Multi-temporal Remote Sensing of Changing Agricultural Land Uses within the Midwestern Corn Belt, 2001-2015

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SCIENTIFIC ABSTRACT

The Midwest US has experienced significant changes in agricultural land use and management practices in recent decades. Cropland expansion, crop rotation change, and crop phenology changes could lead to divergent environmental impacts on linked ecosystems. The overall objective is to examine agricultural land use and management changes and their impacts on water quality in the Midwest US, which is addressed in three separate studies. The first study examined spatial and temporal dimensions of agricultural land use dynamics in east-central Iowa, 2001-2012. Results of this study indicated that increases in corn production in response to US biofuel policies had been achieved mainly by altering crop rotation. This study also examined spatial relationships between cultivated fields and crop rotation practices with respect to underlying soils and terrain. The most intensively cultivated land had shallower slopes and fewer pedologic limitations than others, and the corn was planted on the most suitable soils. The second study characterized key crop phenological parameters (SOS and EOS) for corn and soybean and analyzed their spatial patterns to evaluate their change trends in the Midwest US, 2001-2015. Results showed that MODIS-derived SOS and EOS values are sensitive to input time-series data and threshold values chosen for crop phenology detection. The non-winter MODIS NDVI time-series input data, and a lower threshold value (i.e., 40%) both generated better results for SOS and EOS estimates. Spatial analyses of SOS and EOS values displayed clear south-north gradient for corn and trend analyses of SOS revealed only a small percentage of counties showed statistically significant earlier trends within a user-defined temporal window (2001-2012). The third study integrated remote sensing-derived products from the first two studies with the SWAT model to assess impacts of agricultural management changes on sediment and nutrient yields for three selected watersheds in the Midwest US. With satisfied calibration and validation results for stream flows, sediment and nutrient yields, considered under differing management scenarios, were compared at different spatial scales. Results showed that intensive crop rotation, advancing the planting date with the same length of growing season, and longer growing seasons, dramatically increased, maintained, and slightly reduced sediment, total nitrogen, and total phosphorous yields, respectively. Overall, these studies together illuminate relationships between broad-scale agricultural policies, management decisions, and environmental impacts, and the value of multi-temporal, broad-scale, geospatial analysis of agricultural landscapes.

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GENERAL ABSTRACT

Agricultural land use and management is an important component of how humans use the landscape, as it reflects human actions and values. Changes in agricultural land use and management may have dramatic effects on soil erosion and nutrient export. This research examined agricultural land use and management changes and their impacts on water quality in the Midwest US. Firstly, this research examined spatial and temporal patterns of agricultural extensification and intensification in east-central Iowa, 2001-2012, and related them to variations underlying soils and terrain. This research found that increases in corn production in response to US biofuel policies were realized mainly by altering crop rotation. The most intensively cultivated land had shallower slopes and fewer pedologic limitations than others, and the corn was planted on the most suitable soils. Secondly, this research characterized key crop phenological parameters (start of season (SOS), and end of season (EOS)) for corn and soybean crops in the Midwest US, 2001-2015, and found that remote sensing-derived SOS and EOS values are sensitive to input time-series data and threshold values. With spatial and trend analyses, the south-north gradient for corn SOS and EOS were clearly displayed and only a small percentage of counties showed statistically significant downwards trends for corn and soybean SOS within a user-defined temporal window (2001-2012). Finally, this research assessed impacts of changes of cropping systems and planting/harvest dates under different management scenarios on sediment and nutrient yields for three selected watersheds in the Midwestern US. Intensive crop rotation resulted in greater sediment and nutrient losses while longer growing seasons reduced sediment and nutrient losses slightly.

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Chapter 1 Introduction

1. Research Context and Justification

In United States, total land in crop production has remained roughly constant over the past century, but its distribution and composition have varied (Lubowski et al., 2006). Agricultural management practices have also changed dramatically in recent decades. Changes in agricultural land use and management practices have contributed to substantial environmental issues, such as CO_2 emission, soil degradation, biodiversity loss, and water degradation (Foley et al., 2011). Formation of policy to support sustainable agriculture should be recognized present and future development trends and their potential economic, social and environmental impacts.

As one of the key grain-producing regions of the world, the Midwest US has experienced significant changes in agricultural land use (extensification and intensification) in response to federal policies implemented to encourage production of biofuels (Secchi et al., 2009; Secchi et al., 2011; Stern, Doraiswamy, & Hunt, 2012). The United States Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS) reported that corn acreage in 2007 reached its highest levels since 1944. Increased corn production is generally related to decreases in other agricultural croplands (i.e., soybean and winter wheat), pasture land (Keeney & Hertel, 2009; Westcott, 2007), and marginal lands in the Conservation Reserve Program (CRP) (Langpap & Wu, 2011; Swinton et al., 2011), and replacing standard crop rotation (i.e., corn-soybean/soybean-corn) with continuous corn rotation (Lunetta et al., 2010). Furthermore, elevated corn prices may also promote farmers to plant corn earlier, thereby rising corn yields (Bastidas et al., 2008; Nielsen et al., 2002; Wilcox & Frankenberger, 1987). Current expansion of corn acreage, changing crop rotation practices, changing crop phenological phases in the Midwest US are expected to have significant impacts on sediment and nutrient loading into streams and water bodies, affecting agro-ecosystem functions and services.

My goal for this research is to better understand spatial and temporal dimensions of cropland change, crop rotation change, and crop phenology change in response to changes in ethanol policy, and access their impacts on water quality. Recognition of spatial and temporal dimensions of agricultural land use and management changes is important if we seek to understand local economic and environmental consequences, and to improve predictive models used in decision support.

It is often difficult to obtain detailed agricultural land use and management information, especially for large study areas (Borah & Bera, 2003). Remote sensing can provide detailed and reliable spatial information concerning cropland change, crop rotation patterns, and planting/harvesting dates for corn and soybeans. In this research, I used the Cropland Data Layer (CDL) from 2001 through 2012 produced by USDA NASS to examine changes in cultivated area and crop rotation sequences on a pixel-by-pixel basis. I used Moderate Resolution Imaging Spectroradiometer (MODIS) Normalized Difference Vegetation Index (NDVI) data to estimate planting/harvesting dates for corn and soybeans a pixel-by-pixel basis. In order to access impacts of changes in agricultural land use and management on water quality, I selected the Soil and Water Assessment Tool (SWAT) model. Accurate representation of agricultural management practices like crop rotation and planting/harvest dates are an important component of the SWAT model, however, detailed management map products are often unavailable, or offer limited spatial and temporal coverage. Integrating pixel-by-pixel crop rotation patterns and planting/harvesting dates derived by satellite images, sediment and nutrient yields for current conditions and simulated future agricultural management scenarios were predicted for selected large ungauged watersheds.

2. Dissertation Components, Attribution, and Research Objectives

This dissertation is composed of three manuscript chapters prepared for submission to peer-reviewed academic journals. The three manuscripts present a comprehensive study of changes in agricultural land use and management and their impacts on water quality. The first manuscript (Chapter 2) examines site-specific temporal and spatial patterns of agricultural land use from 2001 to 2012 in a region of East-Central Iowa with USDA-NASS CDLs. This manuscript, with coauthors Dr. James B. Campbell (chair) and Dr. Yang Shao was submitted to *Agricultural Systems*. The second manuscript (Chapter 3) characterizes key crop phenological parameters (SOS and EOS) for corn and soybean crops within the Midwestern US using 250m MODIS 16-day NDVI composites. This manuscript, with coauthors Dr. James B. Campbell (chair) and Dr. Yang Shao was submitted to *Remote Sensing of Environment*. The third manuscript (Chapter 4) examines impacts of changes of cropping systems and planting/harvest dates on sediment and nutrient yields with the SWAT model for selected watersheds in the Midwest US. This manuscript, with coauthors Dr. James B. Campbell (chair) and Dr. Yang Shao is in preparation for submission to a journal yet to be identified.

References

Bastidas, A. M., Setiyono, T. D., Dobermann, A., Cassman, K. G., Elmore, R. W., Graef, G. L., & Specht, J. E. (2008). Soybean Sowing Date: The Vegetative, Reproductive, and Agronomic Impacts. *Crop Science*, *48*(2), 727–740.

Borah, D. K., & Bera, M. (2003). Watershed-scale hydrologic and nonpoint-source pollution models: Review of mathematical bases. *Transactions of the ASAE*, *46*(6), 1553.

Foley, J. a, Ramankutty, N., Brauman, K. a, Cassidy, E. S., Gerber, J. S., Johnston, M., … Zaks, D. P. M. (2011). Solutions for a cultivated planet. *Nature*, *478*(7369), 337–42. doi:10.1038/nature10452

Keeney, R., & Hertel, T. W. (2009). The indirect land use impacts of United States biofuel policies: The importance of acreage, yield, and bilateral trade responses. *American Journal of Agricultural Economics*, *91*(November), 895–909. doi:10.1111/j.1467-8276.2009.01308.x

Langpap, C., & Wu, J. (2011). Potential Environmental Impacts of Increased Reliance on Corn-Based Bioenergy. *Environmental and Resource Economics*, *49*, 147–171. doi:10.1007/s10640-010-9428-8

Lubowski, R. N., Bucholtz, S., Claassen, R., Roberts, M. J., Cooper, J. C., Gueorguieva, A., & Johansson, R. (2006). *Environmental Effects of Agricultural Land-Use The Role of Economics and Policy The Role of Economics and Policy*.

Lunetta, R. S., Shao, Y., Ediriwickrema, J., & Lyon, J. G. (2010). Monitoring agricultural cropping patterns across the Laurentian Great Lakes Basin using MODIS-NDVI data. *International Journal of Applied Earth Observation and Geoinformation*, *12*(2), 81–88. doi:10.1016/j.jag.2009.11.005

Nielsen, R. L., Thomison, P. R., Brown, G. A., Halter, A. L., Wells, J., & Wuethrich, K. L. (2002). Delayed planting effects on flowering and grain maturation of dent corn. *Agronomy Journal*, *94*(3), 549–558.

Secchi, S., Gassman, P. W., Williams, J. R., & Babcock, B. a. (2009). Corn-Based Ethanol Production and Environmental Quality: A Case of Iowa and the Conservation Reserve Program. *Environmental Management*, *44*(4), 732–44. doi:10.1007/s00267-009-9365-x

Secchi, S., Kurkalova, L., Gassman, P. W., & Hart, C. (2011). Land Use Change in a Biofuels Hotspot: The Case of Iowa, USA. *Biomass and Bioenergy*, *35*(6), 2391–2400. doi:10.1016/j.biombioe.2010.08.047

Stern, A. J., Doraiswamy, P. C., & Hunt, E. R. (2012). Changes of crop rotation in Iowa determined from the United States Department of Agriculture , National Agricultural Statistics Service cropland data layer product data layer product. *Journal of Applied Remote Sensing*, *6*(1), 063590–063590. doi:10.1117/1.JRS

Swinton, S. M., Babcock, B. a., James, L. K., & Bandaru, V. (2011). Higher US crop prices trigger little area expansion so marginal land for biofuel crops is limited. *Energy Policy*, *39*(9), 5254–5258. doi:10.1016/j.enpol.2011.05.039

Westcott, P. (2007). *Ethanol Expansion in the United States: How Will the Agricultural Sector Adjust?* Washington DC. Retrieved from http://www.ers.usda.gov/publications/AboutPDF.htm

Wilcox, J. R., & Frankenberger, E. M. (1987). Indeterminate and Determinate Soybean Responses to Planting Date. *Agronomy Journal*, *79*(6), 1074–1078.

Chapter 2 Spatial and Temporal Dimensions of Agricultural Land Use Changes, 2001-2012, East-Central Iowa

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Abstract

In central regions of the U. S. Corn Belt, agricultural production since 2001 has changed in response to federal policies implemented to encourage production of biofuels. As a result, increasing demand for sustainable bioenergy resources has accelerated biofuel production, and led to changes in agricultural land use. This study examines: (1) increases and decreases in cultivated area, and (2) pixel-by-pixel crop rotation sequences within a region of East-Central Iowa. The practice of agriculture brings lands in and out of production in response to variations in local landscapes, markets, and technologies. Further, crops are rotated in response to environmental and market concerns. Knowledge of how such lands are used, and of their topographic and pedologic properties, forms a prerequisite for understanding the context for developing sustainable management practices and policies. This study examines site-specific temporal and spatial patterns of agricultural land use from 2001 to 2012 in a region of East-Central Iowa within United States Department of Agriculture National Agricultural Statistics Service Cropland Data Layer. After 2007, intensity of cultivated land use increased and crop rotation changed from standard corn-soybean or soybean-corn cycles to more intensive rotations. These changes may be correlated with market forces, although variations suggest a multiplicity causes. Intensity of cultivated land use depended on topographic and pedologic properties, although motivations and constraints perceived by producers and managers as they plan their use of landscapes are important.

Keywords: agricultural pattern; land intensification; land extensification; crop rotation; biofuels

1. Introduction

The Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007 requires blending of renewable fuels such as ethanol and biodiesel in transportation fuels, thereby increasing demand for corn and dedicated energy crops such as switchgrass that can supply fuels to meet this requirement. Increased corn production has been achieved through combinations of expansion of cultivated land and intensification of production practices. The former might be based upon cultivation of lands formally held in Conservation Reserve Program (CRP) or upon uses of marginal lands previously devoted to less intensive uses (Langpap & Wu, 2011; Swinton et al., 2011; Westcott, 2007). The latter could be achieved through changes in existing crop rotation practices (Plourde et al., 2013; Stern et al., 2012), or by more intensive use of fertilizers (Simpson et al., 2006).

Broad-scale production of biofuels has wide impacts on agriculture and land use (Keeney & Hertel, 2009; Miao, 2010; Miyake et al., 2012; Mueller & Copenhaver, 2009; Stan et al., 2014; Wallander et al., 2011; Wu et al., 2012). Researchers recognize that meeting increased demand for corn driven by ethanol production must be based upon either extensification or intensification of production, but have disagreed about specifics. Wright and Wimberly (2013) analyzed spatial changes from grassland to cropland between 2006 and 2011 in the western Corn Belt based upon analysis of the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL). They reported that increased corn and soybean production is based upon extensification, not intensification. This study generated a rebuttal from a study in Kansas (Brown et al., 2014). Brown et al. (2014) examined CDL and interview data from Kansas farmers to explore relationships between distance to an ethanol plant and extensification and intensification of corn production at county level between 2007 and 2009. Their study indicated that farmers devoted much more land to intensification than to extensification. In addition, recognition of spatial and temporal dimensions of land use changes in agricultural systems caused by biofuel production is important if we seek to understand local economic and environmental consequences, and to improve predictive models used in decision support. Recent papers have incorporated spatially explicit analyses (Johnston, 2014), focus primarily on particular land use change practices, such as crop rotation or reclamation of CRP lands, and their environmental impacts. For example, Secchi et al. (2011) linked economic, geographical and environmental models by using spatially explicit common units of analysis and used remotely sensed crop cover maps and digitized soils data as inputs. They predict changes in land use, crop rotation, and tillage practice, including the environmental impact of these choices, under different corn price scenarios in Iowa. They assessed environmental impacts on the extensive margin (CRP lands with no cropping) and the intensive margin (lands currently under row crop agriculture) using the Environmental Policy Integrated Climate (EPIC) model. They found that land already in row crops would be converted to continuous corn cropping before any land in CRP would be converted to any corn production. Stern et al. (2012) examined crop rotation practices based upon USDA CDL information, aggregated by county. They examined relationships between corn production increases and crop rotation changes in Iowa, finding regional differences in crop rotation decisions relative to expansion of cultivated land.

There is yet little research devoted to immediate and long-term impacts of increased ethanol production for domestic agriculture, especially the spatial dimensions of these impacts. Spatial details of the crop location, extent and distribution, and patterns of changes in crop rotation illuminate how agricultural practices have responded to changes in ethanol policy. Existing work pays less attention to examine spatial relationships between cultivated fields, and crop rotation practices, with respect to underlying soils and terrain.

We provide an in-depth geographical analysis of land use dynamics to better understand spatial dimensions of cropland change. We examine two hypotheses. First, as there has been a notable increase in biofuel production over previous years, crop production expanded into areas such as those formerly enrolled in the CRP, and into marginal or poor lands that are less suitable for growing crops. Second, as most of the land in Iowa is already used for agriculture, increases in corn production have been largely achieved by altering crop rotation patterns, causing a decline in crop diversity and redistribution of cornfields to most fertile and productive lands. We examine these hypotheses by analyzing 12 years of sequential Landsat imagery of a nine-county region of East-Central Iowa.

2. Study Area

This research investigates a nine-county region in East-Central Iowa (Figure 1), an area of low relief and gentle topography formed as glacial terrain and loess deposits. The southern half (approximately) of this area includes a portion of the Southern Iowa Drift Plain, rolling hills of Wisconsin-aged loess superimposed on Illinoian glacial till, forming some of the world's most productive agricultural land. Here northwest-southeast oriented drainage interfingers into glacial surfaces as forested channels. The southeastern corner includes a section of the Mississippi Alluvial Plain— alluvial deposits associated with the Mississippi River and its tributaries, bordered by limestone and dolomite cliffs. Locally it is formed largely as stream terraces, abandoned river channels, oxbow lakes, and backwater sloughs. The northern edge of the study area is the Iowan Surface, a low-relief surface of glacial till covered by shallow loess.

Approximately 90% of the total land in Iowa is used for agriculture with cropland mainly in private ownership (Petrov & Sugumaran, 2005). Iowa agriculture focuses upon production of cattle, hogs, corn, soybeans, oats, and eggs—a list that includes several products that compete for corn. Iowa is the United States' largest producer of corn and ethanol, and often leads in soybean production. As is typical for Corn Belt agriculture, corn and soybeans are grown in rotation—as noted below, increases in ethanol production have disrupted the accepted corn-soybean rotation, now often replaced by corn-corn-soybean rotation cycles (Bain & Selfa, 2013; Secchi et al., 2011; Stern et al., 2012). The study area covers three main markets for corn inputs (Gallagher, Wisner, & Brubacker, 2005). At least eleven biodiesel and ethanol plants within and near the study area rely upon local corn crops (Figure 2.1), including three established during the past seven years, after the change in biofuel policy (Iowa Department of Natural Resources, 2007). These plants are situated not only in proximity to corn production, but also near transport, including road, rail, and water. Despite the significance of ethanol production, locally and nationally, not all ethanol plants are successful.

3. Methods

3.1 Data

Four sources of data were used to identify changes of agricultural land use. The first set of data was the CDL for Iowa from 2001 through 2012 produced by USDA NASS (http://nassgeodata.gmu.edu/CropScape/). The spatial resolution is 56m for CDLs from 2006 to 2009 and 30m for CDLs from the other years. In order to analyze crop rotation changes over 12 years and compare with other data sets, CDLs from 2006 to 2009 were resampled to 30m. NASS indicates that CDLs have high user's and producer's accuracies for corn and soybeans, usually above 90% for Iowa (Table 2.1). Thus, the CDL appears to be a reliable source of data for crop rotation analysis. The second set was county-level CRP statistics from the US Department of Agriculture and a spatial data of land enrolled in USDA CRP in Iowa in 2008 from University of Iowa. There was no publically available spatial data on CRP lands for other years. The third set was the USGS National Elevation Data (NED) at 30m for Iowa (http://viewer.nationalmap.gov/viewer/), used to extract topographic slope. Lastly, Gridded Soil Survey Geographic (gSSURGO) Database for Iowa produced by USDA Natural Resources Conservation Service (NRCS) was used to identify Corn Suitability Rating (CSR) and land capability class (http://datagateway.nrcs.usda.gov/GDGOrder.aspx).

3.2 Analysis of Land Intensity

The CDLs from 2001 to 2012 were used to identify patterns of summer crops (corn and soybeans) within our region. These CDLs were converted to binary images, labeling pixels classified as corn or soybeans as “1” and labeling other land cover types as “0”. A

3×3 majority filter was applied to all binary images to reduce “salt and pepper” effects. Intensification of production practices for summer crops on a pixel-by-pixel basis were obtained by summarizing lands that were kept in production during 12 years. A five-year moving window (8 windows from 2001 to 2012) was applied to track spatial patterns of such intensification.

3.3 Characterizing Physical Factors

To evaluate the impacts of implementation of 2005/2007 biofuel policies upon long-term sustainability of agricultural land use, we associated land use (re)distribution with land quality and investigated the utilization of lands that have been under the CRP.

Firstly, we used slope, land capability class and CSR to determine whether higher corn prices may have encouraged farmers to use land that is not suited for production. Topographic slope values were extracted from USGS NED 30m DEM. Land capability class values and CSR values were obtained from 10m gSSURGO Database and they were resampled to 30m using the majority class value of 3 by 3 matrixes to represent each new pixel value. Land capability classification shows the suitability of soils for most kinds of field crops which is based on landscape location, slope of the field, depth, texture, and reaction of the soil (Douglas, 1992). It includes eight classes — classes 1 to 4 are arable lands in which classes 3 and 4 have severe to very severe limitations, respectively, and classes 5 to 8 are suitable mainly as pasture or rangeland. The CSR is a standard index of soil suitability for row crop production developed by the Iowa State University Extension (Miller, 2012). This index is based on soil type, slope, drainage, weather, and frequency of use for row crop production. The CSR varies from 0 to 100, where 100 is ideal soil for corn production. CSR for high productivity lands typically exceeds 80, and for low productivity lands generally remains under 65. We computed and compared the percentages of planted corn/soybeans in areas where the CSR was above and below 65 prior and after the implementation of 2005/2007 biofuel policies.

Secondly, we used county-level CRP statistics to determine CRP change pattern during 12 years. This data does not specify the land cover for CRP land as the great majority of CRP land in Iowa is covered with grasses (USDA Farm Service Agency, 2007). We then used 2008 CRP data to determine the overlap with lands planted with corn or other crops to identify weather CRP lands were used in production after the widespread of biofuel production. For our study area, the shapefile has 33,327 polygons covering 223,422 acres. Many of the areas that are set aside for CRP land are wetlands or drainage-ways and therefore are frequently small and irregular in shape. In order to remove these lands from the analysis, any polygons with areas less than 15 acres were excluded. Those remaining were intersected with the 2009 CDL to estimate an amount of 2008 CRP land converted to corn cultivation in 2009.

3.4 Determination of Crop Rotation Patterns

Crop rotation refers to the sequence of crops from year to year for a single field. The standard crop rotation in Iowa has been to alternate between corn and soybeans in consecutive years (Bain & Selfa, 2013; Sahajpal et al., 2014; Stern et al., 2012). Alternatively, some crop producers have chosen to plant corn or soybeans year after year in the same field. For the purpose of this study, CDLs were combined in two ways to determine changes in crop rotation before and after the widespread increases in biofuel production. First, areas with corn for three consecutive years from 2001 to 2012 were measured using conditional statements. A binary classification was created where pixels classified as corn were labeled 1 and other land cover types were labeled 0. Three years were added sequentially and pixels with 3 were considered as continuous corn rotation. Second, we analyzed crop rotation patterns for corn and soybeans over six-year intervals (2002-2007 and 2007-2012), which will give us 64 possible permutations. Except for the standard crop rotation, two or more years of continuous corn provide several choices of rotation sequences. Continuous soybean rotation is not a common occurrence in Iowa (Secchi et al., 2011) because growing soybeans year-after-year in the same field create serious problems with soybean nematodes which have negative effects on soybean yield (Koenning et al., 1995). For a six-year period, we classified all the possible rotation choices into 5 classes by the number of years with corn: corn-soybean/soybean-corn, corn-corn-soybean/soybean-corn-corn, continuous corn, more than three years of continuous corn, and other which including two or more years of continuous soybean.

4. Results

4.1 Intensity of Cultivated Land

Using a five-year moving window, production trends can be analyzed. Over five years, the area in summer crop cultivation for both more than two years and more than three years increased in the period from 2001 to 2012 (Figure 2.2). These trends corresponded to price trends for corn and soybeans based on NASS statistics. From 2001 to 2012, both corn and soybean prices increased from 2009, reaching a maximum in 2012, with, at the state level, other peaks in 2003 and 2007 (USDA National Agricultural

Statistics Service). These trends indicated increases in cultivated land intensity, which may be attributed to the higher demand for corn created by the increasing production capacity of ethanol plants (Renewable Fuels Association, 2013).

Summer crops were cultivated in a way that illustrates place-to-place differences in timing and intensity of land uses (Figure 2.3). Most areas were planted with continuous summer crops, but fragmented terrain bordering rivers and valleys were used less intensively, perhaps because floodplains may be narrow, have steep slopes, or problematic soils. Areas at edges of fields, known as *headlands*, or *turnrows* (narrow, uncropped, strips for turning farm machinery at the ends of rows), were often uncultivated or used less intensively. Together, such conditions may lead these areas to be used for secondary crops, grasslands, or pastures.

At county level, Benton County had the least proportion of area (10.21%), used only for 1 to 3 years while Keokuk County had the most proportion of such areas (27.07%). Cedar County had the most proportion of areas (67.87%) that were used for 11 or 12 years while Keokuk County had the least proportion of such areas (41.86%).

4.2 Cropland Redistribution and Land Suitability

Slope values for areas with different cultivated land intensity within the study area were compared. Land with shallow slopes was used more intensely (Figure 2.4). The most intensively used land (11 or 12 years with summer crop) had slopes of less than six degrees, suitable for mechanization. Slope values of these five classes were significantly different ($P < 0.0001$) according to Wilcoxon Rank Sums/ Kruskal-Wallis Tests. There were less than 0.01% outliers (black crosses in Figure 2.4), most located at edges of fields. Some had extremely high slopes which are impossible for cultivation, perhaps caused by misclassification.

Capability class values for areas with different cultivated land intensities in the study area were compared (Figure 2.5). The smaller the class value designation, the fewer limitations for cultivation. The majority of lands (above 82%) in the study area are arable, within which 56% have few limitations. As land intensity (measured by numbers of years in cultivation) increased, more land with fewer limitations was brought in cultivation (Figure 2.5). Thirty-five percent (35%) of the least intensively used land (1-3 years with summer crops) had fewer limitations while above 63% most intensively used land (11 or 12 years with summer crop) had fewer limitations.

The quality of agricultural land in Iowa is often assessed using CSR for a given type of soil (ISU, 2005). Lands with CSR higher than 65 are generally considered as highly productive lands. The percentage of total corn planted land on high CSR soil increased from 50% in 2000 to 60% in 2007. Since 2007, the percentage of corn on high CSR soil has fluctuated and returned to 50% in 2012. In contrast, the percentage of total soybeans planted land on high CSR soil decreased from 37% in 2000 to 27% in 2007, but has fluctuated and back up to 37% in 2012 (Figure 2.6). At the same time, both area under corn and soybeans planted in low CSR soil remained constant, with about 0.7% increase for corn and about 0.7% decrease for soybeans from 2000 to 2007. These data provide evidence that the most productive lands were used the most intensively (Figure 2.7) and were allocated to grow corn (Figure 2.6). During the interval 2006 to 2007, more and more corn was placed on high-quality soils whereas soybeans were removed from high quality soils. Major corn acreage gains were generally at the expense of soybeans. At the same time, the increasing percentage of corn on low quality soils suggest that expansion of lands used for planting corn also occurred at the expense of other land cover types, such as grasslands (Wright & Wimberly, 2013) and wetlands (Johnston, 2013).

