Spectral Estimates of Crop Residue Cover and Density for Standing and Flat Wheat Stubble

Jonathan Aguilar,* Robert Evans, Merle Vigil, and Craig S. T. Daughtry

ABSTRACT

Crop residue is important for erosion control, soil water storage, filling gaps in various agroecosystem-based modeling, and sink for atmospheric carbon. The use of remote sensing technology provides a fast, objective, and efficient tool for measuring and managing this resource. The challenge is to distinguish the crop residue from the soil and effectively estimate the residue cover across a variety of landscapes. The objective of this study is to assess a select Landsat Thematic Mapper (TM) and hyperspectral-based indices in estimating crop residue cover and amount for both standing and laid flat, and between two winter wheat (*Triticum aestivum* L.) harvest managements (i.e., stripper-header and conventional header) and fallow following proso-millet (*Panicum miliaceum* L.) plots. The primary plots were located in Colorado with additional plots in eastern Montana, Oregon, and Washington states. Data collected include hyperspectral scans, crop residue amount (by weight) and residue cover (by photogrid). Mean analyses, correlation tests, and spectral signature comparison show that the relative position of the crop residues affected the values of some remote sensing indices more than harvest management. Geographical location did not seem to influence the results. There was not enough evidence to support the use of these indices to accurately estimate the amount of residue. Hyperspectral data may deliver better estimates, but in its absence, the use of two or more of these datasets might improve the estimation of residue cover. This information will be useful in guiding analysis of remotely sensed data and in planning data acquisition programs for crop residue, which are essentially nonexistent at present.

Crop residue is an important agricultural C sink component for greenhouse gas (GHG) mitigation. According to Smith et al. (2008), there are three general mechanisms where opportunity for GHG mitigation in agriculture is viable, namely, reducing emission, enhancing removal and avoiding emission. The use of crop residue falls in two of these three mechanisms. Pacala and Socolow (2004) and Caldeira et al. (2004), both identified crop residue as a valuable, rapidly deployable option for GHG mitigation. The Intergovernmental Panel for Climate Change (IPCC) detailed the large mitigation potential of agriculture for short and medium term coming from C sequestration, and to a lesser degree from biomass (from agricultural residues and dedicated energy crops) for bioenergy feedstock (Smith et al., 2007). However, measuring and validating crop residue is limited by measurement uncertainty and monitoring costs (Smith et al., 2007). In addition to the mechanistic variations in C sequestration processes, agricultural systems inherently exhibit several sources of spatial and temporal variability. Increasing the geographical extent and employing remote sensing methodologies in field measurements are some of the options being considered to help address these challenges (Izaurralde and Rice, 2006; Smith et al., 2007). A review on the U.S. C sequestration research needs by Morgan et al. (2010) identifies remote sensing as an important tool for quantifying estimated C fluxes.

Whatever the focus, accurate measurement of the amount of crop residue left in the field after harvest is important. There are several methods to estimate crop residue. One method estimates crop residue from measured yield data for a location using the harvest index (HI). For example, Johnson et al. (2006) used HI to estimate the crop residue and consequently historical C. Although this method is useful for estimating residue in the absence of additional data, accuracy is often questionable because this technique does not incorporate variable harvesting and management practices and may differ depending on environmental conditions and the time of harvest. Another method of estimating the crop residue amount would be through conversion charts relating percent crop residue cover to residue amounts (Sloneker and Moldehauer, 1977; Gregory, 1982; McCool et al., 1995). Adjustment factors associated with tillage operations and implements used in the field are available for wheat (Hickman and Schoenberger, 1989) and for a few other crops (McCool et al., 1995; Kline, 2000).

Remote sensing techniques have been used for many years to measure various agricultural resources at regional scales. Using satellite and aerial images, landscape assessment can be quickly achieved with minimal field sampling. Another advantage of using remote sensing technologies is their capability of monitoring large spatial extents in a relatively short span of time. These tools offer

J. Aguilar, USDA-ARS Northern Plains Laboratory, Mandan ND 58554; R. Evans, USDA-ARS Northern Plains Agricultural Research Laboratory, Sidney, MT 59270; M. Vigil, USDA-ARS Central Great Plains Research Station, Akron, CO 80720; C. Daughtry, USDA-ARS Hydrology and Remote Sensing Laboratory, Beltsville, MD 20705. Received 7 June 2011. *Corresponding author (jonathan.aguilar@ars.usda.gov).

