

ESTIMATES OF CANOPY NITROGEN CONTENT IN HETEROGENEOUS GRASSLANDS
OF KONZA PRAIRIE BY HYPERSPECTRAL REMOTE SENSING

by

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Abstract

Hyperspectral data has been widely used for estimates of canopy biochemical content over the past decades. Most of these studies were conducted in forests or crops with relatively uniform canopies. Feasibility of the use of hyperspectral analysis in heterogeneous canopies with diverse plant species and canopy structures remains uncertain. Spectral data at the canopy level, with mixed background noise, canopy biochemical and biophysical properties create more problems in spectral analysis than that at the leaf level. Complications of heterogeneous canopies make biochemical retrieval through remote sensing even more difficult due to more uneven spatial distribution of biochemical constituents. The objective of my research was to map canopy nitrogen content in tallgrass prairie with mixed canopies by means of hyperspectral data from in-situ and airborne measurements. Research efforts were divided into three steps: (1) the green leaf area index (LAI) retrieval, given LAI is an important parameter in scaling nitrogen content from leaves to canopies; (2) canopy nitrogen modeling from analysis of in-situ hyperspectral data; and (3) canopy nitrogen mapping based on aerial hyperspectral imagery. Research results revealed that a fine chlorophyll absorption feature in the green-yellow region at wavelengths of 562 – 600 nm was sensitive to canopy nitrogen status. Specific spectral features from the normalized spectral data by the first derivative or continuum removal in this narrow spectral region could be selected by multivariate regression for nitrogen modeling. The optimal nitrogen models with high predictive accuracy measured as low values of root-mean-square error (RMSE) were applied to the aerial hyperspectral imagery for canopy nitrogen mapping during the growth seasons from May to September. These maps would be of great value in studies on the interactions between canopy vegetation quality and grazing patterns of large herbivores in tallgrass prairie.

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Chapter 1 - Introduction

Research Background

Interactions between grazing strategies of herbivores and vegetation quality are of great interest in grassland ecosystem science. Grazing activities can shape the structure and composition of grassland vegetation and therefore influence vegetation quality. The grazed site is often of higher nutrition returns with greater plant species diversity than the ungrazed (Collins et al. 1998) due to the capability of plants to overcompensate for low levels of herbivory (McNaughton 1983). Interactively, vegetation quality is one of the major factors that influence grazing strategies of herbivores, and the sites with higher concentration of nutrition are likely to be more frequently used by grazers (Focardi et al. 1996; Post and Klein 1996). Canopy nitrogen content as an important measure of vegetation quality can be linked to grazing patterns, which is of considerable value in studies on the roles of herbivores in grassland ecosystem dynamics.

The traditional method of measuring nitrogen by chemical analysis is tedious and expensive; particularly for a large study site, a great number of foliar samples are required in order to be sufficiently representative of the variability in the whole area (Foley et al. 1998; Mutanga et al. 2005). Hyperspectral remote sensing, a burgeoning technique widely used in detection of vegetation and water resources over the past two decades (Govender et al. 2007), provides a fast and cost-efficient approach to estimating concentration of plant biochemicals (e.g., chlorophyll, protein, nitrogen, calcium, magnesium, etc.) through analysis of the remotely sensed reflected spectral data (Curran et al. 2001; Mutanga et al. 2005).

Early studies used hyperspectral data collected from dried ground foliar samples in laboratory coupled with regression statistics to predict plant biochemistry concentration (Norris et al. 1976). Dried ground leaves are superior to fresh leaves for spectral analysis in that spectral signals may be affected by water and unevenly distributed biochemical constituents in fresh leaf tissues (Yoder and Pettigrew-Crosby 1995). However, this laboratory spectroscopy analysis at the leaf scale was limited when research emphasis shifted to canopy chemistry estimates based on in-situ or aerial imagery spectrometers (Sembiring et al. 1998; Johnson et al. 1994).

Spectral analysis at the canopy scale in the field is more complicated than at the leave scale in the laboratory in that the canopy reflectance spectrum is disturbed by background

variations in the field. Methods of normalizing spectral signals to minimize the background effects have been developed, for example, the first derivative and continuum removal (Kawamura et al. 2008; Kokaly and Clark 1999; Kokaly et al. 2003). The first derivative reflectance characterizes the changes of the original reflectance, by which the background effects are countervailed (Laba et al., 2005). Continuum removal provides a common baseline that allows the spectral features to be standardized and compared (Kokaly 2001; Mutanga et al. 2004).

Additionally, hyperspectral vegetation indices (VIs) integrating spectral values at different wavelengths can normalize spectral features (Daughtry et al. 2000; Wu et al. 2008; Sims and Gamon 2002). The standardized difference between two spectral values is the most commonly used form of VI, due to its inherent scaling of the spectral signals and reduced sensitivity to background variations (Ferwerda et al. 2005; Delalieux et al. 2009).

In addition to disturbance by background variations, spectral mixture of both biochemical (i.e., leaf biochemistry concentration) and biophysical properties (i.e., the biomass and the leaf area index (LAI)) at the canopy level also contributes to complications in changing the scale of analysis from leaf to canopy. The biophysical parameter LAI is an important determinant of canopy nitrogen estimates. A quantitative relationship exists between LAI and nitrogen content in uniform canopies, which varies in response to different developmental phases of the canopy. For a young unclosed canopy, the relation between LAI and canopy nitrogen can be approximated linearly. As the canopy is fully developed with lowest senescent leaves, a logarithmic model fits well into the LAI and canopy nitrogen relation (Yin et al., 2003). Given influences of the biophysical properties, the canopy-integrated method (He and Mui 2010) has been proposed for biochemistry quantification from the leaf to the canopy scale, by which canopy biochemistry content can be calculated as leaf biochemistry concentration multiplied by LAI (Gitelson et al. 2005).

LAI can be measured indirectly by non-destructive means based on theoretical models for LAI estimates in terms of canopy geometry attributes or light extinction (Chen et al. 1997). However, accuracy of the non-destructive LAI measurements is questionable when the canopy structure characteristics don't conform to the assumptions in the theoretical models (He et al. 2007). Alternatively, the normalized difference vegetation index (NDVI) has the potential to be a good indicator of LAI. In general, a linear LAI-NDVI relationship is limited in the closed canopy

due to NDVI saturation, although a linear relationship between NDVI and LAI may occur over a limited range of LAI (Pontauiller et al. 2003). An exponential curve is often used to describe the relation between LAI and NDVI to avoid clear NDVI saturation at the high range of LAI (Fan et al. 2009).

With regard to extraction of spectral features related to plant nitrogen content, since most nitrogen is concentrated in chlorophyll molecules (Yoder and Pettigrew-Crosby 1995), the visible-near infrared (NIR) spectrum region (400 – 1000 nm) with chlorophyll absorption features has been emphasized in a number of previous studies (Peñuelas et al. 1994; Mutanga et al. 2005). The red edge at wavelengths of 680 – 740 nm, the transition between reflectance in the visible and the NIR resulting from strong chlorophyll absorption in the red wavelengths and canopy scattering in the NIR, is an important chlorophyll related spectral feature. As leaf chlorophyll concentration increases, the area of the absorption trough in the spectrum is broaden and the red edge position switches to longer wavelengths (Dawson and Curran, 1998). However, the use of the red edge to estimate chlorophyll content may be limited at the canopy scale due to the influence of spectral mixture in canopies (Curran et al. 1990). The green-yellow region, the downward flank of the major chlorophyll absorption feature in the red wavelengths, is sensitive to pigment concentration in most leaves (Blackburn 2007). This region carries a fine absorption feature at wavelengths of ~ 550 – 600 nm in response to stress of leaf chlorophyll concentration (Carter and Knapp 2001), which is expected to be available in estimates of foliar nitrogen status.

Research Goals

This study was conducted in Konza Prairie Biological Station (KPBS), U.S. KPBS is part of the Flint Hills tallgrass prairie in northeastern Kansas (39°05'N and 96°35'W), characterized by variable continental climate with warm, wet springs, hot summers and dry, cold winters. Mean annual precipitation of 826 mm with ~ 75% falling during April – September supports growth of the vegetation dominated by C_4 grasses of great species diversity in the prairie. KPBS is a site developed for long-term studies on ecological patterns and processes in grassland ecosystem. The site is divided into more than 50 watersheds managed with different frequencies of controlled spring burning (1, 2, 4 and 20 years). 10 contiguous watersheds of ~ 1012 ha are designed to support bison grazing (a large ungulate in North American grassland).

The overarching goal of this study was to map canopy nitrogen content in KPBS based on hyperspectral analysis. Nitrogen maps coupled with data of bison distributions would be of great value in understanding interactions between forage quality and grazing patterns of bison. Challenge in this study was that feasibility of the use of hyperspectral analysis to estimate nitrogen content, though proved by most past studies conducted in forests or crops with relatively uniform canopies (Martin and Aber, 1997; Gong et al., 2002; Sembiring et al., 1998), was uncertain in heterogeneous canopies of KPBS with complicated structure characteristics across mixed plant species. The overarching goal was achieved through three steps:

- Determine the LAI-NDVI relationship at KPBS for retrieval of the canopy biophysical parameter LAI
- Estimate canopy nitrogen content from in-situ hyperspectral data for heterogeneous canopies in KPBS
- Map canopy nitrogen at KPBS using hyperspectral aerial imagery based upon previous analysis of canopy nitrogen retrieval by in-situ measurements

Chapter 2 explored non-destructive methods of LAI retrieval using remote sensing. LAI measurement by the ceptometer was limited in senescent canopies. Empirical LAI-NDVI modeling provided alternative to retrieving LAI. Chapter 3 examined in-situ spectral data in the green-yellow region at wavelengths of 562 – 600 nm. Regression was applied to the normalized spectral features by the first derivative, continuum removal and the standardized difference to select significant spectral features for nitrogen modeling. Chapter 4 compared the spectral data from in-situ and airborne measurements for nitrogen modeling. In-situ spectral features were similar to but not identical with the spectral features from aerial imagery. The fine chlorophyll absorption feature sensitive to nitrogen status in the green-yellow region can be detected in both in-situ data and aerial imagery. Major findings of my research were summarized in Chapter 5.

Chapter 2 - Non-destructive Leaf Area Index Measurements in Heterogeneous Grasslands with Different Fire Frequencies

Abstract

Leaf area index (LAI) is an important variable for studying the biophysical characteristics of vegetation canopy. A number of destructive and non-destructive methods have been developed for LAI measurements. Non-destructive methods based on analysis of remotely sensed measurements of canopy geometry attributes or light extinction have been widely used because of convenience and that there is less impact on the measured canopy compared to the destructive method. This study focused on non-destructive LAI measurements for heterogeneous vegetation canopies in tallgrass prairie. Analysis of ground LAI measurements by the LP-80 ceptometer along with hyperspectral data revealed that senescent leaves accumulated for years in the canopy with low fire frequency could result in overestimates of green LAI. Given the limitations of the ceptometer in senescent canopies, LAI-NDVI relationships were investigated to provide an alternative to LAI estimation. Both the linear and the exponential predictive models for LAI estimation from NDVI were approximated and evaluated by the jackknife cross-validation. The exponential model showed slightly higher predictive accuracy measured as the lower root mean square error (RMSE) than the linear model. This validated exponential LAI-NDVI relationship was expected to be a critical step toward future studies on detection of nitrogen contents in heterogeneous canopy, in that green LAI should be a significant parameter in estimates of canopy nitrogen.

Key words: LAI, NDVI, non-destructive, heterogeneous grasslands, jackknife

Introduction

Leaf area index (LAI), defined as the amount of green leaf area per unit land area in vegetation canopies, is a pivot parameter for studying structural characteristics and biophysical processes of vegetation surfaces. For example, information on LAI is critical in modeling net primary productivity (Prieto-Blanco et al., 2009), growth efficiency (Waring, 1983), ecological and hydrological systems in temperate climates (Breuer et al., 2003), and vegetation-atmosphere

interaction (McWilliam et al., 1993). In addition, LAI is an important determinant of scaling up biochemical content estimation from the leaf to the canopy level (He and Mui, 2010). For homogeneous vegetation surfaces, the canopy-integrated approach has been proposed for chlorophyll quantification, in which the total chlorophyll content in the canopy has been defined as LAI multiplied by the leaf chlorophyll concentration (Gitelson et al., 2005). There have also been investigations into the quantitative relationship between LAI and canopy nitrogen content in uniform vegetation canopies. This relationship varies depending on different developmental phases of the canopy. For a young, unclosed canopy, the relation between LAI and canopy nitrogen can be approximated linearly. As the canopy is fully developed with lowest senescent leaves, a logarithmic model can be a good fit to the LAI and canopy nitrogen relation (Yin et al., 2003).

Given the importance of LAI in studies of biophysical features and processes of vegetation canopies, a variety of destructive and non-destructive methods have been developed to measure LAI directly or indirectly. The destructive method determines LAI directly by calculating the leaf area per unit land surface area of samples taken from the vegetation canopy, an invasive, expensive and time consuming approach, particularly in large study areas. Compared to the destructive method, non-destructive methods are fast and economical, and cause less harm to the terrestrial ecosystems in the vegetation canopies. LAI is determined indirectly by non-destructive means based on theoretical models for LAI estimates in terms of canopy geometry attributes or light extinction, which can be measured by various remote sensors. Due to the efficiency and effectiveness of such non-destructive methods, an increased number of spatial samples widely distributed throughout the whole study area can be obtained. The disadvantage of non-destructive methods is that the LAI values may be underestimated because of the mismatch between the canopy architecture characteristics and the physical model for LAI calculation (He et al., 2007).

Non-destructive methods have been widely used in studies related to various vegetation canopies for reasons of convenience if compared to the destructive method. Commonly used non-destructive LAI instruments include HemiView (Delta-T Devices, Ltd., UK), LAI-2000 plant canopy analyzer (LI-COR, Inc., USA), and AccuPAR LP-80 (Decagon Devices, Inc., USA). These instruments estimate LAI based on inversion models given an assumption of random leaf angle distribution in the canopy (Chen et al., 1997). The gap fraction is an important input

parameter in inversion models. HemiView calculates the gap fraction by measuring the proportion of the visible sky area from the upward-looking hemispherical photography. LAI-2000 measures the transmitted light under the canopy from five angles to calculate the gap fraction for five zenith angle ranges. For LP-80 LAI ceptometers, the gap fraction is determined by the ratio of the photosynthetically active radiation (PAR) under the canopy to the incident PAR above the canopy. Such non-destructive instruments have been playing an increasingly important role in approximating LAI readily and economically.

Another approach to estimating LAI is to investigate relationships between vegetation indices (VIs) and LAI. The advantage of this approach is that the LAI-VI relationships can be applied to mapping LAI distribution over wider areas using hyperspectral or multispectral imagery. Several VIs have been demonstrated to be good indicators of LAI, including the normalized difference vegetation index (NDVI), renormalized difference vegetation index (RDVI), soil-adjusted vegetation index (SAVI), adjusted transformed soil-adjusted vegetation index (ATSAVI), and litter-corrected ATSAVI (L-ATSAVI) (Haboudane et al., 2004; Wang et al., 2005; Reu Jean and Breon, 1995; Huete, 1988; Baret and Guyot, 1991; He et al., 2006). Among these VIs, NDVI has been used most frequently in a large number of studies. In general, a linear LAI-NDVI relationship, although applicable at the lower range of LAI, is limited in closed canopy due to NDVI saturation (Pontauiller et al., 2003). An exponential curve is therefore often used to describe the relationship between LAI and NDVI to avoid clear NDVI saturation at the high range of LAI (Fan et al., 2009).

The objective of this study was to determine the feasibility of non-destructive LAI measurements in heterogeneous grasslands. This would be a critical step toward future studies on detecting nitrogen content in complicated canopy of mixed composition. In this study, in-situ LAI samples were measured using an LP-80 ceptometer, and corresponding hyperspectral data were collected by Analytical Spectral Devices (ASD). Limitations of LP-80 used in mixed grasslands of various structure and composition, in that both green and senescent leaves in the canopy have been measured, were investigated and discussed. Based on this analysis of applicability of LP-80, LAI-NDVI regression models were determined to provide an alternative to LAI estimation. Although LAI-NDVI relationships had been investigated in a great number of previous studies (Colombo et al., 2003; Eklundh et al., 2001; Gong et al., 2003; Lee et al., 2004;

Turner et al., 1999), challenges and opportunities existed given the time and site specificity of those existing empirical models.

Methods

Study Area

The study area is located in Konza Prairie Biological Station (KPBS), the United States. KPBS is part of the Flint Hills tallgrass prairie in northeastern Kansas (39°05'N, 96°35'W), characterized by variable continental climate with warm, wet springs, hot summers and dry, cold winters. Mean annual precipitation is approximately 826 mm with 75% falling during the April to September growing season. Vegetation in this area is dominated by C4 perennial grasses with high species diversity. KPBS consists of more than 50 watersheds managed with different fire frequency and grazing patterns. The area of each watershed ranges from 2 to 200 ha. The in-situ data were collected within three watersheds, N1B, N4D, and N20B, with different fire frequencies. The fire frequency of N1B, N4D and N20B is 1, 4 and 20 years respectively (Fig. 2.1), which contributes to variance in canopy structure and composition of different watersheds.

Data Collection

15 10 m×10 m plots with 6 subplots randomly arrayed around the plot center (Fig. 2.2) were dispersed in each watershed for field data collection (Fig. 2.1). This random sampling was done in order to ensure the range of variability of the collected samples. LAI and hyperspectral data were obtained in 6 subplots to calculate the average for each plot during the canopy growth seasons (June 29 to July 1, and August 1 to August 2, Table 2.1).

An LP-80 ceptometer was used to measure LAI. The LP-80 consists of a data logger and probe with 80 independent sensors mounted as a 0.75 m linear array. These sensors measure PAR in the 400 – 700 nm wavelength, the portion of the spectrum which plants use for photosynthesis. The total incident PAR above canopy and the transmitted PAR below canopy were measured in each subplot. Hyperspectral data were measured to derive NDVI by a portable spectrometer (ASD), approximately 1.5 m above the target surface, yielding a 0.4 m² circular field of view. The spectral resolution, which varies depending on measured wavelengths between 0.3 to 2.5 μm, is approximately 3 nm at the 700 nm wavelength.

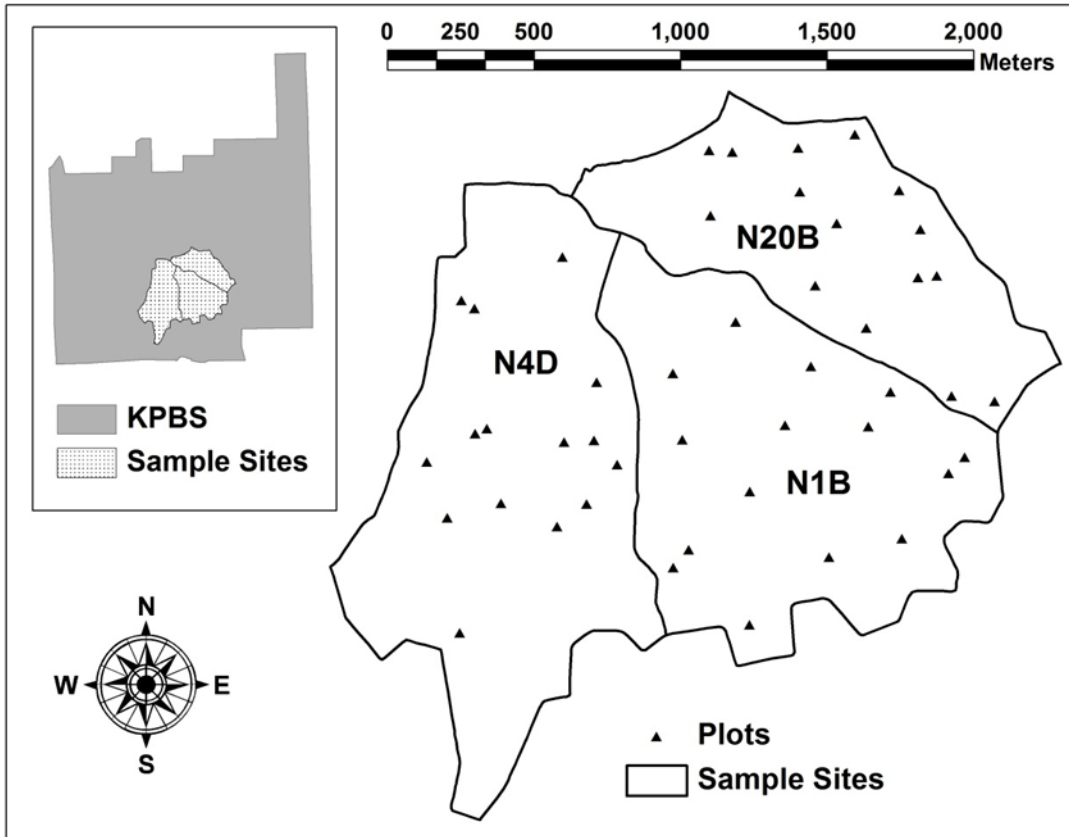


Figure 2.1 Study sites in Konza Prairie Biological Station (KPBS). KPBS includes more than 50 watersheds with different fire frequencies. Samples for this study were collected in three watersheds, N1B, N4D and N20B, with the fire frequency of one year, four years and 20 years respectively.

