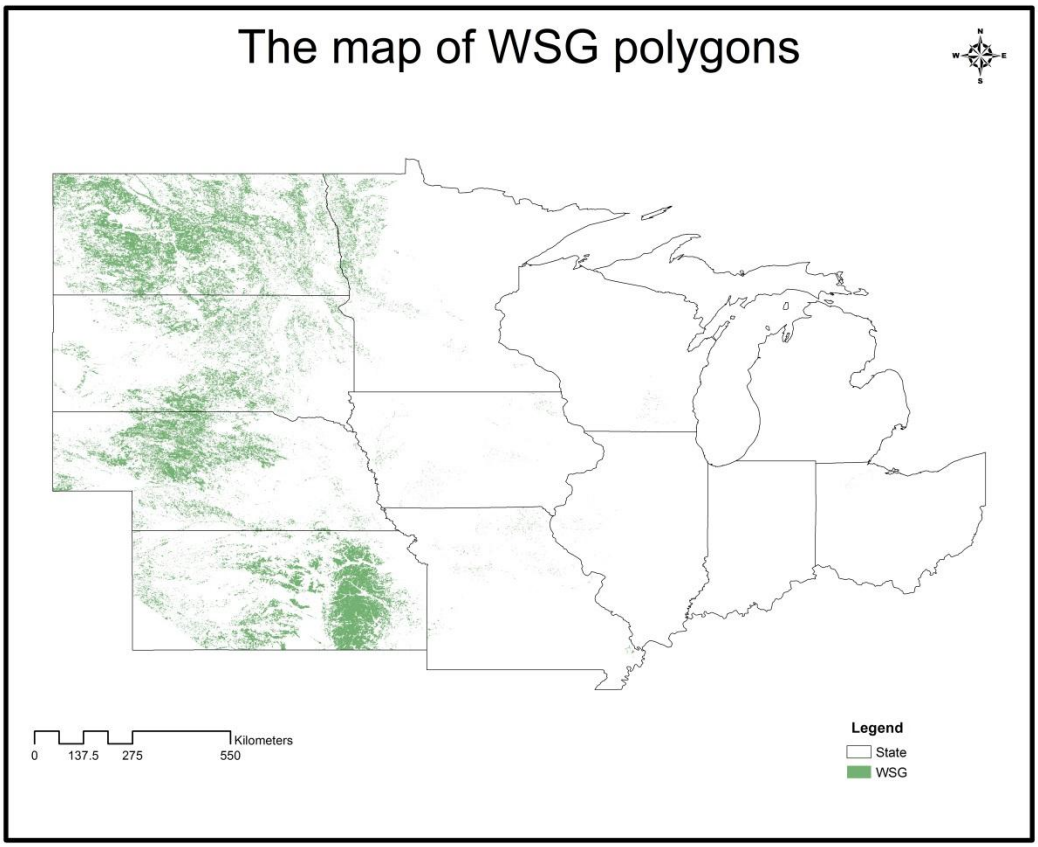


Figure 3-10: The map of WSG polygons

Ground records of WSG production are limited in the Midwest. Moreover, although WSG biomass is recorded in various programs in different states, the measurements are often based on small fields. These records may not be properly applied in this study with a unit size of 500x500m (a MODIS pixel). Here the concept of integral NDVI was regarded as an approximation of vegetation biomass. NDVI is a good measure of green biomass (Rosental et al, 1985), primary productivity and crop yields (Gausman 1974, Sellers 1985, Tucker and Sellers 1986, Goward and Dye 1987,

Sellers et al., 1992). Rojas et al. (2007) studied the relationship between crop yield and cumulative NDVI from onset to end of season. It is found that the integral NDVI reflects biomass accumulation during the growing season. In this study, the integral NDVI of WSG polygons are averaged to represent WSG biomass proximity.

3.3.2 Climate and soil variables

The essential purpose is to evaluate how WSG biomass responds to climate factors including precipitation and temperature and LCC of soil, and to identify the sensitive environmental factors for WSG biomass. Thomson et al. (2009) demonstrated that low precipitation and low pH (soil acidity) may limit the potential production of switchgrass. Tulbure et al. (2012) found that climate variables, such as April-May precipitation, June–September precipitation, and average growing season temperature, can affect switchgrass yields in terms of spatial and temporal variability. Besides, over a four-year period in South Dakota, biomass production was best explained by a linear relationship with April-May precipitation (Lee & Boe, 2005). The relationship of yield with growing season temperature is expected to be “bell shaped”, with higher temperature increasing yield up to a physiological optimum. There was a temperature threshold beyond which grass production could be limited due to increased evapotranspiration and decreased soil moisture (Parrish and Fike, 2005).

With zonal analysis in ArcGIS, the PRISM weather data is averaged in each WSG

polygon (Figure 3-11). The following steps are processed to obtain statistical weather data. The output attributes include monthly maximum temperature and monthly average precipitation for each month in April-October, 2004. These data sets are exported to EXCEL software for statistical analysis.

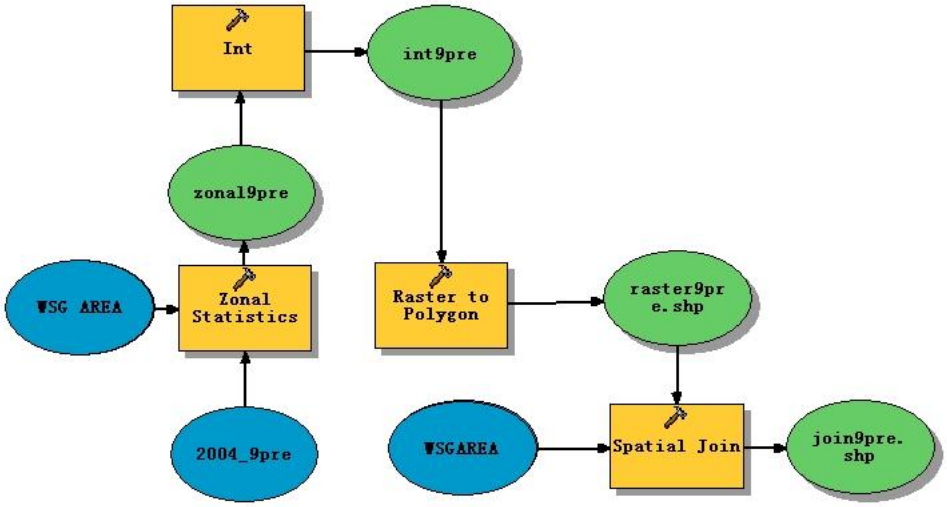


Figure 3-11: Procedures of weather data and soil variable in 2004 (Example of average monthly precipitation of September in 2004)

3.3.3 Statistical analysis

3.3.3.1 Data normalization

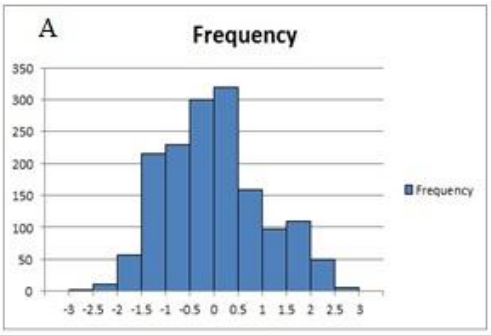
In this study, there are 1555 samples (WSG polygons) that are used to build the Multiple Linear Regression (MLR). Before processing the MLR, WSG biomass, average monthly precipitation from April to September, average monthly maximum temperature from April to September, and the LCC from soil data were normalized in advance.

These data need to be prepared before statistical models can be built (QSARWorld--A Strand Life Sciences Web Resource, http://www.qsarworld.com/qsar-statistics-normalization.php). One of the most commonly applied transformations is normalization, or standardization, to center all variables so they have a zero mean and spread in numbers of standard deviations:

$$z = \frac{x - x_{mean}}{s} \qquad \text{(Eq. 3.3)}$$

Where z is standardizing value; x is value of sample; x_{mean} is average value of samples; s is standard deviation.

Standardization of a variable involves two steps. First, the mean is subtracted from every value, which shifts the central location of the distribution to 0. Then the mean-shifted values are divided by the standard deviation (Frank and Althoen, 1995). A standardized value indicates how many standard deviations an observation is above or below the mean. Figure 3-12 shows the histograms of the standardized values of WSG biomass, LCC, and monthly average maximum temperature and monthly average precipitation in 2004.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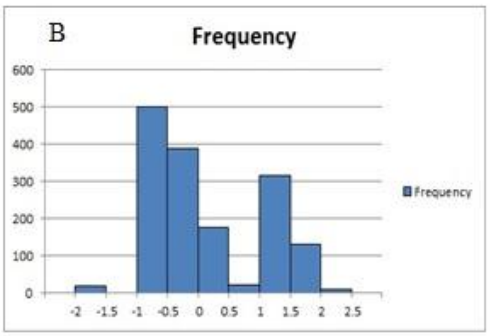
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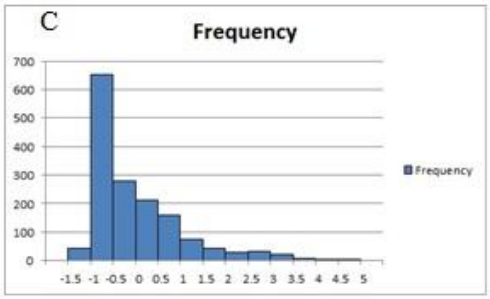
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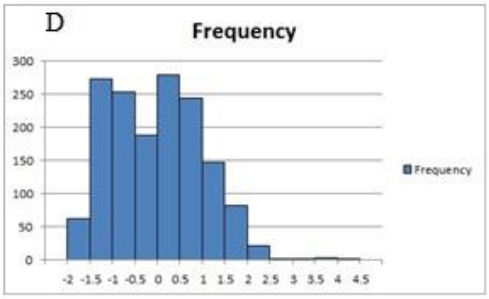
Frequency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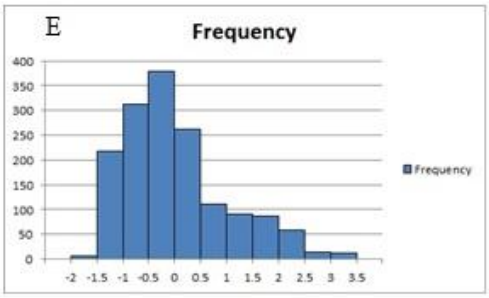
-2 -1.5 -1 -0.5 0 0.5 1 1.5 2 2.5 3 3.5 4 4.5
Frequency