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Abbreviations: ASTER, advanced spaceborne thermal emission and reflection radiometer; an instrument sensor system on board Terra satellite; CAI, cellulose absorption index; GHG, greenhouse gas; HI, harvest index; LAI, leaf area index; LCA, lignin–cellulose absorption index; NDI5, normalized differential index 5; NDI7, normalized differential index 7; NDSVI, normalized differential senescent vegetation index; NDTI, normalized differential tillage index; NDVI, normalized differential vegetation index; SWIR, shortwave infrared; TM, thematic mapper.

analysis of percent cover. At least seven spectroradiometer and digital images were taken per plot.

The soil type in Akron, CO is Weld silt loam (fine, smectitic, mesic Aridic Argiustolls). Other soil types include Dooley sandy loam (fine-loamy, mixed, superactive, frigid Typic Argiustolls) in eastern Montana, Walla-Walla Ritzville silt loam (coarse-silty, mixed, superactive, mesic Typic Calcidic Haploxerolls) in northeastern Oregon and Palouse silt loam (fine-silty, mixed, superactive, mesic Pachic Ultic Haploxerolls) in southeastern Washington. Spectral measurements were done when the soil moisture at the surface (upper 3 cm) was <15% by volume. Soil moisture was vertically measured by a Fieldscout time domain reflectrometry (TDR) 300 soil moisture meter (Spectrum Technologies, Inc., Plainfield, IL) fitted with 3.6-cm long rods.

Laboratory Analysis

The crop residue samples were dried in a forced-air convection oven at 60°C for 5 d or until completely dried. The dry weight was measured and the crop residue density was calculated by dividing the dry weight by two times the ring area or 0.2 m^2.

Soil reflectance spectra were acquired with the spectroradiometer in a laboratory. The samples were illuminated by two 150-W tungsten-halogen lamps at 30° zenith angle 0.3 m away from the target. The bare fiber optic was set at 0.3-m vertical distance and 0° zenith angle which resulted in a 0.13-m diam. field of view. Soil samples were prepared in 26-cm paper plates painted flat black. Soils were passed through a 2-mm sieve and evenly spread on the plate to a depth of 2 to 3 cm. Two to four spectral measurements were made per sample, with the plate rotated under the spectroradiometer setup between samples. Soil spectral signatures were compared before expanding the analysis to other locations.

A randomly-selected digital photographic image of the scenes in the field was cropped to match the field of view of the spectroradiometer. Then, a regular 100-point grid was overlaid on each image using Adobe Photoshop CS4 (v11.0.2 Adobe Systems Incorporated, San Jose, CA). Percent residue cover was estimated by manually counting the number of points underlain with crop residue as described by Laflen et al. (1981). A second count was done by rotating the grid anywhere from 30 to 90 degrees to avoid having the grids in parallel with the crop rows in the photographic image. The average of the two counts was used in the analysis.

Reflectance values were extracted from the measured reflectance measurement corresponding to each image. Remote sensing indices were computed using the following equations (McNairn and Protz, 1993; Daughtry et al., 1996; van Deventer et al., 1997; Qi et al., 2002):

$$\mathrm{CAI} = 100\,[0.5\,(\mathrm{R2.0} + \mathrm{R2.2}) - (\mathrm{R2.1})] \quad [1]$$

$$\mathrm{NDSVI} = (\mathrm{TM5} - \mathrm{TM3})/(\mathrm{TM5} + \mathrm{TM3}) \quad [2]$$

$$\mathrm{NDTI} = (\mathrm{TM5} - \mathrm{TM7})/(\mathrm{TM5} + \mathrm{TM7}) \quad [3]$$

$$\mathrm{NDI5} = (\mathrm{TM4} - \mathrm{TM5})/(\mathrm{TM4} + \mathrm{TM5}) \quad [4]$$