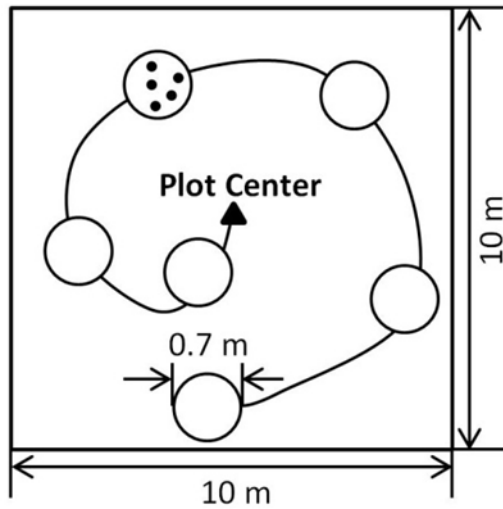


Figure 2.2 Plot design. 15 10 m×10 m plots with 6 subplots spirally arranged around the plot center were set up for data collection in each of the three watersheds. Hyperspectral measurements for each subplot were taken from a 0.4 m² circular field of view with a diameter of 0.7 m. Five foliar samples were clipped in each field of view for chemical analysis of leaf nitrogen concentration.

Table 2.1 Available samples of LAI and corresponding hyperspectral data

<i>Dates</i>	<i>Watersheds</i>	<i>Sample Size</i>
June 29 – July 1	N1B	15
	N4D	15
	N20B	15
August 1 – August 2	N1B	12
	N4D	5
	N20B	15

Data Analysis

LAI Calculation

Calculation of LAI involves application of the Beer-Lambert Law, from which the probability of a ray of light penetrating the canopy can be calculated with an assumption that the elements of a canopy are randomly distributed in space. The probability of penetration is equal to the gap fraction $G(\theta)$ as a function of zenith angle of the solar beam θ (Marshall and Waring, 1986; Martens et al., 1993). Formally:

$$G(\theta) = e^{-K \cdot L} \quad (2.1)$$

Where L is the LAI of the canopy, and K is the extinction coefficient depending on the angle θ and the leaf angle distribution of the canopy. Assuming the angle distribution is spherical, K can be simplified to $K=1/(2\cos\theta)$. $G(\theta)$ is measured by LP-80 ceptometer as the ratio of PAR below canopy (PAR_{below}) to above canopy (PAR_{above}). Solving for LAI gives:

$$L = -2 \cos \theta \cdot \ln \frac{PAR_{below}}{PAR_{above}} \quad (2.2)$$

Analysis of Hyperspectral data

Visible and near infrared (NIR) bands were extracted from hyperspectral data to derive NDVI. The average reflectance values in the green (553 – 558 nm), red (670 – 678 nm) and NIR (780 – 800 nm) regions were calculated respectively to attain robust data of reflectance. NDVI was calculated as the ratio of the difference between NIR and red reflectance to the sum of NIR and the red (Table 2.2).

Regression

In-situ data were grouped by watersheds according to their acquisition dates for analyses of variance at different spatial and temporal scales. In order to determine general models across temporal scales, data collected during two different periods (June 29 – July 1, and August 1 – 2) were put together for each watershed (Table 2.3). Because NDVI is unsaturated in tallgrass prairie, linear regression models were used to approximate LAI-NDVI relationships for each dataset. Exponential regression relationships were also examined to see if they provided better models to describe LAI-NDVI relationships.

Table 2.2 Visible and NIR bands extraction and NDVI calculation

<i>Variables</i>	<i>Calculation</i>
G (Green reflectance)	Average reflectance in the region of 553 – 558 nm
R (Red reflectance)	Average reflectance in the region of 670 – 678 nm
NIR	Average reflectance in the region of 780 – 800 nm
NDVI	$NDVI = (NIR - R) / (NIR + R)$

Table 2.3 Datasets of in-situ LAI and NDVI values

<i>Watersheds</i>	<i>Fire Frequency</i>	<i>Dates</i>	<i>Sample Size</i>
N1B	1 year	June 29 – July 1	15
		August 1 –August 2	12
		June 29 – July 1 & August 1 –August 2	27
N4D	4 years	June 29 – July 1	15
		August 1 –August 2	5
		June 29 – July 1 & August 1 –August 2	20
N20B	20 years	June 29 – July 1	15
		August 1 –August 2	15
		June 29 – July 1 & August 1 –August 2	30

Validation

Given the small sample size of this study, the jackknife, a cross-validation technique, was applied to remove the parameter bias and to assess the performance of the regression model (Abdi and Williams, 2010; Efron and Gong, 1983; Miller, 1974). The jackknife is an iterative leave-one-out procedure, which drops one observation in turn, models from the remaining observations, and then uses the model to estimate the left-out observation each time. In this way, each observation can be compared to its corresponding estimator to evaluate the accuracy of the model.

The applicability of the jackknife is limited in non-linear functions in that the bias is removed by subtraction which is a linear operation. For the exponential models in this study, linear models could be achieved by natural logarithm transformation. The correlation coefficient R was non-linear statistics also. Fisher Z-transformation (Hotelling, 1953) was used to transform the values of R for jackknife estimation. Formally:

$$z = \frac{1}{2} \ln \frac{1+R}{1-R} \quad (2.3)$$

Results and Discussion

Canopy Characteristics

The descriptive statistics of LAI and NDVI in three watersheds with different fire frequencies revealed the canopy characteristics of this site (Table 2.4). Taken as a whole, vegetation canopies were of low LAI ranging from 0.23 to 3.68 and unsaturated NDVI ranging from 0.39 to 0.91. The mean NDVI varied slightly from 0.66 to 0.71 with a range of 0.05.

Among the three watersheds, N1B with the highest mean NDVI of 0.71 was at the lowest ranges of LAI from 0.23 to 2.31 with the mean LAI of 1.28. In contrast, N20B had the lowest mean NDVI of 0.66, but its LAI ranged from 0.95 to 3.68 with the greatest mean of 2.24. This unusual inverse correlation between the mean NDVI and LAI measurements might be explained by taking into account the variance in biophysical characteristics of canopies with different fire frequencies. For canopies in N20B with the fire frequency of 20 years, a great amount of senescent leaves were accumulated continuously for years, which might impact the growth of vegetation canopy by occupying the space where young vegetation was supposed to grow. In this

way, the greenness, reflected by NDVI, in watersheds with low fire frequency was less than with high fire frequency. Meanwhile, the senescent leaves might contribute to the overestimates of green LAI by the LP-80 ceptometer in that these senescent materials could intercept the solar light passing through the canopy, resulting in an underestimated PAR measurement below the canopy.

Also, this influence by the senescent leaves had been shown in anomaly of an evident inverse correlation between LAI and green reflectance for canopies in watershed N20B (Fig. 2.3). High LAI corresponding to low green reflectance indicated that greater part of the dense canopy might consist of senescent leaves.

LAI-NDVI Relationships

Both linear and exponential regressions were applied to fit relationships between LAI and NDVI (Fig. 2.4, Fig. 2.5 and Fig. 2.6). For each watershed, in addition to two individual datasets for different periods, regressions fitted the combined dataset of the two periods, which determined general models to describe LAI-NDVI relationships throughout the growth seasons.

Among the general models for the three watersheds, R^2 values for models in N1B were the greatest (0.67 for the linear model and 0.73 for the exponential model), indicating data of N1B were well approximated by the regression lines. However, regressions were inapplicable in N20B given the low values of R^2 . R^2 close to 0 indicated extremely low proportion of the data can be explained by the regression line. The deteriorated performance of regressions in N20B could be related to the unreliable LAI measurements influenced by senescent leaves due to the low fire frequency.

All the models of N1B had R^2 greater than 0.5, indicating each model in N1B could account for more than 50% of variance in the dataset. In general, exponential relationships were better approximators than linear ones given higher R^2 of exponential models indicated greater proportion of variability in data can be explained by the exponential regression lines. The greatest R^2 existed in models for the dataset of August 1 – 2 in N4D (0.86 for the linear model and 0.85 for the exponential model) (Fig. 2.5 (b)). However, reliability of models for this particular dataset could be greatly compromised by the insufficient sample size.

Table 2.4 Descriptive statistics summary of LAI and NDVI

<i>Watersheds</i>	<i>Sample</i>	<i>LAI(m²·m⁻²)</i>				<i>NDVI</i>			
	<i>Size</i>	Mean	Min.	Max.	Std. Dev.	Mean	Min.	Max.	Std. Dev.
N1B	27	1.28	0.23	2.31	0.60	0.71	0.39	0.91	0.14
N4D	20	1.63	0.63	2.63	0.56	0.69	0.49	0.83	0.10
N20B	30	2.24	0.95	3.68	0.68	0.66	0.47	0.81	0.10

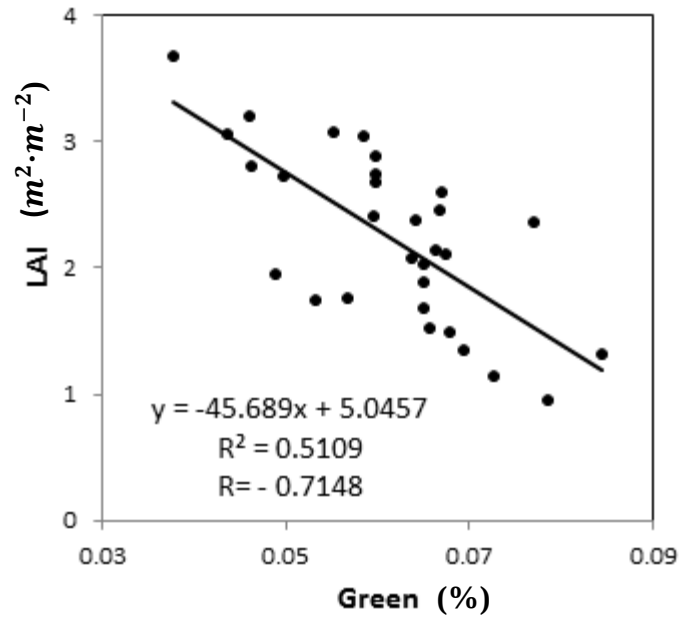


Figure 2.3 Correlation between LAI and the green reflectance (553 – 558 nm) in N20B. Anomaly existed in the negative correlation coefficient that indicated LAI was inversely related to the green reflectance. The overestimated green LAI might result from the influence by the senescent leaves.

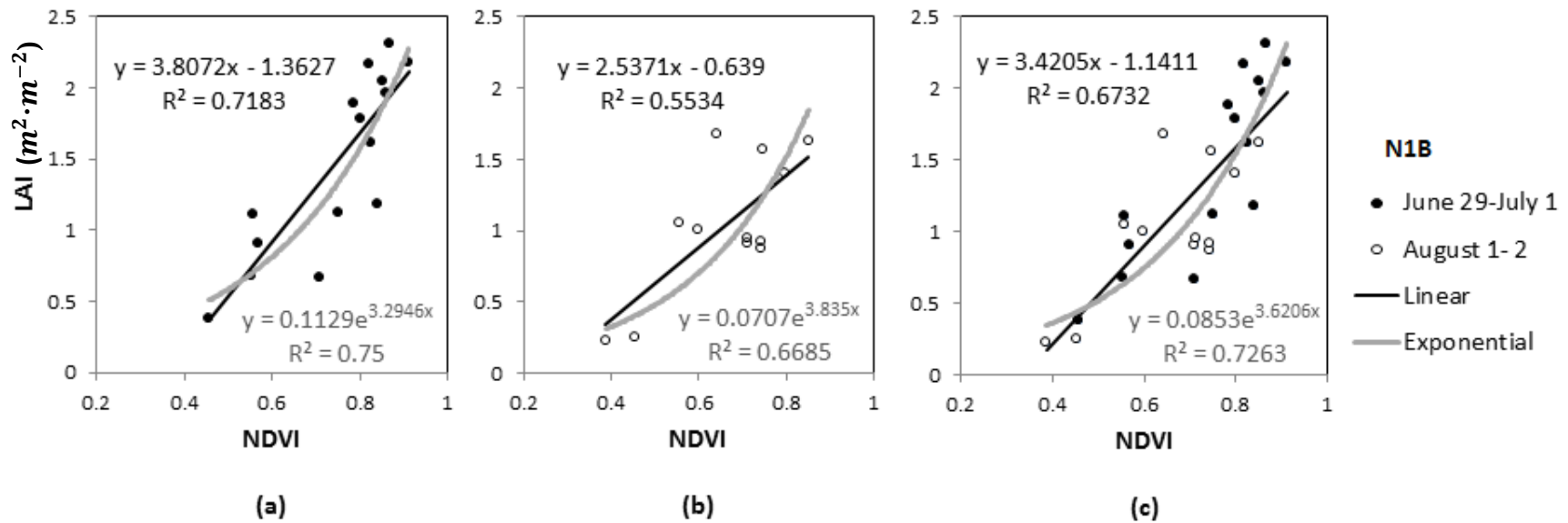
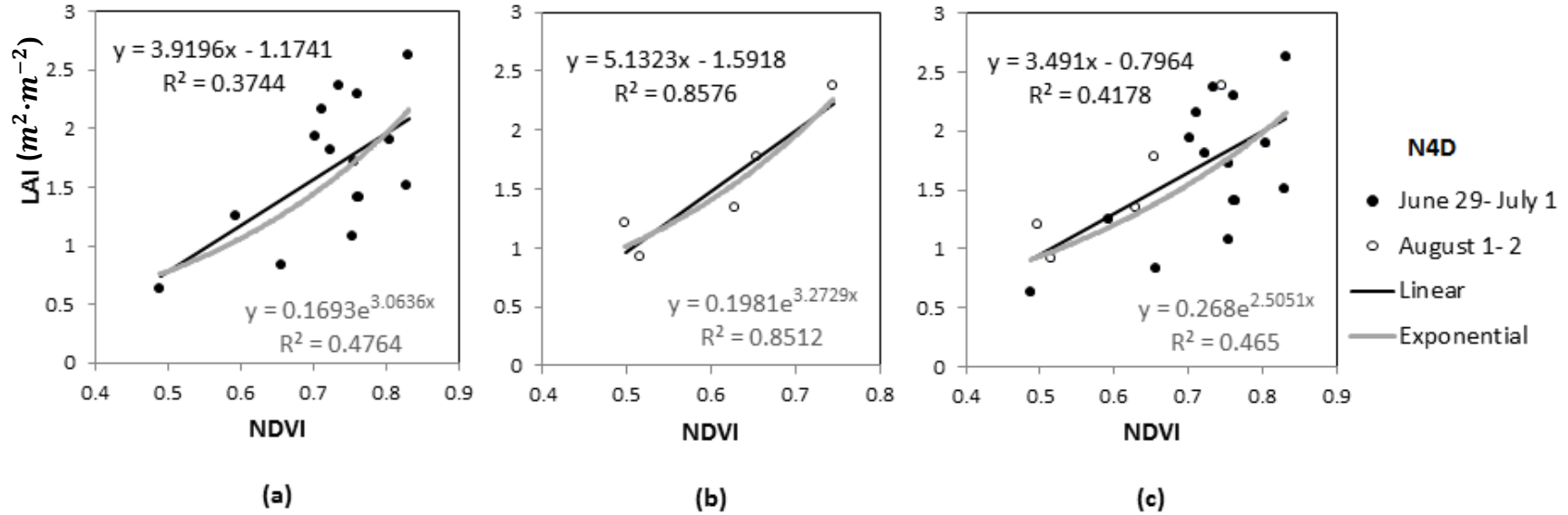


Figure 2.4 Linear and Exponential LAI-NDVI relationships in watershed N1B with fire frequency of 1 year for datasets of (a) June 29 – July 1, (b) August 1 – August 2, and (c) June 29 – July 1 & August 1 – August 2. The empirical coefficients of LAI-NDVI relationships varied slightly over time by comparison of (a) and (b). General linear and exponential models for N1B were determined by fitting the combined dataset (c) of (a) and (b). R^2 of the exponential model was higher than of the linear model in each dataset, indicating that the exponential model could account for greater proportion of variability in the dataset.



20 **Figure 2.5 Linear and Exponential LAI-NDVI relationships in watershed N4D with fire frequency of 4 years for datasets of (a) June 29 – July 1, (b) August 1 – August 2, and (c) June 29 – July 1 & August 1 – August 2. Analysis emphases might be focused on datasets of (a) and (c), in that reliability of models for the dataset (b) though with relatively high R^2 could be compromised by the insufficient sample size.**

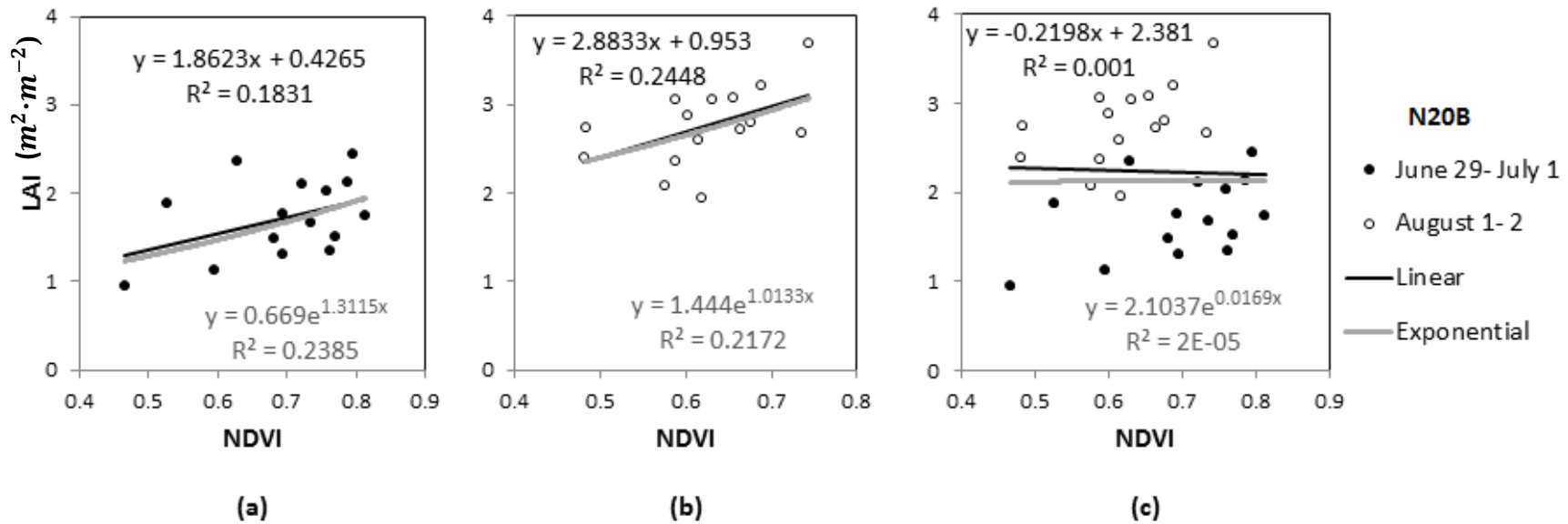


Figure 2.6 Linear and Exponential LAI-NDVI relationships in watershed N20B with fire frequency of 20 years for datasets of (a) June 29 – July 1, (b) August 1 – August 2, and (c) June 29 – July 1 & August 1 – August 2. No feasible regression relationships were determined given the low R^2 for each model. Particularly, R^2 of the model for dataset (c) was close to 0, indicating nearly no relationship existed between LAI and NDVI.

Jackknife Cross-validation

LAI-NDVI relationships could provide an alternative to LAI estimation, which might avoid disadvantages of LAI measurements by the ceptometer. N1B was supposed to be the watershed on which senescent leaves had the least impact, in that an annual burning in the canopy would remove greater part of senescent materials. To get rid of overestimated LAI measurements caused by senescent leaves, only data collected in N1B were taken into account. The jackknife was used to approximate and validate the LAI-NDVI predictive models, based on the standard linear and exponential regressions (Fig. 2.4 (c)) as a preliminary step. Given unfeasibility of the jackknife in non-linear statistics, the correlation coefficient R was transformed using Fisher Z-transformation. The jackknife estimation for the correlation coefficient R^* was calculated from Z-transformed values. In addition, the exponential LAI-NDVI relationship was transformed to linearity by the natural logarithm transformation before jackknife validation. The parameters and biases were then estimated (Table 2.5), and performance of the regressions were evaluated (Fig. 2.7).

