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

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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

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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.

convenience in data gathering and monitoring while reducing the inherent bias in most rapid field survey data or estimates, for example percent crop residue cover. Distinguishing crop residues from soils using remote sensing is a challenge because both materials lack unique spectral signatures in the 400 to 1100 nm wavelength region widely used for remote sensing. They are often spectrally similar, and may differ only in amplitude at certain wavelengths. Complicating the challenge is that crop residues are frequently brighter than the soil shortly after harvest, but as the residues decompose they may become either brighter or darker than the soil (Nagler et al., 2000). Thus, attempts to discriminate crop residues from soils using Landsat TM bands has had mixed success (Daughtry et al., 2005).

Several remote sensing spectral indices reported in the literature are also used to estimate residue cover. Derivation of these indices is based on three general methods: broadband spectral normalized difference indices, reflectance-band height indices, and spectral angle methods (Serbin et al., 2009). Indices using Landsat TM bands, such as the normalized difference tillage index (NDTI; van Deventer et al., 1997), the normalized difference index 5 and 7 (NDI5 and NDI7, respectively; McNairn and Protz, 1993), and the normalized differential senescent vegetation index (NDSVI; Qi et al., 2002) are examples of the broadband spectral category. The lignin–cellulose absorption index (LCA; Daughtry et al., 2005) and the cellulose absorption index (CAI; Daughtry et al., 1996) are examples of reflectance-band height indices category which are both operating in the shortwave infrared (SWIR) region of the spectrum (700–2500 nm). Unfortunately, the TM-broadband spectral indices are not robust across diverse agricultural landscapes and only correlated to crop residue cover for selected soil and crop residue combinations (Daughtry et al., 2005; Serbin et al., 2009). The LCA and CAI seem to work better in distinguishing crop residue from many background soils (Serbin et al., 2009). No investigations have been reported relating all these indices to crop residue amounts.

Exploratory analysis of CAI measurement in the same region (i.e., Pacific Northwest and the central and northern Great Plains) shows that CAI values respond to increasing residue density (Aguilar et al., 2012). Though the coefficient of determination was low ($r^2 = 0.42$), it was strong enough to indicate a relationship between CAI and residue density. Nagler et al. (2003) reported a similar observation on the CAI when they were investigating the performance of CAI against residue cover and density over black soil. It is not surprising that indices such as these could relate to abundance or absence of a particular material. The normalized differential vegetation index (NDVI) derives a similar correlation with the leaf area index (LAI) representing the amount of leaf material in a given landscape. It could be argued that LAI and NDVI do exhibit this relationship due to the vertical orientation and stratification of the plant canopy. In many instances, stratification in the crop residue is still evident in the field after harvest. Relating postharvest crop cover to residue density is not a new principle. Gregory (1982) developed a logarithmic function that accurately estimated percent residue cover from residue density based on the premise that crop residues overlap each other.

There are several factors that spatially and temporally affect the spectral reflectance of a given landscape. Presence, absence, and abundance of a certain elemental composition; mineralogy or chemical bonding; light intensity and angle; absorptive, reflective, and transmittable features of the material; and moisture content of the soil and residue are all factors that alter the spectral response of a particular landscape. The objective of this study was to examine the response of selected remote sensing indices in estimating the percent cover and amount of residue in a field harvested using stripper-header and conventional header methods. The response of CAI, NDSVI, NDTI, NDI5, NDI7, and LCA with varying crop residue orientation, amount, and condition were each investigated as a measure of their capacity to quantify crop residue density. The ability to remotely measure crop residue amount or density in the field will open more opportunities in resource management and improve the accuracy of input parameters for various modeling efforts and systems management.

MATERIALS AND METHODS

Field Data Collection

The study was primarily conducted in the study plots in Akron, CO having a winter wheat–sorghum (*Sorghum bicolor* L.)–proso millet–fallow crop rotation with two harvesting methods, conventional sickle bar reel type header and a stripper-header (Shelbourne Reynolds Engineering Ltd., Shepherds Grove, England). The plots were in randomized complete block design with a split-plot added for this study. Main plot treatments were stripper header and conventional header stubbles, and subplots were laid flat and standing stubbles. Additional sampling and measurements were also done in several wheat and durum (*T. turgidum* L.) experimental plots and farms across the northern Great Plains, the Columbia Basin, and the Palouse region after harvest of the 2010 cropping season. At least two conditions were measured: standing and laid flat stubble. Laid flat stubble were either previously toppled by passing tractor tires and implements or manually toppled before the measurement (e.g., laying wooden board over the stubbles). A third set-up, flailed stubble, found in the field was also measured. Flailed stubbles are mechanically chopped down standing wheat stubbles commonly practiced in the Pacific Northwest region. Crop residues on the soil surface enclosed within two random 0.1 m^2 sampling rings were collected for each sampling location in each plot. Measurements and sampling were conducted within 30 d after harvest or between September to October 2010.

