CHARACTERIZING WOODY ENCROACHMENT IN THE KONZA PRAIRIE USING OBJECT-BASED ANALYSIS OF AERIAL PHOTOGRAPHS

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ABSTRACT

Woody encroachment is a threat to the ecological integrity of tallgrass prairie in Kansas. Encroachment data that covers a large spatial and temporal scale would be valuable to managers of tallgrass prairie, but no such dataset exists. The objective of this research is to develop a replicable technique for creating woody vegetation maps from aerial photographs. Rather than using a traditional pixel-by-pixel approach to classification, this project uses an object-based approach, wherein individual pixels are grouped into meaningful image objects according to user-defined parameters and then classified. I created woody vegetation maps of eight watersheds in the Konza Prairie using imagery from 1978, 1991, 2003, 2006, and 2010. I also determined the efficacy of LIDAR data in classifying the image from 2006. Ground-based vegetation survey data exist for two of the watersheds included in the remote sensing portion of this study. I analyzed the data from the available years nearest to the imagery dates (1983, 1992, 2003, and 2007) in order to provide a measure of validation for the woody vegetation maps. The results of this research were used to determine the applicability of this mapping technique and to draw preliminary conclusions about the landscape-level factors associated with woody encroachment.

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Chapter 1

INTRODUCTION

Grasslands, especially tallgrass prairie, are one of the planet's most threatened ecosystems (Samson and Knopf 1994; White et al. 2000). In addition to the threats to grassland integrity posed by human activities such as ranching and agriculture, grasslands are subject to the encroachment of woody plants and trees. Historically, trees and other woody plants were removed from grasslands through periodic fires both natural and set by Native Americans, leaving behind fire-resistant grasses (Axelrod 1985; Coppedge et al. 2004). Increased European settlement, the subsequent suppression of fire, and the impacts of livestock grazing have created a situation where tree cover in grassland area increases at rates as rapid as 5.8% per year (Briggs et al. 2002). In the central Great Plains of North America the main encroaching tree species is the Eastern Red Cedar (*Juniperus virginiana*) along with woody plants such as Smooth Sumac (*Rhus glabra*), Rough-Leaf Dogwood (*Cornus drummondii*), and American Plum (*Prunus americana*) (Briggs et al. 2005).

Woody encroachment causes a variety of problems in grassland ecosystems beyond conversion to closed canopy forest: degraded soil (McKinley and Blair 2008), loss of suitable nesting areas for grassland birds (Coppedge et al. 2004; Pietz et al. 2009), and the crowding out of grasses by shade trees (Van Auken 2000; Zald 2009; Limb et al. 2010). In sum, the spread of woody plants threatens the ecological balance of grassland areas. The control of woody encroachment is an important issue in grassland management, and good data on the extent and intensity of encroachment would be of great help in planning management strategies. Remote sensing data offer the sort of spatial and temporal coverage useful for monitoring changes in grassland tree cover over large areas. A number of published studies have used satellite image and aerial photographs to study tree encroachment (Laliberte et al. 2004; Sankey and Germino 2008; Zald 2009; Sankey et al. 2010).

Woody plant encroachment is an ongoing problem in the Flint Hills region, which contains the last remaining large stands of tallgrass prairie on the planet (White et al. 2000). Because of its unique ecological characteristics, the area comprised of the Flint Hills of Kansas and the Osage Hills of Oklahoma has been designated as a distinct Level IV Ecoregion by the Environmental Protection Agency (Omernik 1995; Omernik 2010). I chose this area as the focus of this study for two reasons. First, woody encroachment is a significant threat to the ecological integrity of Flint Hills grasslands (Briggs et al. 2002; Michael Estey, personal communication, 2011). Second, the areas of tallgrass prairie included in the Konza Prairie Biological Station (Konza Prairie or KPBS), which is owned by the Nature Conservancy and maintained by Kansas State University as a Long-Term Ecological Research (LTER) site, is documented by extensive ecological data. The availability of high-quality environmental data makes this area ideal for my project.

STUDY AREA

The area of the Flint Hills that this project will consider is a portion of the Konza Prairie, a 3,487 ha (8,617 acre) section of tallgrass prairie located in Riley and Geary Counties in north central Kansas. The KPBS is the focus of the Konza Prairie Long-Term Ecological Research (LTER) station jointly administered by Kansas State University and the Nature Conservancy (Konza Prairie LTER website, http://www.konza.ksu.edu). Because of its status as a research station, the Konza Prairie has been intensively studied. There are existing data from over 20 years of field research, as well as an archive of aerial photographs extending over 60 years into the past (Briggs et al. 2005). The Konza Prairie has experienced a substantial increase in tree cover over time. An analysis of land survey data from 1859 showed a tree cover extent of 5 ha (Abrams 1986). A subsequent study of tree cover in 2002 found a total extent of over 159 ha, an increase of over 30 times (Knight et al. 1994). Its relatively small size and high density of relevant data make the Konza Prairie an ideal area for developing methods of studying tree encroachment throughout the Flint Hills tallgrass prairie.

This project will look specifically at eight watersheds in the Konza Prairie covering a total of 764 ha (1,888 acres) (see Figure 1). Four of the watersheds (N1B, N2B, N4B, and N20B in Figure 1) are located in the portion of the Konza Prairie grazed by bison. The other four watersheds are adjacent to the grazed area but are ungrazed (K1B, K2A, K4A, and K20A in Figure 1). These two groups are symmetrical in the frequency of prescribed burns, as represented by the numbers in the watershed designations (i.e., 1 = annual burns, 2 = burned every 2 years, 4 = burned every 4 years, etc.). The groups cover similar amounts of area: the grazed portion comprises 381 ha (941 acres), versus 384 ha (949 acres) for the ungrazed portion.

RESEARCH QUESTIONS

The first question that this project addresses is the extent to which woody plant cover in the Konza Prairie has changed over time. Remote sensing data provide the spatial and temporal coverage necessary to adequately address this question. Because of their relatively high spatial resolution, aerial photographs are especially well suited for this project. Of particular value are the photos acquired through the U.S. Farm Services Agency's National Agricultural Imagery Program (NAIP). NAIP images for Kansas are available at 2 m (for 2003-2005) and 1 m spatial resolution (for 2006, 2008, and 2010). While the NAIP data are ideal for detecting woody encroachment, their limited historical coverage requires the use of other aerial photographs. Researchers at the Konza Prairie provided me with aerial photographs from 1978, and I downloaded 1991 USGS orthophotos from the Kansas Data Access and Support (DASC) website.

The fine spatial resolution of aerial photographs is useful for detecting individual trees and small groups of trees encroaching into grasslands, but they lack the spectral resolution important for vegetation studies. Because the peak reflectance of vegetation is in the near-infrared (NIR) portion of the electromagnetic spectrum, photographs that only record visible light are at a disadvantage in distinguishing vegetation types. Some NAIP imagery includes an infrared band, but those images are only available for 2008 and 2010 for Kansas. The older panchromatic aerial photographs that this study uses are even more limited, as they only capture vegetation as varying shades of gray. NIR imagery is available for only one of the years included in this study (2010). The study also uses LIDAR data available for 2006. Though it would be ideal for these additional data sources to be available throughout the duration of the time period studied, their limited availability allows me to compare image classifications conducted with and without them, allowing me to evaluate their utility in capturing woody encroachment.

The second question that this project will address is how observed tree encroachment is related to underlying environmental variables. The observed distribution of trees invading the grasslands in the Flint Hills is expected to be nonrandom. Past studies have uncovered a number of different factors that can influence the propensity of grassland to be invaded by trees, such as topography (slope and aspect), soils, grazing intensity, fire frequency, precipitation, and vegetation dynamics (Briggs et al. 2002; Laliberte et al. 2004; Sankey and Germino 2008). There are existing data on all of these factors for the Konza

Prairie, and I use them to draw some tentative conclusions about the relationships between the environment and the spread of woody plants over time and space.

Third, this study evaluates the degree to which the results of the remote sensing analysis agree with vegetation data collected on the ground. Researchers at the Konza Prairie have conducted vegetation surveys in selected watersheds each year from 1983 to the present. Though the vegetation data are only available for two of the watersheds included in my study (N1B and N20B) and the years surveyed mostly do not match the dates of the aerial photographs, the patterns in the data can still help to determine the validity of the remote sensing approach to studying woody encroachment. The level of detail in the vegetation data will also allow for greater insight into the spatial and temporal dynamics of the spread of woody plants.

LITERATURE REVIEW

Data Sources and Analysis

Published studies of tree encroachment have used several forms of remote sensing data with varying levels of success, but aerial photographs are the most commonly used data source. The primary reason for this preference is the greater temporal coverage that aerial photographs provide. In order to assess changes in tree cover given the growth rates of the trees in question, studies need to consider relatively lengthy periods of time. For example, the study area analyzed by Laliberte et al. (2004) had been covered by 37 aerial photography missions from 1936 to 2003, whereas the earliest satellite images of the study area date from the commencement of the Landsat program in 1972. Because of their interests in looking at tree cover over periods beginning as early as the 1930s, other studies have also favored aerial photos over satellite images (Bragg and Hulbert 1976; Archer 1989; Briggs et al. 2002; Zald 2009; Widenmaier and Strong 2010).

The relatively small size of encroaching woody plants tends to require the high spatial resolution that aerial photographs provide. These photographs, however, typically do not include the full range of spectral information available in satellite images. In order to take advantage of the extra spectral data found in satellite images, some studies have worked around the resolution mismatch between Landsat TM data and encroaching junipers. Sankey and Germino (2008) utilized a technique called spectral mixture analysis (SMA) to extract the desired spectral response of evergreen junipers from the background matrix of the 30 m x 30 m TM pixels. The first step of SMA is to identify within the image "pure" pixels that represent the spectral characteristics of the cover types that make up the mixed pixels. "Pure" spectral data for the features of interest can be derived from ground data or from areas of known cover within the image (Chen et al. 2004). By using these known responses, referred to as "endmembers," it is possible to extract the proportional spectral response of the features of interest from the total reflectance of the mixed pixel (Xiao and Moody 2005). In other words, an analyst can use SMA to determine with reasonable accuracy the percentage of trees versus the other cover types found within a 900 m^2 Landsat TM pixel. In a study of tree cover in a complex urban environment, Small and Lu (2006) found a correlation of 0.89 between tree cover estimates derived from SMA of Landsat TM pixels and estimates from 2.8 m resolution QuickBird imagery. The direct application of SMA to tree encroachment has yielded overall accuracy figures ranging from 80% to 92% (Sankey and Germino 2008).

Other tree encroachment studies have sought to exploit the relative advantages of different data sets by analyzing fusions of remote sensing data. Because they provide information on the height of objects on the ground, LIDAR data are particularly useful for studies of tree cover. A fusion of LIDAR height data and Landsat TM spectral information can separate the response of trees from other vegetation types present in mixed pixels. In a study of western juniper encroachment in southeastern Idaho, Sankey et al. (2010) found an overall classification accuracy of 83% for the fused data set versus 71% for Landsat TM data alone. A LIDAR mission flown over part of Kansas in 2006 produced data for the Konza Prairie, and I created a normalized digital surface model (nDSM) from this dataset to assist in the classification of the 2006 NAIP image. Comparison with a classification that does not include LIDAR data should provide some insight into the utility of LIDAR for the detection of aboveground vegetation.

Finally, high-resolution satellite imagery is another data source used in the study of tree encroachment. The advantage of such imagery is that it provides the spatial resolution of aerial photographs along with the spectral information of satellite imagery. In their study of shrub encroachment in an area of southern New Mexico over 12 time points, Laliberte et al. (2004) used a QuickBird image for their final time point. QuickBird is a commercial satellite with a spatial resolution of 2.44 m in the multispectral bands and 0.61 m in the panchromatic band (Jensen 2005). Such high resolution is very well suited to studies of tree encroachment, but the imagery is prohibitively expensive. As such, it was not available for my research.

Change Detection

There are several common techniques for evaluating land cover changes in remote sensing data. One technique used in the tree encroachment literature is multidate composite image change detection, in which classified images from multiple dates are combined into a single data set that is then divided into change and no change classifications (Jensen 2005). In their study of grass bald (i.e., mountaintop grasslands) decline in the Oregon Coast Range, Zald et al. (2009) used aerial photos from four time points, each of which was classified using four categories. The images were combined into a single data set containing 16 possible types of land cover change. These types were then narrowed to those involving change to or from the grass bald land cover type.

The most common change detection technique found in the tree encroachment literature is post-classification comparison change detection. This technique involves separately classifying two or more images and comparing the classified images to produce a pixel-by-pixel map of land cover change (Jensen 2005). Though the accuracy of the change map can be affected by any errors in the original classifications, this form of change detection provides much more robust to-from change information than other techniques. This makes post-classification comparison change detection the favored technique for tree encroachment studies that require determining the land cover types most associated with encroachment (Bragg and Hulbert 1976; Briggs et al. 2002; Sankey and Germino 2008; Sankey et al. 2010; Widenmaier and Strong 2010).

Object-Based and Pixel-Based Image Analysis

As high-resolution imagery has become more common and readily available, pixel-by-pixel (or per-pixel) classification methods have begun to fall out of favor for some applications. This traditional method of image classification, which is used by image processing software such as ERDAS Imagine, groups pixels with similar spectral responses. Similarity is determined either automatically (unsupervised classification) or by reference to user-designated "training" sites for different cover types (supervised classification).

Decreased pixel size (i.e., increased spatial resolution) means that a given ground feature is represented by a greater number of pixels. Smaller pixels are capable of detecting subtle variations in the brightness values of individual ground features, thus increasing the amount of texture in the image. High texture is problematic for pixel-based image classification, which relies on the spectral response of individual pixels to group the image into categories. As the texture of an object increases, there is an increased likelihood that different parts of a single ground feature will be grouped into different categories, and the overall classification accuracy suffers (Blaschke 2010). Another major shortcoming of pixel-by-pixel classification is that the software groups pixels solely on the basis of their brightness values in the different spectral bands: it does not consider other features such as texture and shape. A per-pixel-based method is thus inappropriate for classifying black and white panchromatic historical aerial photographs, in which features are often distinguishable only by their texture (i.e., varying shades of gray) and shape.

An alternative approach to image classification is object-based image analysis (OBIA), in which an image is segmented according to user-defined parameters into polygons comprised of many pixels that are homogeneous on some measure. The polygons are then grouped by the user into meaningful objects, which can then be identified by a computer using context, texture, and shape criteria provided by the user (Blaschke 2010). Because well-defined image objects can have functional meaning, OBIA can go beyond spectral information to include features such as shape, context, and texture in its classification procedures (Blaschke 2010). OBIA is thus well suited for the analysis of high spatial resolution imagery and archival black and white panchromatic imagery (i.e., images lacking spectral information) because of its focus on groups of pixels rather than individual pixels.

Direct comparisons of pixel- and object-based approaches to classification have reported higher accuracies for OBIA. For example, the overall classification accuracy for the interface between wild and urban lands increased from 62% using a pixel-based approach to 80% using OBIA (Cleve et al. 2008). Other studies have found even higher overall classification accuracy through the use of hybrid OBIA/pixel-based methods (Castillejo-Gonzalez et al. 2009; Bernardini et al. 2010).

Because studies of woody encroachment that employ remote sensing techniques tend to use high-resolution aerial photos, OBIA is a promising method. There are few published woody encroachment studies that employ OBIA, but the results present in the literature suggest that it is appropriate for detecting and classifying encroaching woody plants. For instance, Laliberte et al. (2004) employed an object-based approach to their study of shrub encroachment in the semi-arid grasslands of the Jornada Basin in New Mexico. They classified a 2003 QuickBird image of the study area using an object-based approach, and the classified image detected 87% of shrubs present in their ground surveys that were greater than 2 m^2 in area. In their study of tree encroachment in a fescue grassland area in Alberta, Canada, Widenmaier and Strong (2010) segmented aerial photographs into polygons using gray scale thresholds to determine areas of tree cover. They found an average error of 3% in their classified images versus their findings in the field. Though their study was not interested in tree encroachment, Platt and Schoennagel (2009) used OBIA of panchromatic images to determine changes in forest cover in the Colorado Front Range from 1938/1940 to 1999. Their resulting maps matched up favorably with existing USDA forest cover maps and maps derived from manual photo interpretation. In sum, these studies show the usefulness of OBIA for evaluating changes in tree cover over time.

Factors Affecting Woody Plant Encroachment

Published studies have reported dramatic rates of woody encroachment in the tallgrass prairie of the Kansas Flint Hills. A study by Bragg and Hulbert (1976) compared woody plant encroachment rates between burned and unburned prairies in Geary County, Kansas. Over the period 1937-1969, they found a 1% increase in woody plant coverage for burned prairie and a 34% increase for unburned prairie. A more recent study of prairie in Riley and Pottawatomie Counties in Kansas found a 120% increase in coverage over a 15-year period by Eastern Red Cedar alone (Hoch 2000). The same study concluded that unmanaged prairie takes only 30 years to be converted to closed canopy Eastern Red Cedar forest.

Though the literature on woody encroachment into grassland areas is not focused exclusively on the Kansas Flint Hills, studies have determined several widely applicable causal factors responsible for the expansion of tree coverage. One factor influencing the spread of woody plants is grazing by domestic livestock. Sankey and Germino (2008) found a statistically significant relationship between grazing intensity and observed encroachment patterns. Grazing amplifies tree encroachment in two main ways. First, as livestock consume grasses, they reduce the competitive pressures on encroaching trees, thus allowing for more rapid woody plant establishment (Van Auken 2000). As more trees move into a grassland area, the increased shade from the tree canopy further reduces competition and encourages additional encroachment (Zald 2009). In an experimental study of Eastern Red Cedar survival, Schmidt and Stubbendieck (1993) subjected plots of trees to different grazing treatments and found the poorest survival rates in the plots that were not grazed at all, underscoring the importance of the role of grazing in tree encroachment. Second, livestock assist the encroachment process by eating woody plant seeds and depositing them in new locations in their manure (Van Auken 2000). The action of this process is illustrated by Laliberte et al. (2004), who found distinct patterns of mesquite shrub encroachment along old cattle trails in their study area.

Periodic fires, both natural and manmade, are essential for the removal of woody plants from grassland areas (Axelrod 1985). Most of the woody plants encroaching into grasslands are fire intolerant, and those seedlings that are not killed by fire survive as much smaller plants (Van Auken 2000). Bragg and Hulbert (1976) found dramatic differences in tree encroachment rates between burned and unburned prairies, and Archer (1989) found a progressive decrease in the dominance of grasses in prairies as fire frequency decreased. A study of the relationship between fire frequency and shrub cover change in the Konza Prairie found the greatest amount of encroachment in areas burned only every four years (Heisler et al. 2003). Burning frequency is thus an important determinant of tree encroachment patterns.

Though the dynamics are complex and the evidence mixed, there is a consensus in the literature that changing climatic conditions play an important role in the tree encroachment process. In recent years many grassland areas in North America have experienced more frequent and more intense periods of drought, and the drier conditions have tended to favor woody plants over grasses (Van Auken 2000). Overall temperature increases have led to longer growing seasons and snow-free periods that have also favored the establishment of trees (Zald 2009; Widenmaier and Strong 2010). Changes in climate may also threaten the integrity of grasslands that were established under earlier climate conditions (Archer 1989).

Slope and aspect have also been found to influence the likelihood of tree encroachment in a particular area. In their study of experimental Eastern Red Cedar plots in Lincoln and Thomas Counties in west-central Nebraska, Schmitt and Stubbendieck (1993) found higher tree survival rates on north-facing slopes versus south-facing and flat areas. Sankey and Germino (2008) included slope and aspect as independent variables in their study of tree encroachment in southeastern Idaho. The only significant topographical relationships they found were more juniper encroachment in areas of medium slope and westerly aspect and less encroachment in areas with northerly aspect. The contradictions between the results of these studies can likely be attributed to the geographic differences in the study areas. The implication is that there is no universally applicable relationship between topography and tree encroachment rates.

The presence of woody plants in a tallgrass prairie landscape is itself a driver of encroachment. Existing woody plants beget more woody plants through seed dispersal and increasing shade and outcompeting grasses (Van Auken 2000; Zald 2009; Limb et al. 2010). Changes to the soil chemistry in areas surrounding encroaching trees, especially Eastern Red Cedar, create conditions more favorable to tree growth (McKinley and Blair 2008). Woody plants such as Rough-Leaf Dogwood further exacerbate the positive encroachment feedback loop by outcompeting grasses for deep water resources, reproducing clonally, and reducing fuel loads necessary for fires that would eliminate woody species (Ratajczak et al. 2011). Distance from existing trees and woody plants is thus an important factor in the encroachment process.

Finally, soil type is an important dimension of woody encroachment. Gallery forest, the thin bands of trees found around stream channels and in ravines throughout the Flint Hills, tend to grow in soils composed of alluvial and colluvial deposits (Abrams 1986; Knight et al. 1994). Though soil type alone is not sufficient to predict vegetation composition, it can indicate areas of expected tree growth in a tallgrass prairie system and the potential susceptibility of an area to the further growth of trees and shrubs.

METHODS

Imagery and Image Processing

The remote sensing analysis of this project uses aerial photographs. I looked at several time points in order to evaluate the rate and intensity of tree encroachment in the Konza Prairie. The latest time point was be 2010. Imagery from 2003, 2006 and 2010 are NAIP images of Riley County acquired from the Kansas Data Access and Support Center (DASC). I also downloaded a panchromatic 1991 United States Geological Survey (USGS) digital orthophoto from DASC. Older imagery came from the photo archive at the Konza Prairie LTER. The watersheds comprising the study area for this project did not become part of the Konza Prairie until 1978. To complete the temporal image sequence, researchers at the Konza Prairie provided me with aerial photographs from 1978.

An issue that can arise in change detection studies using different data sources is that spatial resolutions may not match up. Conflicting resolutions were an issue for this project. While nearly all of the images analyzed were at 1 m resolution, the NAIP imagery from 2003 was only available at 2 m resolution. Fortunately, this is a common issue, and methods for resampling multitemporal imagery to a common resolution are detailed in several published change detection studies (Laliberte et al. 2004; Narumalani et al. 2004; Bai et al. 2005; Zald 2009; Widenmaier and Strong 2010) follow the approach used by Laliberte et al. (2004), whereby historical images of differing resolutions are resampled to a common resolution that is equal to or less than the size of the encroaching plant species of interest. Laliberte et al. (2004) also suggest filtering the images with a 3x3 low-pass filter in order to reduce the frequency of pixel value changes. The result is a slightly blurred image intended to increase homogeneity within image objects, thus making classification of encroaching trees more accurate. Filtering is more appropriate for the historical imagery, which may tend to be of lower overall quality, and I use a low-pass filter where appropriate.