The jackknife validated linear model was $y = 3.4328x - 1.1477$ with the R^* of 0.8191, in which the bias was reduced by subtraction. Accuracy of the predictive model was assessed by the root-mean-square error (RMSE). Plotting the ground measured versus the jackknife estimated LAI, RMSE for this model was 0.3575, along with the R^2 of 0.6338 (Fig. 2.7 (a)). The unbiased exponential model was $y = 0.08e^{3.706x}$ with the R^* of 0.8513. RMSE between the measure and the estimated LAI was 0.3532, and jackknife estimation for R^2 was 0.6554. The exponential model exhibited better performance for LAI prediction than the linear model given the lower value of RMSE.

Table 2.5 Jackknife estimates of the linear and exponential predictive models. The independent variable x was NDVI, and the dependent variable y was LAI. The bias was calculated as the difference between the estimator in the standard regression and the jackknife estimator. The number of the samples was 27.

<i>Models</i>	<i>Standard Regression</i>		<i>Jackknife</i>		
	<i>Parameters</i>	<i>Estimate</i>	<i>Parameters</i>	<i>Estimate</i>	<i>Bias</i>
$y = ax + b$	a	3.4205	a^*	3.4328	-0.0123
	b	-1.1411	b^*	-1.1477	0.0066
	R	0.8205	R^*	0.8191	0.0014
$y = ae^{bx}$	a	0.0853	a^*	0.0800	0.0053
	b	3.6206	b^*	3.7060	-0.0854
	R	0.8522	R^*	0.8513	0.0009

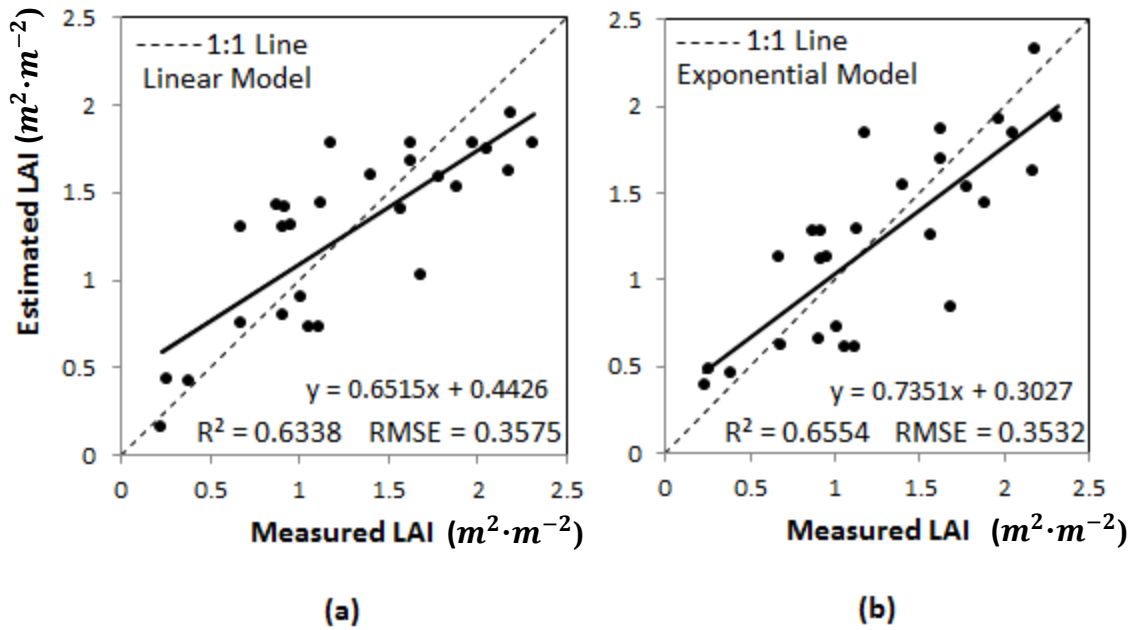


Figure 2.7 Validation for the predictive models. Performance of (a) the linear and (b) exponential regressions was evaluated by comparing the ground measured and the jackknife estimated LAI values. RMSE was calculated to assess the accuracy of the models.

Conclusions

In-situ LAI measurements by the LP-80 ceptometer and hyperspectral data were collected in three watersheds of tallgrass prairie with different fire frequencies. Vegetation canopies in the study site KPBS were of unsaturated NDVI at the lower ranges of LAI. The mean NDVI varied slightly across different watersheds. N20B with the lowest fire frequency had the greatest ranges of LAI measurements. Anomaly in the inverse correlation between LAI and the green reflectance in N20B indicated the canopy might consist of greater proportion of senescent leaves accumulated for years due to the low fire frequency, which contributed to overestimates of green LAI.

LAI-NDVI relationships were investigated to provide an alternative to LAI estimation. The poor performance of regressions in N20B revealed the influence of senescent materials on LAI measurements to some extent. Given limitations of LAI measurements by the ceptometer in senescent canopies, data collected in N1B, the watershed with the least senescent leaves due to an annual burning, were used to fit LAI-NDVI relationships. Both the linear and the exponential relationships were approximated and validated by the jackknife given the small number of the samples. The exponential predictive model showed better performance with the lower RMSE and greater R^2 when compared to the linear model. This determined exponential relationship for LAI estimation from NDVI was expected to be an important step toward future studies on detection of nitrogen contents in heterogeneous canopy, in that green LAI should be a significant parameter in estimates of canopy nitrogen.

Chapter 3 - Canopy Nitrogen Content Estimates of Heterogeneous Grasslands in Konza Prairie by In-situ Hyperspectral Analysis

Abstract

Foliar nitrogen content is an important index for measuring grassland quality. Although the use of hyperspectral analysis for leaf nitrogen retrieval has been developed into an acceptable laboratory method based on a number of previous studies conducted in the forests and crops usually with relatively uniform canopies, the feasibility of nitrogen retrieval by spectral analysis in heterogeneous canopies with varying species composition and canopy structure characteristics remains uncertain. This study attempted to estimate nitrogen content for mixed grasslands with complicated canopies in Konza Prairie by hyperspectral analysis of the in-situ data. The spectral analysis was focused on a fine chlorophyll absorption feature in the green-yellow region at wavelengths of 562 – 600 nm, which carries important information of chlorophyll concentration. Nitrogen content measurements were scaled from the leaf scale to the canopy scale using the canopy-integrated method, which were obtained by multiplying the leaf nitrogen concentration by the LAI. The original reflectance spectra were normalized by the first derivative and the continuum removal to reduce background influence. Multivariate regressions were applied to all possible wavelength combinations in the normalized spectra to determine optimal nitrogen models. Standardized difference was applied to two important features (i.e., the value of the position where the original reflectance decreased fastest, and the minimum of the absorption trough) in the continuum removed spectra. The determined standardized difference vegetation index (SDVI) provided a fast means of estimating nitrogen by bivariate regressions. Monthly models specific for May – September, respectively, and the general models for the whole growth season were determined and validated. Results showed the general relationships between nitrogen content and spectral features across various spatial scales throughout the growth seasons were available.

Key words: hyperspectral, canopy nitrogen, mixed grasslands, the first derivative, continuum removal, SDVI

Introduction

Given interactions between vegetation quality and grazing patterns of herbivores in grasslands, studies of vegetation quality are of great importance in understanding the structure and function of grassland ecosystems (Schimel et al., 1986; Jaramillo and Detling, 1988; Focardi et al., 1996; Post and Klein, 1996). Nitrogen, an indispensable element for composition of amino and nucleic acid in all living organisms on Earth (Bernhard, 2010), is an important index for measuring grassland vegetation quality. Traditional measures of nitrogen concentration, requiring laboratory chemical analysis of foliar samples, are tedious and expensive, especially for a great number of samples in a large study area. High resolution spectra of reflected radiation on the foliar samples carrying detailed properties of plant leaves (Gates et al., 1965), which can be used to detect variation in chlorophyll concentration (Jago et al., 1999; Curran et al., 2001), show great promise in estimates of leaf nitrogen content (Mutanga et al., 2005; Gong et al., 2002; Martin and Aber, 1997) in that most leaf nitrogen is concentrated in chlorophyll molecules (Yoder and Pettigrew-Crosby, 1995). Therefore, analysis of spectral response patterns may provide an effective means of predicting foliar nitrogen contents for a large sample size.

The physical and empirical approaches are two alternatives to nitrogen modeling. Physical models, based on inversion of radiative transfer equations, though claimed to be robust and universal (Goel and Thompson, 2000), require intensive computation. Moreover, physical models are restricted by assumptions of specific canopy structure characteristics, which may be inapplicable for canopy of complicated composition in reality (He and Mui, 2010). Empirical models, though with poor portability, can be readily developed by simply focusing on statistical relationships between nitrogen content and the spectral signals.

Empirical nitrogen retrieval modeling was derived from preceding studies on plant biochemistry estimates by applying stepwise regression to hyperspectral data of dried ground foliage in laboratory (Norris et al., 1976). Dried ground leaves are superior to fresh leaves for spectral analysis, since spectral signals may be influenced by water and unevenly distributed biochemical constituents in fresh leaf tissues (Yoder and Pettigrew-Crosby, 1995). However, laboratory spectroscopy analysis at the leaf scale is limited when research emphasis shifted to canopy chemistry estimates based on in-situ or aerial imagery spectrometers (Sembiring et al., 1998; Johnson et al., 1994).

In order to change the scale of analysis from leaves to canopies, methods for normalization of spectral signal to reduce spectral variations independent of vegetation characteristics have been developed, including the first derivative and continuum removal approaches (Kawamura et al., 2008; Kokaly and Clark, 1999; Kokaly et al., 2003). The first derivative at a point can be approximated as the ratio of the difference in reflectance values at two nearby wavelengths around the given point to the wavelength separation (Laba et al., 2005). The derivative reflectance is possible to remain the plant spectral features, whereas the background effect is separated and removed. Continuum removal uses a convex hull (continuum line) to fit over an absorption feature in the reflectance spectrum. The value in the continuum removed spectrum is calculated by dividing the reflectance in the reflectance spectrum by the value in the continuum line. In this way, spectral features can be compared from a common baseline (Kokaly, 2001; Mutanga et al., 2004).

Vegetation indices (VIs), incorporating spectral values extracted at specific wavelengths, also provide the potential to scale spectral features. A variety of VIs related to chlorophyll concentration have been proposed (Daughtry et al., 2000; Wu et al., 2008; Sims and Gamon, 2002), and are expected to be indicators of nitrogen content. Standardized difference of the spectral values is the commonly used form of VI due to its inherent characteristic of normalizing spectral signals and thus reducing sensitivity to background variations (Ferwerda et al., 2005; Delalieux et al., 2009).

The refined spectral signals from these normalization methods carry information of canopy biochemical content, and are mixed with biophysical properties in addition to biochemical characteristics. For example, the leaf area index (LAI) is a critical biophysical parameter that contributes to complications of canopy reflectance due to its effect on the proportion of reflectance from plant tissues (Yoder and Pettigrew-Crosby, 1995). Given the influences of biophysical properties, the canopy-integrated method (He and Mui, 2010) has been suggested as a way to scale biochemical content from the leaf to the canopy, where canopy biochemical content is calculated as the leaf biochemical concentration multiplied by the canopy biophysical parameter (Gitelson et al. 2005).

The use of hyperspectral data for canopy biochemical content retrieval has been successful in most past studies conducted in forests or crops with uniform canopy structures (Martin and Aber, 1997; Gong et al., 2002; Sembiring et al., 1998), whereas its feasibility for

estimating chemical content in canopies of various structure characteristics across mixed plant species remains uncertain (Ferwerda et al., 2005). This study attempted to estimate canopy nitrogen content from in-situ hyperspectral data for heterogeneous canopies of complicated composition and architecture in Konza Prairie. The canopy-scale nitrogen was calculated as the product of the leaf nitrogen concentration from laboratory chemical analysis and the canopy biophysical parameter LAI. Hyperspectral analysis was focused on the green-yellow region at wavelengths of 562 – 600 nm due to the important chlorophyll absorption features in this spectral region (Carter and Knapp, 2001; Blackburn, 2007). The original reflectance spectra were normalized by the first derivative algorithm and continuum removal. The form of standardized difference VI (SDVI) was applied to features in the continuum removed spectral data to develop the indicator of nitrogen content. Relationships between canopy nitrogen and spectral data of the first derivative, continuum removal or the SDVI were analyzed by examining values of the correlation coefficient (R). Various canopy nitrogen retrieval models were developed by regressions from the first derivative, the continuum removed spectra and the SDVI. Accuracy of these models was assessed by the root-mean-square error (RMSE) between the measured and the estimated canopy nitrogen.

Study Site and Data Collection

Study Site

This study was conducted at Konza Prairie Biological Station (KPBS), near Manhattan, KS (USA). KPBS is located in the Flint Hills tallgrass prairie in northeastern Kansas (39°05'N, 96°35'W), dominated by continental climate with warm, wet springs, hot summers and dry, cold winters. Approximately 75% of 826 mm annual precipitation is concentrated during the April to September, supporting vegetation growth in the prairie. The vegetation in KPBS is characterized by C4 perennial grasses of great species diversity, which results in unevenly distributed biochemical constituents across heterogeneous canopies. KPBS is divided into more than 50 watersheds with different fire frequencies. The in-situ hyperspectral data and foliar samples were collected in three watersheds, N1B, N4D and N20B, with the fire frequency of one year, four years and 20 years respectively (Fig. 2.1). The variations in fire frequency have a great influence

on the proportion of green vegetation to senescent materials in the canopy, which contribute to complications of canopy composition and structure characteristics.

Data Collection

15 10 m×10 m plots dispersed in each of the three watersheds were set up for data collection (Fig. 2.1). For each plot, six subplots were spirally arranged around the center of the plot. In-situ hyperspectral measurements were taken for each subplot by an Analytical Spectral Devices (ASD) FieldSpec Pro portable spectrometer from 1.5 m above the canopy, yielding a 0.4 m² circular field of view with a diameter of 0.7 m. The acquired reflected spectra range from 0.3 to 2.5 μm with a varying spectral resolution which is ~ 3 nm at the 700 nm wavelength and 10 – 12 nm at the wavelengths of 1.05 – 2.5 μm . The hyperspectral data for the vegetation canopy in each plot were obtained by calculating the mean values of the spectra collected from the six subplots.

Five foliar samples, representative of the plant species in the field of view of the spectrometer, were clipped in each subplot for chemical analysis (Fig. 2.2). The fresh green leaves for each subplot were mixed and ground after being dried at 60°C for 48 hours. Foliar nitrogen concentration was determined on the dried ground samples by laboratory elemental analysis using a Costech ECS 4010 (Costech Analytical Technologies Inc., Valencia, CA, USA). Given the chemical nitrogen analysis is expensive and time-consuming, samples randomly selected from three of the six subplots, which were expected to sufficiently characterize the nitrogen status in the whole plot, were used to calculate the mean leaf nitrogen concentration for each plot.

All field data were collected during the vegetation growth seasons in May, July, August and September, 2011. Available samples included 15 for each watershed in May, July, and August respectively; 12 for N1B, 8 for N4D and 7 for N20B in September.

Methods

Canopy Nitrogen

Nitrogen content was scaled from the leaf to the canopy level using the canopy-integrated method, by which canopy nitrogen N_{can} was calculated as the leaf nitrogen N_{leaf} multiplied by the canopy biophysical parameter LAI . Formally:

$$N_{can} = N_{leaf} \cdot LAI \quad (3.1)$$

Where LAI was determined by the empirical LAI - $NDVI$ relationship for Konza Prairie (Chapter 2). Formally:

$$LAI = 0.08e^{3.706 \cdot NDVI} \quad (3.2)$$

Where $NDVI$ was calculated as the ratio of the difference between the near infrared NIR and the red reflectance R to the sum of NIR and R . Formally:

$$NDVI = \frac{NIR - R}{NIR + R} \quad (3.3)$$

Where NIR was the average reflectance at the wavelengths of 780 – 800 nm; R was the average reflectance at the wavelengths of 670 – 678 nm.

Spectrum Smoothing

Given analysis of the first derivative and continuum removal is sensitive to the random noise of the spectral signal, the original reflectance spectra were smoothed by replacing the value at the given wavelength with the mean value of all the wavelengths within a specific moving filter window centered at that wavelength. The filter window for this study was 3. Formally:

$$SR_i = \frac{\sum_{n=i-1}^{i+1} R_n}{3} \quad (3.4)$$

Where SR_i is the smoothed reflectance value at the given wavelength i ; R_n is the original reflectance value at the wavelength n .

The First Derivative of Reflectance

The first derivative of reflectance can separate and remove the variations caused by background influence in the spectra, by which the characteristics of vegetation spectral signals

are refined. The first derivative of a point, defined as the slope of the tangent line at that point, can be approximated by the ratio of the difference in reflectance values at two wavelengths centered at the given point to the wavelength separation. The derivative algorithm was applied to the region of 562 – 600 nm in this study. Formally:

$$D_i = \frac{SR_{i+1} - SR_{i-1}}{\lambda_{i+1} - \lambda_{i-1}} \quad (3.5)$$

Where D_i is the first derivative at the wavelength i ; SR_i is the smoothed reflectance value at the wavelength i ; λ_i is the value of the wavelength i .

Continuum Removal

Continuum removal standardizes the canopy spectral signals using a straight line to fit over the tops of a given absorption feature in the spectrum, in which the continuum removed spectral value at a wavelength is calculated as the ratio of the value in the reflectance spectrum to the corresponding value in the straight line at the given wavelength. The absorption feature selected in this study was in the region of 562 – 600 nm (Fig. 3.1). The continuum removed value at each wavelength in this region was calculated. Formally:

$$CR_i = \frac{SR_i}{SL_i} \quad (3.6)$$

Where CR_i is the continuum removed spectral value at the wavelength i ; SR_i is the smoothed reflectance at the wavelength i ; SL_i is the value at the wavelength i in the straight line fitting over the absorption spectral feature.

SDVI

The SDVI was developed by applying the form of standardized difference to spectral signals based on analysis of features in spectra of the first derivative and continuum removal, which were expected to enhance the nitrogen related features. Formally:

$$SDVI = \frac{S_i - S_j}{S_i + S_j} \quad (3.7)$$

Where S_i is the spectral feature at the wavelength i .

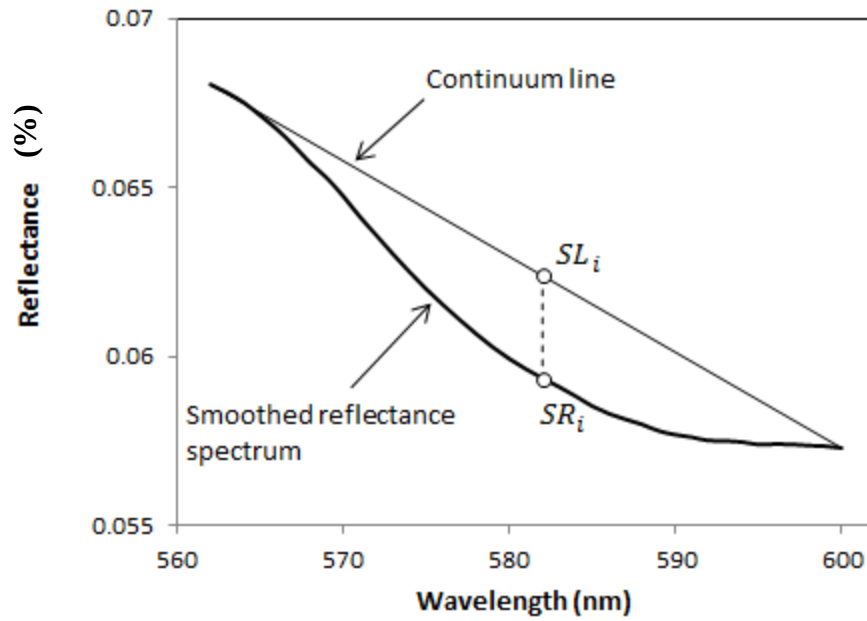


Figure 3.1 Continuum removal applied to the absorption feature in the region of 562 – 600 nm

Empirical Modeling and Validation

30 of 45 samples in May, July, and August respectively, 19 of 27 samples in September, and 109 of 162 samples during May to September were randomly selected to develop monthly models and general models throughout the whole growing seasons. The remaining samples were used for model validation. Regressions were applied to the canopy nitrogen content as the dependent variable and the hyperspectral features as the independent variables. The examined hyperspectral features included all possible wavelength combinations in the first derivative and in the continuum removed spectra, and the SDVI. Models with high values of the coefficient of determination (R^2), a measure of the proportion of variability in the data that can be explained by the regression line, were considered to fit the samples well. The predictive performance of these regression models was validated by comparing the measured nitrogen with the estimated nitrogen. Accuracy of the models was determined by the root-mean-square error (RMSE). Formally:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{\theta}_i - \theta_i)^2}{n}} \quad (3.8)$$

Where $\hat{\theta}_i$ is the estimated canopy nitrogen; θ_i is the measured canopy nitrogen; n is the number of the samples for validation.