Reflectance measurements were conducted during clear sunny days within the 4-h window centered on the local solar noon using an ASD spectroradiometer (FieldSpecPro Full Range, Analytical Spectral Devices, Boulder, CO). The spectroradiometer was capable of measuring the reflectance at 350 to 2500 nm wavelength region with spectral resolutions of 3nm at 700nm band and 10 nm at 1400 and 2100 nm bands. The bare fiber fore optic of the spectroradiometer and a 6.1 megapixel SLR digital camera (Nikon Model D40) were aligned and mounted on a pole at 1.56 m above the soil at a 0° view zenith angle which resulted in a 0.69 m diam. field of view. For calibration, a 30-cm square Spectralon reference panel (Labsphere, Inc., North Sutton, NH) was placed in the field of view of the spectroradiometer at 0.34 m from the optical probe. The spectroradiometer averaged 20 scans per sample reading and multiple sample readings were acquired per plot by walking diagonally across the planted rows. For smaller plots, or subplots, data acquisitions were made by slightly moving the field of view within the experimental setup. Simultaneous digital images were taken by the digital camera on the scenes for comparison and additional 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):

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

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

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

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

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

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

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

Table 1. Comparison of mean indices to residue cover and amount according to management, treatment, and crop and its combinations.

Treatment group	N	Residue cover	Residue density	CAI†	NDSVI	NDTI	NDI5	NDI7	LCA
		%	Mg ha^{-1}						
New harvest only									
Management‡									
Stripper-head (SH)	8	74.1a§	6.18a	8.3a	0.51a	0.060a	–0.334a	–0.28a	–1.85a
Conventional (C)	8	81.1a	4.82b	7.9ab	0.50a	0.016b	–0.336a	–0.32a	–5.59ab
Treatment									
Standing (S)	8	77.8a	5.50a	7.1b	0.56a	0.042a	–0.387b	–0.35b	–2.56a
Laid flat (L)	8	77.4a	5.50a	9.1a	0.45b	0.034a	–0.282a	–0.25a	–4.87a
Combination									
SH × S	4	67.1 b	6.18a	6.7b	0.56a	0.060a	–0.388b	–0.34c	–1.61a
SH × L	4	81.0ab	6.18a	9.9a	0.46b	0.061a	–0.279a	–0.22a	–2.09a
C × S	4	87.8a	4.82a	7.4b	0.55a	0.025ab	–0.386b	–0.36c	–3.52ab
C × L	4	74.5ab	4.82a	8.3ab	0.45b	0.007b	–0.287a	–0.28b	–7.66b
Fallow only									
Management ‡									
SH	4	77.8a	3.93bc	7.4ab	0.50a	–0.018c	–0.332a	–0.35a	–7.75bc
C	4	73.3a	3.49c	6.0b	0.48a	–0.044c	–0.312a	–0.35a	–11.8c
Standing									
Management									
SH	8	72.4a	5.05a	7.1a	0.53a	0.021a	–0.360a	–0.34a	–4.68a
C	8	80.5a	4.16a	6.7a	0.52a	–0.010a	–0.348a	–0.36a	–7.68a
Crop									
Wheat (W)	8	77.4a	5.50a	7.1a	0.56a	0.042a	–0.387b	–0.35a	–2.56a
Fallow (F)	8	75.5a	3.71b	6.7a	0.49 b	–0.031b	–0.322a	–0.35a	–9.80b
Combination									
SH × W	4	67.1a	6.18a	6.7ab	0.56a	0.060a	–0.388b	–0.34a	–1.61a
SH × F	4	77.8a	3.93b	7.4a	0.50b	–0.018b	–0.332a	–0.35a	–7.75bc
C × W	4	87.8a	4.82ab	7.4a	0.55a	0.025a	–0.386b	–0.36a	–3.52ab
C × F	4	73.3a	3.49b	6.0b	0.48b	–0.044b	–0.312a	–0.35a	–11.85c

† 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.

‡ The means of new harvest and fallow managements groups were compared and are reflected by the letters following the values.

