Journal of
Applied Remote Sensing

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Abstract. Bioenergy land use is expanding today as biofuel is consuming higher amount of agricultural production. In 2007, a widespread expansion of corn planting areas was recorded in the United States Department of Agriculture crop census. To better document the corn-related land use change, this study mapped the spatial distributions of four major annual crops (corn, soybean, winter wheat, and spring wheat) and three perennial crops (shortgrass, warm-season tallgrass, and cool-season tallgrass) in the Midwest. From 2006 to 2008, the 8-day, 500-m moderate resolution imaging spectroradiometer (MODIS) surface reflectance products were used to retrieve the normalized difference vegetation index (NDVI) composites. A support vector machine classifier was applied to identify these crops based on their unique growth cycles reflected from NDVI trajectories. The results showed a net increase of 15% of corn fields in 2007 accompanied by a net decrease of 16% in 2008. With the season-long integrated NDVI, this study also explored the geographic context and biomass proxy of native perennial grasses, an important feedstock of cellulosic biofuel. Mostly growing in North Dakota, South Dakota, Nebraska, and Kansas, their biomass quantities increased from west to east. This study indicates that frequent satellite observations may provide an efficient tool for monitoring biomass supplies and land use changes to assist national bioenergy decision-making. [DOI: 10.1117/1.JRS.8.085198]

Keywords: bioenergy; cropland mapping; time series analysis; moderate resolution imaging spectroradiometer.

Paper 14237SS received Apr. 24, 2014; revised manuscript received Sep. 6, 2014; accepted for publication Oct. 2, 2014; published online Nov. 3, 2014.

1 Introduction

Bioenergy land use is of increasing interest in U.S. agriculture today as biomass becomes the largest source of domestic renewable energy in the United States. The Energy Independence and Security Act (EISA) in 2007, following the Energy Policy Act of 2005, mandated 15 billion gallons of biofuels to be used in annual gasoline consumption by 2015.[1] By now corn ethanol remains the primary source of biofuel,[2,3] although agricultural residuals and dedicated energy crops are being explored as a cellulosic feedstock.[4] In 2011, ethanol production consumed >5 billion bushels of corn.[1] A higher need of corn ethanol and higher corn prices encourage farmers to increase corn planting acreage, adjust crop rotations, and convert other lands into corn fields.

Perennial native grasses are also a dedicated energy crop.[5] Since switchgrass (*Panicum virgatum* L.) was identified by the U.S. Department of Energy as a model cellulosic energy crop in early 1990s,[2,6] the adaptability of this native prairie grass to poor soil conditions has led researchers to examine its competitive potentials for cellulosic feedstock on low-productivity croplands.[7,8] Other native prairie grasses, such as big bluestem (*Andropogon gerardi* Vitman),

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little bluestem (*Andropogon scoparius*), and indiangrass [*Sorghastrum nutans* (L.) Nash], also naturally grow throughout the eastern two-thirds of the United States especially the Midwest. These perennial native grasses hold high biomass potentials and environmental implications. With new conversion technologies coming online, the share of cellulosic biofuel from perennial native grasses will increase. The Renewable Fuel Standard (RFS) for cellulosic and other advanced biofuels is set to 20 billion gallons by 2022.[9]

Agricultural land use changes reflect the dynamics of bioenergy expansion. Current knowledge of corn productions and biomass supplies for U.S. bioenergy is mostly gained from cropping surveys by local farmers (e.g., map products). The finest-scale information of crop planting areas, yield and production of annual crops, and perennial forages is mostly available from county-level crop census records at the United States Department of Agriculture (USDA) National Agricultural Statistical Service (NASS). The lack of spatial specificity limits our understanding of energy crop expansion and biomass potentials in major U.S. agricultural regions.

Remote sensing techniques extract regional land use patterns at fine spatial units (meters to kilometers), which provide better estimation of corn cropping and biomass supplies than county-level crop statistics.[10] In recent decades, national land cover products have been periodically developed to assess land cover/use characteristics in the United States. The most commonly applied product is the Landsat-derived National Land Cover Databases in the past three decades.[11] Specifically in agricultural lands, major annual crops in the conterminous United States have been mapped with satellite images since the 1970s in the USDA/NASS Cropland Data Layers (CDL).[12] In recent years, the overall classification accuracies reach 80% to 90% in dominant agricultural lands.[13,14] Perennial native grasses, however, have not been extracted in any U.S. agricultural databases. Because of their spectral similarity, the warm-season native prairie grasses cannot be effectively delineated from cool-season forage grasses in regular satellite images. Therefore, there is a lack of biomass production records of perennial native grasses, which are crucial for accurate assessment of regional biomass supplies.

Regional land cover/use mapping and crop monitoring need frequent and large-coverage observations. Since 2000, the moderate resolution imaging spectroradiometer (MODIS) onboard Terra and Aqua provides satellite images at daily observations and global coverages. These data are thus an ideal source for operational monitoring and assessment of biomass crops in a regional level. Frequent observations along the growing season reveal crop phenology and are able to enhance regional crop mapping.[15] These data products are also the key input to fill in the gaps of perennial biomass crops in current agricultural databases.

Dramatic increase of corn planting areas has been recognized in recent years. Upon the USDA crop census data, the U.S. corn planting areas in 2007 reached a historic record of 93.5 million acres (highest since 1944).[9] This corn boom was apparently driven by the higher demand of corn ethanol after new bioenergy policies such as the Energy Policy Act in 2005 and the EISA in 2007. This study aims to explore the bioenergy-driven land use change in 2007 over the Midwest, the most important U.S. agricultural region. Major annual and perennial crops in the region were extracted from MODIS time series in each year of 2006 to 2008. Spatial distributions of land use change extracted in this study provided quantitative and spatially explicit information for regional bioenergy decision making and sustainable agricultural management.