USDA stated that CRP has shifted from designating entire fields for conservation purposes towards the alternative of implementing high-priority “buffer” practices (e.g., filter strips, grassed waterways) that support working lands by reducing the environmental implications of on-going agricultural production (USDA 2006). CRP statistics show that in 2007 the total amount of area under CRP remained high. CRP land dynamics depend on enrollment and re-enrollment cycles set by a 10-15 year contract that commits CRP status until the expiration date. This 10-year cycle resulted in over 16 million acres enrolled in 1997, potentially expiring in 2007 (Stubbs, 2014). Thus, there were very few CRP contract expirations before the widespread increases in biofuel production. Since 2007, CRP enrollment declined sharply, especially for Iowa County and Keokuk County (USDA Farm Service Agency, 2014). This trend indicates that producers may be allowing their contracts to expire in favor of using productive land for crops. Econometric models also predict that landowners will be likely to withdraw some land from expiring CRP contracts and put the land back into crop production within the high-priced commodity market (Hellerstein & Malcolm, 2011; Secchi et al., 2009).

With spatial data analysis, total amount of CRP land classified as corn in 2009 was extremely small: in 2009 only about 4200 acres of cornfield were in 2008 CRP areas. This area is not significantly large, as it represents only 2% of the total CRP acreage in the study area and could be a result of misclassification. According to 2007 FSA (USDA Farm Service Agency, 2007), only about 2% of corn and soybean farms in 2008 brought

CRP acreage into production between 2006 and 2008. It is very difficult to appropriately attribute certain CRP lands to particular land cover types because of differences in the spatial resolution of CRP data in comparison to CDL data. Thus, there is no indication that the widespread increases in biofuel production have had a particularly negative effect on the CRP program. Given the tendency to plant more corn on higher quality soils that we mentioned earlier, it is unlikely that CRP lands would be used for corn production.

4.3 Crop Rotation

NASS's Prospective Plantings (USDA Agricultural Statistics Board, 2007) report indicated that much of the 2007 increase in corn acreage would come from reduced soybean plantings. Based on our crop rotation analysis over three-year intervals, more crop producers chose to plant corn for three consecutive years in the year of 2007 (Figure 2.8). As mentioned earlier, corn prices were high in 2003, 2007 and after 2009, thus, producers preferred to plant corn in that year and the following year (Wallander et al., 2011).

All 64 possible permutations of corn and soybean rotations were recorded before 2007 but only half of them were used after 2007. Crop producers preferred to plant corn or soybean consecutively after 2007. During the 2002-2007 periods, there was 36.09% cultivated land with standard rotation (either corn-soybean or soybean-corn) (Figure 2.9). These lands were located in the most intensively used lands. Two years of continuous corn was another common occurrence during this period. Both lands with more than three years continuous corn and lands with two or more years of continuous soybeans were less than 10%. During the 2007-2012 periods, standard rotation was replaced by more intensive rotation, such as continuous corn or soybeans for two years, or even longer (Figure 2.10). Two or more years of continuous soybeans also became a common occurrence. As its negative effects on soybean yield (Koenning et al., 1995), this kind of rotation was selected because of high soybean price or because of the classification error of CDLs. During this period, area under corn-corn rotations decreased, while area under three and more years of continuous corn and area under two or more years of continuous soybeans increased. Our results are inconsistent with the rotation change patterns reported in the central US for four-year intervals (2003-2006 and 2007-2010), where area under corn-soybean rotation decreased, and area under corn-corn rotations increased (Plourde et al., 2013). One explanation is that we used six-year intervals, so crop rotation patterns for two or more years of continuous corn during the 2007-2012 periods were determined by the first four years after 2007 — more than 80% of such rotations were during the 2007-2010 periods. After 2010, the standard rotation pattern appeared again.

It is obvious that crop rotation changes after 2007 (Figure 2.11). 59.11% of standard rotation was changed to more two or more years of continuous corn, and 40.89% of standard rotation was changed to two or more years of continuous soybeans. Lands with two or more years of continuous corn were more abundant than lands with two or more years of continuous soybeans. These results clearly indicate that increases in corn production over multiple years have been achieved mainly by altering crop rotation.

5. Discussions[2]

This study examines both spatial and temporal dimensions of agricultural land use dynamics using NASS CDLs. According to the Iowa's CDL metadata, most of the

[2] Additional section for the original manuscript submitted to *Agricultural Systems.*

producer's accuracies and user's accuracies (starting in 2007) for corn and soybeans for each year are above 90% (Table 2.1). When compared to the county-level, survey-based planted acreage data for corn and soybeans for each year (USDA National Agricultural Statistics Service), CDLs underestimate corn and soybeans acreage in most years (Table 2.2). Large differences occur in 2001 (for corn), 2002 (for soybeans), 2003 (for soybeans), and 2007 (for corn and soybeans). The uncertainty caused by misclassification would influence the patterns of total acreage of summer crops within a five-year moving window and land intensity. For example, more land were actually used for summer crops production than CDLs estimates in the 2003-2007 moving window, thus, the total acreage of more than two/three years within five years of summer crops should be larger than the values based on CDLs estimates (Figure 2a). Crop rotation patterns for corn and soybeans over six-year intervals based on these data would be more accurate as the differences have fewer impacts for longer periods.

In order to measure the effect of ethanol plants on land use choices, we calculated land use change from 2004 to 2010 within a 10-mile radius of each ethanol plant. According to the interview response from some farmers in Iowa, farmers would like to sell their corn products directly to ethanol plants if the ethanol plants are not far away (i.e., around 10min driving). Thus, a 10-mile radius is reasonable for our analysis. We first calculated corn acreage and soybean acreage for each year within a 10-mile radius of each ethanol plant. We found that compared to 2006, corn acreage in 2007 increased by 6% while soybean acreage decreased by 29%, and the total summer crop decreased by 11% (Figure 2.12). In 2007, more land was used for corn production and expansion of corn acreage may result from a reduction in soybean acreage. After 2007, corn acreage increased steadily and soybean acreage increased to a stable level. We than examined three crop rotation patterns for corn and soybeans over three-year intervals (i.e., standard corn-soybean/soybean-corn, two years of continuous corn, and continuous corn) within a 10-mile radius of each ethanol plant. We found that land under standard corn-soybean/soybean-corn rotation increased constantly, land under two years of continuous corn rotation reached its highest level in 2006-2008, and land under continuous corn rotation reached its highest level in 2007-2009 (Figure 2.13). The expansion of corn acreage after 2007 was also realized by altering crop rotation patterns to more intensive corn rotation.

6. Conclusions

This study examines both spatial and temporal dimensions of agricultural land use dynamics 2001-2012 in east-central Iowa. This interval includes the years immediately preceding and immediately following changes in US biofuel policy, which has resulted in notable changes in the region's agricultural land use. Agricultural producers can respond to demands or incentives for increased production either through land extensification or land intensification.

From 2001 to 2012, biofuel production has increased in Iowa. As biofuel production increased, demand for corn and its market price have increased, likely leading to changes in land-use intensity and changes in crop rotation. Corn acreage growth occurred generally at the expense of soybeans, other crops, and grasslands. As recorded by NASS CDLs, after 2007, cultivated acreage increased, and standard crop rotation was changed to more intensive series of corn or soybeans plant, on a pixel-by-pixel basis. In addition, area used for both corn cultivation and soybeans cultivation increased. The most intensively cultivated land had shallower slopes and fewer pedologic limitations than others, and the most valuable crop (corn) was planted on the most suitable soils. CRP lands were brought into cultivation since 2007, but they may be used for other crops displaced by corn because they are usually unsuitable for corn production. From our analysis, it is clear that the expansion of corn production after 2007 was realized by altering crop rotation patterns.

However, some producers were not as committed to changes in crop rotation strategies when they applied two years of continuous corn rotation — our analysis shows a pattern that displays coherent groupings that did not change crop rotation strategies. In a small area with similar climate and soil, nearby fields were also applied different types of crop rotation (Figures 2.9, 2.10, and 2.11). Considerations for these differences may include fertilizer application rates, tillage choices, and propinquity to biofuel plants, although specifics are not clear from our analysis. Fertilizer application rates and tillage choices vary spatially and influence yields, which are linked to choices of crop rotation (Katsvairo & Cox, 2000; Vetsch et al., 2007). There is field-level evidence that corn yields under standard crop rotation exceed yields under two or three years of continuous corn (Katsvairo & Cox, 2000; Pikul et al., 2005). Therefore, two or three years of continuous corn tend to be more heavily fertilized in order to increase yields, leading to larger nutrient and soil losses. Production capacities of biofuel plants increased as new plants were constructed in our study region after 2007. Local availability of multiple biofuel plants provided convenient and inexpensive options for the regional corn market, offering alternative choices for corn producers. In the future, we will explore the context in which producers and other agricultural managers are motivated and constrained in their land use and cropping decisions.

References

Bain, C., & Selfa, T. (2013). Framing and reframing the environmental risks and economic benefits of ethanol production in Iowa. *Agriculture and Human Values, 30*(2013), 351–364. doi:10.1007/s10460-012-9401-y

Brown, J. C., Hanley, E., Bergtold, J., Caldas, M., Barve, V., Peterson, D., … Earnhart, D. (2014). Ethanol plant location and intensification vs. extensification of corn cropping in Kansas. *Applied Geography, 53*, 141–148. doi:10.1016/j.apgeog.2014.05.021

Douglas, H. (1992). *Readings in the History of the Soil Conservation Service*.

Gallagher, P., Wisner, R., & Brubacker, H. (2005). Price Relationships in Processors' Input Market Areas: Testing Theories for Corn Prices Near Ethanol Plants. *Canadian Journal of Agricultural Economics/Revue Canadienne D'agroeconomie*, *53*(2-3), 117–139. doi:10.1111/j.1744-7976.2005.00414.x

Hellerstein, D., & Malcolm, S. (2011). *The Influence of Rising Commodity Prices on the Conservation Reserve Program*.

Iowa Department of Natural Resources. (2007). Ethanol and Biodiesel Facilities in Iowa. Retrieved from ftp://ftp.igsb.uiowa.edu/gis_library/ia_state/infrastructure/facilities/ethanol_biodiesel_facilities.zip

Johnston, C. A. (2013). Wetland Losses Due to Row Crop Expansion in the Dakota Prairie Pothole Region. *Wetlands, 33*(1), 175–182. doi:10.1007/s13157-012-0365-x

Johnston, C. A. (2014). Agricultural expansion: land use shell game in the US Northern Plains. *Landscape Ecology*, *29*(1), 81–95.

Katsvairo, T. W., & Cox, W. J. (2000). Economics of cropping systems featuring different rotations, tillage, and management. *Agronomy Journal*, *92*(3), 485–493.

Keeney, R., & Hertel, T. W. (2009). The indirect land use impacts of United States biofuel policies: The importance of acreage, yield, and bilateral trade responses. *American Journal of Agricultural Economics*, *91*(November), 895–909. doi:10.1111/j.1467-8276.2009.01308.x

Koenning, S. R., Schmitt, D. P., Barker, K. R., & Gumpertz, M. L. (1995). Impact of crop rotation and tillage system on Heterodera glycines population density and soybean yield. *Plant Disease*, *79*(3), 282–286.

Langpap, C., & Wu, J. (2011). Potential Environmental Impacts of Increased Reliance on Corn-Based Bioenergy. *Environmental and Resource Economics*, *49*, 147–171. doi:10.1007/s10640-010-9428-8

Miao, R. (2010). The Land-use change effect of ethanol plants in Iowa: 1997–2009, 22. Retrieved from http://www.aeaweb.org/aea/2011conference/program/retrieve.php?pdfid=506

Miller, G. (2012). Corn Suitability Ratings — An Index to Soil Productivity. *Staff General Research Papers. Iowa State University, Department of Agronomy*.

Miyake, S., Renouf, M., Peterson, A., McAlpine, C., & Smith, C. (2012). Land-use and environmental pressures resulting from current and future bioenergy crop expansion: A review. *Journal of Rural Studies*, *28*(4), 650–658. doi:10.1016/j.jrurstud.2012.09.002

Mueller, S., & Copenhaver, K. (2009). *Determining the Land Use Impact of Two Midwestern Corn Ethanol Plants*.

Petrov, A. N., & Sugumaran, R. (2005). Monitoring and Modeling Cropland Loss in Rapidly Growing Urban and Depopulating Rural Counties Using Remotely Sensed Data and GIS. *Geocarto International*, *20*(4), 45–52. doi:10.1080/10106040508542363

Pikul, J. L., Hammack, L., & Riedell, W. E. (2005). Corn yield, nitrogen use, and corn rootworm infestation of rotations in the northern Corn Belt. *Agronomy Journal*, *97*(3), 854–863. doi:10.2134/agronj2004.0263

Plourde, J. D., Pijanowski, B. C., & Pekin, B. K. (2013). Evidence for increased monoculture cropping in the Central United States. *Agriculture, Ecosystems and Environment*, *165*, 50–59. doi:10.1016/j.agee.2012.11.011

Renewable Fuels Association. (2013). Annual Industry Outlook. Retrieved from http://www.ethanolrfa.org/pages/annual-industry-outlook

Sahajpal, R., Zhang, X., Izaurralde, R. C., Gelfand, I., & Hurtt, G. C. (2014). Identifying representative crop rotation patterns and grassland loss in the US Western Corn Belt. *Computers and Electronics in Agriculture*, *108*, 173–182. doi:10.1016/j.compag.2014.08.005

Secchi, S., Gassman, P. W., Williams, J. R., & Babcock, B. a. (2009). Corn-Based Ethanol Production and Environmental Quality: A Case of Iowa and the Conservation Reserve Program. *Environmental Management*, *44*(4), 732–44. doi:10.1007/s00267-009-9365-x

Secchi, S., Kurkalova, L., Gassman, P. W., & Hart, C. (2011). Land Use Change in a Biofuels Hotspot: The Case of Iowa, USA. *Biomass and Bioenergy*, *35*(6), 2391–2400. doi:10.1016/j.biombioe.2010.08.047

Simpson, T. W., Sharpley, A. N., Howarth, R. W., Paerl, H. W., & Mankin, K. R. (2006). The new gold rush: fueling ethanol production while protecting water quality. *Journal of Environmental Quality*, *37*, 318–324. doi:10.2134/jeq2007.0599

Stan, V., Fîntîneru, G., & Ion, V. (2014). Increase of Biofuel Crop Production in Romania over the Last Decades - Possible Impacts on Environment , Greenhouse Gas Emissions and Land Use. *Notulae Botanicae Horti Agrobotanici Cluj-Napoca*, *42*(2), 325–332. doi:10.1583/nbha4229740

Stern, A. J., Doraiswamy, P. C., & Hunt, E. R. (2012). Changes of crop rotation in Iowa determined from the United States Department of Agriculture , National Agricultural Statistics Service cropland data layer product data layer product. *Journal of Applied Remote Sensing*, *6*(1), 063590–063590. doi:10.1117/1.JRS

Stubbs, M. (2014). *Conservation Reserve Program (CRP): Status and Issues*.

Swinton, S. M., Babcock, B. a., James, L. K., & Bandaru, V. (2011). Higher US crop prices trigger little area expansion so marginal land for biofuel crops is limited. *Energy Policy*, *39*(9), 5254–5258. doi:10.1016/j.enpol.2011.05.039

USDA Agricultural Statistics Board. (2007). *Prospective Plantings* (Vol. 4). Washington, D.C.

USDA Farm Service Agency. (2007). *The conservation reserve program: summary and enrollment statistics 2007*. Retrieved from http://www.fsa.usda.gov/Internet/FSA_File/annual_consv_2007.pdf

USDA Farm Service Agency. (2014). *CRP Enrollment and Rental Payments by County, 1986–2013*. Retrieved from www.fsa.usda.gov/FSA/webapp?area=home&subject=copr&topic=crp-st

USDA National Agricultural Statistics Service. (n.d.-a). Acreage. Retrieved from http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1000

USDA National Agricultural Statistics Service. (n.d.-b). Agricultural Prices. Retrieved from http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1002

USDA National Agricultural Statistics Service. (2006). *2007 Farm Bill Theme Papers: Conservation and the Environment*.

Vetsch, J. A., Randall, G. W., & Lamb, J. A. (2007). Corn and soybean production as affected by tillage systems. *Agronomy Journal*, *99*(4), 952–959. doi:10.2134/agronj2006.0149er

Wallander, S., Claassen, R., & Nickerson, C. (2011). *The Ethanol Decade: An Expansion of U.S. Corn Production, 2000-09*. Retrieved from http://www.ers.usda.gov/media/121204/eib79.pdf

Westcott, P. (2007). *Ethanol Expansion in the United States: How Will the Agricultural Sector Adjust?* Washington DC. Retrieved from http://www.ers.usda.gov/publications/AboutPDF.htm

Wright, C. K., & Wimberly, M. C. (2013). Recent land use change in the Western Corn Belt threatens grasslands and wetlands. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(10), 4134–9. doi:10.1073/pnas.1215404110

Wu, Y., Liu, S., & Li, Z. (2012). Identifying potential areas for biofuel production and evaluating the environmental effects: A case study of the James River Basin in the Midwestern United States. *GCB Bioenergy*, *4*, 875–888. doi:10.1111/j.1757-1707.2012.01164.x

Table 2.1. Producer's accuracy (Prod.Acc.) and user's accuracy (User Acc.) for corn and soybeans, and overall accuracy (Overall Acc.) by year for the Iowa Cropland Data Layer (CDL).

	Corn		**Soybeans**		
	Prod.Acc.	**User Acc.**	**Prod.Acc.**	**User Acc.**	**Overall Acc.**
2001	89.6%	NA	91.0%	NA	81.3%
2002	96.3%	NA	95.0%	NA	88.6%
2003	92.5%	NA	93.0%	NA	88.5%
2004	97.4%	NA	98.7%	NA	93.2%
2005	94.0%	NA	95.4%	NA	88.0%
2006	87.5%	NA	86.9%	NA	83.2%
2007	97.5%	97.6%	97.0%	96.7%	97.2%
2008	96.6%	97.9%	96.2%	95.8%	95.7%
2009	97.9%	98.1%	97.0%	97.7%	95.5%
2010	96.6%	97.6%	95.8%	97.3%	93.2%
2011	98.3%	98.4%	97.4%	97.8%	94.3%
2012	96.6%	98.3%	95.6%	97.0%	93.6%

NA: User's accuracies are not provided in CDL metadata from 2001 to 2006.

Table 2.2. Total acreage for corn and soybeans based on Cropland Data Layers (CDLs) and USDA National Agricultural Statistics Service (NASS) Acreage data, and the differences between these two datasets, 2001-2012.

	Corn			Soybeans		
	CDL (acre)	Survey (acre)	Diff	CDL (acre)	Survey (acre)	Diff
2001	892279	1056000	-16%	953263	962000	-1%
2002	1203476	1112500	8%	694836	920000	-24%
2003	1143077	1133500	1%	785676	933000	-16%
2004	1118461	1165000	-4%	908376	897500	1%
2005	1053451	1158000	-9%	831540	884500	-6%
2006	1078191	1125000	-4%	898897	906500	-1%
2007	1161047	1317000	-12%	634356	733500	-14%
2008	1149874	1213000	-5%	780460	838200	-7%
2009	1159278	1243000	-7%	820395	851500	-4%
2010	1253974	1237500	1%	819436	860200	-5%
2011	1263732	1304500	-3%	780382	818900	-5%
2012	1182490	1283000	-8%	776598	844900	-8%

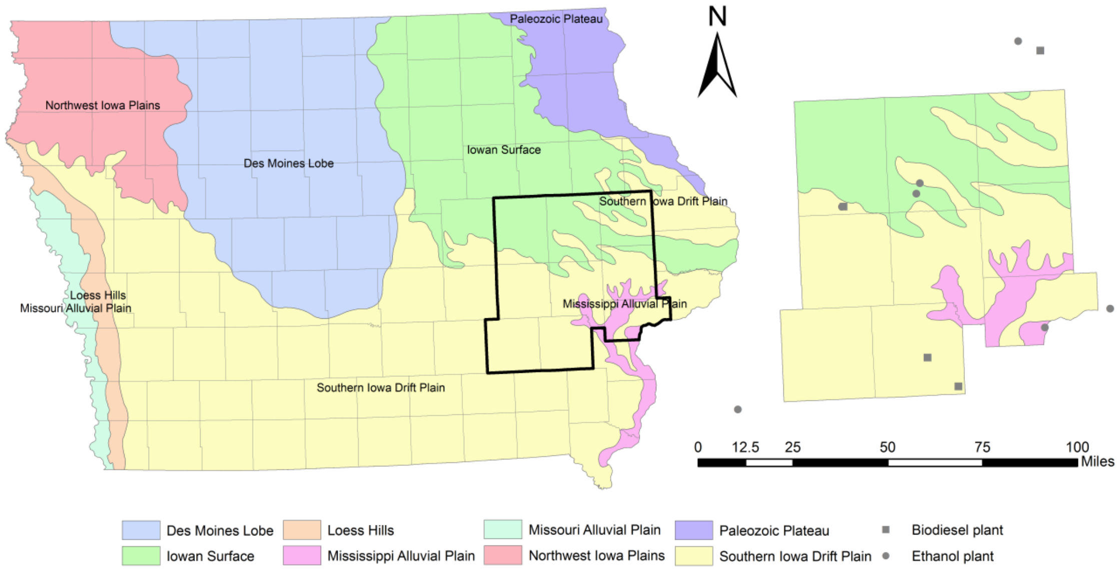

Figure 2.1. Study area in south-eastern Iowa, shown with major landforms of Iowa, adapted from Prior (1991). Locations of ethanol plants are symbolized with grey filled circles and locations of biodiesel plants are symbolized with grey filled boxes.

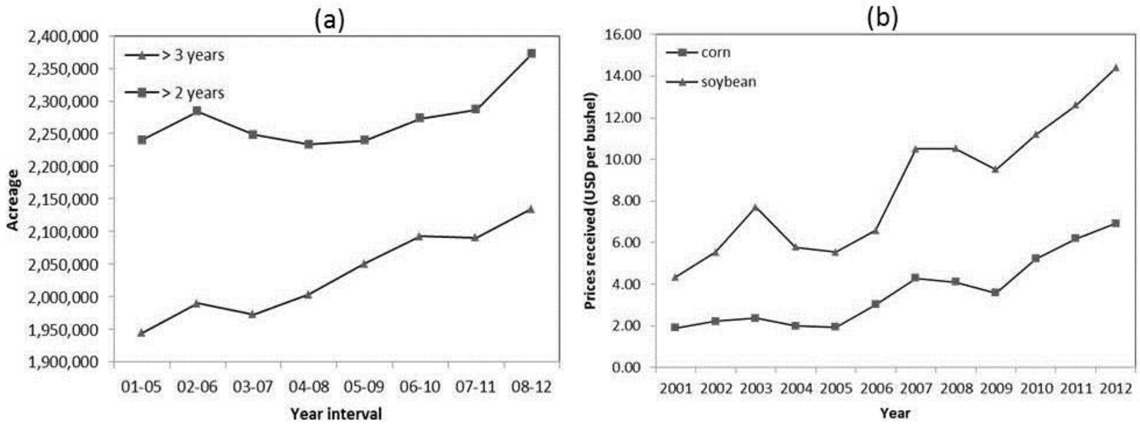

Figure 2.2. Left: Total acres of summer crops by a five-year moving window from 2001 to 2012 in the study area. Lines with black squares indicates more than two years within five years of summer crops, and lines with black triangles indicate more than three years within five years with summer crop within a five-year window. Right: Prices in US dollars (USD) for corn and soybean in Iowa, 2001-2012.

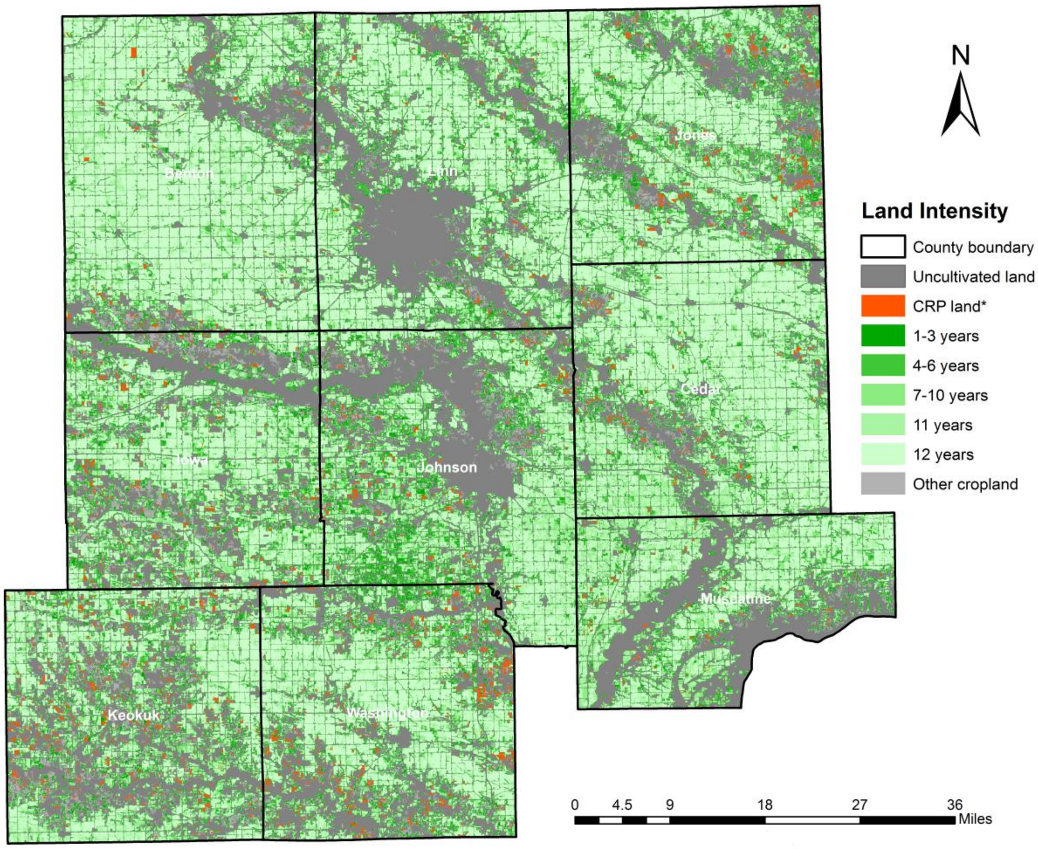

Figure 2.3. Cultivated land intensity class from 2001 to 2012 in the study area, the lighter the color, the more intensively the land in cultivation. CRP land is only for 2008.

