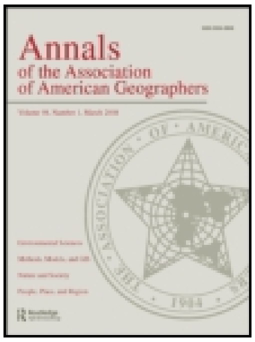

Annals of the Association of American Geographers

ISSN: 0004-5608 (Print) 1467-8306 (Online) Journal homepage: www.tandfonline.com/journals/raag20

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To cite this article: Cuizhen Wang, Felix B. Fritschi, Gary Stacey & ZhengWei Yang (2011) Phenology-Based Assessment of Perennial Energy Crops in North American Tallgrass Prairie, Annals of the Association of American Geographers, 101:4, 742-751, DOI: 10.1080/00045608.2011.567934

To link to this article: https://doi.org/10.1080/00045608.2011.567934

Published online: 28 Apr 2011.

Phenology-Based Assessment of Perennial Energy Crops in North American Tallgrass Prairie

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Biomass is the largest source of renewable energy in the United States, and corn ethanol currently constitutes the vast majority of the country's biofuel. Extended plantation of annual crops for biofuel production, however, has raised concerns about long-term environmental, ecological, and socioeconomic consequences. Switchgrass (*Panicum virgatum* L.), along with other warm-season grasses, is native to the precolonial tallgrass prairie in North America and is identified as an alternative energy crop for cellulosic feedstocks. This article describes a phenology-based geospatial approach to mapping the geographic distribution of this perennial energy crop in the tallgrass prairie. Time series of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery (500-m resolution, eight-day interval) in 2007 were processed to extract five phenology metrics: end of season, season length, peak season, summer dry-down, and cumulative growth. A multitier decision tree was developed to map major crops, especially native prairie grasses in the region. The geographic context of the 20 million ha of perennial native grasses extracted in this study could be combined with economic and environmental considerations in a geographic information system to assist decision making for energy crop development in the prairie region. *Key Words: bioenergy, crop phenology, MODIS imagery, time-series analysis.*

生物量是美国可再生能源的最大来源，玉米乙醇目前占美国生物燃料的绝大部分。然而，用于生物燃料生产的一年生作物的延长种植现象，已经引起了人们对其长期的环境，生态，和社会经济后果的关注。柳枝（柳枝稷属），以及其它暖季型草，原产于北美前殖民地高草草原，被确定为纤维素原料的替代能源作物。本文介绍了一种能够映射此高草草原多年生能源作物之地理分布的，基于物候的地理空间方法。本研究对 2007 年的中分辨率成像光谱仪（MODIS）卫星影像（500 米分辨率，八天间隔）时间系列进行处理，提取了五个物候指标：季节结束期，季节长度，旺季，夏季干萎，和累计增长。并开发了一个多层的决策树以绘制该地区主要作物，特别是原生草原草的地图。在本研究中提取的两千万公顷的天然多年生草本植物的地理背景可结合地理信息系统中的经济和环境的考虑，以协助决策者在草原地区能源作物发展的决策。*关键词：生物能源，作物物候，MODIS 遥感影像，时间序列分析。*

La biomasa es la mayor fuente de energía renovable de los Estados Unidos, y actualmente el etanol de maíz constituye una vasta línea de biocombustibles del país. La ampliación del área de plantación anual para la producción de biocombustible, sin embargo, ha despertado preocupaciones sobre consecuencias ambientales, ecológicas y socioeconómicas a largo plazo. El pasto varilla o "switchgrass" (*Panicum virgatum* L.), junto con otros pastos de estación cálida, es nativo de la pradera de pastos altos en América del Norte y se le identifica como un cultivo energético alternativo para producir concentrados para animales a base de celulosa. Este artículo describe un enfoque geoespacial de base fenológica para cartografiar la distribución geográfica de este pasto energético perenne de la pradera de pastos altos. Se procesaron series de tiempo de imágenes satelitales del Moderate Resolution Imaging Spectroradiometer, o MODIS (resolución de 500-m, a intervalos de ocho días) de 2007, para extraer cinco métricas de fenología: final de la estación, longitud de la estación, estación pico, aridez del verano, y crecimiento acumulativo. Se desarrolló un árbol de decisiones multifila para cartografiar los principales cultivos de la región, especialmente los de pastos nativos de pradera. El contexto geográfico de los 20 millones de hectáreas de pastos nativos perennes considerados en este estudio podría combinarse con consideraciones económicas y ambientales en un sistema de información geográfica, para ayudar en la toma de decisiones sobre desarrollo de cultivos energéticos en la región de las praderas. *Palabras clave: bioenergía, fenología de cosechas, imágenes MODIS, análisis de series de tiempo.*

Annals of the Association of American Geographers, 101(4) 2011, pp. 742–751
Initial submission, March 2010; revised submission, September 2010; final acceptance, December 2010
Published by Taylor & Francis, LLC.

