Estimating Wheat Canopy Cover by Remote Sensing

P.I. Coyne[1] and R.M. Aiken[2]

[1]Agricultural Research Center, Kansas State Univ., Hays 67601 and [2]NW Research-Extension Center, Kansas State Univ., Colby 67701

Abstract

Quantifying crop phenological development prior to attainment of full canopy using light transmission methods to estimate leaf area index (e.g., LI-COR 2000 Plant Canopy Analyzer, LI-COR Biosciences, Lincoln, NE) is challenging. Canopy cover based on a vertical overhead perspective in which land area is classified as either crop canopy or other (bare soil, crop residue, etc.) offers an alternative approach for sparse canopies. We recorded digital images (3 bands: nir, red, green, pixel size=1.6 mm) from 2 m above the crop canopy of winter wheat (*Triticum aestivum* L.) grown under a range of soil moisture and tillage systems. We classified the pixels using two unsupervised multispectral techniques: (1) density slicing (DS) of NDVI (normalized difference vegetation index = [nir-red]/[nir+red]), where pixels classified as canopy had an NDVI≥0.3 and (2) spectral cluster analysis (SCA) using an iterative self-organizing data algorithm (ISODATA). Overall accuracy of the SCA method was estimated at approximately 95% across a wide range of canopy conditions from sparse to dense. The NDVI threshold (0.3) was chosen based on a digital grid overlay using 100 random points, but these reference data were inferior to those used for the SCA method because of the difficulty of manually classifying a single random reference point overlying very small pixels. Therefore, we considered SCA as the more accurate method and compared DS to SCA by correlation (r=0.96). Either method has application as a remotely sensed proxy for canopy development in wheat growth models. While SCA was considered the more accurate method for small pixels, density slicing NDVI is more efficient to implement and, with calibration against SCA, could be used with confidence.

Introduction

Spectral reflectance-based measures of crop canopy formation can facilitate rapid, non-destructive inference of a primary biotic mediator of land-atmosphere exchange processes including energy exchange, primary productivity, and soil erosivity. We used digital color infrared (CIR) images, analyzed by density slicing NDVI and spectral clustering methods to quantify wheat canopy development ranging sparse to dense.

Methods

Crop Culture. Wheat canopy formation was observed within three cropping system studies which investigated 1) tillage and N-levels in continuous wheat, 2) tillage and N application method in a wheat-grain sorghum-fallow sequence, and 3) cropping intensity—involving eight crop sequences under no- till. This provided a wide range of canopy developmental stages against a diverse background varying in amount of exposed bare soil and surface crop residue. Observations were bi-weekly from mid-March to mid-June, 2008.

Digital Images. Color-infrared digital images (260 each) were recorded from a height of 2 m above the crop canopy using a Tetracam ADC multispectral camera (Tetracam Inc. Chatsworth Ca.) equipped with a 1280x1024 pixel Motorola CMOS sensor. The camera was mounted on an adjustable support frame with a rectangular base. Images were cropped to retain the center 1000 x 700 pixels in order to eliminate the frame base and any border effects. Raw images, in DCM format, were converted to JPG images using vendor-supplied software.

Density Slicing (DS) NDVI. NDVI was computed on a pixel basis for each cropped image as [(nir-red)/(nir+red)]. Percent canopy cover (PCC_{ndvi}) was computed as the number of pixels for which LL≤NDVI≤1 divided by the total pixels per image 700,000). This ratio was multiplied by 100. PCC_{ndvi} for a range of NDVI lower limit (LL) thresholds (LL=0 to 0.4 in increments of 0.05) was computed and compared to results from a digital grid overlay (DGO) classification method (Booth et al., 2005) based on 100 manually classified random points from each of the 260 images image. Correlation coefficients (PCC_{ndvi} vs. PC_{dgo}) were used to determine the best (highest r value) NDVI threshold for estimating canopy cover.

