Near-Ground Remote Sensing of Green Area Index on the Shortgrass Prairie

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Abstract

Accurate and efficient leaf area measurements of shortgrass prairie vegetation are difficult to obtain. Few studies have considered the green area index (GAI) as an approximation of the total area of photosynthetically active tissue per unit of ground area. The main objective of this study was to evaluate several near-ground remote sensing methods as reliable and cost efficient measures of GAI on the shortgrass prairie. GAI measured with a standard leaf area meter was compared to 1) spectral vegetation indices calculated from multispectral radiometer data, 2) GAI obtained from laser point-frame measurements, and 3) green cover estimates derived from digital camera images. All methods were assessed for accuracy, time, and cost efficiency. Data were collected in 2001 at the Central Plains Experimental Range in northern Colorado. The standard leaf area meter method was neither time nor cost efficient in comparison with the other methods evaluated in this study. The cost of GAI measurement with the traditional leaf area meter method (\$225 per plot) was 20 times greater than GAI estimation with the multispectral radiometer (\$11 per plot). Comparison of GAI obtained with the standard leaf area meter method with red-band reflectance index values (0.63–0.69 μm) obtained with a portable multispectral radiometer resulted in the best model predictions ($R^2 = 0.76$, Akaike's information corrected criterion [AICC] = 182.9) and the most cost efficient method for GAI estimation. Green cover estimates from digital image analysis resulted in a good correlation with the leaf area meter GAI ($R^2 = 0.72$, AICC = 178.1). However, classification accuracies of digital images were decreased by limited spectral separability between green vegetation, brown vegetation, and soil background. Further calibration and refinement of near-ground remote sensing techniques for vegetation might establish these methods as efficient ground-truth alternatives to satellite-based remote-sensing applications of rangelands such as the shortgrass prairie.

Resumen

En los pastizales de zacates cortos es difícil obtener mediciones certeras y eficientes del área foliar de la vegetación. Pocos estudios han considerado el índice de área verde (GAI) como una aproximación del área total de tejido fotosintéticamente activo por unidad de área de suelo. El principal objetivo de este estudio fue evaluar varios métodos de sensores remotos cercanos al suelo para obtener mediciones, confiables y eficientes en costo, del GAI en pastizales zacates cortos. El GAI obtenido con un medidor estándar de área foliar fue comparado con: índices espectrales de vegetación calculados a partir de datos de un radiómetro multiespectral, 2) GAI obtenido a partir de mediciones del marco de puntos láser y 3) estimaciones de la cobertura de tejido verde derivadas de imágenes de cámara digital. Todos los métodos fueron evaluados para determinar su certeza y eficiencia en tiempo y costo. Los datos fueron colectados en el 2001 en la Estación Experimental de Pastizales Central Plains en el norte de Colorado. El método estándar de medición de área foliar no fue efectivo ni en costo ni en tiempo en comparación con los otros métodos evaluados en este estudio. El costo de las mediciones de GAI con el método tradicional de medición de área foliar (\$225/parcela) fue 20 veces mayor que la estimación de GAI con el radiómetro multiespectral (\$11/parcela). La comparación del GAI obtenido con el medidor estándar de área foliar con los valores del índice RED (Reflejo de la banda roja, 0.63–0.69 μm) obtenidos con un radiómetro multiespectral portátil produjeron el mejor modelo de predicción ($R^2 = 0.76$, AICC = 182.9) y fue el método más efectivo en costo de la estimación de GAI. Las estimaciones de cobertura verde a partir del análisis de las imágenes de la cámara digital produjeron una buena correlación con el GAI del medidor de área foliar ($R^2 = 0.72$, AICC = 178.1). Sin embargo, la clasificación de las certezas de las imágenes de la cámara digital fueron reducidas por la limitada separación espectral entre la vegetación verde, la café y el fondo del suelo. Una mayor calibración y refinamiento de las técnicas de sensores remotos cercanos al suelo pudiera situar a estos métodos como alternativas terrestres verdaderas eficientes para la aplicación de los sensores remotos satelitales en pastizales tal como los de zacates cortos.