Bioenergy is of increasing interest in agriculture as biomass becomes the largest source of renewable energy in the United States. The recent Billion-Ton Annual Supply study (Perlack et al. 2005) estimated that biomass feedstocks (e.g., corn stover, native grasses, and short-rotation woody crops) could replace 30 percent of domestic petroleum consumption by 2030. Corn ethanol is currently the primary source of domestic biofuel (Farrell et al. 2006). The U.S. Department of Agriculture (USDA) Economic Research Service (2010) estimated that U.S. biofuel refiners will buy 4.2 billion bushels of corn in the 2009–2010 marketing year, which accounts for one third of total domestic corn production. Extended acreage of annual crops, however, has raised concerns about long-term environmental, ecological, and socioeconomic consequences (Paine et al. 1996). Increased use of fertilizers and pesticides causes water quality deterioration, and removal of large quantities of residues from croplands promotes nutrient runoff and leads to soil carbon loss, which in turn lowers crop productivity and profitability (Perlack et al. 2005).

Since 1978, the U.S. Department of Energy (DOE) has sponsored research to evaluate a wide variety of bioenergy alternatives (Wright 1994). In the early 1990s, the DOE identified switchgrass (*Panicum virgatum* L.) as a model cellulosic energy crop (McLaughlin and Kszos 2005; Wright 2007). Switchgrass and other warm-season grasses such as big bluestem (*Andropogon gerardi* Vitman), little bluestem (*Andropogon scoparius*), and indiangrass (*Sorghastrum nutans* (L.) Nash) are native to the precolonial tallgrass prairie in North America (Hitchcock 1935). Although lands in the prairie have been largely cultivated, the adaptability of these native grasses to poor soil conditions (e.g., low pH, low fertility) leads researchers to examine their competitive potentials for cellulosic feedstocks on low-productivity croplands (Kort, Collins, and Ditsch 1998; McLaughlin and Kszos 2005). Highly erodible and other environmentally sensitive croplands can be enrolled in the Conservation Reserve Program (CRP) and can be planted to native prairie grasses (Paine et al. 1996). The CRP lands, and amendments to the management of CRP lands permitted in the 2002 Farm Security and Rural Investment Act, could play important roles in determining the acreage planted with native prairie grasses in the future.

Efficient integration of crops into energy supply systems requires their geographic context to assess regional potentials and costs (Gehrung and Scholz 2009). Current predictions of biomass supplies of energy crops, however, are mostly derived from statistical crop production scenarios at county or state levels. The lack of spatially explicit information about energy crops limits our understanding of current and future bioenergy supplies in major U.S. agricultural regions.

Remote sensing (i.e., satellite imagery) techniques could be applied to extract detailed spatial information on biomass supplies in agricultural regions. Such information is essential in moving beyond currently available coarser geographic representations (e.g., county level) to local scales (e.g., fields) to better estimate biomass potential of a region (Gehrung and Scholz 2009). Assisted with satellite images, spatially resolved crop land use and production in the United States are well documented from various analyses and surveys such as the USDA Large Area Crop Inventory (Boatwright and Whitehead 1986) in early years and the Crop Explorer by the USDA Foreign Agricultural Service (FAS 2009; Cropland Explorer 2010). Satellite images acquired in critical stages of a growing season were found especially useful to differentiate major crops such as corn, soybean, and perennial grasses (Chang et al. 2007; Wang, and Spicci 2010). With monthly composites of satellite images acquired in March through October, the U.S. Geological Survey (USGS) created the 1-km land-cover database and identified 159 seasonal land-cover regions in the conterminous United States; each was characterized with internally homogeneous crops or natural land cover types (Loveland et al. 1995). Since the 1970s, the USDA National Agricultural Statistics Service (NASS) has developed annual products of the Cropland Data Layers (CDL) and acreage estimations from fine-resolution (30–56 m), multitemporal satellite images in major U.S. agricultural regions (Allen, Hanuschak, and Craig 2002; NASS 2010b). In crop year 2009 the CDL product covers all forty-eight states in the conterminous United States (Boryan et al. forthcoming). However, warm-season native prairie grasslands have not been specifically mapped in any of the U.S. agricultural databases.

With the availability of coarse-resolution daily observations such as imagery from the National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer (AVHRR) and Terra/Aqua Moderate Resolution Imaging Spectroradiometer (MODIS), phenological variability in cropping systems became well recognized in assisting cropland monitoring in regional scales (Schwartz 1999). Reed et al. (1994) was among the earliest efforts to extract phenological metrics to support vegetation monitoring. Using the AVHRR-extracted normalized difference vegetation index (NDVI) time series, they measured a set of phenological metrics including onset of greenness, time of peak NDVI, rate of greenup/senescence, and integrated NDVI and explored their differences in row crops, grasslands, and deciduous and coniferous forests. Zhang et al. (2003) developed an approach to fitting the NDVI time-series curves into piecewise logistic functions so that phenological metrics can be more accurately extracted. Recently this approach has been well adopted in global phenology (Zhang, Friedl, and Schaaf 2006) and phenology-assisted crop mapping at regional scales (Wardlow, Egbert, and Kastens 2007; Wardlow and Egbert 2008).

Phenology-based time-series analysis could also be performed to identify energy crops and to assess their regional biomass production in a spatially resolved manner. This study aims to apply time-series satellite images to explore current land use patterns of energy crops in the tallgrass prairie. With this information, geospatial and economic tools could be applied to generate spatially explicit data sets to support bioenergy policies in the region.

Study Area and Data Sets

The tallgrass prairie is a triangular region covering ten states in the Midwest and central United States and is extended to Canada in the north (Figure 1).