E
Frequency
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250
200
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50
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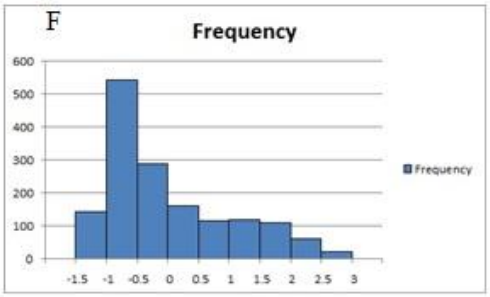
Frequency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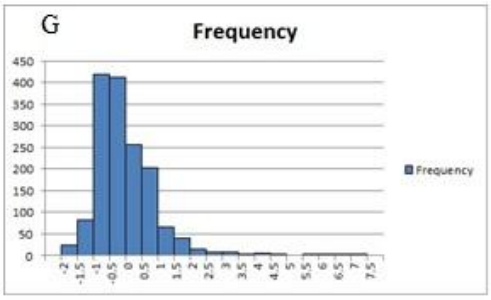
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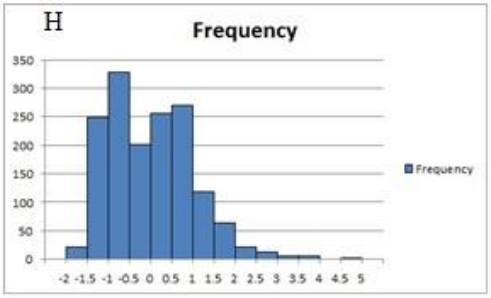
Frequency


H
Frequency
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150
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Frequency

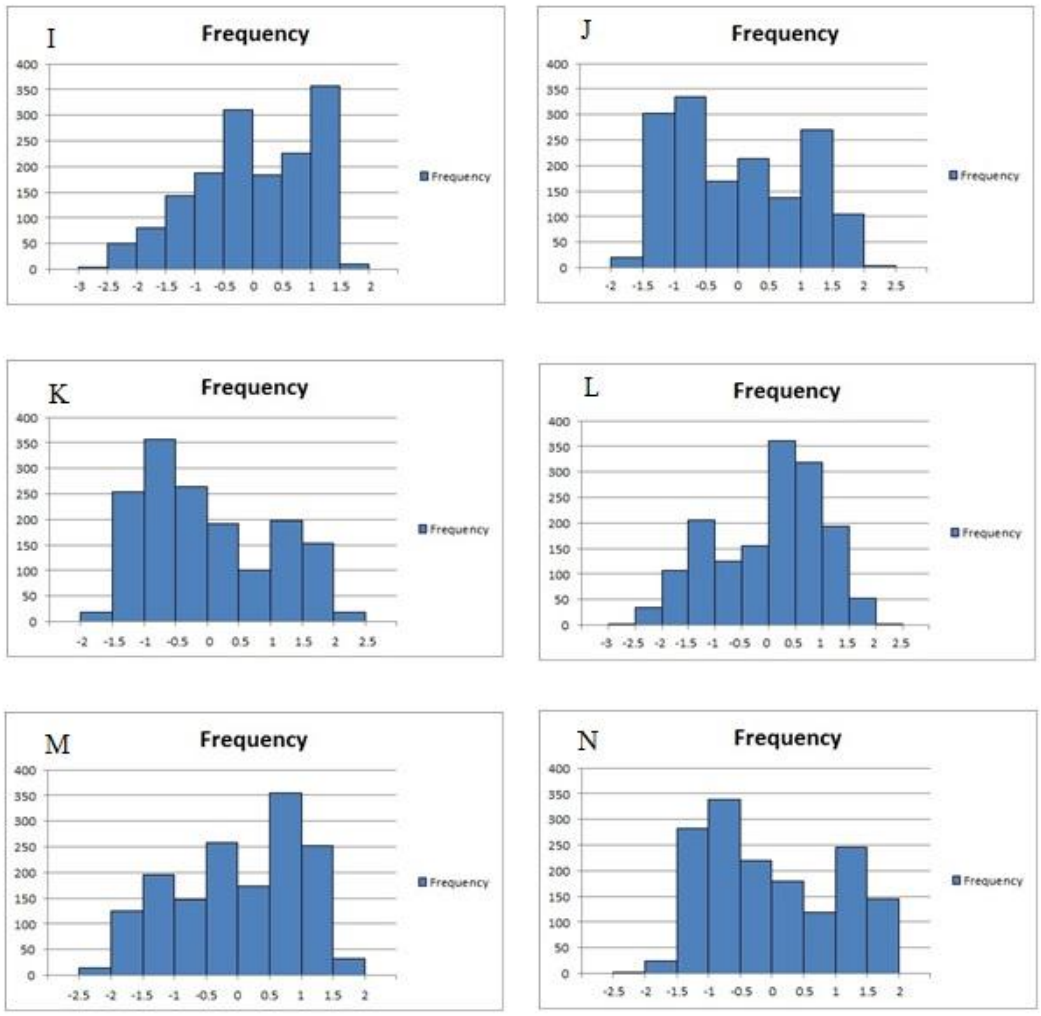

Figure 3-12: After standardizing: A-WSG biomass; B-LCC; C-*The normalized average precipitation in April; D-Average precipitation in May; E-Average precipitation in June; F-Average precipitation in July ; G-Average precipitation in August; H-Average precipitation in September; I-Average maximum temperature in April; J-Average maximum temperature in May; K-Average maximum temperature in June; L-Average maximum temperature in July;* M-*Average maximum temperature in August; N-Average maximum temperature in September*

These histograms display distribution frequency of standardizing of integral NDVI,

LCC of soil, average monthly precipitation from April to September, and average monthly maximum temperature from April to September. Before standardization, the precipitation, temperature and LCC of soil are not normally distributed. Moreover, theses data are sharply changed from minimum value to maximum value. After standardization, they are almost normally distributed, which reduce the impact of statistical analysis. It is significant to decrease impacts for next statistical step of Multiple Linear Regression.

3.3.3.2 Multiple linear regression analysis

This study aims to examine the dependency of WSG biomass to climate and soil factors. MLR is a method to model the linear relationship between a dependent variable and multiple independent variables. The model was built in STATA software (StataCorp., 1985):

$$Biomass_{wsg} = f(Precipitation, temperature, LCC) \quad \text{(Eq. 3.4)}$$

Where WSG biomass is the Integral NDVI, a representation of biomass production of each WSG polygon; Climate parameters are April-September average monthly precipitation and monthly maximum temperature of growing season in 2004, and soil is the STATGO-defined Land Capability classes.

In Eq.3.4, coefficients of independent variables show how the environmental

variables affect WSG biomass. A higher coefficient indicates that this variable is more significant for biomass variation in WSG of the Midwest.

In summary, in this study, major annual (corn & soybean, winter wheat, spring wheat) and perennial (WSG, CSG) crops are first classified based on Phenology-assisted Decision Tree Approach. After extracting NDVI time-series from MODIS data and smoothing the data by Savitzky-Golay method, phenological metrics are extracted by the TIMESAT program. The training data of each crop are selected from CDL maps and published literature. Moreover, a MLR is then implemented to examine the relationship between WSG biomass and environmental factors including monthly average precipitation and monthly average maximum temperature in 2004. By analyzing the relationship and environmental factors, it may be used to evaluate potential biomass in the U.S. Midwest.

Chapter 4 Results

4.1 Crops classification and accuracy assessment

4.1.1 Crops classification

Bioenergy is of increasing interest to agriculture as biomass becomes the largest source of renewable energy in the United States. The Figures 4-1 to 4-10 demonstrate the distributions of WSG, CSG and annual crops in the Midwest and land cover changes from 2001 to 2009.