Key Words: digital imagery, remote sensing, LAI, leaf area, laser point frame, multispectral radiometer

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INTRODUCTION

Traditional methods for estimation of canopy structure variables such as biomass and leaf area index (LAI) on the shortgrass prairie often involve clipping vegetation, which is destructive, time and labor intensive, and often restricted to small areas (Tucker et al. 1975). LAI, an estimate of the total 1-sided leaf area per unit of ground area, is an important canopy variable (Deblonde et al. 1994; Lane et al. 2000) and can be important in studying feedback mechanisms between plant community composition and ecosystem processes (Chapin et al. 1998). Another vegetation area estimator is the green area index (GAI), which considers the total photosynthetically active plant tissue per unit of ground area. Previous studies conducted on the shortgrass prairie have not considered GAI. Even though the same LAI measurement methods can be applied in measurement of GAI, traditional methods often involve clipping vegetation (Tucker et al. 1975). Alternative GAI measurement techniques may be nondestructive and more efficient than clipping. These methods should be objective, reliable, repeatable, time and cost effective, and provide results with acceptable variability (Booth and Tueller 2003).

One alternative method to clipping vegetation to measure GAI is to use the point-frame technique, which is nondestructive, but can be time consuming. The point frame is a point-quadrat technique that considers the average number of contacts per pin at various angles from the horizontal (Warren-Wilson 1963). Point sampling is considered to be an objective technique for vegetation analysis and has been used extensively in quantifying LAI in rangeland studies (Knight 1973; Bonham 1989; Clark and Seyfried 2001; VanAmburg et al. 2005).

Remote sensing has potential applications for rangeland management and monitoring of large areas at a low cost. Research is currently being conducted to develop remote sensing methods to measure indicators of ecosystem health: detection of noxious weeds, estimation of rangeland productivity with radiation use efficiency models of gross primary production, assessment of watershed function, and measurement of canopy structure and soil roughness as indicators of susceptibility to soil erosion (Everitt et al. 1995; Booth and Tueller 2003; Hunt et al. 2003). Remote sensing applications may be effective for GAI estimation on rangelands such as the shortgrass prairie. However, satellite remotely sensed data used to estimate vegetation attributes such as GAI often present a tradeoff between direct but incomplete ground sampling and complete but indirect remote sampling (Friedl et al. 1994). One of the biggest problems in estimation of green vegetation using satellite sensors is that the spatial resolution of the sensors is much larger than vegetation objects (Jensen 1996). As a result, pixel measurements of the sensors represent an integration of sub-pixel reflectance components such as vegetation, shadows, soil, and interaction of soil and vegetation (Huete 1988; Anderson et al. 1993; Todd and Hoffer 1998). Spectral vegetation indices determined from radiometric data from satellite sensors must adequately differentiate vegetation and soil surface features that influence reflectance measures (Hoffer 1978; Todd et al. 1998; Hunt et al. 2003).

Near-ground remote sensing of vegetation with digital cameras could be an effective alternative for estimation of

GAI at a finer resolution than radiometric data from satellites. Digital camera imagery has applications for monitoring forage production, for measuring green cover, for detecting pests and pathogens, and for other management purposes (Adamsen et al. 1999). Digital imagery techniques are nondestructive, can accelerate the process of data collection, can be used for repeated mapping of rangeland vegetation, and can serve as a record of permanent plots.

The objective of this study was to assess the accuracy, precision, and relative costs of labor of the traditional leaf area meter method and various indirect methods for measuring GAI on the shortgrass prairie. The traditional method involved clipping green vegetation and measuring the green plant area with a leaf area meter. This standard method was compared with measurements for the same plots using: 1) a laser point-frame, 2) spectral indices calculated from reflectance measurements obtained with a portable multispectral radiometer, and 3) green cover estimates derived from digital camera images. All methods were also compared qualitatively and were expected to differ in terms of labor necessary for data collection and processing, cost, precision, and repeatability. The leaf area meter method was hypothesized to be least repeatable, most time consuming, and least cost effective.

MATERIALS AND METHODS

Study Site

The field study was conducted at the US Department of Agriculture–Agricultural Research Service Central Plains Experimental Range (CPER) located 60 km northeast of Fort Collins, Colorado (lat 40°49'N, long 107°47'W). The CPER is a 6 280-ha research area and has a long history of moderate grazing by cattle (Todd et al. 1998). The CPER is characterized by a semiarid climate. Mean annual precipitation averages 321 mm and 85% of the precipitation occurs from May through July (Todd et al. 1998). A midsummer senescence caused by drought is common (Anderson et al. 1993). Soils at the CPER are mostly sandy loam.