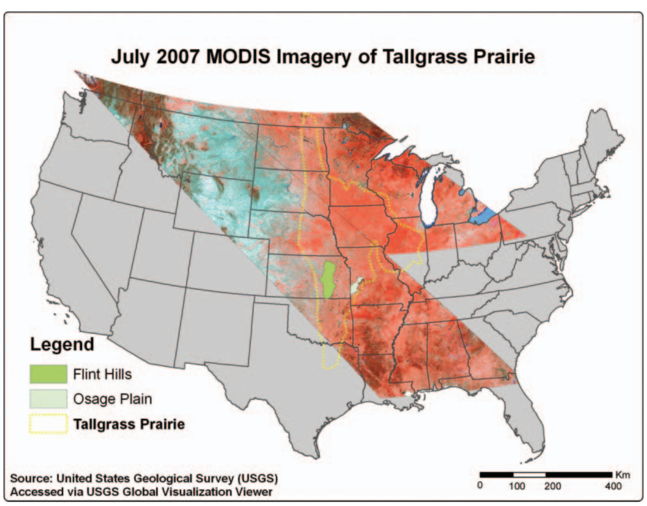

Figure 1. The North American tallgrass prairie and three example Moderate Resolution Imaging Spectroradiometer (MODIS) scenes acquired in July 2007. The color-infrared display of the image shows vegetation in red. Also marked in the figure are the training site (Cherokee Plain, Missouri) and the validation site (Flint Hills, Kansas).

Since European settlement, more than two thirds of the prairie has been converted to annual crops (Schroeder 1983; Risser 1988), primarily corn and soybean in the Corn Belt. Less productive areas tend to be converted to hayfields and pastures of cool-season grass species that were introduced to increase forage production. Native grasses often remain in prairie remnants of the region. Replanted acreages of native grasses also become common in environmentally sensitive croplands designated in federal or state conservation programs.

The tallgrass prairie can be almost fully covered in three MODIS scenes (as shown in Figure 1). In the 500-m MODIS Terra Surface Reflectance products (MOD09A1), each pixel represents a 500×500 m^2 area on the ground. Each image is an eight-day composite by selecting the best pixel value from eight daily images with a maximal value compositing technique (Lovell and Graetz 2001). For each scene, a total of forty-six MOD09A1 composites in 2007 were downloaded from the Land Processes Distributed Active Archive Center (http://lpdaac.usgs.gov). The NDVI time series were then extracted from these image products. The sixteen-day MODIS imagery had been most commonly applied in past studies because it reached better reduction of cloud contamination. It was not used in this study, as subtle phenology variations of perennial crops in critical stages tend to be lost at such intervals.

Crop training data were collected in the Cherokee Plain in southwest Missouri (marked in Figure 1). For annual crops (corn, soybean, and winter wheat), training data were extracted from the CDL map in the Plain that were developed by USDA NASS using 56-m satellite images acquired in 2007 (Cropland Explorer 2010). In previous research funded by the Missouri Department of Conservation (MDC), warm-season native prairie grasses (WSG) and cool-season forage grasses (CSG) were collected during field surveys in 2007 and from the Grassland Coalition Focus Areas managed by MDC (Wang, Jamison, and Spicci 2010). To reduce mixed fields in coarse-resolution MODIS pixels, each data point represented a polygon of at least 1 km^2 (four MODIS pixels). A total of seventeen points for corn, fifteen for soybean, twelve for wheat, twenty-three for WSG, and nineteen for CSG were collected as training data in this study.

The Flint Hills grassland (marked in Figure 1) covers an area of 2.5 million ha in Kansas and is the largest unplowed tallgrass prairie remnant in North America. More than 80 percent of the area is covered with native prairie grasses. Inside the grassland, the 4,500 ha Tallgrass Prairie National Preserve (TPNP) is managed by the National Park Service with a single conservation strategy (Gu et al. 2007). According to the geographic information system (GIS) data downloaded from the Kansas Geological Survey (http://www.kgs.ku.edu), native prairie grass covers 90.95 percent of the TPNP. Moreover, a total of nineteen preserved prairies managed by MDC in southwest Missouri were collected from Wang, Jamison, and Spicci (2010). These prairies served as validation sites of native prairie grasses in this study. The CDL maps of the ten prairie states were also downloaded. As reported in CDL metadata files, the CDL products reached an overall accuracy around 90 percent for major crops (NASS 2010a). Comparing with the 500-m resolution of MODIS imagery, the 56-m CDL map provided fine-scale details and was selected as validation source of annual crops.

Methods

Because of the nature of herbaceous land covers and the spectral similarity of WSG and CSG, the CDL products group them into a single category—pasture/grass. Wang, Jamison, and Spicci (2010), in previous research, found that (1) CSG reached peak NDVI in spring (May), whereas WSG had peak values in early summer (July); and (2) the NDVI of WSG decreased gradually from summer to fall, whereas a second NDVI peak was observed for CSG. Therefore, it was feasible to separate these two grass types based on their phenological features. Phenology of annual crops (corn, soybean, and winter wheat) was also examined in this study. Non-crop land covers (e.g., forest, wetland, water, urban) were extracted from the CDL map and were masked out of the process.