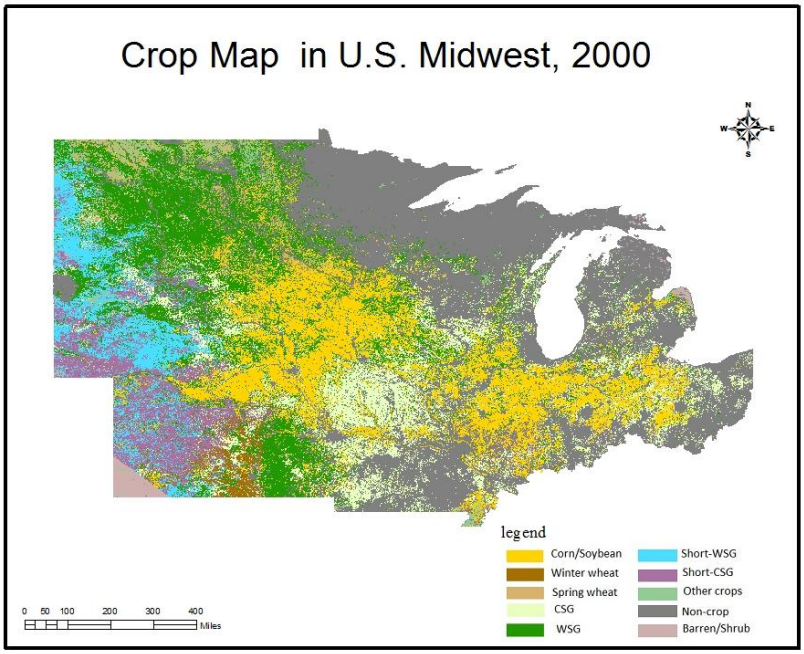

Figure 4-1: The crop map in 2000

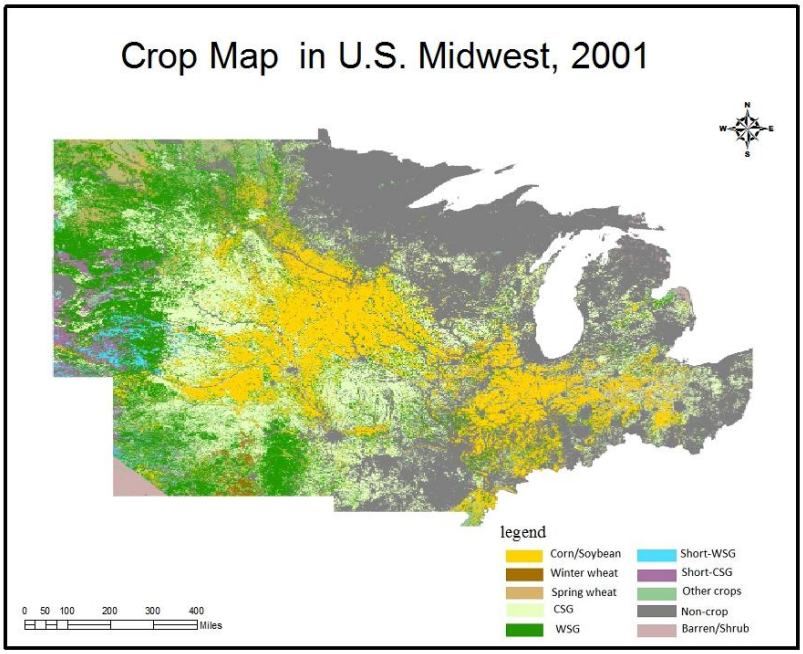

Figure 4-2: The crop map in 2001

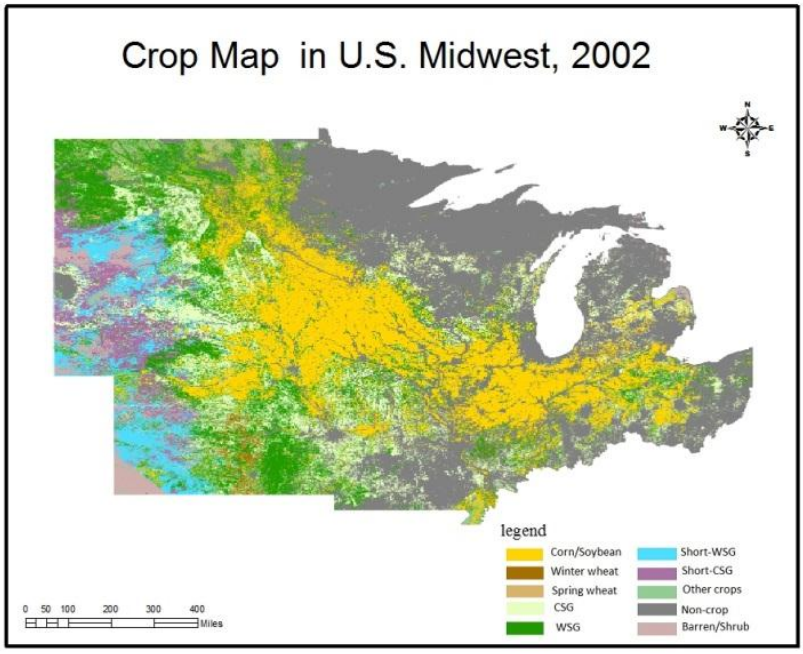

Figure 4-3: The crop map in 2002

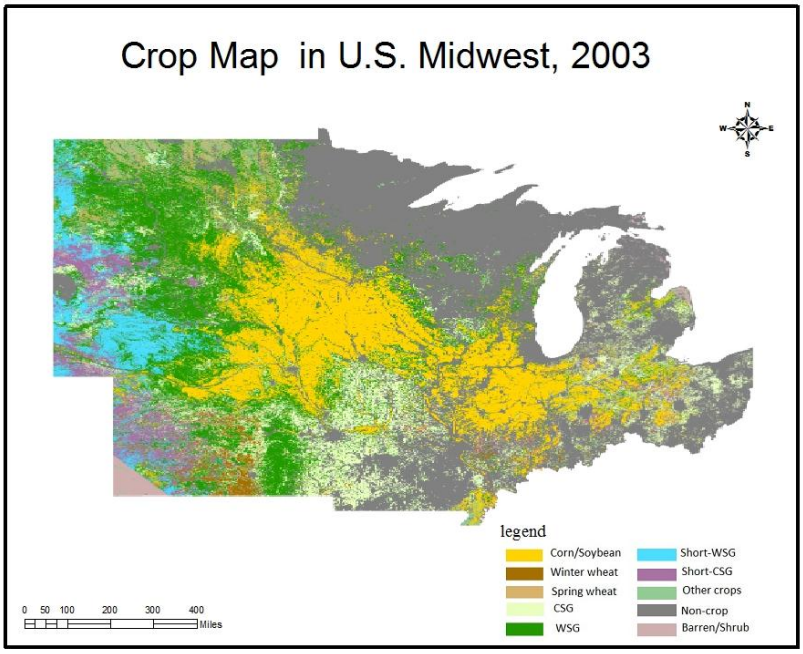

Figure 4-4: The crop map in 2003

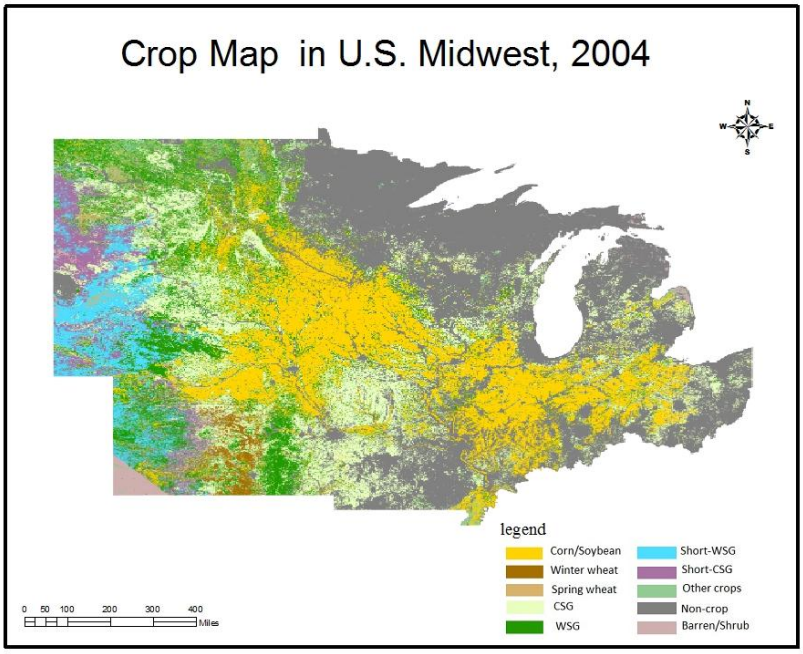

Figure 4-5: The crop map in 2004

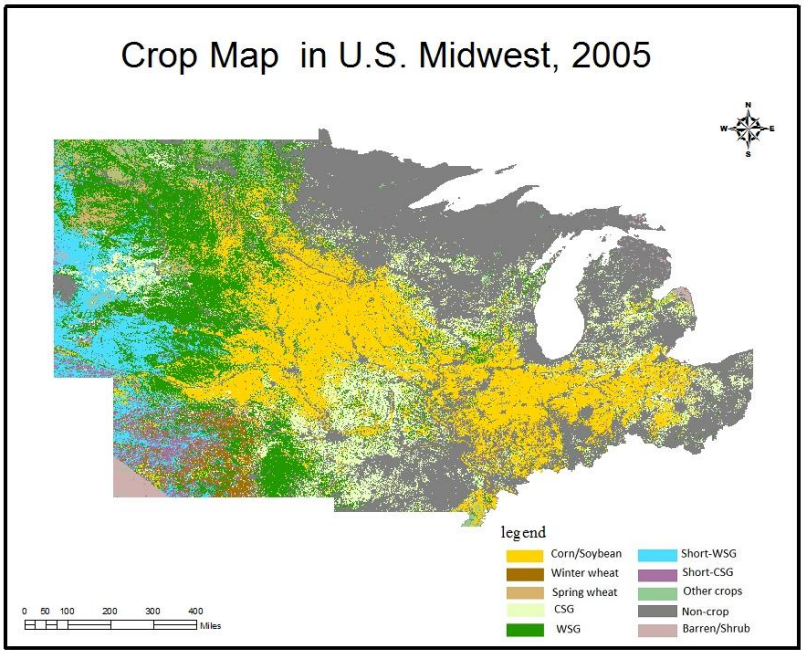

Figure 4-6: The crop map in 2005

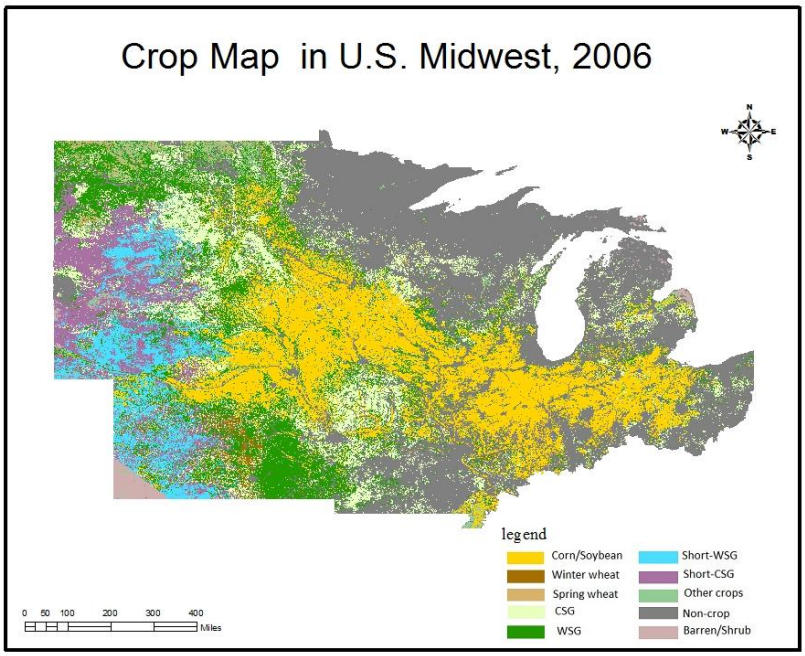

Figure 4-7: The crop map in 2006

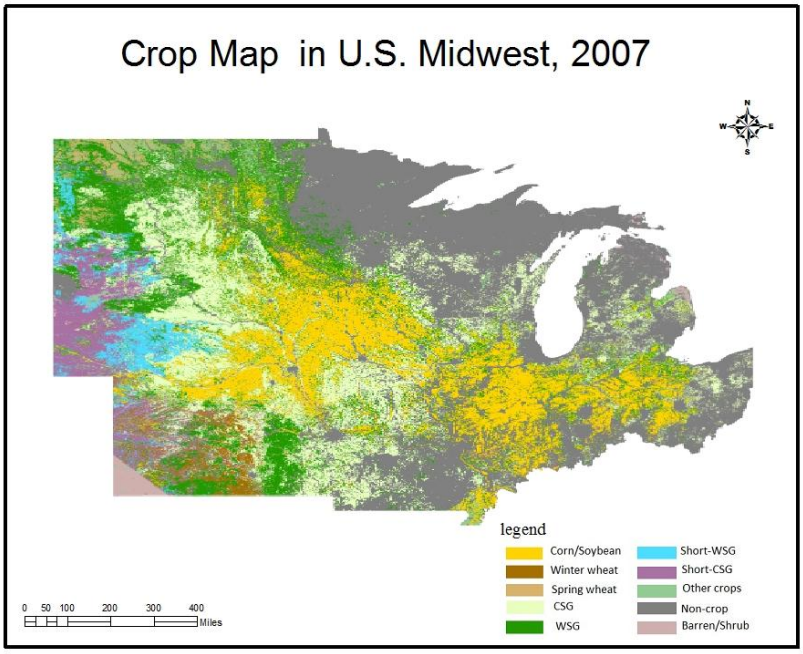

Figure 4-8: The crop map in 2007

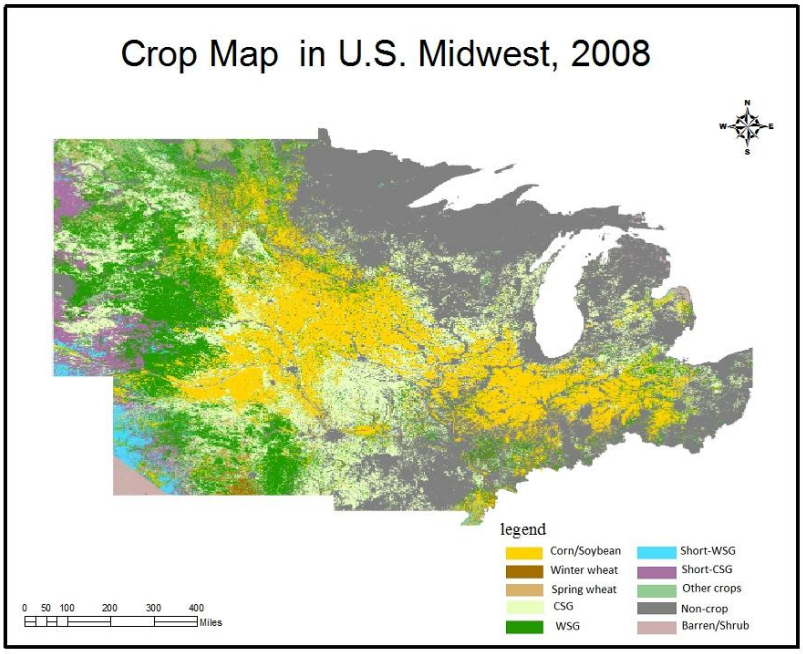

Figure 4-9: The crop map in 2008

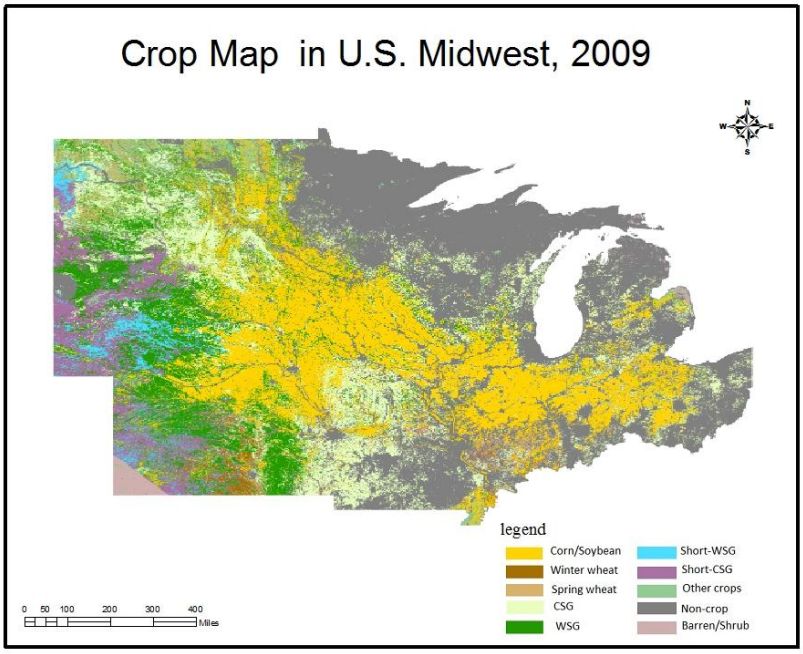

Figure 4-10: The crop map in 2009

4.1.1 Land-use patterns of annual and perennial crops

As shown in Figure 4-1 to 4-10, winter wheat dominates in Kansas and does not change dramatically in different years. Spring wheat is mostly produced in the northern areas such as North Dakota and South Dakota. The Figures also reveal the famous "Corn Belt" in the Midwest. Since the 1850s corn has been the predominant crops in this area. Approximate 40 percent of corn is exported to the world, which has an essential effect on fluctuating of crops prices in the market (NCGA, www.ncga.com). In recent decades corn has grown in higher importance of bioenergy. In the bioenergy report of USDA, by 2022 15 billion gallon of corn ethanol will be produced and serve as domestic biofuel. The classification results in these Figures

illustrate the importance of corn production in the U.S. Midwest.

WSG are mostly distributed in western states such as Missouri, Kansas, Nebraska, North Dakota, and South Dakota. CSG grow all over the agricultural regions in the Midwest. Short-CSG are dominated in the southwestern areas of Midwest such as western region of South Dakota, Nebraska, and Kansas. In addition, there are big areas of growing Short-WSG in Nebraska.

4.1.2 Accuracy assessment

Accuracy assessment is an important part of classification. The accuracy of a class is usually assessed by comparing the classification with reference data that is believed to accurately reflect the real land cover. Sources of reference data include ground observations, higher resolution satellite images, and published maps.