The shortgrass prairie vegetation at the study site was dominated by C₄ blue grama grass (*Bouteloua gracilis* [H.B.K.] Lag.) and C₃ threadleaf sedge (*Carex filifolia* Nutt.). Blue grama accounts for 90% of the total plant basal cover at the CPER (Milchunas et al. 1989). Other prominent species at the study site included prickly pear cactus (*Opuntia polyacantha* Haw.) and fringed sagewort (*Artemisia frigida* [Willd.] Klein) (Hazlett 1998; Todd et al. 1998). Using the point-frame method, Knight (1973) estimated the maximum total green LAI at CPER to be 0.5 in mid-June and Hazlett (1992) estimated it to be 0.55 with peak standing crop occurring in mid-July.

The study site utilized in this study had been moderately grazed by cattle (40% of annual aboveground forage removed) for at least the past 65 years. An ungrazed (control) paddock was established within this site and cattle were introduced into 2 other grazing treatment paddocks within the study site in mid-May 2001. Approximately 40% of forage was removed by cattle in the moderately grazed paddock, and 80% was removed in the heavily grazed paddock. The cattle were scheduled to graze until late September 2001. However, they were

removed in mid-August because of dry conditions and little available forage.

Experimental Design and Data Analysis

A randomized design was used where 3 grazing treatments were sampled at 3 separate times during a growing season. A 90- × 150-m sampling area was established within each grazing treatment paddock at the historically grazed study site. Nine 1-m² plots were located at random within each sampling area for a total of 27 plots for each sampling date. Nine plots per grazing treatment were randomly reselected for each sampling date because vegetation in the plots was clipped during each sampling event. Data were collected from 1-m² plots in May, July, and October 2001.

Data were analyzed using SAS System software (SAS 2001). Multiple regression analysis with backwards elimination was performed where GAI obtained with the leaf area meter was the dependent variable and each method was treated as an independent variable in a mixed-model procedure. Sampling date and grazing treatment were also included as independent variables in multiple regression analyses. It was necessary to transform GAI data in the natural log scale to normalize variance errors. All main effects and interactions were tested for significance at a 95% confidence level. The regression models were compared using R^2 values, Akaike's information corrected criterion (AICC), and standard error.

Cost efficiency analyses considered time and costs to complete each sampling approach. Costs comprised direct costs of field and lab supplies and instruments, as well as labor and time necessary for completion of all fieldwork and lab analyses. Costs of the main instruments and software (laser point-frame, multispectral radiometer, digital camera, image analysis software, and area meter) were prorated on a time basis (hours of use). Total costs were calculated per plot for each sampling method.

Laser Point-Frame

The laser point-frame used has an aluminum bar where traditional pins have been replaced by lasers so that 10 beams of red light intersect the canopy or soil surface at a nadir orientation (VanAmburg et al. 2005). One hundred data points were collected per 1-m² plot in May, and 80 data points per plot were collected in July and October. Readings were reduced from 100 to 80 in July and October after analysis of May data showed no significant differences in results between 100-point and 80-point data ($P = 0.77$). Hits were recorded as the laser beam intersected green vegetation, dead vegetation, litter, rock, or bare ground. GAI for each plot was calculated by dividing the number of laser hits on green vegetation by the total number of observed laser point hits. Six data points (6 plots) were removed from laser point-frame data before statistical analysis. These points appeared as outliers as a result of technician errors in field data collection.

Digital Camera

Color digital images of each 1-m² plot were taken at nadir from a 2-m elevation with an Olympus CAMEDIA E-10

digital camera. The camera recorded images of dimension 2 240 × 1 680 pixels using a 28–80-mm lens with a 30-mm focal length (Fig. 1A). The camera was mounted adjacent to the multispectral radiometer on a telescoping boom and images were acquired remotely between 1100 and 1400 hours to minimize shadow effects.