Crop Phenology Metrics

As illustrated by the jagged NDVI curves in Figure 2, raw NDVI was influenced by cloud residuals as well as atmospheric and sun-sensor illumination conditions. A set of smoothing algorithms have been adopted to reduce these noises. For example, Reed et al. (1994) used a nonlinear median smoother to remove cloud-contaminated NDVI values, although it also reduced peak NDVI values that were assumed noise-free. Gu et al. (2006) applied an upper-envelope three-point smoothing process to provide the local "best estimate" of leaf area index from time-series MODIS products.

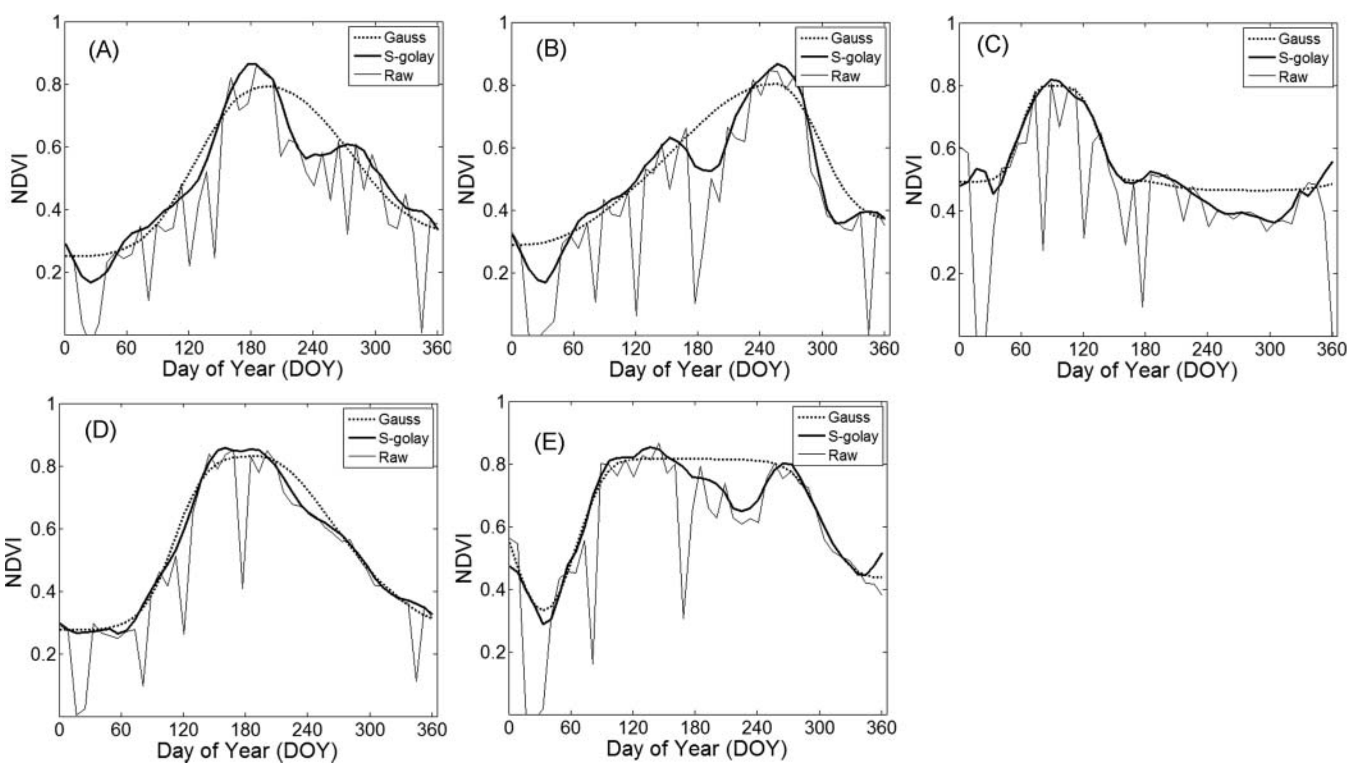

Figure 2. Normalized difference vegetation index (NDVI) variations of major crops in 2007 in the tallgrass prairie: (A) corn, (B) soybean, (C) winter wheat, (D) warm-season native prairie grass, and (E) cool-season forage grass. The three curves are raw NDVI, Savitzky–Golay smoothed NDVI, and asymmetric Gaussian fitted NDVI.

To optimize smoothing process of NDVI curves in this study, a five-point median filter was first applied to remove spikes of heavily contaminated NDVI values. If the filtered NDVI was lower than the original value, it was replaced with the original one to remain peak NDVI points in the curve. Then a commonly applied Savitzky–Golay filtering method (Savitzky and Golay 1964) was used to smooth the time-series curves (Figure 2).

The smoothed data were simulated to extract crop phenology metrics. de Beurs and Henebry (2010) compared a group of thresholding and simulating approaches in phenology studies. Among these, the widely applied ones in crop phenology include piecewise logistic functions (Zhang et al. 2003) and quadratic fitting (De Beurs and Henebry 2004). In this study, however, these approaches turned out to be ill-functioned because grass phenology is often characterized with prolonged growth duration and asymmetric growing trends in early and late seasons. Here we adopted the TIMESAT program (Jonsson and Eklundh 2004) to fit the smoothed MODIS NDVI curves in an asymmetric Gaussian function (Figure 2). The program applied different Gaussian simulation functions to smooth curves before and after growing peak, which was especially useful for crops with asymmetric growing patterns such as perennial grasses and winter wheat.