Results and Discussion

Modeling and Validation

Nitrogen status of grasslands in this study varied across different temporal and spatial scales (Table 3.1). Canopy nitrogen content in the field of view of the spectrometer was determined by the leaf nitrogen concentration varying across different grass species and the amount of green vegetation measured as LAI. High ranges of leaf nitrogen appeared in May, and of LAI appeared in July. Nitrogen content in the canopy was higher in May and July than in other months. Various fire intensity influenced nitrogen spatial distribution in different watersheds. Watershed N1B with high fire frequency of one year had higher levels of canopy nitrogen than the other two watersheds N4D and N20B throughout the vegetation growth seasons from May to September.

Table 3.1 Descriptive statistics summary of canopy nitrogen

Sample Sites	Sample Size	Leaf Nitrogen ($g \cdot m^{-2}$)			LAI ($m^2 \cdot m^{-2}$)			Canopy Nitrogen ($g \cdot m^{-2} \cdot m^2 \cdot m^{-2}$)		
		Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	Mean
May										
N1B	15	2.04	2.96	2.38	0.48	1.64	1.06	1.18	4.18	2.51
N4D	15	1.44	2.10	1.83	0.64	1.67	1.20	1.21	3.06	2.19
N20B	15	1.83	2.41	2.03	0.29	1.41	0.75	0.64	3.06	1.53
July										
N1B	15	1.36	2.15	1.58	0.43	2.35	1.41	0.62	3.48	2.21
N4D	15	1.22	1.80	1.42	0.49	1.74	1.22	0.77	2.57	1.73
N20B	15	1.22	1.82	1.52	0.46	1.63	1.13	0.63	2.71	1.74
August										
N1B	15	1.20	1.89	1.50	0.33	1.87	1.01	0.45	2.80	1.50
N4D	15	1.08	1.53	1.29	0.51	1.50	0.96	0.68	1.81	1.21
N20B	15	1.21	1.65	1.36	0.48	1.27	0.84	0.71	1.82	1.14
September										
N1B	12	0.92	2.05	1.27	0.34	0.97	0.55	0.36	1.17	0.68
N4D	8	0.90	1.61	1.24	0.39	0.76	0.52	0.47	1.09	0.64
N20B	7	0.89	1.50	1.14	0.40	0.72	0.53	0.36	1.07	0.62

Normalized Spectral and the SDVI

The first derivative and continuum removal were applied to the green-yellow region at the wavelengths of 562 – 600 nm to normalize the canopy spectra. The first derivative data (Fig. 3.2), reflecting the rate of change in the spectra, showed the region centered at the wavelength of 572 nm with the highest absolute derivative values was the position where the original reflectance spectral values decreased fastest. The continuum removed data provided standardized reflectance spectra from a common baseline (Fig. 3.3), which showed around the wavelength of 581 nm was at the minimal level of the continuum removed values in the absorption trough. The standardized difference applied to the continuum removed data at wavelengths of 572 nm and 581 nm integrated features of the slope between the two wavelengths and the magnitude of the absorption trough, which was expected to be the indicator of nitrogen retrieval.

Correlations

Analysis of correlations was used to determine the strength of relationships between the nitrogen and the spectral data for each watershed and the three watersheds as a whole in May to September. For the first derivative data (Fig. 3.4), significant wavelengths related to nitrogen content included the regions of 563 – 566 nm and 593 – 596 nm, where the absolute values of R were greater than 0.75 across various watersheds, indicating strong relationships between canopy nitrogen and the first derivative data in the given spectral regions. A common region with relatively low ranges of R was at wavelengths of 569 – 575 nm centered at 572 nm, corresponding to the region with maximum absolute values of the first derivative data, where the original reflectance values decreased fastest. Absolute values of R for the dataset of grouping data across different watersheds throughout the growth seasons from May to September were at high levels of greater than 0.86 (Fig. 3.4 (e)), which indicated a general strong correlation between the nitrogen and the first derivative data in the green-yellow spectral region across various spatial and temporal scales.

For the continuum removed data (Fig. 3.5), spectral features at wavelengths of 569 – 593 nm in May to August with the absolute values of R ranging from 0.83 to 0.89 (Fig. 3.5 (a), (b), and (c)), and of 578 – 593 nm in September with the absolute R of 0.72 – 0.76 (Fig. 3.5 (d)), were strongly related to canopy nitrogen across the three watersheds. Correlations between the nitrogen and the spectral dataset incorporating data for the three watersheds throughout the

whole growth seasons were relatively strong in the region of 569 – 584 nm with the absolute values of R greater than 0.90 (Fig. 3.5 (e)).

The SDVI was developed based on the continuum removed spectral features at the wavelengths of 572 nm and 581 nm, CR_{572} and CR_{581} . Absolute values of R between the canopy nitrogen content N_{can} and the SDVI, though varied slightly across different watersheds and growth seasons, were generally at high ranges from 0.78 to 0.96 (Table 3.2), which suggested the SDVI was possible to be a good indicator of canopy nitrogen.

Canopy Nitrogen Retrieval Modeling and Validation

Monthly models for May, July, August and September respectively, and the general models for the whole growth seasons were determined by regressions for canopy nitrogen retrieval. The predictive performance of the retrieval models was evaluated (Table 3.3).

All possible wavelength combinations in the first derivative and in the continuum removed spectra were examined to develop optimal regression models. Although the model may fit the data better when incorporating more independent variables in the model, the excessive number of the independent variables may result in modeling complications, and even overfitting. Particularly in this study, the independent variables were spectral features concentrated in a narrow region, which usually strongly correlated with each other and thus might not be all statistically significant in the model. Combination of no more than three independent variables in each model might be optimal for this study. If the number of independent variables increased to more than three, the R^2 increased slightly; however, the modeling complication increased, and statistical significance of each independent variable could be hardly ensured. Bivariate regressions were applied to paired data of the canopy nitrogen and the SDVI. These regression models were validated by comparing the measured nitrogen with the estimated nitrogen, the accuracy of which was evaluated by RMSE.

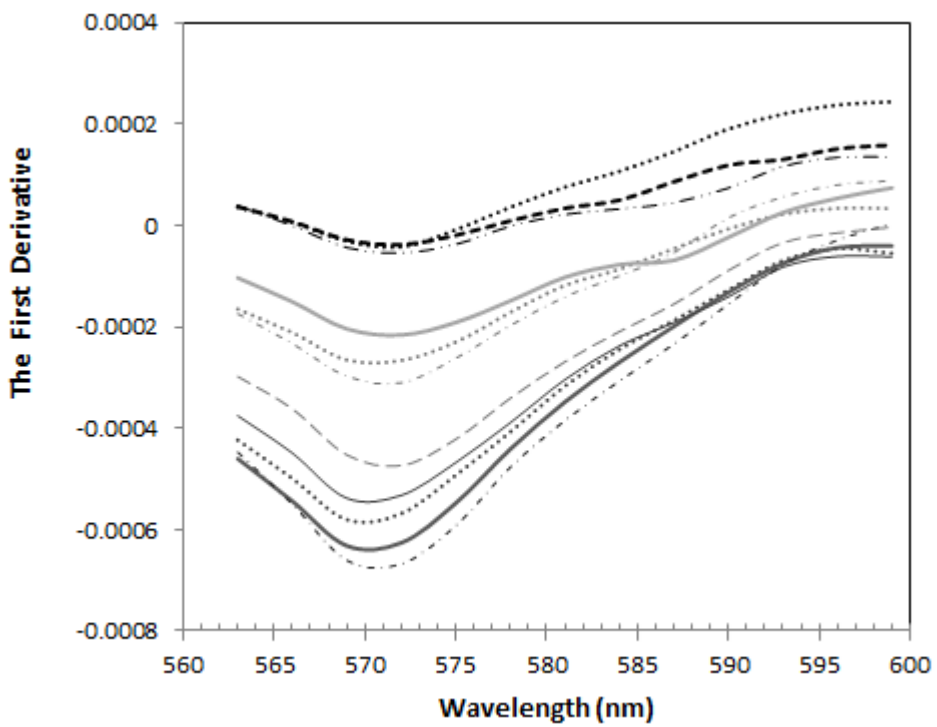


Figure 3.2 The first derivative spectra at the wavelengths of 562 – 600 nm

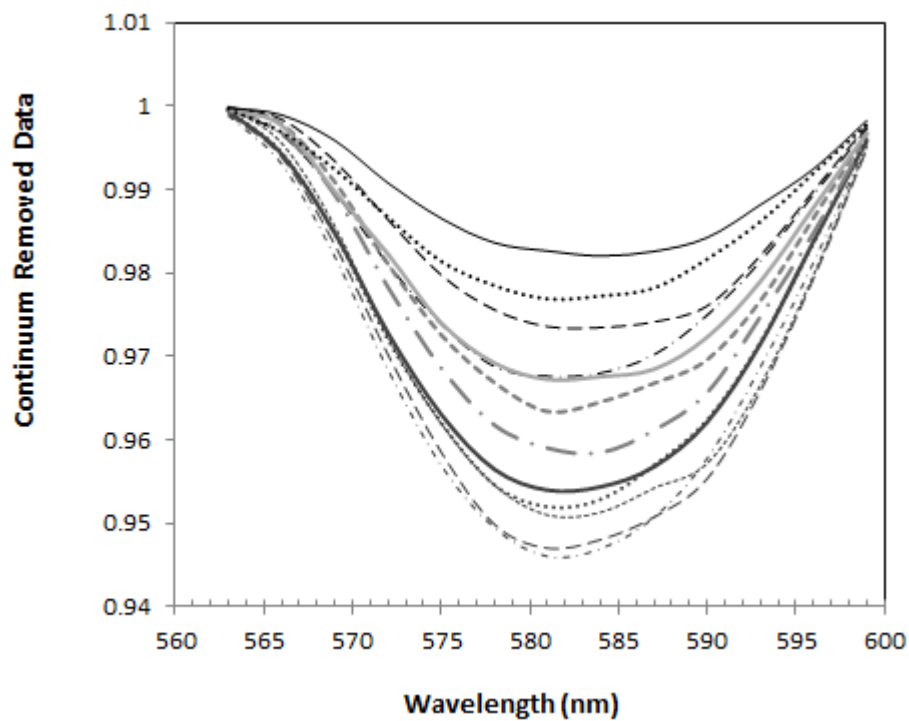


Figure 3.3 The continuum removed spectra at the wavelengths of 562 – 600 nm

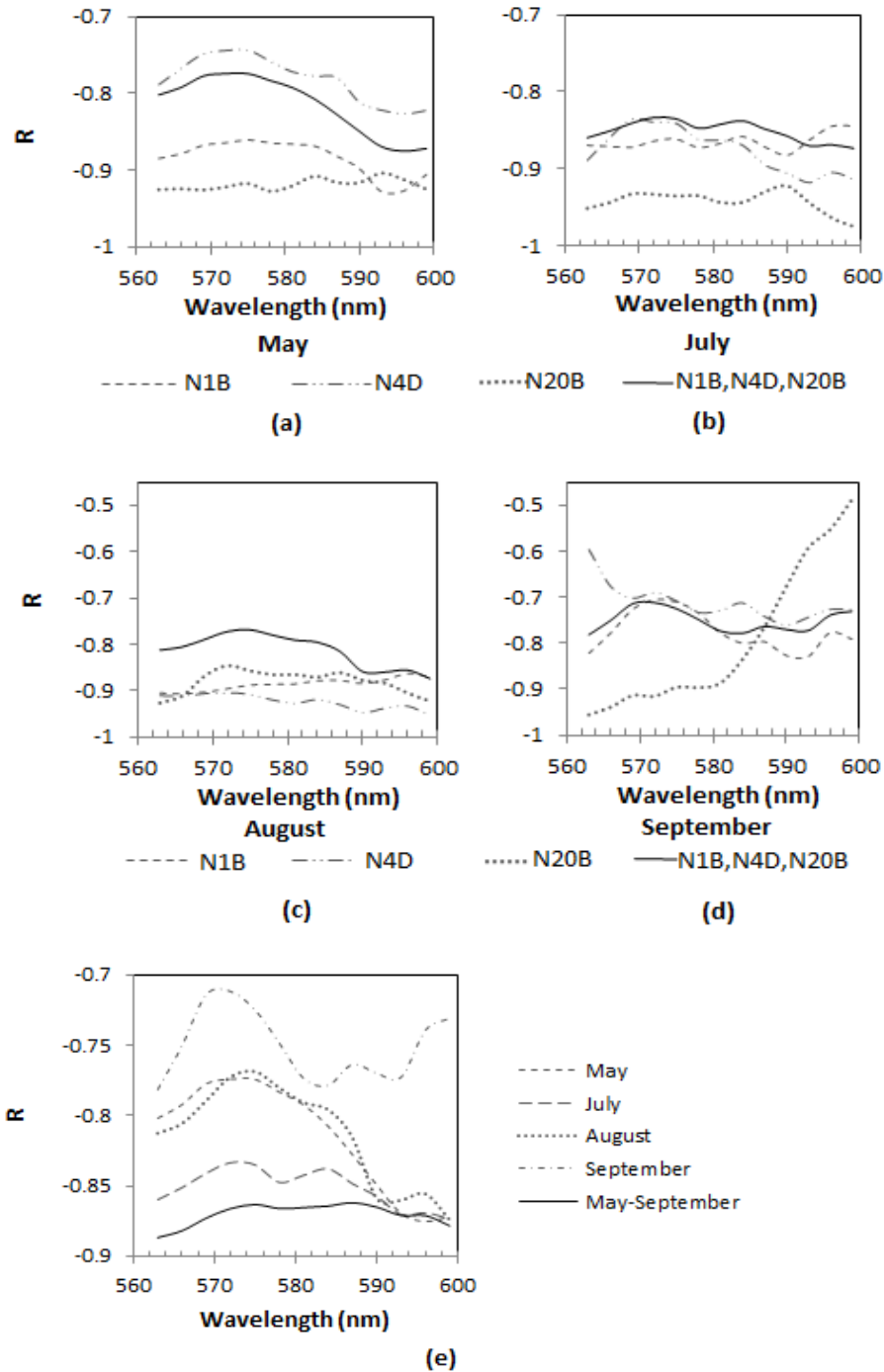


Figure 3.4 Correlations between canopy nitrogen and the first derivative spectral data at the wavelengths of 562 – 600 nm for three watersheds N1B, N4D and N20B respectively and as a whole in (a) May, (b) July, (c) August, (d) September, and for (e) four months respectively and the whole growth seasons from May to September across various watersheds.

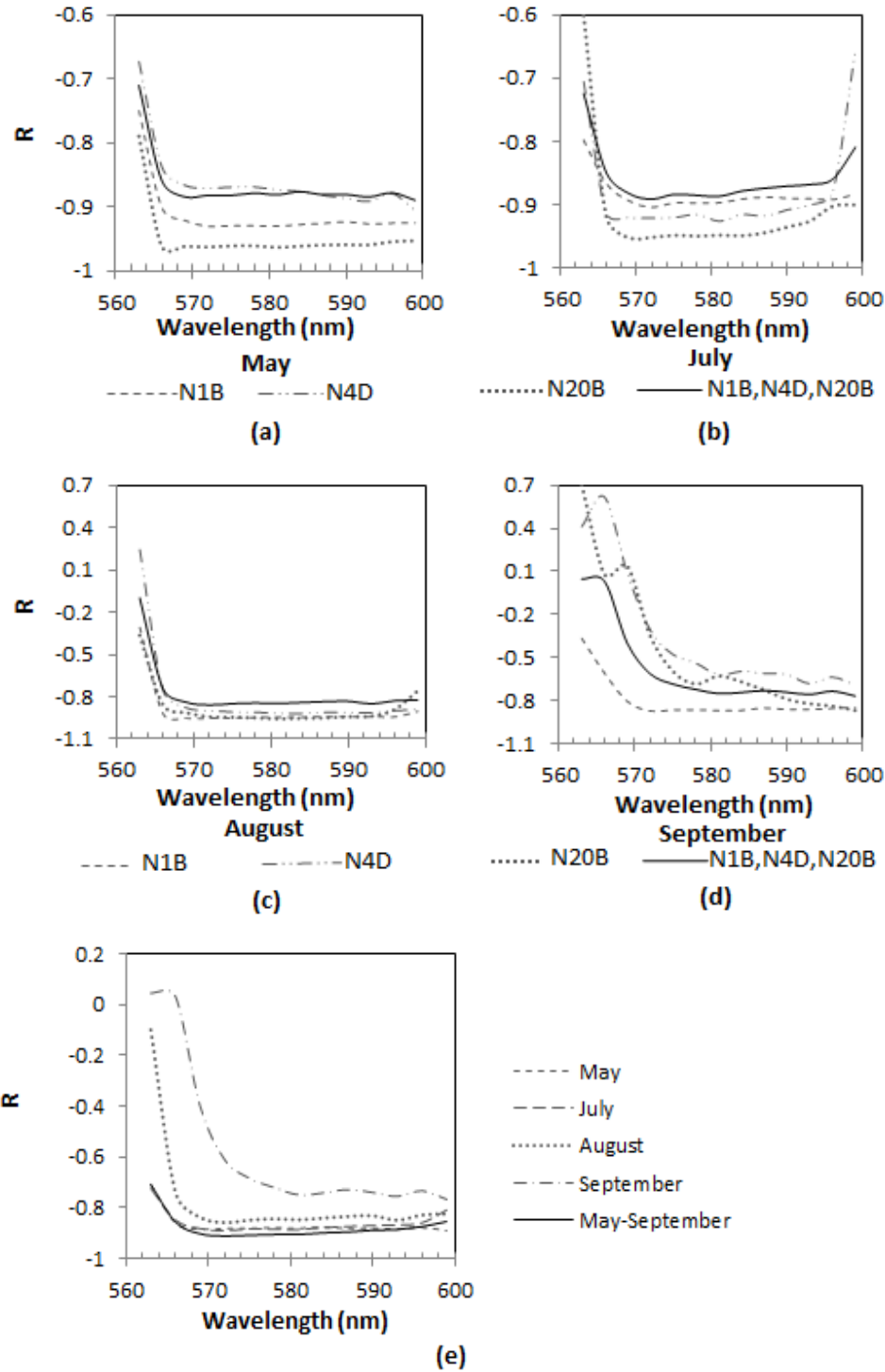


Figure 3.5 Correlations between canopy nitrogen and the continuum removed spectral data at the wavelengths of 562 – 600 nm for three watersheds N1B, N4D and N20B respectively and as a whole in (a) May, (b) July, (c) August, (d) September, and for (e) each of the four months and the whole growth seasons during May to September across various watersheds.

Table 3.2 Correlations between canopy nitrogen N_{can} and the SDVI

<i>Paired Variables</i>	<i>Months</i>	<i>Sites</i>	<i>Sample Size</i>	<i>R</i>
N_{can}	May	N1B	15	0.93
		N4D	15	0.87
		N20B	15	0.96
		N1B,N4D,N20B	30	0.88
	July	N1B	15	0.87
		N4D	15	0.93
		N20B	15	0.94
		N1B,N4D,N20B	30	0.87
	August	N1B	15	0.93
		N4D	15	0.93
		N20B	15	0.96
		N1B,N4D,N20B	30	0.83
$SDVI = \frac{CR_{572} - CR_{581}}{CR_{572} + CR_{581}}$	September	N1B	12	0.85
		N4D	8	0.78
		N20B	7	0.82
		N1B,N4D,N20B	18	0.83
	May – September	N1B,N4D,N20B	108	0.88

Table 3.3 Regression models for canopy nitrogen retrieval and model validation

<i>Months</i>	<i>Modeling</i>				<i>Validation</i>		
	<i>Sample Size</i>	<i>Formula</i>	<i>R²</i>	<i>Adjusted R²</i>	<i>Sample Size</i>	<i>RMSE</i>	<i>R²</i>
May	30	$N_{can} = 2.24 - 27510D_{566} + 35220D_{578} - 17900D_{599}$	0.86	0.84	15	0.50	0.74
		$N_{can} = 46.638 - 442.515CR_{581} + 395.331CR_{584}$	0.81	0.80		0.29	0.94
		$N_{can} = 197.558SDVI$	0.77	0.76		0.21	0.96
July	30	$N_{can} = 2.222 - 8171D_{563} + 18330D_{584} - 18070D_{593}$	0.85	0.84	15	0.35	0.79
		$N_{can} = 21.224 - 230.917CR_{581} + 209.85CR_{587}$	0.85	0.84		0.30	0.86
		$N_{can} = 162.162 SDVI$	0.74	0.73		0.24	0.90
August	30	$N_{can} = 1.553 - 24840D_{569} + 24150D_{572} - 5622D_{599}$	0.86	0.85	15	0.23	0.74
		$N_{can} = 115.57 - 155.35CR_{575} + 325.07CR_{590} - 284.87CR_{593}$	0.84	0.82		0.21	0.78
		$N_{can} = 147.567SDVI$	0.67	0.65		0.16	0.86
September	18	$N_{can} = 1.4045 - 8152D_{563} + 11096D_{569} - 8887D_{578}$	0.77	0.72	9	0.22	0.37
		$N_{can} = 252.05 + 83.51CR_{566} - 335.41CR_{599}$	0.69	0.65		0.17	0.45
		$N_{can} = 137.089SDVI$	0.69	0.67		0.17	0.41
May – September	108	$N_{can} = 1.708 - 13570D_{566} + 14160D_{575} - 7232D_{590}$	0.85	0.85	54	0.28	0.89
		$N_{can} = 38.437 - 311.079CR_{581} + 272.564CR_{584}$	0.86	0.85		0.24	0.92
		$N_{can} = 169.731SDVI$	0.77	0.77		0.25	0.92

Suitable spectral features as the independent variables and corresponding coefficients for nitrogen retrieval modeling varied across different months. Among these monthly models, the values of R^2 for the models based on the first derivative spectra were greater than R^2 for the models based on the continuum removed spectra and the SDVI models, which indicated the modeling datasets were well fitted by the regressions in the first derivative spectral data. However, the values of RMSE in the model validation were higher, indicating lower accuracy of predictive performance. The SDVI models, though with lower R^2 for the regression modeling, showed the lower ranges of RMSE, which indicated higher modeling accuracy. In addition, the bivariate regressions applied to data of the SDVI were simpler than examinations of multivariate regressions applied to all possible combinations in the first derivative and in the continuum removed spectra. Therefore, the SDVI had the potential to provide a means by which canopy nitrogen could be estimated accurately and conveniently.