2 Materials and Methods

2.1 *Study Area and Data Acquisition*

2.1.1 *Study area*

The U.S. Midwest is composed of 12 states across the Corn Belt (Fig. 1). Land used for annual and perennial crops exceeds 70% in the region.[16] Corn-soybean monoculture dominates the Corn Belt in northern and central states. Cool-season forage and warm-season native prairie grasses are popular in western and southern states. In 2000, the Oak Ridge National Lab estimated >200 million acres of land in this region that is suitable for energy crop production. Among national biomass feedstock, 74% of crop residuals and 77% of switchgrass on the Conservation Reserve Program lands are currently from the Midwest.[17] Ten of the 12 Midwestern states [except

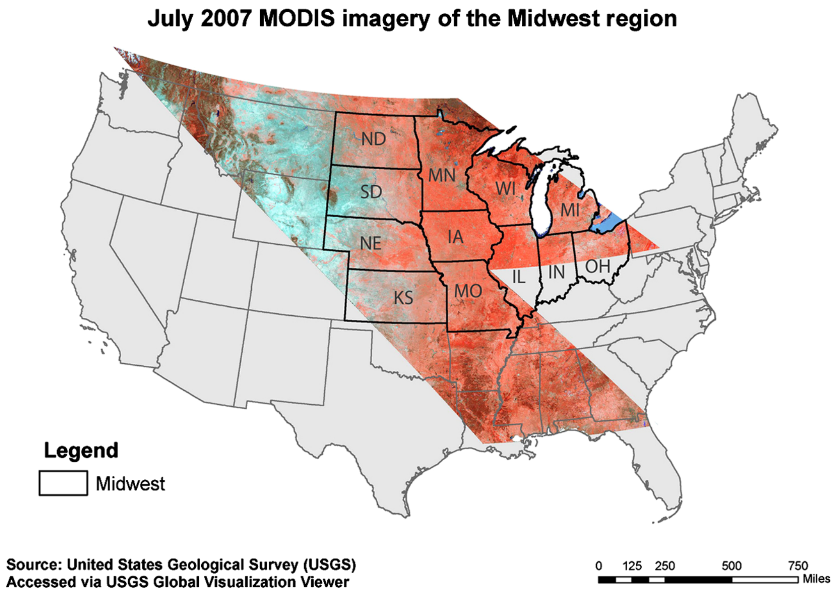

Fig. 1 The 12 states in the Midwest and three example moderate resolution imaging spectroradiometer (MODIS) tiles (acquired in July 2007) in a false-color composite. Vegetation displays in red.

Missouri (MO) and Minnesota (MN)] are marked the nation's top 10 states holding the highest ethanol production capacity.

2.1.2 *Satellite data and published products*

The 500-m, 8-day MODIS surface reflectance products (MOD09A1) in 2006 to 2008 were our primary data source. Datasets at this level of detail are capable of capturing spatial and temporal variations of crop growth at regional scale. The Midwest could be almost fully covered by four MODIS tiles. The three tiles mosaicked in Fig. 1 demonstrate the coverage of each tile in the study region. A total of 46 MOD09A1 scenes per year were acquired for each tile. For each scene, the normalized difference vegetation index (NDVI) was calculated with the red and near-infrared spectral bands of the MOD01A1 imagery. The NDVI is commonly used to represent crop greenness. The 46-point NDVI time series in each year revealed crop development at pixel level. The MOD09A1 products, even after the maximum-value-composite process at 8-day intervals,[18] were strongly influenced by cloud residuals and atmospheric variations. In this study, a modified Savitzky-Golay filtering method[15,19] was applied to smooth the time series, which revealed crop growth cycles in a given year.

The 30 to 56 m CDL products in 2006 to 2008 were available in all Midwestern states (except Michigan in 2006). The background display in Fig. 2 is an example CDL map in 2007 that demonstrated the overall distributions of annual crops and grasses in the Midwest. The USDA NASS also released a 30-m Cultivated Land Mask layer that was extracted from CDL products from 2007 to 2011. This mask was resampled to 500-m pixel size to mask out the noncrop lands (e.g., water, forest, urban). Other crops such as cotton, rice, and sorghum were usually planted in small-size fields and were also masked out. Only primary annual crops (corn, soybean, winter wheat, spring wheat) and grasses were examined in this study. Additionally, to examine weather variations in the Midwest, we downloaded the monthly maximum temperature and monthly minimum temperature records from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) products in the past decade.[20] The PRISM data are in raster format with a grid size of 2.4 arc min (4 km).

2.1.3 *Ground truth samples*

Ground sample points of annual crops in each year were extracted from the CDL products. After resampling the CDL maps to 500-m pixel size, the CDL raster was converted to polygons. For

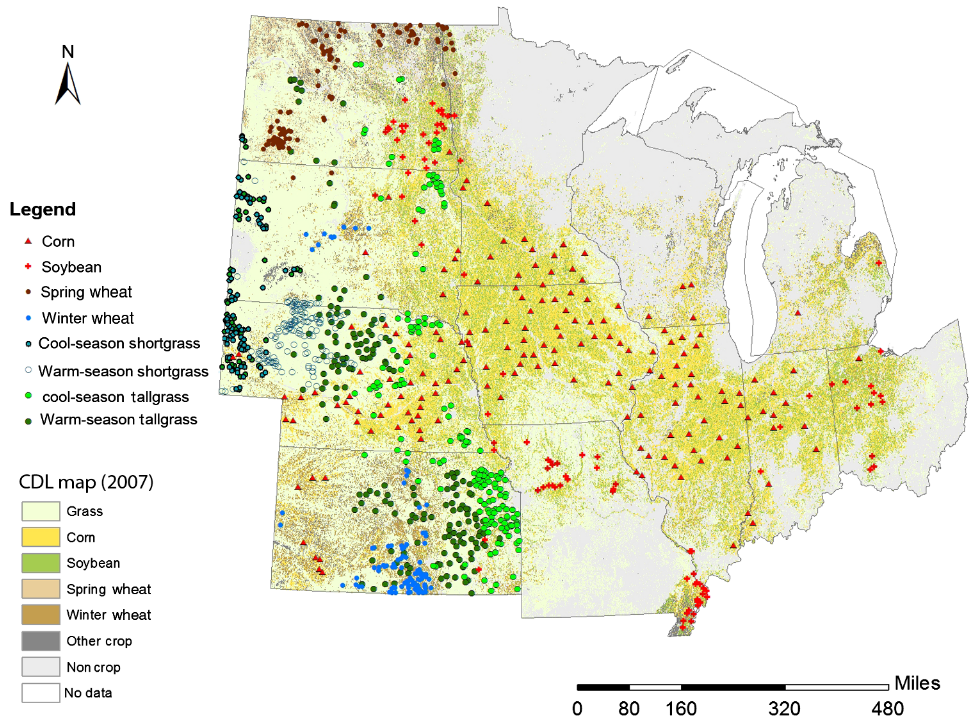

Fig. 2 The 2007 training samples of the eight crops (four annual and four perennial). The background map is the USDA Cropland Data Layers (CDL) map in the same year.

each crop, any polygon with an area larger than 5×5 pixels ($6.25\ km^2$) was extracted, and sample points were randomly selected within the polygon. Points close to polygons borders were not used. Narrow polygons were also excluded to avoid mixed pixels. To reduce spatial autocorrelation, the distance between any two samples was at least 2.5 km (5 pixels). Samples of annual crops varied in each year.