§ Within each column and group, values followed by the same letter are not significantly different at α = 0.05 using the LSD test.

wavelength at TM3, the visible red band, which is intended for chlorophyll content estimation. There is, however, no indication that chlorophyll was active in the scenes. The response of the indices to the treatment and management combinations was apparently influenced more by the stubble treatment than harvest management and it did not necessarily reflect the variations in the residue cover and density. In general, CAI, NDI5, and NDI7 exhibit higher index values for laid flat stubble than standing stubble regardless of harvest management. This is apparently due to angle of reflectance since laid flat stubble have more surface area facing the spectroradiometer than the standing stubble. The NDSVI results were opposite of this general pattern and NDTI showed lower index values for conventional management scenarios. Another plausible explanation for this observation is the interaction of the soil in the scenes. Indices that have SWIR reflectance bands, such as NDTI and LCA, were well correlated with residue cover in laid flat treatments as shown in Table 2. The influence of soil and minerals in the SWIR are diminished when covered with crop residues.

Comparison of fallow to the newly harvest plot data showed a remarkable decrease in residue density but not in the residue cover. Other than the partly decomposed crop residue on the ground, fallow plots also had a considerable amount of weeds, both growing and dead, that partly contributed to the statistically insignificant difference in residue cover. Residue density was not significantly different since the presence of weeds was not sufficiently dense to contribute significantly to the measured amount of biomass in the plots. Of all the indices, LCA and NDTI responded to the change in residue density with a statistically significant decrease in their respective index values. Conventional management had slightly lower residue density and corresponding CAI, NDSVI, NDTI, and LCA values than stripper-header management. Apparently,

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

Location	Crop	Management	Treatment	N	Cover vs. 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 ($\alpha = 0.1$).

** 0.01 level of significance ($\alpha = 0.1$).

*** 0.001 level of significance ($\alpha = 0.1$).

† 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

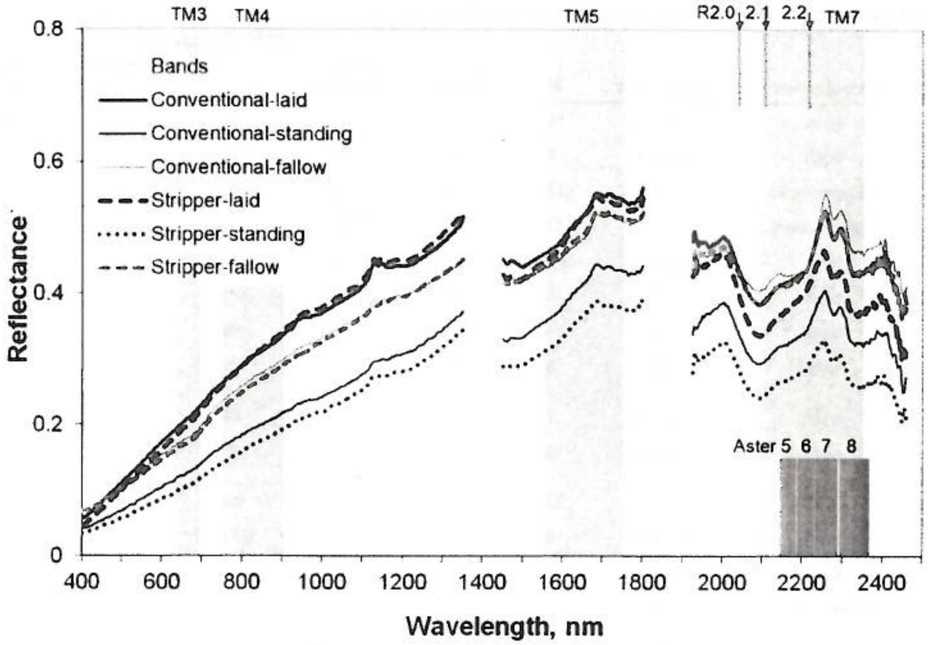

Fig. 1. Field spectral responses of the different setups with the relevant bands on the foreground.

where the conventional had higher reflectance especially in the SWIR region (1400–2500 nm). Conventional harvests tended to leave the crop residue or stubble laying on the ground, which was not the case for the stripper-header harvests.

From these observations, it became more apparent why indices based on broad TM bands showed mixed results in characterizing crop residue lying on the ground. For example, the TM7 band was too broad and off to effectively detect the presence or absence of certain plant materials, that is, cellulose and lignin at the selected wavelengths. The reflectance behavior in visible, near infrared, and portions of the SWIR bands were similar to the crop residue values and were therefore difficult to differentiate from the soil. On the other hand, the narrow bands used in CAI were not performing well in response to the different stubble treatments. Several studies have reported that CAI outperformed indices based on TM bands in distinguishing crop residue against different factors, such as background soil color (Serbin et al., 2009), age of crop residue (Daughtry et al., 2010), and residue moisture content (Nagler et al., 2000, 2003; Daughtry et al., 2004). There is not enough evidence to support that CAI have outperformed the other indices on the harvest management and stubble treatments.