Despite variations in spectral features at different temporal scales, the general models for the whole growth seasons were developed based on the datasets of incorporating the data during May to September. The relatively high ranges of R^2 for the regression modeling suggested the determined general models could account for greater part of variability in the datasets. Strong correlations and low ranges of RMSE between the measured nitrogen values and the estimates by the general models indicated good performance of these models for nitrogen prediction (Fig. 3.6).

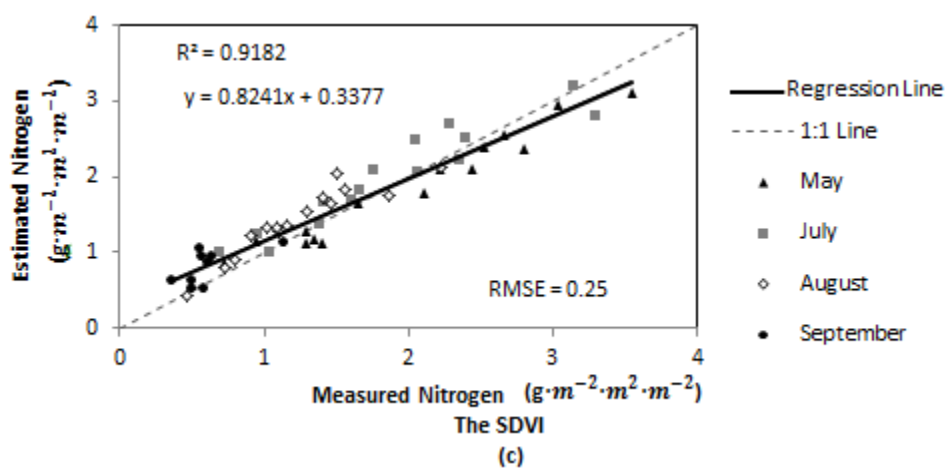
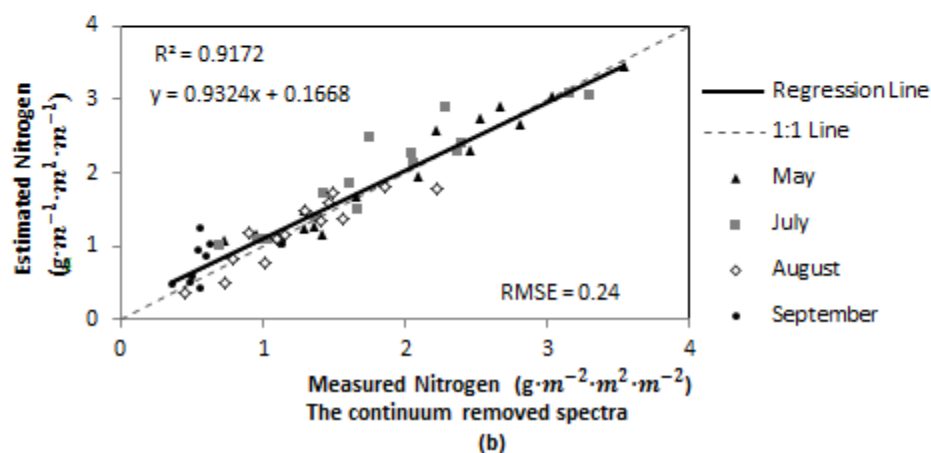
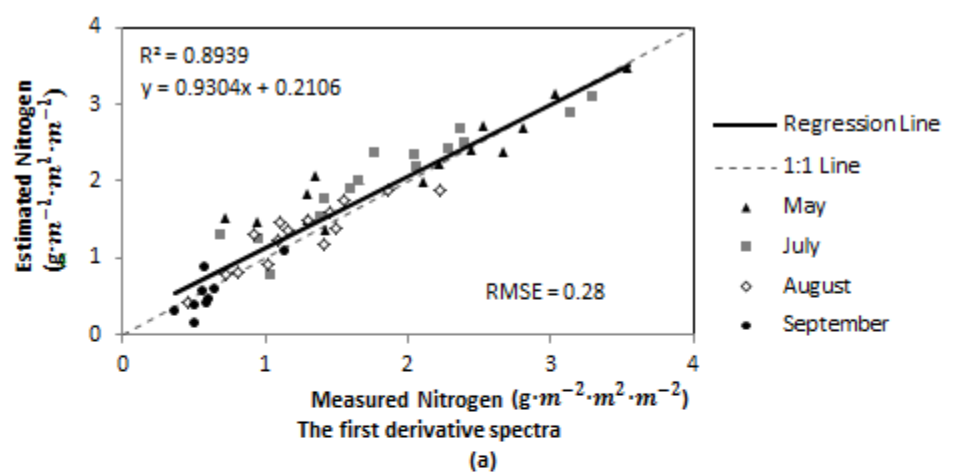


Figure 3.6 Validation of the general predictive models for the whole vegetation growth seasons. The predictive models were developed based on (a) the first derivative spectra, (b) the continuum removed spectra, and (c) the SDVI.

Conclusions

This study examined the use of hyperspectral analysis for nitrogen estimates in heterogeneous tallgrass canopies with various species composition and structure characteristics. The spectral analysis was focused on the fine chlorophyll absorption feature in the green-yellow region at wavelengths of 562 – 600 nm. Different from nitrogen retrieval at the leaf scale, analysis of canopy nitrogen is more complicated in that both the biochemical (i.e., leaf nitrogen concentration) and biophysical (i.e., LAI) canopy features should be taken into account. The canopy-integrated method provided an approach to scaling the nitrogen measurements from the leaf scale to the canopy scale, by which the canopy nitrogen was obtained by the leaf nitrogen concentration multiplied by the LAI. Descriptive statistics of the canopy nitrogen concentration for the three watersheds (N1B, N4D and N20B with fire frequencies of one year, four years and 20 years respectively) revealed variations in vegetation quality influenced by diverse grass species and various fire frequencies in the canopies.

Background influence was another factor that contributed to the complications of canopy spectra. The first derivative and continuum removal were used to reduce the background influence, by which the original spectra were normalized. Multivariate regressions were applied to all possible wavelength combinations in the normalized spectra to determine optimal nitrogen models. The SDVI in this study was developed from two important features (i.e., the value in the position where the original reflectance decreased fastest, and the minimal value in the absorption trough) of the continuum removed spectra, which provided a fast and reliable approach to nitrogen estimates by bivariate regressions.

Despite the canopy heterogeneity due to grass species diversity and variations in canopy architecture that resulted from different fire frequencies, canopy nitrogen modeling fitted well in the datasets incorporating data across the three watersheds for each individual month during the growth seasons from May to September. In addition to models specific for each month, general models for the whole growth seasons were determined. Feasibility of the general models for nitrogen retrieval across various spatial and temporal scales had been proved by the relatively high ranges of R^2 for regression modeling and low ranges of RMSE for model validation.

Chapter 4 - Mapping Canopy Nitrogen at Konza Prairie Biological Station (KPBS): Comparison of In-situ and Airborne Hyperspectral Measurements

Abstract

Hyperspectral analysis of vegetation canopies coupled with regression analysis has been widely used to estimate canopy biochemical concentrations. In this study, canopy reflectance spectral data collected using both in-situ spectrometry and airborne imagery were used to estimate nitrogen levels in heterogeneous canopies in tallgrass prairie. The first derivative and continuum removal were used to minimize background effects and therefore normalize spectral features. For the same sampling plot, the shape of the spectral curve of in-situ data were similar to but not identical with aerial imagery data due to differences in spatial and spectral resolutions between the two instruments. Performance of modeling and validation for canopy nitrogen retrieval from hyperspectral imagery revealed that nitrogen related spectral features could be selected in the green-yellow region at wavelengths of 562 – 600 nm by multivariate regression. The SDVI scaling of the difference between the value at the wavelength where the original reflectance decreased fastest and the minimal value in the continuum removed reflectance curve was demonstrated to be a good indicator of canopy nitrogen. In addition, comparison of spectral data from imagery with spectral resolutions ranging from 3 to 10 nm revealed that the relatively broad channels of 10 nm, though with less subtle features than channels of 3 nm, were feasible in detection of variability in canopy nitrogen concentration. The optimal nitrogen models for individual months during May – September with the lowest ranges of RMSE were applied to the aerial imagery. The generated canopy nitrogen maps coupled with data of grazer distributions would be of great value in studies on interactions between forage quality and grazing patterns of large herbivores in ecosystems of tallgrass prairie.

Key words: canopy nitrogen, hyperspectral, in-situ, aerial imagery, tallgrass prairie

Introduction

Konza Prairie Biological Station (KPBS), a site of C4 dominated grasslands in the Flint Hills of northeastern Kansas is managed as a long-term study site for ecological patterns and processes in tallgrass prairie. Grazing activities can shape vegetation quality in the canopy by increasing plant species diversity (Collins et al. 1998) in that plants have the capability to overcompensate for low levels of herbivory (McNaughton 1983). Interactively, vegetation quality is one of the major factors affecting grazing activities of herbivores which usually prefer sites with high concentration of nutrition (Focardi et al. 1996; Post and Klein 1996). Canopy nitrogen content as an important measure of vegetation quality can be linked to the grazing strategies of herbivores. Mapping canopy nitrogen content coupled with data of tracing bison distributions in KPBS is therefore of considerable value in understanding interactions between forage quality and grazing patterns of bison.

The traditional method of nitrogen measurement requires a great number of foliar samples sufficiently representative of the whole study area for laboratory chemical analysis, which is expensive and time-consuming (Foley et al. 1998; Mutanga et al. 2005). Hyperspectral remote sensing, a technique widely used in detection of vegetation and water resources over the past two decades (Govender et al. 2007), can provide a fast and cost-efficient approach to estimating of biochemical concentrations (e.g., nitrogen, calcium, magnesium, etc.) in the vegetation canopy (Mutanga et al. 2005) by analysis of the remotely sensed reflection spectra.

Hyperspectral remotely sensed data from in-situ and airborne instruments are potential source for estimating canopy nitrogen content. In-situ measurements using portable spectrometers provide a means by which the reflection of electromagnetic radiation on the vegetation canopy in the given sampling plot can be readily recorded. Hyperspectral data from the aircraft flights measure the solar reflected spectrum of a large area through the airborne spectral imaging sensors. The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) designed by the Jet Propulsion Laboratory was the first imaging sensor with the measured spectrum from 400 nm – 2500 nm at 10 nm interval (Green et al. 1998). The narrow channels of hyperspectral data have the potential to show subtle spectral features related to foliar nitrogen concentration which might be obscured by broadband sensors (Schmidt and Skidmore 2001).

Most past studies on nitrogen retrieval modeling by remote sensing have been conducted in either forests or croplands, landscapes featuring relatively uniform canopies (Martin and Aber

1997; Gong et al. 2002; Sembiring et al. 1998). Tallgrass prairie canopies like those at KPBS, however, are notable for their intensive spatial variation in species composition and canopy structure. This canopy heterogeneity makes retrieving canopy nitrogen estimates via remote sensing more challenging, due to the more uneven spatial distribution of biochemical constituents within the diverse canopy. Previous study on canopy nitrogen retrieval in KPBS by in-situ spectral measurements (Chapter 3) revealed that both biochemical and biophysical canopy properties (i.e., leaf nitrogen concentration and LAI) should be taken into account when scaling nitrogen content from the leaf level to the canopy level. The canopy-integrated method (He and Mui 2010) can be used in canopy nitrogen scaling, by which the canopy nitrogen content was calculated as the product of the leaf nitrogen concentration and the LAI (Gitelson et al. 2005). With regard to spectral analysis, the green-yellow spectrum region at the wavelengths of 562 – 600 nm carrying significant chlorophyll absorption features (Carter and Knapp 2001; Blackburn 2007) showed great promise in modeling the scaled canopy nitrogen across heterogeneous canopies.

However, the in-situ canopy nitrogen models determined in the previous study (Chapter 3) might not be directly applied to the airborne imagery, because the spectral features from the airborne imager were similar to but not identical with those of the in-situ data (Rock et al. 1988). This study compared nitrogen related spectral features from the two measurements in the green-yellow region (562 – 600 nm) of canopies in KPBS during May – September in 2011. In addition, imagery spectral resolution of ~ 10 nm at the wavelengths of 562 – 600 nm in September was different from in other months of ~ 3 nm, which provided opportunities to investigate whether important spectral features related to nitrogen retrieval would be masked by the degraded spectral resolution from 3 nm to 10 nm. The objective of this study was to map canopy nitrogen in KPBS based on aerial imagery, which would be a preliminary step toward understanding the grazing patterns in grassland ecosystems of KPBS.

Study Site and Data Collection

KPBS (Fig. 4.1), a tallgrass prairie site located in the Flint Hills of northeastern Kansas (39°05'N, 96°35'W), is characterized by variable continental climate with warm, wet springs, hot summers and dry, cold winters. Mean annual precipitation of 826 mm with 75% falling during April to September can support growth of dominated C4 grasses of great species diversity in

KPBS. KPBS is divided into more than 50 watersheds with the aim of long-term studies on ecological patterns and processes in tallgrass prairie influenced by grazing activities along with fire and climate. 10 contiguous watersheds of ~ 1012 ha are grazed by bison. Fire frequency is controlled in each KPBS watershed, which has a great influence on canopy composition and structure characteristics by affecting the proportion of green vegetation to senescent materials in the canopy.

During May to September in 2011, in-situ hyperspectral data and foliar samples were collected in three grazed watersheds, N1B, N4D and N20B, with the fire frequency of one year, four years and 20 years respectively. Hyperspectral images covering the whole KPBS were captured from aircraft flights carrying a spectroscopy imager. 15 plots, each $10\text{ m} \times 10\text{ m}$ with six subplots spirally arrayed around the plot center, randomly distributed in each watershed, were set up for in-situ data collection. An Analytical Spectral Devices (ASD) FieldSpec Pro portable spectrometer (ASD, Inc., Boulder, CO, USA) was used to measure spectral reflectance data from 1.5 m above the canopy in each subplot, yielding a 0.4 m^2 circular field of view with a diameter of 0.7 m. The spectral resolution, which varies depending on measured wavelengths between 0.3 to $2.5\text{ }\mu\text{m}$, is $\sim 3\text{ nm}$ at the 700 nm wavelength. The mean spectral data of each six subplots was calculated as the spectral reflectance of the given plot. Five foliar samples, representative of the plant species in the field of view of the spectrometer, were clipped in each subplot. Foliar nitrogen concentration was determined from the dried ground samples by laboratory elemental analysis using a Costech ECS 4010 (Costech Analytical Technologies Inc., Valencia, CA, USA). Given the chemical nitrogen analysis is expensive and time-consuming, samples randomly selected from three of the six subplots were used for chemical analysis. The mean nitrogen of the three subplots was expected to sufficiently characterize the leaf nitrogen status in the whole plot. Positions of the plot centers were measured by GPS technology, which allowed the plots to be located on aerial imagery. Available samples included 15 for each watershed in May, July, and August respectively; 12 for N1B, 8 for N4D and 7 for N20B in September.

An AISA camera mounted on a Piper Warrior aircraft was used to capture hyperspectral aerial imagery. 4 – 5 flights covering the whole area of KPBS were conducted in each month during May – September (Fig. 4.2), at an altitude yielding spatial resolution of $2\text{ m} \times 2\text{ m}$ on the imagery. Spectral resolution at the wavelengths of 562 – 600 nm is $\sim 3\text{ nm}$ in May – August, and is $\sim 10\text{ nm}$ in September.

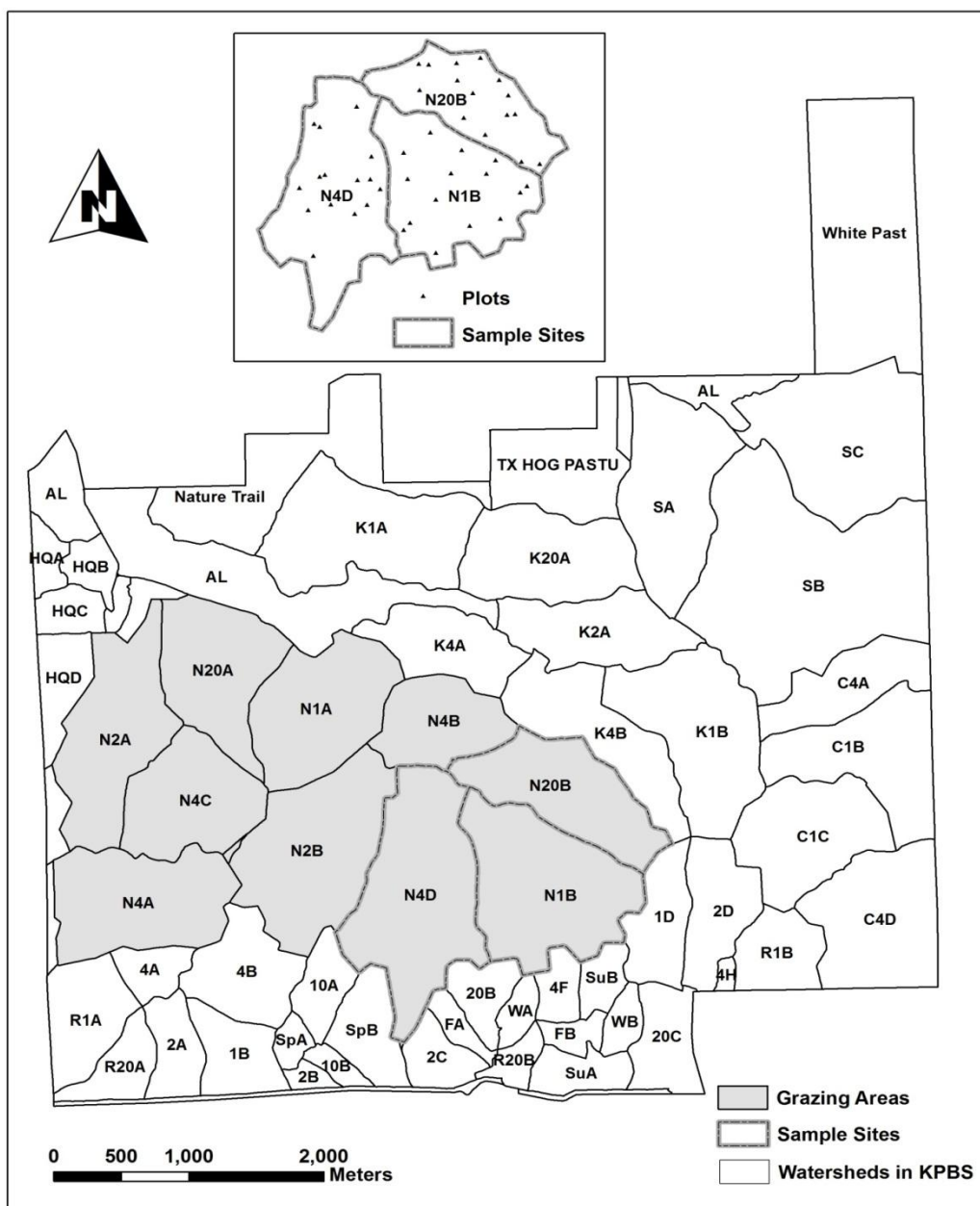
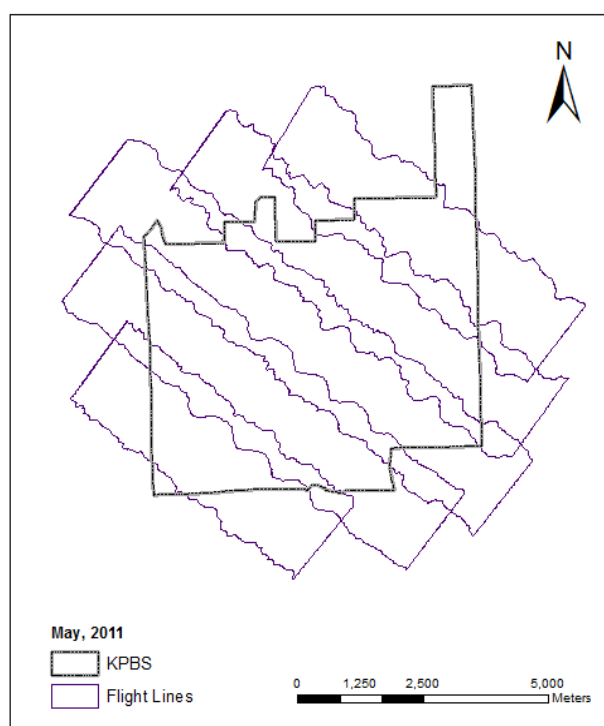
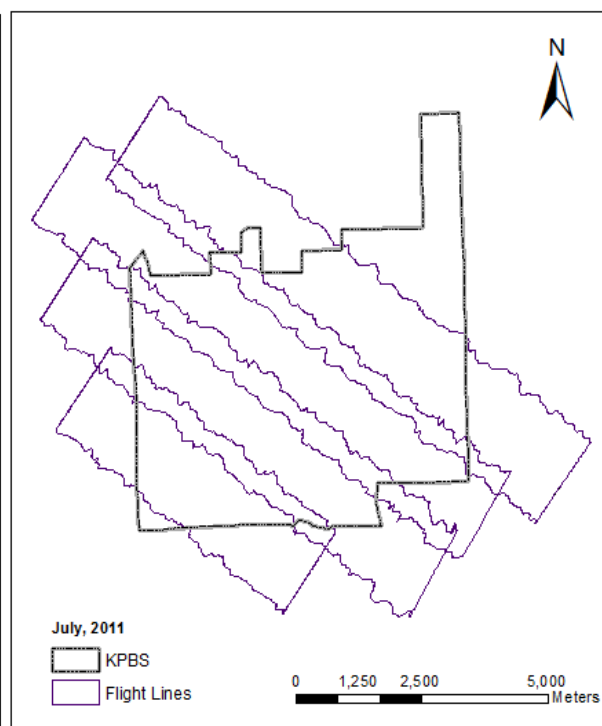