After georeferencing, the corrected images were resampled using cubic convolution, in which the output pixels are assigned the brightness value based on a weighted average of the 16 surrounding pixels. This resampling method has the advantage of producing a relatively smooth output image, which facilitates the OBIA processes of segmentation and classification in a program like eCognition. Because this study will be comparing classified images across time rather than comparing absolute brightness values, atmospheric correction will not be necessary (Laliberte et al. 2004). All image processing involved in this study was done using ArcGIS, ERDAS Imagine, and eCognition.

Image Classification and Change Detection

The aerial photographs were classified using an object-based approach in eCognition. The high spatial resolution of these images allowed for an efficient application of OBIA techniques. Because of the different sensors, acquisition times, and other idiosyncratic features of the different aerial photos used in this project, it was necessary to develop separate processing, segmentation, and classification rule sets for each image. Change detection was conducted using the post-classification comparison method detailed by Jensen (2005). I used ArcGIS 10 to perform the comparisons and generate maps of tree cover over time.

Vegetation Survey Data

I acquired the available vegetation survey data for the 2 watersheds matching my study area (N1B and N20B) for the years most closely matching the dates of the aerial photographs: 1983, 1992, 2003, and 2007. Permanent 50-m long transects have been established in selected watersheds throughout the Konza Prairie. Each watershed contains 4 transects in each of 3 topographic positions, for a total of 12 transects: lowland (Tully soils), upland (Florence soils), and slopes. The lowland and upland surveys have been conducted throughout the duration of the dataset, but slope data are only available for some watersheds and some years. Sampling takes place annually, but not all watersheds are surveyed in a given year. Vegetation species composition is surveyed in May-June and August-September to capture both cool- and warm-season species (Methods Manual Version 2011.1, 2011).

Species composition is determined at 5 permanent plots along each transect, for a total of 20 plots per topographic position. The surveyor estimates the percent cover of each species present in a 10 m^2 area at each plot and assigns a cover class (Table 2) (Bailey and Poulton, 1968). The data for each year are available in a text file containing the cover class of each species for every plot in a given watershed. A blank value for a plot indicates that the species in question was not present. I used Microsoft Excel to sort the data files and isolate only the woody plant species. I was then able to derive cover data for each watershed and for the individual transects. By considering each transect separately, I was better able to compare the results to the woody cover rasters derived from the classifications of the aerial photographs, and I was also able to draw some tentative conclusions regarding the role of topography in the woody cover results.

ANTICIPATED RESULTS AND IMPACTS

This project will produce results that point to a number of conclusions. First, the object-based classification of the aerial photographs are likely to show a more or less constant increase in woody cover over the period studied. The different forms of remote sensing data (panchromatic, full-color NAIP, NIR, and LIDAR) should produce similar woody cover results for the study area. Likewise, the vegetation data from the ground surveys conducted at the Konza Prairie should also show an increase in woody plant cover over time. The different topographic positions surveyed should exhibit different trends in woody cover. Because the dates of the vegetation survey data do not match the dates of the aerial photographs, there will likely be a mismatch between the woody cover figures resulting from the different data sources. There should, however, be some correspondence between the results, both temporally and spatially.

The impacts of this project will be fourfold. First, the project will determine the degree to which OBIA is a useful technique for gathering valid data on woody plant encroachment in areas of tallgrass prairie. Should this technique prove successful, it would be a valuable contribution to both the prairie ecology literature and the practice of grassland management. Second, it will compare the utility of different forms of remote sensing data for the study of vegetation change. If there turns out to be little difference in effectiveness between readily available data such as panchromatic and NAIP imagery and more expensive or less available data like NIR imagery and LIDAR, the approach used here would be ideal for future studies. Third, the Konza Prairie ground-surveyed vegetation data will provide some degree of validation for the results of the remote sensing analysis. This will further enhance the trustworthiness of OBIA as a means of studying vegetation patterns. Finally, this project will produce data on the temporal and spatial trends in woody encroachment in the study area. It will allow for a consideration of changes in woody cover over time and over different spatial and environmental conditions (e.g., topography, burn frequency, grazing, etc.). Woody encroachment is a significant threat to the ecological health of tallgrass prairies, and insofar as this study allows for a better understanding of the spread of woody plants, it will be valuable to the preservation of an important natural, ecological, and cultural resource.

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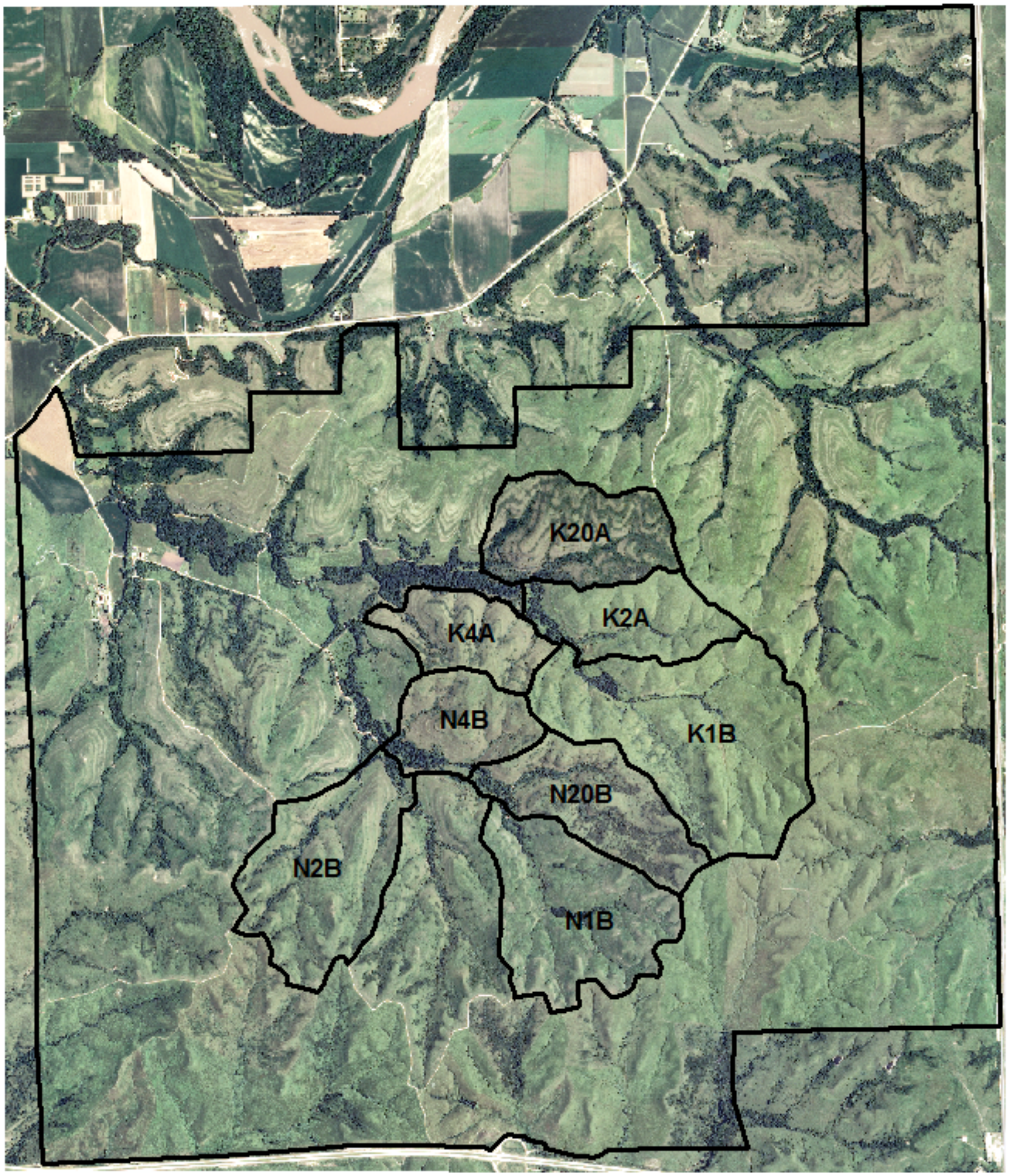
Figure 1
Study area.



Chapter 2

CHARACTERIZING WOODY ENCROACHMENT IN THE KONZA PRAIRIE USING OBJECT-BASED ANALYSIS OF AERIAL PHOTOGRAPHS

INTRODUCTION

Grasslands, especially tallgrass prairie, are one of the planet's most threatened ecosystems (Samson and Knopf, 1994; White et al., 2000). In addition to the threats to grassland integrity posed by human activities such as ranching and agriculture, grasslands are subject to the encroachment of woody plants and trees. Historically, trees and other woody plants were removed from grasslands through periodic fires both natural and set by Native Americans, leaving behind fire-resistant grasses (Axelrod, 1985; Coppedge et al., 2004). Increased European settlement, the subsequent suppression of fire (especially big fires), and the impacts of livestock grazing have created a situation where tree cover in grassland area increases at rates as rapid as 5.8% per year (Briggs et al., 2002). In the central Great Plains of North America the main encroaching tree species are the Eastern Red Cedar (*Juniperus virginiana*) and Osage Orange (*Maclura pomifera*), along with woody plants such as Smooth Sumac (*Rhus glabra*), Rough-Leaf Dogwood (*Cornus drummondii*), and American Plum (*Prunus americana*) (Briggs et al., 2005).

Woody encroachment causes a variety of problems in grassland ecosystems beyond conversion to closed canopy forest: degraded soil (McKinley and Blair, 2008), loss of suitable nesting areas for grassland birds (Coppedge et al., 2004; Pietz et al., 2009), and the crowding out of grasses by shade trees (Van Auken, 2000; Zald, 2009; Limb et al., 2010). In sum, the spread of woody plants threatens the ecological balance of grassland areas. One area particularly affected by woody encroachment is the Flint Hills, which contains the last remaining large stands of tallgrass prairie on the planet (White et al., 2000). Because of its unique ecological characteristics, the area of Kansas and Oklahoma covered by the Flint Hills has been designated as a distinct Level IV Ecoregion by the Environmental Protection Agency (Omernik, 1995; Omernik, 2010).

The control of woody encroachment is an important issue in grassland management, and good data on the extent and intensity of encroachment would be of great help in planning management strategies. Remote sensing data offer the sort of spatial and temporal coverage useful for monitoring changes in woody plant cover over large areas. A number of published studies have used satellite images and aerial photographs to study woody encroachment (Laliberte et al., 2004; Sankey and Germino, 2008; Zald, 2009; Sankey et al., 2010). The goals of this study are twofold: first, to determine the change in woody cover in an area of the Kansas Flint Hills by classifying aerial photographs; and second, to assess the effectiveness of different techniques and forms of data for mapping woody encroachment using remote sensing analysis.

Data Sources and Analysis

Published studies of woody encroachment have used several forms of remote sensing data with varying levels of success, but aerial photographs are the most commonly used data source. The primary reason for this preference is the greater temporal coverage that aerial photographs provide. In order to assess changes in tree cover given the growth rates of the trees in question, studies need to consider relatively lengthy periods of time. For example, the study area analyzed by Laliberte et al. (2004) had been covered by 37 aerial photography missions from 1936 to 2003, whereas the earliest satellite images of the study area date from the commencement of the Landsat program in 1972. Because of their interests in looking at tree cover over periods beginning as early as the 1930s, other studies have also favored aerial photos over satellite images (Bragg and Hulbert, 1976; Archer, 1989; Briggs et al., 2002; Zald, 2009; Widenmaier and Strong, 2010).

The relatively small size of encroaching woody plants also tends to require the high spatial resolution that aerial photographs provide. These photographs, however, typically do not include the full range of spectral information available in satellite images. Fortunately, some dates of National Agricultural Imagery Program (NAIP) imagery contain a near-infrared (NIR) band. For the area of Kansas considered in this study, color infrared (CIR) NAIP imagery is available for 2006 and 2010. The NIR portion of the spectrum is very useful in distinguishing between different types of vegetation because NIR reflectance is directly related to biophysical characteristics such as chlorophyll content that differ between plant species (Jensen, 2000). The availability of NIR data should aid in the production of woody cover classifications. Because NIR data are not always available, a direct comparison of classifications with and without the presence of an NIR band will help determine the value added of NIR data in mapping woody encroachment. To that end, I produced separate classifications for 2010 using RGB and CIR NAIP images.

Other woody encroachment studies have sought to exploit the relative advantages of different datasets by analyzing fusions of remote sensing data. Because they provide information on the height of objects on the ground, LIDAR data are particularly useful for studies of tree cover. A fusion of LIDAR height data and Landsat TM spectral information can separate the response of trees from other vegetation types present in mixed pixels. A study of western juniper encroachment in southeastern Idaho found an overall classification accuracy of 83% (with regard to juniper presence/absence) for the fused dataset versus 71% for Landsat TM data alone (Sankey et al., 2010). A LIDAR mission flown over part of

Kansas in 2006 produced data for the Konza Prairie, and a normalized digital surface model (nDSM) from this dataset can assist in the classification of the 2006 NAIP image. Comparison of classifications that include and omit an nDSM will provide some insight into the utility of LIDAR for the detection of aboveground vegetation.

Object-Based and Pixel-Based Image Analysis

As high-resolution imagery has become more common and readily available, pixel-by-pixel (or per-pixel) classification methods have begun to fall out of favor. This traditional method of image classification, which is used by image processing software such as ERDAS Imagine, groups pixels with similar spectral responses. Similarity is determined either automatically (unsupervised classification) or by reference to user-designated “training” sites for different cover types (supervised classification). Decreased pixel size (i.e., increased spatial resolution) means that a given ground feature is represented by a greater number of pixels. Smaller pixels are capable of detecting subtle variations in the brightness values of individual ground features, thus increasing the amount of texture in the image. High texture is problematic for pixel-based image classification, which relies on the spectral response of individual pixels to group the image into categories. As the texture of an object increases, there is an increased likelihood that different parts of a single ground feature will be grouped into different categories, and the overall classification accuracy suffers (Blaschke, 2010). Another major shortcoming of pixel-by-pixel classification is that the software groups pixels solely on the basis of their brightness values in the different spectral bands: it does not consider other features such as texture and shape. A per-pixel-based method is thus inappropriate for classifying black and white panchromatic historical aerial photographs, in which features are often distinguishable only by their texture (i.e., varying shades of gray) and shape.

An alternative approach to image classification is object-based image analysis (OBIA), in which an image is segmented according to user-defined parameters into polygons comprised of many pixels that are homogeneous on some measure. Several software platforms have OBIA capabilities, including the Trimble eCognition software that I chose to use in my analysis. The polygons are then grouped by the user into meaningful objects, which can then be identified by a computer using context, texture, and shape criteria provided by the user (Blaschke, 2010). Because well-defined image objects can have functional meaning, OBIA can go beyond spectral information to include features such as shape, context, and texture in its classification procedures (Blaschke, 2010). OBIA is thus well suited for the analysis of high spatial resolution imagery and archival black and white panchromatic imagery (i.e., images lacking spectral information) because of its focus on groups of pixels rather than individual pixels.

Direct comparisons of pixel- and object-based approaches to classification have reported higher accuracies for OBIA. For example, the overall classification accuracy for the interface between wild and urban lands increased from 62% using a pixel-based approach to 80% using OBIA (Cleve et al., 2008). Other studies have found even higher overall classification accuracy through the use of hybrid OBIA/pixel-based methods (Castillejo-Gonzalez et al., 2009; Bernardini et al., 2010).

Because studies of tree encroachment employing remote sensing techniques tend to use high-resolution aerial photos, OBIA seems to be a promising classification method. There are few published tree encroachment studies that employ OBIA, but the results in the literature suggest that it is appropriate for detecting and classifying encroaching trees. For instance, an object-based study of shrub encroachment in the semi-arid grasslands of the Jornada Basin in New Mexico using images with sub-meter spatial resolution detected 87% of shrubs present in ground surveys that were greater than 2 m^2 in area (Laliberte et al., 2004). In their study of tree encroachment in a fescue grassland area in Alberta, Canada, Widenmaier and Strong (2010) segmented aerial photographs into polygons using gray scale thresholds to determine areas of tree cover. They found an average error of 3% in their classified images versus their findings in the field. Though their study was not interested in tree encroachment, Platt and Schoennagel (2009) used OBIA of panchromatic images to determine changes in forest cover in the Colorado Front Range from 1938/1940 to 1999. Their resulting maps correlated strongly and significantly (rho=0.88, p~0.000) with existing USDA forest cover maps and maps derived from manual photo interpretation. In sum, these studies show the usefulness of OBIA for evaluating changes in tree cover over time.

METHODS

Study Area

The area of the Flint Hills that this project considered is a portion of the Konza Prairie Biological Station (Konza Prairie or KPBS), a 3,487 ha (8,617 acre) section of tallgrass prairie located in Riley and Geary Counties in north central Kansas. The KPBS is the focus of the Konza Prairie Long-Term Ecological Research (LTER) station jointly administered by Kansas State University and the Nature Conservancy (Konza Prairie LTER website, http://www.konza.ksu.edu). Because of its status as a research station, the Konza Prairie has been intensively studied. There are existing data from over 20 years of field research, as well as an archive of aerial photographs extending over 60 years into the past (Briggs et al., 2005). The decreased burning frequency and altered grazing patters associated with agriculture and livestock production by European settlers have caused a substantial increase in woody plant cover over time in the Konza Prairie. Analysis of land survey data from 1859 shows a tree cover extent of 5 ha (Abrams, 1986). A subsequent study of tree cover in 2002 found a total extent of over 159 ha, an increase of over 30 times (Knight et al., 1994). Its relatively small size and high density of relevant data make the Konza Prairie an ideal area for developing methods of studying tree encroachment throughout the Flint Hills tallgrass prairie.

This project looked specifically at eight watersheds in the Konza Prairie covering a total of 764 ha (1,888 acres). The focus on a carefully selected portion of the entire Konza minimized variability in the causal factors involved in woody encroachment across the study area, thus increasing the validity of any conclusions drawn about observed encroachment patterns. Four of the watersheds (N1B, N2B, N4B, and N20B in Figure 1) are located in the portion of the Konza Prairie grazed by bison. The other four watersheds are adjacent to the grazed area but are ungrazed (K1B, K2A, K4A, and K20A in Figure 1). These two groups are symmetrical in the frequency of prescribed burns, as represented by the numbers in the watershed designations. The groups cover similar amounts of area: the grazed portion comprises 381 ha (941 acres), versus 384 ha (949 acres) for the ungrazed portion.

Image Processing

With the exception of the 1978 image, I downloaded the images used for this project from the Kansas Data Access and Support Center (DASC) at www.kansasgis.org. The 1978 image came from the aerial photo archive held at the KPBS. The 1991 image was a MrSID compressed, 1m spatial resolution USGS Digital Orthophoto of Riley County, Kansas. The other images (2003, 2006, 2010) were MrSID compressed, fully mosaicked images of Riley

County from the U.S. Farm Services Agency's National Agricultural Imagery Program (NAIP). All of the original images were downloaded at 1 m spatial resolution except for the 2003 image, which was at 2 m (see Figures 2-6 for images).

Though most of the images came in preprocessed form, two dates of imagery required mosaicking prior to further analysis. First, the images from 1978 came in the form of scanned aerial photographs from a photo mission flown on November 18, 1978. I first georeferenced each of the four images needed to cover the study area to the 2003 image using a total of 10 ground control points (GCPs). I rectified the images using a second-order polynomial transformation and cubic convolution resampling, and the resulting root mean squared errors (RMSEs) were all less than 9.0. Each of the scanned images contained fiducial marks at their borders, and these needed to be removed prior to mosaicking. Using ArcGIS version 10.1, I created polygon shapefiles representing the footprints of each of the images (i.e., the images minus the fiducial marks) and clipped the images using these footprints. There was sufficient overlap between the images to ensure that no parts of the study area were lost in this clipping procedure. I used the Mosaic Pro utility in ERDAS Imagine 2011 to create the final image of the study area. The seamlines were generated using an automatic "weighted seamline" function, and the image was resampled using cubic convolution with a 0.10 pixel tolerance. No smoothing or feathering functions were applied.

The second image that required mosaicking was the 2010 NAIP CIR image containing an NIR band. I acquired the CIR image in the form of four tiles comprising the USGS 25K Swede Creek quad (i.e., the quad containing the study area). I mosaicked the northeast and northwest tiles of the quad using the mosaic function in ArcGIS, in which the values from the northwest tile were maintained in the areas where they overlapped spatially with the northeast tile (Figure 7).

The first processing step for each of the images was to clip the counties/quads to the study area. I used a shapefile of the KPBS border acquired from DASC to clip the images to rectangles containing the study area. After clipping, I resampled the images to 2 m spatial resolution using cubic convolution. I chose this resolution because it represents the coarsest native resolution among the images I used (2003). The images were then georeferenced using 10-12 GCPs, second- or third-order polynomial transformation (all RMSEs < 0.65), and cubic convolution resampling. The only exception to this ordering of processing steps was the 1978 images. Because the scanned aerial photographs contained no spatial information, they required georeferencing before they could be resampled to 2 m resolution. The 1978 image was thus resampled to 2 m following mosaicking in ERDAS Imagine. Finally, all of the images in compressed format were converted to uncompressed TIFFs to allow for analysis in eCognition.

Because image flaws created problems during initial trials of segmentation and classification in eCognition, two of the images required further processing. Following the procedure used by Laliberte et al. (2004), I applied a 3 x 3 low-pass filter to the 1991 image. A low-pass filter, which reduces the frequency of pixel value changes, produces a slightly blurred image that increases the homogeneity within image objects. The end result is a segmentation in eCognition that better captures ground features and is less likely to split single objects into multiple parts. The 2003 NAIP image also proved problematic in segmentation and classification. The image was highly grainy, and as a result eCognition had considerable trouble distinguishing grassy areas from woody plants. Because of success in working with the panchromatic images that were part of this study (1978, 1991), I decided to perform the segmentation and classification on a single layer of the 2003 image rather than on the entire RGB image. To further improve the segmentation and classification, I also applied a 3 x 3 low-pass filter to the single-layer 2003 image.

LIDAR-Derived Normalized Digital Surface Model (nDSM)

The data used to generate the nDSM came from a LIDAR mission flown in May 2006 over several Kansas counties. I downloaded a total of 19 tiles of “all returns” files in .LAS format from the City of Manhattan section of the LIDAR data found through DASC. To determine which tiles comprised the study area, I downloaded the tile reference and noted those tiles that intersected with any portion of the eight studied watersheds.

All processing of the LIDAR data was done using Quick Terrain (QT) Modeler version 7.1.5 (© Applied Imagery, 2012). The .LAS files were imported into QT Modeler and processed individually to create gridded surface models from the first returns (i.e., the portion of the LIDAR data representing the uppermost parts of aboveground features). The grid sampling was set at 2.0000 m, and holes were filled using the Adaptive Triangulation fill method and Max Z algorithm. The individual gridded surface models were merged with 2.0000 m grid sampling, and because of the non-rectangular study area, hole filling was not applied. I exported the resulting first returns grid in ESRI ASCII Grid format as a .txt file.