Sample points of perennial grasses were extracted from the previously published grass percent map in the Great Plains[21] in which four Midwestern states [North Dakota (ND), South Dakota (SD), Nebraska (NE), and Kansas (KS)] were covered (as shown Fig. 1). In this study, relative abundances of four grass types (shortgrass C3, shortgrass C4, tallgrass C3, and tallgrass C4) were mapped in a range of 0% to 100%. C3 grasses are also regarded as "cool season" plants as they start the growth in early spring and resume in autumn, whereas C4 species are referred to as "warm season" plants that are more photosynthetically active in late spring and summer.[22,23] Tallgrass warm-season species are actually the perennial native grasses that are of great interest in bioenergy. Here, we extracted the polygons with 80% to 100% cover of each grass type as ground truth samples. Similarly, polygons larger than 5×5 pixels were extracted, and sample points of the four grass types were randomly selected with a distance >2.5 km between each other. Subject to classification errors, each sample point was visually checked in the NDVI time series in the 3 years. A skeptical point in any year was removed. Therefore, the final samples of each grass type were the same for all years.

Figure 2 displays all ground samples in 2007. Corn and soybean samples scattered in the Corn Belt, winter wheat in KS (with a few in SD), and spring wheat in ND. Grass samples were clustered and were only available in the four western states (ND, SD, NE, and KS). Please refer to Ref. 21 for detailed information about grass distributions that varied with plant functional types and floristic regions. Finally, the sample points were randomly split into training and validation sets. After visual examination of their NDVI time series, sample points that did not agree with our general understanding of a crop's phenology patterns (e.g., the general crop calendars of planting, silk and harvest as published by the USDA) were removed. The final set of training and validation samples for each crop (four annual and four perennial) is listed in Table 1.

Table 1 Ground truth (training and validation) data of all crop types in each year of 2006 to 2008.

Training/validation	2006	2007	2008
Corn	97/80	101/116	92/107
Soybean	63/43	62/45	58/33
Spring wheat	60/40	67/40	69/66
Winter wheat	56/45	56/43	73/54
Shortgrass C3		83/53	
Shortgrass C4		89/60	
Tallgrass C3		98/88	
Tallgrass C4		93/91	

2.2 *Approaches*

2.2.1 *NDVI Time Series and Adjustment of Crop Calendars*

At an MODIS pixel (with ground area of $500 \times 500\ \mathrm{m}^2$, the smoothed 46-point NDVI time series reveals growing patterns of crops. Using all samples in 2007, the NDVI time series curves of crops are demonstrated in Fig. 3. The mean curve (dark line) was calculated as the average NDVI of all samples at a given time interval in 2007. The trajectory revealed the growth cycles of each crop along the growing season. The 95% envelope embraced the $\pm 1.96 \times$ standard deviation from the mean, representing the NDVI variation of samples at different locations.

As shown in Fig. 3, annual crops have shorter growth seasons and narrower envelops than grasses. Corn was planted slightly earlier than soybean, but the two curves were quite similar. Spring wheat had earlier planting time and shorter length than corn and soybean. Winter wheat was characterized with the earliest peak NDVI (April–May) and the widest envelopes, indicating its large spatial variations of off-season greenness affected by winter snow or green covers (managed or unmanaged) after harvesting. Growing lengths of grasses were longer with higher variation of NDVI than the typical symmetric curves of annual crops. Cool-season grasses started their growth earlier and had apparently a longer season than warm-season grasses. Shortgrass had much lower NDVI than tallgrass types. Therefore, it was feasible to delineate these perennial and annual crops based on these growth patterns.

Geographical shifts of crop calendars and adaptation of native grass cultivars have been observed in large agricultural regions,[24] which may affect growth cycles of the same crop in different areas. For example, planting dates of corn and soybean in the north of the Midwest could be a few weeks later than in southern states. Crop calendars are primarily controlled by weather variation (especially temperature) and reflect the shift of phenological features of a given crop. In this study, we adopted the concept of growing degree days (GDD) to adjust this shift. The GDD is defined as[23]

$$\mathrm{GDD} = \frac{T_{\max} + T_{\min}}{2} - T_{\mathrm{base}}, \tag{1}$$

where $T_{\max}$ and $T_{\min}$ represent the daily maximal and minimal temperatures, respectively. T_{base} is a base temperature that varies for different vegetation types. All units are in °C.

Because both annual and perennial crops in the Midwest were examined in this study, we defined $T_{\mathrm{base}} = 0°\mathrm{C}$ at the regional level. In Eq. (1), the DOY when $\mathrm{GDD} = 0°\mathrm{C}$ is assumed to be the date when the growing cycle of all crops is initiated. Because of weather dynamics, the $\mathrm{GDD} = 0°\mathrm{C}$ dates may vary in different years. Figure 4 demonstrates the range of $\mathrm{GDD} = 0°\mathrm{C}$ distributions extracted from the PRISM monthly highest and lowest temperature in the Midwest. The GDD reached 0°C in January along the southern end of Kansas and Missouri, whereas in