A 95- × 95-cm area within the imaged plot frame was used as a subset for digital image processing. The subset images were processed with ERDAS IMAGINE 8.5 software (ERDAS IMAGINE 1999). Three images were initially classified into 5 classes: green vegetation, brown vegetation, soil, shadow, and saturated pixels, to derive green cover (Fig. 1B). One image from May and 1 image from July were selected and classified respectively with a hybrid classification. Spectral separability of these classes was evaluated with transformed divergence procedures (ERDAS IMAGINE 1999). Mixed classes were further "cluster busted" (Jensen 1996) with the unsupervised procedure to better separate classes, and spectral separability of resultant classes was evaluated again with transformed divergence procedures. The respective signature files were then used in the final supervised classification of the May and July images with a maximum likelihood algorithm. The classifications were assessed for accuracy using 250 randomly stratified points (ERDAS IMAGINE 1999). Accuracy results suggested that it was difficult to accurately discriminate green vegetation pixels from brown vegetation, soil, and shadow pixels. Consequently, the 5 initial classes were amalgamated into 2 classes: green vegetation and other (brown vegetation, soil, shadow, and saturated pixels; Fig. 1C). These respective master signature files were then used to process all May and July images in a supervised classification. Accuracy assessments were performed on 6 images selected at random for each sampling date.

Supervised classification with a maximum likelihood classifier (ERDAS IMAGINE 1999) was completed on October images because of a large decrease in spectral separability (associated with senescence of vegetation) between green vegetation and brown vegetation. Again, accuracy results suggested that it was difficult to accurately discriminate cover components based on 5 classes and therefore they were revised into 2 classes: green and other. This signature file was then used to process the remaining October images in a supervised classification. Accuracy assessments were also performed on 6 images selected at random for this date. Green pixel and all classified pixel counts were used to calculate green cover for all classified images.

Multispectral Radiometer: Spectral Indices

Reflectance measurements were made with a MSR-87 multispectral radiometer (CROPSCAN Inc 2002). The radiometer had a 28° field of view and measured reflected radiation in 8 narrow wavelength bands centered at 0.49 μm , 0.56 μm , 0.66 μm , 0.71 μm , 0.83 μm , 1.10 μm , 1.24 μm , and 1.65 μm . The radiometer was mounted on the telescoping boom at a 2-m elevation over each 1-m² plot. Measurements were taken between 1100 and 1400 hours on clear days and were referenced to a barium sulfate (BaSO₄) panel and a flat black surface panel every 45–60 minutes.

A. Unprocessed Image

B. Hybrid Classification: 5 classes

C. Hybrid Classification: 2 classes

Figure 1. A, Original, unprocessed May digital image. B, C, May image classified with ERDAS IMAGINE 8.5. The original image was initially classified into 5 classes with a hybrid classification (B). The signature file was then revised into 2 classes (C): green vegetation and other, which included brown vegetation, soil, shadow, and saturated pixels.

Spectral indices were calculated from reflectance in the red (RED, 0.66 μm) and near-infrared bands (NIR, 0.83 μm). RED index was simply the measurement of reflectance in the red band. The normalized difference vegetation index (NDVI) and soil adjusted vegetation index (SAVI) were calculated as follows:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad [1]$$

$$SAVI = \frac{(NIR - RED)}{(NIR + RED + L) \cdot (1 + L)} \quad [2]$$

Figure 2. GAI measured with the leaf area meter. There were no significant grazing treatment effects ($P = 0.84$) as indicated by similar letters above the standard error bars for each sampling date.

For SAVI, a correction coefficient (L), $L = 1$, was used to adjust for spectral soil background variations. Because shortgrass prairie LAI was expected to be 0–0.5, L of 1 was chosen based on Huete's (1988) conclusions that an L of 1 was appropriate for low vegetation cover where there is not enough vegetation to cause a canopy-scattered, soil-reflected signal.

Leaf Area Meter

The leaf area meter is the standard method for obtaining LAI of vegetation. Because it is currently the best method available for obtaining near absolute measurements of LAI, the leaf area meter was used as the standard measure of GAI in this study. Vegetation in a 25-cm $\times$ 1-m subplot within each 1-m² plot was clipped at the soil surface for GAI measurements with a LI-3100 leaf area meter (LI-COR Inc 2003). To minimize wilting, vegetation subsamples from each subplot were placed between moist paper towels, put in plastic bags, and placed in a cooler. These vegetation subsamples were manually sorted into green and brown (senesced) components before drying. The remainder of the clipped vegetation from the subplot was also sorted into green and brown components. All vegetation subsamples were oven-dried at 60°C and weighed.