Using ArcGIS, I converted the ASCII Grid into a 2 m resolution floating point raster. To create the nDSM, I used a raster calculation to subtract a 2 m spatial resolution, LIDAR-derived digital elevation model (DEM) for the City of Manhattan area from the first returns grid, yielding a raster in which the cell values represented the average height above the bare earth of that cell in meters. The resulting nDSM contained several errors that needed to be corrected before the nDSM could be finalized. First, a single cell in the nDSM returned a value of 762 m. The lack of any such tall features in the study area, as well as the high value's appearance in a single cell only, indicated the presence of an error. Second, the nDSM contained regions of negative values (i.e., erroneously representing areas as lying below the surface) in homogenous, grassy sections of the study area. The pattern of these negative areas suggested that they were artifacts of the mosaicking process used either to create the DEM or the first returns grid.

To correct the erroneously high and low values, I used simple raster calculations to convert the negatives and the high value to zero values. Comparison with photographs of the study area showed that these errors were in areas containing little to no woody vegetation, so the conversion to zero values did not result in a loss of data. Once the errors had been removed, I georeferenced the nDSM using the same 12 GCPs used to georeference the 2006 NAIP image, a third-order polynomial transformation (RMSE=0.62825), and cubic convolution resampling. Finally, I converted the nDSM to TIFF format to allow for its use as an image layer in eCogntion (Figure 8).

Topographical Data

To allow for a comparison between topographical factors and woody encroachment, I created several data layers from a 2006 LIDAR-derived, 2 m spatial resolution DEM downloaded from DASC and clipped to the study area. First, to aid in visualizing the topography of the study area, I created a hillshade model in ArcGIS using the default settings. Second, I used the DEM to generate slope layers in both percent and degrees, as well as an aspect layer. I reclassified the slope and aspect layers to facilitate analysis following another study of shrub encroachment (Sankey and Germino, 2008). Slope was grouped into three classes: shallow slope (0-10%), moderate slope (10-35%), and steep slope

(>35%). Aspect was grouped into 4 classes: north-facing (315º-45º), east-facing (45º-135º), south-facing (135º-225º), and west-facing (225º-315º).

Image Segmentation

The segmentation and classification of the images used in this project was done using eCognition version 8.7.2 (© Trimble Germany GmbH, 2012). Image segmentation in eCognition takes place according to a series of parameters chosen by the user: scale (determines the size of the image objects), shape/color, and compactness/smoothness. Parameter selection is highly reliant on a number of factors, such as the quality and type of imagery and the end goal of the classification project. As a result, there are a number of different approaches to selecting these parameters. Some object-based studies have used quantitative analysis of local variance within objects created using a variety of scales to determine the optimal scale parameter (Dragut and Eisank, 2012; Tapas et al., 2012). Other studies take a more iterative approach to determining the optimal parameters in which the user attempts a number of different segmentations using different parameters until the image objects capture the features of interest (Platt and Schoennagel, 2009).

I chose to use an iterative approach to select the appropriate segmentation parameters for the images used in this project. The relatively small study area, ease of visual separation between ground features, and small number of classes made a quantitative parameter selection unnecessary. Rather than simply choosing parameters at random, I used the scale, shape/color, and compactness/smoothness values used by Laliberte et al. (2004) as a starting point. Their study had similar objectives in a similar study area (i.e., isolating shrubs from a relatively homogenous background matrix), so it thus seemed appropriate to begin by replicating their segmentation procedure.

Following Laliberte et al. (2004) I originally attempted to isolate individual clumps of woody plants using a two-level segmentation that would allow me to take advantage of the hierarchical relationships that can be used to classify image objects in eCognition. The goal was to isolate the woody plants at the fine segmentation level by relating them to the predominant cover (grass or woody plants/trees) at the coarse level. This approach proved unsuccessful, however, because of the patchy nature of the woody plants in the study area. It was not possible to define image objects at the coarse level that consisted primarily of woody plants and still maintain the intended advantages of the two-level approach.

The final approach used on all the images involved multiple segmentations designed to isolate the woody plants from the grassy background matrix. The process began with a coarse multiresolution segmentation followed by a very fine multiresolution segmentation. Each of these segmentations created a separate object level. Finally, I applied a spectral difference segmentation, in which the image objects at the fine level were merged according to a homogeneity parameter, resulting in a new group of larger objects. The spectral difference was performed on the fine object level for all images except the 1978 and 1991 images, in which the spectral difference segmentation was used to create a third object level. For the RGB and panchromatic images, all the image layers were equally weighted in the segmentation algorithms. For those images containing an NIR layer, that layer was given a weight of 2 (versus 1 for the other layers). I included a thematic layer representing the study area in all of the segmentations to ensure that the resulting image objects would conform to the watershed boundaries (see Table 1 for the segmentation parameters used throughout).

Image Classification

Upon reaching a satisfactory segmentation, the next step in OBIA is to classify the image objects. In this project, the goal was to isolate the woody plants from the grassy background. There are two basic approaches to classification in eCognition: membership functions and thresholds. Membership functions use fuzzy logic to determine via user-defined functions for different image object characteristics (e.g., spectral features, geometry, texture, etc.) the likelihood that a particular object belongs to a defined class (Trimble, 2011, p. 101). This fuzzy approach has the advantage of functioning in a manner akin to the human eye-brain mechanism, in which the observer implicitly weighs a number of different object features to determine its identity. Thresholds, on the other hand, are sharp cutoffs in the values of image object characteristics above or below which the object either does or does not belong to the class in question. Thresholds are much simpler to apply than membership functions, but they are only applicable when the classes are easily distinguishable on a relatively small number of image object characteristics.

I used a few primary image object characteristics to distinguish the woody plants from the grassy areas: mean object brightness or mean pixel value for the panchromatic and RGB images, and normalized difference vegetation index (NDVI) value for the images containing a NIR layer. In the panchromatic and RGB images, the brightness of an image object was the best initial way to capture the sharp visual contrast between the woody plants and the grasses. In the case of the 1991 image, the small size of the woody plants relative to the grassy areas was sufficient in combination with brightness levels to reach a workable classification. NDVI, which is the spectral vegetation index used most commonly in the remote sensing literature, is calculated as the difference between the NIR and red values divided by the sum of the NIR and the red (Rundquist, 2002). It is the best way to distinguish between different types of vegetation (such as woody plants and grasses), though it does require the user to have access to NIR data (Table 2).

Spectral responses alone, whether measured via brightness or NDVI, were not sufficient to isolate the woody plants with the desired degree of precision. Texture is another object feature that clearly differs between woody plants and grasses. In object-based image classification, texture is defined as the distribution in space of gray levels within an object (Haralick et al., 1973). A method of quantifying texture that is available in eCognition is the gray level co-occurrence matrix (GLCM). The GLCM is a measure of the frequency with which different combinations of gray levels occur within an area of interest, such as an image object (Trimble, 2012, p. 320). GLCM values can be quantified in a number of ways, such as homogeneity (the degree of gray level uniformity in the image object) or contrast (the degree of gray level variation in the image object) (Trimble, 2012). The use of texture in image classification is one of the major advantages of OBIA, and it proved to be extremely effective in separating the high-texture, "rough" woody plants from the low-texture, "smooth" grassy areas in many of the images (Table 2).

The final threshold I applied in the classification step was the value of the nDSM layer derived for the 2006 image. The nDSM layer represented the average height above the ground in meters of a particular image object. Because the woody plants tend to be taller and denser than grasses, height is a good way to distinguish between the two. After trying a number of different height thresholds, I settled on a value of 1.0 m (Table 2). Several of the sub-meter thresholds I tested picked up more of the image objects that appeared to be woody vegetation, but the resolution of the LIDAR data used to create the nDSM (horizontal: ~0.6 m; vertical: ~0.25 m) was not suited to such fine distinctions.

After testing and manipulating the various classification algorithms available in eCogntion, I settled on the classifications that contained the fewest false positives and false negatives. The final classifications did, however, contain some readily apparent errors. To remove these errors I used the manual classification tool in eCognition to clean up the maps of woody vegetation. The problem most apparent in each of the images was the appearance of false positives. For example, because woody plants were distinguished from grasses on the basis of their lower brightness levels, some shadowed areas in the 1991 image ended up classified as woody plants. Shadows in ravines and along roads and paths proved to be a consistent problem in each of the classifications. Imperfections in the segmentations also led to the misclassification of some grassy areas immediately adjacent to correctly classified woody plants. In cleaning up the classifications, I removed only obvious false positives, leaving any ambiguous image objects in their original state. False negatives were less of a problem, though they did appear in some areas of dense woody cover (e.g., in watershed K20A) in the 2003 image. I manually assigned these misclassified woody plants to the correct class to the extent that they were easily distinguishable. The 2006 classification that used the LIDAR-derived nDSM did not capture many objects that appeared to be woody plants (i.e., objects classified as woody in the non-nDSM classification). I did not manually correct the nDSM classification so that I could make a more valid assessment of the value added by the inclusion of LIDAR data.

Woody Plant Cover Analysis

After finalizing the classifications in eCognition, I exported the final classes (woody and non-woody) in ArcGIS raster format. I then reclassified the raster values so that all cells classified as woody had a value of 1, and all others had a value of 0. Using the Zonal

Histogram function in ArcGIS with the watersheds as the zonal layer and the classifications as the value layers, I produced a table of the number of woody cells located in each watershed. I replicated this procedure to determine the number of woody cells in each of the slope and aspect classes. After exporting the cell counts into an Excel spreadsheet I calculated the total area of woody cover in each of the watersheds and slope and aspect classes, as well as the percent woody cover in the watersheds.

RESULTS

Changes in Woody Cover

The classifications showed a consistent increase in woody cover in the study area over the period 1978 to 2006, with declines in all but one of the watersheds between 2006 and 2010 (Table 3). Over the entire study area, woody cover increased from 27.86 ha (3.65% of the total area) in 1978 to a peak in 2006 of 154.36 ha (20.2% of the total area), a roughly five-and-half-fold increase over a period of 28 years. Total woody cover in 2010 (116.51 ha, 15.25% of the total area), though less than the observed cover for 2006, still represents a roughly four-fold increase in woody cover over a period of 32 years (see Figures 9-13 for woody cover rasters).

As expected, the largest increases in woody cover over the 1978 to 2010 period were found in the watersheds that were burned least frequently. Watersheds K20A and N20B had the most dramatic increases in woody cover: from 4.15 ha (4.99% of the total area) to a 2006 peak of 40.39 ha (48.59% of the total area), and 1.81 ha (2.15% of the total area) to a 2006 peak of 28.68 ha (33.99% of the total area), respectively. Watershed K20A thus had about ten times more woody cover in 2006 than in 1978, and watershed N20B experienced an increase of about sixteen times over the same period. Interestingly, the smallest increases in woody cover over the periods of the study were found in the watersheds burned biannually (K2A and N2B) rather than in those burned annually (see Table 3). The percent of woody cover by year between the grazed (those with "N" prefixes) and ungrazed (those with "K" prefixes) did not differ consistently (Table 4). Woody cover was somewhat higher in the grazed watersheds during 2003 and 2006, but that trend did not hold up for the other years studied.

Among the different slope classes, the areas with moderate slope (10-35%) saw the largest increases in woody cover (Table 5). As with the watersheds, woody cover peaked in the slope classes in 2006. The moderate slope class increased more than six times from the 1978 minimum to the 2006 maximum, versus an increases of about four times for both the shallow (0-10%) and steep (> 35%) slope classes over the same period. North- and west-facing portions of the study area saw the largest increases in woody cover from the low point in 1978 to the peak in 2006 (Table 6). Each saw increases of six and six-and-a-half times, respectively, versus four times for the east-facing slopes and five times for the south-facing slopes.

Remote Sensing Data Comparison

I produced separate woody cover classifications for 2006 using a CIR image alone and the CIR image in combination with the LIDAR-derived nDSM for the purpose of comparison. The classification using the nDSM showed much lower levels of woody cover than the classification based only on the CIR image (Table 7). Overall woody cover was dramatically different between the classifications without (154.36 ha, 20.2% of the total area, see Figure 12) and with the nDSM (39.65 ha, 5.19% of the total area, see Figure 14). The same trend held for the woody cover figures for each of the individual watersheds.

For the sake of comparison I also produced classifications for 2010 using both RGB and CIR NAIP images of the study area. The woody cover figures for the two classifications were very similar throughout, and the overall numbers did not differ by much: 116.51 ha (15.25% of the total area, see Figure 13) for RGB, and 123.45 ha (16.15% of the total area, see Figure 15) for CIR (Table 8). No clear trend showed up in the woody cover figures for the individual watersheds. The RGB classification yielded higher cover numbers for four of the watersheds, and the CIR classification had the higher numbers for the other four.

DISCUSSION

The observed trends in woody cover with respect to watershed burn frequency echo the findings of other studies of fire and prairie vegetation dynamics. Periodic fires, either natural or manmade, are essential for the removal of woody plants from tallgrass prairies (Axelrod, 1985). Longer intervals between burns tend to favor the establishment and spread of woody plants and shrubs relative to grasses (Archer, 1989). The results of my classifications show the greatest increases in woody cover over the study period in the watersheds that are burned at four- and twenty-year intervals. Interestingly, the smallest increases relative to the amount of woody cover present in 1978 were found in the watersheds burned biannually as opposed to those burned each spring. The relationship between burning frequency and woody encroachment, however, is not deterministic and is highly reliant on the makeup of the vegetation community present prior to the burn. Infrequently burned areas containing few woody plants will show less dramatic increases in woody cover than more frequently burned areas with a higher initial population of woody plants (Heisler et al., 2003). The timing of burns can also impact the presence of woody vegetation, as burning at different times of the year tends to favor different plant species, so burn frequency alone is insufficient to explain prairie species composition (Gibson and Hulbert, 1987). Other factors such as fire intensity and environment (soil moisture, air temperature, wind speed) affect the degree to which burning can kill woody plants. In other words, all burns are not created equal relative to their effects on the presence of woody plants.

Various studies of prairies and shrublands have found statistically significant relationships between grazing and woody encroachment patterns. As grazing livestock consume grasses, they reduce the competitive pressures on woody plants and create conditions for more rapid encroachment (Van Auken, 2000). Livestock also serve as vectors for woody plant seeds, and their presence in a prairie can lead to increased survival rates for encroaching species such as Eastern red cedar (Schmidt and Stubbendieck, 1993; Van Auken, 2000; Laliberte et al., 2004). In contrast to trends observed in the literature, my classifications show little difference in woody cover patterns between the grazed and ungrazed portions of the study area. One potential explanation for this result is that the grazed areas of the Konza Prairie are populated by North American bison (*Bison bison*), a species native to the tallgrass prairies that once covered much of the Great Plains of North America. The relationship established in the literature between grazing and woody encroachment deals largely with cattle rather than native ungulates. There are a number of differences in the grazing behavior of bison and cattle that can have different effects on prairie species composition, and relationships observed for cattle may not hold for bison. Cattle spend more time grazing relative to other activities than bison do. Whereas bison prefer open grassland for grazing, cattle will graze in woody and shrubby areas (Knapp et al., 1999). Both of these differences in the grazing behaviors of cattle and bison indicate that the presence of cattle may be associated with greater degrees of woody encroachment. The latter difference is especially important with regard to the feedback processes involved in woody encroachment whereby the presence of woody plants tends to beget more woody plants (see Chapter 3).

The lack of an observable relationship between grazing and woody encroachment in the results of my study can also be attributed to the artificial nature of the grazing regime at the Konza Prairie. Bison and cattle grazing at the Konza Prairie is not intended to replicate the conditions that prevailed prior to European settlement or to mirror prevailing stocking rates; rather, it is an introduced variable used to investigate impacts on ecological factors such as water quality, mammal populations, and primary production (Methods Manual Version 2011.1, 2011). Also, the "grazed" watersheds are not grazed in their entirety. The grazing animals are confined to clearly delimited areas to allow for better control of grazing as an environmental variable. As such, treating grazed/ungrazed as a dichotomous variable for a given watershed is somewhat misleading. The data presented here are thus of limited utility in illuminating the dynamics of grazing and woody encroachment.

The woody cover classifications show some trends in woody encroachment relative to topographic factors. There were somewhat greater rates of woody cover increase in areas of moderate slope and northerly or westerly aspect than in other areas. There is no uniformity to the findings in the woody encroachment literature regarding the role of topography. Schmitt and Stubbendieck (1993) found the greatest rates of tree survival in a prairie environment on north-facing slopes as opposed to south-facing slopes and flat areas. The only significant encroachment-topography relationships found by Sankey and Germino (2008) were higher encroachment rates in areas of moderate slope and westerly aspect and lower rates in areas with northerly aspect. The inconclusive nature of the relationship is largely due to the complexity of topography's role in determining vegetation communities.

Topography tends to influence vegetation by affecting water flow and soil composition, and local geographic factors (e.g., climate, latitude, soil parent material) may alter the nature of these relationships. Topographic factors also impact different plant species in different ways (Abrams and Hulbert, 1987; Gibson and Hulbert, 1987). It is possible that certain encroaching species favor particular topographic settings in a given area, but detailed field and experimental studies would be needed to determine whether or not this is the case.

One unexpected feature of the woody cover data resulting from the classifications is the almost uniform drop in woody cover across the study area from 2006 to 2010. With the exception of watershed K4A, all of the watersheds had less woody cover in 2010 than they did in 2006. Burning does not explain the drop in woody cover. The frequently burned watersheds were burned on their regular schedule between 2006 and 2010, and neither of the infrequently burned watersheds were burned at all during that period (Konza Prairie Burn History, http://www.konza.ksu.edu/KNZ/pages/research/burnhistory.aspx). The watersheds were not mowed or otherwise treated during that period to remove woody vegetation (Adam Skibbe, personal communication, 2013).

The observed drop in woody cover may have been a function of growing season precipitation in the area. Precipitation amounts for the frost-free May to October growing season as collected at the Manhattan Regional Airport (Weather Underground, 2016), which is directly west of the Konza Prairie, do not contain any anomalies that could adequately explain the changes in woody cover (see Table 9). Though observed precipitation was lower than average in 2006 and 2010, there was no sustained, dramatic change. A more likely explanation is that the low woody cover numbers for 2010 are an artifact of the imagery. A side-by-side comparison of the 2006 and 2010 images shows some differences in the appearance of areas mapped as woody vegetation (Figures 12 and 13). The lower texture in the 2010 image may have led to some errors of omission in the final classification, thus accounting for the observed drop in woody plant coverage.

The substantial differences in woody cover for 2006 produced by the classifications with and without the nDSM are likely an artifact of the source LIDAR data (see Figures 12 and 14). Because of the complex structure of woody plant canopies, a LIDAR point cloud with insufficient density will be unable to capture all of the woody plants present in a study area. In other words, the LIDAR first returns may only capture a fraction of the actual aboveground vegetation in an area, as some of the light pulses will travel through openings in the canopy and strike objects closer to the ground. Other studies that have used LIDAR to map vegetation have encountered similar phenomena. In one study that used LIDAR to map individual shrubs in hilly terrain, the LIDAR data underestimated sagebrush crown area by an average of 49% versus field measurements, and a linear regression of the LIDAR crown area measurements against the field measurements yielded an R^2 value of only 0.33 (Glenn et al., 2011). LIDAR has also been found to consistently underestimate the heights of aboveground vegetation such as trees and shrubs (Streutker and Glenn, 2006; Sankey and Bond, 2011). These problems are common when using raw nDSM values, but they can be alleviated through complex techniques that model tree canopy structure (Hecht et al., 2008).

The separate classifications for 2010 that included and omitted NIR data arrived at very similar woody cover figures, and there was no consistent pattern to the differences that did show up in the data (i.e., neither was consistently higher or lower, see Figures 13 and 15). This result is reflective of one of the major advantages that object-based classifications have over pixel-by-pixel classifications. When classifying imagery using only spectral information, those images containing the most spectral information (i.e., the most bands, the highest radiometric resolution, etc.) will result in the best classification. Additional spectral data provide more ways to distinguish classes from one another in a pixel-by-pixel classification. In object-based classification, however, the inclusion of more bands will not necessarily improve the quality of the classification, as OBIA is not beholden solely to spectral characteristics in separating classes from one another. As a result, it is possible to produce a robust classification using an object-based approach even when the imagery contains no spectral information, as is the case with panchromatic imagery. Though the inclusion of NIR data did not have an appreciable effect on the resulting woody cover classification, it did streamline the classification process. NDVI is still the most straightforward way to distinguish between different forms of vegetation, and the presence of an NIR band thus allows for a much simpler classification that requires fewer steps and fewer cleanups.

CONCLUSIONS

Woody cover in the study area increased about five-and-a-half times from 1978 to a peak in 2006 and about four times to the end of the study in 2010. The watersheds with a twenty-year burn frequency saw the largest increases in woody cover relative to the amounts present in 1978, and the watersheds burned biannually had the smallest increases. Areas with moderate slope, as well as north- and west-facing locations, saw somewhat larger increases in woody cover in comparison to other topographic positions. There was no appreciable difference in woody cover between the grazed and ungrazed portions of the study area. The 2006 classification that used a LIDAR-derived nDSM produced much smaller woody cover numbers than the classification that used only the aerial photograph. Separate classifications for 2010 that included and omitted a NIR band produced very similar woody cover results.

Object-based analysis of high-spatial resolution aerial photographs is an appropriate technique for mapping woody encroachment in tallgrass prairie. OBIA can successfully identify woody plants in whatever aerial imagery is available. The user need not have access to NIR data, and panchromatic imagery does not present a challenge. Though the exact segmentation and classification procedure must be adjusted for each individual date of imagery, the procedures used in this study provide a baseline for future mapping projects. The techniques used in this study could be applied to larger spatial extents and could thus be an important tool for those working to ensure the integrity of the remaining stands of tallgrass prairie.

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Table 1
Segmentation parameters used in eCognition.

Image	Segmentation level	Scale	Spectral difference	Shape	Compactness
1978	1	75		0.8	0.2
	2	5		0.8	0.2
	3		15		
1991	1	75		0.8	0.2
	2	10		0.8	0.2
	3		15		
2003	1	100		0.8	0.2
	2	10	8	0.8	0.2
2006 [a, b]	1	100		0.6	0.2
	2	10	10	0.3	0.7
2010	1	100		0.8	0.2
	2	10	5	0.8	0.2
2010 [a, c]	1	100		0.6	0.2
	2	10	10	0.3	0.7

[a] NIR layer weight = 2; all other layer weights = 1
[b] Same segmentation parameters used both with and without LIDAR
[c] 2010 CIR NAIP image including NIR layer

Table 2
Classification thresholds used in eCognition.