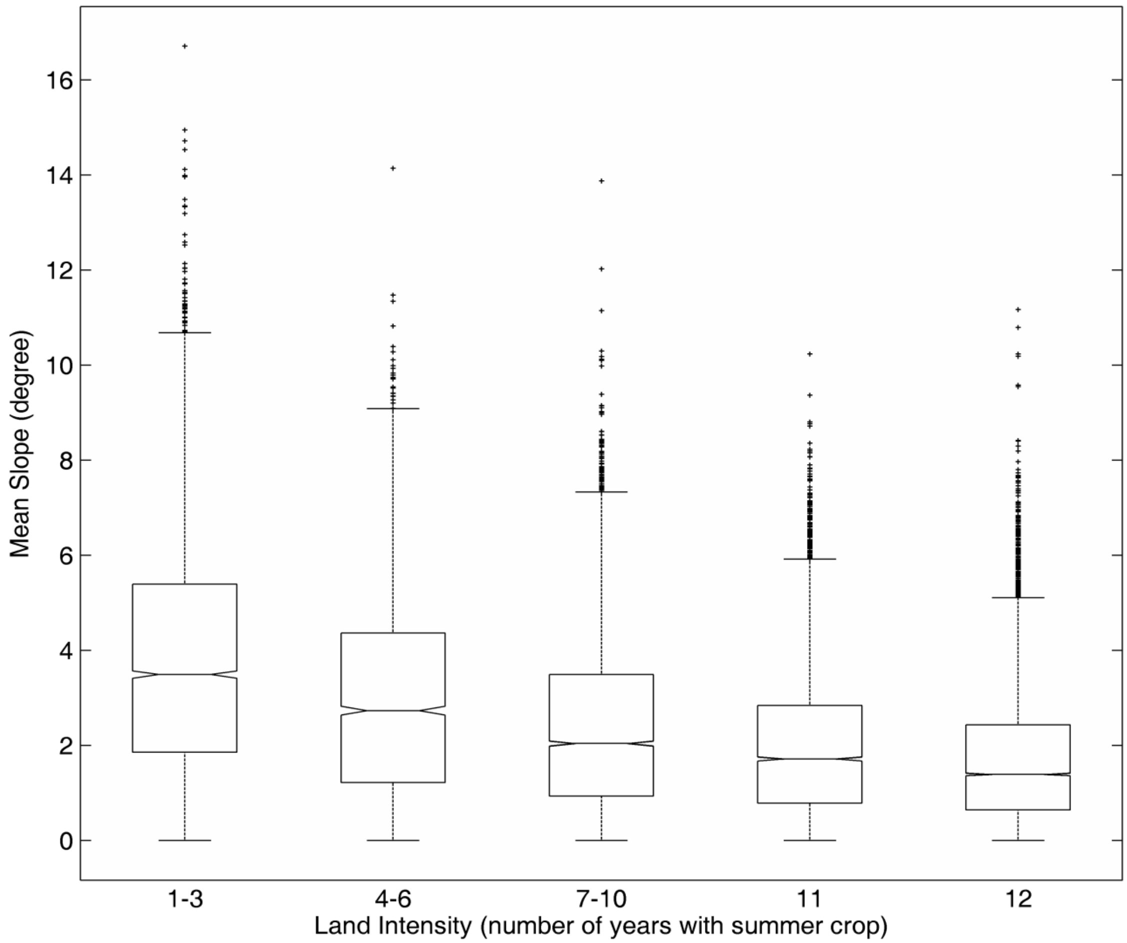

Figure 2.4. Relationships between cultivated land intensity and terrain slope (degrees) within the study area. Lands with shallower slopes are used more intensely. Black crosses represent outliers (they are few in number relative to the totals, almost all located at edges of fields).

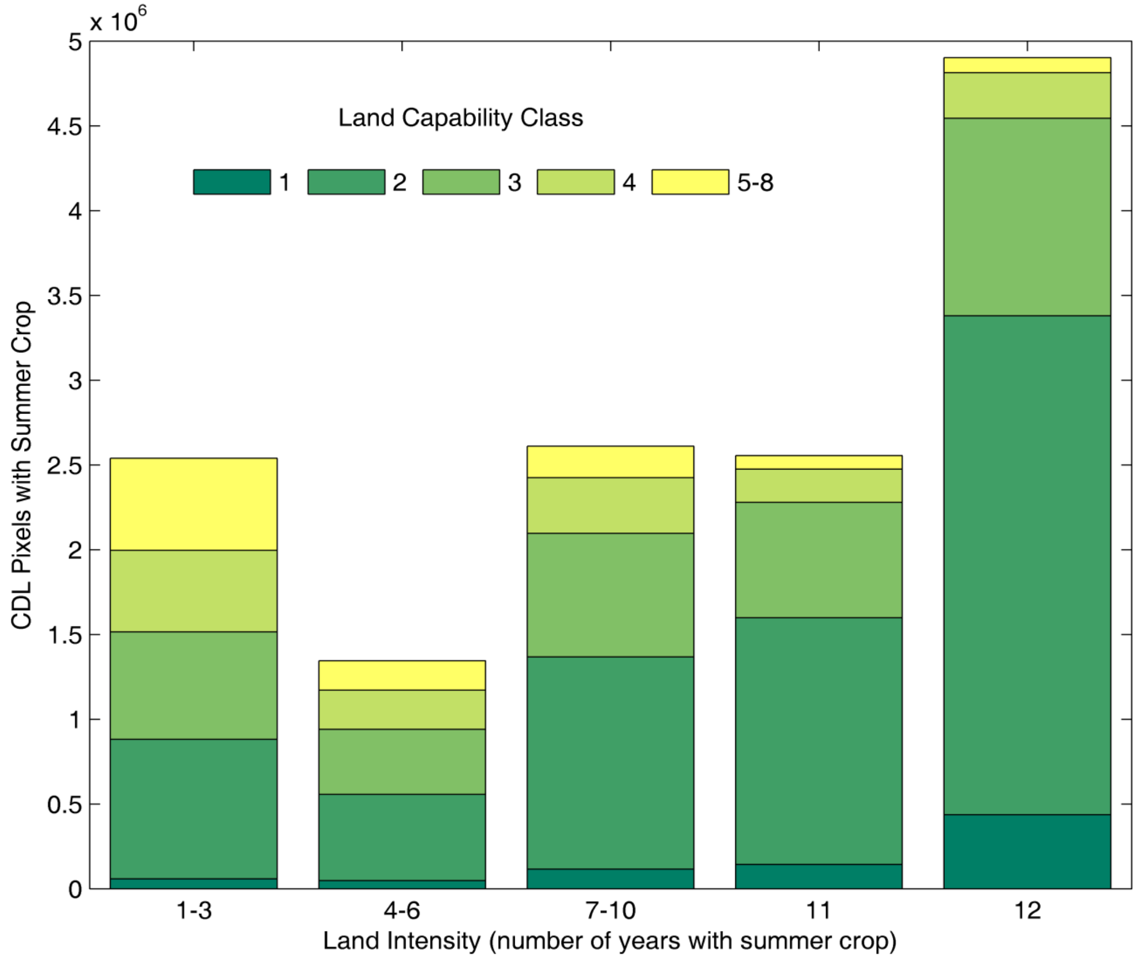

Figure 2.5. Relationships between cultivated land intensity and land capability class within the study area. Land capability classes 1 to 4 are arable lands in which classes 3 and 4 have severe to very severe limitations, respectively, and land capability classes 5 to 8 are suitable mainly as pasture or rangeland. The most intensively used lands tend to have fewer limitations (capability classes 1 and 2).

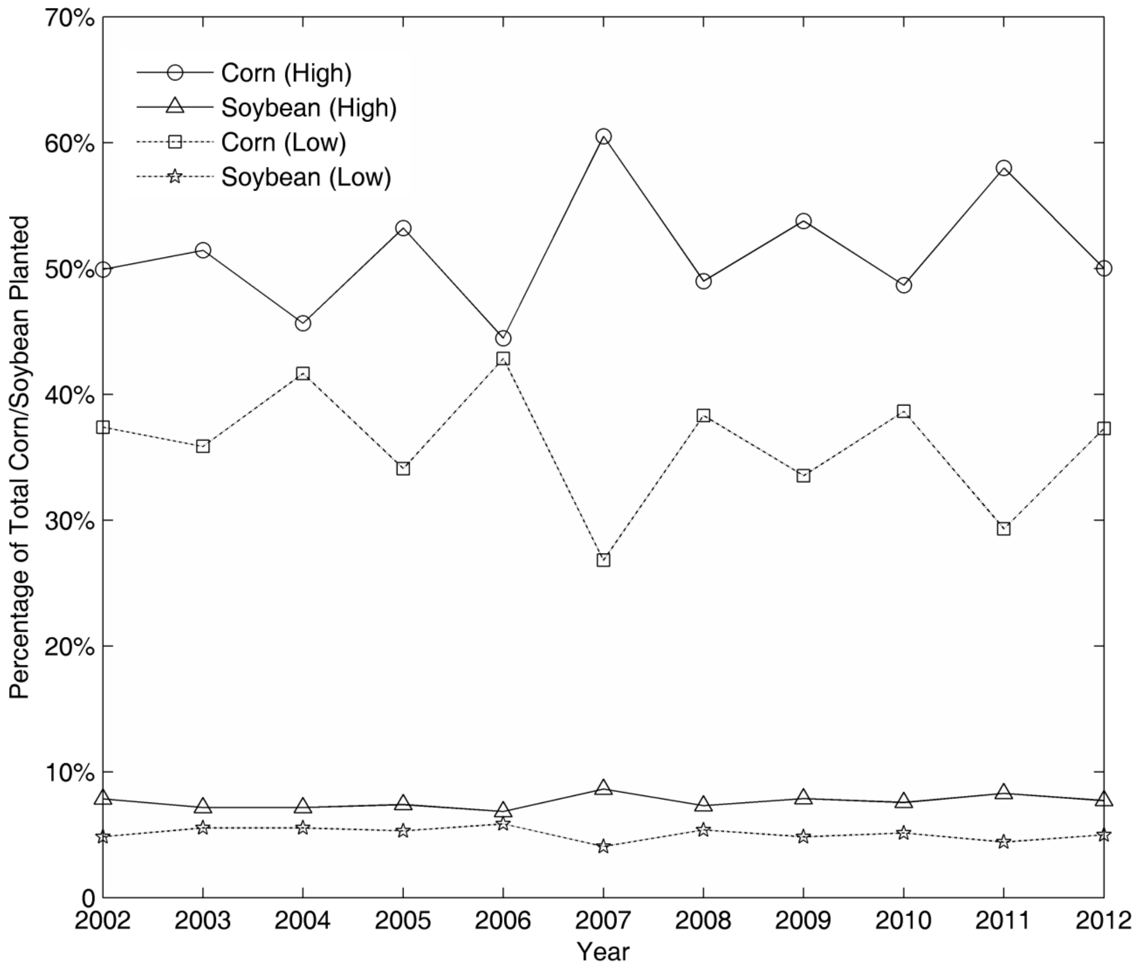

Figure 2.6. The percent of corn and soybeans on high (CSR > 65) and low (CSR < 65) Corn Suitability Rating (CSR) soil for 2002 to 2012. The percentage of total corn-planted land on high CSR soil increased from 2002 to 2007, and then fluctuated; while the percentage of total soybean-planted land on high CSR soil decreased from 2002 to 2007, and then fluctuated thereafter. During the same time, area both under corn and soybeans planted in low CSR soils remained constant.

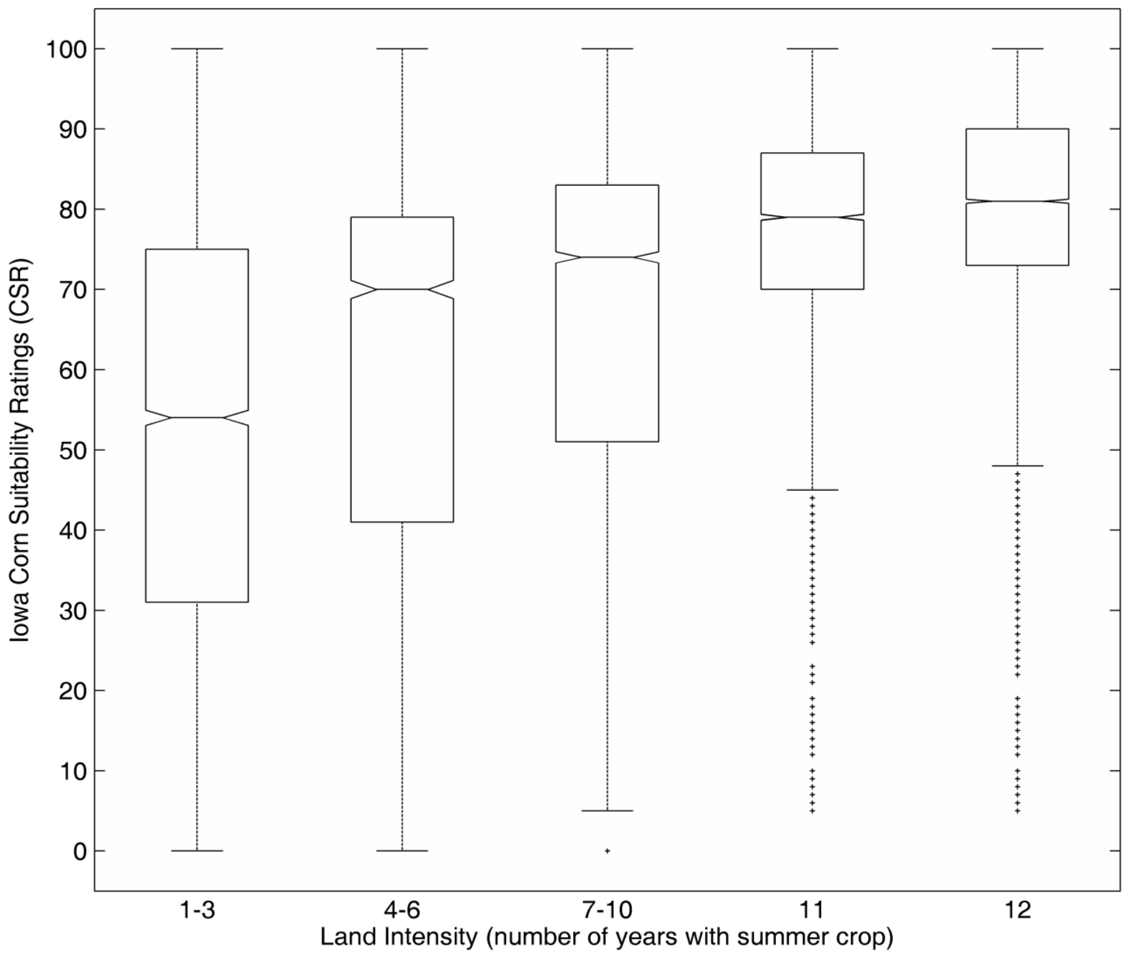

Figure 2.7. Relationship between cultivated land intensity and Corn Suitability Rating (CSR) in the study area. Lands with high CSR soil are used more intensely. Black crosses represent outliers.

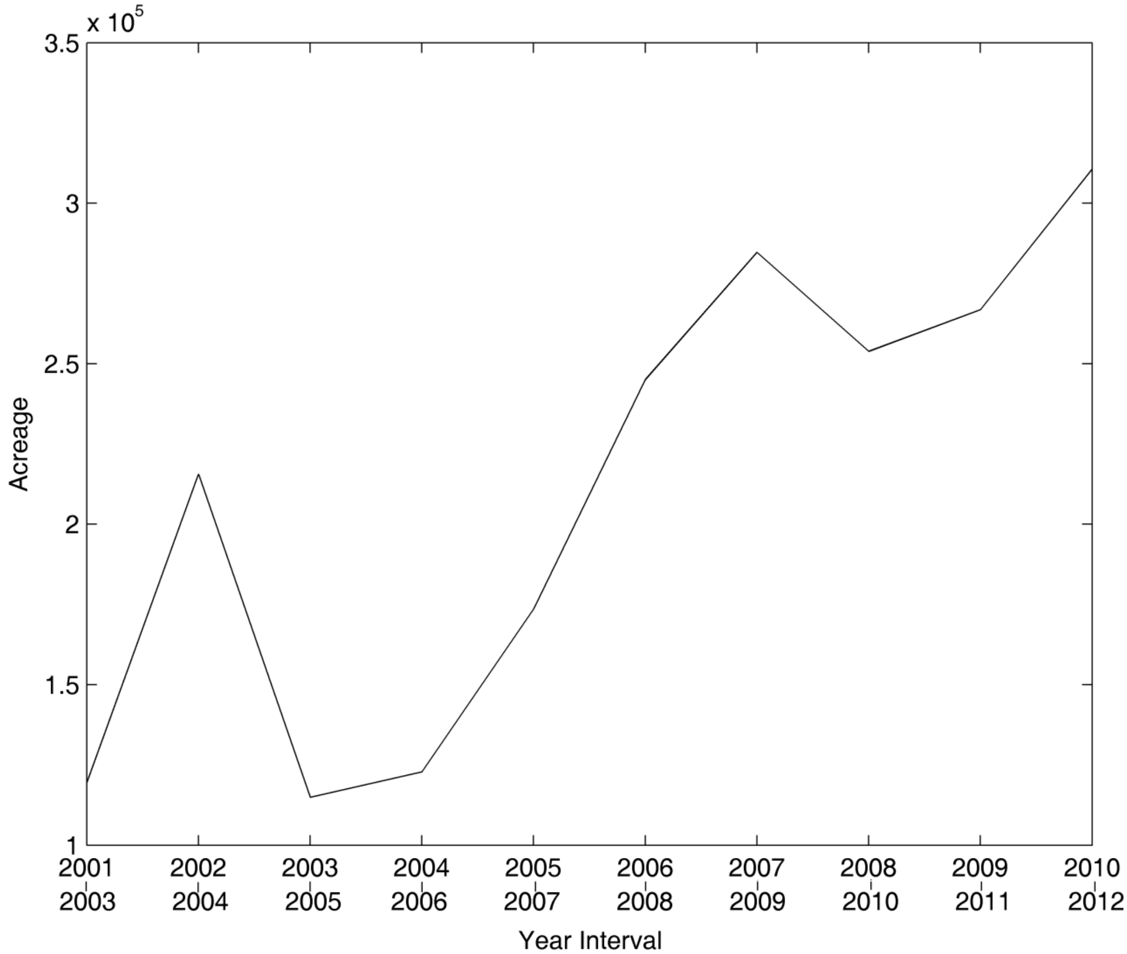

Figure 2.8. Acreage of three-year consecutive plantings of corn in the study area.

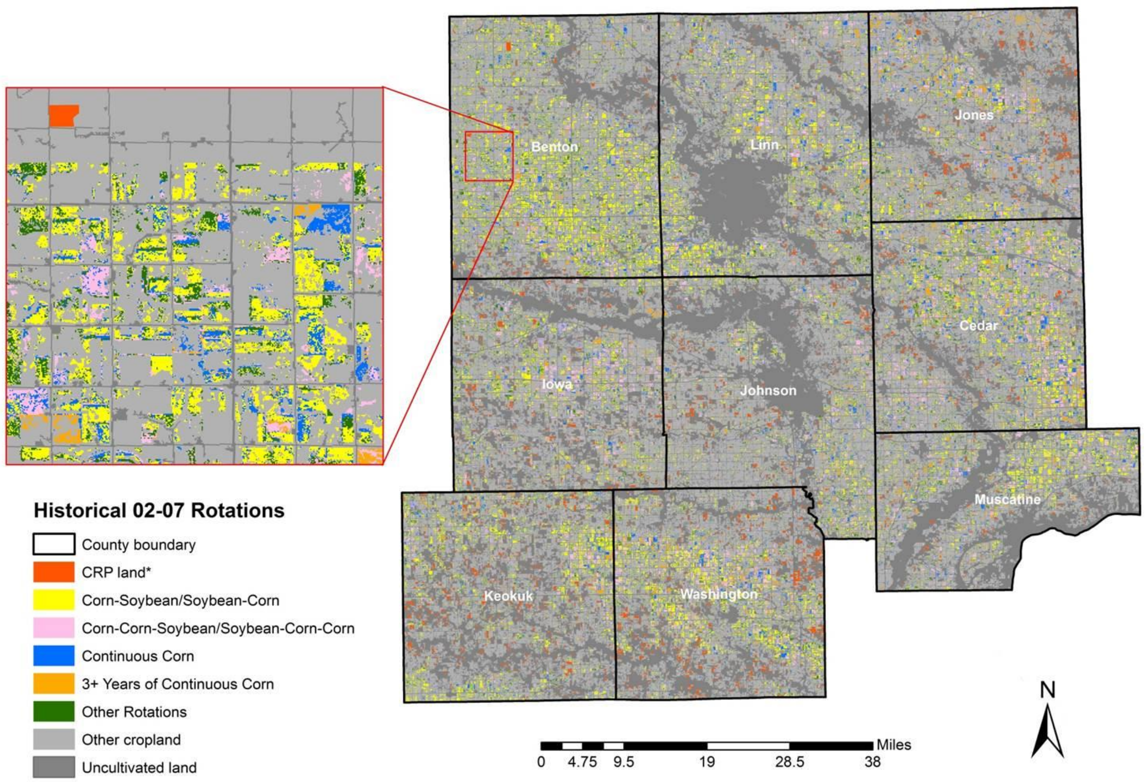

Figure 2.9. Location of 2002-2007 crop rotations in the study area, rotation types include standard rotation (either corn-soybean or soybean-corn), two years of continuous corn, three years of continuous corn, more than three years of continuous corn, and other rotation including two and more years of continuous soybeans. Along with 2008 CRP land.

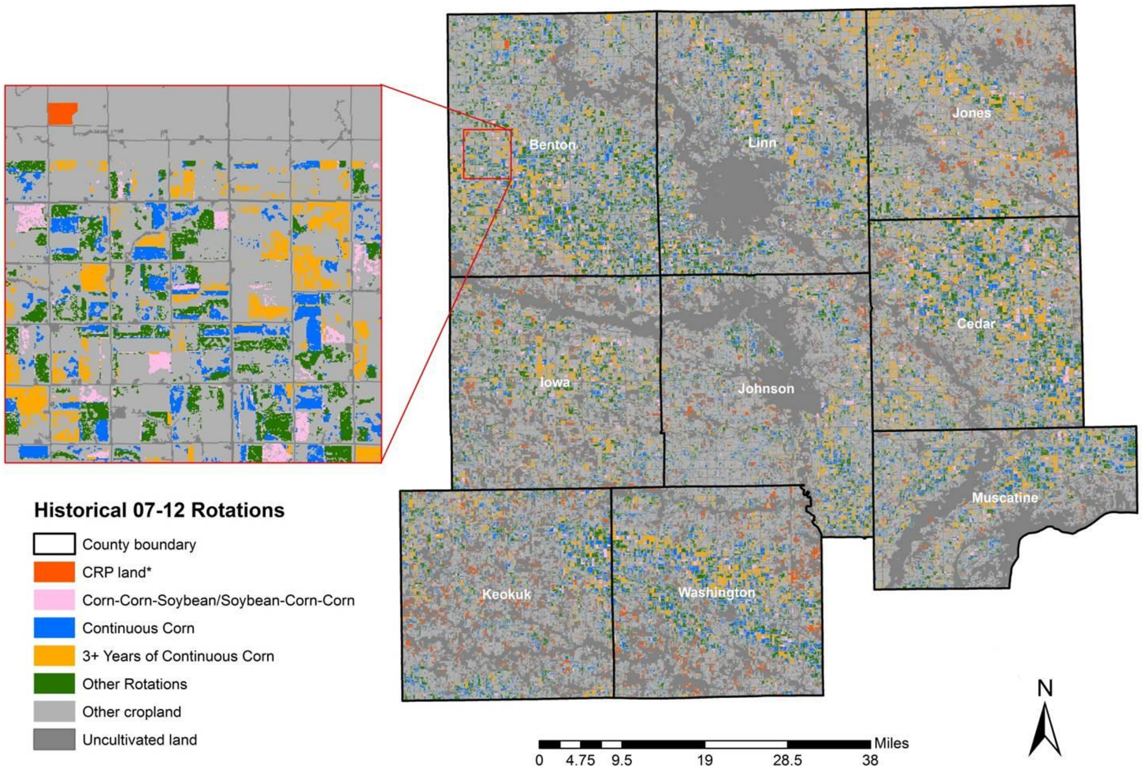

Figure 2.10. Location of 2007-2012 crop rotations in the study area, rotation types include two years of continuous corn, three years of continuous corn, more than three years of continuous corn, and other rotation including two and more years of continuous soybeans. Along with 2008 CRP land.

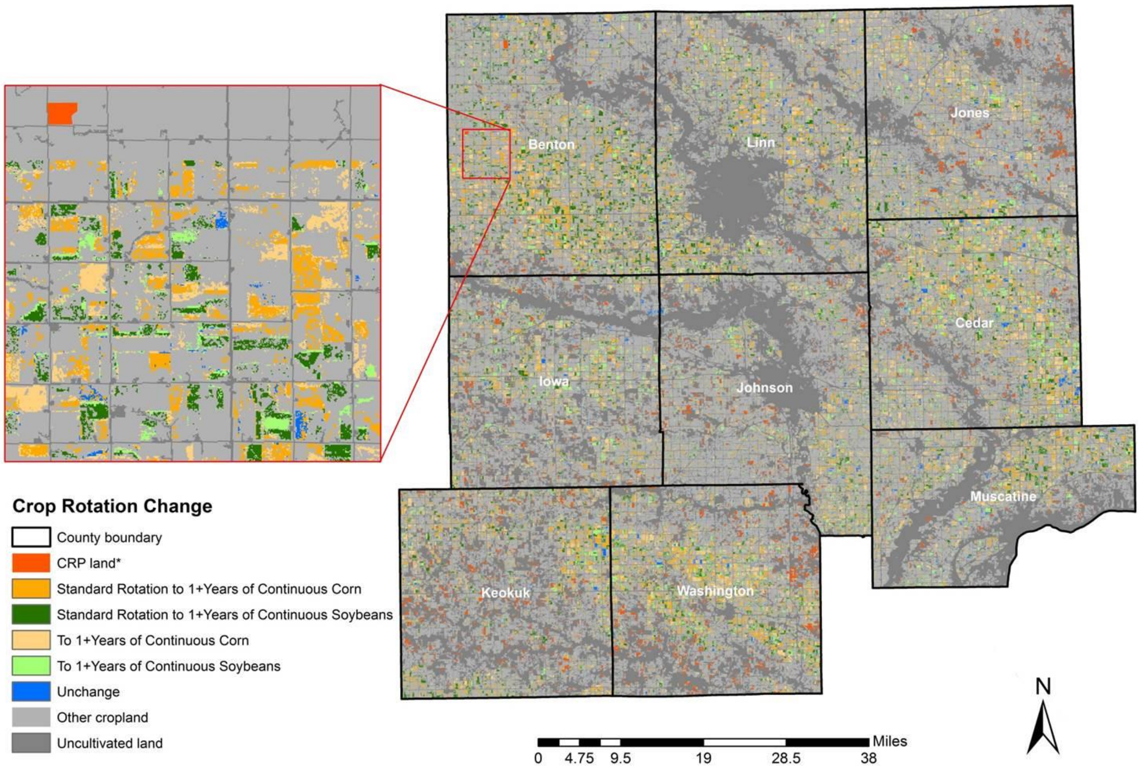

Figure 2.11. Location of crop rotation changes and 2008 CRP land in the study area. Rotation change types include standard rotation to two and more years of continuous corn, standard rotations to two and more years of continuous soybeans, other rotation to two and more years of continuous corn, and other rotations to two and more years of continuous soybeans.