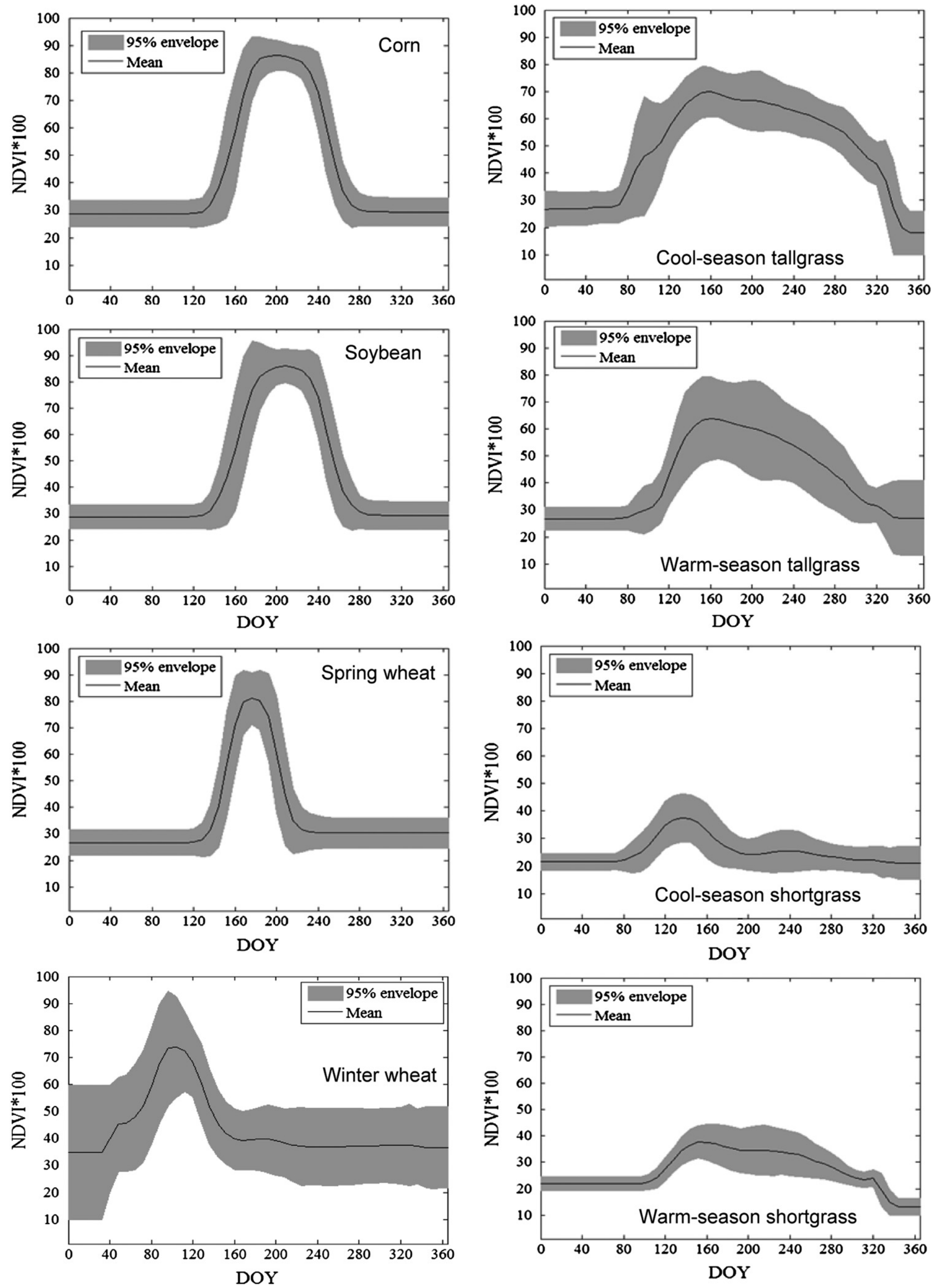

Fig. 3 The 2007 normalized difference vegetation index (NDVI) time series of the eight crops that reveal their growth cycles. Both the mean trajectories (black line) and the 95% envelopes of the variation are displayed.

February, it shifted to the north when the land became warmer. By the end of February, it reached 0°C in northern states such as ND, MN, WI, and MI. In late March, all states in the Midwest reached GDD = 0°C and higher. Therefore, a majority area of the Midwest can be covered by a 1-month shift of crops' start of growth, which agreed with our common understandings of crop calendars in this region. The January GDD = 0°C curve in Fig. 4 served as the base line. The DOY dates of GDD = 0°C were spatially interpolated. For each pixel in the north of the base line, its NDVI time series were adjusted with the days of delay from the base line. The GDD adjustment minimized the geographic variation of the NDVI trajectories, and could improve crop classification in a large region.

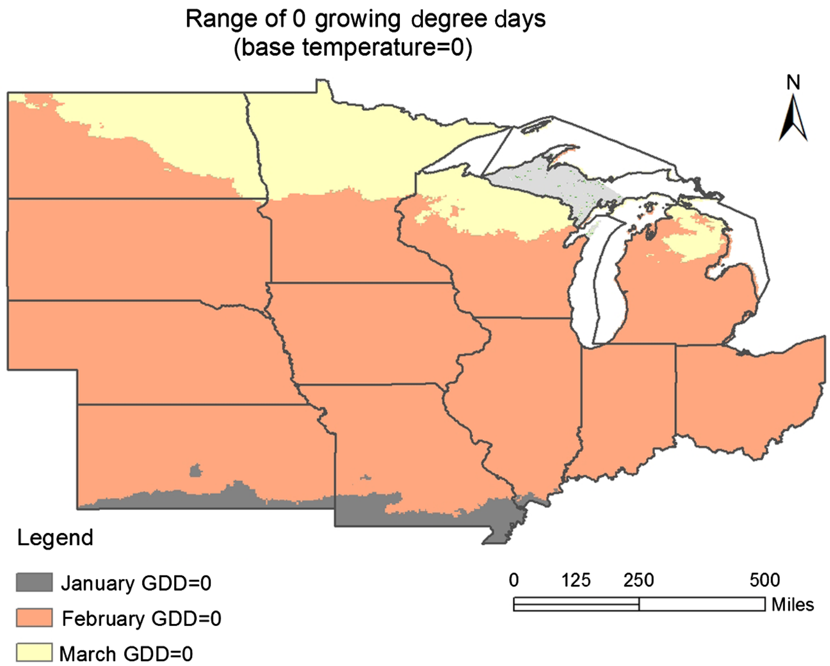

Fig. 4 The ranges of GDD = 0°C in early spring (January–March) of 2007 in the Midwest. The GDD is calculated from the monthly Parameter-elevation Regressions on Independent Slopes Model data.

2.2.2 *Crop classification and corn area change*

Relying on their growth patterns, annual and perennial crops were classified using a commonly applied support vector machine (SVM) approach. As a nonparametric machine learning technique, the SVM optimally discriminates any pair of classes by identifying a linear hyperplane with maximal distances between their training datasets, or a support vector.[25] By controlling the margins of small subsets of sample points, it is less affected by the size, purity, and normality of training samples and is more robust than conventional parametric classifiers.[26,27] Pure, large-size training samples were limited for crops in the coarse-resolution MODIS imagery. Therefore, the SVM was optimal for regional land cover mapping in this study. During the SVM classification, the radial basis function kernel was selected, with which the Gamma function was applied to weight the nearby samples. In each year of 2006 to 2008, the eight crops were classified all over the Midwest. With a unit area of $500 \times 500\ \mathrm{m}^2$, the change of corn plantation in the 3 years was thus quantified.

2.2.3 *Biomass quantification*

Perennial prairie grass holds high potential of biomass feedstock for regional bioenergy. For perennial grasses identified in each year's class map, biomass quantities were approximately evaluated with the NDVI time series. In this study, we used the cumulative NDVI (ΣNDVI) as a biomass proxy of perennial crop pixels:

$$\Sigma\mathrm{NDVI} = 8 \times \int_1^{46} [\mathrm{NDVI}(t) - 0.3]\mathrm{d}t \quad \text{with} \quad \mathrm{NDVI}(t) = 0 \quad \text{when } \mathrm{NDVI}(t) < 0.3, \qquad (2)$$

where t represents the number of intervals ($t \in [1, 46]$ in this study) in a given year. A base value of NDVI = 0.3 is used to approximate the greenness that is not harvested. As demonstrated in Fig. 3, the off-season NDVI values of perennial grasses are often <0.3 and are thus not counted in calculation. The factor 8 is used to project the 8-day NDVI series to daily NDVI accumulation.