Image	Classification thresholds
1978	Mean brightness < 140 GLCM homogeneity < 0.45
1991	Mean pixel value < 100 Number of pixels < 1000
2003	Mean brightness < 100 GLCM contrast < 1.1
2006	NDVI > 0.2 GLCM homogeneity < 0.3
2006 LIDAR	NDVI > 0.2 nDSM > 1.0
2010	Mean brightness < 110 GLCM contrast < 2.1
2010 CIR	NDVI > 0.2 GLCM homogeneity < 0.185

Table 3
Area of woody cover, 1978-2010.

Watershed[a]	**Area (ha)**	**1978 (ha)** *(%)*	**1991 (ha)** *(%)*	**2003 (ha)** *(%)*	**2006 (ha)** *(%)*	**2010 (ha)** *(%)*
K20A	83.13	4.15 *4.99*	6.44 *7.74*	35.61 *42.84*	40.39 *48.59*	33.84 *40.70*
K2A	66.10	4.44 *6.72*	7.05 *10.66*	8.99 *13.60*	14.33 *21.67*	7.36 *11.13*
K4A	53.16	1.22 *2.30*	2.63 *4.95*	10.96 *20.63*	6.21 *11.68*	8.07 *15.18*
K1B	181.26	3.19 *1.76*	9.12 *5.03*	20.37 *11.24*	24.58 *13.56*	9.41 *5.19*
N4B	56.77	3.72 *6.56*	3.33 *5.86*	10.78 *18.99*	11.11 *19.56*	10.64 *18.74*
N20B	84.36	1.81 *2.15*	6.15 *7.29*	23.86 *28.29*	28.68 *33.99*	25.18 *29.84*
N2B	118.78	6.94 *5.84*	10.89 *9.17*	15.11 *12.72*	13.72 *11.55*	13.11 *11.04*
N1B	120.68	2.39 *1.98*	5.61 *4.65*	7.74 *6.41*	15.35 *12.72*	8.90 *7.37*
Total	**764.25**	**27.86** ***3.65***	**51.22** ***6.70***	**133.42** ***17.46***	**154.36** ***20.20***	**116.51** ***15.25***

[a] "K" prefix = ungrazed, "N" prefix = grazed; number = burn frequency (e.g., N4A is grazed and burned every four years)

Table 4
Percent woody cover in grazed and ungrazed watersheds.

Watersheds	1978 (%)	1991 (%)	2003 (%)	2006 (%)	2010 (%)
Grazed [a]	3.91	6.83	15.11	18.09	15.19
Ungrazed [b]	3.39	6.58	19.79	22.29	15.30

[a] Watersheds with "N" prefix
[b] Watersheds with "K" prefix

Table 5
Slope class and woody cover.

Year	0-10% slope (ha)	10-35% slope (ha)	> 35% slope (ha)
1978	10.48	15.24	2.11
1991	16.69	28.98	5.51
2003	38.11	87.61	7.66
2006	44.66	101.30	8.32
2010	34.57	74.97	6.91
% increase	*229.74*	*392.11*	*227.10*

Table 6
Aspect class and woody cover.

Year	North (315º-45º) (ha)	East (45º-135º) (ha)	South (135º-225º) (ha)	West (225º-315º) (ha)
1978	8.89	5.39	5.64	7.93
1991	23.09	9.09	7.24	11.80
2003	46.44	21.83	22.37	42.80
2006	51.71	22.84	28.48	51.32
2010	39.75	17.66	20.68	38.41
% increase	***347.01***	***227.49***	***266.84***	***384.30***

Table 7
2006 woody cover classification with and without LIDAR-derived nDSM.

Watershed	Area (ha)	Without nDSM (ha) *(%)*	With nDSM (ha) *(%)*
K20A	83.13	40.39 *48.59*	5.99 *7.20*
K2A	66.10	14.33 *21.67*	6.12 *9.26*
K4A	53.16	6.21 *11.68*	1.59 *3.00*
K1B	181.26	24.58 *13.56*	5.01 *2.76*
N4B	56.77	11.11 *19.56*	5.30 *9.33*
N20B	84.36	28.68 *33.99*	3.28 *3.89*
N2B	118.78	13.72 *11.55*	7.87 *6.62*
N1B	120.68	15.35 *12.72*	4.49 *3.72*
Total	**764.25**	**154.36** ***20.20***	**39.65** ***5.19***

Table 8
2010 woody cover classification with and without NIR band.

Watershed	Area (ha)	Without NIR (ha) *(%)*	With NIR (ha) *(%)*
K20A	83.13	33.84 *40.70*	32.39 *38.96*
K2A	66.10	7.36 *11.13*	7.24 *10.95*
K4A	53.16	8.07 *15.18*	10.37 *19.51*
K1B	181.26	9.41 *5.19*	13.85 *7.64*
N4B	56.77	10.64 *18.74*	9.02 *15.85*
N20B	84.36	25.18 *29.84*	27.58 *32.69*
N2B	118.78	13.11 *11.04*	14.36 *12.09*
N1B	120.68	8.90 *7.37*	8.65 *7.16*
Total	**764.25**	**116.51** ***15.25***	**123.45** ***16.15***

Table 9
May-October precipitation in Konza Prairie vicinity.

Year	Precipitation (in)
2005	24.69
2006	18.00
2007	24.53
2008	27.77
2009	23.05
2010	18.67

Figure 1
Study area: Konza Prairie watersheds

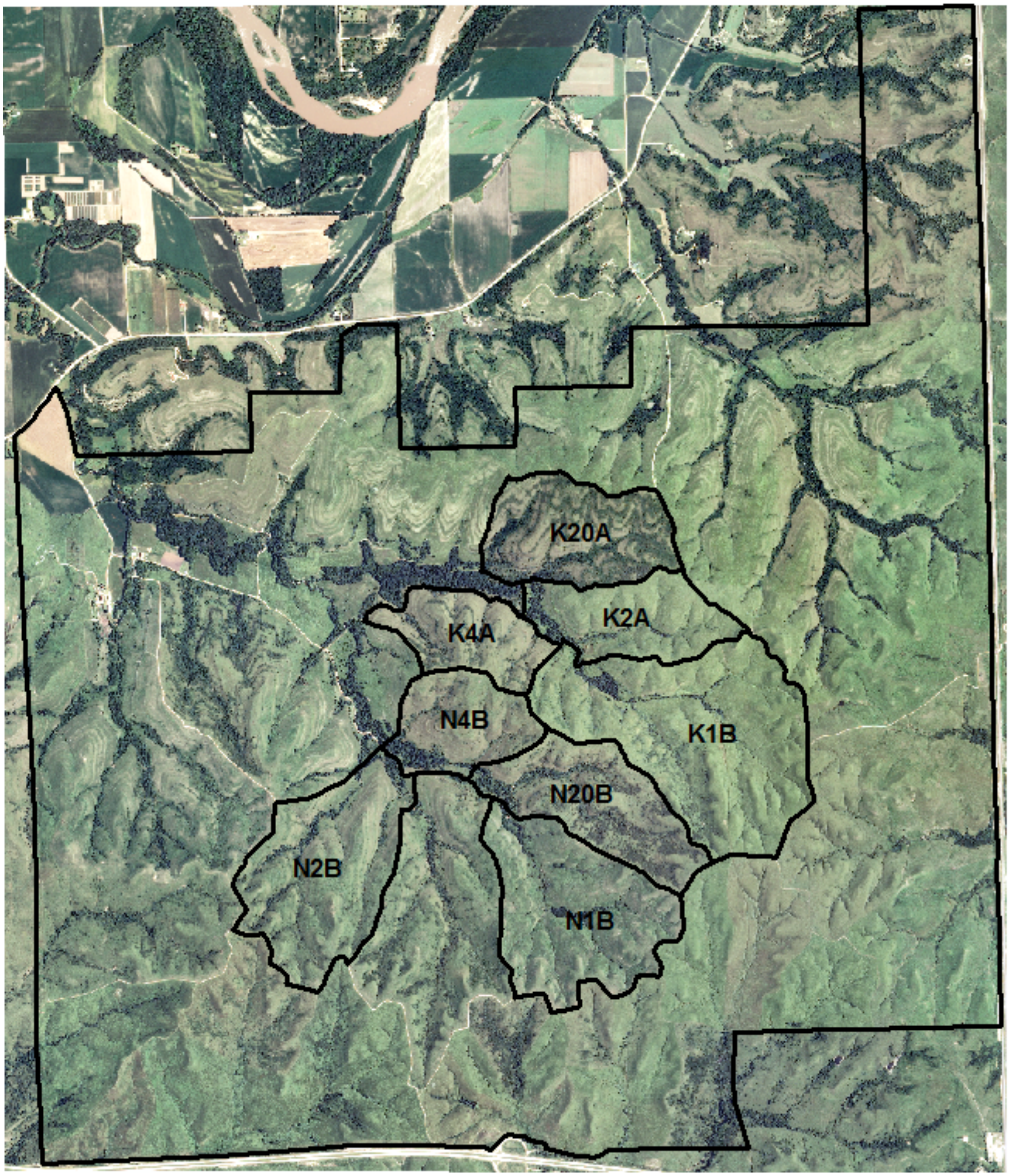


Figure 2
1978 image.

Figure 3
1991 image.

Figure 4
2003 image.

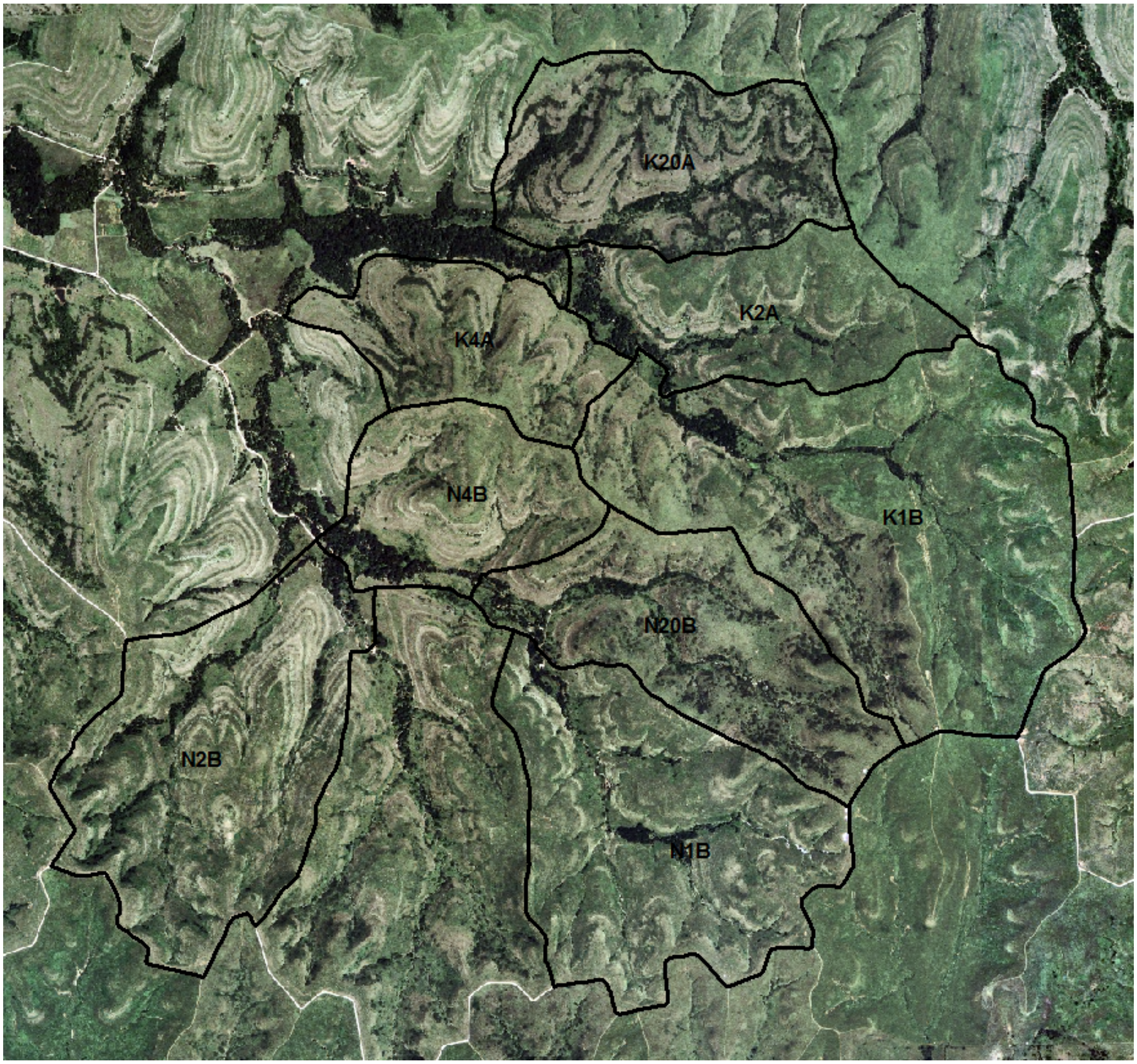


Figure 5
2006 image.

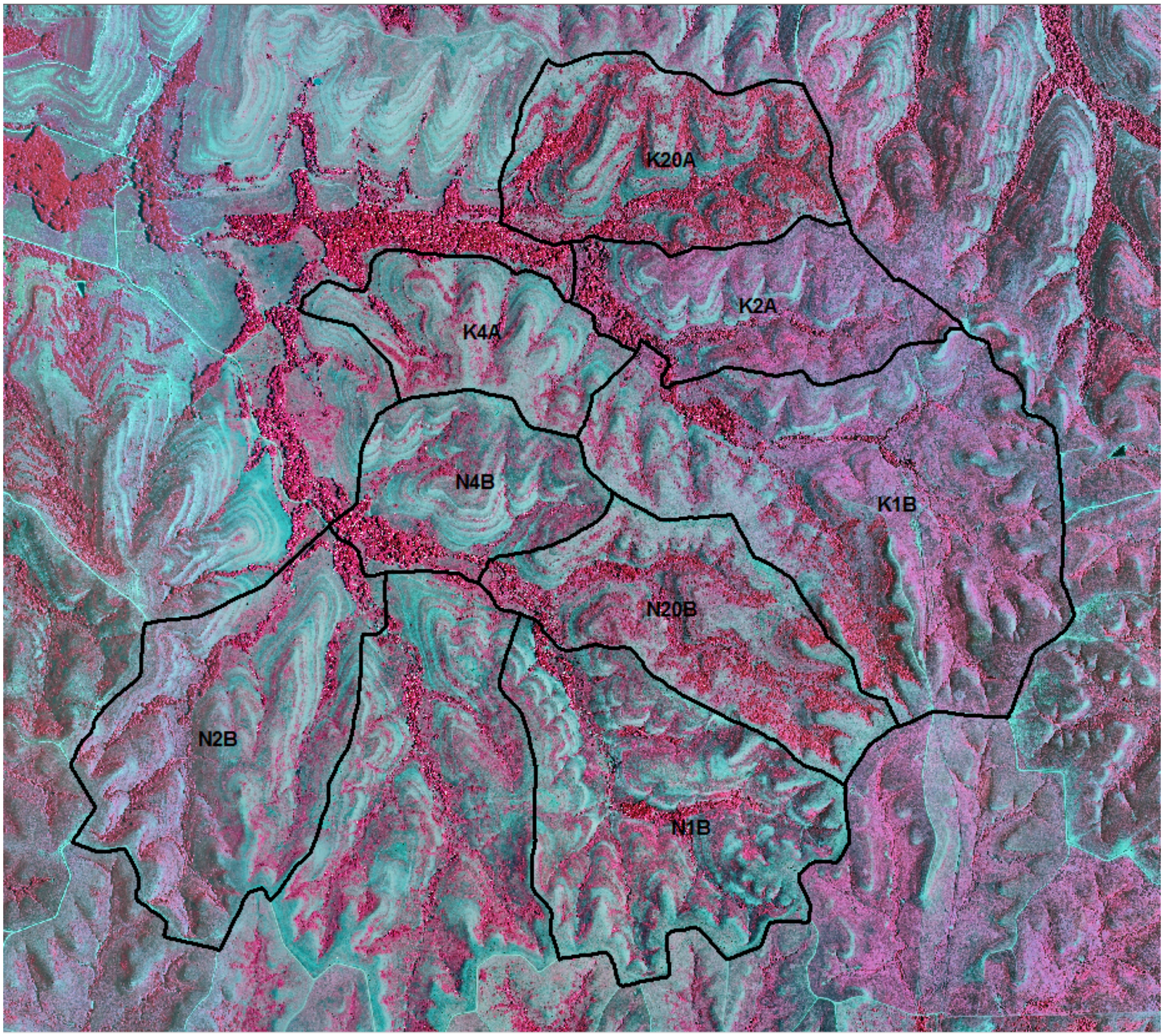


Figure 6
2010 image.

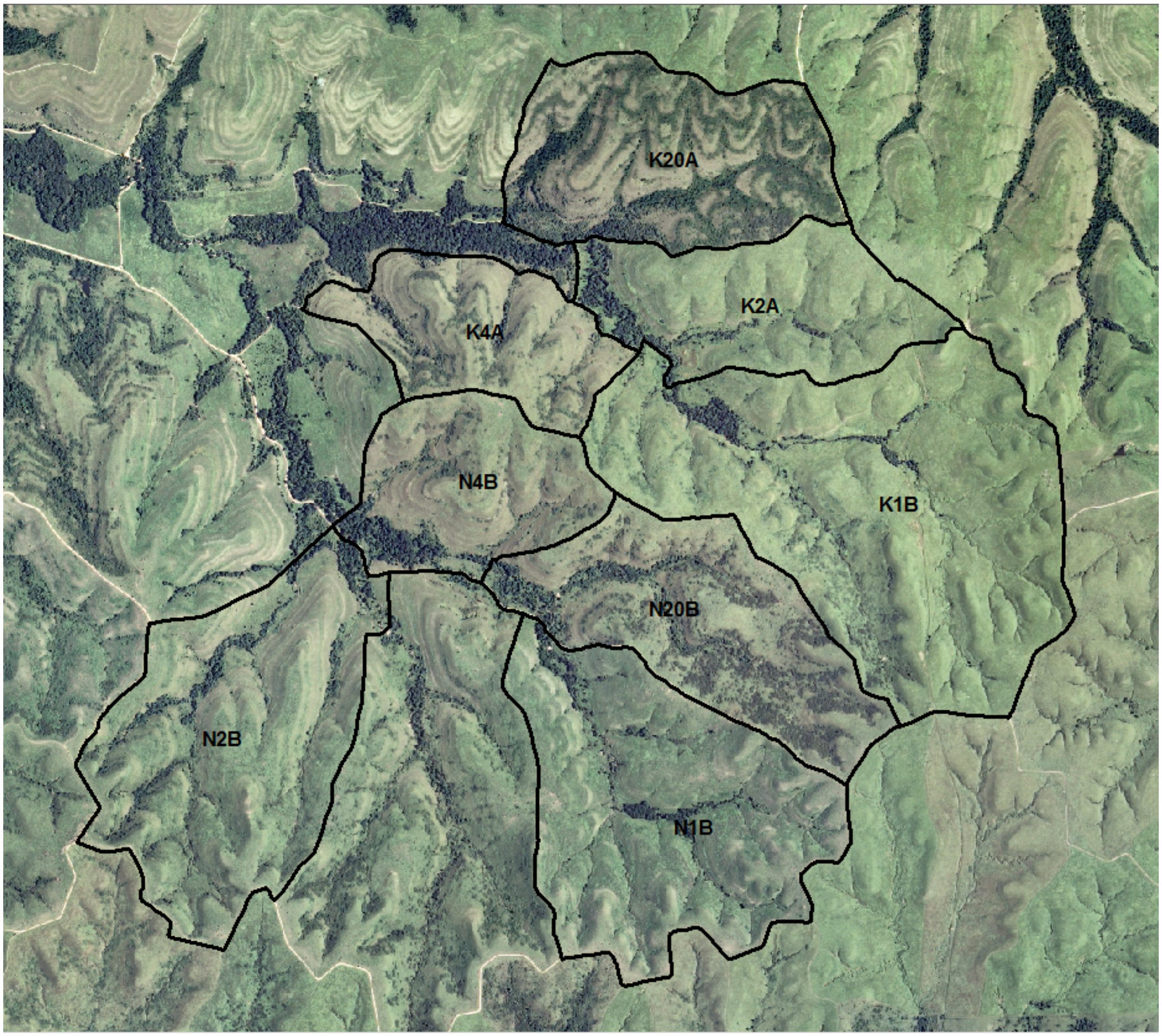


Figure 7
2010 color infrared image.

Figure 8
2006 LIDAR-derived normalized digital surface model (nDSM).

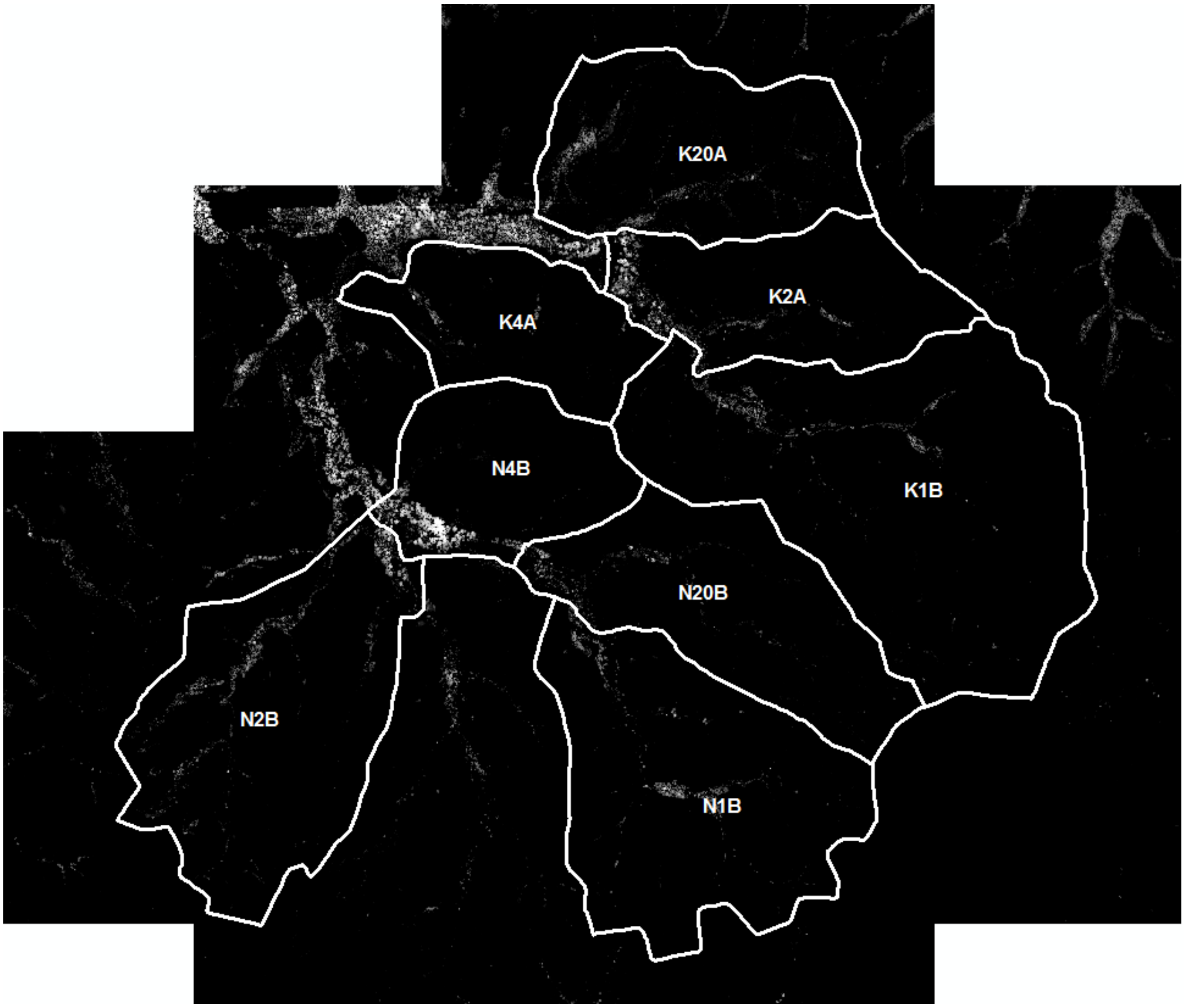


Figure 9
1978 classification.