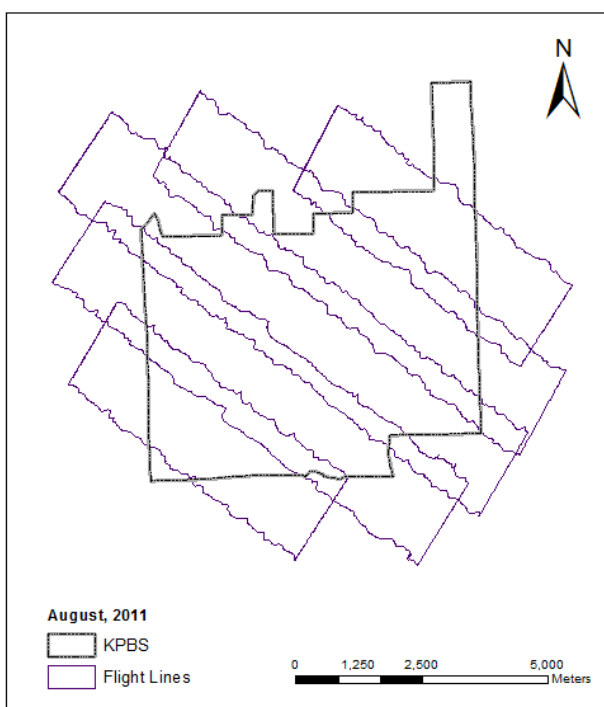
Figure 4.1 Experimental design of the Konza Prairie Biological Station, showing locations where in-situ data were collected. KPBS includes more than 50 watersheds with different fire frequencies. 10 contiguous watersheds are grazed by bison. In-situ data were collected in three watersheds (N1B, N4D and N20B with fire frequency of one year, four years and 20 years respectively). Plots for data collection are randomly distributed to ensure representativeness of the samples.



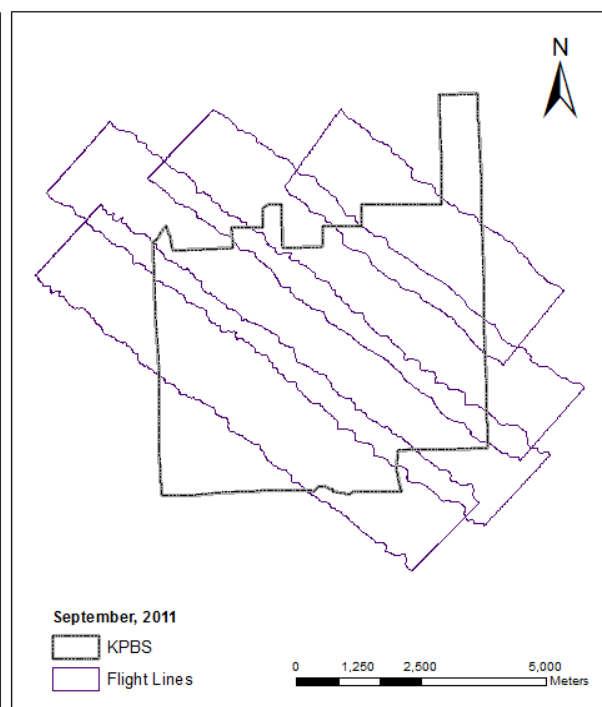
(a) May



(b) July



(c) August



(d) September

Figure 4.2 Flight lines in each month during May – September in 2011

Methods

Spectral Data from Aerial Imagery

Aerial imagery was processed using the ENvironment for Visualizing Images (ENVI) software (Exelis Visual Information Solutions, Inc., Boulder, CO, USA). The FLAASH model was used for atmospheric correction. Canopies on the aerial imagery were classified by gallery forest and grasses using Maximum Likelihood (a supervised classification method). The gallery forest was then removed and not included in subsequent analysis.

Plots for in-situ data collection were located on aerial imagery using location records of the plot centers recorded using a portable GPS receiver. Spectral data from airborne imagery for each plot were obtained by calculating the mean of spectral reflectance data within a window of 5 pixel $\times$ 5 pixel (10 m $\times$ 10 m) centered around the plot center on the imagery.

Canopy Nitrogen Scaling: Leaf to Canopy

Canopy nitrogen was scaled from leaf level to canopy level using the canopy-integrated method, by which canopy nitrogen was calculated as the product of the leaf nitrogen concentration by chemical analysis and the canopy biophysical parameter LAI. LAI was derived from NDVI base on an empirical NDVI-LAI model specific for KPBS (Formula 3.2).

Spectrum Smoothing and Normalization

First derivative (Kawamura et al. 2008; Laba et al. 2005) and continuum removal analysis (Kokaly and Clark 1999; Kokaly et al. 2003), while capable of enhancing fine features of a spectral curve, also tend to enhance the random noise in the curve. Spectral smoothing was therefore a necessary step before these enhancements could be applied. The original reflectance value at the given wavelength was replaced with the mean of values at all the wavelengths within a specific filter window centered at that wavelength. Selection of the size of the smoothing window should take into account both smoothing effectiveness and as small loss of useful spectral features as possible. In this study, the suitable smoothing window size for the spectral imagery of May, July and August was examined to be 5. Formally:

$$SR_i = \frac{\sum_{n=i-2}^{i+2} R_n}{5} \quad (4.1)$$

Where SR_i is the smoothed reflectance value at the given wavelength i ; R_n is the original reflectance value at the wavelength n .

Imagery of September with ~ 10 nm spectral resolution at wavelengths of 562 – 600 nm, which showed stable reflectance signals with less fluctuation caused by random noise in the spectral curves, was unnecessary to be smoothed. The first derivative and continuum removal to normalize spectral features were then applied to the wavelengths of 562 – 600 nm in the smoothed spectral data from imagery. The standardized difference vegetation index (SDVI) (Ferwerda et al., 2005; Delalieux et al., 2009) was used to normalize the difference between two important spectral features. In this study, the two features for SDVI were selected in of the continuum removed spectra, i.e., the value in the position where the spectral reflectance decreased fastest and the minimal value in the absorption trough (Chapter 3). Formally:

$$SDVI = \frac{CR_i - CR_j}{CR_i + CR_j} \quad (4.2)$$

Where CR_i is the continuum removed value at the wavelength i .

Modeling, Validation and Application to Imagery

30 of 45 samples each in May, July, and August, respectively, and 19 of 27 samples in September were randomly selected to develop nitrogen retrieval models for each of the images of individual months. The remaining samples were set aside for model validation. For nitrogen modeling, multivariate regression was applied to all possible combinations at wavelengths of 562 – 600 nm in the first derivative spectra and in the continuum removed spectra; bivariate regression was applied to the SDVI values. The developed models were validated by comparing the measured nitrogen with the estimated nitrogen. Models with high values of the coefficient of determination (R^2) for regression modeling and low values of the root-mean-square error (RMSE) for validation were selected to be optimal. Formulas of the optimal models were applied to the aerial imagery to mapping canopy nitrogen in the whole KPBS.

In addition, modeling and validation were performed on the datasets incorporating samples of May – August (90 samples for modeling and 45 for validation) to develop general nitrogen models for the whole growth seasons. Samples of September were excluded due to inconsistency of the spectral data as the independent variables in datasets of May – August and

September, in that the spectral resolution of 3 nm in May – August was different from that of 10 nm in September.

Results

Descriptive Statistics Summary

Comparison of canopy nitrogen by in-situ and airborne measurements revealed difference in canopy nitrogen distribution between in-situ data and spectral data from aerial imagery (Table 4.1). The difference might be caused by variations in spatial resolution of the two measurements. In-situ data measured canopy nitrogen for each plot by calculating the average of six subplots; spectral data from imagery measured the given plot by calculating the average of the whole area of 10 m × 10 m. Both in-situ data and data from imagery showed watershed N1B with fire frequency of one year had high ranges of mean canopy nitrogen throughout the growth seasons from May to September, which indicated high fire intensity might result in high vegetation nutrient returns.

Analysis of Spectral Features

Random noise in the original spectral data from aerial imagery, which would interfere with retrieval of subtle spectral features associated with nitrogen, was minimized by spectral smoothing with a moving average filter with window size of 5 (Fig. 4.3). For the first derivative spectra from imagery of May – August (Fig. 4.4), the minimal negative values were around the 569 nm wavelength, indicating the wavelength of 569 nm was the position where the original reflectance decreased fastest. This position of 569 nm in the spectral data from imagery shifted slightly to 572 nm in in-situ spectral data (Fig. 4.6 (a)). Continuum removal provided a common baseline that allowed spectral features to be compared (Fig. 4.5). The nadir with minimal values around the wavelength of 581 nm in the continuum removed spectra of in-situ data was close to the nadir centered at 580 nm of the imagery spectral data (Fig. 4.6 (b)). Values at wavelengths of 569 nm and 580 nm in the continuum removed spectra were used to develop the SDVI for canopy nitrogen modeling from aerial imagery of May – August.

Table 4.1 Statistics summary of canopy nitrogen from in-situ spectrometer and airborne imager

Sites	Sample Size	In-situ Canopy Nitrogen ($g \cdot m^{-2} \cdot m^2 \cdot m^{-2}$)			Imagery Canopy Nitrogen ($g \cdot m^{-2} \cdot m^2 \cdot m^{-2}$)		
		Min.	Max.	Mean	Min.	Max.	Mean
May							
N1B	15	1.18	4.18	2.51	1.03	2.51	1.74
N4D	15	1.21	3.06	2.19	0.45	1.95	1.05
N20B	15	0.64	3.06	1.53	0.55	2.29	1.28
July							
N1B	15	0.62	3.48	2.21	0.96	2.72	1.96
N4D	15	0.77	2.57	1.73	1.18	2.84	1.78
N20B	15	0.63	2.71	1.74	1.08	2.46	1.80
August							
N1B	15	0.45	2.80	1.50	0.47	2.55	1.26
N4D	15	0.68	1.81	1.21	0.60	1.39	0.98
N20B	15	0.71	1.82	1.14	0.62	1.37	0.93
September							
N1B	12	0.36	1.17	0.68	0.35	1.22	0.72
N4D	8	0.47	1.09	0.64	0.50	0.94	0.66
N20B	7	0.36	1.07	0.62	0.32	1.06	0.56

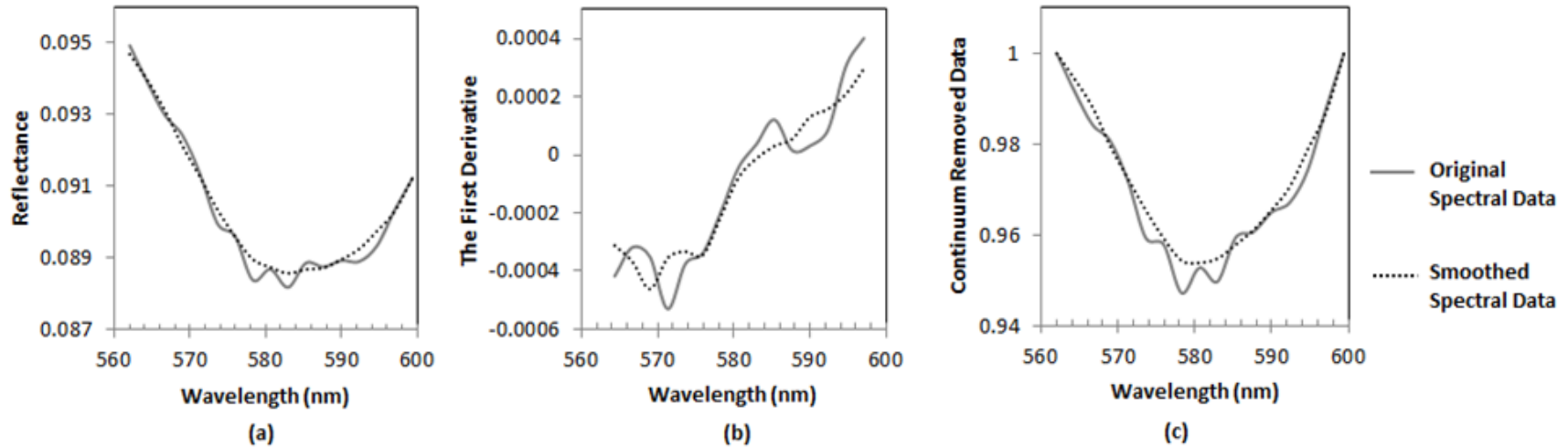


Figure 4.3 Comparison of (a) the reflectance, (b) the first derivative, and (c) the continuum removed data from the original spectra and the smoothed spectra. Spectrum smoothing used to minimize random noise was necessary before performance of the first derivative and continuum removal, in that the first derivative and continuum removal are sensitive to random noise in the spectral data. In this study, the suitable smoothing window size for imagery of May, July and August was examined to be 5. Imagery of September with relatively broad spectral channels of ~ 10 nm at wavelengths of 562 – 600 nm, which showed stable reflectance signals with less fluctuation caused by the random noise, was unnecessary to be smoothed.

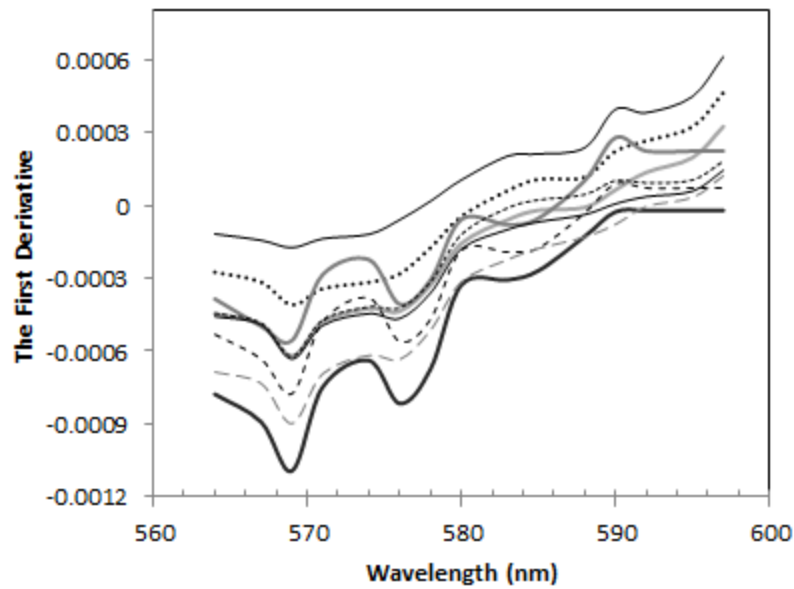


Figure 4.4 The first derivative of the smoothed spectra from imagery of May – August.

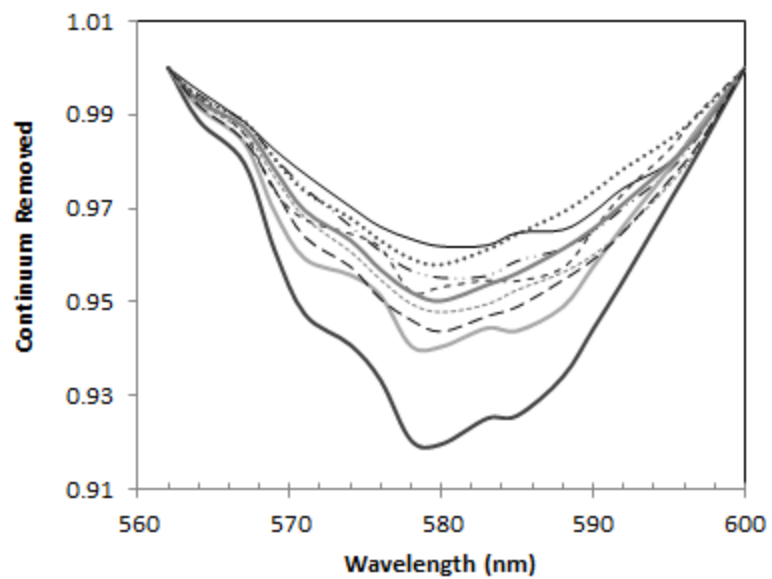


Figure 4.5 The continuum removed data of the smoothed spectra from imagery of May – August.

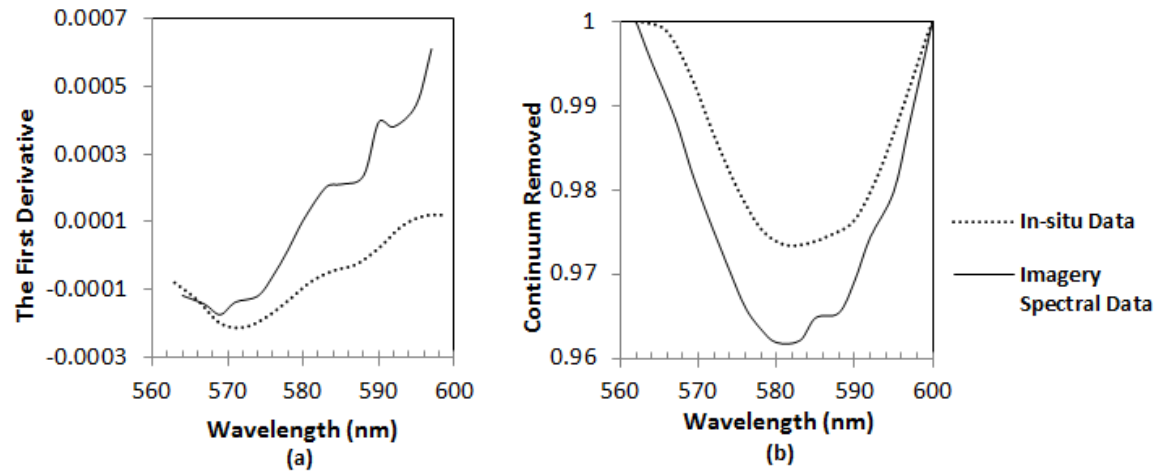


Figure 4.6 Comparison of in-situ data and spectral data from aerial imagery for the same plot. Although the in-situ data were not identical with airborne measurements, the shape and trend of the curves were similar.