4.1.2.1 Reference data

The reference data (WSG and CSG) in this study is collected via published research results. For instance, Mulkey et al. (2008) studied WSG management in Gregory County, South Dakota. In Orr center, Illinois, there are some planting WSG (Benjamin F. Tracy et al., 2010). Because switchgrass is kind of WSG, there are some published research results that are referred as ground data. Tulbure et al. (2012) did switchgrass study in South Dakota (Edmunds county, Clark county, Grant county, Brookings county, Sanborn county), North Dakota (Ramsey county, Morton county, Logan

county), Wisconsin（Sauk county, Columbia county）and Nebraska (Holt county, Pierce county). Moreover, in Prairie State PARK and Osage Prairie, they are dominated by WSG and CSG (Cuizhen Wang et al., 2011). There are the similar situations with selecting training data. These data points hold high uncertainty due to the lack of spatial details in publications.

As Figure 4-12 displayed, from 2000 to 2009, a set of reference points of major crops (corn and soybean--20 points, winter wheat--20 points, spring wheat--20 points, WSG--23 points, CSG--21 points) are randomly selected in the Midwest based on Table 4-1 and phenology features of each crops.

Table 4-1: Reference of accuracy assessment

Type	**Location**
Warm-season Grasses	Gregory County, in South Dakota (Mulkey et al., 2008)
Warm-season grasses	Orr center, Illinois (Tracy et al., 2010)
Switchgrass (Warm-season Grasses)	South Dakota (Edmunds county, Clark county, Grant county, Brookings county, Sanborn county), North Dakota (Ramsey county, Morton county, Logan county), Wisconsin （Sauk county, Columbia county, and Nebraska

	(Holt county, Pierce county). (Tulbure, et al., 2012)
Warm-season grassland, Cool-season grasses	Prairie State PARK, Osage Prairie (Wang et al., 2011)
Warm-season grassland, Cool-season grasses	Central Wisconsin, (Jackson et al., 2010)

Supplementary evidence is also examined from crop calendars in the Midwest as observed at the USDA website (http: //www.usda.gov/nass/). For instance, Figure 4-11 demonstrates the fundamental crop calendars of corn, winter wheat and spring wheat. The indication would be used to select reference points of each crop.