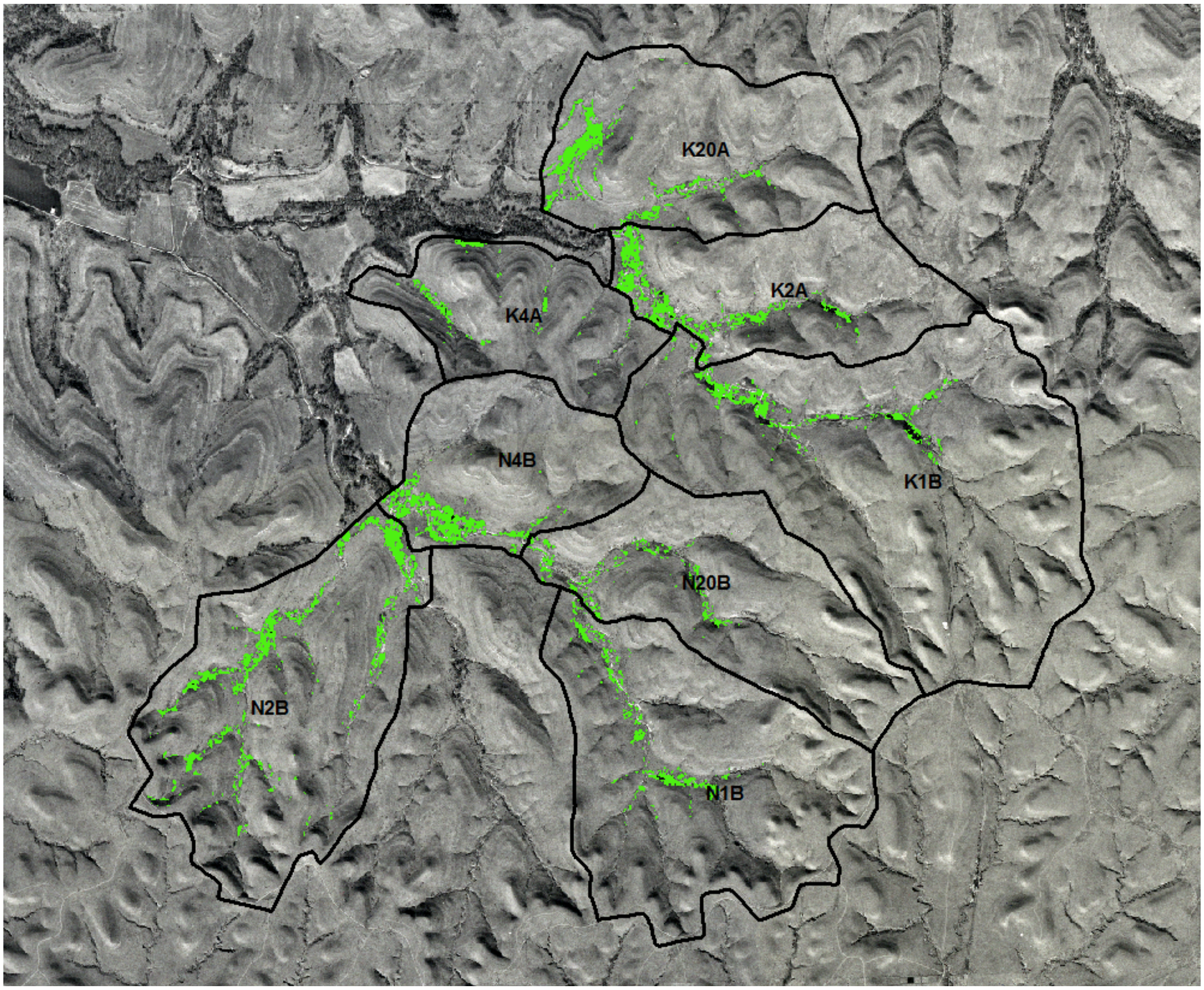


Figure 10
1991 classification.

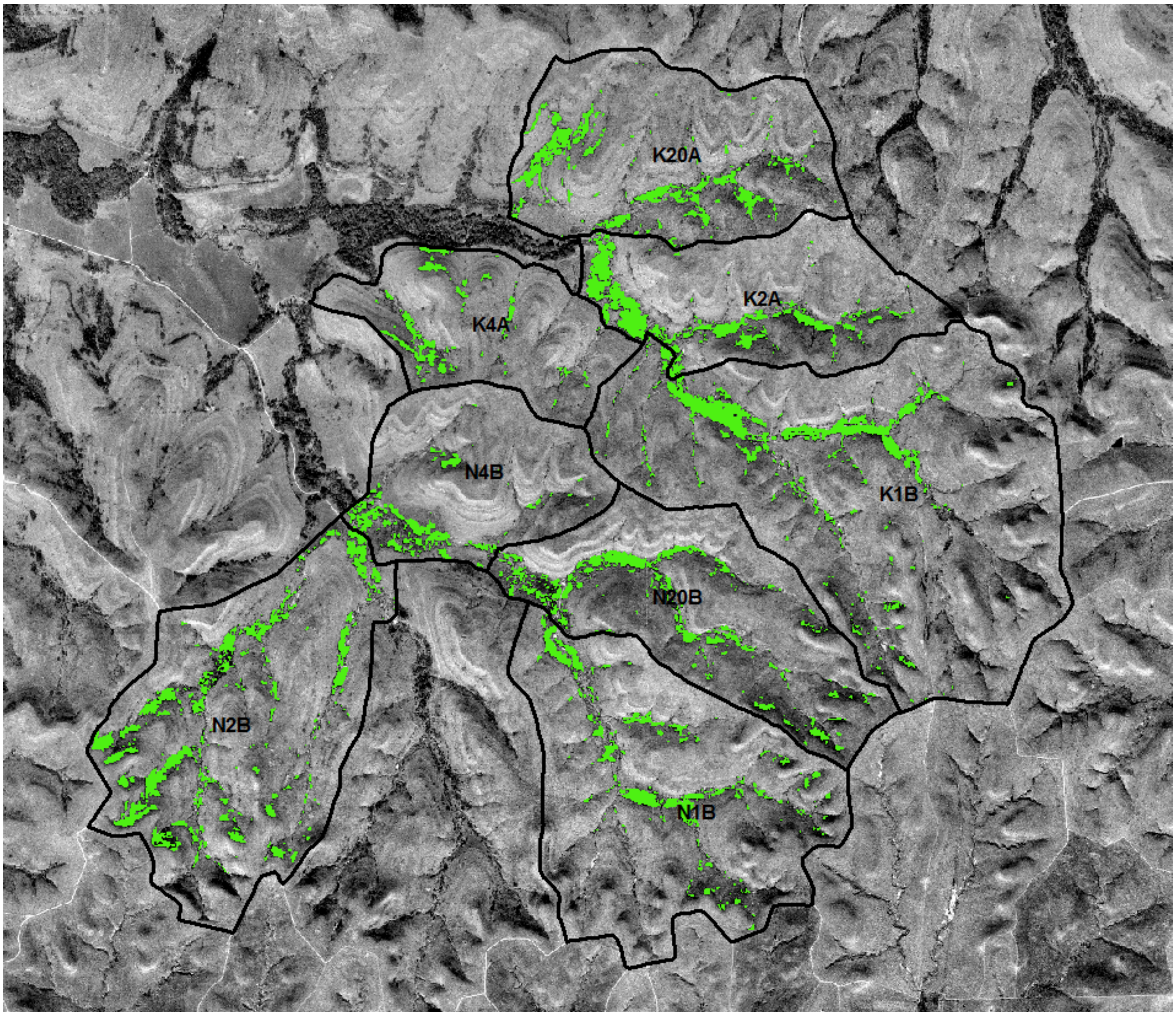


Figure 11
2003 classification.

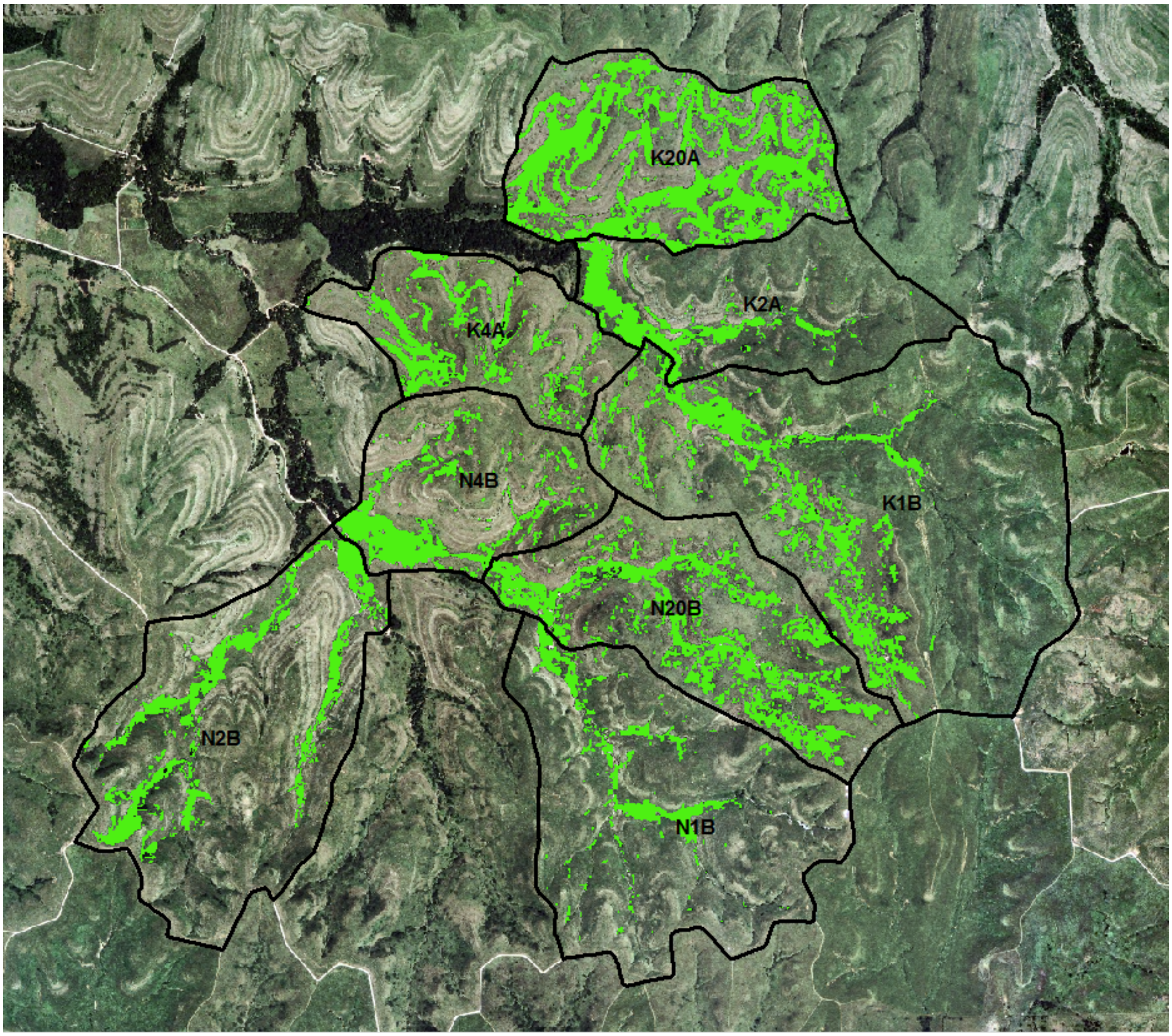


Figure 12
2006 classification.

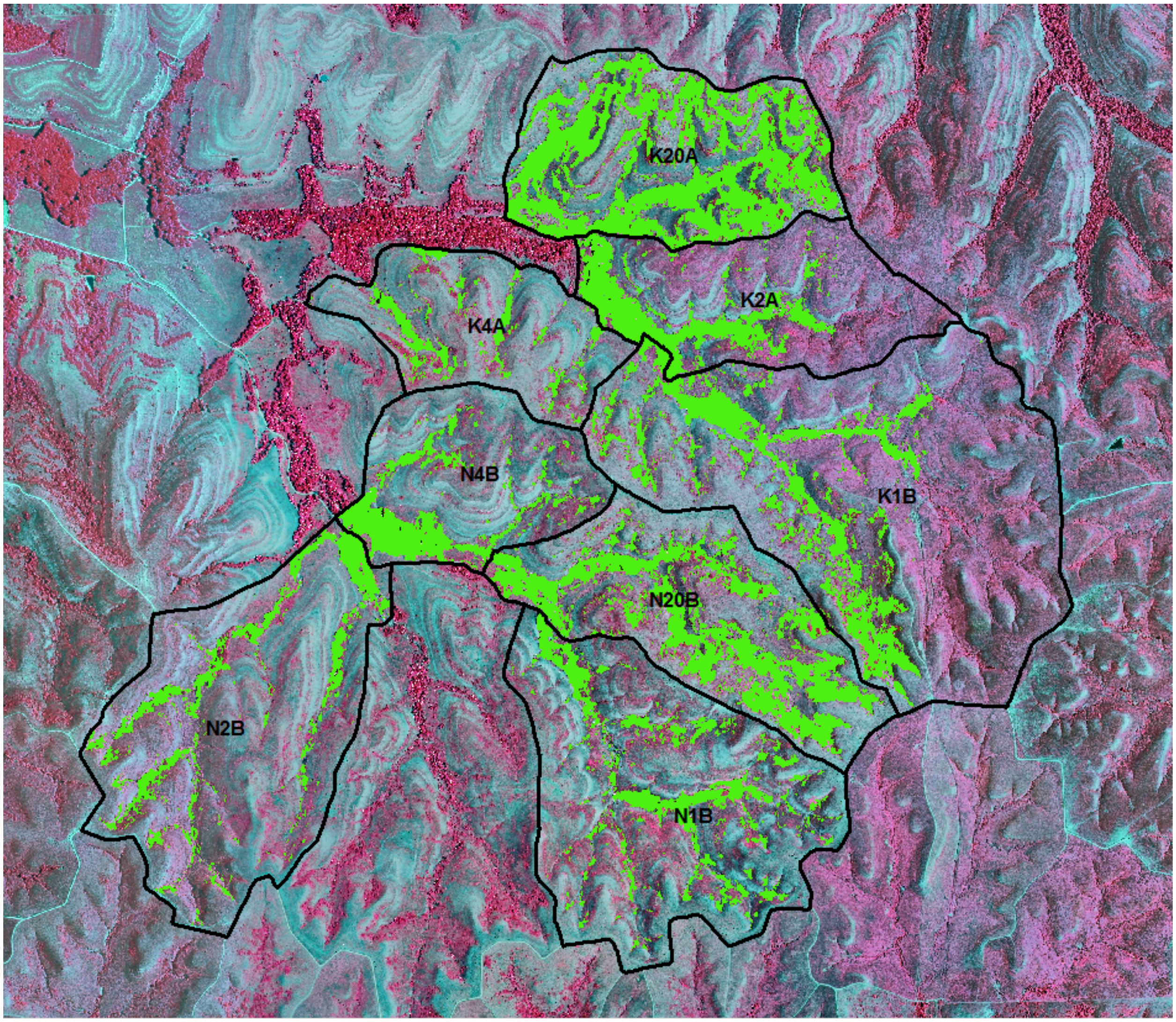


Figure 13
2010 classification.

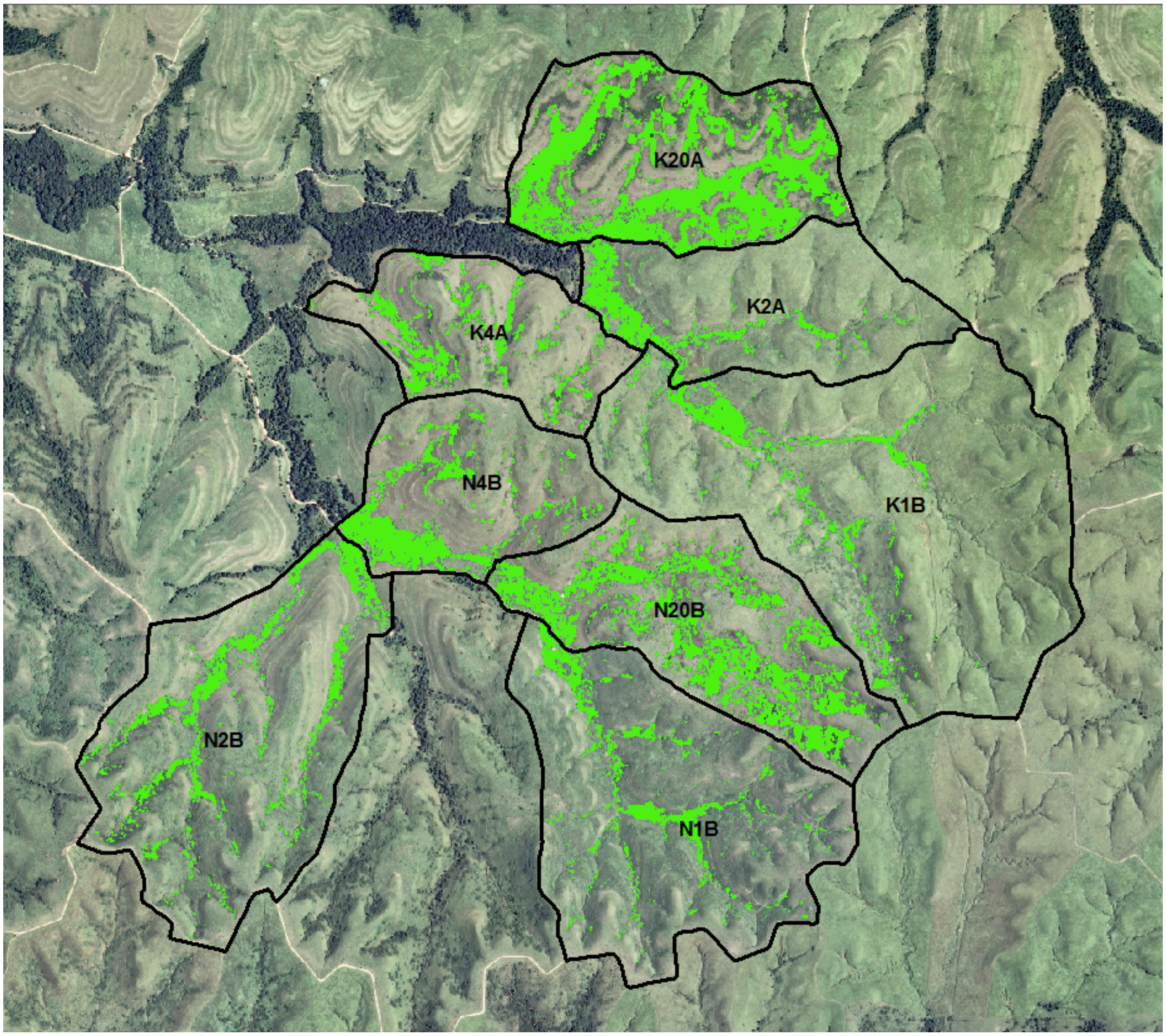


Figure 14
2006 classification from LIDAR-derived nDSM.