Spectral Cluster Analysis (SCA). A schematic of the methods used to calibrate, classify, and assess accuracy of this method is shown in Figure 1. A composited CIR calibration Image was created from four of the 260 individual images selected to span the approximate range of variability in canopy cover and downwelling radiation, which varied throughout the season so that brightness values for the same objects varied in intensity. Three ArcGIS 9.3 (ESRI, Redlands, CA) algorithms (ISO CLUSTER, DENDROGRAM, MAXIMUM LIKELIHOOD CLASSIFIER) were applied to the calibration image. One hundred unique spectral classes (SC) were generated with ISO CLUSTER using all three bands of the calibration CIR image. A dendrogram was generated using the resulting signature table. The dendrogram grouped similar spectral classes together and was used as a guide to visually (manually) assign each spectral class to an information class (IC) index: 1=canopy (wheat leaves/stems) or 2=other (soil, crop residue, etc.). That entailed selecting all pixels of the calibration image having a specific spectral class index (1-100) and blinking them on and off while superimposed on the CIR calibration image at various levels of magnification to determine the probable IC index (1 or 2) represented by a SC. This produced a table that related SC index to IC index, hereafter called the SC➔IC table. The maximum likelihood classifier (MLC) algorithm assigned a spectral class index (1-100) to all pixels in each of the 260 CIR images based on spectral similarity to the 100 spectral classes in the signature table created by ISO CLUSTER. The SC➔IC table was used to map SC to IC. PCC_{sca} was calculated as the number of pixels for which information class index=1 divided by total pixels per image (700,000).

Classification Accuracy Assessment. Classification accuracy for the SCA method was assessed by constructing error matrices for four diverse images—that were different from those used to create the composite calibration image—using the method of Story and Congalton (1986). Both reference and classification data were generated from the same four images (Figure 1). The starting point was images classified by spectral class using the ISO CLUSTER signature table followed by assigning each pixel to a SC using the MLC. The reference dataset was derived by manually mapping SC to IC. The classification data set was derived by automapping SC to IC using the SC➔IC table.

Reference data for the DS method consisted of 100 manually classified random points. While both methods involved observing blinking dots overlaid on the CIR image, the SCA method averaged 7,000 pixels per spectral class making it easy to assign the information class. For the DS method, a single blinking dot was much more difficult to classify overlaid on 1.6 mm pixels. To mitigate this problem, all 260 images are subjected to the DGO classification. Therefore, the correlation of DS with SCA (considered the more accurate method) was calculated rather than an error matrix.

Results and Discussion

Results and Discussion. The calibration composite CIR image is shown in Figure 2 along with NDVI and the density sliced NDVI images. A lower NDVI threshold for NDVI of 0.3 gave the highest correlation with the digital grid overlay estimates (r=0.96 across all 260 images). An example of the classification of a single image by the SCA method is shown in Figure 3.

The accuracy assessment matrix for SCA is shown in Table 1. Producer's accuracy (PA) for canopy classification is a map-based statistic that represents the number of pixels correctly classified as canopy divided by the number of reference pixels in canopy. An error of omission (excluding a pixel that should have been in the canopy class) is computed as 1-PA. User's accuracy (UA) is a reference-based statistic that represents the number of pixels correctly classified as canopy divided by the total number of pixels classified as canopy. An error of commission (classifying a pixel as canopy that was not canopy) is computed as 1-UA. Overall accuracy is simply the number of pixels classified correctly divided by the total number of pixels. The Kappa statistic estimates the improvement of the classified map relative to a random assignment of pixels to information classes.

Overall classification accuracy was about 95% across all four test images and the Kappa statistic showed that the classified map was superior to random classification of pixels. In addition, the UA for classifying a pixel correctly as canopy was almost perfect (i.e., almost no errors of commission), but the PA was more varied across the four images. PA was only 68% in image 21136, but 89-94% for the other three. Thus, errors of omission ranged from 0.06 to 0.32. Image 21136 represented a very sparse canopy case as indicated in rightmost two columns of Table 1. Errors of omission may be larger in very sparse canopies when using such small pixels, as in this study, because it is more difficult to manually assign a spectral class to an information class during calibration. Errors of omission decreased sharply as canopy development increased.

The regression between $PCC_{ndvi\geq 0.3}$ and PCC_{sca} was slightly cuvilinear reflecting the perceived greater classification error for PCC_{ndvi} for images depicting minimal canopy development (positive y-intercept) . The quadric equation had the following form with an R^2 of 0.95.

$$PCC_{ndvi} = 3.499 + 1.854 * PCC_{sca} - 0.0087 * PCC_{sca}^2$$

Conclusions

While SCA was considered superior to DS for estimating canopy cover in this study, because it used all three image bands and was a more rigorous analysis, density slicing of NDVI was nevertheless highly correlated with the SCA results and provides a more general and easily implemented surrogate particularly if adjusted using a DS:SCA regression equation.