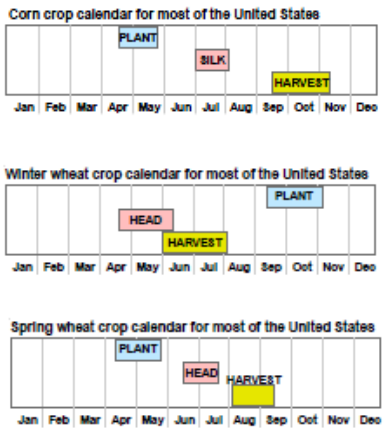

Figure 4-11: Crop calendar of annual crops in the Midwest (USDA-Crop calendar dates are based upon NASS crop progress data from 2000-2004. Crop development stages represent the average time period Source: http://www.usda.gov/nass/)

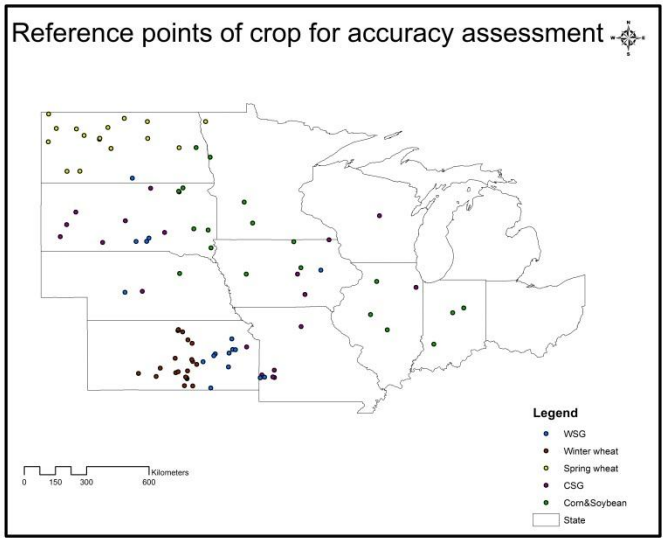

Figure 4-12: Reference points of crops for accuracy assessment

4.1.2.2 Error matrix

The error matrix approach (Congalton 1988) is applied in this study to perform accuracy assessment. Table 4-2 shows the framework of an error matrix which is utilized to calculate classification accuracies of k classes (Jensen 2005). The columns represent ground reference points for each class, and the rows are corresponding points classified from images. The diagonal of matrix summarizes points that are correctly classified. The following calculates a set of accuracies that are derived from the Table:

1) Producer's accuracy (a measure of omission error): refers to the probability that a type of land cover on the ground is classified as such on the image. It is calculated by each diagonal value divided by the corresponding column total:

$$Producer's\ accuracy = \frac{X_{1K}}{X_{+K}} \qquad \text{(Eq. 4.1)}$$

2) User's accuracy (a measure of commission error): refers to the probability that a pixel classified as a land cover type is really this class on the ground. It is calculated by each diagonal value divided by the corresponding row total:

$$User'saccuracy = \frac{X_{IK}}{X_{1+}} \qquad \text{(Eq.4.2)}$$

3) Overall accuracy (a measure for the overall classification accuracy): It can be derived from this Table by counting how many pixels were classified the same in the satellite image and on the ground and dividing this by the total number of pixels:

$$Overall\ accuracy = \frac{(X_{11}+X_{22}+X_{33}+X_{KK})}{N} \qquad \text{(Eq.4.3)}$$

Table 4-2: Error matrix

Class	1	2	3	K	Row total
1	X_{11}	X_{12}	X_{13}	X_{1K}	X_{1+}
2	X_{21}	X_{22}	X_{23}	X_{2K}	X_{2+}
3	X_{31}	X_{32}	X_{33}	X_{3K}	X_{3+}
K	X_{K1}	X_{K2}	X_{K3}	X_{KK}	X_{K+}
Column total	X_{+1}	X_{+2}	X_{+3}	X_{+K}	N

Tables from 4-3 to 4-12 show the results of accuracy assessment.

Table 4-3: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2000

2000 (Year)		Ground reference							
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy	
Image-derived	Corn& Soybean	15					15	1	
	Winter Wheat		18				18	1	
	Spring Wheat			16			16	1	
	WSG	5	1	2	15	1	24	0.625	
	CSG			2	2	18	22	0.8181	
	Other		1		1		2		
	Total	20	20	20	18	19	97	0.8454	Overall accuracy
	Producer's accuracy	0.75	0.9	0.8	0.8333	0.9474			

Table 4-4: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2001

2001 (Year)		Ground reference						
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy
Image-derived	Corn& Soybean	16		1			17	0.9412
	Winter Wheat		14				14	1
	Spring Wheat	1		17			18	0.9444
	WSG	2	4	1	15	1	23	0.6522
	CSG	1	2	1	3	17	24	0.7083

	Other					1	1		
	Total	20	20	20	18	19	97	0.8144	Overall accuracy
	Producer's accuracy	0.8	0.7	0.85	0.8333	0.8947			

Table 4-5: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2002

2002 (Year)		Ground reference							
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy	
Image-derived	Corn& Soybean	19					19	1	
	Winter Wheat		17				17	1	
	Spring Wheat			15			15	1	
	WSG	1		5	16	3	25	0.64	
	CSG		1		1	14	16	0.875	
	Other		2		1	2	5		
	Total	20	20	20	18	19	97	0.8351	Overall accuracy
	Producer's accuracy	0.95	0.85	0.75	0.8889	0.7368			

Table 4-6: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2003

2003 (Year)		Ground reference							
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy	
Image-derived	Corn& Soybean	20				1	21	0.9524	

	Winter Wheat		16				16	1	
	Spring Wheat			17			17	1	
	WSG			2	17	5	24	0.7083	
	CSG		3		1	12	16	0.75	
	Other		1	1		1	3		
	Total	20	20	20	18	19	97	0.8454	Overall accuracy
	Producer's accuracy	1	0.8	0.85	0.9444	0.6316			

Table 4-7: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2004

2004 (Year)		Ground reference							
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy	
Image-derived	Corn& Soybean	20		1			21	0.9524	
	Winter Wheat		18				18	1	
	Spring Wheat			16			16	1	
	WSG		1	3	15		19	0.7895	
	CSG		1		3	19	23	0.8261	
	Other						0		
	Total	20	20	20	18	19	97	0.9072	Overall accuracy
	Producer's accuracy	1	0.9	0.8	0.8333	1			

Table 4-8: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2005

2005 (Year)		Ground reference							
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy	
Image-derived	Corn& Soybean	18			1		19	0.9474	
	Winter Wheat		20				20	1	
	Spring Wheat			18			18	1	
	WSG	2		2	16	3	23	0.6957	
	CSG				1	16	17	0.9412	
	Other						0		
	Total	20	20	20	18	19	97	0.9072	Overall accuracy
	Producer's accuracy	0.9	1	0.9	0.8889	0.8421			

Table 4-9: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2006

2006 (Year)		Ground reference						
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy
Image-derived	Corn& Soybean	19			1		20	0.95
	Winter Wheat		19				19	1
	Spring Wheat			14			14	1
	WSG	1		3	14	1	19	0.7368

	CSG		1	3	3	16	23	0.6957	
	Other					2	2		
	Total	20	20	20	18	19	97	0.8454	Overall accuracy
	Producer's accuracy	0.95	0.95	0.7	0.7778	0.8421			

Table 4-10: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2007

2007 (Year)		Ground reference							
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy	
Image-derived	Corn& Soybean	16					16	1	
	Winter Wheat		19				19	1	
	Spring Wheat			19			19	1	
	WSG	4			14	2	20	0.7	
	CSG		1		4	15	20	0.75	
	Other			1		2	3		
	Total	20	20	20	18	19	97	0.8557	Overall accuracy
	Producer's accuracy	0.8	0.95	0.95	0.7778	0.7895			

Table 4-11: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2008

2008 (Year)		Ground reference							
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy	

Image-derived	Corn& Soybean	19					19	1	
	Winter Wheat		16				16	1	
	Spring Wheat			16			16	1	
	WSG	1		2	16	3	22	0.7273	
	CSG		3	1	2	16	22	0.7273	
	Other		1	1			2		
	Total	20	20	20	18	19	97	0.8557	Overall accuracy
	Producer's accuracy	0.95	0.8	0.8	0.8889	0.8421			

Table 4-12: User's accuracy and Producer's accuracy of crops, and overall accuracy in the U.S. Midwest in 2009

2009 (Year)		Ground reference							
	Class	Corn & Soybean	Winter Wheat	Spring Wheat	WSG	CSG	Total	User's accuracy	
Image-derived	Corn& Soybean	19		3	2		24	0.7917	
	Winter Wheat		18				18	1	
	Spring Wheat			15	1		16	0.9375	
	WSG	1		2	14	4	21	0.6667	
	CSG		1			14	15	0.9333	
	Other		1		1	1	3		
	Total	20	20	20	18	19	97	0.8247	Overall accuracy
	Producer's accuracy	0.95	0.9	0.75	0.7778	0.7369			

Accuracies of annual crops are mostly around 80 percent to 90 percent for ten years. The accuracies of WSG and CSG are relative lower at approximately 70 percent. Table 4-3 to Table 4-12 display the highest overall accuracy is 90.72 percent in 2004 and 2005, when both categories were considered. The lowest overall accuracy is 81.44 in 2001. There are probably several reasons to explain why the accuracies are changed.

Owing to the large pixel size of MODIS imagery (500m * 500 m), the discrepancy might also be caused by mixed pixels. As classification reference, CDL had been transformed to same resolution with MODIS imagery. Therefore, there would be some misclassification of crops. Additionally, based on the analysis of accuracy assessment, some CSG could be misclassified as winter wheat because of their early peak season, and the phenology of winter wheat has a small curve after peak season. The crop phenology approach was inevitably impacted by the shift of crop calendar in a large region.

For WSG, the lowest the user's accuracy was 62.50 percent in 2000, and the lowest producer's accuracy was 77.77 percent in 2006, 2007, and 2009, probably resulting from misclassifying annual crops into perennial crop. Due to relatively similar the length of growth season, the corn and WSG are commission in 2000. There are omission errors between WSG and CSG in 2006 and 2007. One possible reason was

the relatively small area of the prairie and its mixed growth of WSG and CSG species, which resulted in large misclassification in the MODIS map (500m*500m). Although there are some misclassifications, this classification results are good enough for next-step statistical analysis.