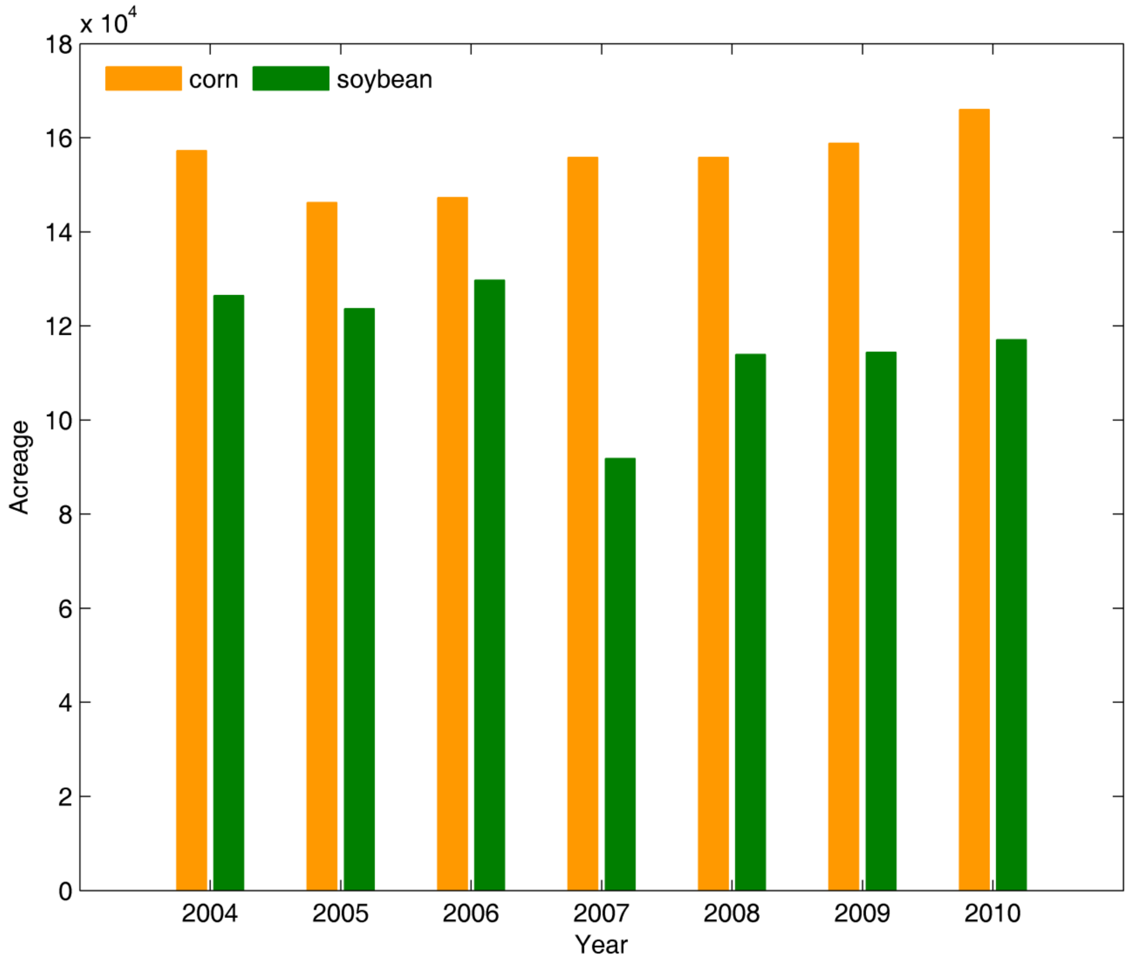

Figure 2.12. Acreage of area planted in corn and soybeans within a 10-mile radius of each ethanol plant, 2004-2010.

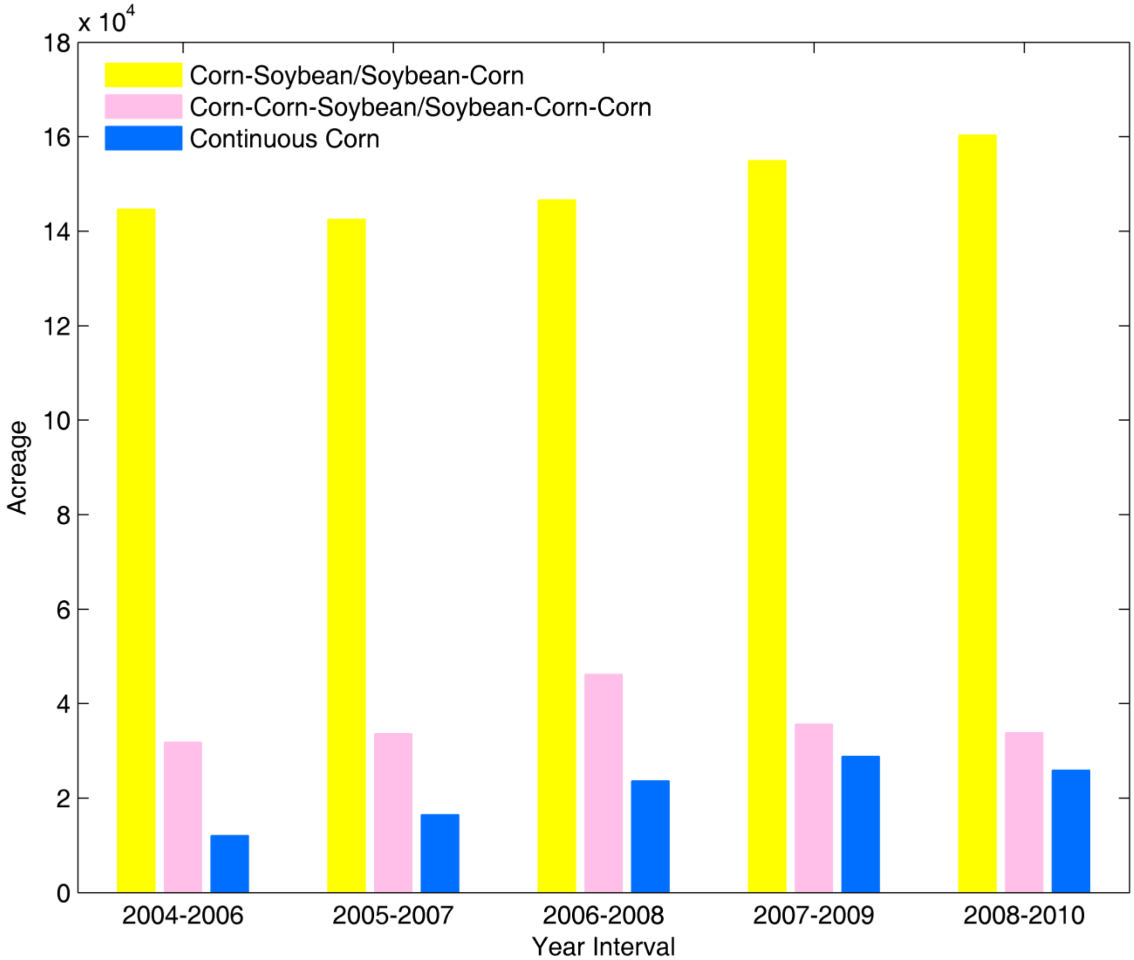

Figure 2.13. Three-year period with acreage of area planted in standard corn-soybean/soybean-corn, two years of continuous corn, and continuous corn within a 10-mile radius of each ethanol plant, 2004-2010.

Chapter 3 Spatial and Temporal Dynamics in the phenology of crops in the Midwestern United States

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Abstract

Understanding crop phenology is fundamental to agricultural production, management, planning and decision-making. This study used 250m 16-day MODIS NDVI time-series data to detect crop phenology across the Midwestern United States, 2001-2015. Key crop phenologial metrics, start of season (SOS) and end of season (EOS), were estimated for corn and soybean. For such a large study region, we found that MODIS-estimated SOS and EOS values are highly depending on the nature of input time-series data and threshold values chosen for crop phenology detection. With the entire sequence of MODIS NDVI time-series data as input, SOS and EOS values were inconsistent compared to crop emerged and crop mature dates from the USDA crop progress reports. However, when winter NDVI images were removed from the time-series data to reduce snow impacts, we obtained good SOS (e.g., R^2 = 0.75 for corn and R^2 = 0.54 for soybean) and EOS (R^2 = 0.83 for corn) estimates. We also examined two threshold values (50% and 40% of seasonal NDVI amplitude) to derive SOS and EOS values. A 40% threshold value generated results better correlated with crop progress report data. We further examined the spatial and temporal patterns of SOS and EOS for both crops. SOS for corn displayed clear south-north gradient: the southern portion of the Midwest US has earlier SOS and EOS dates. Across time, we found a small percentage of counties showed significant ($p<0.05$) downwards trend within a user-defined temporal window (2001-2012). SOS values advanced by approximately 0.66-1.28 and 0.77-1.33 days per year for corn and soybean, respectively. However, such earlier SOS trend did not extend to the recent 2012-2015 study period.

Keywords: MODIS, NDVI time series, crop phenology, growing season

1. Introduction

Knowledge of crop phenology is useful in agricultural production, management, planning, and decision-making (Boschetti et al., 2009; Sakamoto et al., 2005; Xin et al., 2002). Crop phenological parameters such as start of season (SOS), end of season (EOS) and length of growing season (LGS) have been broadly used in studies of climate-crop interactions (Tao et al., 2006), crop yield forecasting (Bolton & Friedl, 2013), crop-specific mapping (Pan et al., 2012; Xiao et al., 2006), and process-based crop simulation models (Doraiswamy et al., 2004; Fang et al., 2011). Crop phenological models can also support early detection of severe weather (Rojas, Vrieling, & Rembold, 2011) and inform national and international responses to food security (Ross et al., 2009). Crop phenological parameters and their spatial-temporal dynamics reveal information not only the usual underlying climatological drivers operating at broad spatial scales, but contributions from local factors such as soil conditions, landscape variations, and management decisions of individual farmers (White & Thomton, 1997).

In the United States, the periodic long-term Crop Progress Report (CPR) of the United States Department of Agriculture (USDA) is often used to support large-scale crop phenological studies. CPRs are field survey-based, including weekly crop management and condition information (e.g., percent corn planted, emerged, matured and harvested) (http://usda.mannlib.cornell.edu/MannUsda/homepage.do). Based on long-term CPR data, several studies indicated that corn planting dates have been progressively earlier over the past several decades (Duvik, 1989; Kucharik, 2006; Lauer, 2001; Shen & Liu, 2015). For example, Kucharik (2006) found that initiation of corn planting in 2005 was approximately 2 weeks earlier compared to the early 1980s for 12 Corn Belt states.

Shifts to earlier planting dates were also reported for soybeans for a few states in the Midwest US (Conley & Santini, 2007; Irwin et al, 2008; Sacks & Kucharik, 2011).

Field survey-based CPRs from USDA are sufficient to characterize general crop conditions and trends at regional and national scales. However, such data have limited spatial detail because crop progress information is based on generalized field observations and subjective assessments by experienced respondents, aggregated and reported at the state level. Crop management and crop conditions may vary substantially within each survey state. The highly-aggregated planting/harvesting dates are clearly inadequate for monitoring and understanding site-specific crop phenological events (Sakamoto et al., 2005). Remote sensing-based phenological estimation may augment CPRs by providing information with improved spatial detail, and potentially reducing costs (Sakamoto et al., 2005; Wardlow et al., 2006).

Time-series remote sensing data are now routinely used for characterizing vegetation phenology (e.g., Becket al., 2006; Eklundh & Olsson, 2003; Heumann et al, 2007; Moody & Johnson, 2001; Moulin et al, 1997; Zhang et al., 2003). Using time-series Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) data, researchers are now developing operational global land surface phenological data for near real-time monitoring (Tan et al., 2011; Zhang et al., 2003). Using time-series remote sensing data to characterize crop phenology, however, presents a significant challenge due to high spatial-temporal dynamics in agricultural landscape (Wardlow et al., 2006). Following Zhang et al. (2003) phenological detection method, Wardlow et al. (2006) derived green-up onset dates for corn, soybean, and sorghum using 16-day MODIS Normalized Difference Vegetation

Index (NDVI) data. They compared MODIS-derived green-up onset dates with the USDA CPR data (e.g., 50% crop emerged) and found large inconsistencies across agricultural statistics districts (ASD). One of the main confounding factors was pre-crop vegetation on the ground. Sakamoto et al. (2010) developed a Two-Step Filtering (TSF) method to detect phenological stages of maize and soybean using 6 years' time-series Wide Dynamic Range Vegetation Index (WDRVI) data derived from MODIS. Their phenological results were highly consistent with ground-based observations for two irrigated sites and one rainfed site in Nebraska. Their crop phenology detection method, however, has yet to be examined for large geographical areas and for longer-term (e.g., > 10~15 years) monitoring. Overall, few published studies focused on crop phenology detection using remote sensing, and validation efforts were largely limited. Accordingly, the spatial-temporal dynamics of crop phenology have not been thoroughly examined through remote sensing approaches.

Accurate detection of key crop phenological phases such as SOS and EOS depend on remote sensing input data and selection of detection algorithms. A large number of phenological models or algorithms have been developed for vegetation phenology, or for land surface phenology in general. Most of such methods involve a two-step procedure of data smoothing and phenological parameter estimation. Data smoothing is important to reduce signal noise caused by clouds and snow in time-series remote sensing data (e.g., Heumann et al., 2007; Sakamoto et al., 2005; Shao et al., 2016) . Phenological parameters are then estimated by using derivatives of the time-series data or applying user-defined thresholds (e.g., 50% of seasonal amplitude) (de Beurs & Henebry, 2010; Gao et al., 2008; Jönsson & Eklundh, 2002; Tan et al., 2011). Among the various methods or tools, TIMESAT is one of the most commonly used packages because it provides an integrated framework for data smoothing and phenological parameter estimation (Jönsson & Eklundh, 2004). Using TIMESAT, Tan et al. (2011) suggested that pre-processing of time-series data, especially for pixels with snow cover, plays a very important role in estimating phenological parameters. For a large study area such as the US Corn Belt, snow cover has significant temporal and spatial variability. There is a need for evaluating how data pre-processing affect performance of crop phenology detection.

The overall objective of this study was to characterize key crop phenological parameters (SOS and EOS) for corn and soybean for the Midwest US using 250m MODIS 16-day NDVI composites. We designed our study to examine spatial distribution and long-term trends of SOS and EOS from 2001 to 2015. Specific objectives were to: (1) examine how input data selection affects crop phenology detection, we compared two sets of time-series NDVI data as input, one used the entire sequence of NDVI time-series data and the other one removed winter images to reduce snow impacts; (2) examine how SOS and EOS estimates vary when TIMESAT threshold values (e.g., percent of seasonal amplitude) are varied; and (3) analyze spatial patterns of SOS and EOS, and evaluate their change trends across time, 2001-2015.

2. Materials and Methods

2.1. Study Area

Our study focuses upon the Midwest US, defined here by the 12 states shown in Figure 3.1. This region is characterized by extensive crop cultivation, and its role as the major producer of US corn and soybean, and half of the nation's wheat (Grace et al., 2011). The Corn Belt located in this region is characterized by climates favoring crop production. Forests are mainly in the southern part of the study area with relatively dense and diverse forest cover, consisting mostly of tall, broadleaf deciduous trees, and needle-leaf conifers. According to US Environmental Protection Agency (EPA) Level III ecoregion classification, it encompasses 42 ecoregions (Commission for Environmental Cooperation, 1997).

2.2. Data and Data preprocessing

MODIS Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V005 (MOD13Q1) acquired from the National Aeronautics and Space Administration (NASA) Reverb (http://reverb.echo.nasa.gov/) for 2001-2015 were used in this study. These high-quality vegetation index products include NDVI, Enhanced Vegetation Index (EVI), and associated reliability index layers. Six MODIS vegetation index tiles were needed to cover the 12-state study area. For a study period of 2001-2015, a total of 2070 MODIS scenes were download. For each composite interval, we used the MODIS Reprojection Tool (MRT) to mosaic NDVI images and project mosaics to an Albers Equal Area Conic (AEA) projection, these image mosaics were then clipped to the 12-state study area boundary and stacked to build time-series NDVI data.

Corn and soybean cropland masks were created with the Cropland Data Layer (CDL) produced by USDA National Agricultural Statistics Service (NASS) (Boryan et al., 2011). Complete CDL coverages for all 12 states are available since 2007. Longer-term complete CDL data collected since 2001 are available for only 3 states – Illinois, Iowa, and North Dakota. NASS reports that CDLs have high levels of user's and producer's accuracies for major crops such as corn and soybeans, usually above 85% for Midwestern states. Thus, CDLs form reliable sources of data for crop-specific phenological analysis. We use CDLs to extract pixels for corn and soybeans from 2007 through 2015 for the entire study area and from 2001 through 2015 for the three states mentioned above. Note that CDLs have different spatial resolutions of 30m-56m, depending on producing year. For each year, we computed corn and soybean proportions within each 250 MODIS grid. Only MODIS pixels with corn or soybean proportions greater than 90% were considered for crop phenology detection and analysis.

CPRs provided by USDA NASS were used to evaluate accuracy of MODIS-derived SOS and EOS estimates for corn and soybean. These progress reports of crop developmental stages are expressed as percentages of completed phases (e.g., 50% corn planted, emerged, and matured).

2.3. Estimate crop phenology using time-series MODIS data

TIMESAT package was used to smooth MODIS NDVI time-series data and detect crop phenology. Three data smoothing algorithms are available in TIMESAT package: adaptive Savitzky–Golay, asymmetric Gaussian, and double-logistic function (Jönsson & Eklundh, 2002). The adaptive Savitzky-Golay (SG) algorithm was used as our primary smoothing algorithm since a recent study of smoothing algorithm comparisons suggested that the SG algorithm better characterizes temporal signals for both corn and soybean (Shao et al., 2016). The SG algorithm basically applies a moving-window quadratic polynomial function to the original time-series data and estimates new values for the center point of each moving-window. Because NDVI signals with cloud contamination are often negatively biased, the TIMESAT package has additional option to adapt fitted values to the upper envelope of the time-series data. Such adaptions were repeated twice to reduce potential impacts from cloud and shadow issues.

For the northern portion of our study area, snow cover presents a significant challenge in curve fitting of time-series NDVI data and subsequent phenological parameter estimation (Tan et al., 2011). We examined two sets of time-series NDVI data for data smoothing and crop phenology detection. In the first set, all NDVI images from 2001 to 2015 were used as input to TIMESAT package. For the second set, we excluded winter season images (Mid-November to Late-March) and the remaining NDVI images (16-day MODIS time series composite periods 7–20) for each year were used as input. Winter season was empirically defined by visual evaluation of snow coverage from time-series NDVI images and previous studies on summer crop mapping and monitoring (Shao et al., 2010).

On the basis of the smoothed NDVI time series data, we first derived MODIS pixel-level (250m resolution) SOS and EOS values using a default threshold (50% of the seasonal amplitude), measured from the left minimum and right minimum, respectively (Jönsson & Eklundh, 2002). It should be noted that such threshold value was user-defined and can be easily adjusted to evaluate their impacts on crop phenology detection. In our study, we tested two threshold values (i.e., 50% and 40%) to see which threshold value generates comparable results of USDA CPRs. With 15 years' NDVI time-series data for a 12-state study area, TIMESAT data smoothing and phenology parameter estimation were computationally expensive. We divided our image processing tasks into 10 small segments and performed parallel processing at the Virginia Tech Advanced Research

Computing’s Blueridge cluster. All data sub-setting and subsequent processing were streamlined using TIMESAT’s setting files and Python scripts.

2.4. Comparison of MODIS-derived crop phenology parameters with CPRs

MODIS-derived phenology metrics of SOS and EOS were compared to crop progress statistics from CPRs. For each year and each state, 50% of corn or soybean emerged dates were extracted from CPRs and serve as reference for SOS comparison (Wardlow et al., 2006). Similarly, 50% corn mature dates were extracted from CPRs and serve as reference for EOS comparison. There was no data available for soybean mature dates in CPRs, thus EOS comparison was conducted for corn only. It should be noted that CPRs are survey-based and only provide weekly ‘snap-shot’ of crop conditions. In many cases, the exact dates for 50% crop emerged or crop mature were not available. We applied linear interpolation to estimate 50% events using the nearest dates (e.g, if the 25% and 75% dates were available) for each crop type. Since CPRs are reported at state level, we averaged MODIS-derived SOS and EOS values for corn and soybean pixels in each state for each study year of 2007 to 2015. The coefficient of determination (R^2) and root-mean-square error (RMSE) were used to compare MODIS-derived crop phenology estimates and CPR values.

2.5. Analysis of Phenological Trends

Analysis of SOS and EOS trends at 250m MODIS pixel scale was confounded by crop rotation (e.g., corn-soybean, corn-corn-hay) issue. Therefore, we examined long-term crop phenological trends at aggregated county-scales. The trend analysis was limited to three states of Illinois, Iowa, and North Dakota, where long-term CDLs were available for generating crop-specific masks. For each year from 2001 to 2015 and for main crop producing counties (defined by > 100 MODIS crop pixels) within the above three states, we computed average SOS (and EOS) for corn and soybean, respectively.

Across time from 2001 to 2015, we applied the non-parametric Mann–Kendall test to calculate the significance of the trend for each main crop-producing county. The Mann–Kendall test is suited to monotonic trend detection independent from its functional nature and, compared to other metrics, is less influenced by the presence of outliers (Lanzante, 1996). The null hypothesis (H_0) of the test states that there is no trend whereas the three alternative hypotheses H_a state that there is a significant negative, non-null, or positive trend. For counties with significant (i.e., $p<0.05$) trends, we fitted simple linear regressions to define coefficients:

$$y = ax + b$$

where y is SOS, EOS, respectively, x is year, a is the slope which represents annual change rate of each phenological metric.

3. Results

3.1. MODIS-derived crop SOS Metrics

Figure 3.2 compares MODIS-derived corn SOS values with 50 percent corn emerged dates from CPRs (2007-2015) using different combinations of time-series input data and threshold values. With all NDVI images as input, MODIS-derived SOS estimates for corn showed large inconsistencies compared to CPR data (Figure 3.2a and 3.2c). R^2 was 0.16 and 0.05 and RMSE was 8.87 and 15.03 days for threshold value of 50% and 40%, respectively. Points that are far away from scatter plot cluster are mainly from SOS estimates for Wisconsin, North Dakoda, and South Dakoda. R^2 increased to 0.75 (RMSE = 11.34) when winter images were removed from time-series data before TIMESAT data smoothing and phenological metric estimation (Figure 3.2b).

With the non-winter MODIS time-series data as input and 0.5 (50% of the NDVI seasonal amplitude) threshold value, on average, MODIS-predicted SOS value for corn was DOY (Day of Year) 154 in the Midwestern region, compared to DOY 143 for 50 percent corn emerged dates from CRP data. When the threshold value was decreased to 0.4 (40% of the seasonal NDVI amplitude), the average MODIS SOS decreased to DOY 147 and RMSE value reduced to 5.73 days (Figure 3.2d).

Figure 3.3 compares MODIS-derived SOS dates with 50 percent emerged dates for soybean from CPRs. With all NDVI images as TIMESAT data smoothing and crop phenology detection, the R^2 was 0.08 and 0.02 for threshold value of 50% and 40%, respectively (Figure 3.3a and 3.3c). There was no clear linear relationship between MODIS-derived SOS dates and CPR dates. Similar to corn, much higher R^2 values (0.54 and 0.50) were obtained when winter NDVI images were removed from input data (Figure 3.3b and 3.3d). Threshold value of 50% seasonal amplitude led to an average SOS value of DOY 165 for soybean, about 8 days later than CPR average value. When a 40% threshold value was applied to detect SOS, the average MODIS-based estimation was DOY 157 for soybean SOS, the same as the CPR value. Overall, the SOS detection for soybean had lower accuracy compared to corn when CPRs are used as references.

3.2. MODIS-derived crop EOS Metrics

Figure 3.4 compares MODIS EOS estimates with 50% corn mature dates from CPRs, 2007- 2015. With all NDVI images as TIMESAT input, R^2 was 0.66 and 0.56 using 50% and 40% threshold value, respectively (Figure 3.4a and 3.4c). Corresponding RMSE values were 10.34 and 19.67 days. By removing winter NDVI images, MODIS EOS estimates were highly consistent with CPR data (Figure 3.4b and 3.4d). R^2 were 0.83 and 0.82 for threshold values of 50% and 40%, respectively. RMSE reduced to 6.88 and 4.97 days. There were a couple outliers where late corn mature dates were reported in CPRs. For instance, the 50% corn mature was recorded on DOY 298 in CPR, while MODIS predicted a much earlier EOS date at DOY 272 or 278 for threshold value of 0.5 and 0.4, respectively. There was no clear explanation for such a large discrepancy. In general, however, MODIS-predicted EOS showed good agreement with CPR data.

The choice of threshold values clearly had large impacts on MODIS EOS estimates. A threshold of 50% led to earlier (7 days on average) EOS dates compared to CPR data, while a threshold value of 40% led to almost the same average EOS date compared to the average value from CPRs. We note that MODIS-derived EOS values for soybean were not compared to the CPRs, since there was no percent soybean mature data in the CPR database.

After evaluating both MODIS input data and threshold value choices for SOS and EOS detection, it was determined that for both corn and soybean, a threshold value of 40% (40% of seasonal amplitude) provided better results compared to the CPR data. More importantly, NDVI images in the winter season need to be removed to achieve consistent SOS and EOS estimates.