$$\mathrm{NDI7} = (\mathrm{TM4} - \mathrm{TM7})/(\mathrm{TM4} + \mathrm{TM7}) \quad [5]$$

$$\mathrm{LCA} = 100\,[\,2\,(\mathrm{A6}) - (\mathrm{A5} + \mathrm{A8})] \quad [6]$$

where

R2.0 = average reflectance at 2025 to 2035 nm band centered at 2000 nm

R2.1 = average reflectance at 2095 to 2105 nm band centered at 2100 nm

R2.2 = average reflectance at 2205 to 2215 nm band centered at 2210 nm

TM3 = average reflectance at 630 to 690 nm band corresponding to TM band 3

TM4 = average reflectance at 750 to 900 nm band corresponding to TM band 4

TM5 = average reflectance at 1550 to1750 nm band corresponding to TM band 5

TM7 = average reflectance at 2090 to 2350 nm band corresponding to TM band 7

A5 = average reflectance at 2145 to 2185 nm band corresponding to Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) sensor's band 5

A6 = average reflectance at 2185 to 2225 nm band corresponding to ASTER sensor's band 6

A8 = average reflectance at 2295 to 2365 nm band corresponding to ASTER sensor's band 8

Statistical analyses were performed using SAS software (Ver. 9.2 SAS Institute Inc., Cary, NC). Most of the analyses were performed using the PROC MIXED model statement. For example, in the Colorado plots, four replications were available and used with management type as the whole plot and stubble treatments as the subplot. PROC CORR statement was used to derive the correlations. Least Significant Difference (LSD) at $\alpha = 0.01$ was the basis in comparing the means of different parameters. Tests of fixed effects were employed in comparing the means at different locations.

RESULTS AND DISCUSSION

Comparison of Means

The selected remote sensing indices had mixed responses on the different management and treatment of crop residues (Table 1). Mean values of residue cover for all management and treatment were not significantly different from each other as measured by photo-grid method. However, four of the indices were able to separate standing stubble from laid flat stubble. Apparently, existing plant litter was sufficient that wheat stubble did not significantly change the percent coverage as measured with the photo-grid method. The stripper-header harvest left significantly higher stubble amount (~20% by weight) than conventional management. The difference is due in part to the higher amount of partly decomposed plant material on the ground from previous cropping season on stripper-head harvested plots. Only the NDTI index showed a significant difference for the two harvest management scenarios.

Surprisingly, despite almost equal values of residue cover and density on both treatments, thus equivalent responses were expected, four of six indices showed significant differences in their index values. The CAI, NDI5, and NDI7 had higher index values for laid flat stubble than standing stubble. The NDTI and LCA did not show any significant difference. The NDSVI, on the other hand, exhibited higher index value for standing stubble. It should be noted that NDSVI was the only index using the shortest than on standing stubbles. Almost the same number of indices was evident for stripper head and conventional management, but the index (i.e., NDSVI, NDI5, and NDI7) values have slightly higher correlation and significance for stripper-head management. Interestingly, NDTI and LCA are negatively or not correlated at all to standing stubble but when the stubble is lying down the correlation is positive. As explained earlier, this may be due to the interaction of soil in the SWIR band.

The correlations of the indices with residue density was barely evident in the Colorado plots, rather most were significant when all locations were considered (Table 4). This could be partly attributed to an increase in the number of samples when all locations are considered. The CAI was negatively correlated to residue density for standing wheat stubbles when with other locations. Most of the broad band indices (i.e., NDSVI, NDTI, NDI5, and NDI7) showed highly significant positive correlations (>0.50) with residue density for the combined locations except for stripper head set-up. The NDSVI exhibited negative correlation on all setups for the combined locations, but was positively correlated when the location was Colorado only. The NDI5 shared a similar but opposite trend with the NDSVI correlations. The LCA was positively correlated to all but one setup in the combined locations, and for a couple more setups in the Colorado plots. In general, there was no definite trend in the correlation of indices to residue density whether the stubble was lying or standing. Low or insignificant correlation existed when the harvest management was stripper head. Percent residue cover and residue density were correlated in only two of the setups, which are positively correlated to lying-down stubbles in the combined locations.