To minimize curling and overlapping, the green vegetation subsamples were arranged on a clear glass plate and scanned with a flatbed scanner. The scans were enhanced in Adobe Photoshop 6.0 (Adobe Photoshop 2000) and printed on transparencies. The transparencies were then read 3 times with the leaf area meter (1-mm² lens resolution) and averaged to obtain subsample green area. LI-COR reports the leaf area meter measurements to be $\pm 7\%$ accurate for 0.5-cm² sample area at the 1-mm² lens resolution (LI-COR Inc 2003). Succulents and round stems were measured directly with the area meter. Spines were removed from cacti, pads were dissected laterally, and half of each pad was scanned through the area meter. Subsample dry weights and dry weights of vegetation from each subplot were used to calculate green vegetation area of each subplot. The green vegetation area of the subplot was then divided by the ground area of the subplot (0.25 m²) to obtain its GAI. This

Table 1. Regression variables for regression models of GAI as predicted by red-band reflectance index (RED), normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), digital camera green cover estimates (Digital camera), and laser point-frame GAI (Laser point-frame). All models were significant at $P \leq 0.05$.

Method	R^2	AICC ¹	SS _E
RED	0.76	182.9	38.57
SAVI	0.73	188.8	44.06
NDVI	0.72	190.0	46.23
Digital camera	0.72	178.1	45.86
Laser point-frame	0.63	199.4	57.76

¹AICC indicates Akaike's information corrected criterion; SS_E, sum of squares error.

GAI of the subplot was assumed to be representative of the entire 1-m² plot.

RESULTS AND DISCUSSION

Leaf Area Meter

GAI as determined with the leaf area meter was greatest in May and decreased with the growing season as vegetation senesced (Fig. 2). The 2001 growing season was not representative of a typical shortgrass prairie growing season at the CPER. The growing season is typically characterized by peak green biomass in mid-June to mid-July and senescence in late summer with possible green-up in the fall (Lauenroth and Milchunas 1992). Despite an atypical growing season, average GAI of 0.52 obtained at the peak of green biomass in May 2001 was consistent with a 0.5 estimate of Knight (1973) and a 0.55 estimate of Hazlett (1992) when green biomass peaked in mid-June and mid-July, respectively. Variance about the mean (SE) was highest in May GAI estimates (0.52 GAI $\pm$ 0.057 SE) and decreased for July (0.15 GAI $\pm$ 0.009 SE) and October estimates (0.04 GAI $\pm$ 0.003 SE). No significant differences in GAI were detected as a result of cattle grazing treatments ($F = 0.18$, $df = 2,72$, $P = 0.84$). Although the leaf area meter method was tedious and expensive, it appeared to provide more precise GAI estimates when areas of small vegetation components were measured from transparencies of vegetation, rather than from actual vegetation. Regression models of leaf area meter GAI as a function of laser point-frame GAI, digital camera green cover estimates, and spectral indices are compared in Table 1 and further discussed below.

Laser Point Frame

The point-frame method, which has been used in numerous rangeland vegetation studies (Levy 1927; Cook and Stubbendieck 1986; Bonham 1989; Clark and Seyfried 2001), was the least effective of all techniques for estimation of GAI in this study. The laser point-frame GAI explained 63% (Table 1) of variability in the natural log of GAI obtained with the leaf area meter (Fig. 3A). Grazing treatment was not significant in the model ($F = 0.93$, $df = 2,6$, $P = 0.45$). The correlation between leaf area meter GAI and laser point-frame GAI might have been improved if more than 80 point observations per sampled plot had been collected in July and October.