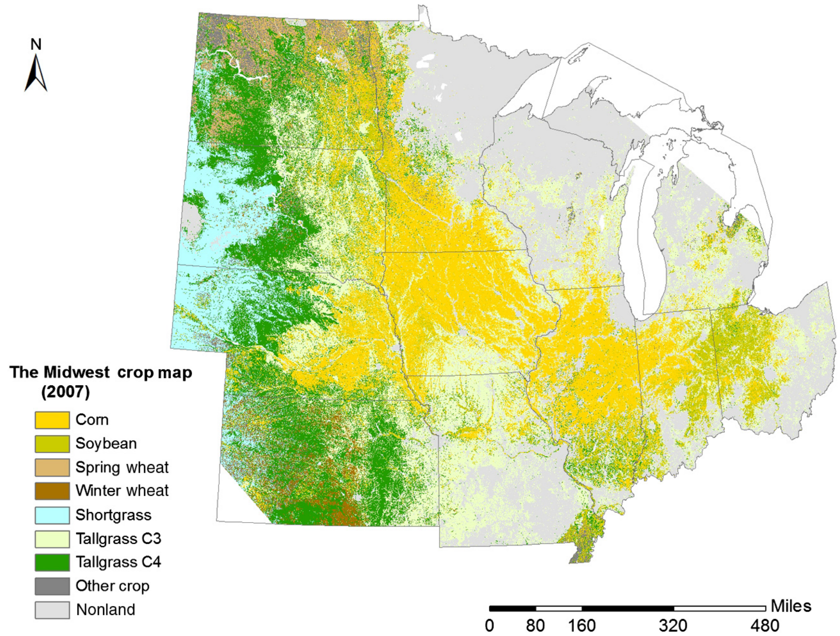

Fig. 5 The MODIS-classified crop map in the Midwest in 2007.

3 Results

3.1 *MODIS-Classified Crop Maps*

Major crops in the Midwest were classified from annual NDVI time series in 2006 to 2008. Using the 2007 map as an example (Fig. 5), distributions of annual crops agreed with our common understanding of crop plantation in the Midwest. Corn and soybean dominated the Corn Belt. More corn fields were identified in the central states such as Iowa (IA), Illinois (IL), eastern NE, and southern MN. Soybean planting areas were larger in southern IL, the eastern (across Indiana and Ohio), and northwestern (across ND, SD, and MN) ends of the region.

The general patterns of annual crops in Fig. 5 were similar to those in the CDL map (the background map in Fig. 2). The individual fields of corn and soybean, however, cannot be effectively revealed in class maps. Corn and soybean grow all over the Corn Belt, but their fields were often smaller than an MODIS pixel. When resampling the CDL raster to 500-m pixel size, small and mixed polygons cannot be used for training point collection. As shown in Fig. 2, most training points of corn were in the central states such as IA, NE, and IL, and most soybean points were clustered in the northwestern and southeastern ends of the Corn Belt (e.g., OH, MO, ND). Therefore, smaller soybean fields cannot be effectively identified in the Central Belt. Winter wheat mostly grew in southern states as KS, and spring wheat was in northern states as ND. Similarly, classification was affected by mixed pixels in the MODIS imagery. The CDL-extracted small polygons were often lost in the MODIS-classified results in Fig. 5.

Perennial grasses dominated the western and southern states of the Midwest. Warm-season and cool-season shortgrasses grew in western states, mostly western KS, NE, SD, and ND. As reported by Wang et al., they naturally grew in the shortgrass steppes and northern upland prairies that had limited productivity. With low biomass (maximum NDVI <0.5), shortgrass was of the least interest in bioenergy. Therefore, the warm-season and cool-season shortgrass pixels were grouped into one class in Fig. 5 and were not further discussed in this study. The eastern states of the Midwest are actually located in the Tallgrass Prairie region. Warm-season tallgrasses still dominated the prairie remnants such as the Flint Hills, KS, and the eastern Sand Hills, NE. In other tallgrass lands, however, cool-season forage species were widely introduced to pasturelands and hayfields because of their improved growth and longer growing season than native grasses.[15] Warm-season and cool-season tallgrasses often grew in mixed conditions with their relative abundance strongly influenced by weather variations in different years. Pasturelands in the eastern states of the region were limited, mostly clustered in MO and IA. These pasturelands were dominated with the introduced cool-season tallgrass species, and had been well-managed for grazing and forage production.

Using the validation points in Table 1, accuracies of the classified results were examined with the confusion matrix approach (Table 2). The misclassification between annual and perennial crops was low. For annual crops, corn and soybean had similar growing cycles and were often misclassified to each other. The commission and omission errors of soybean were always higher than corn, probably from the limited number of soybean samples extracted from the CDL maps. Warm-season and cool-season shortgrasses can be easily misclassified because of their similarly low NDVI values and low trajectory curves (as shown in Fig. 3). Warm-season and cool-season tallgrasses can also be misclassified because of their similar NDVI trajectories. The overall classification accuracies reached 89.21%, 91.22%, and 91.18% in 2006, 2007, and 2008, respectively. The Kappa values of the classifications were relatively stable (0.87 to 0.90) in 3 years. These accuracies may be overestimated because only pure pixels of large crop parcels ($>6.25\ \mathrm{km}^2$) were counted as ground samples. With a unit area of $500 \times 500\ \mathrm{m}^2$ on ground, pixels in cultivated lands were often composed of multiple crop fields. The confusion in these mixed pixels was not able to be evaluated in this study.

Because energy crops are of the major concern of this study, the following analysis was focused on corn, soybean, and grass areas. For these three crops, the state-level planting areas were compared between the MODIS-classified and the CDL maps in each year (Fig. 6). The CDL products did not delineate warm-season and cool-season grasses, and therefore, the comparison of grass was based on the total area of all grass types. A total of 105 points were extracted for three crops in 3 years over the 12 states (11 in 2006). As shown in the scatterplot, the points were generally scattered along the 1:1 line. The planting areas were up to 10 to 20 million acres for corn/soybean and 35 million acres for grasses in the Midwestern states. In comparison with the CDL outputs, corn and grass were overestimated in the states that had larger planting areas (>10 million acres). Soybean in these states mostly had planting areas <10 million acres, and was underestimated in the MODIS classification (below the 1:1 line). When all three crops were considered, the root-mean-square error was 3.28 million acres.

3.2 *Corn-Related Land Use Change in 2006 to 2008*

The corn boom in 2007 recorded in the USDA crop census was further examined. With the classified maps in 2006 to 2008, the land use change between corn and other crops (soybean, grass, and other annual crops) was extracted in 2006 to 2007 and 2007 to 2008 (Fig. 7). To enhance the visualization, other land use patterns were not displayed in this figure. A pie chart was displayed in each map as an inset to categorize the corn-related areas in the region: continuous corn cropping (no change), corn increase (shifted from other crops), and corn decrease (shifted to other crops).