The asymmetric Gaussian fitted curve at each pixel was analyzed in the TIMESAT program to extract a set of phenology metrics. With metrics of all training data, statistical properties revealed that three metrics had significant differences for the five crops (corn, soybean, winter wheat, CSG, and WSG): (1) *end of season*, which represents the date when NDVI has decreased to 20 percent of the amplitude after peak NDVI; (2) *season length*, which represents the dates from start of season (when NDVI has increased to 20 percent of the amplitude) to end of season; and (3) *cumulative growth* ($\Sigma NDVI$), which is calculated as the integral of NDVI from start of season to end of season. Other metrics, such as start of season and derivatives of green-up and brown-down, tend to be overlaid for different crops in their feature spaces and box-plots. These metrics were not used in the study.

The Savitzky–Golay smoothed curves in Figure 2 revealed that annual crops displayed apparent temporal differences in peak NDVI over the course of a growing season, reflecting their variations in growth development. To quantify these differences, three growing stages were defined: early (Day of Year [DOY] 1–161), middle (DOY 145–193), and late (DOY 161–313). Two additional phenology matrices were thus identified: (1) *peak season*, which indicates the date when peak NDVI falls; and (2) *summer dry-down* ($\Delta NDVI$), which is the maximal decrease of NDVI in early-middle stages if peak NDVI falls in the early stage (especially useful for wheat).

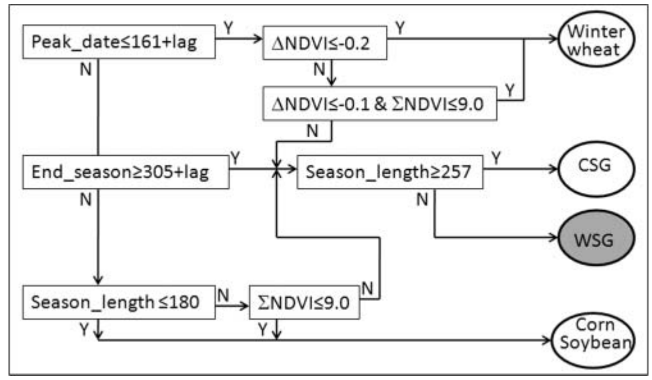

Figure 3. Flowchart of the phenology-based decision tree. The perennial native prairie grass (WSG) is highlighted in the outputs. The numbers 161 and 305 represent Day of Year (DOY). The numbers 180 and 257 represent growth duration (days). NDVI = normalized difference vegetation index; CSG = cool-season grasses; WSG = warm-season grasses.

A Phenology-Based Decision Tree Approach

The selected phenology metrics were put in a decision tree to identify the five crop types in the tallgrass prairie (Figure 3). Winter wheat was first identified because of its early peak season (early spring) and large summer dry-down (dramatic decrease of NDVI) leading to harvest in early summer. Because spring wheat production was limited in the tallgrass prairie, it was grouped into winter wheat and was not further considered in this study. Spring wheat was more commonly grown in northern states, however, and could potentially be misclassified due to temporal shifts in peak greenness. Similar to winter wheat, some CSG as well as a limited number of WSG fields also reached early peak season and were characterized with reduced NDVI after haying or grazing of pastures in late spring to early summer. These grass fields were delineated from winter wheat with a shallower summer dry-down and larger cumulative NDVI ($\Sigma NDVI > 9.0$). Corn and soybean in the prairie often had an early end of season (before DOY 305), shorter season length (< 180 days) and less cumulative NDVI (< 9.0). Corn and soybean were not further separated because the primary concern was native perennial grasses in this study. After annual crops were extracted, WSG was delineated with a shorter growing length (< 257 days) than CSG. The thresholds in the decision tree were selected based on statistical analysis of training data collected in the Cherokee Plain as marked in Figure 1.

Temporal shifts of crop calendars in northern and southern states also need to be considered. It was reported in Zhang et al. (2003) that the onset of greenness for both natural vegetation and agricultural lands displayed a shift of around two days per latitude degree along the 40°–45°N latitude transect. To test temporal shifts in the tallgrass prairie, we randomly selected forty fields for each category (corn, soybean, and grass) from the CDL map. Both WSG and CSG fields were covered in the grass category because they were not specified in the CDL data. In a range of 32°–48°N in the prairie, the peak season had about two days per degree shift for corn (Figure 4A) and soybean (Figure 4B). The shift was slightly larger for grasslands (Figure 4C). There was no apparent shift for end of season of annual crops, whereas a slight shift of 1.7 days was observed in grasslands. The season length did not show apparent shift for all crop types. To be consistent with Zhang et al. (2003), a lag factor was added to peak season and end of season in the decision tree in Figure 3. Based on training data in the Cherokee Plain (around 38°N), the *lag* at each pixel was roughly calculated:

$$\text{Lag} = 2.0 \times \ (\text{latitude} - 38.0) \qquad (1)$$

Results and Discussion

Crop Map and Validation

The MODIS-derived crop map (Figure 5) agreed with the CDL product that corn and soybean were major annual crops, especially in the Corn Belt covering the northern states of the prairie. Clustered wheat fields were mostly found in the southwest (e.g., winter wheat in Kansas and Oklahoma) and the northwest (e.g., spring wheat in Nebraska and South Dakota). For perennial crops, both CSG and WSG grew in grasslands designated in the CDL map. Warm-season native prairie grasses dominated in the south central part of the prairie whereas CSG were in the western and southeastern parts of the prairie.