Figure 3. A, Natural-log-transformed GAI (ln GAI) measured with the leaf area meter vs. GAI obtained with the laser point frame. B, Natural-log-transformed GAI (ln GAI) measured with the leaf area meter vs. green cover estimates calculated from digital camera images. Because sampling date and the interaction between sampling date and green cover had significant effects in the final model, the regression function should be adjusted by sampling date for estimation of GAI using digital camera images: $\ln \text{GAI} = \beta_0 + \beta_{11} (\text{May}_{11}) + \beta_{12} (\text{July}_{12}) + \beta_2 (\text{green cover}_2) + \beta_{31} (\text{May}_{31} \text{ green cover}) + \beta_{32} (\text{July}_{32} \text{ green cover})$, where $\beta_0 = -7.88$; $\beta_{11} = 6.96$; $\beta_{12} = 6.65$; $\beta_2 = 26.98$; $\beta_{31} = -26.30$; $\beta_{32} = -31.47$; $\text{May}_{11} = 1$ if May, 0 otherwise; $\text{July}_{12} = 1$ if July, 0 otherwise; $\text{green cover}_2 = \text{green cover estimate from digital image classified with ERDAS IMAGINE software}$; $\text{May}_{31} \text{ green cover} = 1$ if May, 0 otherwise; $\text{July}_{32} \text{ green cover} = 1$ if July, 0 otherwise.

The results could have further been compromised by the size of the lasers because point sampling may be affected by the diameter of the contact point (Cook and Stubbendieck 1986; VanAmburg et al. 2005). The projected laser dot from the point frame used in this study was 1 mm in diameter (0.8-mm² area), but the center of the laser dot was surrounded by a red halo, which increased the total size of the projected laser dot and may have introduced technician bias during data collection. Nevertheless, point sampling with lasers rather than with traditional metal pins alleviated the problems of bent and blunt pins encountered when using conventional point frames and magnetic point frames (Heady and Rader 1958; Conrad 1969; Taha et al. 1983; VanAmburg et al. 2005). The lasers allowed for more consistent and repeatable collection of vegetation data, especially during windy conditions or when points had to be rerecorded because of technician error.

Digital Camera

Green cover estimates calculated from classified pixel counts of digital images were highest in May and decreased in July and October. Analysis of digital camera images with ERDAS IMAGINE 8.5 produced a model ($R^2 = 0.72$, Table 1) where sampling date ($F = 9.69$, $df = 2,6$, $P < 0.002$), green cover estimates ($F = 4.32$, $df = 1,51$, $P < 0.04$), and the interaction between sampling date and green cover ($F = 4.74$, $df = 2,51$, $P < 0.01$), were all significant in prediction of GAI (Fig. 3B). Therefore, the model should be adjusted to slope and y-intercept values for each sampling period within a growing season in estimation of GAI from digital camera images (Fig. 3B). Paruelo et al. (2000) used a photographic technique and ratios of green, blue, and red bands for pixel intensities to develop an aboveground plant biomass model on the CPER. They also found that the slope and y-intercept of their model differed significantly among sampling dates. The importance of

sampling time in the final model could be attributed to changes in the canopy structure and dominance of functional groups (grasses, forbs, succulents) over the growing season (Hoffer 1978; Weiser et al. 1986; Paruelo et al. 2000).

Most image classification errors occurred in separation of spectrally similar green and brown vegetation pixels. Accuracy assessments with stratified random pixels were completed for 22% of all images. Overall classification accuracies ranged from 79% to 96% and the overall kappa statistic ranged from 0.46 to 0.84. Highest classification accuracies were achieved for October images which can be attributed to the development of a large signature file (184 training samples) used in the supervised classification of October images. This process presented a trade-off between higher classification accuracies and a great amount of time necessary to develop and complete classification processes. Users' accuracies (probability that a pixel classified on an image actually represented that category on the ground) were consistently lower for the green class than for the other class, which included brown vegetation, soil, shadow, and saturated pixels. These lower accuracies were a result of misclassification of green pixels into the other class and indicated the difficulty in distinguishing pixels of green vegetation from pixels of brown or senesced vegetation and pixels of dry, light-colored soil of the shortgrass prairie. The classification errors occurred when different image components (i.e., senescent vegetation, water-stressed vegetation, dry soil) had similar spectral signatures (Hoffer 1978; Jensen 1996). Other rangeland studies on spectral measurements have found that presence of senescent vegetation mixed with soil background interfered with estimation of vegetation attributes from spectral data (Weiser et al. 1986; Frank and Aase 1994; Todd et al. 1998; Booth and Tueller 2003). Shadows caused by shading from standing biomass also decreased classification accuracies and green cover estimates. It was not possible to distinguish all shadow pixels from green vegetation, especially

dark green vegetation pixels bordering shadow pixels that had similar spectral reflectance (Hoffer 1978; Booth and Tueller 2003). This might have resulted in underestimation of green cover from digital images.