3.3 Spatial and temporal patterns of SOS and EOS

The annual SOS and EOS maps derived from 40% thresholding were used to analyze spatial and temporal patterns. For ease of illustration, we focused on county-scale analysis and used 9 years' (2007-2015) average SOS and EOS values for visual assessment (Figure 3.5). For corn, SOS and EOS values increase following the south-north gradient (Figure 3.5a and 3.5c). Earlier SOS in the southern portion of the Midwest US was expected because favorable climates. SOS values for soybean vary substantially (i.e., late April - late June) across the study region (Figure 3.5e). There was no clear south-north gradient and counties located at the edges of Corn Belt appear to have late SOS. For both corn and soybean, the standard deviation values of SOS (and EOS) were higher in the southern portion of the Midwest US, especially for Illinois, Indiana, and Missouri (Figure 3.5b, 3.5d, and 3.5f). Such high inter-annual variability can be attributed to favorable climates in these states. Farmers in this sub-region have more flexibility in managing crop planting and harvesting dates.

SOS and EOS temporal trends were examined for different time periods with the non-parametric Mann–Kendall test (Table 3.1). Because complete CDLs for 2001 to 2015 were only available for North Dakota, Iowa, and Illinois, our SOS and EOS trend analysis was limited to these three states. Among main crop producing counties (e.g., each has greater than 100 MODIS pixels for corn or soybean), only a small percentage of counties showed significant ($p<0.05$) downwards temporal trends for corn and soybean SOS values. Note that the temporal window selected for non-parametric Mann-Kendall test was very important. Most noticeable downwards SOS trends were observed for 2001-2012 temporal window. Within this temporal window, there were 35 (17%) of main corn producing and 22 (9%) main soybean producing counties showed significant downwards trends of SOS (Figure 3.6). All remaining counties did not show significant ($p<0.05$) downwards or upwards trends.

Simple linear trend models were developed for counties with significant temporal trends in 2001-2012. SOS for corn advanced about 0.66-1.28 days per year for these highlighted counties (Figure 3.6). For soybean, SOS advanced about 0.77-1.33 days per year. When all 15 years' data (2001-2015) were included for trend analysis and non-parametric Mann-Kendall test, however, only 2 counties showed downwards trends of SOS for both crops, suggesting that SOS values from 2013 to 2015 did not follow the observable trends of 2001 to 2012. For corn's EOS values, only 5 counties showed significant downwards trends for 2001-2012 and there was no county showing a significant trend for 2001-2015.

4. Discussion

Accurate detection of SOS and EOS for corn and soybean depends on many factors such as input time-series data, smoothing algorithms chosen, and specific threshold values applied to pin-point phenological metrics. For the Midwest US, SOS and EOS estimates were highly sensitive to input data. Initial efforts using the entire sequence of MODIS time-series data generated inconsistent SOS and EOS estimates compared to the USDA CPRs (e.g., SOS: $R^2 = 0.16$ and 0.08 for corn and soybean). Snow cover presents a significant challenge in determining SOS and EOS. Existing time-series data smoothing algorithms provided in TIMESAT cannot recover NDVI temporal profiles for pixels with extended snow period (e.g., 2-3 months). Snow pixels and pixels with partial snow cover will affect seasonal NDVI amplitude estimates, as well as SOS and EOS estimates defined by thresholding of seasonal amplitude. Tan et al. (Tan et al., 2011) used MODIS land surface temperature and MODIS quality assessment (QA) information to define winter season and then applied TIMESAT to derive land surface SOS and EOS. Our method was to remove all winter images from Mid-November to Late-March to reduce snow impacts. This simplified method was designed for major summer crops such as corn and soybean, because their growing season is well-defined and there is no need to incorporate NDVI signals in winter time to estimate SOS and EOS. The non-winter time-series input data provided much improved performance in detecting SOS and EOS for both crops (Figure 3.2, 3.3, and 3.4).

Threshold values used to detection SOS and EOS were also important. For a large study area such as the Midwest US, we were searching for a threshold applicable to the entire study area, rather than variable thresholds across the region. For SOS detection, the default 50% threshold (50% of seasonal NDVI amplitude) generated acceptable results for corn (RMSE = 11.34 days) and soybean (RMSE = 10.76 days). These MODIS-estimated SOS dates were about 11 days later than CPR 50% crop emerged dates. Such results were consistent with Wardlow et al.'s (Wardlow et al., 2006) findings. Crops at the 50% emerged dates are barely detectable (i.e., low NDVI values) and may be affected by soil background. When a lower threshold value (i.e., 40%) was applied, the MODIS-derived SOS matched better (RMSE < 7 days for both crops) with CPR 50% crop emerged dates. The same 40% threshold also generated better results for EOS estimates for corn. We note that MODIS-derived EOS values were compared to 50% crop mature dates, rather than 50% crop harvest dates.

Our study showed that MODIS-derived SOS (EOS) values and CPRs have general agreement at state level, given an appropriate threshold value and time-series data pre-processing steps. Some uncertainties may arise when the pixel-level SOS (EOS) comparison is conducted. For example, Wardlow et al.'s (Wardlow et al., 2006) indicated that pixel-level comparison with field observation may not be appropriate because spatial resolution of MODIS pixel (250m) is rather coarse, thus SOS (EOS) estimates from MODIS could be affected by mixed land cover and soil background. In addition to spatial resolution limitations, SOS and EOS estimates may be affected by MODIS temporal compositing. Although 16-day and 8-day MODIS composite data generally provide sufficient temporal signals for crop monitoring and mapping (Lunetta et al., 2010; Shao et al., 2016), it was not clear how use of different composite data affect SOS and EOS detection. The 8-day composite data theoretically could improve SOS and EOS detection by pinpointing dates at finer temporal resolution, however, the cloud and other noise impacts may increase. In both cases, data smoothing is needed to reduce signal noise and characterize key crop temporal profiles to support crop phenology detection. Future studies are needed to examine how different smoothing algorithms affect SOS and EOS detection for major crops.

Spatial patterns of SOS (EOS) estimates were characterized for 2007-2015. The south-north gradients for SOS and EOS are well defined, especially for corn. Such county-level crop phenological metrics augment the USDA CPRs by providing improved spatial details. Our data support spatial pattern analysis of SOS and EOS at finer resolution (e.g., 250m), however, county-level aggregates may be sufficient to support many agronomic management practices and understand phenological variations due to environmental, social and economic factors. One main challenge in analyzing temporal trends of SOS and EOS is availability of long-term crop-specific map products. For three states with longer-term CDL data (2001-2015), only a small percentage of counties showed significant downwards trend in SOS. More importantly, trend analysis results were largely dependent on the temporal window selected. For 2001-2012, our trend analysis suggested earlier SOS dates for certain counties, which is consistent with Kucharik's (Kucharik, 2006) finding for the Midwest region. Contributing factors may include climate change (e.g., Challinor et al., 2009; Kucharik, 2006; McMaster & Wilhelm, 2003; Oteros et al., 2015; Shen & Liu, 2015) and agronomic management practices to improve crop yields (e.g., Bastidas et al., 2008; Bruns & Abbas, 2006; Kucharik, 2008; Nielsen et al., 2002; Pedersen & Lauer, 2004; Wilcox & Frankenberger, 1987). Other socioeconomic factors such as elevated corn/soybean prices may also promote farmers to potentially plant crops earlier. SOS values in the 2013-2015 interval, however, did not follow the trend. It should be noted that long-term trends of earlier SOS are unrealistic because of climate controls such as freezing temperatures, snow cover, and frozen soils. With consistent and extended MODIS time-series data and improved CDL map products, our spatial-temporal analysis of crop phenology can be expanded in both spatial and temporal domains and further improve our understanding of climate-crop-human interactions.

5. Conclusions

We used 250m MODIS time-series data to estimate annual SOS and EOS for corn and soybean of the 12-state Midwest US, 2001-2015. MODIS-derived SOS and EOS values were compared with the USDA CPR 50% crop emerged dates and 50% crop mature dates, respectively. Inconsistent SOS and EOS values were derived when all NDVI images were used as input to TIMESAT for data smoothing and subsequent phenological parameter estimation. When winter images from Mid-November to Late-March were removed from MODIS time-series data, the agreement between MODIS-derived SOS (and EOS) dates and CPR data substantially improved. We also examined two threshold values (50% and 40% of seasonal NDVI amplitude) for SOS and EOS detection. A threshold value of 40% generated better estimates compared to the default 50% for the Midwest US. Spatial analyses of SOS and EOS values revealed clear south-north gradient for corn – earlier SOS (and EOS) in the south and later SOS (and EOS) in the north portion of the study region. Trend analyses for SOS and EOS were conducted for three states with long-term CDL map products. We found that only a small percentage of counties showed statistically significant downwards trends in SOS for a user-defined temporal window (2001-2012). Within this temporal window, SOS advanced by approximately 0.66-1.28 and 0.77-1.33 days per year for corn and soybean, respectively.

References

Bastidas, A. M., Setiyono, T. D., Dobermann, A., Cassman, K. G., Elmore, R. W., Graef, G. L., & Specht, J. E. (2008). Soybean Sowing Date: The Vegetative, Reproductive, and Agronomic Impacts. *Crop Science*, *48*(2), 727–740.

Beck, P. S., Atzberger, C., Høgda, K. A., Johansen, B., & Skidmore., A. K. (2006). Improved monitoring of vegetation dynamics at very high latitudes: A new method using MODIS NDVI. *Remote Sensing of Environment*, *100*(3), 321–334. doi:10.1016/j.rse.2005.10.021

Bolton, D. K., & Friedl, M. A. (2013). Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics. *Agricultural and Forest Meteorology*, *173*, 74–84.

Boryan, C., Yang, Z., Mueller, R., & Craig, M. (2011). Monitoring US agriculture: the US Department of Agriculture, National Agricultural Statistics Service, Cropland Data Layer Program. *Geocarto International*, *26*(5), 341–358. doi:10.1080/10106049.2011.562309

Boschetti, M., Stroppiana, D., Brivio, P. A., & Bocchi, S. (2009). Multi-year monitoring of rice crop phenology through time series analysis of MODIS images. *International Journal of Remote Sensing*, *30*(18), 4643–4662. doi:10.1080/01431160802632249

Bruns, H. A., & Abbas, H. K. (2006). Planting Date Effects on Bt and Non-Bt Corn in the Mid-South USA. *Agronomy Journal*, *98*(1), 100. doi:10.2134/agronj2005.0143

Challinor, A. J., Ewert, F., Arnold, S., Simelton, E., & Fraser, E. (2009). Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. *Journal of Experimental Botany*, *60*(10), 2775–2789.

doi:10.1093/jxb/erp062

Commission for Environmental Cooperation. (1997). *Ecological Regions of North America: Toward a Common Perspective*.

Conley, S. P., & Santini, J. B. (2007). Crop Management Practices in Indiana Soybean Production Systems. *Crop Management*, *6*(1), 0–0. doi:10.1094/CM-2007-0104-01-RS

de Beurs, K. M., & Henebry, G. M. (2010). Spatio-Temporal Statistical Methods for Modelling Land Surface Phenology. In I. L. Hudson & M. R. Keatley (Eds.), *Phenological Research* (pp. 177–208). Springer Netherlands. doi:10.1007/978-90-481-3335-2

Doraiswamy, P. C., Hatfield, J. L., Jackson, T. J., Akhmedov, B., Prueger, J., & Stern, A. (2004). Crop condition and yield simulations using Landsat and MODIS. *Remote Sensing of Environment*, *92*(4), 548–559.

Duvik, D. N. (1989). 12 Possible Genetic Causes of Increased Variability in US Maize Yields. In J. R. Anderson & P. B. R. Hazell (Eds.), *Variability in grain yields: Implications for agricultural research and policy in developing countries* (pp. 147–156). Baltimore: Johns Hopkins University Press.

Eklundh, L., & Olsson, L. (2003). Vegetation index trends for the African Sahel 1982–1999. *Geophysical Research Letters*, *30*(8).

Fang, H., Liang, S., & Hoogenboom, G. (2011). Integration of MODIS LAI and vegetation index products with the CSM–CERES–Maize model for corn yield estimation. *International Journal of Remote Sensing*, *32*(4), 1039–1065.

Gao, F., Morisette, J. T., Wolfe, R. E., Ederer, G., Pedelty, J., Masuoka, E., …

Nightingale, J. (2008). An Algorithm to Produce Temporally and Spatially Continuous MODIS-LAI Time Series. *IEEE Geoscience and Remote Sensing Letters*, *5*(1), 60–64. doi:10.1109/LGRS.2007.907971

Grace, P. R., Robertson, G. P., Millar, N., Colunga-garcia, M., Basso, B., Gage, S. H., & Hoben, J. (2011). The contribution of maize cropping in the Midwest USA to global warming: A regional estimate. *Agricultural Systems*, *104*(3), 292–296. doi:10.1016/j.agsy.2010.09.001

Heumann, B. W., Seaquist, J. W., Eklundh, L., & Jönsson, P. (2007). AVHRR derived phenological change in the Sahel and Soudan, Africa, 1982–2005. *Remote Sensing of Environment*, *108*(4), 385–392. doi:10.1016/j.rse.2006.11.025

Irwin, S., Good, D., & Tannura, M. (2008). Forming expectations about 2008 US corn and soybean yields—application of crop weather models that incorporate planting progress. *Marketing and Outlook Brief*, *3*.

Jönsson, P., & Eklundh, L. (2002). Seasonality Extraction by Function Fitting to Time-Series of Satellite Sensor Data. *IEEE Transactions on Geoscience and Remote Sensing*, *40*(8), 1824–1832.

Jönsson, P., & Eklundh, L. (2004). TIMESAT—a program for analyzing time-series of satellite sensor data. *Computers & Geosciences*, *30*(8), 833–845. doi:10.1016/j.cageo.2004.05.006

Kucharik, C. J. (2006). A multidecadal trend of earlier corn planting in the central USA. *Agronomy Journal*, *98*, 1544–1550. doi:10.2134/agronj2006.0156

Kucharik, C. J. (2008). Contribution of planting date trends to increased maize yields in the central United States. *Agronomy Journal*, *100*, 328–336.

doi:10.2134/agronj2007.0145

Lanzante, J. R. (1996). Resistant, robust and non-parametric techniques for the analysis of climate data: Theory and examples, including applications to historical radiosonde station data. *International Journal of Climatology*, *16*(11), 1197–1226.

Lauer, J. (2001). Earlier planting dates for corn: Real progress or an effect of global warming? Retrieved from http://corn.agronomy.wisc.edu/WCM/W089.aspx

Lunetta, R. S., Shao, Y., Ediriwickrema, J., & Lyon, J. G. (2010). Monitoring agricultural cropping patterns across the Laurentian Great Lakes Basin using MODIS-NDVI data. *International Journal of Applied Earth Observation and Geoinformation*, *12*(2), 81–88. doi:10.1016/j.jag.2009.11.005

McMaster, G. S., & Wilhelm, W. W. (2003). Phenological responses of wheat and barley to water and temperature: improving simulation models. *The Journal of Agricultural Science*, *141*(02), 129–147. doi:10.1017/S0021859603003460

Moody, A., & Johnson, D. M. (2001). Land-Surface Phenologies from AVHRR Using the Discrete Fourier Transform. *Remote Sensing of Environment*, *75*(3), 305–323. doi:10.1016/S0034-4257(00)00175-9

Moulin, S., Kergoat, L., Viovy, N., & Dedieu, G. (1997). Global-scale assessment of vegetation phenology using NOAA/AVHRR satellite measurements. *Journal of Climate*, *10*(6), 1154–1170.

Nielsen, R. L., Thomison, P. R., Brown, G. A., Halter, A. L., Wells, J., & Wuethrich, K. L. (2002). Delayed planting effects on flowering and grain maturation of dent corn. *Agronomy Journal*, *94*(3), 549–558.

Oteros, J., García-Mozo, H., Botey, R., Mestre, A., & Galán, C. (2015). Variations in cereal crop phenology in Spain over the last twenty-six years (1986–2012). *Climatic Change*, *130*(4), 545–558. doi:10.1007/s10584-015-1363-9

Pan, Y., Li, L., Zhang, J., Liang, S., Zhu, X., & Sulla-menashe, D. (2012). Remote Sensing of Environment Winter wheat area estimation from MODIS-EVI time series data using the Crop Proportion Phenology Index. *Remote Sensing of Environment*, *119*, 232–242. doi:10.1016/j.rse.2011.10.011

Pedersen, P., & Lauer, J. G. (2004). Response of soybean yield components to management system and planting date. *Agronomy Journal*, *96*(5), 1372–1381.

Rojas, O., Vrieling, A., & Rembold, F. (2011). Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. *Remote Sensing of Environment*, *115*(2), 343–352.

Ross, K. W., Brown, M. E., Verdin, J. P., & Underwood, L. W. (2009). Review of FEWS NET biophysical monitoring requirements. *Environmental Research Letters*, *4*(2), 24009.

Sacks, W. J., & Kucharik, C. J. (2011). Crop management and phenology trends in the U.S. Corn Belt: Impacts on yields, evapotranspiration and energy balance. *Agricultural and Forest Meteorology*, *151*(2011), 882–894. doi:10.1016/j.agrformet.2011.02.010

Sakamoto, T., Wardlow, B. D., Gitelson, A. a., Verma, S. B., Suyker, A. E., & Arkebauer, T. J. (2010). A Two-Step Filtering approach for detecting maize and soybean phenology with time-series MODIS data. *Remote Sensing of Environment*, *114*(10), 2146–2159. doi:10.1016/j.rse.2010.04.019

Sakamoto, T., Yokozawa, M., Toritani, H., Shibayama, M., Ishitsuka, N., & Ohno, H.

(2005). A crop phenology detection method using time-series MODIS data. *Remote Sensing of Environment*, *96*(3-4), 366–374. doi:10.1016/j.rse.2005.03.008

Shao, Y., Lunetta, R. S., Ediriwickrema, J., & Iiames, J. (2010). Mapping cropland and major crop types across the Great Lakes Basin using MODIS-NDVI data. *Photogrammetric Engineering and Remote Sensing*, *76*(1), 73–84.

Shao, Y., Lunetta, R. S., Wheeler, B., Iiames, J. S., & Campbell, J. B. (2016). An evaluation of time-series smoothing algorithms for land-cover classifications using MODIS-NDVI multi-temporal data. *Remote Sensing of Environment*, *174*, 258–265. doi:10.1016/j.rse.2015.12.023

Shen, Y., & Liu, X. (2015). Phenological Changes of Corn and Soybeans over U.S. by Bayesian Change-Point Model. *Sustainability*, *7*(6), 6781–6803. doi:10.3390/su7066781

Tan, B., Morisette, J. T., Wolfe, R. E., Gao, F., Ederer, G. A., Nightingale, J., & Pedelty, J. A. (2011). An Enhanced TIMESAT Algorithm for Estimating Vegetation Phenology Metrics From MODIS Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *4*(2), 361–371.

Tao, F., Yokozawa, M., Xu, Y., Hayashi, Y., & Zhang, Z. (2006). Climate changes and trends in phenology and yields of field crops in China, 1981–2000. *Agricultural and Forest Meteorology*, *138*(1), 82–92.

Wardlow, B. D., Kastens, J. H., & Egbert, S. L. (2006). Using USDA Crop Progress Data for the Evaluation of Greenup Onset Date Calculated from MODIS 250-Meter Data. *Photogrammetric Engineering & Remote Sensing*, *72*(11), 1225–1234.

White, A., & Thomton, P. E. (1997). A continental responses phenology model climatic for monitoring variability vegetation to interannual. *Global Biogeochemical Cycles*, *11*(2), 217–234.

Wilcox, J. R., & Frankenberger, E. M. (1987). Indeterminate and Determinate Soybean Responses to Planting Date. *Agronomy Journal*, *79*(6), 1074–1078.

Xiao, X., Boles, S., Frolking, S., Li, C., Babu, J. Y., Salas, W., & Moore, B. (2006). Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images. *Remote Sensing of Environment*, *100*(1), 95–113.

Xin, J., Yu, Z., van Leeuwen, L., & Driessen, P. M. (2002). Mapping crop key phenological stages in the North China Plain using NOAA time series images. *International Journal of Applied Earth Observation and Geoinformation*, *4*(2), 109–117. doi:10.1016/S0303-2434(02)00007-7

Zhang, X., Friedl, M. a., Schaaf, C. B., Strahler, A. H., Hodges, J. C. F., Gao, F., … Huete, A. (2003). Monitoring vegetation phenology using MODIS. *Remote Sensing of Environment*, *84*(3), 471–475. doi:10.1016/S0034-4257(02)00135-9

Table 3.1. Main crop producing counties showed significant (Mann-Kendall test, $p<0.05$) downwards trend of SOS and EOS across different temporal windows.

	2001-2010	**2001-2011**	**2001-2012**	**2001-2013**	**2001-2014**	**2001-2015**
Corn_SOS (n=210)	25	10	35	1	1	2
Soy_SOS (n=244)	10	8	22	2	6	2
Corn_EOS (n=210)	1	2	5	0	1	0

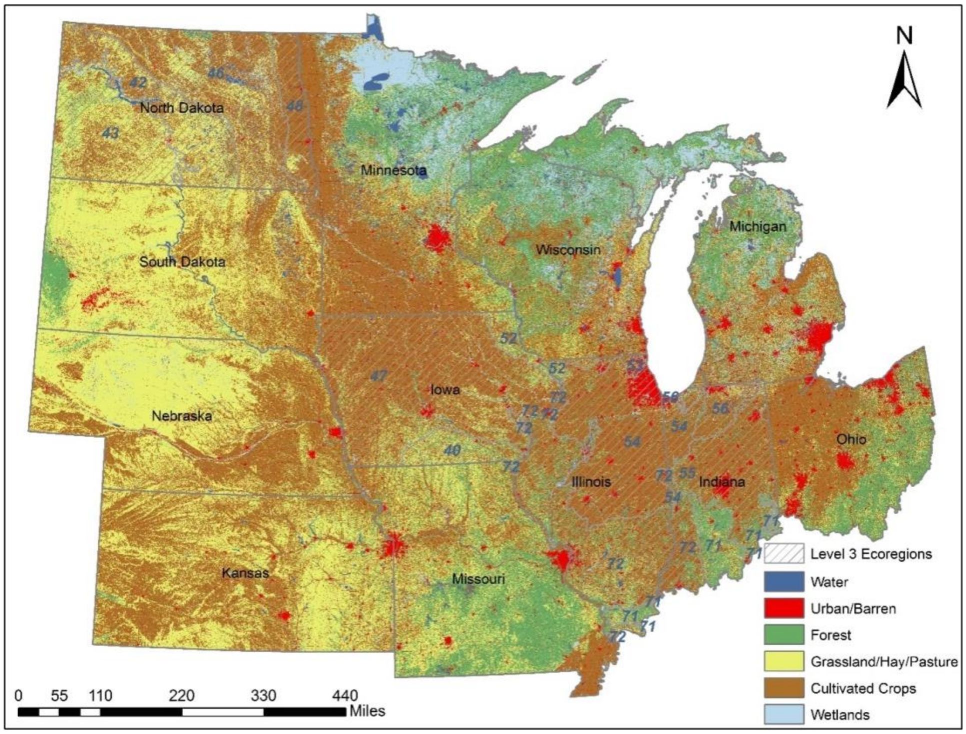

Figure 3.1. Study area with land use type and Level III ecoregions. Each ecoregion is labeled with its US code. (Based upon NLCD 2006 and US EPA Level III ecoregions)

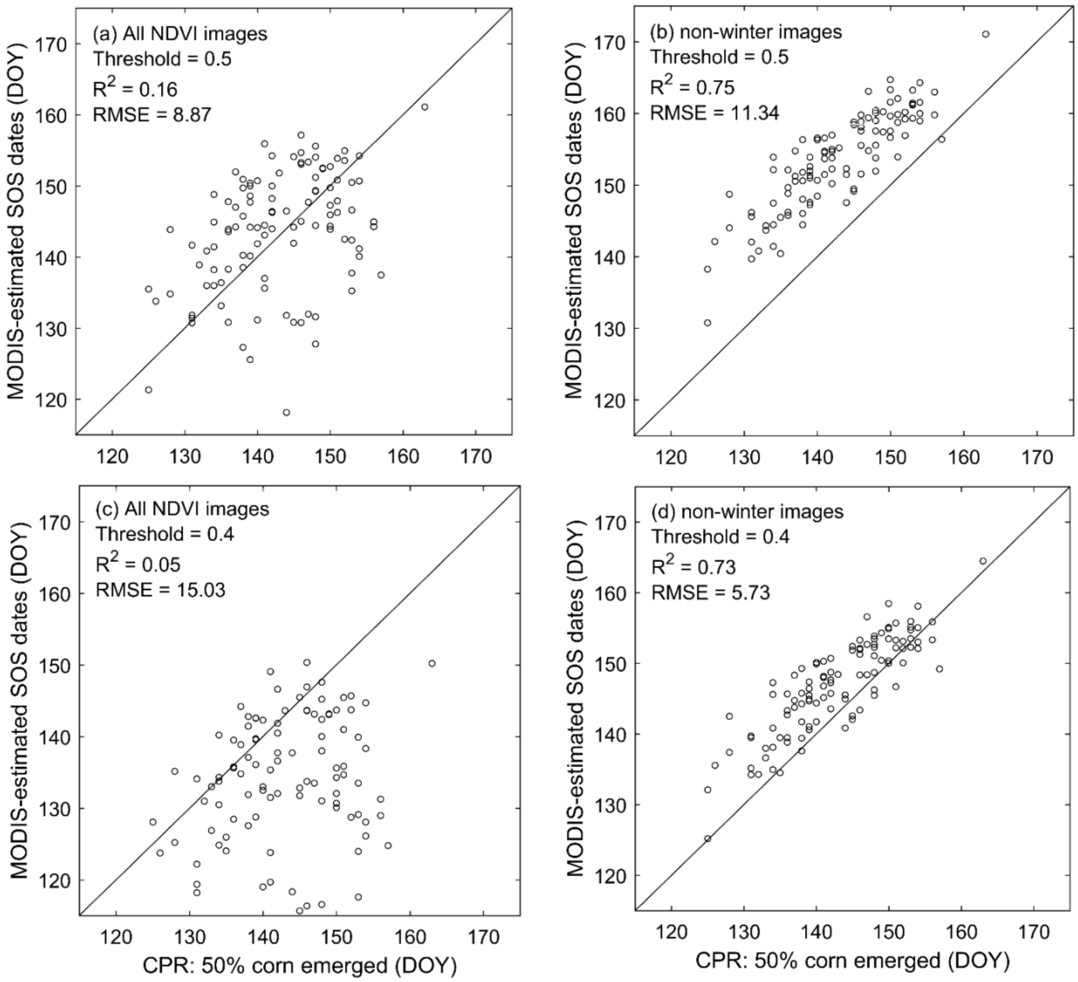

Figure 3.2. Comparison of MODIS-derived SOS values and the USDA CPR survey data of 50% corn emerged dates: (a) all NDVI images as input and threshold value of 0.5, (b) non-winter images as input and threshold value of 0.5, (c) all NDVI images as input and threshold value of 0.4, and (d) non-winter images as input and threshold value of 0.4.