Means by Location

Soil spectral signatures of the sites were not very different from each other (Fig. 2) facilitating the comparisons of means among locations. The means analysis expanded to three more locations showed that the different treatment (i.e., standing and laid flat stubbles) was the prevailing factor influencing changes in the index values (Table 3). Considering conventional harvest only, Type 3 tests of fixed effects showed two parameters, treatment and the combination of treatment and location, were statistically significant to residue cover at $\alpha = 0.01$. Of the indices, only CAI was significant tied to both parameters. This result suggested that CAI could estimate residue cover across the given location, but not residue density.

From the combination parameter, it appears that the flailed plot has the highest (or lowest in the case of NDSVI) value across all indices. At this point we could only speculate that this observation is brought about by high residue density, although it could also be due to residue cover. The mixed model produced nonestimable results in comparing the locations possibly due to inadequate number of samples (Sjöberg, 1995; Gao et al., 2008; SAS, 2011), and therefore it is difficult to derive conclusive statements.

Similar to conventional harvest, stubble treatment on stripper-headed plots was the more dominant factor in the index values rather than location. Tests of fixed effects find NDI7 to be statistically significant parameters in modeling the treatments. If combined with location, CAI, NDSVI, and NDI5 were showing significant effect. Among the indices, only NDI7 showed significantly different index value for the treatment despite a relatively similar crop residue cover and density. The combination of location and treatment shows no consistent observable results.

Correlations

Correlation of the various indices (i.e., CAI, NDSVI, NDTI, NDI5, NDI7, and LCA), residue cover, and residue density against each other (Table 2) revealed some contrasting responses. For the Colorado plots, only CAI and NDI7 was correlated to residue cover for standing stubbles. However, for laid flat stubbles the CAI, NDSVI, NDTI, and LCA were all significantly correlated to residue cover (Table 2). This is another instance where more indices respond or correlates well to residue cover if they are lying on the ground. But when fallow plots are removed from the standing treatment dataset (i.e., wheat, both management and standing treatment), NDTI responds with negative correlation to residue cover. Conventional harvest management shows more indices (i.e., NDSVI, NDTI, and NDI5) to be correlated than the stripper head management (i.e., CAI, NDSVI, and NDI5). Expanding the dataset to include other locations shows a similar trend. More indices with significantly higher correlations show on laid flat stubbles

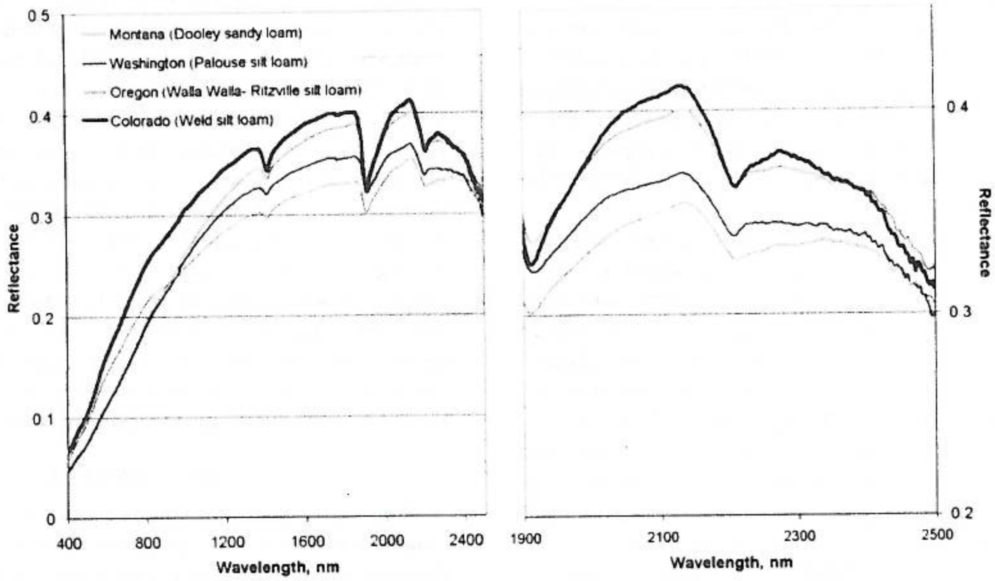

Fig. 2. Spectral signatures of the soil types in the sampling areas measured in the laboratory.