Literature Cited

Booth, D.T., S.E. Cox, and D.E. Johnson. 2005. Detection-threshold calibration and other factors influencing digital measurements of ground cover. Rangeland Ecology and Management 58:598-604.

Story, M., and R.G. Congalton. 1986. Accuracy assessment: A user's perspective. Photogrammetric Engineering and Remote Sensing 52:397-399.

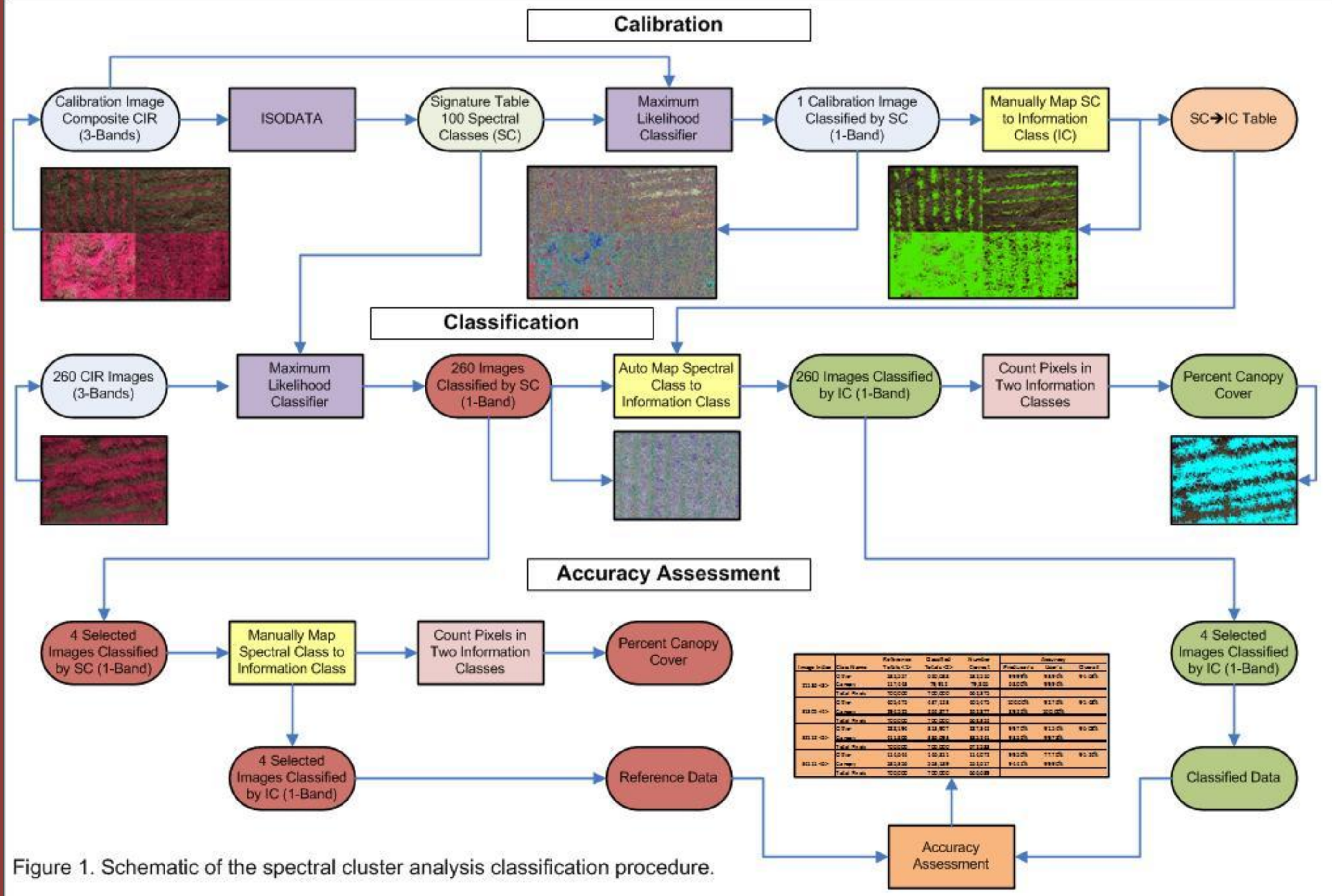

Figure 1. Schematic of the spectral cluster analysis classification procedure.