From 2006 to 2007, a majority of agricultural lands in the Midwest experienced an increase of corn planting shifted from soybean, grass, and other crops [Fig. 7(a)]. Corn decrease was also observed, but the clusters were much smaller and scattered in isolated areas across the region. A large cluster of corn decrease was observed in the western IN and eastern OH. As shown in the pie chart, half of corn fields remained no change from 2006 to 2007, 18% in decrease and 33% in increase.

From 2007 to 2008 [Fig. 7(b)], both corn increase and decrease were observed all over the region, but corn decrease was more predominant, especially in central Corn Belt such as southern MN, southern Wisconsin, northern MO, and all over IA and IL. The areas in western IN and eastern OH, with dramatic corn decrease in 2007, shifted back to corn fields in 2008. In the pie chart, there were about half of corn fields in continuous corn cropping (no change), 38% in decrease and 22% in increase. Figure 7 reveals the corn boom in 2007 and the bounce back next year, which was in agreement with crop census reports.[9] More importantly, it shows detailed spatial distributions of corn change before and after 2007. It also clearly illustrates the corn-soybean rotation pattern in the Midwest.

Figure 8 summarizes the change of corn planting areas of the 12 Midwestern states in the three years. Both corn increase and decrease occurred in each state, but corn increase dominated the period of 2006 to 2007 [Fig. 8(a)], with five states having +3 million acres of corn increase:

Table 2 Error matrices of the SVM class maps derived from the MODIS NDVI time series in 2006, 2007, and 2008. Sample numbers in agreement between the classified and ground references (along the diagonal lines) are marked in bold.

		Ground reference								
		Corn	Soybean	Spr. wheat	Win. wheat	Short C3	Short C4	Tall C3	Tall C4	Commission (%)
Classification in 2006	Corn	**70**	9							11.39
	Soybean	10	**34**							22.73
	Spr. wheat			**34**						0
	Win. wheat				**33**					0
	Short C3			2	5	**46**	4		1	20.69
	Short C4					6	**48**		0	11.11
	Tall C3			1				**82**	3	4.65
	Tall C4			3	2		3	3	**83**	11.7
	Omission (%)	12.5	20.93	15	17.5	11.54	12.73	3.53	4.6	
	Overall classification accuracy: 89.21%; Kappa value: 0.87									
Classification in 2007	Corn	**105**	3							2.78
	Soybean	5	**39**							11.36
	Spr. wheat			**39**						2.5
	Win. wheat				**35**					0
	Short C3				3	**48**	1			7.69
	Short C4	1	1			5	**55**		3	15.38
	Tall C3	1	1	1				**82**	1	4.65
	Tall C4	2	1		2		4	6	**85**	15
	Omission (%)	9.48	13.33	2.5	18.6	9.43	8.33	6.82	5.56	
	Overall classification accuracy: 91.22%; Kappa value: 0.90									
Classification in 2008	Corn	**98**		1						1.01
	Soybean	6	**26**							18.75
	Spr. wheat			**60**	2					3.23
	Win. wheat				**44**					0
	Short C3			3		**42**	2			10.64
	Short C4		3		1	11	**56**		2	23.29
	Tall C3		2	2	1			**84**	3	8.7
	Tall C4		1				2	3	**86**	6.52
	Omission (%)	8.41	18.75	9.09	8.33	20.75	6.67	3.45	5.49	
	Overall classification accuracy: 91.18%; Kappa value: 0.90									

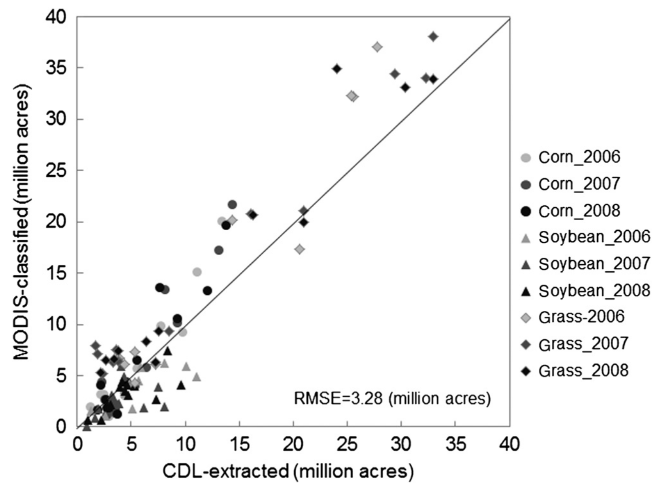

Fig. 6 Scatterplot of the MODIS-classified and CDL-extracted crop areas in the Midwestern states. Summarized for corn, soybean, and perennial grass in each state.

MN, IA, IL, NE, and ND. Corn decrease was more dramatic in 2007 to 2008 [Fig. 8(b)]. The above-mentioned five states had +3 million acres of corn decrease, although the ranks of the change were different in the two periods.

3.3 *Perennial Biomass Quantification in the Midwest*

Different from the interannual shifts of cropping patterns of annual crops, grasses grew perennially in pasturelands and hayfields and usually did not change unless the lands were plowed and converted to annual crops. In the two insets in Fig. 7, there was slightly a higher percentage of grasses shifting to corn in 2007 and a higher percent of corn back to grass in 2008, which may also be related to the corn boom in 2007.

Warm-season tallgrass species provide an alternative of biomass feedstock in the Midwest. With the integrated NDVI along a growing season, biomass quantities of warm-season tallgrass can be approximated, and their spatial distributions were mapped in 2006 [Fig. 9(a)], 2007 [Fig. 9(b)], and 2008 [Fig. 9(c)]. Linking these biomass maps to crop distributions in Fig. 5, warm-season tallgrasses were dominant in the eastern areas of ND, SD, NE, and KS. These areas hold a high potential of cellulosic biofuel, with biomass quantities increasing from the west to east of these states. The legend of Fig. 9 was categorized with the deviation from the mean ΣNDVI in each year. The values of mean/standard deviation of ΣNDVI were 49.44/12.02, 61.71/12.87, and 57.54/14.24 in 2006, 2007, and 2008, respectively. The biomass quantities varied with weather dynamics (e.g., temperature, precipitation) in different years. The relative high biomass in 2007, for example, may be related to a moist year in central United States.[28] For the same reason, more warm-season prairie grasses were classified from cool-season grasses (e.g., those in MN and IL) [Fig. 9(b)]. Satellite time series revealed the interannual variation of biomass production of native prairie tallgrasses that had not been documented in current agricultural databases.