Results of these correlations were by themselves inconclusive. This was because the plots and the sampling designs used in this study were not meant for correlating different residue cover conditions. There were, however, a few valid observations deduced. The CAI and LCA were correlated more to residue cover than for residue density. Broadband indices show good correlations for residue density, especially across locations and when there were more samples, but usually fails when the scene was stripper-head harvested. One caution in using broadband indices is its inconsistent shifting from positive to negative correlation across setups. The interactions between the indices and the different setups shown by this research are reasons enough to justify more investigations on this matter. The given scenarios are particularly important if remote sensing acquisition will be done after harvest where most of the stubble is left standing and mixed scenes cannot be ignored.

CONCLUSIONS

Placement and relative position of the crop residues affected the values of some remote sensing indices more than the influence of the amount of residue on the ground than had been previously hypothesized. From the results of this experiment, it was apparent that the presence of crop residue lying horizontally on the ground could increase the reflectance measurement on a given scene for most indices. This was evident in the laid flat vs. standing stubble, stripper-head harvest vs. conventional harvest, and fallow fields with considerable residue lying on the ground vs. newly harvested field with mostly standing stubble. There was not enough evidence to support the use of remote sensing indices meant to estimate the percent cover of crop residue to accurately estimate the amount of

Table 4. Pearson correlation tests for each index with residue density.

					Residue density vs.						
Location	Crop	Management	Treatment	N	CAI†	NDSVI	NDTI	NDI5	NDI7	LCA	Residue cover
CO	both	both	standing	16	ns‡	0.62**	0.66**	–0.58*	ns	0.58*	ns
		both	laid flat	8	ns	ns	ns	ns	ns	ns	ns
	both	stripper-head	both	12	ns	ns	0.61*	ns	ns	0.53	ns
		conventional	both	12	ns	ns	ns	ns	ns	ns	ns
	wheat	both	standing	8	ns	ns	ns	ns	ns	ns	ns
		both	laid flat	8	ns	ns	ns	ns	ns	ns	ns
	wheat	both	both	16	ns	ns	ns	ns	ns	ns	ns
	fallow	both	both	8	ns	ns	ns	ns	ns	ns	ns
Other	wheat	both	standing	7	–0.74	ns	0.85*	0.68	0.74	ns	ns
		both	laid flat	10	ns	–0.77*	ns	0.79*	0.78*	ns	ns
All	both	both	standing	23	–0.44	–0.53**	0.75***	0.58**	0.71***	0.63**	ns
		both	laid flat	16	ns	–0.75***	0.56*	0.74***	0.73**	0.46	0.47
	both	stripper-head	both	16	ns	ns	ns	ns	ns	ns	ns
		conventional	both	25	ns	–0.71***	0.77***	0.74***	0.80***	0.63***	ns
	wheat	both	standing	15	–0.70**	–0.58*	0.73**	0.62*	0.66**	0.58*	ns
		both	laid flat	16	ns	–0.75***	0.56*	0.74***	0.73**	0.46	0.47

* 0.05 level of significance (α = 0.1).
** 0.01 level of significance (α = 0.1).
*** 0.001 level of significance (α = 0.1).
† CAI, cellulose absorption index; NDSVI, normalized differential senescent vegetation index; NDTI, normalized differential tillage index; NDI5, normalized differential index 5; NDI7, normalized differential index 7; LCA, lignin–cellulose absorption index; CO, Colorado.
‡ ns, not significant.