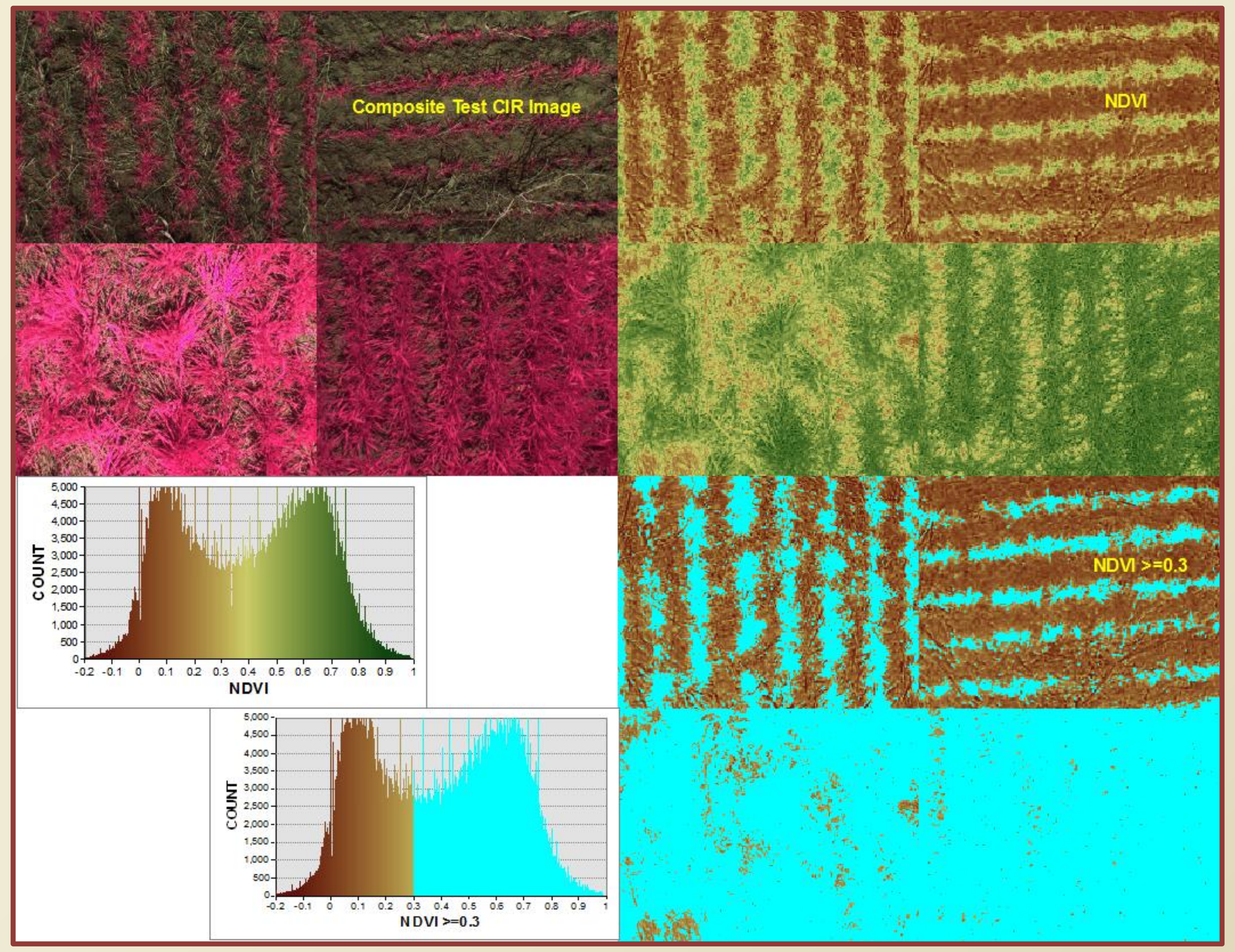

Figure 2. Density slicing NDVI. Percent canopy cover (PCC) based on a lower NDVI threshold of 0.3 was most highly correlated with an independent measure of PCC based on a digital grid overlay and manual classification of 100 random points.