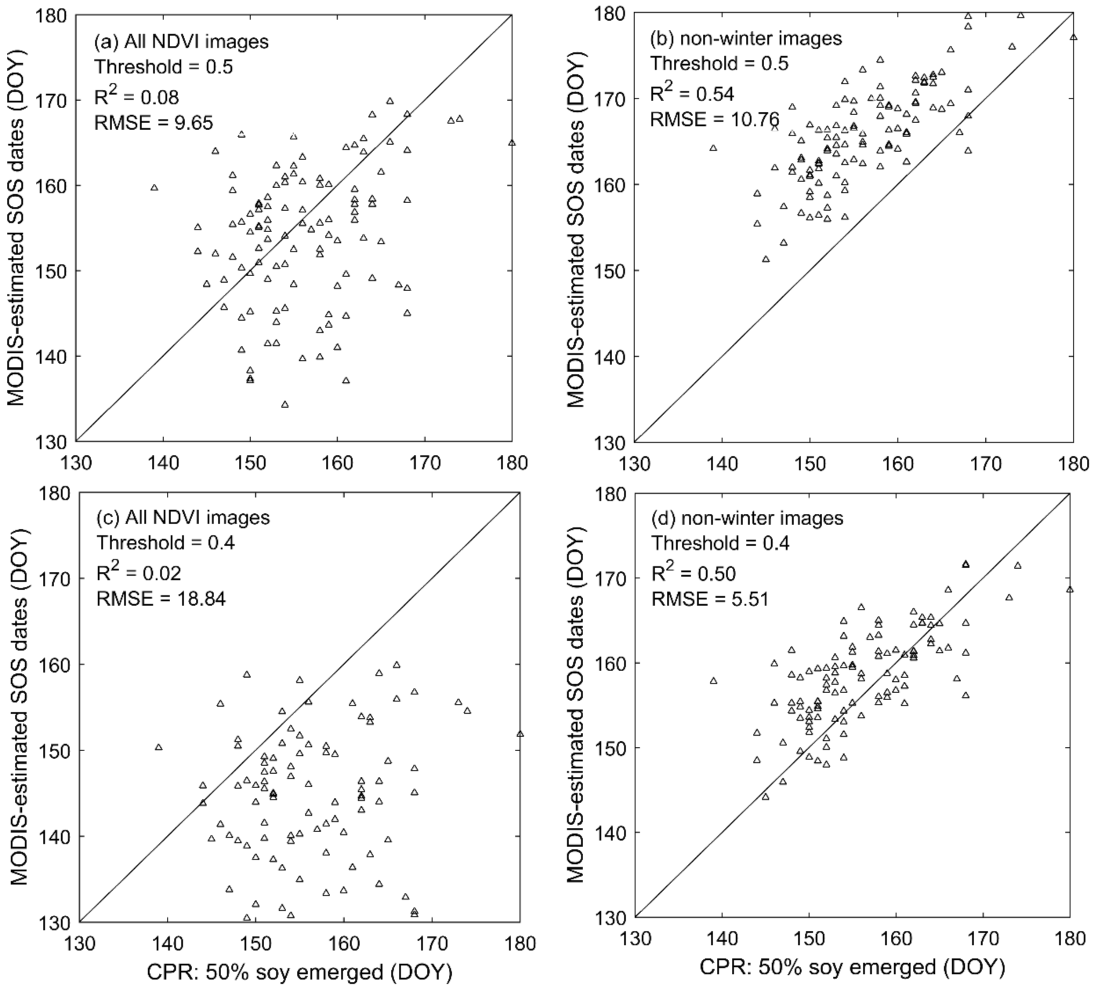

Figure 3.3. Comparison of MODIS-derived SOS values and the USDA CPR survey data of 50% soybean emerged dates: (a) all NDVI images as input and threshold value of 0.5, (b) non-winter images as input and threshold value of 0.5, (c) all NDVI images as input and threshold value of 0.4, and (d) non-winter images as input and threshold value of 0.4.

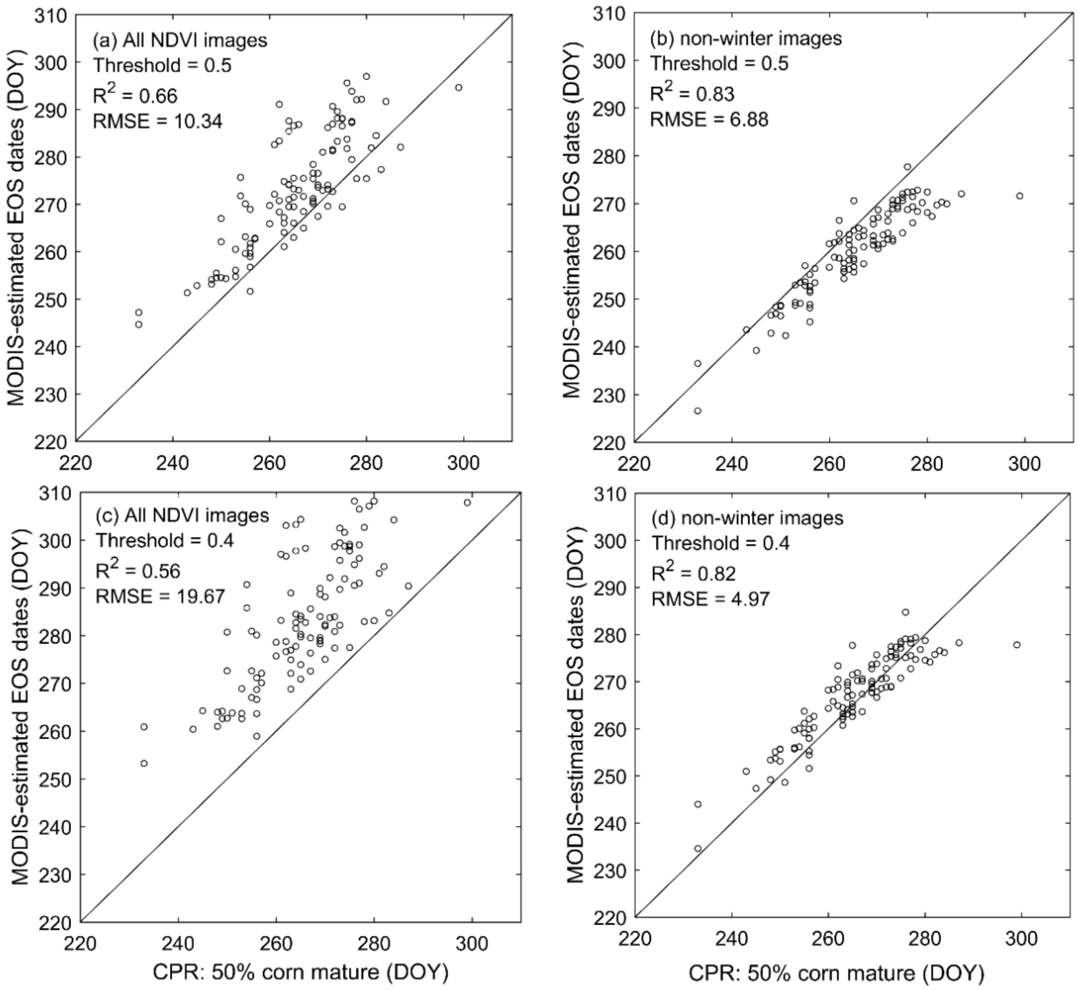

Figure 3.4. Comparison of MODIS-derived EOS values and the USDA CPR survey data of 50% corn mature dates: (a) all NDVI images as input and threshold value of 0.5, (b) non-winter images as input and threshold value of 0.5, (c) all NDVI images as input and threshold value of 0.4, and (d) non-winter images as input and threshold value of 0.4.

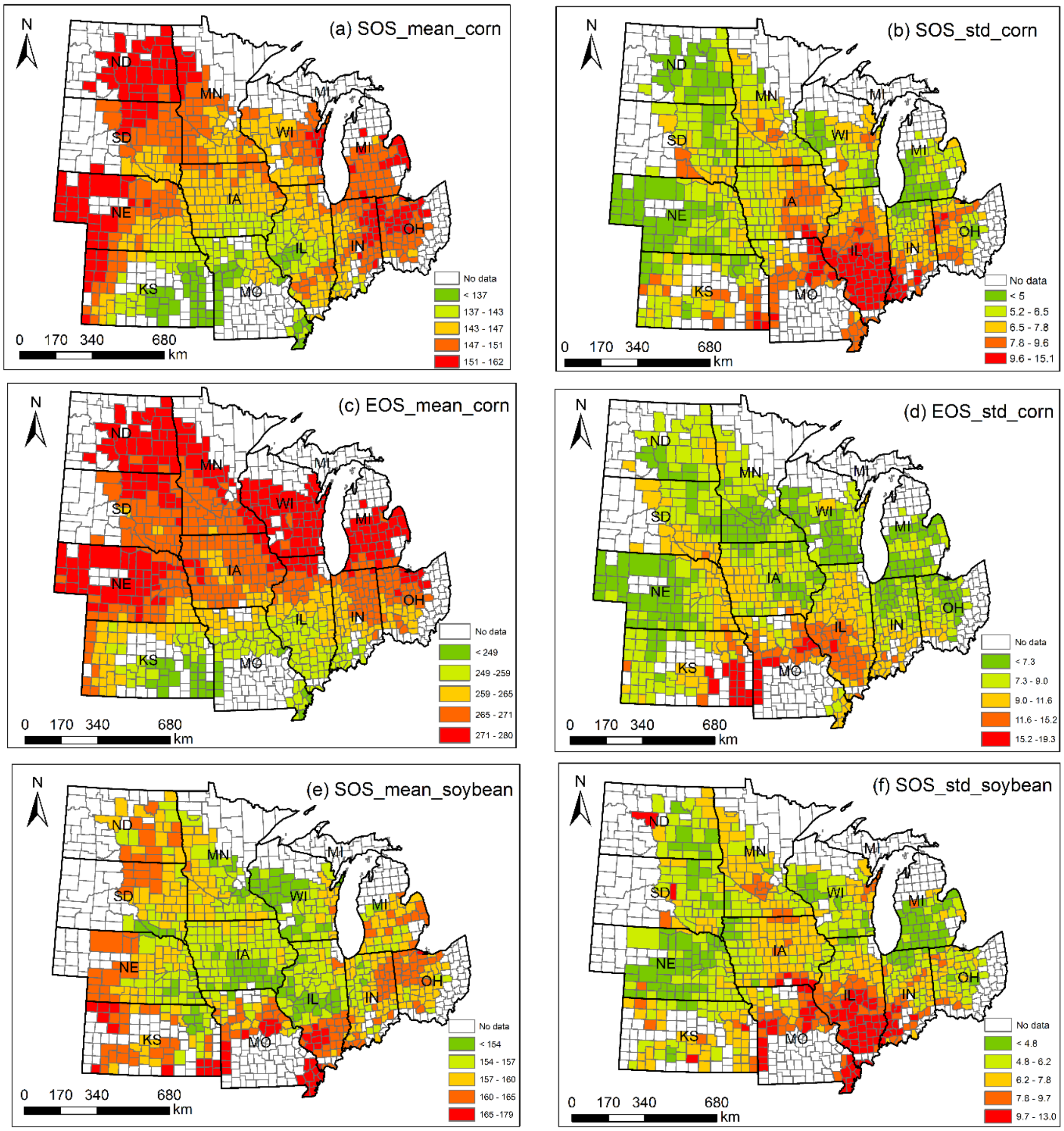

Figure 3.5. County-scale SOS and EOS statistics for 2007-2015: (a) mean SOS for corn; (b) standard deviation of SOS for corn; (c) mean EOS for corn; (d) standard deviation of EOS for corn; (e) mean SOS for soybean; (f) standard deviation of SOS for soybean.

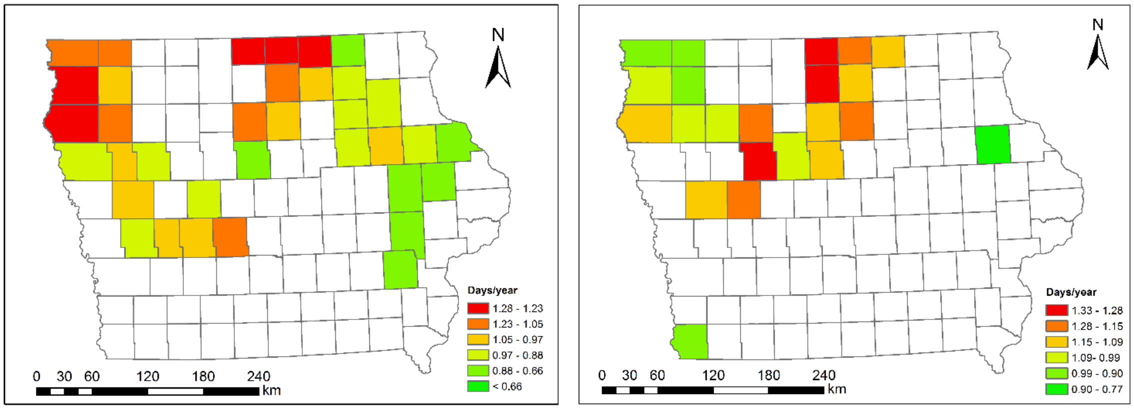

Figure 3.6. Iowa counties showed downwards temporal trends for corn (left) and soybean (right). Results are based on 2001-2012 temporal window.

Chapter 4 Predicting Sediment and Nutrient Loads for Selected Agricultural Watersheds in the Midwestern United States

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In preparation

Abstract

This study integrated remote sensing-derived data for analysis using the Soil and Water Assessment Tool (SWAT) within a geographic information system (GIS) modeling environment to assess impacts of changes of cropping systems and planting/harvest dates within agricultural landscapes of the Central US Corn Belt. Specifically, this analysis examined agricultural impacts upon sediment and nutrient yields in the Embarras, the Upper Scioto, and the Upper White watersheds of the Midwestern US. SWAT models were calibrated using 2000-2005 data and validated using 2006-2010 data for stream flows. For the three selected watersheds, the SWAT model-predicted stream flows matched well with USGS observation data. The R^2 values for the validation period were 0.75, 0.74, and 0.81 and the corresponding NSE values were 0.73, 0.75, and 0.81 for the selected three watersheds, respectively. For the baseline condition, annual sediment yields (tons/ha/year) ranged from 0.89 to 3.98, average annual total nitrogen yields (tons/ha/year) ranged from 8.18 to 13.38 and average annual total phosphorus yields (tons/ha/year) ranged from 1.15 to 1.94. Based on various management scenarios, intensive crop rotation increased sediment and nutrient yields while longer growing seasons for crops decreased sediment and nutrient yields.

Keywords: agricultural management, nutrient loadings, SWAT model, sediment yield

1. Introduction

The 2004 National Water Quality Inventory reports that, in US, agricultural nonpoint source (NPS) pollution forms the principal source of water quality impairment to rivers and streams, the third largest source of impairment to lakes, ponds, and reservoirs, and contributes significantly to ground water contamination and degradation of wetlands (USEPA, 2009). Agricultural production forms a leading contributor to NPS in surface waters, estimated to be the source of 60% of nutrient pollution in streams in the US (Daniel et al., 1998). As one of the key grain-producing regions of the world, the Midwest US has experienced significant changes in agricultural land use and management practices in response to many factors, including advanced technology, improved agronomic management, and changing market force (Schilling et al., 2008). The major changes included the conversion of perennial vegetation to annual row crops (Donner, 2003; Johnston, 2013; Zhang & Schilling, 2006) and the shift from standard corn-soybean/soybean-corn rotation to more intensive corn rotation (Secchi et al., 2011; Stern, Doraiswamy, & Hunt, 2012). Moreover, corn planting dates have been progressively earlier over the past several decades in the Midwest US (Duvik, 1989; June, 2014; Kucharik, 2006; Lauer, 2001). Within a few regions, soybean planting dates have been also occurring at earlier dates for a few states (Conley & Santini, 2007; Irwin, Good, & Tannura, 2008; Sacks & Kucharik, 2011). All of these agriculture activities that magnify the agricultural footprint, in response to increased demand for corn production are expected to have significant impacts on sediment and nutrient loading into streams and water bodies, affecting agro-ecosystem functions and services. Peel (1998) reported that soil erosion could be reduced by more than 50% when corn was rotated with other crops (barley and/or hay) instead of grown continuously. Understanding the magnitude of these changes will be useful for farmers and government agencies to make informed decisions and will be essential for resource managers and policy makers to reduce or control water pollution in agricultural watersheds.

Hydrologic models have been increasingly used to assess hydrologic and biogeochemical responses to land use, land management, and climate change (Aouissi et al., 2014; Boithias et al., 2014; Jha, Gassman, & Arnold, 2007; Oeurng, Sauvage, & Sánchez-pérez, 2011; Santhi et al., 2014; Yang et al., 2015; Zabaleta et al., 2014; Zuo et al., 2016) at various spatial and temporal scales. Use of these watershed models can be very helpful in understanding of interactions between land use and management change, climate variability, water quantity, and water quality issues (Pradhanang et al., 2013). Among these models, Soil and Water Assessment Tool (SWAT) has been successfully implemented all over the world to assess hydrology and water quality in ungauged watersheds (see SWAT Literature database: https://www.card.iastate.edu/swat_articles/). For example, Chiang et al. (2010) assessed individual impacts of land use change and pasture management on sediment, N, and P losses using SWAT with 12 years of detailed spatial land use data. They differentiated impacts of land use changes from conservation practice implementation to determine the relative contributions of sediment and nutrients from pastureland and urban areas. Gassman et al. (2015) simulated alternative cropping systems and management practices scenarios that were analyzed in support of the Master Plan with SWAT for the Raccoon River watershed, west central Iowa, to provide insights of how widespread adoption of these alternative nutrient and cropping system practices could influence water quality.

Furthermore, simulation of hypothetical scenarios in SWAT has proven to be an effective method of evaluating alternative land use and management practices (e.g., conservation, fertilizer, and pesticide management) on water, sediment, and agricultural chemical yields (Gassman et al., 2007). Many studies have investigated effects of cropping systems on sediment and nutrient yields. Shao et al. (2012) accessed the impacts of corn expansion and crop rotation change on sediment yield within four selected watersheds in the Laurentian Great Lakes Basin using SWAT. Results revealed significant increases in average annual sediment yields associated with corn expansion and switching to continuous corn rotation. Mbonimpa et al. (2012) assessed the impacts of various crop rotation patterns on sediment and phosphorus loading in Upper Rock River watershed in Wisconsin with SWAT. They found that conversion of corn-soybean rotation to corn-corn-soybean rotation and continuous corn rotation increased sediment yield and total phosphorus loss. Tong and Naramngam (2007) reported that corn–soybean rotation under no-till significantly reduced sediment, ammonia, and total phosphorus loads in the Little Miami River basin, compared with similar tillage treatments with continuous corn. No study has thus far been discussed impacts of changes of crop planting dates and growing season length on sediment and nutrient yields.

The overall objective of this study was to examine impacts of changes of cropping systems and planting/harvest dates on sediment and nutrient yields with the SWAT model for selected watersheds in the Midwestern US. Specific objectives were: (1) to estimate baseline sediment and nutrient yields under current cropping system and planting/harvest dates, and (2) to predict sediment and nutrient yields for simulated future agricultural management scenarios to quantify impacts of changes of cropping systems and planting/harvest dates on water quality. Borah and Bera (2003, 2004) extensively reviewed eleven continuous simulation models and single-event watershed models for prediction of nutrient export with different land management strategies at a watershed scale. They reported that the SWAT model is better than other models for long-term continuous simulations in predominantly agricultural watersheds. SWAT also allows crop rotation patterns to be defined on a yearly basis, with the timing of planting, harvest, and other operations being specified by the date or by heat units in the model. According to these justifications, the SWAT model was selected for this study.

2. Methods

2.1 Watershed Description

The Midwestern US is one of the world's key grain-producing regions, producing most of US corn and soybeans, and half of the nation's wheat. Since 2005, this region has undergone significant changes in agricultural cropping patterns (Lunetta et al., 2010). We selected three eight-digit Midwestern HUC watersheds to assess impacts of agricultural management on water quality. The three selected watersheds are: the Embarras watershed, east-central Illinois, the Upper Scioto watershed, central Ohio, and the Upper White watershed, central Indiana (Figure 4.1).

The Embarras watershed (Illinois), in the Western Corn Belt Plains, is part of the Wabash River basin, where it covers approximately 6309 km^2 with 73% of agricultural land. Soils within the watershed range from poorly to moderately well-drained. Average annual precipitation is approximately 1041 mm/year and average annual snowfall is approximately 665 mm/year (McConkey & Johanson, 2002). The Upper Scioto watershed (Ohio), in the Eastern Corn Belt Plains, covers roughly 8277 km^2 with 54% of agricultural land. Soils are dominantly moderately or poorly drained. Average annual precipitation is approximately 1022 mm/year and average annual stream flow is approximately 400 mm/year (Xie, 2014). The Upper White watershed (Indiana), in the Central Corn Belt Plains, encompasses approximately 7075 km^2 with 59% of agricultural land. Here, soils are dominantly well drained, principally in cropland. Average annual precipitation is about 1067 mm/year and average annual snowfall is about 737 mm/year (IDEM Office of Water Quality, 2001). Agriculture is the dominant land use within all of the selected watersheds, and large portions (i.e., >50%) of agricultural lands are devoted to corn and soybean production.

2.2 SWAT Model Setup and Description

The SWAT model, developed by the United States Department of Agriculture-Agriculture Research Service (USDA-ARS), is a physically-based, continuous-time, watershed-scale simulation model operating on a daily time step (Arnold et al., 1998; Neitsch et al., 2002). Major components of the model include hydrology, weather, sedimentation, soil temperature, plant growth, nutrients, pesticides, and land management. A complete description of the SWAT model and its components can be found in Arnold et al. (1998) and Neitsch et al. (2002).

We used SWAT 2012, which is compatible with the ArcGIS interface (Neitch et al., 2009), to model water, sediment and nutrient yields. In SWAT 2012, each watershed was divided spatially into subbasins or subwatersheds using a 30 m Digital Elevation Model (DEM) obtained from the USGS Seamless Data Distribution System. The USGS

National Hydrology Dataset was directly overlaid on the DEM for watershed delineation to ensure stream locations were correctly identified. Each subbasin was then subdivided into Hydrologic Response Units (HRUs), defined by homogeneous land use, topography, and soil characteristics. HRUs were created by overlapping the 2006 National Land Cover Dataset (NLCD 2006), the State Soil Geographic dataset (STATSGO), and slope datasets were generated from the DEM using threshold values of 5% for land use, soil and slope. The threshold values were used to preserve the land use and soil properties and to remove minor land use and soil types so that simplified HRU definitions could be achieved (FitzHugh & Mackay, 2000).

The climate data needed by the SWAT model, including daily precipitation, minimum and maximum temperature, were obtained from the USDA-ARS for the period January 1998 to December 2010. In order to improve spatial representation for precipitation and temperature data, all available weather stations within a watershed were used as the input. Wind speed, solar radiation, and relative humidity were estimated using the weather generator built into the SWAT model.

The SWAT model has the ability to define the timing of planting, harvest, and other operations by the date or by heat units. In the SWAT management files, planting/harvest schedules were fixed on specific dates, based on average planting/harvest dates derived from USDA NASS Crop Progress Report (CPR), as follows: planting/beginning of growing season for corn on May 2, 7, and 8, planting/beginning of growing season for soybeans on May 22, 19, and 22, harvest operation and then kill operation to remove corn on October 13, 28, and 22, and harvest operation and then kill operation to remove soybeans on October 11, 12, and 11, for

Embarras, Upper Scioto, and Upper White watersheds, respectively. In order to make our analysis simple, no-till was assumed for all selected cropping systems with default fertilizer application rates.

2.3 SWAT Model Calibration and Validation

The SWAT simulation was executed on a monthly basis from 1998 to 2010, with 1998 to 1999 serving as a two-year warm-up period, 2000 to 2005 as the calibration period and 2006 to 2010 as the validation period. In general, SWAT calibration starts with water balance and stream flow, followed by sediment and nutrients (Arnold et al. 2000; Kirsch et al., 2002; Santhi et al. 2001).

The model was initially calibrated for hydrology using the recommended SWAT model manual calibration approach for water balance and stream flow calibration (Neitsch et al., 2002). Before calibration, SMFMX (melt factor for snow on June 21), SMFMN (melt factor for snow on December 21), and n (Manning's coefficient) were adjusted based on the existing documentation. Key hydrologic parameters such as CN2 (curve number), ESCO (soil evaporation compensation factor), SOL_AWC (soil available water capacity), Alpha_BF (base-flow recession constant), GW_Revap (groundwater ''revap'' coefficient), and REVAPMN (threshold depth of water in the shallow aquifer for "revap" or percolation to the deep aquifer to occur) were manually adjusted to increase or decrease the predicted average annual surface runoff and base flow.

Additional SWAT model parameters, such as SURLAG (surface runoff lag coefficient), were also adjusted to improve the SWAT model performance on monthly basis. Table 4.1 lists descriptions and calibrated values of the common parameters used in Embarras, Upper Scioto, and Upper White watersheds, respectively. Simulated streamflows were compared with corresponding observed data collected at USGS gauge stations 03354000 at Ste. Marie, IL for Embarras River, 03227500 at Columbus, OH for Upper Scioto River, and 03354000 near Centerton, IN for Upper White River from January 1998 to December 2010. The SWAT model-predicted stream flow was evaluated against the observed data at monthly intervals using two most commonly used quantitative statistics, the linear regression coefficient of determination (R^2) and the Nash and Sutcliffe model efficiency coefficient (NSE). According to Moriasi et al. (2007), threshold NSE values of 0.4, 0.5, and 0.7 are used as criteria for accepting stream flow estimations on a daily, monthly, and yearly basis, respectively. The same threshold values were used to judge the model's performance for R^2 (Gassman et al., 2007).

With regard to calibration and validation of sediment and nutrient components, because of insufficient long-term water quality monitoring data at the gauge stations in the selected watersheds, it is not feasible to calibrate predicted sediment and nutrient load. Among the SWAT model parameters that may affect sediment yields, universal soil loss equation practice factor (USLE_P) is commonly adjusted for the sediment-yield calibration. For Upper Scioto watershed, USLE_P was reduced to represent the pre-existing erosion control practices in agricultural lands. A value of 0.39 was applied to fields assigned with no-till practice (Arabi, Frankenberger, Engel, & Arnold, 2008). Default SWAT model parameters were used to estimate nutrient components (i.e., organic N, NO_3, organic P, soluble P).