4 Discussion

The U.S. agricultural patterns are being reshaped by the dramatic increase of biofuel production. The large-scale land use conversion to corn in 2007 in the Midwest was apparently associated with the high price of corn ethanol in 2006, which reached higher than \$4/gallon while the average price was around \$2.[29] Corn decrease in 2008 may be related to the collapse of financial markets and bankruptcies of biofuel producers after corn boom.[30] The fluctuation of corn and gasoline prices and the mandate of updated bioenergy polices (e.g., the RFS in 2010) motivated the corn-related land use. The U.S. corn plantation area in the 2011 to 2012 Crop Year reached

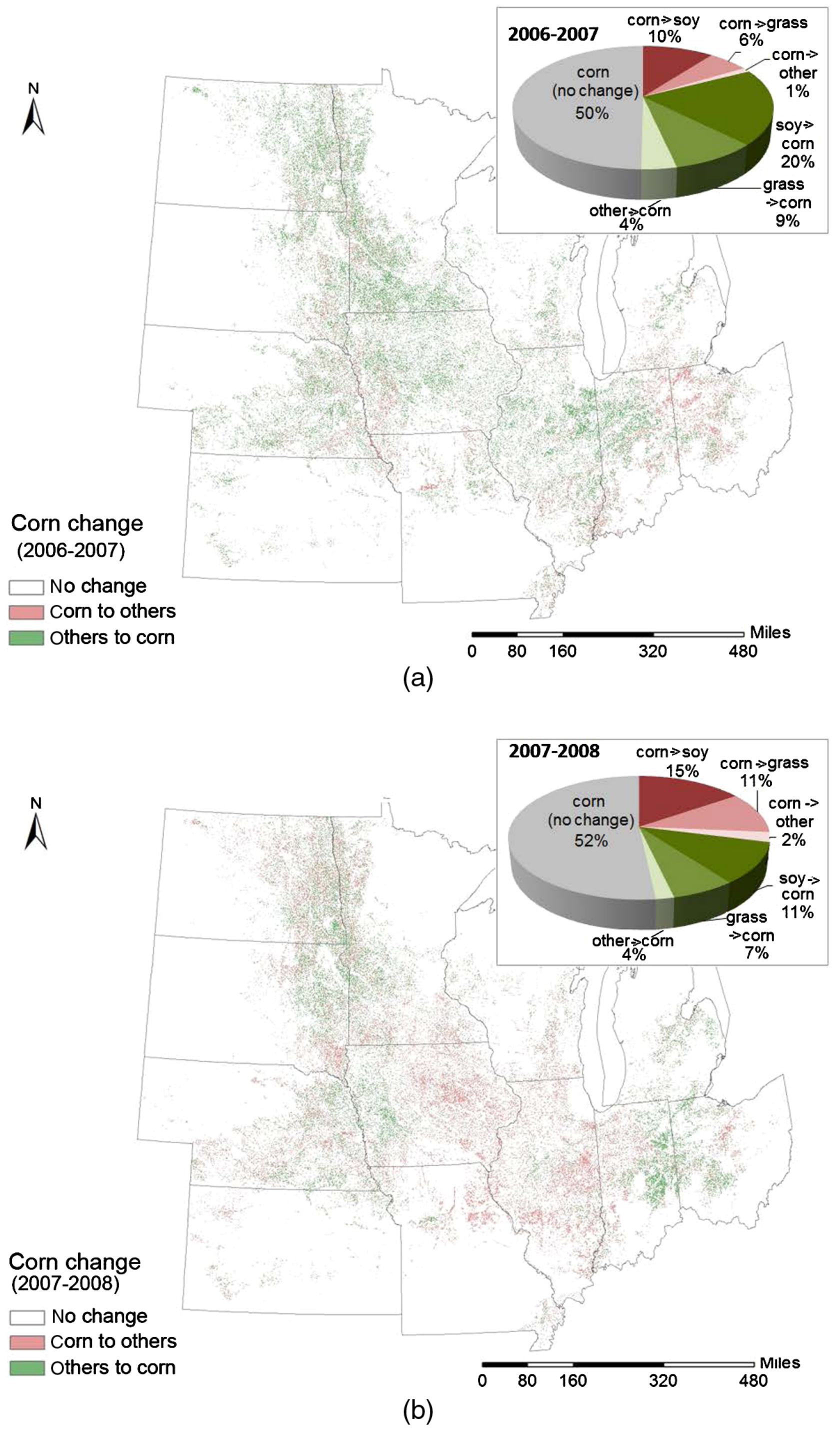

Fig. 7 The change of corn cropping areas between 2006 and 2007 (a) and 2007 to 2008 (b) in the Midwest. The inset charts are summarized from all corn-related fields in 2 years.

92.3 million acres, the second highest below the 2007 corn boom.[29] Satellite-classified crop maps provided more accurate and spatially explicit information of corn acreages than county-level statistical crop census. This fine-scale information in the Midwest better constrains the interactions of prices among ethanol, gasoline, and corn grain, which may help optimizing bioenergy facilities and guiding new policies for long-term decision making.

Although still in its early stage of convention technology, perennial native grass has been designated as a promising source of cellulosic energy crop. While planting acreages of major

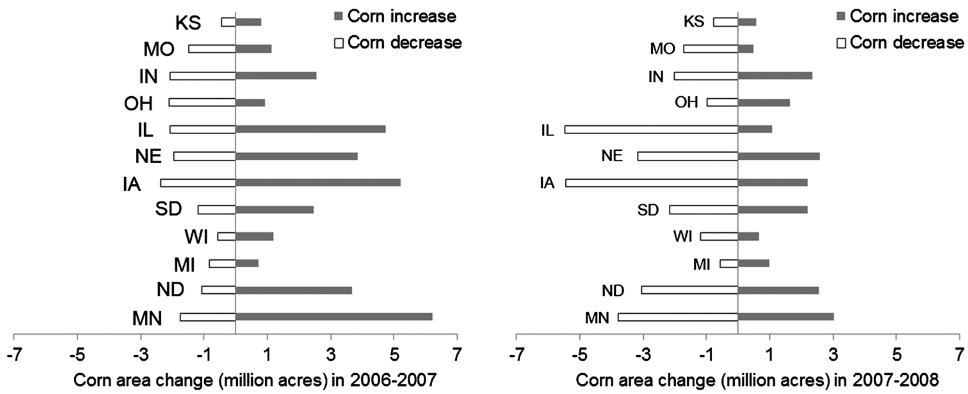

Fig. 8 The increase and decrease of corn cropping areas in 2006 to 2007 (a) and 2007 to 2008 (b) in each Midwestern state.

crops such as corn and soybean in crop census have been commonly used in various reports, perennial grasses in the United States are less documented. The forage acreage records in the crop census are questionable. The spatial distributions of perennial native grasses (warm-season tallgrass) extracted in this study provide some basic information about their current growing patterns in the Midwest. Biomass proxy, represented by the season-long integrated NDVI from the satellite time series, provides relative quantities of biomass potentials in different geographic locations. When ground truth data of grass biomass from local programs (such as the Crop Variety Testing program in various states) become available, this satellite-extracted biomass proxy could be projected to real quantification of biomass feedstock all over the region. Findings in this study indicate that the eastern ND, SD, NE, and KS have the largest coverage of native prairie grasses, with their productivity increasing from the west to east. MO and IA are the two states with apparent land use change from annual to perennial crops since 2006. Beyond this, various programs have been established to promote land conversion to native grasses in U.S. croplands for purposes of environment conservation and bioenergy. Therefore, the satellite time series and the approaches explored in this study could play an important role in quantitative documentation of perennial native grasses at a regional level.