Table 3. Comparison of mean indices to residue cover and amount according to harvest management, location, treatment, and its combinations.

Treatment group	N	Residue cover	Residue density	CAI†	NDSVI	NDTI	NDI5	NDI7	LCA
		%	Mg ha^{-1}						
				By location conventional harvest					
Treatment		‡		‡					
Standing (S)	11	78.8a§	6.79a	4.5b	0.41a	0.148a	−0.22a	−0.08a	4.64a
Laid flat (L)	11	84.6a	7.05a	6.1a	0.35b	0.140a	−0.18a	−0.04a	4.91a
Flailed									
Combination		‡		‡	‡				‡
CO × S	4	87.8ab	4.82a	6.6ab	0.53a	0.091bc	−0.36d	−0.28c	2.62bc
CO × L	4	74.5b	4.82a	6.1abc	0.43b	0.073c	−0.26c	−0.19bc	0.96 c
MT × S	2	68.1b	2.79a	3.8bc	0.44abc	0.131abc	−0.25abcd	−0.13abc	5.64ab
MT × L	2	85.9ab	3.86a	4.6bc	0.43ab	0.155ab	−0.22bc	−0.07ab	5.73a
OR × S	2	72.0ab	10.26a	3.3c	0.29cd	0.19a	−0.11ab	0.08a	4.81ab
OR × L	2	82.3ab	10.26a	6.0abc	0.25d	0.184a	−0.10ab	0.08a	6.46a
WA × S	3	87.3ab	9.28a	4.2bc	0.37d	0.179a	−0.17abc	0.01a	5.49a
WA × L	3	95.9a	9.28a	7.5a	0.28bcd	0.15ab	−0.13ab	0.02a	6.50a
OR × Flailed	1	100.0ab	13.63a	8.5a	0.23d	0.196a	−0.06a	0.14a	7.04a
				By location stripper-head harvest					
Location									
CO	8	74.1a	3.85a	6.0a	0.49a	0.125a	−0.31a	−0.19a	3.85a
MT	3	90.8a	5.93a	6.2a	0.41a	0.173a	−0.20a	−0.04a	5.93a
Treatment		‡					‡	‡	
Standing(S)	5	78.2a	4.51a	6.1a	0.45a	0.138a	−0.28a	−0.15b	4.51a
Laid flat (L)	6	86.6a	5.27a	6.2a	0.45a	0.161a	−0.24a	−0.08a	5.27a
Combination		‡		‡	‡		‡	‡	
CO × S	4	67.1b	3.11a	4.6b	0.53a	0.124a	−0.37b	−0.25b	3.11a
CO × L	4	81.0a	4.60a	7.4a	0.44b	0.126a	−0.26a	−0.13a	4.60a
MT × S	1	89.3a	5.92a	7.5ab	0.35c	0.152a	−0.19a	−0.05a	5.92a
MT × L	2	92.2a	5.94a	4.9b	0.46b	0.195a	−0.22a	−0.02a	5.94a

† 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; MT, Montana; WA, Washington.

‡ Denotes significance on tests of fixed effects for the parameter.

§ Within each column and group, values followed by the same letter are not significantly different at $\alpha = 0.05$ using the LSD test.

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.

residue. Results among indices lack consistency across the treatments. This warrants more investigations especially in probing the spectral responses and improving the response of the indices to residue density. Meanwhile, definite relationships between percent cover and residue density exist and could be computed separately.

Estimating percent residue cover on a regional scale with fields harvested with both conventional and stripper-head methods could pose additional prediction uncertainty. Thus, spot validation of residue levels on representative fields should accompany such remote sensing activities to reduce the inaccuracies brought about by the differences in the position and placement of crop residues. The extent of disparity in index values is affected by many factors other than residue placement and position, but being aware of these possible complications is valuable information for resource management.

Result of this study showed that multispectral remote sensing show some capability of quantifying crop residue cover, but not density, in the field with varying harvest and stubble conditions. Hyperspectral images could deliver better estimates, but the shortage of platforms and sensors inhibit the use of such dataset. Broad Landsat TM and Aster bands could be used in some instances. There are minimal significant developments in putting into orbit sensors that address this need. The use of two or more datasets could possibly improve the accuracy of estimation. Future research on this area should focus on developing other indices primarily aimed at quantifying the amount of crop residue. These data are needed in many emerging and existing studies in C, agroecosystem, and earth systems modeling, but data acquisition programs are minimal to nonexistent (Nowak, 2009; Horowitz et al., 2010).

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