2.4 Future Management Scenarios

The calibrated SWAT models were used to assess the sediment, total nitrogen, and total phosphorus yields for nine simulated future management scenarios. The nine scenarios are grouped according to three main categories based on cropping systems, planting date and length of growing season (Table 4.2). Scenarios 1-3 represent alternative cropping system scenarios in which standard corn-soybean or soybean-corn cropping systems were converted to continuous corn, two years of continuous corn, and two years of continuous soybean cropping systems, respectively. In scenarios 4 to 6, under standard corn-soybean or soybean-corn cropping systems, corn and soybeans were planted one, two, and three weeks earlier and the length of growing season remained the same as those of the baseline condition. Scenarios 7 through 9 advance planting dates and extend the length of growing season. In these scenarios, corn and soybeans were planted one, two, and three weeks earlier but were harvested at the same time as those of the baseline condition, still under the standard corn-soybean or soybean-corn cropping systems. Although these assumed management scenarios are likely unrealistic, our intention was to assess boundary conditions under these extreme scenarios. We replaced the baseline cropping system and operational data with the future cropping system and operational data, and kept other SWAT model inputs and parameters the same as the baseline condition. Sediment, total nitrogen, and total phosphorus yields for future management scenarios were then compared with the baseline yields.

3. Results and Discussion

3.1 SWAT Model Performance

Based on the locations of weather stations, the stream network, and basin topography, the SWAT model watershed-delineation procedure created total numbers of 31, 27, and 26 sub-basins for Embarras, Upper Scioto, and Upper White watersheds, respectively. These basins were further divided into 791, 1008, and 960 HRUs based on land use, soil properties, and slope.

To estimate the impact of management operations on sediment and nutrient yields, stream flows were calibrated and validated by comparing simulated monthly stream flows and observed stream flows at the USGS gauge stations. The statistical performance of the SWAT baseline calibration and validation simulation is shown in Table 4.3. For calibration, the R^2 and NSE values for all three watersheds were greater than 0.5, which is generally viewed as a satisfactory model performance. For validation, a strong correlation was observed for all three watersheds, as indicated by the R^2 and NSE values that ranged between 0.73 and 0.81.

Figure 4.2 shows the comparison of between simulated monthly stream flows and observed values for Embarras watershed, Upper Scioto watershed, and Upper White watershed, respectively. The scatter plots suggested that the SWAT model-predicted stream flows matched USGS observed values reasonably well. The main difficulty was the relatively large scatter for the medium-low stream flow values. For all three watersheds, the SWAT model overestimated low flows during summer months (i.e., July to September) while underestimating peak flows, mostly in the late winter to early spring months (i.e., January to March).

3.2 Sediment Yields under Different Scenarios

For all three watersheds, there were no long-term observation data for calibration of sediment yields. Results from several other studies in similar watersheds were used to guide sediment calibration and determine the appropriate magnitude of sediment yields at annual scales. For the Upper Scioto watershed, annual average sediment yield per unit watershed area was calculated by SWAT with reference to Xie's (2014) study in the same watershed and Whiting's (2003) study in the Great Lakes Basin. The model reported an annual sediment load at 0.89 tons/ha, which is comparable to Xie's results of 0.84 tons/ha and Whiting's results of 0.85 tons/ha to Scioto River at Higby. We used default SWAT model parameters for the Embarras and the Upper White watersheds due to the limited availability of calibration data.

For the baseline condition, the average annual sediment yields (tons/ha/year) were 2.58, 0.89, and 3.98 for the Embarras, the Upper Scioto, and the Upper White watersheds, respectively. Spatial distributions of average annual sediment yields at the sub-basin level for the three watersheds are shown in Figure 4.3. In general, the sediment yields in downstream regions were higher than those in upstream regions and the sub-basins with high sediment yields (i.e., > 2 tons/ha/year) matched well with the location of agricultural lands with relatively high slope values (i.e., > 3% slope). For the Upper White watershed, three sub-basins with high sediment yields (2-3 tons/ha/year) are dominated by forest, which is related to higher slope in these regions. Moreover, there are floodplains in downstream regions with agricultural land. They would result high sediment yields.

Table 4.4 shows average annual sediment yield simulated by the SWAT model under different management scenarios, and total percent change from baseline conditions for selected watersheds. Differences between scenarios 1 to 3 and baseline conditions indicate the impact of cropping systems. Sediment yields increase dramatically as corn production intensifies. When switching baseline crop rotation to continuous corn rotation, average annual sediment yields (tons/ha/year) increased to 4.62, 1.73, and 8.62 for the Embarras, the Upper Scioto, and the Upper White watersheds, respectively. Compared to baseline conditions, average annual sediment yields almost doubled (79-117%). Average annual sediment yields with two years of continuous soybean rotation changed very slightly (< 3%) compared to baseline conditions. This result was similar to that of some other studies. The conversion of corn-soybean rotation to continuous corn rotation resulted in 20% (Intarapapong & Hite, 2002), 24% (Tong & Naramngam, 2007), and 36% (Mbonimpa et al., 2012) increase in sediment yield in Mississippi, Florida, and Wisconsin, respectively, while continuous soybean rotation had the smallest amount of annual sediment loads (Tong & Naramngam, 2007). One possible explanation is that soybeans are usually planted at a higher density and their leaves and roots offer better protection from soil erosion than corn (Tong & Naramngam, 2007). However, this result was the complete opposite of others. Gassman, Secchi, and Jha (2008) found that sediment losses decreased across all of the corn expansion scenarios, with percentage reductions ranging from almost 2 to over 11% for total conversion from corn-soybean rotation into continuous corn rotation. Based on field experiments, corn produces about twice more residue than soybean (Larson, Holt, & Carlson, 1978). Corn residue also decomposes at a slower rate than soybean residue during the first half of the year of decomposition (Ghidey et al., 1985). Together, these two factors would give areas with corn cropping more cover and protection against raindrop detachment during the overwintering period. Moreover, as the additional residue cover with corn cropping, the near soil surface would be better protected and would undergo less weathering and aggregate breakdown when compared to the soil protected by soybean residue (Alberts, Wendt, & Burwell, 1985).

Differences between scenarios 4 to 9 and baseline conditions indicate the impact of planting date and length of growing season. With earlier planting dates (scenarios 4-6, advance planting date 1-3 weeks), average annual sediment yields increased slightly (1-4%). The earlier the planting date, the more the sediment yield. With longer growing seasons (scenarios 7-9), average annual sediment yields increased slightly. Reductions in sediment loss ranged from 2% to 7%. For longer growing seasons, soil surfaces will be covered by crops for longer time, therefore exhibiting lower erosion rates.

3.3 Total Nitrogen Yields under Different Scenarios

For all three watersheds, there were no long-term observational data for calibration of total nitrogen yields. Therefore, we used default SWAT model parameters to estimate total nitrogen yields. For the baseline condition, average annual total nitrogen yields (tons/ha/year) were 8.46, 8.18, and 13.38 for the Embarras, the Upper Scioto, and the Upper White watersheds, respectively. Spatial distributions of average annual total nitrogen yields at the sub-basin level for the three selected watersheds are shown in Figure 4.4. In general, major contributors of total nitrogen were in sub-basins that were dominated by agricultural croplands, especially with relatively high slope values (i.e., > 3% slope). The Upper White watershed had the highest overall total nitrogen yield. In contrast with the other two watersheds, total nitrogen yield in the downstream region was lower than that in the upstream region.

Simulated results of total nitrogen yield under the different scenarios shown in Table 4.4 show that intensive crop rotation increased total nitrogen yield while the longer growing seasons of crops decreased total nitrogen yield. When switching the baseline crop rotation to continuous corn rotation, average annual total nitrogen yields (kgs/ha/year) increased 21-25% for the selected three watersheds. This result can be explained by the fact that legumes (e.g., soybean) can fix large amounts of organic nitrogen which is less susceptible to leaching and increase the available soil nitrogen (Peel, 1998). Additionally, farmers may not have to apply as much inorganic nitrogen fertilizer, which is very soluble and more vulnerable to leaching. For the Upper White watershed, two years of continuous corn rotation had no effect (i.e., < 1% increase) on total nitrogen loss. With earlier planting dates (scenarios 4-6), the average annual total nitrogen yields increased slightly (< 5%) for the Embarras watershed. For the Upper Scioto, and the Upper White watersheds, the average annual total nitrogen yields were almost the same as the baseline condition. Longer growing seasons (scenarios 7-9) also decreased average annual total nitrogen yields slightly for the selected watersheds. Total nitrogen loss reductions ranged from 1% to 3%. Longer growing season which means a longer time of soil cover will reduce total nitrogen loss.

3.4 Total Phosphorus Yields under Different Scenarios

For all three watersheds, there were no long-term observation data for the calibration of total phosphorus yields. We used default SWAT model parameters to estimate total phosphorus yields. For the baseline condition, average annual total phosphorus yields (tons/ha/year) were 1.15, 1.18, and 1.94 for the Embarras, the Upper Scioto, and the Upper White watersheds, respectively. The spatial distributions of average annual total nitrogen yields at the sub-basin level for the three selected watersheds are shown in Figure 4.5. In general, the major sources of total phosphorus were also in sub-basins that were generally dominated by agricultural croplands, especially with relatively high slope values (i.e., > 3% slope). Similar to results of the total nitrogen yield, the Upper White watershed had the highest overall total nitrogen yield. In contrast to the other two watersheds, total phosphorus yield in the downstream region was lower than that in the upstream region.

Simulated results of total phosphorus yield under the different scenarios shown in Table 4.4 are similar to the simulated results of total nitrogen yield. Intensive crop rotation increased total phosphorus yield. When switching the baseline crop rotation to continuous corn rotation, the average annual total phosphorus yields increased 15-19% for the selected three watersheds. The average annual total phosphorus yield with two years of continuous corn rotation for the Upper White watershed was the same as the baseline condition. With earlier planting dates (scenarios 4-6), the average annual total phosphorus yields increased slightly (< 5%) for the Embarras watershed. For the Upper Scioto, and the Upper White watersheds, average annual total phosphorus yields were almost the same as the baseline condition. An longer growing season (scenarios 7-9) also decreased average annual total phosphorus yields due to a longer duration of soil cover. Compared with the baseline condition, annual total phosphorus yields decreased 1-3%.

4. Conclusion

This study assessed the impacts of changes of cropping systems and planting/harvest dates on sediment and nutrient yields in the Embarras, the Upper Scioto, and the Upper White watersheds using the SWAT model. Sediment and nutrient losses under different management scenarios were compared at different spatial scales. At baseline conditions, individual SWAT models were calibrated and validated for stream flows. For the three selected watersheds, the SWAT model-predicted stream flows matched well with the USGS observation data. For the validation period of 2006–2010, the R^2 and NSE values were greater than 0.5, which is generally viewed as a satisfactory model performance.

Effects of changes of cropping systems on sediment and nutrient yields were assessed by using the calibrated SWAT model under three scenarios. Results showed that intensive crop rotation resulted in greater sediment, total nitrogen, and total phosphorus yields, indicating that the increases in sediment, total nitrogen, and total phosphorus losses were mainly due to intensification of corn production. Under the other six scenarios, effects of changes of planting/harvest dates on sediment and nutrient yields were assessed. Results showed that advancing of planting date with the same length of growing season had no effect on water quality. But longer growing seasons reduced sediment yields by 2-7%, total nitrogen by 1-3%, and total phosphorous by 1-3%, indicating that a longer interval with crop cover on the soil helped reduce erosion rates and nutrient losses.

In this study, comparisons of the sediment and nutrient yields were conducted using the same climate conditions for all the management scenarios. The prediction of sediment and nutrient yields for future changes of planting/harvest dates can be complicated by different climate-change scenarios because crop phenology is responsive to long-term variations in climate (White & Thomton, 1997).

References

Alberts, E. E., Wendt, R. C., & Burwell, R. E. (1985). Corn and soybean cropping effects on soil losses and C factors. *Soil Science Society of America Journal*, *49*(3), 721–728.

Aouissi, J., Benabdallah, S., Chabaâne, Z. L., & Cudennec, C. (2014). Modeling water quality to improve agricultural practices and land management in a Tunisian catchment using the Soil and Water Assessment Tool. *Journal of Environmental Quality*, *43*(1), 18–25.

Arabi, M., Frankenberger, J. R., Engel, B. A., & Arnold, J. G. (2008). Representation of agricultural conservation practices with SWAT. *Hydrological Processes*, *22*(16), 3042–3055.

Arnold, J. G., Muttiah, R. S., Srinivasan, R., & Allen, P. M. (2000). Regional estimation of base flow and groundwater recharge in the Upper Mississippi river basin. *Journal of Hydrology*, *227*(1), 21–40.

Arnold, J. G., Srinivasan, R., Muttiah, R. S., & Williams, J. R. (1998). Large area hydrologic modeling and assessment part I: model development. *Journal of the American Water Resources Association*, *34*(1), 73–89.

Boithias, L., Srinivasan, R., Sauvage, S., Macary, F., & Sánchez-Pérez, J. M. (2014). Daily nitrate losses: Implication on long-term river quality in an intensive agricultural catchment of southwestern France. *Journal of Environmental Quality*, *43*(1), 46–54.

Borah, D. K., & Bera, M. (2003). Watershed-scale hydrologic and nonpoint-source pollution models: Review of mathematical bases. *Transactions of the ASAE*, *46*(6), 1553.

Borah, D. K., & Bera, M. (2004). Watershed-scale hydrologic and nonpoint-source pollution models: review of applications. *Transactions of the ASAE*, *47*(3), 789–804.

Chiang, L., Chaubey, I., Gitau, M. W., & Arnold, J. G. (2010). Differentiating impacts of land use changes from pasture management in a CEAP watershed using the SWAT model. *Transactions of the ASABE*, *53*(2), 1569–1584.

Conley, S. P., & Santini, J. B. (2007). Crop Management Practices in Indiana Soybean Production Systems. *Crop Management*, *6*(1), 0–0. doi:10.1094/CM-2007-0104-01-RS

Daniel, T. C., Sharpley, A. N., & Lemunyon, J. L. (1998). Agricultural phosphorus and eutrophication: A symposium overview. *Journal of Environmental Quality*, *27*(2), 251–257.

Donner, S. (2003). The impact of cropland cover on river nutrient levels in the Mississippi River Basin. *Global Ecology and Biogeography*, *12*(4), 341–355.

Duvik, D. N. (1989). 12 Possible Genetic Causes of Increased Variability in US Maize Yields. In J. R. Anderson & P. B. R. Hazell (Eds.), *Variability in grain yields: Implications for agricultural research and policy in developing countries* (pp. 147–156). Baltimore: Johns Hopkins University Press.

FitzHugh, T. W., & Mackay, D. S. (2000). Impacts of input parameter spatial aggregation on an agricultural nonpoint source pollution model. *Journal of Hydrology*, *236*(1), 35–53.

Gassman, P., Jha, M., Wolter, C., & Schilling, K. (2015). Evaluation of Alternative Cropping and Nutrient Management Systems with Soil and Water Assessment Tool for the Raccoon River Watershed Master Plan. *American Journal of Environmental Sciences, 1991*. doi:10.3844/ajessp.2015.227.244

Gassman, P. W., Reyes, M. R., Green, C. H., & Arnold, J. G. (2007). The Soil and Water Assessment Tool : Historical Development , Applications, and Future Research Directions. *Transactions of the ASABE, 50*(4), 1211–1250.

Gassman, P. W., Secchi, S., & Jha, M. (2008). Assessment of Bioenergy-Related Scenarios for the Boone River Watershed in North Central Iowa, (701).

Ghidey, F., Gregory, J. M., McCarty, T. R., & Alberts, E. E. (1985). Residue decay evaluation and prediction. *TRANSACTIONS of the ASAE*, *28*(1), 102–105.

IDEM Office of Water Quality. (2001). *Upper White River Watershed Restoration Action Strategy*.

Intarapapong, W., & Hite, D. (2002). Water quality impacts of conservation practices under environmental constraints: The case of the Mississippi Delta. In *2002 Proceedings of a Regional Workshop SERA-IEG-30, Mississippi State University, Mississippi State, Mississippi*.

Irwin, S., Good, D., & Tannura, M. (2008). Forming expectations about 2008 US corn and soybean yields—application of crop weather models that incorporate planting progress. *Marketing and Outlook Brief, 3*.

Jha, M. K., Gassman, P. W., & Arnold, J. G. (2007). Water quality modeling for the Raccoon River watershed using SWAT. *Transactions of the ASABE, 50*(2), 479–494.

Johnston, C. A. (2013). Wetland Losses Due to Row Crop Expansion in the Dakota Prairie Pothole Region. *Wetlands*, *33*(1), 175–182. doi:10.1007/s13157-012-0365-x

June, C. (2014). *Descriptions of PRISM Spatial Climate Datasets for the Conterminous United States*.

Kirsch, K., Kirsch, A., & Arnold, J. G. (2002). Predicting sediment and phosphorus loads in the Rock River Basin using SWAT. *Transactions of the ASAE*, *45*(6), 1757–1769.

Kucharik, C. J. (2006). A multidecadal trend of earlier corn planting in the central USA. *Agronomy Journal*, *98*, 1544–1550. doi:10.2134/agronj2006.0156

Larson, W. E., Holt, R. F., & Carlson, C. W. (1978). Residues for soil conservation. *Crop Residue Management Systems*, (cropresiduemana), 1–15.

Lauer, J. (2001). Earlier planting dates for corn: Real progress or an effect of global warming? Retrieved from http://corn.agronomy.wisc.edu/WCM/W089.aspx

Lunetta, R. S., Shao, Y., Ediriwickrema, J., & Lyon, J. G. (2010). Monitoring agricultural cropping patterns across the Laurentian Great Lakes Basin using MODIS-NDVI data. *International Journal of Applied Earth Observation and Geoinformation*, *12*(2), 81–88. doi:10.1016/j.jag.2009.11.005

Mbonimpa, E. G., Yuan, Y., Mehaffey, M. H., & Jackson, M. A. (2012). SWAT model application to assess the impact of intensive corn-farming on runoff, sediments and phosphorous loss from an agricultural watershed in Wisconsin. *Journal of Water Resource and Protection*, *4*(7), 423.

McConkey, S. A., & Johanson, M. D. (2002). *Embarras River Watershed Digital Floodplain Mapping, Champaign County, Illinois*. Illinois State Water Survey.

Moriasi, D. N., Arnold, J. G., Liew, M. W. Van, Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE*, *50*(3), 885–900.

Neitch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2009). *Soil and Water Assessment Tool: Theoretical Documentation Version 2009*. College Station, TX.

Neitsch, S. L., Arnold, J. G., Kiniry, J. E. A., Srinivasan, R., & Williams, J. R. (2002). Soil and water assessment tool user's manual version 2000. *GSWRL Report*, *202*(02-06).

Oeurng, C., Sauvage, S., & Sánchez-pérez, J. (2011). Assessment of hydrology, sediment and particulate organic carbon yield in a large agricultural catchment using the SWAT model. *Journal of Hydrology*, *401*(3-4), 145–153. doi:10.1016/j.jhydrol.2011.02.017

Peel, M. D. (1998). *Crop rotations for increased productivity*. NDSU Extension Service.

Pradhanang, S. M., Mukundan, R., Schneiderman, E. M., Zion, M. S., Anandhi, A., Pierson, D. C., … Steenhuis, T. S. (2013). Streamflow responses to climate change: Analysis of hydrologic indicators in a New York City water supply watershed. *JAWRA Journal of the American Water Resources Association*, *49*(6), 1308–1326.

Sacks, W. J., & Kucharik, C. J. (2011). Crop management and phenology trends in the U.S. Corn Belt: Impacts on yields, evapotranspiration and energy balance. *Agricultural and Forest Meteorology*, *151*(2011), 882–894. doi:10.1016/j.agrformet.2011.02.010

Santhi, C., Arnold, J. G., Williams, J. R., Dugus, W. A., Srinivasan, R., & Hauck, L. M. (2001). Validation of the SWAT model on a large river basin with point and nonpoint sources. *Journal of the American Water Resources Association*, *37*(5), 1169–1188.

Santhi, C., Kannan, N., White, M., Di Luzio, M., Arnold, J. G., Wang, X., & Williams, J.

R. (2014). An integrated modeling approach for estimating the water quality benefits of conservation practices at the river basin scale. *Journal of Environmental Quality*, *43*(1), 177–198.

Schilling, K. E., Jha, M. K., Zhang, Y.-K., Gassman, P. W., & Wolter, C. F. (2008). Impact of land use and land cover change on the water balance of a large agricultural watershed: Historical effects and future directions. *Water Resources Research*, *44*, 1–12. doi:10.1029/2007WR006644

Secchi, S., Kurkalova, L., Gassman, P. W., & Hart, C. (2011). Land Use Change in a Biofuels Hotspot: The Case of Iowa, USA. *Biomass and Bioenergy*, *35*(6), 2391–2400. doi:10.1016/j.biombioe.2010.08.047

Shao, Y., Lunetta, R. S., Macpherson, A. J., Luo, J., & Chen, G. (2013). Assessing sediment yield for selected watersheds in the Laurentian Great Lakes Basin under future agricultural scenarios. *Environmental Management*, *51*(1), 59–69. doi:10.1007/s00267-012-9903-9

Stern, A. J., Doraiswamy, P. C., & Hunt, E. R. (2012). Changes of crop rotation in Iowa determined from the United States Department of Agriculture , National Agricultural Statistics Service cropland data layer product data layer product. *Journal of Applied Remote Sensing*, *6*(1), 063590–063590. doi:10.1117/1.JRS

Tong, S. T. Y., & Naramngam, S. (2007). Modeling the impacts of farming practices on water quality in the little Miami River Basin. *Environmental Management*, *39*(6), 853–866.

USEPA. (2009). *National Water Quality Inventory : Report to Congress 2004 Reporting Cycle*. Washington, DC.

White, A., & Thomton, P. E. (1997). A continental responses phenology model climatic for monitoring variability vegetation to interannual. *Global Biogeochemical Cycles*, *11*(2), 217–234.

Whiting, P. J. (2003). *Estimating TMDL background sediment loading from existing data: final report to the Great Lakes commission*. Tech. rep., Great Lakes Commission.

Xie, Y. (2014). *Watershed modeling, farm tenancy and adoption of conservation measures to facilitate water quality trading in the Upper Scioto Watershed, Ohio*. The Ohio State University.

Yang, H., Wang, G., Wang, L., & Zheng, B. (2015). Impact of land use changes on water quality in headwaters of the Three Gorges Reservoir. *Environmental Science and Pollution Research*, 1–13. doi:10.1007/s11356-015-5922-4

Zabaleta, A., Meaurio, M., Ruiz, E., & Antigüedad, I. (2014). Simulation climate change impact on runoff and sediment yield in a small watershed in the Basque Country, northern Spain. *Journal of Environmental Quality*, *43*(1), 235–245.

Zhang, Y.-K., & Schilling, K. E. (2006). Increasing streamflow and baseflow in Mississippi River since the 1940s: Effect of land use change. *Journal of Hydrology*, *324*(1), 412–422.

Zuo, D., Xu, Z., Yao, W., Jin, S., Xiao, P., & Ran, D. (2016). Assessing the effects of changes in land use and climate on runoff and sediment yields from a watershed in the Loess Plateau of China. *Science of the Total Environment*, *544*, 238–250. doi:10.1016/j.scitotenv.2015.11.060

Table 4.1. Parameters used for SWAT model calibration.

Parameter	Description	Embarras	Upper Scioto	Upper White
SMFMX	Melt factor for snow on June 21	7.1	2.5	2.5
SMFMN	Melt factor for snow on December 21	2	2.5	2.5
n	Manning’s coefficient	0.05	0.05	0.05
CN2 (%)	Curve number	-20	-5	-5
GW_REVAP	Groundwater “revap” coefficient	0	0.08	*
GWQMN	Threshold depth of water in shallow aquifer for return flow	*	*	500
REVAPMN	Threshold depth of water in shallow aquifer for percolation	0.2	0.02	0.02
ESCO	Soil evaporation compensation factor	0.9	*	*
SOL_AWC (%)	Soil available water capacity	-5	20	-15
ALPHA_BF	Baseflow alpha factor	0.02	0.02	0.05
SURLAG	Surface runoff lag coefficient	0.5	1	0.5
USLE_P	USLE practice factor	*	0.39	*

Table 4.2. Description of future management scenarios.

Scenario	Scenario cropping system	Scenario planting date (corn/soybean)	Scenario harvest date (corn/soybean)
1	continuous corn	same as baseline	same as baseline
2	c-c-s/s-c-c	same as baseline	same as baseline
3	c-s-s/s-s-c	same as baseline	same as baseline
4	c-s/s-c	one week earlier	one week earlier
5	c-s/s-c	two weeks earlier	two weeks earlier
6	c-s/s-c	three weeks earlier	three weeks earlier
7	c-s/s-c	one week earlier	same as baseline
8	c-s/s-c	two weeks earlier	same as baseline
9	c-s/s-c	three weeks earlier	same as baseline

c-s/s-c: corn-soybean or soybean-corn, *c-c-s/s-c-c*: corn-corn-soybean or soybean-corn-corn, *c-s-s/s-s-c*: corn-soybean-soybean or soybean-soybean-corn

Table 4.3. Assessment of SWAT model performance for the calibration (2000-2005) and validation (2006-2010) periods for the selected watersheds.

Watershed	Calibration (2000-2005)		Validation (2006-2010)	
	R^2	NSE	R^2	NSE
Embarras	0.78	0.77	0.75	0.73
Upper Scioto	0.69	0.67	0.74	0.75
Upper White	0.84	0.83	0.81	0.81

Table 4.4. Average annual sediment, total nitrogen (TN) and total phosphorus (TP) yields under different scenarios and total percent changes from baseline conditions for the selected watersheds.