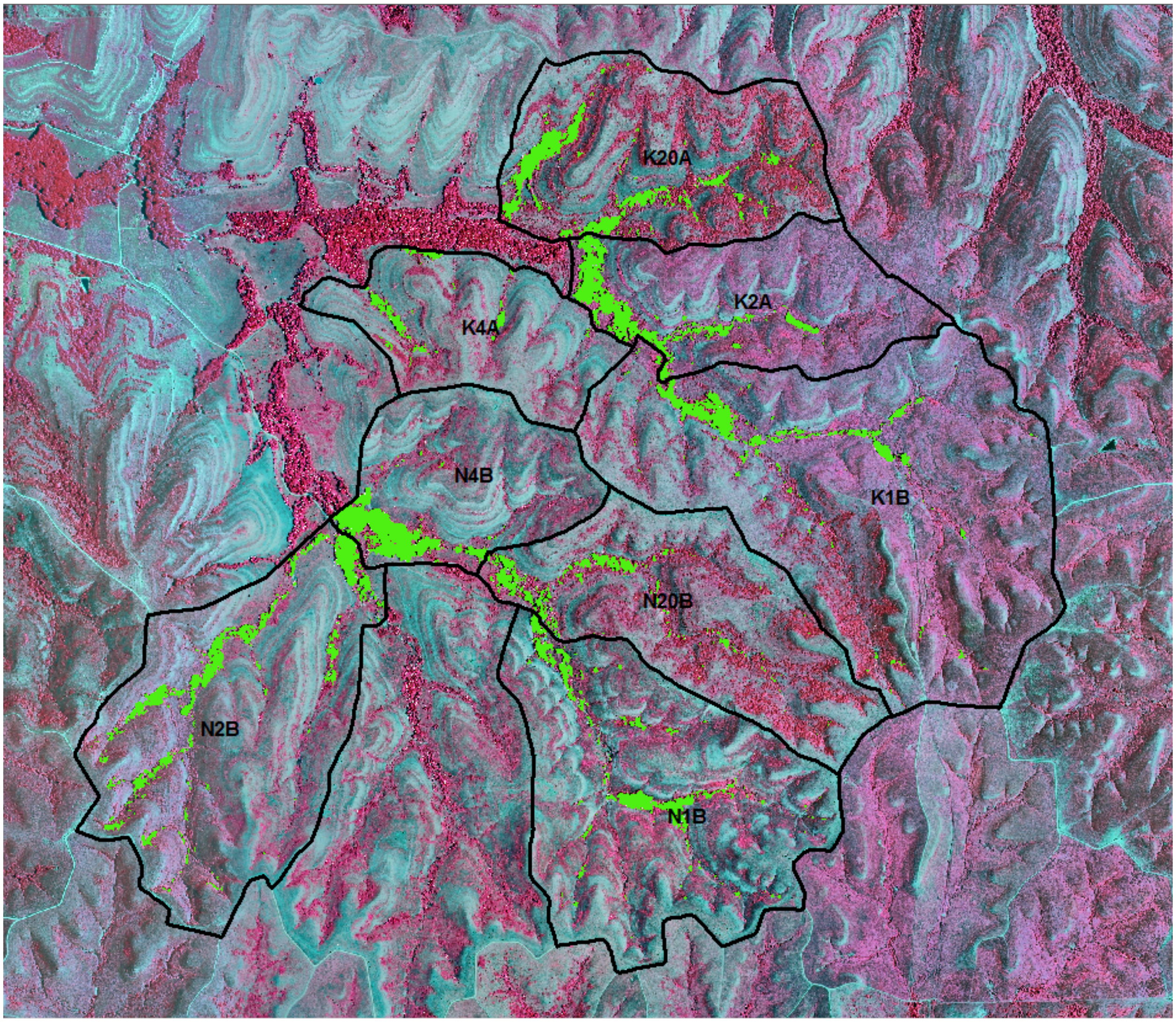
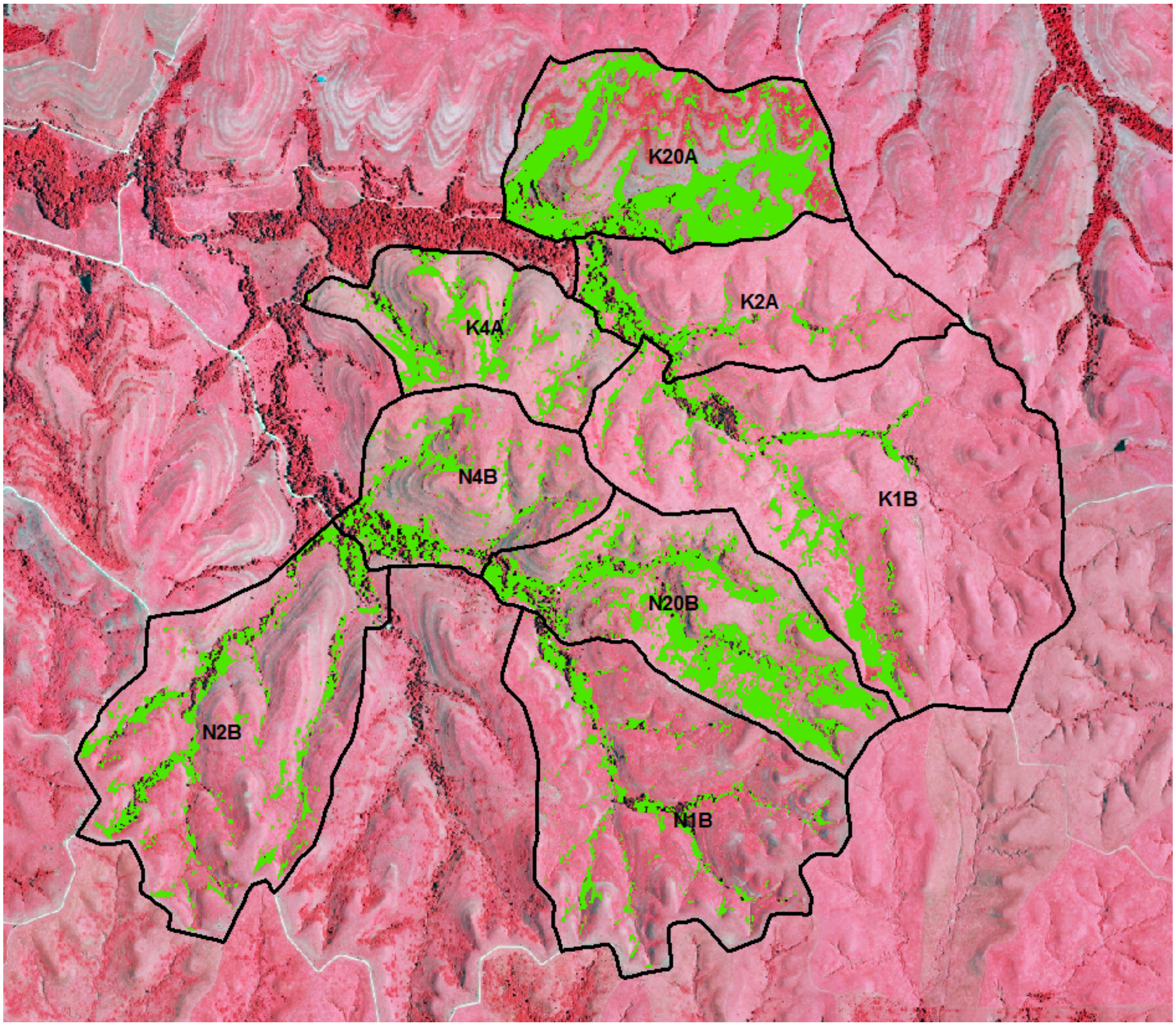


Figure 15
2010 classification using near-infrared (NIR) data.



Chapter 3

EVALUATION OF WOODY ENCROACHMENT IN THE KONZA PRAIRIE USING CLASSIFIED AERIAL PHOTOGRAPHS AND GROUND-BASED VEGETATION SURVEYS

INTRODUCTION

Prior to Euro-American settlement in the latter half of the nineteenth century, the eastern third of Kansas was covered largely by tallgrass prairie (Kindscher et al., 2005). Following the large-scale conversion of tallgrass prairie to agricultural land, most of the remaining tallgrass prairie in the region exists in small, isolated prairie hay meadows under private ownership (Kilroy M., 2010). The largest remaining stand of tallgrass prairie on Earth can be found in the Flint Hills of Kansas and adjoining areas in the Osage Hills of Oklahoma (White et al., 2000).

The remaining North American tallgrass prairie is continually threatened by the encroachment of trees and woody plants that is exacerbated by management practices that encourage woody plant growth. The spread of woody plants degrades the ecological balance of the tallgrass prairie ecosystem in a number of ways: by affecting soil quality (McKinley and Blair, 2008), reducing suitable nesting areas for grassland birds (Coppedge et al., 2001; Coppedge et al., 2004; Pietz et al., 2009), and by crowding out the dominant grass species through increasing resource competition (Van Auken, 2000; Zald, 2009; Limb et al., 2010). The takeover of former prairie by woody plants can be extraordinarily rapid. A study of *Juniperus virginiana* (Eastern Red Cedar) encroachment found a 120% increase the tree's prevalence over a 15-year period, and estimated that it would take as little as 30 years for a prairie to be converted to a closed-canopy Eastern Red Cedar forest in the absence of regular fires (Hoch, 2000). A full understanding of woody encroachment is essential to the maintenance of tallgrass prairie.

The research literature identifies a number of factors involved in the spread of woody plants. The primary driver of the balance between grasses and woody plants is fire, both natural and human caused (Axelrod, 1985). Most woody plants found in tallgrass prairie are fire intolerant, and the seedlings that are not killed by fire survive as much smaller plants (Van Auken, 2000). Several studies have confirmed inverse relationships between fire frequency and intensity and the prevalence of woody plants (Bragg and Hulbert, 1976; Archer, 1989; Heisler et al., 2003). Bragg and Hulbert (1976) observed a 1% increase in woody plant coverage over the period 1937-1969 for regularly burned prairie, versus a 34% increase for unburned prairie.

Topography, expressed in a number of different ways, has also been identified as a factor in the spread of woody plants. Though the applicability of their conclusions is limited by local geographical features, some studies have found relationships between slope and aspect and the prevalence of woody plants (Schmidt and Stubbendieck, 1993; Sankey and Germino, 2008). Other studies have demonstrated a relationship between topographic position (i.e., upland, lowland, slope) and vegetation community makeup, including the prevalence of woody plants (Bragg and Hulbert, 1976; Abrams, 1986; Abrams et al., 1986; Abrams and Hulbert, 1987; Gibson and Hulbert, 1987). Topographical features such as scarps, which act as natural fire breaks and contain soil unfavorable to dense grass coverage, are largely responsible for continued presence over observed ecological history of woodland areas in areas of tallgrass prairie (Wells, 1965).

Most previous studies of woody encroachment in tallgrass prairies have focused on relatively small areas. While small-scale studies are necessary for determining the dynamics at work in the spread of woody plants, a means of acquiring reliable data on the spread of woody plants over large areas would be a useful tool for those managing tallgrass prairies. To that end I applied an object-based classification routine to a series of historical aerial photographs of the Konza Prairie Biological Station (Konza Prairie or KPBS), a 3,487 ha (8,617 acre) section of tallgrass prairie located in Riley and Geary Counties in north central Kansas. The goal was to isolate encroaching woody plants visible in the photographs from the dominant grasses and to determine changes in woody cover over time (see Chapter 2 for procedures and results).

A means of determining changes in woody cover over time for a large spatial area is only useful to the extent that it accurately reflects the situation on the ground. The primary goal of this study is to determine the accuracy and usefulness of my previous remote sensing analysis by comparing it to the available vegetation data for the Konza Prairie. Should the more coarse-grained results of the remote sensing analysis generally match the trends present in the fine-grained in situ vegetation data, that would underscore the reliability of the remote sensing procedure and confirm its potential for future refinement and application.

Beyond its application as a ground data check for my remote sensing analysis, the Konza Prairie vegetation data can also offer some insight into the dynamics of woody encroachment in tallgrass prairie. Another goal of the present study is to draw some conclusions about the factors affecting woody encroachment by looking at trends in woody plant prevalence over time and space (i.e., by watershed and topographic position) in the available vegetation data. This can be a valuable contribution to the literature regarding the dynamics of woody plant encroachment.

METHODS

Konza Prairie Vegetation Data

Scientists at the Konza Prairie LTER have undertaken vegetation surveys each year from 1983 to the present. The data are compiled in the Vegetation Species Composition data set (Data Set Code PVC02). Permanent 50-m long transects have been established in selected watersheds throughout the Konza Prairie. Each watershed contains 4 transects in each of 3 topographic positions, for a total of 12 transects: lowland (Tully soils), upland (Florence soils), and slopes. The lowland and upland surveys have been conducted throughout the duration of the dataset, but slope data are only available for some watersheds and some years. Sampling takes place annually, but not all watersheds are surveyed in a given year. Vegetation species composition is surveyed in May-June and August-September to capture both cool- and warm-season species (Methods Manual Version 2011.1, 2011).

Species composition is determined at 5 permanent plots along each transect, for a total of 20 plots per topographic position. The surveyor estimates the percent cover of each species present in a 10 m^2 area at each plot and assigns a cover class (Table 2) (Bailey and Poulton, 1968). The data for each year are available in a text file containing the cover class of each species for every plot in a given watershed. A blank value for a plot indicates that the species in question was not present.

Analysis of Vegetation Data

Vegetation data were only available for two of the Konza Prairie watersheds that were part of the remote sensing analysis, both of which are grazed: N1B and N20B (1 = burned annually, 2 = burned every 20 years). The available datasets did not completely match the years of the aerial photographs (1978, 1991, 2003, 2010). The earliest aerial photographs classified came from 1978, which predates the commencement of the Vegetation Species Composition dataset. As a result I chose data from the nearest available years: 1983, 1992, 2003, and 2007. Slope transects were available for watershed N20B in 1992, 2003, and 2007 and for N1B in 1992.

The first step in extracting the desired information from the data was to determine the woody plant species present in the dataset. All woody species listed in the Konza Data Catalog for Data Set PVC02 (Data Catalog Version 2011.1, 2011) were analyzed related to their cover and management practices. I then downloaded the text (.txt) files containing the data for each year of interest from the Konza Prairie LTER website (http://www.konza.ksu.edu/knz/pages/data/KnzEntity.aspx?id=PVC021). To allow for sorting by watershed and plant species, I converted the text files into comma-separated value (.csv) files and opened them in Microsoft Excel. Since each species is assigned a three-digit code, I used the code to isolate the cover information for the woody plant species. I refined the data further by separating the trees, shrubs, and woody forbs from one another (Table 1). Not all of the woody species identified initially were present in the watersheds and years analyzed.

Because the cover data for the woody species in Data Set PVC02 is in the form of categorical cover classes, it is not directly comparable to the percent cover figures derived from the classification of aerial photographs. To make the cover classes usable I converted each class value to the midpoint of the class range, expressed as a percentage (Table 2). The result was a spreadsheet containing percent cover values in each plot for all woody plant species found in the two watersheds of interest. I derived aggregate percent woody cover values for each watershed/year by summing the percent cover of all woody plants found in each unique plot and averaging across all the plots. In several plots, summing the percent cover values interpolated from the cover classes yielded woody cover totals over 100%. I assigned a value of 100% to all such plots. I was also able to produce average woody cover by topographic position (upland, slope, and lowland). Because the woody plant species were separated into tree, shrub, and woody forb categories, the analysis yielded percent cover for each type of woody plant.

To compare the vegetation data to the woody cover data derived from the aerial photographs, I created shapefiles for each transect shown on the maps of watersheds N1B and N20B included in the Konza Data Catalog (Data Catalog Version 2011.1, 2011). I represented each transect in ArcMap 10 as a 50 meter-long line, with the position and orientation determined relative to the watershed boundaries as shown on the PDF transect maps. I then attributed each transect with its watershed and a name comprised of the soil type (topographic position) and unique identifier as shown on the map (e.g, N20B F A [Florence A], N1B T A [Tully A]). To allow for a qualitative visual comparison against the woody cover data derived from object-based image analysis (OBIA; see Chapter 2), I created a series of images containing the transect locations paired with the nearest available year's woody cover raster (i.e., 1983 and 1978, 1992 and 1991, etc.), underlain with a hillshade raster (see Figures 1-4). Florence (upland) transects are shown in green, Tully (lowland) in red, and slope in yellow. The available transect maps do not show the locations of the slope transects in N1B, vegetation data for which is available for 1992 only. Because their locations are unknown, these transects were not included in this part of the analysis.

The percent woody cover values derived from the Konza vegetation data and the aerial photographs differ fundamentally in that the former are isolated to the specific locations of each transect surveyed, then extrapolated to describe the entire watershed, while the aerial photo survey includes the entire watershed at the outset. Direct comparison of the data is thus problematic, and some data manipulation is necessary to achieve a fair comparison of the results. To that end I determined the tree and shrub cover for each transect to allow for a more useful comparison of the vegetation data and the remote sensing data. The vegetation data files are arranged in columns with percent cover figures for each species in each plot along each transect. The first five columns represent the plots for transect A for a given topographical position, the second five represent transect B, and so forth through transect D. To derive cover values for each transect, I summed separately the tree and shrub cover for the 5 plots on each transect in each watershed and divided by 5 to yield an average per transect. I then summed the tree and shrub averages to obtain total woody cover values for each transect. Because woody forbs are small and thus unlikely to be distinguishable in the aerial photographs, I did not include them in this part of the analysis.

A more quantitative comparison was possible for 2003, the only year with both an aerial photograph and available vegetation survey data. Having derived average woody cover figures per transect, I used a zonal histogram function in ArcMap 10.2.2 to determine the percentage of cells classified as woody within the area covered by each transect. First, I created a 10 m buffer with rounded ends around each 50 m-long transect line feature to roughly represent the five 10 m^2 survey plots along each transect. I then used the Zonal Histogram tool in ArcMap's Spatial Analyst toolbox with the individual transect buffer polygons as the zonal input and the 2003 woody cover classification as the value raster. The output tables contained the number of woody and non-woody cells in each transect polygon. I then used Microsoft Excel to compute the percent woody cover for each transect, thus allowing a direct comparison between the remote sensing-derived data and the Konza vegetation data.

RESULTS

Transect Locations vs. Woody Cover Classifications

The qualitative comparison of the woody cover rasters to the vegetation data for the nearest available years varied in their degrees of concurrence. The 1978 woody cover raster and the 1983 vegetation data matched relatively well. Woody cover was almost uniformly low during the early years in both datasets, and this is borne out in the comparison. Most of the transects had woody cover percentages near zero, and they fall accordingly in areas classified as non-woody. The few transects containing higher levels of cover (Tully B in N1B, Tully B and C in N20B) fall in areas classified as woody by the remote sensing analysis. A visual comparison does not show any obvious false positives in the woody cover rasters (i.e., areas classified as woody, but containing low cover in the vegetation data) (see Table 6 and Figure 1).

There was substantial divergence between the 1991 woody cover raster and the 1992 vegetation data. The cover values for watershed N1B match fairly well with a few exceptions. According to the vegetation data, the Florence transects contained low levels of woody cover, and they do indeed fall in areas classified as non-woody. The Tully transects have higher amounts of woody cover, and Tully transects B and C fall in ravine areas classified as woody. Transects A and D appear to be in areas classified as non-woody. The major divergence showed up in watershed N20B. The vegetation data show very low cover figures for all transects, while many of the transects fall in areas classified solidly as woody in the 1991 aerial photograph (see Table 6 and Figure 2).

The woody cover raster derived from the 2006 image matched well against the 2007 vegetation data. According to the vegetation data, the majority of the N1B transects contained low amounts of woody cover, and this is largely borne out in the woody cover raster. However, the woody cover raster misses both transects containing higher levels of woody cover (Tully A and B), as both fall in areas classified as non-woody. The woody cover raster matches the vegetation data well for the Tully transects, all of which the 2007 dataset show as having high levels of woody cover. Some of the Florence transects do not match as well, with the woody cover raster appearing to overestimate some (transects D) and underestimate others (transect A) (see Table 6 and Figure 4).

The quantitative comparison of the 2003 woody cover rasters and vegetation data yielded mixed results. Many of the individual transects and topographic positions matched well between the two data sets, while others are in conflict (Table 7). For example, though the numbers do not match up exactly, the four Florence (upland) transects in watershed N1B show closely corresponding low levels of woody cover. The slope transects in watershed N20B show similarly high values for transects A, B, and D, while transect C contains low woody cover in both datasets. Other groups of transects match poorly. The Tully (lowland) transects in N1B show opposite trends in the two datasets. In the vegetation data, transects A and B have high woody cover, and transects C and D have low cover. The exact opposite is true in the woody cover rasters. The Tully transects for N20B are similarly mismatched, with the woody cover rasters overestimating the cover for transects A and C and underestimating transect B versus the vegetation data. With the exception of transect A, which is underestimated, the woody cover rasters overestimate percent cover versus the vegetation data (see Table 7 and Figure 3).

Trees and Shrubs

As expected, the analyzed data showed a general increase in woody cover over time and higher percent cover in the less-frequently burned watershed (N20B). With the exception of a decline between the 1983 and 1992 samples (3.52% to 0.85%, respectively), the analysis of the vegetation survey data showed a consistent increase in percent woody cover for the N20B watershed. The sample plots in this less-frequently burned watershed contained 30.60% woody cover in the final year analyzed (2007). The woody cover trends were more ambiguous for N1B, the annually burned watershed. Woody cover figures ranged from a low of 6.31% in 1992 to a high of 8.78% in 2003. Shrub cover drove much of the variation over time in both watersheds, while percent cover of trees remained low in both watersheds over the sample period. Tree cover never rose above 0.09% for N1B (1983) and 0.19% for N20B (2007). The remainder of the woody cover for each watershed was comprised of shrub cover (Table 3).

Though the percent woody cover relative to topographic position did not exhibit a clear upward trend over time, the numbers for the upland, lowland, and slope classes did vary distinctly from one another. In all years with non-zero percent cover figures, the lowland sample plots contained much higher woody cover than the upland plots. For watershed N1B total woody cover in the lowland plots varied from 12.38% in 1983 to 17.95% in 1992, while woody cover in the upland plots ranged from 0.25% in 2003 to 0.53% in 1992. The trends were similar in N20B, with the lowland plots ranging from 0.00% in 1992 to 48.43% in 2007 versus an upland range of 0.05% in 1983 to 6.60% in 2003. Woody cover data in the slope position was available for only 1992 in the N1B watershed, when it reached 0.45%. Woody cover in the slope plots for N20B occupied a middle range between the upland and lowland classes, ranging from 2.25% in 1992 to 38.68% in 2007 (Table 4).

As was the case with the overall cover figures, the bulk of the total woody cover for the different topographic positions was comprised of shrub cover. No trees were present in the upland plots in either watershed, and the lowland tree cover did not exceed 0.18% (1983)

in N1B and 0.43% (2007) in N20B. The one available slope transect available for N1B also contained no trees. Tree cover in the slope class for N20B did not rise above 0.18% (2003) (Table 4).

Woody Forbs

The woody forb species included in the vegetation data exhibit different percent cover trends both as a function of time and of topography than the tree and shrub species. Woody forb cover increased from the first sample year (1983) to the last sample year (2007) for both watersheds, but the total numbers in the interim years do not follow a constant trend. After starting at a low level in 1983 (2.08%), woody forb cover in watershed N1B stayed relatively stable throughout the other years: 12.16% in 1992, 14.05 % in 2003, and 13.24% in 2007. Watershed N20B displayed a similar trend, but with more variation. Cover was low in 1983 (5.58%) and fluctuated at higher levels throughout the other sampled years: 10.40% in 1992, 24.53% in 2003, and 19.3% in 2007 (see Table 5).

Woody forb cover as a function of topography followed a trend opposite to the one observed for tree and shrub cover. The upland sample plots contained much higher numbers of woody forbs than the lowland plots, and when available, the slope transects contained the most woody forbs. In watershed N1B, woody forb cover in the lowland plots varied from 0.23% (1983) to 1.55% (2003), while the upland plots ranged from 3.9% (1983) to 26.55% (2003). For the only year in which slope plots were available for watershed N1B (1992), those plots contained 20.48% woody forbs versus lowland and upland figures of 1.2% and 14.80% respectively (see Table 5).

The same pattern holds for watershed N20B, where the lowland plots ranged from 0.30% (1992) to 1.43% (2007) versus a range of 9.98% (1983) to 31.10% (2003) for the upland plots. When available, the slope plots contained either the highest or nearly the highest amount of woody forb cover versus the other topographic position. The slope plots ranged from 15.43% in 1992 (against an upland figure of 15.48%, the only sample year in which slope plots didn't contain the greatest amount of cover) to 41.50% in 2003 (see Table 5).