The Flint Hills grassland, the largest remnant of unplowed tallgrass prairie, is marked in Figure 5. Native prairie grasses covered more than 80 percent of the Flint Hills, which was readily identified by the phenology-assisted approach in this study. Limited corn and soybean acreages were found along local river channels in the north of the Flint Hills grassland. This pattern agreed with the CDL map.

Total cropping acreages in the tallgrass prairie were compared between the MODIS-derived and CDL products. The MODIS estimation of corn and soybean was about 3.43 million ha lower than the CDL product (5.61 percent of the tallgrass prairie). The CDL product estimated 25.79 million ha (34.21 percent) of grasslands. In the MODIS crop map, CSG covered 11.82 million ha (15.65 percent), whereas warm-season native grass reached 20.73 million ha (27.45 percent). Combining CSG and WSG, the MODIS map overestimated grasslands by an area of 7.19 million ha. Part of the overestimation might come from acreages of other crops (3.21

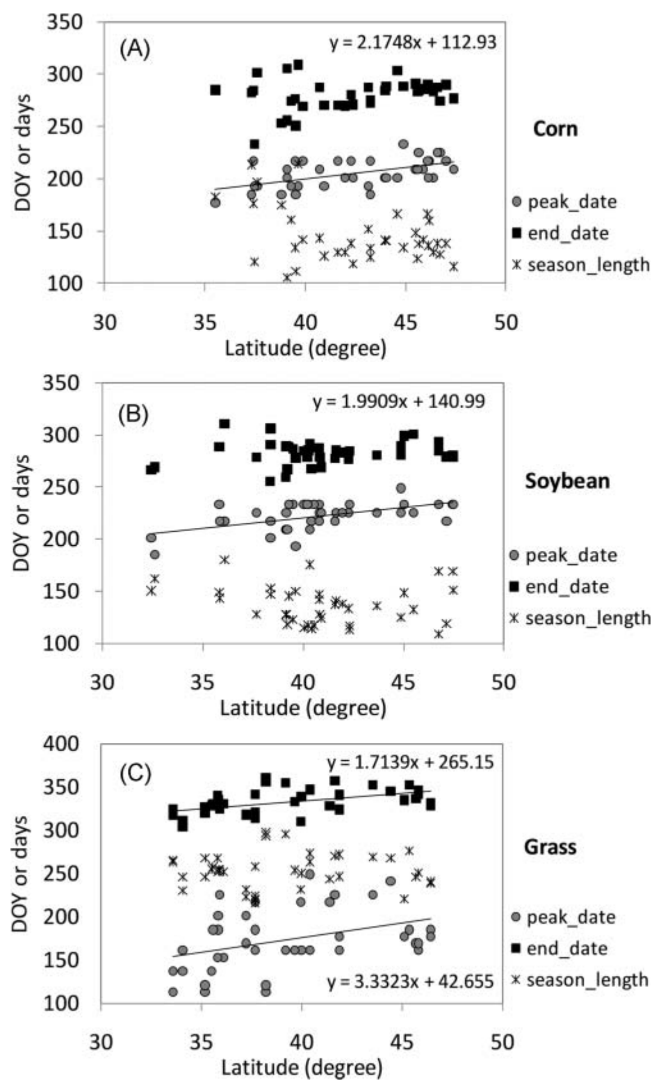

Figure 4. Temporal shifts of phenology metrics of (A) corn, (B) soybean, and (C) grass from randomly selected fields in the tallgrass prairie.

million ha) identified in the CDL product. These crops, such as sorghum, rice, cotton, and vegetables, only covered a small portion of the region and were not specified in this study. In the MODIS crop map, they were often grouped into perennial crops, especially warm-season native grasses because of their short season length. The discrepancy might also come from mixed pixels. Except for the vast landscape of cultivated lands in the Corn Belt, annual crop fields were often small and scattered with grass fields. Although they could be identified in fine-resolution CDL products, these fields were smaller than the 500-m pixel size in the MODIS-derived map. Mixed pixels tend to be classified as grasses because of grass-like phenology metrics such as extended end of season and season length. Therefore, annual crops were underestimated and perennial crops were overestimated in the MODIS-derived map.