Spectral resolution of imagery at wavelengths of 562 – 600 nm varied in different months (~ 3 nm for May – August and ~ 10 nm for September). The spectral curves with the relatively broad spectral resolution of 10 nm (Fig. 4.7) had the similar shape to the curves with the finer resolution of 3 nm (Fig. 4.4 and Fig. 4.5), but revealed less spectral variation. Ranging from 562 nm to 600 nm in the spectra from imagery, the first derivative values were lowest around 596 nm for May – August, and 572 nm for September; the continuum removed values were lowest around 580 nm for May – August, and 582 nm for September (Fig. 4.4, Fig. 4.5 and Fig. 4.7). The SDVIs (scaling the difference between CR_{569} and CR_{580} for May – August, CR_{572} and CR_{582} for September) were examined to model canopy nitrogen on imagery. Previous study on nitrogen modeling from in-situ data revealed that the SDVI scaling difference between continuum removed values at 572 nm and 581 nm was a good indicator of canopy nitrogen in the general model throughout the growth seasons (Chapter 3), which indicated the slight variation in spectral features from the period of May – August (569 nm and 580 nm) to September (571 nm and 580 nm) might result from difference in spectral resolution rather than seasonal variations.

Empirical Regression Modeling and Validation

Given the difference in spatial and spectral resolutions between the in-situ and airborne measurements, the empirical nitrogen models determined from in-situ data in the previous study (Chapter 3) can be hardly directly applied to the aerial imagery. For nitrogen modeling on imagery for individual months, multivariate regression was applied to spectral data of the first derivative and continuum removal in the region of 562 – 600 nm; bivariate regression was applied to the SDVIs. Performance of modeling and validation for nitrogen retrieval (Table 4.2) showed acceptable nitrogen models could be determined from either datasets of the first derivative and continuum removed reflectance or the SDVI values. Feasible models for September suggested the spectral channels of 10 nm, though with less spectral features than channels of 3 nm, were available to be used for nitrogen estimates. Despite variations in selection of wavelength combinations for optimal nitrogen modeling in different months, general nitrogen retrieval models could be developed for the growth seasons during May to August. The models developed from the first derivative and the continuum removed spectral data showed higher ranges of R^2 values for regression modeling and lower ranges of RMSE for model validation than the SDVI model, indicating better performance in canopy nitrogen estimates.

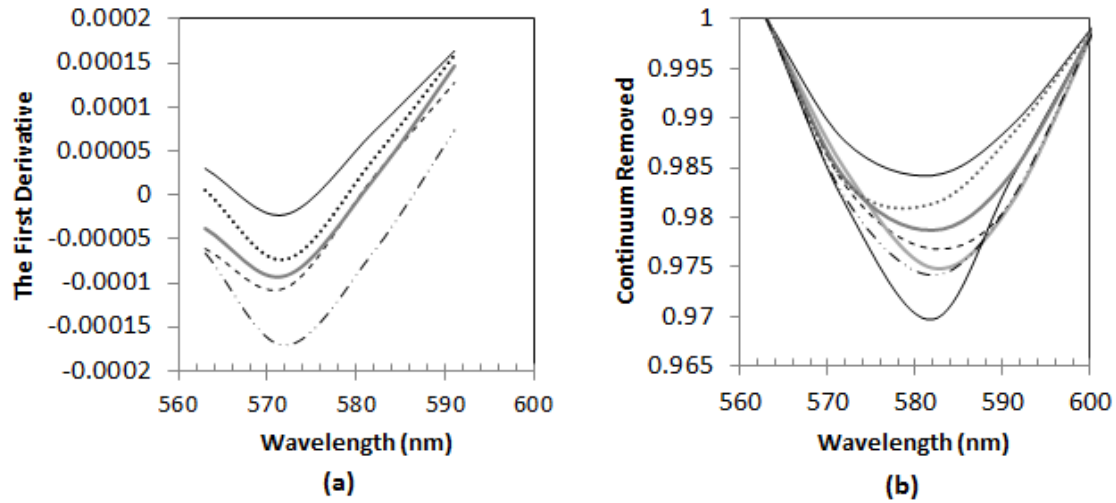


Figure 4.7 Spectral features from imagery of September at wavelengths of 562 – 600 nm with a relatively broad spectral resolution of ~ 10 nm. Subtle features of the first derivative spectra were masked in the relatively broad channels. The continuum removed curves of September with minimal values around the wavelength of 582 nm showed a similar spectral shape to curves of May – September.

Table 4.2 Modeling and validation for canopy nitrogen N_{can} retrieval on imagery. D_i is the value at the wavelength i nm in the first derivative spectra. CR_i is the value at the wavelength i nm in the continuum removed spectra. For May – August, $SDVI = (CR_{569} - CR_{580})/(CR_{569} + CR_{580})$; for September, $SDVI = (CR_{572} - CR_{582})/(CR_{572} + CR_{582})$.

Months	Modeling				Validation		
	Sample Size	Formula	R^2	Adjusted R^2	Sample Size	RMSE	R^2
May	30	$N_{can} = 2.153 + 6267.417D_{567} - 4594.363D_{578}$	0.84	0.82	15	0.23	0.85
		$- 5714.135D_{599}$					
		$N_{can} = 47.876 - 48.496CR_{583}$	0.87	0.86		0.21	0.86
July	30	$N_{can} = 113.466SDVI$	0.84	0.83	15	0.24	0.82
		$N_{can} = 2.447 - 6392D_{595}$	0.72	0.72		0.23	0.82
August	30	$N_{can} = 53.366 - 54.674CR_{583}$	0.67	0.66	15	0.25	0.69
		$N_{can} = 118.366SDVI$	0.59	0.58		0.16	0.79
September	18	$N_{can} = 0.674 - 4597.390D_{564} + 2819.052D_{578}$	0.93	0.92	9	0.20	0.63
		$- 1013.862D_{597}$					
		$N_{can} = 55.579 - 56.496CR_{574}$	0.83	0.83		0.15	0.75
May – August	90	$N_{can} = -0.478 + 109.113SDVI$	0.76	0.75	45	0.18	0.74
		$N_{can} = 1.011 - 2522D_{582}$	0.67	0.65		0.09	0.80
May – August	90	$N_{can} = 72.75CR_{572} - 72.42CR_{582}$	0.59	0.56	45	0.19	0.44
		$N_{can} = 0.329 + 141.617SDVI$	0.58	0.56		0.19	0.45
May – August	90	$N_{can} = 1.401 - 2699D_{583} - 1094D_{592}$	0.81	0.80	45	0.22	0.86
		$N_{can} = 42.897 - 46.717CR_{569} - 174.863CR_{585}$	0.84	0.83		0.24	0.84
		$+ 178.426CR_{588}$					
May – August	90	$N_{can} = -0.332 + 125.381SDVI$	0.60	0.60	45	0.32	0.67

Nitrogen Mapping on Aerial Imagery

Selection of the optimal model for each month should ensure relatively high levels of R^2 in modeling and low levels of RMSE in validation. Higher R^2 indicated that greater proportion of variability in data could be explained by the model, that is, the model fitted the data well. In addition to R^2 , the RMSE as a measure of predictive accuracy of the model was another consideration of even greater importance. Models developed from the continuum removed spectral data for May and August, from the SDVI for July, and from the first derivative spectral data for September with the lowest ranges of RMSE were selected to be used for mapping nitrogen on aerial imagery (Fig. 4.8 – Fig. 4.11). The general model developed from the first derivative spectral data, which had the relatively high R^2 and low RMSE, showed promise in nitrogen estimates throughout the growth seasons from May to August (Fig. 4.12 – Fig. 4.14). The generated nitrogen maps coupled with data of bison distributions would be of considerable value in understanding interactions between forage quality and grazing patterns of large herbivores in grassland ecosystems of KPBS.

Conclusions

Estimates of canopy biochemical content by means of hyperspectral data has developed over the past decades. Spectral data at the canopy level mixed with background noise, canopy biochemical and biophysical properties create more problems in spectral analysis than that at the leaf level. The canopy-integrated method was used in this study to scale analysis from leaves to canopies in terms of the canopy biophysical parameter LAI. Further research efforts could be enhancements in experimental design and algorithm of canopy analysis scaling given complications in heterogeneous canopies with diverse plant species and canopy structures. Other parameters that describe the canopy characteristics, such as the canopy height, could be taken into account on canopy modeling.

Hyperspectral data were collected by in-situ or airborne remote sensors. The shapes of the spectral curves extracted from aerial imagery were similar to but not identical with the in-situ spectral data due to difference in spatial and spectral resolutions of the two measurements. A fine chlorophyll absorption feature in the region of 562 – 600 nm, which could be detected in either in-situ data or aerial imagery, was examined to be sensitive to the canopy nitrogen status.

For each month during May – September, normalized spectral data by the first derivative or continuum removal, in which the background noise was minimized, coupled with multivariate regressions provided opportunities for canopy nitrogen modeling. The SDVI scaling the difference between the value at the wavelength where the original reflectance decreased fastest and the minimal value in the continuum removed reflectance curve was demonstrated to be a good indicator of canopy nitrogen content. Spectral resolution on imagery in September of ~ 10 nm was different from that in other months of ~ 3 nm. Comparison of spectral data with spectral resolutions of 10 nm and 3 nm revealed that the relatively broad channels of 10 nm, though with less subtle features than channels of 3 nm, were feasible in detection of variability in canopy nitrogen concentration. General nitrogen models for the whole growth seasons during May – August could be determined from the first derivative or continuum removed spectral data, indicating specific spectral features could be selected for nitrogen modeling despite the seasonal variations. The optimal models with high predictive accuracy measured as low RMSE were applied to the aerial imagery to generate canopy nitrogen maps for each month, which was a preliminary step toward studies on the interactions between canopy vegetation quality and grazing patterns of large herbivores in tallgrass prairie.

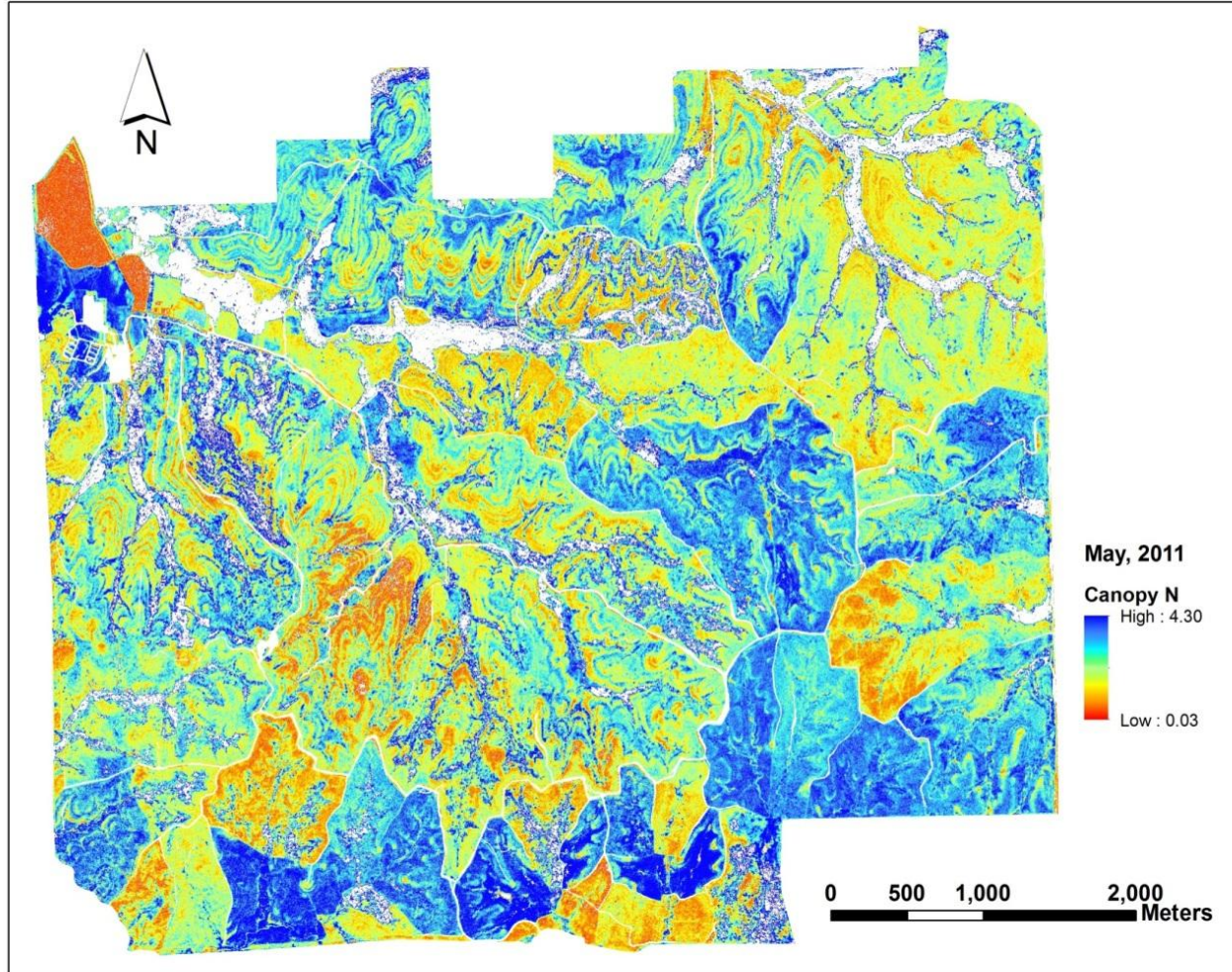


Figure 4.8 Canopy nitrogen map of KPBS in May, 2011, based on the nitrogen retrieval model developed from the continuum removed spectral data ($N_{can} = 47.876 - 48.496CR_{583}$). White areas are where gallery forest was removed (see Methods – Spectral Data from Aerial Imagery).

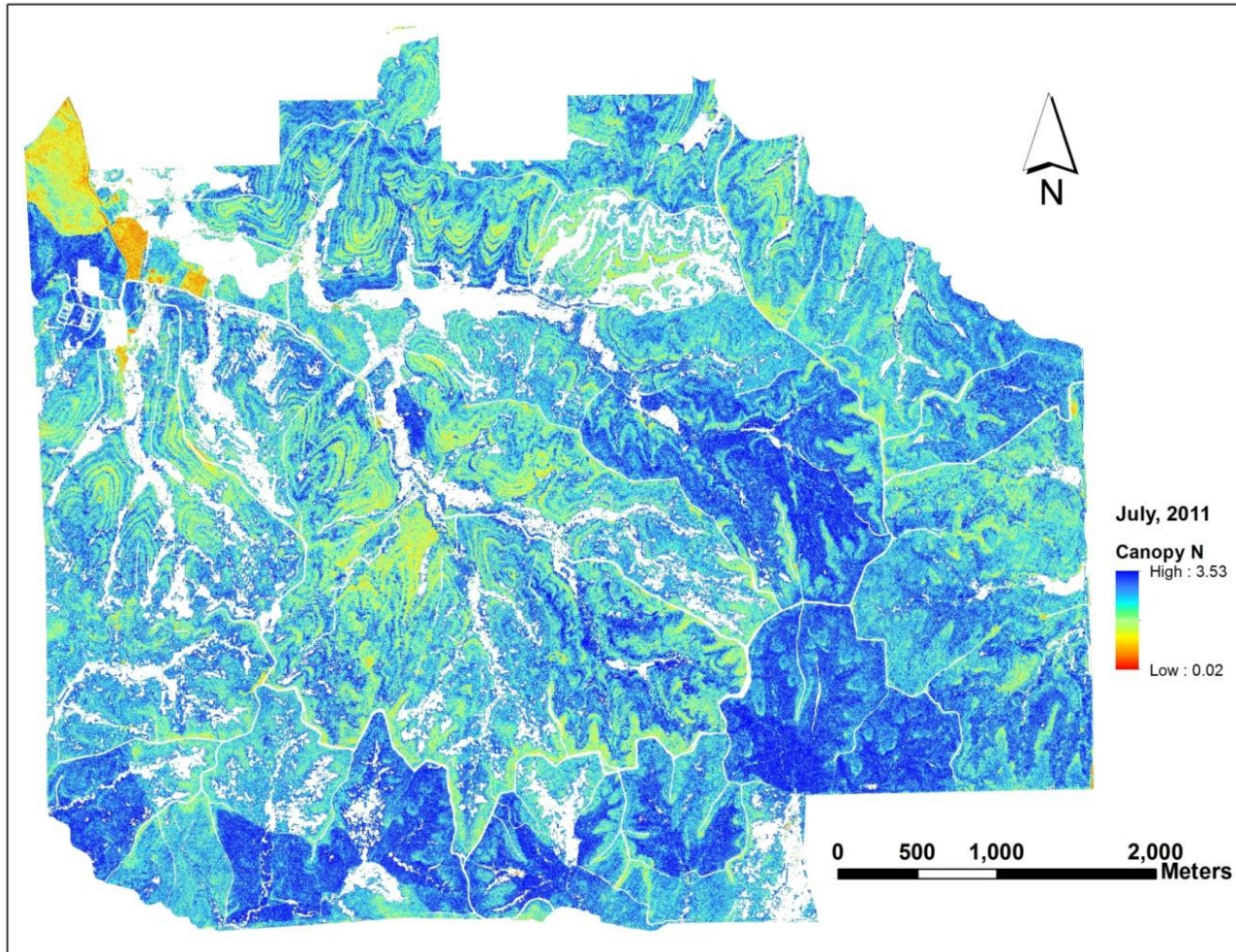


Figure 4.9 Canopy nitrogen map of KPBS in July, 2011, based on the nitrogen retrieval model developed from the SDVI values. The SDVI scaling the difference between CR_{569} and CR_{580} was the indicator in the nitrogen retrieval model ($N_{can} = 118.366SDVI$). White areas are where gallery forest was removed (see Methods – Spectral Data from Aerial Imagery).

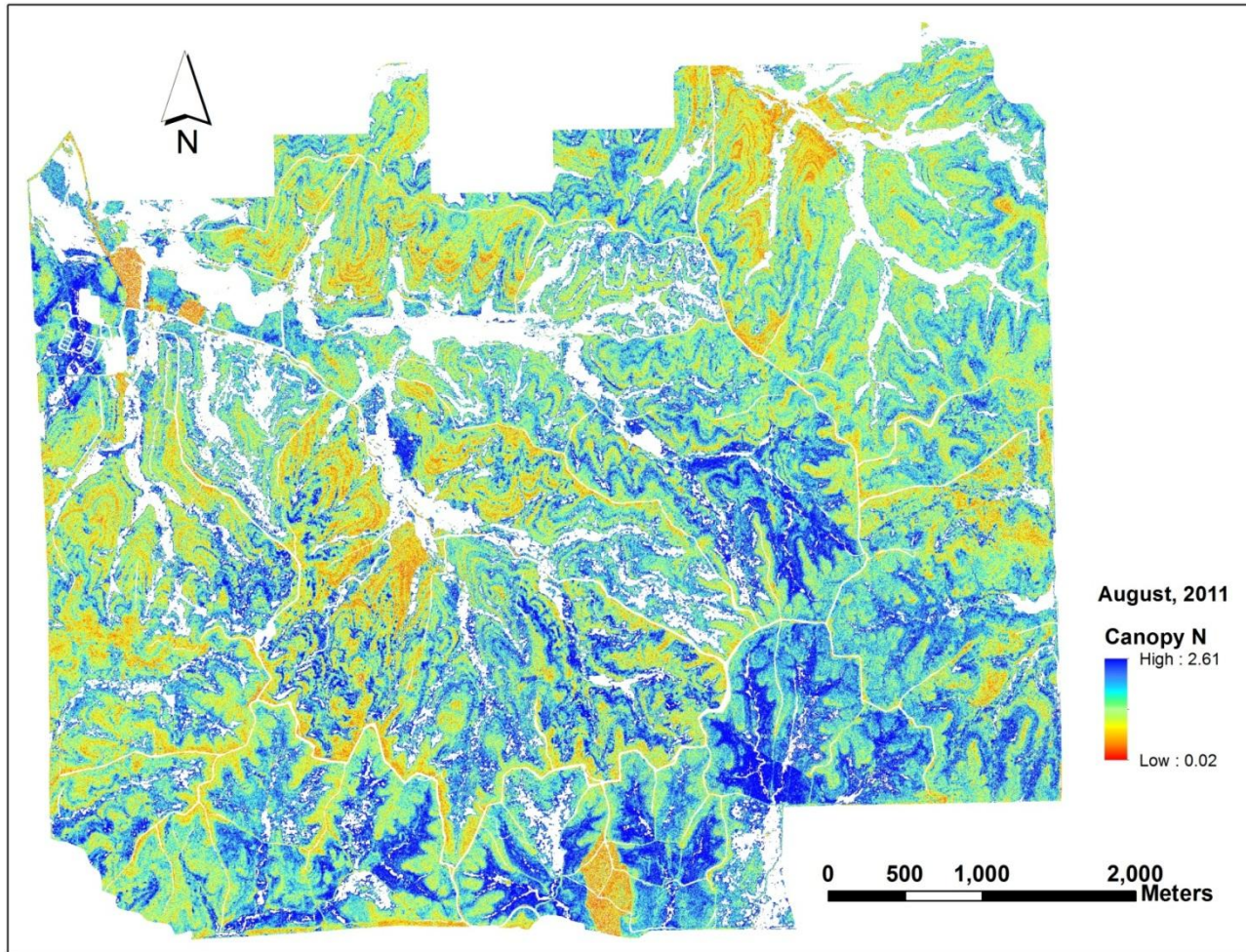


Figure 4.10 Canopy nitrogen map of KPBS in August, 2011, based on the nitrogen retrieval model developed from the continuum removed spectral data ($N_{can} = 55.579 - 56.496CR_{574}$). White areas are where gallery forest was removed (see Methods – Spectral Data from Aerial Imagery).