DISCUSSION

Comparison with Remote Sensing Analysis

The qualitative visual comparison of the aerial image-derived woody cover rasters and the ground-collected vegetation data reveals some mismatches between the two datasets, and indicates a mixed record for the OBIA technique used to classify the images. There are a number of factors inherent in both datasets and the techniques used to analyze them that can explain much of the divergence.

The first and most readily apparent issue is that, with one exception, the woody cover rasters and vegetation data I compared are from different years. Each woody cover raster is a snapshot in time and is unlikely to closely match ground data from a different point in the growing season, let alone a different year. The effects of this temporal mismatch can be best illustrated by comparing the woody cover raster derived from a 1991 aerial photograph to the vegetation data from 1992. The classified data almost uniformly overestimated the amount of woody cover relative to the ground-based vegetation data, especially in watershed N20B. The burn history of the Konza Prairie can explain nearly all of this difference between the datasets. Watershed N20B experienced two unplanned burns between 1991 and 1992, the first on April 5, 1991, and the second on October 20, 1991. Because the exact date of the 1991 image (which is likely a mosaic of images taken on different dates) is unknown, it is unclear whether or not the April 5 burn happened before or after the image. The absence of visual evidence in the image of a recent burn, such as areas blackened with soot, indicates that the image originated either before the burn or long after it. Nevertheless, the watershed was burned at least once before the June 1992 vegetation data collection (Methods Manual Version 2011.1, 2011, Konza Prairie LTER, 2016). These burns would have greatly decreased the amount of woody cover present in 1992 versus the amount of woody cover detected by classifying an image from 1991. Though these unplanned burns complicate a comparison of woody cover relative to burn frequency between watersheds N1B and N20B, the data are still valuable for illustrating woody cover over time as a function of actual burn history. Similar, less obvious dynamics such as climate or local ecological factors could be at work in the other mismatched image-vegetation data pairs. The Konza Prairie vegetation data is thus of limited utility in evaluating the results of the OBIA technique used to derive the woody cover rasters, and the rasters are only somewhat useful as means of extrapolating the transect-based data to entire watersheds.

Setting aside the temporal mismatch responsible for much of the divergence between the two woody cover datasets, some limitations of the remote sensing analysis can also explain the differing woody cover estimates. The first source of inaccurate woody cover rasters is the presence of shadows in the source aerial photographs. Shadows are especially problematic in high-spatial resolution imagery such as aerial photographs, which contain a higher degree of shadow than spatially coarse satellite imagery (Laliberte et al., 2004). Studies of woody encroachment are particularly troubled by shadows, as shadowed areas tend to have spectral characteristics similar to encroaching plants such as juniper, relative to the background matrix (Sankey and Germino, 2008). Shadows can lead to overestimation in which dark areas that resemble trees but are really shadows are classified as encroaching trees or shrubs. Shadowed areas can also lead to underestimation in that they obscure areas containing pixels that would otherwise end up classified as woody plants.

All of the images used in this study contained large areas of shadow in the ravines present in the study area. Shadows can plausibly explain some of the differences between the two datasets. The shadows are concentrated in the areas of lowland (Tully) soils, which happen to be the areas containing the highest levels of woody cover in watersheds N1B and N20B. Some of these shadowed areas would have ended up classified as woody, inflating the woody cover figures represented by the rasters. The results of the 2003 quantitative analysis lend some support to the idea that shadows caused problems in the lowland parts of the classifications. The mismatches between the vegetation data and the woody cover rasters were most pronounced for the Tully transects in both watersheds (see Table 7). Part of the classification cleanup involved manually reclassifying image objects that had been classified as woody but clearly included mostly or entirely shadow pixels. This manual process was imperfect, and it is likely that it erroneously removed some image objects from the woody class. Many of the manual reclassifications may have been correct, but the reclassified shadow objects may have contained woody plants not visible in the aerial photograph. The net result of these errors would be an underestimation of woody cover in some areas.

Another source of potential error in the woody cover classifications relative to the Konza vegetation data is the technique used to classify the objects created by the image segmentation. My classification used three different traits to distinguish woody plants from the grassy matrix surrounding them: brightness, texture, and height. This approach to classification was successful in separating non-grassy areas from the grassy background. The subsequent analyses of the classified data operated under the assumption that two classes were present in the photographs: woody plants and non-woody plants. Such an assumption may not be justified, and it is likely that many of the plants classified as woody are in fact non-woody plants that differ spectrally and texturally from and are taller than grasses. The woody cover rasters would thus contain plant species not classified as woody in the Konza vegetation data (see Table 1), meaning that the results of the remote sensing analysis would end up overestimating the amount of woody cover across the study area. Use of the normalized difference vegetation index (NDVI) could help to minimize the influence of this error, as it is able to distinguish different plant varieties from one another by exploiting their stronger and more varied response in the near-infrared (NIR) spectral band. Unfortunately, NDVI requires access to NIR data, and it was available only for 2006. I did use NDVI where available (2006 and 2010), but direct comparison of the results with and without the NIR data and the NDVI figures did not reveal any great differences in the woody cover figures (see Chapter 2).

In addition to the issues inherent in the image classifications that may lead to inaccuracies when compared to in situ data, features of the 2003 woody cover raster warrant special consideration, especially since 2003 is the only year for which a direct quantitative comparison between the classification and the ground data is available. Initial attempts to segment and classify the 2003 NAIP image in eCognition were unsuccessful because of the graininess (i.e., high spectral variation from pixel to pixel) of the image. The software was unable to distinguish the color and texture of the grass and non-grass areas of the image to create meaningful image objects as it had for the other image years. As a result, it was necessary first to perform the segmentation and classification on only one band of imagery rather than all three (R,G,B) bands, and second, to filter the image with a 3x3 low-pass filter. The end result of these manipulations was an image missing much of its original spectral information and lacking some of its sharpness.

The manipulated image likely produced a less accurate classification of woody and non-woody vegetation relative to conditions on the ground. The lack of multispectral information would have decreased the eCognition software's ability to apply the thresholds used to group pixels into image objects and distinguish them from one another (see Chapter 2 for details on this process). This could have resulted in adjacent woody and non-woody pixels being grouped together, with one or the other type of pixel being subsumed into an object of the other type. This decreased accuracy would cause both errors of commission and omission, with some woody pixels getting lumped into grass objects and vice versa. The lower spatial resolution caused by the filtering process helped to resolve the graininess and allowed for smoother segmentation and classification, but it would have increased the chances of pixels being categorized and classified incorrectly. Overall, the problems with the 2003 image likely led to both over- and underestimation in parts of the study area, thus explaining the discrepancies with the Konza vegetation data.

Temporal and Spatial Variation in Tree and Shrub Cover

Woody cover in the two watersheds surveyed follow expected trends. N1B, the annually burned watershed, contained a consistently low level of both trees and shrubs throughout the study period. N20B, the infrequently burned watershed, contained more woody plants, and woody cover increased steadily over the course of the period studied. Shrubs comprised the majority of the woody cover, while levels of tree cover remained below 1.0% in all of the years studied.

Previous studies of vegetation trends in the Konza Prairie point to fire frequency, topography, and climate as the main drivers of tallgrass prairie species composition (Gibson and Hulbert, 1987). Burn history seems to explain the trends observed in watersheds N1B and N20B over the period 1983 to 2007. Watershed N1B was not burned between April 1973 and April 1988. This lengthy period without any burns would have allowed woody plants, shrubs primarily, to establish a baseline level before annual burns commenced in 1988. Burning took place between February and April in each of the years surveyed between 1992 and 2007. The sample plots in N1B were all surveyed between July and August in the different study years. With the exception of 1983, N1B had thus been burned prior to the vegetation survey. The frequent burns would not have allowed the shrubs to expand beyond the baseline level established prior to 1988. Burn frequency alone cannot explain the rise in shrub cover to 8.78% in 2003 before its return to around 6% in 2007. While burn frequency is an important measure of the role played by fire in tallgrass prairie ecology, the timing of burns during the growing season can determine the degree to which fire affects the balance between grasses and woody plants. The early season burns applied to watershed N1B may be less effective at removing woody plants than late season burns that are intensified by hot, dry weather conditions and higher fuel loads (Briggs et al., 2005). Though burning happened each year in watershed N1B, woody plants may have reached a density during the long, unburned period up to 1988 that made them resistant to weak early-season fires. Fire frequency alone is not sufficient to explain the trends in the data. Fire quality (temperature, intensity), timing of burns within the growing season (i.e., fall vs. spring burns), spatial coverage over the watershed, and environmental factors (soil moisture, air temperature, wind speeds) can limit the degree to which burning kills woody plants. Some interaction between climate, fire dynamics, and the unchanging topography is likely behind the woody cover increase observed over the annually burned period (Konza Prairie LTER, 2016).

As was the case with watershed N1B, N20B was not burned at all during the period prior to 1983, dating back to the beginning of burn history records in 1973. Shrubs were able to establish baseline coverage of around 3% during this period. N20B was burned in October 1991, about ten months prior to the August 1992 vegetation survey. The burn reduced shrub coverage to below 1% (0.85%). The watershed was subject to unplanned burns in September 1992 and March and April 1996, but it has not been burned again up to the present day. As expected, the lack of burning allowed shrub cover to rebound and exceed its previous levels, reaching levels closer to 30% in 2003 and 2007 (Konza Prairie LTER, 2016). The available data cannot explain why the seven unburned years from 1996 to 2003 are associated with a much more dramatic increase in shrub cover versus unburned decade prior to 1983.

Previous studies of woody plant expansion in tallgrass prairies point to some feedback processes that may explain the non-linear increase in woody cover the study period. Clonal woody plant species such as *Cornus drummondii* (roughleaf dogwood), a prime encroacher into tallgrass prairie, expand easily into grassy areas by sharing deep water sources with their clonal offshoots, thus reducing resource competition with grasses and forming shrub "islands" whose diffuse edges are insufficiently dense to support intense fires (Ratajczak et al., 2011). These shrub islands, once established, support higher levels of soil nitrogen, which is the limiting nutrient in the tallgrass prairie environment (Briggs et al., 2005), thus allowing the shrubs to thrive and expand further. Low burn frequency exacerbates these dynamics by allowing shrub islands to form. Once formed, the shrubs cannot be removed by even frequent fires, and these positive feedbacks relative to the surrounding grasses allow them to both remain in place and to expand further. Though trees comprised only a small portion of the woody cover found in the Konza vegetation data, positive feedbacks can allow their cover to increase in a non-linear fashion. Once trees are established, they tend to beget additional trees through seed dispersal and increasing shade and outcompeting grasses (Van Auken, 2000; Zald, 2009; Limb et al., 2010). Eastern Red Cedar, one of the primary encroaching tree species, can also change soil chemistry in a manner that favors future tree growth (McKinley and Blair, 2008; McKinley et al., 2008). All of these feedback processes require the establishment of a baseline population of trees and shrubs, which tends to happen when fire frequency and intensity decrease. Fire frequency thus appears to be a primary determinant of woody cover dynamics across the period studied.

Though the results of this study show noticeable differences in woody cover between different topographic positions, with lowland and slope areas containing more woody plants than upland areas, the relationship does not seem to be causal. Topographic position as expressed in the Konza Prairie vegetation data is in reality a proxy measure of soil type (upland Florence soils and lowland Tully soils) as opposed to other measures of topography such as aspect or degree of slope. Soil type does have an impact on the growth and expansion of so-called gallery forests along stream channels and ravines in the Flint Hills, as the hardwood tree species involved tend to grow in soils comprised of alluvial-colluvial deposits (Abrams, 1986; Knight et al., 1994; Briggs et al., 2005). The available vegetation data for the Konza prairie shows very low cover figures for tree species across the period of my study. Thus, the only species directly affected by topographic position/soil type do not figure in my results.

The observed differences in woody cover across the different topographic positions/soil types are a likely a result of the impacts of fire. Gibson and Hulbert (1987) characterize soil type (as determined by topography) as playing a “secondary role” in species composition in tallgrass prairies; it is, instead, more of a starting condition on which one can compare the impacts of burning, fire being a primary shaper of the vegetation community.

Insofar as soil type affects species composition, it can affect fuel loads and fire intensity (Abrams and Hulbert, 1987; Briggs et al., 2005). Topography, as expressed in my study, is not by itself a determinant or driver of woody plant encroachment.

Woody Forbs

The woody forb cover figures from the Konza Prairie vegetation data cannot be compared directly to the results of the aerial photograph analysis. Woody forb plants are too small (<1 m^2) in area to show up definitively in the photographs used to classify woody cover in the selected watersheds. The finest spatial resolution of the photographs I used in the remote sensing portion of the study was 1 m, which is too coarse to reliably distinguish woody forbs from other plant species found in the study area. The OBIA technique I used to characterize woody encroachment in the Konza Prairie is thus not appropriate for determining changes in woody forb cover over time.

Independent of the remote sensing analysis, the vegetation data reveal some interesting trends in woody forb cover as a function of both time and location. While the percent cover figures fluctuate over the period of the study, the burn histories of the two watersheds seem to explain most of the variation. Previous studies have emphasized fire as the primary determinant of plant community composition in tallgrass prairies, especially with regard to woody plant cover (Abrams and Hulbert, 1987; Gibson and Hulbert, 1987). With the exception of 1983, the N1B transect was burned between February and April of all the years studied (N1B was not burned between April 1973 and April 1988). All of the vegetation surveys took place between July and August of the different years, meaning that N1B had been burned before the data was collected. The woody forb cover figures for all the burned years range only between 12.16% and 14.05%. The lack of burning between

1973 and 1988 likely explains the increase from 2.08% cover in 1983 to 12.16% cover in 1992 (see Table 5). The long, unburned period prior to 1988 seems to have established a higher baseline cover for woody forbs than what existed at the beginning of the study, with the more frequent later burns keeping the cover relatively constant (Konza Prairie LTER, 2016).

The trends over time for N20B also track well with the burn history. The lengthy period with no burns allowed woody forb cover to climb in 1992 to a figure nearly double that found in 1983 (10.40% versus 5.58%; see Table 5). The increase would probably have been even greater had watershed N20B not been burned in October 1991, ten months before the vegetation surveys were conducted. With the exception of three unplanned burns in September 1992 and March and April of 1996, N20B remained unburned for the remainder of the study period (and up to the present day). The lack of burning explains the much higher woody forb cover in 2003 (24.53%), but burning alone cannot explain why the 2007 figure declined to 19.30%. Gibson and Hulbert (1987) identify three major determinants of plant community composition in tallgrass prairies: fire, topography and associated variations in soil type, and climate. Because the first two factors are either known or constant across the period studied, climate is the most likely explanation for any variations that cannot be directly attributed to either fire or topography (Konza Prairie LTER, 2016).

The relationship between woody forb cover and topographical position runs counter to the one observed for trees and shrubs. Whereas trees and shrubs tended to be most dense in lowland areas, woody forbs were most prevalent in the slope and upland areas. Other studies have found a similar relationship between forb density and topographic position, with forbs being most abundant in upland areas (Abrams et al., 1986). Abrams and Hulbert (1987) found a similar trend in their study of the effects of fire and topographical position on various prairie plants. Abundance of *Amorpha canescens* (leadplant), the only woody forb shared between their study and mine, was greater in upland plots when burn frequency was not a factor. They speculate that the higher proportions of forb species in uplands may be a result of the lower productivity of upland soils, which allows more competition with the dominant grasses (pg. 443). Further study would be needed to untangle the relationship between topography, burning, and woody forb prevalence, but the topographical trends in the vegetation data seem to be in agreement with more detailed studies of prairie plant communities.

CONCLUSION

The qualitative comparison of the Konza Prairie vegetation data and the woody cover rasters derived from classified aerial photographs yielded varying results. The 1978 raster matched well with the 1983 vegetation data, as did the 2006 raster with the 2007 vegetation data. Temporal mismatch between the datasets accounts for much of the divergence between the respective woody cover results. For example, the 1991 raster and 1992 vegetation data matched poorly largely because of an unplanned fire in watershed N20B between the 1991 image and the 1992 vegetation data survey. Features of the aerial photographs causing false positives and negatives in the classifications, especially shadows in lowland areas, also explain some of the differences between the results. The object-based classification process used to produce the woody cover rasters, which distinguished only between grasses and non-grasses, may also have produced inaccuracies that caused mismatches with the vegetation data. The quantitative comparison of the 2003 woody cover raster and vegetation data yielded mixed results, with some transects matching well between the datasets, versus others matching very poorly. Problems with the 2003 aerial photograph, combined with the aforementioned issues with the procedure used to produce the rasters, can account for the inconsistent results.

Analysis of the Konza Prairie vegetation data showed consistent increases in tree, shrub, and woody forb cover across the period 1983 to 2007. The woody cover trajectories track well with the burn histories of watersheds N1B and N20B. Decreases in woody cover follow the recorded burns, and the more frequently burned watershed (N1B) contained lower levels of woody cover across the period studied. Woody cover increased in a non-linear fashion from 1983 to 2007, with a much greater rate of increase in the latter part of the time range than at the beginning. This result points to the existence of various positive feedbacks detailed in the woody encroachment literature. Topographic position is associated with differing levels of woody cover. Shrub cover was greatest in lowland areas and lowest in upland areas, with cover on slopes falling in the middle. Tree cover was consistently low (<1%) in all transects and years studied. Woody forb cover displayed an opposite trend, with upland or slope areas having the highest amount of cover and lowlands the lowest.

The object-based technique used to produce the woody cover rasters from historical aerial photographs does appear to have promise as a means of studying woody encroachment over large spatial extents. Further refinement is necessary to reduce the inaccuracies caused by shadows and misclassifications. The Konza Prairie vegetation data serves as a reliable ground dataset that could be used to determine the accuracy and reliability of future iterations of the object-based approach to deriving woody cover rasters. Future studies should focus on years where aerial photographs and vegetation data are both available to allow for the fairest comparison. The Konza Prairie vegetation data, beyond its application as a ground reference for remote sensing analysis, is useful in itself as a way to study woody encroachment trends and dynamics. Vegetation data are available for watersheds beyond N1B and N20B, and the techniques used in this study could be applied to other sections of the Konza Prairie. The continued improvement of the object-based approach to classifying woody plants from aerial photographs, as aided by the Konza Prairie vegetation data, could result in a reliable means of tracking and managing woody encroachment throughout the last remaining stands of the once extensive North American tallgrass prairie.

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Table 1
Common woody plant species in the Konza Prairie.

Scientific name	Common name
Trees	
Ulmus americana	American Elm
Gleditsia triacanthos	Honey Locust
Celtis occidentalis	Common Hackberry
Juniperus virginiana	Eastern Red Cedar
Cercis canadensis	Eastern Redbud
Shrubs	
Symphoricarpos orbiculatus	Coralberry
Prunus americana	American Plum
Cornus drummondii	Roughleaf Dogwood
Rhus glabra	Smooth Sumac
Rhus aromatica	Fragrant Sumac
Zanthoxylum americanum	Common Prickly Ash
Woody Forbs	
Amorpha canescens	Leadplant
Ceanothus herbaceus	Jersey Tea
Rosa arkansana	Wild Prairie Rose

Table 2
Cover classes and interpolated values.

Cover class	Cover (%)	Interpolated values (%)[a]
1	<1	0.5
2	1-5	3
3	5-25	15
4	25-50	37.5
5	50-75	62.5
6	75-95	85
7	95-100	97.5

[a]Values determined from cover class range midpoints

Table 3
Average woody plant coverage in survey plots, 1983-2007.

Year	Tree cover (%)	Shrub cover (%)	Total woody cover (%)
N1B			
1983	0.09	6.25	6.34
1992	0.00	6.31	6.31
2003	0.00	8.78	8.78
2007	0.03	6.53	6.56
N20B			
1983	0.01	3.51	3.52
1992	0.00	0.85	0.85
2003	0.18	27.36	27.54
2007	0.19	30.41	30.60

Table 4
Average woody plant coverage in survey plots by topographic position, 1983-2007.

Year	Topographic position	Tree cover (%)	Shrub cover (%)	Total woody cover (%)
N1B				
1983	Upland	0.00	0.30	0.30
	Lowland	0.18	12.20	12.38
1992	Upland	0.00	0.53	0.53
	Lowland	0.00	17.95	17.95
	Slope	0.00	0.45	0.45
2003	Upland	0.00	0.25	0.25
	Lowland	0.00	17.30	17.30
2007	Upland	0.00	0.50	0.50
	Lowland	0.03	12.55	12.58
N20B				
1983	Upland	0.00	0.05	0.05
	Lowland	0.01	6.98	6.99
1992	Upland	0.00	0.30	0.30
	Lowland	0.00	0.00	0.00
	Slope	0.00	2.25	2.25
2003	Upland	0.00	6.60	6.60
	Lowland	0.38	44.70	45.08
	Slope	0.18	30.78	30.96
2007	Upland	0.00	4.70	4.70
	Lowland	0.43	48.00	48.43
	Slope	0.15	38.53	38.68

Table 5
Average woody forb coverage in survey plots across topographic positions and all plots, 1983-2007.

Year	Topographic position	Woody forb cover (%)
N1B		
1983	Upland	3.90
	Lowland	0.25
	Total	***2.08***
1992	Upland	14.80
	Lowland	1.20
	Slope	20.475
	Total	***12.16***
2003	Upland	26.55
	Lowland	1.55
	Total	***14.05***
2007	Upland	25.18
	Lowland	1.30
	Total	***13.24***
N20B		
1983	Upland	9.98
	Lowland	1.18
	Total	***5.58***
1992	Upland	15.48
	Lowland	0.30
	Slope	15.43
	Total	***10.40***
2003	Upland	31.10
	Lowland	0.98
	Slope	***24.53***
	Total	
2007	Upland	22.60
	Lowland	1.43
	Slope	33.88
	Total	***19.30***

Table 6
Average tree and shrub cover per unique transect, 1983-2007.

Transect [a,b,c]	1983	1992	2003	2007
N1B				
Florence A	0.20	0.70	0.60	0.60
Florence B	0.10	0.00	0.10	0.60
Florence C	0.80	1.30	0.30	0.80
Florence D	0.10	0.10	0.00	0.00
Tully A	2.00	8.40	24.80	20.30
Tully B	43.00	47.10	40.60	26.60
Tully C	1.20	7.90	1.40	1.50
Tully D	3.30	8.40	2.40	1.90
Slope A	-	0.00	-	-
Slope B	-	1.20	-	-
Slope C	-	0.00	-	-
Slope D	-	0.60	-	-
N20B				
Florence A	0.20	0.00	18.30	12.50
Florence B	0.00	0.00	7.50	3.20
Florence C	0.10	1.20	0.60	3.00
Florence D	0.00	0.00	0.00	0.10
Tully A	0.70	0.00	22.40	18.90
Tully B	17.20	0.00	55.20	60.10
Tully C	8.90	0.00	48.50	53.30
Tully D	1.20	0.00	54.20	61.40
Slope A	-	6.60	69.60	75.00
Slope B	-	0.60	23.80	35.40
Slope C	-	1.80	0.30	3.70
Slope D	-	0.00	30.10	40.60

[a] Florence = upland position, Tully = lowland position
[b] Slope transect data unavailable for years marked with dashes
[c] Locations of N1B slope transects unknown

Table 7
Woody cover per transect derived from image classification and vegetation data, 2003.