Due to the large pixel size of MODIS imagery (500×500 m^2), it was difficult to perform ground-based accuracy assessment. This study applied an error matrix approach (Congalton 1988) to compare the accuracies of the MODIS-derived classes against the published CDL products. To be spatially comparable, the CDL map was down-sampled to 500-m resolution with a majority filtering process. Corn and soybean in the CDL map were compared with the class of corn/soybean in the MODIS map, whereas WSG and CSG in the MODIS map (Figure 5) were combined to match the class of grassland in the CDL map. Winter wheat was not considered in the assessment as it covered limited area of the tallgrass prairie. With a stratified random sampling design, a number of 1,448 and 1,077 sample points were selected for corn/soybean and grassland, respectively. The numbers represented 0.1 percent of total pixels for each category in the degraded CDL map. In a two-category error matrix approach, it was found that 428 out of the 1,448 corn/soybean points were misclassified as grass in the MODIS-derived map, whereas 134 out of the 1,077 grass points were misclassified as corn/soybean. The overall accuracy reached 77.74 percent when both categories were considered. For perennial crops, the producer's accuracy was 87.56 percent and the user's accuracy was only 68.78 percent, resulting from misclassifying annual crops into perennial crops in the MODIS-derived map. It should be noted, however, that the "accuracies" discussed here actually represented the agreement between the MODIS-derived map and the published CDL product, which had about 10 percent of uncertainties for classification of major crop types from fine-resolution satellite imagery (NASS 2010a). Further uncertainties were inevitably introduced when the 56-m CDL map was degraded to 500 m for purposes of comparison (Pontius and Cheuk 2006). More ground data will be collected in the future to assess real accuracies of MODIS-derived energy crop map in this study.

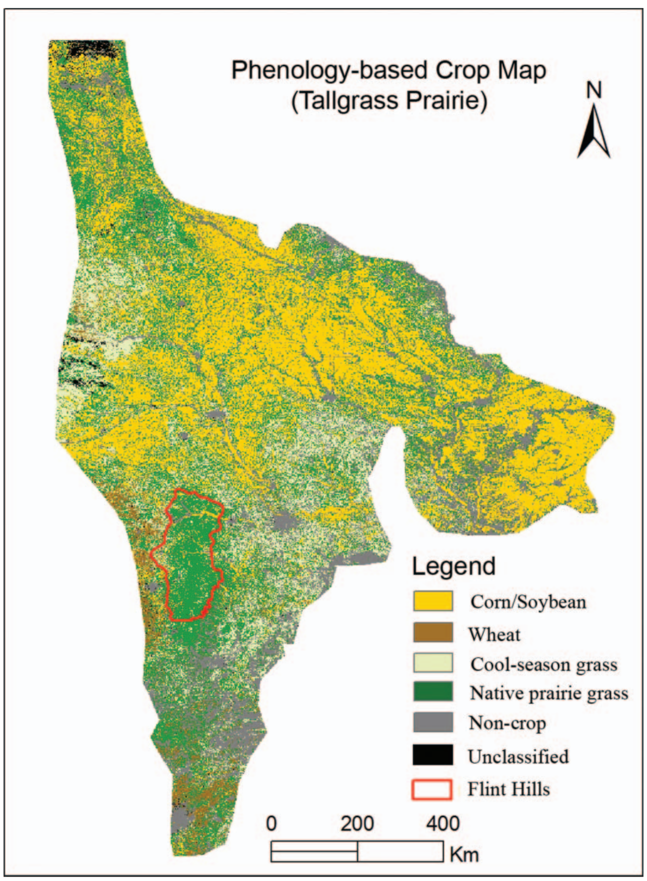

Figure 5. The 2007 crop map of the tallgrass prairie extracted from time series of Moderate Resolution Imaging Spectroradiometer (MODIS) imagery. Outlined in the map is the Flint Hills grassland, the largest validation site of native prairie grass.

Specifically for native prairie grasses, Wang, Jamison, and Spicci (2010) recorded relative abundance of WSG (%) and CSG (%) of the nineteen prairie remnants managed by MDC. In the MODIS-derived map, the percentages were calculated by counting the numbers of WSG and CSG pixels of each prairie. Due to large size of MODIS pixels, the eight prairies less than 100 ha (four MODIS pixels) were not considered. Two large ground truth sites, the Flint Hills grassland (WSG% = 80.00) and the TPNP (WSG% = 90.05) in the grassland, were also examined. Ground-observed and MODIS-calculated relative abundances of these prairies were compared in Figure 6, in which each prairie had two points (WSG% and CSG%) in the scatterplot. It agreed

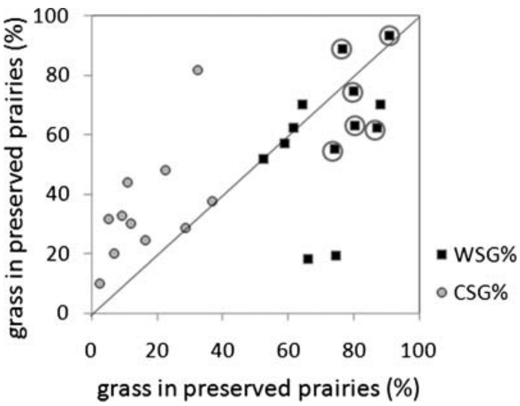

Figure 6. Comparison of ground-observed and Moderate Resolution Imaging Spectroradiometer (MODIS)-derived relative abundance of cool-season grasses (CSG) and warm-season grasses (WSG) in the preserved prairie remnants. The circled points represent the six largest prairies (> 500 ha) in the region.