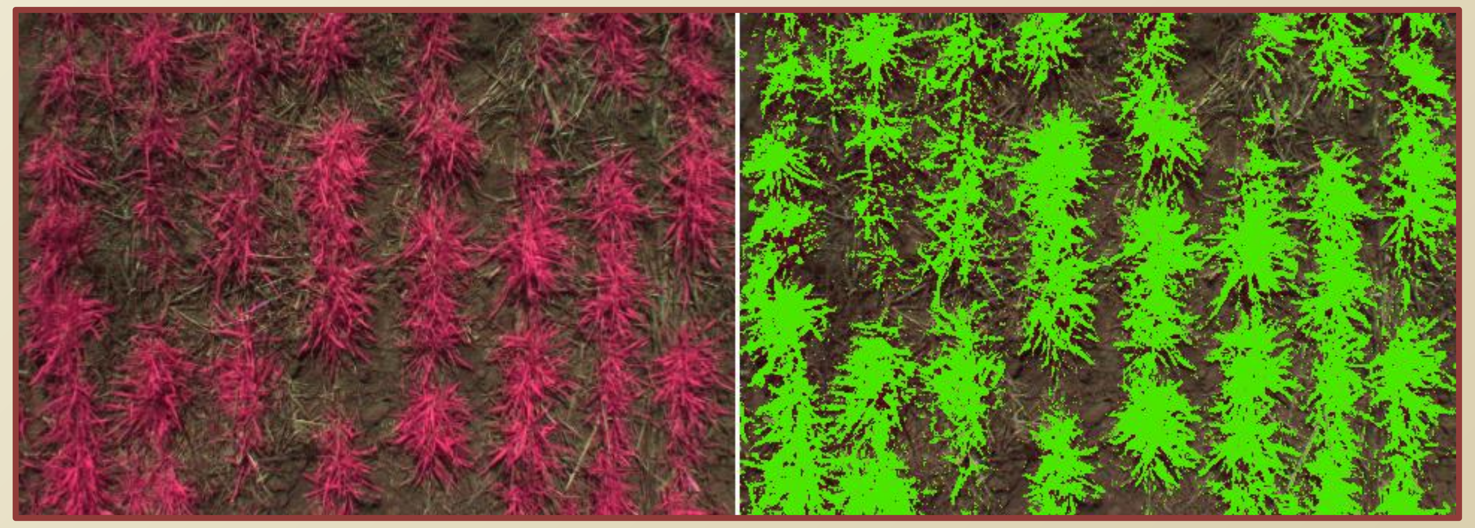

Figure 3. Example of estimating percent canopy cover by the SCA method. PCC_{sca}=43.4%.

Table 1. Accuracy Assessment for ISODATA/MLC Classification Method

Image Index	Class Name	Reference Totals <1>	Classified Totals <2>	Number Correct	Accuracy Producer's	Accuracy User's	Accuracy Overall	Canopy Cover Classification Manual	Canopy Cover Classification Auto
21136	Other	582,557	620,088	582,510	99.99%	93.94%	94.63%	16.78%	11.00%
	Canopy	117,443	79,912	79,865	68.00%	99.94%			
	Total Pixels	700,000	700,000	662,375		Weighted Kappa	0.680		
31305	Other	405,475	437,123	405,475	100.00%	92.76%	95.48%	42.08%	38.00%
	Canopy	294,525	262,877	262,877	89.25%	100.00%			
	Total Pixels	700,000	700,000	668,352		Weighted Kappa	0.893		
32112	Other	288,194	313,907	287,342	99.70%	91.54%	96.08%	58.83%	55.00%
	Canopy	411,806	386,093	385,241	93.55%	99.78%			
	Total Pixels	700,000	700,000	672,583		Weighted Kappa	0.932		
34111	Other	114,644	146,811	114,072	99.50%	77.70%	95.24%	80.08%	79.00%
	Canopy	585,356	553,189	552,617	94.41%	99.90%			
	Total Pixels	700,000	700,000	666,689		Weighted Kappa	0.939		

<1> <2> 100 Spectral classes were generated from the calibration image using ISO CLUSTER; pixels assigned a SC Index using a MLC. Spectral class indices were assigned to each pixel of all CIR images based on the ISO CLUSTER signature table.

<1> Based on manual/visual mapping the spectral classes to information classes using the CIR image.

<2> Based on automapping the spectral classes to information classes using the SC to IC table manually derived from the calibration image.