Transect [a,b,c]	**% cover, image classification**	**% cover, vegetation data**
N1B		
Florence A	0.00	0.60
Florence B	0.00	0.10
Florence C	0.00	0.30
Florence D	0.00	0.00
Tully A	0.00	24.80
Tully B	0.00	40.60
Tully C	27.13	1.40
Tully D	5.26	2.40
Slope A	-	-
Slope B	-	-
Slope C	-	-
Slope D	-	-
N20B		
Florence A	0.00	18.30
Florence B	41.85	7.50
Florence C	21.91	0.60
Florence D	56.17	0.00
Tully A	87.93	22.40
Tully B	15.53	55.20
Tully C	98.75	48.50
Tully D	1.23	0.00
Slope A	81.48	69.60
Slope B	84.26	23.80
Slope C	0.00	0.30
Slope D	16.05	30.10

[a] Florence = upland position, Tully = lowland position
[b] Slope transect data unavailable for years marked with dashes
[c] Locations of N1B slope transects unknown

Figure 1
1978 woody cover raster

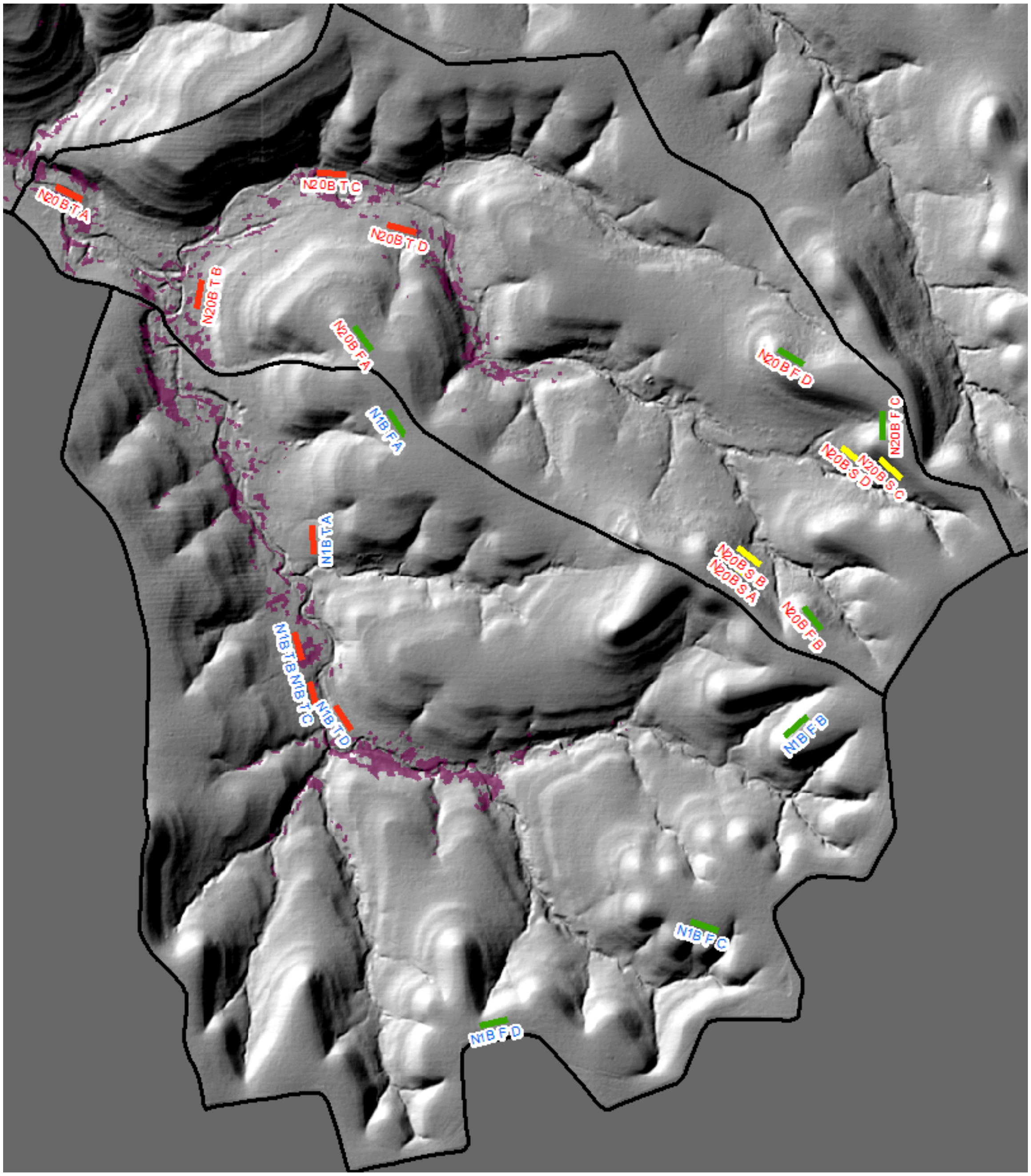


Figure 2
1991 woody cover raster

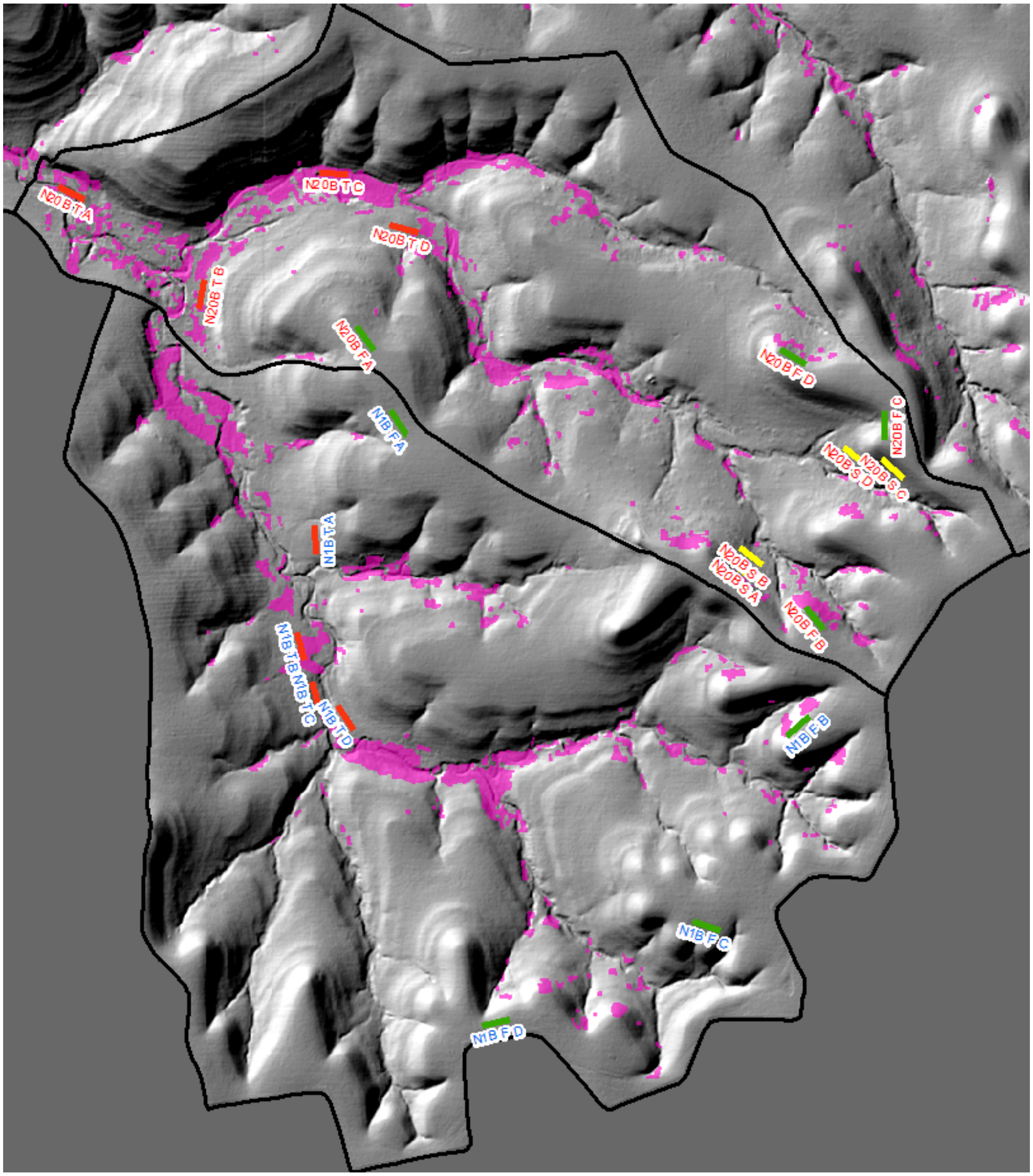


Figure 3
2003 woody cover raster

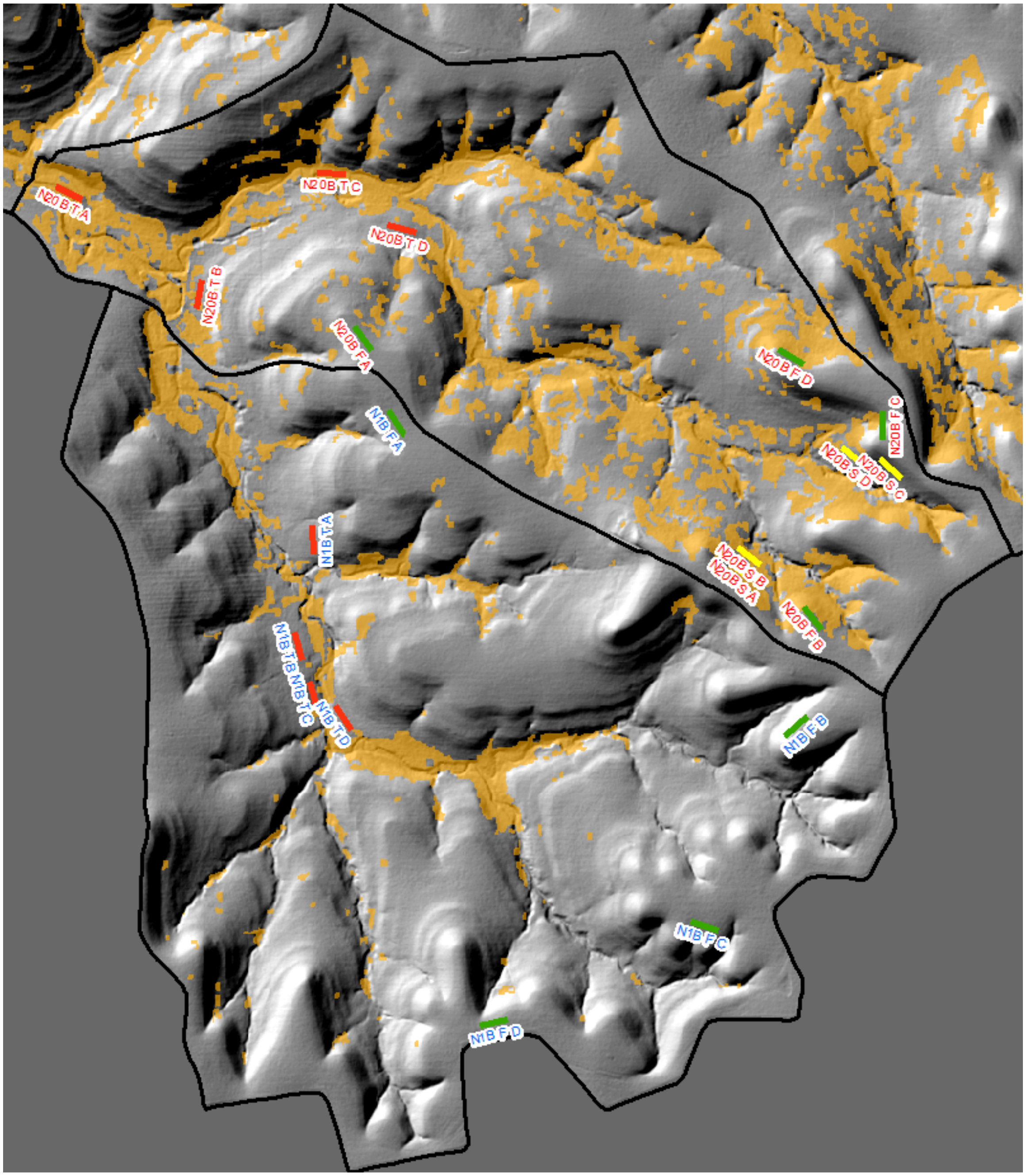
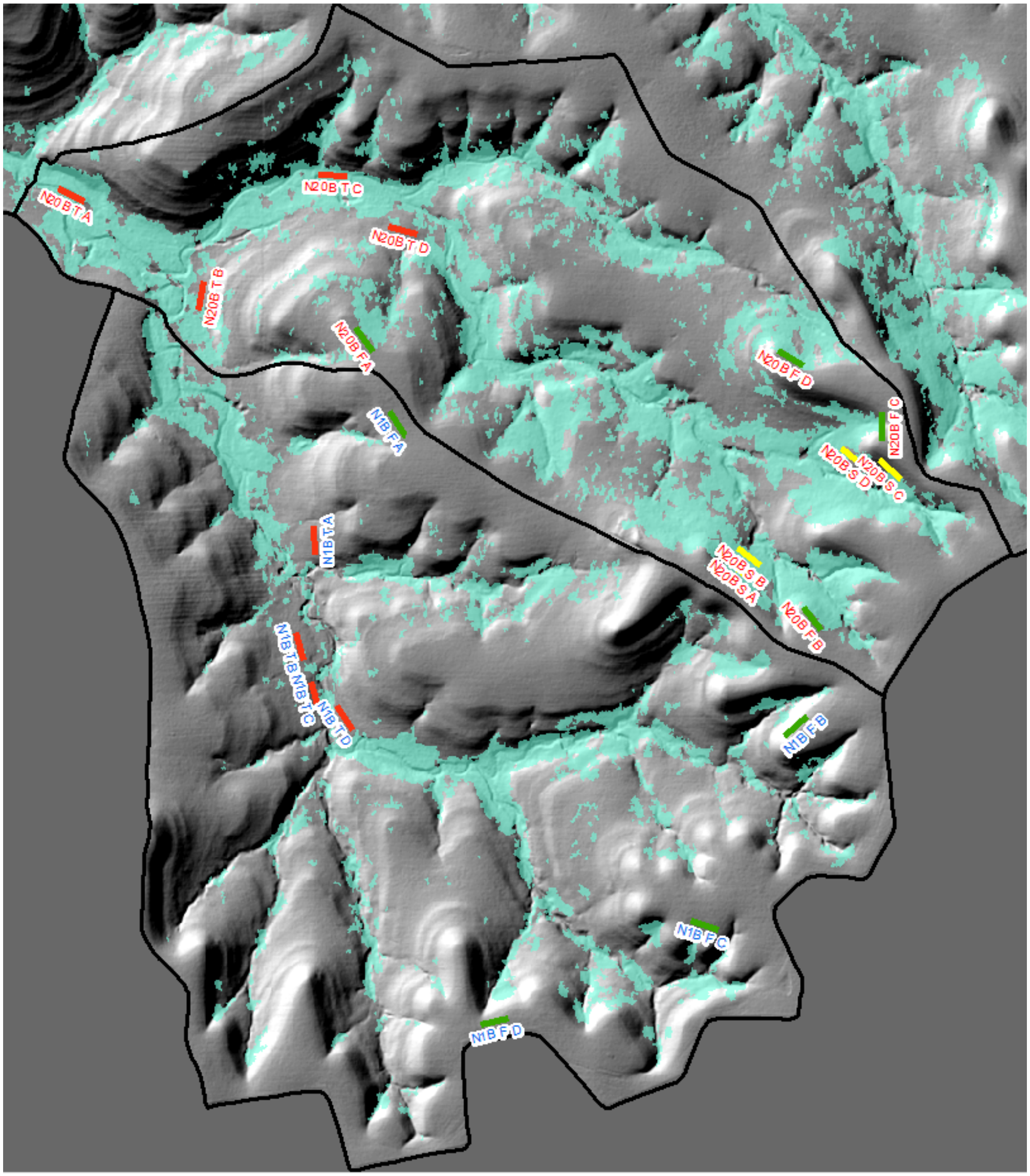


Figure 4
2006 woody cover raster



Chapter 4

CONCLUSIONS

Encroachment by woody plants and trees is one of the primary threats to the ecological health of tallgrass prairie. The control of woody encroachment is a major concern for tallgrass prairie management, and a means of gathering reliable data on encroachment patterns and processes would be a valuable tool for preserving prairies. To that end, this study had two main objectives. First, the study tried to determine the usefulness of an object-based approach to classifying woody plants in historical aerial photographs by looking at the extent of woody cover over time in an area of tallgrass prairie in north central Kansas. Second, the study used ground-based vegetation survey data to provide a measure of validation for the woody cover data derived from the classified aerial photographs and to draw some tentative conclusions about woody encroachment dynamics.

RESULTS

The first portion of this study used object-based image analysis (OBIA) of historical aerial photographs to determine changes in woody plant cover in a portion of the Konza Prairie Biological Station (Konza Prairie) over the period 1978-2010. The resulting classifications showed a substantial increase in woody cover over time, from 3.65% cover in 1978 to a peak cover in 2006 of 20.2% and 15.25% cover in 2010. Of the variables analyzed alongside the classified aerial photographs, burn frequency showed the strongest relationship to observed woody cover. The two watersheds with the lowest burn frequency included in the study (K20A and N20B, both burned every 20 years) showed the most dramatic increases in woody cover. The smallest increases in woody cover were in the watersheds burned every two years (K2A and N2B). The study included several other environmental variables: topography (slope and aspect), presence/absence of grazing, and precipitation. None of these other variables demonstrated a clear relationship with the extent of woody cover.

The OBIA portion of the study included several different forms of remote sensing data: panchromatic (black & white) imagery, full color (RGB) imagery, near-infrared (NIR), and LIDAR. The study thus allowed for a comparison of the relative usefulness of different forms of data for studying woody plant cover. In the years for which multiple forms of remote sensing data were available, the resulting classifications did not reveal any substantial differences. In other words, the inclusion of less commonly available data such as NIR and LIDAR did not provide any added value over more readily available aerial photographs.

The second portion of the study analyzed ground-based vegetation survey data available for the Konza Prairie over the period 1983-2007. The purpose of this analysis was twofold: first, to compare the results on the ground to the results of the raster maps derived from the OBIA, and second, to investigate woody vegetation trends over time and relative to some environmental variables. Direct comparison of the woody cover rasters and the vegetation data was problematic because of mismatches in collection dates and because vegetation data were available for only two of the watersheds (N1B and N20B) included in the first portion of the study. As a result, the comparisons yielded mixed results. However, despite the lack of correspondence between the respective results, the 1978 raster matched well against the 1983 vegetation data, as did the 2006 raster and the 2007 vegetation data. Both a woody cover raster and vegetation data were available for 2003, which allowed for a quantitative transect-by-transect comparison. Because of problems with the quality of the 2003 aerial photograph used to derive the woody cover raster and the simple woody/non-woody schema used to classify the aerial photographs, the quantitative analysis showed close matches between some transects and divergences with others.

Separate from the remote sensing analysis, the Konza Prairie vegetation data showed a consistent increase in woody cover (i.e., cover of trees, shrubs, and woody forbs) over time. Woody cover followed the burn histories of the two watersheds, with cover declining after recorded burns and lower levels across the period studied for the more frequently burned watershed (N1B). The increase in woody cover over the period 1983 to 2007 was not linear. The greatest increases occurred in the later portion of the time period, which provides some indirect evidence for positive feedbacks identified in the literature on woody encroachment dynamics (Van Auken, 2000; Zald, 2009; Limb et al., 2010; Ratajczak et al., 2011). The vegetation data included topographical position (upland, lowland, and slope), and woody cover differed as a function of topography. Shrub cover was greatest in lowland and slope transects and lowest in the upland areas. Woody forb cover displayed an opposite pattern.

SUMMARY

The OBIA approach to classifying aerial photographs is a promising method for studying woody encroachment in grassland areas. Because of its focus on image objects rather than on individual pixels, it is particularly adept at isolating objects that appear clearly against a more or less uniform background matrix (e.g., trees and shrubs in grassy areas). OBIA does not require advanced forms of imagery such as NIR or LIDAR to produce a quality classification. It is thus ideal for studies over extended time periods for which only panchromatic or RGB images are available. The exact segmentation and classification parameters that will best isolate encroaching woody plants in aerial photographs will vary from one study area to another. The present study provides a baseline approach to segmentation and classification that can be adjusted to meet the needs of a particular study. While this study focused on a relatively small area, the techniques used here could be applied to larger spatial extents as needed.

Though data availability limited the validity of the comparisons between the Konza Prairie vegetation data and the woody cover rasters produced by the OBIA analysis, the points where the datasets converge in time and space show promising trends. To the extent that the two datasets allow for comparison, the results demonstrate the promise of OBIA of aerial photographs as a means of studying woody encroachment in tallgrass prairie. The vegetation data available for the Konza Prairie is itself a rich source of information on woody cover over time. The techniques used in this study to isolate the woody plants in the dataset could be used to look at all the available data for the Konza Prairie and draw some broader conclusions.

Future studies could expand upon the techniques used here to gain more detailed knowledge in the dynamics of woody encroachment. First, the OBIA technique could be refined. The comparisons against the Konza Prairie vegetation data revealed two weaknesses in the procedure used to produce the woody cover rasters: the presence of shadows in lowland areas, and the use of a simple woody/non-woody classification scheme. Lowland areas in the Konza Prairie have the highest levels of woody cover, making shadows especially problematic. Future studies could involve additional image processing aimed at reducing the over- and underestimation of woody cover caused by these lowland shadows. A more complex classification scheme may be a way to increase the validity of the woody cover rasters. Though it is not widely available over time, NIR data could provide a means of distinguishing woody plants from other non-grass vegetation present in the aerial photographs. Where it is available LIDAR could also help to filter non-woody plants out of the classification rasters.

Overall, the techniques used in this study show promise for the study of woody encroachment in tallgrass prairies. They provide a starting point that can be improved and expanded into a robust means of analyzing woody plant cover over greater temporal and spatial extents that is not necessary reliant on small-scale and labor intensive ground-based studies. This study is thus of potential value both to the literature on woody encroachment and to the practice of managing the vanishing tallgrass prairies of North America.

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