Multispectral Radiometer: Spectral Indices

Spectral indices were moderately correlated with GAI measured with the leaf area meter method (Table 1). The RED index resulted in the best-fit model ($R^2 = 0.76$; Fig. 4A) where sampling date and RED index were significant variables ($F = 49.66$, $df = 2,16$, $P < 0.0001$; $F = 26.34$, $df = 1,53$, $P < 0.0001$, respectively) but grazing treatment was not ($F = 0.64$, $df = 2,6$, $P = 0.56$). The negative relationship between GAI and the RED index resulted from spectral properties of green vegetation when light-colored soils were present. Because light soils and senesced vegetation had greater reflectance than green vegetation in the red band centered at $0.66 \mu\text{m}$, reflectance in the red wavelength increased as green biomass decreased (Hoffer 1978). The good correlation of the RED index with GAI corresponds to findings of other studies that determined the red waveband ($0.63\text{--}0.66 \mu\text{m}$) to be most sensitive to changes in low levels of photosynthetically active vegetation, whereas the NIR waveband ($0.74\text{--}1.00 \mu\text{m}$) was more sensitive to moderate and high densities of green vegetation (Pearson et al. 1976; Tucker 1977; Frank and Aase 1994).

Regression of NDVI data with GAI resulted in a model where natural-log-transformed NDVI explained 72% of variability in natural-log-transformed GAI ($R^2 = 0.72$; Fig. 4B). Sampling date and grazing treatment effects were not significant in the model ($F = 1.72$, $df = 2,12$, $P = 0.22$; $F = 0.08$, $df = 2,6$, $P = 0.93$, respectively). The natural-log transformations removed errors of variance and curvilinear nature of these data. The positive relationship between NDVI and GAI was a result of spectral reflectance properties of light soils found at the study site and of green vegetation. The index took into consideration NIR reflectance of these substrates. In the NIR portion of the electromagnetic spectrum ($0.83 \mu\text{m}$), green vegetation had higher reflectance than light-colored soil. Thus, as green biomass increased, NIR reflectance increased and red reflectance decreased (Hoffer 1978; Frank and Aase 1994). As a result, NDVI was lowest at the end of the growing season and highest at the beginning of the growing season when GAI was high (Fig. 4B).

Similar to NDVI, natural-log-transformed SAVI explained 73% of the variability in natural-log-transformed GAI values ($R^2 = 0.73$, Fig. 4C). Again, sampling date and grazing treatment were not significant variables in the model ($F = 1.18$, $df = 2,12$, $P = 0.34$; $F = 0.29$, $df = 2,6$, $P = 0.76$, respectively). SAVI was developed from NDVI to more accurately model NIR radiant transfer in fragmented canopies to remove soil background noise caused by differences in soil background properties such as senesced litter or dry and light-colored soils (Huete 1988; Rondeaux et al. 1996; Huete et al. 1997). Thus, the positive relationship between SAVI and GAI can be explained by the same principles as the NDVI and GAI relationship. Results indicated that SAVI did not improve GAI predictions over NDVI. This might be attributed to small variations in soil background among plots within the study area. Huete (1988) and Huete et al. (1997) noted that NDVI was

Figure 4. A, Natural-log-transformed GAI (ln GAI) measured with the leaf area meter vs. the red-band reflectance index values (RED) calculated from spectral reflectance at $0.66 \mu\text{m}$. Because sampling date had a significant effect in this final model, the regression function should be adjusted for a given sampling date: $\ln \text{GAI} = \beta_0 + \beta_1 (\text{May}_1) + \beta_2 (\text{July}_2) + \beta_3 (\text{RED Index}_3)$, where $\beta_0 = 2.52$; $\beta_1 = -0.01$; $\beta_2 = 2.06$; $\beta_3 = 0.47$; $\text{May}_1 = 1$ if May, 0 otherwise; $\text{July}_2 = 1$ if July, 0 otherwise; $\text{RED Index}_3 = \text{Red index value}$. B, Natural-log-transformed GAI (ln GAI) measured with the leaf area meter vs. natural log transformed NDVI (ln NDVI) values. C, Natural-log-transformed GAI (ln GAI) measured with the leaf area meter vs. natural log transformed SAVI (ln SAVI) values.