Table 2. Pearson correlation tests for each index with percent residue cover

					Cover vs.					
Location	Crop	Management	Treatment	N	CAI†	NDSVI	NDTI	NDI5	NDI7	LCA
CO	both	both	standing	16	0.76***	ns‡	ns	ns	–0.47	ns
		both	laid flat	8	0.82*	0.89**	0.75*	ns	ns	0.83**
	both	stripper-head	both	12	0.50	–0.58*	ns	0.51	ns	ns
		conventional	both	12	ns	0.61*	0.52	–0.53	ns	ns
	wheat	both	standing	8	ns	ns	–0.79*	ns	ns	ns
		both	laid flat	8	0.82*	0.89**	0.75*	ns	ns	0.83**
	wheat	both	both	16	ns	ns	ns	ns	ns	ns
	fallow	both	both	8	ns	ns	ns	ns	ns	ns
Other	wheat	both	standing	7	ns	ns	ns	ns	ns	ns
		both	laid flat	8	ns	ns	ns	ns	ns	ns
All	both	both	standing	23	ns	ns	ns	ns	ns	ns
		both	laid flat	18	ns	ns	0.71***	0.44	0.62**	0.79***
	both	stripper-head	both	15	ns	–0.59*	ns	0.72**	0.66**	ns
		conventional	both	26	0.40*	ns	0.37	ns	ns	0.43*
	wheat	both	standing	15	ns	ns	ns	ns	ns	ns
		both	laid flat	18	ns	ns	0.71***	0.44	0.62**	0.79***

* 0.05 level of significance (α = 0.1).
** 0.01 level of significance (α = 0.1).
*** 0.001 level of significance (α = 0.1).
† CAI, cellulose absorption index; NDSVI, normalized differential senescent vegetation index; NDTI, normalized differential tillage index; NDI5, normalized differential index 5; NDI7, normalized differential index 7; LCA, lignin–cellulose absorption index; CO, Colorado.
‡ ns, not significant.

this is due to accelerated decomposition of the conventional harvest stubble compared to the stripper-header plots. The significant decrease in the LCA values partly reflected the decomposition process whereby plant structures, for example, hemicellulose, cellulose, and lignin, responsible for the reflectance absorption at the 2100 nm, were continually being depleted in the different scenes. This residue decomposition was also evident in CAI, but was not statistically significant. Daughtry et al. (2010) reported that for a 79 decomposition-day-old residue, CAI could be underestimated by as much as 21% of its true percent residue cover value. The NDTI measured reflectance near this 2100 nm band, but not as narrow or as specific as the bands used by the LCA and CAI.

Reorganizing the parameters to consider only standing stubble areas in comparing stripper-head with conventional harvest for both fallow and newly harvest wheat plots reaffirmed some initial observations. In these cases, residue cover was not significantly different regardless of harvest management, crop condition (i.e., freshly harvested wheat or fallow) or the combination of both. However, residue density was significantly different in a fallow field that was either harvested as stripper-header or conventional. Of all the indices, only NDI7 did not show any differences in all setups. The NDSVI, NDTI, NDI5, and LCA showed significant changes corresponding to the changes in the residue density, although NDI5's values were negatively correlated to the residue density changes. The CAI did not detect change between fallow and wheat treatments. However, CAI, NDSVI, NDTI, and LCA did show significant changes in the combination of setups attributable to the residue density changes. It appears that residue density was not the only factor that interacted with the indices because NDI5 was negatively correlated and the differences in other indices were barely consistent.

A noteworthy observation was the differences in reflectance behavior of laid flat stubble compared to fallow. From 500 to 1800 nm, laid flat stubble had higher reflectance than fallow, but the pattern inverted after the 2025 nm wavelength (Fig. 1). Compared with fallow, laid flat stubble reflectance dipped significantly at the 2100 nm wavelength, which corresponded to the previously observed wavelengths for cellulose and lignin absorption (Daughtry, 2001). This indicated that the relative abundance of plant structural materials is expected to be much higher shortly after harvest than in fallow.

It was observed in the field that standing stubble inhibited optimal reflection of the light compared with laid flat stubble. Higher than conventional harvest stubble also increased the potential for casting shadows in the target scenes. This would partly explain why three of six indices had significantly higher index values for laid flat compared to standing stubble despite almost identical values of residue cover and density. Inspection of the spectral responses of the different setups (Fig. 1) further supported this observation. Standing stubble had lower reflectance throughout the measured wavelength than laid flat stubble. The same principle was possibly responsible for the higher reflectance in the fallow plots compared to standing wheat plots. Though the fallow plots were generally considered to have standing stubble, much of the stubble was actually lying on the ground due to partial decomposition and from other environmental elements. At this stage, the difference in harvest management is indistinguishable in the spectral signatures. Its relative dryness compared to the newly harvested stubble could also have been responsible for this effect. A similar comparison could be noted on the conventional and stripper-header setup