4.1.3 The 10-year variation of WSG coverage

In each year, planting area of WSG in the Midwest is summarized in Table 4-13. It does not illustrate an apparent trend from 2001 to 2009, although high inter-annual fluctuation is observed in certain years. For example, the area of WSG is 43.2 million hectare in 2003, but the area of WSG reduces to 33.11 million hectare in 2004 based on the classification result. In addition, there is also a high area change from 2006 to 2007. These inter-annual variations may come from some other impacts such as abnormal climate or Classification errors. For example, in 2004, WSG biomass is decreased than other years, which probably results from classification errors. There are more CSG in southeastern of North Dakota and northeastern of South Dakota, but in most of other years, WSG are distributed in these areas.

Table 4-13: WSG biomass assessment in the Midwest

Year	WSG(Million Hectare)
2000	48.56
2001	48.63

2002	41.23
2003	43.20
2004	33.11
2005	47.22
2006	39.83
2007	36.17
2008	45.17
2009	40.27

The average WSG planting areas in 2000-2009 reaches 42.34 million hectare. It indicates the bioenergy potential in this important agricultural region. The spatially explicit information of the WSG maps in the Midwest may also be helpful for biofuels decision-making. For instance, decision makers need to assess where to covert land uses to WSG. A conflict between traditional annual crops and new bioenergy crops, in terms of political ecology, is always concerned among economic profits of land owners, environmental protection, revenue, and program subsidies. For sustainable cropping management in bioenergy, there is a need to leverage these concerns by relying land use conversion and bioenergy crop development on environmentally sensitive areas assisted by the spatial distributions and biomass of WSG polygons. This research performs preliminary examination about the dependency of WSG biomass on a set of environmental factors in next section.

4.2 WSG Biomass proximity

As shown in class maps in 2000-2009, the inter-annual distributions of WSG vary dramatically, due primarily to the WSG/CSG mixed growing environment in grasslands. Interfered with long-term grazing, haying and other management activities, pure WSG fields are rare in the Midwest. Rather, both WSG and CSG species are commonly observed in pasturelands and natural grasslands. Controlled by climate variations, a grass field may grow in phenology features similar to WSG in certain years, while it may grow in similar phenology of CSG in other years. To better represent WSG distributions in the Midwest, I counted the years that a pixel is classified as WSG in the 10-year period. It is defined a WSG pixel if in 6 of 10 years it shows as WSG. In other words, it approximates a field with 60 percent relative abundance. The resulted WSG distributions are displayed in Figure 4-13. The integral NDVI of these WSG pixels thus represents their biomass quantities (Figure 4-14).

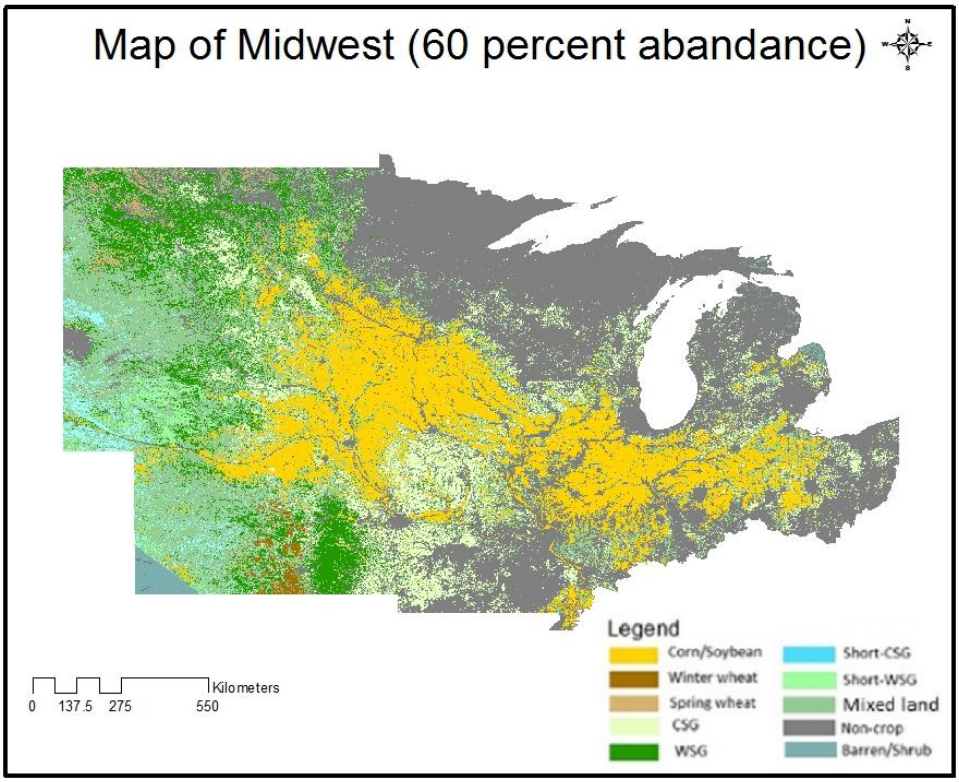

Figure 4-13: Result of classification for WSG of 60 percent abundance (six year)

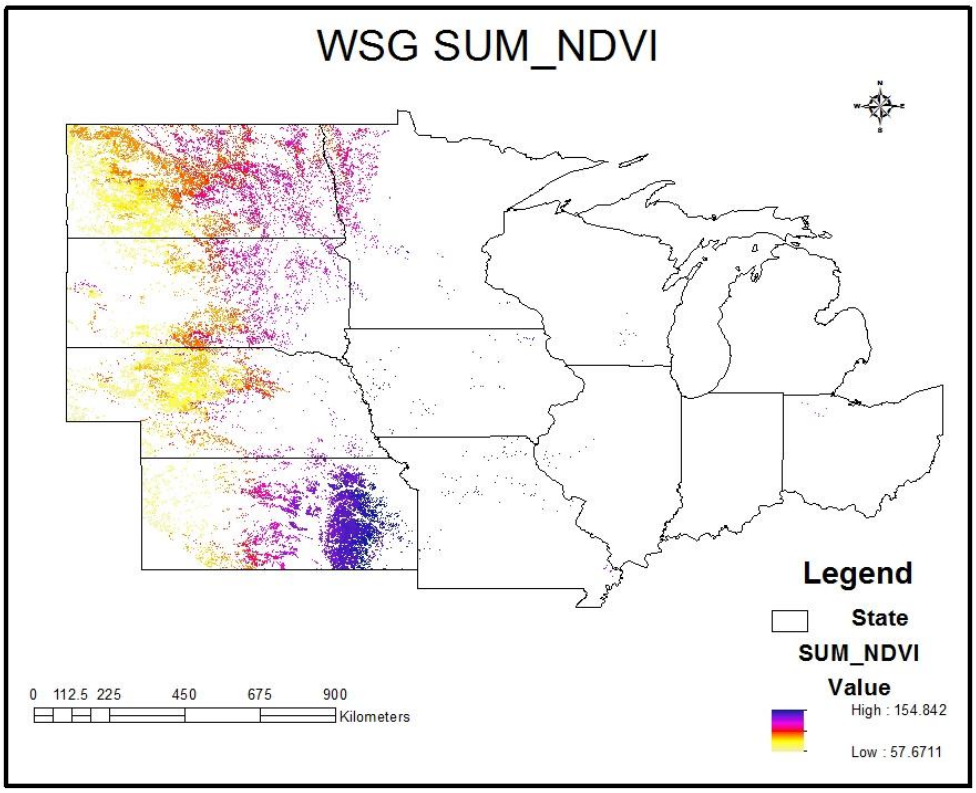

Figure 4-14: Integral NDVI of WSG for WSG of 60 percent abundance (six year)

As shown in Figure 4-14, WSG are primarily distributed in North Dakota, South Dakota, Nebraska and Kansas. The darker color represents higher biomass of WSG fields. This Figure displays that the WSG biomass in western states is lower than eastern states. Especially, the Flint Hills grassland in Kansas reveals the highest biomass because it is a well-reserved tall-grass prairie remnant. Previous researches reveal a similar pattern of WSG distributions in the Midwest.

As described in Chapter 3, the WSG areas in Figure 4-14 are split by soil LCC

polygons (Figure 4-15). Only WSG polygons with areas larger than 1500m*1500m (3 by 3 pixels) are selected as representative WSG points that are used in statistical regression in the next section. Figure 4-16 is an example of average precipitation in theses WSG polygons in June, 2004. Besides, Figure 4-17 displays average maximum temperature in WSG polygons in April, 2004.