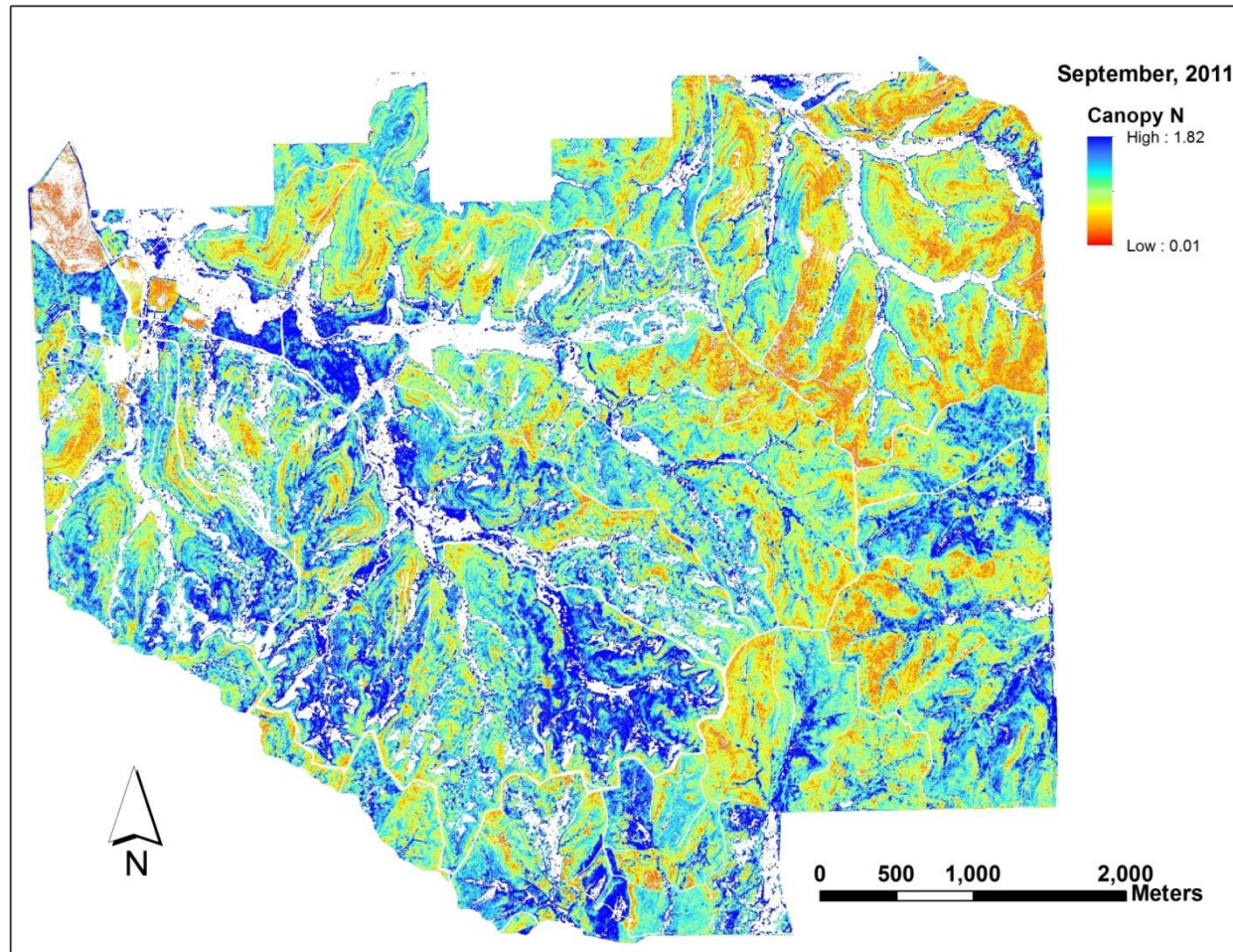


Figure 4.11 Canopy nitrogen map of KPBS in September, 2011, based on the nitrogen retrieval model developed from the first derivative data ($N_{can} = 1.011 - 2522D_{582}$). White areas are where gallery forest was removed (see Methods – Spectral Data from Aerial Imagery).

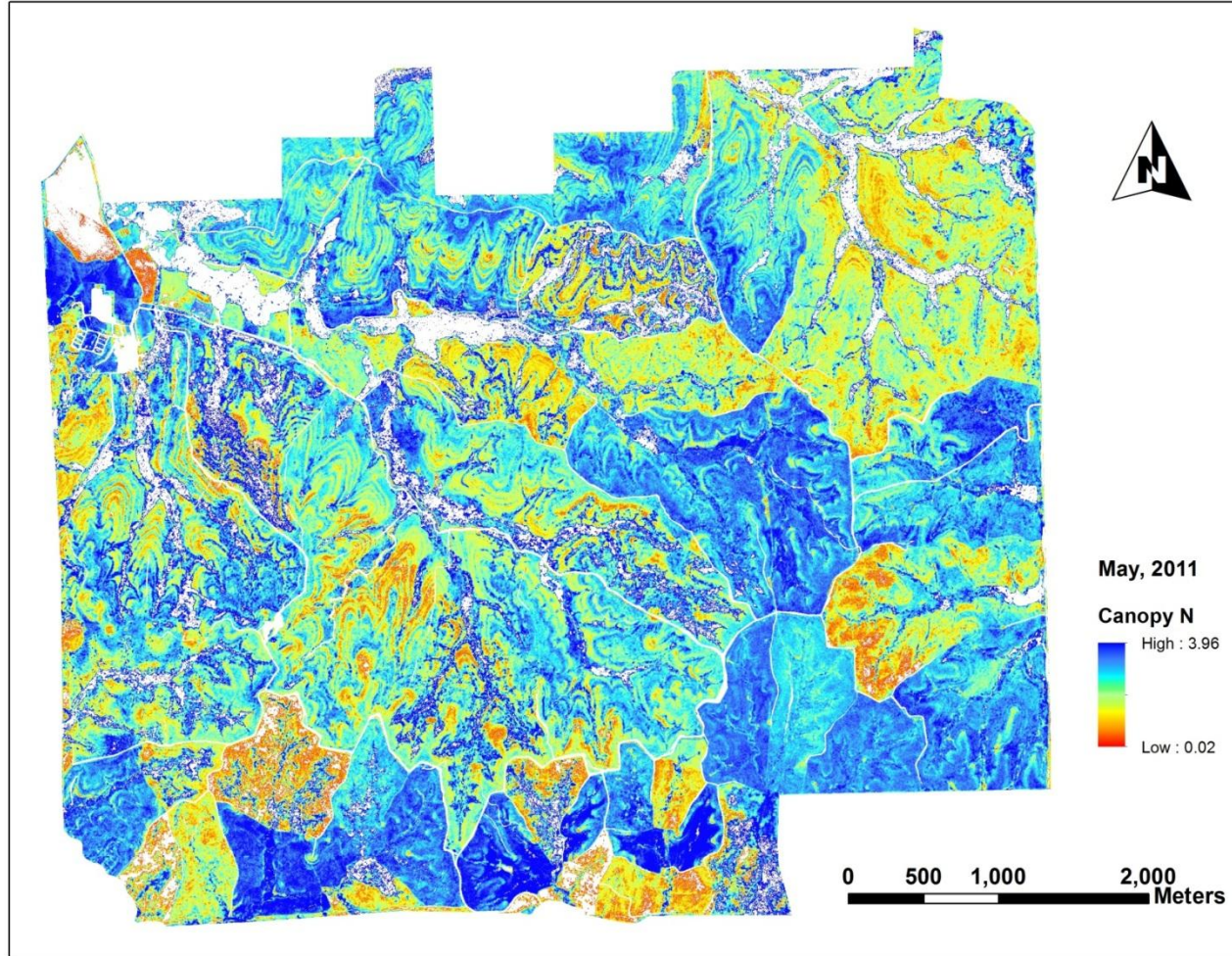


Figure 4.12 Canopy nitrogen map of KPBS in May, 2011, based on the general nitrogen retrieval model for the growth season from May to August ($N_{can} = 1.401 - 2699D_{583} - 1094D_{592}$). White areas are where gallery forest was removed (see Methods – Spectral Data from Aerial Imagery).

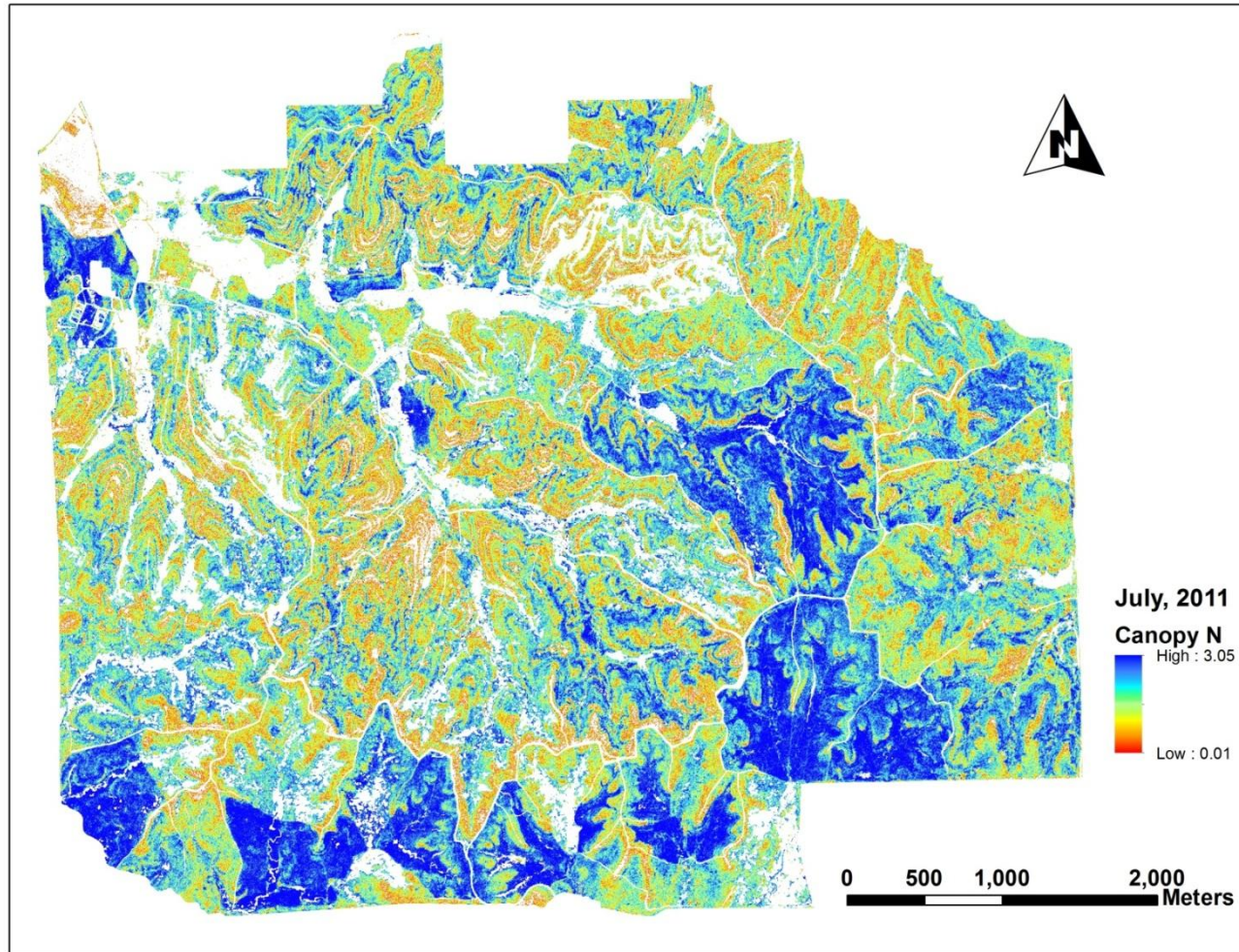


Figure 4.13 Canopy nitrogen map of KPBS in July, 2011, based on the general nitrogen retrieval model for the growth season from May to August was applied to the hyperspectral imagery ($N_{can} = 1.401 - 2699D_{583} - 1094D_{592}$). White areas are where gallery forest was removed (see Methods – Spectral Data from Aerial Imagery).

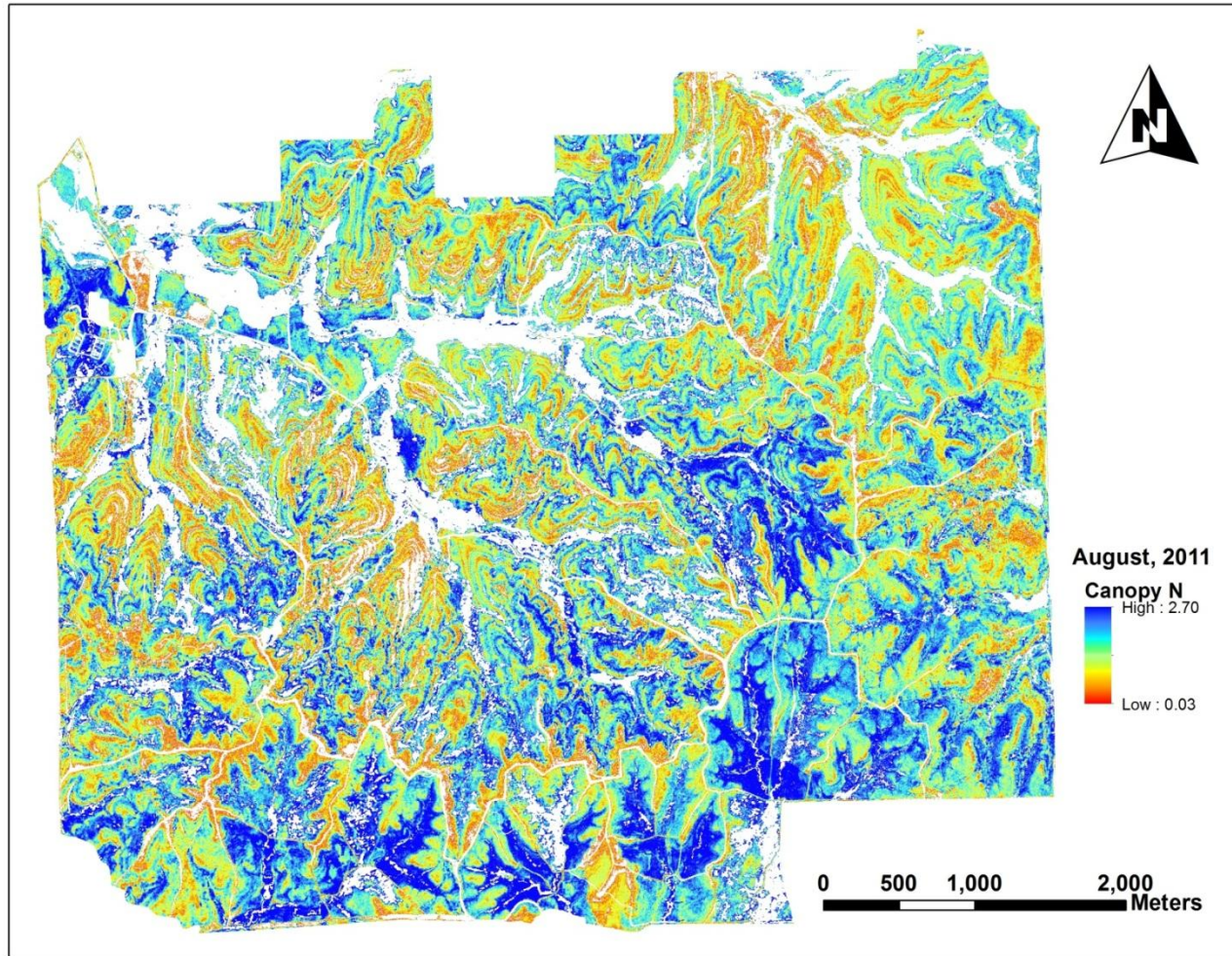


Figure 4.14 Canopy nitrogen map of KPBS in August, 2011, based on the general nitrogen retrieval model for the growth season from May to August was applied to the hyperspectral imagery ($N_{can} = 1.401 - 2699D_{583} - 1094D_{592}$). White areas are where gallery forest was removed (see Methods – Spectral Data from Aerial Imagery).

Chapter 5 - Conclusions

Although hyperspectral remote sensing has been widely used in estimates of biochemical content in uniform canopies such as crops and forests, feasibility of the use of hyperspectral analysis in heterogeneous canopies remains uncertain. My research addressed this problem by estimating nitrogen concentration in mixed grasslands of KPBS based on hyperspectral data from in-situ and airborne measurements. Canopies in KPBS disturbed by fire and ungulate grazing are of various structure characteristics and diverse plant species, resulting in complicated spectral mixture of variable background effects, biochemical (i.e., leaf biochemical concentration) and biophysical properties (i.e., biomass or LAI) at the canopy scale.

Given the green LAI is an important canopy biophysical parameter in nitrogen scaling from the leaf level to the canopy level, chapter 2 explored non-destructive methods for LAI retrieval in heterogeneous canopies. LAI can be measured by the ceptometers based on inversion models of radiative transfer in a fast and cost-efficient way. However, the ceptometer LP-80 used in this study may overestimate green LAI in senescent canopies. LAI calculation by LP-80 is determined by the ratio of the photosynthetically active radiation (PAR) under the canopy to the incident PAR above the canopy. The senescent leaves intercept the solar light passing through the canopy, resulting in an underestimated PAR below the canopy and therefore an overestimated LAI. Given this limitation of the ceptometer, LAI-NDVI relationships have been investigated to provide an alternative to green LAI estimates. Both the linear and the exponential models fitted well into the relations between LAI and NDVI in the unsaturated canopies of KPBS during the vegetation growth seasons. The exponential model showed slight advantages over the linear model in performance of regression modeling and model validation, which was used to retrieve the green LAI in the following studies.

Chapter 3 developed empirical nitrogen models from in-situ hyperspectral data. Nitrogen content was scaled from leaves to canopies using the canopy-integrated methods, by which canopy nitrogen was calculated as the product of the leaf nitrogen concentration and the green LAI. Spectral analysis was focused on a fine chlorophyll absorption feature in the green-yellow region at wavelengths of 562 – 600 nm. The first derivative and continuum removal were examined to be useful in spectral normalization. Significant spectral features related to canopy nitrogen could be selected from the first derivative and the continuum removed spectral data by

multivariate regression. In addition, the SDVI integrating two important features (i.e., the value in the position where the original reflectance decreased fastest, and the minimal value in the absorption pit) from the continuum removed spectral data has been demonstrated to be a good indicator of canopy nitrogen content.

Monthly models during May – September and general models for the whole growth seasons across different watersheds with heterogeneous canopies could be determined from in-situ data. However, these determined in-situ models could be hardly directly applied to the aerial hyperspectral imagery due to differences in spatial and spectral resolutions between the in-situ and airborne measurements. Based on findings from in-situ data in the previous study, research emphasis in chapter 4 of spectral analysis on aerial imagery was still focused on the green-yellow region. Imagery spectral resolution of ~ 10 nm in September was different from in other months of ~ 3 nm. Comparison spectral data with spectral resolutions of 10 nm and 3 nm revealed that the relatively broad channels of 10 nm, though with less subtle features than channels of 3 nm, were feasible in detection of variability in canopy nitrogen concentration.

The optimal nitrogen models from imagery spectral analysis for individual month during May – September with the highest prediction accuracy measured as lowest ranges of RMSE were used to map canopy nitrogen content in KPBS. These maps coupled with data of bison distributions would be of great value in understanding interactions between forage quality and grazing patterns of large herbivores in ecosystems of tallgrass prairie.

On summary, my research showed that the chlorophyll absorption feature in the green-yellow region at wavelength 562 – 600 nm was sensitive to nitrogen status, which could be used in canopy nitrogen estimates. One of the challenges, which still required more research efforts in further studies, was the spectral analysis scaling from the leaf level to the canopy level. Canopy nitrogen scaling in my research was simply based on the canopy-integrated method in terms of the value of LAI. Other parameters that describe the canopy characteristics, such as the canopy height, might improve the nitrogen modeling if taken into account. Additionally, the empirical model for green LAI retrieval should be strengthened and verified further.

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