with Wang, Jamison, and Spicci (2010) that native prairie grasses dominated these prairies. The six largest prairies were circled in the scatterplot: Prairie State Park, Osage Prairie, Wah-Kon-Tah Prairie, Taberville Prairie, TPNP, and Flint Hills grassland. Among the thirteen prairies, only two prairies had apparently different results from ground observations (the two WSG% points in the lower right of the scatterplot). One was the Stony Point Prairie (388.64 ha) in Dade County, Missouri. Upon ground observations it was primarily composed of WSG and CSG, whereas in the CDL map the prairie was largely classified as wetland vegetation, which was masked out in this study. The other one was the Monegow Prairie (108.12 ha) in Cedar County, Missouri. It had much lower WSG% (the lower right in Figure 6) and correspondingly higher CSG% (the upper left in Figure 6) in the MODIS-derived results. One possible reason was the relatively small area of this prairie and its mixed growth of WSG (66.23 percent) and CSG (32.43 percent) species, which resulted in large misclassification in the MODIS-derived map. With all points in Figure 6, the root mean square error (RSME) was 23.47 percent, which explained the overall discrepancy between the MODIS-derived results in this study and the published ground records. When the two outliers were removed, the RMSE dropped to 13.76 percent.

The phenology-based crop mapping approach was inevitably affected by the shift of crop calendar in a large region. Although the shift was compensated for by a lag factor in the decision tree, a large discrepancy was observed in the northern and southern states of the tallgrass prairie. For example, there were considerable amounts of spring wheat acreages in North Dakota (in the very north of the prairie). These fields tend to be misclassified as corn/soybean because they could not meet the decision rule of early peak season in Figure 3. Similarly, some grasslands in Texas (in the very south of the prairie) were misclassified as wheat because of their early peak season. Crops in these states were not further examined because they only cover limited area in the tallgrass prairie.

Biomass Potentials and Environmental and Economic Impacts

Corn has been commercially adopted as a major source of biofuel (e.g., corn ethanol), and native prairie grasses could have high potential as lignocellulosic bioenergy feedstock. The Oak Ridge National Laboratory found that approximately 10 percent of the total suitable land in the Midwest could potentially be used for energy crops without affecting food production (Wright 2007). This study recorded the geographic context of energy crops (an estimation of 26.77 million ha for corn and soybean and 20.73 million ha for native prairie grass) in the tallgrass prairie, a dominant region in the Midwest.

Based on current land use patterns of energy crops, economic and environmental impacts could be assessed for bioenergy viability in the prairie. Economic forces, such as biofuel mandates, tax credits, and tariffs explain the mechanisms through which policy changes cause land use change of energy crops (Thompson, Meyer, and Westhoff 2009). Meanwhile, potential land use change associated with energy crops is determined by crop profitability (net returns) and site-specific environmental factors such as soil quality, water availability, and weather conditions. These economic and environmental factors need to be interactively examined with current cropping activities to project potential land use change and biomass supplies of energy crops. GIS are well suited to integrate disparate data sources in attempts to visualize and analyze geographic phenomena. Similarly, GIS can be manipulated to evaluate land conversion of energy crops in a region to provide spatially explicit information to support decision-making processes such as site selection for power plants (see example studies in Graham, English, and Noon 2000; Voivontas, Assimacopoulos, and Koukios 2001; Vainio et al. 2009).

This study initiated an effort of regional bioenergy land use by taking advantage of coarse-resolution, frequent satellite observations. Only one-year data sets

(2007) were selected because of smooth climate conditions in this year. To continue this investigation, multiyear time-series observations will be applied to explore climate change in agricultural regions as extreme climate conditions and phenology abnormalities can severely affect cropping activities and biomass production. At coarse resolution, MODIS pixels are often a mixture of different fields in agricultural lands. With various linear and nonlinear unmixing techniques, mixed pixels could be decomposed to different crop types at certain percentages, which improves accuracies in estimating energy crop distributions.

Remote sensing of energy crops enhances the documentation and understanding of regional biomass feedstock production. In a long run, other large-scale efforts of phenology studies such as the U.S. National Phenology Network (http://www.uwm.edu/Dept/Geography/npn) and the European Phenology Network (http://www.dow.wau. nl/msa/epn/index.asp) could also be integrated to improve understanding in phenology of land surfaces and to provide a better basis for comparing in situ measurements against remotely sensed observations. Such spatially explicit biomass information is critical for a broad spectrum of planning activities, ranging from policy development, marketing, and siting necessary infrastructure to a variety of security and logistical issues. Therefore, the geospatial approaches initiated in this study could potentially take an important and cross-cutting role in bioenergy policy decision making for federal and state agencies.

Conclusion

This study explored a geospatial assessment of bioenergy land use in the tallgrass prairie. Time series of satellite imagery were analyzed to extract distinct phenology metrics of annual (corn, soybean, wheat) and perennial crops (CSG, WSG) over the course of the growing season in 2007. Five metrics were found to be important in delineating these crops: end of season, season length, peak season, summer dry-down, and cumulative growth. A phenology-based decision tree was developed to identify the five major crops from satellite images. The study revealed the geographic distributions of native prairie grasses, the primary perennial energy crop in the United States. The total acreage of this perennial energy crop was estimated at 20 million ha in the prairie, covering about one quarter of the region. It was demonstrated in this study that time-series MODIS products provided an efficient data source for regional bioenergy studies. If more ground data are available to better understand the uncertainties of MODIS-derived energy crop mapping, the geospatial approach developed and the distributions of energy crops extracted in this study could provide essential information for bioenergy decision making in the prairie region.

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