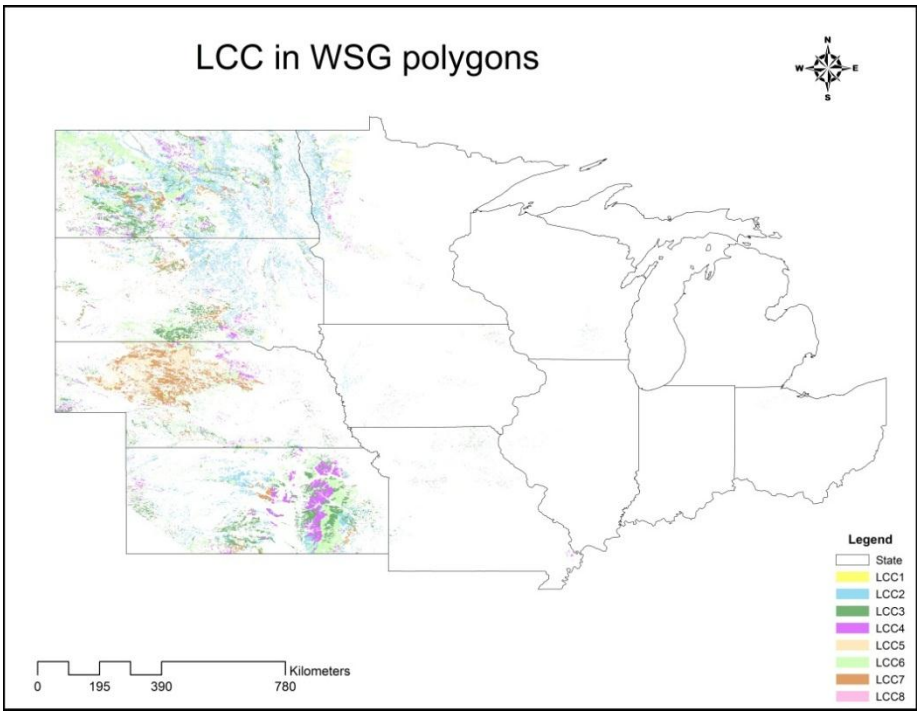

Figure 4-15: LCC distribution in WSG polygons

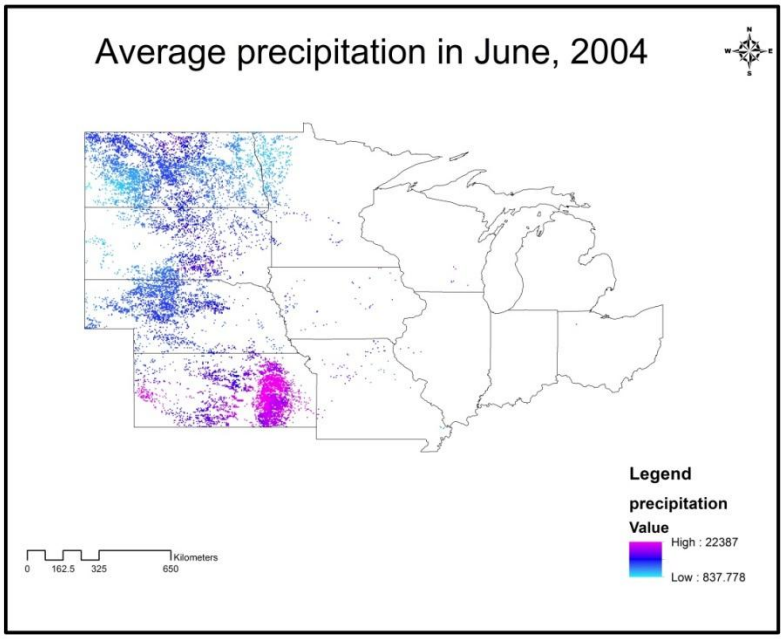

*Figure 4-16: Average precipitation in WSG polygons in June, 2004 (The unit is millimeter*100)*

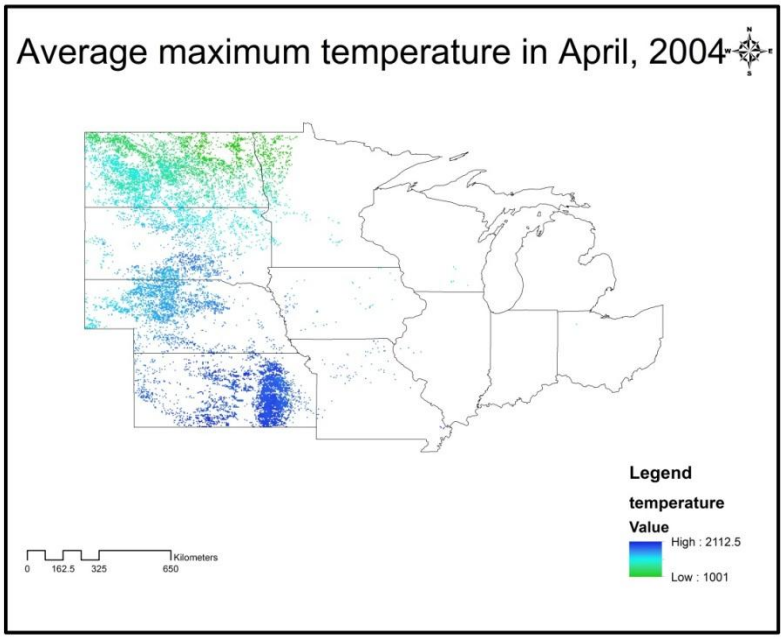

*Figure 4-17: Average maximum temperature in WSG polygons in April, 2004 (The unit is centigrade*100)*

4.3 Environmental dependencies of WSG biomass

There are 1555 samples (WSG polygons) that are used to build the Multiple Linear Regression. In this process, the dependent variable is WSG biomass. The independent variables include average monthly precipitation from April to September, average monthly maximum temperature from April to September, and the LCC from soil data. In the MLR model, the coefficients of all independent variables are listed in Table 4-14. At a confidence interval of 95 percent, a p-value smaller than 0.05 indicates this independent variable plays a statistically significant role in the MLR. As shown in the Table, precipitation in September and temperature in August are not valid in the model. The final equation of the MLR model is thus calculated as:

$$WSG_{biomass} = 0.111PCT_4 + 0.430PCT_5 + 0.200PCT_6 + 0.120PCT_7 + 0.214PCT_8 - 0.017PCT_9 + 0.544TEM_4 - 1.052TPR_5 + 0.374TPR_6 - 0.370TPR_7 + 0.157TPR_8 + 0.440TPR_9 - 0.055LCC$$

(Eq.4.4)

Where WSG biomass is integral NDVI of WSG; PCT_4, PCT_5, PCT_6, PCT_7, PCT_8, PCT_9 are average precipitation in April, May, June, July, August, September in 2004; TPR_4, TPR_5, TPR_6, TPR_7, TPR_8, TPR_9 are average maximum temperature in April, May, June, July, August, September in 2004.

Table 4-14: Coefficients of independent variables in the MLR model **(R-Squared: 0.79)**

Independent	**Coefficient**	**P-value**
Average precipitation of April	0.111	0.000
Average precipitation of May	0.430	0.000
Average precipitation of June	0.200	0.000
Average precipitation of July	0.120	0.000
Average precipitation of August	0.214	0.000
Average precipitation of September	-0.017	0.278
Average maximum temperature of April	0.544	0.000
Average maximum temperature of May	-1.052	0.000
Average maximum temperature of June	0.374	0.000
Average maximum temperature of July	-0.370	0.000
Average maximum temperature of August	0.157	0.153
Average maximum temperature of September	0.440	0.000
LCC of soil	-0.055	0.000

As shown in Table 4-14, The R-Squared value of the regression is approximately 0.8, which indicates that the regression in Eq.4.4 could reasonably explain the dependency of WSG biomass to the list of independent variables.

Different dependencies of WSG biomass to environmental factors may be explained with WSG growth characteristics. Figure 4-18 shows example growth curves of some WSG species (downloaded from the Center for Native Grasslands Management). Generally, switchgrass begins to grow rapidly in late April, slows the pace by late June and becomes semi-dormant in August. Gamagrass begins growing rapidly by mid-April, slows down in June and maintains modest growth until early September. Most of these WSG species go completely dormant during October and start to break dormancy in late March or early April (www.nativegrasses.utk.edu). This information is helpful to understand how WSG growth responds to climate and soil factors.

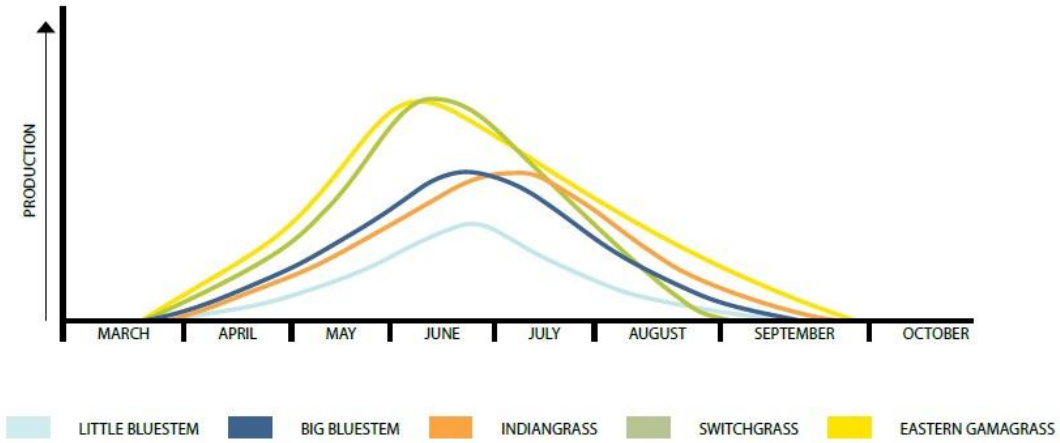

Figure 4-18: Example growth curves of different WSG species (Source: University of Tennessee, Center for Native Grasslands Management)

4.3.1 WSG biomass dependencies on precipitation

In the MLR model, the regression coefficients of precipitation variables are mostly positive (as shown in Table 4-14). The precipitation in May shows dominantly higher influence on WSG biomass than other months (coefficient = 0.430). It is reasonable

because WSG usually start its growth in mid-late April (as shown in Figure 4-18). Sufficient precipitation in this period triggers the early growth and biomass accumulation before reaching its peak growth. Precipitation in September has a negative effect (-0.017) and is statistically insignificant (p-value =0.278). Precipitation in other months also cast positive effects on WSG biomass although the influence is weaker than that of May.

4.3.2 WSG biomass dependencies on temperature

Temperatures in April, June, and September have positive effects on WSG growth. Temperature in April has the strongest effect than other months (coefficient = 0.544). It indicates that increased temperature in start of season of WSG accelerate its growth. On the other hand, temperatures in May and July have negative effects on WSG biomass. Higher temperature in late spring to early summer may restrict WSG growing if it exceeds a physiological optimum or interacts with increased evapotranspiration and reduced soil water availability. The temperature of August does not have a significant effect on WSG growth, when vegetation growth is less active in hot summers.