Water quality	Scenario	Embarras	Upper Scioto	Upper White
Sediment (tons/ha/year)	Baseline	2.58	0.89	3.98
	1	4.62 (+79)	1.73 (+94)	8.62 (+117)
	2	3.03 (+18)	1.04 (+17)	4.83 (+22)
	3	2.61 (+1)	0.89 (0)	3.91 (-2)
	4	2.60 (+1)	0.89 (0)	3.98 (0)
	5	2.64 (+2)	0.90 (+2)	4.02 (+1)
	6	2.68 (+4)	0.91 (+3)	4.06 (+2)
	7	2.52 (-2)	0.87 (-2)	3.87 (-3)
	8	2.46 (-5)	0.86 (-3)	3.79 (-5)
	9	2.39 (-7)	0.85 (-5)	3.71 (-7)
TN (kg/ha/year)	Baseline	8.46	8.18	13.38
	1	10.24 (+21)	10.24 (+25)	16.76 (+25)
	2	8.88 (+5)	8.68 (+6)	13.44 (+0.4)
	3	8.90 (+5)	8.55 (+4)	14.31 (+7)
	4	8.61 (+2)	8.15 (-0.4)	13.35 (-0.2)
	5	8.71 (+3)	8.17 (-0.2)	13.40 (+0.2)
	6	8.77 (+4)	8.19 (+0.1)	13.42 (+0.3)
	7	8.40 (-1)	8.09 (-1)	13.24 (-1)
	8	8.33 (-1)	8.02 (-2)	13.16 (-2)
	9	8.27 (-2)	7.96 (-3)	13.07 (-2)
TP (kg/ha/year)	Baseline	1.15	1.18	1.94
	1	1.33 (+16)	1.40 (+19)	2.22 (+15)
	2	1.20 (+5)	1.25 (+6)	1.94 (0)
	3	1.21 (+5)	1.21 (+3)	2.02 (+4)
	4	1.17 (+2)	1.17 (-0.2)	1.93 (-0.5)
	5	1.185 (+3)	1.18 (0)	1.93 (-0.5)
	6	1.19 (+4)	1.19 (+1)	1.94 (0)
	7	1.14 (-1)	1.16 (-1)	1.91 (-1)
	8	1.13 (-1)	1.15 (-3)	1.90 (-2)
	9	1.12 (-2)	1.14 (-3)	1.88 (-3)

Values in () indicate percent change compared with the baseline condition.

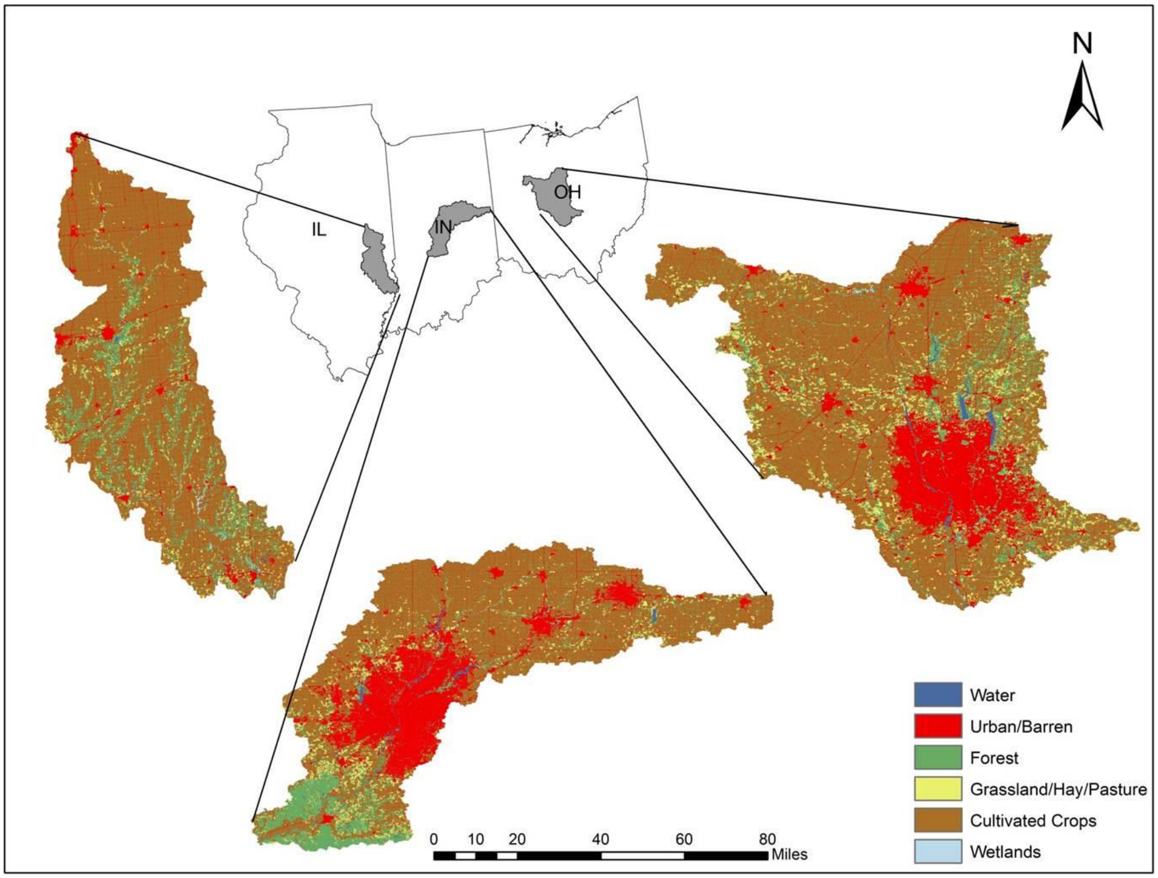

Figure 4.1. Selected watersheds in the Midwestern US, with principal land use (Based upon NLCD 2006). The three selected watersheds are: the Embarras watershed in east-central Illinois, the Upper White watershed in central Indiana, and the Upper Scioto watershed in central Ohio.

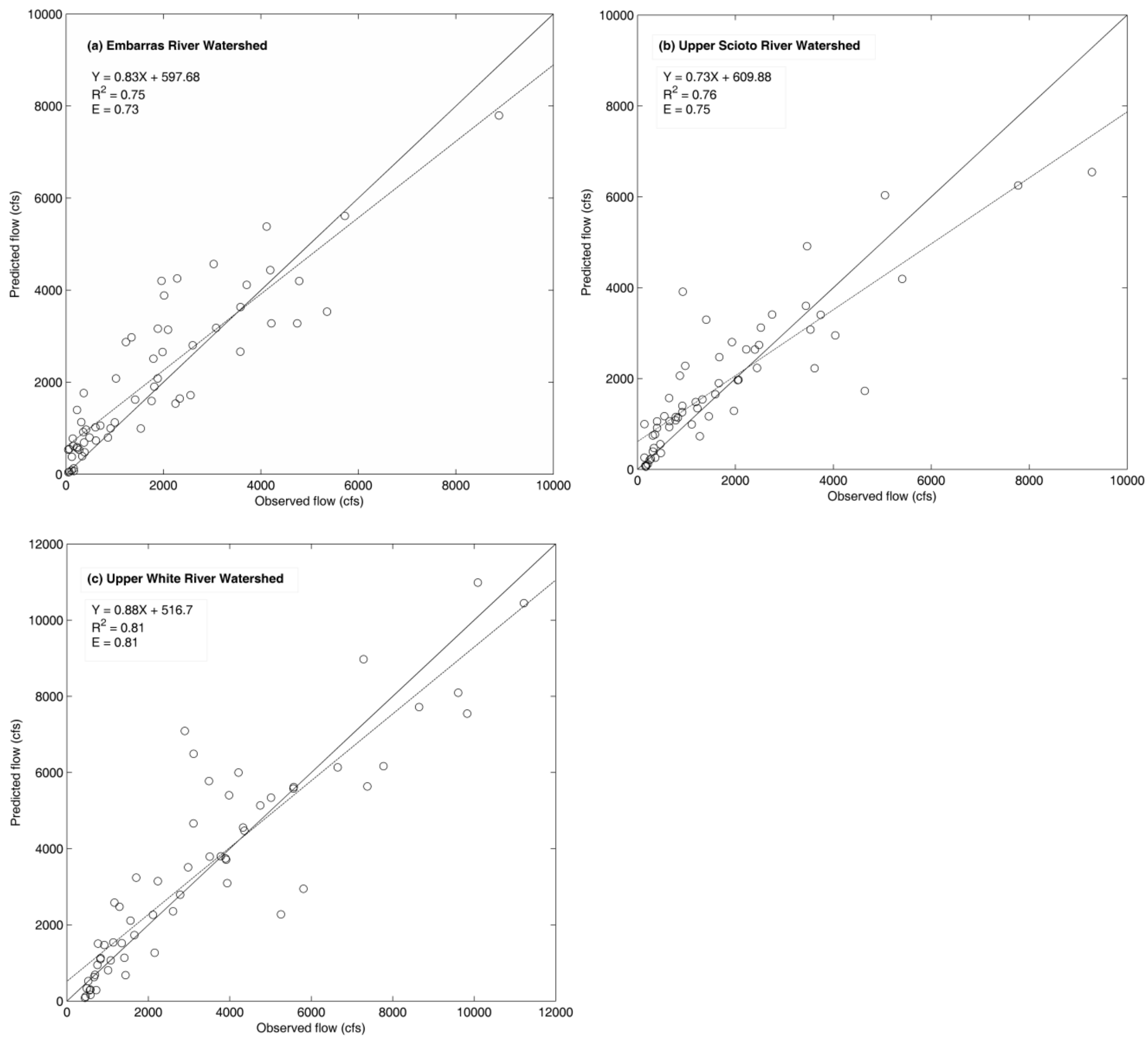

Figure 4.2. Comparisons of monthly stream flow estimates from SWAT model versus the USGS observation data (2006–2010) for the (a) Embarras watershed, (b) Upper Scioto watershed, and (c) Upper White watershed.

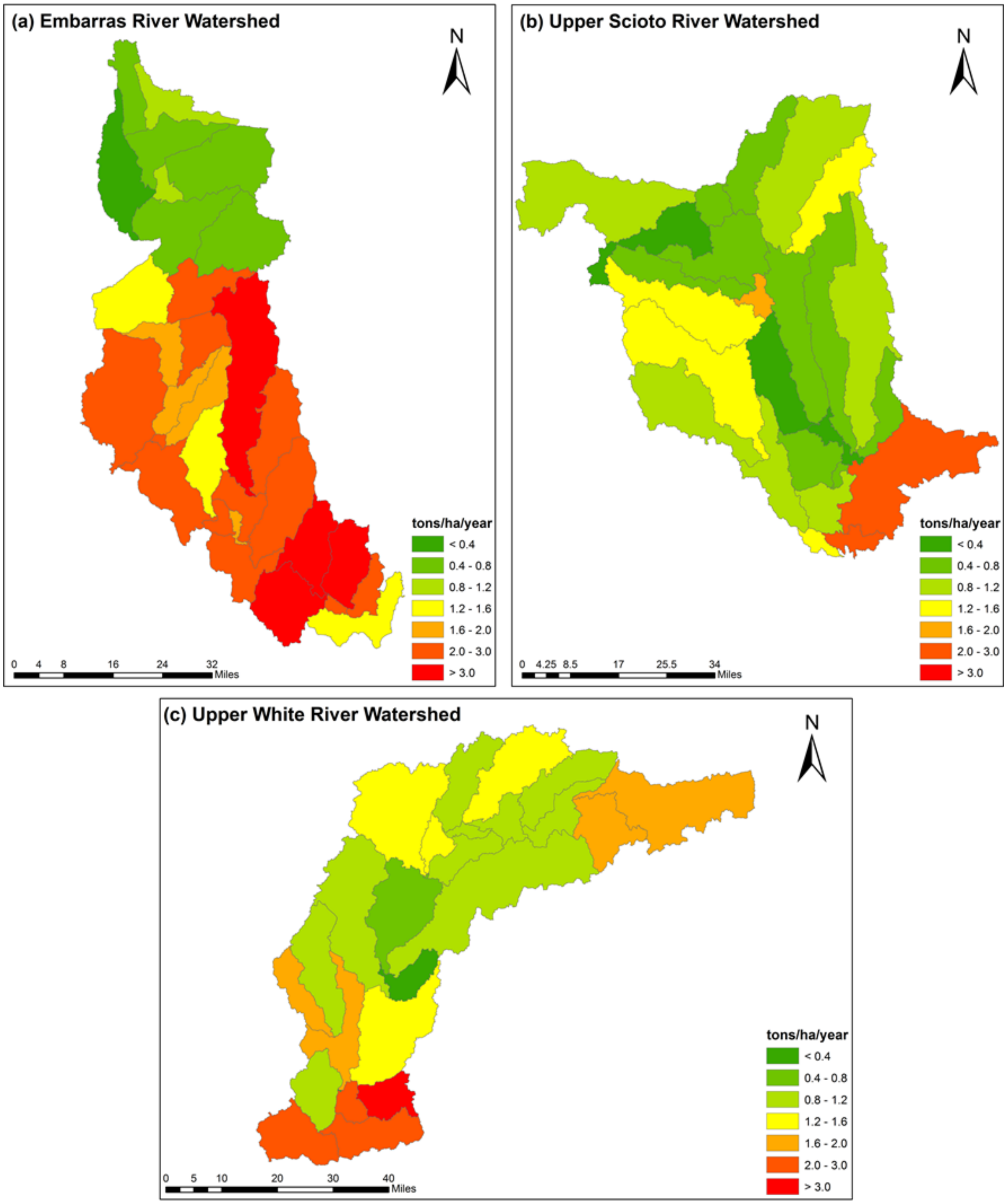

Figure 4.3. Average annual sediment yields from the SWAT model (2000–2010) for the (a) Embarras, (b) Upper Scioto, and (c) Upper White watersheds. The green color means low sediment yields while the red color means high sediment yields.

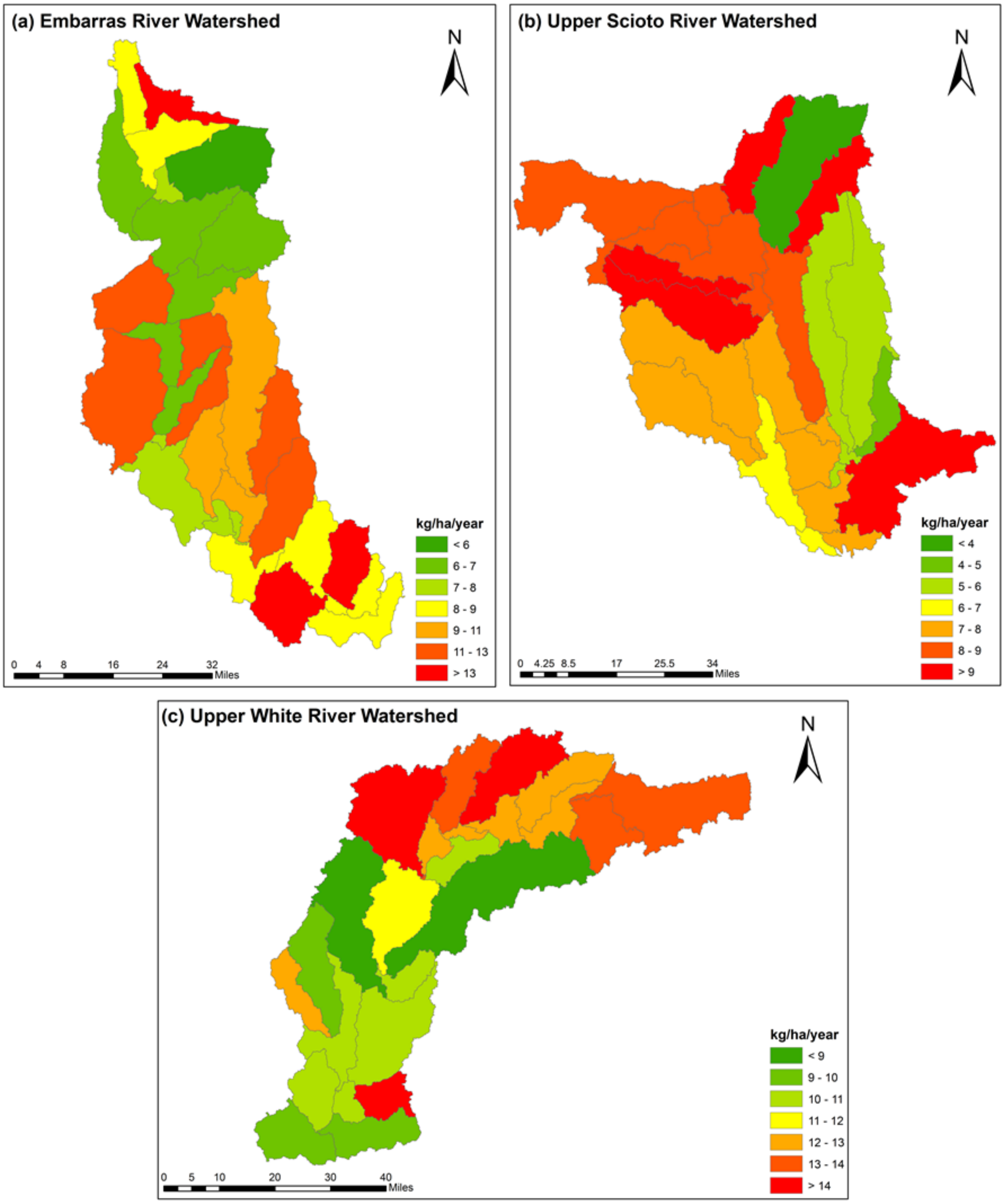

Figure 4.4. Average annual total nitrogen yields from the SWAT model (2000–2010) for the (a) Embarras, (b) Upper Scioto, and (c) Upper White watersheds. The green color means low total nitrogen yields while the red color means high total nitrogen yields.

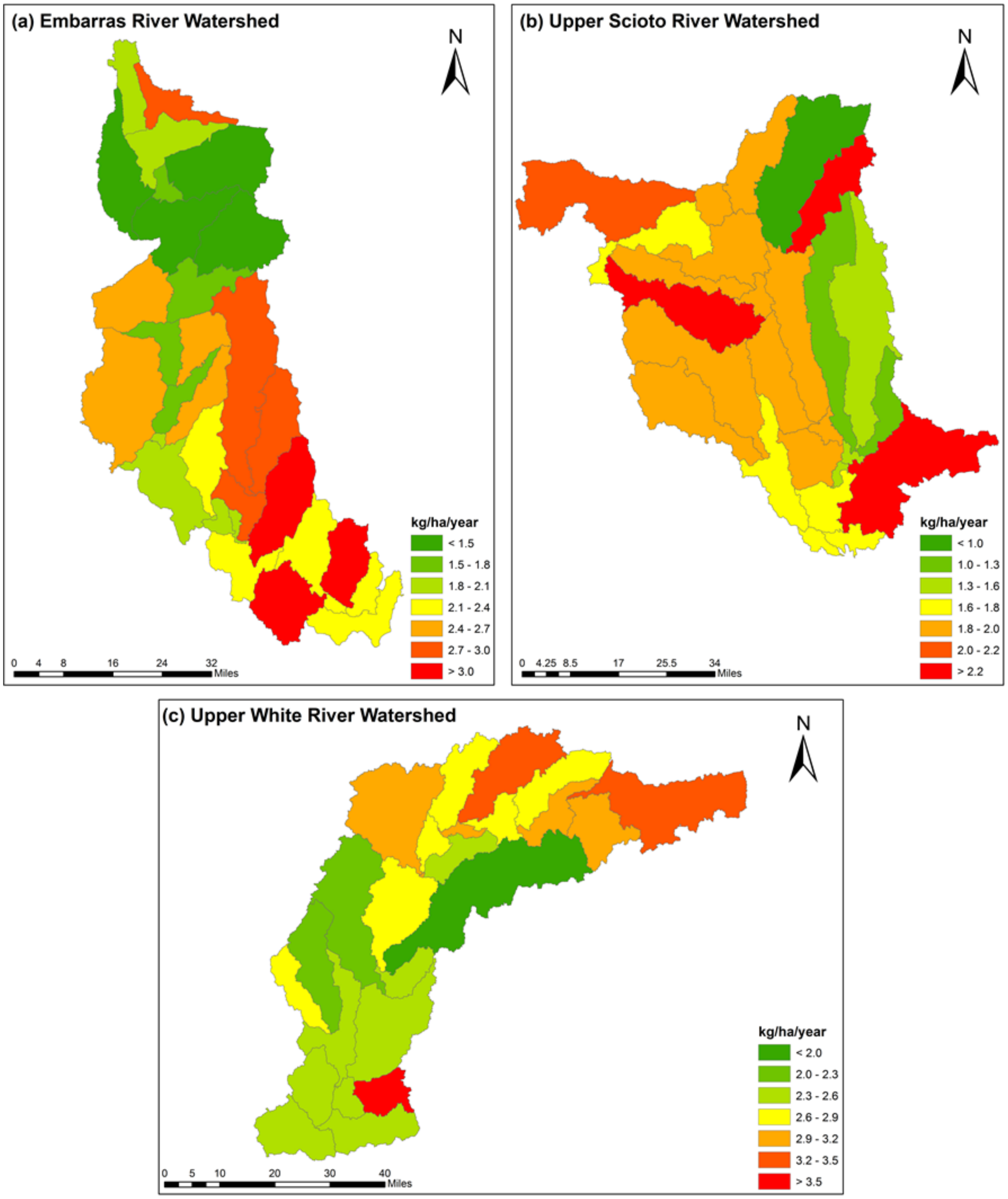

Figure 4.5. Average annual total phosphorus yields from the SWAT model (2000–2010) for the (a) Embarras, (b) Upper Scioto, and (c) Upper White watersheds. The green color means low total phosphorus yields while the red color means high total phosphorus yields.

Chapter 5 Conclusion

1. Summary of Findings

The first study (Chapter 2) examined spatial and temporal dimensions of agricultural land use dynamics, 2001-2012, in east-central Iowa, and spatial relationships between cultivated fields and crop rotation practices, with respect to underlying soils and terrain at a pixel level. Results showed that expansion of corn production perhaps in response to US biofuel policies was implemented by altering crop rotation patterns. As recorded by USDA NASS CDLs, after 2007, cultivated acreage for both corn and soybeans increased, and standard crop rotation (i.e., corn-soybean/soybean-corn) was replaced by more intensive crop rotations. In addition, CRP lands were brought into cultivation since 2007, but they may be used for other crops displaced by corn. The most intensively cultivated land had shallower slopes and fewer pedologic limitations than others, and the most valuable crop (i.e., corn) was planted on the most suitable soils. Spatial patterns of crop rotation sequences before and after 2007 displayed variations in applying crop rotation strategies, suggesting effects of a multiplicity causes (e.g., fertilizer application rates, tillage choices, and propinquity to biofuel plants).

The second study (Chapter 3) estimated annual key crop phenological parameters (SOS and EOS) for corn and soybean in the Midwest US, 2001-2015. Results showed that MODIS-derived SOS and EOS values are highly dependent on the nature of input time-series data and threshold values chosen for crop phenology detection. With the entire sequence of MODIS NDVI time-series data as input, SOS and EOS values were inconsistent compared to the USDA CPRs. However, when winter NDVI images were removed from MODIS time-series data to reduce snow impacts, the agreement between

MODIS-derived SOS/EOS dates and CPR data improved substantially. Two threshold values (50% and 40% of seasonal NDVI amplitude) used to derive SOS and EOS values showed that a 40% threshold value generated better estimates compared to the default 50% threshold value. This study also examined spatial and temporal patterns of SOS and EOS for both crops. SOS and EOS for corn displayed clear south-north gradient: the southern portion of the Midwest US has earlier SOS and EOS dates. Trend analyses for SOS and EOS were conducted for three states with long-term CDL products. For SOS, only a small percentage of counties showed statistically significant downward trends within a user-defined temporal window (2001-2012) and SOS advanced by approximately 0.66-1.28 and 0.77-1.33 days per year for corn and soybean, respectively. However, such earlier SOS trends did not extend to the recent 2012-2015 study period.

The third study (Chapter 4) integrated remote sensing-derived products and the SWAT model to assess impacts of changes in cropping systems and planting/harvest dates on sediment and nutrient yields for three selected watersheds in the Midwest US. At baseline conditions, individual SWAT models were calibrated and validated for stream flows. For the three selected watersheds, the SWAT model-predicted stream flows matched well with the USGS observation data. R^2 and NSE values were greater than 0.5 for calibration and validation periods, values generally viewed as a satisfactory model performance. Sediment and nutrient yields under different management scenarios were compared at different spatial scales. Results showed that intensive crop rotation resulted in greater sediment, total nitrogen, and total phosphorus yields, indicating that increases in sediment, total nitrogen, and total phosphorus losses were mainly due to intensification of corn production. However, advancing of planting date with the same length of growing season had no effect on water quality, while longer growing seasons slightly reduced sediment, total nitrogen, and total phosphorous yields, indicating that a longer interval with crop cover on the soil helped reduce erosion rates and nutrient losses.

2. Contributions and Further Work

My research contributes to an understanding of agricultural systems, and supports development of agricultural policy. It demonstrates the value of remote sensing imagery, specifically sequential imagery, to monitor trends and changes in agricultural land use and management with improved spatial detail, broad coverage, and low costs. Detailed spatial and temporal information of cropland change, crop rotation changes, and crop phenology change illuminate how agricultural practices have responded to changes in biofuel policy. It also provides site-specific agricultural land use and management data for SWAT model to access changes of agricultural land use and management on water quality. The simulation analysis using SWAT model provides boundary information under different management scenarios. This research is useful to guide farmers, policy makers and government officers to use agricultural land and to protect environment.

I see the potential for many further works related to my dissertation. Spatial variations of changes in cropland use, crop rotation, and crop phenology found in the first two studies may be related to multiplicity causes (i.e., climate change, tillage choices, and socioeconomic factors). Interviews and surveys will be used to collect qualitative data to explore the context in which producers and other agricultural managers are motivated and constrained in their land use and cropping decisions.

Accurate detection of SOS and EOS for corn and soybean depends on many factors such as input time-series data, smoothing algorithms chosen, and threshold values applied to pin-point phenological metrics. The second study examined how input data range and threshold selection affect performance of crop phenology detection. Future studies are needed to examine how various spatial resolution and temporal compositing of input data and different smoothing algorithms affect SOS and EOS detection for major crops. The spatial resolution of the MODIS pixel is too coarse to compare with field observations (Wardlow et al., 2006), thus Landsat data, with its relatively high spatial resolution may generate better estimates. Both 16-day and 8-day MODIS composite data are widely used for assessing vegetation phenology, but their performance for crop phenology detection is not clear. Except for Savitzky-Golay algorithm, asymmetric Gaussian and double-logistic function are also needed to evaluate.

In the third study, sediment and nutrient yields were compared using the same climate conditions for all management scenarios. But agriculture is intimately linked to weather and climate. Long-term variations in climate, such as continued warming and intense precipitation, interact with agricultural land use, and management changes may have dramatic effects on soil erosion and nutrient losses. Thus, the prediction of sediment and nutrient yields for future changes of agricultural land use and management can be complicated by different climate-change scenarios.

References

Wardlow, B. D., Kastens, J. H., & Egbert, S. L. (2006). Using USDA Crop Progress Data for the Evaluation of Greenup Onset Date Calculated from MODIS 250-Meter Data. *Photogrammetric Engineering & Remote Sensing*, *72*(11), 1225–1234.