affected by soil background in global data sets where soil types varied across landscapes. Differences between NDVI and SAVI might be greater if plots were larger than 1 m^2 or were distributed over a larger, more diverse study area where SAVI might minimize soil background differences better than NDVI.

Figure 5. Cost per plot for estimation of GAI with spectral indices calculated from radiometer reflectance measurements, laser point-frame GAI, green cover derived from digital images, and the standard leaf area meter method.

Results of this study suggest that the RED index was slightly better than either NDVI or SAVI for GAI estimation over highly reflective light-colored soils found at the shortgrass prairie study site. These results were consistent with results of Graetz et al. (1988) who found the RED index to be better than NDVI for biomass estimation over highly reflective soils on the shortgrass prairie. Todd et al. (1998) also found that the RED index was superior to the Landsat TM Tasseled Cap green vegetation index, the brightness index, the wetness index, and NDVI for estimation of biomass on the CPER shortgrass prairie. The highly reflective light-colored soils found at CPER may be representative of the shortgrass prairie where soils are dry and high in sand content. The RED index may not be as sensitive to vegetation changes in areas where soil texture and moisture is highly variable.

Costs

Cost efficiency analyses demonstrated (Fig. 5) that the traditional leaf area meter approach to GAI estimation was most expensive (\$225 per plot) and time consuming (13.7 h per plot) in comparison with all other methods. The high cost was primarily associated with the large amount of labor necessary to sort clipped vegetation into green and brown components and to measure the area of green vegetation subsamples with a leaf area meter. Analysis of digital images with ERDAS IMAGINE 8.5 software resulted in an intermediate cost (\$53 per plot, 2.5 h per plot). The highest costs in this methodology were associated with development of image analyses protocols. The cost and time for GAI estimation with the laser point frame was \$27 per plot and 1.6 h per plot, respectively. The use of a multispectral radiometer to calculate spectral indices was the most efficient method for GAI estimation in terms of cost (\$11 per plot) and time (0.4 h per plot).

CONCLUSIONS AND MANAGEMENT IMPLICATIONS

The leaf area meter method for GAI estimation was neither time nor cost efficient in comparison with other methods evaluated in this study. The method was destructive, did not permit repeatable measures over time, and was extremely labor

intensive. Error was introduced when plots were not clipped diligently or clipped vegetation was blown away by the wind. Considering these limitations, a method that accurately provides absolute or near-absolute measurements of GAI is needed for a definitive comparison of near-ground remote sensing techniques for GAI estimation on the shortgrass prairie.

Although remote sensing applications often present a trade-off between accuracy and complete ground sampling, results of this study showed promise for near-ground remote sensing of shortgrass prairie canopy variables such as GAI. The RED index was the best predictor of GAI and the most cost efficient and repeatable method for GAI estimation on the CPER shortgrass prairie. Because change in heterogeneous rangeland environments is more difficult to detect than in homogenous environments such as cropping systems, a more detailed study, which would involve more extensive and frequent sampling of shortgrass prairie vegetation throughout the growing season, is needed to establish this method as a reliable GAI estimator that is sensitive to phenological changes of shortgrass prairie vegetation. Moreover, pseudoreplication should be avoided in future studies by establishing replicate treatment paddocks. We utilized 1 sampling area per ungrazed, moderately grazed, and heavily grazed treatment paddock, which constrained the application of our findings to our study site. Replication of sampling areas and treatment paddocks in the future should warrant a wider application of near-ground remote sensing methods across larger landscape scales.

Further calibration and refinement of vegetation near-ground remote sensing applications might establish these methods as efficient ground-truth alternatives for data that are remotely sensed by satellite in comparison with the traditional methods that involve vegetation clipping. These data could be utilized for large-scale monitoring and management of rangelands such as the shortgrass prairie.

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