4.3.3 WSG biomass dependencies on soil properties

The negative coefficient of LCC illustrates that WSG biomass is dependent on soil quality. Good standing LCC produce means that the field favors agricultural growth

and thus produces higher biomass. The coefficient of LCC, however, is quite low in comparison with climate factors. It may indicate that WSG have strong adaption to the growing environment.

Table 4-14 lists the percentage of LCC in the U.S. Midwest. Surprisingly WSG grow in areas with different soil qualities (except areas with LCC of 1, 5 and 8). Lands with LCC=1 may be optimally used for annual crops for high agricultural profits. On the contrary, lands with LCC=8 are not expected to return significant on-site benefits of any crops.

Table 4-14: The percentage of LCC in the U.S. Midwest

LCC of soil	Percentage (percent)
1	1.26
2	38.19
3	18.56
4	10.49
5	2.4
6	18.26
7	10.68
8	0.16

In conclusion, results of this study display the spatial distributions of WSG grasses. By building the Multiple Linear Regression and analyzing the correlations of temperature, precipitation, and LCC of soil, the result demonstrated relationship between biomass supplies and environmental factors. With this information, it is possible to identify potential fields that, under distinct climate conditions and land-use scenarios, may refer to allocation of perennial bioenergy crops.

Chapter 5 Discussion and Future Research

5.1 Discussion

5.1.1 Mapping approach evaluation

For the efforts of classifying land cover/use types in the study region, a decision tree approach is developed based on phenological metrics that are extracted from MODIS products at 500-m spatial resolution. Phenology-based classification is still in its early stage although remote sensing is becoming popular tool and data source in phenology studies. Wang et al. (2011) obtained a relative good mapping result of perennial energy crops in North American tall grass prairie using the phenology analysis approach. There are some well-adopted classification methods such as Maximum Likelihood and Minimum Distance classifier. Satellite imageries at higher spatial resolutions are often processed with these methods. For example, one common application is to compare the Land use and Land cover changes over past years using LANDSAT (30-m) satellite images. Moreover, Spectral Angle Mapping has great advantages with high spectral-resolution or hyperspectral imageries, while Linear Unmixing approaches are often used in mixed lands. The applications of these classifiers in large-area mapping, however, is time consuming and expensive in image acquisition and labor usage. The results may also be questionable because fine- and medium-resolution satellite images cannot be acquired in the same time over a large area. This may raise issues in crop mapping when crop greenness varies quickly in its critical growing stages. Depending on temporal resolutions of satellite sensors and

cloud cover problems, the images in different subsets of a region may be acquired up to months different. Their classification is therefore strongly affected by these uncertainties.

The study implemented crop phenology to perform classification of energy crops in the Midwest region. The advantages of MODIS include daily acquisition, large coverage, and phenological metrics of annual and perennial crops. In this study, the advantages are large-area classification that adopted expert knowledge, which could be used to assist regional cropping statistics such as planting area, production and so on. The results of this study could provide an additional information layer to the current CDL products: WSG/CSG classification. CDL products are not classified as WSG and CSG. Therefore, this study fills the gap of grassland mapping products and their potential applications in domestic bioenergy management.

5.1.2 Land-use policy of WSG-related bioenergy

Based on the classification results, potential bioenergy grass could be found in the U.S. Midwest. In economic perspective, with higher demand of biomass supplies, farmers may prefer planting perennial grass such as switchgrass in environmentally sensitive lands where conventional annual crops may not produce well. On the other hand, farmers might prefer to plant perennial grasses on superior land to get higher yields and greater returns, even though it may harm corn or soybean planting areas

and production. Conversely, large-scale of energy grass planting may also destroy the farmland biodiversity, degrade natural ecosystems, and accelerate soil erosion and water contamination. Therefore, the land-use policy of bioenergy needs to be carefully made to leverage varies factors such as the economic return and environmental protection, the bioenergy development and the sustainability of food security.

According to the class maps in this study, western areas of U.S. Midwest hold high potential in land conversion for biofuels. This study also explores the environmental dependency of WSG production. The relationship was developed in MLR model between WSG biomass and environmental factors including precipitation, temperature and LCC of soil. Along a growing season from April to September, the increasing precipitation could be helpful for WSG growth excluding September. Average monthly maximum temperatures in May and July negatively influence on WSG biomass. Higher temperature could limit crop growing if it exceeds a physiological optimum. Additionally, the negative coefficient of LCC of soil demonstrates that poor standing LCC produce lower WSG biomass. However, farmer could prefer to plant crops that need to grow in higher required condition in good standing LCC. Results from the study would provide helpful information to land decision makers so they could make optimal land-use support and management for cellulosic feedstock development and sustainability.

5.2 Conclusion and future research

This study examines bioenergy-related land cover classification and prediction by considering climate and soil properties using remote sensing and Geographic Information System techniques. One objective is to assess biomass for annual and perennial cops focusing on WSG as a potential bioenergy crop. Another one is to assess the relationships between WSG biomass and climate and soil factors, which could be helpful to land managers and decision makers for effectively and efficiently allocating land-use strategies based on balancing of food storage, livestock and advanced biofuels.

Human behaviors have significant effects on growth of WSG such as selecting cultivar (transgene), plant time, fertility, irrigation, grazing or conversation, and maintenance. For example, if harvested once in fall in mid-September or late-summer, maximum switchgrass biomass could be obtained in different regions (Casler and Boe, 2003). In sum, effective factor of human behavior is not considered how they influence biomass of WSG in Multiple Linear Model.

5.2.1 Major findings

This study explores how the spatial and temporal variability of weather and climate conditions and the LCC of soil conditions affect WSG biomass. Primary findings include:

1) Obtained region-scale crop distributions of corn, soybean, winter wheat, spring wheat, WSG, and CSG owing to their different phenological features using MODIS data from 2000 to 2009 in the U.S. Midwest. The results fill the gap of current crop databases in the U.S.

2) Extracted biomass quantities and spatial distributions of WSG that are needed for assessment of its current bioenergy supplies in the Midwest. In particular, the integral NDVI is assessed as WSG biomass proximity in this study. It is found that in 10-year class maps that WSG are primarily distributed in western region. The average WSG planting areas in 2000-2009 reaches 42.34 million hectare. There are no an apparent trend of WSG from 2001 to 2009, but high inter-annual fluctuation is found in certain years. WSG area is 43.2 million hectare in 2003, whereas the area of WSG reduces to 33.11 million hectare in 2004 based on the classification result. In addition, there is also a high area change from 2006 to 2007. These inter-annual variations may result from some factors such as abnormal climate or Classification errors.

3) Identified the sensitive environmental factors that affect distributions of WSG.

Firstly, the responses of WSG biomass to average monthly precipitation are mostly positive in 2004. Average monthly precipitation in May shows the highest influence

than other months. Along a growing season, the increasing precipitation would be helpful for WSG growth excluding September.

Secondly, the average monthly maximum temperatures in May and July have negative effects on WSG biomass. Higher temperature could limit crop growing if it exceeds a physiological optimum or tolerance range. Moreover, monthly maximum temperatures in May higher effect on WSG biomass because it is the start of season of WSG.

Finally, LCC is a unique and special factor to test how soil controls WSG biomass. Good standing LCC produces higher WSG biomass. The coefficient of LCC, however, is quite low in comparison with climate factors. It probably indicates that WSG have strong adaption of growing environment. In addition, WSG grow in areas with different soil qualities, excluding areas with LCC of 1, 5 and 8.

5.2.2 Research significances

5.2.2.1 Environmental effects

Currently corn is the largest biofuel provision. U.S. Midwest contains the famous "Corn Belt". Other bioenergy crops, such as perennial grasses and short-rotation woody plantation, are in urgent need to reduce risk of corn biofuel in food security and environmental contamination. Moreover, if biofuels replace one part of fossil

fuels, the greenhouse gases such as CO_2 emission will be decreased. Besides, WSG hold a C4 photosynthetic pathway, which differs in carbon exchange and cycle and surface energy flux partitioning from CSG grasses (Foody & Dash, 2007). Therefore, accurate and up-to-date mapping of WSG/CSG delineation provide important information for carbon sequestration in global climate studies.

5.2.2.2 Political and social-economic effects

An energy issue is associated with the political policy. For instance, there is a huge contradiction between developing and developed countries in restricting the emission of CO_2. Developing counties need to develop industry to increase gross domestic product which inevitably involves in higher consumption of fossil fuels. In a way, in place of fossil fuels biofuels could solve some problems on this issue. Energy issues impact international relationships and strategies. For example, European carbon taxes of flights are charged reluctantly because customers from other counties challenge their policy, arisen from the unfair fee. Bioenergy produces less CO_2 than fossil fuels which could resolve some essential political conflicts.

5.2.3 Future work

For next step of this study, there would be some advanced approaches to optimizing the research of the future. Future analyses would do well to consider the following:

1) MODIS images at coarse resolutions are often a mixture of different fields in agricultural lands. With linear and nonlinear unmixing approaches, mixed pixel could be interpreted to different and specific crop types at certain percentages, which improves accuracies of WSG distribution.

2) The method of classification is relatively appropriate and reasonable for the biomass assessment. If there are a large number of ground data of crops and WSG experiments in the Midwest area, the accuracy of classification and biomass estimation could be better.

3) If ten-year data of environmental variables and integral NDVI were considered to the Multiple Linear Model, the panel data knowledge would be added to the analysis. By analysis and comparison of 10-year precipitation and temperature, it could be tested how integral NDVI responds to the tendency of change of environmental variable such as whole growing season of WSG.

In this study, remote sensing techniques provided spatially explicit information. However, there are also some limitations of phenological approaches and misclassifications. Therefore, more in depth research could be done toward a better method to separate the mixed grassland pixel. At large scale region, more factors that have effects on WSG distribution should be considered. More ground data of grasses

could be collected at different time and place to examine specific growth changes in the future.

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