Accuracies of the MODIS-extracted crop maps need to be interpreted with caution. The validation samples were selected from the 56-m CDL products for annual crops and a previously published 500-m percent cover map for grasses. These products were classified from medium- to coarse-resolution satellite images with an overall accuracy of 80% to 90%[14] or a root-mean-square error of 0.22.[21] Uncertainties from these reference data may affect the accuracy assessment in this study. Another concern is the mixed-pixel problem in land cover mapping. In the 500-m MODIS imagery used in this study, a pixel may contain multiple crop fields or noncrop land covers. Although the SVM approach has been proven optimal in past studies and outperformed most other classifiers,[25,26] there remain high omission and commission errors in this binary classification. One example is the corn-soybean shift cropping patterns in the Midwest, which makes it common to cover both fields in one MODIS pixel. Although each crop has its unique phenological features, growth cycles of crops in this region fall in a similar time span. Soybean, for example, is planted only 1 to 2 weeks later than corn. The 8-day interval of the MOD09A1 products further reduces the phenological differences of crops to be extracted from the NDVI time series. Additionally, one MODIS scene has a large swath of 2330×2000 km. The bidirectional reflectance effects in such a large area introduce further uncertainties in image classification. All these aspects may contribute to the high uncertainty of the phenology-assisted crop mapping in this study.

Aside from the multicrop composition in an MODIS pixel, cool-season and warm-season grasses commonly grow in mixed condition in grasslands of the Midwest. Binary classification thus cannot reach optimal results of land cover mapping. In future research, spectral unmixing techniques will be investigated to retrieve the per-pixel percent covers of each crop, which could provide more realistic documentation of crop planting acreages and biomass quantities for bioenergy assessment.

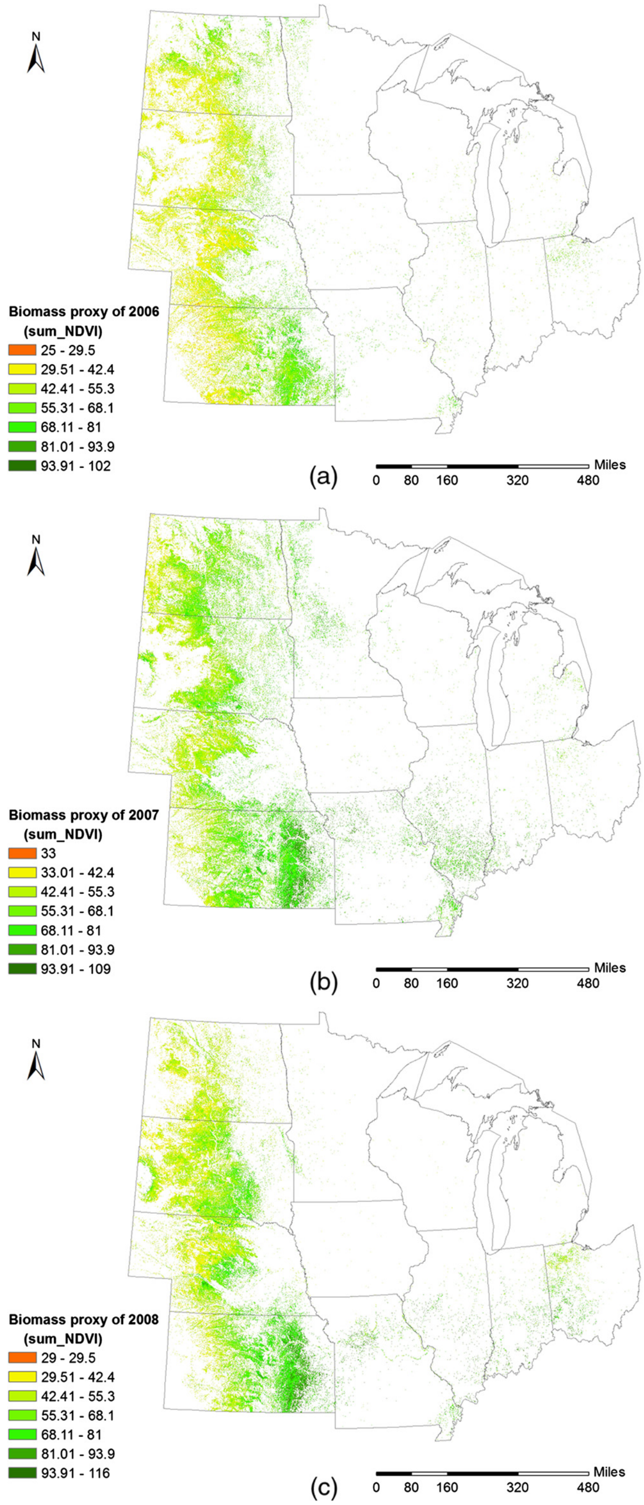

Fig. 9 Spatial distributions and biomass potential of native prairie grasses in 2006 (a), 2007 (b), and 2008 (c) in the Midwest.

5 Conclusions

This study used large-coverage, frequent satellite observations to map major crops in the Midwest and to extract bioenergy-related agricultural land use change in 2006 to 2008. The overall classification accuracy was around 90% although high confusion was observed between corn and soybean. The corn boom in 2007 was observed, and the geographic distributions of land use change were extracted all over the region. A net increase of 15% of corn planting areas was recorded in 2007 accompanied by a 16% net decrease in 2008. Five states (MN, ND, NE, IA, and IL) had the largest amount of corn change, each reached +3 million acres of change (increase in 2007 and decrease in 2008). Biomass proxy of perennial native grasses was represented with the season-long integrated NDVI. At 500-m unit area, it provides basic information about the current distributions of perennial native grasses and the biomass potential of cellulosic biofuel in the Midwest.

Acknowledgments

This research is supported by the USDA-NIFA Grant (Award# 2012-67009-19667) in the project area—Environmental Implications of Direct and Indirect Land Use Change. We thank the USDA NASS for publishing the CDL products and crop census records that serve as an excellent reference in this project.

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